SyriaTel Customer Churn Prediction ¶ (http://localhost:8888/notebooks/Untitled.ipynb?kernel_name=learn-env#SyriaTel-Customer-Churn-Prediction)

In [ ]:
```
# Import Libraries

import numpy as np
import pandas as pd
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
```

In [73]:
```
# Load Dataset

data = pd.read_csv('bigml_59c28831336c6604c800002a.csv')
```

In [74]:
```
data.head(10)
```

Out[74]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...	t c
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	...	
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	
5	AL	118	510	391-8027	yes	no	0	223.4	98	37.98	...	
6	MA	121	510	355-9993	no	yes	24	218.2	88	37.09	...	
7	MO	147	415	329-9001	yes	no	0	157.0	79	26.69	...	
8	LA	117	408	335-4719	no	no	0	184.5	97	31.37	...	
9	WV	141	415	330-8173	yes	yes	37	258.6	84	43.96	...	

10 rows × 21 columns

Finc

10 rows × 21 columns

Finc

In [75]:
```
data.shape
```

Out[75]:
```
(3333, 21)
```

In [76]:
```
print("Number of Rows", data.shape[0])
print("Number of Columns", data.shape[1])
```

```
Number of Rows 3333
Number of Columns 21
```

Get Information about the data set

In [77]:
```
data.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
```

As of now There are 3333 rows and 20 columns in above dataset. Out of which there are 1 boolean data type i.e churn 8 float data type 8 integer data type 3 object data type i.e catagarical value are there There are no missing value present so no need to do the missing value imputation

Check null values in the dataset

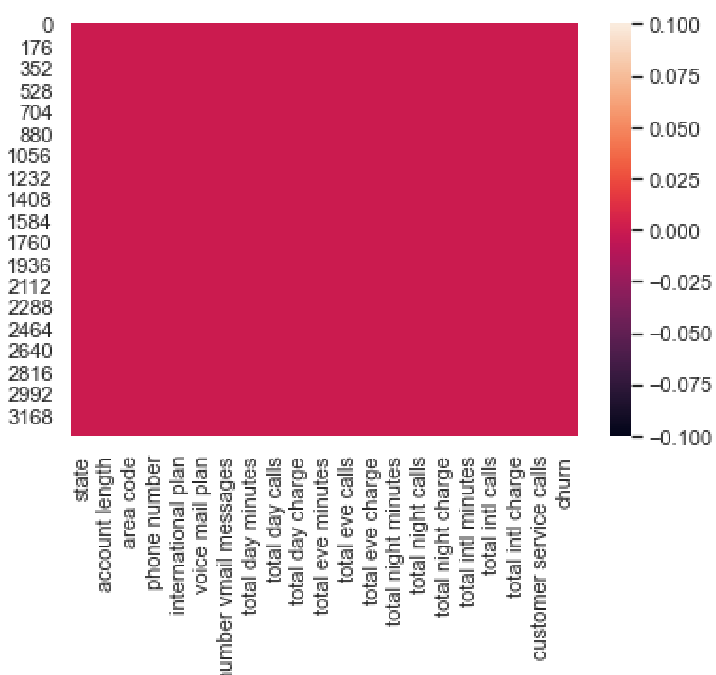
In [78]:
```
data.isnull().sum()
```

In [78]:
```
data.isnull().sum()
```

Out[78]:
```
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
```

In [79]:
```
# Visualizing the missing values
sns.heatmap(data.isnull())
```

Out[79]: <AxesSubplot:>



There is no missing and duplicate values in the dataset.

Get overal statitistic of the dataset

Get overal statitistic of the dataset

In [80]:
```
data.describe()
```

Out[80]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total minu
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.00C
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200.98C
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.713
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.00C
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.60C
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.40C
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.30C
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.70C

Droping irrelevant features

In [81]:
```
data.columns
```

Out[81]:
```
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')
```

Variables Description State :All 51 states

Account Length : How long account has been active

Area Code : Code Number of Area

Intl Plan : International plan activated (yes, no)

VMail Plan : Voice Mail plan activated (yes ,no)

VMail Message : No.of voice mail messages

Day Mins : Total day minutes used
Day Charge : Total day charge

Day calls : Total day calls made
Eve Mins : Total evening minutes

Day Mins : Total day minutes used

Day Charge : Total day charge

Day calls : Total day calls made

Eve Mins : Total evening minutes

Eve Calls : Total evening calls

Eve Charge : Total evening charge

Night Mins : Total night minutes

Night Calls : Total night calls

Night Charge : Total night charge

Intl Mins : Total International minutes used

Intl Calls : Total International calls made

Intl Charge : Total International charge

CustServ calls : Number of customer service calls made

Churn : Customer churn (Target Variable True=1, False=0)

In [82]:
```
data = data.drop(['phone number'], axis=1)
```

In [83]:
```
data
```

Out[83]:

	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	t c
0	KS	128	415	no	yes	25	265.1	110	45.07	197.4	
1	OH	107	415	no	yes	26	161.6	123	27.47	195.5	
2	NJ	137	415	no	no	0	243.4	114	41.38	121.2	
3	OH	84	408	yes	no	0	299.4	71	50.90	61.9	
4	OK	75	415	yes	no	0	166.7	113	28.34	148.3	
...	...	...	...	...	...	...	...	...	...	...	
3328	AZ	192	415	no	yes	36	156.2	77	26.55	215.5	
3329	WV	68	415	no	no	0	231.1	57	39.29	153.4	
3330	RI	28	510	no	no	0	180.8	109	30.74	288.8	
3331	CT	184	510	yes	no	0	213.8	105	36.35	159.6	
3332	TN	74	415	no	yes	25	234.4	113	39.85	265.9	

3333 rows × 20 columns

Encoding of Categorical data

In [84]:
```
#Transforming categorical features into dummy variables as 0 and 1 to be able

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

In [84]:

```
#Transforming categorical features into dummy variables as 0 and 1 to be able

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

Out[84]:

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

In [85]:

```

data['voice mail plan'].unique()
```

Out[85]:

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

In [86]:

```

data['churn'].unique()
```

Out[86]:

```
array([False,  True])
```

In [87]:

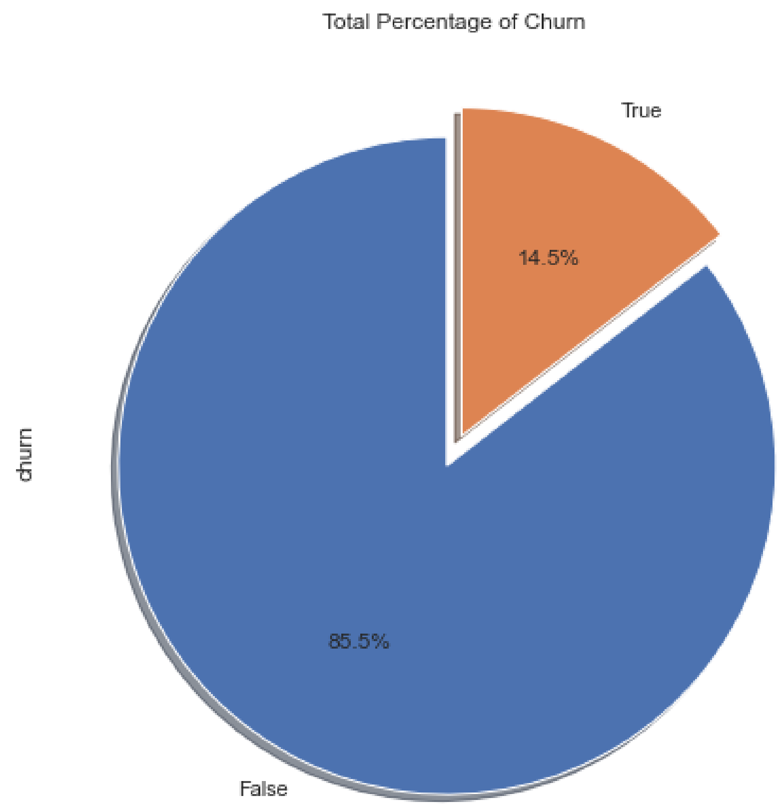
```
print(data.churn.value_counts())
print(" ")
```

```
False    2850
True      483
Name: churn, dtype: int64
```

In [88]:

```
#To get the pie chart to analyze churn
data ['churn'].value_counts().plot.pie(explode=[0.05,0.05], autopct='%1.1f%%'
plt.title('Total Percentage of Churn')
```

In [88]:
```
#To get the pie chart to analyze churn
data ['churn'].value_counts().plot.pie(explode=[0.05,0.05], autopct='%1.1f%%'
plt.title('Total Percentage of Churn')
plt.show()
```



The chart reveals that out of the total dataset, 85.5% (2,850 customers) have not churned, while 14.5% (483 customers) have churned. Although 14.5% might seem like a relatively small number, it's important to note that this figure has risen significantly from its previous level of 1.45%. This indicates a notable increase in customer churn and necessitates prompt attention.

Analyzing "State" column

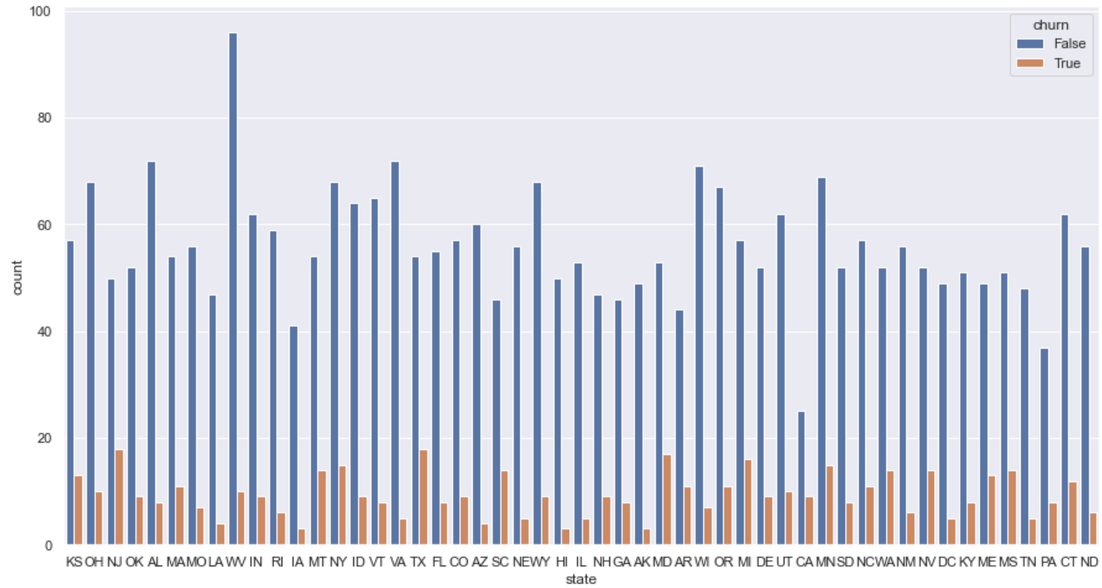
In [89]:
```
data['state'].unique()
```

Out[89]:
```
array(['KS', 'OH', 'NJ', 'OK', 'AL', 'MA', 'MO', 'LA', 'WV', 'IN', 'RI',
       'IA', 'MT', 'NY', 'ID', 'VT', 'VA', 'TX', 'FL', 'CO', 'AZ', 'SC',
       'NE', 'WY', 'HI', 'IL', 'NH', 'GA', 'AK', 'MD', 'AR', 'WI', 'OR',
       'MI', 'DE', 'UT', 'CA', 'MN', 'SD', 'NC', 'WA', 'NM', 'NV', 'DC',
       'KY', 'ME', 'MS', 'TN', 'PA', 'CT', 'ND'], dtype=object)
```

In [90]:
```
#Comparison churn with state by using countplot
sns.set(style="darkgrid")
plt.figure(figsize=(15,8))
```

In [90]:

```
#Comparison churn with state by using countplot
sns.set(style="darkgrid")
plt.figure(figsize=(15,8))
ax = sns.countplot(x='state', hue="churn", data=data)
plt.show()
```



In [91]:

```
#show the most churn state of top 10 by ascending the above list
state_df = data.groupby(['state'])['churn'].mean().sort_values(ascending = Fa
state_df.head(10)
```

Out[91]:

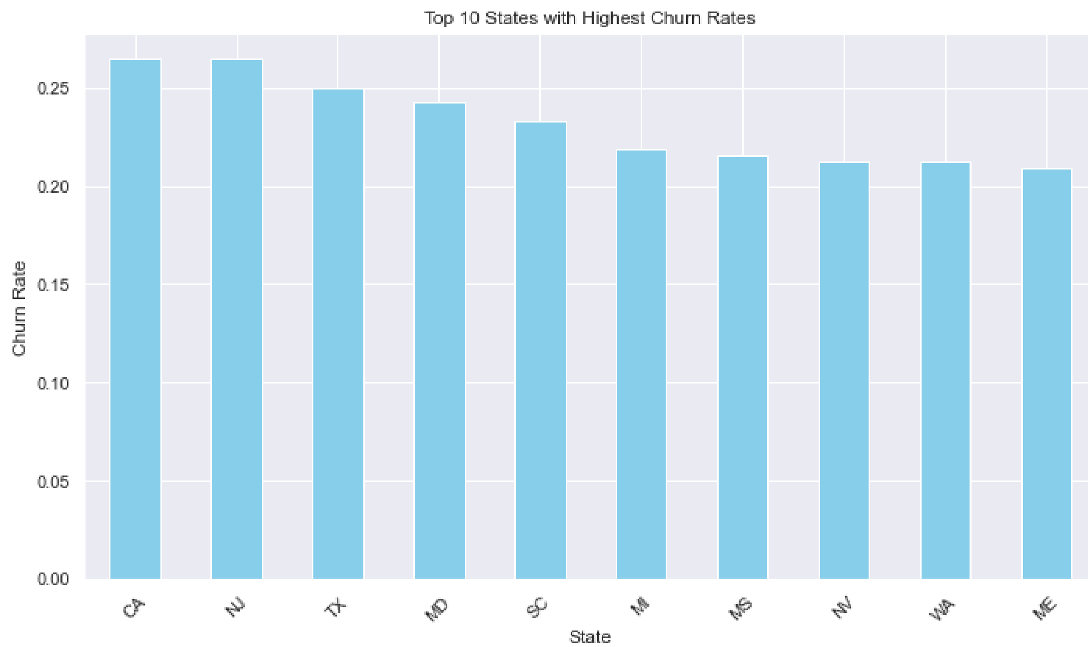
```
state
CA    0.264706
NJ    0.264706
TX    0.250000
MD    0.242857
SC    0.233333
MI    0.219178
MS    0.215385
NV    0.212121
WA    0.212121
ME    0.209677
Name: churn, dtype: float64
```

