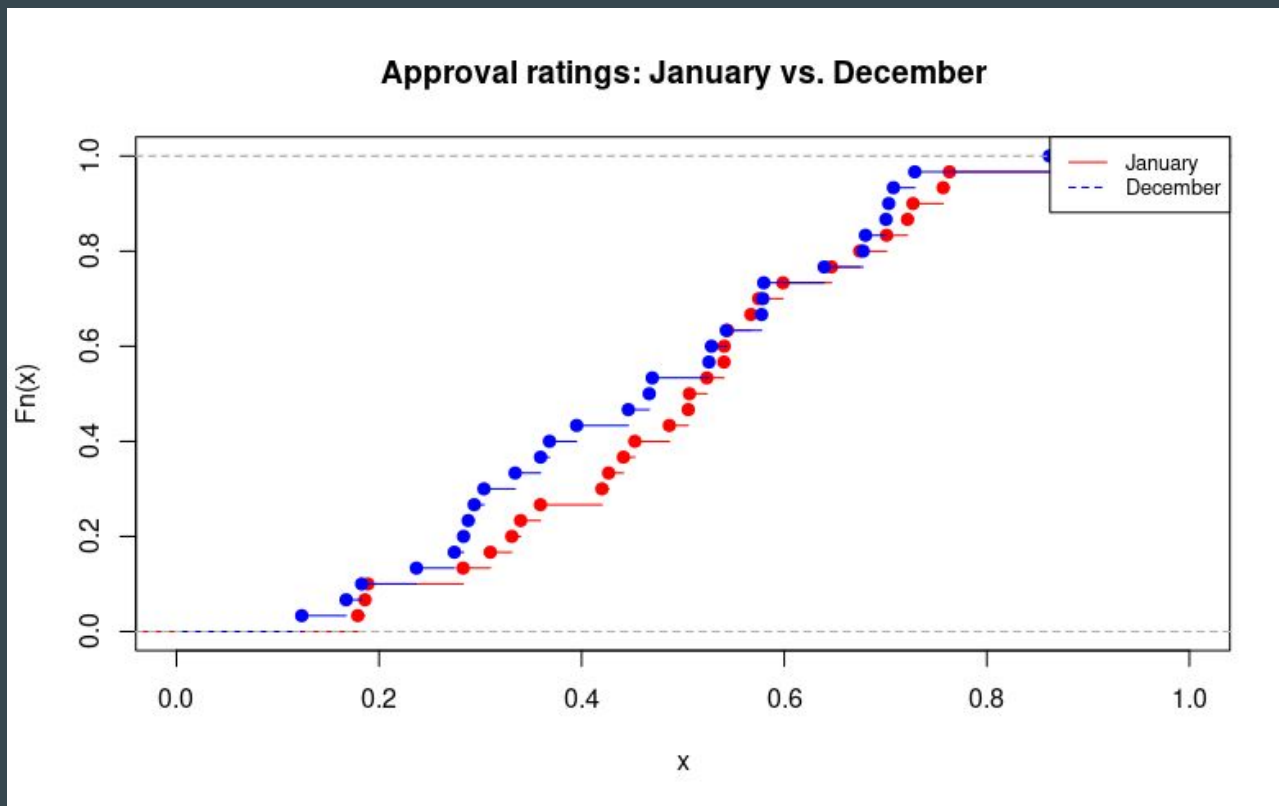


# Useful Probability Distributions

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4 February 2019  
PLSC 309

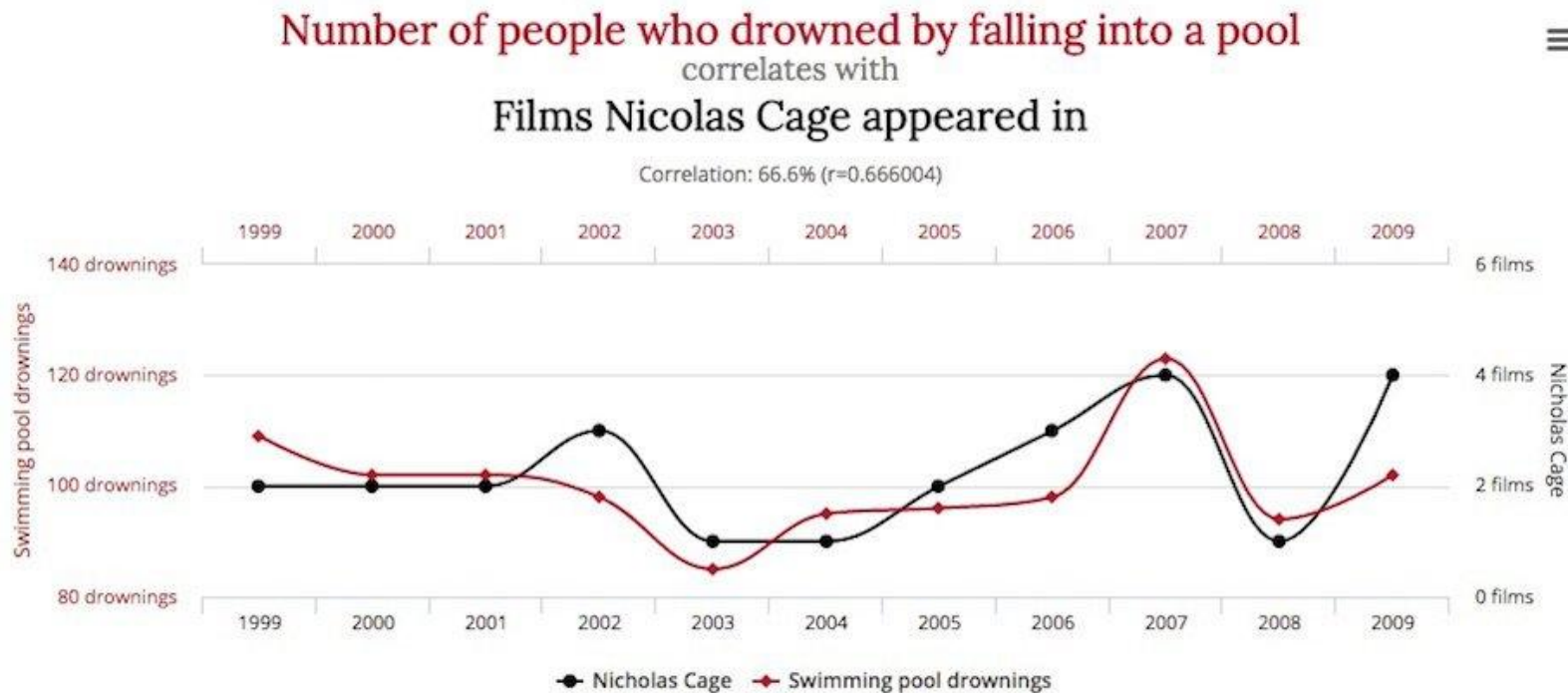
# The fundamental problem of statistics



# The fundamental problem of statistics

*the signal and the noise and the noise and the noise and the noise why so many predictions fail – but some don't the signal and the noise and the noise and the noise nate silver noise noise and the noise*

