

CS 649 Big Data: Tools and Methods  
Fall Semester, 2021  
Doc 13 Statistics, Sampling, Bloom  
Feb 17, 2022

Copyright ©, All rights reserved. 2022 SDSU & Roger Whitney, 5500 Campanile Drive, San Diego, CA 92182-7700 USA. OpenContent (<http://www.opencontent.org/openpub/>) license defines the copyright on this document.

# Descriptive Statistics

mean

median

mode

variance

standard variation

quantiles

# Descriptive Statistics

Arithmetic mean

`mean(numbers) = sum(numbers)/length(numbers)`

`mean([1,7,3,8,5]) == 4.80`

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

median

Middle value of sorted list of numbers

If even number of values then mean of middle two values

`median([1,7,3,8,5]) == 5.00`

mode

Value that appears the most in the data

# Descriptive Statistics

## Variance

Measures the spread in the numbers

$$s^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$$

## Standard Deviation, (SD, s, $\sigma$ )

square root of the variance

# Bessel's Correction

Normally only have a sample of data

Computing mean from sample introduces bias

$$s^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$$

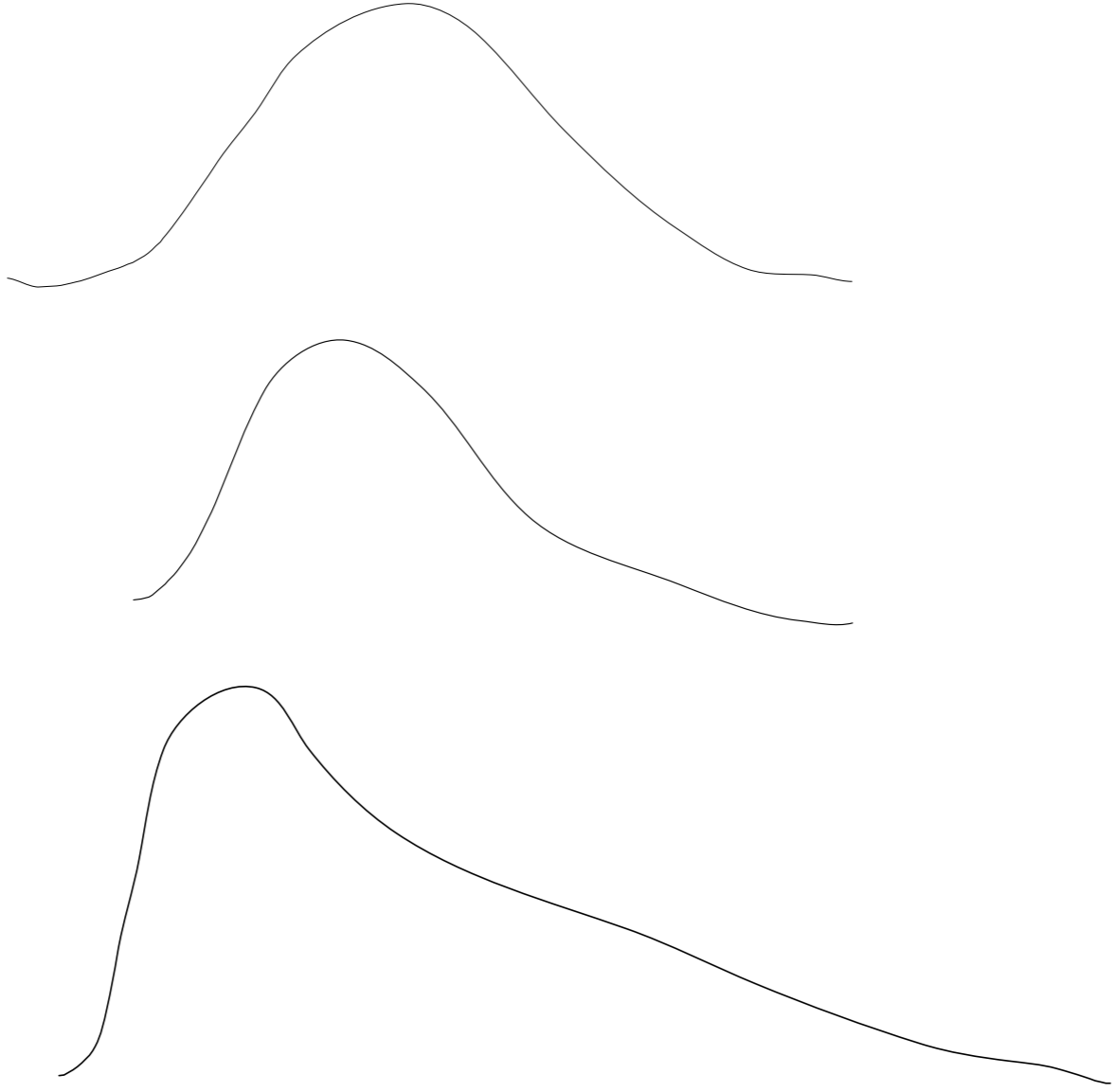
Bessel's correction for this bias

Divide by N-1

For large N this is not needed

$$s^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2.$$

But if underlying distribution is skewed or has long tails (kurtosis) other biases are introduced



# Python functions Use Bessel's correction

```
data = pd.Series([2,4,4,4,5,5,7,9])
```

```
data.var()
```

```
data.std()
```

```
data.mean()
```

```
data.median()
```

```
data.skew()          0.8184875533567997
```

```
pd.Series([1,2,3,4,5,10,20,50,100,1000]).skew()
```

# PySpark

```
from pyspark.sql import SparkSession
import numpy as np
import pandas as ps
spark = SparkSession.builder.getOrCreate()

pdf = ps.DataFrame({'A': np.random.rand(500)})
psdf = spark.createDataFrame(pdf)

import pyspark.sql.functions as F
result_df = (
    psdf
    .select(F.mean('A').alias('mean'),
            F.stddev('A').alias('stddev'),
            F.var_pop('A'),
            F.var_samp('A').alias('variance'))
)
result_df.show()
```



# Me & Bill Gates

mean of mine & Bill Gates net worth = \$39.6 B

variance 3144.2

standard deviation 51.6

mean of Zuckerberg & Carlos Slim net worth = \$52.3 B

variance 11.5

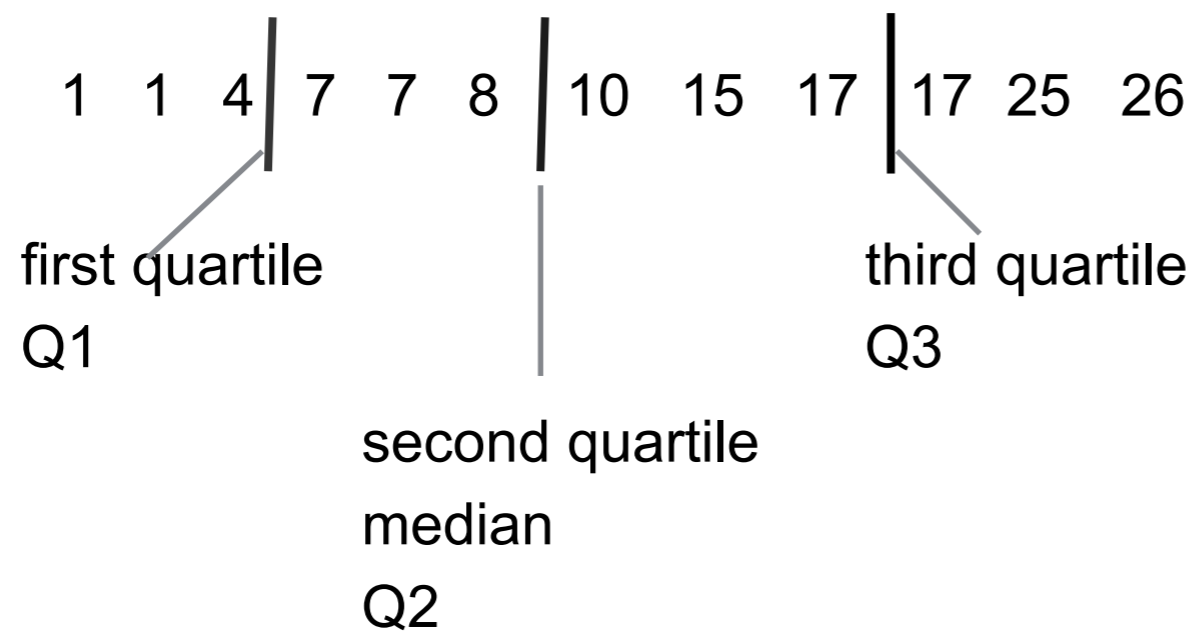
standard deviation 3.39

# Quantiles

q-quantiles

Cutpoints that divide the sorted data into q equal sized groups

4-quantile, quartile



```
pd.Series([1, 1, 4, 7, 7, 8, 10, 15, 17, 17, 25, 26]).quantile([0.25, 0.5, 0.75])
```

```
0.25    6.25
```

```
0.50    9.00
```

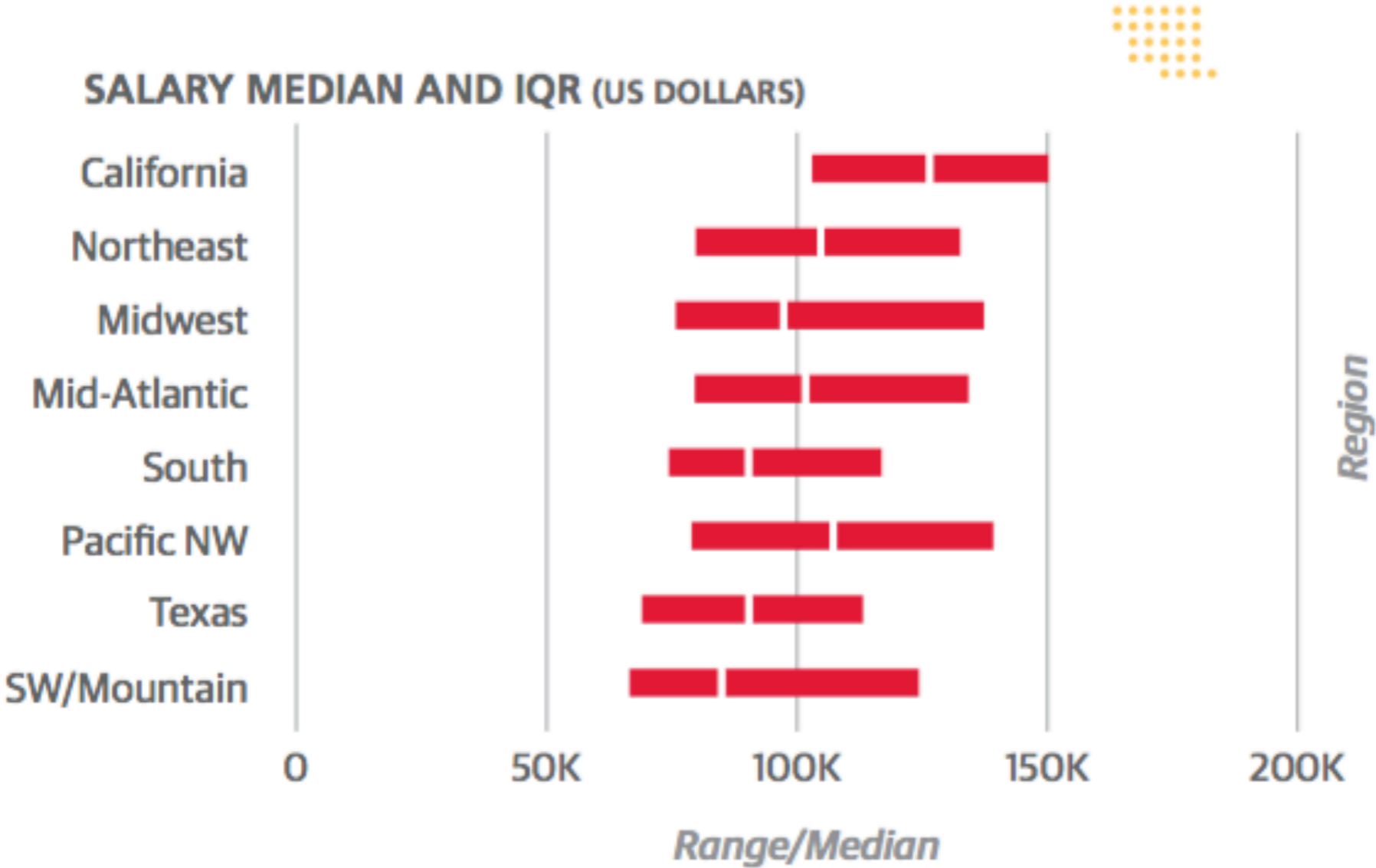
```
0.75   17.00
```

10

```
dtype: float64
```

Red Bar shows middle two quartiles

White bar is median



# 2008-9 Academic Salary

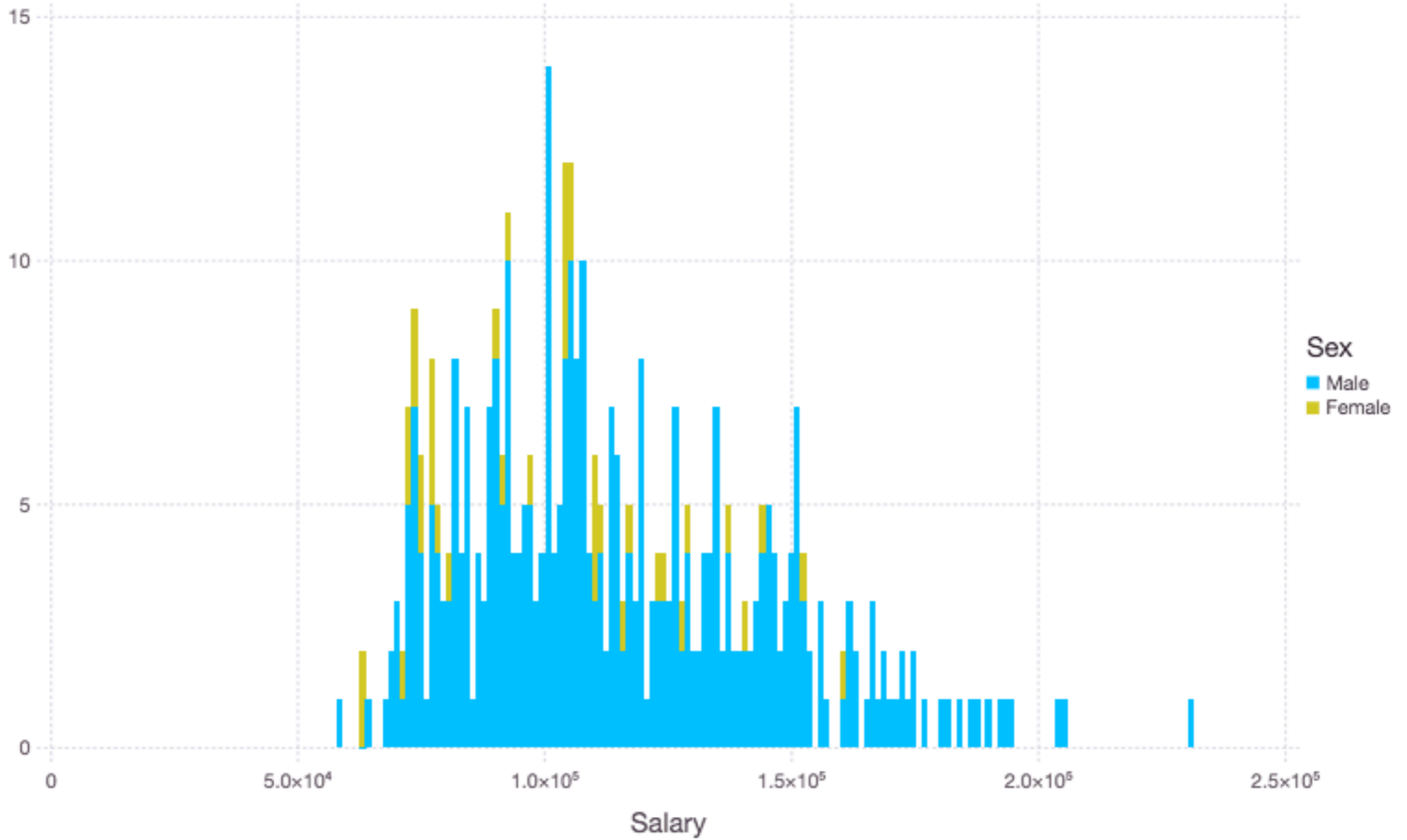
```
salaries_url = "https://vincentarelbundock.github.io/Rdatasets/csv/carData/Salaries.csv"  
salaries = pd.read_csv(salaries_url, index_col=0)
```

