CEE 260/MIE 273: Probability and Statistics in Civil Engineering Lecture M2c: Conditional Probability and Bayes' Theorem

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UMassAmherst

College of Engineering

September 18, 2025

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Outline

- Conditional probability
- 2 Independent events
- Multiplication rule
- 4 Theorem of total probability
- 6 Bayes' theorem
- Outlook

$$P(E) \geq 0$$
 and $P(E) \leq 1$
$$P(S) = 1$$

$$P(E_1 \cup E_2 \cup \cdots \cup E_n) = P(E_1) + P(E_2) + \cdots + P(E_n)$$
 (Mutually exclusive)

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 - Permutations (arrangements) of a subset of k items chosen from set of n items: n!/(n-k)!
 - Combinations (distinct; order not important) of group of k items chosen from set of n items: n!/(k!(n-k)!)

Independent events Multiplication rule Theorem of total probability Bayes' theor



Objectives of today's lecture

Understand conditional probability



- Understand conditional probability
- Grasp the concept of statistical independence

 Independent events
 Multiplication rule
 Theorem of total probability
 Bayes' theorem of total probability

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- Understand Bayes' Theorem and learn how to apply it to solving inverse probability problems

Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlook

Conditional probability

Definition

Conditional probability



 Conditional probability
 Independent events
 Multiplication rule
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Conditional probability

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 = the conditional probability of E_1 given E_2

Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlool

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Conditional probability

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P(E_1|E_2) = the conditional probability of E_1 given E_2 (OR the probability of E_1 conditioned on E_2)
P(E_2|E_1) = the conditional probability of E_2 given E_1
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Independent events Multiplication rule Theorem of total probability Bayes' theorem of total probability 000 000000

Conditional probability (cont.)

Conditional probability

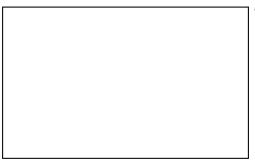
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We can think of $P(E_1|E_2)$ as the probability of realizing sample points of E_1 within the subsample space of E_2 .



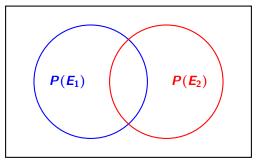
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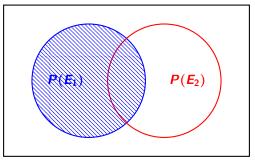
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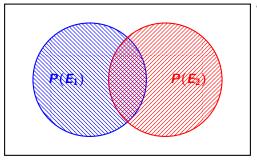


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Independent events Multiplication rule Theorem of total probability Bayes' theorem Outloo

Conditional probability (cont.)

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Conditional probability

$$P(E_1|E_2) = \frac{P(E_1E_2)}{P(E_2)} \tag{1}$$

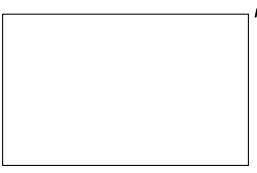
Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlook

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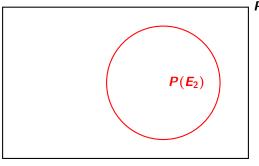
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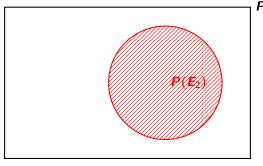
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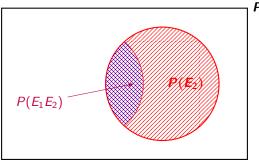
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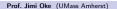
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Useful conditional probability relations



Conditional probability

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 - This means that the event to the right is what goes in the denominator.
 - The numerator is simply the intersection of both events

Conditional probability

Example 1: Highway routes

Conditional probability



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Example 1: Highway routes

Conditional probability

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Conditional probability

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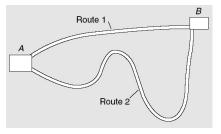


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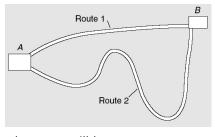


Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlook

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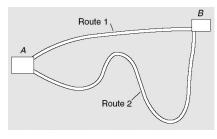
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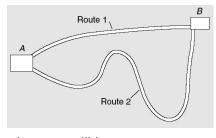
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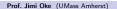
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- (a) What is probability that Route 1 is open during a storm given that Route 2 is also open?
- (b) What is probability that Route 2 is open during a storm conditioned on the event that Route 1 is also open?
- (c) What is probability that Route 1 is closed during a storm given that Route 2 is also closed?