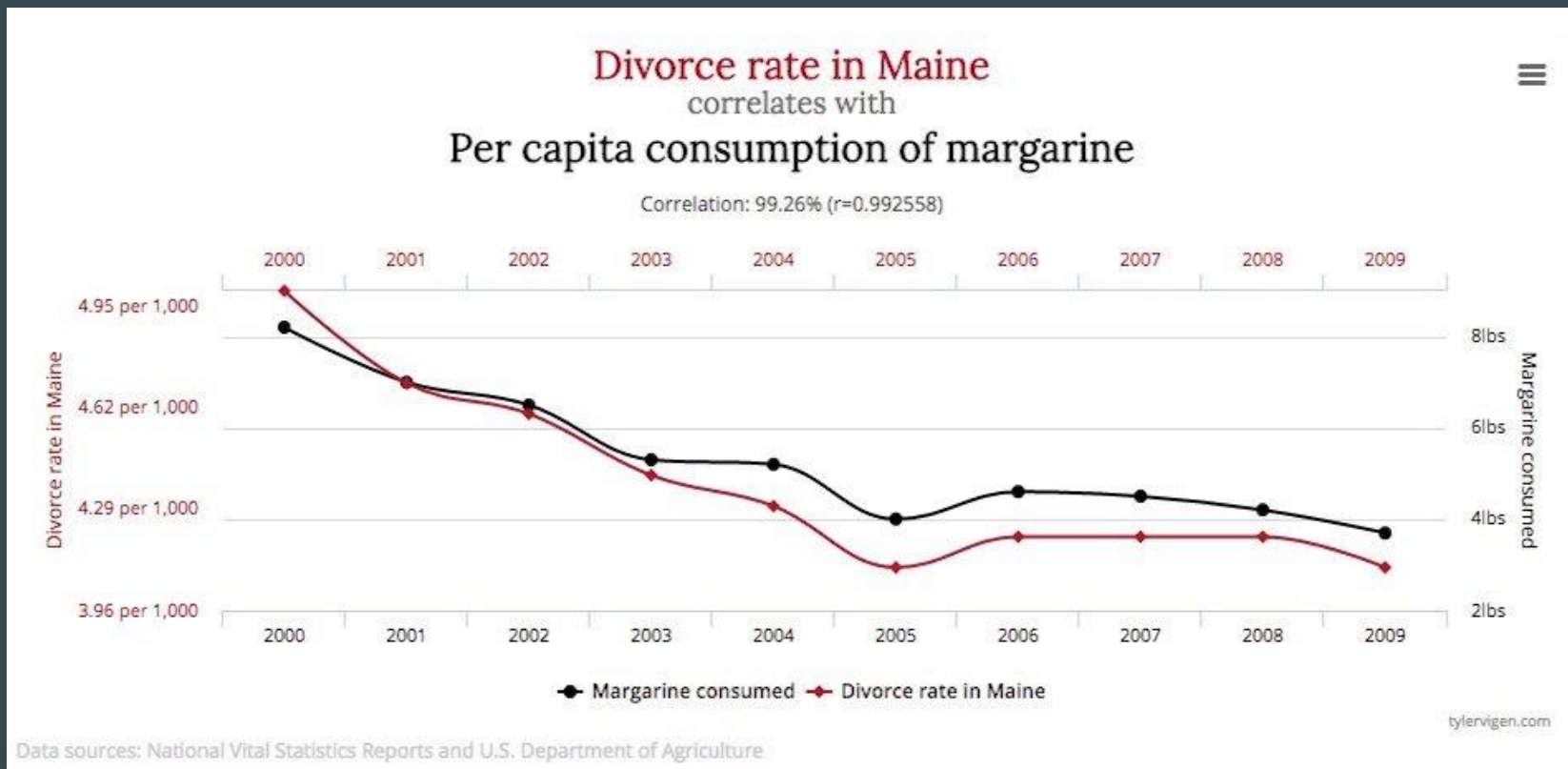
# The fundamental problem of statistics