	<b>rank</b>	<b>discipline</b>	<b>yrs.since.phd</b>	<b>yrs.service</b>	<b>sex</b>	<b>salary</b>
<b>1</b>	Prof	B	19	18	Male	139750
<b>2</b>	Prof	B	20	16	Male	173200
<b>3</b>	AsstProf	B	4	3	Male	79750
<b>4</b>	Prof	B	45	39	Male	115000
<b>5</b>	Prof	B	40	41	Male	141500

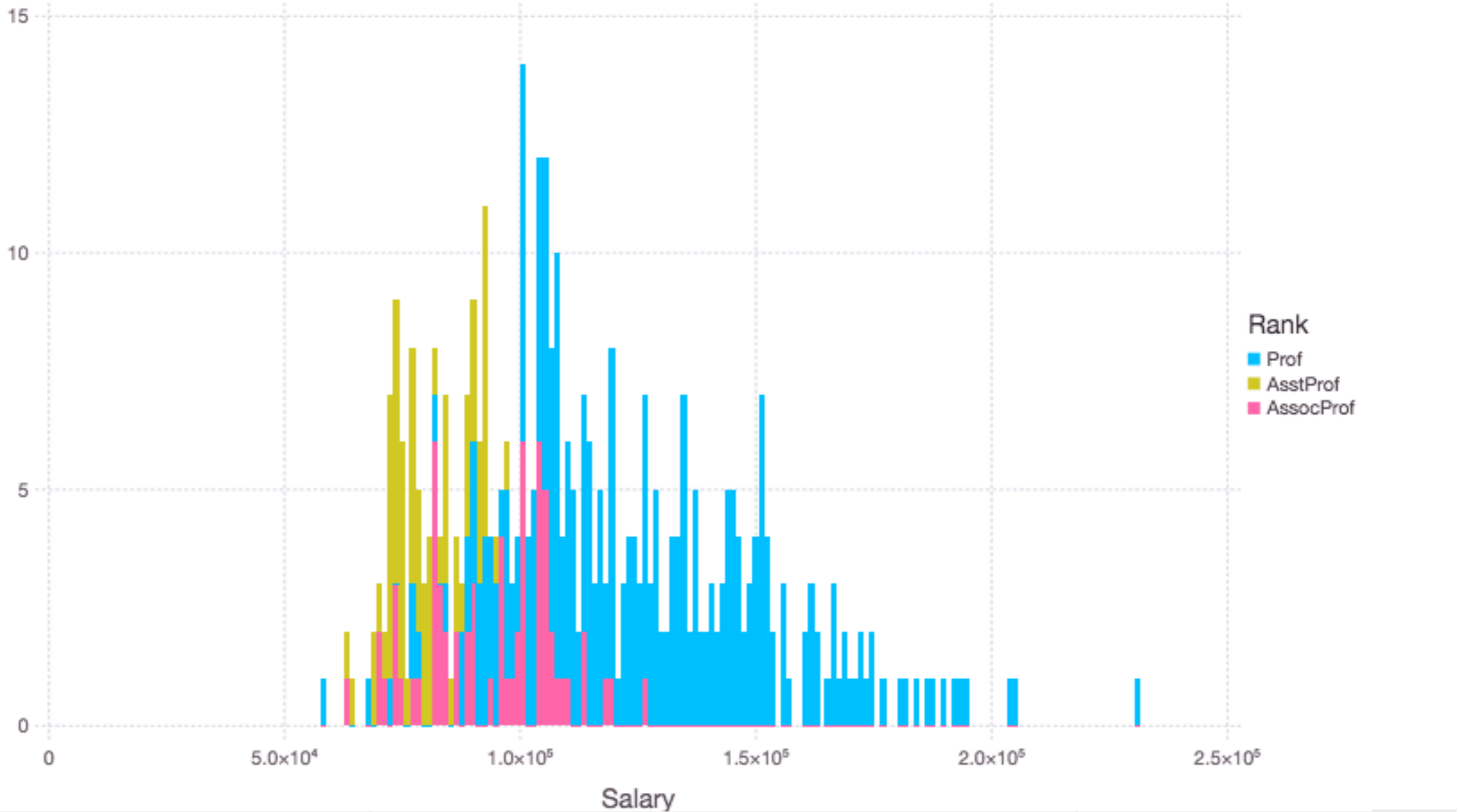
A = Theoretical Department

B = Applied Department

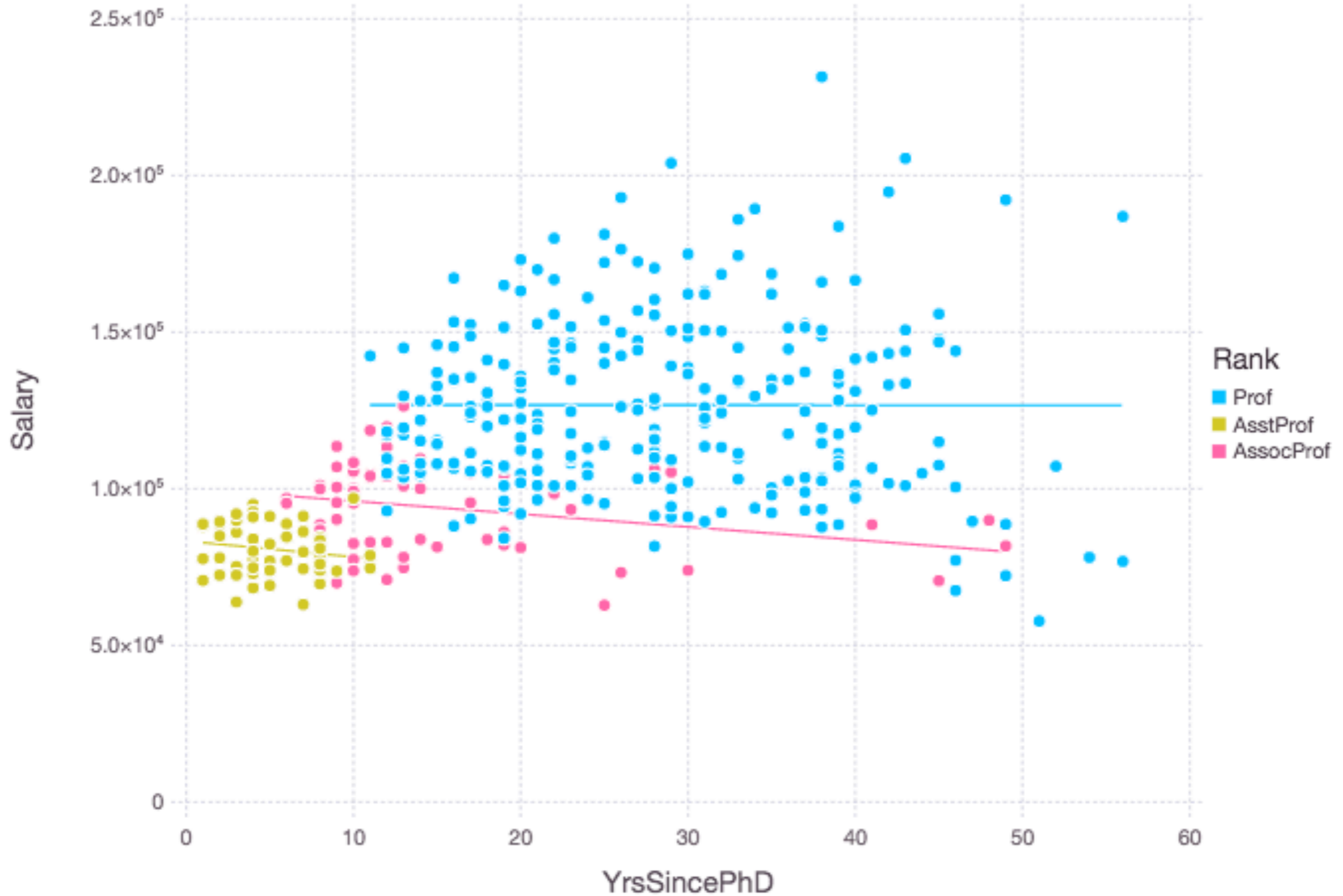
# Salary & Sex



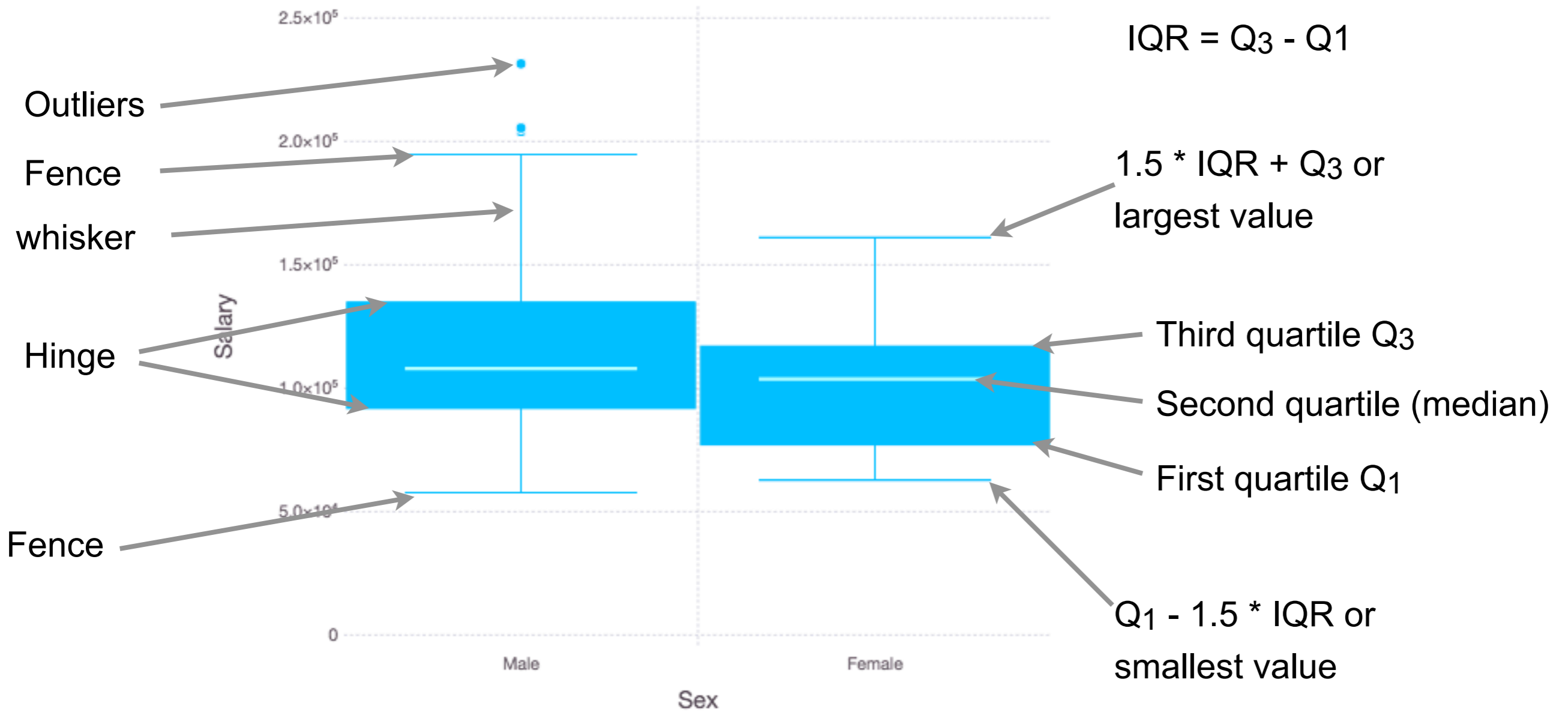
# Salary & Rank



# Scatter Plot: Salary-Years Colored by Rank

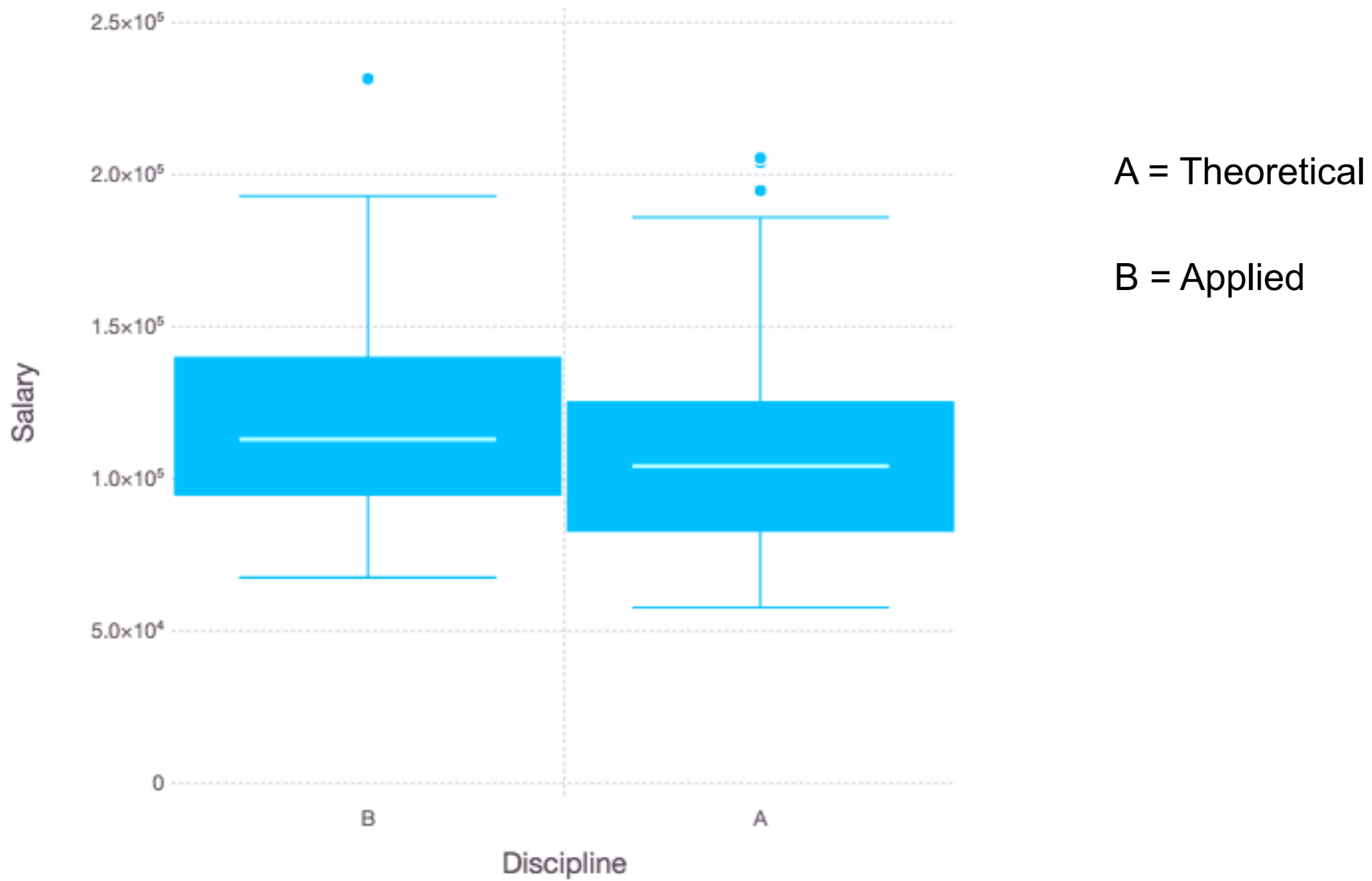