Example 1: Highway routes (cont.)

Conditional probability



Independent events Multiplication rule Theorem of total probability Bayes'

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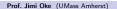
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$$P(\overline{E_1}|\overline{E_2}) = \frac{P(\overline{E_1}\,\overline{E_2})}{P(\overline{E_2})}$$

Conditional probability

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 $P(E_2) = 0.50$ $P(E_1E_2) = 0.40$

$$P(\overline{E_1}|\overline{E_2}) = \frac{P(\overline{E_1}|\overline{E_2})}{P(\overline{E_2})}$$

$$P(\overline{E_1}|\overline{E_2}) = 1 - P(\overline{\overline{E_1}|\overline{E_2}})$$

Conditional probability 000000000

Example 1: Highway routes (cont.)

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$$P(\overline{E_1} \overline{E_2}) = 1 - P(\overline{E_1} \overline{E_2}) \text{ complementary events}$$

$$= 1 - P(E_1 \cup E_2)$$

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Conditional probability 000000000

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$$= 1 - P(E_1 \cup E_2) \text{ De Morgan's Rule}$$

$$= 1 - [P(E_1) + P(E_2) - P(E_1 E_2)]$$

Conditional probability 000000000

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$$= 1 - P(E_1 \cup E_2) \text{ De Morgan's Rule}$$

$$= 1 - [P(E_1) + P(E_2) - P(E_1 E_2)] \text{ addition rule}$$

$$= 1 - (0.75 + 0.50 - 0.40)$$

$$= 1 - 0.85 =$$

Example 1: Highway routes (cont.)

$$P(E_1) = 0.75$$
 $P(E_2) = 0.50$ $P(E_1E_2) = 0.40$

(c) The probability that Route 1 is closed (\overline{E}_1) during a storm given that Route 2 is also closed (\overline{E}_2) is denoted as:

$$\begin{split} P(\overline{E_1}|\overline{E_2}) &= \frac{P(E_1\,E_2)}{P(\overline{E_2})} \\ P(\overline{E_1}\,\overline{E_2}) &= 1 - P(\overline{\overline{E_1}\,\overline{E_2}}) \quad \text{complementary events} \\ &= 1 - P(E_1 \cup E_2) \quad \text{De Morgan's Rule} \\ &= 1 - [P(E_1) + P(E_2) - P(E_1E_2)] \quad \text{addition rule} \\ &= 1 - (0.75 + 0.50 - 0.40) \\ &= 1 - 0.85 = 0.15 \end{split}$$

Thus, we obtain

Conditional probability

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$$P(\overline{E_1}|\overline{E_2}) = \frac{P(\overline{E_1}|\overline{E_2})}{P(\overline{E_2})} =$$

Conditional probability 000000000

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Thus, we obtain

$$P(\overline{E_1}|\overline{E_2}) = \frac{P(\overline{E_1}|\overline{E_2})}{P(\overline{E_2})} = \frac{0.15}{0.50} =$$

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$$= 1 - (0.75 + 0.50 - 0.40)$$

$$= 1 - 0.85 = 0.15$$

Thus, we obtain

$$P(\overline{E_1}|\overline{E_2}) = \frac{P(\overline{E_1}|\overline{E_2})}{P(\overline{E_2})} = \frac{0.15}{0.50} = \boxed{0.30}$$

Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlool

The addition rule

Conditional probability 0000000●



Conditional probability

The addition rule

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Conditioning equally applies to probabilities of events on the same subsample space.

