EECS 491
Artificial Intelligence

Introduction and Overview

Course information

- Instructor:

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  Office hours : Tue, Thu, Fri, Sat 1:00 - 3:00 PM

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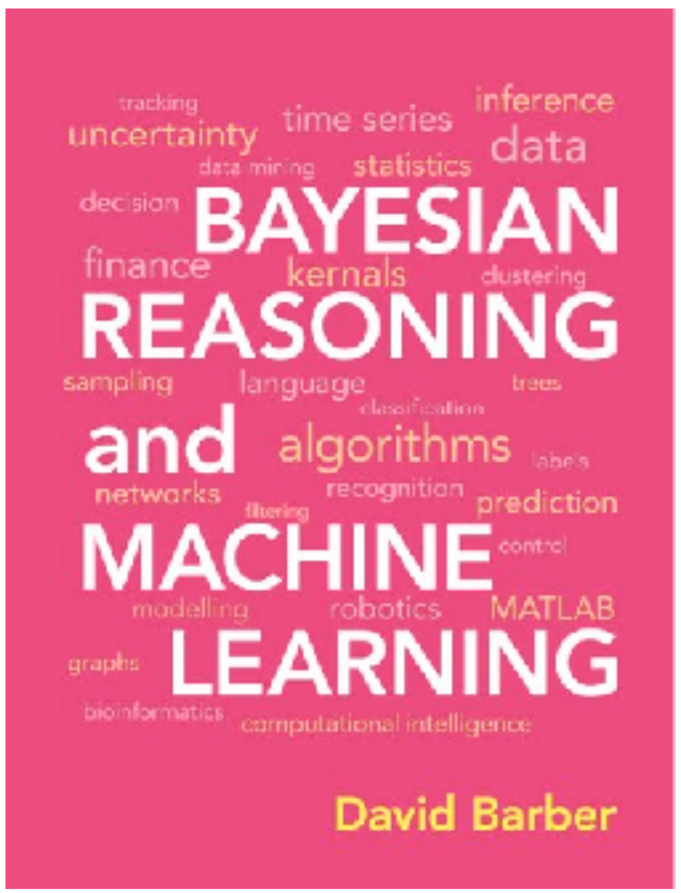
- Class meeting times: MW 12:45 - 2:00 PM
- Class has a canvas course
- Class also has a redmine (git) server : https://csevcs.case.edu

