analyticsedge

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7/2/23

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The Analytics Edge: Introduction

Assignment 1 - An Introduction to Analytics

The following link will lead you to the assignment on the edX website: https://learning.edx.org/course/course-v1:MITx+15.071x+2T2020/block-v1:MITx+15.071x+2T2020+type@sequential+block@a5915d0492804dada5feb1926ba5be7a

An Analytical Detective

There are two main types of crimes: violent crimes, and property crimes. In this problem, we'll focus on one specific type of property crime, called "motor vehicle theft" (sometimes referred to as grand theft auto). This is the act of stealing, or attempting to steal, a car. In this problem, we'll use some basic data analysis in R to understand the motor vehicle thefts in Chicago.

Please download the file mvtWeek1.csv for this problem (do not open this file in any spreadsheet software before completing this problem because it might change the format of the Date field).

Start:
Read the dataset mvtWeek1.csv into R, using the read.csv function, and call the data frame "mvt".

```
mvt <- read.csv("/cloud/project/analyticsedge/Datasets/DatasetsUnit1/mvtWeek1.csv")
```

1.1: How many rows of data (observations) are in this dataset?
Answer: 191641

```
nrow(mvt)
```

```
[1] 191641
```

1.2: How many variables are in this dataset?
Answer: 11

```
ncol(mvt)
```

```
[1] 11
```

1.3: Using the "max" function, what is the maximum value of the variable "ID"?
Answer: 9181151

```r
max(mvt$ID)
```

```
[1] 9181151
```

1.4: What is the minimum value of the variable "Beat"?
Answer: 111

```r
min(mvt$Beat)
```

```
[1] 111
```

1.5: How many observations have value TRUE in the Arrest variable (this is the number of crimes for which an arrest was made)?
Answer: 15536

```r
sum(mvt$Arrest)
```

```
[1] 15536
```

1.6: How many observations have a LocationDescription value of ALLEY?
Answer: 2308

```r
sum(mvt$LocationDescription == "ALLEY")
```

```
[1] 2308
```

2.1: In what format are the entries in the variable Date?
Answer: Month/Day/Year Hour:Minute

```r
mvt$Date[1]
```

```
[1] "12/31/12 23:15"
```

2.2: What is the month and year of the median date in our dataset? Enter your answer as "Month Year", without the quotes.
Answer: May 2006

```r
DateConvert = as.Date(strptime(mvt$Date, "%m/%d/%y %H:%M"))
#summary(DateConvert)
median(DateConvert)
```

```
[1] "2006-05-21"
```

2.3: In which month did the fewest motor vehicle thefts occur?
Answer: February

```r
mvt$Month = months(DateConvert)
mvt$Weekday = weekdays(DateConvert)
mvt$Date = DateConvert
table(mvt$Month)
```

```
    April    August  December  February   January      July      June     March 
    15280     16572     16426     13511     16047     16801     16002     15758 
      May  November   October September 
    16035     16063     17086     16060 
```

2.4: On which weekday did the most motor vehicle thefts occur?
Answer: Friday

```r
table(mvt$Weekday)
```

```
   Friday    Monday  Saturday    Sunday  Thursday   Tuesday Wednesday 
    29284     27397     27118     26316     27319     26791     27416 
```

2.5: Which month has the largest number of motor vehicle thefts for which an arrest was made?
Answer: January

```r
table(mvt$Month, mvt$Arrest)
```

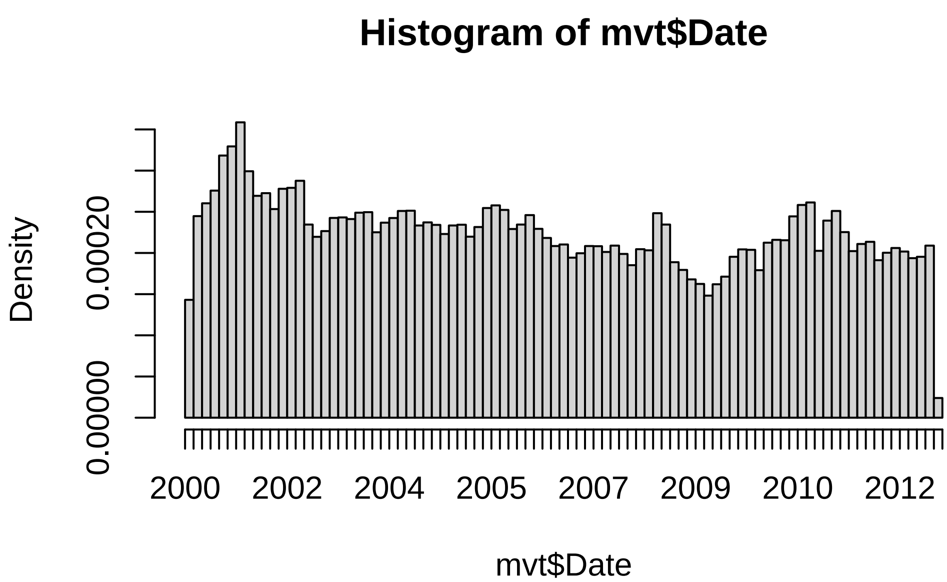
```
          FALSE  TRUE
April     14028  1252
August    15243  1329
December  15029  1397
February  12273  1238
January   14612  1435
July      15477  1324
June      14772  1230
March     14460  1298
May       14848  1187
November  14807  1256
October   15744  1342
September 14812  1248
```

3.1.1: In general, does it look like crime increases or decreases from 2002 - 2012?
Answer: Decreases

3.1.2: In general, does it look like crime increases or decreases from 2005 - 2008?
Answer: Decreases

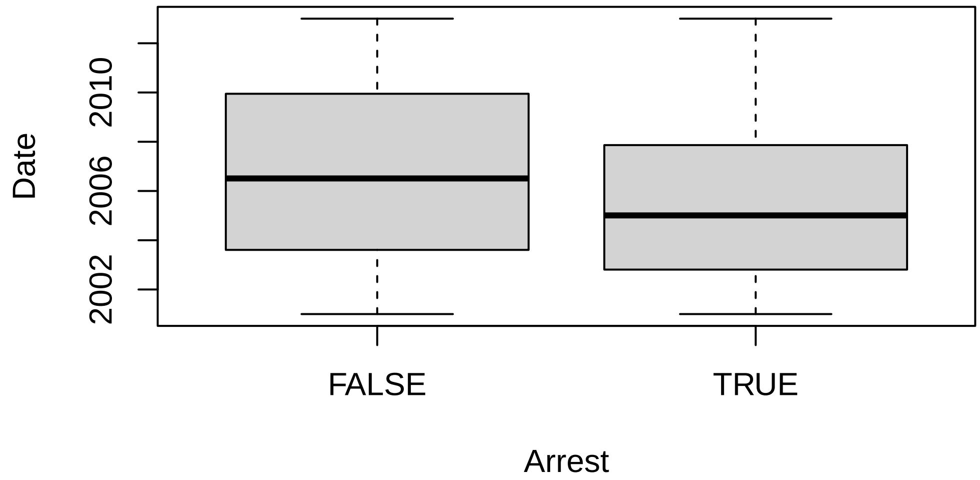
3.1.3: In general, does it look like crime increases or decreases from 2009 - 2011?
Answer: Increases

```r
hist(mvt$Date, breaks=100)
```



3.2: Does it look like there were more crimes for which arrests were made in the first half of the time period or the second half of the time period?
Answer: First half

```r
boxplot(Date ~ Arrest, data = mvt)
```



3.3: For what proportion of motor vehicle thefts in 2001 was an arrest made?
Answer: 0.1041173

```r
tapply(mvt$Arrest, mvt$Year, mean)
```

```
      2001       2002       2003       2004       2005       2006       2007 
0.10411728 0.11278195 0.10794261 0.10040327 0.09269595 0.08087961 0.08487395 
      2008       2009       2010       2011       2012 
0.07061267 0.06903920 0.04523456 0.03996930 0.03902924 
```

3.4: For what proportion of motor vehicle thefts in 2007 was an arrest made?
Answer: 0.08487395

```r
tapply(mvt$Arrest, mvt$Year, mean)
```

```
      2001       2002       2003       2004       2005       2006       2007 
0.10411728 0.11278195 0.10794261 0.10040327 0.09269595 0.08087961 0.08487395 
      2008       2009       2010       2011       2012 
0.07061267 0.06903920 0.04523456 0.03996930 0.03902924 
```

3.5: For what proportion of motor vehicle thefts in 2012 was an arrest made?
Answer: 0.03902924

```
tapply(mvt$Arrest, mvt$Year, mean)
```

```
      2001       2002       2003       2004       2005       2006       2007
0.10411728 0.11278195 0.10794261 0.10040327 0.09269595 0.08087961 0.08487395
      2008       2009       2010       2011       2012
0.07061267 0.06903920 0.04523456 0.03996930 0.03902924
```

4.1: Which locations are the top five locations for motor vehicle thefts, excluding the "Other" category?
Answer: STREET, PARKING LOT/GARAGE(NON.RESID.), ALLEY, GAS STATION, DRIVEWAY - RESIDENTIAL

```
sort(table(mvt$LocationDescription), decreasing = TRUE)
```

```
                                         STREET
                                         156564
                 PARKING LOT/GARAGE(NON.RESID.)
                                          14852
                                          OTHER
                                           4573
                                          ALLEY
                                           2308
                                    GAS STATION
                                           2111
                         DRIVEWAY - RESIDENTIAL
                                           1675
                  RESIDENTIAL YARD (FRONT/BACK)
                                           1536
                                      RESIDENCE
                                           1302
                               RESIDENCE-GARAGE
                                           1176
                                VACANT LOT/LAND
                                            985
                        VEHICLE NON-COMMERCIAL
                                            817
                                       SIDEWALK
                                            462
```

CHA PARKING LOT/GROUNDS
405
AIRPORT/AIRCRAFT
363
POLICE FACILITY/VEH PARKING LOT
266
PARK PROPERTY
255
SCHOOL, PUBLIC, GROUNDS
206
APARTMENT
184
SPORTS ARENA/STADIUM
166
CTA GARAGE / OTHER PROPERTY
148
COMMERCIAL / BUSINESS OFFICE
126
HOTEL/MOTEL
124
SCHOOL, PUBLIC, BUILDING
114
HOSPITAL BUILDING/GROUNDS
101
GROCERY FOOD STORE
80
CHURCH/SYNAGOGUE/PLACE OF WORSHIP
56
RESTAURANT
49
GOVERNMENT BUILDING/PROPERTY
48
COLLEGE/UNIVERSITY GROUNDS
47
CAR WASH
44
CONSTRUCTION SITE
35
SMALL RETAIL STORE
33
OTHER RAILROAD PROP / TRAIN DEPOT
28
AIRPORT EXTERIOR - NON-SECURE AREA

24
SCHOOL, PRIVATE, GROUNDS
23
VEHICLE-COMMERCIAL
23
DEPARTMENT STORE
22
HIGHWAY/EXPRESSWAY
22
NURSING HOME/RETIREMENT HOME
21
TAXICAB
21
MOVIE HOUSE/THEATER
18
RESIDENCE PORCH/HALLWAY
18
BAR OR TAVERN
17
WAREHOUSE
17
FACTORY/MANUFACTURING BUILDING
16
SCHOOL, PRIVATE, BUILDING
14
TAVERN/LIQUOR STORE
14
AIRPORT PARKING LOT
11
AIRPORT VENDING ESTABLISHMENT
10
ATHLETIC CLUB
9
DRUG STORE
8
OTHER COMMERCIAL TRANSPORTATION
8
BANK
7
CONVENIENCE STORE
7
FOREST PRESERVE
6

