

# R Notebook midterm: 419 Survey of Multivariate Methods

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## Top of the world

<https://brand.wsu.edu/visual/colors/>

### TESTING PROCEDURE

This midterm exam (Rnotebook-midterm) is worth 150 points. For each question, review how much the item is worth in terms of points and plan your time wisely.

I would deem it “unwise” to spend hours on a question that is only worth 5 points.

#### Static/Existing Resources Are Allowed

This is an open-book examination. You can use your course notebooks (digital and old-school). You can use Internet resources (stackoverflow, Wikipedia, and Youtube).

#### Dynamic/Living Resources Are \_ NOT\_ Allowed

**You cannot use a living resource on the exam.** That would include a classmate, student, sibling, parent, a tutor, online forums (where you ask the question after the exam period has begun).

If you have questions that need clarifying, please **email the instructor** and he will try to answer them by email or ZOOM. He will be checking his email often during the week of the exam, to make himself available to you.

#### Levels of Mastery

- Do You **Remember**?
- Do You **Understand**?
- Can You **Apply** what you remember/understand to another similar problem?
- Can You **Analyze** and **Synthesize** Data?
- Can You **Evaluate** your analyses?
- Can You **Create** meaningful visualizations and summaries?

#### Rubric of Mastery

For every 10 points, this is the general breakdown.

Emerging	Developing	Mastering
0-4	5-7	8 - 10

## EXPLORATORY DATA ANALYSIS (EDA)

Exploratory data analysis (EDA) is the process of analyzing data to summarize its main characteristics.

Confirmatory data analysis (CDA) is the process of applying specific statistical methods to analyze the data. The goal is also to summarize its main characteristics. We commonly refer to CDA as “statistical hypothesis

testing”. CDA generally makes assumptions about how the data is distributed. Or wants to apply a specific model to the data.

So the two approaches have the same objective: summarize the main characteristics of the data. How they achieve that objective is very different.

## Introduction

### John Tukey

John Tukey is the father of “Exploratory Data Analysis” (EDA) [https://en.wikipedia.org/wiki/John\\_Tukey](https://en.wikipedia.org/wiki/John_Tukey). My favorite statistics book is his 1977 book (not surprising) entitled “Exploratory Data Analysis.”

### Exploratory vs Confirmatory

From Wikipedia (Accessed October 2020): Tukey “also contributed to statistical practice and articulated the important distinction between exploratory data analysis and confirmatory data analysis, **believing that much statistical methodology placed too great an emphasis on the latter.**”

I belong to the “Tukey” camp. I believe too much emphasis is placed on “formal statistical methods and tests”. I believe more emphasis should be placed on the underlying nature of the data. These underlying principles are how the statistical methods developed.

As a data analyst, I believe that first and foremost, we should let the data speak. That is why the first half of the semester started in this form. The second half (confirmatory data analysis) will rely on what is labeled by many as “formal statistical methods”.

### Tukey and “Bell Labs”

In 1965, Tukey divided his time between working at Princeton University and working at Bell Labs (a research think tank).

**Robust Statistics as Nonparametric** Tukey proposed that five summary data are essential to understanding numerical data: `min`, `max`, `median` (technically `Q2`), and `Q1` and `Q3` (the quartiles). In `R`, the function `summary` has only added `mean` to Tukey’s proposal from years ago.

**Box and Whisker Plot** In 1975, Tukey invented the “box and whisker” plot that identifies the median, inter-quartile range (IQR), and outliers of data. The visualization displays the data without making any assumptions about its statistical distribution. The boxplot is a working demonstration of EDA. **Let the data speak!**

### John Chambers and S and R

At the same time as John Tukey, three other men were also working at Bell Labs (John Chambers, Rick Becker, and Allan Wilks) on a statistical programming language `S` that emphasized EDA. This “statistical computing” language was programming mostly in `Fortran` with some `C` programming. Chambers published his first “statistical computing” text in 1977, titled “Computational methods for data analysis” <https://archive.org/details/computationalmet0000cham/page/n11/mode/2up>

Between 1988 and 1991, Chambers updated the engine of `S` to make it more robust. That same engine still powers much of `R` today. That is, much of the base code of `S` was written by Chambers himself. `R` today still uses much of that `S` codebase under the hood.

`R` was an open-source offshoot (a “fork”) of `S` which occurred in the mid 1990s. Today, Chambers is still active in the `S-nowR` community. My favorite book of his is titled (2008): “Software for data analysis programming with `R`”. My second-favorite book of his is titled (1998): “Programming with data: a guide to the `S` language”. In 2016, he authored another book that I still need to read “Extending `R`.”

Modern R is written in **Fortran**, **C**, and **C++**.

Since its foundation is primarily **C**, we can use standard “make” and “make-install” tools to compile R or its packages from the source code. That is why we needed **Rtools** on Windows. The MacOS is now linux based, so no additional tools are required.

## Summary

EDA as exploration is an iterative process.

### Analogy: learning a foreign language

I like to use the analogy of learning a foreign language using the “immersion” approach. For example, I studied Spanish in high school, learned vocabulary and grammar, and really could not speak the language well.

I did learn to speak the language well by being dropped into a foreign country for nearly two years. Some key ingredients to learn a language in an “immersive” environment are listed below:

- surround yourself with others speaking the language to be learned [e.g., I did not spend a lot of time with other Americans speaking English].
- be present when engaged in the language. Listen intently and try to understand as much as you can, not worrying about what you don’t fully understand.
- reflect after language engagement. Try to synthesize what “gaps” you have and then develop study habits to fill in those gaps.
- practice what you have learned.

To some degree, my success was likely accelerated because I had precursory training. Regardless, “immersive” practices benefit learning new languages.

### Proficiency in Data Analytics

[As part of your journey, I have asked you to keep a “paper-and-pencil” notebook to write down words/phrases/ideas. For example, in this section, there may be words/terms/phrases/ideas you don’t fully understand.]

Proficiency requires an iteration of these key features described above. But first, you have to understand what language you are trying to speak. Is it R? Is it Statistics? Mathematics? What exactly is the language?

In my opinion, the language is the “language of data”.

### The “language of data”

How do you think mathematics developed? It likely started with simple data, based on real-world experience: two hands, five fingers on each hand gives me the number ten. Counting in a base-10 system likely resulted. An entire domain of mathematics called “number theory” devotes its studies to these integer values.

How do you think statistics developed? People went out and started measuring things. One person would literally walk down the street in the late 1800s and ask if he could measure a person’s proportions. Another person would study crop yields at different locations and tried to ascertain if they were different.

The foundation of mathematics and statistics is data. So I believe, we should let the data speak.

### Let the data speak

So I am definitely an EDA-guy. Some people are, some people are not. I personally am a strong believer that we should **let the data speak**, learn how to describe the data without imposing any restrictions on it, and always think about the data first and foremost.

I also believe that we should use logic, intuition, and insight before we develop any formal “confirmatory” hypothesis testing. I have intentionally architected this course to emphasize EDA.

### Quality data provenance

I am also very adamant about **data provenance** as I believe the “outputs” of any analysis (whether exploratory or confirmatory) is as only as good as the data quality. I call this **data intimacy**. You should care just as much about the process to get quality data as you do to analyze said data.

The term **GIGO** (garbage-in, garbage-out) in my estimation represents what happens when care for quality data is treated lightly.

### Iterative Exploration

This full EDA approach is a multi-lens approach. View the data from as many different perspectives as possible before arriving at a conclusion. Base your conclusion on a synthesis of what you analyzed from those different perspectives.

- We do initial EDA (using mathematical foundations),
- then we may do confirmatory analyses (traditional statistical methods), and
- then we synthesize our findings and do a higher-ordered EDA using the original analysis and the confirmatory analysis to make final decisions using sound logic and intuition.
- this process will enlighten our understand and possibly help us formulate new suppositions and think about what additional data would inform the topic.

## (10 points) YOUR “EDA” OPINION

[ I have expressed my opinion about the study of data and the importance of EDA in that study. What is your opinion on this topic?

This is worth 10 points, a minimal answer should be at least 3 paragraphs. Agreeing/Disagreeing with my opinion is not how you will be evaluated. How well you express YOUR opinion is what is important.]

## SIMULATING DATA

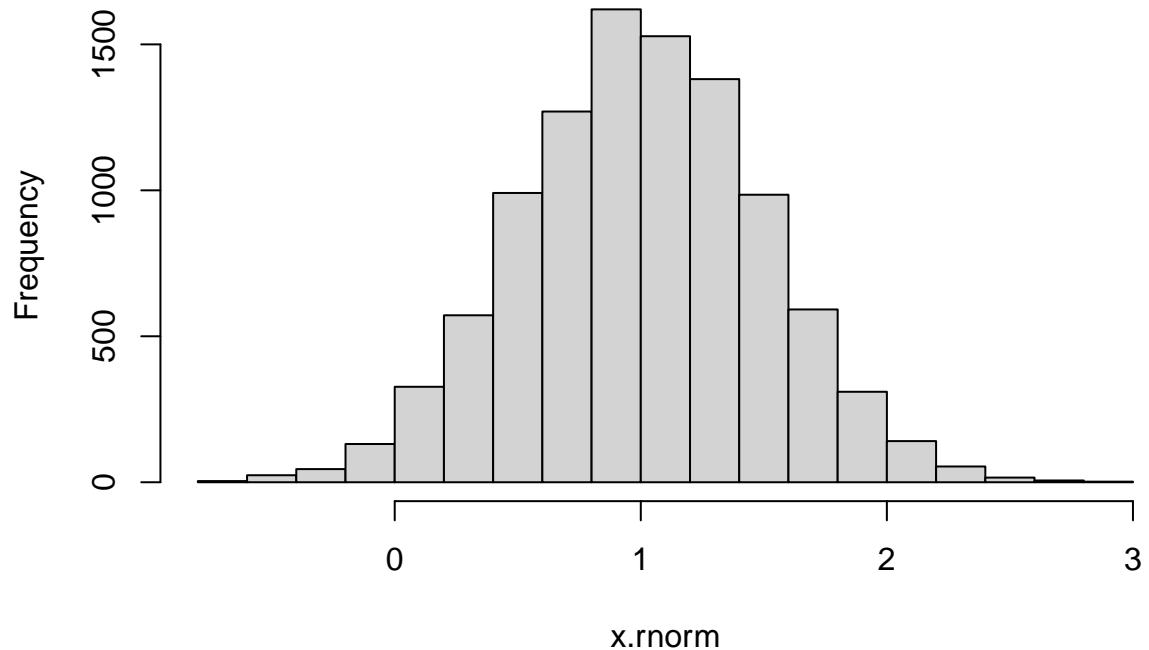
### (10 points) Basic Simulation

- Pick a `set.seed` choice so the code is replicable. Verify that every time you run the commands, the data is not changing with the seed “you chose”.
- Use the functions `rnorm`, `runif` to simulate data.
- Simulate `n=9999`; data for each.
- Call `x.rnorm` the data for the first and `x.runif` the data for the second.
- Plot a histogram `graphics::hist` and report the summary statistics ‘`base::summary` of each.
- Then, plot them using `plot(x.rnorm, x.runif);`.
- Finally, `plot(x.rnorm, sample(x.rnorm) );` and compare it to `plot(x.runif, sample(x.runif) );`.

```
set.seed(1234);

x.rnorm = rnorm(n = 9999, 1, 0.5);
x.runif = runif(n = 9999, 0,1);
graphics::hist(x.rnorm);
```

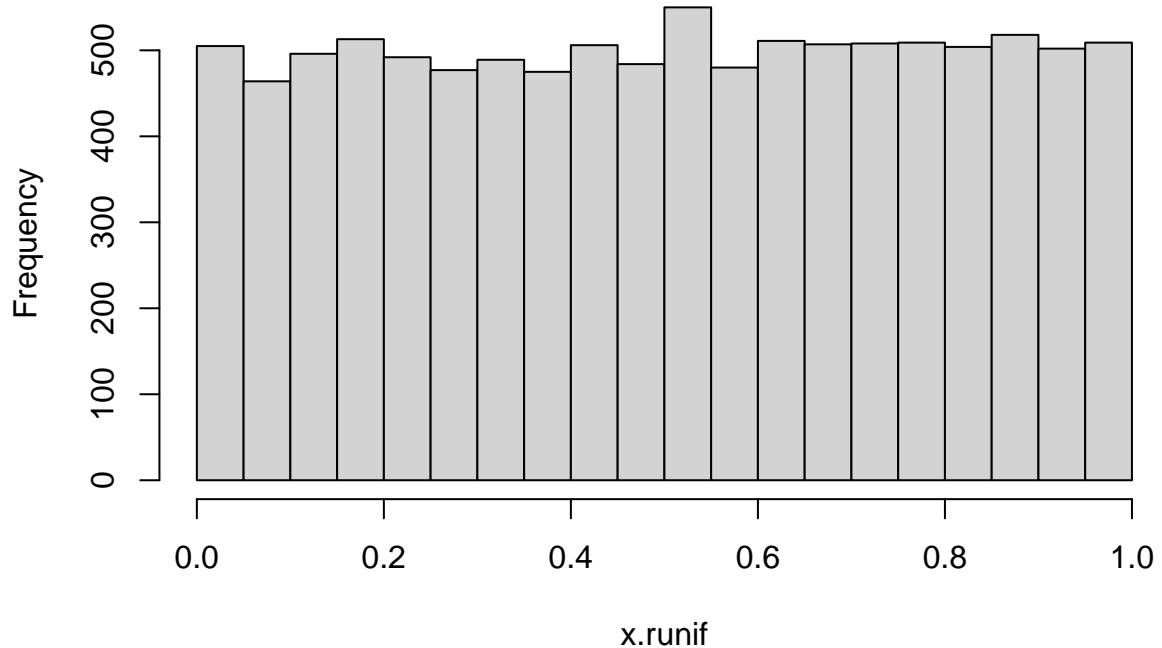
### Histogram of x.rnorm



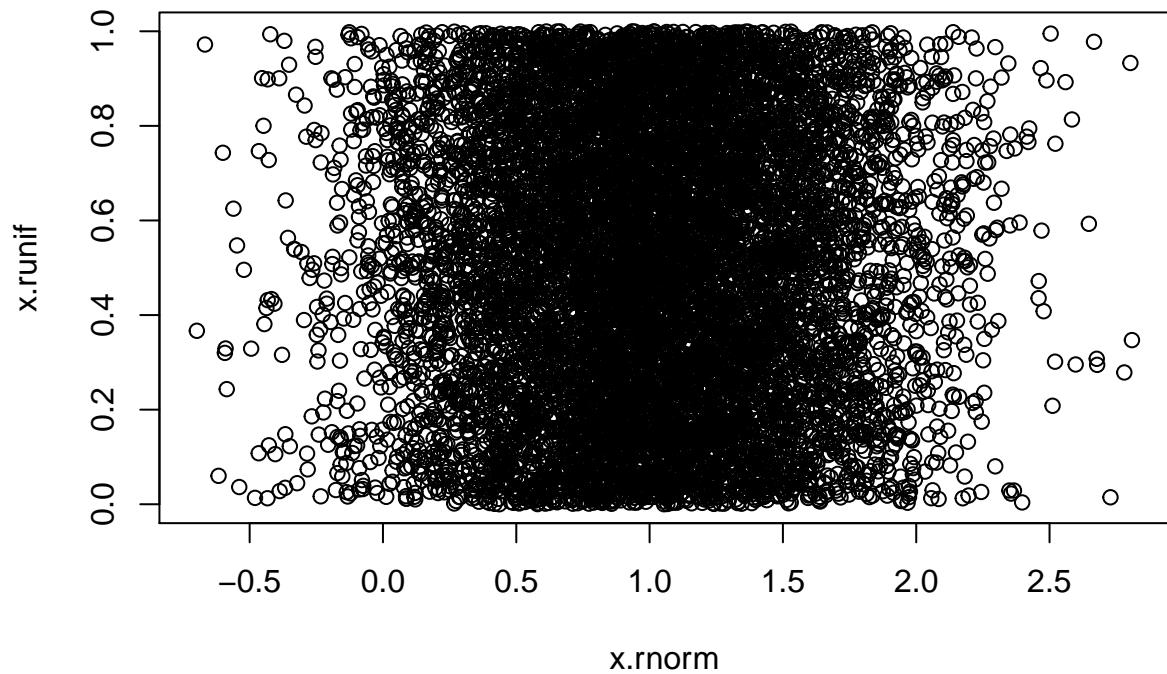
Code of simulation

```
graphics::hist(x.runif);
```

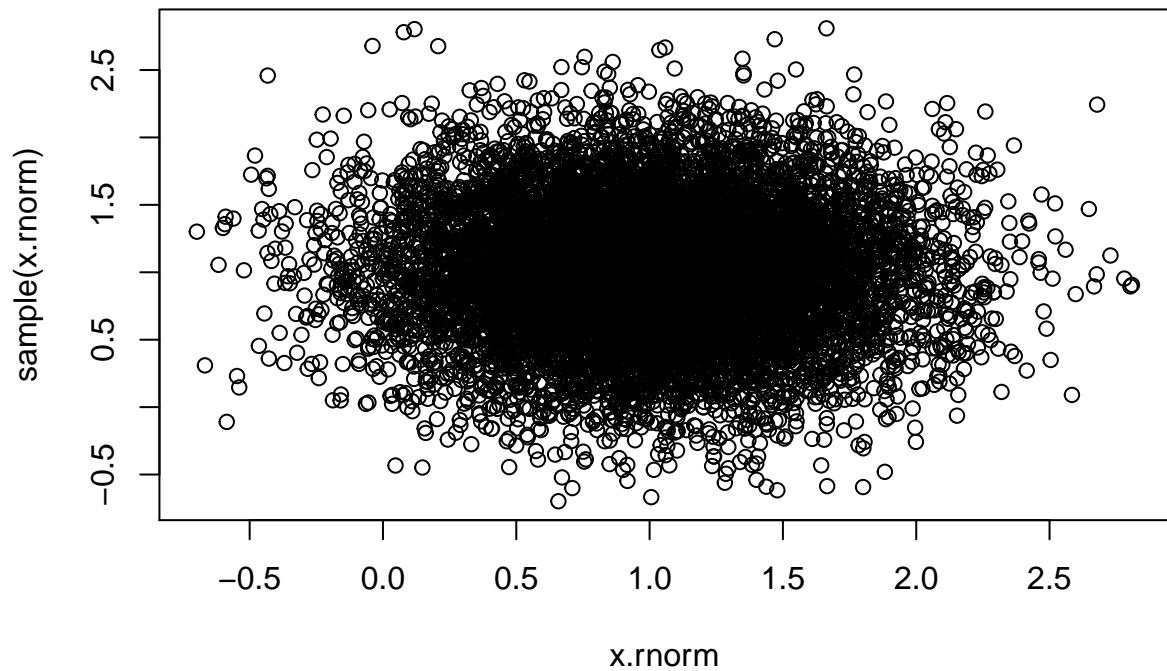
## Histogram of x.runif



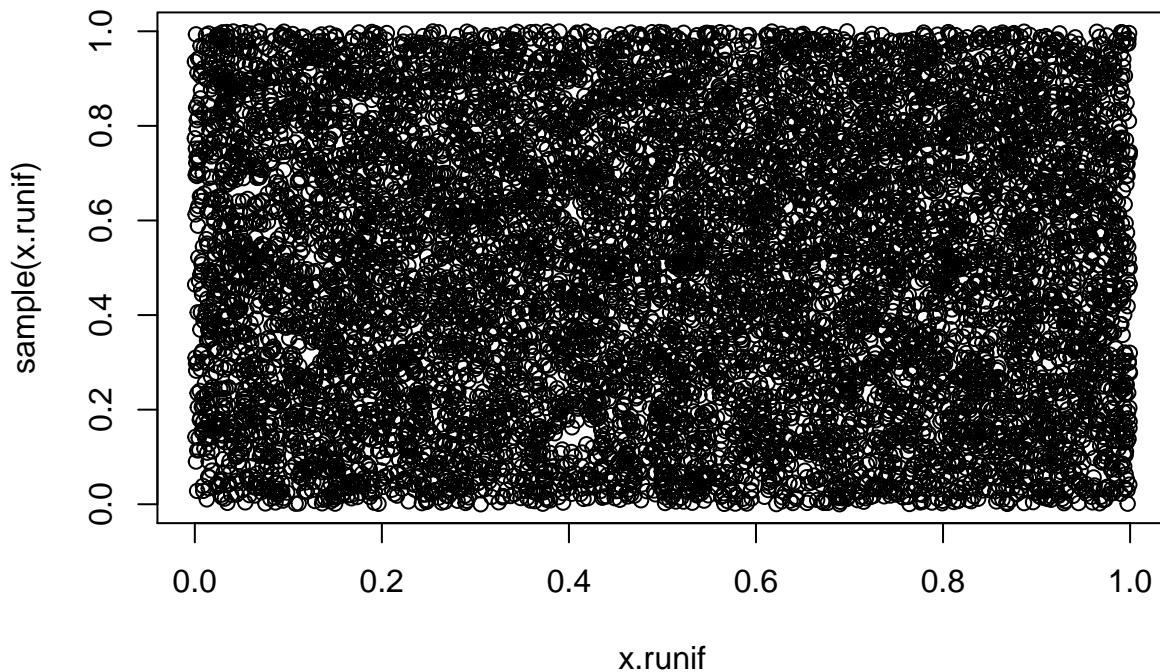
```
base::summary(x.rnorm);  
##      Min.    1st Qu.     Median      Mean    3rd Qu.      Max.  
## -0.6980   0.6696   1.0023   1.0030   1.3347   2.8091  
base::summary(x.runif);  
##      Min.    1st Qu.     Median      Mean    3rd Qu.      Max.  
## 0.0000315 0.2543541 0.5089181 0.5044548 0.7536124 0.9998502  
plot(x.rnorm, x.runif);
```



```
plot(x.rnorm, sample(x.rnorm));
```



```
plot(x.runif, sample(x.runif));
```



#### Describe rnorm, runif

- Describe what each function `rnorm` and `runif` does. How are they similar? How are they different?
- What does the `sample` function do?
- How was `plot(x.rnorm, x.runif);` different from `plot(x.rnorm.sample = sample(x.rnorm) );` and `plot(x.runif.sample = sample(x.runif) );`? How would you describe the shape of each of these plots?

#### (5 points) “Easter-Egg” Simulation

- There was an “Easter Egg” that related to setting the seed `set.seed` using `rbinom`. If you search in the BlackBoard discussion forum for `easter` you will see the discussion about August 25-27.
- In the “Easter Egg”, the goal was to find a scenario using a specific `set.seed` that would simulate flipping a coin 100 times and getting one result (heads/tails) exactly 52 times.
- In this problem, the search criteria has changed. Simulate flipping a coin 1000 times and getting one result (heads/tails) exactly 555 times.
- You need to report 5 values for `set.seed` that achieves this objective. You can report more.
- You should explicitly have the code print `length(x)` where `x` is a vector of the values that meet the objective.

```
nsim = 500000;
y= 1:nsim;
ns = 0;
which = numeric(0);
for(i in y)
```

```

{
  set.seed(i);
  res = rbinom(n = 1, 1000, 0.5);
  if(res == 555)
  {
    cat(i, sep = "\n");
    ns = 1 + ns;
    which = c(which, i);
  }
}

## 49771
## 58927
## 63153
## 64693
## 74842
## 101575
## 103323
## 113838
## 121830
## 152054
## 168654
## 178390
## 211784
## 225908
## 253759
## 298626
## 303566
## 316746
## 317968
## 325175
## 400407
## 491595
## 492805
## 498906

x = which;
length(x);

## [1] 24

```

## Rolling the Dice

- You have 3 dice.
- Each dice has the numbers 1:10 ... they are ten-sided die (“decader” die).
- Write the necessary `for-loops` to capture all possible outcomes of rolling the three dice at the same time.
- A dataframe `myrolls` should have three columns: `dice.1`, `dice.2`, `dice.3` plus a fourth column `roll.total` which is the sum `dice.1 + dice.2 + dice.3` of one iteration of the nested `for` loop.
- Report the dimensions `dim` of `myrolls`.
- Create a table `outcomes.table` that summarizes the counts of the `myrolls$roll.total`
- Transform the table to a dataframe `outcomes.df`. Name the columns: `c("roll.total", "count")`;
- Report the sum of `outcome.df$count`
- Create a new column `outcomes.df$prob` (Probability) that determines the probability of that row given the total sum of the `count` column.

- Display the dataframe.

```
## your code goes here ...

dice.1 = dice.2 = dice.3 = 1:10;

myrolls = NULL;
for(d1 in dice.1)
{
  for(d2 in dice.2)
  {
    for(d3 in dice.3)
    {
      roll.total = d1 + d2 + d3;
      row = c(d1, d2, d3, roll.total);
      myrolls = rbind(myrolls, row);
    }
  }
}

myrolls = as.data.frame(myrolls);
colnames(myrolls) = c("dice.1", "dice.2", "dice.3", "roll.total");

myrolls;
```

### Setting Up the Dice Scenario

	dice.1	dice.2	dice.3	roll.total
## row	1	1	1	3
## row.1	1	1	2	4
## row.2	1	1	3	5
## row.3	1	1	4	6
## row.4	1	1	5	7
## row.5	1	1	6	8
## row.6	1	1	7	9
## row.7	1	1	8	10
## row.8	1	1	9	11
## row.9	1	1	10	12
## row.10	1	2	1	4
## row.11	1	2	2	5
## row.12	1	2	3	6
## row.13	1	2	4	7
## row.14	1	2	5	8
## row.15	1	2	6	9
## row.16	1	2	7	10
## row.17	1	2	8	11
## row.18	1	2	9	12
## row.19	1	2	10	13
## row.20	1	3	1	5
## row.21	1	3	2	6
## row.22	1	3	3	7
## row.23	1	3	4	8
## row.24	1	3	5	9
## row.25	1	3	6	10

## row.26	1	3	7	11
## row.27	1	3	8	12
## row.28	1	3	9	13
## row.29	1	3	10	14
## row.30	1	4	1	6
## row.31	1	4	2	7
## row.32	1	4	3	8
## row.33	1	4	4	9
## row.34	1	4	5	10
## row.35	1	4	6	11
## row.36	1	4	7	12
## row.37	1	4	8	13
## row.38	1	4	9	14
## row.39	1	4	10	15
## row.40	1	5	1	7
## row.41	1	5	2	8
## row.42	1	5	3	9
## row.43	1	5	4	10
## row.44	1	5	5	11
## row.45	1	5	6	12
## row.46	1	5	7	13
## row.47	1	5	8	14
## row.48	1	5	9	15
## row.49	1	5	10	16
## row.50	1	6	1	8
## row.51	1	6	2	9
## row.52	1	6	3	10
## row.53	1	6	4	11
## row.54	1	6	5	12
## row.55	1	6	6	13
## row.56	1	6	7	14
## row.57	1	6	8	15
## row.58	1	6	9	16
## row.59	1	6	10	17
## row.60	1	7	1	9
## row.61	1	7	2	10
## row.62	1	7	3	11
## row.63	1	7	4	12
## row.64	1	7	5	13
## row.65	1	7	6	14
## row.66	1	7	7	15
## row.67	1	7	8	16
## row.68	1	7	9	17
## row.69	1	7	10	18
## row.70	1	8	1	10
## row.71	1	8	2	11
## row.72	1	8	3	12
## row.73	1	8	4	13
## row.74	1	8	5	14
## row.75	1	8	6	15
## row.76	1	8	7	16
## row.77	1	8	8	17
## row.78	1	8	9	18
## row.79	1	8	10	19

## row.80	1	9	1	11
## row.81	1	9	2	12
## row.82	1	9	3	13
## row.83	1	9	4	14
## row.84	1	9	5	15
## row.85	1	9	6	16
## row.86	1	9	7	17
## row.87	1	9	8	18
## row.88	1	9	9	19
## row.89	1	9	10	20
## row.90	1	10	1	12
## row.91	1	10	2	13
## row.92	1	10	3	14
## row.93	1	10	4	15
## row.94	1	10	5	16
## row.95	1	10	6	17
## row.96	1	10	7	18
## row.97	1	10	8	19
## row.98	1	10	9	20
## row.99	1	10	10	21
## row.100	2	1	1	4
## row.101	2	1	2	5
## row.102	2	1	3	6
## row.103	2	1	4	7
## row.104	2	1	5	8
## row.105	2	1	6	9
## row.106	2	1	7	10
## row.107	2	1	8	11
## row.108	2	1	9	12
## row.109	2	1	10	13
## row.110	2	2	1	5
## row.111	2	2	2	6
## row.112	2	2	3	7
## row.113	2	2	4	8
## row.114	2	2	5	9
## row.115	2	2	6	10
## row.116	2	2	7	11
## row.117	2	2	8	12
## row.118	2	2	9	13
## row.119	2	2	10	14
## row.120	2	3	1	6
## row.121	2	3	2	7
## row.122	2	3	3	8
## row.123	2	3	4	9
## row.124	2	3	5	10
## row.125	2	3	6	11
## row.126	2	3	7	12
## row.127	2	3	8	13
## row.128	2	3	9	14
## row.129	2	3	10	15
## row.130	2	4	1	7
## row.131	2	4	2	8
## row.132	2	4	3	9
## row.133	2	4	4	10

## row.134	2	4	5	11
## row.135	2	4	6	12
## row.136	2	4	7	13
## row.137	2	4	8	14
## row.138	2	4	9	15
## row.139	2	4	10	16
## row.140	2	5	1	8
## row.141	2	5	2	9
## row.142	2	5	3	10
## row.143	2	5	4	11
## row.144	2	5	5	12
## row.145	2	5	6	13
## row.146	2	5	7	14
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## row.725	8	3	6	17
## row.726	8	3	7	18
## row.727	8	3	8	19

## row.728	8	3	9	20
## row.729	8	3	10	21
## row.730	8	4	1	13
## row.731	8	4	2	14
## row.732	8	4	3	15
## row.733	8	4	4	16
## row.734	8	4	5	17
## row.735	8	4	6	18
## row.736	8	4	7	19
## row.737	8	4	8	20
## row.738	8	4	9	21
## row.739	8	4	10	22
## row.740	8	5	1	14
## row.741	8	5	2	15
## row.742	8	5	3	16
## row.743	8	5	4	17
## row.744	8	5	5	18
## row.745	8	5	6	19
## row.746	8	5	7	20
## row.747	8	5	8	21
## row.748	8	5	9	22
## row.749	8	5	10	23
## row.750	8	6	1	15
## row.751	8	6	2	16
## row.752	8	6	3	17
## row.753	8	6	4	18
## row.754	8	6	5	19
## row.755	8	6	6	20
## row.756	8	6	7	21
## row.757	8	6	8	22
## row.758	8	6	9	23
## row.759	8	6	10	24
## row.760	8	7	1	16
## row.761	8	7	2	17
## row.762	8	7	3	18
## row.763	8	7	4	19
## row.764	8	7	5	20
## row.765	8	7	6	21
## row.766	8	7	7	22
## row.767	8	7	8	23
## row.768	8	7	9	24
## row.769	8	7	10	25
## row.770	8	8	1	17
## row.771	8	8	2	18
## row.772	8	8	3	19
## row.773	8	8	4	20
## row.774	8	8	5	21
## row.775	8	8	6	22
## row.776	8	8	7	23
## row.777	8	8	8	24
## row.778	8	8	9	25
## row.779	8	8	10	26
## row.780	8	9	1	18
## row.781	8	9	2	19

## row.782	8	9	3	20
## row.783	8	9	4	21
## row.784	8	9	5	22
## row.785	8	9	6	23
## row.786	8	9	7	24
## row.787	8	9	8	25
## row.788	8	9	9	26
## row.789	8	9	10	27
## row.790	8	10	1	19
## row.791	8	10	2	20
## row.792	8	10	3	21
## row.793	8	10	4	22
## row.794	8	10	5	23
## row.795	8	10	6	24
## row.796	8	10	7	25
## row.797	8	10	8	26
## row.798	8	10	9	27
## row.799	8	10	10	28
## row.800	9	1	1	11
## row.801	9	1	2	12
## row.802	9	1	3	13
## row.803	9	1	4	14
## row.804	9	1	5	15
## row.805	9	1	6	16
## row.806	9	1	7	17
## row.807	9	1	8	18
## row.808	9	1	9	19
## row.809	9	1	10	20
## row.810	9	2	1	12
## row.811	9	2	2	13
## row.812	9	2	3	14
## row.813	9	2	4	15
## row.814	9	2	5	16
## row.815	9	2	6	17
## row.816	9	2	7	18
## row.817	9	2	8	19
## row.818	9	2	9	20
## row.819	9	2	10	21
## row.820	9	3	1	13
## row.821	9	3	2	14
## row.822	9	3	3	15
## row.823	9	3	4	16
## row.824	9	3	5	17
## row.825	9	3	6	18
## row.826	9	3	7	19
## row.827	9	3	8	20
## row.828	9	3	9	21
## row.829	9	3	10	22
## row.830	9	4	1	14
## row.831	9	4	2	15
## row.832	9	4	3	16
## row.833	9	4	4	17
## row.834	9	4	5	18
## row.835	9	4	6	19

## row.836	9	4	7	20
## row.837	9	4	8	21
## row.838	9	4	9	22
## row.839	9	4	10	23
## row.840	9	5	1	15
## row.841	9	5	2	16
## row.842	9	5	3	17
## row.843	9	5	4	18
## row.844	9	5	5	19
## row.845	9	5	6	20
## row.846	9	5	7	21
## row.847	9	5	8	22
## row.848	9	5	9	23
## row.849	9	5	10	24
## row.850	9	6	1	16
## row.851	9	6	2	17
## row.852	9	6	3	18
## row.853	9	6	4	19
## row.854	9	6	5	20
## row.855	9	6	6	21
## row.856	9	6	7	22
## row.857	9	6	8	23
## row.858	9	6	9	24
## row.859	9	6	10	25
## row.860	9	7	1	17
## row.861	9	7	2	18
## row.862	9	7	3	19
## row.863	9	7	4	20
## row.864	9	7	5	21
## row.865	9	7	6	22
## row.866	9	7	7	23
## row.867	9	7	8	24
## row.868	9	7	9	25
## row.869	9	7	10	26
## row.870	9	8	1	18
## row.871	9	8	2	19
## row.872	9	8	3	20
## row.873	9	8	4	21
## row.874	9	8	5	22
## row.875	9	8	6	23
## row.876	9	8	7	24
## row.877	9	8	8	25
## row.878	9	8	9	26
## row.879	9	8	10	27
## row.880	9	9	1	19
## row.881	9	9	2	20
## row.882	9	9	3	21
## row.883	9	9	4	22
## row.884	9	9	5	23
## row.885	9	9	6	24
## row.886	9	9	7	25
## row.887	9	9	8	26
## row.888	9	9	9	27
## row.889	9	9	10	28

## row.890	9	10	1	20
## row.891	9	10	2	21
## row.892	9	10	3	22
## row.893	9	10	4	23
## row.894	9	10	5	24
## row.895	9	10	6	25
## row.896	9	10	7	26
## row.897	9	10	8	27
## row.898	9	10	9	28
## row.899	9	10	10	29
## row.900	10	1	1	12
## row.901	10	1	2	13
## row.902	10	1	3	14
## row.903	10	1	4	15
## row.904	10	1	5	16
## row.905	10	1	6	17
## row.906	10	1	7	18
## row.907	10	1	8	19
## row.908	10	1	9	20
## row.909	10	1	10	21
## row.910	10	2	1	13
## row.911	10	2	2	14
## row.912	10	2	3	15
## row.913	10	2	4	16
## row.914	10	2	5	17
## row.915	10	2	6	18
## row.916	10	2	7	19
## row.917	10	2	8	20
## row.918	10	2	9	21
## row.919	10	2	10	22
## row.920	10	3	1	14
## row.921	10	3	2	15
## row.922	10	3	3	16
## row.923	10	3	4	17
## row.924	10	3	5	18
## row.925	10	3	6	19
## row.926	10	3	7	20
## row.927	10	3	8	21
## row.928	10	3	9	22
## row.929	10	3	10	23
## row.930	10	4	1	15
## row.931	10	4	2	16
## row.932	10	4	3	17
## row.933	10	4	4	18
## row.934	10	4	5	19
## row.935	10	4	6	20
## row.936	10	4	7	21
## row.937	10	4	8	22
## row.938	10	4	9	23
## row.939	10	4	10	24
## row.940	10	5	1	16
## row.941	10	5	2	17
## row.942	10	5	3	18
## row.943	10	5	4	19

## row.944	10	5	5	20
## row.945	10	5	6	21
## row.946	10	5	7	22
## row.947	10	5	8	23
## row.948	10	5	9	24
## row.949	10	5	10	25
## row.950	10	6	1	17
## row.951	10	6	2	18
## row.952	10	6	3	19
## row.953	10	6	4	20
## row.954	10	6	5	21
## row.955	10	6	6	22
## row.956	10	6	7	23
## row.957	10	6	8	24
## row.958	10	6	9	25
## row.959	10	6	10	26
## row.960	10	7	1	18
## row.961	10	7	2	19
## row.962	10	7	3	20
## row.963	10	7	4	21
## row.964	10	7	5	22
## row.965	10	7	6	23
## row.966	10	7	7	24
## row.967	10	7	8	25
## row.968	10	7	9	26
## row.969	10	7	10	27
## row.970	10	8	1	19
## row.971	10	8	2	20
## row.972	10	8	3	21
## row.973	10	8	4	22
## row.974	10	8	5	23
## row.975	10	8	6	24
## row.976	10	8	7	25
## row.977	10	8	8	26
## row.978	10	8	9	27
## row.979	10	8	10	28
## row.980	10	9	1	20
## row.981	10	9	2	21
## row.982	10	9	3	22
## row.983	10	9	4	23
## row.984	10	9	5	24
## row.985	10	9	6	25
## row.986	10	9	7	26
## row.987	10	9	8	27
## row.988	10	9	9	28
## row.989	10	9	10	29
## row.990	10	10	1	21
## row.991	10	10	2	22
## row.992	10	10	3	23
## row.993	10	10	4	24
## row.994	10	10	5	25
## row.995	10	10	6	26
## row.996	10	10	7	27
## row.997	10	10	8	28

```

## row.998      10      10      9       29
## row.999      10      10     10       30
print("Dimensions of myrolls");

## [1] "Dimensions of myrolls"
dim(myrolls);

## [1] 1000      4

outcomes.table = table(myrolls$roll.total);
outcomes.df = as.data.frame(outcomes.table);
  colnames(outcomes.df) = c("roll.total", "count");

total.sum = sum(outcomes.df$count);
print("Sum of outcomes.df$count");

## [1] "Sum of outcomes.df$count"
total.sum;

## [1] 1000

outcomes.df$prob = outcomes.df$count / total.sum;
outcomes.df;

##    roll.total count   prob
## 1            3    1 0.001
## 2            4    3 0.003
## 3            5    6 0.006
## 4            6   10 0.010
## 5            7   15 0.015
## 6            8   21 0.021
## 7            9   28 0.028
## 8           10   36 0.036
## 9           11   45 0.045
## 10          12   55 0.055
## 11          13   63 0.063
## 12          14   69 0.069
## 13          15   73 0.073
## 14          16   75 0.075
## 15          17   75 0.075
## 16          18   73 0.073
## 17          19   69 0.069
## 18          20   63 0.063
## 19          21   55 0.055
## 20          22   45 0.045
## 21          23   36 0.036
## 22          24   28 0.028
## 23          25   21 0.021
## 24          26   15 0.015
## 25          27   10 0.010
## 26          28    6 0.006
## 27          29    3 0.003
## 28          30    1 0.001

```

## Viewing a subset of data to answer a question

- How many ways can I roll a 23 when I throw the dice at the same time? What is the probability that I roll a 23 on a single throw?

```
# if you don't have the latest version of humanVerseWSU, you can access the function as follows:  
# library(devtools);  
# source_url(paste0( path.github, "humanVerseWSU/R/functions-dataframe.R" ));  
  
sub.myrolls = subsetDataFrame(myrolls, "roll.total", "==", 23);  
  
sub.myrolls;  
  
##      dice.1 dice.2 dice.3 roll.total  
## row.299     3     10     10     23  
## row.389     4      9     10     23  
## row.398     4     10      9     23  
## row.479     5      8     10     23  
## row.488     5      9      9     23  
## row.497     5     10      8     23  
## row.569     6      7     10     23  
## row.578     6      8      9     23  
## row.587     6      9      8     23  
## row.596     6     10      7     23  
## row.659     7      6     10     23  
## row.668     7      7      9     23  
## row.677     7      8      8     23  
## row.686     7      9      7     23  
## row.695     7     10      6     23  
## row.749     8      5     10     23  
## row.758     8      6      9     23  
## row.767     8      7      8     23  
## row.776     8      8      7     23  
## row.785     8      9      6     23  
## row.794     8     10      5     23  
## row.839     9      4     10     23  
## row.848     9      5      9     23  
## row.857     9      6      8     23  
## row.866     9      7      7     23  
## row.875     9      8      6     23  
## row.884     9      9      5     23  
## row.893     9     10      4     23  
## row.929    10      3     10     23  
## row.938    10      4      9     23  
## row.947    10      5      8     23  
## row.956    10      6      7     23  
## row.965    10      7      6     23  
## row.974    10      8      5     23  
## row.983    10      9      4     23  
## row.992    10     10      3     23  
  
sub.outcomes.df = subsetDataFrame(outcomes.df, "roll.total", "==", 23);  
  
sub.outcomes.df;  
  
##      roll.total count  prob
```

```
## 21      23      36  0.036
```

#### (10 points) Questions from the Dice simulation

##### Roll 23

- How many ways can I roll a 23 when I throw the dice at the same time? What is the probability that I roll a 23 on a single throw?

##### Roll 12 or 22

- What is the probability that I roll a 12 or a 22 on a single throw?

```
## your code goes here ... if necessary

sub.outcomes.df = subsetDataFrame(outcomes.df, "roll.total", "==", 12);

sub.outcomes.df;

##   roll.total count  prob
## 10          12     55 0.055
sub.outcomes.df = subsetDataFrame(outcomes.df, "roll.total", "==", 22);

sub.outcomes.df;

##   roll.total count  prob
## 20          22     45 0.045
```

##### Roll 26 or 29

- What is the probability that I roll a 26 or a 29 on a single throw?

```
## your code goes here ... if necessary
sub.outcomes.df = subsetDataFrame(outcomes.df, "roll.total", "==", 26);

sub.outcomes.df;

##   roll.total count  prob
## 24          26     15 0.015
sub.outcomes.df = subsetDataFrame(outcomes.df, "roll.total", "==", 29);

sub.outcomes.df;

##   roll.total count  prob
## 27          29      3 0.003
```

##### Roll 3 once/twice in a row

- What is the probability that I roll a 3 on a single throw? What is the probability that I roll a 3 twice in a row? First throw = 3 **AND** second throw = 3?

```
## your code goes here ... if necessary
sub.myrolls = subsetDataFrame(myrolls, "roll.total", "==", 3);

sub.myrolls;
```

```

##      dice.1 dice.2 dice.3 roll.total
##  row      1      1      1          3
sub.outcomes.df = subsetDataFrame(outcomes.df, "roll.total", "==", 3);

sub.outcomes.df;

##   roll.total count  prob
## 1            3     1 0.001

```

### Roll 12 or lower

- What is the probability that I roll at most a 12 on a single throw? That is, a 12 or lower ...

```
## your code goes here ... if necessary
```

## INITIAL EXPLORATION OF REAL DATA

We are going to use exploratory techniques to examine some Indeed.com data. If you recall, this job data examines how many jobs reference a certain keyword. Every Monday morning at 12:00:00AM EST (using a scheduler `crontab`), this data collection is performed. A few weeks ago, I added some new keys words. The data set we have consists of 5 weeks: 2020-38 to 2020-42.

- For each “search phrase”, I go to Indeed.com and download the first page of results.
  - From this first page, I grab the “total count”
  - An example is shown in a screenshot, taken this week.

### Source: Data provenance history

#### Import “jobs” data

- Run code to import the data jobs.

```

jobs = utils::read.csv( paste0(path.mshaffer, "_data_/indeed-jobs.txt"), header=TRUE, quote="", sep="|")

colnames(jobs) = c("year.week", "search.query", "job.count");
jobs;

```

##	year.week	search.query	job.count
## 1	2020-38	Excel	375999
## 2	2020-38	Microsoft Office	223663
## 3	2020-38	C++	158317
## 4	2020-38	C#	158317
## 5	2020-38	Database	124631
## 6	2020-38	Computer Science	107584
## 7	2020-38	Data entry	80465
## 8	2020-38	modeling	78330
## 9	2020-38	SQL+	63365
## 10	2020-38	SQL	63365
## 11	2020-38	.NET	62362
## 12	2020-38	Python	56538
## 13	2020-38	Google	50707
## 14	2020-38	Java	49993
## 15	2020-38	Statistics	49383
## 16	2020-38	R	46997
## 17	2020-38	react	41603
## 18	2020-38	Data analysis	38384

## 19	2020-38		HTML	38062
## 20	2020-38		Javascript	35938
## 21	2020-38		Oracle	30143
## 22	2020-38		SAP	29054
## 23	2020-38	Data management		25694
## 24	2020-38	machine learning		23197
## 25	2020-38		scrum	21599
## 26	2020-38	Data analytics		21546
## 27	2020-38		CSS	21303
## 28	2020-38		API	20997
## 29	2020-38		git	18270
## 30	2020-38		Git	18270
## 31	2020-38	Object oriented		17548
## 32	2020-38		PCA	17047
## 33	2020-38		ai	16066
## 34	2020-38		Big data	15737
## 35	2020-38		debugging	15718
## 36	2020-38	Data science		15044
## 37	2020-38		Android	13375
## 38	2020-38		Tableau	13321
## 39	2020-38	agile development		13080
## 40	2020-38	Business intelligence		13032
## 41	2020-38		data sets	12875
## 42	2020-38		full stack	12799
## 43	2020-38		PHP	12367
## 44	2020-38		PhotoShop	12275
## 45	2020-38		iOS	11938
## 46	2020-38		angular	11386
## 47	2020-38		Mysql	10809
## 48	2020-38	design patterns		10689
## 49	2020-38		SAS	10553
## 50	2020-38	Market Research		10489
## 51	2020-38		scrubbing	10141
## 52	2020-38	Database management		10097
## 53	2020-38	artificial intelligence		8968
## 54	2020-38		usability	8680
## 55	2020-38	Business analysis		8674
## 56	2020-38		datasets	8111
## 57	2020-38	Data Visualization		8001
## 58	2020-38	Business Analyst		7932
## 59	2020-38	relational databases		7895
## 60	2020-38		Jquery	7745
## 61	2020-38		regression	7293
## 62	2020-38		version control	7259
## 63	2020-38	Google analytics		6544
## 64	2020-38		unit testing	6530
## 65	2020-38	Data warehouse		6320
## 66	2020-38		Github	6121
## 67	2020-38	relational database		5931
## 68	2020-38		simulations	5749
## 69	2020-38		benchmarking	5566
## 70	2020-38		firmware	5558
## 71	2020-38		Power BI	5266
## 72	2020-38		Postgresql	4824

## 73	2020-38	Data Analyst	4607
## 74	2020-38	Market Analysis	4253
## 75	2020-38	deep learning	4003
## 76	2020-38	Data scientist	3992
## 77	2020-38	Business analytics	3952
## 78	2020-38	Bootstrap	3923
## 79	2020-38	Windows 10	3858
## 80	2020-38	Slack	3492
## 81	2020-38	Data Engineer	3308
## 82	2020-38	arcgis	2846
## 83	2020-38	Visual Basic	2370
## 84	2020-38	natural language processing	2304
## 85	2020-38	clustering	2237
## 86	2020-38	Data manipulation	2159
## 87	2020-38	SPSS	2150
## 88	2020-38	Report generation	2025
## 89	2020-38	Mac OS	1825
## 90	2020-38	Algorithm Design	1734
## 91	2020-38	NLP	1692
## 92	2020-38	merging	1632
## 93	2020-38	statistical modeling	1616
## 94	2020-38	Generating reports	1602
## 95	2020-38	Wireshark	1547
## 96	2020-38	Looker	1388
## 97	2020-38	multivariate	1342
## 98	2020-38	neural networks	1231
## 99	2020-38	Custom reports	1187
## 100	2020-38	Stata	1186
## 101	2020-38	Marketing Research	1036
## 102	2020-38	QlikView	895
## 103	2020-38	Data maintenance	860
## 104	2020-38	D3	765
## 105	2020-38	Statistician	702
## 106	2020-38	Curl	692
## 107	2020-38	C++ programming	688
## 108	2020-38	C programming	688
## 109	2020-38	Spotfire	572
## 110	2020-38	Biostatistician	568
## 111	2020-38	LSA	567
## 112	2020-38	MariaDB	547
## 113	2020-38	decision trees	546
## 114	2020-38	Qualtrics	491
## 115	2020-38	Git version control	490
## 116	2020-38	Delphi	473
## 117	2020-38	Domo	470
## 118	2020-38	TSQL	447
## 119	2020-38	scenario analysis	438
## 120	2020-38	SQLite	400
## 121	2020-38	neural network	399
## 122	2020-38	logistic regression	395
## 123	2020-38	Data wrangling	380
## 124	2020-38	Insights analytics	374
## 125	2020-38	Debian	364
## 126	2020-38	Lab Notebook	364

## 127	2020-38	Sensitivity Analysis	362
## 128	2020-38	Using R	335
## 129	2020-38	well-documented code	229
## 130	2020-38	SVD	226
## 131	2020-38	Actuarial Analyst	208
## 132	2020-38	Power Analysis	200
## 133	2020-38	document code	197
## 134	2020-38	SVM	196
## 135	2020-38	k-means	157
## 136	2020-38	LDA	135
## 137	2020-38	R Studio	132
## 138	2020-38	ggplot	130
## 139	2020-38	plotly	128
## 140	2020-38	SiSense	124
## 141	2020-38	RStudio	117
## 142	2020-38	Web scraping	116
## 143	2020-38	Online analytics	115
## 144	2020-38	Insights Analyst	110
## 145	2020-38	Highcharts	97
## 146	2020-38	Insights analysis	93
## 147	2020-38	Birst	90
## 148	2020-38	Actuarial analysis	80
## 149	2020-38	knn	47
## 150	2020-38	tidyverse	40
## 151	2020-38	spatial statistics	38
## 152	2020-38	R packages	36
## 153	2020-38	Insurance Analyst	34
## 154	2020-38	C++ programmer	25
## 155	2020-38	Insurance analysis	25
## 156	2020-38	C programmer	25
## 157	2020-38	Gauss	24
## 158	2020-38	Insurance analytics	23
## 159	2020-38	GoodData	21
## 160	2020-38	Actuarial analytics	20
## 161	2020-38	R Markdown	17
## 162	2020-38	Data scraping	16
## 163	2020-38	hierarchical clustering	13
## 164	2020-38	kmeans	12
## 165	2020-38	Datawrapper	9
## 166	2020-38	Actuary Analyst	9
## 167	2020-38	FusionCharts	9
## 168	2020-38	Computational Engineer	8
## 169	2020-38	record linkage	7
## 170	2020-38	Insight Squared	5
## 171	2020-38	R Developer	4
## 172	2020-38	Dundas BI	3
## 173	2020-38	Actuary analytics	3
## 174	2020-38	Polling Analyst	2
## 175	2020-38	Highcharter	1
## 176	2020-38	Polling analysis	1
## 177	2020-38	Polling analytics	1
## 178	2020-38	Datapine	1
## 179	2020-38	Analytic Scripting	1
## 180	2020-38	Zebra BI	0

## 181	2020-38	Actuary analysis	0
## 182	2020-39	Excel	385706
## 183	2020-39	Microsoft Office	228397
## 184	2020-39	C++	161156
## 185	2020-39	C#	161156
## 186	2020-39	Database	127108
## 187	2020-39	Computer Science	109819
## 188	2020-39	Data entry	83373
## 189	2020-39	modeling	79713
## 190	2020-39	.NET	65649
## 191	2020-39	SQL	64810
## 192	2020-39	SQL+	64810
## 193	2020-39	Python	57841
## 194	2020-39	Google	51926
## 195	2020-39	Java	51155
## 196	2020-39	Statistics	50588
## 197	2020-39	R	47809
## 198	2020-39	react	42155
## 199	2020-39	Data analysis	39447
## 200	2020-39	HTML	38810
## 201	2020-39	Javascript	36633
## 202	2020-39	Oracle	30729
## 203	2020-39	SAP	29657
## 204	2020-39	Data management	26198
## 205	2020-39	machine learning	24005
## 206	2020-39	Data analytics	22342
## 207	2020-39	scrum	22098
## 208	2020-39	API	21830
## 209	2020-39	CSS	21739
## 210	2020-39	git	18617
## 211	2020-39	Git	18617
## 212	2020-39	Object oriented	18023
## 213	2020-39	PCA	17248
## 214	2020-39	ai	16462
## 215	2020-39	Big data	15997
## 216	2020-39	debugging	15936
## 217	2020-39	Data science	15587
## 218	2020-39	Tableau	13735
## 219	2020-39	Android	13722
## 220	2020-39	Business intelligence	13524
## 221	2020-39	data sets	13445
## 222	2020-39	agile development	13240
## 223	2020-39	full stack	13164
## 224	2020-39	PhotoShop	12622
## 225	2020-39	PHP	12610
## 226	2020-39	iOS	12253
## 227	2020-39	angular	11677
## 228	2020-39	design patterns	11132
## 229	2020-39	SAS	11039
## 230	2020-39	Mysql	10942
## 231	2020-39	Market Research	10748
## 232	2020-39	scrubbing	10364
## 233	2020-39	Database management	10183
## 234	2020-39	artificial intelligence	9426

## 235	2020-39	Business analysis	8873
## 236	2020-39	usability	8847
## 237	2020-39	datasets	8304
## 238	2020-39	Business Analyst	8153
## 239	2020-39	relational databases	8093
## 240	2020-39	Data Visualization	8012
## 241	2020-39	Jquery	7878
## 242	2020-39	version control	7422
## 243	2020-39	regression	7332
## 244	2020-39	Google analytics	6837
## 245	2020-39	unit testing	6669
## 246	2020-39	Data warehouse	6505
## 247	2020-39	Github	6363
## 248	2020-39	relational database	5997
## 249	2020-39	simulations	5861
## 250	2020-39	firmware	5673
## 251	2020-39	benchmarking	5671
## 252	2020-39	Power BI	5456
## 253	2020-39	Postgresql	4943
## 254	2020-39	Data Analyst	4688
## 255	2020-39	Market Analysis	4332
## 256	2020-39	deep learning	4171
## 257	2020-39	Business analytics	4104
## 258	2020-39	Data scientist	4040
## 259	2020-39	Windows 10	4028
## 260	2020-39	Bootstrap	3886
## 261	2020-39	Slack	3600
## 262	2020-39	Data Engineer	3340
## 263	2020-39	arcgis	2898
## 264	2020-39	Visual Basic	2415
## 265	2020-39	natural language processing	2389
## 266	2020-39	clustering	2282
## 267	2020-39	Data manipulation	2247
## 268	2020-39	SPSS	2237
## 269	2020-39	Report generation	2102
## 270	2020-39	Mac OS	1909
## 271	2020-39	Algorithm Design	1760
## 272	2020-39	NLP	1715
## 273	2020-39	statistical modeling	1647
## 274	2020-39	Wireshark	1619
## 275	2020-39	merging	1602
## 276	2020-39	Generating reports	1588
## 277	2020-39	Looker	1423
## 278	2020-39	multivariate	1370
## 279	2020-39	Stata	1271
## 280	2020-39	neural networks	1243
## 281	2020-39	Custom reports	1194
## 282	2020-39	Marketing Research	1120
## 283	2020-39	QlikView	917
## 284	2020-39	Data maintenance	863
## 285	2020-39	D3	771
## 286	2020-39	Curl	753
## 287	2020-39	Statistician	736
## 288	2020-39	C programming	695

