Analysis of Churn Data of a Telecom company

Final Project Submission

Please fill out:

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- Student pace: part time
- Scheduled project review date/time:
- Instructor name:
- Blog post URL:

Business Problem

The bussines problem in this senario is to provide Telecom company a prediction of churn of customers so it can effectively focus a customer retention marketing program. Customer churn is the loss of clients or customers

Introduction

The dataset contains data on the customers of a Telecom company. Each row represents a customer and the columns contain customer's attributes

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn
import seaborn as sns
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
```

Dataloading

In [2]:
```
df = pd.read_csv('churn.csv')
df.head(3)
```

Out[2]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...	to e ca
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	1
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	1

3 rows × 21 columns

Data Understanding

In [3]:
```
#Summary statistics for data
df.describe()
```

Out[3]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total e minut
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.0000
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200.9803
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.7138
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.0000
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.6000
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.4000
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.3000
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.7000

In [4]:
```
df.shape
```

Out[4]:
```
(3333, 21)
```

In [5]:
```
df.columns
```

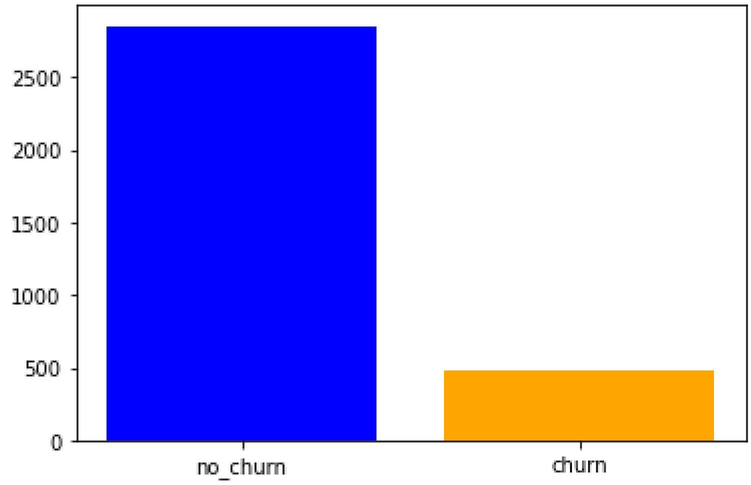
Out[5]:
```
Index(['state', 'account length', 'area code', 'phone number',
       'international plan', 'voice mail plan', 'number vmail messages',
       'total day minutes', 'total day calls', 'total day charge',
       'total eve minutes', 'total eve calls', 'total eve charge',
       'total night minutes', 'total night calls', 'total night charge',
       'total intl minutes', 'total intl calls', 'total intl charge',
       'customer service calls', 'churn'],
      dtype='object')
```

In [6]:
```
#churn count
df['churn'].value_counts()
```

Out[6]:
```
False    2850
True      483
Name: churn, dtype: int64
```

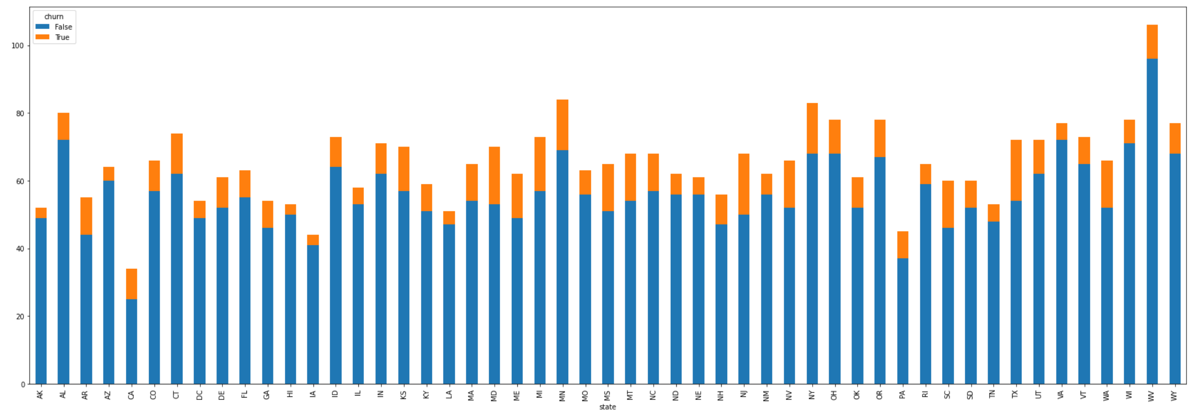
In [7]:
```
#Chart of churn
no_churn = 2850
churn = 483

