

INFSCI 2595

Fall 2019

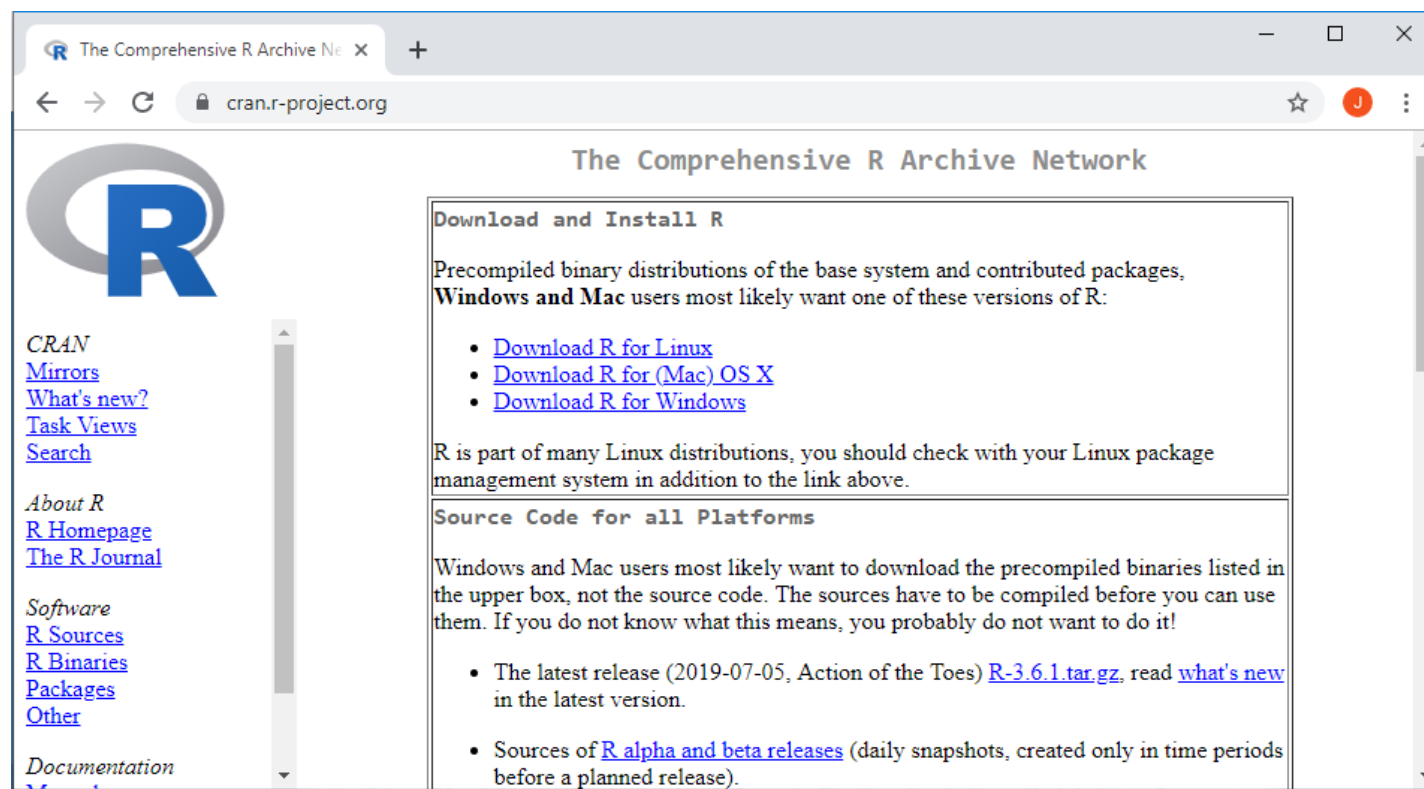
ROOM LOCATION

Lecture 02

Introduction to the R ecosystem

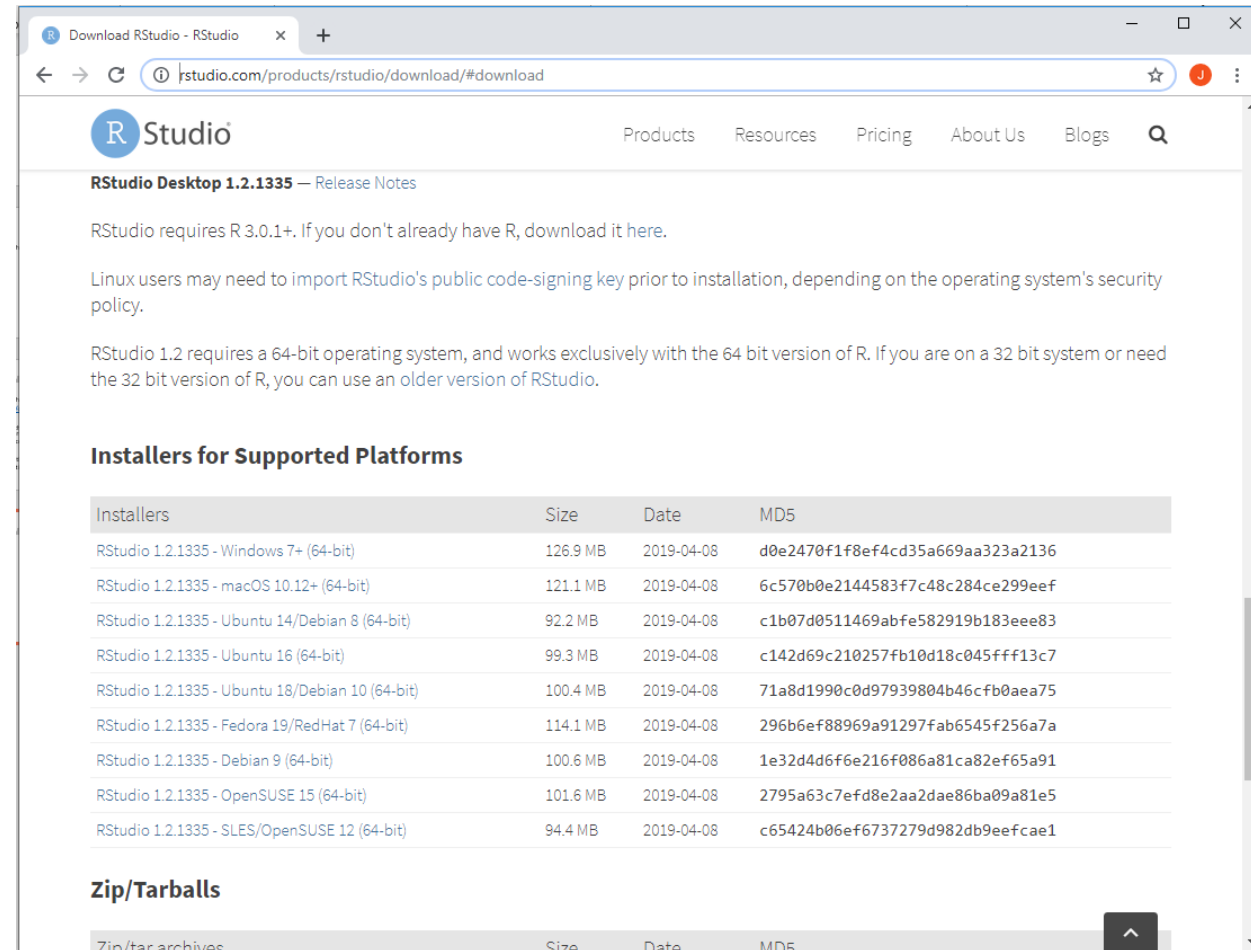
Download and install R

- Go to the CRAN:
- <https://cran.r-project.org/>
- Select the Download link for your operating system of choice.
- Follow the onscreen instructions.



Download and install RStudio

- Go to the following link:
- <https://www.rstudio.com/products/rstudio/download/#download>
- Select the installer for your operating system of choice.
- Follow the onscreen instructions



The screenshot shows the RStudio website's download page. The browser address bar displays 'rstudio.com/products/rstudio/download/#download'. The page header includes the RStudio logo and navigation links: Products, Resources, Pricing, About Us, and Blogs. The main content area is titled 'RStudio Desktop 1.2.1335 — Release Notes'. It contains instructions for users, including a note about R version requirements and a warning for Linux users regarding code-signing keys. Below this, there is a section titled 'Installers for Supported Platforms' which contains a table of download links, sizes, dates, and MD5 hashes for various operating systems. At the bottom, there is a section for 'Zip/Tarballs'.

RStudio Desktop 1.2.1335 — Release Notes

RStudio requires R 3.0.1+. If you don't already have R, download it here.

Linux users may need to import RStudio's public code-signing key prior to installation, depending on the operating system's security policy.

RStudio 1.2 requires a 64-bit operating system, and works exclusively with the 64 bit version of R. If you are on a 32 bit system or need the 32 bit version of R, you can use an older version of RStudio.

Installers for Supported Platforms

Installers	Size	Date	MD5
RStudio 1.2.1335 - Windows 7+ (64-bit)	126.9 MB	2019-04-08	d0e2470f1f8ef4cd35a669aa323a2136
RStudio 1.2.1335 - macOS 10.12+ (64-bit)	121.1 MB	2019-04-08	6c570b0e2144583f7c48c284ce299eef
RStudio 1.2.1335 - Ubuntu 14/Debian 8 (64-bit)	92.2 MB	2019-04-08	c1b07d0511469abfe582919b183eee83
RStudio 1.2.1335 - Ubuntu 16 (64-bit)	99.3 MB	2019-04-08	c142d69c210257fb10d18c045fff13c7
RStudio 1.2.1335 - Ubuntu 18/Debian 10 (64-bit)	100.4 MB	2019-04-08	71a8d1990c0d97939804b46cfb0aea75
RStudio 1.2.1335 - Fedora 19/RedHat 7 (64-bit)	114.1 MB	2019-04-08	296b6ef88969a91297fab6545f256a7a
RStudio 1.2.1335 - Debian 9 (64-bit)	100.6 MB	2019-04-08	1e32d4d6f6e216f086a81ca82ef65a91
RStudio 1.2.1335 - OpenSUSE 15 (64-bit)	101.6 MB	2019-04-08	2795a63c7efd8e2aa2dae86ba09a81e5
RStudio 1.2.1335 - SLES/OpenSUSE 12 (64-bit)	94.4 MB	2019-04-08	c65424b06ef6737279d982db9eefcae1

Zip/Tarballs

Zip/tar archives	Size	Date	MD5
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Cool stuff in R – interactive web applications

- R Shiny allows creating fully interactive visualizations, models, and reports.
 - Essentially converts R to HTML!
- See <https://shiny.rstudio.com/> for examples and a gallery of user created apps.

Quick in-class example

Probability review

We will introduce probability in terms of...

Pitt vs Penn State football!!



Source: <https://heinzfield.com/football/pittsburgh-panthers/>



Source: <https://www.deviantart.com/donatello16/art/We-are-Penn-State-763249687>

Problem statement

- Assumptions:
 - Pitt and Penn State (PSU) are the only college football teams that fans care about in Pennsylvania (PA).
 - We can use attendance to the Pitt vs PSU games to represent the population of PA.
 - We can treat each fan at the game as being independent of all other fans (not true in reality).
- **Objective: Determine the probability that a PA college football fan is a Pitt fan.**

We will assume that we can represent this situation with 2 random variables

- Location – denote as L
 - The game can be played in either Pittsburgh (Pitt's home field) or State College (PSU's home field).
- Fan – denote as F
 - A college football fan in PA can be a fan of either Pitt or PSU.