## 289	2020-39	C++ programming	695
## 290	2020-39	Spotfire	602
## 291	2020-39	LSA	602
## 292	2020-39	Biostatistician	588
## 293	2020-39	MariaDB	582
## 294	2020-39	Qualtrics	568
## 295	2020-39	decision trees	551
## 296	2020-39	Domo	496
## 297	2020-39	Git version control	491
## 298	2020-39	Delphi	481
## 299	2020-39	TSQL	457
## 300	2020-39	scenario analysis	441
## 301	2020-39	SQLite	408
## 302	2020-39	Lab Notebook	400
## 303	2020-39	neural network	397
## 304	2020-39	Data wrangling	391
## 305	2020-39	Debian	387
## 306	2020-39	logistic regression	384
## 307	2020-39	Insights analytics	359
## 308	2020-39	Sensitivity Analysis	357
## 309	2020-39	Using R	341
## 310	2020-39	SVD	230
## 311	2020-39	well-documented code	226
## 312	2020-39	Actuarial Analyst	216
## 313	2020-39	SVM	212
## 314	2020-39	Power Analysis	206
## 315	2020-39	document code	203
## 316	2020-39	Insights Analyst	173
## 317	2020-39	k-means	157
## 318	2020-39	LDA	141
## 319	2020-39	SiSense	141
## 320	2020-39	R Studio	137
## 321	2020-39	Online analytics	132
## 322	2020-39	ggplot	127
## 323	2020-39	plotly	124
## 324	2020-39	RStudio	122
## 325	2020-39	Web scraping	117
## 326	2020-39	Highcharts	100
## 327	2020-39	Insights analysis	100
## 328	2020-39	Birst	96
## 329	2020-39	Actuarial analysis	77
## 330	2020-39	knn	46
## 331	2020-39	R packages	39
## 332	2020-39	tidyverse	38
## 333	2020-39	spatial statistics	37
## 334	2020-39	Insurance Analyst	33
## 335	2020-39	Insurance analytics	27
## 336	2020-39	GoodData	26
## 337	2020-39	Insurance analysis	26
## 338	2020-39	Actuarial analytics	26
## 339	2020-39	Gauss	23
## 340	2020-39	C++ programmer	22
## 341	2020-39	C programmer	22
## 342	2020-39	R Markdown	20

## 343	2020-39	Data scraping	20
## 344	2020-39	hierarchical clustering	14
## 345	2020-39	kmeans	10
## 346	2020-39	record linkage	10
## 347	2020-39	Actuary Analyst	10
## 348	2020-39	Computational Engineer	10
## 349	2020-39	Datawrapper	9
## 350	2020-39	FusionCharts	8
## 351	2020-39	R Developer	5
## 352	2020-39	Insight Squared	5
## 353	2020-39	Actuary analytics	4
## 354	2020-39	Dundas BI	3
## 355	2020-39	Polling Analyst	1
## 356	2020-39	Polling analysis	1
## 357	2020-39	Highcharter	1
## 358	2020-39	Polling analytics	1
## 359	2020-39	Analytic Scripting	1
## 360	2020-39	Datapine	1
## 361	2020-39	Actuary analysis	0
## 362	2020-39	Zebra BI	0
## 363	2020-40	Excel	392715
## 364	2020-40	Microsoft Office	231979
## 365	2020-40	C++	163044
## 366	2020-40	C#	163044
## 367	2020-40	Database	129835
## 368	2020-40	Computer Science	112070
## 369	2020-40	Data entry	84427
## 370	2020-40	modeling	80792
## 371	2020-40	.NET	67350
## 372	2020-40	SQL	66175
## 373	2020-40	SQL+	66175
## 374	2020-40	Python	58898
## 375	2020-40	Google	53052
## 376	2020-40	Java	52113
## 377	2020-40	Statistics	51850
## 378	2020-40	R	49571
## 379	2020-40	react	42576
## 380	2020-40	Data analysis	40455
## 381	2020-40	HTML	40160
## 382	2020-40	Javascript	37554
## 383	2020-40	Oracle	31373
## 384	2020-40	SAP	30335
## 385	2020-40	Data management	26442
## 386	2020-40	machine learning	24489
## 387	2020-40	Data analytics	23044
## 388	2020-40	scrum	22891
## 389	2020-40	API	22159
## 390	2020-40	CSS	21960
## 391	2020-40	git	19232
## 392	2020-40	Object oriented	18296
## 393	2020-40	PCA	17219
## 394	2020-40	ai	16825
## 395	2020-40	Big data	16463
## 396	2020-40	debugging	16386

## 397	2020-40	Data science	15998
## 398	2020-40	Android	14295
## 399	2020-40	Tableau	13943
## 400	2020-40	Business intelligence	13865
## 401	2020-40	data sets	13768
## 402	2020-40	agile development	13570
## 403	2020-40	full stack	13471
## 404	2020-40	PHP	12962
## 405	2020-40	PhotoShop	12824
## 406	2020-40	iOS	12575
## 407	2020-40	angular	11847
## 408	2020-40	design patterns	11364
## 409	2020-40	Mysql	11137
## 410	2020-40	Market Research	11120
## 411	2020-40	SAS	11118
## 412	2020-40	Database management	10613
## 413	2020-40	scrubbing	10526
## 414	2020-40	artificial intelligence	9882
## 415	2020-40	usability	9044
## 416	2020-40	Business analysis	8998
## 417	2020-40	datasets	8394
## 418	2020-40	relational databases	8291
## 419	2020-40	Business Analyst	8278
## 420	2020-40	Data Visualization	8269
## 421	2020-40	Jquery	7986
## 422	2020-40	version control	7588
## 423	2020-40	regression	7529
## 424	2020-40	Google analytics	7026
## 425	2020-40	unit testing	6764
## 426	2020-40	Github	6661
## 427	2020-40	Data warehouse	6539
## 428	2020-40	relational database	6152
## 429	2020-40	simulations	6007
## 430	2020-40	benchmarking	5941
## 431	2020-40	firmware	5796
## 432	2020-40	Power BI	5626
## 433	2020-40	Postgresql	5070
## 434	2020-40	Data Analyst	4786
## 435	2020-40	Business analytics	4285
## 436	2020-40	deep learning	4281
## 437	2020-40	Windows 10	4269
## 438	2020-40	Market Analysis	4260
## 439	2020-40	Data scientist	4084
## 440	2020-40	Bootstrap	3949
## 441	2020-40	Slack	3733
## 442	2020-40	Data Engineer	3428
## 443	2020-40	arcgis	2935
## 444	2020-40	natural language processing	2451
## 445	2020-40	Visual Basic	2438
## 446	2020-40	clustering	2374
## 447	2020-40	SPSS	2372
## 448	2020-40	Data manipulation	2229
## 449	2020-40	Report generation	2193
## 450	2020-40	Mac OS	1902

## 451	2020-40	Algorithm Design	1804
## 452	2020-40	NLP	1768
## 453	2020-40	statistical modeling	1678
## 454	2020-40	Wireshark	1644
## 455	2020-40	merging	1638
## 456	2020-40	Generating reports	1606
## 457	2020-40	Looker	1444
## 458	2020-40	multivariate	1436
## 459	2020-40	neural networks	1348
## 460	2020-40	Stata	1336
## 461	2020-40	Custom reports	1208
## 462	2020-40	Marketing Research	1124
## 463	2020-40	QlikView	920
## 464	2020-40	Data maintenance	850
## 465	2020-40	Curl	784
## 466	2020-40	Statistician	783
## 467	2020-40	D3	779
## 468	2020-40	C programming	718
## 469	2020-40	C++ programming	718
## 470	2020-40	LSA	618
## 471	2020-40	Biostatistician	616
## 472	2020-40	Spotfire	602
## 473	2020-40	decision trees	564
## 474	2020-40	MariaDB	560
## 475	2020-40	Qualtrics	551
## 476	2020-40	Domo	515
## 477	2020-40	Git version control	510
## 478	2020-40	Delphi	499
## 479	2020-40	TSQL	484
## 480	2020-40	scenario analysis	465
## 481	2020-40	Lab Notebook	418
## 482	2020-40	neural network	417
## 483	2020-40	SQLite	416
## 484	2020-40	logistic regression	412
## 485	2020-40	Data wrangling	402
## 486	2020-40	Debian	398
## 487	2020-40	Sensitivity Analysis	363
## 488	2020-40	Using R	355
## 489	2020-40	Insights analytics	350
## 490	2020-40	SVD	239
## 491	2020-40	document code	218
## 492	2020-40	SVM	218
## 493	2020-40	Actuarial Analyst	213
## 494	2020-40	Power Analysis	208
## 495	2020-40	well-documented code	207
## 496	2020-40	k-means	156
## 497	2020-40	SiSense	152
## 498	2020-40	LDA	148
## 499	2020-40	Online analytics	142
## 500	2020-40	plotly	136
## 501	2020-40	R Studio	135
## 502	2020-40	ggplot	133
## 503	2020-40	Insights Analyst	132
## 504	2020-40	RStudio	129

## 505	2020-40	Web scraping	123
## 506	2020-40	Insights analysis	103
## 507	2020-40	Highcharts	97
## 508	2020-40	Birst	84
## 509	2020-40	Actuarial analysis	83
## 510	2020-40	knn	49
## 511	2020-40	tidyverse	40
## 512	2020-40	Insurance Analyst	39
## 513	2020-40	R packages	36
## 514	2020-40	spatial statistics	28
## 515	2020-40	GoodData	28
## 516	2020-40	Insurance analytics	27
## 517	2020-40	Insurance analysis	26
## 518	2020-40	Gauss	26
## 519	2020-40	Actuarial analytics	26
## 520	2020-40	C programmer	22
## 521	2020-40	C++ programmer	22
## 522	2020-40	Data scraping	19
## 523	2020-40	R Markdown	18
## 524	2020-40	hierarchical clustering	15
## 525	2020-40	record linkage	11
## 526	2020-40	kmeans	9
## 527	2020-40	Computational Engineer	8
## 528	2020-40	Datawrapper	8
## 529	2020-40	FusionCharts	8
## 530	2020-40	Actuary Analyst	7
## 531	2020-40	R Developer	6
## 532	2020-40	Insight Squared	4
## 533	2020-40	Actuary analytics	4
## 534	2020-40	Dundas BI	2
## 535	2020-40	Highcharter	1
## 536	2020-40	Datapine	1
## 537	2020-40	Polling analytics	1
## 538	2020-40	Analytic Scripting	1
## 539	2020-40	Polling Analyst	1
## 540	2020-40	Polling analysis	0
## 541	2020-40	Actuary analysis	0
## 542	2020-40	Git	0
## 543	2020-40	Zebra BI	0
## 544	2020-41	Excel	396228
## 545	2020-41	Microsoft Office	232215
## 546	2020-41	C++	164920
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## 548	2020-41	Database	130943
## 549	2020-41	Computer Science	113809
## 550	2020-41	Data entry	85592
## 551	2020-41	modeling	80138
## 552	2020-41	.NET	67493
## 553	2020-41	SQL	67313
## 554	2020-41	SQL+	67313
## 555	2020-41	Python	60241
## 556	2020-41	Google	53377
## 557	2020-41	Java	52872
## 558	2020-41	Statistics	52159

## 559	2020-41	R	49991
## 560	2020-41	react	41047
## 561	2020-41	Data analysis	40836
## 562	2020-41	HTML	39959
## 563	2020-41	Javascript	38358
## 564	2020-41	Oracle	31669
## 565	2020-41	SAP	30495
## 566	2020-41	Data management	26861
## 567	2020-41	machine learning	24859
## 568	2020-41	Data analytics	23491
## 569	2020-41	scrum	23250
## 570	2020-41	API	22313
## 571	2020-41	CSS	22042
## 572	2020-41	git	19532
## 573	2020-41	Git	19528
## 574	2020-41	Object oriented	18612
## 575	2020-41	ai	17491
## 576	2020-41	PCA	17092
## 577	2020-41	debugging	16768
## 578	2020-41	Big data	16619
## 579	2020-41	Data science	16247
## 580	2020-41	Tableau	14430
## 581	2020-41	Android	14225
## 582	2020-41	Business intelligence	14173
## 583	2020-41	agile development	13804
## 584	2020-41	data sets	13773
## 585	2020-41	full stack	13675
## 586	2020-41	PHP	13119
## 587	2020-41	PhotoShop	12880
## 588	2020-41	iOS	12686
## 589	2020-41	angular	11954
## 590	2020-41	design patterns	11495
## 591	2020-41	SAS	11379
## 592	2020-41	Market Research	11366
## 593	2020-41	Mysql	11195
## 594	2020-41	Database management	10594
## 595	2020-41	scrubbing	10486
## 596	2020-41	artificial intelligence	10154
## 597	2020-41	usability	9209
## 598	2020-41	Business analysis	9104
## 599	2020-41	datasets	8553
## 600	2020-41	Data Visualization	8497
## 601	2020-41	Business Analyst	8399
## 602	2020-41	relational databases	8270
## 603	2020-41	Jquery	8014
## 604	2020-41	version control	7648
## 605	2020-41	regression	7561
## 606	2020-41	Google analytics	7060
## 607	2020-41	unit testing	6825
## 608	2020-41	Data warehouse	6763
## 609	2020-41	Github	6593
## 610	2020-41	relational database	6192
## 611	2020-41	benchmarking	6102
## 612	2020-41	simulations	6030

## 613	2020-41	firmware	5944
## 614	2020-41	Power BI	5832
## 615	2020-41	Postgresql	5139
## 616	2020-41	Data Analyst	4817
## 617	2020-41	Market Analysis	4361
## 618	2020-41	Business analytics	4322
## 619	2020-41	deep learning	4316
## 620	2020-41	Data scientist	4210
## 621	2020-41	Windows 10	4173
## 622	2020-41	Bootstrap	3950
## 623	2020-41	Slack	3789
## 624	2020-41	Data Engineer	3504
## 625	2020-41	arcgis	2910
## 626	2020-41	natural language processing	2502
## 627	2020-41	Visual Basic	2482
## 628	2020-41	SPSS	2326
## 629	2020-41	clustering	2319
## 630	2020-41	Data manipulation	2283
## 631	2020-41	Report generation	2196
## 632	2020-41	NLP	1872
## 633	2020-41	Mac OS	1868
## 634	2020-41	Algorithm Design	1813
## 635	2020-41	statistical modeling	1719
## 636	2020-41	Wireshark	1678
## 637	2020-41	merging	1644
## 638	2020-41	Generating reports	1619
## 639	2020-41	multivariate	1450
## 640	2020-41	Looker	1432
## 641	2020-41	Stata	1380
## 642	2020-41	neural networks	1355
## 643	2020-41	Custom reports	1255
## 644	2020-41	Marketing Research	1174
## 645	2020-41	QlikView	944
## 646	2020-41	Data maintenance	856
## 647	2020-41	Curl	792
## 648	2020-41	Statistician	763
## 649	2020-41	D3	758
## 650	2020-41	C programming	720
## 651	2020-41	C++ programming	720
## 652	2020-41	Spotfire	674
## 653	2020-41	Biostatistician	619
## 654	2020-41	decision trees	597
## 655	2020-41	Qualtrics	592
## 656	2020-41	LSA	570
## 657	2020-41	MariaDB	560
## 658	2020-41	Git version control	504
## 659	2020-41	Domo	502
## 660	2020-41	TSQL	494
## 661	2020-41	Delphi	485
## 662	2020-41	scenario analysis	451
## 663	2020-41	Lab Notebook	450
## 664	2020-41	Data wrangling	415
## 665	2020-41	logistic regression	404
## 666	2020-41	neural network	396

## 667	2020-41		Debian	392
## 668	2020-41		SQLite	387
## 669	2020-41	Sensitivity Analysis		373
## 670	2020-41	Insights analytics		364
## 671	2020-41	Using R		351
## 672	2020-41	SVD		243
## 673	2020-41	SVM		236
## 674	2020-41	Actuarial Analyst		232
## 675	2020-41	Power Analysis		227
## 676	2020-41	well-documented code		224
## 677	2020-41	document code		218
## 678	2020-41	k-means		154
## 679	2020-41	SiSense		149
## 680	2020-41	LDA		149
## 681	2020-41	ggplot		143
## 682	2020-41	plotly		136
## 683	2020-41	R Studio		136
## 684	2020-41	RStudio		136
## 685	2020-41	Web scraping		126
## 686	2020-41	Online analytics		124
## 687	2020-41	Insights Analyst		121
## 688	2020-41	Highcharts		99
## 689	2020-41	Actuarial analysis		90
## 690	2020-41	Insights analysis		90
## 691	2020-41	Birst		79
## 692	2020-41	knn		49
## 693	2020-41	tidyverse		39
## 694	2020-41	Insurance Analyst		34
## 695	2020-41	R packages		33
## 696	2020-41	GoodData		30
## 697	2020-41	spatial statistics		30
## 698	2020-41	Insurance analytics		29
## 699	2020-41	Actuarial analytics		29
## 700	2020-41	Data scraping		25
## 701	2020-41	Gauss		24
## 702	2020-41	Insurance analysis		22
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## 705	2020-41	hierarchical clustering		18
## 706	2020-41	R Markdown		17
## 707	2020-41	Computational Engineer		11
## 708	2020-41	record linkage		10
## 709	2020-41	kmeans		9
## 710	2020-41	FusionCharts		8
## 711	2020-41	Datawrapper		8
## 712	2020-41	Actuary Analyst		6
## 713	2020-41	R Developer		6
## 714	2020-41	Actuary analytics		4
## 715	2020-41	Insight Squared		4
## 716	2020-41	Dundas BI		2
## 717	2020-41	Analytic Scripting		1
## 718	2020-41	Polling Analyst		0
## 719	2020-41	Zebra BI		0
## 720	2020-41	Actuary analysis		0

## 721	2020-41	Datapine	0
## 722	2020-41	Highcharter	0
## 723	2020-41	Polling analytics	0
## 724	2020-41	Polling analysis	0
## 725	2020-42	Excel	404527
## 726	2020-42	Microsoft Office	238111
## 727	2020-42	C#	169786
## 728	2020-42	C++	169786
## 729	2020-42	Database	132088
## 730	2020-42	Computer Science	114970
## 731	2020-42	Data entry	87269
## 732	2020-42	modeling	80469
## 733	2020-42	SQL+	68503
## 734	2020-42	SQL	68503
## 735	2020-42	.NET	68052
## 736	2020-42	Python	61021
## 737	2020-42	Google	54741
## 738	2020-42	Statistics	53016
## 739	2020-42	Java	52969
## 740	2020-42	R	49861
## 741	2020-42	react	42006
## 742	2020-42	Data analysis	41620
## 743	2020-42	HTML	40670
## 744	2020-42	Javascript	38637
## 745	2020-42	SAP	31450
## 746	2020-42	Oracle	30632
## 747	2020-42	Data management	27239
## 748	2020-42	machine learning	25172
## 749	2020-42	Data analytics	24058
## 750	2020-42	scrum	23424
## 751	2020-42	API	23097
## 752	2020-42	CSS	22530
## 753	2020-42	Git	19945
## 754	2020-42	git	19943
## 755	2020-42	Object oriented	18572
## 756	2020-42	ai	17947
## 757	2020-42	PCA	17351
## 758	2020-42	Data science	16665
## 759	2020-42	Big data	16518
## 760	2020-42	debugging	16300
## 761	2020-42	Tableau	14707
## 762	2020-42	Android	14618
## 763	2020-42	Business intelligence	14337
## 764	2020-42	data sets	13919
## 765	2020-42	agile development	13896
## 766	2020-42	full stack	13683
## 767	2020-42	PHP	13244
## 768	2020-42	PhotoShop	13081
## 769	2020-42	iOS	12893
## 770	2020-42	angular	12196
## 771	2020-42	Market Research	11698
## 772	2020-42	SAS	11596
## 773	2020-42	design patterns	11457
## 774	2020-42	Mysql	11425

## 775	2020-42	Database management	10664
## 776	2020-42	scrubbing	10422
## 777	2020-42	artificial intelligence	10041
## 778	2020-42	Business analysis	9431
## 779	2020-42	usability	9371
## 780	2020-42	Data Visualization	8666
## 781	2020-42	datasets	8624
## 782	2020-42	relational databases	8610
## 783	2020-42	Business Analyst	8590
## 784	2020-42	Jquery	8165
## 785	2020-42	version control	7727
## 786	2020-42	regression	7658
## 787	2020-42	Google analytics	7197
## 788	2020-42	unit testing	7126
## 789	2020-42	Data warehouse	6970
## 790	2020-42	Github	6735
## 791	2020-42	benchmarking	6262
## 792	2020-42	simulations	6156
## 793	2020-42	firmware	6092
## 794	2020-42	relational database	6070
## 795	2020-42	Power BI	5987
## 796	2020-42	Postgresql	5342
## 797	2020-42	Data Analyst	4924
## 798	2020-42	Business analytics	4406
## 799	2020-42	Market Analysis	4399
## 800	2020-42	Windows 10	4361
## 801	2020-42	deep learning	4316
## 802	2020-42	Data scientist	4274
## 803	2020-42	Bootstrap	4076
## 804	2020-42	Slack	3991
## 805	2020-42	Data Engineer	3451
## 806	2020-42	arcgis	2886
## 807	2020-42	Visual Basic	2536
## 808	2020-42	natural language processing	2478
## 809	2020-42	SPSS	2342
## 810	2020-42	clustering	2289
## 811	2020-42	Data manipulation	2259
## 812	2020-42	Report generation	2232
## 813	2020-42	Mac OS	1960
## 814	2020-42	NLP	1816
## 815	2020-42	Algorithm Design	1791
## 816	2020-42	statistical modeling	1766
## 817	2020-42	Wireshark	1723
## 818	2020-42	merging	1711
## 819	2020-42	Generating reports	1500
## 820	2020-42	multivariate	1490
## 821	2020-42	Looker	1464
## 822	2020-42	Stata	1423
## 823	2020-42	neural networks	1363
## 824	2020-42	Custom reports	1279
## 825	2020-42	Marketing Research	1199
## 826	2020-42	QlikView	1001
## 827	2020-42	Data maintenance	880
## 828	2020-42	D3	794

## 829	2020-42	Curl	792
## 830	2020-42	Statistician	746
## 831	2020-42	C programming	734
## 832	2020-42	C++ programming	734
## 833	2020-42	Spotfire	638
## 834	2020-42	Qualtrics	614
## 835	2020-42	MariaDB	610
## 836	2020-42	Biostatistician	610
## 837	2020-42	decision trees	593
## 838	2020-42	LSA	580
## 839	2020-42	Domo	534
## 840	2020-42	Git version control	519
## 841	2020-42	Delphi	495
## 842	2020-42	scenario analysis	480
## 843	2020-42	TSQL	459
## 844	2020-42	Debian	434
## 845	2020-42	Lab Notebook	433
## 846	2020-42	Data wrangling	421
## 847	2020-42	logistic regression	411
## 848	2020-42	neural network	397
## 849	2020-42	Insights analytics	392
## 850	2020-42	SQLite	380
## 851	2020-42	Using R	373
## 852	2020-42	Sensitivity Analysis	369
## 853	2020-42	Actuarial Analyst	259
## 854	2020-42	SVD	246
## 855	2020-42	Power Analysis	235
## 856	2020-42	well-documented code	231
## 857	2020-42	SVM	230
## 858	2020-42	document code	225
## 859	2020-42	LDA	156
## 860	2020-42	R Studio	149
## 861	2020-42	SiSense	148
## 862	2020-42	RStudio	148
## 863	2020-42	plotly	147
## 864	2020-42	ggplot	147
## 865	2020-42	k-means	144
## 866	2020-42	Web scraping	137
## 867	2020-42	Online analytics	127
## 868	2020-42	Insights Analyst	121
## 869	2020-42	Highcharts	94
## 870	2020-42	Insights analysis	93
## 871	2020-42	Actuarial analysis	88
## 872	2020-42	Birst	86
## 873	2020-42	knn	48
## 874	2020-42	tidyverse	45
## 875	2020-42	R packages	35
## 876	2020-42	spatial statistics	35
## 877	2020-42	GoodData	34
## 878	2020-42	Insurance Analyst	34
## 879	2020-42	Actuarial analytics	27
## 880	2020-42	Insurance analytics	25
## 881	2020-42	Data scraping	25
## 882	2020-42	C programmer	22

```

## 883 2020-42          Gauss      22
## 884 2020-42      C++ programmer 22
## 885 2020-42 hierarchical clustering 20
## 886 2020-42 Insurance analysis 20
## 887 2020-42           R Markdown 19
## 888 2020-42 record linkage 11
## 889 2020-42           kmeans 10
## 890 2020-42 Computational Engineer 10
## 891 2020-42 Datawrapper 8
## 892 2020-42 FusionCharts 8
## 893 2020-42 Actuary Analyst 6
## 894 2020-42 R Developer 5
## 895 2020-42 Insight Squared 4
## 896 2020-42 Actuary analytics 4
## 897 2020-42 Dundas BI 3
## 898 2020-42 Polling Analyst 1
## 899 2020-42 Polling analysis 0
## 900 2020-42 Datapine 0
## 901 2020-42 Analytic Scripting 0
## 902 2020-42 Actuary analysis 0
## 903 2020-42 Polling analytics 0
## 904 2020-42 Zebra BI 0
## 905 2020-42 Highcharter 0

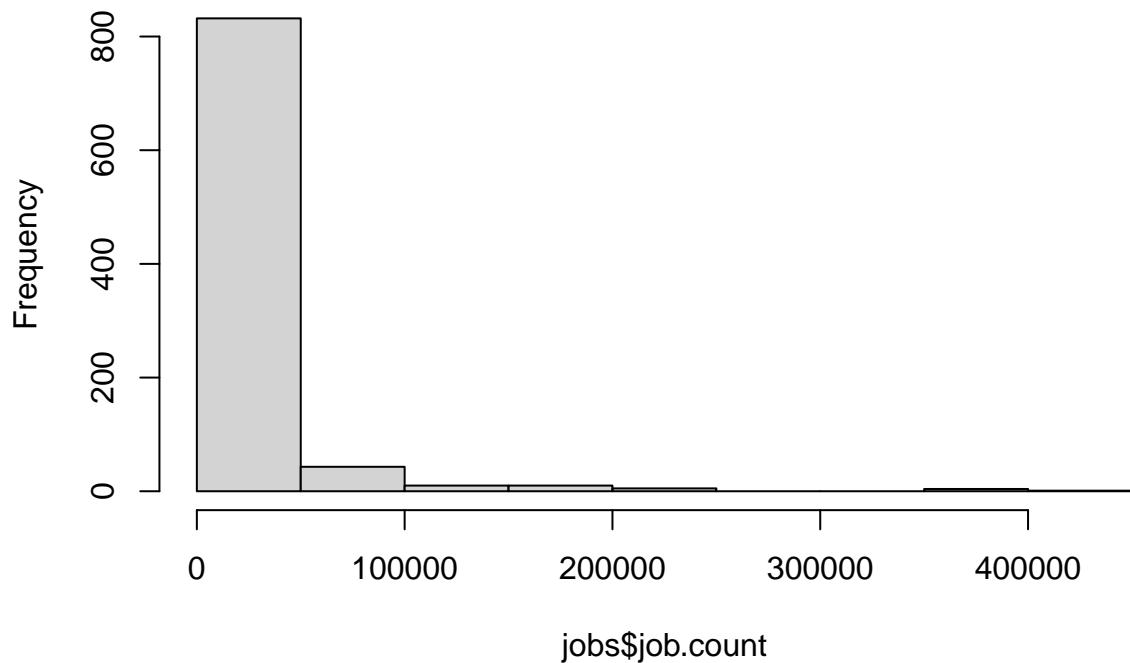
```

- Create a `hist` and `boxplot` and report `summary(jobs$job.count)`.

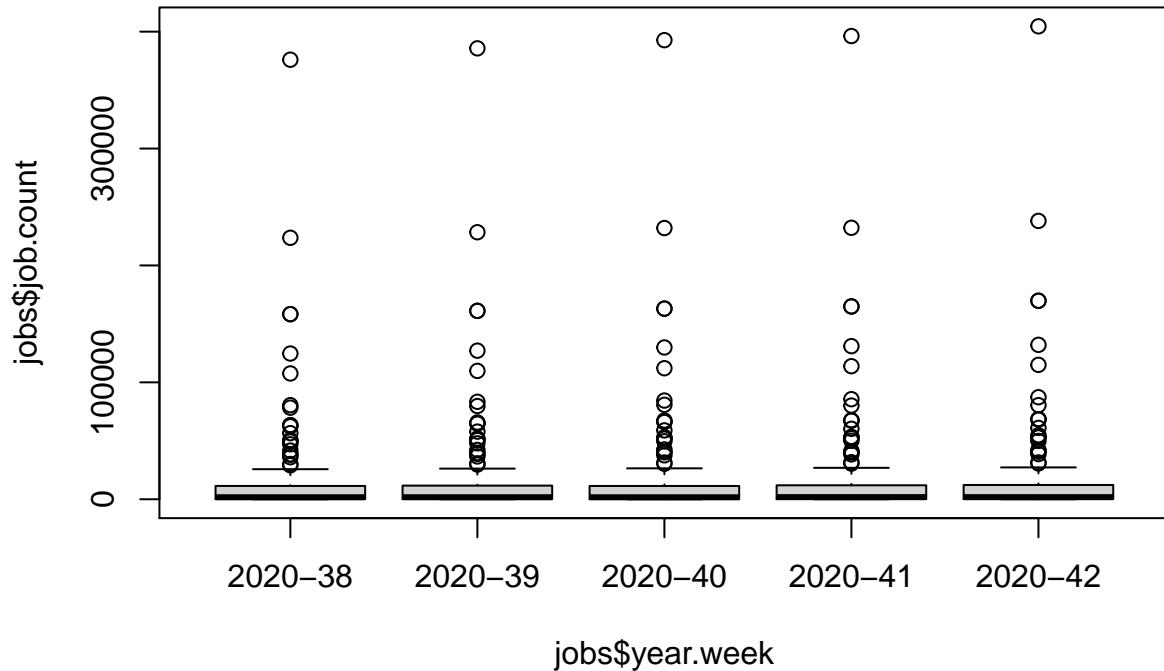
#### (5 points) Histogram and Box Plot

```
hist(jobs$job.count);
```

**Histogram of jobs\$job.count**



```
boxplot(jobs$job.count~jobs$year.week, data = jobs);
```



```
summary(jobs$job.count)
```

```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max. 
##        0      149     1734    15170    11847   404527
```

[What does the histogram tell you about the data? What does the boxplot tell you about the data? What does `summary` tell you about the data?]

Answered this above.

```
deep.dive = c("Microsoft Office", "C++", "SQL", "Computer Science", "Python", "Java", "Statistics", "Da
or = "";
for(search in deep.dive)
{
  or = paste0(or, " jobs$search.query == '",search,"' | ");
}
or = substr(or,0, strlen(or) - 2);

## TODO ... update subsetDataFrame to allow "OR" logic, currently only does "AND" ...

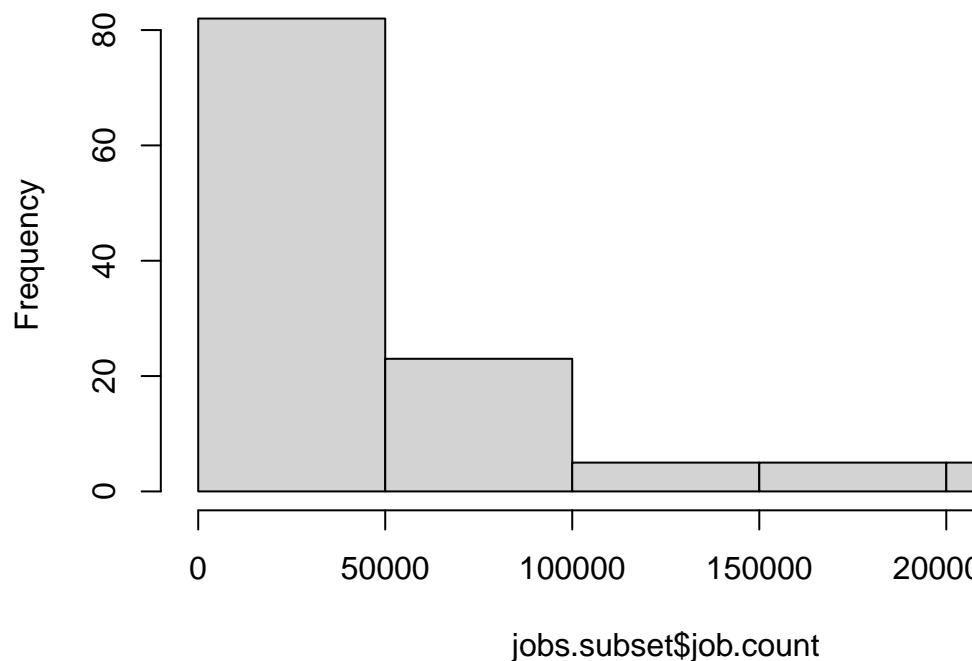
# jobs.subset = jobs[ or , ]; # doesn't work ...
jobs.subset = jobs[ jobs$search.query == 'Microsoft Office' | jobs$search.query == 'C++' | jobs$search
# stem(jobs.subset$job.count);
```

```
# subsetDataFrame(jobs.subset, "job.count", "==", 0);
```

Subset some keywords relevant to this course

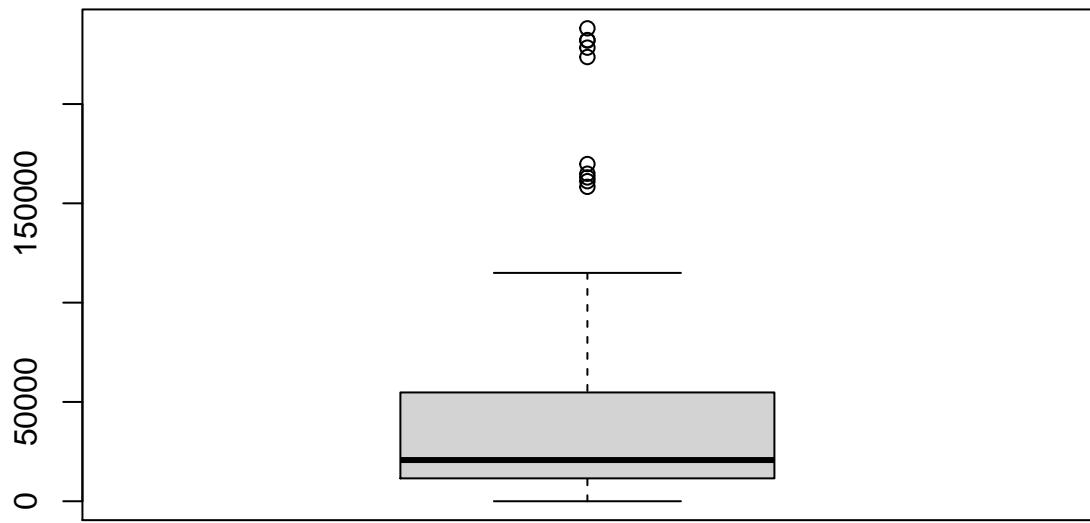
```
hist(jobs.subset$job.count);
```

**Histogram of jobs.subset\$job.count**

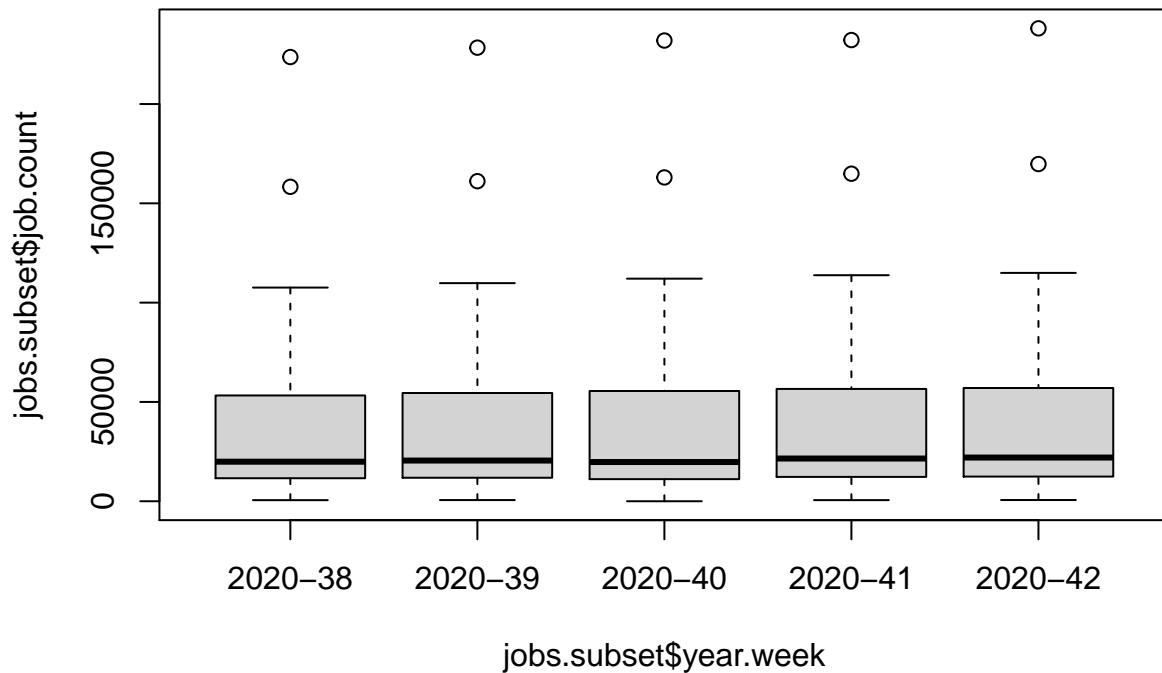


**Histogram and Box Plot of Subset**

```
boxplot(jobs.subset$job.count);
```



```
boxplot(jobs.subset$job.count~jobs.subset$year.week, data = jobs);
```



[What does the histogram tell you about the data? What does the boxplot tell you about the data?]

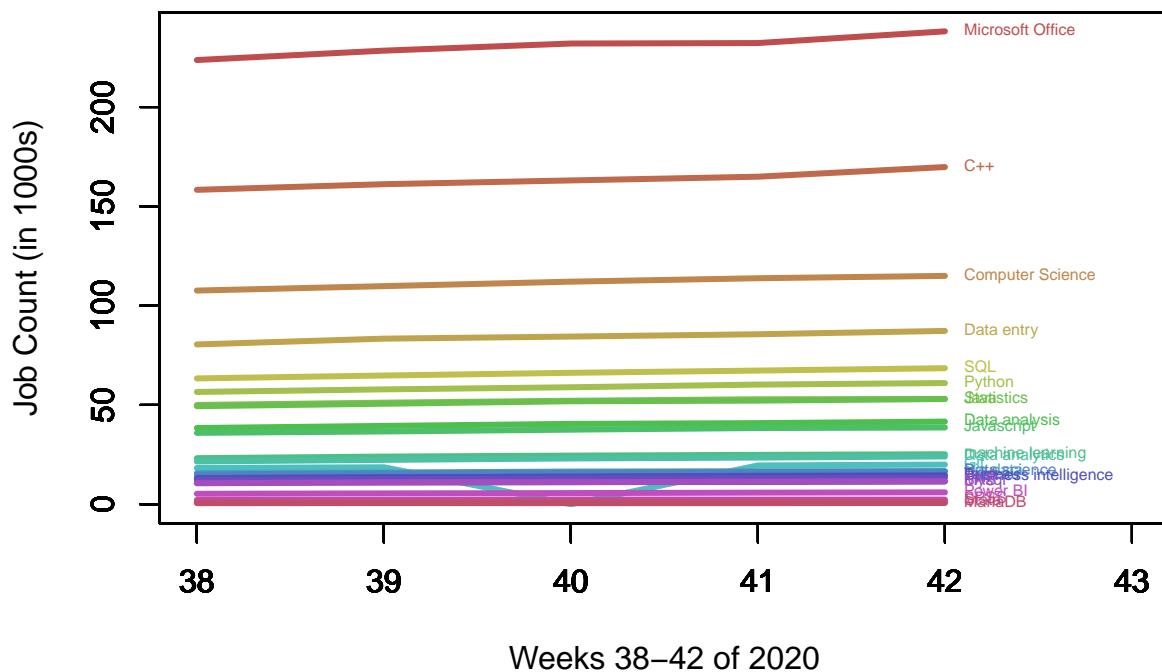
#### (10 points) Trends in Relevant Subset

```
jobs.subset$year.week = as.numeric( gsub("-", ".", jobs.subset$year.week, fixed=TRUE) );

jobs.subset = sortDataFrameByNumericColumns(jobs.subset, c("year.week", "job.count"), c("ASC", "DESC"));
# easier to manage as "how many thousand jobs"
jobs.subset$job.count.k = jobs.subset$job.count / 1000;

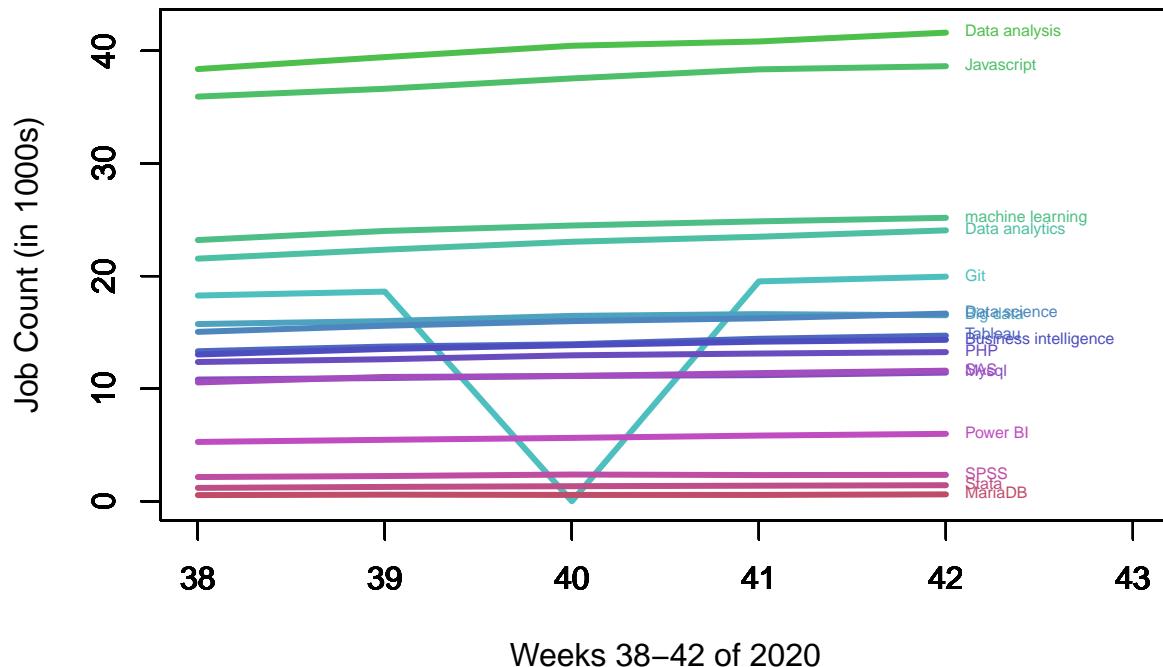
do.nothing = plotJobs(jobs.subset);
```

## Keyword trends in Data Analysis



```
do.nothing = plotJobs(jobs.subset, myy.lim = c(0,42) );
```

## Keyword trends in Data Analysis



**Initial Perspective** [What is your initial “perspective” of this data, now that you see it? Why are the lines “parallel-ish”? What kind of a trend is that?

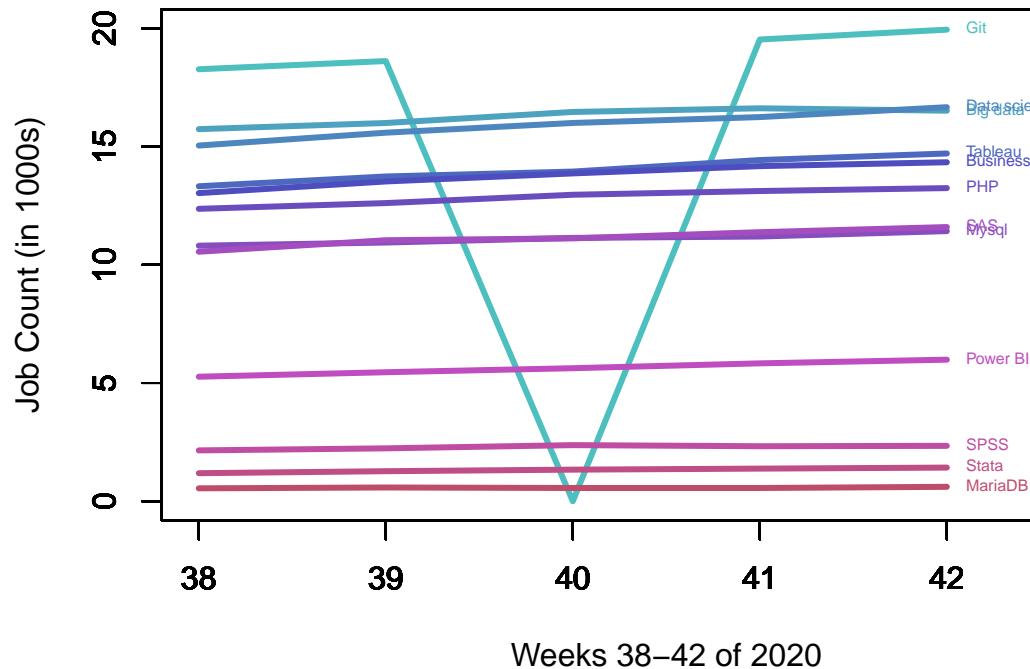
Now comment on the line of data for “Data analysis”. How is it trending? How does it compare to other Search-Query Words?

What is your first perspective?

]

```
do.nothing = plotJobs(jobs.subset, myy.lim = c(0,20) );
```

## Keyword trends in Data Analysis



Missing Data “Git” Week 40?

Git-40/Git-41 data history, notice the date-time and file sizes ...

Source: Data provenance history

Source: Data provenance history

[Is this data missing or did it just drop to zero that week? How does this relate to the other data (remember the idea of “continuity” in mathematics)? What should you do about it?]

```

idxs.week.40 = which(jobs.subset$year.week == 2020.40);
idxs.Git      = which(jobs.subset$search.query == "Git");

# set notation
my.idx = intersect(idxs.Git,idxs.week.40);

jobs.subset[idxs.Git,];

##      year.week search.query job.count job.count.k
## 30    2020.38       Git     18270    18.270
## 211   2020.39       Git     18617    18.617
## 542   2020.40       Git      0       0.000
## 573   2020.41       Git    19528    19.528
## 753   2020.42       Git    19945    19.945

jobs.subset[my.idx,];

##      year.week search.query job.count job.count.k
## 542   2020.4          Git        0         0

```

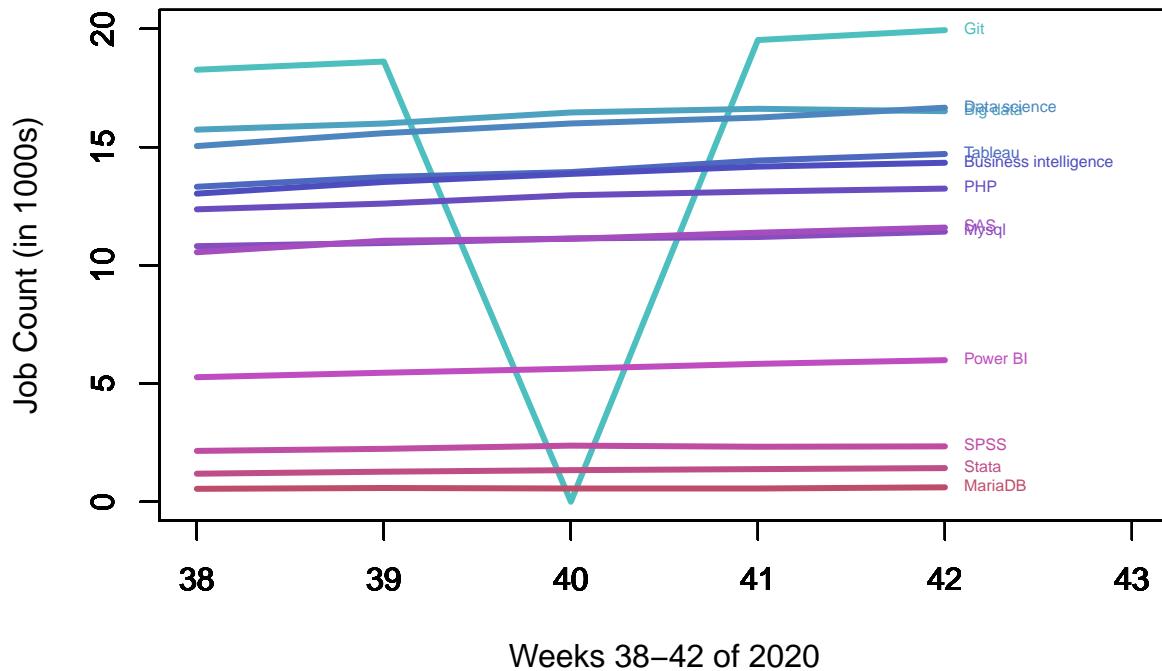
```

## change this if you feel appropriate? To what number?
jobs.subset[my.idx,3] = 0;          # job.count
jobs.subset[my.idx,3] = 0/1000;     # job.count.k (in thousands) ...

do.nothing = plotJobs(jobs.subset, myy.lim = c(0,20) );

```

## Keyword trends in Data Analysis



**Is “Microsoft Office” bigger than “C++”?** I use the term “bigger” or “better” intentionally. We are comparing two items, and these are generic ways of communicating such a comparison. In context of this data problem, a formalized form of the question would be something like: “Utilizing job count for a given search query, determine if the query ‘Microsoft Office’ has a larger job count than the query ‘C++’?” This question will need to be formalized if we are trying to draw specific conclusions, but the initiation of analysis “which is bigger” allows us to understand what the data says or does not say, through exploration.

To answer the question:

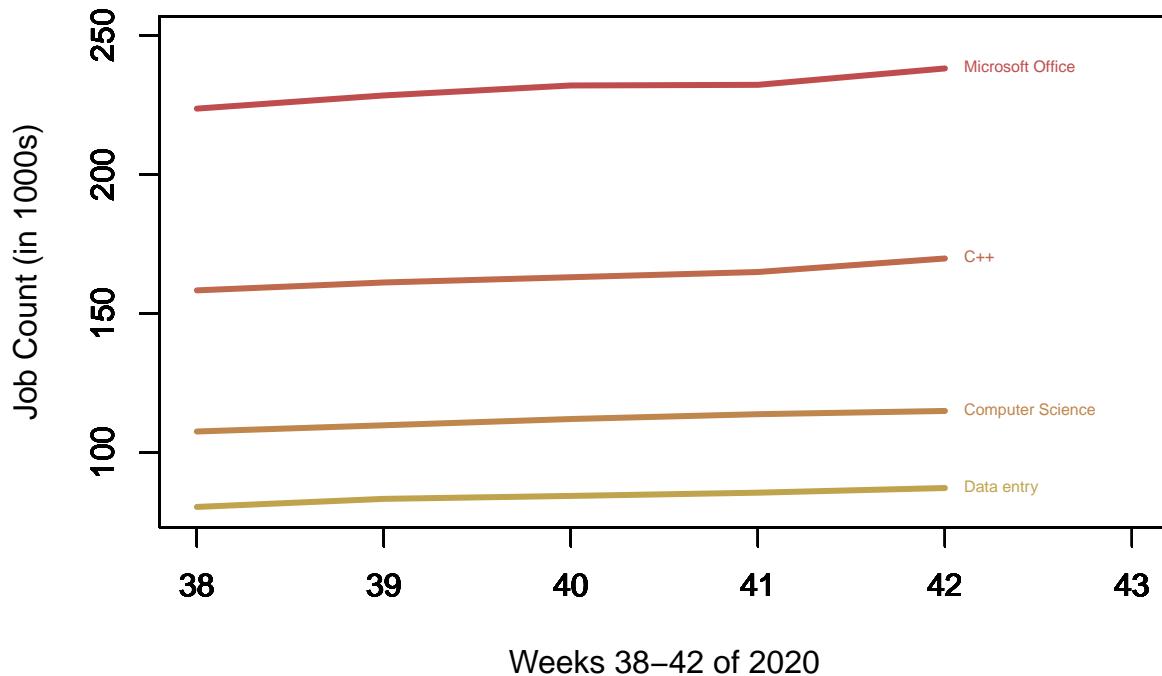
Mathematically, if two lines are parallel, and one is above the other, can we use **distance** to draw a conclusion? Now, many times in statistics we deal with noise in the data, it is not “deterministic” but “stochastic” ... so we need to understand the variability. Based on the data we see, can we not use “parallel-line” logic to conclude that they are different? This is one dimension of EDA, use mathematics. (“mathematics”)

```

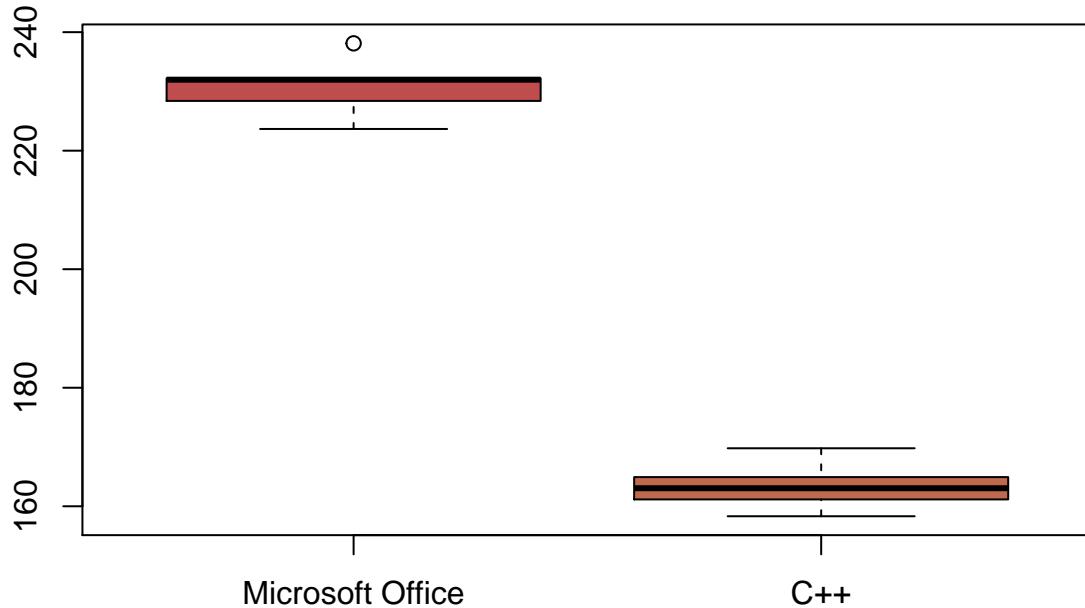
do.nothing = plotJobs(jobs.subset, myy.lim = c(80,250) );

```

## Keyword trends in Data Analysis



```
boxplotJobQueryComparison(jobs.subset, "Microsoft Office", "C++");
```



Tukey invented the boxplot as a nice EDA representation of the data. What logical inference can we make about the distances between the boxplots and the fact that no data is overlapping. This is another dimension of EDA, use “distance” and the boxplot “IQR” to compare two elements. What conclusion would we make? (“boxplot”)

[Can we conclude the data are different based on “mathematics” or “boxplot”?

