Business Understanding

Overview & Background

Business Problem:

SyriaTel is one of many telecommunication companies that runs within a very competitive market. It is currently experiencing frequent customer churn, which leads to lost revenue, which in turn affects other business processes within the company. The needs a method to identify customers at risk of churning so they can implement retention strategies and minimize customer loss.

Proposed solution

To better understand the the factors that influence customer decisions to remain with the company or discontinue using the service, a comprehensive analysis using classification models is required. This model will analyzze historical data maintained by the company about customer demographics and usage patterns to make informed decisions while taking action in order to increase customer retention

Problem statement

SyriaTel, a telecommunications company is experiencing customer churn which leads to loss of revenue. The company lacks a deep understanding of the factors that influence customer decisions to remain with the company or discontinue service use. The company requires to find an informed way to find out the customers at risk of churning so that some retention strategies can be developed or implemented to minimize customer loss and increase revenue.

Objectives

1. To analyze the SyriaTel's customer data dataset to identify statistically significant features that impact customer churn.

2. To yeild visualizations that give insights that can inform actionable strategies

3. To build multiple classification models that predict the binary target variable ,churn, whose coefficients ar easily interpretable

4. To evaluate the model's performance using metrics such as Recall, Precision and F1score

Data Understanding

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```python
import seaborn as sns
from scipy import stats

df = pd.read_csv("Data/bigml_59c28831336c6604c800002a.csv")
df.head()
```

```
  state  account length  area code phone number international plan  \
0    KS             128        415     382-4657                 no   
1    OH             107        415     371-7191                 no   
2    NJ             137        415     358-1921                 no   
3    OH              84        408     375-9999                yes   
4    OK              75        415     330-6626                yes   

  voice mail plan  number vmail messages  total day minutes  total day 
calls  \
0             yes                     25              265.1          
110   
1             yes                     26              161.6          
123   
2              no                      0              243.4          
114   
3              no                      0              299.4          
71   
4              no                      0              166.7          
113   

   total day charge  ...  total eve calls  total eve charge  \
0             45.07  ...               99             16.78   
1             27.47  ...              103             16.62   
2             41.38  ...              110             10.30   
3             50.90  ...               88              5.26   
4             28.34  ...              122             12.61   

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01   
1                254.4                103               11.45   
2                162.6                104                7.32   
3                196.9                 89                8.86   
4                186.9                121                8.41   

   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70   
1                13.7                 3               3.70   
2                12.2                 5               3.29   
3                 6.6                 7               1.78   
4                10.1                 3               2.73   

   customer service calls  churn  
0                       1  False  
1                       1  False  
```

```
2                        0  False
3                        2  False
4                        3  False

[5 rows x 21 columns]

df.shape

(3333, 21)

df. columns

Index(['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 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',
       'customer service calls', 'churn'],
      dtype='object')
```

Data columm descriptions

Account Length: how long account has been active.

VMail Message: Number of voice mail messages send by the customer.

Day Mins: Time spent on day calls.

Eve Mins: Time spent on evening calls.

Night Mins: Time spent on night calls.

Intl Mins: Time spent on international calls.

Day Calls: Number of day calls by customers.

Eve Calls: Number of evening calls by customers.

Intl Calls: Number of international calls.

Night Calls: Number of night calls by customer.

Day Charge: Charges of Day Calls.

Night Charge: Charges of Night Calls.

Eve Charge: Charges of evening Calls.

Intl Charge: Charges of international calls.

VMail Plan: Voice mail plan taken by the customer or not.

State: State in Area of study.

Phone: Phone number of the customer.

Area Code: Area Code of customer.

Intl Plan: Does customer have international plan or not.

CustServ Calls: Number of customer service calls by customer.

Churn : Customers who churned the telecom service or who doesn't(0 ="Churner", 1 ="Non-Churner")

```
df.dtypes
```

```
state                      object
account length              int64
area code                   int64
phone number               object
international plan         object
voice mail plan            object
number vmail messages       int64
total day minutes         float64
total day calls             int64
total day charge          float64
total eve minutes         float64
total eve calls             int64
total eve charge          float64
total night minutes       float64
total night calls           int64
total night charge        float64
total intl minutes        float64
total intl calls            int64
total intl charge         float64
customer service calls      int64
churn                        bool
dtype: object
```

```
df.describe()
```

```
       account length    area code  number vmail messages  total day 
minutes  \
count     3333.000000  3333.000000            3333.000000        
3333.000000   
mean       101.064806   437.182418               8.099010        
179.775098   
std         39.822106    42.371290              13.688365         
54.467389   
min          1.000000   408.000000               0.000000          
0.000000   
25%         74.000000   408.000000               0.000000        
143.700000
```

```
50%        101.000000   415.000000               0.000000
179.400000
75%        127.000000   510.000000              20.000000
216.400000
max        243.000000   510.000000              51.000000
350.800000

       total day calls  total day charge  total eve minutes  total eve
calls  \
count      3333.000000       3333.000000        3333.000000
3333.000000
mean        100.435644         30.562307         200.980348
100.114311
std          20.069084          9.259435          50.713844
19.922625
min           0.000000          0.000000           0.000000
0.000000
25%          87.000000         24.430000         166.600000
87.000000
50%         101.000000         30.500000         201.400000
100.000000
75%         114.000000         36.790000         235.300000
114.000000
max         165.000000         59.640000         363.700000
170.000000

       total eve charge  total night minutes  total night calls  \
count       3333.000000          3333.000000        3333.000000
mean          17.083540           200.872037         100.107711
std            4.310668            50.573847          19.568609
min            0.000000            23.200000          33.000000
25%           14.160000           167.000000          87.000000
50%           17.120000           201.200000         100.000000
75%           20.000000           235.300000         113.000000
max           30.910000           395.000000         175.000000

       total night charge  total intl minutes  total intl calls  \
count         3333.000000         3333.000000       3333.000000
mean             9.039325           10.237294          4.479448
std              2.275873            2.791840          2.461214
min              1.040000            0.000000          0.000000
25%              7.520000            8.500000          3.000000
50%              9.050000           10.300000          4.000000
75%             10.590000           12.100000          6.000000
max             17.770000           20.000000         20.000000

       total intl charge  customer service calls
count        3333.000000             3333.000000
mean            2.764581                1.562856
std             0.753773                1.315491
```

```
min               0.000000                 0.000000
25%               2.300000                 1.000000
50%               2.780000                 1.000000
75%               3.270000                 2.000000
max               5.400000                 9.000000
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   state                   3333 non-null   object
 1   account length          3333 non-null   int64
 2   area code               3333 non-null   int64
 3   phone number            3333 non-null   object
 4   international plan      3333 non-null   object
 5   voice mail plan         3333 non-null   object
 6   number vmail messages   3333 non-null   int64
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64
 20  churn                   3333 non-null   bool
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

Data Cleaning

```
# Checking for missing values
df.isnull().sum()
```

```
state                         0
account length                0
area code                     0
phone number                  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
customer service calls    0
churn                     0
dtype: int64
```

```
# Checking for dupliate values
df.duplicated().sum()
```

```
0
```

```
df['area code'].unique()
```

```
array([415, 408, 510], dtype=int64)
```

```
#Since "area code" is a categorical column, we convert it to string
df['area code'] = df['area code'].astype(str)
df.dtypes
```

```
state                      object
account length              int64
area code                  object
phone number               object
international plan         object
voice mail plan            object
number vmail messages       int64
total day minutes         float64
total day calls             int64
total day charge          float64
total eve minutes         float64
total eve calls             int64
total eve charge          float64
total night minutes       float64
total night calls           int64
total night charge        float64
total intl minutes        float64
total intl calls            int64
total intl charge         float64
customer service calls      int64
churn                        bool
dtype: object
```

