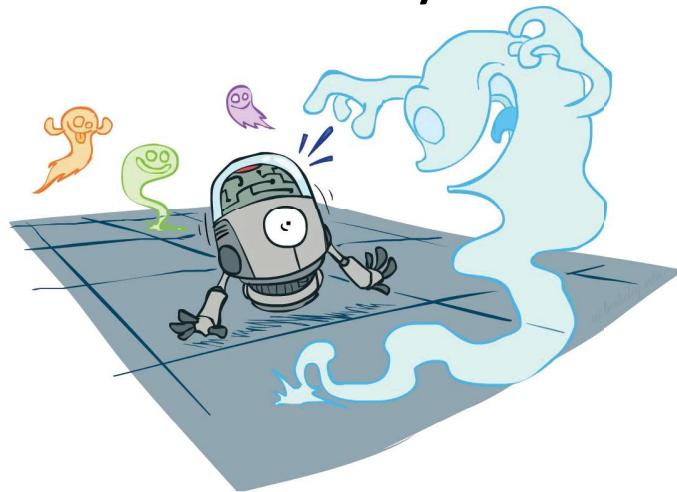


CS 188: Artificial Intelligence

Probability

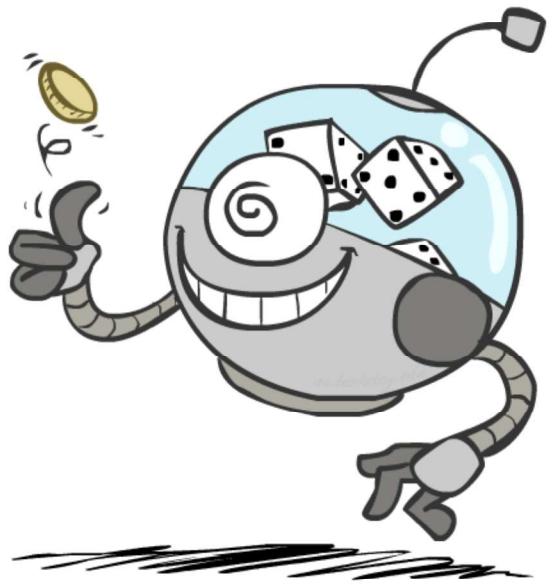


[These slides were created by Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley. All CS188 materials are available at <http://ai.berkeley.edu>.]

Today

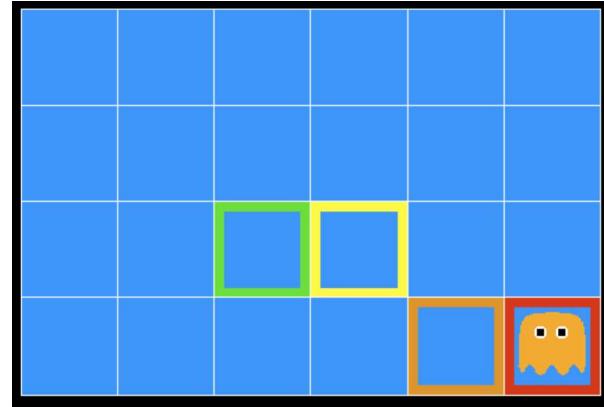
- Probability
 - Random Variables
 - Joint and Marginal Distributions
 - Conditional Distribution
 - Product Rule, Chain Rule, Bayes' Rule
 - Inference by Enumeration

- You'll need all this stuff A LOT for the next few weeks, so make sure you go over it now!



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 $P(\text{Color} \mid \text{Distance})$



$P(\text{red} \mid 3)$	$P(\text{orange} \mid 3)$	$P(\text{yellow} \mid 3)$	$P(\text{green} \mid 3)$
0.05	0.15	0.5	0.3

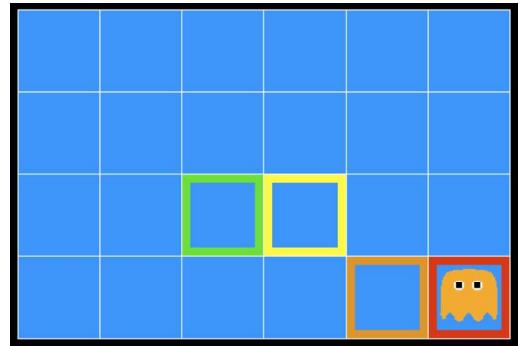
[Demo: Ghostbuster – no probability (L12D1)]