I conclude that the data is different based on the boxplots.

Would a formal “inferential statistical test” tell us something different than logical inference?

I don’t think with this data that inferential statistical tests would tell us anything different than logical inference.

How do you think “formal tests” were derived if not from “mathematics” and “boxplot” (EDA)?]

```
# courage in trusting your intuition may require a fall-back ... for those that need it ...

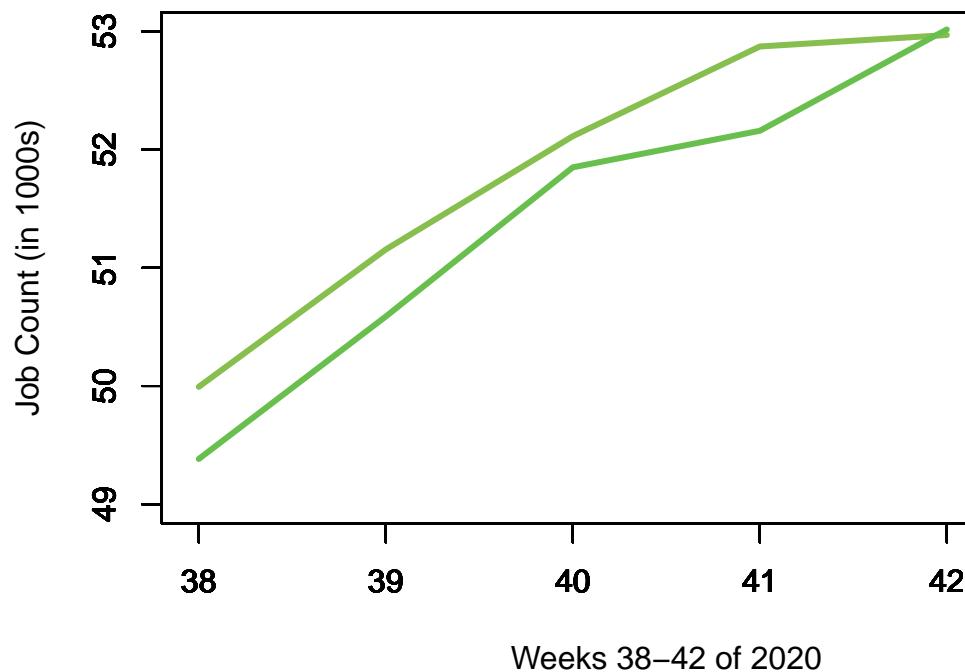
t.test(jobs.subset, "Microsoft Office", "C++");

##
## Welch Two Sample t-test
##
## data: x and y
## t = 22.016, df = 7.6613, p-value = 0.00000003332
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## 60.31098 74.54582
## sample estimates:
## mean of x mean of y
```

```
## 230.8730 163.4446
```

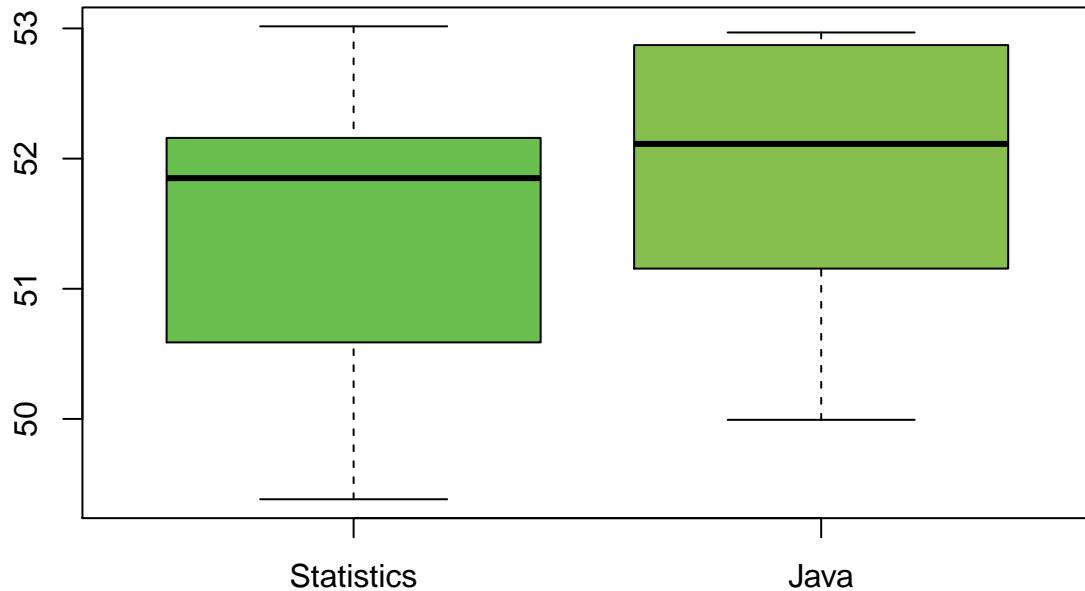
```
do.nothing = plotJobs(jobs.subset, myy.lim = c(49,53) );
```

## Keyword trends in Data Analysis



Is “Statistics” bigger than “Java”?

```
do.nothing = boxplotJobQueryComparison(jobs.subset, "Statistics", "Java");
```



```
t.test(jobs$subset, "Statistics", "Java");

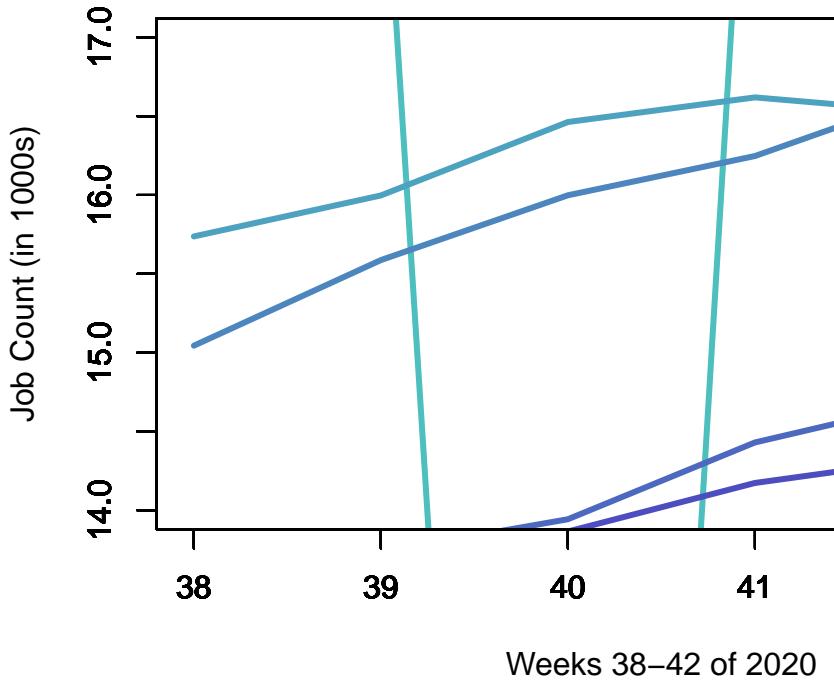
##
##  Welch Two Sample t-test
##
## data: x and y
## t = -0.49621, df = 7.8738, p-value = 0.6333
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -2.384104 1.541704
## sample estimates:
## mean of x mean of y
## 51.3992 51.8204
```

For this data, I can descriptively report that the third-quartile Q3 of “Statistics” is about equal to the median of “Java”. The inter-quartile range (IQR) of each overlap. The minimum value of “Java” is larger than the minimum value of “Statistics”. The maximum value of “Java” is slightly smaller than the maximum value of “Statistics”.

[Use “mathematics” and “boxplot” and “ttest” to answer the question: Is “Statistics” bigger than “Java”?]

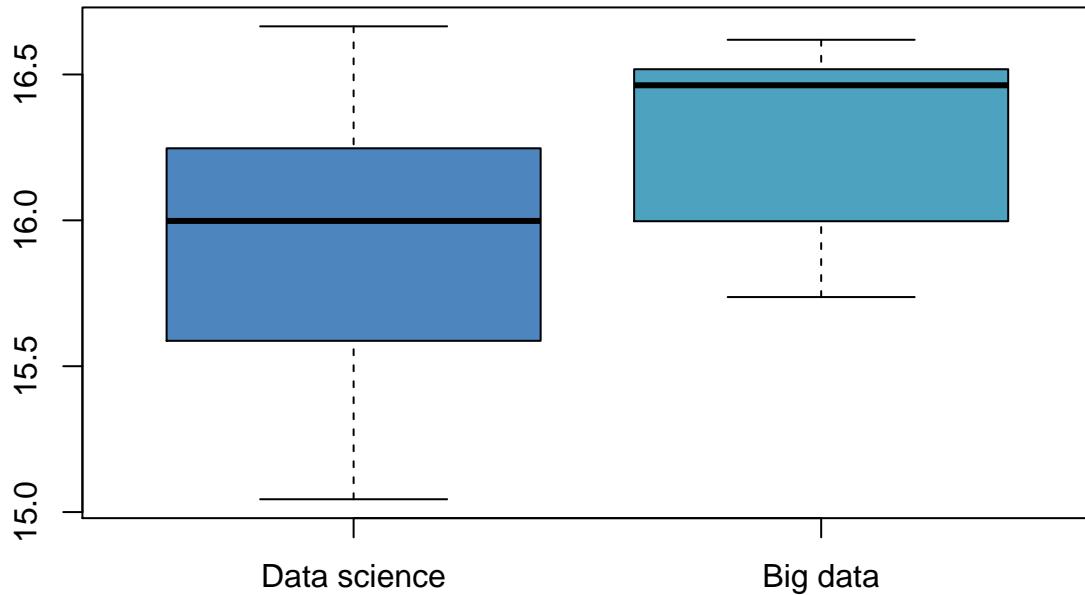
```
do.nothing = plotJobs(jobs$subset, myy.lim = c(14,17) );
```

## Keyword trends in Data Analytics



What about “Data science” and “Big data”?

```
boxplotJobQueryComparison(jobs.subset, "Data science", "Big data");
```



```
t.test(jobs$subset, "Data science", "Big data");

##
##  Welch Two Sample t-test
##
## data:  x and y
## t = -1.1002, df = 6.6285, p-value = 0.3096
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -1.1381677  0.4209677
## sample estimates:
## mean of x mean of y
## 15.9082   16.2668
```

[Use “mathematics” and “boxplot” and “ttest” to make a conclusion.

Next, think carefully about the nature of the data. Is the “collection-approach” flawed to make a conclusion comparing job-counts of these specific keywords? How likely is it that a single-job posting may have both keywords?

This is an example where “data-integrity” knowledge would surpass the other three logical conclusions.

This intuition requires an understanding of what mathematicians call “set theory”. If I am doing an independent search on keywords, is it possible that one job would show up in multiple searches. That is, being counted twice or more.

Intuition and logic would also allow us to conclude that our other comparisons are “very likely okay”. Why?

What would be an improved approach to collecting the data that would allow me to more accurately compare

these two keywords?

This is representative of why exploratory data analysis is essential. It provides us insight into the domain and highlights the need for better data, if we can find it.

]

### Conclusions on logical inference

Distance is a fundamental unit of comparison. We can use our “mathematical” understanding of distance. We can use an “EDA” understanding of the data (e.g., the boxplot). We need to understand the data sourcing and how that will relate to the logical conclusions we are trying to draw.

When we transition to “confirmatory inferential statistics”, we cannot leave our understanding of “maths” and “EDA” behind. They are the foundation from which “inferential statistics” is built. They are “logical inference”.

## COMPUTING DISTANCES

If you recall, we had a notebook on collecting data from Wikipedia. We documented the “data-provenance” protocols to make this happen. We have documented and can replicate our data-collection strategies.

### (10 points) Data Provenance defined

Imagine you are preparing for a job interview. Write a 90-second blurb describing “what is data provenance” and “why it matters”. I would suggest the STAR(S) approach mentioned in one of the notebooks. Reference the “Wikipedia” project as an example of how one can implement the features.

[What is data provenance?

Probably about 200-250 words (with the 90 second limit) ]

### Geospatial distances

“Geo-spatial” studies are becoming much more common in the “data analytics” community, so let’s use basic “latitude/longitude” data to formally talk about “distance.”

So we will look at the 50 state capitals of America (USA). Before that, let’s examine some basic principles of distances using my hometown.

### (5 points) Distance from one input to multiple outputs

#### My Hometown “Columbia Falls, Montana” cfalls

- Find all ZIP codes within 22 miles of Columbia Falls, MT `cfalls` (use lat/long provide from the Wikipedia lookup)... build the bounding “box” and perform the post-hoc “radial distance” computations (as we did in the homework).

```
# copy/paste __student_access__/_SECRET_/_SECRET_database_.txt into console... or this won't work

cfalls.latitude = 48.37028;
cfalls.longitude = -114.18889;
my.radius = 22; my.units = "mi"; #miles

# THIS is where these exam functions live ...
# source_url( paste0(path.github,"misc/functions-midterm-F2000.R") ); # should be 2020 ... oh well

cfalls.info = getNeighborsFromLatLong(22, 48.37028, -114.18889, "mi");

## [1] "The QUERY returned ... 13 ... NEIGHBORS"
```

```

cfalls.info$neighbors;

##      zipcode latitude longitude      city state_long state
## 1      59901  48.21124 -114.2939 KALISPELL MONTANA    MT
## 2      59903  48.19303 -114.3579 KALISPELL MONTANA    MT
## 3      59904  48.19452 -114.3123 KALISPELL MONTANA    MT
## 4      59912  48.36531 -114.1927 COLUMBIA FALLS MONTANA    MT
## 5      59913  48.43674 -114.0507 CORAM     MONTANA    MT
## 6      59916  48.61750 -113.9095 ESSEX     MONTANA    MT
## 7      59919  48.38969 -114.0630 HUNGRY HORSE MONTANA    MT
## 8      59920  48.06516 -114.5023 KILA      MONTANA    MT
## 9      59921  48.62189 -113.8739 LAKE MC DONALD MONTANA    MT
## 10     59926  48.39134 -114.0393 MARTIN CITY MONTANA    MT
## 11     59932  48.07931 -114.2389 SOMERS    MONTANA    MT
## 12     59936  48.49720 -113.9892 WEST GLACIER MONTANA    MT
## 13     59937  48.40834 -114.3522 WHITEFISH MONTANA    MT

##### plotting #####
brown = "#ffe4c4";
green = "#014421";

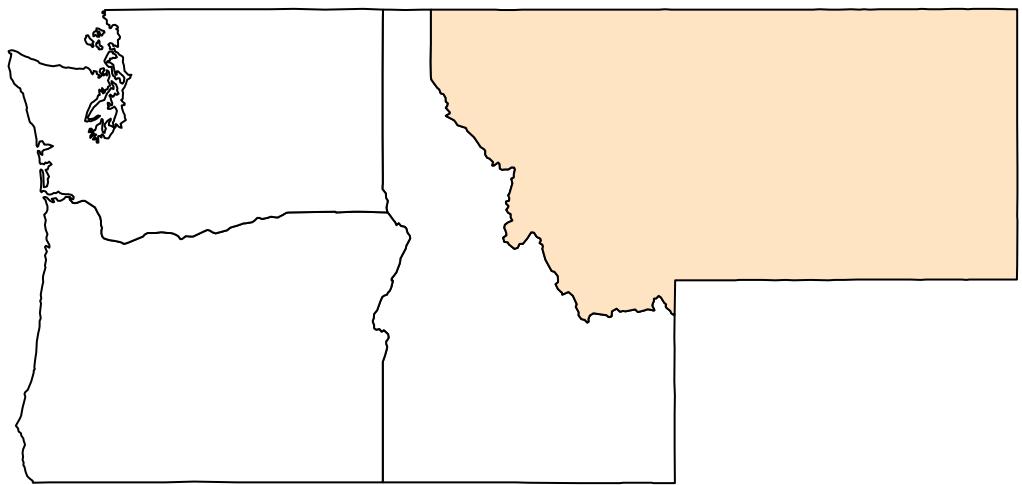
my.state = "montana";
my.state.color = "#ffe4c4";

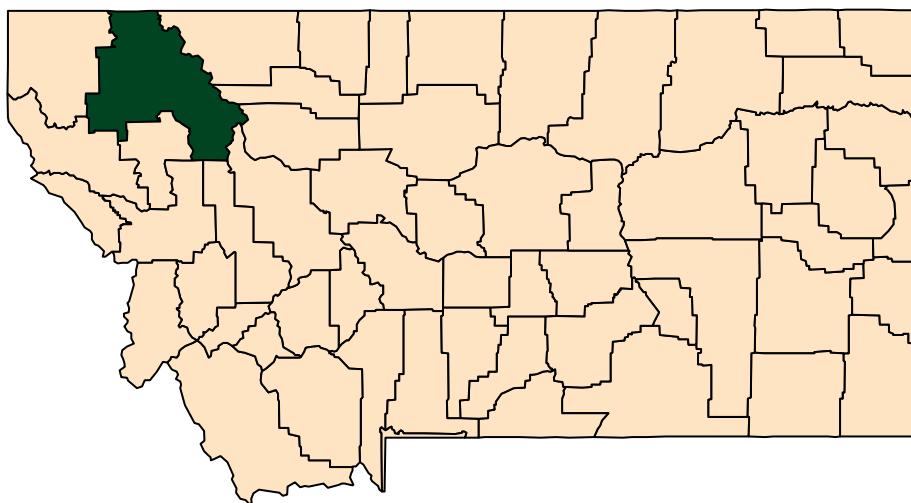
my.county = "flathead";
my.county.color = "#014421";

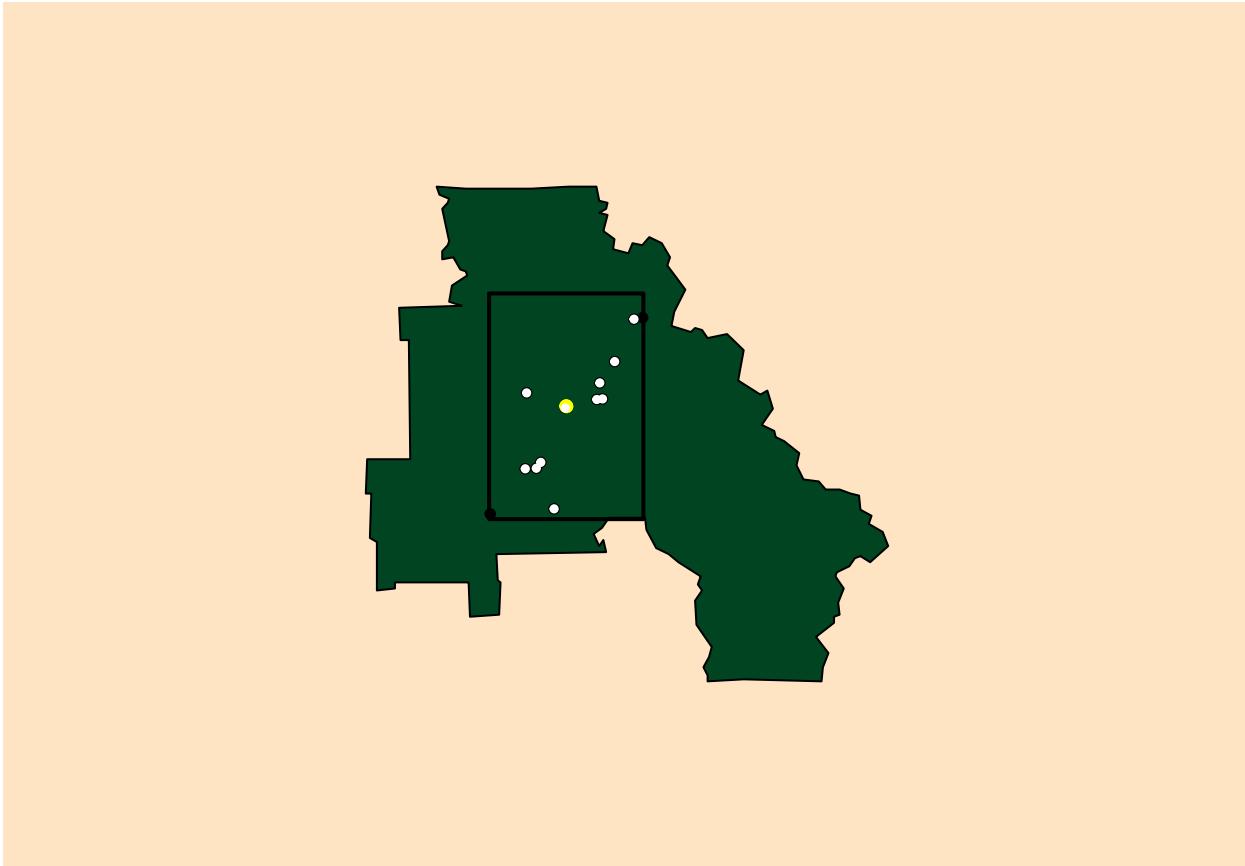
my.nearby.states = c("idaho", "washington", "oregon");

plotNeighbors(cfalls.info,
              state      = my.state,
              state.color = my.state.color,
              state.border = 0.05,
              county     = my.county,
              county.border = 0.05, # if you don't see the box, increase this to like 0.75
              county.color = my.county.color,
              nearby.states = my.nearby.states);

```







[ - why is the box not a square, but a rectangle? ... see `factor.lat` and `factor.long` in function `buildBoundingBoxFromRadiusAndGivenLatitudeLongitude` - critique the visualization ... what do you like? what would make it better?]

**Your Hometown of something like it** Instead of `cfalls.info`, you do `hometown.info`

- a location in the continental US of your choosing (not in Montana, Alaska, or Hawaii). [Graphing will not work for Alaska/Hawaii, Alaska has “boroughs” not counties.]
- find the latitude/longitude of the location you have selected (how and where to look that up?)
- Initially start with a radius of 13 miles
- When you run the code, note how many total “neighbors”; if it is less than 20; increase the “miles” so at least 20 results are returned.
- In the end, you should select a location and radius that works for you. And its visualization also works.
- Be certain to review and update the parameters before calling these functions.

```
hometown.latitude = 00.00000; hometown.longitude = -000.00000; my.radius = 13; my.units = "mi"; #miles
hometown.info = getNeighborsFromLatLong(????); plotNeighbors(hometown.info,????); # you are going
to have to change some of these parameters ...
```

```
hometown.latitude = 48.0518;
hometown.longitude = -122.1771;
my.radius = 20; my.units = "mi"; #miles
hometown.info = getNeighborsFromLatLong(20, 48.0518, -122.1771, "mi");
```

```
## [1] "The QUERY returned ... 35 ... NEIGHBORS"
```

```
hometown.info$neighbors;
```

```
##      zipcode latitude longitude          city state_long state
```

```

## 1 98012 47.84130 -122.2058 BOTHELL WASHINGTON WA
## 2 98020 47.80094 -122.3743 EDMONDS WASHINGTON WA
## 3 98021 47.79165 -122.2174 BOTHELL WASHINGTON WA
## 4 98026 47.84077 -122.3367 EDMONDS WASHINGTON WA
## 5 98036 47.80278 -122.2849 LYNNWOOD WASHINGTON WA
## 6 98037 47.85110 -122.2815 LYNNWOOD WASHINGTON WA
## 7 98043 47.79179 -122.3041 MOUNTLAKE TERRACE WASHINGTON WA
## 8 98046 47.83017 -122.3040 LYNNWOOD WASHINGTON WA
## 9 98082 47.85524 -122.2210 MILL CREEK WASHINGTON WA
## 10 98087 47.87263 -122.2709 LYNNWOOD WASHINGTON WA
## 11 98155 47.76313 -122.2902 SEATTLE WASHINGTON WA
## 12 98160 47.77113 -122.3824 SEATTLE WASHINGTON WA
## 13 98201 47.98859 -122.2018 EVERETT WASHINGTON WA
## 14 98203 47.94596 -122.2299 EVERETT WASHINGTON WA
## 15 98204 47.89843 -122.2548 EVERETT WASHINGTON WA
## 16 98205 47.99055 -122.1141 EVERETT WASHINGTON WA
## 17 98206 47.92563 -122.2264 EVERETT WASHINGTON WA
## 18 98207 47.95998 -122.1968 EVERETT WASHINGTON WA
## 19 98208 47.89491 -122.1934 EVERETT WASHINGTON WA
## 20 98213 47.94082 -122.2347 EVERETT WASHINGTON WA
## 21 98223 48.18180 -121.9796 ARLINGTON WASHINGTON WA
## 22 98236 47.95950 -122.4021 CLINTON WASHINGTON WA
## 23 98238 48.33875 -122.3438 CONWAY WASHINGTON WA
## 24 98258 48.02742 -122.0624 LAKE STEVENS WASHINGTON WA
## 25 98259 48.16499 -122.2992 NORTH LAKWOOD WASHINGTON WA
## 26 98260 48.03366 -122.4502 Langley WASHINGTON WA
## 27 98270 48.06088 -122.1539 MARYSVILLE WASHINGTON WA
## 28 98271 48.09840 -122.2373 MARYSVILLE WASHINGTON WA
## 29 98272 47.85709 -121.9377 MONROE WASHINGTON WA
## 30 98275 47.90714 -122.3091 MUKILTEO WASHINGTON WA
## 31 98287 48.19051 -122.2503 SILVANA WASHINGTON WA
## 32 98290 47.93953 -122.0167 SNOHOMISH WASHINGTON WA
## 33 98291 47.92897 -122.0999 SNOHOMISH WASHINGTON WA
## 34 98292 48.17928 -122.3714 STANWOOD WASHINGTON WA
## 35 98296 47.82290 -122.1182 SNOHOMISH WASHINGTON WA

##### plotting #####
brown = "#ffe4c4";
green = "#014421";

my.state = "washington";
my.state.color = "#ffe4c4";

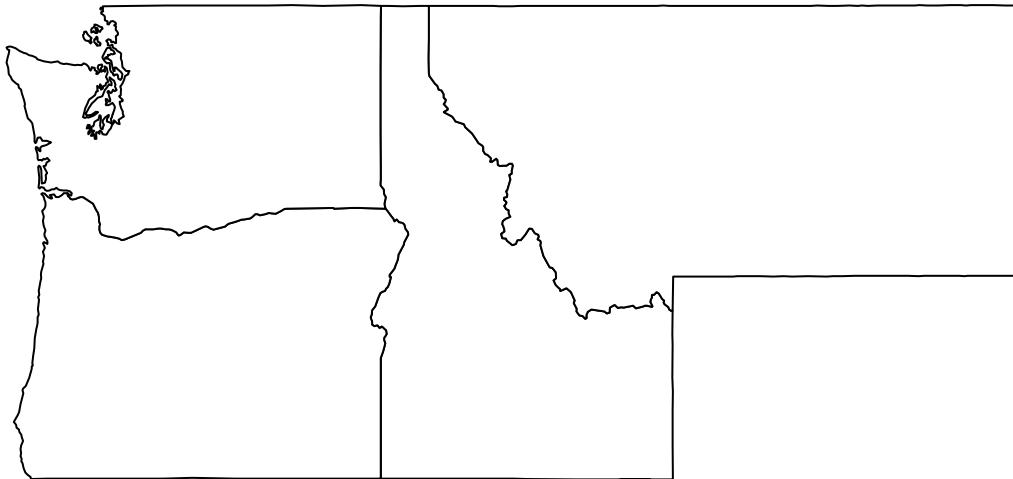
my.county = "snohomish";
my.county.color = "#014421";

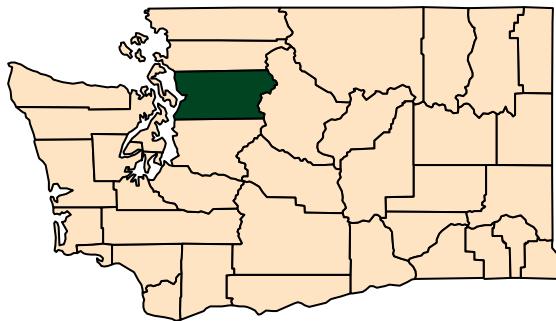
my.nearby.states = c("idaho", "montana", "oregon");

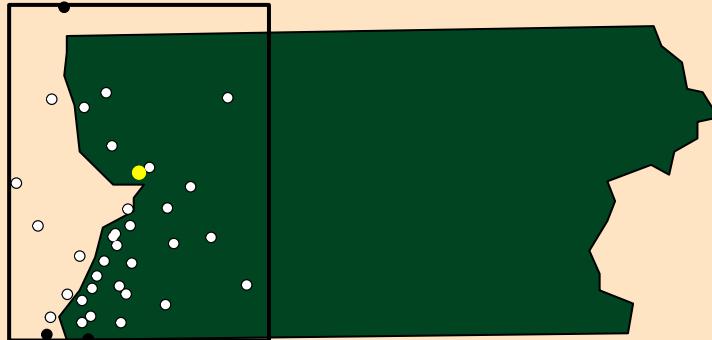
#why wont my box show up?
plotNeighbors(hometown.info,
              state      = my.state,
              state.color = my.state.color,
              state.border = 0.05,
              county     = my.county,

```

```
county.border = 0.25, # if you don't see the box, increase this to like 0.75  
county.color = my.county.color,  
nearby.states = my.nearby.states);
```







### U.S. State Capitals (cities)

From Wikipedia, we grabbed one page that listed the 50 U.S. cities that are designated the capitals of each individual state in America (United States of America).

Using the power of a `for-loop` we make our functions work for us. We now have the data ready to go.

```
capitals = utils::read.csv( paste0(path.mshaffer, "_data_/state-capitals/final/state-capitals.txt"), header=TRUE)

colnames(capitals) = c("state", "capital", "latitude", "longitude", "capital.since", "area.sq.miles", "name")

# hack-add from https://en.wikipedia.org/wiki/ISO_3166-2:US
# TODO, grab this table "appropriately" as a new function
# Is there a dictionary for shortened city names?
# the long-field names is also an issue that needs to be improved upon in the next iteration.

capitals$st = c("AL", "AK", "AZ", "AR", "CA", "CO", "CT", "DE", "FL", "GA", "HI", "ID", "IL", "IN", "IA", "KS", "KY", "LA", "ME", "MD", "MA", "MI", "MN", "MS", "NC", "ND", "NE", "NH", "NI", "NV", "NY", "PA", "PR", "RI", "SD", "TN", "UT", "VA", "VI", "WA", "WI", "WV", "WY")

myLabels = paste0(capitals$capital, ", ", capitals$st);

capitals;

##          state      capital latitude longitude capital.since
## 1      Alabama  Montgomery 32.36167 -86.27917       1846
## 2      Alaska        Juneau 58.30000 -134.41600       1906
## 3     Arizona       Phoenix 33.45000 -112.06700       1912
## 4   Arkansas    Little Rock 34.73611 -92.33111       1821
```

## 5	California	Sacramento	38.58167	-121.49444	1854
## 6	Colorado	Denver	39.73917	-104.99028	1867
## 7	Connecticut	Hartford	41.76250	-72.67417	1875
## 8	Delaware	Dover	39.15806	-75.52444	1777
## 9	Florida	Tallahassee	30.45500	-84.25333	1824
## 10	Georgia	Atlanta	33.75500	-84.39000	1868
## 11	Hawaii	Honolulu	21.30694	-157.85833	1845
## 12	Idaho	Boise	43.61583	-116.20167	1865
## 13	Illinois	Springfield	39.79944	-89.65500	1837
## 14	Indiana	Indianapolis	39.76861	-86.15806	1825
## 15	Iowa	Des Moines	41.59083	-93.62083	1857
## 16	Kansas	Topeka	39.05583	-95.68944	1856
## 17	Kentucky	Frankfort	38.20000	-84.86700	1792
## 18	Louisiana	Baton Rouge	30.44750	-91.17861	1880
## 19	Maine	Augusta	44.31056	-69.77944	1832
## 20	Maryland	Annapolis	38.97306	-76.50111	1694
## 21	Massachusetts	Boston	42.35806	-71.06361	1630
## 22	Michigan	Lansing	42.73361	-84.54667	1847
## 23	Minnesota	Saint Paul	44.94417	-93.09361	1849
## 24	Mississippi	Jackson	32.29889	-90.18472	1821
## 25	Missouri	Jefferson City	38.57667	-92.17361	1826
## 26	Montana	Helena	46.59111	-112.02028	1875
## 27	Nebraska	Lincoln	40.80889	-96.67889	1867
## 28	Nevada	Carson City	39.16444	-119.76694	1861
## 29	New Hampshire	Concord	43.20667	-71.53806	1808
## 30	New Jersey	Trenton	40.22384	-74.76362	1784
## 31	New Mexico	Santa Fe	35.66722	-105.96444	1610
## 32	New York	Albany	42.65250	-73.75722	1797
## 33	North Carolina	Raleigh	35.76700	-78.63300	1792
## 34	North Dakota	Bismarck	46.80833	-100.78361	1883
## 35	Ohio	Columbus	39.96222	-83.00056	1816
## 36	Oklahoma	Oklahoma City	35.46861	-97.52139	1910
## 37	Oregon	Salem	44.93917	-123.03944	1855
## 38	Pennsylvania	Harrisburg	40.26972	-76.87556	1812
## 39	Rhode Island	Providence	41.82361	-71.42222	1900
## 40	South Carolina	Columbia	34.00056	-81.03472	1786
## 41	South Dakota	Pierre	44.37250	-100.32000	1889
## 42	Tennessee	Nashville	36.16667	-86.78333	1826
## 43	Texas	Austin	30.26722	-97.74306	1839
## 44	Utah	Salt Lake City	40.76083	-111.89111	1858
## 45	Vermont	Montpelier	44.25944	-72.57583	1805
## 46	Virginia	Richmond	37.53300	-77.46700	1780
## 47	Washington	Olympia	47.03778	-122.90083	1853
## 48	West Virginia	Charleston	38.34722	-81.63333	1885
## 49	Wisconsin	Madison	43.07472	-89.38417	1838
## 50	Wyoming	Cheyenne	41.14000	-104.82028	1869
##	area.sq.miles	population.2019.est	population.2019.est.MSA		
## 1	159.80	198525		373290	
## 2	2716.70	32113		32113	
## 3	517.60	1680992		4948203	
## 4	116.20	197312		742384	
## 5	97.90	513624		2363730	
## 6	153.30	727211		2967239	
## 7	17.30	122105		1204877	

```

## 8      22.40      38079      180786
## 9      95.70     194500      387227
## 10     133.50     506811      6020364
## 11     68.40      345064      974563
## 12     63.80      228959      749202
## 13     54.00      114230      206868
## 14     361.50     876384      2074537
## 15     75.80      214237      699292
## 16     56.00      125310      231969
## 17     14.70      27679       73663
## 18     76.80      220236      854884
## 19     55.40      18681       122302
## 20     6.73       39174      2800053
## 21     89.60      692600      4873019
## 22     35.00      118210      550391
## 23     52.80      308096      3654908
## 24     104.90     160628      594806
## 25     27.30      42838       151235
## 26     14.00      32315       77414
## 27     74.60      289102      336374
## 28     143.40     55916       55916
## 29     64.30      43627      151391
## 30     7.66       83203      367430
## 31     37.30      84683      150358
## 32     21.40      96460      880381
## 33     114.60     474069      1390785
## 34     26.90      73529      128949
## 35     210.30     898553      2122271
## 36     620.30     655057      1408950
## 37     45.70      174365      433903
## 38     8.11       49528      577941
## 39     18.50      179883      1624578
## 40     125.20     131674      838433
## 41     13.00      13646       20672
## 42     525.90     670820      1934317
## 43     305.10     978908      2227083
## 44     109.10     200567      1232696
## 45     10.20       7855       NA
## 46     60.10      230436      1291900
## 47     16.70      46478       290536
## 48     31.60      46536       257074
## 49     68.70      259680      664865
## 50     21.10      64235       99500
## population.2019.est.CSA city.rank.in.state
## 1          461516      2
## 2             NA      3
## 3          5002221      1
## 4          908941      1
## 5          2639124      6
## 6          3617927      1
## 7          1470083      3
## 8          7209620      2
## 9             NA      7
## 10         6853392      1

```

```

## 11          NA      1
## 12          831235   1
## 13          306399   6
## 14          2457286  1
## 15          877991   1
## 16          NA      4
## 17          745033   15
## 18          NA      2
## 19          NA      8
## 20          9814928  7
## 21          8287710  1
## 22          NA      5
## 23          4027861  2
## 24          674340   1
## 25          NA      15
## 26          NA      6
## 27          357887   2
## 28          637973   6
## 29          8287710  3
## 30          22589036 10
## 31          1158464   4
## 32          1167594   6
## 33          2079687   2
## 34          NA      2
## 35          2525639   1
## 36          1481542   1
## 37          3259710   3
## 38          1271801   9
## 39          8287710   1
## 40          963048    2
## 41          NA      8
## 42          2062547   1
## 43          NA      4
## 44          2641048   1
## 45          NA      6
## 46          NA      4
## 47          4903675   24
## 48          776694    1
## 49          892661    2
## 50          NA      1
##                               url st
## 1          https://en.wikipedia.org/wiki/Montgomery,_Alabama AL
## 2          https://en.wikipedia.org/wiki/Juneau,_Alaska AK
## 3          https://en.wikipedia.org/wiki/Phoenix,_Arizona AZ
## 4          https://en.wikipedia.org/wiki/Little_Rock,_Arkansas AR
## 5          https://en.wikipedia.org/wiki/Sacramento,_California CA
## 6          https://en.wikipedia.org/wiki/Denver CO
## 7          https://en.wikipedia.org/wiki/Hartford,_Connecticut CT
## 8          https://en.wikipedia.org/wiki/Dover,_Delaware DE
## 9          https://en.wikipedia.org/wiki/Tallahassee,_Florida FL
## 10         https://en.wikipedia.org/wiki/Atlanta GA
## 11         https://en.wikipedia.org/wiki/Honolulu HI
## 12         https://en.wikipedia.org/wiki/Boise,_Idaho ID
## 13         https://en.wikipedia.org/wiki/Springfield,_Illinois IL

```

```

## 14      https://en.wikipedia.org/wiki/Indianapolis_IN
## 15      https://en.wikipedia.org/wiki/Des_Moines,_Iowa_IA
## 16      https://en.wikipedia.org/wiki/Topeka,_Kansas_KS
## 17      https://en.wikipedia.org/wiki/Frankfort,_Kentucky_KY
## 18      https://en.wikipedia.org/wiki/Baton_Rouge,_Louisiana_LA
## 19      https://en.wikipedia.org/wiki/Augusta,_Maine_ME
## 20      https://en.wikipedia.org/wiki/Annapolis,_Maryland_MD
## 21      https://en.wikipedia.org/wiki/Boston_MA
## 22      https://en.wikipedia.org/wiki/Lansing,_Michigan_MI
## 23      https://en.wikipedia.org/wiki/Saint_Paul,_Minnesota_MN
## 24      https://en.wikipedia.org/wiki/Jackson,_Mississippi_MS
## 25      https://en.wikipedia.org/wiki/Jefferson_City,_Missouri_MO
## 26      https://en.wikipedia.org/wiki/Helena,_Montana_MT
## 27      https://en.wikipedia.org/wiki/Lincoln,_Nebraska_NE
## 28      https://en.wikipedia.org/wiki/Carson_City,_Nevada_NV
## 29      https://en.wikipedia.org/wiki/Concord,_New_Hampshire_NH
## 30      https://en.wikipedia.org/wiki/Trenton,_New_Jersey_NJ
## 31      https://en.wikipedia.org/wiki/Santa_Fe,_New_Mexico_NM
## 32      https://en.wikipedia.org/wiki/Albany,_New_York_NY
## 33      https://en.wikipedia.org/wiki/Raleigh,_North_Carolina_NC
## 34      https://en.wikipedia.org/wiki/Bismarck,_North_Dakota_ND
## 35      https://en.wikipedia.org/wiki/Columbus,_Ohio_OH
## 36      https://en.wikipedia.org/wiki/Oklahoma_City.OK
## 37      https://en.wikipedia.org/wiki/Salem,_Oregon_OR
## 38      https://en.wikipedia.org/wiki/Harrisburg,_Pennsylvania_PA
## 39      https://en.wikipedia.org/wiki/Providence,_Rhode_Island_RI
## 40      https://en.wikipedia.org/wiki/Columbia,_South_Carolina_SC
## 41      https://en.wikipedia.org/wiki/Pierre,_South_Dakota_SD
## 42      https://en.wikipedia.org/wiki/Nashville,_Tennessee_TN
## 43      https://en.wikipedia.org/wiki/Austin,_Texas_TX
## 44      https://en.wikipedia.org/wiki/Salt_Lake_City_UT
## 45      https://en.wikipedia.org/wiki/Montpelier,_Vermont_VT
## 46      https://en.wikipedia.org/wiki/Richmond,_Virginia_VA
## 47      https://en.wikipedia.org/wiki/Olympia,_Washington_WA
## 48      https://en.wikipedia.org/wiki/Charleston,_West_Virginia_WV
## 49      https://en.wikipedia.org/wiki/Madison,_Wisconsin_WI
## 50      https://en.wikipedia.org/wiki/Cheyenne,_Wyoming_WY

```

## Initial Plotting

- Plot the data on usmap (ggplot2)

```

latlong = removeAllColumnsBut(capitals,c( "state", "st", "capital", "latitude", "longitude", "population"))

# first two elements have to be this
latlong = moveColumnsInDataFrame(latlong, c("longitude","latitude"), "before", "state");

# for transform to work
library(usmap);
latlong.transform = usmap_transform(latlong);
library(ggplot2);

### plot_usmap ...

plot_usmap(fill = "#53565A", alpha = 0.25) +

```

```

ggrepel::geom_label_repel(data = latlong.transform,
  aes(x = longitude.1, y = latitude.1, label = capital),
  size = 3, alpha = 0.8,
  label.r = unit(0.5, "lines"), label.size = 0.5,
  segment.color = "#981E32", segment.size = 1,
  seed = 1002) +
  scale_size_continuous(range = c(1, 16),
  label = scales::comma) +
  labs(title = "U.S. State Capitals",
  subtitle = "Source: Wikipedia (October 2020)") +
  theme(legend.position = "right")

```

## U.S. State Capitals

Source: Wikipedia (October 2020)



- Plot the data using maths voronoi (tripack)

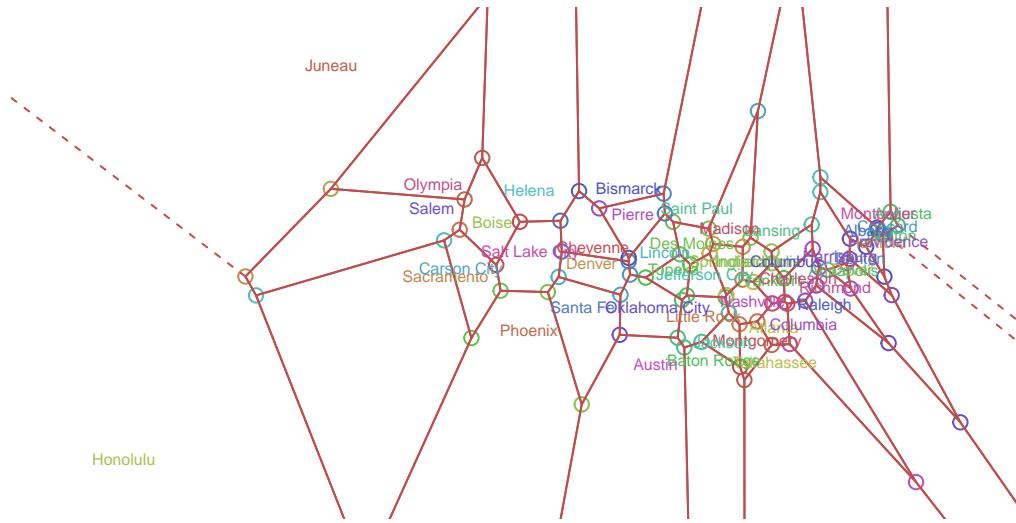
```

colors = rainbow(50, s = 0.6, v = 0.75);

## initial visualization ...
library(tripack);
# plot(voronoi.mosaic(latlong[,4:3], duplicate="remove"), col=colors, xlab="");
plot(voronoi.mosaic(x = latlong$longitude, y = latlong$latitude), col=colors, xlab="");
text(x = latlong$longitude, y = latlong$latitude, labels = latlong$capital, col=colors, cex=0.5);

```

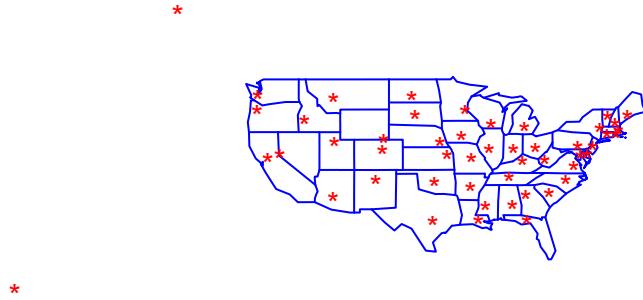
## Voronoi mosaic



```
voronoi.mosaic(x = latlong$longitude, y = latlong$latitude)
```

- Plot the data on `map` (base)

```
### how is any of the other visualizations really any better than a simple map ... with actual location
library(maps);
map('state', plot = TRUE, fill = FALSE,
     col = "blue", myborder = 0.5
   );
points(x = latlong$longitude, y = latlong$latitude,
       col = "red", pch = "*", cex = 1);
```



**(5 points) Comparing “Visualization Options”** Above, the data was displayed using three different visualization packages.

The first `plot_usmap` uses the ‘`ggplot2` methodology which is tied to the “tidyverse” landscape of the R community.

The second `voronoi.mosaic` uses the graph-theory topology known as Voroni partitioning [https://en.wikipedia.org/wiki/Voronoi\\_diagram](https://en.wikipedia.org/wiki/Voronoi_diagram) with the “base” plot function to visualize the topology.

The last one `map` is from the “base” environment.

[ Visually, which is the most appealing to you? Why?

Functionally, which presents the data most effectively? Why?

When we create visualizations, it is essential to portray the data accurately. For example, there are times when putting Alaska/Hawaii next to California might be appropriate, and other times it might not be.

What is a one key factor that would determine this appropriateness?