AIRPORT TERMINAL UPPER LEVEL - NON-SECURE AREA
5
CHA APARTMENT
5
DAY CARE CENTER
5
FIRE STATION
5
ABANDONED BUILDING
4
AIRPORT BUILDING NON-TERMINAL - NON-SECURE AREA
4
BARBERSHOP
4
LAKEFRONT/WATERFRONT/RIVERBANK
4
LIBRARY
4
SAVINGS AND LOAN
4
BOWLING ALLEY
3
CLEANING STORE
3
MEDICAL/DENTAL OFFICE
3
BRIDGE
2
COLLEGE/UNIVERSITY RESIDENCE HALL
2
CURRENCY EXCHANGE
2
AIRPORT BUILDING NON-TERMINAL - SECURE AREA
1
AIRPORT EXTERIOR - SECURE AREA
1
ANIMAL HOSPITAL
1
APPLIANCE STORE
1
CTA TRAIN
1
JAIL / LOCK-UP FACILITY

```
                    1
NEWSSTAND
                    1
```

Create a subset of your data, only taking observations for which the theft happened in one of these five locations, and call this new data set "Top5":

```
Top5 <- subset(mvt, mvt$LocationDescription == "STREET"
       | mvt$LocationDescription == "PARKING LOT/GARAGE(NON.RESID.)"
       | mvt$LocationDescription == "ALLEY"
       | mvt$LocationDescription == "GAS STATION"
       | mvt$LocationDescription == "DRIVEWAY - RESIDENTIAL")
```

4.2: How many observations are in Top5?
Answer: 177510

```
nrow(Top5)
```

```
[1] 177510
```

4.3: One of the locations has a much higher arrest rate than the other locations. Which is it?
Answer: Gas Station (Check percentages)

```
Top5$LocationDescription = factor(Top5$LocationDescription)
table(Top5$LocationDescription, Top5$Arrest)
```

```
                                 FALSE   TRUE
  ALLEY                           2059    249
  DRIVEWAY - RESIDENTIAL          1543    132
  GAS STATION                     1672    439
  PARKING LOT/GARAGE(NON.RESID.) 13249   1603
  STREET                        144969  11595
```

4.4: On which day of the week do the most motor vehicle thefts at gas stations happen?
Answer: Saturday

```
table(Top5$LocationDescription == "GAS STATION", Top5$Weekday)
```

```
       Friday Monday Saturday Sunday Thursday Tuesday Wednesday
 FALSE  26746  25008    24917  24220    24956   24527     25025
 TRUE     332    280      338    336      282     270       273
```

4.5: On which day of the week do the fewest motor vehicle thefts in residential driveways happen?
Answer: Saturday

```
table(Top5$LocationDescription == "DRIVEWAY - RESIDENTIAL", Top5$Weekday)
```

```
       Friday Monday Saturday Sunday Thursday Tuesday Wednesday
 FALSE  26821  25033    25053  24335    24975   24554     25064
 TRUE     257    255      202    221      263     243       234
```

Stock Dynamics

A stock market is where buyers and sellers trade shares of a company, and is one of the most popular ways for individuals and companies to invest money. The size of the world stock market is now estimated to be in the trillions. The largest stock market in the world is the New York Stock Exchange (NYSE), located in New York City. About 2,800 companies are listed on the NYSE. In this problem, we'll look at the monthly stock prices of five of these companies: IBM, General Electric (GE), Procter and Gamble, Coca Cola, and Boeing. The data used in this problem comes from Infochimps.

Please download the following files: IBMStock.csv, GEStock.csv, ProcterGambleStock.csv, CocaColaStock.csv, BoeingStock.csv (do not open these files in any spreadsheet software before completing this problem because it might change the format of the Date field).

Start:
Read the datasets into R, using the read.csv function, and call the data frames "IBM", "GE", "ProcterGamble", "CocaCola", and "Boeing", respectively.

```
IBM <- read.csv("/cloud/project/analyticsedge/Datasets/DatasetsUnit1/IBMStock.csv")
GE <- read.csv("/cloud/project/analyticsedge/Datasets/DatasetsUnit1/GEStock.csv")
ProcterGamble <- read.csv("/cloud/project/analyticsedge/Datasets/DatasetsUnit1/ProcterGamb
CocaCola <- read.csv("/cloud/project/analyticsedge/Datasets/DatasetsUnit1/CocaColaStock.cs
Boeing <- read.csv("/cloud/project/analyticsedge/Datasets/DatasetsUnit1/BoeingStock.csv")
```

Before working with these data sets, we need to convert the dates into a format that R can understand. Take a look at the structure of one of the datasets using the str function. Right now, the date variable is stored as a factor. We can convert this to a "Date" object in R by using the following five commands (one for each data set):

```
IBM$Date = as.Date(IBM$Date, "%m/%d/%y")
GE$Date = as.Date(GE$Date, "%m/%d/%y")
CocaCola$Date = as.Date(CocaCola$Date, "%m/%d/%y")
ProcterGamble$Date = as.Date(ProcterGamble$Date, "%m/%d/%y")
Boeing$Date = as.Date(Boeing$Date, "%m/%d/%y")
```

1.1: Our five datasets all have the same number of observations. How many observations are there in each data set?
Answer: 480

```
nrow(IBM)
```

```
[1] 480
```

1.2: What is the earliest year in our datasets?
Answer: 1970

```
min(IBM$Date)
```

```
[1] "1970-01-01"
```

1.3: What is the latest year in our datasets?
Answer: 2009

```
max(IBM$Date)
```

```
[1] "2009-12-01"
```

1.4: What is the mean stock price of IBM over this time period?
Answer: 144.375

```
mean(IBM$StockPrice)
```

```
[1] 144.375
```

1.5: What is the minimum stock price of General Electric (GE) over this time period?
Answer: 9.293636

```
min(GE$StockPrice)
```

```
[1] 9.293636
```

1.6: What is the maximum stock price of Coca-Cola over this time period?
Answer: 146.5843

```
max(CocaCola$StockPrice)
```

```
[1] 146.5843
```

1.7: What is the median stock price of Boeing over this time period?
Answer:

```
median(Boeing$StockPrice)
```

```
[1] 44.8834
```

1.8: What is the standard deviation of the stock price of Procter & Gamble over this time period?
Answer: 18.19414

```
sd(ProcterGamble$StockPrice)
```

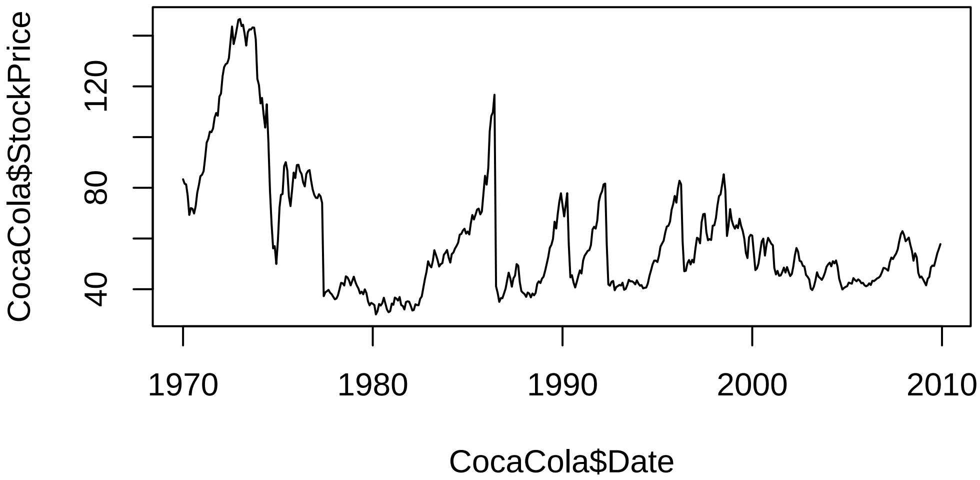
```
[1] 18.19414
```

Side note: According to the assignment, questions 1.2 - 1.7 should've been solved using the summary function. However, I used commands that would give more accurate answer. Along with the commands I used, I also wrote how the assignment could be solved using the summary function.

2.1.1: Around what year did Coca-Cola has its highest stock price in this time period?
Answer: 1973

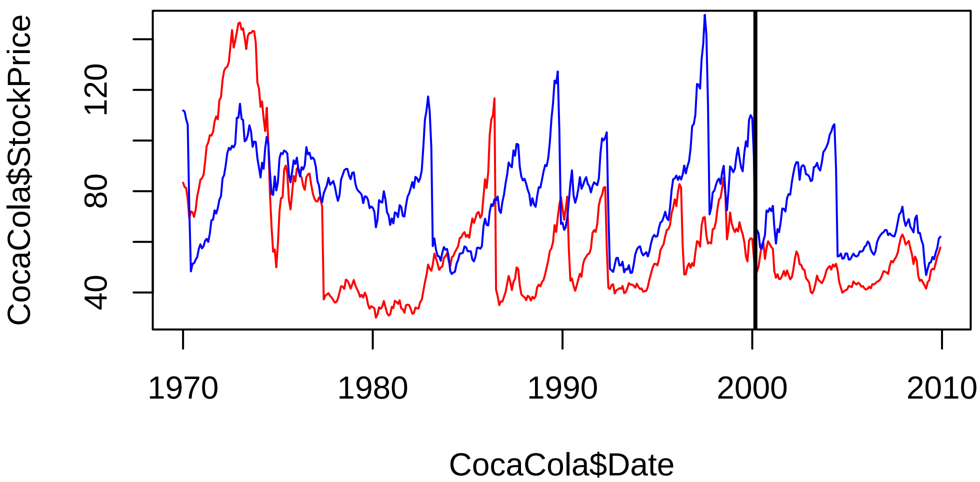
2.1.2: Around what year did Coca-Cola has its lowest stock price in this time period?
Answer: 1980

```
plot(CocaCola$Date, CocaCola$StockPrice, "l")
```



2.2: In March of 2000, the technology bubble burst, and a stock market crash occurred. According to this plot, which company's stock dropped more?
Answer: Procter and Gamble

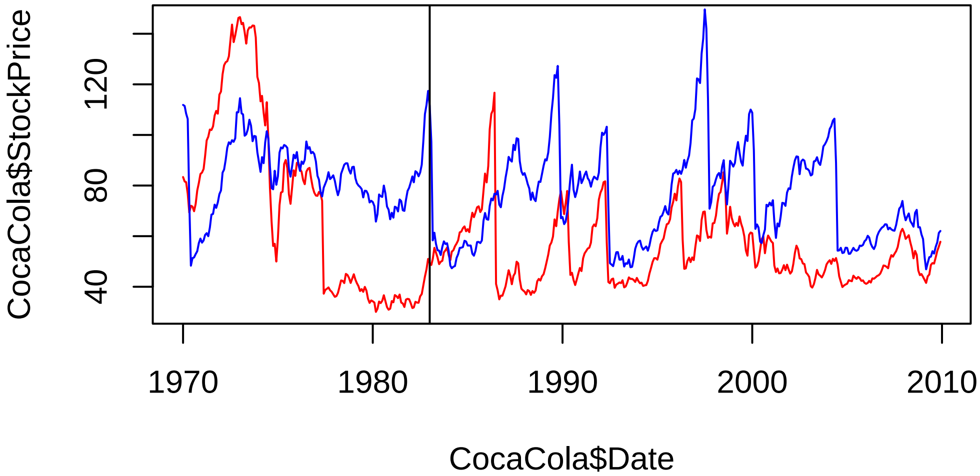
```
plot(CocaCola$Date, CocaCola$StockPrice, "l", col = "red")
lines(ProcterGamble$Date, ProcterGamble$StockPrice, col = "blue")
abline(v=as.Date(c("2000-03-01")), lwd=2)
```



2.3.1: Around 1983, the stock for one of these companies (Coca-Cola or Procter and Gamble) was going up, while the other was going down. Which one was going up?
Answer: CocaCola