Video of Demo Ghostbuster – No probability



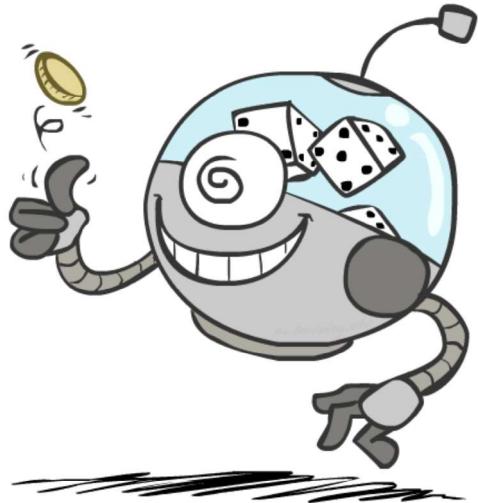
Uncertainty

- General situation:
 - **Observed variables (evidence):** Agent knows certain things about the state of the world (e.g., sensor readings or symptoms)
 - **Unobserved 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 and inference gives us a framework for managing our beliefs and knowledge



Random Variables

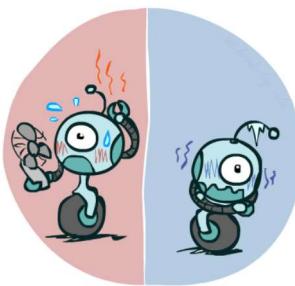
- A **random variable** is some aspect of the world about which we (may) have uncertainty
 - **R** = Is it raining?
 - **T** = Is it hot or cold?
 - **D** = How long will it take to drive to work?
 - **L** = Where is the ghost?
- We denote random variables with capital letters
- Like variables in a CSP, random variables have **domains**
 - **R** in {true, false} (often write as {+r, -r})
 - **T** in {hot, cold}
 - **D** in $[0, \infty)$
 - **L** in possible locations, maybe {(0,0), (0,1), ...}



Probability Distributions

- Associate a probability with each **value** of that **random variable**

- Temperature:



$P(T)$

T	P
hot	0.5
cold	0.5

- Weather:



$P(W)$

W	P
sun	0.6
rain	0.1
fog	0.3
meteor	0.0

Probability Distributions

- Unobserved **random variables** have distributions

T	P
hot	0.5
cold	0.5

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 (of a **lower case value**) is a single number:

$$P(W = \text{rain}) = 0.1$$

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

Shorthand notation:

$P(\text{hot})$ same as $P(T = \text{hot})$

$P(\text{cold})$ same as $P(T = \text{cold})$

$P(\text{rain})$ same as $P(W = \text{rain})$

...

OK if all domain entries are unique

Joint Distributions

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

$$P(X_1 = x_1, X_2 = x_2, \dots, X_N = x_N)$$

$$P(x_1, x_2, \dots, x_N)$$

$$P(T, W)$$

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

- Must obey: $P(x_1, x_2, \dots, x_n) \geq 0$

$$\sum_{(x_1, x_2, \dots, x_n)} P(x_1, x_2, \dots, x_n) = 1$$

- Size of distribution if n variables with domain sizes d?

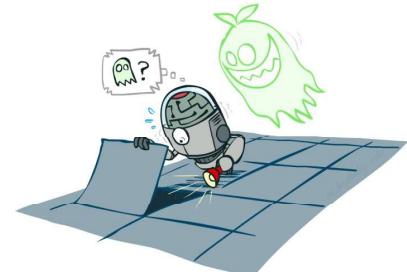
- For all but the smallest distributions, impractical to write out!

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 problems:**
 - Variables with domains
 - Constraints: state whether assignments are possible
 - Ideally: only certain variables directly interact

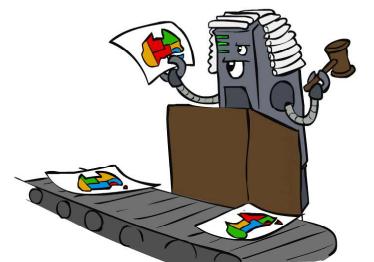
Distribution over T,W

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



Events

- An event is a set E of outcomes

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

- From a joint distribution, we can calculate the probability of any event

- Probability that it's hot AND sunny?
- Probability that it's hot?
- Probability that it's hot OR sunny?

