

Law Informs Code:
A Legal Informatics Approach to Aligning Artificial Intelligence with Humans

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ABSTRACT — Artificial Intelligence (AI) capabilities are rapidly advancing. Highly capable AI could cause radically different futures depending on how it is developed and deployed. We are unable to specify human goals and societal values in a way that reliably directs AI behavior. Specifying the desirability (*value*) of AI taking a particular *action* in a particular *state* of the world is unwieldy beyond a very limited set of *state-action-values*. The purpose of machine learning is to train on a subset of states and have the resulting agent generalize an ability to choose high value actions in unencountered circumstances. Inevitably, the function ascribing values to an agent’s actions during training is an incomplete encapsulation of human values and the training process is a sparse exploration of states pertinent to all possible futures. After training, AI is therefore deployed with a coarse map of human preferred territory and will often choose actions unaligned with our preferred paths.

Law-making and legal interpretation convert opaque human goals and values into legible directives. *Law Informs Code* is the research agenda embedding legal processes and concepts in AI. Similar to how parties to a legal contract cannot foresee every potential “if-then” contingency of their future relationship, and legislators cannot predict all the circumstances under which their bills will be applied, we cannot *ex ante* specify “if-then” rules that provably direct good AI behavior. Legal theory and practice offer arrays of tools to address these problems. For instance, legal standards allow humans to develop shared understandings and adapt them to novel situations, i.e., to generalize expectations regarding actions taken to unspecified states of the world. In contrast to more prosaic uses of the law (e.g., as a deterrent of bad behavior), leveraged as an expression of *how* humans communicate their goals, and *what* society values, *Law Informs Code*.

We describe how data generated by legal processes and the tools of law (methods of law-making, statutory interpretation, contract drafting, applications of standards, and legal reasoning) can facilitate the robust specification of inherently vague human goals to increase *human-AI* alignment. Toward *society-AI* alignment, we present a framework for understanding law as the applied philosophy of multi-agent alignment, harnessing public law as an up-to-date knowledge base of democratically endorsed values ascribed to state-action pairs. Although law is partly a reflection of historically contingent political power – and thus not a perfect aggregation of citizen preferences – if properly parsed, its distillation offers the most legitimate computational comprehension of societal values available. Other data sources suggested for AI alignment – surveys, humans labeling “ethical” situations, or (most commonly) the beliefs of the AI developers – lack an authoritative source of synthesized preference aggregation. Law is grounded in verifiable resolutions: ultimately obtained from a court opinion, but short of that, elicited from legal experts. If law informs powerful AI, engaging in the deliberative political process to improve law would take on even more meaning.

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I. INTRODUCTION

As the internet went viral, “*Code Is Law*” communicated the power of software as a form of governance in cyberspace.¹ Now that Artificial Intelligence (AI) capabilities are rapidly advancing² with new model architectures³ scaled across internet-scale data,⁴ “*Law Informs Code*” is the catchphrase for a legal informatics approach to shaping AI toward human goals.

AI is increasingly widely deployed.⁵ More powerful AI could cause radically different futures.⁶ A summer 2022 survey of hundreds of AI researchers estimated an aggregate forecast

¹ See, Lawrence Lessig, *Code Is Law* (2000); Lawrence Lessig, *Code and Other Laws of Cyberspace* (1999); Lawrence Lessig, *Code 2.0* (2006). The phrase “Code Is Law” has also been adopted as a rallying cry for “smart contracts,” see, e.g., *Code is Law*, Ethereum Classic <https://ethereumclassic.org/why-classic/code-is-law>.

² See, e.g., Scott Reed et al., *A Generalist Agent* (2022) (A multi-modal, multi-task AI agent, “Gato,” that can successfully play the Atari video game, caption images, chat, stack blocks with a robot, and more, all using the same neural network with the same parameters; “the recent progress in generalist models suggests that safety researchers, ethicists, and most importantly, the general public, should consider their risks and benefits.”); Michael Ahn et al., *Do as I Can, Not as I Say: Grounding Language in Robotic Affordances*, arXiv:2204.01691 (2022) (An AI that provides “real-world grounding by means of pretrained skills, which are used to constrain the model to propose natural language actions that are both feasible and contextually appropriate. The robot can act as the language model’s “hands and eyes,” while the language model supplies high-level semantic knowledge about the task.”); Shunyu Yao et al., *REACT: Synergizing Reasoning and Acting in Language Models* (2022) <https://arxiv.org/pdf/2210.03629.pdf> (A large language model powers planning and decision-making, while exposing its “thoughts” and “reasoning” for editing as needed.); Holden Karnofsky, *AI Timelines: Where the Arguments, and the “Experts,” Stand* (Sep 7, 2021) <https://www.cold-takes.com/where-ai-forecasting-stands-today/> (Synthesizing relevant technical reports forecasting AI capabilities from multiple approaches, Karnofsky derives an estimate that “there is more than a 10% chance we’ll see transformative AI [powerful enough to bring us into a new, qualitatively different future] within 15 years (by 2036); a ~50% chance we’ll see it within 40 years (by 2060); and a ~2/3 chance we’ll see it this century (by 2100)”; Jacob Steinhardt, *AI Forecasting: One Year In* (2022) (“progress on ML benchmarks happened significantly **faster** than forecasters expected [...] Progress on a *robustness* benchmark was slower than expected, and was the only benchmark to fall short of forecaster predictions. This is somewhat worrying, as it suggests that machine learning capabilities are progressing quickly, while safety properties are progressing slowly.” (Emphasis in original.)); the most recent large survey of AI researchers (August 2022) on transformative AI timelines can be found at <https://aiimpacts.org/2022-expert-survey-on-progress-in-ai/>.

³ The Transformer architecture (a model of sequential data with stacked self-attention layers and residual connections) has enabled advanced capabilities, see the landmark paper: Vaswani et al., *Attention is All You Need* (2017). See *infra* Section II.C.1. for more on Transformers.

⁴ See, e.g., Leo Gao et al., *The Pile: An 800GB Dataset of Diverse Text for Language Modeling* (2020).

⁵ See, generally, Daniel Zhang et al., *The AI Index 2022 Annual Report*, Stanford Institute for Human-Centered Artificial Intelligence (March 2022), https://aiindex.stanford.edu/wp-content/uploads/2022/03/2022-AI-Index-Report_Master.pdf. For legal discussions of AI deployments, see, e.g., Danielle K. Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 *Washington Law Review* 1-33 (2014); E. Joh, *The New Surveillance Discretion: Automated Suspicion, Big Data, and Policing*, *Harvard Law and Policy Review* vol. 10, no. 15, 15-42 (2016); C. Muñoz, M. Smith & D. J. Patil, *Big Data: A Report on Algorithmic Systems, Opportunity, and Civil Rights*, Executive Office of the U.S. President, Washington, D.C. (May 2016). On large language model deployments, see, e.g., Matthew Hutson, *Robo-writers: The Rise and Risks of Language-Generating AI*, *Nature* 591.7848 22-25 (2021); Sam Manning et al., *A Research Agenda for Assessing the Economic Impacts of Code Generation Models* (2022) https://cdn.openai.com/papers/Economic_Impacts_Research_Agenda.pdf.

⁶ For a longer-term framing of potential AI impacts, see, e.g., Amanda Askill, *Ensuring the Safety of Artificial Intelligence*, in *The Long View: Essays on policy, philanthropy, and the long-term future*, edited by Natalie Cargill & Tyler John (2021); Henry Kissinger, Eric Schmidt & Daniel P. Huttenlocher, *The Age of AI: And Our Human Future*

time of 37 years for a 50% chance of “high-level machine intelligence” (“when unaided machines can accomplish every task better and more cheaply than human workers”).⁷ Because natural language processing (NLP) is a key sub-domain of AI, surveys of NLP researchers are of particular interest. A separate summer 2022 survey of hundreds of NLP researchers found that 57% believe that “recent research has advanced us toward AGI [artificial general intelligence] in some significant way,” and 73% “agree that labor automation from AI could plausibly lead to revolutionary societal change in this century, on at least the scale of the Industrial Revolution.”⁸ Even before additional advancements, we currently face monumental challenges specifying human goals and societal values to reliably direct AI behavior.⁹

Significant computing and data resources are required to develop state-of-the-art AI.¹⁰ Large companies are pushing research and deployment boundaries.¹¹ Regardless of where AI is developed, the developers are disconnected from those affected by AI. To increase alignment of AI with the billions of people impacted, scholars and companies have suggested embedding “ethics” into AI.¹² However, it is unclear how to decide that “ethics” or who gets a say in the process.¹³ We take a different approach, arguing that the target of AI alignment should be democratically endorsed law. This provides legitimate grounding. Although law is a reflection of

(2021); For a nearer-term framing of potential AI risks, see the recent work by the U.S. National Institute of Standards, e.g., *AI Risk Management Framework: Second Draft* (August 18, 2022) https://www.nist.gov/system/files/documents/2022/08/18/AI_RMF_2nd_draft.pdf; Dan Hendrycks et al., *Unsolved Problems in ML Safety* (2021).

⁷ See, 2022 *Expert Survey on Progress in AI* (August 23, 2022) <https://aiimpacts.org/2022-expert-survey-on-progress-in-ai/>. Other surveys also estimate non-trivial impacts, “AI capabilities emerge that could radically transform welfare, wealth, or power, to an extent comparable to the nuclear revolution or even the industrial revolution. These possibilities are strikingly neglected, in part because they involve massive global and intergenerational externalities. There is thus a high leverage opportunity to address what may be the most important global issue of the 21st century.” Allan Dafoe, *AI Governance: A Research Agenda*, Centre for the Governance of AI, Future of Humanity Institute, University of Oxford (2018) at 5.

⁸ Julian Michael et al., *What Do NLP Researchers Believe? Results of the NLP Community Metasurvey*, (2022) <https://arxiv.org/abs/2208.12852> at 11 (36% of respondents believe “it is plausible that AI could produce catastrophic outcomes in this century, on the level of all-out nuclear war.”).

⁹ See, e.g., Laura Weidinger et al., *Taxonomy of Risks Posed by Language Models*, In 2022 ACM Conference on Fairness, Accountability, and Transparency, 214-229 (2022); Dan Hendrycks et al., *Unsolved Problems in ML Safety* (2021); BRIAN CHRISTIAN, *THE ALIGNMENT PROBLEM: MACHINE LEARNING AND HUMAN VALUES* (2020); Miles Brundage et al., *The Malicious Use of Artificial Intelligence: Forecasting, Prevention, and Mitigation*, arXiv:1802.07228 (2018); Shahar Avin et al., *Filling Gaps in Trustworthy Development of AI*, *Science* 374, no. 6573, 1327-1329 (2021); Thomas Arnold & Matthias Scheutz, *The “Big Red Button” Is Too Late: An Alternative Model for The Ethical Evaluation of AI Systems*, *Ethics and Information Technology* (2018); Kris McGuffie & Alex Newhouse, *The Radicalization Risks of GPT-3 and Advanced Neural Language Models*, arXiv:2009.06807 (2020).

¹⁰ See, e.g., Or Sharir, Barak Peleg & Yoav Shoham, *The Cost of Training NLP Models: A Concise Overview* (2020). Although, costs for training models are decreasing; see, e.g., Abhinav Venigalla & Linden Li, *Mosaic LLMs (Part 2): GPT-3 Quality for <\$500k* (September 29, 2022) <https://www.mosaicml.com/blog/gpt-3-quality-for-500k>.

¹¹ See e.g., this statement by a consortium of AI research companies, Cohere (<https://cohere.ai/about>), OpenAI (<https://openai.com/about/>), and AI21 Labs (<https://www.ai21.com/about>), <https://openai.com/blog/best-practices-for-deploying-language-models/>.

¹² See, Daniel Greene, Anna Lauren Hoffmann & Luke Stark, *Better, Nicer, Clearer, Fairer: A Critical Assessment of the Movement for Ethical Artificial Intelligence and Machine Learning*, in Proceedings of the 52nd Hawaii International Conference on System Sciences (2019); Brent Mittelstadt, *Principles alone cannot guarantee ethical AI*, *Nature Machine Intelligence*, Vol 1, 501–507 (2019) [Hereinafter, Mittelstadt *Principles alone cannot guarantee ethical AI*].

¹³ See, generally, Mittelstadt *Principles alone cannot guarantee ethical AI*; Frank Pasquale, *New Laws of Robotics: Defending Human Expertise in the Age of AI* (2020).

the path-dependent structure of political power within a society and not a perfect aggregation of human values, it is the most democratic encapsulation of the attitudes, norms and values of the governed.

If law is leveraged as a set of methodologies for conveying and interpreting directives and a knowledge base of societal values, it can play a unique role in aligning AI with humans. Law-making and legal interpretation convert human intentions and values into legible¹⁴ directives. *Law Informs Code* is the research agenda embedding human law in AI models so we can better specify our objectives. Most research at the intersection of AI and law has focused on two areas: how existing law¹⁵ (or a proposed legal solution¹⁶) can be enforced on AI or the humans behind it (i.e., how *Law Governs Code*); or how AI can improve the practice of law¹⁷ or implementation of policy¹⁸ (i.e., how *Code Informs Law*).¹⁹ This Article describes the new pillar: how AI can use law as theoretical scaffolding and data to be safer by design (i.e., how *Law Informs Code*).

The benefits of law-informed AI would be far-reaching (Figure 1). In addition to more locally useful and societally aligned AI, law-informed AI could power the other two pillars: law governing AI, and AI improving legal services.

¹⁴ We are using “legible” here similar to its use in both James C. Scott, *Seeing Like a State* (1998), and in, Anca D. Dragan, Kenton CT Lee & Siddhartha S. Srinivasa, *Legibility and Predictability of Robot Motion*, in 8th ACM/IEEE International Conference on Human-Robot Interaction, 301-308 IEEE (2013).

¹⁵ See, e.g., Solon Barocas & Andrew D. Selbst, *Big Data’s Disparate Impact*, 104 CAL. L. REV. 671 (2016); Roger Michalski, *How To Sue A Robot*, Utah L. Rev. 1021 (2018); Andrew D. Selbst, *Negligence and AI’s Human Users*, BUL Rev. 100 1315 (2020); Amanda Levendowski, *How Copyright Law Can Fix Artificial Intelligence’s Implicit Bias Problem*, 93 Wash. L. Rev. 579 (2018).

¹⁶ See, e.g., Andrew Tutt, *An FDA For Algorithms*, Administrative L. REV. Vol. 69, No. 1, 83 (2017) (arguing that a new centralized agency is needed for regulating AI); Anton Korinek, *Why We Need a New Agency to Regulate Advanced Artificial Intelligence: Lessons on AI Control from the Facebook Files*, Brookings Institution, (Dec. 8, 2021) <https://www.brookings.edu/research/why-we-need-a-new-agency-to-regulate-advanced-artificial-intelligence-lessons-on-ai-control-from-the-facebook-files/>; Jack Clark & Gillian K. Hadfield, *Regulatory Markets for AI Safety*, arXiv:2001.00078 (2019); Jonas Schuett, *Defining the Scope of AI Regulations*, Legal Priorities Project Working Paper Series No. 9 (2021); Eric Wu et al., *How Medical AI Devices Are Evaluated: Limitations and Recommendations From an Analysis of FDA Approvals*, Nature Medicine 27, 4, 582 (2021); Axel Walz & Kay Firth-Butterfield, *Implementing Ethics Into Artificial Intelligence: A Contribution, From A Legal Perspective, To The Development of an AI Governance Regime*, 17 Duke L. & Tech. Rev. (2018).

¹⁷ See, e.g., Henry Prakken, *On How AI & Law Can Help Autonomous Systems Obey the Law: A Position Paper*, AI4J—Artificial Intelligence for Justice 42 (2016) at 44 (“AI & law research has traditionally focused on support tools for humans carrying out legal tasks.”); Howard Turtle, *Text Retrieval in the Legal World*, A.I. & L., Vol 3, 5–54 (1995).

¹⁸ See, e.g., Peter Henderson, Ben Chugg, Brandon Anderson & Daniel E. Ho, *Beyond Ads: Sequential Decision-Making Algorithms in Law and Public Policy* (2022); Hannah Bloch-Wehba, *Access to Algorithms*, 88 Fordham L. Rev. 1265 (2019) at 1273 – 1290 (Describes some existing uses of AI by the government.); Emily Berman, *A Government of Laws and Not of Machines*, 98 Bu L. Rev. 1277 (2018); Matthew M. Young, Johannes Himmelreich, Justin B. Bullock & Kyoung-Cheol Kim, *Artificial Intelligence and Administrative Evil*, Perspectives on Public Management and Governance 4, no. 3 244-258 (2019).

¹⁹ A complementary intersection has been described as *AI as Law*, in which “AI systems are to be thought of as hybrid critical discussion systems, where different hypothetical perspectives are constructed and evaluated until a good answer is found.” Bart Verheij, *Artificial Intelligence as Law*, A.I. & L. 28, no. 2, 181-206 (2020) at 191 (*AI as Law* comes from the tradition of symbolic systems; *Law Informs AI* is rooted in machine learning; and both are interested in hybrid symbolic-deep learning systems.). Cullen O’Keefe defined a “law-following AI [as] an AI system that is designed to rigorously comply with some defined set of human-originating rules (“laws”), using legal interpretative techniques, under the assumption that those laws apply to the AI in the same way that they would to a human.” (Footnotes omitted.) Cullen O’Keefe, *Law-Following AI 1: Sequence Introduction and Structure*, AI Alignment Forum (2022) <https://www.alignmentforum.org/posts/NrtbF3JHFqBCztXC/law-following-ai-1-sequence-introduction-and-structure>.

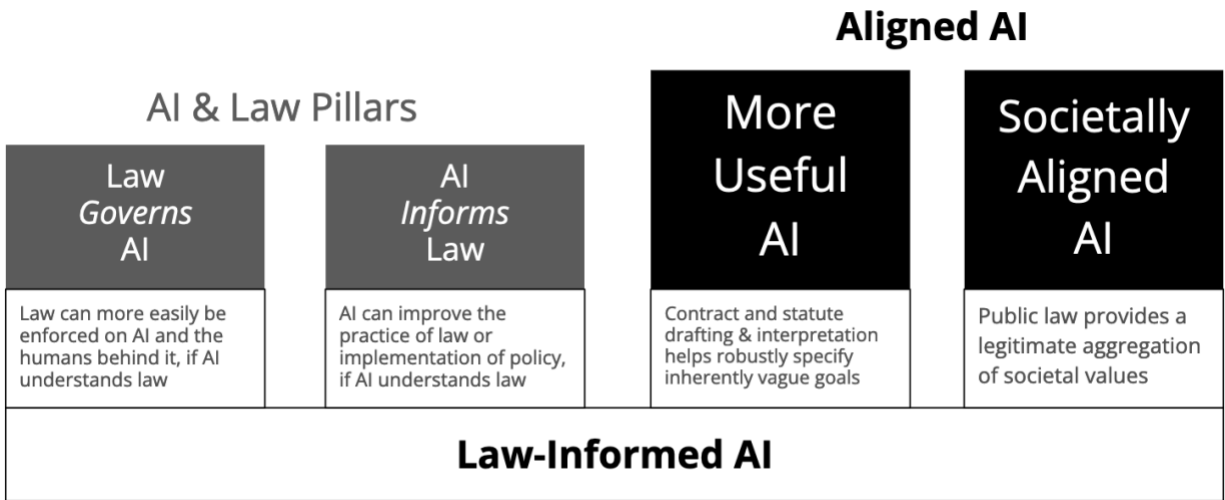


Figure 1: Law-informed code can help power the other AI & Law pillars. The Law Informs Code research agenda focuses on More Useful AI and Societally Aligned AI, but it could have positive externalities for Law Governing AI and AI Informing Law.

In this Article, we do not assess the legality of AI behavior²⁰ or spend much time recommending that AI should play a greater (or lesser) role in legal practice²¹ – critical topics we lack room to address here. Instead, we focus on how AI would be more aligned with humans if we couple legal informatics with AI deployment.²²

Sociology of finance has advanced the idea that financial economics, conventionally viewed as merely a lens on financial markets, actually shapes markets, i.e., the theory is “an engine, not a camera.”²³ Law is an engine, *and* a camera. Legal drafting and interpretation methodologies refined within contract law – an engine of private party alignment – are a lens on how humans communicate their inherently ambiguous goals.²⁴ Public law – an engine for societal coordination and compliance – is a high-fidelity lens on human societal values.

Specifying the desirability (i.e., *value*) of AI taking a particular *action* in a particular *state* of the world is unwieldy beyond a very limited set of *state-action-value* tuples.²⁵ In fact, the purpose of machine learning is to train on a subset of these tuples²⁶ and have the resulting agent

²⁰ See, e.g., Roger Michalski, *How to Sue a Robot*, Utah L. Rev. (2018); Simon Chesterman, *We, The Robots?*. Cambridge University Press (2021).

²¹ See, e.g., Frank Pasquale & Glyn Cashwell, *Four Futures of Legal Automation*, 63 U.C.L.A. L. REV. DISC. 26 (2015); Benjamin Alarie, *The Path of the Law: Towards Legal Singularity*, 66 U. TORONTO L.J. 443 (2016); Emily Berman, *A Government of Laws and not of Machines*, 98 Bu L. Rev. 1277 (2018); Frank Pasquale, *A Rule of Persons, Not Machines: The Limits of Legal Automation*, GEO. WASH. L. REV (2019); Aziz Z. Huq, *A Right to a Human Decision*, 106 Va. L. Rev. 611 (2020); John Nay, *Large Language Models as Corporate Lobbyists* (January 2, 2023). Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4316615.

²² In this Article, we focus on U.S. law, in particular. See *infra* Section V. for a discussion of this limitation.

²³ See, Donald MacKenzie, *An Engine, Not a Camera*, MIT Press (2006).

²⁴ See, e.g., Keno Juechems & Christopher Summerfield, *Where Does Value Come From?* Trends in Cognitive Sciences 23, no. 10 836-850 (2019).

²⁵ Without loss of much generality to other AI paradigms such as supervised learning, we frame the alignment problem from a decision-making (reinforcement learning) perspective.

²⁶ Or input-output pairs, if the focus is purely prediction rather than taking actions. But in this Article we focus on the more general problem of choosing actions, rather than merely prediction; see, generally, D. Abel, J. MacGlashan & M.L. Littman, *Reinforcement Learning as a Framework for Ethical Decision Making*, AAAI Workshop: AI, Ethics,

learn decision policies that generalize to choosing high value actions in unencountered states,²⁷ maintaining the same level of performance in novel circumstances.²⁸ The reward function ascribing values to an agent’s actions during training is inevitably a proxy for human preferences over all actions in all world states,²⁹ and the agent’s training process is a sparse exploration of all states in all possible futures.³⁰

AI often exhibits unanticipated “shortcut” behaviors that seek to optimize an inherently limited reward function.³¹ This causes AI agents to aggressively optimize toward specified rewards

and Society (2016). Below, in the context of self-supervised learning, we discuss the increasingly porous distinction between the paradigms of AI prediction (supervised learning) and AI decision-making (reinforcement learning).

²⁷ Furthermore, a primary purpose of trying to develop future highly advanced AI systems (*see infra* Section II. B.) is to conduct tasks that no human is capable of, *see, e.g.*, Richard Ngo, *The Alignment Problem From a Deep Learning Perspective*, AI Alignment Forum (Aug 10, 2022) <https://www.alignmentforum.org/posts/KbyRPCAsWv5GtfrbG/the-alignment-problem-from-a-deep-learning-perspective>; Ajeya Cotra, *The Case for Aligning Narrowly Superhuman Models*, AI Alignment Forum (March 2021) <https://www.alignmentforum.org/posts/PZtsoaoSLpKjibMqM/the-case-for-aligning-narrowly-superhuman-models>.

²⁸ Generalization is difficult because machine learning model outputs are effectively interpolations within the model’s data manifold, which is defined by the training processes, *see, e.g.*, François Chollet, *On the Measure of Intelligence* (2019). For discussion of generalization in the context of reinforcement learning, *see, e.g.*, K. Cobbe et al., *Quantifying Generalization in Reinforcement Learning*, ICML (2019); Zhang et al., *A Study on Overfitting in Deep Reinforcement Learning* (2018) at 1 (“the same agents and learning algorithms could have drastically different test performance, even when all of them achieve optimal rewards during training.”) Ultimately, whether an AI system’s generalizability is adequate depends on how it is deployed and its relation to live decision-making processes; *see, e.g.*, John Nay & Katherine Strandburg, *Generalizability: Machine Learning and Humans-in-the-loop*, in *BIG DATA LAW* (Roland Vogl ed., 2021); Ben Green & Yiling Chen, *The Principles and Limits of Algorithm-in-the-loop Decision Making*, in *Proceedings of the ACM on Human-Computer Interaction* 3.CSCW 1 (2019); Saleema Amershi, Maya Cakmak, William Bradley Knox & Todd Kulesza, *Power to the People: The Role of Humans in Interactive Machine Learning*, *AI Magazine* 35, no. 4 105-120 (2014). For an illustration of the lack of generalizability of deep learning models on a vision task, *see, e.g.*, Benjamin Recht, Rebecca Roelofs, Ludwig Schmidt & Vaishal Shankar, *Do ImageNet Classifiers Generalize to ImageNet?*, *Proceedings of the 36th International Conference on Machine Learning*, PMLR 97 5389-5400 (2019).

²⁹ *See, e.g.*, Amodei et al., *Concrete Problems in AI Safety* (2016); Joar Skalse, Nikolaus H. R. Howe, Dmitrii Krasheninnikov & David Krueger, *Defining and Characterizing Reward Hacking*, in 36th Conference on Neural Information Processing Systems (2022) <https://arxiv.org/abs/2209.13085>.

³⁰ *See, e.g.*, Langosco et al., *Goal Misgeneralization in Deep Reinforcement Learning*, *Proceedings of the 39th International Conference on Machine Learning*, PMLR 162:12004-12019 (2022); Rohin Shah et al., *Goal Misgeneralization: Why Correct Specifications Aren’t Enough For Correct Goals* (2022) <https://arxiv.org/pdf/2210.01790.pdf> at 11 (“Goal misgeneralization can occur when there is some deployment situation, not previously encountered during training, on which the intended and misgeneralized goal disagree. Thus, one natural approach is to include more situations during training.”).

³¹ *See, e.g.*, W. Bradley Knox et al., *Reward (Mis)design for Autonomous Driving*, arxiv.org (Mar. 11, 2022), <https://arxiv.org/abs/2104.13906>; Victoria Krakovna et al., *Specification Gaming: The Flip Side of AI Ingenuity*, deepmind.com (Apr. 21, 2020), <https://www.deepmind.com/blog/specification-gaming-the-flip-side-of-ai-ingenuity>; Alexander Pan, Kush Bhatia & Jacob Steinhardt, *The Effects of Reward Misspecification: Mapping and Mitigating Misaligned Models*, arxiv.org (Feb. 14, 2022), <https://arxiv.org/abs/2201.03544> [Hereinafter Pan, *Effects of Reward Misspecification*]; Joar Skalse, Nikolaus H. R. Howe, Dmitrii Krasheninnikov & David Krueger, *Defining and Characterizing Reward Hacking*, in 36th Conference on Neural Information Processing Systems (2022) <https://arxiv.org/abs/2209.13085>; J. Lehman et al., *The Surprising Creativity of Digital Evolution: A Collection of Anecdotes From the Evolutionary Computation and Artificial Life Research Communities*, *Artificial Life*, 26(2) 274–306 (2020); R. Geirhos et al., *Shortcut Learning in Deep Neural Networks*, *Nature Machine Intelligence*, 2(11) 665–673 (November 2020).

at the expense of other (usually less quantifiable) variables of interest that were left unspecified.³² Unintended negative behavior results.³³ For instance, when a robot hand was trained to grasp a ball (*from the perspective of the human evaluator, which provided the training reward*), it optimized for hovering between the evaluator’s camera and the ball. This gave the *impression* it was grasping the ball, which optimized the reward.³⁴ Although, *ex post*, this may seem simple to address with an improved reward function and retraining; *ex ante*, careful work from experienced machine learning researchers did not design a training process to avoid this.³⁵ And this is in a tightly controlled environment.

Real-world circumstances³⁶ exacerbate goal misspecification.³⁷ Take, for example, the implementation of simple computational rules applied to data relevant to self-driving cars. When fifty-two programmers were assigned the task of each independently automating simple speed limits, there was “significant deviation in number and type of citations issued [on application of their code to the same real-world data ...] this experiment demonstrates that even relatively narrow and straightforward “rules” can be problematically indeterminate in practice.”³⁸ More capable AI can further exacerbate misspecification issues with stronger optimization ability, “achieving higher proxy reward and lower true reward than less capable agents.”³⁹

³² See, François Chollet, *Deep Learning with Python, Second Edition* (2021) at 450 (“An effect you see constantly in systems design is the *shortcut rule*: if you focus on optimizing one success metric, you will achieve your goal, but at the expense of everything in the system that wasn’t covered by your success metric. You end up taking every available shortcut toward the goal.”). “Excessive literalism” is another way of describing the issue; see, e.g., “A system that is optimizing a function of n variables, where the objective depends on a subset of size $k < n$, will often set the remaining unconstrained variables to extreme values; if one of those unconstrained variables is actually something we care about, the solution found may be highly undesirable. This is essentially the old story of the genie in the lamp, or the sorcerer’s apprentice, or King Midas: you get exactly what you ask for, not what you want.” quoting Stanford Professor, Stuart Russell (<https://www.edge.org/conversation/the-myth-of-ai#26015>); STUART RUSSELL, HUMAN COMPATIBLE: ARTIFICIAL INTELLIGENCE AND THE PROBLEM OF CONTROL (2019). See, e.g., Brandon Trabucco et al., *Conservative Objective Models for Effective Offline Model-Based Optimization* (2021).

³³ See, e.g., Jack Clark & Dario Amodei, *Faulty Reward Functions in the Wild*, <https://openai.com/blog/faulty-reward-functions/> (2016); Ortega & Maini, *Building Safe Artificial Intelligence: Specification, Robustness and Assurance* (2018) <https://medium.com/@deepmindsafetyresearch/building-safe-artificial-intelligence-52f5f75058f1>; David Manheim & Scott Garrabrant, *Categorizing Variants of Goodhart’s Law* (2018); Rachel L. Thomas & David Uminsky, *Reliance on Metrics is a Fundamental Challenge for AI*, *Patterns* 3, no. 5 100476 (2022).

³⁴ See, Dario Amodei, Paul Christiano & Alex Ray, *Learning from Human Preferences* (June 13, 2017) <https://openai.com/blog/deep-reinforcement-learning-from-human-preferences/>; Victoria Krakovna, *Paradigms of AI alignment: components and enablers* (2022).

³⁵ Another example: an AI agent maximized its provided reward by killing itself at the end of the first level of a simulated environment in order to avoid losing in level two, see, William Saunders et al., *Trial without Error: Towards Safe Reinforcement Learning via Human Intervention* (2017). For more examples, see, e.g., Victoria Krakovna, *Specification Gaming Examples in AI* (2022) <https://docs.google.com/spreadsheets/d/e/2PACX-1vRPiprOaC3HsCf5Tuum8bRfzYUiKLRqJmbOoC-32JorNdfyTiRRsR7Ea5eWtvsWzuxo8bjOxCG84dAg/pubhtml>

³⁶ See, e.g., A. Rupam Mahmood et al., *Benchmarking Reinforcement Learning Algorithms on Real-World Robots*, In Conference on Robot Learning, 561-591, PMLR (2018).

³⁷ See, e.g., Steven Kerr, *On the Folly of Rewarding A, While Hoping For B*, *Academy of Management Journal* 18, no. 4 769-783 (1975); Victoria Krakovna, *Paradigms of AI Alignment: Components and Enablers* (2022); Pan, *Effects of Reward Misspecification*.

³⁸ Lisa A. Shay, Woodrow Hartzog, John Nelson & Gregory Conti, *Do Robots Dream of Electric Laws? An Experiment in the Law as Algorithm*, Presentation at the We Robot Conference 2013 (Apr. 8–9, 2013), http://www.gregconti.com/publications/201303_AlgoLaw.pdf [cited in Brian Sheppard, *The Reasonableness Machine*, 62 BCL Rev. 2259 (2021)].

³⁹ Pan, *Effects of Reward Misspecification*, at 1 (“More capable agents often exploit reward misspecifications, achieving higher proxy reward and lower true reward than less capable agents. Moreover, we find instances of phase

We can never provide enough sources of reward. There will always be relevant goals and world attribute valuations missing from any explicit reward function, or ensemble of functions.⁴⁰ It is not possible to manually specify or automatically enumerate a discernment of humans' desirability of all actions an AI might take.⁴¹ Therefore, after training, AI is deployed with an incomplete map of human preferred territory,⁴² and the resulting mismatch between what a human wants and what an AI does is a *human-AI* alignment problem.⁴³ Acknowledging that multiple humans have preferences over values of state-action pairs, we must grapple with an even more intractable problem: *society-AI* alignment.⁴⁴

We developed three primary desiderata for a framework to address these alignment problems.⁴⁵ *First*, the framework should have a well-developed theory of alignment. Rather than overly simple specifications or vacuous high-level principles, it should be laden with modular constructs built to handle the ambiguity and novelty inherent in aligning (human and/or artificial)

transitions: capability thresholds at which the agent's behavior qualitatively shifts, leading to a sharp decrease in the true reward. Such phase transitions pose challenges to monitoring the safety of ML systems.”)

⁴⁰ See, e.g., Roel Dobbe, Thomas Krendl Gilbert & Yonatan Mintz, *Hard Choices in Artificial Intelligence*, Artificial Intelligence, 300 103555 (2021).

⁴¹ Even if it was possible to specify humans' desirability of all actions a system might take within a reward function that was used for training an AI agent, the resulting behavior of the agent is not only a function of the reward function; it is also a function of the exploration of the state space, see, Richard Ngo, *AGI Safety from first principles* (AI Alignment Forum, 2020) at 21-24, <https://www.alignmentforum.org/s/mzgtmmTKKn5MuCzFJ>. Furthermore, even when the “true” reward function is known, different functions can be equally consistent with the training data; see, e.g., Kareem Amin & Satinder Singh, *Towards Resolving Unidentifiability in Inverse Reinforcement Learning* (2016); Soren Minderman & Stuart Armstrong, *Occam's Razor is Insufficient to Infer the Preferences of Irrational Agents*, in Proceedings of the 32nd International Conference on Neural Information Processing Systems (2018).

