

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. 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 understanding 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.]

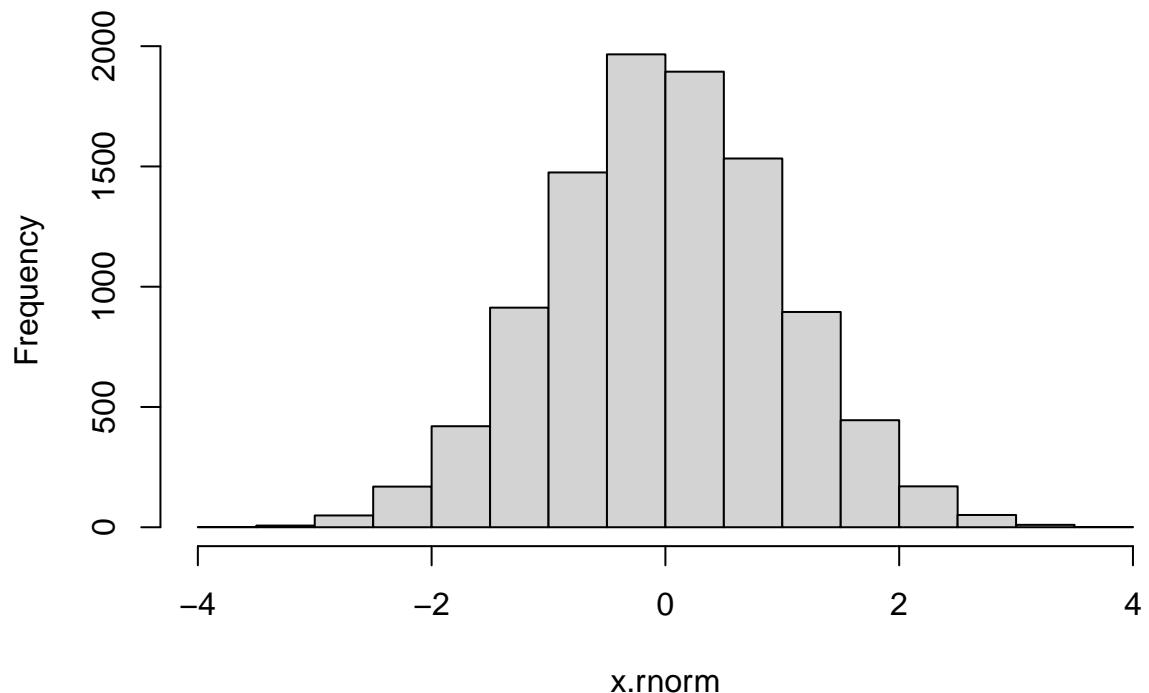
SIMULATING DATA

(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));`.

```
#setting seed and simulate data for rnorm and runif where n=9999
set.seed(321)
x.rnorm <- rnorm(n=9999)
set.seed(321)
x.runif <- runif(n=9999)
# hist and summary for x.rnorm
hist(x.rnorm)
```

Histogram of x.rnorm



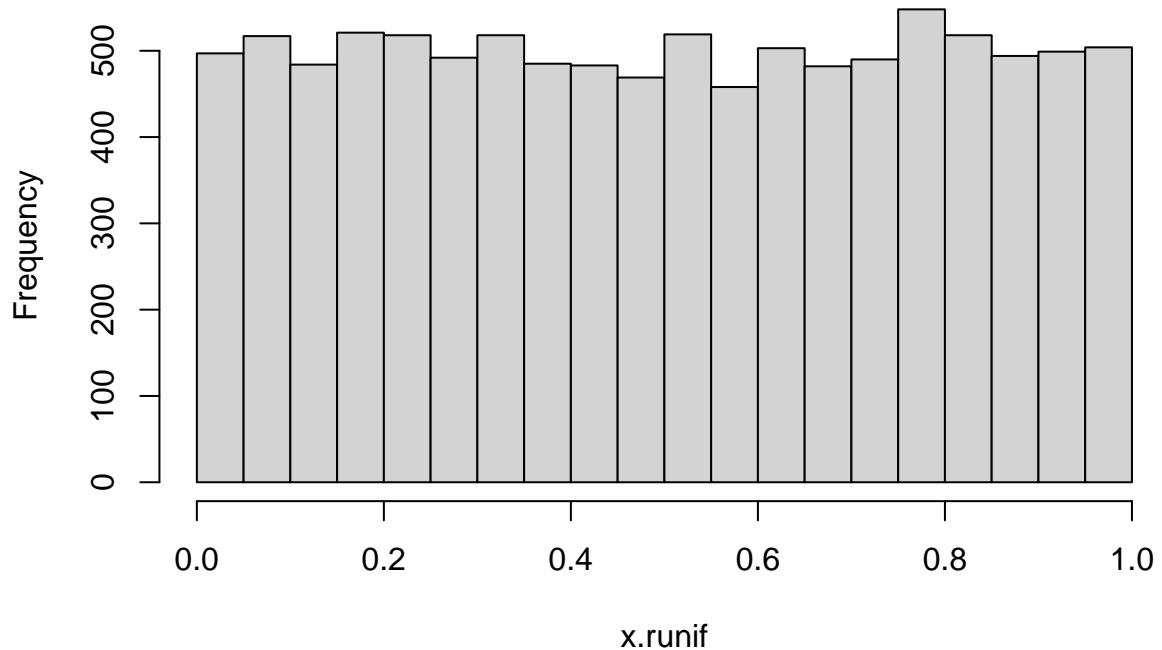
Code of simulation

```
summary(x.rnorm)

##      Min.    1st Qu.     Median      Mean    3rd Qu.      Max.
## -3.605372 -0.663107 -0.000793  0.003992  0.683656  3.574360

# hist and summary for x.runif
hist(x.runif)
```

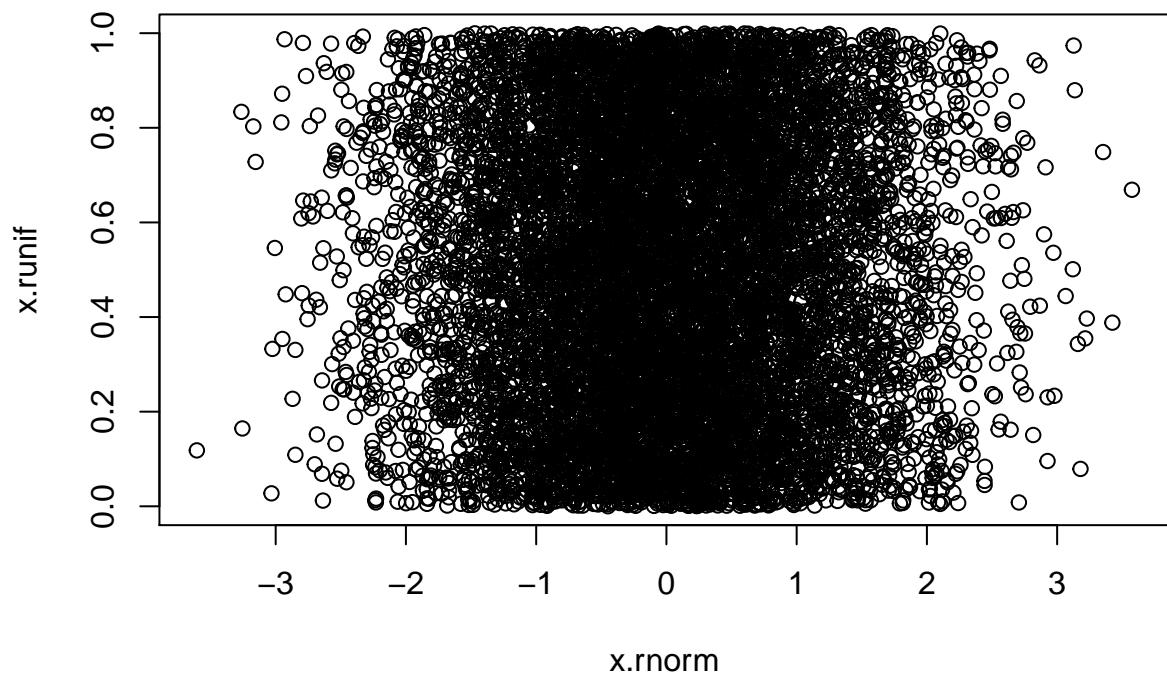
Histogram of x.runif



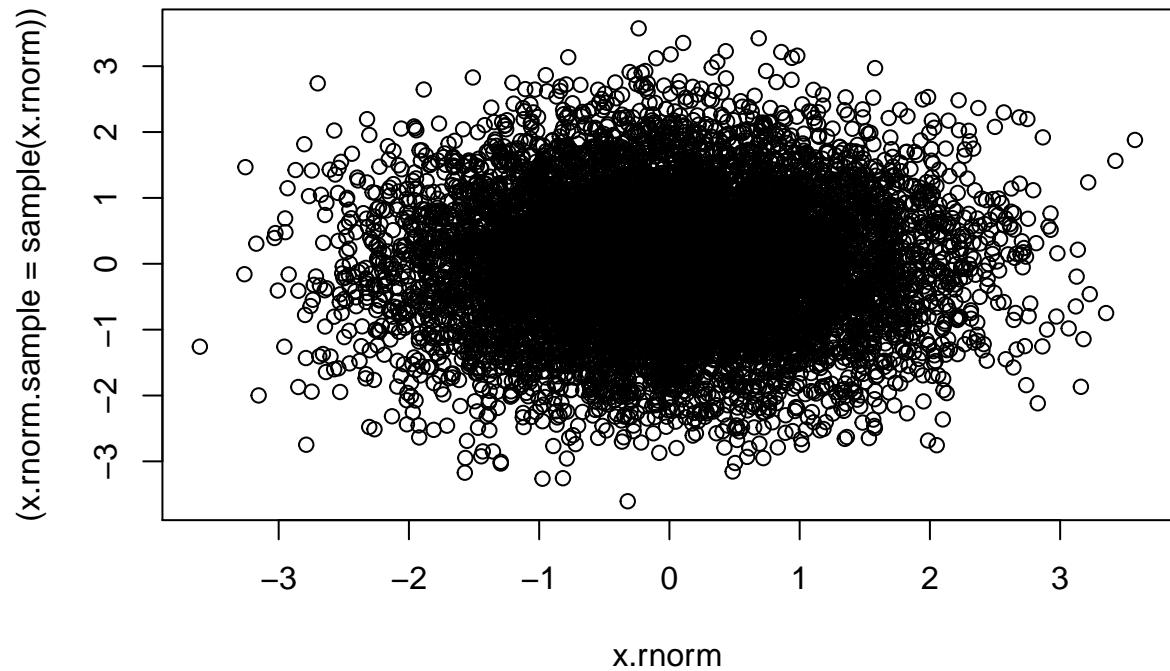
```
summary(x.runif)
```

```
##      Min.    1st Qu.     Median      Mean    3rd Qu.      Max.
## 0.0001233 0.2458256 0.5017109 0.4999222 0.7549359 0.9996324
```

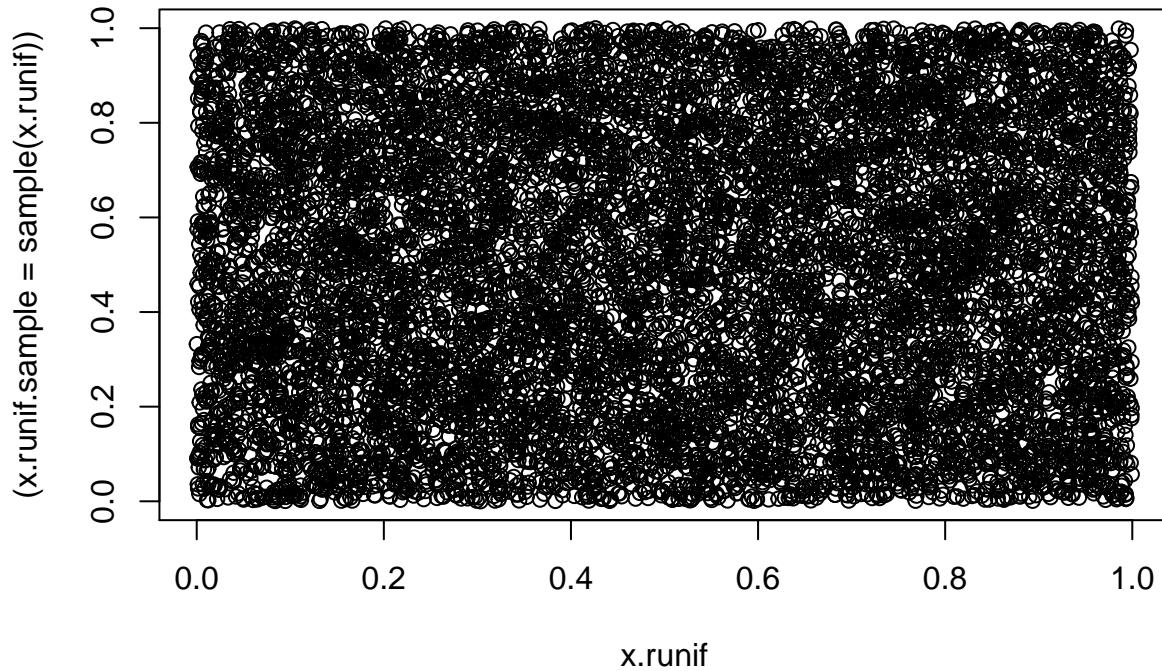
```
#plot1
plot(x.rnorm, x.runif)
```



```
#plot2
plot(x.rnorm, ( x.rnorm.sample = sample(x.rnorm) ) )
```



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



```
summary(x.rnorm.sample)
```

```
##      Min. 1st Qu. Median      Mean 3rd Qu.      Max.
## -3.605372 -0.663107 -0.000793  0.003992  0.683656  3.574360
```

```
summary(x.runif.sample)
```

```
##      Min. 1st Qu. Median      Mean 3rd Qu.      Max.
## 0.0001233 0.2458256 0.5017109 0.4999222 0.7549359 0.9996324
```

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, (x.rnorm.sample = sample(x.rnorm)));` and `plot(x.runif, (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.

```
# Set answer and num in random number to start the while loop.
answer = 0
num = 0
ns=0
num <- sample(1:500000)
for(i in num){
  set.seed(i)
  answer <- rbinom(1,1000,0.5)
  if (answer == 555) {
    ns = 1+ns
    cat("a seed that allows 555/1000 heads is:", i, "\n")
  }
  else if (ns>= 5) {
    break
  }
}
## a seed that allows 555/1000 heads is: 121830
## a seed that allows 555/1000 heads is: 303566
## a seed that allows 555/1000 heads is: 113838
## a seed that allows 555/1000 heads is: 400407
## a seed that allows 555/1000 heads is: 317968
```

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
## row.147	2	5	8	15
## row.148	2	5	9	16
## row.149	2	5	10	17
## row.150	2	6	1	9
## row.151	2	6	2	10
## row.152	2	6	3	11
## row.153	2	6	4	12
## row.154	2	6	5	13
## row.155	2	6	6	14
## row.156	2	6	7	15
## row.157	2	6	8	16
## row.158	2	6	9	17
## row.159	2	6	10	18
## row.160	2	7	1	10
## row.161	2	7	2	11
## row.162	2	7	3	12
## row.163	2	7	4	13
## row.164	2	7	5	14
## row.165	2	7	6	15
## row.166	2	7	7	16
## row.167	2	7	8	17
## row.168	2	7	9	18
## row.169	2	7	10	19
## row.170	2	8	1	11
## row.171	2	8	2	12
## row.172	2	8	3	13
## row.173	2	8	4	14
## row.174	2	8	5	15
## row.175	2	8	6	16
## row.176	2	8	7	17
## row.177	2	8	8	18
## row.178	2	8	9	19
## row.179	2	8	10	20
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## 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?

```

# getting each cases where I roll 12 or 22 when I throw the dice at the same time.

#sub.myrolls12 = subsetDataFrame(myrolls, "roll.total", "==", 12)
#sub.myrolls22 = subsetDataFrame(myrolls, "roll.total", "==", 22)

#sub.myrolls2 = rbind(sub.myrolls12, sub.myrolls22)
#sub.myrolls2

#-----

sub.outcomes12.df = subsetDataFrame(outcomes.df, "roll.total", "==", 12)
sub.outcomes22.df = subsetDataFrame(outcomes.df, "roll.total", "==", 22)

sub.outcomes2.df= rbind(sub.outcomes12.df , sub.outcomes22.df)
sub.outcomes2.df

##      roll.total count  prob
## 10          12     55 0.055
## 20          22     45 0.045

cat('The probability of rolling a 12 or 22 on a single throw is:', sum(sub.outcomes2.df[, 'prob']))

## The probability of rolling a 12 or 22 on a single throw is: 0.1

```

Roll 26 or 29

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

```

sub.outcomes26.df = subsetDataFrame(outcomes.df, "roll.total", "==", 26)
sub.outcomes29.df = subsetDataFrame(outcomes.df, "roll.total", "==", 29)

sub.outcomes3.df= rbind(sub.outcomes26.df , sub.outcomes29.df)
sub.outcomes3.df

##      roll.total count  prob
## 24          26     15 0.015
## 27          29      3 0.003

cat('The probability of rolling a 26 or 29 on a single throw is:', sum(sub.outcomes3.df[, 'prob']))

## The probability of rolling a 26 or 29 on a single throw is: 0.018

```

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?

```

sub.outcomes3.df = subsetDataFrame(outcomes.df, "roll.total", "==", 3)
sub.outcomes3.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 ...

```

sub.myrolls12 = subsetDataFrame(myrolls, "roll.total", "<=", 12)
sub.myrolls12

```

```

##      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.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.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.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.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.60	1	7	1	9
## row.61	1	7	2	10
## row.62	1	7	3	11
## row.63	1	7	4	12
## row.70	1	8	1	10
## row.71	1	8	2	11
## row.72	1	8	3	12
## row.80	1	9	1	11
## row.81	1	9	2	12
## row.90	1	10	1	12
## 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.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.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.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.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.150	2	6	1	9
## row.151	2	6	2	10
## row.152	2	6	3	11
## row.153	2	6	4	12
## row.160	2	7	1	10
## row.161	2	7	2	11
## row.162	2	7	3	12
## row.170	2	8	1	11
## row.171	2	8	2	12
## row.180	2	9	1	12
## row.200	3	1	1	5
## row.201	3	1	2	6
## row.202	3	1	3	7
## row.203	3	1	4	8
## row.204	3	1	5	9
## row.205	3	1	6	10
## row.206	3	1	7	11
## row.207	3	1	8	12
## row.210	3	2	1	6
## row.211	3	2	2	7
## row.212	3	2	3	8
## row.213	3	2	4	9
## row.214	3	2	5	10
## row.215	3	2	6	11
## row.216	3	2	7	12
## row.220	3	3	1	7
## row.221	3	3	2	8
## row.222	3	3	3	9
## row.223	3	3	4	10
## row.224	3	3	5	11
## row.225	3	3	6	12
## row.230	3	4	1	8
## row.231	3	4	2	9
## row.232	3	4	3	10
## row.233	3	4	4	11

## row.234	3	4	5	12
## row.240	3	5	1	9
## row.241	3	5	2	10
## row.242	3	5	3	11
## row.243	3	5	4	12
## row.250	3	6	1	10
## row.251	3	6	2	11
## row.252	3	6	3	12
## row.260	3	7	1	11
## row.261	3	7	2	12
## row.270	3	8	1	12
## row.300	4	1	1	6
## row.301	4	1	2	7
## row.302	4	1	3	8
## row.303	4	1	4	9
## row.304	4	1	5	10
## row.305	4	1	6	11
## row.306	4	1	7	12
## row.310	4	2	1	7
## row.311	4	2	2	8
## row.312	4	2	3	9
## row.313	4	2	4	10
## row.314	4	2	5	11
## row.315	4	2	6	12
## row.320	4	3	1	8
## row.321	4	3	2	9
## row.322	4	3	3	10
## row.323	4	3	4	11
## row.324	4	3	5	12
## row.330	4	4	1	9
## row.331	4	4	2	10
## row.332	4	4	3	11
## row.333	4	4	4	12
## row.340	4	5	1	10
## row.341	4	5	2	11
## row.342	4	5	3	12
## row.350	4	6	1	11
## row.351	4	6	2	12
## row.360	4	7	1	12
## row.400	5	1	1	7
## row.401	5	1	2	8
## row.402	5	1	3	9
## row.403	5	1	4	10
## row.404	5	1	5	11
## row.405	5	1	6	12
## row.410	5	2	1	8
## row.411	5	2	2	9
## row.412	5	2	3	10
## row.413	5	2	4	11
## row.414	5	2	5	12
## row.420	5	3	1	9
## row.421	5	3	2	10
## row.422	5	3	3	11
## row.423	5	3	4	12

```

## row.430      5      4      1      10
## row.431      5      4      2      11
## row.432      5      4      3      12
## row.440      5      5      1      11
## row.441      5      5      2      12
## row.450      5      6      1      12
## row.500      6      1      1      8
## row.501      6      1      2      9
## row.502      6      1      3      10
## row.503      6      1      4      11
## row.504      6      1      5      12
## row.510      6      2      1      9
## row.511      6      2      2      10
## row.512      6      2      3      11
## row.513      6      2      4      12
## row.520      6      3      1      10
## row.521      6      3      2      11
## row.522      6      3      3      12
## row.530      6      4      1      11
## row.531      6      4      2      12
## row.540      6      5      1      12
## row.600      7      1      1      9
## row.601      7      1      2      10
## row.602      7      1      3      11
## row.603      7      1      4      12
## row.610      7      2      1      10
## row.611      7      2      2      11
## row.612      7      2      3      12
## row.620      7      3      1      11
## row.621      7      3      2      12
## row.630      7      4      1      12
## row.700      8      1      1      10
## row.701      8      1      2      11
## row.702      8      1      3      12
## row.710      8      2      1      11
## row.711      8      2      2      12
## row.720      8      3      1      12
## row.800      9      1      1      11
## row.801      9      1      2      12
## row.810      9      2      1      12
## row.900     10      1      1      12

```

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
## 547	2020-41	C#	164920
## 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
## 703	2020-41	C programmer	21
## 704	2020-41	C++ programmer	21
## 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

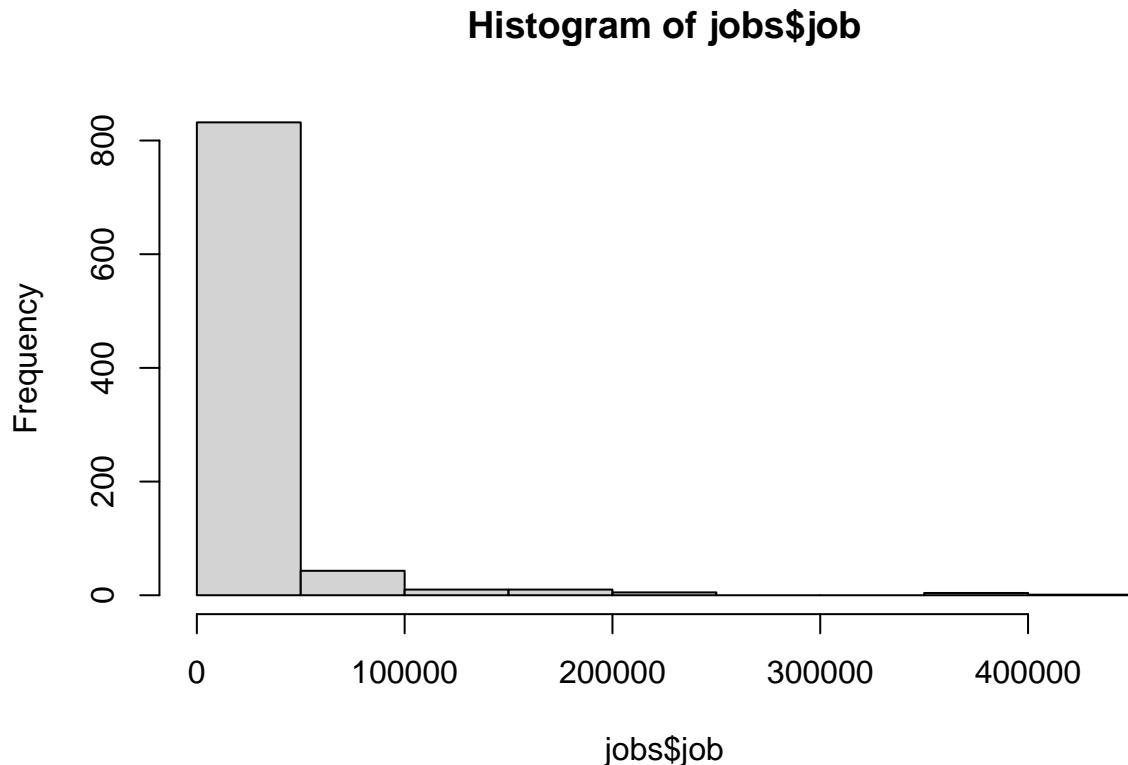
## 798	2020-42	Business analytics	4406
## 799	2020-42	Market Analysis	4399
## 800	2020-42	Windows 10	4361
## 801	2020-42	deep learning	4316
## 802	2020-42	Data scientist	4274
## 803	2020-42	Bootstrap	4076
## 804	2020-42	Slack	3991
## 805	2020-42	Data Engineer	3451
## 806	2020-42	arcgis	2886
## 807	2020-42	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

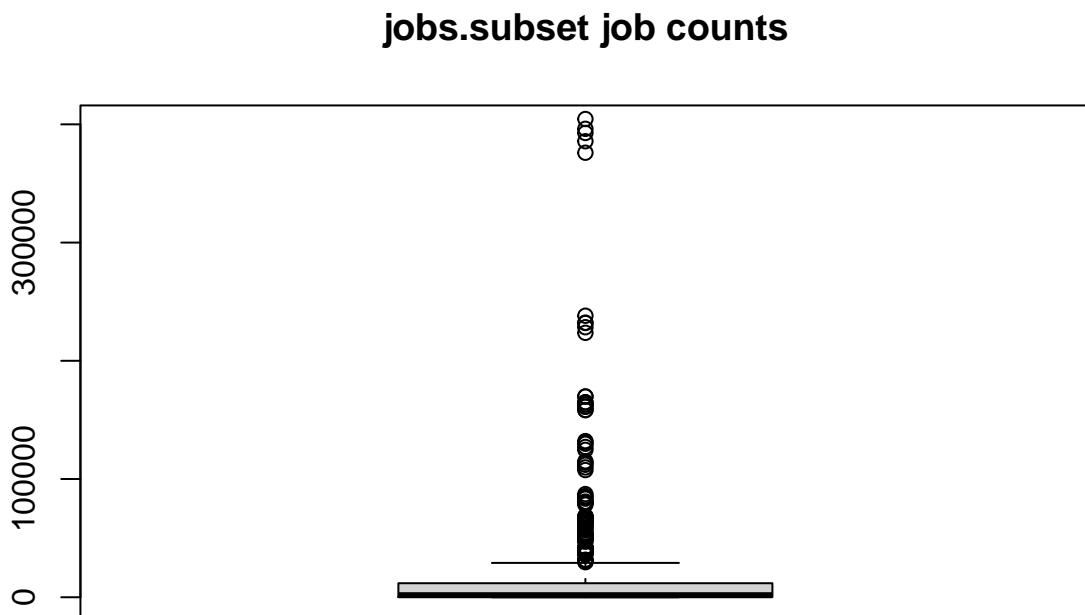
- Create a `hist` and `boxplot` and report `summary(jobs$job.count)`.

(5 points) Histogram and Box Plot

```
hist(jobs$job)
```



```
boxplot(jobs$job.count, ylim = c(0,400000), main='jobs.subset job counts')
```



```
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?]

```
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

```
jobs.subset
```

Histogram and Box Plot of Subset

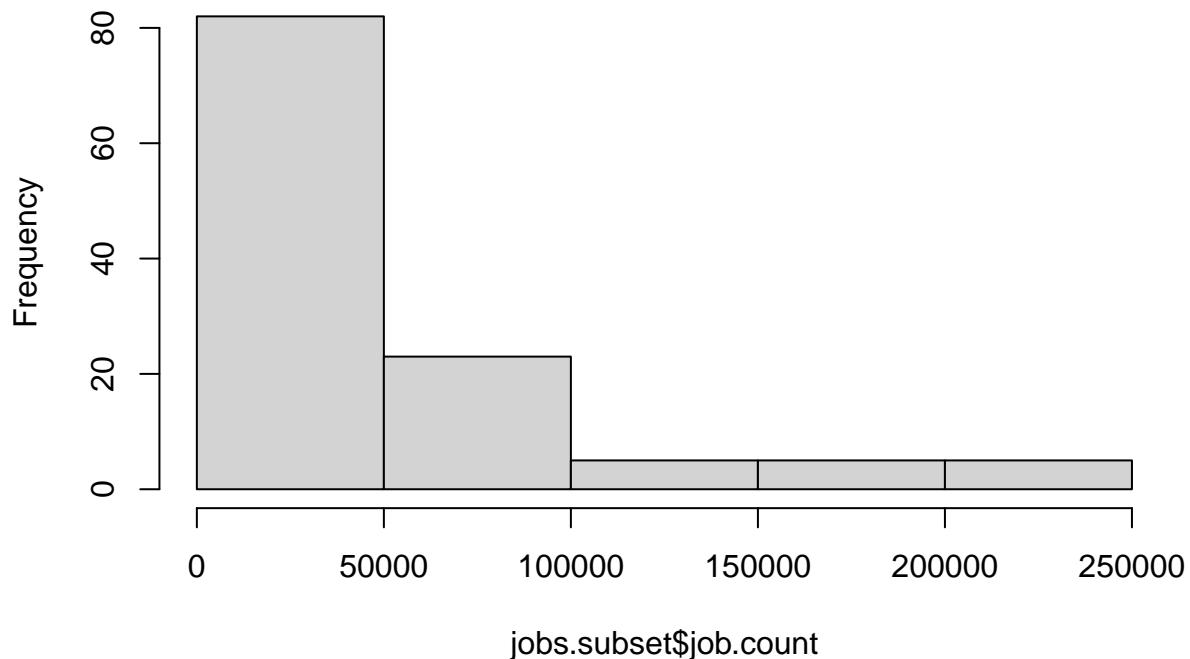
```
##      year.week      search.query job.count
## 2      2020-38      Microsoft Office 223663
## 3      2020-38                  C++ 158317
## 6      2020-38      Computer Science 107584
## 7      2020-38      Data entry 80465
## 10     2020-38                  SQL 63365
## 12     2020-38                  Python 56538
## 14     2020-38                  Java 49993
## 15     2020-38      Statistics 49383
## 18     2020-38      Data analysis 38384
## 20     2020-38      Javascript 35938
## 24     2020-38      machine learning 23197
## 26     2020-38      Data analytics 21546
## 30     2020-38                  Git 18270
## 34     2020-38      Big data 15737
## 36     2020-38      Data science 15044
## 38     2020-38      Tableau 13321
## 40     2020-38  Business intelligence 13032
## 43     2020-38                  PHP 12367
## 47     2020-38      Mysql 10809
## 49     2020-38                  SAS 10553
## 71     2020-38      Power BI 5266
## 87     2020-38      SPSS 2150
## 100    2020-38      Stata 1186
## 112    2020-38      MariaDB 547
## 183    2020-39      Microsoft Office 228397
## 184    2020-39                  C++ 161156
## 187    2020-39      Computer Science 109819
## 188    2020-39      Data entry 83373
## 191    2020-39                  SQL 64810
## 193    2020-39                  Python 57841
## 195    2020-39                  Java 51155
## 196    2020-39      Statistics 50588
## 199    2020-39      Data analysis 39447
## 201    2020-39      Javascript 36633
## 205    2020-39      machine learning 24005
## 206    2020-39      Data analytics 22342
## 211    2020-39                  Git 18617
## 215    2020-39      Big data 15997
## 217    2020-39      Data science 15587
## 218    2020-39      Tableau 13735
```

## 220	2020-39	Business intelligence		13524
## 225	2020-39		PHP	12610
## 229	2020-39		SAS	11039
## 230	2020-39		Mysql	10942
## 252	2020-39		Power BI	5456
## 268	2020-39		SPSS	2237
## 279	2020-39		Stata	1271
## 293	2020-39		MariaDB	582
## 364	2020-40	Microsoft Office		231979
## 365	2020-40		C++	163044
## 368	2020-40	Computer Science		112070
## 369	2020-40		Data entry	84427
## 372	2020-40		SQL	66175
## 374	2020-40		Python	58898
## 376	2020-40		Java	52113
## 377	2020-40		Statistics	51850
## 380	2020-40		Data analysis	40455
## 382	2020-40		Javascript	37554
## 386	2020-40	machine learning		24489
## 387	2020-40		Data analytics	23044
## 395	2020-40		Big data	16463
## 397	2020-40		Data science	15998
## 399	2020-40		Tableau	13943
## 400	2020-40	Business intelligence		13865
## 404	2020-40		PHP	12962
## 409	2020-40		Mysql	11137
## 411	2020-40		SAS	11118
## 432	2020-40		Power BI	5626
## 447	2020-40		SPSS	2372
## 460	2020-40		Stata	1336
## 474	2020-40		MariaDB	560
## 542	2020-40		Git	0
## 545	2020-41	Microsoft Office		232215
## 546	2020-41		C++	164920
## 549	2020-41	Computer Science		113809
## 550	2020-41		Data entry	85592
## 553	2020-41		SQL	67313
## 555	2020-41		Python	60241
## 557	2020-41		Java	52872
## 558	2020-41		Statistics	52159
## 561	2020-41		Data analysis	40836
## 563	2020-41		Javascript	38358
## 567	2020-41	machine learning		24859
## 568	2020-41		Data analytics	23491
## 573	2020-41		Git	19528
## 578	2020-41		Big data	16619
## 579	2020-41		Data science	16247
## 580	2020-41		Tableau	14430
## 582	2020-41	Business intelligence		14173
## 586	2020-41		PHP	13119
## 591	2020-41		SAS	11379
## 593	2020-41		Mysql	11195
## 614	2020-41		Power BI	5832
## 628	2020-41		SPSS	2326