# Box Plots (Tukey Method)

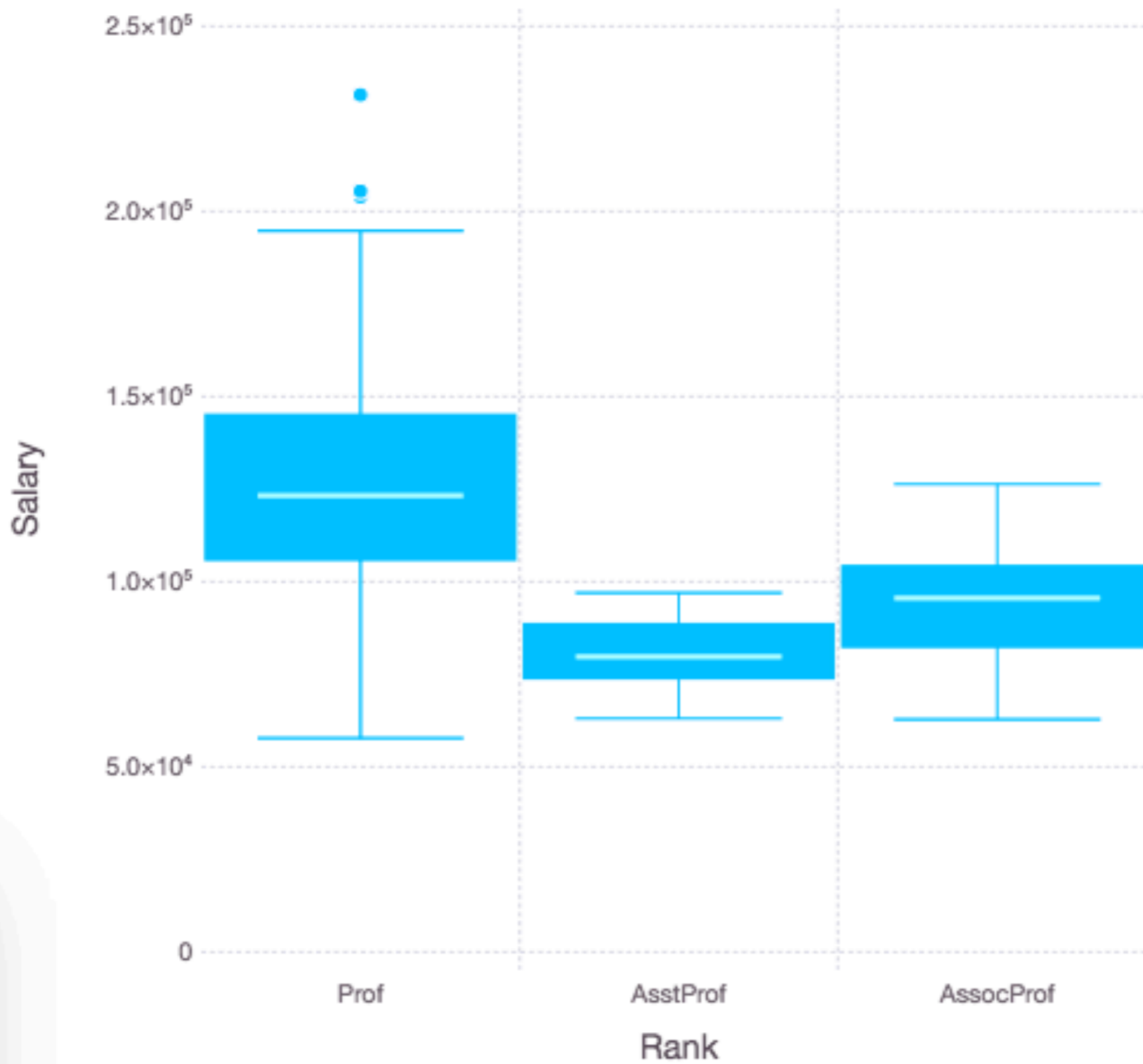




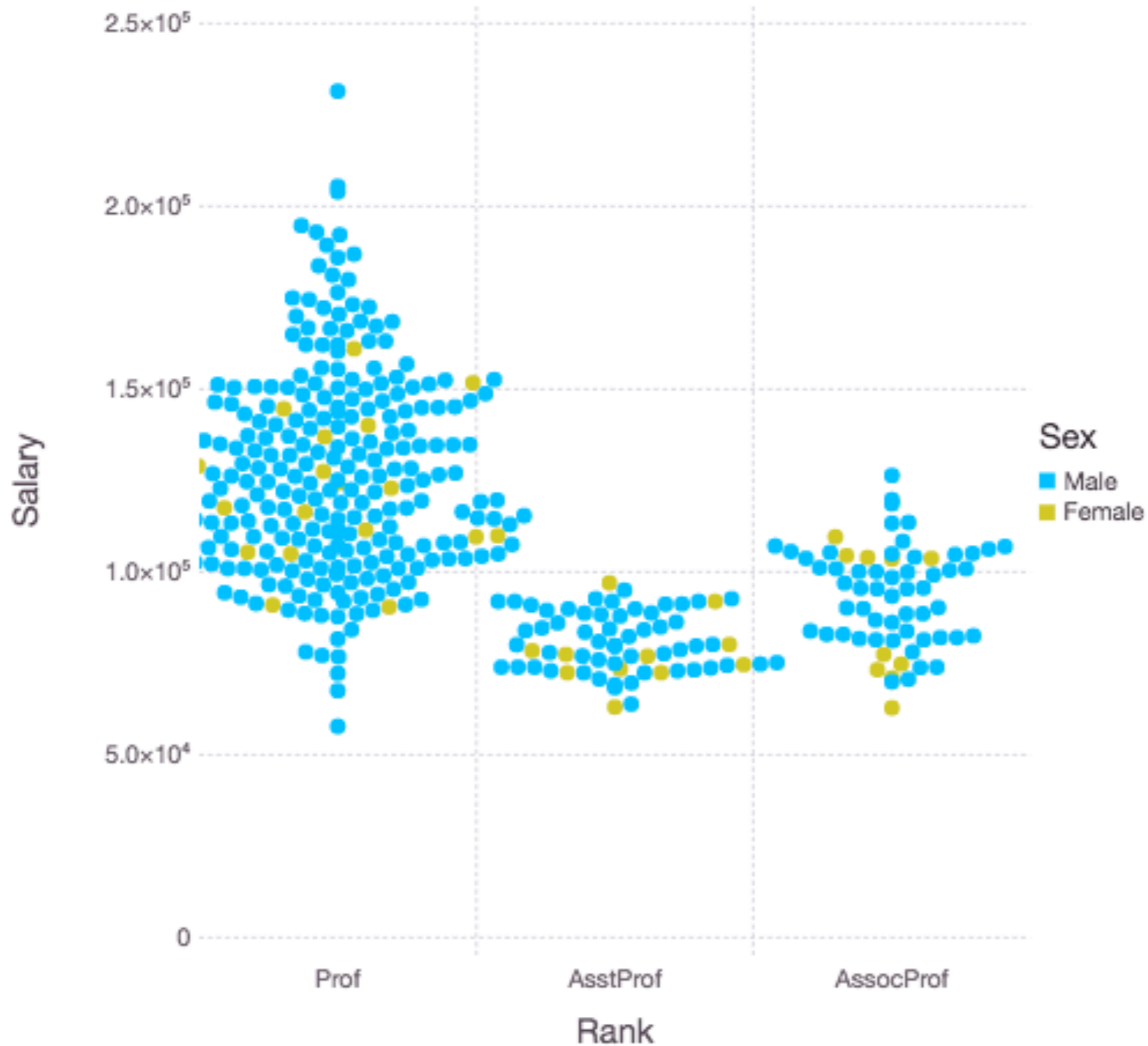
# Salary by Discipline



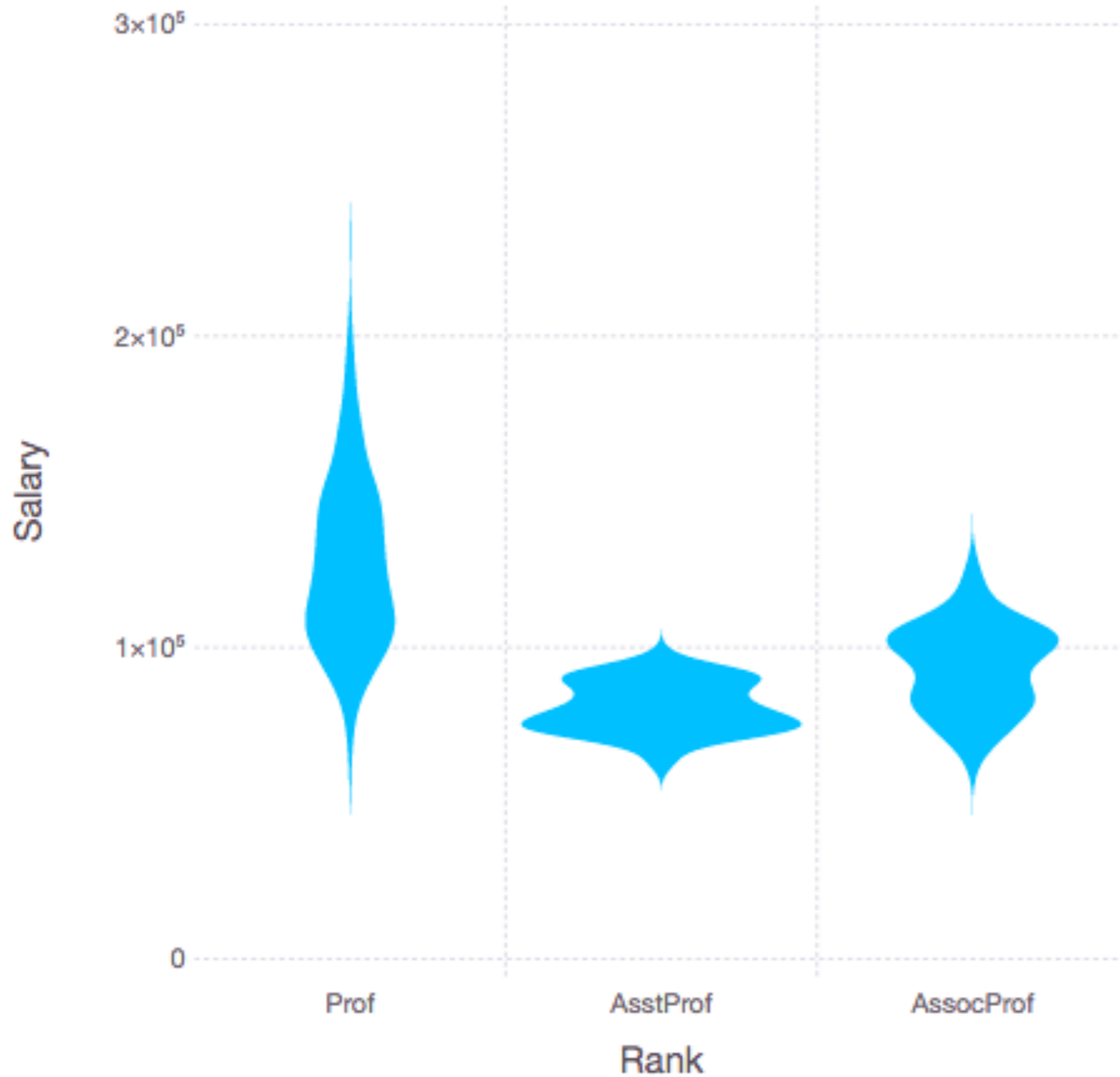
# Salary by Rank



# Beeswarm: Salary by Rank with Sex



# Violin Plot: Salary by Rank



# Distributions

Think in distributions not numbers

## Poincare's Baker

France late 1800's

Bread hand made, regulated

Variation in weight of bread

Poincare suspected baker of cheating

## Dwell Time & A/B Testing of Websites

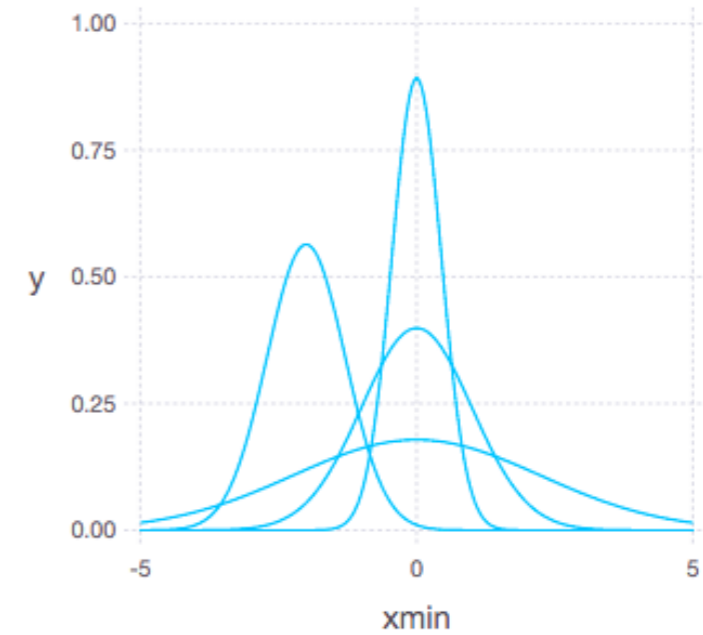
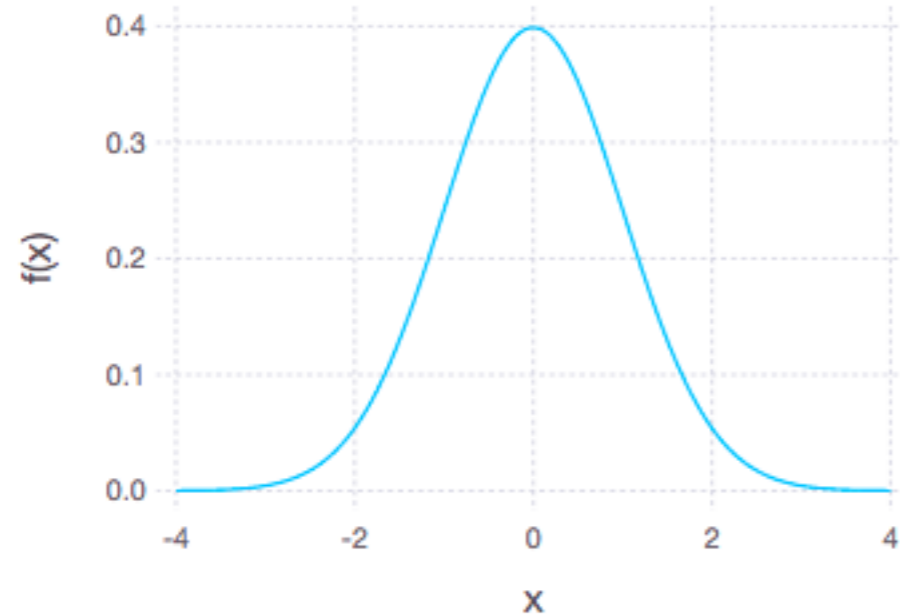
Dwell time - how long people spend on a web page