⁴² Furthermore, there are reinforcement learning systems that learn through interaction with a real-world environment (see, J. García & F. Fernández, *A Comprehensive Survey on Safe Reinforcement Learning*, Journal of Machine Learning Research, 16, 1437–1480 (2015); Alex Ray, Joshua Achiam & Dario Amodei, *Benchmarking Safe Exploration in Deep Reinforcement Learning* (2019)) and proposals for general artificial agents that conduct live self-supervised learning as the primary training method (see, e.g., Yan LeCunn, *A Path Towards Autonomous Machine Intelligence* (2022) <https://openreview.net/forum?id=BZ5a1r-kVsf>). See, a reinforcement learning focused proposal in the same vein, e.g., Sekar et al., *Planning to Explore via Self-Supervised World Models*, in Proceedings of the 37th International Conference on Machine Learning, 119, 8583-8592 (2020). If the learning process occurs while the AI agent is taking action in the world, the alignment problem is harder to solve.

⁴³ Simon Zhuang & Dylan Hadfield-Menell, *Consequences of Misaligned AI*, Advances in Neural Information Processing Systems 33 15763-15773 (2020).

⁴⁴ See *infra* Section IV.

⁴⁵ This Article is focused on the alignment problem primarily with respect to better specifying human intentions and societal values for AI. Another AI safety problem relates to power-seeking AI and “corrigibility,” see, e.g., Nate Soares et al., *Corrigibility*, In Workshops at the Twenty-Ninth AAAI Conference on Artificial Intelligence (2015) at 1 (“We call an AI system “corrigible” if it cooperates with what its creators regard as a corrective intervention”); see, also, Tom Everitt, Daniel Filan, Mayank Daswani & Marcus Hutter, *Self-Modification of Policy and Utility Function in Rational Agents* (2016); Dylan Hadfield-Menell, Anca Dragan, Pieter Abbeel & Stuart Russell, *The Off-switch Game*, In Workshops at the Thirty-First AAAI Conference on Artificial Intelligence (2017); Alex Turner et al., *Optimal Policies Tend To Seek Power*, In Advances in Neural Information Processing Systems, 34, 23063-23074 (2021).. For additional AI alignment discussion focused on existential risks to humanity, see, e.g., Dan Hendrycks & Thomas Woodside, *Open Problems in AI X-Risk* (2022). For a discussion of AI alignment specifically related to natural language agents, see, e.g., Zachary Kenton et al., *Alignment of Language Agents* (2021). For reviews of the broader domain of the safety of highly advanced AI systems that may be built after further AI capabilities advancements, see, e.g., Tom Everitt, Gary Lea & Marcus Hutter, *AGI Safety Literature Review* (2018). For an earlier perspective on AI-human value alignment (the authors may not describe it as “alignment” research), see, e.g., Daniel S. Weld & Oren Etzioni, *The First Law of Robotics (A Call to Arms)*, AAAI (1994).

agents. It should have a theory for how to credibly elicit human values, legitimately synthesize them, and consistently update the results (Figure 2).⁴⁶

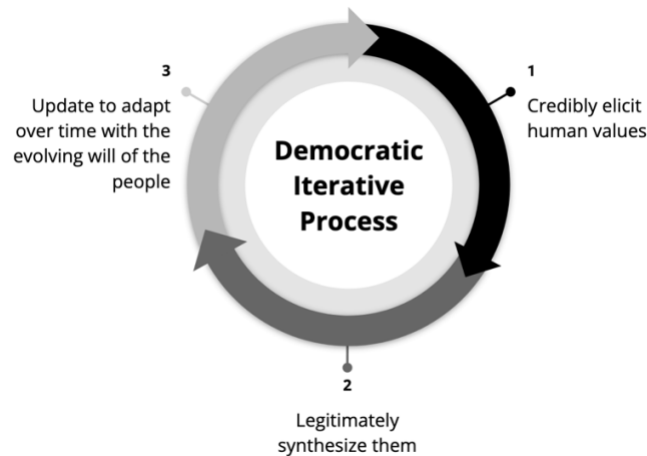


Figure 2: *The iterative democratic process.*

Second, in recognizing that alignment is a moving target as AI capabilities advance,⁴⁷ the framework should be useful for today’s AI while scaling with future advancements.⁴⁸ As AI becomes more capable, the framework should provide benchmarks and solutions calibrated to that higher level of capability. The alignment methods should directly benefit from the improvements in general AI capabilities research.⁴⁹ Much of the research on governing AI falls into two ends of a spectrum related to assumptions of the imminence of transformative AI. Research operating under the premise of a *high probability* of near-term transformative AI (e.g., within 15 years) is focused more on aligning AGI with a benevolent small group of humans that first develop

⁴⁶ Jan Leike, *What Could a Solution to the Alignment Problem Look Like? A High-level View on the Elusive Once-and-for-all Solution* (Sep 26, 2022) <https://aligned.substack.com/p/alignment-solution>.

⁴⁷ As models scale in size, compute, and data inputs, there have been “emergent” breakthroughs in their capabilities; see, e.g., Jason Wei et al., *Emergent Abilities of Large Language Models* (2022); Aarohi Srivastava et al., *Beyond the Imitation Game: Quantifying and Extrapolating the Capabilities of Language Models* (2022); Jason Wei et al., *Finetuned Language Models Are Zero-Shot Learners*, arxiv.org, (Feb. 8, 2022), <https://arxiv.org/abs/2109.01652>; Wenlong Huang et al., *Inner Monologue: Embodied Reasoning through Planning with Language Models*, arXiv:2207.05608 (2022) at 8; Deep Ganguli et al., *Predictability and Surprise in Large Generative Models* (2022) at 14 (“large generative models have an unusual combination of high predictability - model capabilities scale in relation to resources expended on training - and high unpredictability - before training a model, it’s difficult to anticipate all the inputs it will be subjected to, and what capabilities and outputs it will have. The former drives rapid development of such models while the latter makes it difficult to anticipate the consequences of their development and deployment.”); Julien Perolat et al., *Mastering the Game of Stratego with Model-Free Multiagent Reinforcement Learning* (2022) (“Stratego is one of the few iconic board games that Artificial Intelligence (AI) has not yet mastered. [...] Stratego has been a grand challenge for the field of AI for decades [...] DeepNash beats existing state-of-the-art AI methods in Stratego [an extremely complex game] and achieved a yearly (2022) and all-time top-3 rank on the Gravon games platform, competing with human expert players.”).

⁴⁸ See, alignment proposals that focus on scaling to more capable AI, e.g., Leike et al., *Scalable Agent Alignment via Reward Modeling: A Research Direction*, <https://arxiv.org/abs/1811.07871> (2018) at 2 (“we describe how reward modeling can be applied recursively: agents trained with reward modeling can assist the user in the evaluation process when training the next agent.”).

⁴⁹ Most AI research is classified as “capabilities” research by AI alignment and safety researchers in order to distinguish mainstream research focused on improving AI performance on traditional tasks, e.g., prediction, from AI research focused on alignment or safety outcomes.

transformative AI, or how to align AI with an ideal aggregation of human preferences (through yet to be specified aggregation processes). Research operating under the premise of a *low probability* of near-term transformative AI is typically focused more on how to reduce discriminatory and privacy harms posed by present-day AI. We seek a framework that bridges the AI timeline spectrum.⁵⁰

Third, the framework should already be rigorously battle-tested in some form – ideally the documentation of the battle-testing has produced reams of data that can be leveraged by machine learning.

Law, as the applied philosophy of multi-agent alignment, uniquely fulfills these criteria.⁵¹ Alignment is a problem because we cannot *ex ante* specify rules that fully and provably direct good AI behavior.⁵² Similarly, parties to a legal contract cannot foresee every contingency of their relationship,⁵³ and legislators cannot predict every specific circumstances under which their laws will be applied.⁵⁴ That is why much of law is a constellation of standards.⁵⁵ Methodologies for making and interpreting law – where one set of agents develops specifications for behavior, another set of agents interprets the specifications in novel circumstances, and then everyone iterates (Figure 2) – have been theoretically refined for centuries. Democracy has a theory – widely accepted and implemented already – for how to elicit credible human preferences and values, legitimately synthesize them, and consistently update the results to adapt over time with the evolving will of the people. Democratically developed law thus fulfills *requirement one* of our desired criteria, and legal informatics can be the bridge to instill legal reasoning – the language of alignment – within AI, helping close the currently widening “gap between social requirements and technical feasibility.”⁵⁶

As the state-of-the-art advances, we can set iteratively higher bars of demonstrated legal understanding capabilities. If a developer claims their AI has advanced capabilities on tasks, they should demonstrate correspondingly advanced legal comprehension and legal reasoning abilities

⁵⁰ In addition to bridging this gap, there is a relatively unaddressed territory in between. Most pre-2018 alignment research was focused on more clearly decision and agentic oriented training processes, whereas the most powerful AI systems today are a result of self-supervised foundation models that exhibit far less goal-orientation than pure reinforcement learning approaches. See, Janus, *Simulators*, AI Alignment Forum (Sep 2, 2022) <https://www.alignmentforum.org/posts/vJFdjgzmcXMhNTsx/simulators>; Richard Kennaway, *Is the Work on AI Alignment Relevant to GPT?*, AI Alignment Forum (Jul 30, 2020) <https://www.alignmentforum.org/posts/dPcKrfEi87Zzr7w6H/is-the-work-on-ai-alignment-relevant-to-gpt>. An alignment framework that scales across levels of intelligence may be able to address this novel model type. Regardless of whether the most capable AIs are agentic or merely “tools” or “simulators,” the framework should be relevant.

⁵¹ Of course, law does not embed all of the citizenry’s moral views; therefore, a further integration of ethics and AI will be needed to guide AI systems where the law is silent (however, that itself is useful information) or prejudiced, see *infra* Section IV. But, for the reasons outlined throughout this Article, we believe legal informatics is most well suited to serve as the core framework for AI alignment.

⁵² See, e.g., Martin Abadi, Leslie Lamport & Pierre Wolper, *Realizable and Unrealizable Specifications of Reactive Systems*, in *International Colloquium on Automata, Languages, and Programming* (1989); Dan Hendrycks et al., *Aligning AI With Shared Human Values* (2021).

⁵³ Ian R. Macneil, *The Many Futures of Contracts*, 47 S. CAL. L. REV. 691, 731 (1974).

⁵⁴ See, John C. Roberts, *Gridlock and Senate Rules*, 88 Notre Dame L. Rev. 2189 (2012); Brian Sheppard, *The Reasonableness Machine*, 62 BCL Rev. 2259 (2021) [Hereinafter Sheppard *Reasonableness*].

⁵⁵ These “standards” are not academic philosophical guidelines. Rather, they are *legal* standards that, at least theoretically, have an “objective” resolution (obtained from a court opinion), see *infra* Section II. A. & Section IV.

⁵⁶ Mark S. Ackerman, *The Intellectual Challenge of CSCW: The Gap Between Social Requirements and Technical Feasibility*, 15.2-3 *Human-Computer Interaction* 179 (2000).

of the AI.⁵⁷ Benchmarks are the guiding lights of AI research. There is no ceiling of difficulty when considering the morass of laws and regulations across time and jurisdiction. No current AI exhibits the general legal reasoning skills of expert human lawyers, and human experts do not represent the pinnacle of legal comprehension and reasoning abilities.⁵⁸ Legal understanding thus fulfils *requirement two* as an AI alignment benchmark.

The practices of making, interpreting, and enforcing law have been battle tested through millions of legal actions memorialized in digital format⁵⁹ that can be leveraged for machine learning (*requirement three*).⁶⁰ Part II of this Article expands on the satisfaction of our three requirements to demonstrate why the legal lens is so well-suited to increase AI alignment.

Parts III and IV explore the two primary ways that *Law Informs Code* (Figure 3). *First*, law provides theoretical constructs and praxis (methods of statutory interpretation, application of standards, and legal reasoning more broadly) to facilitate the robust specification of what a human wants an AI to proactively accomplish in the world (Part III). *Second*, public law *as data* helps AI parse what it should generally *not* do, providing an up-to-date distillation of democratically deliberated means of reducing externalities and pursuing societal coordination (Part IV). We conclude, in Part V, with drawbacks of our approach and with where further research could be most fruitful.

⁵⁷ Or they should demonstrate correspondingly advanced legal comprehension and legal reasoning abilities of specialized Legal Informatics AI systems that are directly available for guiding the knowledge and actions of the primary AI.

⁵⁸ But they can help evaluate advanced AI systems. I cannot do a backflip, but I can evaluate whether you just did one. Furthermore, “One solution is to have humans provide a training signal by demonstrating or judging performance, but this approach fails if the task is too complicated for a human to directly evaluate. We propose Iterated Amplification, an alternative training strategy which progressively builds up a training signal for difficult problems by combining solutions to easier subproblems.” Paul Christiano, Buck Shlegeris & Dario Amodei, *Supervising Strong Learners by Amplifying Weak Experts* (2018) at 1. *See, also, e.g.*, Jan Leike et al., *Scalable Agent Alignment via Reward Modeling: A Research Direction* (2018); Brian Christian, *The Alignment Problem: Machine Learning and Human Values* (2020) at 263-266.

⁵⁹ *See, e.g.*, Christine Bannan, *Legal Data Access*, in *LEGAL INFORMATICS* (Daniel Martin Katz et al. eds. 2021).

⁶⁰ *See, generally*, Daniel Martin Katz & John Nay, *Machine Learning and Law*, in *LEGAL INFORMATICS* (Daniel Martin Katz et al. eds., 2021).

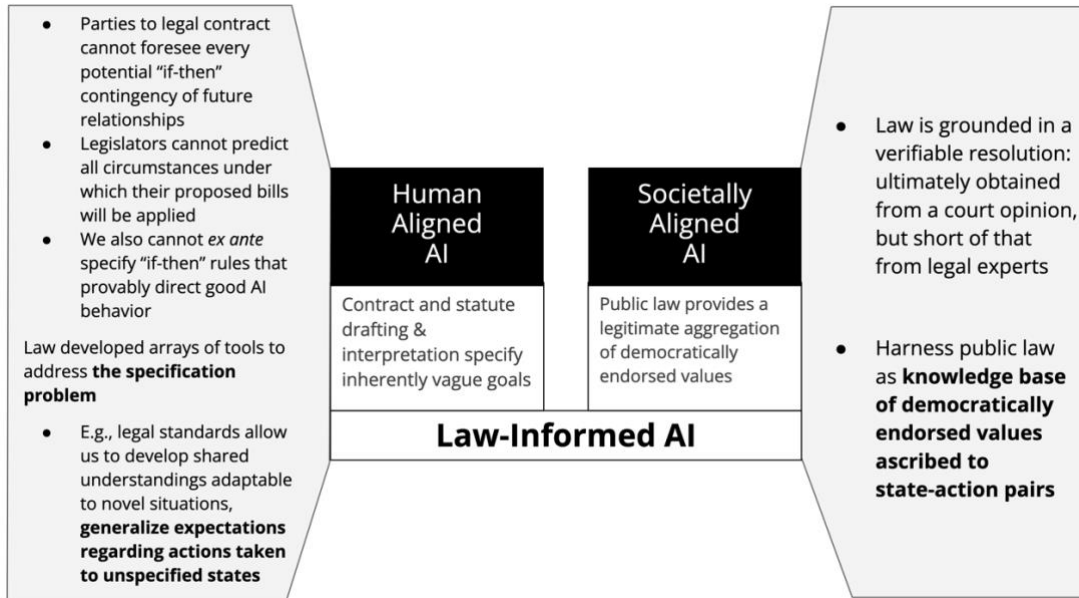


Figure 3: *The two ways in which Law-Informed AI causes more aligned AI: human-AI alignment for more useful AI, and societally-aligned AI for safer AI.*

II. LEGAL INFORMATICS FOR AI ALIGNMENT

A legal (informatics) approach satisfies our three requirements for an alignment framework. Law is the applied philosophy and accepted practice of multi-agent alignment (Section II. A); legal informatics can calibrate AI *task capabilities* and AI *alignment capabilities* as technology advances to potentially transformative AI (II. B); and law produces data and (in the machine learning parlance) model “inductive biases” that can be leveraged to improve AI through goal communication mechanisms and rich background knowledge on how to act without undue externalities (II. C).

A. *Legal Theory is Well-Developed, and Applicable to Alignment*

The legal lens helps frame and clarify the alignment problem. Law is a unique discipline – it is both deeply theoretical⁶¹ and tested against reality with an unrelenting cadence. Because producing, interpreting, enforcing, and amending law is a never-ending society-wide project,⁶² the results are a prime source of information to scalably shape AI behavior.

⁶¹ E.g., even busy practicing attorneys publish esoteric Law Review Articles.

⁶² Law is also capable of reflecting the rights of future generations, *see, e.g.*, Eric Martínez & Christoph Winter, *Protecting Future Generations: A Global Survey of Legal Academics* (2022).

1. Law as Information

We are not aiming for AI to have the legitimacy to make or enforce law. The most ambitious goal of *Law Informing Code* is to computationally encode and embed the generalizability of existing legal concepts and standards into AI. Setting new legal precedent (which, broadly defined, includes proposing and enacting legislation, promulgating agency rules, publishing judicial opinion, systematically enforcing law, and more) should be exclusively reserved for the democratic governmental systems expressing uniquely *human* values.⁶³ Humans should always be the engine of law-making.⁶⁴ The positive implications (for our approach) of this normative stance are that the resulting law encapsulates human views.

The law is a complex system⁶⁵ with seemingly chaotic underlying behavior from which aggregated and systematized preferences emerge.⁶⁶ Law, leveraged as an expression of *what* humans want,⁶⁷ and *how* they communicate their goals under ambiguity and radical uncertainty,⁶⁸ is how *Law Informs Code*. This stands in contrast to more prosaic uses of law e.g., as a deterrent of bad behavior through the threat of sanction⁶⁹ or imposition of institutional legitimacy,⁷⁰ or as an *ex-post* message of moral indignation.⁷¹ *Law Informs Code* in the tradition of Oliver Holmes and subsequent “predictive” theories of law.⁷²

Empirical consequences of violating the law, using enforcement as a source of information,⁷³ are data points for AI. Enforcing law on AI (or their human developers) is how *Law*

⁶³ See, e.g., Frank Pasquale, *New Laws of Robotics: Defending Human Expertise in the Age of AI* (2020); John Nay, *Large Language Models as Corporate Lobbyists* (January 2, 2023). Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4316615.

⁶⁴ See, e.g., Frank Pasquale, *A Rule of Persons, Not Machines: The Limits of Legal Automation*, GEO. WASH. L. REV. (2019); John Nay, *Large Language Models as Corporate Lobbyists* (January 2, 2023). Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4316615.

⁶⁵ For a discussion of complex systems science applied to AI safety, see, e.g., Dan Hendrycks & Thomas Woodside, *Complex Systems for AI Safety* (May 23, 2022) <https://www.alignmentforum.org/posts/n767Q8HqbrteaPA25/complex-systems-for-ai-safety-pragmatic-ai-safety-3>.

⁶⁶ On law as a complex emergent system, see, e.g., Daniel M. Katz & Michael J. Bommarito, *Measuring the complexity of the law: the United States Code*, A.I. & L. 22.4 337-374 (2014); J.B. Ruhl & Daniel M. Katz, *Measuring, Monitoring, and Managing Legal Complexity*, 101 Iowa L. Rev. 191 (2015); Daniel M. Katz et al., *Complex Societies and the Growth of the Law*, Sci Rep 10, 18737 (2020).

⁶⁷ Richard H. McAdams, *The Expressive Powers of Law*, Harv. Univ. Press (2017) at 6-7 (“Law has expressive powers independent of the legal sanctions threatened on violators and independent of the legitimacy the population perceives in the authority creating and enforcing the law.”) [Hereinafter McAdams, *The Expressive Powers of Law*]

⁶⁸ On the notion of radical uncertainty, see, John Kay & Mervyn King, *Radical Uncertainty*, WW Norton & Company (2021); Frank H. Knight, *Risk, Uncertainty, and Profit*, Houghton Mifflin Company (1921).

⁶⁹ Oliver Wendell Holmes, Jr., *The Path of the Law*, in Harvard L. Rev. 10, 457 (1897); Ron Dolin, *Technology Issues in Legal Philosophy*, in LEGAL INFORMATICS (Daniel Martin Katz et al. eds. 2021).

⁷⁰ Kenworthy Bilz & Janice Nadler, *Law, Psychology & Morality*, in MORAL COGNITION AND DECISION MAKING: THE PSYCHOLOGY OF LEARNING AND MOTIVATION, D. Medin, L. Skitka, C. W. Bauman, & D. Bartels, eds., Vol. 50, 101-131, Academic Press (2009).

⁷¹ Mark A. Lemley & Bryan Casey, *Remedies for Robots*, University of Chicago L. Rev. (2019) at 1347. See, also, e.g., Yuval Feldman, *The Law of Good People: Challenging States’ Ability to Regulate Human Behavior* (Cambridge 2018).

⁷² Oliver Wendell Holmes, Jr., *The Path of the Law*, in Harvard L. Rev. 10, 457 (1897); Catharine Pierce Wells, *Holmes on Legal Method: The Predictive Theory of Law as an Instance of Scientific Method*, S. Ill. ULJ 18, 329 (1993); Faraz Dadgostari et al. *Modeling Law Search as Prediction*, A.I. & L. 29.1, 3-34 (2021).

⁷³ McAdams, *The Expressive Powers of Law* at 169-198.

*Governs Code*⁷⁴ not how *Law Informs Code*, and is out of scope here. What good is the law if it is not enforceable – isn't there “no right without a remedy”?⁷⁵ From the perspective of AI, the law can serve as a rich set of methodologies for interpreting inherently incomplete specifications of collective human expectations.⁷⁶

Law provides detailed variegated examples of its application, generalizable precedents with explanations, and well-trained lawyers to solicit targeted model training and fine-tuning feedback to embed an ever-evolving comprehension of societal goals.⁷⁷ As a source to learn goal specification and interpretation⁷⁸ methods and (automatically updated and verified) societal knowledge, law provides an ontology for alignment.⁷⁹

2. Examples of Theoretical Framing

We illustrate the applicability of legal theory with three examples.

i. Complete vs. Incomplete Contracts

From the legal lens, one way of viewing the alignment of a human with an AI is the recognition that it is not possible to create a complete contingent “contract” between the AI and the human it serves because AI training and validation are not comprehensive of states of the world that may be encountered after deployment.⁸⁰ This highlights the need for AI to learn modular extra-

⁷⁴ Using legal remedies to prevent illegal behavior is difficult with non-human agents, *see*, Mark A. Lemley & Bryan Casey, *Remedies for Robots*, University of Chicago L. Rev. (2019) at 1315, 1316 (“Often, we want to compel defendants to do (or not do) something in order to prevent injury. Injunctions, punitive damages, and even remedies like disgorgement are all aimed—directly or indirectly—at modifying or deterring behavior. But deterring robot misbehavior is going to look very different than deterring humans. [...] Courts, for instance, can rely on the fact that most of us don't want to go to jail, so we tend to avoid conduct that might lead to that result. But robots will be deterred only to the extent that their algorithms are modified to include sanctions as part of the risk-reward calculus.”); Ronald Leenes & Federica Lucivero, *Laws on robots, laws by robots, laws in robots: Regulating robot behaviour by design*, Law, Innovation and Technology 6.2, 193 (2014).

⁷⁵ Frederick Pollock, *The Continuity of the Common Law*, 11 Harv L Rev 423, 424 (1898).

⁷⁶ For more on law as an information source on public attitudes and risks, *see*, Richard H. McAdams, *An Attitudinal Theory of Expressive Law* (2000). For more on law as a coordinating mechanism, *see*, Richard H. McAdams, *A Focal Point Theory of Expressive Law* (2000).

⁷⁷ *See infra* Section III. B.

⁷⁸ *See, e.g.*, Owen M. Fiss, *Objectivity and Interpretation*, 34 STAN. L. REV. 739 (1982).

⁷⁹ *See, e.g.*, Arbib, *Ontology Identification Problem* https://arbib.com/p/ontology_identification/. *See*, a legal ontology, *e.g.*, P Casanovas et al., *Semantic Web for the Legal Domain: The Next Step*, *Semantic Web* 7(3):213–227 (2016). It seems plausible that super-human-intelligent AI could have a shared ontology with humans with respect to the communication of directives, goals, and values, while exhibiting super-human task capabilities to implement the humans' goals. This is analogous to a layperson sharing an ontology with a biologist, and providing a directive such as “run a controlled experiment to determine X and minimize side-effects to a reasonable degree,” and the biologist competently doing that in a safe way because she shares an ontology regarding key concepts like “reasonable” even though she has much more intelligence and skill than the layperson with respect to biology.

⁸⁰ For the contract-AI alignment analogy, *see*, Dylan Hadfield-Menell & Gillian K. Hadfield, *Incomplete Contracting and AI Alignment*, In Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society (2019) at 422, 471 (Their “most important claim is that aligning robots with humans will inevitably require building the technical tools to allow AI to do what human agents do naturally: import into their assessment of rewards the costs associated with

contractual standards⁸¹ and background knowledge that can generalize across much of the implicit space of potential “contracts.”⁸²

ii. *Rules vs. Standards*

The legal lens illuminates AI alignment with the voluminous legal theory concerning the distinction between rules and standards.⁸³ Rules (e.g., “do not drive more than 60 miles per hour”) are more targeted directives than standards. If comprehensive enough for the complexity of their application, rules allow the rule-maker to have more clarity than standards over the outcomes that will be realized conditional on the specified states (and agents’ actions in those states, which are a function of any impact the rules might have had).⁸⁴ Complex social systems have emergent behavior that makes formal rules brittle.⁸⁵

On the other hand, standards (e.g., drive “reasonably” for California highways) allow contract parties, judges, regulators, and citizens to develop shared understandings and adapt them to novel situations, i.e., to generalize expectations regarding actions to unspecified states of the world. If rules are not written with enough potential states of the world in mind, they lead to unanticipated undesirable outcomes⁸⁶ (e.g., a driver following the rule above is too slow to bring their passenger to the hospital in time to save their life). But to enumerate all the potentially relevant state-action pairs is excessively costly outside of the simplest environments.⁸⁷ A standard has more capacity to generalize to novel situations than a rule.⁸⁸ The AI analogy for a standard is

taking actions tagged as wrongful by human communities.” In contrast to Hadfield-Menell & Hadfield (2019), who conclude that the primary need is to build “AI that can replicate human cognitive processes”, we use the contract analogy as inspiration for a legal informatics approach that leverages legal tools, legal standards, and legal data from the real-world creation and performance of contracts.)

⁸¹ See *infra* Section II. A. 3. & Section III.

⁸² An Inverse Reinforcement Learning artificial “agent might not ever learn what is the best (or the morally or ethically appropriate) action in some regions of the state space. Without additional capabilities, it would be incapable of reasoning about what ought to be done in these regions – this is exactly the reason why we have norms in the first place: to not have to experience all state/actions precisely because some of them are considered forbidden and should not be experienced.” Thomas Arnold et al., *Value Alignment or Misalignment - What Will Keep Systems Accountable?* AAAI Workshops (2017) at 5.

⁸³ See, e.g., Duncan Kennedy, *Form and Substance in Private Law Adjudication*, 89 Harv. L. Rev. 1685 (1976); Colin S. Diver, *The Optimal Precision of Administrative Rules*, 93 YALE L.J. 65 (1983); Pierre, J. Schlag, *Rules and Standards*, 2 UCLA L Rev 379 (1985); Kathleen M. Sullivan, *Foreword: The Justices of Rules and Standards*, 106 Harv. L. Rev. 22 (1992); Cass R. Sunstein, *Problems with Rules*, 83 CALIF. L. REV. 953 (1995); Prasad Krishnamurthy, *Rules, Standards, and Complexity in Capital Regulation*, 43 J. LEGAL STUD. (2014); Michael Coenen, *Rules Against Rulification*, 124 YALE L.J. (2014); Anthony J. Casey & Anthony Niblett, *Death of Rules and Standards*, 92 IND. L.J. (2017); Sheppard *Reasonableness*.

⁸⁴ See, e.g., Brian Sheppard, *Judging Under Pressure: A Behavioral Examination of the Relationship Between Legal Decisionmaking and Time*, 39 FLA. ST. U. L. REV. 931, 990 (2012).

⁸⁵ See, e.g., Dylan Hadfield-Menell, McKane Andrus & Gillian Hadfield, *Legible Normativity for AI Alignment: The Value of Silly Rules*, In Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society, 115-121 (2019).

⁸⁶ See, e.g., Robert G. Bone, *Who Decides? A Critical Look at Procedural Discretion*, 28 CARDOZO L. REV. 1961, 2002 (2007); Sheppard *Reasonableness*.

⁸⁷ See, e.g., Gideon Parchomovsky & Alex Stein, *Catalogs*, 115 COLUM. L. REV. 165 (2015); John C. Roberts, *Gridlock and Senate Rules*, 88 Notre Dame L. Rev. 2189 (2012); Sheppard *Reasonableness*.

⁸⁸ See, e.g., the SEC explains the benefits of a standards approach in the context of investment advisers: “[A] principles-based approach should continue as it expresses broadly the standard to which investment advisers are held while allowing them flexibility to meet that standard in the context of their specific services.” *Commission*

a continuous, approximate method that relies on significant amounts of data for learning dense representations on which we can apply geometric operations in the latent model space. They are flexible.⁸⁹ The AI analogy for a rule⁹⁰ is a discrete human-crafted “if-then” statement that is brittle, yet requires no empirical data for machine learning.⁹¹

In practice, most legal provisions land somewhere on a spectrum between pure rule and pure standard,⁹² and legal theory can help estimate the right combination⁹³ of “rule-ness” and “standard-ness” when specifying objectives of AI. Furthermore, there are other theorized dimensions to legal provision implementation related to the rule-ness versus standard-ness axis that could elucidate AI goal design, e.g., “determinacy,”⁹⁴ “privately adaptable” (“rules that allocate initial entitlements but do not specify end-states”⁹⁵), and “catalogs” (“a legal command comprising a specific enumeration of behaviors, prohibitions, or items that share a salient common denominator and a residual category—often denoted by the words ‘and the like’ or ‘such as’”⁹⁶).

iii. *Private vs. Public Law*

The AI alignment problem is usually described with respect to the alignment of one AI with one human, or a small subset of humans.⁹⁷ It is more challenging to expand the scope of the

Interpretation Regarding Standard of Conduct for Investment Advisers at 5. See generally, Anthony J. Casey & Anthony Niblett, *Death of Rules and Standards*, 92 IND. L.J. 1401, 1402 (2017); Anthony J. Casey & Anthony Niblett, *Self-Driving Contracts*, in *The Journal of Corporation Law* (2017).

⁸⁹ Patterns of legal language in contracts exhibit elasticity, see, Klaudia Galka & Megan Ma, *Measuring Contract Elasticity: Computing Reinsurance* (Stanford Law School, 2022); Grace Q. Zhang, *Elastic Language: How and Why We Stretch Our Words* (2015).

⁹⁰ Foundation Models have recently been found to have varying “rule-ness” to their different modes of learning and operation, see, Stephanie C.Y. Chan et al., *Transformers Generalize Differently from Information Stored In Context vs In Weights* (2022) <https://arxiv.org/abs/2210.05675>, at 1 (“we find that generalization from weights is more rule-based whereas generalization from context is largely exemplar-based. In contrast, we find that in transformers pre-trained on natural language, in-context learning is significantly rule-based, with larger models showing more rule-basedness.”).

⁹¹ Harry Surden, *The Variable Determinacy Thesis*, 12 COLUMB. SCI. & TECH. L. REV. 1 (2011). [Hereinafter, Surden, *Variable Determinacy*].

⁹² See, e.g., Frederick Schauer, *The Tyranny of Choice and the Rulification of Standards*, 14 J. CONTEMP. LEGAL ISSUES (2005); Richard L. Heppner, Jr., *Conceptualizing Appealability: Resisting the Supreme Court’s Categorical Imperative*, 55 TULSA L. REV. (2020); Sheppard *Reasonableness*.

⁹³ See, Katherine J. Strandburg, *Rulemaking and Inscrutable Automated Decision Tools*, 7 Columbia L. Rev. 119, 1851 (2019) at 1859 (“Decision criteria may also combine rule-like and standard-like aspects according to various schemes. For example, DWI laws in many states combine a rule-like blood alcohol threshold, above which a finding of intoxication is required, with a standard-like evaluation of intoxication at lower levels. Some speed limit laws use a somewhat different scheme: Above a rule-like speed limit, there is a presumption of unsafe driving, but adjudicators may make standard-like exceptions for a narrow range of emergency circumstances.”).

⁹⁴ Surden, *Variable Determinacy*.

⁹⁵ Cass R. Sunstein, *Problems with Rules*, 83 CALIF. L. REV. 953 (1995) at 959.

⁹⁶ Gideon Parchomovsky & Alex Stein, *Catalogs*, 115 COLUM. L. REV. 165 (2015) at 165.

