Cleanup, Review, and Q/A

Bookkeeping

- **Final exam, 12/20 10:30am-12:30pm, this room.**
- Review Session: this Friday, 12/16, 6pm-8pm
  - If you can't make that time, see posted slides.
- Policy on Student Exam Load: (paraphrased)
  - No more than two final exams in one day. Recommended: alternate arrangements for the **second** exam.
  - If you have an 8:00-10:00 exam **and** something after 12, tell me **soon**.

Exam Topics

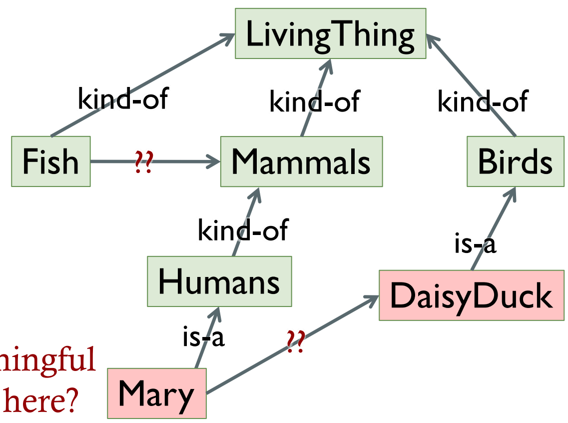
- Multi-Agent Systems
- Knowledge
  - Knowledge-Based Agents
  - Knowledge Representation
  - First-Order Logic
  - Inference
- Planning
  - State spaces
  - PO Planning
  - Probabilistic Planning
- Machine Learning
  - Decision Trees
  - Classification
  - Reinforcement Learning
  - Clustering
  - Bayes' Nets
- Applications
  - Robotics
  - Vision and Deep Learning
  - Natural Language

Knowledge Representation

- Ontologies
  - What would an ontology of "living things" look like?
    - Graphically? As a formal representation?
- Semantic Nets
  - Give an eight-node, nine-arc network about food
    - Graphically? As a formal representation?
- Types of relationships
  - Predicates: return *true* or *false* (a truth value)
  - Functions: return a *value*
  - Common types: is-a, part-of, kind-of, member-of
  - Keep individuals (e.g., Einstein) and groups (e.g., scientists) straight

Ontology: Living Things

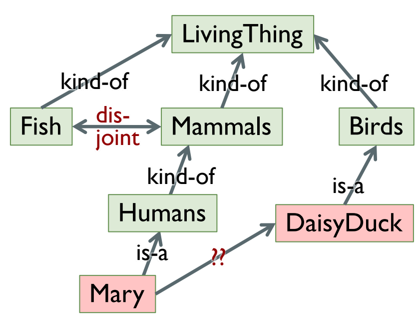
- Ontologies are…
  - Taxonomic
  - Pyramidal (generally)
  - Interconnected
  - Capture semantic (meaningful) relationships
- What other meaningful relationships are here?



Ontology as Text

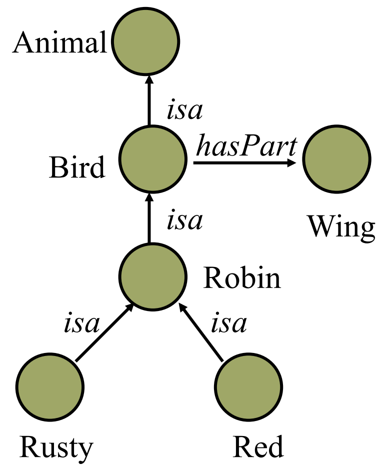
- Statements
  - kind-of(Fish, LivingThing)
  - kind-of(Humans, Mammals)
  - is-a(Mary, Human)
  - is-a(Mammals, Phylum)
  - disjoint(Fish, Mammals)
- Rules
  - disjoint(Fish, Mammals)
  - disjoint(Mammals, Birds) …

    OR…
  - is-a(X,Phylum) ^ is-a(Y,Phylum) ^ (not-equal(X,Y) → disjoint(X,Y)



Semantic Networks

- The ISA (is-a) or AKO (a-kind-of) relation is often used to link instances to classes, classes to superclasses
- Some links (e.g. hasPart) are inherited along ISA paths.
- The semantics of a semantic net can be informal or very formal
  - often defined at the implementation level



Semantic Net: Food

- Give an eight-node, nine-arc network about food.
  - 8 and 9 are minimum

Reasoning and Inference

- Given a formally represented world
  - Agents and their behaviors
  - Goals
  - State spaces
- What is **inference**?
- What kinds of inference can you do?
  - Forward Chaining
  - Backward Chaining