4 possible combinations of these 2 random variables

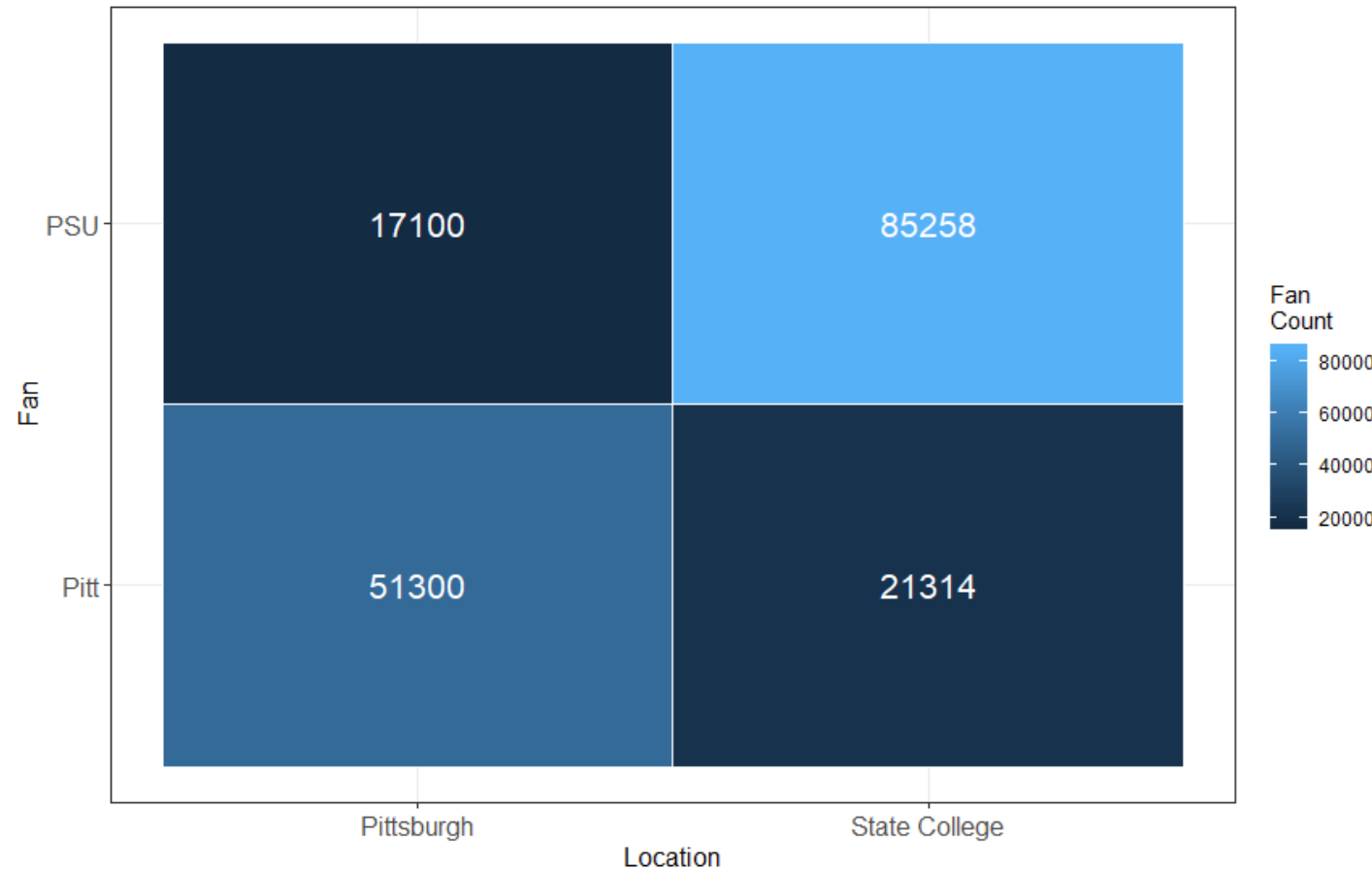
- `L = Pittsburgh & F = Pitt`
- `L = Pittsburgh & F = PSU`
- `L = State College & F = Pitt`
- `L = State College & F = PSU`

Visualize the 4 combinations as a matrix

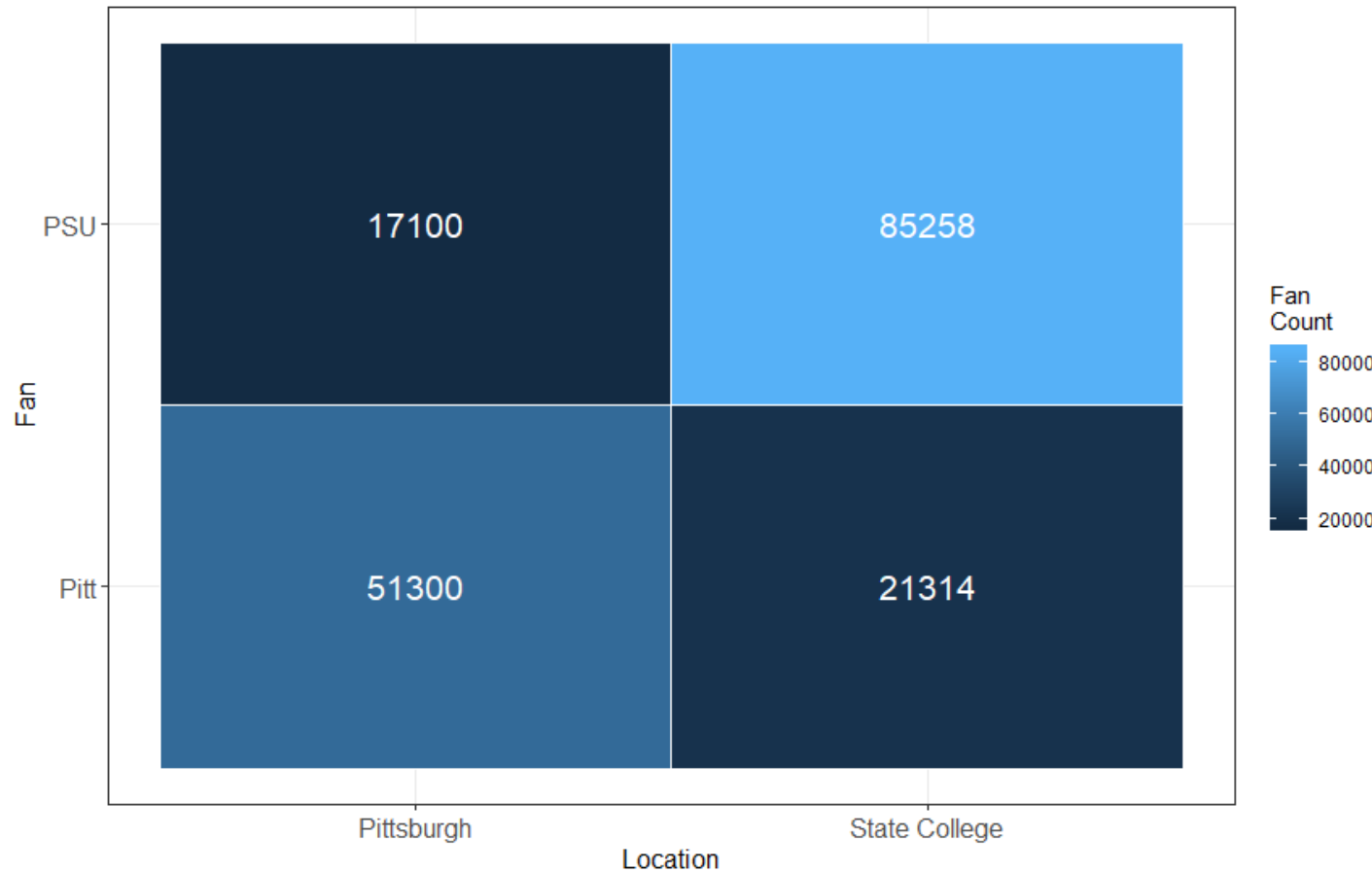
A 2x2 matrix diagram illustrating the combinations of Location and Fan. The vertical axis is labeled 'Fan' with categories 'PSU' and 'Pitt'. The horizontal axis is labeled 'Location' with categories 'Pittsburgh' and 'State College'. The matrix is divided into four quadrants, each containing a text label describing the combination of Location (L) and Fan (F).

	Pittsburgh	State College
PSU	L = Pittsburgh & F = PSU	L = State College & F = PSU
Pitt	L = Pittsburgh & F = Pitt	L = State College & F = Pitt

Include some example values for the number of observations per combination



To meet our objective, we need to first derive several basic probability rules

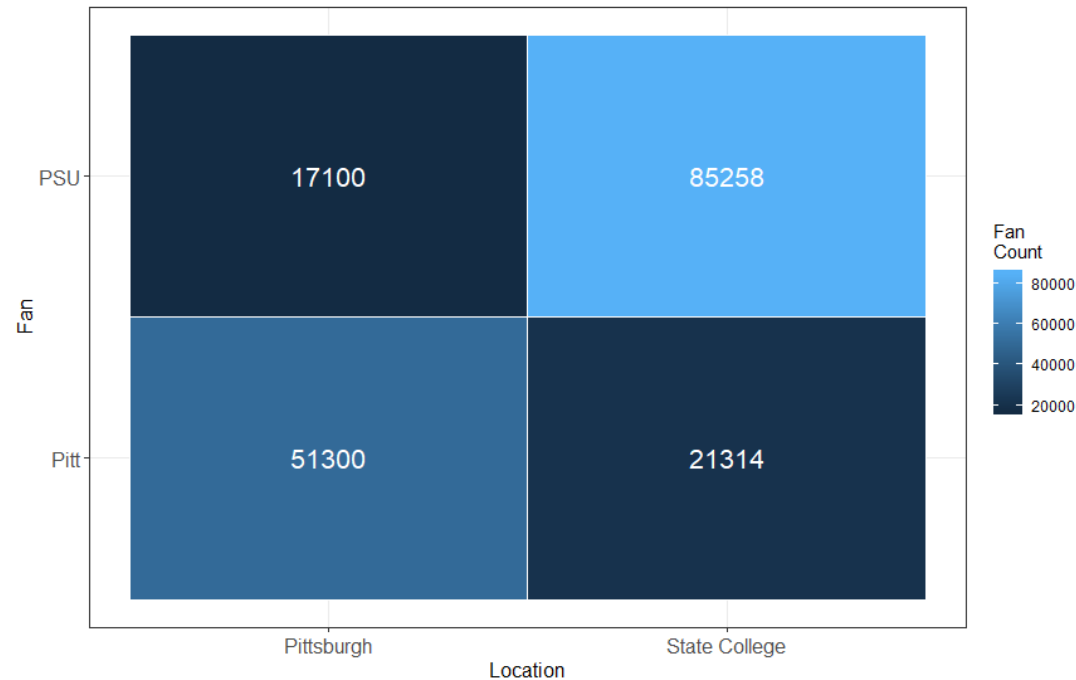


Start with the basic definition of probability

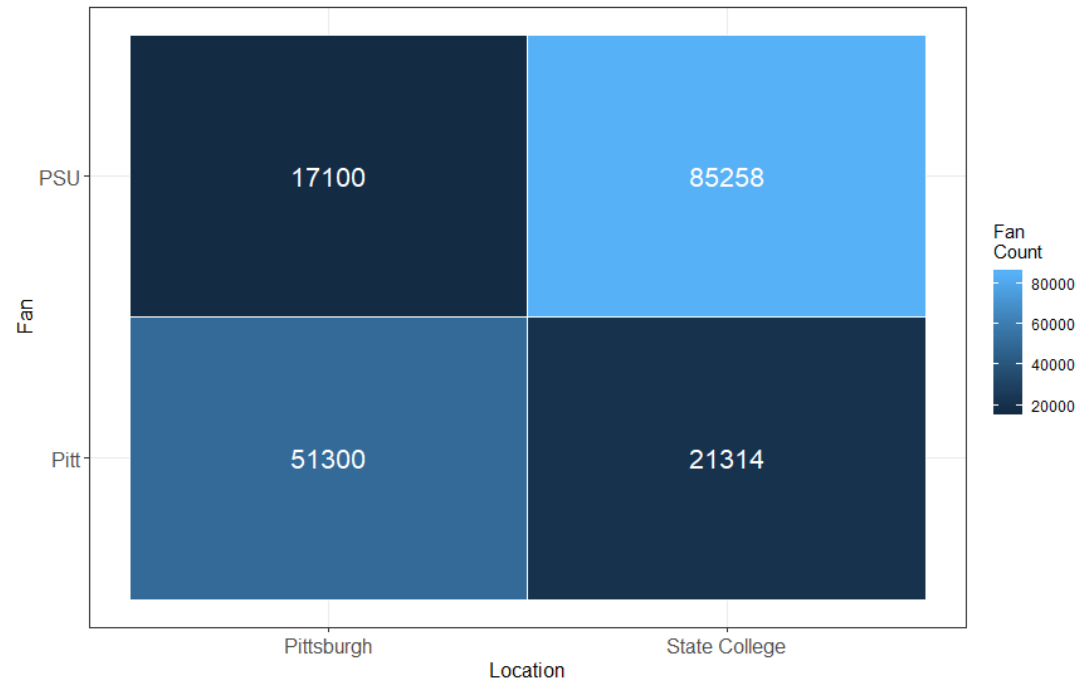
- The probability of an event is the fraction of times that event occurs out of the total number of trials, in the limit that the total number of trials goes to infinity.

In our example, an event is the combination of Location and Fan

- How do we calculate the probability of each event?



