

Probability 1

Lecture 03 : Probability Axioms

Dr. Daniel Flores-Agreda,

(based on the notes of Prof. Davide La Vecchia)

Spring Semester 2021

Objective

- 1 An Axiomatic Definition of Probability
- 2 Implications: Properties of $P(\cdot)$
- 3 Examples and Illustrations
- 4 Conditional Probability
- 5 Independence
- 6 Theorem I: The Theorem of Total Probability
- 7 Theorem II: Bayes' Theorem

- 1 An Axiomatic Definition of Probability
- 2 Implications: Properties of $P(\cdot)$
- 3 Examples and Illustrations
- 4 Conditional Probability
- 5 Independence
- 6 Theorem I: The Theorem of Total Probability
- 7 Theorem II: Bayes' Theorem

An Axiomatic Definition of Probability

Definition

We define probability a set function with values in $[0, 1]$, which satisfies the following axioms:

- (i) $P(A) \geq 0$, for every event A
- (ii) $P(S) = 1$
- (iii) If A_1, A_2, \dots is a sequence of mutually exclusive events (namely $A_i \cap A_j = \emptyset$, for $i \neq j$, and $i, j = 1, 2, \dots$), and such that $A = \bigcup_{i=1}^{\infty} A_i$, then

$$P(A) = P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i). \quad (1)$$

Outline

- 1 An Axiomatic Definition of Probability
- 2 Implications: Properties of $P(\cdot)$**
- 3 Examples and Illustrations
- 4 Conditional Probability
- 5 Independence
- 6 Theorem I: The Theorem of Total Probability
- 7 Theorem II: Bayes' Theorem

Implications: Properties of $P(\cdot)$

One can make use of the three axioms to build more sophisticated statements. For instance,

Theorem (Probability of the Empty Set)

$$P(\emptyset) = 0$$

Proof.

Take $A_1 = A_2 = A_3 = \dots = \emptyset$. Then by (1) in Axiom (ii) we have

$$P(\emptyset) = P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i) = \sum_{i=1}^{\infty} P(\emptyset)$$

which is true only if it is an infinite sum of zeros. Thus

$$P(\emptyset) = 0.$$



Implications: Properties of $P(\cdot)$

Theorem (The Addition Law of Probability)

If A_1, A_2, \dots are mutually exclusive events, then

$$P\left(\bigcup_{i=1}^n A_i\right) = \sum_{i=1}^n P(A_i). \quad (2)$$

Proof.

Let $A_{n+1} = A_{n+2} = \dots = \emptyset$, then $\bigcup_{i=1}^n A_i = \bigcup_{i=1}^{\infty} A_i$, and, from (1) (see Axiom (iii)) it follows

$$P\left(\bigcup_{i=1}^n A_i\right) = P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i) = \sum_{i=1}^n P(A_i) + \underbrace{\sum_{i=n+1}^{\infty} P(A_i)}_{\equiv 0}.$$



Implications: Properties of $P(\cdot)$

Theorem (The Complement Rule)

If A is an event, then $P(A^c) = 1 - P(A)$.

Proof.

Let $A \cup A^c = S$ and $A \cap A^c = \emptyset$, so and

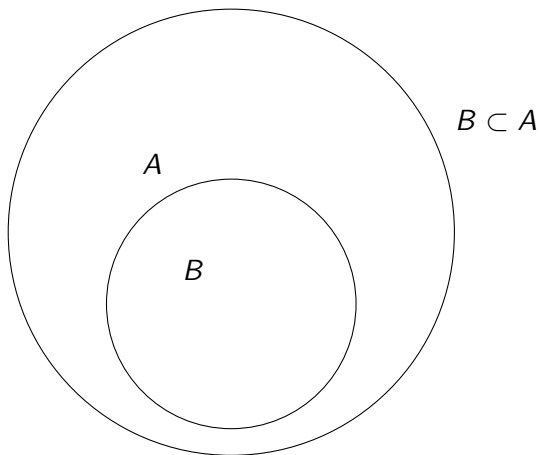
$$P(S) = P(A \cup A^c) = P(A) + P(A^c).$$

By Axiom (i) Axiom (ii) we have $P(S) = 1$, so the desired result follows from:

$$1 = P(A) + P(A^c).$$



Implications: Properties of $P(\cdot)$



Implications: Properties of $P(\cdot)$

Theorem

For any two events A and B , such that $B \subset A$, we have

$$P(A) \geq P(B).$$

Proof.

