

# CS5805 : Machine Learning I

## Lecture # 6

Reza Jafari, Ph.D

Collegiate Associate Professor  
rjafari@vt.edu





# Introduction to Probability

- What is a probability?

# Introduction to Probability

- What is a probability?
- One of the definition is based on the relative frequency :

$$P(E) = \frac{\#times\ an\ E\ occurs}{\#Trials}$$

*as  $\#Trials \rightarrow \infty$*

# Introduction to Probability

- What is a probability?
- One of the definition is based on the relative frequency :

$$P(E) = \frac{\#times\ an\ E\ occurs}{\#Trials}$$

*as  $\#Trials \rightarrow \infty$*

- The problem with this definition is that  $\# Trials \rightarrow \infty$  is impossible.

# Other definition of Probability

- **Axiomatic Probability:**

- ①  $P(E) \geq 0$ , non-negative
- ②  $P(S) = 1$ ,  $S$ : is the sample space
- ③ If  $A_1, A_2, \dots, A_n$  is mutually exclusive ( disjoint) then

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

# Other definition of Probability

- **Axiomatic Probability:**

- ①  $P(E) \geq 0$ , non-negative
- ②  $P(S) = 1$ ,  $S$ : is the sample space
- ③ If  $A_1, A_2, \dots, A_n$  is mutually exclusive ( disjoint) then

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

- Mutually exclusive events: are the events that can not occur simultaneously.

# Other definition of Probability

- **Axiomatic Probability:**

- ①  $P(E) \geq 0$ , non-negative
- ②  $P(S) = 1$ ,  $S$ : is the sample space
- ③ If  $A_1, A_2, \dots, A_n$  is mutually exclusive ( disjoint) then

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

- Mutually exclusive events: are the events that can not occur simultaneously.
- In other words, if one event has already occurred, the other event can not occur.



# Other definition of Probability

- **Axiomatic Probability:**

- ①  $P(E) \geq 0$ , non-negative
- ②  $P(S) = 1$ ,  $S$ : is the sample space
- ③ If  $A_1, A_2, \dots, A_n$  is mutually exclusive ( disjoint) then

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

- Mutually exclusive events: are the events that can not occur simultaneously.
- In other words, if one event has already occurred, the other event can not occur.
- Flipping a coin: Once you get H, there is no way to get T.

# Disjoint Events



# Independence

- Two events are independent, if the probability of the outcome of one event does not influence the probability of outcome of another event.

# Independence

- Two events are independent, if the probability of the outcome of one event does not influence the probability of outcome of another event.
- Let event  $A_1, A_2, \dots, A_n$  are independent events ( meaning occurness one does not depend on the other) then:

$$P(A_1 \cap A_2 \dots \cap A_n) = P(A_1) * P(A_2) \dots * P(A_n)$$

# Independence

- Two events are independent, if the probability of the outcome of one event does not influence the probability of outcome of another event.
- Let event  $A_1, A_2, \dots, A_n$  are independent events ( meaning occurness one does not depend on the other) then:

$$P(A_1 \cap A_2 \dots \cap A_n) = P(A_1) * P(A_2) \dots * P(A_n)$$

- Hence, in order to prove that an event A is independent of event B, it requires to show that

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

# Independence

- Two events are independent, if the probability of the outcome of one event does not influence the probability of outcome of another event.
- Let event  $A_1, A_2, \dots, A_n$  are independent events ( meaning occurness one does not depend on the other) then:

$$P(A_1 \cap A_2 \dots \cap A_n) = P(A_1) * P(A_2) \dots * P(A_n)$$

- Hence, in order to prove that an event A is independent of event B, it requires to show that

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

- Does independence imply disjoint?

# Independence

- Two events are independent, if the probability of the outcome of one event does not influence the probability of outcome of another event.
- Let event  $A_1, A_2, \dots, A_n$  are independent events ( meaning occurness one does not depend on the other) then:

$$P(A_1 \cap A_2 \dots \cap A_n) = P(A_1) * P(A_2) \dots * P(A_n)$$

- Hence, in order to prove that an event A is independent of event B, it requires to show that

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

- Does independence imply disjoint?
- Does disjoint imply independence?