x = ['no_churn','churn']
y = [2850,483]
c = ['blue','orange']

plt.bar(x , y, color=c)
```

Out[7]:
```
<BarContainer object of 2 artists>
```



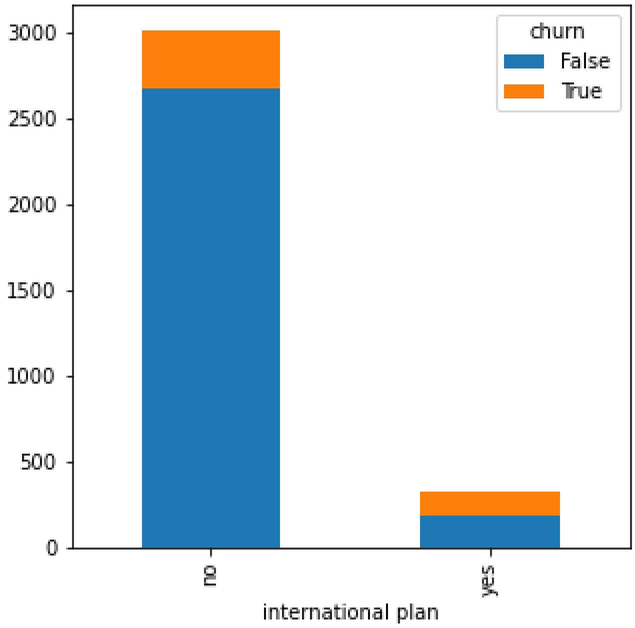
In [8]:
```
#Customer churn by state
df.groupby(["state", "churn"]).size().unstack().plot(kind='bar', stacked=True,
```

Out[8]:
```
<AxesSubplot:xlabel='state'>
```



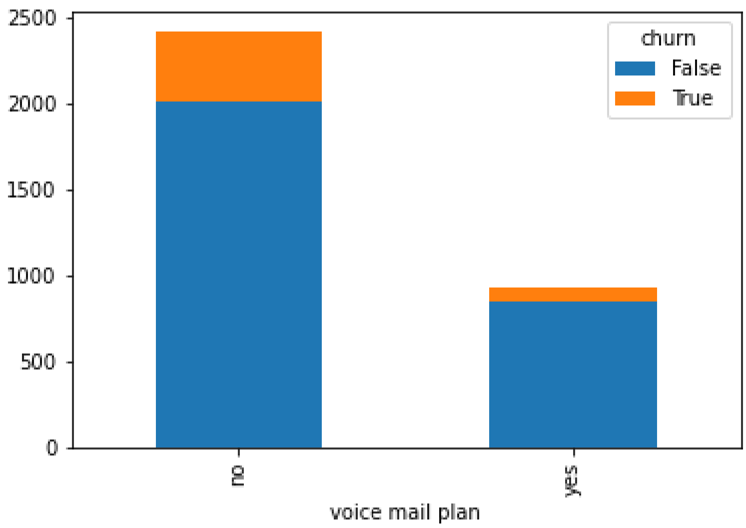
In [9]:
```
#Customer churn with international plan
df.groupby(['international plan','churn']).size().unstack().plot(kind='bar', s
```

Out[9]: <AxesSubplot:xlabel='international plan'>



In [10]:
```
# Customers with voicemail
df.groupby(['voice mail plan','churn']).size().unstack().plot(kind ='bar', sta
```

Out[10]: <AxesSubplot:xlabel='voice mail plan'>



In [11]:
```
#check for null values in dataset

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 Processing

Handling Catagorical data

In [12]:
```
# Handling Catagorical data
df_pre = df.copy()

#Handling state
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
le.fit(df_pre['state'])
df_pre['state'] = le.transform(df_pre['state'])
```

In [13]:
```
#Handling international plan    ,voice mail plan
df_pre["international plan"] = df_pre["international plan"].apply(lambda x: 0
df_pre["voice mail plan"] = df_pre["voice mail plan"].apply(lambda x: 0 if x==
```

In [14]:
```
df_pre.sample(5)
```

Out[14]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...
744	26	78	415	377-7561	0	0	0	191.7	122	32.59	...
1077	34	108	415	344-7197	0	0	0	154.2	123	26.21	...
1827	37	95	415	364-8774	0	0	0	167.6	96	28.49	...
562	50	99	408	389-8606	0	1	28	200.7	88	34.12	...
990	40	38	415	375-5439	0	1	31	197.2	118	33.52	...