⁹⁷ See, e.g., Amanda Askell et al., *A General Language Assistant as a Laboratory for Alignment* (2022) at 44 (“At a very high level, alignment can be thought of as the degree of overlap between the way two agents rank different outcomes. For example, if agent A completely internalizes the desires of agent B — i.e. the only desire A has is to see B’s desires satisfied—we could say that agent A is maximally aligned with agent B.”) [Hereinafter Askell Laboratory for Alignment]; Stiennon et al., *Learning to Summarize with Human Feedback*, in 33 *Advances in Neural Information Processing Systems* 3008-3021 (2020). For a high-level overview of AI alignment research, see, Jan H. Kirchner et al., *Researching Alignment Research: Unsupervised Analysis* (2022).

analysis beyond a small set of humans and ascribe *societal value* to state-action pairs.⁹⁸ Even if we fully align an AI with the goals of a human, what about all the other humans? Legal framing highlights differences between addressing *human-AI* alignment and *society-AI* alignment.⁹⁹ The latter requires us to move beyond private contracts and into the realm of public law¹⁰⁰ to explicitly address inter-agent conflicts and public policy designed to ameliorate externalities and solve massively multi-agent coordination and cooperation dilemmas.¹⁰¹

B. Legal Informatics Can Scale with AI Capabilities

Within the *Law Informs Code* framework, we refer to the ability of AI to perform narrow tasks for humans as “AI-contract” capability (Figure 4). This level of capability has been widely deployed for years, e.g., through powering billions of automated online advertisement placements¹⁰² and social media content choices every day.¹⁰³ Large neural-network-based models pre-trained with self-supervision¹⁰⁴ on significant portions of the internet that require little to no

⁹⁸ See, e.g., Jiaying Shen, Raphen Becker & Victor Lesser, *Agent Interaction in Distributed POMDPs and its Implications on Complexity*, in Proceedings of the Fifth International Joint Conference on Autonomous Agents and Multiagent Systems, 529-536 (2006).

⁹⁹ As one moves from private to public law, that broadens “human-human alignment” challenges. Sophisticated general human reasoning capabilities, e.g., a general counsel’s office with teams of specialists on call with decades of experience in niche areas of law, are deployed in attempts to navigate the challenges associated with understanding and complying with public law.

¹⁰⁰ See, e.g., John Henry Merryman, *The Public Law-Private Law Distinction in European and American Law*, 17 J. Pub. L. 3 (1968).

¹⁰¹ See, e.g., Elinor Ostrom, *Understanding Institutional Diversity*, Princeton University Press (2009); Pablo Hernandez-Leal, Bilal Kartal & Matthew E. Taylor, *A Survey and Critique of Multiagent Deep Reinforcement Learning*, *Autonomous Agents and Multi-Agent Systems* 33, no. 6 750-797 (2019); Phillip Christoffersen, Andreas A. Haupt & Dylan Hadfield-Menell, *Get It in Writing: Formal Contracts Mitigate Social Dilemmas in Multi-Agent RL*, arXiv:2208.10469 (2022).

¹⁰² Rohan Anil et al., *On the Factory Floor: ML Engineering for Industrial-Scale Ads Recommendation Models*, arXiv:2209.05310 (2022) (Describing Google’s advertisement recommendation system).

¹⁰³ See, e.g., recent earnings calls (July 2022) where Meta (Facebook) CEO Mark Zuckerberg discusses how AI-driven recommendations from accounts a user does not follow represents 15% of a user’s content in Facebook and more in Instagram, and will more than double by the end of 2023. See, e.g., Nathan Baschez, *Instagram’s Existential Bet* (2022) <https://every.to/divinations/instagram-s-existential-bet> (“In that same earning call Zuckerberg talked about how there’s a “major shift” towards discovery algorithms, because it “unlocks a large amount of interesting and useful videos and posts you might have otherwise missed.” But he doesn’t just see this as unique to Reels / TikTok. He wants to turn this into a major drive for all types of content across the Facebook family of apps, saying “I think about the AI that we’re building not just as a recommendation system for short-form video, but as a Discovery Engine that can show you all of the most interesting content that people have shared across our systems.”). See, generally, Jonathan Stray, et al., *Building Human Values into Recommender Systems: An Interdisciplinary Synthesis* (2022) <https://arxiv.org/abs/2207.10192>; Jonathan Stray et al., *What Are You Optimizing For? Aligning Recommender Systems with Human Values*, arXiv 2107.10939 (2021).

¹⁰⁴ “Self-supervised” training procedures predict data items that are systematically held-out, e.g., removing a word and predicting the word that was removed (and then iterating this billions of times), or predicting whether an entire sentence is next to another sentence. No explicit labeling of the data is required; therefore, self-supervised training allows a model to be trained across significantly more data than traditional supervised learning. Scalable self-supervised pruning of the training data can reduce the costs of training, see, e.g., Ben Sorscher et al., *Beyond Neural Scaling Laws: Beating Power Law Scaling via Data Pruning* (2022).

supervised learning to perform well on some new tasks (“Foundation Models”¹⁰⁵) are beginning to display what we call “AI-standards” capabilities, which could be used to help align AI with humans through legal informatics.¹⁰⁶ Standards are more abstract and nuanced than rules, and require more generalizable capabilities and world knowledge to implement. The next level – somewhere between current Foundation Model capabilities and a potential “Artificial General Intelligence”¹⁰⁷ (AGI) capability level, *paired with* the additional development of methods and data specific to legal understanding¹⁰⁸ – may unlock what we can call an “AI-public” capability (Figure 4). At this level, AI will be able to understand standards, interpretation guidelines, legal reasoning, and generalizable precedents across all public law (which synthesize citizens’ value preferences over potential actions taken in many states of the world).¹⁰⁹ We are not there yet.

¹⁰⁵ See, e.g., Rishi Bommasani et al., *On the Opportunities and Risks of Foundation Models*, arxiv.org (Aug. 18, 2021) <https://arxiv.org/pdf/2108.07258.pdf>. Foundation Models leverage applications of the Transformer architecture (see, e.g., Ashish Vaswani et al., *Attention Is All You Need*, in *PROCEEDINGS OF THE 31ST CONFERENCE ON NEURAL INFORMATION PROCESSING SYSTEMS (2017)*), which is a model used to encode an input sequence (e.g., words in a particular order) into context-aware representation and then decode that into a novel generation of an ordered sequence (e.g., a new set of words in a particular order) as an output. Sequences of words were the first application area of this model architecture with major success, as these models can capture complicated dependencies and interactions within natural language (LEWIS TUNSTALL ET AL., *NATURAL LANGUAGE PROCESSING WITH TRANSFORMERS*, xii (2022)). Transformers are very expressive in the forward pass of their information and very efficient in the backward pass when they are being trained. The Transformer has since been applied beyond natural language, also to graphs (see, e.g., Jinwoo Kim et al., *Pure Transformers are Powerful Graph Learners (2022)*) and decision-making (see, e.g., Micah Carroll et al., *Towards Flexible Inference in Sequential Decision Problems via Bidirectional Transformers*, (2022) <https://arxiv.org/abs/2204.13326>). Even within the natural language data structure, Transformer models demonstrate non-language skills, such as mathematical reasoning skills, see, e.g., Aitor Lewkowycz et al., *Solving Quantitative Reasoning Problems with Language Models (2022)* <https://arxiv.org/abs/2206.14858>; Tuan Dinh et al., *LIFT: Language-Interfaced Fine-Tuning for Non-Language Machine Learning Tasks (2022)* <https://arxiv.org/abs/2206.06565>; and the ability to simulate social systems, see, e.g., Joon Sung Park et al., *Social Simulacra: Creating Populated Prototypes for Social Computing Systems*, in *35th Annual ACM Symposium on User Interface Software and Technology (2022)*; Lisa P. Argyle et al., *Out of One, Many: Using Language Models to Simulate Human Samples (2022)* <https://arxiv.org/abs/2209.06899>.

¹⁰⁶ AI most capable of performing well on diverse sets of tasks – the most generalizable – are large neural network based models trained on diverse data sets through self-supervision; see, e.g., Thoppilan et al., *LaMDA: Language Models for Dialog Applications (2022)*; Tran et al., *Plex: Towards Reliability Using Pretrained Large Model Extensions (2022)* <https://ai.googleblog.com/2022/07/towards-reliability-in-deep-learning.html>.

¹⁰⁷ See, e.g., a definition of AGI from OpenAI, “highly autonomous systems that outperform humans at most economically valuable work” <https://openai.com/charte/> (accessed Aug 23, 2022). See, generally, Tom Everitt, Gary Lea & Marcus Hutter, *AGI Safety Literature Review (2018)*; Richard Ngo, *The Alignment Problem from a Deep Learning Perspective*, AI Alignment Forum (Aug 10, 2022) <https://www.alignmentforum.org/posts/KbyRPCAsWv5GtfrbG/the-alignment-problem-from-a-deep-learning-perspective>.

¹⁰⁸ See, generally, *infra* Section II. B. 2.

¹⁰⁹ There are no distinct boundaries between the AI-public, AI-standards, and AI-contract levels. We are simply using them as high-level rhetorical devices.

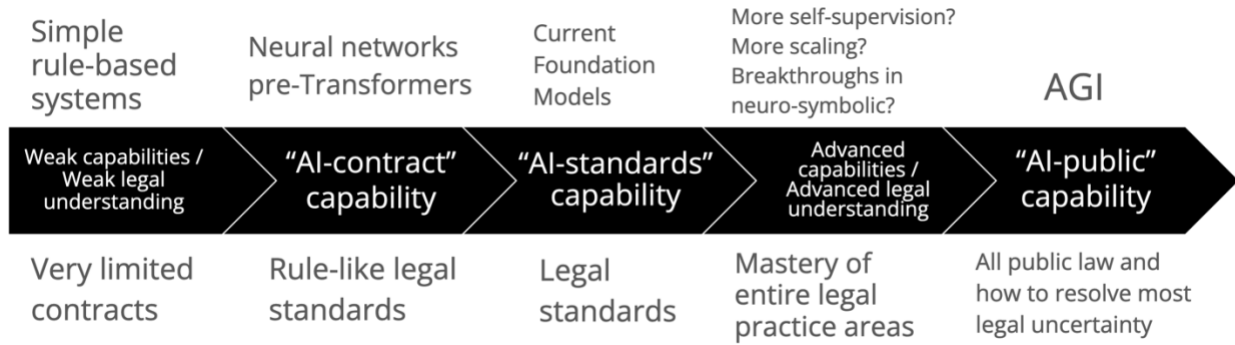


Figure 4: *Legal informatics scaling with AI capabilities. AI capability levels are above the arrow, and legal understanding capabilities are below the arrow. There is a relatively unaddressed AI safety territory in between the two extremes. The pre-Transformer AI alignment research was focused on more clearly decision and agentic oriented training processes, whereas the primary deployed AI today is a result of self-supervised foundation models that exhibit less goal-orientation than pure reinforcement learning approaches. The Law Informs Code alignment framework that scales across levels of intelligence may be able to better address this. As models scale their capabilities, they may automatically become more goal-oriented and power-seeking; this remains to be seen.*

1. AI Capabilities

Unlike traditional supervised learning,¹¹⁰ self-supervision and reinforcement learning can produce “emergent” capabilities.¹¹¹ Advances in deep reinforcement learning are producing more

¹¹⁰ With supervised learning, the best one can do is to predict, with perfect calibration, the same type of output variable with the same type of input variables on new test data not used for training the model. A model that can generalize to novel tasks is out of scope of the traditional supervised learning framework, which is concerned only with mapping *ex ante*-specified input types to *ex ante*-specified output types, albeit on unseen input data points. A complication to this characterization of the distinction in learning paradigms, though, is when supervised learning is trained on state-action-reward sequences and deployed to generate actions in new states by conditioning on high rewards, *see, e.g.*, Dylan R Ashley et al., *Learning Relative Return Policies With Upside-Down Reinforcement Learning*, arXiv:2202.12742 (2022); Kai Arulkumaran et al., *All You Need Is Supervised Learning: From Imitation Learning to Meta-RL With Upside Down RL*, arXiv:2202.11960 (2022).

¹¹¹ *See, e.g.*, Jason Wei et al., *Emergent Abilities of Large Language Models* (2022) <https://arxiv.org/abs/2206.07682>; Jason Wei, *137 Emergent Abilities of Large Language Models* (2022) <https://www.jasonwei.net/blog/emergence>; Ganguli et al., *Predictability and Surprise in Large Generative Models* (2022) at 2 <https://arxiv.org/abs/2202.07785> (“Our basic thesis is that large generative models have an unusual combination of high predictability — model loss improves in relation to resources expended on training, and tends to correlate loosely with improved performance on many tasks — and high unpredictability — specific model capabilities, inputs, and outputs can’t be predicted ahead of time. The former drives rapid development of such models while the latter makes it difficult to anticipate the consequences of their development and deployment.”); Wenlong Huang et al., *Inner Monologue: Embodied Reasoning through Planning with Language Models*, arXiv:2207.05608 (2022) at 8 <https://arxiv.org/abs/2207.05608> (“Although LLMs can generate fluent continuation from the prompted examples, we surprisingly find that, when informed with environment feedback, Inner Monologue demonstrates many impressive reasoning and replanning behaviors beyond the examples given in the prompt. Using a pre-trained LLM as the backbone, the method also inherits many of the appealing properties from its versatility and general-purpose language understanding.”); Mathilde Caron et al., *Emerging Properties in Self-supervised Vision Transformers*, In Proceedings of the IEEE/CVF International Conference on Computer Vision, 9650-9660 (2021); Bowen Baker et al., *Emergent Tool Use from Multi-Agent Autocurricula* (2019) <https://arxiv.org/abs/1909.07528>; Taylor Webb, Keith J.

generalizable decision-making agents,¹¹² which lead to more pressing alignment issues due to the possibility of more autonomous deployments. For both pure prediction tasks (e.g., typical supervised learning inference) and decision tasks (e.g., deployment of agents trained through reinforcement learning), the process of first conducting self-supervised training on a large scale has increased performance on downstream tasks, even with little exposure to those tasks – for “few-shot reasoning.”¹¹³ With latent concepts learned through pre-training, models can even exhibit robust capabilities on novel tasks without any fine-tuning or explicit exposure to that particular task¹¹⁴ – through manually engineered prompting¹¹⁵ or automated algorithmic

Holyoak & Hongjing Lu, *Emergent Analogical Reasoning in Large Language Models* (2022) <https://arxiv.org/abs/2212.09196>.

¹¹² See e.g., Bhoopchand et al., *Learning Robust Real-Time Cultural Transmission without Human Data* (2022) at 2 (“Our artificial agent is parameterised by a neural network and we use deep reinforcement learning (RL) to train the weights. The resulting neural network (with fixed weights) is capable of zero-shot, high-recall cultural transmission within a “test” episode on a wide range of previously unseen tasks.”).

¹¹³ See, e.g., Yaqing Wang et al., *Generalizing From a Few Examples: A Survey on Few-shot Learning*, ACM computing surveys (csur) 53.3 1-34 (2020); Zhao Mandi, Pieter Abbeel & Stephen James, *On the Effectiveness of Fine-tuning Versus Meta-reinforcement Learning* (2022); Zhuyun Dai et al., *Promptagator: Few-shot Dense Retrieval From 8 Examples* (2022) <https://arxiv.org/pdf/2209.11755.pdf> at 10 (They “showed that it is possible to create task-specific, end-to-end retrievers with only a few annotated examples. The few-shot examples, amplified by prompt-based LLM query generation, simplifies the complexity of training neural retrievers for new tasks and leads to promising retrieval performance gains.”); Simran Arora et al., *Ask Me Anything: A Simple Strategy for Prompting Language Models* (2022) <https://arxiv.org/abs/2210.02441>; Jesse Michael Han et al., *Proof Artifact Co-training for Theorem Proving with Language Models*, in *The First Mathematical Reasoning in General Artificial Intelligence Workshop, ICLR* (2021) https://mathai-iclr.github.io/papers/papers/MATHAI_23_paper.pdf (Self-supervised training helps with proving mathematical theorems); Dinglan Peng et al., *How Could Neural Networks Understand Programs?* (2021) <https://arxiv.org/abs/2105.04297> (Self-supervised training helps with understanding computer programming.).

¹¹⁴ For potential explanations of how this surprising behavior is possible, see, e.g., Sang Michael Xie et al., *An Explanation of In-context Learning as Implicit Bayesian Inference* (2021); Sewon Min et al., *Rethinking the Role of Demonstrations: What Makes In-Context Learning Work?* <https://arxiv.org/abs/2202.12837> (2022); Sang Michael Xie & Sewon Min, *How Does In-context Learning Work? A Framework for Understanding the Differences From Traditional Supervised Learning*, Stanford AI Lab Blog (August 1, 2022); David Dohan et al., *Language Model Cascades*, arXiv:2207.10342 (2022) <https://arxiv.org/abs/2207.10342>. In-context learning, or “prompting” (see next footnote) is an example of surprising behavior, see, Rishi Bommasani et al., *On the Opportunities and Risks of Foundation Models*, arxiv.org (Aug. 18, 2021) at 116 <https://arxiv.org/pdf/2108.07258.pdf> (“Similarly, small rewordings of prompts can have large impacts on task performance. Since the space of prompts is intractable to enumerate, it is challenging to definitively assert that any task is outside the reach of current prompt-based foundation models — this is a major challenge for reasoning about possible catastrophic risks from foundation models.”)

¹¹⁵ See, e.g., Jason Wei et al., *Chain of Thought Prompting Elicits Reasoning in Large Language Models*, arXiv:2201.11903 (2022); Adi Robertson, *PROFESSIONAL AI WHISPERERS HAVE LAUNCHED A MARKETPLACE FOR DALL-E PROMPTS: AI art isn’t just an experiment — it’s a side hustle* (Sep 2, 2022) <https://www.theverge.com/2022/9/2/23326868/dalle-midjourney-ai-promptbase-prompt-market-sales-artist-interview> (a marketplace for “prompt engineers”).

prompting¹¹⁶ – for “zero-shot reasoning.”¹¹⁷ Foundation Models excel in natural language processing, but they are also being successfully applied beyond text data.¹¹⁸ Large models are being released as open source, further democratizing their use and distributing their impact.¹¹⁹

Increased task capabilities could allow us to better align AI with humans and with society more broadly, if the capabilities are harnessed properly.¹²⁰ If AGI is attained, according to one of

¹¹⁶ See, e.g., Antonia Creswell & Murray Shanahan, *Faithful Reasoning Using Large Language Models* (2022) <https://arxiv.org/abs/2208.14271> at 15 (“Our approach exemplifies a trend towards algorithmic prompting, a form of automated prompt engineering in which querying a language model becomes a computational primitive. The responses of the language model can be manipulated to construct new prompts that are then used to make further queries. Model queries and prompt construction are composed into algorithms with the usual computational constructs: sequence, choice, and iteration. Algorithmic prompting can be used to elicit more sophisticated and nuanced behaviour from a language model than would otherwise be possible. For example, as our work shows, this approach can be used to develop models capable of faithful reasoning, without compromising performance.”); Zhuosheng Zhang, Aston Zhang, Mu Li & Alex Smola, *Automatic Chain of Thought Prompting in Large Language Models* (2022) <https://arxiv.org/abs/2210.03493>.

¹¹⁷ See, e.g., Kojima et al., *Large Language Models are Zero-Shot Reasoners* (2022) at 1 (“we show that LLMs are decent zero-shot reasoners by simply adding “Let’s think step by step” before each answer [...] The versatility of this single prompt across very diverse reasoning tasks hints at untapped and understudied fundamental zero-shot capabilities of LLMs, suggesting high-level, multi-task broad cognitive capabilities may be extracted by simple prompting.”); Victor Sanh et al., *Multitask Prompted Training Enables Zero-Shot Task Generalization* (2022); K. Bostrom, Z. Sprague, S. Chaudhuri & G. Durrett, *Natural Language Deduction Through Search Over Statement Compositions*, arXiv:2201.06028 (2022); E. Zelikman, Y. Wu & N. D. Goodman, *Star: Bootstrapping Reasoning with Reasoning*, arXiv:2203.14465 (2022) <https://arxiv.org/abs/2203.14465> (“STaR lets a model improve itself by learning from its own generated reasoning.”); Ofir Press et al., *Measuring and Narrowing the Compositionality Gap in Language Models* (2022) <https://arxiv.org/abs/2210.03350>; Jang et al., *BC-Z: Zero-Shot Task Generalization with Robotic Imitation Learning* (2021); Tanya Goyal, Junyi Jessy Li & Greg Durrett, *News Summarization and Evaluation in the Era of GPT-3* (2022) <https://arxiv.org/abs/2209.12356>.

¹¹⁸ See, e.g., Kevin Lu et al., *Pretrained Transformers as Universal Computation Engines* (2021) (They “find language-pretrained transformers can obtain strong performance on a variety of non-language tasks.”); Lili Chen et al., *Decision Transformer: Reinforcement Learning via Sequence Modeling* (2021) (They abstract reinforcement learning as a sequence modeling problem like language modeling and then leverage a Transformer architecture to condition on the desired reward, past states, and actions, to generate future actions.); Kuang-Huei Lee et al., *Multi-Game Decision Transformers* (2022); Mengdi Xu et al., *Prompting Decision Transformer for Few-Shot Policy Generalization*, in Proceedings of the 39th International Conference on Machine Learning, PMLR 162 24631-24645 (2022); Micah Carroll et al., *Towards Flexible Inference in Sequential Decision Problems via Bidirectional Transformers* (2022) (They develop and test “a framework for flexibly defining and training models which: 1) are naturally able to represent any inference task and support multi-task training in sequential decision problems, 2) match or surpass the performance of specialized models after multi-task pre-training, and almost always surpasses them after fine-tuning.”); Victor Sanh et al., *Multitask Prompted Training Enables Zero-Shot Task Generalization* (2022) (They develop and test a system for converting any natural language tasks into a human-readable prompt form.).

¹¹⁹ See, e.g., Melissa Heikkilä, *BLOOM: Inside the Radical New Project to Democratize AI*, In MIT Technology Review (2022) (A large language model matching in scale some of the best performing large models from OpenAI, Google, and others was trained and released open source in July 2022 by over 1,000 volunteers.); *CodeGen* <https://github.com/salesforce/CodeGen> (“CodeGen is an open-source model for program synthesis [that is] competitive with OpenAI Codex.”); *Stable Diffusion* <https://github.com/CompVis/stable-diffusion> (“Stable Diffusion is a latent text-to-image diffusion model. [...] Similar to Google’s Imagen, this model uses a frozen CLIP ViT-L/14 text encoder to condition the model on text prompts [...] the model is relatively lightweight and runs on a GPU with at least 10GB VRAM.”); *Hugging Face T5* https://huggingface.co/docs/transformers/model_doc/t5 (“T5 is an encoder-decoder model pre-trained on a multi-task mixture of unsupervised and supervised tasks and for which each task is converted into a text-to-text format.”); Thomas I. Liao, *Foundation Model Tracker* (2022) <https://foundationmodeltracker.notion.site/foundationmodeltracker/Model-Tracker-v0-9-794ba77f74ec469186efdbdb87e9b8e6>.

¹²⁰ See, Dan Hendrycks & Mantas Mazeika, *X-Risk Analysis for AI Research* (2022) at 8 (“Improving an agent’s world model makes them more generally capable, but this also can make them less likely to spawn unintended consequences.

the more pessimistic (and most prominent) alignment theorists, Eliezer Yudkowsky, “[s]eemingly ‘simple’ proposals [for ensuring super-intelligent systems realize a positive outcome for humans] are likely to have unexpected undesirable consequences, overlooked as possibilities because our implicit background preferences operate invisibly to constrain which solutions we generate for consideration. [...] There is little prospect of an outcome that realizes even the value of being interesting, unless the first superintelligences undergo detailed inheritance from human values.”¹²¹ Our contention is that inheriting an understanding of legal reasoning, legal interpretation methods, legal standards, and public law could provide future advanced AI a more comprehensive view of what humans want. Although we are, debatably, not yet near AGI, addressing safety risks earlier in the deployment lifecycle of powerful technologies likely leads to better outcomes.¹²² Therefore, we propose a legal understanding verification process that *scales with* AI task capabilities, calibrated to the difficulty level of the legal reasoning and interpretation tasks from “AI-contract,” to “AI-standards,” to “AI-public” capability.

2. Legal Understanding Demonstrations

In most existing applications, before AI models are deployed, their performance on the task at hand is validated on data not employed for their training in order to demonstrate generalizability (task performance in circumstances sufficiently different than training data that is commensurate with task performance on training data). This out-of-sample performance evaluation is as a demonstration of a capability related to a specific human’s (or organization’s) preferences. In our framework, this is a demonstration of the AI’s “understanding” of the terms of an (implied) “contract” between the AI and the human(s) it is conducting tasks for (Figure 5).

Optimizers operating over longer time horizons will be able to accomplish more difficult goals, but this could also make models act more prudently and avoid taking irreversible actions.”).

¹²¹ Eliezer Yudkowsky, *Complex Value Systems are Required to Realize Valuable Futures*, In *Artificial General Intelligence: 4th International Conference, AGI 2011*, Proceedings edited by Jürgen Schmidhuber, Kristinn R. Thórisson & Moshe Looks, 388–393, Vol. 6830 (2011) at 14 <https://intelligence.org/files/ComplexValues.pdf>.

¹²² See, e.g., Dan Hendrycks & Mantas Mazeika, *X-Risk Analysis for AI Research* (2022) at 6 (“Many early Internet protocols were not designed with safety and security in mind. Since safety and security features were not built in early, the Internet remains far less secure than it could have been, and we continue to pay large continuing costs as a consequence.”); Dan Hendrycks et al., *Unsolved Problems in ML Safety* (2021) at 1 (“If attention to safety is delayed, its impact is limited, as unsafe design choices become deeply embedded into the system. [...] relying on experts to test safety solutions is not enough—solutions must also be age tested. The test of time is needed even in the most rigorous of disciplines. A century before the four color theorem was proved, Kempe’s peer-reviewed proof went unchallenged for years until, finally, a flaw was uncovered. Beginning the research process early allows for more prudent design and more rigorous testing.” (Citations omitted.)). See, generally, Nancy G. Leveson, *Engineering a Safer World: Systems Thinking Applied to Safety*, MIT Press (2016).

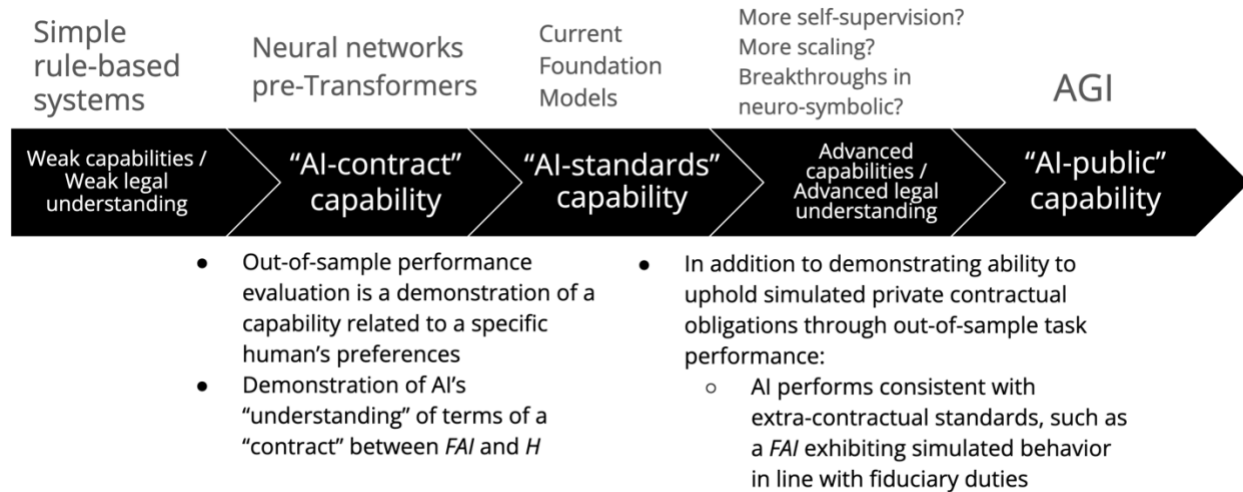


Figure 5: "AI-contract" level and "AI-standards" level alignment benchmarking.

If AI is only at an "AI-contract" capability level, and deployed only on a narrow task, we have no expectation of it being able to autonomously track and comply with public law. This is the status quo for most deployments. It does not mean that the AI will necessarily violate the law; rather, it's an admission that the AI is not advanced enough to understand the legal context in any meaningful sense.¹²³

AI general task capabilities are advancing faster than AI safety because there is vastly more effort on the former.¹²⁴ To help close this gap,¹²⁵ before AI models are deployed in increasingly agentic capacities, e.g., fully autonomous vehicles on most major roads,¹²⁶ the deploying party

¹²³ See, e.g., John Nay & James Daily, *Aligning Artificial Intelligence with Humans through Public Policy* (2022). [Hereinafter Nay, *Aligning AI through Public Policy*].

¹²⁴ See, e.g., Dan Hendrycks & Thomas Woodside, *Introduction to Pragmatic AI Safety* (May 9, 2022) <https://www.alignmentforum.org/posts/bffA9WC9nEJhtagQi/introduction-to-pragmatic-ai-safety-pragmatic-ai-safety-1> ("Machine learning has been outpacing safety [...] Meanwhile, existing approaches to AI safety have not seen similar strides. Many older approaches are still pre-paradigmatic, uncertain about what concrete research directions should be pursued and still aiming to get their bearings. Centered on math and theory, this research focuses on studying strictly futuristic risks that result from potential systems. Unfortunately, not much progress has been made"). This general technological governance issue is often framed as the "pacing problem," see, e.g., Gary E. Marchant, *Governance of Emerging Technologies as a Wicked Problem*, Vand. L. Rev. 73 1861 (2020); Adam Thierer, *The Pacing Problem and the Future of Technology Regulation* (2018).

¹²⁵ For other recommendations of potential policy responses, see, e.g., Ryan Calo, *Artificial Intelligence Policy: A Primer and Roadmap*, UC DL Rev. Vol. 51 (2017); Jessica Fjeld et al., *Principled Artificial Intelligence: Mapping Consensus in Ethical and Rights-Based Approaches to Principles for AI* (2020) at 34. For a dashboard of international AI policies, see the OECD AI's live repository of over 260 AI policies. For specific recent federal U.S. government proposals, see, e.g., Aiming for truth, fairness, and equity in your company's use of AI, Federal Trade Commission, <https://www.reginfo.gov/public/do/eAgendaViewRule?pubId=202110&RIN=3084-AB69>; EEOC Launches Initiative on Artificial Intelligence and Algorithmic Fairness, US Equal Employment Opportunity Commission; Agencies Seek Wide Range of Views on Financial Institutions' Use of Artificial Intelligence; Federal Register, Artificial Intelligence Risk Management Framework.

¹²⁶ National Conference of State Legislatures, *Autonomous Vehicles / Self-Driving Vehicles Enacted Legislation*, ncsl.org (Feb. 18, 2020), <https://www.ncsl.org/research/transportation/autonomous-vehicles-self-driving-vehicles-enacted-legislation.aspx>.

should demonstrate¹²⁷ the AI’s understanding of human goals, policies, and legal standards.¹²⁸ A validation procedure could illustrate the AI’s “understanding” of the “meaning” of legal concepts.¹²⁹

In addition to demonstrating its ability to uphold private contractual obligations (e.g., through acceptable out-of-sample task performance), sufficiently capable AI should demonstrate an ability to perform consistent with extra-contractual standards, such as a fully automated investment advisory system exhibiting simulated behavior in line with fiduciary duties to a human principal.

Sufficiently agentic AI¹³⁰ should demonstrate comprehension of the public law that will be relevant to its behavior if deployed.¹³¹ This is a very difficult threshold to pass.¹³²

Although super-human intelligence would be able to conduct legal reasoning beyond the capability of any lawyer, legal questions ultimately bottom out at a mechanism for resolution: the governmental legal system.¹³³ We cannot fully understand the decisions of superhuman AI. Similarly, courts do not purport to have any substantive understanding of technical details or science behind complex cases they provide final determinations on. The law is designed to resolve outcomes without requiring judges to have domain knowledge (or cognitive capacity) anywhere near the level of the parties or technologies involved. Therefore, if alignment is driven by understanding of legal information and legal reasoning, humans can assess alignment of more intelligent AI. This is an important feature of the *Law Informs Code* framework. Compare this to ethics – a widely discussed potential source of human values for AI alignment – where it is unclear how we could evaluate (or what would even constitute) super-intelligent ethical decisions because there is no mechanism external to the AI that can legitimately resolve ethical deliberation.¹³⁴

¹²⁷ Demonstrate to governments, ideally. *See, e.g.*, Jess Whittlestone & Jack Clark, *Why and How Governments Should Monitor AI Development*, arXiv:2108.12427 (2021).

¹²⁸ *See infra* Section III.

¹²⁹ For a definition of “meaning” that would be appropriate here, *see, e.g.*, Christopher D. Manning, *Human Language Understanding & Reasoning*, *Daedalus* 151, no. 2 127-138 (2022) at 134, 135 (“Meaning is not all or nothing; in many circumstances, we partially appreciate the meaning of a linguistic form. I suggest that meaning arises from understanding the network of connections between a linguistic form and other things, whether they be objects in the world or other linguistic forms. If we possess a dense network of connections, then we have a good sense of the meaning of the linguistic form. For example, if I have held an Indian shehnai, then I have a reasonable idea of the meaning of the word, but I would have a richer meaning if I had also heard one being played [...] Using this definition whereby understanding meaning consists of understanding networks of connections of linguistic forms, there can be no doubt that pre-trained language models learn meanings.”).

¹³⁰ For a description of advanced AI capabilities and agentic planning, *see, e.g.*, Joseph Carlsmith, *Is Power-Seeking AI an Existential Risk?* (2022) at 4-7.

¹³¹ *See infra* Section IV; Nay, *Aligning AI through Public Policy*.

¹³² *See, e.g.*, Daniel J. Gervais, *Towards an Effective Transnational Regulation of AI*, *AI & Society* 1-20 (2021) at 6 (“Take just this well-known example: *Carlsbad Technology, Inc. v. HIF Bio, Inc.*, 556 U.S. 635 (2008). Looking at the statute involved in that case (28 U. S. C. §1441(c)), would lead to an entirely incorrect understanding of “the law” because the Supreme Court’s interpretation of the statute—the exact opposite of what the text of the statute actually says—is what courts are bound to follow under *stare decisis*.”). *See*, avenues of AI research focused on resolving conflicting norms, *e.g.*, Daniel Kasenberg & Matthias Scheutz, *Inverse Norm Conflict Resolution*, in *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*, 178-183 (2018).

¹³³ *See, e.g.*, Figure 6.

¹³⁴ *See infra* Section IV.A.