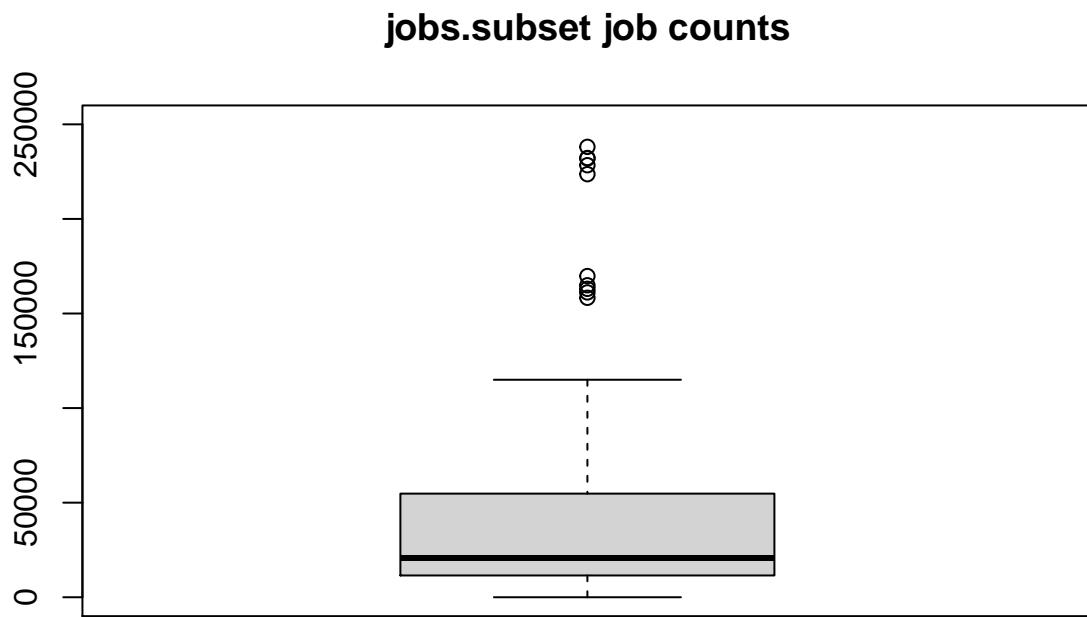
```
## 641 2020-41 Stata 1380
## 657 2020-41 MariaDB 560
## 726 2020-42 Microsoft Office 238111
## 728 2020-42 C++ 169786
## 730 2020-42 Computer Science 114970
## 731 2020-42 Data entry 87269
## 734 2020-42 SQL 68503
## 736 2020-42 Python 61021
## 738 2020-42 Statistics 53016
## 739 2020-42 Java 52969
## 742 2020-42 Data analysis 41620
## 744 2020-42 Javascript 38637
## 748 2020-42 machine learning 25172
## 749 2020-42 Data analytics 24058
## 753 2020-42 Git 19945
## 758 2020-42 Data science 16665
## 759 2020-42 Big data 16518
## 761 2020-42 Tableau 14707
## 763 2020-42 Business intelligence 14337
## 767 2020-42 PHP 13244
## 772 2020-42 SAS 11596
## 774 2020-42 Mysql 11425
## 795 2020-42 Power BI 5987
## 809 2020-42 SPSS 2342
## 822 2020-42 Stata 1423
## 835 2020-42 MariaDB 610
```

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

Histogram of jobs.subset\$job.count



```
boxplot(jobs.subset$job.count, ylim = c(0,250000), main='jobs.subset job counts')
```



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

```
##      Min. 1st Qu. Median      Mean 3rd Qu.      Max.
##        0    11553   20746   44306   53897  238111
```

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

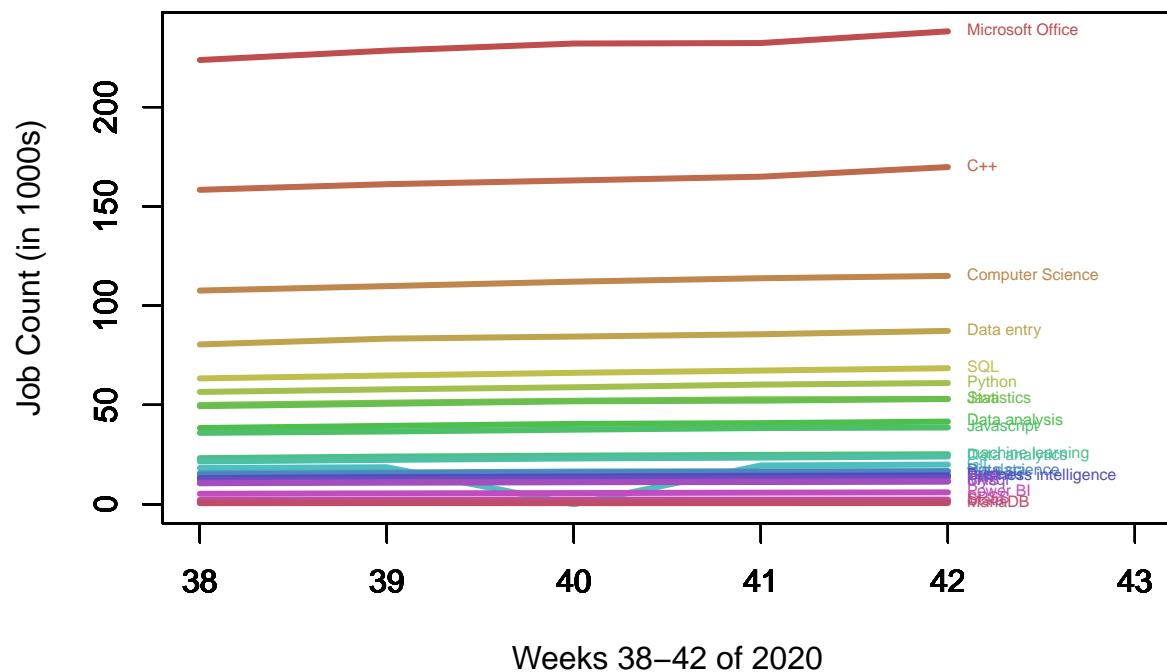
(10 points) Trends in Relevant Subset

```
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;

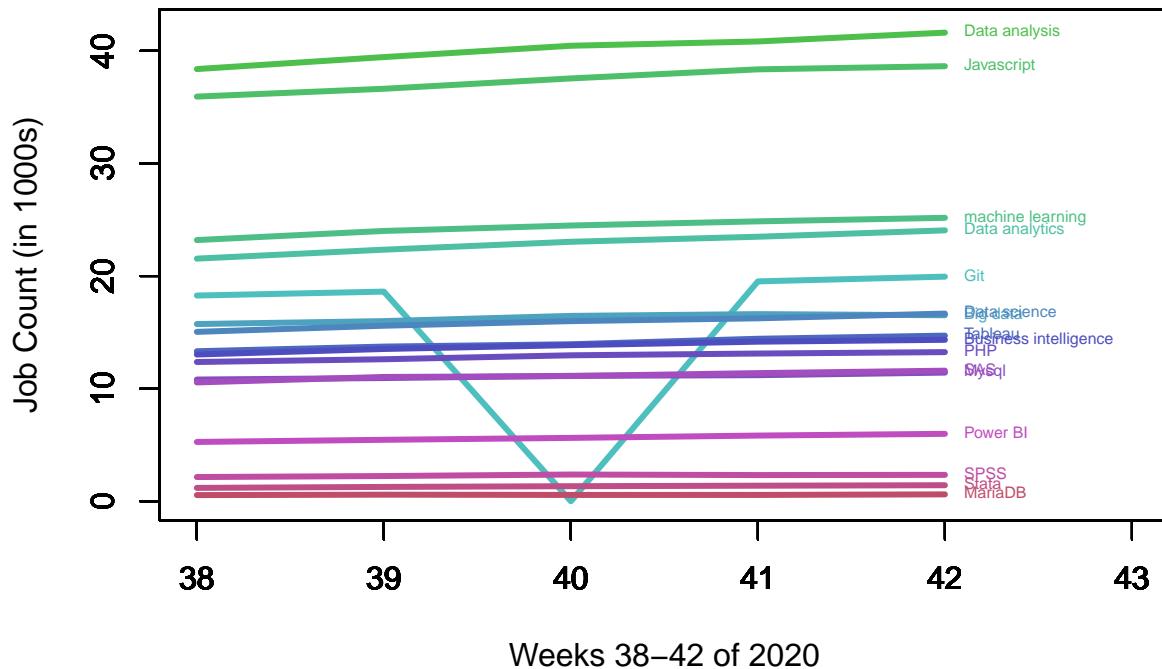
do.nothing = plotJobs(jobs.subset);
```

Keyword trends in Data Analysis



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

Keyword trends in Data Analysis



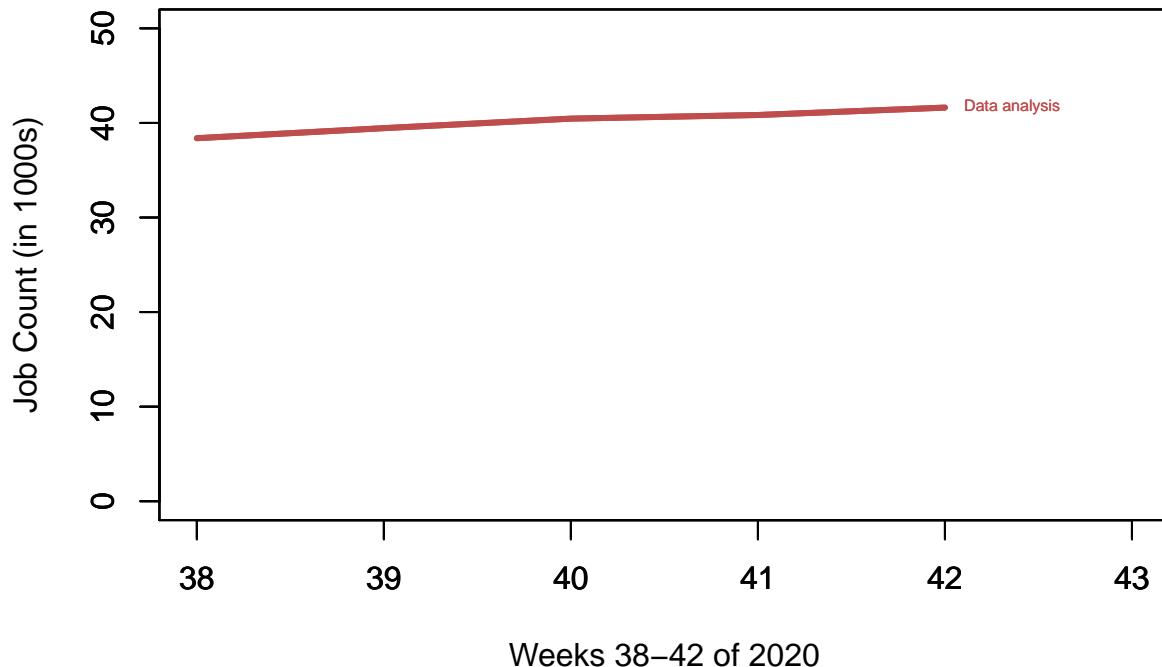
```
jobs.da <- subset(jobs.subset, search.query=='Data analysis')
jobs.da
```

Initial Perspective

```
##      year.week search.query job.count job.count.k
## 18    2020.38 Data analysis     38384     38.384
## 199   2020.39 Data analysis     39447     39.447
## 380   2020.40 Data analysis     40455     40.455
## 561   2020.41 Data analysis     40836     40.836
## 742   2020.42 Data analysis     41620     41.620
```

```
jobs.da$job.count.k = jobs.da$job.count / 1000;
plotJobs(jobs.da, myy.lim = c(0,50))
```

Keyword trends in Data Analysis



```
## $colors
## [1] "#BF4D4D"
##
## $search
## [1] "Data analysis"
```

[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?

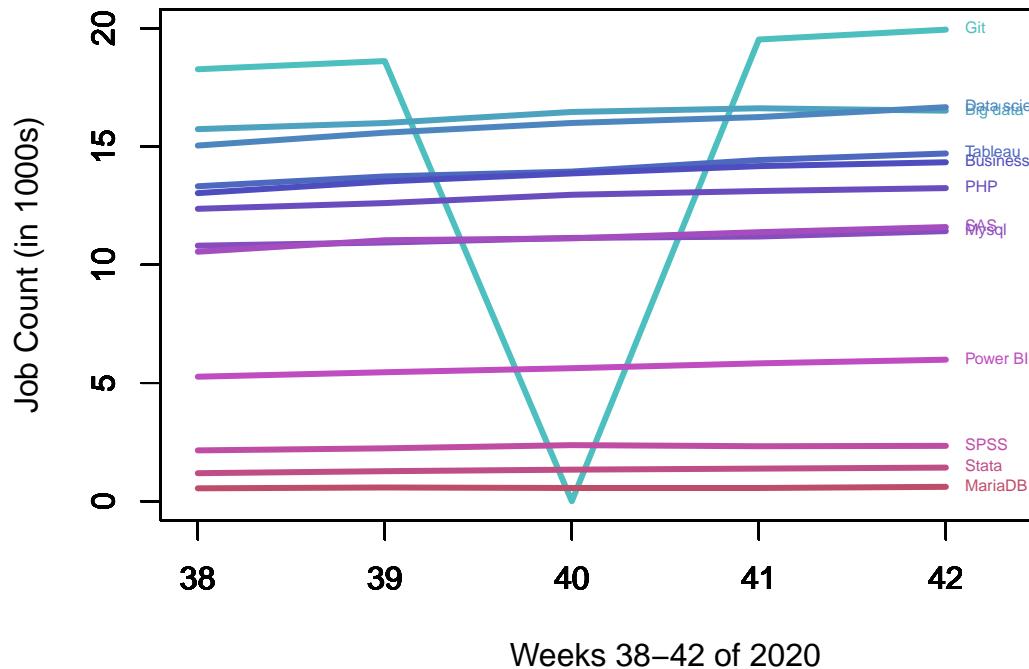
Now comment on the line of data for “Data analysis”. How is it trending? How does it compare to other Search-Query Words?

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      0.000    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      0.000    0.000
```

```

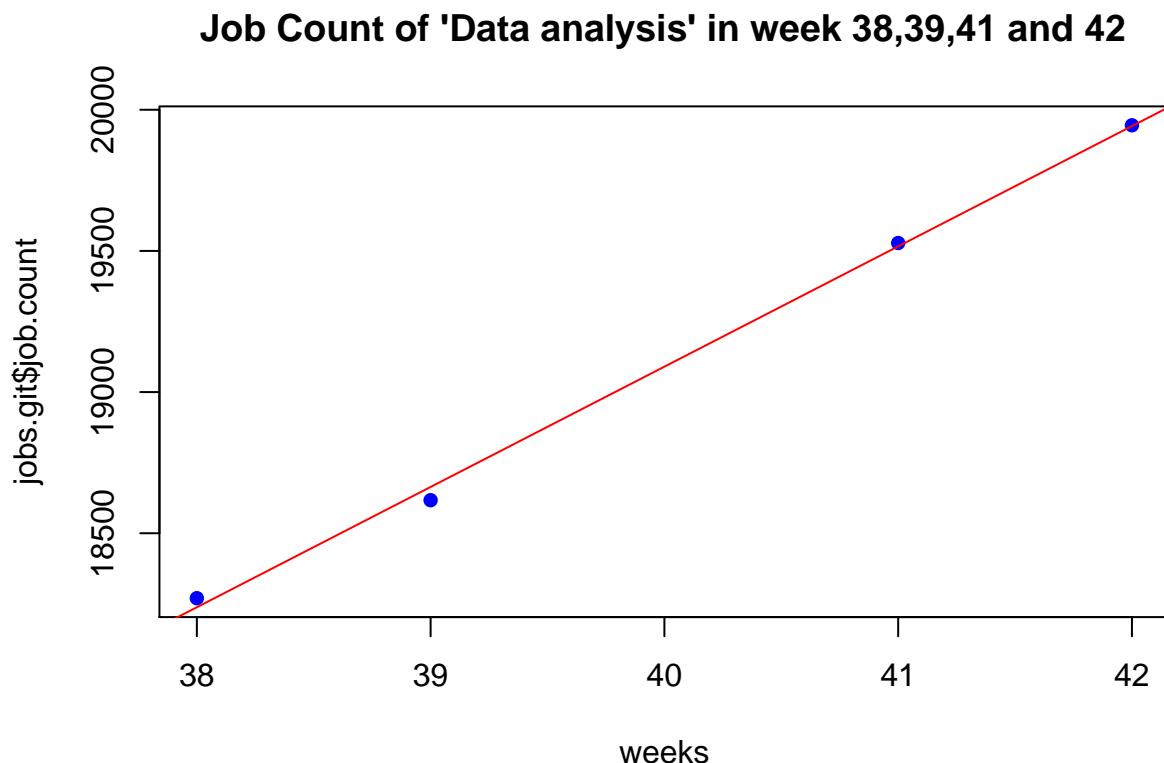
## change this if you feel appropriate? To what number?

## I can use the data points that aren't missing to find the best fit line, then find a value the week
# Creating subset of data excluding week40
jobs.git <- jobs.subset[idxs.Git,][ -c(3),]
jobs.git

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

# Plot the jobs.git with best fit line
weeks <- c(38,39,41,42)
plot(weeks, jobs.git$job.count, pch=16, col="blue", main = "Job Count of 'Data analysis' in week 38,39,41 and 42")
abline(lm(jobs.git$job.count ~ weeks), col="red")

```



```

lm(jobs.git$job.count ~ weeks)

##
## Call:
## lm(formula = jobs.git$job.count ~ weeks)
##
```

```

## Coefficients:
## (Intercept)      weeks
## 2046.0          426.1

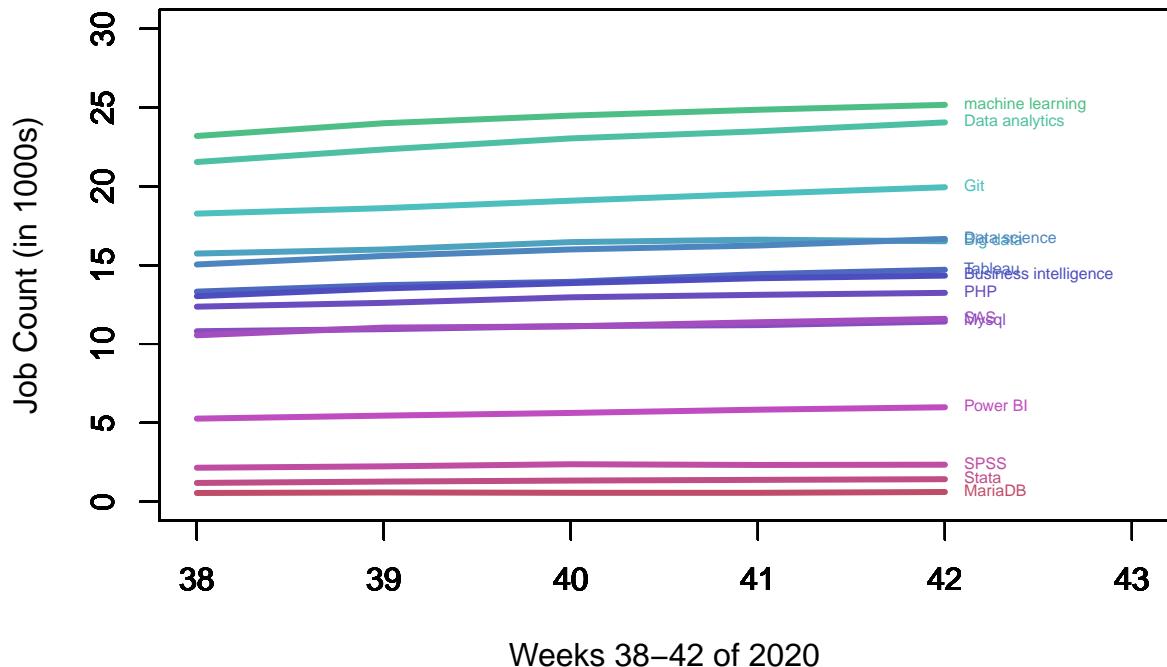
# now we found the linear model : 2046.0 + 426.1*(week)
# find value for the week 40 using the equation above
jobcount.40 <- 2046.0 + 426.1*40

jobs.subset[my.idx,3] <- jobcount.40      # job.count
jobs.subset[my.idx,4] <- jobcount.40/1000  # job.count.k (in thousands) ...

do.nothing = plotJobs(jobs.subset, myy.lim = c(0,30) )

```

Keyword trends in Data Analysis



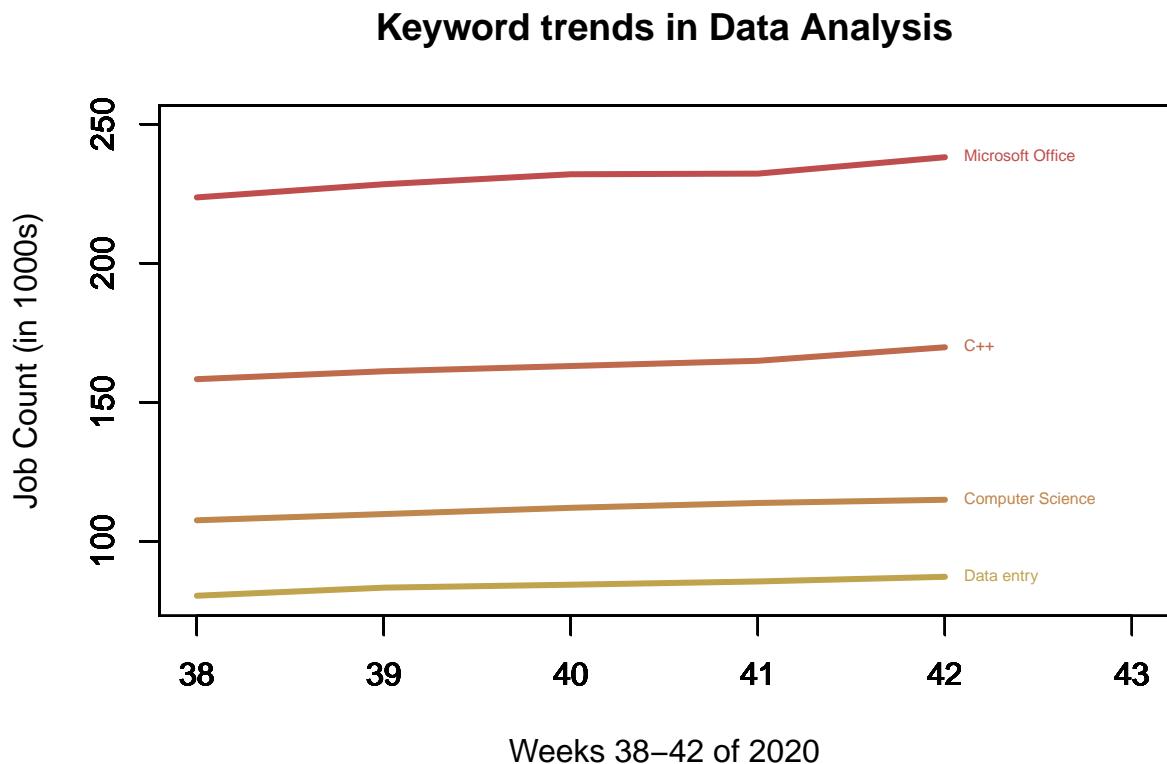
Is “Microsoft Office” bigger than “C++”? I use the term “bigger” or “better” intentionally. We are comparing two items, and these are generic ways of communicating such a comparison. In context of this data problem, a formalized form of the question would be something like: “Utilizing job count for a 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:

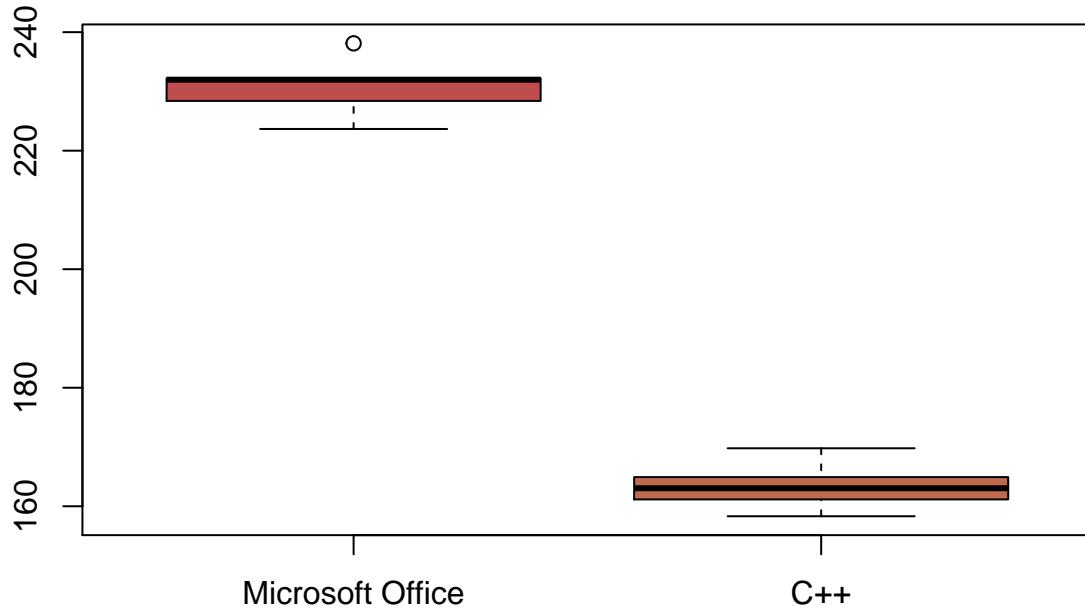
Mathematically, if two lines are parallel, and one is above the other, can we use **distance** to draw a conclusion? Now, many times in statistics we deal with noise in the data, it is not “deterministic” but “stochastic” ... so we need to understand the variability. Based on the data we see, can we 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) );
```



```
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”)

```
msoffice <- jobs.subset[which(jobs.subset$search.query == "Microsoft Office"),]
c <- jobs.subset[which(jobs.subset$search.query == "C++"),]
```

```
summary(msoffice$job.count.k)
```

```
##      Min. 1st Qu.  Median      Mean 3rd Qu.      Max.
##    223.7   228.4   232.0   230.9   232.2   238.1
```

```
summary(c$job.count.k)
```

```
##      Min. 1st Qu.  Median      Mean 3rd Qu.      Max.
##    158.3   161.2   163.0   163.4   164.9   169.8
```

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

Would a formal “inferential statistical test” tell us something 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 ...

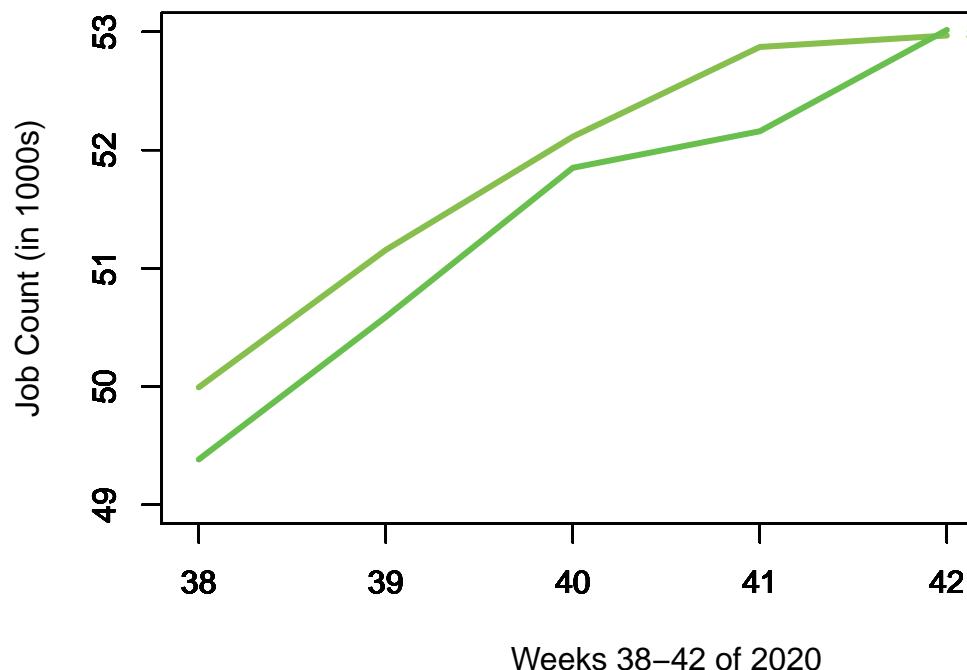
t.test.jobs(jobs.subset, "Microsoft Office", "C++");

## 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

```

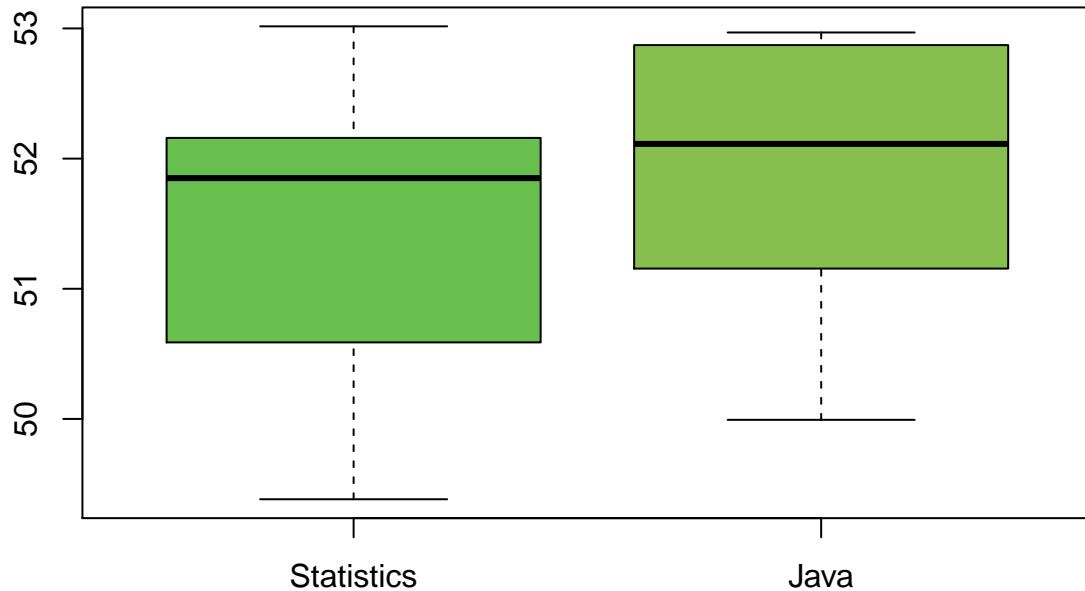
```
do.nothing = plotJobs(jobs.subset, myy.lim = c(49,53) );
```

Keyword trends in Data Analysis



Is “Statistics” bigger than “Java”?

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



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”.

```
summary(jobs.subset[which(jobs.subset$search.query == "Statistics"),]$job.count.k)
```

```
##      Min. 1st Qu. Median      Mean 3rd Qu.      Max.
## 49.38    50.59  51.85    51.40  52.16    53.02
```

```
summary(jobs.subset[which(jobs.subset$search.query == "Java"),]$job.count.k)
```

```
##      Min. 1st Qu. Median      Mean 3rd Qu.      Max.
## 49.99    51.16  52.11    51.82  52.87    52.97
```

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

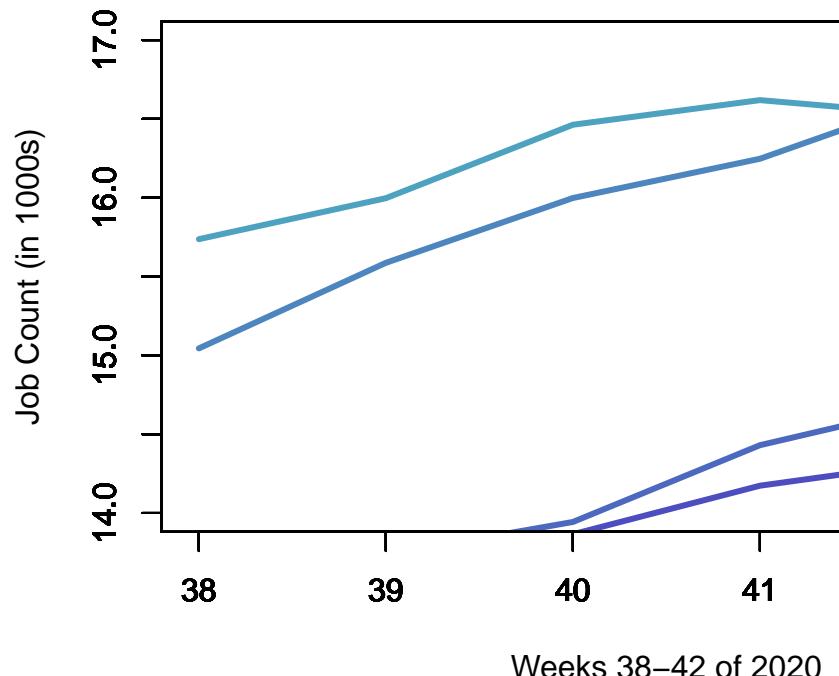
```
##
##  Welch Two Sample t-test
##
## data: x and y
## t = -0.49621, df = 7.8738, p-value = 0.6333
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
```

```
## -2.384104 1.541704
## sample estimates:
## mean of x mean of y
## 51.3992 51.8204
```

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

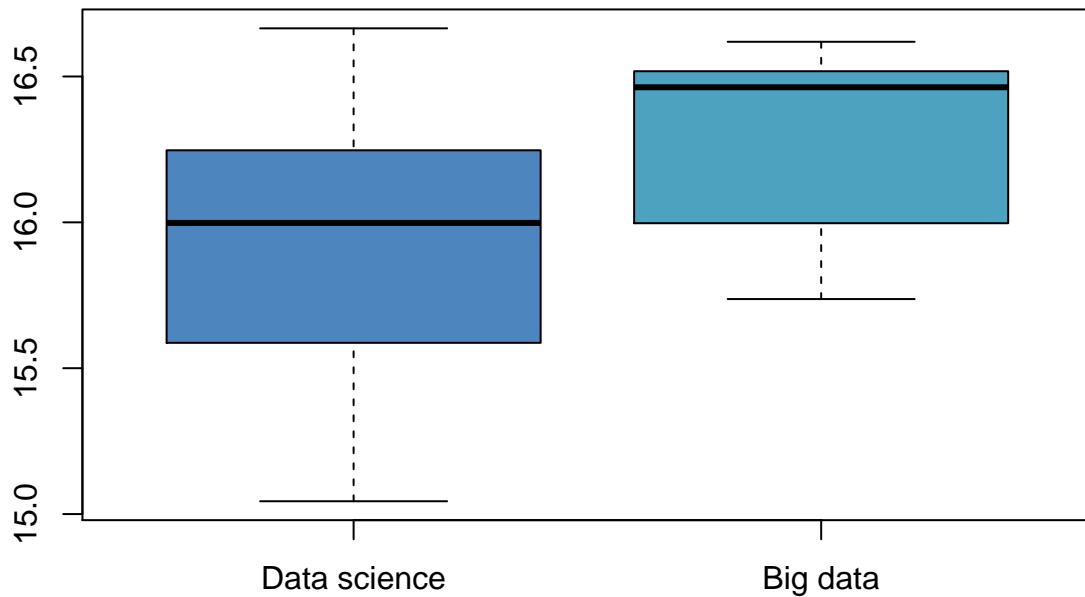
```
do.nothing = plotJobs(jobs.subset, myy.lim = c(14,17) );
```

Keyword trends in Data Analytics



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

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



```

summary(jobs.subset[which(jobs.subset$search.query == "Data science"),]$job.count.k)

##      Min. 1st Qu.  Median      Mean 3rd Qu.      Max.
##  15.04   15.59   16.00   15.91   16.25   16.66

summary(jobs.subset[which(jobs.subset$search.query == "Big data"),]$job.count.k)

##      Min. 1st Qu.  Median      Mean 3rd Qu.      Max.
##  15.74   16.00   16.46   16.27   16.52   16.62

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

```

From the box plot, we can see that the median value of ‘Big data’ slightly larger than the Q3 value of ‘Data Science’. The whiskers(maximum to the minimum values) shows that ‘Data Science’ data has a wider distribution, that is. more scattered compared to the ‘Big data’ data. After looking at the plot and the boxplot, We get a sense that these two data might not differ much from each other. We can verify this by looking at the Welch two-sample t-test results. The p-value = 0.3096 and the significance level = 0.05. Thus, we cannot reject the null hypothesis of no difference between the true averages of the two groups at the significance level of 0.05.

