Outline

- Uncertainty
- Probability
- Syntax and Semantics
- Inference
- Independence and Bayes' Rule

Includes many slides by Russell & Norvig

Uncertain Actions

- So far, our agents believe that
  - logical statements are true or false (maybe unknown)
  - actions will always do what they think they do
- Unfortunately, the real world is not like that
  - agents almost never have access to the whole truth about the world

  → agents must deal with uncertainty
- Example:
  - We many different actions for getting us to the airport:
    - action A_t = leave for the airport t minutes before departure
  - Typical problems:
    - Will a given action A_t get me to the airport in time?
    - Which action is the best choice for getting me to the airport?

Problems with Uncertainty

- Risks involved in the plan A_{90} will get me to the airport
  - partial observability (road state, other drivers' plans, etc.)
  - noisy sensors (traffic reports may be wrong)
  - uncertainty in action outcomes (flat tire, accident, etc.)
  - immense complexity of modeling and predicting traffic
- A logically correct plan:

  A_{90} will get me to the airport as long as my car doesn't break down, I don't run out of gas, no accident, the bridge doesn't fall down, etc.

  - impossible to model all things that can go wrong
    - → qualification problem
- A more cautious plan:

  A_{1440} will get me to the airport

  - will certainly succeed, but clearly suboptimal
    - e.g., we have to pay for a night in a hotel

Probabilities

- Probabilities are one way of handling uncertainty
  - e.g. A_{90} will get me to the airport with probability 0.5
- The probability summarizes effects that are due to
  - Laziness
    - I don't want to list all things that must not go wrong
  - Theoretical Ignorance
    - Some things just can't be known
      - e.g.: We cannot completely model the weather
  - Practical Ignorance
    - Some things might not be known about the particular situation
      - e.g. Is there a traffic jam at A5?

Probabilities and Beliefs

- Probabilities that are related to one's beliefs
  - a probability p attached to a statement means that I believe that the statement will be true in $p \cdot 100\%$ of the cases
    - there is traffic jam on the A5 in 10% of the cases (meaning: there might be jam, but usually there is none)
  - it does not mean that it is true with $p\%$
    - the traffic on the A5 is jammed with a degree of 10% (meaning: there's a jam, but it could be worse...)

→ Probability theory is about degree of belief
  - other techniques (e.g., Fuzzy logic) deal with degree of truth
- Probabilities of propositions change with new evidence:
  - $P(A_{25}$ gets me there in time $|$ no reported accidents$) = 0.06$
    - in 6% of the days I get there in 25 mins if no accidents reported
  - $P(A_{25}$ gets me there in time $|$ no reported accidents, 5 a.m.$) = 0.15$
    - chances are higher at 5 in the morning...

Making Decisions under Uncertainty

- Suppose I believe the following:
  - P(A_{25} gets me there on time | …) = 0.04
  - P(A_{90} gets me there on time | …) = 0.70
  - P(A_{120} gets me there on time | …) = 0.95
  - P(A_{1440} gets me there on time | …) = 0.9999

  Which action should I choose?

- The choice depends on my preferences
  - how bad is to miss the flight?
  - how bad is it to wait for an hour at the airport?
- Utility theory is used to represent and infer preferences
- Decision theory = probability theory + utility theory

Probability Basics

Begin with a set Ω—the sample space

e.g., 6 possible rolls of a die.

$\omega \in \Omega$ is a sample point/possible world/atomic event

A probability space or probability model is a sample space with an assignment $P(\omega)$ for every $\omega \in \Omega$ s.t.

$0 \leq P(\omega) \leq 1$

$\Sigma_\omega P(\omega) = 1$

e.g., $P(1) = P(2) = P(3) = P(4) = P(5) = P(6) = 1/6$.

An event A is any subset of Ω

$$P(A) = \Sigma_{\{\omega \in A\}} P(\omega)$$

E.g., $P(\text{die roll} < 4) = P(1) + P(2) + P(3) = 1/6 + 1/6 + 1/6 = 1/2$

Kolmogorov's Axioms of Probability

1. All probabilities are between 0 and 1

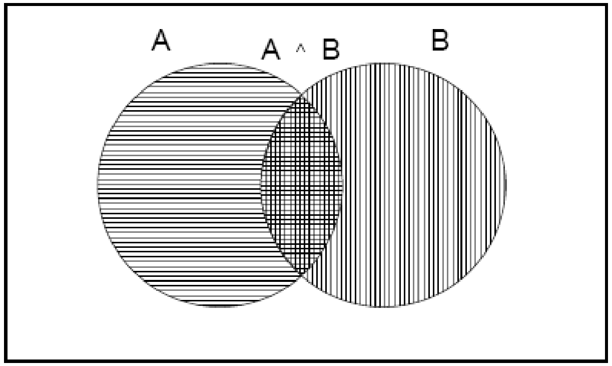
$$0 \leq P(a) \leq 1$$

2. Necessarily true propositions have probability 1, necessarily false propositions have probability 0

$$P(\mathit{false}) = 0 \qquad P(\mathit{true}) = 1$$

3. The probability of a disjunction is

$$P(a \vee b) = P(a) + P(b) - P(a \wedge b)$$



These axioms restrict the set of probabilistic beliefs that an agent can (reasonably) hold

- similar to logical constraints like A and $\neg A$ can't both be true

Violation of Axioms of Probability

Bruno de Finetti (1931)

- an agent who bets according to probabilities that violate the axioms of probability can be forced to bet so as to lose money *regardless of outcome!*

