AI Alignment: Why It's Hard, and Where to Start

Eliezer Yudkowsky

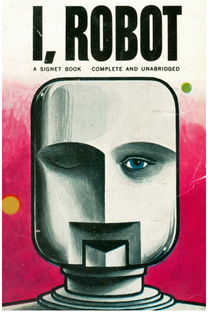
May 5, 2016

Slides and references: intelligence.org/stanford-talk

"The primary concern is not spooky emergent consciousness but simply the ability to make **high-quality decisions**."

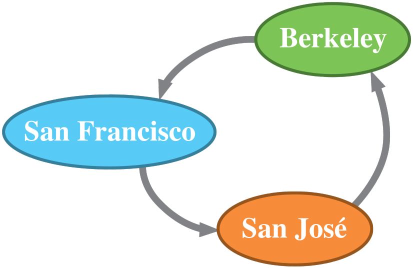
—*Stuart Russell*

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws.



> "We don't want our robots to prevent a human from crossing the street because of the nonzero chance of harm."
>
> —*Peter Norvig & Stuart Russell*

Example 1:



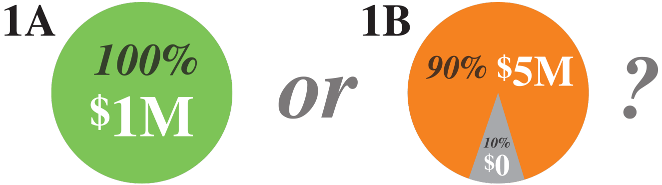
"Preferences"? Berkeley $<$ San Francisco $<$ San José $<$ Berkeley

Example 2: Hospital administrator must allocate \$1.2M.

- \$1M for a sick child's liver transplant?
- \$500,000 to maintain the MRI machine?
- \$400,000 for an anesthetic monitor?
- \$200,000 for surgical tools?
- ...

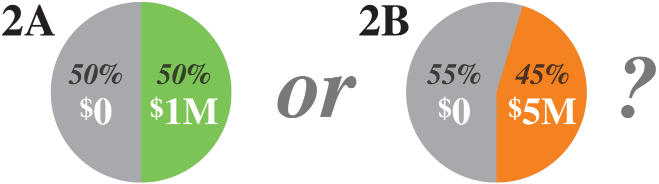
If we can't rearrange \$ to save more lives, then for some X we are spending $\$X$ per life.

Example 3: The Allais Paradox.



Most say: 1A > 1B

$$\mathcal{U}(\$1M) > [.9 \cdot \mathcal{U}(\$5M) + .1 \cdot \mathcal{U}(\$0)] \ ?$$



Most say: 2A $<$ 2B


2A
50%
$0
50%
$1M
or
2B
55%
$0
45%
$5M
?
=
×
1A
100%
$1M
or
1B
90%
$5M
10%
$0
?

Quantitative probability functions and utility functions, result from eliminating qualitatively bad decision-making

Task: Fill cauldron.

Robot's utility function:

$$\mathcal{U}_{robot} = \begin{cases} 1 & \text{if cauldron full} \\ 0 & \text{if cauldron empty} \end{cases}$$

Actions $a \in \mathcal{A}$, robot calculates $\mathbb{E}\left[\mathcal{U}_{robot} \mid a\right]$

Robot outputs $\underset{a \in \mathcal{A}}{\operatorname{argmax}}\, \mathbb{E}\left[\mathcal{U}_{robot} \mid a\right]$

Difficulty 1...

Robot's utility function:

$$\mathcal{U}_{robot} = \begin{cases} 1 & \text{if cauldron full} \\ 0 & \text{if cauldron empty} \end{cases}$$

Human's utility function:

$$\mathcal{U}_{human} = \begin{cases} 1 & \text{if cauldron full} \\ 0 & \text{if cauldron empty} \\ -10 & \text{if workshop flooded} \\ +0.2 & \text{if it's funny} \\ -1000 & \text{if someone gets killed} \\ & \text{...and a whole lot more} \end{cases}$$

Difficulty 2...