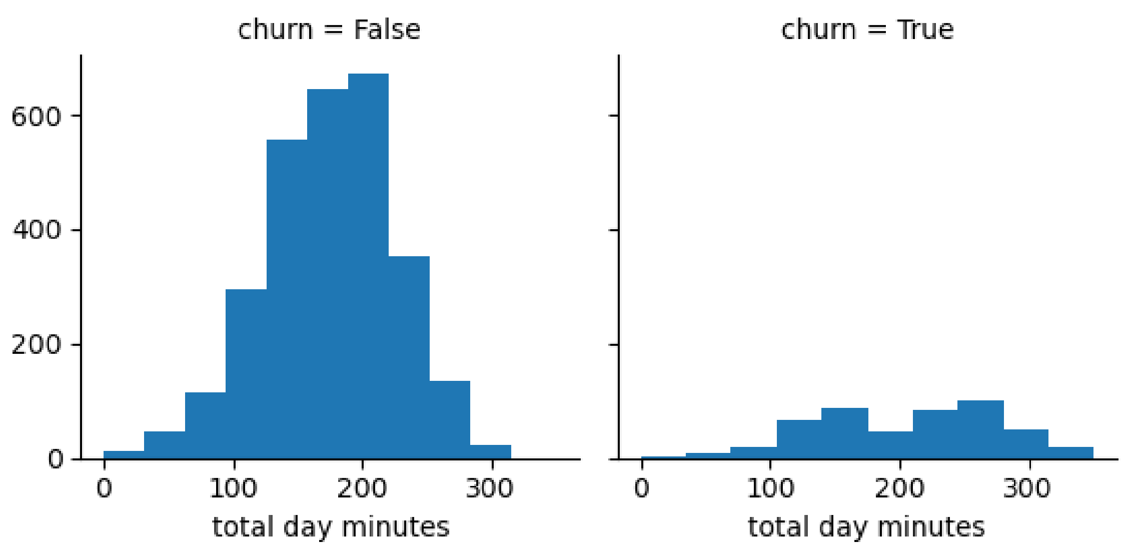
EDA

Univariate Analysis

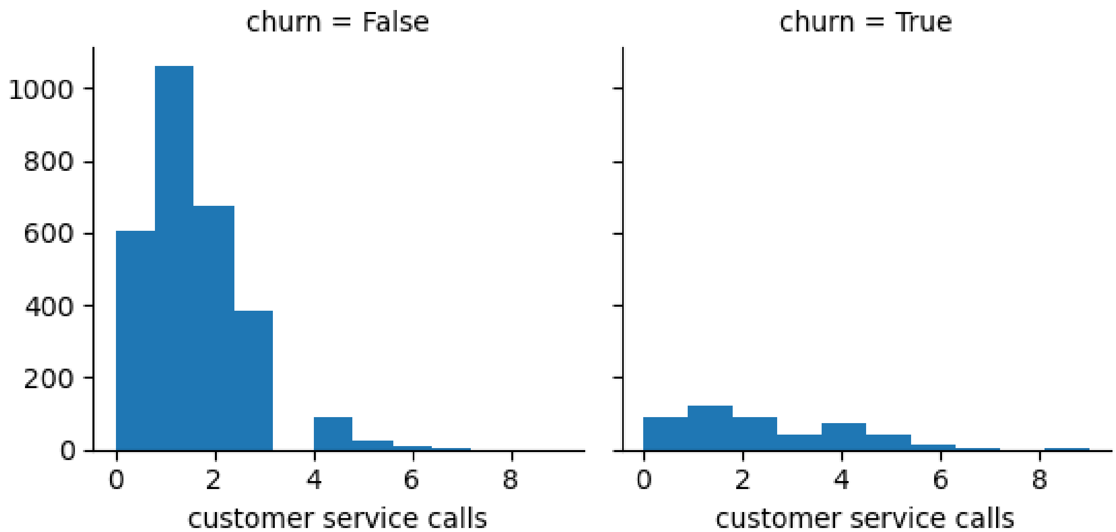
Studying the distribution of a single continuous numerical value

Is there a significant difference in the average daily call duration between churning and non-churning customers?

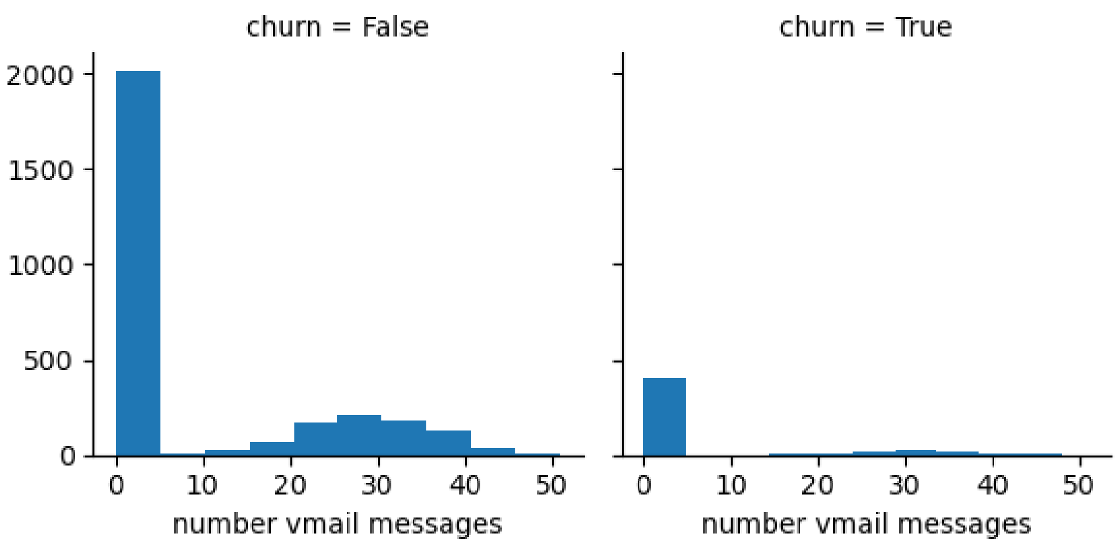
```
from project_funcitons import UnivariateAnalysis

analysis = UnivariateAnalysis(df)
analysis.plot_distribution("Total Day Minutes", "total day minutes")
```



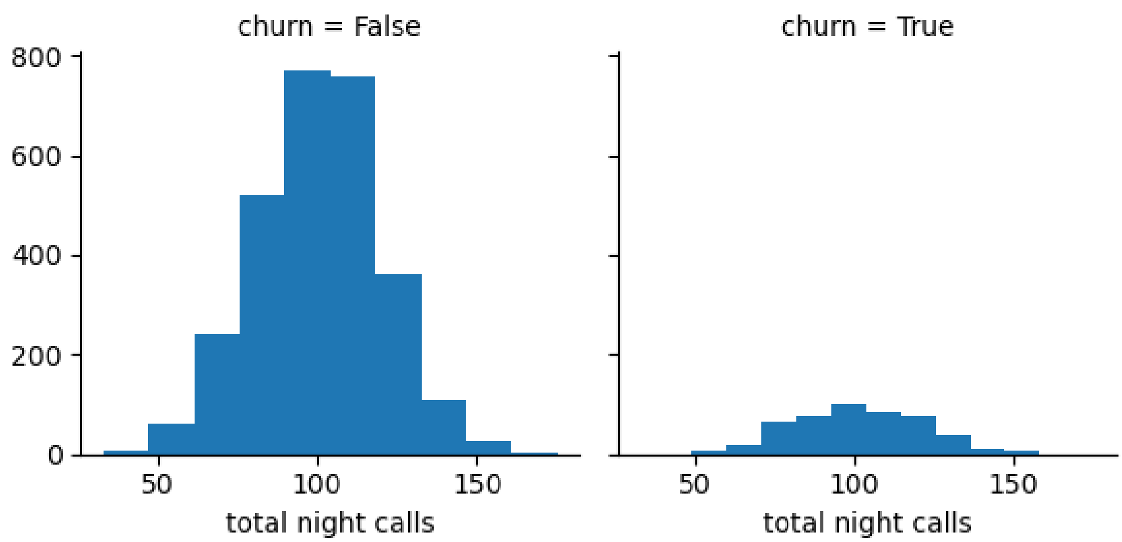

```
analysis.plot_distribution("Customer Service Calls", "customer service calls")
```




```
analysis.plot_distribution("Number of Voicemail Messages", "number
vmail messages")
```