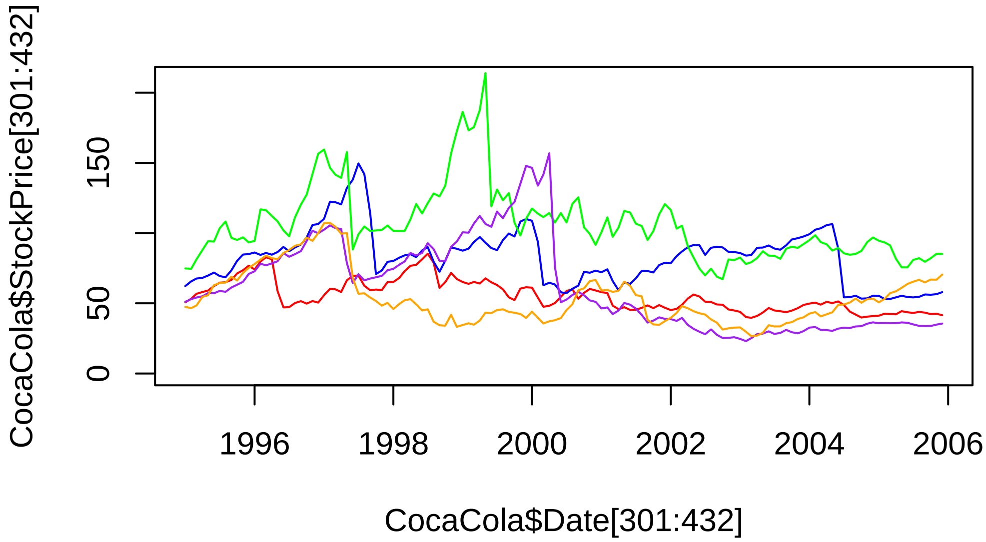
2.3.1: In the time period shown in the plot, which stock generally has lower values?
Answer: CocaCola

```
plot(CocaCola$Date, CocaCola$StockPrice, "l", col = "red")
lines(ProcterGamble$Date, ProcterGamble$StockPrice, col = "blue")
abline(v=as.Date(c("1983-01-01")))
```



Plot to answer the following questions:

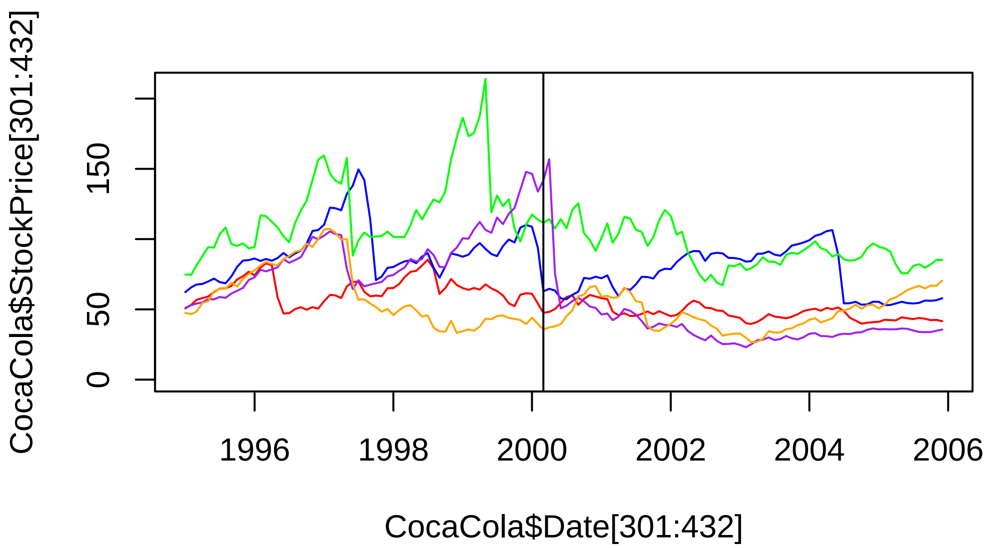
```
plot(CocaCola$Date[301:432], CocaCola$StockPrice[301:432], type="l", col="red", ylim=c(0,2
lines(ProcterGamble$Date[301:432], ProcterGamble$StockPrice[301:432], col = "blue")
lines(IBM$Date[301:432], IBM$StockPrice[301:432], col = "green")
lines(GE$Date[301:432], GE$StockPrice[301:432], col = "purple")
lines(Boeing$Date[301:432], Boeing$StockPrice[301:432], col = "orange")
```



3.1: Which stock fell the most right after the technology bubble burst in March 2000?

Answer: General Electric (GE)

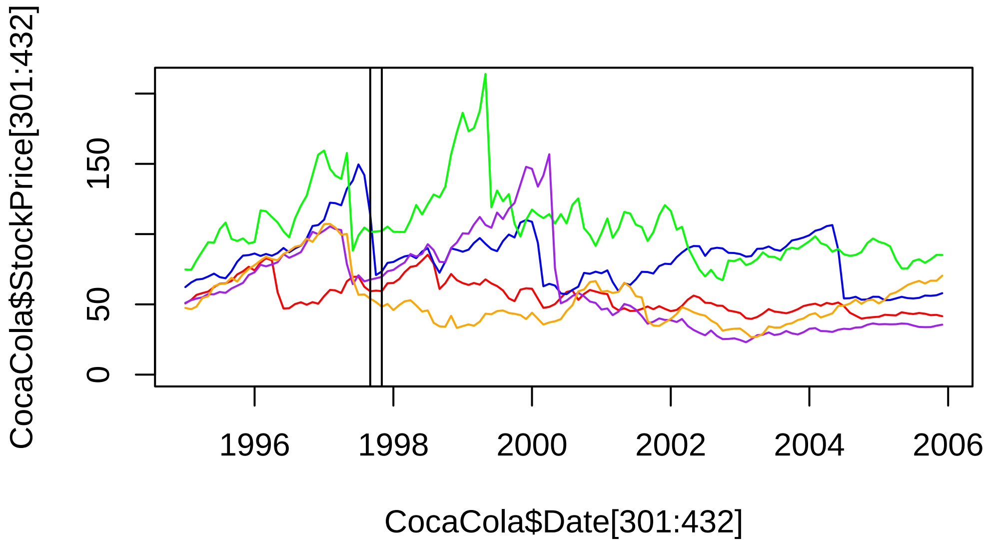
```
plot(CocaCola$Date[301:432], CocaCola$StockPrice[301:432], type="l", col="red", ylim=c(0,2
lines(ProcterGamble$Date[301:432], ProcterGamble$StockPrice[301:432], col = "blue")
lines(IBM$Date[301:432], IBM$StockPrice[301:432], col = "green")
lines(GE$Date[301:432], GE$StockPrice[301:432], col = "purple")
lines(Boeing$Date[301:432], Boeing$StockPrice[301:432], col = "orange")
abline(v = as.Date(c("2000-03-01")))
```



3.2: Which stock reaches the highest value in the time period 1995-2005?
Answer: IBM

3.3: Comparing September 1997 to November 1997, which companies saw a decreasing trend in their stock price?
Answer: Procer and Gamble, Boeing

```
plot(CocaCola$Date[301:432], CocaCola$StockPrice[301:432], type="l", col="red", ylim=c(0,2
lines(ProcterGamble$Date[301:432], ProcterGamble$StockPrice[301:432], col = "blue")
lines(IBM$Date[301:432], IBM$StockPrice[301:432], col = "green")
lines(GE$Date[301:432], GE$StockPrice[301:432], col = "purple")
lines(Boeing$Date[301:432], Boeing$StockPrice[301:432], col = "orange")
abline(v = as.Date(c("1997-09-1")))
abline(v = as.Date(c("1997-11-1")))
```



3.4: In the last two years of this time period (2004 and 2005) which stock seems to be performing the best, in terms of increasing stock price?
Answer: Boeing

4.1: In which months has IBM historically had a higher stock price (on average)?
Answer: January, February, March, April, May

```
tapply(IBM$StockPrice, months(IBM$Date), mean) > mean(IBM$StockPrice)
```

```
    April    August  December  February   January      July      June     March 
     TRUE     FALSE     FALSE      TRUE      TRUE     FALSE     FALSE      TRUE 
```

```
      May  November   October September 
     TRUE     FALSE     FALSE     FALSE 
```

4.2: General Electric and Coca-Cola both have their highest average stock price in the same month. Which month is this?
Answer: April

```r
tapply(GE$StockPrice, months(GE$Date), mean) == max(tapply(GE$StockPrice, months(GE$Date),
```

```
    April    August  December  February   January      July      June     March 
     TRUE     FALSE     FALSE     FALSE     FALSE     FALSE     FALSE     FALSE 
      May  November   October September 
    FALSE     FALSE     FALSE     FALSE 
```

4.3: For the months of December and January, every company's average stock is higher in one month and lower in the other. In which month are the stock prices lower?
Answer: December

```r
tapply(GE$StockPrice, months(GE$Date), mean)
```

```
    April    August  December  February   January      July      June     March 
 64.48009  56.50315  59.10217  62.52080  62.04511  56.73349  56.46844  63.15055 
      May  November   October September 
 60.87135  57.28879  56.23897  56.23913 
```

Demographics and Employment in the United States

In the wake of the Great Recession of 2009, there has been a good deal of focus on employment statistics, one of the most important metrics policymakers use to gauge the overall strength of the economy. In the United States, the government measures unemployment using the Current Population Survey (CPS), which collects demographic and employment information from a wide range of Americans each month. In this exercise, we will employ the topics reviewed in the lectures as well as a few new techniques using the September 2013 version of this rich, nationally representative dataset (available online).

The observations in the dataset represent people surveyed in the September 2013 CPS who actually completed a survey. While the full dataset has 385 variables, in this exercise we will use a more compact version of the dataset.

Please dowload the following file: CPSData.csv

Start:
Load the dataset from CPSData.csv into a data frame called CPS.

```
CPS <- read.csv("/cloud/project/analyticsedge/Datasets/DatasetsUnit1/CPSData.csv")
```

1.1: How many interviewees are in the dataset?
Answer: 131302

```
nrow(CPS)
```

```
[1] 131302
```

1.2: Among the interviewees with a value reported for the Industry variable, what is the most common industry of employment?
Answer: Educational and health services

```
head(sort(table(CPS$Industry), decreasing = TRUE), 1)
```

```
Educational and health services
                          15017
```

1.3.1: Which state has the fewest interviewees?
Answer: New Mexico

```
tail(sort(table(CPS$State), decreasing = TRUE), 1)
```

```
New Mexico
      1102
```

1.3.2: Which state has the largest number of interviewees?
Answer: California

```
head(sort(table(CPS$State), decreasing = TRUE), 1)
```

```
California
     11570
```

1.4: What proportion of interviewees are citizens of the United States?
Answer: 0.9421943

```r
table(CPS$Citizenship)
```

```

    Citizen, Native Citizen, Naturalized          Non-Citizen
             116639                 7073                 7590
```

```r
(116639 + 7073)/nrow(CPS)
```

```
[1] 0.9421943
```

1.5: For which races are there at least 250 interviewees in the CPS dataset of Hispanic ethnicity?
Answer: American Indian, Black, Multiracial, White

```r
table(CPS$Race, CPS$Hispanic) > 250
```

```

                      0     1
  American Indian  TRUE  TRUE
  Asian            TRUE FALSE
  Black            TRUE  TRUE
  Multiracial      TRUE  TRUE
  Pacific Islander TRUE FALSE
  White            TRUE  TRUE
```

2.1: Which variables have at least one interviewee with a missing (NA) value?
Answer: MetroAreaCode, Married, Education, EmploymentStatus, Industry

```r
names(which(colSums(is.na(CPS)) > 0))
```

```
[1] "MetroAreaCode"    "Married"          "Education"        "EmploymentStatus"
[5] "Industry"
```

2.2: We will try to determine if there is a pattern in the missing values of the Married variable.
Answer: The Married variable being missing is related to the Age value for the interviewee.

```r
table(CPS$Region, is.na(CPS$Married))
```

```
          FALSE  TRUE
Midwest   24609  6075
Northeast 21432  4507
South     33535  7967
West      26388  6789
```

```r
table(CPS$Sex, is.na(CPS$Married))
```

```
       FALSE  TRUE
Female 55264 12217
Male   50700 13121
```

```r
table(CPS$Age, is.na(CPS$Married))
```

```
   FALSE TRUE
0      0 1283
1      0 1559
2      0 1574
3      0 1693
4      0 1695
5      0 1795
6      0 1721
7      0 1681
8      0 1729
9      0 1748
10     0 1750
11     0 1721
12     0 1797
13     0 1802
14     0 1790
15  1795    0
16  1751    0
17  1764    0
18  1596    0
19  1517    0
20  1398    0
21  1525    0
22  1536    0
23  1638    0
```

