

UNCERTAINTY - PROBABILITY

### UNCERTAINTY

Let action At = leave for airport t minutes before flight Will At get me there on time?

#### **Problems:**

- 1. partial observability (road state, etc.)
- 2. multi-agent problem (other drivers' plans)
- 3. noisy sensors (uncertain traffic reports)
- 4. uncertainty in action outcomes (flat tire, etc.)
- 5. immense complexity of modeling and predicting traffic

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#### Hence a purely logical approach either

- 1. risks falsehood: "A25will get me there on time", or
- 2. leads to conclusions that are too weak for decision making:

"A25will get me there on time if there's no accident on the bridge and it doesn't rain and my tires remain intact, etc., etc."

"A1440 should get me there on time but I'd have to stay overnight in the airport."

## PROPOSITIONAL LOGIC AND PROBABILITY

Their ontological commitments are the same

The world is a set of facts that do or do not hold

**Ontology** is the philosophical study of the nature of being, becoming, existence, or reality; what exists in the world?

Their epistemological commitments differ

- **Logic agent** believes true, false, or no opinion
- Probabilistic agent has a numerical degree of belief between 0 (false) and 1 (true)
  - **Epistemology** is the philosophical study of the nature and scope of knowledge; how, and in what way, do we know about the world?

## UNCERTAINTY IN THE WORLD

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  - Randomness
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- Probability gives
  - natural way to describe our assumptions
  - rules for how to combine information
- Subjective probability
  - Relate to agent's own state of knowledge: P(A25 | no accidents) = 0.05
  - Not assertions about the world; indicate degrees of belief
  - Change with new evidence: P(A25 | no accidents, 5am) = 0.20

### MAKING DECISIONS UNDER UNCERTAINTY

- Suppose I believe the following:
  - P(A25 gets me there on time | ...) = 0.04
  - P(A90 gets me there on time | ...) = 0.70
  - P(A120 gets me there on time | ...) = 0.95
  - P(A1440 gets me there on time | ...) = 0.9999
- Which action to choose?

### MAKING DECISIONS UNDER UNCERTAINTY

- Which action to choose?
- Depends on my preferences for missing flight vs. time spent waiting, etc.
  - Utility theory is used to represent and infer preferences
  - Decision theory= probability theory + utility theory
- Expected utility of action a in state s
  - =  $\sum_{\text{outcome in Results(s,a)}} P(\text{outcome}) * Utility(\text{outcome})$
- A rational agent acts to maximize expected utility

### **EX: AIRPORT**

- Suppose I believe the following:
  - P(A25 gets me there on time | ...) = 0.04
  - P(A90 gets me there on time | ...) = 0.70
  - P(A120 gets me there on time  $| ... \rangle = 0.95$
  - P(A1440 gets me there on time | ...) = 0.9999
  - Utility(on time) = \$1,000
  - Utility(not on time) = -\$10,000
- Expected utility of action a in state s

= 
$$\sum_{\text{outcome in Results(s,a)}} P(\text{outcome}) * Utility(\text{outcome})$$

$$E(Utility(A25)) = 0.04*\$1,000 + 0.96*(-\$10,000) = -\$9,560$$

$$E(Utility(A90)) = 0.7*\$1,000 + 0.3*(-\$10,000) = -\$2,300$$

$$E(Utility(A120)) = 0.95*\$1,000 + 0.05*(-\$10,000) = \$450$$

$$E(Utility(A1440)) = 0.9999*\$1,000 + 0.0001*(-\$10,000) = \$998.90$$

Have not yet accounted for disutility of staying overnight at the airport, etc.

### **PROBABILITY**

- P(a) is the probability of proposition "a"
- E.g., P(it will rain in London tomorrow)
  - The proposition "a" is actually true or false in the real world
  - P(a) is our <u>degree of belief</u> that proposition "a" is true in the real world
  - P(a) = "prior" or marginal or unconditional probability
  - Assumes no other information is available
- Axioms of probability:
  - $0 \le P(a) \le 1$
  - P(NOT(a)) = 1 P(a)
  - P(true) = 1
  - P(false) = 0
  - P(a OR b) = P(a) + P(b) P(a AND b)

## INTERPRETATIONS OF PROBABILITY

- Relative Frequency: Usually taught in school
  - P(a) represents the frequency that event a will happen in repeated trials.
  - Requires event a to have happened enough times for data to be collected.
- Degree of Belief: A more general view of probability
  - P(a) represents an agent's degree of belief that event a is true.
  - Can predict probabilities of events that occur rarely or have not yet occurred.
  - Does not require new or different rules, just a different interpretation.

#### • Examples:

- a = "life exists on another planet"
  - What is P(a)? We all will assign different probabilities
- a = "California will secede from the US"
  - What is P(a)?
- a = "over 50% of the students in this class will get A's"
  - What is P(a)?

