CS 188: Artificial Intelligence
Spring 2010

Lecture 13: Probability
3/2/2010

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Many slides adapted from Dan Klein.

Announcements

- Upcoming
  - **new** Tomorrow/Wednesday: probability review session
    - 7:30-9:30pm in 306 Soda
  - P3 due on Thursday (3/4)
  - W4 going out on Thursday, due next week Thursday (3/11)
  - Midterm in evening of 3/18

Today

- We're almost done with search and planning!
  - MDP's: policy search wrap-up
- Next, we'll start studying how to reason with probabilities
  - Diagnosis
  - Tracking objects
  - Speech recognition
  - Robot mapping
  - … lots more!
- Third part of course: machine learning

Policy Search

MDPs recap

- MDP recap: (S, A, T, R, s_0, γ)

  distance from target * (-1)

  $\in \mathbb{R}^{12}$ $\in \mathbb{R}^4$ physics $\in (0,1)$
  - In small MDPs: can find V(s) and/or Q(s,a)
    - Known T, R: value iteration, policy iteration
    - Unknown T, R: Q learning
  - In large MDPs: cannot enumerate all states

Function Approximation

$$Q(s,a) = w_1 f_1(s,a) + w_2 f_2(s,a) + \ldots + w_n f_n(s,a)$$

- Q-learning with linear q-functions:

  $transition = (s,a,r,s')$

  difference $= \left[r + \gamma \max_{a'} Q(s',a')\right] - Q(s,a)$

  $Q(s,a) \leftarrow Q(s,a) + \alpha$ [difference] Exact Q's

  $w_i \leftarrow w_i + \alpha$ [difference] $f_i(s,a)$ Approximate Q's
- Intuitive interpretation:
  - Adjust weights of active features
  - E.g. if something unexpectedly bad happens, disprefer all states with that state's features
- Formal justification: online least squares

Policy Search Idea

- Problem: often the feature-based policies that work well aren't the ones that approximate V / Q best
- Solution: learn the policy that maximizes rewards rather than the value that predicts rewards

$\pi(s) = \arg\max_a \sum_i w_i f_i(s,a)$

- This is the idea behind policy search, such as what controlled the upside-down helicopter

Policy search

Init weights as $w^{(0)}$ random

$V^{(0)} = \text{Evaluate}(w^{(0)})$

For $j = 1 : \text{num\_iters}$

$w^{(j)} = w^{(j-1)} +$ small perturbation

$V^{(j)} := \text{Evaluate}(w^{(j)})$

if $(V^{(j)} > V^{(j-1)})$

"keep"

else

$V^{(j)} = V^{(j-1)}$

$w^{(j)} = w^{(j-1)}$

→ "pegasus" Ng & Jordan

Run K simulations and return average of sum of accumulated rewards

Policy Search

- Simplest policy search: $\{w_i\}$
  - Start with an initial linear value function or Q-function
  - Nudge each feature weight up and down and see if your policy is better than before
- Problems:
  - How do we tell the policy got better?
  - Need to run many sample episodes!
  - If there are a lot of features, this can be impractical

→ Mostly applicable when prior knowledge allows one to choose a representation with a very small number of free parameters to be learned

Toddler (Tedrake et al.)

Take a Deep Breath…

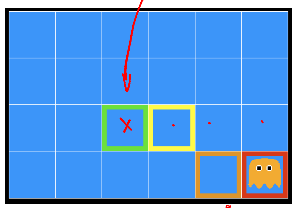
- We're done with search and planning!
- Next, we'll look at how to reason with probabilities
  - Diagnosis
  - Tracking objects
  - Speech recognition
  - Robot mapping
  - … lots more!
- Third part of course: machine learning

Today

- Probability
  - Random Variables
  - Joint and Marginal Distributions
  - Conditional Distribution
  - Product Rule, Chain Rule, Bayes' Rule
  - Inference
  - Independence
- You'll need all this stuff A LOT for the next few weeks, so make sure you go over it now!
- **Probability review session tomorrow 7:30-9:30pm in 306 Soda --- you will benefit from it for many lectures/assignments/exam questions if any of the material we are about to go over today is not completely trivial!!**

Inference in Ghostbusters

- A ghost is in the grid somewhere
- Sensor readings tell how close a square is to the ghost
  - On the ghost: red
  - 1 or 2 away: orange
  - 3 or 4 away: yellow
  - 5+ away: green

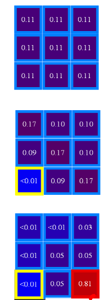


- Sensors are noisy, but we know P(Color | Distance)

P(red | 3)	P(orange | 3)	P(yellow | 3)	P(green | 3)
0.05	0.15	0.5	0.3

Uncertainty

- General situation:
  - **Evidence**: Agent knows certain things about the state of the world (e.g., sensor readings or symptoms)
  - **Hidden variables**: Agent needs to reason about other aspects (e.g. where an object is or what disease is present)
  - **Model**: Agent knows something about how the known variables relate to the unknown variables
- Probabilistic reasoning gives us a framework for managing our beliefs and knowledge