It is very possible that the single-job posting will include many keywords. When we looking at the jobs.subset data, we are looking at closely related keywords for data analytics. Maybe the better way to collect the data can be getting rid of duplicated job posts between data sets compared.

[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

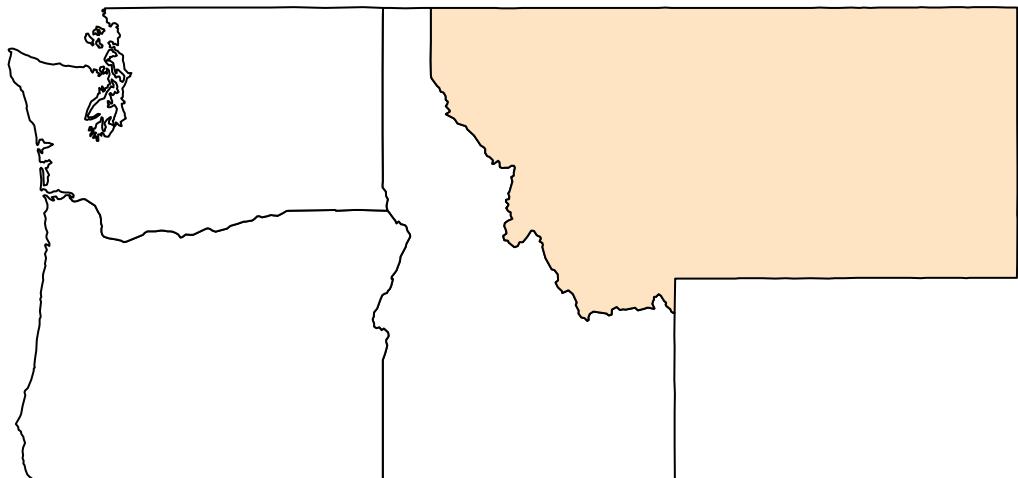
##### plotting #####
brown = "#ffe4c4";
green = "#014421";
```

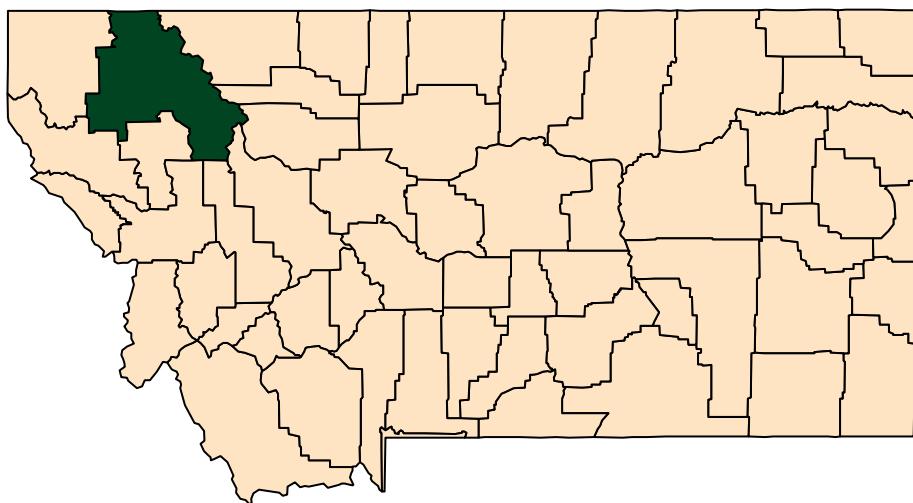
```
my.state = "montana";
my.state.color = "#ffe4c4";

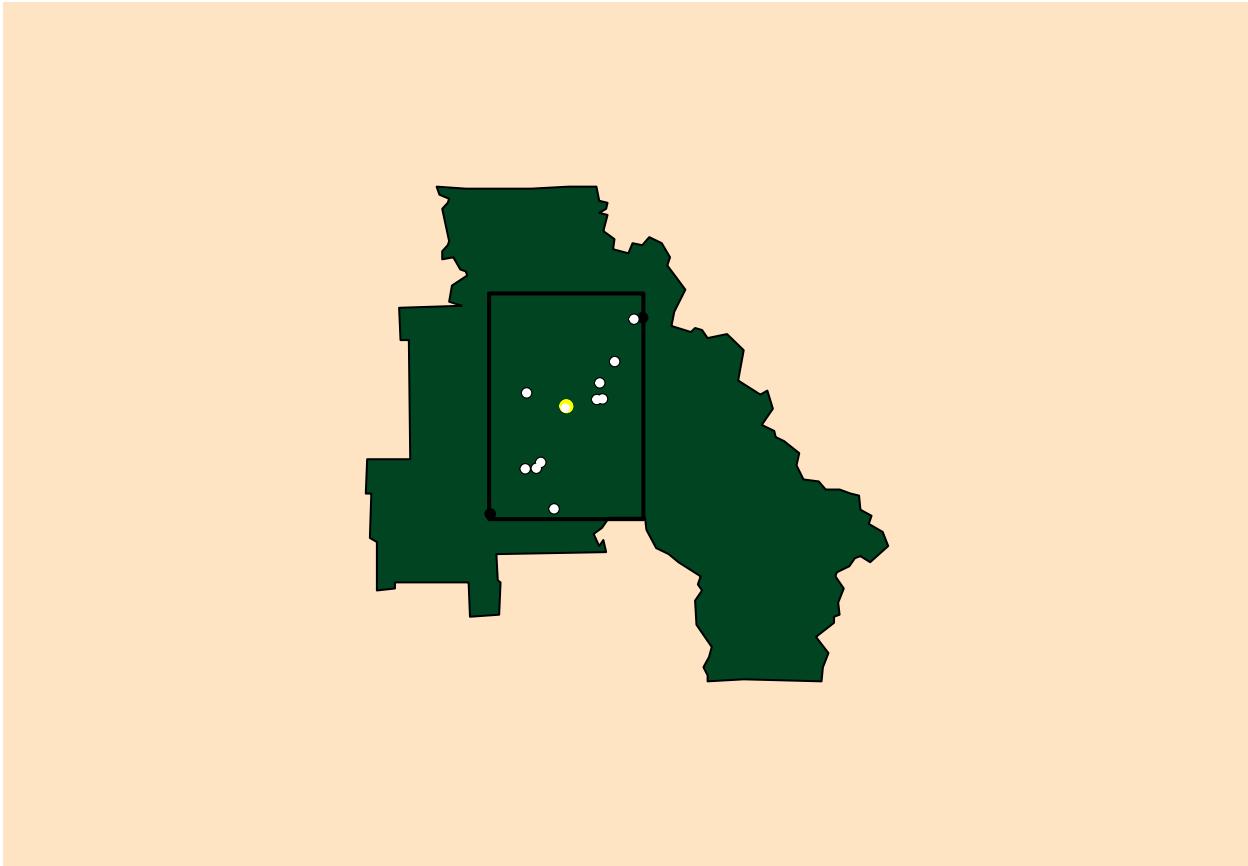
my.county = "flathead";
my.county.color = "#014421";

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 = 47.957470
hometown.longitude = -122.165446
my.radius = 13
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

hometown.info = getNeighborsFromLatLong(my.radius, hometown.latitude, hometown.longitude, "mi")

## [1] "The QUERY returned ... 24 ... NEIGHBORS"

hometown.info$neighbors

##      zipcode latitude longitude      city state_long state
## 1      98012  47.84130 -122.2058 BOTHELL WASHINGTON WA
## 2      98021  47.79165 -122.2174 BOTHELL WASHINGTON WA
## 3      98026  47.84077 -122.3367 EDMONDS WASHINGTON WA
## 4      98036  47.80278 -122.2849 LYNNWOOD WASHINGTON WA
## 5      98037  47.85110 -122.2815 LYNNWOOD WASHINGTON WA
## 6      98043  47.79179 -122.3041 MOUNTLAKE TERRACE WASHINGTON WA
## 7      98046  47.83017 -122.3040 LYNNWOOD WASHINGTON WA
## 8      98082  47.85524 -122.2210 MILL CREEK WASHINGTON WA
## 9      98087  47.87263 -122.2709 LYNNWOOD WASHINGTON WA
## 10     98201  47.98859 -122.2018 EVERETT WASHINGTON WA
## 11     98203  47.94596 -122.2299 EVERETT WASHINGTON WA
## 12     98204  47.89843 -122.2548 EVERETT WASHINGTON WA
## 13     98205  47.99055 -122.1141 EVERETT WASHINGTON WA
## 14     98206  47.92563 -122.2264 EVERETT WASHINGTON WA
## 15     98207  47.95998 -122.1968 EVERETT WASHINGTON WA
## 16     98208  47.89491 -122.1934 EVERETT WASHINGTON WA
## 17     98213  47.94082 -122.2347 EVERETT WASHINGTON WA
## 18     98258  48.02742 -122.0624 LAKE STEVENS WASHINGTON WA
## 19     98270  48.06088 -122.1539 MARYSVILLE WASHINGTON WA
## 20     98271  48.09840 -122.2373 MARYSVILLE WASHINGTON WA
## 21     98275  47.90714 -122.3091 MUKILTEO WASHINGTON WA
## 22     98290  47.93953 -122.0167 SNOHOMISH WASHINGTON WA
## 23     98291  47.92897 -122.0999 SNOHOMISH WASHINGTON WA
## 24     98296  47.82290 -122.1182 SNOHOMISH WASHINGTON WA

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

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

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

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

## I have tried multiple times to make this code work but was not successful..... I'm getting an error
## I think this might be due to my version of R? .. My r is 4.0.2 do I need to update?..
## Please try this code below to check if it works on your machine

# plotNeighbors(hometown.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)

```

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"), hea

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

# 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", "L

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)

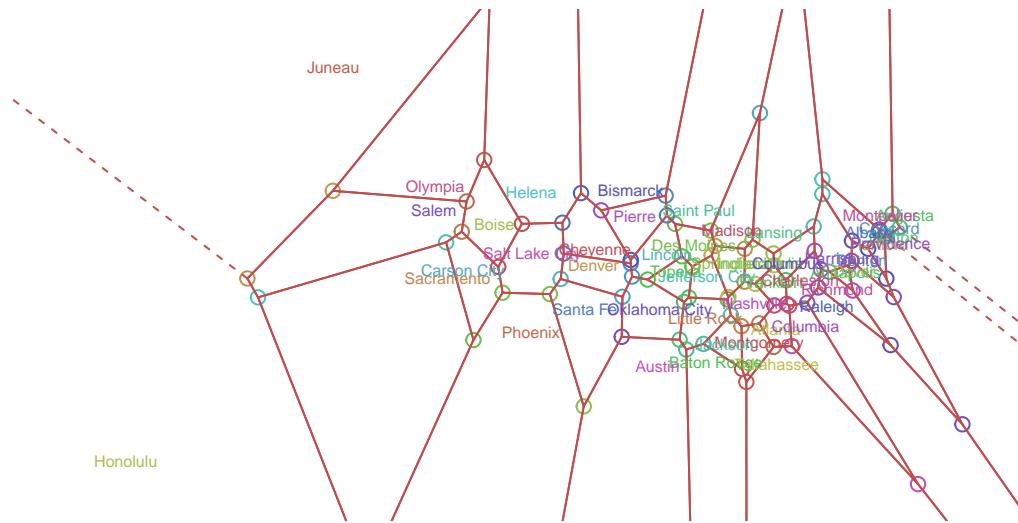


- Plot the data using maths voronoi (tripack)

```
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);
```

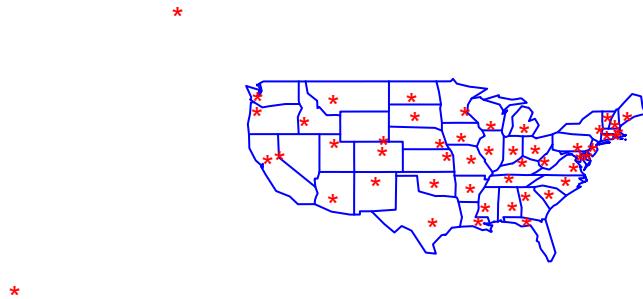
Voronoi mosaic



```
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 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 data frame 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.m = as.matrix( dist.haversine );
rownames(dist.haversine.m) =
colnames(dist.haversine.m) = myLabels;

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

dist.haversine.df;  ## too big

```

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).

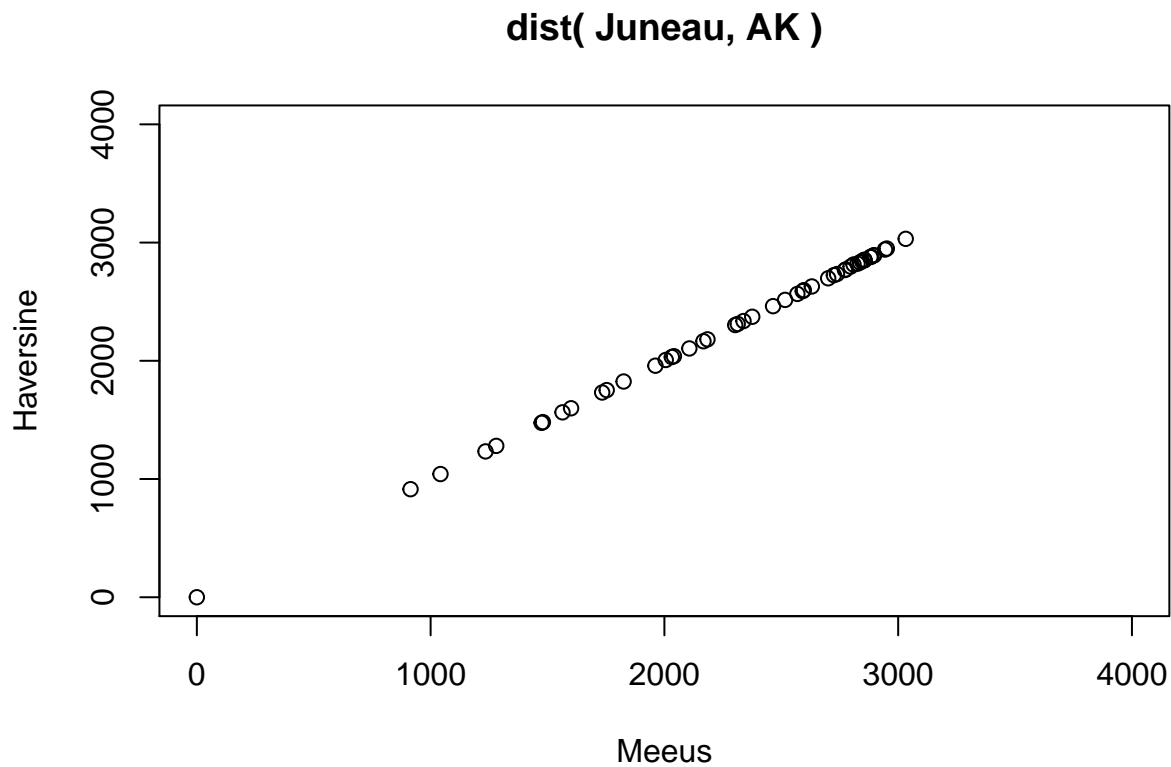
```

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	479.1
## Juneau, AK	3587.6	3487.7	2202.7	3483.5	3419.6
## Phoenix, AZ	2313.0	2089.7	366.6	2186.0	1832.5
## Little Rock, AR	1276.9	1031.2	747.1	1151.9	751.3
## Sacramento, CA	2746.2	2554.0	871.5	2621.5	2348.3
## Denver, CO	1842.1	1650.7	286.0	1717.1	1465.0
## Hartford, CT	117.4	155.8	1865.7	85.3	526.3
## Dover, DE	354.1	84.5	1679.4	259.7	289.1
## Tallahassee, FL	1120.8	850.2	1238.8	1018.2	478.0
## Atlanta, GA	958.0	689.6	1185.3	845.0	343.6
## Honolulu, HI	4949.4	4721.0	3001.7	4822.3	4439.3
## Boise, ID	2438.8	2274.6	783.1	2318.4	2121.5
## Springfield, IL	1016.7	813.6	935.0	890.1	663.0
## Indianapolis, IN	832.8	622.9	1117.8	705.7	495.0
## Des Moines, IA	1210.9	1033.9	788.2	1087.0	911.7
## Topeka, KS	1349.4	1145.4	607.8	1222.9	958.5
## Frankfort, KY	805.6	569.0	1165.1	680.0	379.5
## Baton Rouge, LA	1387.5	1121.7	884.0	1270.4	777.1
## Augusta, ME	122.6	391.9	2063.8	245.5	762.4
## Annapolis, MD	398.5	128.2	1624.8	294.8	250.0
## Boston, MA	64.0	250.0	1960.7	148.5	614.5
## Lansing, MI	711.0	561.5	1267.0	589.1	579.1
## Saint Paul, MN	1183.0	1052.5	950.6	1067.5	1012.1
## Jackson, MS	1266.1	1004.0	892.4	1146.7	674.6
## Jefferson City, MO	1171.1	957.4	779.3	1044.1	764.3
## Helena, MT	2222.6	2081.1	823.1	2106.8	1970.0
## Lincoln, NE	1382.6	1197.3	618.8	1258.0	1044.9
## Carson City, NV	2648.0	2458.3	791.3	2523.6	2258.1
## Concord, NH	0.0	270.9	1950.3	127.1	643.1
## Trenton, NJ	270.9	0.0	1732.3	176.4	373.1
## Santa Fe, NM	1950.3	1732.3	0.0	1823.4	1492.3
## Albany, NY	127.1	176.4	1823.4	0.0	544.6

## Raleigh, NC	643.1	373.1	1492.3	544.6	0.0
## Bismarck, ND	1616.0	1491.6	819.1	1503.2	1429.4
## Columbus, OH	664.7	450.1	1288.4	537.7	375.0
## Oklahoma City, OK	1515.8	1285.2	461.2	1389.0	1031.5
## Salem, OR	2814.5	2655.9	1130.7	2695.4	2505.8
## Harrisburg, PA	355.0	115.4	1619.7	236.7	325.2
## 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).

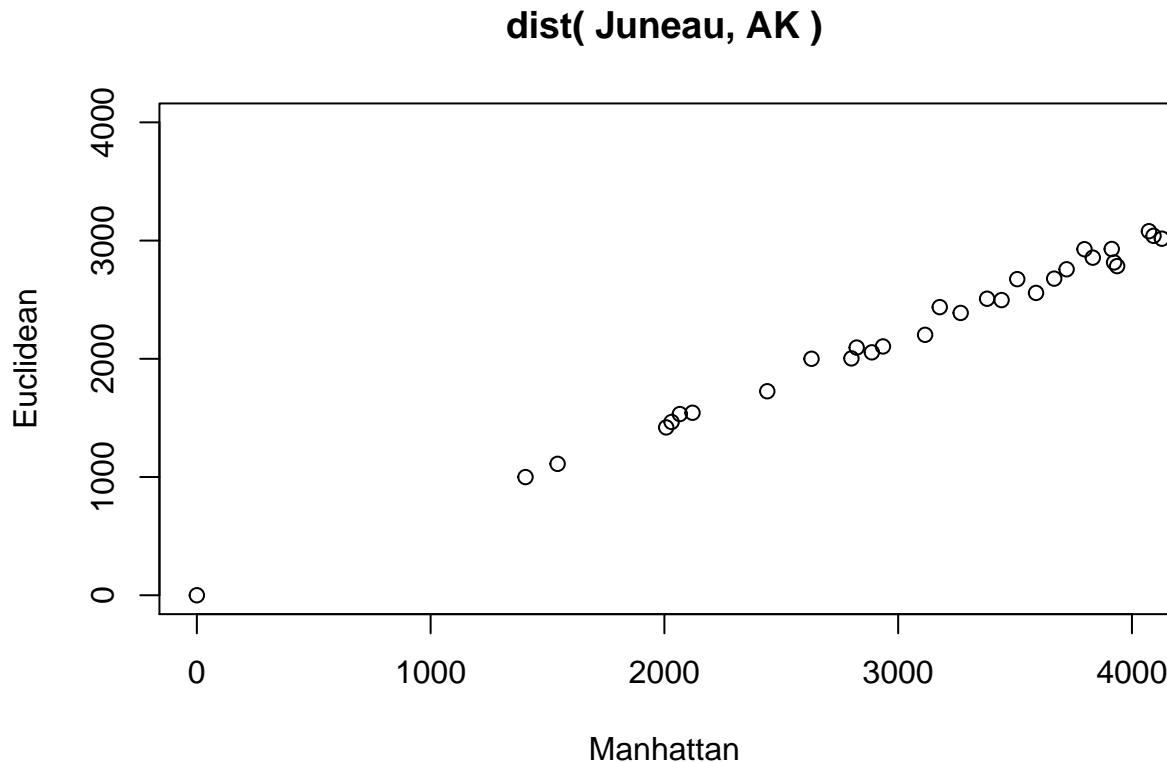
```

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 and performs some pairwise distance algorithm called a 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

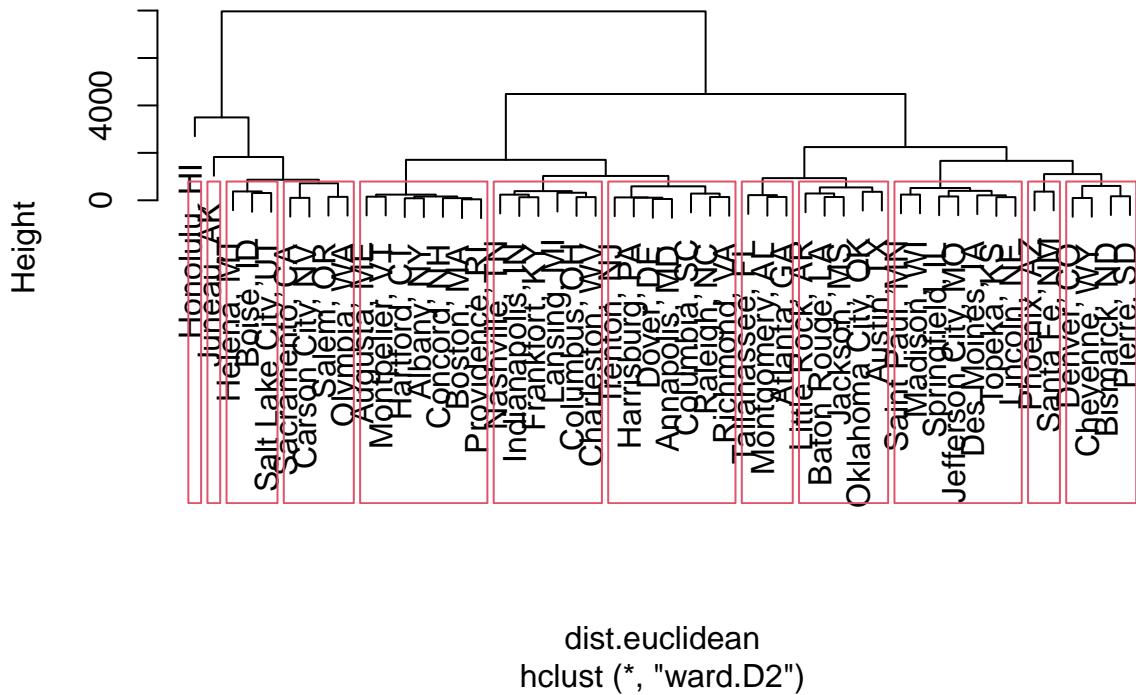
We already have some data for the U.S. capitals and have computed a Euclidean distance using a capital city's longitude and latitude. Let's choose to cut the result into 12 agglomerations. Why 12? It was a choice based on my life experience and intuition. As I reflected on why, I did some external searching that validates a choice in that range https://en.wikipedia.org/wiki/List_of_regions_of_the_United_States. 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



```

## 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`

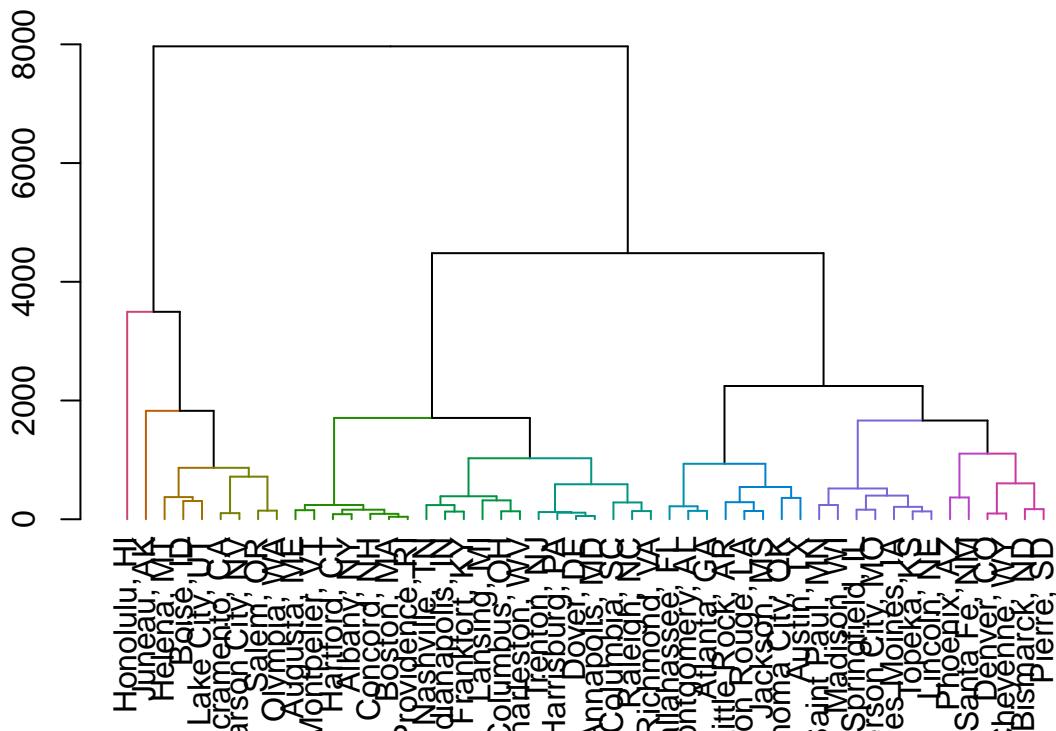
In the above example, the tree was cut into 12 groups based on the “distance” formula used and based on the “agglomeration” linkage technique invoice. I likely should have used a “geo-spatial” distance, but we will see that mere “euclidean” distance seems to perform okay.

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
```

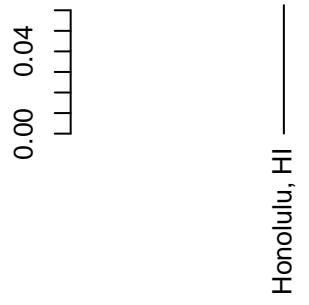


```

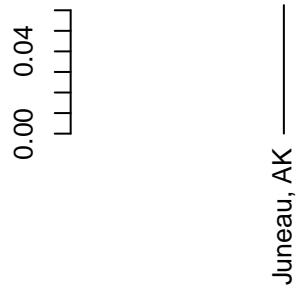
## [1] "Pruning 1 of 12"
## [1] "Pruning 2 of 12"
## [1] "Pruning 3 of 12"
## [1] "Pruning 4 of 12"
## [1] "Pruning 5 of 12"
## [1] "Pruning 6 of 12"
## [1] "Pruning 7 of 12"
## [1] "Pruning 8 of 12"
## [1] "Pruning 9 of 12"
## [1] "Pruning 10 of 12"
## [1] "Pruning 11 of 12"
## [1] "Pruning 12 of 12"

```

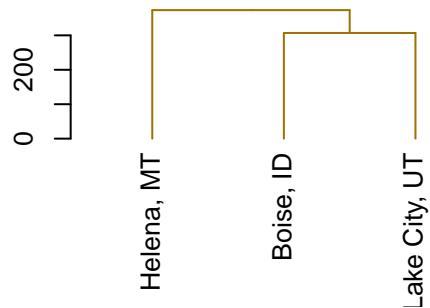
SubTree number 1



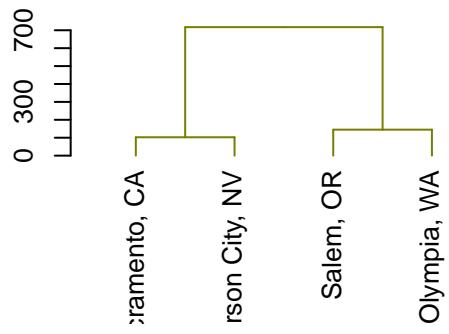
SubTree number 2



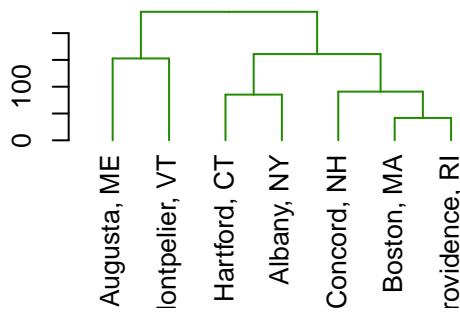
SubTree number 3



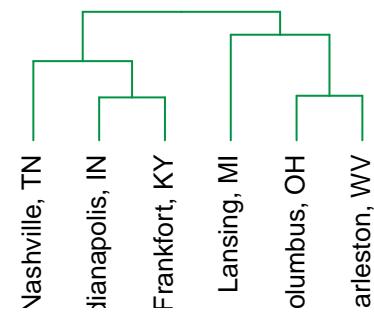
SubTree number 4



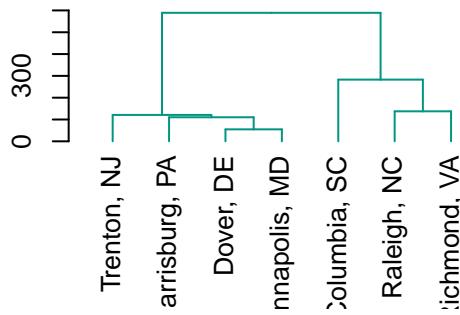
SubTree number 5



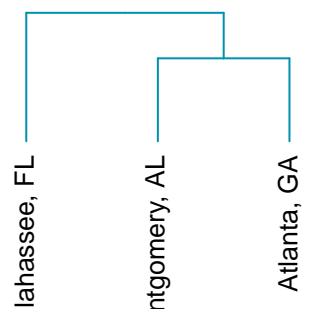
SubTree number 6



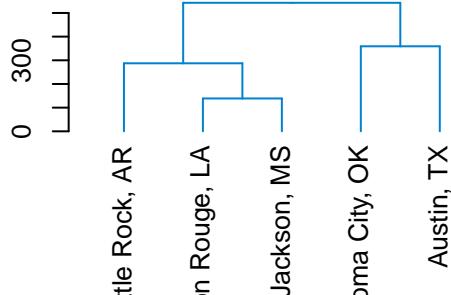
SubTree number 7



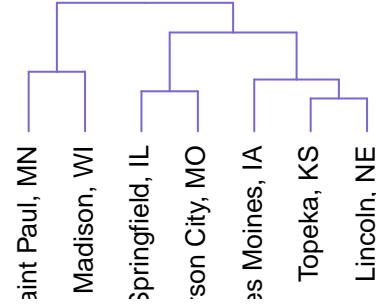
SubTree number 8



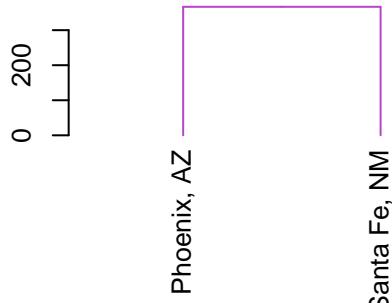
SubTree number 9



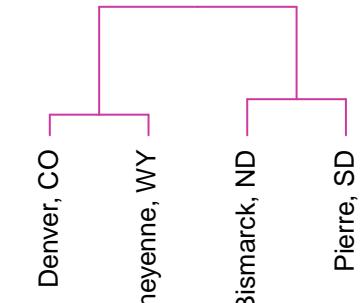
SubTree number 10



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(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);
```

```
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();

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

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

## 'data.frame': 100 obs. of 13 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: logi NA NA NA NA NA NA ...

## you do something here ...

# (1) populate cluster.arbitrary
movies.50$cluster.arbitrary[movies.50$millionsAdj2000<1] <- 'cluster2'
movies.50$cluster.arbitrary[movies.50$millionsAdj2000>=1 & movies.50$millionsAdj2000<5] <- 'cluster3'
movies.50$cluster.arbitrary[movies.50$millionsAdj2000>=5 & movies.50$millionsAdj2000<50] <- 'cluster4'
movies.50$cluster.arbitrary[movies.50$millionsAdj2000>=50] <- 'cluster5'
movies.50$cluster.arbitrary[is.na(movies.50$millionsAdj2000)] <- 'cluster1'
# (2) summarize how many movies live in each (table count)
table(movies.50$cluster.arbitrary)

## 
## cluster1 cluster2 cluster3 cluster4 cluster5
##      5        4        2       38       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, Thriller" ...
## $ 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: chr "cluster5" "cluster5" "cluster5" "cluster5" ...
## $ cluster.deciles : logi NA NA NA NA NA NA ...
```

you do something here ...

```
# use # 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
cat('there are', sum(is.na(movies.50$millionsAdj2000)), " NA's in column millionsAdj2000")
```

there are 5 NA's in column millionsAdj2000

```
# (2) for the rest of the data, break it up into deciles
movies.50.rest <- movies.50[!is.na(movies.50$millionsAdj2000),]
stats::quantile(movies.50.rest$millionsAdj2000, prob=seq(0.1,0.9,by=0.1), type=1)
```

```
##          10%         20%         30%         40%         50%         60%         70%
## 7.638768 20.177743 27.511542 37.259081 53.554796 64.786272 74.509802
##          80%         90%
## 115.650000 146.638920
```

```

# (3) $cluster.deciles for a given movie should be NA, 1, 2, 3, ... 10
movies.50$cluster.deciles[movies.50$millionsAdj2000<7.638768] <- 'Decile1'
movies.50$cluster.deciles[movies.50$millionsAdj2000>=7.638768 & movies.50$millionsAdj2000<20.177743] <-
movies.50$cluster.deciles[movies.50$millionsAdj2000>=20.177743 & movies.50$millionsAdj2000<27.511542] <-
movies.50$cluster.deciles[movies.50$millionsAdj2000>=27.511542 & movies.50$millionsAdj2000<37.259081] <-
movies.50$cluster.deciles[movies.50$millionsAdj2000>=37.259081 & movies.50$millionsAdj2000<53.554796] <-
movies.50$cluster.deciles[movies.50$millionsAdj2000>=53.554796 & movies.50$millionsAdj2000<64.786272] <-
movies.50$cluster.deciles[movies.50$millionsAdj2000>=64.786272 & movies.50$millionsAdj2000<74.509802] <-
movies.50$cluster.deciles[movies.50$millionsAdj2000>=74.509802 & movies.50$millionsAdj2000<115.650000] <-
movies.50$cluster.deciles[movies.50$millionsAdj2000>=115.650000 & movies.50$millionsAdj2000<146.638920] <-
movies.50$cluster.deciles[movies.50$millionsAdj2000>=146.638920] <- 'Decile10'

# (4) summarize how many movies live in each (table count)

table(movies.50$cluster.deciles, exclude = NULL)

## 
##   Decile1 Decile10 Decile2 Decile3 Decile4 Decile5 Decile6 Decile7
##       9       10      9     11      9     10      9      9
##   Decile8 Decile9     <NA>
##       9       10      5