5 rows × 21 columns

Checking for null values

In [15]:
```
df_pre.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   int32  
 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   int64  
 5   voice mail plan         3333 non-null   int64  
 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), int32(1), int64(10), object(1)
memory usage: 511.1+ KB
```

Checking for duplicates

In [16]:
```
#check for duplicate
df_pre.duplicated()
```

Out[16]:
```
0       False
1       False
2       False
3       False
4       False
        ...
3328    False
3329    False
3330    False
3331    False
3332    False
Length: 3333, dtype: bool
```

Dropping columns that are not needed

In [17]:
```
#drop phone number
df_pre = df_pre.drop(['phone number'],axis =1)
df_pre.columns
```

Out[17]:
```
Index(['state', 'account length', 'area code', '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')
```

Modeling

Classification task

In [18]:
```
#defining x and y
y = df_pre['churn']
X = df_pre.drop(['churn'],axis=1)
```

In [19]:
```
#Standadize data
scaler = StandardScaler()
X = scaler.fit_transform(X)
X
```

Out[19]:
```
array([[-0.6786493 ,  0.67648946, -0.52360328, ..., -0.60119509,
        -0.0856905 , -0.42793202],
       [ 0.6031696 ,  0.14906505, -0.52360328, ..., -0.60119509,
         1.2411686 , -0.42793202],
       [ 0.33331299,  0.9025285 , -0.52360328, ...,  0.21153386,
         0.69715637, -1.1882185 ],
       ...,
       [ 0.87302621, -1.83505538,  1.71881732, ...,  0.61789834,
         1.3871231 ,  0.33235445],
       [-1.35329082,  2.08295458,  1.71881732, ...,  2.24335625,
        -1.87695028,  0.33235445],
       [ 1.07541867, -0.67974475, -0.52360328, ..., -0.19483061,
         1.2411686 , -1.1882185 ]])
```

In [20]:
```
#make train test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
```

Baseline Model

Logistical regression model

In [21]:
```
#Logistical regression model
clf = LogisticRegression(random_state=0)
model_log = clf.fit(X_train, y_train)
model_log
```

Out[21]:
```
LogisticRegression(random_state=0)
```

In [22]:
```
#model evalutaion on train data
clf.score(X_train, y_train)
```

Out[22]:
```
0.8595438175270108
```

We have an 85% accuracy in our model with train data

In [23]:
```
#model evalutaion on test data
clf.score(X_test, y_test)
```

Out[23]:
```
0.8669064748201439
```

We have an 86% accuracy in our model with test data This means the model has an 86% accuracy when pedicting customer churn.

Descision Trees

In [24]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn import tree
```

In [25]:
```
#Fit data
dtree = DecisionTreeClassifier(random_state=0)
dtree.fit(X_train,y_train)
```

Out[25]:
```
DecisionTreeClassifier(random_state=0)
```

In [26]:
```
#use test data for accuracy measurement
dtree.score(X_test, y_test)
```

Out[26]:
```
0.9184652278177458
```

In [27]:
```
#Accuracy test
y_pred_test = dtree.predict(X_test)
Accuracy = accuracy_score(y_test, y_pred_test)
Accuracy
```

Out[27]:
```
0.9184652278177458
```

This means the model has a 91.8% chance of acccuracy when pedicting customer churn.

KNN Classifier

In [28]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [29]:
```
#fit data
#default neighbours = 5
neigh = KNeighborsClassifier(n_neighbors=5)
neigh.fit(X_train,y_train)
```

Out[29]:
```
KNeighborsClassifier()
```

In [30]:
```
#use train data for accuracy measurement
neigh.score(X_train,y_train)
```

Out[30]:
```
0.9187675070028011
```

In [31]:
```
#use test data for accuracy measurement
neigh.score(X_test, y_test)
```

Out[31]:
```
0.9064748201438849
```

In [32]:
```
#accuracy
y_pred_test = neigh.predict(X_test)
Accuracy = accuracy_score(y_test, y_pred_test)
Accuracy
```

Out[32]:
```
0.9064748201438849
```

This means the model has a 90.6% chance of acccuracy when pedicting customer churn.

Conclusion

Logistical regression : 86%

Decision Tree : 91.8%

KNN Classifier: 90.6%

Our goal was to identify clients which are likely to churn, so we can do special-purpose marketing strategies to avoid the churn event. For this we evaluated differently preprocessed datasets and different classifiers. In the classification chapter we have trained several different classifiers, including a Logistic Regression, a K-Nearest Neighbors Classifier and Decision Tree.

Concluding, we suggest the Telecom company to use the Decision Tree model to identify potential churn customers and according to the customers life-time value present them special offers.