The Essence of Intelligence is Appropriate Action (not thinking, reasoning, learning or language) and other things every student of AI should know

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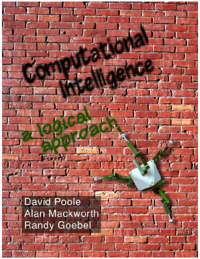
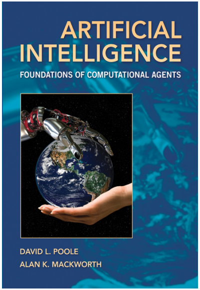
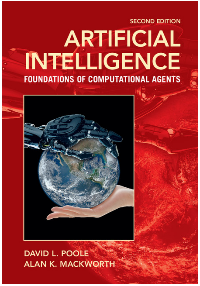
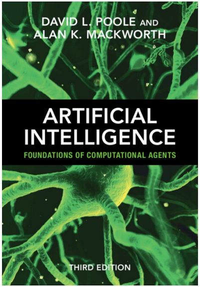
Books and online resources









`https://artint.info` – full text online
`https://www.aispace.org` – Java apps for learning AI
`http://aipython.org` – open source Python code

Audience Question

Humans evolved intelligence because

A it was selected for when finding a suitable mate

B it enabled behavior that helped humans to survive and flourish

C it enabled them to spread gossip and misinformation

D it enabled people to have deep inner thoughts

E it was just random

Outline

Agents

What should an agent believe?

What should an agent do?

Where do values/goals/preferences come from?

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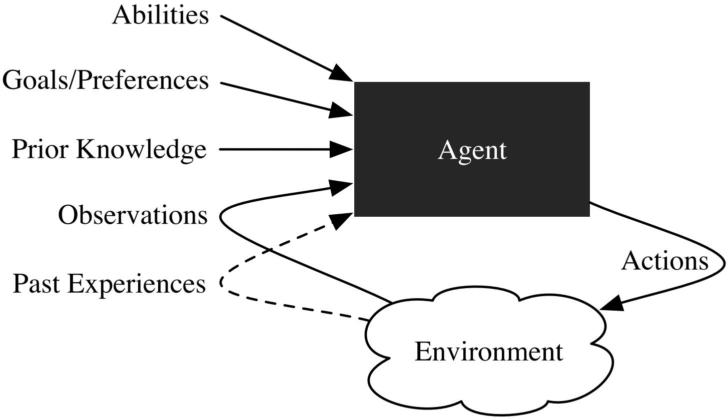
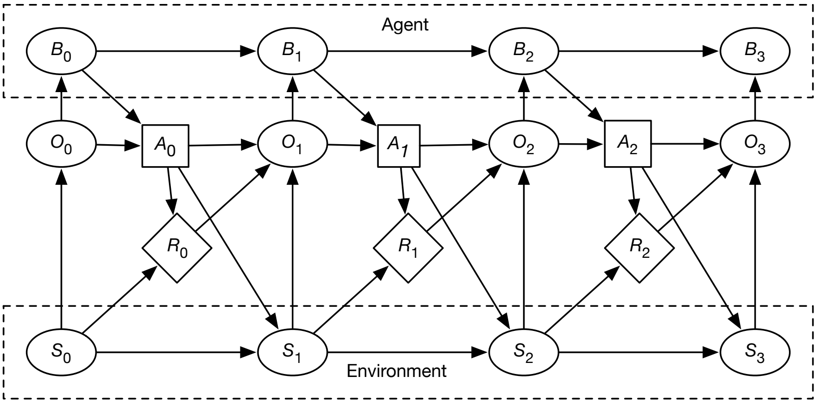


An agent situated in time



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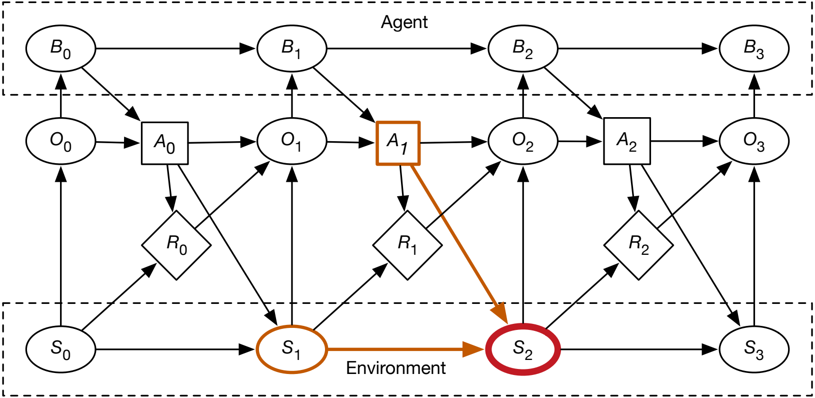