# Conditional Probability

- The conditional probability of an event B is the probability that the event will occur given the knowledge that an event A has already occurred.

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



# Conditional Probability

- The conditional probability of an event B is the probability that the event will occur given the knowledge that an event A has already occurred.

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

- Or the joint probability between A and B can be calculated as

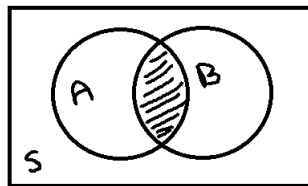
$$P(A \cap B) = P(B|A) * P(A)$$

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

# Example

- A and B are not mutually exclusive in below venn diagram, hence:

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



# Example

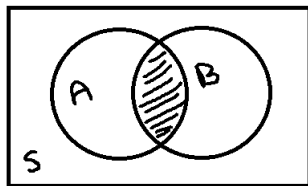
- A and B are not mutually exclusive in below venn diagram, hence:

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

- If A and B are independent then  $P(B|A) = P(B)$  because:

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

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



# Example

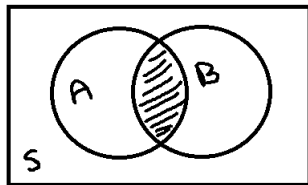
- A and B are not mutually exclusive in below venn diagram, hence:

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

- If A and B are independent then  $P(B|A) = P(B)$  because:

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

- Similarly  $P(A|B) = P(A)$
- Conditional Probability is extremely important in parameter estimation and forecasting of time-series model.



# Theorem of Total Probability

- If  $B_1, B_2, B_3, \dots$  is a partition of the sample space  $S$ , then for any event  $A$  we have:

$$P(A) = \sum_i P(A \cap B_i) = \sum_i P(A|B_i)P(B_i)$$

# Theorem of Total Probability

- If  $B_1, B_2, B_3, \dots$  is a partition of the sample space  $S$ , then for any event  $A$  we have:

$$P(A) = \sum_i P(A \cap B_i) = \sum_i P(A|B_i)P(B_i)$$

- **Example:** There are three bags that each contain 100 marbles:
  - Bag 1 has 75 red and 25 blue marbles;
  - Bag 2 has 60 red and 40 blue marbles;
  - Bag 3 has 45 red and 55 blue marbles;

I choose one of the bags at random and then pick a marble from the chosen bag, also at random. What is the probability that the chosen marble is red?

# Total Probability and Decision tree

- The decision tree is a simple and convenient method of visualizing problem with the total probability rule.

# Total Probability and Decision tree

- The decision tree is a simple and convenient method of visualizing problem with the total probability rule.
- The decision tree depicts all possible events in the sequence and quickly identify the relationships between events and calculate the conational probability.

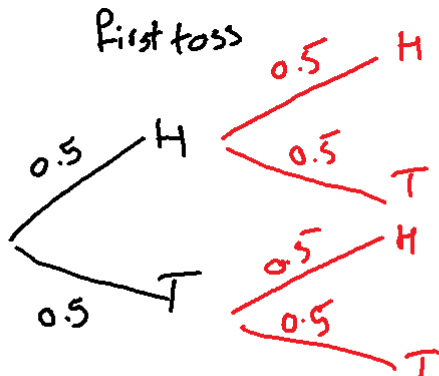


# Total Probability and Decision tree

- The decision tree is a simple and convenient method of visualizing problem with the total probability rule.
- The decision tree depicts all possible events in the sequence and quickly identify the relationships between events and calculate the conational probability.
- Let toss a fair coin twice. What is the probability of getting TT?

# Total Probability and Decision tree

- The decision tree is a simple and convenient method of visualizing problem with the total probability rule.
- The decision tree depicts all possible events in the sequence and quickly identify the relationships between events and calculate the conational probability.
- Let toss a fair coin twice. What is the probability of getting TT?



# Example

- You are a stock analyst for a company. You discovered that the company is planning to launch a new project that is likely to affect the company stock price. You identified the following probabilities:
  - 1 There is a 60% probability of launching a new project.
  - 2 If a company launches the project, there is a 75% chance that the company stock will increase.
  - 3 If a company does not launch the project, there is a 30% chance probability that company stock price will increase.