A/B testing - Showing two versions of a page to different people

How to tell if dwell time differs from between versions

# Normal (Gaussian) Distribution

---

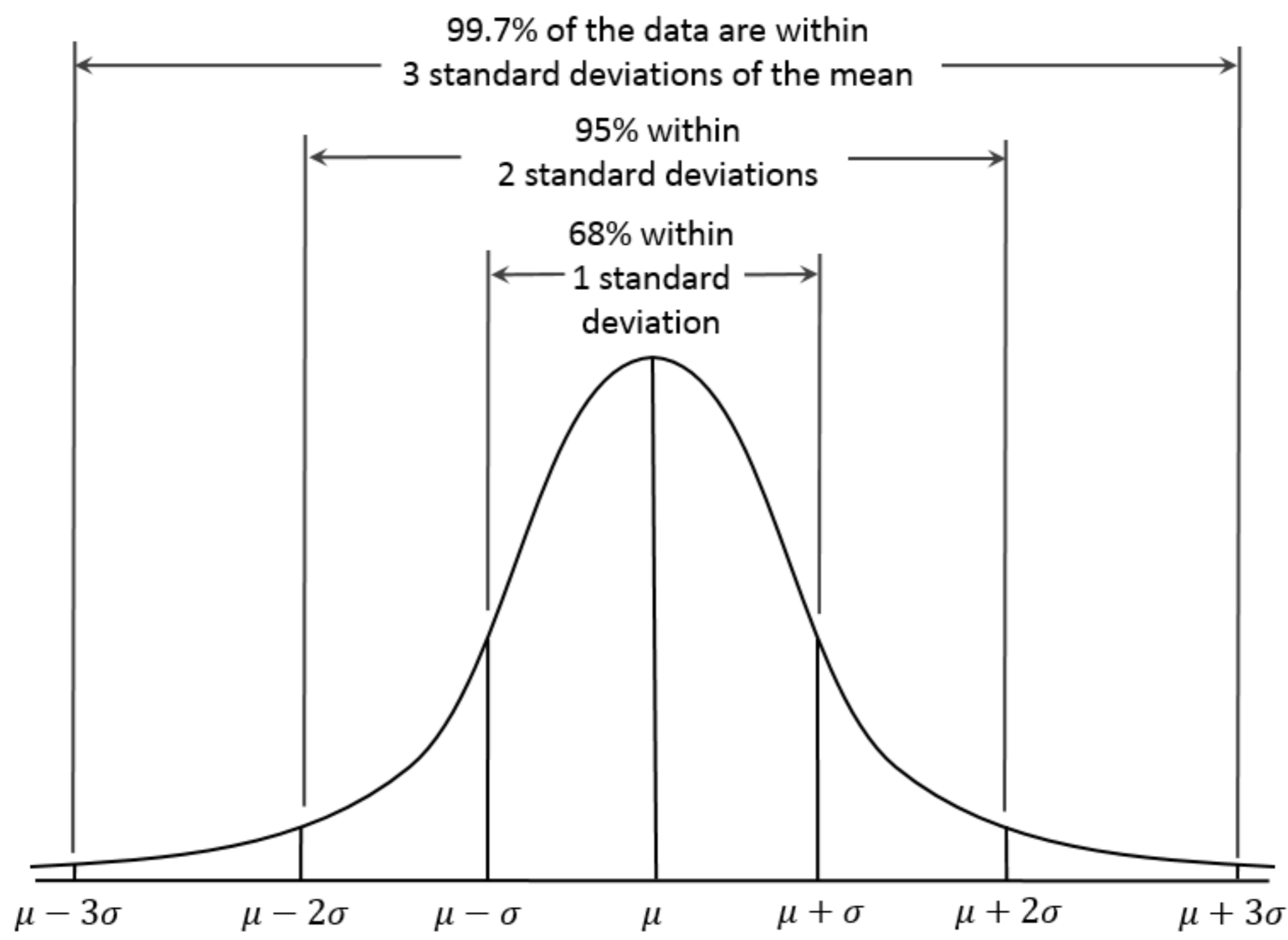


$$f(x | \mu, \sigma^2) = \frac{1}{\sqrt{2\sigma^2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Normal distribution is specified by

$\mu$  - mean, central point

$\sigma$  - standard deviation



# Populations & Samples

Populations - all the items

Sample - set of representative items

*Standard Error of sample =  $\sigma_x/\text{sqrt}(n)$*

*Standard Error of mean (SEM)*

Measure	Sample statistic	Population parameter
Number of items	n	N
Mean	$\bar{x}$	$\mu_x$
Standard deviation	$S_x$	$\sigma_x$
Standard error	$S_{\bar{x}}$	

Standard deviation of the sample-mean estimate of a population mean

Note to decrease the SE by 2 we need to increase the sample size by factor of 4



# Hypothesis Testing

H<sub>0</sub> - Status quo

Null hypothesis

Poincare's Baker bread weight  
is correct

People spend the same amount of  
time on version A and B of the website

alpha - probability that H<sub>1</sub> is false

0.05

0.01

0.001

H<sub>1</sub> - What you are trying to prove

Alternative hypothesis

Poincare's Baker bread weight is  
less than it should be

People spend the more time on  
version A than B of the website

Sample N loaves of bread compute mean  
If probability of that mean occurring from  
properly manufactured bread is less than 0.05  
we accept H<sub>1</sub>

# Types of Errors

False Positive (FP), type I error

Accepting  $H_1$  when it is not true

Smaller alpha values reduce FP

False Negative (FN), type II error

Rejecting  $H_1$  when it is true

Small alphas increase FN

# Causation & Correlation

## Statistics

Does not prove that one thing is caused by another  
Demonstrates that events are rare

If we accept  $H_1$  with  $\alpha = 0.05$

5% chance that  $H_1$  is wrong

If 100 studies accept  $H_1$  with  $\alpha = 0.05$

Expect about 5 of them are false positives

# Bonus Slide

Center For Open Science

<https://cos.io/our-services/research/>

Reproduced 100 published Psychology studies

97 original studies had significant results  $p < .05$

36 reproduced studies had significant results  $p < .05$

47 original effects sizes were in the 95% confidence interval of replication

## Bonus Slide - 2

John P. A. Ioannidis      Why Most Published Research Findings Are False  
PLoS Med. 2005 Aug; 2(8): e124.

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1182327/>

Dr. Russell Schierling

Why Can't We Reproduce Biomedical Research?

<https://bit.ly/2X15u03>

Replication crisis

[https://en.wikipedia.org/wiki/Replication\\_crisis](https://en.wikipedia.org/wiki/Replication_crisis)

primarily affecting parts of the social and life sciences in which scholars have found that the results of many scientific studies are difficult or impossible to replicate or reproduce on subsequent investigation

# Sensitivity & Specificity

Sensitivity

$$\frac{\text{Correctly predicted H}_1 \text{ cases}}{\text{Total number of H}_1 \text{ cases}}$$

Specificity

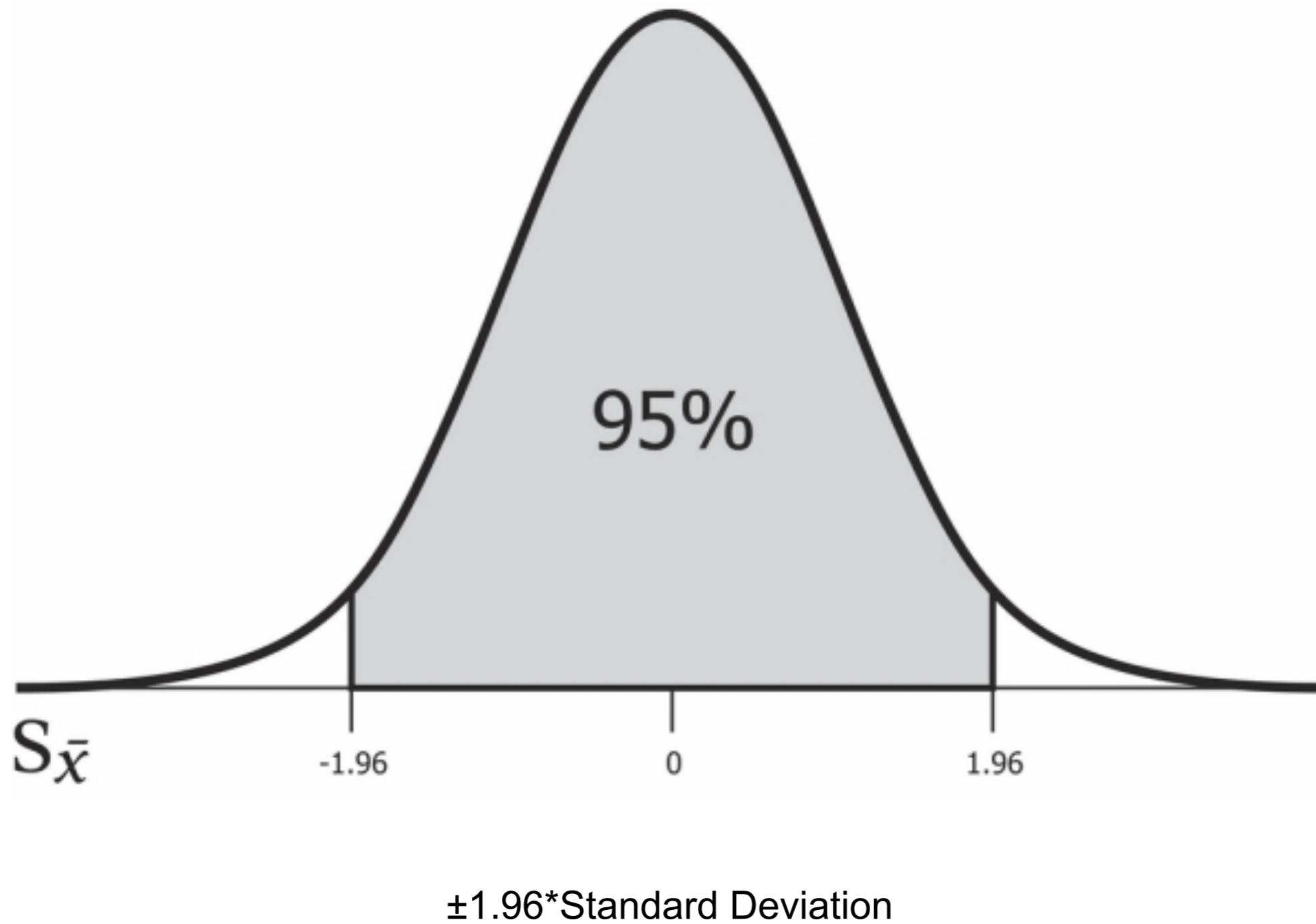
$$\frac{\text{Correctly predicted non-H}_1 \text{ cases}}{\text{Total number of non-H}_1 \text{ cases}}$$

# Confidence Interval

Given a distribution and a  $p$  value

The interval that will contain  $1-p$  of the values

# 95% Confidence, $p = 0.05$





# Poincare's Baker

How to check for Cheating Bakers

Weigh  $N$  samples of bread

Compute confidence interval of the mean of the sample

See if expected mean is in confidence interval

# Poincare's Baker

Assume

Bread weight supposed to be 1000g

Standard deviation of 30g

Baker makes bread 20g lighter

10 Samples

Confidence interval of mean

974.0 990.0

972.5 988.0

966.0 983.0

Random sample

100 items

Mean 1000 - 20

Standard deviation 30

971.2 985.0

972.8 988.0

972.1 988.0

973.3 989.0

Compute the confidence interval for mean

970.5 988.0

971.9 986.0

Repeat 10 times

970.8 986.0

using Distributions

using HypothesisTests

```
d = Normal(980,30)
```

```
fake_sample = rand(d,100)
```

```
(a,b) = ci(OneSampleTTest(fake_sample),0.01)
```

# Poincare's Baker

Assume

Bread weight supposed to be 1000g

Standard deviation of 30g

Baker makes bread 10g lighter

10 Samples

a	b
978.6	995.0
983.2	998.0
983.1	998.0
979.7	997.0
982.7	999.0
986.8	1000.0
983.7	999.0
979.9	995.0
981.3	997.0
984.8	1002.0

Random sample

100 items

Mean 1000 - 10

Standard deviation 30

Compute the confidence interval for mean

Repeat 10 times

using Distributions

using HypothesisTests

```
d = Normal(990,30)
```

```
fake_sample = rand(d,100)
```

