Advances in Data Sciences

Final Project Report

Team 8

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Rossmann Store Sales Analysis

1.1 Problem Statement

Rossmann operates over 3,000 drug stores in 7 European countries. Currently, Rossmann store managers are tasked with predicting their daily sales for up to six weeks in advance. Store sales are influenced by many factors, including promotions, competition, school and state holidays, seasonality, and locality. With thousands of individual managers predicting sales based on their unique circumstances, the accuracy of results can be quite varied. In this case study, we focus on daily sales for 1,115 stores located across Germany.

1.2 Background and Summary

Rossmann is Germany's second-largest drug store chain, with other 3,000 stores in 7 European countries. Rossmann Store sells prescription drugs and a wide assortment of general merchandise, including over-the-counter drugs, beauty products and cosmetics. It also provides healthcare services through its more than 1000 MinuteClinic medical clinics as well as their Diabetes Care Centers. Currently, Rossmann store managers are tasked with predicting their daily sales for up to six weeks in advance. Store sales are influenced by many factors, including promotions, competition, school and state holidays, seasonality, and locality. With thousands of individual managers predicting sales based on their unique circumstances, the accuracy of results can be quite varied.

1.3 Dataset

Most of the fields are self-explanatory. The following are descriptions for those that aren't.

- **Id** - an Id that represents a (Store, Date) duple within the test set
- **Store** - a unique Id for each store
- **Sales** - the turnover for any given day (this is what you are predicting)

- **Customers** - the number of customers on a given day
- **Open** - an indicator for whether the store was open: 0 = closed, 1 = open
- **StateHoliday** - indicates a state holiday. Normally all stores, with few exceptions, are closed on state holidays. Note that all schools are closed on public holidays and weekends. a = public holiday, b = Easter holiday, c = Christmas, 0 = None
- **SchoolHoliday** - indicates if the (Store, Date) was affected by the closure of public schools
- **StoreType** - differentiates between 4 different store models: a, b, c, d
- **Assortment** - describes an assortment level: a = basic, b = extra, c = extended
- **CompetitionDistance** - distance in meters to the nearest competitor store
- **CompetitionOpenSince[Month/Year]** - gives the approximate year and month of the time the nearest competitor was opened
- **Promo** - indicates whether a store is running a promo on that day
- **Promo2** - Promo2 is a continuing and consecutive promotion for some stores: 0 = store is not participating, 1 = store is participating
- **Promo2Since[Year/Week]** - describes the year and calendar week when the store started participating in Promo2
- **PromoInterval** - describes the consecutive intervals Promo2 is started, naming the months the promotion is started anew. E.g. "Feb,May,Aug,Nov" means each round starts in February, May, August, November of any given year for that store

1.4 Evaluation Criteria

Predictions are evaluated on the Root Mean Square Percentage Error(RMSPE). Lower the score better will be the prediction.

$$\mathrm{RMSPE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2},$$

where Sales denotes the sales of a single store on a single day and PredSales denotes the corresponding prediction. Store with 0 sales is ignored in scoring.

1.5 Impact of Solution

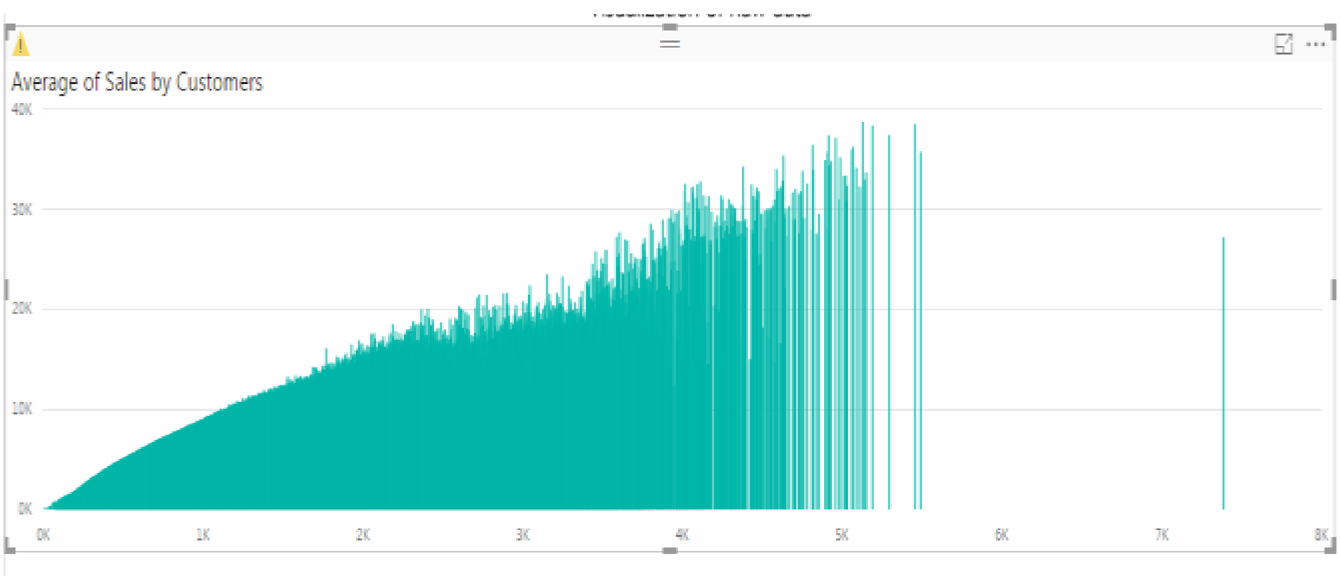
- Better management of staff schedules.
- Provide enough time to store managers to focus on customers and their teams.
- Increase efficiency of employees.

1.6 Power BI Analysis

1.6.1 Visualization of Raw Input File

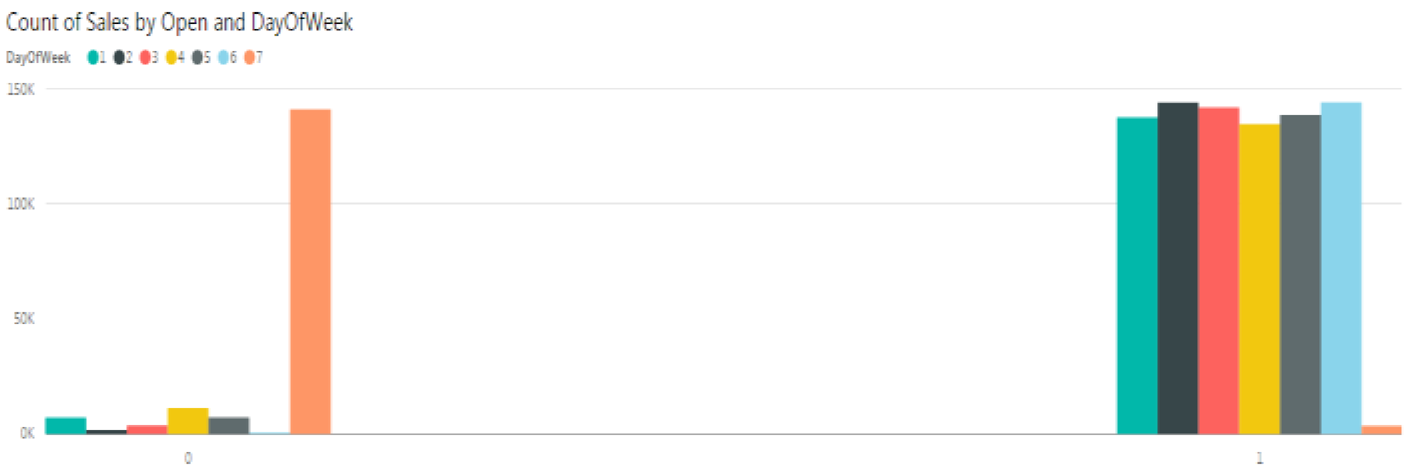
Graph1: Average Sales as per customers

- This graph shows that Average sales vary as per the number of customers in the store. Sales depends on various other factors like date, Day of Week, it's a holiday or not, etc.



Graph 2: Count of Sales by Open and DayofWeek

- This graph represents how sales varies as per ‘Open’ status and which Dayof Week it is. Sales is more on weekends as well as when the ‘Open’ status is 1.

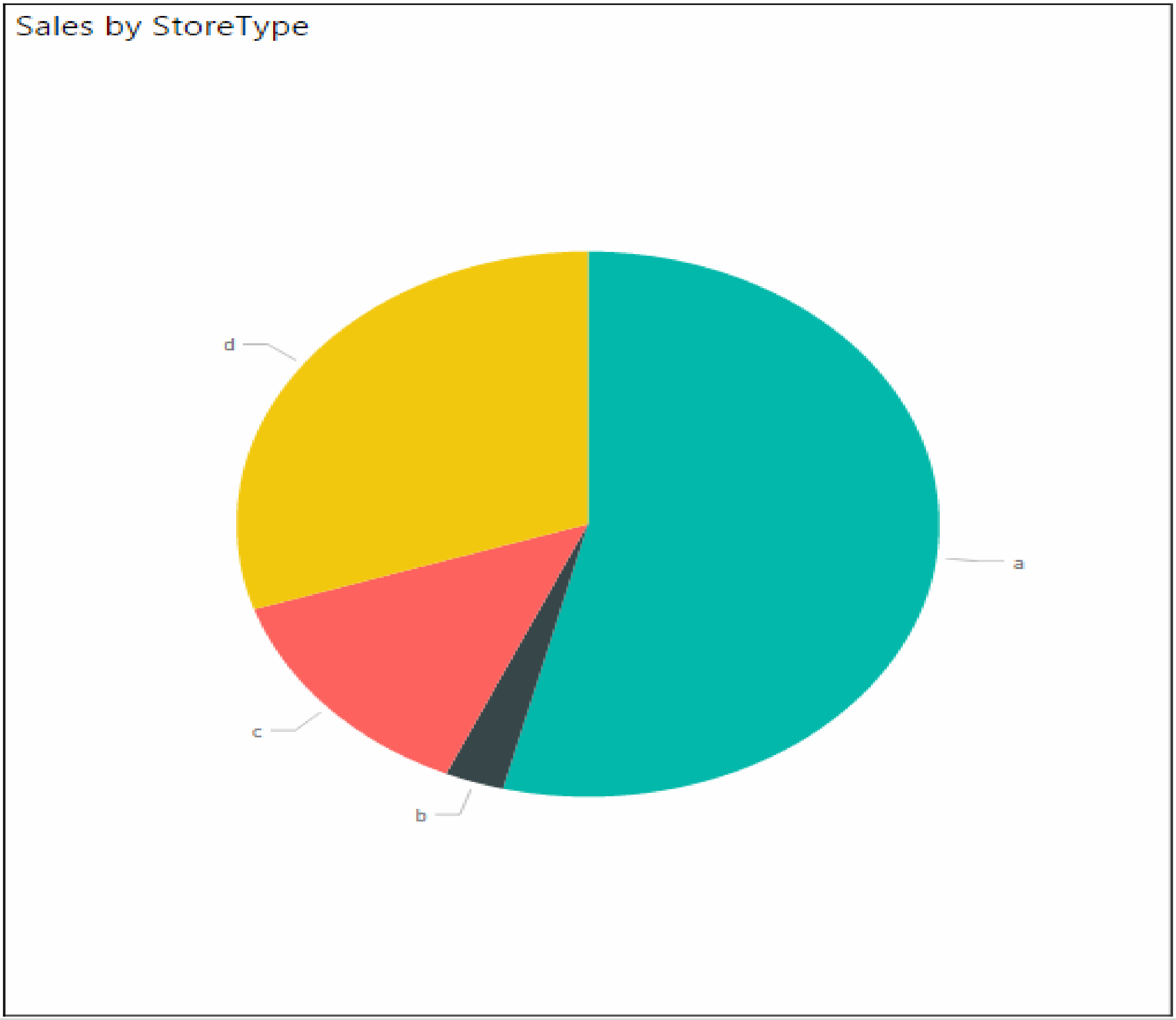


Graph 3: Count of Store by Store Type

- This graph represents the number of stores as per the Store Type. Various Store Types are a,b,c and d.

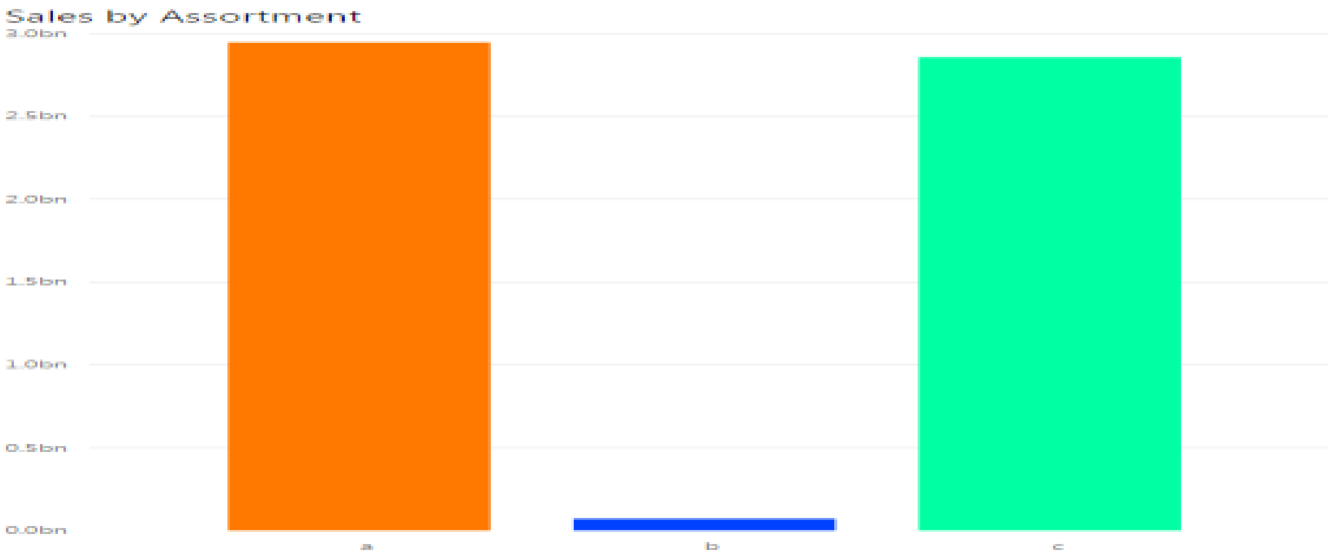
Graph 4: Sales by Store Type

- This graph represents Average of Sales as per each store. So on an average Store Type b have maximum sales.



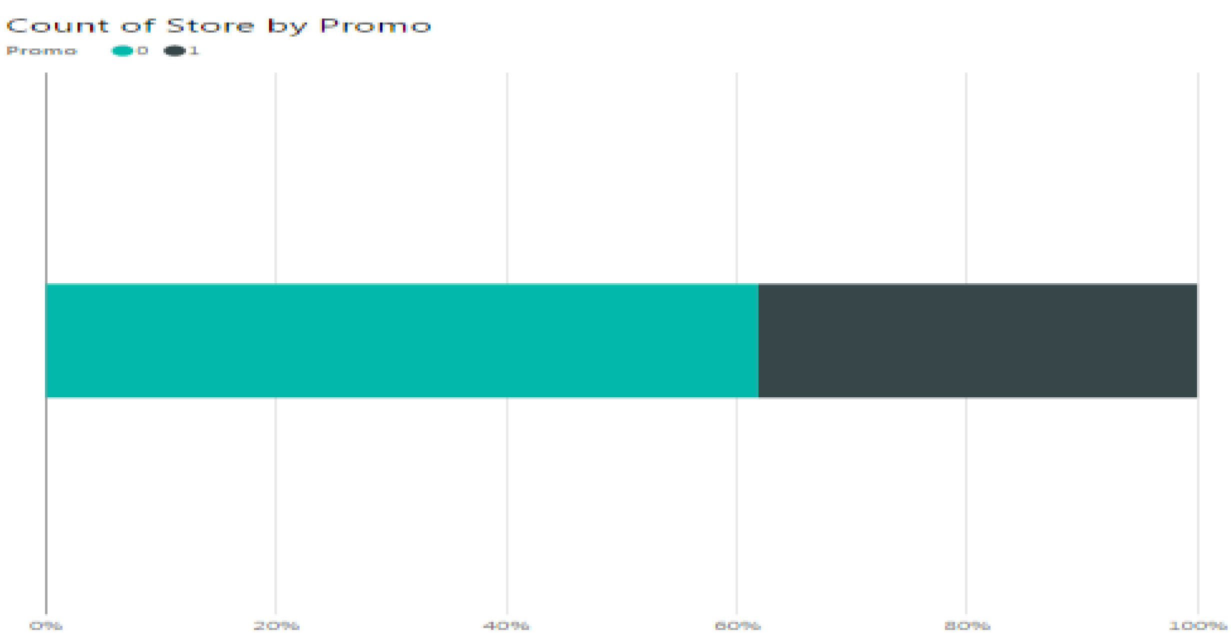
Graph 5: Count of Sales by Assortment

➢ Assortment basically specifies the type of store i.e. if its Basic,extra or extender. This graph shows Sales as per Assortment Type.



Graph 6: Count of Store by Promo

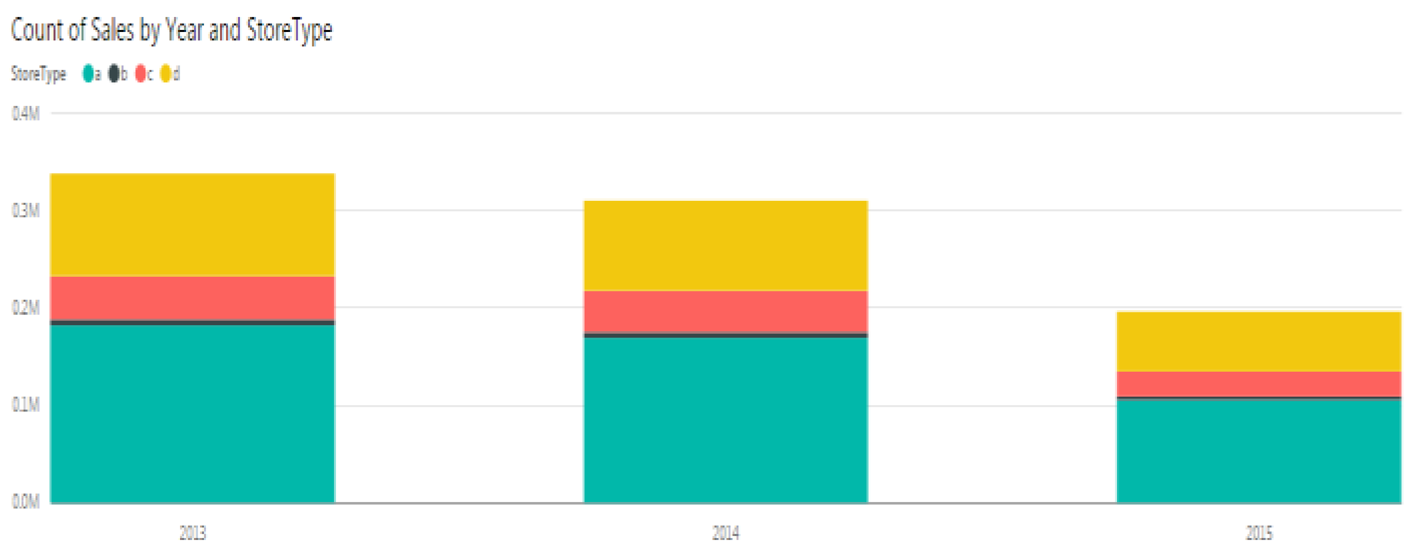
➢ **This graph displays the count of store by promo. It shows that there are more stores which do not offer any promotions.**



1.6.2 Visualization on Cleaned File

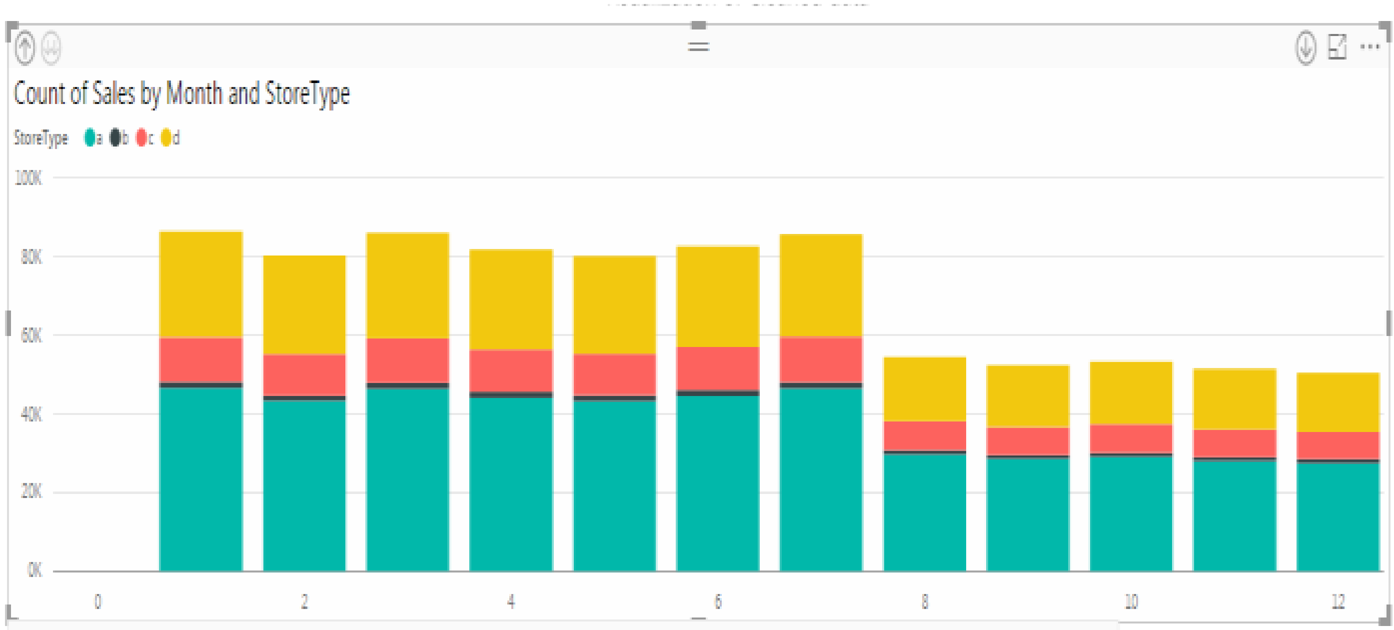
Graph 1: Count of Sales by Year and Store Type

- This graph shows Sales count for every year as per the Store Type.