# Example

- You are a stock analyst for a company. You discovered that the company is planning to launch a new project that is likely to affect the company stock price. You identified the following probabilities:
  - ① There is a 60% probability of launching a new project.
  - ② If a company launches the project, there is a 75% chance that the company stock will increase.
  - ③ If a company does not launch the project, there is a 30% chance probability that company stock price will increase.
- Find the probability that company's stock will increase?

# Example

- You are a stock analyst for a company. You discovered that the company is planning to launch a new project that is likely to affect the company stock price. You identified the following probabilities:
  - ① There is a 60% probability of launching a new project.
  - ② If a company launches the project, there is a 75% chance that the company stock will increase.
  - ③ If a company does not launch the project, there is a 30% chance probability that company stock price will increase.
- Find the probability that company's stock will increase?
- Find the probability that company's stock will increase given that new project is launched?

# Example

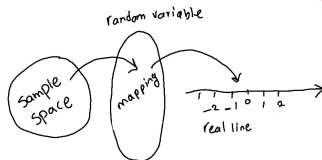
- You are a stock analyst for a company. You discovered that the company is planning to launch a new project that is likely to affect the company stock price. You identified the following probabilities:
  - ① There is a 60% probability of launching a new project.
  - ② If a company launches the project, there is a 75% chance that the company stock will increase.
  - ③ If a company does not launch the project, there is a 30% chance probability that company stock price will increase.
- Find the probability that company's stock will increase?
- Find the probability that company's stock will increase given that new project is launched?
- Find the probability that company's stock will increase given that new project is not launched?

# Example

- You are a stock analyst for a company. You discovered that the company is planning to launch a new project that is likely to affect the company stock price. You identified the following probabilities:
  - ① There is a 60% probability of launching a new project.
  - ② If a company launches the project, there is a 75% chance that the company stock will increase.
  - ③ If a company does not launch the project, there is a 30% chance probability that company stock price will increase.
- Find the probability that company's stock will increase?
- Find the probability that company's stock will increase given that new project is launched?
- Find the probability that company's stock will increase given that new project is not launched?
- Should the company launch the project or not?

# Random Variable

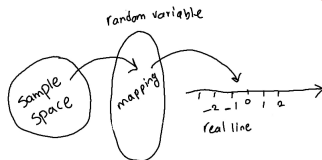
- Given an experiment with events and their associated probabilities. A random variable is a mapping from a sample space to the real line.





# Random Variable

- Given an experiment with events and their associated probabilities. A random variable is a mapping from a sample space to the real line.



- Random variables map events to numbers where functions map numbers to numbers. For example:

$$y = \sin\left(\frac{\pi}{2}\right) \quad (1)$$

# Probability Distribution Function

- What is the purpose of this mapping?

$$F_x(\lambda) = P(\{S : X(s) \leq \lambda\}) \quad (2)$$

# Probability Distribution Function

- What is the purpose of this mapping?
  - It shows probability distribution function.

$$F_x(\lambda) = P(\{S : X(s) \leq \lambda\}) \quad (2)$$

# Probability Distribution Function

- What is the purpose of this mapping?
  - It shows probability distribution function.

$$F_x(\lambda) = P(\{S : X(s) \leq \lambda\}) \quad (2)$$

- $\lambda$  is the dummy variable and  $X$  is the random variable.

# Probability Distribution Function

- What is the purpose of this mapping?
  - It shows probability distribution function.

$$F_x(\lambda) = P(\{S : X(s) \leq \lambda\}) \quad (2)$$

- $\lambda$  is the dummy variable and  $X$  is the random variable.
- It is very important to use different letters for random variable ( $X$ ) and dummy variable ( $\lambda$ )

# Probability Distribution Function

- What is the purpose of this mapping?
  - It shows probability distribution function.

$$F_x(\lambda) = P(\{S : X(s) \leq \lambda\}) \quad (2)$$

- $\lambda$  is the dummy variable and  $X$  is the random variable.
- It is very important to use different letters for random variable ( $X$ ) and dummy variable ( $\lambda$ )
- Random variable is a mapping and the dummy variable is the place holder.