24	1627	0
25	1604	0
26	1643	0
27	1657	0
28	1736	0
29	1645	0
30	1854	0
31	1762	0
32	1790	0
33	1804	0
34	1653	0
35	1716	0
36	1663	0
37	1531	0
38	1530	0
39	1542	0
40	1571	0
41	1673	0
42	1711	0
43	1819	0
44	1764	0
45	1749	0
46	1665	0
47	1647	0
48	1791	0
49	1989	0
50	1966	0
51	1931	0
52	1935	0
53	1994	0
54	1912	0
55	1895	0
56	1935	0
57	1827	0
58	1874	0
59	1758	0
60	1746	0
61	1735	0
62	1595	0
63	1596	0
64	1519	0
65	1569	0
66	1577	0

```
67  1227    0
68  1130    0
69  1062    0
70  1195    0
71  1031    0
72   941    0
73   896    0
74   842    0
75   763    0
76   729    0
77   698    0
78   659    0
79   661    0
80  2664    0
85  2446    0
```

```
table(CPS$Citizenship, is.na(CPS$Married))
```

```
                     FALSE  TRUE
Citizen, Native      91956 24683
Citizen, Naturalized  6910   163
Non-Citizen           7098   492
```

2.3.1: How many states had all interviewees living in a non-metropolitan area (aka they have a missing MetroAreaCode value)? For this question, treat the District of Columbia as a state (even though it is not technically a state).
Answer: 2

2.3.2: How many states had all interviewees living in a metropolitan area? Again, treat the District of Columbia as a state.
Answer: 3

```
table(CPS$State, is.na(CPS$MetroAreaCode))
```

```
                     FALSE  TRUE
Alabama               1020   356
Alaska                   0  1590
Arizona               1327   201
Arkansas               724   697
California           11333   237
```

Colorado	2545	380
Connecticut	2593	243
Delaware	1696	518
District of Columbia	1791	0
Florida	4947	202
Georgia	2250	557
Hawaii	1576	523
Idaho	761	757
Illinois	3473	439
Indiana	1420	584
Iowa	1297	1231
Kansas	1234	701
Kentucky	908	933
Louisiana	1216	234
Maine	909	1354
Maryland	2978	222
Massachusetts	1858	129
Michigan	2517	546
Minnesota	2150	989
Mississippi	376	854
Missouri	1440	705
Montana	199	1015
Nebraska	816	1133
Nevada	1609	247
New Hampshire	1148	1514
New Jersey	2567	0
New Mexico	832	270
New York	5144	451
North Carolina	1642	977
North Dakota	432	1213
Ohio	2754	924
Oklahoma	1024	499
Oregon	1519	424
Pennsylvania	3245	685
Rhode Island	2209	0
South Carolina	1139	519
South Dakota	595	1405
Tennessee	1149	635
Texas	6060	1017
Utah	1455	387
Vermont	657	1233
Virginia	2367	586
Washington	1937	429

```
West Virginia           344  1065
Wisconsin              1882   804
Wyoming                   0  1624
```

2.4: Which region of the United States has the largest proportion of interviewees living in a non-metropolitan area?
Answer: Midwest

```
table(CPS$Region, is.na(CPS$MetroAreaCode))
```

```
          FALSE  TRUE
Midwest   20010 10674
Northeast 20330  5609
South     31631  9871
West      25093  8084
```

2.5.1: Which state has a proportion of interviewees living in a non-metropolitan area closest to 30%?
Answer: Wisconsin

2.5.2: Which state has the largest proportion of non-metropolitan interviewees, ignoring states where all interviewees were non-metropolitan?
Answer: Montana

```
sort(tapply(is.na(CPS$MetroAreaCode), CPS$State, mean))
```

```
District of Columbia           New Jersey         Rhode Island
          0.00000000           0.00000000           0.00000000
          California              Florida        Massachusetts
          0.02048401           0.03923092           0.06492199
            Maryland             New York          Connecticut
          0.06937500           0.08060769           0.08568406
            Illinois             Colorado              Arizona
          0.11221881           0.12991453           0.13154450
              Nevada                Texas            Louisiana
          0.13308190           0.14370496           0.16137931
        Pennsylvania             Michigan           Washington
          0.17430025           0.17825661           0.18131868
             Georgia             Virginia                 Utah
          0.19843249           0.19844226           0.21009772
              Oregon             Delaware           New Mexico
```

```
     0.21821925           0.23396567           0.24500907
         Hawaii                 Ohio              Alabama
     0.24916627           0.25122349           0.25872093
        Indiana            Wisconsin       South Carolina
     0.29141717           0.29932986           0.31302774
      Minnesota             Oklahoma             Missouri
     0.31506849           0.32764281           0.32867133
      Tennessee               Kansas       North Carolina
     0.35594170           0.36227390           0.37304315
           Iowa             Arkansas                Idaho
     0.48694620           0.49049965           0.49868248
       Kentucky        New Hampshire             Nebraska
     0.50678979           0.56874530           0.58132376
          Maine              Vermont          Mississippi
     0.59832081           0.65238095           0.69430894
   South Dakota         North Dakota        West Virginia
     0.70250000           0.73738602           0.75585522
        Montana               Alaska              Wyoming
     0.83607908           1.00000000           1.00000000
```

Codes like MetroAreaCode and CountryOfBirthCode are a compact way to encode factor variables with text as their possible values, and they are therefore quite common in survey datasets. In fact, all but one of the variables in this dataset were actually stored by a numeric code in the original CPS datafile.

When analyzing a variable stored by a numeric code, we will often want to convert it into the values the codes represent. To do this, we will use a dictionary, which maps the the code to the actual value of the variable. We have provided dictionaries MetroAreaCodes.csv and CountryCodes.csv, which respectively map MetroAreaCode and CountryOfBirthCode into their true values. **Read these two dictionaries into data frames MetroAreaMap and CountryMap:**

```
MetroAreaMap <- read.csv("/cloud/project/analyticsedge/Datasets/DatasetsUnit1/MetroAreaCod
CountryMap <- read.csv("/cloud/project/analyticsedge/Datasets/DatasetsUnit1/CountryCodes.c
```

3.1.1: How many observations (codes for metropolitan areas) are there in MetroAreaMap?
Answer: 271

```
nrow(MetroAreaMap)
```

```
[1] 271
```

3.1.2: How many observations (codes for countries) are there in CountryMap?
Answer: 149

```r
nrow(CountryMap)
```

```
[1] 149
```

To merge in the metropolitan areas, we want to connect the field MetroAreaCode from the CPS data frame with the field Code in MetroAreaMap. The following command merges the two data frames on these columns, overwriting the CPS data frame with the result:

```r
CPS = merge(CPS, MetroAreaMap, by.x = "MetroAreaCode", by.y = "Code", all.x = TRUE)
```

3.2.1: hat is the name of the variable that was added to the data frame by the merge() operation?
Answer: MetroArea

```r
str(CPS)
```

```
'data.frame':   131302 obs. of  15 variables:
 $ MetroAreaCode     : int  10420 10420 10420 10420 10420 10420 10420 10420 10420 10420 ...
 $ PeopleInHousehold : int  4 4 2 4 1 3 4 4 2 3 ...
 $ Region            : chr  "Midwest" "Midwest" "Midwest" "Midwest" ...
 $ State             : chr  "Ohio" "Ohio" "Ohio" "Ohio" ...
 $ Age               : int  2 9 73 40 63 19 30 6 60 32 ...
 $ Married           : chr  NA NA "Married" "Married" ...
 $ Sex               : chr  "Male" "Male" "Female" "Female" ...
 $ Education         : chr  NA NA "Some college, no degree" "High school" ...
 $ Race              : chr  "White" "White" "White" "White" ...
 $ Hispanic          : int  0 0 0 0 0 0 0 1 0 0 ...
 $ CountryOfBirthCode: int  57 57 57 362 57 57 203 57 57 57 ...
 $ Citizenship       : chr  "Citizen, Native" "Citizen, Native" "Citizen, Native" "Citizen, 
 $ EmploymentStatus  : chr  NA NA "Retired" "Not in Labor Force" ...
 $ Industry          : chr  NA NA NA NA ...
 $ MetroArea         : chr  "Akron, OH" "Akron, OH" "Akron, OH" "Akron, OH" ...
```

3.2.2: How many interviewees have a missing value for the new metropolitan area variable?
Answer: 34238

```r
sum(is.na(CPS$MetroArea))
```

```
[1] 34238
```

3.3: Which of the following metropolitan areas has the largest number of interviewees?
Answer: Boston-Cambridge-Quincy, MA-NH

```r
sort(table(CPS$MetroArea), decreasing = TRUE)
```

```
New York-Northern New Jersey-Long Island, NY-NJ-PA
                                              5409
      Washington-Arlington-Alexandria, DC-VA-MD-WV
                                              4177
              Los Angeles-Long Beach-Santa Ana, CA
                                              4102
          Philadelphia-Camden-Wilmington, PA-NJ-DE
                                              2855
               Chicago-Naperville-Joliet, IN-IN-WI
                                              2772
              Providence-Fall River-Warwick, MA-RI
                                              2284
                    Boston-Cambridge-Quincy, MA-NH
                                              2229
            Minneapolis-St Paul-Bloomington, MN-WI
                                              1942
                   Dallas-Fort Worth-Arlington, TX
                                              1863
                    Houston-Baytown-Sugar Land, TX
                                              1649
                                      Honolulu, HI
                                              1576
             Miami-Fort Lauderdale-Miami Beach, FL
                                              1554
                Atlanta-Sandy Springs-Marietta, GA
                                              1552
                                 Denver-Aurora, CO
                                              1504
                              Baltimore-Towson, MD
                                              1483
```

San Francisco-Oakland-Fremont, CA
1386
Detroit-Warren-Livonia, MI
1354
Las Vegas-Paradise, NV
1299
Riverside-San Bernardino, CA
1290
Seattle-Tacoma-Bellevue, WA
1255
Portland-Vancouver-Beaverton, OR-WA
1089
Phoenix-Mesa-Scottsdale, AZ
971
Kansas City, MO-KS
962
Omaha-Council Bluffs, NE-IA
957
St. Louis, MO-IL
956
San Diego-Carlsbad-San Marcos, CA
907
Hartford-West Hartford-East Hartford, CT
885
Tampa-St. Petersburg-Clearwater, FL
842
Pittsburgh, PA
732
Bridgeport-Stamford-Norwalk, CT
730
Salt Lake City, UT
723
Cincinnati-Middletown, OH-KY-IN
719
Milwaukee-Waukesha-West Allis, WI
714
Portland-South Portland, ME
701
Cleveland-Elyria-Mentor, OH
681
San Jose-Sunnyvale-Santa Clara, CA
670
Sacramento-Arden-Arcade-Roseville, CA

667
Burlington-South Burlington, VT
657
Boise City-Nampa, ID
644
Orlando, FL
610
Albuquerque, NM
609
San Antonio, TX
607
Oklahoma City, OK
604
Virginia Beach-Norfolk-Newport News, VA-NC
597
Sioux Falls, SD
595
Indianapolis, IN
570
Columbus, OH
551
Louisville, KY-IN
519
Charlotte-Gastonia-Concord, NC-SC
517
Austin-Round Rock, TX
516
New Haven, CT
506
Nashville-Davidson-Murfreesboro, TN
505
Des Moines, IA
501
Richmond, VA
490
Dover, DE
456
Fargo, ND-MN
432
Wichita, KS
427
Ogden-Clearfield, UT
423

