Bayes Theorem

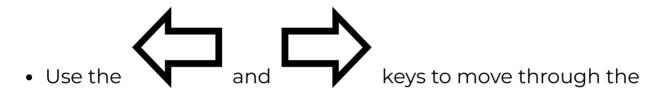
Applied To Data Analysis

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How To Navigate This Presentation



presentation.

• Press o for panel overview.

Derivation

	D=1	D=0
H=1	P(D,H)	$P(\mathrm{not}D,H)$
H=0	$P(D, \mathrm{not} H)$	$P(\mathrm{not}D,\mathrm{not}H)$

From the definition of conditional probability:

$$P(D|H) = P(D,H)/P(H)$$

$$P(H|D) = P(D,H)/P(D)$$

Then:

$$P(D|H)P(H) = P(D,H)$$

$$P(H|D)P(D) = P(D,H)$$

Then:

$$P(D|H)P(H) = P(H|D)P(D)$$

Bayes Theorem:

$$P(H|D) = rac{P(D|H)P(H)}{P(D)}$$

In Words:

posterior \propto likelihood \times prior

Example

Consider an example using 1,000 hypothetical studies. We imagine that only 10% of interventions are likely to have results. We adopt standard assumptions of adopting an α , or chance of detecting an effect when one is not there of 5%. We similarly assume 80% power β , or a 20% chance of failing to detect an effect when it is not present.

Data (D)	D=1 (effect)	D=0 (no effect)
Hypothesis (H)	100 effects	900 non-effects
H=1 (conclude effect)	80 true positives	45 false positives
H=0 (conclude no effect)	20 false negatives	855 true negatives

With thanks to the Wikipedia article on this topic for inspiration for this example.

Visualization

Calculations

$$P(H=1|D=1) = \frac{P(D=1|H=1)P(H=1)}{P(D)}$$

$$= \frac{P(D=1|H=1)P(H=1)}{P(D=1|H=1)P(H=1) + P(D=0|H=1)P(H=1)}$$

$$P(H=1|D=1) = \frac{.8 \times .1}{.08 + .045} = .64$$

See also Thinking Through Bayesian Ideas

Discussion

- Calculations suggest that a true effect is likely in 64% of the cases where one concludes the presence of an effect.
- Consequently, calculations suggest that 36% of the time, when one concludes there is an effect, there is actually no effect.
- Put another way, despite setting lpha=.05, 36% of cases result in a false positive.
- Notice how the Bayesian approach lets us estimate the probability of different hypotheses given the data. In some cases, this may afford us the opportunity to accept our null hypothesis H_0 .