

Lecture 4

Probability II

Lecture Information

Ceng272 *Statistical Computations* at March 8, 2010

Additive Rules

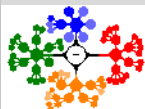
Conditional Probability

Multiplicative Rules

Bayes' Rules

Dr. Cem Özdoğan
Computer Engineering Department
Çankaya University

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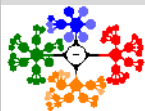
4 Bayes'Rules

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- **Theorem 2.10:**

If A and B are any two events, then

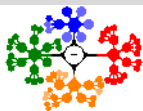
$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

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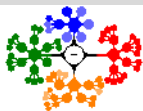
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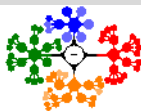
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- **Theorem 2.10:**

If A and B are any two events, then

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

- **Corollary 1:**

If A and B are mutually exclusive, then

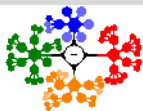
$$P(A \cup B) = P(A) + P(B)$$

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If A and B are mutually exclusive, then

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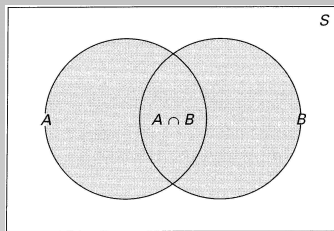
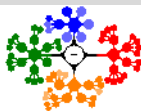


Figure: Additive rule of probability.



- **Corollary 2:**

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

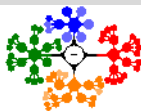
$$P(A_1 \cup A_2 \cup \dots \cup A_n) = P(A_1) + P(A_2) + \dots + P(A_n)$$

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

$$P(A_1 \cup A_2 \cup \dots \cup A_n) = P(A_1) + P(A_2) + \dots + P(A_n)$$

- **Corollary 3:**

If A_1, A_2, \dots, A_n , is a partition of a sample space S , then

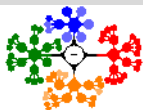
$$\begin{aligned} P(A_1 \cup A_2 \cup \dots \cup A_n) &= P(A_1) + P(A_2) + \dots + P(A_n) \\ &= P(S) = 1 \end{aligned}$$

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- **Theorem 2.11:** (an extension of Theorem 2.10)

For three events A , B , and C ,

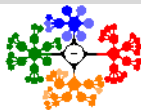
$$P(A \cup B \cup C) = P(A) + P(B) + P(C) - P(A \cap B) - P(A \cap C) \\ - P(B \cap C) + P(A \cap B \cap C)$$

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- **Theorem 2.12:**

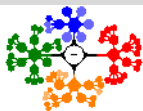
If A and A' are complementary events, then

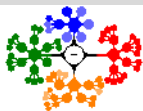
$$P(A) + P(A') = 1$$

Proof : Since $A \cup A' = S$ and $A \cap A' = \emptyset$, then

$$1 = P(S) = P(A \cup A') = P(A) + P(A')$$

- **Example 2.32:** The probability that the production procedure meets specification ($2000 \pm 10 \text{ mm}$) is known to be 0.99. Small cable is just as likely to be defective as large cable.





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- What is the probability that a cable selected randomly is too large?

Let M be the event that a cable meets spec. Let S and L be the events that the cable is too small and too large, respectively. Then

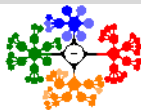
$$P(M) = 0.99 \text{ and } P(S) = P(L) = (1 - 0.99)/2 = 0.0005$$

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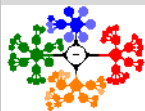
- What is the probability that a cable selected randomly is larger than 1990 mm?

$$P(X \geq 1990) = 1 - P(S) = 0.995$$

where X is the length of a randomly selected cable.

Conditional Probability I

- **Conditional probability:** $P(B|A)$



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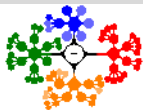
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Conditional Probability I

- **Conditional probability:** $P(B|A)$
 - Sometimes the occurrence of an event is influenced or related with some other event.