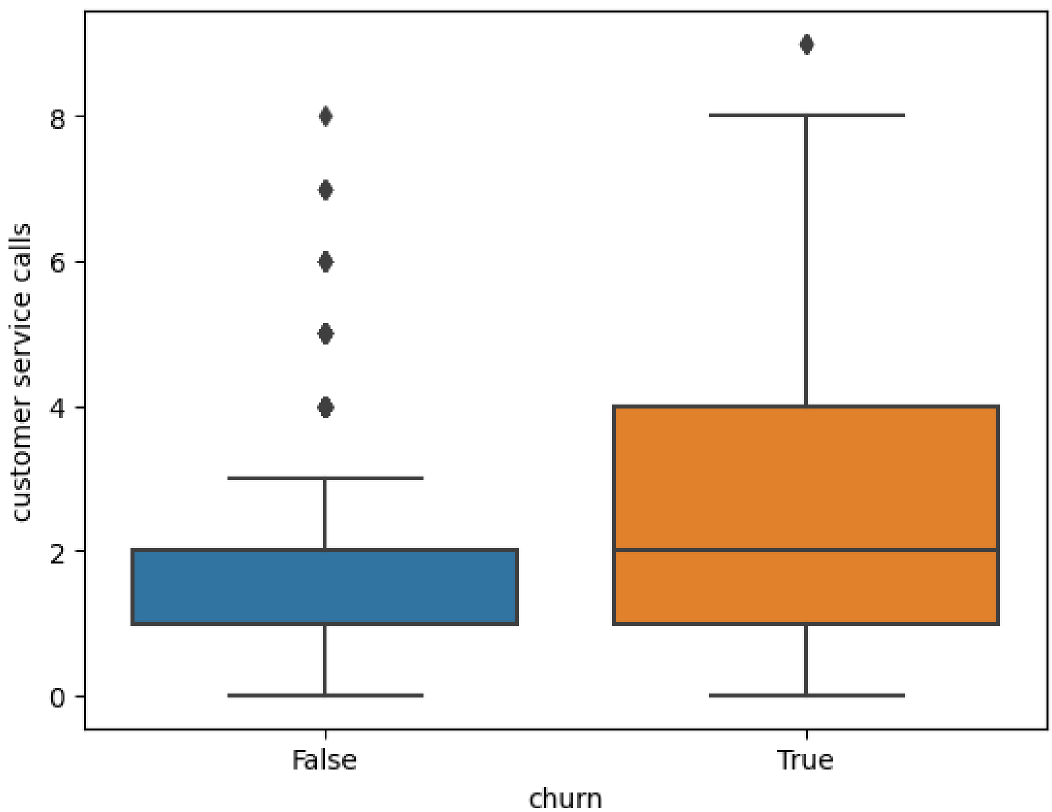



```
analysis.plot_distribution("total night calls", "total night calls")
```




```
sns.boxplot(x = 'churn' , y = "customer service calls" , data=df)
```

```
<Axes: xlabel='churn', ylabel='customer service calls'>
```



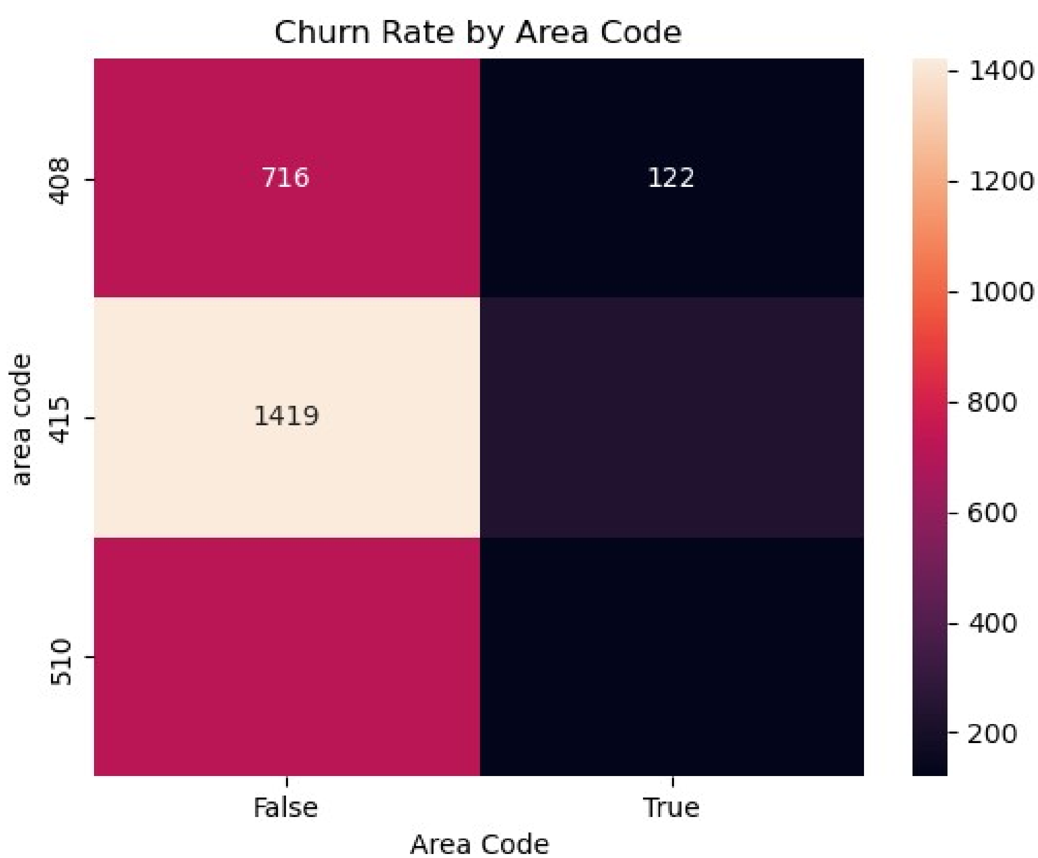
Area codes where Churners and Non-churners are observed

```
crosstab1= pd.crosstab(df['area code'],df['churn'])
crosstab1
```

```
churn      False  True
area code
408          716   122
415         1419   236
510          715   125
```

Histogram and Heatmap to show churners per area code

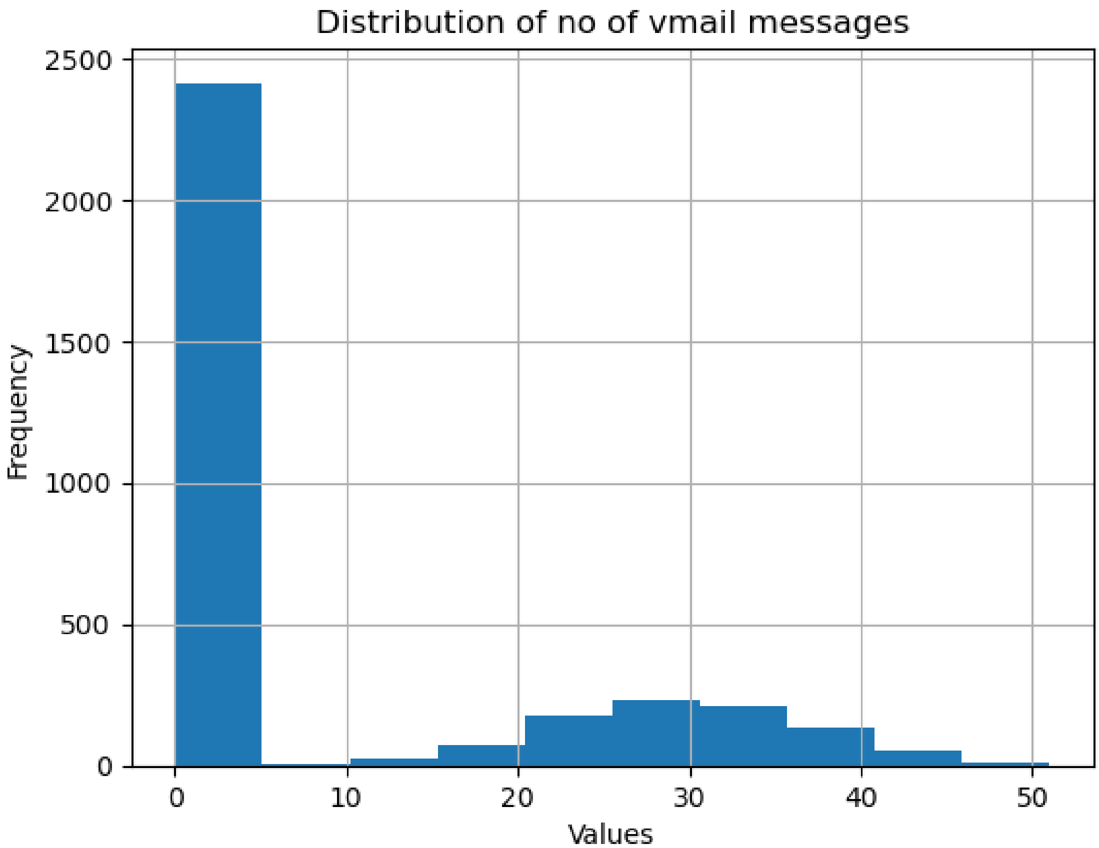
```
sns.heatmap(crosstab1, annot=True, fmt="d")

plt.title("Churn Rate by Area Code")
plt.xlabel("Area Code")

plt.show()
```



