

# Probability Theory for EOR

How to describe the distribution

Distributions determine probability values of events generated by random variables. We distinguish random variables by their distributions.

How do we describe distributions: e.g., the shape of PDF/PMF?

## Median and mode

## Median.

- ▶  $c$  (may not be unique for a given r.v.) is a median if  $\mathbb{P}(X \leq c) \geq 1/2$  and  $\mathbb{P}(X \geq c) \geq 1/2$ .
- ▶ Median  $c$  is different from mean/expectation  $\mu$ .
  - ▶ The value that minimizes the mean squared error,  $\mathbb{E}(X - x)^2$ , is the **mean**  $\mu$ .  
*Sketch of proof:*  $\mathbb{E}(X - x)^2 = \mathbb{E}(X - \mu + (\mu - x))^2 = \mathbb{E}(X - \mu)^2 + 2\mathbb{E}((X - \mu)(\mu - x)) + \mathbb{E}(\mu - x)^2 = \text{Var}(X) + (\mu - x)^2$ .
  - ▶ A value that minimizes the mean absolute error,  $\mathbb{E}|X - x|$ , is a **median**  $c$ .  
*Sketch of proof:* compare  $\mathbb{E}|X - x|$  with  $\mathbb{E}|X - c|$  for  $x < c$  and  $x > c$ .

## Example:

- ▶ Median for Bern( $p$ )-distributed  $X$  with  $p = 1/2$ :  
 $\forall c \in [0, 1]$ .
- ▶ Median for a constant  $c$  (degenerated random variable  $X$ ,  $P(X = c) = 1$ ):  
 $c$ .

## Mode.

- ▶  **$c$  (may not be unique for a given r.v.)** is a mode if the PMF/PDF takes its maximum value at  $c$ .

### Example:

- ▶ Mode for  $\text{Bern}(p)$ -distributed  $X$  with  $p > 1/2$ :  
 $c = 1$ . (Unimodal distribution, a probability distribution with a PDF/PMF which has a single peak).
- ▶ Mode for  $\text{Bern}(p)$ -distributed  $X$  with  $p = 1/2$ :  
 $\{0, 1\}$ . (Multimodal distribution, a probability distribution with a PDF/PMF which has multiple peaks, here we have a bimodal case).
- ▶ Mode for a constant  $c$  (degenerated random variable  $X$ ,  $P(X = c) = 1$ ):  
 $c$ .
- ▶ Mode for  $N(\mu, \sigma^2)$ -distributed  $X$ :

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \text{ takes its maximum at } c = \mu.$$

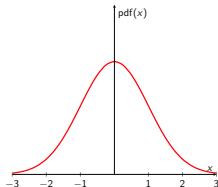
# Symmetry and skewness

## Symmetry.

- We say that an r.v.  $X$  has a symmetric distribution about  $\mu$  (or  $X$  is symmetric) if  $X - \mu$  has the same/identical distribution as  $\mu - X$ .

### Example:

- If  $Z \sim N(0, 1)$ , both  $Z$  and  $-Z$  have the identical **PDF**:



$$\psi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}.$$

- Flip one coin, betting on the head is the same as betting on the bottom. Here we may consider  $X = I_{head}$  (Bern(1/2)).

Symmetric as **PMF** satisfies

$$P(X - \mu = k) = P(\mu - X = k).$$

*What else?*

$$\mathbb{E}(X - \mu) \equiv 0, \quad \mathbb{E}(X - \mu)^3 = 0, \quad \mathbb{E}(X - \mu)^5 = 0, \dots$$

## Skewness.

- ▶ The skewness of an r.v.  $X$  with  $\mu, \sigma^2$  is:

$$\text{Skew}(X) = \mathbb{E} \left( \frac{X - \mu}{\sigma} \right)^3$$

- ▶ We normalize by  $\sigma$  since a good measure of the symmetry should give the same number to measure the symmetry of  $X$  and  $Y = bX$ :  
**skewness is a third standardized moment.**

Symmetry implies that  $\text{Skew}(X) = 0$ ;  
 **$\text{Skew}(X) \neq 0$  implies asymmetry.**