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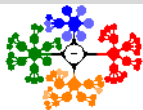
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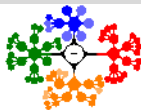
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 - **The probability of an event B occurring when it is known that some event A has occurred.**



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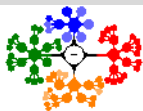
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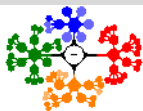
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 - **The notion of conditional probability provides the capability of re-evaluating the idea of probability of an event in light of additional information.**



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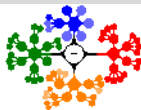
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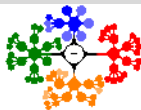
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- **Example:**

$$S = \{1, 2, 3, 4, 5, 6\}, A = \{4, 5, 6\}, B = \{1, 3, 5\}, \implies P(B|A)?$$





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- **Example:**

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- **Definition 2.9:**

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

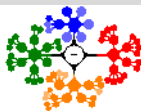
provided $P(A) > 0$

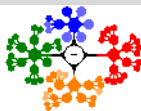
Conditional Probability II

- **Example:** Our sample space S is the population of adults in a small town. They can be categorized according to gender and employment status (see Table 1).

Table: Categorized adult population in a small town.

	Employed	Unemployed	Total
Male	460	40	500
Female	140	260	400
Total	600	300	900





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- One individual is to be selected at random for a publicity tour.

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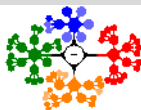
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- One individual is to be selected at random for a publicity tour.
- **The concerned events**

$$P(M|E) = \frac{460}{600} = \frac{23}{30}$$

$$P(M|E) = \frac{n(E \cap M)/n(S)}{n(E)/n(S)} = \frac{P(E \cap M)}{P(E)} = \frac{\frac{460}{900}}{\frac{600}{900}} = \frac{23}{30}$$



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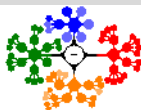
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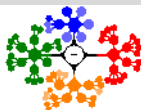
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 - E : the one chosen is employed

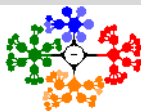
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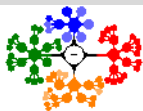
Conditional Probability III

- **Example 2.33:** The probability that a regularly scheduled flight departs on time is $P(D) = 0.83$;



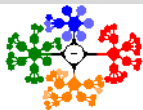
Conditional Probability III

- **Example 2.33:** The probability that a regularly scheduled flight departs on time is $P(D) = 0.83$;
- the probability that arrives on time is $P(A) = 0.82$;



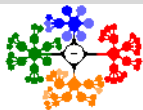
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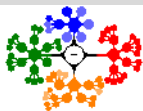
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Conditional Probability III

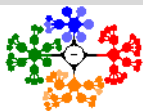
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- Find the probability that a plane



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- the probability that it departs and arrives on time is $P(D \cap A) = 0.78$.
- Find the probability that a plane
 - arrives on time given that it departed on time, and

$$P(A|D) = \frac{P(D \cap A)}{P(D)} = \frac{0.78}{0.83} = 0.94$$



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- departed on time given that it has arrived on time.

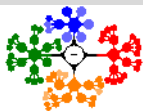
$$P(D|A) = \frac{P(D \cap A)}{P(A)} = \frac{0.78}{0.82} = 0.95$$

- **Definition 2.10:**

Two events A and B are said to be **independent** if and only if

$$P(B|A) = P(B) \text{ or } P(A|B) = P(A).$$

Otherwise, A and B are **dependent**.

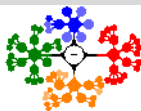


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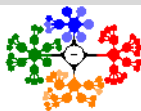
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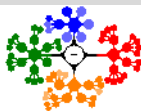
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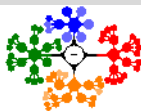
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- **Example:** Two cards are drawn in succession, with replacement



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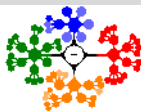
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- **Example:** Two cards are drawn in succession, with replacement
 - **Event A :** the first card is an ace



Additive Rules

Conditional Probability

Multiplicative Rules

Bayes' Rules

- **Definition 2.10:**

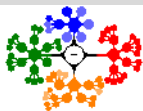
Two events A and B are said to be **independent** if and only if

$$P(B|A) = P(B) \text{ or } P(A|B) = P(A).$$

Otherwise, A and B are **dependent**.

