Problem Statement

Churn (loss of customers to competition) is a problem for companies because it is more expensive to acquire a new customer than to keep your existing one from leaving. This problem statement is targeted at enabling churn reduction using analytics concepts.

Target Variable – Churn

Exploratory Data Analysis - It includes following steps Looking into the data means visualizing the data through graphs and analyzing all variables.

- Visualization
- Missing value analysis
- Outlier analysis
- Correlation
- Feature scaling
- Dummy data create
- Feature sampling

Models:- Applied below models on preprocessed data

- KNN
- Logistic Regression
- Random forest
- Linear regression

Loading Dataset

train_original = pd.read_csv("Train_data.csv")

test_original = pd.read_csv("Test_data.csv")

Exploring Data

train.head(5)

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...	total eve calls	total eve charge	total night minutes	total night calls	total night charge	total intl minutes	total intl calls	total intl charge	c
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.78	244.7	91	11.01	10.0	3	2.70	
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.62	254.4	103	11.45	13.7	3	3.70	
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.30	162.6	104	7.32	12.2	5	3.29	
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.26	196.9	89	8.86	6.6	7	1.78	
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.61	186.9	121	8.41	10.1	3	2.73	

#Checking info of data as data types and rows n cols

train.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
state                             3333 non-null object
account length                    3333 non-null int64
area code                         3333 non-null int64
phone number                      3333 non-null object
international plan                3333 non-null object
voice mail plan                   3333 non-null object
number vmail messages             3333 non-null int64
total day minutes                 3333 non-null float64
total day calls                   3333 non-null int64
total day charge                  3333 non-null float64
total eve minutes                 3333 non-null float64
total eve calls                   3333 non-null int64
total eve charge                  3333 non-null float64
total night minutes               3333 non-null float64
total night calls                 3333 non-null int64
total night charge                3333 non-null float64
total intl minutes                3333 non-null float64
total intl calls                  3333 non-null int64
total intl charge                 3333 non-null float64
number customer service calls     3333 non-null int64
Churn                             3333 non-null object
dtypes: float64(8), int64(8), object(5)
memory usage: 546.9+ KB
```

train.describe()

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total eve charge	total night minutes	total night calls	total ch
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.00
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200.980348	100.114311	17.083540	200.872037	100.107711	9.03
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.713844	19.922625	4.310668	50.573847	19.568609	2.27
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	23.200000	33.000000	1.04
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.600000	87.000000	14.160000	167.000000	87.000000	7.52
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.400000	100.000000	17.120000	201.200000	100.000000	9.05
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.300000	114.000000	20.000000	235.300000	113.000000	10.59
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.700000	170.000000	30.910000	395.000000	175.000000	17.77

To check unique values now

for i in train.columns:

print(i,' -- ',len(train[i].value_counts()))

```
state  --  51
account length  --  212
area code  --  3
phone number  --  3333
international plan  --  2
voice mail plan  --  2
number vmail messages  --  46
total day minutes  --  1667
total day calls  --  119
total day charge  --  1667
total eve minutes  --  1611
total eve calls  --  123
total eve charge  --  1440
total night minutes  --  1591
total night calls  --  120
total night charge  --  933
total intl minutes  --  162
total intl calls  --  21
total intl charge  --  162
number customer service calls  --  10
Churn  --  2
```

Replacing spaces from columns name with underscore

train.columns = train.columns.str.replace(" ","_")

test.columns = test.columns.str.replace(" ","_") Changing area_code type to categorical in both test and train data set

train['area_code'] = train['area_code'].astype('object')

test['area_code'] = test['area_code'].astype('object')

Droping phone_number

train = train.drop('phone_number',axis=1)

test = test.drop('phone_number',axis=1)

All categorical var and removing target var

cat_names = train.select_dtypes(exclude=np.number).columns.tolist()

cat_names.remove('Churn')

cat_names

```
['account_length', 'number_vmail_messages', 'total_day_minutes',
'total_day_calls', 'total_day_charge', 'total_eve_minutes',
'total_eve_calls', 'total_eve_charge', 'total_night_minutes',
'total_night_calls', 'total_night_charge', 'total_intl_minutes',
'total_intl_calls', 'total_intl_charge', 'number_customer_service_calls']

['state', 'area_code', 'international_plan', 'voice_mail_plan']
```

Checking Missing Value in Data

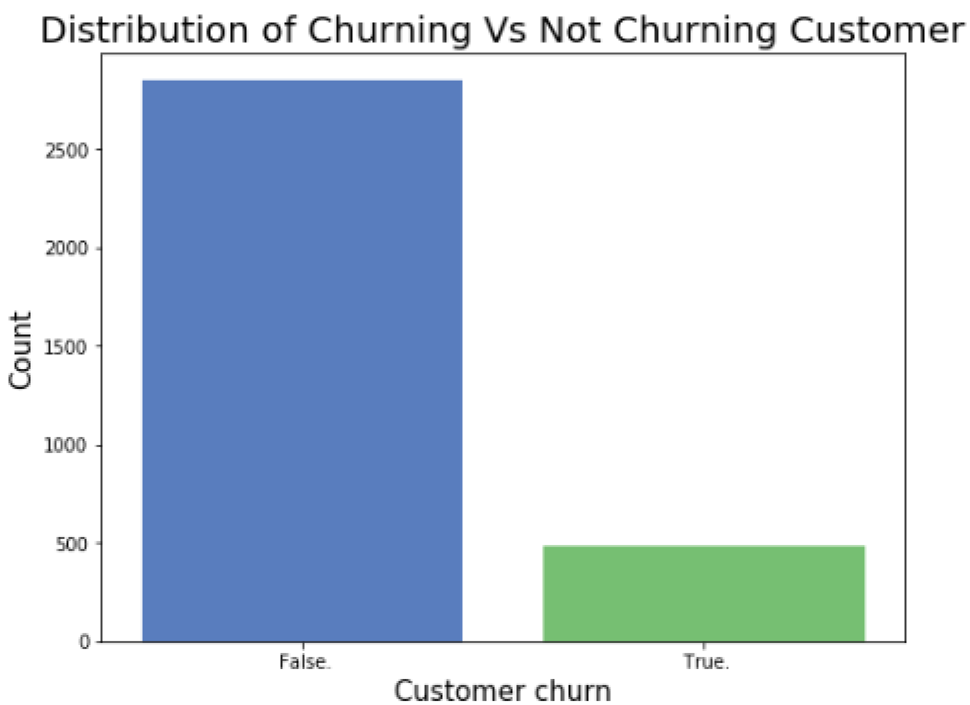
print(train.isnull().sum())

```
state                            0
account_length                   0
area_code                        0
international_plan               0
voice_mail_plan                  0
number_vmail_messages            0
total_day_minutes                0
total_day_calls                  0
total_day_charge                 0
total_eve_minutes                0
total_eve_calls                  0
total_eve_charge                 0
total_night_minutes              0
total_night_calls                0
total_night_charge               0
```

```
total_intl_minutes                0
total_intl_calls                  0
total_intl_charge                 0
number_customer_service_calls     0
Churn                             0
dtype: int64
```

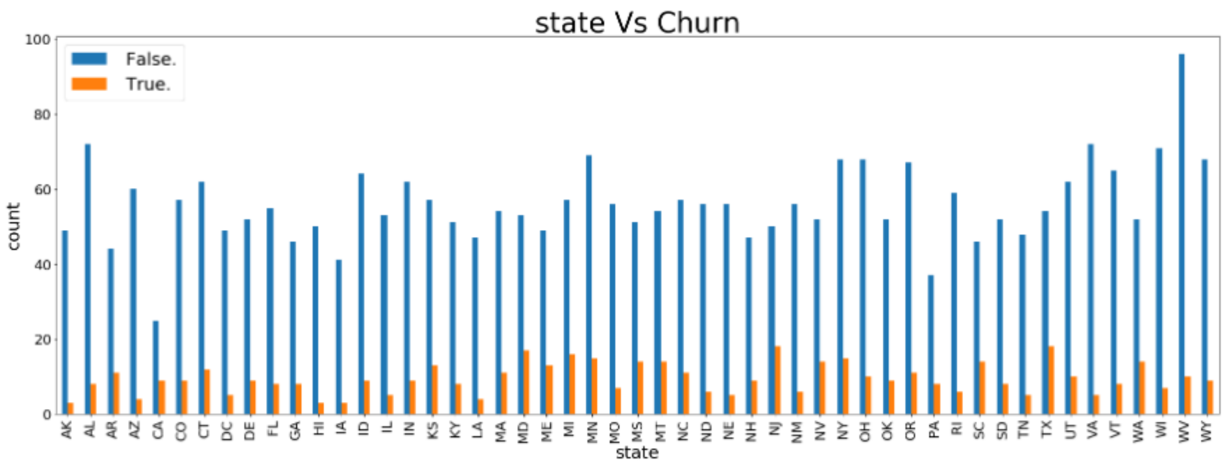
Visualizing data

```
plt.figure(figsize=(8,6))

sns.countplot(x = train.Churn,palette='muted')

plt.xlabel('Customer churn', fontsize= 15)

plt.ylabel('Count', fontsize= 15)

plt.title("Distribution of Churning Vs Not Churning Customer",fontsize= 20)