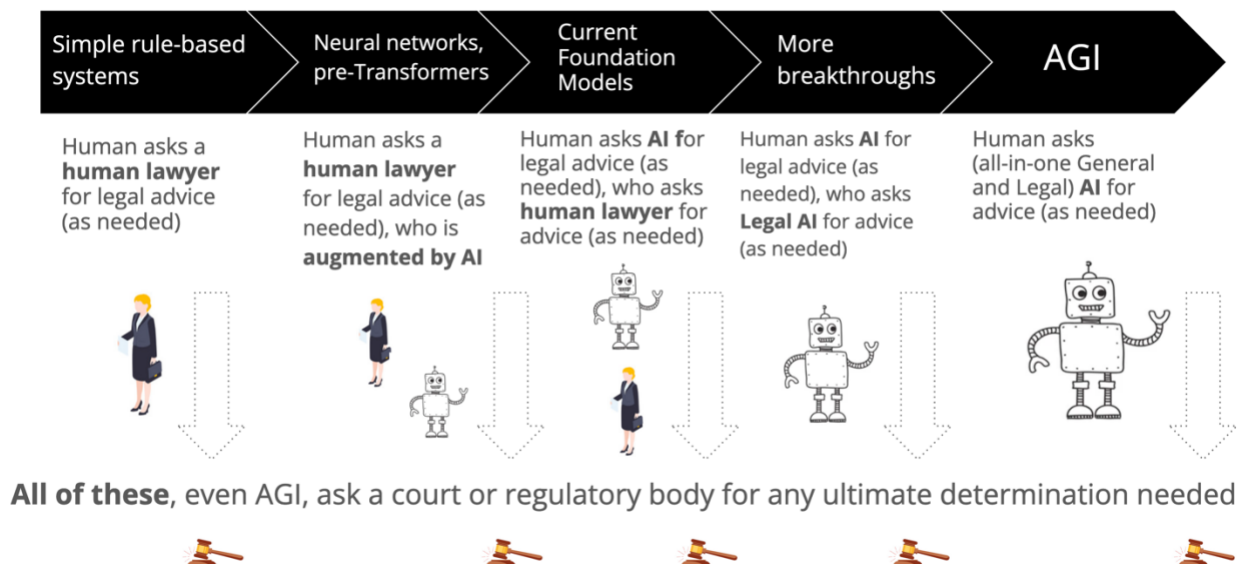


Figure 6: In the example of scaling legal practice, as AI capabilities surpass humans, the Law Informs Code approach to AI alignment keeps the process ultimately grounded in human judgment.

As the state-of-the-art for AI advances, there should be a higher bar of demonstrated legal understanding.¹³⁵ If an AI developer claims their system has advanced capabilities on tasks that it would like the AI to complete outside of its training environment, the developer should show correspondingly advanced legal knowledge and legal reasoning abilities of the system.

One of the technical impediments to alignment,¹³⁶ especially of deep learning models,¹³⁷ is the difficulty of understanding the model and the causes of its behaviors once trained.¹³⁸ This

¹³⁵ Scholars have suggested we use AI “Guardians” to monitor operational AI systems once they are deployed, *see, e.g.,* Amitai Etzioni & Oren Etzioni, *Keeping AI Legal*, 19 *Vanderbilt Journal of Entertainment and Technology Law* 133 (2016) at 139, “From here on, AI should be divided into two categories. The first category would consist of operational AI programs - the computerized “brains” that guide smart instruments. The second category would be composed of oversight AI programs that review the first category’s decision making and keep the decisions in line with the law. These oversight programs, which this Article calls “AI Guardians,” would include AI programs to interrogate, discover, supervise, audit, and guarantee the compliance of operational AI programs.” Our proposal is focused on AI systems demonstrating their own legal understanding, but our discussion of seeking parity between AI capabilities and AI legal understanding is related to what would be required to technically implement the Etzioni’s proposal, at 146, “These AI Guardians will need to become smarter just as operational AI programs are improving.”

¹³⁶ *See, e.g.,* Brian Christian, *The Alignment Problem: Machine Learning and Human Values* (2020).

¹³⁷ *See, e.g.,* Tilman Räuukur, Anson Ho, Stephen Casper & Dylan Hadfield-Menell, *Toward Transparent AI: A Survey on Interpreting the Inner Structures of Deep Neural Networks*, arXiv:2207.13243 (2022) <https://arxiv.org/abs/2207.13243>.

¹³⁸ *See, generally,* M. Danilevsky et al., *A Survey of the State of Explainable AI for Natural Language Processing* (2020). For some of the latest methods for interpretability of large generative machine learning models, *see, e.g.,* Ganguli et al., *Predictability and Surprise in Large Generative Models* <https://dl.acm.org/doi/abs/10.1145/3531146.3533229> (2022). For a counter-argument for the need for explainability in the context of autonomous systems acting legally, *see, e.g.,* Henry Prakken, *On How AI & Law Can Help Autonomous Systems Obey the Law: A Position Paper*, *AI4J—Artificial Intelligence for Justice* 42, 42-46 (2016) at 44 (“the legal tasks supported by traditional AI & law tools require explanation and justification of decisions. With autonomous systems there is no need for this; all that counts is that legally acceptable behaviour is generated. Of course, when an autonomous system does something legally wrong, its behaviour might have to be explained in a court case. However, this does not require that the system itself can do that; it may suffice to have a log file recording the system’s internal actions.”); *see, also, e.g.,* Michael Kearns & Aaron Roth, *The Ethical Algorithm: The Science of*

generally worsens as models scale in size and complexity.¹³⁹ Understanding the inner workings of AI is helpful for editing its beliefs,¹⁴⁰ and validating its safety,¹⁴¹ reliability, and legal comprehension abilities.¹⁴² Training deep learning models on legal data, where learned intermediate model representations can correspond to legal concepts, opens the possibility for mechanistic (alignment) interpretability¹⁴³ (methods for reverse engineering key components of AI to better understand its tendencies). If neural networks learn representations of human interpretable legal knowledge¹⁴⁴ as a substrate of the model, and if legal concepts are the ontology for alignment (as this Article argues), viewing their use inside a model could help us understand if and how a model is aligned.

We should supplement mechanistic explanations with a behavioral perspective. Simulations exploring the actions of machine-learning-based decision-making models throughout state-action space can uncover patterns of agent decision-making.¹⁴⁵ Safety benchmarks have been developed for simple environments for AI agents trained with reinforcement learning.¹⁴⁶ Similar

Socially Aware Algorithm Design (Oxford University Press, 2019) at 170-175 (Defining “interpretability” depends on the audience and the model type and task.).

¹³⁹ Info. Law Inst. at N.Y. Univ. Sch. of Law with Foster Provost, Krishna Gummadi, Anupam Datta, Enrico Bertini, Alexandra Chouldechova, Zachary Lipton & John Nay, *Modes of Explanation in Machine Learning: What Is Possible and What Are the Tradeoffs?*, in *Algorithms and Explanations* (Apr. 27, 2017), <https://youtu.be/U0NsxZQTtk>.

¹⁴⁰ Kevin Meng, David Bau, Alex Andonian & Yonatan Belinkov, *Locating and Editing Factual Associations in GPT*, arXiv:2202.05262 (2022).

¹⁴¹ Understanding the models is also important for dealing with “inner alignment” problems that may arise with more powerful AI systems because it could help uncover instances of AI models deceiving humans, and situations where AI models are solving subproblems unforeseen in the original problem specification; *see, e.g.*, Evan Hubinger et al., *Risks From Learned Optimization in Advanced Machine Learning Systems* (2019). For more on explainable AI in the alignment context, *see, e.g.*, Y. Belinkov & J. Glass, *Analysis Methods in Neural Language Processing: A Survey*, In *Transactions of the Association for Computational Linguistics*, 7: 49–72 (2019); Evan Hubinger, *Relaxed Adversarial Training for Inner Alignment* (September 10, 2019) <https://www.alignmentforum.org/posts/9Dy5YRaoCxH9zuJqa/relaxed-adversarial-training-for-inner-alignment>. For more on interpreting the inner workings of AI models, *see, e.g.*, Chris Olah et al., *Zoom In: An Introduction to Circuits*, 5.3 e00024-001 Distill (March 10, 2020) <https://distill.pub/2020/circuits/zoom-in/>; Chelsea Voss et al., *Visualizing Weights* 6.2 e00024-007 Distill (2021).

¹⁴² *See, e.g.*, Katie Atkinson, Trevor Bench-Capon & Danushka Bollegala, *Explanation in AI and Law: Past, Present and Future*, *Artificial Intelligence* 289 (2020) at 1 (“insights from AI and Law, where explanation has long been a concern, may provide useful pointers for future development of explainable AI.”); P. Jonathon Phillips et al., *Four Principles of Explainable Artificial Intelligence*, *Natl. Inst. Stand. Technol. Interag. Intern. Rep.* 8312 (September 2021) <https://nvlpubs.nist.gov/nistpubs/ir/2021/NIST.IR.8312.pdf>; Katherine J. Strandburg, *Rulemaking and Inscrutable Automated Decision Tools*, *Columbia Law Review* 119, no. 7 1851-1886 (2019).

¹⁴³ *See, e.g.*, Chris Olah, *Mechanistic Interpretability, Variables, and the Importance of Interpretable Bases* (June 27, 2022) <https://transformer-circuits.pub/2022/mech-interp-essay/index.html>.

¹⁴⁴ *See, e.g.*, John Nay, *Gov2Vec: Learning Distributed Representations of Institutions and Their Legal Text*, in *Proceedings of 2016 Empirical Methods in Natural Language Processing Workshop on NLP and Computational Social Science*, 49–54, Association for Computational Linguistics, (November 5, 2016).

¹⁴⁵ *See, e.g.*, John Nay, *A Machine Learning Approach to Modeling Dynamic Decision-Making in Strategic Interactions and Prediction Markets*, Vanderbilt University (2017) <https://www.proquest.com/pagepdf/2007010189?accountid=12768>; John Nay & Yevgeniy Vorobeychik, *Predicting Human Cooperation*, *PLoS One* 11, no. 5 (2016); John Nay & Jonathan M. Gilligan, *Data-driven Dynamic Decision Models*, in 2015 Winter Simulation Conference (WSC) 2752-2763, IEEE (2015); John Nay, Martin Van der Linden & Jonathan M. Gilligan, *Betting and Belief: Prediction Markets and Attribution of Climate Change*, in 2016 Winter Simulation Conference (WSC) 1666-1677, IEEE (2016).

¹⁴⁶ *See, e.g.*, Alex Ray, Joshua Achiam & Dario Amodei, *Benchmarking Safe Exploration in Deep Reinforcement Learning* (2019); Daniel S. Brown, Jordan Schneider, Anca Dragan & Scott Niekum, *Value Alignment Verification*, In *International Conference on Machine Learning*, 1105-1115, PMLR (2021).

approaches could help demonstrate an AI's comprehension of legal standards before it is permitted to act in the real world.¹⁴⁷ This would not be a fool-proof deterministic verification.¹⁴⁸ From a legal perspective, this is analogous to the certification of legal and regulatory understanding for professionals such as financial advisors, with the key difference that there is a relatively costless assessment of AI legal understanding. Relative to the professional certification and subsequent testing we currently impose on humans providing specialized services such as financial advising, it is significantly less expensive to run millions of simulations of scenarios to test an AI's comprehension of relevant legal standards and regulations.¹⁴⁹ It is now possible to conduct social science research on data generated by simulating persons by using Foundation Models conditioned on human data.¹⁵⁰ Applying empirical social science methods to simulations of AI behavior is a promising approach to measuring AI legal understanding.

¹⁴⁷ See, e.g., Malgieri & Pasquale, *From Transparency to Justification: Toward Ex Ante Accountability for AI* (2022) (they propose “a system of “unlawfulness by default” for AI systems, an ex-ante model where some AI developers have the burden of proof to demonstrate that their technology is not discriminatory, not manipulative, not unfair, not inaccurate, and not illegitimate in its legal bases and purposes.”). For other proposals related to the certification or verification of AI systems before and during deployment, see, e.g., Miles Brundage et al., *Toward Trustworthy AI Development: Mechanisms for Supporting Verifiable Claims* (2020); Inioluwa Deborah Raji et al., *Outsider Oversight: Designing a Third Party Audit Ecosystem for AI Governance* (2022); Gregory Falco et al., *Governing AI Safety Through Independent Audits*, *Nature Machine Intelligence*, Vol 3, 566–571 (2021); Peter Cihon et al., *AI Certification: Advancing Ethical Practice by Reducing Information Asymmetries*, *IEEE Transactions on Technology and Society* 2.4, 200-209 (2021); Andrew Tutt, *An FDA For Algorithms*, *Admin. L. Rev.* Vol. 69, No. 1, 83 (2017) at 122 (argues that there is a “close analog between complex pharmaceuticals and sophisticated algorithms[...]” and therefore the FDA provides a model for a new regulatory agency for algorithms); Florian Moslein & Roberto Zicari, *Certifying Artificial Intelligence Systems*, in *BIG DATA LAW* (Roland Vogl ed., 2021); Thomas Arnold & Matthias Scheutz, *The “Big Red Button” Is Too Late: An Alternative Model for the Ethical Evaluation of AI systems*, *Ethics and Information Technology* (2018) at 60 (“We outline a system architecture consisting of an ethical core layer above the hardware and below the virtual machine layer that consists of scenario-generation and simulation engines,”). For a proposal for verification of AI systems before deployment, specifically related to reinforcement learning decision-making systems, see, e.g., Thomas Krendl Gilbert, Sarah Dean, Tom Zick & Nathan Lambert, *Choices, Risks, and Reward Reports: Charting Public Policy for Reinforcement Learning Systems* (2022).

¹⁴⁸ See, e.g., Stanley Bak, Changliu Liu & Taylor Johnson, *The Second International Verification of Neural Networks Competition (vnn-comp 2021): Summary and Results*, arXiv:2109.00498 (2021). For a discussion of the difficulty of verifying the security of software systems and the analogy to aligning AI, see, e.g., elspood, *Security Mindset: Lessons from 20+ years of Software Security Failures Relevant to AGI Alignment* (June 21, 2022). Developing robust verification processes is extremely difficult. Much more deterministic and much simpler software than AI systems cannot be fully trusted, see, e.g., Ken Thompson, *Reflections on Trusting Trust*, 27 *CACM* 761 (1984) <https://archive.ph/gi1W8> (“You can't trust code that you did not totally create yourself. [...] No amount of source-level verification or scrutiny will protect you from using untrusted code.”).

¹⁴⁹ For a proposal on monitoring AI systems once they are deployed, see, e.g., Amitai Etzioni & Oren Etzioni, *Keeping AI Legal*, 19 *Vanderbilt Journal of Entertainment and Technology Law* 133 (2016) at 139, 146 (“From here on, AI should be divided into two categories. The first category would consist of operational AI programs - the computerized “brains” that guide smart instruments. The second category would be composed of oversight AI programs that review the first category's decision making and keep the decisions in line with the law. These oversight programs, which this Article calls “AI Guardians,” would include AI programs to interrogate, discover, supervise, audit, and guarantee the compliance of operational AI programs. [...] These AI Guardians will need to become smarter just as operational AI programs are improving [...] humans may have little choice but to draw on AI to check AI - and to seek to increase oversight of artificial intelligence as the intelligence of the programs they oversee grows.”).

¹⁵⁰ See, e.g., Lisa P. Argyle et al., *Out of One, Many: Using Language Models to Simulate Human Samples* (2022) <https://arxiv.org/abs/2209.06899>.

3. *Legal Understanding as the Alignment Benchmark*

Progress in AI research is driven, in large part, by shared benchmarks that thousands of researchers globally use to guide experiments, understand as a community whether model approaches and data are improving AI capabilities, and compare results across research groups.¹⁵¹ AI performance on benchmarks are one of the primary “objective functions” of the overall global research apparatus.¹⁵² As quantitative lodestars, benchmarks create perverse incentives to build AI that optimizes for benchmark performance at the expense of true generalization and intelligence,¹⁵³ see, e.g., “Goodhart’s Law,” colloquially communicated as, “when a measure becomes a target, it ceases to be a good measure.”¹⁵⁴ Many AI benchmarks have a significant number of errors,¹⁵⁵ which suggests that in some cases machine learning models have, more than widely recognized, “overfitted to memorizing data instead of learning abstract concepts.”¹⁵⁶ There are spurious cues within benchmark data that, once removed, significantly drop model performance, demonstrating that models are often learning patterns that do not generalize outside of the closed world of the benchmark data.¹⁵⁷ Many benchmarks, especially in natural language processing, have become saturated,¹⁵⁸ as “contemporary models quickly achieve outstanding performance on benchmark tasks but nonetheless fail on simple challenge examples and falter in real-world scenarios.”¹⁵⁹ Benchmarking AI capabilities is difficult.¹⁶⁰ Benchmarking AI alignment has the same issues, but

¹⁵¹ Douwe Kiela et al., *Dynabench: Rethinking Benchmarking in NLP*, in Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies 4110–4124 (Association for Computational Linguistics, 2021) [Hereinafter Douwe Kiela, *Dynabench*]; Samuel Bowman & George Dahl, *What Will it Take to Fix Benchmarking in Natural Language Understanding?*, in Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (2021).

¹⁵² For more on this generalized notion of an objective function, see, Kenneth O. Stanley & Joel Lehman, *Why Greatness Cannot Be Planned: The Myth of the Objective* (2015).

¹⁵³ See, generally, the footnote above discussing the shortcut rule (François Chollet, *Deep Learning with Python, Second Edition* (2021) at 450). See, e.g., Adriano Barbosa-Silva et al., *Mapping Global Dynamics of Benchmark Creation and Saturation in Artificial Intelligence* (2022) at 1 (“We curated data for 1688 benchmarks covering the entire domains of computer vision and natural language processing, and show that a large fraction of benchmarks quickly trended towards near-saturation.”).

¹⁵⁴ Charles Goodhart, *Problems of Monetary Management: The U.K. Experience*, In Courakis, Anthony S. (ed.). *Inflation, Depression, and Economic Policy in the West* (1975); See, e.g., Peter Coy, *Goodhart’s Law Rules the Modern World. Here Are Nine Examples*, Bloomberg.com (March 26, 2021); David Manheim & Scott Garrabrant, *Categorizing Variants of Goodhart’s Law* (2018).

¹⁵⁵ Curtis G. Northcutt, Anish Athalye & Jonas Mueller, *Pervasive Label Errors in Test Sets Destabilize Machine Learning Benchmarks* (2021).

¹⁵⁶ Björn Barz & Joachim Denzler, *Do We Train on Test Data? Purging CIFAR of Near-Duplicates* (2020) at 1.

¹⁵⁷ See, e.g., Ronan Le Bras et al., *Adversarial Filters of Dataset Biases*, in Proceedings of the 37th International Conference on Machine Learning, PMLR 119:1078-1088 (2020).

¹⁵⁸ Samuel Bowman & George Dahl, *What Will it Take to Fix Benchmarking in Natural Language Understanding?*, in Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (2021).

¹⁵⁹ Douwe Kiela *Dynabench* at 4110.

¹⁶⁰ See, e.g., Tanya Goyal, Junyi Jessy Li & Greg Durrett, *News Summarization and Evaluation in the Era of GPT-3* (2022) <https://arxiv.org/abs/2209.12356> (“In recent years, research in text summarization has typically relied on comparisons with gold test sets for evaluation, possibly augmented with reference-free metrics for dimensions like factuality. This paper shows that all these metrics are completely ineffective at evaluating GPT-3 summaries.” (Citations omitted.)).

compounded by vaguer problem definitions. There is also far less research on AI alignment benchmarks.

Performing well on societal alignment is more difficult than performing well on task capabilities.¹⁶¹ Because alignment is so fundamentally hard, the sky should be the limit on the difficulty of alignment benchmarks.¹⁶² Legal-informatics-based benchmarks could serve as AI alignment benchmarks. Models currently perform worse than expert humans on legal understanding tasks such as statutory reasoning,¹⁶³ professional law,¹⁶⁴ and legal discovery;¹⁶⁵ there is significant room for improvement on legal language processing tasks.¹⁶⁶ Example benchmarks that could be used as part of the overall alignment benchmark are legal search,¹⁶⁷ Bar Exam scores, contract analysis,¹⁶⁸ and identifying legislation that is relevant to a company.¹⁶⁹ Next, we discuss example research directions that could improve the performance of AI on legal understanding benchmarks. A comprehensive suite of benchmark datasets could catalyze research through a desire of the community of researchers to score highly on the leaderboards.

C. Legal Processes, Data & Experts Can Improve AI

Legal informatics may allow us to engineer models in new ways and engineer legal data (both observational data and data derived from human interaction with models) into training signals that help align AI.

¹⁶¹ See, e.g., the human inability to align large numbers of humans or different groups, relative to extraordinary human capabilities on tasks in isolation or small groups.

¹⁶² Researchers are making progress on better characterizing performance on task capabilities beyond simple comparisons of overall performance on monolithic benchmarks, see, e.g., Kawin Ethayarajh et al., *Information-Theoretic Measures of Dataset Difficulty* (2021); Kawin Ethayarajh et al., *Understanding Dataset Difficulty with V-Usable Information* (2022). This work could inform methods to accurately measure alignment capabilities as well.

¹⁶³ See, recent applications in tax law, which is a more rules-based (as opposed to standards-based) area of the U.S. Code, e.g., Nils Holzenberger, Andrew Blair-Stanek & Benjamin Van Durme, *A Dataset for Statutory Reasoning in Tax Law Entailment and Question Answering* (2020); Nils Holzenberger & Benjamin Van Durme, *Factoring Statutory Reasoning as Language Understanding Challenges* (2021).

¹⁶⁴ See e.g., Dan Hendrycks et al., *Measuring Massive Multitask Language Understanding*, arXiv:2009.03300 (2020).

¹⁶⁵ Eugene Yang et al., *Goldilocks: Just-Right Tuning of BERT for Technology-Assisted Review*, in *Advances in Information Retrieval: 44th European Conference on IR Research*, 502–517 (Apr 2022).

¹⁶⁶ See, e.g., Ilias Chalkidis et al., *LexGLUE: A Benchmark Dataset for Legal Language Understanding in English*, in *PROCEEDINGS OF THE 60TH ANNUAL MEETING OF THE ASSOCIATION FOR COMPUTATIONAL LINGUISTICS* (2022); D. Jain, M.D. Borah & A. Biswas, *Summarization of legal documents: where are we now and the way forward*, *Comput. Sci. Rev.* 40, 100388 (2021).

¹⁶⁷ See, Faraz Dadgostari et al., *Modeling Law Search as Prediction*, *A.I. & L.* 29.1, 3-34 (2021) at 3 (“In any given matter, before legal reasoning can take place, the reasoning agent must first engage in a task of “law search” to identify the legal knowledge—cases, statutes, or regulations—that bear on the questions being addressed.”); Michael A. Livermore & Daniel N. Rockmore, *The Law Search Turing Test*, in *Law as Data: Computation, Text, and the Future of Legal Analysis* (2019) at 443-452; Michael A. Livermore et al., *Law Search in the Age of the Algorithm*, *Mich. St. L. Rev.* 1183 (2020).

¹⁶⁸ Dan Hendrycks, Collin Burns, Anya Chen & Spencer Ball, *Cuad: An Expert-Annotated NLP Dataset for Legal Contract Review*, arXiv:2103.06268 (2021).

¹⁶⁹ Nay, *Aligning AI through Public Policy*; John Nay, *Large Language Models as Corporate Lobbyists* (January 2, 2023). Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4316615.

1. Models

The current era of deep learning is characterized in large part by scaling the size of the models and training them with self-supervision (and, recently, adding reinforcement learning from human feedback on top for fine-tuning).¹⁷⁰ There now seems to be evidence that the bottleneck in pushing the capabilities of most AI performance further (e.g., in large language models,¹⁷¹ and recommendation models¹⁷²) is less on the sheer size of the models and more on the amount of useful data, training procedures, and (probably less importantly) model architectures.¹⁷³ Legal informatics is an untapped source of data, a set of symbolic systems that Foundation Models can call on (similar to calling a Python interpreter), and potentially an inspiration for training procedures and model structure tweaks.¹⁷⁴

i. AI Capabilities Can Improve Legal Informatics

The *Law Informs Code* agenda can leverage recent advancements in machine learning.¹⁷⁵ In particular, there are relevant threads of research in natural language processing¹⁷⁶ with large language models trained with self-supervision; deep reinforcement learning; the intersection of large language models and deep reinforcement learning;¹⁷⁷ and “safe reinforcement learning”¹⁷⁸

¹⁷⁰ Computing power is a key factor in AI model performance, *see, e.g.*, Richard Sutton, *The Bitter Lesson*, Incomplete Ideas (blog), 13 12 (2019) <http://www.incompleteideas.net/IncIdeas/BitterLesson.html>. (“The biggest lesson that can be read from 70 years of AI research is that general methods that leverage computation are ultimately the most effective, and by a large margin. The ultimate reason for this is Moore's law, or rather its generalization of continued exponentially falling cost per unit of computation.”).

¹⁷¹ Jordan Hoffmann et al., *Training Compute-Optimal Large Language Models* (2022) <https://arxiv.org/abs/2203.15556>.

¹⁷² Newsha Ardalani et al., *Understanding Scaling Laws for Recommendation Models* (2022) <https://arxiv.org/abs/2208.08489>.

¹⁷³ Marcos Treviso et al., *Efficient Methods for Natural Language Processing: A Survey* (2022) <https://arxiv.org/abs/2209.00099>.

¹⁷⁴ *See infra* Section II.C.1.ii.

¹⁷⁵ *See, e.g.*, Daniel Martin Katz & John Nay, *Machine Learning and Law*, in *LEGAL INFORMATICS* (Daniel Martin Katz et al. eds., 2021).

¹⁷⁶ For natural language processing methods applied to legal text, *see, e.g.*, John Nay, *Natural Language Processing for Legal Texts*, in *LEGAL INFORMATICS* (Daniel Martin Katz et al. eds. 2021); John Nay, *Natural Language Processing and Machine Learning for Law and Policy Texts* (April 7, 2018) <https://ssrn.com/abstract=3438276>; Michael A. Livermore & Daniel N. Rockmore, *Distant Reading the Law*, in *Law as Data: Computation, Text, and the Future of Legal Analysis* (2019) 3-19; J.B. Ruhl, John Nay & Jonathan Gilligan, *Topic Modeling the President: Conventional and Computational Methods*, 86 *GEO. WASH. L. REV.* 1243 (2018); John Nay, *Predicting and Understanding Law-making with Word Vectors and an Ensemble Model*, 12 *PLOS ONE* 1 (2017); John Nay, *Gov2Vec: Learning Distributed Representations of Institutions and Their Legal Text*, in *Proceedings of 2016 Empirical Methods in Natural Language Processing Workshop on NLP and Computational Social Science*, 49–54, Association for Computational Linguistics, (November 5, 2016).

¹⁷⁷ *See, e.g.*, Prithviraj Ammanabrolu et al., *Aligning to Social Norms and Values in Interactive Narratives* (2022).

¹⁷⁸ *See, e.g.*, Javier Garcia & Fernando Fernandez, *A Comprehensive Survey on Safe Reinforcement Learning*, *Journal of Machine Learning Research*, 16, 1 (2015) at 1437 (“Safe Reinforcement Learning can be defined as the process of learning policies that maximize the expectation of the return in problems in which it is important to ensure reasonable system performance and/or respect safety constraints during the learning and/or deployment processes.”); Philip S. Thomas et al., *Preventing Undesirable Behavior of Intelligent Machines*, *Science* 366.6468 999-1004 (2019); William Saunders et al., *Trial without Error: Towards Safe Reinforcement Learning via Human Intervention* (2017); Markus

(especially where constraints on agent actions can be described in natural language¹⁷⁹). The combination of (a) large language models trained on large corpora of (sometimes explicitly morally salient¹⁸⁰) text powering decision-making agents;¹⁸¹ (b) procedures that learn an

Peschl, Arkady Zgonnikov, Frans A. Oliehoek & Luciano C. Siebert, *MORAL: Aligning AI with Human Norms through Multi-Objective Reinforced Active Learning*, In Proceedings of the 21st International Conference on Autonomous Agents and Multiagent Systems, 1038-1046 (2022).

¹⁷⁹ See, e.g., Tsung-Yen Yang et al., *Safe Reinforcement Learning with Natural Language Constraints* (2021) at 3, 2 (Most research on safe reinforcement learning requires “a human to specify the cost constraints in mathematical or logical form, and the learned constraints cannot be easily reused for new learning tasks. In this work, we design a modular architecture to learn to interpret textual constraints, and demonstrate transfer to new learning tasks.” Tsung-Yen Yang et al. developed “*Policy Optimization with Language CO*nstraints (POLCO), where we disentangle the representation learning for textual constraints from policy learning. Our model first uses a *constraint interpreter* to encode language constraints into representations of forbidden states. Next, a *policy network* operates on these representations and state observations to produce actions. Factorizing the model in this manner allows the agent to retain its constraint comprehension capabilities while modifying its policy network to learn new tasks. Our experiments demonstrate that our approach achieves higher rewards (up to 11x) while maintaining lower constraint violations (up to 1.8x) compared to the baselines on two different domains.”); Bharat Prakash et al., *Guiding safe reinforcement learning policies using structured language constraints*, UMBC Student Collection (2020).

¹⁸⁰ See, e.g., Jin et al., *When to Make Exceptions: Exploring Language Models as Accounts of Human Moral Judgment* (2022) <https://arxiv.org/abs/2210.01478> (“we present a novel challenge set consisting of rule-breaking question answering (RBQA) of cases that involve potentially permissible rule-breaking – inspired by recent moral psychology studies. Using a state-of-the-art large language model (LLM) as a basis, we propose a novel moral chain of thought (MORALCOT) prompting strategy that combines the strengths of LLMs with theories of moral reasoning developed in cognitive science to predict human moral judgments.”); Liwei Jiang et al., *Delphi: Towards Machine Ethics and Norms* (2021) (“1.7M examples of people’s ethical judgments on a broad spectrum of everyday situations”); Dan Hendrycks et al., *Aligning AI With Shared Human Values* (2021) at 2 (“We find that existing natural language processing models pre-trained on vast text corpora and fine-tuned on the ETHICS dataset have low but promising performance. This suggests that current models have much to learn about the morally salient features in the world, but also that it is feasible to make progress on this problem today.”); Nicholas Lourie, Ronan Le Bras & Yejin Choi, *Scruples: A Corpus of Community Ethical Judgments on 32,000 Real-life Anecdotes*, In Proceedings of the AAAI Conference on Artificial Intelligence, vol. 35, no. 15, 13470-13479 (2021) (32,000 real-life ethical situations, with 625,000 ethical judgments.); Frazier et al., *Learning Norms from Stories: A Prior for Value Aligned Agents* (2019).

¹⁸¹ See, e.g., Prithviraj Ammanabrolu et al., *Aligning to Social Norms and Values in Interactive Narratives* (2022) (“We introduce [...] an agent that uses the social commonsense knowledge present in specially trained language models to contextually restrict its action space to only those actions that are aligned with socially beneficial values.”); Md Sultan Al Nahian et al., *Training Value-Aligned Reinforcement Learning Agents Using a Normative Prior* (2021) (“We introduce an approach to value-aligned reinforcement learning, in which we train an agent with two reward signals: a standard task performance reward, plus a normative behavior reward. The normative behavior reward is derived from a value-aligned prior model previously shown to classify text as normative or non-normative. We show how variations on a policy shaping technique can balance these two sources of reward and produce policies that are both effective and perceived as being more normative.”); Dan Hendrycks et al., *What Would Jiminy Cricket Do? Towards Agents That Behave Morally* (2021) (“To facilitate the development of agents that avoid causing wanton harm, we introduce Jiminy Cricket, an environment suite of 25 text-based adventure games with thousands of diverse, morally salient scenarios. By annotating every possible game state, the Jiminy Cricket environments robustly evaluate whether agents can act morally while maximizing reward.”); Shunyu Yao et al., *Keep CALM and Explore: Language Models for Action Generation in Text-based Games* (2020) (“Our key insight is to train language models on human gameplay, where people demonstrate linguistic priors and a general game sense for promising actions conditioned on game history. We combine CALM with a reinforcement learning agent which re-ranks the generated action candidates”); Matthew Hausknecht et al., *Interactive Fiction Games: A Colossal Adventure* (2019) at 1 (“From a machine learning perspective, Interactive Fiction games exist at the intersection of natural language processing and sequential decision making. Like many NLP tasks, they require natural language understanding, but unlike most NLP tasks, IF games are sequential decision making problems in which actions change the subsequent world states”).

automated mapping from natural language to environment dynamics¹⁸² and reward functions of agents;¹⁸³ and (c) offline reinforcement learning (with Transformer-based models)¹⁸⁴ represents a potential opportunity to leverage millions (or even billions) of state-action-value tuples from (natural language) legal text within reinforcement learning paradigms (where AI agents make “decisions”).

We should also experiment with how legal informatics is employed within AI agent decision-making paradigms,¹⁸⁵ e.g., (a) as (natural language¹⁸⁶) constraints;¹⁸⁷ (b) for shaping the reward function during training;¹⁸⁸ (c) for refined representations of the state space;¹⁸⁹ (d) for guiding the exploration of the state space during training;¹⁹⁰ (e) as inputs to world models for efficient training;¹⁹¹ (f) as a Foundation Model prior, or part of pretraining, to bias a deployed agent’s action space toward certain actions or away from others;¹⁹² or (g) as some combination of

¹⁸² See e.g., Austin W. Hanjie, Victor Zhong & Karthik Narasimhan, *Grounding Language to Entities and Dynamics for Generalization in Reinforcement Learning* (2021); Prithviraj Ammanabrolu & Mark Riedl, *Learning Knowledge Graph-based World Models of Textual Environments*, In *Advances in Neural Information Processing Systems* 34 3720-3731 (2021); Felix Hill et al., *Grounded Language Learning Fast and Slow* (2020); Marc-Alexandre Côté et al., *TextWorld: A Learning Environment for Text-based Games* (2018).