Example:

- suppose Agent 1 believes the following
  $P(a)=0.4 \quad P(b)=0.3 \quad P(a \vee b)=0.8$

axioms of probability are violated because
$P(a \vee b) > P(a)+P(b)$

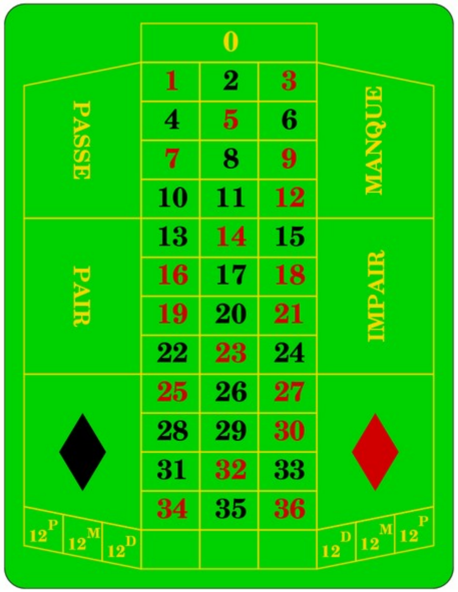
- Agent 2 can now select a set of events and bet on them according to these probabilities so that she cannot loose

Agent 1		Agent 2		Outcome for Agent 1			
proposition	belief	bet	stakes	$a \wedge b$	$a \wedge \neg b$	$\neg a \wedge b$	$\neg a \wedge \neg b$
a	0.4	a	4:6	-6	-6	4	4
b	0.3	b	3:7	-7	3	-7	3
$a \vee b$	0.8	$\neg(a \vee b)$	2:8	2	2	2	-8
				-11	**-1**	**-1**	**-1**

Random Variables

- A random variable is a function from atomic events to some range of values
- Example: Roulette
  - atomic events: numbers 0-36
  - random variables with outcomes true or false
    - rouge / noir, pair / impair, passe / manque
    - transversale, carre, cheval
    - douzaines premier/milieu/dernier
    - etc.

  e.g. $\mathrm{rouge}(36) = \mathrm{true}$



- The probablity function P over atomic events induces a probability distribution over all random variables X

$$P(X = x_i) = \sum_{\{\omega : X(\omega) = x_i\}} P(\omega)$$

  - $P(Rouge = true) = P(1) + P(3) + \ldots + P(34) + P(36) = \frac{1}{37} + \frac{1}{37} + \ldots + \frac{1}{37} + \frac{1}{37} = \frac{18}{37}$

Propositions

Think of a proposition as the event (set of sample points) where the proposition is true

Given Boolean random variables A and B:

event a = set of sample points where $A(\omega) = true$

event $\neg a$ = set of sample points where $A(\omega) = false$

event $a \wedge b$ = points where $A(\omega) = true$ and $B(\omega) = true$

Often in AI applications, the sample points are **defined** by the values of a set of random variables, i.e., the sample space is the Cartesian product of the ranges of the variables

With Boolean variables, sample point = propositional logic model

e.g., $A = true$, $B = false$, or $a \wedge \neg b$.

Proposition = disjunction of atomic events in which it is true

e.g., $(a \vee b) \equiv (\neg a \wedge b) \vee (a \wedge \neg b) \vee (a \wedge b)$

$\Rightarrow P(a \vee b) = P(\neg a \wedge b) + P(a \wedge \neg b) + P(a \wedge b)$

Syntax for Propositions

Propositional or Boolean random variables

- e.g., $Cavity$ (do I have a cavity?)
- $Cavity = true$ is a proposition, also written $cavity$

Discrete random variables (finite or infinite)

- e.g., $Weather$ is one of $\langle sunny, rain, cloudy, snow \rangle$
- $Weather = rain$ is a proposition
- Values must be exhaustive and mutually exclusive

Continuous random variables (bounded or unbounded)

- e.g., $Temp = 21.6$; also allow, e.g., $Temp < 22.0$.

Arbitrary Boolean combinations of basic propositions

Prior Probabilities

P denotes a probability distribution

P denotes a probability

Prior or unconditional probabilities of propositions

e.g., $P(Cavity = true) = 0.1$ and $P(Weather = sunny) = 0.72$

correspond to belief prior to arrival of any (new) evidence

Probability distribution gives values for all possible assignments:

$\mathbf{P}(Weather) = \langle 0.72, 0.1, 0.08, 0.1 \rangle$ (normalized, i.e., sums to 1)

Joint probability distribution for a set of r.v.s gives the probability of every atomic event on those r.v.s (i.e., every sample point)

$\mathbf{P}(Weather, Cavity) =$ a 4×2 matrix of values:

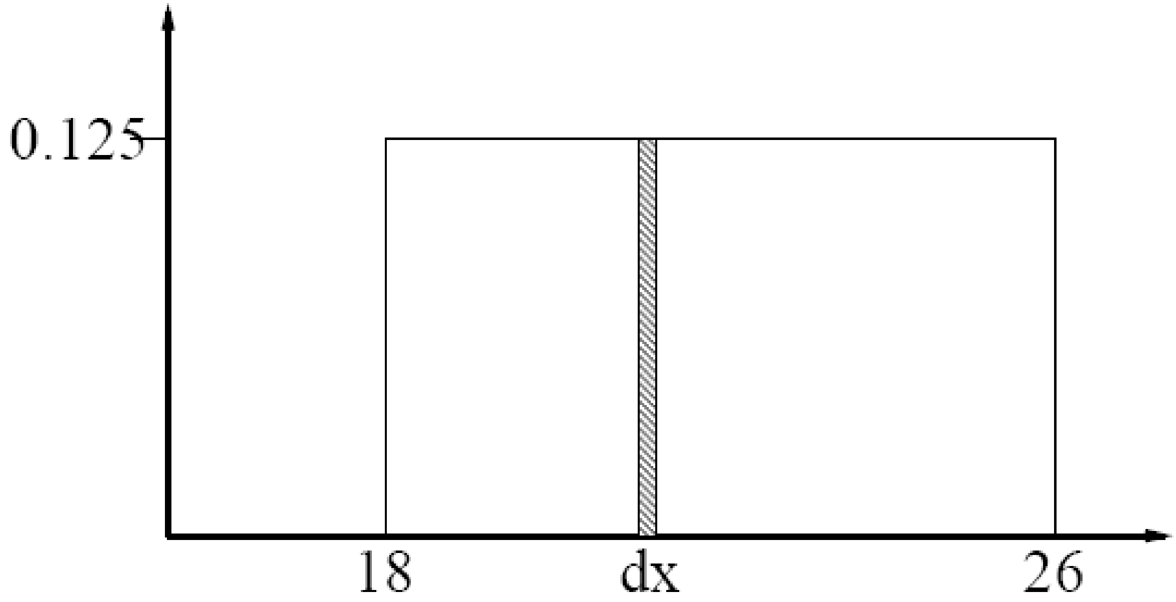
$Weather =$	$sunny$	$rain$	$cloudy$	$snow$
$Cavity = true$	0.144	0.02	0.016	0.02
$Cavity = false$	0.576	0.08	0.064	0.08

Note: If we know the joint probability for a set of random variables, we can answer all questions, because each event is a union of sample points

Probability for Continuous Variables

Express distribution as a parameterized function of value:

$P(X=x) = U[18,26](x)$ = uniform density between 18 and 26



Here P is a density; integrates to 1.

$P(X=20.5) = 0.125$ really means

$$\lim_{dx \to 0} P(20.5 \leq X \leq 20.5 + dx)/dx = 0.125$$

Marginalization (Summing Out)

Marginalization (aka *Summing Out*)

- For any set of variables $\mathbf{Y}$ and $\mathbf{Z}$

$$\mathbf{P}(\mathbf{Y}) = \sum_z \mathbf{P}(\mathbf{Y}, z)$$

- In particular, this means that given the joint probability distribution, the probability distribution of any random variable can be computed by summing out
  - the resulting distribution is then also called marginal distribution and its probabilities the marginal probabilities

Conditioning

- A variant of the above rule that uses conditional probabilities

$$\mathbf{P}(\mathbf{Y}) = \sum_z \mathbf{P}(\mathbf{Y} | z) \cdot P(z)$$

Marginalization

Start with the joint distribution:

	toothache		*¬ toothache*	
	catch	*¬ catch*	*catch*	*¬ catch*
cavity	.108	.012	.072	.008
¬ cavity	.016	.064	.144	.576

For any proposition ϕ, sum the atomic events where it is true:

$P(\phi) = \Sigma_{\omega:\omega \models \phi} P(\omega)$

Marginalization

Start with the joint distribution:

	toothache		¬ *toothache*	
	catch	¬ *catch*	*catch*	¬ *catch*
cavity	.108	.012	.072	.008
¬ *cavity*	.016	.064	.144	.576

For any proposition ϕ, sum the atomic events where it is true:

$$P(\phi) = \Sigma_{\omega:\omega \models \phi} P(\omega)$$

$$P(toothache) = 0.108 + 0.012 + 0.016 + 0.064 = 0.2$$

Inference by Enumeration

Start with the joint distribution:

	toothache		¬ *toothache*	
	catch	¬ *catch*	*catch*	¬ *catch*
cavity	.108	.012	.072	.008
¬ *cavity*	.016	.064	.144	.576

For any proposition ϕ, sum the atomic events where it is true:

$$P(\phi) = \Sigma_{\omega:\omega\models\phi} P(\omega)$$

$$P(cavity \lor toothache) = 0.108 + 0.012 + 0.072 + 0.008 + 0.016 + 0.064 = 0.28$$

Conditional Probabilities

$\mathbf{P}(Cavity, Toothache)$	$toothache$	$\neg\, toothache$
$cavity$	0.12	0.08
$\neg\, cavity$	0.08	0.72

Conditional or posterior probabilities

e.g., $P(cavity|toothache) = 0.8$

i.e., **given that** $toothache$ **is all I know**

NOT "if $toothache$ then 80% chance of $cavity$"

(Notation for conditional distributions:

$\mathbf{P}(Cavity|Toothache)$ = 2-element vector of 2-element vectors)

$$\mathbf{P}(Cavity|Toothache) = \langle\langle 0.6, 0.4 \rangle, \langle 0.1, 0.9 \rangle\rangle$$

If we know more, e.g., $cavity$ is also given, then we have

$P(cavity|toothache, cavity) = 1$

Note: the less specific belief **remains valid** after more evidence arrives, but is not always **useful**

New evidence may be irrelevant, allowing simplification, e.g.,

$P(cavity|toothache, 49ersWin) = P(cavity|toothache) = 0.8$

This kind of inference, sanctioned by domain knowledge, is crucial

Definition of Conditional Probability

Definition of conditional probability:

$$P(a|b) = \frac{P(a \wedge b)}{P(b)} \text{ if } P(b) \neq 0$$

Product rule gives an alternative formulation:

$$P(a \wedge b) = P(a|b)P(b) = P(b|a)P(a)$$

A general version holds for whole distributions, e.g.,

$$\mathbf{P}(Weather, Cavity) = \mathbf{P}(Weather|Cavity)\mathbf{P}(Cavity)$$

(View as a 4×2 set of equations, not matrix mult.)