plt.show()
```



#State Wise Churning of customer

diff_bar('state','Churn')

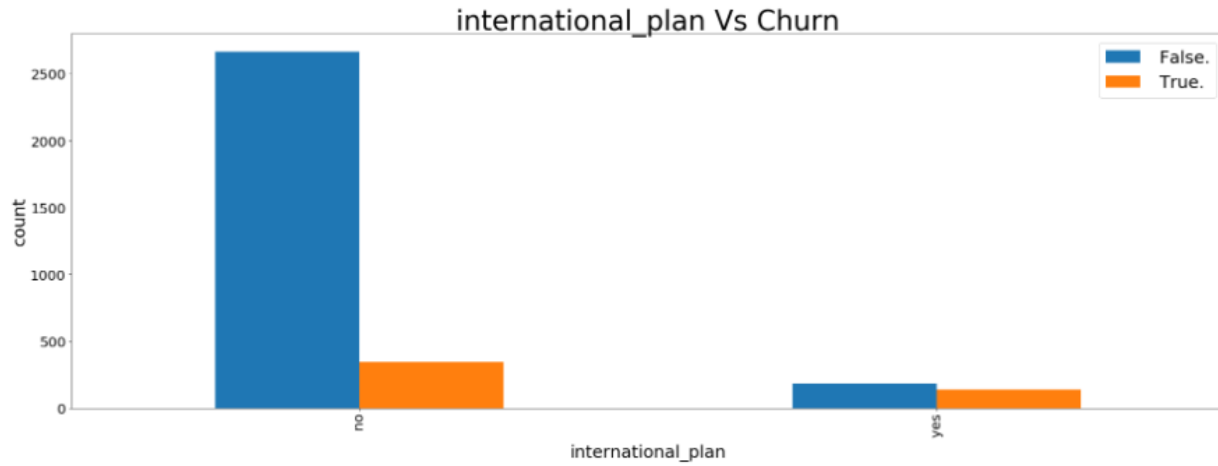


#area_code Wise Churning of customer

diff_bar('area_code','Churn')

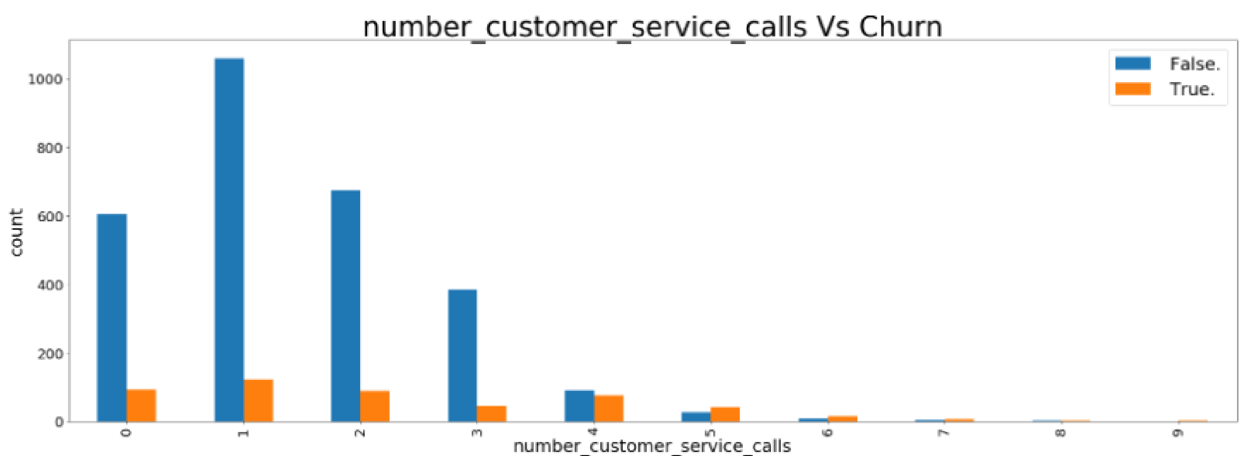
#International_Plan Wise Churning of customer

diff_bar('international_plan','Churn')



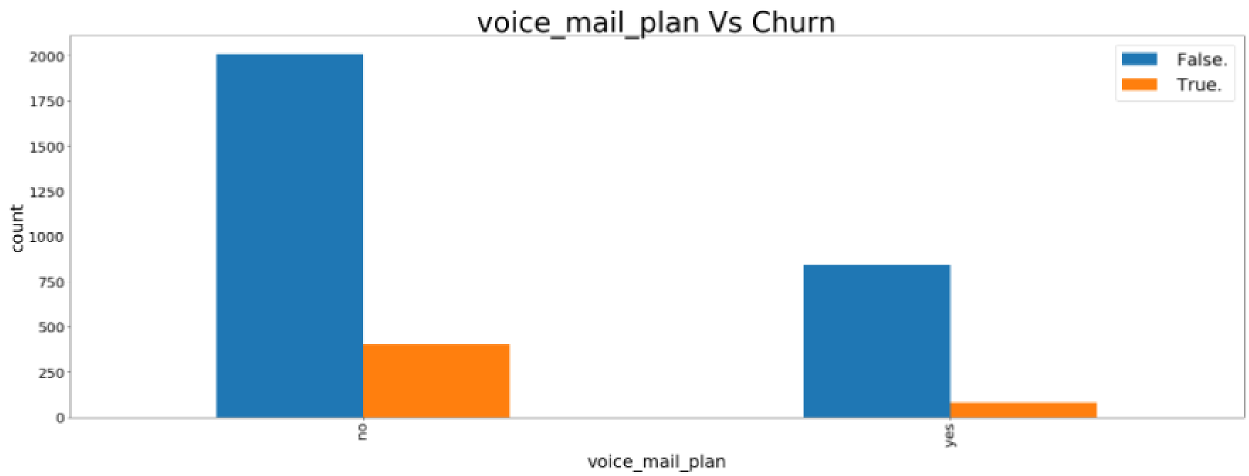
#Number of Customer_Service Call Wise Churning of customer

diff_bar('number_customer_service_calls','Churn')



#No. of Customer Churning and had a Voice mail plan

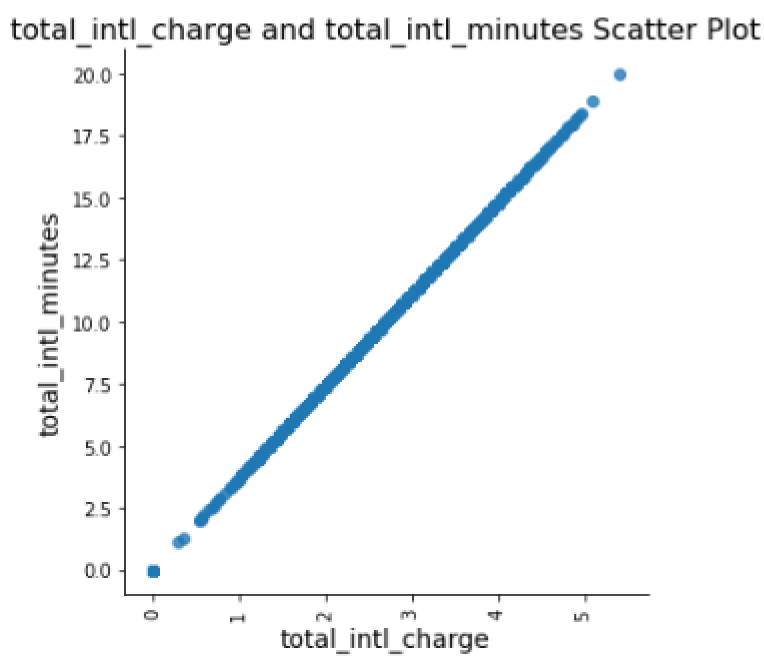
diff_bar('voice_mail_plan','Churn')



Pairplot

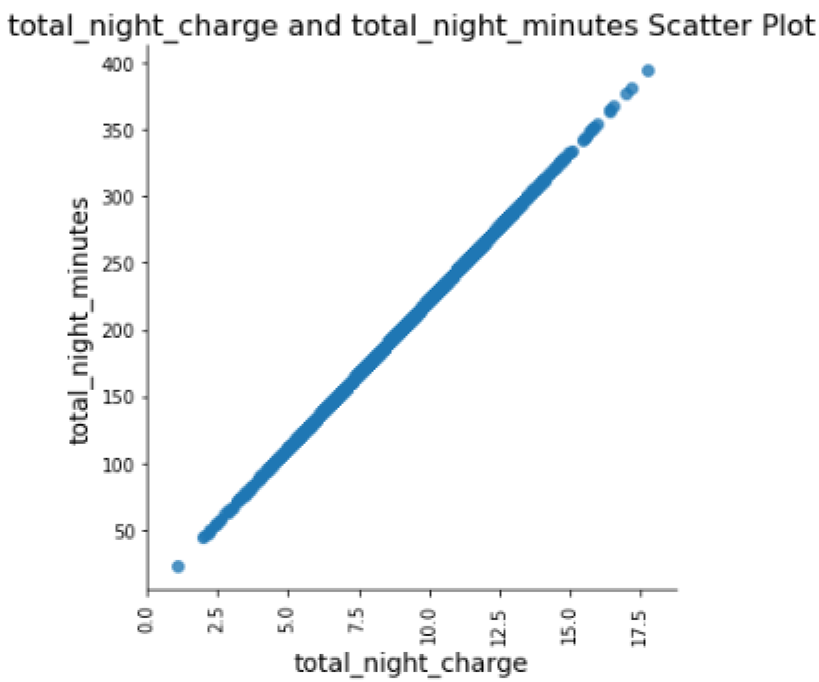
#Total intl charge and Total intl Minute

diff_scattr('total_intl_charge','total_intl_minutes')



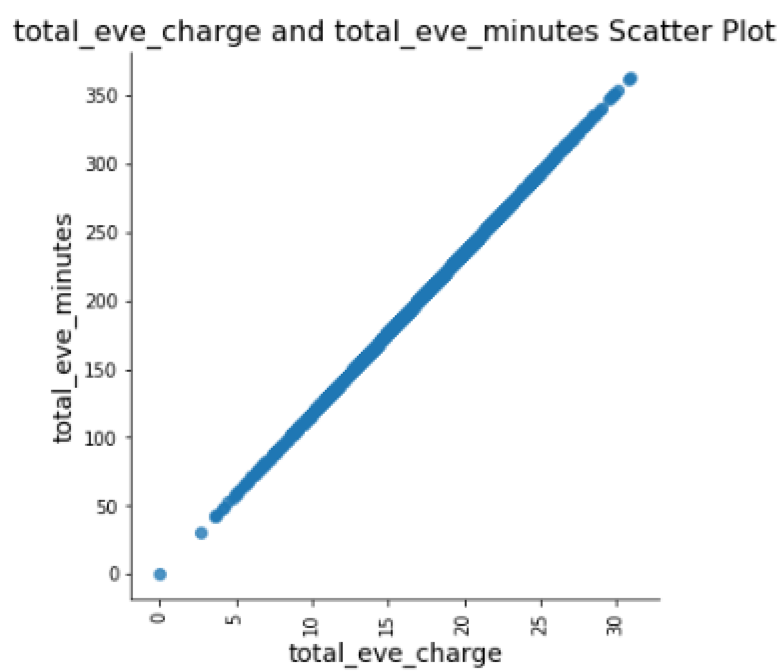
Total night charge and Total night Minute

diff_scattr('total_night_charge','total_night_minutes')



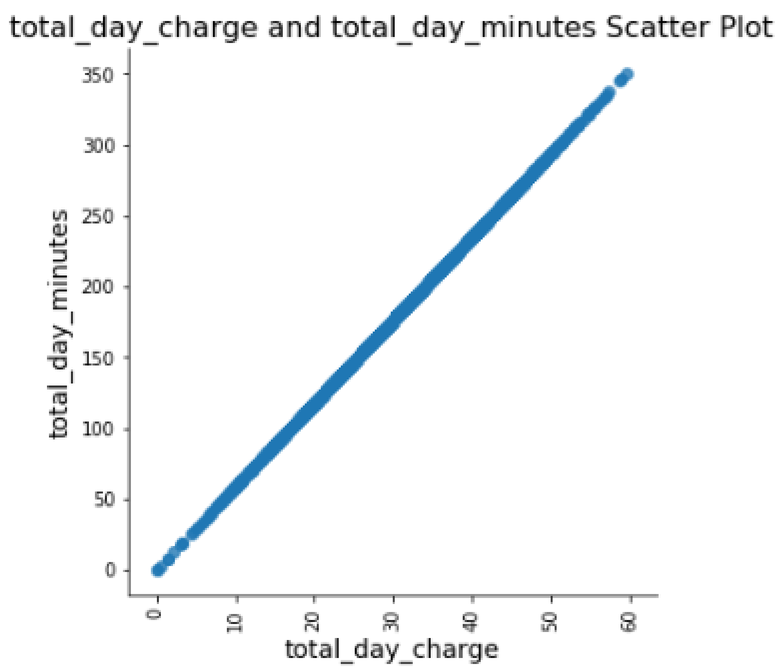
#Total eve charge and Total eve Minute

diff_scattr('total_eve_charge','total_eve_minutes')



#Total day charge and Total Day Minute

diff_scattr('total_day_charge','total_day_minutes')



Changing Categorical colum values to numeric codes

#function for converting cat to num codes