In [92]:

```
# Plot the bar chart

plt.figure(figsize=(10, 6))
```

In [92]:

```
# Plot the bar chart

plt.figure(figsize=(10, 6))
state_df.head(10).plot(kind='bar', color='skyblue')
plt.title('Top 10 States with Highest Churn Rates')
plt.xlabel('State')
plt.ylabel('Churn Rate')
plt.xticks(rotation=45)
plt.tight_layout()

# Show the plot
plt.show()
```



There are 51 unique state present who have different churn rate.

From the above analysis CA, NJ, TX, MD, SC, MI are the ones who have a higher churn rate of more than 22%

Area Code Analysis

In [93]:

```
# Area Code wise churn Percentage
area_code_churn_perc = (data.groupby(['area code'])['churn'].mean()*100).rese
area_code_churn_perc
```

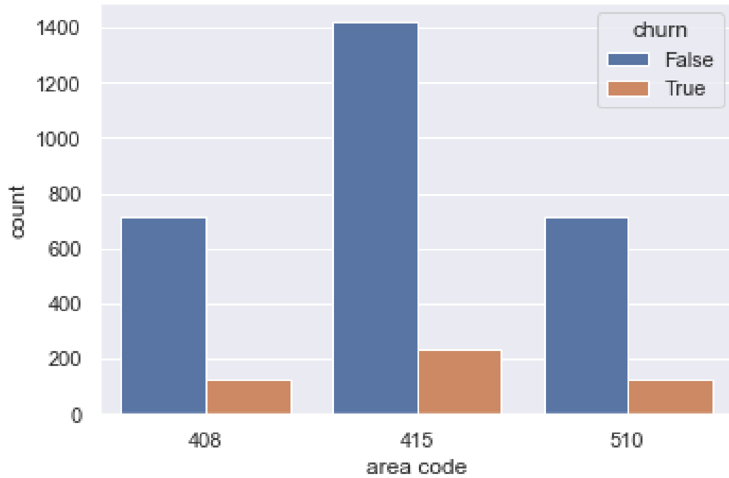
Out[93]:

	area code	churn
0	408	14.558473
1	415	14.259819
2	510	14.880952

In [94]:

```
sns.set(style="darkgrid")
ax = sns.countplot(x='area code', hue="churn", data=data)
plt.show()
```

In [94]:
```
sns.set(style="darkgrid")
ax = sns.countplot(x='area code', hue="churn", data=data)
plt.show()
```



In the above data, we notice that there is only 3 unique value are there i.e 408,415,51

International Plan Analysis

In [95]:
```
data['international plan'].unique()
```

Out[95]: array(['no', 'yes'], dtype=object)

In [96]:
```
data
```

Out[96]:

	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	t c
0	KS	128	415	no	yes	25	265.1	110	45.07	197.4	
1	OH	107	415	no	yes	26	161.6	123	27.47	195.5	
2	NJ	137	415	no	no	0	243.4	114	41.38	121.2	
3	OH	84	408	yes	no	0	299.4	71	50.90	61.9	
4	OK	75	415	yes	no	0	166.7	113	28.34	148.3	
...	...	...	...	...	...	...	...	...	...	...	
3328	AZ	192	415	no	yes	36	156.2	77	26.55	215.5	
3329	WV	68	415	no	no	0	231.1	57	39.29	153.4	
3330	RI	28	510	no	no	0	180.8	109	30.74	288.8	
3331	CT	184	510	yes	no	0	213.8	105	36.35	159.6	
3332	TN	74	415	no	yes	25	234.4	113	39.85	265.9	

3333 rows × 20 columns

In [97]:
```
#Show count value of 'yes','no'

data['international plan'].value_counts()
```

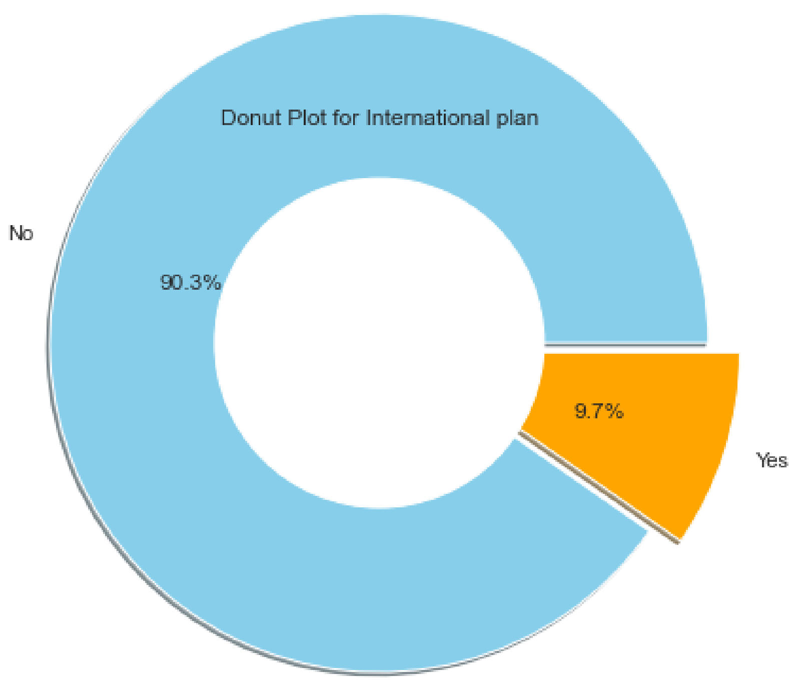
In [97]:
```
#Show count value of 'yes','no'

data['international plan'].value_counts()
```

