Exploratory data analysis, prinicipal component analysis and linear regression with R

Code ▾

In this notebook, we will conduct an exploratory data analysis and linear regression with R using the Walmart sales data set from this Kaggle link (https://www.kaggle.com/datasets/yasserh/walmart-dataset?select=Walmart.csv). For that let's load the important libraries for data analysis. Here we will use *pacman* package for managing add on packages. If the packages already exist, it will load them, otherwise it will download and load the packages.

Hide

```
#use require() or library() to load the base packages
require(pacman) # gives a confirmation message
```

```
Loading required package: pacman
```

Hide

```
library(pacman) # load the package, but no confirmation message
```

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```
# We can load all these packages at at time which are commonly used
pacman::p_load(pacman, dplyr, GGally, ggplot2, ggthemes,
  ggvis, httr, lubridate, plotly, rio, rmarkdown, shiny,
  stringr, tidyr)
# you can install the packages independently via " install.packages("package_name")
```

Now let's read in the Walmart dataset and conduct some exploratory data analysis and visualizations. We will utilize the *import* function from rio library to import files like csv, xlsx, txt, etc. Other wise we need to use specific functions like read.csv, read.table, etc.

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```
data1 <- import('../../datasets/Walmart.csv') # specify the path location

# Alternatively we could also use the read.csv(filepath, header = True) option
#data1 = read.csv('../../datasets/Walmart.csv', header = TRUE)
```

Hide

```
# disaplay the first 20 entries of the data
head(data1,20)
```

	Store <int>	Date <chr>	Weekly_Sales <dbl>	Holiday_Flag <int>	Temperature <dbl>	Fuel_Price <dbl>	CPI <dbl>	Unemployment <dbl>
1	1	05-02-2010	1643691	0	42.31	2.572	211.0964	8.106
2	1	12-02-2010	1641957	1	38.51	2.548	211.2422	8.106
3	1	19-02-2010	1611968	0	39.93	2.514	211.2891	8.106
4	1	26-02-2010	1409728	0	46.63	2.561	211.3196	8.106
5	1	05-03-2010	1554807	0	46.50	2.625	211.3501	8.106
6	1	12-03-2010	1439542	0	57.79	2.667	211.3806	8.106
7	1	19-03-2010	1472516	0	54.58	2.720	211.2156	8.106
8	1	26-03-2010	1404430	0	51.45	2.732	211.0180	8.106
9	1	02-04-2010	1594968	0	62.27	2.719	210.8204	7.808
10	1	09-04-2010	1545419	0	65.86	2.770	210.6229	7.808

1-10 of 20 rows   Previous **1** 2 Next

Hide

```
# dimension of the dataset
dim(data1)
```

```
[1] 6435    8
```

The dataset has 6435 rows and 8 columns which correspond to the following attribute

- Store - the store number
- Date - the week of sales
- Weekly_Sales - sales for the given store
- Holiday_Flag - whether the week is a special holiday week 1 – Holiday week 0 – Non-holiday week
- Temperature - Temperature on the day of sale
- Fuel_Price - Cost of fuel in the region
- CPI – Prevailing consumer price index
- Unemployment - Prevailing unemployment rate
- Holiday Events
 Super Bowl: 12-Feb-10, 11-Feb-11, 10-Feb-12, 8-Feb-13
 Labour Day: 10-Sep-10, 9-Sep-11, 7-Sep-12, 6-Sep-13
 Thanksgiving: 26-Nov-10, 25-Nov-11, 23-Nov-12, 29-Nov-13
 Christmas: 31-Dec-10, 30-Dec-11, 28-Dec-12, 27-Dec-13

````
```r
summary(data1)
```
````

````
```
     Store         Date             Weekly_Sales      Holiday_Flag      Temperature       Fuel_Price
 Min.   : 1   Length:6435       Min.   : 209986   Min.   :0.00000   Min.   : -2.06   Min.   :2.472
 1st Qu.:12   Class :character  1st Qu.: 553350   1st Qu.:0.00000   1st Qu.: 47.46   1st Qu.:2.933
 Median :23   Mode  :character  Median : 960746   Median :0.00000   Median : 62.67   Median :3.445
 Mean   :23                     Mean   :1046965   Mean   :0.06993   Mean   : 60.66   Mean   :3.359
 3rd Qu.:34                     3rd Qu.:1420159   3rd Qu.:0.00000   3rd Qu.: 74.94   3rd Qu.:3.735
 Max.   :45                     Max.   :3818686   Max.   :1.00000   Max.   :100.14   Max.   :4.468
      CPI          Unemployment
 Min.   :126.1   Min.   : 3.879
 1st Qu.:131.7   1st Qu.: 6.891
 Median :182.6   Median : 7.874
 Mean   :171.6   Mean   : 7.999
 3rd Qu.:212.7   3rd Qu.: 8.622
 Max.   :227.2   Max.   :14.313
```
````

Since it it is little bit cluttered, let’s take a look at the weekly sales column.

Hide

```
summary(data1$Weekly_Sales)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
 209986  553350  960746 1046965 1420159 3818686 
```

Hide

```
# Let's get the unique store values
unique(data1$Store)
```

```
 [1]  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35
36 37
[38] 38 39 40 41 42 43 44 45
```

So there are 45 Walmart stores in this data set. We need to aggregate the data by store number and add the weekly sales to see if certain stores have more sales compared to others. In order to do this, we will utilize the *group_by* function from dplyr library. Let’s group the data by store number and store the sum of weekly sales into another data frame, gdf.

‘%>%’ is used to combine different functions in R.

