

# Central Limit Theorem

...

11 Monday 2019  
PLSC 309

# Roadmap

1. Law of large numbers (sample converges to population as sample gets larger)
2. What happens to distributions of sums?
  - a. Bernoulli sums
  - b. Random walk
  - c. Exponential sums
  - d. Poisson sums
3. CLT

# Review: sampling distribution

Respondent	Age
1	20
2	18
3	22
4	23
5	17
6	21
7	20

Sample	Mean
1	20.14

# Review: sampling distribution

Respondent	Age
8	22
9	19
10	24
11	16
12	20
13	18
14	21

Sample	Mean
1	20.14
2	20

# Review: sampling distribution

Respondent	Age
15	18
16	22
17	19
18	21
19	19
20	23
21	20

Sample	Mean
1	20.14
2	20
3	20.28

# Review: sampling distribution

Respondent	Age
22	23
23	16
24	18
25	22
26	23
27	17
28	19

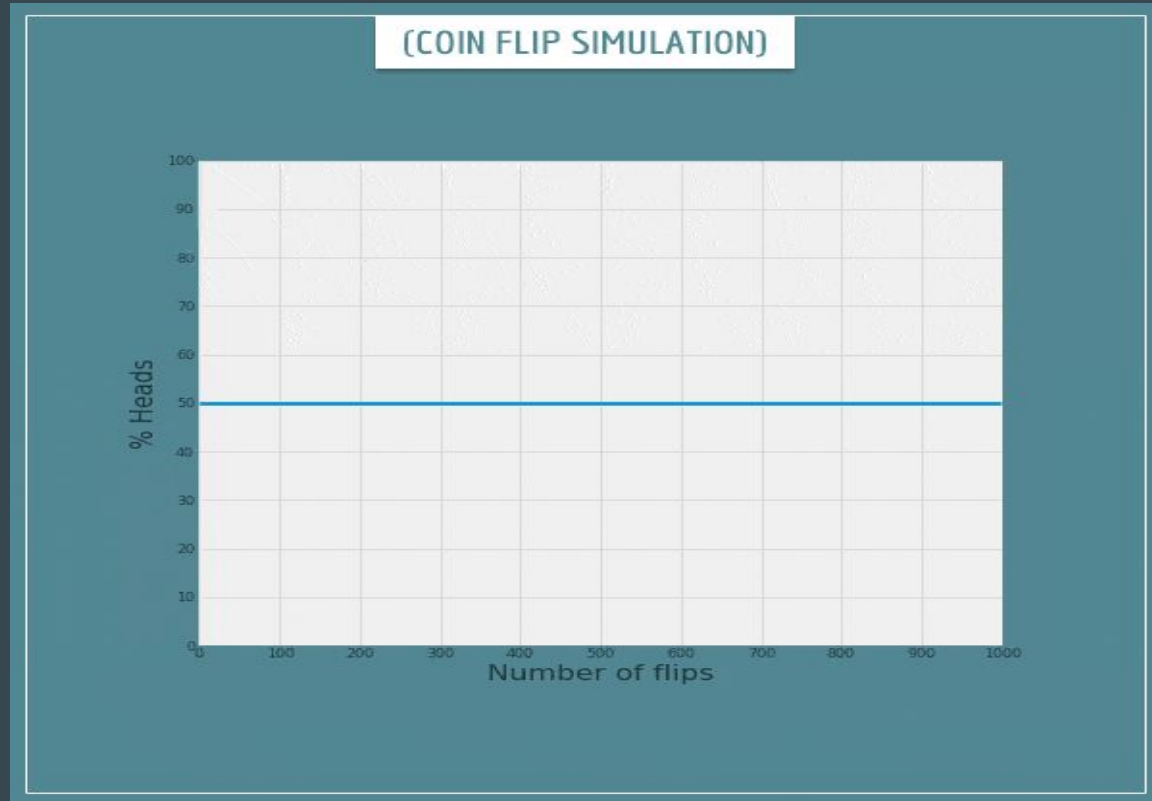
Sample	Mean
1	20.14
2	20
3	20.28
4	19.71

# Review: sampling distribution

Respondent	Age
29	18
30	21
31	20
32	23
33	19
34	21
35	22

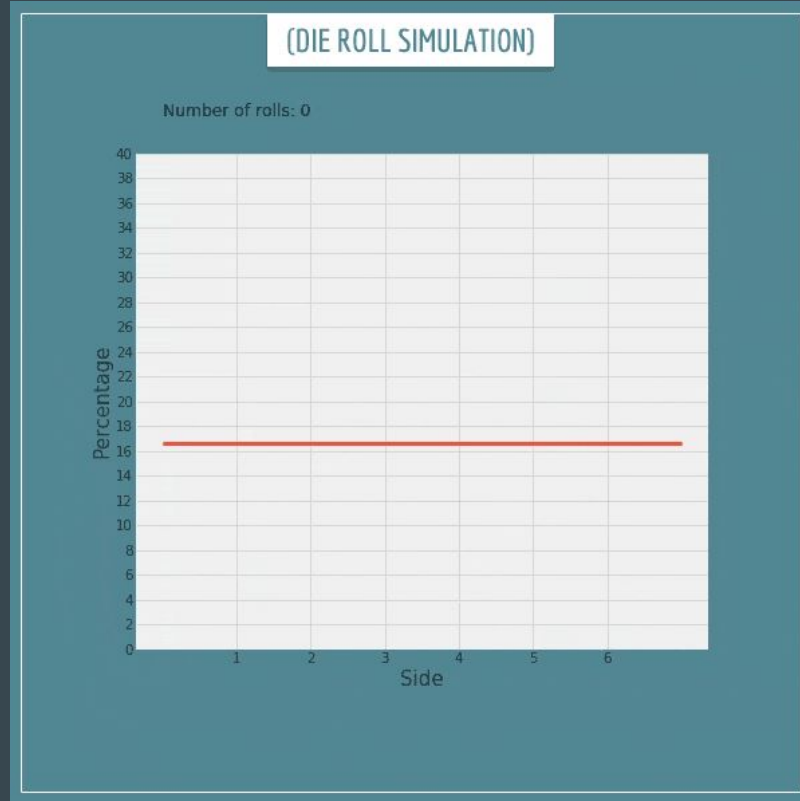
Sample	Mean
1	20.14
2	20
3	20.28
4	19.71
5	20.57

# Law of Large Numbers





# Law of Large Numbers



# Law of Large Numbers

As  $N$  increases, mean of  $X$  approaches  $E(X)$

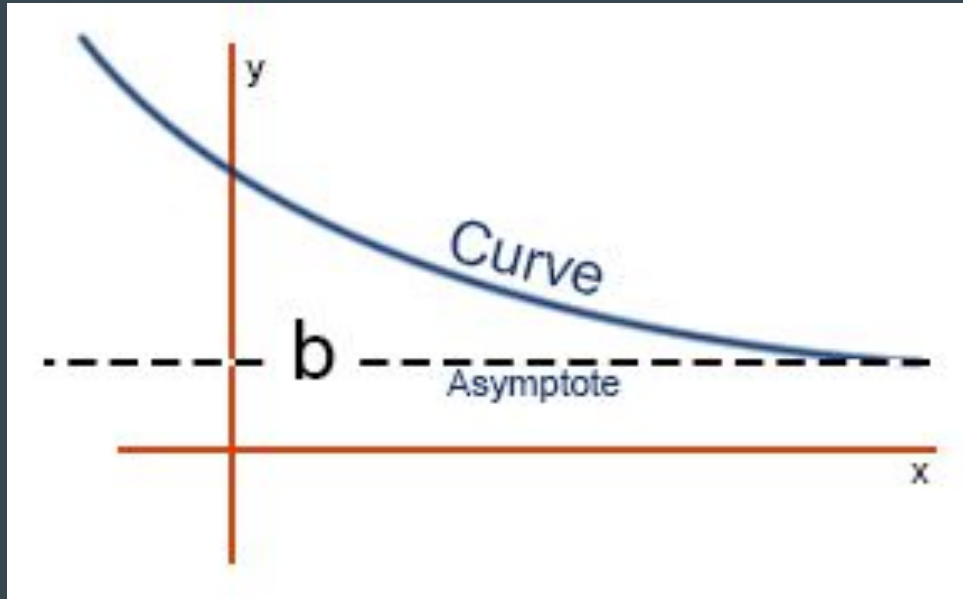
# Law of Large Numbers

$$\sum (X_i = \text{outcome}) / N = P(X = \text{outcome})$$

As  $N \rightarrow \infty$

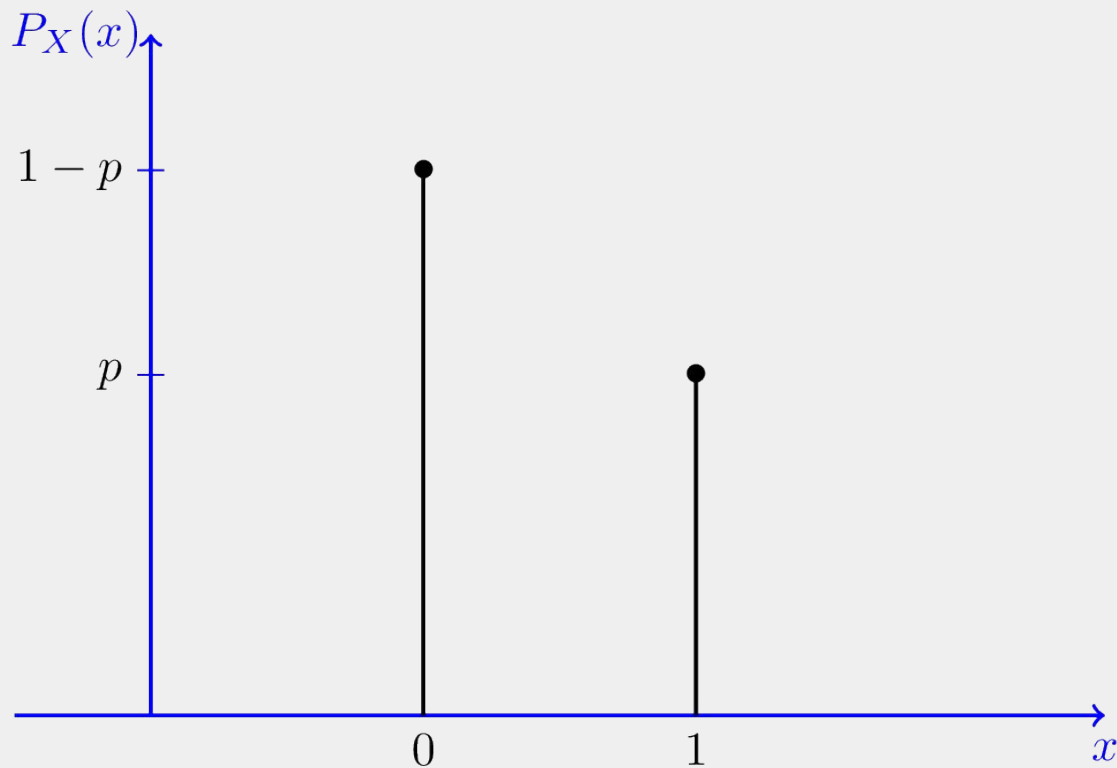
# What are asymptotics?