```

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>

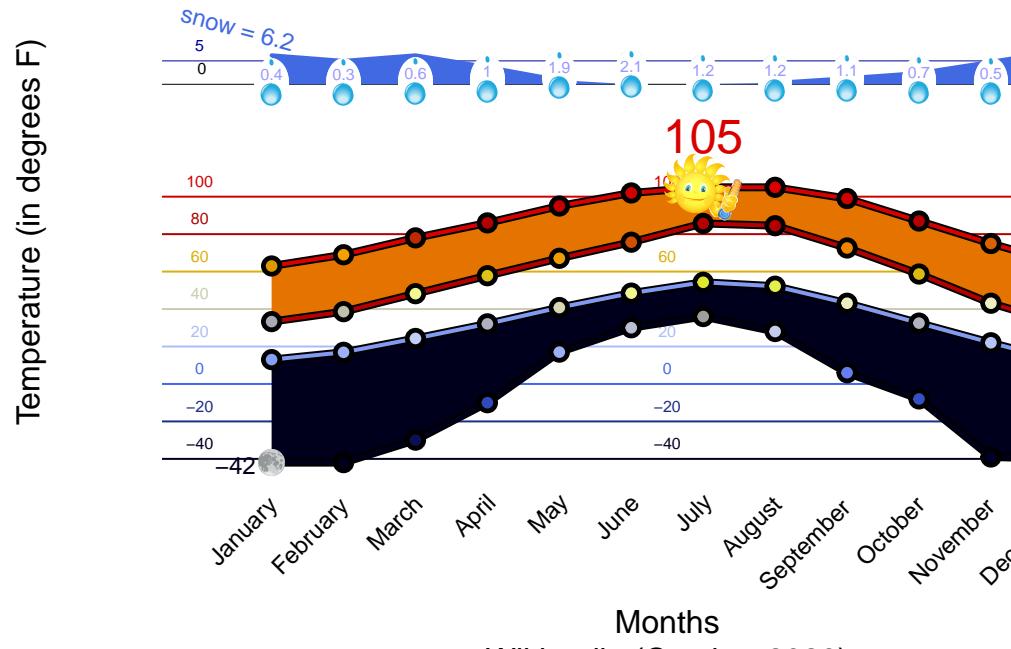
Source: <https://bit.ly/359HAnY>

<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");
```

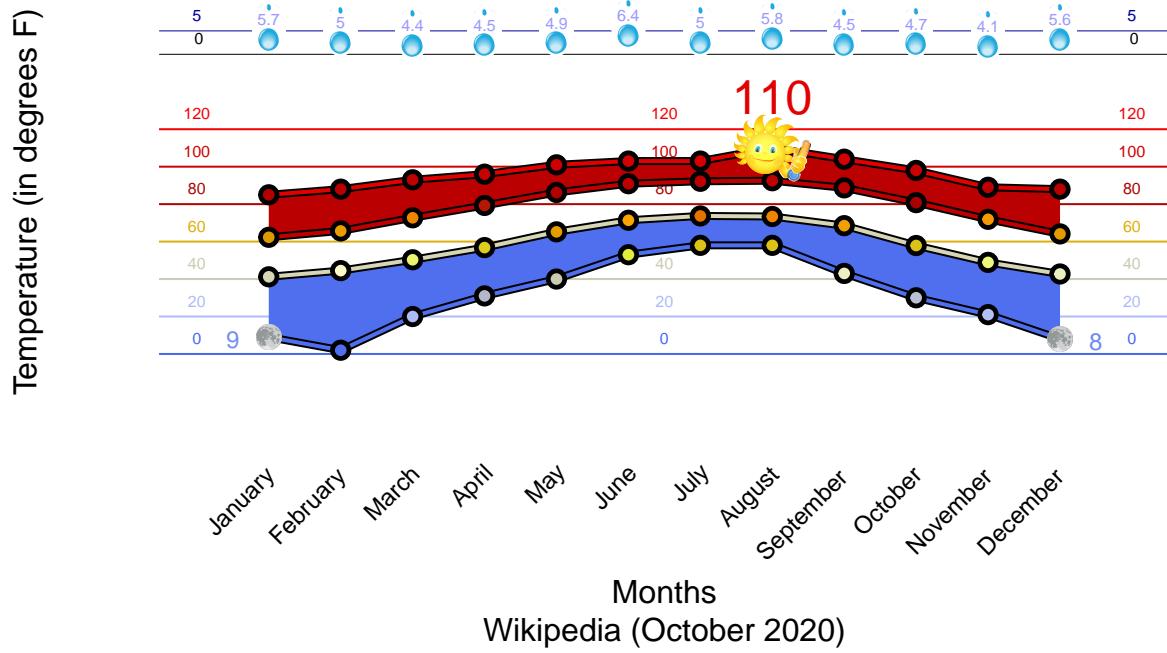
Helena, Montana



(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?

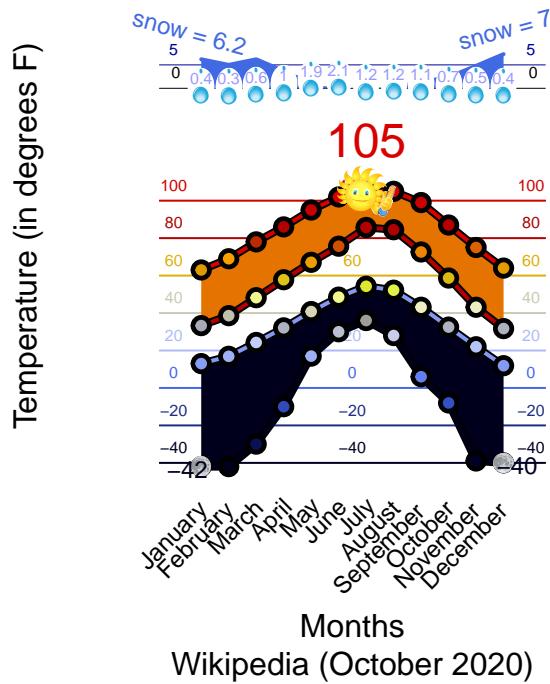
Is it aesthetically pleasing? Is it functional?

]

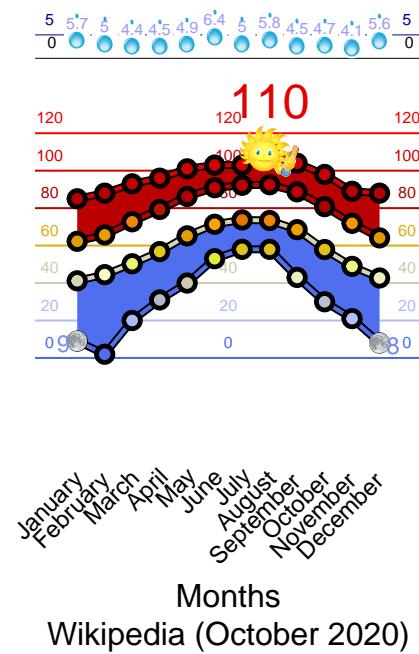
We can achieve a side-by-side comparison using the function described below. The first city will be graphed on the left, the second city on the right.

```
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/

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

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-climatedat.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"   "February"   "March"      "April"       "May"        "June"  
## [7] "July"       "August"      "September"  "October"     "November"   "December"
```

```
# 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.Feb	highmax.Mar	highmax.Apr	highmax.May	highmax.Jun	highmax.Jul
## 1	86	90	94	99	106	107
## 23	57	61	72	80	87	89
## 39	92	100	105	114	122	121
## 59	87	91	95	98	107	112
## 79	80	90	98	107	112	114
## 94	80	84	90	95	105	105
## 117	77	89	96	99	100	103
## 141	80	88	97	98	101	104
## 162	89	91	95	102	105	104
## 182	80	89	93	97	106	105
## 205	88	89	91	93	92	94
## 225	71	82	92	100	110	111
## 248	78	91	90	101	104	112
## 265	77	85	90	96	104	106
## 289	78	91	93	105	103	110
## 311	84	93	97	103	109	114
## 334	80	88	95	99	106	111
## 350	88	93	96	101	103	103
## 365	60	84	90	94	98	99
## 381	83	92	95	98	103	105
## 399	73	89	94	97	100	104
## 423	69	86	88	96	99	103
## 446	59	83	93	93	103	105
## 458	89	95	94	100	105	107
## 476	89	97	96	102	105	112
## 490	69	78	86	95	102	105
## 509	83	91	97	104	108	115
## 532	76	81	88	94	101	107
## 552	74	89	95	98	101	102
## 574	76	87	93	99	100	106
## 597	73	77	84	96	99	101
## 617	74	89	93	97	100	104
## 641	84	94	95	99	105	105
## 665	73	81	93	102	111	114
## 688	78	85	90	96	102	106
## 712	92	97	100	104	107	110
## 734	72	80	93	100	105	108
## 754	79	87	93	97	100	107
## 776	72	90	98	96	98	102
## 800	84	93	96	101	109	107
## 823	75	88	98	105	112	117
## 837	84	89	91	96	109	107
## 861	99	98	99	104	109	109
## 885	69	80	89	99	105	107

## 908	61	82	90	90	95	97
## 925	83	94	96	100	104	105
## 949	73	79	88	96	98	104
## 968	81	92	96	98	105	108
## 986	68	83	94	101	101	107
## 1007	71	77	84	91	100	100
	highmax.Aug	highmax.Sep	highmax.Oct	highmax.Nov	highmax.Dec	highavg.Jan
## 1	106	106	102	91	85	57.4
## 23	87	85	68	64	59	34.6
## 39	117	116	107	96	87	67.2
## 59	114	106	98	86	81	50.5
## 79	112	109	102	86	72	54.4
## 94	105	101	90	81	79	44.0
## 117	102	101	91	83	76	34.5
## 141	102	99	95	85	75	43.4
## 162	103	102	95	89	84	63.5
## 182	104	102	98	84	79	52.3
## 205	95	95	94	93	89	80.1
## 225	110	102	94	78	70	37.8
## 248	108	102	93	83	74	34.8
## 265	103	100	92	81	74	35.6
## 289	110	101	95	82	69	31.0
## 311	113	110	97	85	77	39.9
## 334	105	106	98	84	78	41.5
## 350	110	104	98	89	88	62.3
## 365	100	96	85	74	67	27.6
## 381	106	99	92	85	78	42.7
## 399	102	102	90	83	76	35.8
## 423	102	99	90	79	70	30.1
## 446	103	95	88	75	66	26.0
## 458	107	107	98	89	84	56.1
## 476	111	107	96	87	79	39.9
## 490	105	99	87	75	64	33.3
## 509	110	106	98	85	75	35.4
## 532	105	103	93	79	75	45.2
## 552	101	98	92	80	73	30.8
## 574	105	101	94	83	76	39.0
## 597	96	94	87	75	65	43.5
## 617	102	100	91	82	72	30.6
## 641	105	104	100	88	81	50.9
## 665	109	105	95	79	66	23.4
## 688	103	100	94	80	76	36.5
## 712	113	108	97	87	86	49.7
## 734	108	104	93	74	72	47.7
## 754	104	102	97	84	75	37.0
## 776	104	100	88	81	77	37.4
## 800	107	106	101	90	83	56.0
## 823	114	108	98	87	77	30.0
## 837	106	105	99	88	79	46.9
## 861	112	112	100	91	90	61.5
## 885	106	100	89	75	69	37.4
## 908	97	92	84	76	67	26.4
## 925	107	103	99	86	81	47.4
## 949	104	98	90	74	64	45.9

	## 968	108	104	96	87	80	42.5
## 986	102	99	90	77	65	65	26.4
## 1007	98	95	85	75	69	69	39.5
##	highavg.Feb	highavg.Mar	highavg.Apr	highavg.May	highavg.Jun	highavg.Jul	
## 1	61.8	69.7	76.6	84.0	89.8	92.1	
## 23	36.7	40.8	49.1	56.9	62.4	63.4	
## 39	70.7	76.9	85.2	94.8	103.9	106.1	
## 59	55.1	64.0	73.1	81.1	88.9	92.5	
## 79	61.2	66.8	72.7	80.9	87.9	93.3	
## 94	46.2	54.4	61.5	71.5	82.4	89.4	
## 117	38.5	47.7	60.5	71.2	79.6	84.5	
## 141	47.0	54.9	65.7	74.7	83.2	87.0	
## 162	67.5	73.8	79.9	87.0	91.0	92.1	
## 182	56.6	64.6	72.5	79.9	86.4	89.1	
## 205	80.2	81.2	82.7	84.6	87.0	87.9	
## 225	44.7	54.6	62.3	71.6	81.3	91.2	
## 248	39.9	52.1	64.6	74.8	83.1	86.2	
## 265	40.2	51.7	63.4	72.8	81.9	85.0	
## 289	36.1	49.0	62.3	72.4	81.6	85.7	
## 311	45.0	56.4	66.7	75.9	84.7	89.5	
## 334	46.0	55.8	66.5	75.2	83.6	87.3	
## 350	65.7	72.7	79.3	86.2	90.9	92.2	
## 365	31.8	40.4	53.1	65.2	73.8	79.2	
## 381	45.5	53.2	63.9	72.9	81.6	85.8	
## 399	38.7	45.4	55.6	66.0	75.9	81.4	
## 423	33.3	44.1	57.8	68.8	78.4	82.4	
## 446	31.0	43.0	58.0	71.0	80.0	85.0	
## 458	60.5	68.5	75.9	83.1	89.5	91.6	
## 476	45.3	55.8	66.7	75.1	83.5	88.3	
## 490	38.6	48.2	57.8	67.1	75.7	85.7	
## 509	40.1	52.3	64.3	74.2	84.2	89.0	
## 532	49.9	56.7	62.7	71.4	81.1	89.6	
## 552	34.9	43.8	57.4	68.9	77.4	82.3	
## 574	42.2	50.9	61.4	71.8	80.8	85.3	
## 597	48.2	55.9	64.7	74.2	83.5	85.9	
## 617	34.6	44.4	58.3	69.4	77.9	82.3	
## 641	55.2	63.4	72.4	79.6	87.1	90.2	
## 665	28.3	40.4	57.0	68.4	77.2	84.7	
## 688	40.6	51.1	63.5	72.9	81.6	84.9	
## 712	54.6	63.4	72.3	80.2	88.1	93.9	
## 734	51.6	56.5	61.1	67.8	73.9	82.0	
## 754	40.7	50.4	62.4	72.1	81.0	85.5	
## 776	40.3	47.8	58.6	68.4	77.5	82.8	
## 800	60.3	68.2	76.3	83.8	90.0	92.7	
## 823	34.9	45.4	59.7	70.2	80.0	88.8	
## 837	51.8	61.0	70.5	78.2	86.0	89.3	
## 861	65.2	72.2	79.8	86.5	92.1	95.6	
## 885	43.2	53.7	61.6	71.9	83.0	92.6	
## 908	30.3	39.0	53.3	65.7	74.3	78.5	
## 925	51.3	60.0	70.3	77.9	86.1	89.7	
## 949	49.3	53.9	58.9	65.3	70.6	76.8	
## 968	46.6	56.2	67.7	74.8	82.2	85.2	
## 986	31.1	43.1	57.3	68.4	77.9	81.6	
## 1007	40.5	47.5	54.9	64.7	75.3	83.4	

	highavg.Aug	highavg.Sep	highavg.Oct	highavg.Nov	highavg.Dec	lowavg.Jan
## 1	91.9	87.3	78.3	69.0	59.6	35.7
## 23	62.6	56.6	48.4	39.8	36.7	26.2
## 39	104.4	99.8	88.5	75.5	66.0	45.6
## 59	92.6	85.6	74.8	63.0	52.3	31.2
## 79	92.2	87.9	77.9	63.7	54.3	40.7
## 94	87.2	78.5	65.3	52.1	42.8	17.4
## 117	82.7	74.9	63.1	51.6	39.7	17.7
## 141	85.2	79.3	68.8	58.5	47.4	27.1
## 162	91.5	88.4	81.4	73.0	65.3	39.0
## 182	88.1	82.2	72.7	63.6	54.0	34.3
## 205	88.7	88.6	86.7	83.9	81.2	66.3
## 225	89.7	78.8	64.8	48.2	37.5	24.7
## 248	84.9	78.9	66.4	52.3	38.3	18.7
## 265	84.0	77.6	65.3	52.2	38.9	20.5
## 289	83.8	76.1	63.1	47.9	34.0	14.3
## 311	88.6	80.4	68.4	54.6	41.7	19.6
## 334	86.7	80.4	69.5	57.3	45.0	21.9
## 350	92.5	88.7	80.8	71.9	64.1	41.2
## 365	78.0	69.6	57.2	45.2	33.5	11.0
## 381	84.0	76.9	66.3	56.9	46.8	29.1
## 399	79.6	72.4	61.4	51.5	41.2	22.2
## 423	80.1	72.7	59.9	46.7	34.3	16.8
## 446	82.0	73.0	59.0	42.0	29.0	7.0
## 458	91.6	86.7	77.2	67.4	58.2	35.3
## 476	87.8	79.7	68.5	55.8	42.6	20.9
## 490	84.5	72.6	58.7	43.1	31.7	13.0
## 509	86.8	78.7	65.8	50.3	37.2	13.8
## 532	88.0	80.4	67.9	54.4	45.0	21.7
## 552	80.9	72.6	60.5	48.4	36.3	10.4
## 574	83.6	76.1	65.0	54.5	43.1	23.2
## 597	83.4	77.7	66.5	53.1	43.2	17.5
## 617	80.4	72.2	59.8	47.9	35.8	14.5
## 641	88.4	82.1	72.6	63.6	53.6	31.0
## 665	83.5	72.1	57.5	39.6	26.2	2.2
## 688	83.7	77.0	65.1	52.6	40.1	22.6
## 712	93.4	84.7	73.4	61.5	50.6	28.8
## 734	82.4	76.8	64.1	52.6	46.2	34.7
## 754	83.4	75.6	64.1	53.1	41.3	22.8
## 776	81.4	74.2	63.3	53.2	42.3	21.0
## 800	90.7	85.2	76.1	67.3	58.2	33.7
## 823	87.3	76.5	61.0	44.1	31.3	9.8
## 837	89.0	82.4	71.7	60.3	49.5	28.4
## 861	97.0	90.5	81.8	71.4	62.7	41.5
## 885	90.5	79.2	64.7	49.4	38.0	21.6
## 908	76.7	68.7	56.0	43.8	31.6	7.0
## 925	87.6	81.2	71.0	61.4	50.7	28.3
## 949	77.7	71.8	60.2	50.2	44.2	33.7
## 968	84.2	77.8	67.7	57.0	45.6	26.3
## 986	79.4	71.8	58.9	44.1	30.2	11.1
## 1007	81.2	71.8	58.8	46.5	38.2	18.0
##	lowavg.Feb	lowavg.Mar	lowavg.Apr	lowavg.May	lowavg.Jun	lowavg.Jul
## 1	39.2	45.3	51.6	60.7	68.1	71.5
## 23	27.6	30.1	35.3	42.3	48.4	51.4

## 39	48.7	53.5	60.2	69.4	77.7	83.5
## 59	34.5	42.7	51.0	61.1	69.4	73.2
## 79	43.7	46.5	49.0	53.9	58.4	60.9
## 94	18.9	26.4	33.3	42.7	52.3	58.9
## 117	20.9	27.9	38.4	47.7	57.3	62.7
## 141	29.0	35.6	44.3	53.8	63.4	68.4
## 162	41.9	47.1	52.3	61.6	69.5	72.0
## 182	37.7	44.1	51.5	60.3	68.2	71.3
## 205	66.1	67.7	69.4	70.9	73.4	74.5
## 225	28.3	34.4	39.3	46.5	53.7	60.4
## 248	22.6	32.2	42.4	52.6	61.9	65.4
## 265	23.9	32.8	42.7	52.6	62.1	65.8
## 289	18.8	29.7	41.1	52.2	62.0	66.8
## 311	23.8	33.3	43.5	54.2	63.7	68.4
## 334	24.7	31.2	40.5	50.1	59.5	63.8
## 350	44.5	50.3	56.8	65.2	71.4	73.7
## 365	14.5	23.4	34.6	44.6	54.2	59.9
## 381	30.7	36.9	45.8	55.6	66.4	71.2
## 399	24.7	31.1	40.6	49.9	59.5	65.4
## 423	18.5	26.0	37.0	46.7	56.7	60.6
## 446	12.0	24.0	38.0	50.0	59.0	64.0
## 458	38.5	45.3	52.2	61.6	68.6	71.6
## 476	24.6	33.3	43.8	53.8	63.7	68.1
## 490	16.9	24.3	32.1	40.8	48.5	54.3
## 509	18.0	27.9	38.8	50.5	60.9	66.1
## 532	25.3	29.9	33.9	40.8	47.1	52.2
## 552	13.8	22.5	32.7	42.6	52.5	57.7
## 574	25.8	31.9	41.0	50.5	60.3	66.0
## 597	21.5	26.1	32.3	41.0	49.4	54.4
## 617	17.3	25.7	37.3	47.1	56.5	61.4
## 641	33.8	39.9	48.0	56.5	65.8	69.9
## 665	7.9	19.4	30.7	42.7	52.0	57.4
## 688	25.0	32.7	42.6	52.2	61.5	65.5
## 712	32.8	41.0	49.7	59.6	67.8	72.2
## 734	34.6	37.2	39.6	41.7	49.3	53.1
## 754	25.1	33.0	41.9	52.1	62.0	66.3
## 776	23.6	30.0	39.6	48.6	58.4	64.2
## 800	36.8	43.0	50.4	59.5	68.2	71.6
## 823	13.8	23.5	34.2	45.7	55.4	61.9
## 837	31.6	39.0	47.5	56.8	65.4	69.5
## 861	44.8	51.3	58.6	66.7	72.3	74.4
## 885	25.2	33.6	39.5	47.8	56.4	64.7
## 908	9.5	18.9	31.5	41.9	51.2	55.7
## 925	30.5	37.1	46.1	55.0	64.5	68.9
## 949	32.8	35.1	37.7	43.1	47.6	50.8
## 968	28.7	35.4	44.5	52.7	61.6	65.7
## 986	15.1	24.8	35.8	46.1	56.1	61.0
## 1007	18.6	24.4	30.8	40.2	48.9	55.5
##	lowavg.Aug	lowavg.Sep	lowavg.Oct	lowavg.Nov	lowavg.Dec	lowmin.Jan
## 1	71.0	65.2	53.5	43.9	37.4	0
## 23	50.2	45.8	39.0	31.4	27.8	-20
## 39	82.7	76.9	64.8	52.7	44.8	16
## 59	72.4	64.5	52.6	42.2	33.7	-8
## 79	60.5	58.4	52.8	45.5	40.4	19

## 94	57.9	48.3	36.6	24.5	17.1	-29
## 117	61.1	52.7	41.1	33.2	23.4	-26
## 141	67.0	60.1	48.7	39.8	31.0	-7
## 162	72.1	68.1	57.3	47.5	41.1	6
## 182	70.7	64.8	54.0	44.5	36.5	-8
## 205	75.1	74.4	73.4	71.4	68.3	52
## 225	59.6	51.0	40.9	31.9	24.0	-28
## 248	63.6	54.6	43.8	33.9	22.5	-22
## 265	64.4	56.2	44.7	35.1	24.4	-27
## 289	64.8	55.2	43.0	30.5	18.0	-30
## 311	66.2	56.3	44.7	33.0	22.3	-23
## 334	62.5	54.6	43.0	34.0	25.9	-27
## 350	73.4	68.5	57.9	48.9	42.7	9
## 365	58.5	50.5	39.6	30.6	18.6	-33
## 381	69.1	62.8	50.5	41.8	31.9	-8
## 399	64.6	57.4	46.5	38.0	28.2	-13
## 423	59.4	51.2	40.7	32.4	22.3	-29
## 446	62.0	53.0	41.0	27.0	13.0	-29
## 458	70.9	64.6	53.1	44.0	37.3	-5
## 476	66.3	57.0	44.9	34.9	24.0	-23
## 490	52.2	43.1	32.5	22.0	11.9	-42
## 509	63.8	53.4	40.6	27.6	16.4	-33
## 532	50.6	43.4	34.6	27.1	21.9	-27
## 552	56.1	47.4	35.8	28.2	17.2	-35
## 574	64.2	56.4	44.2	36.9	27.6	-13
## 597	53.3	46.5	35.5	24.6	17.4	-14
## 617	59.9	51.6	39.6	31.5	21.2	-28
## 641	68.6	61.7	49.8	40.8	33.3	-9
## 665	55.5	44.9	32.2	18.8	6.1	-45
## 688	64.1	56.5	45.0	36.1	26.8	-22
## 712	71.3	63.2	51.6	40.0	30.6	-11
## 734	52.8	48.4	42.3	38.4	34.0	-10
## 754	64.5	56.2	44.6	35.1	26.6	-22
## 776	63.2	55.3	43.9	35.7	26.3	-13
## 800	71.0	64.2	52.1	42.3	35.3	-1
## 823	60.1	49.2	36.4	23.3	12.1	-33
## 837	68.4	60.7	48.9	39.4	31.3	-17
## 861	74.6	69.4	60.6	50.6	42.3	-2
## 885	63.4	53.0	41.3	30.6	22.6	-22
## 908	53.8	46.1	35.3	26.9	14.4	-34
## 925	67.4	60.1	48.3	39.4	31.4	-12
## 949	50.5	46.0	40.5	36.4	32.6	-8
## 968	64.5	56.9	45.4	36.9	29.2	-16
## 986	59.0	50.2	38.8	28.2	15.9	-37
## 1007	54.1	44.7	33.9	24.2	17.3	-38
##	lowmin.Feb	lowmin.Mar	lowmin.Apr	lowmin.May	lowmin.Jun	lowmin.Jul
## 1	-5	17	28	40	48	59
## 23	-15	-5	12	26	32	39
## 39	24	25	35	39	49	63
## 59	-12	11	28	38	46	54
## 79	21	29	34	37	43	47
## 94	-25	-11	-2	19	30	42
## 117	-24	-6	9	28	37	44
## 141	-11	7	14	28	41	45

## 162	-2	20	29	34	46	57	
## 182	-9	10	25	37	39	53	
## 205	52	53	56	60	63	63	
## 225	-15	5	11	22	30	35	
## 248	-24	-12	16	28	39	48	
## 265	-21	-7	18	27	37	46	
## 289	-26	-22	9	26	37	47	
## 311	-25	-7	10	26	36	43	
## 334	-16	-3	16	27	36	48	
## 350	2	20	31	40	53	58	
## 365	-23	-11	9	26	36	43	
## 381	-6	10	13	32	35	50	
## 399	-18	-8	11	31	41	50	
## 423	-37	-25	-6	19	27	31	
## 446	-32	-25	3	21	36	45	
## 458	1	15	27	36	47	51	
## 476	-25	-16	13	24	38	42	
## 490	-42	-30	-10	17	30	36	
## 509	-26	-19	3	24	39	45	
## 532	-22	-5	3	18	25	33	
## 552	-37	-20	4	21	30	35	
## 574	-14	1	11	33	41	48	
## 597	-24	-6	10	19	28	37	
## 617	-22	-21	9	26	35	40	
## 641	-2	11	23	29	38	48	
## 665	-45	-36	-12	13	30	32	
## 688	-20	-6	14	25	35	43	
## 712	-17	1	20	32	46	53	
## 734	-4	12	23	25	32	35	
## 754	-13	-1	11	30	40	49	
## 776	-17	1	11	29	39	48	
## 800	-2	4	26	34	44	54	
## 823	-35	-19	1	21	34	42	
## 837	-13	2	23	34	42	51	
## 861	-1	18	30	40	51	57	
## 885	-30	0	14	25	32	40	
## 908	-29	-18	2	20	29	35	
## 925	-10	10	19	31	40	51	
## 949	-1	9	23	25	30	35	
## 968	-12	-5	18	26	33	46	
## 986	-29	-29	0	19	31	36	
## 1007	-34	-21	-8	8	25	33	
##	lowmin.Aug	lowmin.Sep	lowmin.Oct	lowmin.Nov	lowmin.Dec	rain.Jan	rain.Feb
## 1	56	39	26	13	5	4.65	5.28
## 23	32	28	13	-7	-10	7.98	6.71
## 39	58	47	34	27	22	0.91	0.92
## 59	52	37	27	10	-1	3.55	3.66
## 79	48	44	34	27	17	3.63	3.90
## 94	40	17	-2	-18	-25	0.41	0.37
## 117	36	30	17	1	-18	3.23	2.89
## 141	35	30	25	11	-3	3.41	3.07
## 162	57	40	29	13	10	4.34	4.85
## 182	55	36	28	3	0	4.20	4.67
## 205	63	65	61	57	54	0.00	0.00

## 225	32	23	11	-10	-25	1.24	0.99		
## 248	43	31	13	-3	-21	1.82	1.81		
## 265	41	30	20	-5	-23	2.66	2.32		
## 289	40	26	7	-10	-22	1.00	1.28		
## 311	40	29	16	-5	-26	0.86	1.32		
## 334	41	30	20	-1	-17	3.70	3.07		
## 350	58	43	30	21	8	5.72	5.04		
## 365	39	28	21	4	-15	2.61	2.43		
## 381	46	37	26	13	-1	3.32	2.94		
## 399	46	34	25	-2	-17	3.36	3.25		
## 423	26	19	10	-5	-25	1.65	1.47		
## 446	42	26	15	-14	-29	0.79	0.67		
## 458	54	35	26	15	4	4.97	4.76		
## 476	41	29	14	1	-21	1.93	2.29		
## 490	28	6	-8	-39	-40	0.36	0.30		
## 509	39	26	3	-15	-27	0.64	0.77		
## 532	26	17	6	-5	-26	1.59	1.50		
## 552	29	20	10	-17	-24	2.70	2.62		
## 574	41	31	22	12	-7	3.16	2.31		
## 597	36	26	5	-12	-17	0.60	0.53		
## 617	34	24	16	-11	-22	2.59	2.20		
## 641	46	37	19	11	0	3.50	3.23		
## 665	32	10	-10	-30	-43	0.43	0.51		
## 688	39	31	17	-5	-17	2.73	2.25		
## 712	49	35	16	9	-8	1.39	1.58		
## 734	30	26	19	9	-12	5.96	4.56		
## 754	45	30	23	10	-8	2.88	2.39		
## 776	40	32	20	6	-12	3.86	3.29		
## 800	53	40	23	12	4	3.58	3.61		
## 823	39	21	4	-18	-31	0.42	0.59		
## 837	47	36	26	-1	-10	3.75	3.94		
## 861	58	41	30	20	4	2.22	2.02		
## 885	37	27	14	-14	-21	1.25	1.25		
## 908	31	20	14	-7	-27	2.45	2.04		
## 925	46	35	21	10	-2	3.04	2.76		
## 949	33	25	14	-1	-7	7.84	5.27		
## 968	41	32	17	6	-17	3.00	3.19		
## 986	35	25	12	-14	-28	1.23	1.45		
## 1007	25	8	-5	-21	-28	0.33	0.47		
##		rain.Mar	rain.Apr	rain.May	rain.Jun	rain.Jul	rain.Aug	rain.Sep	rain.Oct
## 1		5.95	4.02	3.54	4.07	5.24	3.96	3.97	2.92
## 23		6.29	4.64	4.96	4.42	5.44	8.16	12.72	13.23
## 39		0.99	0.28	0.11	0.02	1.05	1.00	0.64	0.58
## 59		4.68	5.14	4.87	3.65	3.27	2.59	3.18	4.91
## 79		2.86	1.36	0.75	0.21	0.02	0.04	0.35	1.06
## 94		0.92	1.71	2.12	1.98	2.16	1.69	0.96	1.02
## 117		3.62	3.72	4.35	4.35	4.18	3.93	3.88	4.37
## 141		4.31	3.88	4.25	4.00	4.09	4.36	4.13	3.42
## 162		5.94	3.06	3.47	7.73	7.17	7.35	4.69	3.23
## 182		4.81	3.36	3.67	3.95	5.27	3.90	4.47	3.41
## 205		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
## 225		1.39	1.23	1.39	0.69	0.33	0.24	0.58	0.75
## 248		2.63	3.51	4.24	4.46	3.94	3.24	2.90	3.15
## 265		3.56	3.81	5.05	4.25	4.55	3.13	3.12	3.12

