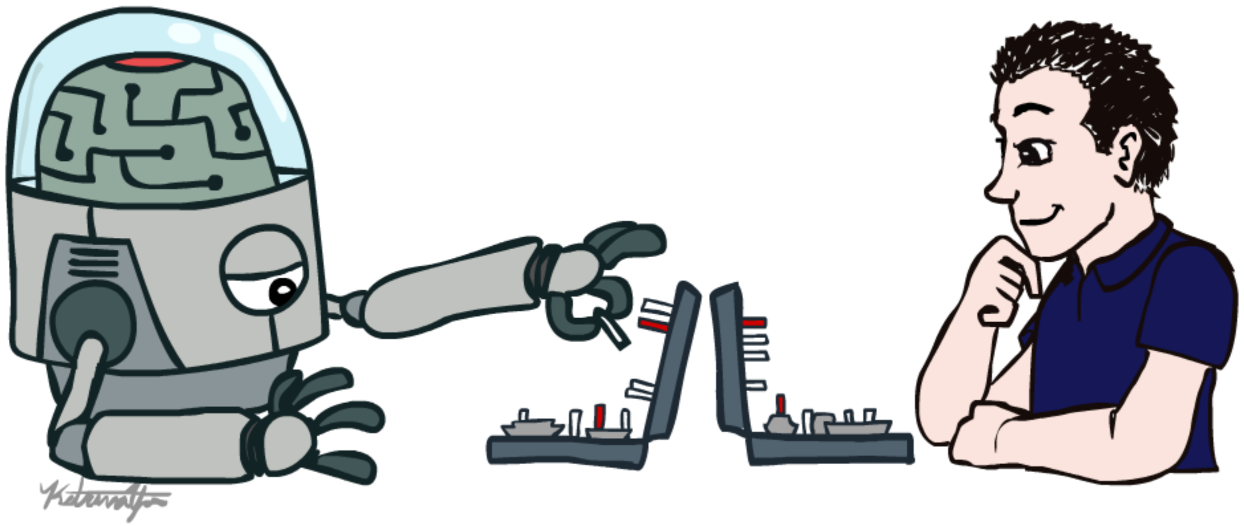
Artificial Intelligence

Introduction and Rationality



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(slides adapted from Dan Klein, Pieter Abbeel, Anca Dragan, Stuart Russell)

SS

What is artificial intelligence?

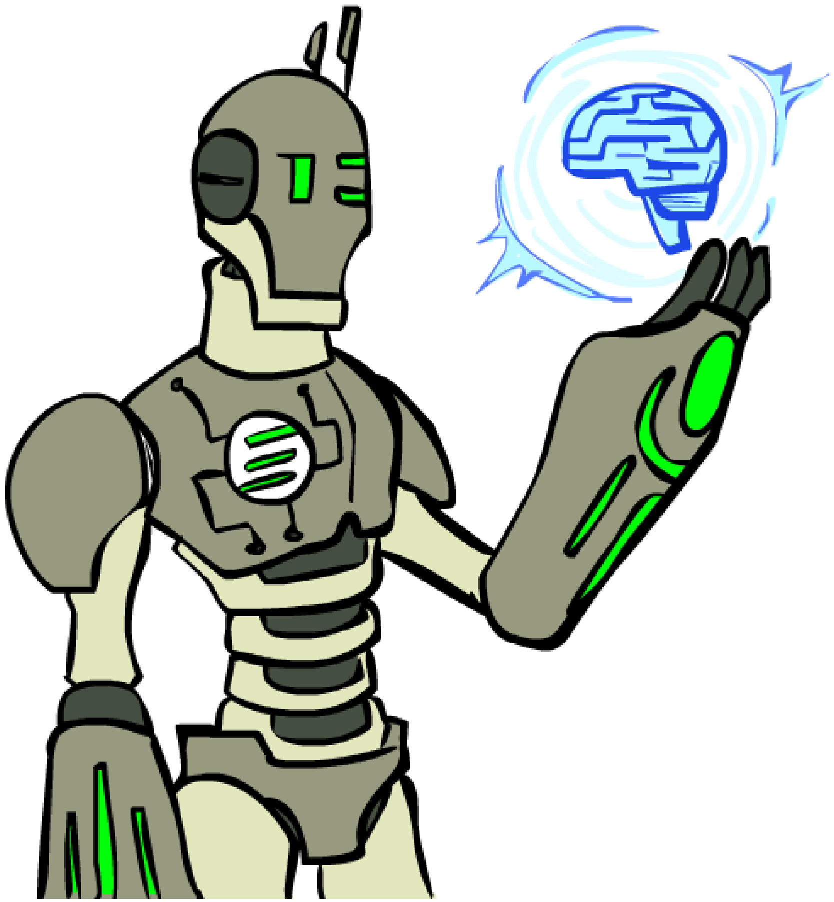
Artificial intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think and learn like humans. It is a broad field of computer science that focuses on creating intelligent machines capable of performing tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, problem-solving, and language translation.

AI encompasses various subfields and techniques, including machine learning, natural language processing, computer vision, expert systems, and robotics. These approaches enable AI systems to acquire knowledge, process information, reason, and make predictions or decisions based on the available data.

Machine learning, a key component of AI, involves training algorithms to recognize patterns in large amounts of data and make predictions or take actions without being explicitly programmed. This ability to learn from experience and adapt to new situations is what sets AI apart from traditional software systems.

In these slides…

- What is artificial intelligence?
- Where did it come from/What can AI do?
  - What should we and shouldn't we worry about?
- Utilities and Rationality



What is AI?

The science of making machines that:

Rational Decisions

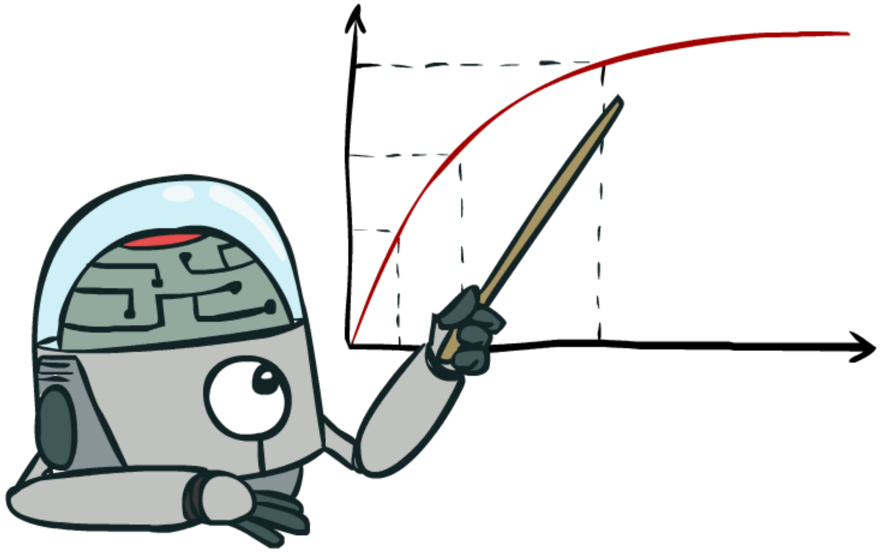
We'll use the term **rational** in a very specific, technical way:

- Rational: maximally achieving pre-defined goals
- Rationality only concerns what decisions are made (not the thought process behind them)
- Goals are expressed in terms of the **utility** of outcomes
- Being rational means **maximizing your expected utility**

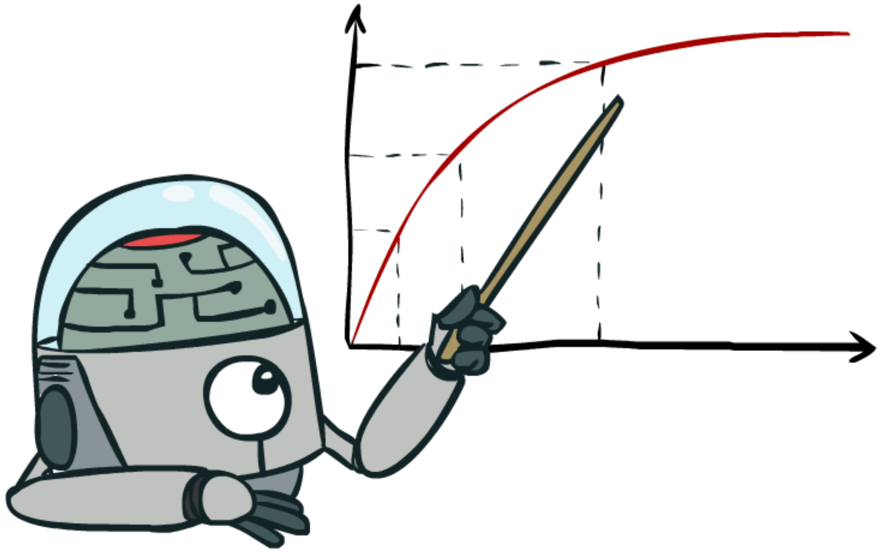
A better title for this course would be:

Computational Rationality

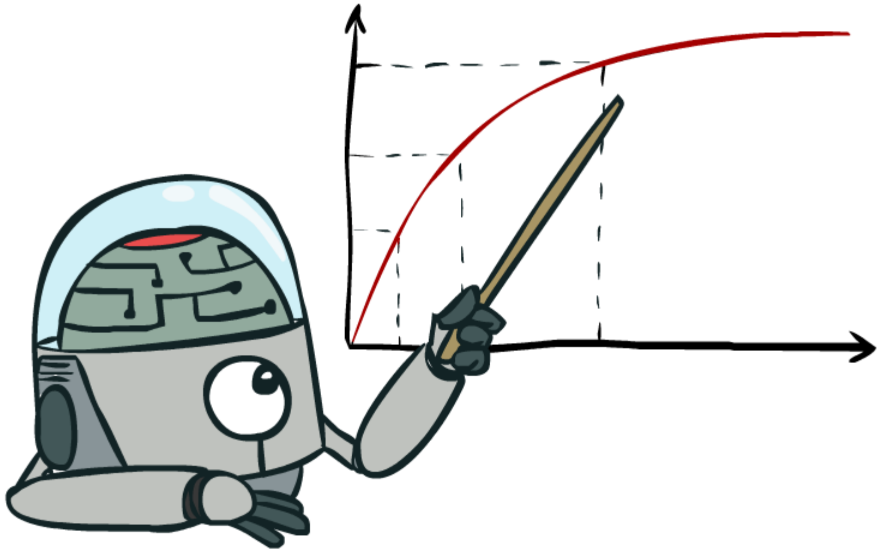
Maximize Your Expected Utility



Maximize Your Expected Utility



Maximize Your Expected Utility

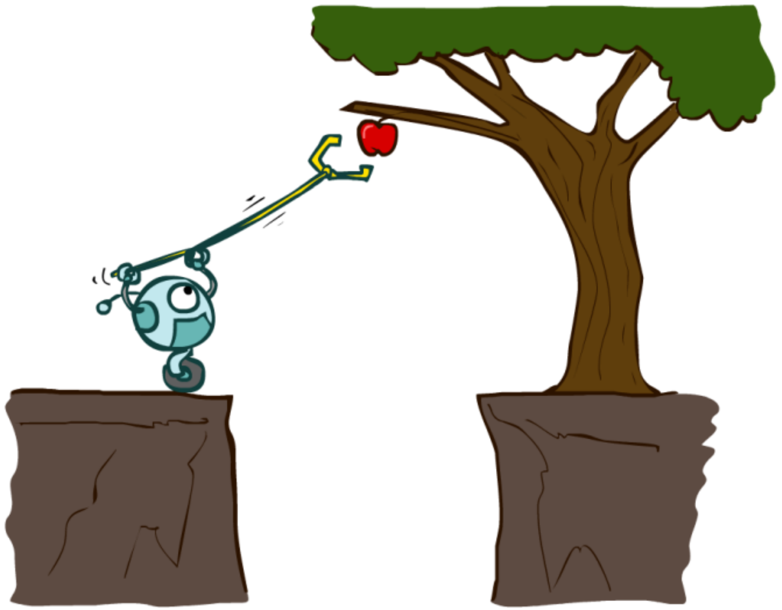


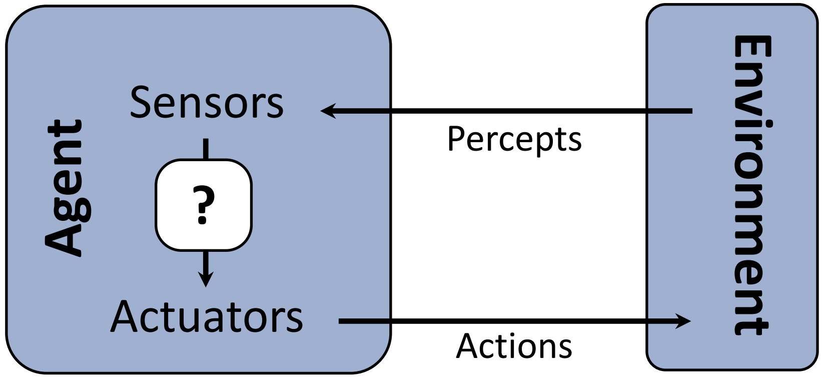
What About the Brain?