In our example, an event is the combination of Location and Fan

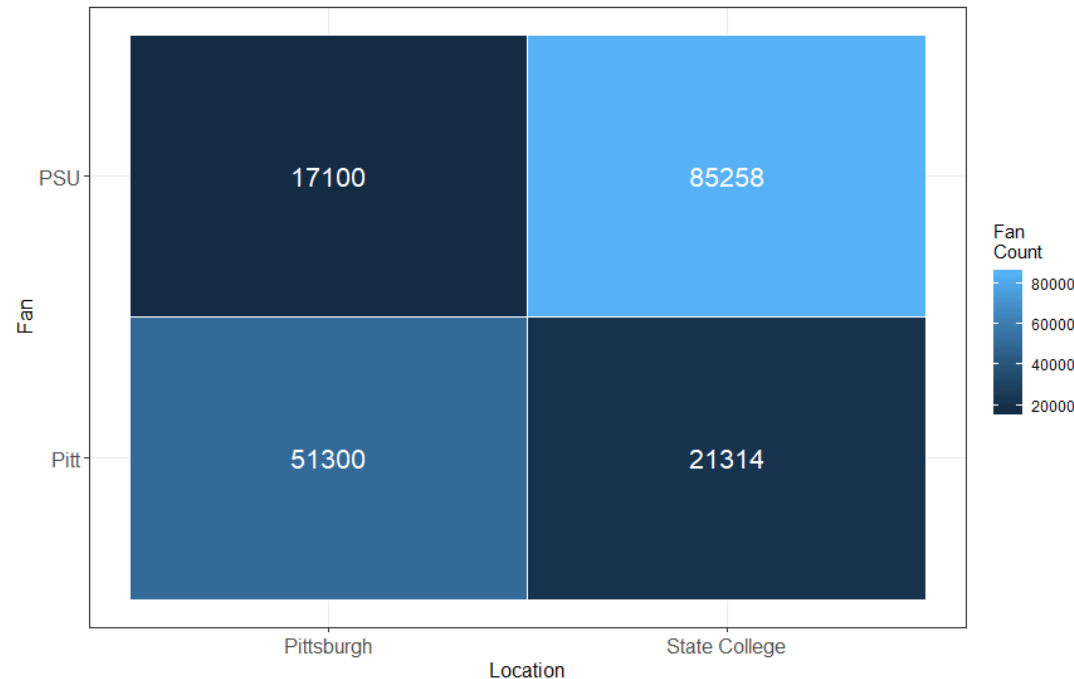


- How do we calculate the probability of each event?

$$P(\text{event}) = \frac{\text{number of times event occurs}}{\text{total number of trials}}$$

- Total number of trials in our example?

In our example, an event is the combination of Location and Fan

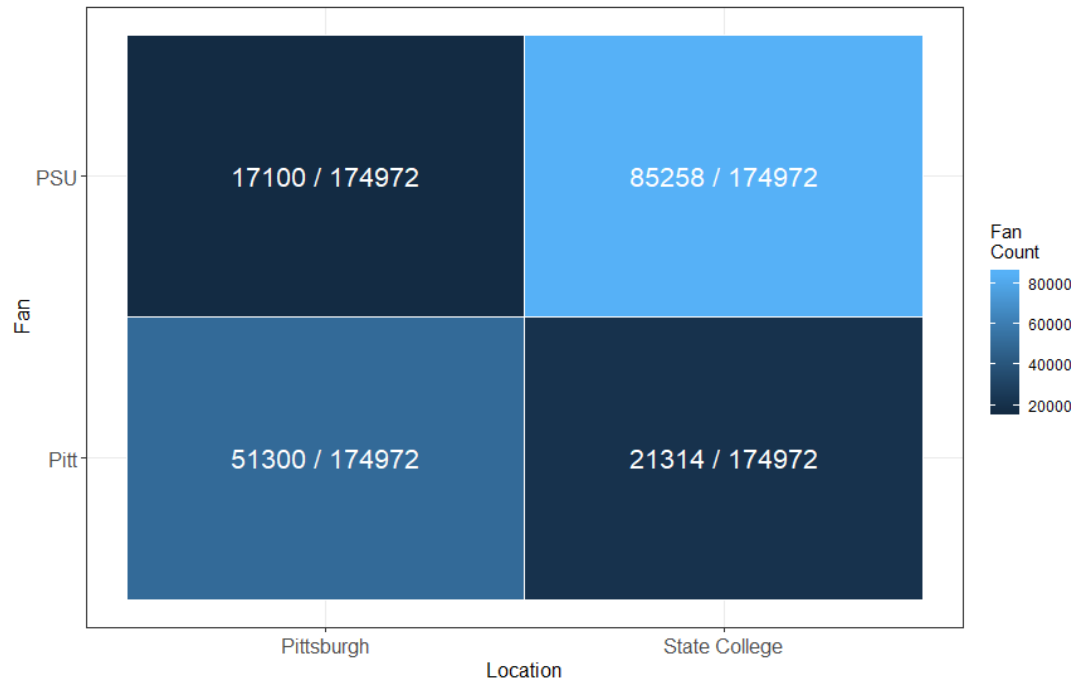


- How do we calculate the probability of each event?

$$P(\text{event}) = \frac{\text{number of times event occurs}}{\text{total number of trials}}$$

- Total number of trials in our example?
- Sum up the counts across the 4 combinations!

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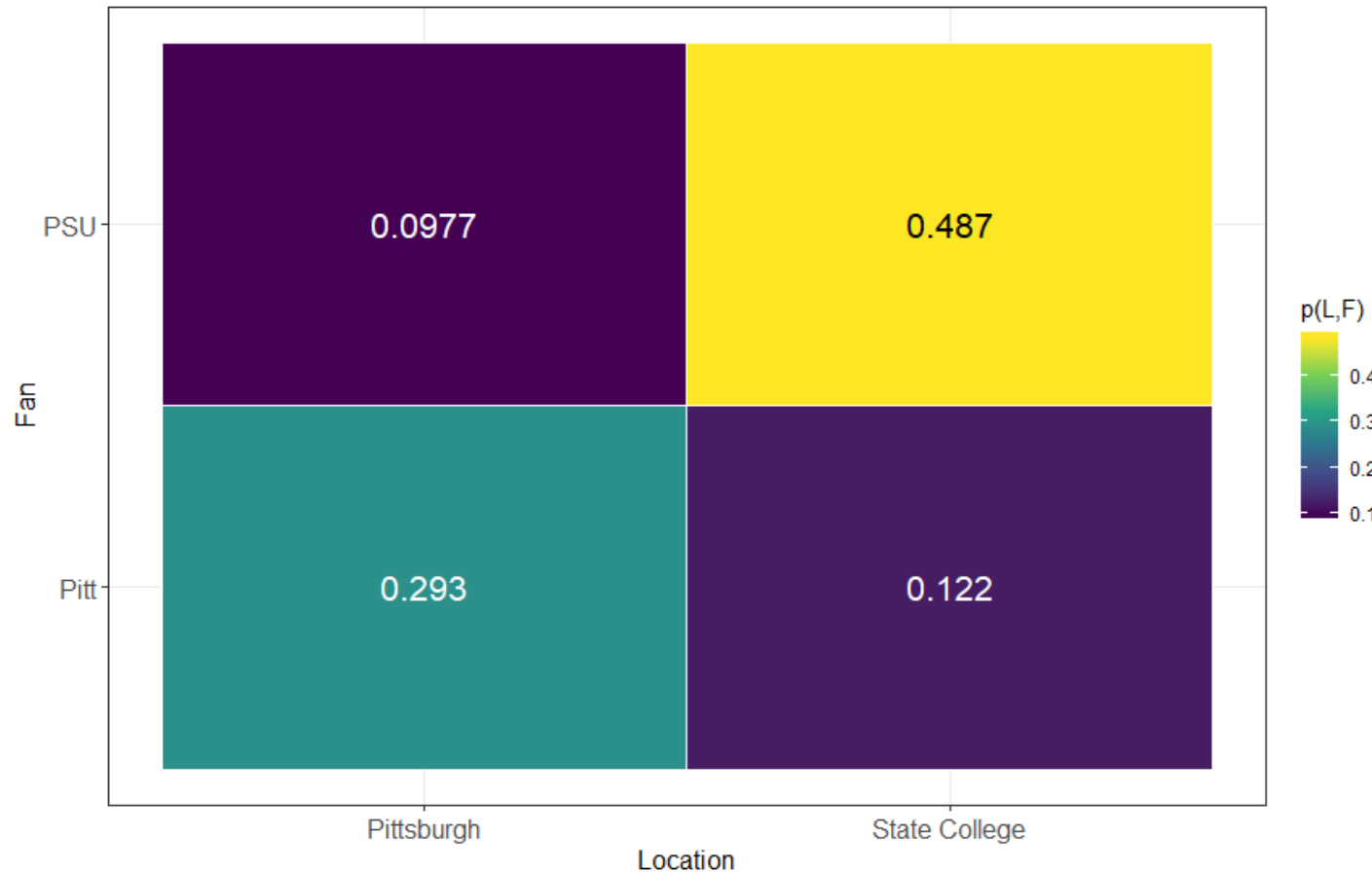
- How do we calculate the probability of each event?

$$P(\text{event}) = \frac{\text{number of times event occurs}}{\text{total number of trials}}$$

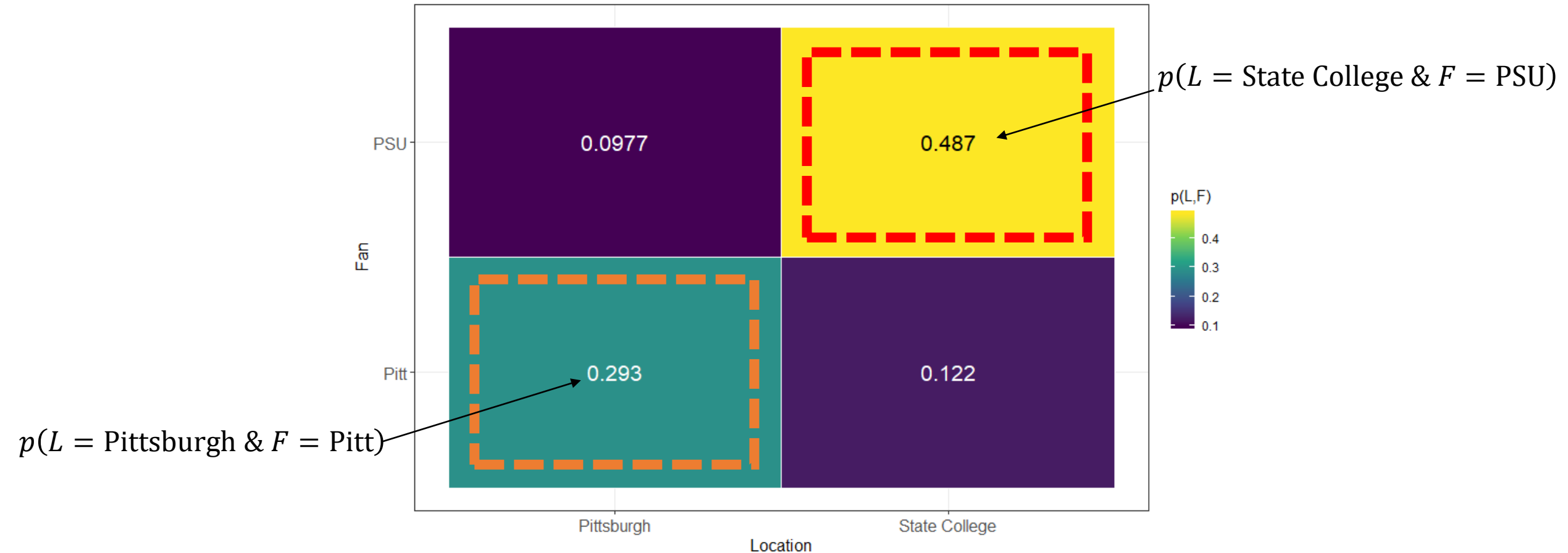
- Total number of trials in our example?
- Sum up the counts across the 4 combinations!
- Total number of trials = 174972

For now, allow 174972 to be represent approaching infinity...

