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Predicting Customer Churn

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Acknowledgement

I take this opportunity to express my profound gratitude and deep regards to my faculty (**Anubhav Chaturvedi**) for his exemplary guidance, monitoring and constant encouragement throughout the course of this project. The blessing, help and guidance given by him/her time to time shall carry me a long way in the journey of life on which I am about to embark.

I am obliged to my project team members for the valuable information provided by them in their respective fields. I am grateful for their cooperation during the period of my assignment.

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Project Objective

- **The Business Problem:** Predicting Churn at a Telecom Service Provider
- **Project Objective:** Our objective is to understand which of the factors contribute most to customer churn and to predict which customers will potentially churn based on service-related factors.
- **About the Dataset**
 - It consists of information for 5,000 customers and includes independent variables such as account length, number of voicemail messages, total daytime charge, total evening charge, total night charge, total international charge, and number of customer service calls. The dependent variable in the dataset is whether the customer churned or not, which is indicated by a 1 for "yes" and 0 for "no."

Project Scope

Following is the description of all column of the dataset:

- It consists of information for 5,000 customers
- account_length-account length
- number_vmail_messages-number of voicemail messages
- total_day_charge-total daytime charge
- total_eve_charge-total evening charge
- total_night_charge-total night charge
- total_intl_charge-total international charge
- number_customer_service_calls-number of customer service calls.
- churn-The dependent variable in the dataset is whether the customer churned or not, which is indicated by a 1 for "yes" and 0 for "no."

Data description

	number_vmail_messages	total_day_charge	total_eve_charge	total_night_charge	total_intl_charge	number_customer_service_calls	churn
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000
mean	7.755200	30.649668	17.054322	9.017732	2.771196	1.570400	0.141400
std	13.546393	9.162069	4.296843	2.273763	0.745514	1.306363	0.348469
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	24.430000	14.140000	7.510000	2.300000	1.000000	0.000000
50%	0.000000	30.620000	17.090000	9.020000	2.780000	1.000000	0.000000
75%	17.000000	36.750000	19.900000	10.560000	3.240000	2.000000	0.000000
max	52.000000	59.760000	30.910000	17.770000	5.400000	9.000000	1.000000

Model Building

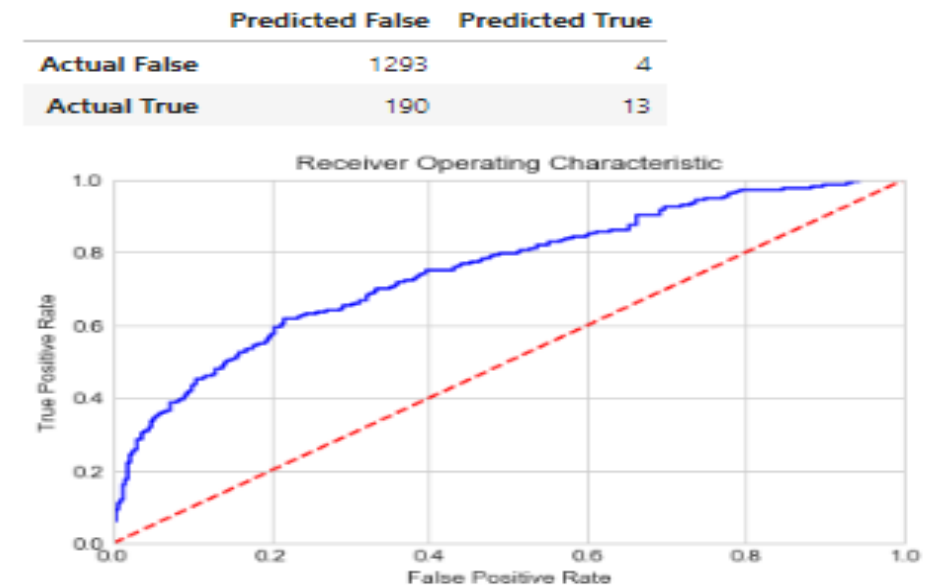
Logistic Regression

- ✓ Logistic regression is used to describe data and to explain the relationship between one dependent binary variable and one or more nominal, ordinal, interval or ratio-level independent variables.