Targeted campaigns could be done in area codes with high number of churners

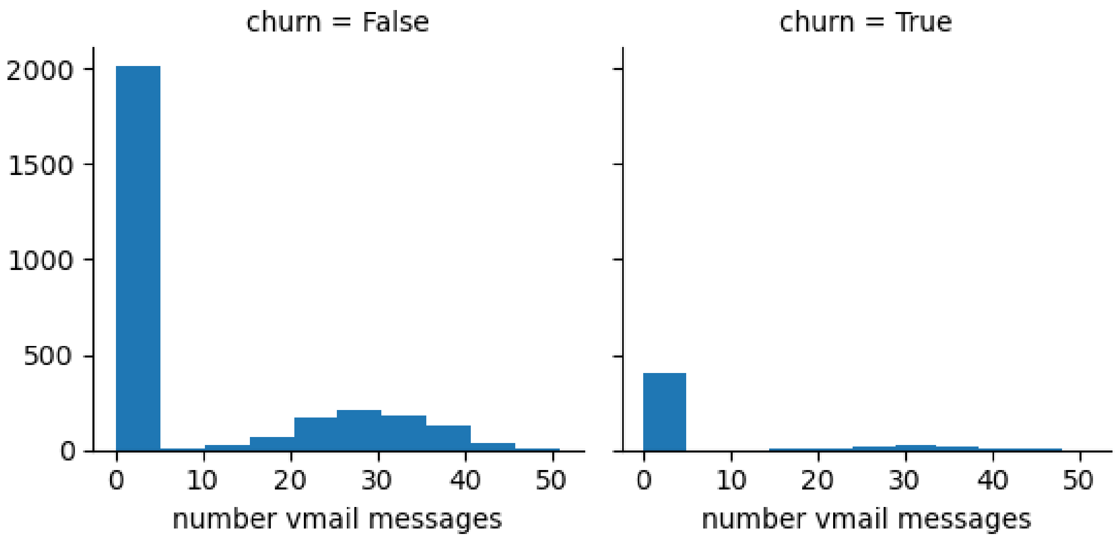
```
df['number vmail messages'].hist()
plt.xlabel('Values')
plt.ylabel('Frequency')
```

```
plt.title('Distribution of no of vmail messages')
plt.show()
```




```
vmail = sns.FacetGrid(df, col="churn")
vmail.map(plt.hist, "number vmail messages")
```

```
<seaborn.axisgrid.FacetGrid at 0x28aadb18cd0>
```




```
#plt.figure(figsize=(12,8))
#sns.scatterplot(x='account length', y='total charge')
df['number vmail messages'].skew()

1.2648236337102594
```