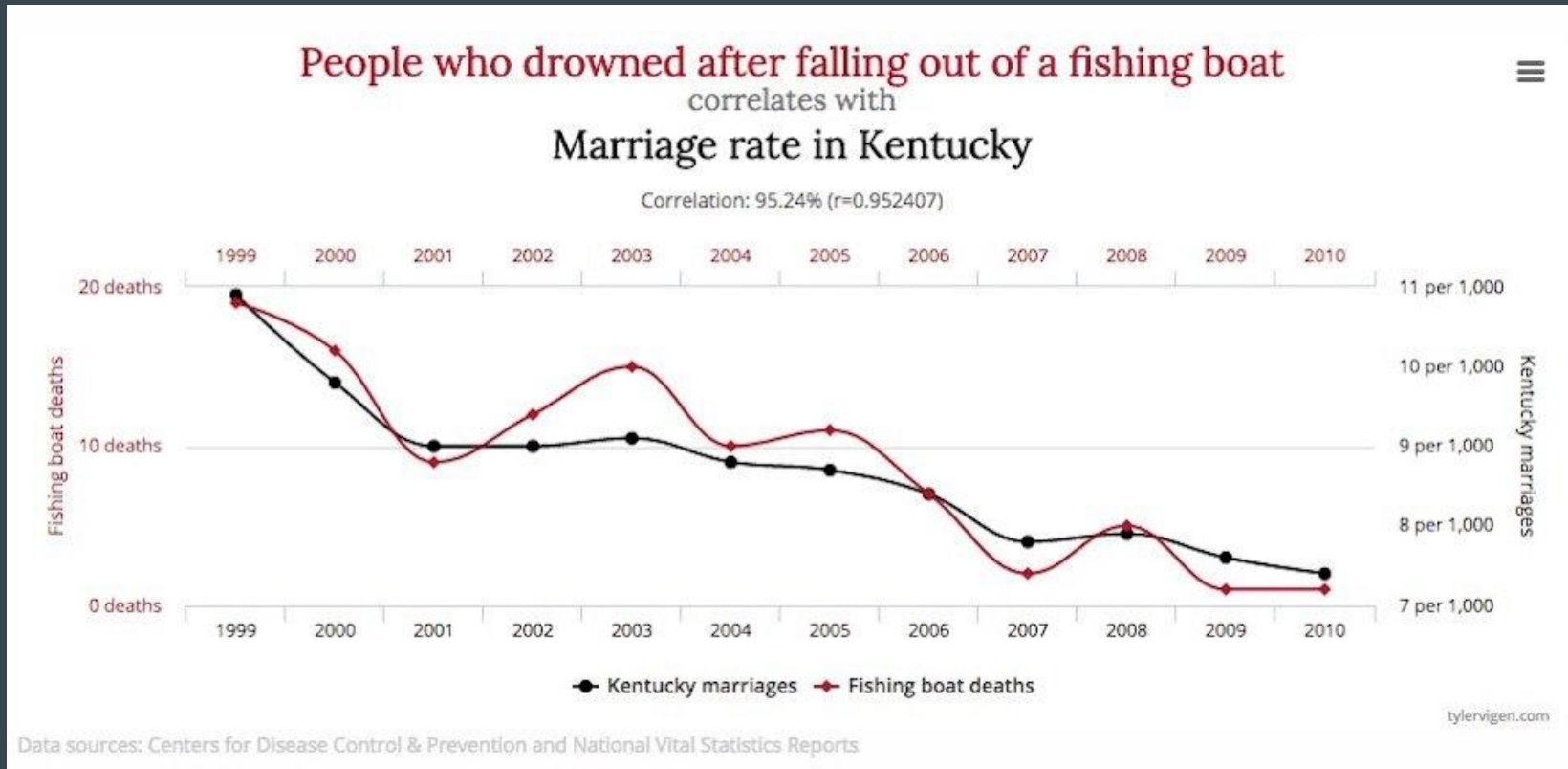
Data sources: Centers for Disease Control & Prevention and Internet Movie Database