The addition rule

Conditional probability

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 (6)

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Conditional probability

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 (6)

$$P(A \cup B|E) = P(A|E) + P(B|E) - P(AB|E)$$
(7)

 Independent events
 Multiplication rule
 Theorem of total probability

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Statistically independent events



Independent events Multiplication rule

Statistically independent events

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Statistical independence

Statistically independent events

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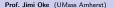
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Examples of independent events

• The outcomes of a die rolled twice in succession.

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 The outcomes of a die rolled twice in succession. The result of the first roll does not affect the result of the other.

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- The event that it will be cloudy in Amherst tomorrow and the event that the number of births in California tomorrow will increase compared to that of today.

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- The ages of a random sample of Pioneer Valley residents

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- Generally, all elements of a random sample are assumed independent

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 Independent events
 Multiplication rule
 Theorem of total probability
 Bayes' theorem of total probability

Example 2: Rolling two dice



 Independent events
 Multiplication rule
 Theorem of total probability
 Bayes' theorem
 Outlook

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Example 2: Rolling two dice

Let X and Y represent the outcomes of rolling two dice.



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(a) What is the probability that the first die X is 1?



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$$P(X=1) = \frac{1}{6}$$

(b) What is the probability that both X and Y are 1?

Let *X* and *Y* represent the outcomes of rolling two dice.

(a) What is the probability that the first die *X* is 1?

$$P(X=1) = \frac{1}{6}$$

(b) What is the probability that both *X* and *Y* are 1?

Let X and Y represent the outcomes of rolling two dice.

(a) What is the probability that the first die X is 1?

$$P(X=1) = \frac{1}{6}$$

(b) What is the probability that both *X* and *Y* are 1?

$$P(X = 1 \cap Y = 1) = P(X = 1) \times P(Y = 1)$$

Let X and Y represent the outcomes of rolling two dice.

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$$P(X = 1 \cap Y = 1) = P(X = 1) \times P(Y = 1)$$

= $\frac{1}{6} \times \frac{1}{6} =$

Let X and Y represent the outcomes of rolling two dice.

(a) What is the probability that the first die X is 1?

$$P(X=1) = \frac{1}{6}$$

(b) What is the probability that both *X* and *Y* are 1?

$$P(X = 1 \cap Y = 1) = P(X = 1) \times P(Y = 1)$$

= $\frac{1}{6} \times \frac{1}{6} = \frac{1}{36}$

 Independent events
 Multiplication rule
 Theorem of total probability
 Bayes' theorem of total probability

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Example 2: Rolling two dice (cont.)



$$P(Y = 1|X = 1) = \frac{P(Y = 1 \cap Y = 1)}{P(X = 1)}$$

$$P(Y = 1 | X = 1) = \frac{P(Y = 1 \cap Y = 1)}{P(X = 1)}$$
$$= \frac{P(Y = 1) \times P(X = 1)}{P(X = 1)}^{1}$$

$$P(Y = 1 | X = 1) = \frac{P(Y = 1 \cap Y = 1)}{P(X = 1)}$$
$$= \frac{P(Y = 1) \times P(X = 1)}{P(X = 1)^{-1}}$$

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$$= P(Y = 1)$$

$$P(Y = 1 | X = 1) = \frac{P(Y = 1 \cap Y = 1)}{P(X = 1)}$$

$$= \frac{P(Y = 1) \times P(X = 1)}{P(X = 1)^{-1}}$$

$$= P(Y = 1)$$

(d) Why is
$$P(Y = 1|X = 1) = P(Y = 1)$$
?