- As a function gets infinitely large it approaches infinity



# Bernoulli Distribution

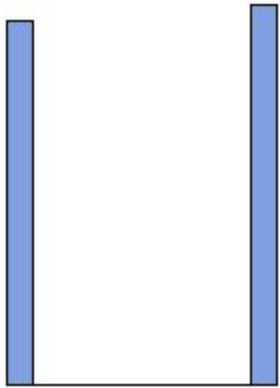
$$X \sim \text{Bernoulli}(p)$$



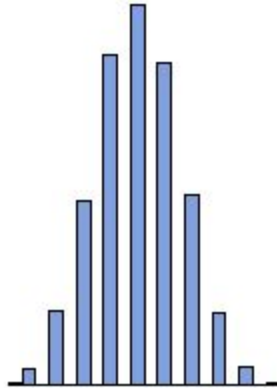
$$\begin{cases} q = 1 - p & \text{if } k = 0 \\ p & \text{if } k = 1 \end{cases}$$

# Series of bernoulli trials

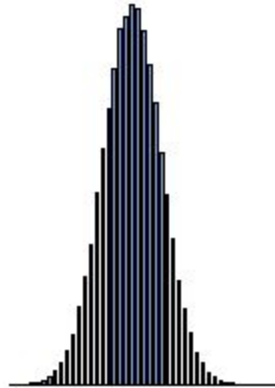
Trials = 1



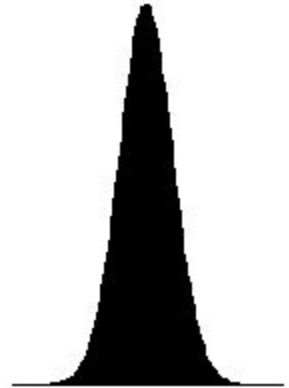
Trials = 10



Trials = 100



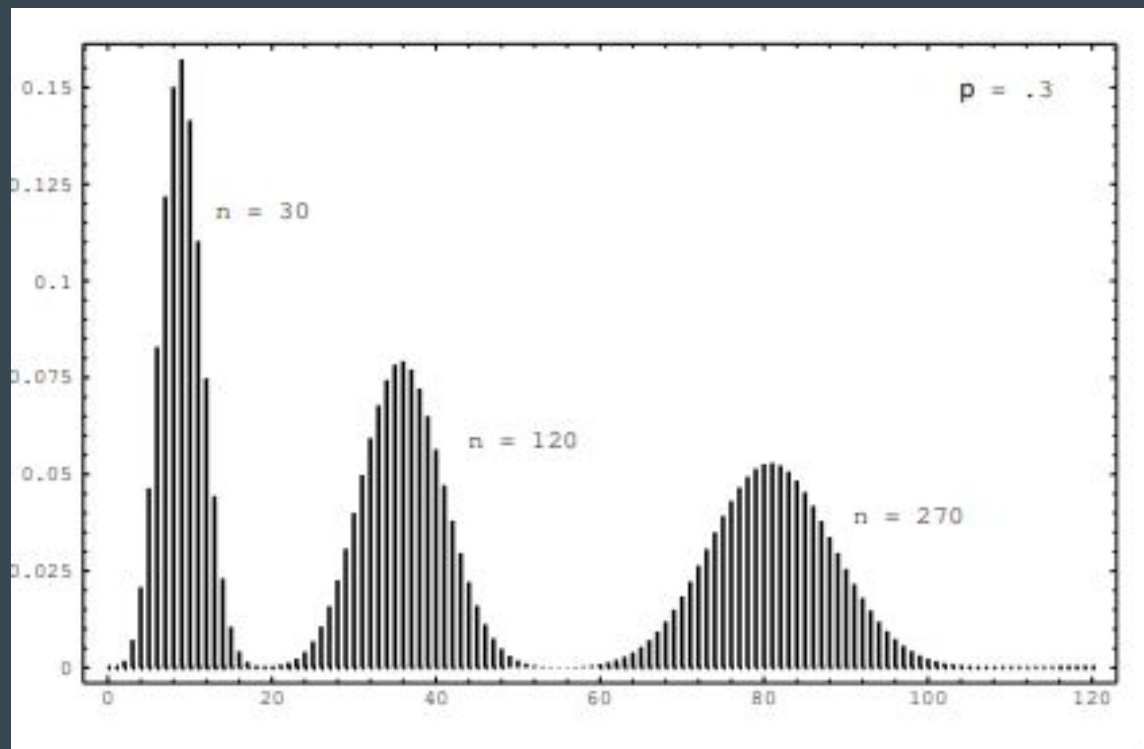
Trials = 1000



# Binomial distribution is a sum of Bernoullis

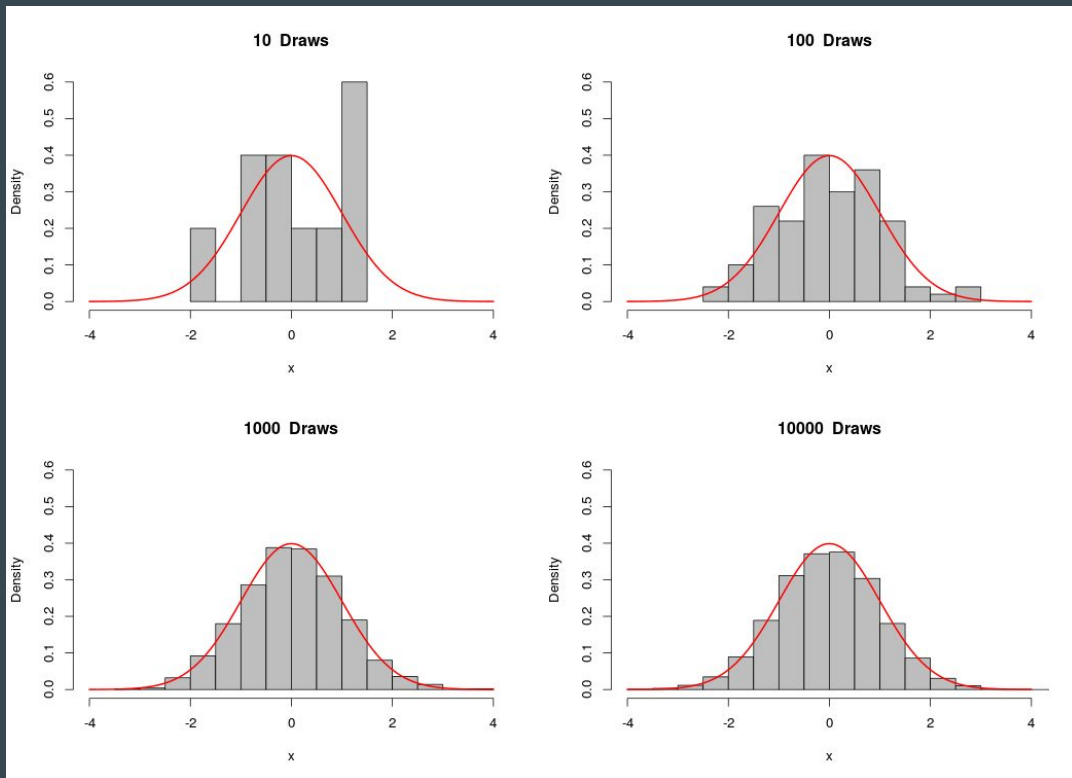
- If  $X$  is a series of Bernoulli trials, each  $X_i$  is a 0 or 1
  - $X = \{0, 1, 0, 1, 1, 0, 1, 0, 0\}$
- A binomial trial is predicting  $k$  successes out of  $n$  trials
- So a binomial expected value is just the sum of a Bernoulli variable
  - $k = \sum(X)$
  - $k = np = E(X)$