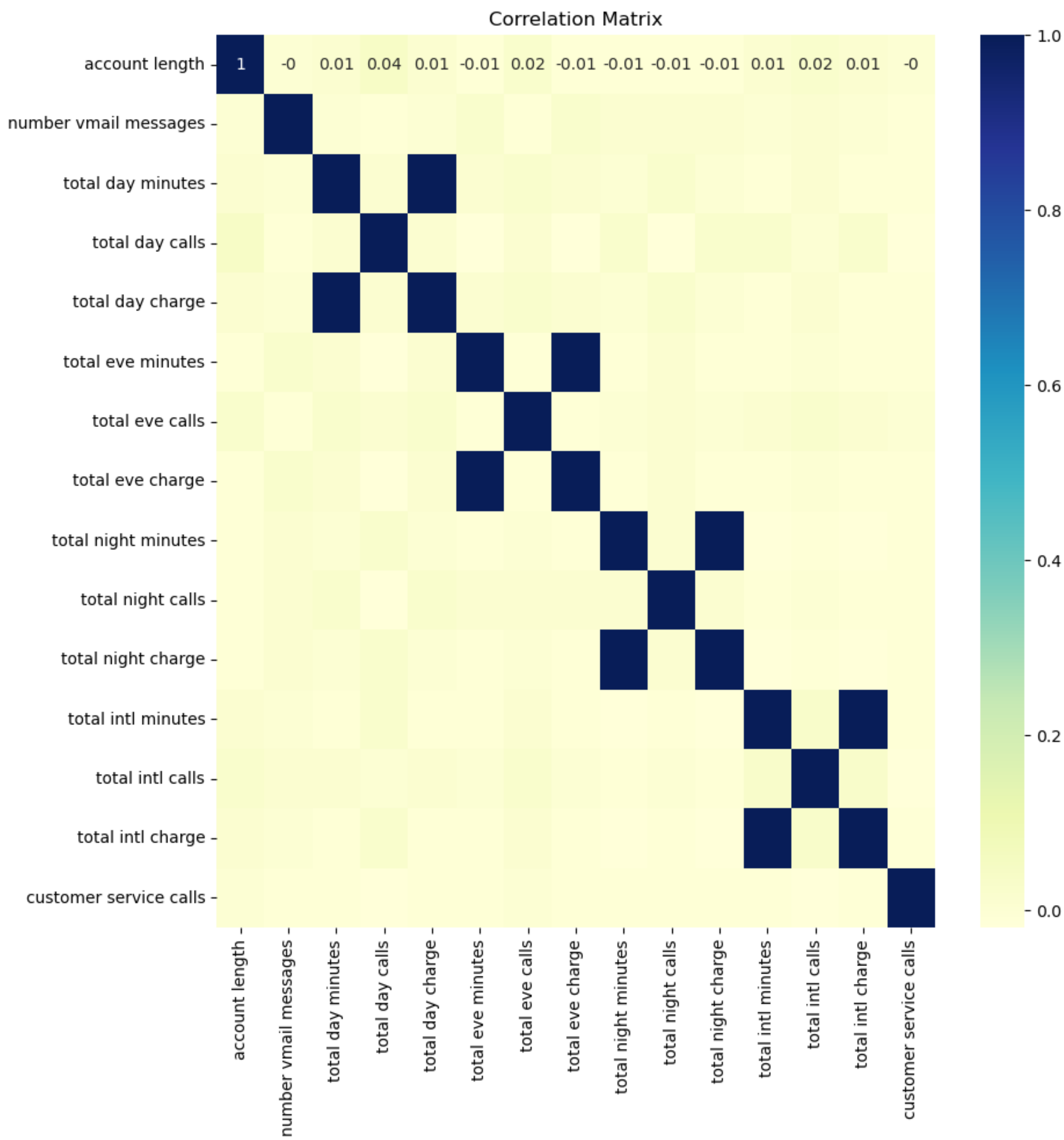
Correlation Analysis

```
df_numeric = df.select_dtypes(include=[np.number])

cor = df_numeric.corr()
cor

                        account length  number vmail messages  \
account length                1.000000              -0.004628
number vmail messages        -0.004628               1.000000
total day minutes             0.006216               0.000778
total day calls               0.038470              -0.009548
total day charge              0.006214               0.000776
total eve minutes            -0.006757               0.017562
total eve calls               0.019260              -0.005864
total eve charge             -0.006745               0.017578
total night minutes          -0.008955               0.007681
total night calls            -0.013176               0.007123
total night charge           -0.008960               0.007663
total intl minutes            0.009514               0.002856
total intl calls              0.020661               0.013957
total intl charge             0.009546               0.002884
customer service calls       -0.003796              -0.013263

                        total day minutes  total day calls  total day
charge  \
```

```
account length                      0.006216         0.038470
0.006214
number vmail messages               0.000778        -0.009548
0.000776
total day minutes                   1.000000         0.006750
1.000000
total day calls                     0.006750         1.000000
0.006753
total day charge                    1.000000         0.006753
1.000000
total eve minutes                   0.007043        -0.021451
0.007050
total eve calls                     0.015769         0.006462
0.015769
total eve charge                    0.007029        -0.021449
0.007036
total night minutes                 0.004323         0.022938
0.004324
total night calls                   0.022972        -0.019557
0.022972
total night charge                  0.004300         0.022927
0.004301
total intl minutes                 -0.010155         0.021565          -
0.010157
total intl calls                    0.008033         0.004574
0.008032
total intl charge                  -0.010092         0.021666          -
0.010094
customer service calls             -0.013423        -0.018942          -
0.013427

                        total eve minutes  total eve calls  total eve
charge  \
account length                     -0.006757         0.019260          -
0.006745
number vmail messages               0.017562        -0.005864
0.017578
total day minutes                   0.007043         0.015769
0.007029
total day calls                    -0.021451         0.006462          -
0.021449
total day charge                    0.007050         0.015769
0.007036
total eve minutes                   1.000000        -0.011430
1.000000
total eve calls                    -0.011430         1.000000          -
0.011423
total eve charge                    1.000000        -0.011423
1.000000
```

```
total night minutes              -0.012584        -0.002093         -
0.012592
total night calls                 0.007586         0.007710
0.007596
total night charge               -0.012593        -0.002056         -
0.012601
total intl minutes               -0.011035         0.008703         -
0.011043
total intl calls                  0.002541         0.017434
0.002541
total intl charge                -0.011067         0.008674         -
0.011074
customer service calls           -0.012985         0.002423         -
0.012987

                        total night minutes  total night calls  \
account length                    -0.008955          -0.013176
number vmail messages              0.007681           0.007123
total day minutes                  0.004323           0.022972
total day calls                    0.022938          -0.019557
total day charge                   0.004324           0.022972
total eve minutes                 -0.012584           0.007586
total eve calls                   -0.002093           0.007710
total eve charge                  -0.012592           0.007596
total night minutes                1.000000           0.011204
total night calls                  0.011204           1.000000
total night charge                 0.999999           0.011188
total intl minutes                -0.015207          -0.013605
total intl calls                  -0.012353           0.000305
total intl charge                 -0.015180          -0.013630
customer service calls            -0.009288          -0.012802

                        total night charge  total intl minutes  \
account length                   -0.008960            0.009514
number vmail messages             0.007663            0.002856
total day minutes                 0.004300           -0.010155
total day calls                   0.022927            0.021565
total day charge                  0.004301           -0.010157
total eve minutes                -0.012593           -0.011035
total eve calls                  -0.002056            0.008703
total eve charge                 -0.012601           -0.011043
total night minutes               0.999999           -0.015207
total night calls                 0.011188           -0.013605
total night charge                1.000000           -0.015214
total intl minutes               -0.015214            1.000000
total intl calls                 -0.012329            0.032304
total intl charge                -0.015186            0.999993
customer service calls           -0.009277           -0.009640

                        total intl calls  total intl charge  \
```

```
account length                   0.020661         0.009546
number vmail messages            0.013957         0.002884
total day minutes                0.008033        -0.010092
total day calls                  0.004574         0.021666
total day charge                 0.008032        -0.010094
total eve minutes                0.002541        -0.011067
total eve calls                  0.017434         0.008674
total eve charge                 0.002541        -0.011074
total night minutes             -0.012353        -0.015180
total night calls                0.000305        -0.013630
total night charge              -0.012329        -0.015186
total intl minutes               0.032304         0.999993
total intl calls                 1.000000         0.032372
total intl charge                0.032372         1.000000
customer service calls          -0.017561        -0.009675

                        customer service calls
account length                       -0.003796
number vmail messages                -0.013263
total day minutes                    -0.013423
total day calls                      -0.018942
total day charge                     -0.013427
total eve minutes                    -0.012985
total eve calls                       0.002423
total eve charge                     -0.012987
total night minutes                  -0.009288
total night calls                    -0.012802
total night charge                   -0.009277
total intl minutes                   -0.009640
total intl calls                     -0.017561
total intl charge                    -0.009675
customer service calls                1.000000

#Heatmap
plt.figure(figsize=(10, 10))
sns.heatmap(cor.round(2), annot=True, cmap='YlGnBu')
plt.title("Correlation Matrix")
plt.show()
```



Total day charge & Total day minutes are highly correlated

Total eve charge and Total eve minutes are highly correlated

Total night charge & Total night minutes are highly correlated

Total intl charge & Total intl minutes are highly correlated

For each pair, one variable can be eliminated.

```
columns_to_drop = ['total day charge' ,'total eve charge', 'total
night charge', 'total intl charge', ]
df_numeric_dropped= df_numeric.drop(columns_to_drop, axis=1)

df_numeric_dropped.columns
```

```
Index(['account length', 'number vmail messages', 'total day minutes',
       'total day calls', 'total eve minutes', 'total eve calls',
       'total night minutes', 'total night calls', 'total intl
minutes',
       'total intl calls', 'customer service calls'],
      dtype='object')
```

For Numeric columns:

H0 - There is no statistical significant correlation between the feature and the target variable.

Ha - There is a significant correlation between the feature and the target variable

If pvalue>0.05 = accept the null hypothesis

If pvalue <0.05 = reject the null hypothesis

```
numeric_cols = df_numeric_dropped.columns.to_list()

numeric_cols
```

```
['account length',
 'number vmail messages',
 'total day minutes',
 'total day calls',
 'total eve minutes',
 'total eve calls',
 'total night minutes',
 'total night calls',
 'total intl minutes',
 'total intl calls',
 'customer service calls']
```

```
y = df['churn']
selected_columns = None
from sklearn.feature_selection import f_classif
fval,pval = f_classif(df_numeric_dropped,y)
for i in range(len(numeric_cols)):
    print(numeric_cols[i],pval[i])
```

```
account length 0.33976000705720666
number vmail messages 2.1175218402696038e-07
total day minutes 5.300278227509361e-33
total day calls 0.28670102402211844
total eve minutes 8.011338561256927e-08
```

```
total eve calls 0.5941305829720491
total night minutes 0.04046648463758881
total night calls 0.7230277872081609
total intl minutes 8.05731126549437e-05
total intl calls 0.002274701409850077
customer service calls 3.900360240185746e-34
```

```
df.head()
```

```
  state  account length  area code phone number international plan  \
0    KS             128        415     382-4657                 no
1    OH             107        415     371-7191                 no
2    NJ             137        415     358-1921                 no
3    OH              84        408     375-9999                yes
4    OK              75        415     330-6626                yes

  voice mail plan  number vmail messages  total day minutes  total day
calls  \
0             yes                     25              265.1
110
1             yes                     26              161.6
123
2              no                      0              243.4
114
3              no                      0              299.4
71
4              no                      0              166.7
113

   total day charge  ...  total eve calls  total eve charge  \
0             45.07  ...               99             16.78
1             27.47  ...              103             16.62
2             41.38  ...              110             10.30
3             50.90  ...               88              5.26
4             28.34  ...              122             12.61

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01
1                254.4                103               11.45
2                162.6                104                7.32
3                196.9                 89                8.86
4                186.9                121                8.41

   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70
1                13.7                 3               3.70
2                12.2                 5               3.29
3                 6.6                 7               1.78
4                10.1                 3               2.73
```

```
   customer service calls  churn
0                       1  False
1                       1  False
2                       0  False
3                       2  False
4                       3  False

[5 rows x 21 columns]
```

