

- Expected value
 - Weighted average

$$E(X) = \sum_{X \in \text{Vals}(X)} X * P(X)$$

ex for die $X = \{1, 2, \dots, 6\}$

$$\begin{aligned} \sum_{X \in \{1, \dots, 6\}} X * P(X) &= 1 * \frac{1}{6} + 2 * \frac{1}{6} + \dots + 6 * \frac{1}{6} \\ &= \frac{1}{6} + \frac{2}{6} + \frac{3}{6} + \frac{4}{6} + \frac{5}{6} + \frac{6}{6} \\ &= \frac{21}{6} = 3.5 \end{aligned}$$

So $E(X) = 3.5$

Weighted die: $P(1, \dots, 5) = 0.1$
 $P(6) = 0.5$

$$\begin{aligned} E(X) &= \sum_{X \in \text{Vals}(X)} X * P(X) = 1 * \frac{1}{10} + 2 * \frac{1}{10} + 3 * \frac{1}{10} + 4 * \frac{1}{10} + 5 * \frac{1}{10} + 6 * \frac{5}{10} \\ &= \frac{1}{10} + \frac{2}{10} + \frac{3}{10} + \frac{4}{10} + \frac{5}{10} + \frac{30}{10} \\ &= \frac{45}{10} = 4.5 \end{aligned}$$

- Sample (empirical) mean:
 - If you don't know probabilities for weighted die, you can roll it a bunch of times

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$$

- Variance

$$\text{Var}(X) = E\left[\underbrace{(X - \mu)^2}_{\text{spread}}\right] = \sum_{x \in \text{Vals}(X)} (x - \mu)^2 p(x)$$

Fair die

$$E[X_{\text{fair}}] = 3.5$$

$$\text{Var}(X_{\text{fair}}) = \sum_{x \in \text{Vals}(X)} (x - 3.5)^2 \frac{1}{6} = \frac{1}{6} [(1-3.5)^2 + \dots + (6-3.5)^2] \approx 2.92$$

Weighted die

$$E[X_w] = 4.5$$

$$p(1, \dots, 5) = \frac{1}{10}$$

$$p(6) = \frac{1}{2}$$

$$\text{Var}(X_w) = \sum_{x \in \text{Vals}(X)} (x - 4.5)^2 p(x) = \frac{1}{10} [(1-4.5)^2 + \dots + (5-4.5)^2] + \frac{1}{2} (6-4.5)^2 = 3.25$$

- Sample (empirical) variance

$$\text{Var}(X) = \frac{1}{n-1} \sum_{i=1}^n (X_i - \mu)^2$$

- Trying to estimate population variance based on sample

- Central limit theorem

- If X_1, X_2, \dots, X_n are samples from a population with expected value μ and finite variance σ^2 , and \bar{X}_n is the sample mean, then:

$$Z = \lim_{n \rightarrow \infty} \left(\frac{\bar{X}_n - \mu}{\sigma / \sqrt{n}} \right)$$

mean
↑
→ Variance

is a standard normal distribution $N(0, 1)$

Central Limit theorem: if the population is not normal, when n is large, the sample mean is approximately normal

-Even if the original data isn't normal, the mean of the samples (\bar{X}) will always converge to a normal distribution as n approaches infinity

If you don't normalize the distribution to Z as $N(0,1)$ then we end up with: $N(\bar{X}_n, \frac{\sigma^2}{n})$, with $\frac{\sigma^2}{n}$ as ^{sample} variance, $\frac{\sigma}{\sqrt{n}}$ as standard deviation, and \bar{X}_n as mean. It's the same, just dealing with means of samples instead of z values for the data.

- Z score
 - Tells us how many standard deviation the sample mean is away from the expected value
 - A z score of 0 means the sample mean is the same as expected value

- Hypothesis testing
 - H_0 : null hypothesis (eg die is fair)
 - H_1 : alternative hypothesis (eg die is weighted towards higher values)
 - Apply central limit theorem:

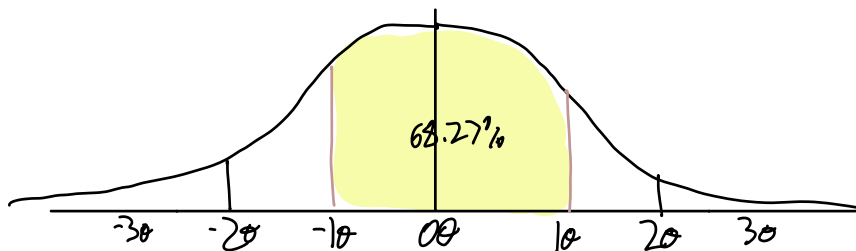
$$z\text{-score} = \frac{\bar{X}_n - \mu}{\sigma / \sqrt{n}} \quad \text{sample: } n=20 \quad \bar{X}_n=4.2$$

$$z\text{-score (test statistic)} = \frac{4.2 - 3.5}{2.92 / \sqrt{20}} \approx 1.83$$

- P-value
 - Probability of observing a result as or more extreme than our under the null hypothesis
 - Probability density function

$$pdf = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

area under curve within some range



68.27% fall within 1σ of mean

- Hypothesis testing

$$\text{test-statistic} = 1.43$$

$$p\text{-value} = \int_{1.43}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx \approx 0.033$$

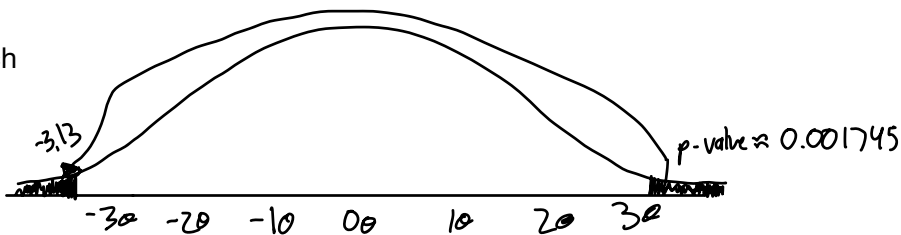
- Usually compare p-value to alpha value of 0.05 (significance level)
- Since p-value = 0.033 < 0.05, we reject the null hypothesis

Handout 17

1. $E[X] = 0.5$
2. $\text{Var}(X) = 1/2[(1-.5)^2 + (0-.5)^2] = 0.25$
3. Sample mean $\bar{X} = 54/80 = 0.675$

$$4. \text{Test statistic} = \sqrt{80} \left(\frac{0.675 - 0.5}{\sqrt{0.25}} \right) = 3.13$$

5. Sketch



6. Since p-value = 0.001745 < 0.05, we reject the null hypothesis