# Sum of $n$ Bernoulli trials





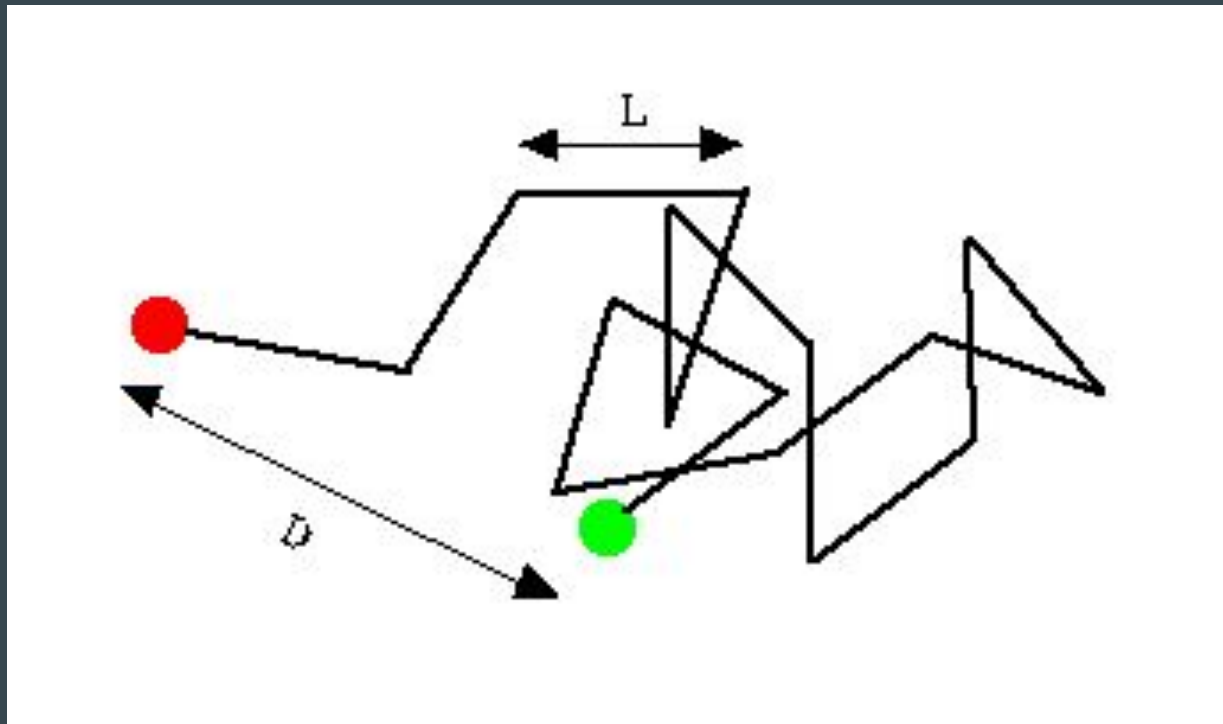
# Normal approximation to binomial



# Random walks

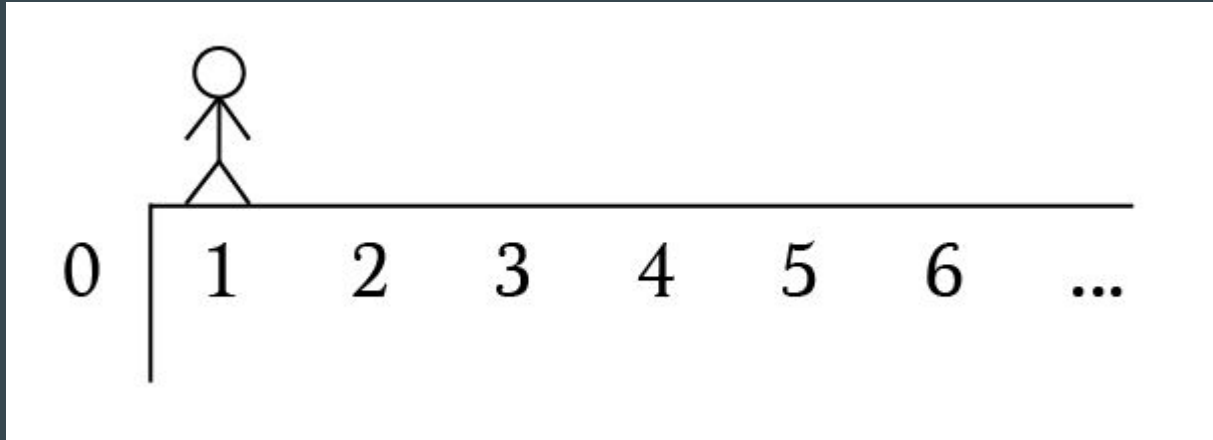
- For an  $N$  dimensional space
- Move some fixed distance  $b$
- With direction a random variable  $p$

# Random walks

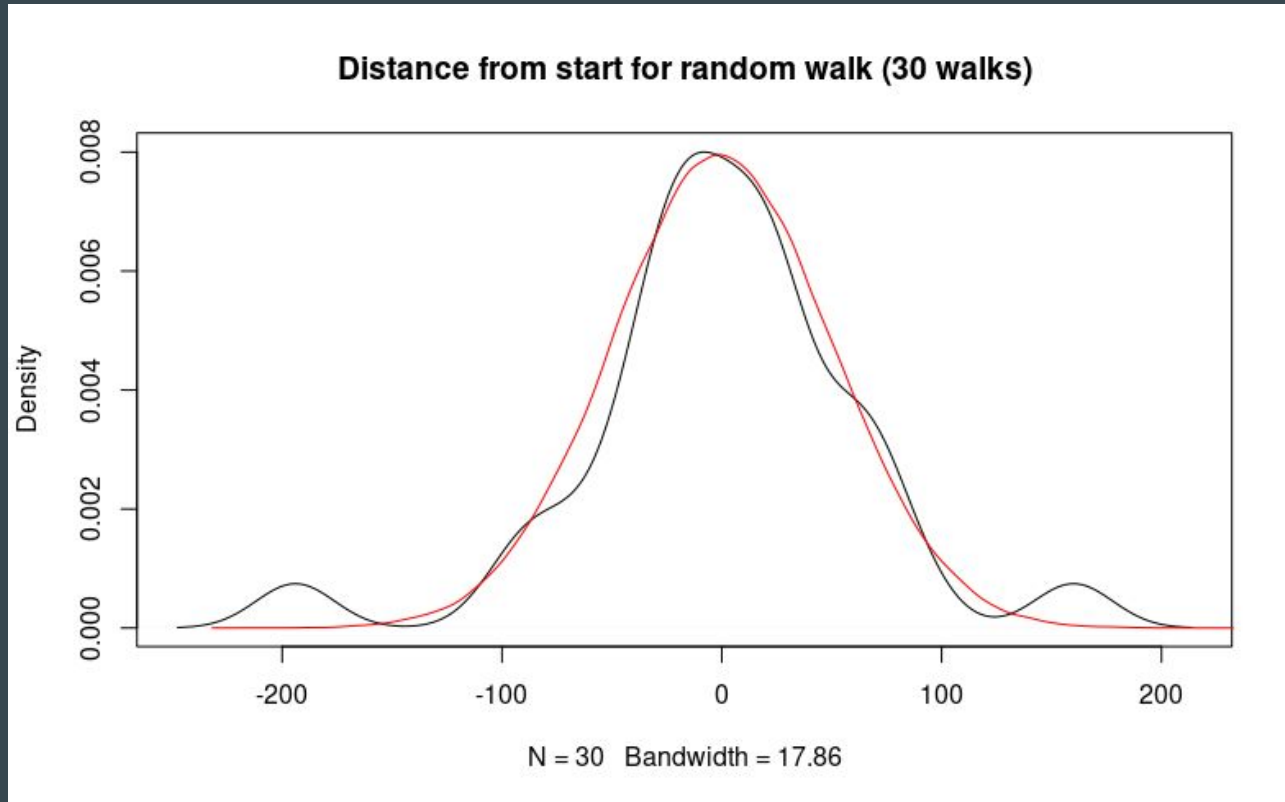


# One dimensional random walk

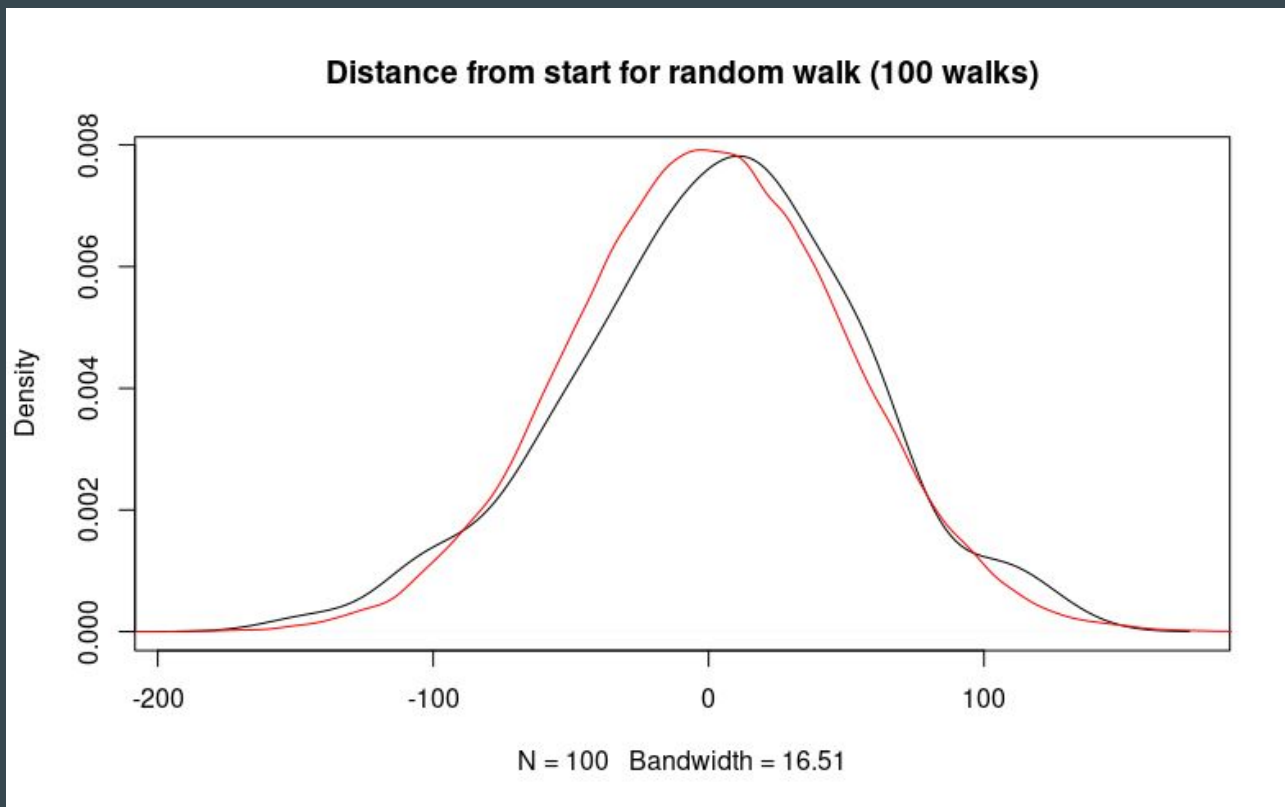
- Move one integer with probability  $p$  for either direction