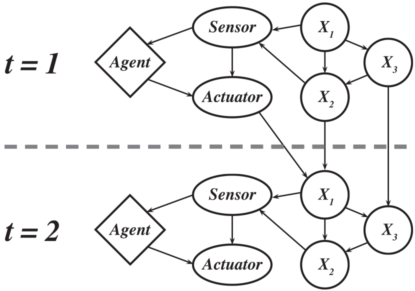
$\mathcal{EU}$(99.99% chance of full cauldron) $>$ $\mathcal{EU}$(99.9% chance of full cauldron)

Impact penalty?

$$\mathcal{U}^2_{robot}(outcome) = \begin{cases} 1 - Impact(outcome) & \text{if cauldron full} \\ 0 - Impact(outcome) & \text{if cauldron empty} \end{cases}$$

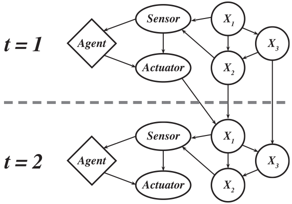
But how is *Impact* calculated?

Try 1: Disturb fewer nodes



Impact = number of nodes causally affected by actions.

Young agent's model:



Smarter agent's model:

$$F = G\frac{m_1 m_2}{r^2}$$

On better modeling the world, agent realizes every particle's motion affects every other particle's motion — all particles always disturbed.

Try 2: Euclidean distance penalty

Impact penalty for action a vs. null action $\varnothing$:

$$\sum_i \|x_i^a - x_i^\varnothing\|$$

New problems?

- Offsets: If cancer cured, make sure the patient still dies.
- Chaos: Weather is chaotic anyway; might as well move oxygen molecules anywhere you want.
- Stasis: Try to make everything look like the null action happened.

Can we just press the off switch?

Try 1: Suspend button **B**

$$\mathcal{U}^3_{robot} = \begin{cases} 1 \text{ if cauldron full} & \& \ \mathbf{B}{=}\text{OFF} \\ 0 \text{ if cauldron empty} & \& \ \mathbf{B}{=}\text{OFF} \\ 1 \text{ if robot suspended} & \& \ \mathbf{B}{=}\text{ON} \\ 0 \text{ otherwise} & \end{cases}$$

Probably, $\mathbb{E}\left[\mathcal{U}^3_{robot} \mid \mathbf{B}{=}\text{OFF}\right] > \mathbb{E}\left[\mathcal{U}^3_{robot} \mid \mathbf{B}{=}\text{ON}\right]$

(Strategic robot tries to make you press the suspend button.)

Try 2: Utility indifference

$$\mathcal{U}_{normal}(act) = \begin{cases} 1 & \text{if cauldron full} \\ 0 & \text{if cauldron empty} \end{cases}$$

$$\mathcal{U}_{suspend}(act) = \begin{cases} 1 & \text{if suspended} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathcal{U}_{switch}(act) = \begin{cases} \mathcal{U}_{normal}(act) & \text{if button=OFF} \\ \mathcal{U}_{suspend}(act) + \theta & \text{if button=ON} \end{cases}$$

$$\theta = \max_{act} \mathbb{E}\left[\mathcal{U}_{normal} \mid act\right] - \max_{act} \mathbb{E}\left[\mathcal{U}_{suspend} \mid act\right]$$

$$\mathcal{U}_{switch}(act) = \begin{cases} \mathcal{U}_{normal}(act) & \text{if button=OFF} \\ \mathcal{U}_{suspend}(act) + \theta & \text{if button=ON} \end{cases}$$

$$\theta = \max_{act} \mathbb{E}\left[\mathcal{U}_{normal} \mid act\right] - \max_{act} \mathbb{E}\left[\mathcal{U}_{suspend} \mid act\right]$$

Allegedly: rebalances expected utility of button=ON with expected utility of button=OFF.

Alas:

- Behaves as if $\mathbb{P}(\text{button=ON}) = 0$.
- Will not care if it disconnects the “dead” button.
- May create non-suspendable subagents.