# Probability Density Function

- The derivative of probability distribution function is defined as probability density function:

$$f_x(\lambda) = \frac{d}{d\lambda} F_x(\lambda) \quad (3)$$

or

$$F_x(\lambda) = \int_{-\infty}^{\lambda} f_x(\mu) d\mu \quad (4)$$

# Probability Density Function

- The derivative of probability distribution function is defined as probability density function:

$$f_x(\lambda) = \frac{d}{d\lambda} F_x(\lambda) \quad (3)$$

or

$$F_x(\lambda) = \int_{-\infty}^{\lambda} f_x(\mu) d\mu \quad (4)$$

- In other word the area under the density function shows probability of the event occur. Hence, the area under the density function from  $-\infty$  to  $\infty$  must be equal to 1.



# Probability Density Function

- The derivative of probability distribution function is defined as probability density function:

$$f_x(\lambda) = \frac{d}{d\lambda} F_x(\lambda) \quad (3)$$

or

$$F_x(\lambda) = \int_{-\infty}^{\lambda} f_x(\mu) d\mu \quad (4)$$

- In other word the area under the density function shows probability of the event occur. Hence, the area under the density function from  $-\infty$  to  $\infty$  must be equal to 1.
- In order to define a random variable, the density function is needed.

# Probability Density Function

- The derivative of probability distribution function is defined as probability density function:

$$f_x(\lambda) = \frac{d}{d\lambda} F_x(\lambda) \quad (3)$$

or

$$F_x(\lambda) = \int_{-\infty}^{\lambda} f_x(\mu) d\mu \quad (4)$$

- In other word the area under the density function shows probability of the event occur. Hence, the area under the density function from  $-\infty$  to  $\infty$  must be equal to 1.
- In order to define a random variable, the density function is needed.
- Knowing density function, reveal all information about the random variable.

Consider a continuous random variable  $X$  with probability density function  $f_X(\lambda)$ . We have:

①  $f_X(\lambda) \geq 0$  for all  $\lambda$  in  $\mathbb{R}$

②  $\int_{-\infty}^{\infty} f_X(\lambda) d\lambda = 1$

③  $P(a < X \leq b) = F_X(b) - F_X(a) = \int_a^b f_X(\lambda) d\lambda$

# Example

Let consider a uniform density function for a random variable  $X$ . This random variable is said to have *Uniform*( $a, b$ ) distribution. Or it can mathematically to be written as:

$$f_X(\lambda) = \begin{cases} c, & 0 < a < \lambda < b \\ 0, & \text{Else} \end{cases}$$

Graph the above density function and find  $c$  in terms if  $a$  and  $b$ .

# Example

Let  $X$  be a continuous random variable with the following pdf:

$$f_X(\lambda) = \begin{cases} ce^{-\lambda}, & \lambda \geq 0 \\ 0, & \text{Else} \end{cases}$$

- 1 Find  $c$ .
- 2 Find the probability distribution function  $F_X(\lambda)$
- 3 Find  $P(1 < X \leq 3)$
- 4 Find  $P(X = 2)$
- 5 Find  $P(X \in [0, 1] \cup [3, 4])$

# Example

Let  $X$  be a continuous random variable that is equally likely to be any value between 80 and 100.

- 1 Graph the corresponding probability density function.
- 2 Find  $P(90 < X \leq 95)$

# Joint Random Variables

- Two random variables  $X$  and  $Y$  are jointly continuous if they have a joint probability distribution function defined as:

$$F_{X,Y}(\lambda_1, \lambda_2) = P(\{s : X(s) \leq \lambda_1\} \cap \{t : Y(t) \leq \lambda_2\})$$

# Joint Random Variables

- Two random variables  $X$  and  $Y$  are jointly continuous if they have a joint probability distribution function defined as:

$$F_{X,Y}(\lambda_1, \lambda_2) = P(\{s : X(s) \leq \lambda_1\} \cap \{t : Y(t) \leq \lambda_2\})$$

- where the joint density function is defined as:

$$f_{X,Y}(\lambda_1, \lambda_2) = \frac{\partial^2 F_{X,Y}(\lambda_1, \lambda_2)}{\partial \lambda_1 \partial \lambda_2}$$