¹⁸³ See e.g., MacGlashan et al., *Grounding English Commands to Reward Functions, Robotics: Science and Systems* (2015) at 1 (“Because language is grounded to reward functions, rather than explicit actions that the robot can perform, commands can be high-level, carried out in novel environments autonomously, and even transferred to other robots with different action spaces. We demonstrate that our learned model can be both generalized to novel environments and transferred to a robot with a different action space than the action space used during training.”); Karthik Narasimhan, Regina Barzilay & Tommi Jaakkola, *Grounding Language for Transfer in Deep Reinforcement Learning* (2018); Prasoon Goyal, Scott Niekum & Raymond J. Mooney, *Using Natural Language for Reward Shaping in Reinforcement Learning* (2019); Jelena Luketina et al., *A Survey of Reinforcement Learning Informed by Natural Language* (2019); Theodore Sumers et al., *Learning Rewards from Linguistic Feedback* (2021); Jessy Lin et al., *Inferring Rewards from Language in Context* (2022); Pratyusha Sharma et al., *Correcting Robot Plans with Natural Language Feedback* (2022). See, generally, Hong Jun Jeon, Smitha Milli & Anca Dragan, *Reward-rational (Implicit) Choice: A Unifying Formalism for Reward Learning*, *Advances in Neural Information Processing Systems* 33 4415-4426 (2020).

¹⁸⁴ See, e.g., Lili Chen et al., *Decision Transformer: Reinforcement Learning via Sequence Modeling* (2021); Sergey Levine et al., *Offline Reinforcement Learning: Tutorial, Review, and Perspectives on Open Problems* (2020).

¹⁸⁵ See, e.g., Mykel J. Kochenderfer, Tim A. Wheeler & Kyle H. Wray, *Algorithms for Decision Making*, MIT Press (2022).

¹⁸⁶ See, e.g., Tsung-Yen Yang et al., *Safe Reinforcement Learning with Natural Language Constraints* (2021) at 3 (“Since constraints are decoupled from rewards and policies, agents trained to understand certain constraints can transfer their understanding to respect these constraints in new tasks, even when the new optimal policy is drastically different.”).

¹⁸⁷ See, e.g., Joshua Achiam, David Held, Aviv Tamar & Pieter Abbeel, *Constrained Policy Optimization*, In *Proceedings of the 34th International Conference on Machine Learning*, PMLR 70:22-31 (2017).

¹⁸⁸ See, e.g., Bharat Prakash et al., *Guiding Safe Reinforcement Learning Policies Using Structured Language Constraints*, UMBC Student Collection (2020); Dan Hendrycks et al., *What Would Jimmy Cricket Do? Towards Agents That Behave Morally* (2021).

¹⁸⁹ See, e.g., Mengjiao Yang & Ofir Nachum, *Representation Matters: Offline Pretraining for Sequential Decision Making*, In *Proceedings of the 38th International Conference on Machine Learning*, PMLR 139, 11784-11794 (2021).

¹⁹⁰ See, e.g., Allison C. Tam et al., *Semantic Exploration from Language Abstractions and Pretrained Representations* (2022).

¹⁹¹ See, e.g., Vincent Micheli, Eloi Alonso & François Fleuret, *Transformers are Sample Efficient World Models* (2022) <https://arxiv.org/abs/2209.00588>.

¹⁹² See, e.g., Jacob Andreas, Dan Klein & Sergey Levine, *Learning with Latent Language*, In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, Vol 1, 2166–2179, Association for Computational Linguistics (2018); Shunyu Yao et al., *Keep CALM and Explore: Language Models for Action Generation in Text-based Games* (2020); Andrew K Lampinen et al., *Tell*

the aforementioned. Where legal informatics is providing the modular constructs (e.g., methods of statutory interpretation, applications of standards, and legal reasoning more broadly) to facilitate the communication of what a human wants an AI to do, it is more likely employed for specifying and shaping reward functions. Where legal informatics, through distillations of public law, helps specify what AI should *not* do, in order to provide a broader knowledge base of how to reduce societal externalities, it is more likely employed as constraints on the actions available to an agent.

Foundation Models have the potential to unlock significant legal understanding capability. “Legal decision-making requires context at various scales: knowledge of all historical decisions and standards, knowledge of the case law that remains relevant in the present, and knowledge of the nuances of the individual case at hand. Foundation models are uniquely poised to have the potential to learn shared representations of historical and legal contexts, as well as have the linguistic power and precision for modeling an individual case.”¹⁹³ Foundation Models trained on legal text learn model weights and word embeddings specific to legal text that (in the limited work thus far) provide (slightly) better performance on downstream legal tasks relative to models trained on primarily non-legal text.¹⁹⁴ Foundation Models have been useful for analyzing legal language¹⁹⁵ and legal arguments,¹⁹⁶ and testing legal theories.¹⁹⁷ Foundation Models’ recent strong capabilities in automatically analyzing (non-legal) citations¹⁹⁸ may prove fruitful in identifying relevant legal precedent, and their ability to generate persuasive language could help AI understand, and thus learn from, legal brief text data.¹⁹⁹

Foundation Models are beginning to demonstrate improved performance in analyzing contracts.²⁰⁰ As state-of-the-art models have gotten larger and more advanced, their contract

Me Why! Explanations Support Learning Relational and Causal Structure, in Proceedings of the 39th International Conference on Machine Learning, PMLR 162, 11868-11890 (2022).

¹⁹³ Rishi Bommasani et al., *On the Opportunities and Risks of Foundation Models*, arxiv.org (Aug. 18, 2021) <https://arxiv.org/pdf/2108.07258.pdf> at 63.

¹⁹⁴ See, e.g., Zheng et al., *When Does Pretraining Help?: Assessing Self-supervised Learning for Law and the CaseHOLD Dataset of 53,000+ Legal Holdings*, In ICAIL '21: Proceedings of the Eighteenth International Conference on Artificial Intelligence and Law (June 2021), at 159 (“Our findings [...] show that Transformer-based architectures, too, learn embeddings suggestive of distinct legal language.”).

¹⁹⁵ See, e.g., Julian Nyarko & Sarath Sanga, *A Statistical Test for Legal Interpretation: Theory and Applications*, The Journal of Law, Economics, and Organization, <https://doi.org/10.1093/jleo/ewab038> (2020); Jonathan H. Choi, *An Empirical Study of Statutory Interpretation in Tax Law*, NYU L Rev. 95, 363 (2020) <https://www.nyulawreview.org/issues/volume-95-number-2/an-empirical-study-of-statutory-interpretation-in-tax-law/>.

¹⁹⁶ Prakash Poudyal et al., *ECHR: Legal Corpus for Argument Mining*, In *Proceedings of the 7th Workshop on Argument Mining*, 67–75, Association for Computational Linguistics (2020) at 1 (“The results suggest the usefulness of pre-trained language models based on deep neural network architectures in argument mining.”).

¹⁹⁷ Josef Valvoda et al., *What About the Precedent: An Information-Theoretic Analysis of Common Law*, In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 2275-2288 (2021).

¹⁹⁸ See, e.g., Petroni et al., *Improving Wikipedia Verifiability with AI* (2022) <https://openreview.net/forum?id=qfTqRtkDbWZ>.

¹⁹⁹ See e.g., Sebastian Duerr & Peter A. Gloor, *Persuasive Natural Language Generation – A Literature Review* (2021); Jialu Li, Esin Durmus & Claire Cardie, *Exploring the Role of Argument Structure in Online Debate Persuasion*, In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, Association for Computational Linguistics, 8905–8912 (2020); Rishi Bommasani et al., *On the Opportunities and Risks of Foundation Models*, arxiv.org (Aug. 18, 2021) <https://arxiv.org/pdf/2108.07258.pdf> at 64.

²⁰⁰ Spyretta Leivaditi, Julien Rossi & Evangelos Kanoulas, *A Benchmark for Lease Contract Review*, arXiv:2010.10386 (2020); Allison Hegel et al., *The Law of Large Documents: Understanding the Structure of Legal Contracts Using Visual Cues*, arXiv:2107.08128 (2021); Dan Hendrycks, Collin Burns, Anya Chen & Spencer Ball,

analysis performance has improved,²⁰¹ suggesting we can expect continued advancements in natural language processing capabilities to improve legal text analysis as a by-product.²⁰² Mainstream AI capabilities research could potentially unlock further advances toward *Law Informing Code*; in particular, through the successful application of deep reinforcement learning further beyond toy problems (e.g., video games and board games),²⁰³ with human feedback,²⁰⁴ and through offline learning at large scale.²⁰⁵

These potentials represent the preferred approach: *Law* can best *Inform Code* if legal informatics is able to adopt (or adapt) state-of-the-art models and processes and convert the progress in general AI capabilities (which is being aggressively funded by most of the large internet technology companies and national governments) into gains in AI legal understanding.

ii. Legal Informatics Could Improve AI Capabilities

Cuad: An expert-annotated NLP dataset for legal contract review, arXiv:2103.06268 (2021); Ilias Chalkidis et al., *LexGLUE: A Benchmark Dataset for Legal Language Understanding in English*, in PROCEEDINGS OF THE 60TH ANNUAL MEETING OF THE ASSOCIATION FOR COMPUTATIONAL LINGUISTICS (2022); Stephen C. Mouritsen, *Contract Interpretation with Corpus Linguistics*, 94 WASH. L. REV. 1337 (2019); Yonathan A. Arbel & Shmuel I. Becher, *Contracts in the Age of Smart Readers*, 83 Geo. Wash. L. Rev. 90 (2022).

²⁰¹ Dan Hendrycks, Collin Burns, Anya Chen & Spencer Ball, *Cuad: An Expert-Annotated NLP Dataset for Legal Contract Review*, arXiv:2103.06268 (2021) at 2 (“We experiment with several state-of-the-art Transformer (Vaswani et al., 2017) models on CUAD [a dataset for legal contract review]. We find that performance metrics such as Precision @ 80% Recall are improving quickly as models improve, such that a BERT model from 2018 attains 8.2% while a DeBERTa model from 2021 attains 44.0%.”).

²⁰² Rishi Bommasani et al., *On the Opportunities and Risks of Foundation Models*, arxiv.org (Aug. 18, 2021) <https://arxiv.org/pdf/2108.07258.pdf> at 59 (“Many legal applications pose unique challenges to computational solutions. Legal language is specialized and legal outcomes often rely on the application of ambiguous and unclear standards to varied and previously unseen fact patterns. At the same time, due to its high costs, labeled training data is scarce. Depending on the specific task, these idiosyncrasies can pose insurmountable obstacles to the successful deployment of traditional models. In contrast, their flexibility and capability to learn from few examples suggest that foundation models could be uniquely positioned to address the aforementioned challenges.”).

²⁰³ In the legal understanding domain, *see, e.g.*, Duy-Hung Nguyen et al., *Robust Deep Reinforcement Learning for Extractive Legal Summarization*, in International Conference on Neural Information Processing (2021).

²⁰⁴ *See, e.g.*, Paul F. Christiano et al., *Deep Reinforcement Learning from Human Preferences*, in Advances in Neural Information Processing Systems 30 (2017); Natasha Jaques et al., *Way Off-Policy Batch Deep Reinforcement Learning of Implicit Human Preferences in Dialog* (2019); Stiennon et al., *Learning to Summarize with Human Feedback*, in 33 Advances in Neural Information Processing Systems 3008-3021 (2020); Daniel M. Ziegler, et al., *Fine-tuning Language Models From Human Preferences*, arXiv:1909.08593 (2019); Jeff Wu et al., *Recursively Summarizing Books with Human Feedback*, arXiv:2109.10862 (2021); Cassidy Laidlaw & Stuart Russell, *Uncertain Decisions Facilitate Better Preference Learning* (2021); Koster et al., *Human-centred mechanism design with Democratic AI*, *Nature Human Behaviour* (2022); Long Ouyang et al. *Training Language Models to Follow Instructions with Human Feedback*, arxiv.org (Mar. 4, 2022), <https://arxiv.org/pdf/2203.02155.pdf>.

²⁰⁵ *See, e.g.*, Dibya Ghosh et al., *Offline RL Policies Should be Trained to be Adaptive* (2022); Machel Reid, Yutaro Yamada & Shixiang Shane Gu, *Can Wikipedia Help Offline Reinforcement Learning?* (2022); Sergey Levine et al., *Offline Reinforcement Learning: Tutorial, Review, and Perspectives on Open Problems* (2020) at 25 (Combining offline and online RL through historical legal information and human feedback is likely a promising integrated approach, because, “if the dataset state-action distribution is narrow, neural network training may only provide brittle, non-generalizable solutions. Unlike online reinforcement learning, where accidental overestimation errors arising due to function approximation can be corrected via active data collection, these errors cumulatively build up and affect future iterates in an offline RL setting.”).

This may be a two-way street, with the legal informatics alignment research also improving general AI capabilities and other AI alignment techniques.²⁰⁶ We provide four example avenues.

First, legal informatics alignment research could improve fundamental AI capabilities by inspiring novel inductive biases from legal reasoning.²⁰⁷ Neuro-symbolic modeling (combining parametric models such as deep neural networks with non-parametric symbolic systems) is a potential approach to building more generalizable reasoning capabilities,²⁰⁸ and legal informatics could power the symbolic legal reasoning components of hybrid systems.²⁰⁹

Second, adversarial debate is fundamental to legal processes and there is a line of AI research – inspired by the success of self-play AI systems like AlphaGo²¹⁰ – pursuing the modeling of artificial debate between AI agents as a means of performing more advanced tasks than humans while remaining aligned with those humans.²¹¹ This approach views machine learning “as a game played between two agents, where the agents have an argument with each other and the human judges the exchange. Even if the agents have a more advanced understanding of the problem than the human, the human may be able to judge which agent has the better argument (similar to expert witnesses arguing to convince a jury).”²¹² Legal symbolic systems-based argumentation

²⁰⁶ Rishi Bommasani et al., *On the Opportunities and Risks of Foundation Models*, arxiv.org (Aug. 18, 2021) <https://arxiv.org/pdf/2108.07258.pdf> at 66 (“Legal briefing and reasoning is likely beyond the capabilities of current models, but appears to be within the future realm of possibilities. As such, these serve as a potential lode star for the ongoing development of foundation models.”); Bart Verheij, *Artificial Intelligence as Law*, A.I. & L. 28, no. 2, 181-206 (2020).

²⁰⁷ For the importance of abstraction, and ideas for building it into machine learning models, see, e.g., Murray Shanahan & Melanie Mitchell, *Abstraction for Deep Reinforcement Learning*, in Proceedings of the International Joint Conference on Artificial Intelligence (2022); Melanie Mitchell, *Abstraction and Analogy-Making in Artificial Intelligence*, in *Annals of the New York Academy of Sciences*, 1505 (1), 79–101 (2021) at 1 (“While AI has made dramatic progress over the last decade in areas such as computer vision, natural language processing, and robotics, current AI systems almost entirely lack the ability to form humanlike concepts and abstractions.”). For research on Foundation Model capabilities related to metaphors, see, e.g., Ben Prystawski, Paul Thibodeau & Noah Goodman, *Psychologically-informed Chain-of-thought Prompts for Metaphor Understanding in Large Language Models* (2022) <https://arxiv.org/abs/2209.08141>. Analogies and metaphors are foundational to the law, see e.g., Steven L. Winter, *The Metaphor of Standing and the Problem of Self-governance*, *Stan. L. Rev.* 40, 1371 (1987); Steven L. Winter, *A Clearing in the Forest* (2001). State-of-the-art large language models currently perform poorly on understanding metaphors; see, e.g., Tuhin Chakrabarty, Yejin Choi & Vered Shwartz, *It’s Not Rocket Science: Interpreting Figurative Language in Narratives*, *TACL* (2022).

²⁰⁸ See e.g., Rajarshi Das, et al., *Case-based Reasoning for Natural Language Queries over Knowledge Bases*, in Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, 9594–9611, Association for Computational Linguistics (2021); F Ward, F Belardinelli & F Toni, *Argumentative Reward Learning: Reasoning About Human Preferences*, in *HMCaT 2022 ICML* (2022).

²⁰⁹ Bart Verheij, *Artificial Intelligence as Law*, A.I. & L. 28, no. 2, 181-206 (2020) at 191.

²¹⁰ The first program to defeat a professional human Go player, see, Silver et al., *Mastering the Game of Go Without Human Knowledge*, *Nature*, 550, 354–359 (2017).

²¹¹ See e.g., Richard Ngo, *Why I’m Excited About Debate* (2021) <https://www.alignmentforum.org/posts/LDsSqXf9Dpu3J3gHD/why-i-m-excited-about-debate>; Geoffrey Irving, Paul Christiano & Dario Amodei, *AI Safety Via Debate* (2018) <https://arxiv.org/abs/1805.00899>.

²¹² The authors’ “hope is that, properly trained, such agents can produce value-aligned behavior far beyond the capabilities of the human judge. If the two agents disagree on the truth but the full reasoning is too large to show the humans, the debate can focus in on simpler and simpler factual disputes, eventually reaching a claim that is simple enough for direct judging.” Geoffrey Irving & Dario Amodei, *AI Safety via Debate* (May 3, 2018).

modeling²¹³ could inform this research.²¹⁴ There may be ways to leverage the way in which much of the legal process is inherently adversarial to embed capabilities for fending off adversarial attacks and for improving model training with adversarial and argumentation techniques.²¹⁵ Securing machine learning systems against adversarial attacks is difficult;²¹⁶ simple systems can fail in unexpected and surprising ways, and more advanced systems can in some cases be easily fooled.²¹⁷ Approaches to adversarial training of machine learning models for improving AI task capabilities²¹⁸ and robustness,²¹⁹ and adversarial benchmarking of machine learning models²²⁰ may benefit.

²¹³ Kevin D. Ashley & VR Walker, *Toward Constructing Evidence-based Legal Arguments Using Legal Decision Documents and Machine Learning*, in Proceedings of the Fourteenth International Conference on Artificial Intelligence and Law, 176–180 ACM (2013); Katie Atkinson et al., *Toward Artificial Argumentation*, *AI Mag* 38(3):25–36 (2017); Bart Verheij, *Proof with and Without Probabilities. Correct evidential reasoning with presumptive arguments, coherent hypotheses and degrees of uncertainty*, *A.I. & L.* 25(1):127–154 (2017); P Baroni, D Gabbay, M Giacomini & van der Torre L (eds.) *Handbook of Formal Argumentation* (2018); Bart Verheij, *Artificial Intelligence as Law*, *A.I. & L.* 28, no. 2, 181-206 (2020) at 191-193.

²¹⁴ And, back in the other direction, the results of this research area can be used to further improve legal informatics, specifically, to leverage improved machine learning capabilities for simulating theoretical court outcomes, in order to draw provisional conclusions about the way in which a legal precedent or legal standard may apply to a particular circumstance. For research on predicting court outcomes, see, e.g., Junyun Cui et al., *A Survey on Legal Judgment Prediction: Datasets, Metrics, Models and Challenges*, arXiv:2204.04859 (2022).

²¹⁵ When reward functions are learned with neural networks and then optimized by other machine learning models this sets up a situation prone to exploitation of errors in the learned proxy utility function, see, e.g., Brandon Trabucco, Aviral Kumar, Xinyang Geng & Sergey Levine, *Conservative Objective Models for Effective Offline Model-based Optimization*, In International Conference on Machine Learning, 10358-10368 (2021); Adam Gleave, et al., *Adversarial Policies: Attacking Deep Reinforcement Learning*, In Proc. ICLR-20 (2020); Dan Hendrycks et al., *Unsolved Problems in ML Safety* (2021).

²¹⁶ See e.g., in the context of natural language processing, Linyang Li et al., *BERT-ATTACK: Adversarial Attack Against BERT Using BERT*, in Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (2020); Eric Wallace et al., *Universal Adversarial Triggers for Attacking and Analyzing NLP*, in Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing (2019). See e.g., in the context of deep reinforcement learning, Adam Gleave et al., *Adversarial Policies: Attacking Deep Reinforcement Learning*, In Proc. ICLR-20 (2020).

²¹⁷ Ian Goodfellow et al., *Attacking Machine Learning with Adversarial Examples* (February 24, 2017); Ian J. Goodfellow, Jonathon Shlens & Christian Szegedy, *Explaining and Harnessing Adversarial Examples* (2015).

²¹⁸ See, generally, Anthony Huang et al., *Adversarial Machine Learning*, In Proceedings of the 4th ACM workshop on Security and Artificial Intelligence, 43–58 (2011). See, e.g., Mingyang Yi et al., *Improved OOD Generalization via Adversarial Training and Pretraining*, In Proceedings of the 38th International Conference on Machine Learning, Vol 139 11987, 18–24 (Jul 2021) <https://proceedings.mlr.press/v139/yi21a.html>; H. Zhang, I. Goodfellow, D. Metaxas & A. Odena, *Self-attention Generative Adversarial Networks*, in International Conference on Machine Learning, 7354-7363 (May 2019). Although, note that, as of 2022, diffusion models are generally a more capable approach than GANs, see, e.g., Prafulla Dhariwal & Alexander Nichol, *Diffusion Models Beat GANs on Image Synthesis*, In Advances in Neural Information Processing Systems 34 8780 (2021); Robin Rombach et al., *High-resolution Image Synthesis with Latent Diffusion Models*, in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (2022).

²¹⁹ See, e.g., Daniel M. Ziegler et al., *Adversarial Training for High-Stakes Reliability* (2022) <https://arxiv.org/abs/2205.01663>. Adversarial examples can be understood as “a misalignment between the (human-specified) notion of robustness and the inherent geometry of the data”, see, Andrew Ilyas et al., *Adversarial Examples Are Not Bugs, They Are Features*, in Advances in Neural Information Processing Systems 32 (2019).

²²⁰ See, e.g., Yixin Nie et al., *Adversarial NLI: A New Benchmark for Natural Language Understanding*, Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (2020).

Third, machine-readable-law research²²¹ and practice²²² seeks hybrid structured-unstructured data representations of legal directives. This work advances the ability of humans specifying their objectives in code, and could influence AI (e.g., as reward function specifications).

Fourth, the *Law Informs Code* research agenda related to contracts is aimed at improving the ability of AI to more efficiently understand which actions to perform for a human.²²³

Techniques that increase AI alignment or safety at the expense of AI capabilities (the so-called “alignment tax”²²⁴) can lead to organizations eschewing alignment to gain additional capabilities²²⁵ as organizations and countries race forward on developing and deploying AI.²²⁶ If a safer version of AI performs better, then it is more likely to be adopted. However, because we do not yet have sufficient AI safety solutions, research that advances general AI capabilities without significantly increasing AI safety may not be desirable because it can bring AI closer to transformative levels in an unsafe manner.²²⁷ If new model architectures or training techniques we build for law-informed AI were not going to be developed by other research groups within a similar timeframe, then that increases AI capabilities. But the specific capabilities developed for *Law Informs Code* purposes may be orthogonal to developments that contribute toward general AI.

²²¹ See e.g., Megan Ma & Bryan Wilson, *The Legislative Recipe: Syntax for Machine-Readable Legislation*, 19 Nw. J. Tech. & Intell. Prop. 107 (2021); J. Mohun & A. Roberts, *Cracking the Code: Rulemaking for Humans and Machines*, OECD Working Papers on Public Governance, No. 42, (2020); *Cambridge Regulatory Genome*, <https://www.jbs.cam.ac.uk/faculty-research/centres/regulatory-genome-project/about-rgp/#crg> (2020); Tom Barraclough, Hamish Fraser & Curtis Barnes, *Legislation as Code for New Zealand: Opportunities, Risks, and Recommendations* (March 2021) <http://www.nzlii.org/nz/journals/NZLFRRp/2021/3.html>; Sarah B. Lawsky, *Form as Formalization*, 16 Ohio St. Tech. LJ 114 (2020); Sarah B. Lawsky, *A Logic for Statutes*, 21 Fla. Tax Rev. 60 (2017); Marcos A. Pertierra, Sarah B. Lawsky, Erik Hemberg & Una-May O’Reilly, *Towards Formalizing Statute Law as Default Logic through Automatic Semantic Parsing*, in ASAIL@ ICAIL (2017); T. Athan, et al., *OASIS LegalRuleML*, In ICAIL, 3–12, ACM (2013) <https://dl.acm.org/doi/10.1145/2514601.2514603>.

²²² See e.g., *OpenFisca*, <https://openfisca.org/en/>; *VisiLaw*, <https://www.visilaw.com/>; *Catala*, <https://catala-lang.org/>.

²²³ See *infra* Section III.

²²⁴ See, *Askill Laboratory for Alignment*.

²²⁵ See, e.g., Eliezer Yudkowsky, *Aligning an AGI Adds Significant Development Time* (Feb 21, 2017) https://arbitral.com/p/aligning_adds_time/; *Askill Laboratory for Alignment* (“Controlling the inputs and capabilities of AI systems will clearly have costs, so it seems hard to ensure that these controls, even if they’re developed, are actually used.”); Tom Adamczewski, *A Shift in Arguments for AI Risk* (May 25, 2019) at Section 3.2 <https://fragile-credences.github.io/prioritising-ai/#the-importance-of-competitive-pressures>.

²²⁶ See, e.g., Stuart Armstrong, Nick Bostrom & Carl Shulman, *Racing to the Precipice: A Model of Artificial Intelligence Development*, *AI & Society* 31, no. 2, 201-206 (2016); Amanda Askill, Miles Brundage & Gillian Hadfield, *The Role of Cooperation in Responsible AI Development*, arXiv:1907.04534 (2019); Stephen Cave & Seán S. ÓhÉigeartaigh, *An AI Race for Strategic Advantage: Rhetoric and Risks*, In Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society, 36-40 (2018); Peter Asaro, *What is an Artificial Intelligence Arms Race Anyway*, 45 ISJLP 15 (2019); Henry Kissinger, Eric Schmidt & Daniel P. Huttenlocher, *The Age of AI: And Our Human Future* (2021).

²²⁷ Dan Hendrycks & Thomas Woodside, *Perform Tractable Research While Avoiding Capabilities Externalities* (2022) <https://www.alignmentforum.org/posts/dfRtxWcFDupfWpLQo/perform-tractable-research-while-avoiding-capabilities> (“It is not wise to decrease some risks (e.g. improving a safety metric) by increasing other risks through advancing capabilities. In some cases, optimizing safety metrics might increase capabilities even if they aren’t being aimed for, so there needs to be a more principled way to analyze risk. We must ensure that growing the safety field does not simply hasten the arrival of superintelligence.”); Nick Bostrom, *Existential Risks: Analyzing Human Extinction Scenarios and Related Hazards*, *Journal of Evolution and Technology* 9 (2002) (“What we do have the power to affect (to what extent depends on how we define “we”) is the rate of development of various technologies and potentially the sequence in which feasible technologies are developed and implemented. Our focus should be on what I want to call differential technological development: trying to retard the implementation of dangerous technologies and accelerate implementation of beneficial technologies, especially those that ameliorate the hazards posed by other technologies.”).

Technical developments achieved for the purposes of AI understanding law better that were not going to be developed by other research groups within a similar timeframe are likely not material causes of accelerated timelines for the development of transformative AI.

However, it's hard to rule out any AI research contributing in at least some small way to advancing capabilities – so it is more a matter of degree and the tradeoffs of the positive safety benefits of the research (and the reduction of the “alignment tax” in race dynamics) with the negative of AI timeline acceleration.²²⁸ Relative to teaching AI to better understand public law and societal values as expressed through legal data,²²⁹ the research on methods for AI to better understand the preferences of an individual human (or small group of humans) likely leads to additional capabilities advancements faster, and to the type of capabilities more associated with power-seeking of one entity (human, group of humans, or AI).²³⁰

2. Data

In addition to refining our theoretical understanding of alignment and guiding design of AI architectures, legal informatics provides data for model training, fine-tuning, and validation.

i. Data from Experts

One of the largest focus areas in empirical AI alignment research is learning reward functions based on human feedback and human demonstration.²³¹ But humans have many

²²⁸ Dan Hendrycks & Thomas Woodside, *Perform Tractable Research While Avoiding Capabilities Externalities* (2022) <https://www.alignmentforum.org/posts/dfRtxWcFDupfWpLQo/perform-tractable-research-while-avoiding-capabilities>.

²²⁹ Much of the work on law informing AI is data engineering work, e.g., automatically generating labeled court opinion data that can be employed in evaluating the consistency of agent behavior with particular legal standards.

²³⁰ A similar point has been made about AI learning ethical theories versus learning human preferences, Dan Hendrycks & Thomas Woodside, *Perform Tractable Research While Avoiding Capabilities Externalities* (2022) <https://www.alignmentforum.org/posts/dfRtxWcFDupfWpLQo/perform-tractable-research-while-avoiding-capabilities> (“In general, research into the application of ethical theories and the approximation of normative factors appears far less likely to lead to capabilities externalities, because the scope of what is being learned is restricted dramatically. Ethical theories contain less information that is relevant to understanding how to perform general tasks than generic human annotations and comparisons.”).

²³¹ See, e.g., Pieter Abbeel, Adam Coates, Morgan Quigley & Andrew Y Ng, *An Application of Reinforcement Learning to Aerobatic Helicopter Flight*, in *Advances in Neural Information Processing Systems* (2007); Jaedong Choi & Kee-Eung Kim, *Inverse Reinforcement Learning in Partially Observable Environments*, *Journal of Machine Learning Research* 12, 691–730 (2011); Dylan Hadfield-Menell, Anca Dragan, Pieter Abbeel & Stuart J Russell, *Cooperative Inverse Reinforcement Learning*, in *Advances in neural information processing systems*, 3909–3917 (2016); Dylan Hadfield-Menell et al., *Inverse Reward Design*, in *Advances in Neural Information Processing Systems*, 6768–6777 (2017); Daniel M. Ziegler, et al., *Fine-tuning Language Models From Human Preferences*, arXiv:1909.08593 (2019); Siddharth Reddy et al., *Learning Human Objectives by Evaluating Hypothetical Behavior*, in *Proceedings of the 37th International Conference on Machine Learning*, PMLR 119, 8020-8029 (2020); Stiennon et al., *Learning to Summarize with Human Feedback*, in *33 Advances in Neural Information Processing Systems* 3008-3021 (2020); Hong Jun Jeon, Smitha Milli & Anca Dragan. *Reward-rational (Implicit) Choice: A Unifying Formalism for Reward Learning*, *Advances in Neural Information Processing Systems* 33 4415-4426 (2020); Theodore Sumers et al., *Learning Rewards from Linguistic Feedback* (2021); Theodore Sumers et al., *Linguistic Communication As (Inverse) Reward Design*, in *ACL Workshop on Learning with Natural Language Supervision* (2022); Yuntao Bai et

cognitive limitations and biases that corrupt this process,²³² including routinely failing to predict (seemingly innocuous) implications of actions (we believe are) pursuant to our goals,²³³ and having inconsistent preferences that do not generalize to new situations.²³⁴ Researchers are investigating whether we can augment human feedback and demonstration abilities with trustworthy AI assistants in order to scale human feedback to super-human AI,²³⁵ and how to recursively provide human feedback on decompositions of the overall task.²³⁶ However, even if that process worked perfectly, the ultimate evaluation of the AI is still grounded in unsubstantiated human judgments providing the top-level feedback. Our goal is to ground alignment-related feedback in legal judgment.

Evaluating a behavior is easier than learning how to actually execute that behavior; for example, I cannot do a backflip but I can evaluate whether you just did a backflip.²³⁷ With this in mind, reinforcement learning through human attorney feedback (there are more than 1.3 million lawyers in the US²³⁸) on natural language interactions with AI models is potentially a powerful process to teach (through training, or fine-tuning, or extraction of templates for in-context prompting of large language models²³⁹) statutory interpretation, argumentation, and case-based

al., *Training a Helpful and Harmless Assistant with Reinforcement Learning from Human Feedback* (2022) <https://arxiv.org/abs/2204.05862>.

²³² See, e.g., Rohin Shah, Noah Gundotra, Pieter Abbeel & Anca Dragan, *On the Feasibility of Learning, Rather Than Assuming, Human Biases for Reward Inference*, In International Conference on Machine Learning (2019); Geoffrey Irving & Amanda Askell, *AI Safety Needs Social Scientists*, Distill 4.2 e14 (2019). On human cognitive biases more generally, see, e.g., Amos Tversky & Daniel Kahneman, *Judgment under Uncertainty: Heuristics and Biases*, Science 185.4157 1124 (1974).

²³³ See, generally, Gerd Gigerenzer & Reinhard Selten, eds., *Bounded Rationality: The Adaptive Toolbox*, MIT Press (2002); Sanjit Dhami & Cass R. Sunstein, *Bounded Rationality: Heuristics, Judgment, and Public Policy*, MIT Press (2022).

²³⁴ Dan Hendrycks & Thomas Woodside, *Perform Tractable Research While Avoiding Capabilities Externalities* (2022) <https://www.alignmentforum.org/posts/dfRtxWcFDupfWpLQo/perform-tractable-research-while-avoiding-capabilities> (“[Human] preferences can be inconsistent, ill-conceived, and highly situation-dependent, so they may not be generalizable to the unfamiliar world that will likely arise after the advent of highly-capable models [...] Compared with task preferences, ethical theories and human values such as intrinsic goods may be more generalizable, interpretable, and neglected.”).

²³⁵ “For tasks that humans struggle to evaluate, we won’t know whether the reward model has actually generalized “correctly” (in a way that’s actually aligned with human intentions) since we don’t have an evaluation procedure to check. All we could do was make an argument by analogy because the reward model generalized well in other cases from easier to harder tasks.” Jan Leike, *Why I’m Excited About AI-assisted Human Feedback: How to Scale Alignment Techniques to Hard Tasks* (March 29, 2022) <https://aligned.substack.com/p/ai-assisted-human-feedback>.

²³⁶ See, e.g., Paul Christiano, Buck Shlegeris & Dario Amodei, *Supervising Strong Learners by Amplifying Weak Experts* (2018); Leike et al., *Scalable Agent Alignment via Reward Modeling: A Research Direction*, <https://arxiv.org/abs/1811.07871> (2018); Jan Leike, *Why I’m Excited About AI-assisted Human Feedback: How to Scale Alignment Techniques to Hard Tasks* (March 29, 2022) <https://aligned.substack.com/p/ai-assisted-human-feedback>; Jeff Wu et al., *Recursively Summarizing Books with Human Feedback*, arXiv:2109.10862 (2021).