tylervigen.com

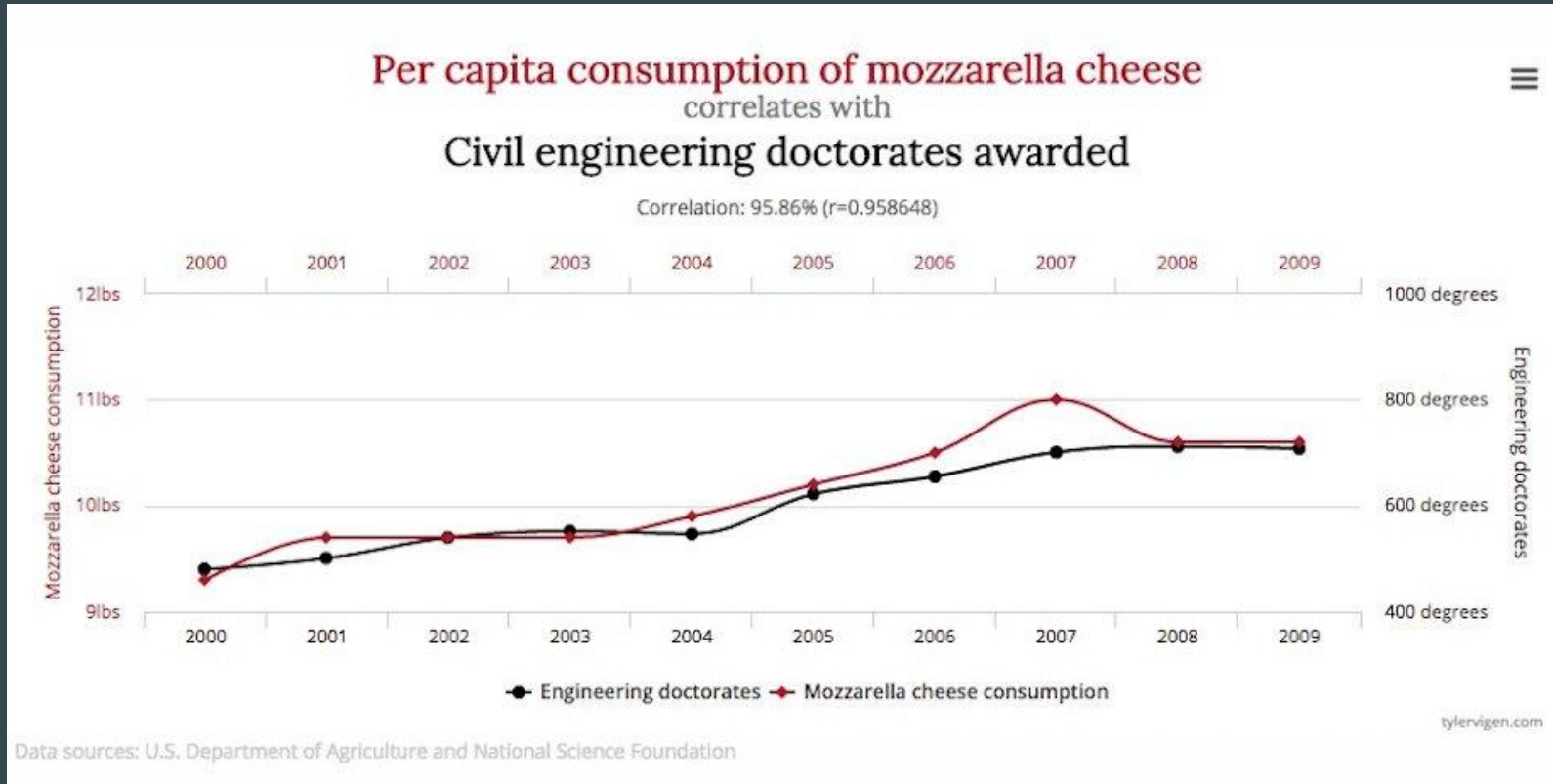
# The fundamental problem of statistics



# The fundamental problem of statistics



# The fundamental problem of statistics



# The fundamental problem of statistics

- We need to distinguish random noise from systematic changes
- If we assume a probability distribution for what we're trying to explain...
- ...we have a good guess for what the random noise will be!



# Preview

- It is difficult to directly estimate a probability distribution from data
- Instead we look for *naturally occurring distributions*
- We then make an assumption (backed up by evidence) that our data is drawn from one of those distributions

# But first, some vocabulary

- We have seen random variables, which we typically label  $X$
- The distributions we see have other mathematical variables called *parameters*
  - These are usually constants
  - They determine the shape of the distribution
  - These can be calculated or directly estimated from data