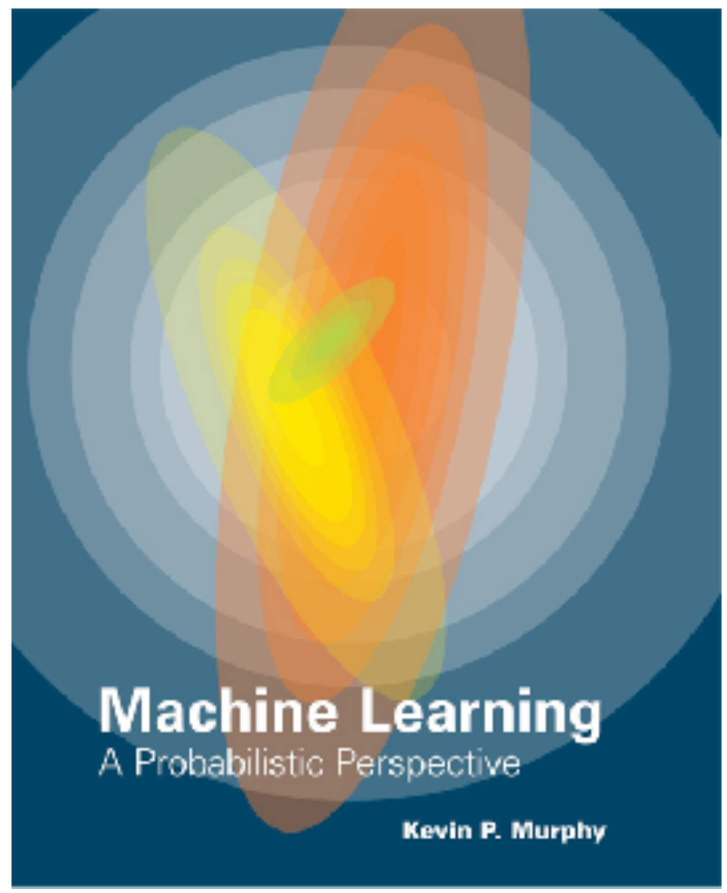
Outline and key concepts

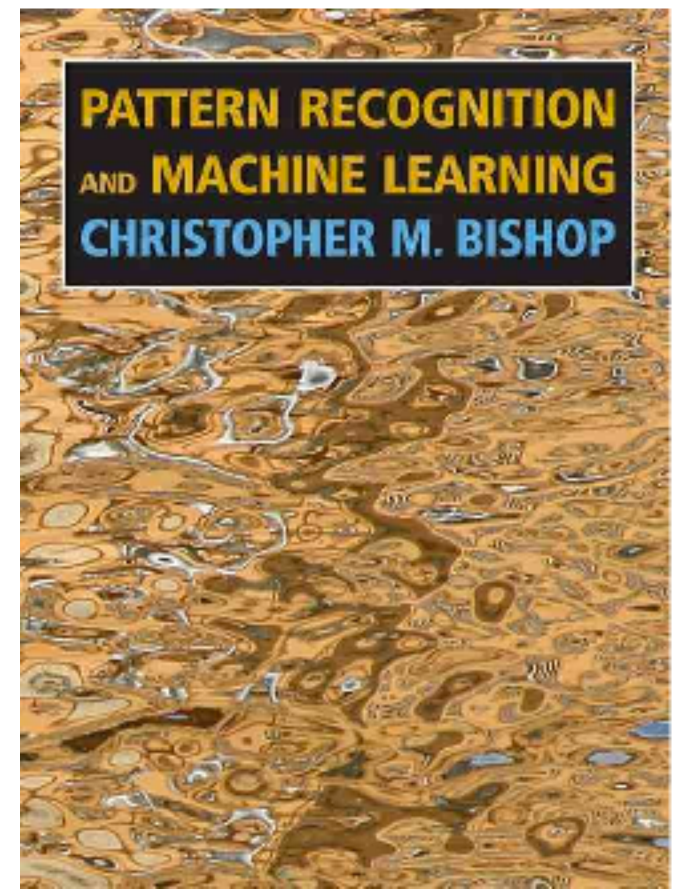
- Course introduction and organization
- Introduction to Artificial Intelligence (AI)
  - Intelligent systems
  - definition, examples
- Roles of probability and inference in AI:
  - rational (and optimal) way to deal with uncertainty
  - natural extension of logical inference
- Environment Setup and Test Case of Notebook

Course textbooks (no, we're not covering everything)

- *Bayesian Reasoning and Machine Learning* by Barber, Cambridge 2012
  Available online: http://www.cs.ucl.ac.uk/staff/d.barber/brml/
- Also recommended:
  Machine Learning: A Probabilistic Perspective by Murphy, MIT Press, 2012
  Pattern Recognition and Machine Learning by Bishop, Springer, 2006







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- Learn general methods and models representing probabilistic information
- Learn a range of inference and learning methods for these models
- Implement and apply these techniques to practical problems
- Implement and explain your idea to others

Course Design

- a portfolio based course and emphasizes creative exploration
- preferred form for assignments will be notebooks (default python in Jupyter)
- The notebooks you will create for each exercise in an assignment will consist of
  - conceptual background (text)
  - mathematical background (equations, must use latex)
  - code (e,g., python)
  - plots or results (could be table)
- no final exam
- course projects will be presented during the final exam period.
- peer discussion and feedback
- your assignments will be largely graded by peer review