Hide

```
gdf <- data1 %>% group_by(data1$Store) %>%
       summarise(Total_sales = sum(Weekly_Sales))
gdf
```

data1$Store <int>	Total_sales <dbl>
1	222402809
2	275382441
3	57586735
4	299543953
5	45475689
6	223756131
7	81598275
8	129951181
9	77789219
10	271617714

1-10 of 45 rows Previous **1** 2 3 4 5 Next

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```
# plot the sales as a function of store number
plot(gdf, col = 'blue', type = 'h', pch = 19, main = "Total Sales", xlab = "Store Number", ylab= "Sales")
```

As we can see, some of the stores have higher cumulative sales compared to others and this could be a regional factor as well. Now let’s see how the sales change as a function of date for a single store, e.g. store 1. For this we will use the *plot_ly* tool in the plotly library.

Hide

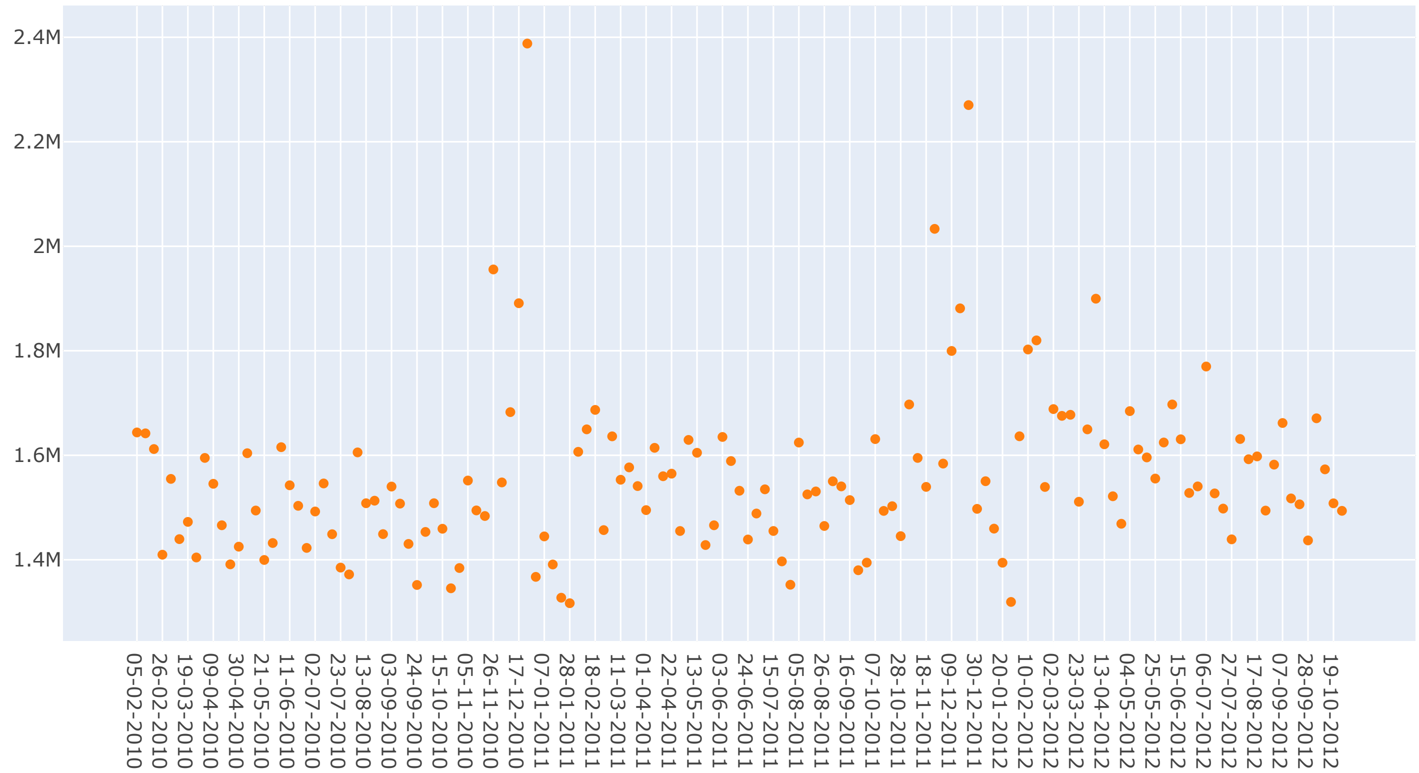
```
#plot the sales as a function of the date as well
fig <- plot_ly(data1, type = 'scatter', mode = 'markers')%>%
  add_trace(x = data1$Date[data1$Store == 1], y = data1$Weekly_Sales[data1$Store == 1])%>%
  layout(showlegend = F)
fig <- fig %>%
  layout(
         xaxis = list(zerolinecolor = '#ffff',
                      zerolinewidth = 2,
                      gridcolor = 'ffff'),
         yaxis = list(zerolinecolor = '#ffff',
                      zerolinewidth = 2,
                      gridcolor = 'ffff'),
         plot_bgcolor='#e5ecf6', width = 900)
```

```
Warning: Specifying width/height in layout() is now deprecated.
Please specify in ggplotly() or plot_ly()
```

Hide

```
fig
```

```
Warning: Can't display both discrete & non-discrete data on same axisWarning: Can't display both discrete & no
n-discrete data on same axis
```



Interesting there is a spike in the weeky sales during the time between Thanksgiving and Christmas in 2010 and 2011. For that we will group the data by date. Let’s plot the same for all stores here.

Hide

```
#plot the sales as a function of the date as well
fig <- plot_ly(data1, type = 'scatter', mode = 'markers')%>%
  add_trace(x = data1$Date, y = data1$Weekly_Sales)%>%
  layout(showlegend = F)
fig <- fig %>%
  layout(
         xaxis = list(zerolinecolor = '#ffff',
                      zerolinewidth = 2,
                      gridcolor = 'ffff'),
         yaxis = list(zerolinecolor = '#ffff',
                      zerolinewidth = 2,
                      gridcolor = 'ffff'),
         plot_bgcolor='#e5ecf6', width = 900)
```

```
Warning: Specifying width/height in layout() is now deprecated.
Please specify in ggplotly() or plot_ly()
```

Hide

