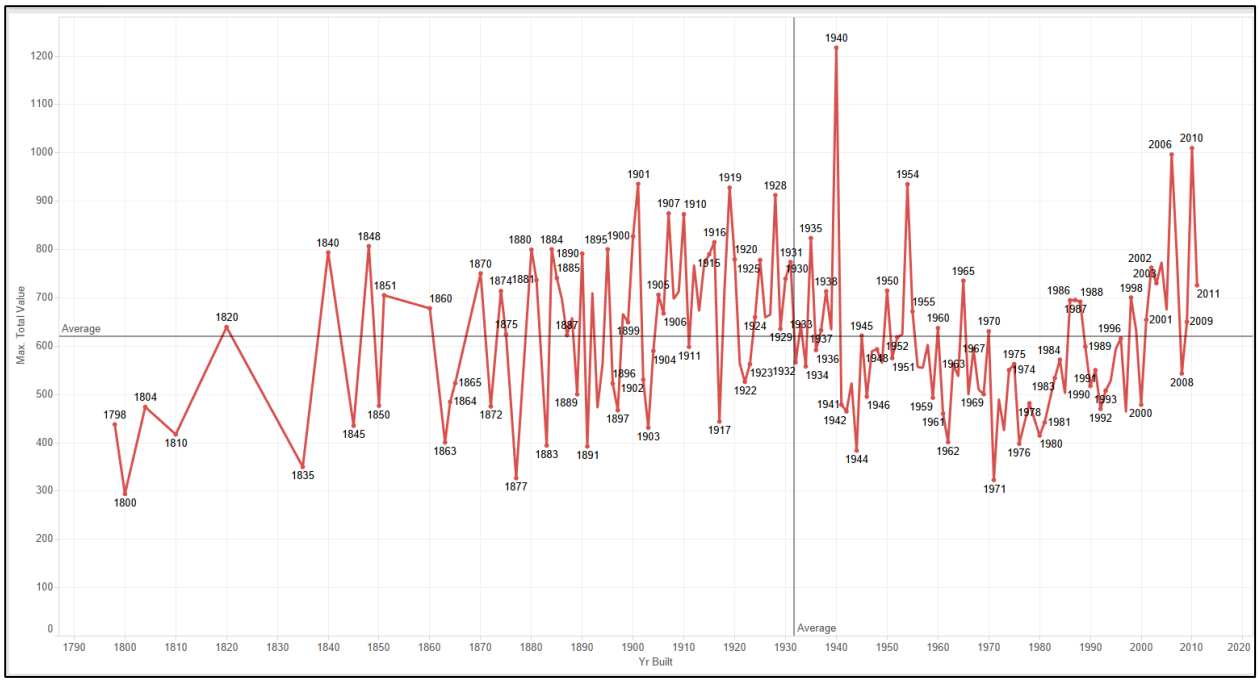
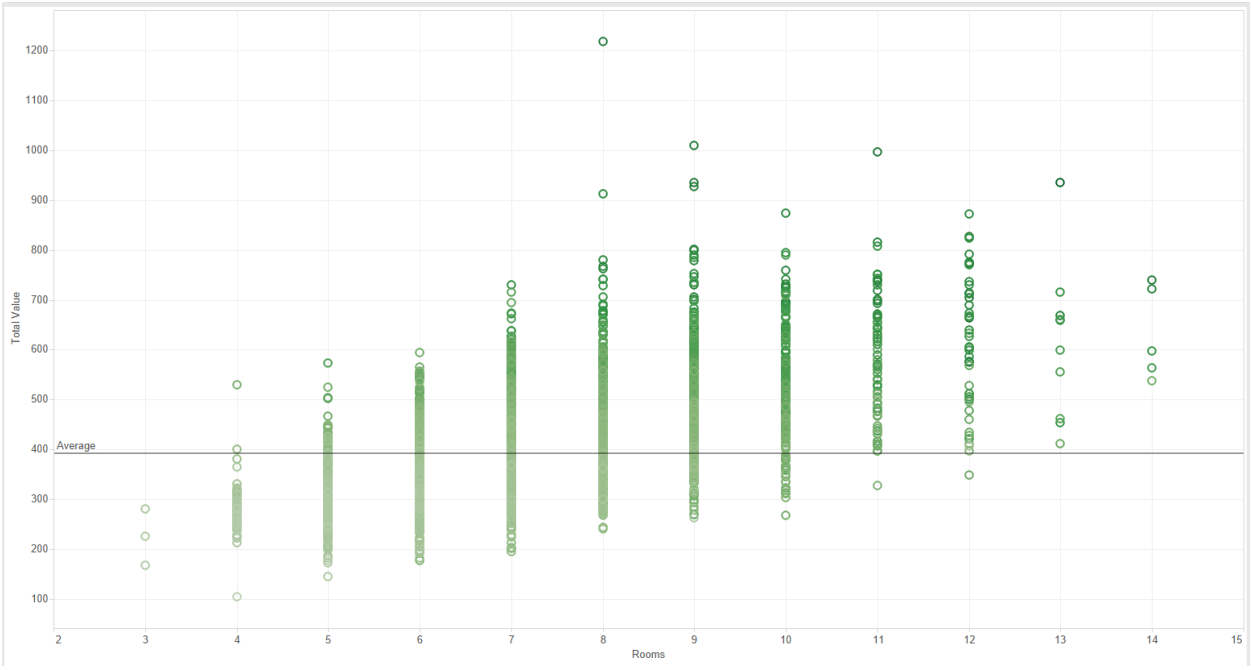
Question 1:

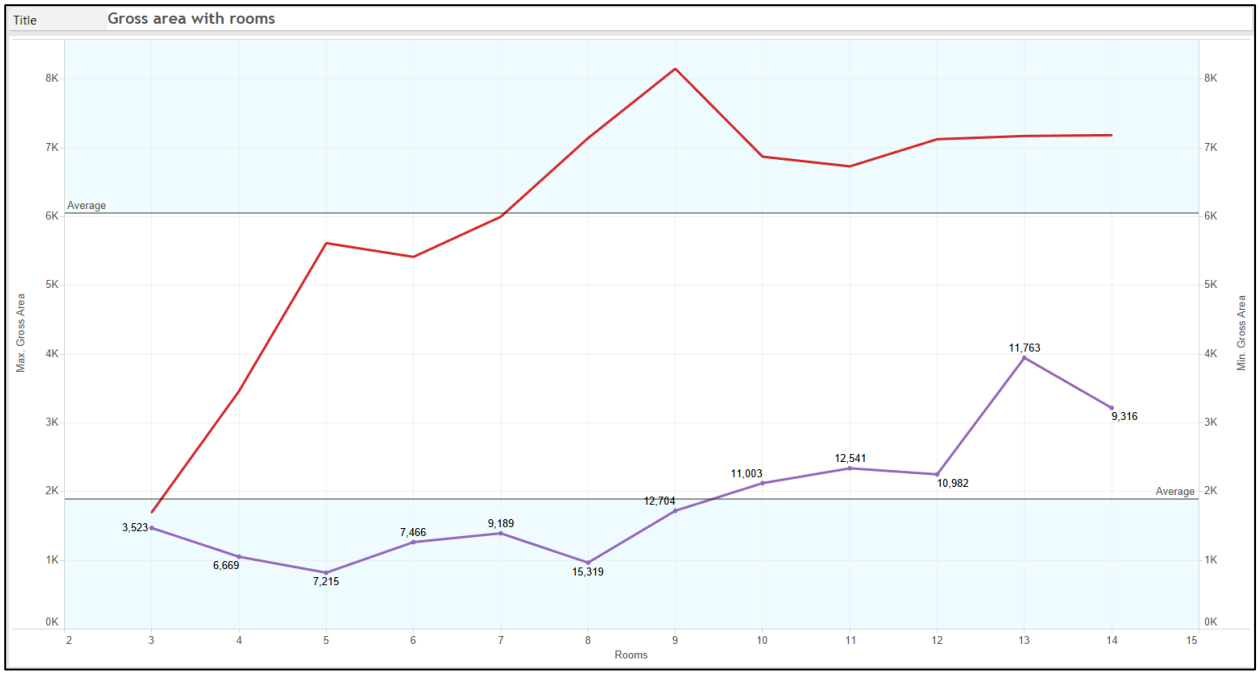
Cleaning data:

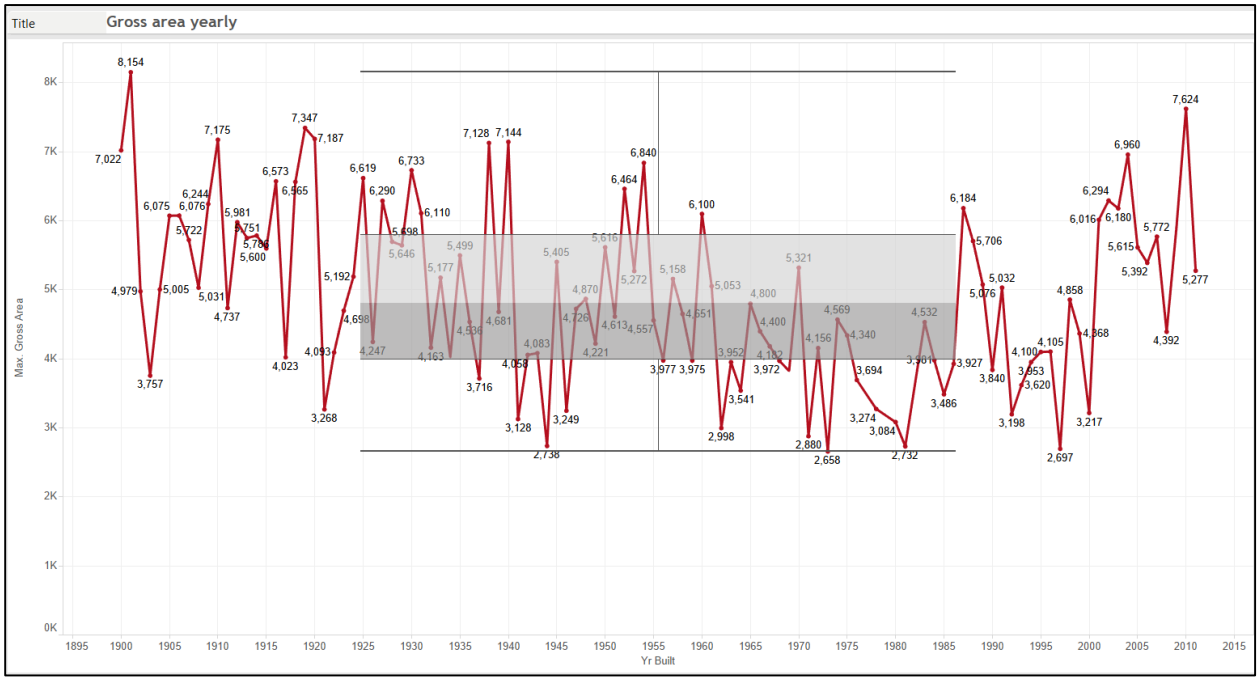
Imported the data set into Wrangler, default datatype for columns was integer. The datatype was changed to decimal to correct the mismatched values in the columns.

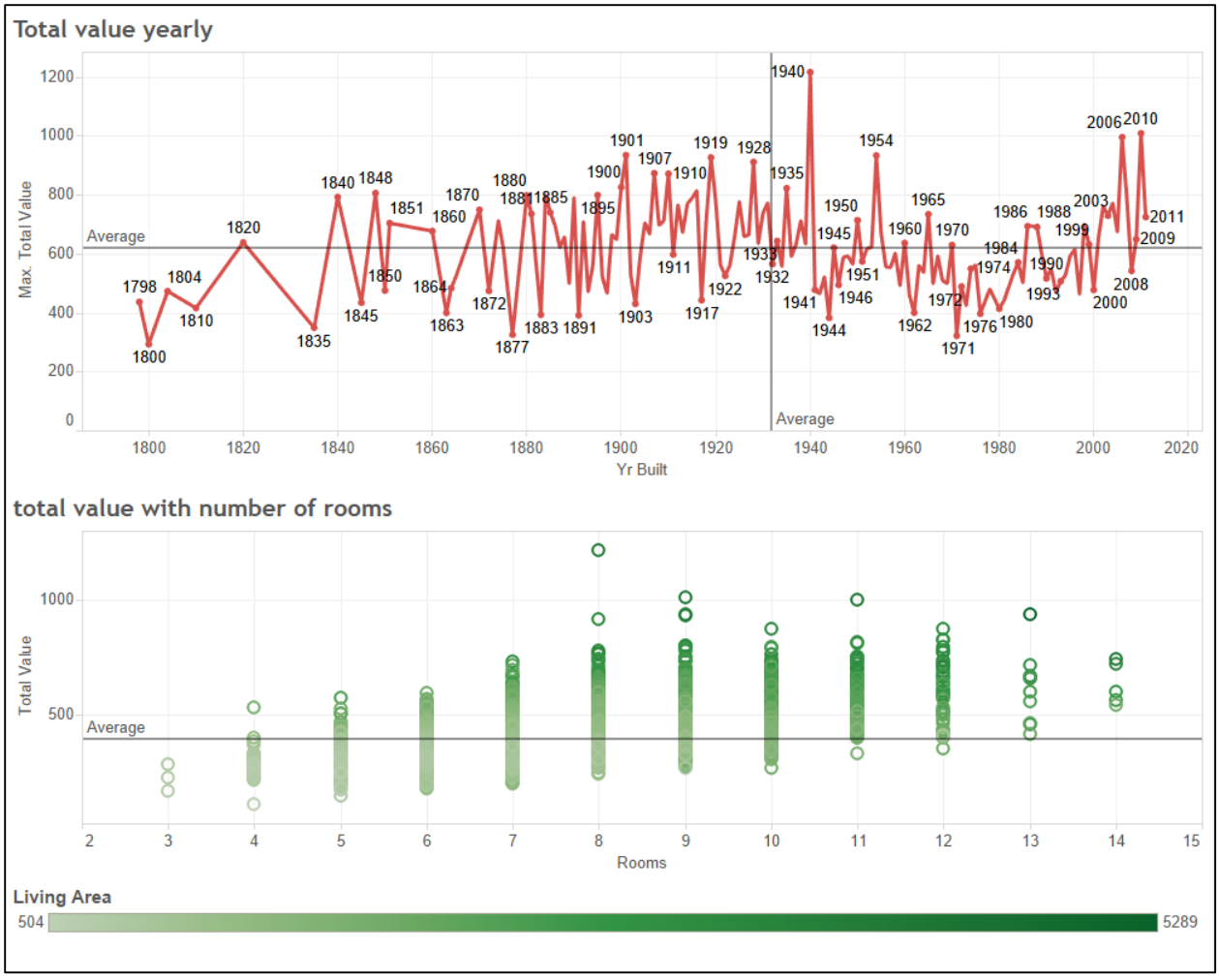
Exploratory analysis:






Title
Gross area with rooms
Max. Gross Area
Min. Gross Area
Rooms
Average
Average
8K
7K
6K
5K
4K
3K
2K
1K
0K
2
3
4
5
6
7
8
9
10
11
12
13
14
15
3,523
6,669
7,215
7,466
9,189
15,319
12,704
11,003
12,541
10,982
11,763
9,316


Title
Gross area yearly
Max. Gross Area
Yr Built
8K
7K
6K
5K
4K
3K
2K
1K
0K
1895
1900
1905
1910
1915
1920
1925
1930
1935
1940
1945
1950
1955
1960
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015


Total value yearly
Max. Total Value
Yr Built
Average
total value with number of rooms
Total Value
Rooms
Average
Living Area
504
5289


Living area with rooms
Median
Average
Rooms
Measure Names
Min. Living Area
Gross area with rooms
Max. Gross Area
Min. Gross Area
Average
Rooms
Gross area yearly
Max. Gross Area
Yr Built

Creating dummies:

Variables REMODEL, FLOORS, ROOMS, BEDROOMS,FULL_BATH, HALF_BATH, KITCHEN, FIREPLACE had categorical values. Created dummy variables for the mentioned variables. FIREPLACE and FLOORS were ignored as their value did not bring significant change to the result.

Partitioning the data:

Partitioned data into 60% and 40%.

60% partition is used as training data and 40% partition is used as validation data.

MULTIPLE LINEAR REGRESSION:

The cutoff probability value for success was kept at 0.5.

Training Data Scoring - Summary Report

Total sum of squared errors	RMS Error	Average Error
2.08232	0.022644	6.55428E-14

Validation Data Scoring - Summary Report

Total sum of squared errors	RMS Error	Average Error
0.904658	0.022802	-0.00256916

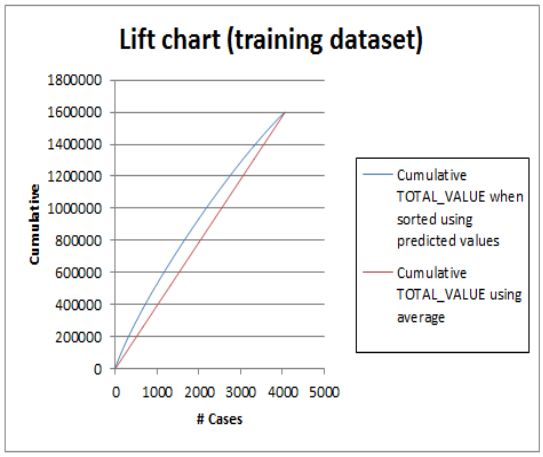
ANOVA

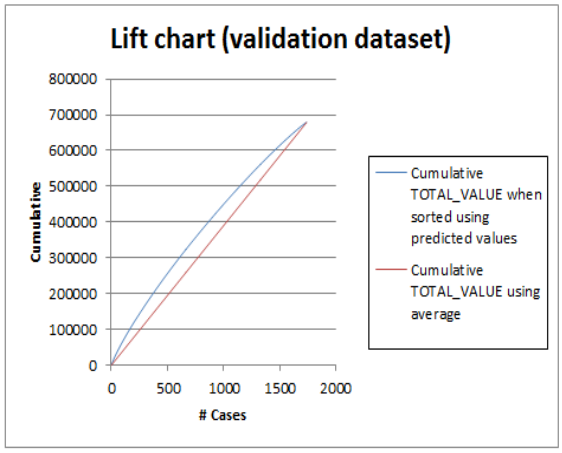
Source	DF	SS	MS	F-Statistic	P-Value
Regression	33	39498956.35	1196938.071	2314759305	0
Error	4027	2.0823	0.0005		
Total	4060	39498958.43	1196938.072		

The RMS Error for training data set is 0.0226 whereas for validation data set it is 0.0228.

Used ANOVA to perform regression.

Lift Chart:

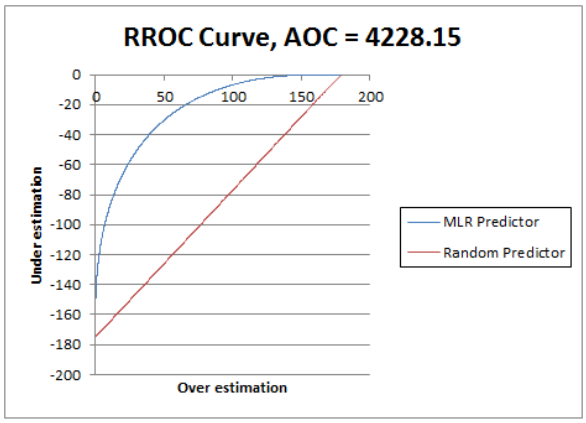


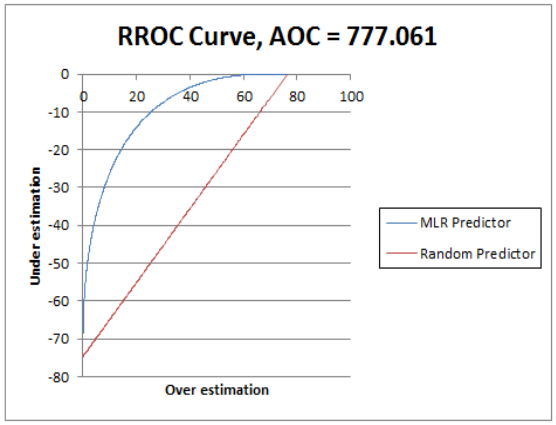


A lift chart is the graphical way to assess the predictive performance of a model. It compares the model with the baseline model that has no predictors. It can be said that model's predictive performance is better than baseline model.

ROC Curve:

Training dataset and Validation dataset:





The ROC (Receiver Operating Characteristic) curve plots the sensitivity and 1-specificity. Better performance are given by the curves that are near the Y axis. Area under the Curve is 777.061 for validation data set as shown in the figure.

CART

The cutoff probability value for success was kept at 0.5.

Training Data scoring - Summary Report (Using Best Pruned Tree)

Total sum of squared errors	RMS Error	Average Error
1524663	19.37628	7.08478E-14

Validation Data scoring - Summary Report (Using Best Pruned Tree)

Total sum of squared errors	RMS Error	Average Error
966744.6	23.57118	-0.08632458

The RMS Error for training data set is 19.37 whereas for validation data set it is 23.57.

Best Pruned Tree:

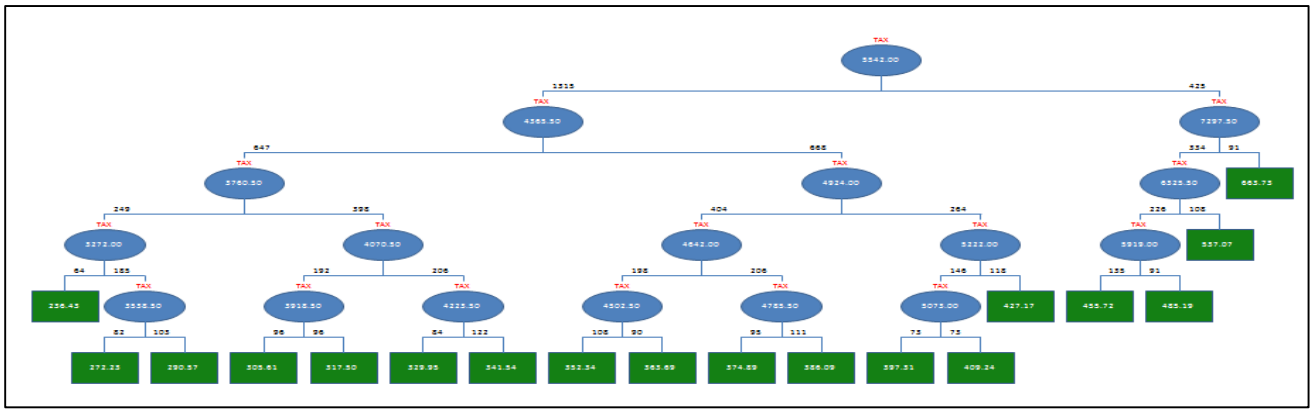
Best Pruned Tree Rules (Using Validation Data)

#Decision Nodes	12	#Terminal Nodes	13

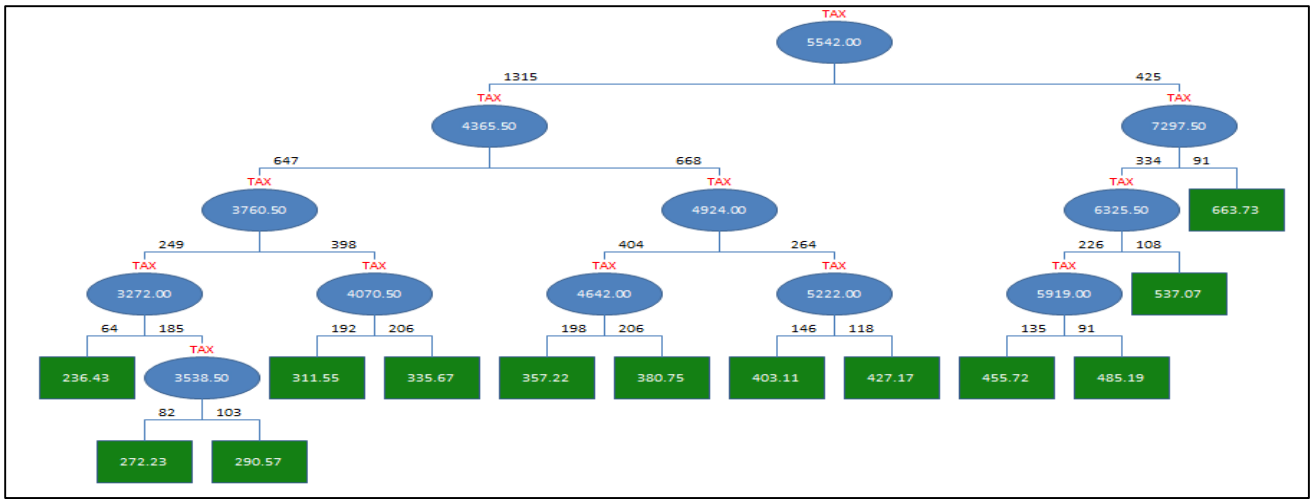
Level	NodeID	ParentID	SplitVar	litValue/S	Cases	LeftChild	RightChil	PredVal	Node Type
0	0	N/A	TAX	5542	1740	1	2	393.77	Decision
1	1	0	TAX	4365.5	1315	3	4	349.92	Decision
1	2	0	TAX	7297.5	425	5	6	531.45	Decision
2	3	1	TAX	3760.5	647	7	8	304.41	Decision
2	4	1	TAX	4924	668	9	10	389.61	Decision
2	5	2	TAX	6325.5	334	11	12	495.64	Decision
2	6	2	N/A	N/A	91	N/A	N/A	663.73	Terminal
3	7	3	TAX	3272	249	13	14	273.95	Decision
3	8	3	TAX	4070.5	398	15	16	323.97	Decision
3	9	4	TAX	4642	404	17	18	369.03	Decision
3	10	4	TAX	5222	264	19	20	413.93	Decision
3	11	5	TAX	5919	226	21	22	468.43	Decision
3	12	5	N/A	N/A	108	N/A	N/A	537.07	Terminal
4	13	7	N/A	N/A	64	N/A	N/A	236.43	Terminal
4	14	7	TAX	3538.5	185	23	24	283.62	Decision
4	15	8	N/A	N/A	192	N/A	N/A	311.55	Terminal
4	16	8	N/A	N/A	206	N/A	N/A	335.67	Terminal
4	17	9	N/A	N/A	198	N/A	N/A	357.22	Terminal
4	18	9	N/A	N/A	206	N/A	N/A	380.75	Terminal
4	19	10	N/A	N/A	146	N/A	N/A	403.11	Terminal
4	20	10	N/A	N/A	118	N/A	N/A	427.17	Terminal
4	21	11	N/A	N/A	135	N/A	N/A	455.72	Terminal
4	22	11	N/A	N/A	91	N/A	N/A	485.19	Terminal
5	23	14	N/A	N/A	82	N/A	N/A	272.23	Terminal
5	24	14	N/A	N/A	103	N/A	N/A	290.57	Terminal