(c) Use the conditional probability formula to find P(Y = 1|X = 1)

$$P(Y = 1 | X = 1) = \frac{P(Y = 1 \cap Y = 1)}{P(X = 1)}$$

$$= \frac{P(Y = 1) \times P(X = 1)}{P(X = 1)^{-1}}$$

$$= P(Y = 1)$$

(d) Why is P(Y = 1|X = 1) = P(Y = 1)? X and Y are independent events.

Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlool

The multiplication rule

Conditional probability



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The multiplication rule

The probability of the intersection of two events is



onditional probability Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlook

The multiplication rule

The probability of the intersection of two events is

$$P(E_1 E_2) = P(E_1 | E_2) P(E_2)$$
 (10)

onditional probability Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlool

The multiplication rule

The probability of the intersection of two events is

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Equivalently:

Conditional probability Independent events Multiplication rule

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The multiplication rule

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 (10)

Equivalently:

$$P(AB) = P(B|A)P(A) \tag{11}$$

Conditional probability Independent events Multiplication rule Theorem of total probability Bayes' theorem Outloo

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Statistically independent events

IF A and B are statistically independent, the multiplication rule becomes:

onditional probability Independent events Multiplication rule Theorem of total probability Bayes' theorem Outloo

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Statistically independent events

IF A and B are statistically independent, the multiplication rule becomes:

$$P(AB) = P(A)P(B) \tag{12}$$

Inditional probability Independent events Multiplication rule Theorem of total probability Bayes' theorem Outloo

The multiplication rule

The probability of the intersection of two events is

$$P(E_1 E_2) = P(E_1 | E_2) P(E_2)$$
 (10)

Equivalently:

$$P(AB) = P(B|A)P(A) \tag{11}$$

Statistically independent events

IF A and B are statistically independent, the multiplication rule becomes:

$$P(AB) = P(A)P(B) \tag{12}$$

That is, the joint probability of two statistically independent events is the product of their individual probabilities.

The probability of the joint occurrence of three events is:



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$$P(ABC) = P(A|BC)P(BC)$$

= $P(A|BC)P(B|C)P(C)$ (13)

The probability of the joint occurrence of three events is:

$$P(ABC) = P(A|BC)P(BC)$$

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Statistically independent events

If the three events are statistically independent, then:

The probability of the joint occurrence of three events is:

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Statistically independent events

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$$P(ABC) =$$

The probability of the joint occurrence of three events is:

$$P(ABC) = P(A|BC)P(BC)$$

= $P(A|BC)P(B|C)P(C)$ (13)

Statistically independent events

If the three events are statistically independent, then:

$$P(ABC) = P(A)P(B)P(C)$$
(14)

The multiplication rule: conditional probabilities

Equally applies to probabilities of events conditioned on the same subsample space.



Conditional probability Independent events Multiplication rule Theorem of total probability Bayes' theorem Outloo

The multiplication rule: conditional probabilities

Equally applies to probabilities of events conditioned on the same subsample space.

$$P(AB|E) = P(A|B|E)P(B|E)$$
(15)

The multiplication rule: conditional probabilities

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Statistically independent events

If A and B are statistically independent, the multiplication rule for two events conditioned on the same space becomes:

The multiplication rule: conditional probabilities

Equally applies to probabilities of events conditioned on the same subsample space.

$$P(AB|E) = P(A|B|E)P(B|E)$$
(15)

Statistically independent events

If A and B are statistically independent, the multiplication rule for two events conditioned on the same space becomes:

$$P(AB|E) = P(A|E)P(B|E)$$
(16)

Example 3: Airline industry strikes



Example 3: Airline industry strikes

The airline industry in a certain country is subject to labor strikes by the pilots (event A), mechanics (event B) or flight attendants (event C).



Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlook

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Example 3: Airline industry strikes

The airline industry in a certain country is subject to labor strikes by the pilots (event A), mechanics (event B) or flight attendants (event C).

The probability of strikes by each of the individual groups in the next 3 years is given by:

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The airline industry in a certain country is subject to labor strikes by the pilots (event A), mechanics (event B) or flight attendants (event C).