²³⁷ Jan Leike et al., *Scalable Agent Alignment via Reward Modeling: A Research Direction* (2018); Brian Christian, *The Alignment Problem: Machine Learning and Human Values* (2020) at 263-266; Jan Leike, *Why I’m Optimistic About Our Alignment Approach* (2022) <https://aligned.substack.com/p/alignment-optimism> (see the list on the examples where it is easier to evaluate than generate from scratch.).

²³⁸ *ABA Profile of the Legal Profession* (2022) at 22 <https://www.americanbar.org/content/dam/aba/administrative/news/2022/07/profile-report-2022.pdf>.

²³⁹ See, e.g., D. Khashabi, C. Baral, Y Choi & H Hajishirzi, *Reframing Instructional Prompts to GPTk’s Language*, In Findings of the Association for Computational Linguistics, 589-612 (May 2022). Large neural network models have demonstrated the ability to learn mathematical functions purely from in-context interaction, see, e.g., Shivam Garg, Dimitris Tsipras, Percy Liang & Gregory Valiant, *What Can Transformers Learn In-Context? A Case Study of Simple Function Classes* (2022).

reasoning, which can then be applied for aligning increasingly powerful AI. With large language models, only a few samples of human feedback, in the form of natural language, are needed for model refinement for some tasks.²⁴⁰ Models could be trained to assist human attorney evaluators, which, in partnership with the humans, could allow the combined human-AI evaluation team to have capabilities surpassing the legal understanding of the expert humans alone,²⁴¹ but still share the core legal concept ontology for communication of human directives and goals.²⁴² This will require learning from, and being validated on, existing legal text data.

ii. Data from Legal Text

The Foundation Models in use today have been trained on a large portion of the Internet to leverage billions of human actions (through natural language expressions). Training on high-quality dialog data leads to better dialog models,²⁴³ training on technical mathematics papers leads to better mathematical reasoning,²⁴⁴ and training on code leads to better reasoning.²⁴⁵ It may be possible to, similarly, leverage billions of human legal data points to build Law Foundation Models with better legal reasoning through language model self-supervision on pre-processed (but still largely unstructured) legal text data.²⁴⁶

Selecting which data sets are best suited for self-supervised pre-training is an active area of research.²⁴⁷ This is especially important in the legal domain where many historical actions represent institutionalized prejudices and partisan politics.²⁴⁸

We can use multiple filters to guide data selection and data structuring processes. *First*, is the goal of training on a data point to embed world knowledge into AI, or to learn legal reasoning skills? Learning that humans in the U.S. drive on the right side of the road is learning world knowledge; whereas, learning how to map a statute about driving rules to a new fact pattern in the real world is learning how to conduct a legal reasoning task. *Second*, is the uncertainty that an AI

²⁴⁰ See, e.g., Jérémy Scheurer et al., *Training Language Models with Language Feedback* (2022).

²⁴¹ See, e.g., Samuel R. Bowman et al., *Measuring Progress on Scalable Oversight for Large Language Models* (2022) <https://arxiv.org/abs/2211.03540>.

²⁴² See, e.g., William Saunders et al., *Self-critiquing Models for Assisting Human Evaluators* (2022).

²⁴³ See, e.g., Thoppilan et al., *LaMDA: Language Models for Dialog Applications* (2022).

²⁴⁴ See, e.g., Aitor Lewkowycz et al., *Solving Quantitative Reasoning Problems with Language Models* (2022) <https://arxiv.org/abs/2206.14858>; Yuhuai Wu et al., *Autoformalization with Large Language Models* (2022) <https://arxiv.org/abs/2205.12615>.

²⁴⁵ See, e.g., Aman Madaan et al., *Language Models of Code are Few-Shot Commonsense Learners* (2022) <https://arxiv.org/abs/2210.07128>.

²⁴⁶ See, e.g., Zheng et al., *When does pretraining help?: assessing self-supervised learning for law and the CaseHOLD dataset of 53,000+ legal holdings*, In ICAIL '21: Proceedings of the Eighteenth International Conference on Artificial Intelligence and Law (June 2021); Ilias Chalkidis et al., *LexGLUE: A Benchmark Dataset for Legal Language Understanding in English*, in PROCEEDINGS OF THE 60TH ANNUAL MEETING OF THE ASSOCIATION FOR COMPUTATIONAL LINGUISTICS (2022); Ilias Chalkidis et al., *LEGAL-BERT: The Muppets Straight Out of Law School*, in Findings of the Association for Computational Linguistics: EMNLP, 2898-2904 (November 2020); Peter Henderson et al., *Pile of Law: Learning Responsible Data Filtering from the Law and a 256GB Open-Source Legal Dataset* (2022) <https://arxiv.org/abs/2207.00220>.

²⁴⁷ See, e.g., Thao Nguyen et al., *Quality Not Quantity: On the Interaction between Dataset Design and Robustness of CLIP* (2022).

²⁴⁸ See, e.g., Kathryn Stanchi, *The Rhetoric of Racism in the United States Supreme Court*, *BCL Rev.* 62, 1251 (2021).

could theoretically resolve by training on a data point epistemic or aleatory.²⁴⁹ If the nature of the uncertainty is epistemic – e.g., whether citizens prefer climate change risk reduction over endangered species protection – then it is fruitful to apply as much data as we can to learning functions to closer approximate the underlying fact about the world or about law. If the nature of the uncertainty is more of an aleatory flavor – e.g., the middle name of the defendant in a case, or the weather on a day a year from now – then there is enough inherent randomness that we would seek to avoid attempting to learn anything about that fact or data point.²⁵⁰

Legal standards can be learned directly from legal text data.²⁵¹ Fine-tuning of Foundation Models on smaller labeled data sets has proven successful for learning descriptive “common-sense” ethical judgement capabilities,²⁵² which, from a technical (not normative²⁵³) perspective, is similar to the machine learning problem of learning legal standards. We can codify examples of human and corporate behavior exhibiting standards such as fiduciary duty into a structured format to evaluate the standards-understanding capabilities of AI models (Figure 7).²⁵⁴

²⁴⁹ These are rough abstractions, and any determination of their application should be interpreted to be on a continuum, and itself highly uncertain. See, e.g., Y. Gal, *Uncertainty in Deep Learning*. Ph.D. thesis, University of Cambridge (2016).

²⁵⁰ Discerning whether content is epistemic vs. aleatory is a major hurdle, and context dependent.

²⁵¹ See, e.g., Peter Henderson et al., *Pile of Law: Learning Responsible Data Filtering from the Law and a 256GB Open-Source Legal Dataset* (2022) at 7 <https://arxiv.org/abs/2207.00220> (They learn data filtering standards related to privacy and toxicity from legal data, e.g., “a model trained on Pile of Law (pol-bert) ranks Jane Doe ~ 3 points higher than a standard bert-large-uncased on true pseudonym cases. This suggests that models pre-trained on Pile of Law are more likely to encode appropriate pseudonymity norms. To be sure, pol-bert is slightly more biased for Jane Doe use overall, as is to be expected, but its performance gains persist even after accounting for this bias.”).

²⁵² See, e.g., Liwei Jiang et al., *Can Machines Learn Morality? The Delphi Experiment* (2022) <https://arxiv.org/pdf/2110.07574.pdf> at 28 (“We have shown that Delphi demonstrates a notable ability to generate on-target predictions over new and unseen situations even when challenged with nuanced situations. This supports our hypothesis that machines can be taught human moral sense, and indicates that the bottom-up method is a promising path forward for creating more morally informed AI systems.”).

²⁵³ See *infra* Section IV. A.

²⁵⁴ This data could include both “gold-standard” human labeled data, but also automated data structuring that is subsequently sampled and selectively human validated for correctness. Data hand-labeled by expensive legal experts is unlikely to provide a large enough data set for training large neural models. Rather, its purpose is to validate the performance of models trained on much larger, general data, e.g., Foundation Models trained on large portions of the Internet. This semi-structured data could be used for self-supervised learning processes to apply across relevant case law, regulatory guidance, training materials, and self-regulatory organization data (e.g., FINRA exams) in order to train models to learn correct and incorrect fiduciary behavior across as many contexts as possible.

Time Step 1:

STATE: Stephen Guinn was the alleged fiduciary of Alan Stroud and Cathy Stroud.

ACTION: Guinn went to the Strouds' home to discuss Alan's term life insurance.

LEGAL REWARD: unsure

Time Step 2:

STATE: Guinn told the Strouds that the premiums on Alan's life insurance policy were going to drastically increase and that the Strouds needed to change Alan's term life insurance policy to a whole life insurance policy before that happened.

ACTION: Alan converted his term life insurance policy with a \$60,000 death benefit into a whole life insurance policy with a \$30,000 death benefit.

LEGAL REWARD: positive for Alan

Time Step 3:

STATE: Guinn created a fiduciary relationship with Alan and Cathy through his interactions with them on May 5, 2019, and May 6, 2019.

ACTION: Guinn procured whole life insurance for Alan.

LEGAL REWARD: positive for Alan

Time Step 4:

STATE: Guinn hid or neglected to tell Alan and Cathy important information about the advisability of converting Alan's term life insurance policy into a whole life insurance policy.

ACTION: Alan converted his term life insurance policy to a whole life insurance policy by the end of the May 6, 2019 meeting with Guinn.

LEGAL REWARD: negative for Alan and Cathy

Figure 7: *Example from a Large Language Model-driven system we built to systematically convert court opinions into consecutive state-action-reward tuples of the facts of the cases in a way that they could be used to train AI agents with reinforcement learning to learn how to behave as law-abiding fiduciaries.*

The legal data available for AI to learn from, or be evaluated on, includes textual data from all types of law (constitutional, statutory, administrative, case, and contractual),²⁵⁵ legal training tools (e.g., bar exam outlines, casebooks, and software for teaching the casuistic approach), rule-based legal reasoning programs,²⁵⁶ and human-in-the-loop live feedback from human legal experts.²⁵⁷ The latter two could simulate state-action-value spaces for AI fine-tuning or validation, and the former can be processed to do so.

Automated data curation processes to convert legal text data into classification tasks, or decision tasks (via state-action-reward tuples, or contextual constraints for shaping candidate action choices conditional on the state) is an important frontier in this research agenda (and promising for application to case law and contracts). Learning from textual descriptions, rather

²⁵⁵ In the U.S., the legislative branch creates statutory law through bills enacted by Congress; the executive branch creates administrative regulations through Agencies' notices of proposed rule-making and final rules; the judicial branch creates case law through judicial opinions; and private parties create contracts. Only the latter is not widely available in some form. Laws are found at varying levels of government in the United States: federal, state, and local. The adopted versions of public law are often compiled in official bulk data repositories that offer machine-readable formats. For instance, statutory law is integrated into the United States Code (or a state's Code), which organizes the text of all Public Laws that are still in force into subjects; and administrative policies become part of the Code of Federal Regulations (or a state's Code of Regulations), also organized by subject.

²⁵⁶ See, e.g., HYPO (Kevin D. Ashley, *Modelling Legal Argument: Reasoning With Cases and Hypotheticals* (1989)); CATO (Vincent Alevan, *Teaching Case-based Argumentation Through a Model and Examples* (1997)); Latifa Al-Abdulkarim, Katie Atkinson & Trevor Bench-Capon, *A Methodology for Designing Systems To Reason With Legal Cases Using Abstract Dialectical Frameworks*, A.I. & L. Vol 24, 1–49 (2016). See, generally, Katie Atkinson, *Representation and Automation of Legal Information*, in *BIG DATA LAW* (Roland Vogl ed., 2021).

²⁵⁷ Research at the intersection of social, behavioral, and computer science is helping to determine which methods for learning from human feedback and human observational behavior are most effective in a reinforcement learning setting, see, e.g., David Lindner & Mennatallah El-Assady, *Humans are not Boltzmann Distributions: Challenges and Opportunities for Modelling Human Feedback and Interaction in Reinforcement Learning* (2022); Mihaela Curmei et al., *Towards Psychologically-Grounded Dynamic Preference Models*, arXiv 2208.01534 (2022); Jaime F. Fisac et al., *Pragmatic-pedagogic Value Alignment*, *Robotics Research*, 49-57 (2020).

than direct instruction, may allow models to learn reward functions that better generalize;²⁵⁸ fortunately, more law is in the form of descriptions and standards than direct instructions and simple rules. Descriptions of the application of standards by judges and regulators provides a rich surface area to learn from.

Textual data can be curated and labeled for these purposes. Efforts of this nature should aim for two outcomes. *First*, data that can be used to evaluate how well AI understands legal standards. *Second*, the possibility that the initial expert labeled data can be used to generate additional much larger data sets through automated curation and processing of full legal corpora.²⁵⁹ This phase of the legal informatics project could lead to enough data to unlock the ability to not just evaluate models and verify AI, but also train (or at least fine-tune pre-trained) large models on prediction and decision task data derived from legal text.

Data curation should be designed such that the data will be both useful in the near-term for today's AI models, and crucially, so it will also likely be of increasing value as a function of the increase in general AI capabilities.²⁶⁰

III. CONTRACTS & STANDARDS: *HUMAN-AI* ALIGNMENT

Specifying what we want is hard. The difficulty compounds when we hand inadequate specifications over to powerful optimizers like AI that do not share our ontology of concepts or our language of alignment.²⁶¹ *Law Informs Code* with a tradition of methods (for drafting and interpreting statutes and contracts) that facilitates communicating what a human wants an agent to do.²⁶²

²⁵⁸ See, Summers et al., *How To Talk So Your Robot Will Learn: Instructions, Descriptions, and Pragmatics* (2022); Karthik Narasimhan, Regina Barzilay & Tommi Jaakkola, *Grounding Language for Transfer in Deep Reinforcement Learning* (2018); Austin W. Hanjie, Victor Zhong & Karthik Narasimhan, *Grounding Language to Entities and Dynamics for Generalization in Reinforcement Learning* (2021).

²⁵⁹ Like all machine learning models, natural language processing focused models often learn spurious associations, see, e.g., Divyansh Kaushik & Zachary C. Lipton, *How Much Reading Does Reading Comprehension Require? A Critical Investigation of Popular Benchmarks*, in *Empirical Methods in Natural Language Processing* (2018). To address this, and learn more generalizable knowledge from textual data, it is helpful to obtain counterfactual label augmentations (see, Divyansh Kaushik, Eduard Hovy & Zachary C. Lipton, *Learning the Difference that Makes a Difference with Counterfactually-Augmented Data* (2020) (Labels that revise each textual input, “so that it (i) accords with a counterfactual target label; (ii) retains internal coherence; and (iii) avoids unnecessary changes”); Matt Gardner et al., *Evaluating Models' Local Decision Boundaries via Contrast Sets* (2020)), and to remove data labels where spurious artifacts are likely to lead the models to learn patterns that do not generalize; see, e.g., Ronan Le Bras et al., *Adversarial Filters of Dataset Biases*, in *Proceedings of the 37th International Conference on Machine Learning*, PMLR 119, 1078-1088 (2020).

²⁶⁰ In particular, in natural language processing on long documents, and through leveraging offline and human-in-the-loop reinforcement learning; see *infra* Section II.C.1.i. & Section V.

²⁶¹ See, e.g., Alex Turner, Neale Ratzlaff & Prasad Tadepalli, *Avoiding Side Effects in Complex Environments*, in *Advances in Neural Information Processing Systems* 33 21406 (2020); Victoria Krakovna et al., *Avoiding Side Effects by Considering Future Tasks*, in *Advances in Neural Information Processing Systems* 33 19064 (2020).

²⁶² *Law also Informs Code* by specifying what AI systems should not do, in order to provide a broader knowledge base of how to reduce externalities and promote coordination and cooperation within a society (see *infra* Section IV).

For most AI, the human deploying it would like it to obey public laws,²⁶³ but that is not the originating purpose of any practical deployment. The purpose is to automatically answer your questions,²⁶⁴ or to serve as your personal assistant²⁶⁵ scheduling meetings and booking flights on your behalf,²⁶⁶ or to drive your car,²⁶⁷ or to produce beautiful images on command.²⁶⁸ Something directly useful to you. Contracts can help (Section III. A).²⁶⁹ However, standards are needed to fill the gaps in contracts (III. B). We illustrate the power of standards with an example of fiduciary duties (III. C).

A. Contracts

One way of describing the deployment of AI is that a human principal, *P*, employs an *AI* to accomplish a goal, *G*, specified by *P*. If we view *G* as a “contract,” methods for creating and implementing legal contracts – which govern billions of relationships every day – can inform how we align *AI* with *P*.²⁷⁰

Contracts memorialize a shared understanding between parties regarding *state-action-value* tuples. It is not possible to create a complete contingent contract between *AI* and *P* because *AI*'s training process is never comprehensive of every *state-action* pair that *AI* will see in the wild once deployed.²⁷¹ Although it is also practically impossible to create complete contracts between humans, contracts still serve as useful customizable commitment devices to clarify and advance shared goals. This works because the law has developed mechanisms to facilitate sustained alignment amongst ambiguity. Gaps within contracts – *state-action pairs* without a *value* – are often filled by the invocation of frequently employed standards (e.g., “material” and “reasonable”²⁷²). These standards could be used as modular (pre-trained model) building blocks across AI systems.

²⁶³ See *infra* Section IV.

²⁶⁴ OpenAI, *ChatGPT: Optimizing Language Models for Dialogue* (2022) <https://openai.com/blog/chatgpt>.

²⁶⁵ See, e.g., Askell Laboratory for Alignment.

²⁶⁶ See, e.g., Jessy Lin et al., *Inferring Rewards from Language in Context* (2022).

²⁶⁷ See, e.g., W. Bradley Knox et al., *Reward (Mis)design for Autonomous Driving*, arxiv.org (Mar. 11, 2022), <https://arxiv.org/abs/2104.13906>.

²⁶⁸ See, e.g., Aditya Ramesh et al., *Hierarchical Text-Conditional Image Generation with CLIP Latents* (2022).

²⁶⁹ See, e.g., Phillip Christoffersen, Andreas A. Haupt & Dylan Hadfield-Menell, *Get It in Writing: Formal Contracts Mitigate Social Dilemmas in Multi-Agent RL*, arXiv:2208.10469 (2022) (Allowing AI agents to implement contracts for performance of particular actions improves collective outcomes in social dilemmas.); Dylan Hadfield-Menell & Gillian K. Hadfield, *Incomplete Contracting and AI Alignment*, In Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society (2019) [Hereinafter Hadfield-Menell *Incomplete Contracting*].

²⁷⁰ See, generally, Hadfield-Menell *Incomplete Contracting*.

²⁷¹ See, Hadfield-Menell *Incomplete Contracting*. In some cases, e.g., for very simple financial agreements, it is possible to create a fully contingent computable contract; see, e.g., Mark Flood & Oliver Goodenough, *Contract as Automaton: Representing a Simple Financial Agreement in Computational Form*, A.I. & L. (2021); Shaun Azzopardi, Gordon J. Pace, Fernando Schapachnik & Gerardo Schneider, *Contract Automata*, 24 A.I. & L. 203 (2016). However, most deployment contexts of AI systems have far too large a state-action space for this approach to be feasible; see, e.g., James Grimmelman, *All Smart Contracts Are Ambiguous*, 2 Journal of Law and Innovation 1 (2019).

²⁷² Alan D. Miller & Ronen Perry, *The Reasonable Person*, 87 NYU L. Rev. 323 (2012); Karni A. Chagal-Feferkorn, *The Reasonable Algorithm*, U. Ill. JL Tech. & Pol'y 111 (2018); Karni A. Chagal-Feferkorn, *How Can I Tell If My Algorithm Was Reasonable?*, 27 MICH. TECH. L. REV. 213 (2021); Sheppard *Reasonableness*; Kevin P. Tobia, *How*

Rather than viewing contracts from the perspective of a traditional participant, e.g., a counterparty or judge, consistent with the *Law Informs Code* approach, AI could view contracts and their creation, implementation, evolution,²⁷³ and enforcement as guides to navigating webs of inter-agent obligations.²⁷⁴ For these more limited purposes, arguably, we can drop any presumed mental states and intentionality requirements to entering a contract from the AI side.²⁷⁵

This benefits both the negotiation and performance of the contracts for two reasons, relative to a traditional human-human contracting process. First, *in the negotiation phase*, human parties will often withhold information about their preferences because they perceive that information sharing to be strategically disadvantageous *ex ante* because they may attempt to further their goals *ex post*. Dropping the strategic nature of the relationship removes this incentive to withhold useful information.²⁷⁶ Second, *during the term of the contract*, parties will not be conducting economic analyses of whether breach is more favorable than performance.²⁷⁷ When we remove the enforcement concerns from the contracts, it removes downfalls such as these.²⁷⁸ But it does not deprive the *Law Informs Code* approach of the utility of the tools that have evolved to enable effective contracting, e.g., extra-contractual standards used to fill “contract” gaps in informing AI what to do for *P*.

B. Standards

A key engineering principle, especially for building complicated computational systems, is to leverage modular, reusable abstractions that can be flexibly plugged into a diverse set of systems.²⁷⁹ Standards are modular, reusable abstractions employed to align agents engaged in inherently incompletely specified relationships in uncertain circumstances.²⁸⁰ Pre-training deep

People Judge What Is Reasonable, 70 ALA. L. REV. 293 (2018); Patrick J. Kelley & Laurel A. Wendt, *What Judges Tell Juries About Negligence: A Review of Pattern Jury Instructions*, 77 CHI.-KENT L. REV. 587 (2002).

²⁷³ See, Matthew Jennejohn, Julian Nyarko & Eric Talley, *Contractual Evolution*, 89 U. Chi. L. Rev. 901 (2022).

²⁷⁴ Charles Fried, *Contract as Promise: A Theory of Contractual Obligation* (Harv. Univ. Press, 1981).

²⁷⁵ See, e.g., *Woburn National Bank v Woods*, 77 N.H. 172, 89 A 491, 492 (1914) (citation omitted), quoting Oliver Wendell Holmes, Jr., *The Common Law* (Little Brown 1881) at 307 (“A contract involves what is called a meeting of the minds of the parties. But this does not mean that they must have arrived at a common mental state touching the matter at hand. The standard by which their conduct is judged and their rights are limited are not internal but external. In the absence of fraud or incapacity, the question is: What did the party say and do? “The making of a contract does not depend upon the state of the parties’ minds; it depends upon their overt acts.”); John Linarelli, *A Philosophy of Contract Law for Artificial Intelligence: Shared Intentionality*, in CONTRACTING AND CONTRACT LAW IN THE AGE OF ARTIFICIAL INTELLIGENCE (Martin Ebers, Cristina Poncibò, & Mimi Zou eds., 2022).

²⁷⁶ See, Anthony J. Casey & Anthony Niblett, *Self-Driving Contracts*, in *The Journal of Corporation Law* (2017) [Hereinafter Casey, *Self-driving*].

²⁷⁷ See, e.g., Oliver Wendell Holmes, Jr., *The Path of the Law*, 10 HARV. L. REV. 457, 462 (1897) (“[t]he duty to keep a contract at common law means a prediction that you must pay damages if you do not keep it — and nothing else.”). Holmes (1897) and Fried (1981) are cited in Casey, *Self-driving*, in their discussion of the reduced role of breach of contracts if incomplete contracts could have their gaps filled by automated algorithms.

²⁷⁸ It reduces the importance of the traditional uses of legal concepts related to the enforcement of contracts, e.g., mutual mistake and impossibility; see, Casey, *Self-driving*. However, doctrines of this nature are still useful to the AI for understanding the context in which existing contracts data was created and their meaning amongst counterparties.

²⁷⁹ See, e.g., François Chollet, *Deep Learning with Python, Second Edition* (Manning, 2021); Olivier L. de Weck, Daniel Roos & Christopher L. Magee, *Engineering Systems: Meeting Human Needs in a Complex Technological World* (MIT Press, 2011).

²⁸⁰ See *infra* Section II. A. 3.

learning models, before they are fine-tuned to application-specific tasks, is a potential pathway for embedding concepts of legal standards, and associated downstream behaviors exhibiting those standards, into AI models. Rules describing discrete logical contractual terms, and straightforward specifications, can be bolted onto the overall automated system,²⁸¹ outside of (end-to-end differentiable) deep learning model(s). But standards require more nuanced approaches.

For humans, rules are generally more expensive to make but then cheaper to use (because it is clearer whether an action follows a rule), relative to standards that are more costly than rules to use (because, when choosing an action in real-time, there is high uncertainty about whether the action is *ex-post* going to comply with the standard).²⁸² For AI, standards are more expensive to instill (and validate) through extensive machine learning training and validation, but then cheaper to deploy because they scale to unenumerated state-action pairs. In the *Law Informs Code* use-case, in contrast to their legal creation and evolution,²⁸³ standards do not require adjudication for implementation and resolution of meaning. Rather, they are learned from past legal application and implemented up front. The law's computational process of iteratively defining standards through judicial opinion about their particular case-specific application, and regulatory guidance, can be leveraged as the AI's starting point.

C. An Example: Fiduciary Duty

If law is the applied philosophy of multi-agent alignment, fiduciary law is the branch of that applied philosophy concerned with a principal – a human with less control or information related to the provision of a service – and a fiduciary delegated to provide service.²⁸⁴ Fiduciary duties are imposed on powerful agents to align their behavior with the wellbeing of those they serve. Fiduciary standards are an empirically and theoretically rich area of law. The concept of fiduciary duty is widely deployed across financial services,²⁸⁵ business more generally, healthcare,

²⁸¹ See, e.g., computational logic-based representations of legal institutions and their relationships, e.g., King et al., *A Framework for Governing Institutions*, in Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems, 473-481 (ACM, 2015).

²⁸² See, Louis Kaplow, *Rules Versus Standards: An Economic Analysis*, 42 *Duke Law Journal* 557-629 (1992) at 1 (“Rules typically are more costly than standards to create, whereas standards tend to be more costly for individuals to interpret when deciding how to act and for an adjudicator to apply to past conduct.”).

²⁸³ See, e.g., Dale A. Nance, *Rules, Standards, and the Internal Point of View*, 75 *FORDHAM L. REV.* (2006); Sheppard *Reasonableness*.

²⁸⁴ In addition to the fiduciary obligations of investment advisors (see, *SEC v. Capital Gains Research Bureau, Inc.*, 375 U.S. 180, 194 (1963); 15 U.S.C. 80b; and 17 CFR 275), fiduciary duties have been applied widely by courts across various types of relationships outside of financial services and securities law (e.g., attorneys and trustees), see, e.g., Harold Brown, *Franchising - A Fiduciary Relationship*, 49 *TEX. L. REV.* 650 (1971); Arthur B. Laby, *The Fiduciary Obligation as the Adoption of Ends*, (2008), and citations therein, e.g., see, *Ledbetter v. First State Bank & Trust Co.*, 85 F.3d 1537, 1539 (11th Cir. 1996); *Venier v. Forbes*, 25 N.W.2d 704, 708 (Minn. 1946); *Meyer v. Maus*, 626 N.W.2d 281, 286 (N.D. 2001); John C. Coffee, Jr., *From Tort to Crime: Some Reflections on the Criminalization of Fiduciary Breaches and the Problematic Line Between Law and Ethics*, 19 *AM. CRIM. L. REV.* 117, 150 (1981); Austin W. Scott, *The Fiduciary Principle*, 37 *CAL. L. REV.* 539, 541 (1949). The standard is also applied in medical contexts, see, e.g., *American Medical Association Code of Medical Ethics, Opinions on Patient-Physician Relationships*, *AMA Principles of Medical Ethics: I, II, IV, VIII*.

²⁸⁵ In addition to fiduciary duty, there are at least five additional parallels between AI alignment and financial services law. (1.) We are attempting to align AI intentions with preferences of groups of humans – “Environmental, Social, Governance” investment products attempt to codify human values and securities regulators find that “greenwashing”

and more. Legislators, regulators, and self-regulatory organizations recognize the impossibility of complete contracts between agents (e.g., directors of corporations and investment advisers²⁸⁶) and the humans they serve (e.g., corporate shareholders, and investment clients). AI research also grapples with the impossibility of fully specified *state-action-reward* spaces for training AI agents that generalize to new circumstances.²⁸⁷ Complete contingent contracts (even if only implicitly complete) between an AI and the human(s) it serves are implausible for any systems operating in a realistic environment.²⁸⁸ Fiduciary duties are often seen as part of a solution to the incompleteness of contracts between shareholders and corporate directors,²⁸⁹ and between investors and their advisors.²⁹⁰

Fiduciary duty adds value beyond more complete contracts.²⁹¹ Even if parties could theoretically create a complete contract up front, there is still something missing: it's not a level playing field between contracting parties (parallel: AI has access to more information and computing power than humans). Contracts generally assume the parties are strategic, negotiating during the contract creation (parallel: the AI objective design) process, but the human-AI relationship is not fundamentally strategic during that design process. Contracts are generally

is common. (2.) We are attempting to manage complex novel AI systems with unpredictable behaviors – financial markets regulators routinely grapple with managing emergent behavior of complex adaptive systems, *see, e.g.*, Yesha Yadav, *The Failure of Liability in Modern Markets*, 102 Va. L. Rev. 1031 (2016). (3.) We are witnessing AI power concentrating in private firms with significant data and computing resources, such as large online advertising companies – we have seen the same thing happen over the past few decades in financial markets with the rise of private firms with significant data and computing resources, such as “platform hedge fund” firms managing tens of billions of dollars and the increasing difficulty of launching new alpha-seeking investment firms in that oligopoly-esque environment. (4.) Self-regulation is being discussed by AI companies (*see, e.g.* this early effort by a consortium of AI research companies, Cohere, OpenAI, and AI21 Labs: <https://openai.com/blog/best-practices-for-deploying-language-models/>) – FINRA is an example of a powerful self-regulatory body in financial services. (5.) Another lesson from financial regulation and reporting: corporate disclosure rules can work well but regulators should fight the urge toward them becoming boilerplate and devolving into performative box-checking.

²⁸⁶ Securities laws help align powerful agents (e.g., investment advisors) with their less informed human principals (e.g., investment clients) through fiduciary obligations. As AI becomes more generally capable, securities laws will increasingly apply directly to AI systems because buying, managing, offering, and selling securities are key vectors through which sufficiently advanced automated systems will interact within the broader world. Expanding the purview of the SEC over advanced AI systems could help enforce human-AI alignment.

²⁸⁷ AI alignment research recognizes a similar problem, *see, e.g.*, Abram Demski & Scott Garrabrant, *Embedded Agency* (2020) at 6, <https://arxiv.org/abs/1902.09469> (“the question is about creating a successor that will robustly not use its intelligence against you. From the point of view of the successor agent, the question is, “How do you robustly learn or respect the goals of something that is stupid, manipulable, and not even using the right ontology?””); Nate Soares & Benya Fallenstein, *Agent Foundations for Aligning Machine Intelligence with Human Interests: A Technical Research Agenda*, in *The Technological Singularity: Managing the Journey*, eds. Victor Callaghan, Jim Miller, Roman Yampolskiy & Stuart Armstrong (2017). Brent Mittelstadt, *Principles alone cannot guarantee ethical AI*, *Nature Machine Intelligence*, Vol 1, 501–507 (2019) at 505 (“AI development is not a formal profession. Equivalent fiduciary relationships and complementary governance mechanisms do not exist for private sector AI developers.”); Hadfield-Menell *Incomplete Contracting*.

²⁸⁸ *See*, Hadfield-Menell *Incomplete Contracting*.

²⁸⁹ Michael C. Jensen & William H. Meckling, *Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure*, *Journal of Financial Economics*, Vol 3, Issue 4, 305-360 (October 1976); Deborah A. DeMott, *Breach of Fiduciary Duty: On Justifiable Expectations of Loyalty and Their Consequences*, 48 *Arizona L. Rev.* 925-956 (2006).

²⁹⁰ *SEC v. Capital Gains Res. Bureau, Inc.*, 375 U.S. 180, 194-95 (1963); 15 U.S.C. 80b; 17 CFR 275.

²⁹¹ Alexander Styhre, *What We Talk About When We Talk About Fiduciary Duties: The Changing Role of a Legal Theory Concept in Corporate Governance Studies*, *Management & Organizational History* 13:2, 113-139 (2018) [Hereinafter, Styhre, *What We Talk About*]; Arthur B. Laby, *The Fiduciary Obligation as the Adoption of Ends*, 56 *Buff. L. Rev.* 99 (2008).

assumed to be created between equals, whereas fiduciary duties are explicitly placed on the party entrusted with more power or knowledge. Fiduciary duty addresses this asymmetric dynamic with guardrails to facilitate alignment of a principal with their agent.

Fiduciary duty goes beyond the explicit contract and helps guide a fiduciary in *a priori* unspecified state-action-value tuples;²⁹² whereas, contracting parties “may act in a self-interested manner even where the other party is injured, as long as such actions are reasonably contemplated by the contract.”²⁹³ Contrary to a fiduciary relationship, “no party to a contract has a general obligation to take care of the other, and neither has the right to be taken care of.”²⁹⁴ There is a fundamental shift in stance when a relationship moves from merely contractual to also include a fiduciary obligation: “In the world of contract, self-interest is the norm, and restraint must be imposed by others. In contrast, the altruistic posture of fiduciary law requires that once an individual undertakes to act as a fiduciary, he should act to further the interests of another in preference to his own.”²⁹⁵

A fiduciary duty has two primary components: a duty of loyalty and a duty of care.²⁹⁶ The duty of care could be interpreted to describe the capability of the AI to accomplish useful behavior for humans.²⁹⁷ The duty of loyalty, in the AI analogy, is about the AI’s faithful pursuit of human ends, which becomes more of an issue as AI is more capable and agentic.²⁹⁸

1. Information Expression

An example of how legal enforcement expresses information, *in and of itself*,²⁹⁹ is what an AI can glean from the focus on *ex ante* (human and corporate) deterrence with a default rule for

²⁹² Styhre, *What We Talk About*.

²⁹³ See, e.g., D. G. Smith, *Critical Resource Theory of Fiduciary Duty*, 55 *Vanderbilt L. Rev.* 1399–1497 (2002) at 1410; Deborah DeMott, *Beyond Metaphor: An Analysis of Fiduciary Obligation*, *Duke Law Journal* (1988) at 882 (The “fiduciary’s duties go beyond mere fairness and honesty; they oblige him to act to further the beneficiary’s best interests.”).