Features to be used

```
X_features = df[['area code', 'international plan','number vmail 
messages','total day minutes','total eve minutes',
     'total night minutes','total intl minutes','customer service 
calls']]
y = df['churn']

X_features.head()

  area code international plan  number vmail messages  total day 
minutes  \
0       415                 no                     25      
265.1   
1       415                 no                     26      
161.6   
2       415                 no                      0      
243.4   
3       408                yes                      0      
299.4   
4       415                yes                      0      
166.7   

   total eve minutes  total night minutes  total intl minutes  \
0              197.4                244.7                10.0   
1              195.5                254.4                13.7   
2              121.2                162.6                12.2   
3               61.9                196.9                 6.6   
4              148.3                186.9                10.1   

   customer service calls  
0                       1  
1                       1  
2                       0  
3                       2  
4                       3  

X_features.dtypes

area code                  object
international plan         object
```

```
number vmail messages       int64
total day minutes         float64
total eve minutes         float64
total night minutes       float64
total intl minutes        float64
customer service calls      int64
dtype: object
```

```
X_features['international plan'].unique()
```

```
array(['no', 'yes'], dtype=object)
```

Preprocessing

```
# label encoding for area code column
from sklearn.preprocessing import LabelEncoder

encoder= LabelEncoder()
X_features.loc[:, 'area_code_encoded'] =
encoder.fit_transform(X_features['area code'])

X_features.tail()
```

```
C:\Users\user\AppData\Local\Temp\ipykernel_15336\184457964.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  X_features.loc[:, 'area_code_encoded'] =
encoder.fit_transform(X_features['area code'])
```

```
     area code international plan  number vmail messages  total day
minutes  \
3328       415                 no                     36
156.2
3329       415                 no                      0
231.1
3330       510                 no                      0
180.8
3331       510                yes                      0
213.8
3332       415                 no                     25
234.4

      total eve minutes  total night minutes  total intl minutes  \
3328              215.5                279.1                 9.9
3329              153.4                191.3                 9.6
3330              288.8                191.9                14.1
```

```
3331              159.6                 139.2                  5.0
3332              265.9                 241.4                 13.7

      customer service calls  area_code_encoded
3328                       2                  1
3329                       3                  1
3330                       2                  2
3331                       2                  2
3332                       0                  1

#Mapping international plan
internationalPlan_mapping = {"yes": 1, "no": 0}
X_features.loc[:, 'international plan'] = X_features['international
plan'].replace(internationalPlan_mapping)

X_features.head()

  area code international plan  number vmail messages  total day
minutes  \
0       415                  0                     25
265.1
1       415                  0                     26
161.6
2       415                  0                      0
243.4
3       408                  1                      0
299.4
4       415                  1                      0
166.7

   total eve minutes  total night minutes  total intl minutes  \
0              197.4                244.7                10.0
1              195.5                254.4                13.7
2              121.2                162.6                12.2
3               61.9                196.9                 6.6
4              148.3                186.9                10.1

   customer service calls  area_code_encoded
0                       1                  1
1                       1                  1
2                       0                  1
3                       2                  0
4                       3                  1

X_features= X_features.drop('area code', axis=1)

X_features.head()

  international plan  number vmail messages  total day minutes  \
0                  0                     25              265.1
1                  0                     26              161.6
```

```
2                    0                       0               243.4
3                    1                       0               299.4
4                    1                       0               166.7

   total eve minutes  total night minutes  total intl minutes  \
0              197.4                244.7                10.0
1              195.5                254.4                13.7
2              121.2                162.6                12.2
3               61.9                196.9                 6.6
4              148.3                186.9                10.1

   customer service calls  area_code_encoded
0                       1                  1
1                       1                  1
2                       0                  1
3                       2                  0
4                       3                  1
```

Scaling & Train_test_Split

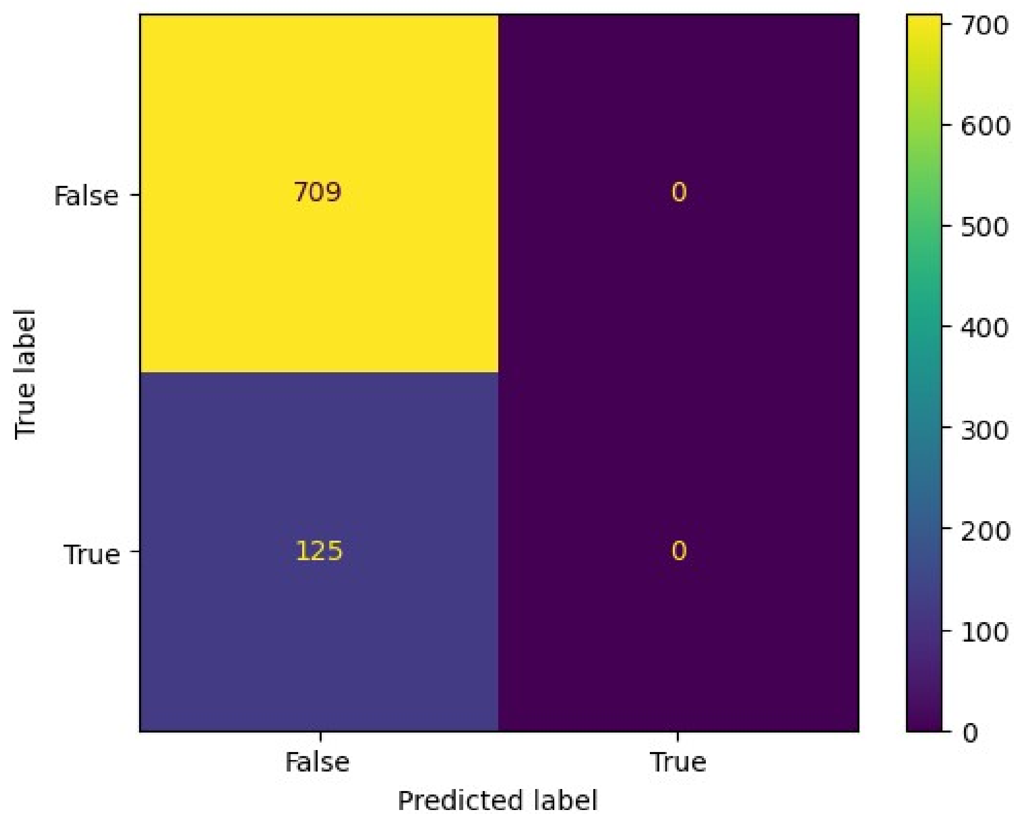
```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

X = X_features.copy()
y = df['churn']

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size= 0.25, random_state=42)

np.bincount(y_test)

# 0 - "churner"  1 - "Non-Churner"

array([709, 125], dtype=int64)

print("X_train: ", X_train.shape)
print("X_test: ", X_test.shape)
print('y: ', y.shape)
print("y_train:", y_train.shape)
print("y_test: ",y_test.shape)

X_train:  (2499, 8)
X_test:  (834, 8)
y:  (3333,)
y_train: (2499,)
y_test:  (834,)
```

Modelling

Logistic regression

Baseline evaluation metric - DummyClassifier that always predicts class 0 (Churner)

```
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.dummy import DummyClassifier

ConfusionMatrixDisplay.from_estimator(estimator=DummyClassifier(strate
gy='constant', constant=0).fit(X_train, y_train),
                                       X=X_test, y=y_test);
```




```
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
dummy_model = DummyClassifier(strategy='constant',
constant=0).fit(X_train, y_train)

dummy_accuracy = dummy_model.score(X_test, y_test)

print("Dummy Classifier Accuracy:", dummy_accuracy)
```

```
Dummy Classifier Accuracy: 0.8501199040767387
```

Fitted logistic regression model

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression(class_weight='balanced')
model.fit(X_train,y_train)

LogisticRegression(class_weight='balanced')

from sklearn.model_selection import cross_val_score

# Perform cross-validation
cv_scores = cross_val_score(model, X_train, y_train, cv=5)
cv_scores

array([0.754     , 0.758     , 0.758     , 0.768     , 0.77755511])

y_pred = model.predict(X_test)
model.score(X_test, y_test)

0.7877697841726619
```

The test set performance is similar to thhe cross-validation scores obtained earlier on the training set. This suggests this model generalizes reasonably well.