$$P(T, W)$$

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

- Typically, the events we care about are *partial assignments*, like $P(T=\text{hot})$

Quiz: Events

■ $P(+x, +y) ?$

$P(X, Y)$

■ $P(+x) ?$

■ $P(-y \text{ OR } +x) ?$

X	Y	P
+x	+y	0.2
+x	-y	0.3
-x	+y	0.4
-x	-y	0.1

Quiz: Events

- $P(+x, +y) ?$ 0.2
- $P(+x) ?$ $0.2 + 0.3 = 0.5$
- $P(-y \text{ OR } +x) ?$ $0.1 + 0.3 + 0.2 = 0.6$

$P(X, Y)$

X	Y	P
+x	+y	0.2
+x	-y	0.3
-x	+y	0.4
-x	-y	0.1

Marginal Distributions

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

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

$$P(T) = \sum_w P(t, w)$$

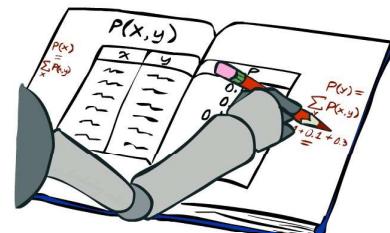
T	P
hot	0.5
cold	0.5

$$P(W) = \sum_t P(t, w)$$

W	P
sun	0.6
rain	0.4

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

hidden (unobserved) variables



Quiz: Marginal Distributions

X	Y	P
+x	+y	0.2
+x	-y	0.3
-x	+y	0.4
-x	-y	0.1

$$P(x) = \sum_y P(x, y)$$

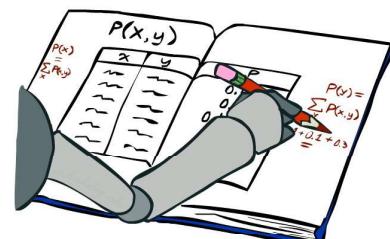
→

$$P(y) = \sum_x P(x, y)$$

→

X	P
+x	
-x	

Y	P
+y	
-y	



Quiz: Marginal Distributions

X	Y	P
+x	+y	0.2
+x	-y	0.3
-x	+y	0.4
-x	-y	0.1

$$P(x) = \sum_y P(x, y)$$

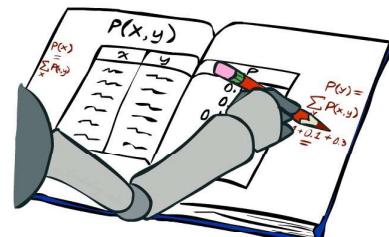
→

$$P(y) = \sum_x P(x, y)$$

→

X	P
+x	0.5
-x	0.5

Y	P
+y	0.6
-y	0.4



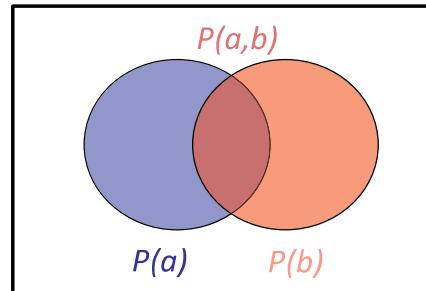
Conditional Probabilities

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

evidence

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

query = (proportion of b where a holds)



Conditional Probabilities

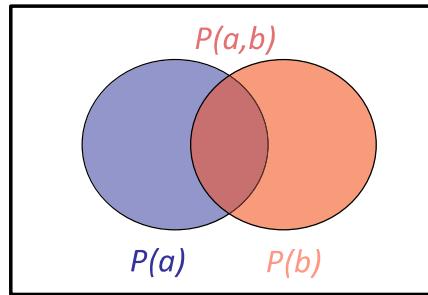
- A simple relation between joint and conditional probabilities
 - In fact, this is taken as the *definition* of a conditional probability

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

= (proportion of b where a holds)