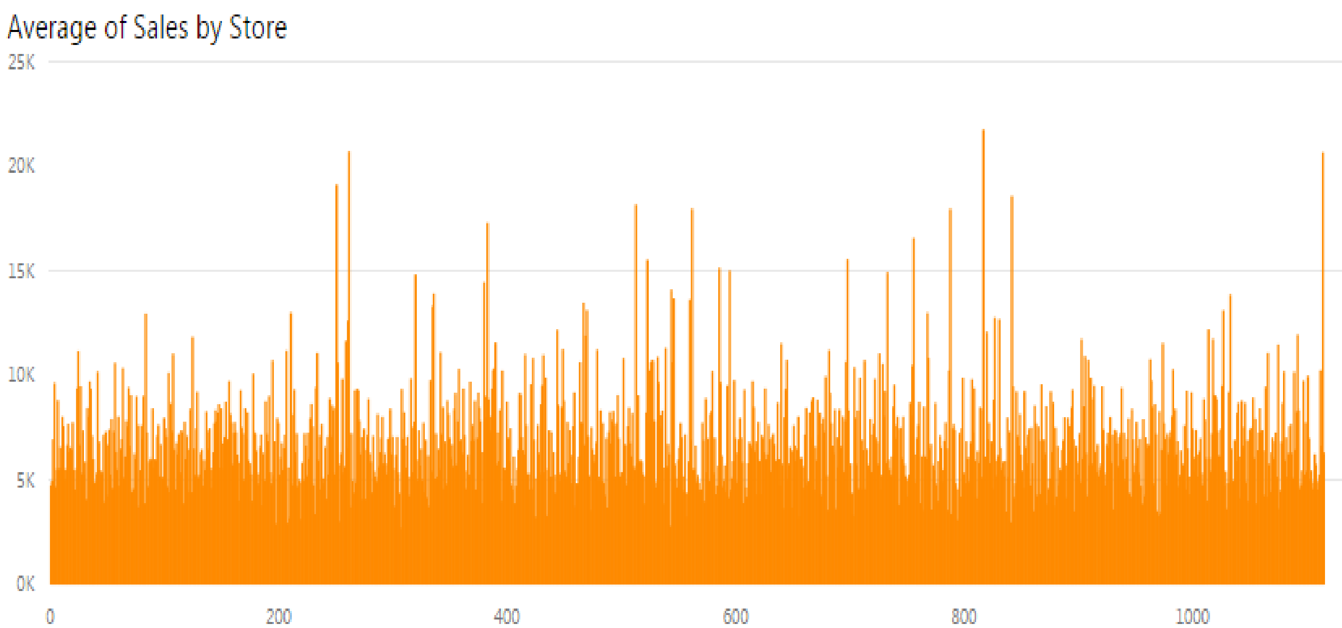
Graph 2: Count of Sales by Month and Store Type

- This graph shows Sales count for every month as per the Store Type.



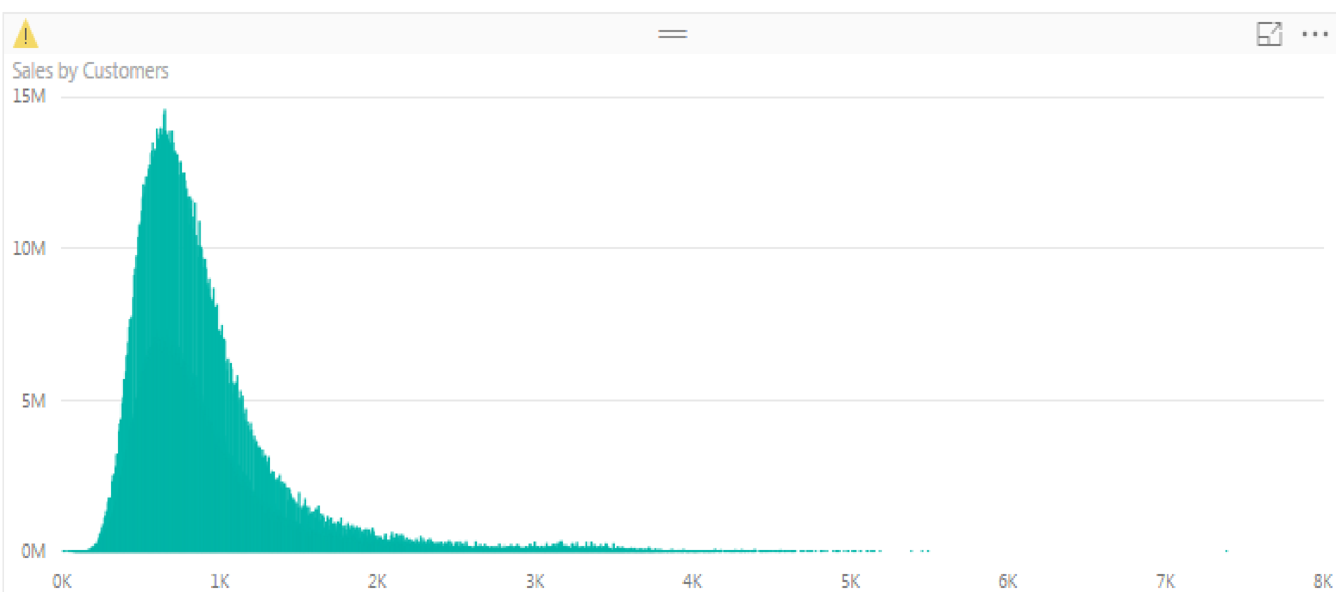
Graph 3: Sales by Store

- This graph shows Average Sales by each Store.



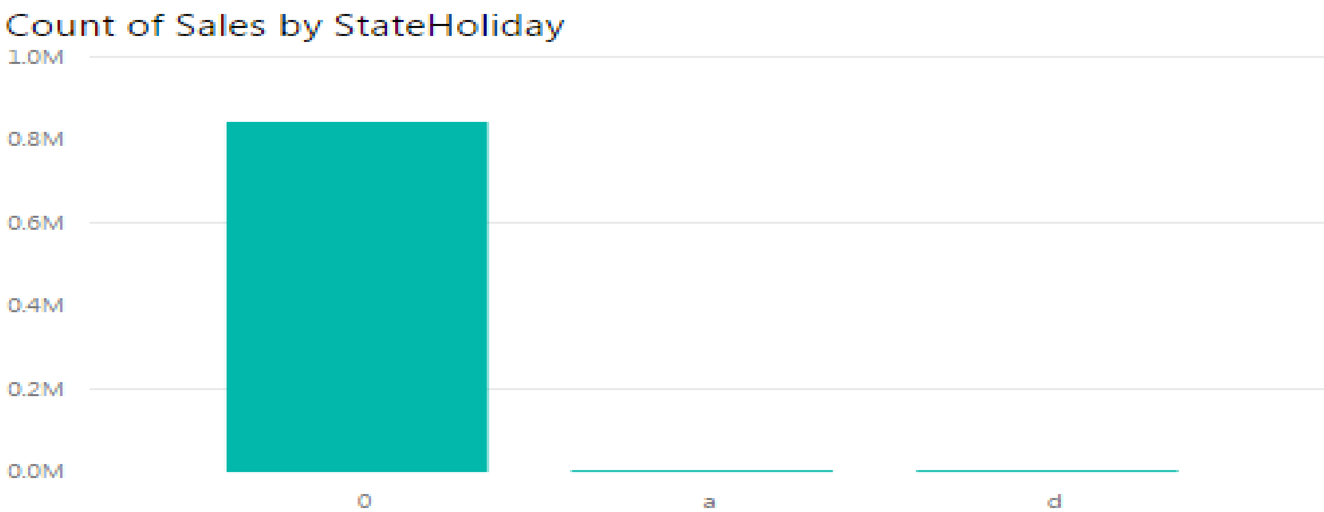
Graph 4: Sales by Customers

- This graph shows the Sales count as per number of Customers.



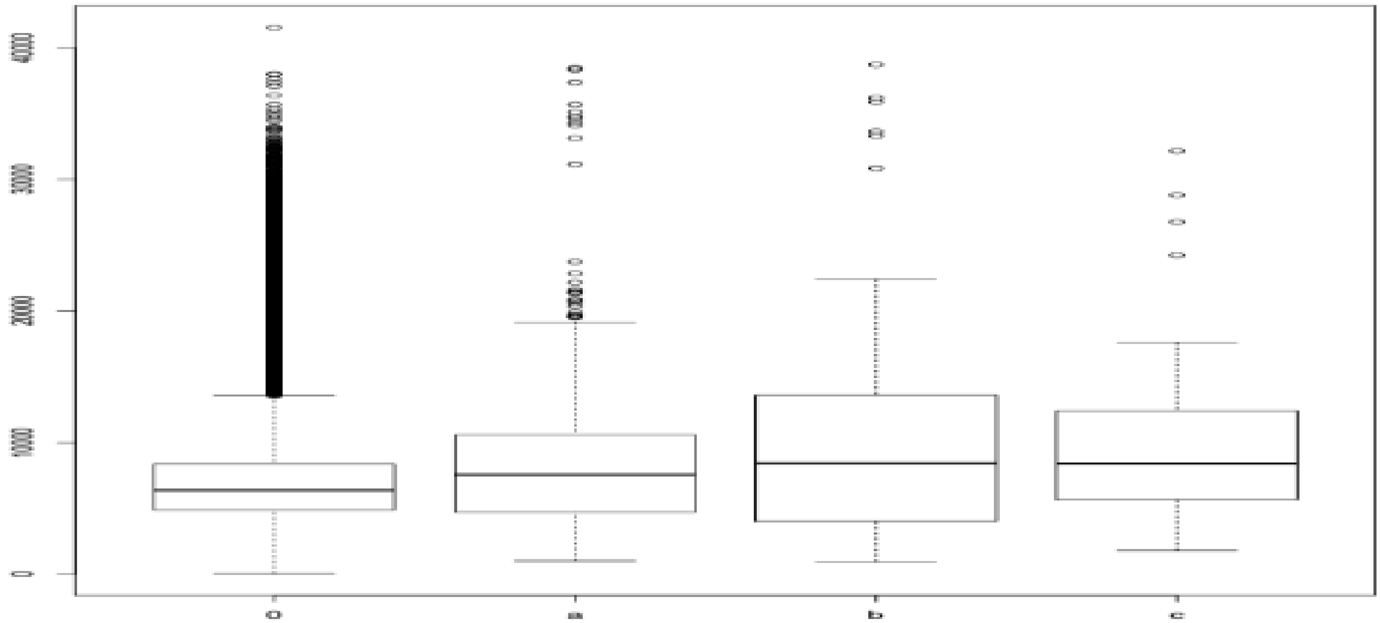
Graph 5: Sales by State Holiday

- **This graph shows the Count of Sales as per the type of State Holidays.**

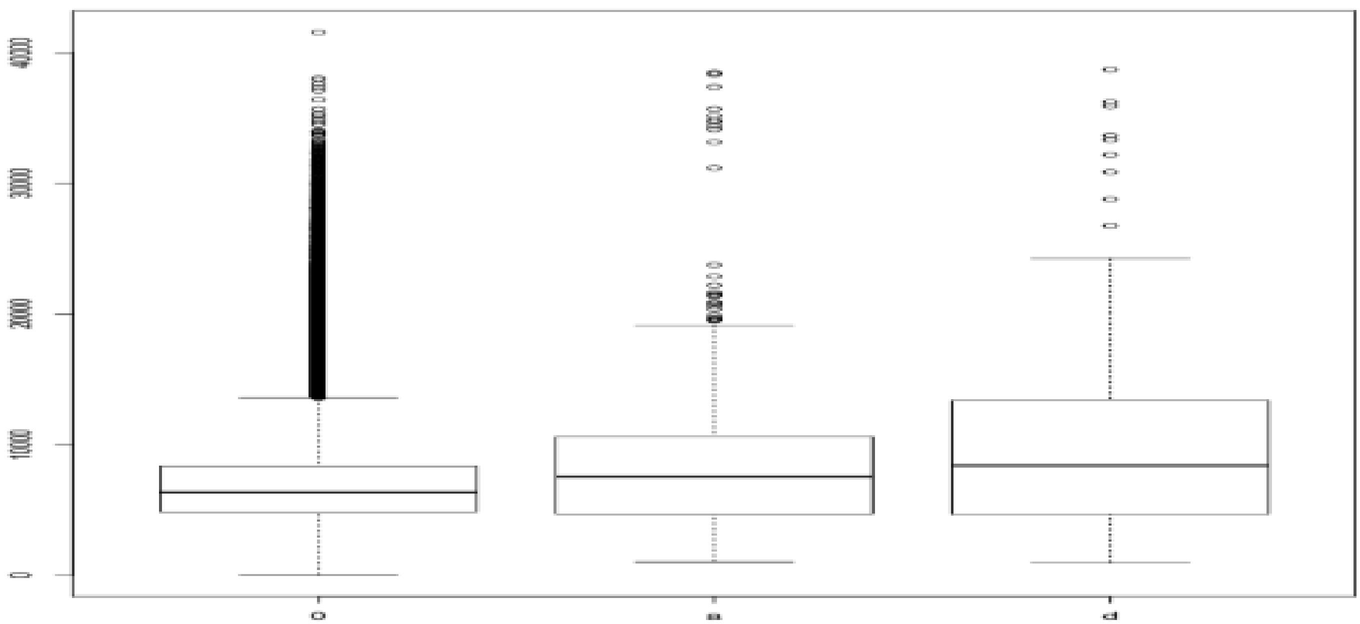


a= Public Holiday, 0= no holiday, d= Combination of Easter Holiday and Christmas Holiday

<u>Note</u>: We have combined StateHoliday for b=Easter Holiday and c=Christmas Holiday as d because State Holiday a, b, c's sales distribution is not similar. However, State Holiday==b only has 145 data points. StateHoliday==c only has 71 data points. Since the training data points are not large, we combined State Holiday b and c as one category as depicted in the boxplot below.



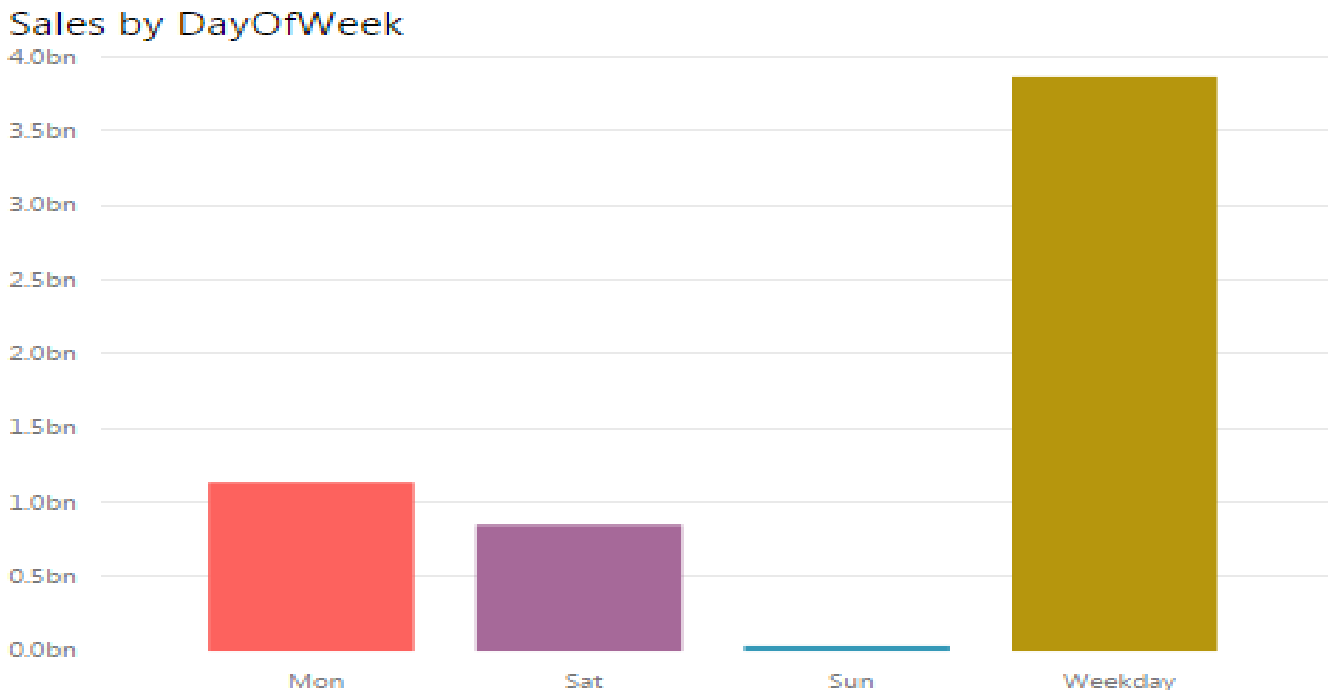
Boxplot of Sales as per StateHoliday in uncleaned dataset



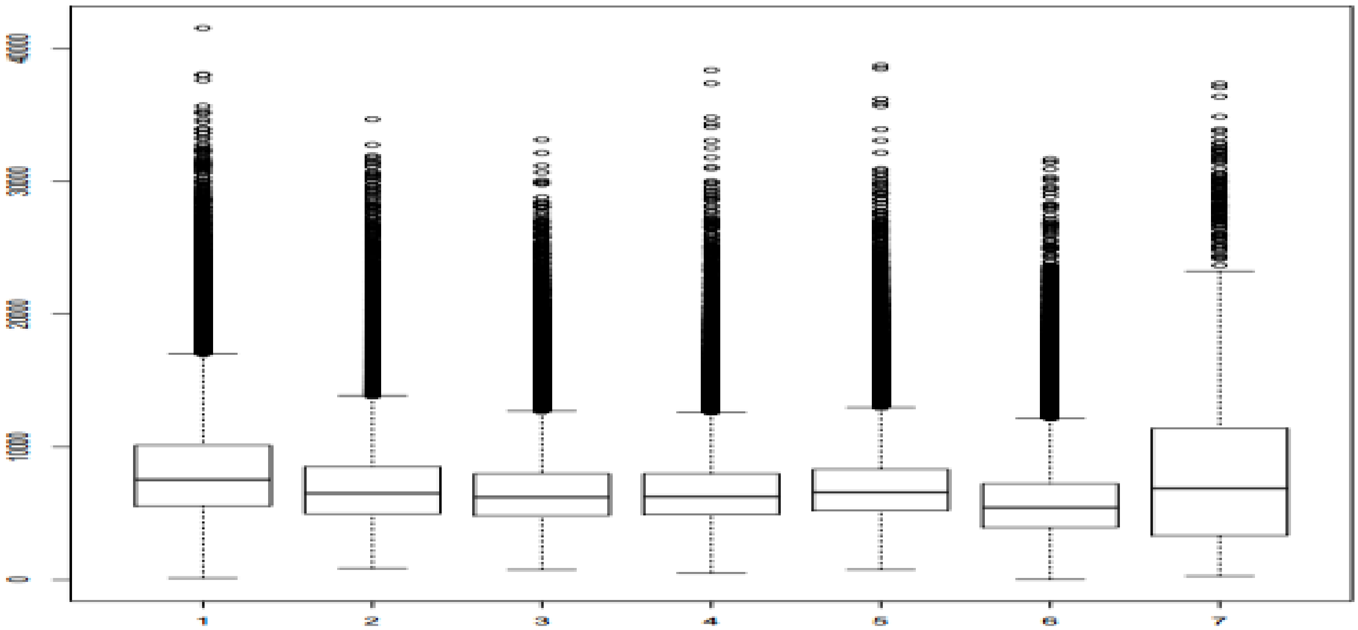
Boxplot of Sales as per StateHoliday in cleaned dataset

Graph 6: Sales by DayofWeek

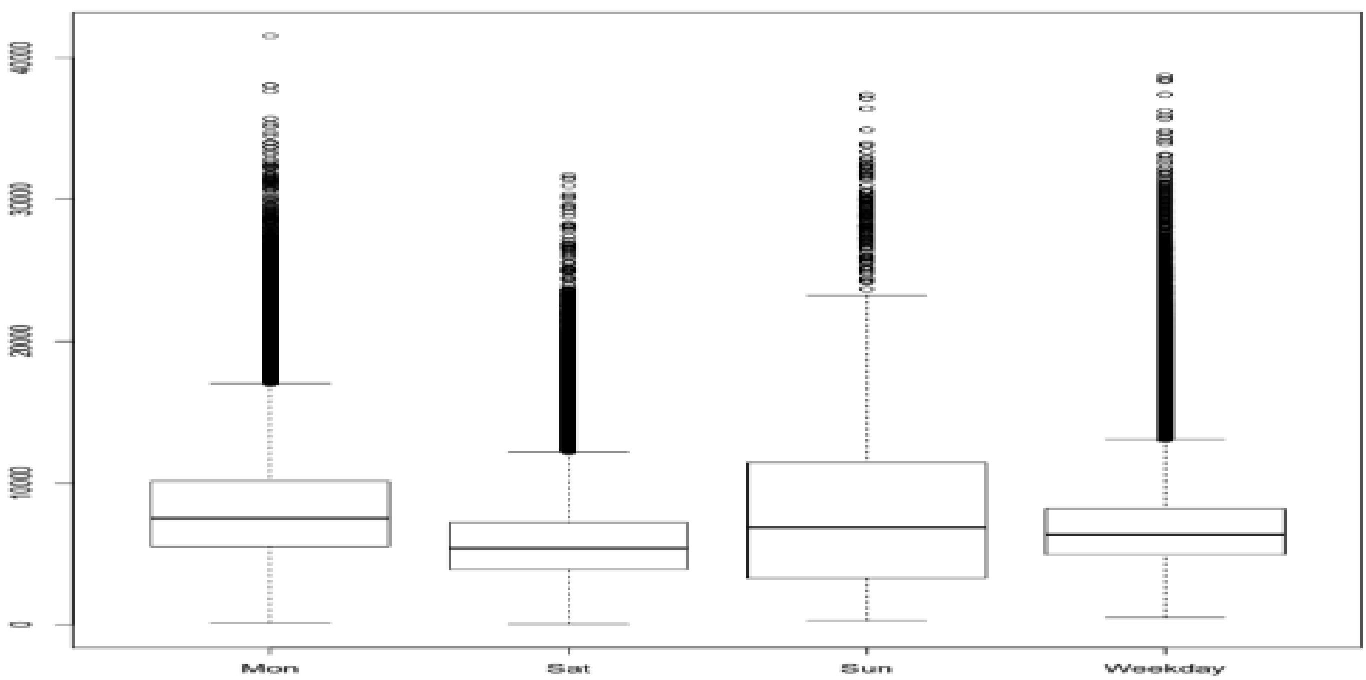
- This graph depicts Sales by each day of week.