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- **Example:** Two cards are drawn in succession, with replacement
 - Event A : the first card is an ace
 - Event B : the second card is a spade

$$P(B|A) = \frac{P(A \cap B)}{P(A)} = \frac{1/52}{4/52} = \frac{13}{52} = \frac{1}{4} \text{ and } P(B) = \frac{13}{52} = \frac{1}{4}$$



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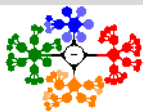
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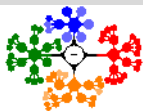
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- Since $P(B|A) = P(B)$, these two events are independent.

[Additive Rules](#)[Conditional Probability](#)[Multiplicative Rules](#)[Bayes' Rules](#)

Multiplicative Rules I

- Multiplying the formula of Definition 2.9 by $P(A)$, we obtain the **multiplicative rule**, which enables us to calculate the probability that two events will both occur.

[Additive Rules](#)[Conditional Probability](#)[Multiplicative Rules](#)[Bayes' Rules](#)

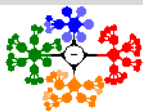
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- Multiplying the formula of Definition 2.9 by $P(A)$, we obtain the **multiplicative rule**, which enables us to calculate the probability that two events will both occur.
- **Theorem 2.13:**

If in an experiment the events A and B can both occur, then

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

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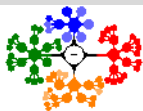
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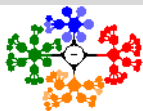
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- **Example 2.35:** Suppose that we have a fuse box containing 20 fuses, of which 5 are defective. If 2 fuses are selected at random and removed from the box in succession *without replacing* the first.



Additive Rules

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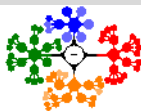
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Additive Rules

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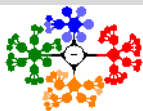
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Additive Rules

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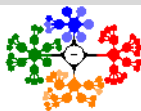
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- **Example 2.35:** Suppose that we have a fuse box containing 20 fuses, of which 5 are defective. If 2 fuses are selected at random and removed from the box in succession *without replacing* the first.
- What is the probability that both fuses are defective?
 - Event A : the first fuse is defective
 - Event B : the second fuse is defective. Hence,

$$P(A \cap B) = P(A) * P(B|A) = \frac{1}{4} * \frac{4}{19} = \frac{1}{19}$$

Multiplicative Rules II

- **Example 2.36:** One bag contains 4 white balls and 3 black balls. A second bag contains 3 white balls and 5 black balls.



Multiplicative Rules II

- **Example 2.36:** One bag contains 4 white balls and 3 black balls. A second bag contains 3 white balls and 5 black balls.
- One ball is drawn from the first bag and placed unseen in the second bag. What is the probability that a ball now drawn from the second bag is black?





Additive Rules

Conditional Probability

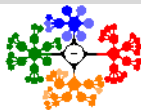
Multiplicative Rules

Bayes' Rules

- **Example 2.36:** One bag contains 4 white balls and 3 black balls. A second bag contains 3 white balls and 5 black balls.
- One ball is drawn from the first bag and placed unseen in the second bag. What is the probability that a ball now drawn from the second bag is black?
- **Solution:** Let B_1 , B_2 , and W_1 represent, respectively, the drawing of a black ball from bag 1, a black ball from bag 2, and a white ball from bag 1.

$$\begin{aligned}P[(B_1 \cap B_2) \cup (W_1 \cap B_2)] &= P(B_1 \cap B_2) + P(W_1 \cap B_2) \\&= P(B_1)P(B_2|B_1) + P(W_1)P(B_2|W_1) \\&= \frac{3}{7} * \frac{6}{9} + \frac{4}{7} * \frac{5}{9} = \frac{38}{63}\end{aligned}$$

Multiplicative Rules III



Additive Rules

Conditional Probability

Multiplicative Rules

Bayes' Rules

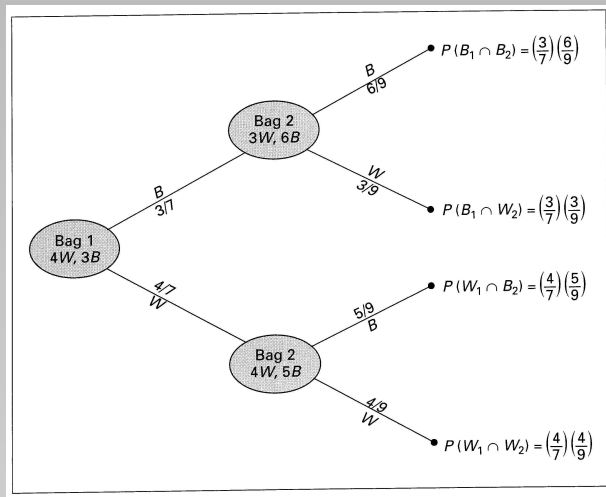


Figure: Tree diagram for Example 2.36.