Peer Feedback

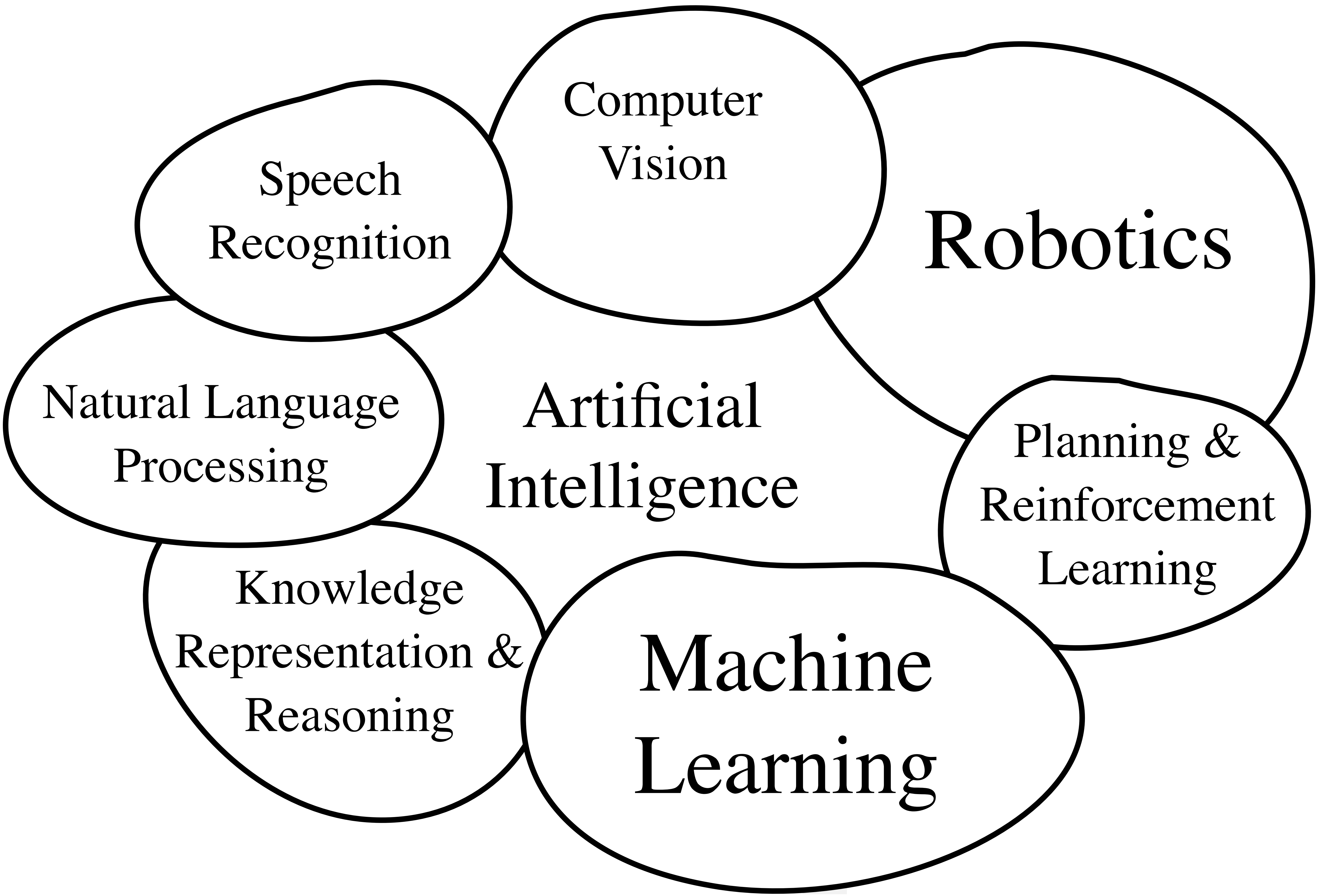
- use git repository for exercises (CSEVCS Redmine)
- must use version control: we need to see both your progress and how you addressed feedback from discussion sessions
- this allows for creative exploration, which we encourage

Collaboration and Cheating

- Collaboration to discuss the assignments and problems is encouraged.
- You *must* generate and write up the solutions yourself
- We expect that you can write on the explanation and code yourself, starting from a blank page without reference.
- Anything less is cheating.
- You are not allowed to copy code.

Course Schedule

	Date	Topics	Readings	Assignment due dates: out	Assignment due dates: group disc.	Assignment due dates: due
1	Mon, Jan 22	**Introduction and Overview** - course topics overview, applications, examples of probabilistic modeling and inference, workflow example: notebook, redmine, git	chapter introductions in Barber, M.1	A0		
2	Wed, Jan 24	**Probabilistic Reasoning** - basic probability review, reasoning with Bayes' rule	B.1.1-2, M.2.1-2		A0	
3	Mon, Jan 29	**Reasoning with Continuous Variables** - probability distribution functions, prior, likelihood, and posterior, model-based inference	B.1.3, background B.8, B.9.1, M.2.1-4			
4	Wed, Jan 31	**Belief Networks** - representing probabilistic relations with graphs, basic graph concepts, independence relationships, examples and limitations of BNs	B.2, B.3, M.10.1-2	A1		
5	Mon, Feb 5	**Graphical Models** - Markov networks, Ising model and Hopfield nets, Boltzmann machines, chain graphs, factor graphs, expressiveness of graphical models	B.4, B9.6, M.19.1-4, B.28.4		A1	
6	Wed, Feb 7	**Inference in Belief Nets** - variable elimination, sampling methods, Markov Chain Monte Carlo (MCMC), Gibbs Sampling	B.5.1.1, M10.3, M20.3, B.27.1-3			
7	Mon, Feb 12	**Inference in Graphical Models 1** - message passing, factor graphs	B.5.1-2, M.20, Bishop Ch.8		A1	
8	Wed, Feb 14	**Inference in Graphical Models 2** - sum-product algorithm, belief propagation	B.5.1-2, M.20, Bishop Ch.8	A2		A1