```
# Analysis on train data
from sklearn.metrics import accuracy_score, recall_score, f1_score,
precision_score

y_pred2 = model.predict(X_train)
print("Accuracy : ", accuracy_score(y_train,y_pred2))
print("Recall : ", recall_score(y_train,y_pred2))
print("F1 score : ", f1_score(y_train,y_pred2))
print("Precision : ", precision_score(y_train,y_pred2))

Accuracy :  0.7643057222889156
Recall :  0.7346368715083799
F1 score :  0.4717488789237669
Precision :  0.3474240422721268

# performance analysis
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred))

              precision    recall  f1-score   support

       False       0.95      0.79      0.86       709
        True       0.40      0.78      0.53       125

    accuracy                           0.79       834
   macro avg       0.67      0.79      0.69       834
```

```
weighted avg       0.87      0.79      0.81       834
```

Precision is low: Model identifies many customers as churn risks, but a large portion of them don't actually churn

Logistic regression with different train_test_split (80/20)

Model 2

```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

X = X_features.copy()
y = df['churn']

scaler = StandardScaler()
Xscaled = scaler.fit_transform(X)

Xtrain, Xtest, ytrain, ytest = train_test_split(Xscaled, y, test_size=
0.3, random_state=42, stratify=y)

model2 = LogisticRegression(class_weight='balanced')
model2.fit(Xtrain,ytrain)
```

```
LogisticRegression(class_weight='balanced')
```

```
y_pred3 = model2.predict(Xtest)
model2.score(Xtest, ytest)
```

```
0.762
```

```
print(classification_report(ytest, y_pred3))
```

```
              precision    recall  f1-score   support

       False       0.95      0.76      0.85       855
        True       0.35      0.77      0.48       145

    accuracy                           0.76      1000
   macro avg       0.65      0.77      0.67      1000
weighted avg       0.86      0.76      0.79      1000
```

Logistic regression evaluation

0.77 Recall - The model correctly identifies 77% of the actual churners. The model seems effective at capturing a significant portion of customers who are about to churn.

0.35 Precision - The model generates a significant number of false positives. (65%). These are customers flagged as churn risks who don't actually churn.

Decision Tree Classifier

Model 3

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

X = X_features.copy()
y = df['churn']

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size= 0.25, random_state=42)

dtmodel =
DecisionTreeClassifier(random_state=10,class_weight={0:0.5,1:0.5})
dtmodel.fit(X_train,y_train)
```

```
DecisionTreeClassifier(class_weight={0: 0.5, 1: 0.5}, random_state=10)
```

```
dt_y_pred = dtmodel.predict(X_test)
dtmodel.score(X_test, y_test)
```

```
0.8896882494004796
```

```
#Analysis on testing data
print(classification_report(y_test, dt_y_pred))
```

```
              precision    recall  f1-score   support

       False       0.94      0.93      0.94       709
        True       0.63      0.64      0.63       125

    accuracy                           0.89       834
   macro avg       0.78      0.79      0.78       834
weighted avg       0.89      0.89      0.89       834
```

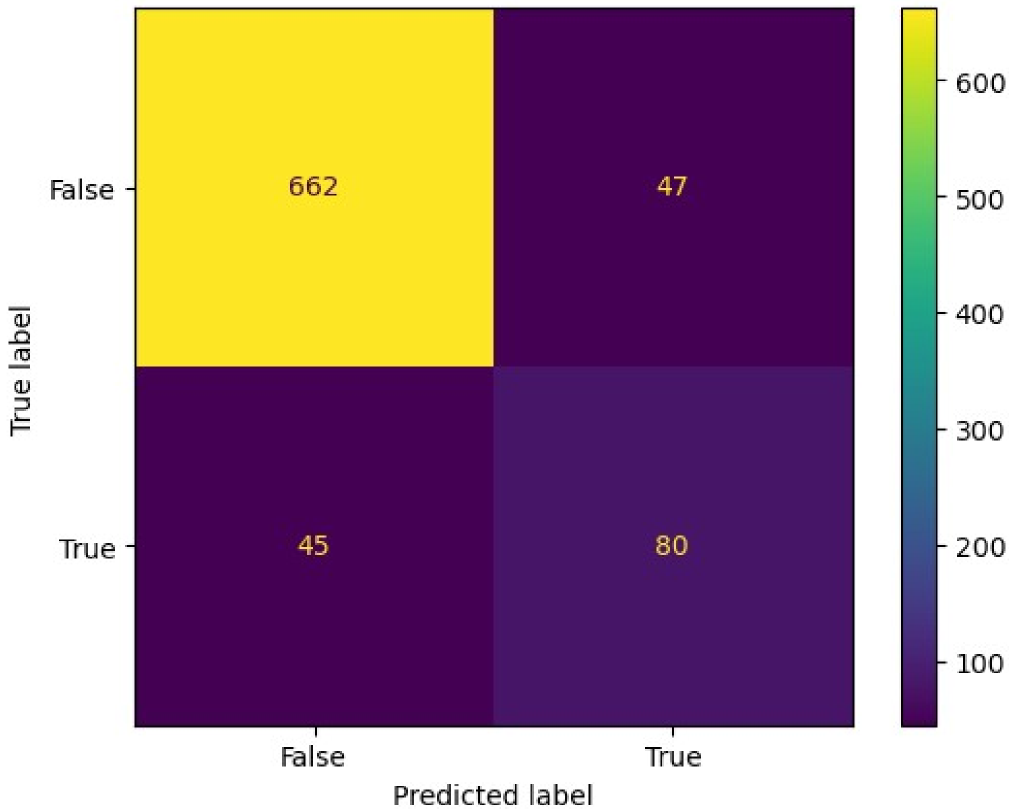
Decision tree evaluation

Model is overfitting on training data. To handle overfitting, decrease the value of max_depth, increase min_samples_leaf and min_samples_split

Recall - 0.64: The model correctly identifies 64% of the actual churners Precision - 0.63 : Out of every 100 customers the model identifies as likely to churn, only 63 of them actually churn

```
import matplotlib.pyplot as plt

from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

```
dt_cm = confusion_matrix(y_test, dt_y_pred)
dt_cm_display = ConfusionMatrixDisplay(dt_cm,
display_labels=y.unique())
dt_cm_display.plot(values_format='d')
plt.show()
```



Hyper-Parameter Tuning for Decision tree

Model 4

```
from sklearn.model_selection import GridSearchCV
dt_param_grid = {'max_depth':[2,3,4,5,6], 'min_samples_split':
[10,15,20,30,40] }
grid_dtmodel=GridSearchCV(dtmodel, dt_param_grid)
grid_dtmodel.fit(X_train, y_train)

best_tree = grid_dtmodel.best_estimator_
best_tree


DecisionTreeClassifier(class_weight={0: 0.5, 1: 0.5}, max_depth=6,
                       min_samples_split=10, random_state=10)
```

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
y_pred_best = best_tree.predict(X_test)

dt_best_accuracy= accuracy_score(y_test, y_pred_best)

dt_best_recall = recall_score(y_test, y_pred_best)
dt_best_precision = precision_score(y_test, y_pred_best)
print("Accuracy is: ", dt_best_accuracy, " | precision_score is: 
",dt_best_precision, " | recall_score is : ", dt_best_recall)
```

```
Accuracy is:  0.9292565947242206  | precision_score is:  0.875  | 
recall_score is :  0.616
```