$P(T, W)$

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



$$P(W = s | T = c) = \frac{P(W = s, T = c)}{P(T = c)} = \frac{0.2}{0.5} = 0.4$$

$$= P(W = s, T = c) + P(W = r, T = c)$$

$$= 0.2 + 0.3 = 0.5$$

Quiz: Conditional Probabilities

- $P(+x \mid +y) ?$

$$P(X, Y)$$

X	Y	P
+x	+y	0.2
+x	-y	0.3
-x	+y	0.4
-x	-y	0.1

- $P(-x \mid +y) ?$

- $P(-y \mid +x) ?$

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

Quiz: Conditional Probabilities

■ $P(+x \mid +y) ?$ $0.2 / 0.6 = 1/3$

$P(X, Y)$

X	Y	P
+x	+y	0.2
+x	-y	0.3
-x	+y	0.4
-x	-y	0.1

■ $P(-x \mid +y) ?$ $0.4 / 0.6 = 2/3$

■ $P(-y \mid +x) ?$ $0.3 / 0.5 = 3/5$

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

Conditional Distributions

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

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

Conditional Distributions

$$P(W|T = \text{hot})$$

W	P
sun	0.8
rain	0.2

$$P(W|T = \text{cold})$$

W	P
sun	0.4
rain	0.6

$P(W|T)$

Joint Distribution

$$P(T, W)$$

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

Normalization Trick

$P(T, W)$

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

$$\begin{aligned}
 P(W = s|T = c) &= \frac{P(W = s, T = c)}{P(T = c)} \\
 &= \frac{P(W = s, T = c)}{P(W = s, T = c) + P(W = r, T = c)} \\
 &= \frac{0.2}{0.2 + 0.3} = 0.4
 \end{aligned}$$

$P(W|T = c)$

W	P
sun	0.4
rain	0.6

$$\begin{aligned}
 P(W = r|T = c) &= \frac{P(W = r, T = c)}{P(T = c)} \\
 &= \frac{P(W = r, T = c)}{P(W = s, T = c) + P(W = r, T = c)} \\
 &= \frac{0.3}{0.2 + 0.3} = 0.6
 \end{aligned}$$

Normalization Trick

$$\begin{aligned}
 P(W = s|T = c) &= \frac{P(W = s, T = c)}{P(T = c)} \\
 &= \frac{P(W = s, T = c)}{P(W = s, T = c) + P(W = r, T = c)} \\
 &= \frac{0.2}{0.2 + 0.3} = 0.4
 \end{aligned}$$

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

SELECT the joint probabilities matching the evidence

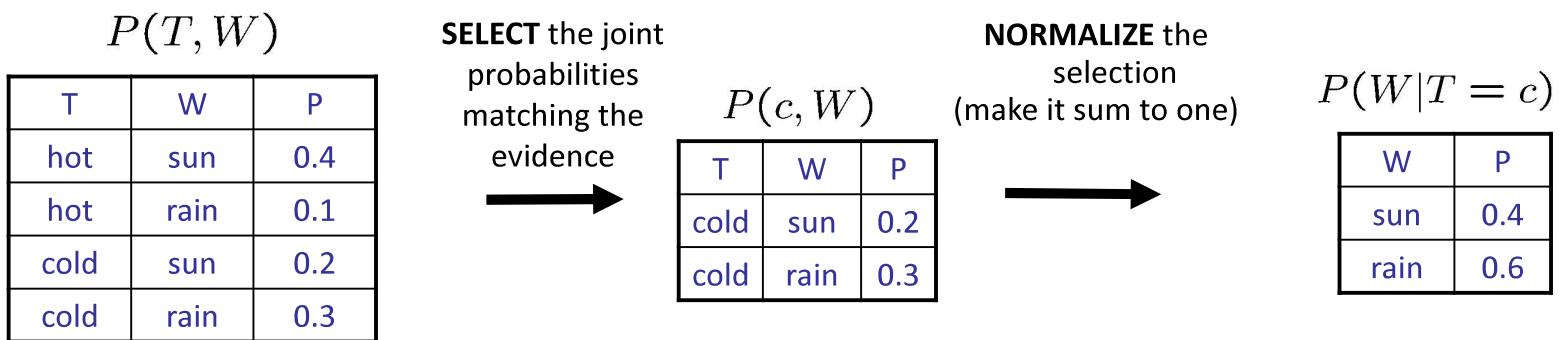
T	W	P
cold	sun	0.2
cold	rain	0.3

NORMALIZE the selection
(make it sum to one)

W	P
sun	0.4
rain	0.6

$$\begin{aligned}
 P(W = r|T = c) &= \frac{P(W = r, T = c)}{P(T = c)} \\
 &= \frac{P(W = r, T = c)}{P(W = s, T = c) + P(W = r, T = c)} \\
 &= \frac{0.3}{0.2 + 0.3} = 0.6
 \end{aligned}$$