```
fig
```

```
Warning: Can't display both discrete & non-discrete data on same axisWarning: Can't display both discrete & no
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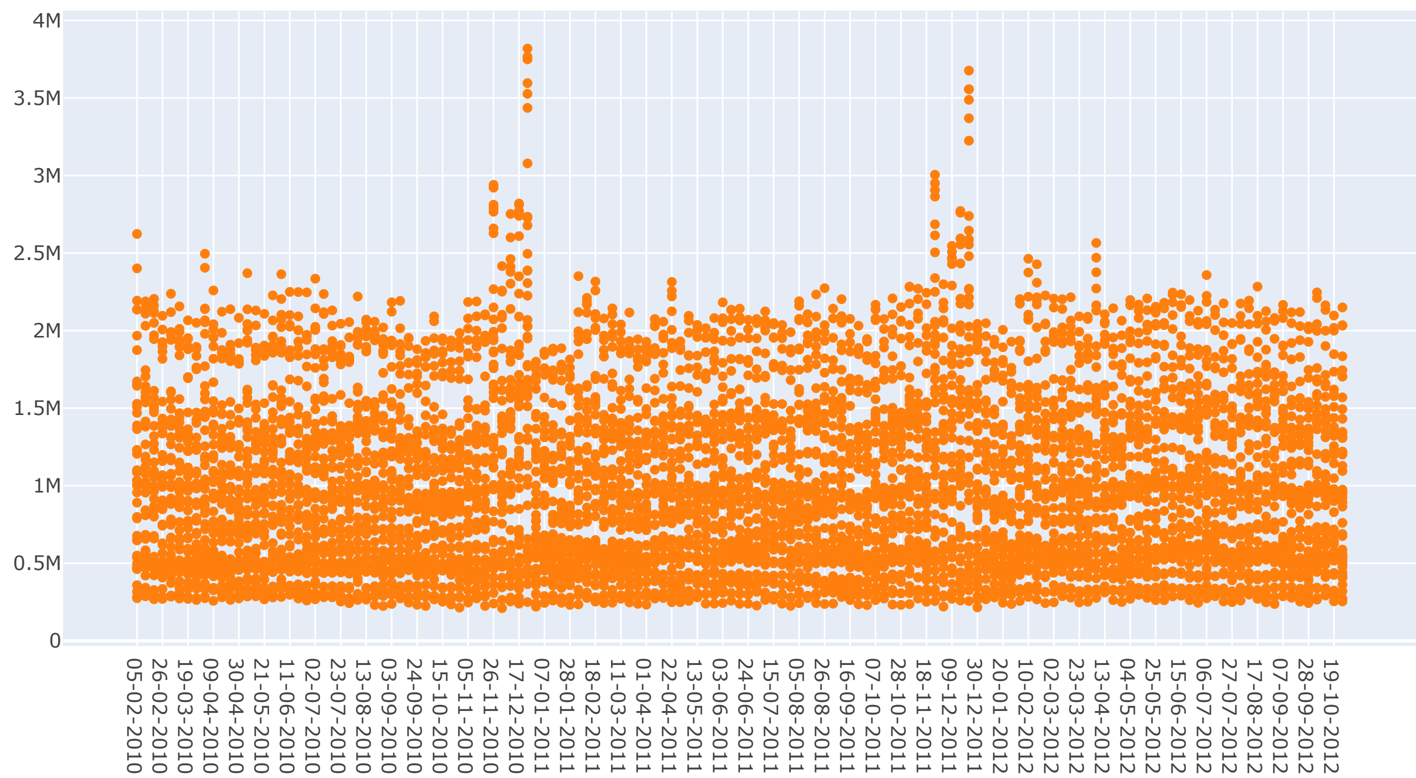

If we look at the holiday events,

- Super Bowl: 12-Feb-10, 11-Feb-11, 10-Feb-12, 8-Feb-13
- Labour Day: 10-Sep-10, 9-Sep-11, 7-Sep-12, 6-Sep-13
- Thanksgiving: 26-Nov-10, 25-Nov-11, 23-Nov-12, 29-Nov-13
- Christmas: 31-Dec-10, 30-Dec-11, 28-Dec-12, 27-Dec-13

We can clearly see an increase in Sales during the holiday season and it always reaches a peak during the time between Thanksgiving and Christmas.

Let’s make a scatter plot of Weekly sales and temperature.

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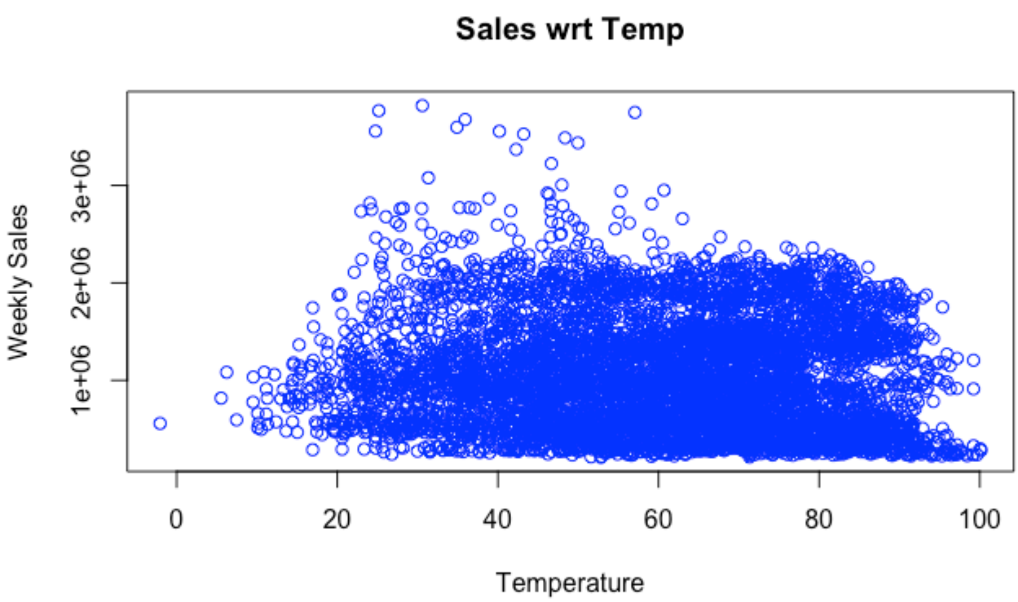
```
plot( data1$Temperature, data1$Weekly_Sales, col = 'blue', main = 'Sales wrt Temp', ylab = "Weekly Sales", xlab = "Temperature")
```



The Weekly sales and temperature seems to be not correlate with each other. Let' make do some more plotting in subplots format to look for correlations using the plotly library

