

Course Notes Summary

Focus Area: Brief summary of main formulas

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Prepared for quick revision and reference

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

Brief summary of main formulas — Bayes' theorem (study notes)

1. Core definitions - Event intersection: $A \cap B$ = both A and B occur. - Conditional probability: $P(B | A)$ = probability B occurs given A has occurred. - Prior probability: the initial probability of an event before new evidence (notation: $P(A)$). - Posterior probability: the revised probability after observing evidence (notation: $P(A | B)$). - Likelihood: $P(B | A)$ — probability of observed evidence B under hypothesis A.

2. Fundamental formulas - Conditional probability (definition) - $P(B | A) = P(A \cap B) / P(A)$, provided $P(A) > 0$.

- Symmetry for intersection - $P(A \cap B) = P(A) P(B | A) = P(B) P(A | B)$.

- Bayes' theorem (basic two-event form) - $P(A | B) = [P(A) P(B | A)] / P(B)$.

- Law of total probability (useful for the denominator) - If A_1, A_2, \dots, A_k is a partition (mutually exclusive and exhaustive), then - $P(B) = \sum_{i=1}^k P(A_i) P(B | A_i)$.

- Bayes' theorem (generalized / k events / partition form) - For A_j in a partition A_1, \dots, A_k ,
- $P(A_j | B) = [P(A_j) P(B | A_j)] / \sum_{i=1}^k P(A_i) P(B | A_i)$.

3. Derivation idea (short) - From $P(A \cap B) = P(A) P(B | A) = P(B) P(A | B)$ $P(A | B) = P(A) P(B | A) / P(B)$. - Denominator $P(B)$ expanded by law of total probability when multiple causes exist.

4. Intuitive / counting method (recommended for calculation) - Steps: 1. Choose a convenient total population N (e.g., 100, 1,000 or 10,000). 2. Convert priors $P(A_i)$ into counts: $\text{count}(A_i) = N \times P(A_i)$. 3. For each A_i , compute counts of evidence B: $\text{count}(A_i \text{ and } B) = \text{count}(A_i) \times P(B | A_i)$. 4. Sum counts for B: $\text{count}(B) = \sum \text{count}(A_i \text{ and } B)$. 5. Posterior $P(A_j | B) = \text{count}(A_j \text{ and } B) / \text{count}(B)$. - This produces the same numeric result as the formula and is less error-prone.

5. Worked examples (compact)

Example A — Industrial quality (ELT manufacturers) - Given: - $P(A)=0.80$, $P(B)=0.15$, $P(C)=0.05$ - $P(D | A)=0.04$, $P(D | B)=0.06$, $P(D | C)=0.09$ (D = defective) - Using Bayes' theorem for $P(A | D)$: - Numerator = $0.80 \times 0.04 = 0.032$ - Denominator = $0.032 + (0.15 \times 0.06) + (0.05 \times 0.09) = 0.032 + 0.009 + 0.0045 = 0.0455$ - $P(A | D) = 0.032 / 0.0455 \approx 0.703$ - Counting method (N = 10,000) gives the same: 320 defective from A out of 455 total defective 320/455 ≈ 0.703 .

Example B — Smoking and gender (Orange County) - Given: - $P(\text{Male})=0.51$, $P(\text{Female})=0.49$ - $P(\text{Cigar} | \text{Male})=0.095$, $P(\text{Cigar} | \text{Female})=0.017$ - Compute $P(\text{Male} | \text{Cigar})$: - Numerator = $0.51 \times 0.095 = 0.04845$ - Denominator = $0.04845 + (0.49 \times 0.017 = 0.00833) = 0.05678$ - $P(\text{Male} | \text{Cigar}) = 0.04845 / 0.05678 \approx 0.854$ - Counting method (N = 100,000) — 4,845 cigar-smoking males / 5,678 total cigar smokers ≈ 0.854 .

6. Important relationships insights - Posterior = Prior \times Likelihood: - $P(A_j | B) = P(A_j) \times P(B | A_j)$. Normalize by dividing by $\sum_i P(A_i) P(B | A_i)$. — *Bayes' theorem is a formal statement of updating belief about hypothesis. Law of total probability is essential to compute the marginal probability of evidence $P(B)$. — When the partition is on the event form.*

7. Common conditions and pitfalls - Denominator must be > 0 ($P(B) > 0$). - The set A_1, \dots, A_k used in the denominator must be mutually exclusive and collectively exhaustive (a partition). - Confuse $P(B | A)$ with $P(A | B)$ — they are generally not equal. - Use counts/intuitive table to reduce algebraic substitution errors.

8. Quick checklist for solving Bayes problems 1. Identify hypotheses A_j and evidence/event B. 2. Write priors $P(A_j)$ and likelihoods $P(B | A_j)$. 3. Compute marginal $P(B) = \sum P(A_i) P(B | A_i)$. 4. Compute posterior $P(A_j | B) = P(A_j) P(B | A_j) / P(B)$. 5. Optionally, verify with a counting/table approach.

9. Useful mnemonic - “Posterior = Prior \times Likelihood” — multiply prior probability by how likely the evidence is under that hypothesis, then normalize.

Use this sheet to revise formulas quickly and to guide computations; when in doubt, convert probabilities to counts and construct a small contingency table — it's often the fastest, least error-prone route.