Chain rule is derived by successive application of product rule:

$$\begin{aligned}\mathbf{P}(X_1, \ldots, X_n) &= \mathbf{P}(X_1, \ldots, X_{n-1})\ \mathbf{P}(X_n|X_1, \ldots, X_{n-1})\\ &= \mathbf{P}(X_1, \ldots, X_{n-2})\ \mathbf{P}(X_{n_1}|X_1, \ldots, X_{n-2})\ \mathbf{P}(X_n|X_1, \ldots, X_{n-1})\\ &= \ldots\\ &= \prod_{i=1}^{n} \mathbf{P}(X_i|X_1, \ldots, X_{i-1})\end{aligned}$$

Inference by Enumeration

Start with the joint distribution:

	toothache		¬ *toothache*	
	catch	¬ *catch*	*catch*	¬ *catch*
cavity	.108	.012	.072	.008
¬ *cavity*	.016	.064	.144	.576

Can also compute conditional probabilities:

$$P(\neg cavity | toothache) = \frac{P(\neg cavity \wedge toothache)}{P(toothache)}$$

$$= \frac{0.016 + 0.064}{0.108 + 0.012 + 0.016 + 0.064} = 0.4$$

Normalization

Start with the joint distribution:

	toothache		¬ *toothache*	
	catch	¬ *catch*	*catch*	¬ *catch*
cavity	.108	.012	.072	.008
¬ *cavity*	.016	.064	.144	.576

Denominator can be viewed as a normalization constant α

$$\mathbf{P}(Cavity|toothache) = \alpha\, \mathbf{P}(Cavity, toothache)$$
$$= \alpha\, [\mathbf{P}(Cavity, toothache, catch) + \mathbf{P}(Cavity, toothache, \neg catch)]$$
$$= \alpha\, [\langle 0.108, 0.016\rangle + \langle 0.012, 0.064\rangle]$$
$$= \alpha\, \langle 0.12, 0.08\rangle = \langle 0.6, 0.4\rangle$$

General idea: compute distribution on query variable
by fixing evidence variables and summing over hidden variables

Inference by Enumeration (Ctd.)

Let $\mathbf{X}$ be all the variables. Typically, we want
the posterior joint distribution of the query variables $\mathbf{Y}$
given specific values $\mathbf{e}$ for the evidence variables $\mathbf{E}$

Let the hidden variables be $\mathbf{H} = \mathbf{X} - \mathbf{Y} - \mathbf{E}$

Then the required summation of joint entries is done by summing out the hidden variables:

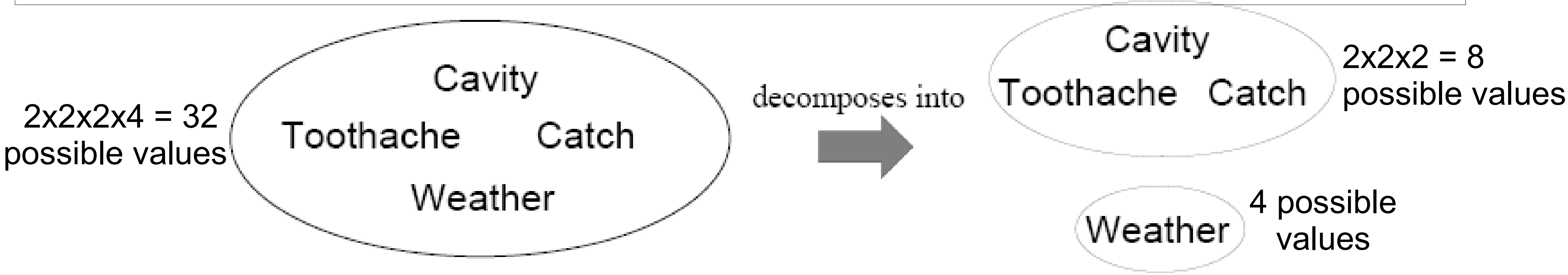
$$\mathbf{P}(\mathbf{Y}|\mathbf{E}=\mathbf{e}) = \alpha\mathbf{P}(\mathbf{Y}, \mathbf{E}=\mathbf{e}) = \alpha\Sigma_{\mathbf{h}}\mathbf{P}(\mathbf{Y}, \mathbf{E}=\mathbf{e}, \mathbf{H}=\mathbf{h})$$

The terms in the summation are joint entries because $\mathbf{Y}$, $\mathbf{E}$, and $\mathbf{H}$ together exhaust the set of random variables

Obvious problems:
1) Worst-case time complexity $O(d^n)$ where d is the largest arity
2) Space complexity $O(d^n)$ to store the joint distribution
3) How to find the numbers for $O(d^n)$ entries???

Independence

A and B are **independent** iff
$\mathbf{P}(A|B) = \mathbf{P}(A)$ or $\mathbf{P}(B|A) = \mathbf{P}(B)$ or $\mathbf{P}(A,B) = \mathbf{P}(A)\mathbf{P}(B)$



$$\mathbf{P}(Toothache, Catch, Cavity, Weather) = \mathbf{P}(Toothache, Catch, Cavity)\mathbf{P}(Weather)$$

32 entries reduced to 12; for n independent biased coins, $2^n \rightarrow n$

Absolute independence powerful but rare

Dentistry is a large field with hundreds of variables, none of which are independent. What to do?