Hide

```
#Initialize figures
fig1 <- plot_ly(x = data1$Holiday_Flag, y = data1$Weekly_Sales, type = 'scatter', name = 'holiday', mode = 'markers') %>%
  layout(xaxis = list(title = 'Holiday Flag'), yaxis = list(title = 'Weekly Sales'))

fig2 <- plot_ly(x = data1$Fuel_Price, y = data1$Weekly_Sales, type = 'scatter', name = 'Fuel', mode = 'markers') %>%
  layout(xaxis = list(title = 'Fuel Price'), yaxis = list(title = 'Weekly Sales'))

fig3 <- plot_ly(x = data1$CPI, y = data1$Weekly_Sales, type = 'scatter', name = 'CPI',  mode = 'markers') %>%
  layout(xaxis = list(title = 'CPI'), yaxis = list(title = 'Weekly Sales'))

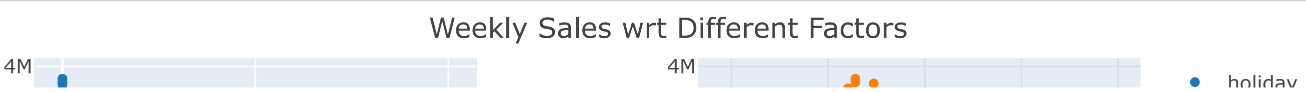
fig4 <- plot_ly(x = data1$Unemployment, y = data1$Weekly_Sales, type = 'scatter', name = 'Unemployment', mode = 'markers') %>%
  layout(xaxis = list(title = 'Unemployment'), yaxis = list(title = 'Weekly Sales'))

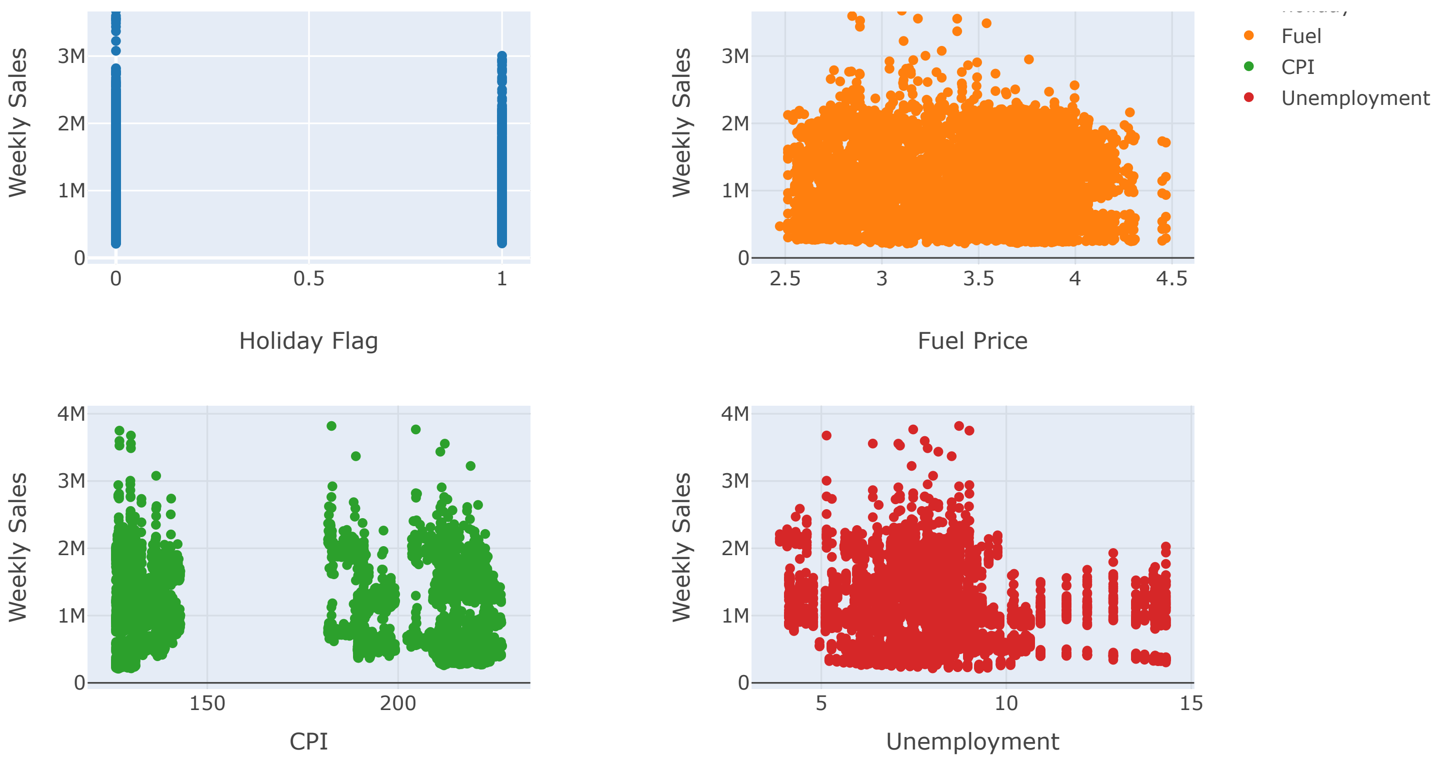
#creating subplot
fig <- subplot(fig1, fig2, fig3, fig4, nrows = 2, titleY = TRUE, titleX = TRUE, margin = 0.1 )
fig <- fig %>%layout(title = 'Weekly Sales wrt Different Factors',
                     plot_bgcolor='#e5ecf6',
         xaxis = list(
           zerolinecolor = '#ffff',
           zerolinewidth = 2,
           gridcolor = 'ffff'),
         yaxis = list(
           zerolinecolor = '#ffff',
           zerolinewidth = 2,
           gridcolor = 'ffff'), autosize = F, width = 900, height = 500)
```

```
Warning: Specifying width/height in layout() is now deprecated.
Please specify in ggplotly() or plot_ly()
```

Hide

```
fig
```





As we can see the weekly sales is not directly correlated with holiday flag, fuel price, CPI. The weekly sales goes down as the unemployment rates go up.

From our primary exploratory data analysis, what we can understand is that the Weekly sales mainly depend on the holiday time and the geographical location/store number in this data set. Also, the Sales are better during lower unemployment index.