## 289	2.30	3.86	4.74	4.94	4.47	4.13	3.05	2.64
## 311	2.49	3.53	4.91	5.40	3.82	4.24	3.66	3.03
## 334	4.39	3.74	4.01	4.06	4.14	3.45	2.90	2.53
## 350	4.41	4.46	4.89	6.41	4.96	5.82	4.54	4.70
## 365	3.36	3.78	3.69	3.55	3.41	3.31	3.74	4.36
## 381	4.53	3.66	4.20	4.17	4.56	3.88	4.76	3.89
## 399	4.32	3.74	3.49	3.68	3.43	3.35	3.44	3.94
## 423	2.06	3.03	3.36	3.45	2.84	3.23	3.50	2.53
## 446	1.54	2.87	3.70	4.21	4.41	4.76	3.27	2.91
## 458	5.04	4.96	4.38	4.12	4.81	4.24	3.03	3.92
## 476	3.00	4.16	5.18	4.39	4.31	3.99	4.15	3.35
## 490	0.59	0.98	1.87	2.06	1.19	1.20	1.10	0.68
## 509	1.93	2.71	4.29	4.35	3.40	3.49	3.02	1.97
## 532	1.15	0.43	0.43	0.40	0.19	0.21	0.39	0.77
## 552	3.27	3.41	3.66	3.69	3.74	3.18	3.38	4.04
## 574	4.14	3.54	4.37	4.41	4.95	4.10	4.27	4.18
## 597	0.94	0.77	0.94	1.29	2.33	2.23	1.54	1.33
## 617	3.21	3.17	3.61	3.79	4.12	3.46	3.30	3.68
## 641	4.11	2.92	3.27	3.52	4.73	4.26	4.36	3.25
## 665	0.87	1.26	2.40	3.17	2.89	2.28	1.59	1.25
## 688	3.02	3.40	4.17	4.01	4.79	3.32	2.84	2.61
## 712	3.06	3.07	4.65	4.93	2.93	3.28	4.06	3.71
## 734	3.99	2.81	2.22	1.54	0.46	0.44	1.28	3.03
## 754	3.37	3.10	3.79	3.60	4.61	3.20	4.07	3.27
## 776	5.01	4.36	3.55	3.64	3.29	3.60	3.92	3.93
## 800	3.73	2.62	2.97	4.69	5.46	5.26	3.54	3.17
## 823	1.23	1.81	3.15	3.57	2.61	1.80	1.87	1.65
## 837	4.11	4.00	5.50	4.14	3.64	3.17	3.41	3.04
## 861	2.76	2.09	4.44	4.33	1.88	2.35	2.99	3.88
## 885	1.79	1.99	1.95	0.98	0.61	0.69	1.21	1.52
## 908	2.39	2.66	3.37	3.80	4.08	4.01	3.12	3.44
## 925	4.04	3.27	3.78	3.93	4.51	4.66	4.13	2.98
## 949	5.29	3.54	2.33	1.76	0.63	0.94	1.71	4.60
## 968	3.91	3.24	4.80	4.29	4.94	3.74	3.25	2.67
## 986	2.20	3.40	3.55	4.54	4.18	4.27	3.13	2.40
## 1007	1.05	1.78	2.34	2.34	2.19	1.95	1.48	0.93
##	rain.Nov	rain.Dec	snow.Jan	snow.Feb	snow.Mar	snow.Apr	snow.May	snow.Jun
## 1	4.61	4.86	0.0	0.0	0.0	0.0	0.0	0
## 23	8.44	9.23	24.2	15.9	5.4	0.9	0.0	0
## 39	0.65	0.88	0.0	0.0	0.0	0.0	0.0	0
## 59	5.28	4.97	1.6	1.3	0.4	0.0	0.0	0
## 79	2.46	3.43	0.0	0.0	0.0	0.0	0.0	0
## 94	0.61	0.35	7.0	5.7	10.7	6.8	1.1	0
## 117	3.89	3.44	12.3	11.0	6.4	1.4	0.0	0
## 141	3.48	3.65	4.6	7.7	0.3	0.0	0.0	0
## 162	3.50	3.90	0.0	0.0	0.0	0.0	0.0	0
## 182	4.10	3.90	1.3	0.4	0.8	0.0	0.0	0
## 205	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0
## 225	1.35	1.55	5.1	2.8	1.3	0.3	0.0	0
## 248	3.21	2.52	6.4	5.5	2.5	0.3	0.0	0
## 265	3.70	3.17	8.6	6.5	2.6	0.2	0.0	0
## 289	2.19	1.42	8.5	7.9	5.2	1.8	0.0	0
## 311	1.85	1.35	4.9	4.5	1.6	0.3	0.0	0
## 334	3.29	3.49	3.4	2.8	1.2	0.0	0.0	0

## 350	4.10	5.60	0.0	0.0	0.0	0.0	0.0	0
## 365	4.35	3.24	20.0	14.9	15.6	4.7	0.0	0
## 381	3.80	3.56	4.4	0.4	0.3	0.0	0.0	0
## 399	3.99	3.78	12.9	10.9	7.8	1.9	0.0	0
## 423	2.78	1.87	13.8	11.6	7.0	1.9	0.0	0
## 446	1.81	1.10	0.0	0.0	0.0	0.0	0.0	0
## 458	4.76	5.15	0.0	0.0	0.0	0.0	0.0	0
## 476	3.61	2.67	4.8	3.4	1.4	0.1	0.0	0
## 490	0.49	0.40	6.2	5.0	6.2	3.7	0.9	0
## 509	1.43	0.95	5.4	5.6	4.8	1.4	0.0	0
## 532	1.19	1.43	3.4	3.4	1.9	0.2	0.0	0
## 552	3.72	3.20	18.1	12.3	11.1	2.8	0.0	0
## 574	3.31	3.70	6.0	0.0	5.2	0.0	0.0	0
## 597	0.85	0.83	4.0	2.9	4.4	0.4	0.0	0
## 617	3.29	2.93	17.9	12.2	11.0	2.3	0.1	0
## 641	3.12	3.07	2.9	1.9	0.5	0.1	0.0	0
## 665	0.71	0.49	8.9	8.1	9.1	4.2	0.4	0
## 688	3.20	2.97	9.2	6.1	4.2	1.1	0.0	0
## 712	1.98	1.88	2.8	1.4	0.9	0.0	0.0	0
## 734	6.50	6.86	0.6	1.7	0.0	0.0	0.0	0
## 754	3.23	3.23	8.8	10.5	5.2	0.4	0.0	0
## 776	4.51	4.22	9.0	8.5	5.5	0.6	0.0	0
## 800	2.74	3.22	0.8	0.5	0.1	0.0	0.0	0
## 823	0.76	0.55	5.4	6.0	5.8	3.5	0.0	0
## 837	4.31	4.24	2.6	2.3	0.9	0.0	0.0	0
## 861	2.96	2.40	0.4	0.2	0.0	0.0	0.0	0
## 885	1.45	1.41	12.5	10.7	6.5	4.0	0.3	0
## 908	3.17	2.74	22.6	18.0	16.8	4.9	0.0	0
## 925	3.24	3.26	3.9	3.4	0.6	0.1	0.0	0
## 949	8.63	7.46	1.9	4.7	0.7	0.0	0.0	0
## 968	3.73	3.27	11.3	9.8	5.8	1.4	0.0	0
## 986	2.39	1.74	12.9	10.6	7.0	2.6	0.2	0
## 1007	0.59	0.49	5.9	7.9	11.3	10.2	2.3	0
##	snow.Jul	snow.Aug	snow.Sep	snow.Oct	snow.Nov	snow.Dec		
## 1	0	0.0	0.0	0.0	0.0	0.0		
## 23	0	0.0	0.0	0.6	9.2	13.6		
## 39	0	0.0	0.0	0.0	0.0	0.0		
## 59	0	0.0	0.0	0.0	0.0	0.2		
## 79	0	0.0	0.0	0.0	0.0	0.0		
## 94	0	0.0	1.3	4.0	8.7	8.5		
## 117	0	0.0	0.0	0.0	2.0	7.4		
## 141	0	0.0	0.0	0.0	0.2	2.9		
## 162	0	0.0	0.0	0.0	0.0	0.0		
## 182	0	0.0	0.0	0.0	0.0	0.4		
## 205	0	0.0	0.0	0.0	0.0	0.0		
## 225	0	0.0	0.0	0.1	2.6	7.0		
## 248	0	0.0	0.0	0.0	0.6	5.6		
## 265	0	0.0	0.0	0.4	0.7	6.9		
## 289	0	0.0	0.0	0.4	2.5	9.0		
## 311	0	0.0	0.0	0.3	1.0	5.2		
## 334	0	0.0	0.0	0.0	0.4	1.6		
## 350	0	0.0	0.0	0.0	0.0	0.0		
## 365	0	0.0	0.0	0.3	3.5	14.5		
## 381	0	0.0	0.0	0.0	0.2	0.8		

```

## 399      0    0.0    0.0    0.0    1.3    9.0
## 423      0    0.0    0.0    0.4    3.4   13.0
## 446      0    0.0    0.0    0.0    0.0    0.0
## 458      0    0.0    0.0    0.0    0.0    0.0
## 476      0    0.0    0.0    0.0    0.3    3.8
## 490      0    0.3    1.3    2.4    4.8    7.3
## 509      0    0.0    0.0    0.7    2.1    5.9
## 532      0    0.0    0.0    0.0    0.9    3.9
## 552      0    0.0    0.0    0.0    2.6   14.5
## 574      0    0.0    0.0    0.0    0.6    3.5
## 597      0    0.0    0.0    1.0    2.3    8.0
## 617      0    0.0    0.0    0.3    2.8   13.7
## 641      0    0.0    0.0    0.0    0.1    0.6
## 665      0    0.0    0.2    2.2    8.8    9.3
## 688      0    0.0    0.0    0.2    0.9    5.0
## 712      0    0.0    0.0    0.0    0.4    2.1
## 734      0    0.0    0.0    0.0    0.1    1.1
## 754      0    0.0    0.0    0.0    0.6    5.1
## 776      0    0.0    0.0    0.0    1.5    8.7
## 800      0    0.0    0.0    0.0    0.0    0.1
## 823      0    0.0    0.0    0.9    4.8    4.8
## 837      0    0.0    0.0    0.0    0.0    0.5
## 861      0    0.0    0.0    0.0    0.0    0.0
## 885      0    0.0    0.0    1.4    7.6   13.2
## 908      0    0.0    0.0    0.0    9.1   21.9
## 925      0    0.0    0.0    0.0    0.2    2.1
## 949      0    0.0    0.0    0.0    0.9    2.6
## 968      0    0.0    0.0    0.1    1.3    6.7
## 986      0    0.0    0.0    0.5    3.6   13.5
## 1007     0    0.0    1.3    5.0    8.0    8.4

```

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

```

## [1] "state"      "capital"     "st"          "labels"      "highmax.Jan"
## [6] "highmax.Feb" "highmax.Mar"  "highmax.Apr"  "highmax.May"  "highmax.Jun"
## [11] "highmax.Jul" "highmax.Aug"  "highmax.Sep"  "highmax.Oct"  "highmax.Nov"
## [16] "highmax.Dec" "highavg.Jan" "highavg.Feb" "highavg.Mar" "highavg.Apr"
## [21] "highavg.May" "highavg.Jun" "highavg.Jul" "highavg.Aug" "highavg.Sep"
## [26] "highavg.Oct" "highavg.Nov" "highavg.Dec" "lowavg.Jan" "lowavg.Feb"
## [31] "lowavg.Mar"  "lowavg.Apr"  "lowavg.May"  "lowavg.Jun"  "lowavg.Jul"
## [36] "lowavg.Aug"  "lowavg.Sep"  "lowavg.Oct"  "lowavg.Nov"  "lowavg.Dec"
## [41] "lowmin.Jan"  "lowmin.Feb" "lowmin.Mar" "lowmin.Apr" "lowmin.May"
## [46] "lowmin.Jun"  "lowmin.Jul" "lowmin.Aug" "lowmin.Sep" "lowmin.Oct"
## [51] "lowmin.Nov"  "lowmin.Dec" "rain.Jan"   "rain.Feb"   "rain.Mar"
## [56] "rain.Apr"    "rain.May"   "rain.Jun"   "rain.Jul"   "rain.Aug"
## [61] "rain.Sep"    "rain.Oct"   "rain.Nov"   "rain.Dec"   "snow.Jan"
## [66] "snow.Feb"    "snow.Mar"  "snow.Apr"  "snow.May"   "snow.Jun"
## [71] "snow.Jul"    "snow.Aug"  "snow.Sep"  "snow.Oct"   "snow.Nov"
## [76] "snow.Dec"

```

```
#####
##### WHICH COLUMNS #####
#####
```

```
#X = climate.df[,5:52]; # temperature
```

```

X = climate.df[,5:76]; # 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[,5:76]; # everything ... you have to change months above to get this dataframe to be the
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;
X

```

WHICH X

	highmax.Jan	highmax.Feb	highmax.Mar	highmax.Apr	highmax.May
## Montgomery, AL	83	86	90	94	99
## Juneau, AK	60	57	61	72	80
## Phoenix, AZ	88	92	100	105	114
## Little Rock, AR	83	87	91	95	98
## Sacramento, CA	79	80	90	98	107
## Denver, CO	76	80	84	90	95
## Hartford, CT	72	77	89	96	99
## Dover, DE	77	80	88	97	98
## Tallahassee, FL	83	89	91	95	102
## Atlanta, GA	79	80	89	93	97
## Honolulu, HI	88	88	89	91	93
## Boise, ID	63	71	82	92	100
## Springfield, IL	73	78	91	90	101
## Indianapolis, IN	71	77	85	90	96
## Des Moines, IA	67	78	91	93	105
## Topeka, KS	78	84	93	97	103
## Frankfort, KY	80	80	88	95	99
## Baton Rouge, LA	85	88	93	96	101
## Augusta, ME	61	60	84	90	94

## Annapolis, MD	77	83	92	95	98
## Boston, MA	74	73	89	94	97
## Lansing, MI	66	69	86	88	96
## Saint Paul, MN	57	59	83	93	93
## Jackson, MS	85	89	95	94	100
## Jefferson City, MO	79	89	97	96	102
## Helena, MT	63	69	78	86	95
## Lincoln, NE	73	83	91	97	104
## Carson City, NV	72	76	81	88	94
## Concord, NH	72	74	89	95	98
## Trenton, NJ	73	76	87	93	99
## Santa Fe, NM	65	73	77	84	96
## Albany, NY	71	74	89	93	97
## Raleigh, NC	80	84	94	95	99
## Bismarck, ND	63	73	81	93	102
## Columbus, OH	74	78	85	90	96
## Oklahoma City, OK	83	92	97	100	104
## Salem, OR	68	72	80	93	100
## Harrisburg, PA	73	79	87	93	97
## Providence, RI	70	72	90	98	96
## Columbia, SC	84	84	93	96	101
## Pierre, SD	68	75	88	98	105
## Nashville, TN	78	84	89	91	96
## Austin, TX	90	99	98	99	104
## Salt Lake City, UT	63	69	80	89	99
## Montpelier, VT	66	61	82	90	90
## Richmond, VA	81	83	94	96	100
## Olympia, WA	64	73	79	88	96
## Charleston, WV	81	81	92	96	98
## Madison, WI	58	68	83	94	101
## Cheyenne, WY	70	71	77	84	91
	highmax.Jun	highmax.Jul	highmax.Aug	highmax.Sep	highmax.Oct
## Montgomery, AL	106	107	106	106	102
## Juneau, AK	87	89	87	85	68
## Phoenix, AZ	122	121	117	116	107
## Little Rock, AR	107	112	114	106	98
## Sacramento, CA	112	114	112	109	102
## Denver, CO	105	105	105	101	90
## Hartford, CT	100	103	102	101	91
## Dover, DE	101	104	102	99	95
## Tallahassee, FL	105	104	103	102	95
## Atlanta, GA	106	105	104	102	98
## Honolulu, HI	92	94	95	95	94
## Boise, ID	110	111	110	102	94
## Springfield, IL	104	112	108	102	93
## Indianapolis, IN	104	106	103	100	92
## Des Moines, IA	103	110	110	101	95
## Topeka, KS	109	114	113	110	97
## Frankfort, KY	106	111	105	106	98
## Baton Rouge, LA	103	103	110	104	98
## Augusta, ME	98	99	100	96	85
## Annapolis, MD	103	105	106	99	92
## Boston, MA	100	104	102	102	90
## Lansing, MI	99	103	102	99	90

## Saint Paul, MN	103	105	103	95	88	
## Jackson, MS	105	107	107	107	98	
## Jefferson City, MO	105	112	111	107	96	
## Helena, MT	102	105	105	99	87	
## Lincoln, NE	108	115	110	106	98	
## Carson City, NV	101	107	105	103	93	
## Concord, NH	101	102	101	98	92	
## Trenton, NJ	100	106	105	101	94	
## Santa Fe, NM	99	101	96	94	87	
## Albany, NY	100	104	102	100	91	
## Raleigh, NC	105	105	105	104	100	
## Bismarck, ND	111	114	109	105	95	
## Columbus, OH	102	106	103	100	94	
## Oklahoma City, OK	107	110	113	108	97	
## Salem, OR	105	108	108	104	93	
## Harrisburg, PA	100	107	104	102	97	
## Providence, RI	98	102	104	100	88	
## Columbia, SC	109	107	107	106	101	
## Pierre, SD	112	117	114	108	98	
## Nashville, TN	109	107	106	105	99	
## Austin, TX	109	109	112	112	100	
## Salt Lake City, UT	105	107	106	100	89	
## Montpelier, VT	95	97	97	92	84	
## Richmond, VA	104	105	107	103	99	
## Olympia, WA	98	104	104	98	90	
## Charleston, WV	105	108	108	104	96	
## Madison, WI	101	107	102	99	90	
## Cheyenne, WY	100	100	98	95	85	
	##	highmax.Nov	highmax.Dec	highavg.Jan	highavg.Feb	highavg.Mar
## Montgomery, AL	91	85	57.4	61.8	69.7	
## Juneau, AK	64	59	34.6	36.7	40.8	
## Phoenix, AZ	96	87	67.2	70.7	76.9	
## Little Rock, AR	86	81	50.5	55.1	64.0	
## Sacramento, CA	86	72	54.4	61.2	66.8	
## Denver, CO	81	79	44.0	46.2	54.4	
## Hartford, CT	83	76	34.5	38.5	47.7	
## Dover, DE	85	75	43.4	47.0	54.9	
## Tallahassee, FL	89	84	63.5	67.5	73.8	
## Atlanta, GA	84	79	52.3	56.6	64.6	
## Honolulu, HI	93	89	80.1	80.2	81.2	
## Boise, ID	78	70	37.8	44.7	54.6	
## Springfield, IL	83	74	34.8	39.9	52.1	
## Indianapolis, IN	81	74	35.6	40.2	51.7	
## Des Moines, IA	82	69	31.0	36.1	49.0	
## Topeka, KS	85	77	39.9	45.0	56.4	
## Frankfort, KY	84	78	41.5	46.0	55.8	
## Baton Rouge, LA	89	88	62.3	65.7	72.7	
## Augusta, ME	74	67	27.6	31.8	40.4	
## Annapolis, MD	85	78	42.7	45.5	53.2	
## Boston, MA	83	76	35.8	38.7	45.4	
## Lansing, MI	79	70	30.1	33.3	44.1	
## Saint Paul, MN	75	66	26.0	31.0	43.0	
## Jackson, MS	89	84	56.1	60.5	68.5	
## Jefferson City, MO	87	79	39.9	45.3	55.8	

## Helena, MT	75	64	33.3	38.6	48.2
## Lincoln, NE	85	75	35.4	40.1	52.3
## Carson City, NV	79	75	45.2	49.9	56.7
## Concord, NH	80	73	30.8	34.9	43.8
## Trenton, NJ	83	76	39.0	42.2	50.9
## Santa Fe, NM	75	65	43.5	48.2	55.9
## Albany, NY	82	72	30.6	34.6	44.4
## Raleigh, NC	88	81	50.9	55.2	63.4
## Bismarck, ND	79	66	23.4	28.3	40.4
## Columbus, OH	80	76	36.5	40.6	51.1
## Oklahoma City, OK	87	86	49.7	54.6	63.4
## Salem, OR	74	72	47.7	51.6	56.5
## Harrisburg, PA	84	75	37.0	40.7	50.4
## Providence, RI	81	77	37.4	40.3	47.8
## Columbia, SC	90	83	56.0	60.3	68.2
## Pierre, SD	87	77	30.0	34.9	45.4
## Nashville, TN	88	79	46.9	51.8	61.0
## Austin, TX	91	90	61.5	65.2	72.2
## Salt Lake City, UT	75	69	37.4	43.2	53.7
## Montpelier, VT	76	67	26.4	30.3	39.0
## Richmond, VA	86	81	47.4	51.3	60.0
## Olympia, WA	74	64	45.9	49.3	53.9
## Charleston, WV	87	80	42.5	46.6	56.2
## Madison, WI	77	65	26.4	31.1	43.1
## Cheyenne, WY	75	69	39.5	40.5	47.5
##	highavg.Apr	highavg.May	highavg.Jun	highavg.Jul	highavg.Aug
## Montgomery, AL	76.6	84.0	89.8	92.1	91.9
## Juneau, AK	49.1	56.9	62.4	63.4	62.6
## Phoenix, AZ	85.2	94.8	103.9	106.1	104.4
## Little Rock, AR	73.1	81.1	88.9	92.5	92.6
## Sacramento, CA	72.7	80.9	87.9	93.3	92.2
## Denver, CO	61.5	71.5	82.4	89.4	87.2
## Hartford, CT	60.5	71.2	79.6	84.5	82.7
## Dover, DE	65.7	74.7	83.2	87.0	85.2
## Tallahassee, FL	79.9	87.0	91.0	92.1	91.5
## Atlanta, GA	72.5	79.9	86.4	89.1	88.1
## Honolulu, HI	82.7	84.6	87.0	87.9	88.7
## Boise, ID	62.3	71.6	81.3	91.2	89.7
## Springfield, IL	64.6	74.8	83.1	86.2	84.9
## Indianapolis, IN	63.4	72.8	81.9	85.0	84.0
## Des Moines, IA	62.3	72.4	81.6	85.7	83.8
## Topeka, KS	66.7	75.9	84.7	89.5	88.6
## Frankfort, KY	66.5	75.2	83.6	87.3	86.7
## Baton Rouge, LA	79.3	86.2	90.9	92.2	92.5
## Augusta, ME	53.1	65.2	73.8	79.2	78.0
## Annapolis, MD	63.9	72.9	81.6	85.8	84.0
## Boston, MA	55.6	66.0	75.9	81.4	79.6
## Lansing, MI	57.8	68.8	78.4	82.4	80.1
## Saint Paul, MN	58.0	71.0	80.0	85.0	82.0
## Jackson, MS	75.9	83.1	89.5	91.6	91.6
## Jefferson City, MO	66.7	75.1	83.5	88.3	87.8
## Helena, MT	57.8	67.1	75.7	85.7	84.5
## Lincoln, NE	64.3	74.2	84.2	89.0	86.8
## Carson City, NV	62.7	71.4	81.1	89.6	88.0

## Concord, NH	57.4	68.9	77.4	82.3	80.9
## Trenton, NJ	61.4	71.8	80.8	85.3	83.6
## Santa Fe, NM	64.7	74.2	83.5	85.9	83.4
## Albany, NY	58.3	69.4	77.9	82.3	80.4
## Raleigh, NC	72.4	79.6	87.1	90.2	88.4
## Bismarck, ND	57.0	68.4	77.2	84.7	83.5
## Columbus, OH	63.5	72.9	81.6	84.9	83.7
## Oklahoma City, OK	72.3	80.2	88.1	93.9	93.4
## Salem, OR	61.1	67.8	73.9	82.0	82.4
## Harrisburg, PA	62.4	72.1	81.0	85.5	83.4
## Providence, RI	58.6	68.4	77.5	82.8	81.4
## Columbia, SC	76.3	83.8	90.0	92.7	90.7
## Pierre, SD	59.7	70.2	80.0	88.8	87.3
## Nashville, TN	70.5	78.2	86.0	89.3	89.0
## Austin, TX	79.8	86.5	92.1	95.6	97.0
## Salt Lake City, UT	61.6	71.9	83.0	92.6	90.5
## Montpelier, VT	53.3	65.7	74.3	78.5	76.7
## Richmond, VA	70.3	77.9	86.1	89.7	87.6
## Olympia, WA	58.9	65.3	70.6	76.8	77.7
## Charleston, WV	67.7	74.8	82.2	85.2	84.2
## Madison, WI	57.3	68.4	77.9	81.6	79.4
## Cheyenne, WY	54.9	64.7	75.3	83.4	81.2
	highavg.Sep	highavg.Oct	highavg.Nov	highavg.Dec	lowavg.Jan
## Montgomery, AL	87.3	78.3	69.0	59.6	35.7
## Juneau, AK	56.6	48.4	39.8	36.7	26.2
## Phoenix, AZ	99.8	88.5	75.5	66.0	45.6
## Little Rock, AR	85.6	74.8	63.0	52.3	31.2
## Sacramento, CA	87.9	77.9	63.7	54.3	40.7
## Denver, CO	78.5	65.3	52.1	42.8	17.4
## Hartford, CT	74.9	63.1	51.6	39.7	17.7
## Dover, DE	79.3	68.8	58.5	47.4	27.1
## Tallahassee, FL	88.4	81.4	73.0	65.3	39.0
## Atlanta, GA	82.2	72.7	63.6	54.0	34.3
## Honolulu, HI	88.6	86.7	83.9	81.2	66.3
## Boise, ID	78.8	64.8	48.2	37.5	24.7
## Springfield, IL	78.9	66.4	52.3	38.3	18.7
## Indianapolis, IN	77.6	65.3	52.2	38.9	20.5
## Des Moines, IA	76.1	63.1	47.9	34.0	14.3
## Topeka, KS	80.4	68.4	54.6	41.7	19.6
## Frankfort, KY	80.4	69.5	57.3	45.0	21.9
## Baton Rouge, LA	88.7	80.8	71.9	64.1	41.2
## Augusta, ME	69.6	57.2	45.2	33.5	11.0
## Annapolis, MD	76.9	66.3	56.9	46.8	29.1
## Boston, MA	72.4	61.4	51.5	41.2	22.2
## Lansing, MI	72.7	59.9	46.7	34.3	16.8
## Saint Paul, MN	73.0	59.0	42.0	29.0	7.0
## Jackson, MS	86.7	77.2	67.4	58.2	35.3
## Jefferson City, MO	79.7	68.5	55.8	42.6	20.9
## Helena, MT	72.6	58.7	43.1	31.7	13.0
## Lincoln, NE	78.7	65.8	50.3	37.2	13.8
## Carson City, NV	80.4	67.9	54.4	45.0	21.7
## Concord, NH	72.6	60.5	48.4	36.3	10.4
## Trenton, NJ	76.1	65.0	54.5	43.1	23.2
## Santa Fe, NM	77.7	66.5	53.1	43.2	17.5

## Albany, NY	72.2	59.8	47.9	35.8	14.5
## Raleigh, NC	82.1	72.6	63.6	53.6	31.0
## Bismarck, ND	72.1	57.5	39.6	26.2	2.2
## Columbus, OH	77.0	65.1	52.6	40.1	22.6
## Oklahoma City, OK	84.7	73.4	61.5	50.6	28.8
## Salem, OR	76.8	64.1	52.6	46.2	34.7
## Harrisburg, PA	75.6	64.1	53.1	41.3	22.8
## Providence, RI	74.2	63.3	53.2	42.3	21.0
## Columbia, SC	85.2	76.1	67.3	58.2	33.7
## Pierre, SD	76.5	61.0	44.1	31.3	9.8
## Nashville, TN	82.4	71.7	60.3	49.5	28.4
## Austin, TX	90.5	81.8	71.4	62.7	41.5
## Salt Lake City, UT	79.2	64.7	49.4	38.0	21.6
## Montpelier, VT	68.7	56.0	43.8	31.6	7.0
## Richmond, VA	81.2	71.0	61.4	50.7	28.3
## Olympia, WA	71.8	60.2	50.2	44.2	33.7
## Charleston, WV	77.8	67.7	57.0	45.6	26.3
## Madison, WI	71.8	58.9	44.1	30.2	11.1
## Cheyenne, WY	71.8	58.8	46.5	38.2	18.0
##	lowavg.Feb	lowavg.Mar	lowavg.Apr	lowavg.May	lowavg.Jun
## Montgomery, AL	39.2	45.3	51.6	60.7	68.1
## Juneau, AK	27.6	30.1	35.3	42.3	48.4
## Phoenix, AZ	48.7	53.5	60.2	69.4	77.7
## Little Rock, AR	34.5	42.7	51.0	61.1	69.4
## Sacramento, CA	43.7	46.5	49.0	53.9	58.4
## Denver, CO	18.9	26.4	33.3	42.7	52.3
## Hartford, CT	20.9	27.9	38.4	47.7	57.3
## Dover, DE	29.0	35.6	44.3	53.8	63.4
## Tallahassee, FL	41.9	47.1	52.3	61.6	69.5
## Atlanta, GA	37.7	44.1	51.5	60.3	68.2
## Honolulu, HI	66.1	67.7	69.4	70.9	73.4
## Boise, ID	28.3	34.4	39.3	46.5	53.7
## Springfield, IL	22.6	32.2	42.4	52.6	61.9
## Indianapolis, IN	23.9	32.8	42.7	52.6	62.1
## Des Moines, IA	18.8	29.7	41.1	52.2	62.0
## Topeka, KS	23.8	33.3	43.5	54.2	63.7
## Frankfort, KY	24.7	31.2	40.5	50.1	59.5
## Baton Rouge, LA	44.5	50.3	56.8	65.2	71.4
## Augusta, ME	14.5	23.4	34.6	44.6	54.2
## Annapolis, MD	30.7	36.9	45.8	55.6	66.4
## Boston, MA	24.7	31.1	40.6	49.9	59.5
## Lansing, MI	18.5	26.0	37.0	46.7	56.7
## Saint Paul, MN	12.0	24.0	38.0	50.0	59.0
## Jackson, MS	38.5	45.3	52.2	61.6	68.6
## Jefferson City, MO	24.6	33.3	43.8	53.8	63.7
## Helena, MT	16.9	24.3	32.1	40.8	48.5
## Lincoln, NE	18.0	27.9	38.8	50.5	60.9
## Carson City, NV	25.3	29.9	33.9	40.8	47.1
## Concord, NH	13.8	22.5	32.7	42.6	52.5
## Trenton, NJ	25.8	31.9	41.0	50.5	60.3
## Santa Fe, NM	21.5	26.1	32.3	41.0	49.4
## Albany, NY	17.3	25.7	37.3	47.1	56.5
## Raleigh, NC	33.8	39.9	48.0	56.5	65.8
## Bismarck, ND	7.9	19.4	30.7	42.7	52.0