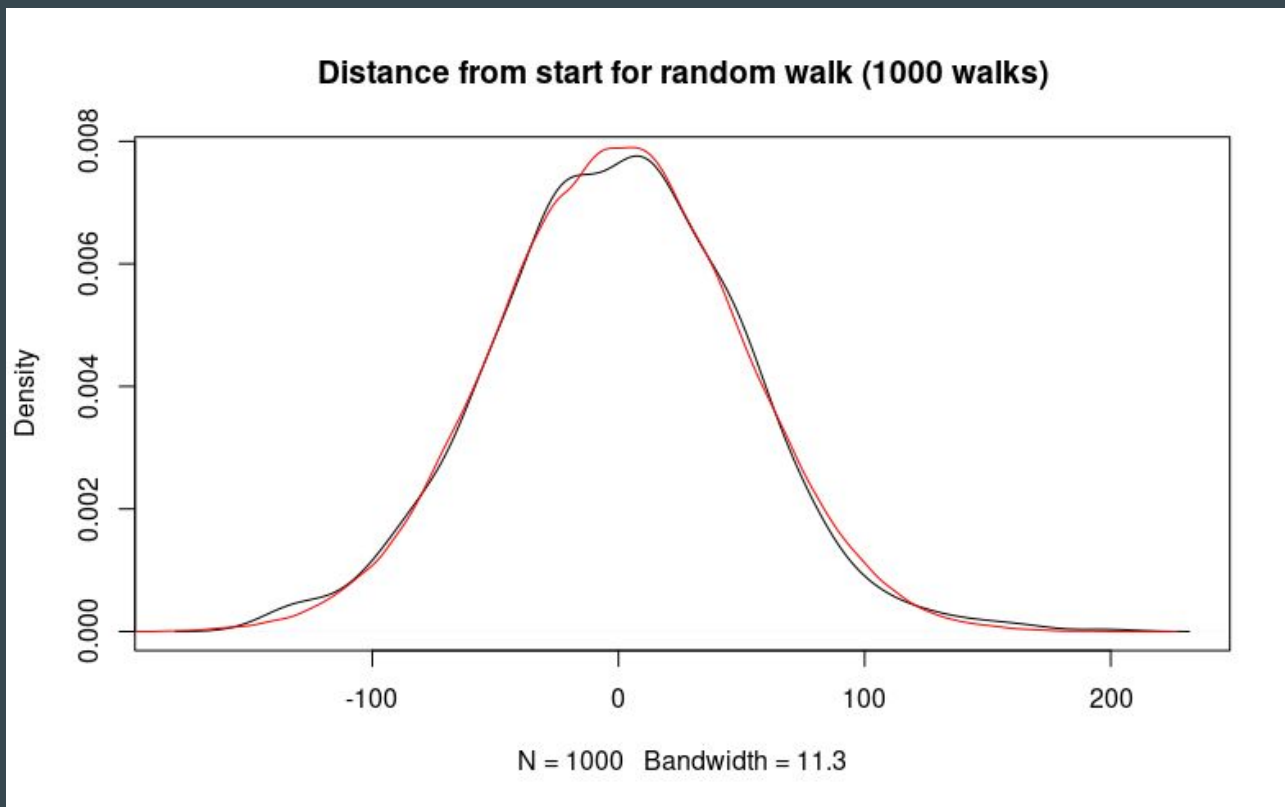
# Distance from start for random walk



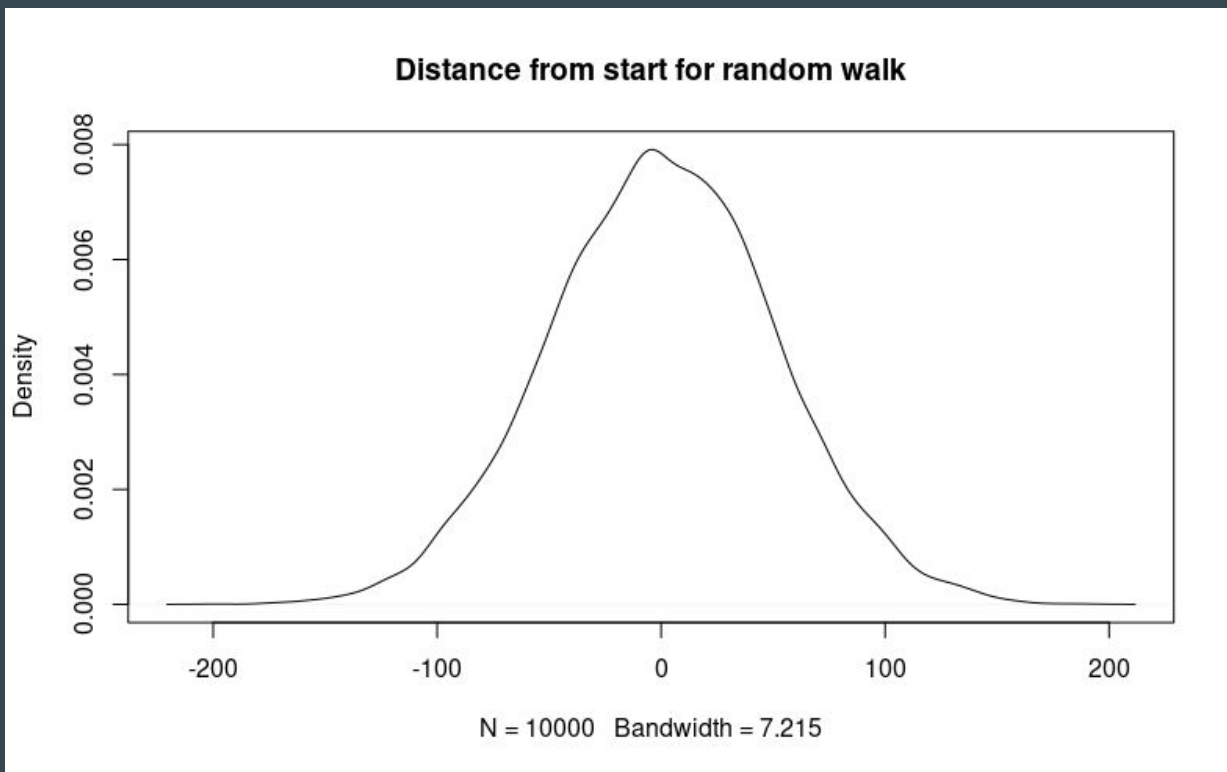
# Distance from start for random walk



# Distance from start for random walk



# Why is this useful?

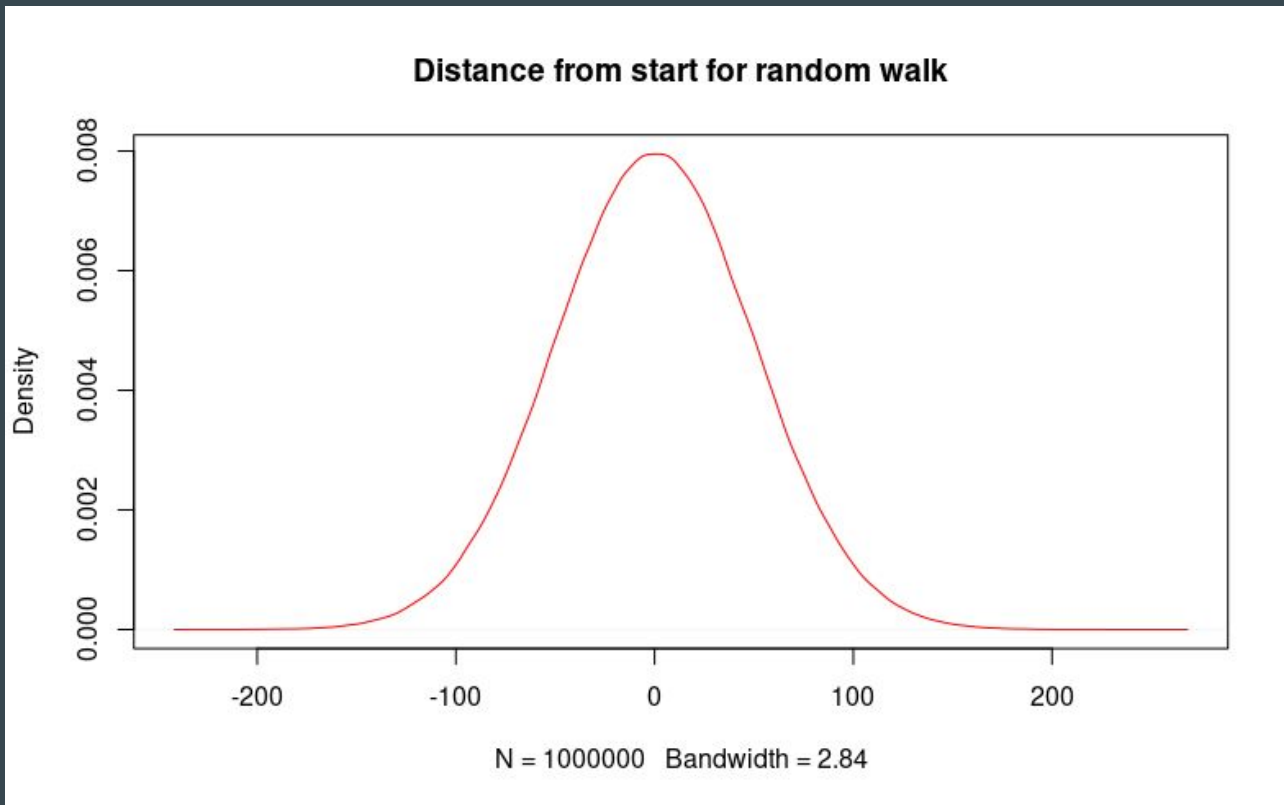


D = distance from  
center

$$P(D < -100) = 2.92\%$$



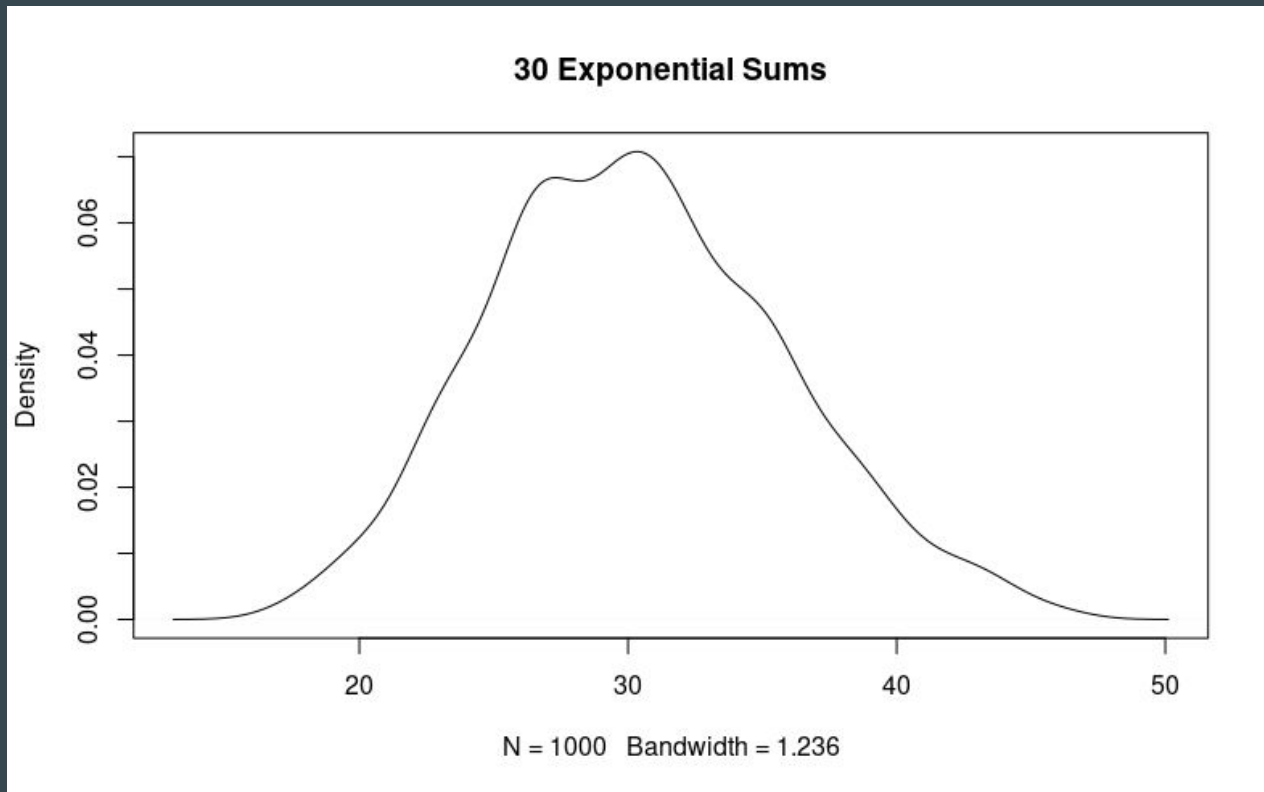
# Why is this useful?



