

Lecture Slides for

# EXPECTATION AND LAW OF LARGE NUMBERS

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# Expectation

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- Random variables, by definition, result in different outcomes
- The variation in random variables is captured by their **distribution**
  - **Probability Mass function** for Discrete variables
  - **Probability Density function** for Continuous variables
- We use summary statistics such as **expectation** (mean) and **variance** to capture some overall properties of the distribution/variable
- **Expectation** gives mean/average/expected value of the random variable given the distribution
  - E.g : Expected returns on a certain investment in the market
  - E.g : Expected rainfall during coming monsoon

# Expectation

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- The **expectation**, or **expected value**, of some function  $f(x)$  with respect to a probability distribution  $P(x)$  is the average value of  $f(x)$  when  $x$  is drawn from  $P$   $[x \sim P]$

Denoted by  $\mathbb{E}_{x \sim P}[f(x)]$

- If  $P$  is clear from the context  $\mathbb{E}_x[f(x)]$
- If  $x$  is also clear from the context  $\mathbb{E}[f(x)]$
- Sometimes, simply denoted as  $\mathbb{E}[f]$

- Mathematically,

$$\begin{aligned} \text{Discrete} \quad \mathbb{E}_{x \sim P}[f(x)] &= \sum_x P(x) f(x) && \text{p.m.f} \\ \text{Continuous} \quad \mathbb{E}_{x \sim P}[f(x)] &= \int_x p(x) f(x) dx && \text{p.d.f} \end{aligned}$$

# Multivariate Expectation

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- For a multivariate random variable  $x$  we can interpret the variable and the expectations by considering each component separately

That is, if  $x = \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_D \end{bmatrix} \in \mathbb{R}^D$  then

$$\mathbb{E}_x[f(x)] = \begin{bmatrix} \mathbb{E}_{x_1}[f(x_1)] \\ \mathbb{E}_{x_2}[f(x_2)] \\ \dots \\ \mathbb{E}_{x_D}[f(x_D)] \end{bmatrix}$$

vector  $\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$

$\vec{x} = \begin{bmatrix} \text{Temp} \\ \text{Press} \\ \text{Humidity} \end{bmatrix}$   $\begin{bmatrix} E_{\text{temp}}[f(\text{temp})] \\ E_{\text{press}}[f(\text{press})] \\ \vdots \end{bmatrix}$

# Examples

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- What is the expected value of a coin toss for a fair coin assuming that Heads=1 and Tails=0?

$x$	0	1
$P(x)$	$\frac{1}{2}$	$\frac{1}{2}$

Ans: Random variable  $X \in \{0,1\}$ .

*Identity random var*

*Calculate P-distribution*

$P$  is a **uniform** distribution with both states having probability  $\frac{1}{2}$

$$\text{So, } \mathbb{E}_{x \sim P}[x] = \sum_x xP(x) = \left[0 \times \frac{1}{2} + 1 \times \frac{1}{2}\right] = \frac{1}{2} \quad \checkmark$$

- Similarly, the expected value of a fair dice throw is?

Random variable  $X \in \{1,2,3,4,5,6\}$ .  $P$  is uniform with probability  $\frac{1}{6}$

$$\text{So, } \mathbb{E}_{x \sim P}[x] = \sum_x xP(x) = \left[1 \times \frac{1}{6} + 2 \times \frac{1}{6} + \dots + 6 \times \frac{1}{6}\right] = 3.5$$

# Examples

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- What is the expected value of the sum of two dice thrown together?

**Ans:** Random variable  $x \in \{2, 3, \dots, 12\}$ .

What is the probability distribution?

- Note : P is not uniform

Distribution						
x	2, 12	3, 11	4, 10	5, 9	6, 8	7
P(x)	$\frac{1}{36}$	$\frac{2}{36}$	$\frac{3}{36}$	$\frac{4}{36}$	$\frac{5}{36}$	$\frac{6}{36}$

$$\text{So, } \mathbb{E}_{x \sim P}[x] = \sum_x xP(x) = \left[ 2 \times \frac{1}{36} + 3 \times \frac{2}{36} + \dots + 12 \times \frac{1}{36} \right] = 7$$

Question : Is there an easier way of calculating this case?



# Linearity of Expectation

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- Important Property of expectation  
The Expectation Operator is linear

$E[\cdot]$

Linear Comb

- Mathematically, if  $f(x) = \alpha g(x) + \beta h(x)$  is a multivariate function with  $\alpha, \beta \in \mathbb{R}$  being scalars, then

$$\mathbb{E}[f] = \alpha \mathbb{E}[g] + \beta \mathbb{E}[h]$$

Note the use of compact notation

Applying this to our example, we note that  $X = D_1 + D_2$  where  $D_1$  and  $D_2$  are the number obtained on the first and second dice respectively.

$$E[X] = E[D_1 + D_2] = E[D_1] + E[D_2]$$

$$\text{Then, } \mathbb{E}[X] = \mathbb{E}[D_1] + \mathbb{E}[D_2] = \underline{3.5} + 3.5 = 7$$

Note : Much simpler, since the distribution of  $X$  need not be found

# Proof of Linearity of Expectation

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**Linearity:** If  $f(x) = \alpha g(x) + \beta h(x)$  is a multivariate function with  $\alpha, \beta \in \mathbb{R}$  being scalars, then

$$\mathbb{E}[f] = \alpha \mathbb{E}[g] + \beta \mathbb{E}[h] \rightarrow \text{Claim}$$

**Proof:** For continuous distributions

$$\begin{aligned} \mathbb{E}[f] &= \int f(x)p(x)dx \rightarrow \text{Definition} & \mathbb{E}[f] &= \sum f(x)p(x) \\ &= \int (\alpha g(x) + \beta h(x))p(x)dx \\ &= \alpha \int \underbrace{g(x)p(x)dx}_{\mathbb{E}[g]} + \beta \int \underbrace{h(x)p(x)dx}_{\mathbb{E}[h]} \\ \Rightarrow \mathbb{E}[f] &= \alpha \mathbb{E}[g] + \beta \mathbb{E}[h] \end{aligned}$$

Discrete can be proved similarly – Try it as an exercise!



# Law of large numbers

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⊛ Law of large No.

$$E(x) = 0.5$$

	H	T	
10 →	2	8	0.2
100 →	40	60	0.4
1000 →	550	450	0.55

# Mixture distribution

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- ▶ Mixture distribution is a way of combining many distributions.
- ▶  $c_1 = \mathcal{N}(x; \mu_1, \sigma_1^2)$ ,  $c_2 = \mathcal{N}(x; \mu_2, \sigma_2^2)$ .
- ▶ Prior probability:  $\alpha_1 = P(c = c_1)$ ,  $\alpha_2 = P(c = c_2)$
- ▶ Posterior Probability:  $P(c|x)$
- ▶ Mixture distribution:  $P(x) = \sum_i P(c = c_i)P(x|c)$ .