Little Rock-North Little Rock, AR
404
Jacksonville, FL
393
Birmingham-Hoover, AL
392
Colorado Springs, CO
372
New Orleans-Metairie-Kenner, LA
367
Memphis, TN-MS-AR
348
Buffalo-Niagara Falls, NY
344
Raleigh-Cary, NC
336
Allentown-Bethlehem-Easton, PA-NJ
334
Tulsa, OK
323
Reno-Sparks, NV
310
Provo-Orem, UT
309
Rochester, NY
307
Grand Rapids-Wyoming, MI
304
Fresno, CA
303
Tucson, AZ
302
Columbia, SC
291
Madison, WI
284
Albany-Schenectady-Troy, NY
268
Dayton, OH
268
Oxnard-Thousand Oaks-Ventura, CA
267
Baton Rouge, LA

262
Charleston, WV
262
Rochester-Dover, NH-ME
262
Greensboro-High Point, NC
251
Bakersfield, CA
245
El Paso, TX
244
Davenport-Moline-Rock Island, IA-IL
240
Toledo, OH
235
Charleston-North Charleston, SC
232
Akron, OH
231
Syracuse, NY
223
Jackson, MS
222
Fayetteville-Springdale-Rogers, AR-MO
215
Bangor, ME
208
Fort Collins-Loveland, CO
206
Norwich-New London, CT-RI
203
Savannah, GA
202
Poughkeepsie-Newburgh-Middletown, NY
201
Billings, MT
199
Lexington-Fayette, KY
198
Cedar Rapids, IA
196
Eugene-Springfield, OR
196

McAllen-Edinburg-Pharr, TX
195
Stockton, CA
193
Sarasota-Bradenton-Venice, FL
192
Durham, NC
189
Greenville, SC
185
Topeka, KS
182
Lafayette, LA
181
Monroe, LA
179
Scranton-Wilkes Barre, PA
176
Harrisburg-Carlisle, PA
174
Boulder, CO
171
Salem, OR
170
Knoxville, TN
168
Palm Bay-Melbourne-Titusville, FL
168
Chattanooga, TN-GA
167
Greeley, CO
162
Augusta-Richmond County, GA-SC
161
Springfield, MO
161
Modesto, CA
158
Waterbury, CT
157
Lancaster, PA
156
Spokane, WA

156
Waterloo-Cedar Falls, IA
156
Springfield, MA-CT
155
Youngstown-Warren-Boardman, OH
153
Lakeland-Winter Haven, FL
149
Cape Coral-Fort Myers, FL
146
Shreveport-Bossier City, LA
146
Worcester, MA-CT
144
Reading, PA
142
Bend, OR
140
Deltona-Daytona Beach-Ormond Beach, FL
140
Fort Wayne, IN
136
Green Bay, WI
136
Vallejo-Fairfield, CA
133
Corpus Christi, TX
132
Santa Barbara-Santa Maria-Goleta, CA
132
Iowa City, IA
131
Pueblo, CO
130
Santa Rosa-Petaluma, CA
129
Kalamazoo-Portage, MI
127
Winston-Salem, NC
127
Duluth, MN-WI
126

Appleton,WI
125
Beaumont-Port Author, TX
123
Champaign-Urbana, IL
122
Visalia-Porterville, CA
121
Lansing-East Lansing, MI
119
Racine, WI
119
Canton-Massillon, OH
118
Coeur d'Alene, ID
117
Huntsville, AL
117
York-Hanover, PA
117
Asheville, NC
116
Victoria, TX
116
La Crosse, WI
114
Rockford, IL
114
Danbury, CT
112
Peoria, IL
112
Yakima, WA
112
Atlantic City, NJ
111
Eau Claire, WI
110
Mobile, AL
110
Port St. Lucie-Fort Pierce, FL
109
Las Cruses, NM

107
Pensacola-Ferry Pass-Brent, FL
107
Merced, CA
106
Fort Smith, AR-OK
105
Bloomington, IN
104
Salinas, CA
104
Montgomery, AL
103
Flint, MI
102
Myrtle Beach-Conway-North Myrtle Beach, SC
102
Killeen-Temple-Fort Hood, TX
101
El Centro, CA
99
Evansville, IN-KY
99
Janesville, WI
99
Olympia, WA
99
Spartanburg, SC
99
Lawrence, KS
98
Lawton, OK
97
Decatur, Al
96
Wausau, WI
96
Trenton-Ewing, NJ
91
Harrisonburg, VA
90
Muskegon-Norton Shores, MI
90

Laredo, TX
89
Amarillo, TX
88
Bremerton-Silverdale, WA
87
Erie, PA
87
Kankakee-Bradley, IL
87
Kingston, NY
87
Hagerstown-Martinsburg, MD-WV
86
Ann Arbor, MI
85
Oshkosh-Neenah, WI
85
Altoona, PA
82
Huntington-Ashland, WV-KY-OH
82
Medford, OR
82
Naples-Marco Island, FL
82
St. Cloud, MN
82
Decatur, IL
81
Lake Charles, LA
81
South Bend-Mishawaka, IN-MI
81
Fort Walton Beach-Crestview-Destin, FL
80
Utica-Rome, NY
80
Brownsville-Harlingen, TX
79
Vero Beach, FL
79
Waco, TX

79
Holland-Grand Haven, MI
78
Tuscaloosa, AL
78
Fayetteville, NC
77
Michigan City-La Porte, IN
77
San Luis Obispo-Paso Robles, CA
77
Ocala, FL
76
Springfield, IL
76
Barnstable Town, MA
75
Saginaw-Saginaw Township North, MI
74
Salisbury, MD
74
Binghamton, NY
73
Lynchburg, VA
73
Bellingham, WA
70
Gainesville, FL
70
Jackson, MI
70
Albany, GA
68
Kingsport-Bristol, TN-VA
67
Leominster-Fitchburg-Gardner, MA
66
Roanoke, VA
66
Santa-Cruz-Watsonville, CA
66
Athens-Clark County, GA
65

Gulfport-Biloxi, MS
65
Longview, TX
65
Macon, GA
65
Anderson, SC
64
Farmington, NM
64
Florence, AL
63
Jacksonville, NC
63
Johnstown, PA
63
Lubbock, TX
63
Monroe, MI
63
Anderson, IN
62
Anniston-Oxford, AL
61
Napa, CA
61
Chico, CA
60
Columbus, GA-AL
59
Joplin, MO
59
Panama City-Lynn Haven, FL
59
Hickory-Morgantown-Lenoir, NC
57
Madera, CA
57
Prescott, AZ
54
Vineland-Millville-Bridgeton, NJ
54
Johnson City, TN

```
                                                    52
                                          Santa Fe, NM
                                                    52
                                           Midland, TX
                                                    51
                             Niles-Benton Harbor, MI
                                                    51
                                       Punta Gorda, FL
                                                    48
                                          Columbia, MO
                                                    47
                                       Tallahassee, FL
                                                    43
                                          Valdosta, GA
                                                    42
                                     Warner Robins, GA
                                                    42
                               Bloomington-Normal IL
                                                    40
                                       Springfield, OH
                                                    34
                                        Ocean City, NJ
                                                    30
                                     Bowling Green, KY
                                                    29
```

3.4: Which metropolitan area has the highest proportion of interviewees of Hispanic ethnicity?
Answer: Laredo, TX

```
head(sort(tapply(CPS$Hispanic, CPS$MetroArea, mean), decreasing = TRUE), 1)
```

```
Laredo, TX
 0.9662921
```

3.5: Determine the number of metropolitan areas in the United States from which at least 20% of interviewees are Asian.
Answer: 4

```
sum(sort(tapply(CPS$Race == "Asian", CPS$MetroArea, mean), decreasing = TRUE) > 0.2)
```

```
[1] 4
```

3.6: Determine which metropolitan area has the smallest proportion of interviewees who have received no high school diploma.
Answer: Iowa City, IA

```
head(sort(tapply(CPS$Education == "No high school diploma", CPS$MetroArea, mean, na.rm = T
```

```
Iowa City, IA
   0.02912621
```

Just as we did with the metropolitan area information, merge in the country of birth information from the CountryMap data frame, replacing the CPS data frame with the result:

```
CPS = merge(CPS, CountryMap, by.x = "CountryOfBirthCode", by.y = "Code", all.x = TRUE)
```

4.1.1: What is the name of the variable added to the CPS data frame by this merge operation?
Answer: Country

```
str(CPS)
```

```
'data.frame':   131302 obs. of  16 variables:
 $ CountryOfBirthCode: int  57 57 57 57 57 57 57 57 57 57 ...
 $ MetroAreaCode     : int  10420 71650 10420 10420 10420 10420 10420 10420 10420 10420 ...
 $ PeopleInHousehold : int  2 4 5 2 2 3 1 3 4 4 ...
 $ Region            : chr  "Midwest" "Northeast" "Midwest" "Midwest" ...
 $ State             : chr  "Ohio" "New Hampshire" "Ohio" "Ohio" ...
 $ Age               : int  73 5 10 30 30 0 34 32 6 9 ...
 $ Married           : chr  "Married" NA NA "Married" ...
 $ Sex               : chr  "Female" "Female" "Female" "Female" ...
 $ Education         : chr  "Some college, no degree" NA NA "Associate degree" ...
 $ Race              : chr  "White" "White" "White" "White" ...
 $ Hispanic          : int  0 0 0 0 0 0 0 0 1 0 ...
 $ Citizenship       : chr  "Citizen, Native" "Citizen, Native" "Citizen, Native" "Citizen, 
 $ EmploymentStatus  : chr  "Retired" NA NA "Employed" ...
 $ Industry          : chr  NA NA NA "Trade" ...
 $ MetroArea         : chr  "Akron, OH" "Boston-Cambridge-Quincy, MA-NH" "Akron, OH" "Akron, 
 $ Country           : chr  "United States" "United States" "United States" "United States"
```

4.1.2: How many interviewees have a missing value for the new country of birth variable?
Answer: 176

```
sum(is.na(CPS$Country))
```

```
[1] 176
```

4.2: Among all interviewees born outside of North America, which country was the most common place of birth?
Answer: Philippines

```
head(sort(table(CPS$Country), decreasing = TRUE), 3)
```

```
United States        Mexico   Philippines
       115063          3921           839
```

4.3: What proportion of the interviewees from the "New York-Northern New Jersey-Long Island, NY-NJ-PA" metropolitan area have a country of birth that is not the United States? For this computation, don't include people from this metropolitan area who have a missing country of birth.
Answer: 0.3086603

```
tapply(CPS$Country != "United States", CPS$MetroArea == "New York-Northern New Jersey-Long
```

```
    FALSE      TRUE
0.1392772 0.3086603
```

4.4: Which metropolitan area has the largest number (note – not proportion) of interviewees with a country of birth... 4.4.1: ...in India?
Answer: New York-Northern New Jersey-Long Island, NY-NJ-PA

```
tail(sort(tapply(CPS$Country == "India", CPS$MetroArea, sum, na.rm = TRUE)), 1)
```

```
New York-Northern New Jersey-Long Island, NY-NJ-PA
                                                96
```

4.4.2: ...in Brazil?
Answer: Boston-Cambridge-Quincy, MA-NH

```r
tail(sort(tapply(CPS$Country == "Brazil", CPS$MetroArea, sum, na.rm = TRUE)), 1)
```

```
Boston-Cambridge-Quincy, MA-NH
                            18
```

4.4.3: …in Somalia?
Answer: Minneapolis-St Paul-Bloomington, MN-WI

```r
tail(sort(tapply(CPS$Country == "Somalia", CPS$MetroArea, sum, na.rm = TRUE)), 1)
```

```
Minneapolis-St Paul-Bloomington, MN-WI
                                    17
```

Internet Privacy Poll (OPTIONAL)

Internet privacy has gained widespread attention in recent years. To measure the degree to which people are concerned about hot-button issues like Internet privacy, social scientists conduct polls in which they interview a large number of people about the topic. In this assignment, we will analyze data from a July 2013 Pew Internet and American Life Project poll on Internet anonymity and privacy, which involved interviews across the United States. While the full polling data can be found here, we will use a more limited version of the results, available in AnonymityPoll.csv.