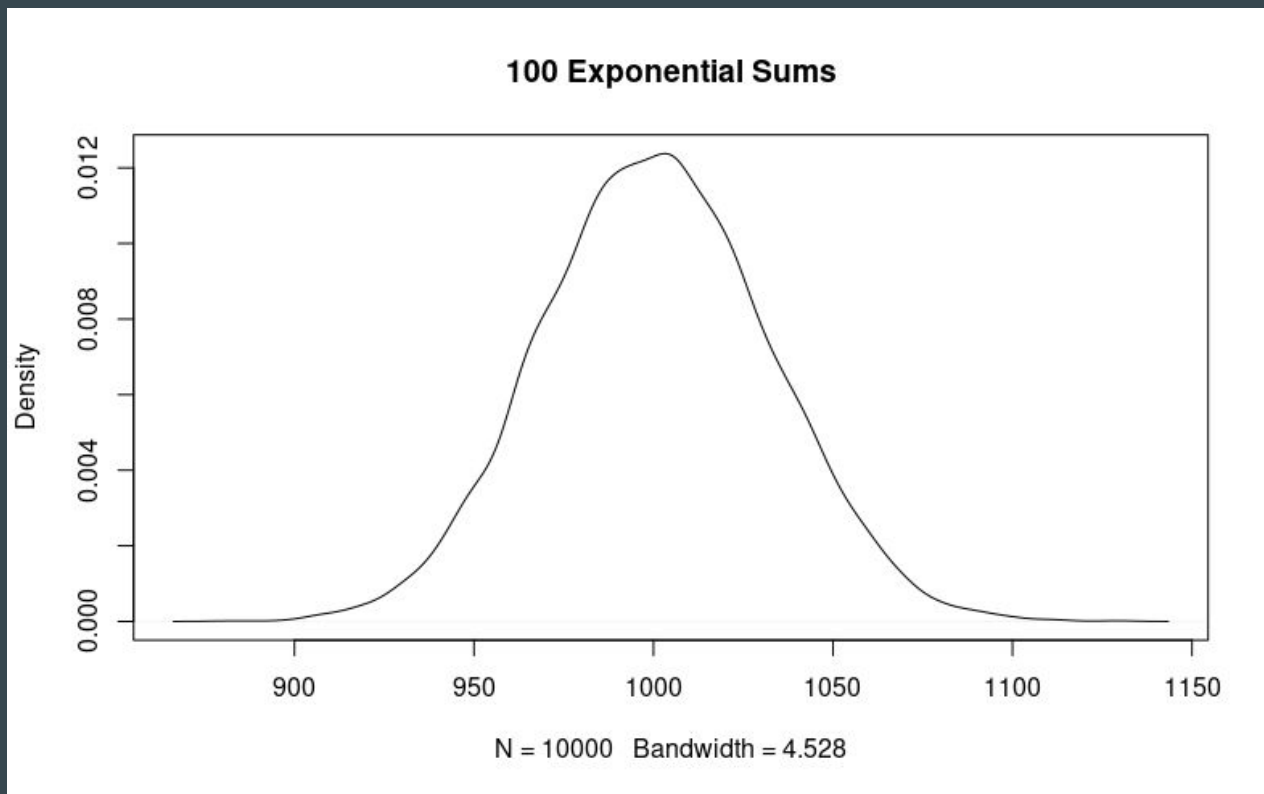
D = distance from  
center

$$P(D < -100) = 3\%$$

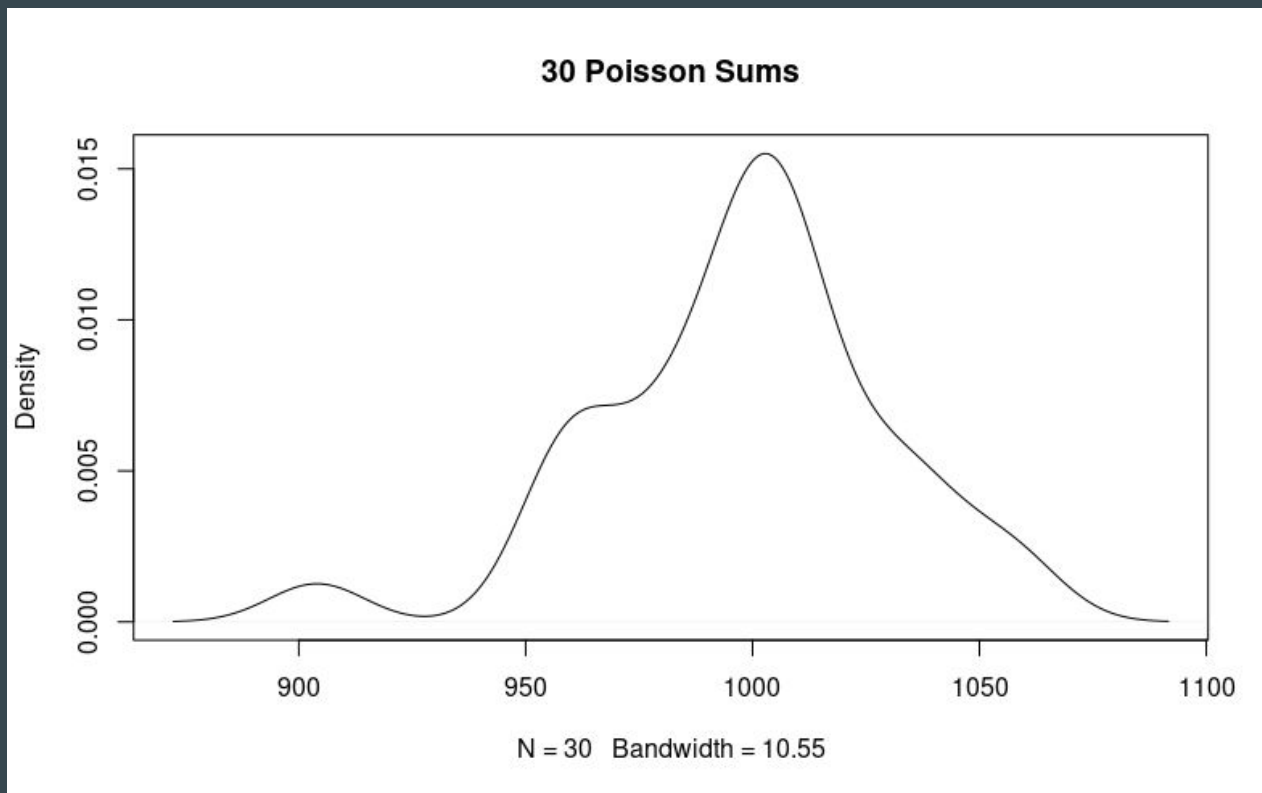
# Exponential sums



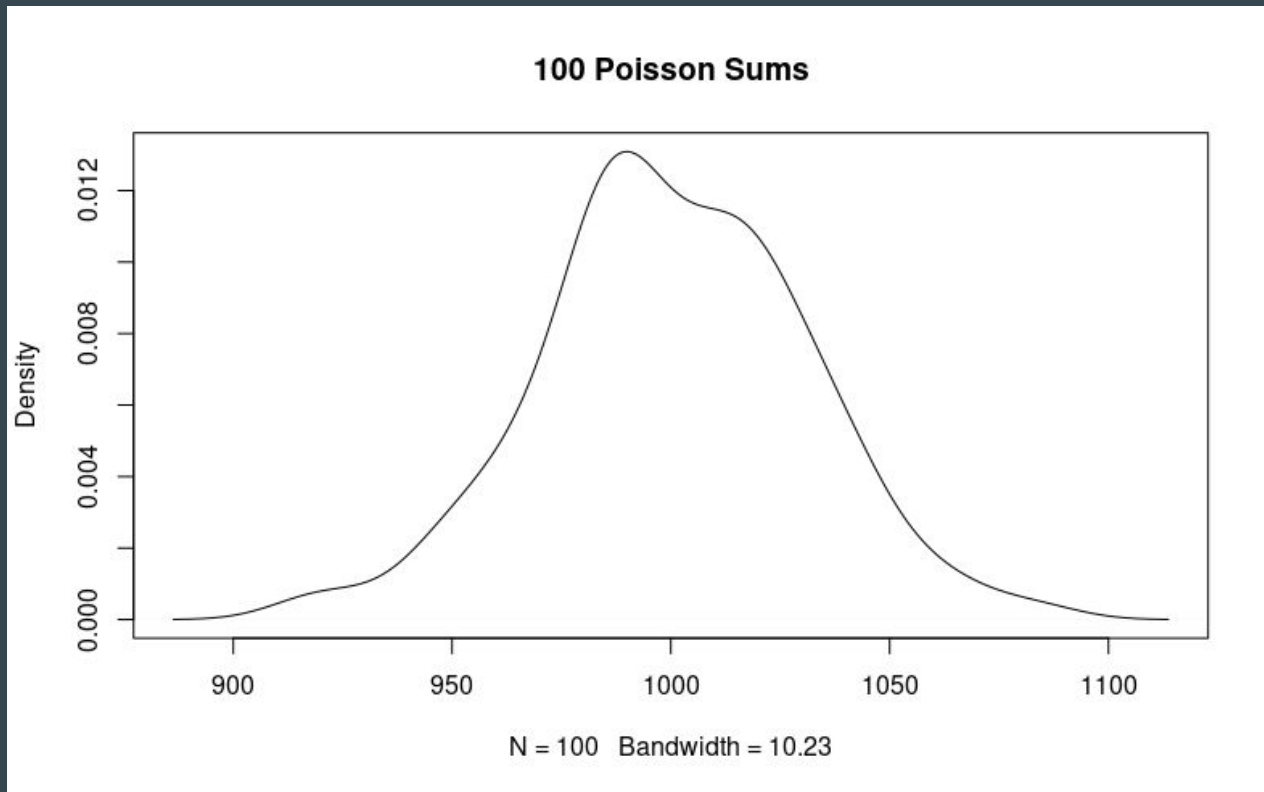
# Exponential sums



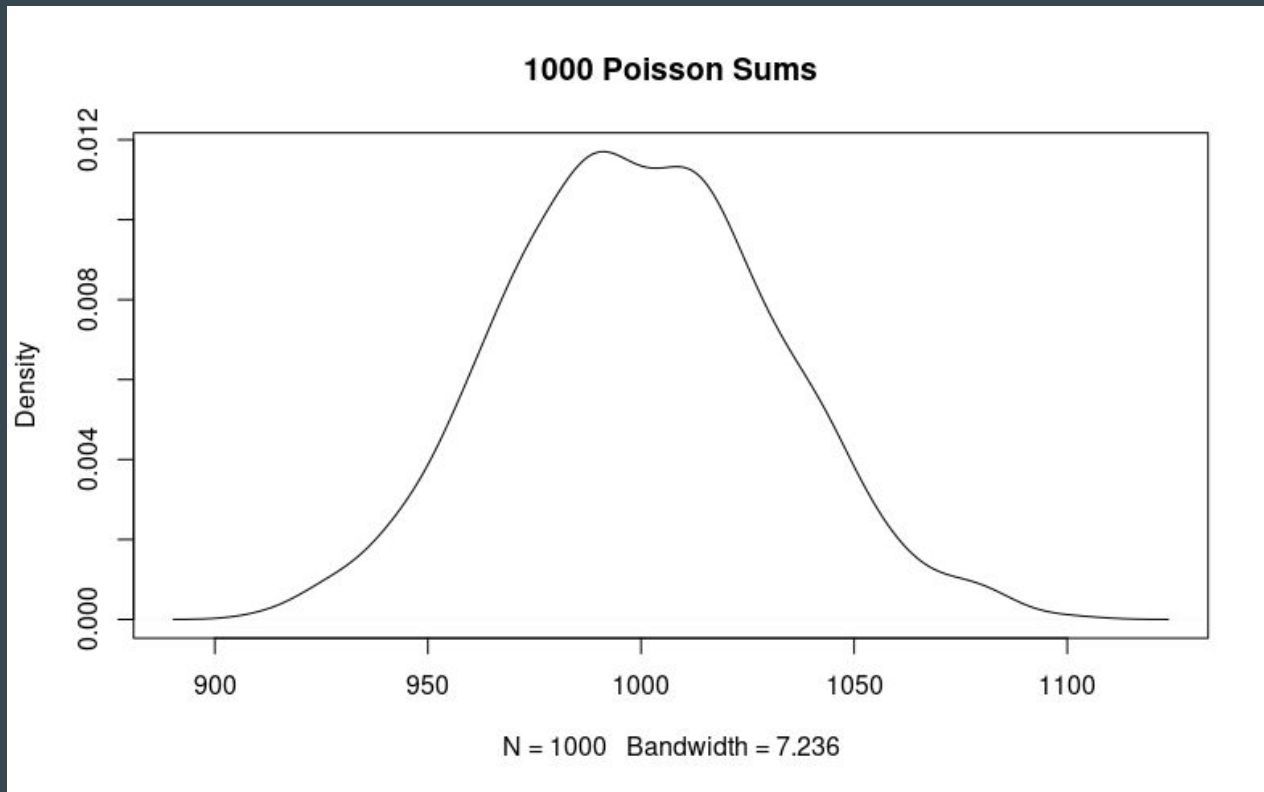
# Poisson sums



# Poisson sums



# Poisson sums



# Central Limit Theorem

For any i.i.d. variables, given a large enough sample size, any sums drawn from those variables will be normally distributed.

