



## Course Notes Summary

Focus Area: Summary of main formulas please

<b>Source:</b>	BayesTheorem.pdf
<b>Generated:</b>	2025-09-05 15:53:31
<b>Summary Type:</b>	Comprehensive

Prepared for quick revision and reference

Use this sheet as a step-by-step guide when solving problems.

## 1 Section 1.

### 1.1 Subsection 1.1

- Key definitions
  - Prior probability: initial probability before new information (e.g.,  $P(A)$ ).
  - Posterior probability: revised probability after incorporating new information (e.g.,  $P(A | B)$ ).
  - Likelihood: probability of observed evidence given a hypothesis (e.g.,  $P(B | A)$ ).
  - Marginal (or total) probability: overall probability of evidence (e.g.,  $P(B)$ ).
  - Conditional probability: probability of one event given another ( $P(B | A)$ ).
- Fundamental formulas
  - Conditional probability (definition):
    - \* 
$$P(B | A) = \frac{P(A \cap B)}{P(A)}$$
  - Product rule (relates joint and conditional probabilities):
    - \* 
$$P(A \cap B) = P(A)P(B | A) = P(B)P(A | B)$$
  - Independence criterion:
    - \*  $A$  and  $B$  independent  $\Leftrightarrow P(A \cap B) = P(A)P(B)$
    - \* Equivalently  $P(B | A) = P(B)$  (when independent)

### 1.2 Subsection 1.2

- Bayes' theorem (two events)
  - $$P(A | B) = \frac{P(B | A)P(A)}{P(B)}$$
  - Use when you want posterior  $P(A | B)$  and you know prior  $P(A)$  and likelihood  $P(B | A)$ .
- Law of total probability (two-event form):
  - $$P(B) = P(A)P(B | A) + P(A^c)P(B | A^c)$$
- Generalized Bayes (partition  $A_1, \dots, A_n$ )
  - Law of total probability (general):
    - \* 
$$P(B) = \sum_i P(A_i)P(B | A_i)$$
  - Bayes' theorem (generalized):
    - \* 
$$P(A_k | B) = \frac{P(A_k)P(B | A_k)}{\sum_i P(A_i)P(B | A_i)}$$
  - Compact relationship (proportional form):
    - \* 
$$P(A_k | B) \propto P(A_k) P(B | A_k)$$
 (normalize by sum over  $k$ )

## 2 Section 2.

### 2.1 Subsection 2.1

- Stepwise procedure to apply Bayes' theorem (ordered)
  1. List hypotheses (partition)  $A_1, \dots, A_n$  and their priors  $P(A_i)$ .
  2. For each hypothesis, list the likelihood  $P(B | A_i)$ .
  3. Compute marginal  $P(B) = \sum_i P(A_i)P(B | A_i)$ .
  4. Compute posterior  $P(A_k | B) = \frac{P(A_k)P(B | A_k)}{P(B)}$ .
- Intuitive (frequency/table) method
  - Assume a convenient total  $N$  (e.g., 1000 or 100000).
  - Convert priors to counts:  $\text{count}(A_i) = N \cdot P(A_i)$ .
  - For each  $A_i$ , compute  $\text{count}(A_i \wedge B) = \text{count}(A_i) \cdot P(B | A_i)$ .
  - Marginal count( $B$ ) =  $\sum_i \text{count}(A_i \wedge B)$ .
  - Posterior =  $\frac{\text{count}(A_k \wedge B)}{\text{count}(B)}$ .
- Short example 1 (Orange County cigar smokers)
  - Given:  $P(\text{male}) = 0.51$ ,  $P(\text{cigar} | \text{male}) = 0.095$ ,  $P(\text{cigar} | \text{female}) = 0.017$ .
  - Compute  $P(\text{male} | \text{cigar})$ :
    - \* Numerator =  $0.095 \times 0.51 = 0.04845$
    - \* Denominator =  $0.04845 + 0.017 \times 0.49 = 0.04845 + 0.00833 = 0.05678$
    - \*  $P(\text{male} | \text{cigar}) = \frac{0.04845}{0.05678} \approx 0.853$
- Short example 2 (ELT manufacturers and defectives)
  - Given:  $P(A) = 0.80$ ,  $P(B) = 0.15$ ,  $P(C) = 0.05$ ; defect rates  $P(D | A) = 0.04$ ,  $P(D | B) = 0.06$ ,  $P(D | C) = 0.09$ .
  - Compute  $P(A | D)$ :
    - \* Numerator =  $0.80 \times 0.04 = 0.032$
    - \* Denominator =  $0.032 + 0.15 \times 0.06 + 0.05 \times 0.09 = 0.032 + 0.009 + 0.0045 = 0.0455$
    - \*  $P(A | D) = \frac{0.032}{0.0455} \approx 0.703$
  - Equivalent frequency-table example ( $N = 10,000$ ): defective counts  $A = 320$ ,  $B = 90$ ,  $C = 45$ , total defective = 455  $\Rightarrow P(A | D) = 320/455 \approx 0.703$ .

### 2.2 Subsection 2.2

- Important relationships and connections
  - Prior  $\rightarrow$  Likelihood  $\rightarrow$  Posterior: Bayes updates prior by weighting it with the likelihood of observed evidence.
  - Denominator role:  $P(B)$  is the marginal likelihood; it ensures posterior probabilities sum to 1 across hypotheses.
  - Proportionality: Posterior is proportional to prior  $\times$  likelihood; normalization uses total probability.

- Generalization: Bayes works with any finite partition of hypotheses; use law of total probability for the denominator.
- Practical tips and common pitfalls
  - Tip: Use the frequency/table method when formulas feel error-prone; it is less error-prone and intuitive.
  - Tip: Keep track of which event is the hypothesis ( $A_i$ ) and which is the evidence ( $B$ ).
  - Pitfall: Confusing  $P(B | A)$  (likelihood) with  $P(A | B)$  (posterior).
  - Pitfall: Forgetting to include all partition events in the denominator (use full partition).
- Compact summary of main formulas (for quick revision)

$$\begin{aligned} - P(B | A) &= \frac{P(A \cap B)}{P(A)} \\ - P(A \cap B) &= P(A)P(B | A) = P(B)P(A | B) \\ - P(A | B) &= \frac{P(B | A)P(A)}{P(B)} \\ - P(B) &= \sum_i P(A_i)P(B | A_i) \\ - P(A_k | B) &= \frac{P(A_k)P(B | A_k)}{\sum_i P(A_i)P(B | A_i)} \end{aligned}$$