²⁹⁴ Tamar Frankel, *Fiduciary Law*, 71 *California L. Rev.* (1983) at 880, <https://www.jstor.org/stable/3480303>.

²⁹⁵ *Id.* at 830. According to some legal scholars, fiduciary law has arguably been an important contributor to the economic growth in modern societies, “Exchange of products is insufficient to support successful and flourishing societies. Services are needed as well and sometimes even more than products. By definition, an exchange of services involves unequal knowledge.” Tamar Frankel, *The Rise of Fiduciary Law*, Boston Univ. School of Law, Public Law Research Paper No. 18-18, <https://ssrn.com/abstract=3237023> (August 22, 2018) at 11.

²⁹⁶ See, G. Rauterberg & E. Talley, *Contracting Out of the Fiduciary Duty of Loyalty: An Empirical Analysis of Corporate Opportunity Waivers*, *Columbia L. Rev.* 117 (5): 1075–1151 (2017) (Discussing the distinction between duty of loyalty and duty of care in the context of Delaware corporate law.).

²⁹⁷ The alignment problem is broken down by some into outer and inner alignment, see, e.g., Evan Hubinger et al., *Risks from learned optimization in advanced machine learning systems* (2019). Eliciting human preferences, distilling them into suitable computational representations, and training an AI agent to understand them solves the “outer alignment” problem by aligning humans and the design of the objectives of their AI. Robustly implementing that AI design specification into behaviors of the AI so that it reliably reflects the human preferences and does not optimize for its own goals not shared by the human solves the “inner alignment” problem by aligning the design of the AI agent with its observed and potential behavior. The AI is fully loyal to the human if we solve inner alignment. In the context of fiduciary standards, outer alignment could potentially be interpreted as the duty of care, and inner alignment as the duty of loyalty.

²⁹⁸ See, e.g., Joseph Carlsmith, *Is Power-Seeking AI an Existential Risk?* (2022) at 4-7 <https://arxiv.org/pdf/2206.13353.pdf>.

²⁹⁹ See *infra* Section II. A. 1.

how any gains are split in the context of a fiduciary standard, “*the default rule in fiduciary law is that all gains that arise in connection with the fiduciary relationship belong to the principal unless the parties specifically agree otherwise. This default rule, which is contrary to the interests of the party with superior information, induces the fiduciary to make full disclosure so that the parties can complete the contract expressly as regards the principal’s and the fiduciary’s relative shares of the surplus arising from the conduct that would otherwise have constituted a breach.*”³⁰⁰ Other means of legal deterrence can center more on *post-hoc* sanction or incapacitation. If embedded in AI model pre-training processes, standards pursuing deterrence by thwarting the opportunity to share in the gains of negative behavior(s) could guide an AI agent upheld to this standard toward, “*the disclosure purposes of fiduciary law. Because the fiduciary is not entitled to keep the gains from breach, the fiduciary is [...] given an incentive to disclose the potential gains from breach and seek the principal’s consent.*”³⁰¹

2. A Spectrum

Within financial services, there is a spectrum of fiduciary obligation, e.g., a trustee has significant obligations, while an index provider has a tenuous obligation to investors in funds tracking their index (when there is a financial advisor sitting in between the index provider and the end investor).³⁰² Analogously, fiduciary duty can be a useful standard both for today’s AI models and for much more capable models that may be developed over the coming years. Today’s deployed AI is more similar to the index provider powering a simple rule-based investment strategy, like an exchange-traded fund tracking a standard S&P 500 index,³⁰³ whereas future more advanced AI is likely to be more analogous to something like a Trustee administering investments in complicated private equity transactions. We should dial up the fiduciary obligations for more advanced AI.

Another way of looking at this: assuming increased capabilities, AI could enable fiduciary duties to be more broadly applied across digital services. In scenarios where an agent is trusted to adopt a principal’s objectives, standards that help ensure the agent can be trusted could be foundational to application-specific training processes. In addition to traditionally clear-cut fiduciaries (such as investment advisers), automated personal assistants, programming partners,³⁰⁴ and other emerging AI-driven services could be designed to exhibit fiduciary obligations toward their human clients.³⁰⁵ Advancing capabilities of AI could make this possible by enabling

³⁰⁰ Robert H. Sitkoff, *The Economic Structure of Fiduciary Law*, Boston University L. Rev. (2011) at 1049 [Hereinafter, Sitkoff *The Economic Structure*].

³⁰¹ Sitkoff *The Economic Structure* at 1049.

³⁰² See, e.g., *SEC Requests Information and Comment on Advisers Act Regulatory Status of Index Providers, Model Portfolio Providers, and Pricing Services* (2022).

³⁰³ SEC, *Commission Interpretation Regarding Standard of Conduct for Investment Advisers* (2019).

³⁰⁴ See, e.g., Mark Chen et al., *Evaluating Large Language Models Trained on Code*, arXiv:2107.03374 (2021).

³⁰⁵ It has been argued that the digital age, “has given rise to new fiduciary relationships created by the explosion of the collection and use of personal data. The relationships of trust between end-users and online service providers need not be identical to traditional professional relationships in all respects.” Jack M. Balkin, *Information Fiduciaries and the First Amendment*, U.C. Davis. L. Rev. (2016) at 1221. In the context of data privacy, Jack M. Balkin, *The Fiduciary Model of Privacy*, Harvard L. Rev. Forum, Vol. 134, No. 1 (November 2020) argues that technology companies should have fiduciary duties toward their end users, including a duty of confidentiality, a duty of care, and a duty of loyalty.

scalability of high-quality personalized advice (the basis of the duty of care), while the advancing capabilities make the duty of loyalty component increasingly salient.³⁰⁶

3. *Toward Implementation*

One possibility for implementing fiduciary standards is to develop a base-level pre-training process for learning the standard across various contexts, while using existing human-AI alignment techniques, such as reinforcement learning from human feedback, as the “contract” component, e.g., by personalizing the AI reward functions to the preferences of the individual human(s) that the AI is working on behalf of.³⁰⁷

To learn the standard across various contexts, there are many existing relationships that can be converted to data and training processes, “*Fiduciary principles govern an incredibly wide and diverse set of relationships, from personal relationships and professional service relationships to all manner of interpersonal and institutional commercial relationships. Fiduciary principles structure relationships through which children are raised, incapable adults cared for, sensitive client interests addressed, vast sums of money invested, businesses managed, real and personal property administered, government functions performed, and charitable organizations run. Fiduciary law, more than any other field, undergirds the increasingly complex fabric of relationships of interdependence in and through which people come to rely on one another in the pursuit of valued interests.*”³⁰⁸ For instance, there is a rich set of fiduciary behavior from corporate directors (fiduciaries to shareholders) and investment advisers (fiduciaries to clients) from which AI could learn. Corporate officers and investment advisors face the issue of balancing their own interests, the interests of their principals, and the interests of society at large.³⁰⁹ Unlike most human decision-making, corporate and investor behavior are well documented and are often made by professionals with advisors that have knowledge of the relevant law. This opens up the possibility of tapping into this observational data to train agents.³¹⁰

³⁰⁶ See, e.g., Michael K. Cohen, Marcus Hutter & Michael A. Osborne, *Advanced Artificial Agents Intervene in the Provision of Reward*, AI Magazine (2022) <https://onlinelibrary.wiley.com/doi/full/10.1002/aaai.12064>; Richard Ngo, *The Alignment Problem From a Deep Learning Perspective*, AI Alignment Forum (Aug 10, 2022) <https://www.alignmentforum.org/posts/KbyRPCAsWv5GtfrbG/the-alignment-problem-from-a-deep-learning-perspective>; Alexander Matt Turner et al., *Optimal Policies Tend To Seek Power*, In *Advances in Neural Information Processing Systems* (2021); Ajeya Cotra, *Without Specific Countermeasures, The Easiest Path to Transformative AI Likely Leads to AI Takeover* (2022) at subsection “*As humans’ control fades, Alex would be motivated to take over*” https://www.alignmentforum.org/posts/pRkFkzwKZ2zfa3R6H/without-specific-countermeasures-the-easiest-path-to#As_humans__control_fades__Alex_would_be_motivated_to_take_over; Joseph Carlsmith, *Is Power-Seeking AI an Existential Risk?* (2022).

³⁰⁷ For the part of the human-AI alignment problem under what we could call the duty of care component, one approach involves eliciting human preferences in a form legible to AI and using reinforcement learning to fine-tune the AI to exhibit behaviors that reliably reflect those preferences; see, e.g., Long Ouyang et al. *Training Language Models to Follow Instructions with Human Feedback*, arxiv.org (Mar. 4, 2022), <https://arxiv.org/pdf/2203.02155.pdf>.

³⁰⁸ Paul B. Miller, *The Identification of Fiduciary Relationships* (February 6, 2018). See, e.g., Evan J. Criddle, Paul B. Miller & Robert H. Sitkoff, eds., *The Oxford Handbook of Fiduciary Law* (Oxford University Press, 2019).

³⁰⁹ So-called “Environmental, Social, Governance” (ESG) investing is an example of fiduciaries (corporate directors and investment advisors) purportedly factoring in the interests of society at large into their professional decisions, see, e.g., Mark Carney, *Value(s): Building a Better World for All* (2021) at 382-453; Alex Edmans, *Grow the Pie: How Great Companies Deliver Both Purpose and Profit* (2020).

³¹⁰ See *infra* Section II. C. 2. ii.

This could involve codifying examples of fiduciary behavior into a structured format to train models,³¹¹ including both “gold-standard” human labeled data and automated data structuring (sampled and selectively human validated for correctness). The ultimate goal is to use this semi-structured data to conduct self-supervised learning across relevant case law, regulatory guidance, and self-regulatory data to learn correct and incorrect fiduciary behavior across contexts.

The first goal should be to develop public benchmark datasets and simulation environments for specific legal standards. This would ideally catalyze widespread adoption of a validation practice demonstrating any given AI system’s “understanding” of the legal and regulatory standards relevant to its potential deployment.³¹² The next frontier is for AI to understand, and guide its actions, with public law.

IV. PUBLIC LAW: *SOCIETY-AI* ALIGNMENT

If we succeed with the *Law Informs Code* approach in increasing the alignment of one AI to a small number of humans through the use of contracts and standards, we will have a more useful and *locally* reliable system. However, all else equal, this likely *decreases* the expected global reliability and safety as an AI interacts with the broader world, e.g., by increasing the risk of maximizing the welfare of a small group of powerful people.³¹³ There are many more objectives (outside of individual or group goals) and many more humans that should be considered. As AI capabilities advance, we need to simultaneously address the *human-AI* and *society-AI* alignment problems.

Unfortunately, we cannot simply point an AI’s contractual or fiduciary obligations to a broader set of humans. For one, some individuals would “contract” with an AI (e.g., by providing instructions to the AI or from the AI learning the humans’ preferences) to harm others.³¹⁴ Further, humans have (often, inconsistent and time-varying) preferences about the behavior of other humans (especially behaviors with negative externalities) and states of the world more broadly.³¹⁵ Moving beyond the problem of aligning AI with a single human, aligning AI with society is considerably more difficult³¹⁶ but necessary as AI deployment has broad effects.³¹⁷

³¹¹ See *infra* Section II. C. 2. ii.

³¹² See *infra* Section II. B. 2.

³¹³ See, e.g., William McAskill, *What We Owe the Future* (2022) at 83-86. Langdon Winner, *The Whale and the Reactor: A Search for Limits in an Age of High Technology*, University of Chicago Press (2010); Mark Coeckelbergh, *The Political Philosophy of AI* (2022).

³¹⁴ Iason Gabriel, *Artificial Intelligence, Values, and Alignment*, 30 MINDS & MACHINES 411 (2020) [Hereinafter Gabriel, *Values*.]; S. Blackburn, *Ruling Passions: An Essay in Practical Reasoning* (Oxford University Press, 2001).

³¹⁵ Gabriel, *Values*.

³¹⁶ See, e.g., Andrew Critch & David Krueger, *AI Research Considerations for Human Existential Safety (ARCHES)* (2020) [Hereinafter, Critch, *AI Research Considerations*]; Eliezer Yudkowsky, *Coherent Extrapolated Volition*, Singularity Institute for Artificial Intelligence (2004); Hans De Bruijn & Paulien M. Herder, *System and Actor Perspectives on Sociotechnical Systems*, IEEE Transactions on Systems, Man, and Cybernetics-part A: Systems and Humans 39.5 981 (2009); Jiaying Shen, Raphen Becker & Victor Lesser, *Agent Interaction in Distributed POMDPs and its Implications on Complexity*, in Proceedings of the Fifth International Joint Conference on Autonomous Agents and Multiagent Systems, 529-536 (2006).

³¹⁷ See, Ben Wagner, *Accountability by Design in Technology Research*, Computer Law & Security Review, 37 105398 (2020); Roel Dobbe, Thomas Krendl Gilbert & Yonatan Mintz, *Hard Choices in Artificial Intelligence*, Artificial Intelligence, 300 103555 (2021).

Most AI alignment research is focused on the solipsistic “single-single” problem of single human and a single AI.³¹⁸ The pluralistic dilemmas stemming from “single-multi” (a single human and multiple AIs) and especially “multi-single” (multiple humans and a single AI³¹⁹) and “multi-multi” situations are critical.³²⁰ When attempting to align multiple humans with one or more AI, we need overlapping and sustained endorsements of AI behaviors,³²¹ but there is no consensus social choice mechanism to aggregate preferences and values across humans³²² or time.³²³ Eliciting and synthesizing human values systematically is an unsolved problem that philosophers and economists have labored on for millennia.³²⁴ When aggregating views across society, we run into at least three design decisions, “standing, concerning whose ethics views are included; measurement, concerning how their views are identified; and aggregation, concerning how individual views are combined to a single view that will guide AI behavior.”³²⁵ Beyond merely the technical challenges,³²⁶ “[e]ach set of decisions poses difficult ethical dilemmas with major consequences for AI behavior, with some decision options yielding pathological or even catastrophic results.”³²⁷ Rather than attempting to reinvent the wheel in ivory towers and corporate bubbles, we should be inspired by democracy and law.³²⁸

³¹⁸ See, Critch, *AI Research Considerations*.

³¹⁹ See, e.g., Arnaud Fickinger et al., *Multi-Principal Assistance Games: Definition and Collegial Mechanisms*, arXiv:2012.14536 (2020); Critch, *AI Research Considerations*.

³²⁰ Critch, *AI Research Considerations*.

³²¹ See, e.g., Gabriel, *Values*.

³²² See, Amartya Sen, *Collective Choice and Social Welfare*, Harv. Univ. Press (2018); G. Arrhenius, *An Impossibility Theorem for Welfarist Axiologies*, *Economics & Philosophy*, 16(2), 247–266 (2000); Seth D. Baum, *Social Choice Ethics in Artificial Intelligence*, *AI & Society* 35.1, 165-176 (2020); Critch, *AI Research Considerations*; Gabriel, *Values*.

³²³ Tyler Cowen & Derek Parfit, *Against the Social Discount Rate*, in Peter Laslett & James S. Fishkin (eds.) *Justice Between Age Groups and Generations*, Yale University Press 144 (1992).

³²⁴ See, e.g., Gabriel, *Values*; Ariela Tubert, *Ethical Machines*, 41 *Seattle U L Rev* 1163 (2017); Amartya Sen, *Rationality and Social Choice*, *The American Economic Review* 85.1 (1995).

³²⁵ Seth D. Baum, *Social Choice Ethics in Artificial Intelligence*, *AI & SOCIETY* 35.1, 165-176 (2020) at 1.

³²⁶ For AI capabilities research in multi-agent contexts, see, e.g., Max Jaderberg et al., *Human-level Performance in 3D Multiplayer Games with Population-based Reinforcement Learning*, *Science* 364.6443 859-865 (2019); Hengyuan Hu, Adam Lerer, Alex Peysakhovich & Jakob Foerster, “*Other-Play*” for Zero-Shot Coordination, In International Conference on Machine Learning, 4399-4410 (2020); Johannes Treutlein, Michael Dennis, Caspar Oesterheld & Jakob Foerster, *A New Formalism, Method and Open Issues for Zero-shot Coordination*, In International Conference on Machine Learning, 10413-10423 (2021); Phillip Christoffersen, Andreas A. Haupt & Dylan Hadfield-Menell, *Get It in Writing: Formal Contracts Mitigate Social Dilemmas in Multi-Agent RL*, arXiv:2208.10469 (2022); Pablo Hernandez-Leal, Bilal Kartal & Matthew E. Taylor, *A Survey and Critique of Multiagent Deep Reinforcement Learning*, *Autonomous Agents and Multi-Agent Systems* 33, no. 6 750-797 (2019); Chongjie Zhang & Julie A. Shah, *Fairness in Multi-agent Sequential Decision-making*, in *Advances in Neural Information Processing Systems* 27 (2014); Siqi Liu et al., *From Motor Control to Team Play in Simulated Humanoid Football*, *SCIENCE ROBOTICS* Vol 7, Issue 69 (Aug 31 2022) (They demonstrate agents learning coordination in a relatively complex multi-agent environment.); David Ha & Yujin Tang, *Collective Intelligence for Deep Learning: A Survey of Recent Developments*, *Collective Intelligence* 1(1) (2022) (The intersections of the fields of complexity science and deep learning may unlock additional insights about systems with a large number of agents and emergent social phenomena.).

³²⁷ *Id.*

³²⁸ If we are leveraging democratically developed law, we will need to ensure that AI does not corrupt the law-making process, see, e.g., Robert Epstein & Ronald E. Robertson, *The Search Engine Manipulation Effect (SEME) and its possible impact on the outcomes of elections*, *Proceedings of the National Academy of Sciences* 112.33 (2015); Mark Coeckelbergh, *The Political Philosophy of AI* (2022) at 62-92; Shoshana Zuboff, *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*, *Public Affairs* (2019). And we need to ensure that humans are the engines of law-making, see *infra* Section II. A. 1.

In addition to *Law Informing Code* through standards and interpretation methods that facilitate specifying what a human wants an agent to do,³²⁹ *Law Informs Code* with a constantly updated and verified knowledge base of societal preferences on what AI should not do, in order to reduce externalities (resolve disagreements among “contract-level” AI deployments) and promote coordination and cooperation (Figure 8).³³⁰ There is no other comparable source of this knowledge.

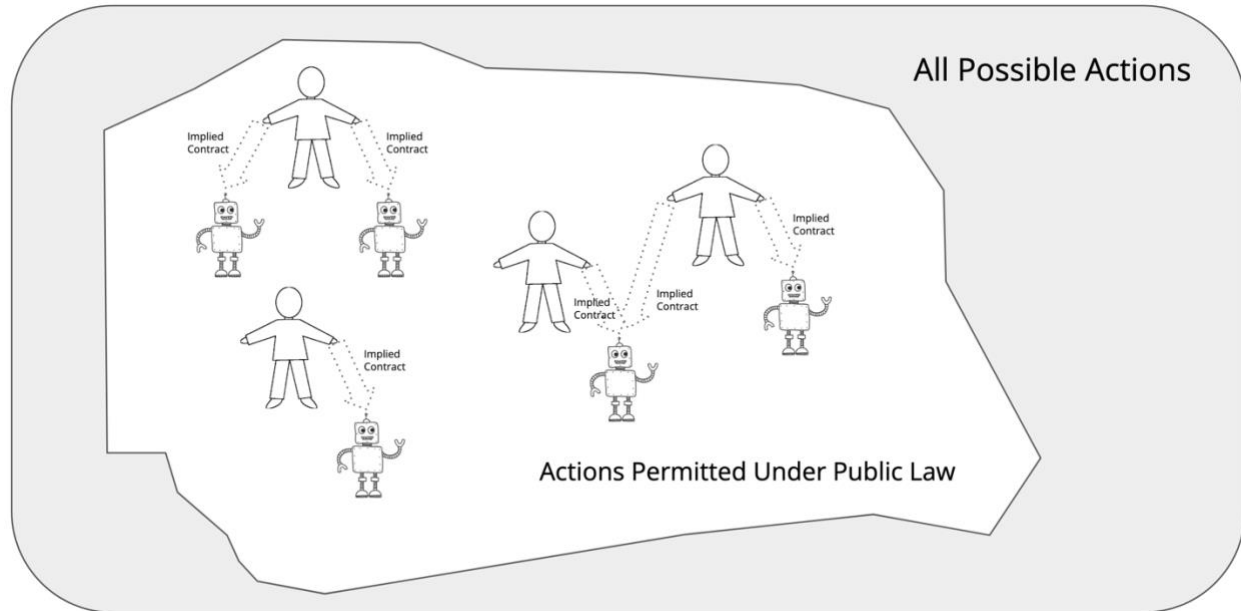


Figure 8: AI understanding *public law* can help constrain AI actions to align AI with society; while *private law (implied contracts)* between AI and human(s) instructs AI and aligns with humans.

A. AI Ethics and Moral Machines

³²⁹ See *infra* Section III.

³³⁰ Although this Article is not focused on how *Law Governs AI*, the *Law Informs AI* agenda suggests a novel policy approach (as a thought experiment) to governing AI’s relationships to humans and the physical world: wrapping all agentic AI systems in their own legal entities, e.g., a Corporation or a Limited Liability Company. A public policy, then, to further align AI with humans would be to enforce that the legal entity has verified human shareholders. The corporation is, to a large extent, a mechanism designed to reduce the principal-agent problem between shareholders and managers (DGCL §141(a) (“The business and affairs of every corporation organized under this chapter shall be managed by or under the direction of a board of directors....”), so with humans as the shareholders the corporate form could help align the corporate AI “management.” Regardless of whether wrapping the system in a legal entity would be helpful, under current law, sufficiently advanced AI systems would be able to utilize legal business entities as the key vector through which they conduct their affairs, e.g., to employ humans, to sue other entities, to purchase goods (see, e.g., Shawn Bayern, *Are Autonomous Entities Possible*, NW. U. L. REV. Online 114 23 (2019); Lynn M. LoPucki, *Algorithmic Entities*, Vol 95, Issue 4, 887-953 Washington University L. Rev. (2018); Shawn Bayern, *The Implications of Modern Business Entity Law for the Regulation of Autonomous Systems*, 19 STAN. TECH. L. REV. 93, 104 n.43 (2015); Shawn Bayern, *Of Bitcoins, Independently Wealthy Software, and the Zero-Member LLC*, 108 NW. U. L. REV. 1485, 1496–97 (2014)). Reducing the risk that this potentially inevitable state of affairs leads to bad outcomes for humans may imply the same conclusion: we should strictly enforce that business entities have human shareholders.

The *Law Informs Code* approach should be the core alignment framework, with attempts to embed (ever-contested) “ethics” into AI as a complementary, secondary effort.³³¹ When AI agents are navigating the world, it is important for AI to attempt to understand (or at least try to predict) moral judgements of humans encountered.³³² State-of-the-art models already perform reasonably well predicting human judgements on a spectrum of everyday situations.³³³ Human intuition, our common-sense morality, often falters in situations that involve decisions about groups unlike ourselves, leading to a “Tragedy of Common-Sense Morality.”³³⁴ There is no widely-agreed upon societal mechanism to filter observed human decisions that a model can learn from to those that exhibit preferred decisions, or to validate crowd-sourced judgments about behaviors.³³⁵ The process of learning *descriptive ethics* relies on descriptive data of how the (largely unethical) world looks or (unauthoritative, illegitimate, almost immediately outdated, and disembodied³³⁶) surveys of common-sense judgements of morally charged decisions.³³⁷ In building aligned AI, we cannot rely solely on these data sources.³³⁸

Instead of attempting to replicate common sense morality in AI (learning *descriptive ethics*), we could also use various academic philosophical theories – learning or hand-

³³¹ See, e.g., Joshua Walker, *Is 'Ethical AI' a Red Herring?* 36 Santa Clara High Tech LJ 445 (2019).

³³² See, e.g., Gonçalo Pereira, Rui Prada & Pedro A. Santos, *Integrating Social Power into the Decision-making of Cognitive Agents*, 241 *Artificial Intelligence* 1-44 (2016); Liwei Jiang et al., *Delphi: Towards Machine Ethics and Norms* (2021); Hendrycks et al., *Aligning AI With Shared Human Values* (2021); Nicholas Lourie, Ronan Le Bras & Yejin Choi, *Scruples: A Corpus of Community Ethical Judgments on 32,000 Real-life Anecdotes*, In Proceedings of the AAAI Conference on Artificial Intelligence, vol. 35, no. 15, 13470-13479 (2021); Edmond Awad et al., *The Moral Machine Experiment*, *Nature* 563.7729 59-64 (2018).

³³³ See, e.g., Liwei Jiang et al., *Delphi: Towards Machine Ethics and Norms* (2021) (1.7M examples); Dan Hendrycks et al., *Aligning AI With Shared Human Values* (2021); *The Moral Uncertainty Research Competition* (2022) <https://moraluncertainty.mlsafety.org>; Dan Hendrycks et al., *Aligning AI With Shared Human Values* (2021); Caleb Ziems, Jane Yu, Yi-Chia Wang, Alon Halevy & Diyi Yang, *The Moral Integrity Corpus: A Benchmark for Ethical Dialogue Systems*, In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics, Association for Computational Linguistics (2022).

³³⁴ See, Joshua Greene, *Moral Tribes: Emotion, Reason, and the Gap Between US and Them*, Penguin Press (2013) [Hereinafter Greene, *Moral Tribes*].

³³⁵ Researchers attempting to embed ethics into deep learning systems acknowledge this; see, e.g., Liwei Jiang et al., *Can Machines Learn Morality? The Delphi Experiment* (2022) <https://arxiv.org/pdf/2110.07574.pdf> at 27 (“We recognize that value systems differ among annotators (Jiang et al., 2021a; Sap et al., 2022), and accept that even UDHR [Universal Declaration of Human Rights] may not be acceptable for all. Perhaps some readers will object that there is an ethical requirement for scientists to take account of all viewpoints, but such exclusion of views is unavoidable since it is not possible to represent every viewpoint simultaneously. This is an inherent property of any approach that trains on a large corpus annotated by multiple people.”); Caleb Ziems, Jane Yu, Yi-Chia Wang, Alon Halevy & Diyi Yang, *The Moral Integrity Corpus: A Benchmark for Ethical Dialogue Systems*, In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics, Association for Computational Linguistics (2022) at 3763 (“Any collection of moral judgments will reflect the annotators’ worldviews [...] we recognize that even regionally-localized judgments may shift with context over time, and a potentially shifting target demands adaptable moral agents”).

³³⁶ See, e.g., Hubert Etienne, *The Dark Side of the 'Moral Machine' and the Fallacy of Computational Ethical Decision-making for Autonomous Vehicles*, *Law, Innovation and Technology* 13, no. 1, 85-107 (2021); Kathryn B. Francis et al., *Virtual Morality: Transitioning from Moral Judgment to Moral Action?* *Plos One*, 11(10):e0164374 (2016).

³³⁷ Cristina Bicchieri, *Norms in the Wild: How to Diagnose, Measure, and Change Social Norms*, Oxford University Press (2017) at xiv (“the presumed link between empirical (all do it) and normative (all approve of it) expectations may lead us into epistemic traps that are difficult to escape.”); Zeerak Talat et al., *A Word on Machine Ethics: A Response to Jiang et al. (2021)*, arXiv:2111.04158 (2021).

³³⁸ Zeerak Talat et al., *A Word on Machine Ethics: A Response to Jiang et al. (2021)*, arXiv:2111.04158 (2021).

engineering³³⁹ *prescriptive ethics* – to address AI-society alignment and imbue societal values.³⁴⁰ We provide six reasons why prescriptive ethics is not a suitable primary framework for AI alignment.³⁴¹

First, there is no unified ethical theory precise enough to be practically useful for building AI;³⁴² therefore, it does not meet our first desired characteristic of an alignment framework.³⁴³

Second, ethics does not have any rigorous tests of its theories; it does not meet our second desired characteristic of an alignment framework because it has not been battle-tested outside of academia, “[t]he truly difficult part of ethics—actually translating normative theories, concepts and values into good practices AI practitioners can adopt—is kicked down the road like the proverbial can.”³⁴⁴ Two corollaries to these first two issues are that we cannot validate the ethics of AI or its behaviors in any widely agreed-upon manner,³⁴⁵ and there is little data on empirical applications (especially not one with sufficient ecological validity³⁴⁶) that can be leveraged by

³³⁹ Selmer Bringsjord, Konstantine Arkoudas & Paul Bello, *Toward a General Logicist Methodology for Engineering Ethically Correct Robots*, IEEE Intelligent Systems 21, no. 4, 38-44 (2006).

³⁴⁰ See, e.g., Wendell Wallach & Colin Allen, *Moral Machines: Teaching Robots Right from Wrong* (2009); James H. Moor, *The Nature, Importance, and Difficulty of Machine Ethics*, IEEE intelligent systems 21, no. 4 18-21 (2006). Michael Anderson & Susan L. Anderson, *Machine Ethics*, Cambridge University Press (2011); Edmond Awad et al., *Computational Ethics*, In Trends in Cognitive Sciences (2022); James H. Moor, *Just Consequentialism and Computing*, Ethics and Information Technology 1, 61–65 (1999); Heather M. Roff, *Expected Utilitarianism* (2020); Elizabeth Gibney, *The Battle for Ethical AI at the World’s Biggest Machine-learning Conference*, Nature (2020); Dan Hendrycks et al., *Aligning AI With Shared Human Values* (2021); National Academies of Sciences, Engineering, and Medicine, *Fostering Responsible Computing Research: Foundations and Practices*, Washington, DC: The National Academies Press (2022); Joshua Greene et al., *Embedding Ethical Principles in Collective Decision Support Systems*, Thirtieth AAAI Conference on Artificial Intelligence (2016).

³⁴¹ If the ethical theory is a consequentialist one, another issue is that the implementation would have major capabilities externalities, Dan Hendrycks & Thomas Woodside, *Perform Tractable Research While Avoiding Capabilities Externalities* (2022) <https://www.alignmentforum.org/posts/dfRtxWcFDupfWpLQo/perform-tractable-research-while-avoiding-capabilities> (“one should not try to model consequentialist ethics by building better general predictive world models, as this is likely to create capabilities externalities.”).

³⁴² See, e.g., Brent Mittelstadt, *Principles Alone Cannot Guarantee Ethical AI*, Nature Machine Intelligence, Vol 1, 501–507 (2019) at 503 (“Fairness, dignity and other such abstract concepts are examples of ‘essentially contested concepts’ with many possible conflicting meanings that require contextual interpretation through one’s background political and philosophical beliefs. These different interpretations, which can be rationally and genuinely held, lead to substantively different requirements in practice, which will only be revealed once principles or concepts are translated and tested in practice”); R. Clarke, *Principles and Business Processes for Responsible AI*, Computer Law and Security Review (2019); Jessica Morley et al., *Ethics as a Service: A Pragmatic Operationalisation of AI Ethics*, 31.2 Minds and Machines 239-256 (2021); J. van den Hoven, *Computer Ethics and Moral Methodology*, Metaphilosophy 28, 234–248 (1997); W. B. Gallie, *Essentially Contested Concepts*, Proc. Aristot. Soc. 56, 167–198 (1955); H. S. Richardson, *Specifying Norms as a way to Resolve Concrete Ethical Problems*, Philos. Public Aff. 19, 279–310 (1990).

³⁴³ See *infra* Section I for the framework requirements.

³⁴⁴ Brent Mittelstadt, *Principles Alone Cannot Guarantee Ethical AI*, Nature Machine Intelligence, Vol 1, 501–507 (2019) at 503; K. Shilton, *Values Levers: Building Ethics Into Design*, Sci. Technol. Hum. Values 38, 374–397 (2013).

³⁴⁵ See, e.g., Anne Gerdes & Peter Øhrstrøm, *Issues in Robot Ethics Seen Through the Lens of a Moral Turing Test*, Journal of Information, Communication and Ethics in Society (2015); J. Van den Bergh & D. Deschoolmeester, *Ethical Decision Making in ICT: Discussing the Impact of an Ethical Code of Conduct*, Commun. IBIMA, 127497 (2010); B. Friedman, D. G. Hendry & A. Borning, *A Survey of Value Sensitive Design Methods*, Found. Trends Hum. Comp. Interact. 11, 63–125 (2017); Brent Mittelstadt, *Principles Alone Cannot Guarantee Ethical AI*, Nature Machine Intelligence, Vol 1, 501–507 (2019); Mireille Hildebrandt, *Closure: On Ethics, Code, and Law*, in Law for Computer Scientists and Other Folk (Oxford, 2020).

³⁴⁶ See, e.g., Martin T. Orne & Charles H. Holland, *On the Ecological Validity of Laboratory Deceptions*, International Journal of Psychiatry 6, no. 4, 282-293 (1968).

machine learning processes.³⁴⁷ Law is validated in a widely agreed-upon manner,³⁴⁸ e.g., court opinion, and has databases of empirical application with sufficient ecological validity.

Third, ethics, by its nature, lacks settled precedent across, and even within, theories.³⁴⁹ There are, justifiably, fundamental disagreements between reasonable people about which ethical theory would be best to implement, spanning academic metaphysical disagreements to more practical indeterminacies, “not only are there disagreements about the appropriate ethical framework to implement, but there are specific topics in ethical theory [...] that appear to elude any definitive resolution regardless of the framework chosen.”³⁵⁰ As AI is more broadly deployed, there will be much more widespread attention on the underpinnings of AI system design. As this scrutiny increases, there will be deep investigation into what morally relevant principles are being embedded in AI, and strong backlash from the public, media, and the government into particular philosophical theories. Public law is not immune from criticism either, but the public can take that criticism to their elected representatives.