Out[97]:
```
no     3010
yes     323
Name: international plan, dtype: int64
```

In [98]:
```
#Calculate the International Plan vs Churn percentage

International_plan_data = pd.crosstab(data["international plan"],data["churn"
International_plan_data['Percentage Churn'] = International_plan_data.apply(I
print(International_plan_data)
```

```
churn               False  True  Percentage Churn
international plan
no                   2664   346         11.495017
yes                   186   137         42.414861
```

In [99]:
```
#To get the Donut Plot to analyze International Plan
data_plan = data['international plan'].value_counts()
explode = (0, 0.2)
plt.pie(data_plan, explode = explode,autopct='%1.1f%%',shadow=True,radius = 2
circle = plt.Circle( (0,0), 1, color='white')
p=plt.gcf()
p.gca().add_artist(circle)
plt.title('Donut Plot for International plan')
plt.show()
```



In this analysis, 3010 dont have an international plan, 323 have an international plan.
Correlation Heatmap

In this analysis, 3010 dont have an international plan, 323 have an international plan.
Correlation Heatmap

In [100]:
```
data
```

Out[100]:

	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	t c
0	KS	128	415	no	yes	25	265.1	110	45.07	197.4	
1	OH	107	415	no	yes	26	161.6	123	27.47	195.5	
2	NJ	137	415	no	no	0	243.4	114	41.38	121.2	
3	OH	84	408	yes	no	0	299.4	71	50.90	61.9	
4	OK	75	415	yes	no	0	166.7	113	28.34	148.3	
...	...	...	...	...	...	...	...	...	...	...	
3328	AZ	192	415	no	yes	36	156.2	77	26.55	215.5	
3329	WV	68	415	no	no	0	231.1	57	39.29	153.4	
3330	RI	28	510	no	no	0	180.8	109	30.74	288.8	
3331	CT	184	510	yes	no	0	213.8	105	36.35	159.6	
3332	TN	74	415	no	yes	25	234.4	113	39.85	265.9	

3333 rows × 20 columns

In [117]:
```
corr = data.corr()
corr
```

In [117]:
```
corr = data.corr()
corr
```

Out[117]:

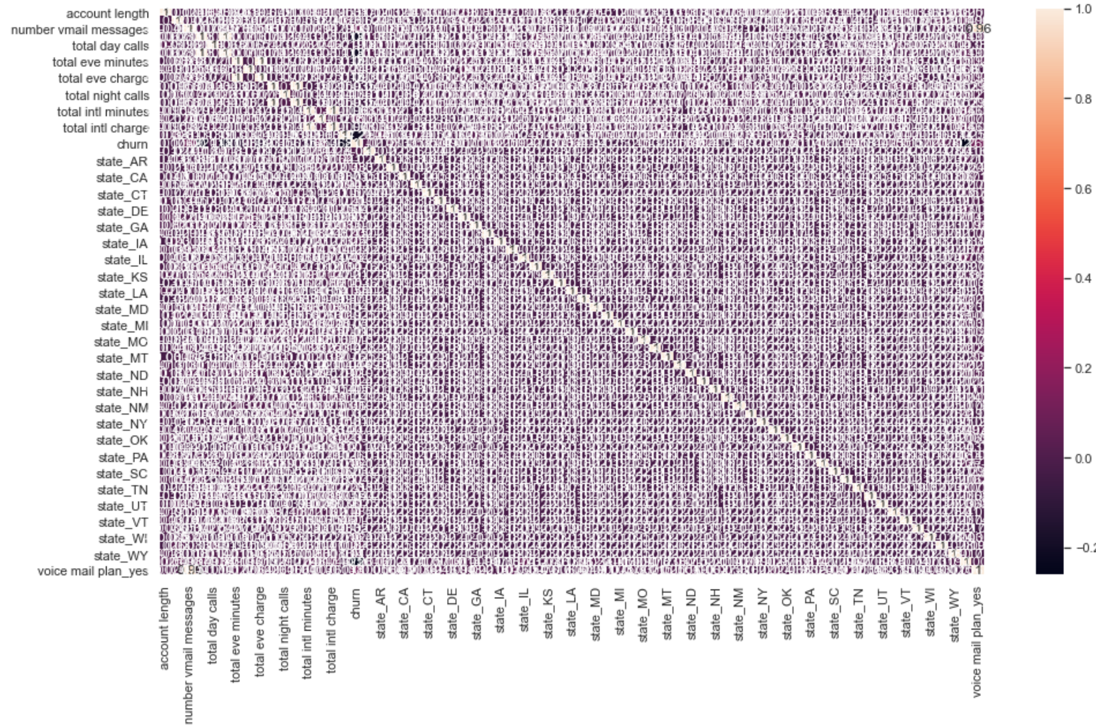
	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total c
account length	1.000000	-0.012463	-0.004628	0.006216	0.038470	0.006214	-0.006757	0.019
area code	-0.012463	1.000000	-0.001994	-0.008264	-0.009646	-0.008264	0.003580	-0.011
number vmail messages	-0.004628	-0.001994	1.000000	0.000778	-0.009548	0.000776	0.017562	-0.005
total day minutes	0.006216	-0.008264	0.000778	1.000000	0.006750	1.000000	0.007043	0.015
total day calls	0.038470	-0.009646	-0.009548	0.006750	1.000000	0.006753	-0.021451	0.006
...	...	...	...	...	...	...	...	
state_WI	-0.008476	0.005189	0.002070	-0.001832	-0.028977	-0.001839	-0.010750	-0.004
state_WV	-0.025631	0.029812	0.008308	-0.019383	0.030234	-0.019380	-0.044919	-0.018
state_WY	0.018058	-0.001039	-0.017748	0.001115	0.013681	0.001107	0.014704	-0.006
international plan_yes	0.024735	0.048551	0.008745	0.049396	0.003755	0.049398	0.019100	0.006
voice mail plan_yes	0.002918	-0.000747	0.956927	-0.001684	-0.011086	-0.001686	0.021545	-0.006

69 rows × 69 columns

In [118]:
```
plt.figure(figsize=(16,9))
sns.heatmap(corr, annot = True)
```

In [118]:
```
plt.figure(figsize=(16,9))
sns.heatmap(corr, annot = True)
```

Out[118]: <AxesSubplot:>



In [101]:
```
data = pd.get_dummies(data, drop_first=True)
```

In [102]:
```
data.head(10)
```

Out[102]:

	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	...	stat
0	128	415	25	265.1	110	45.07	197.4	99	16.78	244.7	...	
1	107	415	26	161.6	123	27.47	195.5	103	16.62	254.4	...	
2	137	415	0	243.4	114	41.38	121.2	110	10.30	162.6	...	
3	84	408	0	299.4	71	50.90	61.9	88	5.26	196.9	...	
4	75	415	0	166.7	113	28.34	148.3	122	12.61	186.9	...	
5	118	510	0	223.4	98	37.98	220.6	101	18.75	203.9	...	
6	121	510	24	218.2	88	37.09	348.5	108	29.62	212.6	...	
7	147	415	0	157.0	79	26.69	103.1	94	8.76	211.8	...	
8	117	408	0	184.5	97	31.37	351.6	80	29.89	215.8	...	
9	141	415	37	258.6	84	43.96	222.0	111	18.87	326.4	...	