# What is i.i.d.?

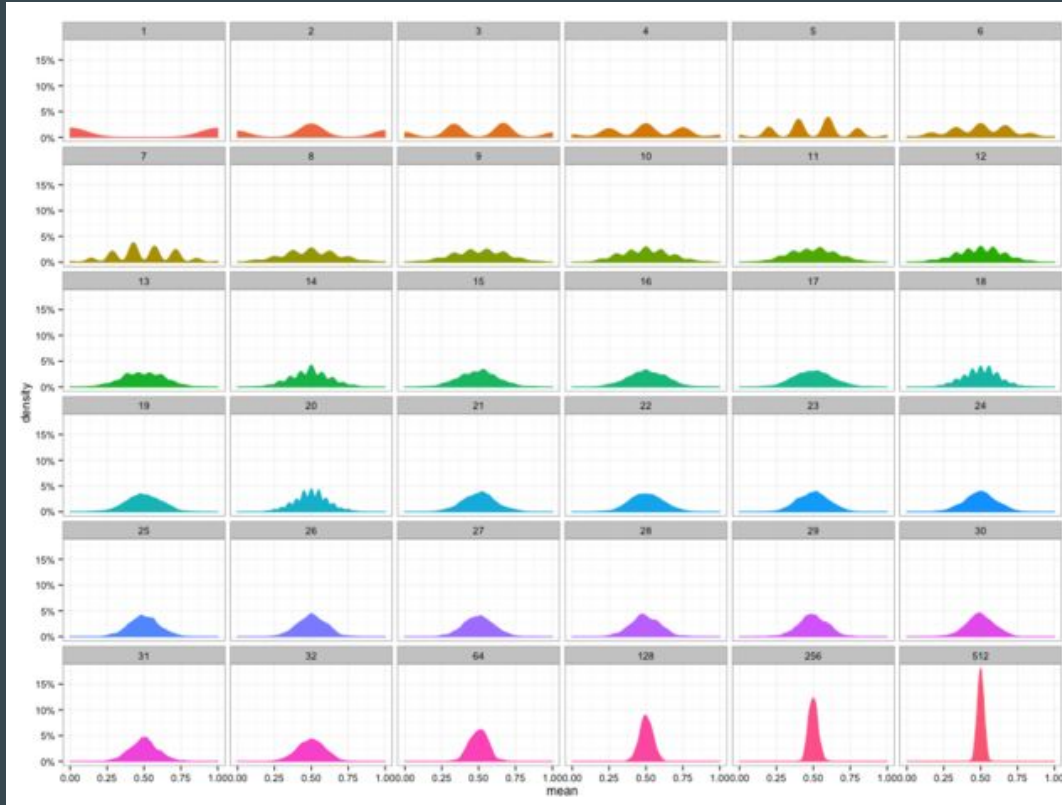
- Stands for Independently and Identically Distributed
  - Independent: the value of one observation does not affect the other
  - Identically distributed: all variables are generated by the same distribution
- Practically, we are way more concerned about *independence* than *identically distributed*