Cleaning the data

Let' see if the data has any missing values or Nan values before modeling the data. We will use the *filter* function to filter missing/Nan values and use the *mutate* to replace the bad values.

Hide

```
data1 %>%
  summarise(count = sum(is.na(data1)))
```

count <int>
0

1 row

This data was taken from Kaggle and does not contain any NA/Nan values. But we could introduce some Nan values and clean the data set.

Hide

```
data1[5,5] <- NA
data1[9,5] <- NaN
head(data1, 10)
```

	Store <int>	Date <chr>	Weekly_Sales <dbl>	Holiday_Flag <int>	Temperature <dbl>	Fuel_Price <dbl>	CPI <dbl>	Unemployment <dbl>
1	1	05-02-2010	1643691	0	42.31	2.572	211.0964	8.106
2	1	12-02-2010	1641957	1	38.51	2.548	211.2422	8.106
3	1	19-02-2010	1611968	0	39.93	2.514	211.2891	8.106
4	1	26-02-2010	1409728	0	46.63	2.561	211.3196	8.106
5	1	05-03-2010	1554807	0	NA	2.625	211.3501	8.106
6	1	12-03-2010	1439542	0	57.79	2.667	211.3806	8.106

7	1	19-03-2010	1472516	0	54.58	2.720	211.2156	8.106
8	1	26-03-2010	1404430	0	51.45	2.732	211.0180	8.106
9	1	02-04-2010	1594968	0	NaN	2.719	210.8204	7.808
10	1	09-04-2010	1545419	0	65.86	2.770	210.6229	7.808

1-10 of 10 rows

Now let's try again for NA/NaN values. *is.na* would check for both NA and NaN values while *is.nan* will only check for NaN values.

Hide

```
data1 %>%
  summarise(count = sum(is.na(data1)))
```

count <int>
2

1 row

Hide

```
#is.nan requires a list of data
data1 %>%
  summarise(count = sum(is.nan(data1$Temperature)))
```

count <int>
1

1 row

Let's replace the NA/NaNs with the median values in the data set.

Hide

```
data1 <- data1 %>%
        mutate(Temperature = replace(Temperature, is.na(Temperature), median(Temperature, na.rm = TRUE)))
head(data1, 10)
```

	Store <int>	Date <chr>	Weekly_Sales <dbl>	Holiday_Flag <int>	Temperature <dbl>	Fuel_Price <dbl>	CPI <dbl>	Unemployment <dbl>
1	1	05-02-2010	1643691	0	42.31	2.572	211.0964	8.106
2	1	12-02-2010	1641957	1	38.51	2.548	211.2422	8.106
3	1	19-02-2010	1611968	0	39.93	2.514	211.2891	8.106
4	1	26-02-2010	1409728	0	46.63	2.561	211.3196	8.106
5	1	05-03-2010	1554807	0	62.68	2.625	211.3501	8.106
6	1	12-03-2010	1439542	0	57.79	2.667	211.3806	8.106
7	1	19-03-2010	1472516	0	54.58	2.720	211.2156	8.106
8	1	26-03-2010	1404430	0	51.45	2.732	211.0180	8.106
9	1	02-04-2010	1594968	0	62.68	2.719	210.8204	7.808
10	1	09-04-2010	1545419	0	65.86	2.770	210.6229	7.808

1-10 of 10 rows

Preprocessing

Before modeling the data, we need to convert the dates into a more meaning full numbers. In our case, rather than converting days into some numbers, we need it as a cyclic variable going from 1-365 as our sales are a function of different time of an year, especially the holiday time. Let's write a function to do that.

Hide

```
#defining a function to convert the dates into day in a year
date_to_number <- function(dates){
  num_date <- c()
  #print(length(num_date))
  for (i in seq(1:length(dates))){
      date <-  dates[i]
      d <- strtoi(substr(date, 1, 2), 10) # getting the string values and converting to integers, using base 1
0 here.
      m <- strtoi(substr(date, 4, 5), 10)
      y <- strtoi(substr(date, 7, 10), 10)

      num_date <- append(num_date, m*30 + d)

      #cat(i, date, num_date[[i]], "\n")
  }
  return (num_date)
}

new_dates <- date_to_number(data1$Date)
#print(new_dates)

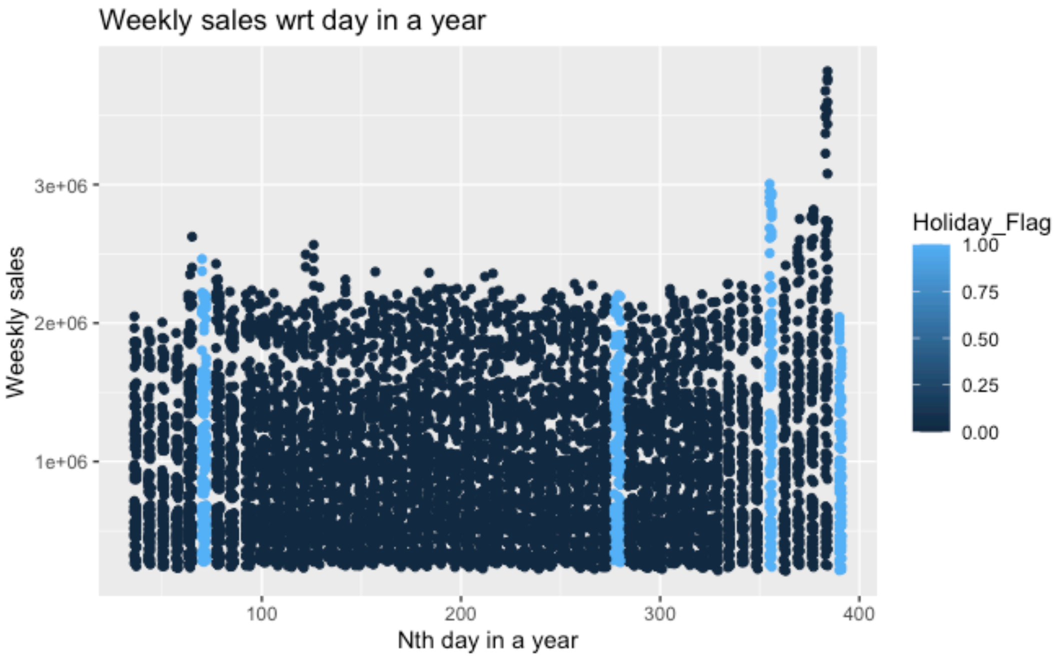
# add the new date numbers to the dataframe
data1 <- data1 %>%
         mutate(date_number = new_dates)
head(data1,6)
```