Conditional Independence

$\mathbf{P}(Toothache, Cavity, Catch)$ has $2^3 - 1 = 7$ independent entries

If I have a cavity, the probability that the probe catches in it doesn't depend on whether I have a toothache:

(1) $P(catch|toothache, cavity) = P(catch|cavity)$

The same independence holds if I haven't got a cavity:

(2) $P(catch|toothache, \neg cavity) = P(catch|\neg cavity)$

$Catch$ is conditionally independent of $Toothache$ given $Cavity$:

$\mathbf{P}(Catch|Toothache, Cavity) = \mathbf{P}(Catch|Cavity)$

Equivalent statements:

$\mathbf{P}(Toothache|Catch, Cavity) = \mathbf{P}(Toothache|Cavity)$

$\mathbf{P}(Toothache, Catch|Cavity) = \mathbf{P}(Toothache|Cavity)\mathbf{P}(Catch|Cavity)$

Analogous to:

$\mathbf{P}(A|B) = \mathbf{P}(A)$ or $\mathbf{P}(B|A) = \mathbf{P}(B)$ or $\mathbf{P}(A, B) = \mathbf{P}(A)\mathbf{P}(B)$

Conditional Independence (Ctd.)

Write out full joint distribution using chain rule:

$$\begin{aligned}&\mathbf{P}(Toothache, Catch, Cavity)\\ &= \mathbf{P}(Toothache|Catch, Cavity)\mathbf{P}(Catch, Cavity)\\ &= \mathbf{P}(Toothache|Catch, Cavity)\mathbf{P}(Catch|Cavity)\mathbf{P}(Cavity)\\ &= \mathbf{P}(Toothache|Cavity)\mathbf{P}(Catch|Cavity)\mathbf{P}(Cavity)\end{aligned}$$

I.e., $2 + 2 + 1 = 5$ independent numbers (equations 1 and 2 remove 2)

In most cases, the use of conditional independence reduces the size of the representation of the joint distribution from exponential in n to linear in n.

Conditional independence is our most basic and robust form of knowledge about uncertain environments.

Bayes Rule

Product rule $P(a \wedge b) = P(a|b)P(b) = P(b|a)P(a)$

$\Rightarrow$ Bayes' rule $P(a|b) = \dfrac{P(b|a)P(a)}{P(b)}$

or in distribution form

$$\mathbf{P}(Y|X) = \frac{\mathbf{P}(X|Y)\mathbf{P}(Y)}{\mathbf{P}(X)} = \alpha\mathbf{P}(X|Y)\mathbf{P}(Y)$$

Useful for assessing diagnostic probability from causal probability:

$$P(Cause|Effect) = \frac{P(Effect|Cause)P(Cause)}{P(Effect)}$$

E.g., let M be meningitis, S be stiff neck:

$$P(m|s) = \frac{P(s|m)P(m)}{P(s)} = \frac{0.8 \times 0.0001}{0.1} = 0.0008$$

Note: posterior probability of meningitis still very small!

Example: AIDS-Test

- event *Aids* = a person has Aids or not
- event *Positive* = a person has a positive test result

- The test has the following characteristics:
  - $P(positive|aids) = 0.99$
  - $P(negative|aids) = 0.01$

    The test makes 1% mistakes for people that have aids
  - $P(positive|\neg aids) = 0.005$
  - $P(negative|\neg aids) = 0.995$

    The test makes 0,5% mistakes for people that don't have aids

- Looks like a pretty reliable test?

Example: AIDS-Test

- event *Aids* = a person has Aids or not
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- The test has the following characteristics:
  - $P(positive|aids) = 0.99$
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  - $P(positive|\neg aids) = 0.005$
  - $P(negative|\neg aids) = 0.995$

The test makes 1% mistakes for people that have aids

The test makes 0,5% mistakes for people that don't have aids

- Now suppose you are in a low-risk group (low a priori probability of having Aids, say $P(aids) = 0.0001$) and have a positive test result. Should you panic?

$$P(a|p) = \frac{P(p|a) \cdot P(a)}{P(p)} = \frac{P(p|a) \cdot P(a)}{P(p|a) \cdot P(a) + P(p|\neg a) \cdot P(\neg a)} = \frac{0.99 \cdot 0.0001}{0.99 \cdot 0.0001 + 0.005 \cdot 0.9999} = 0.0194$$