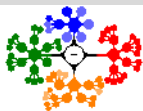
Multiplicative Rules IV

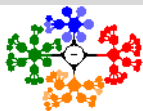
- **Theorem 2.14:**

Two events A and B are (statistically or probabilistically) independent if and only if

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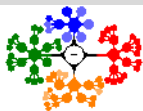
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Multiplicative Rules IV

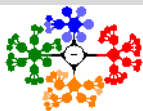
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Multiplicative Rules IV

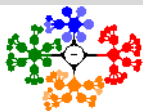
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- **Example 2.37:** A small town has one fire engine and one ambulance available for emergencies.
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Multiplicative Rules IV

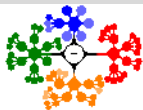
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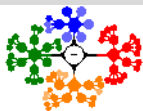
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 - In the event of an injury resulting from a burning building, find the probability that both the ambulance and the fire engine will be available.
- **Solution:** Let A and B represent the respective events that the fire engine and the ambulance are available. Then

$$P(A \cap B) = P(A)P(B) = 0.98 * 0.92 = 0.9016.$$

Multiplicative Rules V

- **Example 2.38:** Find the probability that



Additive Rules

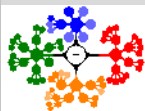
Conditional Probability

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Additive Rules

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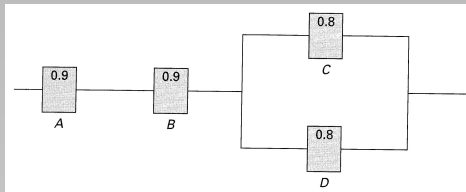
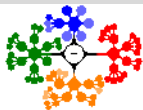


Figure: An electrical system for Example 2.38.



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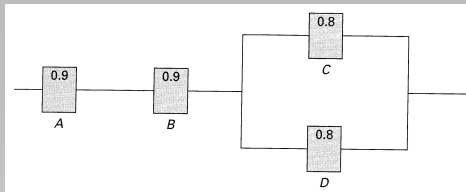
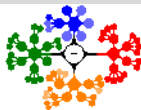


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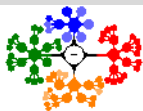


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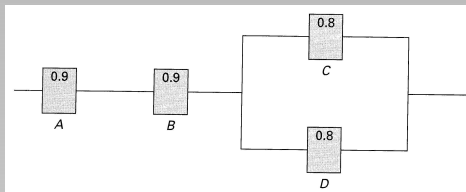
Multiplicative Rules

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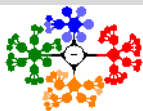
Multiplicative Rules V

- **Example 2.38:** Find the probability that



- the entire system works

Figure: An electrical system for Example 2.38.

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Multiplicative Rules V

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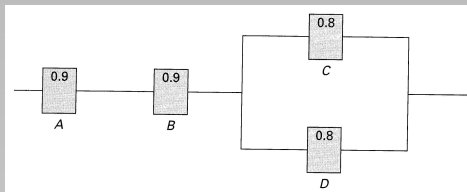
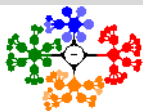


Figure: An electrical system for Example 2.38.

- the entire system works
- the component **C** does not work, given that the entire system works



Additive Rules

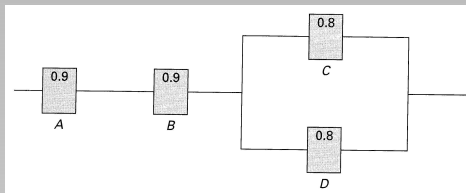
Conditional Probability

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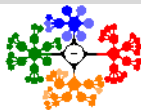


- the entire system works
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Figure: An electrical system for Example 2.38.