# Decision Nodes	Cost Complexity	Train. MSE	Valid. MSE			
0	6037.647977	9726.41183	10078.52			
1	2739.582377	3688.76385	4030.297			
2	3433.257121	2318.97266	2695.818			
3	857.1945374	1174.55362	1424.932			
4	1052.656643	964.022294	1209.558			
5	1216.713172	761.236765	944.861			
6	350.9038504	546.938131	756.5727			
7	250.1528075	496.80901	681.2771			
8	273.2196347	465.539909	644.2812			
9	265.9572705	435.182171	614.0293			
10	268.9524265	408.586444	592.0313			
11	104.3526456	384.136224	564.0785			
12	48.39243006	375.44017	555.6003	<-- Best Pruned		
13	51.64564057	371.751196	551.5966			
14	54.51257387	368.028701	547.2672			
15	55.23720552	364.576376	544.466			
16	58.56194024	361.131556	541.2391			
17	0	357.497384	537.7855	<-- Min Error Tree	Std. Error	23.1902

Minimum Error Tree

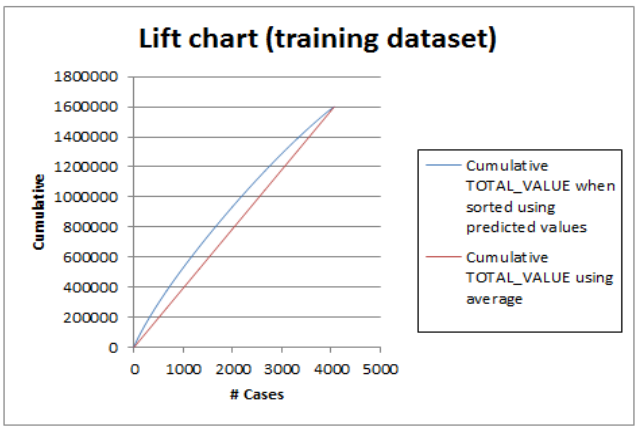


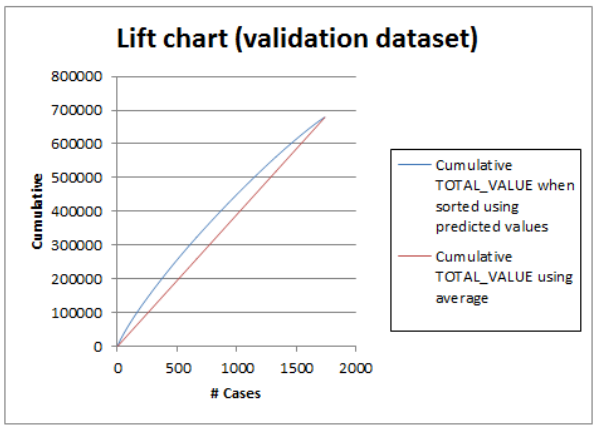
Best Pruned Tree:



Lift Chart:

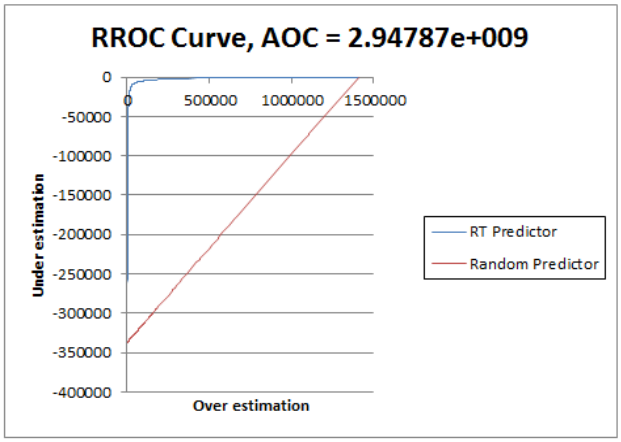
Training dataset and Validation dataset:

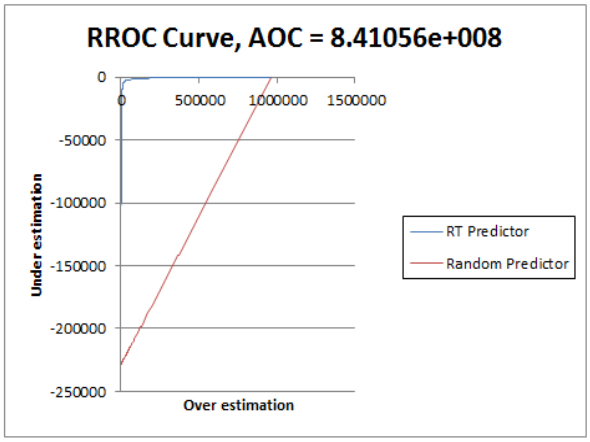




ROC Curve:

Training dataset and Validation dataset:





Random Forest:

Training Data scoring - Summary Report

Total sum of squared errors	RMS Error	Average Error
1358439	18.28957	0.14333

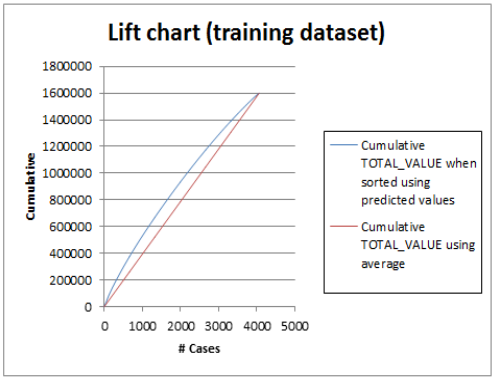
Validation Data scoring - Summary Report

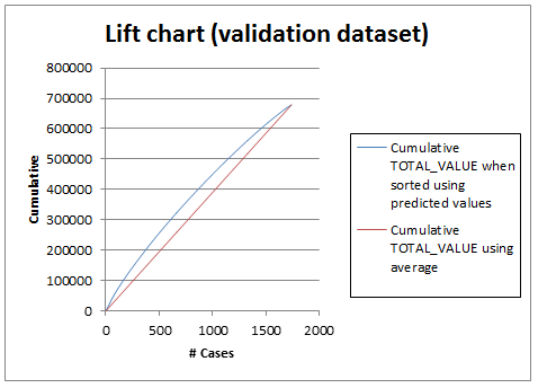
Total sum of squared errors	RMS Error	Average Error
928208.3	23.0966	-0.18956

The RMS Error for training data set is 18.28957 whereas for validation data set it is 23.0966.

Lift Chart:

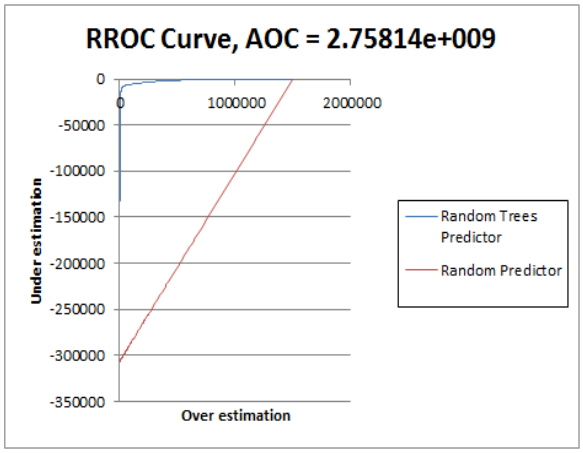
Training dataset and Validation dataset:

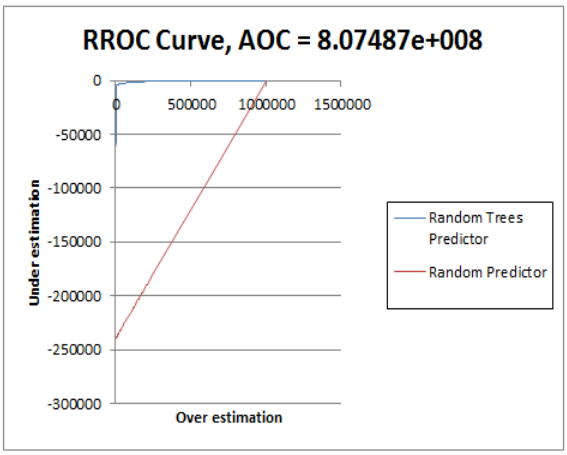




ROC Curve:

Training dataset and Validation dataset:





Comparison between the models:

Based on overall percentage error for validation datasets and maximum area under the curve (ROC), Random Forest turns out to be the best model amongst all models.

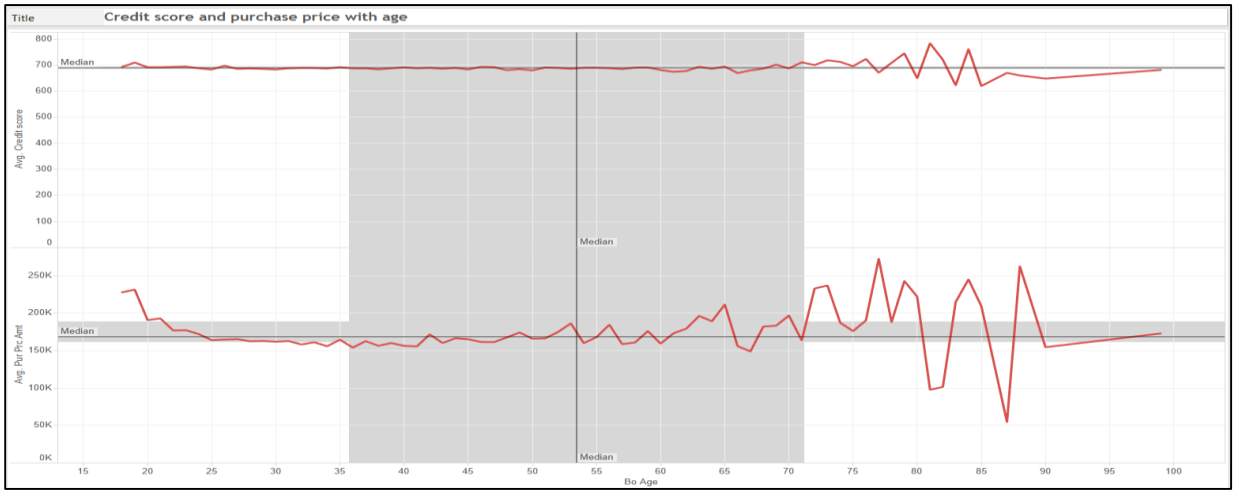
To calculate the Value of a home, random forest model is useful because it gives minimum RMS error and the validation data set has an average error of -0.18.

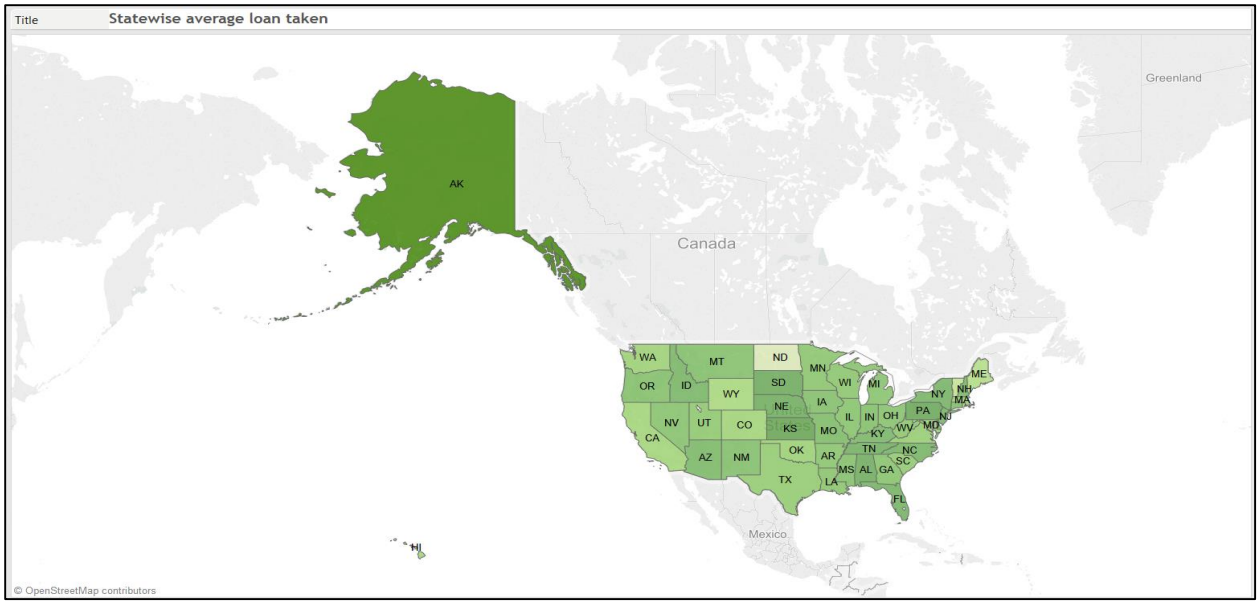
Question 2:

Cleaning data:

Imported the data set into Wrangler. Some columns had no data and some had missing and mismatched values. Columns without data were dropped missing values were deleted.

Exploratory analysis:




Title
Statewise average loan taken
Greenland
AK
Canada
WA
MT
ND
MN
OR
ID
SD
WI
MI
WY
NY
NH
ME
MA
NE
IA
NV
UT
CO
KS
IL
IN
OH
PA
NJ
MD
WV
CA
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NM
OK
AR
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SC
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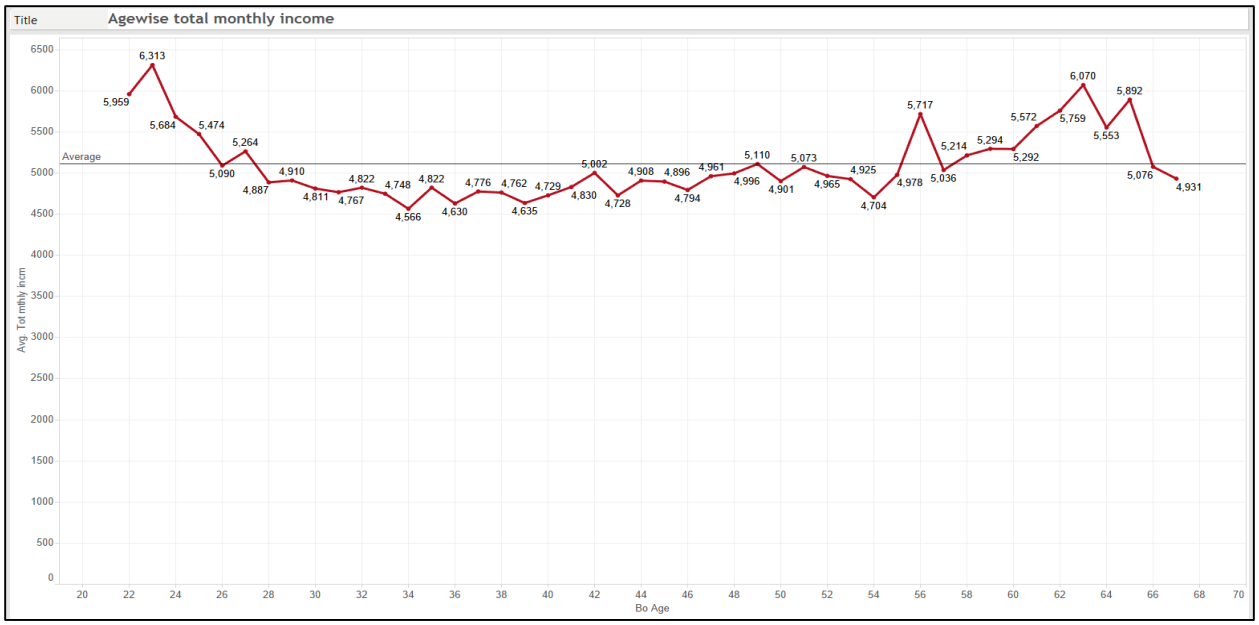
AL
GA
TX
LA
FL
HI
Mexico
© OpenStreetMap contributors


Title
Agewise total monthly income
Average
Avg. Tot mthly incm
Bo Age
6500
6000
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
20
22
24
26
28
30
32
34
36
38
40
42
44
46
48
50
52
54
56
58
60
62
64
66
68
70
5,959
6,313
5,684
5,474
5,090
5,264
4,887
4,910
4,811
4,822
4,767
4,748
4,566
4,822
4,630
4,776
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4,635
4,729
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4,728
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4,896
4,794
4,961
4,996
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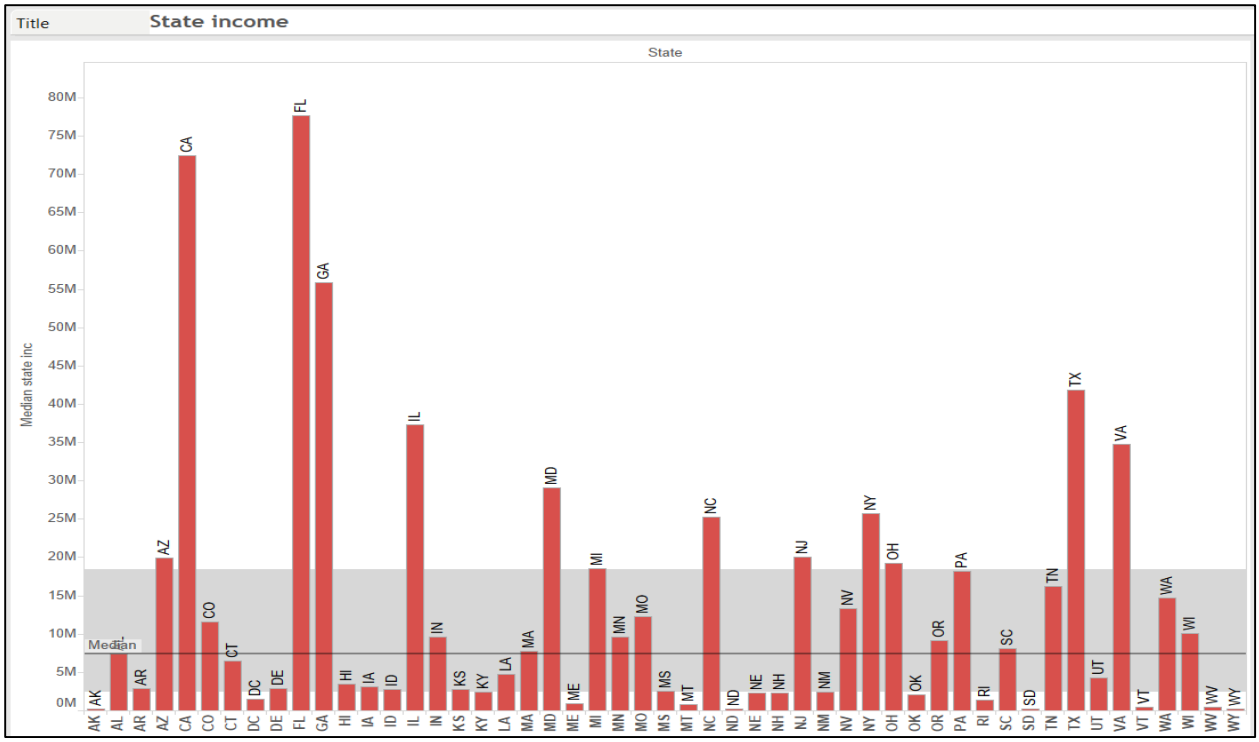
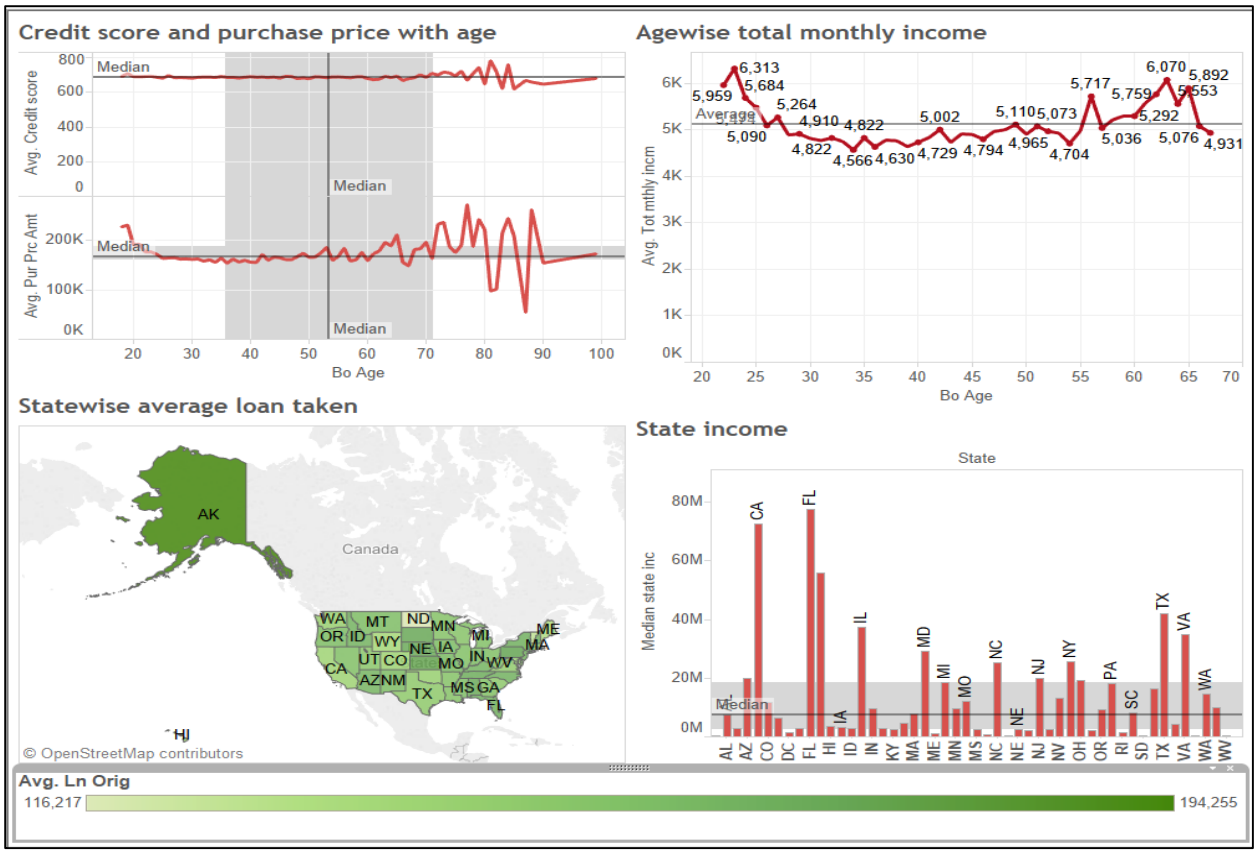
5,076
4,931


Title
State income
State
Median state inc
Median

Dashboard:


Credit score and purchase price with age
Avg. Credit score
Avg. Pur Prc Amt
Median
Bo Age
Agewise total monthly income
Avg. Tot mthly incm
Average
Bo Age
Statewise average loan taken
AK
Canada
© OpenStreetMap contributors
Avg. Ln Orig
116,217
194,255
State income
State
Median state inc
Median

Creating dummies:

There were several categorical variables like First_home, Status, OUTCOME, UPB_Appraisal. Created dummy variables for the mentioned categorical variables.

Partitioning the data:

Partitioned data into 60% and 40%. 60% partition is used as training data and 40% partition is used as validation data.

Logistic Regression:

The cutoff probability value for success was kept at 0.5.

Training Data Scoring - Summary Report

Cutoff probability value for success (UPDATABLE)	0.5	Updating the value here will NOT update value in detailed report

Confusion Matrix

	Predicted Class	
Actual Class	1	0
1	5020	0
0	0	4060

Error Report

Class	# Cases	# Errors	% Error
1	5020	0	0
0	4060	0	0
Overall	9080	0	0

Performance

Success Class	1
Precision	1
Recall (Sensitivity)	1
Specificity	1
F1-Score	1

The overall % error rate is 0.00 and model classifies 5020 as Default Outcome and 982 NON Default Outcome correctly.

Validation Data Scoring - Summary Report

Cutoff probability value for success (UPDATABLE)	0.5	Updating the value here will NOT update value in detailed report

Confusion Matrix

	Predicted Class	
Actual Class	1	0
1	3294	3
0	3	2754

Error Report

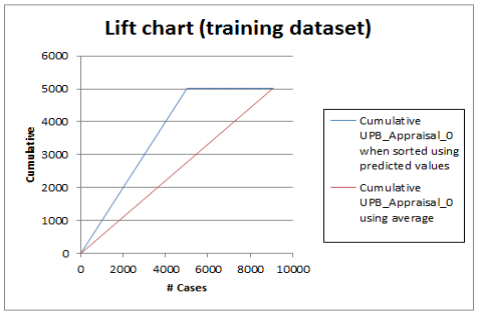
Class	# Cases	# Errors	% Error
1	3297	3	0.090991811
0	2757	3	0.108813928
Overall	6054	6	0.099108028

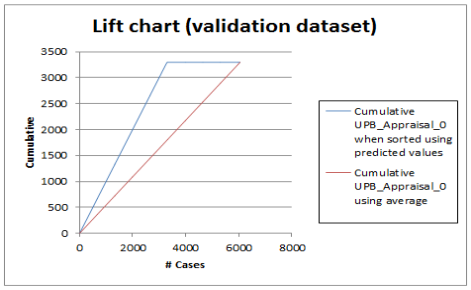
Performance

Success Class	1
Precision	0.99909
Recall (Sensitivity)	0.99909
Specificity	0.998912
F1-Score	0.99909

The overall error rate 0.099% and the model classify 3294 as Default Outcome and 2754 NON Default Outcome correctly.

Lift Chart:



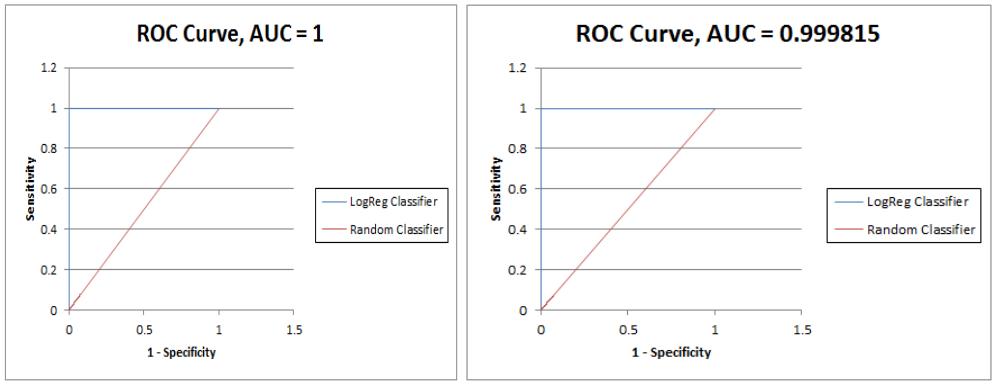


A lift chart is the graphical way to assess the predictive performance of a model. It compares the model with the baseline model that has no predictors.