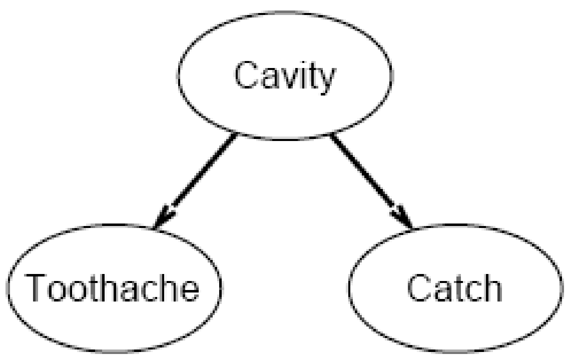
Bayes Rule and Independence

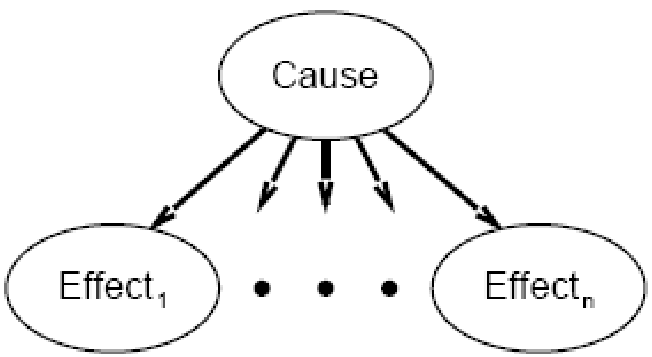
$$\mathbf{P}(Cavity|toothache \wedge catch)$$
$$= \alpha\, \mathbf{P}(toothache \wedge catch|Cavity)\mathbf{P}(Cavity)$$
$$= \alpha\, \mathbf{P}(toothache|Cavity)\mathbf{P}(catch|Cavity)\mathbf{P}(Cavity)$$

The model is naïve because it assumes that all effects are independent given the cause (which is often not true)

This is an example of a naive Bayes model:

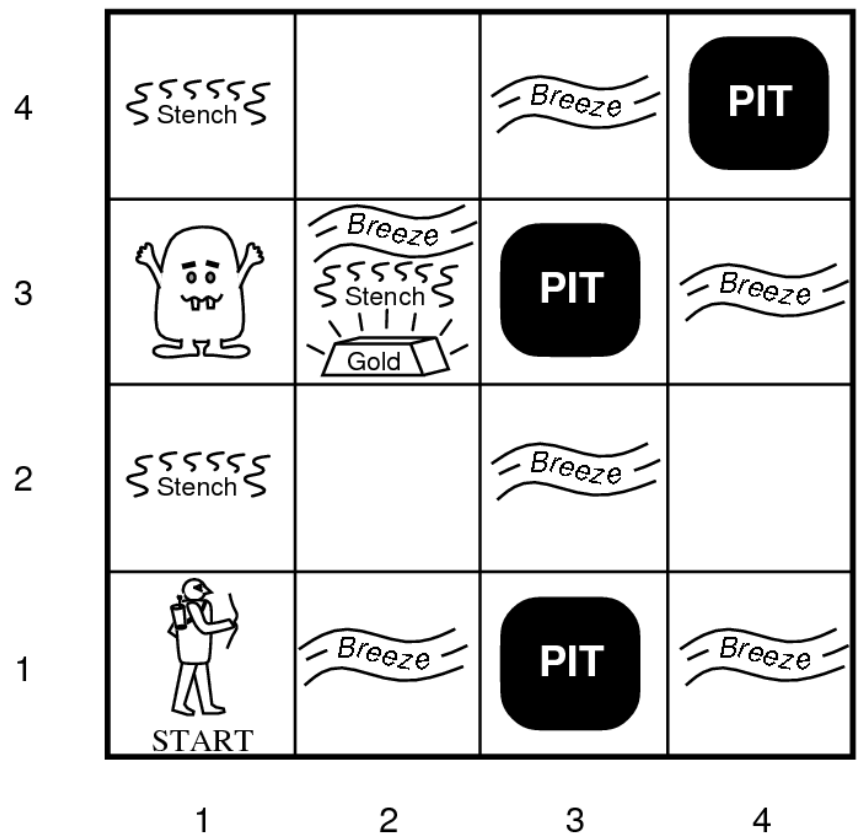
$$\mathbf{P}(Cause, Effect_1, \ldots, Effect_n) = \mathbf{P}(Cause)\Pi_i \mathbf{P}(Effect_i|Cause)$$





Total number of parameters is linear in n

Example: Wumpus World



Performance measure
gold +1000, death -1000
-1 per step, -10 for using the arrow

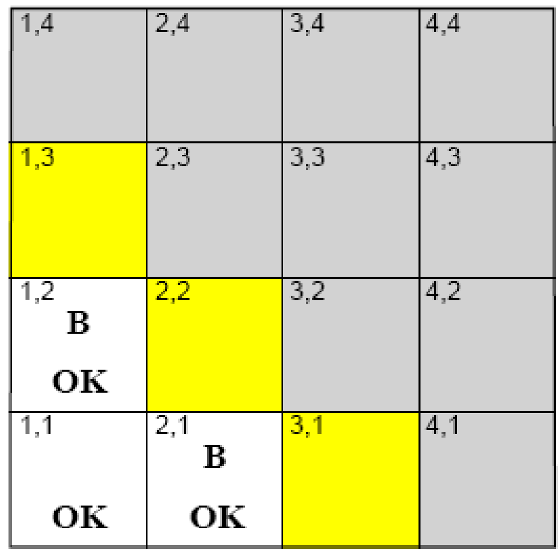
Environment
Squares adjacent to wumpus are smelly
Squares adjacent to pit are breezy
Glitter iff gold is in the same square
Shooting kills wumpus if you are facing it
Shooting uses up the only arrow
Grabbing picks up gold if in same square
Releasing drops the gold in same square

Actuators Left turn, Right turn,
Forward, Grab, Release, Shoot

Sensors Breeze, Glitter, Smell

Example: Wumpus World

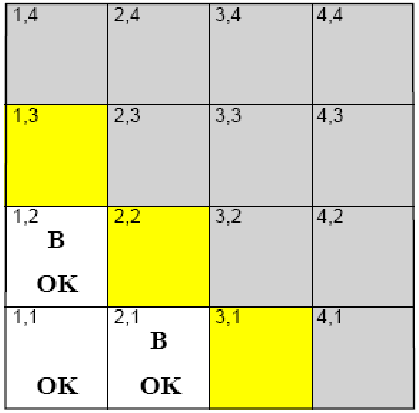
Current knowledge of the agent about the world



- the agent has visited the squares [1,1], [1,2], [2,1]
- it found a breeze in [1,2] and one in [2,1].
- therefore, no safe explorative step is possible
  - all yellow squares might contain a pit

→ Which of the yellow squares is the safest?