```
def cat_to_num(df):
    for i in range(0, df.shape[1]):
        #print(i)
        if(df.iloc[:,i].dtypes == 'object'):
            df.iloc[:,i] = pd.Categorical(df.iloc[:,i])
            df.iloc[:,i] = df.iloc[:,i].cat.codes
            df.iloc[:,i] = df.iloc[:,i].astype('object')
    return df
```

Feature Selection

#Setting up the pane or matrix size

f, ax = plt.subplots(figsize=(18,12)) #Width,height

#Generate Corelation Matrix

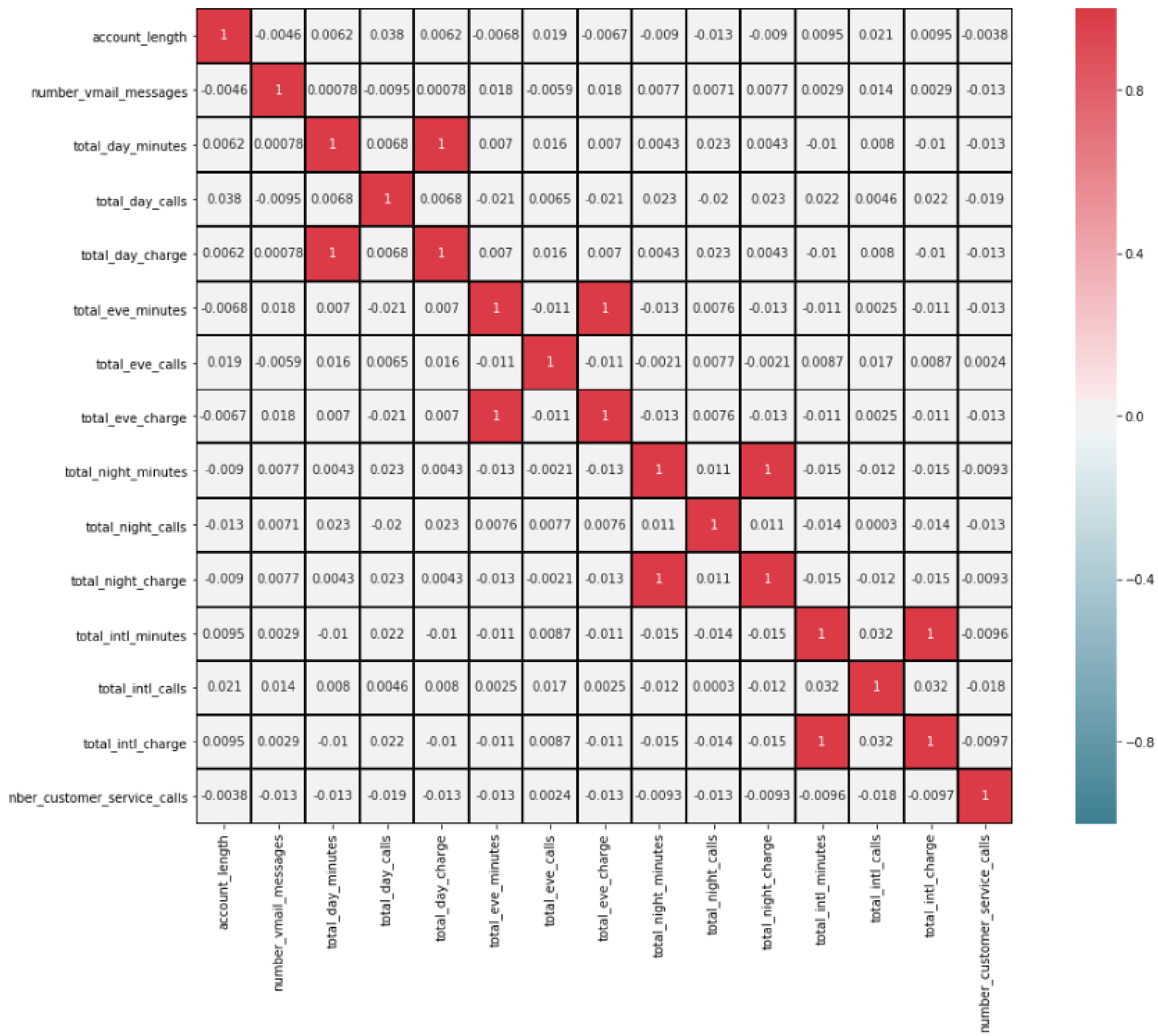
corr = train[cname].corr()

#Plot using Seaborn library

sns.heatmap(corr,mask=np.zeros_like(corr, dtype=np.bool),
cmap=sns.diverging_palette(220,10, as_cmap=True),\

square=True, ax=ax,annot=True,linewidths=1 , linecolor= 'black',vmin = -1, vmax = 1)

plt.show()



Chi-Square for Categorical variables

```
from scipy.stats import chi2_contingency

for i in cat_names:

   print(i)

   #As we know imput to chi square is always a contiguency table so we generating it using crostab function present in pd

   chi2, p, dof, ex =chi2_contingency(pd.crosstab(train['Churn'],train[i]))
```

#as above pd.crosstab(dependent variable , independent variable)

print(p)

```
state
0.002296221552011188
area_code
0.9150556960243712
international_plan
2.4931077033159556e-50
voice_mail_plan
5.15063965903898e-09
```

#Remove correlated variable & the variable which doesn't contain any meaning full info

rmev = ['state','total_day_charge','total_eve_charge','total_night_charge','total_intl_charge']

train = train.drop(rmev,axis=1)

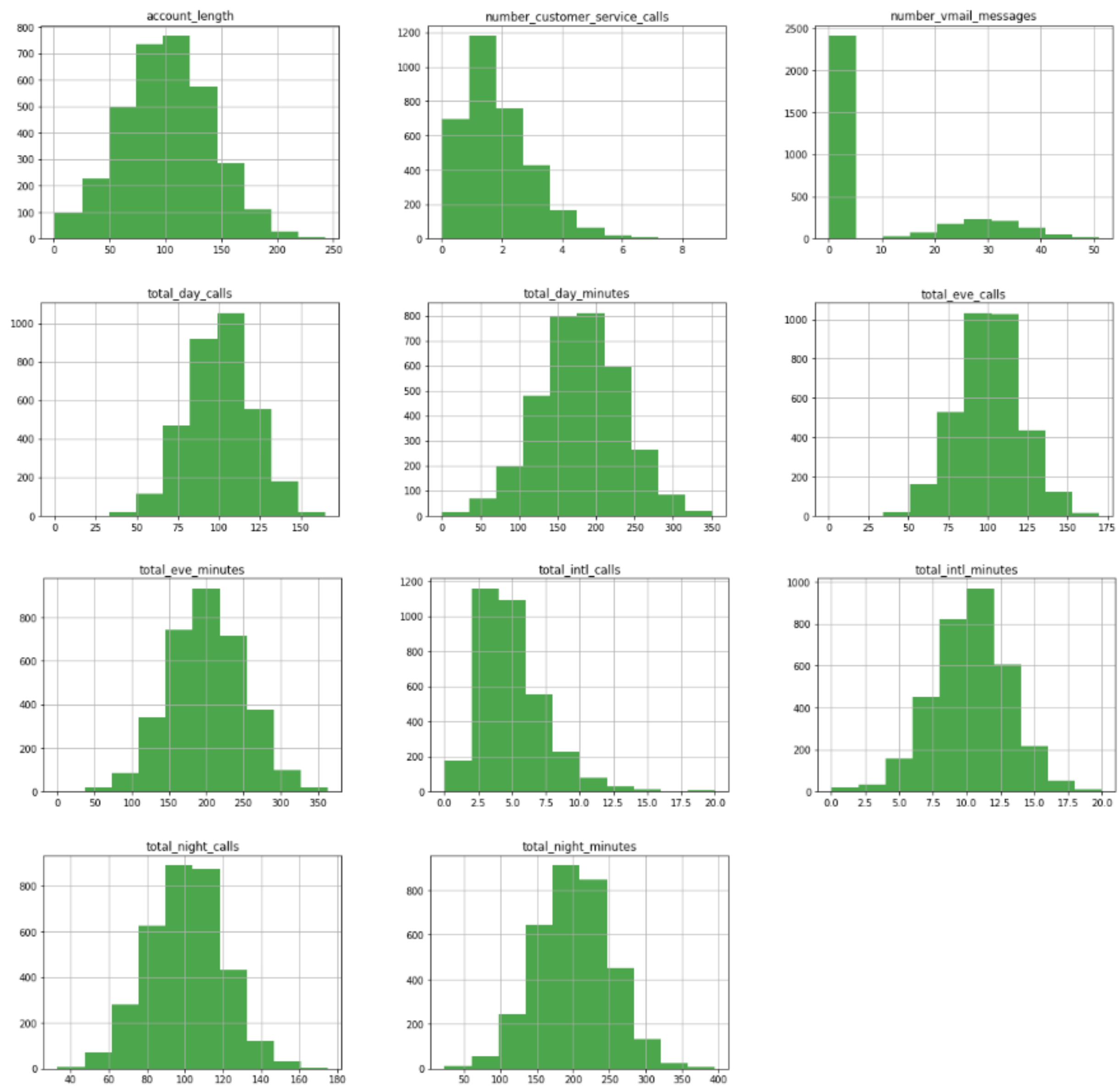
test = test.drop(rmev,axis=1)

Feature Scaling

#Check distribution of data via pandas visualization

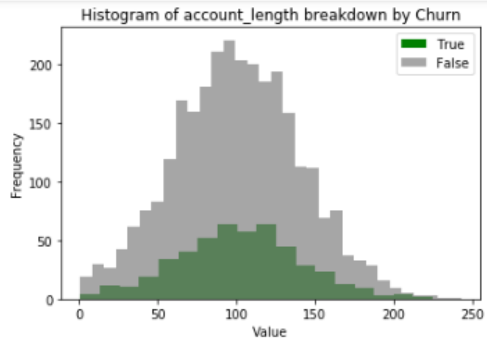
train[cname].hist(figsize=(20,20),color='g',alpha = 0.7)

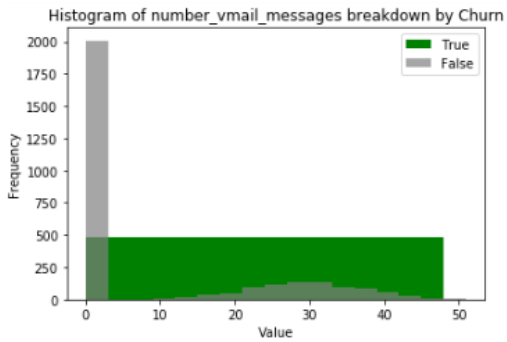
plt.show()

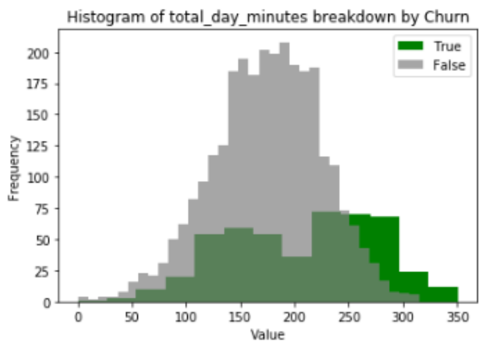


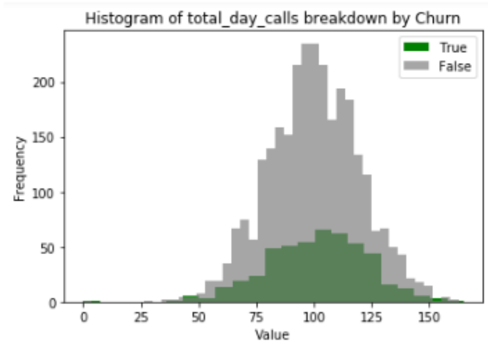