## **CONCEPTS OF PROBABILITY**

#### Unconditional Probability

- P(a), the probability of "a" being true, or P(a=True)
- Does not depend on anything else to be true (unconditional)
- Represents the probability prior to further information that may adjust it (prior)
- Also sometimes "marginal" probability (vs. joint probability)

## **CONCEPTS OF PROBABILITY**

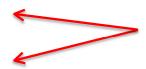
#### Conditional Probability

- P(a|b), the probability of "a" being true, given that "b" is true
- Relies on "b" = true (conditional)
- Represents the prior probability adjusted based upon new information "b" (posterior)
- Can be generalized to more than 2 random variables:
  - e.g. P(a|b, c, d)

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We often use comma to abbreviate AND.

- Joint Probability
- P(a, b) = P(a ^b), the probability of "a" and "b" both being true
- Can be generalized to more than 2 random variables:
  - e.g. P(a, b, c, d)

### RANDOM VARIABLES

- Random Variable:
  - Basic element of probability assertions
  - Similar to CSP variable, but values reflect probabilities not constraints.
    - Variable: A
    - Domain: {a<sub>1</sub>, a<sub>2</sub>, a<sub>3</sub>} <-- events / outcomes</p>
- Types of Random Variables:
  - Boolean random variables : { true, false }
    - e.g., Cavity (= do I have a cavity?)
  - Discrete random variables : one value from a set of values
    - e.g., Weather is one of {sunny, rainy, cloudy ,snow}
  - Continuous random variables : a value from within constraints
    - e.g., Current temperature is bounded by (10°, 200°)
- Domain values must be exhaustive and mutually exclusive:
  - One of the values must always be the case (Exhaustive)
  - Two of the values cannot both be the case (Mutually Exclusive)

### RANDOM VARIABLES

```
Example: Coin flipVariable = R, the result of the coin flip

Domain = {heads, tails, edge}
P(R = heads) = 0.4999
P(R = tails) = 0.4999
P(R = edge) = 0.0002

                                                              <-- must be exhaustive
                                                             } <-- must be exclusive</pre>
```

- Shorthand is often used for simplicity:
  - Upper-case letters for variables, lower-case letters for values.

```
\equiv <P(A=a1), P(A=a2), ..., P(A=an)>  for all n values in Domain(A)
             P(A)
– E.g.,
                         \equiv P(A = a)

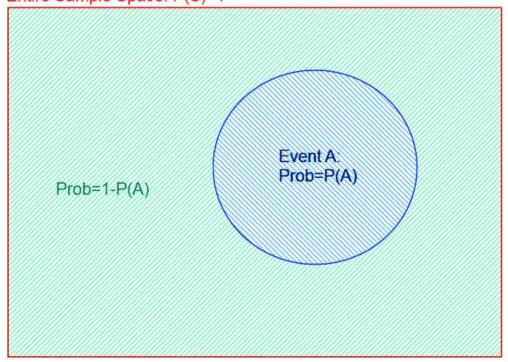
\equiv P(A=a | B=b)

\equiv P(A=a \lambda B=b)
             P(a)
E.g.,
```

- Two kinds of probability propositions:
  - Elementary propositions are an assignment of a value to a random variable:
    - e.g., Weather = sunny; e.g., Cavity = false (abbreviated as ¬cavity)
  - Complex propositions are formed from elementary propositions and standard logical connectives:
    - e.g., Cavity = false Weather = sunny

## PROBABILITY SPACE

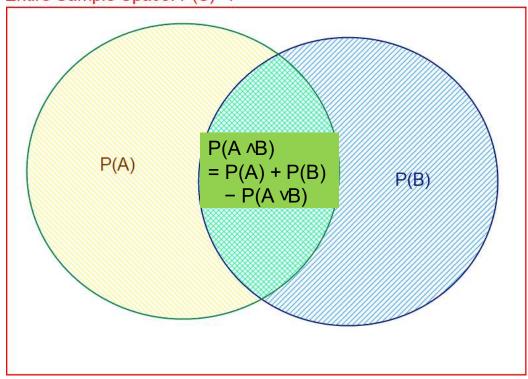
$$P(A) + P(\neg A) = 1$$



Area = Probability of Event

## AND PROBABILITY

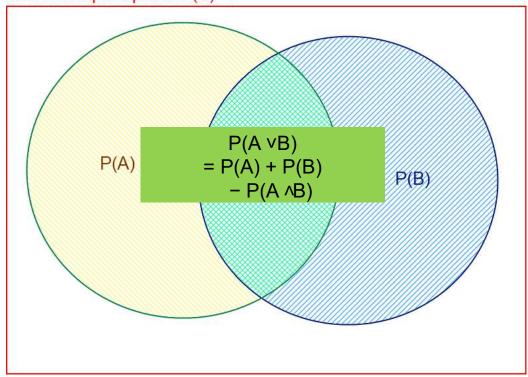
$$P(A, B) = P(A ^B) = P(A) + P(B) - P(A ^B)$$