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,  
    intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,  
    penalty='l2', random_state=None, solver='liblinear', tol=0.0001,  
    verbose=0, warm_start=False)
```

	precision	recall	f1-score	support
0	0.87	1.00	0.93	1297
1	0.76	0.06	0.12	203
avg / total	0.86	0.87	0.82	1500

ROC Curve



Model Building

KNN

- ✓ K nearest neighbors is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions).

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',  
                    metric_params=None, n_jobs=1, n_neighbors=1, p=2,  
                    weights='uniform')
```

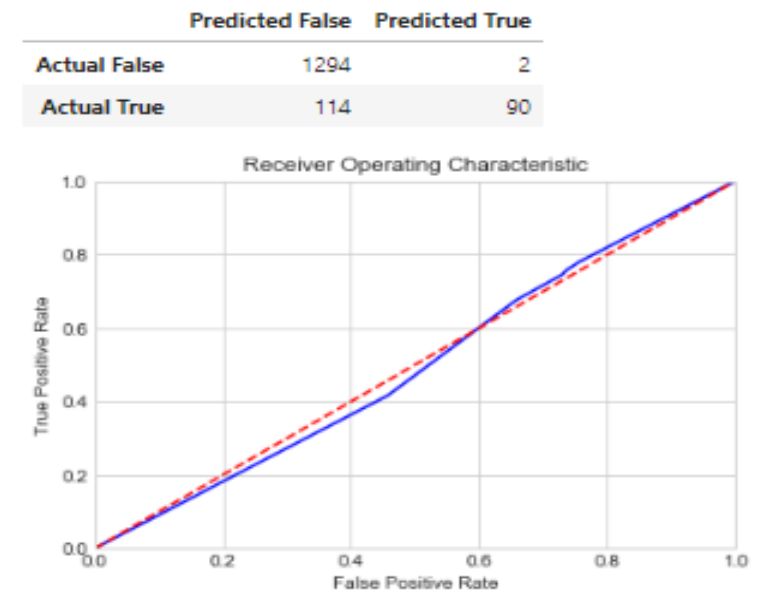
WITH K=8

```
[[1282    5]  
 [ 134   79]]
```

	precision	recall	f1-score	support
0	0.91	1.00	0.95	1287
1	0.94	0.37	0.53	213
avg / total	0.91	0.91	0.89	1500

Accuracy of KNN classifier : 0.9073333333333333

ROC Curve



Model Building

Naïve Bayes

- ✓ A naive Bayes classifier is an algorithm that uses Bayes' theorem to classify objects. Naive Bayes classifiers assume strong, or naive, independence between attributes of data points.

For Account Length	precision	recall	f1-score	support
0	0.86	1.00	0.92	3677
1	0.00	0.00	0.00	616
avg / total	0.73	0.86	0.79	4293

number_vmail_messages	precision	recall	f1-score	support
0	0.86	1.00	0.92	3677
1	0.00	0.00	0.00	616
avg / total	0.73	0.86	0.79	4293

total_day_charge	precision	recall	f1-score	support
0	0.86	1.00	0.92	3677
1	0.00	0.00	0.00	616
avg / total	0.74	0.85	0.79	4293

total_eve_charge	precision	recall	f1-score	support
0	0.86	1.00	0.92	3677
1	0.00	0.00	0.00	616
avg / total	0.73	0.86	0.79	4293

total_night_charge	precision	recall	f1-score	support
0	0.86	1.00	0.92	3677
1	0.00	0.00	0.00	616
avg / total	0.73	0.86	0.79	4293

total_intl_charge	precision	recall	f1-score	support
0	0.86	1.00	0.92	3677
1	0.00	0.00	0.00	616
avg / total	0.73	0.86	0.79	4293

number_customer_service_calls	precision	recall	f1-score	support
0	0.86	0.99	0.92	3677
1	0.14	0.01	0.02	616
avg / total	0.75	0.85	0.79	4293