The probability of strikes by each of the individual groups in the next 3 years is given by:

$$P(A) = 0.03$$
 $P(B) = 0.05$ $P(C) = 0.06$

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The airline industry in a certain country is subject to labor strikes by the pilots (event A), mechanics (event B) or flight attendants (event C).

The probability of strikes by each of the individual groups in the next 3 years is given by:

$$P(A) = 0.03$$
 $P(B) = 0.05$ $P(C) = 0.06$

Assuming that events A, B and C are statistically independent, find

- (a) the probability that all groups will strike in the next 3 years
- (b) the probability of a labor strike in the airline industry in the next 3 years.

Independent events Multiplication rule OOO Theorem of total probability Bayes' theorem of total probability OOO OOOOOO

Example 3: Airline industry strikes (cont.)



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$$P(A) = 0.03$$
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Example 3: Airline industry strikes (cont.)

$$P(A) = 0.03$$
 $P(B) = 0.05$ $P(C) = 0.06$

$$P(ABC) = P(A)P(B)P(C)$$

Example 3: Airline industry strikes (cont.)

$$P(A) = 0.03$$
 $P(B) = 0.05$ $P(C) = 0.06$

$$P(ABC) = P(A)P(B)P(C)$$
 statistical independence

Example 3: Airline industry strikes (cont.)

$$P(A) = 0.03$$
 $P(B) = 0.05$ $P(C) = 0.06$

$$P(ABC) = P(A)P(B)P(C)$$
 statistical independence
= 0.03(0.05)(0.06)

$$P(A) = 0.03$$
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(a) The probability that all 3 groups will strike in the next 3 years is given by:

$$P(ABC) = P(A)P(B)P(C)$$
 statistical independence
= $0.03(0.05)(0.06)$
= 0.00009 =

$$P(A) = 0.03$$
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(a) The probability that all 3 groups will strike in the next 3 years is given by:

$$P(ABC) = P(A)P(B)P(C)$$
 statistical independence
= $0.03(0.05)(0.06)$
= $0.00009 = 9.0 \times 10^{-5}$

Independent events Multiplication rule OOO Theorem of total probability Bayes' theorom of total probability OOO OOOOO

Example 3: Airline industry strikes (cont.)



Independent events Multiplication rule OOO Theorem of total probability Bayes' theorem OOO OOOOOOO

Example 3: Airline industry strikes (cont.)

$$P(A) = 0.03$$
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Example 3: Airline industry strikes (cont.)

$$P(A) = 0.03$$
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(b) The probability of a labor strike is the probability that any combination of the groups will strike.



Example 3: Airline industry strikes (cont.)

$$P(A) = 0.03$$
 $P(B) = 0.05$ $P(C) = 0.06$

(b) The probability of a labor strike is the probability that any combination of the groups will strike.

(Step 1) Formulate the desired probability:

$$P(A) = 0.03$$
 $P(B) = 0.05$ $P(C) = 0.06$

(b) The probability of a labor strike is the probability that any combination of the groups will strike.

(Step 1) Formulate the desired probability:

$$P(A \cup B \cup C)$$

Example 3: Airline industry strikes (cont.)

$$P(A) = 0.03$$
 $P(B) = 0.05$ $P(C) = 0.06$

(b) The probability of a labor strike is the probability that any combination of the groups will strike.

(Step 1) Formulate the desired probability:

$$P(A \cup B \cup C)$$

$$P(A) = 0.03$$
 $P(B) = 0.05$ $P(C) = 0.06$

(b) The probability of a labor strike is the probability that any combination of the groups will strike.

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$$= \boxed{0.134}$$

nditional probability Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlook

Total probability

Useful in situations where the probability of an event cannot be directly determined but its conditional probabilities are known.