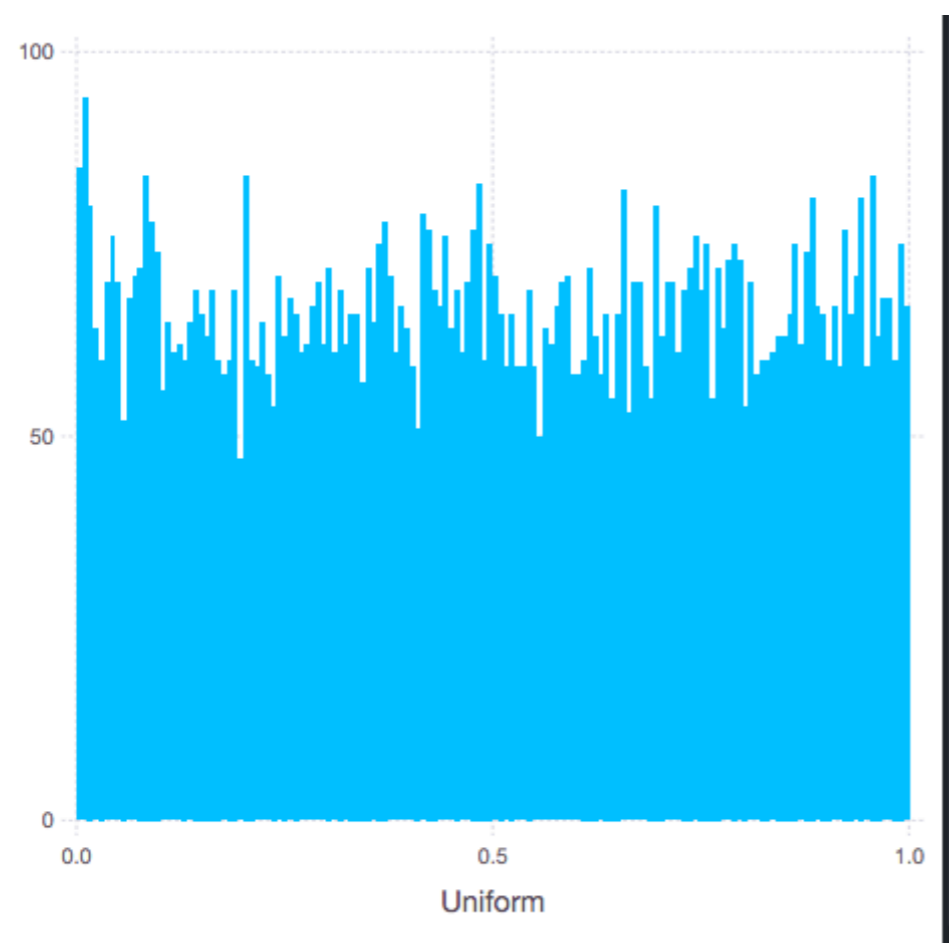
```
(a,b) = ci(OneSampleTTest(fake_sample),0.01)
```

# Central Limit Theorem

Plot 10\_000 random integers

Between 0 and 1

Bin the results



# Central Limit Theorem

Let

$X_1, X_2, \dots, X_N$  random sample

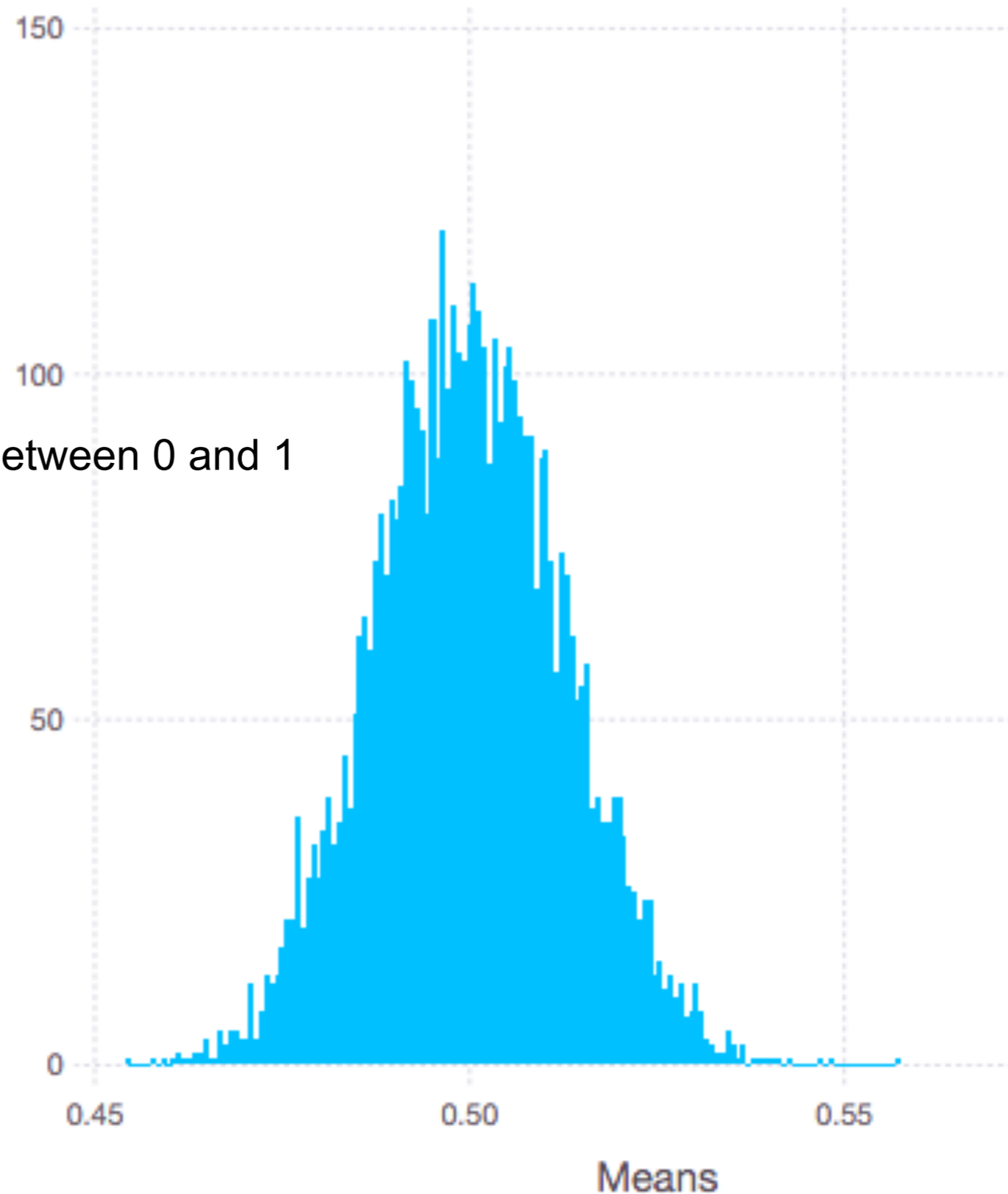
$$S_N = (X_1 + \dots + X_N)/N$$

Then as  $N$  gets large  $S_N$  approximates the normal distribution

Compute the mean of 500 random numbers between 0 and 1

Repeat 5000 times

Plot the sums



# Poincare's Baker - Part Two

After being fined the baker still cheated

But always gave Poincare the heaviest loaf

Poincare still caught him!

# Dwell Times on Web sites

Look at Dwell data of website

Don't know the distribution of the dwell times

But daily mean of dwell times will be normally distributed

# Dwell Data

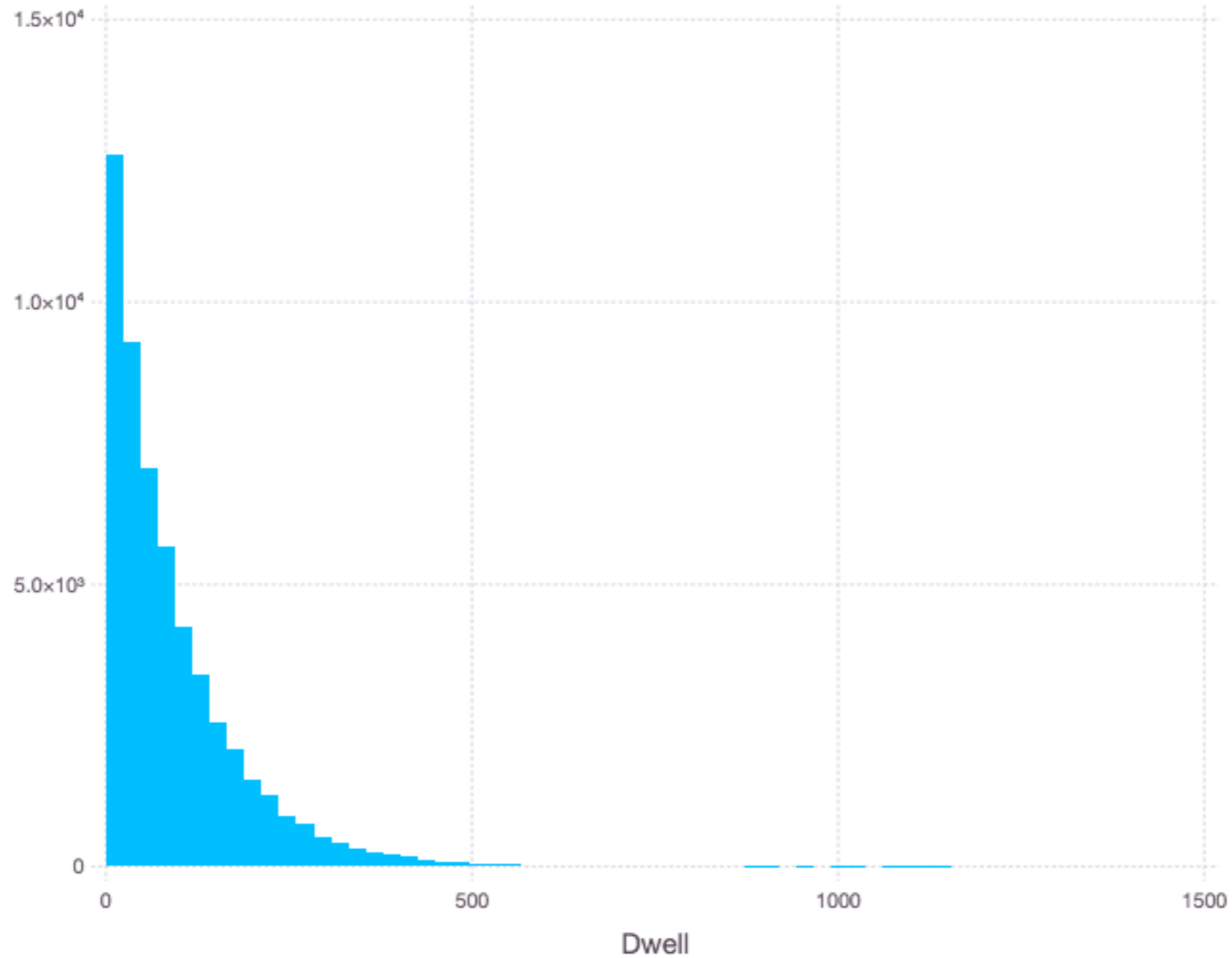
54000x2 DataFrames.DataFrame

Row	date	Dwell
1	"2015-01-01T00:03:43Z"	74
2	"2015-01-01T00:32:12Z"	109
3	"2015-01-01T01:52:18Z"	88
4	"2015-01-01T01:54:30Z"	17

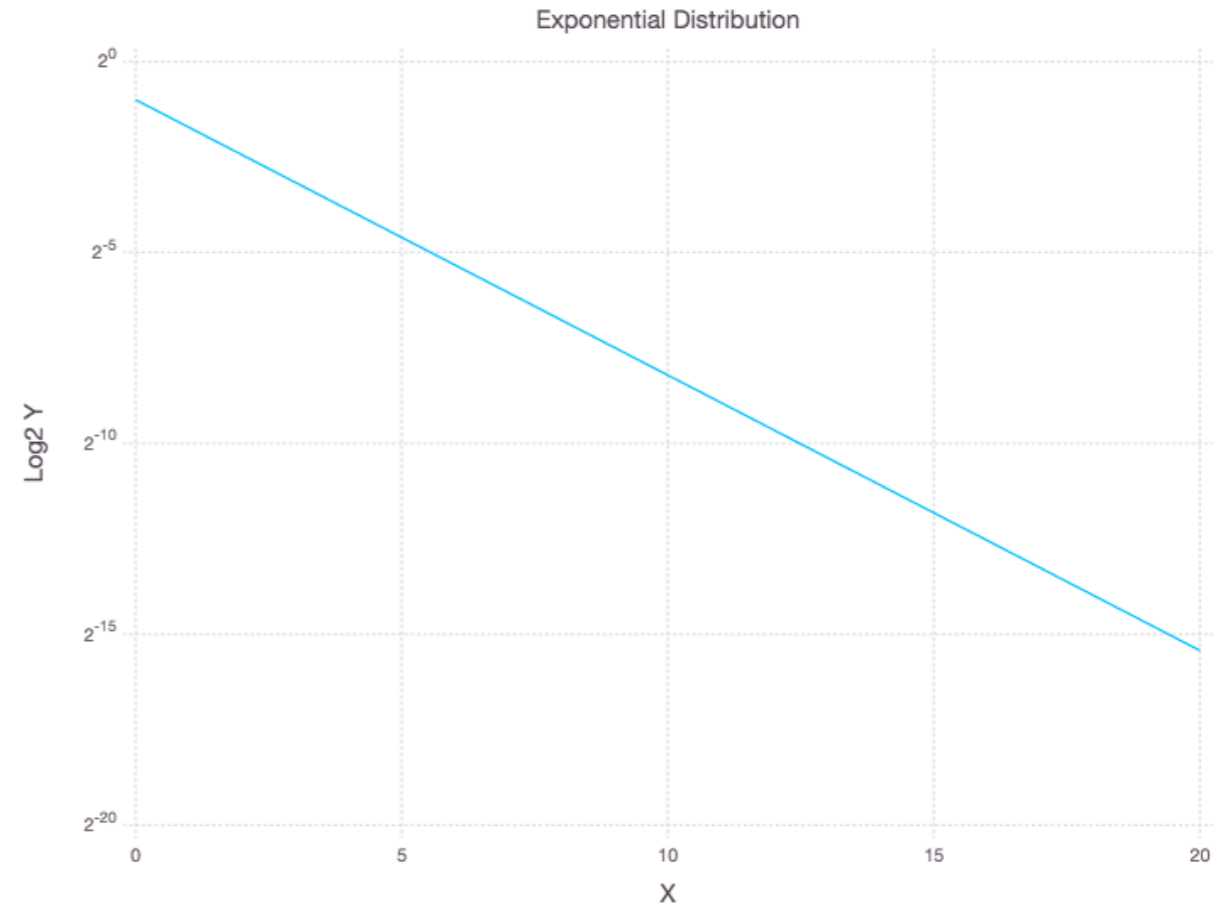
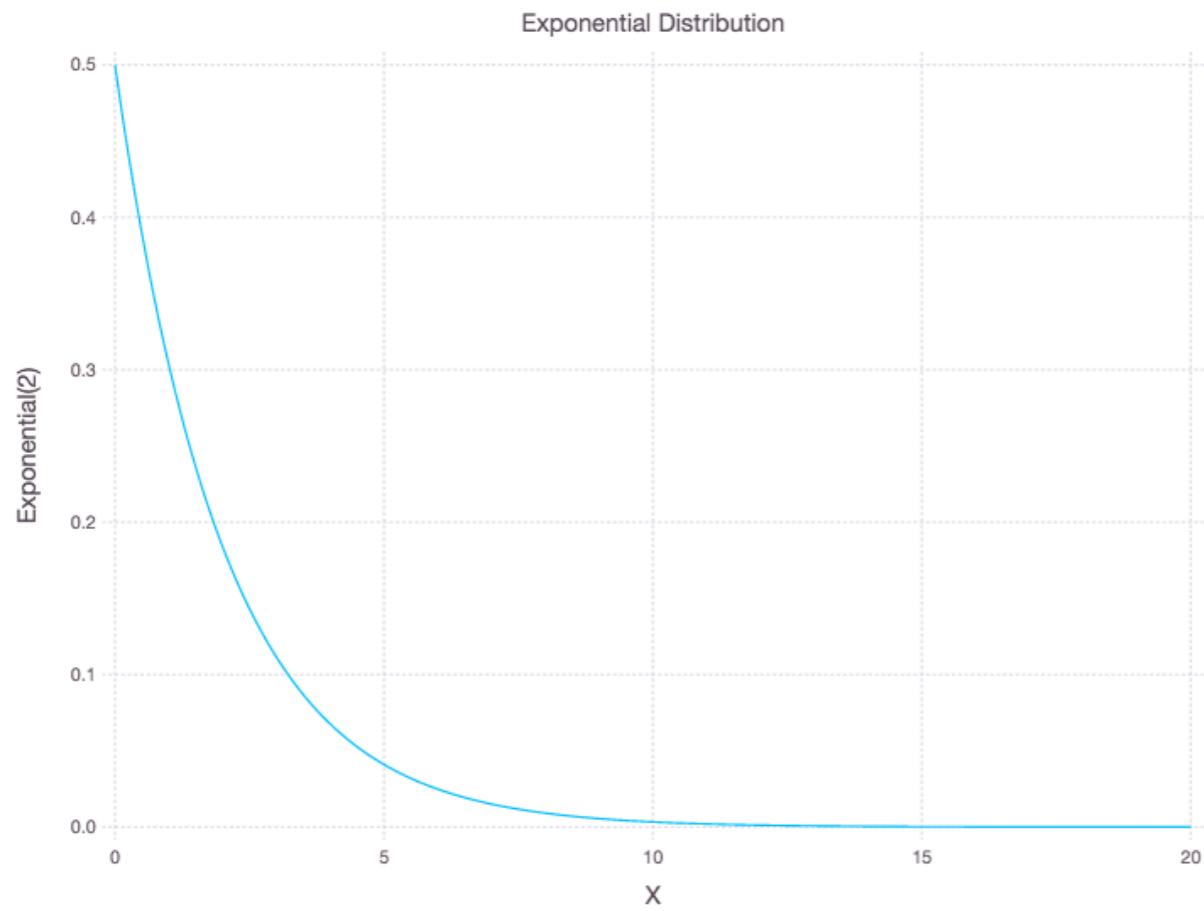