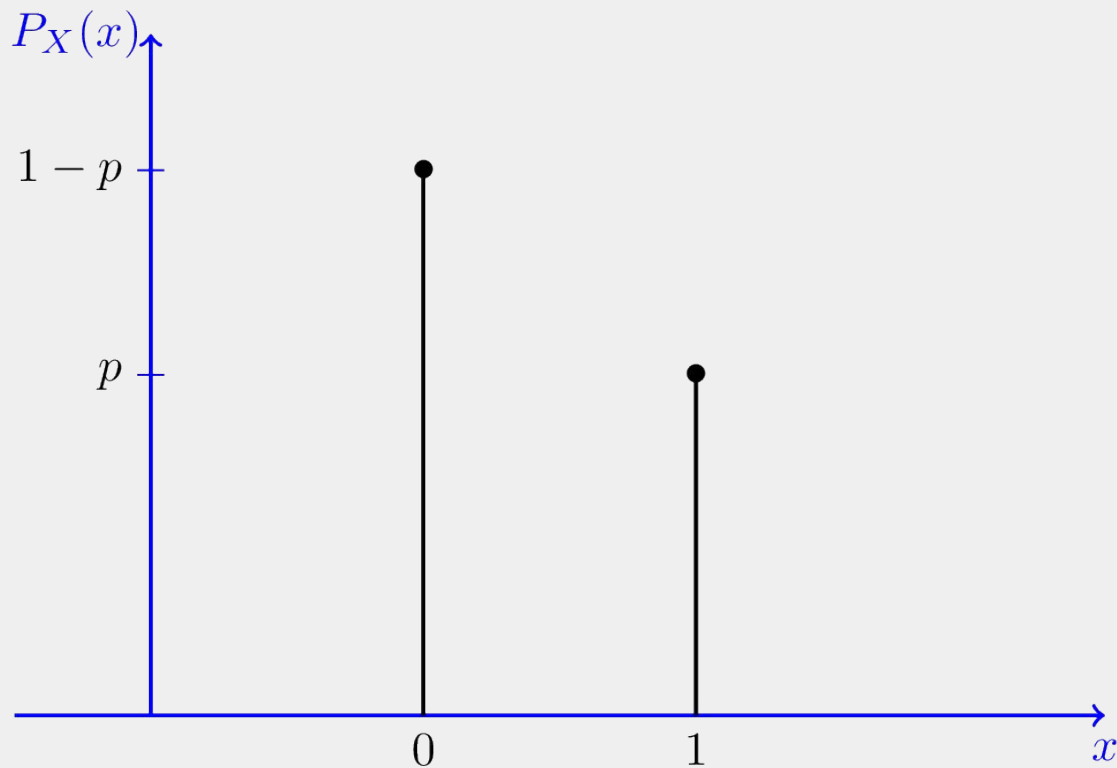
# Bernoulli Distribution

# Successes and failures

- A Bernoulli distribution describes any event with a binary outcome
  - Outcome = 1 (*success*)
  - Outcome = 0 (*failure*)
- Two parameters
  - $p$ : probability of success
  - $q$ : probability of failure (equivalent to  $1-p$ )

# Bernoulli Distribution

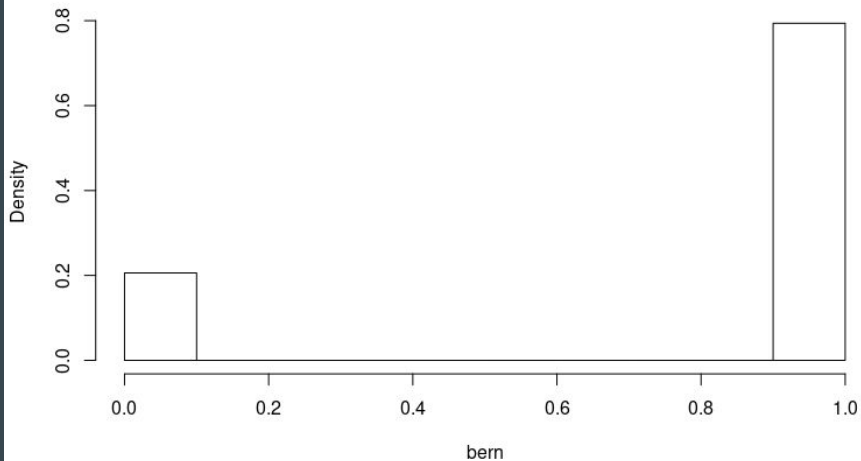
$$X \sim \text{Bernoulli}(p)$$



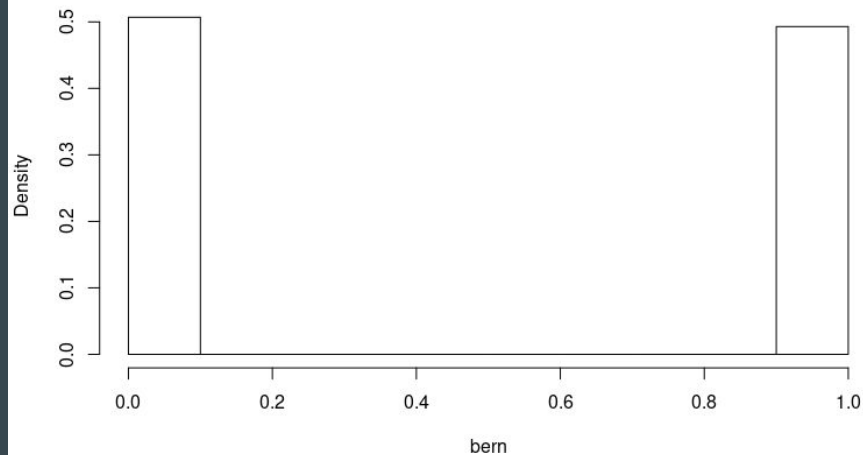
$$\begin{cases} q = 1 - p & \text{if } k = 0 \\ p & \text{if } k = 1 \end{cases}$$

# Changing parameter $p$

Bernoulli with  $p = 0.8$



Bernoulli with  $p = 0.5$



# Mean and Variance for Bernoulli

- A bernoulli distribution is one trial that ends in either a success or a failure
- Each trial is independent from the other
- $E(X) = p$
- $\text{Var}(X) = p(1-p)$  or  $pq$

# Examples of Bernoulli processes

- A candidate is running for election. The chance they win is 70%
  - 0 = candidate loses
  - 1 = candidate wins
  - $p = .7$
  - $E(X) = .7$
  - $\text{Var}(X) = .21$
- There is a 5% chance of a coup in Thailand
  - 0 = no coup
  - 1 = coup
  - $P = .05$
  - $E(X) = .05$
  - $\text{Var}(X) = .0475$