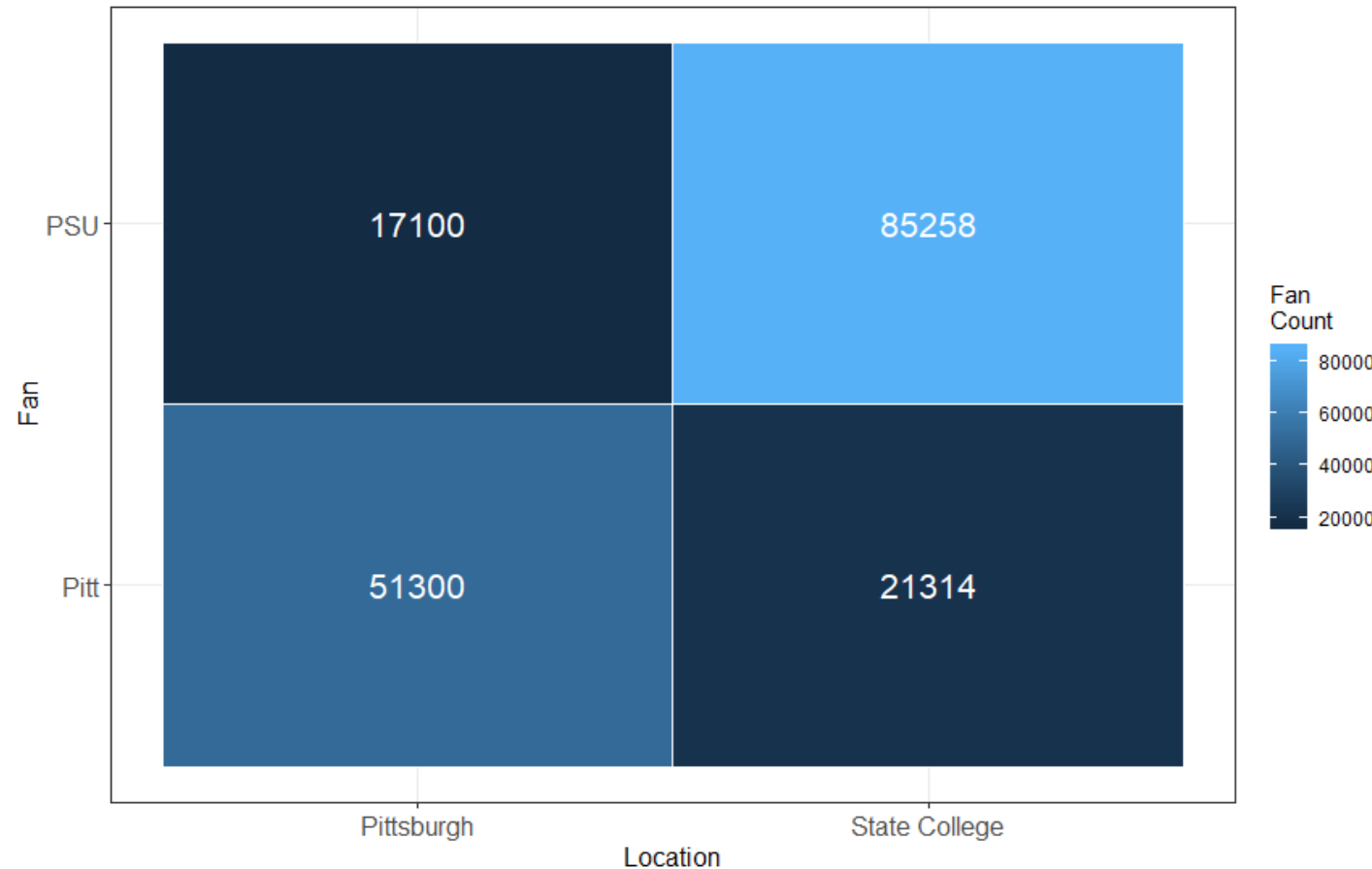
The probability of each combination is the referred to as the joint probability



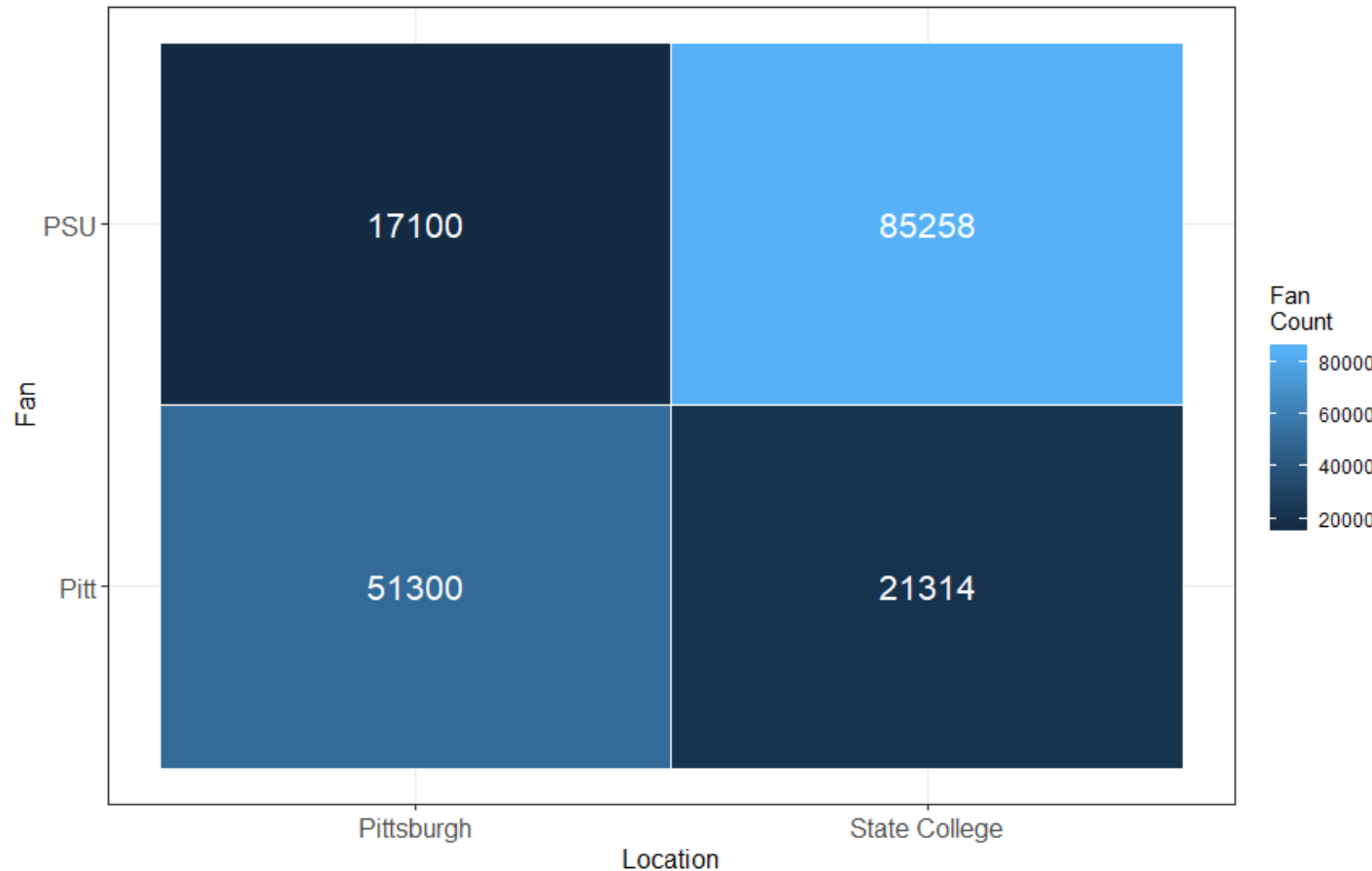
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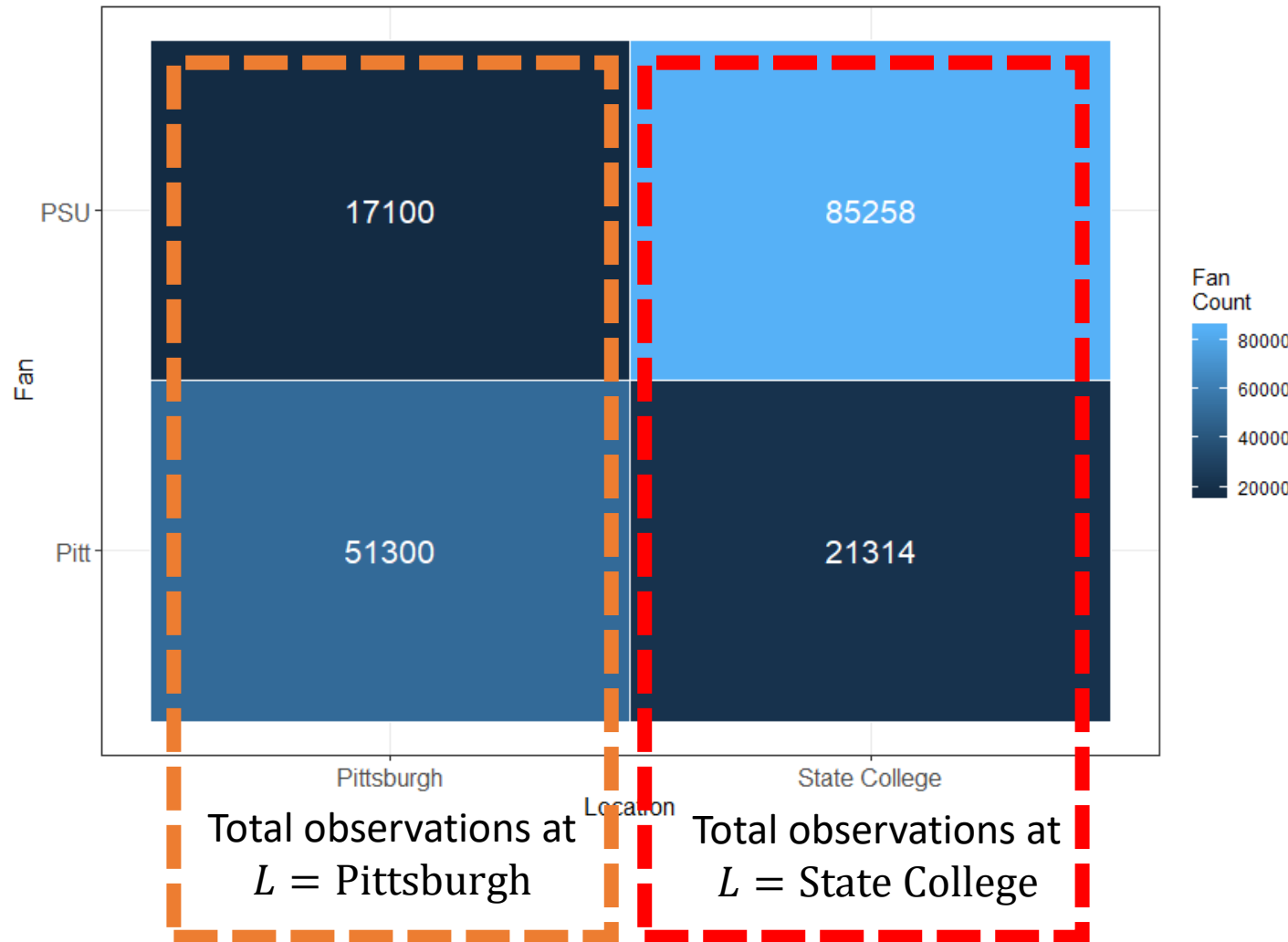
However, rather than working with the joint probabilities, we will work with the counts directly.



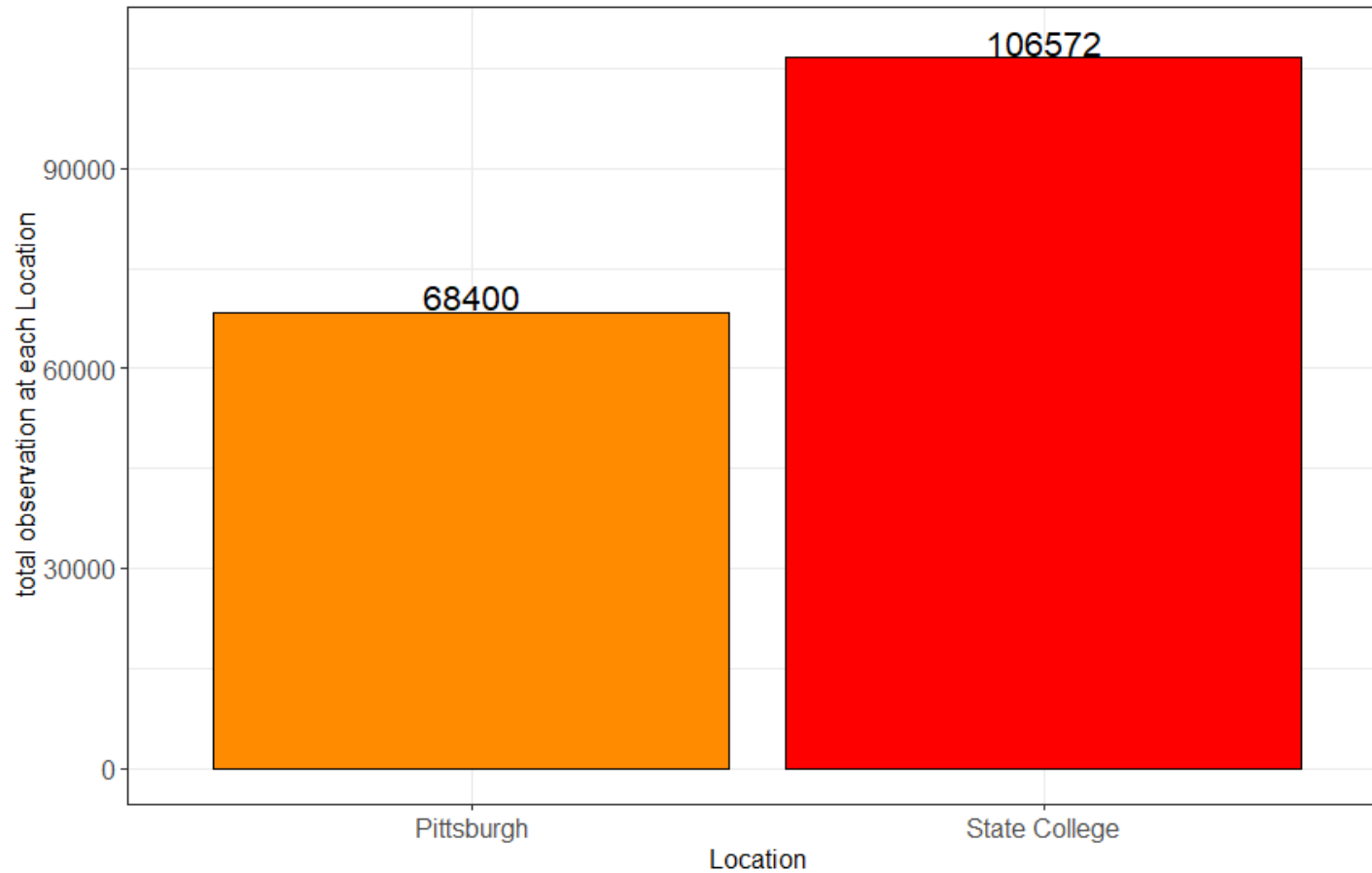
How would we calculate $p(L = \text{Pittsburgh})$, irrespective of the value of Fan?