```
#Histogram break down

def plot_hist_y(x,y):

    plt.hist(list(x[y == 1]),color='green',label='True',bins='auto')

    plt.hist(list(x[y == 0]),color='grey', alpha = 0.7, label='False',bins='auto')

    plt.title("Histogram of {var} breakdown by {Y}".format(var = x.name,Y=y.name))

    plt.xlabel("Value")
```

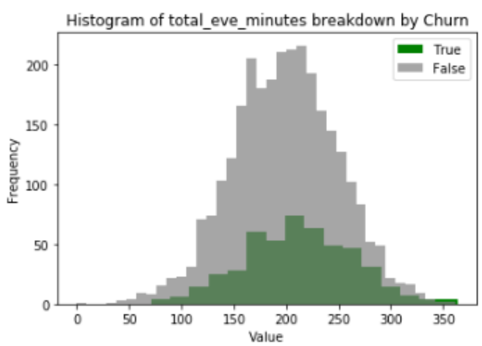
```
    plt.ylabel("Frequency")
    plt.legend(loc="upper right")
    plt.savefig("Histogram of {var} breakdown by {Y}.png".format(var = x.name,Y=y.name))
    plt.show()

for i in cname:
    #print(i)
    plot_hist_y(train[i],train.Churn)
```

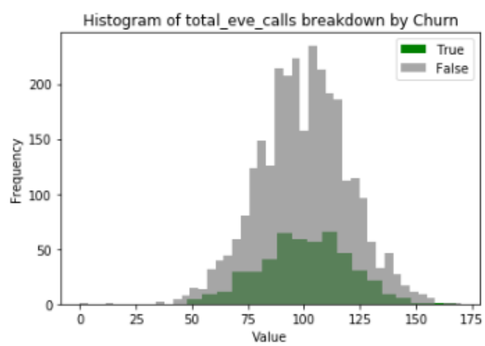

Histogram of account_length breakdown by Churn
True
False
Frequency
Value

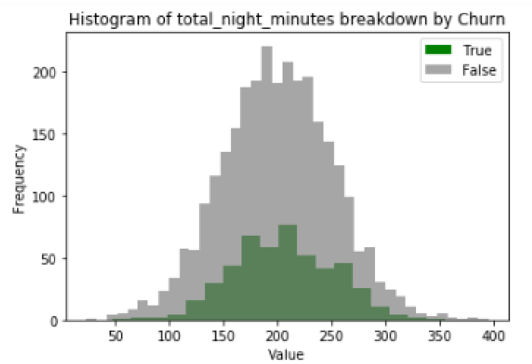

Histogram of number_vmail_messages breakdown by Churn
True
False
Frequency
Value

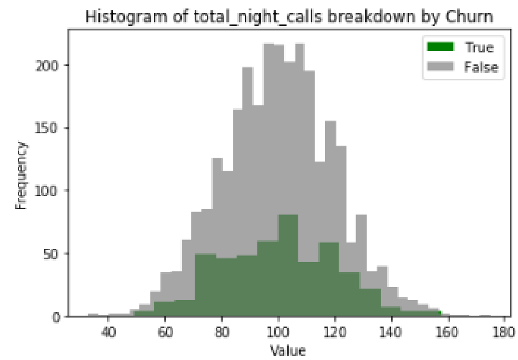

Histogram of total_day_minutes breakdown by Churn
True
False
Frequency
Value

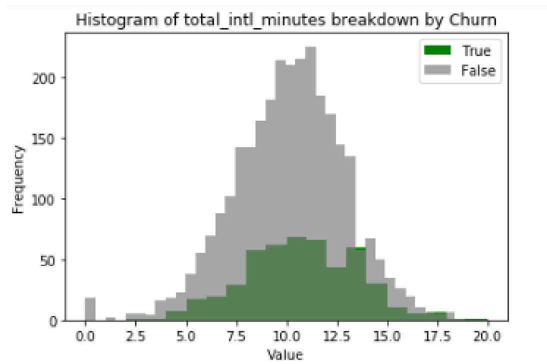

Histogram of total_day_calls breakdown by Churn
True
False
Frequency
Value

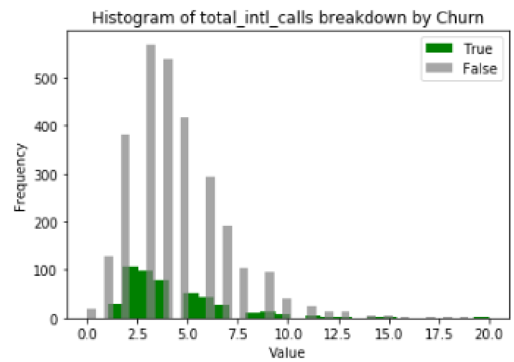

Histogram of total_eve_minutes breakdown by Churn
True
False
Frequency
Value

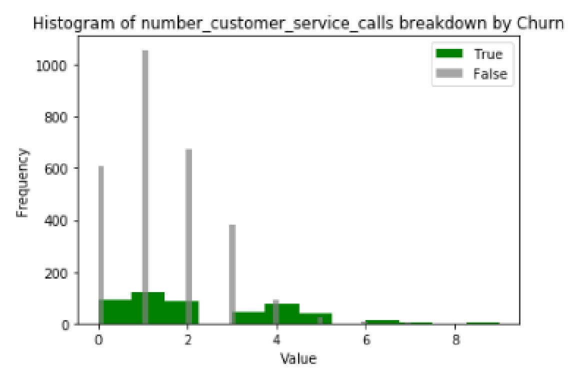

Histogram of total_eve_calls breakdown by Churn
True
False
Frequency
Value











#Applying standarization as most of the variables are normalized

```
def scale_standard(df):
  for i in cname:
    #print(i)
    df[i] = (df[i] - df[i].mean())/df[i].std()
  return df
```

Sampling Data For Train and Test

```
#Using train test split functionality for creatuing sampling

X = train.iloc[:,:14]

y = train.iloc[:,14]

y=y.astype('int')

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=101)


(X_train.shape),(y_train.shape)
```

```
((2233, 14), (2233,))
```

Using SMOTE (SMOTE: Synthetic Minority Over-sampling Technique)

Due to target variable is imbalance

```
Smo = SMOTE(random_state=101)

X_train_res, y_train_res = Smo.fit_sample(X_train,y_train)

(X_train_res.shape,y_train_res.shape)
```

```
((3790, 14), (3790,))
```

Prediction function

```
def pred(model_object,predictors,compare):
    """1.model_object = model name
       2.predictors = data to be predicted
       3.compare = y_train"""
    predicted = model_object.predict(predictors)
    # Determine the false positive and true positive rates
    fpr, tpr, _ = roc_curve(compare, model_object.predict_proba(predictors)[:,1])
    cm = pd.crosstab(compare,predicted)
    TN = cm.iloc[0,0]
    FN = cm.iloc[1,0]
    TP = cm.iloc[1,1]
    FP = cm.iloc[0,1]
    print("CONFUSION MATRIX ------- ")
    print(cm)
    print()

    ##check accuracy of model
    print('Classification paradox :-------')
    print('Accuracy :- ', round(((TP+TN)*100)/(TP+TN+FP+FN),2))
    print()
    print('Specificity //  True Negative Rate :- ',round((TN*100)/(TN+FP),2))
    print()
    print('Sensivity // True Positive Rate // Recall :- ',round((TP*100)/(FN+TP),2))
    print()
    print('False Negative Rate :- ',round((FN*100)/(FN+TP),2))
    print()
    print('False Postive Rate :- ',round((FP*100)/(FP+TN),2))
    print()
    print(classification_report(compare,predicted))
    print()
    # Calculate the AUC
    print ('AUC -: %0.2f' % auc(fpr, tpr))
```

RandomForest