Normalization Trick



- Why does this work? Sum of selection is $P(\text{evidence})!$ ($P(T=c)$, here)

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

Quiz: Normalization Trick

- $P(X | Y=-y) ?$

$P(X, Y)$		
X	Y	P
+x	+y	0.2
+x	-y	0.3
-x	+y	0.4
-x	-y	0.1

SELECT the joint probabilities matching the evidence



NORMALIZE the selection
(make it sum to one)



Quiz: Normalization Trick

- $P(X | Y=-y) ?$

$P(X, Y)$

X	Y	P
+x	+y	0.2
+x	-y	0.3
-x	+y	0.4
-x	-y	0.1

SELECT the joint probabilities matching the evidence



X	Y	P
+x	-y	0.3
-x	-y	0.1

NORMALIZE the selection
(make it sum to one)



X	P
+x	0.75
-x	0.25

To Normalize

- (Dictionary) To bring or restore to a **normal condition**

All entries sum to ONE

- Procedure:

- Step 1: Compute $Z = \text{sum over all entries}$
- Step 2: Divide every entry by Z

- Example 1

W	P
sun	0.2
rain	0.3

Normalize \rightarrow
 $Z = 0.5$

W	P
sun	0.4
rain	0.6

- Example 2

T	W	P
hot	sun	20
hot	rain	5
cold	sun	10
cold	rain	15

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

Probabilistic Inference

- *Probabilistic inference*: compute a desired probability from other known probabilities (e.g. conditional from joint)
- We generally compute conditional probabilities
 - $P(\text{on time} \mid \text{no reported accidents}) = 0.90$
 - These represent the agent's *beliefs* given the evidence
- Probabilities change with new evidence:
 - $P(\text{on time} \mid \text{no accidents, 5 a.m.}) = 0.95$
 - $P(\text{on time} \mid \text{no accidents, 5 a.m., raining}) = 0.80$
 - Observing new evidence causes *beliefs to be updated*



Inference by Enumeration

- $P(W)$?

S	T	W	P
summer	hot	sun	0.30
summer	hot	rain	0.05
summer	cold	sun	0.10
summer	cold	rain	0.05
winter	hot	sun	0.10
winter	hot	rain	0.05
winter	cold	sun	0.15
winter	cold	rain	0.20

Inference by Enumeration

- $P(W)?$



query

S	T	W	P
summer	hot	sun	0.30
summer	hot	rain	0.05
summer	cold	sun	0.10
summer	cold	rain	0.05
winter	hot	sun	0.10
winter	hot	rain	0.05
winter	cold	sun	0.15
winter	cold	rain	0.20

Inference by Enumeration

- $P(W)$?

$$P(\text{sun}) = 0.3 + 0.1 + 0.1 + 0.15 = 0.65$$

S	T	W	P
summer	hot	sun	0.30
summer	hot	rain	0.05
summer	cold	sun	0.10
summer	cold	rain	0.05
winter	hot	sun	0.10
winter	hot	rain	0.05
winter	cold	sun	0.15
winter	cold	rain	0.20

Inference by Enumeration

- $P(W)$?

$$P(\text{sun}) = 0.3 + 0.1 + 0.1 + 0.15 = 0.65$$

$$P(\text{rain}) = 0.05 + 0.05 + 0.05 + 0.20 = 0.35$$

S	T	W	P
summer	hot	sun	0.30
summer	hot	rain	0.05
summer	cold	sun	0.10
summer	cold	rain	0.05
winter	hot	sun	0.10
winter	hot	rain	0.05
winter	cold	sun	0.15
winter	cold	rain	0.20

Inference by Enumeration

- evidence
↓
- $P(W | \text{winter, hot})?$
- ↑
query

S	T	W	P
summer	hot	sun	0.30
summer	hot	rain	0.05
summer	cold	sun	0.10
summer	cold	rain	0.05
winter	hot	sun	0.10
winter	hot	rain	0.05
winter	cold	sun	0.15
winter	cold	rain	0.20