# Joint Random Variables

- Two random variables  $X$  and  $Y$  are jointly continuous if they have a joint probability distribution function defined as:

$$F_{X,Y}(\lambda_1, \lambda_2) = P(\{s : X(s) \leq \lambda_1\} \cap \{t : Y(t) \leq \lambda_2\})$$

- where the joint density function is defined as:

$$f_{X,Y}(\lambda_1, \lambda_2) = \frac{\partial^2 F_{X,Y}(\lambda_1, \lambda_2)}{\partial \lambda_1 \partial \lambda_2}$$

- properties of Joint density function is

1

$$f_{X,Y}(\lambda_1, \lambda_2) \geq 0 \quad \forall \lambda_1 \text{ and } \lambda_2$$

2

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(\lambda_1, \lambda_2) d\lambda_1 d\lambda_2 = 1$$

# Example

Let  $X$  and  $Y$  be two jointly continuous random variables (uniformly distributed) with joint probability density function:

$$f_{XY}(\lambda_1, \lambda_2) = \begin{cases} \lambda_1 + c\lambda_2^2, & 0 \leq \lambda_1 \leq 1, 0 \leq \lambda_2 \leq 1 \\ 0, & \text{Else} \end{cases}$$

- 1 Find  $c$ .
- 2 Find  $P(0 < X \leq \frac{1}{2}, 0 < Y \leq \frac{1}{2})$

# Example

Let  $X$  and  $Y$  be two jointly continuous random variables with the joint probability density function:

$$f_{XY}(\lambda_1, \lambda_2) = \begin{cases} c\lambda_1^2 + \frac{\lambda_1\lambda_2}{3}, & 0 \leq \lambda_1 \leq 1, 0 \leq \lambda_2 \leq 2 \\ 0, & \text{Else} \end{cases}$$

- 1 Find  $c$ .
- 2 Find  $P(X + Y \geq 1)$

# Marginal Probability Density Function

- We can find the marginal probability density functions of random variable  $X$  and  $Y$  from their joint density function.

$$f_X(\lambda_1) = \int_{-\infty}^{\infty} f_{X,Y}(\lambda_1, \lambda_2) d\lambda_2$$

$$f_Y(\lambda_2) = \int_{-\infty}^{\infty} f_{X,Y}(\lambda_1, \lambda_2) d\lambda_1$$

- In general, we say a set of random variables  $X_1(\lambda_1) \dots X_n(\lambda_n)$  is (mutually) **independent** if

$$f_{X_1, \dots, X_n}(\lambda_1 \dots \lambda_n) = \prod_{i=1}^n f_{X_i}(\lambda_i)$$

# Marginal Probability Density Function

- We can find the marginal probability density functions of random variable  $X$  and  $Y$  from their joint density function.

$$f_X(\lambda_1) = \int_{-\infty}^{\infty} f_{X,Y}(\lambda_1, \lambda_2) d\lambda_2$$

$$f_Y(\lambda_2) = \int_{-\infty}^{\infty} f_{X,Y}(\lambda_1, \lambda_2) d\lambda_1$$

- To check if random variable  $X$  and  $Y$  are independent, it requires to show:

$$f_{XY}(\lambda_1, \lambda_2) \stackrel{?}{=} f_X(\lambda_1) * f_Y(\lambda_2)$$

- In general, we say a set of random variables  $X_1(\lambda_1) \dots X_n(\lambda_n)$  is (mutually) **independent** if

$$f_{X_1, \dots, X_n}(\lambda_1 \dots \lambda_n) = \prod_{i=1}^n f_{X_i}(\lambda_i)$$

# Example

- Let consider two random variables  $X$  and  $Y$  with the following joint probability density function:

$$f_{XY}(\lambda_1, \lambda_2) = \begin{cases} c, & -1 \leq \lambda_1 \leq 0, 0 \leq \lambda_2 \leq 1 \\ 0, & \text{Else} \end{cases}$$



# Example

- Let consider two random variables  $X$  and  $Y$  with the following joint probability density function:

$$f_{XY}(\lambda_1, \lambda_2) = \begin{cases} c, & -1 \leq \lambda_1 \leq 0, 0 \leq \lambda_2 \leq 1 \\ 0, & \text{Else} \end{cases}$$



- Find the constant  $c$ .