Note: We have combined Tue, Wed, Thurs and Fri as Weekday because Tue through Fri Sales distributions are very close. Mon, Sat and Sun's Sales distributions are unique. In dataset, DayofWeek is represented as numeric number 1-7. From intuitive, we know that there is no linear relationship from 1-7 number to Sales data. We treat DayofWeek as four factors,Mon,Weekday(Tue-Fri), Sat, Sun as depicted in the boxplot below.



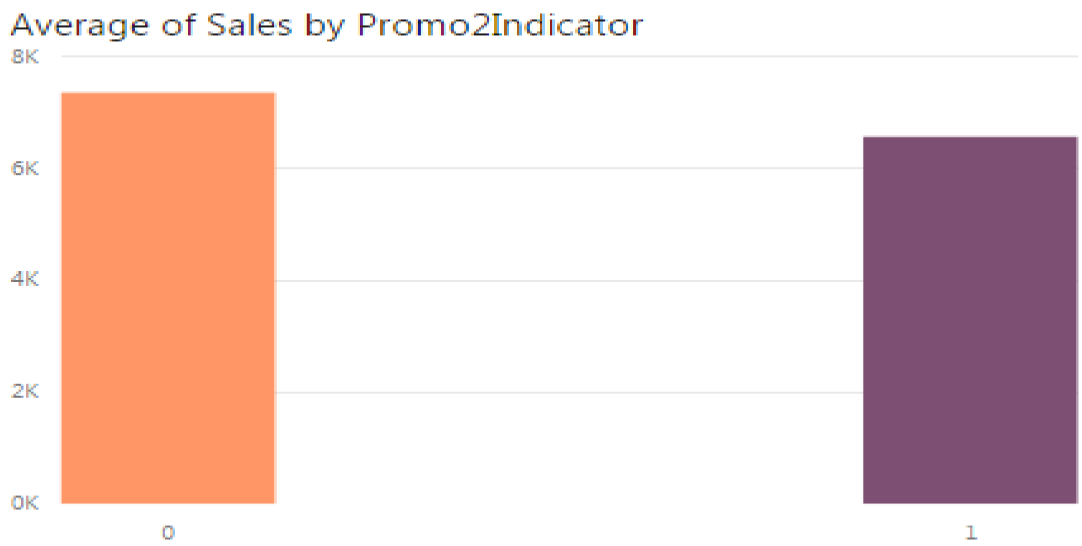
Boxplot of Sales as per DayofWeek in uncleaned dataset



Boxplot of Sales as per DayofWeek in cleaned dataset

Graph 7: Average of Sales by Promo2Indicator

- This graph indicates average of sales as per Promotion-2 indicator.



<u>Note</u>: We combined Promo2, Promo2SinceWeek, Promo2SinceYear and Promointerval to a Promo2indicator in historical sales data. The indicator indicates on a certain day whether a certain store is on promotion 2.

1.7 Data Cleansing

Data cleansing is divided into two parts:

RStudio:

- Read the train.csv file.
- Read the store.csv file.
- Merge data from train and store file.
- Write merged data to merged_data_train_updated.csv file.

```
#ROSSMANN SALES DATASET : Data Cleansing

#Train dataset as input
rossmann_data<-read.csv(file.choose(), header=TRUE)

#Store dataset as input
store_data<-read.csv(file.choose(), header=TRUE)

#Merging Train dataset with the Store dataset
merged_data<-merge(rossmann_data,store_data,by='Store',all.x=T)

#write merged data to csv file
write.csv(merged_data,"merged_data_train_updated.csv",row.names=FALSE)
```

Microsoft Azure ML:

- Read merged_data_train_updated.csv file.
- Remove outliers.

  Remove the rows where store is open and sales value is zero.

  Remove the rows where sales<0 when customers visit the store.

```
#Removing rows where sales=0 and Open=1
order_data<-merged_data[!(merged_data$Open==1 & merged_data$Sales==0),]

#Remove the rows where sales<0 when customers visit the store
order_data<-merged_data[(merged_data$Sales>0),]
```

- Extract Day, month, year and week from each date.
- Rename the DayofWeek column.

  Note: We have combined Tue, Wed, Thurs and Fri as Weekday because Tue through Fri Sales distributions are very close. Mon, Sat and Sun's Sales distributions are unique. In dataset, DayofWeek is represented as numeric number 1-7. From intuitive, we know that there is no linear relationship from 1-7 number to Sales data. We treat DayofWeek as four factors,Mon,Weekday(Tue-Fri), Sat, Sun.

```
#Separated Date column into year, month and day for prediction variables
library(lubridate)
data_year<-year(order_data$Date)
data_month<-month(order_data$Date)
data_day<-day(order_data$Date)
data_week<-week(order_data$Date)

#Combining the 3 different columns - month, day and year with the order_data data frame
combined_data<-cbind(order_data[1:3], data_year, data_month, data_day, data_week, order_data[4:18])


#Changing number of days in a week with the corresponding character names - sales on Monday, Saturday, Sunday and rest of the weekdays are different
combined_data$DayOfWeek<-as.numeric(combined_data$DayOfWeek)
combined_data$DayOfWeek[combined_data$DayOfWeek==1]<-"Mon"
combined_data$DayOfWeek[combined_data$DayOfWeek==2 | combined_data$DayOfWeek==3 | combined_data$DayOfWeek==4 |combined_data$DayOfWeek==5 ]<-"Weekday"
combined_data$DayOfWeek[combined_data$DayOfWeek==6]<-"Sat"
combined_data$DayOfWeek[combined_data$DayOfWeek==7]<-"Sun"
combined_data$DayOfWeek<-as.factor(combined_data$DayOfWeek)
```

- **Feature Engineering:** Combine Competition Distance, CompetitionOpenSince Month, CompetitionOpenSinceYear to a HaveCompetitor. The HaveCompetitor indicator indicates on a certain day whether a certain store has a competitor.

```
#Added a new column based on values in CompetitionOpenSinceMonth and CompetitionOpenSinceYear - FEATURE ENGINEERING
combined_data$HaveCompetitor<-ifelse((is.na(combined_data$CompetitionOpenSinceMonth) & is.na(combined_data$CompetitionOpenSinceYear)& is.na(combined_data$CompetitionDistance)), 0, 1)
```

- Cleaning on StateHoliday column in dataset.
- Cleaning on CompetitionDistance column in dataset. In this column we replace NAs with CompetitionDistance as a large number 100000. This method enables us to only one CompetitionDistance feature. It also models the no competitor case by weakening CompetitionDistance impact.

```
#Merging b and c columns of StateHoliday because they have similar sales value as compared to others, a = public holiday, b = Easter holiday, c = Christmas, 0 = None
combined_data$StateHoliday<-as.character(combined_data$StateHoliday)
combined_data$StateHoliday[combined_data$StateHoliday=="b"|combined_data$StateHoliday=="c"]<-"d"
combined_data$StateHoliday<-as.factor(combined_data$StateHoliday)

#CompetitionDistance - replacing NAs with 100000 where HaveCompetitor = 0
combined_data$CompetitionDistance[(combined_data$HaveCompetitor==0)]<-100000
```

- **Feature Engineering:** Combine Promo2, Promo2SinceWeek, Promo2SinceYear and Promointerval to a promo2 indicator in historical sales data. The indicator indicates on a certain day whether a certain store is on promotion 2.

```
#Combine Promo2, Promo2SinceWeek, Promo2SinceYear and Promointerval to a promotion 2 indicator in historical sales data. The indicator indicates on a certain day whether a certain store is
combined_data$Promo2Indicator<-ifelse(((combined_data$Promo2==0) & (is.na(combined_data$Promo2SinceYear)) & (is.na(combined_data$Promo2SinceWeek))
                                    & (combined_data$PromoInterval=="")), 0, 1)
```

- **Feature Engineering:** Adding a Promo2Month column

  PromoInterval records the first month of each email marketing, replaced it with Promo2Month, which has number of months when the store conducted the most recent email promotion.

  Steps for adding Promo2month column:

1. Extract each month name from PromoInterval column and treat them as promointerval quarters.

```
#PromoInterval records the first month of each email marketing, replaced it with Promo2Month, which has number of months when the store conducted the most recent email promotion
library(stringi)

# Extracting each month name from PromoIntervalcolumn and treat them as promointerval quarters
#Fourth Quarter
w<-as.character(combined_data$PromoInterval)
promo_month<-function(w,n){substr(w,nchar(w)-n+1,nchar(w))}
combined_data$QuarterFour<-promo_month(w,3)

#Third Quarter
x<-as.character(combined_data$PromoInterval)
promo_month3<-function(x,n){substr(x,nchar(x)-n+1,nchar(x))}
combined_data$QuarterThree<-promo_month3(x,7)
combined_data$QuarterThree<-stri_sub(combined_data$QuarterThree,1,3)

#Second Quarter
y<-as.character(combined_data$PromoInterval)
promo_month2<-function(y,n){substr(y,nchar(y)-n+1,nchar(y))}
combined_data$QuarterTwo<-promo_month2(y,11)
combined_data$QuarterTwo<-stri_sub(combined_data$QuarterTwo,1,3)

#First Quarter
z<-as.character(combined_data$PromoInterval)
promo_month1<-function(z,n){substr(z,nchar(z)-n+1,nchar(z))}
combined_data$QuarterOne<-promo_month1(z,15)
combined_data$QuarterOne<-stri_sub(combined_data$QuarterOne,1,3)
```

2. Changing the month names in corresponding columns to numeric values as per the months in a year.

```
#Changing the month names in corresponding columns to numeric values as per the months in a year
combined_data$QuarterFour[which(combined_data$QuarterFour=="Oct")]<-"10"
combined_data$QuarterFour[which(combined_data$QuarterFour=="Nov")]<-"11"
combined_data$QuarterFour[which(combined_data$QuarterFour=="Dec")]<-"12"
combined_data$QuarterThree[which(combined_data$QuarterThree=="Jul")]<-"7"
combined_data$QuarterThree[which(combined_data$QuarterThree=="Aug")]<-"8"
combined_data$QuarterThree[which(combined_data$QuarterThree=="Sep")]<-"9"
combined_data$QuarterTwo[which(combined_data$QuarterTwo=="Apr")]<-"4"
combined_data$QuarterTwo[which(combined_data$QuarterTwo=="May")]<-"5"
combined_data$QuarterTwo[which(combined_data$QuarterTwo=="Jun")]<-"6"
combined_data$QuarterOne[which(combined_data$QuarterOne=="Jan")]<-"1"
combined_data$QuarterOne[which(combined_data$QuarterOne=="Feb")]<-"2"
combined_data$QuarterOne[which(combined_data$QuarterOne=="Mar")]<-"3"
```

3. Converting the four quarter columns to numeric value columns.

```
#Converting the four quarter columns to numeric value columns
combined_data$QuarterFour<-as.numeric(combined_data$QuarterFour)
combined_data$QuarterThree<-as.numeric(combined_data$QuarterThree)
combined_data$QuarterTwo<-as.numeric(combined_data$QuarterTwo)
combined_data$QuarterOne<-as.numeric(combined_data$QuarterOne)
```

4. Calculating the number of months by applying the following formula to data_year, data_month, Promo2SinceYear and QuarterFour columns

```
#Calculating the number of months by applying the following formula to data_year, data_month, Promo2SinceYear and QuarterFour columns
combined_data$Promo2SinceYear<-as.numeric(combined_data$Promo2SinceYear)
b<-(12 * (combined_data$data_year - combined_data$Promo2SinceYear)) + (combined_data$data_month - combined_data$QuarterFour)
c<-(12 * (combined_data$data_year - combined_data$Promo2SinceYear)) + (combined_data$data_month - combined_data$QuarterThree)
d<-(12 * (combined_data$data_year - combined_data$Promo2SinceYear)) + (combined_data$data_month - combined_data$QuarterTwo)
e<-(12 * (combined_data$data_year - combined_data$Promo2SinceYear)) + (combined_data$data_month - combined_data$QuarterOne)
```

5. Running the for-loop for taking out the positive number of months for the duration when the store performed most recent promotion

   Taking out negative values (starting promotion before shop opened)

```
#Running the for-loop for taking out the positive number of months for the duration when the store performed most recent promotion
#Taking out negative values (starting promotion before shop opened)
combined_data$PromoMonth<-ifelse(combined_data$Promo2SinceYear>combined_data$data_year,0,
       ifelse(combined_data$QuarterFour<=combined_data$data_month, b,
              ifelse(combined_data$QuarterThree<=combined_data$data_month, c,
                     ifelse(combined_data$QuarterTwo<=combined_data$data_month, d,
                            ifelse(combined_data$QuarterOne<=combined_data$data_month, e,
                                   0)))))
```

6. Replacing the NAs with zero in the PromoMonth Column

```
#Replacing the NAs with zero in the PromoMonth Column
combined_data$PromoMonth[is.na(combined_data$PromoMonth)]<-0
```

- **Feature Engineering:** Creating new column Expected_Sales.

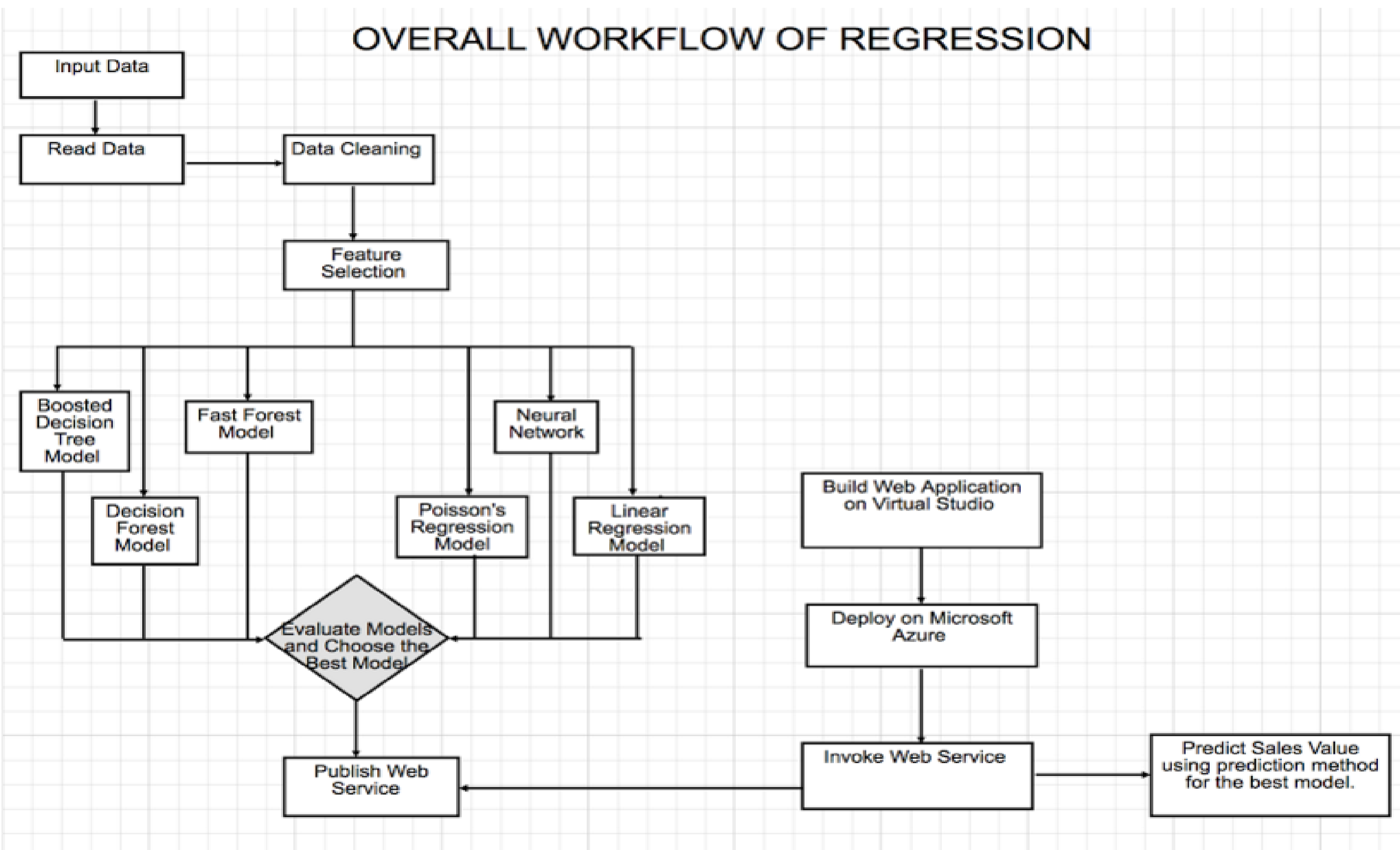
```
#Taking the mean of Sales
mean<-mean(combined_data$Sales)

#Creating new column Expected_Sales
combined_data$Expected_Sales<-ifelse(combined_data$Sales<mean,0,1)
combined_data$Expected_Sales<-factor(combined_data$Expected_Sales, levels=c(0,1),labels=c("Below Average", "Above Average"))
```

- Write data to csv file named **cleanedData_RossmannSales.csv** file.