Code

```
In [1]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve
import matplotlib
import matplotlib.pyplot as plt
from IPython.display import display, HTML
```

Preparing the Data

```
In [2]: ch=pd.read_csv("churn.csv")
ch1=pd.read_csv("churn.csv")
ch.head()
```

```
Out[2]:
```

	account_length	number_vmail_messages	total_day_charge	total_eve_charge	total_night_charge	total_intl_charge	number_customer_service_calls	churn
0	128	25	45.07	16.78	11.01	2.70	1	0
1	107	26	27.47	16.62	11.45	3.70	1	0
2	137	0	41.38	10.30	7.32	3.29	0	0
3	84	0	50.90	5.26	8.86	1.78	2	0
4	75	0	28.34	12.61	8.41	2.73	3	0

```
In [3]: ch.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 5000 entries, 0 to 4999  
Data columns (total 8 columns):  
account_length      5000 non-null int64  
number_vmail_messages  5000 non-null int64  
total_day_charge    5000 non-null float64  
total_eve_charge    5000 non-null float64  
total_night_charge  5000 non-null float64  
total_intl_charge   5000 non-null float64  
number_customer_service_calls  5000 non-null int64  
churn              5000 non-null int64  
dtypes: float64(4), int64(4)  
memory usage: 312.6 KB
```

```
In [4]: ch.describe()
```

Out[4]:

	account_length	number_vmail_messages	total_day_charge	total_eve_charge	total_night_charge	total_intl_charge	number_customer_service_calls	churn
count	5000.00000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000
mean	100.25860	7.755200	30.649668	17.054322	9.017732	2.771196	1.570400	0.141400
std	39.69456	13.546393	9.162069	4.296843	2.273763	0.745514	1.306363	0.348469
min	1.00000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	73.00000	0.000000	24.430000	14.140000	7.510000	2.300000	1.000000	0.000000
50%	100.00000	0.000000	30.620000	17.090000	9.020000	2.780000	1.000000	0.000000
75%	127.00000	17.000000	36.750000	19.900000	10.560000	3.240000	2.000000	0.000000
max	243.00000				17.770000	5.400000	9.000000	1.000000



EDA

```
In [5]: #Distribution of churn
print('Distribution of churn : ')
print(ch['churn'].value_counts())
print('\n\nProportion for Distribution of churn : ')
print(ch['churn'].value_counts(normalize=True))
```

Distribution of churn :

0 4293

1 707

Name: churn, dtype: int64

Proportion for Distribution of churn :

0 0.8586

1 0.1414

Name: churn, dtype: float64

```
In [6]: #what is the proportion of churned users in our dataframe?
ch['churn'].mean()
```

Out[6]: 0.1414

In [7]: *#What are average values of numerical variables for churned users?*

```
ch[ch['churn'] == 1].mean()
```

Out[7]:

account_length	102.332390
number_vmail_messages	4.496464
total_day_charge	35.338416
total_eve_charge	17.999562
total_night_charge	9.273607
total_intl_charge	2.887426
number_customer_service_calls	2.254597
churn	1.000000

dtype: float64

In [8]: *#maximum day,evening,night,international charges who are loyal*

```
print("Maximum Day charge : ",ch[(ch['churn'] == 0)][['total_day_charge']].max())  
print("Maximum Evening charge : ",ch[(ch['churn'] == 0)][['total_eve_charge']].max())  
print("Maximum Night charge : ",ch[(ch['churn'] == 0)][['total_night_charge']].max())  
print("Maximum International charge : ",ch[(ch['churn'] == 0)][['total_intl_charge']].max())
```

Maximum Day charge : 53.65

Maximum Evening charge : 30.75

Maximum Night charge : 17.77

Maximum Intern:

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```
In [9]: #grouping the data according to the values of the Churn variable and display statistics of all columns in each group:
col= ['number_vmail_messages', 'total_day_charge', 'total_eve_charge', 'total_night_charge', 'total_intl_charge', 'number_customer_service_calls']
ch.groupby(['churn'])[col].describe(percentiles=[])
```