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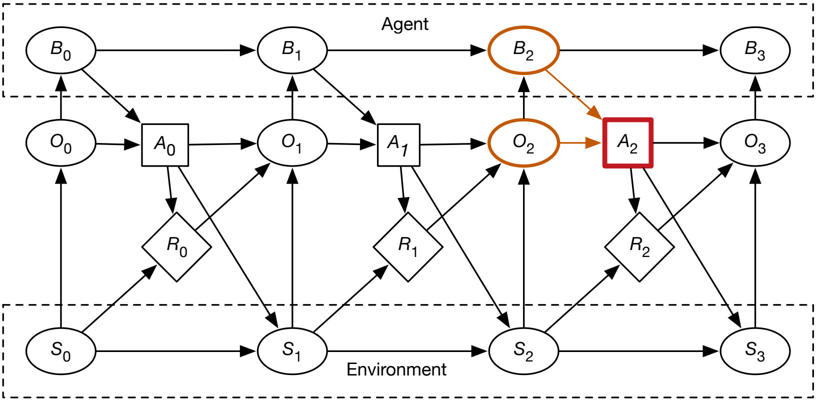

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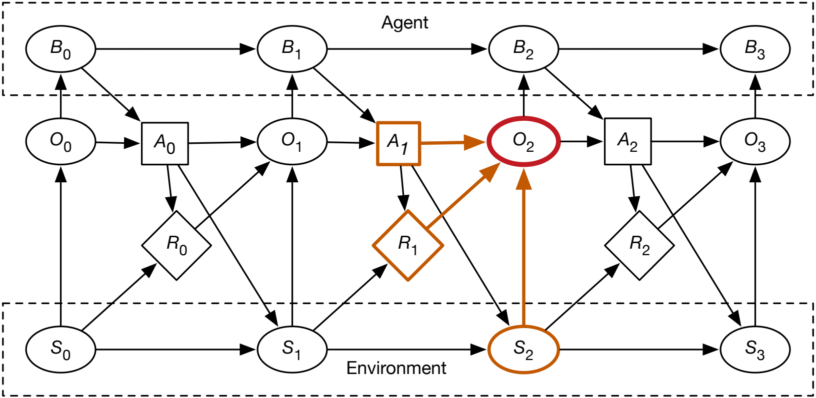

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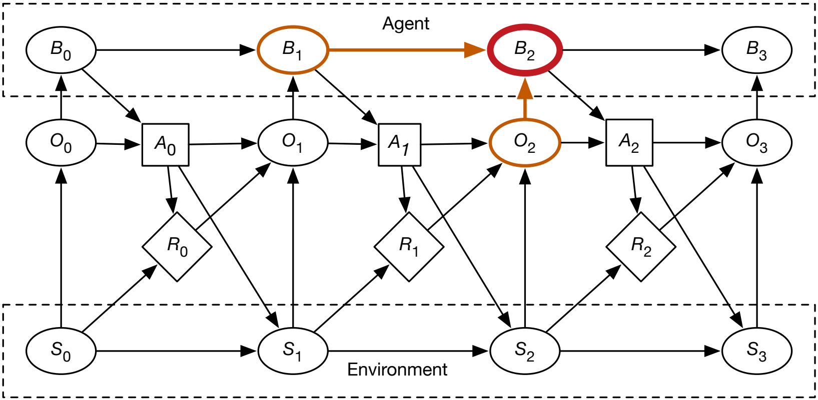

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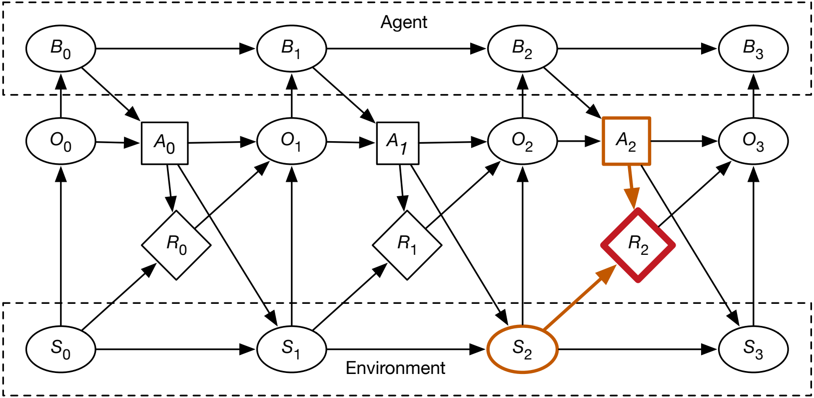