Start:
Using read.csv(), load the dataset from AnonymityPoll.csv into a data frame called poll.

```r
poll <- read.csv("/cloud/project/analyticsedge/Datasets/DatasetsUnit1/AnonymityPoll.csv")
```

1.1: How many people participated in the poll?
Answer: 1002

```r
nrow(poll)
```

```
[1] 1002
```

1.2.1: How many interviewees responded that they use a smartphone?
Answer: 487

```r
sum(poll$Smartphone, na.rm = TRUE)
```

```
[1] 487
```

1.2.2: How many interviewees responded that they don't use a smartphone?
Answer: 472

```r
table(poll$Smartphone)
```

```
  0   1 
472 487 
```

1.2.3: How many interviewees did not respond to the question, resulting in a missing value, or NA, in the summary() output?
Answer: 43

```r
sum(is.na(poll$Smartphone))
```

```
[1] 43
```

1.3.1: Which of the following are states in the Midwest census region?
Answer: Kansas, Missouri, Ohio

1.3.2: Which was the state in the South census region with the largest number of interviewees?
Answer: Texas

```r
table(poll$Region, poll$State)
```

```
           
            Alabama Arizona Arkansas California Colorado Connecticut Delaware
  Midwest         0       0        0          0        0           0        0
  Northeast       0       0        0          0        0           8        0
  South          11       0       10          0        0           0        6
  West            0      24        0        103       19           0        0
           
            District of Columbia Florida Georgia Idaho Illinois Indiana Iowa
  Midwest                      0       0       0     0       32      27   14
  Northeast                    0       0       0     0        0       0    0
```

South	2	42	34	0	0	0	0
West	0	0	0	8	0	0	0

	Kansas	Kentucky	Louisiana	Maine	Maryland	Massachusetts	Michigan
Midwest	14	0	0	0	0	0	31
Northeast	0	0	0	4	0	19	0
South	0	25	17	0	18	0	0
West	0	0	0	0	0	0	0

	Minnesota	Mississippi	Missouri	Montana	Nebraska	Nevada
Midwest	15	0	26	0	11	0
Northeast	0	0	0	0	0	0
South	0	11	0	0	0	0
West	0	0	0	5	0	8

	New Hampshire	New Jersey	New Mexico	New York	North Carolina
Midwest	0	0	0	0	0
Northeast	7	16	0	60	0
South	0	0	0	0	32
West	0	0	5	0	0

	North Dakota	Ohio	Oklahoma	Oregon	Pennsylvania	Rhode Island
Midwest	5	38	0	0	0	0
Northeast	0	0	0	0	45	4
South	0	0	14	0	0	0
West	0	0	0	20	0	0

	South Carolina	South Dakota	Tennessee	Texas	Utah	Vermont	Virginia
Midwest	0	3	0	0	0	0	0
Northeast	0	0	0	0	0	3	0
South	12	0	17	72	0	0	31
West	0	0	0	0	11	0	0

	Washington	West Virginia	Wisconsin	Wyoming
Midwest	0	0	23	0
Northeast	0	0	0	0
South	0	5	0	0
West	28	0	0	7

2.1.1: How many interviewees reported not having used the Internet and not having used a smartphone?
Answer: 186

```r
tapply(poll$Internet.Use == 0, poll$Smartphone == 0, sum, na.rm = TRUE)
```

```
FALSE  TRUE
   17   186
```

2.1.2: How many interviewees reported having used the Internet and having used a smartphone?
Answer: 470

```r
tapply(poll$Internet.Use, poll$Smartphone, sum, na.rm = TRUE)
```

```
  0   1
285 470
```

2.1.3: How many interviewees reported having used the Internet but not having used a smartphone?
Answer: 285

```r
tapply(poll$Internet.Use == 1, poll$Smartphone == 0, sum, na.rm = TRUE)
```

```
FALSE  TRUE
  470   285
```

2.1.4: How many interviewees reported having used a smartphone but not having used the Internet?
Answer: 17

```r
tapply(poll$Internet.Use == 0, poll$Smartphone == 1, sum, na.rm = TRUE)
```

```
FALSE  TRUE
  186    17
```

```r
# Alternative to all 4 above questions: table(poll$Internet.Use, poll$Smartphone)
```

2.2.1: How many interviewees have a missing value for their Internet use?
Answer: 1

```r
sum(is.na(poll$Internet.Use))
```

```
[1] 1
```

2.2.2: How many interviewees have a missing value for their smartphone use?
Answer: 43

```r
sum(is.na(poll$Smartphone))
```

```
[1] 43
```

Use the subset function to obtain a data frame called "limited", which is limited to interviewees who reported Internet use or who reported smartphone use:

```r
limited <- subset(poll, poll$Internet.Use == 1
                        |poll$Smartphone == 1)
# Alternative: limited = subset(poll, Internet.Use == 1 | Smartphone == 1)
```

2.3: How many interviewees are in the new data frame?
Answer: 792

```r
nrow(limited)
```

```
[1] 792
```

3.1: Which variables have missing values in the limited data frame?
Answer: *Check output*

```r
names(which(colSums(is.na(limited)) > 0))
```

```
[1] "Smartphone"             "Age"                    "Conservativeness"
[4] "Worry.About.Info"       "Privacy.Importance"     "Anonymity.Possible"
[7] "Tried.Masking.Identity" "Privacy.Laws.Effective"
```

3.2: What is the average number of pieces of personal information on the Internet, according to the Info.On.Internet variable?
Answer: 3.795455

```r
mean(limited$Info.On.Internet)
```

```
[1] 3.795455
```

3.3.1: How many interviewees reported a value of 0 for Info.On.Internet?
Answer: 105

```r
sum(limited$Info.On.Internet == 0)
```

```
[1] 105
```

3.3.2: How many interviewees reported the maximum value of 11 for Info.On.Internet?
Answer: 8

```r
sum(limited$Info.On.Internet == 11)
```

```
[1] 8
```

3.4: What proportion of interviewees who answered the Worry.About.Info question worry about how much information is available about them on the Internet?
Answer: 0.4886076

```r
table(limited$Worry.About.Info)
```

```
  0   1
404 386
```

```r
386/(404 + 386)
```

```
[1] 0.4886076
```

3.5: What proportion of interviewees who answered the Anonymity.Possible question think it is possible to be completely anonymous on the Internet?
Answer: 0.3691899

```r
table(limited$Anonymity.Possible)
```

```
  0   1 
475 278 
```

```r
278/(475 + 278)
```

```
[1] 0.3691899
```

3.6: What proportion of interviewees who answered the Tried.Masking.Identity question have tried masking their identity on the Internet?
Answer: 0.1632653

```r
table(limited$Tried.Masking.Identity)
```

```
  0   1 
656 128 
```

```r
128/(656 + 128)
```

```
[1] 0.1632653
```

3.7: What proportion of interviewees who answered the Privacy.Laws.Effective question find United States privacy laws effective?
Answer: 0.2558459

```r
table(limited$Privacy.Laws.Effective)
```

```
  0   1 
541 186 
```

```r
186/(541 + 186)
```

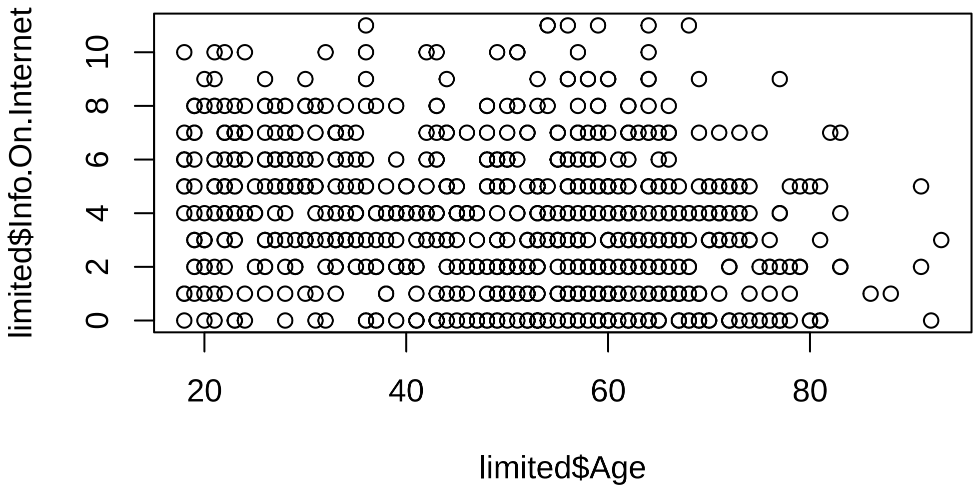
```
[1] 0.2558459
```

4.1: Build a histogram of the age of interviewees. What is the best represented age group in the population?
Answer: People aged about 60 years old.

```
hist(limited$Age)
```

Both Age and Info.On.Internet are variables that take on many values, so a good way to observe their relationship is through a graph. We learned in lecture that we can plot Age against Info.On.Internet with the command `plot(limited$Age, limited$Info.On.Internet)`. However, because Info.On.Internet takes on a small number of values, multiple points will be plotted in exactly the same location on this graph, making the distribution hard to see:

```
plot(limited$Age, limited$Info.On.Internet)
```



4.2: What is the largest number of interviewees that have exactly the same value in their Age variable AND the same value in their Info.On.Internet variable?
Answer: 6

```
max(table(limited$Age, limited$Info.On.Internet))
```

```
[1] 6
```

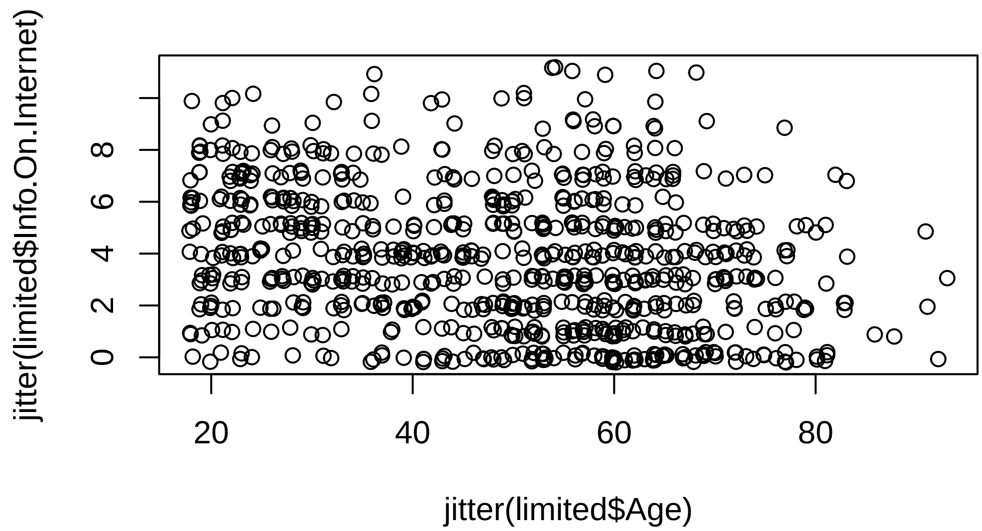
4.3: Experimenting with the command jitter(c(1, 2, 3)), what appears to be the functionality of the jitter command?
Answer: jitter adds or subtracts a small amount of random noise to the values passed to it, and two runs will yield different results.

```
jitter(c(1, 2, 3))
```

```
[1] 0.8283179 2.0098571 3.0930231
```

4.4: What relationship to you observe between Age and Info.On.Internet?
Answer: Older age seems moderately associated with a smaller value for Info.On.Internet.

```
plot(jitter(limited$Age), jitter(limited$Info.On.Internet))
```



4.5.1: What is the average Info.On.Internet value for smartphone users?
Answer: 4.367556

4.5.2: What is the average Info.On.Internet value for non-smartphone users?
Answer: 2.922807

```
tapply(limited$Info.On.Internet, limited$Smartphone, mean, na.rm = TRUE)
```

```
       0        1 
2.922807 4.367556 
```

4.6.1: What proportion of smartphone users who answered the Tried.Masking.Identity question have tried masking their identity when using the Internet?
Answer: 0.1925466

4.6.2: What proportion of non-smartphone users who answered the Tried.Masking.Identity question have tried masking their identity when using the Internet?
Answer: 0.1174377

```
tapply(limited$Tried.Masking.Identity, limited$Smartphone, mean, na.rm = TRUE)
```

```
        0         1 
0.1174377 0.1925466 
```

And we're done! That was all for Assignment 1!