Computer Vision
Speech Recognition
Robotics
Natural Language Processing
Artificial Intelligence
Planning & Reinforcement Learning
Knowledge Representation & Reasoning
Machine Learning

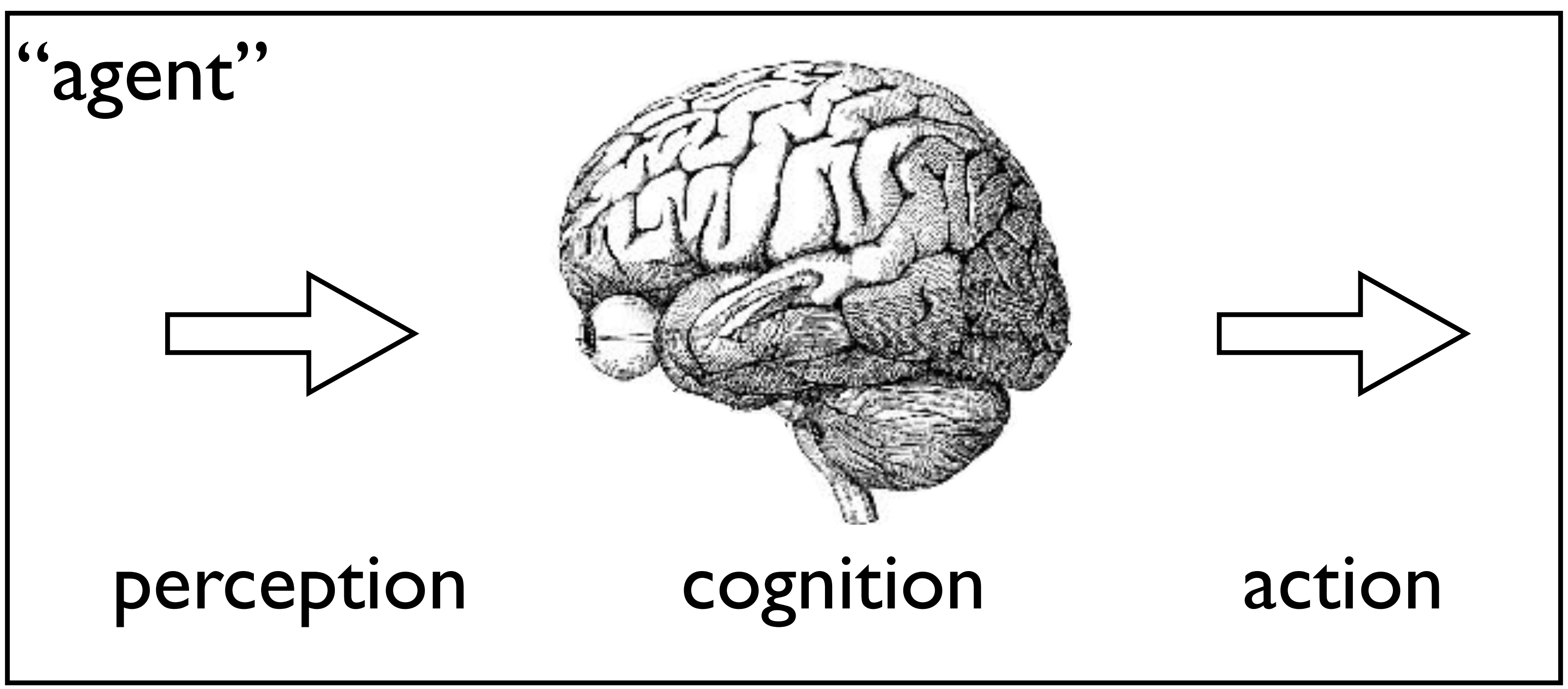
How this is different from 391 and 440?