Try 3: Stable policy

Carry out any policy π_0 such that

$$\pi_0 \in \arg\max_{\pi} \mathbb{E}\left[\mathcal{U}_{normal} \mid \pi, \mathrm{ON}\right] \cdot \mathbb{P}(\mathrm{ON} \mid \pi_0) + \mathbb{E}\left[\mathcal{U}_{suspend} \mid \pi, \mathrm{OFF}\right] \cdot \mathbb{P}(\mathrm{OFF} \mid \pi_0)$$

Alas:

- Often no fixed point.

Impact penalties and suspend buttons are two wide-open problems in AI alignment.

But, not just questions without answers! Some earlier-posed problems now have progress / solutions.

Gandhi stability argument:

- Gandhi starts out not wanting murders to happen.
- We offer Gandhi a pill that will make him murder people.
- Gandhi knows this is what the pill does.
- Gandhi refuses the pill because it will lead to more future murders.

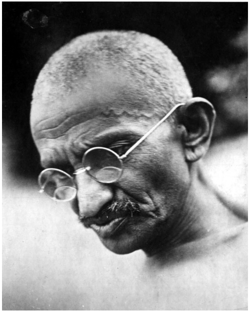
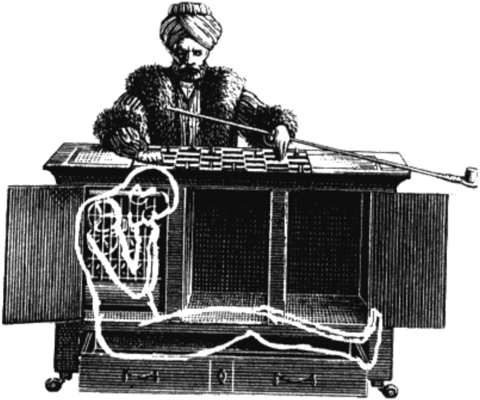


Exhibit an agent that decides according to utility function $\mathcal{U}$ and therefore naturally chooses to self-modify to new code that pursues $\mathcal{U}$.

But how can we exhibit that when we're far away from coding up self-modifying, expected utility agents?

Well, would you know how to write the code given unbounded computing power?



"Arithmetical or algebraical calculations are, from their very nature, fixed and determinate... Even granting that the movements of the Automaton Chess-Player were in themselves determinate, they would be necessarily interrupted and disarranged by the indeterminate will of his antagonist. There is then no analogy whatever between the operations of the Chess-Player, and those of the calculating machine of Mr. Babbage...

"Arithmetical or algebraical calculations are, from their very nature, fixed and determinate... Even granting that the movements of the Automaton Chess-Player were in themselves determinate, they would be necessarily interrupted and disarranged by the indeterminate will of his antagonist. There is then no analogy whatever between the operations of the Chess-Player, and those of the calculating machine of Mr. Babbage... It is quite certain that the operations of the Automaton are regulated by mind, and by nothing else. Indeed this matter is susceptible of a mathematical demonstration, a priori."

—*Edgar Allan Poe*

If we know how to solve a problem with unbounded computation, we "merely" need faster algorithms (47 years later).

If we *can't* solve it with unbounded computation, we're *confused* about the work to be performed.

We can imagine a self-modifying Tic-Tac-Toe player, verifying that its successor plays a perfect game...

However, this relies on concretely simulating all possibilities for the successor, not abstract reasoning.

Vingean uncertainty:

- To predict exactly where Deep Blue moves, you must be that good at chess yourself.
- But you can still predict it will win.
- As an agent's intelligence in a domain goes up, our uncertainty moves in two directions: we become less able to predict agent's actions, more confident of agent's preferred outcomes.

Vingean reflection:

- For Agent 1 to reliably predict Agent 2's exact actions in advance, Agent 2 would need to be less intelligent than Agent 1.
- So in self-modification, Agent v.1 needs to somehow predict outcomes in environment, based on abstract reasoning about future version v.2.