```
#Random Forest Model
rf_model = RandomForestClassifier(n_estimators=100,random_state=101).fit(X_train_res,y_train_res)

#Model Score on Valdation Data Set
pred(rf_model,X_test,y_test)

# Accuracy :-  94.73
# Specificity //  True Negative Rate :-  96.86
# Sensivity // True Positive Rate // Recall :-  80.69
# False Negative Rate :-  19.31
# False Postive Rate :-  3.14
# AUC -: 0.91
```

```
CONFUSION MATRIX ------->>
col_0    0    1
Churn
0      925   30
1       28  117

Classification paradox :------->>
Accuracy :-  94.73

Specificity //  True Negative Rate :-  96.86

Sensivity // True Positive Rate // Recall :-  80.69

False Negative Rate :-  19.31

False Postive Rate :-  3.14

             precision    recall  f1-score   support

          0       0.97      0.97      0.97       955
          1       0.80      0.81      0.80       145

avg / total       0.95      0.95      0.95      1100
```

AUC -: 0.91

Logistic Regression

In [115]:
```
#logistic without binaries
logit_model = LogisticRegression(random_state=101).fit(X_train_res,y_train_res)

#Model Score on Valdation Data Set
pred(logit_model,X_test,y_test)

# Classification paradox :------->>
# Accuracy :-  78.18
# Specificity //  True Negative Rate :-  78.74
# Sensivity // True Positive Rate // Recall :-  74.48
# False Negative Rate :-  25.52
# False Postive Rate :-  21.26
#AUC -: 0.81
```

```
CONFUSION MATRIX ------->>
col_0    0    1
Churn
0      752  203
1       37  108

Classification paradox :------->>
Accuracy :-  78.18

Specificity //  True Negative Rate :-  78.74

Sensivity // True Positive Rate // Recall :-  74.48

False Negative Rate :-  25.52

False Postive Rate :-  21.26



             precision    recall  f1-score   support

          0       0.95      0.79      0.86       955
          1       0.35      0.74      0.47       145

avg / total       0.87      0.78      0.81      1100


AUC -: 0.81
```

KNN

```
#KNN Model Development
KNN_Model = KNeighborsClassifier(n_neighbors=5).fit(X_train_res,y_train_res)

#Model Score on Valdation Data Set
pred(KNN_Model,X_test,y_test)

# Classification paradox :------->>
# Accuracy :-  78.09
# Specificity //  True Negative Rate :-  79.48
# Sensivity // True Positive Rate // Recall :-  68.97
# False Negative Rate :-  31.03
# False Postive Rate :-  20.52
# AUC = 0.80
```

```
CONFUSION MATRIX ------->>
col_0    0    1
Churn
0      759  196
1       45  100

Classification paradox :------->>
Accuracy :-  78.09

Specificity //  True Negative Rate :-  79.48

Sensivity // True Positive Rate // Recall :-  68.97

False Negative Rate :-  31.03

False Postive Rate :-  20.52


             precision    recall  f1-score   support

          0       0.94      0.79      0.86       955
          1       0.34      0.69      0.45       145

avg / total       0.86      0.78      0.81      1100


AUC -: 0.80
```

Navie Bayes

```
#Navie Model Development
Naive_model = GaussianNB().fit(X_train_res,y_train_res)

#Model Score on Valdation Data Set
pred(Naive_model,X_test,y_test)

# Classification paradox :------->>
# Accuracy :-  78.64
# Specificity //  True Negative Rate :-  78.95
# Sensivity // True Positive Rate // Recall :-  76.55
# False Negative Rate :-  23.45
# False Postive Rate :-  21.05
# AUC = 0.82
```

```
CONFUSION MATRIX ------->>
col_0    0    1
Churn
0      754  201
1       34  111

Classification paradox :------->>
Accuracy :-  78.64

Specificity //  True Negative Rate :-  78.95

Sensivity // True Positive Rate // Recall :-  76.55

False Negative Rate :-  23.45

False Postive Rate :-  21.05


             precision    recall  f1-score   support

          0       0.96      0.79      0.87       955
          1       0.36      0.77      0.49       145

avg / total       0.88      0.79      0.82      1100


AUC -: 0.82
```

Final Model :- Random Forest

As above random forest fits best for out dataset out of our tested models

Hyper Parameter Optimization with RandomSeacrhCV

below code will take time to execute so just made it commented

In [119]:
```
# Training Final Model With Optimum Parameters
final_Model = RandomForestClassifier(random_state=101, n_estimators = 500,n_jobs=-1)
final_Model.fit(X_train_res,y_train_res)
```

Out[119]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=500, n_jobs=-1,
            oob_score=False, random_state=101, verbose=0, warm_start=False)
```

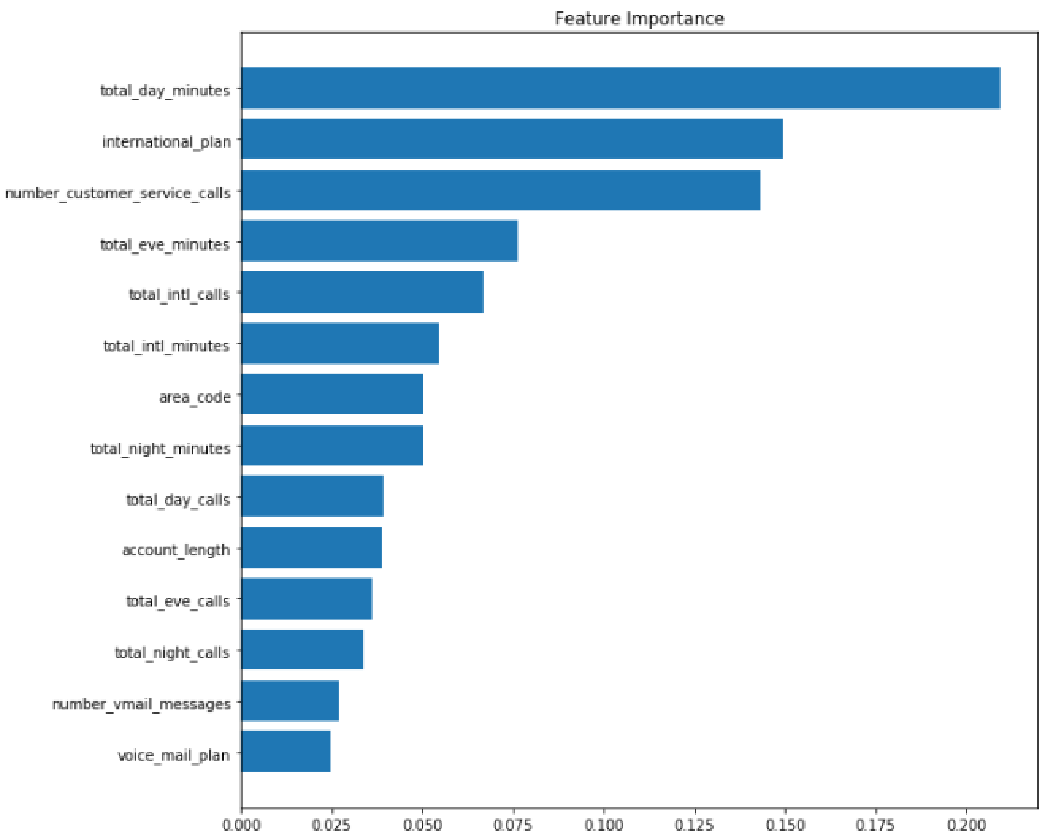
In [120]:
```
#Validating Predictions
pred(final_Model,X_test,y_test)
```

```
CONFUSION MATRIX ------->>
col_0    0    1
Churn
0      927   28
1       26  119

Classification paradox :------->>
Accuracy :-  95.09
```

```
Specificity //  True Negative Rate :-  97.07

Sensivity // True Positive Rate // Recall :-  82.07

False Negative Rate :-  17.93

False Postive Rate :-  2.93

             precision    recall  f1-score   support

          0       0.97      0.97      0.97       955
          1       0.81      0.82      0.82       145

avg / total       0.95      0.95      0.95      1100


AUC -: 0.91
```

Features Importance

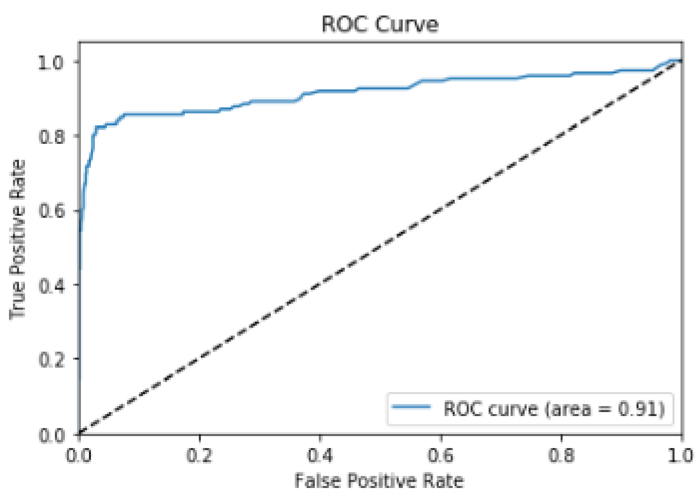
```
#Calculating feature importances
importances = final_Model.feature_importances_

# Sort feature importances in descending order
indices = np.argsort(importances)[::1]

# Rearrange feature names so they match the sorted feature importances
names = [train.columns[i] for i in indices]

# Creating plot
fig = plt.figure(figsize=(10,10))
plt.title("Feature Importance")

# Add horizontal bars
plt.barh(range(X.shape[1]),importances[indices],align = 'center')
plt.yticks(range(X.shape[1]), names)
plt.show()
#fig.savefig('feature_importance.png')
```



AUC & ROC Curve

```
#from sklearn.metrics import roc_curve,auc,roc_auc_score
# Determine the false positive and true positive rates
fpr, tpr, _ = roc_curve(y_test, final_Model.predict_proba(X_test)[:,1])
# Calculate the AUC
roc_auc = auc(fpr, tpr)
print ('ROC AUC: %0.2f' % roc_auc)

# Plot of a ROC curve for a specific class
plt.figure()
plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc="lower right")
plt.show()
```

```
ROC AUC: 0.91
```