10 rows × 69 columns

In [103]:
```
data.columns
```

In [103]:
```
data.columns
```

Out[103]:
```
Index(['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 night charge',
       'total intl minutes', 'total intl calls', 'total intl charge',
       'customer service calls', 'churn', 'state_AL', 'state_AR', 'state_A
Z',
       'state_CA', 'state_CO', 'state_CT', 'state_DC', 'state_DE', 'state_F
L',
       'state_GA', 'state_HI', 'state_IA', 'state_ID', 'state_IL', 'state_I
N',
       'state_KS', 'state_KY', 'state_LA', 'state_MA', 'state_MD', 'state_M
E',
       'state_MI', 'state_MN', 'state_MO', 'state_MS', 'state_MT', 'state_N
C',
       'state_ND', 'state_NE', 'state_NH', 'state_NJ', 'state_NM', 'state_N
V',
       'state_NY', 'state_OH', 'state_OK', 'state_OR', 'state_PA', 'state_R
I',
       'state_SC', 'state_SD', 'state_TN', 'state_TX', 'state_UT', 'state_V
A',
       'state_VT', 'state_WA', 'state_WI', 'state_WV', 'state_WY',
       'international plan_yes', 'voice mail plan_yes'],
      dtype='object')
```

In [104]:
```
#Check Unique Values for each variable.
for i in data.columns:
    print(i, "is", data[i].nunique())
```

In [104]:

```
#Check Unique Values for each variable.
for i in data.columns:
  print(i,"is", data[i].nunique())
```

```
account length is 212
area code is 3
number vmail messages is 46
```

```
account length is 212
area code is 3
number vmail messages is 46
total day minutes is 1667
total day calls is 119
total day charge is 1667
total eve minutes is 1611
total eve calls is 123
total eve charge is 1440
total night minutes is 1591
total night calls is 120
total night charge is 933
total intl minutes is 162
total intl calls is 21
total intl charge is 162
customer service calls is 10
churn is 2
state_AL is 2
state_AR is 2
state_AZ is 2
state_CA is 2
state_CO is 2
state_CT is 2
state_DC is 2
state_DE is 2
state_FL is 2
state_GA is 2
state_HI is 2
state_IA is 2
state_ID is 2
state_IL is 2
state_IN is 2
state_KS is 2
state_KY is 2
state_LA is 2
state_MA is 2
state_MD is 2
state_ME is 2
state_MI is 2
state_MN is 2
state_MO is 2
state_MS is 2
state_MT is 2
state_NC is 2
state_ND is 2
state_NE is 2
state_NH is 2
state_NJ is 2
state_NM is 2
state_NV is 2
state_NY is 2
state_OH is 2
state_OK is 2
state_OR is 2
state_PA is 2
state_RI is 2
state_SC is 2
state_SD is 2
state_UT is 2
state_TN is 2
state_VA is 2
state_TX is 2
state_VT is 2
state_WA is 2
```

```
state_SD is 2
state_TN is 2
state_TX is 2
state_UT is 2
state_VA is 2
state_VT is 2
state_WA is 2
state_WI is 2
state_WV is 2
state_WY is 2
international plan_yes is 2
voice mail plan_yes is 2
```

In [105]:

```
data['churn'] = pd.get_dummies(data['churn'])
```

In [106]:

```
data['churn'].value_counts()
```

Out[106]:

```
1    2850
0     483
Name: churn, dtype: int64
```

In [107]:

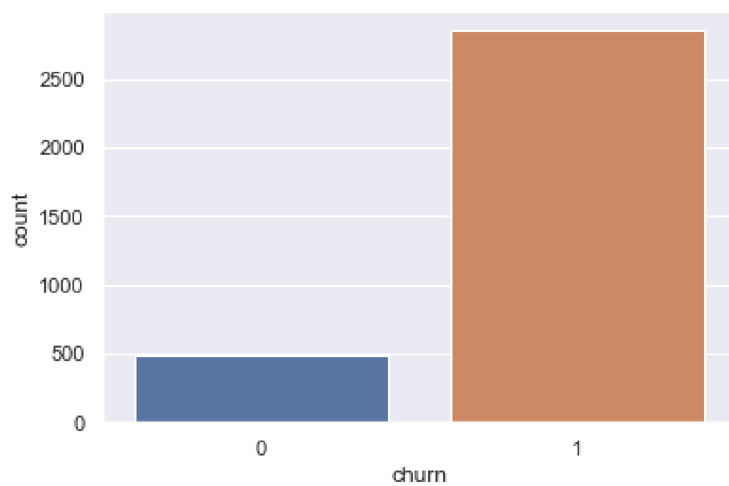
```
import seaborn as sns
```

In [108]:

```
sns.countplot(data['churn'])
```

```
C:\Users\Allan\anaconda3\envs\learn-env\lib\site-packages\seaborn\_decorato
rs.py:36: FutureWarning: Pass the following variable as a keyword arg: x. F
rom version 0.12, the only valid positional argument will be `data`, and pa
ssing other arguments without an explicit keyword will result in an error o
r misinterpretation.
  warnings.warn(
```

Out[108]: <AxesSubplot:xlabel='churn', ylabel='count'>



In [109]:

```
X = data.drop('churn', axis = 1)
y = data['churn']
```

Handling Imbalanced data with SMOTE

In [113]:

```
#SMOTE technique to deal with unbalanced data problem

from imblearn.over_sampling import SMOTE
```

In [113]:
```
#SMOTE technique to deal with unbalanced data problem

from imblearn.over_sampling import SMOTE
```

In [114]:
```
X_res, y_res = SMOTE().fit_resample(X, y)
```

In [115]:
```
y_res.value_counts()
```

Out[115]:
```
1    2850
0    2850
Name: churn, dtype: int64
```

In [ ]:
```

```

Splitting the dataset into training set and test set

In [119]:
```
from sklearn.model_selection import train_test_split
```

In [120]:
```
X_train,X_test,y_train,y_test = train_test_split(X_res,y_res,test_size=0.2,ra
```

In [121]:
```
X_test.shape
```

Out[121]:
```
(1140, 68)
```

Feature Scaling

In [122]:
```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
```

In [123]:
```
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [124]:
```
X_train
```

Out[124]:
```
array([[ 1.57038483, -0.51181663, -0.53516577, ..., -0.12486072,
        -0.30881049, -0.4783088 ],
       [ 1.19782731, -0.51181663, -0.53516577, ..., -0.12486072,
        -0.30881049, -0.4783088 ],
       [-0.63834908,  1.74949111,  1.83419115, ..., -0.12486072,
        -0.30881049,  2.09069958],
       ...,
       [-0.10612404, -0.6784393 , -0.53516577, ..., -0.12486072,
        -0.30881049, -0.4783088 ],
       [ 0.53254601, -0.63083282, -0.53516577, ..., -0.12486072,
        -0.30881049, -0.4783088 ],
       [ 1.8098861 , -0.51181663, -0.53516577, ..., -0.12486072,
        -0.30881049, -0.4783088 ]])
```