Forward Chaining

sneeze(Lise) ← infer truth of (query)

- Find and apply relevant rules

variable binding

cat(Y) ∧ allergic-cats(X) → allergies(X) ∧ cat(Felix)

→

cat(Felix) ∧ allergic-cats(X) → allergies(X) ∧ allergic-cats(Lise)

→

allergies(Lise) ∧ allergies(X) → sneeze(X)

→

sneeze(Lise) ✓

add new sentence to KB

Knowledge Base

1. Allergies lead to sneezing.
   allergies(X) → sneeze(X)
2. Cats cause allergies if allergic to cats.
   cat(Y) ∧ allergic-cats(X) → allergies(X)
3. Felix is a cat.
   cat(Felix)
4. Lise is allergic to cats.
   allergic-cats(Lise)

Last Time: Inference

Knowledge Base

1. Allergies lead to sneezing.
   allergies(X) → sneeze(X)
2. Cats cause allergies if allergic to cats.
   cat(Y) ∧ allergic-cats(X) → allergies(X)
3. Felix is a cat.
   cat(Felix)
4. Lise is allergic to cats.
   allergic-cats(Lise)

sneeze(Lise) ← query

- Backward Chaining: apply rules that end with the goal

variable binding

allergies(X) → sneeze(X) + sneeze(Lise)
new query: allergies(Lise)?

cat(Y) ∧ allergic-cats(X) → allergies(X) + allergies(Lise)
new query: cat(Y) ∧ allergic-cats(Lise)?

cat(Felix) + cat(Y) ∧ allergic-cats(Lise)
new sentence: cat(Felix) ∧ allergic-cats(Lise) ✓

Uses of Inference

- Ontologies
  - Conclude new information
  - Sanity check
- Semantic Networks
  - Conclude new information
  - Build out network
  - Maintain probabilities
- Planning

Planning

- Classical Planning
- Partial-order planning
- Probabilistic planning

Planning Problem

- Find a **sequence of actions** [operations] that achieves a **goal** when executed from the **initial world state**.
- That is, given:
  - A set of operator descriptions (possible primitive actions by the agent)
  - An initial state description
  - A goal state (description or predicate)
- Compute a **plan**, which is
  - A sequence of operator instances [**operations**]
  - Executing them in initial state → state satisfying description of goal-state

With "Situations"

- **Initial state** and **Goal state** with explicit situations

  At(Home, S_0) ∧ ¬Have(Milk, S_0) ∧ ¬Have(Bananas, S_0) ∧ ¬Have(Drill, S_0)

  (∃s) At(Home,s) ∧ Have(Milk,s) ∧ Have(Bananas,s) ∧ Have(Drill,s)

- **Operators:**

  ∀(a,s) Have(Milk,Result(a,s)) ⇔
  ((a=Buy(Milk) ∧ At(Grocery,s)) ∨
  (Have(Milk, s) ∧ a ≠ Drop(Milk)))

  ∀(a,s) Have(Drill,Result(a,s)) ⇔
  ((a=Buy(Drill) ∧ At(HardwareStore,s)) ∨
  (Have(Drill, s) ∧ a ≠ Drop(Drill)))

With Implicit Situations

- **Initial state**

  At(Home) ∧ ¬Have(Milk) ∧ ¬Have(Bananas) ∧ ¬Have(Drill)

- **Goal state**

  At(Home) ∧ Have(Milk) ∧ Have(Bananas) ∧ Have(Drill)

- **Operators:**

  Have(Milk) ⇔
  ((a=Buy(Milk) ∧ At(Grocery)) ∨ (Have(Milk) ∧ a ≠ Drop(Milk)))

  Have(Drill) ⇔
  ((a=Buy(Drill) ∧ At(HardwareStore)) ∨ (Have(Drill) ∧ a ≠ Drop(Drill)))

Planning as Inference

At(Home) ∧ ¬Have(Milk) ∧ ¬Have(Drill)
At(Home) ∧ Have(Milk) ∧ Have(Drill)

- Knowledge Base for MilkWorld
  - What do we have? Not have?
  - How does one "have" things? (2 rules recommended)
  - Where are drills sold?
  - Where is milk sold?
  - What actions do we have available?