Final Test Data Predictions

```
# #Test Data Spliting parts target and Predictors
XX = test.iloc[:,:14].values  #predictors
yy = test.iloc[:,14].values   #target
yy=yy.astype('int')
```

```
#Predicting test data
#pred(model_object=final_Model,predictors=XX,compare=yy)

Churn_Pred = final_Model.predict(XX)
cm = pd.crosstab(yy,Churn_Pred)
TN = cm.iloc[0,0]
FN = cm.iloc[1,0]
TP = cm.iloc[1,1]
FP = cm.iloc[0,1]
print("CONFUSION MATRIX ----->> ")
print(cm)
print()
##check accuracy of model
print('Accuracy :- ', round(((TP+TN)*100)/(TP+TN+FP+FN),2))
print('False Negative Rate :- ',round((FN*100)/(FN+TP),2))
print('False Postive Rate :- ',round((FP*100)/(FP+TN),2))
```

```
CONFUSION MATRIX ----->>
col_0     0    1
row_0
0      1331  112
1        37  187

Accuracy :-  91.06
False Negative Rate :-  16.52
False Postive Rate :-  7.76
```

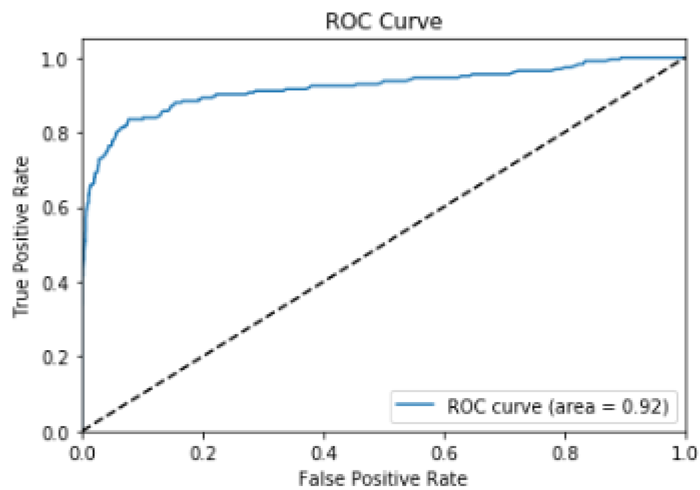
```
print(classification_report(yy,Churn_Pred))
```

```
             precision    recall  f1-score   support

          0       0.97      0.92      0.95      1443
          1       0.63      0.83      0.72       224

avg / total       0.93      0.91      0.92      1667
```

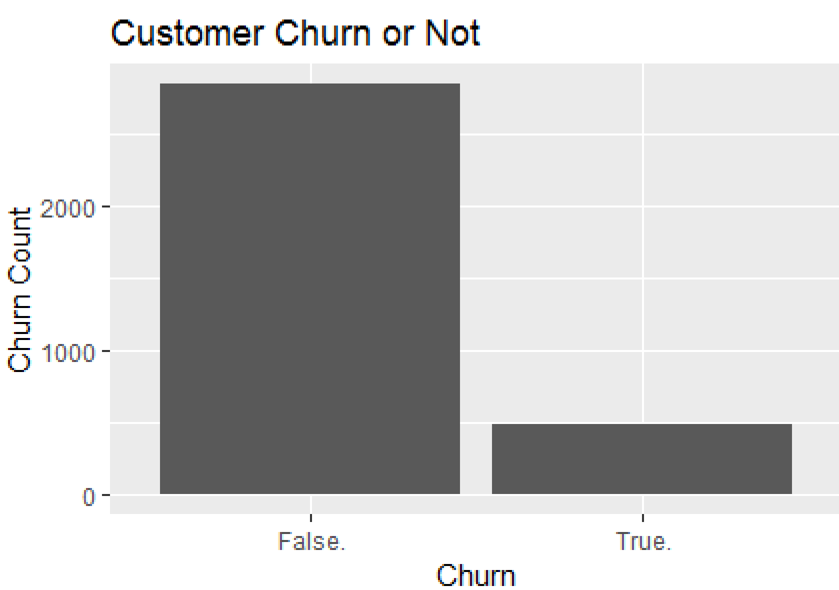
AUC & ROC over Test Data

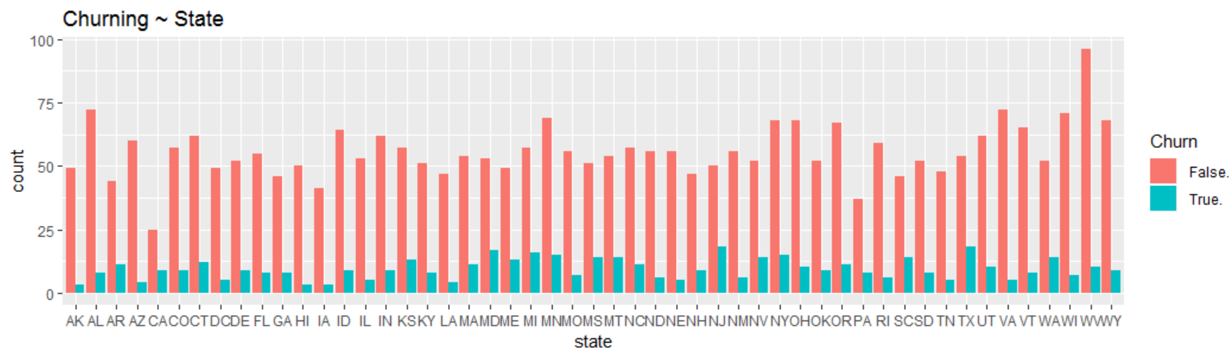
```
from sklearn.metrics import roc_curve,auc,roc_auc_score
# Determine the false positive and true positive rates
fpr, tpr, _ = roc_curve(yy, final_Model.predict_proba(XX)[:,1])
# Calculate the AUC
roc_auc = auc(fpr, tpr)
print ('ROC AUC: %0.2f' % roc_auc)

# Plot of a ROC curve for a specific class
plt.figure()
plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc="lower right")
plt.show()
```