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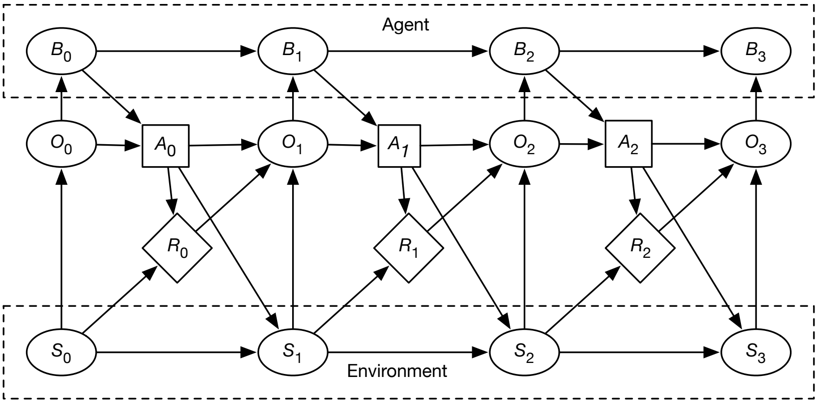

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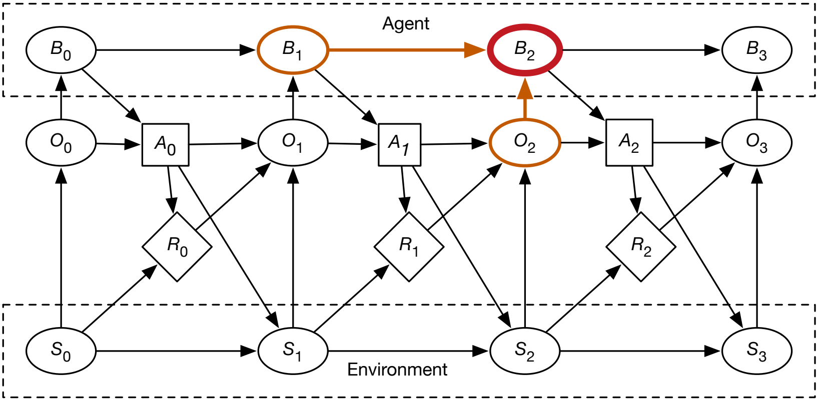

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- Common: end-to-end (monolithic) learning: learn everything at once.

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$\boxed{\text{Do we just need to learn with more data?}}$

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- Same argument goes for symptoms.

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Avoiding the combinatorics $P(Diseases \mid Symptoms, Location, \dots)$

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- What happens when a new virus arrives?

Context and Independence

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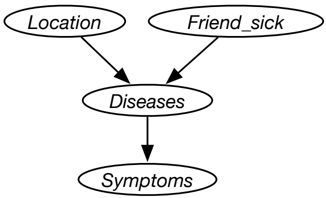

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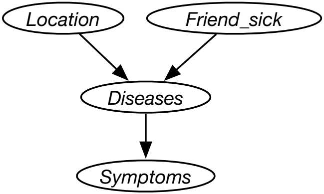

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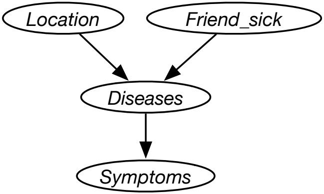
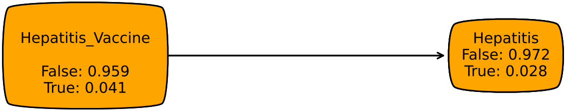


- modular, transportable
- can be learned from data

Determining the Effects of Acting

$P(Hepatitis)$, $P(Hepatitis\_Vaccine)$ – fictional probabilities



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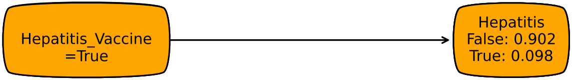