	Store <int>	Date <chr>	Weekly_Sales <dbl>	Holiday_Flag <int>	Temperature <dbl>	Fuel_Price <dbl>	CPI <dbl>	Unemployment <dbl>
1	1	05-02-2010	1643691	0	42.31	2.572	211.0964	8.106
2	1	12-02-2010	1641957	1	38.51	2.548	211.2422	8.106
3	1	19-02-2010	1611968	0	39.93	2.514	211.2891	8.106
4	1	26-02-2010	1409728	0	46.63	2.561	211.3196	8.106
5	1	05-03-2010	1554807	0	62.68	2.625	211.3501	8.106
6	1	12-03-2010	1439542	0	57.79	2.667	211.3806	8.106

6 rows | 1-9 of 9 columns

Hide

```
# Now let's make a plot using ggplot to plot the sales as a fuction of the new date numbers we created
ggplot(data = data1, mapping = aes(y = Weekly_Sales, x = date_number, color = Holiday_Flag)) + geom_point() +
labs(title = "Weekly sales wrt day in a year", x = "Nth day in a year", y = "Weeskly sales")
```



One interesting thing to note here is that, some of the high sales time between after Thanksgiving and before Christmas has been marked as not a holiday flag which might affect the modeling of the data.

Correlation calculation

Let's build a correlation matrix first using the Pearson correlation coefficient.

Hide

```
data_new <- data1[-2] # removing the dates column
head(data_new)
```

	Store <int>	Weekly_Sales <dbl>	Holiday_Flag <int>	Temperature <dbl>	Fuel_Price <dbl>	CPI <dbl>	Unemployment <dbl>	date_number <dbl>
1	1	1643691	0	42.31	2.572	211.0964	8.106	65
2	1	1641957	1	38.51	2.548	211.2422	8.106	72
3	1	1611968	0	39.93	2.514	211.2891	8.106	79
4	1	1409728	0	46.63	2.561	211.3196	8.106	86
5	1	1554807	0	62.68	2.625	211.3501	8.106	95
6	1	1439542	0	57.79	2.667	211.3806	8.106	102

6 rows

Hide

```
#use the cor function to get the correlation of features in the data frame
res = cor(data_new)
round(res,2)
```

```
             Store Weekly_Sales Holiday_Flag Temperature Fuel_Price   CPI Unemployment date_number
Store         1.00        -0.34         0.00       -0.02       0.06 -0.21         0.22        0.00
Weekly_Sales -0.34         1.00         0.04       -0.06       0.01 -0.07        -0.11        0.07
Holiday_Flag  0.00         0.04         1.00       -0.16      -0.08  0.00         0.01        0.13
Temperature  -0.02        -0.06        -0.16        1.00       0.14  0.18         0.10        0.24
Fuel_Price    0.06         0.01        -0.08        0.14       1.00 -0.17        -0.03       -0.04
CPI          -0.21        -0.07         0.00        0.18      -0.17  1.00        -0.30        0.01
Unemployment  0.22        -0.11         0.01        0.10      -0.03 -0.30         1.00       -0.01
date_number   0.00         0.07         0.13        0.24      -0.04  0.01        -0.01        1.00
```

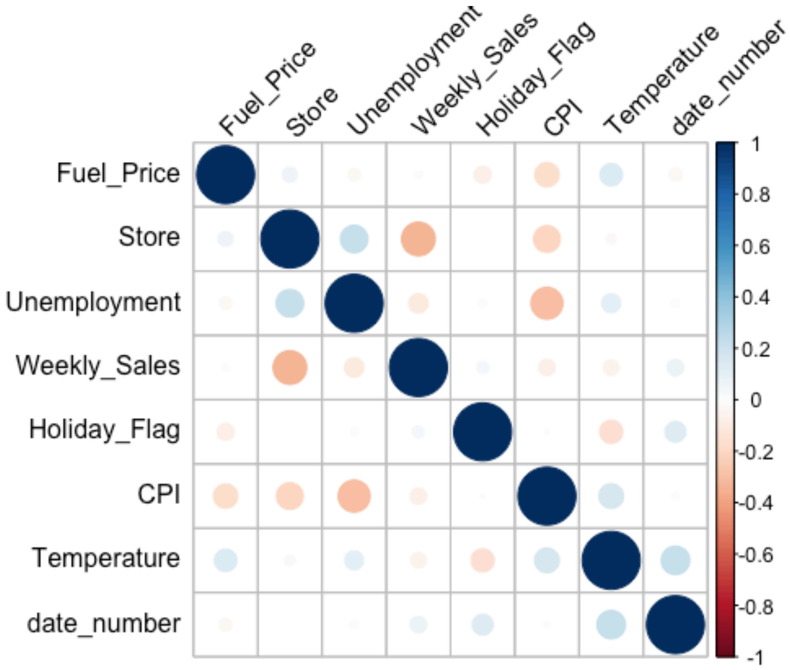
Hide

```
# Let's import the corrplot library for the visualization of the correlation
library(corrplot)
```

```
corrplot 0.92 loaded
```

Hide

```
corrplot(res, type = "full", order = "hclust",
         tl.col = "black", tl.srt = 45)
```



In this correlogram, the radius of the circle represent the correlation strength and the colors represents the positive/negative correlation. As we can see, for the weekly sales has some correlation with the store number and it weakly/not correlated with the rest of features.

Principal component analysis

Before modeling of the data, let's do principal component analysis (PCA) of the data for visualization and understand the correlation within the data set.