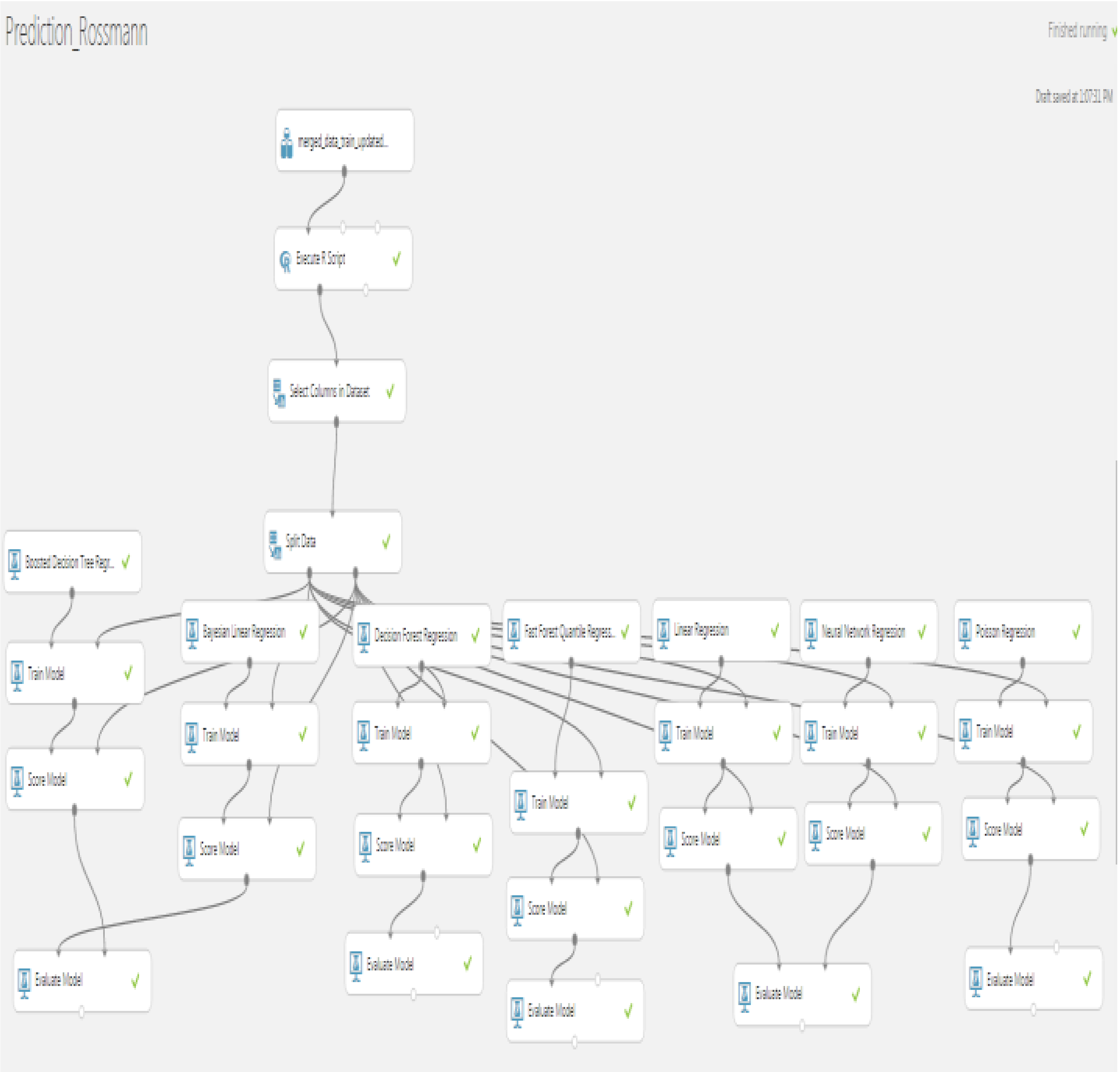
1.8 Regression Models

1.8.1 Overall Design

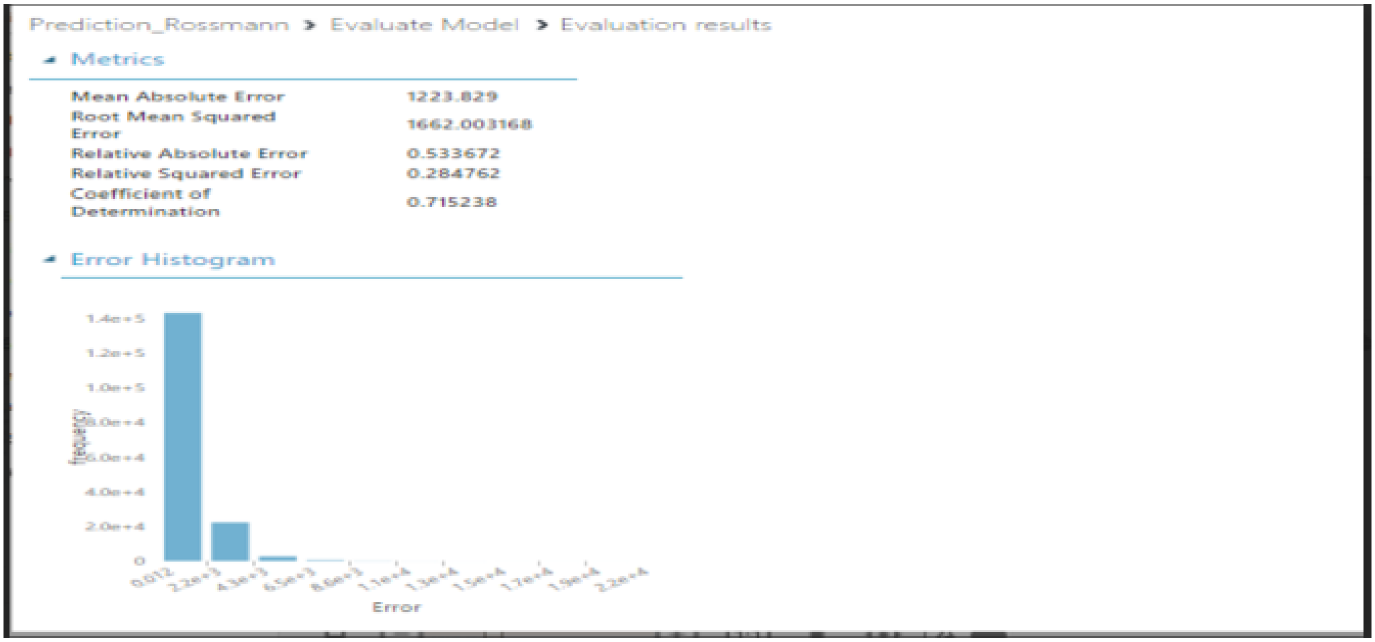
- Read the Rossmann Sales Data.
- Cleanse the data as explained in Data Cleansing section.
- Implement various regression models.
- Compare the models through MAE (mean absolute error) and RMSPE (Root Mean Square Percentage Error) and choose the best model.
- Deploy the best regression model as a web service.
- Build web application using visual studio and deploy it on Microsoft Azure.
- Predict value of Sales through this web application.



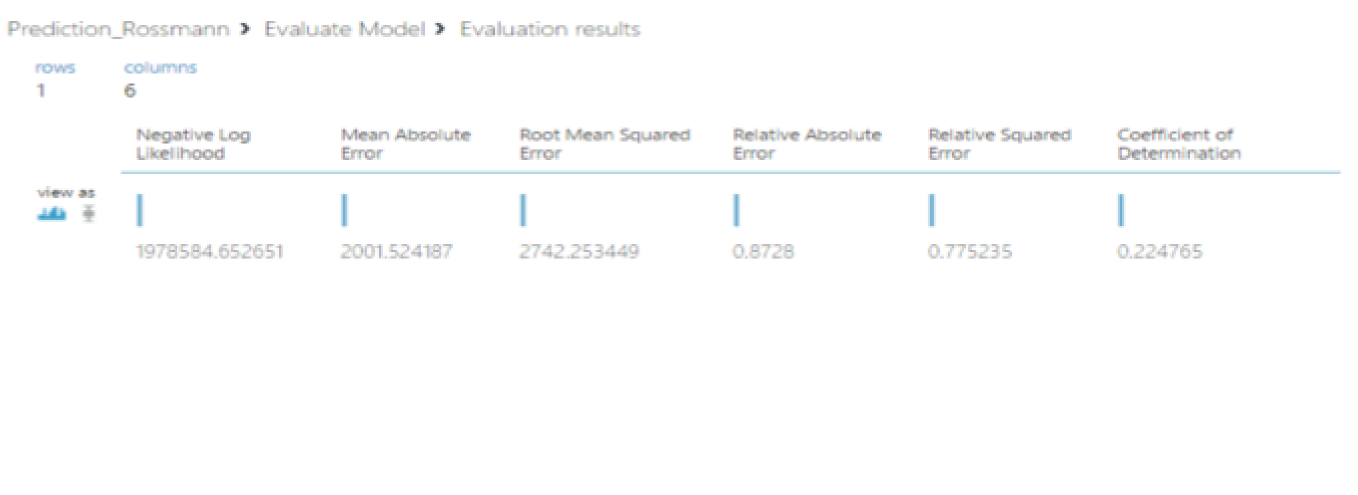
1.8.2 Azure Models



1.8.3 Boosted Decision Tree Regression



1.8.4 Bayesian Linear Regression

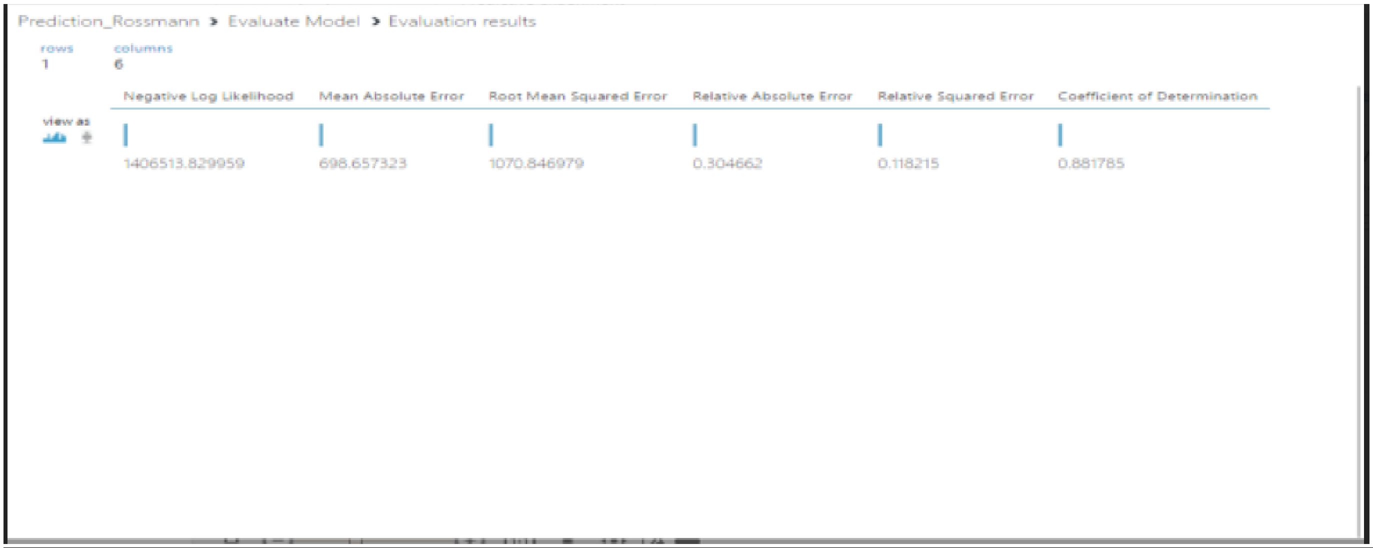


Prediction_Rossmann › Evaluate Model › Evaluation results

rows 1 columns 6

Negative Log Likelihood	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error	Relative Squared Error	Coefficient of Determination
1978584.652651	2001.524187	2742.253449	0.8728	0.775235	0.224765

1.8.5 Decision Forest Regression

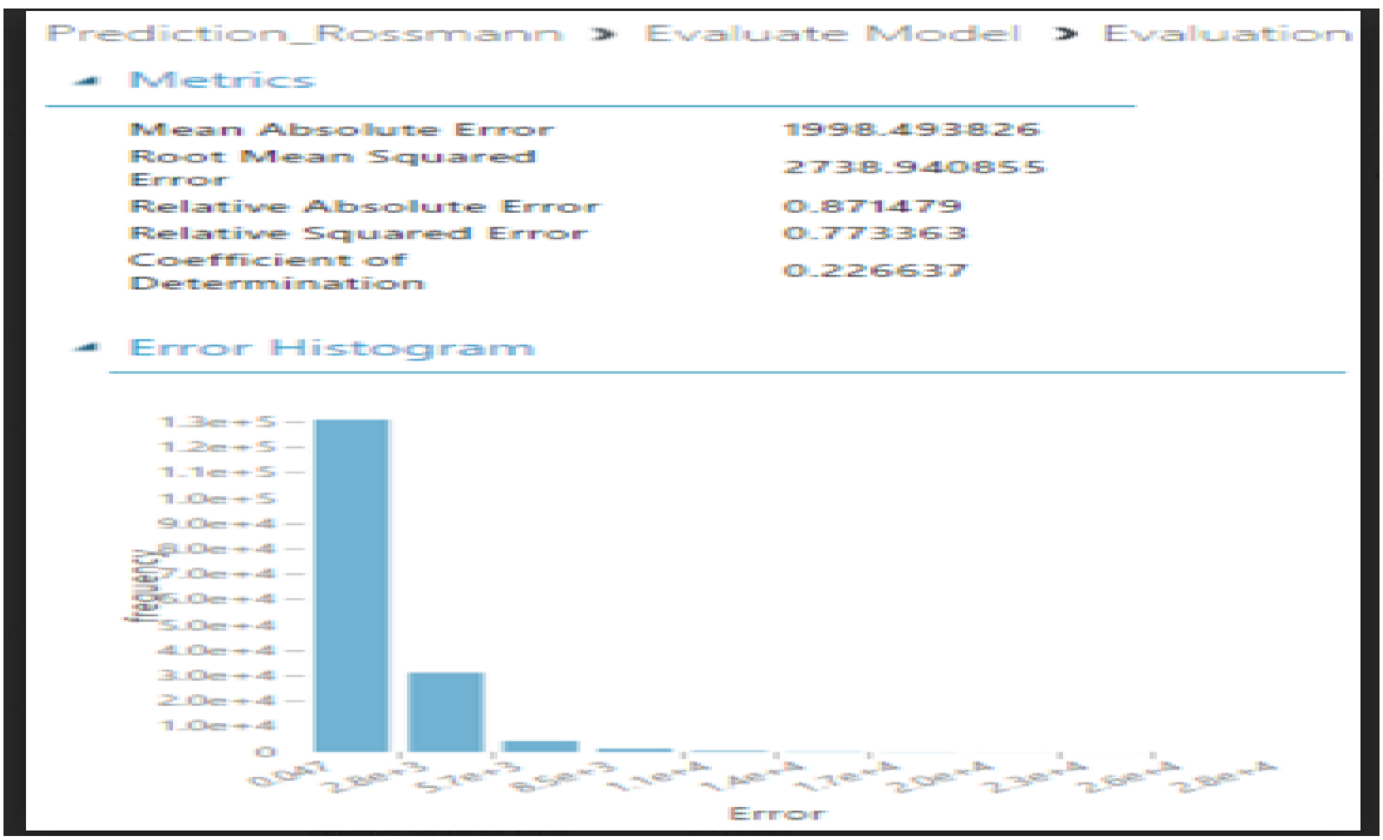


Prediction_Rossmann > Evaluate Model > Evaluation results

rows 1 columns 6

Negative Log Likelihood	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error	Relative Squared Error	Coefficient of Determination
1406513.829959	698.657323	1070.846979	0.304662	0.118215	0.881785

1.8.6 Linear Regression



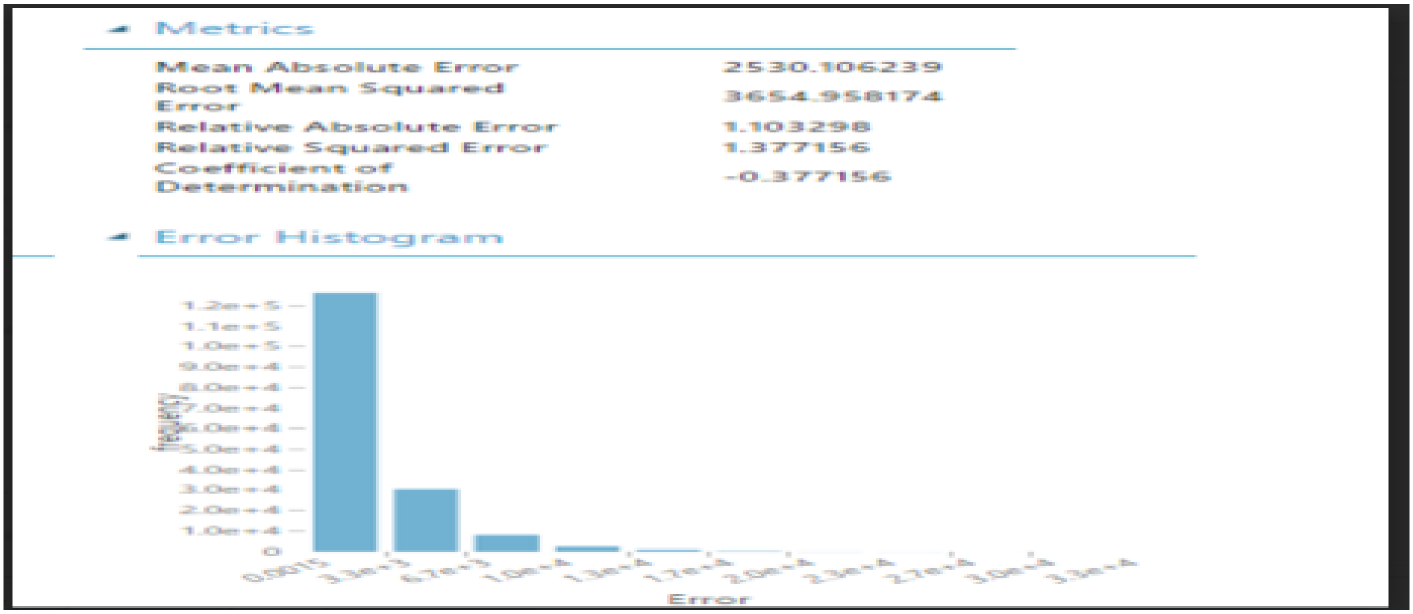
Prediction_Rossmann > Evaluate Model > Evaluation

Metrics

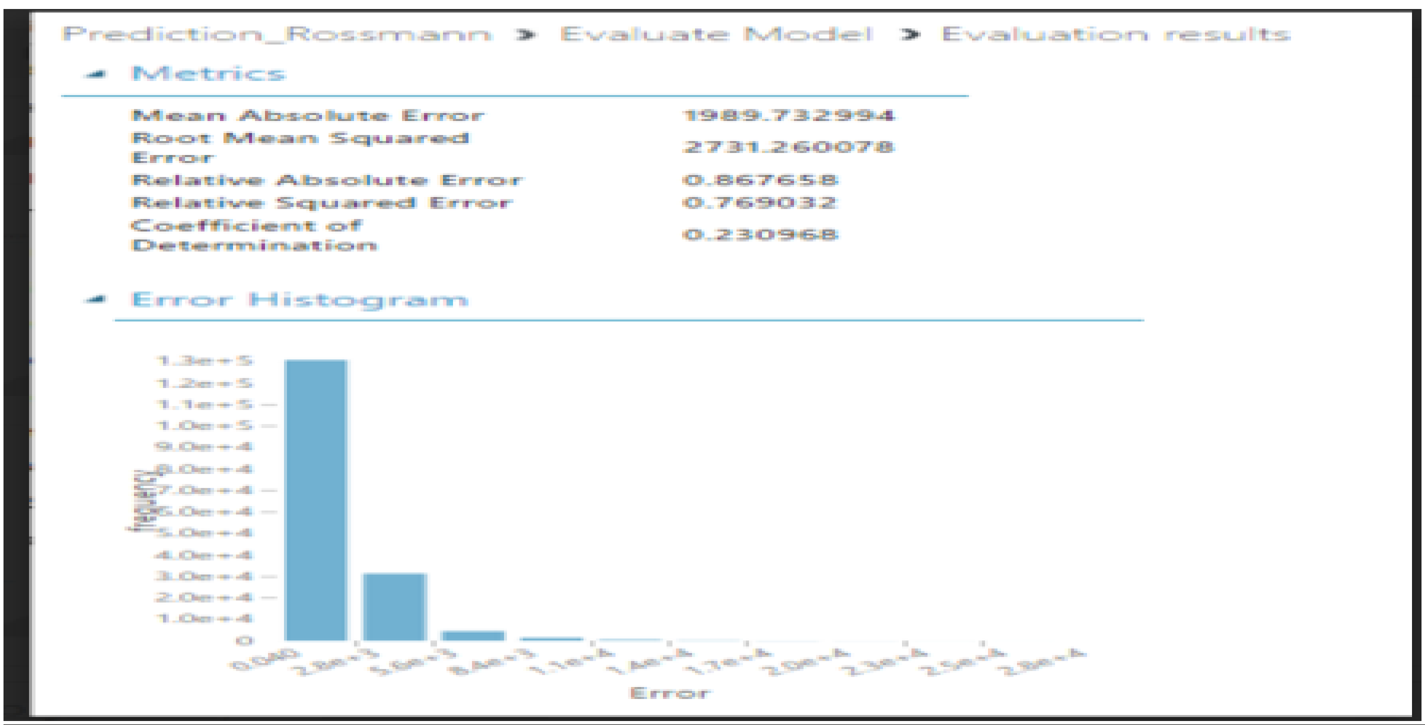
Mean Absolute Error	1998.493826
Root Mean Squared Error	2738.940855
Relative Absolute Error	0.871479
Relative Squared Error	0.773363
Coefficient of Determination	0.226637