```
Out[9]:
```

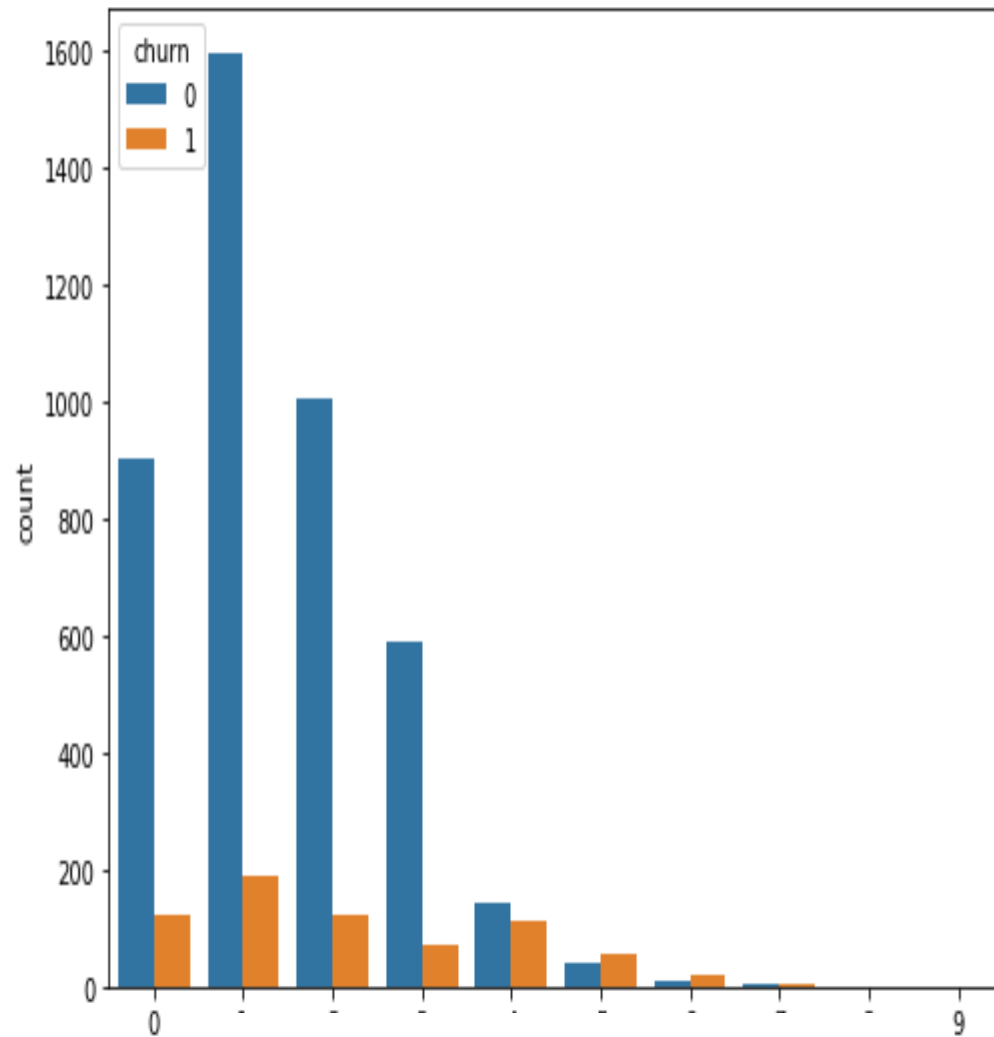
	number_vmail_messages						total_day_charge						...	total_intl_charge						number_customer_service_calls					
	count	mean	std	min	50%	max	count	mean	std	min	...	std	min	50%	max	count	mean	std	min	50%	max				
churn																									
0	4293.0	8.291870	13.809408	0.0	0.0	52.0	4293.0	29.877494	8.437810	0.0	...	0.742443	0.0	2.78	5.32	4293.0	1.457722	1.164236	0.0	1.0	8.0				
1	707.0	4.496464	11.297719	0.0	0.0	48.0	707.0	35.338416	11.658195	0.0	...	0.754057	0.0	2.86	5.40	707.0	2.254597	1.815956	0.0	2.0	9.0				

2 rows × 36 columns