]

**(5 points) Building the distance matrix** The dataframe we are using has been named `latlong` to represent the latitudes and longitudes of the 50 U.S. cities in America.

```
# manual conversion
# how many miles is 1 degree of latitude
latitude.factor = 69; # rough mile estimate # 68.703 ?
latlong$x.lat = latlong$latitude * latitude.factor;
```

```

longitude.factor = 54.6; # rough mile estimate
latlong$y.long = latlong$longitude * longitude.factor;

latlong = moveColumnsInDataFrame(latlong, c("y.long","x.lat"), "before", "longitude");

```

Let's start with geo-spatial distances. I will do `distMeeus` and you will do `distHaversine`

**Meeus** These distance formulas can utilize the true geo-spatial coordinates. The distance table is getting large, so there is a helper function to lookup a certain value.

```

library(geosphere);
library(measurements);

dist.meeus = conv_unit( distm( latlong[,3:4],
                               fun=distMeeus), "m", "mi"); # default meters to miles

dist.meeus.m = as.matrix( dist.meeus );
rownames(dist.meeus.m) =
colnames(dist.meeus.m) = myLabels;

dist.meeus.df = as.data.frame( round( dist.meeus.m, digits=1 ) );

dist.meeus.df; ## too big

```

	Montgomery, AL	Juneau, AK	Phoenix, AZ	Little Rock, AR
## Montgomery, AL	0.0	2855.6	1497.1	385.6
## Juneau, AK	2855.6	0.0	2005.8	2516.3
## Phoenix, AZ	1497.1	2005.8	0.0	1133.4
## Little Rock, AR	385.6	2516.3	1133.4	0.0
## Sacramento, CA	2018.8	1480.3	635.1	1634.7
## Denver, CO	1161.4	1825.6	585.2	777.6
## Hartford, CT	990.5	2855.1	2215.2	1170.3
## Dover, DE	763.8	2881.2	2062.7	977.2
## Tallahassee, FL	177.7	3032.3	1642.0	555.6
## Atlanta, GA	145.7	2845.3	1591.5	459.4
## Honolulu, HI	4408.0	2809.0	2910.9	4040.4
## Boise, ID	1795.1	1280.7	735.9	1413.7
## Springfield, IL	546.4	2338.4	1316.1	379.0
## Indianapolis, IN	510.7	2464.8	1498.7	485.8
## Des Moines, IA	754.3	2106.8	1154.9	478.0
## Topeka, KS	701.4	2167.1	991.0	351.1
## Frankfort, KY	410.3	2591.8	1556.0	479.2
## Baton Rouge, LA	318.1	2796.7	1242.3	303.1
## Augusta, ME	1213.3	2836.7	2370.3	1367.5
## Annapolis, MD	713.6	2855.0	2010.2	923.1
## Boston, MA	1081.8	2884.4	2299.3	1261.7
## Lansing, MI	721.6	2375.7	1621.6	693.0
## Saint Paul, MN	942.1	1961.5	1285.2	705.4
## Jackson, MS	228.5	2725.0	1272.6	208.7
## Jefferson City, MO	542.0	2313.6	1166.3	265.0
## Helena, MT	1677.8	1234.8	906.7	1312.5
## Lincoln, NE	819.6	2040.7	987.5	481.6
## Carson City, NV	1927.5	1474.7	582.6	1542.6

## Concord, NH	1097.1	2826.1	2277.8	1258.1
## Trenton, NJ	839.5	2855.3	2103.4	1034.8
## Santa Fe, NM	1150.5	2031.7	380.0	773.5
## Albany, NY	986.3	2772.4	2162.9	1139.4
## Raleigh, NC	497.2	2943.7	1903.0	777.2
## Bismarck, ND	1257.7	1600.9	1095.9	942.4
## Columbus, OH	555.1	2568.8	1666.8	626.9
## Oklahoma City, OK	680.1	2303.0	841.2	298.3
## Salem, OR	2146.1	1042.2	985.5	1764.9
## Harrisburg, PA	755.8	2776.0	1991.9	929.3
## Providence, RI	1045.8	2897.5	2279.9	1233.3
## Columbia, SC	324.2	2951.4	1780.7	647.3
## Pierre, SD	1122.7	1733.9	982.0	789.0
## Nashville, TN	263.8	2630.7	1445.5	328.1
## Austin, TX	692.9	2596.4	869.6	441.1
## Salt Lake City, UT	1530.8	1564.2	504.3	1145.8
## Montpelier, VT	1105.1	2738.3	2231.8	1238.6
## Richmond, VA	613.7	2893.7	1959.9	852.4
## Olympia, WA	2171.6	914.1	1096.3	1795.8
## Charleston, WV	488.8	2700.6	1732.1	644.7
## Madison, WI	758.0	2184.2	1394.4	596.6
## Cheyenne, WY	1190.0	1753.3	663.3	811.4
##	Sacramento, CA Denver, CO Hartford, CT Dover, DE			
## Montgomery, AL	2018.8	1161.4	990.5	763.8
## Juneau, AK	1480.3	1825.6	2855.1	2881.2
## Phoenix, AZ	635.1	585.2	2215.2	2062.7
## Little Rock, AR	1634.7	777.6	1170.3	977.2
## Sacramento, CA	0.0	888.7	2558.5	2452.1
## Denver, CO	888.7	0.0	1691.6	1569.4
## Hartford, CT	2558.5	1691.6	0.0	234.2
## Dover, DE	2452.1	1569.4	234.2	0.0
## Tallahassee, FL	2181.2	1333.2	1011.7	777.8
## Atlanta, GA	2086.5	1211.9	845.0	618.1
## Honolulu, HI	2461.8	3343.9	5018.8	4912.6
## Boise, ID	443.7	638.1	2194.7	2114.9
## Springfield, IL	1702.3	815.5	899.4	756.0
## Indianapolis, IN	1886.8	1001.0	719.9	569.8
## Des Moines, IA	1485.1	610.4	1081.2	967.7
## Topeka, KS	1388.2	499.8	1224.4	1081.6
## Frankfort, KY	1975.1	1086.5	691.5	509.2
## Baton Rouge, LA	1808.7	1009.1	1291.6	1071.2
## Augusta, ME	2669.3	1824.8	228.9	463.1
## Annapolis, MD	2404.2	1520.3	278.9	54.1
## Boston, MA	2631.2	1769.7	92.5	321.7
## Lansing, MI	1946.8	1082.0	612.0	532.2
## Saint Paul, MN	1522.9	706.2	1048.8	985.4
## Jackson, MS	1809.3	973.2	1163.9	948.4
## Jefferson City, MO	1580.7	692.4	1052.8	897.5
## Helena, MT	733.2	591.0	1962.3	1903.8
## Lincoln, NE	1327.0	445.2	1247.2	1125.8
## Carson City, NV	101.5	790.4	2457.2	2351.7
## Concord, NH	2596.2	1740.9	115.3	348.1
## Trenton, NJ	2474.4	1596.8	152.3	84.0
## Santa Fe, NM	879.6	285.9	1835.3	1683.7

## Albany, NY	2492.3	1631.0	82.8	258.3
## Raleigh, NC	2351.8	1463.5	523.7	289.6
## Bismarck, ND	1192.5	531.9	1428.7	1377.1
## Columbus, OH	2050.2	1166.5	554.7	402.9
## Oklahoma City, OK	1338.8	504.4	1407.2	1234.8
## Salem, OR	445.9	988.8	2505.8	2441.0
## Harrisburg, PA	2364.7	1485.9	242.5	105.2
## Providence, RI	2620.9	1755.3	64.8	283.7
## Columbia, SC	2262.0	1380.1	703.1	469.2
## Pierre, SD	1165.3	399.8	1404.0	1325.0
## Nashville, TN	1906.3	1022.4	850.8	650.3
## Austin, TX	1467.2	770.9	1603.7	1400.2
## Salt Lake City, UT	533.3	371.5	2025.4	1920.1
## Montpelier, VT	2533.0	1686.2	172.4	383.6
## Richmond, VA	2378.8	1490.9	387.8	153.9
## Olympia, WA	588.0	1029.5	2469.5	2418.7
## Charleston, WV	2144.4	1256.6	529.9	334.6
## Madison, WI	1700.6	841.4	857.9	771.0
## Cheyenne, WY	902.5	97.1	1659.8	1549.8
##	Tallahassee, FL	Atlanta, GA	Honolulu, HI	Boise, ID
## Montgomery, AL	177.7	145.7	4408.0	1795.1
## Juneau, AK	3032.3	2845.3	2809.0	1280.7
## Phoenix, AZ	1642.0	1591.5	2910.9	735.9
## Little Rock, AR	555.6	459.4	4040.4	1413.7
## Sacramento, CA	2181.2	2086.5	2461.8	443.7
## Denver, CO	1333.2	1211.9	3343.9	638.1
## Hartford, CT	1011.7	845.0	5018.8	2194.7
## Dover, DE	777.8	618.1	4912.6	2114.9
## Tallahassee, FL	0.0	227.5	4549.8	1968.8
## Atlanta, GA	227.5	0.0	4499.8	1835.5
## Honolulu, HI	4549.8	4499.8	0.0	2835.4
## Boise, ID	1968.8	1835.5	2835.4	0.0
## Springfield, IL	712.8	508.7	4159.3	1391.7
## Indianapolis, IN	651.0	426.1	4344.9	1567.8
## Des Moines, IA	928.6	739.4	3946.6	1156.3
## Topeka, KS	878.9	727.3	3838.8	1109.0
## Frankfort, KY	535.0	307.6	4426.8	1671.8
## Baton Rouge, LA	413.2	458.6	4142.8	1644.5
## Augusta, ME	1240.0	1068.5	5118.9	2284.0
## Annapolis, MD	733.8	567.9	4864.0	2070.8
## Boston, MA	1099.1	936.2	5089.5	2260.7
## Lansing, MI	846.8	619.3	4407.8	1590.8
## Saint Paul, MN	1108.9	900.5	3975.7	1146.0
## Jackson, MS	372.8	351.0	4182.9	1611.2
## Jefferson City, MO	718.8	547.3	4029.5	1296.5
## Helena, MT	1855.1	1696.3	3095.1	289.8
## Lincoln, NE	997.3	832.4	3786.8	1017.8
## Carson City, NV	2091.5	1992.4	2562.8	358.7
## Concord, NH	1124.2	952.1	5052.0	2220.3
## Trenton, NJ	859.6	693.9	4936.2	2126.5
## Santa Fe, NM	1306.9	1232.6	3268.4	772.7
## Albany, NY	1022.0	842.1	4951.0	2123.3
## Raleigh, NC	490.0	355.6	4795.1	2055.2
## Bismarck, ND	1433.3	1244.7	3617.5	782.7

## Columbus, OH	659.2	434.9	4510.0	1721.6
## Oklahoma City, OK	843.7	757.0	3743.7	1141.4
## Salem, OR	2319.9	2184.7	2560.8	351.2
## Harrisburg, PA	793.9	611.5	4826.3	2020.4
## Providence, RI	1060.3	900.2	5080.7	2254.7
## Columbia, SC	308.5	193.6	4686.2	1993.1
## Pierre, SD	1299.9	1123.5	3617.8	792.1
## Nashville, TN	419.9	214.7	4340.3	1635.7
## Austin, TX	805.4	819.2	3755.2	1369.4
## Salt Lake City, UT	1701.0	1583.4	2995.0	296.2
## Montpelier, VT	1146.1	962.0	4984.9	2150.9
## Richmond, VA	623.9	468.4	4833.2	2061.3
## Olympia, WA	2347.5	2200.4	2636.9	402.7
## Charleston, WV	564.1	352.2	4599.2	1830.1
## Madison, WI	915.1	697.3	4161.3	1345.8
## Cheyenne, WY	1364.7	1229.4	3364.0	606.4
##	Springfield, IL	Indianapolis, IN	Des Moines, IA	Topeka, KS
## Montgomery, AL	546.4	510.7	754.3	701.4
## Juneau, AK	2338.4	2464.8	2106.8	2167.1
## Phoenix, AZ	1316.1	1498.7	1154.9	991.0
## Little Rock, AR	379.0	485.8	478.0	351.1
## Sacramento, CA	1702.3	1886.8	1485.1	1388.2
## Denver, CO	815.5	1001.0	610.4	499.8
## Hartford, CT	899.4	719.9	1081.2	1224.4
## Dover, DE	756.0	569.8	967.7	1081.6
## Tallahassee, FL	712.8	651.0	928.6	878.9
## Atlanta, GA	508.7	426.1	739.4	727.3
## Honolulu, HI	4159.3	4344.9	3946.6	3838.8
## Boise, ID	1391.7	1567.8	1156.3	1109.0
## Springfield, IL	0.0	186.1	242.2	326.8
## Indianapolis, IN	186.1	0.0	411.5	512.2
## Des Moines, IA	242.2	411.5	0.0	206.2
## Topeka, KS	326.8	512.2	206.2	0.0
## Frankfort, KY	280.3	128.6	520.4	588.2
## Baton Rouge, LA	650.4	702.4	780.3	646.3
## Augusta, ME	1065.6	897.2	1219.0	1382.2
## Annapolis, MD	705.8	519.7	920.9	1030.7
## Boston, MA	984.6	807.2	1159.5	1308.2
## Lansing, MI	334.2	221.1	472.3	635.6
## Saint Paul, MN	396.2	503.3	233.0	427.7
## Jackson, MS	518.0	562.1	668.2	559.1
## Jefferson City, MO	159.4	333.2	221.6	192.6
## Helena, MT	1217.7	1381.2	975.7	976.4
## Lincoln, NE	377.4	560.2	168.3	131.9
## Carson City, NV	1602.8	1787.0	1384.4	1290.2
## Concord, NH	966.7	793.7	1131.9	1287.4
## Trenton, NJ	789.6	605.0	989.7	1116.5
## Santa Fe, NM	936.1	1118.8	781.8	611.5
## Albany, NY	850.0	675.4	1020.9	1172.1
## Raleigh, NC	663.7	495.6	902.8	963.7
## Bismarck, ND	739.6	881.1	505.9	593.9
## Columbus, OH	353.8	168.4	567.9	680.4
## Oklahoma City, OK	524.4	689.6	472.1	267.2
## Salem, OR	1732.2	1904.5	1493.6	1457.6

## Harrisburg, PA	677.9	493.4	879.7	1004.8
## Providence, RI	964.2	784.6	1144.9	1289.1
## Columbia, SC	622.2	488.4	863.6	885.5
## Pierre, SD	631.9	793.2	389.9	438.0
## Nashville, TN	295.5	250.8	524.9	527.4
## Austin, TX	800.5	926.1	814.0	617.0
## Salt Lake City, UT	1173.8	1357.0	952.5	867.6
## Montpelier, VT	929.1	763.5	1080.3	1244.2
## Richmond, VA	676.8	494.5	905.3	994.4
## Olympia, WA	1731.3	1897.1	1489.9	1474.3
## Charleston, WV	442.6	262.3	673.9	760.6
## Madison, WI	226.5	283.0	239.9	430.3
## Cheyenne, WY	803.4	986.3	582.7	504.4
##	Frankfort, KY Baton Rouge, LA Augusta, ME Annapolis, MD			
## Montgomery, AL	410.3	318.1	1213.3	713.6
## Juneau, AK	2591.8	2796.7	2836.7	2855.0
## Phoenix, AZ	1556.0	1242.3	2370.3	2010.2
## Little Rock, AR	479.2	303.1	1367.5	923.1
## Sacramento, CA	1975.1	1808.7	2669.3	2404.2
## Denver, CO	1086.5	1009.1	1824.8	1520.3
## Hartford, CT	691.5	1291.6	228.9	278.9
## Dover, DE	509.2	1071.2	463.1	54.1
## Tallahassee, FL	535.0	413.2	1240.0	733.8
## Atlanta, GA	307.6	458.6	1068.5	567.9
## Honolulu, HI	4426.8	4142.8	5118.9	4864.0
## Boise, ID	1671.8	1644.5	2284.0	2070.8
## Springfield, IL	280.3	650.4	1065.6	705.8
## Indianapolis, IN	128.6	702.4	897.2	519.7
## Des Moines, IA	520.4	780.3	1219.0	920.9
## Topeka, KS	588.2	646.3	1382.2	1030.7
## Frankfort, KY	0.0	644.4	889.8	455.9
## Baton Rouge, LA	644.4	0.0	1508.7	1019.3
## Augusta, ME	889.8	1508.7	0.0	506.4
## Annapolis, MD	455.9	1019.3	506.4	0.0
## Boston, MA	782.7	1383.8	149.5	368.9
## Lansing, MI	313.3	923.2	748.7	494.7
## Saint Paul, MN	630.5	1005.2	1146.5	946.5
## Jackson, MS	505.7	140.4	1377.8	895.6
## Jefferson City, MO	397.4	563.2	1223.7	845.7
## Helena, MT	1495.5	1576.5	2034.6	1863.4
## Lincoln, NE	655.8	778.1	1387.2	1077.4
## Carson City, NV	1876.4	1724.1	2567.9	2304.0
## Concord, NH	779.3	1393.6	116.4	390.3
## Trenton, NJ	559.5	1143.2	380.4	126.7
## Santa Fe, NM	1178.3	929.1	1992.5	1631.4
## Albany, NY	660.7	1278.9	230.4	291.8
## Raleigh, NC	383.4	813.8	752.6	250.3
## Bismarck, ND	1003.8	1240.2	1504.1	1338.8
## Columbus, OH	157.6	801.9	741.4	354.1
## Oklahoma City, OK	725.6	505.3	1585.8	1181.3
## Salem, OR	2012.5	1993.0	2578.2	2398.9
## Harrisburg, PA	451.7	1051.6	458.0	91.7
## Providence, RI	754.8	1349.6	190.7	332.3
## Columbia, SC	360.2	642.2	931.6	425.6

## Pierre, SD	908.1	1082.3	1504.5	1282.3
## Nashville, TN	175.6	468.9	1057.0	596.3
## Austin, TX	916.3	392.3	1806.0	1346.5
## Salt Lake City, UT	1449.7	1360.6	2139.8	1872.8
## Montpelier, VT	763.5	1392.4	138.7	417.5
## Richmond, VA	407.1	924.9	616.4	112.4
## Olympia, WA	2010.2	2038.6	2529.0	2378.9
## Charleston, WV	176.1	769.8	740.2	280.9
## Madison, WI	411.6	876.3	983.4	729.3
## Cheyenne, WY	1080.5	1060.8	1782.9	1502.2
##	Boston, MA	Lansing, MI	Saint Paul, MN	Jackson, MS
## Montgomery, AL	1081.8	721.6	942.1	228.5
## Juneau, AK	2884.4	2375.7	1961.5	2725.0
## Phoenix, AZ	2299.3	1621.6	1285.2	1272.6
## Little Rock, AR	1261.7	693.0	705.4	208.7
## Sacramento, CA	2631.2	1946.8	1522.9	1809.3
## Denver, CO	1769.7	1082.0	706.2	973.2
## Hartford, CT	92.5	612.0	1048.8	1163.9
## Dover, DE	321.7	532.2	985.4	948.4
## Tallahassee, FL	1099.1	846.8	1108.9	372.8
## Atlanta, GA	936.2	619.3	900.5	351.0
## Honolulu, HI	5089.5	4407.8	3975.7	4182.9
## Boise, ID	2260.7	1590.8	1146.0	1611.2
## Springfield, IL	984.6	334.2	396.2	518.0
## Indianapolis, IN	807.2	221.1	503.3	562.1
## Des Moines, IA	1159.5	472.3	233.0	668.2
## Topeka, KS	1308.2	635.6	427.7	559.1
## Frankfort, KY	782.7	313.3	630.5	505.7
## Baton Rouge, LA	1383.8	923.2	1005.2	140.4
## Augusta, ME	149.5	748.7	1146.5	1377.8
## Annapolis, MD	368.9	494.7	946.5	895.6
## Boston, MA	0.0	687.9	1115.1	1256.3
## Lansing, MI	687.9	0.0	453.3	783.0
## Saint Paul, MN	1115.1	453.3	0.0	886.2
## Jackson, MS	1256.3	783.0	886.2	0.0
## Jefferson City, MO	1139.4	492.5	442.0	447.1
## Helena, MT	2022.6	1372.5	919.6	1519.2
## Lincoln, NE	1326.5	640.1	338.5	688.6
## Carson City, NV	2529.8	1845.5	1421.5	1720.4
## Concord, NH	63.4	659.6	1076.4	1263.4
## Trenton, NJ	242.4	536.1	987.5	1017.6
## Santa Fe, NM	1919.6	1244.2	931.6	934.1
## Albany, NY	139.1	549.0	977.4	1147.5
## Raleigh, NC	609.8	575.5	989.1	704.1
## Bismarck, ND	1489.0	844.9	392.5	1147.5
## Columbus, OH	643.5	207.5	619.3	663.3
## Oklahoma City, OK	1495.8	857.2	694.2	474.8
## Salem, OR	2566.7	1911.6	1460.2	1962.0
## Harrisburg, PA	334.9	432.6	885.7	922.4
## Providence, RI	41.2	674.9	1108.7	1223.3
## Columbia, SC	790.7	631.7	990.6	543.0
## Pierre, SD	1472.2	798.7	358.2	996.6
## Nashville, TN	943.0	468.5	690.2	330.1
## Austin, TX	1695.8	1127.9	1043.4	468.5

## Salt Lake City, UT	2098.7	1413.6	994.8	1336.5
## Montpelier, VT	151.8	610.2	1010.6	1258.9
## Richmond, VA	475.6	518.6	958.8	806.3
## Olympia, WA	2526.2	1886.7	1433.5	1997.7
## Charleston, WV	622.2	339.2	746.6	637.7
## Madison, WI	932.0	246.6	225.4	744.5
## Cheyenne, WY	1735.2	1048.0	648.4	1013.4
## Jefferson City, MO	542.0	1677.8	819.6	1927.5
## Juneau, AK	2313.6	1234.8	2040.7	1474.7
## Phoenix, AZ	1166.3	906.7	987.5	582.6
## Little Rock, AR	265.0	1312.5	481.6	1542.6
## Sacramento, CA	1580.7	733.2	1327.0	101.5
## Denver, CO	692.4	591.0	445.2	790.4
## Hartford, CT	1052.8	1962.3	1247.2	2457.2
## Dover, DE	897.5	1903.8	1125.8	2351.7
## Tallahassee, FL	718.8	1855.1	997.3	2091.5
## Atlanta, GA	547.3	1696.3	832.4	1992.4
## Honolulu, HI	4029.5	3095.1	3786.8	2562.8
## Boise, ID	1296.5	289.8	1017.8	358.7
## Springfield, IL	159.4	1217.7	377.4	1602.8
## Indianapolis, IN	333.2	1381.2	560.2	1787.0
## Des Moines, IA	221.6	975.7	168.3	1384.4
## Topeka, KS	192.6	976.4	131.9	1290.2
## Frankfort, KY	397.4	1495.5	655.8	1876.4
## Baton Rouge, LA	563.2	1576.5	778.1	1724.1
## Augusta, ME	1223.7	2034.6	1387.2	2567.9
## Annapolis, MD	845.7	1863.4	1077.4	2304.0
## Boston, MA	1139.4	2022.6	1326.5	2529.8
## Lansing, MI	492.5	1372.5	640.1	1845.5
## Saint Paul, MN	442.0	919.6	338.5	1421.5
## Jackson, MS	447.1	1519.2	688.6	1720.4
## Jefferson City, MO	0.0	1149.0	285.2	1482.8
## Helena, MT	1149.0	0.0	863.9	645.4
## Lincoln, NE	285.2	863.9	0.0	1227.0
## Carson City, NV	1482.8	645.4	1227.0	0.0
## Concord, NH	1123.5	1978.5	1299.7	2494.8
## Trenton, NJ	937.2	1907.0	1151.7	2373.6
## Santa Fe, NM	786.7	816.7	616.6	795.7
## Albany, NY	1006.1	1887.5	1188.1	2390.9
## Raleigh, NC	771.1	1876.3	1038.5	2253.9
## Bismarck, ND	716.7	533.8	462.1	1093.2
## Columbus, OH	500.8	1523.6	723.3	1950.0
## Oklahoma City, OK	365.1	1075.1	371.2	1248.1
## Salem, OR	1643.3	544.2	1362.0	432.6
## Harrisburg, PA	825.7	1805.1	1040.9	2263.9
## Providence, RI	1117.6	2020.0	1311.2	2519.5
## Columbia, SC	696.6	1836.5	978.3	2166.4
## Pierre, SD	581.5	588.1	308.1	1064.0
## Nashville, TN	340.0	1486.7	624.2	1810.0
## Austin, TX	654.8	1361.9	729.2	1390.5
## Salt Lake City, UT	1059.7	402.6	796.9	432.2
## Montpelier, VT	1087.6	1904.8	1248.5	2431.6
## Richmond, VA	804.4	1866.2	1053.8	2279.4

## Olympia, WA	1654.4	516.5	1369.8	566.0	
## Charleston, WV	571.5	1641.4	819.9	2045.1	
## Madison, WI	343.0	1134.2	406.9	1599.3	
## Cheyenne, WY	694.6	520.1	426.2	801.9	
##	Concord, NH	Trenton, NJ	Santa Fe, NM	Albany, NY	Raleigh, NC
## Montgomery, AL	1097.1	839.5	1150.5	986.3	497.2
## Juneau, AK	2826.1	2855.3	2031.7	2772.4	2943.7
## Phoenix, AZ	2277.8	2103.4	380.0	2162.9	1903.0
## Little Rock, AR	1258.1	1034.8	773.5	1139.4	777.2
## Sacramento, CA	2596.2	2474.4	879.6	2492.3	2351.8
## Denver, CO	1740.9	1596.8	285.9	1631.0	1463.5
## Hartford, CT	115.3	152.3	1835.3	82.8	523.7
## Dover, DE	348.1	84.0	1683.7	258.3	289.6
## Tallahassee, FL	1124.2	859.6	1306.9	1022.0	490.0
## Atlanta, GA	952.1	693.9	1232.6	842.1	355.6
## Honolulu, HI	5052.0	4936.2	3268.4	4951.0	4795.1
## Boise, ID	2220.3	2126.5	772.7	2123.3	2055.2
## Springfield, IL	966.7	789.6	936.1	850.0	663.7
## Indianapolis, IN	793.7	605.0	1118.8	675.4	495.6
## Des Moines, IA	1131.9	989.7	781.8	1020.9	902.8
## Topeka, KS	1287.4	1116.5	611.5	1172.1	963.7
## Frankfort, KY	779.3	559.5	1178.3	660.7	383.4
## Baton Rouge, LA	1393.6	1143.2	929.1	1278.9	813.8
## Augusta, ME	116.4	380.4	1992.5	230.4	752.6
## Annapolis, MD	390.3	126.7	1631.4	291.8	250.3
## Boston, MA	63.4	242.4	1919.6	139.1	609.8
## Lansing, MI	659.6	536.1	1244.2	549.0	575.5
## Saint Paul, MN	1076.4	987.5	931.6	977.4	989.1
## Jackson, MS	1263.4	1017.6	934.1	1147.5	704.1
## Jefferson City, MO	1123.5	937.2	786.7	1006.1	771.1
## Helena, MT	1978.5	1907.0	816.7	1887.5	1876.3
## Lincoln, NE	1299.7	1151.7	616.6	1188.1	1038.5
## Carson City, NV	2494.8	2373.6	795.7	2390.9	2253.9
## Concord, NH	0.0	264.9	1898.8	118.9	637.6
## Trenton, NJ	264.9	0.0	1723.6	175.6	372.9
## Santa Fe, NM	1898.8	1723.6	0.0	1783.6	1531.7
## Albany, NY	118.9	175.6	1783.6	0.0	542.1
## Raleigh, NC	637.6	372.9	1531.7	542.1	0.0
## Bismarck, ND	1445.4	1376.4	814.4	1353.7	1374.4
## Columbus, OH	634.1	436.7	1287.0	515.2	375.0
## Oklahoma City, OK	1483.3	1283.1	475.6	1365.0	1061.9
## Salem, OR	2522.7	2447.3	1102.1	2431.4	2395.7
## Harrisburg, PA	342.2	111.7	1612.0	230.7	325.0
## Providence, RI	95.6	206.6	1900.1	132.7	570.6
## Columbia, SC	815.8	551.1	1417.8	715.2	182.9
## Pierre, SD	1434.3	1334.6	670.7	1334.0	1288.3
## Nashville, TN	944.5	710.8	1074.6	826.9	457.5
## Austin, TX	1695.2	1463.5	605.0	1576.8	1170.1
## Salt Lake City, UT	2064.6	1941.4	476.7	1959.7	1829.7
## Montpelier, VT	89.3	300.3	1854.2	125.8	667.8
## Richmond, VA	500.9	236.0	1583.5	404.1	137.9
## Olympia, WA	2479.6	2419.7	1174.9	2393.0	2391.8
## Charleston, WV	626.1	390.2	1354.2	509.9	243.2
## Madison, WI	900.5	780.8	1021.6	792.9	763.8

## Cheyenne, WY	1703.4	1572.3	382.6	1596.1	1461.8
##	Bismarck, ND	Columbus, OH	Oklahoma City, OK	Salem, OR	
## Montgomery, AL	1257.7	555.1	680.1	2146.1	
## Juneau, AK	1600.9	2568.8	2303.0	1042.2	
## Phoenix, AZ	1095.9	1666.8	841.2	985.5	
## Little Rock, AR	942.4	626.9	298.3	1764.9	
## Sacramento, CA	1192.5	2050.2	1338.8	445.9	
## Denver, CO	531.9	1166.5	504.4	988.8	
## Hartford, CT	1428.7	554.7	1407.2	2505.8	
## Dover, DE	1377.1	402.9	1234.8	2441.0	
## Tallahassee, FL	1433.3	659.2	843.7	2319.9	
## Atlanta, GA	1244.7	434.9	757.0	2184.7	
## Honolulu, HI	3617.5	4510.0	3743.7	2560.8	
## Boise, ID	782.7	1721.6	1141.4	351.2	
## Springfield, IL	739.6	353.8	524.4	1732.2	
## Indianapolis, IN	881.1	168.4	689.6	1904.5	
## Des Moines, IA	505.9	567.9	472.1	1493.6	
## Topeka, KS	593.9	680.4	267.2	1457.6	
## Frankfort, KY	1003.8	157.6	725.6	2012.5	
## Baton Rouge, LA	1240.2	801.9	505.3	1993.0	
## Augusta, ME	1504.1	741.4	1585.8	2578.2	
## Annapolis, MD	1338.8	354.1	1181.3	2398.9	
## Boston, MA	1489.0	643.5	1495.8	2566.7	
## Lansing, MI	844.9	207.5	857.2	1911.6	
## Saint Paul, MN	392.5	619.3	694.2	1460.2	
## Jackson, MS	1147.5	663.3	474.8	1962.0	
## Jefferson City, MO	716.7	500.8	365.1	1643.3	
## Helena, MT	533.8	1523.6	1075.1	544.2	
## Lincoln, NE	462.1	723.3	371.2	1362.0	
## Carson City, NV	1093.2	1950.0	1248.1	432.6	
## Concord, NH	1445.4	634.1	1483.3	2522.7	
## Trenton, NJ	1376.4	436.7	1283.1	2447.3	
## Santa Fe, NM	814.4	1287.0	475.6	1102.1	
## Albany, NY	1353.7	515.2	1365.0	2431.4	
## Raleigh, NC	1374.4	375.0	1061.9	2395.7	
## Bismarck, ND	0.0	1009.2	800.6	1077.7	
## Columbus, OH	1009.2	0.0	852.5	2053.9	
## Oklahoma City, OK	800.6	852.5	0.0	1491.2	
## Salem, OR	1077.7	2053.9	1491.2	0.0	
## Harrisburg, PA	1276.6	325.1	1173.2	2343.8	
## Providence, RI	1486.3	619.2	1471.7	2563.8	
## Columbia, SC	1359.1	425.2	942.5	2339.6	
## Pierre, SD	169.7	937.8	631.9	1116.8	
## Nashville, TN	1030.0	333.2	604.6	1983.1	
## Austin, TX	1152.6	1067.1	358.7	1705.6	
## Salt Lake City, UT	693.9	1518.9	862.5	634.7	
## Montpelier, VT	1372.8	611.7	1450.7	2448.9	
## Richmond, VA	1350.2	342.6	1123.3	2395.5	
## Olympia, WA	1043.4	2040.1	1533.7	145.1	
## Charleston, WV	1133.7	133.4	900.7	2166.6	
## Madison, WI	614.9	394.5	681.7	1670.0	
## Cheyenne, WY	439.9	1148.3	556.7	956.7	
##	Harrisburg, PA	Providence, RI	Columbia, SC	Pierre, SD	
## Montgomery, AL	755.8	1045.8	324.2	1122.7	

## Juneau, AK	2776.0	2897.5	2951.4	1733.9
## Phoenix, AZ	1991.9	2279.9	1780.7	982.0
## Little Rock, AR	929.3	1233.3	647.3	789.0
## Sacramento, CA	2364.7	2620.9	2262.0	1165.3
## Denver, CO	1485.9	1755.3	1380.1	399.8
## Hartford, CT	242.5	64.8	703.1	1404.0
## Dover, DE	105.2	283.7	469.2	1325.0
## Tallahassee, FL	793.9	1060.3	308.5	1299.9
## Atlanta, GA	611.5	900.2	193.6	1123.5
## Honolulu, HI	4826.3	5080.7	4686.2	3617.8
## Boise, ID	2020.4	2254.7	1993.1	792.1
## Springfield, IL	677.9	964.2	622.2	631.9
## Indianapolis, IN	493.4	784.6	488.4	793.2
## Des Moines, IA	879.7	1144.9	863.6	389.9
## Topeka, KS	1004.8	1289.1	885.5	438.0
## Frankfort, KY	451.7	754.8	360.2	908.1
## Baton Rouge, LA	1051.6	1349.6	642.2	1082.3
## Augusta, ME	458.0	190.7	931.6	1504.5
## Annapolis, MD	91.7	332.3	425.6	1282.3
## Boston, MA	334.9	41.2	790.7	1472.2
## Lansing, MI	432.6	674.9	631.7	798.7
## Saint Paul, MN	885.7	1108.7	990.6	358.2
## Jackson, MS	922.4	1223.3	543.0	996.6
## Jefferson City, MO	825.7	1117.6	696.6	581.5
## Helena, MT	1805.1	2020.0	1836.5	588.1
## Lincoln, NE	1040.9	1311.2	978.3	308.1
## Carson City, NV	2263.9	2519.5	2166.4	1064.0
## Concord, NH	342.2	95.6	815.8	1434.3
## Trenton, NJ	111.7	206.6	551.1	1334.6
## Santa Fe, NM	1612.0	1900.1	1417.8	670.7
## Albany, NY	230.7	132.7	715.2	1334.0
## Raleigh, NC	325.0	570.6	182.9	1288.3
## Bismarck, ND	1276.6	1486.3	1359.1	169.7
## Columbus, OH	325.1	619.2	425.2	937.8
## Oklahoma City, OK	1173.2	1471.7	942.5	631.9
## Salem, OR	2343.8	2563.8	2339.6	1116.8
## Harrisburg, PA	0.0	304.3	489.4	1229.2
## Providence, RI	304.3	0.0	752.0	1464.7
## Columbia, SC	489.4	752.0	0.0	1253.4
## Pierre, SD	1229.2	1464.7	1253.4	0.0
## Nashville, TN	608.4	912.6	358.3	910.3
## Austin, TX	1361.4	1665.6	1011.5	982.9
## Salt Lake City, UT	1831.9	2087.9	1750.9	640.1
## Montpelier, VT	352.6	178.0	840.0	1368.7
## Richmond, VA	191.5	437.3	315.4	1280.0
## Olympia, WA	2319.1	2525.7	2347.0	1104.0
## Charleston, WV	287.4	591.4	301.6	1053.7
## Madison, WI	674.8	920.4	771.4	554.4
## Cheyenne, WY	1462.3	1722.9	1389.9	319.6
##	Nashville, TN	Austin, TX	Salt Lake City, UT	Montpelier, VT
## Montgomery, AL	263.8	692.9	1530.8	1105.1
## Juneau, AK	2630.7	2596.4	1564.2	2738.3
## Phoenix, AZ	1445.5	869.6	504.3	2231.8
## Little Rock, AR	328.1	441.1	1145.8	1238.6

## Sacramento, CA	1906.3	1467.2	533.3	2533.0
## Denver, CO	1022.4	770.9	371.5	1686.2
## Hartford, CT	850.8	1603.7	2025.4	172.4
## Dover, DE	650.3	1400.2	1920.1	383.6
## Tallahassee, FL	419.9	805.4	1701.0	1146.1
## Atlanta, GA	214.7	819.2	1583.4	962.0
## Honolulu, HI	4340.3	3755.2	2995.0	4984.9
## Boise, ID	1635.7	1369.4	296.2	2150.9
## Springfield, IL	295.5	800.5	1173.8	929.1
## Indianapolis, IN	250.8	926.1	1357.0	763.5
## Des Moines, IA	524.9	814.0	952.5	1080.3
## Topeka, KS	527.4	617.0	867.6	1244.2
## Frankfort, KY	175.6	916.3	1449.7	763.5
## Baton Rouge, LA	468.9	392.3	1360.6	1392.4
## Augusta, ME	1057.0	1806.0	2139.8	138.7
## Annapolis, MD	596.3	1346.5	1872.8	417.5
## Boston, MA	943.0	1695.8	2098.7	151.8
## Lansing, MI	468.5	1127.9	1413.6	610.2
## Saint Paul, MN	690.2	1043.4	994.8	1010.6
## Jackson, MS	330.1	468.5	1336.5	1258.9
## Jefferson City, MO	340.0	654.8	1059.7	1087.6
## Helena, MT	1486.7	1361.9	402.6	1904.8
## Lincoln, NE	624.2	729.2	796.9	1248.5
## Carson City, NV	1810.0	1390.5	432.2	2431.6
## Concord, NH	944.5	1695.2	2064.6	89.3
## Trenton, NJ	710.8	1463.5	1941.4	300.3
## Santa Fe, NM	1074.6	605.0	476.7	1854.2
## Albany, NY	826.9	1576.8	1959.7	125.8
## Raleigh, NC	457.5	1170.1	1829.7	667.8
## Bismarck, ND	1030.0	1152.6	693.9	1372.8
## Columbus, OH	333.2	1067.1	1518.9	611.7
## Oklahoma City, OK	604.6	358.7	862.5	1450.7
## Salem, OR	1983.1	1705.6	634.7	2448.9
## Harrisburg, PA	608.4	1361.4	1831.9	352.6
## Providence, RI	912.6	1665.6	2087.9	178.0
## Columbia, SC	358.3	1011.5	1750.9	840.0
## Pierre, SD	910.3	982.9	640.1	1368.7
## Nashville, TN	0.0	753.1	1392.8	934.0
## Austin, TX	753.1	0.0	1074.1	1678.6
## Salt Lake City, UT	1392.8	1074.1	0.0	2002.8
## Montpelier, VT	934.0	1678.6	2002.8	0.0
## Richmond, VA	524.6	1264.9	1850.5	529.9
## Olympia, WA	1993.9	1771.8	698.8	2402.9
## Charleston, WV	321.2	1074.3	1616.4	622.7
## Madison, WI	496.3	996.5	1167.5	844.8
## Cheyenne, WY	1031.8	848.0	370.8	1645.0
##				
## Montgomery, AL	613.7	2171.6	488.8	758.0
## Juneau, AK	2893.7	914.1	2700.6	2184.2
## Phoenix, AZ	1959.9	1096.3	1732.1	1394.4
## Little Rock, AR	852.4	1795.8	644.7	596.6
## Sacramento, CA	2378.8	588.0	2144.4	1700.6
## Denver, CO	1490.9	1029.5	1256.6	841.4
## Hartford, CT	387.8	2469.5	529.9	857.9

## Dover, DE	153.9	2418.7	334.6	771.0
## Tallahassee, FL	623.9	2347.5	564.1	915.1
## Atlanta, GA	468.4	2200.4	352.2	697.3
## Honolulu, HI	4833.2	2636.9	4599.2	4161.3
## Boise, ID	2061.3	402.7	1830.1	1345.8
## Springfield, IL	676.8	1731.3	442.6	226.5
## Indianapolis, IN	494.5	1897.1	262.3	283.0
## Des Moines, IA	905.3	1489.9	673.9	239.9
## Topeka, KS	994.4	1474.3	760.6	430.3
## Frankfort, KY	407.1	2010.2	176.1	411.6
## Baton Rouge, LA	924.9	2038.6	769.8	876.3
## Augusta, ME	616.4	2529.0	740.2	983.4
## Annapolis, MD	112.4	2378.9	280.9	729.3
## Boston, MA	475.6	2526.2	622.2	932.0
## Lansing, MI	518.6	1886.7	339.2	246.6
## Saint Paul, MN	958.8	1433.5	746.6	225.4
## Jackson, MS	806.3	1997.7	637.7	744.5
## Jefferson City, MO	804.4	1654.4	571.5	343.0
## Helena, MT	1866.2	516.5	1641.4	1134.2
## Lincoln, NE	1053.8	1369.8	819.9	406.9
## Carson City, NV	2279.4	566.0	2045.1	1599.3
## Concord, NH	500.9	2479.6	626.1	900.5
## Trenton, NJ	236.0	2419.7	390.2	780.8
## Santa Fe, NM	1583.5	1174.9	1354.2	1021.6
## Albany, NY	404.1	2393.0	509.9	792.9
## Raleigh, NC	137.9	2391.8	243.2	763.8
## Bismarck, ND	1350.2	1043.4	1133.7	614.9
## Columbus, OH	342.6	2040.1	133.4	394.5
## Oklahoma City, OK	1123.3	1533.7	900.7	681.7
## Salem, OR	2395.5	145.1	2166.6	1670.0
## Harrisburg, PA	191.5	2319.1	287.4	674.8
## Providence, RI	437.3	2525.7	591.4	920.4
## Columbia, SC	315.4	2347.0	301.6	771.4
## Pierre, SD	1280.0	1104.0	1053.7	554.4
## Nashville, TN	524.6	1993.9	321.2	496.3
## Austin, TX	1264.9	1771.8	1074.3	996.5
## Salt Lake City, UT	1850.5	698.8	1616.4	1167.5
## Montpelier, VT	529.9	2402.9	622.7	844.8
## Richmond, VA	0.0	2382.7	234.4	735.5
## Olympia, WA	2382.7	0.0	2157.7	1650.1
## Charleston, WV	234.4	2157.7	0.0	521.2
## Madison, WI	735.5	1650.1	521.2	0.0
## Cheyenne, WY	1480.0	984.6	1246.1	803.3
## Cheyenne, WY				
## Montgomery, AL	1190.0			
## Juneau, AK	1753.3			
## Phoenix, AZ	663.3			
## Little Rock, AR	811.4			
## Sacramento, CA	902.5			
## Denver, CO	97.1			
## Hartford, CT	1659.8			
## Dover, DE	1549.8			
## Tallahassee, FL	1364.7			
## Atlanta, GA	1229.4			

```

## Honolulu, HI           3364.0
## Boise, ID              606.4
## Springfield, IL        803.4
## Indianapolis, IN       986.3
## Des Moines, IA          582.7
## Topeka, KS              504.4
## Frankfort, KY          1080.5
## Baton Rouge, LA         1060.8
## Augusta, ME             1782.9
## Annapolis, MD           1502.2
## Boston, MA              1735.2
## Lansing, MI              1048.0
## Saint Paul, MN           648.4
## Jackson, MS              1013.4
## Jefferson City, MO       694.6
## Helena, MT              520.1
## Lincoln, NE              426.2
## Carson City, NV           801.9
## Concord, NH              1703.4
## Trenton, NJ              1572.3
## Santa Fe, NM              382.6
## Albany, NY              1596.1
## Raleigh, NC              1461.8
## Bismarck, ND              439.9
## Columbus, OH              1148.3
## Oklahoma City, OK          556.7
## Salem, OR              956.7
## Harrisburg, PA             1462.3
## Providence, RI             1722.9
## Columbia, SC              1389.9
## Pierre, SD              319.6
## Nashville, TN              1031.8
## Austin, TX              848.0
## Salt Lake City, UT          370.8
## Montpelier, VT              1645.0
## Richmond, VA              1480.0
## Olympia, WA              984.6
## Charleston, WV              1246.1
## Madison, WI              803.3
## Cheyenne, WY                  0.0

lookupPairwiseValue(dist.meeus.df, "Juneau, AK", "Montgomery, AL");

## [1] 2855.6

dist.haversine = conv_unit( distm(latlong[,3:4],
                                    fun=distHaversine), "m", "mi"); # default meters to miles

dist.haversine.h = as.matrix( dist.haversine );
rownames(dist.haversine.h) =
colnames(dist.haversine.h) = myLabels;

dist.haversine.df = as.data.frame( round( dist.haversine.h, digits=1 ) );

```

```
dist.haversine.df;
```

## Haversine

	Montgomery, AL	Juneau, AK	Phoenix, AZ	Little Rock, AR
## Montgomery, AL	0.0	2854.6	1495.6	385.5
## Juneau, AK	2854.6	0.0	2007.1	2515.3
## Phoenix, AZ	1495.6	2007.1	0.0	1132.2
## Little Rock, AR	385.5	2515.3	1132.2	0.0
## Sacramento, CA	2016.9	1481.3	635.2	1632.9
## Denver, CO	1161.1	1824.8	585.9	777.3
## Hartford, CT	991.1	2850.8	2213.1	1169.6
## Dover, DE	764.2	2877.7	2060.6	976.4
## Tallahassee, FL	178.0	3031.6	1640.6	555.8
## Atlanta, GA	145.9	2843.8	1589.8	459.0
## Honolulu, HI	4405.8	2814.2	2910.1	4038.5
## Boise, ID	1794.3	1280.3	737.6	1412.9
## Springfield, IL	547.9	2336.0	1315.1	379.9
## Indianapolis, IN	512.4	2462.1	1497.4	486.3
## Des Moines, IA	755.7	2104.5	1154.6	479.3
## Topeka, KS	702.0	2165.4	990.5	351.8
## Frankfort, KY	411.6	2589.3	1554.5	479.1
## Baton Rouge, LA	318.1	2796.7	1241.3	304.1
## Augusta, ME	1214.1	2831.8	2368.1	1367.0
## Annapolis, MD	714.1	2851.6	2008.2	922.4
## Boston, MA	1082.4	2879.9	2297.1	1261.0
## Lansing, MI	723.7	2372.4	1620.6	693.9
## Saint Paul, MN	944.1	1958.6	1285.4	707.2
## Jackson, MS	228.3	2724.4	1271.4	209.1
## Jefferson City, MO	542.9	2311.7	1165.4	265.8
## Helena, MT	1677.8	1233.5	909.0	1312.6
## Lincoln, NE	820.4	2038.8	987.4	482.5
## Carson City, NV	1925.8	1475.4	583.1	1541.0
## Concord, NH	1097.9	2821.5	2275.7	1257.6
## Trenton, NJ	840.1	2851.5	2101.3	1034.1
## Santa Fe, NM	1149.5	2031.9	379.9	772.6
## Albany, NY	987.2	2768.1	2161.0	1139.0
## Raleigh, NC	497.2	2941.1	1901.0	776.4
## Bismarck, ND	1259.1	1598.6	1097.4	943.8
## Columbus, OH	556.6	2565.8	1665.4	627.1
## Oklahoma City, OK	679.7	2302.4	840.4	298.0
## Salem, OR	2144.8	1042.1	986.7	1763.6
## Harrisburg, PA	756.7	2772.4	1990.0	928.8
## Providence, RI	1046.3	2893.2	2277.7	1232.5
## Columbia, SC	324.0	2949.4	1778.8	646.6
## Pierre, SD	1123.8	1731.8	983.1	790.2
## Nashville, TN	264.8	2628.8	1444.1	327.8
## Austin, TX	692.4	2597.2	869.0	441.7
## Salt Lake City, UT	1529.9	1563.9	505.8	1145.0
## Montpelier, VT	1106.2	2733.7	2229.9	1238.4
## Richmond, VA	614.0	2890.6	1957.9	851.6
## Olympia, WA	2170.6	913.8	1097.9	1794.8
## Charleston, WV	489.8	2697.8	1730.4	644.3
## Madison, WI	760.1	2181.3	1393.9	598.1

## Cheyenne, WY	1189.9	1752.1	664.2	811.4
##	Sacramento, CA	Denver, CO	Hartford, CT	Dover, DE
## Montgomery, AL	2016.9	1161.1	991.1	764.2
## Juneau, AK	1481.3	1824.8	2850.8	2877.7
## Phoenix, AZ	635.2	585.9	2213.1	2060.6
## Little Rock, AR	1632.9	777.3	1169.6	976.4
## Sacramento, CA	0.0	887.5	2555.0	2448.9
## Denver, CO	887.5	0.0	1689.2	1567.3
## Hartford, CT	2555.0	1689.2	0.0	234.4
## Dover, DE	2448.9	1567.3	234.4	0.0
## Tallahassee, FL	2179.5	1333.1	1013.1	779.0
## Atlanta, GA	2084.3	1211.1	845.5	618.3
## Honolulu, HI	2462.7	3343.5	5016.3	4910.1
## Boise, ID	444.1	637.6	2191.3	2112.0
## Springfield, IL	1700.0	814.3	898.2	754.9
## Indianapolis, IN	1884.3	999.6	718.9	569.1
## Des Moines, IA	1483.1	609.6	1079.6	966.5
## Topeka, KS	1386.4	499.2	1222.8	1080.1
## Frankfort, KY	1972.6	1085.1	690.9	508.6
## Baton Rouge, LA	1807.5	1009.9	1292.2	1071.5
## Augusta, ME	2665.6	1822.2	229.1	463.4
## Annapolis, MD	2401.1	1518.2	279.1	54.0
## Boston, MA	2627.6	1767.2	92.4	321.8
## Lansing, MI	1944.2	1080.6	611.1	531.9
## Saint Paul, MN	1521.1	705.8	1047.3	984.5
## Jackson, MS	1807.7	973.2	1164.1	948.4
## Jefferson City, MO	1578.7	691.5	1051.5	896.3
## Helena, MT	733.6	591.4	1959.3	1901.4
## Lincoln, NE	1325.2	444.6	1245.4	1124.2
## Carson City, NV	101.4	789.3	2453.8	2348.6
## Concord, NH	2592.7	1738.5	115.5	348.5
## Trenton, NJ	2471.1	1594.6	152.4	84.1
## Santa Fe, NM	878.7	286.7	1833.3	1681.7
## Albany, NY	2488.9	1628.7	82.9	258.8
## Raleigh, NC	2349.0	1461.9	524.4	290.0
## Bismarck, ND	1191.7	532.7	1426.6	1375.7
## Columbus, OH	2047.4	1164.9	554.0	402.4
## Oklahoma City, OK	1337.4	504.5	1405.9	1233.5
## Salem, OR	446.9	987.8	2501.9	2437.5
## Harrisburg, PA	2361.5	1483.8	242.3	105.3
## Providence, RI	2617.3	1752.9	64.7	283.8
## Columbia, SC	2259.6	1379.0	704.0	469.8
## Pierre, SD	1164.1	400.2	1401.9	1323.4
## Nashville, TN	1904.0	1021.3	850.4	649.8
## Austin, TX	1466.6	772.6	1603.6	1400.0
## Salt Lake City, UT	532.7	371.0	2022.5	1917.5
## Montpelier, VT	2529.5	1683.9	172.8	384.2
## Richmond, VA	2375.8	1489.0	388.1	154.1
## Olympia, WA	589.2	1028.7	2465.7	2415.4
## Charleston, WV	2141.6	1254.9	529.5	334.2
## Madison, WI	1698.4	840.5	856.7	770.2
## Cheyenne, WY	901.4	97.3	1657.4	1547.7
##	Tallahassee, FL	Atlanta, GA	Honolulu, HI	Boise, ID
## Montgomery, AL	178.0	145.9	4405.8	1794.3

## Juneau, AK	3031.6	2843.8	2814.2	1280.3
## Phoenix, AZ	1640.6	1589.8	2910.1	737.6
## Little Rock, AR	555.8	459.0	4038.5	1412.9
## Sacramento, CA	2179.5	2084.3	2462.7	444.1
## Denver, CO	1333.1	1211.1	3343.5	637.6
## Hartford, CT	1013.1	845.5	5016.3	2191.3
## Dover, DE	779.0	618.3	4910.1	2112.0
## Tallahassee, FL	0.0	228.4	4547.4	1968.2
## Atlanta, GA	228.4	0.0	4497.5	1834.2
## Honolulu, HI	4547.4	4497.5	0.0	2836.7
## Boise, ID	1968.2	1834.2	2836.7	0.0
## Springfield, IL	714.6	509.6	4157.7	1389.8
## Indianapolis, IN	653.1	427.3	4343.1	1565.6
## Des Moines, IA	930.3	740.2	3945.5	1154.6
## Topeka, KS	879.7	727.3	3837.5	1107.8
## Frankfort, KY	536.9	308.6	4424.7	1669.8
## Baton Rouge, LA	412.9	458.7	4140.7	1644.7
## Augusta, ME	1241.6	1069.0	5116.4	2280.3
## Annapolis, MD	735.2	568.2	4861.5	2068.0
## Boston, MA	1100.5	936.6	5086.9	2257.2
## Lansing, MI	849.5	621.1	4406.1	1588.3
## Saint Paul, MN	1111.2	901.9	3974.9	1144.1
## Jackson, MS	372.7	350.8	4180.8	1610.7
## Jefferson City, MO	720.0	547.5	4028.0	1295.0
## Helena, MT	1855.5	1695.7	3096.4	289.8
## Lincoln, NE	998.4	832.6	3785.8	1016.4
## Carson City, NV	2090.0	1990.3	2563.6	359.1
## Concord, NH	1125.8	952.8	5049.5	2216.8
## Trenton, NJ	861.0	694.3	4933.7	2123.4
## Santa Fe, NM	1306.1	1231.4	3267.5	773.2
## Albany, NY	1023.8	842.9	4948.6	2119.9
## Raleigh, NC	490.8	355.4	4792.6	2052.9
## Bismarck, ND	1435.0	1245.5	3617.7	781.6
## Columbus, OH	661.4	436.2	4507.9	1719.2
## Oklahoma City, OK	843.5	756.3	3742.2	1141.0
## Salem, OR	2318.8	2182.9	2563.1	350.7
## Harrisburg, PA	795.6	612.2	4823.9	2017.5
## Providence, RI	1061.6	900.5	5078.1	2251.3
## Columbia, SC	309.2	193.4	4683.7	1991.3
## Pierre, SD	1301.3	1123.9	3617.5	790.8
## Nashville, TN	421.2	215.0	4338.3	1634.1
## Austin, TX	804.8	818.8	3753.4	1370.4
## Salt Lake City, UT	1700.4	1582.1	2995.3	296.2
## Montpelier, VT	1148.0	962.9	4982.6	2147.4
## Richmond, VA	625.0	468.5	4830.7	2058.7
## Olympia, WA	2346.7	2198.8	2639.6	402.5
## Charleston, WV	565.9	353.0	4597.0	1827.7
## Madison, WI	917.6	698.8	4160.0	1343.6
## Cheyenne, WY	1364.9	1228.8	3363.7	605.7
##	Springfield, IL	Indianapolis, IN	Des Moines, IA	Topeka, KS
## Montgomery, AL	547.9	512.4	755.7	702.0
## Juneau, AK	2336.0	2462.1	2104.5	2165.4
## Phoenix, AZ	1315.1	1497.4	1154.6	990.5
## Little Rock, AR	379.9	486.3	479.3	351.8

## Sacramento, CA	1700.0	1884.3	1483.1	1386.4
## Denver, CO	814.3	999.6	609.6	499.2
## Hartford, CT	898.2	718.9	1079.6	1222.8
## Dover, DE	754.9	569.1	966.5	1080.1
## Tallahassee, FL	714.6	653.1	930.3	879.7
## Atlanta, GA	509.6	427.3	740.2	727.3
## Honolulu, HI	4157.7	4343.1	3945.5	3837.5
## Boise, ID	1389.8	1565.6	1154.6	1107.8
## Springfield, IL	0.0	185.9	242.1	326.4
## Indianapolis, IN	185.9	0.0	411.1	511.5
## Des Moines, IA	242.1	411.1	0.0	206.5
## Topeka, KS	326.4	511.5	206.5	0.0
## Frankfort, KY	280.1	128.8	520.1	587.5
## Baton Rouge, LA	652.6	704.2	782.7	648.0
## Augusta, ME	1064.3	896.2	1217.2	1380.5
## Annapolis, MD	704.9	519.1	919.7	1029.4
## Boston, MA	983.3	806.2	1157.8	1306.5
## Lansing, MI	334.2	221.5	471.7	635.1
## Saint Paul, MN	396.8	503.5	233.5	428.5
## Jackson, MS	519.7	563.5	670.1	560.2
## Jefferson City, MO	159.3	332.9	222.1	192.3
## Helena, MT	1216.4	1379.7	974.5	975.9
## Lincoln, NE	376.9	559.4	168.1	132.1
## Carson City, NV	1600.6	1784.6	1382.6	1288.5
## Concord, NH	965.5	792.8	1130.2	1285.8
## Trenton, NJ	788.5	604.2	988.3	1115.0
## Santa Fe, NM	935.3	1117.7	781.6	611.1
## Albany, NY	848.9	674.7	1019.4	1170.6
## Raleigh, NC	663.3	495.6	902.3	962.7
## Bismarck, ND	739.6	880.6	506.0	594.8
## Columbus, OH	353.3	168.2	567.2	679.5
## Oklahoma City, OK	524.5	689.3	473.0	267.8
## Salem, OR	1729.9	1901.9	1491.4	1455.8
## Harrisburg, PA	677.0	492.7	878.5	1003.4
## Providence, RI	962.9	783.6	1143.2	1287.4
## Columbia, SC	622.6	489.2	863.9	885.1
## Pierre, SD	631.6	792.5	389.6	438.5
## Nashville, TN	296.0	251.5	525.3	527.0
## Austin, TX	802.0	927.2	816.3	619.0
## Salt Lake City, UT	1172.1	1355.1	951.2	866.4
## Montpelier, VT	928.1	762.8	1078.7	1242.8
## Richmond, VA	676.1	494.1	904.4	993.2
## Olympia, WA	1729.1	1894.6	1487.7	1472.8
## Charleston, WV	442.2	262.1	673.2	759.6
## Madison, WI	227.0	283.3	239.7	430.4
## Cheyenne, WY	802.4	984.9	581.8	503.9
##	Frankfort, KY	Baton Rouge, LA	Augusta, ME	Annapolis, MD
## Montgomery, AL	411.6	318.1	1214.1	714.1
## Juneau, AK	2589.3	2796.7	2831.8	2851.6
## Phoenix, AZ	1554.5	1241.3	2368.1	2008.2
## Little Rock, AR	479.1	304.1	1367.0	922.4
## Sacramento, CA	1972.6	1807.5	2665.6	2401.1
## Denver, CO	1085.1	1009.9	1822.2	1518.2
## Hartford, CT	690.9	1292.2	229.1	279.1

## Dover, DE	508.6	1071.5	463.4	54.0
## Tallahassee, FL	536.9	412.9	1241.6	735.2
## Atlanta, GA	308.6	458.7	1069.0	568.2
## Honolulu, HI	4424.7	4140.7	5116.4	4861.5
## Boise, ID	1669.8	1644.7	2280.3	2068.0
## Springfield, IL	280.1	652.6	1064.3	704.9
## Indianapolis, IN	128.8	704.2	896.2	519.1
## Des Moines, IA	520.1	782.7	1217.2	919.7
## Topeka, KS	587.5	648.0	1380.5	1029.4
## Frankfort, KY	0.0	645.8	889.2	455.3
## Baton Rouge, LA	645.8	0.0	1509.4	1019.8
## Augusta, ME	889.2	1509.4	0.0	506.6
## Annapolis, MD	455.3	1019.8	506.6	0.0
## Boston, MA	782.0	1384.3	149.7	368.9
## Lansing, MI	314.0	925.4	747.6	494.5
## Saint Paul, MN	630.9	1008.1	1144.6	945.8
## Jackson, MS	506.6	140.9	1378.1	895.7
## Jefferson City, MO	396.9	565.1	1222.4	844.6
## Helena, MT	1494.1	1577.7	2031.2	1861.0
## Lincoln, NE	655.1	780.1	1385.3	1076.0
## Carson City, NV	1874.0	1723.2	2564.3	2300.9
## Concord, NH	778.8	1394.3	116.4	390.6
## Trenton, NJ	558.9	1143.7	380.6	126.7
## Santa Fe, NM	1176.9	928.8	1990.4	1629.6
## Albany, NY	660.4	1279.8	230.2	292.2
## Raleigh, NC	383.3	813.8	753.4	250.8
## Bismarck, ND	1003.5	1242.8	1501.6	1337.6
## Columbus, OH	157.8	803.4	740.7	353.7
## Oklahoma City, OK	724.9	505.9	1584.6	1180.1
## Salem, OR	2009.9	1992.7	2573.9	2395.6
## Harrisburg, PA	451.3	1052.4	457.9	91.9
## Providence, RI	754.1	1350.0	191.0	332.3
## Columbia, SC	360.8	642.1	932.5	426.3
## Pierre, SD	907.5	1084.6	1502.0	1280.8
## Nashville, TN	175.9	470.0	1056.7	595.8
## Austin, TX	916.8	392.0	1806.0	1346.3
## Salt Lake City, UT	1447.8	1360.7	2136.7	1870.2
## Montpelier, VT	763.3	1393.4	138.5	418.1
## Richmond, VA	406.6	925.1	616.9	112.6
## Olympia, WA	2007.8	2038.6	2524.7	2375.6
## Charleston, WV	175.9	770.7	740.0	280.5
## Madison, WI	412.1	879.0	981.9	728.7
## Cheyenne, WY	1079.1	1061.8	1780.3	1500.2
##	Boston, MA	Lansing, MI	Saint Paul, MN	Jackson, MS
## Montgomery, AL	1082.4	723.7	944.1	228.3
## Juneau, AK	2879.9	2372.4	1958.6	2724.4
## Phoenix, AZ	2297.1	1620.6	1285.4	1271.4
## Little Rock, AR	1261.0	693.9	707.2	209.1
## Sacramento, CA	2627.6	1944.2	1521.1	1807.7
## Denver, CO	1767.2	1080.6	705.8	973.2
## Hartford, CT	92.4	611.1	1047.3	1164.1
## Dover, DE	321.8	531.9	984.5	948.4
## Tallahassee, FL	1100.5	849.5	1111.2	372.7
## Atlanta, GA	936.6	621.1	901.9	350.8

