Theorem: Bayes' Theorem

Bayes' Theorem provides a way to calculate Conditional Probability in the "reverse" direction. It relates P(A|B) to P(B|A), allowing us to update beliefs based on new evidence.

Statement

For Events A and B with P(A) > 0 and P(B) > 0:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

Alternative Forms

Using Law of Total Probability

If $\{A_1,A_2,...,A_n\}$ form a partition of the sample space:

$$P(A_i|B) = \frac{P(B|A_i) \cdot P(A_i)}{\sum_{i=1}^n P(B|A_i) \cdot P(A_i)}$$

Binary Case

For event A and its complement A^c :

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B|A) \cdot P(A) + P(B|A^c) \cdot P(A^c)}$$

Proof

From the definition of conditional probability: 1. $P(A|B) = \frac{P(A \cap B)}{P(B)}$ 2. $P(B|A) = \frac{P(A \cap B)}{P(A)}$

From (2): $P(A \cap B) = P(B|A) \cdot P(A)$

Substituting into (1):

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

Terminology

- P(A): **Prior probability** of A
- P(A|B): Posterior probability of A given evidence B
- P(B|A): **Likelihood** of observing B given A
- P(B): Marginal probability or normalizing constant

Applications

Medical Diagnosis

- A: Patient has disease
- B: Test is positive
- Calculate P(Disease|Positive test) from known test accuracy

Machine Learning

- Naive Bayes classifiers
- Bayesian inference and parameter estimation
- Updating model beliefs with new data

Example: Medical Test

Given: - Disease prevalence: P(D)=0.001~(0.1%) - Test sensitivity: P(+|D)=0.99~(99%) - Test specificity: $P(-|D^c)=0.95$, so $P(+|D^c)=0.05$

Find P(D|+):

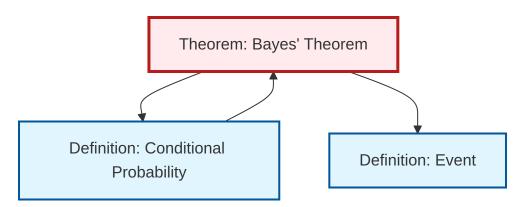
$$P(D|+) = \frac{0.99 \times 0.001}{0.99 \times 0.001 + 0.05 \times 0.999} = \frac{0.00099}{0.05094} \approx 0.0194$$

Despite a positive test, the probability of having the disease is only about 1.94%!

Bayesian Updating

Bayes' theorem enables iterative belief updating: 1. Start with prior P(A) 2. Observe evidence B 3. Update to posterior P(A|B) 4. Use posterior as new prior for next observation

Dependency Graph



Local dependency graph