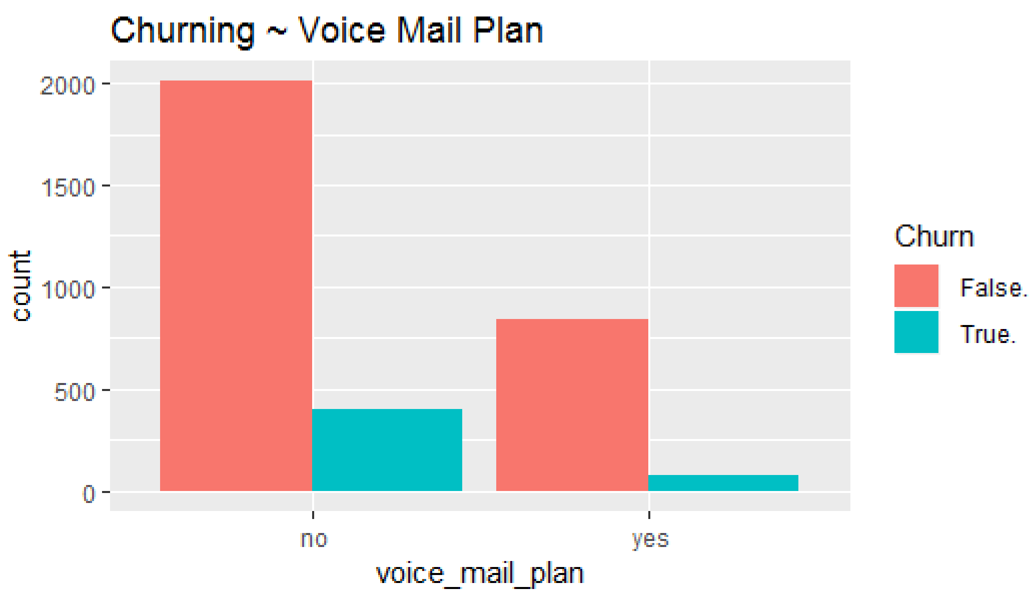
```
ROC AUC: 0.92
```

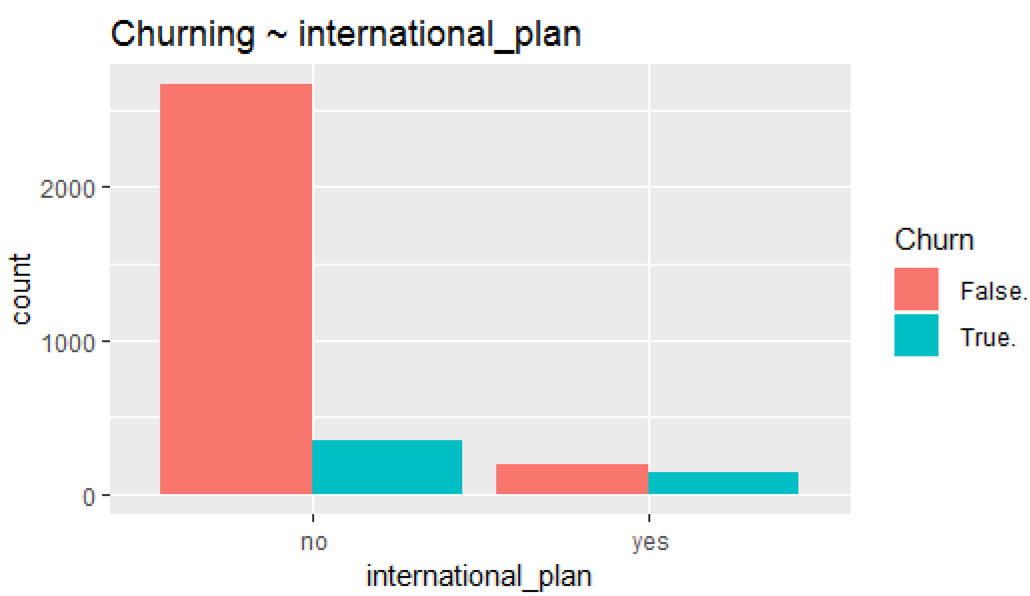


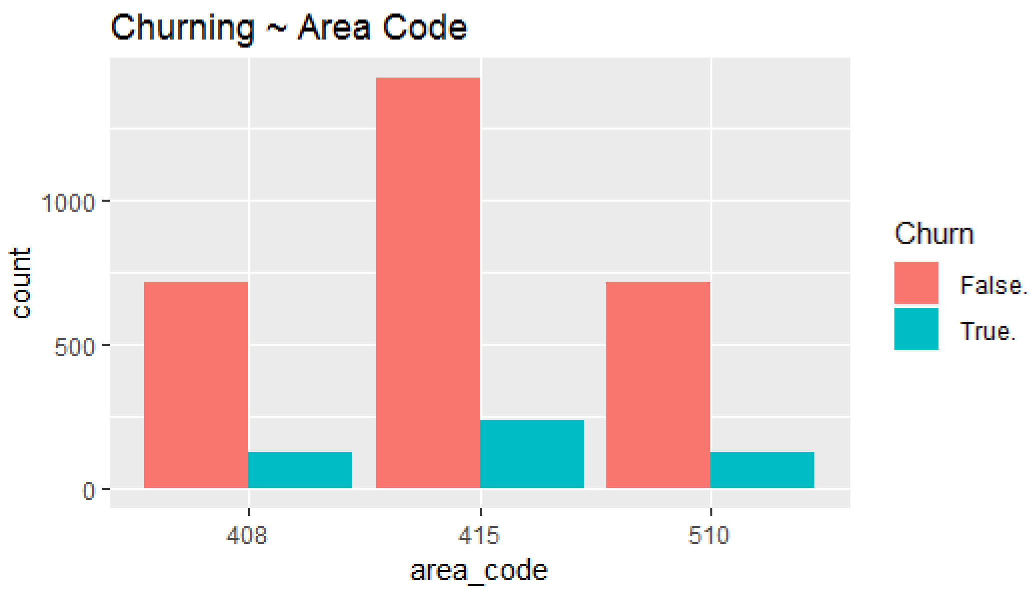
Extra Figures of R code

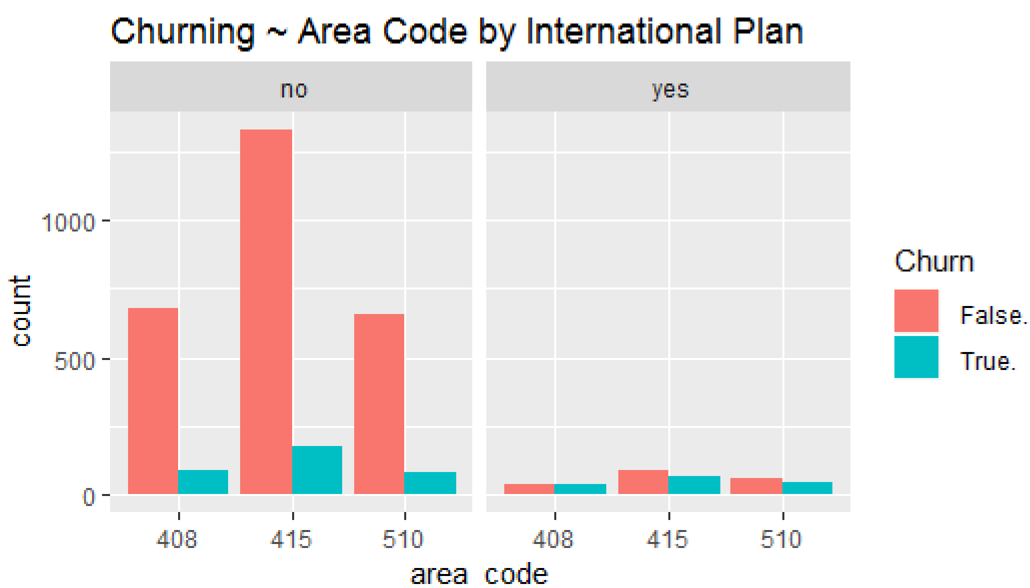


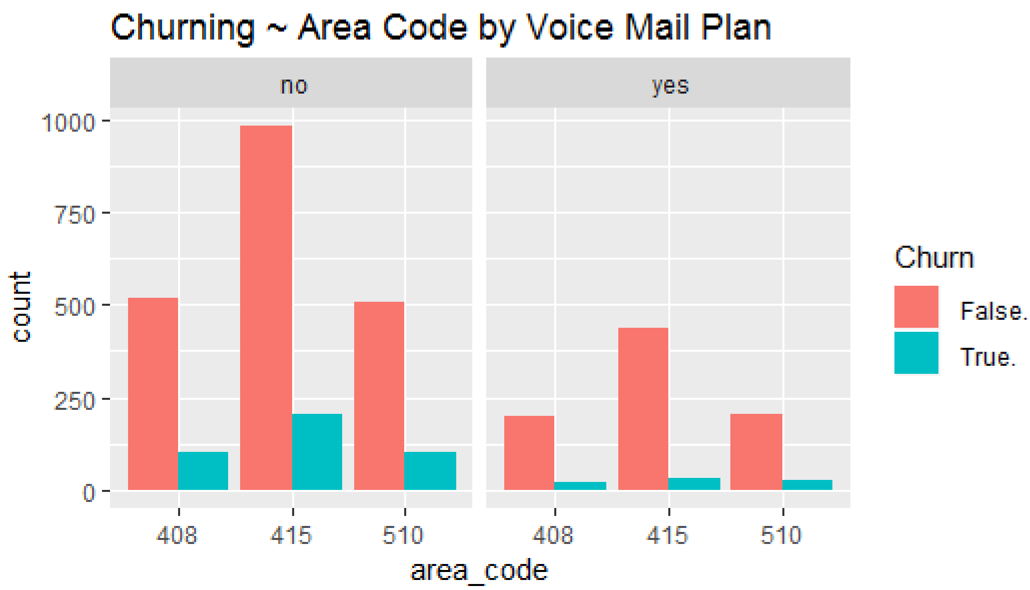

Churning ~ State
count
state
Churn
False.
True.

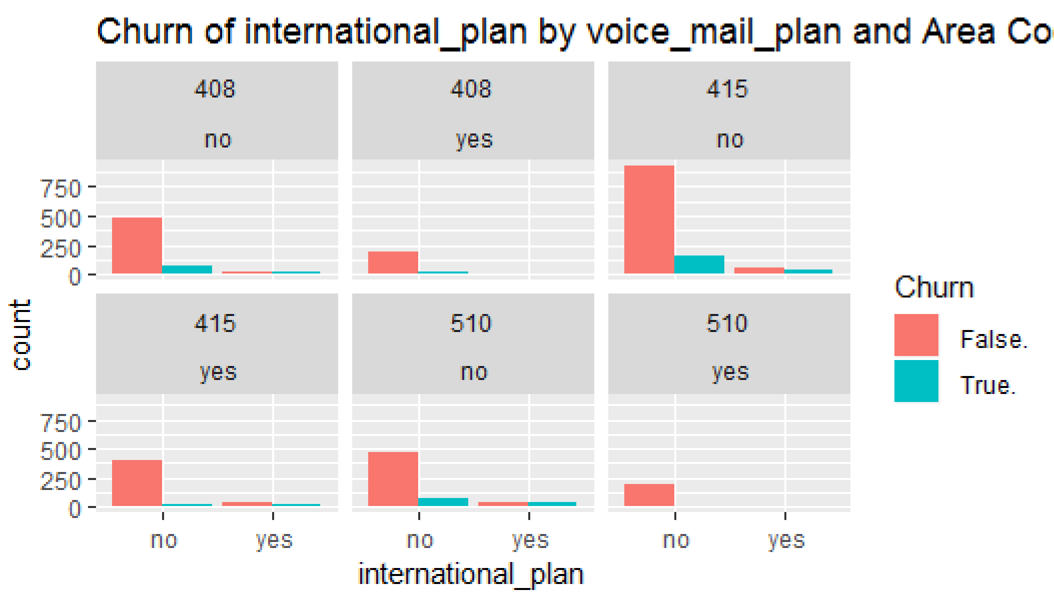

Churning ~ Voice Mail Plan
count
no
yes
voice_mail_plan
Churn
False.
True.

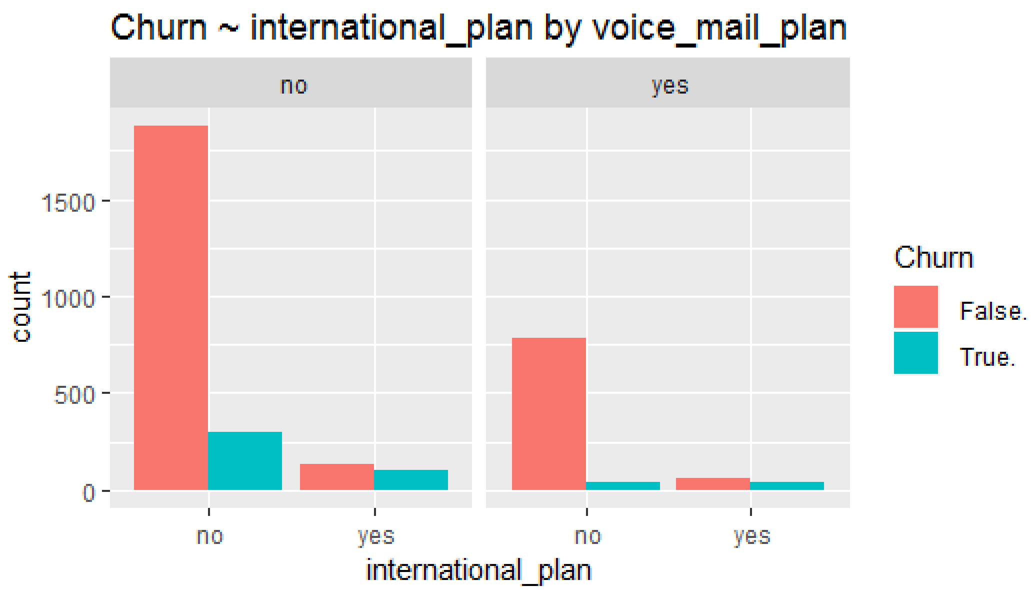

Churning ~ international_plan
count
no
yes
international_plan
Churn
False.
True.