Lift chart is based on 6000 validation records. It can be said that model's predictive performance is better than baseline model.

ROC Curve:

Training dataset and Validation dataset:



The ROC (Receiver Operating Characteristic) curve plots the sensitivity and 1-specificity. Better performance are given by the curves that are near the Y axis. Area under the Curve for validation dataset is 0.999 as shown in the figure.

CART

The cutoff probability value for success was kept at 0.5.

Training Data scoring - Summary Report (Using Full-Grown Tree)

Cutoff probability value for success (UPDATABLE) 0.5 Updating the value here will NOT update value in detailed report

Confusion Matrix

	Predicted Class	
Actual Class	1	0
1	4812	208
0	470	3590

Error Report

Class	# Cases	# Errors	% Error
1	5020	208	4.143426
0	4060	470	11.57635
Overall	9080	678	7.46696

Performance

Success Class	1
Precision	0.911019
Recall (Sensitivity)	0.958566
Specificity	0.884236
F1-Score	0.934188

The overall % error rate 7.46 and model classifies 4812 as Default Outcome and 3590 as NON Default Outcome correctly.

Validation Data scoring - Summary Report (Using Best Pruned Tree)

Cutoff probability value for success (UPDATABLE) 0.5 Updating the value here will NOT update value in detailed report

Confusion Matrix

	Predicted Class	
Actual Class	1	0
1	3141	156
0	318	2439

Error Report

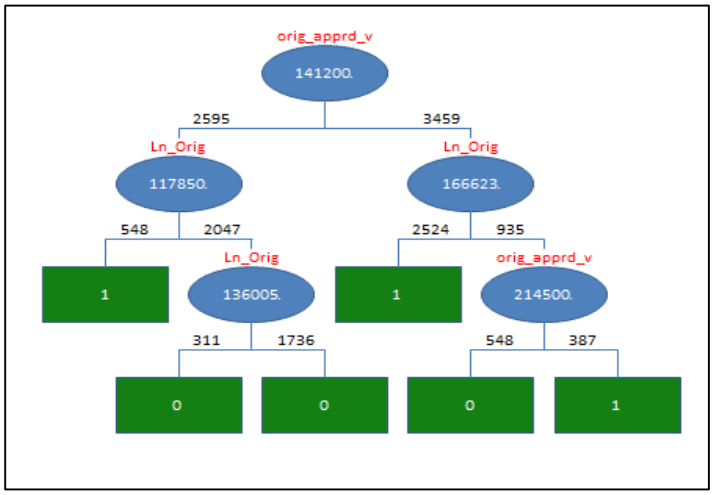
Class	# Cases	# Errors	% Error
1	3297	156	4.731574
0	2757	318	11.53428
Overall	6054	474	7.829534

Performance

Success Class	1
Precision	0.908066
Recall (Sensitivity)	0.952684
Specificity	0.884657
F1-Score	0.92984

The overall % error rate is 7.829 and model classifies 3141 as Default Outcome and 2439 as NON Default Outcome correctly.

Best Pruned tree:

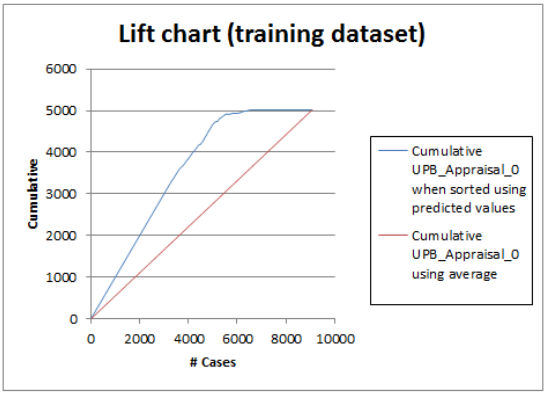


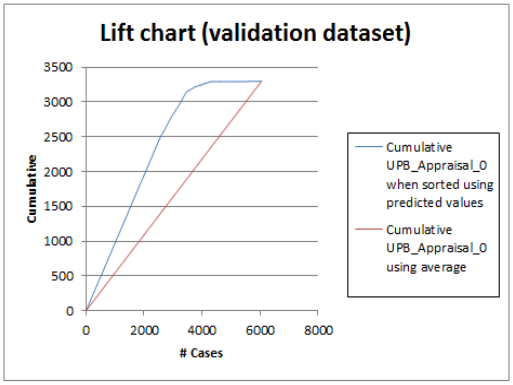
Best-Pruned Tree Rules (Using Validation Data)

#Decision Nodes	5	#Terminal Nodes	6

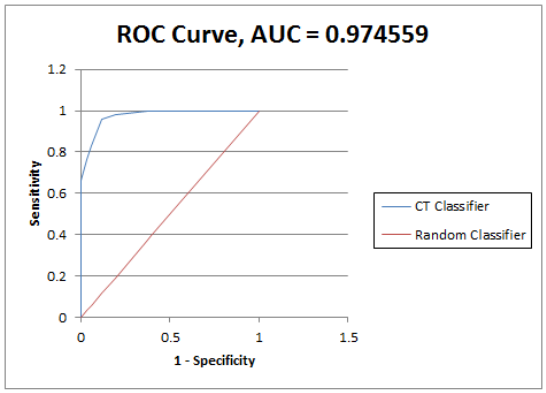
NodeID	Level	ParentID	LeftChild	RightChild	SplitVar	plitValue/Se	Cases	sclassificatic	Class	Node Type
0	0	N/A	1	2	apprd_val	141200.5	6054	0.447137	1	Decision
1	1	0	3	4	Ln_Orig	117850	2595	0.084581	0	Decision
2	1	0	5	6	Ln_Orig	166623.5	3459	0.105727	1	Decision
3	2	1	N/A	N/A	N/A	N/A	548	0.02533	1	Terminal
4	2	1	7	8	Ln_Orig	136005	2047	0.012335	0	Decision
5	2	2	N/A	N/A	N/A	N/A	2524	0.011674	1	Terminal
6	2	2	9	10	apprd_val	214500	935	0.064978	0	Decision
7	3	4	N/A	N/A	N/A	N/A	311	0.011454	0	Terminal
8	3	4	N/A	N/A	N/A	N/A	1736	0.000881	0	Terminal
9	3	6	N/A	N/A	N/A	N/A	548	0.010573	0	Terminal
10	3	6	N/A	N/A	N/A	N/A	387	0.014758	1	Terminal

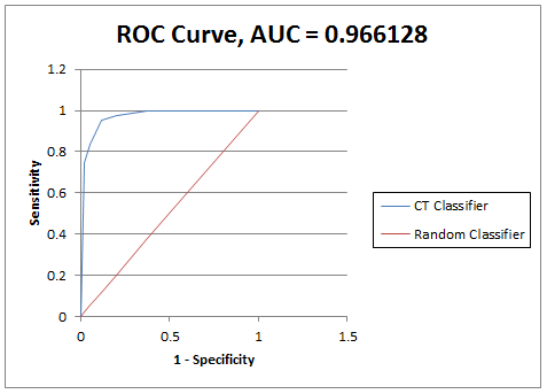
Lift Chart:





ROC Curve:





RANDOM TREE:

The cutoff probability value for success was kept at 0.5.

Training Data scoring - Summary Report

Cutoff probability value for success (UPDATABLE)	0.5	Updating the value here will NOT update value in detailed report

Confusion Matrix

	Predicted Class	
Actual Class	1	0
1	4784	236
0	306	3754

Error Report

Class	# Cases	# Errors	% Error
1	5020	236	4.701195
0	4060	306	7.536946
Overall	9080	542	5.969163

Performance

Success Class	1
Precision	0.939882
Recall (Sensitivity)	0.952988
Specificity	0.924631
F1-Score	0.94639

The overall % error rate 5.96 and model classifies 4784 as Default Outcome and 3754 as NON Default Outcome correctly.

Validation Data scoring - Summary Report

Cutoff probability value for success (UPDATABLE)	0.5	Updating the value here will NOT update value in detailed report

Confusion Matrix

	Predicted Class	
Actual Class	1	0
1	3097	200
0	201	2556

Error Report

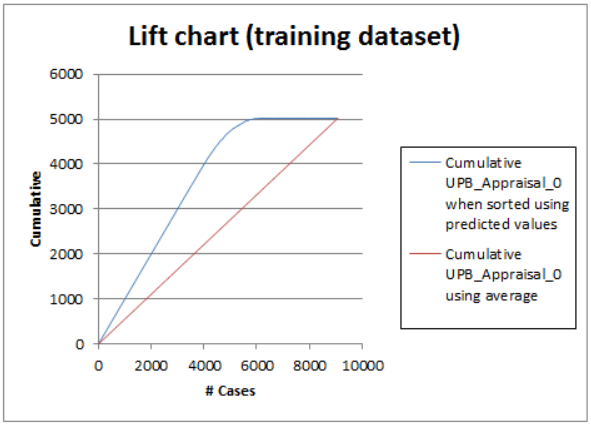
Class	# Cases	# Errors	% Error
1	3297	200	6.066121
0	2757	201	7.290533
Overall	6054	401	6.62372

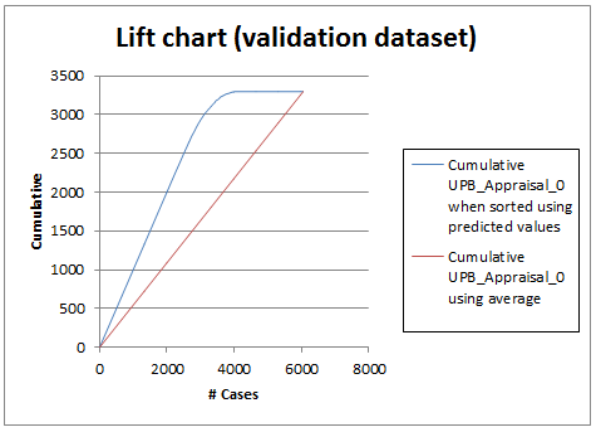
Performance

Success Class	1
Precision	0.939054
Recall (Sensitivity)	0.939339
Specificity	0.927095
F1-Score	0.939196

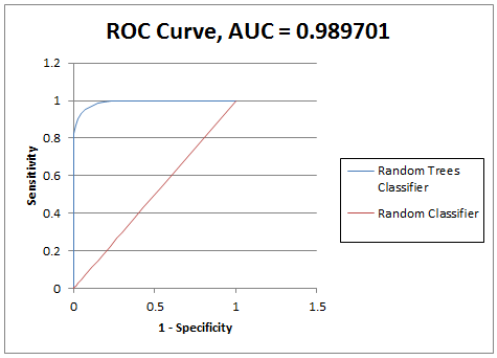
The overall % error rate is 6.623 and model classifies 3097 as Default Outcome and 2556 as NON Default Outcome correctly.

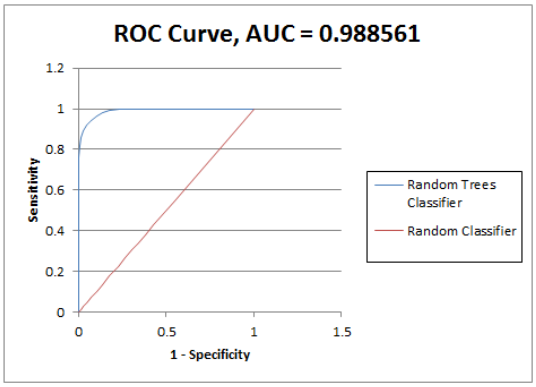
Lift Chart:





ROC Curve:





Comparison between the models:

Based on overall percentage error for validation datasets and maximum area under the curve (ROC), Random Forest turns out to be the best model amongst all models.

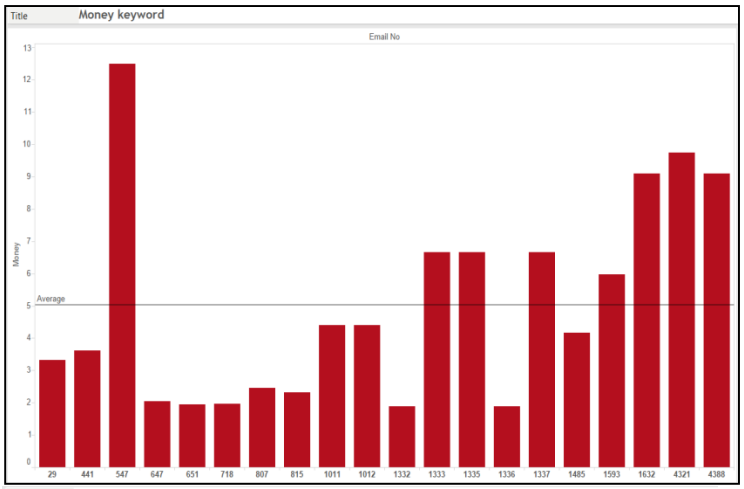
Considering detecting the Default Outcome, random forest model is useful because it gives minimum error rate and Outcome are classified in a better way as Default and Non-default. Logistic Regression gives 0% error rate but that model is ignored because it is too over-fitted a model.

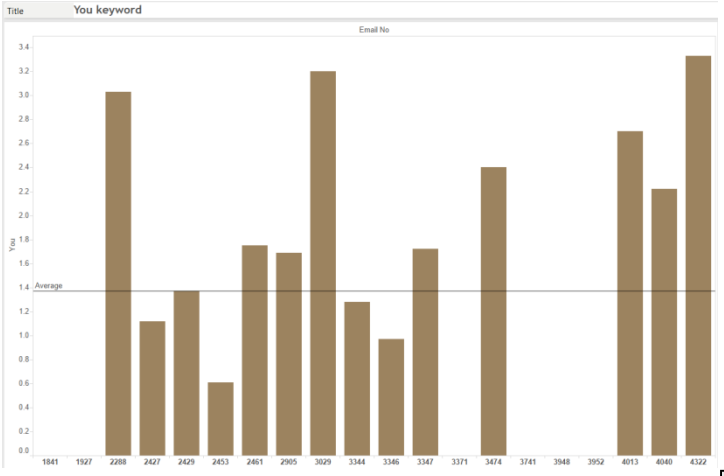
Question 3:

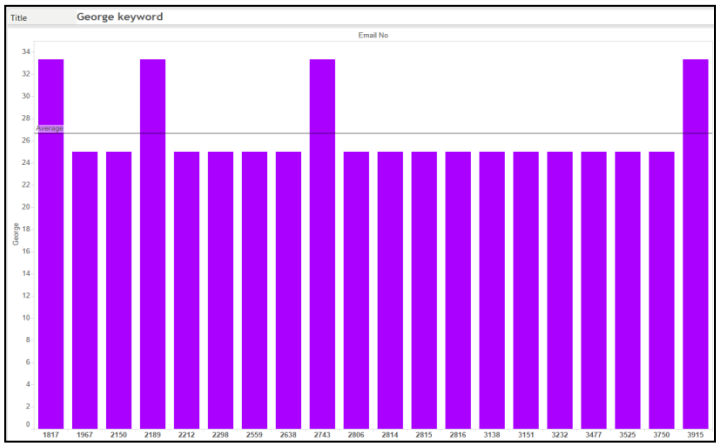
Cleaning data:

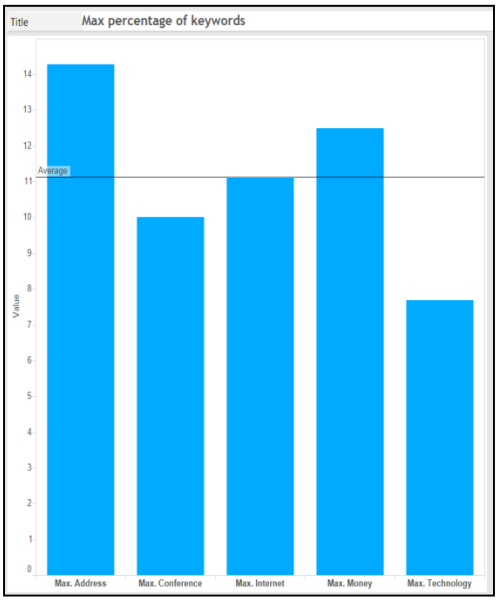
Imported the data set into Wrangler, default datatype for columns was integer. The datatype was changed to decimal to correct the mismatched values in the columns.

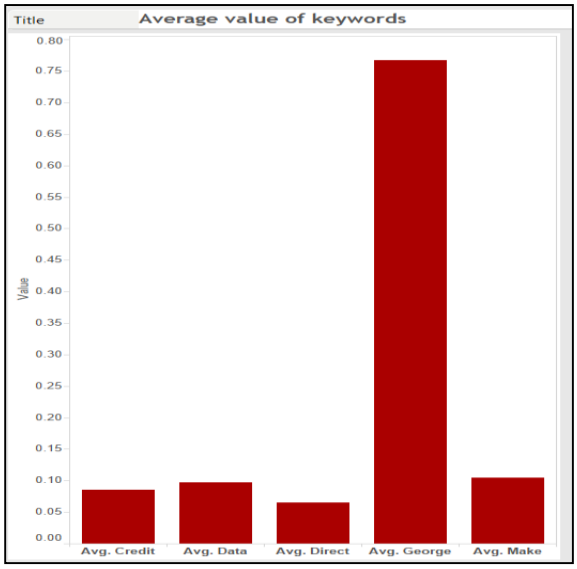
Exploratory analysis:







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0.45
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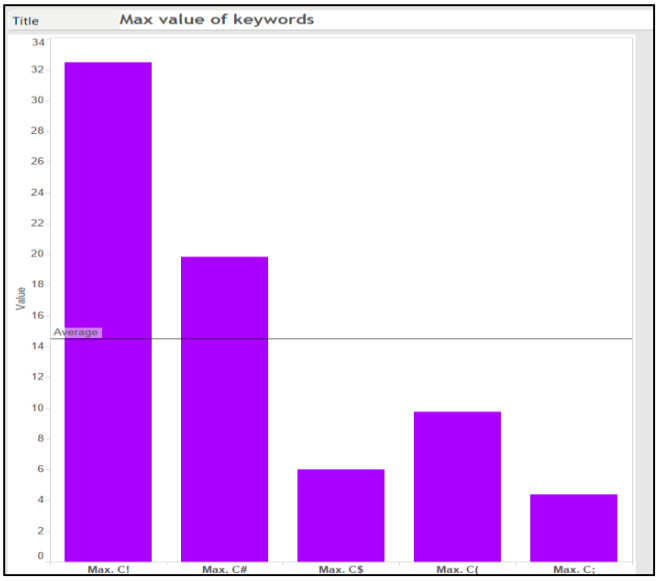
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Avg. Credit
Avg. Data
Avg. Direct
Avg. George
Avg. Make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Value
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30
28
26
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22
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18
16
14
12
10
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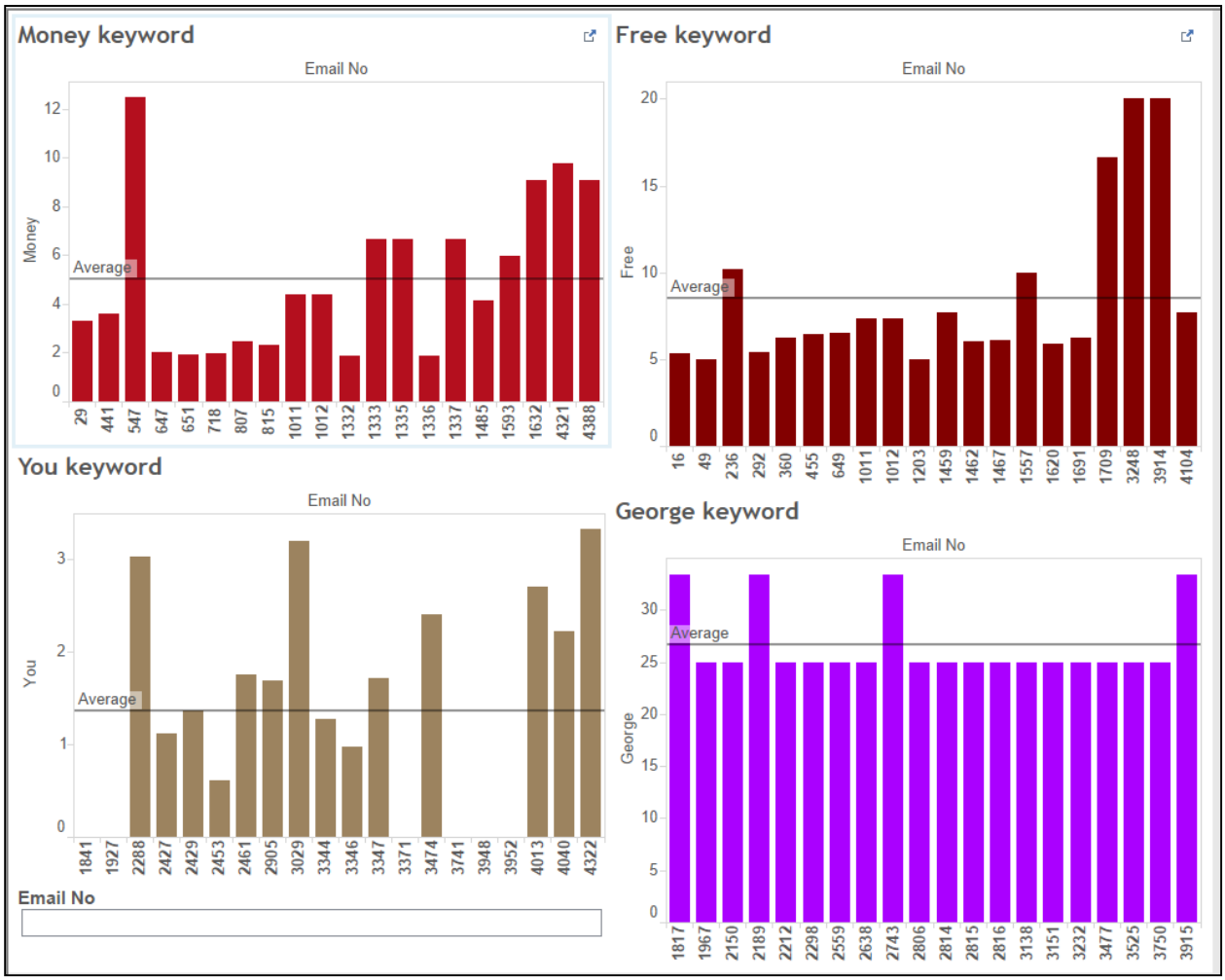
Dashboard 1:


Money keyword
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647
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807
815
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1012
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1333
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1485
1593
1632
4321
4388
Free keyword
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Free
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49
236
292
360
455
649
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1012
1203
1459
1462
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1557
1620
1691
1709
3248
3914
4104
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You
Average
1841
1927
2288
2427
2429
2453
2461
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2189
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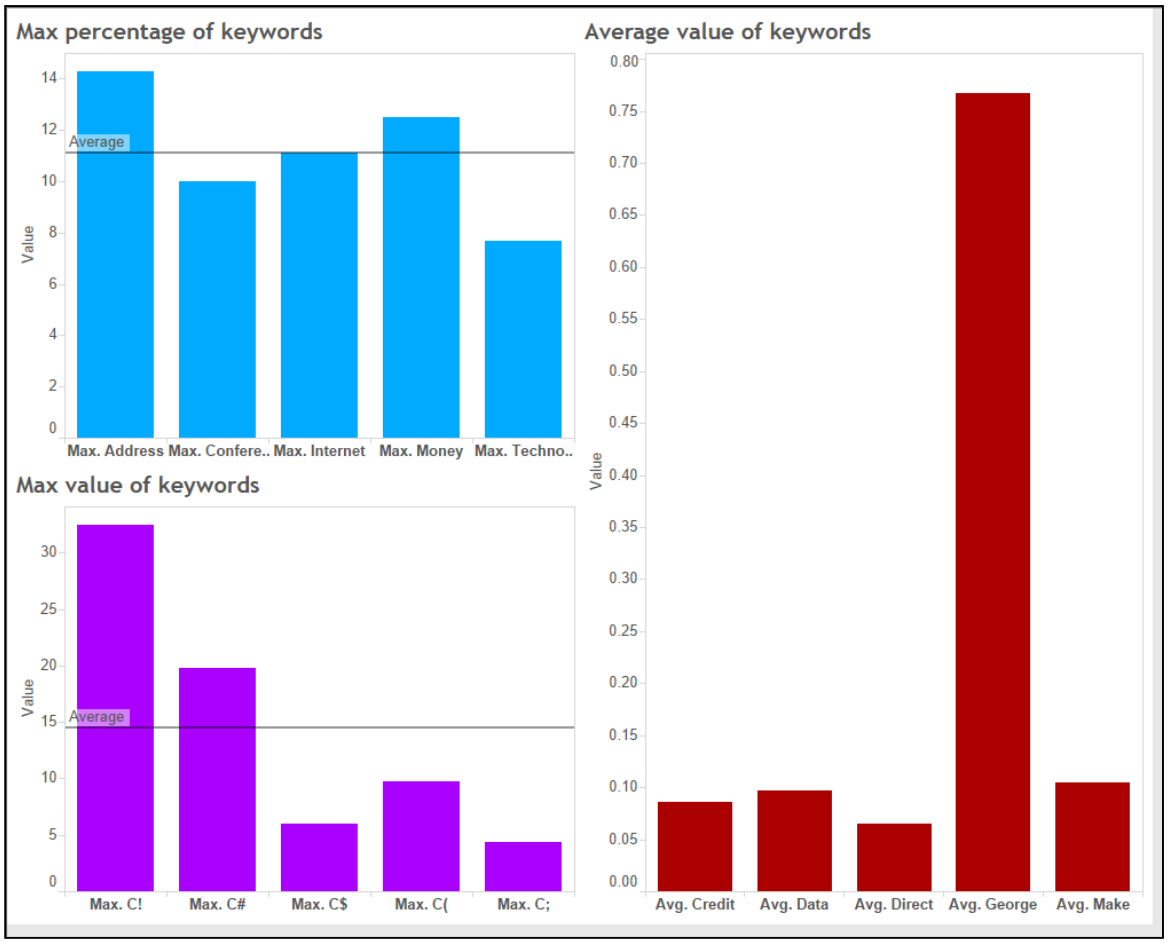
Dashboard 2:



Creating dummies:

The only categorical variable is SPAM. Created dummy variables from the categorical variable SPAM.