- **Solution:**

$$\begin{aligned}
 P(A \cap B \cap (C \cup D)) &= P(A) * P(B) * P(C \cup D) \\
 &= P(A) * P(B) * (1 - P(C' \cap D')) = P(A) * P(B) * (1 - P(C') * P(D')) \\
 &= 0.9 * 0.9 * (1 - (1 - 0.8) * (1 - 0.8)) = 0.7776
 \end{aligned}$$



Additive Rules

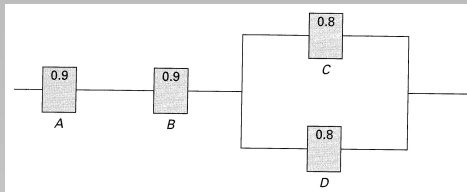
Conditional Probability

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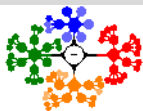
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 \end{aligned}$$

- $$P = \frac{P(\text{the system works but } C \text{ does not work})}{P(\text{the system works})}$$

$$= \frac{P(A \cap B \cap C' \cap D)}{P(A \cap B \cap (C \cup D))} = \frac{0.9 * 0.9 * (1 - 0.8) * 0.8}{0.7776} = 0.1667$$

Multiplicative Rules VI

- **Independence** is often easy to grasp intuitively.



Additive Rules

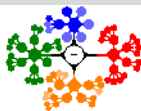
Conditional Probability

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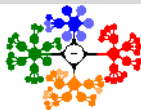
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- For example, if the occurrence of two events is governed by distinct and non-interacting physical processes, such events will turn out to be independent.



Multiplicative Rules VI

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- **On the other hand, independence is not easily visualized in terms of the sample space.**



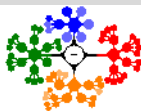
Additive Rules

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Multiplicative Rules VI



Additive Rules

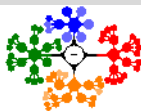
Conditional Probability

Multiplicative Rules

Bayes' Rules

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- On the other hand, independence is not easily visualized in terms of the sample space.
- A common fallacy (wrong idea) is that two events are independent if they are disjoint, but in fact *the opposite is true*:

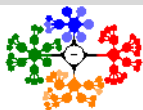
Two disjoint events A and B with $P(A) > 0$ and $P(B) > 0$ are never independent, since their intersection $A \cap B$ is empty and has probability 0.

[Additive Rules](#)[Conditional Probability](#)[Multiplicative Rules](#)[Bayes' Rules](#)

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Two disjoint events A and B with $P(A) > 0$ and $P(B) > 0$ are never independent, since their intersection $A \cap B$ is empty and has probability 0.

- We note that



Additive Rules

Conditional Probability

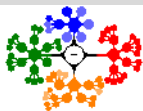
Multiplicative Rules

Bayes' Rules

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 - (i) independent events are never mutually exclusive,



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- **Independence** is often easy to grasp intuitively.
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- We note that
 - (i) independent events are never mutually exclusive,
 - (ii) **two mutually exclusive events are always dependent.**

Multiplicative Rules VII

- Theorem 2.15:**

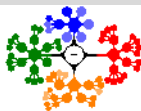
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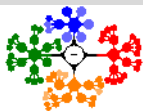
$$P(A_1 \cap A_2 \cap \dots \cap A_k) = P(A_1)P(A_2|A_1)P(A_3|A_1 \cap A_2)$$

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$$P(A_k|A_1 \cap A_2 \cap \dots \cap A_k) = P(A_1)P(A_2) \dots P(A_k) = \prod_{n=1}^k P(A_n)$$



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Multiplicative Rules VII

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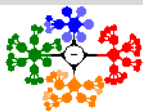
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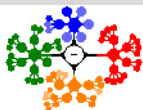
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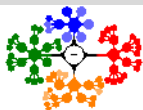
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- **Example 2.39:** Three cards are drawn in succession without replacement. Find the probability that the event

$A_1 \cap A_2 \cap A_3$ occurs, where

- A_1 : the first card is red ace
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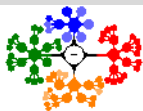
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- Solution:**

$$P(A_1 \cap A_2 \cap A_3) = P(A_1)P(A_2|A_1)P(A_3|A_1 \cap A_2) \\ = \frac{2}{52} * \frac{8}{51} * \frac{12}{50} = \frac{8}{5525}$$