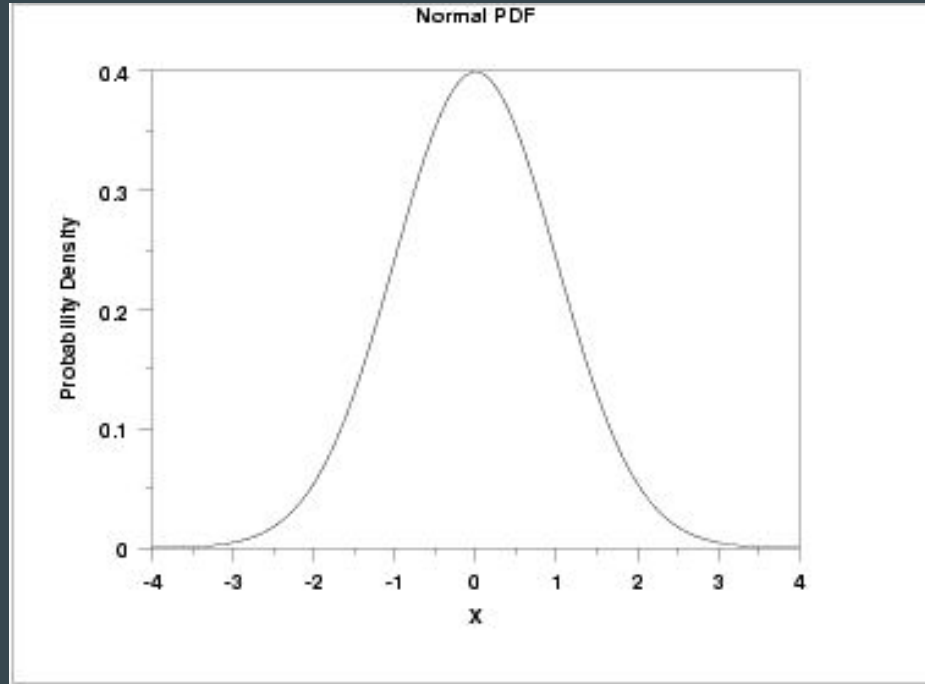
# Central Limit Theorem

Given a large enough sample size, the sample means will be normally distributed.

# Central Limit Theorem

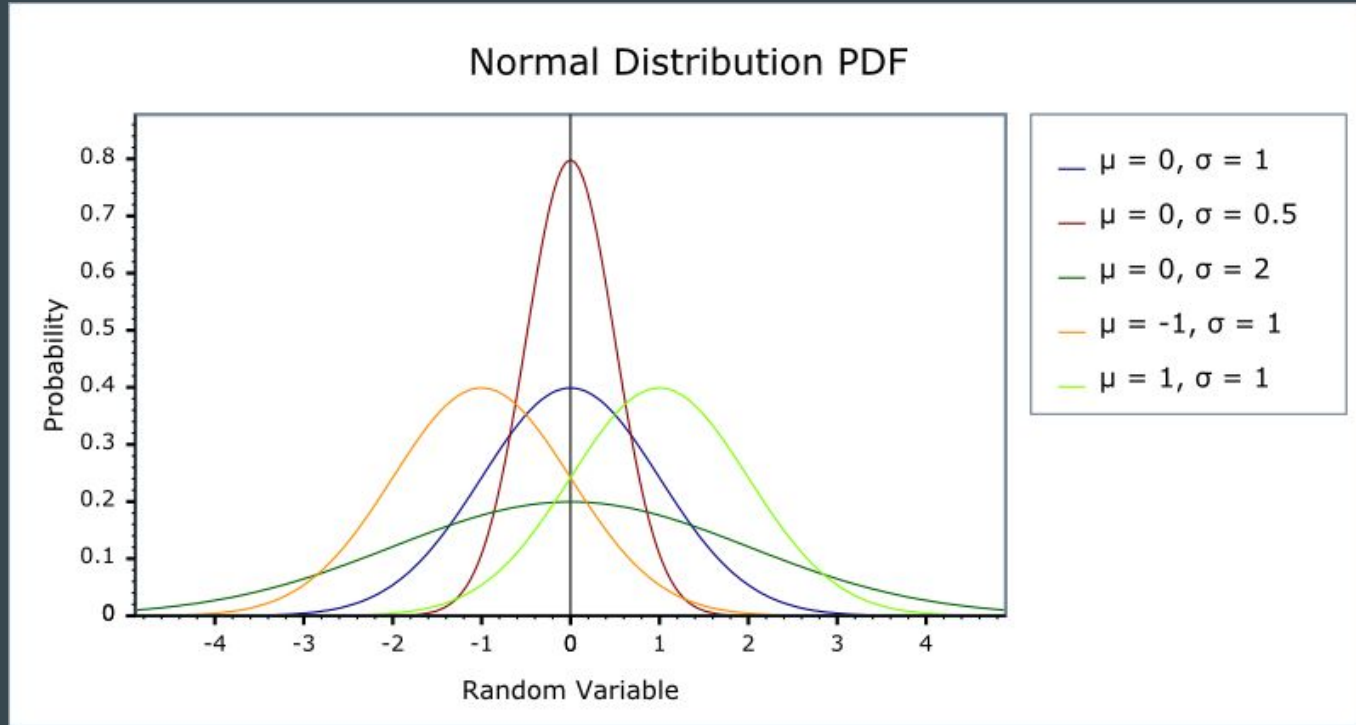


# Normal distribution



$$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

# Changing normal parameters



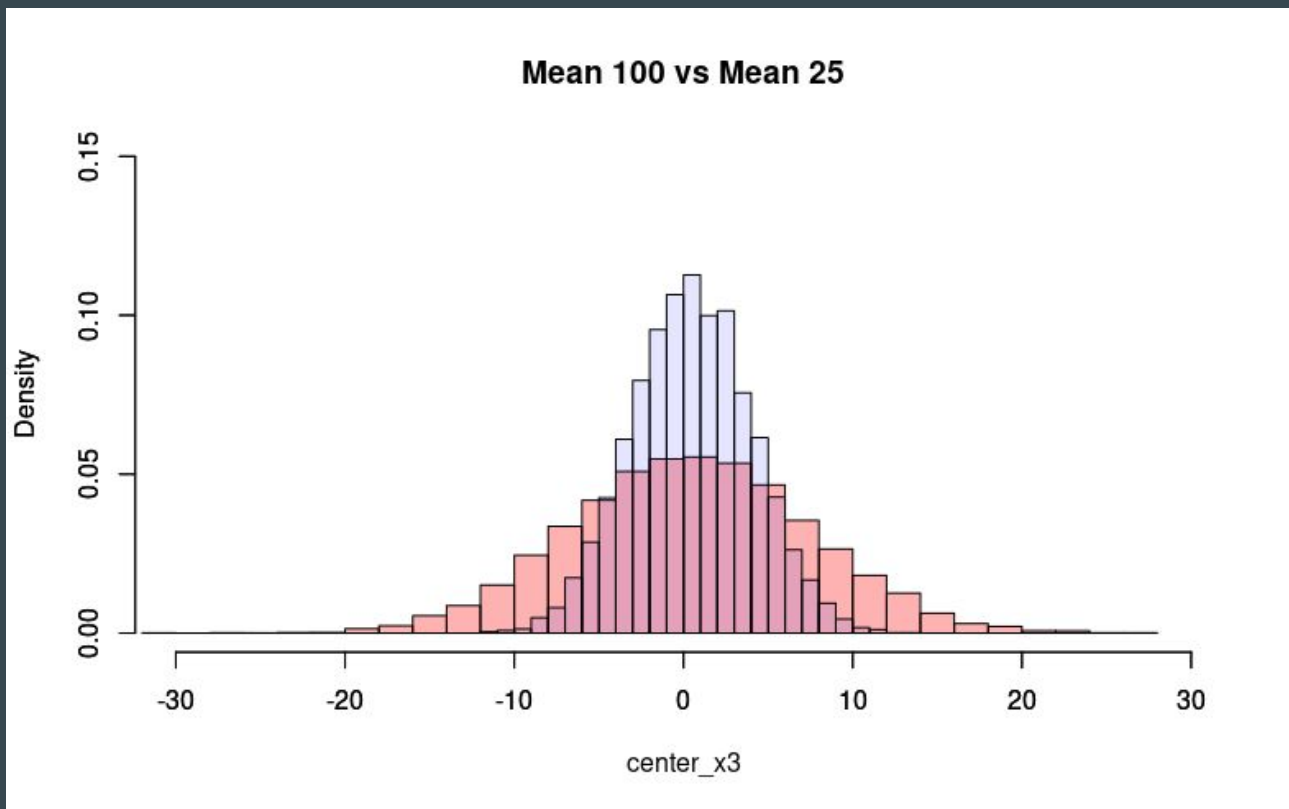
# Standardizing distributions

- Take two sets of data from the same distribution
- Two parts of standardization
  - Centering data (lining up  $E(X)$ )
  - Scaling data (line up the variance)
- Standardized variables have mean 1, variance 0