- Brains (human minds) are very good at making rational decisions, but not perfect
- Brains aren't as modular as software, so hard to reverse engineer!
- "Brains are to intelligence as wings are to flight"
- Lessons learned from the brain: memory and simulation are key to decision making

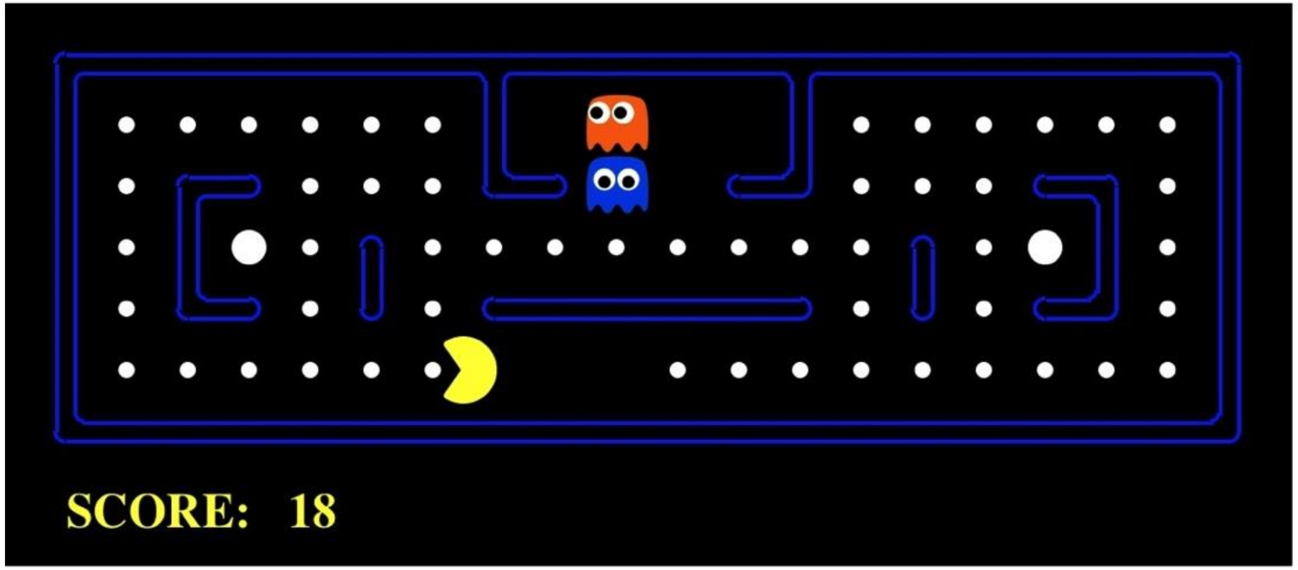
Designing Rational Agents

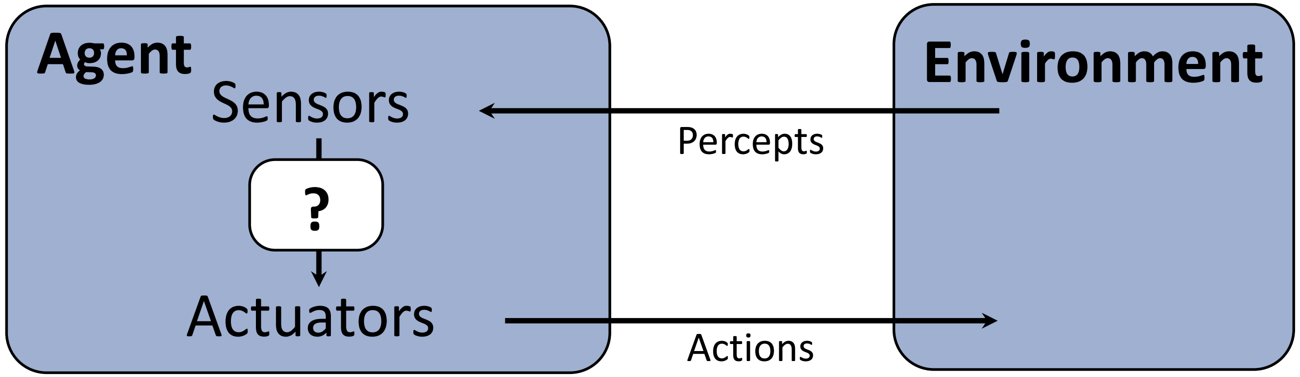
- An **agent** is an entity that *perceives* and *acts*.
- A **rational agent** selects actions that maximize its (expected) **utility**.
- Characteristics of the **percepts, environment,** and **action space** dictate techniques for selecting rational actions
- **This course** is about:
  - General AI techniques for a variety of problem types
  - Learning to recognize when and how a new problem can be solved with an existing technique





Pac-Man as an Agent

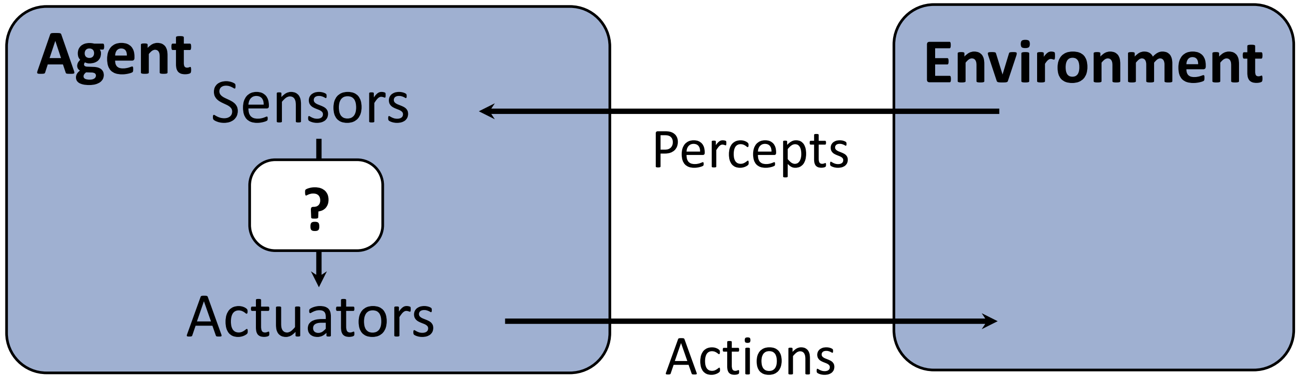




Pac-Man is a registered trademark of Namco-Bandai Games, used here for educational purposes

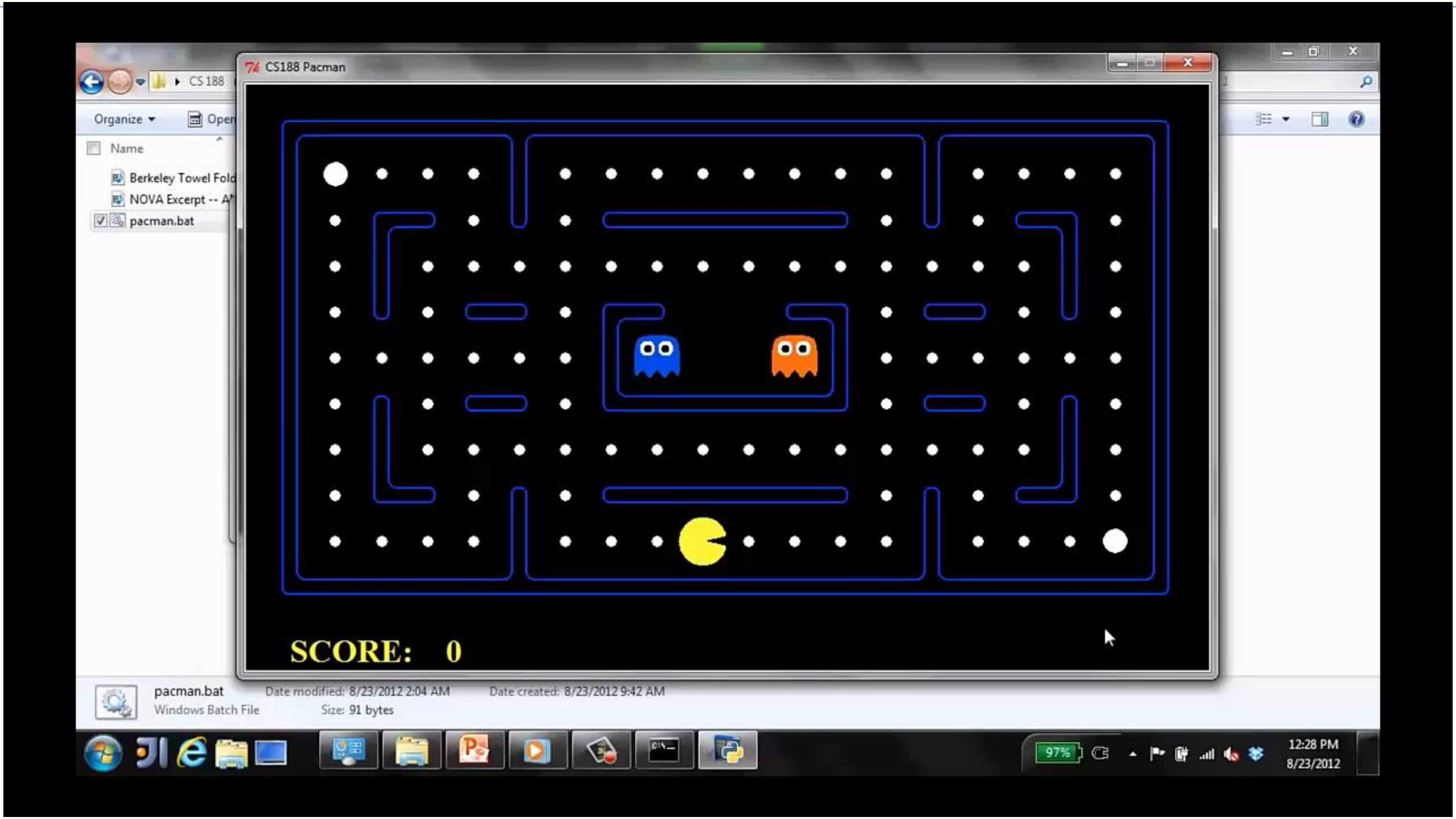
Demo1: pacman-l1.mp4

Agents and environments



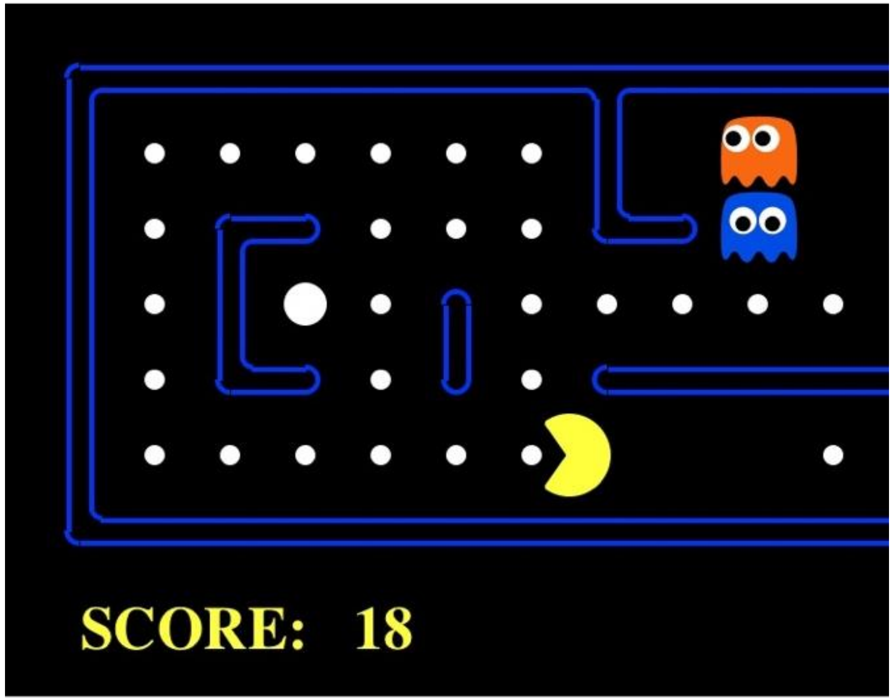
- An agent ***perceives*** its environment through ***sensors*** and ***acts*** upon it through ***actuators*** (or *effectors*, depending on whom you ask)
- The *agent function* maps percept sequences to actions
- It is generated by an *agent program* running on a ***machine***

A human agent in Pacman



The task environment - PEAS

- Performance measure
  - -1 per step; + 10 food; +500 win; -500 die; +200 hit scared ghost
- Environment
  - Pacman dynamics (incl ghost behavior)
- Actuators
  - Left Right Up Down or NSEW
- Sensors
  - Entire state is visible (except power pellet duration)



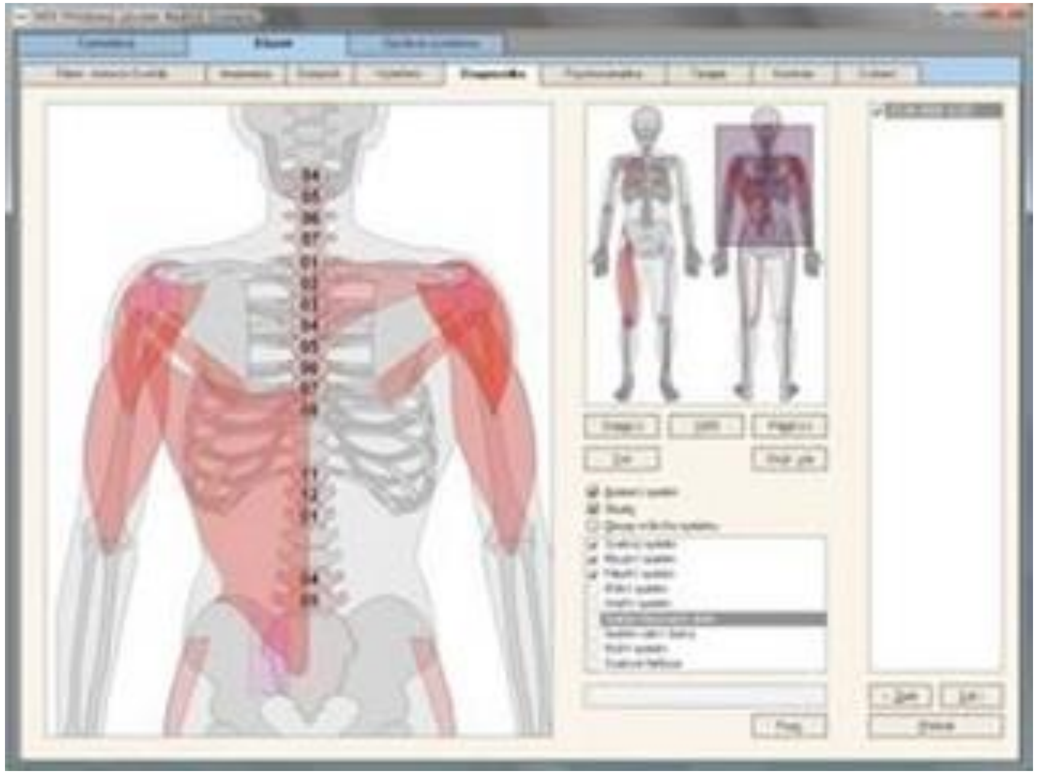
PEAS: Automated taxi

- Performance measure
  - Income, happy customer, vehicle costs, fines, insurance premiums
- Environment
  - US streets, other drivers, customers, weather, police…
- Actuators
  - Steering, brake, gas, display/speaker
- Sensors
  - Camera, radar, accelerometer, engine sensors, microphone, GPS

Image: http://nypost.com/2014/06/21/how-google-might-put-taxi-drivers-out-of-business/

PEAS: Medical diagnosis system

- Performance measure
  - Patient health, cost, reputation
- Environment
  - Patients, medical staff, insurers, courts
- Actuators
  - Screen display, email
- Sensors
  - Keyboard/mouse



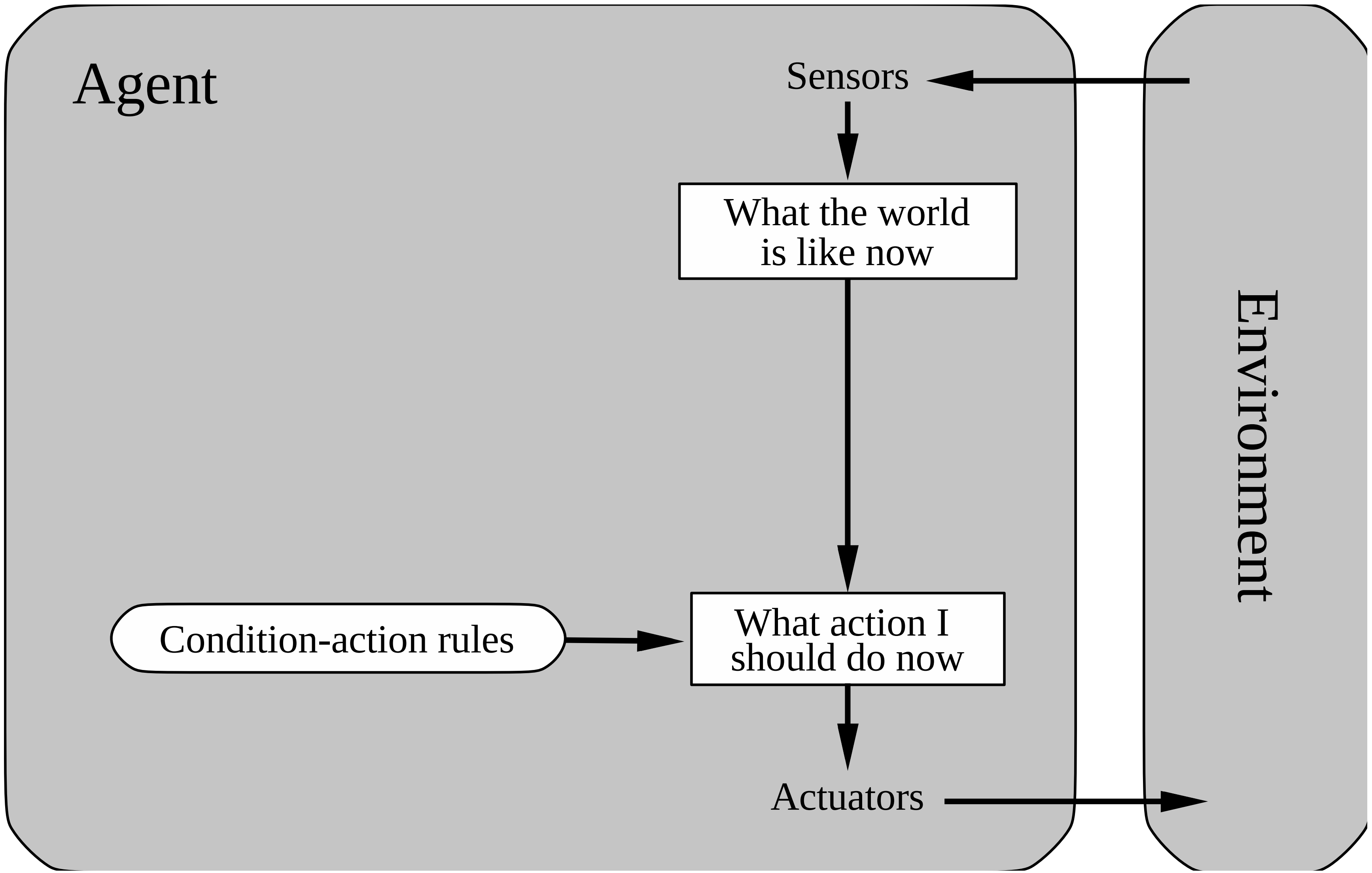
Environment types

	Pacman	Diagnosis	Taxi
Fully or partially observable			
Single-agent or multiagent			
Deterministic or stochastic			
Static or dynamic			
Discrete or continuous			
Known physics?			
Known perf. measure?			

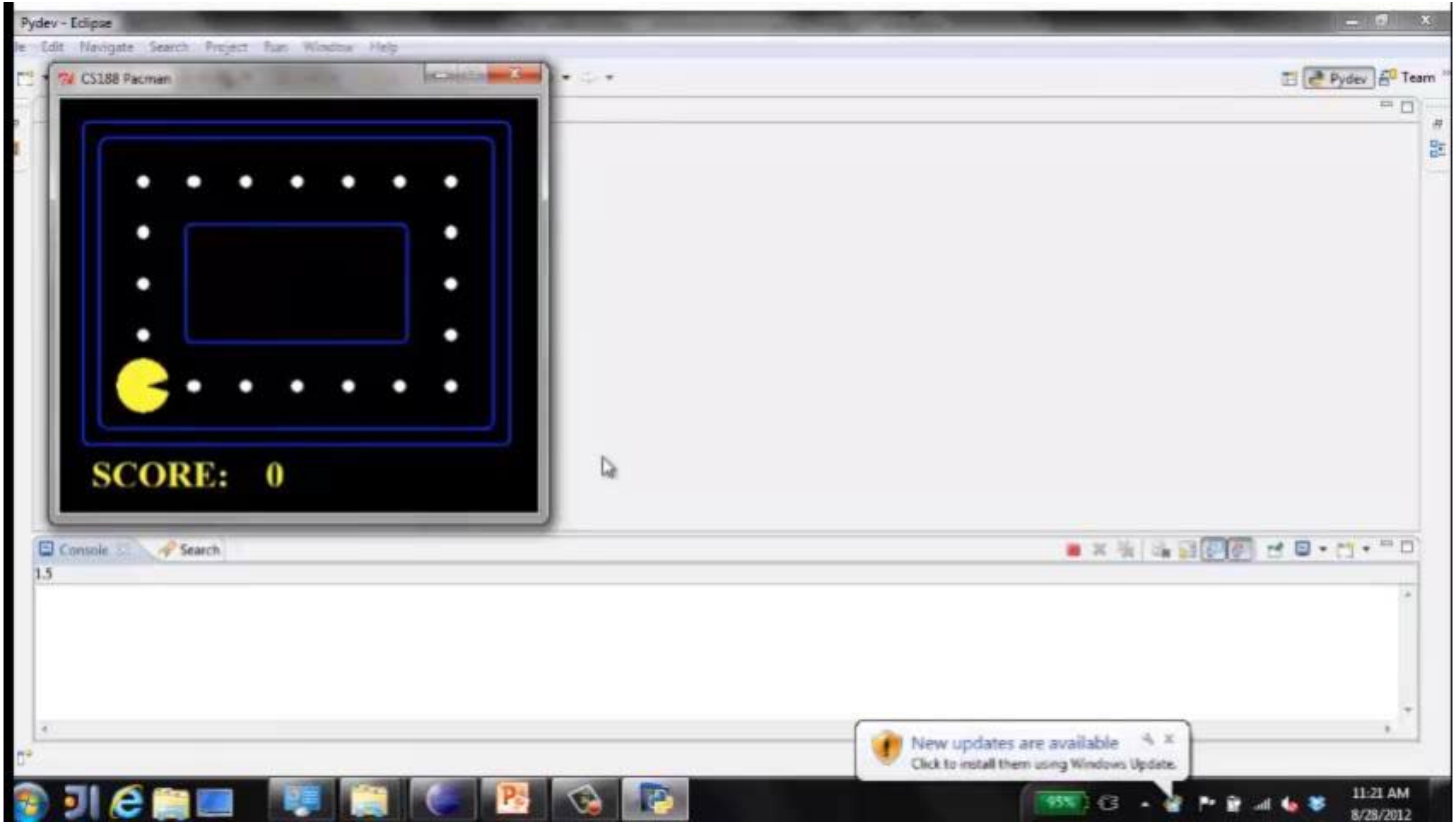
Agent design

- **The environment type largely determines the agent design**
  - ***Partially observable*** => agent requires ***memory*** (internal state)
  - ***Stochastic*** => agent may have to prepare for ***contingencies***
  - ***Multi-agent*** => agent may need to behave ***randomly***
  - ***Static*** => agent has time to compute a rational decision
  - ***Continuous time*** => continuously operating ***controller***
  - ***Unknown physics*** => need for ***exploration***
  - ***Unknown perf. measure*** => observe/interact with ***human principal***

Simple reflex agents



Eat adjacent dot, if any



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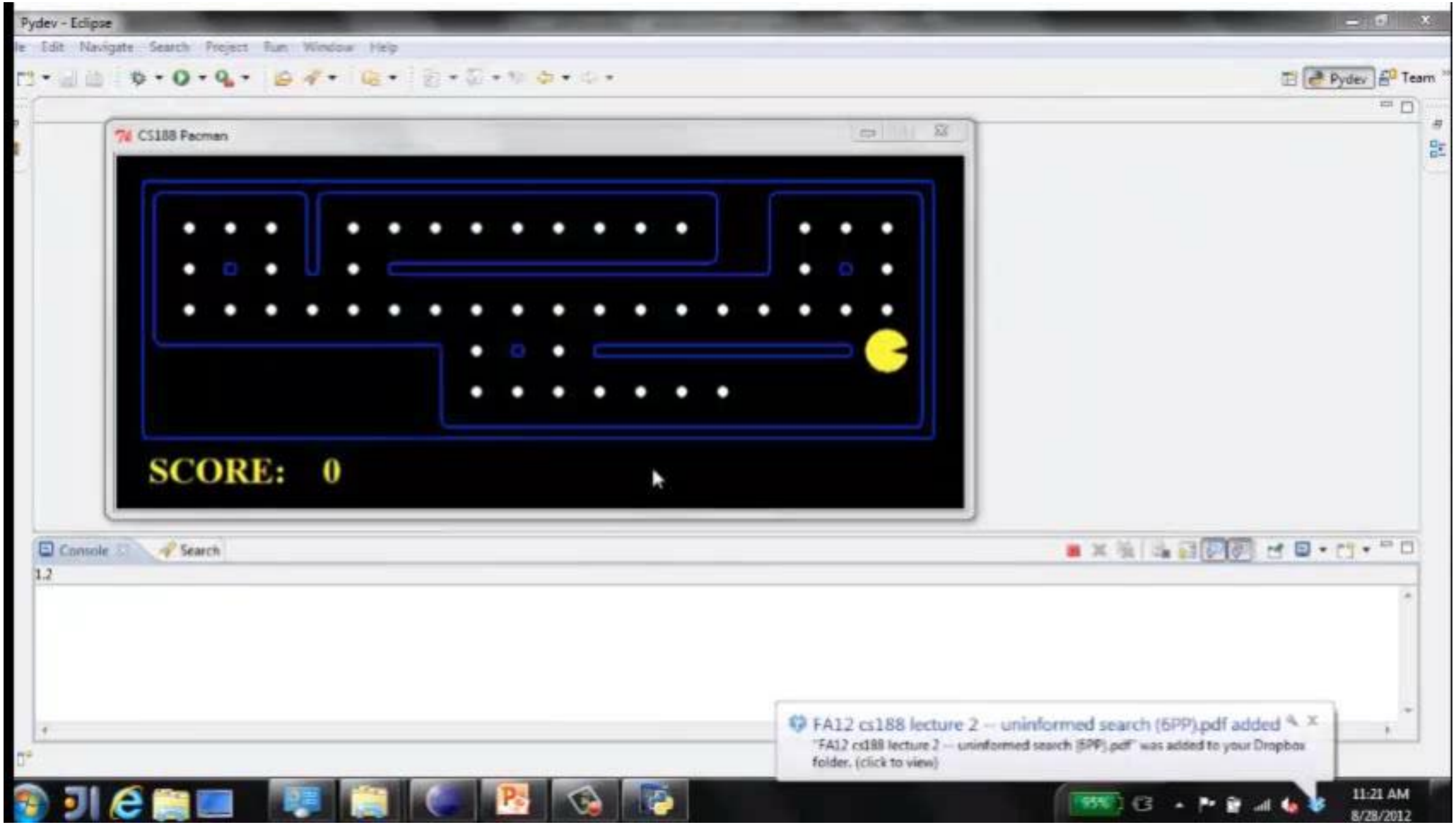
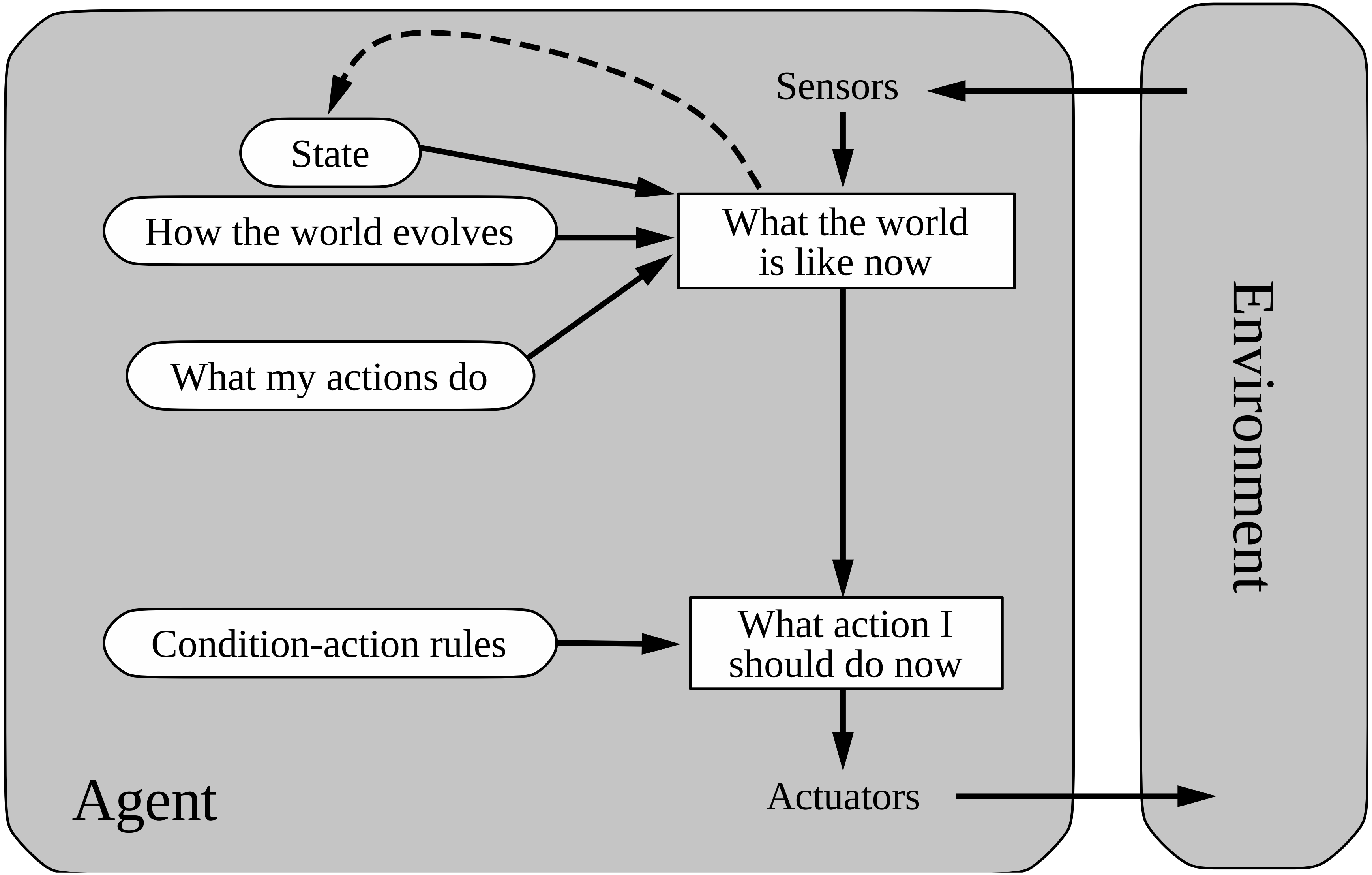


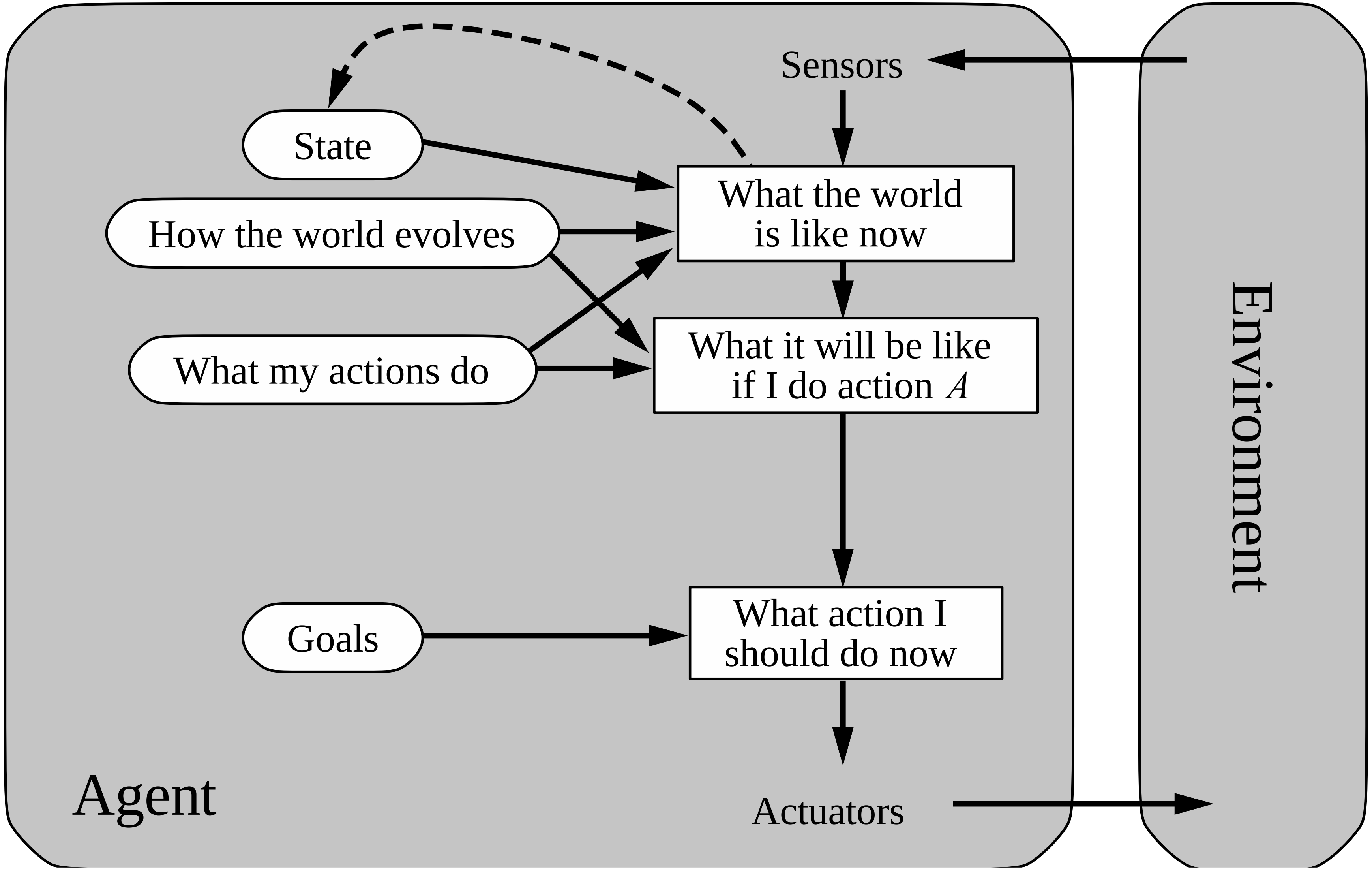
Pacman agent contd.

- Can we (in principle) extend this reflex agent to behave well in all standard Pacman environments?
  - No – Pacman is not quite fully observable (power pellet duration)
  - Otherwise, yes – we can (*in principle*) make a lookup table…..
  - *How large would it be?*

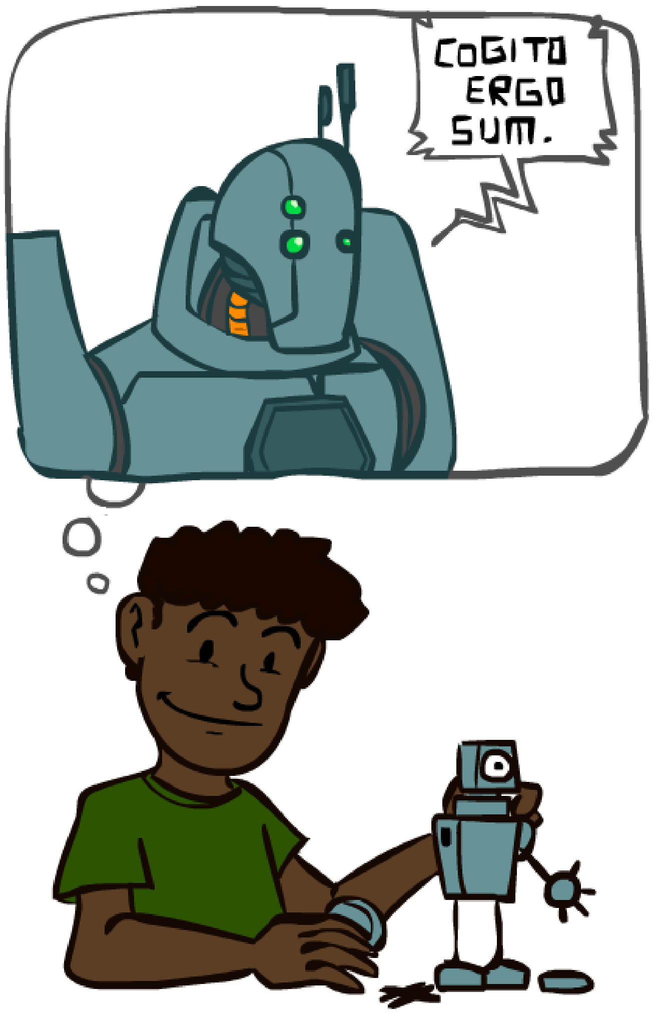
Reflex agents with state



Goal-based agents

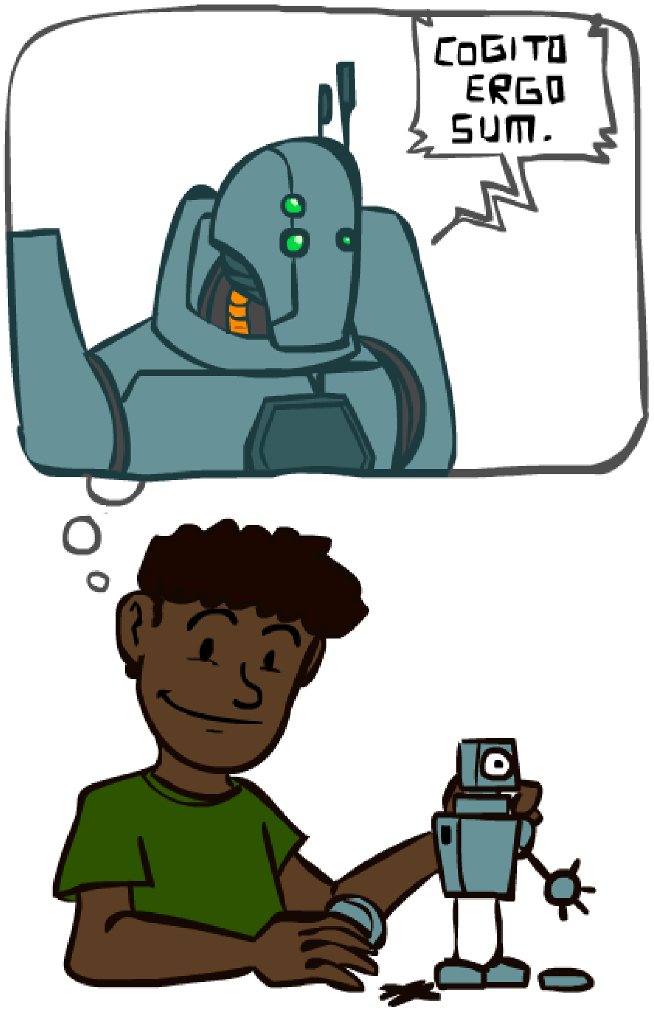


A (Short) History of AI



A (Short) History of AI

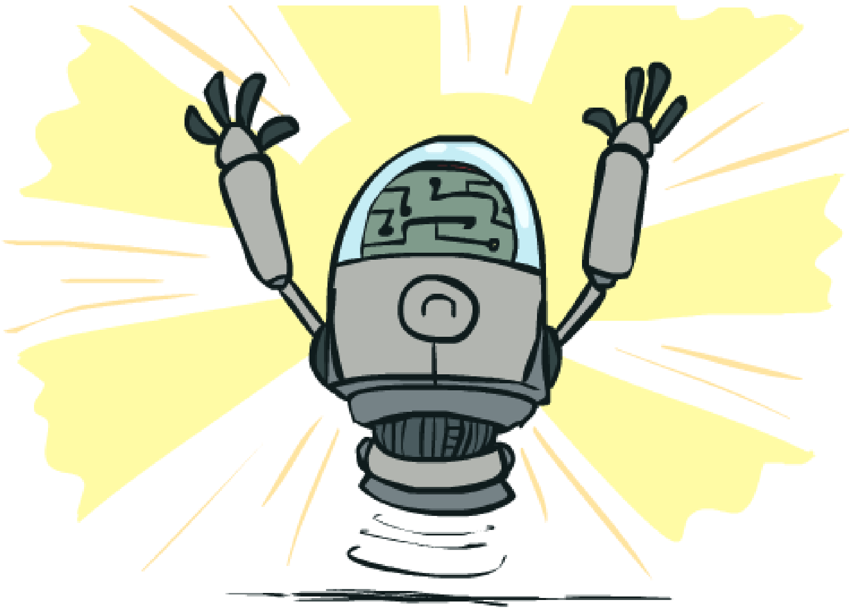
- 1940-1950: Early days
  - 1943: McCulloch & Pitts: Boolean circuit model of brain
  - 1950: Turing's "Computing Machinery and Intelligence"
- 1950—70: Excitement: Look, Ma, no hands!
  - 1950s: Early AI programs, including Samuel's checkers program, Newell & Simon's Logic Theorist, Gelernter's Geometry Engine
  - 1956: Dartmouth meeting: "Artificial Intelligence" adopted
  - 1965: Robinson's complete algorithm for logical reasoning
- 1970—90: Knowledge-based approaches
  - 1969—79: Early development of knowledge-based systems
  - 1980—88: Expert systems industry booms
  - 1988—93: Expert systems industry busts: "AI Winter"
- 1990—: Statistical approaches
  - Resurgence of probability, focus on uncertainty
  - General increase in technical depth
  - Agents and learning systems… "AI Spring"?
- 2000—: Where are we now?



What Can AI Do?

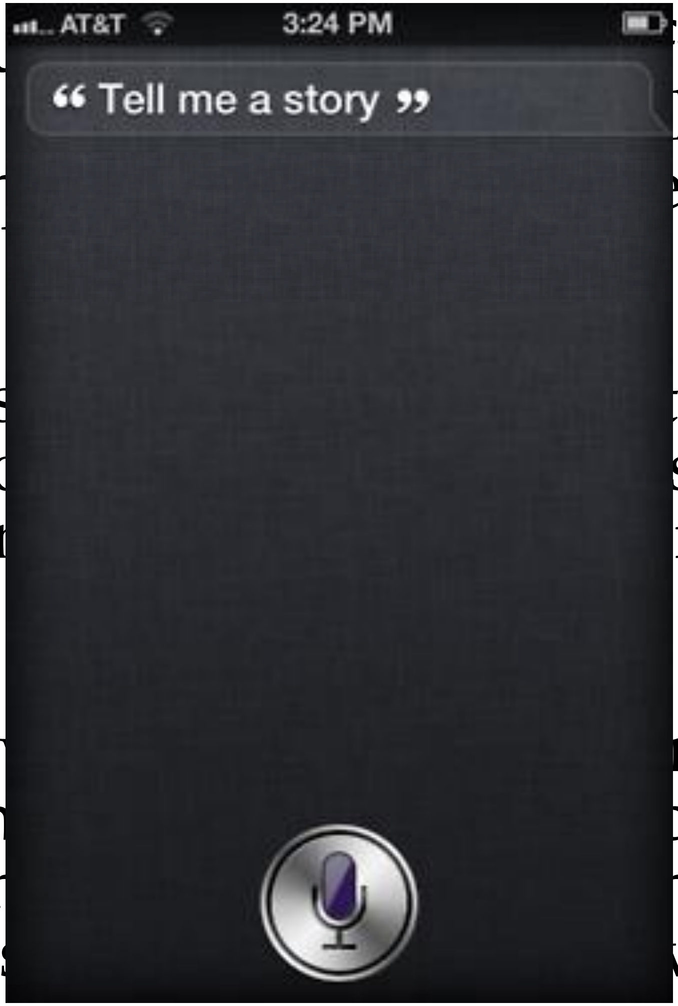
Quiz: Which of the following can be done at present?

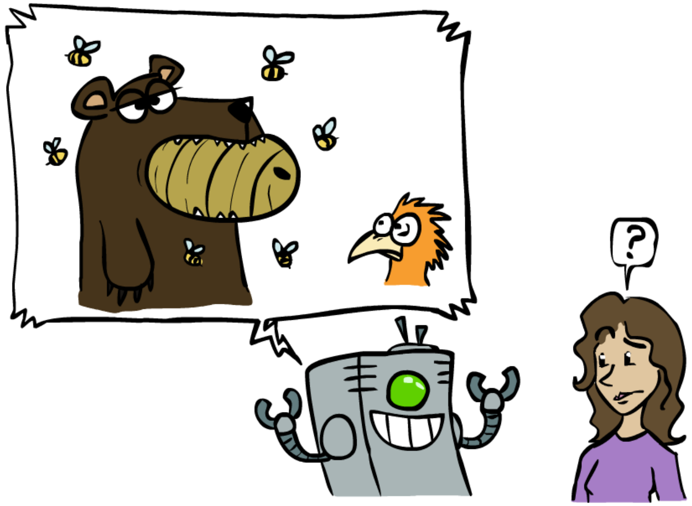
- ✓ 玩一场像样的 Jeopardy 游戏?
- ✓ 在国际象棋中战胜任何人?
- ✓ 在围棋中战胜最优秀的人类?
- ✓ 打一场像样的网球比赛?
- ✓ 拿起一个特定的杯子，把它放在架子上?
- ✗ 卸载任何家庭中的任何洗碗机?
- ? 沿着高速公路安全行驶?
- ✗ 沿着广州大道安全行驶?
- ✓ 在网上购买一周的杂货?
- ✗ 在杂货店购买一周的杂货?
- ? 发现并证明一个新的数学定理?
- ✗ 进行外科手术?
- ✗ 与人合作卸载已知的洗碗机?
- ✓ 实时将中文口语翻译成英语口语?
- ? 写一个故意搞笑的故事?



Unintentionally Funny Stories

- One day Joe Bear was hu … riend
  Irving Bird where some … ld him
  there was a beehive in th … ed to
  the oak tree. He ate the …





- Henry Squirrel was thirs … to the
  river bank where his goo … s sitting.
  Henry slipped and fell in … rowned.
  The End.

- Once upon a time there … nd a vain crow. One day
  the crow was sitting in h … ce of cheese in his mouth.
  He noticed that he was h … heese. He became hungry,
  and swallowed the chees … ver to the crow. The End.

[Shank, Tale-Spin System, 1984]

Game Agents

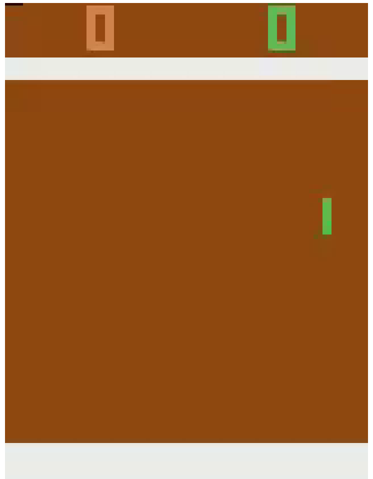
- Classic Moment: May, '97: Deep Blue vs. Kasparov
  - First match won against world champion
  - "Intelligent creative" play
  - 200 million board positions per second
  - Humans understood 99.9 of Deep Blue's moves
  - Can do about the same now with a PC cluster

- 1996: Kasparov Beats Deep Blue
  "I could feel --- I could smell --- a new kind of intelligence across the table."
- 1997: Deep Blue Beats Kasparov
  "Deep Blue hasn't proven anything."

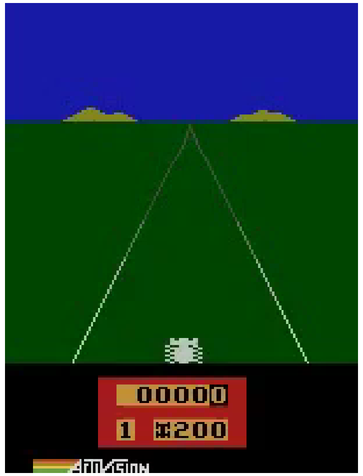
Text from Bart Selman, image from IBM's Deep Blue pages

Game Agents

- Reinforcement learning

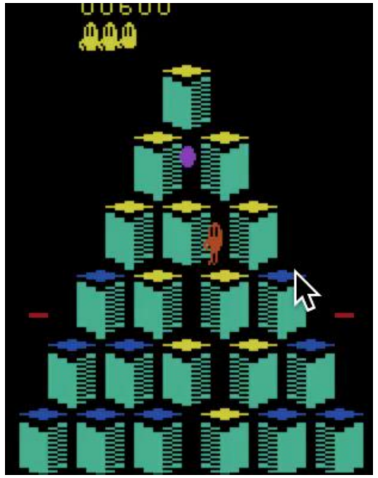


Pong



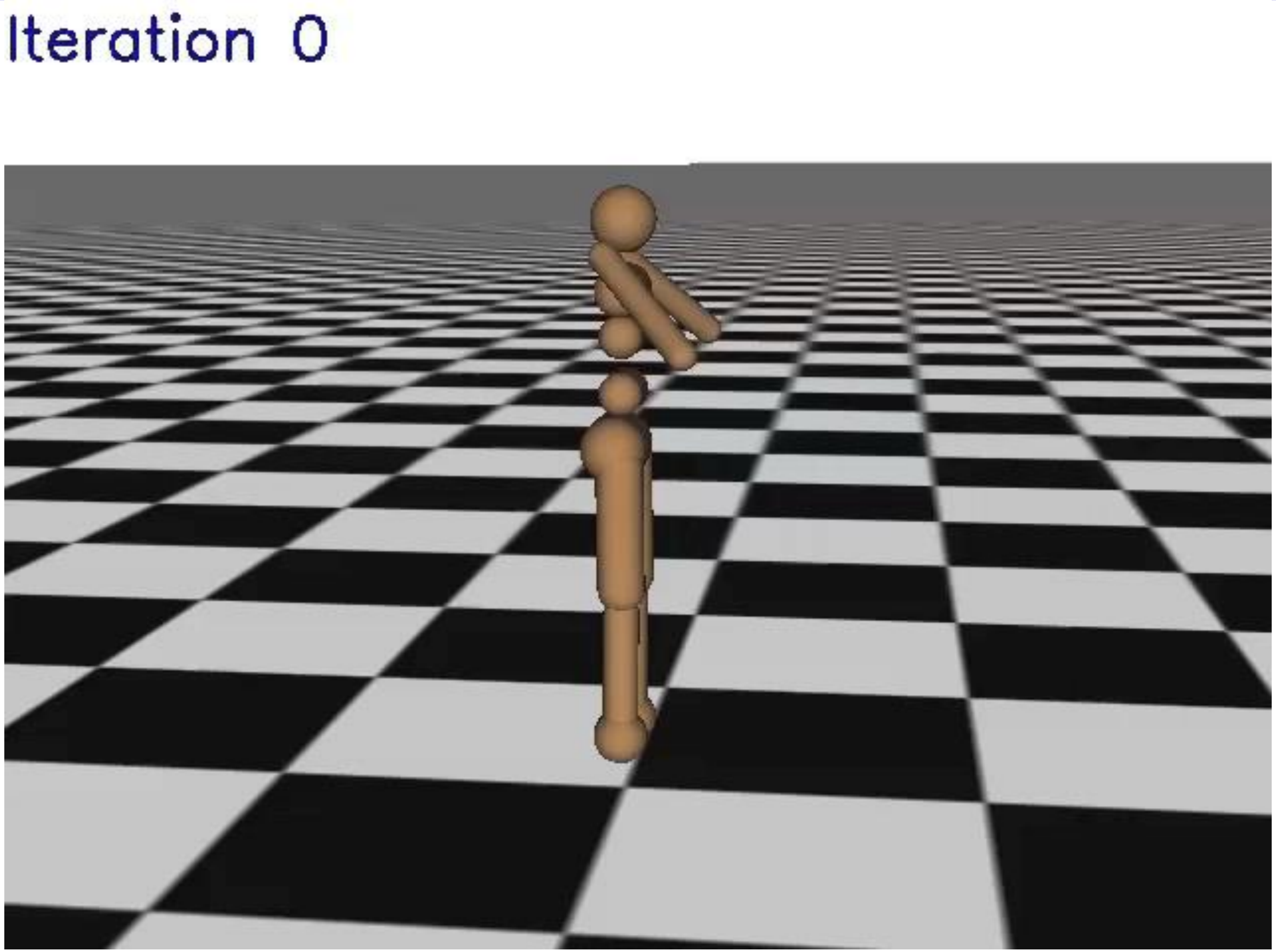
Enduro赛车

Beamrider



Q*bert

Simulated Agents



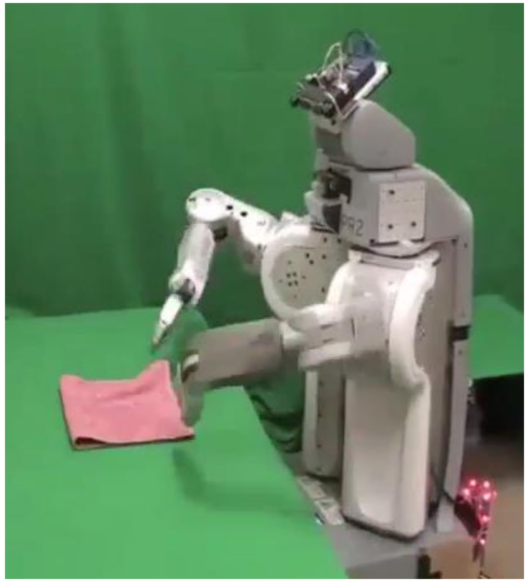
[Schulman, Moritz, Levine, Jordan, Abbeel, ICLR 2016]

Robotics

- Robotics
  - Part mech. eng.
  - Part AI
  - Reality much harder than simulations!

- Technologies
  - Vehicles
  - Rescue
  - Help in the home
  - Lots of automation…

- In this class:
  - We ignore mechanical aspects
  - Methods for planning
  - Methods for control

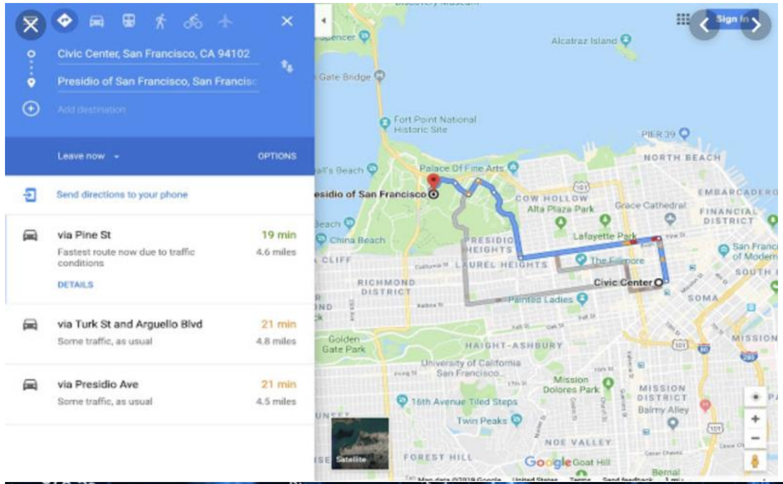


Utility?

Clear utility function

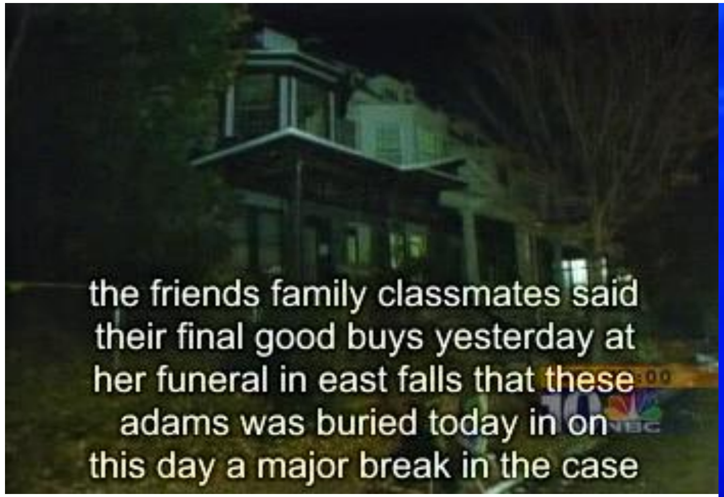
Not so clear utility function

Tools for Predictions & Decisions



Natural Language

- Speech technologies (e.g. Siri)
  - Automatic speech recognition (ASR)
  - Text-to-speech synthesis (TTS)
  - Dialog systems



- Language processing technologies
  - Question answering
  - Machine translation

  - Web search
  - Text classification, spam filtering, etc…

Computer Vision

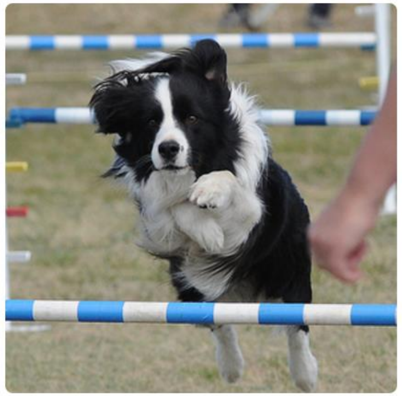
"man in black shirt is playing guitar."

"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

"boy is doing backflip on wakeboard."

"girl in pink dress is jumping in air."



"black and white dog jumps over bar."

"young girl in pink shirt is swinging on swing."

"man in blue wetsuit is surfing on wave."

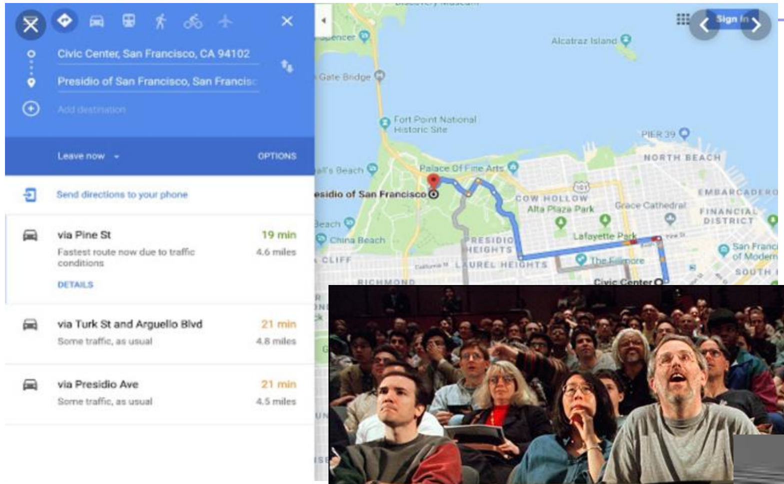
Should I take this course?

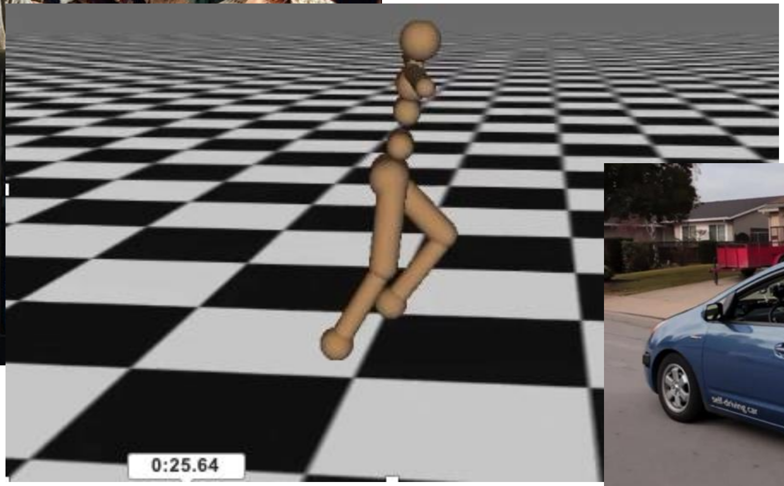
- Yes, if you want to know how to design rational agents!
  - This course also teaches you a different way of thinking.
  - Powerful ideas without too much math rigor
- Disclaimer: If you're interested in making yourself more competitive for industry jobs, various courses in Data Science and the School of Information are a much better fit.

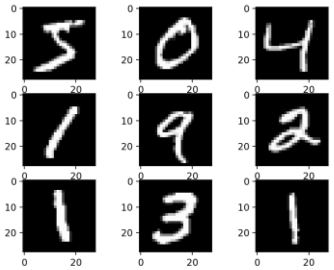
Topics

- Utilities and Rationality, Search and Planning
- Constraint Satisfaction Programming
- Game Trees, Minimax, Pruning, Monte-Carlo Tree Search
- Probabilistic Inference, Bayesian Networks, Markov Models
- Decision Networks and Value of Perfect Information
- Markov Decision Processes and Reinforcement Learning
- Supervised Machine Learning, MLE and MAP
- Optimization Theory, Neural Networks
- Survey of Modern Problems and Topics

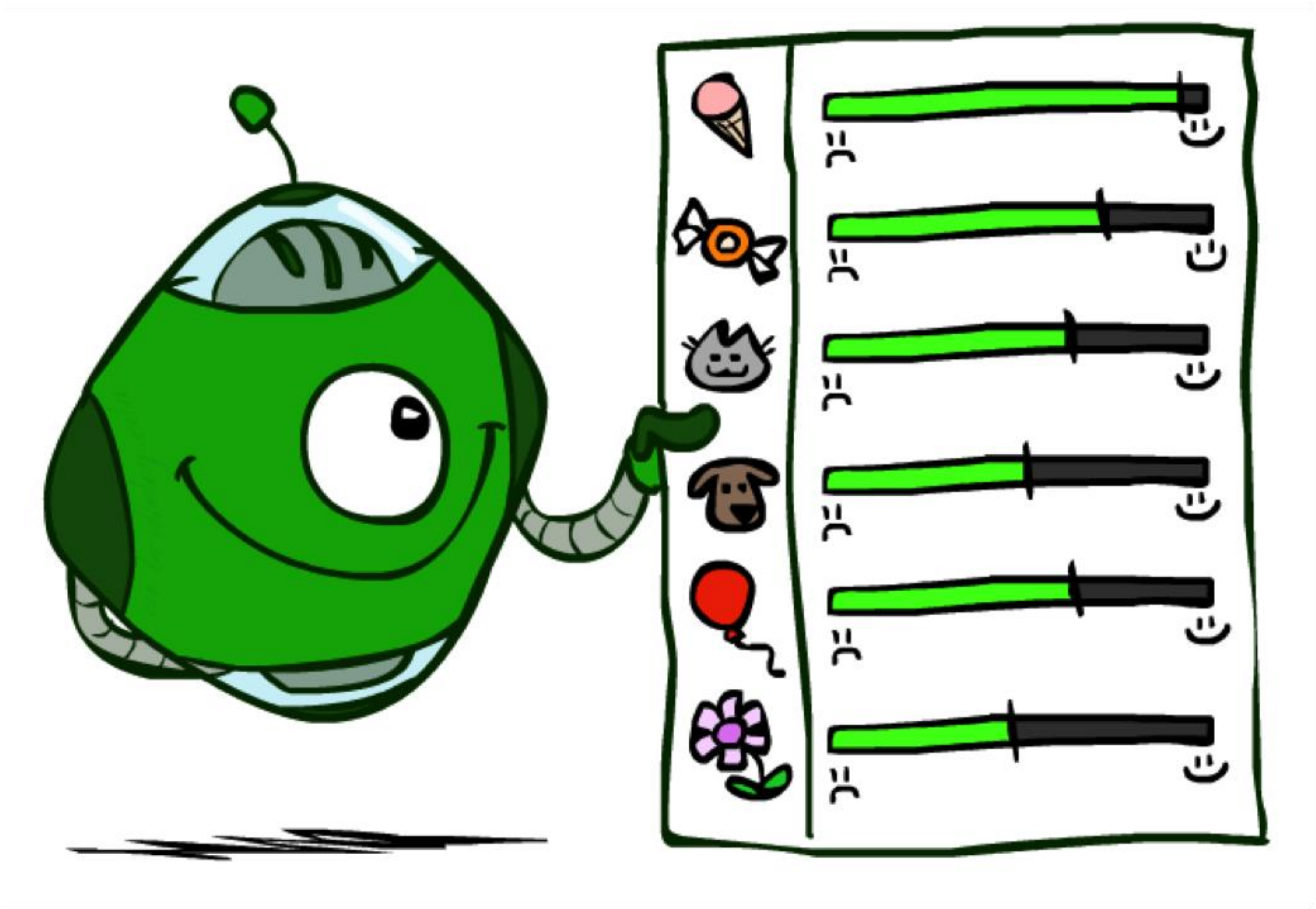
The kinds of AI problems in this course







Utilities



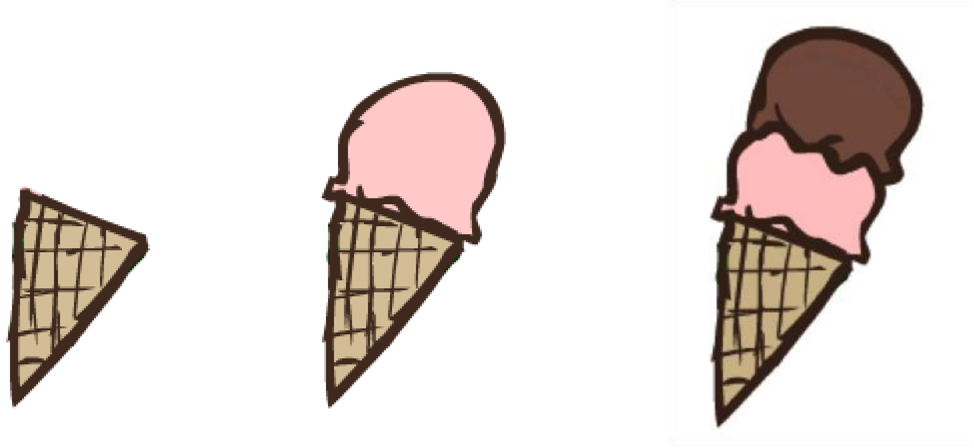
Maximum Expected Utility

- Principle of maximum expected utility:
  - A rational agent should choose the action that maximizes its expected utility, given its knowledge

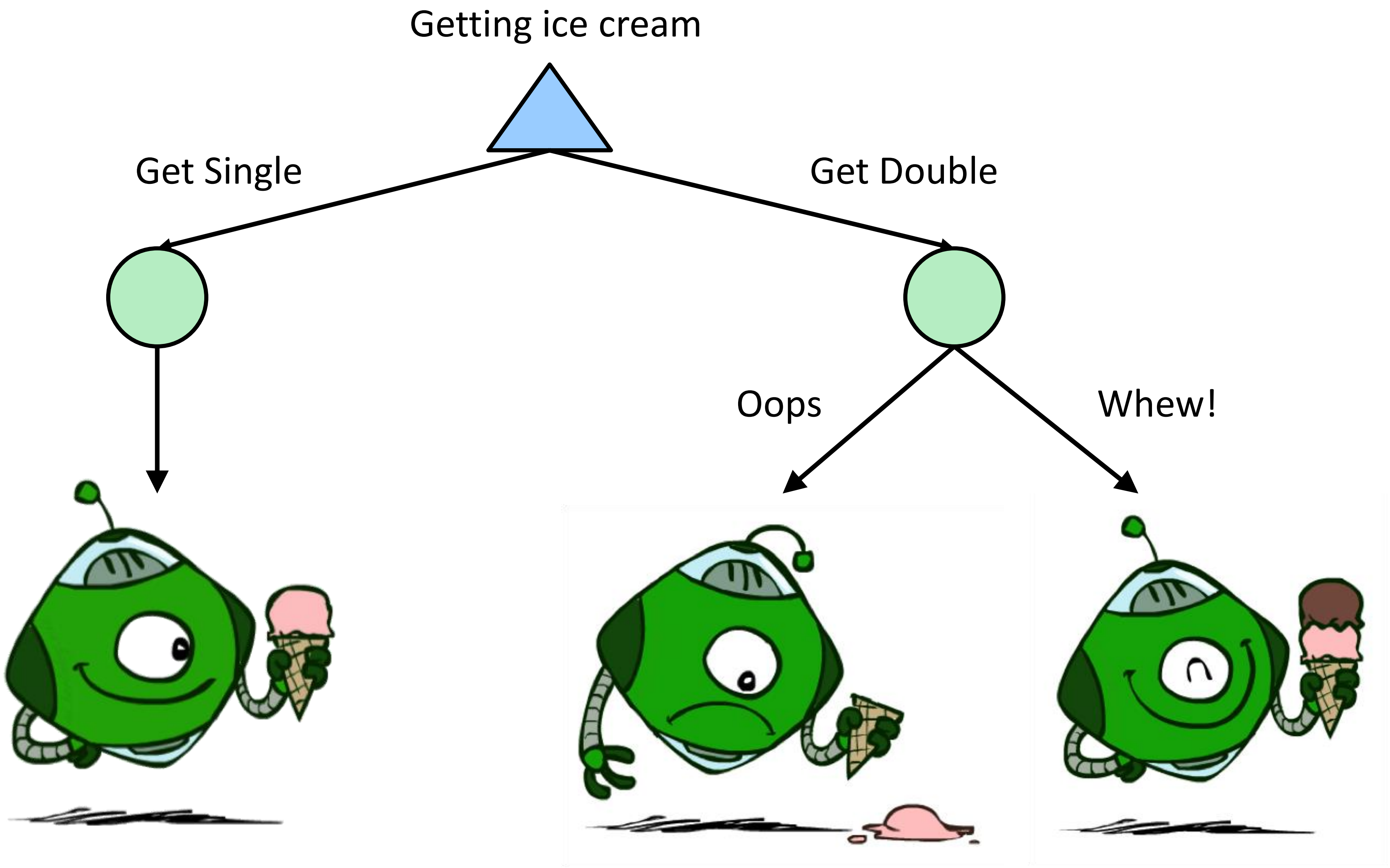
- Questions:
  - Where do utilities come from?
  - How do we know such utilities even exist?
  - How do we know that averaging even makes sense?
  - What if our behavior (preferences) can't be described by utilities?

Utilities

- Utilities are functions from outcomes (states of the world) to real numbers that describe an agent's preferences
- Where do utilities come from?
  - In a game, may be simple (+1/-1)
  - Utilities summarize the agent's goals
  - Theorem: any "rational" preferences can be summarized as a utility function
- We hard-wire utilities and let behaviors emerge
  - Why don't we let agents pick utilities?
  - Why don't we prescribe behaviors?



Utilities: Uncertain Outcomes



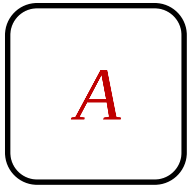
Preferences

- An agent must have preferences among:
  - Prizes: *A, B*, etc.
  - Lotteries: situations with uncertain prizes

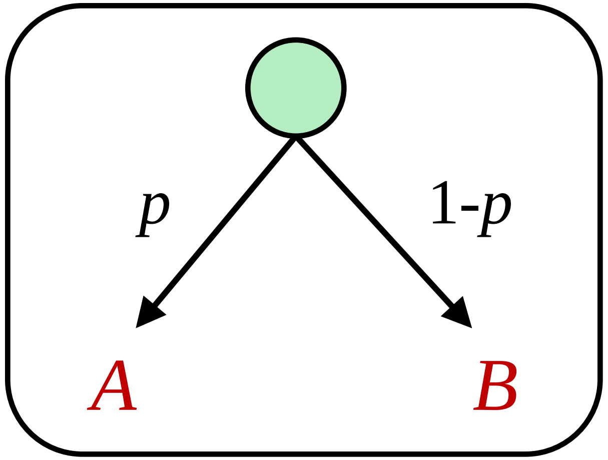
    $L = [p, A;\ (1\text{-}p), B]$

- Notation:
  - Preference: $A > B$
  - Indifference: $A \sim B$

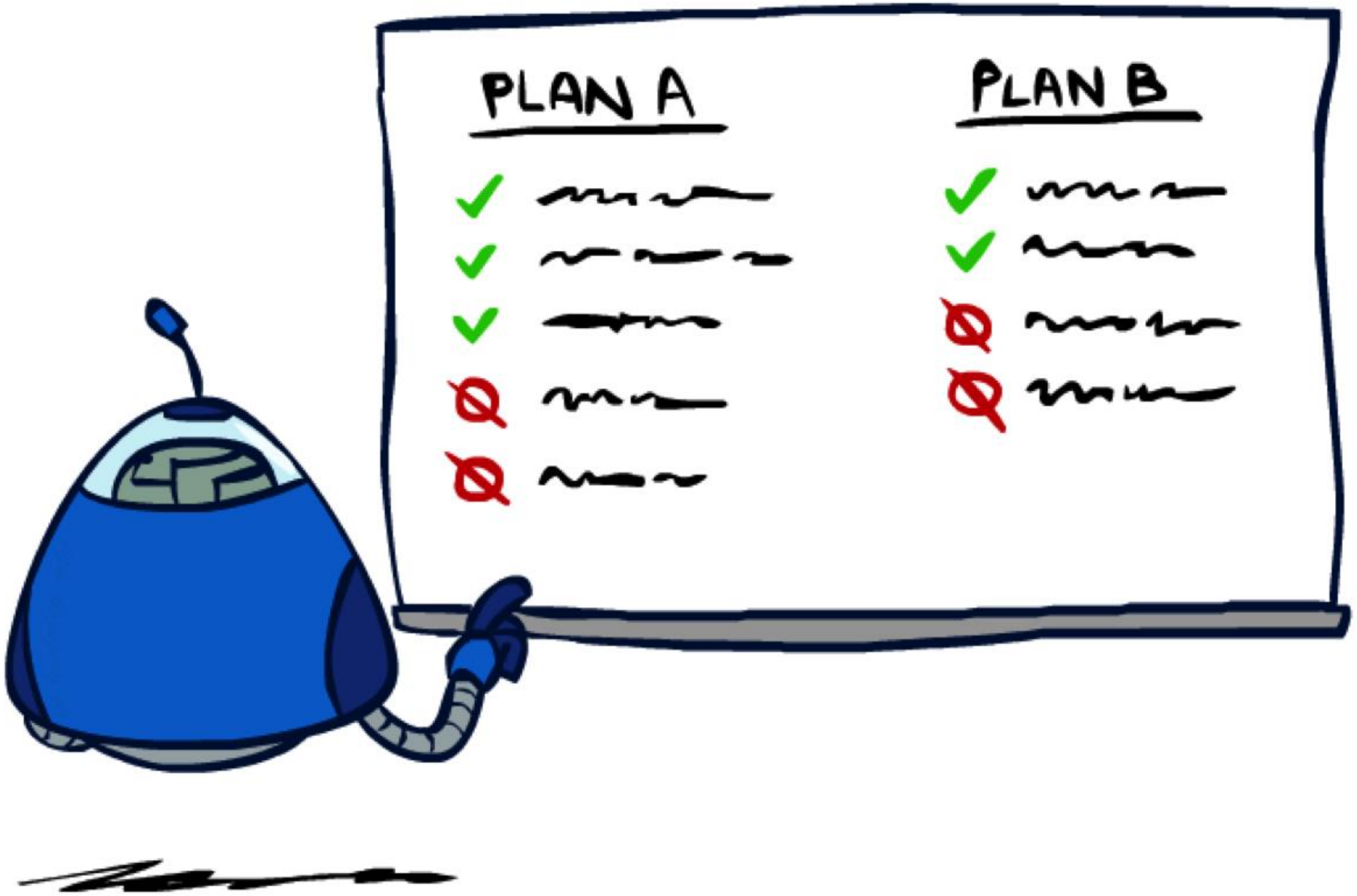
A Prize



A Lottery



Rationality

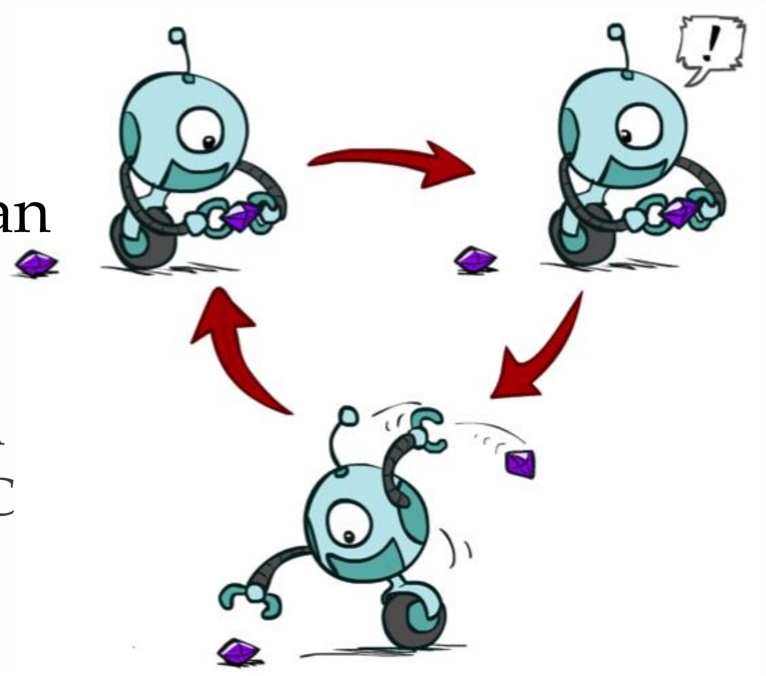


Rational Preferences

- We want some constraints on preferences before we call them rational, such as:

$$\text{Axiom of Transitivity: } (A \succ B) \wedge (B \succ C) \Rightarrow (A \succ C)$$

- For example: an agent with intransitive preferences can be induced to give away all of its money
  - If B > C, then an agent with C would pay (say) 1 cent to get B
  - If A > B, then an agent with B would pay (say) 1 cent to get A
  - If C > A, then an agent with A would pay (say) 1 cent to get C



Rational Preferences

The Axioms of Rationality

Orderability:

$$(A > B) \vee (B > A) \vee (A \sim B)$$

Transitivity:

$$(A > B) \wedge (B > C) \Rightarrow (A > C)$$

Continuity:

$$(A > B > C) \Rightarrow \exists p\ [p, A;\ 1\text{-}p, C] \sim B$$

Substitutability:

$$(A \sim B) \Rightarrow [p, A;\ 1\text{-}p, C] \sim [p, B;\ 1\text{-}p, C]$$

Monotonicity:

$$(A > B) \Rightarrow$$
$$(p \geq q) \Leftrightarrow [p, A;\ 1\text{-}p, B] \geq [q, A;\ 1\text{-}q, B]$$

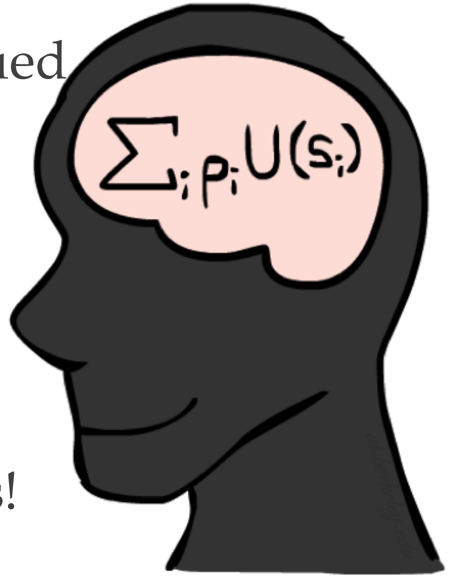
Theorem: Rational preferences imply behavior describable as maximization of expected utility

MEU Principle

- Theorem [Ramsey, 1931; von Neumann & Morgenstern, 1944]
  - Given any preferences satisfying these constraints, there exists a real-valued function U such that:

$$U(A) \geq U(B) \;\Leftrightarrow\; A \succeq B$$

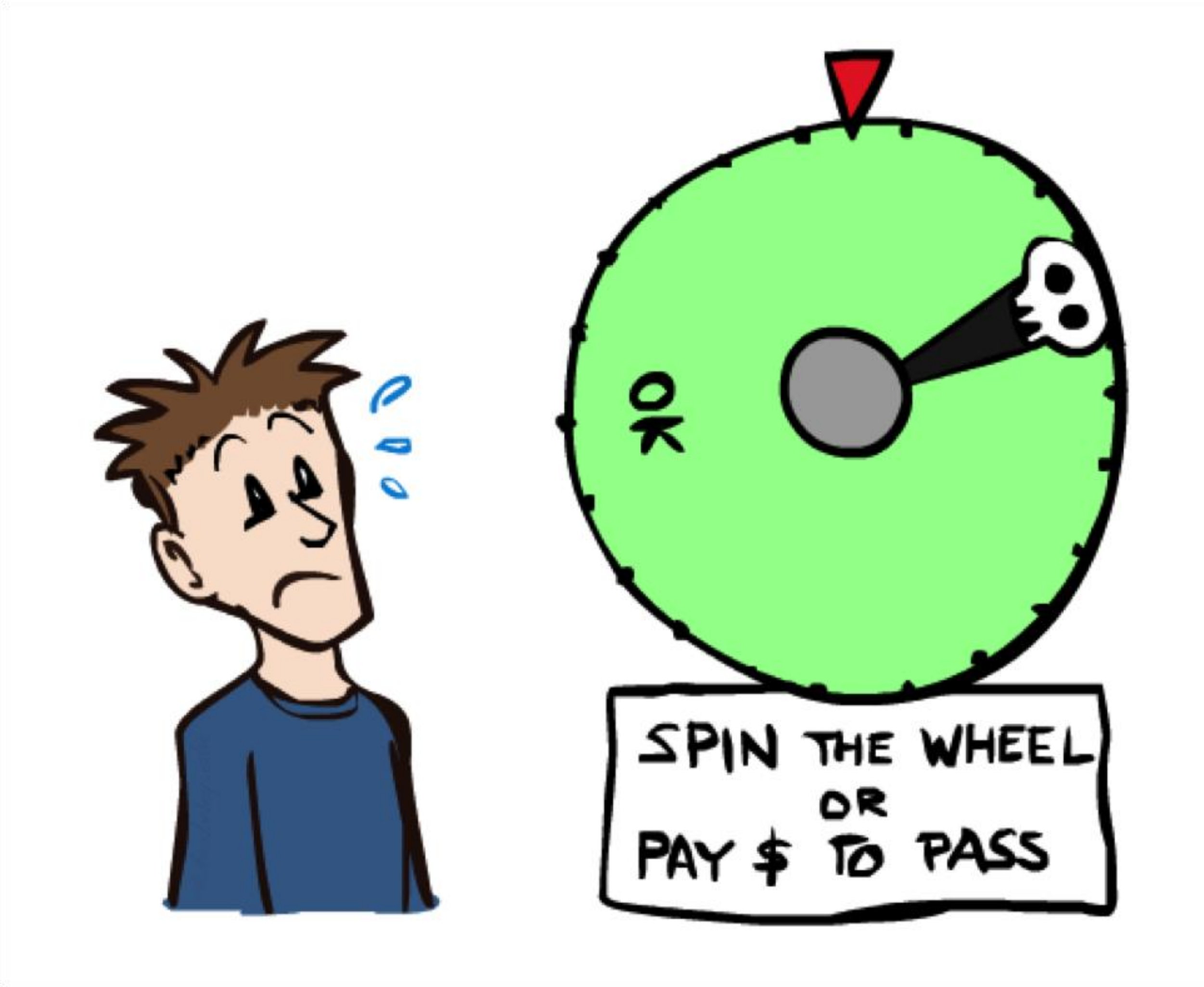
$$U([p_1,S_1;\ \ldots\ ;p_n,S_n]) = p_1 U(S_1) + \ldots + p_n U(S_n)$$



  - I.e. values assigned by U preserve preferences of both prizes and lotteries!

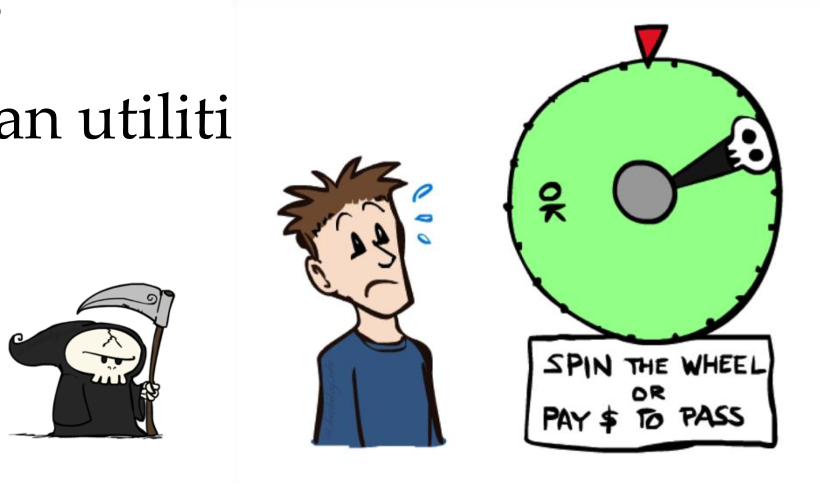
- Maximum expected utility (MEU) principle:
  - Choose the action that maximizes expected utility
  - Note: rationality does ***not*** require representing or manipulating utilities and probabilities
    - E.g., a lookup table for perfect tic-tac-toe

Human Utilities



Human Utilities

- Utilities map states to real numbers. Which numbers?
- Standard approach to assessment (elicitation) of human utiliti
  - Compare a prize A to a ***standard lottery*** L_p between
    - "best possible prize" $u_{\top}$ with probability p
    - "worst possible catastrophe" $u_{\bot}$ with probability $1\text{-}p$
  - Adjust lottery probability p until indifference: $A \sim L_p$
  - Resulting p is a utility in $[0,1]$



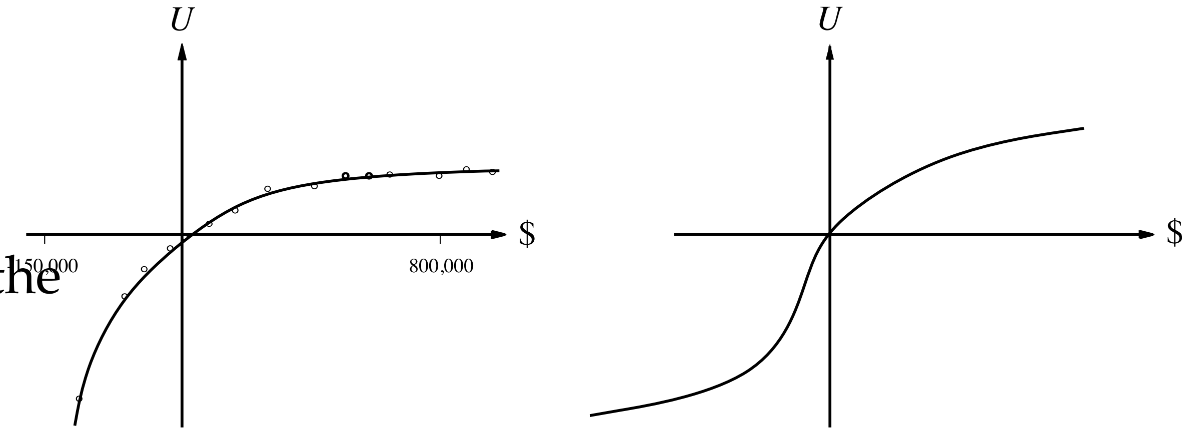
Pay $50 ~

0.999999 → *No change*

0.000001 → *Instant death*

Money

- Money ***does not*** behave as a utility function, but we can talk about the utility of having money (or being in debt)
- Given a lottery $L = [p, \$X; (1\text{-}p), \$Y]$
  - The ***expected monetary value*** $\text{EMV}(L) = pX + (1\text{-}p)Y$
  - The utility is $U(L) = pU(\$X) + (1\text{-}p)U(\$Y)$
  - Typically, $U(L) < U(\text{ EMV}(L)\ )$
  - In this sense, people are ***risk-averse***
  - E.g., how much would you pay for a lottery ticket $L=[0.5, \$10{,}000;\ 0.5, \$0]$?
  - The ***certainty equivalent*** of a lottery $\text{CE}(L)$ is the cash amount such that $\text{CE}(L) \sim L$
  - The ***insurance premium*** is $\text{EMV}(L) - \text{CE}(L)$
  - If people were risk-neutral, this would be zero!



(a) (b)