CS 260: Foundations of Data Science

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HAVERFORD COLLEGE

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Admin

- **Lab 5** grades & feedback posted on Moodle
- **Lab 7** due tonight at midnight
- **Lab 8** posted (due next Tuesday)
- **Final Project proposal** due Friday (Nov 7)

Outline for today

- Recap PCA
- Begin: statistics and hypothesis testing
- Central limit theorem

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Principal Component Analysis (PCA)

- Transforms *p*-dimensional data so that the new first dimension explains as much of the variation as possible, the new second explains as much of the remaining variation as possible, and so on

- PCA is a linear transformation

- Typically, we look at the first few dimensions of the transformed data as a means of dimensionality reduction and visualization

- PCA is often used for:
  - Data visualization
  - Infer qualitative relationships between groups

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Motivation for studying statistics

1) I have a new method that achieves 95% accuracy on a dataset. The previous best method achieved 92% accuracy. Is my method significantly better?

2) I have created a new treatment for high blood pressure. Did it significantly lower the blood pressure of the treatment group over the control group?

3) Which variants in the genome are statistically correlated with a specific disease?

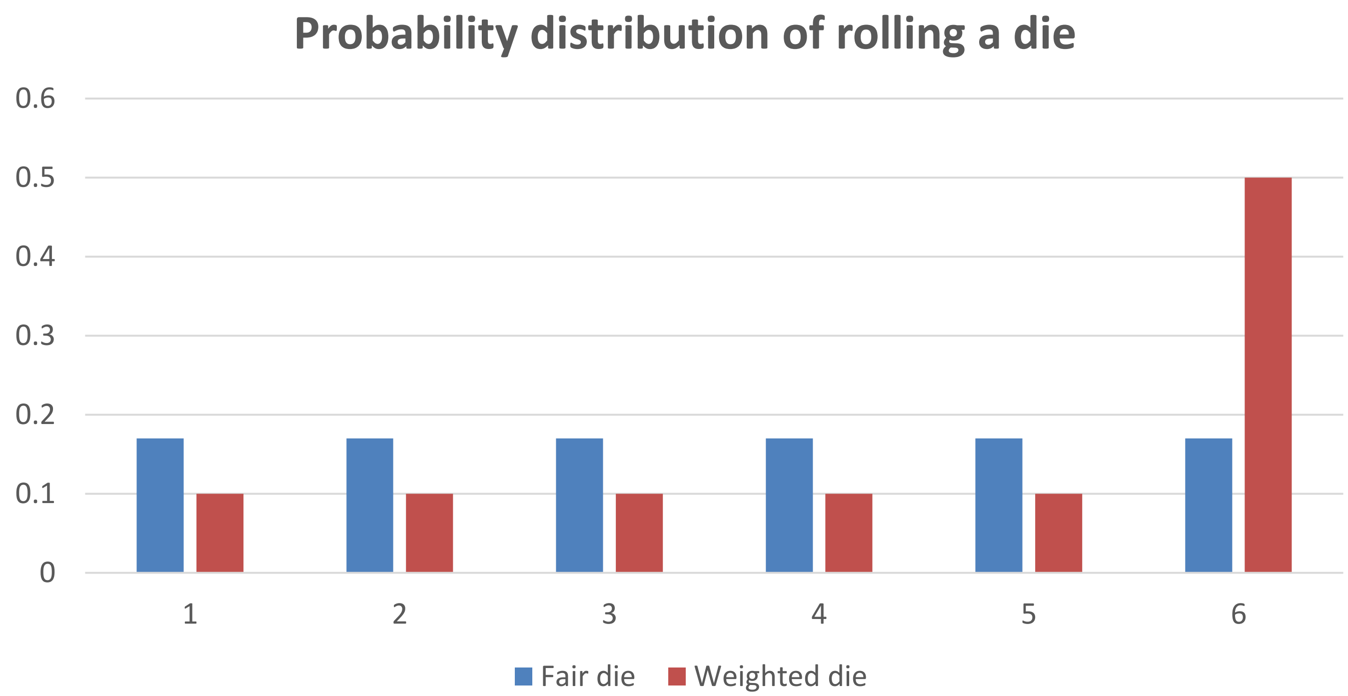
Motivation for studying statistics

- In general there are many questions that can only be answered properly with statistics.