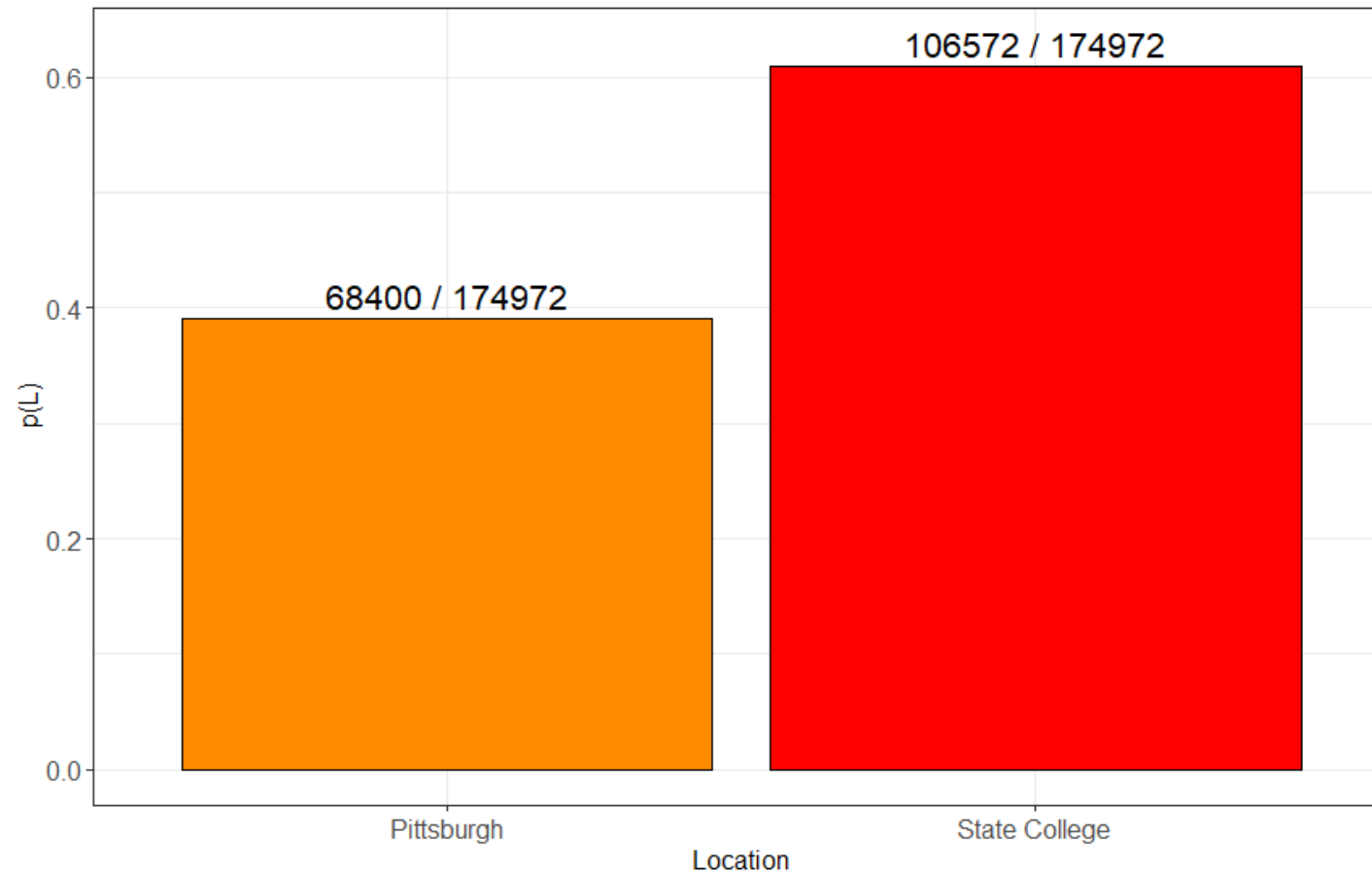
How would we calculate $p(L = \text{Pittsburgh})$, irrespective of the value of Fan?



Sum up the counts at each Location



Divide the total observations at each `Location` by the total number of trials



Work through the steps with the example values...

- Sum up the counts:

$$68400 = 51300 + 17100$$

- Divide by the total number of trials:

$$\frac{68400}{174972} = \frac{51300}{174972} + \frac{17100}{174972}$$

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What are these quantities?

Work through the steps with the example values...

- Sum up the counts:

$$68400 = 51300 + 17100$$

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$p(L = \text{Pittsburgh} \ \& \ F = \text{Pitt})$

$p(L = \text{Pittsburgh} \ \& \ F = \text{PSU})$

Joint probabilities!

Work through the steps with the example values...

- Sum up the counts:

$$68400 = 51300 + 17100$$

- Divide by the total number of trials:

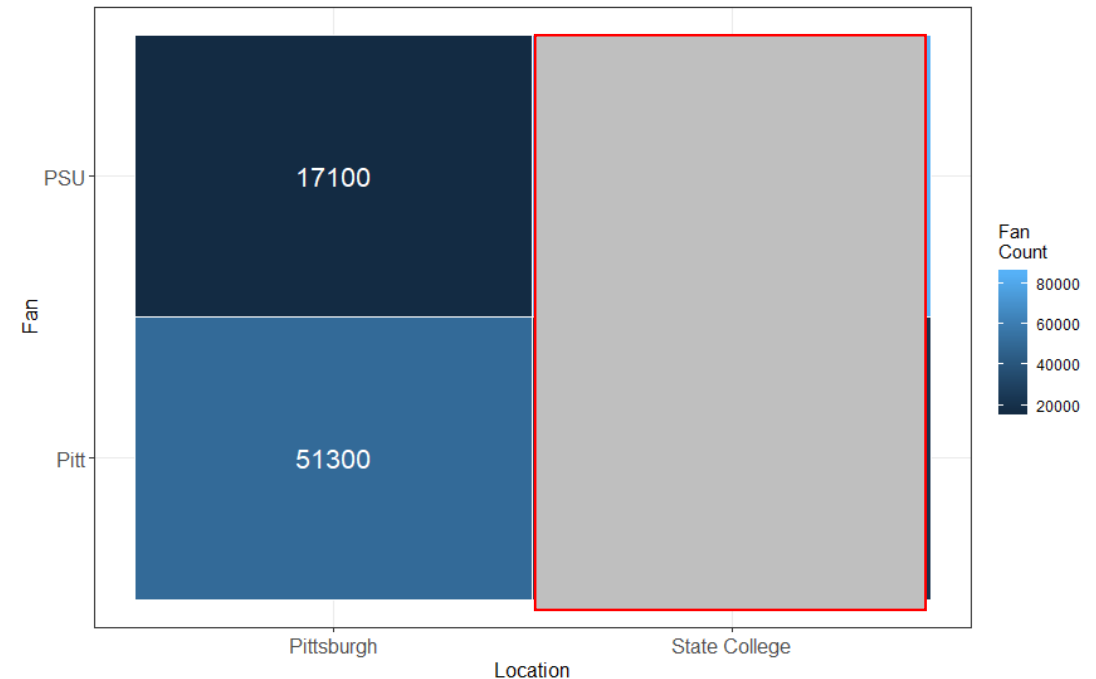
$$\frac{68400}{174972} = \frac{51300}{174972} + \frac{17100}{174972}$$

$$p(L = \text{Pittsburgh}) = p(L = \text{Pittsburgh} \ \& \ F = \text{Pitt}) + p(L = \text{Pittsburgh} \ \& \ F = \text{PSU})$$

The **sum rule** of probability -> *marginalize* or sum out the other variables

Next, focus on $L = \text{Pittsburgh}$. What is the probability of each Fan GIVEN the Location?

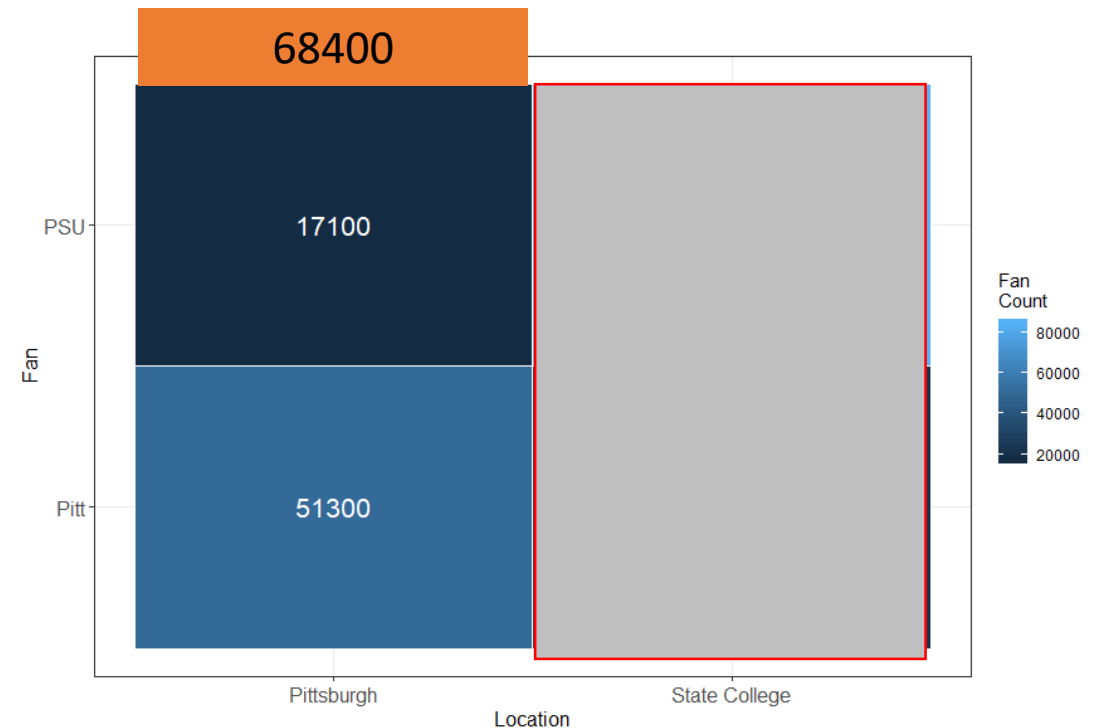
- The basic definition of probability remains the same.
- Has the total number of trials changed?



Next, focus on $L = \text{Pittsburgh}$. What is the probability of each Fan GIVEN the Location?