Error Histogram

1.8.5 Neural Network Regression



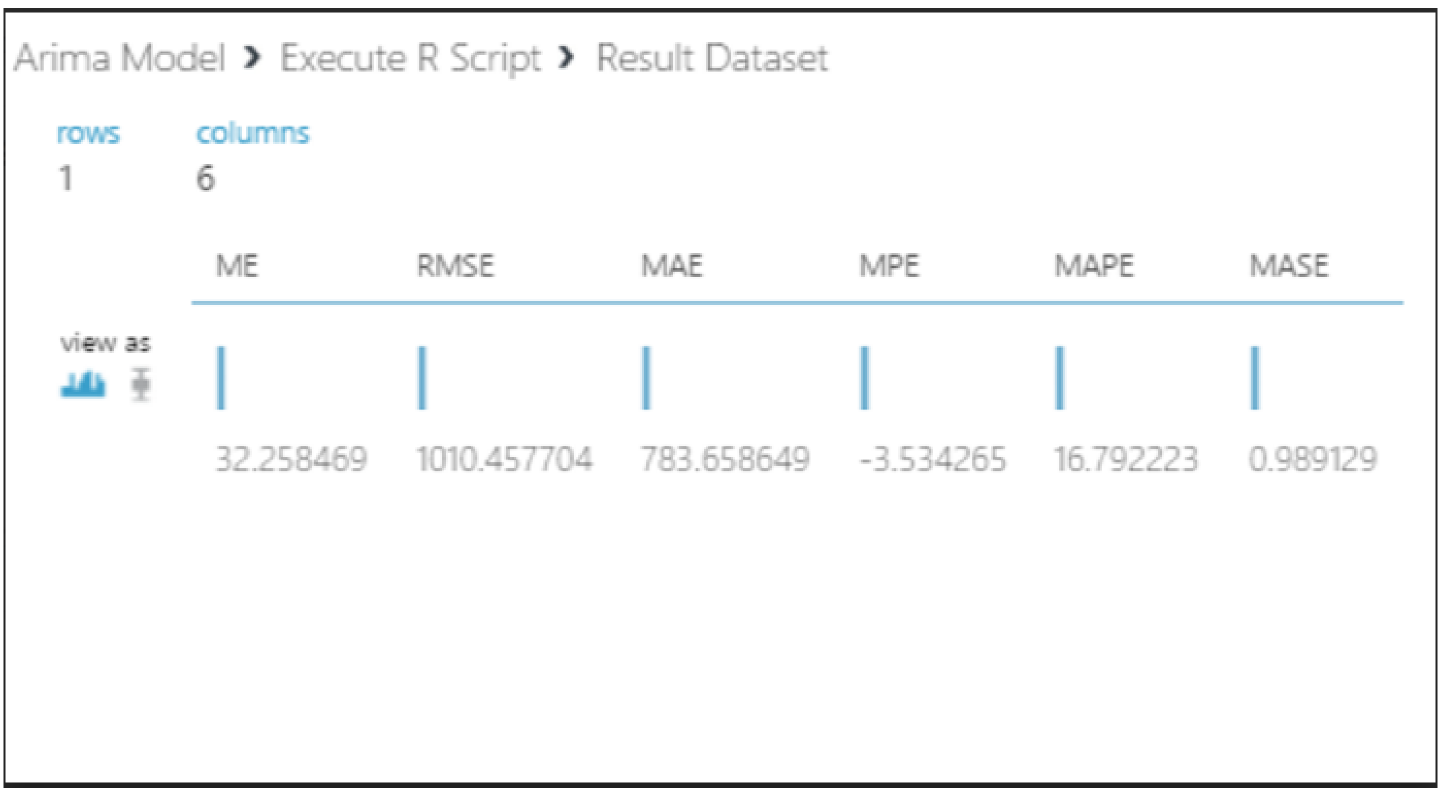
1.8.8 Poisson Regression



1.8.9 ARIMA Model

ARIMA model is a generalization of an autoregressive moving average (ARMA) model. Both of these models are fitted to time series data either to better understand the data or to predict future points in the series (forecasting). ARIMA models are applied in some cases where data show evidence of non-stationarity, where an initial differencing step (corresponding to the "integrated" part of the model) can be applied to reduce the non-stationarity.[1]

The AR part of ARIMA indicates that the evolving variable of interest is regressed on its own lagged (i.e., prior) values. The MA part indicates that the regression error is actually a linear combination of error terms whose values occurred contemporaneously and at various times in the past. The I (for "integrated") indicates that the data values have been replaced with the difference between their values and the previous values (and this differencing process may have been performed more than once). The purpose of each of these features is to make the model fit the data as well as possible.


Arima Model › Execute R Script › Result Dataset

rows 1 columns 6

ME	RMSE	MAE	MPE	MAPE	MASE
32.258469	1010.457704	783.658649	-3.534265	16.792223	0.989129

1.8.10 Summary

Model Name	MAE	RMSE
Boosted Decision Tree Regression	**1,224**	**1,662 (Approx. RMSPE = 14.64%)**
Bayesian Linear Regression	**2,001**	**2,742 (Approx. RMSPE = 23.58%)**
Decision Forest Regression	**698**	**1,070 (Approx. RMSPE = 11.74%)**
Linear Regression	**1,998**	**2,738 (Approx. RMSPE = 23.16%)**
Neural Network Regression	**2,530**	**3,654 (Approx. RMSPE = 34.93%)**
Poisson Regression	**1,989**	**2,731 (Approx. RMSPE = 26.89%)**
ARIMA Model	**7,83**	**1,010 (Approx. RMSPE = 10.55%)**

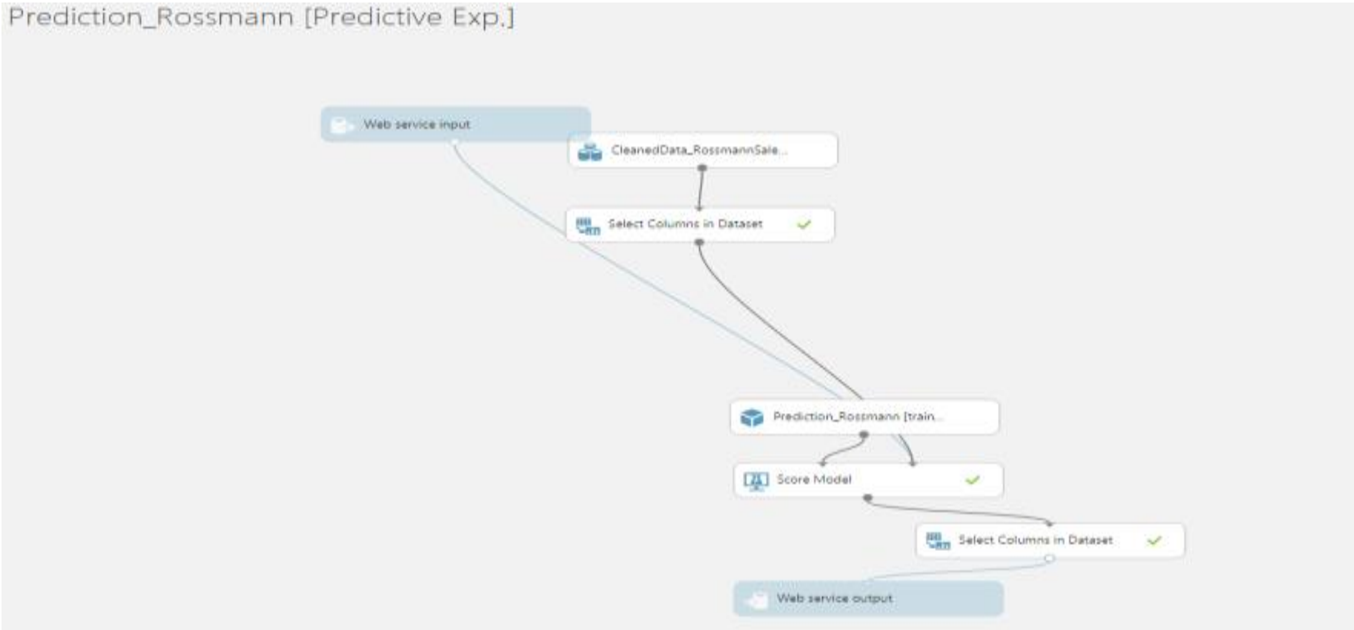
1.8.11 Conclusion

Out of all these models we chose Decision Forest Regression Model because it had minimum MAPE i.e. **698** and minimum RMSE i.e. **1,070.** It had the best combination amongst all the other models.

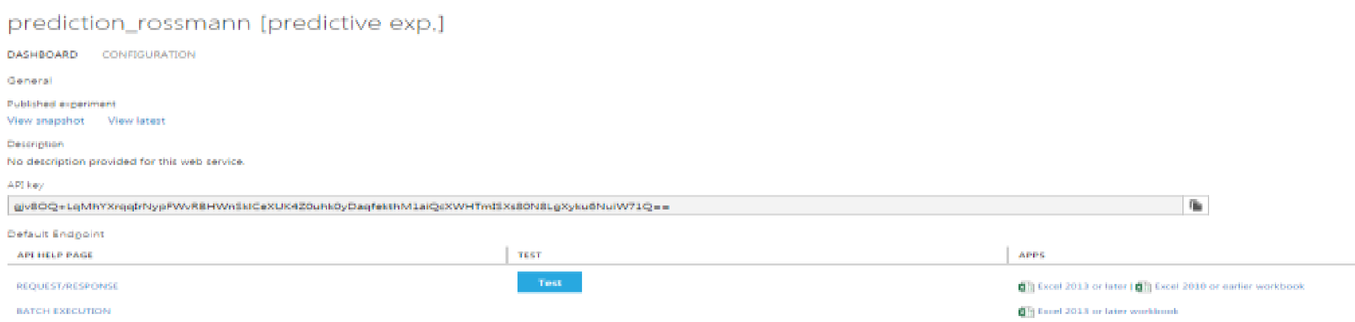
1.8.12 Web Service

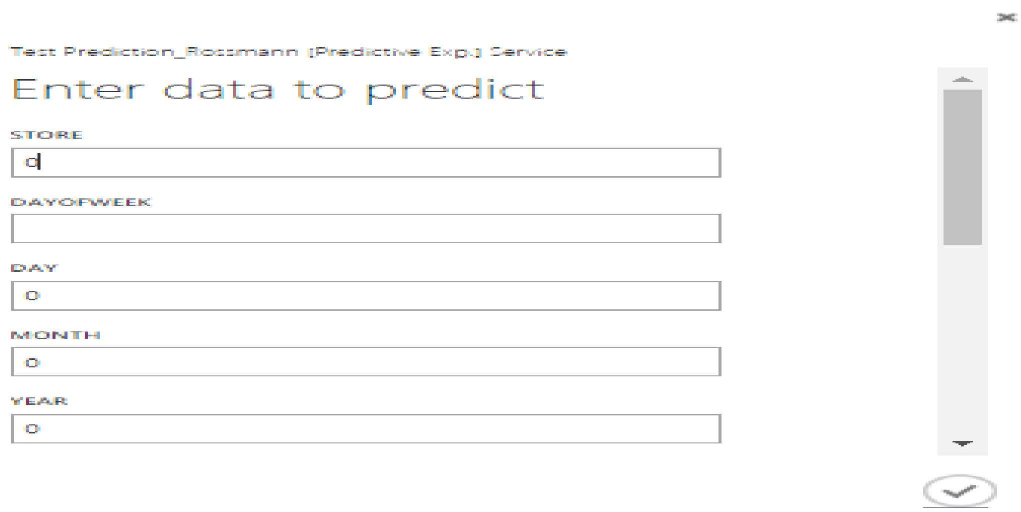
Below are the steps to create a web service of Regression model:

- Set-up web service
- Save Decision Forest Regression Model's train model as a Trained Model.
- Modules that were used for training are removed. Specifically:
    - Decision Forest Regression Model
    - Train Model
    - Split Data



- Then Web Service input and Web Service output is added.
- Service is deployed.

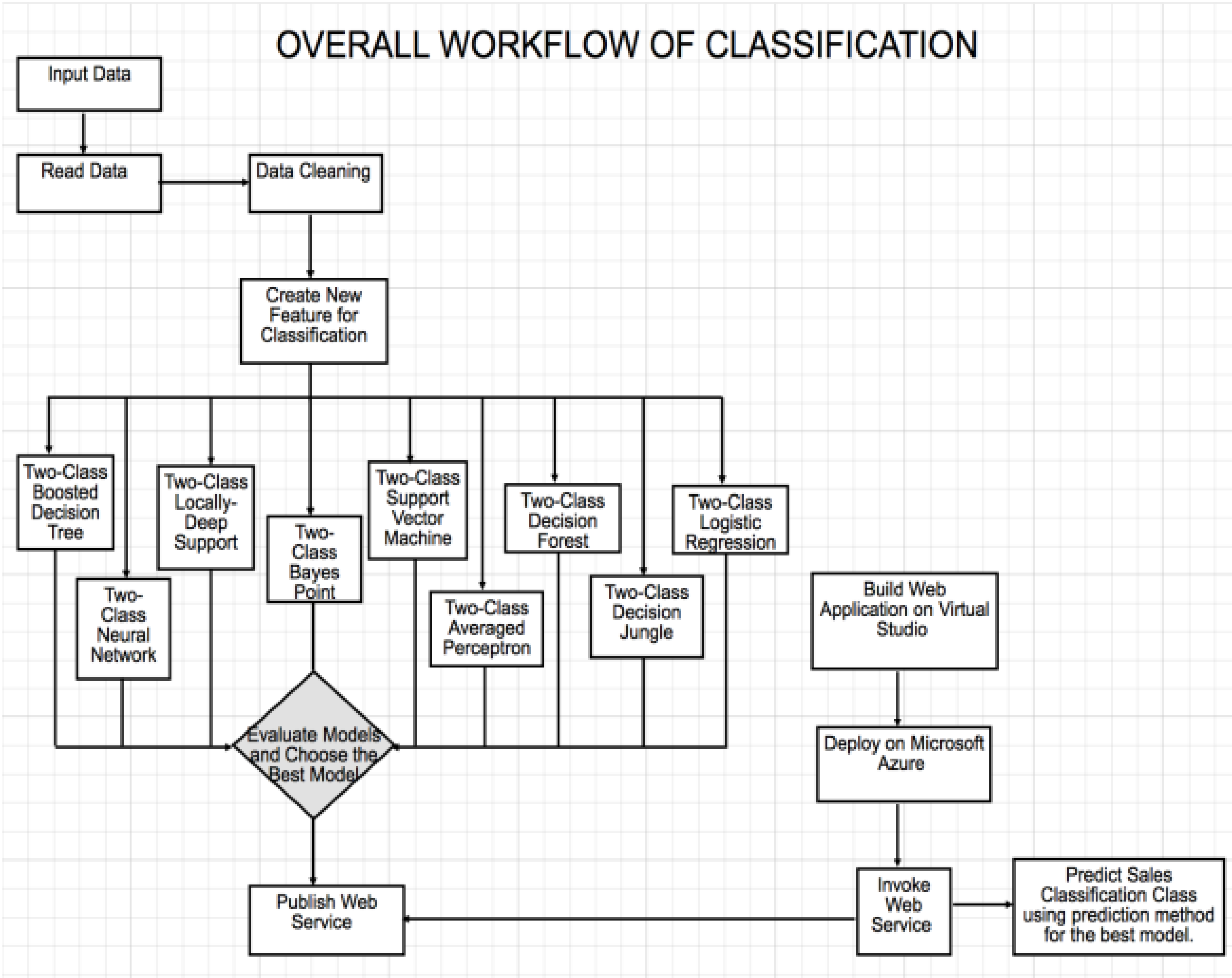




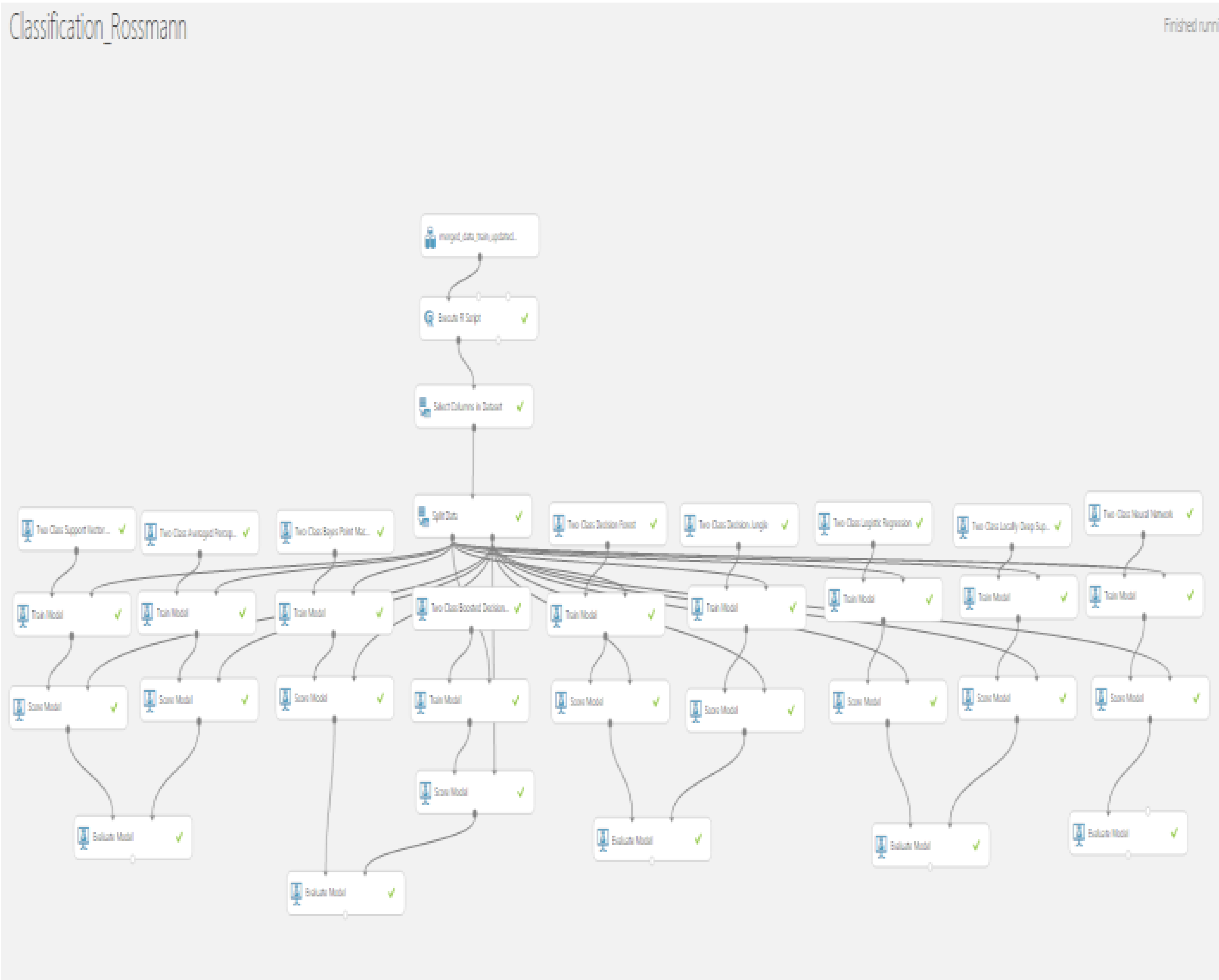
1.9 Classification Models

1.9.1 Overall Design

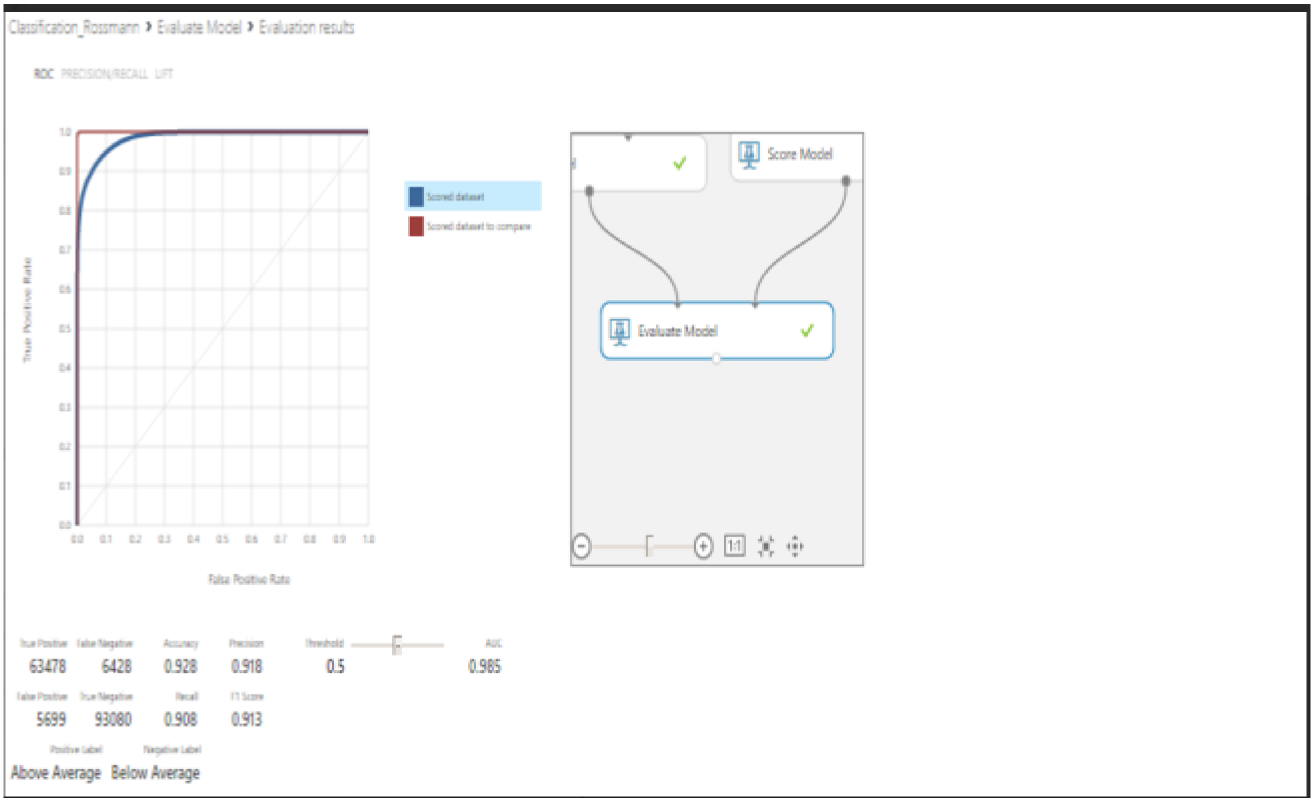
- Read the Rossmann Sales Data.
- Cleanse the data as explained in Data Cleansing section.
- Implement various classification models.
- Compare the models through Error Percentage, Accuracy and Precision to choose the best model.
- Deploy the best classification model as a web service.
- Build web application using visual studio and deploy it on Microsoft Azure.
- Predict the class of predicted sales value through this web application.