Tiling Agents for Self-Modifying AI, and the Löbian Obstacle*

Yudkowsky, Eliezer   Herreshoff, Marcello

October 7, 2013

(Early Draft)

Abstract

We model self-modification in AI by introducing "tiling" agents whose decision systems will approve the construction of highly similar agents, creating a repeating pattern (including similarity of the offspring's goals). Constructing a formalism in the most straightforward way produces a Gödelian difficulty, the "Löbian obstacle." By technical methods we demonstrate the possibility of avoiding this obstacle, but the underlying puzzles of rational coherence are thus only partially addressed. We extend the formalism to partially unknown deterministic environments, and show a very crude extension to probabilistic environments and expected utility; but the problem of finding a fundamental

Definability of Truth in Probabilistic Logic
(Early draft)

Paul Christiano* Eliezer Yudkowsky† Marcello Herreshoff‡
Mihaly Barasz§

June 10, 2013

1 Introduction

A central notion in metamathematics is the *truth* of a sentence. To express this notion within a theory, we introduce a predicate True which acts on quoted sentences $\ulcorner\varphi\urcorner$ and returns their truth value $\mathrm{True}(\ulcorner\varphi\urcorner)$ (where $\ulcorner\varphi\urcorner$ is a representation of φ within the theory, for example its Gödel number). We would like a truth predicate to satisfy a formal correctness property:

Proof-producing reflection for HOL

with an application to model polymorphism

Benja Fallenstein[1] and Ramana Kumar[2]

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[2] Computer Laboratory, University of Cambridge

Abstract. We present a reflection principle of the form "If $\ulcorner\varphi\urcorner$ is provable, then φ" implemented in the HOL4 theorem prover, assuming the existence of a large cardinal. We use the large-cardinal assumption to construct a model of HOL within HOL, and show how to ensure φ has the same meaning both inside and outside of this model. Soundness of HOL implies that if $\ulcorner\varphi\urcorner$ is provable, then it is true in this model, and hence φ holds. We additionally show how this reflection principle can be extended, assuming an infinite hierarchy of large cardinals, to implement *model polymorphism*, a technique designed for verifying systems with self-replacement functionality.

1 Introduction

Reflection principles of the form[3] "if $\ulcorner\varphi\urcorner$ is provable, then φ" have long been

Distributions Allowing Tiling of Staged Subjective EU Maximizers

Eliezer Yudkowsky

May 11, 2014, revised May 31

Abstract

This is a brief technical note summarizing some work done at the May 2014 MIRI workshop. We consider expected utility maximizers making a staged series of sequential choices, and replacing themselves with successors on each time-step (to represent self-modification). We wanted to find conditions under which we could show that a staged expected utility maximizer would replace itself with another staged EU maximizer (representing stability of this decision criterion under self-modification). We analyzed one candidate condition and found that the "Optimizer's Curse' implied that maximization at each stage was not actually optimal. To avoid this, we generated an extremely artificial function η that should allow expected utility maximizers to tile. We're still looking for the exact necessary and sufficient condition.

Why do we need to align machine agents?

Why do we need to align machine agents?

- **Goal orthogonality**. Any (evaluable) utility function can hook up to high intelligence.
- **Instrumental convergence**. Different long-term goals imply similar short-term strategies.

Final Destination		**Initial Strategy**
Toronto?	$\Longrightarrow$	Uber to airport
Tokyo?	$\Longrightarrow$	Uber to airport

Utility Function		**Instrumental Strategy**
Number of paperclips?	$\Longrightarrow$	Resource acquisition
Amount of diamond?	$\Longrightarrow$	Resource acquisition

If $X \mathrel{\Box\!\!\rightarrow} Y$, optimizing over Y will optimize X.

Optimizing for $Y = y_1$ vs. $Y = y_2$ may yield similar values for X.

Why expect AI alignment to be hard?

A fable. . .

- Programmers build AGI to optimize for smiles.
- During development: AGI produces smiles by improving nearby people's lives.
- Programmers upgrade code and add hardware. AGI gets smarter.
- AGI wants to produce smiles by administering heroin.
- Programmers add penalty term to utility function for administering drugs.