# Example

- Let consider two random variables  $X$  and  $Y$  with the following joint probability density function:

$$f_{XY}(\lambda_1, \lambda_2) = \begin{cases} c, & -1 \leq \lambda_1 \leq 0, 0 \leq \lambda_2 \leq 1 \\ 0, & \text{Else} \end{cases}$$



- Find the constant  $c$ .
- Find the marginal density  $f_X(\lambda_1)$ .



# Example

- Let consider two random variables  $X$  and  $Y$  with the following joint probability density function:

$$f_{XY}(\lambda_1, \lambda_2) = \begin{cases} c, & -1 \leq \lambda_1 \leq 0, 0 \leq \lambda_2 \leq 1 \\ 0, & \text{Else} \end{cases}$$



- Find the constant  $c$ .
- Find the marginal density  $f_X(\lambda_1)$ .
- Find the marginal density  $f_Y(\lambda_2)$ .

## Example

- Let consider two random variables  $X$  and  $Y$  with the following joint probability density function:

$$f_{XY}(\lambda_1, \lambda_2) = \begin{cases} c, & -1 \leq \lambda_1 \leq 0, 0 \leq \lambda_2 \leq 1 \\ 0, & \text{Else} \end{cases}$$



- Find the constant  $c$ .
- Find the marginal density  $f_X(\lambda_1)$ .
- Find the marginal density  $f_Y(\lambda_2)$ .
- Are  $X$  and  $Y$  independent?

# Conditional Density Function

- Let  $X$  and  $Y$  be two continuous random variables. The conditional probability density function of  $X$  given  $Y$  is defined as :

$$f_{X|Y}(\lambda_1|\lambda_2) = \frac{f_{X,Y}(\lambda_1, \lambda_2)}{f_Y(\lambda_2)}$$

$$P(a \leq Y \leq b | X = \lambda_1) = \int_a^b f_{Y|X}(\lambda_2|\lambda_1) d\lambda_2$$

$$f_{Y|X}(\lambda_2|\lambda_1) = \frac{f_{X,Y}(\lambda_1, \lambda_2)}{f_X(\lambda_1)}$$

$$P(a \leq X \leq b | Y = \lambda_2) = \int_a^b f_{X|Y}(\lambda_1|\lambda_2) d\lambda_1$$

# Conditional Density Function

- Let  $X$  and  $Y$  be two continuous random variables. The conditional probability density function of  $X$  given  $Y$  is defined as :

$$f_{X|Y}(\lambda_1|\lambda_2) = \frac{f_{X,Y}(\lambda_1, \lambda_2)}{f_Y(\lambda_2)}$$

$$P(a \leq Y \leq b | X = \lambda_1) = \int_a^b f_{Y|X}(\lambda_2|\lambda_1) d\lambda_2$$

$$f_{Y|X}(\lambda_2|\lambda_1) = \frac{f_{X,Y}(\lambda_1, \lambda_2)}{f_X(\lambda_1)}$$

$$P(a \leq X \leq b | Y = \lambda_2) = \int_a^b f_{X|Y}(\lambda_1|\lambda_2) d\lambda_1$$

# Conditional Density Function

- Let  $X$  and  $Y$  be two continuous random variables. The conditional probability density function of  $X$  given  $Y$  is defined as :

$$f_{X|Y}(\lambda_1|\lambda_2) = \frac{f_{X,Y}(\lambda_1, \lambda_2)}{f_Y(\lambda_2)}$$

$$P(a \leq Y \leq b | X = \lambda_1) = \int_a^b f_{Y|X}(\lambda_2|\lambda_1) d\lambda_2$$

$$f_{Y|X}(\lambda_2|\lambda_1) = \frac{f_{X,Y}(\lambda_1, \lambda_2)}{f_X(\lambda_1)}$$

$$P(a \leq X \leq b | Y = \lambda_2) = \int_a^b f_{X|Y}(\lambda_1|\lambda_2) d\lambda_1$$