- This one week on statistics is not a substitute for a full stats course, which I recommend everyone take!

- We’re going to do a few key examples now to build up intuition, but this is a huge field and not my main area of research.

Distributions



Probability mass function (pmf): $p(x)$

$$\sum_{x \in vals(X)} p(x) = 1$$

Expected Value

Weighted average:

$$E[X] = \sum_{x \in vals(X)} x * p(x)$$

$$E[X_f] = 1 * \frac{1}{6} + 2 * \frac{1}{6} + \cdots + 6 * \frac{1}{6} = 3.5$$

$$E[X_w] = (1 + 2 + \cdots + 5) * \frac{1}{10} + 6 * \frac{1}{2} = 4.5$$

Sample (empirical) mean:

$$\overline{X_n} = \frac{1}{n} \sum_{i=1}^{n} x_i$$

Variance

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

$$Var(X_f) = \frac{1}{6}[(1 - 3.5)^2 + \cdots + (6 - 3.5)^2] \approx 2.92$$

$$Var(X_w) = \frac{1}{10}[(1 - 4.5)^2 + \cdots + (5 - 4.5)^2] + \frac{1}{2}(6 - 4.5)^2 = 3.25$$

Sample (empirical) variance:

$$Var(X) = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \overline{X_n})^2$$

Outline for today

- Recap PCA and Handout 16
- Begin: statistics and hypothesis testing
- Central limit theorem

Central Limit Theorem

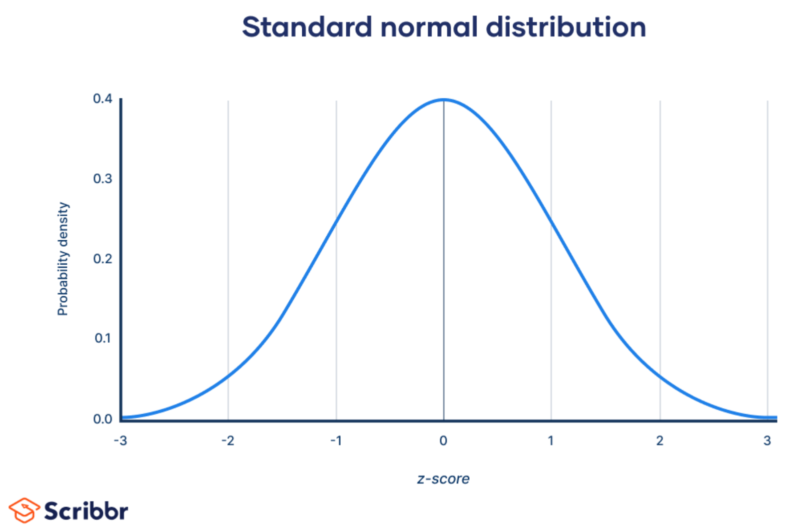
If $x_1, x_2, \ldots, x_n$ are samples from a population with expected value μ and finite variance σ^2, and $\overline{X_n}$ is the sample mean, then

$$Z = \lim_{n \to \infty} \left(\frac{\overline{X_n} - \mu}{\sigma / \sqrt{n}} \right)$$

Normalized sample mean

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

mean variance



Hypothesis testing

- H_0: null hypothesis (e.g. die is fair)
- H_1: alternative hypothesis (e.g. die is weighted towards higher values)