Planning as Inference

At(Home) ∧ ¬Have(Milk) ∧ ¬Have(I
At(Home) ∧ Have(Milk) ∧ Have(Dril

- Knowledge Base for MilkW
  - What do we have? Not have?
  - How does one "have" things? (
  - Where are drills sold?
  - Where is milk sold?
  - What actions do we have avail

<u>Knowledge Base</u>

1. We're currently home.
2. We don't have anything.
3. One has things when they are bought at *appropriate* places.
4. One has things one already has and hasn't dropped.
5. Hardware stores sell drills.
6. Groceries sell milk.
7. Our actions are:

Inference

- What two things do we combine first (by number)?
  - How about 1 and 7(a)?
  - action 1 = Go(GS)
  - action 2 = Buy(Drill)
- What then changes in the knowledge base?
  - ¬At(X)
  - At(GS)

And so on…

Knowledge Base

1. We're currently home.
   At(Home)
2. We don't have anything.
   ¬Have(Drill)
   ¬Have(Milk)
3. One has things when they are bought at *appropriate* places.
   Have(X) ⇔
   (At(Y) ∧ (Sells(X,Y) ∧ (a=Buy(X))
4. You have things you already have and haven't dropped.
   (Have(X) ∧ a ≠ Drop(X)))
5. Hardware stores sell drills.
   (Sells(Drill,HWS)
6. Groceries sell milk.
   (Sells(Milk,GS)
7. Our actions are:
   At(X) ∧ Go(Y) => At(Y) ∧ ¬At(X)
   Drop(X) => ¬Have(X)
   Buy(X) [defined above]

Partial-Order Planning

Partial-Order Planning

- A **linear planner** builds a plan as a **totally ordered sequence** of plan steps
- A **non-linear planner (aka partial-order planner)** builds up a plan as a set of steps with some temporal constraints
  - E.g., S1<S2 (step S1 must come before S2)
- Partially ordered plan (POP) **refined** by either:
  - adding a new **plan step**, or
  - adding a new **constraint** to the steps already in the plan.
- A POP can be **linearized** (converted to a totally ordered plan) by topological sorting*

* from search - *R&N 223*

Non-Linear Plan: Steps

- A non-linear plan consists of

  (1) A set of **steps** $\{S_1, S_2, S_3, S_4 \ldots\}$

  Each step has an **operator description**, **preconditions** and **post-conditions**

  (2) A set of **causal links** $\{ \ldots (S_i,C,S_j) \ldots\}$

  (One) goal of step S_i is to achieve precondition C of step S_j

  (3) A set of **ordering constraints** $\{ \ldots S_i<S_j \ldots \}$

  if step S_i must come before step S_j

Back to Milk World…

- Actions:
  1. Go(GS)
  2. Buy(Milk)
  3. Go(HWS)
  4. Buy(Drill)
  5. Go(Home)
- Does ordering matter?

Knowledge Base

1. We're currently home.
   At(Home) ← this was not true throughout!
2. We have milk and a drill.
   Have(Drill)
   Have(Milk)

None of these has changed.

3. One has things when they are bought at *appropriate* places.
   Have(X) ⇔
   (At(Y) ∧ (Sells(X,Y) ∧ (a=Buy(X))
4. You have things you already have and haven't dropped.
   (Have(X) ∧ a ≠ Drop(X)))
5. Hardware stores sell drills.
   (Sells(Drill,HWS)
6. Groceries sell milk.
   (Sells(Milk,GS)
7. Our actions are:
   At(X) ∧ Go(Y) => At(Y) ∧ ¬At(X)
   Drop(X) => ¬Have(X)
   Buy(X) [defined above]

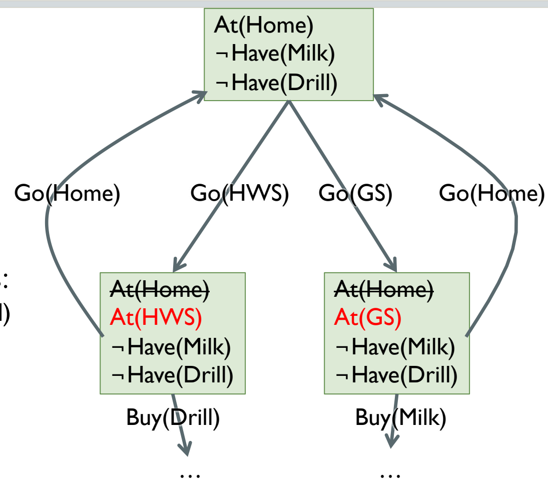
Specifying Steps and Constraints

- Go(X)
  - Preconditions: ¬At(X)
  - Postconditions: At(X)
- Buy(T)
  - Preconditions: At(Z) ^ Sells(T, Z)
  - Postconditions: Have(T)
- Causal Links: Go(X) → At(X)
- Ordering Constraints: Go(X) < At(X)