# Conditional Density Function

- Let  $X$  and  $Y$  be two continuous random variables. The conditional probability density function of  $X$  given  $Y$  is defined as :

$$f_{X|Y}(\lambda_1|\lambda_2) = \frac{f_{X,Y}(\lambda_1, \lambda_2)}{f_Y(\lambda_2)}$$

$$P(a \leq Y \leq b | X = \lambda_1) = \int_a^b f_{Y|X}(\lambda_2|\lambda_1) d\lambda_2$$

$$f_{Y|X}(\lambda_2|\lambda_1) = \frac{f_{X,Y}(\lambda_1, \lambda_2)}{f_X(\lambda_1)}$$

$$P(a \leq X \leq b | Y = \lambda_2) = \int_a^b f_{X|Y}(\lambda_1|\lambda_2) d\lambda_1$$

- For example want to know the probability density function of the outside temperature given that the humidity is known to be below 50%

# Example

- Let consider a random variable  $X$  and  $Y$  with the following joint density function as follow and the plot given in the previous example. Find the conditional density function  $f_{X|Y}(\lambda_1|\lambda_2)$  and  $f_{Y|X}(\lambda_2|\lambda_1)$

$$f_{X,Y}(\lambda_1, \lambda_2) = \begin{cases} 2 : & -1 \leq \lambda_1 \leq 0 \text{ and } 0 \leq \lambda_2 \leq 1 \\ 0 : & \text{Otherwise} \end{cases}$$

# Example

- $R$  is a random variable that is equally likely to be any value between 80 and 100.
  - Find  $P(90 \leq R \leq 95)$
  - Find  $P(90 \leq R \leq 95 | 85 \leq R \leq 95)$



# Expectation

- Expected value of a random variable  $X$  reduces density function to one number which is the mean value of

$$\mu_x = E[x] = \int_{-\infty}^{\infty} \lambda f_X(\lambda) d\lambda$$

# Expectation

- Expected value of a random variable  $X$  reduces density function to one number which is the mean value of

$$\mu_x = E[x] = \int_{-\infty}^{\infty} \lambda f_X(\lambda) d\lambda$$

- Similarly the variance of random variable  $X$  is defined as :

$$\sigma_x^2 = E[(x - \mu_x)^2] = \int_{-\infty}^{\infty} (\lambda - \mu_x)^2 f_X(\lambda) d\lambda = E[x^2] - \mu_x^2$$

# Expectation

- Expected value of a random variable  $X$  reduces density function to one number which is the mean value of

$$\mu_x = E[x] = \int_{-\infty}^{\infty} \lambda f_X(\lambda) d\lambda$$

- Similarly the variance of random variable  $X$  is defined as :

$$\sigma_x^2 = E[(x - \mu_x)^2] = \int_{-\infty}^{\infty} (\lambda - \mu_x)^2 f_X(\lambda) d\lambda = E[x^2] - \mu_x^2$$

- Covariance between two random variable  $X$  and  $Y$  is defined as :

$$\sigma_{xy} = E[(x - \mu_x)(y - \mu_y)]$$

# Expectation

- Expected value of a random variable  $X$  reduces density function to one number which is the mean value of

$$\mu_x = E[x] = \int_{-\infty}^{\infty} \lambda f_X(\lambda) d\lambda$$

- Similarly the variance of random variable  $X$  is defined as :

$$\sigma_x^2 = E[(x - \mu_x)^2] = \int_{-\infty}^{\infty} (\lambda - \mu_x)^2 f_X(\lambda) d\lambda = E[x^2] - \mu_x^2$$

- Covariance between two random variable  $X$  and  $Y$  is defined as :

$$\sigma_{xy} = E[(x - \mu_x)(y - \mu_y)]$$

- For uncorrelated random variables  $X$  and  $Y$ , the covariance is zero hence the correlation coefficient is zero.

# Example

- Let consider a continuous random variable  $X$  to be defined uniformly between 0 and 10. What is the mean of  $X$  and what is the variance?

# Example

- Let consider a continuous random variable  $X$  to be defined uniformly between 0 and 10. What is the mean of  $X$  and what is the variance?
- **Answer** :  $\mu_x = 5$  and  $\sigma_x^2 = 8.3$