Let us write

$$A = B \cup (B^c \cap A)$$

and notice that $B \cap (B^c \cap A) = \phi$, so that

$$\begin{aligned} P(A) &= P\{B \cup (B^c \cap A)\} \\ &= P(B) + P(B^c \cap A) \end{aligned}$$

which implies (since $P(B^c \cap A) \geq 0$) that

$$P(A) \geq P(B).$$



Implications: Properties of $P(\cdot)$

Theorem

For any two events A and B then

$$P(A \cup B) = P(A) + P(B) - P(A \cap B).$$

Proof.

Consider that $A \cup B = A \cup (A^c \cap B)$, and $A \cap (A^c \cap B) = \emptyset$. Now remember^a that $A^c \cap B = B - (A \cap B)$, so,

$$\begin{aligned} P(A \cup B) &= P(A) + P(A^c \cap B) \\ &= P(A) + P(B) - P(A \cap B). \end{aligned}$$



^aSee Lecture 1 for the meaning of set difference.

Implications: Properties of $P(\cdot)$

Theorem (Boole's inequality)

For the events A_1, A_2, \dots, A_n ,

$$P(A_1 \cup A_2 \cup \dots \cup A_n) \leq \sum_{i=1}^n P(A_i).$$

For instance, let us consider $n = 2$. Then we have:

$$P(A_1 \cup A_2) = P(A_1) + P(A_2) - P(A_1 \cap A_2) \leq P(A_1) + P(A_2)$$

since $P(A_1 \cap A_2) \geq 0$ by definition.

Remark

It is worth notice that if $A_j \cap A_i = \emptyset$, for every i and j , with $i \neq j$, then $P(A_1 \cup A_2 \cup \dots \cup A_n) = \sum_{i=1}^n P(A_i)$, as stated in (2).

Outline

- 1 An Axiomatic Definition of Probability
- 2 Implications: Properties of $P(\cdot)$
- 3 Examples and Illustrations**
- 4 Conditional Probability
- 5 Independence
- 6 Theorem I: The Theorem of Total Probability
- 7 Theorem II: Bayes' Theorem

Example (Flipping a coin twice)

If we flip a balanced coin twice, what is the probability of getting at least one head?

- The sample space is: $S = \{HH, HT, TH, TT\}$
- Balanced coin: outcomes are equally likely and $p_{HH} = p_{HT} = p_{TH} = p_{TT} = p = 1/4$
- Let A denote the event **obtaining at least one Head**, i.e. $H = \{HH, HT, TH\}$

$$\begin{aligned} Pr(A) &= Pr(\{HH \cup HT \cup TH\}) \\ &= Pr(\{HH\}) + Pr(\{HT\}) + Pr(\{TH\}) \\ &= \frac{1}{4} + \frac{1}{4} + \frac{1}{4} = \frac{3}{4} \end{aligned}$$

Example (Detecting Shoppers)

Shopper TRK is an electronic device that counts the number of shoppers entering a shopping centre.

Two shoppers enter the shopping centre together, one walking in front of the other:

- 1. There is a 0.98 probability that the first shopper is detected*
- 2. There is a 0.94 probability that the second shopper is detected.*
- 3. There is a 0.93 probability that both shoppers are detected.*

What is the probability that the device will detect at least one of the two shoppers entering?

Example (Detecting Shoppers, continued)

Define the **events**:

- D (shopper is detected) and
- U (shopper is undetected).

Then, the Sample Space is $S = \{DD, DU, UD, UU\}$

Define the **probabilities**:

- $Pr(DD \cup DU) = 0.98$
- $Pr(DD \cup UD) = 0.94$
- $Pr(DD) = 0.93$

Example (Detecting Shoppers, continued)

$$\begin{aligned}Pr(DD \cup UD \cup DU) &= Pr(\{DD \cup UD\} \cup \{DD \cup DU\}) \\&= Pr(\{DD \cup UD\}) + Pr(\{DD \cup DU\}) \\&\quad - Pr(\{DD \cup UD\} \cap \{DD \cup DU\})\end{aligned}$$

The only missing probability is : $P\{DD \cup UD\} \cap \{DD \cup DU\} = ?$

To compute it, let's use the fact that **the union is distributive with respect to the intersection** (see Ch 2):

$$(DD \cup UD) \cap (DD \cup DU) = DD \cup (UD \cap DU) = DD \cup \emptyset = DD$$

Example (Detecting Shoppers, continued)

Graphically:

DD	DU
UD	UU

So, the desired probability is:

$$\begin{aligned}Pr(DD \cup UD \cup DU) &= Pr(\{DD \cup UD\}) + Pr(\{DD \cup DU\}) - Pr(DD) \\&= 0.98 + 0.94 - 0.93 \\&= 0.99\end{aligned}$$

Example (De Morgan's law)

Given $P(A \cup B) = 0.7$ and $P(A \cup B^c) = 0.9$, find $P(A)$.

