Conditional Probability¹ STA 256: Fall 2018

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Conditional Probability: The idea

- If event *B* has occurred, maybe the probability of *A* is different from the probability of *A* overall.
- Maybe the chances of an auto insurance claim are different depending on the type of car.
- We will talk about the *conditional* probability of an insurance claim *given* that the car is a Dodge Charger.

Restrict the sample space

To condition on the event B, make B the new, restricted sample space.



Express the probability of A as a fraction of the probability of B, provided the probability of B is not zero.

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

Definition: The probability of A given B

If
$$P(B) > 0$$
, $P(A|B) = \frac{P(A \cap B)}{P(B)}$
 M
 F
 $A = HFV Pos_{1} + IVO$
 0.04
 0.01
 0.46
 0.49

$$P(A|F) = \frac{P(A \cap F)}{P(F)} = \frac{0.01}{0.50} = 0.02$$

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Multiplication Law $P(A|B) = \frac{P(A \cap B)}{P(B)} \Rightarrow P(A \cap B) = P(A|B)P(B)$

$P(A \cap B) = P(A|B)P(B)$

Useful for sequential experiments. A jar contains 15 red balls and 5 blue balls. What is the probability of randomly drawing a red and then a blue?

$$P(R_1 \cap B_2) = P(R_1)P(B_2|R_1) = \frac{15}{20} \frac{5}{19} = \frac{15}{76} \approx 0.197$$

Make a Tree Justified by the multiplication principle

$$P(A_1) = P(A_1 \cap B_1)$$

$$P(A_1) = P(A_1 \cap B_1)$$

$$P(A_1) = P(A_1 \cap B_2)$$

$$P(A_2) = P(A_2 \cap B_1)$$

$$P(A_2) = P(A_2 \cap B_1)$$

$$P(B_1 \cap A_2) = P(A_2 \cap B_1)$$

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$$P(B_2 \cap A_2) = P(A_2 \cap B_1)$$

$$P(B_2 \cap A_2)$$

$$P(B_3 \cap A_2) = P(A_2 \cap B_1)$$

$$P(B_3 \cap A_2)$$

$$P(B_3 \cap A_2) = P(A_2 \cap B_3)$$

- Can be extended to more than 2 stages.
- Are best for *small* sequential experiments.
- Can allow you to side-step two important theorems, if the problem is set up nicely for you.
 - The Law of Total Probability
 - Bayes' Theorem.

Partition Ω , into B_1, B_2, \ldots, B_n , disjoint, with $P(B_k) > 0$ for all k.



$$A = \bigcup_{k=1}^{n} (A \cap B_k), \text{ disjoint}$$
$$P(A) = \sum_{k=1}^{n} P(A \cap B_k)$$
$$= \sum_{k=1}^{n} P(A|B_k)P(B_k)$$

In the 2 coins and one die example, we got $P(2) = \frac{7}{18}$ from a tree.

$$P(2) = P(2|\text{Coin 1}) P(\text{Coin 1}) + P(2|\text{Coin 2}) P(\text{Coin 2}) + P(2|\text{Die}) P(\text{Die}) = \frac{1}{2} \cdot \frac{1}{3} + \frac{1}{2} \cdot \frac{1}{3} + \frac{1}{6} \cdot \frac{1}{3} = \frac{7}{18}$$

Let $\Omega = \bigcup_{k=1}^{\infty} B_k$, disjoint, with $P(B_k) > 0$ for all k. Then

$$P(A) = \sum_{k=1}^{\infty} P(A|B_k) P(B_k)$$

Bayes' Theorem allows you to turn conditional probability around, and obtain P(B|A) from P(A|B).

Thomas Bayes (1701-1761) Image from the Wikipedia



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Let $\Omega = \bigcup_{k=1}^{\infty} B_k$, disjoint, with $P(B_k) > 0$ for all k. Then

$$P(B_j|A) = \frac{P(A|B_j)P(B_j)}{\sum_{k=1}^{\infty} P(A|B_k)P(B_k)}$$

An important special case is

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

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http://www.utstat.toronto.edu/~brunner/oldclass/256f18