Inference by Enumeration

- $P(W \mid \text{winter, hot})?$

unnormalized $P(\text{sun} \mid \text{winter, hot}) = 0.10$

unnormalized $P(\text{rain} \mid \text{winter, hot}) = 0.05$

$$P(\text{sun} \mid \text{winter, hot}) = 0.10 / 0.15 = 2/3$$

$$P(\text{rain} \mid \text{winter, hot}) = 0.05 / 0.15 = 1/3$$

S	T	W	P
summer	hot	sun	0.30
summer	hot	rain	0.05
summer	cold	sun	0.10
summer	cold	rain	0.05
winter	hot	sun	0.10
winter	hot	rain	0.05
winter	cold	sun	0.15
winter	cold	rain	0.20

Inference by Enumeration

- evidence
↓
■ $P(W | \text{winter})?$
- ↑
query hidden (unobserved) variable: T

S	T	W	P
summer	hot	sun	0.30
summer	hot	rain	0.05
summer	cold	sun	0.10
summer	cold	rain	0.05
winter	hot	sun	0.10
winter	hot	rain	0.05
winter	cold	sun	0.15
winter	cold	rain	0.20

Inference by Enumeration

- $P(W | \text{winter})?$

$$\text{unnormalized } P(\text{sun} | \text{winter}) = 0.1 + 0.15 = 0.25$$

S	T	W	P
summer	hot	sun	0.30
summer	hot	rain	0.05
summer	cold	sun	0.10
summer	cold	rain	0.05
winter	hot	sun	0.10
winter	hot	rain	0.05
winter	cold	sun	0.15
winter	cold	rain	0.20

Inference by Enumeration

- $P(W | \text{winter})?$

$$\text{unnormalized } P(\text{sun} | \text{winter}) = 0.1 + 0.15 = 0.25$$

$$\text{unnormalized } P(\text{rain} | \text{winter}) = 0.05 + 0.20 = 0.25$$

S	T	W	P
summer	hot	sun	0.30
summer	hot	rain	0.05
summer	cold	sun	0.10
summer	cold	rain	0.05
winter	hot	sun	0.10
winter	hot	rain	0.05
winter	cold	sun	0.15
winter	cold	rain	0.20

Inference by Enumeration

- $P(W | \text{winter})?$

$$\text{unnormalized } P(\text{sun} | \text{winter}) = 0.1 + 0.15 = 0.25$$

$$\text{unnormalized } P(\text{rain} | \text{winter}) = 0.05 + 0.20 = 0.25$$

$$P(\text{sun} | \text{winter}) = 0.25 / 0.50 = 0.5$$

$$P(\text{rain} | \text{winter}) = 0.25 / 0.50 = 0.5$$

S	T	W	P
summer	hot	sun	0.30
summer	hot	rain	0.05
summer	cold	sun	0.10
summer	cold	rain	0.05
winter	hot	sun	0.10
winter	hot	rain	0.05
winter	cold	sun	0.15
winter	cold	rain	0.20

Inference by Enumeration

- General case:

- Evidence variables: $E_1 \dots E_k = e_1 \dots e_k$
- Query* variable: Q
- Hidden variables: $H_1 \dots H_r$

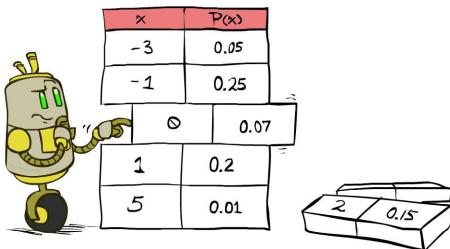
$$\left. \begin{array}{l} E_1 \dots E_k = e_1 \dots e_k \\ Q \\ H_1 \dots H_r \end{array} \right\} \begin{array}{l} X_1, X_2, \dots, X_n \\ \text{All variables} \end{array}$$

* Works fine with multiple query variables, too

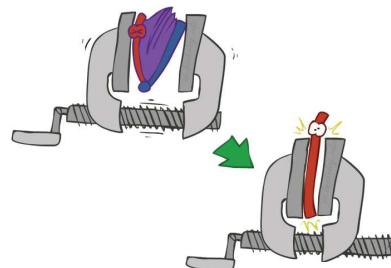
- We want:

$$P(Q|e_1 \dots e_k)$$

- Step 1: Select the entries consistent with the evidence



- Step 2: Sum out H to get joint of Query and evidence



$$P(Q, e_1 \dots e_k) = \sum_{h_1 \dots h_r} \underbrace{P(Q, h_1 \dots h_r, e_1 \dots e_k)}_{X_1, X_2, \dots, X_n}$$

