

## Week 02

### 1) Expected Value (mean)

- \* The expected value is the long-run average outcome of a random variable if we repeated an experiment infinitely many times
- \* Theoretical Mean = Expected Value

For Discrete  $\Rightarrow$

$$E[X] = \mu = \sum_i x_i p_i$$

$x_i$  = values

$p_i$  = probabilities

ex: Toss a fair dice

$$E[X] = \frac{1}{6} (1+2+3+4+5+6) = 3.5$$

- \* 3.5 not an actual value, but the expected outcome over many trials

For Continuous  $\Rightarrow$

$$E[X] = \mu = \int_{-\infty}^{\infty} x f(x) dx$$

ex: For a uniform distribution  $[0, 1]$

$$E[X] = \int_0^1 x 1 dx = \frac{1}{2}$$

- \* Mean / Balancing point
- \* Defined for discrete and continuous variables
- \* Weighted average of the PMF / PDF
- \* Very high because of outliers

## 2) Central Tendency : Median and Mode

- \* Central tendency is a statistical concept that describes the center point or typical value of a dataset or a probability distribution

### Median

- \* The median is the middle value when data is sorted
- \* If n is odd  $\rightarrow$  middle element
- \* If n is even  $\rightarrow$  average of the two middle elements
- \* less affected by outliers (better for skewed data)

### Mode

- \* The mode is the value that occurs more frequently
- \* A distribution can be :
  - Unimodal  $\rightarrow$  1 mode
  - Bimodal  $\rightarrow$  2 peaks
  - Multimodal  $\rightarrow$  more than 2 peaks
- \* Works well for categorical data ( fav color, product preference )

### 3) Expected value of a function

$X \Rightarrow g(X)$   
variable      function

Discrete case  $\Rightarrow$

$X$  takes values  $x_i$ , probabilities  $p_i$   
then

$$E[g(X)] = \sum g(x_i) \cdot p_i$$

example: Dice roll (1-6)

$$\therefore \text{mean of } X = E[X] = 3.5$$

$$\therefore g(x) = x^2$$

$$E[x^2] = \frac{1}{6} (1^2 + 2^2 + 3^2 + 4^2 + 5^2 + 6^2) = 15.17$$

$\Rightarrow$  Expected square of the roll is 15.17

Continuous case  $\Rightarrow$

If  $X$  has PDF  $f(x)$

$$E[g(x)] = \int_{-\infty}^{\infty} g(x) \cdot f(x) dx$$

ex: Uniform (0, 1),  $g(x) = x^2$

$$E[x^2] = \int_0^1 x^2 \cdot (1) dx = \frac{1}{3}$$

In general :

$$E[aX+b] = aE[X] + b$$

$$E[aX] = aE[X]$$

$$E[b] = b$$

#### 4] Sum of expectations

$$E[X_1 + X_2 + \dots + X_n] = E[X_1] + E[X_2] + \dots + E[X_n]$$

- \* This works always, regardless of whether  $X$  and  $Y$  are independent or not

#### 5] Variance

- \* Variance measures how spread out the values of a random variable are around the mean.

• Mean  $\rightarrow$  tell us the center of data

• Variance  $\rightarrow$  tell us how far the data is spread from the mean

\* If data points are close to the mean (low variance)

\* If data points are far away (high variance)

For a random variable  $X$  with mean  $\mu = E(X)$

$$\text{Var}(X) = E[(X - \mu)^2]$$

$$= E[X^2] - (E[X])^2$$

- 1] Find  $X$ 's mean
- 2] Find the deviation from that mean for every value of  $X$
- 3] Square those ~~univariate~~ deviations
- 4] Average those squared deviations

"Average Squared deviation"

## b) Standard deviation

- \* Standard deviation is a measure of how spread out the data is around the mean.

$$\sigma = \sqrt{\text{Var}(\mu)} = \sqrt{E[(X-\mu)^2]}$$

- \* Variance is in squared units (height in  $\text{cm}^2$ )
- \* Standard deviation brings it back to the original units, making it easier to interpret

## 7] Sum of gaussians (Normal distributions)

- \* If  $X$  and  $Y$  are independent gaussians, then their sum is also gaussian.

$$X \sim N(\mu_1, \sigma_1^2)$$

$$Y \sim N(\mu_2, \sigma_2^2)$$

$$Z = X + Y$$

$$Z \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$

- \* A gaussian curve is "stable" under addition
- \* Adding two independent gaussians just shifts the center (mean) and increase the spread (variance)
- \* This is a special case of the central Limit Theorem (CLT): adding many independent random variables tends toward a normal distribution.
- 8] Standardizing a distribution
- \* Standardizing means transforming a random variable or dataset so that:
  - Its mean becomes 0
  - Its standard deviation becomes 1

$$Z(\text{standardized variable}) = \frac{X - \mu}{\sigma}$$

- ⇒ Subtracting  $\mu$  = shifts the distribution so it's centered at 0
- ⇒ Dividing by  $\sigma$  = rescales the spread so Variance = 0
- \* In ML standardizing can improve the convergence rate of optimization algorithms (gradient descent, SVM, PCA) and prevent some features from dominating others, leading to improved model.