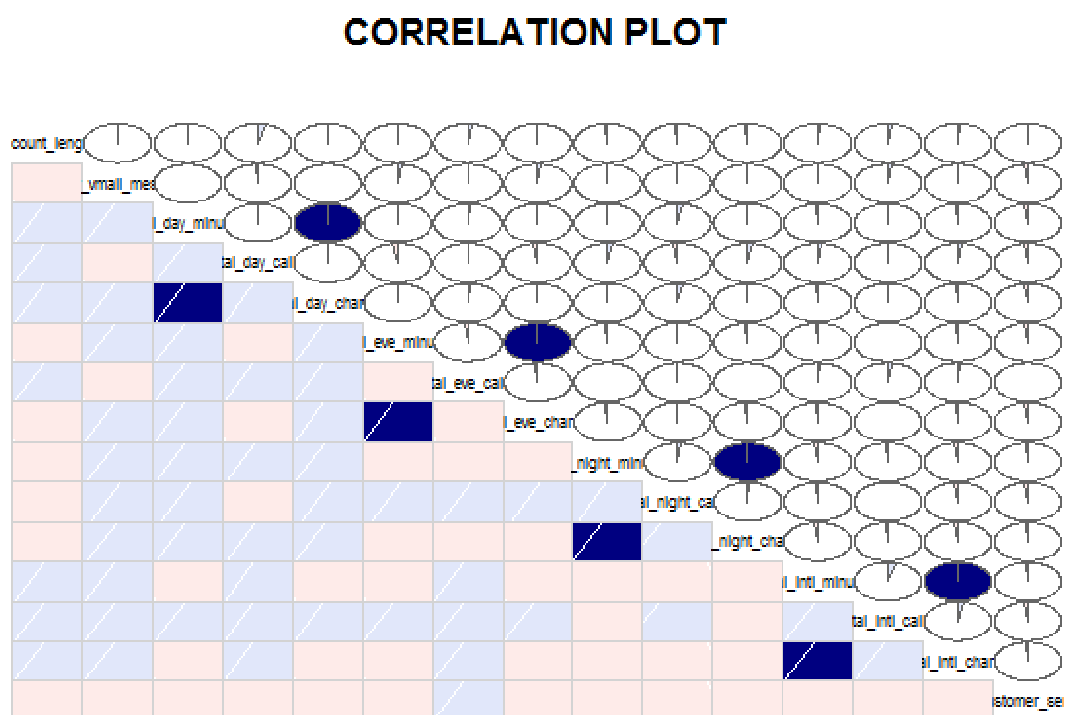

Churning ~ Area Code
count
1000
500
0
408
415
510
area_code
Churn
False.
True.

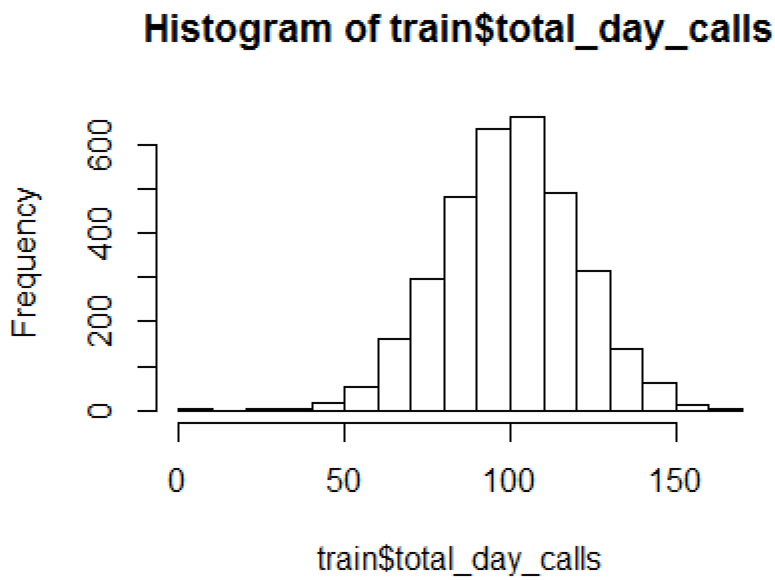

Churning ~ Area Code by International Plan
no
yes
count
1000
500
0
408
415
510
408
415
510
area_code
Churn
False.
True.

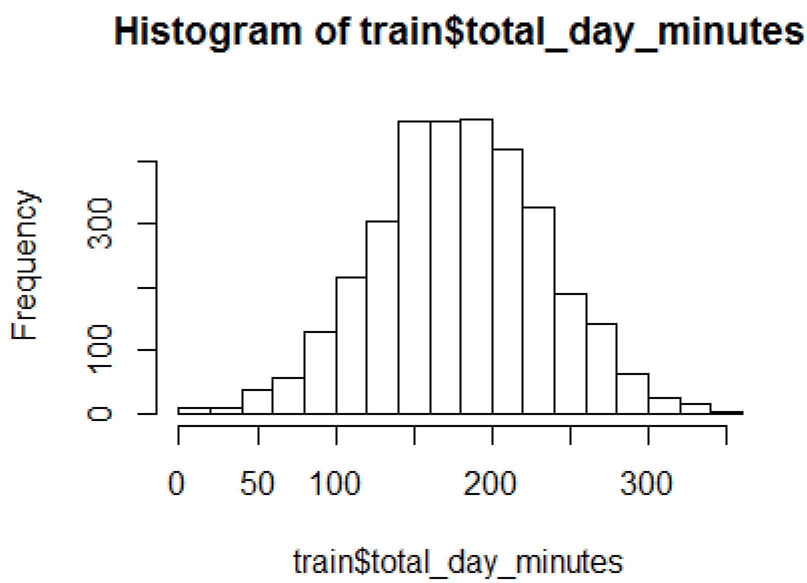

Churning ~ Area Code by Voice Mail Plan
no
yes
1000
750
500
250
0
count
408
415
510
area_code
Churn
False.
True.

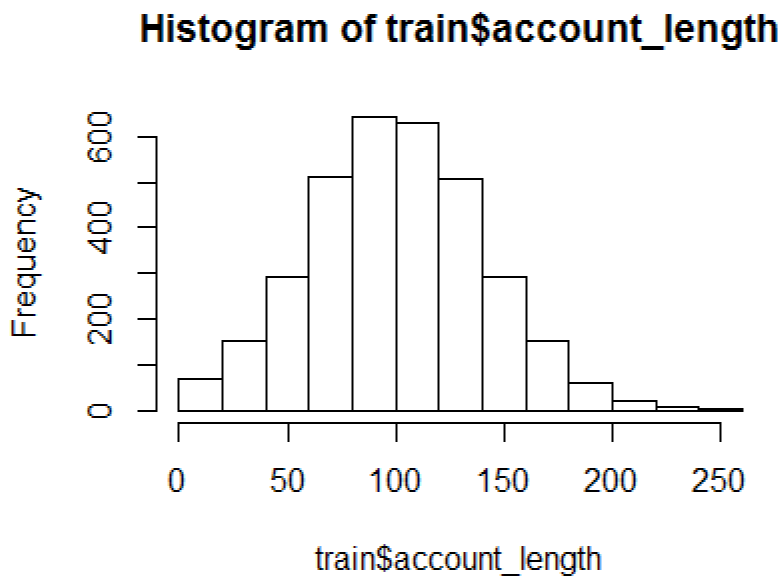

Churn of international_plan by voice_mail_plan and Area Co
408
no
408
yes
415
no
415
yes
510
no
510
yes
750
500
250
0
count
international_plan
Churn
False.
True.

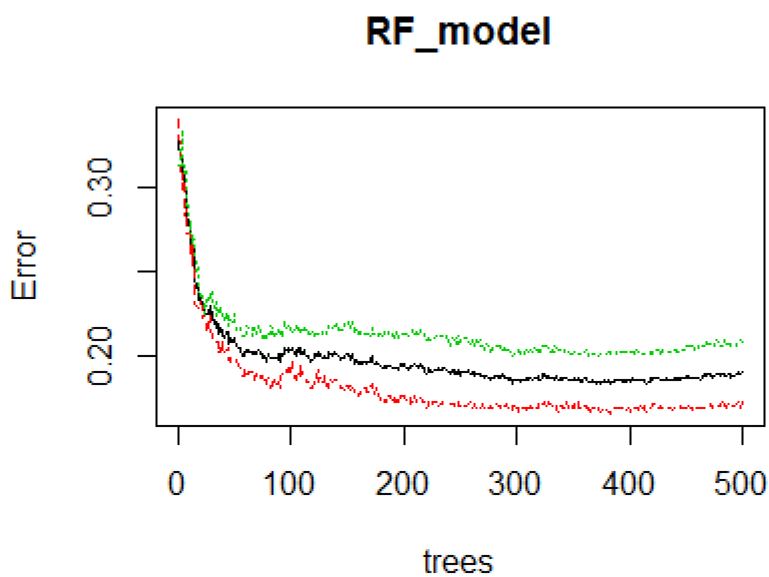

Churn ~ international_plan by voice_mail_plan
no
yes
count
1500
1000
500
0
no
yes
no
yes
international_plan
Churn
False.
True.

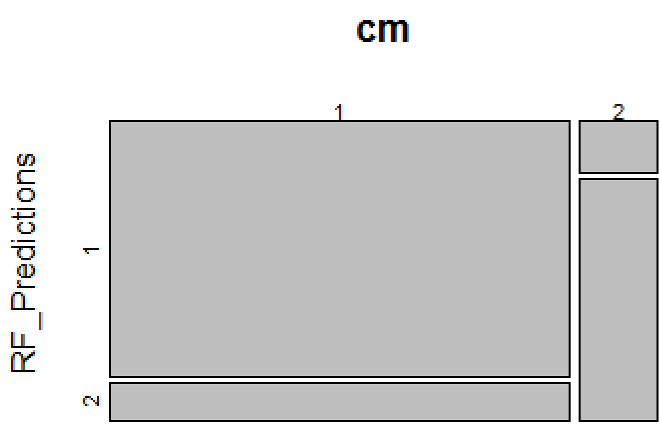

CORRELATION PLOT

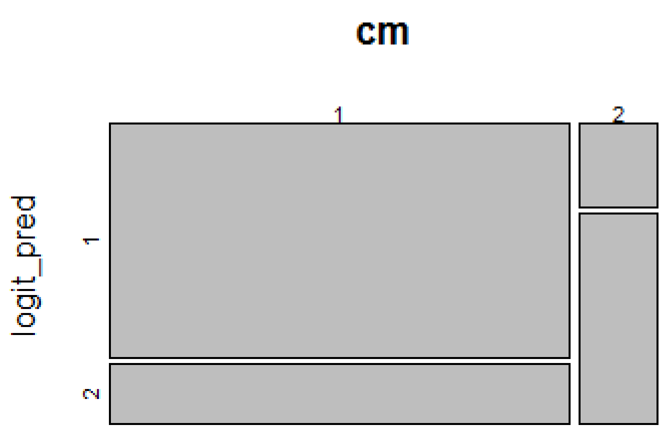

Histogram of train$total_day_calls
Frequency
0
200
400
600
0
50
100
150
train$total_day_calls


Histogram of train$total_day_minutes
Frequency
0
100
300
0
50
100
200
300
train$total_day_minutes


Histogram of train$account_length
Frequency
0
200
400
600
0
50
100
150
200
250
train$account_length


RF_model
Error
0.20
0.30
0
100
200
300
400
500
trees


cm
1
2
RF_Predictions
1
2


cm
1
2
logit_pred
1
2