- Apply CLT:

$$\text{Z-score} = \frac{\overline{X_n} - \mu}{\sqrt{\sigma^2/n}}$$

test statistic

$$\approx \frac{4.2 - 3.5}{\sqrt{2.92/20}} \approx 1.83$$

n=20

$\overline{X_n} = 4.2$

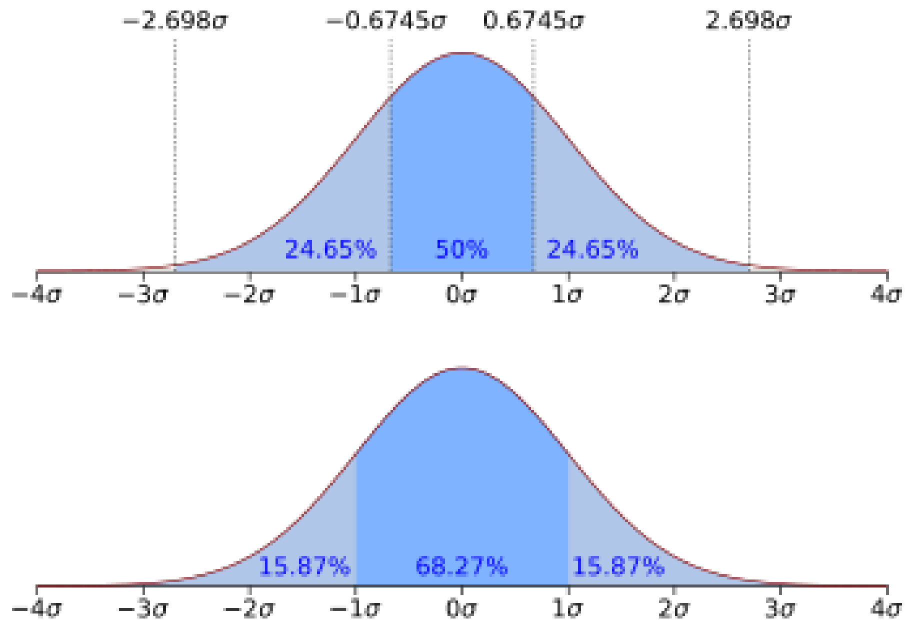
p-value

- Probability of observing a result as or more extreme than ours **under the null hypothesis**

- Probability density function for the standard normal distribution:

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

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-x^2/2}\, dx = 1$$



Wikipedia

Hypothesis testing

- p-value $= \int_{1.83}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-x^2/2}\, dx \approx 0.033$

- Usually compare with $\alpha = 0.05$ (significance level)

- $0.033 \leq 0.05 \Rightarrow$ reject the null hypothesis

Handout 16

Handout 17

(1) $E[X] = \sum_{x} x \cdot p(x) = 0 \cdot \frac{1}{2} + 1 \cdot \frac{1}{2} = \boxed{\frac{1}{2} = \mu}$

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

$= \sum_{x} (x-\mu)^2 \, p(x)$

$= \left(0 - \frac{1}{2}\right)^2 \cdot \frac{1}{2} + \left(1 - \frac{1}{2}\right)^2 \cdot \frac{1}{2}$

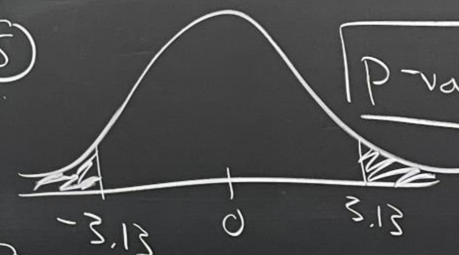
$= \boxed{\frac{1}{4} = \sigma^2}$

(3) $\bar{X}_n = \frac{54}{80} = 0.675$

(4) $z = \frac{\bar{X}_n - \mu}{\sqrt{\frac{\sigma^2}{n}}} = \frac{0.675 - 0.5}{\sqrt{\frac{0.25}{80}}}$

$\boxed{z \approx 3.13}$

(5)



$\boxed{\text{p-value} = 0.001745}$

≤ 0.05

(6) reject H_0!