```
[ 1.8098861 , -0.31181603, -0.55516577, ..., -0.12486072,
 -0.30881049, -0.4783088 ]])
```

Apply Machine Learning Models

Logistic Regression

In [131]:
```
from sklearn.linear_model import LogisticRegression
```

In [132]:
```
log = LogisticRegression()
```

In [133]:
```
log.fit(X_train, y_train)
```

Out[133]: LogisticRegression()

In [227]:
```
y_pred = log.predict(X_test)
```

In [230]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1
```

In [160]:
```
acc = accuracy_score(y_test, y_pred)
acc
```

Out[160]: 0.9087719298245615

In [231]:
```
prec = precision_score(y_test, y_pred)
prec
```

Out[231]: 0.8897893030794165

In [232]:
```
rel = recall_score(y_test, y_pred)
rel
```

Out[232]: 0.9384615384615385

In [233]:
```
f1  = f1_score(y_test, y_pred)
f1
```

Out[233]: 0.9134775374376041

In [164]:
```
import pandas as pd

results = pd.DataFrame([['Logistic Regression', acc, prec, rel, f1]],
```

In [164]:
```
import pandas as pd

results = pd.DataFrame([['Logistic Regression', acc, prec, rel, f1]],
                       columns=['Model', 'Accuracy', 'Precision', 'Recall', '
results
```

Out[164]:

	Model	Accuracy	Precision	Recall	F1
0	Logistic Regression	0.908772	0.889789	0.938462	0.913478

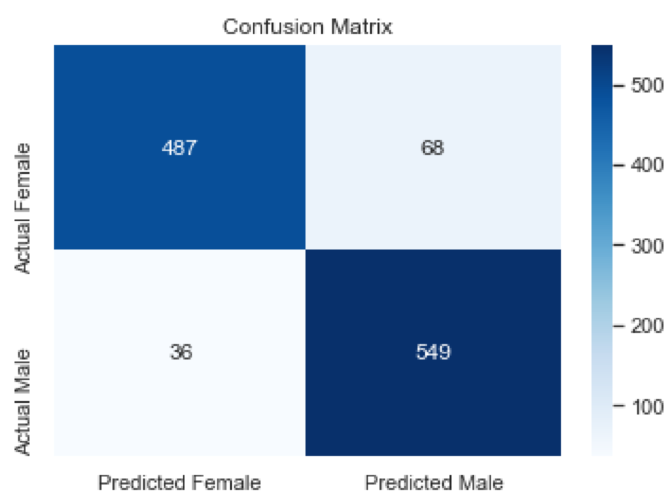
In [185]:
```
from sklearn.metrics import confusion_matrix, classification_report

conf_matrix = confusion_matrix(y_test, y_pred)

print(conf_matrix)
```

```
[[487  68]
 [ 36 549]]
```

In [186]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.93      0.88      0.90       555
           1       0.89      0.94      0.91       585

    accuracy                           0.91      1140
   macro avg       0.91      0.91      0.91      1140
weighted avg       0.91      0.91      0.91      1140
```

In [187]:
```
# Display the confusion matrix using seaborn
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", xticklabels=['Pre
plt.title('Confusion Matrix')
plt.show()
```



Model accuracy is 90.1%, which isn't bad. F1 score is only 91.3%

Predicted Female Predicted Male

Model accuracy is 90.1%, which isn't bad. F1 score is only 91.3%

Support Vector Classifier

In [145]:
```
from sklearn import svm
```

In [146]:
```
svm = svm.SVC()
```

In [147]:
```
svm.fit(X_train, y_train)
```

Out[147]:
```
SVC()
```

In [174]:
```
y_pred_svc = svm.predict(X_test)
```

In [175]:
```
acc = accuracy_score(y_test, y_pred_svc)
acc
```

Out[175]:
```
0.8991228070175439
```

In [176]:
```
prec = precision_score(y_test, y_pred_svc)
prec
```

Out[176]:
```
0.8528528528528528
```

In [177]:
```
rel = recall_score(y_test, y_pred_svc)
rel
```

Out[177]:
```
0.9709401709401709
```

In [178]:
```
f1  = f1_score(y_test, y_pred_svc)
f1
```

Out[178]:
```
0.9080735411670664
```

In [188]:
```

results2 = pd.DataFrame([['SVC', acc, prec, rel, f1]],
                       columns=['Model', 'Accuracy', 'Precision', 'Recall', '
results2
```

Out[188]:

	Model	Accuracy	Precision	Recall	F1
0	SVC	0.899123	0.852853	0.97094	0.908074

In [234]:
```
conf_matrix_svc = confusion_matrix(y_test, y_pred_svc)

print(conf_matrix_svc)
```

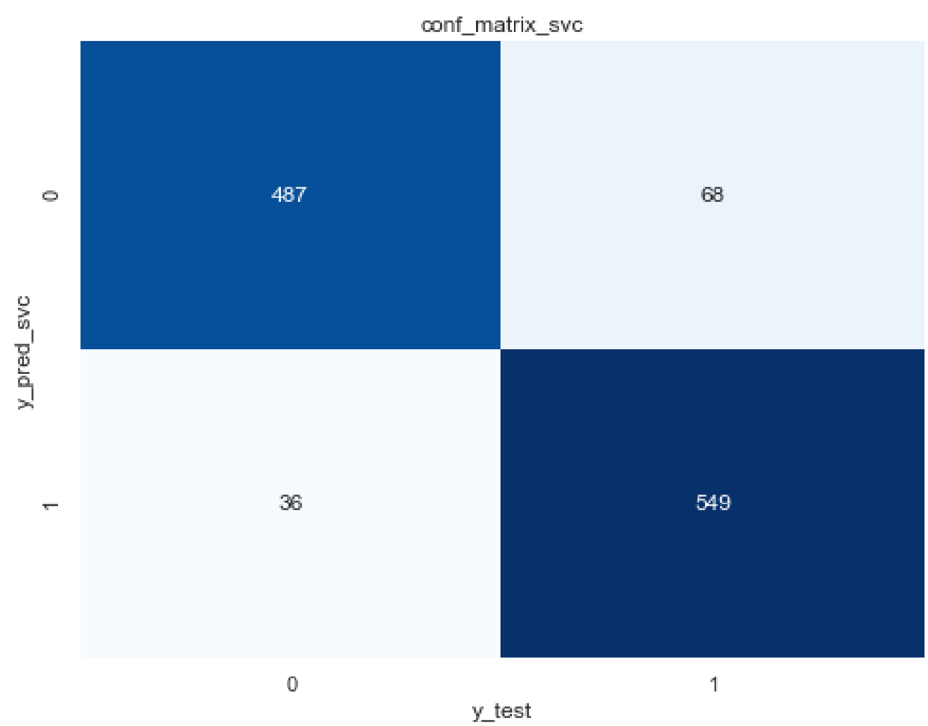
In [234]:
```
conf_matrix_svc = confusion_matrix(y_test, y_pred_svc)

print(conf_matrix_svc)
```

```
[[457  98]
 [ 17 568]]
```

In [235]:
```
print(classification_report(y_test, y_pred_svc))
```