# Dwell Times

Divide the range of data into 50 equal bins  
Plot the number of items in each bin



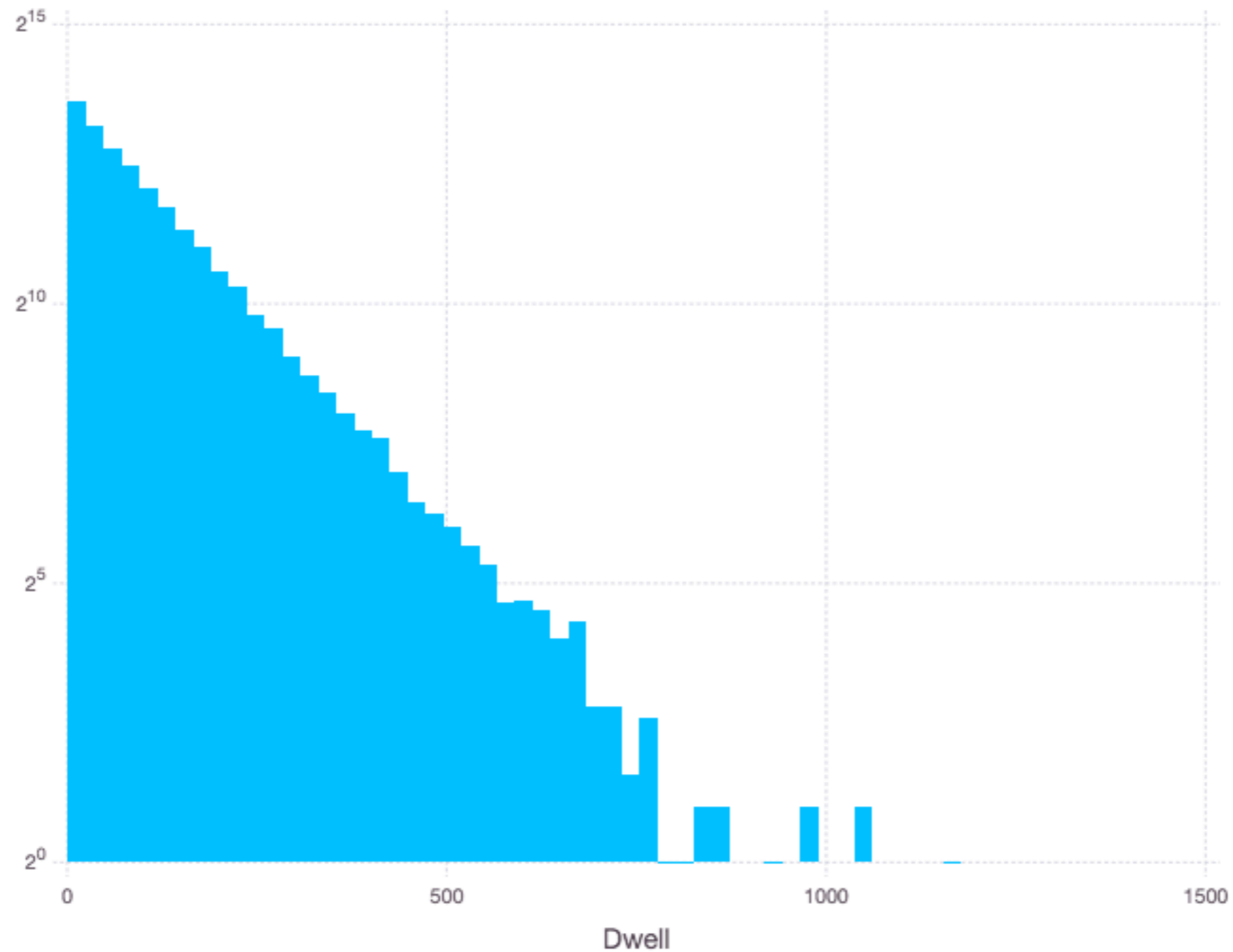
# Exponential Distribution



$Log_2(Y)$

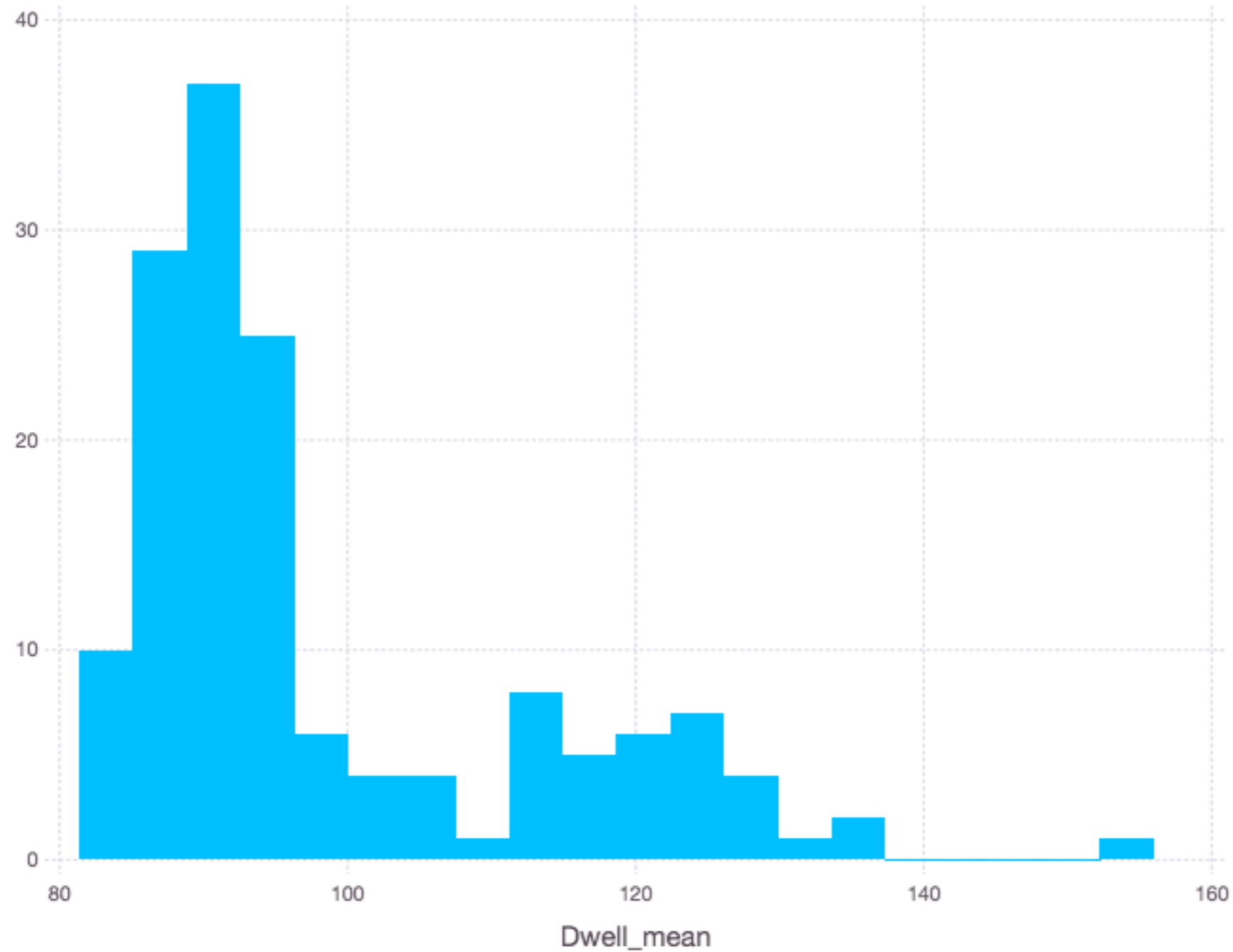
# Log Scale - So Dwell Time is Exponential Dist.

```
plot(dwell_times, x="Dwell", Geom.histogram(bincount = 50), Scale.y_log2)
```