## Honolulu, HI	5086.9	4406.1	3974.9	4180.8
## Boise, ID	2257.2	1588.3	1144.1	1610.7
## Springfield, IL	983.3	334.2	396.8	519.7
## Indianapolis, IN	806.2	221.5	503.5	563.5
## Des Moines, IA	1157.8	471.7	233.5	670.1
## Topeka, KS	1306.5	635.1	428.5	560.2
## Frankfort, KY	782.0	314.0	630.9	506.6
## Baton Rouge, LA	1384.3	925.4	1008.1	140.9
## Augusta, ME	149.7	747.6	1144.6	1378.1
## Annapolis, MD	368.9	494.5	945.8	895.7
## Boston, MA	0.0	686.9	1113.4	1256.4
## Lansing, MI	686.9	0.0	452.7	784.8
## Saint Paul, MN	1113.4	452.7	0.0	888.5
## Jackson, MS	1256.4	784.8	888.5	0.0
## Jefferson City, MO	1138.0	492.5	443.0	448.4
## Helena, MT	2019.4	1370.4	918.1	1519.7
## Lincoln, NE	1324.6	639.3	338.8	689.9
## Carson City, NV	2526.3	1843.0	1419.8	1719.0
## Concord, NH	63.4	658.6	1074.7	1263.7
## Trenton, NJ	242.4	535.5	986.4	1017.6
## Santa Fe, NM	1917.5	1243.3	932.1	933.4
## Albany, NY	138.9	548.2	975.9	1148.0
## Raleigh, NC	610.3	576.3	989.3	703.7
## Bismarck, ND	1486.8	843.8	391.9	1149.4
## Columbus, OH	642.7	207.8	619.0	664.4
## Oklahoma City, OK	1494.4	857.2	695.6	474.7
## Salem, OR	2562.7	1908.5	1457.7	1961.0
## Harrisburg, PA	334.6	432.2	884.8	922.8
## Providence, RI	41.3	673.9	1107.1	1223.3
## Columbia, SC	791.4	633.2	991.5	542.6
## Pierre, SD	1469.9	797.5	357.6	998.2
## Nashville, TN	942.5	469.6	691.3	330.7
## Austin, TX	1695.6	1129.4	1046.2	468.3
## Salt Lake City, UT	2095.7	1411.5	993.5	1336.0
## Montpelier, VT	152.0	609.3	1008.9	1259.5
## Richmond, VA	475.9	518.9	958.4	806.1
## Olympia, WA	2522.2	1883.8	1431.0	1997.0
## Charleston, WV	621.8	339.8	746.5	638.2
## Madison, WI	930.5	246.2	225.3	746.6
## Cheyenne, WY	1732.6	1046.4	647.8	1013.8
##	Jefferson City, MO Helena, MT Lincoln, NE Carson City, NV			
## Montgomery, AL	542.9	1677.8	820.4	1925.8
## Juneau, AK	2311.7	1233.5	2038.8	1475.4
## Phoenix, AZ	1165.4	909.0	987.4	583.1
## Little Rock, AR	265.8	1312.6	482.5	1541.0
## Sacramento, CA	1578.7	733.6	1325.2	101.4
## Denver, CO	691.5	591.4	444.6	789.3
## Hartford, CT	1051.5	1959.3	1245.4	2453.8
## Dover, DE	896.3	1901.4	1124.2	2348.6
## Tallahassee, FL	720.0	1855.5	998.4	2090.0
## Atlanta, GA	547.5	1695.7	832.6	1990.3
## Honolulu, HI	4028.0	3096.4	3785.8	2563.6
## Boise, ID	1295.0	289.8	1016.4	359.1
## Springfield, IL	159.3	1216.4	376.9	1600.6

## Indianapolis, IN	332.9	1379.7	559.4	1784.6	
## Des Moines, IA	222.1	974.5	168.1	1382.6	
## Topeka, KS	192.3	975.9	132.1	1288.5	
## Frankfort, KY	396.9	1494.1	655.1	1874.0	
## Baton Rouge, LA	565.1	1577.7	780.1	1723.2	
## Augusta, ME	1222.4	2031.2	1385.3	2564.3	
## Annapolis, MD	844.6	1861.0	1076.0	2300.9	
## Boston, MA	1138.0	2019.4	1324.6	2526.3	
## Lansing, MI	492.5	1370.4	639.3	1843.0	
## Saint Paul, MN	443.0	918.1	338.8	1419.8	
## Jackson, MS	448.4	1519.7	689.9	1719.0	
## Jefferson City, MO	0.0	1148.2	285.1	1480.8	
## Helena, MT	1148.2	0.0	863.1	645.9	
## Lincoln, NE	285.1	863.1	0.0	1225.3	
## Carson City, NV	1480.8	645.9	1225.3	0.0	
## Concord, NH	1122.2	1975.3	1297.8	2491.3	
## Trenton, NJ	936.0	1904.4	1150.1	2370.3	
## Santa Fe, NM	785.9	818.2	616.7	795.0	
## Albany, NY	1004.9	1884.5	1186.4	2387.6	
## Raleigh, NC	770.4	1874.7	1037.6	2251.2	
## Bismarck, ND	717.3	532.8	462.6	1092.4	
## Columbus, OH	500.2	1521.7	722.3	1947.4	
## Oklahoma City, OK	365.2	1075.7	372.2	1246.8	
## Salem, OR	1641.3	543.4	1360.1	433.3	
## Harrisburg, PA	824.7	1802.6	1039.5	2260.9	
## Providence, RI	1116.2	2016.9	1309.3	2516.0	
## Columbia, SC	696.4	1835.5	978.1	2164.1	
## Pierre, SD	581.7	587.2	308.4	1062.9	
## Nashville, TN	339.9	1485.8	624.0	1807.9	
## Austin, TX	656.4	1364.0	731.6	1390.2	
## Salt Lake City, UT	1058.4	403.3	795.7	431.7	
## Montpelier, VT	1086.6	1901.6	1246.8	2428.2	
## Richmond, VA	803.4	1864.2	1052.6	2276.5	
## Olympia, WA	1652.6	515.6	1368.1	567.0	
## Charleston, WV	570.8	1639.7	818.9	2042.4	
## Madison, WI	343.6	1132.5	406.5	1597.1	
## Cheyenne, WY	693.8	520.2	425.6	800.9	
##	Concord, NH	Trenton, NJ	Santa Fe, NM	Albany, NY	Raleigh, NC
## Montgomery, AL	1097.9	840.1	1149.5	987.2	497.2
## Juneau, AK	2821.5	2851.5	2031.9	2768.1	2941.1
## Phoenix, AZ	2275.7	2101.3	379.9	2161.0	1901.0
## Little Rock, AR	1257.6	1034.1	772.6	1139.0	776.4
## Sacramento, CA	2592.7	2471.1	878.7	2488.9	2349.0
## Denver, CO	1738.5	1594.6	286.7	1628.7	1461.9
## Hartford, CT	115.5	152.4	1833.3	82.9	524.4
## Dover, DE	348.5	84.1	1681.7	258.8	290.0
## Tallahassee, FL	1125.8	861.0	1306.1	1023.8	490.8
## Atlanta, GA	952.8	694.3	1231.4	842.9	355.4
## Honolulu, HI	5049.5	4933.7	3267.5	4948.6	4792.6
## Boise, ID	2216.8	2123.4	773.2	2119.9	2052.9
## Springfield, IL	965.5	788.5	935.3	848.9	663.3
## Indianapolis, IN	792.8	604.2	1117.7	674.7	495.6
## Des Moines, IA	1130.2	988.3	781.6	1019.4	902.3
## Topeka, KS	1285.8	1115.0	611.1	1170.6	962.7

## Frankfort, KY	778.8	558.9	1176.9	660.4	383.3
## Baton Rouge, LA	1394.3	1143.7	928.8	1279.8	813.8
## Augusta, ME	116.4	380.6	1990.4	230.2	753.4
## Annapolis, MD	390.6	126.7	1629.6	292.2	250.8
## Boston, MA	63.4	242.4	1917.5	138.9	610.3
## Lansing, MI	658.6	535.5	1243.3	548.2	576.3
## Saint Paul, MN	1074.7	986.4	932.1	975.9	989.3
## Jackson, MS	1263.7	1017.6	933.4	1148.0	703.7
## Jefferson City, MO	1122.2	936.0	785.9	1004.9	770.4
## Helena, MT	1975.3	1904.4	818.2	1884.5	1874.7
## Lincoln, NE	1297.8	1150.1	616.7	1186.4	1037.6
## Carson City, NV	2491.3	2370.3	795.0	2387.6	2251.2
## Concord, NH	0.0	265.1	1896.8	118.7	638.4
## Trenton, NJ	265.1	0.0	1721.7	175.9	373.4
## Santa Fe, NM	1896.8	1721.7	0.0	1781.7	1529.9
## Albany, NY	118.7	175.9	1781.7	0.0	543.0
## Raleigh, NC	638.4	373.4	1529.9	543.0	0.0
## Bismarck, ND	1443.1	1374.8	815.9	1351.7	1374.0
## Columbus, OH	633.4	436.1	1285.6	514.7	375.5
## Oklahoma City, OK	1482.0	1281.9	475.1	1363.9	1060.7
## Salem, OR	2518.6	2443.7	1102.1	2427.5	2393.0
## Harrisburg, PA	342.2	111.5	1610.3	230.8	325.8
## Providence, RI	95.8	206.5	1898.0	132.6	571.1
## Columbia, SC	816.8	551.9	1416.3	716.4	183.0
## Pierre, SD	1432.0	1332.8	671.9	1331.9	1287.6
## Nashville, TN	944.2	710.3	1073.3	826.7	457.0
## Austin, TX	1695.2	1463.3	605.5	1577.0	1169.5
## Salt Lake City, UT	2061.6	1938.7	477.1	1956.9	1827.6
## Montpelier, VT	89.4	300.8	1852.4	126.0	668.9
## Richmond, VA	501.4	236.3	1581.7	404.8	138.2
## Olympia, WA	2475.5	2416.2	1175.2	2389.2	2389.3
## Charleston, WV	625.9	389.9	1352.7	509.8	243.5
## Madison, WI	899.1	779.9	1021.3	791.7	764.1
## Cheyenne, WY	1700.9	1570.1	383.6	1593.8	1460.3
##	Bismarck, ND	Columbus, OH	Oklahoma City, OK	Salem, OR	
## Montgomery, AL	1259.1	556.6	679.7	2144.8	
## Juneau, AK	1598.6	2565.8	2302.4	1042.1	
## Phoenix, AZ	1097.4	1665.4	840.4	986.7	
## Little Rock, AR	943.8	627.1	298.0	1763.6	
## Sacramento, CA	1191.7	2047.4	1337.4	446.9	
## Denver, CO	532.7	1164.9	504.5	987.8	
## Hartford, CT	1426.6	554.0	1405.9	2501.9	
## Dover, DE	1375.7	402.4	1233.5	2437.5	
## Tallahassee, FL	1435.0	661.4	843.5	2318.8	
## Atlanta, GA	1245.5	436.2	756.3	2182.9	
## Honolulu, HI	3617.7	4507.9	3742.2	2563.1	
## Boise, ID	781.6	1719.2	1141.0	350.7	
## Springfield, IL	739.6	353.3	524.5	1729.9	
## Indianapolis, IN	880.6	168.2	689.3	1901.9	
## Des Moines, IA	506.0	567.2	473.0	1491.4	
## Topeka, KS	594.8	679.5	267.8	1455.8	
## Frankfort, KY	1003.5	157.8	724.9	2009.9	
## Baton Rouge, LA	1242.8	803.4	505.9	1992.7	
## Augusta, ME	1501.6	740.7	1584.6	2573.9	

## Annapolis, MD	1337.6	353.7	1180.1	2395.6
## Boston, MA	1486.8	642.7	1494.4	2562.7
## Lansing, MI	843.8	207.8	857.2	1908.5
## Saint Paul, MN	391.9	619.0	695.6	1457.7
## Jackson, MS	1149.4	664.4	474.7	1961.0
## Jefferson City, MO	717.3	500.2	365.2	1641.3
## Helena, MT	532.8	1521.7	1075.7	543.4
## Lincoln, NE	462.6	722.3	372.2	1360.1
## Carson City, NV	1092.4	1947.4	1246.8	433.3
## Concord, NH	1443.1	633.4	1482.0	2518.6
## Trenton, NJ	1374.8	436.1	1281.9	2443.7
## Santa Fe, NM	815.9	1285.6	475.1	1102.1
## Albany, NY	1351.7	514.7	1363.9	2427.5
## Raleigh, NC	1374.0	375.5	1060.7	2393.0
## Bismarck, ND	0.0	1008.4	802.4	1075.9
## Columbus, OH	1008.4	0.0	851.9	2050.9
## Oklahoma City, OK	802.4	851.9	0.0	1490.3
## Salem, OR	1075.9	2050.9	1490.3	0.0
## Harrisburg, PA	1275.1	324.6	1172.1	2340.3
## Providence, RI	1484.1	618.4	1470.3	2559.8
## Columbia, SC	1359.4	426.4	941.6	2337.4
## Pierre, SD	170.0	936.7	633.4	1114.9
## Nashville, TN	1030.5	333.6	603.9	1981.0
## Austin, TX	1155.7	1067.8	360.0	1706.1
## Salt Lake City, UT	693.6	1516.8	862.0	634.2
## Montpelier, VT	1370.6	611.3	1449.7	2444.8
## Richmond, VA	1349.3	342.5	1122.0	2392.4
## Olympia, WA	1041.5	2037.3	1533.0	145.3
## Charleston, WV	1133.0	133.6	899.8	2163.8
## Madison, WI	614.2	394.4	682.4	1667.3
## Cheyenne, WY	440.4	1146.7	557.1	955.5
##	Harrisburg, PA Providence, RI Columbia, SC Pierre, SD			
## Montgomery, AL	756.7	1046.3	324.0	1123.8
## Juneau, AK	2772.4	2893.2	2949.4	1731.8
## Phoenix, AZ	1990.0	2277.7	1778.8	983.1
## Little Rock, AR	928.8	1232.5	646.6	790.2
## Sacramento, CA	2361.5	2617.3	2259.6	1164.1
## Denver, CO	1483.8	1752.9	1379.0	400.2
## Hartford, CT	242.3	64.7	704.0	1401.9
## Dover, DE	105.3	283.8	469.8	1323.4
## Tallahassee, FL	795.6	1061.6	309.2	1301.3
## Atlanta, GA	612.2	900.5	193.4	1123.9
## Honolulu, HI	4823.9	5078.1	4683.7	3617.5
## Boise, ID	2017.5	2251.3	1991.3	790.8
## Springfield, IL	677.0	962.9	622.6	631.6
## Indianapolis, IN	492.7	783.6	489.2	792.5
## Des Moines, IA	878.5	1143.2	863.9	389.6
## Topeka, KS	1003.4	1287.4	885.1	438.5
## Frankfort, KY	451.3	754.1	360.8	907.5
## Baton Rouge, LA	1052.4	1350.0	642.1	1084.6
## Augusta, ME	457.9	191.0	932.5	1502.0
## Annapolis, MD	91.9	332.3	426.3	1280.8
## Boston, MA	334.6	41.3	791.4	1469.9
## Lansing, MI	432.2	673.9	633.2	797.5

## Saint Paul, MN	884.8	1107.1	991.5	357.6
## Jackson, MS	922.8	1223.3	542.6	998.2
## Jefferson City, MO	824.7	1116.2	696.4	581.7
## Helena, MT	1802.6	2016.9	1835.5	587.2
## Lincoln, NE	1039.5	1309.3	978.1	308.4
## Carson City, NV	2260.9	2516.0	2164.1	1062.9
## Concord, NH	342.2	95.8	816.8	1432.0
## Trenton, NJ	111.5	206.5	551.9	1332.8
## Santa Fe, NM	1610.3	1898.0	1416.3	671.9
## Albany, NY	230.8	132.6	716.4	1331.9
## Raleigh, NC	325.8	571.1	183.0	1287.6
## Bismarck, ND	1275.1	1484.1	1359.4	170.0
## Columbus, OH	324.6	618.4	426.4	936.7
## Oklahoma City, OK	1172.1	1470.3	941.6	633.4
## Salem, OR	2340.3	2559.8	2337.4	1114.9
## Harrisburg, PA	0.0	304.0	490.4	1227.6
## Providence, RI	304.0	0.0	752.7	1462.5
## Columbia, SC	490.4	752.7	0.0	1253.4
## Pierre, SD	1227.6	1462.5	1253.4	0.0
## Nashville, TN	608.1	912.0	358.1	910.4
## Austin, TX	1361.4	1665.4	1010.9	985.8
## Salt Lake City, UT	1829.3	2084.9	1749.3	639.5
## Montpelier, VT	352.9	178.3	841.3	1366.5
## Richmond, VA	192.0	437.6	315.9	1278.8
## Olympia, WA	2315.8	2521.8	2345.1	1102.3
## Charleston, WV	287.2	591.0	302.5	1052.8
## Madison, WI	674.0	919.1	772.4	553.6
## Cheyenne, WY	1460.3	1720.4	1388.9	319.6
##	Nashville, TN Austin, TX Salt Lake City, UT Montpelier, VT			
## Montgomery, AL	264.8	692.4	1529.9	1106.2
## Juneau, AK	2628.8	2597.2	1563.9	2733.7
## Phoenix, AZ	1444.1	869.0	505.8	2229.9
## Little Rock, AR	327.8	441.7	1145.0	1238.4
## Sacramento, CA	1904.0	1466.6	532.7	2529.5
## Denver, CO	1021.3	772.6	371.0	1683.9
## Hartford, CT	850.4	1603.6	2022.5	172.8
## Dover, DE	649.8	1400.0	1917.5	384.2
## Tallahassee, FL	421.2	804.8	1700.4	1148.0
## Atlanta, GA	215.0	818.8	1582.1	962.9
## Honolulu, HI	4338.3	3753.4	2995.3	4982.6
## Boise, ID	1634.1	1370.4	296.2	2147.4
## Springfield, IL	296.0	802.0	1172.1	928.1
## Indianapolis, IN	251.5	927.2	1355.1	762.8
## Des Moines, IA	525.3	816.3	951.2	1078.7
## Topeka, KS	527.0	619.0	866.4	1242.8
## Frankfort, KY	175.9	916.8	1447.8	763.3
## Baton Rouge, LA	470.0	392.0	1360.7	1393.4
## Augusta, ME	1056.7	1806.0	2136.7	138.5
## Annapolis, MD	595.8	1346.3	1870.2	418.1
## Boston, MA	942.5	1695.6	2095.7	152.0
## Lansing, MI	469.6	1129.4	1411.5	609.3
## Saint Paul, MN	691.3	1046.2	993.5	1008.9
## Jackson, MS	330.7	468.3	1336.0	1259.5
## Jefferson City, MO	339.9	656.4	1058.4	1086.6

## Helena, MT	1485.8	1364.0	403.3	1901.6
## Lincoln, NE	624.0	731.6	795.7	1246.8
## Carson City, NV	1807.9	1390.2	431.7	2428.2
## Concord, NH	944.2	1695.2	2061.6	89.4
## Trenton, NJ	710.3	1463.3	1938.7	300.8
## Santa Fe, NM	1073.3	605.5	477.1	1852.4
## Albany, NY	826.7	1577.0	1956.9	126.0
## Raleigh, NC	457.0	1169.5	1827.6	668.9
## Bismarck, ND	1030.5	1155.7	693.6	1370.6
## Columbus, OH	333.6	1067.8	1516.8	611.3
## Oklahoma City, OK	603.9	360.0	862.0	1449.7
## Salem, OR	1981.0	1706.1	634.2	2444.8
## Harrisburg, PA	608.1	1361.4	1829.3	352.9
## Providence, RI	912.0	1665.4	2084.9	178.3
## Columbia, SC	358.1	1010.9	1749.3	841.3
## Pierre, SD	910.4	985.8	639.5	1366.5
## Nashville, TN	0.0	753.4	1391.3	934.0
## Austin, TX	753.4	0.0	1075.1	1678.9
## Salt Lake City, UT	1391.3	1075.1	0.0	1999.9
## Montpelier, VT	934.0	1678.9	1999.9	0.0
## Richmond, VA	524.0	1264.5	1848.2	530.7
## Olympia, WA	1992.1	1772.6	698.6	2398.8
## Charleston, WV	321.1	1074.5	1614.3	622.8
## Madison, WI	497.5	998.7	1165.9	843.5
## Cheyenne, WY	1030.9	849.9	370.2	1642.5
##	Richmond, VA Olympia, WA Charleston, WV Madison, WI			
## Montgomery, AL	614.0	2170.6	489.8	760.1
## Juneau, AK	2890.6	913.8	2697.8	2181.3
## Phoenix, AZ	1957.9	1097.9	1730.4	1393.9
## Little Rock, AR	851.6	1794.8	644.3	598.1
## Sacramento, CA	2375.8	589.2	2141.6	1698.4
## Denver, CO	1489.0	1028.7	1254.9	840.5
## Hartford, CT	388.1	2465.7	529.5	856.7
## Dover, DE	154.1	2415.4	334.2	770.2
## Tallahassee, FL	625.0	2346.7	565.9	917.6
## Atlanta, GA	468.5	2198.8	353.0	698.8
## Honolulu, HI	4830.7	2639.6	4597.0	4160.0
## Boise, ID	2058.7	402.5	1827.7	1343.6
## Springfield, IL	676.1	1729.1	442.2	227.0
## Indianapolis, IN	494.1	1894.6	262.1	283.3
## Des Moines, IA	904.4	1487.7	673.2	239.7
## Topeka, KS	993.2	1472.8	759.6	430.4
## Frankfort, KY	406.6	2007.8	175.9	412.1
## Baton Rouge, LA	925.1	2038.6	770.7	879.0
## Augusta, ME	616.9	2524.7	740.0	981.9
## Annapolis, MD	112.6	2375.6	280.5	728.7
## Boston, MA	475.9	2522.2	621.8	930.5
## Lansing, MI	518.9	1883.8	339.8	246.2
## Saint Paul, MN	958.4	1431.0	746.5	225.3
## Jackson, MS	806.1	1997.0	638.2	746.6
## Jefferson City, MO	803.4	1652.6	570.8	343.6
## Helena, MT	1864.2	515.6	1639.7	1132.5
## Lincoln, NE	1052.6	1368.1	818.9	406.5
## Carson City, NV	2276.5	567.0	2042.4	1597.1

## Concord, NH	501.4	2475.5	625.9	899.1
## Trenton, NJ	236.3	2416.2	389.9	779.9
## Santa Fe, NM	1581.7	1175.2	1352.7	1021.3
## Albany, NY	404.8	2389.2	509.8	791.7
## Raleigh, NC	138.2	2389.3	243.5	764.1
## Bismarck, ND	1349.3	1041.5	1133.0	614.2
## Columbus, OH	342.5	2037.3	133.6	394.4
## Oklahoma City, OK	1122.0	1533.0	899.8	682.4
## Salem, OR	2392.4	145.3	2163.8	1667.3
## Harrisburg, PA	192.0	2315.8	287.2	674.0
## Providence, RI	437.6	2521.8	591.0	919.1
## Columbia, SC	315.9	2345.1	302.5	772.4
## Pierre, SD	1278.8	1102.3	1052.8	553.6
## Nashville, TN	524.0	1992.1	321.1	497.5
## Austin, TX	1264.5	1772.6	1074.5	998.7
## Salt Lake City, UT	1848.2	698.6	1614.3	1165.9
## Montpelier, VT	530.7	2398.8	622.8	843.5
## Richmond, VA	0.0	2379.7	234.1	735.2
## Olympia, WA	2379.7	0.0	2155.0	1647.5
## Charleston, WV	234.1	2155.0	0.0	521.2
## Madison, WI	735.2	1647.5	521.2	0.0
## Cheyenne, WY	1478.2	983.6	1244.5	802.2
##	Cheyenne, WY			
## Montgomery, AL	1189.9			
## Juneau, AK	1752.1			
## Phoenix, AZ	664.2			
## Little Rock, AR	811.4			
## Sacramento, CA	901.4			
## Denver, CO	97.3			
## Hartford, CT	1657.4			
## Dover, DE	1547.7			
## Tallahassee, FL	1364.9			
## Atlanta, GA	1228.8			
## Honolulu, HI	3363.7			
## Boise, ID	605.7			
## Springfield, IL	802.4			
## Indianapolis, IN	984.9			
## Des Moines, IA	581.8			
## Topeka, KS	503.9			
## Frankfort, KY	1079.1			
## Baton Rouge, LA	1061.8			
## Augusta, ME	1780.3			
## Annapolis, MD	1500.2			
## Boston, MA	1732.6			
## Lansing, MI	1046.4			
## Saint Paul, MN	647.8			
## Jackson, MS	1013.8			
## Jefferson City, MO	693.8			
## Helena, MT	520.2			
## Lincoln, NE	425.6			
## Carson City, NV	800.9			
## Concord, NH	1700.9			
## Trenton, NJ	1570.1			
## Santa Fe, NM	383.6			

```

## Albany, NY          1593.8
## Raleigh, NC        1460.3
## Bismarck, ND        440.4
## Columbus, OH       1146.7
## Oklahoma City, OK      557.1
## Salem, OR           955.5
## Harrisburg, PA      1460.3
## Providence, RI      1720.4
## Columbia, SC       1388.9
## Pierre, SD           319.6
## Nashville, TN       1030.9
## Austin, TX            849.9
## Salt Lake City, UT     370.2
## Montpelier, VT      1642.5
## Richmond, VA         1478.2
## Olympia, WA           983.6
## Charleston, WV       1244.5
## Madison, WI            802.2
## Cheyenne, WY            0.0

lookupPairwiseValue(dist.haversine.df, "Juneau, AK", "Montgomery, AL");

## [1] 2854.6

```

You can compare the two with the code below (currently in comments).

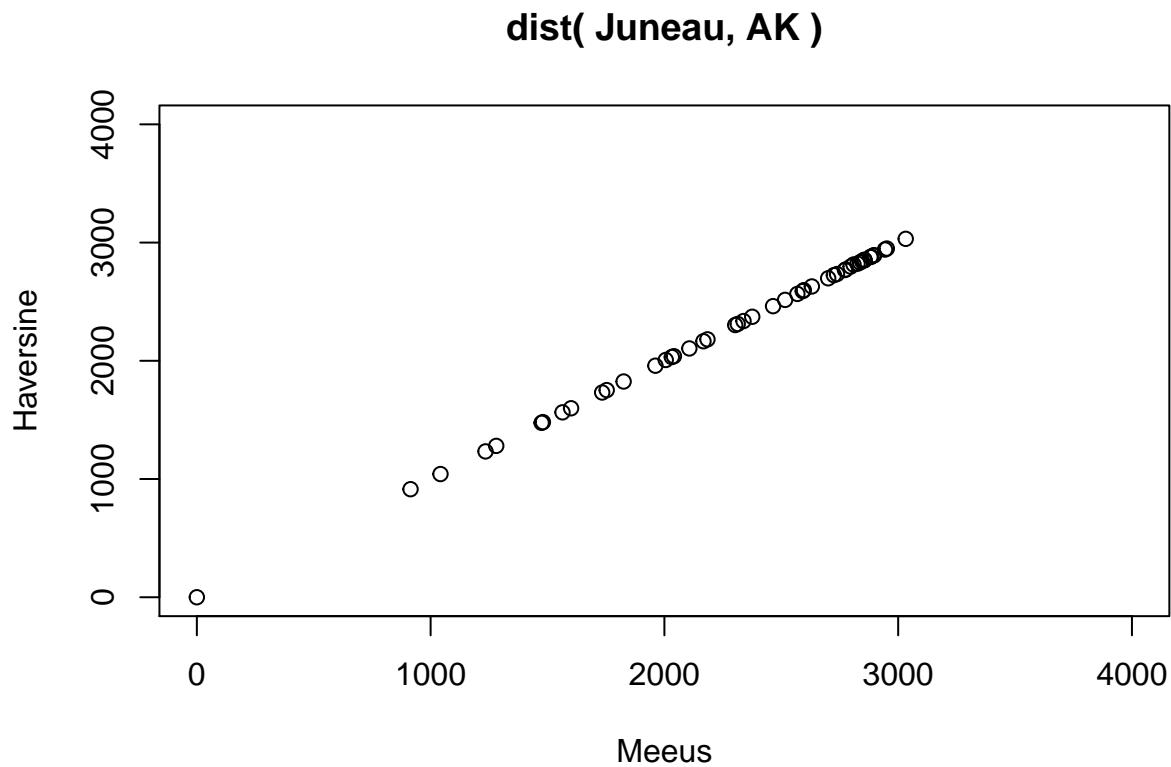
```

#View(dist.meeus.df)
x = dist.meeus.df[,2]; # Juneau ... pick one location
y = dist.haversine.df[,2];

my.lim = c(0, 4000 );

plot(x, y,
      xlab="Meeus",
      ylab="Haversine",
      main="dist( Juneau, AK )",
      xlim=my.lim,
      ylim=my.lim);

```



```
plotXYwithBoxPlots(x, y,
  xlab="Meeus",
  ylab="Haversine",
  main="dist( Juneau, AK )",
  xlim=my.lim,
  ylim=my.lim);
```

[ Examining the data above, is there much difference between these two calculations?

What is the conceptual difference between these two calculations? Try `?distMeeus` or `?distHaversine`

Are the results similar?

Is there a more accurate distance algorithm for geo-spatial calculations? If so, what is it?

]

Let's now do `manhattan` and `euclidean` which are more common in the "statistical clustering" domain. I will do `euclidean`.

```
dist.manhattan = dist( latlong[,1:2],
  method="manhattan", diag=TRUE, upper=TRUE);
dist.manhattan.m = as.matrix( dist.manhattan );
rownames(dist.manhattan.m) =
colnames(dist.manhattan.m) = myLabels;

dist.manhattan.df = as.data.frame( round( dist.manhattan.m, digits=1) );
```

```
dist.manhattan.df; ## too big
```

## Manhattan

	Montgomery, AL	Juneau, AK	Phoenix, AZ	Little Rock, AR
## Montgomery, AL	0.0	4418.0	1483.1	494.3
## Juneau, AK	4418.0	0.0	2934.9	3923.7
## Phoenix, AZ	1483.1	2934.9	0.0	1166.3
## Little Rock, AR	494.3	3923.7	1166.3	0.0
## Sacramento, CA	2351.9	2066.1	868.8	1857.7
## Denver, CO	1530.7	2887.3	820.3	1036.4
## Hartford, CT	1391.5	4512.2	2724.4	1558.1
## Dover, DE	1056.2	4536.3	2389.1	1222.8
## Tallahassee, FL	242.2	4660.2	1725.3	736.4
## Atlanta, GA	199.3	4425.0	1532.2	501.3
## Honolulu, HI	4671.0	3832.5	3338.1	4504.4
## Boise, ID	2410.3	2007.7	927.2	1916.0
## Springfield, IL	697.5	3720.5	1661.8	495.5
## Indianapolis, IN	517.7	3913.5	1850.6	684.3
## Des Moines, IA	1037.7	3380.3	1568.9	543.4
## Topeka, KS	975.7	3442.3	1281.0	481.4
## Frankfort, KY	479.9	4092.3	1812.9	646.5
## Baton Rouge, LA	399.6	4282.6	1347.7	358.8
## Augusta, ME	1725.4	4494.4	3058.3	1892.0
## Annapolis, MD	990.1	4495.7	2323.0	1156.7
## Boston, MA	1520.5	4559.0	2853.4	1687.1
## Lansing, MI	810.3	3796.9	2143.2	976.9
## Saint Paul, MN	1240.3	3177.8	1829.0	746.0
## Jackson, MS	217.6	4209.1	1274.2	285.4
## Jefferson City, MO	750.7	3667.3	1439.9	273.6
## Helena, MT	2387.3	2030.7	909.3	1893.0
## Lincoln, NE	1150.7	3267.3	1348.0	656.4
## Carson City, NV	2297.8	2120.2	814.7	1803.6
## Concord, NH	1553.2	4474.6	2886.1	1719.8
## Trenton, NJ	1171.2	4504.3	2504.2	1337.8
## Santa Fe, NM	1302.9	3115.1	486.2	808.6
## Albany, NY	1393.8	4391.6	2726.7	1560.4
## Raleigh, NC	652.4	4600.5	1985.4	819.0
## Bismarck, ND	1788.8	2629.3	1537.8	1294.5
## Columbus, OH	703.5	4072.6	2036.4	870.0
## Oklahoma City, OK	828.2	3589.8	933.5	333.9
## Salem, OR	2875.0	1543.1	1391.8	2380.7
## Harrisburg, PA	1059.1	4385.8	2392.0	1225.7
## Providence, RI	1464.1	4576.3	2797.0	1630.7
## Columbia, SC	399.4	4591.3	1732.4	667.5
## Pierre, SD	1595.4	2822.6	1395.0	1101.1
## Nashville, TN	290.1	4127.9	1567.9	401.6
## Austin, TX	770.4	3936.6	1001.7	603.8
## Salt Lake City, UT	1978.0	2440.1	514.1	1483.7
## Montpelier, VT	1569.1	4345.3	2902.1	1735.7
## Richmond, VA	838.0	4542.3	2170.9	1004.6
## Olympia, WA	3012.2	1405.8	1529.1	2517.9
## Charleston, WV	666.7	4258.7	1999.6	833.3
## Madison, WI	908.7	3509.3	1902.6	736.3

## Cheyenne, WY	1618.0	2800.0	926.3	1123.8
##	Sacramento, CA	Denver, CO	Hartford, CT	Dover, DE
## Montgomery, AL	2351.9	1530.7	1391.5	1056.2
## Juneau, AK	2066.1	2887.3	4512.2	4536.3
## Phoenix, AZ	868.8	820.3	2724.4	2389.1
## Little Rock, AR	1857.7	1036.4	1558.1	1222.8
## Sacramento, CA	0.0	981.0	2885.1	2549.7
## Denver, CO	981.0	0.0	1904.1	1648.9
## Hartford, CT	2885.1	1904.1	0.0	335.3
## Dover, DE	2549.7	1648.9	335.3	0.0
## Tallahassee, FL	2594.1	1772.8	1412.4	1077.1
## Atlanta, GA	2358.9	1537.7	1192.2	856.9
## Honolulu, HI	3177.4	4158.4	6062.5	5727.2
## Boise, ID	636.3	879.6	2504.5	2528.6
## Springfield, IL	1822.5	841.5	1062.6	815.8
## Indianapolis, IN	2011.3	1030.3	873.8	622.7
## Des Moines, IA	1729.5	748.5	1155.5	1155.9
## Topeka, KS	1441.7	555.0	1443.4	1108.1
## Frankfort, KY	2026.2	1204.9	911.5	576.2
## Baton Rouge, LA	2216.5	1395.2	1791.1	1455.7
## Augusta, ME	3218.9	2237.9	333.9	669.2
## Annapolis, MD	2483.6	1608.4	401.4	66.1
## Boston, MA	3014.1	2033.1	129.0	464.4
## Lansing, MI	2303.8	1322.8	715.2	739.3
## Saint Paul, MN	1989.7	1008.7	1334.4	1358.5
## Jackson, MS	2143.0	1321.8	1609.1	1273.7
## Jefferson City, MO	1601.3	780.0	1284.5	949.2
## Helena, MT	1069.9	856.6	2481.5	2505.6
## Lincoln, NE	1508.6	527.6	1376.5	1268.9
## Carson City, NV	134.5	846.5	2750.5	2416.1
## Concord, NH	3046.7	2065.7	161.7	497.0
## Trenton, NJ	2664.8	1683.8	220.3	115.1
## Santa Fe, NM	1049.0	334.2	2238.2	1902.9
## Albany, NY	2887.3	1906.3	120.5	337.6
## Raleigh, NC	2534.4	1713.2	739.0	403.7
## Bismarck, ND	1698.5	717.5	1882.9	1907.0
## Columbus, OH	2197.0	1216.0	688.0	463.7
## Oklahoma City, OK	1523.7	702.5	1790.9	1455.6
## Salem, OR	523.0	1344.3	2969.1	2993.2
## Harrisburg, PA	2552.7	1571.7	332.4	150.5
## Providence, RI	2957.6	1976.6	72.6	407.9
## Columbia, SC	2525.2	1703.9	992.1	656.7
## Pierre, SD	1555.7	574.7	1689.6	1713.6
## Nashville, TN	2061.9	1240.6	1156.5	821.1
## Austin, TX	1870.5	1049.3	2161.9	1826.6
## Salt Lake City, UT	674.7	447.3	2210.4	2096.2
## Montpelier, VT	3062.7	2081.7	177.7	513.0
## Richmond, VA	2476.3	1655.0	553.5	218.2
## Olympia, WA	660.3	1481.5	3106.4	3130.5
## Charleston, WV	2192.6	1371.3	724.8	389.5
## Madison, WI	2063.2	1082.2	1002.9	1027.0
## Cheyenne, WY	1086.9	105.9	1798.1	1736.3
##	Tallahassee, FL	Atlanta, GA	Honolulu, HI	Boise, ID
## Montgomery, AL	242.2	199.3	4671.0	2410.3

## Juneau, AK	4660.2	4425.0	3832.5	2007.7
## Phoenix, AZ	1725.3	1532.2	3338.1	927.2
## Little Rock, AR	736.4	501.3	4504.4	1916.0
## Sacramento, CA	2594.1	2358.9	3177.4	636.3
## Denver, CO	1772.8	1537.7	4158.4	879.6
## Hartford, CT	1412.4	1192.2	6062.5	2504.5
## Dover, DE	1077.1	856.9	5727.2	2528.6
## Tallahassee, FL	0.0	235.2	4650.0	2652.5
## Atlanta, GA	235.2	0.0	4870.3	2417.3
## Honolulu, HI	4650.0	4870.3	0.0	3813.8
## Boise, ID	2652.5	2417.3	3813.8	0.0
## Springfield, IL	939.7	704.5	4999.9	1712.8
## Indianapolis, IN	746.6	511.5	5188.7	1905.8
## Des Moines, IA	1279.8	1044.7	4907.0	1372.6
## Topeka, KS	1217.9	982.7	4619.1	1434.6
## Frankfort, KY	567.9	332.7	5150.9	2084.6
## Baton Rouge, LA	378.6	598.9	4271.4	2274.9
## Augusta, ME	1746.3	1526.1	6396.4	2582.6
## Annapolis, MD	1011.0	790.8	5661.1	2488.0
## Boston, MA	1541.5	1321.2	6191.5	2551.3
## Lansing, MI	863.2	628.1	5481.3	1789.2
## Saint Paul, MN	1482.4	1247.3	5167.1	1353.4
## Jackson, MS	451.1	416.9	4453.4	2201.4
## Jefferson City, MO	992.8	757.7	4778.0	1659.6
## Helena, MT	2629.5	2394.3	4247.4	433.6
## Lincoln, NE	1392.9	1157.7	4686.0	1259.6
## Carson City, NV	2540.0	2304.8	3312.0	501.8
## Concord, NH	1574.1	1353.9	6224.2	2466.9
## Trenton, NJ	1192.2	972.0	5842.2	2496.6
## Santa Fe, NM	1545.1	1309.9	3824.3	1107.4
## Albany, NY	1414.7	1194.5	6064.8	2383.9
## Raleigh, NC	673.4	453.2	5323.4	2592.8
## Bismarck, ND	2030.9	1795.8	4875.9	1062.1
## Columbus, OH	724.4	504.2	5374.4	2064.9
## Oklahoma City, OK	1070.4	835.2	4271.6	1582.1
## Salem, OR	3117.1	2882.0	3531.7	464.7
## Harrisburg, PA	1080.0	859.8	5730.1	2378.1
## Providence, RI	1485.0	1264.8	6135.1	2568.6
## Columbia, SC	420.4	200.1	5070.4	2583.6
## Pierre, SD	1837.5	1602.4	4733.1	919.3
## Nashville, TN	532.2	297.1	4906.0	2120.2
## Austin, TX	749.5	969.7	3900.6	1928.9
## Salt Lake City, UT	2220.1	1985.0	3852.1	432.4
## Montpelier, VT	1590.1	1369.9	6240.1	2426.4
## Richmond, VA	858.9	638.7	5509.0	2534.6
## Olympia, WA	3254.4	3019.2	3684.1	601.9
## Charleston, WV	687.6	467.4	5337.7	2251.0
## Madison, WI	1150.9	915.7	5240.7	1501.6
## Cheyenne, WY	1860.2	1625.1	4264.4	792.3
##	Springfield, IL	Indianapolis, IN	Des Moines, IA	Topeka, KS
## Montgomery, AL	697.5	517.7	1037.7	975.7
## Juneau, AK	3720.5	3913.5	3380.3	3442.3
## Phoenix, AZ	1661.8	1850.6	1568.9	1281.0
## Little Rock, AR	495.5	684.3	543.4	481.4

## Sacramento, CA	1822.5	2011.3	1729.5	1441.7
## Denver, CO	841.5	1030.3	748.5	555.0
## Hartford, CT	1062.6	873.8	1155.5	1443.4
## Dover, DE	815.8	622.7	1155.9	1108.1
## Tallahassee, FL	939.7	746.6	1279.8	1217.9
## Atlanta, GA	704.5	511.5	1044.7	982.7
## Honolulu, HI	4999.9	5188.7	4907.0	4619.1
## Boise, ID	1712.8	1905.8	1372.6	1434.6
## Springfield, IL	0.0	193.1	340.1	380.8
## Indianapolis, IN	193.1	0.0	533.2	569.6
## Des Moines, IA	340.1	533.2	0.0	287.9
## Topeka, KS	380.8	569.6	287.9	0.0
## Frankfort, KY	371.8	178.7	711.9	650.0
## Baton Rouge, LA	728.5	917.3	902.2	840.3
## Augusta, ME	1396.5	1207.7	1489.4	1777.3
## Annapolis, MD	775.2	582.2	1115.4	1053.4
## Boston, MA	1191.6	1002.8	1284.6	1572.4
## Lansing, MI	481.4	292.6	574.3	862.2
## Saint Paul, MN	542.7	735.8	260.2	548.0
## Jackson, MS	546.5	735.3	828.8	766.8
## Jefferson City, MO	221.9	410.7	287.0	225.0
## Helena, MT	1689.8	1882.8	1349.6	1411.6
## Lincoln, NE	453.2	646.2	220.9	175.0
## Carson City, NV	1687.9	1876.7	1595.0	1322.1
## Concord, NH	1224.3	1035.5	1317.2	1605.1
## Trenton, NJ	842.4	653.5	1123.9	1223.1
## Santa Fe, NM	1175.6	1364.4	1082.7	794.8
## Albany, NY	1064.9	876.1	1157.8	1445.7
## Raleigh, NC	880.0	687.0	1220.2	1158.2
## Bismarck, ND	1091.2	1284.3	751.1	813.1
## Columbus, OH	374.6	185.8	692.2	755.4
## Oklahoma City, OK	728.3	917.1	635.4	347.5
## Salem, OR	2177.4	2370.5	1837.3	1899.3
## Harrisburg, PA	730.2	541.4	1005.4	1111.0
## Providence, RI	1135.2	946.4	1228.1	1516.0
## Columbia, SC	870.8	677.7	1210.9	1149.0
## Pierre, SD	897.9	1090.9	557.7	619.7
## Nashville, TN	407.5	282.7	747.6	685.6
## Austin, TX	1099.3	1288.1	1006.4	718.5
## Salt Lake City, UT	1280.4	1473.5	1054.8	1002.3
## Montpelier, VT	1240.3	1051.5	1333.2	1621.1
## Richmond, VA	821.8	628.8	1162.0	1100.0
## Olympia, WA	2314.7	2507.7	1974.5	2036.5
## Charleston, WV	538.2	345.1	878.3	816.4
## Madison, WI	240.8	404.3	333.7	621.6
## Cheyenne, WY	920.5	1113.6	642.6	642.4
##	Frankfort, KY	Baton Rouge, LA	Augusta, ME	Annapolis, MD
## Montgomery, AL	479.9	399.6	1725.4	990.1
## Juneau, AK	4092.3	4282.6	4494.4	4495.7
## Phoenix, AZ	1812.9	1347.7	3058.3	2323.0
## Little Rock, AR	646.5	358.8	1892.0	1156.7
## Sacramento, CA	2026.2	2216.5	3218.9	2483.6
## Denver, CO	1204.9	1395.2	2237.9	1608.4
## Hartford, CT	911.5	1791.1	333.9	401.4

## Dover, DE	576.2	1455.7	669.2	66.1
## Tallahassee, FL	567.9	378.6	1746.3	1011.0
## Atlanta, GA	332.7	598.9	1526.1	790.8
## Honolulu, HI	5150.9	4271.4	6396.4	5661.1
## Boise, ID	2084.6	2274.9	2582.6	2488.0
## Springfield, IL	371.8	728.5	1396.5	775.2
## Indianapolis, IN	178.7	917.3	1207.7	582.2
## Des Moines, IA	711.9	902.2	1489.4	1115.4
## Topeka, KS	650.0	840.3	1777.3	1053.4
## Frankfort, KY	0.0	879.5	1245.4	510.1
## Baton Rouge, LA	879.5	0.0	2124.9	1389.7
## Augusta, ME	1245.4	2124.9	0.0	735.3
## Annapolis, MD	510.1	1389.7	735.3	0.0
## Boston, MA	1040.6	1920.1	204.8	530.5
## Lansing, MI	330.3	1209.8	915.1	698.8
## Saint Paul, MN	914.5	1104.8	1316.7	1318.0
## Jackson, MS	697.5	182.0	1942.9	1207.6
## Jefferson City, MO	424.9	615.2	1618.4	883.1
## Helena, MT	2061.6	2251.9	2463.7	2465.0
## Lincoln, NE	824.9	1015.3	1710.3	1228.4
## Carson City, NV	1972.1	2162.4	3084.4	2375.5
## Concord, NH	1073.2	1952.8	172.2	563.1
## Trenton, NJ	691.3	1570.8	554.1	181.2
## Santa Fe, NM	1326.7	1167.5	2572.1	1836.8
## Albany, NY	913.8	1793.4	331.6	403.7
## Raleigh, NC	508.3	1052.0	1072.9	337.6
## Bismarck, ND	1463.0	1653.3	1865.2	1866.5
## Columbus, OH	223.5	1103.0	1021.9	423.1
## Oklahoma City, OK	879.4	692.8	2124.8	1389.5
## Salem, OR	2549.2	2739.5	2951.4	2952.7
## Harrisburg, PA	579.1	1458.7	666.3	109.9
## Providence, RI	984.1	1863.7	261.3	474.0
## Columbia, SC	499.0	799.0	1325.9	590.6
## Pierre, SD	1269.6	1459.9	1671.8	1673.1
## Nashville, TN	244.9	634.6	1490.3	755.1
## Austin, TX	1250.4	370.9	2495.8	1760.5
## Salt Lake City, UT	1652.2	1842.5	2544.2	2055.7
## Montpelier, VT	1089.2	1968.7	156.2	579.1
## Richmond, VA	450.1	1237.6	887.4	152.1
## Olympia, WA	2686.5	2876.8	3088.6	3089.9
## Charleston, WV	186.7	1066.3	1058.7	323.4
## Madison, WI	583.0	969.3	1155.7	986.4
## Cheyenne, WY	1292.3	1482.6	2132.0	1695.7
##	Boston, MA	Lansing, MI	Saint Paul, MN	Jackson, MS
## Montgomery, AL	1520.5	810.3	1240.3	217.6
## Juneau, AK	4559.0	3796.9	3177.8	4209.1
## Phoenix, AZ	2853.4	2143.2	1829.0	1274.2
## Little Rock, AR	1687.1	976.9	746.0	285.4
## Sacramento, CA	3014.1	2303.8	1989.7	2143.0
## Denver, CO	2033.1	1322.8	1008.7	1321.8
## Hartford, CT	129.0	715.2	1334.4	1609.1
## Dover, DE	464.4	739.3	1358.5	1273.7
## Tallahassee, FL	1541.5	863.2	1482.4	451.1
## Atlanta, GA	1321.2	628.1	1247.3	416.9

## Honolulu, HI	6191.5	5481.3	5167.1	4453.4
## Boise, ID	2551.3	1789.2	1353.4	2201.4
## Springfield, IL	1191.6	481.4	542.7	546.5
## Indianapolis, IN	1002.8	292.6	735.8	735.3
## Des Moines, IA	1284.6	574.3	260.2	828.8
## Topeka, KS	1572.4	862.2	548.0	766.8
## Frankfort, KY	1040.6	330.3	914.5	697.5
## Baton Rouge, LA	1920.1	1209.8	1104.8	182.0
## Augusta, ME	204.8	915.1	1316.7	1942.9
## Annapolis, MD	530.5	698.8	1318.0	1207.6
## Boston, MA	0.0	762.1	1381.3	1738.1
## Lansing, MI	762.1	0.0	619.2	1027.8
## Saint Paul, MN	1381.3	619.2	0.0	1031.3
## Jackson, MS	1738.1	1027.8	1031.3	0.0
## Jefferson City, MO	1413.5	703.3	489.6	541.8
## Helena, MT	2528.3	1766.2	1147.0	2178.4
## Lincoln, NE	1505.5	795.2	481.1	941.8
## Carson City, NV	2879.6	2169.3	1855.2	2088.9
## Concord, NH	84.5	742.9	1296.8	1770.7
## Trenton, NJ	349.3	707.3	1326.5	1388.8
## Santa Fe, NM	2367.3	1657.0	1342.9	1094.0
## Albany, NY	167.4	594.7	1213.9	1611.3
## Raleigh, NC	868.1	803.6	1422.8	870.0
## Bismarck, ND	1929.8	1167.7	548.5	1579.9
## Columbus, OH	817.1	275.6	894.8	921.0
## Oklahoma City, OK	1920.0	1209.7	895.6	619.3
## Salem, OR	3016.0	2253.9	1635.4	2666.0
## Harrisburg, PA	461.4	588.9	1208.0	1276.7
## Providence, RI	56.5	779.4	1398.6	1681.6
## Columbia, SC	1121.1	794.3	1413.5	617.0
## Pierre, SD	1736.4	974.3	434.0	1386.5
## Nashville, TN	1285.5	575.2	950.2	452.6
## Austin, TX	2291.0	1580.7	1266.6	552.9
## Salt Lake City, UT	2339.4	1629.1	1315.0	1769.0
## Montpelier, VT	213.8	758.9	1167.5	1786.7
## Richmond, VA	682.6	745.4	1364.6	1055.5
## Olympia, WA	3153.2	2391.1	1771.9	2803.3
## Charleston, WV	853.9	461.7	1080.9	884.2
## Madison, WI	1049.8	287.7	331.5	787.2
## Cheyenne, WY	1927.2	1216.9	902.8	1409.1
##	Jefferson City, MO Helena, MT Lincoln, NE Carson City, NV			
## Montgomery, AL	750.7	2387.3	1150.7	2297.8
## Juneau, AK	3667.3	2030.7	3267.3	2120.2
## Phoenix, AZ	1439.9	909.3	1348.0	814.7
## Little Rock, AR	273.6	1893.0	656.4	1803.6
## Sacramento, CA	1601.3	1069.9	1508.6	134.5
## Denver, CO	780.0	856.6	527.6	846.5
## Hartford, CT	1284.5	2481.5	1376.5	2750.5
## Dover, DE	949.2	2505.6	1268.9	2416.1
## Tallahassee, FL	992.8	2629.5	1392.9	2540.0
## Atlanta, GA	757.7	2394.3	1157.7	2304.8
## Honolulu, HI	4778.0	4247.4	4686.0	3312.0
## Boise, ID	1659.6	433.6	1259.6	501.8
## Springfield, IL	221.9	1689.8	453.2	1687.9

## Indianapolis, IN	410.7	1882.8	646.2	1876.7	
## Des Moines, IA	287.0	1349.6	220.9	1595.0	
## Topeka, KS	225.0	1411.6	175.0	1322.1	
## Frankfort, KY	424.9	2061.6	824.9	1972.1	
## Baton Rouge, LA	615.2	2251.9	1015.3	2162.4	
## Augusta, ME	1618.4	2463.7	1710.3	3084.4	
## Annapolis, MD	883.1	2465.0	1228.4	2375.5	
## Boston, MA	1413.5	2528.3	1505.5	2879.6	
## Lansing, MI	703.3	1766.2	795.2	2169.3	
## Saint Paul, MN	489.6	1147.0	481.1	1855.2	
## Jackson, MS	541.8	2178.4	941.8	2088.9	
## Jefferson City, MO	0.0	1636.6	400.0	1547.2	
## Helena, MT	1636.6	0.0	1236.6	935.4	
## Lincoln, NE	400.0	1236.6	0.0	1374.1	
## Carson City, NV	1547.2	935.4	1374.1	0.0	
## Concord, NH	1446.2	2443.9	1538.1	2912.2	
## Trenton, NJ	1064.2	2473.6	1236.9	2530.3	
## Santa Fe, NM	953.7	1084.4	861.8	994.9	
## Albany, NY	1286.8	2360.9	1378.7	2752.8	
## Raleigh, NC	933.2	2569.8	1333.2	2480.3	
## Bismarck, ND	1038.1	628.5	638.1	1563.9	
## Columbus, OH	596.5	2041.9	805.3	2062.5	
## Oklahoma City, OK	506.4	1559.1	414.5	1469.6	
## Salem, OR	2124.3	715.6	1724.3	577.1	
## Harrisburg, PA	952.1	2355.1	1118.5	2418.1	
## Providence, RI	1357.1	2545.6	1449.0	2823.1	
## Columbia, SC	923.9	2560.6	1323.9	2471.1	
## Pierre, SD	844.7	791.9	444.7	1421.2	
## Nashville, TN	460.6	2097.2	860.6	2007.8	
## Austin, TX	877.4	1905.9	785.5	1816.4	
## Salt Lake City, UT	1227.3	409.3	833.9	540.2	
## Montpelier, VT	1462.1	2314.6	1554.1	2928.2	
## Richmond, VA	875.0	2511.6	1275.0	2422.1	
## Olympia, WA	2261.5	624.9	1861.5	714.4	
## Charleston, WV	591.3	2228.0	991.3	2138.5	
## Madison, WI	462.7	1478.6	554.6	1928.7	
## Cheyenne, WY	867.4	769.2	467.4	952.4	
##	Concord, NH	Trenton, NJ	Santa Fe, NM	Albany, NY	Raleigh, NC
## Montgomery, AL	1553.2	1171.2	1302.9	1393.8	652.4
## Juneau, AK	4474.6	4504.3	3115.1	4391.6	4600.5
## Phoenix, AZ	2886.1	2504.2	486.2	2726.7	1985.4
## Little Rock, AR	1719.8	1337.8	808.6	1560.4	819.0
## Sacramento, CA	3046.7	2664.8	1049.0	2887.3	2534.4
## Denver, CO	2065.7	1683.8	334.2	1906.3	1713.2
## Hartford, CT	161.7	220.3	2238.2	120.5	739.0
## Dover, DE	497.0	115.1	1902.9	337.6	403.7
## Tallahassee, FL	1574.1	1192.2	1545.1	1414.7	673.4
## Atlanta, GA	1353.9	972.0	1309.9	1194.5	453.2
## Honolulu, HI	6224.2	5842.2	3824.3	6064.8	5323.4
## Boise, ID	2466.9	2496.6	1107.4	2383.9	2592.8
## Springfield, IL	1224.3	842.4	1175.6	1064.9	880.0
## Indianapolis, IN	1035.5	653.5	1364.4	876.1	687.0
## Des Moines, IA	1317.2	1123.9	1082.7	1157.8	1220.2
## Topeka, KS	1605.1	1223.1	794.8	1445.7	1158.2