$$Z = \sum_q P(Q, e_1 \dots e_k)$$

$$P(Q|e_1 \dots e_k) = \frac{1}{Z} P(Q, e_1 \dots e_k)$$

$$\times \frac{1}{Z}$$

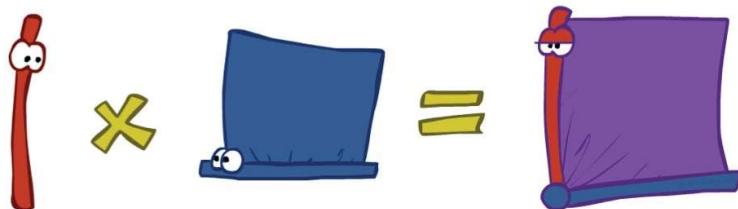
Inference by Enumeration

- Obvious problems:
 - Worst-case time complexity $O(d^n)$
 - Space complexity $O(d^n)$ to store the joint distribution

The Product Rule

- Sometimes have conditional distributions but want the joint

$$P(y)P(x|y) = P(x, y) \quad \leftrightarrow \quad P(x|y) = \frac{P(x, y)}{P(y)}$$



The Product Rule

$$P(y)P(x|y) = P(x, y)$$

- Example:

$P(W)$		$P(D W)$			$P(D, W)$		
D	W	P	D	W	P	D	W
wet	sun	0.1					
dry	sun	0.9					
wet	rain	0.7					
dry	rain	0.3					

The Chain Rule

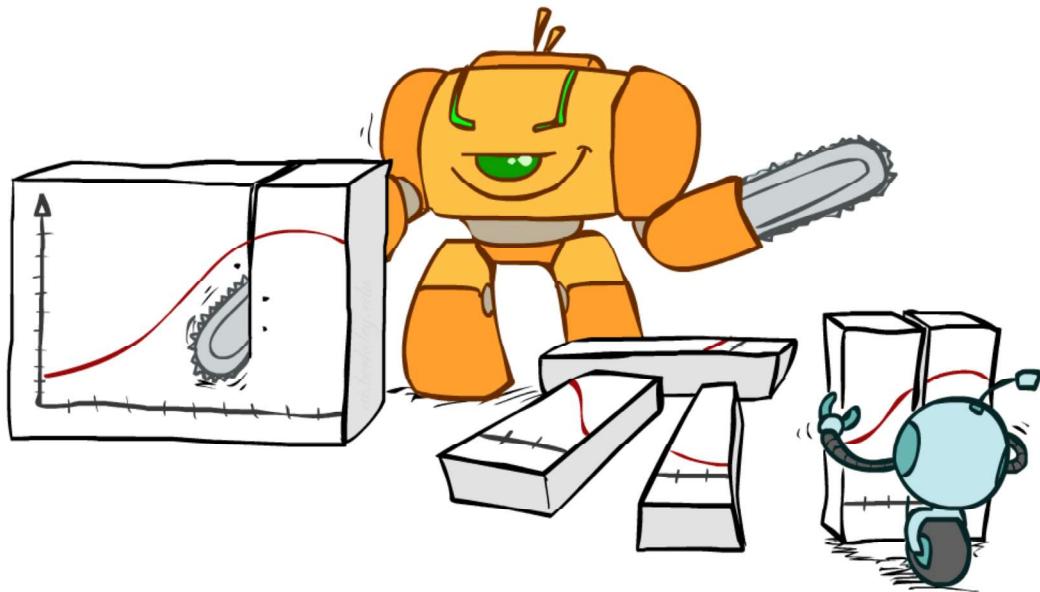
- More generally, can always write any joint distribution as an incremental product of conditional distributions

$$P(x_1, x_2, x_3) = P(x_1)P(x_2|x_1)P(x_3|x_1, x_2)$$

$$P(x_1, x_2, \dots, x_n) = \prod_i P(x_i|x_1 \dots x_{i-1})$$

- Why is this always true?

Bayes Rule



Bayes' Rule

- Two ways to factor a joint distribution over two variables:

$$P(x, y) = P(x|y)P(y) = P(y|x)P(x)$$

That's my rule!

- Dividing, we get:

$$P(x|y) = \frac{P(y|x)}{P(y)}P(x)$$

- Why is this at all helpful?