By De Morgan's law,

$$P(A^c \cap B^c) = P((A \cup B)^c) = 1 - P(A \cup B) = 1 - 0.7 = 0.3$$

and similarly

$$P(A^c \cap B) = 1 - P(A \cup B^c) = 1 - 0.9 = 0.1.$$

Thus,

$$P(A^c) = P(A^c \cap B^c) + P(A^c \cap B) = 0.3 + 0.1 = 0.4,$$

so

$$P(A) = 1 - 0.4 = 0.6.$$

Example (Probability, union, and complement)

John is taking two books along on his holiday vacation. With probability 0.5, he will like the first book; with probability 0.4, he will like the second book; and with probability 0.3, he will like both books. What is the probability that he likes neither book?

Let A_i be the event that John likes book i , for $i = 1, 2$. Then the probability that he likes at least one book is:

$$\begin{aligned} P\left(\bigcup_{i=1}^2 A_i\right) &= P(A_1 \cup A_2) = P(A_1) + P(A_2) - P(A_1 \cap A_2) \\ &= 0.5 + 0.4 - 0.3 = 0.6. \end{aligned}$$

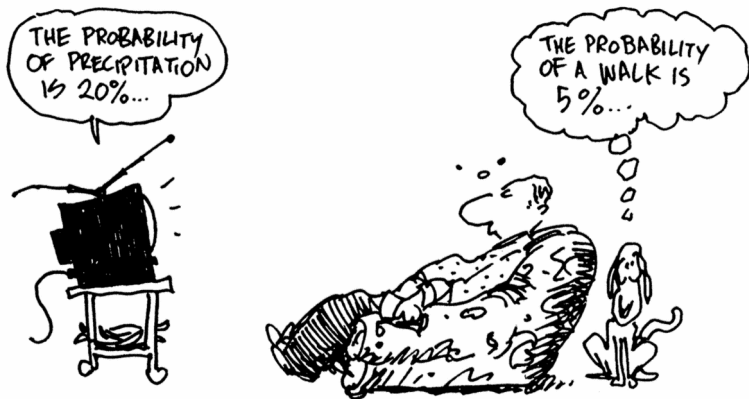
Because the event the John likes neither books is the complement of the event that he likes at least one of them (namely $A_1 \cup A_2$), we have

$$P(A_1^c \cap A_2^c) = P((A_1 \cup A_2)^c) = 1 - P(A_1 \cup A_2) = 0.4.$$

Outline

- 1 An Axiomatic Definition of Probability
- 2 Implications: Properties of $P(\cdot)$
- 3 Examples and Illustrations
- 4 Conditional Probability**
- 5 Independence
- 6 Theorem I: The Theorem of Total Probability
- 7 Theorem II: Bayes' Theorem

Conditional Probability



Conditional Probability

Sometimes, probability depends on the information available.

Example

Suppose you have two dice and throw them; the possible outcomes are:

(1,1)	(1,2)	(1,3)	(1,4)	(1,5)	(1,6)
(2,1)	(2,2)	(2,3)	(2,4)	(2,5)	(2,6)
(3,1)	(3,2)	(3,3)	(3,4)	(3,5)	(3,6)
(4,1)	(4,2)	(4,3)	(4,4)	(4,5)	(4,6)
(5,1)	(5,2)	(5,3)	(5,4)	(5,5)	(6,5)
(6,1)	(6,2)	(6,3)	(6,4)	(6,5)	(6,6)

Conditional Probability

Example (cont'd)

Consider the event $A = \text{getting } 5$, or equivalently $A = \{5\}$.
What is $P(A)$, namely, the probability of getting 5?