- The basic definition of probability remains the same.
- Has the total number of trials changed?
 - YES!

$$p(F = \text{Pitt} | L = \text{Pittsburgh}) = \frac{51300}{68400}$$

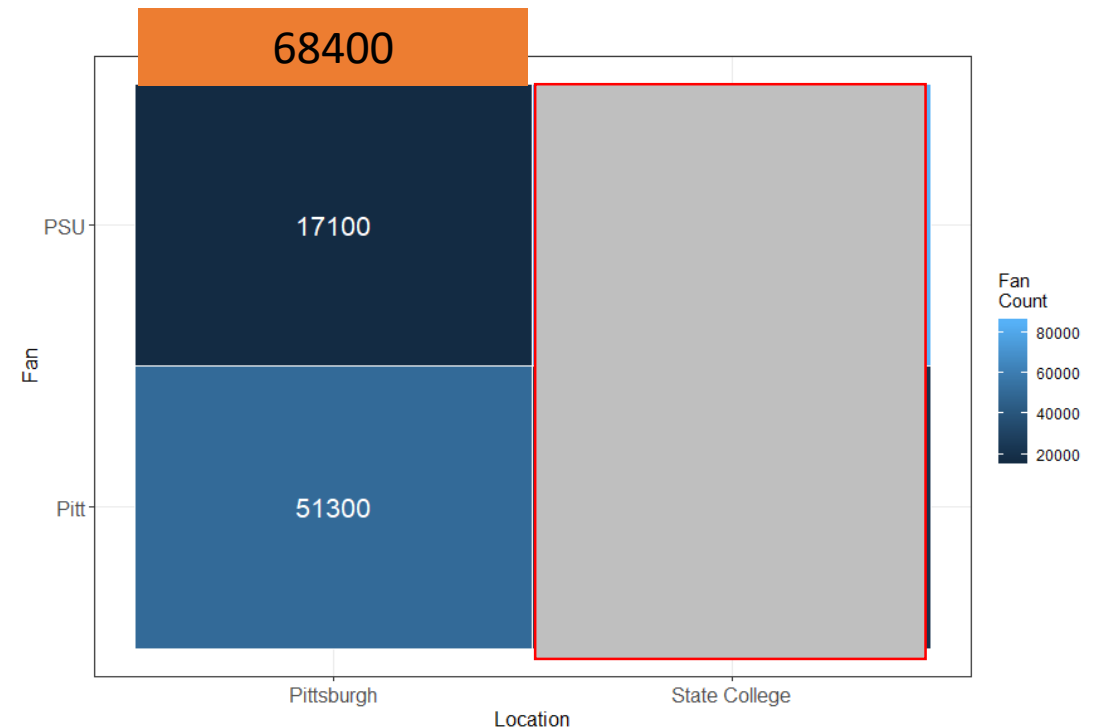


Next, focus on $L = \text{Pittsburgh}$. What is the probability of each Fan GIVEN the Location?

- The basic definition of probability remains the same.
- Has the total number of trials changed?
 - **YES!**

$$p(F = \text{Pitt} | L = \text{Pittsburgh}) = \frac{51300}{68400}$$

Conditional probability of F given L



Revisit the joint probability

$$p(L = \text{Pittsburgh} \ \& \ F = \text{Pitt}) = \frac{51300}{174972}$$

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$$p(L = \text{Pittsburgh} \& F = \text{Pitt}) = \frac{51300}{174972}$$

Multiply by $1 = 68400/68400$:

$$p(L = \text{Pittsburgh} \& F = \text{Pitt}) = \frac{51300}{174972} = \frac{51300}{68400} \cdot \frac{68400}{174972}$$

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$$p(F = \text{Pitt} | L = \text{Pittsburgh}) \cdot p(L = \text{Pittsburgh})$$

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$$p(L = \text{Pittsburgh} \& F = \text{Pitt}) = \frac{51300}{174972} = \frac{51300}{68400} \cdot \frac{68400}{174972}$$

$$p(L = \text{Pittsburgh} \& F = \text{Pitt}) = p(F = \text{Pitt} | L = \text{Pittsburgh}) \cdot p(L = \text{Pittsburgh})$$

PRODUCT RULE

Using these rules we can calculate $p(F = \text{Pitt})$

- Start with the sum rule:

$$p(F = \text{Pitt}) = p(L = \text{Pittsburgh}, F = \text{Pitt}) + p(L = \text{State College}, F = \text{Pitt})$$

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$$p(F = \text{Pitt}) = p(L = \text{Pittsburgh}, F = \text{Pitt}) + p(L = \text{State College}, F = \text{Pitt})$$

- Substitute in the product rule:

$$p(L = \text{Pittsburgh}, F = \text{Pitt}) = p(F = \text{Pitt} | L = \text{Pittsburgh})p(L = \text{Pittsburgh})$$

$$p(L = \text{State College}, F = \text{Pitt}) = p(F = \text{Pitt} | L = \text{State College})p(L = \text{State College})$$

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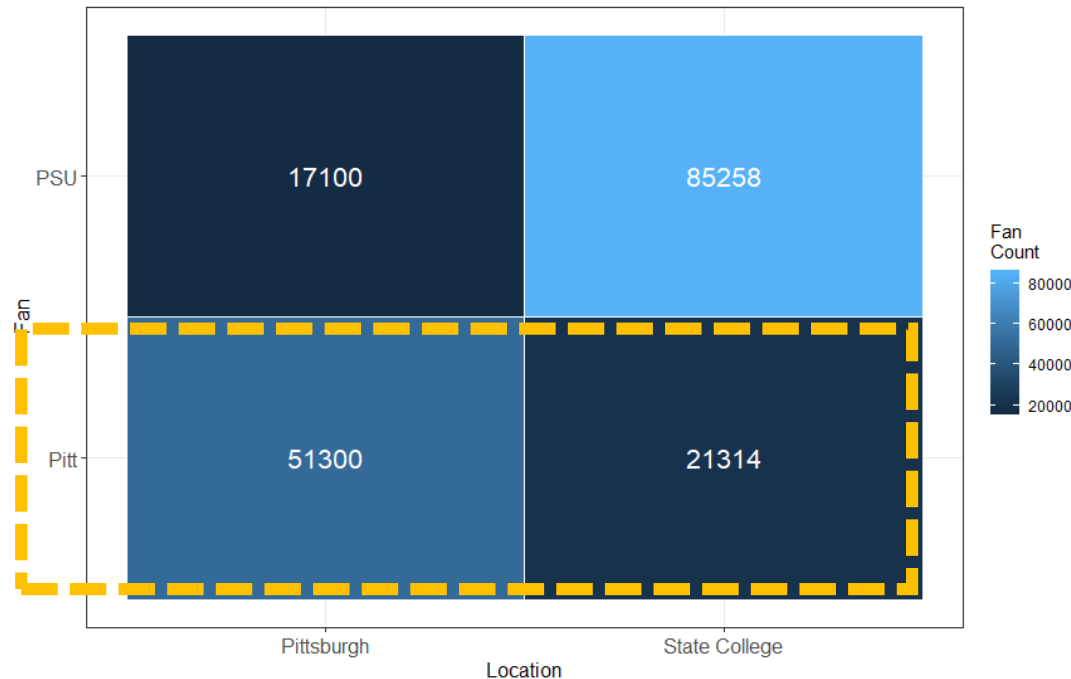
$$p(L = \text{Pittsburgh}, F = \text{Pitt}) = p(F = \text{Pitt} | L = \text{Pittsburgh})p(L = \text{Pittsburgh})$$

$$p(L = \text{State College}, F = \text{Pitt}) = p(F = \text{Pitt} | L = \text{State College})p(L = \text{State College})$$

- Substitute in the example values:

$$p(F = \text{Pitt}) = \frac{51300}{68400} \cdot \frac{68400}{174972} + \frac{21314}{106572} \cdot \frac{106572}{174972} = 0.415$$

Why is the product rule important?



- In this simple example, we could have calculated $p(F = \text{Pitt})$ using the sum rule alone.
- Follow the same steps we used to calculate $p(L = \text{Pittsburgh})$.
- Sum over the \mathbb{L} variable, for the fixed $F = \text{Pitt}$ value.

In this simple example, we know all quantities, but in a real problem...

- The sum and product rules allow us to rewrite a probability in terms of other probabilities.
- Thus, we can use these rules to write a probability we **DO NOT** know in terms of probabilities we **DO** know!
- Essentially, break a hard problem up into smaller easier pieces to work with.

Let's use this concept to ask a different question: What is the probability $L = \text{Pittsburgh}$, given $F = \text{Pitt}$?

- Start with the joint probability we described previously:

$$p(L = \text{Pittsburgh}, F = \text{Pitt}) = p(F = \text{Pitt} | L = \text{Pittsburgh})p(L = \text{Pittsburgh})$$

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- We can also write:

$$p(F = \text{Pitt}, L = \text{Pittsburgh}) = p(L = \text{Pittsburgh} | F = \text{Pitt})p(F = \text{Pitt})$$

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- We can also write:

$$p(F = \text{Pitt}, L = \text{Pittsburgh}) = p(L = \text{Pittsburgh} | F = \text{Pitt})p(F = \text{Pitt})$$

- Use the **symmetry property**:

$$p(L = \text{Pittsburgh}, F = \text{Pitt}) = p(F = \text{Pitt}, L = \text{Pittsburgh})$$

Substitute in the product rule relationships
into each side of the symmetry property

$$p(L = \text{Pittsburgh} | F = \text{Pitt})p(F = \text{Pitt}) = p(F = \text{Pitt} | L = \text{Pittsburgh})p(L = \text{Pittsburgh})$$

Substitute in the product rule relationships into each side of the symmetry property

$$p(L = \text{Pittsburgh} | F = \text{Pitt})p(F = \text{Pitt}) = p(F = \text{Pitt} | L = \text{Pittsburgh})p(L = \text{Pittsburgh})$$

- Rearrange to write the probability of interest in terms of probabilities we already know:

$$p(L = \text{Pittsburgh} | F = \text{Pitt}) = \frac{p(F = \text{Pitt} | L = \text{Pittsburgh})p(L = \text{Pittsburgh})}{p(F = \text{Pitt})}$$

Substitute in the product rule relationships into each side of the symmetry property

$$p(L = \text{Pittsburgh} | F = \text{Pitt})p(F = \text{Pitt}) = p(F = \text{Pitt} | L = \text{Pittsburgh})p(L = \text{Pittsburgh})$$

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The above relationship is **BAYES' THEOREM!!!!**

Evaluate using the example values

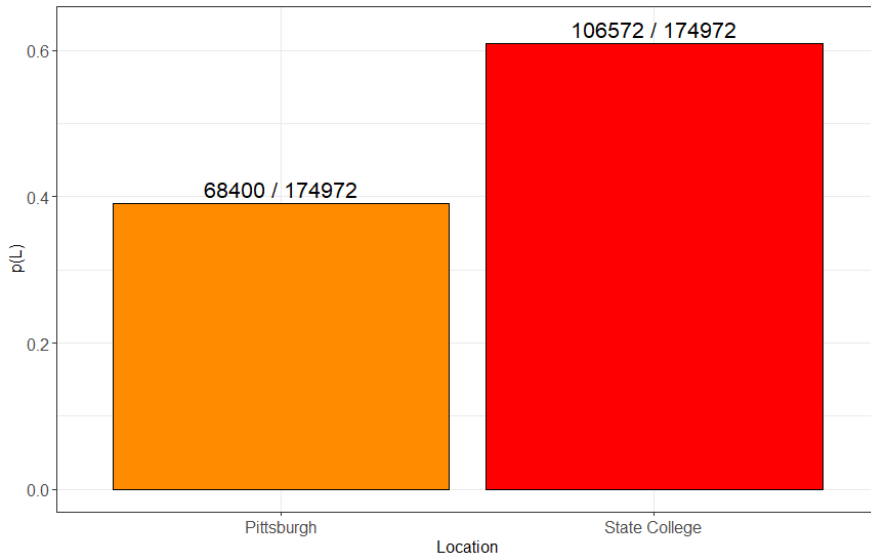
$$p(L = \text{Pittsburgh} | F = \text{Pitt}) = \frac{\frac{51300}{68400} \cdot \frac{68400}{174972}}{0.415} = 0.706$$

But, what does $p(L = \text{Pittsburgh} | F = \text{Pitt})$ represent?

- Consists of three terms.

But, what does $p(L = \text{Pittsburgh} | F = \text{Pitt})$ represent?

Initially, we know the counts at
Pittsburgh and State College.