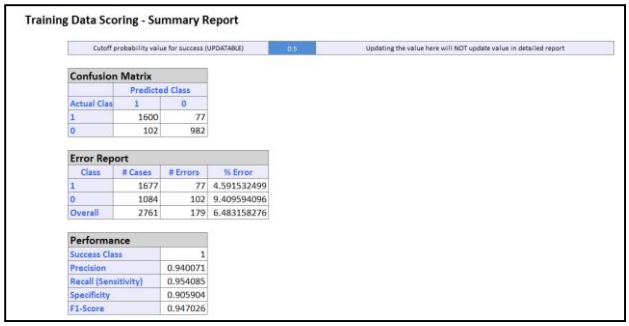
Partitioning the data:

Partitioned data into 60% and 40%.

60% partition is used as training data and 40% partition is used as validation data.

Logistic Regression:

The cutoff probability value for success was kept at 0.5.



Training Data Scoring - Summary Report

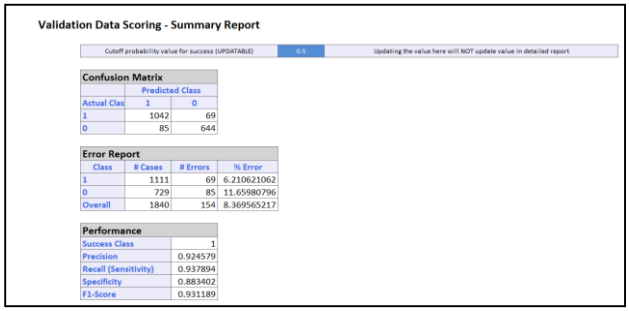
Cutoff probability value for success (UPDATABLE) 0.5 Updating the value here will NOT update value in detailed report

Confusion Matrix	Predicted Class	
Actual Clas	1	0
1	1600	77
0	102	982

Error Report			
Class	# Cases	# Errors	% Error
1	1677	77	4.591532499
0	1084	102	9.409594096
Overall	2761	179	6.483158276

Performance	
Success Class	1
Precision	0.940071
Recall (Sensitivity)	0.954085
Specificity	0.905904
F1-Score	0.947026

The overall % error rate is 6.48 and model classifies 1600 SPAM emails and 982 NON SPAM emails correctly.



Validation Data Scoring - Summary Report

Cutoff probability value for success (UPDATABLE) 0.5 Updating the value here will NOT update value in detailed report

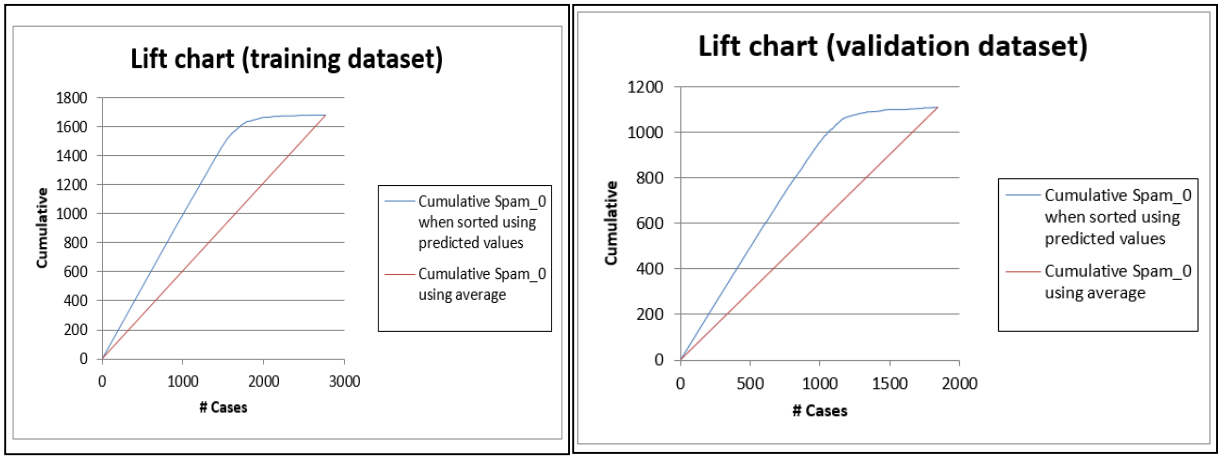
Confusion Matrix	Predicted Class	
Actual Clas	1	0
1	1042	69
0	85	644

Error Report			
Class	# Cases	# Errors	% Error
1	1111	69	6.210621062
0	729	85	11.65980796
Overall	1840	154	8.369565217

Performance	
Success Class	1
Precision	0.924579
Recall (Sensitivity)	0.937894
Specificity	0.883402
F1-Score	0.931189

The overall error rate 8.36% and the model classifies 1042 SPAM emails and 644 NON SPAM emails

Lift Chart:

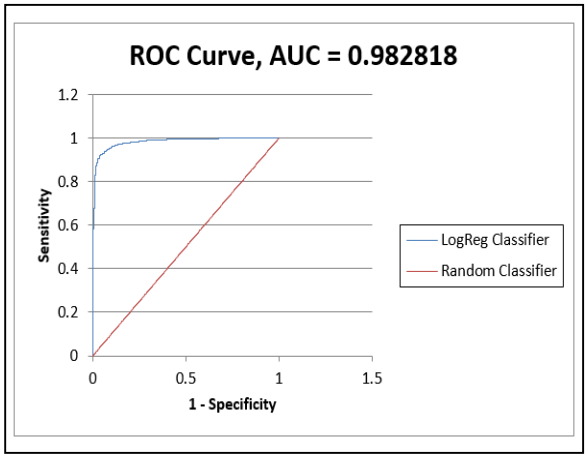


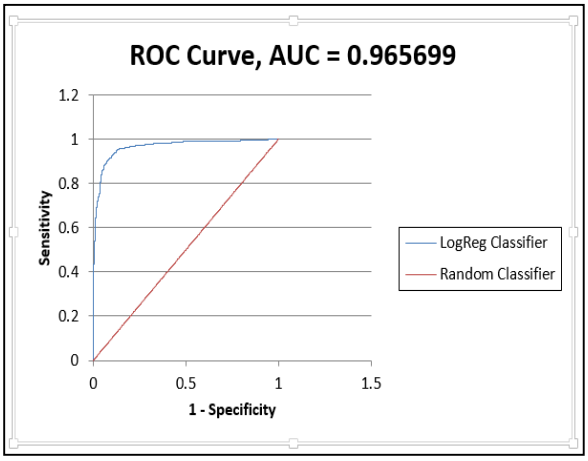
A lift chart is the graphical way to assess the predictive performance of a model. It compares the model with the baseline model that has no predictors.

Lift chart is based on 1800 validation records. It can be said that model's predictive performance is better than baseline model.

ROC Curve:

Training dataset and Validation dataset:

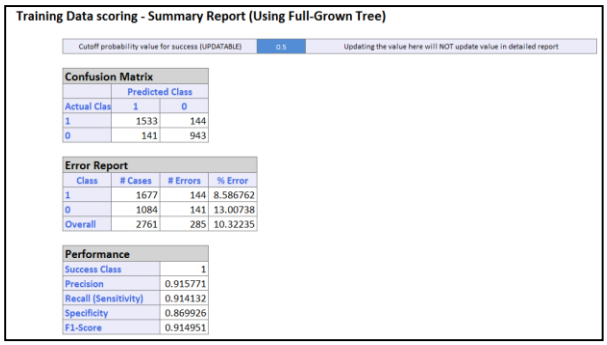




The ROC (Receiver Operating Characteristic) curve plots the sensitivity and 1-specificity. Better performance are given by the curves that are near the Y axis. Area under the Curve is 0.96 as shown in the figure.

CART

The cutoff probability value for success was kept at 0.5.



Training Data scoring - Summary Report (Using Full-Grown Tree)

Cutoff probability value for success (UPDATABLE) 0.5 Updating the value here will NOT update value in detailed report

Confusion Matrix		
	Predicted Class	
Actual Clas	1	0
1	1533	144
0	141	943

Error Report			
Class	# Cases	# Errors	% Error
1	1677	144	8.586762
0	1084	141	13.00738
Overall	2761	285	10.32235

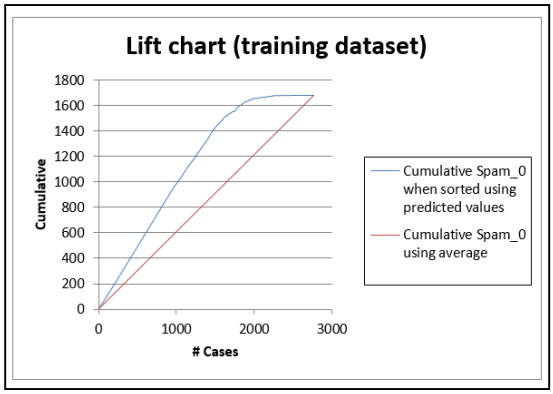
Performance	
Success Class	1
Precision	0.915771
Recall (Sensitivity)	0.914132
Specificity	0.869926
F1-Score	0.914951

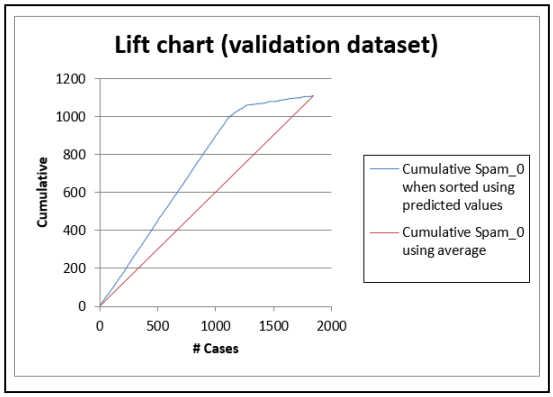
The overall % error rate is 10.32 and model classifies 1533 SPAM emails and 943 NON SPAM emails correctly.

The overall % error rate is 12.39 and model classifies 993 SPAM emails and 619 NON SPAM emails correctly.

Lift Chart:

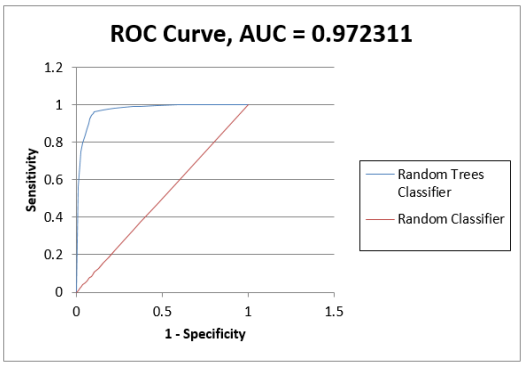
Training dataset and Validation dataset:

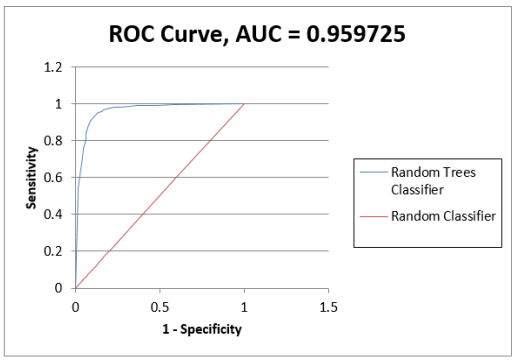




ROC Curve:

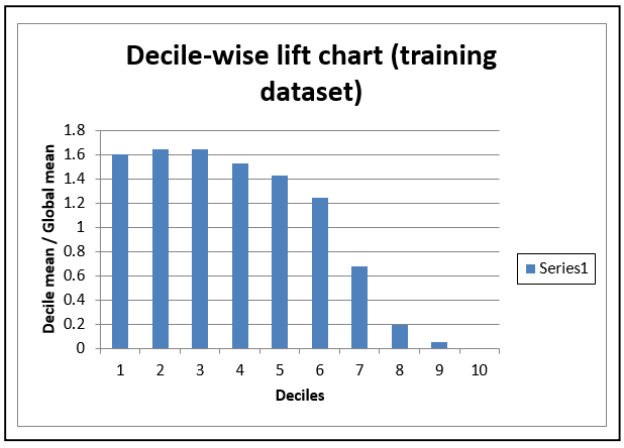
Training dataset and Validation dataset:

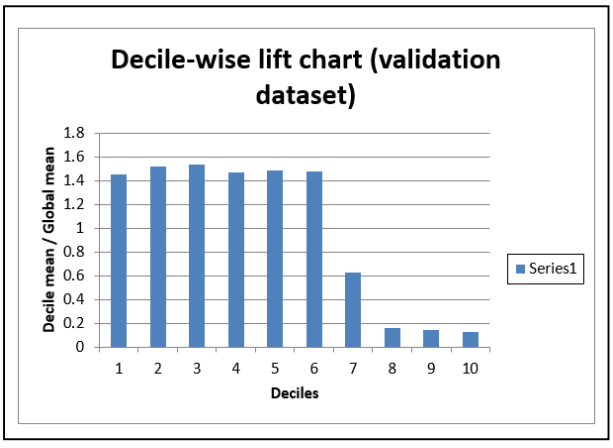




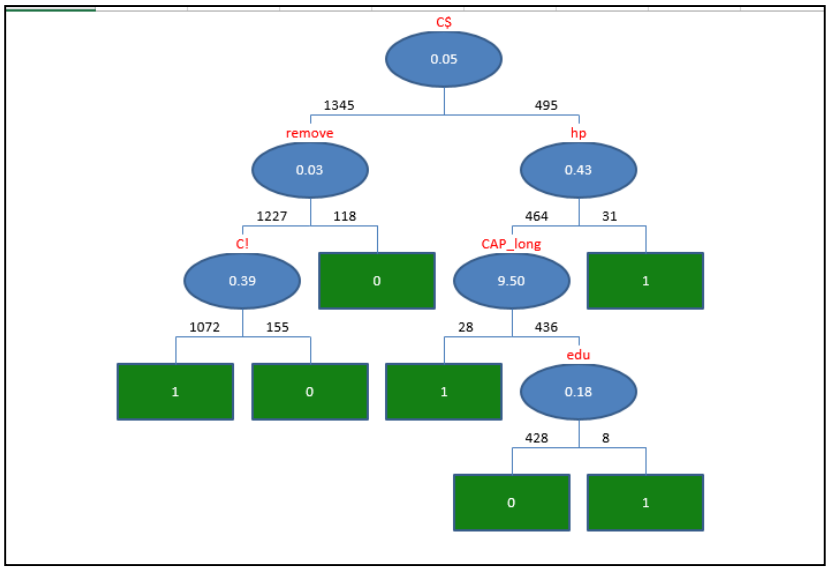
Decile chart:

Training dataset and Validation dataset:

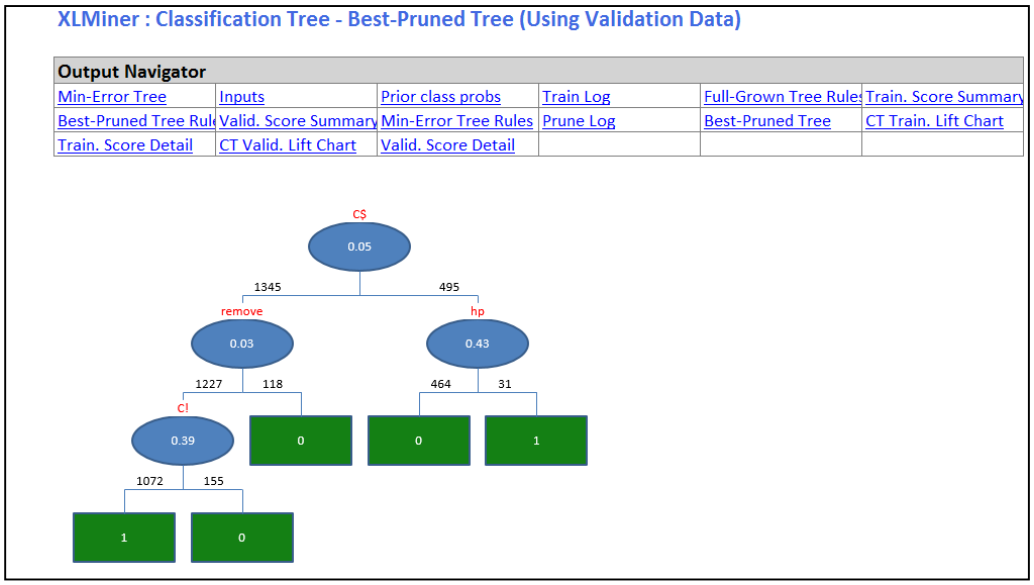




Minimum Error Tree:



Pruned tree:



Random Forest:

The cutoff probability value for success was kept at 0.5.

Training Data scoring - Summary Report

Cutoff probability value for success (UPDATABLE)	0.5	Updating the value here will NOT update value in detailed report

Confusion Matrix

	Predicted Class	
Actual Clas	1	0
1	1599	78
0	104	980

Error Report

Class	# Cases	# Errors	% Error
1	1677	78	4.651163
0	1084	104	9.594096
Overall	2761	182	6.591815

Performance

Success Class	1
Precision	0.938931
Recall (Sensitivity)	0.953488
Specificity	0.904059
F1-Score	0.946154

The overall % error rate is 6.59 and model classifies 1599 SPAM emails and 980 NON SPAM emails correctly.

Validation Data scoring - Summary Report

Cutoff probability value for success (UPDATABLE)	0.5	Updating the value here will NOT update value in detailed report

Confusion Matrix

	Predicted Class	
Actual Clas	1	0
1	1044	67
0	85	644

Error Report

Class	# Cases	# Errors	% Error
1	1111	67	6.030603
0	729	85	11.65981
Overall	1840	152	8.26087

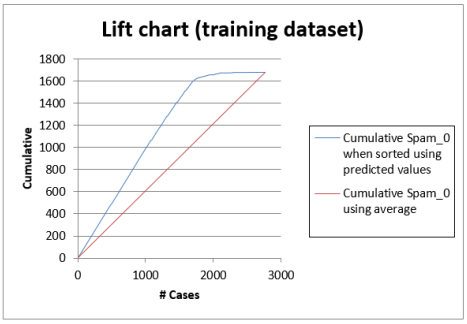
Performance

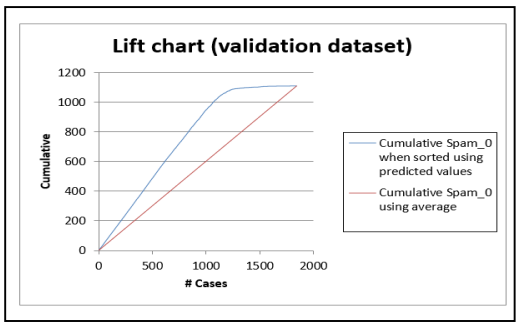
Success Class	1
Precision	0.924712
Recall (Sensitivity)	0.939694
Specificity	0.883402
F1-Score	0.932143

The overall % error rate is 8.26 and model classifies 1044 SPAM emails and 644 NON SPAM emails correctly.

Lift Chart:

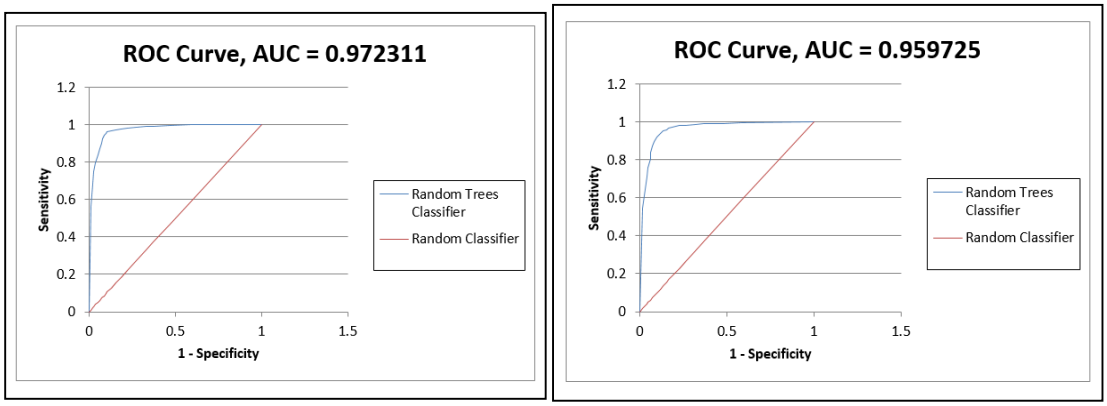
Training dataset and Validation dataset:





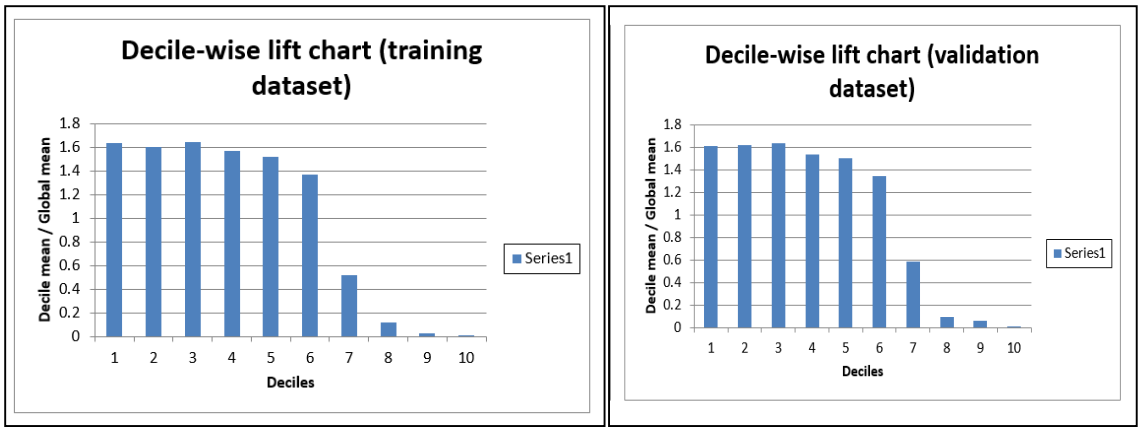
ROC Curve:

Training dataset and Validation dataset:



Decile **chart:**

Training dataset and Validation dataset:



Comparison between the models:

Based on overall percentage error for validation datasets and maximum area under the curve (ROC), Random Forest turns out to be the best model amongst all models.

Considering detecting the SPAM mails, random forest model is useful because it gives minimum error rate and emails are classified in a better way as SPAM and NON SPAM.

Problem 4

The blog feedback dataset contains following attributes:

1-50 : Average, standard deviation, min, max and median of the Attributes 51…60

51: Total number of comments before basetime

52: Number of comments in the last 24 hours before the basetime

53: Let T1 denote the datetime 48 hours before basetime, Let T2 denote the datetime 24 hours before basetime. This attribute is the number of comments in the time period between T1 and T2

54: Number of comments in the first 24 hours after the publication of the blog post, but before basetime

55: The difference of Attribute 52 and Attribute 53

56…60: The same features as the attributes 51…55, but features 56…60 refer to the number of links (trackbacks),

61: The length of time between the publication of the blog post and basetime

62: The length of the blog post

63…262: The 200 bag of words features for 200 frequent words of the text of the blog post

263…269: binary indicator features (0 or 1) for the weekday (Monday…Sunday) of the basetime

270…276: binary indicator features (0 or 1) for the weekday (Monday…Sunday) of the date of publication of the blog post

277: Number of parent pages: we consider a blog post P as a parent of blog post B, if B is a reply (trackback) to blog post P.