(1,1)	(1,2)	(1,3)	(1,4)	(1,5)	(1,6)
(2,1)	(2,2)	(2,3)	(2,4)	(2,5)	(2,6)
(3,1)	(3,2)	(3,3)	(3,4)	(3,5)	(3,6)
(4,1)	(4,2)	(4,3)	(4,4)	(4,5)	(4,6)
(5,1)	(5,2)	(5,3)	(5,4)	(5,5)	(5,6)
(6,1)	(6,2)	(6,3)	(6,4)	(6,5)	(6,6)

Example (cont'd)

The dice are fair so we can get 36 events with equal probability $1/36$.
Namely:

$$Pr(i, j) = \frac{1}{36}, \quad \text{for } i, j = 1, \dots, 6$$

Thus, we can make use of the highlighted probabilities

$$\begin{aligned} P(5) &= Pr\{(1, 4) \cup (2, 3) \cup (3, 2) \cup (4, 1)\} \\ &= Pr\{(1, 4)\} + Pr\{(2, 3)\} + Pr\{(3, 2)\} + Pr\{(4, 1)\} \\ &= 1/36 + 1/36 + 1/36 + 1/36 \\ &= 4/36 \\ &= 1/9. \end{aligned}$$

Conditional Probability

Example (cont'd)

Now, suppose that we throw the die first and we get 2.

What is the probability of getting 5 given that we have observed 2 in the first throw?

(1,1)	(1,2)	(1,3)	(1,4)	(1,5)	(1,6)
(2,1)	(2,2)	(2,3)	(2,4)	(2,5)	(2,6)
(3,1)	(3,2)	(3,3)	(3,4)	(3,5)	(3,6)
(4,1)	(4,2)	(4,3)	(4,4)	(4,5)	(4,6)
(5,1)	(5,2)	(5,3)	(5,4)	(5,5)	(5,6)
(6,1)	(6,2)	(6,3)	(6,4)	(6,5)	(6,6)

$$\Pr\{\text{getting 5 given 2 in the first throw}\} = \Pr\{\text{getting 3 in the second throw}\} = 1/6$$

Conditional Probability

Remark

- *Information changes the probability*
- *By knowing that we got 2 in the first throw, we have changed the sample space:*

(1,1)	(1,2)	(1,3)	(1,4)	(1,5)	(1,6)
(2,1)	(2,2)	(2,3)	(2,4)	(2,5)	(2,6)
(3,1)	(3,2)	(3,3)	(3,4)	(3,5)	(3,6)
(4,1)	(4,2)	(4,3)	(4,4)	(4,5)	(4,6)
(5,1)	(5,2)	(5,3)	(5,4)	(5,5)	(6,5)
(6,1)	(6,2)	(6,3)	(6,4)	(6,5)	(6,6)

- *Probability can change drastically — e.g., suppose that in our example we have 6 in the first throw \Rightarrow the probability of observing 5 in two draws ... is zero !!!*

Definition

Let A and B be two events. The conditional probability of event A given event B , denoted by $P(A|B)$, is defined by:

$$P(A|B) = \frac{P(A \cap B)}{P(B)}, \quad \text{if } P(B) > 0,$$

and it is left undefined if $P(B) = 0$.

Conditional Probability

Example (A check)

Let us define the set B as:

(1,1)	(1,2)	(1,3)	(1,4)	(1,5)	(1,6)
(2,1)	(2,2)	(2,3)	(2,4)	(2,5)	(2,6)
(3,1)	(3,2)	(3,3)	(3,4)	(3,5)	(3,6)
(4,1)	(4,2)	(4,3)	(4,4)	(4,5)	(4,6)
(5,1)	(5,2)	(5,3)	(5,4)	(5,5)	(6,5)
(6,1)	(6,2)	(6,3)	(6,4)	(6,5)	(6,6)

So we have

$$\begin{aligned}P(B) &= Pr\{(2,1) \cup (2,2) \cup (2,3) \cup (2,4) \cup (2,5) \cup (2,6)\} \\&= Pr(2,1) + Pr(2,2) + Pr(2,3) + Pr(2,4) + Pr(2,5) + Pr(2,6) \\&= 6/36 = 1/6\end{aligned}$$

Conditional Probability

Example (A check)

and consider $A \cap B$

(1,1)	(1,2)	(1,3)	(1,4)	(1,5)	(1,6)
(2,1)	(2,2)	(2,3)	(2,4)	(2,5)	(2,6)
(3,1)	(3,2)	(3,3)	(3,4)	(3,5)	(3,6)
(4,1)	(4,2)	(4,3)	(4,4)	(4,5)	(4,6)
(5,1)	(5,2)	(5,3)	(5,4)	(5,5)	(5,6)
(6,1)	(6,2)	(6,3)	(6,4)	(6,5)	(6,6)