# Binomial Distribution

# An extension of the Bernoulli

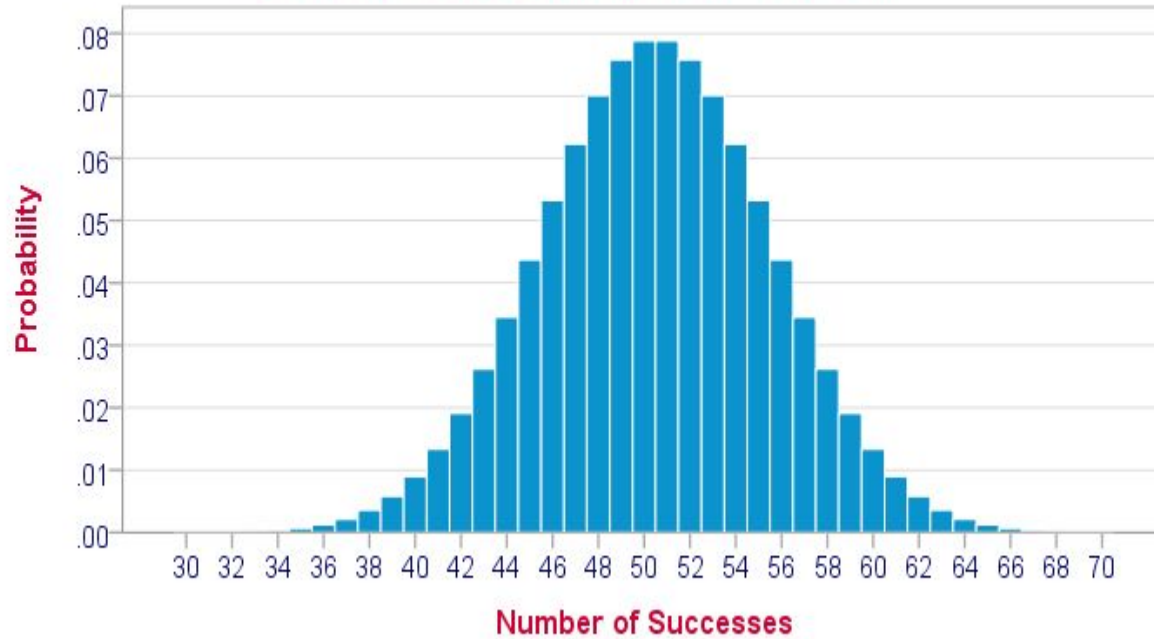
- In the Bernoulli, we had one event that yields an outcome of success or failure
- What if we had a bunch of events that yielded 0-1 outcomes?
- In other words, given a series of  $n$  trials, what is the probability that we have  $k$  successes?
- Three parameters
  - $p$ : probability of success
  - $n$ : number of trials
  - $k$ : number of successes

## Interlude: combinations

$$\binom{n}{k} = \frac{n!}{k!(n-k)!}$$

# Binomial Distribution

Binomial Probability Distribution | N = 100, P = 0.5



$$\binom{n}{k} p^k (1 - p)^{n-k}$$

# Binomial PMF

Let's say we're trying to flip a coin ten times. A success is a heads. We only get one head. Probability of success is  $p$ . Probability of failure is  $1-p$ .

$$\{S, F, F, F, F, F, F, F, F, F\} = p * (1-p)^9$$

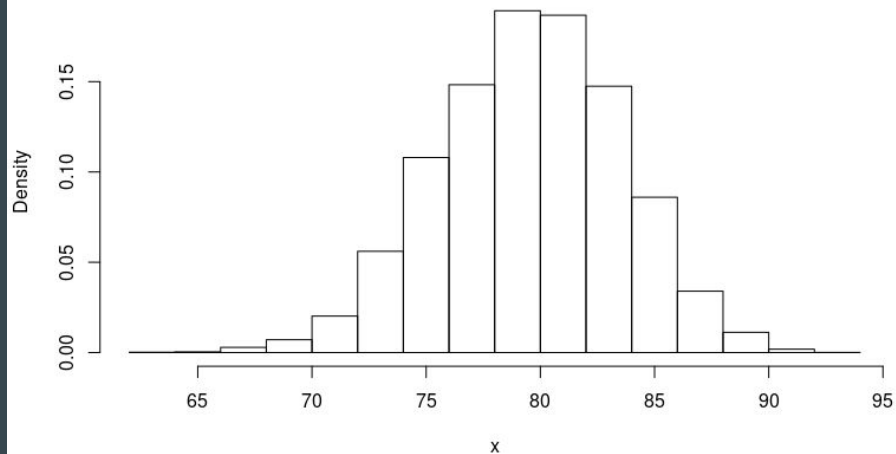
$$\{F, S, F, F, F, F, F, F, F, F\} = (1-p) * p * (1-p)^8 = p * (1-p)^9$$

$$\{F, F, S, F, F, F, F, F, F, F\} = (1-p)^2 * p * (1-p)^7 = p * (1-p)^9$$

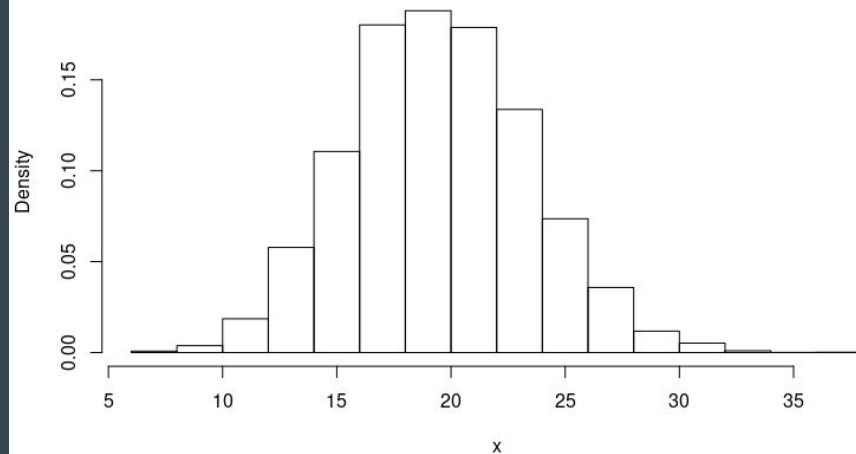
In other words, each different way of getting one success has a probability of  $p * (1-p)^9$ . Summing all these up we get  $10 * p * (1-p)^9$ .  $10 \text{ choose } 1 = 10$ .