- EECS 391 is designed as a introductory course that covers a broad range of topics (e.g. Russell and Norvig):
  - problem solving by search
  - game theory, game trees, alpha-beta pruning
  - constraint satisfaction
  - logic, decision making, Bayes nets
  - reinforcement learning
- EECS 440
  - decision trees, classification
  - neural networks, support vector machines
  - learning theory, relational learning
- EECS 491 expands on subset of these topics: reasoning and decision making (but not machine learning, which is EECS 440)

What are intelligent systems?

Three key steps of a knowledge-based agent (Craik, 1943):

1. the stimulus (or world or problem space) must be translated into an internal representation
2. the representation is manipulated by cognitive processes to derive new internal representations
3. these in turn are translated into action



Representation

All AI problems require some form of representation.

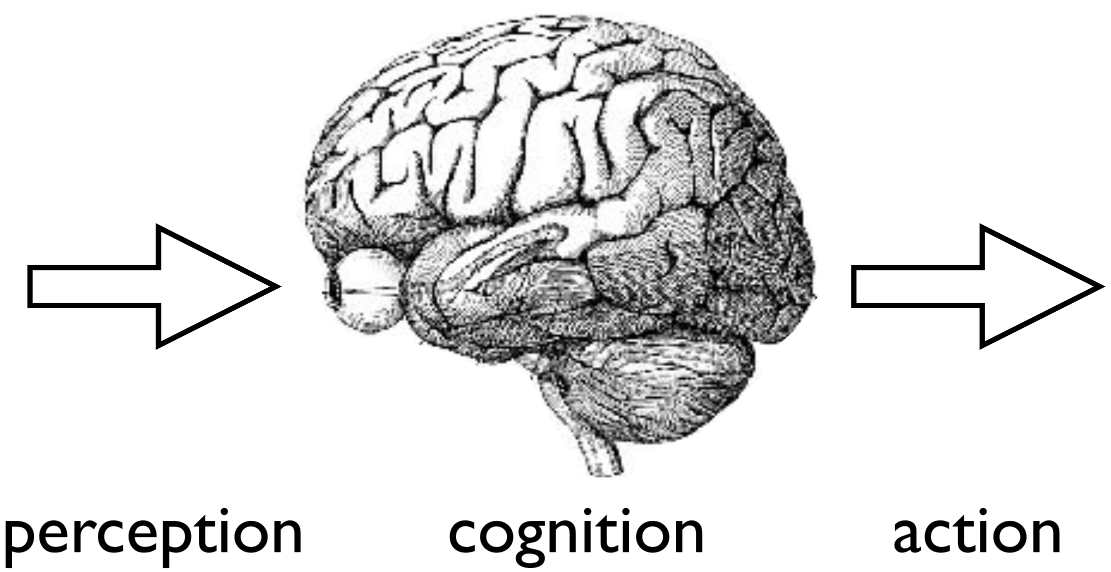
- chess board
- maze
- text
- object
- room
- sound
- visual scene

A major part AI is representing the data space to allow reasoning and inference

Sometimes the representation is the output. E.g., discovering "patterns".

Output

The output action can also be complex.