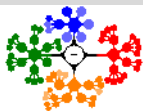
Multiplicative Rules VIII

- **Independence of Several Events:**

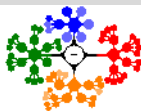
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Multiplicative Rules VIII

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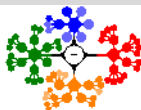
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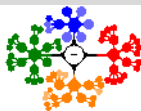
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Multiplicative Rules IX

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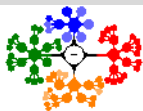
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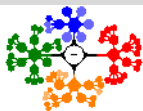
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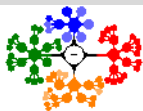
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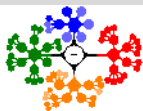
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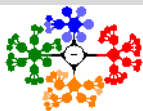
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Multiplicative Rules IX

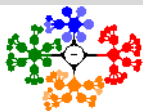
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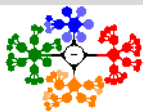
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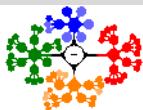
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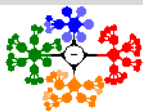
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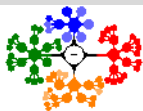
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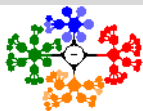
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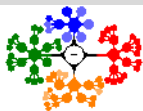
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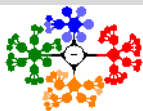
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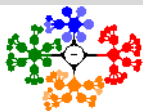
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Bayes' Rules I

- Our sample space S is the population of adults in a small town. They can be categorized according to employment status.

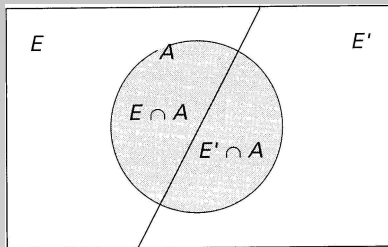
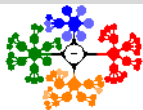
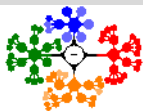


Figure: Venn diagram for the events A , E , and E' .



Additive Rules

Conditional Probability

Multiplicative Rules

Bayes' Rules

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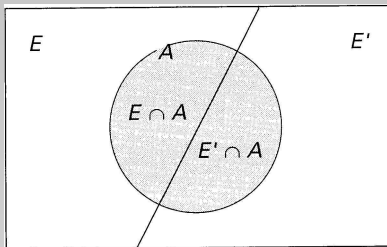
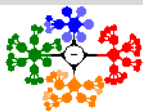


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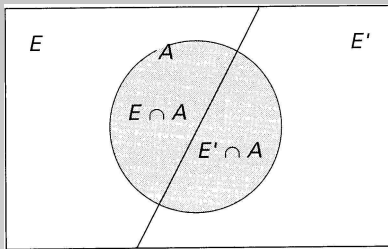
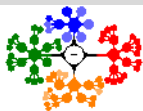


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- Our sample space S is the population of adults in a small town. They can be categorized according to employment status.
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 - The concerned event E : the one chosen is employed
 - Give the additional information that 36 of those employed and 12 of those unemployed are members of the Rotary Club.

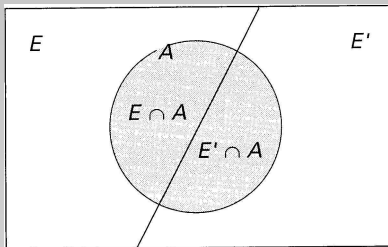
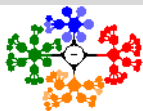


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- One individual is to be selected at random for a publicity tour.
 - The concerned event E : the one chosen is employed
 - Give the additional information that 36 of those employed and 12 of those unemployed are members of the Rotary Club.
 - Find the probability of the event A that individual selected is a member of the Rotary Club.