OVERALL WORKFLOW OF CLASSIFICATION
Input Data
Read Data
Data Cleaning
Create New Feature for Classification
Two-Class Boosted Decision Tree
Two-Class Neural Network
Two-Class Locally-Deep Support
Two-Class Bayes Point
Two-Class Support Vector Machine
Two-Class Averaged Perceptron
Two-Class Decision Forest
Two-Class Decision Jungle
Two-Class Logistic Regression
Evaluate Models and Choose the Best Model
Publish Web Service
Build Web Application on Virtual Studio
Deploy on Microsoft Azure
Invoke Web Service
Predict Sales Classification Class using prediction method for the best model.

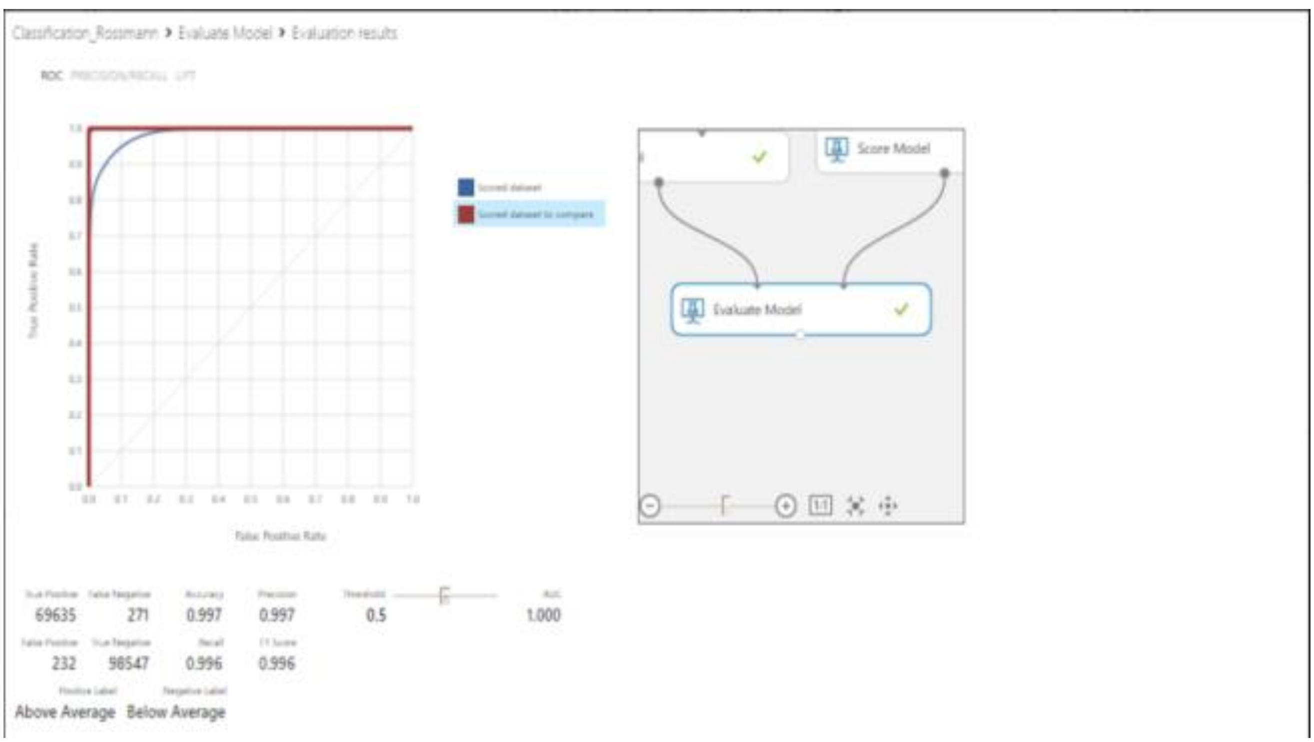
1.9.2 Azure Models



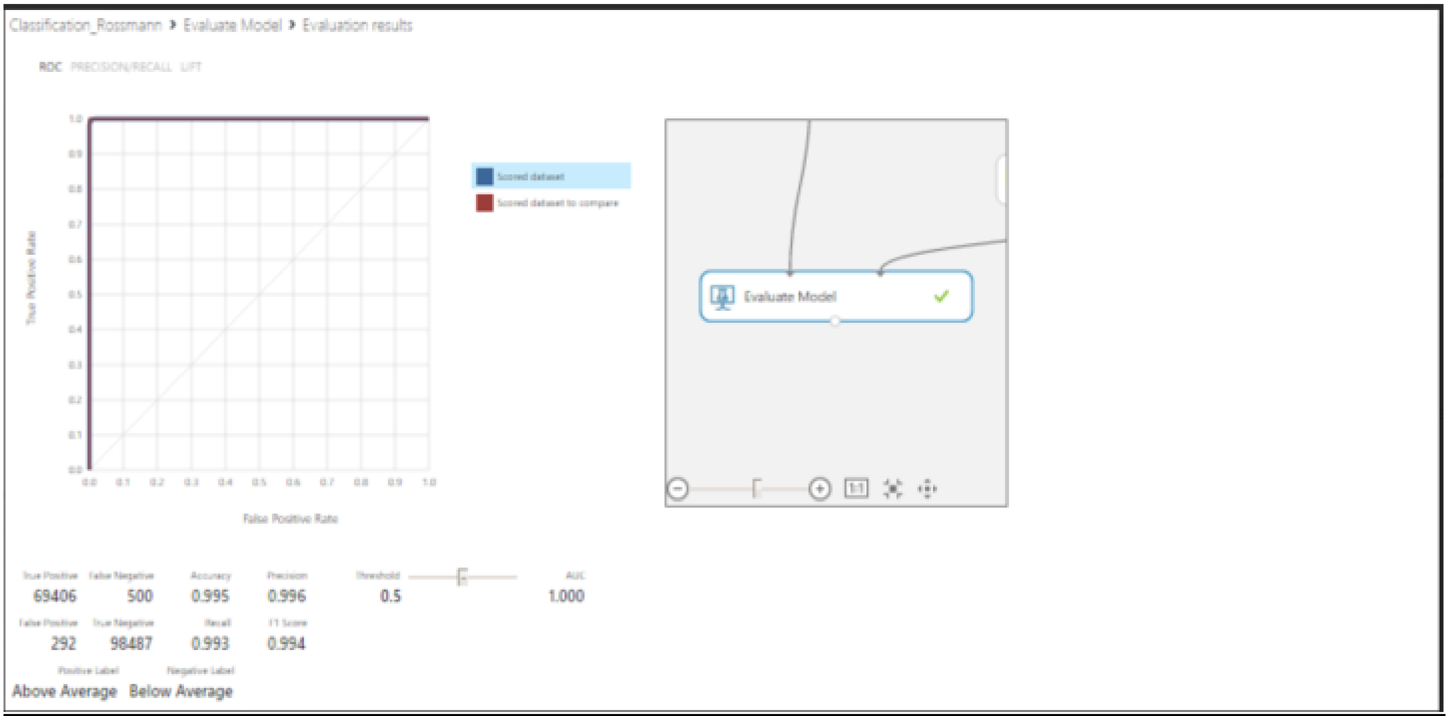
1.9.3 Two-Class Support Vector Machine



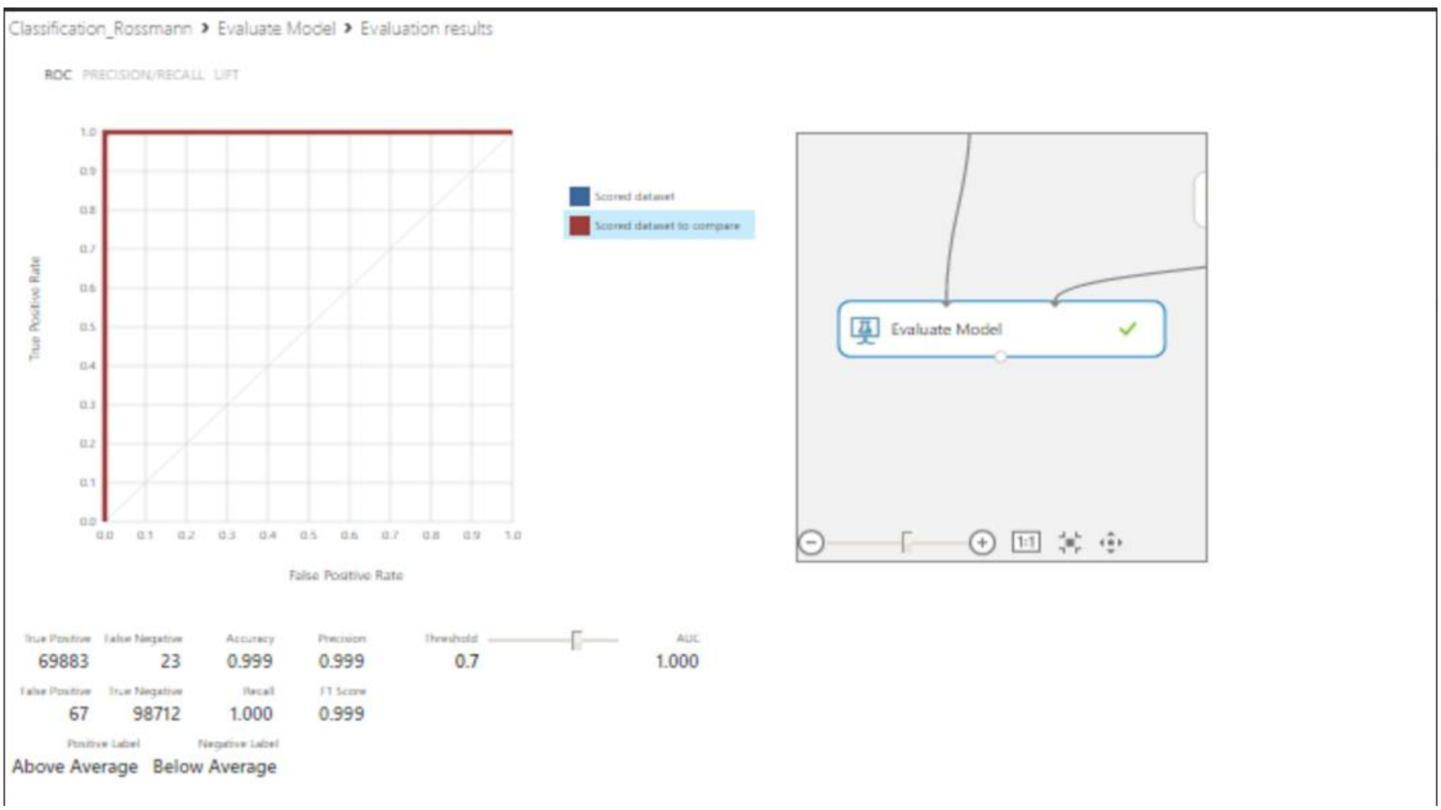
1.9.4 Two-Class Averaged Perceptron



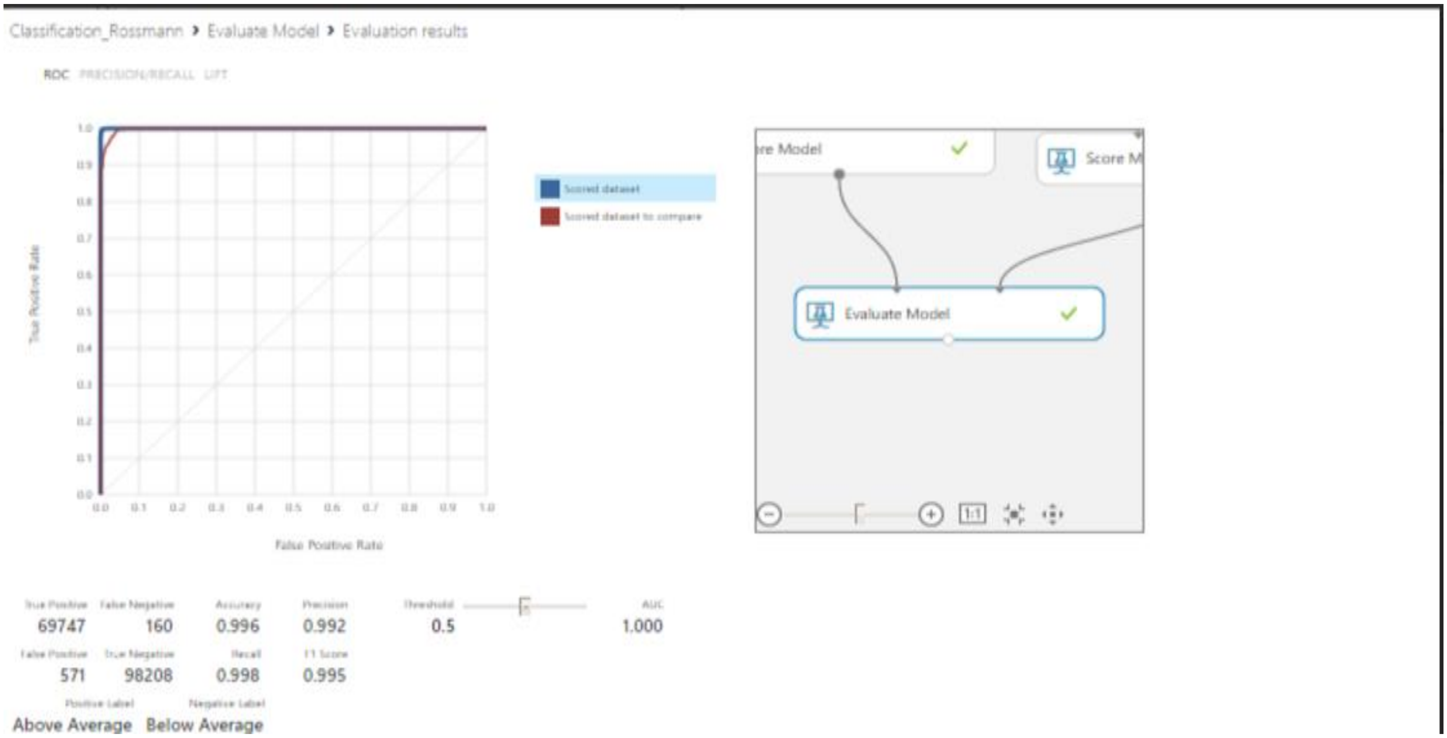
1.9.5 Two-Class Bayes Point Machine



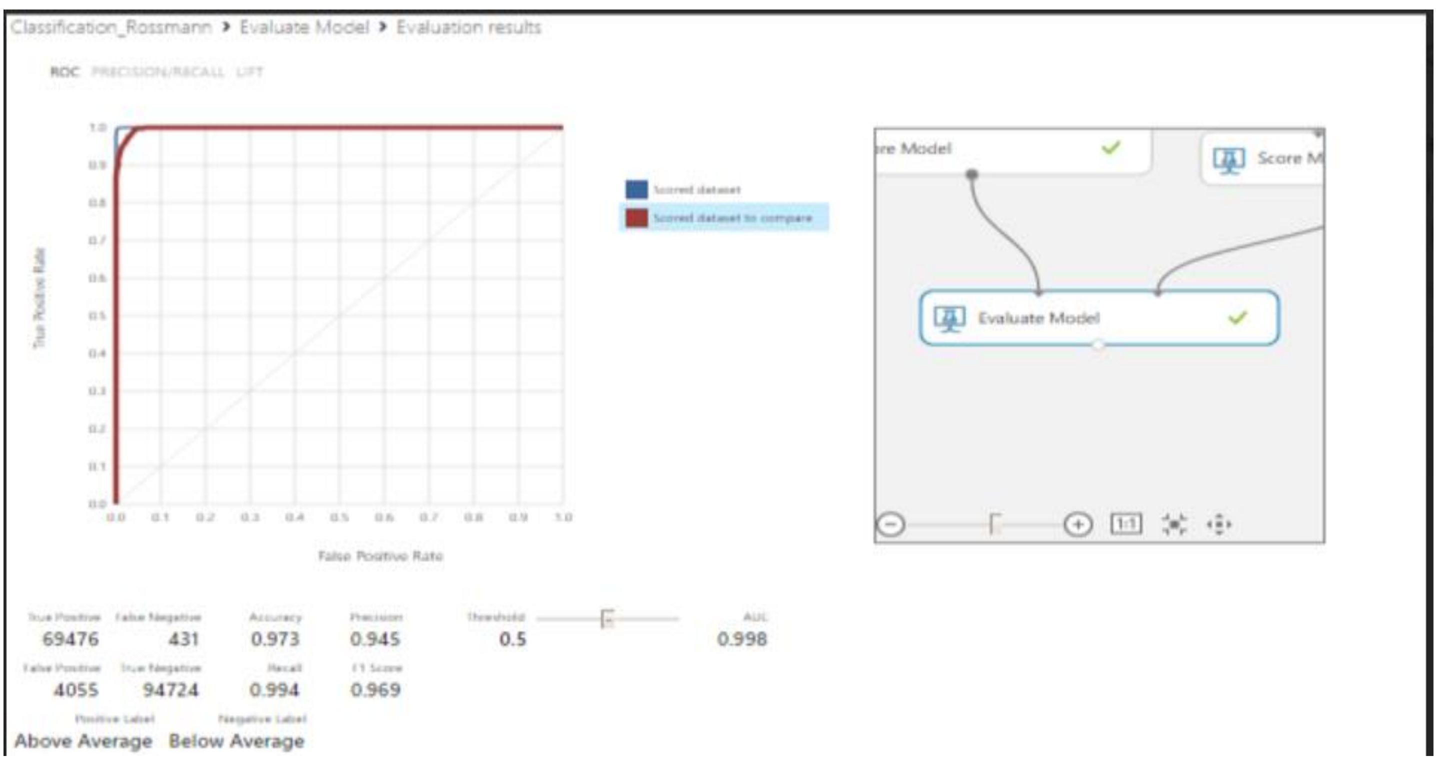
1.9.6 Two-Class Boosted Decision Tree



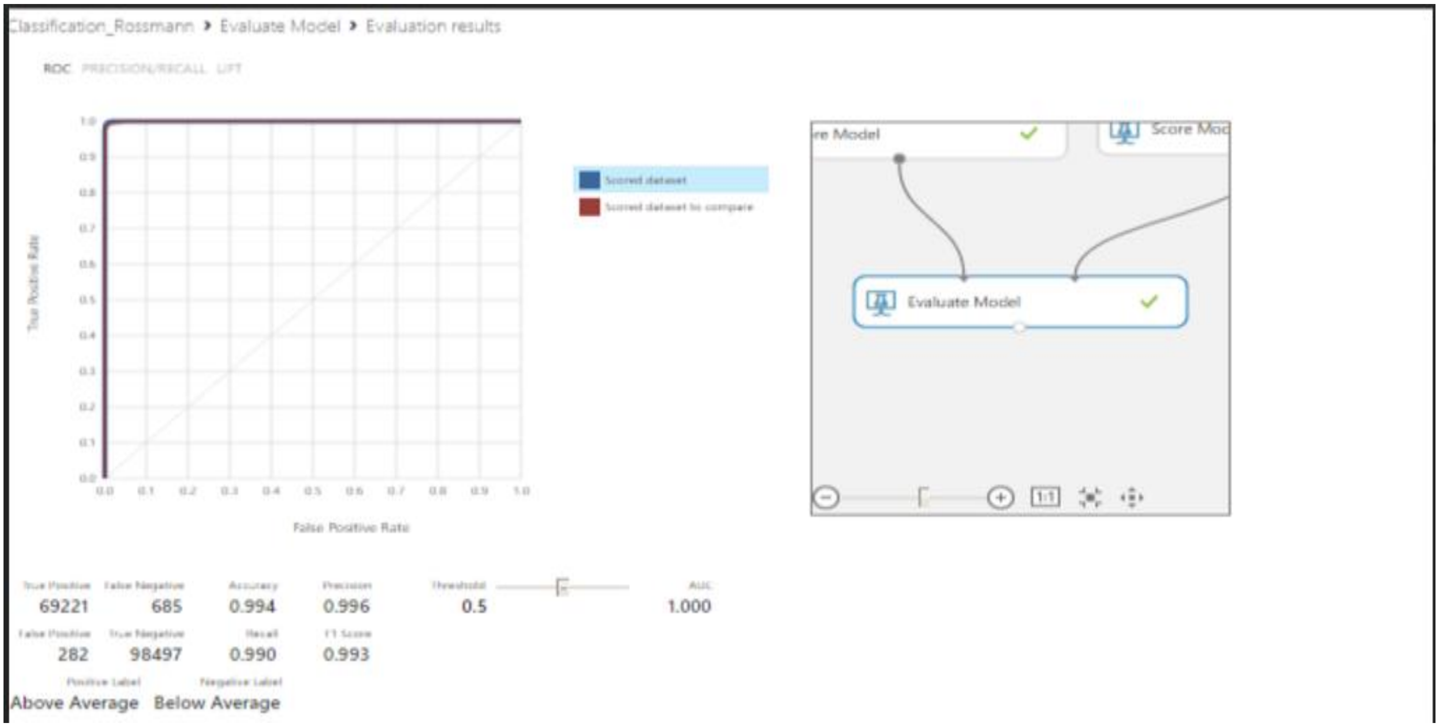
1.9.7 Two-Class Decision Forest



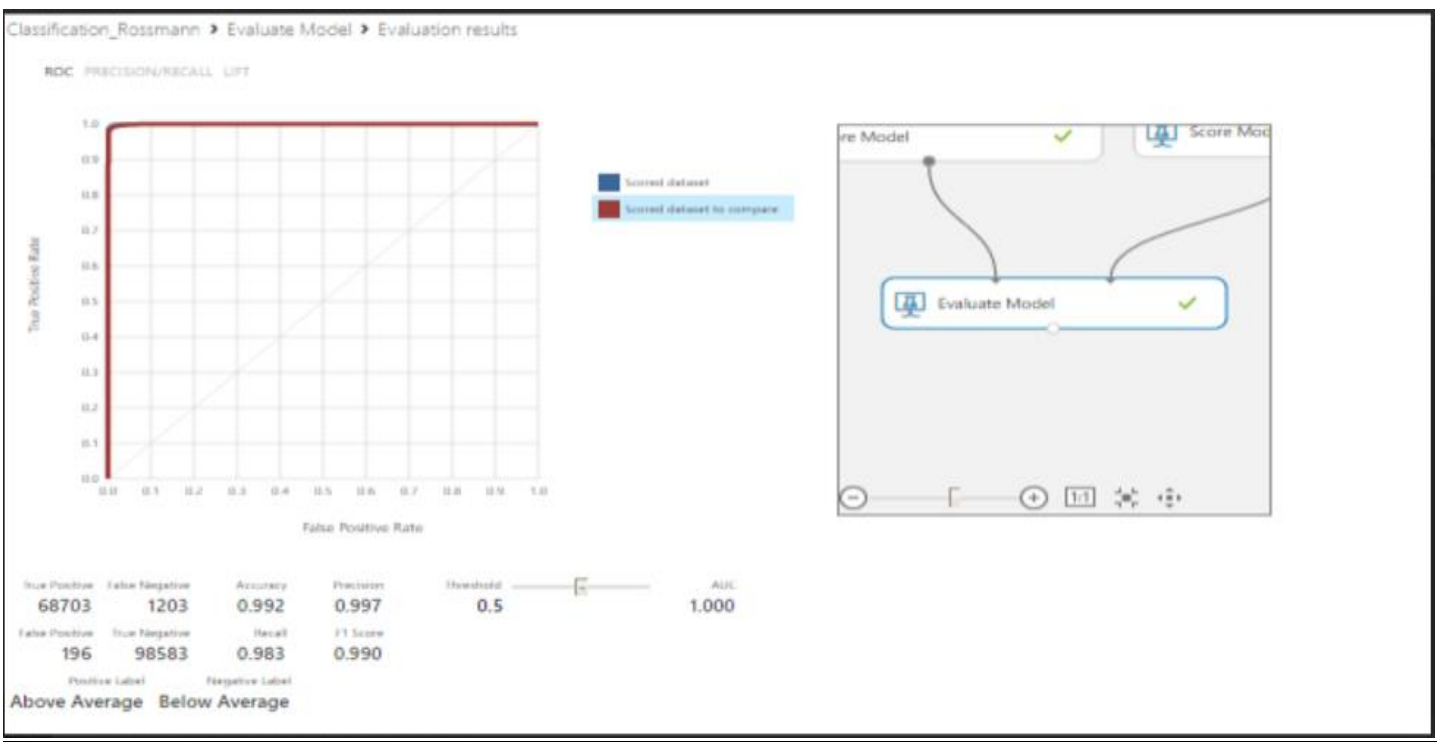
1.9.8 Two-Class Decision Jungle



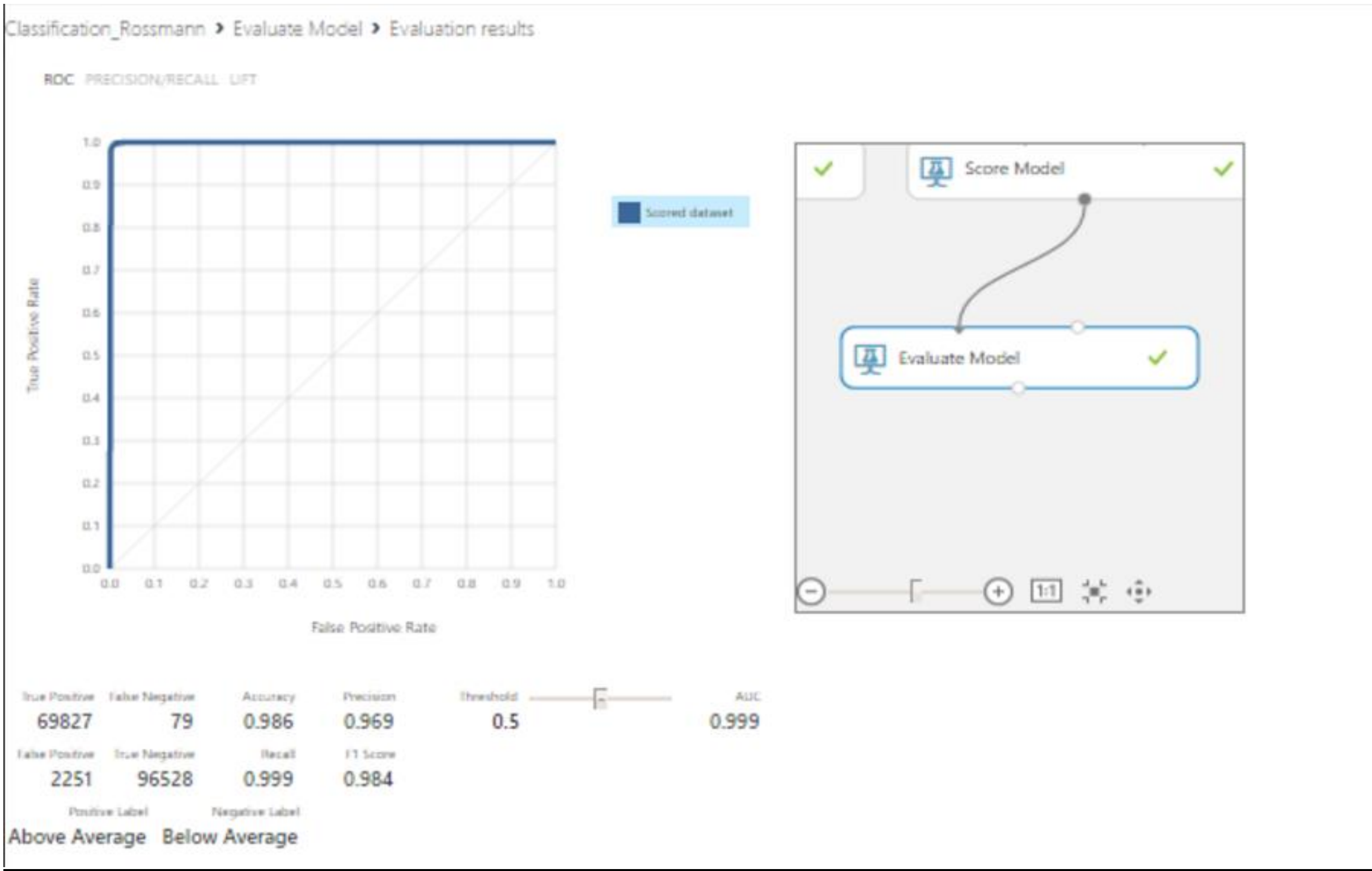
1.9.9 Two-Class Logistic Regression



1.9.10 Two-Class Locally-Deep Support Vector Machine



1.9.11Two Class Neural Network



1.9.12 Summary

Model Name	Accuracy	Precision	Error Percentage
Two Class Support Vector Machine	0.928	0.918	0.71
Two Class Averaged Perceptron	0.997	0.997	0.3
Two Class Bayes Point Machine	0.995	0.996	0.4
Two Class Boosted Decision Tree	0.999	0.999	0.05
Two Class Decision Forest	0.996	0.992	0.43
Two Class Decision Jungle	0.973	0.945	2.6
Two Class Logistic Regression	0.994	0.996	0.5

Two Class Locally Deep SVM	**0.992**	**0.997**	**0.8**
Two Class Neural Network	**0.986**	**0.969**	**1.3**

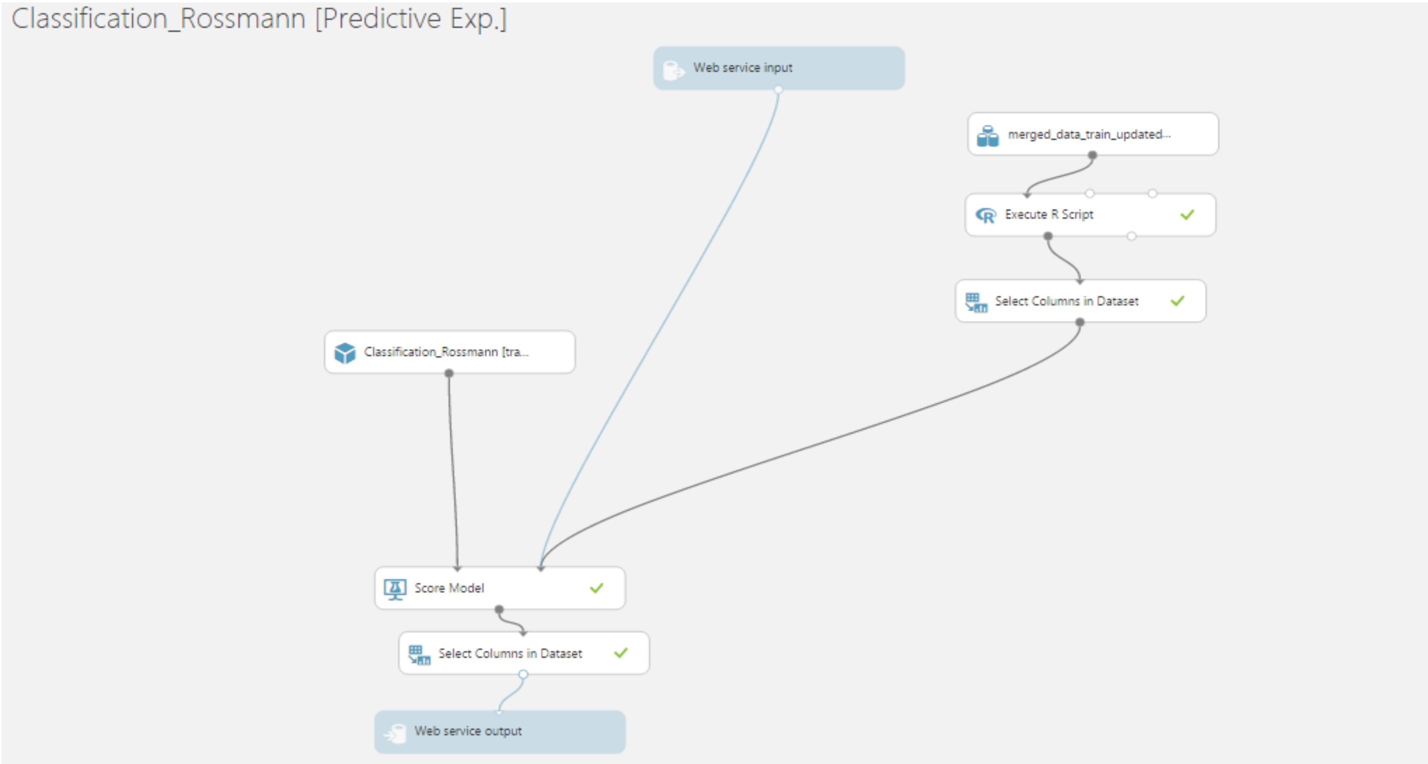
1.9.13 Conclusion

So we chose Two-Class Boosted Decision Tree classification model over all other models as it has the best accuracy and precision and less error percentage.