**Area = Probability of Event** 

## OR PROBABILITY

$$P(A \lor B) = P(A) + P(B) - P(A \lor B)$$

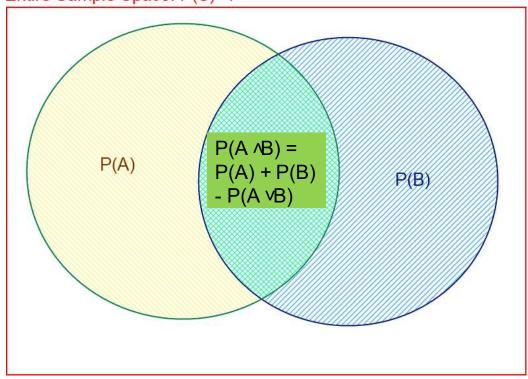


**Area = Probability of Event** 

# CONDITIONAL PROBABILITY

We often use comma to abbreviate AND.

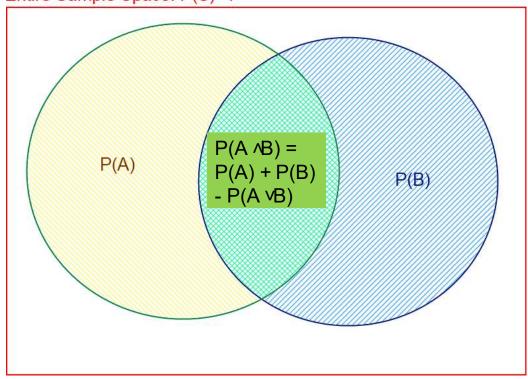
 $P(A \mid B) = P(A, B)/P(B)$ 



**Area = Probability of Event** 

## PRODUCT RULE

$$P(A,B) = P(A|B) P(B)$$



**Area = Probability of Event** 

#### USING THE PRODUCT RULE

- Applies to any number of variables:
  - P(a, b, c) = P(a, b|c) P(c) = P(a|b, c) P(b, c)
  - P(a, b, c | d, e) = P(a | b, c, d, e) P(b, c | d, e)
- Factoring: (AKA Chain Rule for probabilities)
  - By the product rule, we can always write:

$$P(a, b, c, ... z) = P(a | b, c, ... z) P(b, c, ... z)$$

We often use comma to abbreviate AND.

Repeatedly applying this idea, we can write:

$$P(a, b, c, ... z) = P(a | b, c, .... z) P(b | c, ... z) P(c | ... z) ... P(z)$$

This holds for any ordering of the variables

Start with the joint distribution:

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

For any proposition  $\phi$ , sum the atomic events where it is true:

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

Start with the joint distribution:

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

For any proposition  $\phi$ , sum the atomic events where it is true:

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

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

Start with the joint distribution:

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

For any proposition  $\phi$ , sum the atomic events where it is true:

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

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

Start with the joint distribution:

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

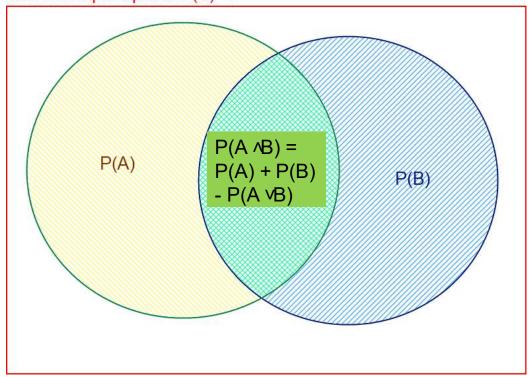
Can also compute conditional probabilities:

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

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

## BAYES' RULE

# P(B|A) = P(A|B) P(B) / P(A)Entire Sample Space: P(S)=1



**Area = Probability of Event** 

### DERIVATION OF BAYES' RULE

Start from Product Rule:

$$- P(a, b) = P(a|b) P(b) = P(b|a) P(a)$$

Isolate Equality on Right Side:

$$-P(a|b) P(b) = P(b|a) P(a)$$

Divide through by P(b):

$$- P(a|b) = P(b|a) P(a) / P(b)$$
 <-- Bayes' Rule

## BAYES' RULE

Product rule 
$$P(a \wedge b) = P(a|b)P(b) = P(b|a)P(a)$$
  
 $\Rightarrow$  Bayes' rule  $P(a|b) = \frac{P(b|a)P(a)}{P(b)}$ 

or in distribution form

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

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!