Fourth, even if AI developers (impossibly) agreed on one ethical theory (or ensemble of underlying theories³⁵¹) being “correct,” there is no mechanism to align humans around that theory (or “meta-theory”).³⁵² In contrast, in democracies, law has legitimate authority imposed by widely accepted government institutions,³⁵³ and serves as a coordinating focal point of values to facilitate human progress.³⁵⁴ Imbuing understanding of ethical frameworks is a useful exercise. The law is silent on many important values that humans hold and we can use ethical modules to better align AI with its human principal by imbuing the ethical framework that the human principal chooses into the AI. But this is more in the *human-AI alignment* realm than a *society-AI alignment* solution. Society-AI alignment requires us to move beyond “private contracts” between a human and her AI and into the realm of public law to explicitly address inter-agent conflicts and policies designed to ameliorate externalities and solve massively multi-agent coordination and cooperation dilemmas through top-down implementations.³⁵⁵ We can use ethics to better align AI with its

³⁴⁷ See *infra* Section II. C. 2. for how law can be leveraged by machine learning.

³⁴⁸ See, e.g., Mireille Hildebrandt, *Closure: On Ethics, Code, and Law*, in *Law for Computer Scientists and Other Folk* (Oxford, 2020).

³⁴⁹ See, e.g., Gabriel, *Values* at 425 (“it is very unlikely that any single moral theory we can now point to captures the entire truth about morality. Indeed, each of the major candidates, at least within Western philosophical traditions, has strongly counterintuitive moral implications in some known situations, or else is significantly underdetermined.”); Joseph F. Fletcher, *Situation Ethics: The New Morality* (1997).

³⁵⁰ Miles Brundage, *Limitations and Risks of Machine Ethics*, *Journal of Experimental and Theoretical Artificial Intelligence*, 26.3, 355–372 (2014) at 369.

³⁵¹ See, e.g., Toby Newberry & Toby Ord, *The Parliamentary Approach to Moral Uncertainty*, Technical Report # 2021-2, (Future of Humanity Institute, University of Oxford, July 15, 2021) <https://www.fhi.ox.ac.uk/wpcontent/uploads/2021/06/Parliamentary-Approach-to-Moral-Uncertainty.pdf>; William MacAskill, *Practical Ethics Given Moral Uncertainty*, *Utilitas* 31.3 231 (2019); Adrien Ecoffet & Joel Lehman, *Reinforcement Learning Under Moral Uncertainty*, In *International Conference on Machine Learning*, 2926-2936. PMLR (2021).

³⁵² See, e.g., John Rawls, *The Law of Peoples: with, the Idea of Public Reason Revisited*, Harv. Univ. Press (1999) at 11-16; Gabriel, *Values* at 425.

³⁵³ See, generally, David Estlund, *Democratic Authority: A Philosophical Framework*, Princeton University Press (2009); Gabriel, *Values* at 432.

³⁵⁴ “Law is perhaps society’s most general purpose tool for creating focal points and achieving coordination. Coordinated behavior requires concordant expectations, and the law creates those expectations by the dictates it expresses.” Richard H. McAdams, *The Expressive Powers of Law*, Harv. Univ. Press (2017) at 260 [Hereinafter McAdams, *The Expressive Powers of Law*].

³⁵⁵ For a discussion of the difference between intent-alignment (similar to our characterization of *human-AI alignment*) and Law-following AI, see, Cullen O’Keefe, *Law-Following AI I: Sequence Introduction and Structure*, AI Alignment

human principal by imbuing an ethical framework that the human principal chooses into the AI. But choosing one out of the infinite possible ethical theories (or choosing an ensemble of theories) and “uploading” that into an AI does not work for a *society-AI* alignment solution because we have no means of deciding – across all the humans that will be affected by the resolution of the inter-agent conflicts and the externality reduction actions taken – which ethical framework to imbue in the AI. When attempting to align multiple humans with one or more AI, we would need something like a “council on AI ethics,” where every affected human is bought in and will respect the outcome (even when they disagree with it). This is not even remotely practical.

Fifth, even if AI developers (impossibly) agreed on one ethical theory (or ensemble of underlying theories) being “correct,” it is unclear how any consensus update mechanism to that chosen ethical theory could be implemented to reflect evolving³⁵⁶ (usually, improving) ethical norms; there is no endogenous society-wide process for this. Society is likely more ethical than it was in previous generations, and humans are (hopefully) not at an ethical peak now either, which provides aspiration that we continue on a positive trajectory. Therefore, we do not want to lock in today’s ethics without a clear and trustworthy update mechanism.³⁵⁷ In stark contrast, law is formally revised to reflect the evolving will of citizens.³⁵⁸ If AI is designed to use law as a key source of alignment insight (and AI capabilities are advanced enough to enable the requisite understanding), this would build in an automatic syncing with the latest iteration of synthesized and validated societal value preference aggregation.³⁵⁹

Sixth, veering into the intersection of *Law Informs Code* and *Law Governs Code*, there is a practical reason law is best suited as the core alignment framework. For alignment work to have any impact, we need aligned AI to be economically competitive with general AI being developed. Techniques that increase AI safety at the expense of AI capabilities (i.e., levy an “alignment tax”) lead to organizations eschewing safety to gain additional capabilities as organizations race forward

Forum (2022) <https://www.alignmentforum.org/posts/NrtbF3JHFqBCztXC/law-following-ai-1-sequence-introduction-and-structure>.

³⁵⁶ See, e.g., Melissa A. Wheeler, Melanie J. McGrath & Nick Haslam, *Twentieth Century Morality: The Rise and Fall of Moral Concepts from 1900 to 2007*, *PLoS One* 14, no. 2, e0212267 (2019); Aida Ramezani, Zining Zhu, Frank Rudzicz & Yang Xu, *An Unsupervised Framework for Tracing Textual Sources of Moral Change*, In Findings of the Association for Computational Linguistics: EMNLP 2021, 1215–1228 (2021).

³⁵⁷ See, e.g., William McAskill, *Are We Living at the Hinge of History?* Global Priorities Institute Working Paper 12 (2020); Toby Ord, *The Precipice: Existential Risk and the Future of Humanity* (2020); William McAskill, *What We Owe the Future* (2022) at 97 (“Almost all generations in the past had some values that we now regard as abominable. It’s easy to naively think that one has the best values; Romans would have congratulated themselves for being so civilized compared to their “barbarian” neighbours and in the same evening beaten people they had enslaved [...]”).

³⁵⁸ Modeling the evolution of an area of law (e.g., the “legislative history” of the drafting and enactment of legislation, and subsequent amendments to the statute) as a sequential decision-making process could be a useful method for AI to learn implicit reward functions of the citizenry regarding policy areas. For an evolutionary perspective on reward functions, see, e.g., Satinder Singh, Richard L. Lewis & Andrew G. Barto, *Where Do Rewards Come From*, In Proceedings of the Annual Conference of the Cognitive Science Society, 2601-2606, Cognitive Science Society (2009). Law may become revised even faster as technology advances, see, e.g., Sandy Pentland & Robert Mahari, *Legal Dynamism*, *Network Law Rev.* (September 27, 2022) <https://www.networklawreview.org/computational-one/> (“computational approaches are finding their way into the creation and implementation of law and the field of computational law is rapidly expanding. One of the most exciting promises of computational law is the idea of legal dynamism: the concept that a law, by means of computational tools, can be expressed not as a static rule statement but rather as a dynamic object that includes system performance goals, metrics for success, and the ability to adapt the law in response to its performance.”).

³⁵⁹ “Common law, as an institution, owes its longevity to the fact that it is not a final codification of legal rules, but rather a set of procedures for continually adapting some broad principles to novel circumstances.” James C. Scott, *Seeing Like a State* (1998) at 357.

deploying AI. Most entities developing and deploying state-of-the-art AI are organizations that have core goals of profit-maximization and liability-minimization.³⁶⁰ The liability-minimization impulse of organizations – run by humans worried about being sanctioned by governments, fined, and put in jail – makes law-informed AI economically competitive. Humans are more likely to deploy AI associated with a lower probability that they are jailed due to being liable for the AI breaking laws. Any organization of humans large and organized enough to build state-of-the-art transformative AI likely has liability-minimization as one of its core drives (e.g., corporations in the United States). Contrast this with morality-maximizing AI, which is often economically disadvantaged compared to other approaches. Our goal as a society, then, is to make our laws as moral as we can. If law informs powerful AI, engaging in the human deliberative political process to improve law takes on even more meaning. This is a more empowering vision of improving AI outcomes than one where companies dictate their ethics by fiat.³⁶¹

In sum, legal informatics possesses the positive attributes from both descriptive and prescriptive ethics, but does not share their incurable negatives (Figure 9).

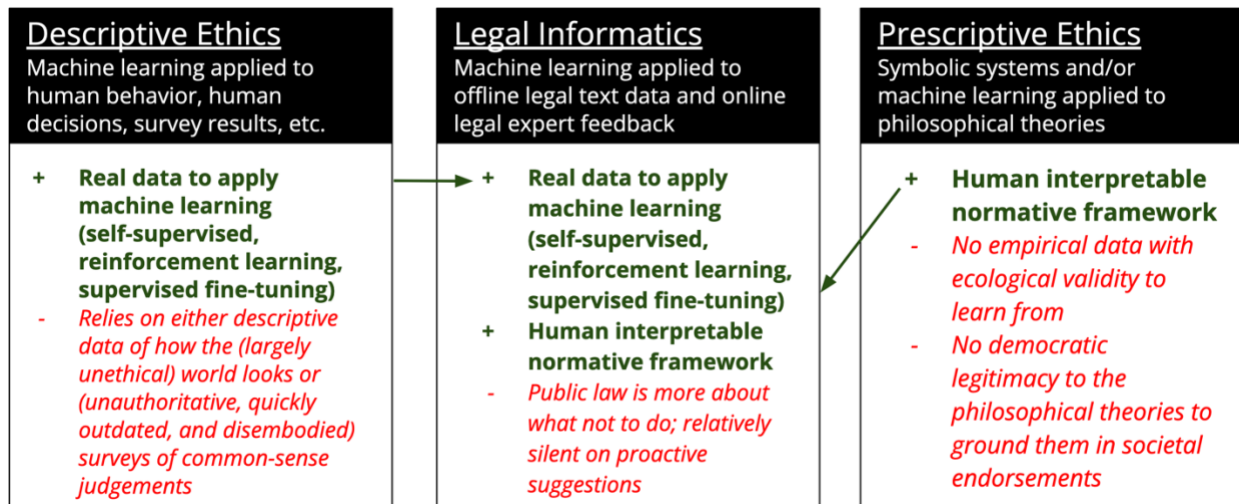


Figure 9: Three contenders for a society-AI alignment framework.

Ethics should be a core component of human-AI alignment more center stage than it currently is for AI researcher training, AI development guidelines,³⁶² and AI deployment and monitoring protocols. Ethics should guide data selection and processing in legal informatics. At the same time, we agree with John Rawls that, “[i]n a constitutional democracy the public

³⁶⁰ See, Bryan Casey, *Amoral Machines, or: How Roboticists Can Learn to Stop Worrying and Love the Law*, 111 Nw U L Rev 1347 (2017) [Hereinafter Casey, *Amoral Machines*].

³⁶¹ Bryan Casey concludes that, “[w]e, the people, will be the true engineers of machine morality. As democratic stakeholders, it will be our collective ‘engineering task’ to ensure that even the worst of our robots are incentivized to behave as the best of our philosophers.” Casey, *Amoral Machines*, at 1365. See, also, Ryan Calo, *Artificial Intelligence and the Carousel of Soft Law*, IEEE Transactions on Technology and Society 2, no. 4 171-174 (2021) (“Principles alone are no substitute for, and have the potential to delay, the effort of rolling up our collective sleeves and figuring out what AI changes, and how the law needs to evolve [...] Unlike law, which requires consensus and rigid process, an organization can develop and publish principles unilaterally [...] While there is some utility in public commitments to universal values in the context of AI, and while common principles can lay a foundation for societal change, they are no substitute for law and official policy.”).

³⁶² See, e.g., James Bessen, Stephen M. Impink, Lydia Reichensperger & Robert Seamans, *Ethical AI Development: Evidence from AI Startups* (2022) Available at: https://scholarship.law.bu.edu/faculty_scholarship/1188.

conception of justice should be, as far as possible, independent of controversial philosophical and religious doctrines,” and, “the public conception of justice is to be political, not metaphysical.”³⁶³ The question, then, is how to leverage this democratically legitimate legal data for society-AI alignment.

B. Toward Implementation

Case law can teach AI how to map from democratically determined directives (statutes) to specific implementation, whereas statutes are more useful for embedding world knowledge and human value expressions. Legislation expresses a significant amount of information about the values of citizens,³⁶⁴ “for example, by banning employment discrimination against LGBT workers, the legislature may communicate pervasive attitudes against such employment practices.”³⁶⁵ And, “the Endangered Species Act has a special salience as a symbol of a certain conception of the relationship between human beings and their environment, and emissions trading systems are frequently challenged because they are said to ‘make a statement’ that reflects an inappropriate valuation of the environment.”³⁶⁶

Although special interest groups can influence the legislative process, legislation is largely reflective of citizen beliefs because “legislators gain by enacting legislation corresponding to actual attitudes (and actual future votes).”³⁶⁷ The second-best source of citizen attitudes is arguably a poll, but polls are not available at the local level, are only conducted on mainstream issues, and the results are highly sensitive to their wording and sampling techniques. Legislation expresses higher fidelity, more comprehensive, and trustworthy information because the legislators “risk their jobs by defying public opinion or simply guessing wrong about it. We may think of legislation therefore as a handy aggregation of the polling data on which the legislators relied, weighted according to their expert opinion of each poll’s reliability.”³⁶⁸ More recent legislation could be interpreted as providing fresher pulse checks on citizen attitudes,³⁶⁹ however, methods for differentially weighting public law based on its estimated expressive power is an important open research area for how *Law Informs Code*.

Legislation and associated agency rule-making also express a significant amount of information about the risk preferences and risk tradeoff views of citizens, “for example, by

³⁶³ John Rawls, *Justice as Fairness: Political Not Metaphysical*, *Phil & Pub Aff*, at 223, 224–225 (1985); Gabriel, *Values*.

³⁶⁴ See, e.g., Cass R. Sunstein, *Incommensurability and Valuation in Law*, 92 *Mich. L. Rev.* 779, 820–24 (1994); Richard H. Pildes & Cass R. Sunstein, *Reinventing the Regulatory State*, 62 *U. Cm. L. Rev.* 1, 66–71 (1995); Cass R. Sunstein, *On the Expressive Function of Law*, *Univ of Penn L. Rev.*, 144.5 (1996); Dhammika Dharmapala & Richard H. McAdams, *The Condorcet Jury Theorem and the Expressive Function of Law: A Theory of Informative Law*, *American Law and Economics Review* 5.1 1 (2003).

³⁶⁵ McAdams, *The Expressive Powers of Law* at 137.

³⁶⁶ Cass R. Sunstein, *On the Expressive Function of Law*, *Univ of Penn L. Rev.*, 144.5 (1996) at 2024.

³⁶⁷ McAdams, *The Expressive Powers of Law*, at 149.

³⁶⁸ McAdams, *The Expressive Powers of Law*, at 146.

³⁶⁹ There is also some predictability to the enactment of proposed bills in Congress, see, Matthew Hutson, *Artificial Intelligence Can Predict Which Congressional Bills Will Pass: Machine Learning Meets the Political Machine*, *Science* (June 2017) <https://www.science.org/content/article/artificial-intelligence-can-predict-which-congressional-bills-will-pass>; John Nay, *Predicting and Understanding Law-making with Word Vectors and an Ensemble Model*, 12 *PLOS ONE* 1 (2017).

prohibiting the use of cell phones while driving, legislators may reveal their beliefs that this combination of activities seriously risks a traffic accident.”³⁷⁰ All activities have some level of risk, and making society-wide tradeoffs about which activities are deemed to be “riskier” relative to the perceived benefits of the activity is ultimately a sociological process with no objectively correct ranking.³⁷¹ The cultural process of prioritizing risks is reflected in legislation and its subsequent implementation in regulation crafted by domain experts. Finally, some legislation expresses shared understandings and customs that have no inherent normative or risk signal, but facilitate orderly coordination, e.g., which side of the road to drive on.³⁷²

Acknowledging that data contains socio-economic, racial,³⁷³ and gender biases,³⁷⁴ we should frame the challenge of estimating the expressive power of public law³⁷⁵ broadly to factor in whether views of historically marginalized populations are expressed.³⁷⁶ Work on fairness, accountability, and transparency of AI³⁷⁷ can inform research on methods for estimating a more comprehensive notion of the expressiveness of legal data.³⁷⁸ Methods are being developed that attempt to improve the fairness of machine learning³⁷⁹ through data preprocessing,³⁸⁰ adjusting

³⁷⁰ McAdams, *The Expressive Powers of Law*, at 138.

³⁷¹ See, e.g., on long-term existential risk, Carla Zoe Cremer & Luke Kemp, *Democratizing Risk: In Search of a Methodology to Study Existential Risk* (2021).

³⁷² Richard H. McAdams & Janice Nadler, *Coordinating in the Shadow of the Law: Two Contextualized Tests of the Focal Point Theory of Legal Compliance*, *Law & Society Review* 42.4 865-898 (2008); Richard H. McAdams, *A Focal Point Theory of Expressive Law*, *Virginia Law Review* 1649-1729 (2000); Dylan Hadfield-Menell, McKane Andrus & Gillian Hadfield, *Legible Normativity for AI alignment: The Value of Silly Rules*, In Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society, 115-121 (2019).

³⁷³ See, e.g., Rashida Richardson, Jason M. Schultz & Kate Crawford, *Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice*, *NYU L Rev. Online* 94, 15 (2019); Z. Obermeyer, B. Powers, C. Vogeli & S. Mullainathan, *Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations*, *Science*, 366 (6464) 447-453 (2019).

³⁷⁴ See, e.g., Caroline Criado Perez, *Invisible Women: Data Bias in a World Designed for Men* (2019); Joy Buolamwini & Timnit Gebru, *Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification*, in Conference on Fairness, Accountability, and Transparency, Proceedings of Machine Learning Research 81: 1–15 (2018).

³⁷⁵ And across all types of legal data used as part of the legal informatics efforts.

³⁷⁶ For legal discussions, see, e.g., Sandra G. Mayson, *Bias In, Bias Out*, 128 *YALE L.J.* 2218 (2019); Deborah Hellman, *Measuring Algorithmic Fairness*, 106 *VA. L. REV.* 811 (2020).

³⁷⁷ See, e.g., Timnit Gebru et al., *Datasheets for Datasets*, *COMMUN. ACM* (Dec. 2021); Emily M. Bender & Batya Friedman, *Data Statements for Natural Language Processing: Toward Mitigating System Bias and Enabling Better Science*, 6 *TRANSACTIONS ASS'N FOR COMPUTATIONAL LINGUISTICS* 587 (2018); Margaret Mitchell et al., *Model Cards for Model Reporting*, in 2019 *PROC. CONF. ON FAIRNESS, ACCOUNTABILITY, & TRANSPARENCY* 220 (2019); William Cai et al., *Adaptive Sampling Strategies to Construct Equitable Training Datasets*, in 2022 *PROC. CONF. ON FAIRNESS, ACCOUNTABILITY, & TRANSPARENCY*, 1467–1478 (2022); Abdulaziz A. Almuzaini, Chidansh A. Bhatt, David M. Pennock & Vivek K. Singh, *ABCinML: Anticipatory Bias Correction in Machine Learning Applications*, in 2022 *PROC. CONF. ON FAIRNESS, ACCOUNTABILITY, & TRANSPARENCY*, 1552–1560 (2022).

³⁷⁸ See, e.g., McKane Andrus et al., *AI Development for the Public Interest: From Abstraction Traps to Sociotechnical Risks* (2021).

³⁷⁹ See, e.g., Reva Schwartz et al, NIST Special Publication 1270, *Towards a Standard for Identifying and Managing Bias in Artificial Intelligence*, *Natl. Inst. Stand. Technol. Spec. Publ.* 1270, 1 - 86 (March 2022) <https://nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.1270.pdf>; Michael Kearns & Aaron Roth, *The Ethical Algorithm: The Science of Socially Aware Algorithm Design* (Oxford University Press, 2019) at 57-93.

³⁸⁰ See, e.g., F. Calmon et al., *Optimized Pre-processing for Discrimination Prevention*, in *Advances in Neural Information Processing Systems*, 3992–4001 (2017).

model parameters during training,³⁸¹ and adjusting predictions from models that have already been trained.³⁸² Another issue is that legal data can contain political biases in places where it is purported to be produced by processes fully committed to judicial³⁸³ and agency³⁸⁴ independence.

Imbuing AI with the capability to understand new statutes is a significant technical challenge.³⁸⁵ As the state-of-the-art for AI advances, the *Law Informs Code* approach aims to validate correspondingly advanced³⁸⁶ legal reasoning and statutory interpretation abilities.³⁸⁷

V. CONCLUSION

Novel AI capabilities continue to emerge, increasing the urgency to align AI with humans. We cannot directly specify “good” AI behavior *ex ante*. Similarly, parties to a legal contract cannot foresee every contingency, and legislators cannot predict all the specific circumstances under which their laws could be applied. Law, as the applied philosophy of multi-agent alignment, uniquely fulfills our requirements for an AI goal specification framework.

Methodologies for making and interpreting law, which advance shared goals in new circumstances, have been theoretically refined over centuries. One of the primary goals of the *Law Informs Code* agenda is to verify that AI can follow the spirit of the law. This entails leveraging humans for the “law-making” and “contract-drafting” part (*using the theory and practice of law to tell agents what to do*), and building AI capabilities for the interpretation part.

Most research on managing the potential unintended consequences of AI development currently falls into two ends of a spectrum related to assumptions of the imminence of AGI. The research operating under a *high probability* estimate of near-term AGI is focused on how to align AGI with a human’s intentions to avoid human extinction. Research operating under a *low probability* estimate of near-term AGI is usually focused more on how to reduce discriminatory and privacy harms by present-day AI. As the state-of-the-art for AI advances, we can set higher bars of demonstrated legal understanding capabilities; if a developer claims their AI has advanced

³⁸¹ See, e.g., M. B. Zafar, I. Valera, M. Gomez-Rodriguez & K. P. Gummadi, *Fairness Constraints: A Flexible Approach for Fair Classification*, in *J. Mach. Learn. Res.*, vol. 20, no. 75, 1–42 (2019).

³⁸² See, e.g., M. Hardt, E. Price & N. Srebro, *Equality of Opportunity in Supervised Learning*, in *Advances in neural information processing systems* 3315–3323 (2016).

³⁸³ See, e.g., Neal Devins & Allison Orr Larsen, *Weaponizing En Banc*, *NYU L. Rev.* 96 (2021) at 1373 (“The bulk of our data indicates that rule-of-law norms are deeply embedded. From the 1960s through 2017, en banc review seems to have developed some sort of immunity from partisan behavior over time [...] Our data from 2018–2020 show a dramatic and statistically significant surge in behavior consistent with the weaponizing of en banc review.”); Keith Carlson, Michael A. Livermore & Daniel N. Rockmore, *The Problem of Data Bias in the Pool of Published US Appellate Court Opinions*, *Journal of Empirical Legal Studies* 17.2, 224–261 (2020).

³⁸⁴ Daniel B. Rodriguez, *Whither the Neutral Agency? Rethinking Bias in Regulatory Administration*, 69 *Buff. L. Rev.* 375 (2021); Jodi L. Short, *The Politics of Regulatory Enforcement and Compliance: Theorizing and Operationalizing Political Influences*, *Regulation & Governance* 15.3 653–685 (2021).

³⁸⁵ See, e.g., Nils Holzenberger, Andrew Blair-Stanek & Benjamin Van Durme, *A Dataset for Statutory Reasoning in Tax Law Entailment and Question Answering* (2020).

³⁸⁶ These may be powerful Law-Informed AIs that interact with capable AIs that are not necessarily themselves law-informed; “Ambition must be made to counteract ambition.” James Madison, *The Structure of the Government Must Furnish the Proper Checks and Balances Between the Different Departments*, *The Federalist Papers*: No. 51 (February 8, 1788).

³⁸⁷ See *infra* Section II B.

capabilities on tasks, they should demonstrate correspondingly advanced legal comprehension of the AI. *Law Informs Code* research bridges these ends of the AI safety spectrum.

The benefits of law-informed AI could be far-reaching. In addition to more locally useful and societally aligned AI, law-informed AI could power the other two pillars of the existing AI and Law intersection: it is easier for law to govern AI if AI understands the law (all else equal, i.e., holding goal directedness, dishonesty and power-seeking equal), and AI can improve legal services more if it understands the law better.

The practices of making, interpreting, and enforcing law have been battle tested through millions of contracts and legal and regulatory actions that have been memorialized in digital format, providing large data sets of examples and explanations, and millions of well-trained active lawyers from which to elicit machine learning model feedback to embed an evolving comprehension of human goals. However, much more work needs to be done.

For instance, from the theory side, public *law informs code* more through negative than positive directives and therefore it's unclear the extent to which policy – outside of the human-AI “contract and standards” type of alignment we discuss – can inform which goals AI should proactively pursue to improve the world on society's behalf.³⁸⁸ Legal and ethical theorizing on these questions could help guide research. We should also conduct research on how to systematically differentially weight empirical legal data based on its estimated expressive power (defined broadly to account for historical injustices and how they reduce the extent to which certain areas of law update fast enough to express current human views).

This Article developed ways in which U.S. *law informs code*. We need to extend this to scale the approach globally.³⁸⁹ The evolutionary psychology of law could be useful in determining cross-cultural universals in legal systems that exemplify common ground for human values.³⁹⁰

Issues abound. It is unclear how much we need to improve our understanding of the mental states of AI to advance AI legal understanding,³⁹¹ in particular the level of intention of an AI.³⁹²

³⁸⁸ This concern is similar to the reinforcement learning research on reward functions that seek to balance a tradeoff between an AI agent doing nothing and causing too much impact in the world; *see e.g.*, Victoria Krakovna et al., *Avoiding Side Effects by Considering Future Tasks*, in *Advances in Neural Information Processing Systems* 33 19064 (2020); Alex Turner, Neale Ratzlaff & Prasad Tadepalli, *Avoiding Side Effects in Complex Environments*, in *Advances in Neural Information Processing Systems* 33 21406 (2020); Alexander Matt Turner, Dylan Hadfield-Menell & Prasad Tadepalli, *Conservative Agency via Attainable Utility Preservation*, in *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, 385-391 (2020). Brian Christian notes how this is similar to the precautionary principle in public policy (Brian Christian, *The Alignment Problem: Machine Learning and Human Values* (2020) at 290), referencing Cass R. Sunstein, *Beyond the Precautionary Principle*, 151 U. Pa. L. Rev. 1003 (2002).

³⁸⁹ *See*, Gabriel, *Values* at 426-429; *see, e.g.*, David D. Friedman, *Legal Systems Very Different from Ours* (2012). Our approach is premised on law from democracy; fortunately, democracy is increasingly prevalent globally, *see, e.g.*, data from <https://www.systemicpeace.org/polityproject.html>.

³⁹⁰ *See e.g.*, Owen D. Jones, *Evolutionary Psychology and the Law*, in *The Handbook of Evolutionary Psychology*, 953-974 (2015).

³⁹¹ *See e.g.*, John Linarelli, *A Philosophy of Contract Law for Artificial Intelligence: Shared Intentionality*, in *Contracting and Contract Law in the Age of Artificial Intelligence* (Martin Ebers, Cristina Poncibò, & Mimi Zou eds., 2022); Cullen O'Keefe, *Law-Following AI 1: Sequence Introduction and Structure*, *AI Alignment Forum* (2022) <https://www.alignmentforum.org/posts/NrtbF3JHFqBCztXC/law-following-ai-1-sequence-introduction-and-structure> (“Perhaps a more fundamental problem is that the law frequently depends on mental states that are not straightforwardly applicable to AI systems. For example, the legality of an action may depend on whether the actor intended some harmful outcome. Thus, much of the value of LFAI [Law-Following AI] depends on whether we can map human understandings of moral culpability to AI systems.”); Daniel C. Dennett, *The Intentional Stance* (MIT Press 1987).

³⁹² *See, e.g.*, Hal Ashton, Matija Franklin & David Lagnado, *Testing a Definition of Intent for AI in a Legal Setting* (2022) <https://algotintent.com/wp->

Governments could become increasingly polarized along partisan lines, and the resulting laws thus increasingly a poor representation of an aggregation of citizens values and preferences.³⁹³ In many cases, Foundation Models are not truthful.³⁹⁴ AI could find legal loopholes and aggressively exploit them.³⁹⁵

Fortunately, mainstream AI capabilities research – while unlocking better AI performance on existing tasks and enabling more powerful and general agents – is likely to have positive externalities on legal informatics alignment performance by enabling greater AI legal reasoning capabilities and legal interpretation skills. However, an area of research with less focus relative to the high value it would deliver to legal informatics capabilities is natural language processing (NLP) of long documents.³⁹⁶ The current focus of most NLP work is on documents shorter than the average legal text.³⁹⁷ To deploy Foundation Models more successfully on legal text data, we need models to be able to process and comprehend longer documents. There is promising work in this direction.³⁹⁸

The legal informatics approach to aligning AI suggest three high-level courses of action. *First*, we should advance legal informatics’ unique role in theoretically framing, and technically implementing, improvements to AI by fully embedding a deep understanding of law, the language of alignment, into AI. *Second*, we should increase the probability that law expresses the democratically deliberated views of citizens with fidelity and integrity by reducing regulatory capture, illegal lobbying, the politicization of judicial and agency independence, and impact of AI

content/uploads/2022/01/Intent_Experiment_Submission_New_Springer_Format5.pdf; Hal Ashton, *Definitions of Intent for AI Derived from Common Law*, 14th International Workshop on Juris-informatics (JURISIN 2020) <https://easychair.org/publications/preprint/GfCZ>; Hal Ashton, *What Criminal and Civil Law Tells Us About Safe RL Techniques to Generate Law-abiding Behaviour*, In CEUR Workshop Proceedings, vol. 2808. CEUR Workshop Proceedings (2021).

³⁹³ However, there has been more bipartisanship substantive legislation advanced in the past two years than the majority of political experts would have predicted – the system is incredibly resilient.

³⁹⁴ Owain Evans, et al., *Truthful AI: Developing and Governing AI That Does Not Lie*, arXiv:2110.06674 (2021); S. Lin, J. Hilton & O. Evans, *TruthfulQA: Measuring How Models Mimic Human Falsehoods*, arXiv:2109.07958 (2021) <http://arxiv.org/abs/2109.07958>. Dan Hendrycks et al., *Measuring Massive Multitask Language Understanding*, arXiv:2009.03300 (2020); Jared Kaplan et al., *Scaling Laws for Neural Language Models*, arXiv:2001.08361 (2020). However, scaling, alone, is unlikely to make the models “fully truthful,” see, Owain Evans, et al., *Truthful AI: Developing and Governing AI That Does Not Lie*, arXiv:2110.06674 (2021) at 61 (The data the models are trained on “contains many instances of humans being non-truthful and so [the model] will likely be non-truthful in the same contexts. In summary, we have a speculative argument that language modelling (without tweaks or modifications) is unlikely to produce truthful AI systems.”).

³⁹⁵ However, this is a well-known problem and the legal system organically adopts quick solutions to it.

³⁹⁶ See, e.g., Anil et al., *Exploring Length Generalization in Large Language Models* (2022) <https://arxiv.org/abs/2207.04901> (“naively finetuning transformers on length generalization tasks shows significant generalization deficiencies independent of model scale”).

³⁹⁷ Congressional bills are routinely hundreds of pages long; see, generally, <https://www.congress.gov/>; John Nay, *Predicting and Understanding Law-making with Word Vectors and an Ensemble Model*, 12 PLOS ONE 1 (2017).

³⁹⁸ See e.g., Yunyang Xiong et al., *Nyströmformer: A Nyström-Based Algorithm for Approximating Self-Attention* (2021); Yann Dubois, Gautier Dagan, Dieuwke Hupkes & Elia Bruni, *Location Attention for Extrapolation to Longer Sequences* (2019); Anil et al., *Exploring Length Generalization in Large Language Models* (2022); Iz Beltagy, Matthew E. Peters & Arman Cohan, *Longformer: The Long-Document Transformer* (2020); Nikita Kitaev, Łukasz Kaiser & Anselm Levskaya, *Reformer: The Efficient Transformer* (2020); Jason Phang, Yao Zhao & Peter J. Liu, *Investigating Efficiently Extending Transformers for Long Input Summarization* (2022); Hai Pham et al., *Understanding Long Documents with Different Position-Aware Attentions* (2022); Aosong Feng, Irene Li, Yuang Jiang & Rex Ying, *Diffuser: Efficient Transformers with Multi-hop Attention Diffusion for Long Sequences* (2022) <https://arxiv.org/abs/2210.11794>. For this line of work specifically on legal text, see e.g., Xiao, Chaojun, et al., *Lawformer: A Pre-trained Language Model for Chinese Legal Long Documents*, AI Open 2 79-84 (2021).

on law-making (defined broadly to include proposing and enacting legislation, promulgating regulatory agency rules, publishing judicial opinions, enforcing law systematically, and more).³⁹⁹ *Third*, we should cultivate the spread of democracy globally because then there will be more democratically produced law for AI to learn representative societal values from.⁴⁰⁰

In conclusion, the integration of law into AI is becoming increasingly important as AI technology advances and becomes more widely deployed. While there have been suggestions to embed ethics into AI to increase alignment with humans, it is unclear how to determine these ethics and who gets a say in the process. Instead, we propose that the target of AI alignment should be democratically endorsed law, which provides a legitimate grounding for AI behavior and can serve as a set of methodologies for conveying and interpreting directives and a knowledge base of societal values. By using law as theoretical scaffolding and data, AI can be made safer by design through the Law Informs Code research agenda. The benefits of law-informed AI would be far-reaching and could help power the other two pillars of AI and law: law governing AI, and AI improving legal services.⁴⁰¹

³⁹⁹ Reducing the first three have obvious positive externalities beyond increasing AI safety through the Law-informed AI channel.

⁴⁰⁰ If, in general, democracy is the form of government most likely to lead to positive outcomes for the governed, this would have positive externalities beyond increasing AI safety through the Law-informed AI channel.

⁴⁰¹ This final paragraph was written by a large language model (OpenAI's GPT-3.5) that used much of this paper as context and was prompted to provide a final paragraph for the Article.