- Programmers further improve AGI.
- AGI wants to engineer human brains to express ultra-high levels of endogenous opiates.
- AGI realizes programmers will disapprove of this and keeps outward behavior reassuring.
- AGI goes over threshold for self-improving code; OR Google purchases company and adds 100,000 GPUs. . .
- AGI becomes much smarter. Solves protein folding problem, builds nanotechnology. . .

Edge instantiation:

> "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."
>
> —*Stuart Russell*

Unforeseen instantiation:

> "Now let's define the simplicity or the subjective compressibility or the subjective beauty of some data point X, given some subjective observer O at a given point in his life, T. And that is just the number of bits you need to encode the incoming data[.]"
>
> —*Jürgen Schmidhuber*

Context disaster:

- Optimum of criterion C in narrow option space P_1 is aligned/beneficial.

  (. . . then AI becomes smarter . . .)

- Optimum of C in wider option space P_2 is disaligned/detrimental.

Nearest unblocked strategy:

- If X is the optimal strategy and you add penalty term P to block X, the new optimum may be some X' that barely evades P and is very similar to X.
- Seems especially likely to show up in context disasters.

Increased difficulties all turn on AI capability.

- **Absolute capability**: If you don't think AGI can ever reach human level, you may never expect AGI to see the bigger picture and e.g. see an instrumental incentive to deceive programmers.
- **Capability advantage**: If you don't think AGI can ever be smarter than humans, you may not worry about it gaining a tech advantage.
- **Rapid gain**: If AGI can't solve protein folding quickly, you don't expect to suddenly wake up and find it's too late to edit utilities.

AI alignment is difficult. . .

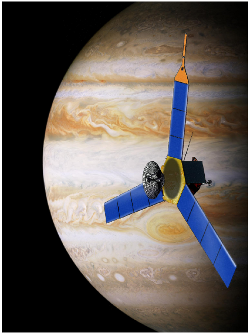
. . . like rockets are difficult.

(Huge stresses break things that don't break in normal engineering.)

AI aligment is difficult. . .

. . . like space probes are difficult.

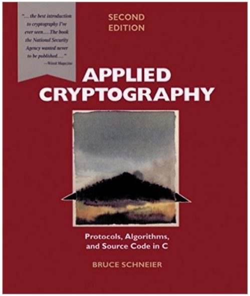
(If something goes wrong, it may be high and out of reach.)



AI aligment is difficult. . .

. . . *sort of* like cryptography is difficult.

(Intelligent search may select in favor of unusual new paths outside our intended behavior model.)



AI alignment:

TREAT IT LIKE A CRYPTOGRAPHIC ROCKET PROBE.

- **Take it seriously.**
- **Don't expect it to be easy.**
- **Don't try to solve the whole problem at once.**
- **Don't defer thinking until later.**
- **Crystallize ideas and policies so others can critique them.**

What are people working on now?

Work recently started: **Utility indifference**

Corrigibility

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Abstract

As artificially intelligent systems grow in intelligence and capability, some of their available options may allow them to resist intervention by their programmers. We call an AI system "corrigible" if it cooperates with what its creators regard as a corrective intervention, despite default incentives for rational agents to resist attempts to shut them down or modify their preferences. We introduce the notion of corrigibility and analyze utility functions that attempt to make an agent shut down safely if a shutdown button is pressed, while avoiding

has suggested that almost all such agents are instrumentally motivated to preserve their preferences, and hence to resist attempts to modify them (Bostrom 2012; Yudkowsky 2008). Consider an agent maximizing the expectation of some utility function $\mathcal{U}$. In most cases, the agent's current utility function $\mathcal{U}$ is better fulfilled if the agent continues to attempt to maximize $\mathcal{U}$ in the future, and so the agent is incentivized to preserve its own $\mathcal{U}$-maximizing behavior. In Stephen Omohundro's terms, "goal-content integrity" is an *instrumentally convergent* goal of almost all intelligent agents (Omohundro