## Frankfort, KY	1073.2	691.3	1326.7	913.8	508.3
## Baton Rouge, LA	1952.8	1570.8	1167.5	1793.4	1052.0
## Augusta, ME	172.2	554.1	2572.1	331.6	1072.9
## Annapolis, MD	563.1	181.2	1836.8	403.7	337.6
## Boston, MA	84.5	349.3	2367.3	167.4	868.1
## Lansing, MI	742.9	707.3	1657.0	594.7	803.6
## Saint Paul, MN	1296.8	1326.5	1342.9	1213.9	1422.8
## Jackson, MS	1770.7	1388.8	1094.0	1611.3	870.0
## Jefferson City, MO	1446.2	1064.2	953.7	1286.8	933.2
## Helena, MT	2443.9	2473.6	1084.4	2360.9	2569.8
## Lincoln, NE	1538.1	1236.9	861.8	1378.7	1333.2
## Carson City, NV	2912.2	2530.3	994.9	2752.8	2480.3
## Concord, NH	0.0	381.9	2399.9	159.4	900.7
## Trenton, NJ	381.9	0.0	2018.0	222.5	518.8
## Santa Fe, NM	2399.9	2018.0	0.0	2240.5	1499.2
## Albany, NY	159.4	222.5	2240.5	0.0	741.3
## Raleigh, NC	900.7	518.8	1499.2	741.3	0.0
## Bismarck, ND	1845.3	1875.0	1051.6	1762.4	1971.3
## Columbus, OH	849.7	467.8	1550.2	690.3	527.9
## Oklahoma City, OK	1952.6	1570.7	474.7	1793.2	1051.9
## Salem, OR	2931.5	2961.2	1572.1	2848.6	3057.5
## Harrisburg, PA	494.1	118.5	1905.8	334.7	406.6
## Providence, RI	101.8	292.8	2310.8	184.7	811.6
## Columbia, SC	1153.7	771.8	1476.2	994.3	253.0
## Pierre, SD	1651.9	1681.6	908.9	1569.0	1777.9
## Nashville, TN	1318.2	936.2	1081.8	1158.7	472.6
## Austin, TX	2323.6	1941.7	821.5	2164.2	1422.9
## Salt Lake City, UT	2372.0	2064.2	675.1	2212.6	2160.5
## Montpelier, VT	129.3	397.9	2415.9	175.4	916.7
## Richmond, VA	715.2	333.3	1684.7	555.8	185.5
## Olympia, WA	3068.8	3098.5	1709.3	2985.8	3194.7
## Charleston, WV	886.5	504.6	1513.4	727.1	341.9
## Madison, WI	983.5	995.0	1416.4	882.4	1091.2
## Cheyenne, WY	1959.8	1704.3	440.1	1800.4	1800.6
##		Bismarck, ND	Columbus, OH	Oklahoma City, OK	Salem, OR
## Montgomery, AL	1788.8	703.5		828.2	2875.0
## Juneau, AK	2629.3	4072.6		3589.8	1543.1
## Phoenix, AZ	1537.8	2036.4		933.5	1391.8
## Little Rock, AR	1294.5	870.0		333.9	2380.7
## Sacramento, CA	1698.5	2197.0		1523.7	523.0
## Denver, CO	717.5	1216.0		702.5	1344.3
## Hartford, CT	1882.9	688.0		1790.9	2969.1
## Dover, DE	1907.0	463.7		1455.6	2993.2
## Tallahassee, FL	2030.9	724.4		1070.4	3117.1
## Atlanta, GA	1795.8	504.2		835.2	2882.0
## Honolulu, HI	4875.9	5374.4		4271.6	3531.7
## Boise, ID	1062.1	2064.9		1582.1	464.7
## Springfield, IL	1091.2	374.6		728.3	2177.4
## Indianapolis, IN	1284.3	185.8		917.1	2370.5
## Des Moines, IA	751.1	692.2		635.4	1837.3
## Topeka, KS	813.1	755.4		347.5	1899.3
## Frankfort, KY	1463.0	223.5		879.4	2549.2
## Baton Rouge, LA	1653.3	1103.0		692.8	2739.5
## Augusta, ME	1865.2	1021.9		2124.8	2951.4

## Annapolis, MD	1866.5	423.1	1389.5	2952.7
## Boston, MA	1929.8	817.1	1920.0	3016.0
## Lansing, MI	1167.7	275.6	1209.7	2253.9
## Saint Paul, MN	548.5	894.8	895.6	1635.4
## Jackson, MS	1579.9	921.0	619.3	2666.0
## Jefferson City, MO	1038.1	596.5	506.4	2124.3
## Helena, MT	628.5	2041.9	1559.1	715.6
## Lincoln, NE	638.1	805.3	414.5	1724.3
## Carson City, NV	1563.9	2062.5	1469.6	577.1
## Concord, NH	1845.3	849.7	1952.6	2931.5
## Trenton, NJ	1875.0	467.8	1570.7	2961.2
## Santa Fe, NM	1051.6	1550.2	474.7	1572.1
## Albany, NY	1762.4	690.3	1793.2	2848.6
## Raleigh, NC	1971.3	527.9	1051.9	3057.5
## Bismarck, ND	0.0	1443.3	960.6	1344.1
## Columbus, OH	1443.3	0.0	1102.9	2529.5
## Oklahoma City, OK	960.6	1102.9	0.0	2046.8
## Salem, OR	1344.1	2529.5	2046.8	0.0
## Harrisburg, PA	1756.5	355.6	1458.5	2842.7
## Providence, RI	1947.1	760.6	1863.5	3033.3
## Columbia, SC	1962.0	518.7	1001.5	3048.2
## Pierre, SD	193.4	1250.0	767.2	1279.6
## Nashville, TN	1498.7	468.4	634.5	2584.9
## Austin, TX	1307.4	1473.9	371.0	2393.5
## Salt Lake City, UT	1023.7	1632.5	1149.7	897.0
## Montpelier, VT	1716.0	865.7	1968.6	2802.2
## Richmond, VA	1913.1	469.7	1237.4	2999.3
## Olympia, WA	1223.4	2666.8	2184.0	152.4
## Charleston, WV	1629.4	186.1	1066.1	2715.6
## Madison, WI	880.0	563.3	969.1	1966.2
## Cheyenne, WY	611.5	1272.6	789.8	1256.9
##	Harrisburg, PA Providence, RI Columbia, SC Pierre, SD			
## Montgomery, AL	1059.1	1464.1	399.4	1595.4
## Juneau, AK	4385.8	4576.3	4591.3	2822.6
## Phoenix, AZ	2392.0	2797.0	1732.4	1395.0
## Little Rock, AR	1225.7	1630.7	667.5	1101.1
## Sacramento, CA	2552.7	2957.6	2525.2	1555.7
## Denver, CO	1571.7	1976.6	1703.9	574.7
## Hartford, CT	332.4	72.6	992.1	1689.6
## Dover, DE	150.5	407.9	656.7	1713.6
## Tallahassee, FL	1080.0	1485.0	420.4	1837.5
## Atlanta, GA	859.8	1264.8	200.1	1602.4
## Honolulu, HI	5730.1	6135.1	5070.4	4733.1
## Boise, ID	2378.1	2568.6	2583.6	919.3
## Springfield, IL	730.2	1135.2	870.8	897.9
## Indianapolis, IN	541.4	946.4	677.7	1090.9
## Des Moines, IA	1005.4	1228.1	1210.9	557.7
## Topeka, KS	1111.0	1516.0	1149.0	619.7
## Frankfort, KY	579.1	984.1	499.0	1269.6
## Baton Rouge, LA	1458.7	1863.7	799.0	1459.9
## Augusta, ME	666.3	261.3	1325.9	1671.8
## Annapolis, MD	109.9	474.0	590.6	1673.1
## Boston, MA	461.4	56.5	1121.1	1736.4
## Lansing, MI	588.9	779.4	794.3	974.3

## Saint Paul, MN	1208.0	1398.6	1413.5	434.0
## Jackson, MS	1276.7	1681.6	617.0	1386.5
## Jefferson City, MO	952.1	1357.1	923.9	844.7
## Helena, MT	2355.1	2545.6	2560.6	791.9
## Lincoln, NE	1118.5	1449.0	1323.9	444.7
## Carson City, NV	2418.1	2823.1	2471.1	1421.2
## Concord, NH	494.1	101.8	1153.7	1651.9
## Trenton, NJ	118.5	292.8	771.8	1681.6
## Santa Fe, NM	1905.8	2310.8	1476.2	908.9
## Albany, NY	334.7	184.7	994.3	1569.0
## Raleigh, NC	406.6	811.6	253.0	1777.9
## Bismarck, ND	1756.5	1947.1	1962.0	193.4
## Columbus, OH	355.6	760.6	518.7	1250.0
## Oklahoma City, OK	1458.5	1863.5	1001.5	767.2
## Salem, OR	2842.7	3033.3	3048.2	1279.6
## Harrisburg, PA	0.0	405.0	659.7	1563.2
## Providence, RI	405.0	0.0	1064.6	1753.7
## Columbia, SC	659.7	1064.6	0.0	1768.6
## Pierre, SD	1563.2	1753.7	1768.6	0.0
## Nashville, TN	824.1	1229.0	463.3	1305.3
## Austin, TX	1829.5	2234.5	1169.9	1114.0
## Salt Lake City, UT	1945.7	2282.9	2151.2	881.0
## Montpelier, VT	510.1	231.1	1169.7	1522.6
## Richmond, VA	221.1	626.1	438.5	1719.7
## Olympia, WA	2980.0	3170.5	3185.5	1416.8
## Charleston, WV	392.4	797.4	332.6	1436.0
## Madison, WI	876.5	1067.0	1082.0	686.6
## Cheyenne, WY	1585.8	1870.7	1791.3	468.8
##	Nashville, TN Austin, TX Salt Lake City, UT Montpelier, VT			
## Montgomery, AL	290.1	770.4	1978.0	1569.1
## Juneau, AK	4127.9	3936.6	2440.1	4345.3
## Phoenix, AZ	1567.9	1001.7	514.1	2902.1
## Little Rock, AR	401.6	603.8	1483.7	1735.7
## Sacramento, CA	2061.9	1870.5	674.7	3062.7
## Denver, CO	1240.6	1049.3	447.3	2081.7
## Hartford, CT	1156.5	2161.9	2210.4	177.7
## Dover, DE	821.1	1826.6	2096.2	513.0
## Tallahassee, FL	532.2	749.5	2220.1	1590.1
## Atlanta, GA	297.1	969.7	1985.0	1369.9
## Honolulu, HI	4906.0	3900.6	3852.1	6240.1
## Boise, ID	2120.2	1928.9	432.4	2426.4
## Springfield, IL	407.5	1099.3	1280.4	1240.3
## Indianapolis, IN	282.7	1288.1	1473.5	1051.5
## Des Moines, IA	747.6	1006.4	1054.8	1333.2
## Topeka, KS	685.6	718.5	1002.3	1621.1
## Frankfort, KY	244.9	1250.4	1652.2	1089.2
## Baton Rouge, LA	634.6	370.9	1842.5	1968.7
## Augusta, ME	1490.3	2495.8	2544.2	156.2
## Annapolis, MD	755.1	1760.5	2055.7	579.1
## Boston, MA	1285.5	2291.0	2339.4	213.8
## Lansing, MI	575.2	1580.7	1629.1	758.9
## Saint Paul, MN	950.2	1266.6	1315.0	1167.5
## Jackson, MS	452.6	552.9	1769.0	1786.7
## Jefferson City, MO	460.6	877.4	1227.3	1462.1

## Helena, MT	2097.2	1905.9	409.3	2314.6
## Lincoln, NE	860.6	785.5	833.9	1554.1
## Carson City, NV	2007.8	1816.4	540.2	2928.2
## Concord, NH	1318.2	2323.6	2372.0	129.3
## Trenton, NJ	936.2	1941.7	2064.2	397.9
## Santa Fe, NM	1081.8	821.5	675.1	2415.9
## Albany, NY	1158.7	2164.2	2212.6	175.4
## Raleigh, NC	472.6	1422.9	2160.5	916.7
## Bismarck, ND	1498.7	1307.4	1023.7	1716.0
## Columbus, OH	468.4	1473.9	1632.5	865.7
## Oklahoma City, OK	634.5	371.0	1149.7	1968.6
## Salem, OR	2584.9	2393.5	897.0	2802.2
## Harrisburg, PA	824.1	1829.5	1945.7	510.1
## Providence, RI	1229.0	2234.5	2282.9	231.1
## Columbia, SC	463.3	1169.9	2151.2	1169.7
## Pierre, SD	1305.3	1114.0	881.0	1522.6
## Nashville, TN	0.0	1005.5	1687.9	1334.1
## Austin, TX	1005.5	0.0	1496.5	2339.6
## Salt Lake City, UT	1687.9	1496.5	0.0	2388.0
## Montpelier, VT	1334.1	2339.6	2388.0	0.0
## Richmond, VA	602.9	1608.4	2102.3	731.2
## Olympia, WA	2722.1	2530.8	1034.2	2939.5
## Charleston, WV	431.6	1437.1	1818.6	902.5
## Madison, WI	618.7	1340.1	1388.5	999.5
## Cheyenne, WY	1328.0	1136.6	412.2	1975.8
##	Richmond, VA Olympia, WA Charleston, WV Madison, WI			
## Montgomery, AL	838.0	3012.2	666.7	908.7
## Juneau, AK	4542.3	1405.8	4258.7	3509.3
## Phoenix, AZ	2170.9	1529.1	1999.6	1902.6
## Little Rock, AR	1004.6	2517.9	833.3	736.3
## Sacramento, CA	2476.3	660.3	2192.6	2063.2
## Denver, CO	1655.0	1481.5	1371.3	1082.2
## Hartford, CT	553.5	3106.4	724.8	1002.9
## Dover, DE	218.2	3130.5	389.5	1027.0
## Tallahassee, FL	858.9	3254.4	687.6	1150.9
## Atlanta, GA	638.7	3019.2	467.4	915.7
## Honolulu, HI	5509.0	3684.1	5337.7	5240.7
## Boise, ID	2534.6	601.9	2251.0	1501.6
## Springfield, IL	821.8	2314.7	538.2	240.8
## Indianapolis, IN	628.8	2507.7	345.1	404.3
## Des Moines, IA	1162.0	1974.5	878.3	333.7
## Topeka, KS	1100.0	2036.5	816.4	621.6
## Frankfort, KY	450.1	2686.5	186.7	583.0
## Baton Rouge, LA	1237.6	2876.8	1066.3	969.3
## Augusta, ME	887.4	3088.6	1058.7	1155.7
## Annapolis, MD	152.1	3089.9	323.4	986.4
## Boston, MA	682.6	3153.2	853.9	1049.8
## Lansing, MI	745.4	2391.1	461.7	287.7
## Saint Paul, MN	1364.6	1771.9	1080.9	331.5
## Jackson, MS	1055.5	2803.3	884.2	787.2
## Jefferson City, MO	875.0	2261.5	591.3	462.7
## Helena, MT	2511.6	624.9	2228.0	1478.6
## Lincoln, NE	1275.0	1861.5	991.3	554.6
## Carson City, NV	2422.1	714.4	2138.5	1928.7

## Concord, NH	715.2	3068.8	886.5	983.5
## Trenton, NJ	333.3	3098.5	504.6	995.0
## Santa Fe, NM	1684.7	1709.3	1513.4	1416.4
## Albany, NY	555.8	2985.8	727.1	882.4
## Raleigh, NC	185.5	3194.7	341.9	1091.2
## Bismarck, ND	1913.1	1223.4	1629.4	880.0
## Columbus, OH	469.7	2666.8	186.1	563.3
## Oklahoma City, OK	1237.4	2184.0	1066.1	969.1
## Salem, OR	2999.3	152.4	2715.6	1966.2
## Harrisburg, PA	221.1	2980.0	392.4	876.5
## Providence, RI	626.1	3170.5	797.4	1067.0
## Columbia, SC	438.5	3185.5	332.6	1082.0
## Pierre, SD	1719.7	1416.8	1436.0	686.6
## Nashville, TN	602.9	2722.1	431.6	618.7
## Austin, TX	1608.4	2530.8	1437.1	1340.1
## Salt Lake City, UT	2102.3	1034.2	1818.6	1388.5
## Montpelier, VT	731.2	2939.5	902.5	999.5
## Richmond, VA	0.0	3136.5	283.7	1033.1
## Olympia, WA	3136.5	0.0	2852.9	2103.5
## Charleston, WV	283.7	2852.9	0.0	749.4
## Madison, WI	1033.1	2103.5	749.4	0.0
## Cheyenne, WY	1742.4	1394.1	1458.7	976.3
##	Cheyenne, WY			
## Montgomery, AL	1618.0			
## Juneau, AK	2800.0			
## Phoenix, AZ	926.3			
## Little Rock, AR	1123.8			
## Sacramento, CA	1086.9			
## Denver, CO	105.9			
## Hartford, CT	1798.1			
## Dover, DE	1736.3			
## Tallahassee, FL	1860.2			
## Atlanta, GA	1625.1			
## Honolulu, HI	4264.4			
## Boise, ID	792.3			
## Springfield, IL	920.5			
## Indianapolis, IN	1113.6			
## Des Moines, IA	642.6			
## Topeka, KS	642.4			
## Frankfort, KY	1292.3			
## Baton Rouge, LA	1482.6			
## Augusta, ME	2132.0			
## Annapolis, MD	1695.7			
## Boston, MA	1927.2			
## Lansing, MI	1216.9			
## Saint Paul, MN	902.8			
## Jackson, MS	1409.1			
## Jefferson City, MO	867.4			
## Helena, MT	769.2			
## Lincoln, NE	467.4			
## Carson City, NV	952.4			
## Concord, NH	1959.8			
## Trenton, NJ	1704.3			
## Santa Fe, NM	440.1			

```

## Albany, NY           1800.4
## Raleigh, NC         1800.6
## Bismarck, ND        611.5
## Columbus, OH        1272.6
## Oklahoma City, OK   789.8
## Salem, OR            1256.9
## Harrisburg, PA       1585.8
## Providence, RI       1870.7
## Columbia, SC         1791.3
## Pierre, SD            468.8
## Nashville, TN        1328.0
## Austin, TX            1136.6
## Salt Lake City, UT   412.2
## Montpelier, VT        1975.8
## Richmond, VA          1742.4
## Olympia, WA            1394.1
## Charleston, WV         1458.7
## Madison, WI             976.3
## Cheyenne, WY              0.0

lookupPairwiseValue(dist.manhattan.df, "Juneau, AK", "Montgomery, AL");

## [1] 4418

```

**Euclidean** We have converted the true latitude/longitude to a miles-type format, so the resulting table will report miles.

```

dist.euclidean = dist(latlong[,1:2],
                      method="euclidean", diag=TRUE, upper=TRUE);
dist.euclidean.m = as.matrix( dist.euclidean );
rownames(dist.euclidean.m) =
colnames(dist.euclidean.m) = myLabels;

dist.euclidean.df = as.data.frame( round( dist.euclidean.m, digits=1) );

dist.euclidean.df; ## too big

```

	Montgomery, AL	Juneau, AK	Phoenix, AZ	Little Rock, AR
## Montgomery, AL	0.0	3179.8	1410.0	368.8
## Juneau, AK	3179.8	0.0	2104.5	2814.9
## Phoenix, AZ	1410.0	2104.5	0.0	1081.2
## Little Rock, AR	368.8	2814.9	1081.2	0.0
## Sacramento, CA	1970.1	1532.6	624.8	1614.3
## Denver, CO	1141.4	2054.6	581.0	772.6
## Hartford, CT	986.2	3559.0	2226.0	1177.7
## Dover, DE	751.5	3476.2	2033.7	967.0
## Tallahassee, FL	171.9	3345.6	1532.6	530.8
## Atlanta, GA	141.0	3213.9	1511.3	438.8
## Honolulu, HI	3982.0	2855.5	2636.9	3695.8
## Boise, ID	1808.9	1419.7	736.9	1440.2
## Springfield, IL	545.3	2757.3	1299.8	378.7
## Indianapolis, IN	511.1	2928.8	1480.3	483.9
## Des Moines, IA	752.5	2508.1	1153.2	478.2
## Topeka, KS	690.9	2496.8	974.3	349.9
## Frankfort, KY	410.2	3040.2	1520.9	472.5

## Baton Rouge, LA	298.3	3044.1	1159.2	302.5
## Augusta, ME	1221.2	3658.8	2427.5	1397.4
## Annapolis, MD	702.2	3431.8	1978.9	912.4
## Boston, MA	1079.8	3629.7	2321.6	1274.7
## Lansing, MI	721.9	2927.1	1633.5	696.5
## Saint Paul, MN	944.6	2437.2	1304.7	705.6
## Jackson, MS	213.3	3008.5	1197.4	205.0
## Jefferson City, MO	536.2	2678.0	1142.3	265.1
## Helena, MT	1714.4	1465.6	906.7	1350.9
## Lincoln, NE	813.7	2387.9	981.7	481.6
## Carson City, NV	1887.7	1543.7	576.4	1528.8
## Concord, NH	1099.0	3587.6	2313.0	1276.9
## Trenton, NJ	830.4	3487.7	2089.7	1031.2
## Santa Fe, NM	1098.7	2202.7	366.6	747.1
## Albany, NY	985.7	3483.5	2186.0	1151.9
## Raleigh, NC	479.1	3419.6	1832.5	751.3
## Bismarck, ND	1273.1	2000.2	1108.7	952.3
## Columbus, OH	554.1	3079.3	1649.4	624.2
## Oklahoma City, OK	650.2	2557.3	806.3	287.9
## Salem, OR	2186.7	1111.6	993.7	1818.5
## Harrisburg, PA	749.2	3379.1	1978.2	926.2
## Providence, RI	1041.3	3622.5	2293.2	1242.0
## Columbia, SC	307.9	3362.5	1694.8	618.9
## Pierre, SD	1129.0	2095.0	989.6	795.2
## Nashville, TN	264.0	3016.0	1393.2	318.6
## Austin, TX	642.4	2784.0	812.3	427.1
## Salt Lake City, UT	1513.7	1725.4	504.5	1146.0
## Montpelier, VT	1110.7	3512.7	2281.6	1263.0
## Richmond, VA	599.0	3423.7	1910.1	834.2
## Olympia, WA	2241.3	999.6	1108.6	1872.5
## Charleston, WV	484.7	3193.9	1695.7	635.0
## Madison, WI	758.4	2673.8	1405.3	597.4
## Cheyenne, WY	1179.7	2003.3	661.9	812.6
##	Sacramento, CA	Denver, CO	Hartford, CT	Dover, DE
## Montgomery, AL	1970.1	1141.4	986.2	751.5
## Juneau, AK	1532.6	2054.6	3559.0	3476.2
## Phoenix, AZ	624.8	581.0	2226.0	2033.7
## Little Rock, AR	1614.3	772.6	1177.7	967.0
## Sacramento, CA	0.0	904.7	2674.6	2510.3
## Denver, CO	904.7	0.0	1770.0	1609.3
## Hartford, CT	2674.6	1770.0	0.0	237.7
## Dover, DE	2510.3	1609.3	237.7	0.0
## Tallahassee, FL	2109.3	1300.9	1004.2	766.7
## Atlanta, GA	2053.1	1198.2	845.3	611.0
## Honolulu, HI	2315.8	3154.4	4860.5	4661.1
## Boise, ID	451.9	668.0	2380.0	2242.2
## Springfield, IL	1740.5	837.3	937.0	772.8
## Indianapolis, IN	1931.1	1028.2	749.0	582.1
## Des Moines, IA	1536.0	633.8	1143.7	1002.2
## Topeka, KS	1409.3	510.0	1270.4	1101.0
## Frankfort, KY	2000.0	1103.9	709.7	514.4
## Baton Rouge, LA	1747.8	989.8	1276.8	1044.9
## Augusta, ME	2851.2	1948.2	236.4	474.1
## Annapolis, MD	2456.8	1556.4	284.1	54.8

## Boston, MA	2765.8	1861.2	97.1	328.7
## Lansing, MI	2037.6	1135.2	651.7	550.9
## Saint Paul, MN	1611.6	742.2	1136.3	1039.0
## Jackson, MS	1763.6	957.6	1157.8	929.9
## Jefferson City, MO	1600.9	704.4	1087.1	909.9
## Helena, MT	757.0	609.0	2174.0	2057.6
## Lincoln, NE	1363.6	459.8	1312.3	1160.6
## Carson City, NV	102.5	807.8	2577.5	2415.6
## Concord, NH	2746.2	1842.1	117.4	354.1
## Trenton, NJ	2554.0	1650.7	155.8	84.5
## Santa Fe, NM	871.5	286.0	1865.7	1679.4
## Albany, NY	2621.5	1717.1	85.3	259.7
## Raleigh, NC	2348.3	1465.0	526.3	289.1
## Bismarck, ND	1265.3	539.1	1573.8	1476.7
## Columbus, OH	2103.9	1200.7	577.3	412.0
## Oklahoma City, OK	1326.4	503.1	1424.5	1227.7
## Salem, OR	446.7	1048.8	2758.7	2624.8
## Harrisburg, PA	2439.0	1535.5	251.5	106.4
## Providence, RI	2743.1	1838.5	68.5	289.8
## Columbia, SC	2231.6	1366.6	703.7	466.0
## Pierre, SD	1223.2	408.9	1520.2	1400.8
## Nashville, TN	1902.5	1024.2	861.7	648.5
## Austin, TX	1418.1	764.0	1582.0	1359.4
## Salt Lake City, UT	545.5	383.3	2142.4	1988.7
## Montpelier, VT	2699.5	1797.1	172.4	387.1
## Richmond, VA	2405.0	1510.5	392.0	154.3
## Olympia, WA	588.5	1100.0	2766.4	2643.3
## Charleston, WV	2176.5	1278.9	543.0	338.2
## Madison, WI	1780.4	882.6	916.8	803.5
## Cheyenne, WY	927.4	97.1	1755.7	1605.4
##	Tallahassee, FL	Atlanta, GA	Honolulu, HI	Boise, ID
## Montgomery, AL	171.9	141.0	3982.0	1808.9
## Juneau, AK	3345.6	3213.9	2855.5	1419.7
## Phoenix, AZ	1532.6	1511.3	2636.9	736.9
## Little Rock, AR	530.8	438.8	3695.8	1440.2
## Sacramento, CA	2109.3	2053.1	2315.8	451.9
## Denver, CO	1300.9	1198.2	3154.4	668.0
## Hartford, CT	1004.2	845.3	4860.5	2380.0
## Dover, DE	766.7	611.0	4661.1	2242.2
## Tallahassee, FL	0.0	227.8	4068.1	1966.6
## Atlanta, GA	227.8	0.0	4102.3	1865.4
## Honolulu, HI	4068.1	4102.3	0.0	2746.4
## Boise, ID	1966.6	1865.4	2746.4	0.0
## Springfield, IL	709.0	506.5	3936.4	1473.2
## Indianapolis, IN	651.0	426.0	4116.9	1661.7
## Des Moines, IA	923.0	739.2	3776.3	1240.8
## Topeka, KS	861.4	717.2	3608.6	1163.3
## Frankfort, KY	535.5	307.8	4152.3	1751.2
## Baton Rouge, LA	378.1	435.3	3694.9	1640.8
## Augusta, ME	1240.4	1080.2	5064.3	2535.1
## Annapolis, MD	724.3	561.4	4606.3	2191.2
## Boston, MA	1092.3	939.0	4956.6	2466.1
## Lansing, MI	847.4	619.6	4267.1	1729.4
## Saint Paul, MN	1110.2	906.6	3894.2	1265.0

## Jackson, MS	347.9	332.0	3772.0	1621.0
## Jefferson City, MO	707.9	539.7	3779.2	1357.2
## Helena, MT	1881.0	1749.4	3050.8	307.0
## Lincoln, NE	985.2	828.9	3601.2	1083.4
## Carson City, NV	2030.0	1967.3	2417.4	363.6
## Concord, NH	1120.8	958.0	4949.4	2438.8
## Trenton, NJ	850.2	689.6	4721.0	2274.6
## Santa Fe, NM	1238.8	1185.3	3001.7	783.1
## Albany, NY	1018.2	845.0	4822.3	2318.4
## Raleigh, NC	478.0	343.6	4439.3	2121.5
## Bismarck, ND	1444.9	1269.8	3578.7	870.2
## Columbus, OH	659.6	435.0	4285.1	1830.2
## Oklahoma City, OK	802.8	726.7	3436.3	1164.6
## Salem, OR	2341.7	2246.9	2504.6	384.3
## Harrisburg, PA	788.0	608.6	4611.2	2159.6
## Providence, RI	1051.7	900.7	4927.2	2448.1
## Columbia, SC	301.2	184.0	4285.0	2031.5
## Pierre, SD	1300.7	1137.2	3521.7	868.7
## Nashville, TN	417.6	211.6	4013.9	1686.5
## Austin, TX	736.7	767.8	3340.0	1365.3
## Salt Lake City, UT	1668.2	1577.5	2846.2	306.9
## Montpelier, VT	1146.2	970.3	4918.4	2382.4
## Richmond, VA	613.0	459.2	4529.9	2156.2
## Olympia, WA	2400.4	2293.8	2606.8	435.4
## Charleston, WV	563.0	350.8	4324.8	1922.1
## Madison, WI	914.7	698.5	4029.1	1464.7
## Cheyenne, WY	1343.3	1226.4	3202.9	644.5
##	Springfield, IL Indianapolis, IN Des Moines, IA Topeka, KS			
## Montgomery, AL	545.3	511.1	752.5	690.9
## Juneau, AK	2757.3	2928.8	2508.1	2496.8
## Phoenix, AZ	1299.8	1480.3	1153.2	974.3
## Little Rock, AR	378.7	483.9	478.2	349.9
## Sacramento, CA	1740.5	1931.1	1536.0	1409.3
## Denver, CO	837.3	1028.2	633.8	510.0
## Hartford, CT	937.0	749.0	1143.7	1270.4
## Dover, DE	772.8	582.1	1002.2	1101.0
## Tallahassee, FL	709.0	651.0	923.0	861.4
## Atlanta, GA	506.5	426.0	739.2	717.2
## Honolulu, HI	3936.4	4116.9	3776.3	3608.6
## Boise, ID	1473.2	1661.7	1240.8	1163.3
## Springfield, IL	0.0	190.9	249.3	333.5
## Indianapolis, IN	190.9	0.0	426.4	522.7
## Des Moines, IA	249.3	426.4	0.0	208.2
## Topeka, KS	333.5	522.7	208.2	0.0
## Frankfort, KY	283.8	129.2	532.2	593.8
## Baton Rouge, LA	650.6	699.1	780.4	643.0
## Augusta, ME	1129.0	947.6	1315.2	1460.4
## Annapolis, MD	720.5	530.1	952.0	1047.7
## Boston, MA	1030.3	843.3	1232.8	1363.7
## Lansing, MI	344.6	222.7	501.7	659.2
## Saint Paul, MN	401.6	520.5	233.2	430.3
## Jackson, MS	518.3	560.3	668.0	554.7
## Jefferson City, MO	161.3	338.6	222.5	194.8
## Helena, MT	1308.0	1488.5	1062.2	1032.2

## Lincoln, NE	389.8	578.9	175.5	132.5
## Carson City, NV	1644.7	1835.5	1437.4	1314.7
## Concord, NH	1016.7	832.8	1210.9	1349.4
## Trenton, NJ	813.6	622.9	1033.9	1145.4
## Santa Fe, NM	935.0	1117.8	788.2	607.8
## Albany, NY	890.1	705.7	1087.0	1222.9
## Raleigh, NC	663.0	495.0	911.7	958.5
## Bismarck, ND	776.6	934.7	531.6	602.9
## Columbus, OH	363.5	172.9	590.7	695.6
## Oklahoma City, OK	523.2	687.7	473.1	267.0
## Salem, OR	1857.0	2045.1	1622.8	1547.5
## Harrisburg, PA	698.5	508.0	918.8	1030.6
## Providence, RI	1005.3	817.0	1212.2	1338.7
## Columbia, SC	617.8	486.5	864.0	872.9
## Pierre, SD	662.3	836.0	413.1	445.5
## Nashville, TN	295.7	250.9	528.6	525.6
## Austin, TX	792.2	911.0	813.1	616.7
## Salt Lake City, UT	1215.9	1406.7	999.2	892.4
## Montpelier, VT	982.0	803.7	1163.7	1312.1
## Richmond, VA	683.6	499.0	925.4	1000.5
## Olympia, WA	1882.7	2067.9	1642.3	1584.5
## Charleston, WV	449.3	265.8	691.7	769.0
## Madison, WI	226.5	288.2	253.0	442.1
## Cheyenne, WY	833.2	1023.3	612.3	518.9
##	Frankfort, KY Baton Rouge, LA Augusta, ME Annapolis, MD			
## Montgomery, AL	410.2	298.3	1221.2	702.2
## Juneau, AK	3040.2	3044.1	3658.8	3431.8
## Phoenix, AZ	1520.9	1159.2	2427.5	1978.9
## Little Rock, AR	472.5	302.5	1397.4	912.4
## Sacramento, CA	2000.0	1747.8	2851.2	2456.8
## Denver, CO	1103.9	989.8	1948.2	1556.4
## Hartford, CT	709.7	1276.8	236.4	284.1
## Dover, DE	514.4	1044.9	474.1	54.8
## Tallahassee, FL	535.5	378.1	1240.4	724.3
## Atlanta, GA	307.8	435.3	1080.2	561.4
## Honolulu, HI	4152.3	3694.9	5064.3	4606.3
## Boise, ID	1751.2	1640.8	2535.1	2191.2
## Springfield, IL	283.8	650.6	1129.0	720.5
## Indianapolis, IN	129.2	699.1	947.6	530.1
## Des Moines, IA	532.2	780.4	1315.2	952.0
## Topeka, KS	593.8	643.0	1460.4	1047.7
## Frankfort, KY	0.0	636.3	925.4	459.9
## Baton Rouge, LA	636.3	0.0	1510.0	994.1
## Augusta, ME	925.4	1510.0	0.0	519.9
## Annapolis, MD	459.9	994.1	519.9	0.0
## Boston, MA	806.4	1371.7	151.9	377.7
## Lansing, MI	313.3	921.8	813.6	510.2
## Saint Paul, MN	646.8	1005.7	1273.7	995.2
## Jackson, MS	500.1	138.8	1388.6	877.7
## Jefferson City, MO	399.8	563.5	1285.1	856.2
## Helena, MT	1591.6	1592.4	2311.7	2009.3
## Lincoln, NE	669.6	775.4	1488.5	1109.0
## Carson City, NV	1906.7	1672.8	2752.3	2362.4
## Concord, NH	805.6	1387.5	122.6	398.5

## Trenton, NJ	569.0	1121.7	391.9	128.2
## Santa Fe, NM	1165.1	884.0	2063.8	1624.8
## Albany, NY	680.0	1270.4	245.5	294.8
## Raleigh, NC	379.5	777.1	762.4	250.0
## Bismarck, ND	1052.6	1244.8	1701.6	1431.8
## Columbus, OH	158.7	794.0	781.7	361.4
## Oklahoma City, OK	716.2	489.9	1633.0	1172.9
## Salem, OR	2135.5	2006.5	2908.3	2574.1
## Harrisburg, PA	459.1	1034.0	477.3	91.8
## Providence, RI	775.5	1334.1	193.6	340.0
## Columbia, SC	357.4	605.7	940.1	423.1
## Pierre, SD	945.1	1082.7	1667.5	1352.8
## Nashville, TN	175.0	461.9	1085.2	593.9
## Austin, TX	891.0	358.6	1808.3	1306.1
## Salt Lake City, UT	1486.1	1336.2	2312.3	1936.2
## Montpelier, VT	790.7	1392.8	152.7	423.1
## Richmond, VA	406.7	894.2	628.4	112.5
## Olympia, WA	2164.3	2076.1	2906.5	2593.8
## Charleston, WV	176.9	754.1	766.9	283.5
## Madison, WI	417.1	876.8	1073.8	758.2
## Cheyenne, WY	1108.2	1048.4	1925.7	1553.4
##	Boston, MA	Lansing, MI	Saint Paul, MN	Jackson, MS
## Montgomery, AL	1079.8	721.9	944.6	213.3
## Juneau, AK	3629.7	2927.1	2437.2	3008.5
## Phoenix, AZ	2321.6	1633.5	1304.7	1197.4
## Little Rock, AR	1274.7	696.5	705.6	205.0
## Sacramento, CA	2765.8	2037.6	1611.6	1763.6
## Denver, CO	1861.2	1135.2	742.2	957.6
## Hartford, CT	97.1	651.7	1136.3	1157.8
## Dover, DE	328.7	550.9	1039.0	929.9
## Tallahassee, FL	1092.3	847.4	1110.2	347.9
## Atlanta, GA	939.0	619.6	906.6	332.0
## Honolulu, HI	4956.6	4267.1	3894.2	3772.0
## Boise, ID	2466.1	1729.4	1265.0	1621.0
## Springfield, IL	1030.3	344.6	401.6	518.3
## Indianapolis, IN	843.3	222.7	520.5	560.3
## Des Moines, IA	1232.8	501.7	233.2	668.0
## Topeka, KS	1363.7	659.2	430.3	554.7
## Frankfort, KY	806.4	313.3	646.8	500.1
## Baton Rouge, LA	1371.7	921.8	1005.7	138.8
## Augusta, ME	151.9	813.6	1273.7	1388.6
## Annapolis, MD	377.7	510.2	995.2	877.7
## Boston, MA	0.0	736.6	1216.0	1253.7
## Lansing, MI	736.6	0.0	491.0	783.0
## Saint Paul, MN	1216.0	491.0	0.0	886.9
## Jackson, MS	1253.7	783.0	886.9	0.0
## Jefferson City, MO	1181.8	505.7	442.2	446.6
## Helena, MT	2255.2	1523.5	1039.6	1547.2
## Lincoln, NE	1402.7	675.6	346.0	685.9
## Carson City, NV	2668.3	1938.7	1510.0	1683.2
## Concord, NH	64.0	711.0	1183.0	1266.1
## Trenton, NJ	250.0	561.5	1052.5	1004.0
## Santa Fe, NM	1960.7	1267.0	950.6	892.4
## Albany, NY	148.5	589.1	1067.5	1146.7

## Raleigh, NC	614.5	579.1	1012.1	674.6
## Bismarck, ND	1651.5	930.1	439.1	1156.4
## Columbus, OH	672.4	209.0	649.5	658.4
## Oklahoma City, OK	1520.8	867.8	697.1	456.4
## Salem, OR	2843.5	2107.2	1635.0	1994.7
## Harrisburg, PA	348.5	452.0	942.4	911.3
## Providence, RI	41.8	719.3	1202.7	1217.1
## Columbia, SC	793.1	632.4	1001.8	513.2
## Pierre, SD	1603.4	868.6	396.5	1000.1
## Nashville, TN	958.7	469.3	696.8	325.1
## Austin, TX	1678.7	1122.1	1044.0	435.8
## Salt Lake City, UT	2231.9	1499.2	1066.2	1321.2
## Montpelier, VT	155.0	662.0	1121.3	1267.1
## Richmond, VA	482.8	527.4	994.7	782.7
## Olympia, WA	2848.7	2115.1	1633.9	2055.5
## Charleston, WV	640.0	341.9	773.8	626.2
## Madison, WI	1001.5	265.2	240.1	744.8
## Cheyenne, WY	1845.0	1112.4	692.0	1005.3
##	Jefferson City, MO Helena, MT Lincoln, NE Carson City, NV			
## Montgomery, AL	536.2	1714.4	813.7	1887.7
## Juneau, AK	2678.0	1465.6	2387.9	1543.7
## Phoenix, AZ	1142.3	906.7	981.7	576.4
## Little Rock, AR	265.1	1350.9	481.6	1528.8
## Sacramento, CA	1600.9	757.0	1363.6	102.5
## Denver, CO	704.4	609.0	459.8	807.8
## Hartford, CT	1087.1	2174.0	1312.3	2577.5
## Dover, DE	909.9	2057.6	1160.6	2415.6
## Tallahassee, FL	707.9	1881.0	985.2	2030.0
## Atlanta, GA	539.7	1749.4	828.9	1967.3
## Honolulu, HI	3779.2	3050.8	3601.2	2417.4
## Boise, ID	1357.2	307.0	1083.4	363.6
## Springfield, IL	161.3	1308.0	389.8	1644.7
## Indianapolis, IN	338.6	1488.5	578.9	1835.5
## Des Moines, IA	222.5	1062.2	175.5	1437.4
## Topeka, KS	194.8	1032.2	132.5	1314.7
## Frankfort, KY	399.8	1591.6	669.6	1906.7
## Baton Rouge, LA	563.5	1592.4	775.4	1672.8
## Augusta, ME	1285.1	2311.7	1488.5	2752.3
## Annapolis, MD	856.2	2009.3	1109.0	2362.4
## Boston, MA	1181.8	2255.2	1402.7	2668.3
## Lansing, MI	505.7	1523.5	675.6	1938.7
## Saint Paul, MN	442.2	1039.6	346.0	1510.0
## Jackson, MS	446.6	1547.2	685.9	1683.2
## Jefferson City, MO	0.0	1216.6	290.2	1507.1
## Helena, MT	1216.6	0.0	927.8	664.5
## Lincoln, NE	290.2	927.8	0.0	1265.7
## Carson City, NV	1507.1	664.5	1265.7	0.0
## Concord, NH	1171.1	2222.6	1382.6	2648.0
## Trenton, NJ	957.4	2081.1	1197.3	2458.3
## Santa Fe, NM	779.3	823.1	618.8	791.3
## Albany, NY	1044.1	2106.8	1258.0	2523.6
## Raleigh, NC	764.3	1970.0	1044.9	2258.1
## Bismarck, ND	737.3	613.7	470.7	1163.0
## Columbus, OH	509.9	1649.2	749.1	2008.2

## Oklahoma City, OK	362.3	1102.6	371.3	1241.1
## Salem, OR	1741.5	612.3	1467.2	436.7
## Harrisburg, PA	843.4	1967.8	1081.9	2343.1
## Providence, RI	1155.0	2240.9	1380.8	2646.0
## Columbia, SC	685.3	1901.8	974.8	2144.6
## Pierre, SD	598.1	656.9	316.2	1121.0
## Nashville, TN	338.0	1554.4	628.1	1812.7
## Austin, TX	649.0	1369.8	729.7	1350.1
## Salt Lake City, UT	1087.1	402.4	830.6	443.9
## Montpelier, VT	1139.6	2159.7	1337.4	2600.5
## Richmond, VA	806.2	1987.4	1073.0	2312.3
## Olympia, WA	1776.4	594.9	1494.8	569.6
## Charleston, WV	575.7	1753.9	838.9	2082.9
## Madison, WI	345.7	1259.5	427.9	1680.7
## Cheyenne, WY	712.8	544.1	445.1	827.4
##	Concord, NH Trenton, NJ Santa Fe, NM Albany, NY Raleigh, NC			
## Montgomery, AL	1099.0	830.4	1098.7	985.7
## Juneau, AK	3587.6	3487.7	2202.7	3483.5
## Phoenix, AZ	2313.0	2089.7	366.6	2186.0
## Little Rock, AR	1276.9	1031.2	747.1	1151.9
## Sacramento, CA	2746.2	2554.0	871.5	2621.5
## Denver, CO	1842.1	1650.7	286.0	1717.1
## Hartford, CT	117.4	155.8	1865.7	85.3
## Dover, DE	354.1	84.5	1679.4	259.7
## Tallahassee, FL	1120.8	850.2	1238.8	1018.2
## Atlanta, GA	958.0	689.6	1185.3	845.0
## Honolulu, HI	4949.4	4721.0	3001.7	4822.3
## Boise, ID	2438.8	2274.6	783.1	2318.4
## Springfield, IL	1016.7	813.6	935.0	890.1
## Indianapolis, IN	832.8	622.9	1117.8	705.7
## Des Moines, IA	1210.9	1033.9	788.2	1087.0
## Topeka, KS	1349.4	1145.4	607.8	1222.9
## Frankfort, KY	805.6	569.0	1165.1	680.0
## Baton Rouge, LA	1387.5	1121.7	884.0	1270.4
## Augusta, ME	122.6	391.9	2063.8	245.5
## Annapolis, MD	398.5	128.2	1624.8	294.8
## Boston, MA	64.0	250.0	1960.7	148.5
## Lansing, MI	711.0	561.5	1267.0	589.1
## Saint Paul, MN	1183.0	1052.5	950.6	1067.5
## Jackson, MS	1266.1	1004.0	892.4	1146.7
## Jefferson City, MO	1171.1	957.4	779.3	1044.1
## Helena, MT	2222.6	2081.1	823.1	2106.8
## Lincoln, NE	1382.6	1197.3	618.8	1258.0
## Carson City, NV	2648.0	2458.3	791.3	2523.6
## Concord, NH	0.0	270.9	1950.3	127.1
## Trenton, NJ	270.9	0.0	1732.3	176.4
## Santa Fe, NM	1950.3	1732.3	0.0	1823.4
## Albany, NY	127.1	176.4	1823.4	0.0
## Raleigh, NC	643.1	373.1	1492.3	544.6
## Bismarck, ND	1616.0	1491.6	819.1	1503.2
## Columbus, OH	664.7	450.1	1288.4	537.7
## Oklahoma City, OK	1515.8	1285.2	461.2	1389.0
## Salem, OR	2814.5	2655.9	1130.7	2695.4
## Harrisburg, PA	355.0	115.4	1619.7	236.7

## Providence, RI	95.6	213.2	1933.3	139.7	574.2
## Columbia, SC	820.0	549.2	1366.0	717.1	179.0
## Pierre, SD	1573.6	1424.4	675.1	1455.2	1324.6
## Nashville, TN	963.8	713.5	1047.9	840.3	445.9
## Austin, TX	1686.5	1430.5	583.4	1563.8	1110.3
## Salt Lake City, UT	2209.7	2027.5	477.7	2086.2	1848.3
## Montpelier, VT	92.1	303.0	1917.0	128.3	672.9
## Richmond, VA	508.0	237.2	1561.3	407.2	137.5
## Olympia, WA	2816.8	2670.0	1212.7	2700.2	2539.1
## Charleston, WV	645.2	396.8	1341.3	522.7	241.9
## Madison, WI	974.4	822.2	1039.6	853.7	773.8
## Cheyenne, WY	1822.8	1642.3	382.8	1699.3	1477.1
## Bismarck, ND	Columbus, OH Oklahoma City, OK Salem, OR				
## Montgomery, AL	1273.1	554.1	650.2	2186.7	
## Juneau, AK	2000.2	3079.3	2557.3	1111.6	
## Phoenix, AZ	1108.7	1649.4	806.3	993.7	
## Little Rock, AR	952.3	624.2	287.9	1818.5	
## Sacramento, CA	1265.3	2103.9	1326.4	446.7	
## Denver, CO	539.1	1200.7	503.1	1048.8	
## Hartford, CT	1573.8	577.3	1424.5	2758.7	
## Dover, DE	1476.7	412.0	1227.7	2624.8	
## Tallahassee, FL	1444.9	659.6	802.8	2341.7	
## Atlanta, GA	1269.8	435.0	726.7	2246.9	
## Honolulu, HI	3578.7	4285.1	3436.3	2504.6	
## Boise, ID	870.2	1830.2	1164.6	384.3	
## Springfield, IL	776.6	363.5	523.2	1857.0	
## Indianapolis, IN	934.7	172.9	687.7	2045.1	
## Des Moines, IA	531.6	590.7	473.1	1622.8	
## Topeka, KS	602.9	695.6	267.0	1547.5	
## Frankfort, KY	1052.6	158.7	716.2	2135.5	
## Baton Rouge, LA	1244.8	794.0	489.9	2006.5	
## Augusta, ME	1701.6	781.7	1633.0	2908.3	
## Annapolis, MD	1431.8	361.4	1172.9	2574.1	
## Boston, MA	1651.5	672.4	1520.8	2843.5	
## Lansing, MI	930.1	209.0	867.8	2107.2	
## Saint Paul, MN	439.1	649.5	697.1	1635.0	
## Jackson, MS	1156.4	658.4	456.4	1994.7	
## Jefferson City, MO	737.3	509.9	362.3	1741.5	
## Helena, MT	613.7	1649.2	1102.6	612.3	
## Lincoln, NE	470.7	749.1	371.3	1467.2	
## Carson City, NV	1163.0	2008.2	1241.1	436.7	
## Concord, NH	1616.0	664.7	1515.8	2814.5	
## Trenton, NJ	1491.6	450.1	1285.2	2655.9	
## Santa Fe, NM	819.1	1288.4	461.2	1130.7	
## Albany, NY	1503.2	537.7	1389.0	2695.4	
## Raleigh, NC	1429.4	375.0	1031.5	2505.8	
## Bismarck, ND	0.0	1079.8	802.5	1222.0	
## Columbus, OH	1079.8	0.0	851.3	2212.9	
## Oklahoma City, OK	802.5	851.3	0.0	1538.9	
## Salem, OR	1222.0	2212.9	1538.9	0.0	
## Harrisburg, PA	1381.1	335.1	1174.9	2541.1	
## Providence, RI	1639.6	645.1	1491.0	2826.5	
## Columbia, SC	1394.2	425.1	905.9	2414.5	
## Pierre, SD	170.0	993.4	633.1	1241.1	

## Nashville, TN	1059.9	333.5	588.3	2070.1
## Austin, TX	1153.3	1046.6	359.1	1712.5
## Salt Lake City, UT	736.2	1578.4	865.4	673.5
## Montpelier, VT	1550.2	641.8	1491.0	2755.7
## Richmond, VA	1424.9	345.5	1104.2	2540.2
## Olympia, WA	1207.7	2232.6	1599.2	145.0
## Charleston, WV	1197.6	134.1	889.9	2306.1
## Madison, WI	673.6	409.4	687.6	1842.1
## Cheyenne, WY	448.9	1194.1	558.5	1028.7
##	Harrisburg, PA	Providence, RI	Columbia, SC	Pierre, SD
## Montgomery, AL	749.2	1041.3	307.9	1129.0
## Juneau, AK	3379.1	3622.5	3362.5	2095.0
## Phoenix, AZ	1978.2	2293.2	1694.8	989.6
## Little Rock, AR	926.2	1242.0	618.9	795.2
## Sacramento, CA	2439.0	2743.1	2231.6	1223.2
## Denver, CO	1535.5	1838.5	1366.6	408.9
## Hartford, CT	251.5	68.5	703.7	1520.2
## Dover, DE	106.4	289.8	466.0	1400.8
## Tallahassee, FL	788.0	1051.7	301.2	1300.7
## Atlanta, GA	608.6	900.7	184.0	1137.2
## Honolulu, HI	4611.2	4927.2	4285.0	3521.7
## Boise, ID	2159.6	2448.1	2031.5	868.7
## Springfield, IL	698.5	1005.3	617.8	662.3
## Indianapolis, IN	508.0	817.0	486.5	836.0
## Des Moines, IA	918.8	1212.2	864.0	413.1
## Topeka, KS	1030.6	1338.7	872.9	445.5
## Frankfort, KY	459.1	775.5	357.4	945.1
## Baton Rouge, LA	1034.0	1334.1	605.7	1082.7
## Augusta, ME	477.3	193.6	940.1	1667.5
## Annapolis, MD	91.8	340.0	423.1	1352.8
## Boston, MA	348.5	41.8	793.1	1603.4
## Lansing, MI	452.0	719.3	632.4	868.6
## Saint Paul, MN	942.4	1202.7	1001.8	396.5
## Jackson, MS	911.3	1217.1	513.2	1000.1
## Jefferson City, MO	843.4	1155.0	685.3	598.1
## Helena, MT	1967.8	2240.9	1901.8	656.9
## Lincoln, NE	1081.9	1380.8	974.8	316.2
## Carson City, NV	2343.1	2646.0	2144.6	1121.0
## Concord, NH	355.0	95.6	820.0	1573.6
## Trenton, NJ	115.4	213.2	549.2	1424.4
## Santa Fe, NM	1619.7	1933.3	1366.0	675.1
## Albany, NY	236.7	139.7	717.1	1455.2
## Raleigh, NC	325.2	574.2	179.0	1324.6
## Bismarck, ND	1381.1	1639.6	1394.2	170.0
## Columbus, OH	335.1	645.1	425.1	993.4
## Oklahoma City, OK	1174.9	1491.0	905.9	633.1
## Salem, OR	2541.1	2826.5	2414.5	1241.1
## Harrisburg, PA	0.0	316.5	488.6	1311.0
## Providence, RI	316.5	0.0	752.9	1587.6
## Columbia, SC	488.6	752.9	0.0	1273.2
## Pierre, SD	1311.0	1587.6	1273.2	0.0
## Nashville, TN	610.6	925.1	347.6	931.1
## Austin, TX	1332.1	1643.5	947.9	983.4
## Salt Lake City, UT	1912.1	2210.8	1748.1	679.2

