

# STAB57: An Introduction to Statistics

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Week 1 (Introduction and Review of STAB52)



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# Acknowledgement

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# Review: Probability

- The **probability measure**  $P$  for each **event**  $A$  defined on **sample space**  $\Omega$  satisfies the following properties:
  - $P(A)$  is non-negative and  $0 \leq P(A) \leq 1$
  - $P(A) = 0$  when  $A$  is empty
  - $P(A) = 1$  when  $A$  is the entire sample space  $\Omega$
  - $P$  is (*countably*) additive.

$X$  is the outcome of rolling a fair dice.

What is the probability that it's an even number?

$$\Omega = \{1,2,3,4,5,6\}, A = \{2,4,6\}$$

$$\implies P(A) = 3/6 = 1/2$$

# Review: Expectation

- **Expected value/ mean/ average** of random variable ( $X$ ) is defined as
  - $E[X] = \int_{-\infty}^{\infty} xf(x)dx$  when  $X$  is continuous or
  - $E[X] = \sum_i x_i P[X = x_i]$  when  $X$  is discrete

$X$  is the outcome of rolling a fair dice.

What is the expected value of  $X$ ?

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

- Expectation is a **linear operator**
  - Let  $X$  and  $Y$  are two random variables and  $a$ ,  $b$  and  $c$  are few constants. Then
  - $E[aX + bY + c] = aE[X] + bE[Y] + c$

# Indicator Function

- If  $A$  is any event, we can define the **indicator function of  $A$ , written  $I_A$** , to be the random variable for all  $s \in \Omega$

$$I_A(s) = \begin{cases} 1, & \text{if } s \in A \\ 0, & \text{if } s \notin A \end{cases}$$

## Probability expressed as the expectation of Indicator function

Using the same example as before: We are rolling a dice and  $A = \{2, 4, 6\}$

| Random variable X | 1 | 2 | 3 | 4 | 5 | 6 |
|-------------------|---|---|---|---|---|---|
| $I_A$             | 0 | 1 | 0 | 1 | 0 | 1 |

$$E[I_A] = \frac{1}{6}(0 + 1 + 0 + 1 + 0 + 1) = \frac{3}{6} = \frac{1}{2} = P[A]$$

# Review: LLN

- **Law of Large Number (LLN)**

- Let  $X_1, X_2, \dots, X_i$  be a sequence of independent random variables with  $E[X_i] = \mu$ .
- Let  $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$
- Then  $\bar{X}_n \xrightarrow{P} \mu$  as  $n \rightarrow \infty$
- **In naive words:** sample mean approaches the population mean as the sample size increases.

We are rolling a fair dice repeatedly and calculating the mean

| Sample size (n) | Observations  | Sample mean ( $\bar{X}_n$ ) |
|-----------------|---------------|-----------------------------|
| 3               | 3,4,1         | $8/3=2.67$                  |
| 5               | 3,4,1,6,5     | $19/5 = 3.8$                |
| ...             | ...           | ...                         |
| 800             | 3,4,1,...,2,5 | 3.49                        |

NOTE: population average = 3.5

# LLN in graph

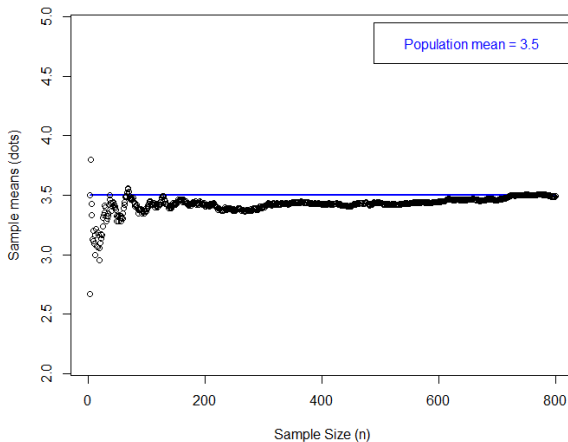


Figure: Trace of sample mean from repeatedly rolling a fair dice

# Review: Central Limit Theorem (CLT)

- Suppose  $X_1, X_2, \dots$  is an i.i.d. sequence of random variables each having finite mean  $\mu$  and finite variance  $\sigma^2$
- Let  $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$  i.e. sample mean
- Then according to the Central Limit Theorem as  $n \rightarrow \infty$ ,

$$\bar{X}_n \xrightarrow{D} N\left(\mu, \frac{\sigma^2}{n}\right)$$

or

$$\frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} \xrightarrow{D} N(0, 1)$$

- **In naive words:** A random variable ( $X$ ) can follow *some distribution* with mean  $\mu$  and variance  $\sigma^2$ . If we pick a *fixed number of samples ( $n$ )* and *calculate the sample mean repeatedly*, then those sample means will have a **Normal distribution** with mean  $\mu$  and variance  $\sigma^2/n$