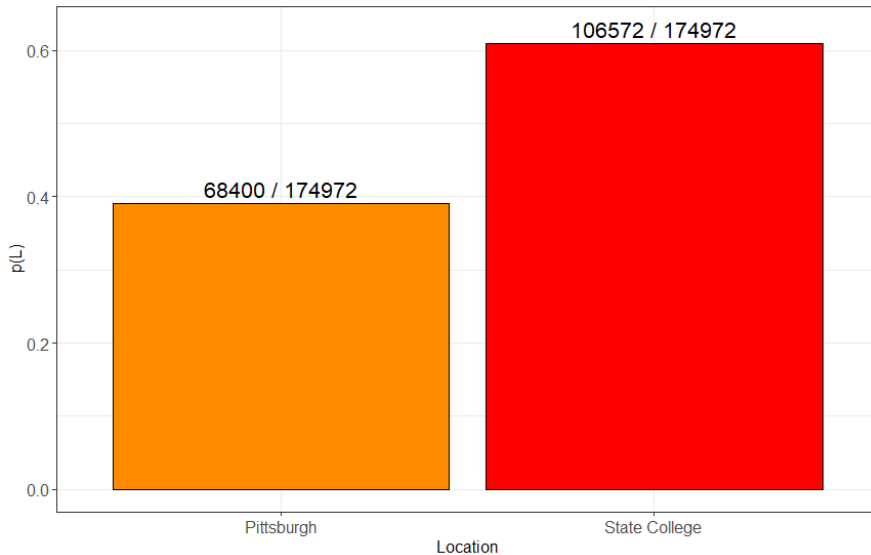


$$p(L = \text{Pittsburgh}) = \frac{68400}{174972} = 0.391$$

$p(L = \text{Pittsburgh})$ is the **PRIOR**
probability, *before* saying
anything about the Fan type.

But, what does $p(L = \text{Pittsburgh} | F = \text{Pitt})$ represent?

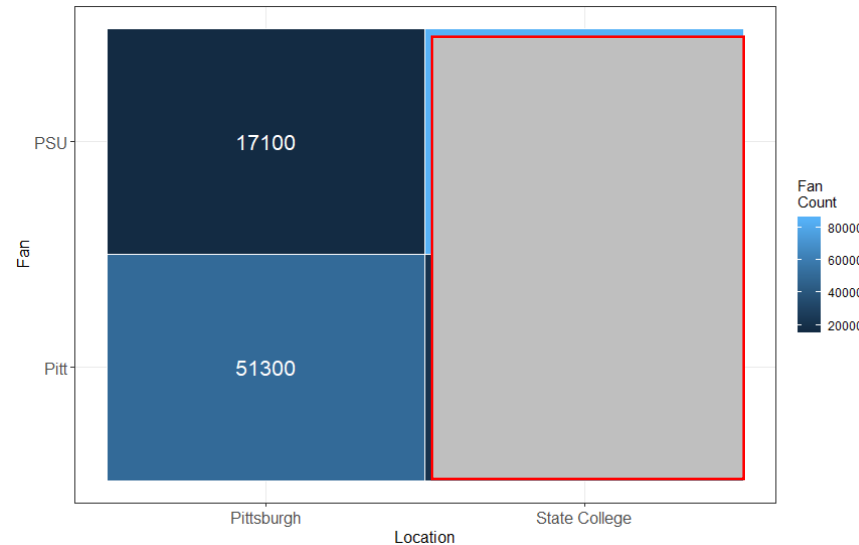
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Fixing $L = \text{Pittsburgh}$ changes
the total number of trials!

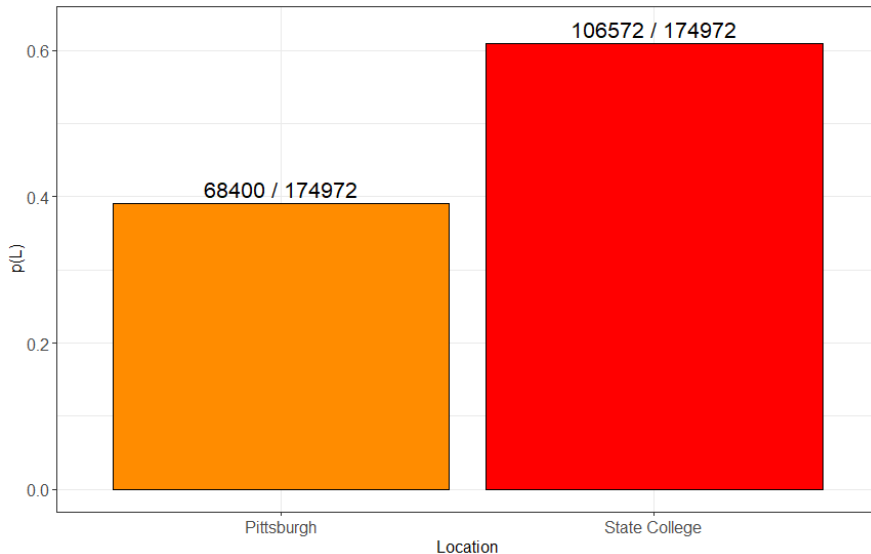


Total number of trials is now 68400

$p(F = \text{Pitt} | L = \text{Pittsburgh})$
is called the **LIKELIHOOD**.

But, what does $p(L = \text{Pittsburgh} | F = \text{Pitt})$ represent?

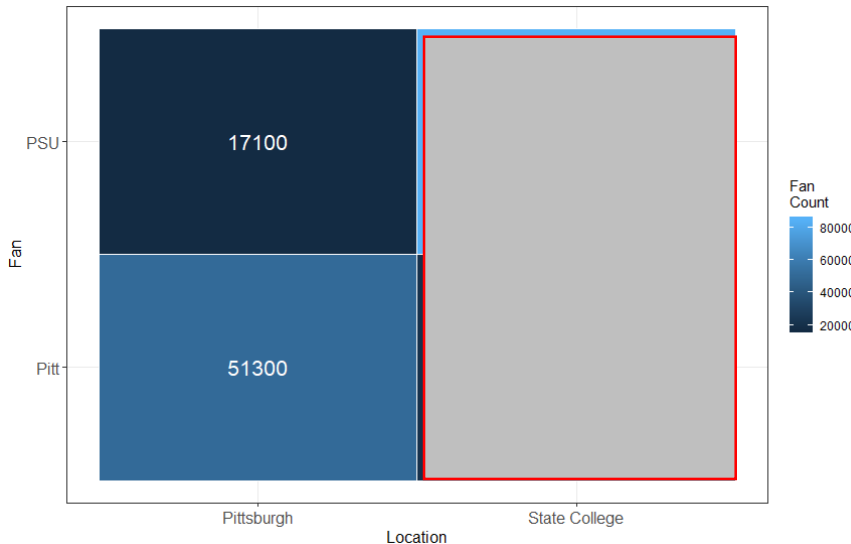
Initially, we know the counts at Pittsburgh and State College.



$$p(L = \text{Pittsburgh}) = \frac{68400}{174972} = 0.391$$

$p(L = \text{Pittsburgh})$ is the **PRIOR** probability, *before* saying anything about the Fan type.

Fixing $L = \text{Pittsburgh}$ changes the total number of trials!



Total number of trials is now 68400

$p(F = \text{Pitt} | L = \text{Pittsburgh})$ is called the **LIKELIHOOD**.

$p(F = \text{Pitt})$ is the **average** probability of a Pitt fan.

Compute using the sum and product rule, as we did previously.

Serves as the normalizing constant that guarantees the probability is between 0 and 1.

$p(F = \text{Pitt})$ referred to as the **EVIDENCE** or **MARGINAL LIKELIHOOD**.

Combining the PRIOR, LIKELIHOOD, and EVIDENCE yields the POSTERIOR

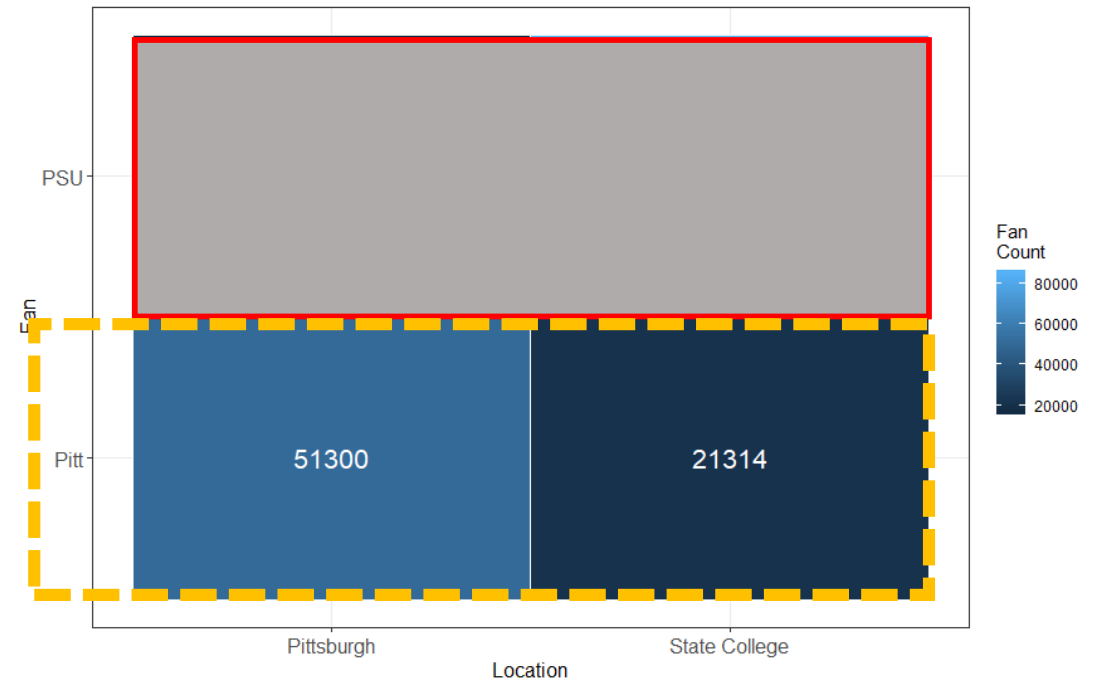
$$\text{Posterior} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Evidence}}$$

We updated our prior ***belief*** given the observations!

The calculations and terminology may seem a little confusing, but we already knew how to calculate $p(L = \text{Pittsburgh} | F = \text{Pitt})$...

- Follow the same conditioning procedure we saw earlier.
- Fixing $F = \text{Pitt}$ changes the total number of trials to 72614.
- The conditional probability is:

$$\frac{51300}{72614} = 0.706$$



In many respects, probability is just counting!

- Get the bookkeeping correct, and the rest basically takes care of itself.
- In this course, we will use a lot of math.
- If the math appears overwhelming, just remember we're just counting!

Probability distributions

In our college football example, we were given counts for each of the 4 combinations.

- Beaver Stadium at State College has a capacity 106572 fans.
- We won't be able to ask everyone there!
- How can we represent the population attending the game?

In our college football example, we were given counts for each of the 4 combinations.

- Beaver Stadium at State College has a capacity 106572 fans.
- We won't be able to ask everyone there!
- How can we represent the population attending the game?
 - **SAMPLING!!!!**

Assumptions

- Maintain the assumption that all fans are independent.
- Assume our sample size is very small relative to the population size.

Notation

- Instead of denoting F_{an} as F , we will now use the general variable x .
- Encode $F_{an=Pitt}$ as $x = 1$ and $F_{an=PSU}$ as $x = 0$.

The probability of $\text{Fan} = \text{Pitt}$, $x = 1$, will be denoted by the parameter μ

- The above statement can be written as:

$$p(x = 1|\mu) = \mu$$

The probability of $\text{Fan} = \text{Pitt}$, $x = 1$, will be denoted by the parameter μ