## Montpelier, VT	361.8	179.5	845.2	1514.9
## Richmond, VA	191.6	443.4	312.0	1334.0
## Olympia, WA	2556.0	2833.7	2456.5	1246.6
## Charleston, WV	291.7	606.9	301.7	1101.7
## Madison, WI	709.9	984.5	774.5	603.8
## Cheyenne, WY	1527.0	1824.1	1389.0	331.8
##	Nashville, TN	Austin, TX	Salt Lake City, UT	Montpelier, VT
## Montgomery, AL	264.0	642.4	1513.7	1110.7
## Juneau, AK	3016.0	2784.0	1725.4	3512.7
## Phoenix, AZ	1393.2	812.3	504.5	2281.6
## Little Rock, AR	318.6	427.1	1146.0	1263.0
## Sacramento, CA	1902.5	1418.1	545.5	2699.5
## Denver, CO	1024.2	764.0	383.3	1797.1
## Hartford, CT	861.7	1582.0	2142.4	172.4
## Dover, DE	648.5	1359.4	1988.7	387.1
## Tallahassee, FL	417.6	736.7	1668.2	1146.2
## Atlanta, GA	211.6	767.8	1577.5	970.3
## Honolulu, HI	4013.9	3340.0	2846.2	4918.4
## Boise, ID	1686.5	1365.3	306.9	2382.4
## Springfield, IL	295.7	792.2	1215.9	982.0
## Indianapolis, IN	250.9	911.0	1406.7	803.7
## Des Moines, IA	528.6	813.1	999.2	1163.7
## Topeka, KS	525.6	616.7	892.4	1312.1
## Frankfort, KY	175.0	891.0	1486.1	790.7
## Baton Rouge, LA	461.9	358.6	1336.2	1392.8
## Augusta, ME	1085.2	1808.3	2312.3	152.7
## Annapolis, MD	593.9	1306.1	1936.2	423.1
## Boston, MA	958.7	1678.7	2231.9	155.0
## Lansing, MI	469.3	1122.1	1499.2	662.0
## Saint Paul, MN	696.8	1044.0	1066.2	1121.3
## Jackson, MS	325.1	435.8	1321.2	1267.1
## Jefferson City, MO	338.0	649.0	1087.1	1139.6
## Helena, MT	1554.4	1369.8	402.4	2159.7
## Lincoln, NE	628.1	729.7	830.6	1337.4
## Carson City, NV	1812.7	1350.1	443.9	2600.5
## Concord, NH	963.8	1686.5	2209.7	92.1
## Trenton, NJ	713.5	1430.5	2027.5	303.0
## Santa Fe, NM	1047.9	583.4	477.7	1917.0
## Albany, NY	840.3	1563.8	2086.2	128.3
## Raleigh, NC	445.9	1110.3	1848.3	672.9
## Bismarck, ND	1059.9	1153.3	736.2	1550.2
## Columbus, OH	333.5	1046.6	1578.4	641.8
## Oklahoma City, OK	588.3	359.1	865.4	1491.0
## Salem, OR	2070.1	1712.5	673.5	2755.7
## Harrisburg, PA	610.6	1332.1	1912.1	361.8
## Providence, RI	925.1	1643.5	2210.8	179.5
## Columbia, SC	347.6	947.9	1748.1	845.2
## Pierre, SD	931.1	983.4	679.2	1514.9
## Nashville, TN	0.0	723.7	1407.1	955.8
## Austin, TX	723.7	0.0	1058.8	1679.4
## Salt Lake City, UT	1407.1	1058.8	0.0	2160.1
## Montpelier, VT	955.8	1679.4	2160.1	0.0
## Richmond, VA	517.3	1215.3	1892.7	535.5
## Olympia, WA	2109.9	1796.1	740.9	2754.4

## Charleston, WV	318.9	1041.4	1660.4	641.1
## Madison, WI	497.4	994.6	1239.2	921.4
## Cheyenne, WY	1042.9	843.9	387.0	1773.7
##	Richmond, VA Olympia, WA Charleston, WV Madison, WI			
## Montgomery, AL	599.0	2241.3	484.7	758.4
## Juneau, AK	3423.7	999.6	3193.9	2673.8
## Phoenix, AZ	1910.1	1108.6	1695.7	1405.3
## Little Rock, AR	834.2	1872.5	635.0	597.4
## Sacramento, CA	2405.0	588.5	2176.5	1780.4
## Denver, CO	1510.5	1100.0	1278.9	882.6
## Hartford, CT	392.0	2766.4	543.0	916.8
## Dover, DE	154.3	2643.3	338.2	803.5
## Tallahassee, FL	613.0	2400.4	563.0	914.7
## Atlanta, GA	459.2	2293.8	350.8	698.5
## Honolulu, HI	4529.9	2606.8	4324.8	4029.1
## Boise, ID	2156.2	435.4	1922.1	1464.7
## Springfield, IL	683.6	1882.7	449.3	226.5
## Indianapolis, IN	499.0	2067.9	265.8	288.2
## Des Moines, IA	925.4	1642.3	691.7	253.0
## Topeka, KS	1000.5	1584.5	769.0	442.1
## Frankfort, KY	406.7	2164.3	176.9	417.1
## Baton Rouge, LA	894.2	2076.1	754.1	876.8
## Augusta, ME	628.4	2906.5	766.9	1073.8
## Annapolis, MD	112.5	2593.8	283.5	758.2
## Boston, MA	482.8	2848.7	640.0	1001.5
## Lansing, MI	527.4	2115.1	341.9	265.2
## Saint Paul, MN	994.7	1633.9	773.8	240.1
## Jackson, MS	782.7	2055.5	626.2	744.8
## Jefferson City, MO	806.2	1776.4	575.7	345.7
## Helena, MT	1987.4	594.9	1753.9	1259.5
## Lincoln, NE	1073.0	1494.8	838.9	427.9
## Carson City, NV	2312.3	569.6	2082.9	1680.7
## Concord, NH	508.0	2816.8	645.2	974.4
## Trenton, NJ	237.2	2670.0	396.8	822.2
## Santa Fe, NM	1561.3	1212.7	1341.3	1039.6
## Albany, NY	407.2	2700.2	522.7	853.7
## Raleigh, NC	137.5	2539.1	241.9	773.8
## Bismarck, ND	1424.9	1207.7	1197.6	673.6
## Columbus, OH	345.5	2232.6	134.1	409.4
## Oklahoma City, OK	1104.2	1599.2	889.9	687.6
## Salem, OR	2540.2	145.0	2306.1	1842.1
## Harrisburg, PA	191.6	2556.0	291.7	709.9
## Providence, RI	443.4	2833.7	606.9	984.5
## Columbia, SC	312.0	2456.5	301.7	774.5
## Pierre, SD	1334.0	1246.6	1101.7	603.8
## Nashville, TN	517.3	2109.9	318.9	497.4
## Austin, TX	1215.3	1796.1	1041.4	994.6
## Salt Lake City, UT	1892.7	740.9	1660.4	1239.2
## Montpelier, VT	535.5	2754.4	641.1	921.4
## Richmond, VA	0.0	2565.9	234.3	754.7
## Olympia, WA	2565.9	0.0	2331.6	1850.3
## Charleston, WV	234.3	2331.6	0.0	534.3
## Madison, WI	754.7	1850.3	534.3	0.0
## Cheyenne, WY	1514.1	1067.8	1280.6	853.3

```

##                               Cheyenne, WY
## Montgomery, AL           1179.7
## Juneau, AK                2003.3
## Phoenix, AZ               661.9
## Little Rock, AR            812.6
## Sacramento, CA             927.4
## Denver, CO                 97.1
## Hartford, CT              1755.7
## Dover, DE                 1605.4
## Tallahassee, FL             1343.3
## Atlanta, GA                1226.4
## Honolulu, HI               3202.9
## Boise, ID                  644.5
## Springfield, IL              833.2
## Indianapolis, IN            1023.3
## Des Moines, IA              612.3
## Topeka, KS                  518.9
## Frankfort, KY                1108.2
## Baton Rouge, LA              1048.4
## Augusta, ME                  1925.7
## Annapolis, MD                1553.4
## Boston, MA                  1845.0
## Lansing, MI                  1112.4
## Saint Paul, MN                692.0
## Jackson, MS                  1005.3
## Jefferson City, MO            712.8
## Helena, MT                  544.1
## Lincoln, NE                  445.1
## Carson City, NV                827.4
## Concord, NH                  1822.8
## Trenton, NJ                  1642.3
## Santa Fe, NM                  382.8
## Albany, NY                  1699.3
## Raleigh, NC                  1477.1
## Bismarck, ND                  448.9
## Columbus, OH                  1194.1
## Oklahoma City, OK                558.5
## Salem, OR                  1028.7
## Harrisburg, PA                1527.0
## Providence, RI                1824.1
## Columbia, SC                  1389.0
## Pierre, SD                  331.8
## Nashville, TN                1042.9
## Austin, TX                  843.9
## Salt Lake City, UT                387.0
## Montpelier, VT                1773.7
## Richmond, VA                  1514.1
## Olympia, WA                  1067.8
## Charleston, WV                1280.6
## Madison, WI                  853.3
## Cheyenne, WY                  0.0

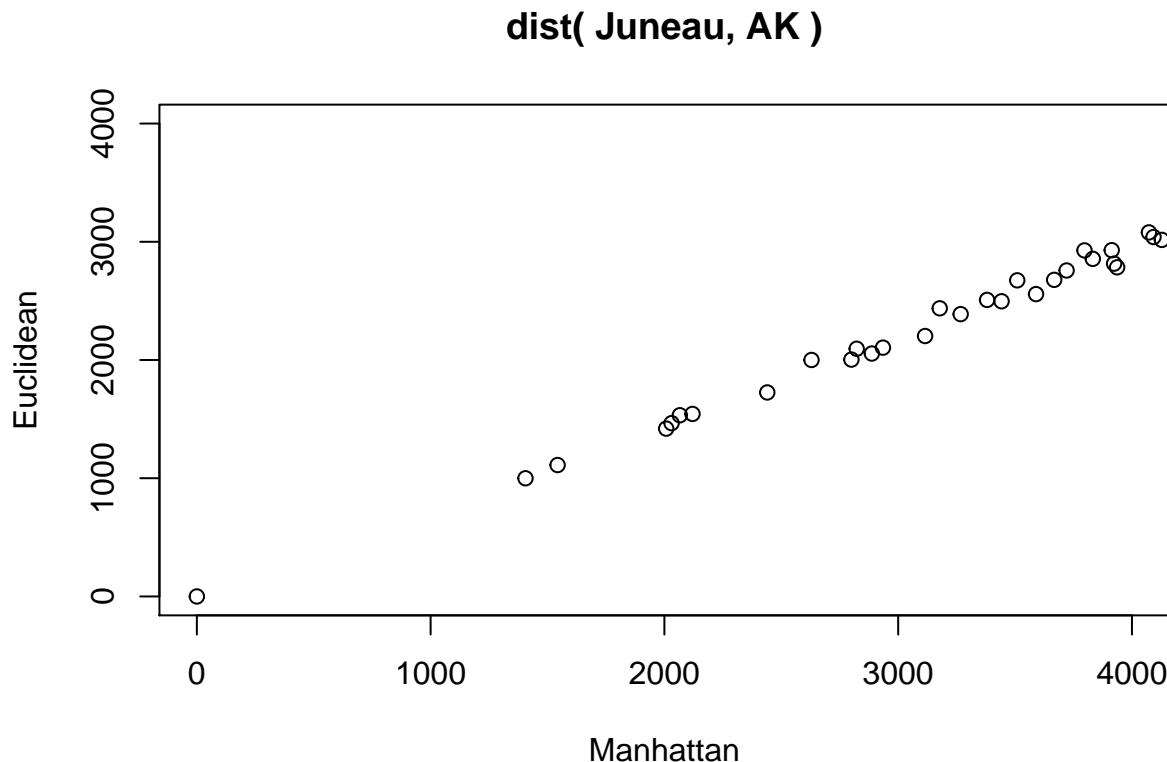
```

```
lookupPairwiseValue(dist.euclidean.df, "Juneau, AK", "Montgomery, AL");
```

```
## [1] 3179.8
```

You can compare the two with the code below (currently in comments).

```
x = dist.manhattan.df[,2]; # Juneau ... pick one location  
y = dist.euclidean.df[,2];  
  
my.lim = c(0, 4000);  
  
plot(x, y,  
      xlab="Manhattan",  
      ylab="Euclidean",  
      main="dist( Juneau, AK )",  
      xlim=my.lim,  
      ylim=my.lim);
```



```
plotXYwithBoxPlots(x, y,  
                     xlab="Manhattan",  
                     ylab="Euclidean",  
                     main="dist( Juneau, AK )",  
                     xlim=my.lim,  
                     ylim=my.lim);
```

[ What is the difference between these two calculations?

Are the results similar?

]

## HIERARCHICAL clustering as a function of distance

Aggregating or agglomerating data is typically called “clustering” and is generally considered to be a “unsupervised learning” method.

### Introduction

We use `hclust` to perform Hierarchical Clustering. The word “hierarchical” is used because the nature of the data is organized like a family genealogy. The bottom of the tree represents the descendants that eventually “link” to a common ancestor.

If you type `?hclust` you can review the parameter options which we explored in a notebook. `hclust` is primarily a function of `dist()` [distance], and we have just computed some distances, so we could try and apply `hclust` to our data to see if our state capitals will cluster into meaningful regions.

There are several agglomeration methods (“linkage”) one could choose from. Each method takes the `dist` [https://en.wikipedia.org/wiki/Hierarchical\\_clustering#Metric](https://en.wikipedia.org/wiki/Hierarchical_clustering#Metric) and performs some pairwise distance algorithm called a linkage criteria [https://en.wikipedia.org/wiki/Hierarchical\\_clustering#Linkage\\_criteria](https://en.wikipedia.org/wiki/Hierarchical_clustering#Linkage_criteria).

I generally use either the “complete” linkage method or the “ward.D2” linkage method. You can read help `?hclust` to better appreciate why: “A number of different clustering methods are provided. Ward’s minimum variance method aims at finding compact, spherical clusters. The complete linkage method finds similar clusters.”

If you are trying to link binary data (zeroes and ones) or genomic data (where the distances were computed using a genetic-distance algorithm), you may want to try the UPGMA approach: “average” or “centroid”.

### Analogy of Family

Since I am from a large family, I will make a family tree analogy. For me, I am the 5th of 11 siblings (5 brothers, 5 sisters). If I wanted to cluster the siblings in a pair-wise fashion, how would I begin?

First, I would ask, which other sibling is most like me? Since this is a pair-wise approach, and there are 11 siblings, maybe at the initial stage, I will not be paired with another sibling.

In fact, at least one will not be paired because the total number is 11. And maybe more than one will not be paired in the initial stage. Remember “similarity” is being defined based on some distance-linkage method. And to use this approach, “similarity” needs to numerical data.

At each stage, pair-wise joining occurs until there is nothing left to join. The tree contains all of the elements. Every element (branch) eventually joins the main branch (trunk) of the tree.

### Clustering U.S. capital cities based on latitude, longitude

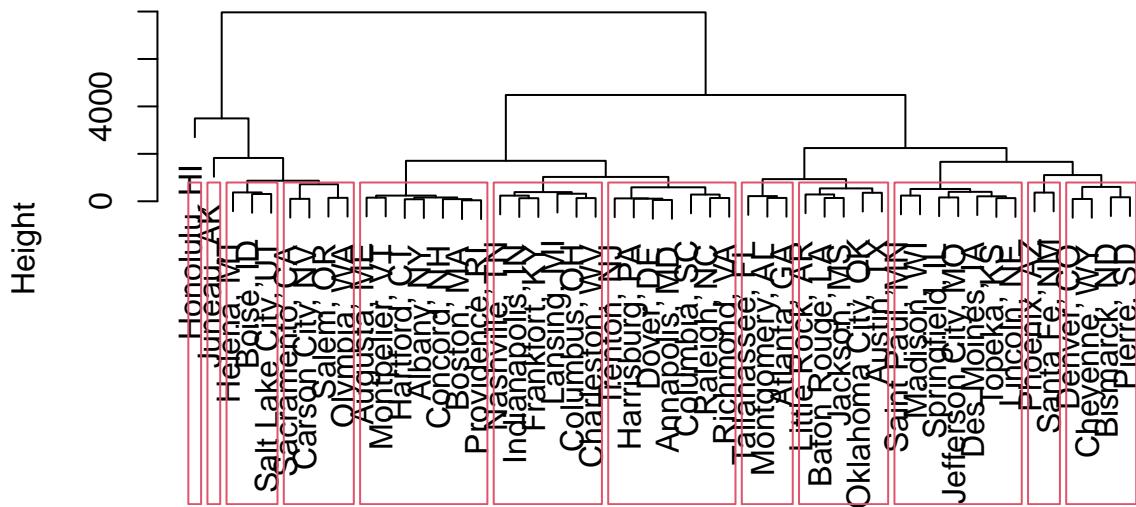
We already have some data for the U.S. capitals and have computed a Euclidean distance using a capital-city’s longitude and latitude. Let’s choose to cut the result into 12 agglomerations. Why 12? It was a choice based on my life experience and intuition. As I reflected on why, I did some external searching that validates a choice in that range [https://en.wikipedia.org/wiki/List\\_of\\_regions\\_of\\_the\\_United\\_States](https://en.wikipedia.org/wiki/List_of_regions_of_the_United_States). You certainly could run this analysis with another choice. It is exploratory, and your intuition matters.

Geographically, I am saying the capital-city does represent the state. An ideal representation may be in the center (centroid) of the state. Remember this when we see the linkages with “New York”, the city is Albany, not Manhattan.

```
## ward.D2
hclust.ward2.dist.euclidean = hclust(dist.euclidean, method="ward.D2");

plot( hclust.ward2.dist.euclidean,
      labels= myLabels );
rect.hclust( hclust.ward2.dist.euclidean, k=12 );
```

## Cluster Dendrogram



```
dist.euclidean  
hclust (*, "ward.D2")
```

```
## complete
#
#hclust.complete.dist.euclidean = hclust(dist.euclidean, method="complete");
#
#plot( hclust.ward2.dist.euclidean,
#      labels= myLabels );
#rect.hclust( hclust.ward2.dist.euclidean, k=12 );
```

### Understanding the cutree

In the above example, the tree was cut into 12 groups based on the “distance” formula used and based on the “agglomeration” linkage technique invoice. I likely should have used a “geo-spatial” distance, but we will see that mere “euclidean” distance seems to perform okay.

A fancy word for this statistical tree is a “dendrogram”. I call each element of the tree a branch. The smallest branches (twigs) are the fundamental elements, in this case the cities. Over time, they merge with other small branches, and so on.

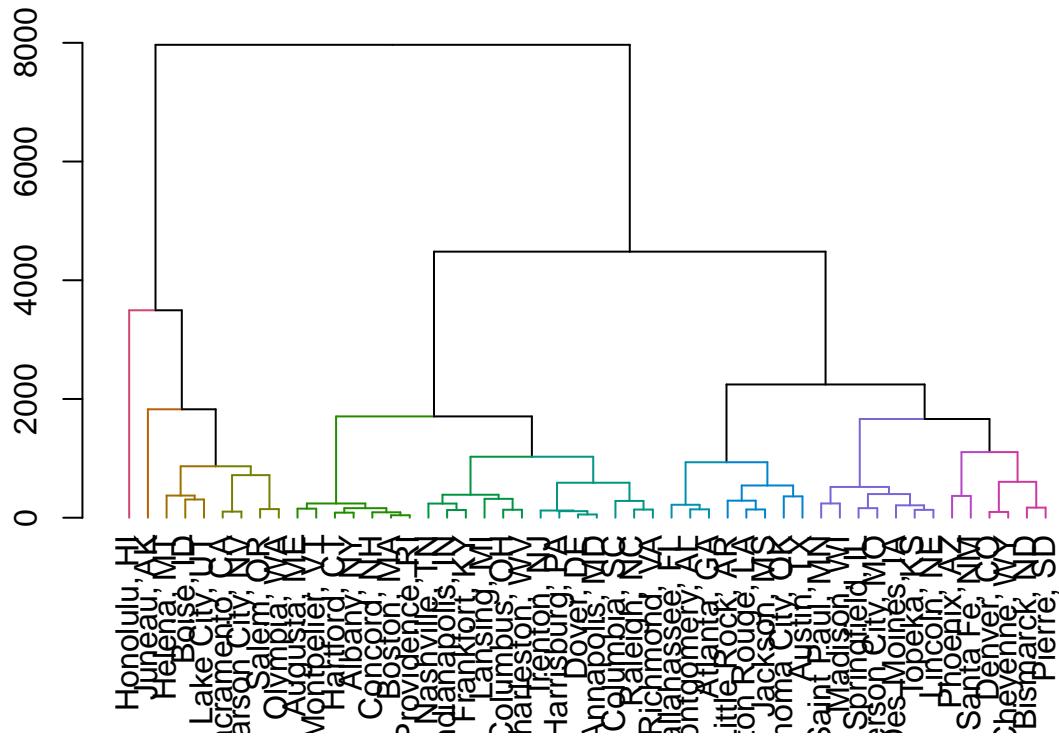
The relative height when this smallest branch merges with another branch demonstrates when the branch has found a similar pair-wise match (with another smallest branch or a merging branch). I call “Honolulu Hawaii” an isolate because the vertical height when it merges with another branch is the highest of all of the smallest branches (e.g., cities). “Juneau Alaska” is another isolate, but it does merge before “Hawaii”.

It would be nice if we could decompose this information and look at one `cutree` at a time. And color-code the distinctions. Using the function `plot.hclust.sub` we can do this.

```
source_url( paste0(path.github, "humanVerseWSU/R/functions-EDA.R") ); # EDA functions ...
## SHA-1 hash of file is dd72e464241952b23d5b08d2213099eccf7a86f6
```

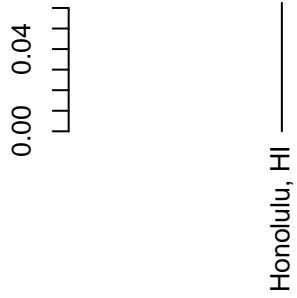
```
hclust.ward2.dist.euclidean$labels = myLabels;
plot.hclust.sub(hclust.ward2.dist.euclidean, k=12);

## Registered S3 method overwritten by 'dendextend':
##   method      from
##   text.pvclust pvclust
```

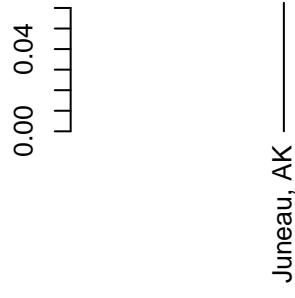


```
## [1] "Pruning 1 of 12"  
## [1] "Pruning 2 of 12"  
## [1] "Pruning 3 of 12"  
## [1] "Pruning 4 of 12"  
## [1] "Pruning 5 of 12"  
## [1] "Pruning 6 of 12"  
## [1] "Pruning 7 of 12"  
## [1] "Pruning 8 of 12"  
## [1] "Pruning 9 of 12"  
## [1] "Pruning 10 of 12"  
## [1] "Pruning 11 of 12"  
## [1] "Pruning 12 of 12"
```

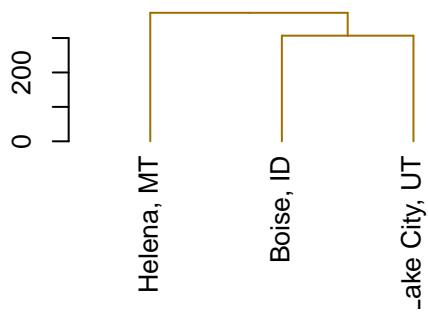
**SubTree number 1**



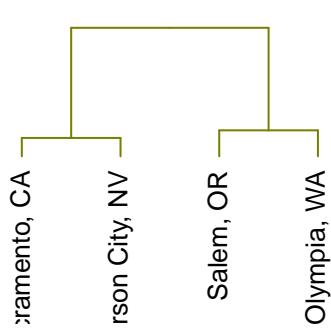
**SubTree number 2**



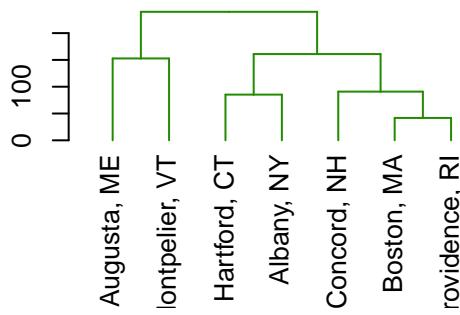
**SubTree number 3**



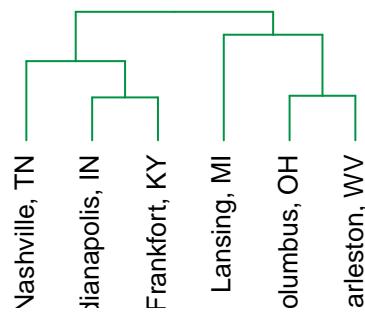
**SubTree number 4**



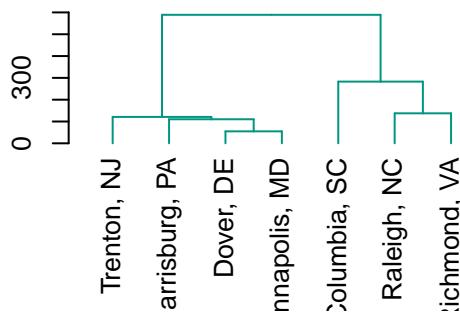
**SubTree number 5**



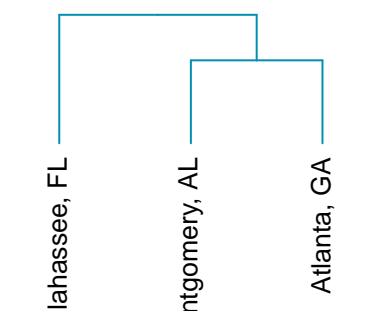
**SubTree number 6**

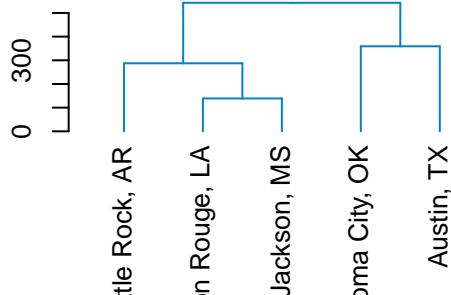
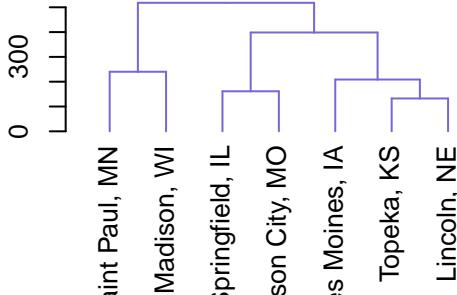
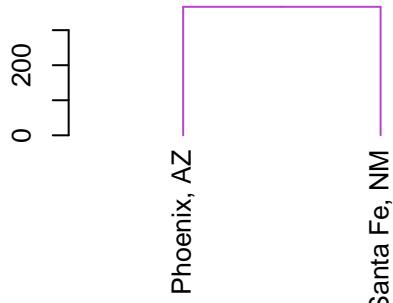
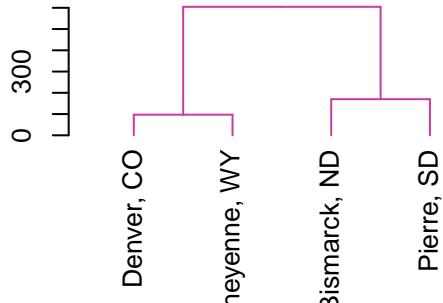


**SubTree number 7**



**SubTree number 8**



**SubTree number 9****SubTree number 10****SubTree number 11****SubTree number 12**

```
#plot.hclust.sub(hclust.complete.dist.euclidean, k=12);
```

### (10 points) Review one clustering tree (dendrogram)

Choose either `hclust.ward2.dist.euclidean` or `hclust.complete.dist.euclidean` and review how the U.S. state capitals are clustered. [I commented out one form, so you will have to re-run if you want to select that one.]

Comment on the “face validity” of this approach based on your understanding about how the U.S. regions are defined? Are the North/South Dakotas together? What about the North/South Carolinas? What about the Pacific Northwest? While living in Kentucky, some people called the area “Kentuckiana” meaning Kentucky/Indiana. Does that show up? Also note anything that seems peculiar.

### Additional remarks about `hclust`

I find `hclust` to be a nice initial perusal of the data.

If you want to understand the stability of a particular `hclust` to use it for something other than an “initial perusal of the data,” I would recommend `pvclust` which I introduced in the weekly notebooks. It is often used in peer-reviewed research, as it provides a p-value of sorts regarding the **stability** of the `hclust` structure.

## GENERIC clustering

Aggregating or agglomerating data is typically called “clustering”. In exploration, we can create some generic clustering techniques. Below we will create two adhoc clustering rules.

## Arbitrary Aggregation

Recall the “movie dataset” with “Will Smith” and “Denzel Washington”. We have a collection of movies, and how much money each movie made at the box office. We could organize those movies by some arbitrary rules. For example:

- Cluster 1: NA. We have missing data regarding the money. So let’s put all movies that are NA into that cluster.
- Cluster 2: Under a million dollars
- Cluster 3: 1-4.99... million dollars (greater than or equal to one, but less than 5)
- Cluster 4: 5-49.99...
- Cluster 5: 50+

```
library(plyr)
library(dplyr)
library(devtools);
source_url( paste0(path.mshaffer, "will") );
```

(5 points) Movie Aggregation [Arbitrary] for Will and Denzel

```
## SHA-1 hash of file is 3c1c97d961577e9b47a12faa20dca74bfe755c87
source_url( paste0(path.mshaffer, "denzel") );
```

```
## SHA-1 hash of file is 6692d8c5629db1ae023691bb55de2664a48cdde0
```

```
movies.50 = rbind(will$movies.50, denzel$movies.50);
#View(denzel$movies.50)
unique(movies.50$ttid); # are they in any shared movies ???
```

```
## [1] "tt0480249" "tt1386697" "tt0116629" "tt0119654" "tt0343818" "tt0454921"
## [7] "tt0448157" "tt0120912" "tt1409024" "tt0386588" "tt0814314" "tt0112442"
## [13] "tt0172156" "tt0120660" "tt6139732" "tt0145660" "tt2381941" "tt1815862"
## [19] "tt1596350" "tt1229340" "tt5519340" "tt0307453" "tt1155076" "tt0120891"
## [25] "tt0120783" "tt1502397" "tt0248667" "tt4682786" "tt3322364" "tt1025100"
## [31] "tt0114558" "tt0300051" "tt0284490" "tt0146984" "tt1837709" "tt0338466"
## [37] "tt0947802" "tt1823664" "tt0268397" "tt1082886" "tt5814534" "tt3721964"
## [43] "tt0416212" "tt0108149" "tt0328099" "tt0167427" "tt0466839" "tt0107478"
## [49] "tt7255568" "tt0466856" "tt0765429" "tt0139654" "tt0454848" "tt0455944"
## [55] "tt0328107" "tt1907668" "tt0453467" "tt1037705" "tt0107818" "tt1599348"
## [61] "tt0210945" "tt1272878" "tt1111422" "tt0477080" "tt2404435" "tt0145681"
## [67] "tt3766354" "tt0251160" "tt0097441" "tt0368008" "tt0112740" "tt2671706"
## [73] "tt0174856" "tt0104797" "tt0107798" "tt0119099" "tt0133952" "tt0313443"
## [79] "tt0427309" "tt0115956" "tt0107616" "tt0124718" "tt0168786" "tt6000478"
## [85] "tt0114857" "tt0112857" "tt0102789" "tt0092804" "tt0100168" "tt0117372"
## [91] "tt0088146" "tt0097880" "tt0102456" "tt0099750" "tt0091786" "tt0082138"
## [97] "tt0097373" "tt4283892" "tt1698652" "tt0118783"
```

```
loadInflationData();
#View(denzel$movies.50)
```

```
movies.50 = standardizeDollarsInDataFrame(movies.50,
                                           2000,
                                           "millions",
                                           "year",
                                           "millionsAdj2000");
```

```

movies.50$cluster.arbitrary = NA;

## you do something here ..

# (1) populate cluster.arbitrary
# (2) summarize how many movies live in each (table count)

movies.50$cluster.arbitrary[is.na(movies.50$millionsAdj2000)] = 1

movies.50$cluster.arbitrary[movies.50$millionsAdj2000 < 1] = 2

movies.50$cluster.arbitrary[movies.50$millionsAdj2000 < 5 & movies.50$millionsAdj2000 >= 1] = 3

movies.50$cluster.arbitrary[movies.50$millionsAdj2000 >= 5 & movies.50$millionsAdj2000 < 50] = 4

movies.50$cluster.arbitrary[movies.50$millionsAdj2000 >= 50 & movies.50$millionsAdj2000 >= 50] = 5

View(movies.50)

count(movies.50, "cluster.arbitrary")

##   cluster.arbitrary freq
## 1                  1    5
## 2                  2    4
## 3                  3    2
## 4                  4   38
## 5                  5   51

```

## Aggregating using Quantiles

John Tukey emphasized that ordering the data and then splitting it based on the ordering was a fundamental premise of exploratory data analysis.

**Tukey's Summary Data** John Tukey proposed five elements as primary data for analysis.

- the minimum `min`
- the maximum `max`

Sorting the data makes it easiest to find these data, and will be useful to find the other three exploratory summary features.

This is what I would call “slice and dice”. The data is cut in half, and the value of that middle “cutting point” is the `Q2` which we call the `median`.

Next, the lower half could also be cut in half, and the value of that middle “cutting” point is `Q1`.

Then, the upper half could also be cut in half, and the value of that middle “cutting” point is `Q3`.

A common metric derived from this “median-split” procedure is called the interquartile range `IQR` which is defined as the distance between `Q3` and `Q1`. It literally represents the middle 50% of the data; 50% of the elements of the dataset are between `Q3` and `Q1`.

```

x = 1:99;
length(x);

```

## Quartile Example

```

## [1] 99
median(x);

## [1] 50
x[50];

## [1] 50
median(x[1:49]);

## [1] 25
x[25];

## [1] 25
median(x[51:99]);

## [1] 75
x[75];

## [1] 75
# probability-approach ...
# algorithm: the default type=7
stats::quantile(x, prob = c(0.25, 0.5, 0.75), type=1);

## 25% 50% 75%
## 25 50 75

```

Algorithms address various issues associated with dividing numbers and whether or not to include the dividing number in the subset division, but the principle holds.

We can generalize this idea by not always cutting the data in half (median-split as  $n=2$ , median-median-split as  $n=4$ ). Instead, we could cut by tens (we call them deciles). Or we could cut by hundreds (we call them centiles). The function `quantile` performs this operation, and if you dig into the `doStatsSummary` function used in this course, you can see its application.

```

movies.50$cluster.deciles = NA;
str(movies.50);

```

### (5 points) Movie Aggregation [Decile] for Will and Denzel

```

## 'data.frame':   100 obs. of  14 variables:
## $ rank           : num  1 2 3 4 5 6 7 8 9 10 ...
## $ title          : chr  "I Am Legend" "Suicide Squad" "Independence Day" "Men in Black" ...
## $ ttid           : chr  "tt0480249" "tt1386697" "tt0116629" "tt0119654" ...
## $ year           : num  2007 2016 1996 1997 2004 ...
## $ rated          : chr  "PG-13" "PG-13" "PG-13" "PG-13" ...
## $ minutes         : num  101 123 145 98 115 117 92 88 106 118 ...
## $ genre           : chr  "Action, Adventure, Drama" "Action, Adventure, Fantasy" "Action, Adventure, Fantasy" ...
## $ ratings         : num  7.2 6 7 7.3 7.1 8 6.4 6.2 6.8 6.6 ...
## $ metacritic      : num  65 40 59 71 59 64 49 49 58 58 ...
## $ votes           : num  675193 588111 520657 507618 491489 ...
## $ millions        : num  256 325 306 251 145 ...
## $ millionsAdj2000 : num  213 233 336 269 132 ...
## $ cluster.arbitrary: num  5 5 5 5 5 5 5 5 5 ...

```

```

## $ cluster.deciles : logi NA NA NA NA NA NA ...
# 1 number of NA's
sum(is.na(movies.50$cluster.deciles))

## [1] 100
#View(movies.50)

## you do something here ...

#stats::quantile(x, prob=seq(0.1,0.9,by=0.1), type=1 );

# (1) how many NA's are there ... keep them NA's
# (2) for the rest of the data, break it up into deciles
# (3) $cluster.deciles for a given movie should be NA, 1, 2, 3, ... 10
# (4) summarize how many movies live in each (table count)

```

## CENTROID clustering (k-means) as a function of distance

### Introduction

Rather than clustering on distance-linkage in a pair-wise fashion, we can cluster based on randomly selecting just **k** points in our data and begin identifying their nearest neighbors using some distance approach.

For example, if **k**=3, we would randomly select three of our data points. We would then compute the distances from all of the remaining points to these 3 anchor points. The points that are closest to a given anchor will be assigned to that anchor. At the end of the stage, we now have new data, so a new centroid is determined. At this point, the centroid <https://en.wikipedia.org/wiki/Centroid> is likely not one of our data points, but a location within the given centroid cluster. In the “naive” approach, you merely take an average (mean) of all the members of your cluster. More advanced approaches (the default “Hartigan-Wong” of **kmeans**) utilize deviations from the average, called a sum-of-squares approach. This is why in our **kmeans-notebook** we analyzed the **wss** to ascertain how many clusters **k** should we use.

Regardless, after the new centroids (centers) for the clusters are determined, the process iterates. All distances are computed from all points to the new centroids; points are assigned to a given centroid cluster (in this example: 1, 2, 3); a new centroid center is computed, and we repeat the process until a stopping rule is reached: maybe we have exhausted the number of iterations allowed (**iter.max** parameter of **kmeans**)? Or maybe we are not changing membership of any of the data points? Or maybe we have met some objective (like **wss**)?

It is possible to get a **kmeans** result by merely starting with 3 different random points. In general, **kmeans** is fast (and our computers are so much faster than the computers of 1990: the first computer I built in 1995 had 32MB of RAM, a Pentium processor <https://en.wikipedia.org/wiki/Pentium> and a 900MB Cheetah hard-drive).

Anyway, we can utilize the parameter **nstart** to try many different starting values, and let the program identify the best, most consistent solution.

### My recommendations

I would recommend the default algorithm Hartigan-Wong with **iter.max**=100 and **nstart**=100. You can test the timings from the default values: **iter.max**=10 and **nstart**=1. Since the data is likely multidimensional **stars** are the best way to summary the results and membership of **kmeans**. Please see the “kmeans-notebook” for examples.

## WIKIPEDIA CLIMATE DATA

For the 50 U.S. cities, we harvested climate data. In the “Wikipedia” notebook, details of that data provenance were outlined. If we want to compare the cities using the climate data, we have to build a matching dataframe, which means we have to select features that exist in each city’s climate data set.

There are four temperature features that are always present:

- Record high F (C) ... we will call it “high.max”
- Average high F (C) ... we will call it “high.avg”
- Average low F (C) ... we will call it “low.avg”
- Record low F (C) ... we will call it “low.max” [probably not the best name choice, but it is parallel in form to the first element]

Additionally, for precipitation we have:

- Average precipitation inches (mm) ... we will call it “rain”
- Average snowfall inches (cm) ... we will call it “snow”

For each of these features we have 12 months of data. This is a nice dataset. Let’s see what we can do with it.

**Basic Background Research** We should begin by doing a bit of peripheral research on the topic, to gain “domain knowledge” so we know what to do with the data. A few elements that would benefit.

<https://www.forbes.com/sites/brianbrettschneider/2018/07/08/when-does-the-hottest-day-of-the-year-usually-occur/#78141f47548c>

**Source:** <https://bit.ly/359HAnY>

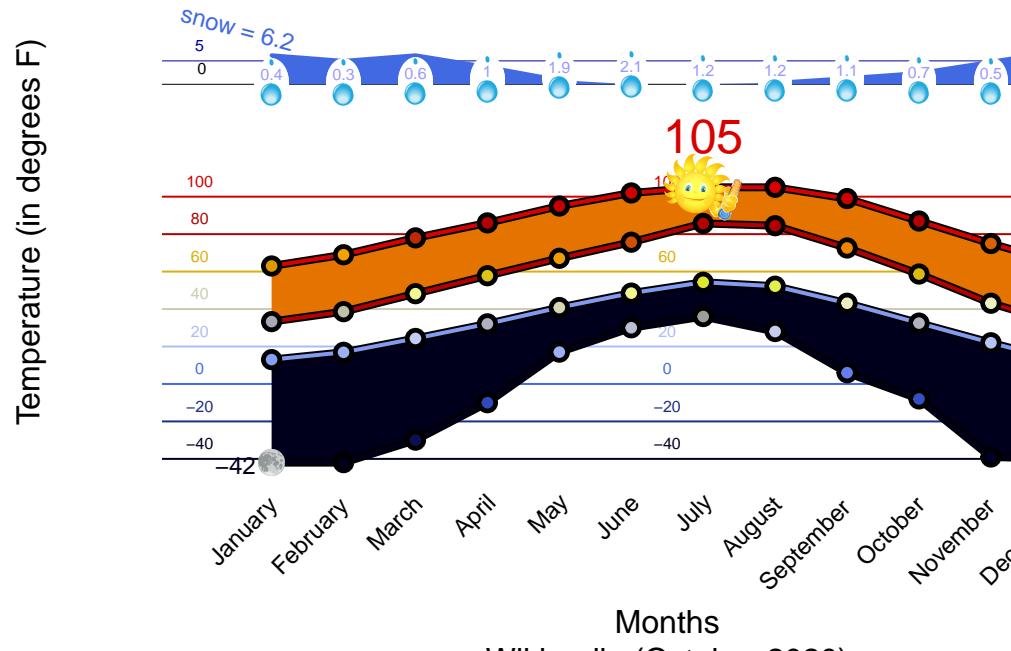
<https://www.climate.gov/news-features/featured-images/whats-coldest-day-year>

**One Graph** When graphing data to visualize, it is essential that you keep the scales uniform so quick-visual comparisons are accurate. I gave you a task to practice the idea of creation that “one informative” research graphic. And I now present my version for you to use and critique based on your efforts. I am a plot guy, so some of you may have a different ‘ggplot2 type solution. Ultimately, the intent of this graphic is to best summarize the data in a meaningful way for exploratory analysis.

```
climate = utils::read.csv( paste0(path.mshaffer, "_data_/state-capitals/final/state-capitals-climatedata.csv"))

plotTemperatureFromWikipediaData(climate, city.key="capital", city.val="Helena");
```

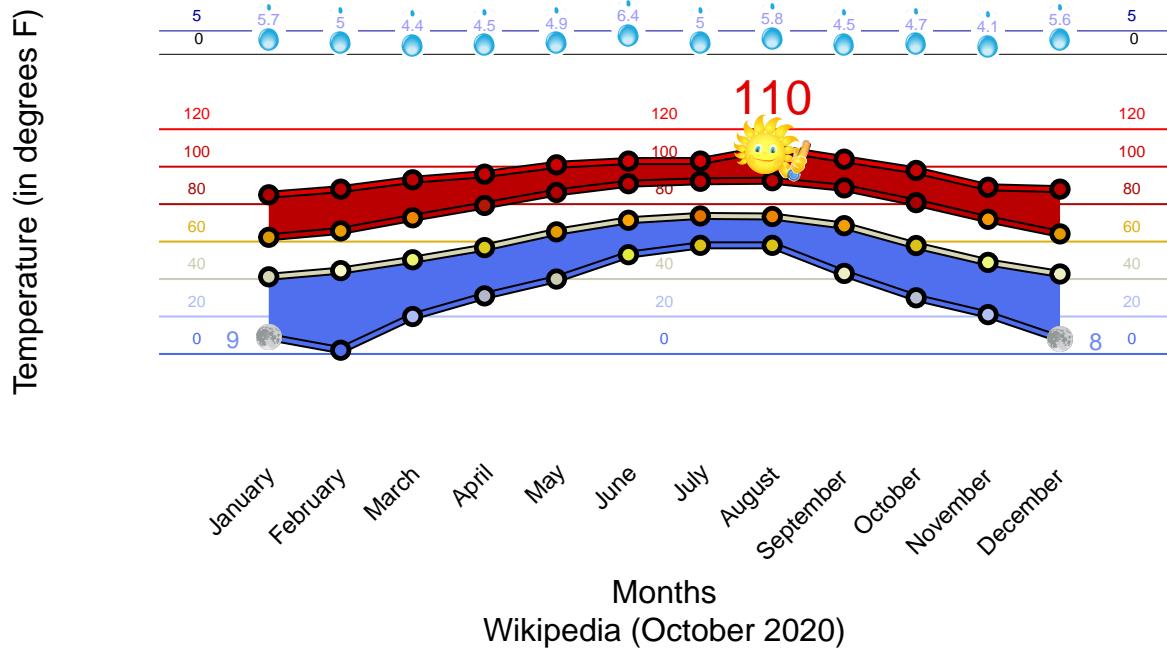
## Helena, Montana



(5 points) One Research Graph

```
plotTemperatureFromWikipediaData(climate, city.key="capital", city.val="Baton Rouge");
```

## Baton Rouge, Louisiana



[ What do you like about this graphic?

What do you dislike?

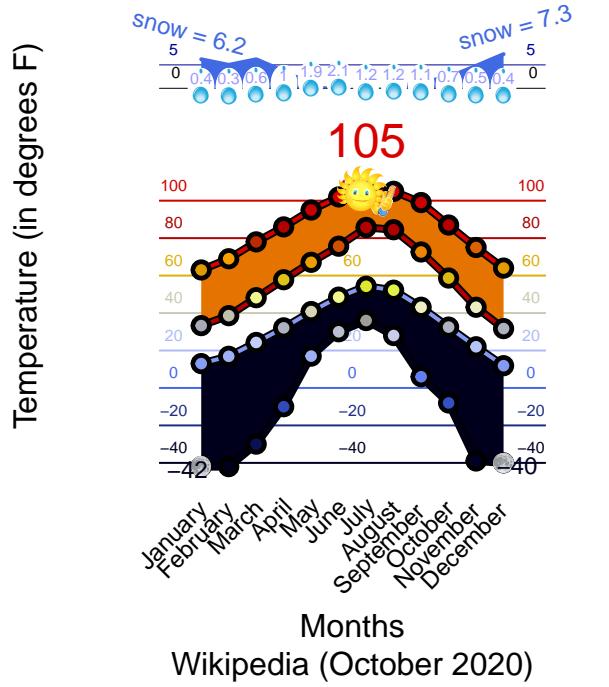
Is it aesthetically pleasing? Is it functional?

]

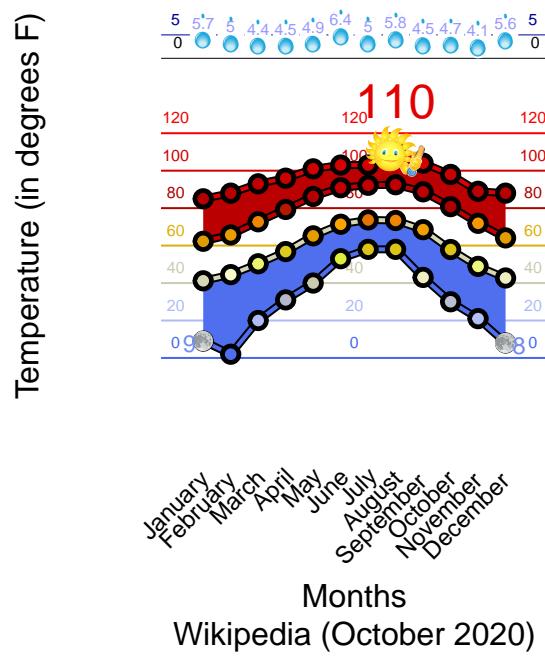
We can achieve a side-by-side comparison using the function described below. The first city will be graphed on the left, the second city on the right.

```
compareTwoCitiesClimates(climate, city.key="capital", city.1="Helena", city.2="Baton Rouge");
```

## Helena, Montana



## Baton Rouge, Louisiana



[ What do you like about this graphic?

What do you dislike?

Are the y-axis the same scale? Are the visible gridlines for each the same?

What is the difference between rain and snow on the graphic? Was that a good approach? How would you have done it?

]

**(5 points) One Publication Graph** We are in exploration, so the “one” research graphic may be very different than the “one” formal graphic designed for a client. Typically, the final graphic needs to meet certain criteria:

- Very pleasing aesthetically
- Interactive if possible
- Live data feeds if possible
- Served in a secure, safe, private location (if required by the client)

To demonstrate the differences, I created a mockup of our 50 U.S. cities and put it into a nice finalized product form called “highcharts”.

[http://md5.mshaffer.com/WSU\\_STATS419/\\_EXAMPLES\\_/fiddle\\_usmap/](http://md5.mshaffer.com/WSU_STATS419/_EXAMPLES_/fiddle_usmap/)

It pulls data in real time (using AJAX) to grab the weather at the latitudes/longitudes we defined in our Wikipedia notebook.

- You can use your mouse to draw a box to zoom in.

- The third-wheel on the mouse also helps you zoom in/out.
- Hold down CNTRL with your left hand and use your mouse key to drag the map. It seems to only “pan” in the x-direction at the moment.
- The data in the popup displayed can be customized. I report the temperature in Celsius/Fahrenheit and also display the population data we gathered from Wikipedia.

Once you have a template built, it is rather easy to modify it. Here I changed the background map, and all of the data/features stay the same:

[http://md5.mshaffer.com/WSU\\_STATS419/\\_EXAMPLES\\_/fiddle\\_usmap/world.html](http://md5.mshaffer.com/WSU_STATS419/_EXAMPLES_/fiddle_usmap/world.html)

### Which Features to Include in the Analysis

- months, you can pick all of them 1:12 or maybe just one month per season (April, July, October, January)
- X, depending on what you chose for months, you can now select what climate columns you want to use
  - Some of Temperature Data
  - All of Temperature Data
  - Precipitation Data
  - Everything (All of Temperature Data, Precipitation Data)

If we want to cluster cities, which decisions seem best? Why? As you can see from the code below, you just comment out two options, and can quickly rerun the analysis.