Hide

```
# using prcomp function for PCA
pc <- prcomp(data_new,
        center = TRUE,  # Centers means to 0 (optional)
        scale = TRUE)   # Sets unit variance (helpful)

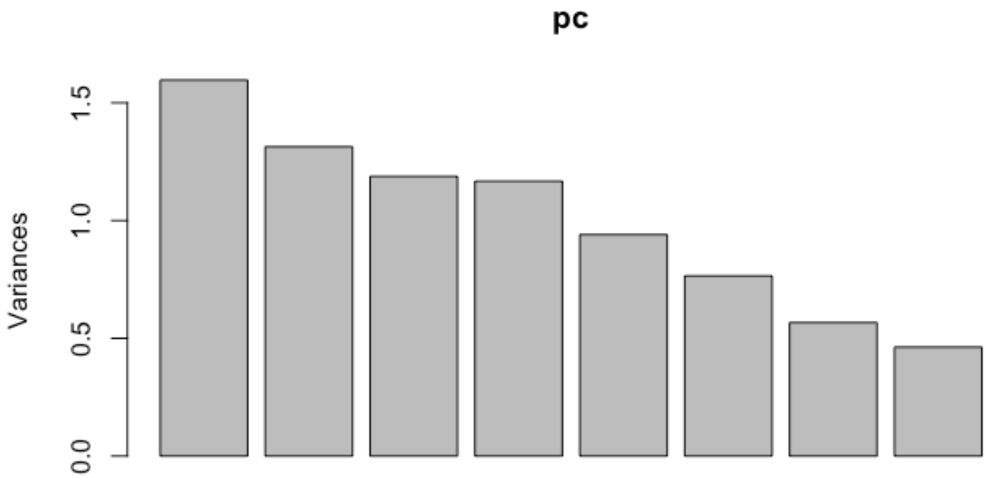
# Get summary stats
summary(pc)
```

```
Importance of components:
                          PC1    PC2    PC3    PC4    PC5     PC6     PC7     PC8
Standard deviation     1.2636 1.1461 1.0898 1.0803 0.9697 0.87475 0.75293 0.68023
Proportion of Variance 0.1996 0.1642 0.1484 0.1459 0.1176 0.09565 0.07086 0.05784
Cumulative Proportion  0.1996 0.3638 0.5122 0.6581 0.7756 0.87130 0.94216 1.00000
```

As you can see the variance is mostly spread out and the data is not much correlated.

Hide

```
#Screeplot for number of components
plot(pc)
```



Hide

```
# Get standard deviations and rotation
pc
```

```
Standard deviations (1, .., p=8):
[1] 1.2636174 1.1460754 1.0897825 1.0802661 0.9697365 0.8747479 0.7529284 0.6802261

Rotation (n x k) = (8 x 8):
                     PC1         PC2        PC3        PC4         PC5         PC6         PC7          PC8
Store        -0.58302714  0.06282082  0.1876872  0.1645521 -0.23624741 -0.32652943  0.65674624 -0.008894007
Weekly_Sales  0.37061204 -0.24412301 -0.5807988 -0.1815134  0.21885436 -0.05564072  0.61394405 -0.069684476
Holiday_Flag  0.04756473 -0.31022505 -0.1891669  0.5898542 -0.45713176  0.51900724  0.07426895  0.184206619
Temperature   0.01940246  0.75361202 -0.1550988  0.0101879  0.13179102  0.28400046  0.18263804  0.525500962
Fuel_Price   -0.16554419  0.21550230 -0.3006047 -0.5389580 -0.61367045  0.23289369 -0.05610621 -0.333670674
CPI           0.47216154  0.30498145  0.4688994  0.1664354 -0.04469587  0.22873143  0.30464448 -0.537920392
Unemployment -0.51150062  0.02703337 -0.2094692  0.1523670  0.52771281  0.44046373 -0.03216957 -0.443868529
date_number   0.09007179  0.36345716 -0.4620599  0.5005512 -0.11349736 -0.48958352 -0.23641808 -0.295411396
```

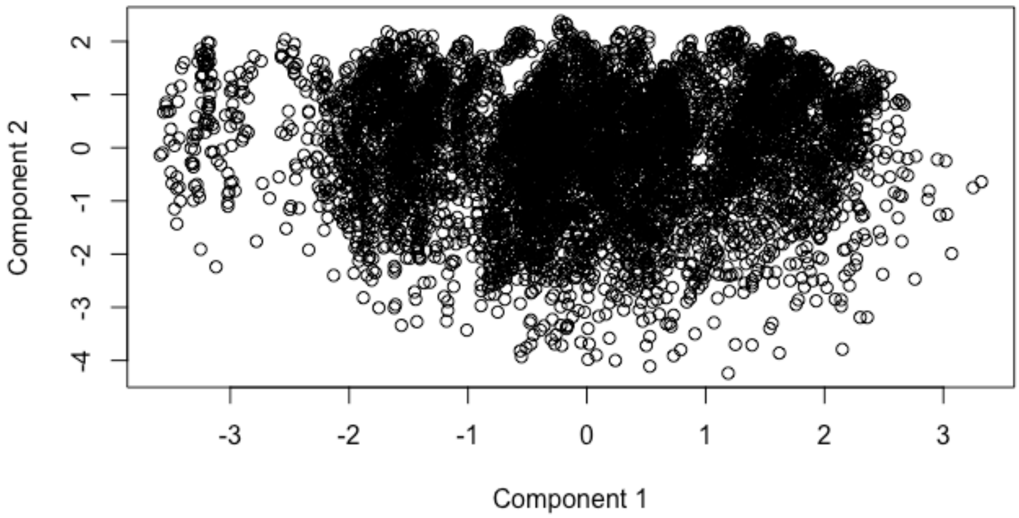
Hide

```
# See how cases load on PCs
pre <- predict(pc) %>% round(2)
dim(pre)
```

```
[1] 6435    8
```