Assignment 2 - Linear Regression

The following link will lead you to the assignment on the edX website: https://learning.edx.org/course/course-v1:MITx+15.071x+2T2020/block-v1:MITx+15.071x+2T2020+type@sequential+block@60d93a44280348d7a0a16663f92af0f7

Climate Change

There have been many studies documenting that the average global temperature has been increasing over the last century. The consequences of a continued rise in global temperature will be dire. Rising sea levels and an increased frequency of extreme weather events will affect billions of people.

In this problem, we will attempt to study the relationship between average global temperature and several other factors.

The file climate_change.csv contains climate data from May 1983 to December 2008.

Start:
We are interested in how changes in these variables affect future temperatures, as well as how well these variables explain temperature changes so far. To do this, first read the dataset climate_change.csv into R.

```
climateChange <- read.csv("/cloud/project/analyticsedge/Datasets/DatasetsUnit2/climate_cha
```

Then, split the data into a *training set*, consisting of all the observations up to and including 2006, and a *testing set* consisting of the remaining years (hint: use subset). A training set refers to the data that will be used to build the model (this is the data we give to the lm() function), and a testing set refers to the data we will use to test our predictive ability.

```
climateTrain <- subset(climateChange, Year <=2006)
climateTest <- subset(climateChange, Year > 2006)
```

Next, build a linear regression model to predict the dependent variable Temp, using MEI, CO2, CH4, N2O, CFC.11, CFC.12, TSI, and Aerosols as independent variables (Year and Month should NOT be used in the model). Use the training set to build the model.

```r
climateModel1 <- lm(Temp ~ MEI + CO2 + CH4 + N2O + CFC.11 + CFC.12 + TSI + Aerosols, data
```

1.1: What is the model R2 (the "Multiple R-squared" value)?
Answer: 0.7509

1.2: Which variables are significant in the model?
Answer: MEI, CO2, CFC.11, CFC.12, TSI, Aerosols

```r
summary(climateModel1)
```

```
Call:
lm(formula = Temp ~ MEI + CO2 + CH4 + N2O + CFC.11 + CFC.12 +
    TSI + Aerosols, data = climateTrain)

Residuals:
     Min       1Q   Median       3Q      Max
-0.25888 -0.05913 -0.00082  0.05649  0.32433

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.246e+02  1.989e+01  -6.265 1.43e-09 ***
MEI          6.421e-02  6.470e-03   9.923  < 2e-16 ***
CO2          6.457e-03  2.285e-03   2.826  0.00505 **
CH4          1.240e-04  5.158e-04   0.240  0.81015
N2O         -1.653e-02  8.565e-03  -1.930  0.05467 .
CFC.11      -6.631e-03  1.626e-03  -4.078 5.96e-05 ***
CFC.12       3.808e-03  1.014e-03   3.757  0.00021 ***
TSI          9.314e-02  1.475e-02   6.313 1.10e-09 ***
Aerosols    -1.538e+00  2.133e-01  -7.210 5.41e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.09171 on 275 degrees of freedom
Multiple R-squared:  0.7509,    Adjusted R-squared:  0.7436
F-statistic: 103.6 on 8 and 275 DF,  p-value: < 2.2e-16
```

Current scientific opinion is that nitrous oxide and CFC-11 are greenhouse gases: gases that are able to trap heat from the sun and contribute to the heating of the Earth. However, the regression coefficients of both the N2O and CFC-11 variables are *negative*, indicating that increasing atmospheric concentrations of either of these two compounds is associated with lower global temperatures.

2.1: What is the simplest correct explanation for this contradiction?
Answer: All of the gas concentration variables reflect human development - N2O and CFC.11 are correlated with other variables in the data set.

2.2.1: Which of the following independent variables is N2O highly correlated with (absolute correlation greater than 0.7)?
Answer: CO2, CH4, CFC.12

2.2.2: Which of the following independent variables is CFC.11 highly correlated with?
Answer: CH4, CFC.12

```r
cor(climateTrain)
```

```
                Year         Month           MEI         CO2         CH4
Year      1.00000000 -0.0279419602 -0.0369876842  0.98274939  0.91565945
Month    -0.02794196  1.0000000000  0.0008846905 -0.10673246  0.01856866
MEI      -0.03698768  0.0008846905  1.0000000000 -0.04114717 -0.03341930
CO2       0.98274939 -0.1067324607 -0.0411471651  1.00000000  0.87727963
CH4       0.91565945  0.0185686624 -0.0334193014  0.87727963  1.00000000
N2O       0.99384523  0.0136315303 -0.0508197755  0.97671982  0.89983864
CFC.11    0.56910643 -0.0131112236  0.0690004387  0.51405975  0.77990402
CFC.12    0.89701166  0.0006751102  0.0082855443  0.85268963  0.96361625
TSI       0.17030201 -0.0346061935 -0.1544919227  0.17742893  0.24552844
Aerosols -0.34524670  0.0148895406  0.3402377871 -0.35615480 -0.26780919
Temp      0.78679714 -0.0998567411  0.1724707512  0.78852921  0.70325502
                 N2O      CFC.11        CFC.12         TSI    Aerosols
Year      0.99384523  0.56910643  0.8970116635  0.17030201 -0.34524670
Month     0.01363153 -0.01311122  0.0006751102 -0.03460619  0.01488954
MEI      -0.05081978  0.06900044  0.0082855443 -0.15449192  0.34023779
CO2       0.97671982  0.51405975  0.8526896272  0.17742893 -0.35615480
CH4       0.89983864  0.77990402  0.9636162478  0.24552844 -0.26780919
N2O       1.00000000  0.52247732  0.8679307757  0.19975668 -0.33705457
CFC.11    0.52247732  1.00000000  0.8689851828  0.27204596 -0.04392120
CFC.12    0.86793078  0.86898518  1.0000000000  0.25530281 -0.22513124
TSI       0.19975668  0.27204596  0.2553028138  1.00000000  0.05211651
Aerosols -0.33705457 -0.04392120 -0.2251312440  0.05211651  1.00000000
Temp      0.77863893  0.40771029  0.6875575483  0.24338269 -0.38491375
                Temp
Year      0.78679714
Month    -0.09985674
MEI       0.17247075
CO2       0.78852921
```

```
CH4         0.70325502
N2O         0.77863893
CFC.11      0.40771029
CFC.12      0.68755755
TSI         0.24338269
Aerosols -0.38491375
Temp        1.00000000
```

Given that the correlations are so high, let us focus on the N2O variable and build a model with only MEI, TSI, Aerosols and N2O as independent variables. Remember to use the training set to build the model:

```r
climateModel2 <- lm(Temp ~ MEI + N2O + TSI + Aerosols, data = climateTrain)
```

3.1: What is the coefficient of N2O in this reduced model?
Answer: 2.532e-02 (0.02532)

3.2: What is the model R^2?
Answer: 0.7261

```r
summary(climateModel2)
```

```

Call:
lm(formula = Temp ~ MEI + N2O + TSI + Aerosols, data = climateTrain)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.27916 -0.05975 -0.00595  0.05672  0.34195 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -1.162e+02  2.022e+01  -5.747 2.37e-08 ***
MEI          6.419e-02  6.652e-03   9.649  < 2e-16 ***
N2O          2.532e-02  1.311e-03  19.307  < 2e-16 ***
TSI          7.949e-02  1.487e-02   5.344 1.89e-07 ***
Aerosols    -1.702e+00  2.180e-01  -7.806 1.19e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.09547 on 279 degrees of freedom
Multiple R-squared:  0.7261,    Adjusted R-squared:  0.7222 
F-statistic: 184.9 on 4 and 279 DF,  p-value: < 2.2e-16
```

We have many variables in this problem, and as we have seen above, dropping some from the model does not decrease model quality. R provides a function, step, that will automate the procedure of trying different combinations of variables to find a good compromise of model simplicity and R2. This trade-off is formalized by the Akaike information criterion (AIC) - it can be informally thought of as the quality of the model with a penalty for the number of variables in the model.

Use the step function in R to derive a new model, with the full model as the initial model:

```r
climateModel <- step(climateModel1)
```

```
Start:  AIC=-1348.16
Temp ~ MEI + CO2 + CH4 + N2O + CFC.11 + CFC.12 + TSI + Aerosols

           Df Sum of Sq    RSS     AIC
- CH4       1   0.00049 2.3135 -1350.1
<none>                  2.3130 -1348.2
- N2O       1   0.03132 2.3443 -1346.3
- CO2       1   0.06719 2.3802 -1342.0
- CFC.12    1   0.11874 2.4318 -1335.9
- CFC.11    1   0.13986 2.4529 -1333.5
- TSI       1   0.33516 2.6482 -1311.7
- Aerosols  1   0.43727 2.7503 -1301.0
- MEI       1   0.82823 3.1412 -1263.2

Step:  AIC=-1350.1
Temp ~ MEI + CO2 + N2O + CFC.11 + CFC.12 + TSI + Aerosols

           Df Sum of Sq    RSS     AIC
<none>                  2.3135 -1350.1
- N2O       1   0.03133 2.3448 -1348.3
- CO2       1   0.06672 2.3802 -1344.0
- CFC.12    1   0.13023 2.4437 -1336.5
- CFC.11    1   0.13938 2.4529 -1335.5
- TSI       1   0.33500 2.6485 -1313.7
- Aerosols  1   0.43987 2.7534 -1302.7
- MEI       1   0.83118 3.1447 -1264.9
```

4.1: What is the R^2 value of the model produced by the step function?
Answer: 0.7508

4.2: Which of the variable(s) were eliminated from the full model by the step function?

Answer: CH4

```
summary(climateModel)
```

```
Call:
lm(formula = Temp ~ MEI + CO2 + N2O + CFC.11 + CFC.12 + TSI +
    Aerosols, data = climateTrain)

Residuals:
     Min       1Q   Median       3Q      Max
-0.25770 -0.05994 -0.00104  0.05588  0.32203

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.245e+02  1.985e+01  -6.273 1.37e-09 ***
MEI          6.407e-02  6.434e-03   9.958  < 2e-16 ***
CO2          6.402e-03  2.269e-03   2.821 0.005129 **
N2O         -1.602e-02  8.287e-03  -1.933 0.054234 .
CFC.11      -6.609e-03  1.621e-03  -4.078 5.95e-05 ***
CFC.12       3.868e-03  9.812e-04   3.942 0.000103 ***
TSI          9.312e-02  1.473e-02   6.322 1.04e-09 ***
Aerosols    -1.540e+00  2.126e-01  -7.244 4.36e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.09155 on 276 degrees of freedom
Multiple R-squared:  0.7508,    Adjusted R-squared:  0.7445
F-statistic: 118.8 on 7 and 276 DF,  p-value: < 2.2e-16
```

5: Using the model produced from the step function, calculate temperature predictions for the testing data set, using the predict function. What is the testing set R^2?

Answer: 0.6286051

```
predictTemp <- predict(climateModel, newdata = climateTest)
SSE = sum((predictTemp - climateTest$Temp)^2)
SST = sum((mean(climateTrain$Temp) - climateTest$Temp)^2)
R2 = 1 - SSE/SST
R2
```

```
[1] 0.6286051
```

Reading Test Scores

The Programme for International Student Assessment (PISA) is a test given every three years to 15-year-old students from around the world to evaluate their performance in mathematics, reading, and science. This test provides a quantitative way to compare the performance of students from different parts of the world. In this homework assignment, we will predict the reading scores of students from the United States of America on the 2009 PISA exam.