# Centering variables

$$X - \text{mean}(X)$$

# Centering variables



# Scaling Variables

$$X / \text{sqrt}(\text{Var}(X))$$



# Scaling formula / z-score

$$z = \frac{x - \mu}{\sigma}$$

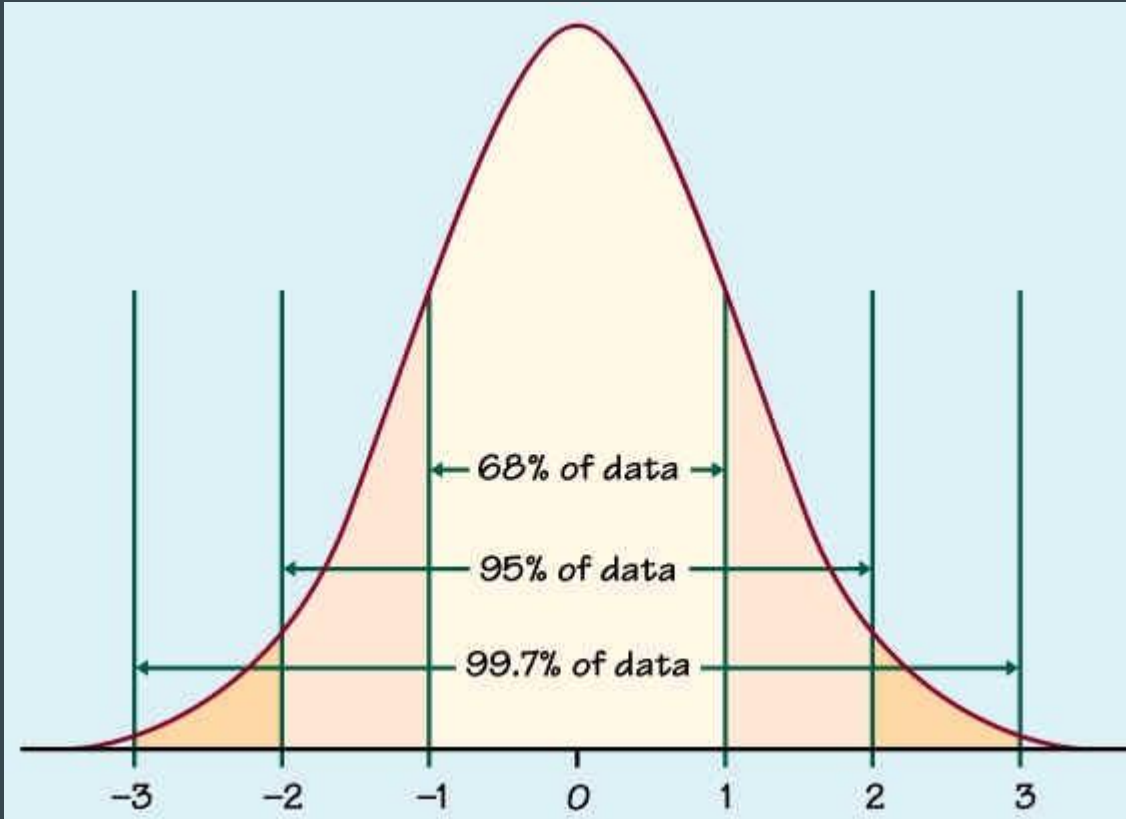
$\mu$  = Mean

$\sigma$  = Standard Deviation

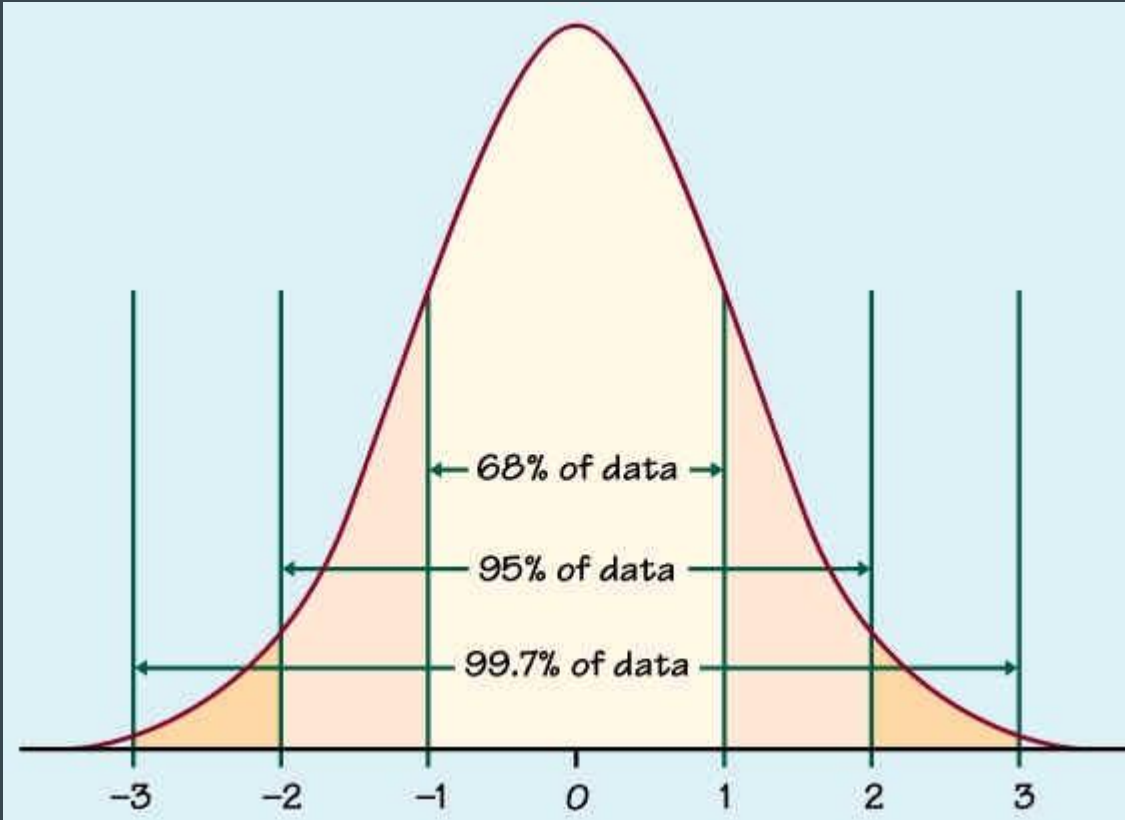
# Use of z-scores

- Z-scores allow us to determine the probability of only a single observation
  - If you assume the normal distribution
- Mean of 0 and Variance of 1 provided simple interpretation

# Interpretation of z-score

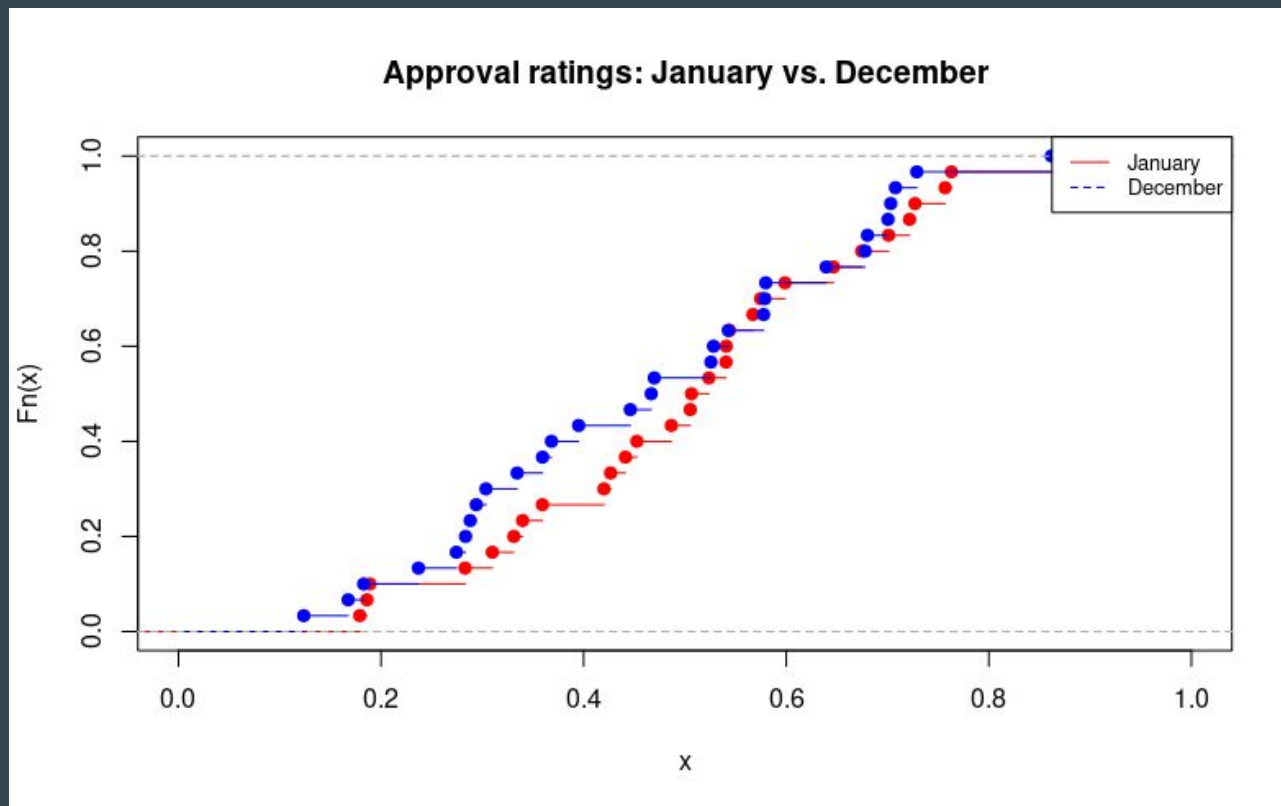


# Interpretation of z-score



- $-1 < z < 1$ 
  - 68% chance
- $-2 < z < 2$ 
  - 95% chance
- $-3 < z < 3$ 
  - 99.7% chance

# Let's take a step back



# Use of the normal

- If we are interested in the mean of a sample with sufficient size all we need is...
  - Expected Value (mean)
  - Variance (standard deviation)
- ...and we can assign it a probability
  - Answer questions whether something changed in the population or random chance
- We don't need to know the distribution of our data, or anything else about the population

# Z-scores in action

After opening a new school, a city wants to determine if the new school is performing well. The average school in the district has a graduation rate of 74%, with a standard deviation of 8%. The new school's graduation rate is 82%.

$$z = x - \text{mean}(x) / \text{stdev}(x)$$

$$z = (.82 - .74) / .08 = -1$$

# Review

- Assuming i.i.d, any type of sums drawn from any type of distribution will be normally distributed, given a large enough sample
- Z-scores rescale distributions to have:
  - $E(X) = 0$
  - $\text{Var}(X) = 1$
- Z-scores allow us to determine probability *without* knowing what distribution it came from