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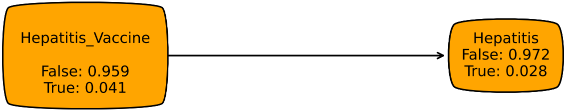

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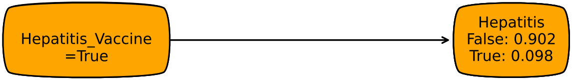

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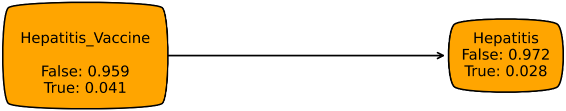

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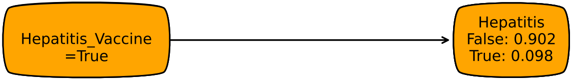

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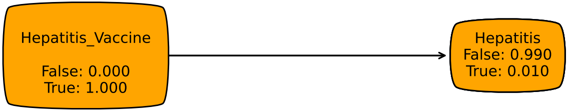

Pearl's do notation $P(Hepatitis \mid do(Hepatitis\_Vaccine))$

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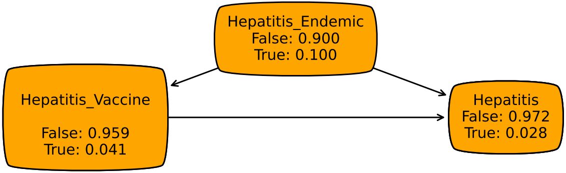

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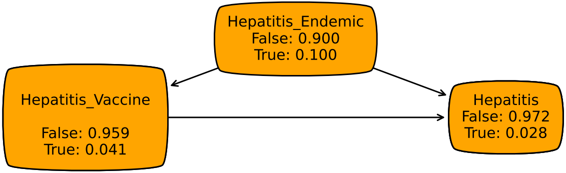

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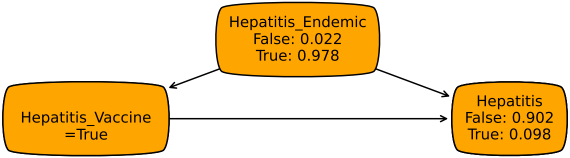

A causal model predicts the effects of an action
Hepatitis_Endemic is a confounder.
Open source code at AIPython.org

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- It needs a real body to carry out experiments in its world
- It could use all connected sensors and actuators, as long as it can control the actuators.

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Model/find out why data is missing!

Audience Question

What is the real world made of?

A Features or random variables

B Words, pixels, phonemes ...

C Entities and events (e.g., plants, people, diseases, talks, conferences)

D Huh? There is a real world?

Relational Models

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Also statistical relational AI,
relational probabilistic models,
logic learning

Relations and Knowledge Graphs

- Example relation:

Patient	Test	Technician	Result	DateTime
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- E.g, (54326353202601220945, patient, 54326)
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- Number of triples for reified tuple = number of columns

Relations and Knowledge Graphs

- Example relation:

Patient	Test	Technician	Result	DateTime
54326	353	99807	1	202601220945
54326	353	87601	0	202601250830
...				

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- In Wikidata over 98% of entities are reified with 10 or fewer triples.

From Knowledge Graphs to Random Variables

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  e.g.: *has-streamed*
- $\longrightarrow$ relational probabilistic models represent how these random variables interrelate,
  independently of the actual entities: "logic variables", "universal quantification", "lifted", "exchangeable", "parameter sharing", "weight tying", "convolutional"

Determining Truth

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What should an agent do?

Where do values/goals/preferences come from?

Preferences

Alice . . . went on "Would you please tell me, please, which way I ought to go from here?"
"That depends a good deal on where you want to get to," said the Cat.
"I don't much care where —" said Alice.
"Then it doesn't matter which way you go," said the Cat.

Alice's Adventures in Wonderland, Lewis Carroll, 1865

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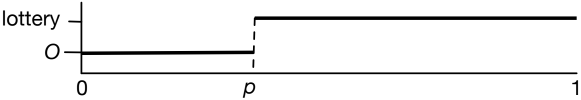

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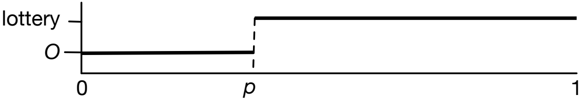

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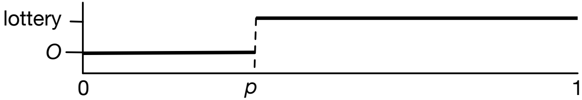

- The p where preference flips is the utility of the outcome O.
- A few intuitive(?) assumptions $\Rightarrow$ prefer outcome iff higher expected utility

Utility and time

- How would you compare the following sequences of rewards (per week):

  A: \$1,000,000, \$0, \$0, \$0, \$0, \$0,...
  B: \$1000, \$1000, \$1000, \$1000, \$1000,...