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Theorem of total probability

onditional probability Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlook

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$$P(A) = P(A|E_1)P(E_1) + P(A|E_2)P(E_2) + \dots + P(A|E_n)P(E_n)$$
 (17)

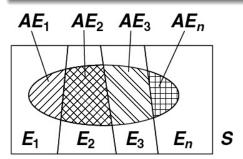
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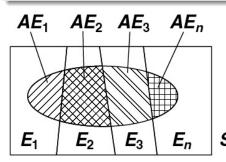


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The probability of an event A conditioned on the mutually exclusive and collectively exhaustive events E_1, E_2, \ldots, E_n is given by

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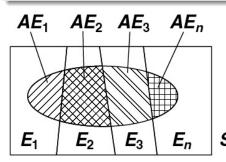
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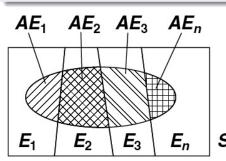


$$P(A) = P(AE_1) +$$

Useful in situations where the probability of an event cannot be directly determined but its conditional probabilities are known.

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$$P(A) = P(AE_1) + P(AE_2)$$

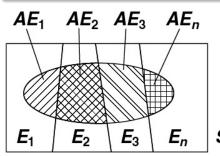
Inditional probability Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlook

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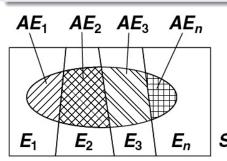
$$P(A) = P(AE_1) + P(AE_2) + P(AE_2)$$

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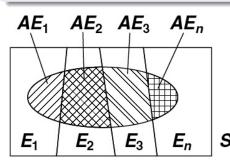
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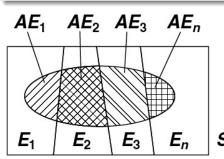
Note that:

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$$P(A) = P(AE_1) + P(AE_2) + P(AE_3) + \cdots + P(AE_n)$$

Note that:

$$P(AE_1) = P(A|E_1)P(E_1),$$
 etc.

Example 4: Flooding and snow accumulation



The flooding of a river in the spring season (event F) will depend on the accumulation of snow in the mountain during the past winter.



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$$P(F|H) = 0.90$$
 $P(F|N) = 0.40$ $P(F|L) = 0.10$

and in the winter

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$$P(H) = 0.20$$
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Find the probability of flooding in the river during the spring season P(F).

Example 4: Flooding and snow accumulation (cont.)



Example 4: Flooding and snow accumulation (cont.)



$$P(F) = P(F|H)P(H) + P(F|N)P(N) + P(F|L)P(L)$$

Example 4: Flooding and snow accumulation (cont.)

$$P(F) = P(F|H)P(H) + P(F|N)P(N) + P(F|L)P(L)$$

= 0.90(0.20) + 0.40(0.50) + 0.10(0.30)

Example 4: Flooding and snow accumulation (cont.)

$$P(F) = P(F|H)P(H) + P(F|N)P(N) + P(F|L)P(L)$$

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= 0.41

Independent events Multiplication rule Theorem of total probability

OOO OOOOO OOO OOO

Bayes' theorem
OOOOOOOO

Derivation of Bayes' theorem



Independent events Multiplication rule OOO Theorem of total probability Nultiplication rule OOO Shapes' theorem OOO OOO

Derivation of Bayes' theorem

Recall from the multiplication rule that:



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$$P(B|A) = \frac{P(A|B)P(B)}{P(A)} \tag{21}$$

ability Independent events Multiplication rule Theorem of total probability OOO OOOOO

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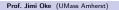
This is in essence Bayes' Theorem

Independent events Multiplication rule Theorem of total probability Bayes' theorem

OOO OOO OOO OOO OOOOOO

Bayes' theorem

Conditional probability



Bayes' theorem



Bayes' theorem

$$P(A_i|E) = \frac{P(E|A_i)P(A_i)}{\sum_{j=1}^{n} P(E|A_j)P(A_j)} =$$

Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlook

OOO OOO OOO OOO OOO OO

Bayes' theorem

$$P(A_i|E) = \frac{P(E|A_i)P(A_i)}{\sum_{j=1}^{n} P(E|A_j)P(A_j)} = \frac{P(E|A_i)P(A_i)}{P(E)}$$
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oility Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlook

Bayes' theorem

Bayes' Theorem allows for the computation of an inverse probability, e.g. given P(E|A), can we find P(A|E)?