- Lets us build one conditional from its reverse
- Often one conditional is tricky but the other one is simple
- Foundation of many systems we'll see later (e.g. ASR, MT)



- In the running for most important AI equation!

Bayes' Rule

- Two ways to factor a joint distribution over two variables:

$$P(x, y) = P(x|y)P(y) = P(y|x)P(x)$$

- Dividing, we get:

$$P(x|y) = \frac{P(y|x)}{P(y)} P(x) \quad P(\text{cause}|\text{effect}) = \frac{P(\text{effect}|\text{cause})P(\text{cause})}{P(\text{effect})}$$

- Why is this at all helpful?

- Lets us build one conditional from its reverse
- Often one conditional is tricky but the other one is simple
- Foundation of many systems we'll see later (e.g. ASR, MT)

- In the running for most important AI equation!

Inference with Bayes' Rule

- Example: Diagnostic probability from causal probability:

$$P(\text{cause}|\text{effect}) = \frac{P(\text{effect}|\text{cause})P(\text{cause})}{P(\text{effect})}$$

- Example:

- M: meningitis, S: stiff neck

$$\left. \begin{array}{l} P(+m) = 0.0001 \\ P(+s|m) = 0.8 \\ P(+s|-m) = 0.01 \end{array} \right\} \text{Example givens}$$

$$P(+m|s) = \frac{P(+s|m)P(+m)}{P(+s)} = \frac{P(+s|m)P(+m)}{P(+s|m)P(+m) + P(+s|-m)P(-m)} = \frac{0.8 \times 0.0001}{0.8 \times 0.0001 + 0.01 \times 0.999}$$

Quiz: Bayes' Rule

- Given:

$P(W)$	
R	P
sun	0.8
rain	0.2

$P(D W)$		
D	W	P
wet	sun	0.1
dry	sun	0.9
wet	rain	0.7
dry	rain	0.3

- What is $P(W | \text{dry})$?

Quiz: Bayes' Rule

- Given:

$P(W)$	
R	P
sun	0.8
rain	0.2

$P(D W)$		
D	W	P
wet	sun	0.1
dry	sun	0.9
wet	rain	0.7
dry	rain	0.3

- What is $P(W | \text{dry})$?

$$\text{unnormalized } P(\text{sun} | \text{dry}) = P(\text{dry} | \text{sun}) * P(\text{sun}) = 0.9 * 0.8 = 0.72$$

$$\text{unnormalized } P(\text{rain} | \text{dry}) = P(\text{dry} | \text{rain}) * P(\text{rain}) = 0.3 * 0.2 = 0.06$$

$$P(\text{sun} | \text{dry}) = 0.72 / 0.78 = 12 / 13$$

$$P(\text{rain} | \text{dry}) = 0.06 / 0.78 = 1 / 13$$

Ghostbusters, Revisited

- Let's say we have two distributions:
 - Prior distribution over ghost location: $P(G)$
 - Let's say this is uniform
 - Sensor reading model: $P(R | G)$
 - Given: we know what our sensors do
 - R = reading color measured at (1,1)
 - E.g. $P(R = \text{yellow} | G=(1,1)) = 0.1$
- We can calculate the posterior distribution $P(G|r)$ over ghost locations given a reading using Bayes' rule:

$$\text{unnormalized } P(g|r) = P(r|g)P(g)$$

$P(G)$	<table border="1"> <tr><td>0.11</td><td>0.11</td><td>0.11</td></tr> <tr><td>0.11</td><td>0.11</td><td>0.11</td></tr> <tr><td>0.11</td><td>0.11</td><td>0.11</td></tr> </table>	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
0.11	0.11	0.11								
0.11	0.11	0.11								
0.11	0.11	0.11								
$P(G r)$	<table border="1"> <tr><td>0.17</td><td>0.10</td><td>0.10</td></tr> <tr><td>0.09</td><td>0.17</td><td>0.10</td></tr> <tr><td><0.01</td><td>0.09</td><td>0.17</td></tr> </table>	0.17	0.10	0.10	0.09	0.17	0.10	<0.01	0.09	0.17
0.17	0.10	0.10								
0.09	0.17	0.10								
<0.01	0.09	0.17								

[Demo: Ghostbuster – with probability (L12D2)]

Video of Demo Ghostbusters with Probability



Next Time: Bayes' Nets
