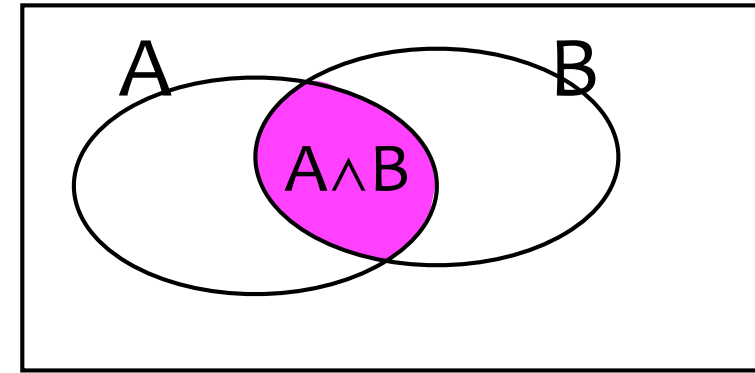


Probability of combined propositions

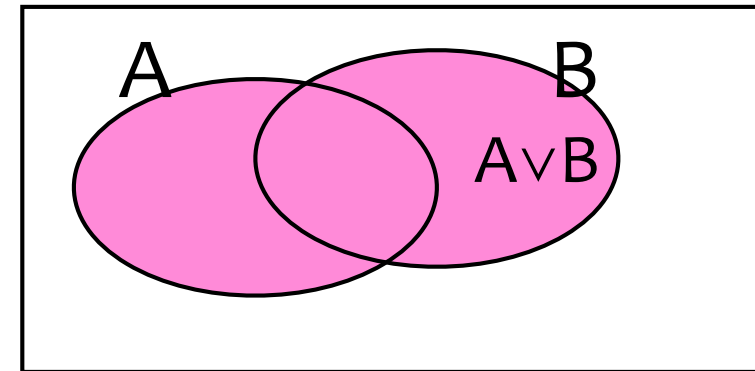
- $p(A \wedge B)$ = probability both A and B are true.
- $A \wedge B$ is a subset of A, so



Conjunction of A and B

$$0 \leq p(A \wedge B) \leq p(A) \quad \text{Conjunction rule}$$

- $A \vee B$ is a superset of A, so
- $p(A) \leq p(A \vee B) \leq 1$ Disjunction rule

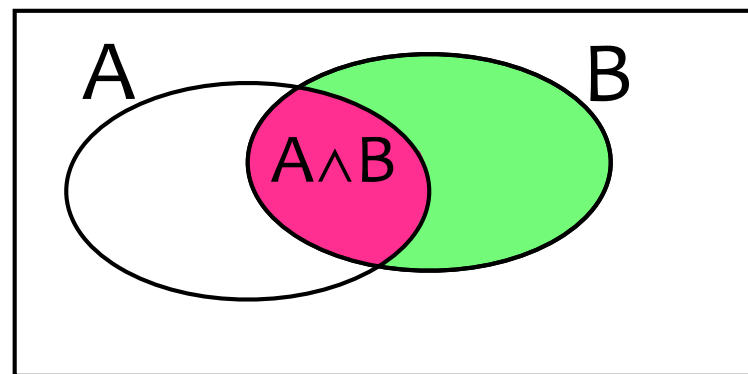


Disjunction of A and B

- $p(A \vee B) = p(A) + p(B) - p(A \wedge B)$ Relation between \wedge and \vee

Conditional probability

- $p(A|B)$ means “probability of A given B is true”
- Definition: $p(A|B) = \frac{p(A \wedge B)}{p(B)}$



Probability tables

Gallup 2009

		B		
		T	F	
A	T	10	20	30
	F	40	30	70
		50	50	

$$p(A|B) = 10/50 = .2$$

		Sex		
		M	F	
Party	D	27	31	58
	R	23	19	42
		50	50	

$$p(D|F) = 31/50 = .62$$

$$p(F|D) = 31/58 = .53$$

Bayes' rule

- Conditional probability is the basis for inductive inference
- The conditional probability of a conclusion (**hypothesis**) H given premise (data) D is:

The diagram illustrates Bayes' rule with the formula $p(H|D) = \frac{p(H)p(D|H)}{p(D)}$. The components are annotated as follows:

- Prior probability** (blue text): $p(H)$, described as "belief in H before the data". A blue arrow points from this text to the $p(H)$ term in the numerator.
- Likelihood** (red text): $p(D|H)$, described as "fit of H to the data". A red arrow points from this text to the $p(D|H)$ term in the numerator.
- Posterior probability** (pink text): $p(H|D)$, described as "belief in H after the data". A pink arrow points from this text to the $p(H|D)$ term on the left side of the equation.

- This is called **Bayes' rule** and is incredibly useful for deciding how strongly to believe any inductive hypothesis on the basis of evidence and prior knowledge.
- Bayes' rule says: the posterior is proportional to the **product** of the prior and the likelihood (fit to the evidence).