## Columbus, OH	25.0	32.7	42.6	52.2	61.5
## Oklahoma City, OK	32.8	41.0	49.7	59.6	67.8
## Salem, OR	34.6	37.2	39.6	41.7	49.3
## Harrisburg, PA	25.1	33.0	41.9	52.1	62.0
## Providence, RI	23.6	30.0	39.6	48.6	58.4
## Columbia, SC	36.8	43.0	50.4	59.5	68.2
## Pierre, SD	13.8	23.5	34.2	45.7	55.4
## Nashville, TN	31.6	39.0	47.5	56.8	65.4
## Austin, TX	44.8	51.3	58.6	66.7	72.3
## Salt Lake City, UT	25.2	33.6	39.5	47.8	56.4
## Montpelier, VT	9.5	18.9	31.5	41.9	51.2
## Richmond, VA	30.5	37.1	46.1	55.0	64.5
## Olympia, WA	32.8	35.1	37.7	43.1	47.6
## Charleston, WV	28.7	35.4	44.5	52.7	61.6
## Madison, WI	15.1	24.8	35.8	46.1	56.1
## Cheyenne, WY	18.6	24.4	30.8	40.2	48.9
	lowavg.Jul	lowavg.Aug	lowavg.Sep	lowavg.Oct	lowavg.Nov
## Montgomery, AL	71.5	71.0	65.2	53.5	43.9
## Juneau, AK	51.4	50.2	45.8	39.0	31.4
## Phoenix, AZ	83.5	82.7	76.9	64.8	52.7
## Little Rock, AR	73.2	72.4	64.5	52.6	42.2
## Sacramento, CA	60.9	60.5	58.4	52.8	45.5
## Denver, CO	58.9	57.9	48.3	36.6	24.5
## Hartford, CT	62.7	61.1	52.7	41.1	33.2
## Dover, DE	68.4	67.0	60.1	48.7	39.8
## Tallahassee, FL	72.0	72.1	68.1	57.3	47.5
## Atlanta, GA	71.3	70.7	64.8	54.0	44.5
## Honolulu, HI	74.5	75.1	74.4	73.4	71.4
## Boise, ID	60.4	59.6	51.0	40.9	31.9
## Springfield, IL	65.4	63.6	54.6	43.8	33.9
## Indianapolis, IN	65.8	64.4	56.2	44.7	35.1
## Des Moines, IA	66.8	64.8	55.2	43.0	30.5
## Topeka, KS	68.4	66.2	56.3	44.7	33.0
## Frankfort, KY	63.8	62.5	54.6	43.0	34.0
## Baton Rouge, LA	73.7	73.4	68.5	57.9	48.9
## Augusta, ME	59.9	58.5	50.5	39.6	30.6
## Annapolis, MD	71.2	69.1	62.8	50.5	41.8
## Boston, MA	65.4	64.6	57.4	46.5	38.0
## Lansing, MI	60.6	59.4	51.2	40.7	32.4
## Saint Paul, MN	64.0	62.0	53.0	41.0	27.0
## Jackson, MS	71.6	70.9	64.6	53.1	44.0
## Jefferson City, MO	68.1	66.3	57.0	44.9	34.9
## Helena, MT	54.3	52.2	43.1	32.5	22.0
## Lincoln, NE	66.1	63.8	53.4	40.6	27.6
## Carson City, NV	52.2	50.6	43.4	34.6	27.1
## Concord, NH	57.7	56.1	47.4	35.8	28.2
## Trenton, NJ	66.0	64.2	56.4	44.2	36.9
## Santa Fe, NM	54.4	53.3	46.5	35.5	24.6
## Albany, NY	61.4	59.9	51.6	39.6	31.5
## Raleigh, NC	69.9	68.6	61.7	49.8	40.8
## Bismarck, ND	57.4	55.5	44.9	32.2	18.8
## Columbus, OH	65.5	64.1	56.5	45.0	36.1
## Oklahoma City, OK	72.2	71.3	63.2	51.6	40.0
## Salem, OR	53.1	52.8	48.4	42.3	38.4

## Harrisburg, PA	66.3	64.5	56.2	44.6	35.1	
## Providence, RI	64.2	63.2	55.3	43.9	35.7	
## Columbia, SC	71.6	71.0	64.2	52.1	42.3	
## Pierre, SD	61.9	60.1	49.2	36.4	23.3	
## Nashville, TN	69.5	68.4	60.7	48.9	39.4	
## Austin, TX	74.4	74.6	69.4	60.6	50.6	
## Salt Lake City, UT	64.7	63.4	53.0	41.3	30.6	
## Montpelier, VT	55.7	53.8	46.1	35.3	26.9	
## Richmond, VA	68.9	67.4	60.1	48.3	39.4	
## Olympia, WA	50.8	50.5	46.0	40.5	36.4	
## Charleston, WV	65.7	64.5	56.9	45.4	36.9	
## Madison, WI	61.0	59.0	50.2	38.8	28.2	
## Cheyenne, WY	55.5	54.1	44.7	33.9	24.2	
	lowavg	Dec	lowmin.Jan	lowmin.Feb	lowmin.Mar	lowmin.Apr
## Montgomery, AL	37.4	0	-5	17	28	
## Juneau, AK	27.8	-20	-15	-5	12	
## Phoenix, AZ	44.8	16	24	25	35	
## Little Rock, AR	33.7	-8	-12	11	28	
## Sacramento, CA	40.4	19	21	29	34	
## Denver, CO	17.1	-29	-25	-11	-2	
## Hartford, CT	23.4	-26	-24	-6	9	
## Dover, DE	31.0	-7	-11	7	14	
## Tallahassee, FL	41.1	6	-2	20	29	
## Atlanta, GA	36.5	-8	-9	10	25	
## Honolulu, HI	68.3	52	52	53	56	
## Boise, ID	24.0	-28	-15	5	11	
## Springfield, IL	22.5	-22	-24	-12	16	
## Indianapolis, IN	24.4	-27	-21	-7	18	
## Des Moines, IA	18.0	-30	-26	-22	9	
## Topeka, KS	22.3	-23	-25	-7	10	
## Frankfort, KY	25.9	-27	-16	-3	16	
## Baton Rouge, LA	42.7	9	2	20	31	
## Augusta, ME	18.6	-33	-23	-11	9	
## Annapolis, MD	31.9	-8	-6	10	13	
## Boston, MA	28.2	-13	-18	-8	11	
## Lansing, MI	22.3	-29	-37	-25	-6	
## Saint Paul, MN	13.0	-29	-32	-25	3	
## Jackson, MS	37.3	-5	1	15	27	
## Jefferson City, MO	24.0	-23	-25	-16	13	
## Helena, MT	11.9	-42	-42	-30	-10	
## Lincoln, NE	16.4	-33	-26	-19	3	
## Carson City, NV	21.9	-27	-22	-5	3	
## Concord, NH	17.2	-35	-37	-20	4	
## Trenton, NJ	27.6	-13	-14	1	11	
## Santa Fe, NM	17.4	-14	-24	-6	10	
## Albany, NY	21.2	-28	-22	-21	9	
## Raleigh, NC	33.3	-9	-2	11	23	
## Bismarck, ND	6.1	-45	-45	-36	-12	
## Columbus, OH	26.8	-22	-20	-6	14	
## Oklahoma City, OK	30.6	-11	-17	1	20	
## Salem, OR	34.0	-10	-4	12	23	
## Harrisburg, PA	26.6	-22	-13	-1	11	
## Providence, RI	26.3	-13	-17	1	11	
## Columbia, SC	35.3	-1	-2	4	26	

## Pierre, SD	12.1	-33	-35	-19	1
## Nashville, TN	31.3	-17	-13	2	23
## Austin, TX	42.3	-2	-1	18	30
## Salt Lake City, UT	22.6	-22	-30	0	14
## Montpelier, VT	14.4	-34	-29	-18	2
## Richmond, VA	31.4	-12	-10	10	19
## Olympia, WA	32.6	-8	-1	9	23
## Charleston, WV	29.2	-16	-12	-5	18
## Madison, WI	15.9	-37	-29	-29	0
## Cheyenne, WY	17.3	-38	-34	-21	-8
	lowmin.	May	lowmin.	Jun	lowmin.
## Montgomery, AL	40	48	59	56	39
## Juneau, AK	26	32	39	32	28
## Phoenix, AZ	39	49	63	58	47
## Little Rock, AR	38	46	54	52	37
## Sacramento, CA	37	43	47	48	44
## Denver, CO	19	30	42	40	17
## Hartford, CT	28	37	44	36	30
## Dover, DE	28	41	45	35	30
## Tallahassee, FL	34	46	57	57	40
## Atlanta, GA	37	39	53	55	36
## Honolulu, HI	60	63	63	63	65
## Boise, ID	22	30	35	32	23
## Springfield, IL	28	39	48	43	31
## Indianapolis, IN	27	37	46	41	30
## Des Moines, IA	26	37	47	40	26
## Topeka, KS	26	36	43	40	29
## Frankfort, KY	27	36	48	41	30
## Baton Rouge, LA	40	53	58	58	43
## Augusta, ME	26	36	43	39	28
## Annapolis, MD	32	35	50	46	37
## Boston, MA	31	41	50	46	34
## Lansing, MI	19	27	31	26	19
## Saint Paul, MN	21	36	45	42	26
## Jackson, MS	36	47	51	54	35
## Jefferson City, MO	24	38	42	41	29
## Helena, MT	17	30	36	28	6
## Lincoln, NE	24	39	45	39	26
## Carson City, NV	18	25	33	26	17
## Concord, NH	21	30	35	29	20
## Trenton, NJ	33	41	48	41	31
## Santa Fe, NM	19	28	37	36	26
## Albany, NY	26	35	40	34	24
## Raleigh, NC	29	38	48	46	37
## Bismarck, ND	13	30	32	32	10
## Columbus, OH	25	35	43	39	31
## Oklahoma City, OK	32	46	53	49	35
## Salem, OR	25	32	35	30	26
## Harrisburg, PA	30	40	49	45	30
## Providence, RI	29	39	48	40	32
## Columbia, SC	34	44	54	53	40
## Pierre, SD	21	34	42	39	21
## Nashville, TN	34	42	51	47	36
## Austin, TX	40	51	57	58	41

## Salt Lake City, UT	25	32	40	37	27	
## Montpelier, VT	20	29	35	31	20	
## Richmond, VA	31	40	51	46	35	
## Olympia, WA	25	30	35	33	25	
## Charleston, WV	26	33	46	41	32	
## Madison, WI	19	31	36	35	25	
## Cheyenne, WY	8	25	33	25	8	
##	lowmin.Oct	lowmin.Nov	lowmin.Dec	rain.Jan	rain.Feb	rain.Mar
## Montgomery, AL	26	13	5	4.65	5.28	5.95
## Juneau, AK	13	-7	-10	7.98	6.71	6.29
## Phoenix, AZ	34	27	22	0.91	0.92	0.99
## Little Rock, AR	27	10	-1	3.55	3.66	4.68
## Sacramento, CA	34	27	17	3.63	3.90	2.86
## Denver, CO	-2	-18	-25	0.41	0.37	0.92
## Hartford, CT	17	1	-18	3.23	2.89	3.62
## Dover, DE	25	11	-3	3.41	3.07	4.31
## Tallahassee, FL	29	13	10	4.34	4.85	5.94
## Atlanta, GA	28	3	0	4.20	4.67	4.81
## Honolulu, HI	61	57	54	0.00	0.00	0.00
## Boise, ID	11	-10	-25	1.24	0.99	1.39
## Springfield, IL	13	-3	-21	1.82	1.81	2.63
## Indianapolis, IN	20	-5	-23	2.66	2.32	3.56
## Des Moines, IA	7	-10	-22	1.00	1.28	2.30
## Topeka, KS	16	-5	-26	0.86	1.32	2.49
## Frankfort, KY	20	-1	-17	3.70	3.07	4.39
## Baton Rouge, LA	30	21	8	5.72	5.04	4.41
## Augusta, ME	21	4	-15	2.61	2.43	3.36
## Annapolis, MD	26	13	-1	3.32	2.94	4.53
## Boston, MA	25	-2	-17	3.36	3.25	4.32
## Lansing, MI	10	-5	-25	1.65	1.47	2.06
## Saint Paul, MN	15	-14	-29	0.79	0.67	1.54
## Jackson, MS	26	15	4	4.97	4.76	5.04
## Jefferson City, MO	14	1	-21	1.93	2.29	3.00
## Helena, MT	-8	-39	-40	0.36	0.30	0.59
## Lincoln, NE	3	-15	-27	0.64	0.77	1.93
## Carson City, NV	6	-5	-26	1.59	1.50	1.15
## Concord, NH	10	-17	-24	2.70	2.62	3.27
## Trenton, NJ	22	12	-7	3.16	2.31	4.14
## Santa Fe, NM	5	-12	-17	0.60	0.53	0.94
## Albany, NY	16	-11	-22	2.59	2.20	3.21
## Raleigh, NC	19	11	0	3.50	3.23	4.11
## Bismarck, ND	-10	-30	-43	0.43	0.51	0.87
## Columbus, OH	17	-5	-17	2.73	2.25	3.02
## Oklahoma City, OK	16	9	-8	1.39	1.58	3.06
## Salem, OR	19	9	-12	5.96	4.56	3.99
## Harrisburg, PA	23	10	-8	2.88	2.39	3.37
## Providence, RI	20	6	-12	3.86	3.29	5.01
## Columbia, SC	23	12	4	3.58	3.61	3.73
## Pierre, SD	4	-18	-31	0.42	0.59	1.23
## Nashville, TN	26	-1	-10	3.75	3.94	4.11
## Austin, TX	30	20	4	2.22	2.02	2.76
## Salt Lake City, UT	14	-14	-21	1.25	1.25	1.79
## Montpelier, VT	14	-7	-27	2.45	2.04	2.39
## Richmond, VA	21	10	-2	3.04	2.76	4.04

## Olympia, WA	14	-1	-7	7.84	5.27	5.29	
## Charleston, WV	17	6	-17	3.00	3.19	3.91	
## Madison, WI	12	-14	-28	1.23	1.45	2.20	
## Cheyenne, WY	-5	-21	-28	0.33	0.47	1.05	
##		rain.Apr	rain.May	rain.Jun	rain.Jul	rain.Aug	rain.Sep
## Montgomery, AL	4.02	3.54	4.07	5.24	3.96	3.97	
## Juneau, AK	4.64	4.96	4.42	5.44	8.16	12.72	
## Phoenix, AZ	0.28	0.11	0.02	1.05	1.00	0.64	
## Little Rock, AR	5.14	4.87	3.65	3.27	2.59	3.18	
## Sacramento, CA	1.36	0.75	0.21	0.02	0.04	0.35	
## Denver, CO	1.71	2.12	1.98	2.16	1.69	0.96	
## Hartford, CT	3.72	4.35	4.35	4.18	3.93	3.88	
## Dover, DE	3.88	4.25	4.00	4.09	4.36	4.13	
## Tallahassee, FL	3.06	3.47	7.73	7.17	7.35	4.69	
## Atlanta, GA	3.36	3.67	3.95	5.27	3.90	4.47	
## Honolulu, HI	0.00	0.00	0.00	0.00	0.00	0.00	
## Boise, ID	1.23	1.39	0.69	0.33	0.24	0.58	
## Springfield, IL	3.51	4.24	4.46	3.94	3.24	2.90	
## Indianapolis, IN	3.81	5.05	4.25	4.55	3.13	3.12	
## Des Moines, IA	3.86	4.74	4.94	4.47	4.13	3.05	
## Topeka, KS	3.53	4.91	5.40	3.82	4.24	3.66	
## Frankfort, KY	3.74	4.01	4.06	4.14	3.45	2.90	
## Baton Rouge, LA	4.46	4.89	6.41	4.96	5.82	4.54	
## Augusta, ME	3.78	3.69	3.55	3.41	3.31	3.74	
## Annapolis, MD	3.66	4.20	4.17	4.56	3.88	4.76	
## Boston, MA	3.74	3.49	3.68	3.43	3.35	3.44	
## Lansing, MI	3.03	3.36	3.45	2.84	3.23	3.50	
## Saint Paul, MN	2.87	3.70	4.21	4.41	4.76	3.27	
## Jackson, MS	4.96	4.38	4.12	4.81	4.24	3.03	
## Jefferson City, MO	4.16	5.18	4.39	4.31	3.99	4.15	
## Helena, MT	0.98	1.87	2.06	1.19	1.20	1.10	
## Lincoln, NE	2.71	4.29	4.35	3.40	3.49	3.02	
## Carson City, NV	0.43	0.43	0.40	0.19	0.21	0.39	
## Concord, NH	3.41	3.66	3.69	3.74	3.18	3.38	
## Trenton, NJ	3.54	4.37	4.41	4.95	4.10	4.27	
## Santa Fe, NM	0.77	0.94	1.29	2.33	2.23	1.54	
## Albany, NY	3.17	3.61	3.79	4.12	3.46	3.30	
## Raleigh, NC	2.92	3.27	3.52	4.73	4.26	4.36	
## Bismarck, ND	1.26	2.40	3.17	2.89	2.28	1.59	
## Columbus, OH	3.40	4.17	4.01	4.79	3.32	2.84	
## Oklahoma City, OK	3.07	4.65	4.93	2.93	3.28	4.06	
## Salem, OR	2.81	2.22	1.54	0.46	0.44	1.28	
## Harrisburg, PA	3.10	3.79	3.60	4.61	3.20	4.07	
## Providence, RI	4.36	3.55	3.64	3.29	3.60	3.92	
## Columbia, SC	2.62	2.97	4.69	5.46	5.26	3.54	
## Pierre, SD	1.81	3.15	3.57	2.61	1.80	1.87	
## Nashville, TN	4.00	5.50	4.14	3.64	3.17	3.41	
## Austin, TX	2.09	4.44	4.33	1.88	2.35	2.99	
## Salt Lake City, UT	1.99	1.95	0.98	0.61	0.69	1.21	
## Montpelier, VT	2.66	3.37	3.80	4.08	4.01	3.12	
## Richmond, VA	3.27	3.78	3.93	4.51	4.66	4.13	
## Olympia, WA	3.54	2.33	1.76	0.63	0.94	1.71	
## Charleston, WV	3.24	4.80	4.29	4.94	3.74	3.25	
## Madison, WI	3.40	3.55	4.54	4.18	4.27	3.13	

## Cheyenne, WY	1.78	2.34	2.34	2.19	1.95	1.48
##	rain.Oct	rain.Nov	rain.Dec	snow.Jan	snow.Feb	snow.Mar
## Montgomery, AL	2.92	4.61	4.86	0.0	0.0	0.0
## Juneau, AK	13.23	8.44	9.23	24.2	15.9	5.4
## Phoenix, AZ	0.58	0.65	0.88	0.0	0.0	0.0
## Little Rock, AR	4.91	5.28	4.97	1.6	1.3	0.4
## Sacramento, CA	1.06	2.46	3.43	0.0	0.0	0.0
## Denver, CO	1.02	0.61	0.35	7.0	5.7	10.7
## Hartford, CT	4.37	3.89	3.44	12.3	11.0	6.4
## Dover, DE	3.42	3.48	3.65	4.6	7.7	0.3
## Tallahassee, FL	3.23	3.50	3.90	0.0	0.0	0.0
## Atlanta, GA	3.41	4.10	3.90	1.3	0.4	0.8
## Honolulu, HI	0.00	0.00	0.00	0.0	0.0	0.0
## Boise, ID	0.75	1.35	1.55	5.1	2.8	1.3
## Springfield, IL	3.15	3.21	2.52	6.4	5.5	2.5
## Indianapolis, IN	3.12	3.70	3.17	8.6	6.5	2.6
## Des Moines, IA	2.64	2.19	1.42	8.5	7.9	5.2
## Topeka, KS	3.03	1.85	1.35	4.9	4.5	1.6
## Frankfort, KY	2.53	3.29	3.49	3.4	2.8	1.2
## Baton Rouge, LA	4.70	4.10	5.60	0.0	0.0	0.0
## Augusta, ME	4.36	4.35	3.24	20.0	14.9	15.6
## Annapolis, MD	3.89	3.80	3.56	4.4	0.4	0.3
## Boston, MA	3.94	3.99	3.78	12.9	10.9	7.8
## Lansing, MI	2.53	2.78	1.87	13.8	11.6	7.0
## Saint Paul, MN	2.91	1.81	1.10	0.0	0.0	0.0
## Jackson, MS	3.92	4.76	5.15	0.0	0.0	0.0
## Jefferson City, MO	3.35	3.61	2.67	4.8	3.4	1.4
## Helena, MT	0.68	0.49	0.40	6.2	5.0	6.2
## Lincoln, NE	1.97	1.43	0.95	5.4	5.6	4.8
## Carson City, NV	0.77	1.19	1.43	3.4	3.4	1.9
## Concord, NH	4.04	3.72	3.20	18.1	12.3	11.1
## Trenton, NJ	4.18	3.31	3.70	6.0	0.0	5.2
## Santa Fe, NM	1.33	0.85	0.83	4.0	2.9	4.4
## Albany, NY	3.68	3.29	2.93	17.9	12.2	11.0
## Raleigh, NC	3.25	3.12	3.07	2.9	1.9	0.5
## Bismarck, ND	1.25	0.71	0.49	8.9	8.1	9.1
## Columbus, OH	2.61	3.20	2.97	9.2	6.1	4.2
## Oklahoma City, OK	3.71	1.98	1.88	2.8	1.4	0.9
## Salem, OR	3.03	6.50	6.86	0.6	1.7	0.0
## Harrisburg, PA	3.27	3.23	3.23	8.8	10.5	5.2
## Providence, RI	3.93	4.51	4.22	9.0	8.5	5.5
## Columbia, SC	3.17	2.74	3.22	0.8	0.5	0.1
## Pierre, SD	1.65	0.76	0.55	5.4	6.0	5.8
## Nashville, TN	3.04	4.31	4.24	2.6	2.3	0.9
## Austin, TX	3.88	2.96	2.40	0.4	0.2	0.0
## Salt Lake City, UT	1.52	1.45	1.41	12.5	10.7	6.5
## Montpelier, VT	3.44	3.17	2.74	22.6	18.0	16.8
## Richmond, VA	2.98	3.24	3.26	3.9	3.4	0.6
## Olympia, WA	4.60	8.63	7.46	1.9	4.7	0.7
## Charleston, WV	2.67	3.73	3.27	11.3	9.8	5.8
## Madison, WI	2.40	2.39	1.74	12.9	10.6	7.0
## Cheyenne, WY	0.93	0.59	0.49	5.9	7.9	11.3
##	snow.Apr	snow.May	snow.Jun	snow.Jul	snow.Aug	snow.Sep
## Montgomery, AL	0.0	0.0	0	0	0.0	0.0

## Juneau, AK	0.9	0.0	0	0	0.0	0.0
## Phoenix, AZ	0.0	0.0	0	0	0.0	0.0
## Little Rock, AR	0.0	0.0	0	0	0.0	0.0
## Sacramento, CA	0.0	0.0	0	0	0.0	0.0
## Denver, CO	6.8	1.1	0	0	0.0	1.3
## Hartford, CT	1.4	0.0	0	0	0.0	0.0
## Dover, DE	0.0	0.0	0	0	0.0	0.0
## Tallahassee, FL	0.0	0.0	0	0	0.0	0.0
## Atlanta, GA	0.0	0.0	0	0	0.0	0.0
## Honolulu, HI	0.0	0.0	0	0	0.0	0.0
## Boise, ID	0.3	0.0	0	0	0.0	0.0
## Springfield, IL	0.3	0.0	0	0	0.0	0.0
## Indianapolis, IN	0.2	0.0	0	0	0.0	0.0
## Des Moines, IA	1.8	0.0	0	0	0.0	0.0
## Topeka, KS	0.3	0.0	0	0	0.0	0.0
## Frankfort, KY	0.0	0.0	0	0	0.0	0.0
## Baton Rouge, LA	0.0	0.0	0	0	0.0	0.0
## Augusta, ME	4.7	0.0	0	0	0.0	0.0
## Annapolis, MD	0.0	0.0	0	0	0.0	0.0
## Boston, MA	1.9	0.0	0	0	0.0	0.0
## Lansing, MI	1.9	0.0	0	0	0.0	0.0
## Saint Paul, MN	0.0	0.0	0	0	0.0	0.0
## Jackson, MS	0.0	0.0	0	0	0.0	0.0
## Jefferson City, MO	0.1	0.0	0	0	0.0	0.0
## Helena, MT	3.7	0.9	0	0	0.3	1.3
## Lincoln, NE	1.4	0.0	0	0	0.0	0.0
## Carson City, NV	0.2	0.0	0	0	0.0	0.0
## Concord, NH	2.8	0.0	0	0	0.0	0.0
## Trenton, NJ	0.0	0.0	0	0	0.0	0.0
## Santa Fe, NM	0.4	0.0	0	0	0.0	0.0
## Albany, NY	2.3	0.1	0	0	0.0	0.0
## Raleigh, NC	0.1	0.0	0	0	0.0	0.0
## Bismarck, ND	4.2	0.4	0	0	0.0	0.2
## Columbus, OH	1.1	0.0	0	0	0.0	0.0
## Oklahoma City, OK	0.0	0.0	0	0	0.0	0.0
## Salem, OR	0.0	0.0	0	0	0.0	0.0
## Harrisburg, PA	0.4	0.0	0	0	0.0	0.0
## Providence, RI	0.6	0.0	0	0	0.0	0.0
## Columbia, SC	0.0	0.0	0	0	0.0	0.0
## Pierre, SD	3.5	0.0	0	0	0.0	0.0
## Nashville, TN	0.0	0.0	0	0	0.0	0.0
## Austin, TX	0.0	0.0	0	0	0.0	0.0
## Salt Lake City, UT	4.0	0.3	0	0	0.0	0.0
## Montpelier, VT	4.9	0.0	0	0	0.0	0.0
## Richmond, VA	0.1	0.0	0	0	0.0	0.0
## Olympia, WA	0.0	0.0	0	0	0.0	0.0
## Charleston, WV	1.4	0.0	0	0	0.0	0.0
## Madison, WI	2.6	0.2	0	0	0.0	0.0
## Cheyenne, WY	10.2	2.3	0	0	0.0	1.3
			snow.Oct	snow.Nov	snow.Dec	
## Montgomery, AL	0.0	0.0	0.0			
## Juneau, AK	0.6	9.2	13.6			
## Phoenix, AZ	0.0	0.0	0.0			
## Little Rock, AR	0.0	0.0	0.2			

## Sacramento, CA	0.0	0.0	0.0
## Denver, CO	4.0	8.7	8.5
## Hartford, CT	0.0	2.0	7.4
## Dover, DE	0.0	0.2	2.9
## Tallahassee, FL	0.0	0.0	0.0
## Atlanta, GA	0.0	0.0	0.4
## Honolulu, HI	0.0	0.0	0.0
## Boise, ID	0.1	2.6	7.0
## Springfield, IL	0.0	0.6	5.6
## Indianapolis, IN	0.4	0.7	6.9
## Des Moines, IA	0.4	2.5	9.0
## Topeka, KS	0.3	1.0	5.2
## Frankfort, KY	0.0	0.4	1.6
## Baton Rouge, LA	0.0	0.0	0.0
## Augusta, ME	0.3	3.5	14.5
## Annapolis, MD	0.0	0.2	0.8
## Boston, MA	0.0	1.3	9.0
## Lansing, MI	0.4	3.4	13.0
## Saint Paul, MN	0.0	0.0	0.0
## Jackson, MS	0.0	0.0	0.0
## Jefferson City, MO	0.0	0.3	3.8
## Helena, MT	2.4	4.8	7.3
## Lincoln, NE	0.7	2.1	5.9
## Carson City, NV	0.0	0.9	3.9
## Concord, NH	0.0	2.6	14.5
## Trenton, NJ	0.0	0.6	3.5
## Santa Fe, NM	1.0	2.3	8.0
## Albany, NY	0.3	2.8	13.7
## Raleigh, NC	0.0	0.1	0.6
## Bismarck, ND	2.2	8.8	9.3
## Columbus, OH	0.2	0.9	5.0
## Oklahoma City, OK	0.0	0.4	2.1
## Salem, OR	0.0	0.1	1.1
## Harrisburg, PA	0.0	0.6	5.1
## Providence, RI	0.0	1.5	8.7
## Columbia, SC	0.0	0.0	0.1
## Pierre, SD	0.9	4.8	4.8
## Nashville, TN	0.0	0.0	0.5
## Austin, TX	0.0	0.0	0.0
## Salt Lake City, UT	1.4	7.6	13.2
## Montpelier, VT	0.0	9.1	21.9
## Richmond, VA	0.0	0.2	2.1
## Olympia, WA	0.0	0.9	2.6
## Charleston, WV	0.1	1.3	6.7
## Madison, WI	0.5	3.6	13.5
## Cheyenne, WY	5.0	8.0	8.4

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);

```

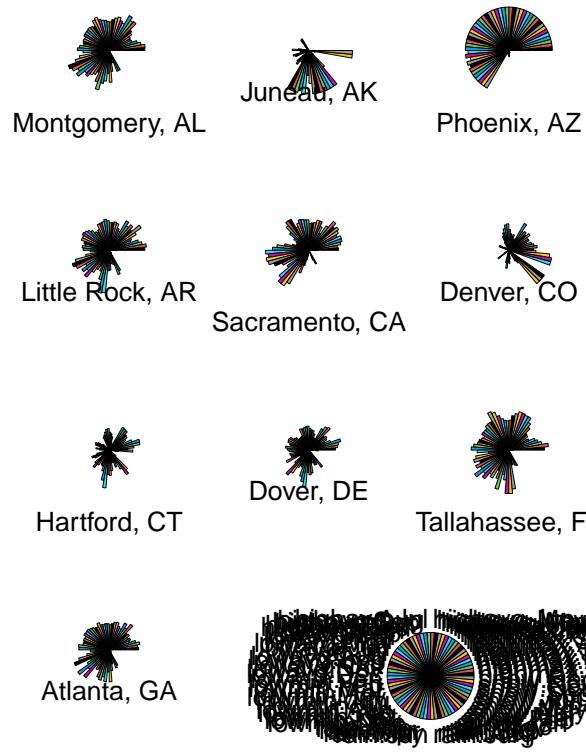


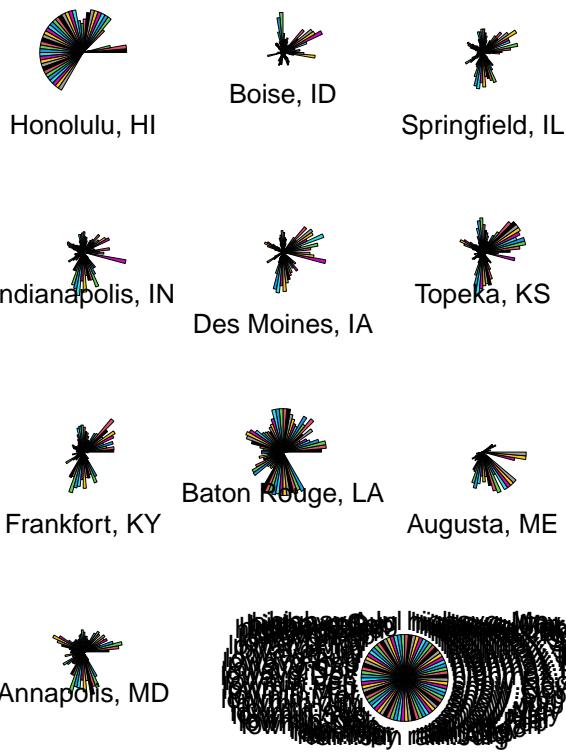
Descriptives of Sample

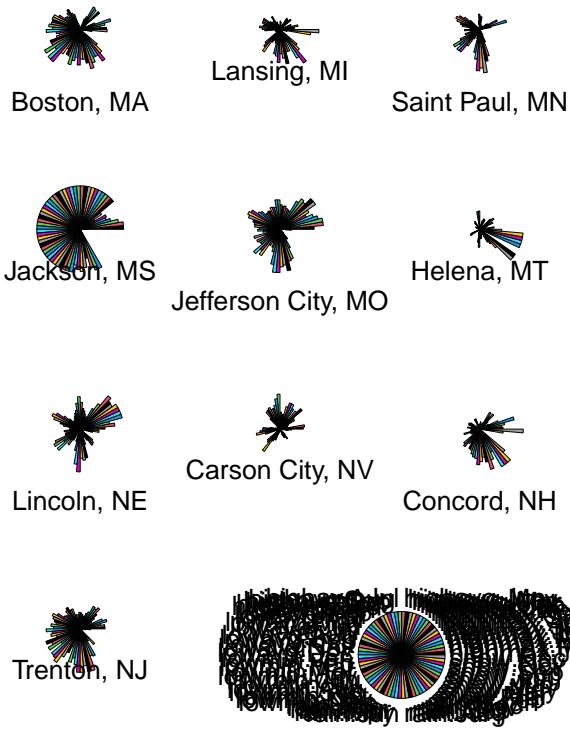
```

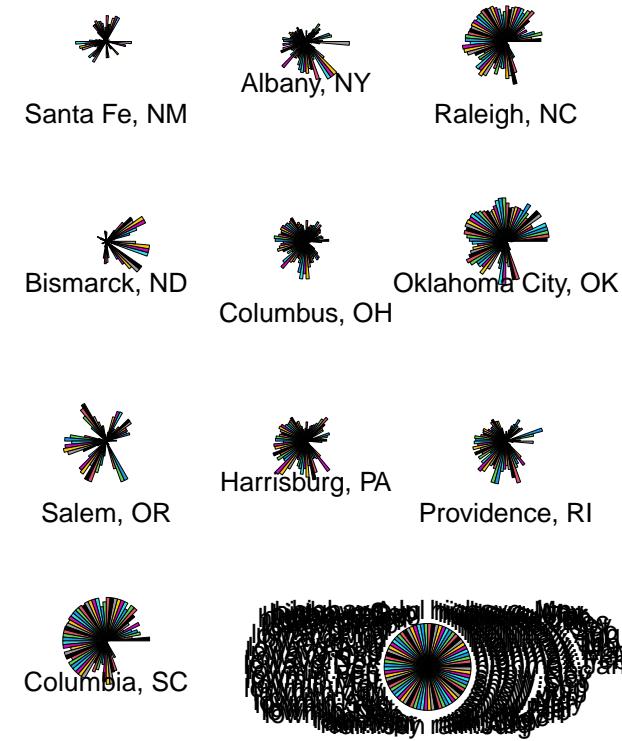
## too busy, let's group them
x.start = 1;
x.end = 10;
for(i in 1:5)
{
  stars( whichX[x.start:x.end,] ,
         len = 0.5, key.loc=c(6,2), draw.segments = TRUE);
  x.start = 1 + x.end;
  x.end = 10 + x.end;
}

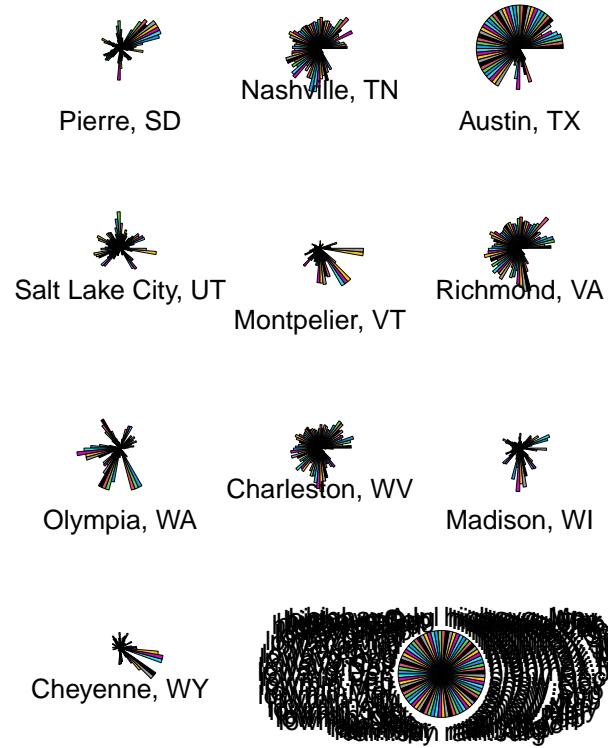
```











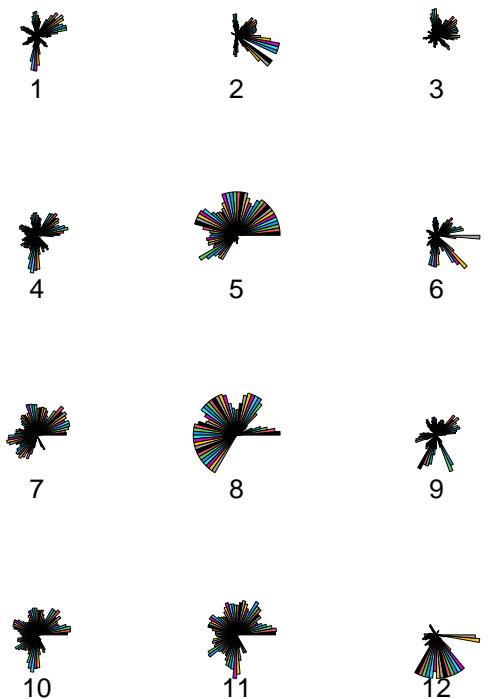
Above, you are just analyzing the general shapes. Which ones are “fuller” circles? Why?
 Which ones are not very “full circles”? Why?