278…280: Minimum, maximum, average number of comments that the parents received

281: The target: the number of comments in the next 24 hours (relative to basetime)

Setting the work directory and reading the training data csv.

```
setwd("C:/Users/Mushtaq/Downloads/ADS/Week 4/R-tutorial")
blogtrain<-read.csv("blogData_train.csv",header = T)
```

Lets create the test data:

```
blogtest1<-read.csv("blogData_test-2012.02.01.00_00.csv",header=T)
blogtest2<-read.csv("blogData_test-2012.02.02.00_00.csv",header=T)
names(blogtest2)<-names(blogtest1)
blogtest3<-read.csv("blogData_test-2012.02.03.00_00.csv",header=T)
```

```
names(blogtest3)<-names(blogtest1)
blogtest4<-read.csv("blogData_test-2012.02.04.00_00.csv",header=T)
names(blogtest4)<-names(blogtest1)
blogtest5<-read.csv("blogData_test-2012.02.05.00_00.csv",header=T)
names(blogtest5)<-names(blogtest1)
blogtest6<-read.csv("blogData_test-2012.02.06.00_00.csv",header=T)
names(blogtest6)<-names(blogtest1)
blogtest7<-read.csv("blogData_test-2012.02.07.00_00.csv",header=T)
names(blogtest7)<-names(blogtest1)
blogtest8<-read.csv("blogData_test-2012.02.08.00_00.csv",header=T)
names(blogtest8)<-names(blogtest1)
blogtest9<-read.csv("blogData_test-2012.02.09.00_00.csv",header=T)
names(blogtest9)<-names(blogtest1)
blogtest10<-read.csv("blogData_test-2012.02.10.00_00.csv",header=T)
names(blogtest10)<-names(blogtest1)
blogtest11<-read.csv("blogData_test-2012.02.11.00_00.csv",header=T)
names(blogtest11)<-names(blogtest1)
blogtest12<-read.csv("blogData_test-2012.02.12.00_00.csv",header=T)
names(blogtest12)<-names(blogtest1)
blogtest13<-read.csv("blogData_test-2012.02.13.00_00.csv",header=T)
names(blogtest13)<-names(blogtest1)
blogtest14<-read.csv("blogData_test-2012.02.14.00_00.csv",header=T)
names(blogtest14)<-names(blogtest1)
blogtest15<-read.csv("blogData_test-2012.02.15.00_00.csv",header=T)
names(blogtest15)<-names(blogtest1)
blogtest16<-read.csv("blogData_test-2012.02.16.00_00.csv",header=T)
names(blogtest16)<-names(blogtest1)
blogtest17<-read.csv("blogData_test-2012.02.17.00_00.csv",header=T)
names(blogtest17)<-names(blogtest1)
blogtest18<-read.csv("blogData_test-2012.02.18.00_00.csv",header=T)
names(blogtest18)<-names(blogtest1)
blogtest19<-read.csv("blogData_test-2012.02.19.00_00.csv",header=T)
names(blogtest19)<-names(blogtest1)
blogtest20<-read.csv("blogData_test-2012.02.20.00_00.csv",header=T)
```

```
names(blogtest20)<-names(blogtest1)
blogtest21<-read.csv("blogData_test-2012.02.21.00_00.csv",header=T)
names(blogtest21)<-names(blogtest1)
blogtest22<-read.csv("blogData_test-2012.02.22.00_00.csv",header=T)
names(blogtest22)<-names(blogtest1)
blogtest23<-read.csv("blogData_test-2012.02.23.00_00.csv",header=T)
names(blogtest23)<-names(blogtest1)
blogtest24<-read.csv("blogData_test-2012.02.24.00_00.csv",header=T)
names(blogtest24)<-names(blogtest1)
blogtest25<-read.csv("blogData_test-2012.02.25.00_00.csv",header=T)
names(blogtest25)<-names(blogtest1)
blogtest26<-read.csv("blogData_test-2012.02.26.00_00.csv",header=T)
names(blogtest26)<-names(blogtest1)
blogtest27<-read.csv("blogData_test-2012.02.27.00_00.csv",header=T)
names(blogtest27)<-names(blogtest1)
blogtest28<-read.csv("blogData_test-2012.02.28.00_00.csv",header=T)
names(blogtest28)<-names(blogtest1)
blogtest29<-read.csv("blogData_test-2012.02.29.00_00.csv",header=T)
names(blogtest29)<-names(blogtest1)
blogtest30<-read.csv("blogData_test-2012.03.01.00_00.csv",header=T)
names(blogtest30)<-names(blogtest1)
blogtest31<-read.csv("blogData_test-2012.03.02.00_00.csv",header=T)
names(blogtest31)<-names(blogtest1)
blogtest32<-read.csv("blogData_test-2012.03.03.00_00.csv",header=T)
names(blogtest32)<-names(blogtest1)
blogtest33<-read.csv("blogData_test-2012.03.04.00_00.csv",header=T)
names(blogtest33)<-names(blogtest1)
blogtest34<-read.csv("blogData_test-2012.03.05.00_00.csv",header=T)
names(blogtest34)<-names(blogtest1)
blogtest35<-read.csv("blogData_test-2012.03.06.00_00.csv",header=T)
names(blogtest35)<-names(blogtest1)
blogtest36<-read.csv("blogData_test-2012.03.07.00_00.csv",header=T)
names(blogtest36)<-names(blogtest1)
blogtest37<-read.csv("blogData_test-2012.03.08.00_00.csv",header=T)
```

```
names(blogtest37)<-names(blogtest1)
blogtest38<-read.csv("blogData_test-2012.03.09.00_00.csv",header=T)
names(blogtest38)<-names(blogtest1)
blogtest39<-read.csv("blogData_test-2012.03.10.00_00.csv",header=T)
names(blogtest39)<-names(blogtest1)
blogtest40<-read.csv("blogData_test-2012.03.11.00_00.csv",header=T)
names(blogtest40)<-names(blogtest1)
blogtest41<-read.csv("blogData_test-2012.03.12.00_00.csv",header=T)
names(blogtest41)<-names(blogtest1)
blogtest42<-read.csv("blogData_test-2012.03.13.00_00.csv",header=T)
names(blogtest42)<-names(blogtest1)
blogtest43<-read.csv("blogData_test-2012.03.14.00_00.csv",header=T)
names(blogtest43)<-names(blogtest1)
blogtest44<-read.csv("blogData_test-2012.03.15.00_00.csv",header=T)
names(blogtest44)<-names(blogtest1)
blogtest45<-read.csv("blogData_test-2012.03.16.00_00.csv",header=T)
names(blogtest45)<-names(blogtest1)
blogtest46<-read.csv("blogData_test-2012.03.17.00_00.csv",header=T)
names(blogtest46)<-names(blogtest1)
blogtest47<-read.csv("blogData_test-2012.03.18.00_00.csv",header=T)
names(blogtest47)<-names(blogtest1)
blogtest48<-read.csv("blogData_test-2012.03.19.00_00.csv",header=T)
names(blogtest48)<-names(blogtest1)
blogtest49<-read.csv("blogData_test-2012.03.20.00_00.csv",header=T)
names(blogtest49)<-names(blogtest1)
blogtest50<-read.csv("blogData_test-2012.03.21.00_00.csv",header=T)
names(blogtest50)<-names(blogtest1)
blogtest51<-read.csv("blogData_test-2012.03.22.00_00.csv",header=T)
names(blogtest51)<-names(blogtest1)
blogtest52<-read.csv("blogData_test-2012.03.23.00_00.csv",header=T)
names(blogtest52)<-names(blogtest1)
blogtest53<-read.csv("blogData_test-2012.03.24.00_00.csv",header=T)
names(blogtest53)<-names(blogtest1)
blogtest54<-read.csv("blogData_test-2012.03.25.00_00.csv",header=T)
```

```
names(blogtest54)<-names(blogtest1)
blogtest55<-read.csv("blogData_test-2012.03.26.01_00.csv",header=T)
names(blogtest55)<-names(blogtest1)
blogtest56<-read.csv("blogData_test-2012.03.27.01_00.csv",header=T)
names(blogtest56)<-names(blogtest1)
blogtest57<-read.csv("blogData_test-2012.03.28.01_00.csv",header=T)
names(blogtest57)<-names(blogtest1)
blogtest58<-read.csv("blogData_test-2012.03.29.01_00.csv",header=T)
names(blogtest58)<-names(blogtest1)
blogtest59<-read.csv("blogData_test-2012.03.30.01_00.csv",header=T)
names(blogtest59)<-names(blogtest1)
blogtest60<-read.csv("blogData_test-2012.03.31.01_00.csv",header=T)
names(blogtest60)<-names(blogtest1)
```

Combining all test csv files into 1.

```
blogtest<-rbind(blogtest1,blogtest2,blogtest3,blogtest4,blogtest5,blogtest6,b
logtest7,blogtest8,blogtest9,blogtest10,blogtest11,blogtest12,blogtest13,blog
test14,blogtest15,blogtest16,blogtest17,blogtest18,blogtest19,blogtest20,blog
test21,blogtest22,blogtest23,blogtest24,blogtest25,blogtest26,blogtest27,blog
test28,blogtest29,blogtest30,blogtest31,blogtest32,blogtest33,blogtest34,blog
test35,blogtest36,blogtest37,blogtest38,blogtest39,blogtest40,blogtest41,blog
test42,blogtest43,blogtest44,blogtest45,blogtest46,blogtest47,blogtest48,blog
test49,blogtest50,blogtest51,blogtest52,blogtest53,blogtest54,blogtest55,blog
test56,blogtest57,blogtest58,blogtest59,blogtest60)
names(blogtest)<-names(blogtrain)
```

The target is the number of feedbacks that the blog-entry will receive in the next H hours. Most regression algorithms assume that the instances are vectors. Furthermore, it is assumed that the value of the target is known for some (sufficiently enough) instances, and based on this information, we want to predict the value of the target for those cases where it is unknown. First, using the cases where the target is known, a prediction model, regressor, is constructed. Then, the regressor is used to predict the value of the target for the instances with unknown valued target.

Now we will extract some features from the document and build models from those features:

1. Basic features: Number of links and comments
2. Textual features: The most discriminative bag of words features
3. Weekday features: Binary indicator features that describe on which day of the week the main text of the document was published and for which day of the week the prediction has to be calculated

We will create three models as follows: 1. Using only basic features. 2. Using basic and weekday features. 3. Using basic and textual features.

Applying multi linear Regression,

Taking the columns of only basic features,

```
blogtrain_basic<-blogtrain[,c(51:60,281)]
blogtest_basic<-blogtest[,c(51:60,281)]
```

Creating the regression model using lm()

```
regression_basic<-lm(blogtrain_basic$X1.0.2~.,data=blogtrain_basic)
regression_basic
```

```
##
## Call:
## lm(formula = blogtrain_basic$X1.0.2 ~ ., data = blogtrain_basic)
##
## Coefficients:
## (Intercept)       X2.0.1       X2.0.2      X0.0.14       X2.0.3
##     2.13989      0.08007      0.29936     -0.01698     -0.08807
##      X2.0.4      X0.0.15      X0.0.16      X0.0.17      X0.0.18
##          NA     -2.99623      1.12627      0.22766      3.21444
##     X0.0.19
##          NA
```

```
summary(regression_basic)
```

```
##
## Call:
## lm(formula = blogtrain_basic$X1.0.2 ~ ., data = blogtrain_basic)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -288.85   -2.51   -2.14   -1.60 1421.28
##
## Coefficients: (2 not defined because of singularities)
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.139890   0.156311  13.690  < 2e-16 ***
## X2.0.1       0.080070   0.007243  11.055  < 2e-16 ***
```

```
## X2.0.2       0.299357   0.004620  64.793  < 2e-16 ***
## X0.0.14     -0.016978   0.005273  -3.220 0.001282 **
## X2.0.3      -0.088074   0.007404 -11.896  < 2e-16 ***
## X2.0.4             NA         NA      NA       NA
## X0.0.15     -2.996227   0.596173  -5.026 5.03e-07 ***
## X0.0.16      1.126266   0.301542   3.735 0.000188 ***
## X0.0.17      0.227656   0.317478   0.717 0.473329
## X0.0.18      3.214440   0.586787   5.478 4.32e-08 ***
## X0.0.19            NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 33.19 on 52387 degrees of freedom
## Multiple R-squared:  0.2255, Adjusted R-squared:  0.2254
## F-statistic:  1906 on 8 and 52387 DF,  p-value: < 2.2e-16
```

Time to predict the model using test data,

```
predictions_basic=predict.lm(regression_basic,blogtest_basic)
## Warning in predict.lm(regression_basic, blogtest_basic): prediction from a
## rank-deficient fit may be misleading
summary(predictions_basic)
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -19.010   2.140   2.140   6.040   3.305 381.500
```

Now lets build the model by using basic and weekday features.

```
blogtrain_basicweekday<-blogtrain[,c(51:60,270:276,281)]
blogtest_basicweekday<-blogtest[,c(51:60,270:276,281)]
```

Creating the regression model using lm()

```
regression_basicweekday<-lm(blogtrain_basicweekday$X1.0.2~.,data=blogtrain_ba
sicweekday)
summary(regression_basicweekday)
##
## Call:
```

```
## lm(formula = blogtrain_basicweekday$X1.0.2 ~ ., data = blogtrain_basicweek
day)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -288.66   -2.81   -2.11   -1.60 1420.70
##
## Coefficients: (3 not defined because of singularities)
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.358680   0.488838   4.825 1.40e-06 ***
## X2.0.1       0.079686   0.007244  11.001  < 2e-16 ***
## X2.0.2       0.299144   0.004621  64.737  < 2e-16 ***
## X0.0.14     -0.017121   0.005273  -3.247 0.001167 **
## X2.0.3      -0.087358   0.007408 -11.792  < 2e-16 ***
## X2.0.4             NA         NA      NA       NA
## X0.0.15     -3.014114   0.596276  -5.055 4.32e-07 ***
## X0.0.16      1.129878   0.301546   3.747 0.000179 ***
## X0.0.17      0.234097   0.317485   0.737 0.460914
## X0.0.18      3.228334   0.586902   5.501 3.80e-08 ***
## X0.0.19            NA         NA      NA       NA
## X0.0.227    -0.482932   0.607259  -0.795 0.426463
## X0.0.228    -0.174627   0.601699  -0.290 0.771647
## X0.0.229    -0.630579   0.599466  -1.052 0.292850
## X1.0.1      -0.676346   0.605175  -1.118 0.263741
## X0.0.230     0.361581   0.610383   0.592 0.553596
## X0.0.231     0.472711   0.674555   0.701 0.483447
## X0.0.232           NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 33.19 on 52381 degrees of freedom
## Multiple R-squared:  0.2256, Adjusted R-squared:  0.2254
## F-statistic:  1090 on 14 and 52381 DF,  p-value: < 2.2e-16
```

Time to predict the model using test data,

```
predictions_basicweekday=predict.lm(regression_basicweekday,blogtest_basicweekday)
```

```
## Warning in predict.lm(regression_basicweekday, blogtest_basicweekday):
## prediction from a rank-deficient fit may be misleading
```

```
summary(predictions_basicweekday)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -18.470   1.876   2.359   6.016   3.354 381.200
```

Now lets build the model by using basic and textual features.

```
blogtrain_basictextual<-blogtrain[,c(51:60,63:262,281)]
blogtest_basictextual<-blogtest[,c(51:60,63:262,281)]
```

Creating the regression model using lm()

```
regression_basictextual<-lm(blogtrain_basictextual$X1.0.2~.,data=blogtrain_basictextual)
summary(regression_basictextual)
```

```
##
## Call:
## lm(formula = blogtrain_basictextual$X1.0.2 ~ ., data = blogtrain_basictextual)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -282.48   -3.97   -1.28   -0.03 1422.58
##
## Coefficients: (24 not defined because of singularities)
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.847466   0.257653   3.289  0.00101 **
## X2.0.1        0.069047   0.007252   9.522  < 2e-16 ***
## X2.0.2        0.296531   0.004633  64.003  < 2e-16 ***
## X0.0.14      -0.016684   0.005281  -3.159  0.00158 **
## X2.0.3       -0.079922   0.007438 -10.745  < 2e-16 ***
## X2.0.4              NA         NA      NA       NA
## X0.0.15      -3.021667   0.595823  -5.071 3.96e-07 ***
## X0.0.16       1.063574   0.300987   3.534  0.00041 ***
```

```
## X0.0.17       0.189247   0.316930   0.597  0.55043
## X0.0.18       3.263229   0.586404   5.565 2.64e-08 ***
## X0.0.19             NA         NA      NA       NA
## X0.0.21       1.634112   3.727680   0.438  0.66112
## X0.0.22       0.254961   0.432977   0.589  0.55596
## X0.0.23      91.005797  78.572981   1.158  0.24677
## X0.0.24      -1.773220   9.628151  -0.184  0.85388
## X0.0.25       0.083152   0.404283   0.206  0.83704
## X0.0.26      -0.690242   0.449794  -1.535  0.12489
## X0.0.27       1.114260   0.403991   2.758  0.00582 **
## X0.0.28      -2.114230   3.018516  -0.700  0.48367
## X0.0.29      -2.472069   2.567957  -0.963  0.33572
## X0.0.30       1.125333   0.922655   1.220  0.22260
## X0.0.31             NA         NA      NA       NA
## X0.0.32      -2.666658   6.273503  -0.425  0.67079
## X0.0.33      -0.032282   2.250852  -0.014  0.98856
## X0.0.34             NA         NA      NA       NA
## X0.0.35       2.137198   1.278763   1.671  0.09467 .
## X0.0.36      -1.331027   3.992618  -0.333  0.73885
## X0.0.37      -0.068728   0.416024  -0.165  0.86879
## X0.0.38             NA         NA      NA       NA
## X0.0.39             NA         NA      NA       NA
## X0.0.40      -2.349633   2.645408  -0.888  0.37444
## X0.0.41      -3.175498   3.894631  -0.815  0.41487
## X0.0.42       2.886833  13.591126   0.212  0.83179
## X0.0.43      17.084271   9.808063   1.742  0.08154 .
## X0.0.44      -0.614141   1.038096  -0.592  0.55412
## X0.0.45     -16.593124  14.067201  -1.180  0.23818
## X0.0.46       2.547900   1.380803   1.845  0.06501 .
## X0.0.47      -1.560294   0.629263  -2.480  0.01316 *
## X0.0.48      -1.223018  19.153603  -0.064  0.94909
## X0.0.49      -4.037526   9.776702  -0.413  0.67963
## X0.0.50      27.407495  11.065273   2.477  0.01326 *
## X0.0.51      -2.680592   2.145608  -1.249  0.21155
```

```
## X0.0.52             NA         NA      NA       NA
## X0.0.53      -1.955333  13.565093  -0.144  0.88539
## X0.0.54       0.027526   0.543952   0.051  0.95964
## X0.0.55             NA         NA      NA       NA
## X0.0.56      10.426064   8.107211   1.286  0.19844
## X0.0.57      -3.407066   8.676028  -0.393  0.69454
## X0.0.58      -2.820556   4.863682  -0.580  0.56197
## X0.0.59       0.143375   0.495200   0.290  0.77218
## X0.0.60       2.374018   0.575715   4.124 3.74e-05 ***
## X0.0.61       0.153296   0.873826   0.175  0.86074
## X0.0.62      -0.617930   0.729507  -0.847  0.39697
## X0.0.63       1.712855   2.727239   0.628  0.52997
## X0.0.64      -5.503326   4.261663  -1.291  0.19659
## X0.0.65      -4.604709   2.798933  -1.645  0.09994 .
## X0.0.66      -1.721541   1.183777  -1.454  0.14588
## X0.0.67      -2.466834  19.230565  -0.128  0.89793
## X0.0.68      -0.884397   0.949867  -0.931  0.35182
## X0.0.69      -2.124992  13.545456  -0.157  0.87534
## X0.0.70      -4.718432   7.867139  -0.600  0.54867
## X0.0.71      -6.453293   9.777555  -0.660  0.50925
## X0.0.72      -0.978981   0.456613  -2.144  0.03204 *
## X0.0.73       0.100316   0.611783   0.164  0.86975
## X0.0.74      -0.074516   1.041480  -0.072  0.94296
## X0.0.75      -2.804185   3.725117  -0.753  0.45159
## X0.0.76      -0.048611   1.365339  -0.036  0.97160
## X0.0.77      -2.013840   0.703618  -2.862  0.00421 **
## X0.0.78      -0.148625   0.442138  -0.336  0.73676
## X0.0.79       0.293380   0.803951   0.365  0.71517
## X0.0.80      -0.816797   0.402981  -2.027  0.04268 *
## X0.0.81      -3.215536   7.696830  -0.418  0.67611
## X0.0.82      22.634374  19.743769   1.146  0.25163
## X0.0.83       7.316953   1.474151   4.964 6.95e-07 ***
## X0.0.84       8.584089   7.598044   1.130  0.25858
## X0.0.85      -3.248480   1.991073  -1.632  0.10279
```

```
## X0.0.86       0.180822   1.334370   0.136  0.89221
## X0.0.87       0.224165  19.127505   0.012  0.99065
## X0.0.88             NA         NA      NA       NA
## X0.0.89      -2.243392   2.145862  -1.045  0.29582
## X0.0.90             NA         NA      NA       NA
## X0.0.91       0.235560   6.615317   0.036  0.97159
## X0.0.92       0.839249   0.784453   1.070  0.28469
## X0.0.93      -0.508768   0.924780  -0.550  0.58222
## X0.0.94       0.529696   0.722997   0.733  0.46378
## X0.0.95       3.644237   2.430729   1.499  0.13382
## X0.0.96       2.265292   0.878289   2.579  0.00991 **
## X0.0.97       0.227358   0.404013   0.563  0.57361
## X0.0.98      -0.396488   0.578616  -0.685  0.49320
## X0.0.99      -0.027882   0.583320  -0.048  0.96188
## X0.0.100     -2.026450   2.996871  -0.676  0.49892
## X0.0.101     -0.111257   0.575560  -0.193  0.84672
## X0.0.102     -1.266460   1.675217  -0.756  0.44965
## X0.0.103     -2.905214   2.650662  -1.096  0.27307
## X0.0.104     -3.555265   2.672780  -1.330  0.18347
## X0.0.105     -3.047814   2.091392  -1.457  0.14504
## X0.0.106    -10.292553  11.378679  -0.905  0.36571
## X0.0.107            NA         NA      NA       NA
## X0.0.108     -1.988575   3.146963  -0.632  0.52745
## X0.0.109      0.559923   0.384870   1.455  0.14572
## X0.0.110     -3.746630   3.287103  -1.140  0.25438
## X0.0.111     -1.071550   0.712518  -1.504  0.13262
## X0.0.112      8.345845   0.846661   9.857  < 2e-16 ***
## X0.0.113     -8.210874  19.144145  -0.429  0.66800
## X0.0.114            NA         NA      NA       NA
## X0.0.115     -1.331595   1.613187  -0.825  0.40912
## X0.0.116      0.787977   0.395376   1.993  0.04627 *
## X0.0.117      0.470369   0.521865   0.901  0.36742
## X0.0.118     -3.082727   4.554453  -0.677  0.49850
## X0.0.119            NA         NA      NA       NA
```

```
## X0.0.120     -1.371580   0.892809  -1.536  0.12448
## X0.0.121      0.305643   0.935719   0.327  0.74394
## X0.0.122     -1.298528   1.990649  -0.652  0.51420
## X0.0.123     -5.526628   4.214885  -1.311  0.18979
## X0.0.124            NA         NA      NA       NA
## X0.0.125     -4.128919   4.255301  -0.970  0.33190
## X0.0.126     -5.180522  10.540813  -0.491  0.62309
## X0.0.127            NA         NA      NA       NA
## X0.0.128     -1.084212   0.439125  -2.469  0.01355 *
## X0.0.129     11.787163   5.389462   2.187  0.02874 *
## X0.0.130            NA         NA      NA       NA
## X0.0.131     -3.876353   9.628152  -0.403  0.68724
## X0.0.132     -1.305413   1.251473  -1.043  0.29691
## X0.0.133      2.375786   2.869448   0.828  0.40770
## X0.0.134     -4.713524   4.526261  -1.041  0.29771
## X0.0.135     -2.614264   2.446024  -1.069  0.28517
## X0.0.136     -4.509309   7.836970  -0.575  0.56503
## X0.0.137            NA         NA      NA       NA
## X0.0.138      0.410619   0.538753   0.762  0.44597
## X0.0.139     -0.972983   0.753665  -1.291  0.19671
## X0.0.140     -1.135507   1.495399  -0.759  0.44766
## X0.0.141     -0.157578   0.594603  -0.265  0.79100
## X0.0.142      2.602058   0.512454   5.078 3.83e-07 ***
## X0.0.143      1.842455   8.647188   0.213  0.83127
## X0.0.144     -1.630391   1.263717  -1.290  0.19700
## X0.0.145     -1.354175   1.086279  -1.247  0.21254
## X0.0.146     -2.491832   1.965856  -1.268  0.20496
## X0.0.147     -0.054989   1.237245  -0.044  0.96455
## X0.0.148            NA         NA      NA       NA
## X0.0.149      1.351434   0.509246   2.654  0.00796 **
## X0.0.150     -1.047553   1.176250  -0.891  0.37315
## X0.0.151      0.522369   0.475811   1.098  0.27228
## X0.0.152      0.922745   0.452164   2.041  0.04128 *
## X0.0.153      4.331742   1.051065   4.121 3.77e-05 ***
```

```
## X0.0.154      0.805796   1.149698   0.701  0.48338
## X0.0.155     -0.494108   0.593075  -0.833  0.40478
## X0.0.156            NA         NA      NA       NA
## X0.0.157      3.043259   9.715558   0.313  0.75410
## X0.0.158            NA         NA      NA       NA
## X0.0.159     -3.234341   2.411269  -1.341  0.17981
## X0.0.160      0.449904   0.441576   1.019  0.30827
## X0.0.161     -3.886129   5.382312  -0.722  0.47029
## X0.0.162     -2.769249   4.119496  -0.672  0.50144
## X0.0.163      1.031387   1.464316   0.704  0.48122
## X0.0.164      2.941547   2.303257   1.277  0.20156
## X0.0.165      1.692388   0.709554   2.385  0.01708 *
## X0.0.166      1.722219   1.370116   1.257  0.20876
## X0.0.167     -2.778269   4.383498  -0.634  0.52621
## X0.0.168      0.996222   0.398155   2.502  0.01235 *
## X0.0.169     -1.652474   2.963244  -0.558  0.57708
## X0.0.170            NA         NA      NA       NA
## X0.0.171     -0.741194   0.410733  -1.805  0.07115 .
## X0.0.172      4.079053   7.250672   0.563  0.57373
## X0.0.173      1.535999   2.343600   0.655  0.51221
## X0.0.174     -1.019412   0.625632  -1.629  0.10323
## X0.0.175     -5.777633   6.442594  -0.897  0.36984
## X0.0.176      4.241928   3.210602   1.321  0.18643
## X0.0.177      4.032759   0.910521   4.429 9.48e-06 ***
## X0.0.178     -2.133954   3.567160  -0.598  0.54969
## X0.0.179      1.529311   0.753262   2.030  0.04234 *
## X0.0.180     -3.828366   4.027636  -0.951  0.34185
## X0.0.181     -4.936244  19.948654  -0.247  0.80456
## X0.0.182     -2.904884   9.708709  -0.299  0.76479
## X0.0.183     -1.161862   1.847412  -0.629  0.52941
## X0.0.184     -0.457575   0.414406  -1.104  0.26952
## X0.0.185      1.576523   2.031672   0.776  0.43777
## X0.0.186     -1.799460   0.467737  -3.847  0.00012 ***
## X0.0.187     -3.463498   3.802995  -0.911  0.36244
```

```
## X0.0.188     -0.370631   0.487494  -0.760  0.44709
## X0.0.189     -3.229403   2.287928  -1.411  0.15810
## X0.0.190      1.190554   0.395009   3.014  0.00258 **
## X0.0.191      0.153285   0.446654   0.343  0.73146
## X0.0.192     -1.226597   0.766750  -1.600  0.10966
## X0.0.193     -0.584177   4.078497  -0.143  0.88611
## X0.0.194            NA         NA      NA       NA
## X0.0.195     -1.706313   2.087091  -0.818  0.41361
## X0.0.196     -3.493958   3.164329  -1.104  0.26952
## X0.0.197     -3.065526   5.066545  -0.605  0.54515
## X0.0.198     -2.344982   3.499284  -0.670  0.50278
## X0.0.199      1.807940   0.917461   1.971  0.04878 *
## X0.0.200     -1.653323   1.277912  -1.294  0.19575
## X0.0.201            NA         NA      NA       NA
## X0.0.202     -6.637217  19.371897  -0.343  0.73189
## X0.0.203     -0.667033   1.054266  -0.633  0.52693
## X0.0.204      0.357972   0.568618   0.630  0.52899
## X0.0.205     -0.142610   0.480832  -0.297  0.76678
## X0.0.206      0.707324   0.412222   1.716  0.08619 .
## X0.0.207     -1.459573   1.759229  -0.830  0.40673
## X0.0.208            NA         NA      NA       NA
## X0.0.209     -2.748764   1.220132  -2.253  0.02427 *
## X0.0.210      4.552534   1.859707   2.448  0.01437 *
## X0.0.211    -16.134111  13.617969  -1.185  0.23612
## X0.0.212      0.374160   0.946792   0.395  0.69271
## X0.0.213     -0.611701   1.330699  -0.460  0.64574
## X0.0.214     -3.411174  11.182840  -0.305  0.76034
## X0.0.215      0.475560   0.781941   0.608  0.54307
## X0.0.216     -1.969372   3.127245  -0.630  0.52886
## X0.0.217      0.278107   2.549547   0.109  0.91314
## X0.0.218      0.624875   2.905938   0.215  0.82974
## X0.0.219      1.563589   1.623596   0.963  0.33553
## X0.0.220     -8.435505   9.585418  -0.880  0.37884
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 33.08 on 52209 degrees of freedom
## Multiple R-squared:  0.2333, Adjusted R-squared:  0.2306
## F-statistic:  85.4 on 186 and 52209 DF,  p-value: < 2.2e-16
```