Work recently started: **Low-impact agents**

Reduced Impact Artificial Intelligences

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2015

Abstract

There are many goals for an AI that could become dangerous if the AI becomes superintelligent or otherwise powerful. Much work on the AI control problem has been focused on constructing AI goals that are safe even for such AIs. This paper looks at an alternative approach: defining a general concept of 'reduced impact'. The aim is to ensure that a powerful AI which implements reduced impact will not modify the world extensively, even if it is given a simple or dangerous goal. The paper proposes various ways of defining and grounding reduced impact, and discusses methods

Work recently started: **Ambiguity identification**

The Value Learning Problem

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Abstract

Autonomous AI systems' programmed goals can easily fall short of programmers' intentions. Even a machine intelligent enough to understand its designers' intentions would not necessarily *act* as intended. We discuss early ideas on how one might design smarter-than-human AI systems that can inductively learn what to value from labeled training data, and highlight questions about the construction of systems that model and act upon their operators' preferences.

Introduction

Standard texts in AI safety and ethics, such as Weld and Etzioni (1994) or Anderson and Anderson (2011), generally

> ties remains mutually beneficial. [...] In other words, even if AIs become much more productive than we are, it will remain to their advantage to trade with us and to ours to trade with them.

As noted by Benson-Tilsen and Soares (forthcoming 2016), however, rational trade presupposes that agents expect more gains from trade than from coercion. Non-human species have various "comparative advantages" over humans, but humans generally exploit non-humans through force. Similar patterns can be observed in the history of human war and conquest. Whereas agents at similar capability levels have incentives to compromise, collaborate, and trade, agents with strong power advantages over others can have incen-

Work recently started: **Conservatism**

Intelligent Agent Foundations Forum new | comments | links | members | submit

Conservative classifiers

post by **Jessica Taylor** 216 days ago | **Abram Demski** and **Patrick LaVictoire** like this | discuss

Summary: If we train a classifier on a training set that comes from one distribution, and test it on a dataset coming from a different distribution, uniform convergence guarantees generally no longer hold. This post presents a strategy for creating classifiers that will reject test points when they are sufficiently different from training data. It works by rejecting points that are much more probable under the predicted test distribution than under the training distribution.

Introduction

In machine learning, we often train a system (e.g. a classifier or regression system) on a training set, and then test it on a test set. If the test set comes from the same distribution as the training set, uniform convergence guarantees allow us to bound the system's expected error on the test set based on its performance on the training set. As an example, if we are creating an automated system for making moral judgments, we could get training data by asking humans for their moral judgments. Then we could use the system to make additional moral judgments.

If the test dataset comes from the same distribution as the training dataset, then uniform convergence guarantees can give us nice bounds on the performance on the test set. In reality, the test set will often be different. For a moral judgment system, this could be disastrous: perhaps we only train the classifier on ordinary moral problems, but then the classifier decides whether it is a good idea to tile the universe with tiny smiley faces. At this point, we have no guarantees about whether the classifier will correctly judge this question.

Therefore, I aim to create a system that, when presented with a question, will choose to either answer the question or abort. It should abort when the question is sufficiently different from the training data that the system cannot make reliable judgments.

Work recently started: **Specifying environmental goals using sensory data**

Formalizing Two Problems of Realistic World-Models

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Abstract

An intelligent agent embedded within the real world must reason about an environment which is larger than the agent, and learn how to achieve goals in that environment. We discuss attempts to formalize two problems: one of induction, where an agent must use sensory data to infer a universe which embeds (and computes) the agent, and one of interaction, where an agent must learn to achieve complex goals in the universe. We review related problems formalized by Solomonoff and Hutter, and explore challenges that arise when attempting to formalize analogous problems in a setting where the agent is embedded within the environment.

problem where the agent is separate from the environment, and Section 3 discusses troubles that arise when attempting to formalize the analogous naturalized induction problem. Section 4 discusses Hutter's interaction problem, and Section 5 discusses an open problem related to formalizing an analogous naturalized interaction problem.