Rewards and Values

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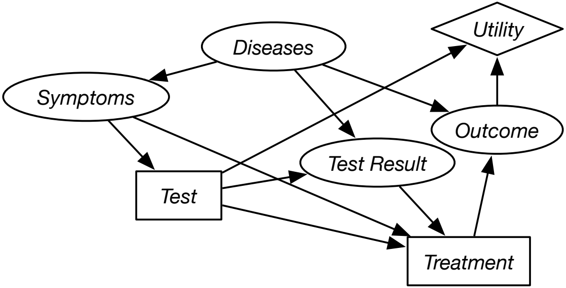
- Discount γ is not a hyperparameter to be optimized, but specifies how much future rewards are worth.

Decision Network



- Ellipses are random variables
- Rectangles are decisions
- Diamond is utility
- Arc means "can depend on"

Decision Processes

- For artificial domains, such as games and factory floors, a agent can observe state of environment: fully observable

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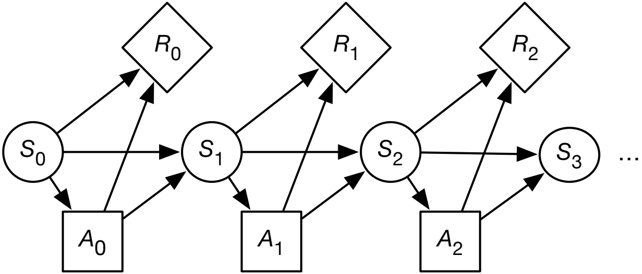
- A fully-observable Markov decision process can go on indefinitely:



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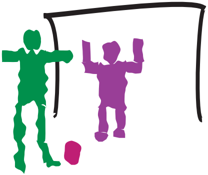
Multiple Agent Example: Football Penalty Kick



		goalkeeper left	goalkeeper right
kicker	left	0.6	0.2
	right	0.3	0.9

Probability of a goal.

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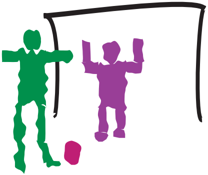

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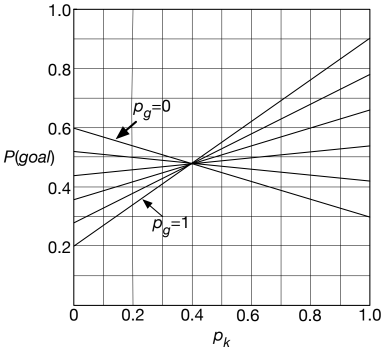

p_k is $P(kicker = right)$
p_j is $P(goalkeeper = right)$

Multiagent Example: Tragedy of the Commons

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Mechanism design: design the rules. E.g., maximize common good.

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- Non-consenting people and/or the environment may be impacted.
  E.g., driving, building sewage treatment centre

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- How to make it fair when the people acting and people impacted are in different socioeconomic groups or different countries or not-yet-born?

Moral Decisions

". . . self-driving cars . . . what are the values that we're going to embed in the cars? There are gonna be a bunch of choices that you have to make, the classic problem being: If the car is driving, you can swerve to avoid hitting a pedestrian, but then you might hit a wall and kill yourself. It's a moral decision, and who's setting up those rules?"

Barack Obama, 2016

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- Determining which values to use, and how preferences can be established fairly, is a major non-technical challenge.

Conclusions

- Agents are judged by their actions.
- Acting under uncertainty is gambling. Probability is the calculus of gambling.
- It is impossible to learn the effects of actions from observations alone: you need a causal model. An agent needs to act in the world with a real body.
- Determining truth is the realm of science. Use all available evidence. Have diverse hypotheses. Carry out experiments. Always be open to new evidence and hypotheses. Be skeptical.
- What an agent should do depends on its preferences and others affected by its actions.
- Determining which values to use, and how preferences can be established fairly, is a major non-technical challenge.
- The essence of (artificial) intelligence is action.