Time to predict the model using test data,

```
predictions_basictextual=predict.lm(regression_basictextual,blogtest_basictextual)
## Warning in predict.lm(regression_basictextual, blogtest_basictextual):
## prediction from a rank-deficient fit may be misleading
summary(predictions_basictextual)
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -28.7200   0.8475   1.7870   5.8950   5.1320 376.5000
```

Lets continue building the model using CART algorithm. Importing all the reuired libraries

```
library(rpart)
library(rpart.plot)
## Warning: package 'rpart.plot' was built under R version 3.2.4
library(ROCR)
## Warning: package 'ROCR' was built under R version 3.2.4
## Loading required package: gplots
## Warning: package 'gplots' was built under R version 3.2.4
##
## Attaching package: 'gplots'
## The following object is masked from 'package:stats':
##
##     lowess
library(party)
## Warning: package 'party' was built under R version 3.2.4
## Loading required package: grid
## Loading required package: mvtnorm
## Loading required package: modeltools
## Loading required package: stats4
```

```
## Loading required package: strucchange
## Warning: package 'strucchange' was built under R version 3.2.4
## Loading required package: zoo
##
## Attaching package: 'zoo'
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
## Loading required package: sandwich
```

Lets create CART model using basic features only

```
blogtrain_basic<-blogtrain[,c(51:60,281)]
blogtest_basic<-blogtest[,c(51:60,281)]
```

Creating the CART model using rpart

```
tree_basic<-rpart(blogtrain_basic$X1.0.2~.,data=blogtrain_basic, method =  "anova",control=rpart.control(cp=0.001))
printcp(tree_basic)
```

```
##
## Regression tree:
## rpart(formula = blogtrain_basic$X1.0.2 ~ ., data = blogtrain_basic,
##     method = "anova", control = rpart.control(cp = 0.001))
##
## Variables actually used in tree construction:
## [1] X0.0.14 X0.0.15 X0.0.16 X0.0.18 X0.0.19 X2.0.1  X2.0.2  X2.0.3  X2.0.4
##
## Root node error: 74495814/52396 = 1421.8
##
## n= 52396
##
##           CP nsplit rel error  xerror     xstd
## 1  0.1601367      0   1.00000 1.00002 0.066871
## 2  0.0356080      1   0.83986 0.84826 0.061039
## 3  0.0208948      2   0.80426 0.80975 0.059376
```

```
## 4  0.0089661      3   0.78336 0.79373 0.058969
## 5  0.0048979      4   0.77439 0.78757 0.059284
## 6  0.0045895      5   0.76950 0.78643 0.059365
## 7  0.0043841      6   0.76491 0.78946 0.059430
## 8  0.0035830      7   0.76052 0.78468 0.059286
## 9  0.0024613     11   0.74619 0.78365 0.059307
## 10 0.0024404     13   0.74127 0.78696 0.059280
## 11 0.0023383     15   0.73639 0.78715 0.059274
## 12 0.0021951     16   0.73405 0.78913 0.059329
## 13 0.0020115     17   0.73185 0.78757 0.059237
## 14 0.0017869     19   0.72783 0.78578 0.059151
## 15 0.0017494     24   0.71852 0.78507 0.059155
## 16 0.0012456     25   0.71677 0.78380 0.059163
## 17 0.0012077     29   0.71179 0.79028 0.059260
## 18 0.0011379     31   0.70937 0.79199 0.059199
## 19 0.0011267     32   0.70823 0.79224 0.059137
## 20 0.0010000     34   0.70598 0.79065 0.058687
```

Calculating the best complexity parameter of the model

```
bestcp_basic <-tree_basic$cptable[which.min(tree_basic$cptable[,"xerror"]),"CP"]
bestcp_basic
```

```
## [1] 0.002461266
```

Pruning the tree to avoid overfitting

```
tree.pruned_basic <- prune(tree_basic, cp=bestcp_basic)
summary(tree.pruned_basic)
```

```
## Call:
## rpart(formula = blogtrain_basic$X1.0.2 ~ ., data = blogtrain_basic,
##     method = "anova", control = rpart.control(cp = 0.001))
##   n= 52396
##
##            CP nsplit rel error    xerror       xstd
## 1 0.160136685      0 1.0000000 1.0000151 0.06687132
```

```
## 2 0.035607988      1 0.8398633 0.8482630 0.06103885
## 3 0.020894750      2 0.8042553 0.8097497 0.05937646
## 4 0.008966101      3 0.7833606 0.7937338 0.05896866
## 5 0.004897880      4 0.7743945 0.7875707 0.05928377
## 6 0.004589499      5 0.7694966 0.7864310 0.05936519
## 7 0.004384053      6 0.7649071 0.7894595 0.05942969
## 8 0.003582984      7 0.7605230 0.7846781 0.05928645
## 9 0.002461266     11 0.7461911 0.7836451 0.05930677
##
## Variable importance
##  X2.0.2  X2.0.4  X2.0.3  X2.0.1 X0.0.16 X0.0.19 X0.0.18 X0.0.15
##      42      36       6       6       3       3       2       2
##
## Node number 1: 52396 observations,    complexity param=0.1601367
##   mean=6.764829, MSE=1421.784
##   left son=2 (51595 obs) right son=3 (801 obs)
##   Primary splits:
##       X2.0.2  < 221.5 to the left,  improve=0.16013670, (0 missing)
##       X2.0.4  < 185.5 to the left,  improve=0.12456960, (0 missing)
##       X2.0.3  < 279.5 to the left,  improve=0.07712658, (0 missing)
##       X2.0.1  < 352.5 to the left,  improve=0.07535665, (0 missing)
##       X0.0.16 < 2.5   to the left,  improve=0.04953726, (0 missing)
##   Surrogate splits:
##       X2.0.4  < 221.5 to the left,  agree=0.996, adj=0.760, (0 split)
##       X2.0.1  < 818.5 to the left,  agree=0.986, adj=0.055, (0 split)
##       X2.0.3  < 788   to the left,  agree=0.985, adj=0.029, (0 split)
##       X0.0.16 < 9.5   to the left,  agree=0.985, adj=0.019, (0 split)
##       X0.0.19 < 10.5  to the left,  agree=0.985, adj=0.017, (0 split)
##
## Node number 2: 51595 observations,    complexity param=0.03560799
##   mean=4.884756, MSE=843.6107
##   left son=4 (45388 obs) right son=5 (6207 obs)
##   Primary splits:
##       X2.0.4  < 7.5   to the left,  improve=0.06094381, (0 missing)
```

```
##       X2.0.2  < 20.5  to the left,  improve=0.05892590, (0 missing)
##       X2.0.3  < 14.5  to the left,  improve=0.02121635, (0 missing)
##       X2.0.1  < 14.5  to the left,  improve=0.02009537, (0 missing)
##       X0.0.19 < 0.5   to the left,  improve=0.01385694, (0 missing)
##   Surrogate splits:
##       X2.0.2  < 14.5  to the left,  agree=0.938, adj=0.483, (0 split)
##       X0.0.19 < 1.5   to the left,  agree=0.891, adj=0.092, (0 split)
##       X0.0.16 < 1.5   to the left,  agree=0.888, adj=0.068, (0 split)
##
## Node number 3: 801 observations,    complexity param=0.02089475
##   mean=127.8664, MSE=23770.55
##   left son=6 (575 obs) right son=7 (226 obs)
##   Primary splits:
##       X2.0.2  < 427.5 to the left,  improve=0.08175181, (0 missing)
##       X2.0.4  < 421   to the left,  improve=0.07196278, (0 missing)
##       X2.0.3  < 430   to the left,  improve=0.06611954, (0 missing)
##       X2.0.1  < 430.5 to the left,  improve=0.05480402, (0 missing)
##       X0.0.18 < 1.5   to the left,  improve=0.04451982, (0 missing)
##   Surrogate splits:
##       X2.0.4  < 427.5 to the left,  agree=0.939, adj=0.783, (0 split)
##       X2.0.3  < 427.5 to the left,  agree=0.843, adj=0.442, (0 split)
##       X2.0.1  < 427.5 to the left,  agree=0.813, adj=0.336, (0 split)
##       X0.0.16 < 7.5   to the left,  agree=0.757, adj=0.137, (0 split)
##       X0.0.19 < 7.5   to the left,  agree=0.757, adj=0.137, (0 split)
##
## Node number 4: 45388 observations,    complexity param=0.00489788
##   mean=2.233167, MSE=336.933
##   left son=8 (45220 obs) right son=9 (168 obs)
##   Primary splits:
##       X2.0.2  < 107.5 to the left,  improve=0.023859180, (0 missing)
##       X2.0.1  < 400.5 to the left,  improve=0.011253080, (0 missing)
##       X0.0.14 < 187.5 to the left,  improve=0.009131713, (0 missing)
##       X2.0.4  < 1.5   to the left,  improve=0.009126476, (0 missing)
##       X2.0.3  < 343.5 to the left,  improve=0.007968743, (0 missing)
```

```
##   Surrogate splits:
##       X0.0.14 < 655.5 to the left,  agree=0.996, adj=0.018, (0 split)
##
## Node number 5: 6207 observations,    complexity param=0.004589499
##   mean=24.27421, MSE=4121.272
##   left son=10 (3562 obs) right son=11 (2645 obs)
##   Primary splits:
##       X2.0.4  < 42.5  to the left,  improve=0.013365470, (0 missing)
##       X2.0.2  < 103.5 to the left,  improve=0.011946390, (0 missing)
##       X2.0.3  < 42.5  to the left,  improve=0.011160650, (0 missing)
##       X2.0.1  < 42.5  to the left,  improve=0.009678477, (0 missing)
##       X0.0.14 < 0.5   to the right, improve=0.007272552, (0 missing)
##   Surrogate splits:
##       X2.0.2  < 42.5  to the left,  agree=0.973, adj=0.936, (0 split)
##       X2.0.3  < 42.5  to the left,  agree=0.955, adj=0.895, (0 split)
##       X2.0.1  < 42.5  to the left,  agree=0.951, adj=0.885, (0 split)
##       X0.0.19 < 2.5   to the left,  agree=0.616, adj=0.099, (0 split)
##       X0.0.16 < 2.5   to the left,  agree=0.614, adj=0.095, (0 split)
##
## Node number 6: 575 observations,    complexity param=0.003582984
##   mean=100.2296, MSE=16396.05
##   left son=12 (184 obs) right son=13 (391 obs)
##   Primary splits:
##       X2.0.3  < 276.5 to the left,  improve=0.02100116, (0 missing)
##       X0.0.18 < 0.5   to the left,  improve=0.01977664, (0 missing)
##       X0.0.15 < 0.5   to the left,  improve=0.01941526, (0 missing)
##       X2.0.1  < 353.5 to the left,  improve=0.01664092, (0 missing)
##       X2.0.2  < 354.5 to the left,  improve=0.01289905, (0 missing)
##   Surrogate splits:
##       X2.0.1 < 276.5 to the left,  agree=0.951, adj=0.848, (0 split)
##       X2.0.2 < 276.5 to the left,  agree=0.880, adj=0.625, (0 split)
##       X2.0.4 < 276.5 to the left,  agree=0.718, adj=0.120, (0 split)
##
## Node number 7: 226 observations,    complexity param=0.008966101
```

```
##   mean=198.1814, MSE=35645.6
##   left son=14 (61 obs) right son=15 (165 obs)
##   Primary splits:
##       X0.0.18 < 2.5   to the left,  improve=0.08291271, (0 missing)
##       X0.0.15 < 2.5   to the left,  improve=0.07893757, (0 missing)
##       X0.0.16 < 2.5   to the left,  improve=0.05969577, (0 missing)
##       X2.0.2  < 666.5 to the left,  improve=0.04538495, (0 missing)
##       X0.0.19 < 2.5   to the left,  improve=0.04426379, (0 missing)
##   Surrogate splits:
##       X0.0.15 < 2.5   to the left,  agree=0.996, adj=0.984, (0 split)
##       X0.0.16 < 2.5   to the left,  agree=0.889, adj=0.590, (0 split)
##       X0.0.19 < 2.5   to the left,  agree=0.850, adj=0.443, (0 split)
##       X2.0.3  < 433.5 to the left,  agree=0.743, adj=0.049, (0 split)
##       X2.0.1  < 433.5 to the left,  agree=0.739, adj=0.033, (0 split)
##
## Node number 8: 45220 observations
##   mean=2.060349, MSE=311.8869
##
## Node number 9: 168 observations
##   mean=48.75, MSE=4906.652
##
## Node number 10: 3562 observations
##   mean=17.87872, MSE=3641.125
##
## Node number 11: 2645 observations
##   mean=32.88696, MSE=4638.619
##
## Node number 12: 184 observations
##   mean=73.17935, MSE=13359.72
##
## Node number 13: 391 observations,    complexity param=0.003582984
##   mean=112.9591, MSE=17318.54
##   left son=26 (106 obs) right son=27 (285 obs)
##   Primary splits:
```

```
##       X0.0.18 < 0.5   to the left,  improve=0.04192850, (0 missing)
##       X0.0.15 < 0.5   to the left,  improve=0.04103568, (0 missing)
##       X0.0.19 < 0.5   to the left,  improve=0.02890781, (0 missing)
##       X0.0.16 < 0.5   to the left,  improve=0.02322103, (0 missing)
##       X2.0.1  < 288.5 to the right, improve=0.02304655, (0 missing)
##   Surrogate splits:
##       X0.0.15 < 0.5   to the left,  agree=0.997, adj=0.991, (0 split)
##       X0.0.16 < 0.5   to the left,  agree=0.847, adj=0.434, (0 split)
##
## Node number 14: 61 observations,    complexity param=0.004384053
##   mean=108.7705, MSE=39642.87
##   left son=28 (54 obs) right son=29 (7 obs)
##   Primary splits:
##       X2.0.4  < 702.5 to the left,  improve=0.13505570, (0 missing)
##       X2.0.2  < 694   to the left,  improve=0.07957718, (0 missing)
##       X2.0.3  < 722   to the left,  improve=0.06185540, (0 missing)
##       X0.0.14 < 5.5   to the right, improve=0.05540664, (0 missing)
##       X2.0.1  < 764.5 to the right, improve=0.03749789, (0 missing)
##   Surrogate splits:
##       X2.0.2 < 694   to the left,  agree=0.967, adj=0.714, (0 split)
##       X2.0.3 < 722   to the left,  agree=0.951, adj=0.571, (0 split)
##       X2.0.1 < 934   to the left,  agree=0.902, adj=0.143, (0 split)
##
## Node number 15: 165 observations
##   mean=231.2364, MSE=30119.72
##
## Node number 26: 106 observations
##   mean=68.77358, MSE=8636.892
##
## Node number 27: 285 observations,    complexity param=0.003582984
##   mean=129.393, MSE=19551.28
##   left son=54 (263 obs) right son=55 (22 obs)
##   Primary splits:
##       X2.0.1  < 291.5 to the right, improve=0.04152467, (0 missing)
```

```
##       X2.0.3  < 290   to the right, improve=0.03675561, (0 missing)
##       X0.0.14 < 0.5   to the right, improve=0.02339020, (0 missing)
##       X2.0.2  < 288.5 to the right, improve=0.01363084, (0 missing)
##       X0.0.17 < 1.5   to the right, improve=0.01008088, (0 missing)
##   Surrogate splits:
##       X2.0.3 < 288.5 to the right, agree=0.986, adj=0.818, (0 split)
##
## Node number 28: 54 observations
##   mean=82.42593, MSE=22460.02
##
## Node number 29: 7 observations
##   mean=312, MSE=125540
##
## Node number 54: 263 observations
##   mean=121.1521, MSE=16487.41
##
## Node number 55: 22 observations,    complexity param=0.003582984
##   mean=227.9091, MSE=45661.17
##   left son=110 (13 obs) right son=111 (9 obs)
##   Primary splits:
##       X2.0.4  < 282.5 to the left,  improve=0.35277120, (0 missing)
##       X2.0.2  < 284   to the left,  improve=0.25578780, (0 missing)
##       X2.0.3  < 284.5 to the left,  improve=0.25578780, (0 missing)
##       X2.0.1  < 282.5 to the left,  improve=0.15519920, (0 missing)
##       X0.0.18 < 2.5   to the right, improve=0.06292435, (0 missing)
##   Surrogate splits:
##       X2.0.2 < 282.5 to the left,  agree=0.955, adj=0.889, (0 split)
##       X2.0.3 < 284.5 to the left,  agree=0.955, adj=0.889, (0 split)
##       X2.0.1 < 282.5 to the left,  agree=0.909, adj=0.778, (0 split)
##
## Node number 110: 13 observations
##   mean=122.3077, MSE=17903.14
##
## Node number 111: 9 observations
```

```
##   mean=380.4444, MSE=46381.14
```

Predict the model using test data

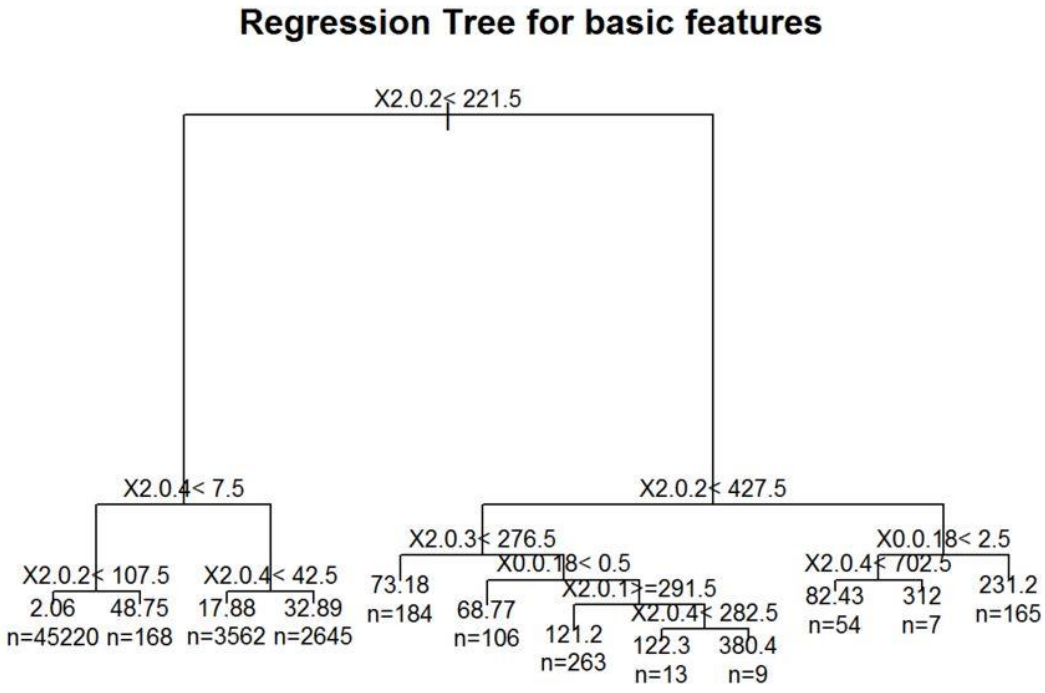
```
blogtrain_basic<-blogtrain_basic[-c(7565:52396),]

pred_basic<-predict(tree.pruned_basic,blogtest_basic,type = "vector")
```

Developing the confusion matrix

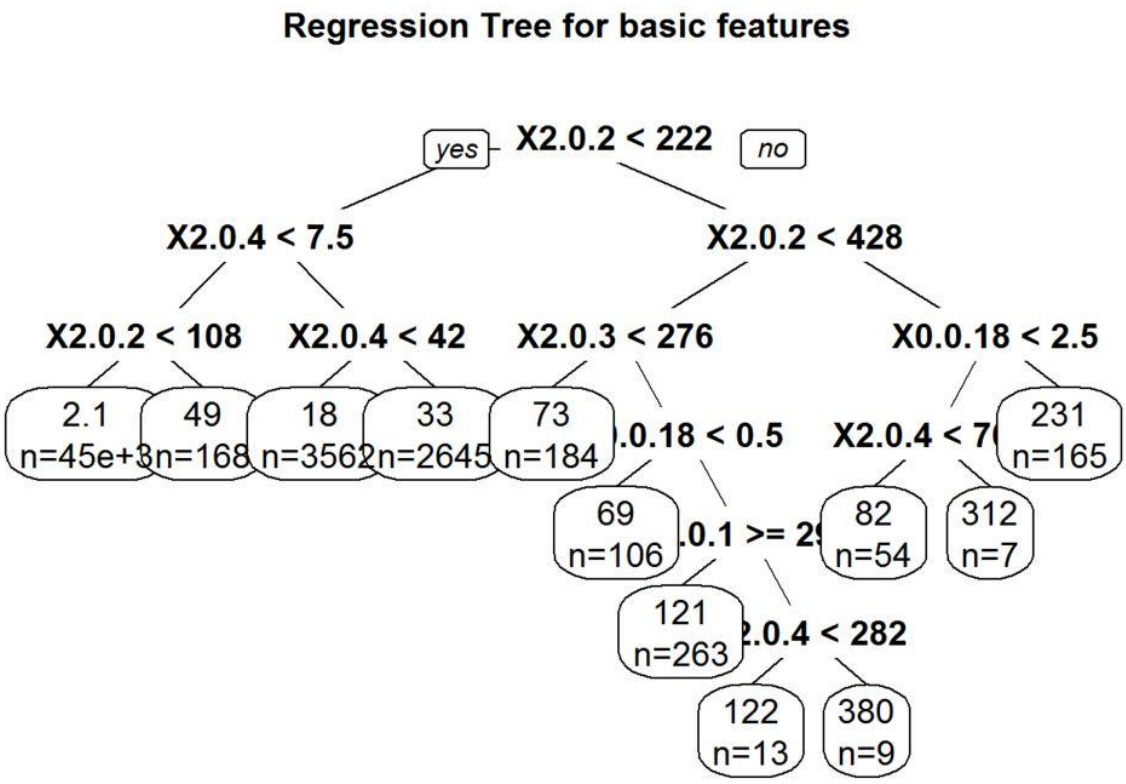
```
conf.matrix_basic<-table(blogtrain_basic$X1.0.2,pred_basic)

rownames(conf.matrix_basic) <- paste("Actual", rownames(conf.matrix_basic), s
ep=":")

colnames(conf.matrix_basic) <- paste("Predicted", colnames(conf.matrix_basic)
, sep=":")

#print(conf.matrix_basic)
```

Plotting the regression tree for basic features

```
plot(tree.pruned_basic, main="Regression Tree for basic features")

text(tree.pruned_basic,cex=0.8,use.n=TRUE,xpd=TRUE)
```



```
prp(tree.pruned_basic,faclen=0,tweak=1.5,extra=1,main="Regression Tree for ba
sic features")
```



Finding out the R squared value

```
tmp_basic<-printcp(tree_basic)
```

```
##
## Regression tree:
## rpart(formula = blogtrain_basic$X1.0.2 ~ ., data = blogtrain_basic,
##     method = "anova", control = rpart.control(cp = 0.001))
##
## Variables actually used in tree construction:
## [1] X0.0.14 X0.0.15 X0.0.16 X0.0.18 X0.0.19 X2.0.1  X2.0.2  X2.0.3  X2.0.4
##
## Root node error: 74495814/52396 = 1421.8
##
## n= 52396
##
```

```
##           CP nsplit rel error  xerror     xstd
## 1  0.1601367      0   1.00000 1.00002 0.066871
## 2  0.0356080      1   0.83986 0.84826 0.061039
## 3  0.0208948      2   0.80426 0.80975 0.059376
## 4  0.0089661      3   0.78336 0.79373 0.058969
## 5  0.0048979      4   0.77439 0.78757 0.059284
## 6  0.0045895      5   0.76950 0.78643 0.059365
## 7  0.0043841      6   0.76491 0.78946 0.059430
## 8  0.0035830      7   0.76052 0.78468 0.059286
## 9  0.0024613     11   0.74619 0.78365 0.059307
## 10 0.0024404     13   0.74127 0.78696 0.059280
## 11 0.0023383     15   0.73639 0.78715 0.059274
## 12 0.0021951     16   0.73405 0.78913 0.059329
## 13 0.0020115     17   0.73185 0.78757 0.059237
## 14 0.0017869     19   0.72783 0.78578 0.059151
## 15 0.0017494     24   0.71852 0.78507 0.059155
## 16 0.0012456     25   0.71677 0.78380 0.059163
## 17 0.0012077     29   0.71179 0.79028 0.059260
## 18 0.0011379     31   0.70937 0.79199 0.059199
## 19 0.0011267     32   0.70823 0.79224 0.059137
## 20 0.0010000     34   0.70598 0.79065 0.058687
```

```
rsq.val_basic<-1-tmp_basic[,c(3,4)]
rsq.val_basic<-rsq.val_basic[nrow(rsq.val_basic)]
rsq.val_basic
```

```
## [1] 0.2940199
```

Lets build the model using basic and weekday features

```
blogtrain_basicweekday<-blogtrain[,c(51:60,270:276,281)]
blogtest_basicweekday<-blogtest[,c(51:60,270:276,281)]
```

Creating the CART model using rpart

```
tree_basicweekday<-rpart(blogtrain_basicweekday$X1.0.2~.,data=blogtrain_basic
weekday, method = "anova",control=rpart.control(cp=0.001))
printcp(tree_basicweekday)
```

```
##
## Regression tree:
## rpart(formula = blogtrain_basicweekday$X1.0.2 ~ ., data = blogtrain_basicw
eekday,
##     method = "anova", control = rpart.control(cp = 0.001))
##
## Variables actually used in tree construction:
## [1] X0.0.14 X0.0.15 X0.0.16 X0.0.18 X0.0.19 X2.0.1  X2.0.2  X2.0.3  X2.0.4
##
## Root node error: 74495814/52396 = 1421.8
##
## n= 52396
##
##           CP nsplit rel error  xerror     xstd
## 1  0.1601367      0   1.00000 1.00002 0.066871
## 2  0.0356080      1   0.83986 0.84554 0.060959
## 3  0.0208948      2   0.80426 0.80694 0.059507
## 4  0.0089661      3   0.78336 0.79174 0.058932
## 5  0.0048979      4   0.77439 0.78235 0.059284
## 6  0.0045895      5   0.76950 0.78189 0.059400
## 7  0.0043841      6   0.76491 0.77941 0.059384
## 8  0.0035830      7   0.76052 0.78171 0.059427
## 9  0.0024613     11   0.74619 0.78005 0.059351
## 10 0.0024404     13   0.74127 0.78202 0.059316
## 11 0.0023383     15   0.73639 0.78478 0.059289
## 12 0.0021951     16   0.73405 0.78637 0.059298
## 13 0.0020115     17   0.73185 0.78618 0.059439
## 14 0.0017869     19   0.72783 0.78323 0.059312
## 15 0.0017494     24   0.71852 0.77994 0.059246
## 16 0.0012456     25   0.71677 0.78700 0.059362
## 17 0.0012077     29   0.71179 0.79016 0.059285
## 18 0.0011379     31   0.70937 0.79236 0.059343
## 19 0.0011267     32   0.70823 0.79430 0.059334
## 20 0.0010000     34   0.70598 0.79835 0.059345
```