Eventually…

1. Go(GS)
2. Buy(Milk)
3. Go(HWS)
4. Buy(Drill)
5. Go(Home)

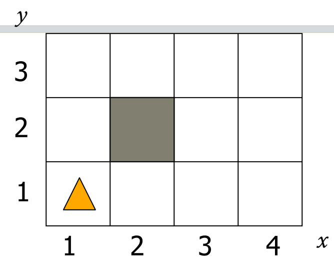
- Ordering is not strict.
- Go(HWS) preconditions:
  - ¬At(HWS) ^ ¬Have(Drill)
- So, 1<2, 3<4
- How many non-loopy paths – i.e., plans?



Probabilistic Planning

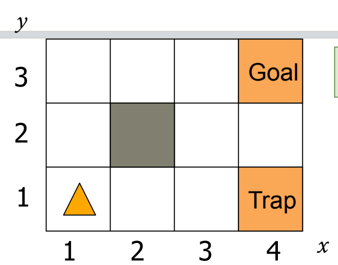
- Core idea: instead of actions having single effects:
  - a1: A → B   a2: B → C
- Actions have possible effect**s**, requiring a table:
  - a1: A → B: 80%   a2: B → C: 80%
  - a1: A → A: 20%   a2: B → B: 20%
- At each plan step, propagate probabilities forward
  - Where am I now, **with what probability?**

Transition Model in Practice



- In each state, the possible actions are U, D, R, and L
- The effect of U is as follows (transition model):
  - With probability 0.8, the robot moves up one square (if the robot is already in the top row, then it does not move)
  - With probability 0.1, the robot moves right one square (if the robot is already in the rightmost row, then it does not move)
  - With probability 0.1, the robot moves left one square (if the robot is already in the leftmost row, then it does not move)
- D, R, and L have similar probabilistic effects

Transition Model in Practice



- In each state, possible actions are U, D, R, and L
- The transition model) of U is:
  - up: 0.8
  - left: 0.1
  - right: 0.1
- D, R, and L have similar probabilistic effects

Plan: U, U, R, R, R

- Where am I?
  - Step 1: (1,2): 0.8   (1,1): 0.1   (2,1): 0.1
  - Step 2: (1,2) → (1,3): 0.8
    (1,2) → (1,2): 0.1
    (1,2) → (1,2): 0.1
    (1,1) → (1,1): 0.1
    (1,1) → (1,2): 0.8
    (1,1) → (2,1): 0.1
    …
- Now: What are the odds I'm at 1,3? 1,2?

What does that mean?

- We must evaluate each sequence of actions
  - "Utility"
- Based on what we believe about events
  - But we can replan throughout
- In practice, we define (or learn) a *policy*.
  - I'm at X. What's best at X?
    - And does it matter how I got there? No – this is a Markovian problem.
- Value Iteration?
  - 17.13, 17.17

Machine Learning

- Supervised vs. Unsupervised
  - What is classification?
  - What is clustering?
  - Exploitation v. Exploration
  - K-Means, EM, and failure modes

Reinforcement Learning

- **Reinforcement learning systems**
  - Learn **series** of actions or decisions, rather than a single decision
  - Based on feedback given at the end of the series
- A reinforcement learner has
  - A goal
  - Carries out trial-and-error search
  - Finds the best paths toward that goal