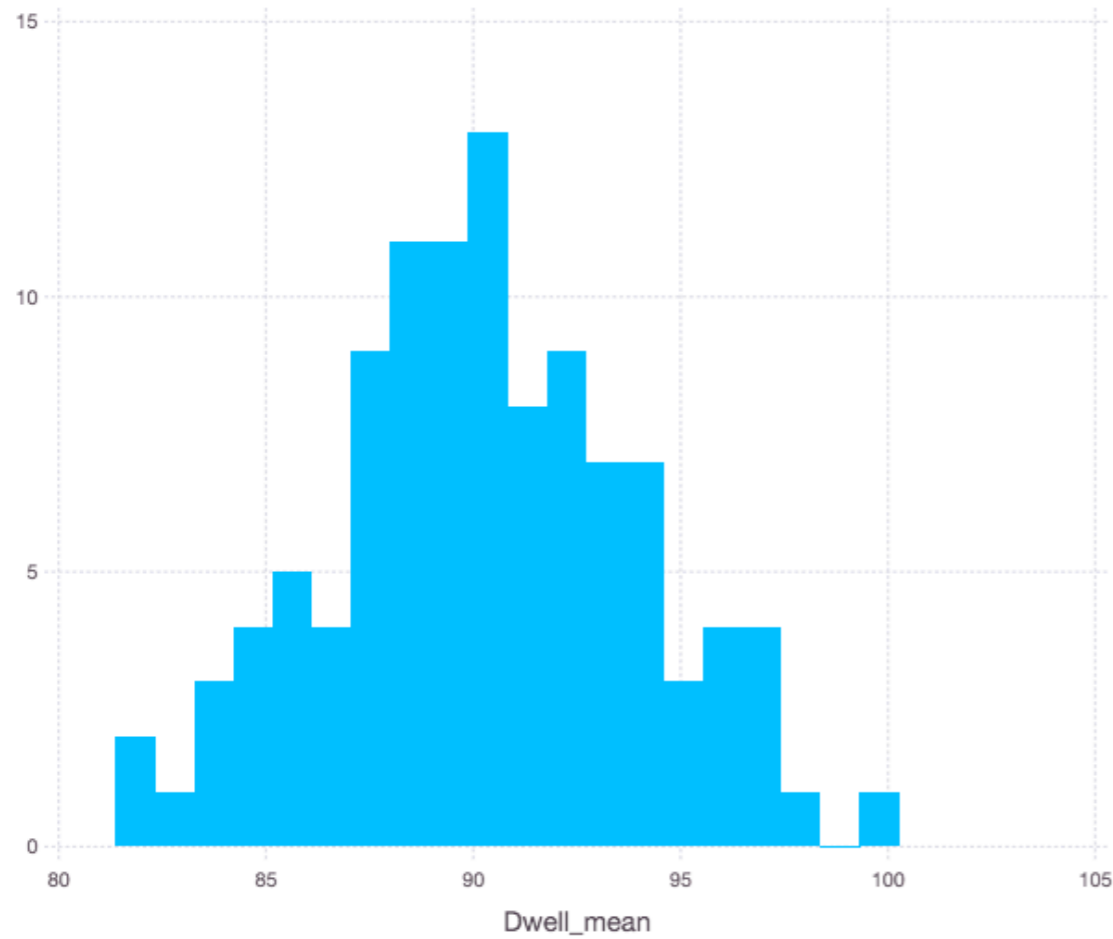


# Compute Daily Mean Dwell Time

```
plot(daily_dwll, x="Dwell_mean", Geom.histogram(bincount=20))
```



## Week Days



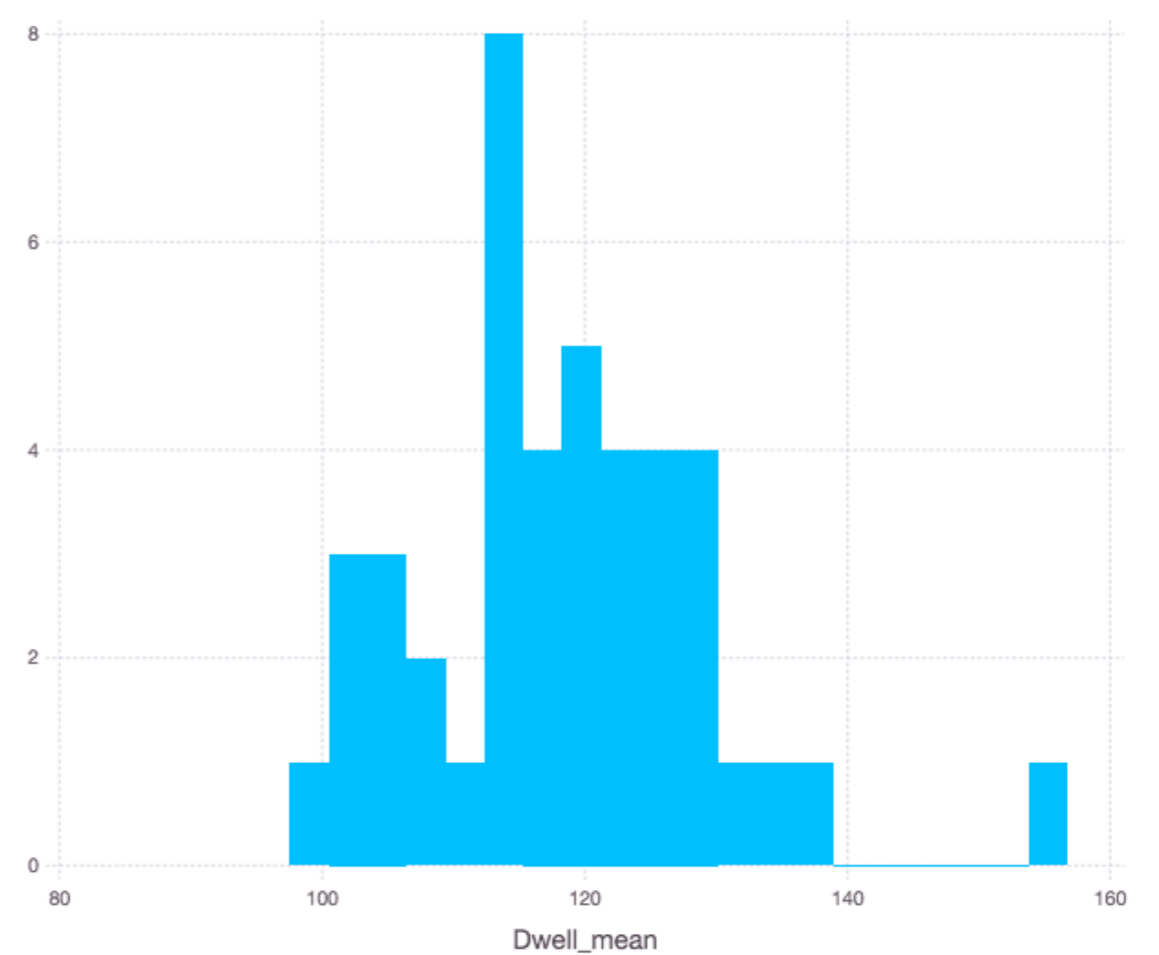
sample size = 107

mean = 90.2

std = 3.7

CI of mean  $p = 0.05$  (115,122)

## Weekends



sample size = 107

mean = 118.3

std = 11.0

CI of mean  $p = 0.05$  (89.5 ,90.9)

# Sampling - Motivation

How to find mean and median of 1 Billion values?

Web browser wants to warn user when they request a known malicious website

Could be millions of malicious websites

Don't want to check server for each URL

Web Crawler

Visit page A

Extract all links from page A

Repeat process on all links from page A

How to know if you have already visited a page?

Google indexes ~45 Billion web pages

# Populations & Samples

Populations - all the items

Sample - set of representative items

*Standard Error of sample =  $\sigma_x/\text{sqrt}(n)$*

*Standard Error of mean (SEM)*

Measure	Sample statistic	Population parameter
Number of items	n	N
Mean	$\bar{x}$	$\mu_x$
Standard deviation	$S_x$	$\sigma_x$
Standard error	$S_{\bar{x}}$	

Standard deviation of the sample-mean estimate of a population mean

Note to decrease the SE by 2 we need to increase the sample size by factor of 4

# Sampling

100,000 data points

Compute the average

Take random sample of 1000 compute average

How close will sample average be to actual average?

Let  $\bar{s}$  = average of the sample

$n$  = sample size = 1000

Standard Error = standard deviation =  $s/\sqrt{n}$



# Sampling

Let  $\bar{s}$  = average of the sample

$n$  = sample size = 1000

Standard Error = standard deviation =  $s/\sqrt{n}$

Confidence Interval  $(\bar{s} - z*s/\sqrt{n}, \bar{s} + z*s/\sqrt{n})$

Width of confidence interval =  $\bar{s} + z*s/\sqrt{n} - (\bar{s} - z*s/\sqrt{n})$   
=  $\bar{s} + z*s/\sqrt{n} - \bar{s} + z*s/\sqrt{n}$   
=  $z*s/\sqrt{n} + z*s/\sqrt{n}$   
=  $2z*s/\sqrt{n}$

# Sampling

Confidence Interval  $(s - z*s/\sqrt{n}, s + z*s/\sqrt{n})$

Experiment

100,000 random integer between 0 and 1000

Sample size 1,000

Sample mean ( $s$ ) = 532.33

Confidence Interval at 95% = (499.3, 565.3)

Actual mean = 501.4

# What if we want sample to be within 10?

Width of confidence interval =  $W = 2z*s/\text{sqrt}(n)$

$$\begin{aligned}n &= 4z^2s^2/W^2 \\ &= 4 * 1.96^2 * 501.4^2/10^2 \\ &\approx 39000\end{aligned}$$

Mean of samples of size 39000

502.37	Population mean
500.795	
503.108	501.4
502.488	
499.351	
499.907	
500.791	
501.248	
501.814	
501.707	
⋮	
504.143	
500.595	

---

# Bloom Filter

Burton Bloom - 1970

Space-efficient probabilistic data structure

Test whether an element is in a set

Bloom filter does not contain the elements in the set

False positive matches are possible

Possibly in set

False negatives are not possible

Definitely not in set

# Types of Errors

False Positive (FP), type I error

Accepting a statement as true when it is not true

False Negative (FN), type II error

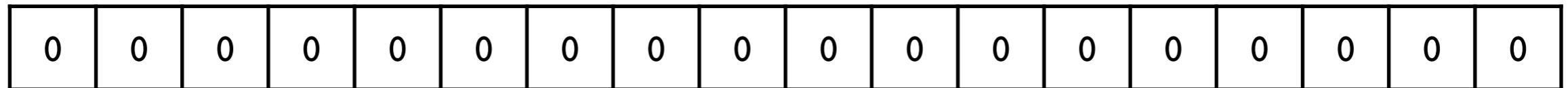
Accepting a statement as false when it is true

# Bloom Filter - How it works

Empty Bloom filter

m bits all 0

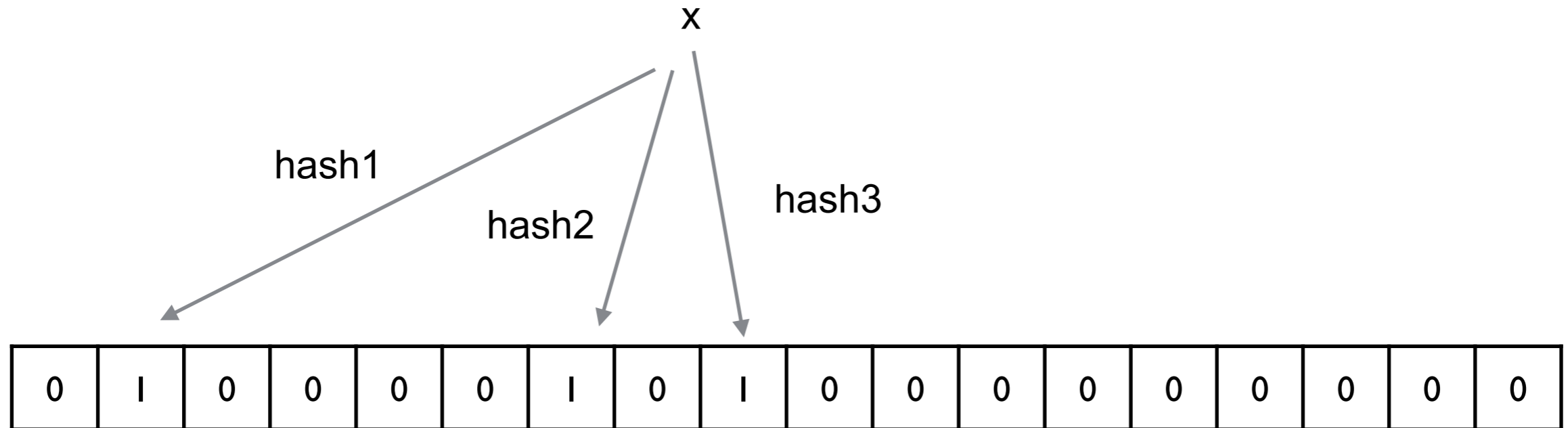
k different hash functions



# Bloom Filter - How it works

$m = 18$   
 $k = 3$

Insert x



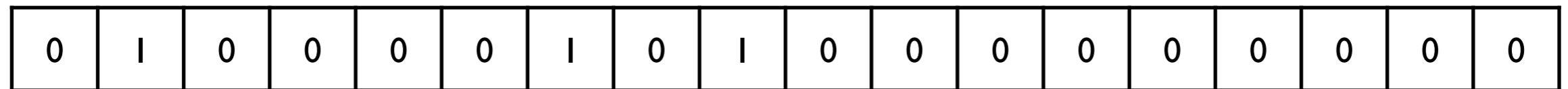
# Bloom Filter - How it works

$m = 18$

$k = 3$

Contains  $y$ ?

$\{x\}$



Does not contain  $y$

$y$



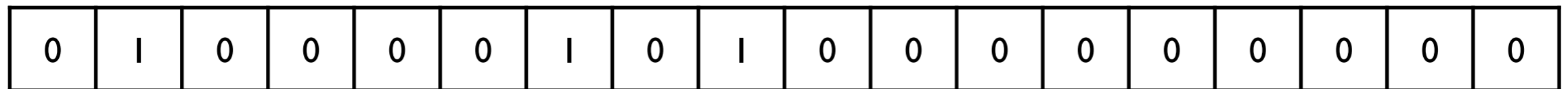
# Bloom Filter - How it works

$m = 18$

$k = 3$

Contains  $x$ ?

$\{x\}$



Possibly as all hash locations are 1

$x$

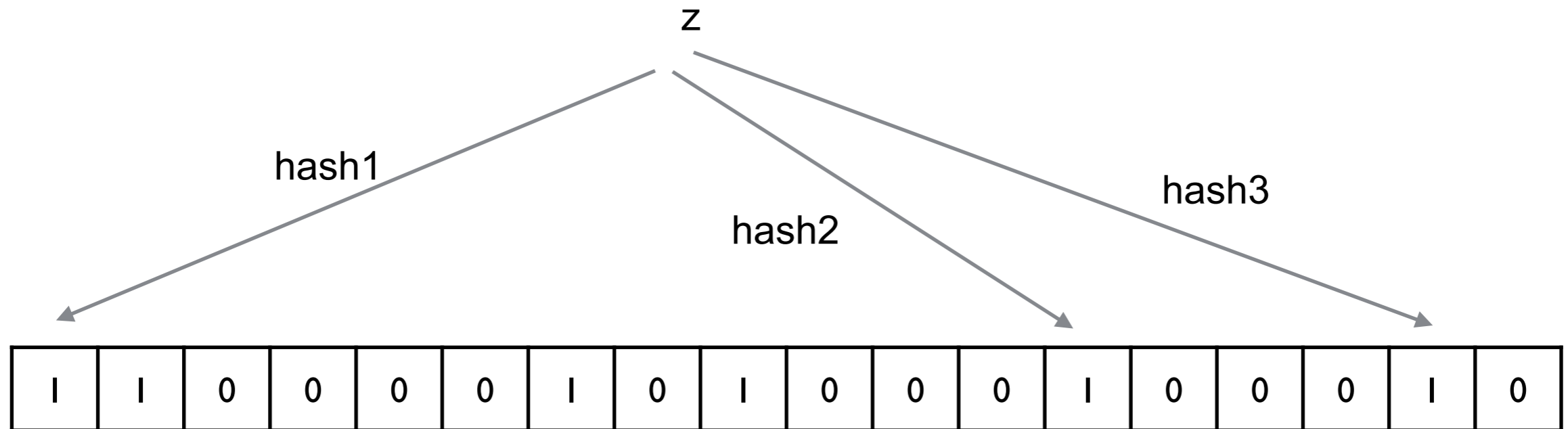
# Bloom Filter - How it works

$m = 18$

$k = 3$

Insert z

{x}



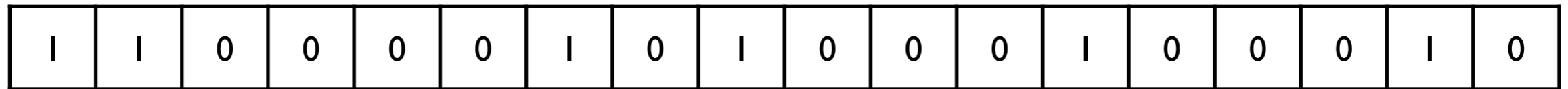
# Bloom Filter - How it works

$m = 18$

$k = 3$

Contains  $y$ ?

$\{x, z\}$



Might contain  $y$

Two hash functions had same value as  $x$

One hash function had same value of  $z$

$y$

# Bloom Filter - How it works

Larger  $m$

- Decreases false positives

- Increases table size - fewer collisions

Larger  $k$

- Decreases false positives up to a point

- But fills table faster

# Bloom filter for Scala

<https://github.com/alexandrnikitin/bloom-filter-scala>

```
// Create a Bloom filter
val expectedElements = 1000000
val falsePositiveRate = 0.1
val bf = BloomFilter[String](expectedElements, falsePositiveRate)

// Put an element
bf.add(element)

// Check whether an element in a set
bf.mightContain(element)

// Dispose the instance
bf.dispose()
```

# Bloom Filter - Sample Uses

## Akamai's web servers

- Some pages are only accessed once - One-hit-wonders

- Only cache web page after second time it is accessed

- Use bloom filter to determine if page has been seen before

## Google BigTable, Apache HBase and Apache Cassandra, and Postgresql

- Use Bloom filters to see if rows or columns exist

- Avoid costly disk access on nonexistent rows

## Google Chrome web browser

- Use Bloom filter to identify malicious URLs

- If filter contains the url then check server to make sure

## Medium

- Uses Bloom filters to avoid recommending articles a user has previously read

# Heavy Hitters Problem

Streaming  
Real time

Computing popular products

Given the page views on Amazon which products are viewed the most?

Computing frequent search queries

Given the stream of Google searches what are the popular searches  
3.5 billion searches per day

View Tweets

How often are tweets viewed? What the most popular tweets?

Heavy Network flows

Given packet count source and destination through switch

Where is the traffic the heaviest?