Example: Wumpus World Specifying the Probability Model



$P_{ij} = true$ iff $[i, j]$ contains a pit

$B_{ij} = true$ iff $[i, j]$ is breezy
Include only $B_{1,1}, B_{1,2}, B_{2,1}$ in the probability model

The full joint distribution is $\mathbf{P}(P_{1,1}, \ldots, P_{4,4}, B_{1,1}, B_{1,2}, B_{2,1})$

Apply product rule: $\mathbf{P}(B_{1,1}, B_{1,2}, B_{2,1} \mid P_{1,1}, \ldots, P_{4,4})\mathbf{P}(P_{1,1}, \ldots, P_{4,4})$

(Do it this way to get $P(Effect|Cause)$.)

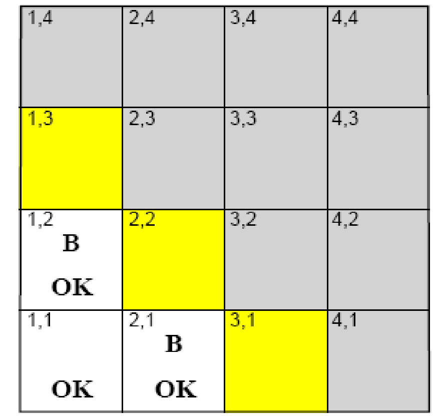
First term: 1 if pits are adjacent to breezes, 0 otherwise

Second term: pits are placed randomly, probability 0.2 per square:

$$\mathbf{P}(P_{1,1}, \ldots, P_{4,4}) = \prod_{i,j=1,1}^{4,4} \mathbf{P}(P_{i,j}) = 0.2^n \times 0.8^{16-n}$$

for n pits.

Example: Wumpus World Observations and Queries



$P_{ij} = true$ iff $[i, j]$ contains a pit

$B_{ij} = true$ iff $[i, j]$ is breezy

Include only $B_{1,1}, B_{1,2}, B_{2,1}$ in the probability model

We know the following facts:

$$b = \neg b_{1,1} \wedge b_{1,2} \wedge b_{2,1}$$

$$known = \neg p_{1,1} \wedge \neg p_{1,2} \wedge \neg p_{2,1}$$

Query is $\mathbf{P}(P_{1,3}|known, b)$ ← What is the probability distribution for a pit on [1,3]?

Define $Unknown$ = P_{ij}s other than $P_{1,3}$ and $Known$

For inference by enumeration, we have

$$\mathbf{P}(P_{1,3}|known, b) = \alpha \Sigma_{unknown} \mathbf{P}(P_{1,3}, unknown, known, b)$$

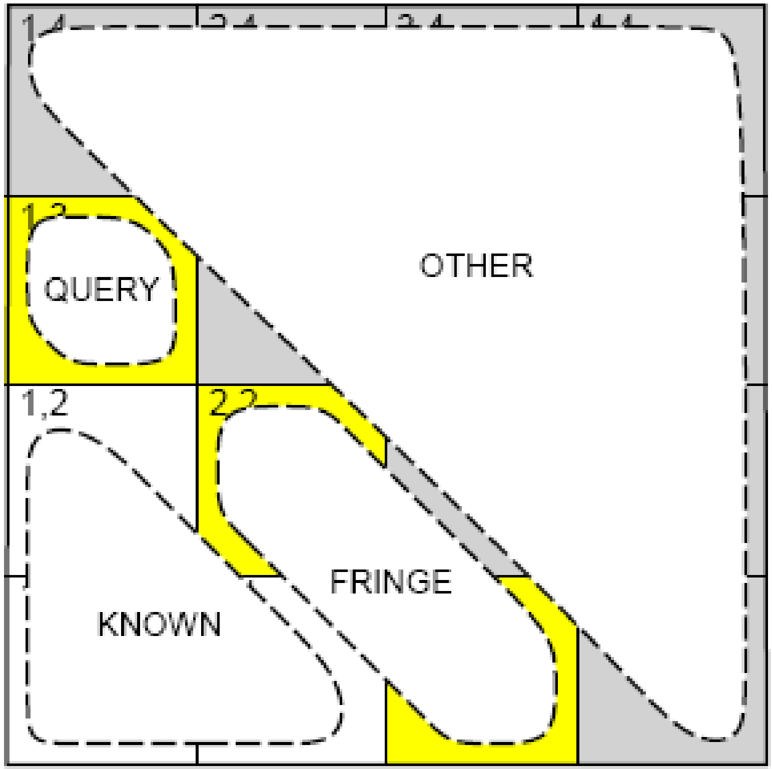
Grows exponentially with number of squares!

Example: Wumpus World Using Conditional Independence

Basic insight: observations are conditionally independent of other hidden squares given neighbouring hidden squares

The square [4,4] will not have an influence on whether the agent has noticed a breeze on [1,2] or not.

In fact, none of the squares in the *Other* region may have influenced the observations in [1,1], [1,2] and [2,1].