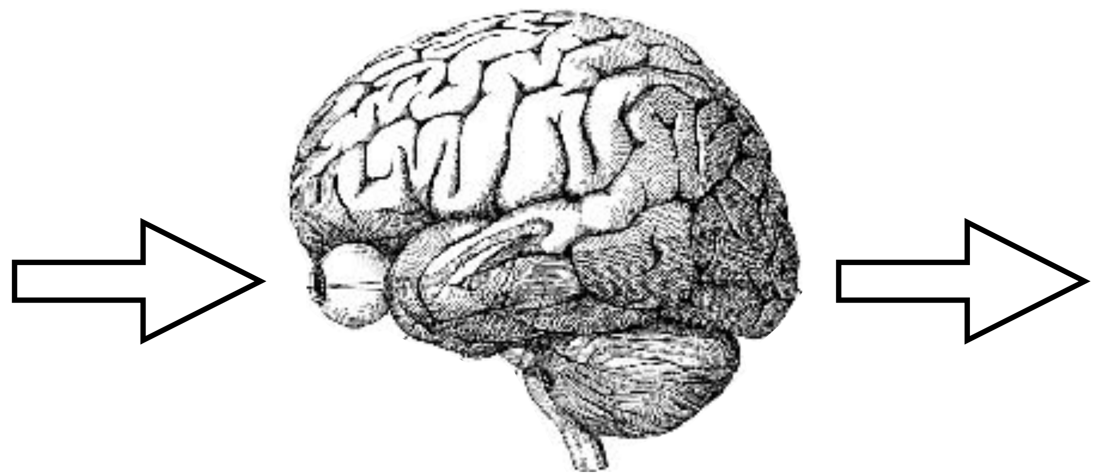


- next move
- text
- label
- actuator
- movement

From a simple chess move to a motor sequence to grasp an object.

Reasoning

Reasoning can be thought of as constructing an accurate world model.



perception   cognition   action

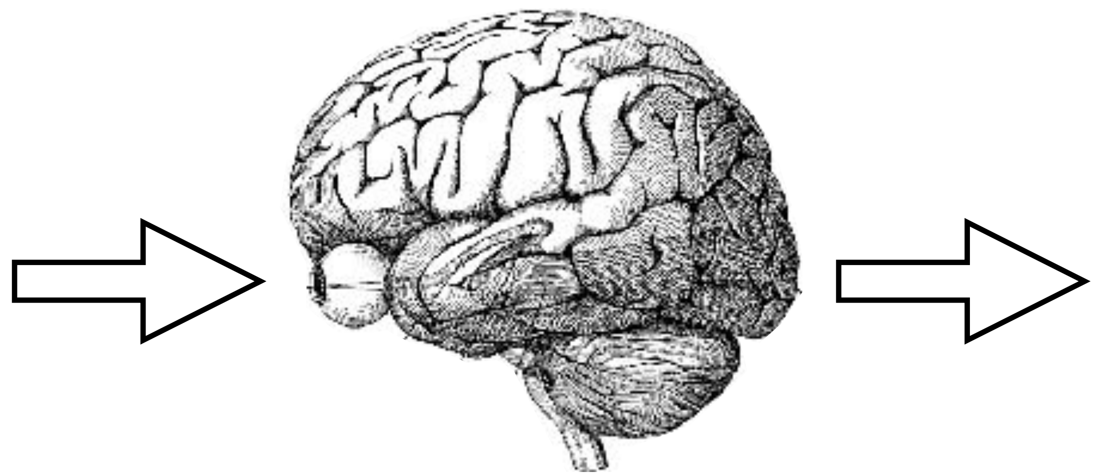
- facts
- observations
- "wet ground"

- logical consequences
- inferences
- "it rained" or "sprinkler" ?

Rational inference:
What can be logically inferred give available information?

Reasoning with uncertain information

Most facts are not concrete and are not known with certainty.



perception   cognition   action

- facts
- observations
- “fever”
- “aches”
- platelet count=N

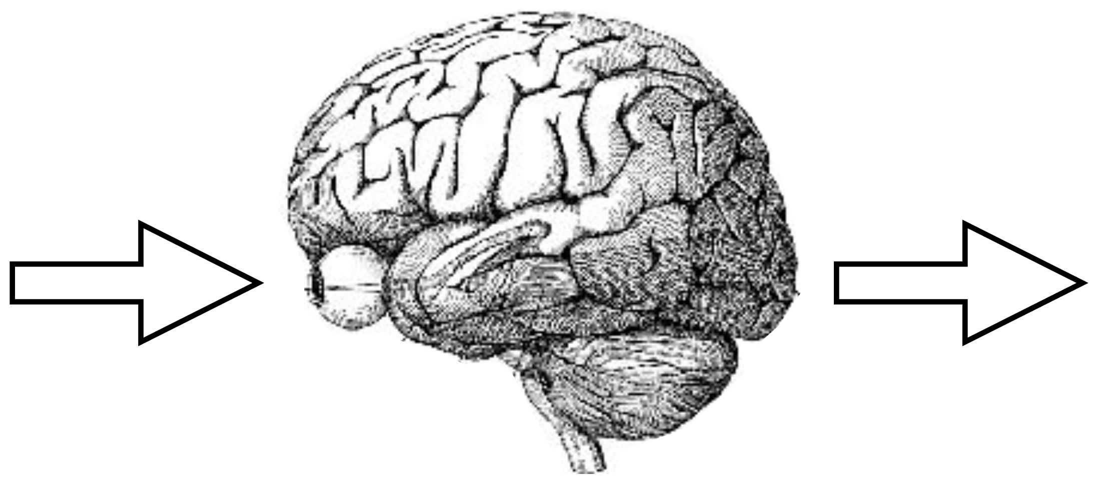
- inferences
- What disease?
- What causes?