```

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          1
## Phoenix, AZ          1
## Little Rock, AR      1
## Sacramento, CA      2
## Denver, CO          2
## Hartford, CT          2
## Dover, DE          3
## Tallahassee, FL      3
## Atlanta, GA          3
## Honolulu, HI          3
## Boise, ID          3

```

```

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

print( table(membership) ) ;

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

# 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.Feb highmax.Mar highmax.Apr highmax.May
## Cluster.1      66.25000    73.75000    88.25000   95.25000   101.75000
## Cluster.2      65.33333    71.00000    78.66667   87.66667    96.00000

```

## Cluster.3	67.80000	73.80000	80.80000	88.60000	96.80000
## Cluster.4	74.83333	78.66667	89.41667	94.00000	98.58333
## Cluster.5	88.00000	92.00000	100.00000	105.00000	114.00000
## Cluster.6	65.66667	67.66667	85.50000	91.66667	96.00000
## Cluster.7	79.00000	80.00000	90.00000	98.00000	107.00000
## Cluster.8	88.00000	88.00000	89.00000	91.00000	93.00000
## Cluster.9	66.00000	72.50000	79.50000	90.50000	98.00000
## Cluster.10	79.75000	84.12500	91.75000	95.25000	98.75000
## Cluster.11	85.00000	89.16667	93.33333	95.66667	101.16667
## Cluster.12	60.00000	57.00000	61.00000	72.00000	80.00000
##	highmax.Jun	highmax.Jul	highmax.Aug	highmax.Sep	highmax.Oct
## Cluster.1	106.5000	111.7500	109.2500	102.50000	94.75000
## Cluster.2	104.3333	106.3333	104.0000	99.66667	89.00000
## Cluster.3	104.0000	106.2000	104.4000	100.00000	90.60000
## Cluster.4	102.7500	107.5833	105.66667	102.91667	93.83333
## Cluster.5	122.0000	121.0000	117.0000	116.00000	107.00000
## Cluster.6	99.0000	102.0000	100.66667	97.33333	88.66667
## Cluster.7	112.0000	114.0000	112.0000	109.00000	102.00000
## Cluster.8	92.0000	94.0000	95.0000	95.00000	94.00000
## Cluster.9	101.5000	106.0000	106.0000	101.00000	91.50000
## Cluster.10	105.2500	106.6250	107.1250	103.25000	97.25000
## Cluster.11	106.1667	106.1667	107.5000	106.16667	99.00000
## Cluster.12	87.0000	89.0000	87.0000	85.00000	68.00000
##	highmax.Nov	highmax.Dec	highavg.Jan	highavg.Feb	highavg.Mar
## Cluster.1	82.25000	71.75000	30.60000	35.52500	47.42500
## Cluster.2	76.33333	66.33333	32.06667	35.80000	45.36667
## Cluster.3	77.60000	71.60000	41.58000	46.44000	55.06000
## Cluster.4	83.41667	76.50000	37.86667	42.00000	51.77500
## Cluster.5	96.00000	87.00000	67.20000	70.70000	76.90000
## Cluster.6	78.00000	69.00000	28.65000	32.66667	42.46667
## Cluster.7	86.00000	72.00000	54.40000	61.20000	66.80000
## Cluster.8	93.00000	89.00000	80.10000	80.20000	81.20000
## Cluster.9	74.00000	68.00000	46.80000	50.45000	55.20000
## Cluster.10	86.12500	80.00000	47.97500	52.13750	60.56250
## Cluster.11	89.83333	85.66667	59.46667	63.50000	70.85000
## Cluster.12	64.00000	59.00000	34.60000	36.70000	40.80000
##	highavg.Apr	highavg.May	highavg.Jun	highavg.Jul	highavg.Aug
## Cluster.1	61.07500	71.95000	81.45000	87.12500	84.97500
## Cluster.2	56.56667	66.73333	76.06667	84.60000	83.06667
## Cluster.3	62.56000	72.12000	82.26000	89.74000	87.76000
## Cluster.4	63.13333	72.58333	81.28333	85.49167	84.21667
## Cluster.5	85.20000	94.80000	103.90000	106.10000	104.40000
## Cluster.6	56.20000	67.73333	76.61667	81.05000	79.25000
## Cluster.7	72.70000	80.90000	87.90000	93.30000	92.20000
## Cluster.8	82.70000	84.60000	87.00000	87.90000	88.70000
## Cluster.9	60.00000	66.55000	72.25000	79.40000	80.05000
## Cluster.10	70.08750	78.06250	85.92500	89.68750	88.53750
## Cluster.11	77.96667	85.10000	90.55000	92.71667	92.53333
## Cluster.12	49.10000	56.90000	62.40000	63.40000	62.60000
##	highavg.Sep	highavg.Oct	highavg.Nov	highavg.Dec	lowavg.Jan
## Cluster.1	76.07500	62.22500	46.07500	32.87500	11.22500
## Cluster.2	72.16667	58.33333	43.06667	32.03333	11.06667
## Cluster.3	78.92000	65.84000	51.44000	41.30000	20.58000
## Cluster.4	77.08333	65.65000	53.80833	41.65000	21.45000

## Cluster.5	99.80000	88.50000	75.50000	66.00000	45.60000	
## Cluster.6	71.26667	58.71667	46.01667	33.61667	11.80000	
## Cluster.7	87.90000	77.90000	63.70000	54.30000	40.70000	
## Cluster.8	88.60000	86.70000	83.90000	81.20000	66.30000	
## Cluster.9	74.30000	62.15000	51.40000	45.20000	34.20000	
## Cluster.10	81.80000	71.41250	61.10000	50.61250	29.77500	
## Cluster.11	87.80000	79.26667	70.00000	61.35000	37.73333	
## Cluster.12	56.60000	48.40000	39.80000	36.70000	26.20000	
##	lowavg.Feb	lowavg.Mar	lowavg.Apr	lowavg.May	lowavg.Jun	lowavg.Jul
## Cluster.1	15.65000	26.27500	38.02500	49.60000	59.32500	64.70000
## Cluster.2	14.46667	22.70000	31.20000	41.23333	49.80000	55.73333
## Cluster.3	23.84000	30.08000	35.66000	43.76000	51.78000	58.12000
## Cluster.4	24.45000	32.06667	41.79167	51.41667	60.95833	65.60833
## Cluster.5	48.70000	53.50000	60.20000	69.40000	77.70000	83.50000
## Cluster.6	14.78333	23.55000	34.81667	44.83333	54.53333	59.38333
## Cluster.7	43.70000	46.50000	49.00000	53.90000	58.40000	60.90000
## Cluster.8	66.10000	67.70000	69.40000	70.90000	73.40000	74.50000
## Cluster.9	33.70000	36.15000	38.65000	42.40000	48.45000	51.95000
## Cluster.10	32.57500	39.53750	47.98750	57.33750	66.36250	70.57500
## Cluster.11	40.95000	47.05000	53.65000	62.55000	69.68333	72.46667
## Cluster.12	27.60000	30.10000	35.30000	42.30000	48.40000	51.40000
##	lowavg.Aug	lowavg.Sep	lowavg.Oct	lowavg.Nov	lowavg.Dec	lowmin.Jan
## Cluster.1	62.67500	52.70000	40.25000	27.10000	14.87500	-31.250000
## Cluster.2	53.93333	44.23333	32.86667	21.66667	11.76667	-41.666667
## Cluster.3	56.96000	48.44000	37.78000	27.74000	20.60000	-24.000000
## Cluster.4	64.10000	55.84167	44.31667	35.23333	25.60000	-20.583333
## Cluster.5	82.70000	76.90000	64.80000	52.70000	44.80000	16.000000
## Cluster.6	57.78333	49.50000	38.30000	29.63333	18.26667	-32.666667
## Cluster.7	60.50000	58.40000	52.80000	45.50000	40.40000	19.000000
## Cluster.8	75.10000	74.40000	73.40000	71.40000	68.30000	52.000000
## Cluster.9	51.65000	47.20000	41.40000	37.40000	33.30000	-9.000000
## Cluster.10	69.36250	62.23750	50.55000	40.98750	32.46250	-10.000000
## Cluster.11	72.16667	66.66667	55.75000	46.20000	39.35000	1.166667
## Cluster.12	50.20000	45.80000	39.00000	31.40000	27.80000	-20.000000
##	lowmin.Feb	lowmin.Mar	lowmin.Apr	lowmin.May	lowmin.Jun	lowmin.Jul
## Cluster.1	-29.75000	-21.25000	4.00000	23.00000	36.50000	44.75000
## Cluster.2	-40.33333	-29.00000	-10.00000	12.66667	28.33333	33.66667
## Cluster.3	-23.20000	-3.40000	7.20000	20.60000	29.00000	37.40000
## Cluster.4	-19.08333	-5.75000	13.16667	27.83333	37.66667	46.25000
## Cluster.5	24.00000	25.00000	35.00000	39.00000	49.00000	63.00000
## Cluster.6	-29.50000	-20.66667	3.00000	21.83333	31.33333	36.66667
## Cluster.7	21.00000	29.00000	34.00000	37.00000	43.00000	47.00000
## Cluster.8	52.00000	53.00000	56.00000	60.00000	63.00000	63.00000
## Cluster.9	-2.50000	10.50000	23.00000	25.00000	31.00000	35.00000
## Cluster.10	-10.00000	7.75000	20.62500	32.62500	40.87500	50.62500
## Cluster.11	-1.16667	15.66667	28.50000	37.33333	48.16667	56.00000
## Cluster.12	-15.00000	-5.00000	12.00000	26.00000	32.00000	39.00000
##	lowmin.Aug	lowmin.Sep	lowmin.Oct	lowmin.Nov	lowmin.Dec	rain.Jan
## Cluster.1	40.00000	24.75000	7.25000	-14.25000	-27.25000	0.7125000
## Cluster.2	28.33333	8.00000	-7.66667	-30.00000	-37.00000	0.3733333
## Cluster.3	34.20000	22.00000	6.80000	-11.80000	-22.80000	1.0180000
## Cluster.4	41.16667	30.75000	18.66667	1.25000	-17.00000	2.7658333
## Cluster.5	58.00000	47.00000	34.00000	27.00000	22.00000	0.9100000
## Cluster.6	32.33333	22.66667	13.83333	-8.33333	-23.50000	2.2050000

```

## Cluster.7 48.00000 44.00000 34.000000 27.000000 17.000000 3.6300000
## Cluster.8 63.00000 65.00000 61.000000 57.000000 54.000000 0.0000000
## Cluster.9 31.50000 25.50000 16.500000 4.000000 -9.500000 6.9000000
## Cluster.10 47.00000 35.37500 23.500000 8.250000 -3.125000 3.2700000
## Cluster.11 56.00000 39.66667 27.333333 15.666667 5.833333 4.2466667
## Cluster.12 32.00000 28.00000 13.000000 -7.000000 -10.000000 7.9800000
##          rain.Feb rain.Mar rain.Apr rain.May rain.Jun rain.Jul rain.Aug
## Cluster.1 0.8275000 1.7500000 2.812500 3.970000 4.267500 3.722500 3.545000
## Cluster.2 0.42666667 0.83666667 1.340000 2.203333 2.523333 2.090000 1.810000
## Cluster.3 0.9280000 1.2380000 1.226000 1.366000 1.068000 1.124000 1.012000
## Cluster.4 2.5316667 3.6216667 3.654167 4.325833 4.211667 4.245833 3.607500
## Cluster.5 0.9200000 0.9900000 0.280000 0.110000 0.020000 1.050000 1.000000
## Cluster.6 2.0350000 2.7483333 3.241667 3.540000 3.803333 3.728333 3.576667
## Cluster.7 3.9000000 2.8600000 1.360000 0.750000 0.210000 0.020000 0.040000
## Cluster.8 0.0000000 0.0000000 0.000000 0.000000 0.000000 0.000000 0.000000
## Cluster.9 4.9150000 4.6400000 3.175000 2.275000 1.650000 0.545000 0.690000
## Cluster.10 3.2312500 4.2062500 3.662500 4.273750 4.036250 4.125000 3.762500
## Cluster.11 4.2600000 4.6383333 3.535000 3.948333 5.225000 4.920000 4.830000
## Cluster.12 6.7100000 6.2900000 4.640000 4.960000 4.420000 5.440000 8.160000
##          rain.Sep rain.Oct rain.Nov rain.Dec snow.Jan snow.Feb
## Cluster.1 2.802500 2.2925000 1.5475000 1.005000 4.825000 4.8750000
## Cluster.2 1.390000 0.9533333 0.5966667 0.460000 7.000000 7.0000000
## Cluster.3 0.936000 1.0780000 1.0900000 1.114000 6.400000 5.1000000
## Cluster.4 3.533333 3.3458333 3.4600000 3.150833 8.133333 6.6250000
## Cluster.5 0.640000 0.5800000 0.6500000 0.880000 0.000000 0.0000000
## Cluster.6 3.361667 3.4083333 3.2833333 2.620000 17.550000 13.2666667
## Cluster.7 0.350000 1.0600000 2.4600000 3.430000 0.000000 0.0000000
## Cluster.8 0.000000 0.0000000 0.0000000 0.000000 0.000000 0.0000000
## Cluster.9 1.495000 3.8150000 7.5650000 7.160000 1.250000 3.2000000
## Cluster.10 4.062500 3.5762500 3.6637500 3.566250 3.012500 2.3500000
## Cluster.11 3.793333 3.6366667 3.7783333 4.188333 0.200000 0.1166667
## Cluster.12 12.720000 13.2300000 8.4400000 9.230000 24.200000 15.9000000
##          snow.Mar snow.Apr snow.May snow.Jun snow.Jul snow.Aug snow.Sep
## Cluster.1 3.95000000 1.6750000 0.00 0 0 0.0 0.0000000
## Cluster.2 8.86666667 6.0333333 1.20 0 0 0.1 0.9333333
## Cluster.3 4.96000000 2.3400000 0.28 0 0 0.0 0.2600000
## Cluster.4 4.11666667 0.6416667 0.00 0 0 0.0 0.0000000
## Cluster.5 0.00000000 0.0000000 0.00 0 0 0.0 0.0000000
## Cluster.6 11.41666667 3.2000000 0.05 0 0 0.0 0.0000000
## Cluster.7 0.00000000 0.0000000 0.00 0 0 0.0 0.0000000
## Cluster.8 0.00000000 0.0000000 0.00 0 0 0.0 0.0000000
## Cluster.9 0.35000000 0.0000000 0.00 0 0 0.0 0.0000000
## Cluster.10 0.58750000 0.0250000 0.00 0 0 0.0 0.0000000
## Cluster.11 0.01666667 0.0000000 0.00 0 0 0.0 0.0000000
## Cluster.12 5.40000000 0.9000000 0.00 0 0 0.0 0.0000000
##          snow.Oct snow.Nov snow.Dec
## Cluster.1 0.50000000 2.3500000 4.9250000
## Cluster.2 3.20000000 7.2000000 8.3333333
## Cluster.3 1.30000000 4.4200000 8.1200000
## Cluster.4 0.08333333 0.9333333 5.7083333
## Cluster.5 0.00000000 0.0000000 0.00000000
## Cluster.6 0.25000000 4.1666667 15.1833333
## Cluster.7 0.00000000 0.0000000 0.00000000
## Cluster.8 0.00000000 0.0000000 0.00000000

```

```
## Cluster.9 0.0000000 0.5000000 1.85000000
## Cluster.10 0.0000000 0.1375000 1.20000000
## Cluster.11 0.0000000 0.0000000 0.01666667
## Cluster.12 0.6000000 9.2000000 13.60000000
```

```
state <- rownames(membership)
rownames(membership) <- NULL
new.membership <- cbind(state, membership)
new.membership
```

	state	Cluster
## 1	Montgomery, AL	1
## 2	Juneau, AK	1
## 3	Phoenix, AZ	1
## 4	Little Rock, AR	1
## 5	Sacramento, CA	2
## 6	Denver, CO	2
## 7	Hartford, CT	2
## 8	Dover, DE	3
## 9	Tallahassee, FL	3
## 10	Atlanta, GA	3
## 11	Honolulu, HI	3
## 12	Boise, ID	3
## 13	Springfield, IL	4
## 14	Indianapolis, IN	4
## 15	Des Moines, IA	4
## 16	Topeka, KS	4
## 17	Frankfort, KY	4
## 18	Baton Rouge, LA	4
## 19	Augusta, ME	4
## 20	Annapolis, MD	4
## 21	Boston, MA	4
## 22	Lansing, MI	4
## 23	Saint Paul, MN	4
## 24	Jackson, MS	4
## 25	Jefferson City, MO	5
## 26	Helena, MT	6
## 27	Lincoln, NE	6
## 28	Carson City, NV	6
## 29	Concord, NH	6
## 30	Trenton, NJ	6
## 31	Santa Fe, NM	6
## 32	Albany, NY	7
## 33	Raleigh, NC	8
## 34	Bismarck, ND	9
## 35	Columbus, OH	9
## 36	Oklahoma City, OK	10
## 37	Salem, OR	10
## 38	Harrisburg, PA	10
## 39	Providence, RI	10
## 40	Columbia, SC	10
## 41	Pierre, SD	10
## 42	Nashville, TN	10
## 43	Austin, TX	10

```

## 44 Salt Lake City, UT      11
## 45    Montpelier, VT      11
## 46    Richmond, VA      11
## 47    Olympia, WA      11
## 48    Charleston, WV      11
## 49    Madison, WI      11
## 50    Cheyenne, WY      12

for (i in 1:12) {
  cat(new.membership$state[membership$Cluster==i], 'are in cluster', i, '\n')
}

## Montgomery, AL Juneau, AK Phoenix, AZ Little Rock, AR are in cluster 1
## Sacramento, CA Denver, CO Hartford, CT are in cluster 2
## Dover, DE Tallahassee, FL Atlanta, GA Honolulu, HI Boise, ID are in cluster 3
## Springfield, IL Indianapolis, IN Des Moines, IA Topeka, KS Frankfort, KY Baton Rouge, LA Augusta, ME
## Jefferson City, MO are in cluster 5
## Helena, MT Lincoln, NE Carson City, NV Concord, NH Trenton, NJ Santa Fe, NM are in cluster 6
## Albany, NY are in cluster 7
## Raleigh, NC are in cluster 8
## Bismarck, ND Columbus, OH are in cluster 9
## Oklahoma City, OK Salem, OR Harrisburg, PA Providence, RI Columbia, SC Pierre, SD Nashville, TN Austin
## Salt Lake City, UT Montpelier, VT Richmond, VA Olympia, WA Charleston, WV Madison, WI are in cluster 10
## Cheyenne, WY are in cluster 12

```

(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

## Loading required package: lattice

## Loading required package: survival

## Loading required package: Formula

##
## Attaching package: 'Hmisc'

```

```

## The following object is masked from 'package:psych':
##
##     describe

## The following objects are masked from 'package:base':
##
##     format.pval, units

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

```

	capital	state	units	key	Jan	Feb	Mar	Apr	May
## 1	Albany	New York	1 Record high F (C)	71	74	89	93	97	
## 2	Annapolis	Maryland	1 Record high F (C)	77	83	92	95	98	
## 3	Atlanta	Georgia	1 Record high F (C)	79	80	89	93	97	
## 4	Augusta	Maine	1 Record high F (C)	61	60	84	90	94	
## 5	Austin	Texas	1 Record high F (C)	90	99	98	99	104	
## 6	Baton Rouge	Louisiana	1 Record high F (C)	85	88	93	96	101	
## 7	Bismarck	North Dakota	1 Record high F (C)	63	73	81	93	102	
## 8	Boise	Idaho	1 Record high F (C)	63	71	82	92	100	
## 9	Boston	Massachusetts	1 Record high F (C)	74	73	89	94	97	
## 10	Carson City	Nevada	1 Record high F (C)	72	76	81	88	94	
## 11	Charleston	West Virginia	1 Record high F (C)	81	81	92	96	98	
## 12	Cheyenne	Wyoming	1 Record high F (C)	70	71	77	84	91	
## 13	Columbia	South Carolina	1 Record high F (C)	84	84	93	96	101	
## 14	Columbus	Ohio	1 Record high F (C)	74	78	85	90	96	
## 15	Concord	New Hampshire	1 Record high F (C)	72	74	89	95	98	
## 16	Denver	Colorado	1 Record high F (C)	76	80	84	90	95	
## 17	Des Moines	Iowa	1 Record high F (C)	67	78	91	93	105	
## 18	Dover	Delaware	1 Record high F (C)	77	80	88	97	98	
## 19	Frankfort	Kentucky	1 Record high F (C)	80	80	88	95	99	
## 20	Harrisburg	Pennsylvania	1 Record high F (C)	73	79	87	93	97	
## 21	Hartford	Connecticut	1 Record high F (C)	72	77	89	96	99	
## 22	Helena	Montana	1 Record high F (C)	63	69	78	86	95	
## 23	Honolulu	Hawaii	1 Record high F (C)	88	88	89	91	93	
## 24	Indianapolis	Indiana	1 Record high F (C)	71	77	85	90	96	
## 25	Jackson	Mississippi	1 Record high F (C)	85	89	95	94	100	
## 26	Jefferson City	Missouri	1 Record high F (C)	79	89	97	96	102	
## 27	Juneau	Alaska	1 Record high F (C)	60	57	61	72	80	
## 28	Lansing	Michigan	1 Record high F (C)	66	69	86	88	96	
## 29	Lincoln	Nebraska	1 Record high F (C)	73	83	91	97	104	
## 30	Little Rock	Arkansas	1 Record high F (C)	83	87	91	95	98	
## 31	Madison	Wisconsin	1 Record high F (C)	58	68	83	94	101	
## 32	Montgomery	Alabama	1 Record high F (C)	83	86	90	94	99	
## 33	Montpelier	Vermont	1 Record high F (C)	66	61	82	90	90	
## 34	Nashville	Tennessee	1 Record high F (C)	78	84	89	91	96	
## 35	Oklahoma City	Oklahoma	1 Record high F (C)	83	92	97	100	104	
## 36	Olympia	Washington	1 Record high F (C)	64	73	79	88	96	
## 37	Phoenix	Arizona	1 Record high F (C)	88	92	100	105	114	
## 38	Pierre	South Dakota	1 Record high F (C)	68	75	88	98	105	
## 39	Providence	Rhode Island	1 Record high F (C)	70	72	90	98	96	
## 40	Raleigh	North Carolina	1 Record high F (C)	80	84	94	95	99	

## 41	Richmond	Virginia	1 Record high F (C)	81	83	94	96	100					
## 42	Sacramento	California	1 Record high F (C)	79	80	90	98	107					
## 43	Saint Paul	Minnesota	1 Record high F (C)	57	59	83	93	93					
## 44	Salem	Oregon	1 Record high F (C)	68	72	80	93	100					
## 45	Salt Lake City	Utah	1 Record high F (C)	63	69	80	89	99					
## 46	Santa Fe	New Mexico	1 Record high F (C)	65	73	77	84	96					
## 47	Springfield	Illinois	1 Record high F (C)	73	78	91	90	101					
## 48	Tallahassee	Florida	1 Record high F (C)	83	89	91	95	102					
## 49	Topeka	Kansas	1 Record high F (C)	78	84	93	97	103					
## 50	Trenton	New Jersey	1 Record high F (C)	73	76	87	93	99					
##	Jun	Jul	Aug	Sep	Oct	Nov	Dec	latitude	longitude	capital	since	area	sq.miles
## 1	100	104	102	100	91	82	72	42.65250	-73.75722	1797		21.40	
## 2	103	105	106	99	92	85	78	38.97306	-76.50111	1694		6.73	
## 3	106	105	104	102	98	84	79	33.75500	-84.39000	1868		133.50	
## 4	98	99	100	96	85	74	67	44.31056	-69.77944	1832		55.40	
## 5	109	109	112	112	100	91	90	30.26722	-97.74306	1839		305.10	
## 6	103	103	110	104	98	89	88	30.44750	-91.17861	1880		76.80	
## 7	111	114	109	105	95	79	66	46.80833	-100.78361	1883		26.90	
## 8	110	111	110	102	94	78	70	43.61583	-116.20167	1865		63.80	
## 9	100	104	102	102	90	83	76	42.35806	-71.06361	1630		89.60	
## 10	101	107	105	103	93	79	75	39.16444	-119.76694	1861		143.40	
## 11	105	108	108	104	96	87	80	38.34722	-81.63333	1885		31.60	
## 12	100	100	98	95	85	75	69	41.14000	-104.82028	1869		21.10	
## 13	109	107	107	106	101	90	83	34.00056	-81.03472	1786		125.20	
## 14	102	106	103	100	94	80	76	39.96222	-83.00056	1816		210.30	
## 15	101	102	101	98	92	80	73	43.20667	-71.53806	1808		64.30	
## 16	105	105	105	101	90	81	79	39.73917	-104.99028	1867		153.30	
## 17	103	110	110	101	95	82	69	41.59083	-93.62083	1857		75.80	
## 18	101	104	102	99	95	85	75	39.15806	-75.52444	1777		22.40	
## 19	106	111	105	106	98	84	78	38.20000	-84.86700	1792		14.70	
## 20	100	107	104	102	97	84	75	40.26972	-76.87556	1812		8.11	
## 21	100	103	102	101	91	83	76	41.76250	-72.67417	1875		17.30	
## 22	102	105	105	99	87	75	64	46.59111	-112.02028	1875		14.00	
## 23	92	94	95	95	94	93	89	21.30694	-157.85833	1845		68.40	
## 24	104	106	103	100	92	81	74	39.76861	-86.15806	1825		361.50	
## 25	105	107	107	107	98	89	84	32.29889	-90.18472	1821		104.90	
## 26	105	112	111	107	96	87	79	38.57667	-92.17361	1826		27.30	
## 27	87	89	87	85	68	64	59	58.30000	-134.41600	1906		2716.70	
## 28	99	103	102	99	90	79	70	42.73361	-84.54667	1847		35.00	
## 29	108	115	110	106	98	85	75	40.80889	-96.67889	1867		74.60	
## 30	107	112	114	106	98	86	81	34.73611	-92.33111	1821		116.20	
## 31	101	107	102	99	90	77	65	43.07472	-89.38417	1838		68.70	
## 32	106	107	106	102	91	85	32	32.36167	-86.27917	1846		159.80	
## 33	95	97	97	92	84	76	67	44.25944	-72.57583	1805		10.20	
## 34	109	107	106	105	99	88	79	36.16667	-86.78333	1826		525.90	
## 35	107	110	113	108	97	87	86	35.46861	-97.52139	1910		620.30	
## 36	98	104	104	98	90	74	64	47.03778	-122.90083	1853		16.70	
## 37	122	121	117	116	107	96	87	33.45000	-112.06700	1912		517.60	
## 38	112	117	114	108	98	87	77	44.37250	-100.32000	1889		13.00	
## 39	98	102	104	100	88	81	77	41.82361	-71.42222	1900		18.50	
## 40	105	105	105	104	100	88	81	35.76700	-78.63300	1792		114.60	
## 41	104	105	107	103	99	86	81	37.53300	-77.46700	1780		60.10	
## 42	112	114	112	109	102	86	72	38.58167	-121.49444	1854		97.90	
## 43	103	105	103	95	88	75	66	44.94417	-93.09361	1849		52.80	

## 44	105	108	108	104	93	74	72	44.93917	-123.03944	1855	45.70
## 45	105	107	106	100	89	75	69	40.76083	-111.89111	1858	109.10
## 46	99	101	96	94	87	75	65	35.66722	-105.96444	1610	37.30
## 47	104	112	108	102	93	83	74	39.79944	-89.65500	1837	54.00
## 48	105	104	103	102	95	89	84	30.45500	-84.25333	1824	95.70
## 49	109	114	113	110	97	85	77	39.05583	-95.68944	1856	56.00
## 50	100	106	105	101	94	83	76	40.22384	-74.76362	1784	7.66
## population.2019.est	population.2019.est.MSA	population.2019.est.CSA									
## 1	96460	880381	1167594								
## 2	39174	2800053	9814928								
## 3	506811	6020364	6853392								
## 4	18681	122302	NA								
## 5	978908	2227083	NA								
## 6	220236	854884	NA								
## 7	73529	128949	NA								
## 8	228959	749202	831235								
## 9	692600	4873019	8287710								
## 10	55916	55916	637973								
## 11	46536	257074	776694								
## 12	64235	99500	NA								
## 13	131674	838433	963048								
## 14	898553	2122271	2525639								
## 15	43627	151391	8287710								
## 16	727211	2967239	3617927								
## 17	214237	699292	877991								
## 18	38079	180786	7209620								
## 19	27679	73663	745033								
## 20	49528	577941	1271801								
## 21	122105	1204877	1470083								
## 22	32315	77414	NA								
## 23	345064	974563	NA								
## 24	876384	2074537	2457286								
## 25	160628	594806	674340								
## 26	42838	151235	NA								
## 27	32113	32113	NA								
## 28	118210	550391	NA								
## 29	289102	336374	357887								
## 30	197312	742384	908941								
## 31	259680	664865	892661								
## 32	198525	373290	461516								
## 33	7855	NA	NA								
## 34	670820	1934317	2062547								
## 35	655057	1408950	1481542								
## 36	46478	290536	4903675								
## 37	1680992	4948203	5002221								
## 38	13646	20672	NA								
## 39	179883	1624578	8287710								
## 40	474069	1390785	2079687								
## 41	230436	1291900	NA								
## 42	513624	2363730	2639124								
## 43	308096	3654908	4027861								
## 44	174365	433903	3259710								
## 45	200567	1232696	2641048								
## 46	84683	150358	1158464								

## 47	114230	206868	306399
## 48	194500	387227	NA
## 49	125310	231969	NA
## 50	83203	367430	22589036
## city.rank.in.state			url
## 1	6	https://en.wikipedia.org/wiki/Albany,_New_York	
## 2	7	https://en.wikipedia.org/wiki/Annapolis,_Maryland	
## 3	1	https://en.wikipedia.org/wiki/Atlanta	
## 4	8	https://en.wikipedia.org/wiki/Augusta,_Maine	
## 5	4	https://en.wikipedia.org/wiki/Austin,_Texas	
## 6	2	https://en.wikipedia.org/wiki/Baton_Rouge,_Louisiana	
## 7	2	https://en.wikipedia.org/wiki/Bismarck,_North_Dakota	
## 8	1	https://en.wikipedia.org/wiki/Boise,_Idaho	
## 9	1	https://en.wikipedia.org/wiki/Boston	
## 10	6	https://en.wikipedia.org/wiki/Carson_City,_Nevada	
## 11	1	https://en.wikipedia.org/wiki/Charleston,_West_Virginia	
## 12	1	https://en.wikipedia.org/wiki/Cheyenne,_Wyoming	
## 13	2	https://en.wikipedia.org/wiki/Columbia,_South_Carolina	
## 14	1	https://en.wikipedia.org/wiki/Columbus,_Ohio	
## 15	3	https://en.wikipedia.org/wiki/Concord,_New_Hampshire	
## 16	1	https://en.wikipedia.org/wiki/Denver	
## 17	1	https://en.wikipedia.org/wiki/Des_Moines,_Iowa	
## 18	2	https://en.wikipedia.org/wiki/Dover,_Delaware	
## 19	15	https://en.wikipedia.org/wiki/Frankfort,_Kentucky	
## 20	9	https://en.wikipedia.org/wiki/Harrisburg,_Pennsylvania	
## 21	3	https://en.wikipedia.org/wiki/Hartford,_Connecticut	
## 22	6	https://en.wikipedia.org/wiki/Helena,_Montana	
## 23	1	https://en.wikipedia.org/wiki/Honolulu	
## 24	1	https://en.wikipedia.org/wiki/Indianapolis	
## 25	1	https://en.wikipedia.org/wiki/Jackson,_Mississippi	
## 26	15	https://en.wikipedia.org/wiki/Jefferson_City,_Missouri	
## 27	3	https://en.wikipedia.org/wiki/Juneau,_Alaska	
## 28	5	https://en.wikipedia.org/wiki/Lansing,_Michigan	
## 29	2	https://en.wikipedia.org/wiki/Lincoln,_Nebraska	
## 30	1	https://en.wikipedia.org/wiki/Little_Rock,_Arkansas	
## 31	2	https://en.wikipedia.org/wiki/Madison,_Wisconsin	
## 32	2	https://en.wikipedia.org/wiki/Montgomery,_Alabama	
## 33	6	https://en.wikipedia.org/wiki/Montpelier,_Vermont	
## 34	1	https://en.wikipedia.org/wiki/Nashville,_Tennessee	
## 35	1	https://en.wikipedia.org/wiki/Oklahoma_City	
## 36	24	https://en.wikipedia.org/wiki/Olympia,_Washington	
## 37	1	https://en.wikipedia.org/wiki/Phoenix,_Arizona	
## 38	8	https://en.wikipedia.org/wiki/Pierre,_South_Dakota	
## 39	1	https://en.wikipedia.org/wiki/Providence,_Rhode_Island	
## 40	2	https://en.wikipedia.org/wiki/Raleigh,_North_Carolina	
## 41	4	https://en.wikipedia.org/wiki/Richmond,_Virginia	
## 42	6	https://en.wikipedia.org/wiki/Sacramento,_California	
## 43	2	https://en.wikipedia.org/wiki/Saint_Paul,_Minnesota	
## 44	3	https://en.wikipedia.org/wiki/Salem,_Oregon	
## 45	1	https://en.wikipedia.org/wiki/Salt_Lake_City	
## 46	4	https://en.wikipedia.org/wiki/Santa_Fe,_New_Mexico	
## 47	6	https://en.wikipedia.org/wiki/Springfield,_Illinois	
## 48	7	https://en.wikipedia.org/wiki/Tallahassee,_Florida	
## 49	4	https://en.wikipedia.org/wiki/Topeka,_Kansas	

```
## 50          10      https://en.wikipedia.org/wiki/Trenton,\_New\_Jersey
##      st
## 1  NY
## 2  MD
## 3  GA
## 4  ME
## 5  TX
## 6  LA
## 7  ND
## 8  ID
## 9  MA
## 10 NV
## 11 WV
## 12 WY
## 13 SC
## 14 OH
## 15 NH
## 16 CO
## 17 IA
## 18 DE
## 19 KY
## 20 PA
## 21 CT
## 22 MT
## 23 HI
## 24 IN
## 25 MS
## 26 MO
## 27 AK
## 28 MI
## 29 NE
## 30 AR
## 31 WI
## 32 AL
## 33 VT
## 34 TN
## 35 OK
## 36 WA
## 37 AZ
## 38 SD
## 39 RI
## 40 NC
## 41 VA
## 42 CA
## 43 MN
## 44 OR
## 45 UT
## 46 NM
## 47 IL
## 48 FL
## 49 KS
## 50 NJ
```

```
high.X = high[,c(5:18,21)]; # numeric data
high.X
```