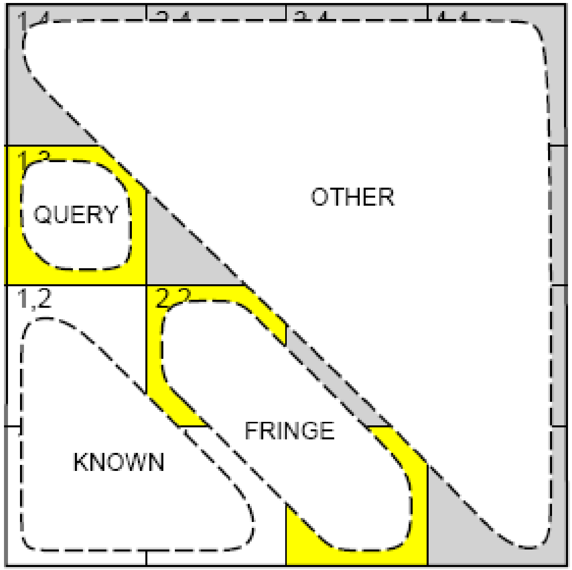


Define $Unknown = Fringe \cup Other$

$\mathbf{P}(b|P_{1,3}, Known, Unknown) = \mathbf{P}(b|P_{1,3}, Known, Fringe)$

Manipulate query into a form where we can use this!

Example: Wumpus World Computation



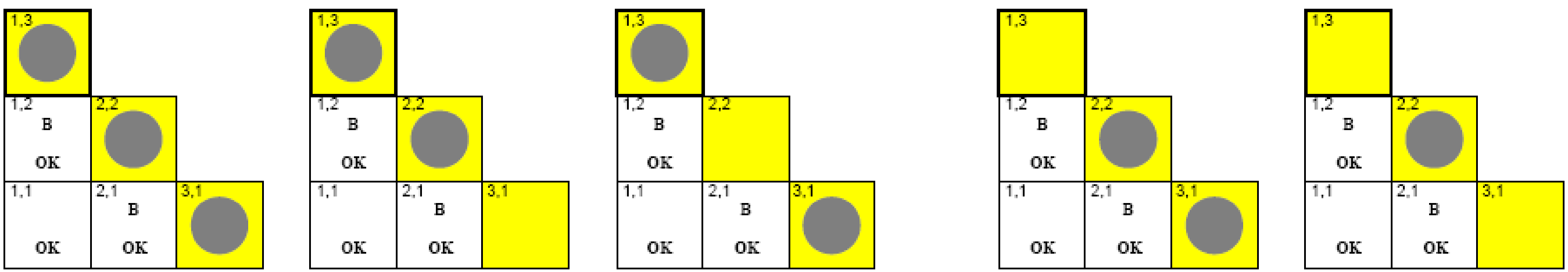
The query $\mathbf{P}(P_{1,3}|known,b)$ is now transformed in a way so that we can use the equation from the previous slide

$$\mathbf{P}(P_{1,3}|known,b) = \alpha \sum_{unknown} \mathbf{P}(P_{1,3}, unknown, known, b)$$
$$= \alpha \sum_{unknown} \mathbf{P}(b|P_{1,3}, known, unknown)\mathbf{P}(P_{1,3}, known, unknown)$$
$$= \alpha \sum_{fringe} \sum_{other} \mathbf{P}(b|known, P_{1,3}, fringe, other)\mathbf{P}(P_{1,3}, known, fringe, other)$$
$$= \alpha \sum_{fringe} \sum_{other} \mathbf{P}(b|known, P_{1,3}, fringe)\mathbf{P}(P_{1,3}, known, fringe, other)$$
$$= \alpha \sum_{fringe} \mathbf{P}(b|known, P_{1,3}, fringe) \sum_{other} \mathbf{P}(P_{1,3}, known, fringe, other)$$
$$= \alpha \sum_{fringe} \mathbf{P}(b|known, P_{1,3}, fringe) \sum_{other} \mathbf{P}(P_{1,3})P(known)P(fringe)P(other)$$
$$= \alpha\, P(known)\mathbf{P}(P_{1,3}) \sum_{fringe} \mathbf{P}(b|known, P_{1,3}, fringe)P(fringe) \sum_{other} P(other)$$
$$= \alpha'\, \mathbf{P}(P_{1,3}) \sum_{fringe} \mathbf{P}(b|known, P_{1,3}, fringe)P(fringe)$$

Example: Wumpus World Computation

is 1 if the breeze observations b are consistent with the fringe, 0 otherwise

$$\mathbf{P}(P_{1,3}|known, b) = \alpha' \mathbf{P}(P_{1,3}) \sum_{fringe} \mathbf{P}(b|known, P_{1,3}, fringe) P(fringe)$$



0.2 x 0.2 = 0.04 | 0.2 x 0.8 = 0.16 | 0.8 x 0.2 = 0.16 | 0.2 x 0.2 = 0.04 | 0.2 x 0.8 = 0.16

$$\begin{aligned} \mathbf{P}(P_{1,3}|known, b) &= \alpha' \langle 0.2(0.04+0.16+0.16),\ 0.8(0.04+0.16) \rangle \\ &\approx \langle 0.31, 0.69 \rangle \end{aligned}$$

$$\mathbf{P}(P_{2,2}|known, b) \approx \langle 0.86, 0.14 \rangle$$ (by analogous computation)

Summary

- Probability is a rigorous formalism for uncertain knowledge
- Joint probability distribution specifies probability of every atomic event
- Queries can be answered by summing over atomic events
- For nontrivial domains, we must find a way to reduce the joint size
- Independence and conditional independence provide the tools