The datasets pisa2009train.csv and pisa2009test.csv contain information about the demographics and schools for American students taking the exam, derived from 2009 PISA Public-Use Data Files distributed by the United States National Center for Education Statistics (NCES). While the datasets are not supposed to contain identifying information about students taking the test, by using the data you are bound by them NCES data use agreement, which prohibits any attempt to determine the identity of any student in the datasets.

Start:
Load the training and testing sets pisa2009train.csv and pisa2009test.csv using the read.csv() function, and save them as variables with the names pisaTrain and pisaTest.

```
pisaTrain <- read.csv("/cloud/project/analyticsedge/Datasets/DatasetsUnit2/pisa2009train.c
pisaTest <- read.csv("/cloud/project/analyticsedge/Datasets/DatasetsUnit2/pisa2009test.csv
```

1.1: How many students are there in the training set?
Answer: 3663

```
nrow(pisaTrain)
```

```
[1] 3663
```

1.2.1: Using tapply() on pisaTrain, what is the average reading test score of males
Answer: 483.5325

1.2.2: Using tapply() on pisaTrain, what is the average reading test score of females?
Answer: 512.9406

```
tapply(pisaTrain$readingScore, pisaTrain$male, mean)
```

```
       0        1
512.9406 483.5325
```

1.3: Which variables are missing data in at least one observation in the training set?
Answer: *Check output*

```
names(which(colSums(is.na(pisaTrain)) > 0))
```

```
 [1] "raceeth"               "preschool"              "expectBachelors"
 [4] "motherHS"              "motherBachelors"        "motherWork"
 [7] "fatherHS"              "fatherBachelors"        "fatherWork"
[10] "selfBornUS"            "motherBornUS"           "fatherBornUS"
[13] "englishAtHome"         "computerForSchoolwork" "read30MinsADay"
[16] "minutesPerWeekEnglish" "studentsInEnglish"     "schoolHasLibrary"
[19] "schoolSize"
```

Linear regression discards observations with missing data, so we will remove all such observations from the training and testing sets:

```
pisaTrain <- na.omit(pisaTrain)
pisaTest <- na.omit(pisaTest)
```

1.4: How many observations are now in the training/testing set?
Answer: 2414/990 respectively

```
nrow(pisaTrain)
```

```
[1] 2414
```

```
nrow(pisaTest)
```

```
[1] 990
```

2.1: Which of the variables *grade*, *male* and *raceeth* is an unordered or ordered factor with a min. of 3 values
Answer: grade - ordered (ex. 8, 9, 10, 11) male - only has 2 values raceeth - unordered (no way to sepcifically order it)

How to include unordered factors in a linear regression model:
To include unordered factors in a linear regression model, we define one level as the "reference level" and add a binary variable for each of the remaining levels. In this way, a factor with n levels is replaced by n-1 binary variables. The reference level is typically selected to be the most frequently occurring level in the dataset.

As an example, consider the unordered factor variable "color", with levels "red", "green", and "blue". If "green" were the reference level, then we would add binary variables `colorred` and `colorblue` to a linear regression problem. All red examples would have `colorred = 1` and `colorblue = 0`. All blue examples would have `colorred = 0` and `colorblue = 1`. All green examples would have `colorred = 0` and `colorblue = 0`.

Now, consider the variable "raceeth" in our problem, which has levels "American Indian/Alaska Native", "Asian", "Black", "Hispanic", "More than one race", "Native Hawaiian/Other Pacific Islander", and "White". Because it is the most common in our population, we will select White as the reference level.

2.2: Which binary variables will be included in the regression model?
Answer: We create a binary variable for each level except the reference level, so we would create all these variables except for raceethWhite.

2.3: For a student who is Asian, which binary variables would be set to 0? What about a student who is white?
Answer: An Asian student will have raceethAsian set to 1 and all other raceeth binary variables set to 0. Since "White" is the reference level, a white student will have all raceeth binary variables set to 0.

Because the race variable takes on text values, it was loaded as a factor variable when we read in the dataset with read.csv() – you can see this when you run str(pisaTrain) or str(pisaTest). However, by default R selects the first level alphabetically ("American Indian/Alaska Native") as the reference level of our factor instead of the most common level ("White"). **Set the reference level of the factor by typing the following two lines in your R console:**

```
pisaTrain$raceeth = relevel(factor(pisaTrain$raceeth), "White")
pisaTest$raceeth = relevel(factor(pisaTest$raceeth), "White")
```

Now, build a linear regression model (call it lmScore) using the training set to predict readingScore using all the remaining variables:

```r
lmScore <- lm(readingScore ~ ., data = pisaTrain)
```

3.1: What is the Multiple R-squared value of lmScore on the training set?
Answer: 0.3251

```r
summary(lmScore)
```

```
Call:
lm(formula = readingScore ~ ., data = pisaTrain)

Residuals:
    Min      1Q  Median      3Q     Max 
-247.44  -48.86    1.86   49.77  217.18 

Coefficients:
                                                Estimate Std. Error t value
(Intercept)                                   143.766333  33.841226   4.248
grade                                          29.542707   2.937399  10.057
male                                          -14.521653   3.155926  -4.601
raceethAmerican Indian/Alaska Native          -67.277327  16.786935  -4.008
raceethAsian                                   -4.110325   9.220071  -0.446
raceethBlack                                  -67.012347   5.460883 -12.271
raceethHispanic                               -38.975486   5.177743  -7.528
raceethMore than one race                     -16.922522   8.496268  -1.992
raceethNative Hawaiian/Other Pacific Islander  -5.101601  17.005696  -0.300
preschool                                      -4.463670   3.486055  -1.280
expectBachelors                                55.267080   4.293893  12.871
motherHS                                        6.058774   6.091423   0.995
motherBachelors                                12.638068   3.861457   3.273
motherWork                                     -2.809101   3.521827  -0.798
fatherHS                                        4.018214   5.579269   0.720
fatherBachelors                                16.929755   3.995253   4.237
fatherWork                                      5.842798   4.395978   1.329
selfBornUS                                     -3.806278   7.323718  -0.520
motherBornUS                                   -8.798153   6.587621  -1.336
fatherBornUS                                    4.306994   6.263875   0.688
englishAtHome                                   8.035685   6.859492   1.171
computerForSchoolwork                          22.500232   5.702562   3.946
read30MinsADay                                 34.871924   3.408447  10.231
minutesPerWeekEnglish                           0.012788   0.010712   1.194
studentsInEnglish                              -0.286631   0.227819  -1.258
```

```
schoolHasLibrary                                 12.215085   9.264884   1.318
publicSchool                                    -16.857475   6.725614  -2.506
urban                                            -0.110132   3.962724  -0.028
schoolSize                                        0.006540   0.002197   2.977
                                                Pr(>|t|)
(Intercept)                                     2.24e-05 ***
grade                                            < 2e-16 ***
male                                            4.42e-06 ***
raceethAmerican Indian/Alaska Native            6.32e-05 ***
raceethAsian                                     0.65578
raceethBlack                                     < 2e-16 ***
raceethHispanic                                 7.29e-14 ***
raceethMore than one race                        0.04651 *
raceethNative Hawaiian/Other Pacific Islander    0.76421
preschool                                        0.20052
expectBachelors                                  < 2e-16 ***
motherHS                                         0.32001
motherBachelors                                  0.00108 **
motherWork                                       0.42517
fatherHS                                         0.47147
fatherBachelors                                 2.35e-05 ***
fatherWork                                       0.18393
selfBornUS                                       0.60331
motherBornUS                                     0.18182
fatherBornUS                                     0.49178
englishAtHome                                    0.24153
computerForSchoolwork                           8.19e-05 ***
read30MinsADay                                   < 2e-16 ***
minutesPerWeekEnglish                            0.23264
studentsInEnglish                                0.20846
schoolHasLibrary                                 0.18749
publicSchool                                     0.01226 *
urban                                            0.97783
schoolSize                                       0.00294 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 73.81 on 2385 degrees of freedom
Multiple R-squared:  0.3251,    Adjusted R-squared:  0.3172
F-statistic: 41.04 on 28 and 2385 DF,  p-value: < 2.2e-16
```

3.2: What is the training-set root-mean squared error (RMSE) of lmScore?
Answer: 73.36555

```r
sqrt(mean(lmScore$residuals^2))
```

```
[1] 73.36555
```

3.3: Consider two students A and B. They have all variable values the same, except that student A is in grade 11 and student B is in grade 9. What is the predicted reading score of student A minus the predicted reading score of student B?
Answer: 59.08541 *(The coefficient of the variable grade is 29.542707, meaning that it affects the reading score by that value, if someone is a grade higher or lower. Since student A is 2 grades higher than student B, we have to multiply this value by 2.)*

```r
29.542707*2
```

```
[1] 59.08541
```

3.4: What is the meaning of the coefficient associated with variable raceethAsian?
Answer: Predicted difference in the reading score between an Asian student and a white student who is otherwise identical

3.5: Based on the significance codes, which variables are candidates for removal from the model?
Answer: preschool, expectBachelors, motherHS, motherWork, fatherHS, fatherWork, selfBornUS, motherBornUS, fatherBornUS, englishAtHome, minutesPerWeekEnglish, studentsInEnglish, schoolHasLibrary, urban

```r
summary(lmScore)
```

```
Call:
lm(formula = readingScore ~ ., data = pisaTrain)

Residuals:
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```
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preschool                                   -4.463670   3.486055  -1.280
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selfBornUS                                  -3.806278   7.323718  -0.520
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                                           Pr(>|t|)
(Intercept)                                2.24e-05 ***
grade                                       < 2e-16 ***
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preschool                                   0.20052
expectBachelors                             < 2e-16 ***
motherHS                                    0.32001
motherBachelors                             0.00108 **
motherWork                                  0.42517
fatherHS                                    0.47147
```

```
fatherBachelors                                    2.35e-05 ***
fatherWork                                          0.18393
selfBornUS                                          0.60331
motherBornUS                                        0.18182
fatherBornUS                                        0.49178
englishAtHome                                       0.24153
computerForSchoolwork                              8.19e-05 ***
read30MinsADay                                      < 2e-16 ***
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studentsInEnglish                                   0.20846
schoolHasLibrary                                    0.18749
publicSchool                                        0.01226 *
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schoolSize                                          0.00294 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 73.81 on 2385 degrees of freedom
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F-statistic: 41.04 on 28 and 2385 DF,  p-value: < 2.2e-16
```

Using the "predict" function and supplying the "newdata" argument, use the lmScore model to predict the reading scores of students in pisaTest. Call this vector of predictions "predTest": *(Do not change the variables in the model (for example, do not remove variables that we found were not significant in the previous part of this problem))*

```r
predTest <- predict(lmScore, newdata = pisaTest)
```

4.1: What is the range between the maximum and minimum predicted reading score on the test set?

Answer: 284.4683

```r
max(predTest) - min(predTest)
```

```
[1] 284.4683
```

4.2.1: What is the sum of squared errors (SSE) of lmScore on the testing set?

Answer: 5762082

```r
SSE <- sum((predTest - pisaTest$readingScore)^2)
SSE
```

```
[1] 5762082
```

4.2.2: What is the root-mean squared error (RMSE) of lmScore on the testing set?
Answer: 76.29079

```r
sqrt(SSE/nrow(pisaTest))
```

```
[1] 76.29079
```

4.3.1: What is the predicted test score used in the baseline model?
Answer: 517.9629

```r
mean(pisaTrain$readingScore)
```

```
[1] 517.9629
```

4.3.2: What is the total sum of squares (SST) on the testing-set?
Answer: 7802354

```r
SST <- sum((mean(pisaTrain$readingScore)-pisaTest$readingScore)^2)
SST
```

```
[1] 7802354
```

4.4: What is the test-set R-squared value of lmScore?
Answer: 0.2614944

```r
R2 <- 1 - SSE/SST
R2
```

```
[1] 0.2614944
```