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Random Variables

- A random variable is some aspect of the world about which we (may) have uncertainty
  - R = Is it raining?
  - D = How long will it take to drive to work?
  - L = Where am I?
- We denote random variables with capital letters
- Like variables in a CSP, random variables have domains
  - R in {true, false} (sometimes write as {+r, ¬r})
  - D in [0, ∞)
  - L in possible locations, maybe {(0,0), (0,1), …}

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Probability Distributions

- Unobserved random variables have distributions

$P(T)$

T	P
warm	0.5
cold	0.5

0.5+0.5=1.0
0.5 ≥ 0

$P(W)$

W	P
sun	0.6
rain	0.1
fog	0.3
meteor	0.0

- A distribution is a TABLE of probabilities of values
- A probability (lower case value) is a single number

$P(W = rain) = 0.1$ $\quad P(rain) = 0.1$ $\quad P(r)=0.1$

- Must have: $\forall x \; P(x) \geq 0$ $\quad \sum_x P(x) = 1$

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Joint Distributions

- A *joint distribution* over a set of random variables: $X_1, X_2, \ldots X_n$ specifies a real number for each assignment (or *outcome*):

$$P(X_1 = x_1, X_2 = x_2, \ldots X_n = x_n)$$
$$P(x_1, x_2, \ldots x_n)$$

n=2, d=2

$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

- Size of distribution if n variables with domain sizes d? d^n
- Must obey:

$$P(x_1, x_2, \ldots x_n) \geq 0$$
$$\sum_{(x_1, x_2, \ldots x_n)} P(x_1, x_2, \ldots x_n) = 1$$

- For all but the smallest distributions, impractical to write out

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Probabilistic Models

- A probabilistic model is a joint distribution over a set of random variables
- Probabilistic models:
  - (Random) variables with domains
  - Assignments are called *outcomes*
  - Joint distributions: say whether assignments (outcomes) are likely
  - *Normalized:* sum to 1.0
  - Ideally: only certain variables directly interact
- Constraint satisfaction probs:
  - Variables with domains
  - Constraints: state whether assignments are possible
  - Ideally: only certain variables directly interact

Distribution over T,W

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

Constraint over T,W

T	W	P
hot	sun	T
hot	rain	F
cold	sun	F
cold	rain	T

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Events

- An *event* is a set E of outcomes

$$P(E) = \sum_{(x_1 \ldots x_n) \in E} P(x_1 \ldots x_n)$$

- From a joint distribution, we can calculate the probability of any event
  - Probability that it's hot AND sunny? $= 0.4$
  - Probability that it's hot? $= P(T=hot, W=sun) + P(T=hot, W=rain) = 0.4 + 0.1 = 0.5$
  - Probability that it's hot OR sunny? $= P(h,s) + P(h,r) + P(c,s) = 0.4 + 0.1 + 0.2 = 0.7$
- Typically, the events we care about are *partial assignments*, like P(T=hot)

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

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Marginal Distributions

- Marginal distributions are sub-tables which eliminate variables
- Marginalization (summing out): Combine collapsed rows by adding

$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

$$P(t) = \sum_s P(t, s)$$

$P(T)$

T	P
hot	0.5
cold	0.5

$$P(s) = \sum_t P(t, s)$$

$P(W)$

W	P
sun	0.6
rain	0.4

$$P(X_1 = x_1) = \sum_{x_2} P(X_1 = x_1, X_2 = x_2)$$

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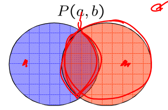
Conditional Probabilities

- A simple relation between joint and conditional probabilities
  - In fact, this is taken as the *definition* of a conditional probability

$$P(a|b) = \frac{P(a,b)}{P(b)}$$



$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

$P(W = r | T = c) = ???$

$$\frac{P(W=r, T=c)}{P(T=c)} = \frac{P(W=r, T=c)}{P(T=c, W=r) + P(T=c, W=s)} = \frac{0.3}{0.3 + 0.2} = \frac{0.3}{0.5} = .6$$

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Conditional Distributions

- Conditional distributions are probability distributions over some variables given fixed values of others

Conditional Distributions

$P(W|T)$

$P(W|T = hot)$

W	P
sun	0.8
rain	0.2

$P(W|T = cold)$

W	P
sun	0.4
rain	0.6

Joint Distribution

$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

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Normalization Trick

- A trick to get a whole conditional distribution at once:
  - Select the joint probabilities matching the evidence
  - Normalize the selection (make it sum to one)

$P(T, W)$

T	W	P
hot	sun	0.4
hot	rain	0.1
cold	sun	0.2
cold	rain	0.3

Select

unnormalized table

$P(T, r)$

T	R	P
hot	rain	0.1
cold	rain	0.3

Normalize

$P(T|r)$

T	P
hot	0.25
cold	0.75

$$P(h|r) = \frac{P(h,r)}{P(h,r) + P(c,r)}$$

- Why does this work? Sum of selection is P(evidence)! (P(r), here)

$$P(x_1|x_2) = \frac{P(x_1, x_2)}{P(x_2)} = \frac{P(x_1, x_2)}{\sum_{x_1} P(x_1, x_2)}$$

$$P(c|r) = \frac{P(c,r)}{P(h,r) + P(c,r)}$$

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