## 9] Moments of a distribution

- \* ) Moments are numerical values that describe the shape and characteristics of a probability distribution.
- \* ) They are essentially expected values of powers (or functions) of the random variable.

$$M_r = E[x^r] = r^{\text{th}} \text{ raw moment}$$

$$E[x] = p_1 x_1 + p_2 x_2 + \dots + p_n x_n$$

(1st moment)

$$E[x^2] = p_1 x_1^2 + p_2 x_2^2 + \dots + p_n x_n^2$$

(2nd moment)

$$E[x^k] = p_1 x_1^k + p_2 x_2^k + \dots + p_n x_n^k$$

(k<sup>th</sup> moment)

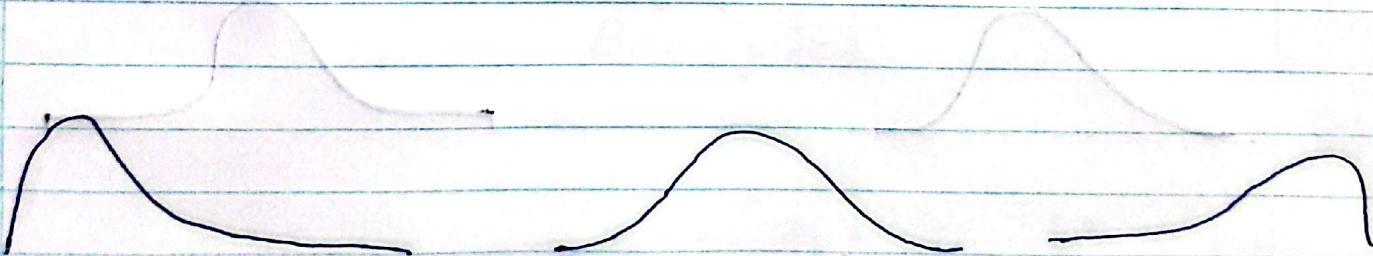
## 10] Skewness

First moment  $\Rightarrow M_1 = E[x]$  (Mean)

Second moment  $\Rightarrow M_2 = E[(x - \mu)^2] = \text{Var}(x)$

- \* Skewness is the third moment where we go if two distributions have same moment 1 and 2.
- \* Skewness is a measure of the asymmetry of a probability distribution around its mean.

$$\boxed{\text{Skewness} = E\left[\frac{(x - \mu)^3}{\sigma}\right]}$$



→ positively skewed

Not skewed

←  
Negatively skewed

$$E\left[\left(\frac{x - \mu}{\sigma}\right)^3\right] > 0$$

$$E\left[\left(\frac{x - \mu}{\sigma}\right)^3\right] = 0$$

$$E\left[\left(\frac{x - \mu}{\sigma}\right)^3\right] < 0$$

## ii) kurtosis

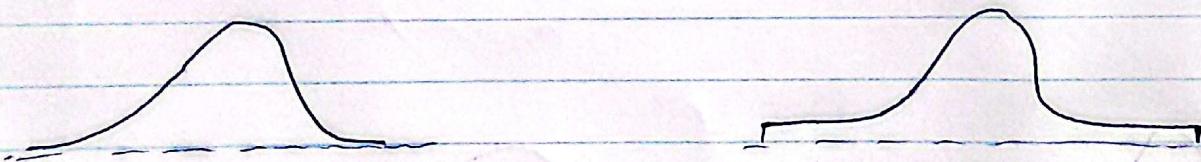
examined (a)

- \* kurtosis measures the "tailedness" of a probability distribution
- \* Basically how heavy or light the tails are compared to a normal distribution
- \* This is the fourth central moment

$$\text{kurtosis} = E \left[ \frac{(X-\mu)^4}{\sigma^4} \right]$$

Thin  
tails

Thick  
tails



$$E \left[ \left( \frac{x-\mu}{\sigma} \right)^4 \right] = \text{small}$$

$$E \left[ \left( \frac{x-\mu}{\sigma} \right)^4 \right] = \text{large}$$

Even if they have  
same variances

## 12] Quantiles and Box plots

\* Quantiles are values that divide a dataset or probability distribution into equal parts.

25% quantile (First quantile -  $Q_1$ )

50% quantile (median -  $Q_2$ )

75% quantile (Third quantile -  $Q_3$ )

Interquartile range (IQR) =  $Q_3 - Q_1$

Ex:

$$Q_1 = 18.35$$

$$IQR = 34.6$$

$$Q_2 = 27.8$$

$$x_{\min} = 8.7$$

$$Q_3 = 52.95$$

$$x_{\max} = 75$$

Box plot