Cisco Nexus 9500 - 172.8 Tbps

Useful to detect DoS attacks

Volatile Stocks

Given stream of stock transactions which stocks are

Traded the most

Change prices the most

# Count-Min Sketch

Graham Cormode and S. Muthu Muthukrishnan - 2003

Consume a stream of events

Count the frequency of the different types of events in the stream

Does not store the events

Counts for each event type

- Estimate of actual count

- Within given range of actual count with given probability



# Count-Min Sketch - How it works

Initial count-min sketch

w - columns

d - rows

d different hash functions

All entries integers = 0

w determines

Interval length containing actual count

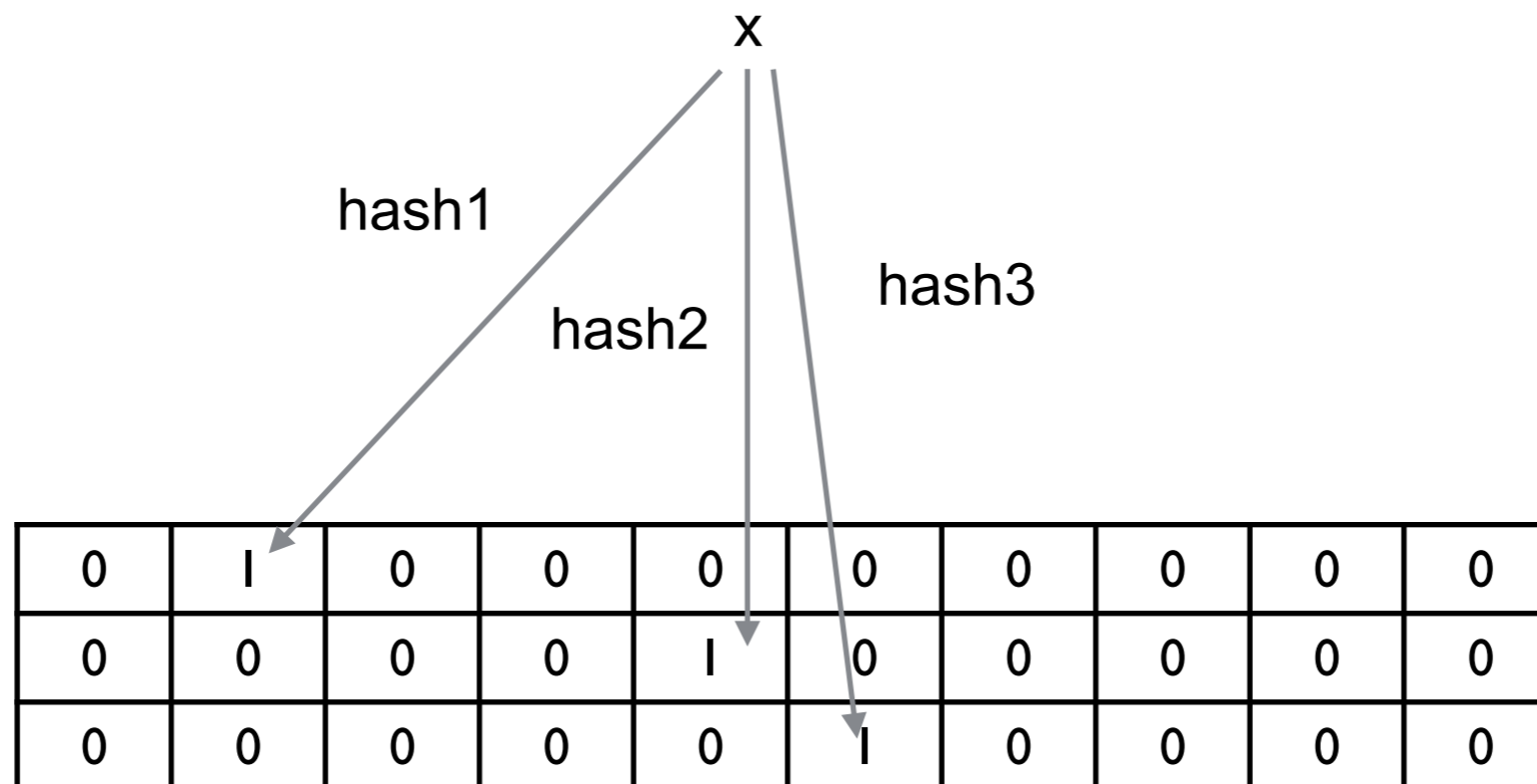
d determines

Probability that actual count is in interval

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

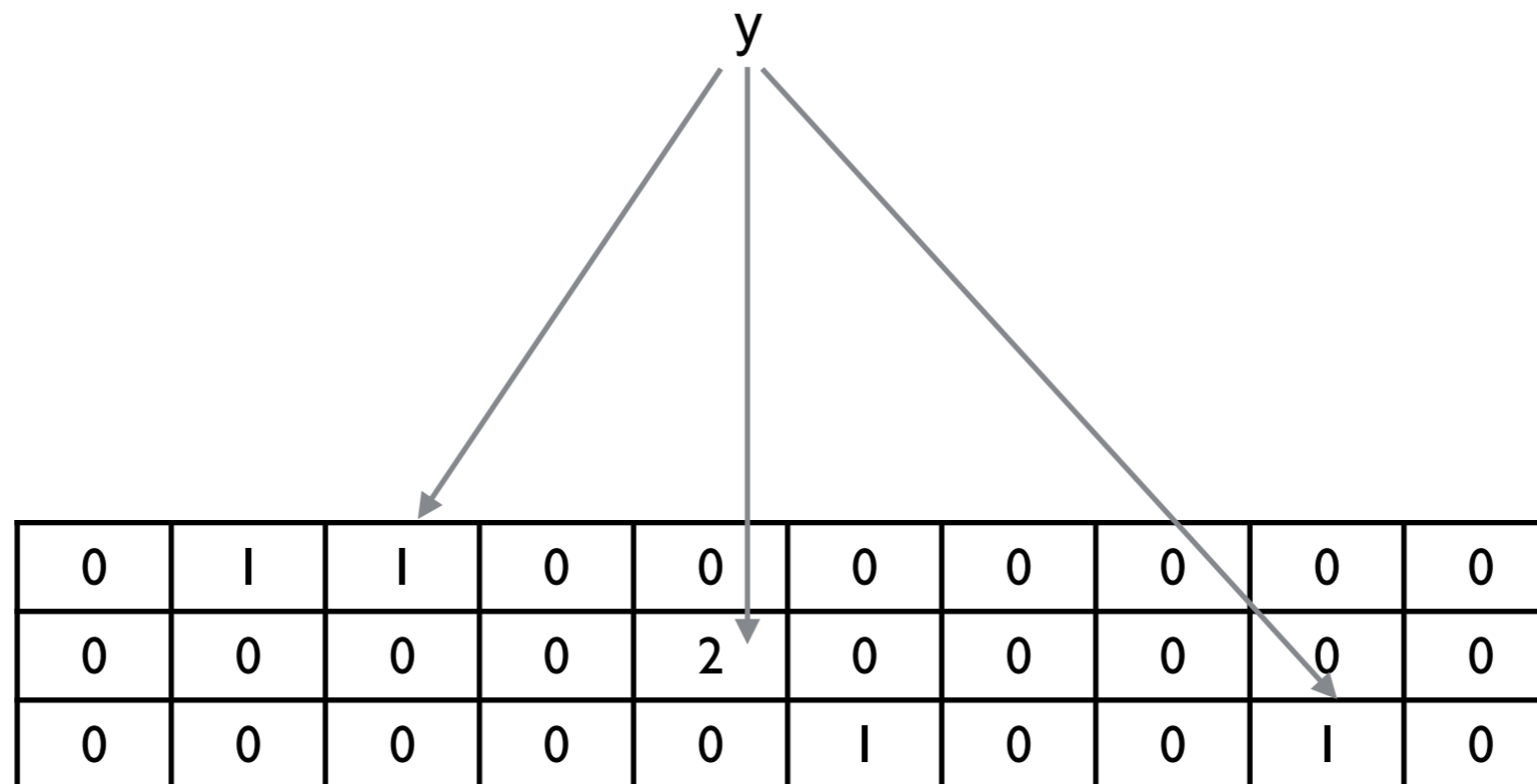
# Count-Min Sketch - How it works

Event x



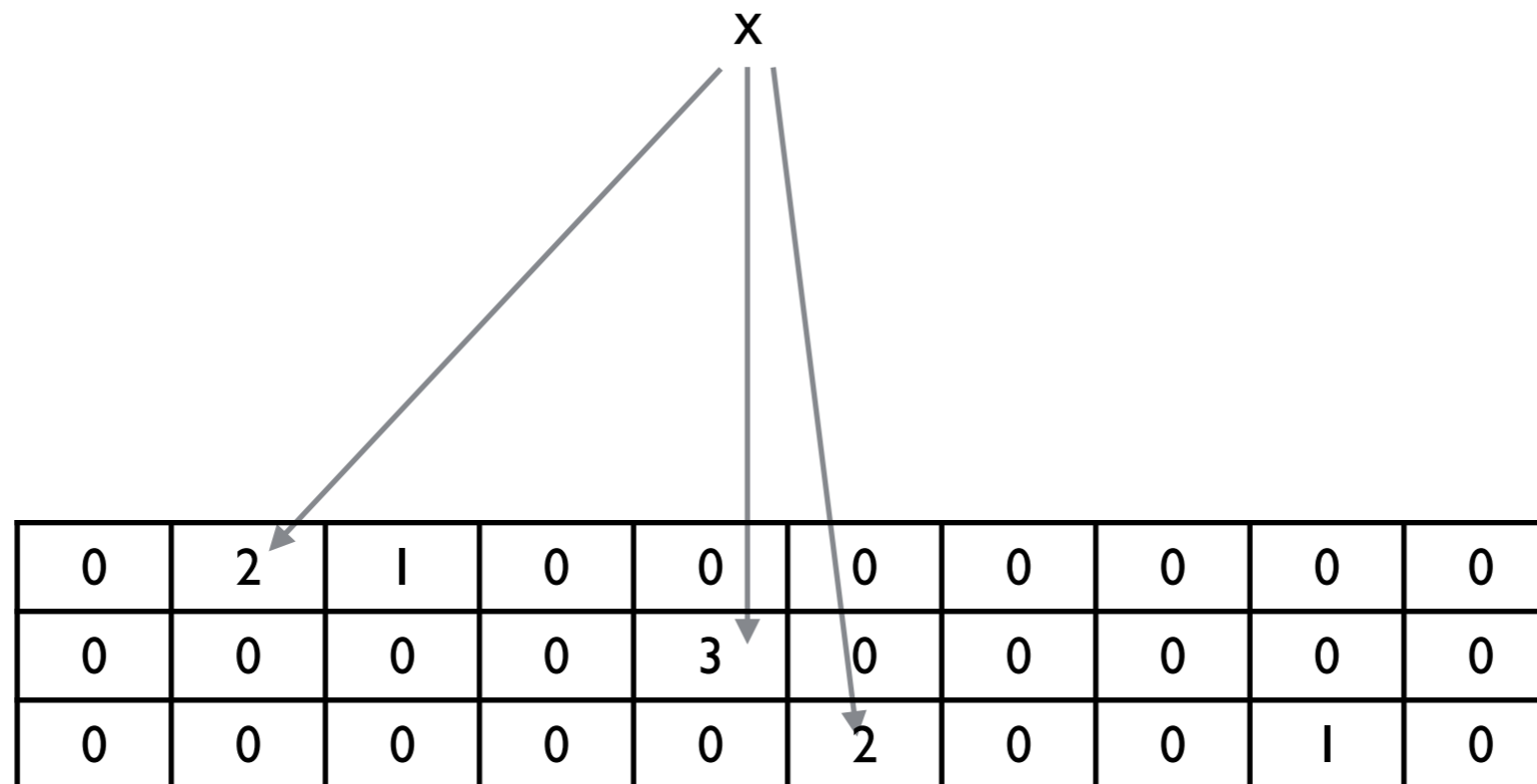
# Count-Min Sketch - How it works

Event  $y$



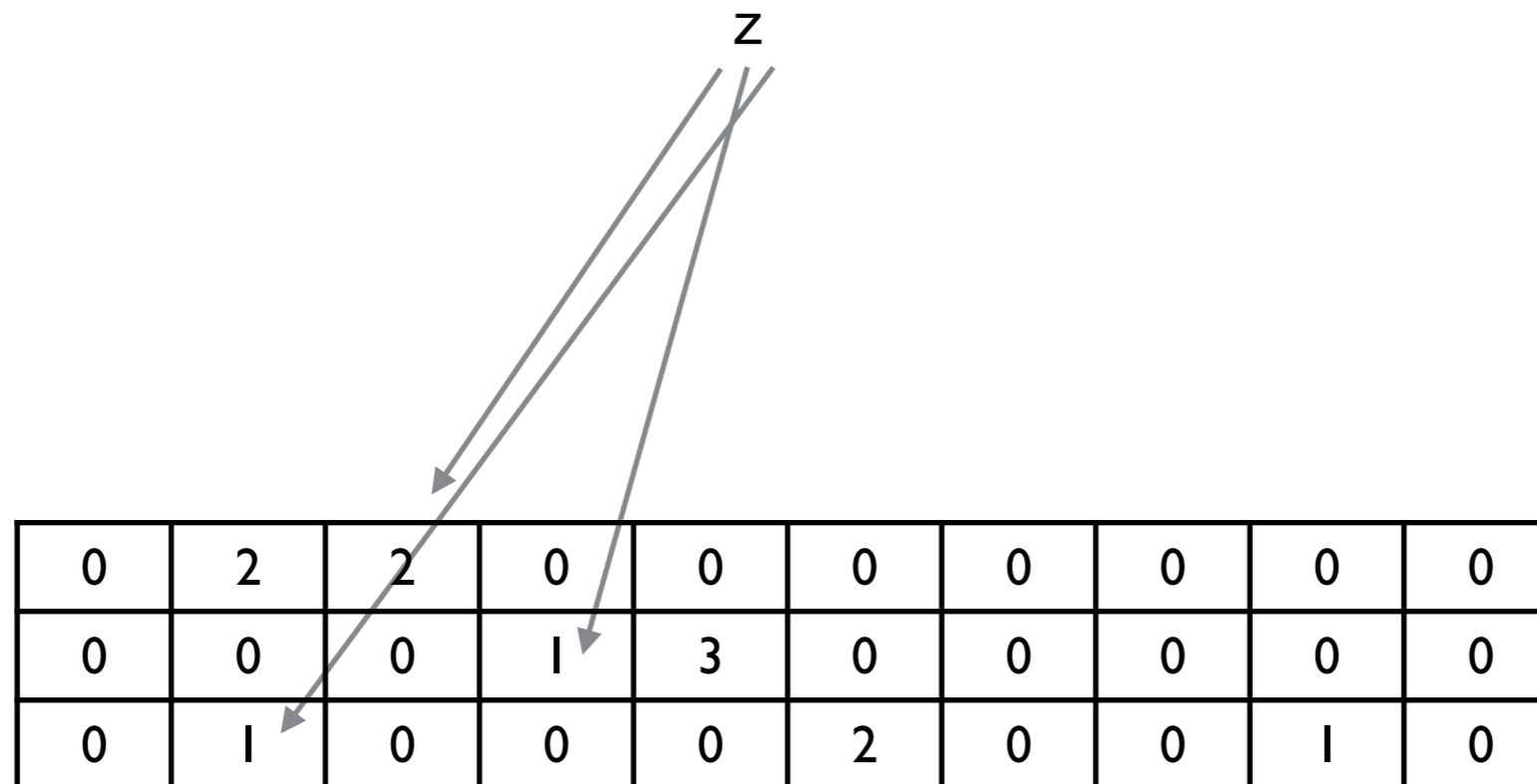
# Count-Min Sketch - How it works

Event x



# Count-Min Sketch - How it works

Event z



# Count-Min Sketch - How it works

How often did x occur?

Look at counts for x in each row  
Return the minimum count