```
              precision    recall  f1-score   support

           0       0.96      0.82      0.89       555
           1       0.85      0.97      0.91       585

    accuracy                           0.90      1140
   macro avg       0.91      0.90      0.90      1140
weighted avg       0.91      0.90      0.90      1140
```

In [193]:
```
plt.figure(figsize=(8, 6))  # Set the figure size as needed
sns.heatmap(conf_matrix_svc, annot=True, fmt='d', cmap='Blues', cbar=False)

# Add labels and a title
plt.xlabel('y_test')
plt.ylabel('y_pred_svc')
plt.title('conf_matrix_svc')

# Show the heatmap
plt.show()
```



KNeighbors Classifier

KNeighbors Classifier

In [150]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [152]:
```
knn = KNeighborsClassifier()
```

In [153]:
```
knn.fit(X_train, y_train)
```

Out[153]:
```
KNeighborsClassifier()
```

In [213]:
```
pred_knn = knn.predict(X_test)
```

In [214]:
```
acc = accuracy_score(y_test, pred_knn)
acc
```

Out[214]:
```
0.9105263157894737
```

In [215]:
```
prec = precision_score(y_test, pred_knn)
prec
```

Out[215]:
```
0.8732612055641422
```

In [216]:
```
rel = recall_score(y_test, pred_knn)
rel
```

Out[216]:
```
0.9658119658119658
```

In [217]:
```
f1  = f1_score(y_test, pred_knn)
f1
```

Out[217]:
```
0.9172077922077922
```

In [218]:
```
print(classification_report(y_test, pred_knn))
```

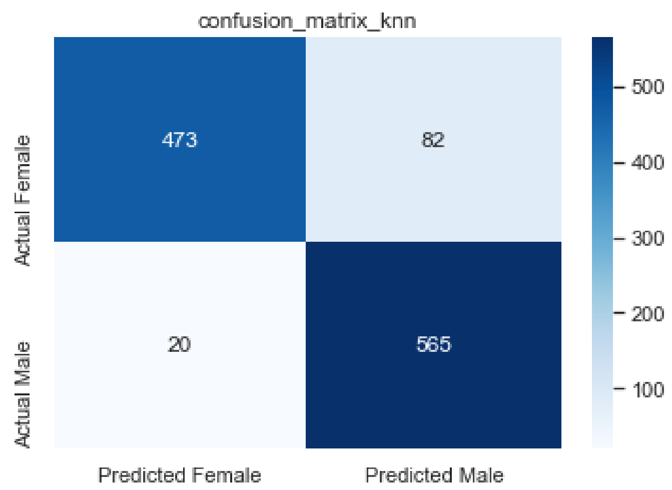
```
              precision    recall  f1-score   support

           0       0.96      0.85      0.90       555
           1       0.87      0.97      0.92       585

    accuracy                           0.91      1140
   macro avg       0.92      0.91      0.91      1140
weighted avg       0.92      0.91      0.91      1140
```

In [219]:
```
confusion_matrix_knn = confusion_matrix(y_test, pred_knn)
confusion_matrix_knn
```

Out[219]:
```
array([[473,  82],
       [ 20, 565]], dtype=int64)
```

In [220]:
```
# Display the confusion matrix using seaborn
sns.heatmap(confusion_matrix_knn, annot=True, fmt="d", cmap="Blues", xticklab
plt.title('confusion matrix knn')
```

In [220]:
```
# Display the confusion matrix using seaborn
sns.heatmap(confusion_matrix_knn, annot=True, fmt="d", cmap="Blues", xticklab
plt.title('confusion_matrix_knn')
plt.show()
```



DecisionTreeClassifier

In [194]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [195]:
```
dt  = DecisionTreeClassifier()
```

In [196]:
```
dt.fit(X_train, y_train)
```

Out[196]: DecisionTreeClassifier()

In [201]:
```
y_pred_dt = dt.predict(X_test)
```

In [202]:
```
accuracy_score(y_test, y_pred_dt)
```

Out[202]: 0.8868421052631579

In [203]:
```
precision_score(y_test, y_pred_dt)
```

Out[203]: 0.9175824175824175

In [204]:
```
recall_score(y_test, y_pred_dt)
```

Out[204]: 0.8564102564102564

In [205]:
```
f1_score(y_test, y_pred_dt)
```

Out[205]: 0.8859416445623343

In [206]:
```
print(classification_report(y_test, y_pred_dt))
```

Out[205]: 0.8859416445623343

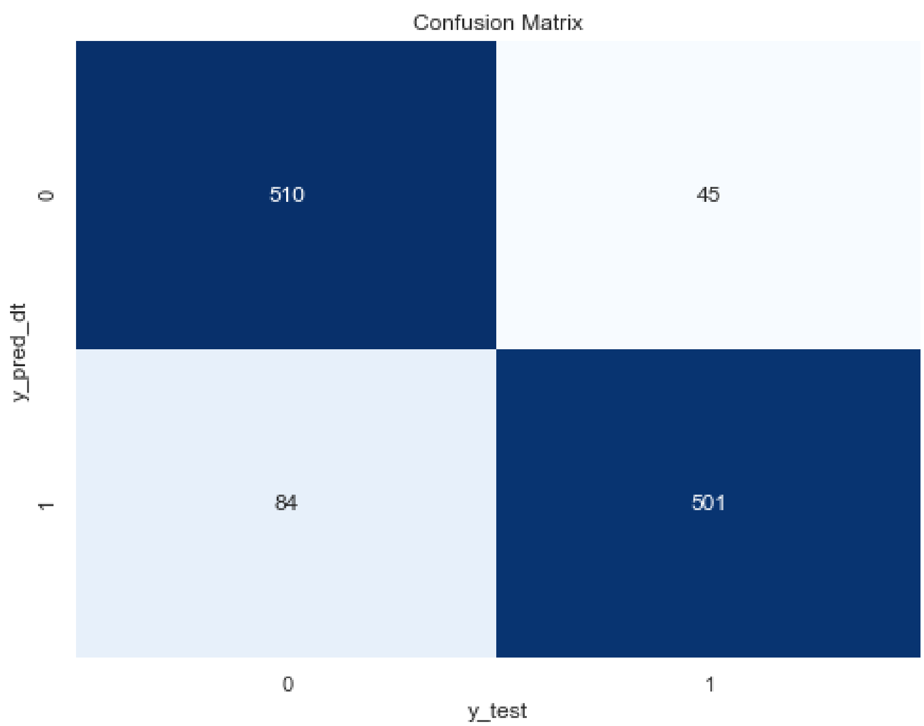
In [206]:
```
print(classification_report(y_test, y_pred_dt))
```