Reinforcement Learning

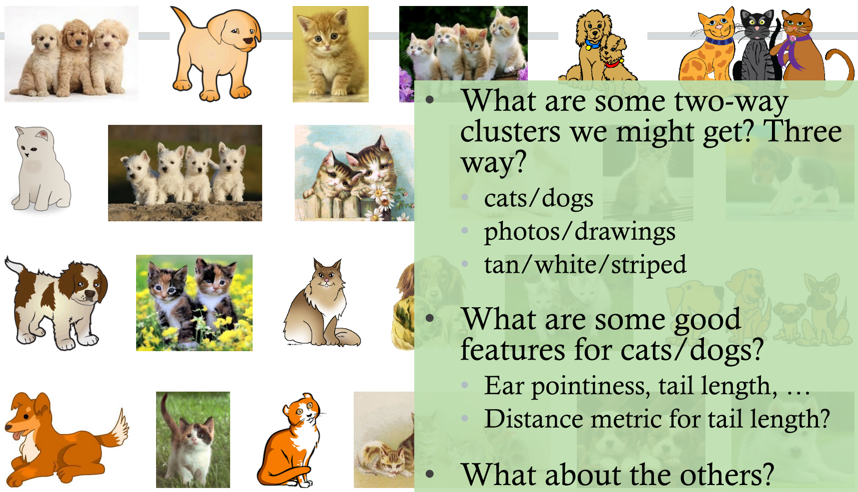
- A typical reinforcement learning system is an active agent, interacting with its environment.
- It must balance
  - Exploration: trying different actions and sequences of actions to discover which ones work best
  - Exploitation (achievement): using sequences which have worked well so far
- Must learn **successful sequences of actions** in an uncertain environment

Clustering

- Given some instances with examples
  - But no labels!
  - Unsupervised learning — the instances do not include a "class"
- Group instances such that:
  - Examples within a group (cluster) are similar
  - Examples in different groups (cluster) are different
- According to some *measure of similarity*, or **distance metric**.
  - Finding the right **features** and **distance metric** are important!

Example

Example

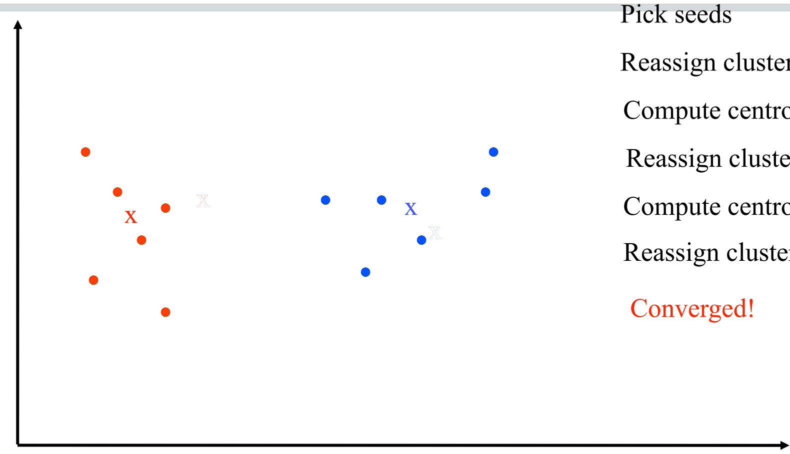


- What are some two-way clusters we might get? Three way?
  - cats/dogs
  - photos/drawings
  - tan/white/striped
- What are some good features for cats/dogs?
  - Ear pointiness, tail length, …
  - Distance metric for tail length?
- What about the others?

K-Means Clustering

- Provide number of desired clusters, k.
- Randomly choose k instances as seeds.
- Form initial clusters based on these seeds.
- Calculate the centroid of each cluster.
- Iterate, repeatedly reallocating instances to closest centroids and calculating the new centroids
- Stop when clustering converges or after a fixed number of iterations.

K Means Example (K=2)



Pick seeds

Reassign clusters

Compute centroids

Reassign clusters

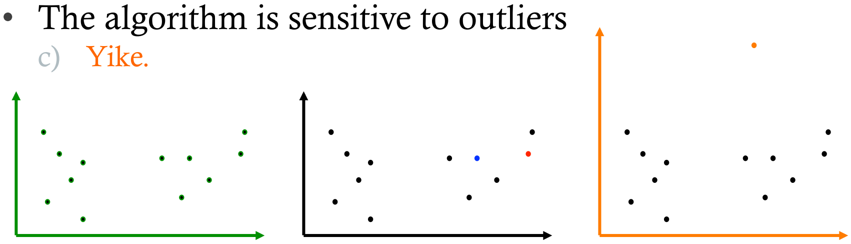
Compute centroids

Reassign clusters

Converged!

K-Means

- Tradeoff: more clusters (better focused clusters) and too many clusters (overfitting)
  a) What would we likely get for 3 clusters? 4?
- Results can vary based on random seed selection
  b) What if these were our starting points?
- The algorithm is sensitive to outliers
  c) Yike.



(a) (b) (c)

EM Summary

- Basically a probabilistic K-Means.
- Has many of same advantages and disadvantages
  - Results are easy to understand
  - Have to choose k ahead of time
- Useful in domains where we would prefer the likelihood that an instance can belong to more than one cluster
  - Natural language processing for instance