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Rev. Thomas Bayes (1701-61)

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- likelihood: $P(E|A_i)$



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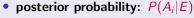


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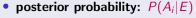


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$$P(A|E) = \frac{P(E|A)P(A)}{P(E|A)P(A) + P(E|B)P(B)}$$
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Bayes' theorem 00000000

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Independent events Multiplication rule Theorem of total probability Bayes' theorem Outloo OO OO OO OO

Example 5: Construction supplies

Aggregates for the construction of a reinforced concrete building are supplied by two companies.



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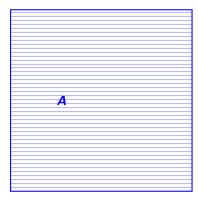
E = aggregates are substandard

Example 5: Construction supplies (cont.)

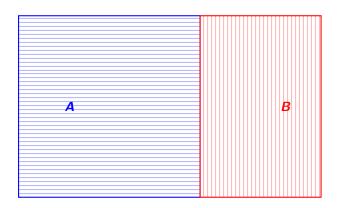


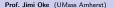
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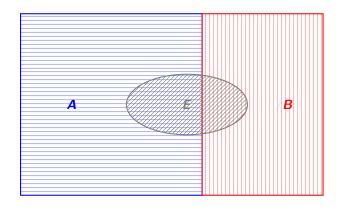
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Bayes' theorem

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Bayes' theorem

Independent events Multiplication rule OOOOOO Theorem of total probability OOO ■ OO



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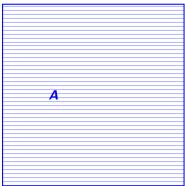
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Bayes' theorem 0000●000

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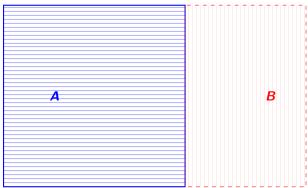




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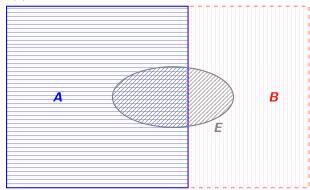
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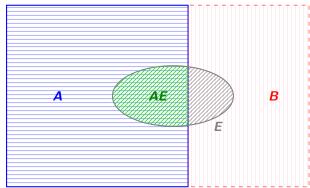
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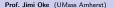




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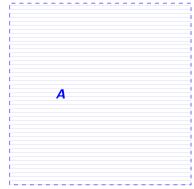


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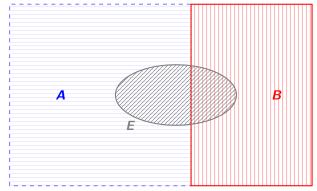




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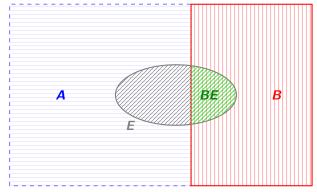
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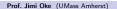
$$= 0.818 \approx \boxed{0.82}$$

P(A|E) is the posterior probability of A having observed E. In other words, having prior knowledge of A (i.e. P(A) and the likelihood of E given A, we can update our knowledge of A (posterior probability) based on these observations.

Conditional probability Independent events Multiplication rule Theorem of total probability Bayes' theorem Outlook

Recap

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Recap (cont.)

Total probability:

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Outlook

Outlook 0

Recap (cont.)

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$$P(A_1|E) = \frac{P(E|A_1)P(A_1)}{P(E|A_1)P(A_1) + P(E|A_2)P(A_2) + \dots + P(E|A_n)P(A_n)}$$
(30)