# Effect of parameters on Binomial Distribution

Binomial with  $n=100$ ,  $p=0.8$



Binomial with  $n=100$ ,  $p=0.2$



# Mean and Variance for Binomial distribution

- Binomial distribution extends the Bernoulli to  $n$  trials
  - $E(X)$  for Bernoulli was  $p$
  - ... $E(X)$  for Binomial is  $np$
- $\text{Var}(X) = np(1-p)$

# Examples of Binomial processes

- 18 candidates are running for office. Incumbents win 90% of the time. How many incumbents will win?
  - $E(X) = np = 16.2$
  - $\text{Var}(X) = np(1-p) = 1.62$
- A political party needs has 60 senators in Congress. Senators vote with their own party 92% of the time. What is the probability they get 60 votes?
  - $E(X) = np = 55.2$
  - $\text{Var}(X) = 4.416$



# Multinomial Distribution

# Categories as binary choices

- The binomial distribution dealt with  $k$  success from  $n$  trials
- A multinomial distribution is about choosing from  $k$  categories in  $n$  trials
- If there are  $k$  categories, each category has a probability,  $p_i$

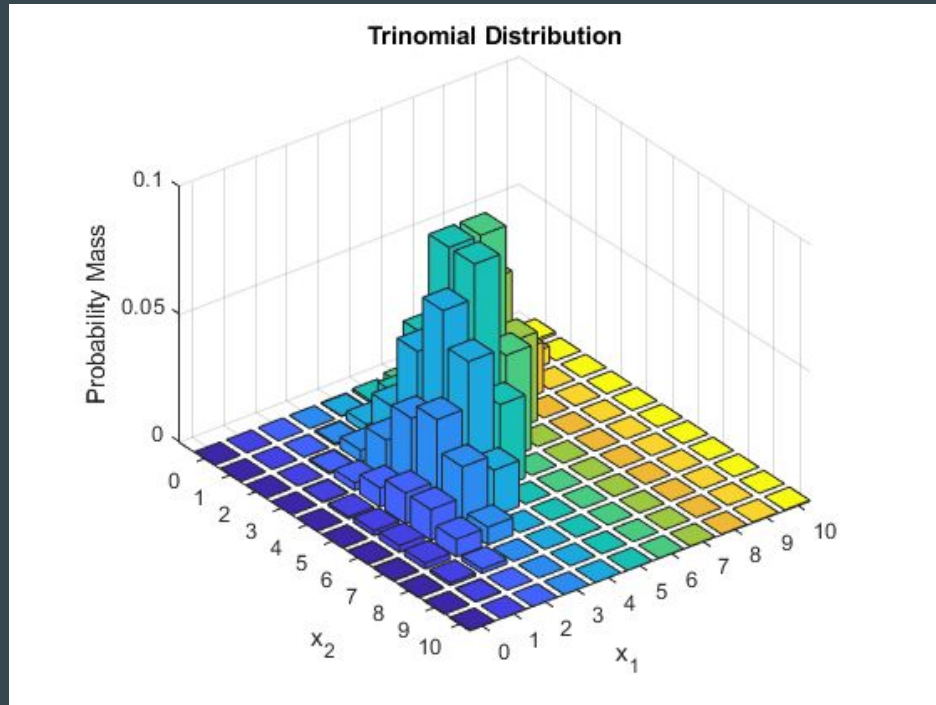
# Categorical variables are condensed binary outcomes

Political party: 0 = Democrat; 1 = Republican; 2 = Green

Political Party
0
2
1

Democrat	Republican	Green
1	0	0
0	0	1
0	1	0

# Multinomial Distribution



$$\frac{n!}{x_1! \cdots x_k!} p_1^{x_1} \cdots p_k^{x_k}$$

# Mean and Variance for Multinomial distribution

- There is no global expected value or variance, just one for each category
- Calculations are exactly the same as the binomial distribution
  - $E(X_i) = np_i$
  - $\text{Var}(X_i) = np_i(1-p_i)$

# Examples of Multinomial Processes

- Any consumer choice
  - Type of car to buy
  - Type of phone to buy
  - Etc.
- The Green, Democrat, and Republican party candidates are running against one another in a district with 1000 voters. The probability that someone votes Green is 2%, Democrat is 49%, and Republican is 49%.
  - $E(\text{Green}) = np_i = 20$
  - $E(\text{Dem}) = np_i = 490$