Bayesian inference

- Given some data D and various hypotheses that might explain the data, Bayesian inference allows you to compute **how strongly to believe H** as a function of
 - the degree to which H fits the evidence (**likelihood**), and
 - the **prior probability** of H (how likely it was before the evidence).
- Given data D , **Bayes' rule** lets you calculate the **posterior probability** of H (the probability of H given the data D).
- Bayesian inference simply uses the mathematical laws of probability to decide what to believe

Bayesian inference: examples

- A random person. Is he/she a democrat?

prior probability = $p(D) = 58\%$ [58% of random people are democrats]

Oh, she's a woman? Ok,

$$p(D|F) = p(F|D)p(D)/p(F)$$

$$= (.53)(.58)/(.5) = .615$$

Bayes' rule



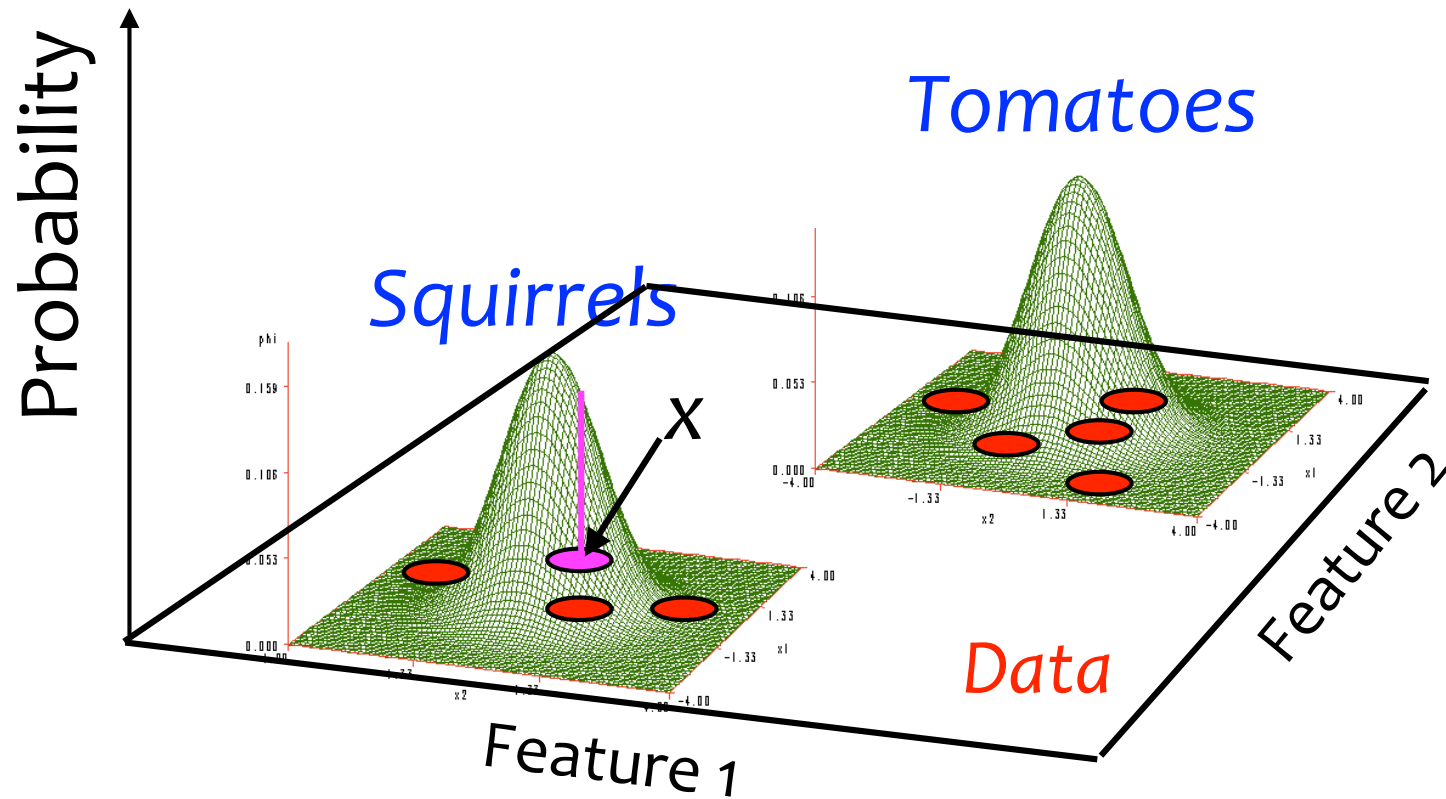
- A guy named Joe. Is he a symphony conductor?

$p(SC) = .0001$ [low prior — very few people are symphony conductors]

Oh, he likes music? $p(SC|Likes\ music) =$

$p(LM|SC)p(SC)/p(LM) = (1)(.0001)/(1/2) = .0002$ (assuming 50% of people like music!)

Bayesian concept learning



$$p(\text{squirrel}|x) = \frac{p(x|\text{squirrel})p(\text{squirrel})}{p(x|\text{squirrel})p(\text{squirrel}) + p(x|\text{tomato})p(\text{tomato})}$$

prior of squirrel
prior of tomato

Conditional probability in reasoning

Deduction

- Modus ponens

$A, A \rightarrow B;$

B

- Modus tollens

$A \rightarrow B, \sim B;$

$\sim A$

Probabilistic reasoning

- “probabilistic modus ponens”

$A, p(B|A) \text{ high};$

$p(B) \text{ high}$

- “probabilistic modus tollens”

$p(B|A) \text{ low}, B;$

$p(A) \text{ low}$

Bayesian inference and rationality

- Bayesian inference is the rational method for drawing inferences from experience—rational induction
- Bayesian inference is considered normative,
 - i.e. “objectively correct.” This is really important!
- If people are “Bayesian”, that means they form beliefs in a way that is optimal given the information available to them
- If not, people are irrational, which means that they form in a way that is incoherent or internally inconsistent.
- So: are people Bayesian?