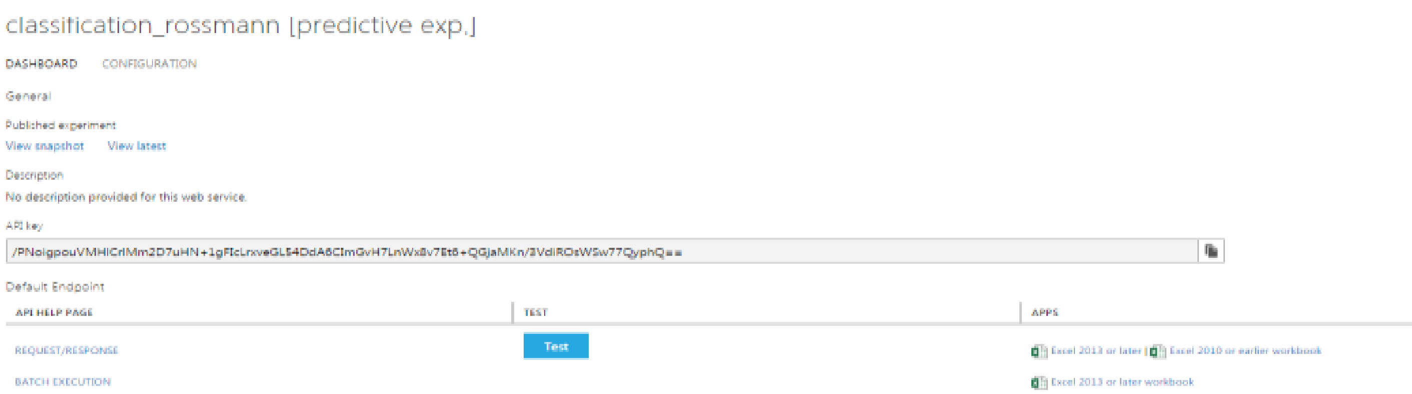
1.9.14 Web Service

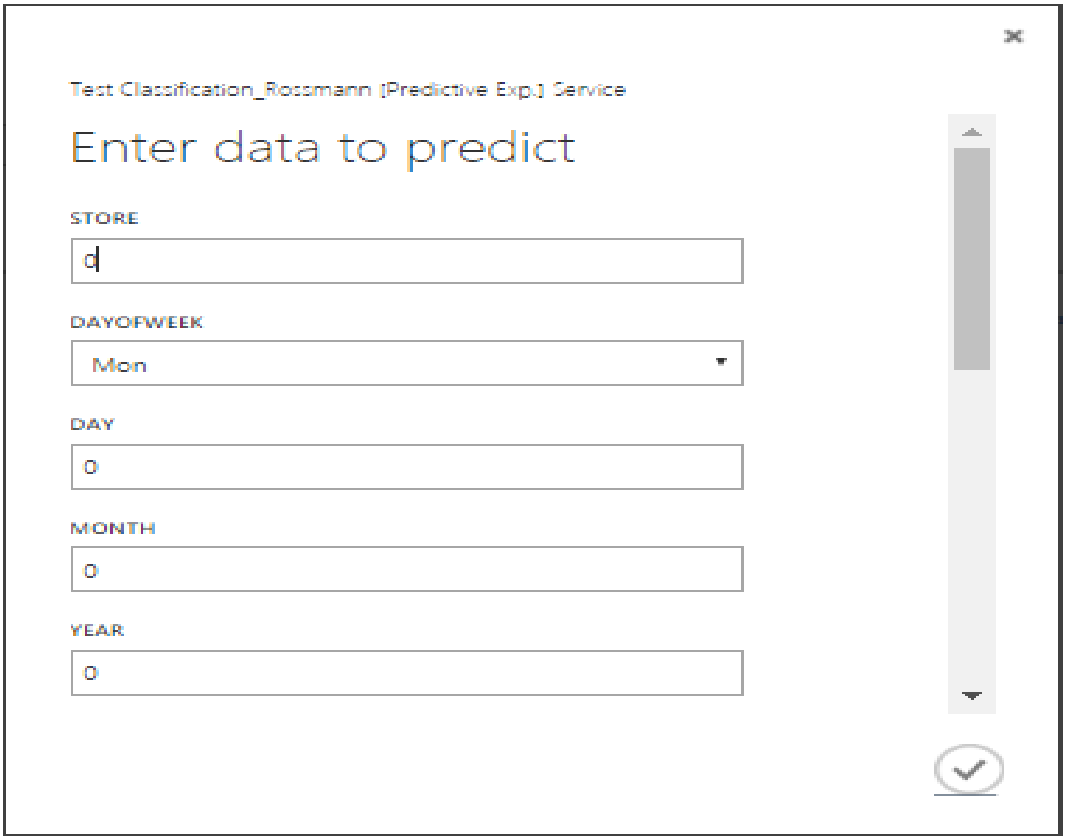
Below are the steps to create a web service of classification model:

- Set-up web service
- Save Two-Class Boosted Decision Tree’s train model as a Trained Model.
- Modules that were used for training are removed. Specifically:
    - Boosted Decision Tree Model
    - Train Model
    - Split Data



- ➢ Then Web Service input and Web Service output is added.
- ➢ Service is deployed.




Test Classification_Rossmann [Predictive Exp.] Service
Enter data to predict
STORE
0
DAYOFWEEK
Mon
DAY
0
MONTH
0
YEAR
0

1.10 Clustering

Clustering can be considered the most important ***unsupervised learning*** problem; so, as every other problem of this kind, it deals with finding a structure in a collection of unlabeled data.
A loose definition of clustering could be 'the process of organizing objects into groups whose members are similar in some way'.
A ***cluster*** is therefore a collection of objects which are 'similar' between them and are 'dissimilar' to the objects belonging to other clusters.

1.10.1 The Algorithm: K-Means Clustering

K-means is one of the simplest unsupervised learning algorithms that solve the well-known clustering problems. The algorithm follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. This algorithm aims at minimizing an *objective function*, in this case a squared error function. The objective function

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2$$

where $\left\| x_i^{(j)} - c_j \right\|^2$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j, is an indicator of the distance of the *n* data points from their respective cluster centres.

1.10.2 Web Service

Below are the steps to create a web service of classification model:

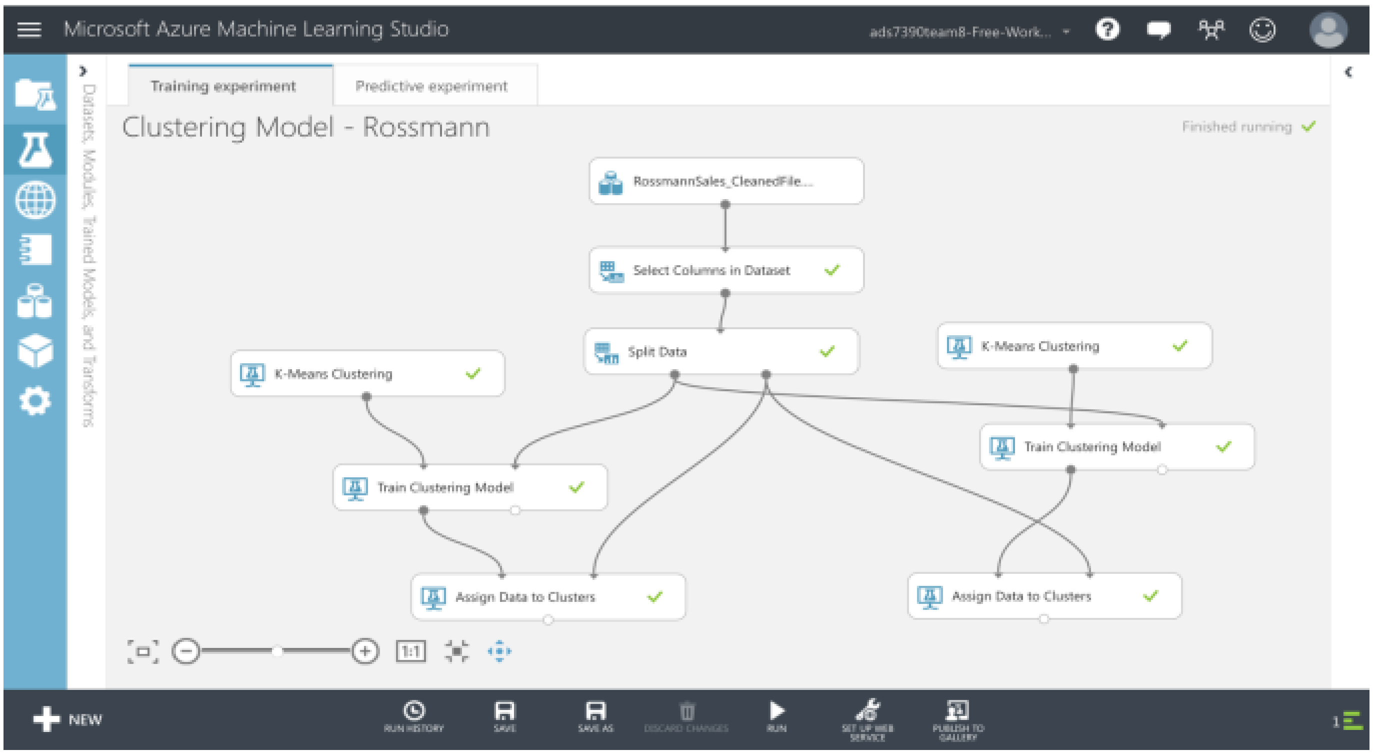
- Set-up web service
- Add dataset to be used for training clustering model.