Probabilistic inference:
How do we give the proper weight to each observation?

What is ideal?

Learning

What if your world is changing? How do we maintain an accurate model?



perception cognition action

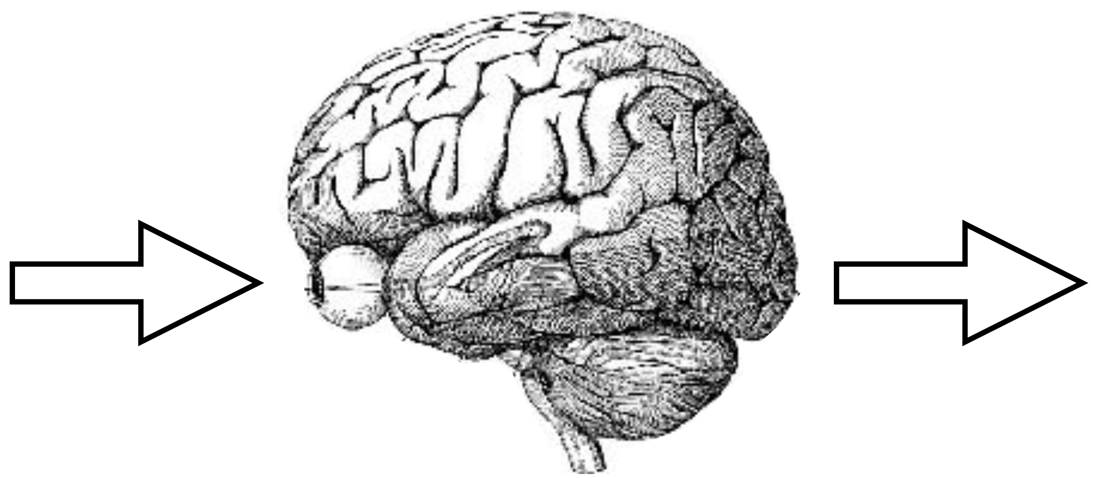
- chess board
- maze
- text
- object
- room
- sound
- visual scene

Learning:
adapt internal representation so that it is as accurate as possible.

Can also adapt our models of other agents.

Thinking

What do you do once you have a representation? This requires a goal.



perception cognition action

- chess board
- maze
- text
- object
- room
- sound
- visual scene

- find best move
- shortest path
- semantic parsing
- recognition
- object localization
- speech recognition
- path navigation

Rational behavior:
choose actions that maximize goal achievement given available information

Where can this go?

- Robotics
- Internet search
- Scheduling
- Planing
- Logistics
- HCI
- Games
- Auction design
- Diagnosis
- General reasoning

In class, we will focus on general methods for problem representation, inference, and learning.

What is the role of probability and inference in AI?

- Many algorithms are designed as if knowledge is perfect, but it rarely is.
- There are almost always things that are unknown, or not precisely known.

- Examples:
  - bus schedule
  - quickest way to the airport
  - sensor networks

- An agent making optimal decisions must take into account *uncertainty*.

Making rational decisions when faced with uncertainty

- *Probability*

  the precise representation of knowledge and uncertainty
- *Probability theory*

  how to optimally update your knowledge based on new information
- *Decision theory: probability theory + utility theory*

  how to use this information to achieve maximum expected utility

- Consider a bus schedule. What's the utility function?
  - Suppose the schedule says the bus comes at 8:05.
  - Situation A: You have a class at 8:30.
  - Situation B: You have a class at 8:30, and it's cold and raining.
  - Situation C: You have a final exam at 8:30.

Probability of uncountable events

- How do we calculate probability that it will rain tomorrow?
  - Look at historical trends?
  - Assume it generalizes?

- What's the probability that there was life on Mars?
- What's the probability that candidate X will win the election?
- What was the probability the sea level will rise 1 meter within the century?

Notebook Sample