So we have $P(A \cap B) = Pr(2, 3) = 1/36$ so,

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{1/36}{1/6} = \frac{1}{6}.$$

- 1 An Axiomatic Definition of Probability
- 2 Implications: Properties of $P(\cdot)$
- 3 Examples and Illustrations
- 4 Conditional Probability
- 5 Independence**
- 6 Theorem I: The Theorem of Total Probability
- 7 Theorem II: Bayes' Theorem

Definition

Two events A and B are independent if the occurrence of one event has no effect on the probability of occurrence of the other event. Thus,

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

or equivalently

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

Clearly, if $P(A|B) \neq P(A)$, then A and B are *dependent*.

Independence

A second characterisation

Two events A and B are independent if

$$P(A|B) = P(A),$$

now by definition of conditional probability we know that

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

so we have

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

and rearranging the terms, we find that two events are independent iif

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

Example

A coin is tossed three times and the eight possible outcomes
HHH, HHT, HTH, THH, HTT, THT, TTH, TTT
are assumed to be equally likely with probability $1/8$

Define

A = an H occurs on each of the first two tosses

B = T occurs in the third toss

D = two Ts occur in the three tosses

Q1: Are A and B independent?

Q2: Are B and D independent?

Example (cont'd)

We have

$$A = \{HHH, HHT\}$$

$$\Pr\{A\} = 2/8 = 1/4$$

$$B = \{HHT, HTT, THT, TTT\}$$

$$\Pr\{B\} = 4/8 = 1/2$$

$$D = \{HTT, THT, TTH\}$$

$$\Pr\{D\} = 3/8$$

$$A \cap B = \{HHT\}$$

$$\Pr\{A \cap B\} = 1/8$$

$$B \cap D = \{HTT, THT\}$$

$$\Pr\{B \cap D\} = 2/8 = 1/4$$

$$\Pr\{A\}\Pr\{B\} = \frac{1}{4} \times \frac{1}{2} = \frac{1}{8} \quad \Pr\{A \cap B\} = \frac{1}{8} \Rightarrow A, B \text{ independent}$$

$$\Pr\{B\}\Pr\{D\} = \frac{1}{2} \times \frac{3}{8} = \frac{3}{16} \quad \Pr\{B \cap D\} = \frac{1}{4} \Rightarrow B \text{ and } D \text{ dependent}$$

Outline

- 1 An Axiomatic Definition of Probability
- 2 Implications: Properties of $P(\cdot)$
- 3 Examples and Illustrations
- 4 Conditional Probability
- 5 Independence
- 6 Theorem I: The Theorem of Total Probability**
- 7 Theorem II: Bayes' Theorem

Theorem I: The Theorem of Total Probability

Theorem (Total Probabilities)

Let $B_1, B_2, \dots, B_k, \dots, B_n$ be mutually disjoint events, satisfying $S = \cup_{i=1}^n B_i$, and $P(B_i) > 0$, for every $i = 1, 2, \dots, n$ then for every A we have that:

$$P(A) = \sum_{i=1}^n P(A|B_i)P(B_i). \quad (3)$$

Proof.

Write $A = A \cap S = A \cap (\cup_{i=1}^n B_i) = \cup_{i=1}^n (A \cap B_i)$. Since the $\{B_i \cap A\}$ are mutually disjoint, we have

$$P(A) = P(\cup_{i=1}^n (A \cap B_i)) = \sum_{i=1}^n P(A \cap B_i) = \sum_{i=1}^n P(A|B_i)P(B_i).$$



Theorem I: The Theorem of Total Probability

Remark. The theorem remains valid even if $n = \infty$ in Eq. (3). (Double check, and re-do the proof using $n = \infty$.)

Corollary

Let B satisfy $0 < P(B) < 1$; then for every event A :

$$P(A) = P(A|B)P(B) + P(A|B^c)P(B^c)$$

Proof.

Exercise [Hint: $S = B \cup B^c$].



Outline

- 1 An Axiomatic Definition of Probability
- 2 Implications: Properties of $P(\cdot)$
- 3 Examples and Illustrations
- 4 Conditional Probability
- 5 Independence
- 6 Theorem I: The Theorem of Total Probability
- 7 Theorem II: Bayes' Theorem**

Theorem II: Bayes' Theorem

Theorem I can be applied to derive the well-celebrated Bayes' Theorem.