- WHICH MONTHS
- WHICH COLUMNS

```
climate = utils::read.csv( paste0(path.mshaffer, "_data_/state-capitals/final/state-capitals-climatedata.csv"))

##### WHICH MONTHS #####
##### months = 1:12; # all the data #####
months = c(1,4,7,10); # one month of each of the four seasons
#####

month.abb; # ?month.abb

WHICH MONTHS & WHICH COLUMNS

## [1] "Jan" "Feb" "Mar" "Apr" "May" "Jun" "Jul" "Aug" "Sep" "Oct" "Nov" "Dec"
month.name;

## [1] "January"   "February"   "March"      "April"       "May"        "June"
## [7] "July"       "August"      "September"  "October"     "November"   "December"
month.name[months]; # these are the names of the months you are selecting ...

## [1] "January"   "April"      "July"       "October"
# this function would allow us to use different months as criteria and different climate-data keys. It

climate.df = buildClimateDataFrame(climate, months, keys=c("Record high F (C)", "Average high F (C)", "A
climate.df;
```

##	state	capital	st	labels	highmax.	Jan						
## 1	Alabama	Montgomery	AL	Montgomery,	AL	83						
## 23	Alaska	Juneau	AK	Juneau,	AK	60						
## 39	Arizona	Phoenix	AZ	Phoenix,	AZ	88						
## 59	Arkansas	Little Rock	AR	Little Rock,	AR	83						
## 79	California	Sacramento	CA	Sacramento,	CA	79						
## 94	Colorado	Denver	CO	Denver,	CO	76						
## 117	Connecticut	Hartford	CT	Hartford,	CT	72						
## 141	Delaware	Dover	DE	Dover,	DE	77						
## 162	Florida	Tallahassee	FL	Tallahassee,	FL	83						
## 182	Georgia	Atlanta	GA	Atlanta,	GA	79						
## 205	Hawaii	Honolulu	HI	Honolulu,	HI	88						
## 225	Idaho	Boise	ID	Boise,	ID	63						
## 248	Illinois	Springfield	IL	Springfield,	IL	73						
## 265	Indiana	Indianapolis	IN	Indianapolis,	IN	71						
## 289	Iowa	Des Moines	IA	Des Moines,	IA	67						
## 311	Kansas	Topeka	KS	Topeka,	KS	78						
## 334	Kentucky	Frankfort	KY	Frankfort,	KY	80						
## 350	Louisiana	Baton Rouge	LA	Baton Rouge,	LA	85						
## 365	Maine	Augusta	ME	Augusta,	ME	61						
## 381	Maryland	Annapolis	MD	Annapolis,	MD	77						
## 399	Massachusetts	Boston	MA	Boston,	MA	74						
## 423	Michigan	Lansing	MI	Lansing,	MI	66						
## 446	Minnesota	Saint Paul	MN	Saint Paul,	MN	57						
## 458	Mississippi	Jackson	MS	Jackson,	MS	85						
## 476	Missouri	Jefferson City	MO	Jefferson City,	MO	79						
## 490	Montana	Helena	MT	Helena,	MT	63						
## 509	Nebraska	Lincoln	NE	Lincoln,	NE	73						
## 532	Nevada	Carson City	NV	Carson City,	NV	72						
## 552	New Hampshire	Concord	NH	Concord,	NH	72						
## 574	New Jersey	Trenton	NJ	Trenton,	NJ	73						
## 597	New Mexico	Santa Fe	NM	Santa Fe,	NM	65						
## 617	New York	Albany	NY	Albany,	NY	71						
## 641	North Carolina	Raleigh	NC	Raleigh,	NC	80						
## 665	North Dakota	Bismarck	ND	Bismarck,	ND	63						
## 688	Ohio	Columbus	OH	Columbus,	OH	74						
## 712	Oklahoma	Oklahoma City	OK	Oklahoma City,	OK	83						
## 734	Oregon	Salem	OR	Salem,	OR	68						
## 754	Pennsylvania	Harrisburg	PA	Harrisburg,	PA	73						
## 776	Rhode Island	Providence	RI	Providence,	RI	70						
## 800	South Carolina	Columbia	SC	Columbia,	SC	84						
## 823	South Dakota	Pierre	SD	Pierre,	SD	68						
## 837	Tennessee	Nashville	TN	Nashville,	TN	78						
## 861	Texas	Austin	TX	Austin,	TX	90						
## 885	Utah	Salt Lake City	UT	Salt Lake City,	UT	63						
## 908	Vermont	Montpelier	VT	Montpelier,	VT	66						
## 925	Virginia	Richmond	VA	Richmond,	VA	81						
## 949	Washington	Olympia	WA	Olympia,	WA	64						
## 968	West Virginia	Charleston	WV	Charleston,	WV	81						
## 986	Wisconsin	Madison	WI	Madison,	WI	58						
## 1007	Wyoming	Cheyenne	WY	Cheyenne,	WY	70						
##	highmax.	Apr	highmax.	Jul	highmax.	Oct	highavg.	Jan	highavg.	Apr	highavg.	Jul
## 1		94		107		102		57.4		76.6		92.1
## 23		72		89		68		34.6		49.1		63.4

## 39	105	121	107	67.2	85.2	106.1
## 59	95	112	98	50.5	73.1	92.5
## 79	98	114	102	54.4	72.7	93.3
## 94	90	105	90	44.0	61.5	89.4
## 117	96	103	91	34.5	60.5	84.5
## 141	97	104	95	43.4	65.7	87.0
## 162	95	104	95	63.5	79.9	92.1
## 182	93	105	98	52.3	72.5	89.1
## 205	91	94	94	80.1	82.7	87.9
## 225	92	111	94	37.8	62.3	91.2
## 248	90	112	93	34.8	64.6	86.2
## 265	90	106	92	35.6	63.4	85.0
## 289	93	110	95	31.0	62.3	85.7
## 311	97	114	97	39.9	66.7	89.5
## 334	95	111	98	41.5	66.5	87.3
## 350	96	103	98	62.3	79.3	92.2
## 365	90	99	85	27.6	53.1	79.2
## 381	95	105	92	42.7	63.9	85.8
## 399	94	104	90	35.8	55.6	81.4
## 423	88	103	90	30.1	57.8	82.4
## 446	93	105	88	26.0	58.0	85.0
## 458	94	107	98	56.1	75.9	91.6
## 476	96	112	96	39.9	66.7	88.3
## 490	86	105	87	33.3	57.8	85.7
## 509	97	115	98	35.4	64.3	89.0
## 532	88	107	93	45.2	62.7	89.6
## 552	95	102	92	30.8	57.4	82.3
## 574	93	106	94	39.0	61.4	85.3
## 597	84	101	87	43.5	64.7	85.9
## 617	93	104	91	30.6	58.3	82.3
## 641	95	105	100	50.9	72.4	90.2
## 665	93	114	95	23.4	57.0	84.7
## 688	90	106	94	36.5	63.5	84.9
## 712	100	110	97	49.7	72.3	93.9
## 734	93	108	93	47.7	61.1	82.0
## 754	93	107	97	37.0	62.4	85.5
## 776	98	102	88	37.4	58.6	82.8
## 800	96	107	101	56.0	76.3	92.7
## 823	98	117	98	30.0	59.7	88.8
## 837	91	107	99	46.9	70.5	89.3
## 861	99	109	100	61.5	79.8	95.6
## 885	89	107	89	37.4	61.6	92.6
## 908	90	97	84	26.4	53.3	78.5
## 925	96	105	99	47.4	70.3	89.7
## 949	88	104	90	45.9	58.9	76.8
## 968	96	108	96	42.5	67.7	85.2
## 986	94	107	90	26.4	57.3	81.6
## 1007	84	100	85	39.5	54.9	83.4
##	highavg.Oct	lowavg.Jan	lowavg.Apr	lowavg.Jul	lowavg.Oct	lowmin.Jan
## 1	78.3	35.7	51.6	71.5	53.5	0
## 23	48.4	26.2	35.3	51.4	39.0	-20
## 39	88.5	45.6	60.2	83.5	64.8	16
## 59	74.8	31.2	51.0	73.2	52.6	-8
## 79	77.9	40.7	49.0	60.9	52.8	19

## 94	65.3	17.4	33.3	58.9	36.6	-29	
## 117	63.1	17.7	38.4	62.7	41.1	-26	
## 141	68.8	27.1	44.3	68.4	48.7	-7	
## 162	81.4	39.0	52.3	72.0	57.3	6	
## 182	72.7	34.3	51.5	71.3	54.0	-8	
## 205	86.7	66.3	69.4	74.5	73.4	52	
## 225	64.8	24.7	39.3	60.4	40.9	-28	
## 248	66.4	18.7	42.4	65.4	43.8	-22	
## 265	65.3	20.5	42.7	65.8	44.7	-27	
## 289	63.1	14.3	41.1	66.8	43.0	-30	
## 311	68.4	19.6	43.5	68.4	44.7	-23	
## 334	69.5	21.9	40.5	63.8	43.0	-27	
## 350	80.8	41.2	56.8	73.7	57.9	9	
## 365	57.2	11.0	34.6	59.9	39.6	-33	
## 381	66.3	29.1	45.8	71.2	50.5	-8	
## 399	61.4	22.2	40.6	65.4	46.5	-13	
## 423	59.9	16.8	37.0	60.6	40.7	-29	
## 446	59.0	7.0	38.0	64.0	41.0	-29	
## 458	77.2	35.3	52.2	71.6	53.1	-5	
## 476	68.5	20.9	43.8	68.1	44.9	-23	
## 490	58.7	13.0	32.1	54.3	32.5	-42	
## 509	65.8	13.8	38.8	66.1	40.6	-33	
## 532	67.9	21.7	33.9	52.2	34.6	-27	
## 552	60.5	10.4	32.7	57.7	35.8	-35	
## 574	65.0	23.2	41.0	66.0	44.2	-13	
## 597	66.5	17.5	32.3	54.4	35.5	-14	
## 617	59.8	14.5	37.3	61.4	39.6	-28	
## 641	72.6	31.0	48.0	69.9	49.8	-9	
## 665	57.5	2.2	30.7	57.4	32.2	-45	
## 688	65.1	22.6	42.6	65.5	45.0	-22	
## 712	73.4	28.8	49.7	72.2	51.6	-11	
## 734	64.1	34.7	39.6	53.1	42.3	-10	
## 754	64.1	22.8	41.9	66.3	44.6	-22	
## 776	63.3	21.0	39.6	64.2	43.9	-13	
## 800	76.1	33.7	50.4	71.6	52.1	-1	
## 823	61.0	9.8	34.2	61.9	36.4	-33	
## 837	71.7	28.4	47.5	69.5	48.9	-17	
## 861	81.8	41.5	58.6	74.4	60.6	-2	
## 885	64.7	21.6	39.5	64.7	41.3	-22	
## 908	56.0	7.0	31.5	55.7	35.3	-34	
## 925	71.0	28.3	46.1	68.9	48.3	-12	
## 949	60.2	33.7	37.7	50.8	40.5	-8	
## 968	67.7	26.3	44.5	65.7	45.4	-16	
## 986	58.9	11.1	35.8	61.0	38.8	-37	
## 1007	58.8	18.0	30.8	55.5	33.9	-38	
##	lowmin.Apr	lowmin.Jul	lowmin.Oct	rain.Jan	rain.Apr	rain.Jul	rain.Oct
## 1	28	59	26	4.65	4.02	5.24	2.92
## 23	12	39	13	7.98	4.64	5.44	13.23
## 39	35	63	34	0.91	0.28	1.05	0.58
## 59	28	54	27	3.55	5.14	3.27	4.91
## 79	34	47	34	3.63	1.36	0.02	1.06
## 94	-2	42	-2	0.41	1.71	2.16	1.02
## 117	9	44	17	3.23	3.72	4.18	4.37
## 141	14	45	25	3.41	3.88	4.09	3.42

## 162	29	57	29	4.34	3.06	7.17	3.23
## 182	25	53	28	4.20	3.36	5.27	3.41
## 205	56	63	61	0.00	0.00	0.00	0.00
## 225	11	35	11	1.24	1.23	0.33	0.75
## 248	16	48	13	1.82	3.51	3.94	3.15
## 265	18	46	20	2.66	3.81	4.55	3.12
## 289	9	47	7	1.00	3.86	4.47	2.64
## 311	10	43	16	0.86	3.53	3.82	3.03
## 334	16	48	20	3.70	3.74	4.14	2.53
## 350	31	58	30	5.72	4.46	4.96	4.70
## 365	9	43	21	2.61	3.78	3.41	4.36
## 381	13	50	26	3.32	3.66	4.56	3.89
## 399	11	50	25	3.36	3.74	3.43	3.94
## 423	-6	31	10	1.65	3.03	2.84	2.53
## 446	3	45	15	0.79	2.87	4.41	2.91
## 458	27	51	26	4.97	4.96	4.81	3.92
## 476	13	42	14	1.93	4.16	4.31	3.35
## 490	-10	36	-8	0.36	0.98	1.19	0.68
## 509	3	45	3	0.64	2.71	3.40	1.97
## 532	3	33	6	1.59	0.43	0.19	0.77
## 552	4	35	10	2.70	3.41	3.74	4.04
## 574	11	48	22	3.16	3.54	4.95	4.18
## 597	10	37	5	0.60	0.77	2.33	1.33
## 617	9	40	16	2.59	3.17	4.12	3.68
## 641	23	48	19	3.50	2.92	4.73	3.25
## 665	-12	32	-10	0.43	1.26	2.89	1.25
## 688	14	43	17	2.73	3.40	4.79	2.61
## 712	20	53	16	1.39	3.07	2.93	3.71
## 734	23	35	19	5.96	2.81	0.46	3.03
## 754	11	49	23	2.88	3.10	4.61	3.27
## 776	11	48	20	3.86	4.36	3.29	3.93
## 800	26	54	23	3.58	2.62	5.46	3.17
## 823	1	42	4	0.42	1.81	2.61	1.65
## 837	23	51	26	3.75	4.00	3.64	3.04
## 861	30	57	30	2.22	2.09	1.88	3.88
## 885	14	40	14	1.25	1.99	0.61	1.52
## 908	2	35	14	2.45	2.66	4.08	3.44
## 925	19	51	21	3.04	3.27	4.51	2.98
## 949	23	35	14	7.84	3.54	0.63	4.60
## 968	18	46	17	3.00	3.24	4.94	2.67
## 986	0	36	12	1.23	3.40	4.18	2.40
## 1007	-8	33	-5	0.33	1.78	2.19	0.93
##		snow.Jan	snow.Apr	snow.Jul	snow.Oct		
## 1		0.0	0.0	0	0.0		
## 23		24.2	0.9	0	0.6		
## 39		0.0	0.0	0	0.0		
## 59		1.6	0.0	0	0.0		
## 79		0.0	0.0	0	0.0		
## 94		7.0	6.8	0	4.0		
## 117		12.3	1.4	0	0.0		
## 141		4.6	0.0	0	0.0		
## 162		0.0	0.0	0	0.0		
## 182		1.3	0.0	0	0.0		
## 205		0.0	0.0	0	0.0		

```

## 225      5.1      0.3      0      0.1
## 248      6.4      0.3      0      0.0
## 265      8.6      0.2      0      0.4
## 289      8.5      1.8      0      0.4
## 311      4.9      0.3      0      0.3
## 334      3.4      0.0      0      0.0
## 350      0.0      0.0      0      0.0
## 365     20.0      4.7      0      0.3
## 381      4.4      0.0      0      0.0
## 399     12.9      1.9      0      0.0
## 423     13.8      1.9      0      0.4
## 446      0.0      0.0      0      0.0
## 458      0.0      0.0      0      0.0
## 476      4.8      0.1      0      0.0
## 490      6.2      3.7      0      2.4
## 509      5.4      1.4      0      0.7
## 532      3.4      0.2      0      0.0
## 552     18.1      2.8      0      0.0
## 574      6.0      0.0      0      0.0
## 597      4.0      0.4      0      1.0
## 617     17.9      2.3      0      0.3
## 641      2.9      0.1      0      0.0
## 665      8.9      4.2      0      2.2
## 688      9.2      1.1      0      0.2
## 712      2.8      0.0      0      0.0
## 734      0.6      0.0      0      0.0
## 754      8.8      0.4      0      0.0
## 776      9.0      0.6      0      0.0
## 800      0.8      0.0      0      0.0
## 823      5.4      3.5      0      0.9
## 837      2.6      0.0      0      0.0
## 861      0.4      0.0      0      0.0
## 885     12.5      4.0      0      1.4
## 908     22.6      4.9      0      0.0
## 925      3.9      0.1      0      0.0
## 949      1.9      0.0      0      0.0
## 968     11.3      1.4      0      0.1
## 986     12.9      2.6      0      0.5
## 1007     5.9     10.2      0      5.0

names(climate.df); # this helps you see the indexes ...

```

```

## [1] "state"        "capital"       "st"           "labels"        "highmax.Jan"
## [6] "highmax.Apr"  "highmax.Jul"   "highmax.Oct"   "highavg.Jan"   "highavg.Apr"
## [11] "highavg.Jul"  "highavg.Oct"   "lowavg.Jan"    "lowavg.Apr"    "lowavg.Jul"
## [16] "lowavg.Oct"   "lowmin.Jan"    "lowmin.Apr"    "lowmin.Jul"    "lowmin.Oct"
## [21] "rain.Jan"     "rain.Apr"      "rain.Jul"      "rain.Oct"      "snow.Jan"
## [26] "snow.Apr"     "snow.Jul"      "snow.Oct"

#View(climate.df)
#####
##### WHICH COLUMNS #####
#####
#X = climate.df[,5:52]; # temperature
#X = climate.df[,5:76]; # was 76 everything (includes rain)
#X = climate.df[,5:20]; # temperature, 1 month per season

```

```
X = climate.df[,5:28]; # everything (includes rain), 1 month per season
#####
#####
```

```
rownames(X) = climate.df$labels;
Xs = scale(X);
```

### To scale or not to scale, that is the question

```
X = climate.df[,5:28]; # everything ... you have to change months above to get this dataframe to be the same
rownames(X) = climate.df$labels;
Xs = scale(X);
```

So let's do some analysis with all of the data available to us. Most of the data is in Temperature, with ranges from -42 degrees Fahrenheit (Helena, Montana) to 122 (Phoenix, Arizona).

The precipitation data (rain and snow) is measured in inches. So should we scale the data. The answer in PCA and orthogonal projections is absolutely YES, but for `hclust` and `kmeans` is that always the case?

You can make a choice below, and observe how it influences your answers.

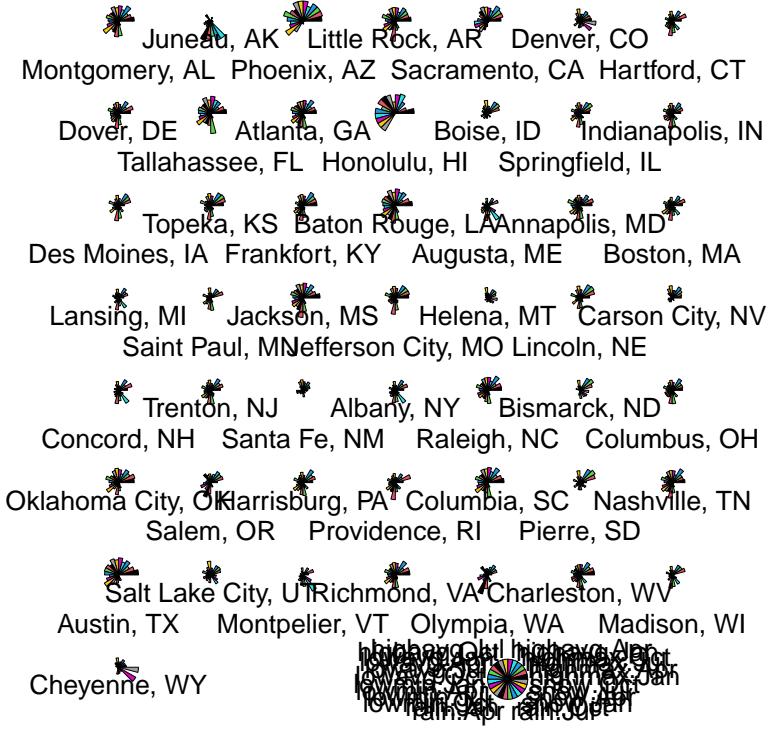
```
whichX = X;
#whichX = Xs;
```

### WHICH X

#### Perform k-means on All Climate Features

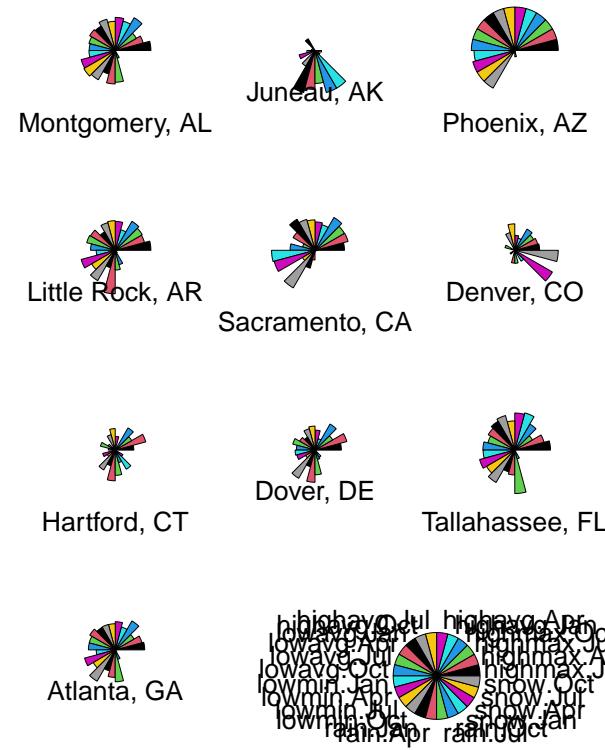
With the selected features let's perform k-means. Let's select k=12. I will select all of the features, but you can change that if you wish.

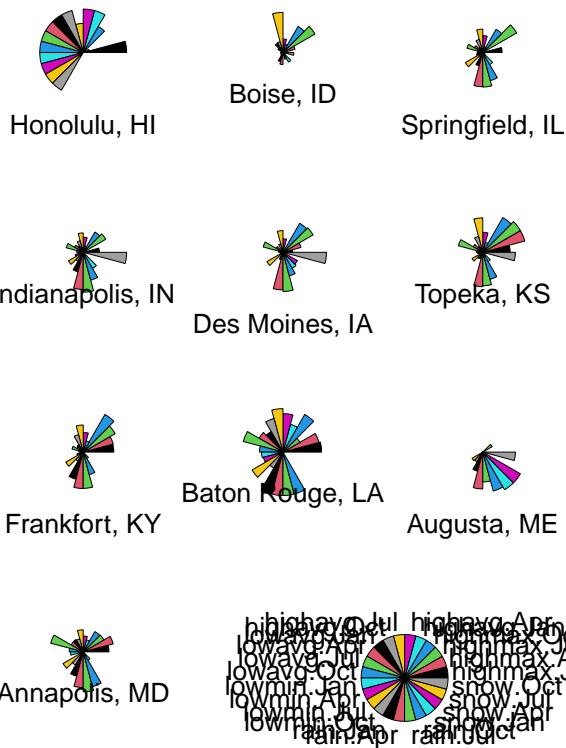
```
colors = rainbow(50, s = 0.6, v = 0.75); # 50 colors for 50 states
# descriptive star plot to start
stars(whichX, len = 0.5, key.loc=c(12,2), draw.segments = TRUE);
```

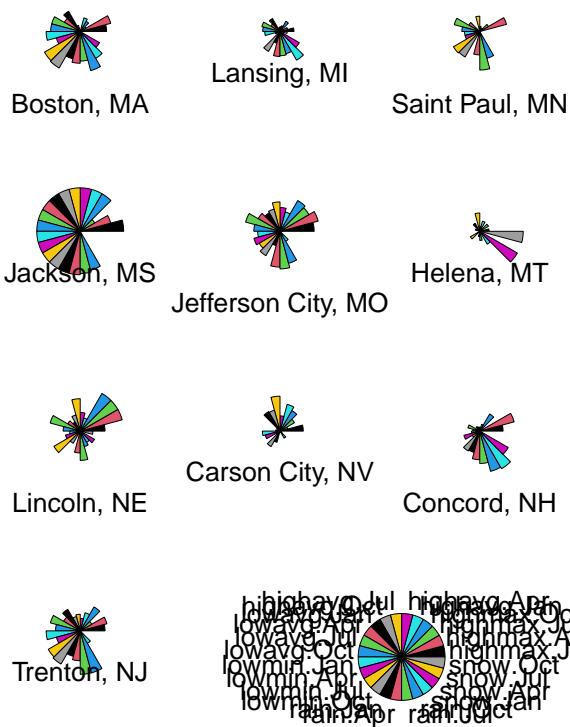


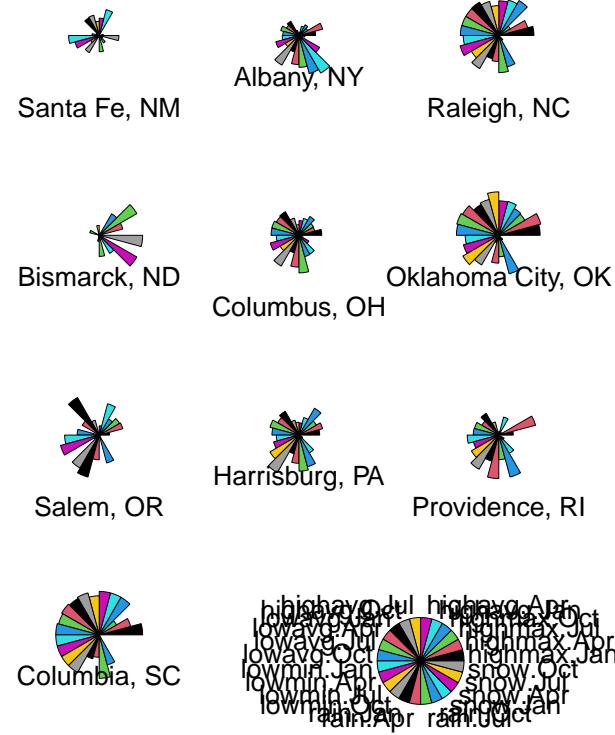
### Descriptives of Sample

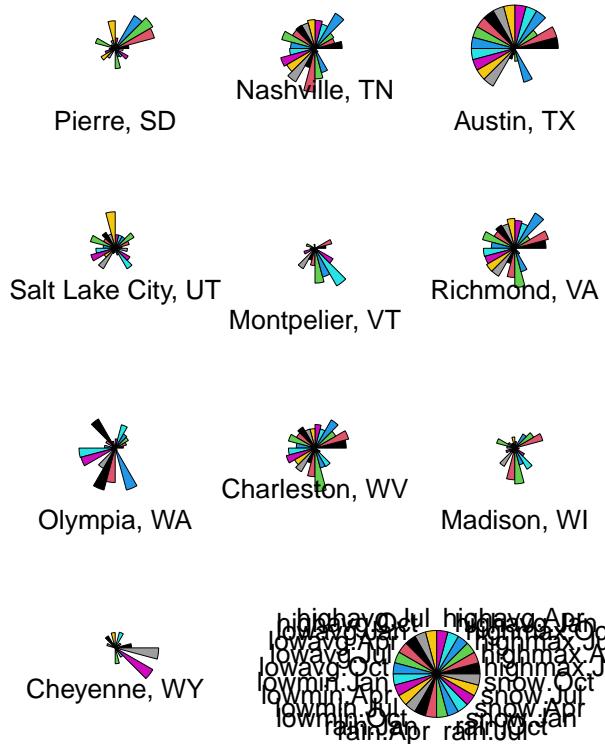
```
## too busy, let's group them
x.start = 1;
x.end = 10;
for(i in 1:5)
{
  stars( whichX[x.start:x.end,] ,
         len = 0.5, key.loc=c(6,2), draw.segments = TRUE);
  x.start = 1 + x.end;
  x.end = 10 + x.end;
}
```











Above, you are just analyzing the general shapes. Which ones are “fuller” circles? Why?

Circles representing Arizona and Hawaii are both “fuller” because they’re representing hotter temperatures throughout the year. The bigger the slice the higher the correlation for that month.

Which ones are not very “full circles”? Why?

Circles representing Montana and Maine show not very “full circles” because they’re implying throughout the year the temperatures not extremely hot (probably cold), and shows rain/snow there spiking in the later months Oct-Dec. Another conclusion I would draw from this is ones with less full circles that dont have spikes in temperature, they have more consistent cold weather.

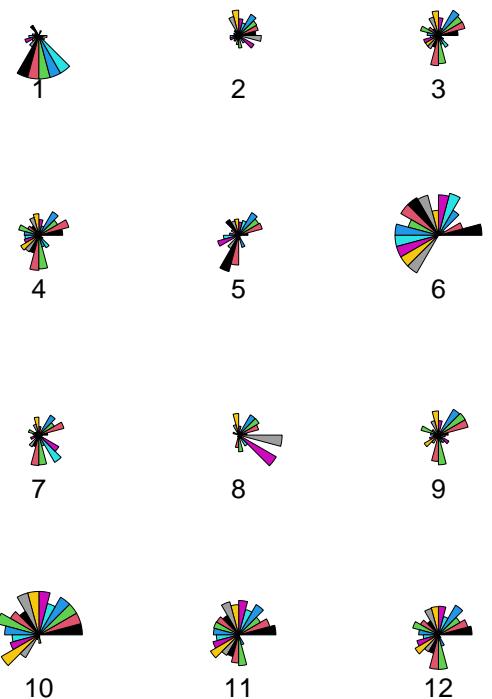
```

k = 12;
iterations = 100;
number.starts = 100;

whichX.kmeans = kmeans(whichX, 12,
                      iter.max=iterations,
                      nstart = number.starts); # default algorithm
stars(whichX.kmeans$centers, len = 0.5, key.loc = c(10, 3),
      main = "Algorithm: DEFAULT [Hartigan-Wong] \n Stars of KMEANS=12", draw.segments = TRUE);

```

## Algorithm: DEFAULT [Hartigan–Wong Stars of KMEANS=12



### Computation of Clusters/Centroids

```

membership = matrix( whichX.kmeans$cluster, ncol=1);
membership = membership[order(membership),];
membership = as.data.frame(membership);
rownames(membership) = climate.df$labels;
colnames(membership) = c("Cluster");

membership;

```

### Cluster Membership and Centroid Attributes

```

##           Cluster
## Montgomery, AL      1
## Juneau, AK          2
## Phoenix, AZ          2
## Little Rock, AR      2
## Sacramento, CA      3
## Denver, CO          3
## Hartford, CT         3
## Dover, DE          3
## Tallahassee, FL      3
## Atlanta, GA          3
## Honolulu, HI         3
## Boise, ID          3
## Springfield, IL      3
## Indianapolis, IN      3

```

```

## Des Moines, IA          4
## Topeka, KS             4
## Frankfort, KY          4
## Baton Rouge, LA         4
## Augusta, ME             4
## Annapolis, MD           4
## Boston, MA              5
## Lansing, MI             5
## Saint Paul, MN          6
## Jackson, MS             7
## Jefferson City, MO      7
## Helena, MT              7
## Lincoln, NE             7
## Carson City, NV          7
## Concord, NH             7
## Trenton, NJ              8
## Santa Fe, NM             8
## Albany, NY              8
## Raleigh, NC              9
## Bismarck, ND             9
## Columbus, OH             9
## Oklahoma City, OK        9
## Salem, OR                10
## Harrisburg, PA            11
## Providence, RI            11
## Columbia, SC              11
## Pierre, SD                11
## Nashville, TN              11
## Austin, TX                12
## Salt Lake City, UT        12
## Montpelier, VT             12
## Richmond, VA              12
## Olympia, WA                12
## Charleston, WV             12
## Madison, WI                12
## Cheyenne, WY                12

print( table(membership) ) ;

## membership
##  1  2  3  4  5  6  7  8  9 10 11 12
##  1  3 10  6  2  1  6  3  4  1  5  8

# I believe in an older version of R these were called $centroids
attributes = as.data.frame( whichX.kmeans$centers );
  rownames(attributes) = paste0("Cluster.",1:12);
  attributes;

##          highmax.Jan highmax.Apr highmax.Jul highmax.Oct highavg.Jan
## Cluster.1      60.00000    72.00000    89.00000   68.00000   34.60000
## Cluster.2      71.00000    87.33333   104.33333   90.00000   44.23333
## Cluster.3      72.60000    92.80000   108.90000   94.10000   37.49000
## Cluster.4      75.33333    95.50000   104.83333   92.50000   40.13333
## Cluster.5      66.00000    90.50000   106.00000   91.50000   46.80000
## Cluster.6      88.00000    91.00000    94.00000   94.00000   80.10000

```

```

## Cluster.7    65.66667    91.66667    102.0000    88.66667    28.65000
## Cluster.8    65.33333    87.66667    106.3333    89.00000    32.06667
## Cluster.9    66.25000    95.25000    111.7500    94.75000    30.60000
## Cluster.10   88.00000    105.00000    121.0000    107.00000    67.20000
## Cluster.11   84.00000    96.40000    107.4000    99.40000    59.82000
## Cluster.12   81.62500    95.00000    107.2500    98.75000    51.22500
##          highavg.Apr highavg.Jul highavg.Oct lowavg.Jan lowavg.Apr lowavg.Jul
## Cluster.1    49.10000    63.40000    48.40000    26.20000    35.30000    51.40000
## Cluster.2    62.96667    88.30000    66.56667    18.86667    33.16667    55.16667
## Cluster.3    63.82000    87.50000    65.99000    21.10000    41.46000    65.11000
## Cluster.4    62.15000    84.58333    65.41667    24.81667    42.63333    66.81667
## Cluster.5    60.00000    79.40000    62.15000    34.20000    38.65000    51.95000
## Cluster.6    82.70000    87.90000    86.70000    66.30000    69.40000    74.50000
## Cluster.7    56.20000    81.05000    58.71667    11.80000    34.81667    59.38333
## Cluster.8    56.56667    84.60000    58.33333    11.06667    31.20000    55.73333
## Cluster.9    61.07500    87.12500    62.22500    11.22500    38.02500    64.70000
## Cluster.10   85.20000    106.10000    88.50000    45.60000    60.20000    83.50000
## Cluster.11   77.66000    93.06000    80.04000    39.62000    53.66000    70.50000
## Cluster.12   72.91250    91.12500    73.68750    31.37500    49.55000    71.02500
##          lowavg.Oct lowmin.Jan lowmin.Apr lowmin.Jul lowmin.Oct rain.Jan
## Cluster.1    39.00000   -20.00000   12.000000   39.00000   13.000000  7.9800000
## Cluster.2    35.56667   -23.33333   3.666667   37.33333   3.000000  0.8666667
## Cluster.3    43.40000   -24.20000   13.200000   43.80000   16.500000  2.2300000
## Cluster.4    46.53333   -11.66667   13.000000   47.83333   22.500000  3.3516667
## Cluster.5    41.40000   -9.00000   23.000000   35.00000   16.500000  6.9000000
## Cluster.6    73.40000   52.00000   56.000000   63.00000   61.000000  0.0000000
## Cluster.7    38.30000   -32.66667   3.000000   36.66667   13.833333  2.2050000
## Cluster.8    32.86667   -41.66667   -10.000000  33.66667   -7.666667  0.3733333
## Cluster.9    40.25000   -31.25000   4.000000   44.75000   7.250000  0.7125000
## Cluster.10   64.80000   16.00000   35.000000   63.00000   34.000000  0.9100000
## Cluster.11   56.42000   6.40000   30.400000   55.60000   29.800000  4.1120000
## Cluster.12   51.30000   -8.87500   23.875000   51.87500   23.250000  3.4975000
##          rain.Apr rain.Jul rain.Oct snow.Jan snow.Apr snow.Jul snow.Oct
## Cluster.1    4.640000  5.440000  13.2300000  24.200000  0.9000000      0 0.600000000
## Cluster.2    0.970000  1.560000  1.0400000  4.800000  2.4666667      0 1.666666667
## Cluster.3    3.219000  3.528000  2.7700000  7.600000  0.8100000      0 0.240000000
## Cluster.4    3.736667  4.210000  3.6716667  8.033333  0.6500000      0 0.016666667
## Cluster.5    3.175000  0.545000  3.8150000  1.250000  0.0000000      0 0.000000000
## Cluster.6    0.000000  0.000000  0.0000000  0.000000  0.0000000      0 0.000000000
## Cluster.7    3.241667  3.728333  3.4083333  17.550000  3.2000000      0 0.250000000
## Cluster.8    1.340000  2.090000  0.9533333  7.000000  6.0333330      0 3.200000000
## Cluster.9    2.812500  3.722500  2.2925000  4.825000  1.6750000      0 0.500000000
## Cluster.10   0.280000  1.050000  0.5800000  0.000000  0.0000000      0 0.000000000
## Cluster.11   2.998000  3.854000  3.1580000  0.080000  0.0000000      0 0.000000000
## Cluster.12   3.667500  4.327500  3.5487500  1.987500  0.0250000      0 0.000000000

```

### (10 points) Summarize Findings

- Identify which states share a common cluster.
- For a given cluster, what are its primary characteristics

[ Summarize your k-means findings for 12 clusters.]

## (15 points) Correlation

Correlation, like distance, is an important feature of multivariate analysis. So let's review some basic correlation related to our climate data. For simplicity, let's consider "Record High Temperature" and "Record Low Temperature" and see how they correlate with other factors we have gathered from Wikipedia.

Recall, in this table, "Jan-Dec" are different months of the same temperature variable.

```
library(Hmisc); # p-values for correlation

high = subsetDataFrame(climate, c("key", "units"), "==", c("Record high F (C)",1));
high = merge(high, capitals, by=c("capital","state"));

high.X = high[,c(5:18,21)]; # numeric data
high.cor = round( cor(high.X), digits=2);
# high.cor.p = rcorr(as.matrix(high.X), type="pearson"); # p-values for statistical significance ... #

# examine July (idx = 7)

as.data.frame( high.cor ) ; # so it will render nicely in RStudio
```

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct
## Jan	1.00	0.92	0.76	0.57	0.43	0.39	0.25	0.41	0.62	0.71
## Feb	0.92	1.00	0.80	0.63	0.62	0.53	0.45	0.59	0.74	0.79
## Mar	0.76	0.80	1.00	0.87	0.73	0.56	0.53	0.67	0.76	0.82
## Apr	0.57	0.63	0.87	1.00	0.82	0.68	0.65	0.75	0.79	0.81
## May	0.43	0.62	0.73	0.82	1.00	0.83	0.85	0.85	0.86	0.81
## Jun	0.39	0.53	0.56	0.68	0.83	1.00	0.90	0.86	0.87	0.78
## Jul	0.25	0.45	0.53	0.65	0.85	0.90	1.00	0.91	0.86	0.73
## Aug	0.41	0.59	0.67	0.75	0.85	0.86	0.91	1.00	0.90	0.78
## Sep	0.62	0.74	0.76	0.79	0.86	0.87	0.86	0.90	1.00	0.88
## Oct	0.71	0.79	0.82	0.81	0.81	0.78	0.73	0.78	0.88	1.00
## Nov	0.89	0.89	0.89	0.76	0.65	0.56	0.46	0.57	0.74	0.86
## Dec	0.94	0.89	0.81	0.65	0.46	0.41	0.27	0.46	0.65	0.72
## latitude	-0.83	-0.80	-0.68	-0.49	-0.40	-0.30	-0.15	-0.29	-0.46	-0.67
## longitude	0.07	0.01	0.39	0.34	0.08	0.01	0.02	0.04	0.07	0.14
## population.2019.est	0.40	0.42	0.36	0.35	0.38	0.48	0.31	0.31	0.44	0.39
##			Nov	Dec	latitude	longitude	population.2019.est			
## Jan	0.89	0.94	-0.83	0.07			0.40			
## Feb	0.89	0.89	-0.80	0.01			0.42			
## Mar	0.89	0.81	-0.68	0.39			0.36			
## Apr	0.76	0.65	-0.49	0.34			0.35			
## May	0.65	0.46	-0.40	0.08			0.38			
## Jun	0.56	0.41	-0.30	0.01			0.48			
## Jul	0.46	0.27	-0.15	0.02			0.31			
## Aug	0.57	0.46	-0.29	0.04			0.31			
## Sep	0.74	0.65	-0.46	0.07			0.44			
## Oct	0.86	0.72	-0.67	0.14			0.39			
## Nov	1.00	0.91	-0.82	0.17			0.40			
## Dec	0.91	1.00	-0.85	0.12			0.42			
## latitude	-0.82	-0.85	1.00	0.01			-0.34			
## longitude	0.17	0.12	0.01	1.00			-0.10			
## population.2019.est	0.40	0.42	-0.34	-0.10			1.00			

```
high.cor.july = high.cor[,7];
high.cor.july;
```

```

##          Jan        Feb        Mar        Apr
## 0.25      0.45      0.53      0.65
## May       Jun       Jul       Aug
## 0.85      0.90      1.00      0.91
## Sep       Oct       Nov       Dec
## 0.86      0.73      0.46      0.27
## latitude   longitude population.2019.est
## -0.15      0.02      0.31

```

**#View(high.cor.july)**

Describe the correlation of July in “Record high F (C)” to the other numeric factors printed above.

**x is correlated with y (0.00). This correlation is positive/negative which means ... This correlation is strong/weak because ... overall, this suggests ...**

- July perfectly correlates with July (1.00). This correlation is positive and very strong. This is because they are the same data.
- With the months, you can note each, or plot a trend showing them, and discussing them briefly as a trend.
- latitude is a measure of north/south, so be certain to apply the correlation value with some meaning. be certain you know which direction is positive or negative to correctly interpret the sign of the correlation.
- longitude is a measure of east/west, so be certain ...
- population is the size of the city
- intuitively, which months do you think correlate most with latitude for this data? which correlate the least? is the correlation always the same sign (positive/negative), or does it change?

[You can use the dataframe output to do this analysis, or create your own subset]

```

library(Hmisc); # p-values for correlation

low = subsetDataFrame(climate, c("key", "units"), "==", c("Record low F (C)",1));
low = merge(low, capitals, by=c("capital","state"));

low.X = low[,c(5:18,21)]; # numeric data
low.cor = round( cor(low.X), digits=2);
# low.cor.p = rcorr(as.matrix(low.X), type="pearson"); # p-values for statistical significance ... # s

# examine Jan (idx = 1)

as.data.frame( low.cor ) ; # so it will render nicely in RStudio

```

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct
## Jan	1.00	0.95	0.93	0.92	0.89	0.80	0.74	0.77	0.90	0.87
## Feb	0.95	1.00	0.94	0.92	0.86	0.75	0.70	0.72	0.88	0.86
## Mar	0.93	0.94	1.00	0.92	0.85	0.73	0.71	0.72	0.85	0.85
## Apr	0.92	0.92	0.92	1.00	0.91	0.82	0.78	0.81	0.93	0.89
## May	0.89	0.86	0.85	0.91	1.00	0.93	0.88	0.88	0.95	0.93
## Jun	0.80	0.75	0.73	0.82	0.93	1.00	0.92	0.91	0.88	0.82
## Jul	0.74	0.70	0.71	0.78	0.88	0.92	1.00	0.96	0.87	0.77
## Aug	0.77	0.72	0.72	0.81	0.88	0.91	0.96	1.00	0.87	0.77
## Sep	0.90	0.88	0.85	0.93	0.95	0.88	0.87	0.87	1.00	0.94
## Oct	0.87	0.86	0.85	0.89	0.93	0.82	0.77	0.77	0.94	1.00
## Nov	0.91	0.92	0.90	0.89	0.89	0.81	0.75	0.75	0.92	0.93

```

## Dec          0.97  0.95  0.93  0.92  0.91  0.82  0.78  0.79  0.91  0.90
## latitude     -0.72 -0.64 -0.69 -0.71 -0.72 -0.75 -0.75 -0.80 -0.72 -0.66
## longitude    -0.33 -0.36 -0.31 -0.25 -0.12 -0.05  0.09  0.02 -0.09 -0.04
## population.2019.est 0.34  0.37  0.32  0.37  0.35  0.39  0.46  0.46  0.40  0.32
##           Nov   Dec  latitude longitude population.2019.est
## Jan          0.91  0.97  -0.72  -0.33           0.34
## Feb          0.92  0.95  -0.64  -0.36           0.37
## Mar          0.90  0.93  -0.69  -0.31           0.32
## Apr          0.89  0.92  -0.71  -0.25           0.37
## May          0.89  0.91  -0.72  -0.12           0.35
## Jun          0.81  0.82  -0.75  -0.05           0.39
## Jul          0.75  0.78  -0.75  0.09            0.46
## Aug          0.75  0.79  -0.80  0.02            0.46
## Sep          0.92  0.91  -0.72  -0.09           0.40
## Oct          0.93  0.90  -0.66  -0.04           0.32
## Nov          1.00  0.94  -0.70  -0.12           0.28
## Dec          0.94  1.00  -0.71  -0.24           0.33
## latitude     -0.70 -0.71  1.00   0.01          -0.34
## longitude    -0.12 -0.24  0.01   1.00          -0.10
## population.2019.est 0.28  0.33  -0.34  -0.10           1.00

```

```

low.cor.january = low.cor[,1];
low.cor.january;

```

```

##           Jan      Feb      Mar      Apr
## Jan       1.00
## May        0.95    0.93
## May        0.93    0.95    0.92
## Jun        0.80    0.74    0.77
## Sep        0.80    0.74    0.77
## Sep        0.77    0.80    0.89
## Oct        0.87    0.91    0.90
## Oct        0.90    0.87    0.89
## Dec        0.87    0.91    0.92
## Dec        0.92    0.90    0.87
##           latitude longitude population.2019.est
## latitude    -0.72   -0.33    0.34
## longitude   -0.33    0.34   -0.72
## population.2019.est 0.34   -0.72   -0.33

```

Describe the correlation of January in “Record low F (C)” to the other numeric factors printed above.

Similar to “high” writeup, but for the “low” data.

## “So What” is DATA ANALYSIS?

In the social sciences (e.g., Karl Weick), the concept of “sense making” refers to “the process by which people give meaning to their collective experiences”. I have used this framework in my high-technology innovation research (See Figure 1 of <http://www.mshaffer.com/arizona/pdf/LoneGenius.pdf>, my rubric concept comes from learning-theory growth models: Nascent, Adolescent, Mature.)

This final topic is reflective: we are thinking about how we think.

## Statistics

The syllabus defined statistics as “the discipline that concerns the collection, organization, analysis, interpretation and presentation of data.” (See <https://en.wikipedia.org/wiki/Statistics>)

There are 5 elements mentioned: collection, organization, analysis, interpretation, and presentation of “data”. Are those equally weighted? That is, should we devote 20% of our time to each of those? Now, consider the “analysis” stage. I have suggested there are two camps: exploratory and confirmatory data analysis. Are those equally weighted? That is, should we devote 50% of our time to each of those? Now, in an “equally-likely” scenario, we would have.

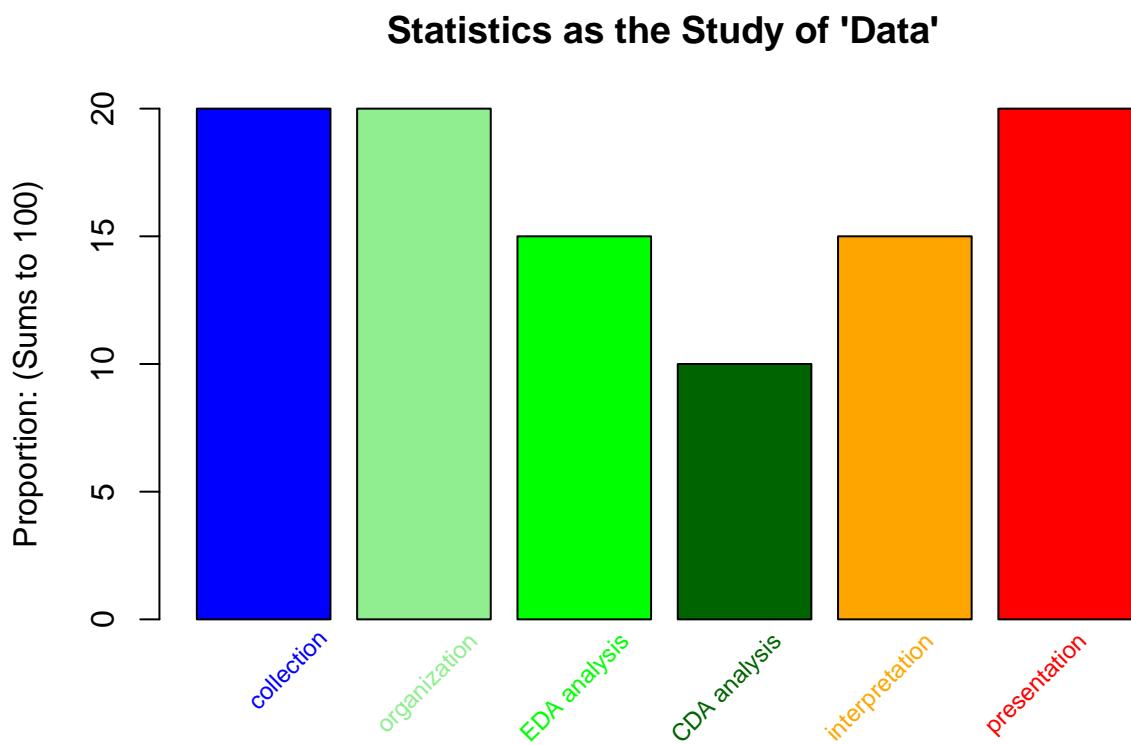
```

x = c(20,20,15,10,15,20);
x.labels = c("collection", "organization", "EDA analysis", "CDA analysis", "interpretation", "presentation");
x.colors = c("blue", "lightgreen", "green", "darkgreen", "orange", "red");

barplot(x,
        col = x.colors,
        ylim = c(0, 20),
        ylab = "Proportion: (Sums to 100)",
        main="Statistics as the Study of 'Data'");

text(1.14*(1:6), par("usr")[3], col = x.colors, labels = x.labels, srt = 45, adj = c(1.1,1.1), xpd = TRUE)

```



## Data Analytics

Source: <https://data-analytics.wsu.edu/197-2/> (Accessed October 2010)

“Data analytics is the application of powerful new methods—drawn from computer science, mathematics and statistics, and domain sciences—to collect, curate, analyze, discover and communicate knowledge from ‘big data.’” <https://data-analytics.wsu.edu/> (Accessed October 2010)

**Importance of ‘Data’** I love data.

I also love math/physics. I also love exploratory data analysis. I also love computational statistics or statistical computing [https://en.wikipedia.org/wiki/Computational\\_statistics](https://en.wikipedia.org/wiki/Computational_statistics). I also love thinking about developing the one graphic to summarize data most effectively.

**Apprenticeship as Learning a Trade** The idea of sharing in the learning process is an important aspect of the apprenticeship model. You are learning a trade (data analytics). I have experience in this trade. My job as the instructor is to provide you with a variety of “situated-learning” experiences To help you understand the nature of the trade. This exam is an example of such an experience.

**Tools of the Trade** Below are the core requirements for the data analytics program:

- Calculus and linear algebra (10 credits)
- Computer science fundamentals (11 credits)
- Machine learning and data management (9 credits)
- Statistics (15 credits)
- Data analytics introduction, ethics & project-focused \* capstone experience (9 credits)

These are not the tools of the trade, but hopefully, they introduce you to key tools of the trade. What exactly are tools of the trade? [You will have an opportunity to write a response below.]

**Dimensional Reduction, an Axiomatic View** This video was recently shared with me that highlights some distinctions among persons practicing various forms of data analysis <https://www.youtube.com/watch?v=uHGICi9jOWY>. As an orthogonal projection, I would create two axes. On the horizontal axis (x-axis), I would place “theory of data” to the left and “application of data” toward the right. On the vertical axis (y-axis), I would place “care for data integrity” at the top and “less care for data integrity” at the bottom.

**Skills of the Trade** As someone that is coming from industry, having hired young people like you out of Computer Science, Electrical-Computer Engineering, I have opinions related to skills of the trade.

- Can you acquire an appreciation for “data intimacy”?
- Can you track and document how data is curated?
- Can you track and document the analyses you perform? Can you recreate them? Do you have basic version-control protocols in place?
- Can you view data from multiple perspectives and synthesize those perspectives to identify the central them of the data? Can you be objective? Can you try and identify objective metrics to enlighten your understanding about the essence of data?
- Can you experiment with different visualizations in search of an optimal “one graphic” result? Do you have practice using various visualization tools? Can you comprehend which visualization tool is appropriate for messaging (communicating results) to a particular audience?
- Can you communicate and defend your findings to a particular audience? Are your communications professional? Is the final work product both simple and comprehensive: simple in its summary findings and comprehensive in its ability to be replicated and audited as necessary.

## (20 points) YOUR OPINION OF DATA ANALYTICS

[This is worth 20 points.

Specifically, address:

- (1) what proportion of “statistics” should be divided among: collection, organization, analysis, interpretation, and presentation of “data” ... providing a `barplot` of your opinion within your response would seem appropriate

```
x = c(20,20,15,10,15,20); ## change these values and discuss ...
x.labels = c("collection", "organization", "EDA analysis", "CDA analysis", "interpretation", "presentation");
x.colors = c("blue", "lightgreen", "green", "darkgreen", "orange", "red");

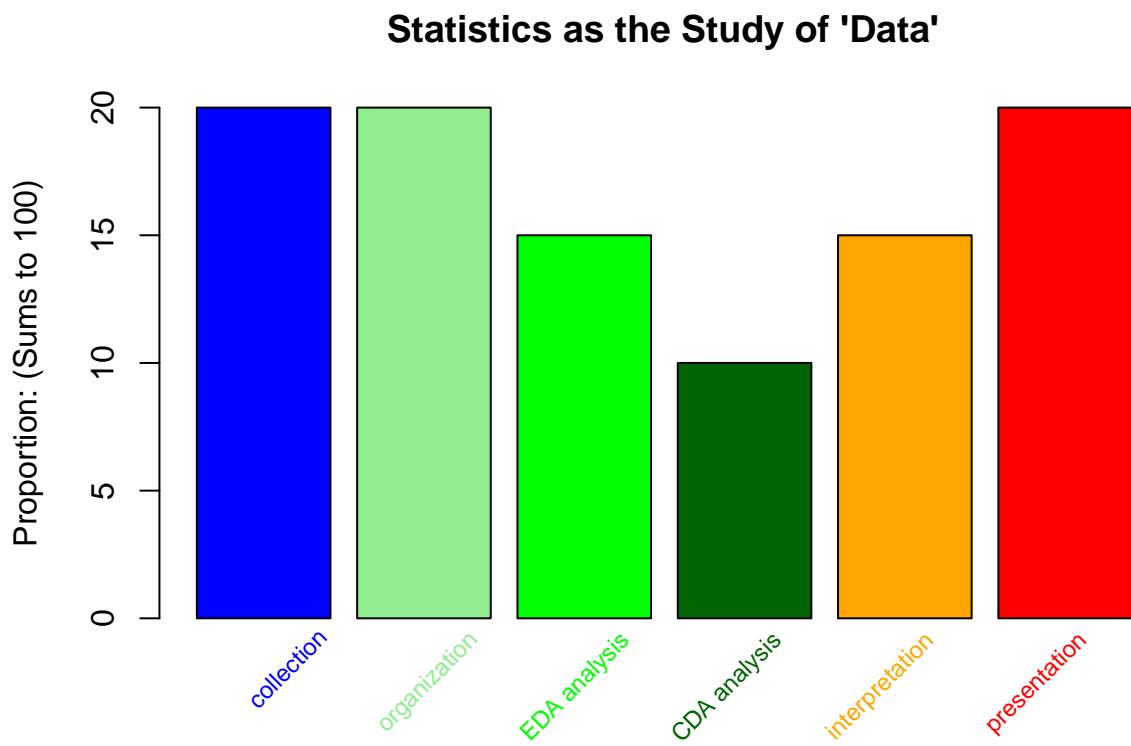
barplot(x,
        col = x.colors,
        ylim = c(0, max(x)),
        ylab = "Proportion: (Sums to 100)",
```

```

main="Statistics as the Study of 'Data'");

text(1.14*(1:6), par("usr")[3], col = x.colors, labels = x.labels, srt = 45, adj = c(1.1,1.1), xpd = T)

```



- (2) what tools of the trade should you be acquiring from the core courses? how are you doing in that acquisition process (e.g., tool X is ... and right now I feel like my understanding/proficiency of tool X ... ) ...
- (3) utilize the provided `plot` script to place the course-course categories on the proposed x-y graph related to analytics practice (Applied vs Theoretical) and care of data integrity (Great Care vs Little Care) ... Also place your personal assessment on the plot script provided
- (4) evaluate your skill-level on the six “skills of the trade”: Emerging (Nascent), Developing (Adolescent), Mastering (Mature). explain your evaluation and include other important skills you believe are relevant that are not included
- (5) Any other comments you would like to share.

]

```

# x is -1 for perfectly theoretical
# x is 1 for perfectly applied

# y is -1 for no care whatsoever for data integrity
# y is 1 is perfect care for data integrity

##### basic plot setup #####

```

```

plot(0,0, col="white",
  ylim=c(-1.5,1.5), xlim=c(-1.5,1.5),
  xlab = "",
  ylab = "",
  xaxt = 'n', bty = 'n', yaxt = 'n',
  main = "Axiomatic Perspective on Practice/Care",
  );
segments(-1,0,1,0, col="#999999");
segments(0,-1,0,1, col="#999999");
text(-1.1,0, "Theoretical Data Practice", cex=0.5, srt = 90);
text(1.1,0, "Applied Data Practice", cex=0.5, srt = -90);
text(0,1.1, "Great Care for Data Integrity", cex=0.5, srt = 0);
text(0,-1.1, "Little Care for Data Integrity", cex=0.5, srt = 0);
##### basic plot setup #####
##### you can add elements here #####
## this point represents the professor's self-perception
points(0.45, 0.90, pch=20, col="blue");
text(0.50, 0.90, "Nic", col="blue", cex=0.45, srt = 45, pos=3);

```

## Axiomatic Perspective on Practice/Care



##### TODO ##### ... maybe change color for each data point

```

# https://brand.wsu.edu/visual/colors/
# crimson = #981e32
# you need to change the x,y from 0,0 ...

```

```

# you can change col ... cex (font size), srt (angle), and pos = 1,2,3,4
#
# points(0, 0, pch=20, col="#981e32");
# text(0, 0, "Student (self)", col="#981e32", cex=0.75, srt = 45, pos=3);
#
# ## evaluate the Course Categories of Tools of the Trade
# ## give them a score
#
# points(0, 0, pch=20, col="#981e32");
# text(0, 0, "Math(s)", col="#981e32", cex=0.5, srt = 45, pos=3);
#
#
# points(0, 0, pch=20, col="#981e32");
# text(0, 0, "Computer Science", col="#981e32", cex=0.5, srt = 45, pos=3);
#
# points(0, 0, pch=20, col="#981e32");
# text(0, 0, "Machine learning", col="#981e32", cex=0.5, srt = 45, pos=3);
#
# points(0, 0, pch=20, col="#981e32");
# text(0, 0, "Statistics", col="#981e32", cex=0.5, srt = 45, pos=3);
#
# points(0, 0, pch=20, col="#981e32");
# text(0, 0, "Data analytics", col="#981e32", cex=0.5, srt = 45, pos=3);
#
# # You have a track (e.g., Business)
# points(0, 0, pch=20, col="#981e32");
# text(0, 0, "Core discipline", col="#981e32", cex=0.5, srt = 45, pos=3);

```