```
              precision    recall  f1-score   support

           0       0.86      0.92      0.89       555
           1       0.92      0.86      0.89       585

    accuracy                           0.89      1140
   macro avg       0.89      0.89      0.89      1140
weighted avg       0.89      0.89      0.89      1140
```

In [208]:
```
confusion_matrix_dtc = confusion_matrix(y_test, y_pred_dt)
confusion_matrix_dtc
```

Out[208]:
```
array([[510,  45],
       [ 84, 501]], dtype=int64)
```

In [210]:
```
# Create a heatmap of the confusion matrix
plt.figure(figsize=(8, 6))  # Set the figure size as needed
sns.heatmap(confusion_matrix_dtc, annot=True, fmt='d', cmap='Blues', cbar=Fal

# Add labels and a title
plt.xlabel('y_test')
plt.ylabel('y_pred_dt')
plt.title('Confusion Matrix')

# Show the heatmap
plt.show()
```

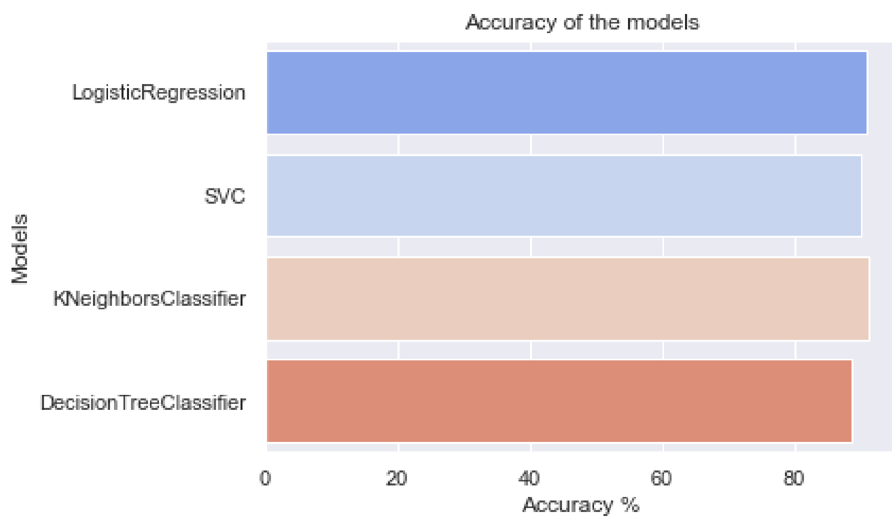


Model Comparisons - Accuracy

Model Comparisons - Accuracy

In [221]:

```
models = [log,svm,knn, dt]

result = []
results = pd.DataFrame(columns= ["Models","Accuracy"])

for model in models:
    names = model.__class__.__name__
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    result = pd.DataFrame([[names, accuracy*100]], columns= ["Models","Accura
    results = results.append(result)


sns.barplot(x= 'Accuracy', y = 'Models', data=results, palette="coolwarm")
plt.xlabel('Accuracy %')
plt.title('Accuracy of the models');
```



In [222]:

```
results.sort_values(by="Accuracy",ascending=False)
```

Out[222]:

	Models	Accuracy
0	KNeighborsClassifier	91.052632
0	LogisticRegression	90.877193
0	SVC	89.912281
0	DecisionTreeClassifier	88.684211

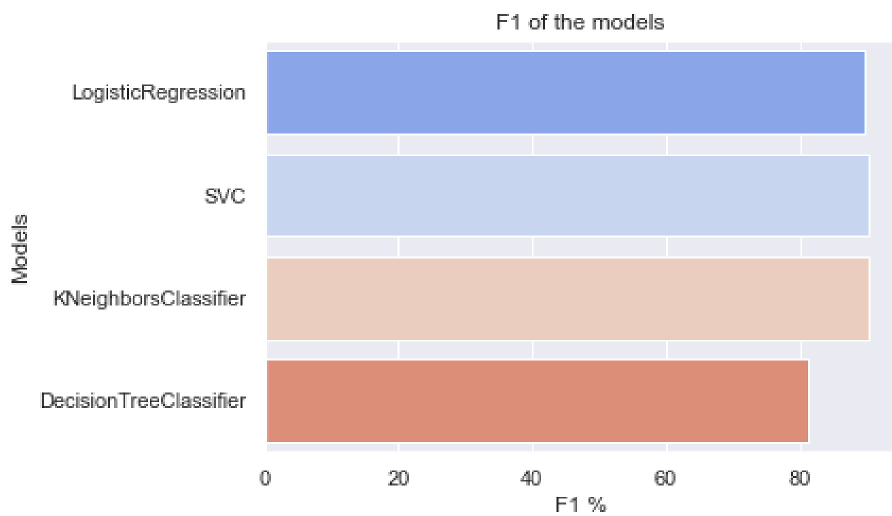
Accuracy allows one to measure the total number of prediction a model gets right. The best performing model will have the highest accuracy. Of the four models tested, KNeighborsClassifier classifier has the highest accuracy.

Model Comparisons - F1 Score

Model Comparisons - F1 Score

In [224]:
```
from sklearn.model_selection import train_test_split,cross_val_score
```

In [236]:
```
models = [log,svm,knn, dt]

result = []
results = pd.DataFrame(columns= ["Models","F1"])

for model in models:
    names = model.__class__.__name__
    y_pred = model.predict(X_test)
    f1 = cross_val_score(model,X_test,y_test,cv=10,scoring="f1_weighted").mea
    result = pd.DataFrame([[names, f1*100]], columns= ["Models","F1"])
    results = results.append(result)

sns.barplot(x= 'F1', y = 'Models', data=results, palette="coolwarm")
plt.xlabel('F1 %')
plt.title('F1 of the models');
```



In [238]:
```
results.sort_values(by="F1",ascending=False)
```

Out[238]:

	Models	F1
0	KNeighborsClassifier	90.092238
0	SVC	90.079953
0	LogisticRegression	89.543552
0	DecisionTreeClassifier	81.279757

F1 score measures the harmonic mean between precision and recall It is a value between 0 and 1, with 1 being a perfect score and an indication everything was observed correctly. KNeighborsClassifier classifier had the highest F1 score.

Conclusion

Conclusion

The company should improve on customer retention and reduce customer churn. This project analyzed a churn dataset to identify the main factors contributing to churn and gain valuable insights.

Through exploratory data analysis, we were able to gain insight into the Syrialtel churn dataset.

The churn pie chart reveals that out of the total dataset, 85.5% (2,850 customers) have not churned, while 14.5% (483 customers) have churned. This indicates a notable increase in customer churn and necessitates prompt attention.

CA, NJ, TX, MD, SC, MI are the states who have a higher churn rate of more than 22%.

The area code may not be relevant and can be excluded

In [ ]: