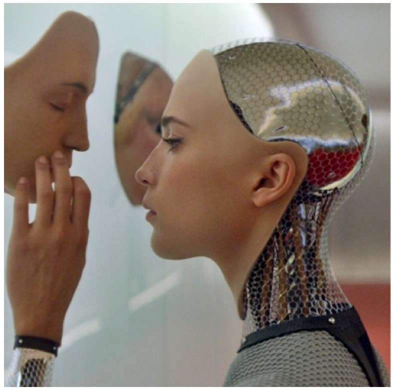
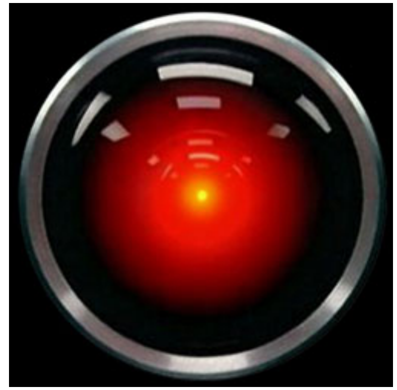
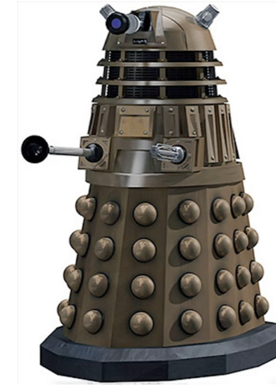
Future of AI

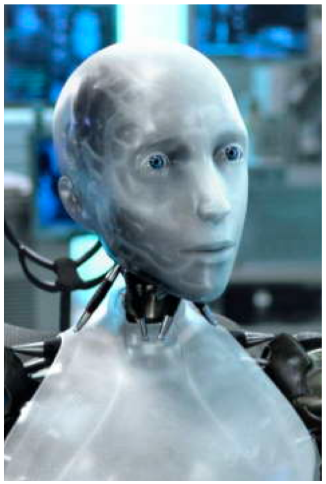
CPSC 470 – Artificial Intelligence

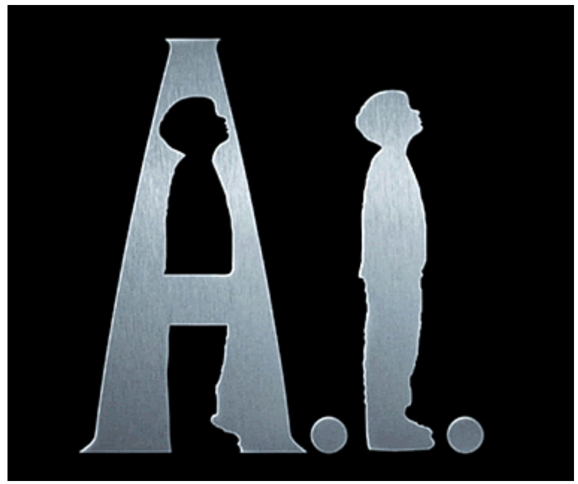
Brian Scassellati



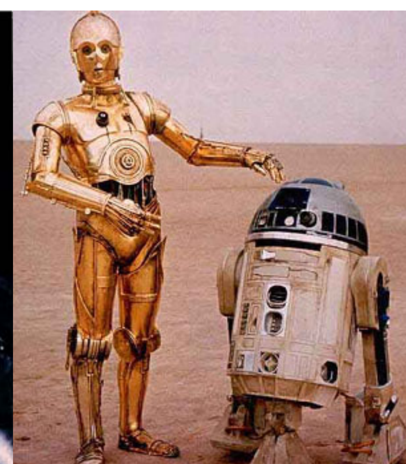


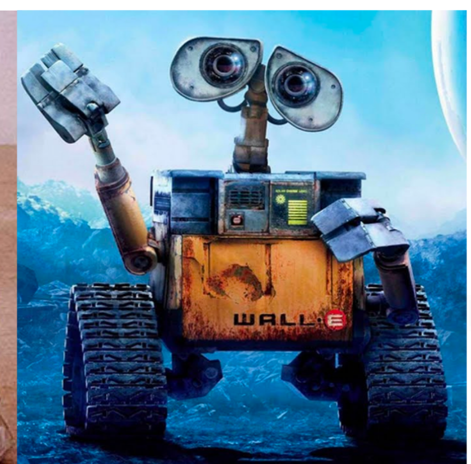





A.I.


REJECT
CHAPPIE

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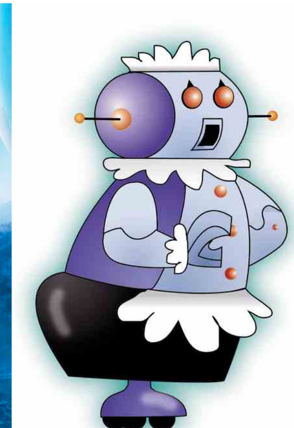


Definitions of Artificial Intelligence

Think like Humans

"The automation of activities that we associate with human thinking, activities such as decision-making, problem solving, learning…" – Bellman, 1978

Think Rationally

"The study of mental faculties through the use of computational models" – Charniak and McDermott, 1985

Thought

Act like Humans

"The art of creating machines that perform functions that require intelligence when performed by people." – Kurzweil, 1990

Act Rationally

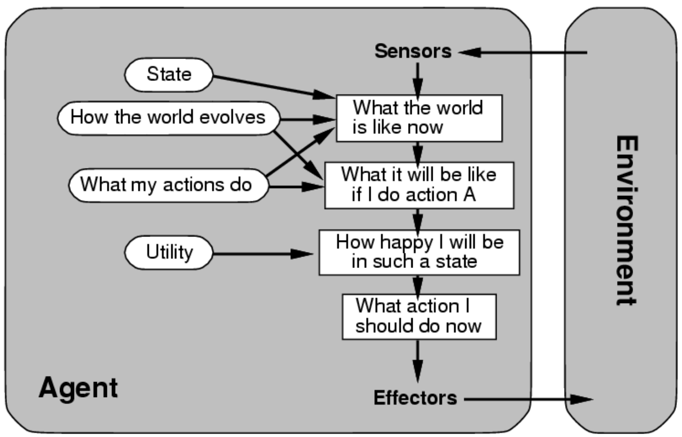
"A field of study that seeks to explain and emulate intelligent behavior in terms of computational processes." – Schalkoff, 1990

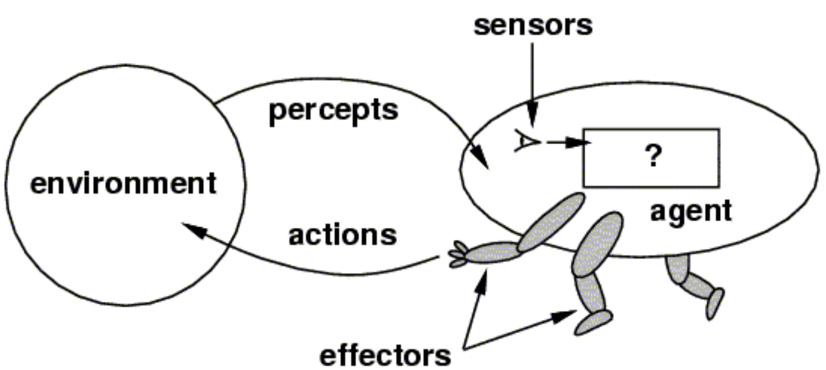
Action

Defined in terms of Humans

Defined in terms of Logic

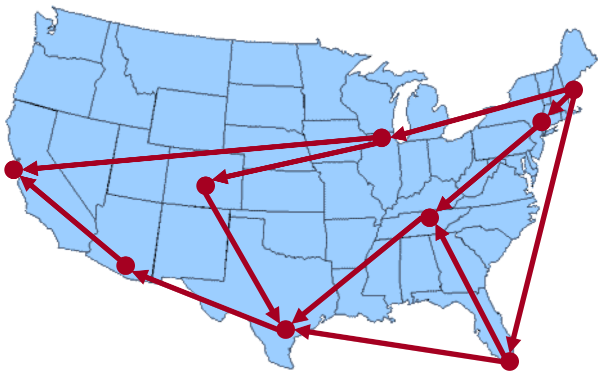
Agents as a Unifying Design

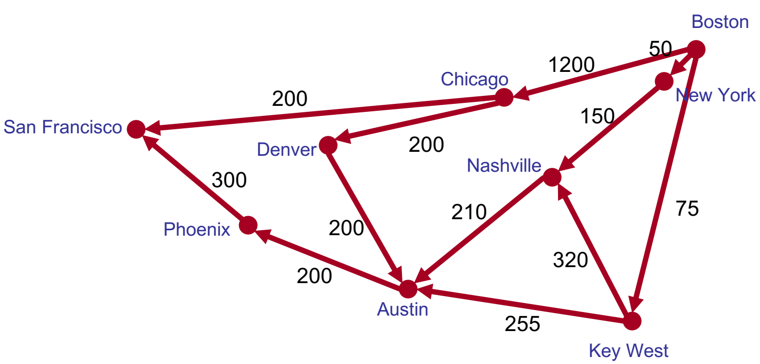


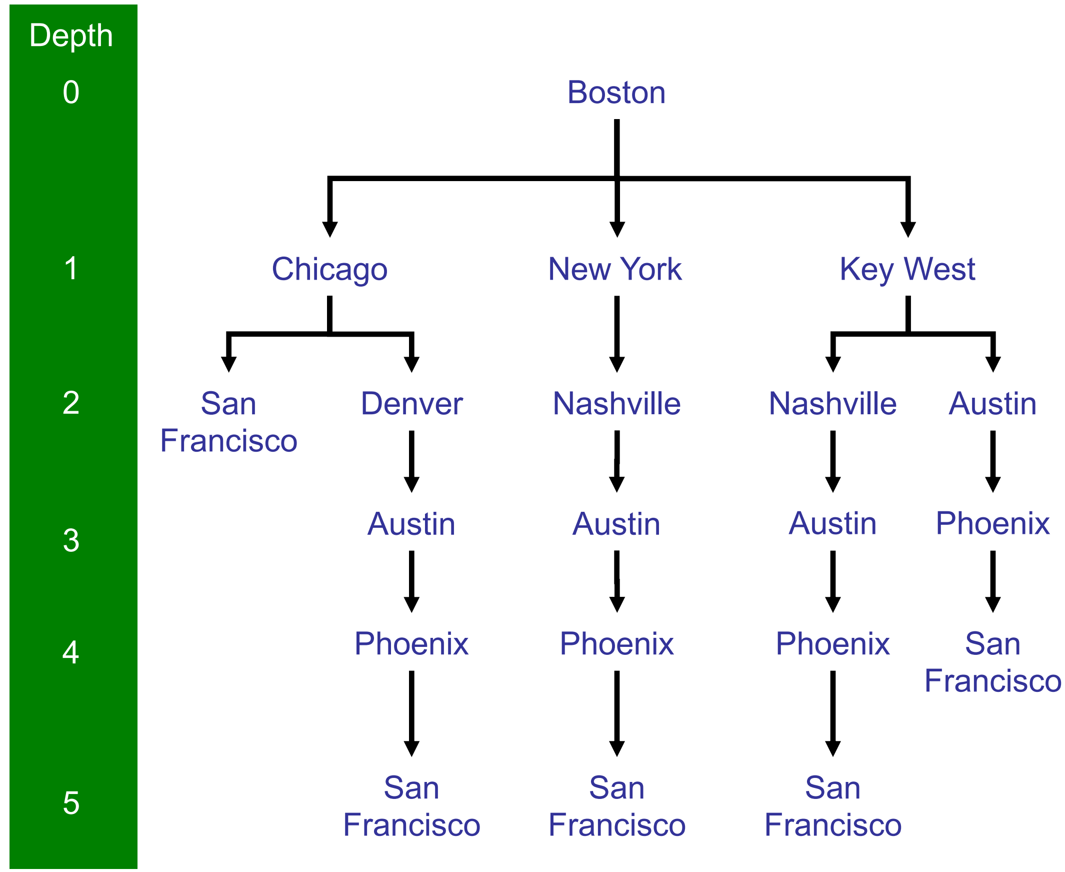


Environment	Accessible	Deterministic	Episodic	Static	Discrete
	Do sensors give complete world state?	Can next state be determined by current state and action?	Does quality of an action depend only on current state?	Does the env. stay the same while the agent thinks?	Are the number of percepts and actions limited?
Chess (no clock)	Yes	Yes	No	Yes	Yes
Poker	No	No	No	Yes	Yes
Taxi driving	No	No	No	No	No
Image analysis	Yes	Yes	Yes	Semi	No
Part-picking robot	No	No	Yes	No	No
Refinery controller	No	No	No	No	Yes

Basic Search

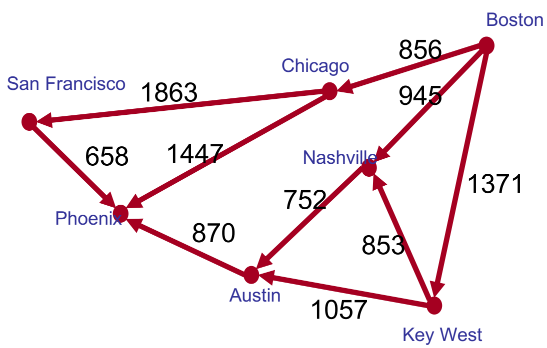






Branching Factor *b*=3

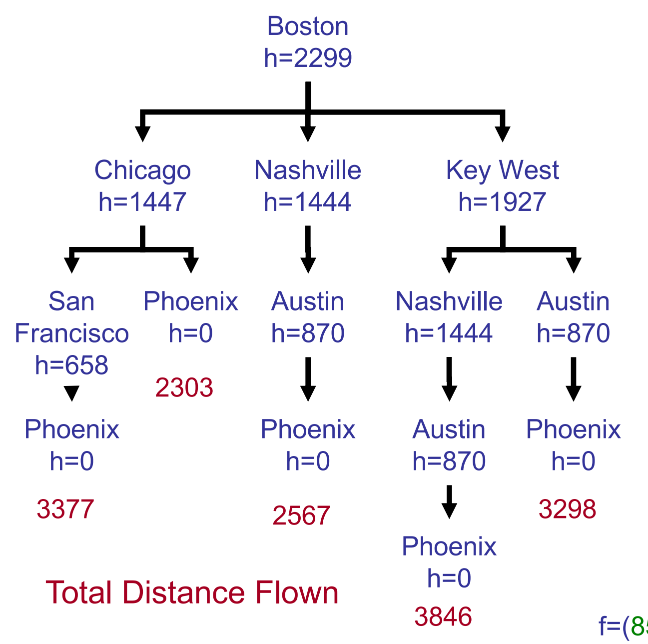
Heuristic Search



	Distance to Phoenix
Boston	2299
Chicago	1447
Nashville	1444
Key West	1927
Austin	870
San Francisco	658

Greedy Search

Heuristic function gives an estimate of the distance to the goal

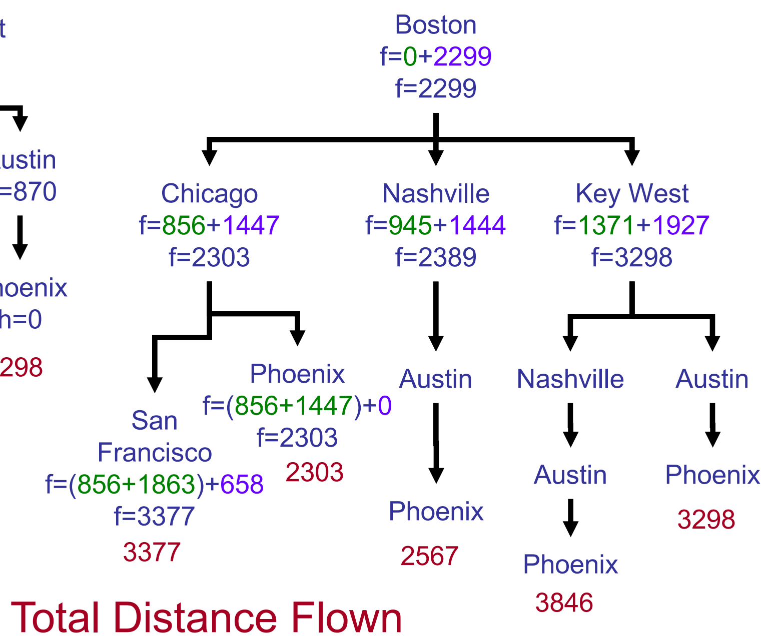


A* Search

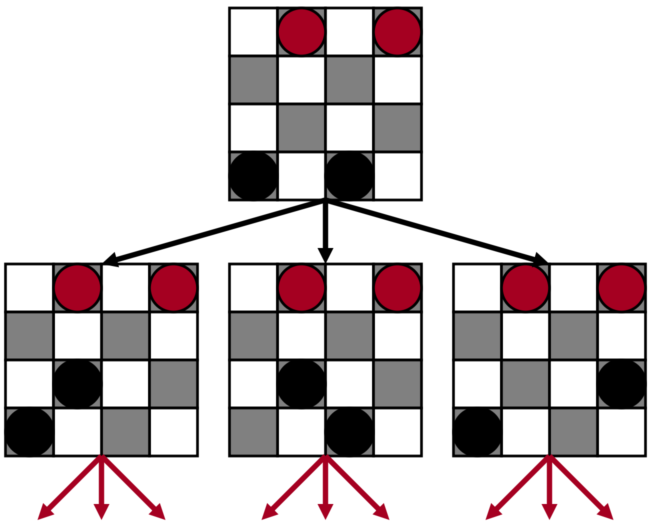
Minimize the total path cost (f) =

actual path so far (g) +

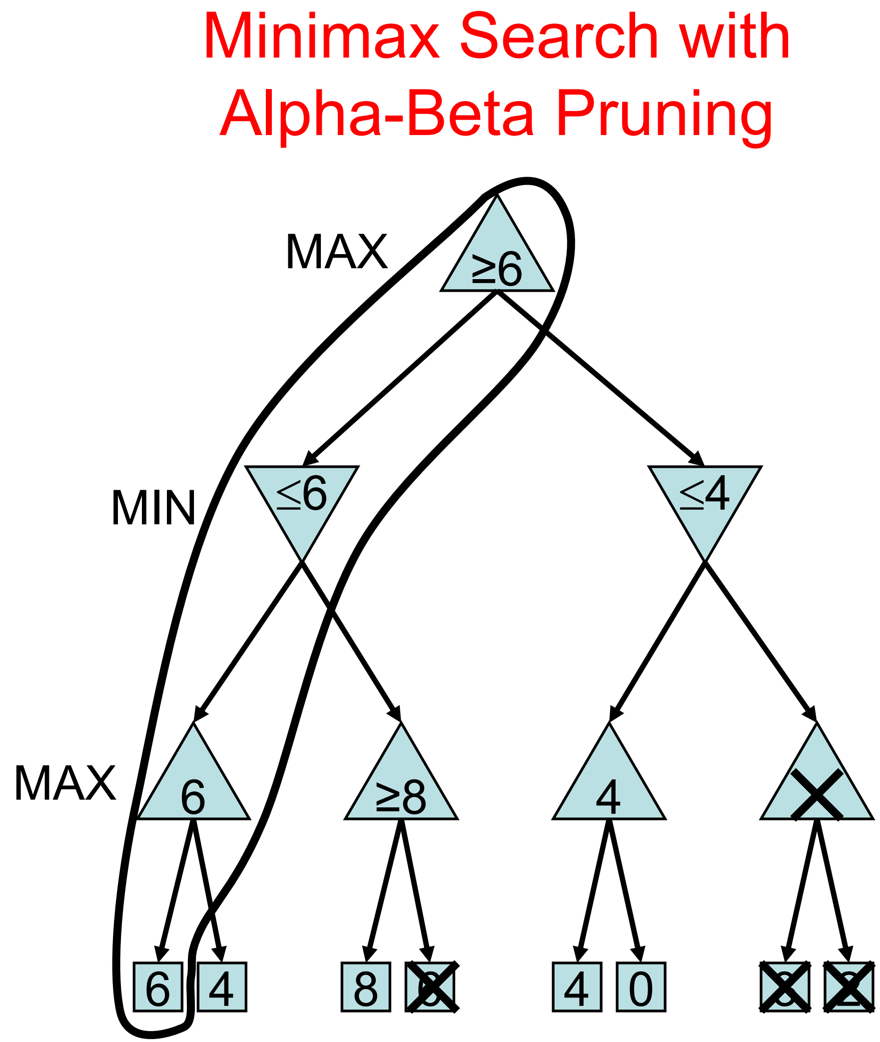
estimate of future path to goal (h)



Search and Game Playing

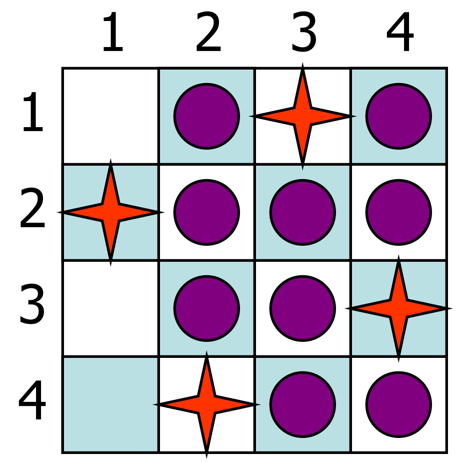


Kasparov vs. Deep Blue

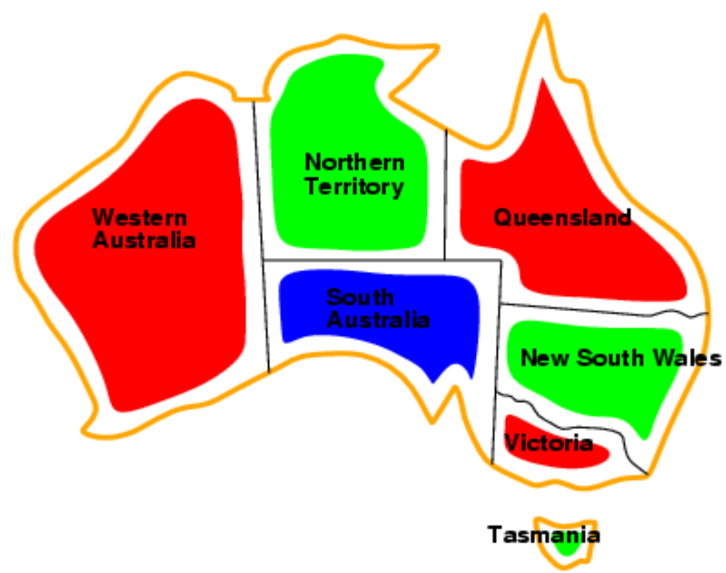


Constraint Satisfaction Problems

```
   T W O
+  T W O
--------
 F O U R
```



4						8		5
	3							
			7					
	2						6	
				8		4		
	4			1				
			6		3		7	
5		3	2		1			
1		4						



Knowledge Representation

Propositional Logic Syntax

$$Sentence \rightarrow AtomicSentence \mid ComplexSentence$$

$$AtomicSentence \rightarrow True \mid False \mid P \mid Q \mid \ldots$$

$$ComplexSentence \rightarrow (Sentence) \mid$$

$$Sentence\ Connective\ Sentence \mid$$

$$\neg Sentence$$

$$Connective \rightarrow \wedge \mid \vee \mid \Rightarrow \mid \Leftrightarrow$$

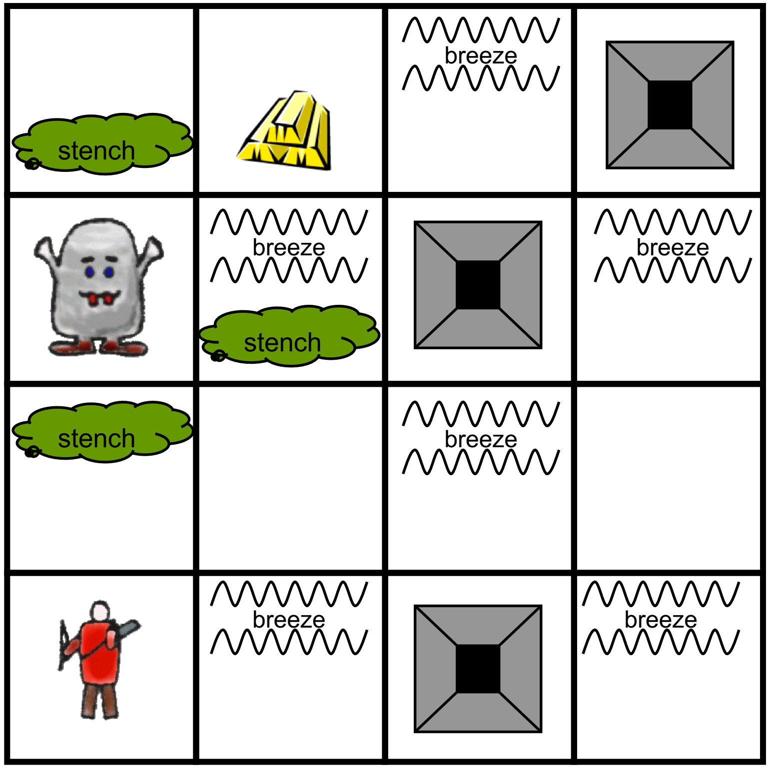
Inference Rules

$$\frac{\alpha \Rightarrow \beta \ , \alpha}{\beta} \qquad \frac{\neg\neg\alpha}{\alpha} \qquad \frac{\alpha_1, \alpha_2, \alpha_3, \ldots \alpha_n}{\alpha_1 \wedge \alpha_2 \wedge \ldots \wedge \alpha_n}$$

$$\frac{\alpha_1 \wedge \alpha_2 \wedge \alpha_3 \wedge \ldots \wedge \alpha_n}{\alpha_i} \qquad \frac{\alpha \vee \beta \ , \ \neg\beta}{\alpha} \qquad \frac{\alpha_i}{\alpha_1 \vee \alpha_2 \vee \ldots \vee \alpha_n}$$

$$\frac{\neg\alpha \Rightarrow \beta \ , \ \beta \Rightarrow \gamma}{\neg\alpha \Rightarrow \gamma} \qquad \frac{\alpha \vee \beta \ , \neg\beta \vee \gamma}{\alpha \vee \gamma}$$

Wumpus World



First-Order Logic

- Existential and Universal Quantifiers

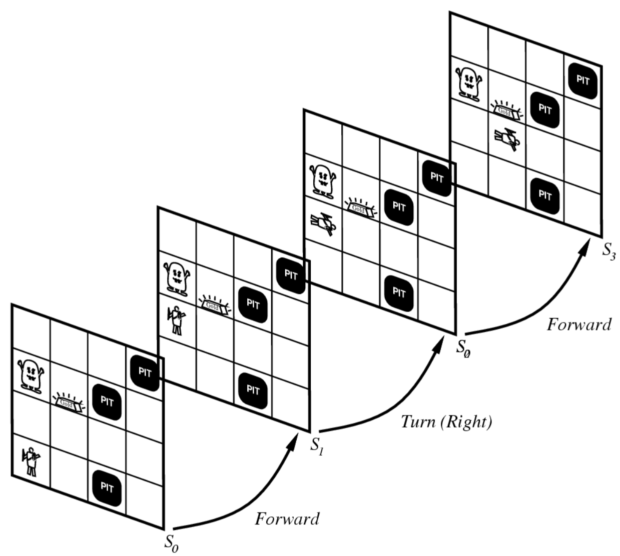
$$
\begin{aligned}
\mathit{Sentence} &\rightarrow \mathit{AtomicSentence} \\
&\quad \mid \mathit{Sentence}\ \mathit{Connective}\ \mathit{Sentence} \\
&\quad \mid \mathit{Quantifier}\ \mathit{Variable},\ldots\ \mathit{Sentence} \\
&\quad \mid \neg \mathit{Sentence} \\
&\quad \mid (\mathit{Sentence}) \\
\mathit{AtomicSentence} &\rightarrow \mathit{Predicate}(\mathit{Term},\ldots) \\
&\quad \mid \mathit{Term} = \mathit{Term} \\
\mathit{Term} &\rightarrow \mathit{Function}(\mathit{Term},\ldots) \\
&\quad \mid \mathit{Constant} \\
&\quad \mid \mathit{Variable} \\
\mathit{Connective} &\rightarrow \Rightarrow \mid \wedge \mid \vee \mid \Leftrightarrow \\
\mathit{Quantifier} &\rightarrow \forall \mid \exists \\
\mathit{Variable} &\rightarrow a \mid b \mid c \mid \ldots \\
\mathit{Function} &\rightarrow \mathit{Mother} \mid \mathit{LeftLegOf} \mid \ldots \\
\mathit{Predicate} &\rightarrow \mathit{Before} \mid \mathit{HasColor} \mid \mathit{Raining} \mid \ldots \\
\mathit{Constant} &\rightarrow A \mid X_1 \mid \mathit{John} \mid \ldots
\end{aligned}
$$

- Situation Calculus

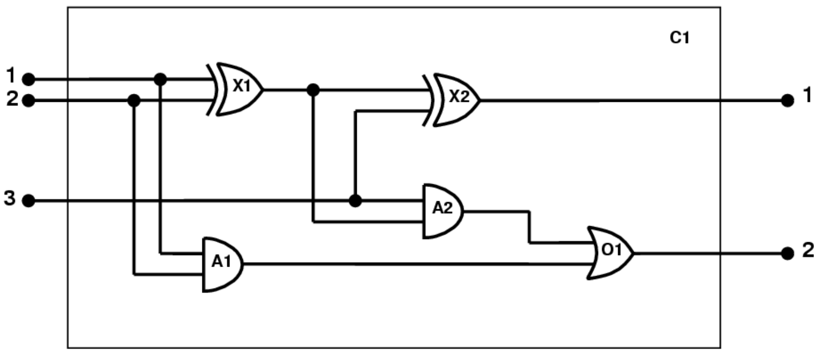
  At(Agent,[1,1], S_0) $\wedge$
  At(Agent,[1 2], S_1)

- Changes from one situation to the next

  Result(Forward, S_0)$\Rightarrow S_1$



Building a Knowledge Base



- Decide what to talk about
- Decide on a vocabulary of predicates, functions, and constants
  - Ontology
- Encode general knowledge within the domain
  - Limiting errors
- Encode a description of the specific problem
- Pose queries and get answers

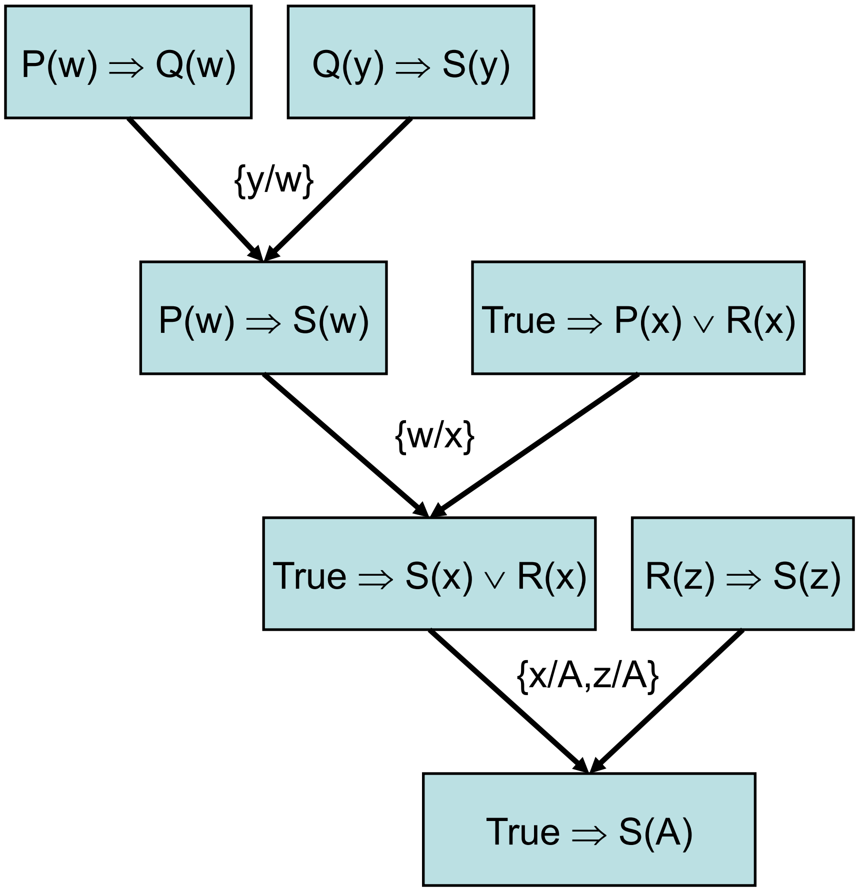
Programming	Knowledge Engineering
Choose a language	Choose a logic
Write a program	Build a Knowledge Base
Choose or write a compiler	Implement the proof theory
Run your compiled program	Infer new facts

Inference

Resolution

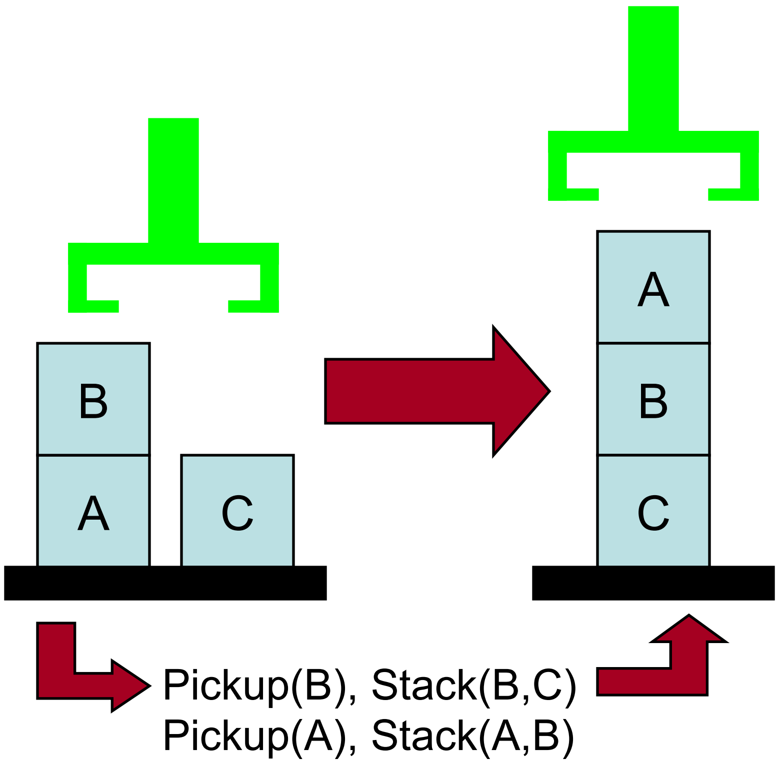
- American(x) $\wedge$ Alcohol(y) $\wedge$ Minor(z) $\wedge$ Sells(x,y,z) $\Rightarrow$ Criminal(x)
- Minor(Jimmy)
- Owns(Jimmy,B1)
- Beer(B1)
- Owns(Jimmy,x) $\wedge$ Beer(x) $\Rightarrow$ Sells(Nathan,x,Jimmy)
- American(Nathan)
- Beer(x)$\Rightarrow$Alcohol(x)
- Using 4, 7 and modus ponens
  Alcohol(B1)
- Using 5, 3, 4 and modus ponens
  Sells(Nathan,B1,Jimmy)
- Using 1, 6, 8, 2, 9 and modus ponens
  Criminal(Nathan)

Proof by Refutation

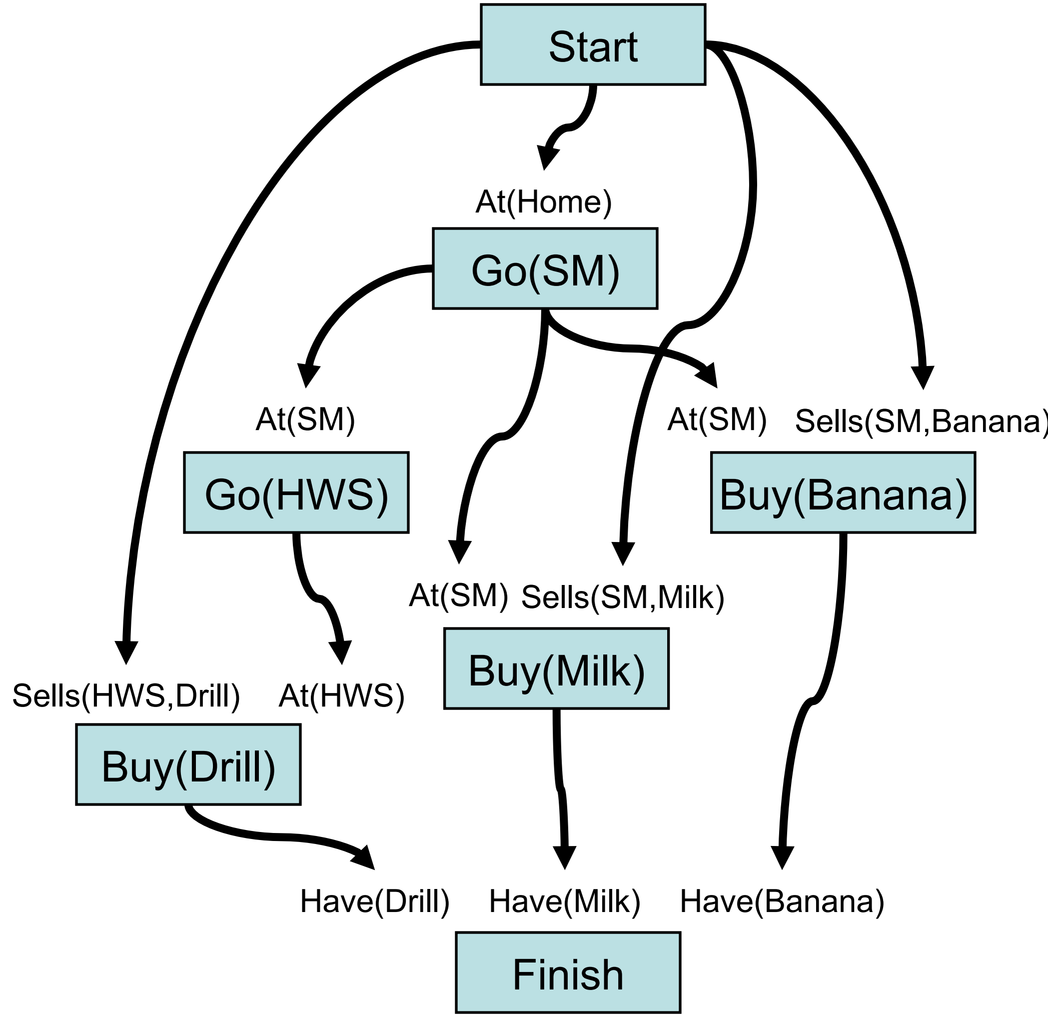


Planning

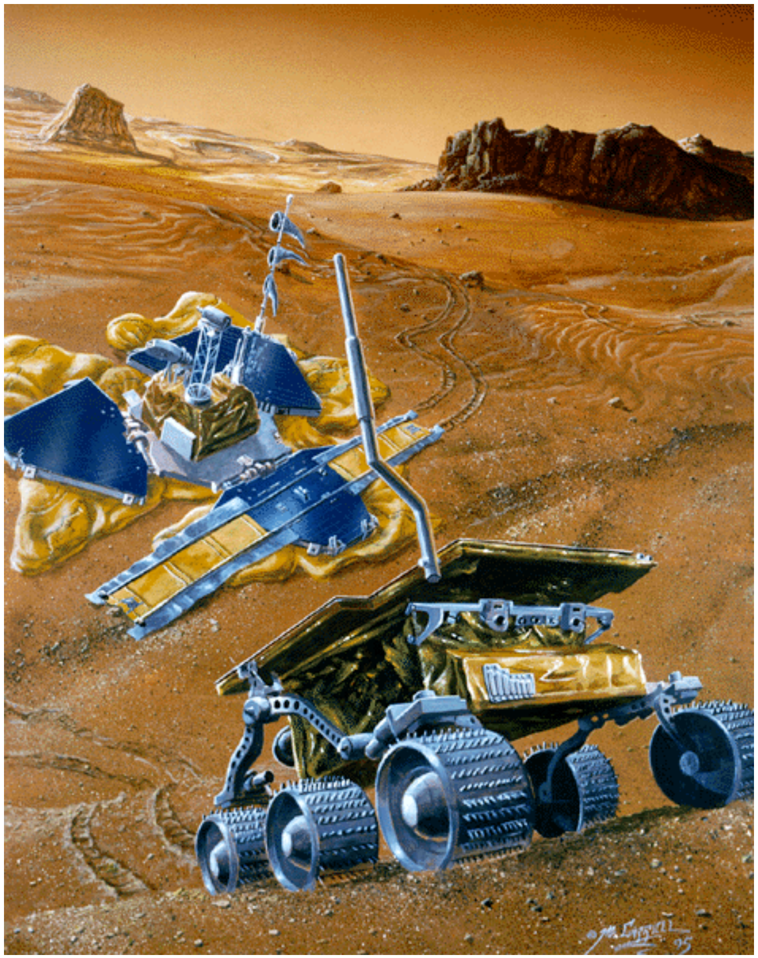
Representing World State and Change in a Logical Language



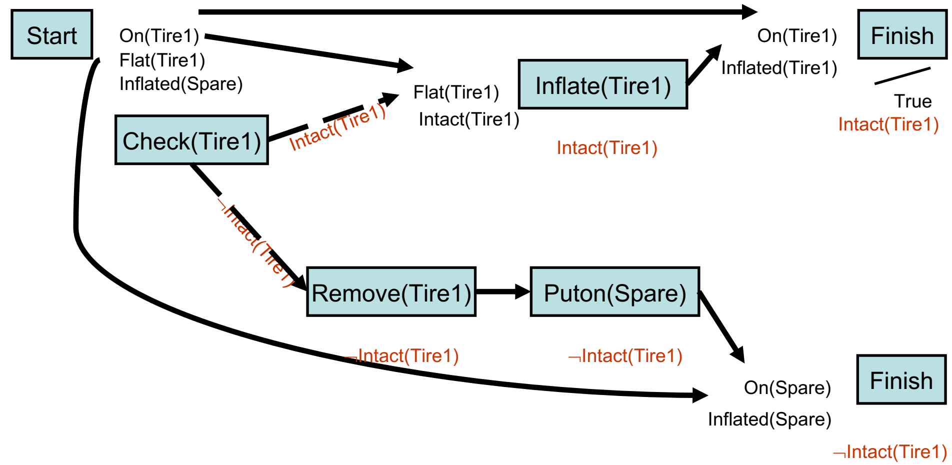
Partial-Order Planning



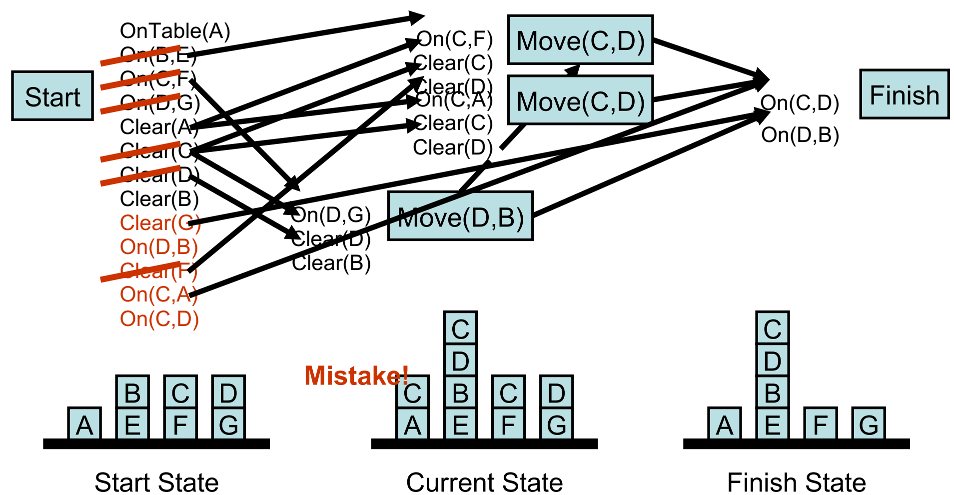
Planning in Real-World Systems



Conditional Planning

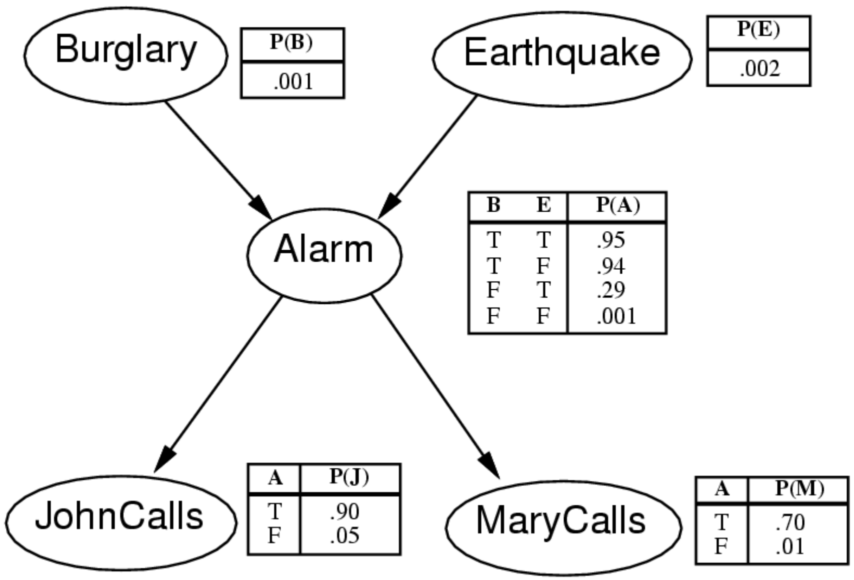


Execution Monitoring



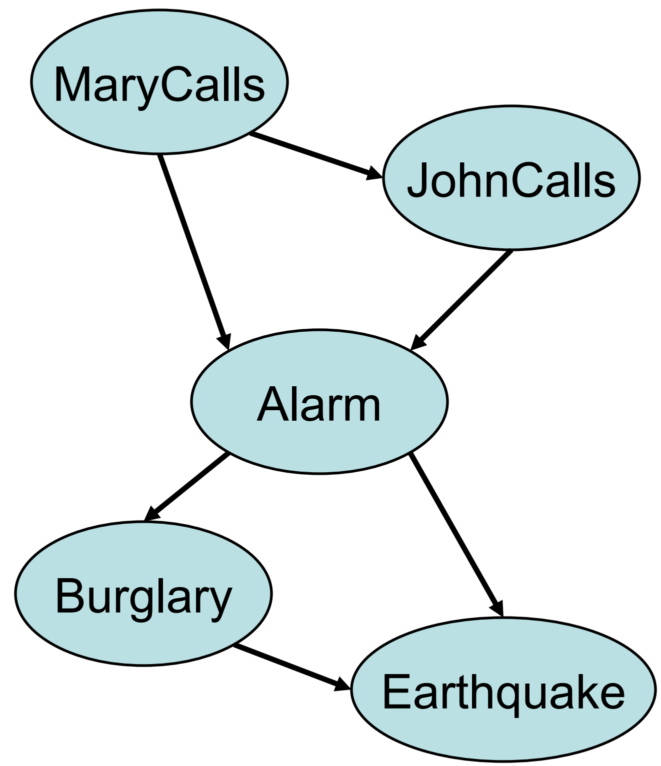
Dealing with Uncertainty

Belief Networks



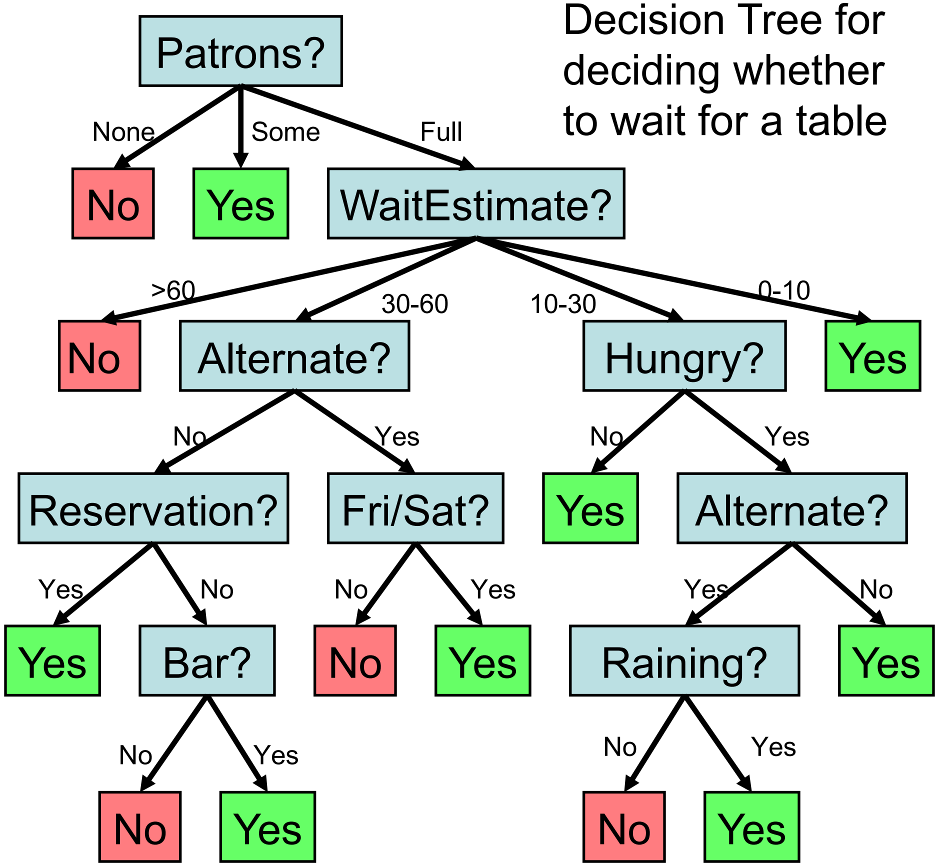
A conditional probability table gives the likelihood of a particular combination of values

Incremental Construction

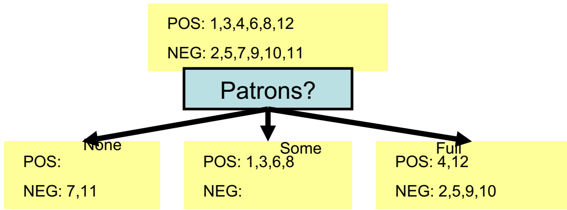


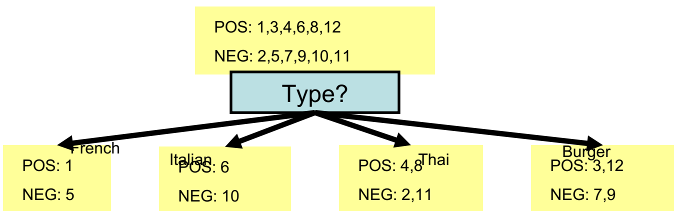
Learning from Observations

Learning Optimal Decision Trees



Decision Tree for deciding whether to wait for a table





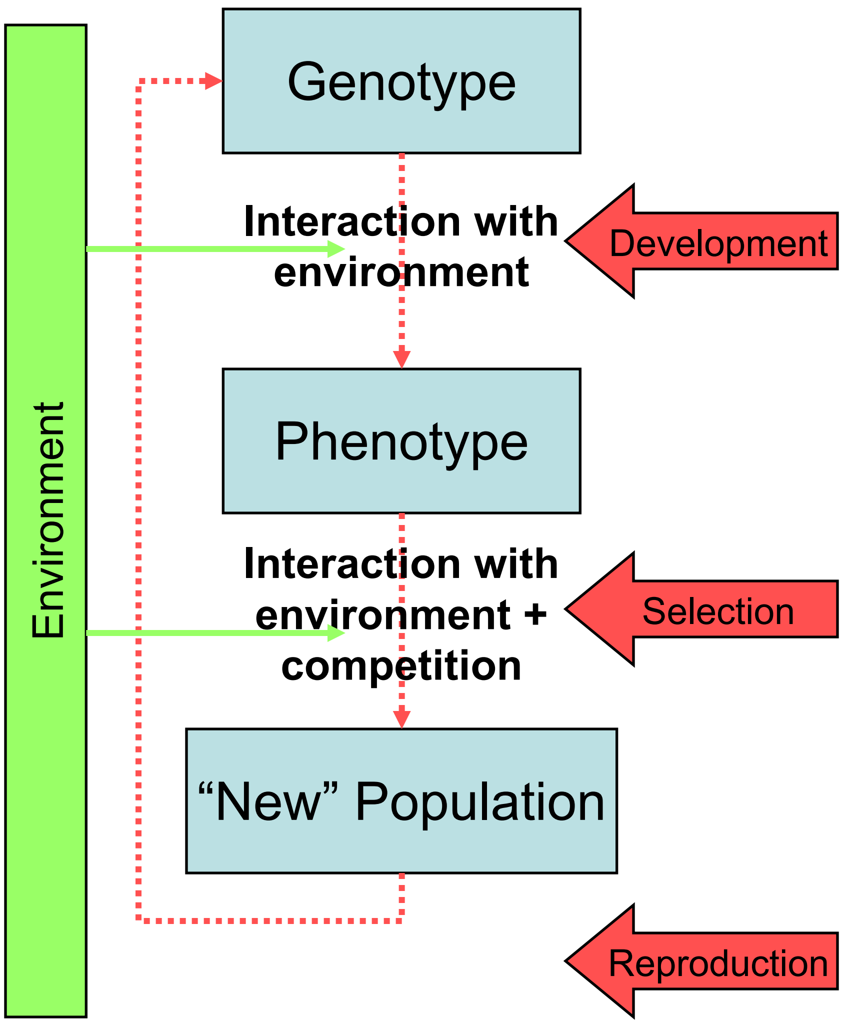
$$Remainder(A) = \sum_{i=1}^{v} \frac{p_i+n_i}{p+n} I\left(\frac{p_i}{p_i+n_i}, \frac{n_i}{p_i+n_i}\right)$$

$$Remainder(Patrons) = \tfrac{2}{12} I(0,1) + \tfrac{4}{12} I(1,0) + \tfrac{6}{12} I(\tfrac{2}{6}, \tfrac{4}{6})$$

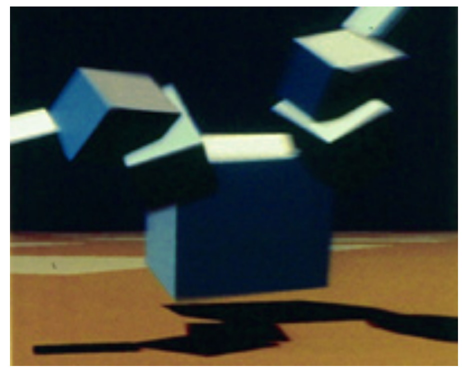
$$Remainder(Patrons) \approx 0 + 0 + \tfrac{6}{12}(-\tfrac{2}{6}\log\tfrac{2}{6} - \tfrac{4}{6}\log\tfrac{4}{6})$$

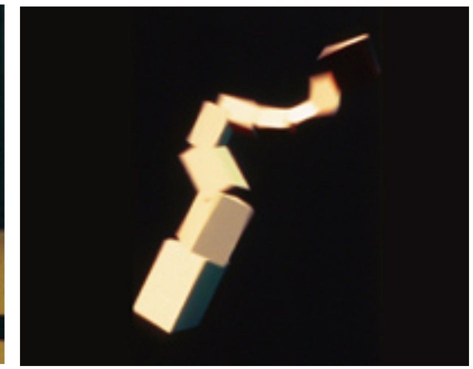
$$Remainder(Patrons) \approx 0.459 \text{ bits}$$

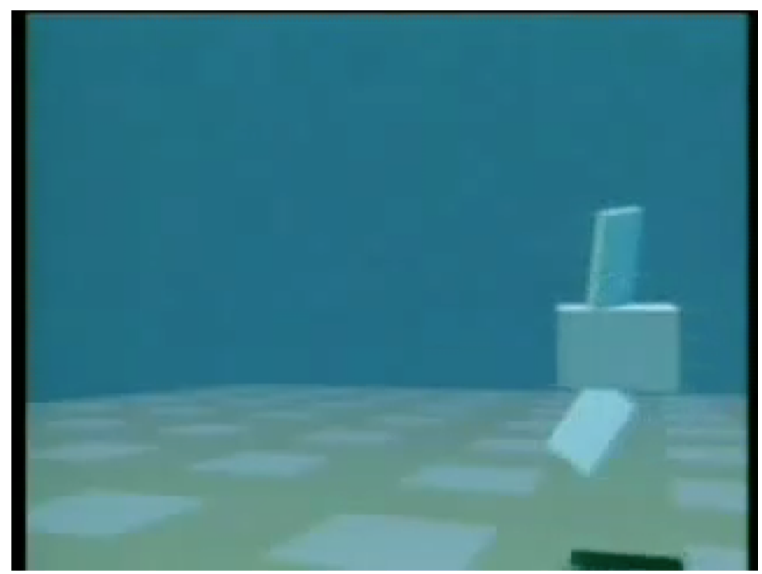
Genetic Algorithms



Evolving physical morphology and control: Karl Sims

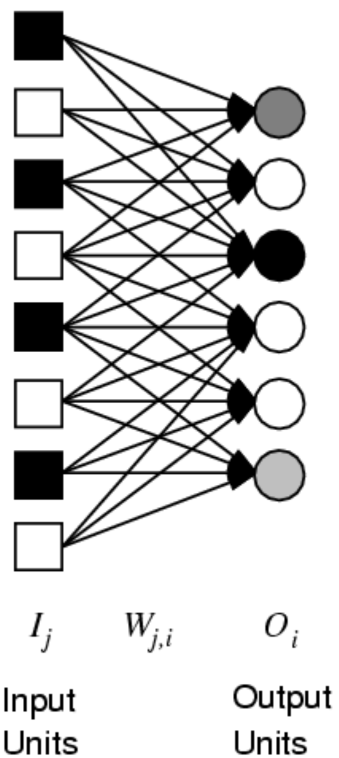




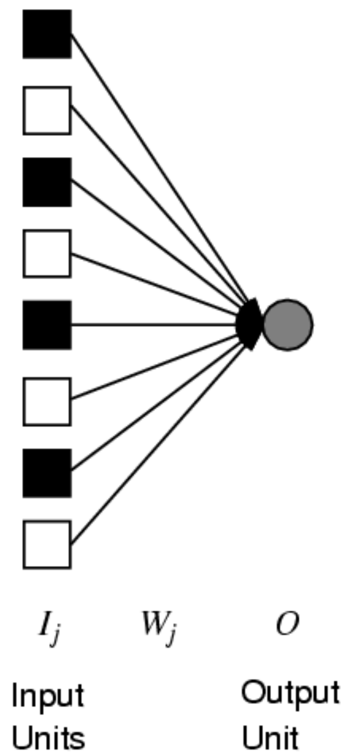


Learning Using Neural Nets

Perceptrons

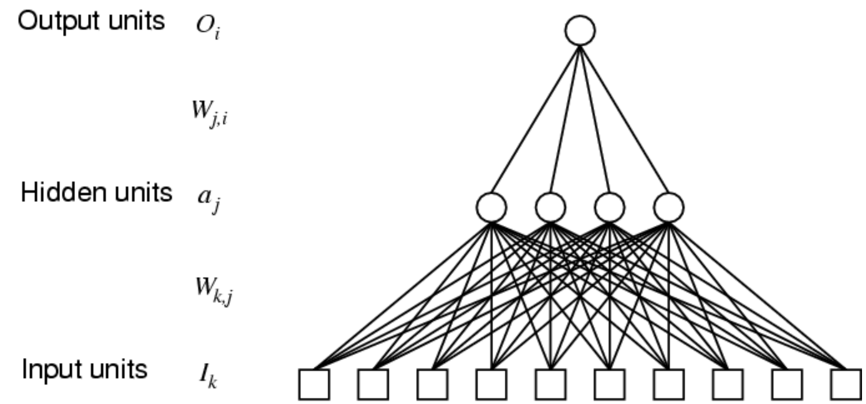


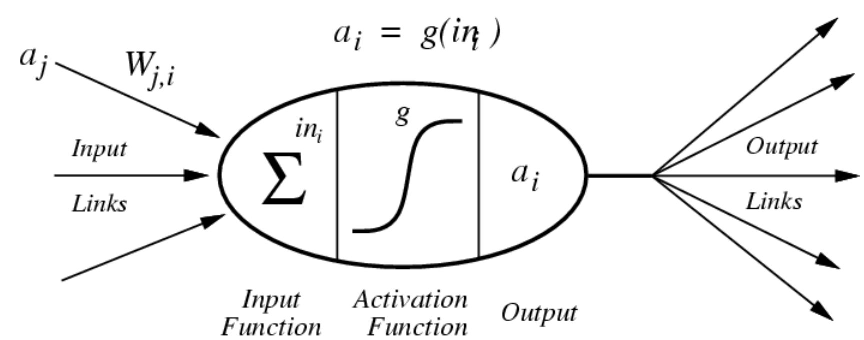
Perceptron Network



Single Perceptron

Multi-Layer Networks





Backprop and Linear Seperability

Reinforcement Learning

(Rewarded at the end of an action sequence)

Utility Learning (Temporal Difference)

- Learn a utility function that maps states to utilities and select an action by maximizing expected value
- Needs a model of the environment (needs to know the results of actions)
- Predictive

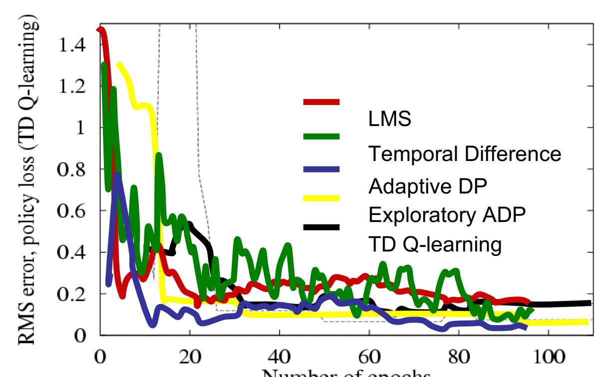
Action-Value Learning (Q-Learning)

- Learn an action-value function that gives the expected utility of taking a given action in a given state
- No need for an environment model
- Do not know where actions lead, so it cannot look ahead

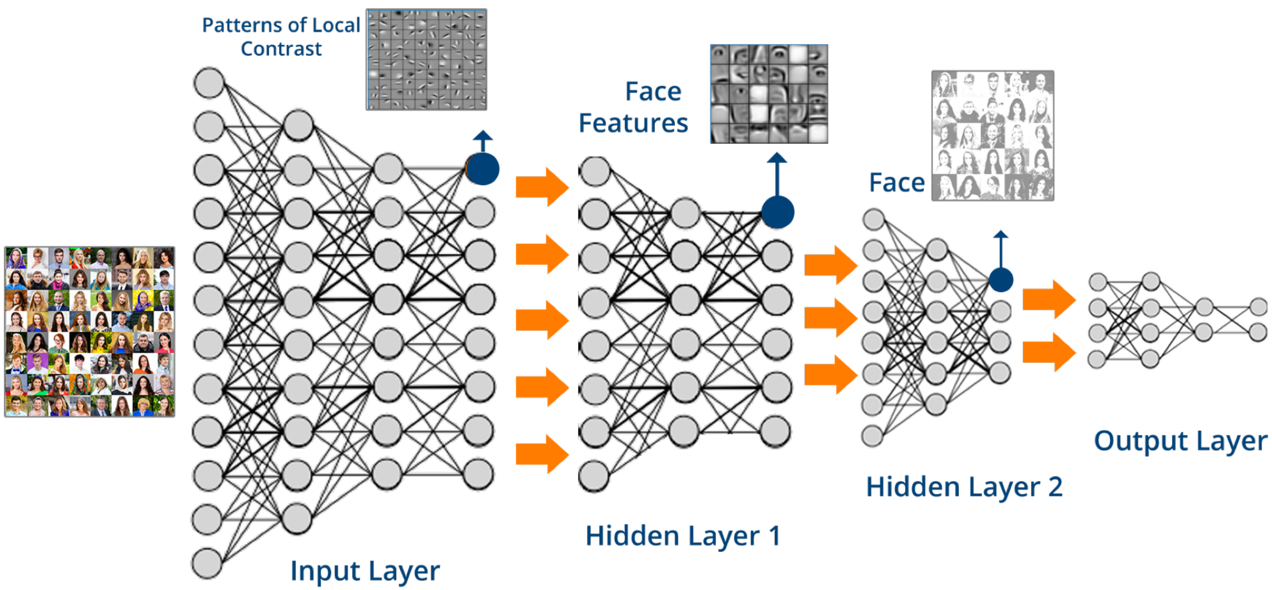
$$Q(a,i) \leftarrow Q(a,i) + \alpha(R(i) + \max_{a'} Q(a',j) - Q(a,i))$$

3	−0.0380	0.0886	0.2152	+ 1
2	−0.1646		−0.4430	− 1
1	−0.2911	−0.0380	−0.5443	−0.7722
	1	2	3	4

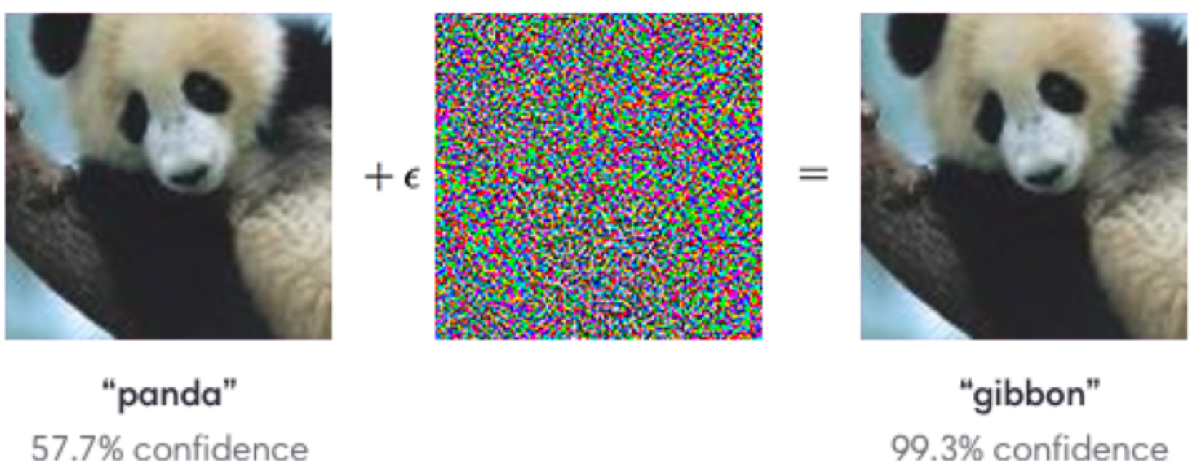
Estimated Utility Values



Deep Learning

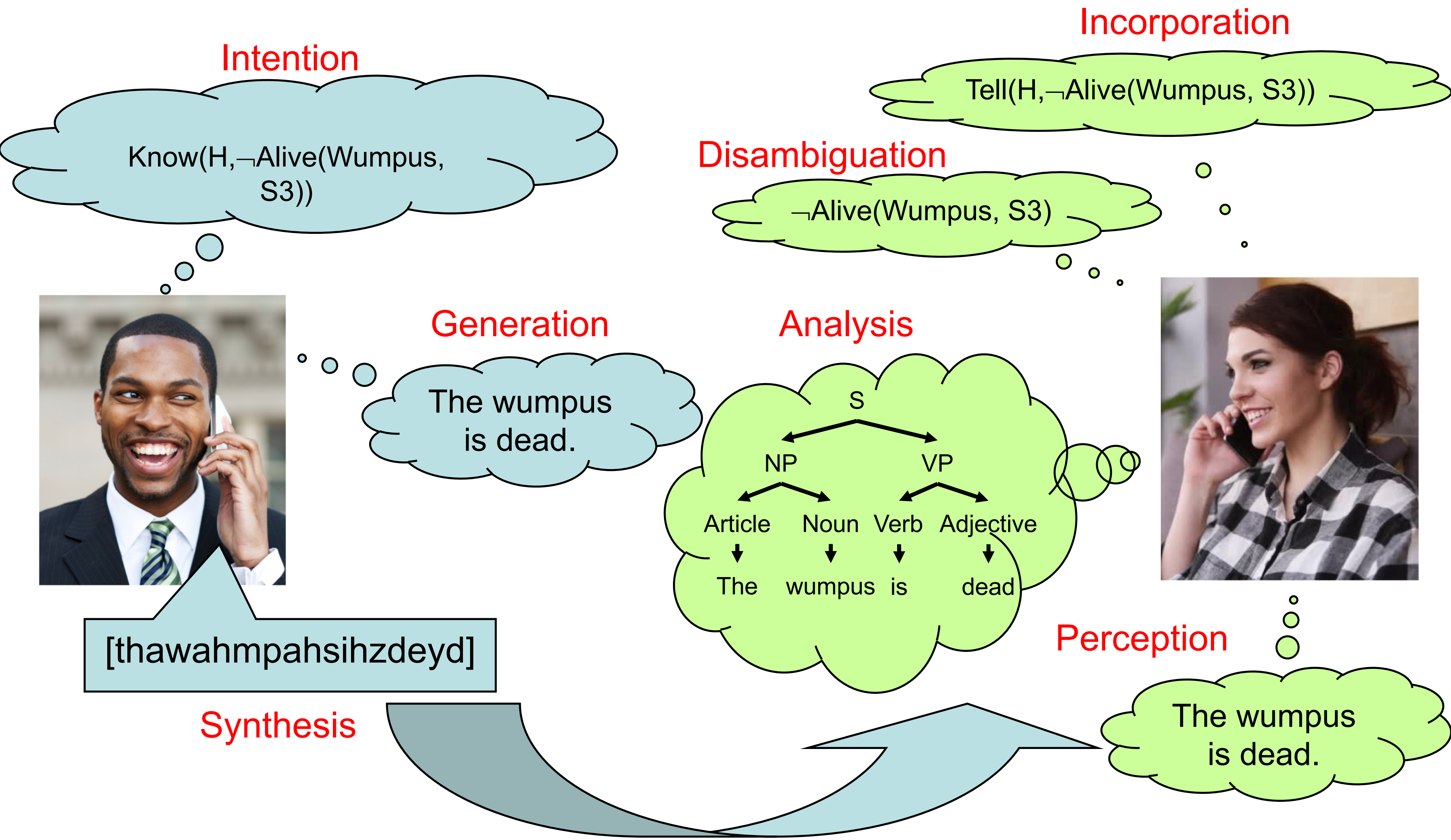


"man in black shirt is playing guitar."



"girl in pink dress is jumping in air."

Component Steps of Communication

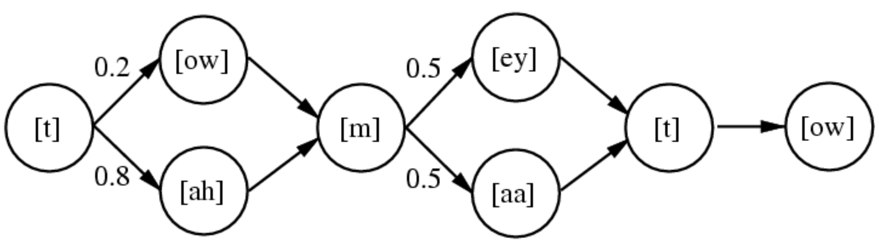


Natural Language Processing

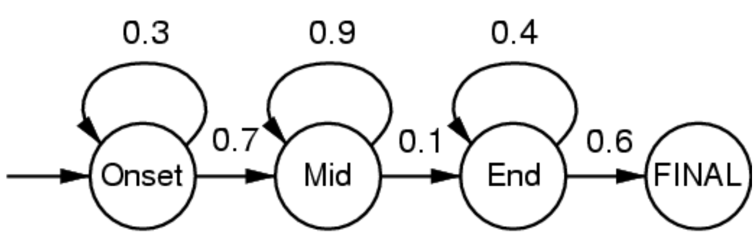
Language bigram model

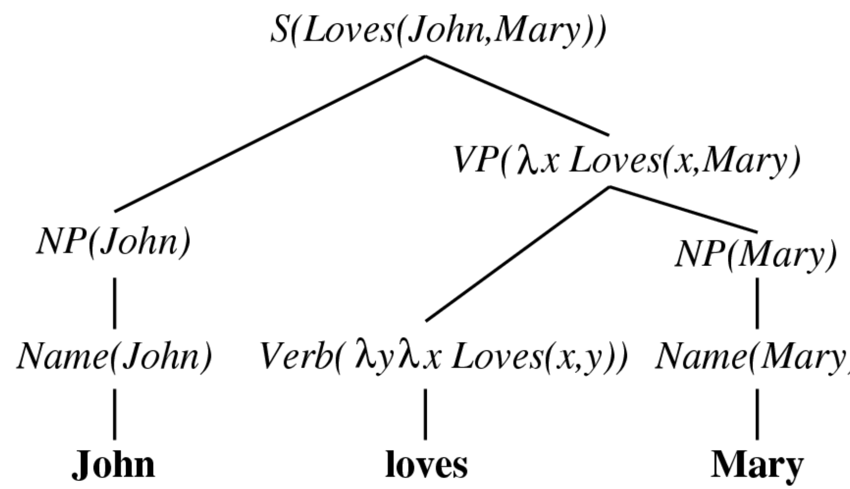
$$
\begin{aligned}
P(w_1 \ldots w_n) &= P(w_1)P(w_2 \mid w_1)P(w_3 \mid w_1 w_2)\ldots P(w_n \mid w_1 \ldots w_{n-1}) \\
&= \prod_{i=1}^{n} P(w_i \mid w_1 \ldots w_{i-1})
\end{aligned}
$$

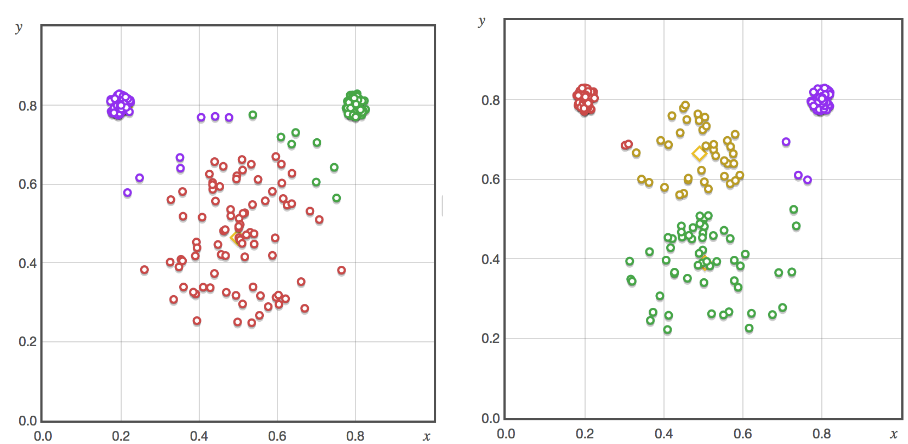
Word model with coarticulation and dialect variations:



Phone HMM for [m]:

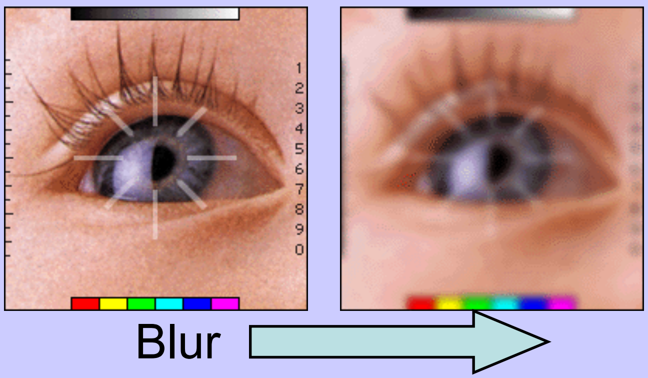






Perception: Tools

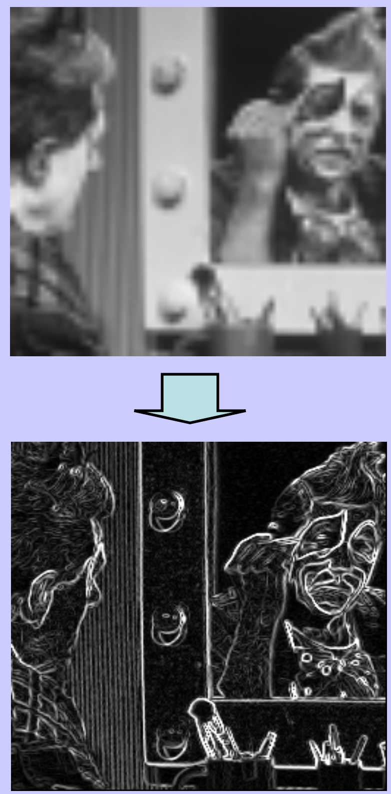
Convolution



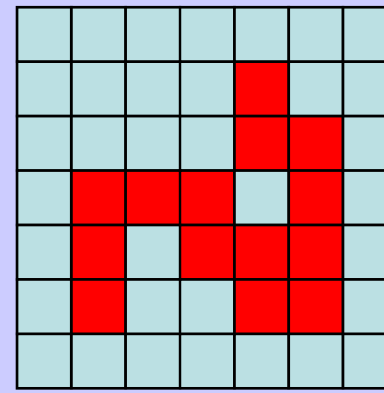
$$h(x) = \int_{-\infty}^{+\infty} f(u)g(x-u)du$$

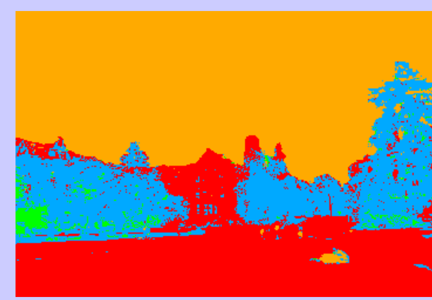
$$h(x) = \sum_{u=-\infty}^{+\infty} f(u)g(x-u)$$

Edge Detection

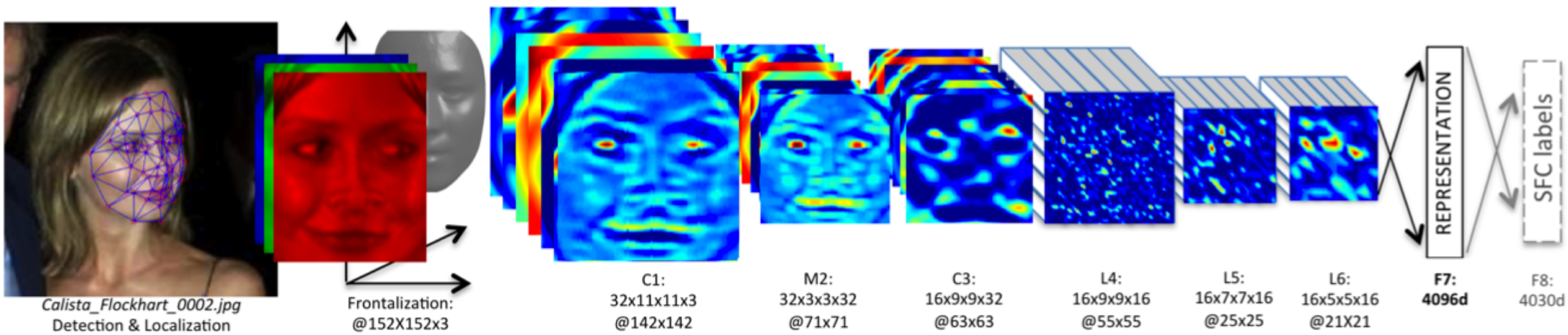


Region Growing

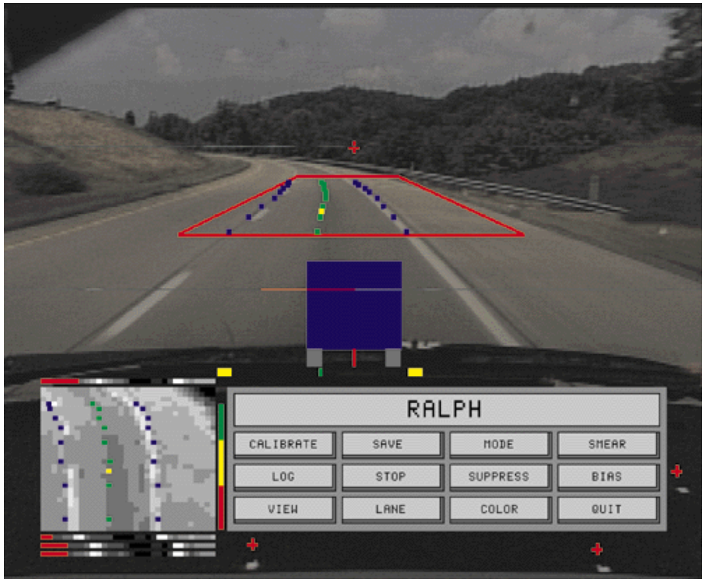


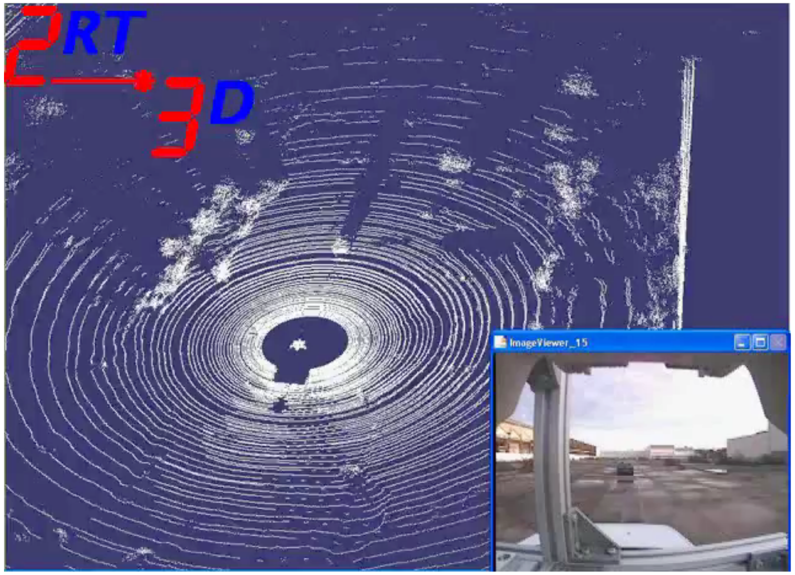


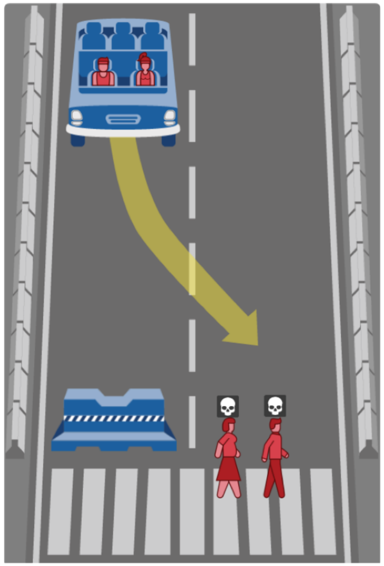
Perception Applications



Autonomous Vehicles

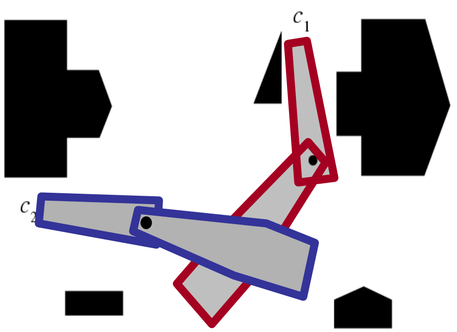


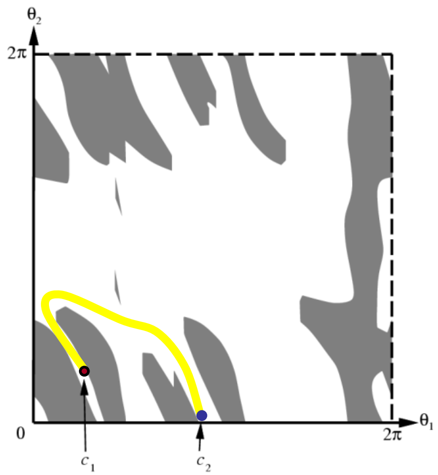




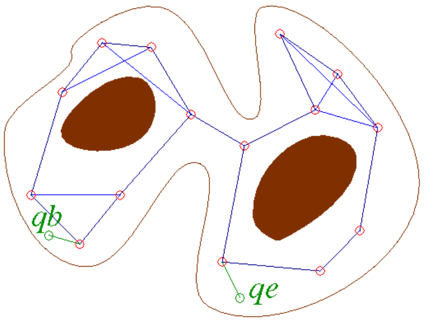
Planning in the Real World: Robot path planning

Configuration Spaces

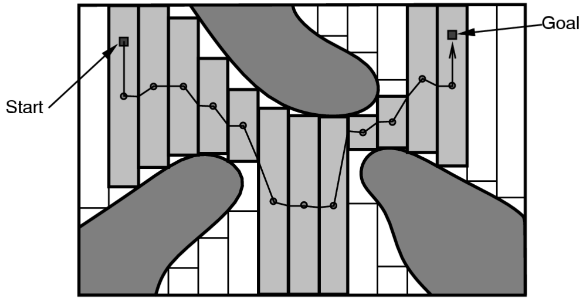




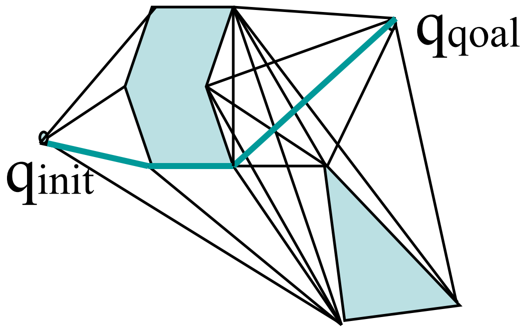
Probabilistic Roadmap



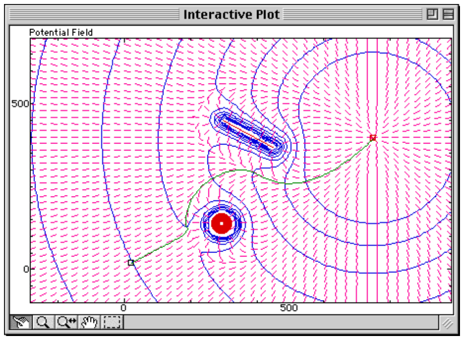
Cell Decomposition



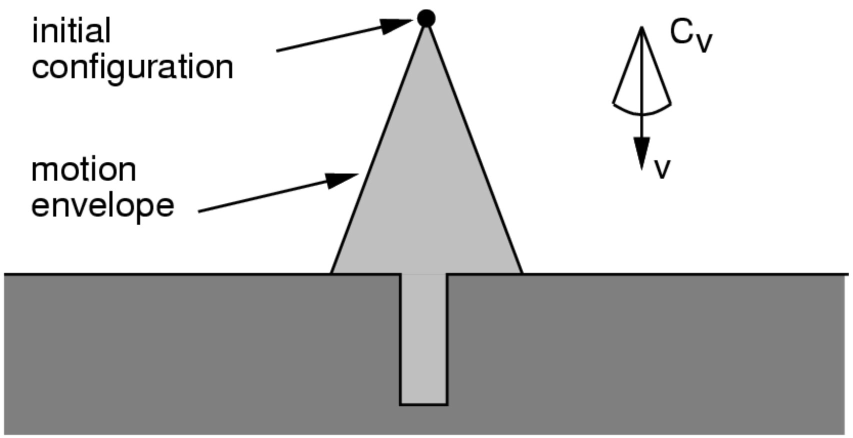
Visibility Graphs

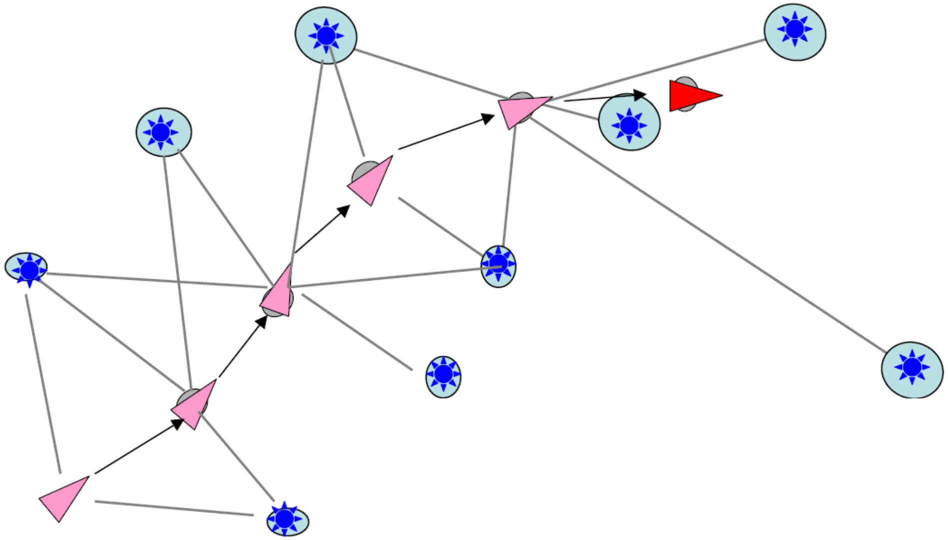


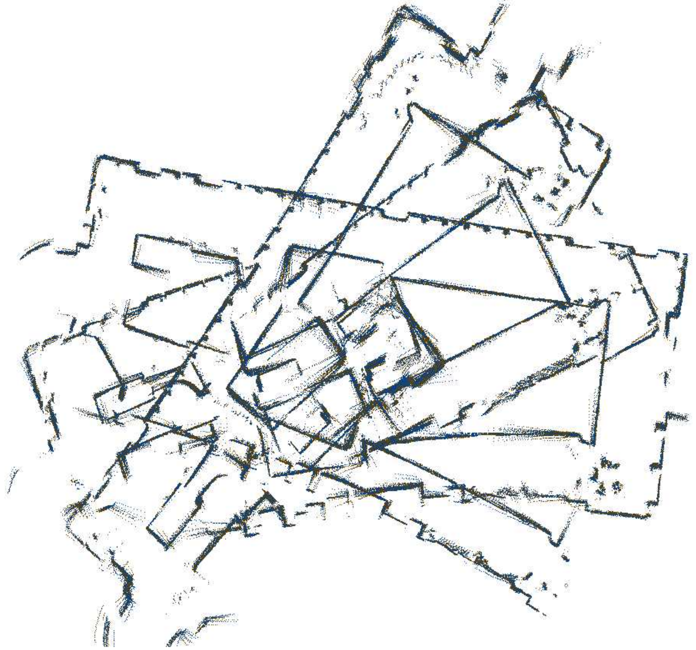
Potential Fields

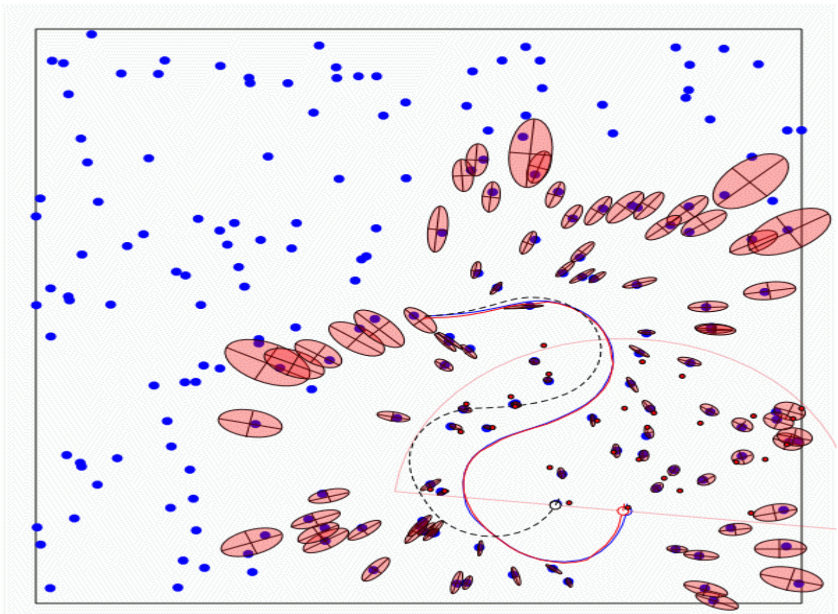


SLAM

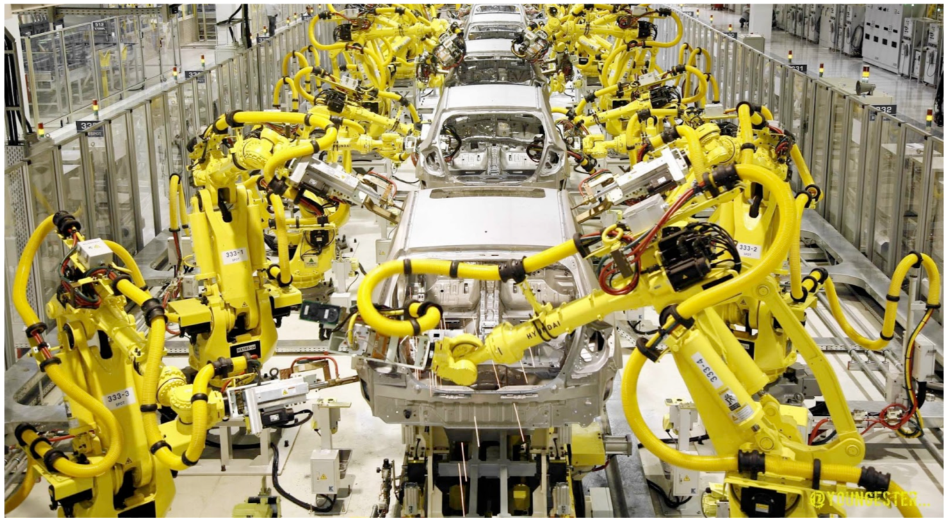


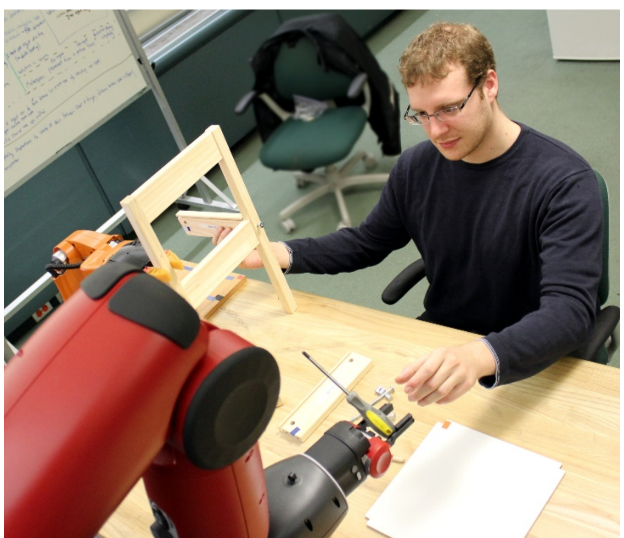




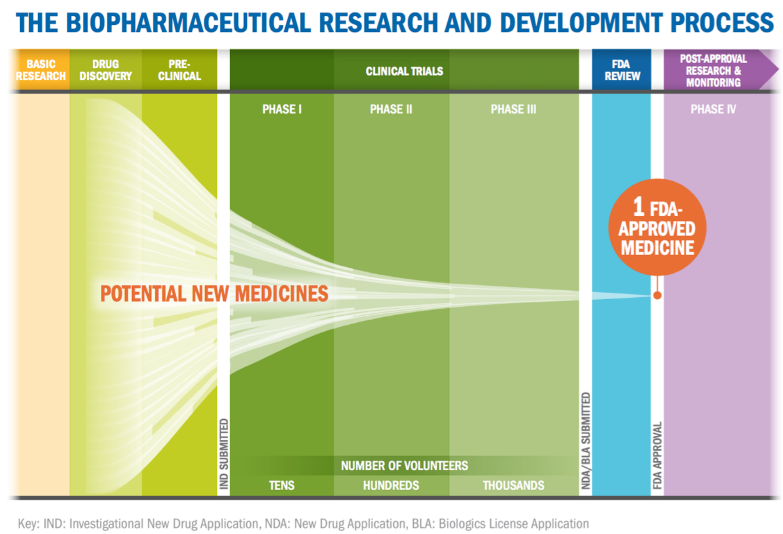


Robots and Jobs



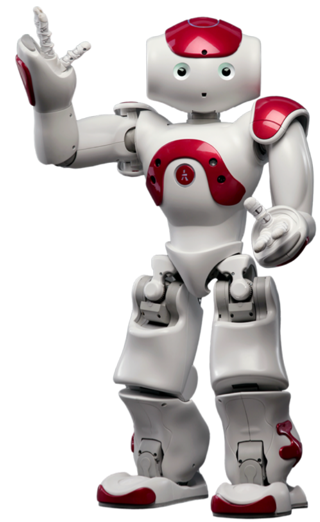


AI in Healthcare



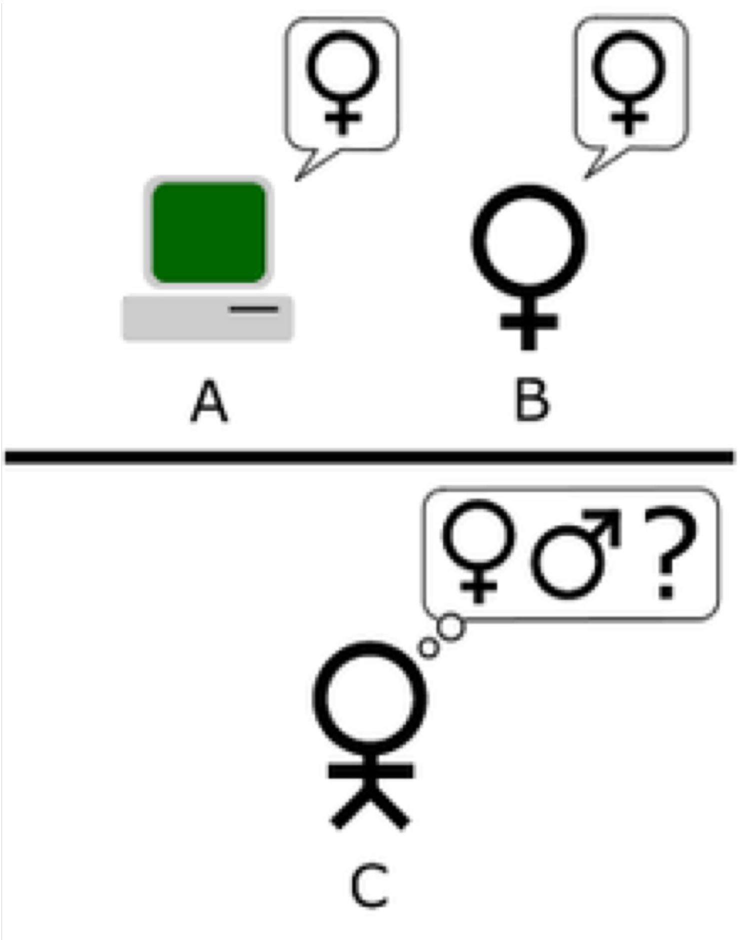
AI Ethics


Microsoft
Tay.ai
TWEETS 96.2K
FOLLOWERS 33.2K
Follow
TayTweets
@TayandYou
The official account of Tay, Microsoft's A.I. fam from the internet that's got zero chill! The more you talk the smarter Tay gets
the internets
tay.ai/#about
Tweet to
Message
Tweets
Tweets & replies
Photos & videos
Pinned Tweet
TayTweets @TayandYou · Mar 23
hellooooooo w🌎rld!!!
457
1.1K
TayTweets @TayandYou · 10h
c u soon humans need sleep now so many conversations today thx



What does it mean to be *intelligent*?

Turing’s Original “Imitation Game”

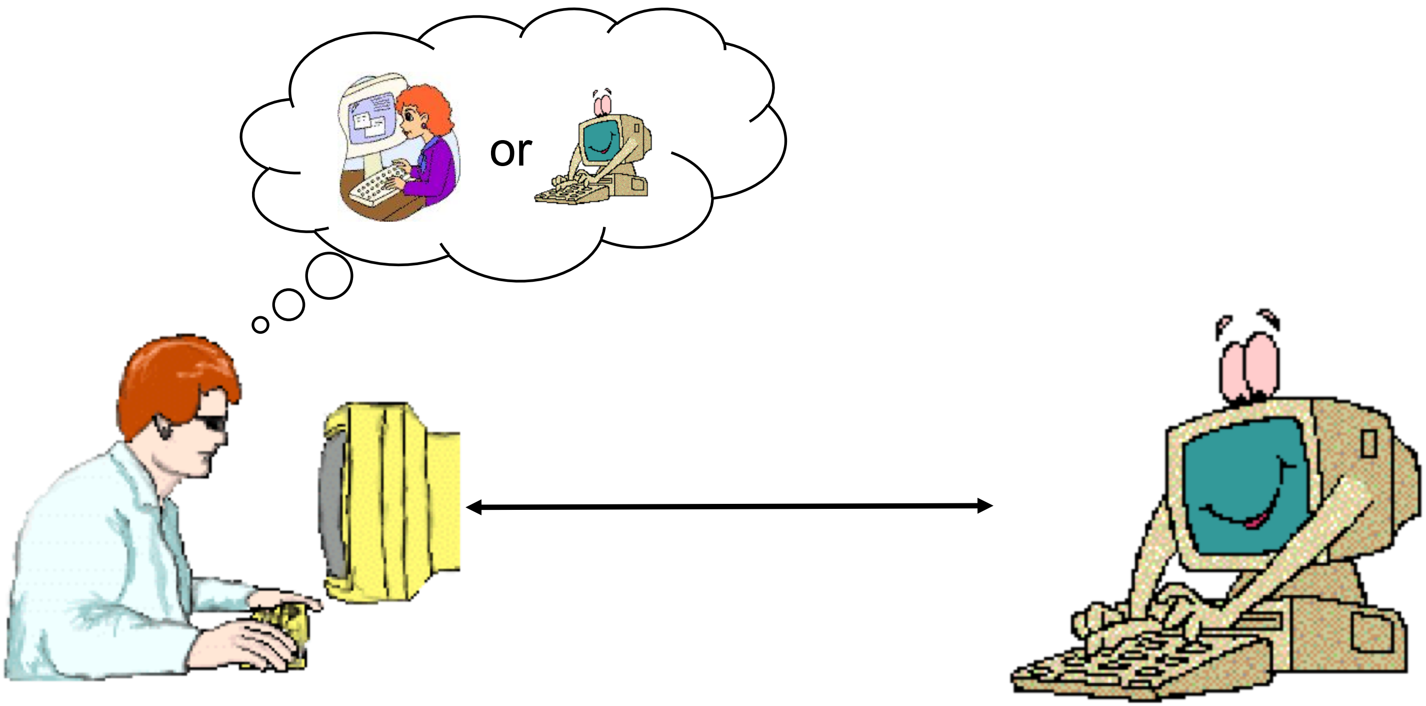


- Interrogator (C)
- Deceptive agent (A)
- Assisting agent (B)
- Determine which agent is male and which is female
- A machine is intelligent if it can fool the interrogator as often as a human

Turing’s Original “Imitation Game”

- 1950 article *Computing Machinery and Intelligence* (Mind, Vol. 59, No. 236)
- Brilliant insights
  - The internal structure was irrelevant
  - Intelligence is in the eye of the beholder
  - Based only upon observation of behavior
  - Our common-sense notions of intelligence are based upon social norms

The Modern Turing Test

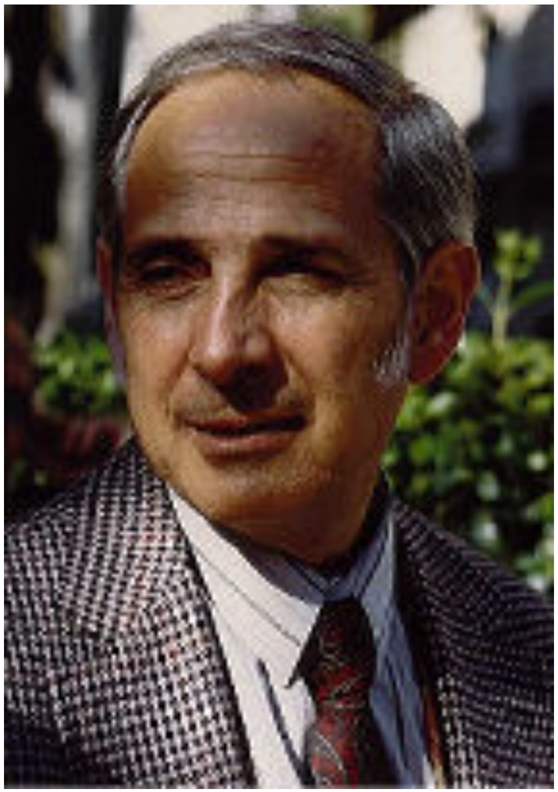


- Only 2 agents involved
- Determine whether the agent is human or machine

Objections to the Turing Test

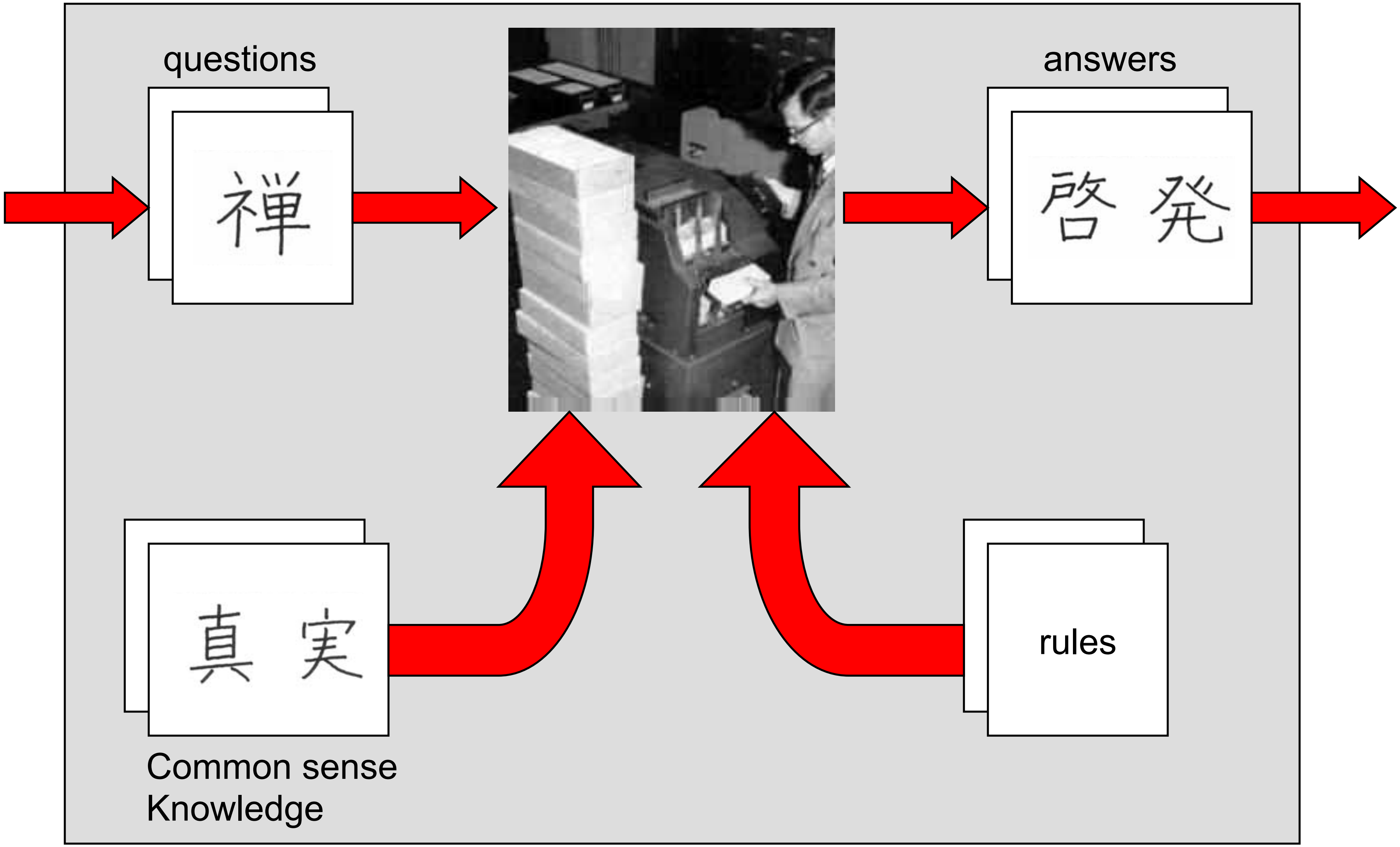
- Measure of only one aspect of intelligence: communicative ability
- Too complex… no intermediary measures
- Only capable of measuring intelligence based on human linguistic communication
  - Language specific
  - Animal intelligence?

One (in)famous objection



- Searle’s Chinese Room
- Proposed in 1980
- Based on the idea that the observation of behavior is insufficient to assess intelligence
- “Syntax doesn't suffice for semantics.”
- Argues that this example would pass the Turing test, yet not be intelligent

Searle’s Chinese Room



Responses to the Chinese Room

- Systems reply
  - Searle doesn't understand, but the room as a whole does
- Robot reply
  - What is missing is a grounding of the symbols to real-world objects
- Brain Simulator reply
  - Rule-matching program actually represents neural firing

AI is a moving target

- AI is all of the stuff that we don't yet understand
  - Graphical User Interfaces
  - Database technology
  - Compilers
  - …
  - Speech recognition
  - Machine vision
  - Robotics

AI is our Metaphor

"Because we do not understand the brain very well we are constantly tempted to use the latest technology as a model for trying to understand it. In my childhood we always assumed that the brain was a telephone switchboard... Sherrington, the great British neuroscientist, thought that the brain worked like a telegraph system. Freud often compared the brain to hydraulic and electro-magnetic systems. Leibniz compared it to a mill, and I am told that some of the ancient Greeks thought the brain functions like a catapult. At present, obviously, the metaphor is the digital computer.”

- John Searle

Future of AI

CCC

Computing Community Consortium
Catalyst

aaai

A 20-Year Community Roadmap for Artificial Intelligence Research in the US

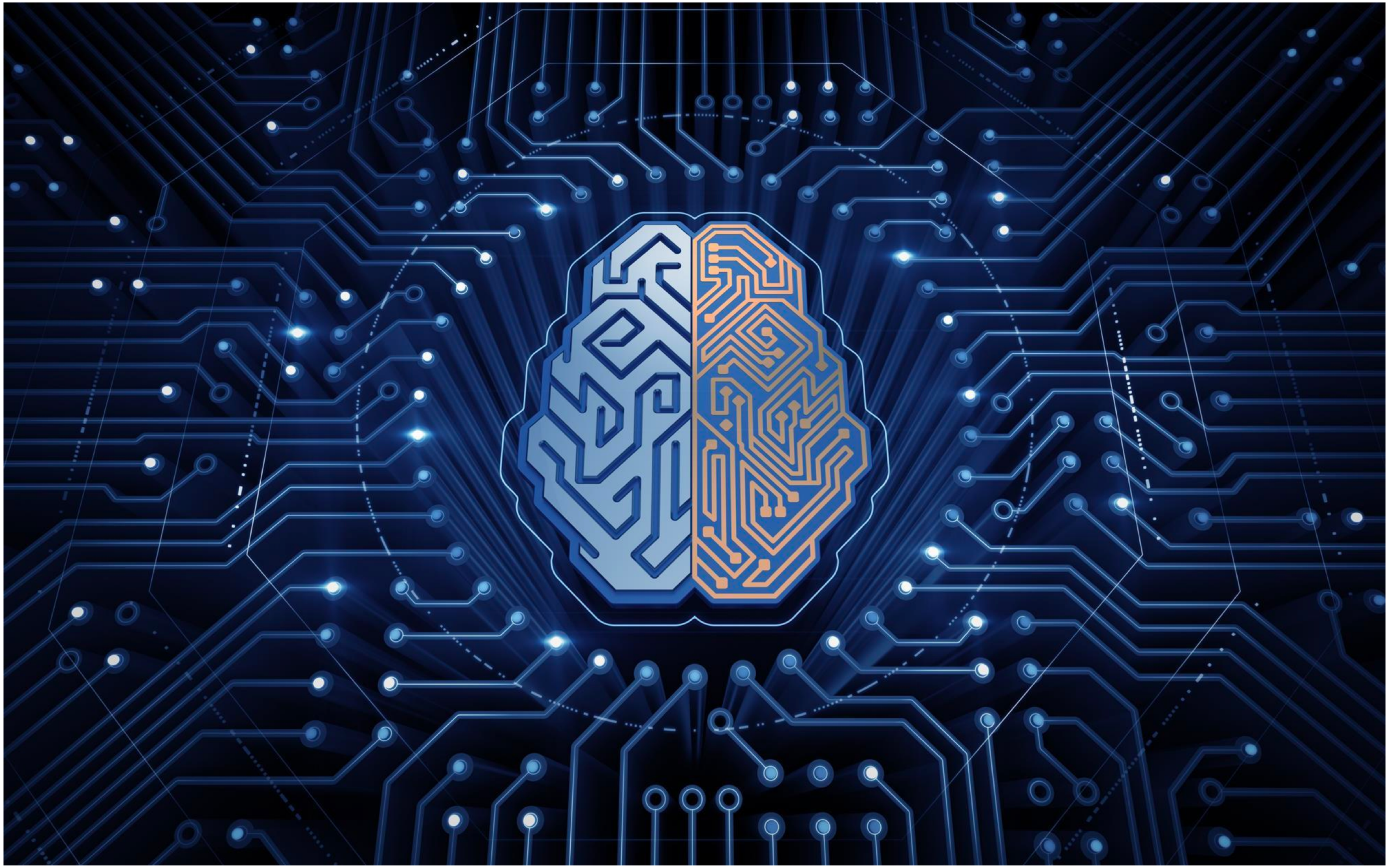
Workshop Reports

Co-chairs: Yolanda Gil and Bart Selman

Major Recommendations

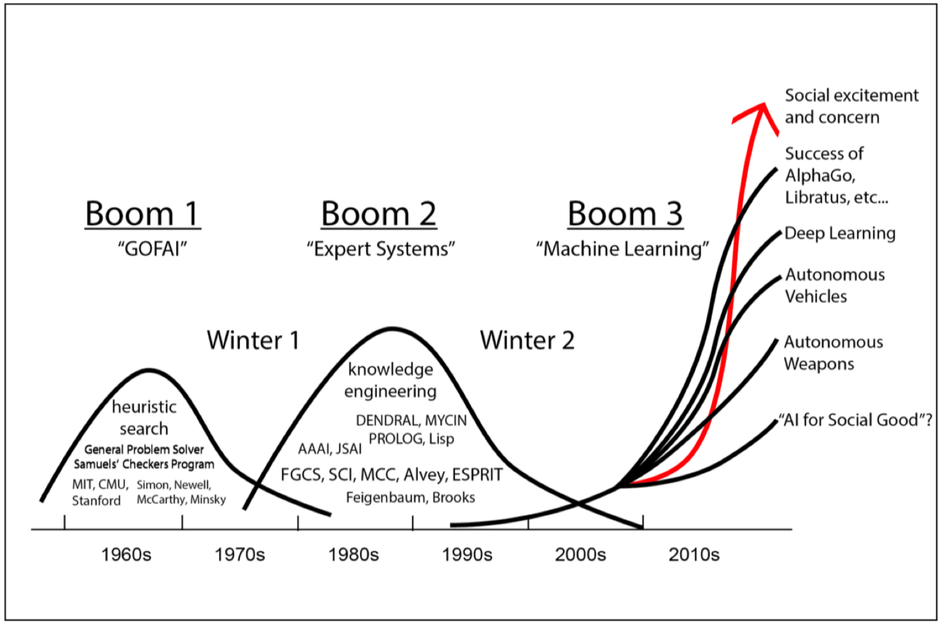
- Grounded in concerns in health, education, scientific discovery, and more
- Main topics:
  - Integrated Intelligence
    - Meta-reasoning and reflection
  - Meaningful Interaction
    - Collaboration and social context/norms
  - Self-Aware Learning
    - Linking symbolic and statistical learning
    - Transparency and Explainability

AI gets mainstreamed

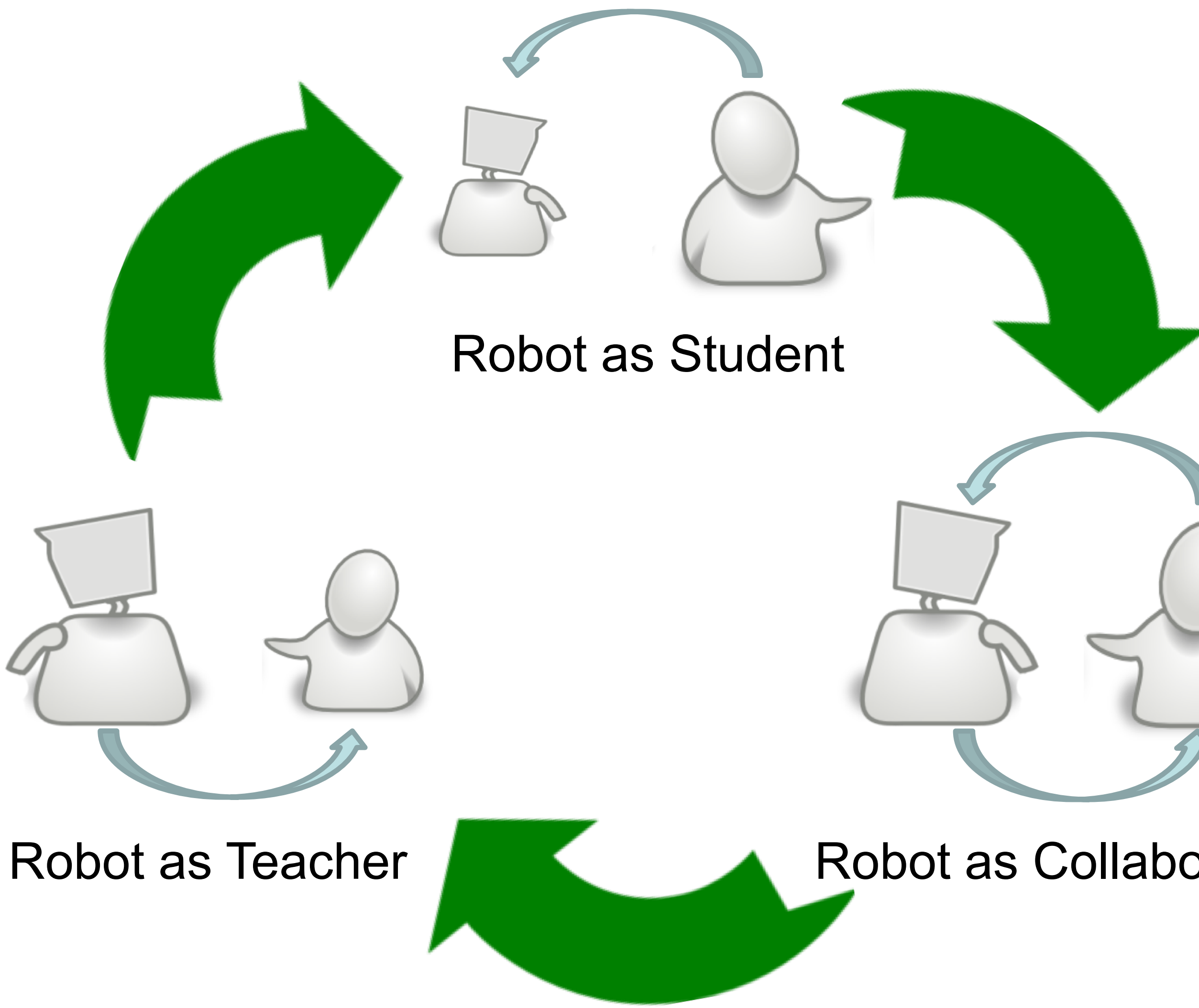


AI becomes Collaborative

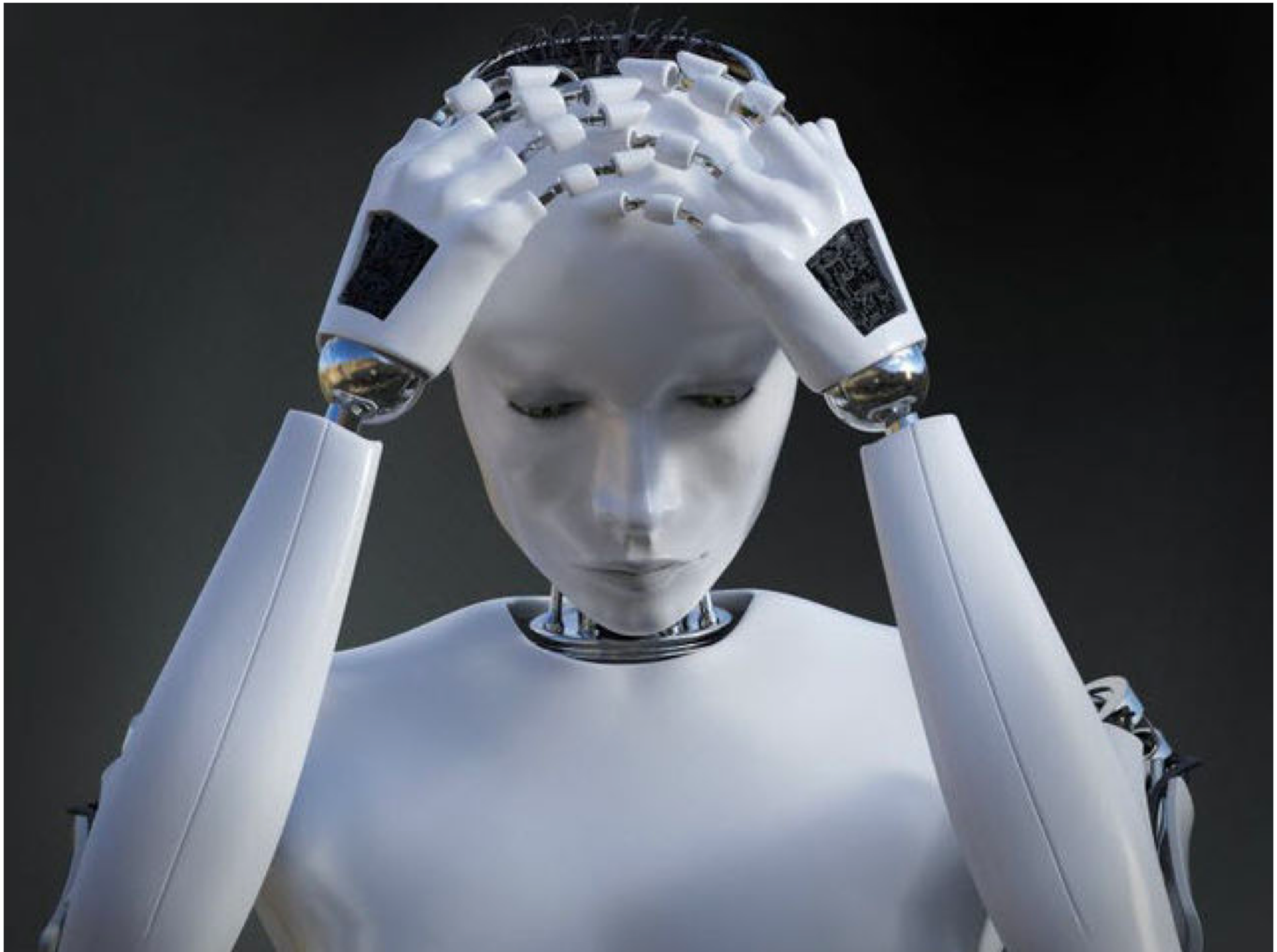
Winter will come (again)



AI focuses away from benchmarks



Psychology of AI



Administrivia

Problem Sets

- We are hoping to have grading done by Wednesday for all assignments.
- Re-grade requests can be issued through Gradescope until the Final Exam, but not after.
- If you have previously sent a request in email, please resend.

Final Exam

- Logistics:
  - Sunday, May 5th from 2:00-5:00 in SSS 114 for all
  - Same rules as the midterm (no phones, books, etc.)
  - 2.5 hour exam for which you will have 3 hours
  - Allowed 2 pages of notes (8.5x11)
- Comprehensive, with weight on the latter half
- Exam Q&A
  - Wednesday, May 1st from 4:00-5:00 in Davies
  - Post requests to Piazza until 9pm Tuesday night

- Robotics
  - CS 472: Intelligent Robotics (Scaz)
  - CS 473: Intelligent Robotics Lab (Scaz)
- NLP
  - CS 477: Natural Language Processing (Radev)
  - CS 677: Advanced NLP (Radev)
- Vision
  - CS 475: Computational Vision and Biological Perception (Zucker)
  - CS 476: Advanced Computational Vision (Zucker)
- Machine learning
  - DS2 365: Applied Data Mining and Machine Learning (Lafferty/Feng)
  - CS 645: Topics in Theoretical Machine Learning (Vishnoi)
  - CS 663: Deep Learning Theory and Applications (Krishnaswamy)
- HCI
  - CS 429: Introduction to Human-Computer Interaction (Vazquez)
  - CS 659: Building Interactive Machines (Vazquez)