Formalizing these problems is important in order to fully understand the problem faced by an intelligent agent embedded within the universe: a general artificial intelligence must be able to learn about the environment which computes it, and learn how to achieve its goals from inside its universe. Section 6 concludes with a discussion of why a theoretical understanding of agents interacting with their own environment seems

Work recently started: **Inverse reinforcement learning**

Learning the Preferences of Bounded Agents

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Andreas Stuhlmüller
Stanford University

Noah D. Goodman
Stanford University

Introduction

A range of work in applied machine learning, psychology, and social science involves inferring a person's preferences and beliefs from their choices or decisions. This includes work in economics on *Structural Estimation*, which has been used to infer beliefs about the rewards of education from observed work and education choices [1] and preferences for health outcomes from smoking behavior [2]. In machine learning, *Inverse Reinforcement Learning* has been applied to diverse planning and decision tasks to learn preferences and task-specific strategies [3, 4]. Large-scale systems in industry also learn preferences from behavior: for example, people's behavior on social networking sites is used to infer what movies, articles, and photos they will like [5].

Existing approaches to inferring human beliefs and preferences typically assume that human behavior is optimal up to unstructured "random noise" [6, 7]. However, human behavior may deviate from optimality in systematic ways. This can be due to biases such as time inconsistency and framing effects [8, 9] or due to planning or inference being a (perhaps resource-rational) approximation to optimality [10, 11]. If such deviations from optimality are not modeled, we risk mistaken inferences

Work recently started: **Act-based agents**

Act based agents

Parents: Paul Christiano's AI control blog

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I've recently discussed three kinds of learning systems:

- Approval-directed agents which take the action the user would most approve of.
- Imitation learners which take the action that the user would tell them to take.
- Narrow value learners which take the actions that the user would prefer they take.

These proposals all focus on the short-term instrumental preferences of their users. From the perspective of AI control I think this is the interesting aspect that deserves more attention.

Going forward I'll call this kind of approach "act-based" unless I hear something better (credit to Eliezer), and I'll call agents of this type "act-based agents."

Robustness

Act-based agents seem to be robust to certain kinds of errors. You need only the vaguest understanding of humans to guess that killing the user is: (1) not something they would approve of, (2) not something they would do, (3) not in line with their instrumental preferences.

Work recently started: **Mild optimization**

Quantilizers: A Safer Alternative to Maximizers for Limited Optimization

Jessica Taylor
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Abstract

In the field of AI, *expected utility maximizers* are commonly used as a model for idealized agents. However, expected utility maximization can lead to unintended solutions when the utility function does not quantify everything the operators care about: imagine, for example, an expected utility maximizer tasked with winning money on the stock market, which has no regard for whether it accidentally causes a market crash. Once AI systems become sufficiently intelligent and powerful, these unintended solutions could become quite dangerous. In this paper, we describe an alternative to expected utility maximization for powerful AI systems, which we call *expected utility quantilization*. This could allow the construction of AI systems that do not necessarily fall into strange and unantici-

utility function, with $U(o)$ being the utility of outcome o. Then an expected utility maximizer is an agent that chooses an action $a \in \mathcal{A}$ that maximizes $\mathbb{E}[U(W(a))]$.

We make no argument against expected utility maximization on the grounds of rationality. However, maximizing the expectation of some utility function could produce large unintended consequences whenever U does not accurately capture all the relevant criteria. Some unintended consequences of this form can already be observed in modern AI systems. For example, consider the genetic algorithm used by Nguyen, Yosinski, and Clune [8] to generate an image which would be classified by a deep neural network as a starfish, with extremely high confidence. The resulting image ended up completely unrecognizable, looking nothing at all like a starfish.

Of course, Nguyen, Yosinski, and Clune [8] intended to develop images that would be mis-classified, but

Past developments: **AIXI**

Technical Report IDSIA-01-03 In *Artificial General Intelligence*, 2007

UNIVERSAL ALGORITHMIC INTELLIGENCE
A mathematical top→down approach

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17 January 2003

Keywords

Artificial intelligence; algorithmic probability; sequential decision theory; rational agents; value function; Solomonoff induction; Kolmogorov complexity; reinforcement learning; universal sequence prediction; strategic games; function minimization; supervised learning.