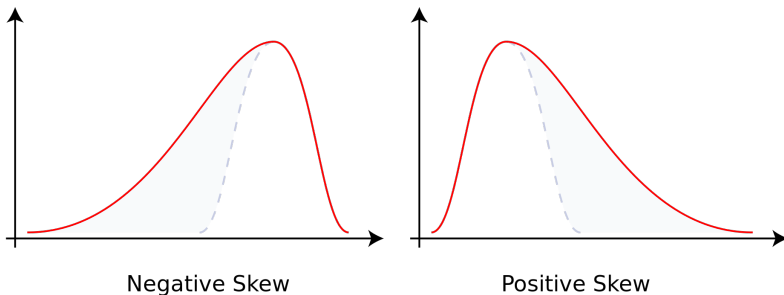
### Example:

- ▶ Consider  $Y \sim \text{Bern}(1/2)$ ,  $\mathbb{E} \left( \frac{Y - 1/2}{1/2} \right)^3 = -1 \times 1/2 + 1 \times 1/2 = 0$ .
- ▶  **$\text{Skew}(X) = 0$  does not necessarily imply symmetry:**  
Consider a discrete r.v.  $X$  such that  $\text{supp}(X) = \{-1, -2, 3\}$  with **PMF**  
 $p_X(x) = 1/3, x \in \{-1, -2, 3\}$ ,  $X$  is not symmetric.



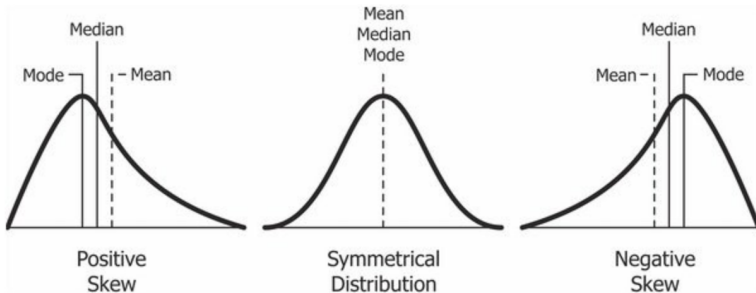
## Example figure 1:

Figures from wikipedia (<https://en.wikipedia.org/wiki/Skewness>) on **negative (left) skewed** and **positive (right) skewed** distributions.



## Example figure II:

Figures from wikipedia (<https://en.wikipedia.org/wiki/Skewness>) on **negative (left) skewed** and **positive (right) skewed unimodal** distributions.



Median and mode  
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Symmetry and skewness  
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Tail and Kurtosis  
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## Tail and Kurtosis

## Kurtosis.

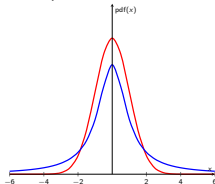
- ▶ The Kurtosis of an r.v.  $X$  with  $\mu$ ,  $\sigma^2$  is (**fourth standardized moment shifted by 3**):

$$\text{Kurt}(X) = \mathbb{E} \left( \frac{X - \mu}{\sigma} \right)^4 - 3$$

- ▶ A measure of how heavy the tail of the probability distribution of a real-valued random variable is.

## Example:

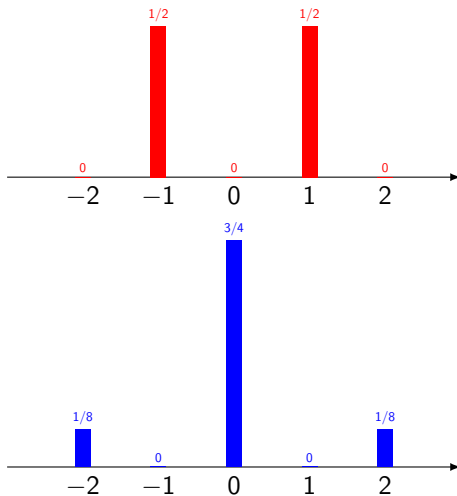
- ▶ **Student-t(n)** PDF ( $n=5$ ) (Kurtosis is 5) and **standard normal bell-shape PDF** (Kurtosis is 0)



## Student-t(n) PDF:

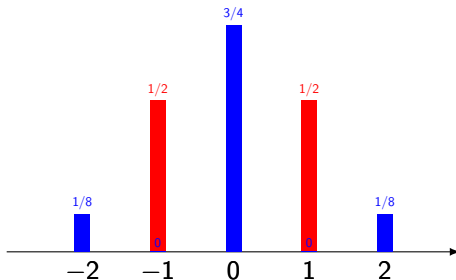
## Example:

**Fair coin** v.s. **unfair 3-sided die**



## Example:

**Fair coin** v.s. **unfair 3-sided die**



1. Mean the same
2. Variance the same
3. Symmetric (Skew zero)
4. \*\*  $\text{Kurt}(\text{red}) < \text{Kurt}(\text{blue})$