- The above statement can be written as:

$$p(x = 1|\mu) = \mu$$

- Since we have either $x = 1$ or $x = 0$, the probability that $x = 0$ is:

$$p(x = 0|\mu) = 1 - \mu$$

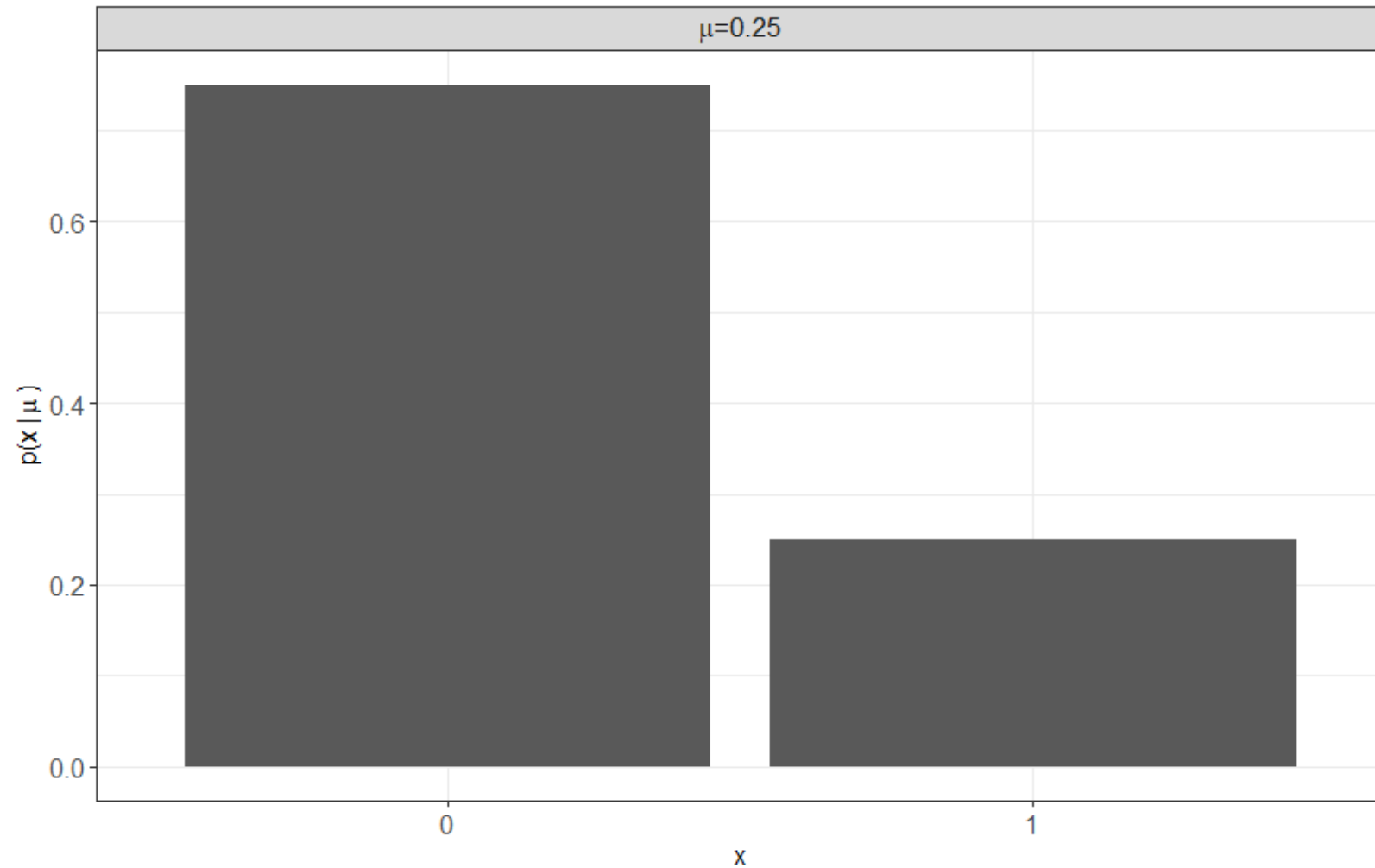
The probability mass function over possible outcomes can be more compactly written as:

$$p(x|\mu) = \text{Bernoulli}(x|\mu) = \mu^x(1 - \mu)^{1-x}$$

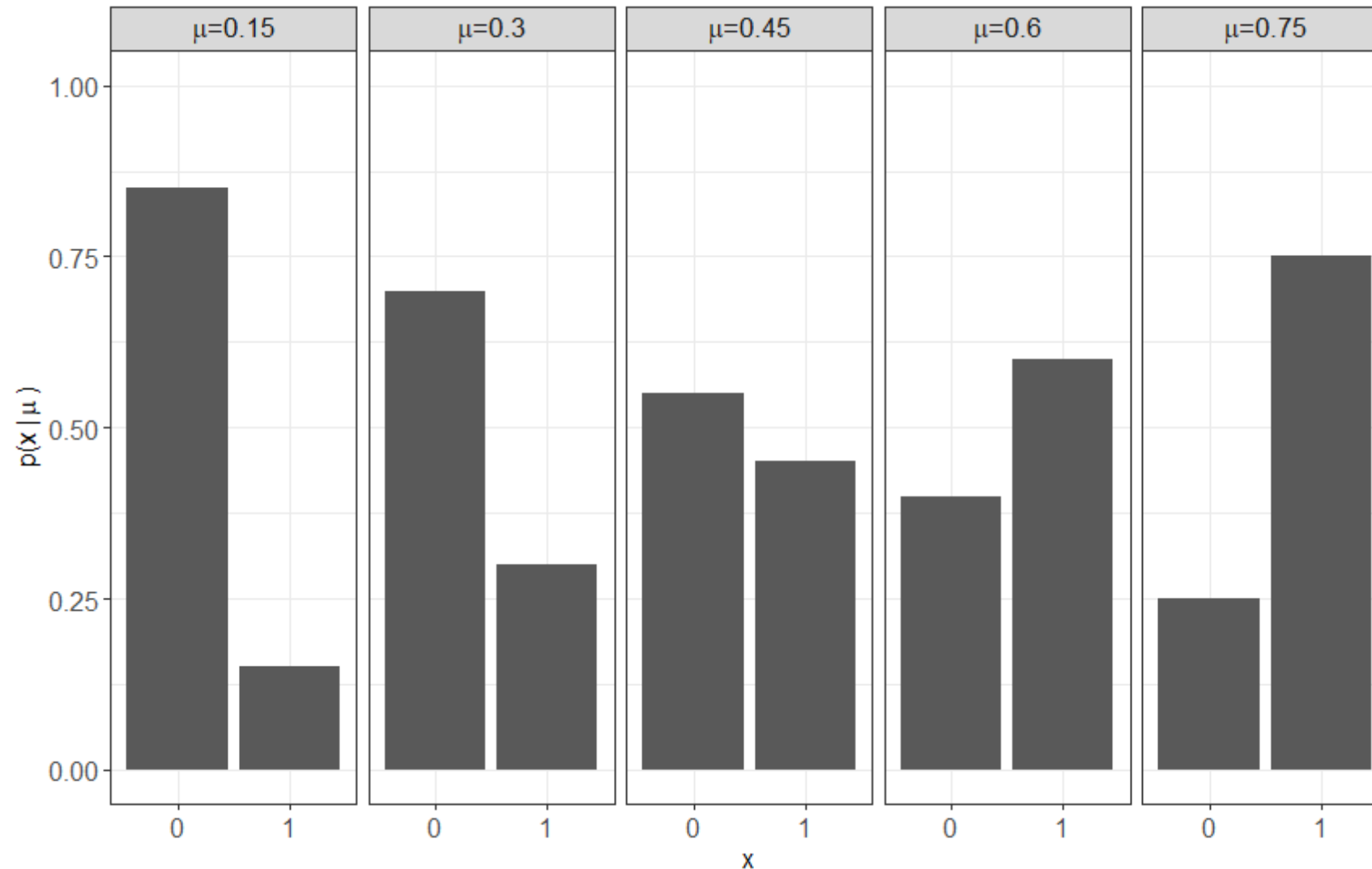
Referred to as the Bernoulli distribution after Jacob Bernoulli

Note: μ is a probability and so is bounded: $0 \leq \mu \leq 1$

The Bernoulli distribution PMF for a single μ



Bernoulli PMF for multiple μ values



The Bernoulli distribution can be used to represent many different real-life applications

- Today we introduced the concept in terms of college football fans.
- Typically, the Bernoulli distribution is introduced with the canonical **coin flip** example.
- Applicable in sports, engineering, manufacturing, medicine, marketing, etc...

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- Today we introduced the concept in terms of college football fans.
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- Applicable in sports, engineering, manufacturing, medicine, marketing, etc...
- The Bernoulli distribution is applicable for many **BINARY OUTCOME** situations.

Back to our college football example...

- Suppose we ask 4 random people which team they are cheering for, and we get the following answers:

Person	Fan
1	PSU
2	PSU
3	Pitt
4	PSU

In terms of the encoded variable x :

Person	Fan	x
1	PSU	0
2	PSU	0
3	Pitt	1
4	PSU	0

What is the probability of the sequence we observed?

- Start with the joint distribution:

$$p(x_1 = 0, x_2 = 0, x_3 = 1, x_4 = 0 | \mu)$$

- Assuming each person is **independent** we can factorize the joint distribution into:

$$p(x_1 = 0, x_2 = 0, x_3 = 1, x_4 = 0 | \mu) = p(x_1 = 0) p(x_2 = 0) p(x_3 = 1) p(x_4 = 0)$$

Drop μ on the right-hand side (RHS) to save space

Substitute in the expression from the Bernoulli PMF for each person

$$p(x_1 = 0)p(x_2 = 0)p(x_3 = 1)p(x_4 = 0) = (1 - \mu)(1 - \mu)\mu(1 - \mu)$$

Drop μ to save space

Now generalize from asking 4 people, to asking N people

- Denote the sequence of responses as: $\mathbf{x} = \{x_1, x_2, \dots, x_n, \dots, x_N\}$
- Assuming each person is **independent** we can factorize the joint distribution just as we did before:

$$p(\mathbf{x}|\mu) = \prod_{n=1}^N \{\mu^{x_n} (1 - \mu)^{1-x_n}\} = \prod_{n=1}^N \text{Bernoulli}(x_n|\mu)$$

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Likelihood Function!!!

What happens when μ is unknown?

- If we have the observed sequence $\mathbf{x} = \{x_1, x_2, \dots, x_n, \dots, x_N\}$ we can estimate μ from the data.
- Which value of μ is best?

What happens when μ is unknown?

- If we have the observed sequence $\mathbf{x} = \{x_1, x_2, \dots, x_n, \dots, x_N\}$ we can estimate μ from the data.
- Which value of μ is best?
- The value that **MAXIMIZES** the likelihood!

$$\hat{\mu} = \mu_{ML} = \operatorname{argmax}_{\mu \in [0,1]} p(\mathbf{x}|\mu)$$

Rather than working with the likelihood directly...we will maximize the *log-likelihood*

- The log-likelihood for the N independent observations:

$$\log[p(\mathbf{x}|\mu)] = \sum_{n=1}^N \{x_n \log[\mu] + (1 - x_n) \log[1 - \mu]\}$$

Rearrange the log-likelihood

$$\log[p(\mathbf{x}|\mu)] = \log[\mu] \sum_{n=1}^N \{x_n\} + \log[1 - \mu] \sum_{n=1}^N \{1 - x_n\}$$

Rearrange the log-likelihood

$$\log[p(\mathbf{x}|\mu)] = \log[\mu] \underbrace{\sum_{n=1}^N \{x_n\}}_{\text{Number of Pitt fans, or more generally number of events } M} + \log[1 - \mu] \underbrace{\sum_{n=1}^N \{1 - x_n\}}_{\text{Number of PSU fans, or more generally number of times we did not observe the event } N - M}$$

Number of Pitt fans,
or more generally
number of events M .

Number of PSU fans, or
more generally number of
times we **did not** observe
the event $N - M$.

Rearrange the log-likelihood

$$\log[p(\mathbf{x}|\mu)] = \log[\mu] \cdot M + \log[1 - \mu] \cdot (N - M)$$

To optimize, calculate the derivative of the log-likelihood with respect to μ

$$\frac{\partial}{\partial \mu} \{\log[p(\mathbf{x}|\mu)]\} = \frac{\partial}{\partial \mu} \{\log[\mu] \cdot M\} + \frac{\partial}{\partial \mu} \{\log[1 - \mu] \cdot (N - M)\}$$

To optimize, calculate the derivative of the log-likelihood with respect to μ

$$\frac{\partial}{\partial \mu} \{\log[p(\mathbf{x}|\mu)]\} = \underbrace{\frac{\partial}{\partial \mu} \{\log[\mu] \cdot M\}}_{\frac{M}{\mu}} + \underbrace{\frac{\partial}{\partial \mu} \{\log[1 - \mu] \cdot (N - M)\}}_{\frac{-(N - M)}{1 - \mu}}$$

Set the derivative equal to zero and solve for μ_{ML}

$$\frac{\partial}{\partial \mu} \{\log[p(\mathbf{x}|\mu)]\} = 0 = \frac{M}{\mu_{ML}} - \frac{N - M}{1 - \mu_{ML}}$$

Set the derivative equal to zero and solve for μ_{ML}

$$\frac{\partial}{\partial \mu} \{\log[p(\mathbf{x}|\mu)]\} = 0 = \frac{M}{\mu_{ML}} - \frac{N - M}{1 - \mu_{ML}}$$



$$\frac{(1 - \mu_{ML}) \cdot M - \mu_{ML} \cdot (N - M)}{\mu_{ML} \cdot (1 - \mu_{ML})} = 0$$

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$$\frac{\partial}{\partial \mu} \{\log[p(\mathbf{x}|\mu)]\} = 0 = \frac{M}{\mu_{ML}} - \frac{N - M}{1 - \mu_{ML}}$$



$$\frac{(1 - \mu_{ML}) \cdot M - \mu_{ML} \cdot (N - M)}{\mu_{ML} \cdot (1 - \mu_{ML})} = 0$$



$$M - \mu_{ML}M - \mu_{ML}N + \mu_{ML}M = 0 \rightarrow M - \mu_{ML}N = 0$$

The maximum likelihood estimate (MLE) for μ is just based on counting!

$$\mu_{ML} = \frac{M}{N} = \frac{1}{N} \sum_{n=1}^N \{x_n\}$$