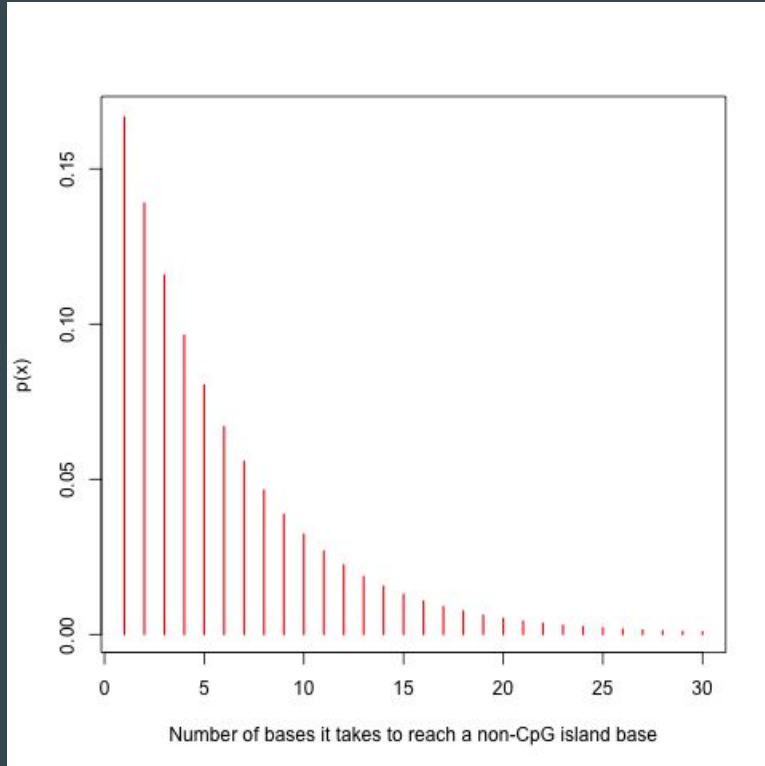
# Geometric Distribution

# How long does it take to get a success?

- For  $k$  trials, how long does it take to get to one success?
- Bernoulli: one trial, one success
- Binomial:  $n$  trials,  $k$  successes
- Geometric:  $k$  trials, one success
  - $p$ : probability of success
  - $k$ : how many trials it takes to get to one success



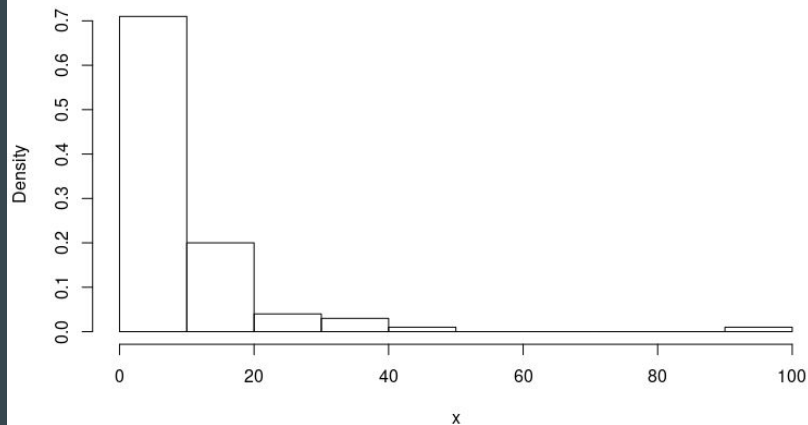
# Geometric distribution



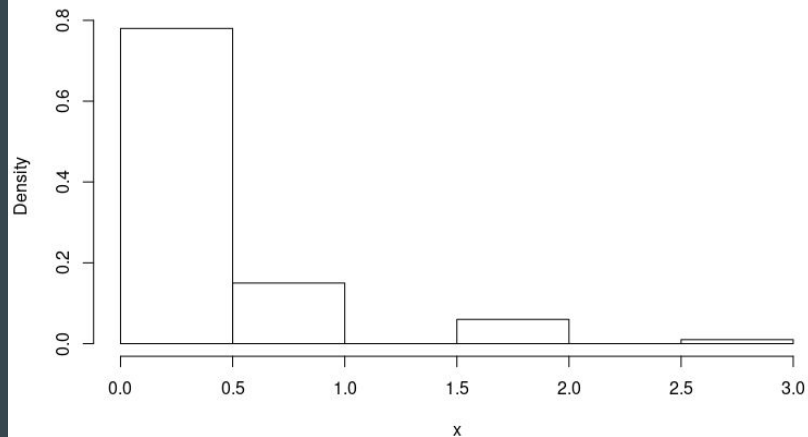
$$(1 - p)^{k-1} p$$

# Changing parameters for geometric

Geometric with  $p=0.1$



Geometric with  $p=0.9$



# Mean and Variance for the geometric distribution

- Expected value for the geometric is telling us, on average, how many trials we should expect to do before we come to a single success
  - $E(X) = 1/p$
- $\text{Var}(X) = (1-p) / p^2$

# Examples of geometric processes

- A factory is making widgets. Their failure rate is 0.01. How many trials will it take until there is a failure?
  - $E(X) = 1/p = 100$
  - $\text{Var}(X) = (1-p) / p^2 = 9900$
- Somebody won't stop gambling until they win at blackjack. The chance you win at blackjack is 49%. How many hands will they sit through until they win?
  - $E(X) = 1/p = 2.04$
  - $\text{Var}(X) = (1-p) / p^2 = 2.12$

# Review

Today we learned about commonly occurring discrete distributions:

- Bernoulli - a single trial that can end in either success or failure
- Binomial - a collection of Bernoulli trials
- Multinomial - a categorical extension of the binomial distribution
- Geometric - number of times it takes for a series of Bernoulli trials to produce a success