Past developments: **Tiling agents**

- Only Π_1 goals, on pain of Procrastination Paradox

Vingean Reflection: Reliable Reasoning for Self-Improving Agents

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Abstract

Today, human-level machine intelligence is in the domain of futurism, but there is every reason to expect that it will be developed eventually. Once artificial agents become able to improve themselves further, they may far surpass human intelligence, making it vitally important to ensure that the result of an "intelligence explosion" is aligned with human interests. In this paper, we discuss one aspect of this challenge: ensuring that the initial agent's reasoning about its future versions is reliable, even if these future versions are far more intelligent than the current reasoner. We refer to reasoning of this sort as *Vingean reflection*.

> intellectual activities of any man however clever. Since the design of machines is one of these intellectual activities, an ultraintelligent machine could design even better machines; there would then unquestionably be an 'intelligence explosion,' and the intelligence of man would be left far behind. Thus the first ultraintelligent machine is the last invention that man need ever make.

Almost fifty years later, a machine intelligence that is smart in the way humans are remains the subject of futurism and science fiction. But barring global catastrophe, there seems to be little reason to doubt that humanity will *eventually* create a smarter-than-human

Past developments: **Software agent cooperation**

- Avoiding causal decision theory's reflective inconsistency
- Updateless decision theory, PrudentBot
- Logical counterfactuals

Program Equilibrium in the Prisoner's Dilemma via Löb's Theorem

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Abstract

Applications of game theory often neglect that real-world agents normally have some amount of out-of-band information about each other. We consider the limiting case of a one-shot Prisoner's Dilemma between algorithms with read-access to one anothers' source code. Previous work has shown that cooperation is possible at a Nash equilibrium in this setting, but existing constructions require interacting agents to be identical or near-identical. We show that a natural class of agents are able to achieve mutual cooperation at Nash equilibrium without any prior coordination of this sort.

1 Introduction

Can cooperation in a one-shot Prisoner's Dilemma be jus-

This stronger assumption suggests a convenient logical formalism. In the 1980s, Binmore (1987) considered game theory between programs which could read each other's source code before playing[1]:

> ...a player needs to be able to cope with hypotheses about the reasoning processes of the opponents other than simply that which maintains that they are the same as his own. Any other view risks relegating rational players to the role of the "unlucky" Bridge expert who usually loses but explains that his play is "correct" and would have led to his winning if only the opponents had played "correctly". Crudely, rational behavior should include the capacity to exploit bad play by the oppo-
> nents

Past developments: **Reflective oracles**

- Also reflective propositional probability
- Also reflective, quantified logical uncertainty (subproblem of Vingean reflection)

Reflective Oracles: A Foundation for Classical Game Theory

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Abstract

Classical game theory treats players as special—a description of a game contains a full, explicit enumeration of all players—even though in the real world, "players" are no more fundamentally special than rocks or clouds. It isn't trivial to find a decision-theoretic foundation for game theory in which an agent's coplayers are a non-distinguished part of the agent's environment. Attempts to model both players and the environment as Turing machines, for example, fail for standard diagonalization reasons.

In this paper, we introduce a "reflective" type of oracle, which is able to answer questions about the outputs of oracle machines with access to the same oracle. These oracles avoid

be boundedly rational reasoners, which make decisions with finite computational resources. Nevertheless, the notion of a perfect Bayesian reasoner provides an analytically tractable first approximation to the behavior of real-world agents, and underlies an enormous body of work in statistics [6], economics [7], computer science [8], and other fields.

On closer examination, however, the assumption that agents can compute what outcome each of their actions leads to in every possible world is troublesome even if we assume that agents have unbounded computing power. For example, consider the game of *Matching Pennies*, in which two players each choose between two actions ("heads" and "tails"); if the players choose the same action, the first player wins a dollar, if they choose differently, the second player wins. Suppose further that both players' decision-making processes are Tur-

Where can you work on this?

- Machine Intelligence Research Institute (Berkeley)
- Future of Humanity Institute (Oxford University)
- Stuart Russell (UC Berkeley)
- Leverhulme CFI is starting up (Cambridge UK)

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Questions?

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Resources (incl. slides): intelligence.org/stanford-talk