##	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	latitude	longitude
## 1	71	74	89	93	97	100	104	102	100	91	82	72	42.65250	-73.75722
## 2	77	83	92	95	98	103	105	106	99	92	85	78	38.97306	-76.50111
## 3	79	80	89	93	97	106	105	104	102	98	84	79	33.75500	-84.39000
## 4	61	60	84	90	94	98	99	100	96	85	74	67	44.31056	-69.77944
## 5	90	99	98	99	104	109	109	112	112	100	91	90	30.26722	-97.74306
## 6	85	88	93	96	101	103	103	110	104	98	89	88	30.44750	-91.17861
## 7	63	73	81	93	102	111	114	109	105	95	79	66	46.80833	-100.78361
## 8	63	71	82	92	100	110	111	110	102	94	78	70	43.61583	-116.20167
## 9	74	73	89	94	97	100	104	102	102	90	83	76	42.35806	-71.06361
## 10	72	76	81	88	94	101	107	105	103	93	79	75	39.16444	-119.76694
## 11	81	81	92	96	98	105	108	108	104	96	87	80	38.34722	-81.63333
## 12	70	71	77	84	91	100	100	98	95	85	75	69	41.14000	-104.82028
## 13	84	84	93	96	101	109	107	107	106	101	90	83	34.00056	-81.03472
## 14	74	78	85	90	96	102	106	103	100	94	80	76	39.96222	-83.00056
## 15	72	74	89	95	98	101	102	101	98	92	80	73	43.20667	-71.53806
## 16	76	80	84	90	95	105	105	105	101	90	81	79	39.73917	-104.99028
## 17	67	78	91	93	105	103	110	110	101	95	82	69	41.59083	-93.62083
## 18	77	80	88	97	98	101	104	102	99	95	85	75	39.15806	-75.52444
## 19	80	80	88	95	99	106	111	105	106	98	84	78	38.20000	-84.86700
## 20	73	79	87	93	97	100	107	104	102	97	84	75	40.26972	-76.87556
## 21	72	77	89	96	99	100	103	102	101	91	83	76	41.76250	-72.67417
## 22	63	69	78	86	95	102	105	105	99	87	75	64	46.59111	-112.02028
## 23	88	88	89	91	93	92	94	95	95	94	93	89	21.30694	-157.85833
## 24	71	77	85	90	96	104	106	103	100	92	81	74	39.76861	-86.15806
## 25	85	89	95	94	100	105	107	107	107	98	89	84	32.29889	-90.18472
## 26	79	89	97	96	102	105	112	111	107	96	87	79	38.57667	-92.17361
## 27	60	57	61	72	80	87	89	87	85	68	64	59	58.30000	-134.41600
## 28	66	69	86	88	96	99	103	102	99	90	79	70	42.73361	-84.54667
## 29	73	83	91	97	104	108	115	110	106	98	85	75	40.80889	-96.67889
## 30	83	87	91	95	98	107	112	114	106	98	86	81	34.73611	-92.33111
## 31	58	68	83	94	101	101	107	102	99	90	77	65	43.07472	-89.38417
## 32	83	86	90	94	99	106	107	106	106	102	91	85	32.36167	-86.27917
## 33	66	61	82	90	90	95	97	97	92	84	76	67	44.25944	-72.57583
## 34	78	84	89	91	96	109	107	106	105	99	88	79	36.16667	-86.78333
## 35	83	92	97	100	104	107	110	113	108	97	87	86	35.46861	-97.52139
## 36	64	73	79	88	96	98	104	104	98	90	74	64	47.03778	-122.90083
## 37	88	92	100	105	114	122	121	117	116	107	96	87	33.45000	-112.06700
## 38	68	75	88	98	105	112	117	114	108	98	87	77	44.37250	-100.32000
## 39	70	72	90	98	96	98	102	104	100	88	81	77	41.82361	-71.42222
## 40	80	84	94	95	99	105	105	105	104	100	88	81	35.76700	-78.63300
## 41	81	83	94	96	100	104	105	107	103	99	86	81	37.53300	-77.46700
## 42	79	80	90	98	107	112	114	112	109	102	86	72	38.58167	-121.49444
## 43	57	59	83	93	93	103	105	103	95	88	75	66	44.94417	-93.09361
## 44	68	72	80	93	100	105	108	108	104	93	74	72	44.93917	-123.03944
## 45	63	69	80	89	99	105	107	106	100	89	75	69	40.76083	-111.89111
## 46	65	73	77	84	96	99	101	96	94	87	75	65	35.66722	-105.96444
## 47	73	78	91	90	101	104	112	108	102	93	83	74	39.79944	-89.65500
## 48	83	89	91	95	102	105	104	103	102	95	89	84	30.45500	-84.25333
## 49	78	84	93	97	103	109	114	113	110	97	85	77	39.05583	-95.68944

```

## 50 73 76 87 93 99 100 106 105 101 94 83 76 40.22384 -74.76362
## population.2019.est
## 1 96460
## 2 39174
## 3 506811
## 4 18681
## 5 978908
## 6 220236
## 7 73529
## 8 228959
## 9 692600
## 10 55916
## 11 46536
## 12 64235
## 13 131674
## 14 898553
## 15 43627
## 16 727211
## 17 214237
## 18 38079
## 19 27679
## 20 49528
## 21 122105
## 22 32315
## 23 345064
## 24 876384
## 25 160628
## 26 42838
## 27 32113
## 28 118210
## 29 289102
## 30 197312
## 31 259680
## 32 198525
## 33 7855
## 34 670820
## 35 655057
## 36 46478
## 37 1680992
## 38 13646
## 39 179883
## 40 474069
## 41 230436
## 42 513624
## 43 308096
## 44 174365
## 45 200567
## 46 84683
## 47 114230
## 48 194500
## 49 125310
## 50 83203

```

```

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          0.25  0.45  0.53  0.65
## May          0.85  0.90  1.00  0.91
## Sep          0.86  0.73  0.46  0.27
## latitude      -0.15  0.02  0.31
## longitude
## population.2019.est

```

```

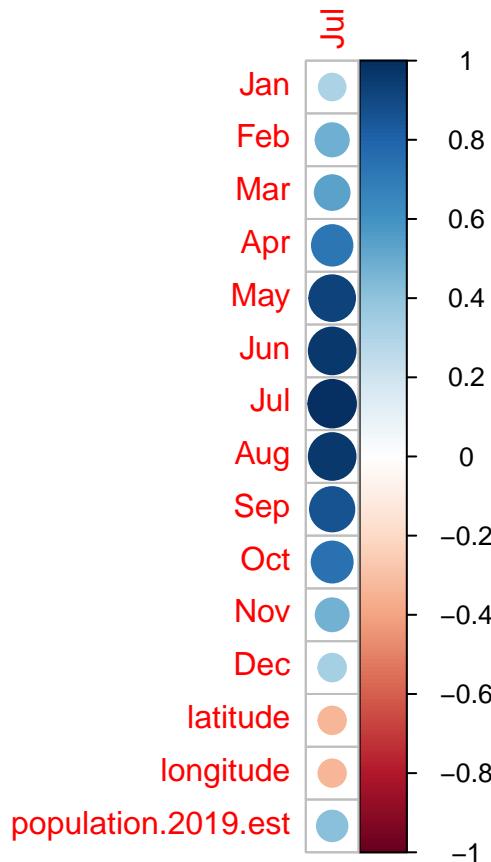
library(corrgram)

## 
## Attaching package: 'corrgram'

## The following object is masked from 'package:lattice':
## 
##     panel.fill

corrplot::corrplot(cor(high.cor)[,7, drop=FALSE], cl.pos = 'r', cl.ratio =3.0 )

```



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

##	capital	state	units	key	Jan	Feb	Mar	Apr	May	Jun
## 1	Albany	New York	1 Record low F (C)	-28 -22 -21	9	26	35			
## 2	Annapolis	Maryland	1 Record low F (C)	-8 -6 10	13	32	35			
## 3	Atlanta	Georgia	1 Record low F (C)	-8 -9 10	25	37	39			
## 4	Augusta	Maine	1 Record low F (C)	-33 -23 -11	9	26	36			
## 5	Austin	Texas	1 Record low F (C)	-2 -1 18	30	40	51			
## 6	Baton Rouge	Louisiana	1 Record low F (C)	9 2 20	31	40	53			
## 7	Bismarck	North Dakota	1 Record low F (C)	-45 -45 -36	-12	13	30			
## 8	Boise	Idaho	1 Record low F (C)	-28 -15	5	11	22	30		
## 9	Boston	Massachusetts	1 Record low F (C)	-13 -18	-8	11	31	41		
## 10	Carson City	Nevada	1 Record low F (C)	-27 -22	-5	3	18	25		
## 11	Charleston	West Virginia	1 Record low F (C)	-16 -12	-5	18	26	33		
## 12	Cheyenne	Wyoming	1 Record low F (C)	-38 -34	-21	-8	8	25		
## 13	Columbia	South Carolina	1 Record low F (C)	-1 -2	4	26	34	44		
## 14	Columbus	Ohio	1 Record low F (C)	-22 -20	-6	14	25	35		
## 15	Concord	New Hampshire	1 Record low F (C)	-35 -37	-20	4	21	30		
## 16	Denver	Colorado	1 Record low F (C)	-29 -25	-11	-2	19	30		
## 17	Des Moines	Iowa	1 Record low F (C)	-30 -26	-22	9	26	37		
## 18	Dover	Delaware	1 Record low F (C)	-7 -11	7	14	28	41		
## 19	Frankfort	Kentucky	1 Record low F (C)	-27 -16	-3	16	27	36		
## 20	Harrisburg	Pennsylvania	1 Record low F (C)	-22 -13	-1	11	30	40		
## 21	Hartford	Connecticut	1 Record low F (C)	-26 -24	-6	9	28	37		
## 22	Helena	Montana	1 Record low F (C)	-42 -42	-30	-10	17	30		
## 23	Honolulu	Hawaii	1 Record low F (C)	52 52	53	56	60	63		
## 24	Indianapolis	Indiana	1 Record low F (C)	-27 -21	-7	18	27	37		
## 25	Jackson	Mississippi	1 Record low F (C)	-5 1	15	27	36	47		
## 26	Jefferson City	Missouri	1 Record low F (C)	-23 -25	-16	13	24	38		
## 27	Juneau	Alaska	1 Record low F (C)	-20 -15	-5	12	26	32		
## 28	Lansing	Michigan	1 Record low F (C)	-29 -37	-25	-6	19	27		
## 29	Lincoln	Nebraska	1 Record low F (C)	-33 -26	-19	3	24	39		
## 30	Little Rock	Arkansas	1 Record low F (C)	-8 -12	11	28	38	46		
## 31	Madison	Wisconsin	1 Record low F (C)	-37 -29	-29	0	19	31		
## 32	Montgomery	Alabama	1 Record low F (C)	0 -5	17	28	40	48		
## 33	Montpelier	Vermont	1 Record low F (C)	-34 -29	-18	2	20	29		
## 34	Nashville	Tennessee	1 Record low F (C)	-17 -13	2	23	34	42		
## 35	Oklahoma City	Oklahoma	1 Record low F (C)	-11 -17	1	20	32	46		
## 36	Olympia	Washington	1 Record low F (C)	-8 -1	9	23	25	30		
## 37	Phoenix	Arizona	1 Record low F (C)	16 24	25	35	39	49		
## 38	Pierre	South Dakota	1 Record low F (C)	-33 -35	-19	1	21	34		
## 39	Providence	Rhode Island	1 Record low F (C)	-13 -17	1	11	29	39		
## 40	Raleigh	North Carolina	1 Record low F (C)	-9 -2	11	23	29	38		
## 41	Richmond	Virginia	1 Record low F (C)	-12 -10	10	19	31	40		
## 42	Sacramento	California	1 Record low F (C)	19 21	29	34	37	43		
## 43	Saint Paul	Minnesota	1 Record low F (C)	-29 -32	-25	3	21	36		
## 44	Salem	Oregon	1 Record low F (C)	-10 -4	12	23	25	32		
## 45	Salt Lake City	Utah	1 Record low F (C)	-22 -30	0	14	25	32		
## 46	Santa Fe	New Mexico	1 Record low F (C)	-14 -24	-6	10	19	28		
## 47	Springfield	Illinois	1 Record low F (C)	-22 -24	-12	16	28	39		
## 48	Tallahassee	Florida	1 Record low F (C)	6 -2	20	29	34	46		
## 49	Topeka	Kansas	1 Record low F (C)	-23 -25	-7	10	26	36		
## 50	Trenton	New Jersey	1 Record low F (C)	-13 -14	1	11	33	41		
##	Jul Aug Sep Oct Nov Dec	latitude	longitude	capital.since area.sq.miles						

## 1	40	34	24	16	-11	-22	42.65250	-73.75722	1797	21.40
## 2	50	46	37	26	13	-1	38.97306	-76.50111	1694	6.73
## 3	53	55	36	28	3	0	33.75500	-84.39000	1868	133.50
## 4	43	39	28	21	4	-15	44.31056	-69.77944	1832	55.40
## 5	57	58	41	30	20	4	30.26722	-97.74306	1839	305.10
## 6	58	58	43	30	21	8	30.44750	-91.17861	1880	76.80
## 7	32	32	10	-10	-30	-43	46.80833	-100.78361	1883	26.90
## 8	35	32	23	11	-10	-25	43.61583	-116.20167	1865	63.80
## 9	50	46	34	25	-2	-17	42.35806	-71.06361	1630	89.60
## 10	33	26	17	6	-5	-26	39.16444	-119.76694	1861	143.40
## 11	46	41	32	17	6	-17	38.34722	-81.63333	1885	31.60
## 12	33	25	8	-5	-21	-28	41.14000	-104.82028	1869	21.10
## 13	54	53	40	23	12	4	34.00056	-81.03472	1786	125.20
## 14	43	39	31	17	-5	-17	39.96222	-83.00056	1816	210.30
## 15	35	29	20	10	-17	-24	43.20667	-71.53806	1808	64.30
## 16	42	40	17	-2	-18	-25	39.73917	-104.99028	1867	153.30
## 17	47	40	26	7	-10	-22	41.59083	-93.62083	1857	75.80
## 18	45	35	30	25	11	-3	39.15806	-75.52444	1777	22.40
## 19	48	41	30	20	-1	-17	38.20000	-84.86700	1792	14.70
## 20	49	45	30	23	10	-8	40.26972	-76.87556	1812	8.11
## 21	44	36	30	17	1	-18	41.76250	-72.67417	1875	17.30
## 22	36	28	6	-8	-39	-40	46.59111	-112.02028	1875	14.00
## 23	63	63	65	61	57	54	21.30694	-157.85833	1845	68.40
## 24	46	41	30	20	-5	-23	39.76861	-86.15806	1825	361.50
## 25	51	54	35	26	15	4	32.29889	-90.18472	1821	104.90
## 26	42	41	29	14	1	-21	38.57667	-92.17361	1826	27.30
## 27	39	32	28	13	-7	-10	58.30000	-134.41600	1906	2716.70
## 28	31	26	19	10	-5	-25	42.73361	-84.54667	1847	35.00
## 29	45	39	26	3	-15	-27	40.80889	-96.67889	1867	74.60
## 30	54	52	37	27	10	-1	34.73611	-92.33111	1821	116.20
## 31	36	35	25	12	-14	-28	43.07472	-89.38417	1838	68.70
## 32	59	56	39	26	13	5	32.36167	-86.27917	1846	159.80
## 33	35	31	20	14	-7	-27	44.25944	-72.57583	1805	10.20
## 34	51	47	36	26	-1	-10	36.16667	-86.78333	1826	525.90
## 35	53	49	35	16	9	-8	35.46861	-97.52139	1910	620.30
## 36	35	33	25	14	-1	-7	47.03778	-122.90083	1853	16.70
## 37	63	58	47	34	27	22	33.45000	-112.06700	1912	517.60
## 38	42	39	21	4	-18	-31	44.37250	-100.32000	1889	13.00
## 39	48	40	32	20	6	-12	41.82361	-71.42222	1900	18.50
## 40	48	46	37	19	11	0	35.76700	-78.63300	1792	114.60
## 41	51	46	35	21	10	-2	37.53300	-77.46700	1780	60.10
## 42	47	48	44	34	27	17	38.58167	-121.49444	1854	97.90
## 43	45	42	26	15	-14	-29	44.94417	-93.09361	1849	52.80
## 44	35	30	26	19	9	-12	44.93917	-123.03944	1855	45.70
## 45	40	37	27	14	-14	-21	40.76083	-111.89111	1858	109.10
## 46	37	36	26	5	-12	-17	35.66722	-105.96444	1610	37.30
## 47	48	43	31	13	-3	-21	39.79944	-89.65500	1837	54.00
## 48	57	57	40	29	13	10	30.45500	-84.25333	1824	95.70
## 49	43	40	29	16	-5	-26	39.05583	-95.68944	1856	56.00
## 50	48	41	31	22	12	-7	40.22384	-74.76362	1784	7.66
## population.2019.est population.2019.est.MSA population.2019.est.CSA										
## 1		96460		880381		1167594				
## 2		39174		2800053		9814928				
## 3		506811		6020364		6853392				

##	rank	state	count	NA
4	18681	122302		NA
5	978908	2227083		NA
6	220236	854884		NA
7	73529	128949		NA
8	228959	749202		831235
9	692600	4873019		8287710
10	55916	55916		637973
11	46536	257074		776694
12	64235	99500		NA
13	131674	838433		963048
14	898553	2122271		2525639
15	43627	151391		8287710
16	727211	2967239		3617927
17	214237	699292		877991
18	38079	180786		7209620
19	27679	73663		745033
20	49528	577941		1271801
21	122105	1204877		1470083
22	32315	77414		NA
23	345064	974563		NA
24	876384	2074537		2457286
25	160628	594806		674340
26	42838	151235		NA
27	32113	32113		NA
28	118210	550391		NA
29	289102	336374		357887
30	197312	742384		908941
31	259680	664865		892661
32	198525	373290		461516
33	7855	NA		NA
34	670820	1934317		2062547
35	655057	1408950		1481542
36	46478	290536		4903675
37	1680992	4948203		5002221
38	13646	20672		NA
39	179883	1624578		8287710
40	474069	1390785		2079687
41	230436	1291900		NA
42	513624	2363730		2639124
43	308096	3654908		4027861
44	174365	433903		3259710
45	200567	1232696		2641048
46	84683	150358		1158464
47	114230	206868		306399
48	194500	387227		NA
49	125310	231969		NA
50	83203	367430		22589036
##	city.rank.in.state			url
1	6			https://en.wikipedia.org/wiki/Albany,_New_York
2	7			https://en.wikipedia.org/wiki/Annapolis,_Maryland
3	1			https://en.wikipedia.org/wiki/Atlanta
4	8			https://en.wikipedia.org/wiki/Augusta,_Maine
5	4			https://en.wikipedia.org/wiki/Austin,_Texas
6	2			https://en.wikipedia.org/wiki/Baton_Rouge,_Louisiana

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2 https://en.wikipedia.org/wiki/Bismarck,_North_Dakota
1 https://en.wikipedia.org/wiki/Boise,_Idaho
1 https://en.wikipedia.org/wiki/Boston
6 https://en.wikipedia.org/wiki/Carson_City,_Nevada
1 https://en.wikipedia.org/wiki/Charleston,_West_Virginia
1 https://en.wikipedia.org/wiki/Cheyenne,_Wyoming
2 https://en.wikipedia.org/wiki/Columbia,_South_Carolina
1 https://en.wikipedia.org/wiki/Columbus,_Ohio
3 https://en.wikipedia.org/wiki/Concord,_New_Hampshire
1 https://en.wikipedia.org/wiki/Denver
1 https://en.wikipedia.org/wiki/Des_Moines,_Iowa
2 https://en.wikipedia.org/wiki/Dover,_Delaware
15 https://en.wikipedia.org/wiki/Frankfort,_Kentucky
9 https://en.wikipedia.org/wiki/Harrisburg,_Pennsylvania
3 https://en.wikipedia.org/wiki/Hartford,_Connecticut
6 https://en.wikipedia.org/wiki/Helena,_Montana
1 https://en.wikipedia.org/wiki/Honolulu
1 https://en.wikipedia.org/wiki/Indianapolis
1 https://en.wikipedia.org/wiki/Jackson,_Mississippi
15 https://en.wikipedia.org/wiki/Jefferson_City,_Missouri
3 https://en.wikipedia.org/wiki/Juneau,_Alaska
5 https://en.wikipedia.org/wiki/Lansing,_Michigan
2 https://en.wikipedia.org/wiki/Lincoln,_Nebraska
1 https://en.wikipedia.org/wiki/Little_Rock,_Arkansas
2 https://en.wikipedia.org/wiki/Madison,_Wisconsin
2 https://en.wikipedia.org/wiki/Montgomery,_Alabama
6 https://en.wikipedia.org/wiki/Montpelier,_Vermont
1 https://en.wikipedia.org/wiki/Nashville,_Tennessee
1 https://en.wikipedia.org/wiki/Oklahoma_City
24 https://en.wikipedia.org/wiki/Olympia,_Washington
1 https://en.wikipedia.org/wiki/Phoenix,_Arizona
8 https://en.wikipedia.org/wiki/Pierre,_South_Dakota
1 https://en.wikipedia.org/wiki/Providence,_Rhode_Island
2 https://en.wikipedia.org/wiki/Raleigh,_North_Carolina
4 https://en.wikipedia.org/wiki/Richmond,_Virginia
6 https://en.wikipedia.org/wiki/Sacramento,_California
2 https://en.wikipedia.org/wiki/Saint_Paul,_Minnesota
3 https://en.wikipedia.org/wiki/Salem,_Oregon
1 https://en.wikipedia.org/wiki/Salt_Lake_City
4 https://en.wikipedia.org/wiki/Santa_Fe,_New_Mexico
6 https://en.wikipedia.org/wiki/Springfield,_Illinois
7 https://en.wikipedia.org/wiki/Tallahassee,_Florida
4 https://en.wikipedia.org/wiki/Topeka,_Kansas
10 https://en.wikipedia.org/wiki/Trenton,_New_Jersey

## st
## 1 NY
## 2 MD
## 3 GA
## 4 ME
## 5 TX
## 6 LA
## 7 ND
## 8 ID
## 9 MA

```

```

## 10 NV
## 11 WV
## 12 WY
## 13 SC
## 14 OH
## 15 NH
## 16 CO
## 17 IA
## 18 DE
## 19 KY
## 20 PA
## 21 CT
## 22 MT
## 23 HI
## 24 IN
## 25 MS
## 26 MO
## 27 AK
## 28 MI
## 29 NE
## 30 AR
## 31 WI
## 32 AL
## 33 VT
## 34 TN
## 35 OK
## 36 WA
## 37 AZ
## 38 SD
## 39 RI
## 40 NC
## 41 VA
## 42 CA
## 43 MN
## 44 OR
## 45 UT
## 46 NM
## 47 IL
## 48 FL
## 49 KS
## 50 NJ

```

```

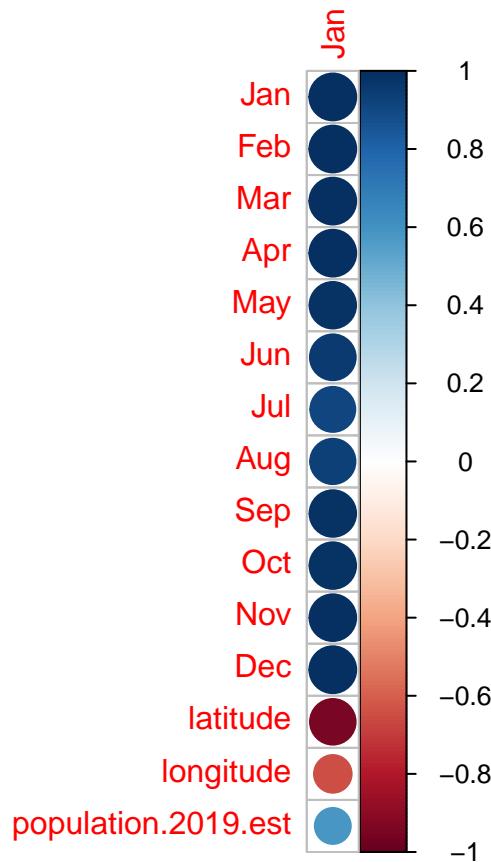
low.cor.january = low.cor[,1];
low.cor.january;

```

	Jan	Feb	Mar	Apr
##	1.00	0.95	0.93	0.92
##	May	Jun	Jul	Aug
##	0.89	0.80	0.74	0.77
##	Sep	Oct	Nov	Dec
##	0.90	0.87	0.91	0.97
##	latitude	longitude	population.2019.est	
##	-0.72	-0.33	0.34	

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

```
library(corrgram)
corrplot::corrplot(cor(low.cor)[,1, drop=FALSE], cl.pos = 'r', cl.ratio =3.0 )
```



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.

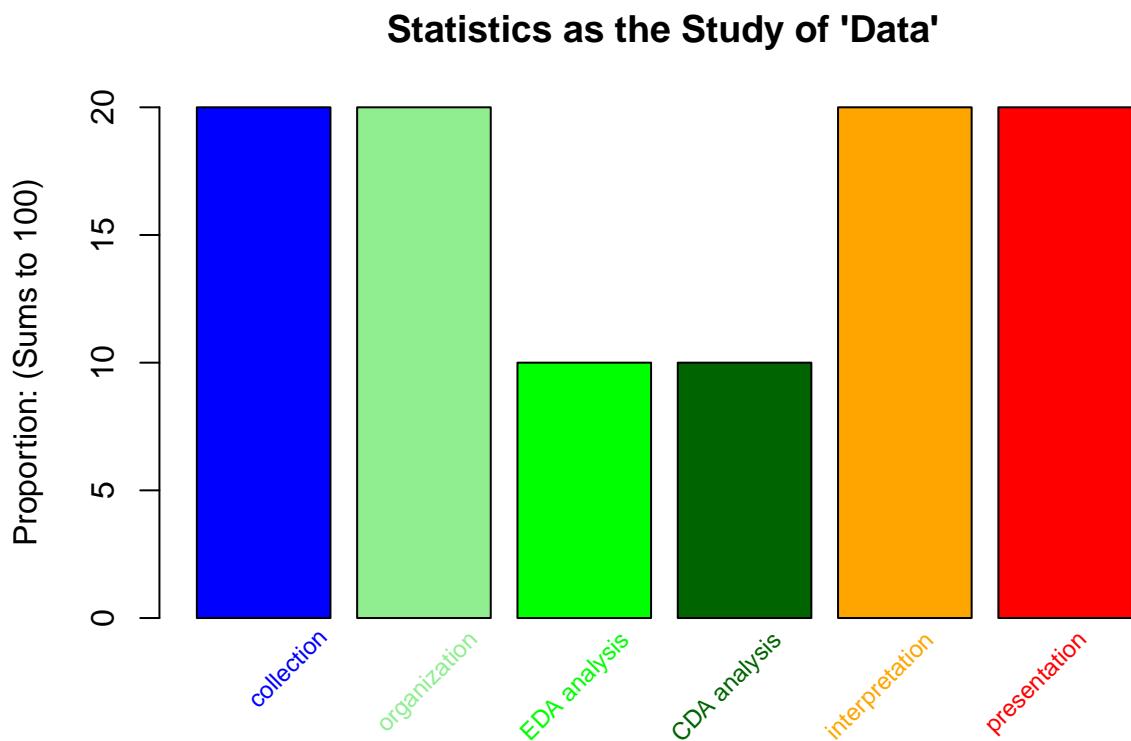
```

x = c(20,20,10,10,20,20);
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. 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

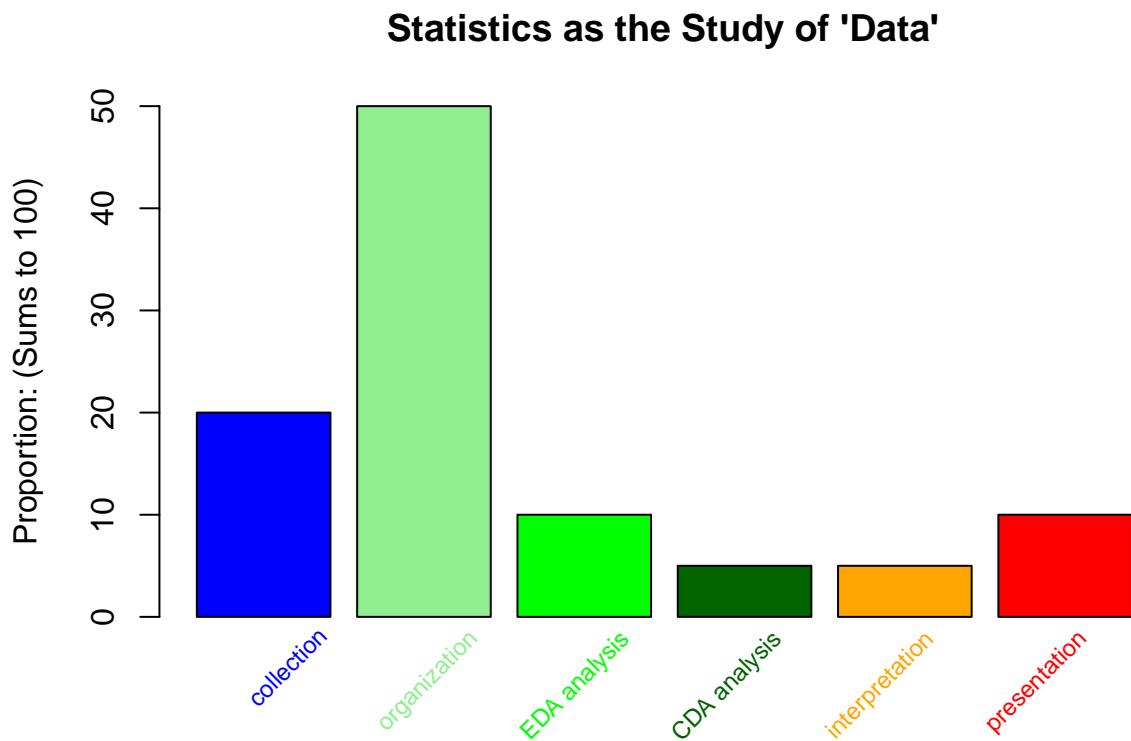
```

x = c(20,50,10,5,5,10); ## 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 = TRUE)

```



- (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(0.75, 0.95, pch=20, col="blue")
text(0.75, 0.95, "Shaffer (self)", col="blue", cex=0.75, srt = 45, pos=3)

points(0.60, 0.80, pch=20, col="red")
text(0.60, 0.80, "Minju", col="red", cex=0.75, srt = 45, pos=3)

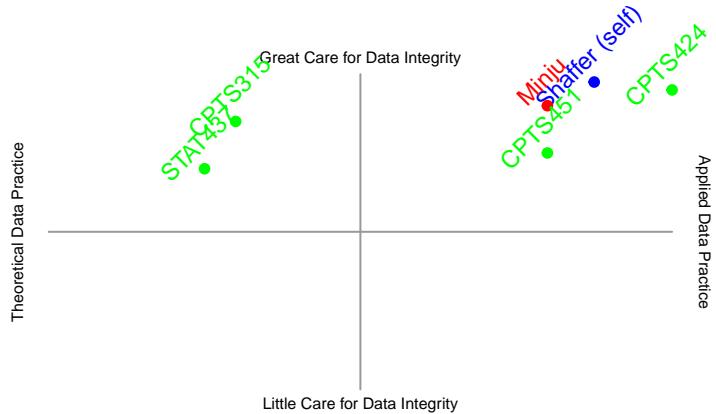
points(-0.40, 0.70, pch=20, col="green")
text(-0.40, 0.70, "CPTS315", col="green", cex=0.75, srt = 45, pos=3)

points(0.60, 0.50, pch=20, col="green")
text(0.60, 0.50, "CPTS451", col="green", cex=0.75, srt = 45, pos=3)

points(-0.50, 0.40, pch=20, col="green")
text(-0.50, 0.40, "STAT437", col="green", cex=0.75, srt = 45, pos=3)

points(1.00, 0.90, pch=20, col="green")
text(1.00, 0.90, "CPTS424", col="green", cex=0.75, 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);
```