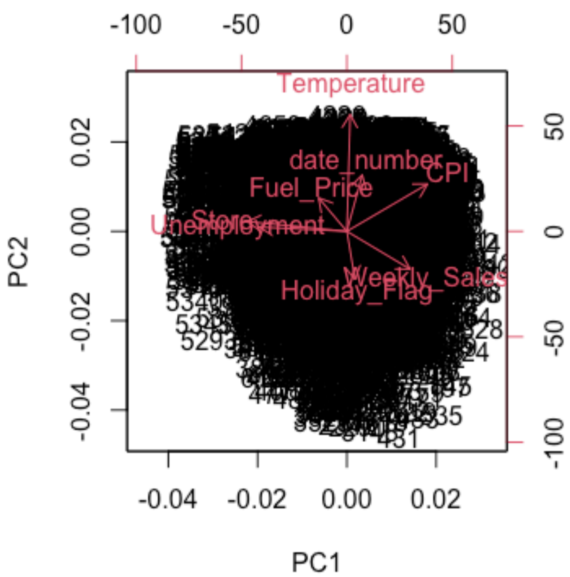
Hide

```
#plotting the first 2 components
plot(pre[,1], pre[,2], xlab = "Component 1", ylab = "Component 2")
```



Hide

```
# Biplot of first two components
biplot(pc)
```



As you can see, there the first 2 principal components only explains only 36% of the data and they don't have any linear correlation as well. Here in the biplot, length of vectors denote how much it has contributed to the component and cos(angle between vectors) is proportional to the correlation between them. As you can see, the weekly sales and holiday flag are correlated.

Multivariate linear regression

Now let's do the multivariate modeling of the data. For that let's define the x and y data.

Hide

```
# Let's shuffle the dataset before splitting
data_shuff <- data1[sample(1:nrow(data1)),]

# define x and y values
x = data_shuff[c(-2, -3)]
x <- as.matrix(x)
y <- data_shuff$Weekly_Sales

# let's split the data into test, validatation and test datasets with 70:20:10 ratio
# In total the dataset has 6435 rows
xtrain <- x[1:4504,]
ytrain <- y[1:4504]

xval <- x[4505:5792, ]
yval <- x[4505:5792]

xtest <- x[5793:6435,]
ytest <- y[5793:6435]
```

Hide

```
# Now let's use a linear model on the test dataset first
reg_test <- lm(ytrain ~ xtrain)

reg_test # print the coefficients only
```

```
Call:
lm(formula = ytrain ~ xtrain)

Coefficients:
       (Intercept)         xtrainStore  xtrainHoliday_Flag   xtrainTemperature    xtrainFuel_Price
           1913703              -15449               11643               -2114               15201
         xtrainCPI  xtrainUnemployment   xtraindate_number
             -2304              -18689                 522
```

Hide

```
summary(reg_test)  # Inferential tests
```

```
Call:
lm(formula = ytrain ~ xtrain)

Residuals:
     Min       1Q   Median       3Q      Max
-1078640  -381087   -50982   378883  2578371

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)        1913702.51   91775.33  20.852  < 2e-16 ***
xtrainStore         -15449.14     622.81 -24.806  < 2e-16 ***
xtrainHoliday_Flag   11642.94   31222.65   0.373    0.709
xtrainTemperature    -2113.65     464.28  -4.552 5.44e-06 ***
xtrainFuel_Price     15201.16   17800.35   0.854    0.393
xtrainCPI            -2304.11     219.76 -10.485  < 2e-16 ***
xtrainUnemployment  -18689.43    4537.29  -4.119 3.87e-05 ***
xtraindate_number      521.95      83.43   6.256 4.31e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 521700 on 4496 degrees of freedom
Multiple R-squared:  0.1492,    Adjusted R-squared:  0.1479
F-statistic: 112.7 on 7 and 4496 DF,  p-value: < 2.2e-16
```

Let’ look at the actaual weekly sales and predicted weekly sales from the training data

Hide

```
pred_ytrain <- predict(reg_test, newdata = as.data.frame(xtrain))

for (i in seq(1:30)){
  str <- sprintf("Actual : %f, predicted :%f \n", ytrain[i], pred_ytrain[i])
  cat(str)
}
```

```
Actual : 326469.430000, predicted :768448.919239
Actual : 897032.190000, predicted :1287480.554505
Actual : 679481.900000, predicted :1296819.114757
Actual : 1019555.510000, predicted :1192692.926764
Actual : 514731.600000, predicted :1252493.799091
Actual : 966817.240000, predicted :1176342.965302
Actual : 688958.750000, predicted :958557.542685
Actual : 1442873.220000, predicted :1178406.498477
Actual : 706924.020000, predicted :926379.794751
Actual : 650263.950000, predicted :626701.311367
Actual : 948977.500000, predicted :1210529.606338
Actual : 1974646.780000, predicted :1321350.866209
Actual : 1946070.880000, predicted :1224361.821098
Actual : 877423.450000, predicted :624935.747533
Actual : 933924.440000, predicted :918810.396511
Actual : 891148.550000, predicted :1186539.269679
Actual : 1408016.100000, predicted :1246706.498348
Actual : 466594.890000, predicted :1263417.682197
Actual : 1377593.100000, predicted :1299543.055120
Actual : 1391256.120000, predicted :1247528.898717
Actual : 316203.640000, predicted :1214197.533739
Actual : 1840491.410000, predicted :1296546.653124
Actual : 351925.360000, predicted :911242.126161
Actual : 2135982.790000, predicted :1092136.394474
Actual : 2205919.860000, predicted :1190321.481930
Actual : 670993.010000, predicted :548445.285882
Actual : 1052895.250000, predicted :1107792.718489
Actual : 1593655.960000, predicted :1077762.430768
Actual : 1418697.050000, predicted :1086498.351999
Actual : 611390.670000, predicted :1242934.794579
```

The R statistics should be close to 1 and in our case we are getting 0.14. Also the residual error is really high. Maybe our simple multivariate regression model is not good enough for the prediction purpose here which is also evident after looking at the first 30 actual weekly sales and predicted sales. Feature engineering could have been done if some of the features exhibited some non-linear relationship with the Weekly sales.

We will revisit this problem with a polynomial regression and decision tree regression in the future.

Hide

```
# How to clear packages
#p_unload(dplyr, tidyr, stringr) # Clear specific packages
p_unload(all)  # Easier: clears all add-ons
```

```
The following packages have been unloaded:
corrplot, tidyr, stringr, shiny, rmarkdown, rio, plotly, lubridate, httr, ggvis, ggthemes, GGally, ggplot2, d
plyr, pacman
```

Hide

```
#detach("package:datasets", unload = TRUE)  # For base packages

# Clear console
#cat("\014")  # ctrl+L
```