Random Forest

Model 5

```
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier()

from sklearn.model_selection import RandomizedSearchCV

param_grid = [{
    'n_estimators': [100,500,1000],
    'criterion' : ['entropy', 'gini'],
    'min_samples_split' : [2, 4, 7],
    'min_samples_leaf': [2,4],
    'max_depth': [8,10, 11],
    'class_weight': [{0: 1, 1: 3}, {0: 1, 1: 5}]
}]


random_grid_search = RandomizedSearchCV(rf,
                                        param_grid,
                                        cv=5,
                                        scoring='accuracy',
                                        n_jobs= -1,
                                        random_state=26
                                        )


random_grid_search.fit(X_train, y_train)
```

```
RandomizedSearchCV(cv=5, estimator=RandomForestClassifier(), n_jobs=-
1,
                   param_distributions=[{'class_weight': [{0: 1, 1: 
3},
                                                          {0: 1, 1: 
```

```
5}],
                                         'criterion': ['entropy',
'gini'],
                                         'max_depth': [8, 10, 11],
                                         'min_samples_leaf': [2, 4],
                                         'min_samples_split': [2, 4,
7],
                                         'n_estimators': [100, 500,
1000]}],
                   random_state=26, scoring='accuracy')
```

```
random_grid_search.best_score_
```

```
0.935576753507014
```

```
random_grid_search.best_params_
```

```
{'n_estimators': 100,
 'min_samples_split': 2,
 'min_samples_leaf': 2,
 'max_depth': 11,
 'criterion': 'gini',
 'class_weight': {0: 1, 1: 3}}
```

```
best_random_forest = random_grid_search.best_estimator_

y_pred = best_random_forest.predict(X_test)

print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

       False       0.94      0.98      0.96       709
        True       0.88      0.66      0.76       125

    accuracy                           0.94       834
   macro avg       0.91      0.82      0.86       834
weighted avg       0.93      0.94      0.93       834
```

```
from sklearn.metrics import roc_curve, auc

tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()

# False Positive Rate (FPR) and True Positive Rate (TPR)
fpr, tpr, thresholds = roc_curve(y_test, y_pred)

# Area Under the ROC Curve (AUC)
roc_auc = auc(fpr, tpr)
print("AUC:", roc_auc)
```

```
AUC: 0.8242425952045135
```

This AUC value:0.807537376586742 is high. This indicates better overall model performance in distinguishing positive and negative cases than a random classifier.

KNN

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.utils.class_weight import compute_class_weight


knn = KNeighborsClassifier(n_neighbors=4)

knn.fit(X_train, y_train)
```

```
KNeighborsClassifier(n_neighbors=4)
```

```
knn_y_pred= knn.predict(X_test)

knn.score(X_test, y_test)
```

```
0.8908872901678657
```

```
knn_cm = confusion_matrix(y_test, knn_y_pred)
knn_cm
```

```
array([[704,   5],
       [ 86,  39]], dtype=int64)
```

```
print(classification_report(y_test, knn_y_pred))
```

```
              precision    recall  f1-score   support

       False       0.89      0.99      0.94       709
        True       0.89      0.31      0.46       125

    accuracy                           0.89       834
   macro avg       0.89      0.65      0.70       834
weighted avg       0.89      0.89      0.87       834
```

```
import sklearn as sk; print(sk.__version__)
```

```
1.2.2
```

Using different distance metrics and using weights

```
from sklearn.neighbors import KNeighborsClassifier

euclidean_distance = KNeighborsClassifier(metric='euclidean')
manhattan_distance = KNeighborsClassifier(metric='manhattan')
minkowski_distance = KNeighborsClassifier(metric='minkowski', p=5)  #
You can adjust the p value (power)
```

```python
euclidean_distance.fit(X_train, y_train)
manhattan_distance.fit(X_train, y_train)
minkowski_distance.fit(X_train, y_train)


y_pred_euclidean = euclidean_distance.predict(X_test)
print("Euclidean Distance Classification Report:")
print(classification_report(y_test, y_pred_euclidean))
```

```
Euclidean Distance Classification Report:
              precision    recall  f1-score   support

       False       0.90      0.98      0.94       709
        True       0.82      0.39      0.53       125

    accuracy                           0.90       834
   macro avg       0.86      0.69      0.74       834
weighted avg       0.89      0.90      0.88       834
```

```python
y_pred_manhattan = manhattan_distance.predict(X_test)
print("Manhattan Distance Classification Report:")
print(classification_report(y_test, y_pred_manhattan))
```

```
Manhattan Distance Classification Report:
              precision    recall  f1-score   support

       False       0.90      0.98      0.94       709
        True       0.80      0.35      0.49       125

    accuracy                           0.89       834
   macro avg       0.85      0.67      0.71       834
weighted avg       0.88      0.89      0.87       834
```

```python
y_pred_minkowski = minkowski_distance.predict(X_test)
print("Minkowski Distance Classification Report:")
print(classification_report(y_test, y_pred_minkowski))
```

```
Minkowski Distance Classification Report:
              precision    recall  f1-score   support

       False       0.90      0.98      0.94       709
        True       0.82      0.39      0.53       125

    accuracy                           0.90       834
   macro avg       0.86      0.69      0.74       834
weighted avg       0.89      0.90      0.88       834
```

```
df.dtypes
```

```
state                      object
account length              int64
area code                  object
phone number               object
international plan         object
voice mail plan            object
number vmail messages       int64
total day minutes         float64
total day calls             int64
total day charge          float64
total eve minutes         float64
total eve calls             int64
total eve charge          float64
total night minutes       float64
total night calls           int64
total night charge        float64
total intl minutes        float64
total intl calls            int64
total intl charge         float64
customer service calls      int64
churn                        bool
dtype: object
```

All 3 KNN using different distance metrics give very low recall. Model cannt be used to make predictions.

Summary

The following are the models that were evaluated: Logistic regression, decision tree, tuned decision tree, kNN model and tuned random forest.

The metrics used to evaluate these models areprecision, recall, F1 score, and AUC. For our particular business problem, the cost of a cutomer leaving is high. Therefore, priority will be given to recall over precision in the precision- recall trade-off.

MODEL1 - FITTED LOGISTIC REGRESSION (75-25 split) The model's performance was evaluated using 5-fold cross-validation on the training data. The average accuracy score across the folds was 0.762 with a standard deviation of 0.008. The model achieved an accuracy of 0.788 on the held-out test set." The precision however is low. Precision - Precision : 0.347 and a moderately high recall of 0.734

Model 2- FITTED LOGISTIC REGRESSION (8-/20 split) Very low precision of 0.35 and moderate recall of 0.77.

Although these first two models give high recall, the very low precision will lead to wasted resources by the company as these models flag customers as churn risks who don't actually churn.

Model 3 - Decision tree Recall - 0.64: The model correctly identifies 64% of the actual churners Precision - 0.63 : Out of every 100 customers the model identifies as likely to churn, only 63 of them actually churn This model also has an accuracy of 89% This model has better precision and accuracy than the logistic model

Model 4 - Tuned decision tree Using GridSearchCV, the parameters tuned on this tree were "max_depth" and 'min_samples_split'. the model had precision_score of 0.875 and recall of 0.616

Model5 -Tuned Random Forest The parameters tunes for this model include 'n_estimators', 'min_samples_split', 'min_samples_leaf, 'max_depth' and 'class_weight' It was evaluated using 5-fold cross-validation on the training data. It had a precision of 0.87 and recall of 0.66. and AUC of 0.820. This AUC indicates better overall model performance in distinguishing positive and negative cases than a random classifier.

Model 6 - KNN This model had the lowest recall of all models. Recall of o.31 and precision of 0.89. Since it is crucial to our business that churned customers are identified, this model will NOT be used.

After evaluating all models, the best the tuned random forest achieved the highest F1 score. Though other models have higher recall, it is at the expense of missclassifying non-churners as churners. This model also has a high AUC of 0.820. This is therefore the best model.