Calculating the best complexity parameter of the model

```
bestcp_basicweekday <-tree_basicweekday$cptable[which.min(tree_basicweekday$cptable[,"xerror"]),"CP"]

bestcp_basicweekday
```

```
## [1] 0.004384053
```

Pruning the tree to avoid overfitting

```
tree.pruned_basicweekday <- prune(tree_basicweekday, cp=bestcp_basicweekday)

summary(tree.pruned_basicweekday)
```

```
## Call:

## rpart(formula = blogtrain_basicweekday$X1.0.2 ~ ., data = blogtrain_basicweekday,

##     method = "anova", control = rpart.control(cp = 0.001))

##   n= 52396

##

##            CP nsplit rel error    xerror       xstd

## 1 0.160136685      0 1.0000000 1.0000150 0.06687054

## 2 0.035607988      1 0.8398633 0.8455374 0.06095860

## 3 0.020894750      2 0.8042553 0.8069393 0.05950731

## 4 0.008966101      3 0.7833606 0.7917356 0.05893210

## 5 0.004897880      4 0.7743945 0.7823488 0.05928438

## 6 0.004589499      5 0.7694966 0.7818918 0.05939956

## 7 0.004384053      6 0.7649071 0.7794079 0.05938418

##

## Variable importance

##  X2.0.2  X2.0.4  X2.0.1  X2.0.3 X0.0.16 X0.0.19 X0.0.18 X0.0.15

##      44      38       4       4       3       3       2       2

##

## Node number 1: 52396 observations,    complexity param=0.1601367

##   mean=6.764829, MSE=1421.784

##   left son=2 (51595 obs) right son=3 (801 obs)

##   Primary splits:

##       X2.0.2  < 221.5 to the left,  improve=0.16013670, (0 missing)

##       X2.0.4  < 185.5 to the left,  improve=0.12456960, (0 missing)
```

```
##       X2.0.3  < 279.5 to the left,  improve=0.07712658, (0 missing)
##       X2.0.1  < 352.5 to the left,  improve=0.07535665, (0 missing)
##       X0.0.16 < 2.5   to the left,  improve=0.04953726, (0 missing)
##   Surrogate splits:
##       X2.0.4  < 221.5 to the left,  agree=0.996, adj=0.760, (0 split)
##       X2.0.1  < 818.5 to the left,  agree=0.986, adj=0.055, (0 split)
##       X2.0.3  < 788   to the left,  agree=0.985, adj=0.029, (0 split)
##       X0.0.16 < 9.5   to the left,  agree=0.985, adj=0.019, (0 split)
##       X0.0.19 < 10.5  to the left,  agree=0.985, adj=0.017, (0 split)
##
## Node number 2: 51595 observations,    complexity param=0.03560799
##   mean=4.884756, MSE=843.6107
##   left son=4 (45388 obs) right son=5 (6207 obs)
##   Primary splits:
##       X2.0.4  < 7.5   to the left,  improve=0.06094381, (0 missing)
##       X2.0.2  < 20.5  to the left,  improve=0.05892590, (0 missing)
##       X2.0.3  < 14.5  to the left,  improve=0.02121635, (0 missing)
##       X2.0.1  < 14.5  to the left,  improve=0.02009537, (0 missing)
##       X0.0.19 < 0.5   to the left,  improve=0.01385694, (0 missing)
##   Surrogate splits:
##       X2.0.2  < 14.5  to the left,  agree=0.938, adj=0.483, (0 split)
##       X0.0.19 < 1.5   to the left,  agree=0.891, adj=0.092, (0 split)
##       X0.0.16 < 1.5   to the left,  agree=0.888, adj=0.068, (0 split)
##
## Node number 3: 801 observations,    complexity param=0.02089475
##   mean=127.8664, MSE=23770.55
##   left son=6 (575 obs) right son=7 (226 obs)
##   Primary splits:
##       X2.0.2  < 427.5 to the left,  improve=0.08175181, (0 missing)
##       X2.0.4  < 421   to the left,  improve=0.07196278, (0 missing)
##       X2.0.3  < 430   to the left,  improve=0.06611954, (0 missing)
##       X2.0.1  < 430.5 to the left,  improve=0.05480402, (0 missing)
##       X0.0.18 < 1.5   to the left,  improve=0.04451982, (0 missing)
##   Surrogate splits:
```

```
##       X2.0.4  < 427.5 to the left,  agree=0.939, adj=0.783, (0 split)
##       X2.0.3  < 427.5 to the left,  agree=0.843, adj=0.442, (0 split)
##       X2.0.1  < 427.5 to the left,  agree=0.813, adj=0.336, (0 split)
##       X0.0.16 < 7.5   to the left,  agree=0.757, adj=0.137, (0 split)
##       X0.0.19 < 7.5   to the left,  agree=0.757, adj=0.137, (0 split)
##
## Node number 4: 45388 observations,    complexity param=0.00489788
##   mean=2.233167, MSE=336.933
##   left son=8 (45220 obs) right son=9 (168 obs)
##   Primary splits:
##       X2.0.2  < 107.5 to the left,  improve=0.023859180, (0 missing)
##       X2.0.1  < 400.5 to the left,  improve=0.011253080, (0 missing)
##       X0.0.14 < 187.5 to the left,  improve=0.009131713, (0 missing)
##       X2.0.4  < 1.5   to the left,  improve=0.009126476, (0 missing)
##       X2.0.3  < 343.5 to the left,  improve=0.007968743, (0 missing)
##   Surrogate splits:
##       X0.0.14 < 655.5 to the left,  agree=0.996, adj=0.018, (0 split)
##
## Node number 5: 6207 observations,    complexity param=0.004589499
##   mean=24.27421, MSE=4121.272
##   left son=10 (3562 obs) right son=11 (2645 obs)
##   Primary splits:
##       X2.0.4  < 42.5  to the left,  improve=0.013365470, (0 missing)
##       X2.0.2  < 103.5 to the left,  improve=0.011946390, (0 missing)
##       X2.0.3  < 42.5  to the left,  improve=0.011160650, (0 missing)
##       X2.0.1  < 42.5  to the left,  improve=0.009678477, (0 missing)
##       X0.0.14 < 0.5   to the right, improve=0.007272552, (0 missing)
##   Surrogate splits:
##       X2.0.2  < 42.5  to the left,  agree=0.973, adj=0.936, (0 split)
##       X2.0.3  < 42.5  to the left,  agree=0.955, adj=0.895, (0 split)
##       X2.0.1  < 42.5  to the left,  agree=0.951, adj=0.885, (0 split)
##       X0.0.19 < 2.5   to the left,  agree=0.616, adj=0.099, (0 split)
##       X0.0.16 < 2.5   to the left,  agree=0.614, adj=0.095, (0 split)
##
```

```
## Node number 6: 575 observations
##   mean=100.2296, MSE=16396.05
##
## Node number 7: 226 observations,    complexity param=0.008966101
##   mean=198.1814, MSE=35645.6
##   left son=14 (61 obs) right son=15 (165 obs)
##   Primary splits:
##       X0.0.18 < 2.5   to the left,  improve=0.08291271, (0 missing)
##       X0.0.15 < 2.5   to the left,  improve=0.07893757, (0 missing)
##       X0.0.16 < 2.5   to the left,  improve=0.05969577, (0 missing)
##       X2.0.2  < 666.5 to the left,  improve=0.04538495, (0 missing)
##       X0.0.19 < 2.5   to the left,  improve=0.04426379, (0 missing)
##   Surrogate splits:
##       X0.0.15 < 2.5   to the left,  agree=0.996, adj=0.984, (0 split)
##       X0.0.16 < 2.5   to the left,  agree=0.889, adj=0.590, (0 split)
##       X0.0.19 < 2.5   to the left,  agree=0.850, adj=0.443, (0 split)
##       X2.0.3  < 433.5 to the left,  agree=0.743, adj=0.049, (0 split)
##       X2.0.1  < 433.5 to the left,  agree=0.739, adj=0.033, (0 split)
##
## Node number 8: 45220 observations
##   mean=2.060349, MSE=311.8869
##
## Node number 9: 168 observations
##   mean=48.75, MSE=4906.652
##
## Node number 10: 3562 observations
##   mean=17.87872, MSE=3641.125
##
## Node number 11: 2645 observations
##   mean=32.88696, MSE=4638.619
##
## Node number 14: 61 observations
##   mean=108.7705, MSE=39642.87
##
```

```
## Node number 15: 165 observations
##   mean=231.2364, MSE=30119.72
```

Predict the model using test data

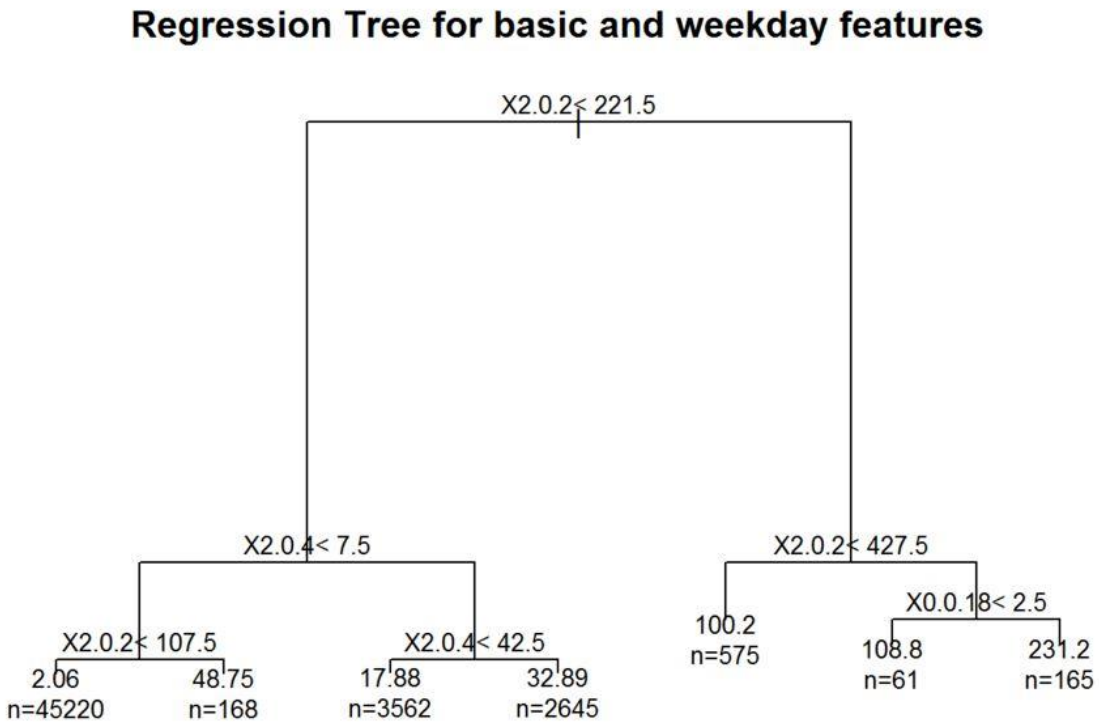
```
blogtrain_basicweekday<-blogtrain_basicweekday[-c(7565:52396),]
pred_basicweekday<-predict(tree.pruned_basicweekday,blogtest_basicweekday,type = "vector")
#print(tree.pruned_basicweekday)
```

Developing the confusion matrix

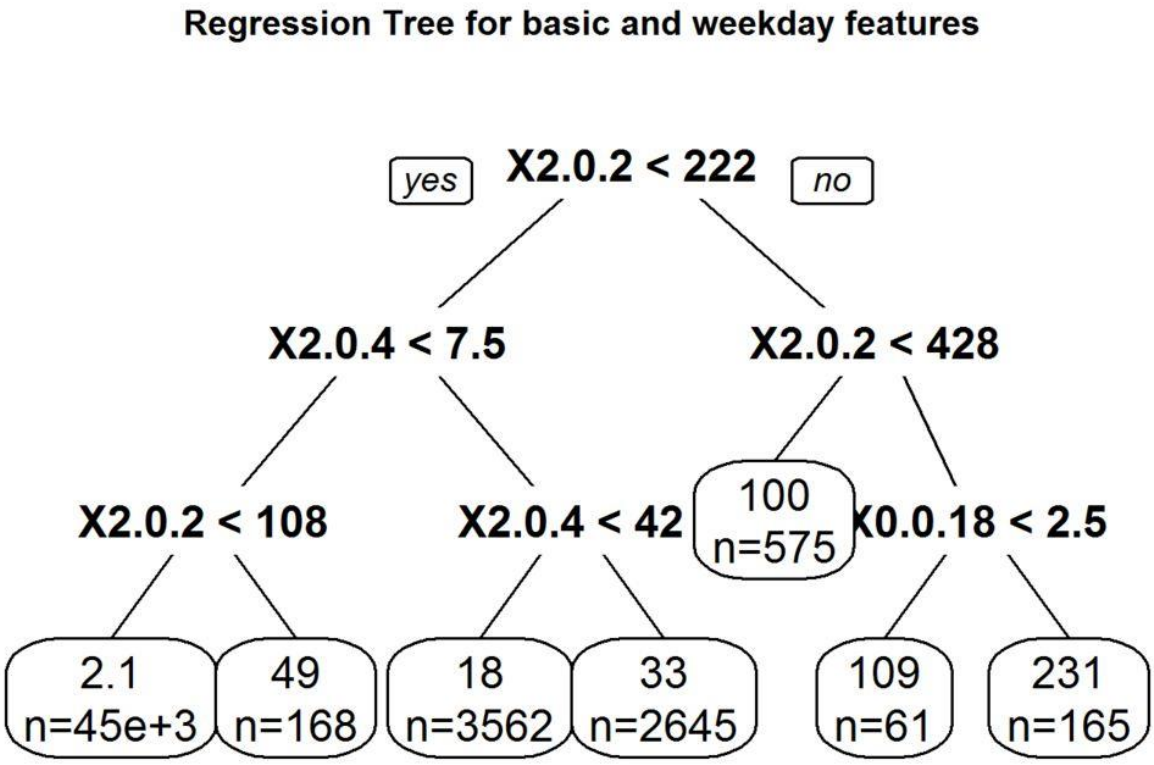
```
conf.matrix_basicweekday<-table(blogtrain_basicweekday$X1.0.2,pred_basicweekday)
rownames(conf.matrix_basicweekday) <- paste("Actual", rownames(conf.matrix_basicweekday), sep=":")
colnames(conf.matrix_basicweekday) <- paste("Predicted", colnames(conf.matrix_basicweekday), sep=":")
#print(conf.matrix_basic)
```

Plotting the regression tree for basic features

```
plot(tree.pruned_basicweekday, main="Regression Tree for basic and weekday features")
text(tree.pruned_basicweekday,cex=0.8,use.n=TRUE,xpd=TRUE)
```




```
prp(tree.pruned_basicweekday,faclen=0,tweak=1.5,extra=1,main="Regression Tree
for basic and weekday features")
```



Finding out the R squared value

```
tmp_basicweekday<-printcp(tree_basicweekday)
```

```
##
## Regression tree:
## rpart(formula = blogtrain_basicweekday$X1.0.2 ~ ., data = blogtrain_basicw
eekday,
##     method = "anova", control = rpart.control(cp = 0.001))
##
## Variables actually used in tree construction:
## [1] X0.0.14 X0.0.15 X0.0.16 X0.0.18 X0.0.19 X2.0.1  X2.0.2  X2.0.3  X2.0.4
##
## Root node error: 74495814/52396 = 1421.8
##
## n= 52396
##
##           CP nsplit rel error  xerror     xstd
## 1  0.1601367      0   1.00000 1.00002 0.066871
```

```
## 2  0.0356080      1   0.83986 0.84554 0.060959
## 3  0.0208948      2   0.80426 0.80694 0.059507
## 4  0.0089661      3   0.78336 0.79174 0.058932
## 5  0.0048979      4   0.77439 0.78235 0.059284
## 6  0.0045895      5   0.76950 0.78189 0.059400
## 7  0.0043841      6   0.76491 0.77941 0.059384
## 8  0.0035830      7   0.76052 0.78171 0.059427
## 9  0.0024613     11   0.74619 0.78005 0.059351
## 10 0.0024404     13   0.74127 0.78202 0.059316
## 11 0.0023383     15   0.73639 0.78478 0.059289
## 12 0.0021951     16   0.73405 0.78637 0.059298
## 13 0.0020115     17   0.73185 0.78618 0.059439
## 14 0.0017869     19   0.72783 0.78323 0.059312
## 15 0.0017494     24   0.71852 0.77994 0.059246
## 16 0.0012456     25   0.71677 0.78700 0.059362
## 17 0.0012077     29   0.71179 0.79016 0.059285
## 18 0.0011379     31   0.70937 0.79236 0.059343
## 19 0.0011267     32   0.70823 0.79430 0.059334
## 20 0.0010000     34   0.70598 0.79835 0.059345
```

```
rsq.val_basicweekday<-1-tmp_basicweekday[,c(3,4)]
rsq.val_basicweekday<-rsq.val_basicweekday[nrow(rsq.val_basicweekday)]
rsq.val_basicweekday
```

```
## [1] 0.2940199
```

Lets build the model using basic and textual features

```
blogtrain_basictextual<-blogtrain[,c(51:60,281)]
blogtest_basictextual<-blogtest[,c(51:60,63:262,281)]
```

Creating the CART model using rpart

```
tree_basictextual<-rpart(blogtrain_basictextual$X1.0.2~.,data=blogtrain_basic
textual, method = "anova",control=rpart.control(cp=0.001))
printcp(tree_basictextual)
```

```
##
## Regression tree:
```

```
## rpart(formula = blogtrain_basictextual$X1.0.2 ~ ., data = blogtrain_basict
extual,
##     method = "anova", control = rpart.control(cp = 0.001))
##
## Variables actually used in tree construction:
## [1] X0.0.14 X0.0.15 X0.0.16 X0.0.18 X0.0.19 X2.0.1  X2.0.2  X2.0.3  X2.0.4
##
## Root node error: 74495814/52396 = 1421.8
##
## n= 52396
##
##           CP nsplit rel error  xerror     xstd
## 1  0.1601367      0   1.00000 1.00001 0.066871
## 2  0.0356080      1   0.83986 0.84496 0.061011
## 3  0.0208948      2   0.80426 0.81139 0.059991
## 4  0.0089661      3   0.78336 0.79204 0.059210
## 5  0.0048979      4   0.77439 0.78251 0.059505
## 6  0.0045895      5   0.76950 0.78218 0.059299
## 7  0.0043841      6   0.76491 0.78033 0.059353
## 8  0.0035830      7   0.76052 0.78100 0.059393
## 9  0.0024613     11   0.74619 0.77988 0.059330
## 10 0.0024404     13   0.74127 0.78017 0.059194
## 11 0.0023383     15   0.73639 0.77882 0.059169
## 12 0.0021951     16   0.73405 0.78078 0.059356
## 13 0.0020115     17   0.73185 0.78196 0.059368
## 14 0.0017869     19   0.72783 0.78427 0.059370
## 15 0.0017494     24   0.71852 0.78563 0.059399
## 16 0.0012456     25   0.71677 0.78849 0.059026
## 17 0.0012077     29   0.71179 0.79699 0.059276
## 18 0.0011379     31   0.70937 0.79688 0.059264
## 19 0.0011267     32   0.70823 0.79721 0.059263
## 20 0.0010000     34   0.70598 0.80232 0.059384
```

Calculating the best complexity parameter of the model

```
bestcp_basictextual <-tree_basictextual$cptable[which.min(tree_basictextual$cptable[,"xerror"]),"CP"]

bestcp_basictextual
```

```
## [1] 0.002338311
```