➢ Modules that were used for training are removed. Specifically:

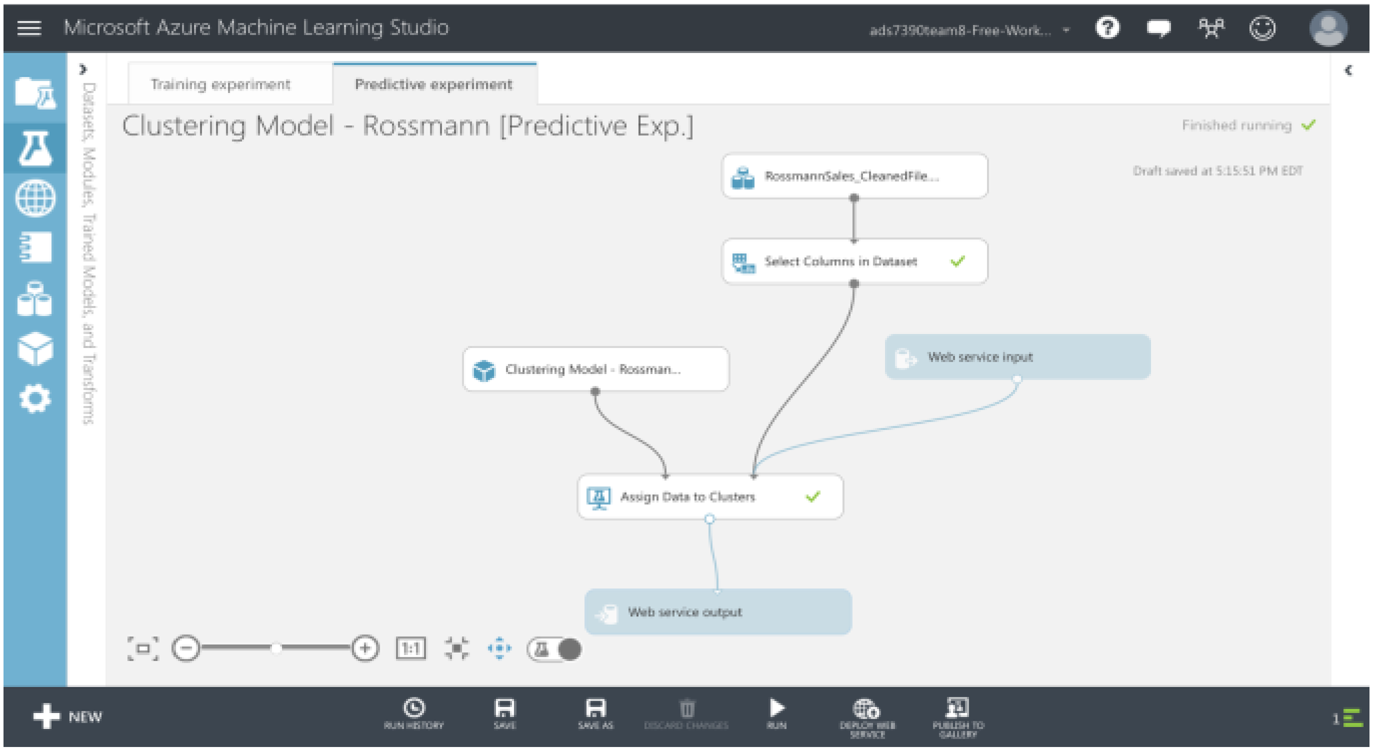
- K-Means Clustering
- Train Clustering Model
- Split
- Assign to Clusters

Experiments -

✓ Training Experiment:



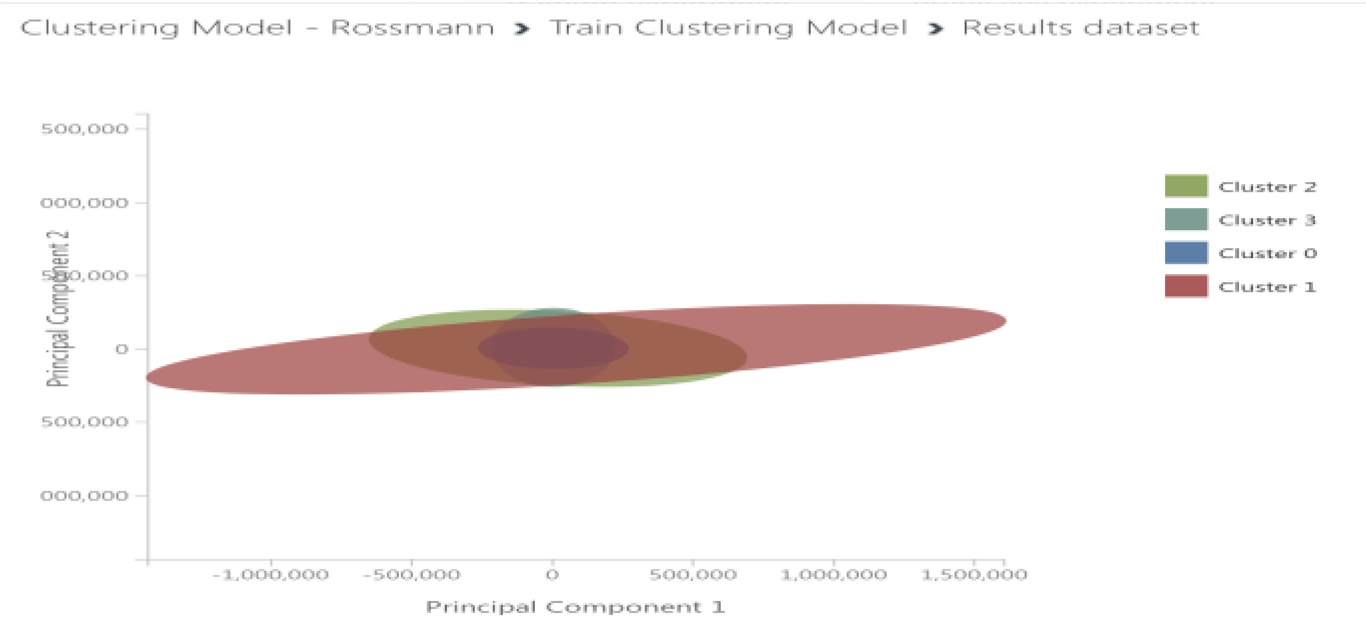
✓ Predictive Experiment:



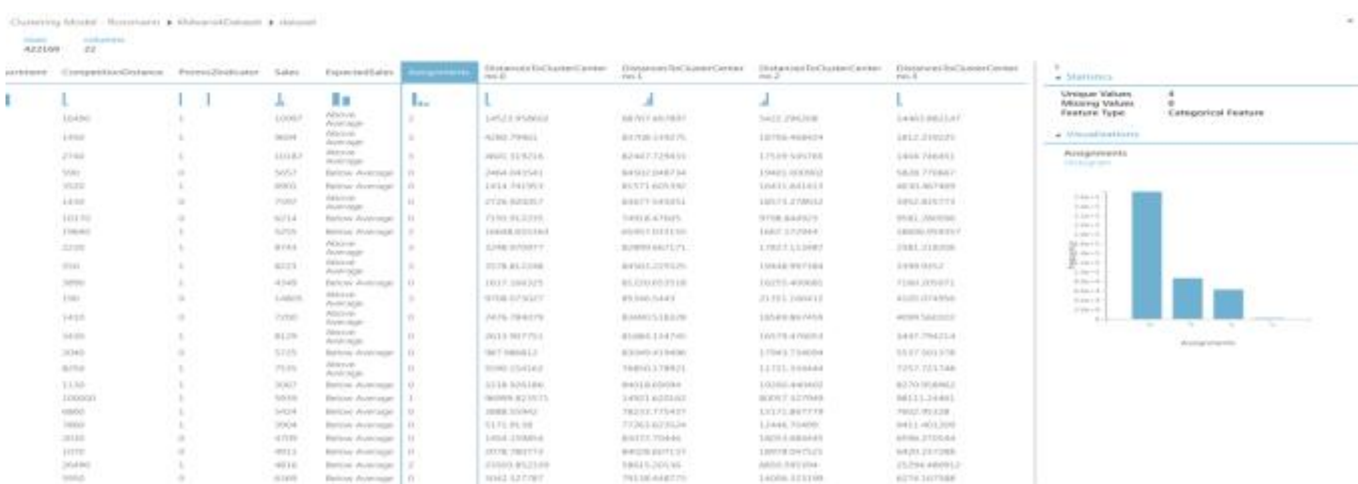
1.10.2 Cluster Formation

- **K = 4**

➢ The following is the clustering graph which depicts the K-Means Clustering for 17 variables in the cleaned train dataset. Here the **K = 4** called as centroids. The clusters show the overall similarity between the values.

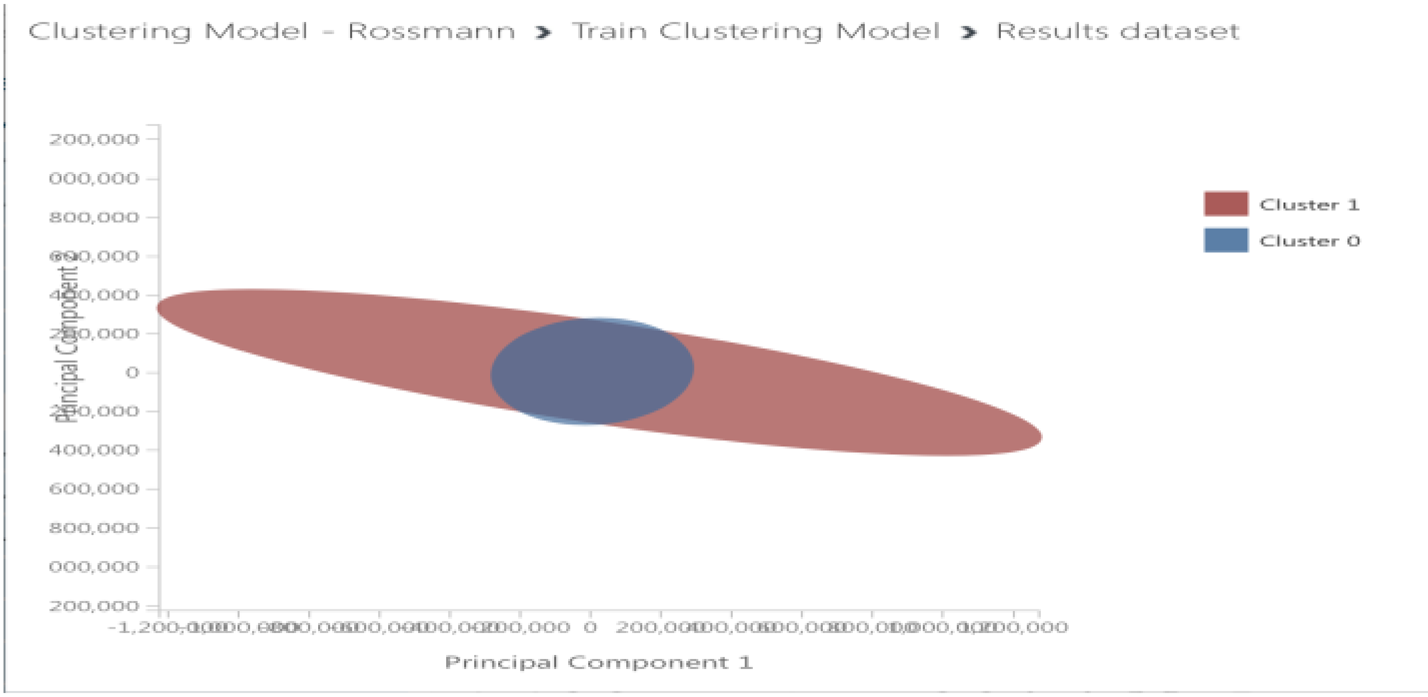


➢ The following is the dataset obtained by training the clustering model with Rossmann sales dataset with K=4. The 'Assignments' column designates which cluster does the value of the particular row belongs to.

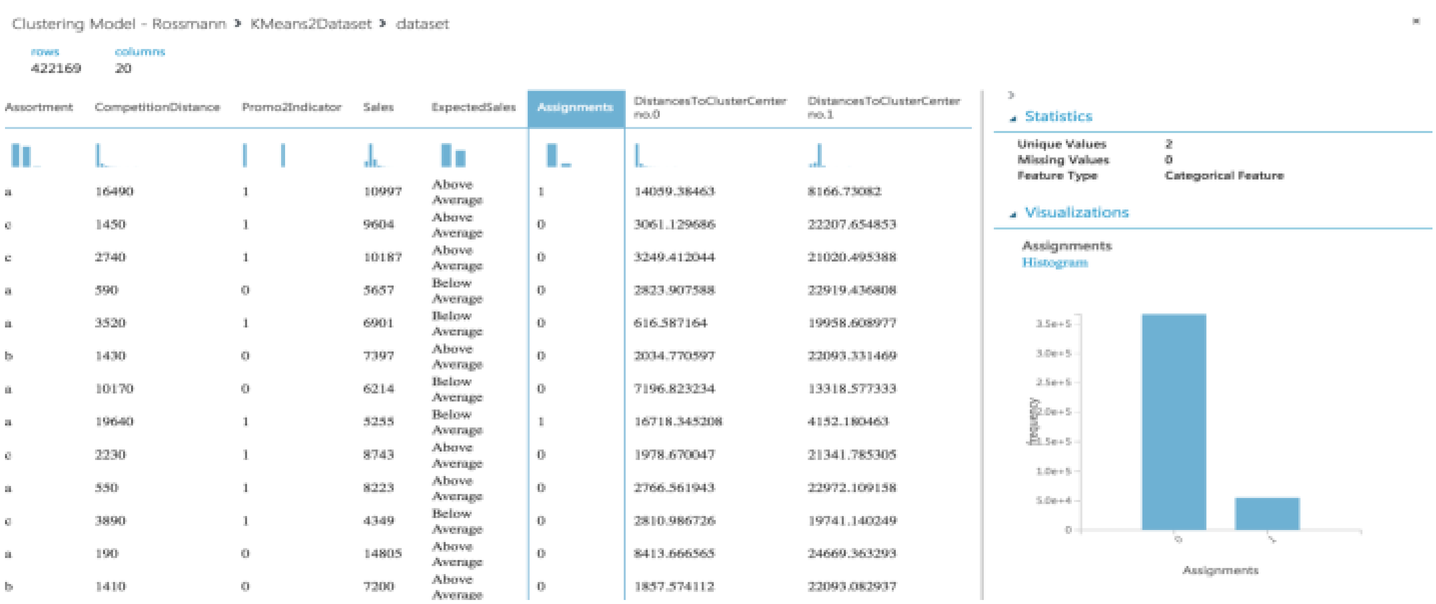


- **K = 2**

The following is the clustering graph which depicts the K-Means Clustering for 17 variables in the cleaned train dataset. Here the **K = 2** called as centroids. The clusters show the overall similarity between the values.

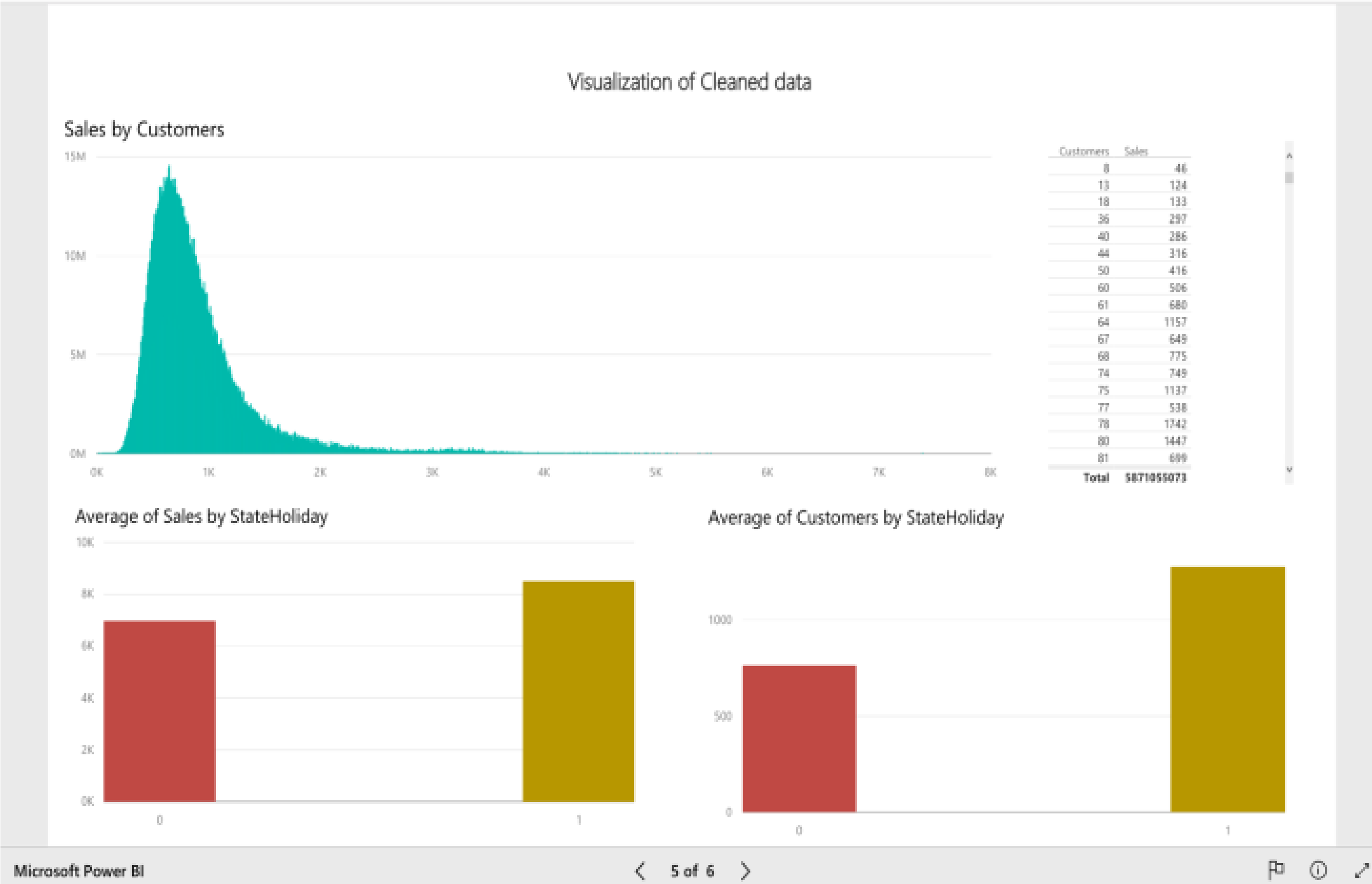


- ➢ The following is the dataset obtained by training the clustering model with Rossmann sales dataset with K=2. The 'Assignments' column designates which cluster does the value of the particular row belongs to.



Assortment	CompetitionDistance	Promo2Indicator	Sales	ExpectedSales	Assignments	DistancesToClusterCenter no.0	DistancesToClusterCenter no.1
a	16490	1	10997	Above Average	1	14059.38463	8166.73082
c	1450	1	9604	Above Average	0	3061.129686	22207.654853
c	2740	1	10187	Above Average	0	3249.412044	21020.495388
a	590	0	5657	Below Average	0	2823.907588	22919.436808
a	3520	1	6901	Below Average	0	616.587164	19958.608977
b	1430	0	7397	Above Average	0	2034.770597	22093.331469
a	10170	0	6214	Below Average	0	7196.823234	13318.577333
a	19640	1	5255	Below Average	1	16718.345208	4152.180463
c	2230	1	8743	Above Average	0	1978.670047	21341.785305
a	550	1	8223	Above Average	0	2766.561943	22972.109158
c	3890	1	4349	Below Average	0	2810.986726	19741.140249
a	190	0	14805	Above Average	0	8413.666565	24669.363293
b	1410	0	7200	Above Average	0	1857.574112	22093.082937

1.11 Power Bi integration with Web Application



1.12 References

1. https://www.kaggle.com/c/rossmann-store-sales
2. https://en.wikipedia.org/wiki/Autoregressive_integrated_moving_average
3. https://www-users.cs.umn.edu/~kumar/dmbook/ch8.pdf
4. http://sutlib2.sut.ac.th/sut_contents/H99006.pdf
5. https://www.coursera.org/learn/machine-learning