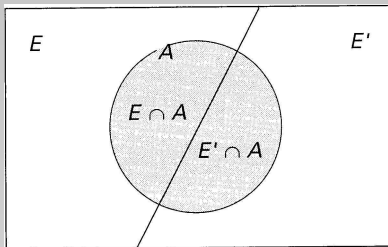


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Bayes' Rules II

- Event A is the union of the two mutually exclusive events $E \cap A$ and $E' \cap A$. Hence,

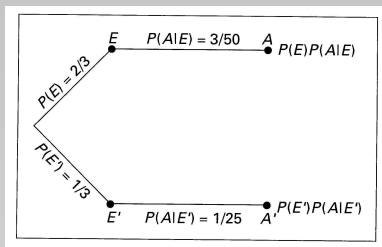
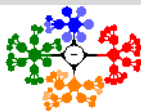


Figure: Tree diagram for the data.



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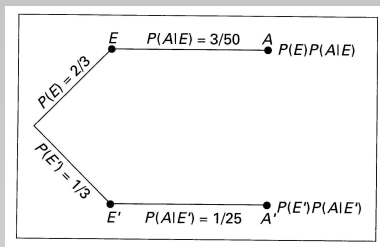
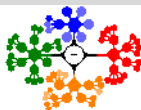
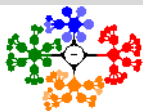


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$$A = (E \cap A) \cup (E' \cap A)$$

$$\begin{aligned} P(A) &= P[(E \cap A) \cup (E' \cap A)] \\ &= P(E \cap A) + P(E' \cap A) \\ &= P(E)P(A|E) + P(E')P(A|E') \end{aligned}$$

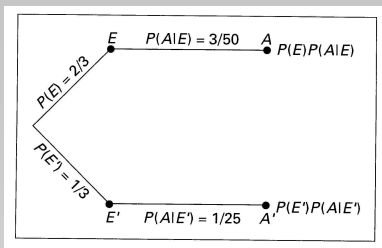
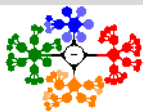


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$$\bullet P(E) = \frac{600}{900} = \frac{2}{3}, P(A|E) = \frac{36}{600} = \frac{3}{50}$$

$$\bullet P(E') = \frac{1}{3}, P(A|E') = \frac{12}{300} = \frac{1}{25}$$

$$\bullet P(A) = \frac{2}{3} * \frac{3}{50} + \frac{1}{3} * \frac{1}{25} = \frac{4}{75}$$

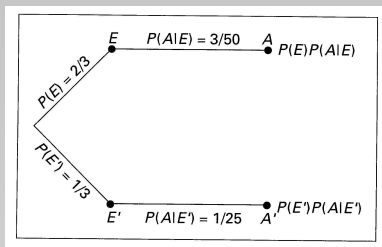


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Bayes' Rules III

- Theorem 2.16: (Theorem of total probability or rule of elimination)**

If the events B_1, B_2, \dots, B_k constitute a partition of the sample space S such that $P(B_i) \neq 0$ for $i = 1, 2, \dots, k$, then for any event A of S ,

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

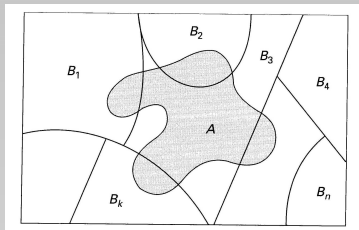
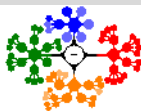
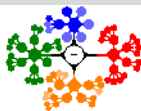


Figure: Partitioning the sample space S .



Bayes' Rules IV

- **Example 2.41:** In a certain assembly plant, three machines, B_1 , B_2 and B_3 make 30%, 45% and 25%, respectively, of the products.



Additive Rules

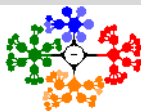
Conditional Probability

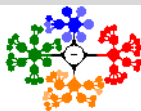
Multiplicative Rules

Bayes' Rules

Bayes' Rules IV

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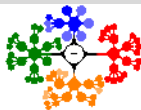


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- Now, suppose that a finished product is randomly selected. What is the probability that it is defective?

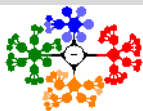
$$\begin{aligned}P(A) &= P(B_1)P(A|B_1) + P(B_2)P(A|B_2) + P(B_3)P(A|B_3) \\ &= 0.3 * 0.02 + 0.45 * 0.03 + 0.25 * 0.02 = 0.0245\end{aligned}$$

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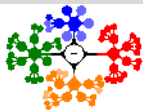
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- **Solution:**
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- **Event B :** the product is made by machine B_i



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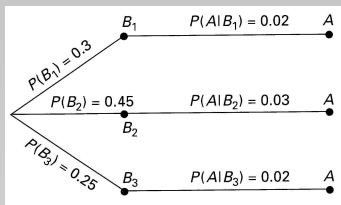
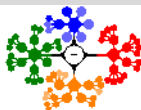


Figure: Tree diagram for Example 2.41.