Pruning the tree to avoid overfitting

```
tree.pruned_basictextual <- prune(tree_basictextual, cp=bestcp_basictextual)

summary(tree.pruned_basictextual)
```

```
## Call:

## rpart(formula = blogtrain_basictextual$X1.0.2 ~ ., data = blogtrain_basictextual,

##     method = "anova", control = rpart.control(cp = 0.001))

##   n= 52396

##

##             CP nsplit rel error    xerror       xstd

## 1  0.160136685      0 1.0000000 1.0000137 0.06687109

## 2  0.035607988      1 0.8398633 0.8449633 0.06101065

## 3  0.020894750      2 0.8042553 0.8113902 0.05999129

## 4  0.008966101      3 0.7833606 0.7920366 0.05921012

## 5  0.004897880      4 0.7743945 0.7825115 0.05950489

## 6  0.004589499      5 0.7694966 0.7821795 0.05929944

## 7  0.004384053      6 0.7649071 0.7803322 0.05935308

## 8  0.003582984      7 0.7605230 0.7810036 0.05939342

## 9  0.002461266     11 0.7461911 0.7798818 0.05932994

## 10 0.002440411     13 0.7412686 0.7801736 0.05919357

## 11 0.002338311     15 0.7363878 0.7788202 0.05916928

##

## Variable importance

##  X2.0.2  X2.0.4  X2.0.1  X2.0.3 X0.0.16 X0.0.19 X0.0.18 X0.0.15 X0.0.14

##      40      36       7       6       3       2       2       2       1

##

## Node number 1: 52396 observations,    complexity param=0.1601367

##   mean=6.764829, MSE=1421.784

##   left son=2 (51595 obs) right son=3 (801 obs)

##   Primary splits:
```

```
##       X2.0.2  < 221.5  to the left,  improve=0.16013670, (0 missing)
##       X2.0.4  < 185.5  to the left,  improve=0.12456960, (0 missing)
##       X2.0.3  < 279.5  to the left,  improve=0.07712658, (0 missing)
##       X2.0.1  < 352.5  to the left,  improve=0.07535665, (0 missing)
##       X0.0.16 < 2.5    to the left,  improve=0.04953726, (0 missing)
##   Surrogate splits:
##       X2.0.4  < 221.5  to the left,  agree=0.996, adj=0.760, (0 split)
##       X2.0.1  < 818.5  to the left,  agree=0.986, adj=0.055, (0 split)
##       X2.0.3  < 788    to the left,  agree=0.985, adj=0.029, (0 split)
##       X0.0.16 < 9.5    to the left,  agree=0.985, adj=0.019, (0 split)
##       X0.0.19 < 10.5   to the left,  agree=0.985, adj=0.017, (0 split)
##
## Node number 2: 51595 observations,    complexity param=0.03560799
##   mean=4.884756, MSE=843.6107
##   left son=4 (45388 obs) right son=5 (6207 obs)
##   Primary splits:
##       X2.0.4  < 7.5    to the left,  improve=0.06094381, (0 missing)
##       X2.0.2  < 20.5   to the left,  improve=0.05892590, (0 missing)
##       X2.0.3  < 14.5   to the left,  improve=0.02121635, (0 missing)
##       X2.0.1  < 14.5   to the left,  improve=0.02009537, (0 missing)
##       X0.0.19 < 0.5    to the left,  improve=0.01385694, (0 missing)
##   Surrogate splits:
##       X2.0.2  < 14.5   to the left,  agree=0.938, adj=0.483, (0 split)
##       X0.0.19 < 1.5    to the left,  agree=0.891, adj=0.092, (0 split)
##       X0.0.16 < 1.5    to the left,  agree=0.888, adj=0.068, (0 split)
##
## Node number 3: 801 observations,    complexity param=0.02089475
##   mean=127.8664, MSE=23770.55
##   left son=6 (575 obs) right son=7 (226 obs)
##   Primary splits:
##       X2.0.2  < 427.5  to the left,  improve=0.08175181, (0 missing)
##       X2.0.4  < 421    to the left,  improve=0.07196278, (0 missing)
##       X2.0.3  < 430    to the left,  improve=0.06611954, (0 missing)
##       X2.0.1  < 430.5  to the left,  improve=0.05480402, (0 missing)
```

```
##       X0.0.18 < 1.5    to the left,  improve=0.04451982, (0 missing)
##   Surrogate splits:
##       X2.0.4  < 427.5  to the left,  agree=0.939, adj=0.783, (0 split)
##       X2.0.3  < 427.5  to the left,  agree=0.843, adj=0.442, (0 split)
##       X2.0.1  < 427.5  to the left,  agree=0.813, adj=0.336, (0 split)
##       X0.0.16 < 7.5    to the left,  agree=0.757, adj=0.137, (0 split)
##       X0.0.19 < 7.5    to the left,  agree=0.757, adj=0.137, (0 split)
##
## Node number 4: 45388 observations,    complexity param=0.00489788
##   mean=2.233167, MSE=336.933
##   left son=8 (45220 obs) right son=9 (168 obs)
##   Primary splits:
##       X2.0.2  < 107.5  to the left,  improve=0.023859180, (0 missing)
##       X2.0.1  < 400.5  to the left,  improve=0.011253080, (0 missing)
##       X0.0.14 < 187.5  to the left,  improve=0.009131713, (0 missing)
##       X2.0.4  < 1.5    to the left,  improve=0.009126476, (0 missing)
##       X2.0.3  < 343.5  to the left,  improve=0.007968743, (0 missing)
##   Surrogate splits:
##       X0.0.14 < 655.5  to the left,  agree=0.996, adj=0.018, (0 split)
##
## Node number 5: 6207 observations,    complexity param=0.004589499
##   mean=24.27421, MSE=4121.272
##   left son=10 (3562 obs) right son=11 (2645 obs)
##   Primary splits:
##       X2.0.4  < 42.5   to the left,  improve=0.013365470, (0 missing)
##       X2.0.2  < 103.5  to the left,  improve=0.011946390, (0 missing)
##       X2.0.3  < 42.5   to the left,  improve=0.011160650, (0 missing)
##       X2.0.1  < 42.5   to the left,  improve=0.009678477, (0 missing)
##       X0.0.14 < 0.5    to the right, improve=0.007272552, (0 missing)
##   Surrogate splits:
##       X2.0.2  < 42.5   to the left,  agree=0.973, adj=0.936, (0 split)
##       X2.0.3  < 42.5   to the left,  agree=0.955, adj=0.895, (0 split)
##       X2.0.1  < 42.5   to the left,  agree=0.951, adj=0.885, (0 split)
##       X0.0.19 < 2.5    to the left,  agree=0.616, adj=0.099, (0 split)
```

```
##       X0.0.16 < 2.5    to the left,  agree=0.614, adj=0.095, (0 split)
##
## Node number 6: 575 observations,    complexity param=0.003582984
##   mean=100.2296, MSE=16396.05
##   left son=12 (184 obs) right son=13 (391 obs)
##   Primary splits:
##       X2.0.3  < 276.5  to the left,  improve=0.02100116, (0 missing)
##       X0.0.18 < 0.5    to the left,  improve=0.01977664, (0 missing)
##       X0.0.15 < 0.5    to the left,  improve=0.01941526, (0 missing)
##       X2.0.1  < 353.5  to the left,  improve=0.01664092, (0 missing)
##       X2.0.2  < 354.5  to the left,  improve=0.01289905, (0 missing)
##   Surrogate splits:
##       X2.0.1 < 276.5  to the left,  agree=0.951, adj=0.848, (0 split)
##       X2.0.2 < 276.5  to the left,  agree=0.880, adj=0.625, (0 split)
##       X2.0.4 < 276.5  to the left,  agree=0.718, adj=0.120, (0 split)
##
## Node number 7: 226 observations,    complexity param=0.008966101
##   mean=198.1814, MSE=35645.6
##   left son=14 (61 obs) right son=15 (165 obs)
##   Primary splits:
##       X0.0.18 < 2.5    to the left,  improve=0.08291271, (0 missing)
##       X0.0.15 < 2.5    to the left,  improve=0.07893757, (0 missing)
##       X0.0.16 < 2.5    to the left,  improve=0.05969577, (0 missing)
##       X2.0.2  < 666.5  to the left,  improve=0.04538495, (0 missing)
##       X0.0.19 < 2.5    to the left,  improve=0.04426379, (0 missing)
##   Surrogate splits:
##       X0.0.15 < 2.5    to the left,  agree=0.996, adj=0.984, (0 split)
##       X0.0.16 < 2.5    to the left,  agree=0.889, adj=0.590, (0 split)
##       X0.0.19 < 2.5    to the left,  agree=0.850, adj=0.443, (0 split)
##       X2.0.3  < 433.5  to the left,  agree=0.743, adj=0.049, (0 split)
##       X2.0.1  < 433.5  to the left,  agree=0.739, adj=0.033, (0 split)
##
## Node number 8: 45220 observations
##   mean=2.060349, MSE=311.8869
```

```
##
## Node number 9: 168 observations
##   mean=48.75, MSE=4906.652
##
## Node number 10: 3562 observations
##   mean=17.87872, MSE=3641.125
##
## Node number 11: 2645 observations
##   mean=32.88696, MSE=4638.619
##
## Node number 12: 184 observations
##   mean=73.17935, MSE=13359.72
##
## Node number 13: 391 observations,    complexity param=0.003582984
##   mean=112.9591, MSE=17318.54
##   left son=26 (106 obs) right son=27 (285 obs)
##   Primary splits:
##       X0.0.18 < 0.5    to the left,  improve=0.04192850, (0 missing)
##       X0.0.15 < 0.5    to the left,  improve=0.04103568, (0 missing)
##       X0.0.19 < 0.5    to the left,  improve=0.02890781, (0 missing)
##       X0.0.16 < 0.5    to the left,  improve=0.02322103, (0 missing)
##       X2.0.1  < 288.5  to the right, improve=0.02304655, (0 missing)
##   Surrogate splits:
##       X0.0.15 < 0.5    to the left,  agree=0.997, adj=0.991, (0 split)
##       X0.0.16 < 0.5    to the left,  agree=0.847, adj=0.434, (0 split)
##
## Node number 14: 61 observations,    complexity param=0.004384053
##   mean=108.7705, MSE=39642.87
##   left son=28 (54 obs) right son=29 (7 obs)
##   Primary splits:
##       X2.0.4  < 702.5  to the left,  improve=0.13505570, (0 missing)
##       X2.0.2  < 694    to the left,  improve=0.07957718, (0 missing)
##       X2.0.3  < 722    to the left,  improve=0.06185540, (0 missing)
##       X0.0.14 < 5.5    to the right, improve=0.05540664, (0 missing)
```

```
##       X2.0.1  < 764.5  to the right, improve=0.03749789, (0 missing)
##   Surrogate splits:
##       X2.0.2 < 694    to the left,  agree=0.967, adj=0.714, (0 split)
##       X2.0.3 < 722    to the left,  agree=0.951, adj=0.571, (0 split)
##       X2.0.1 < 934    to the left,  agree=0.902, adj=0.143, (0 split)
##
## Node number 15: 165 observations,    complexity param=0.002461266
##   mean=231.2364, MSE=30119.72
##   left son=30 (11 obs) right son=31 (154 obs)
##   Primary splits:
##       X2.0.4  < -16    to the left,  improve=0.029056610, (0 missing)
##       X2.0.3  < 445.5  to the left,  improve=0.025428800, (0 missing)
##       X2.0.2  < 666.5  to the left,  improve=0.022494830, (0 missing)
##       X2.0.1  < 445.5  to the left,  improve=0.019468590, (0 missing)
##       X0.0.14 < 558.5  to the right, improve=0.009872295, (0 missing)
##   Surrogate splits:
##       X0.0.14 < 558.5  to the right, agree=0.976, adj=0.636, (0 split)
##       X0.0.16 < 0.5    to the left,  agree=0.970, adj=0.545, (0 split)
##       X2.0.1  < 1553.5 to the right, agree=0.952, adj=0.273, (0 split)
##       X0.0.19 < -2.5   to the left,  agree=0.939, adj=0.091, (0 split)
##
## Node number 26: 106 observations
##   mean=68.77358, MSE=8636.892
##
## Node number 27: 285 observations,    complexity param=0.003582984
##   mean=129.393, MSE=19551.28
##   left son=54 (263 obs) right son=55 (22 obs)
##   Primary splits:
##       X2.0.1  < 291.5  to the right, improve=0.04152467, (0 missing)
##       X2.0.3  < 290    to the right, improve=0.03675561, (0 missing)
##       X0.0.14 < 0.5    to the right, improve=0.02339020, (0 missing)
##       X2.0.2  < 288.5  to the right, improve=0.01363084, (0 missing)
##       X0.0.17 < 1.5    to the right, improve=0.01008088, (0 missing)
##   Surrogate splits:
```

```
##       X2.0.3 < 288.5  to the right, agree=0.986, adj=0.818, (0 split)
##
## Node number 28: 54 observations
##   mean=82.42593, MSE=22460.02
##
## Node number 29: 7 observations
##   mean=312, MSE=125540
##
## Node number 30: 11 observations
##   mean=120.5455, MSE=22304.43
##
## Node number 31: 154 observations,    complexity param=0.002461266
##   mean=239.1429, MSE=29740.27
##   left son=62 (137 obs) right son=63 (17 obs)
##   Primary splits:
##       X2.0.1  < 1021.5 to the left,  improve=0.04853794, (0 missing)
##       X0.0.14 < 463.5  to the left,  improve=0.03582062, (0 missing)
##       X2.0.3  < 445.5  to the left,  improve=0.03236608, (0 missing)
##       X2.0.4  < 219.5  to the right, improve=0.02494573, (0 missing)
##       X0.0.17 < 1.5    to the left,  improve=0.02038482, (0 missing)
##   Surrogate splits:
##       X0.0.14 < 426.5  to the left,  agree=0.942, adj=0.471, (0 split)
##       X2.0.3  < 1038   to the left,  agree=0.942, adj=0.471, (0 split)
##       X2.0.2  < 955.5  to the left,  agree=0.929, adj=0.353, (0 split)
##       X2.0.4  < 1028   to the left,  agree=0.929, adj=0.353, (0 split)
##       X0.0.17 < 4.5    to the left,  agree=0.916, adj=0.235, (0 split)
##
## Node number 54: 263 observations
##   mean=121.1521, MSE=16487.41
##
## Node number 55: 22 observations,    complexity param=0.003582984
##   mean=227.9091, MSE=45661.17
##   left son=110 (13 obs) right son=111 (9 obs)
##   Primary splits:
```

```
##       X2.0.4  < 282.5  to the left,  improve=0.35277120, (0 missing)
##       X2.0.2  < 284    to the left,  improve=0.25578780, (0 missing)
##       X2.0.3  < 284.5  to the left,  improve=0.25578780, (0 missing)
##       X2.0.1  < 282.5  to the left,  improve=0.15519920, (0 missing)
##       X0.0.18 < 2.5    to the right, improve=0.06292435, (0 missing)
##   Surrogate splits:
##       X2.0.2 < 282.5  to the left,  agree=0.955, adj=0.889, (0 split)
##       X2.0.3 < 284.5  to the left,  agree=0.955, adj=0.889, (0 split)
##       X2.0.1 < 282.5  to the left,  agree=0.909, adj=0.778, (0 split)
##
## Node number 62: 137 observations,    complexity param=0.002440411
##   mean=225.7591, MSE=28820.46
##   left son=124 (27 obs) right son=125 (110 obs)
##   Primary splits:
##       X2.0.4  < 447    to the left,  improve=0.03170966, (0 missing)
##       X2.0.3  < 445.5  to the left,  improve=0.02902210, (0 missing)
##       X2.0.1  < 445.5  to the left,  improve=0.02206072, (0 missing)
##       X2.0.2  < 445.5  to the left,  improve=0.02049825, (0 missing)
##       X0.0.18 < 8.5    to the right, improve=0.01489800, (0 missing)
##   Surrogate splits:
##       X2.0.2  < 445.5  to the left,  agree=0.898, adj=0.481, (0 split)
##       X0.0.14 < 173.5  to the right, agree=0.883, adj=0.407, (0 split)
##       X2.0.1  < 445.5  to the left,  agree=0.876, adj=0.370, (0 split)
##       X2.0.3  < 445.5  to the left,  agree=0.876, adj=0.370, (0 split)
##       X0.0.16 < 2.5    to the left,  agree=0.847, adj=0.222, (0 split)
##
## Node number 63: 17 observations
##   mean=347, MSE=24076.12
##
## Node number 110: 13 observations
##   mean=122.3077, MSE=17903.14
##
## Node number 111: 9 observations
##   mean=380.4444, MSE=46381.14
```

```
##
## Node number 124: 27 observations
##   mean=164.7407, MSE=11699.53
##
## Node number 125: 110 observations,    complexity param=0.002440411
##   mean=240.7364, MSE=31884.67
##   left son=250 (96 obs) right son=251 (14 obs)
##   Primary splits:
##       X2.0.1  < 482.5  to the right, improve=0.06797177, (0 missing)
##       X2.0.2  < 481    to the right, improve=0.06797177, (0 missing)
##       X2.0.4  < 466.5  to the right, improve=0.05472211, (0 missing)
##       X2.0.3  < 482    to the right, improve=0.03704196, (0 missing)
##       X0.0.16 < 8.5    to the right, improve=0.03339207, (0 missing)
##   Surrogate splits:
##       X2.0.2 < 481    to the right, agree=1.000, adj=1.000, (0 split)
##       X2.0.3 < 480    to the right, agree=0.982, adj=0.857, (0 split)
##       X2.0.4 < 470    to the right, agree=0.982, adj=0.857, (0 split)
##
## Node number 250: 96 observations
##   mean=222.9583, MSE=27779.44
##
## Node number 251: 14 observations
##   mean=362.6429, MSE=43006.37
```

Predict the model using test data

```
blogtrain_basictextual<-blogtrain_basictextual[-c(7565:52396),]
pred_basictextual<-predict(tree.pruned_basictextual,blogtest_basictextual,type = "vector")
print(tree.pruned_basictextual)
```

```
## n= 52396
##
## node), split, n, deviance, yval
##       * denotes terminal node
##
```

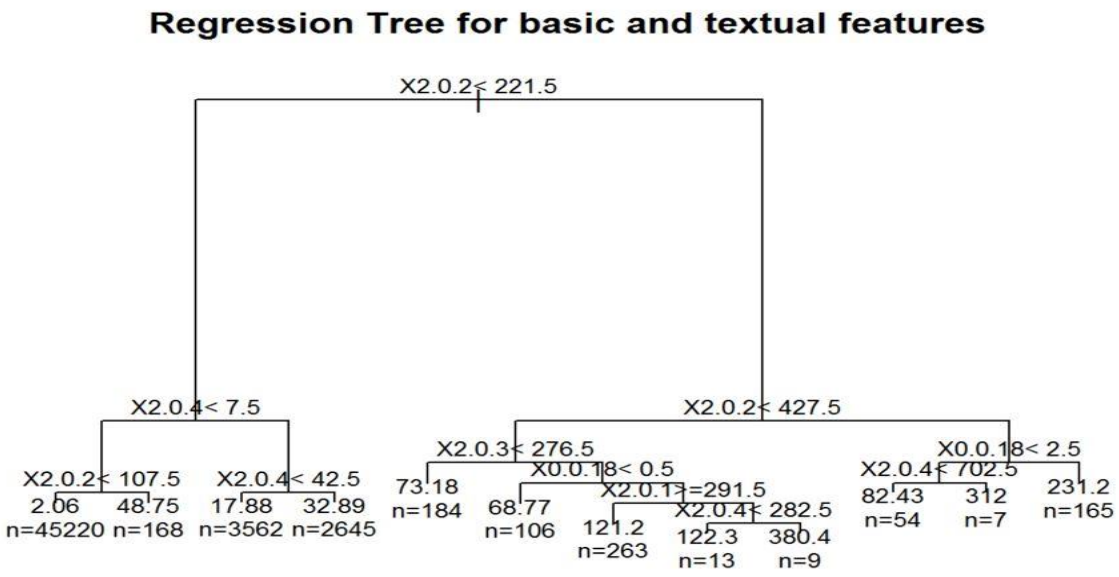
```
##   1) root 52396 74495810.0   6.764829
##     2) X2.0.2< 221.5 51595 43526090.0   4.884756
##       4) X2.0.4< 7.5 45388 15292720.0   2.233167
##         8) X2.0.2< 107.5 45220 14103530.0   2.060349 *
##         9) X2.0.2>=107.5 168   824317.5  48.750000 *
##       5) X2.0.4>=7.5 6207 25580730.0  24.274210
##        10) X2.0.4< 42.5 3562 12969690.0  17.878720 *
##        11) X2.0.4>=42.5 2645 12269150.0  32.886960 *
##     3) X2.0.2>=221.5 801 19040210.0 127.866400
##       6) X2.0.2< 427.5 575  9427730.0 100.229600
##        12) X2.0.3< 276.5 184  2458189.0  73.179350 *
##        13) X2.0.3>=276.5 391  6771547.0 112.959100
##          26) X0.0.18< 0.5 106   915510.6  68.773580 *
##          27) X0.0.18>=0.5 285  5572116.0 129.393000
##            54) X2.0.1>=291.5 263  4336190.0 121.152100 *
##            55) X2.0.1< 291.5 22  1004546.0 227.909100
##             110) X2.0.4< 282.5 13   232740.8 122.307700 *
##             111) X2.0.4>=282.5 9   417430.2 380.444400 *
##       7) X2.0.2>=427.5 226  8055906.0 198.181400
##        14) X0.0.18< 2.5 61  2418215.0 108.770500
##          28) X2.0.4< 702.5 54  1212841.0  82.425930 *
##          29) X2.0.4>=702.5 7   878780.0 312.000000 *
##        15) X0.0.18>=2.5 165  4969754.0 231.236400
##          30) X2.0.4< -16 11   245348.7 120.545500 *
##          31) X2.0.4>=-16 154  4580001.0 239.142900
##            62) X2.0.1< 1021.5 137  3948403.0 225.759100
##             124) X2.0.4< 447 27   315887.2 164.740700 *
##             125) X2.0.4>=447 110  3507313.0 240.736400
##               250) X2.0.1>=482.5 96  2666826.0 222.958300 *
##               251) X2.0.1< 482.5 14   602089.2 362.642900 *
##            63) X2.0.1>=1021.5 17   409294.0 347.000000 *
```

Developing the confusion matrix

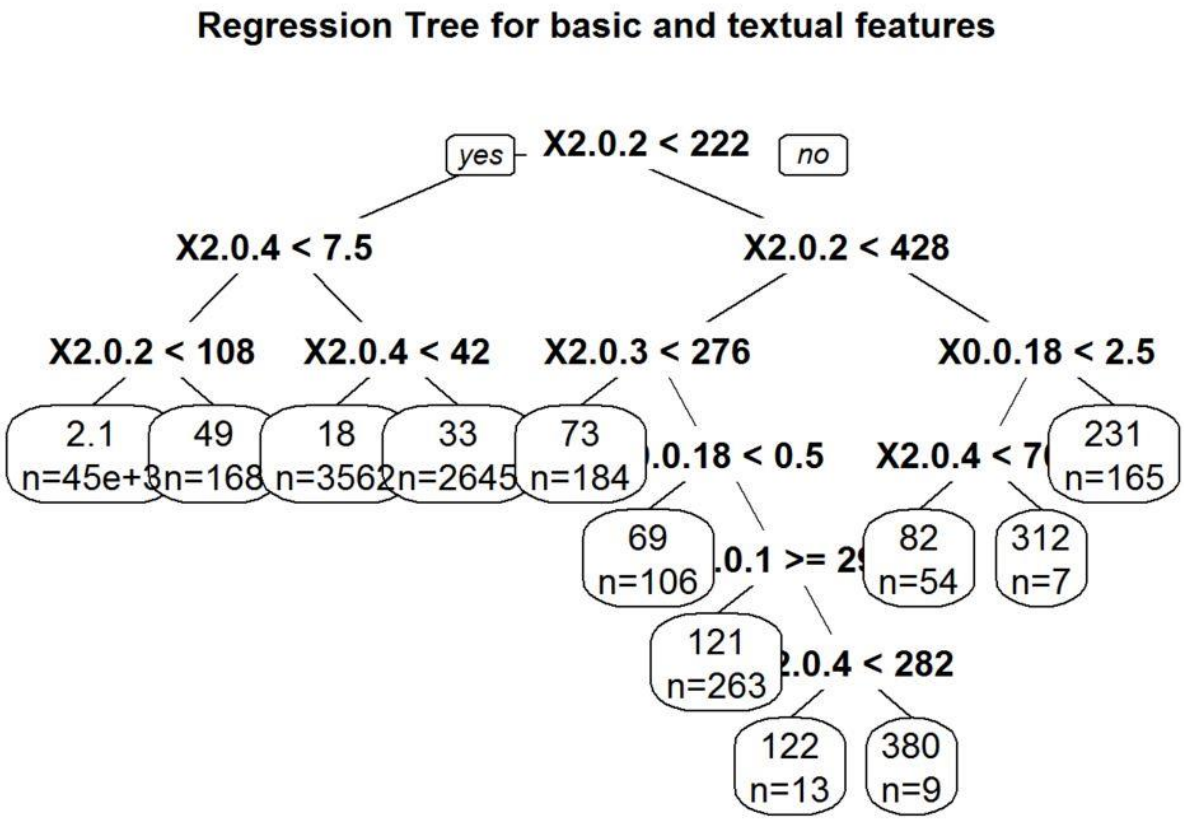
```
conf.matrix_basictextual<-table(blogtrain_basictextual$X1.0.2,pred_basictextual)

rownames(conf.matrix_basictextual) <- paste("Actual", rownames(conf.matrix_basictextual), sep=":")

colnames(conf.matrix_basictextual) <- paste("Predicted", colnames(conf.matrix_basictextual), sep=":")

##print(conf.matrix_basic)
```

Plotting the regression tree for basic features

```
plot(tree.pruned_basic, main="Regression Tree for basic and textual features")

text(tree.pruned_basic,cex=0.8,use.n=TRUE,xpd=TRUE)
```




```
prp(tree.pruned_basic,faclen=0,tweak=1.5,extra=1,main="Regression Tree for basic and textual features")
```



Finding out the R squared value

```
tmp_basictextual<-printcp(tree_basictextual)
```

```
##
## Regression tree:
## rpart(formula = blogtrain_basictextual$X1.0.2 ~ ., data = blogtrain_basict
extual,
##     method = "anova", control = rpart.control(cp = 0.001))
##
## Variables actually used in tree construction:
## [1] X0.0.14 X0.0.15 X0.0.16 X0.0.18 X0.0.19 X2.0.1  X2.0.2  X2.0.3  X2.0.4
##
## Root node error: 74495814/52396 = 1421.8
##
## n= 52396
##
##           CP nsplit rel error  xerror     xstd
```

```
## 1  0.1601367      0   1.00000 1.00001 0.066871
## 2  0.0356080      1   0.83986 0.84496 0.061011
## 3  0.0208948      2   0.80426 0.81139 0.059991
## 4  0.0089661      3   0.78336 0.79204 0.059210
## 5  0.0048979      4   0.77439 0.78251 0.059505
## 6  0.0045895      5   0.76950 0.78218 0.059299
## 7  0.0043841      6   0.76491 0.78033 0.059353
## 8  0.0035830      7   0.76052 0.78100 0.059393
## 9  0.0024613     11   0.74619 0.77988 0.059330
## 10 0.0024404     13   0.74127 0.78017 0.059194
## 11 0.0023383     15   0.73639 0.77882 0.059169
## 12 0.0021951     16   0.73405 0.78078 0.059356
## 13 0.0020115     17   0.73185 0.78196 0.059368
## 14 0.0017869     19   0.72783 0.78427 0.059370
## 15 0.0017494     24   0.71852 0.78563 0.059399
## 16 0.0012456     25   0.71677 0.78849 0.059026
## 17 0.0012077     29   0.71179 0.79699 0.059276
## 18 0.0011379     31   0.70937 0.79688 0.059264
## 19 0.0011267     32   0.70823 0.79721 0.059263
## 20 0.0010000     34   0.70598 0.80232 0.059384
```

```
rsq.val_basictextual<-1-tmp_basictextual[,c(3,4)]
rsq.val_basictextual<-rsq.val_basictextual[nrow(rsq.val_basictextual)]
rsq.val_basictextual
```

```
## [1] 0.2940199
```

Lets build models using random forest algorithm

```
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 3.2.4
```

```
## randomForest 4.6-12
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
set.seed(400)
```

Creating the training and test data of basic features only

```
blogtrain_basic<-blogtrain[,c(51:60,281)]
```

```
blogtest_basic<-blogtest[,c(51:60,281)]
```

Using randomForest()

```
randomforest_basic<-randomForest(blogtrain_basic$X1.0.2~.,data=blogtrain_basic,importance=TRUE,ntree=50)
print(randomforest_basic)
```

```
##
## Call:
##  randomForest(formula = blogtrain_basic$X1.0.2 ~ ., data = blogtrain_basic,      importance = TRUE, ntree = 50)
##                Type of random forest: regression
##                      Number of trees: 50
## No. of variables tried at each split: 3
##
##           Mean of squared residuals: 1135.312
##                     % Var explained: 20.15
```

```
importance(randomforest_basic)
```

```
##           %IncMSE IncNodePurity
## X2.0.1  4.8664667     5267405.7
## X2.0.2  6.5607866    10202230.5
## X0.0.14 4.5601105     1675205.2
## X2.0.3  3.2092975     5638494.7
## X2.0.4  4.9623873     9853232.9
## X0.0.15 3.1881349     1198775.0
## X0.0.16 1.0897886     1663224.1
## X0.0.17 2.4482372      387600.7
## X0.0.18 3.6970186     1459824.3
## X0.0.19 0.2207321     1560206.5
```

Predicting using test data

```
predictions_basic<-predict(randomforest_basic,blogtest_basic)
summary(predictions_basic)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   1.041   1.041   6.078   3.044 280.400
```

```
blogtrain_basic<-blogtrain_basic[-c(7565:52396),]
```

Creating the confirmation matrix

```
confmatrix_basic<-table(blogtrain_basic$X1.0.2,predictions_basic)

rownames(confmatrix_basic) <- paste("Actual", rownames(confmatrix_basic), sep
=":")

colnames(confmatrix_basic) <- paste("Predicted", colnames(confmatrix_basic),
sep=":")

#print(confmatrix_basic)
```

Creating the training and test data of basic and weekday features

```
blogtrain_basicweekday<-blogtrain[,c(51:60,270:276,281)]

blogtest_basicweekday<-blogtest[,c(51:60,270:276,281)]
```

Using randomForest()

```
randomforest_basicweekday<-randomForest(blogtrain_basicweekday$X1.0.2~.,data=
blogtrain_basicweekday,importance=TRUE,ntree=50)

print(randomforest_basicweekday)
```

```
##

## Call:

##  randomForest(formula = blogtrain_basicweekday$X1.0.2 ~ ., data = blogtrai
n_basicweekday,      importance = TRUE, ntree = 50)

##                Type of random forest: regression

##                      Number of trees: 50

## No. of variables tried at each split: 5

##

##           Mean of squared residuals: 1153.45

##                     % Var explained: 18.87
```

```
importance(randomforest_basicweekday)
```

```
##              %IncMSE IncNodePurity

## X2.0.1    8.28360729     5474937.5

## X2.0.2    7.12132657    11258256.1

## X0.0.14   2.82422601     1509583.8

## X2.0.3    6.02552296     6119372.0

## X2.0.4    4.47786177     8423455.6
```

```
## X0.0.15   4.76204712     1197774.4
## X0.0.16   4.47502991     1544939.7
## X0.0.17   1.54761778      334115.4
## X0.0.18   3.15753880     1470783.3
## X0.0.19   1.81934863     1912855.4
## X0.0.227  0.90022649      738938.6
## X0.0.228 -0.03103034      648746.3
## X0.0.229 -0.75762494      969809.5
## X1.0.1    1.87161750      872882.6
## X0.0.230 -0.53249118      823952.4
## X0.0.231 -0.04719097      470063.9
## X0.0.232 -1.20131681      483520.1
```

Predicting using test data

```
predictions_basicweekday<-predict(randomforest_basicweekday,blogtest_basicweekday)

summary(predictions_basicweekday)
```

```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
##    0.0000    0.8047    1.1030    6.1090    2.7240  316.6000
```

```
blogtrain_basicweekday<-blogtrain_basicweekday[-c(7565:52396),]
```

Creating the confusion matrix

```
confmatrix_basicweekday<-table(blogtrain_basicweekday$X1.0.2,predictions_basicweekday)

rownames(confmatrix_basicweekday) <- paste("Actual", rownames(confmatrix_basicweekday), sep=":")

colnames(confmatrix_basicweekday) <- paste("Predicted", colnames(confmatrix_basicweekday), sep=":")

#print(confmatrix_basicweekday)
```

Following is the table of comparison of R squared vales:

	Regression	CART
Basic features	0.2255	0.294
Basic + Weekday Features	0.2256	0.294
Basic + Textual Features	0.233	0.294

Comparison of R squared values obtained in Regression and CART. By looking at these values, we can infer that CART is the better model among them as it has R squared value closer to 1.