Theorem (Bayes' Theorem)

Let $B_1, B_2, \dots, B_k, \dots, B_n$ be mutually disjoint events, satisfying

$$S = \cup_{i=1}^n B_i,$$

and $P(B_i) > 0$, for every $i = 1, 2, \dots, n$. Then for every event A for which $P(A) > 0$, we have that

$$P(B_k|A) = \frac{P(A|B_k)P(B_k)}{\sum_{i=1}^n P(A|B_i)P(B_i)}. \quad (4)$$

Theorem II: Bayes' Theorem

Proof.

Let us write

$$\begin{aligned}P(B_k|A) &= \frac{P(A \cap B_k)}{P(A)} \\&= \frac{P(A \cap B_k)}{\sum_{i=1}^n P(A|B_i)P(B_i)} \\&= \frac{P(A|B_k)P(B_k)}{\sum_{i=1}^n P(A|B_i)P(B_i)}\end{aligned}$$

That concludes the proof. □

Theorem II: Bayes' Theorem

Example

Let us consider a special case, where we have only two events A and B .

From the definition of conditional probability

$$\Pr\{A|B\} = \frac{\Pr\{A \cap B\}}{\Pr\{B\}} \qquad \Pr\{B|A\} = \frac{\Pr\{A \cap B\}}{\Pr\{A\}}$$

This can be written as

$$\Pr\{A \cap B\} = \Pr\{A|B\} \Pr\{B\} \qquad \Pr\{A \cap B\} = \Pr\{B|A\} \Pr\{A\}$$

That is

$$\Pr\{A|B\} \Pr\{B\} = \Pr\{B|A\} \Pr\{A\}$$

Rearranging this we have

$$\Pr\{A|B\} = \frac{\Pr\{A\}}{\Pr\{B\}} \times \Pr\{B|A\} \quad \Leftarrow \text{Bayes' Theorem}$$

... so thanks to Bayes' Theorem we can reverse the role of $A|B$ and $B|A$.

Theorem II: Bayes' Theorem

Application

Example (Guessing in a multiple choice exam)

Example 1.13 In answering a question on a multiple choice test a student either knows the answer or he guesses. Let p be the probability that she knows the answer and $1 - p$ the probability that she guesses. Assume that a student who guesses at the answer will be correct with probability $1/m$, where m is the number of multiple-choice alternatives. What is the conditional probability that a student knew the answer to a question given that she answered it correctly?

Solution: Let C and K denote respectively the event that the student answers the question correctly and the event that she actually knows the answer. Now

$$\begin{aligned} P(K|C) &= \frac{P(KC)}{P(C)} = \frac{P(C|K)P(K)}{P(C|K)P(K) + P(C|K^c)P(K^c)} \\ &= \frac{p}{p + (1/m)(1 - p)} \\ &= \frac{mp}{1 + (m - 1)p} \end{aligned}$$

Thus, for example, if $m = 5$, $p = \frac{1}{2}$, then the probability that a student knew the answer to a question she correctly answered is $\frac{5}{6}$. ♦

Theorem II: Bayes' Theorem

Application

Example

Members of a consulting firm in Geneva rent cars from two rental agencies:

- 60% from AVIS
- 40% from Mobility

Now consider that

- 9% of the cars from AVIS need a tune-up
- 20% of the cars from Mobility need a tune-up

If a car delivered to the consulting firm needs a tune-up, what is the probability that the care came from AVIS?

Aim

$A := \{\text{car rented from AVIS}\}$ and $B := \{\text{car needs a tune-up}\}$. We know $P(B|A)$ and we look for $P(A|B) \Rightarrow$ Bayes' theorem!!

Theorem II: Bayes' Theorem

Application

Example (cont'd)

$$\Pr\{A\}=0.6$$

$$\Pr\{B|A\}=0.09$$

$$\Pr\{B|A^C\}=0.2$$

$$\Pr\{B\}=\Pr\{(B\cap A)\cup(B\cap A^C)\}$$

$$=\Pr\{B\cap A\}+\Pr\{B\cap A^C\}$$

$$=\Pr\{B|A\}\Pr\{A\}+\Pr\{B|A^C\}\Pr\{A^C\}$$

$$=0.09\times 0.6+0.2\times 0.4$$

$$=0.134$$

$$\Pr\{A|B\}=\frac{\Pr\{A\}}{\Pr\{B\}}\times\Pr\{B|A\}=\frac{0.6}{0.134}0.09=0.402985$$

Wrap-up