# Review: Linear Combination of Normal variables

- Let  $X_i \sim N(\mu_i, \sigma_i^2)$  where  $i = 1, 2, \dots, n$  and  $X_i$ 's are independent.
- Let  $Y$  be a linear combination of all the  $X_i$ 's with

$$Y = a_1X_1 + a_2X_2 + \dots + a_nX_n + b = \sum_{i=1}^n a_iX_i + b$$

where  $a_1, a_2, \dots, a_n, b$  are constants

- Then,

$$Y \sim N\left(\sum_{i=1}^n a_i\mu_i + b, \sum_{i=1}^n a_i^2\sigma_i^2\right)$$

## Example

Let,  $X_1 \sim N(10, 2)$  and  $X_2 \sim N(20, 3)$  and  $Y = 0.4X_1 + 0.6X_2$   
Then  $Y \sim N(, )$  with mean  $= 0.4 * 10 + 0.6 * 20 = 16$  and  
variance  $= (0.4)^2 * 2 + (0.6)^2 * 3 = 1.4$

# Review: Some common distributions

| Distribution               | pdf or pmf   | mean           | variance                    | MGF  |
|----------------------------|--|----------------|-----------------------------|--|
| Bernoulli( $\theta$ )      | $\theta^x(1-\theta)^{1-x}$   | $\theta$       | $\theta(1-\theta)$          | $(1-\theta) + \theta e^t$  |
| Binomial ( $m, \theta$ )   | $\binom{m}{x} \theta^x (1-\theta)^{m-x}$                                   | $m\theta$      | $m\theta(1-\theta)$         | $[(1-\theta) + \theta e^t]^m$  |
| Poisson( $\lambda$ )       | $\frac{e^{-\lambda} \lambda^x}{x!}$  | $\lambda$      | $\lambda$                   | $\exp[\lambda(e^t - 1)]$   |
| Uniform $[a, b]$           | $1/(b-a)$  | $(a+b)/2$      | $(b-a)^2/12$                | $\begin{cases} (e^{tb} - e^{ta})/t(b-a) & , t \neq 0 \\ 1 & , t = 0 \end{cases}$                     |
| Normal ( $\mu, \sigma^2$ ) | $(2\pi\sigma^2)^{-1/2} \exp[-\frac{1}{2\sigma^2}(x-\mu)^2]$                | $\mu$          | $\sigma^2$                  | $\exp[\mu t + \sigma^2 t^2/2]$   |
| Exponential( $\beta$ )     | $\beta e^{-\beta x}$   | $1/\beta$      | $1/\beta^2$                 | $(1-t/\beta)^{-1}$   |
| Exponential( $\theta$ )    | $\frac{1}{\theta} e^{-\frac{x}{\theta}}$                                   | $\theta$       | $\theta^2$                  | $(1-t\theta)^{-1}$   |
| Gamma( $\alpha, \beta$ )   | $\frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$            | $\alpha/\beta$ | $\alpha/\beta^2$            | $(1-t/\beta)^{-\alpha}, t < \beta$   |
| Gamma( $\alpha, \theta$ )  | $\frac{1}{\Gamma(\alpha)\theta^\alpha} x^{\alpha-1} e^{-\frac{x}{\theta}}$ | $\alpha\theta$ | $\alpha\theta^2$            | $(1-t\theta)^{-\alpha}, t < 1/\theta$  |
| Beta( $a, b$ )             | $\frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} x^{a-1} (1-x)^{b-1}$               | $a/(a+b)$      | $\frac{ab}{(a+b)^2(a+b+1)}$ | $1 + \sum_{k=1}^{\infty} \left( \prod_{r=0}^{k-1} \frac{a+r}{\alpha+\beta+r} \right) \frac{t^k}{k!}$ |

# Review: $Z$ and $\chi^2$ distribution

- **Standard Normal/  $N(0,1)$  /  $Z$  distribution**

- If  $X \sim N(\mu, \sigma^2)$  then  $\frac{X-\mu}{\sigma} \sim N(0,1)$
- $Z = \frac{X-\mu}{\sigma}$

- **$\chi^2$  distribution**

- Let  $U = Z^2$  where  $Z$  is a Standard Normal variable
- $U \sim \chi^2$  distribution with 1 degrees of freedom. (written as  $\chi^2_{(1)}$ )
- Additive property: If  $X \sim \chi^2_{(m)}$  and  $Y \sim \chi^2_{(n)}$  then  $X + Y \sim \chi^2_{(m+n)}$
- If  $X \sim \chi^2_{(m)}$  then  $E[X] = m$

# Review: $t$ and $F$ distribution

- **$t$  distribution**

- Let  $Z$  and  $U$  are two independent variables
- where  $Z \sim N(0, 1)$  and  $U \sim \chi^2_{(m)}$
- $\frac{Z}{\sqrt{U/m}} \sim t$ -distribution with  $m$  degrees of freedom. (written as  $t_{(m)}$ )

- **$F$  distribution**

- Let  $X$  and  $Y$  are two independent variables
- where  $X \sim \chi^2_{(m)}$  and  $Y \sim \chi^2_{(n)}$
- Then  $\frac{X/m}{Y/n} \sim F$  distribution with degrees of freedom  $(m, n)$

# Homework (Non-credit)

Evans and Rosenthal

Exercise: 3.4.21, 3.4.23, 4.6.1 - 4.6.10

Rice

Chapter 6, Exercise: 3, 5, 6