- Theorem 2.17:** (Bayes' Rule)

If the events B_1, B_2, \dots, B_k constitute a partition of the sample space S such that $P(B_i) \neq 0$ for $i = 1, 2, \dots, k$, then

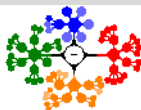
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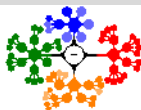
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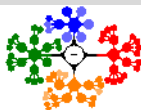
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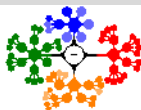
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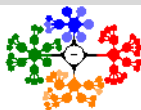
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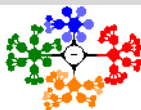
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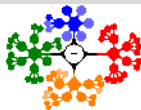
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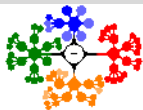
- **Example 2.42:** With reference to Example 2.41, if a product were chosen randomly and found to be defective, what is the probability that it was made by machine B_3

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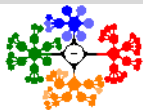
Bayes' Rules

- **Example 2.42:** With reference to Example 2.41, if a product were chosen randomly and found to be defective, what is the probability that it was made by machine B_3
- Using Bayes' rule,

$$\begin{aligned}P(B_3|A) &= \frac{P(B_3)P(A|B_3)}{P(B_1)P(A|B_1) + P(B_2)P(A|B_2) + P(B_3)P(A|B_3)} \\ &= \frac{0.005}{0.006 + 0.0135 + 0.005} = \frac{10}{49}\end{aligned}$$

Bayes' Rules VII

- **Example 2.43:** A manufacturing firm employs three analytical plans for the design and development of a particular product.



Additive Rules

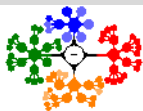
Conditional Probability

Multiplicative Rules

Bayes' Rules

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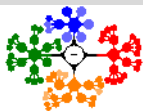
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- The “defect rate” is different for the three procedures as follows:

$$P(D|P_1) = 0.01, P(D|P_2) = 0.03, P(D|P_3) = 0.5$$

where $P(D|P_j)$ is the probability of a defective product, given plan j .



Bayes' Rules VII

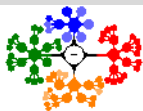
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- For cost reasons, all three are used at varying times. In fact, plans 1, 2, and 3 are used for 30%, 20%, and 50% of the products respectively.
- The “defect rate” is different for the three procedures as follows:

$$P(D|P_1) = 0.01, \quad P(D|P_2) = 0.03, \quad P(D|P_3) = 0.5$$

where $P(D|P_j)$ is the probability of a defective product, given plan j .

- If a random product was observed and found to be defective, which plan was most likely used and thus responsible?





Additive Rules

Conditional Probability

Multiplicative Rules

Bayes' Rules

Bayes' Rules VII

- **Example 2.43:** A manufacturing firm employs three analytical plans for the design and development of a particular product.
- For cost reasons, all three are used at varying times. In fact, plans 1, 2, and 3 are used for 30%, 20%, and 50% of the products respectively.
- The “defect rate” is different for the three procedures as follows:

$$P(D|P_1) = 0.01, \quad P(D|P_2) = 0.03, \quad P(D|P_3) = 0.05$$

where $P(D|P_j)$ is the probability of a defective product, given plan j .

- If a random product was observed and found to be defective, which plan was most likely used and thus responsible?
- **Solution:** $P(P_1) = 0.3, P(P_2) = 0.2, P(P_3) = 0.5$

$$P(P_i|D) = \frac{P(P_i)P(D|P_i)}{\sum_{j=1}^3 P(P_j)P(D|P_j)} = \frac{(0.30)(0.01)}{(0.3)(0.01) + (0.20)(0.03) + (0.50)(0.05)} = \frac{0.003}{0.019}$$

$$P(P_1|D) = 0.158, \quad P(P_2|D) = 0.316, \quad P(P_3|D) = 0.526.$$