```
In [10]: #lets see how number of customer service calls effect churn
pd.crosstab(ch['churn'], ch['number_customer_service_calls'], margins=True)
```

```
Out[10]: number_customer_service_calls 0 1 2 3 4 5 6 7 8 9 All
churn
0 902 1596 1005 592 141 38 12 6 1 0 4293
1 121 190 122 73 111 58 22 7 1 2 707
2 2 2 5000
```

```
In [11]: plt.rcParams['figure.figsize'] = (8, 6)
sns.countplot(x='number_customer_service_calls', hue='churn', data=ch);
```



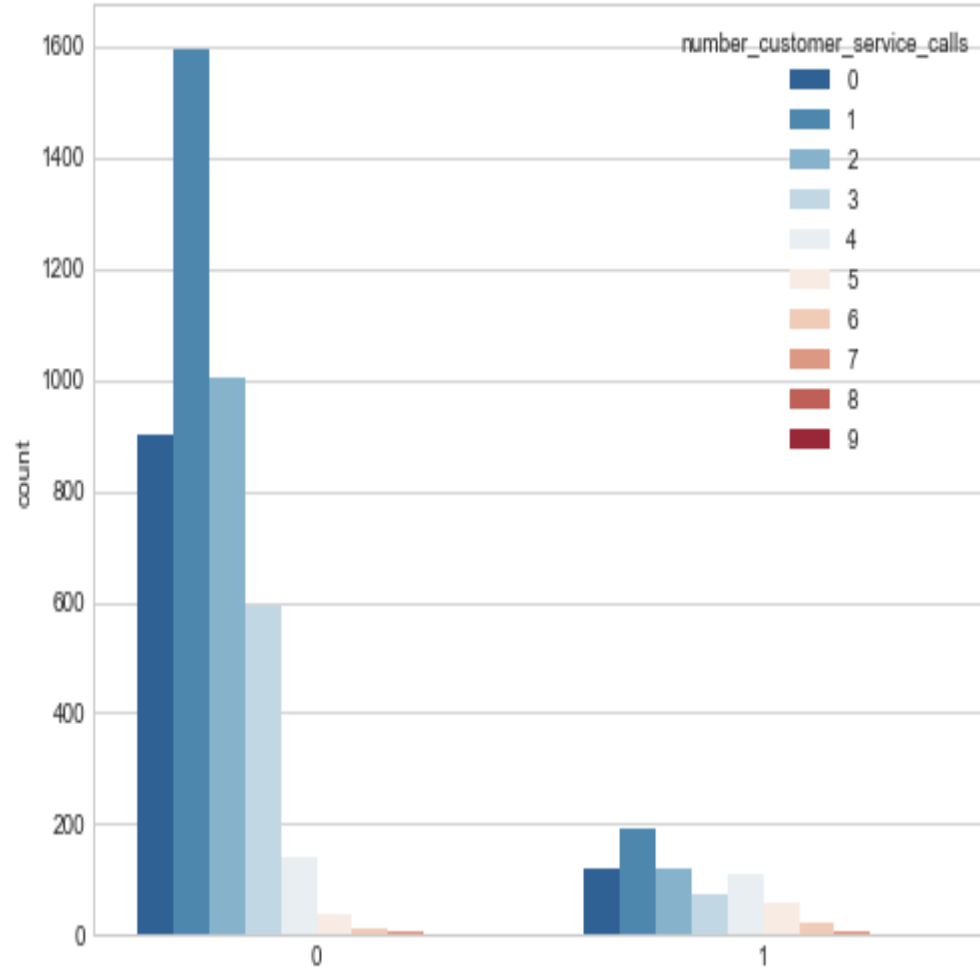
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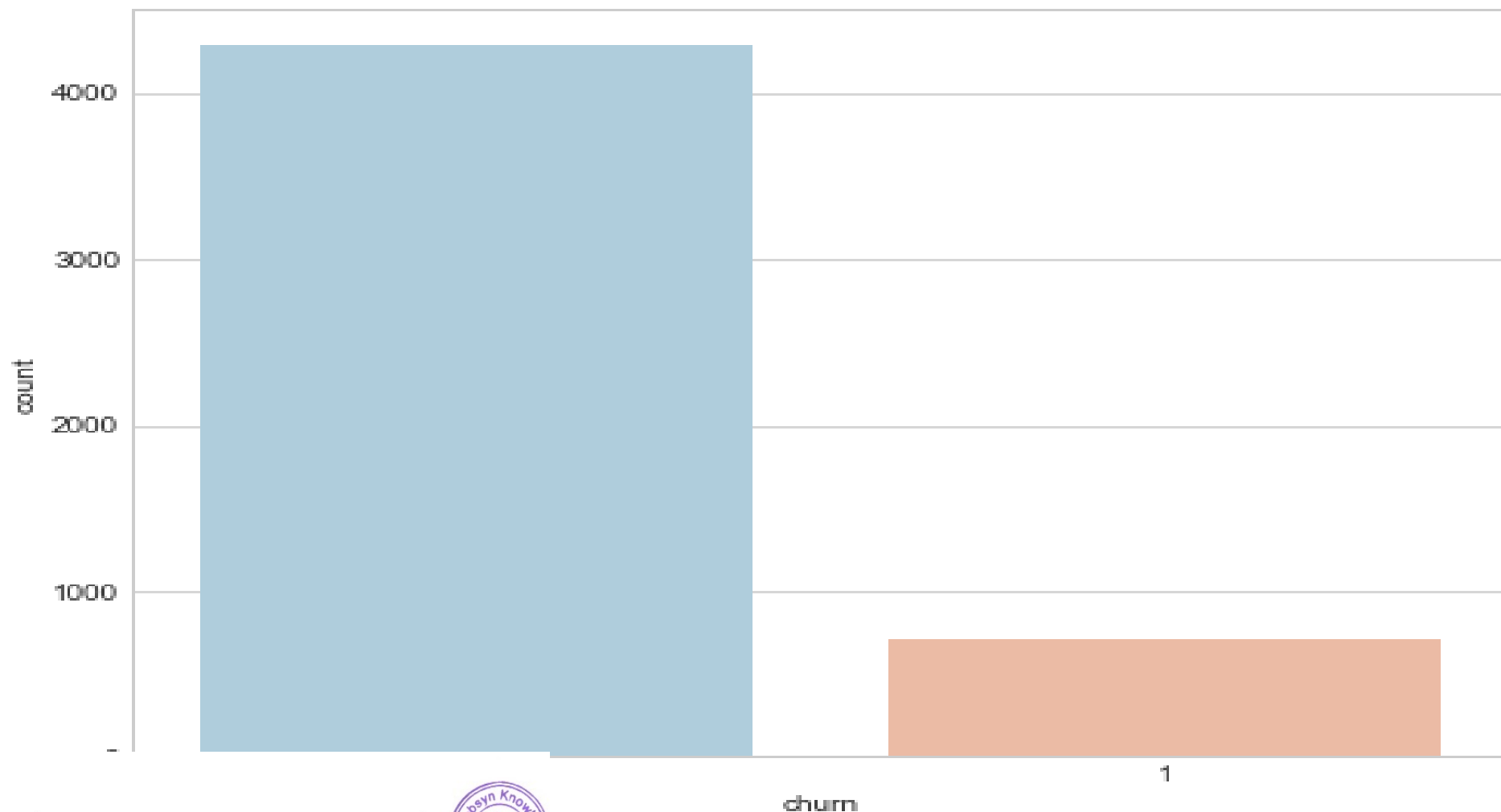
```
In [12]: sns.set_style('whitegrid')
sns.countplot(x='churn',hue='number_customer_service_calls',data=ch,palette='RdBu_r')
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0xef071c07b8>



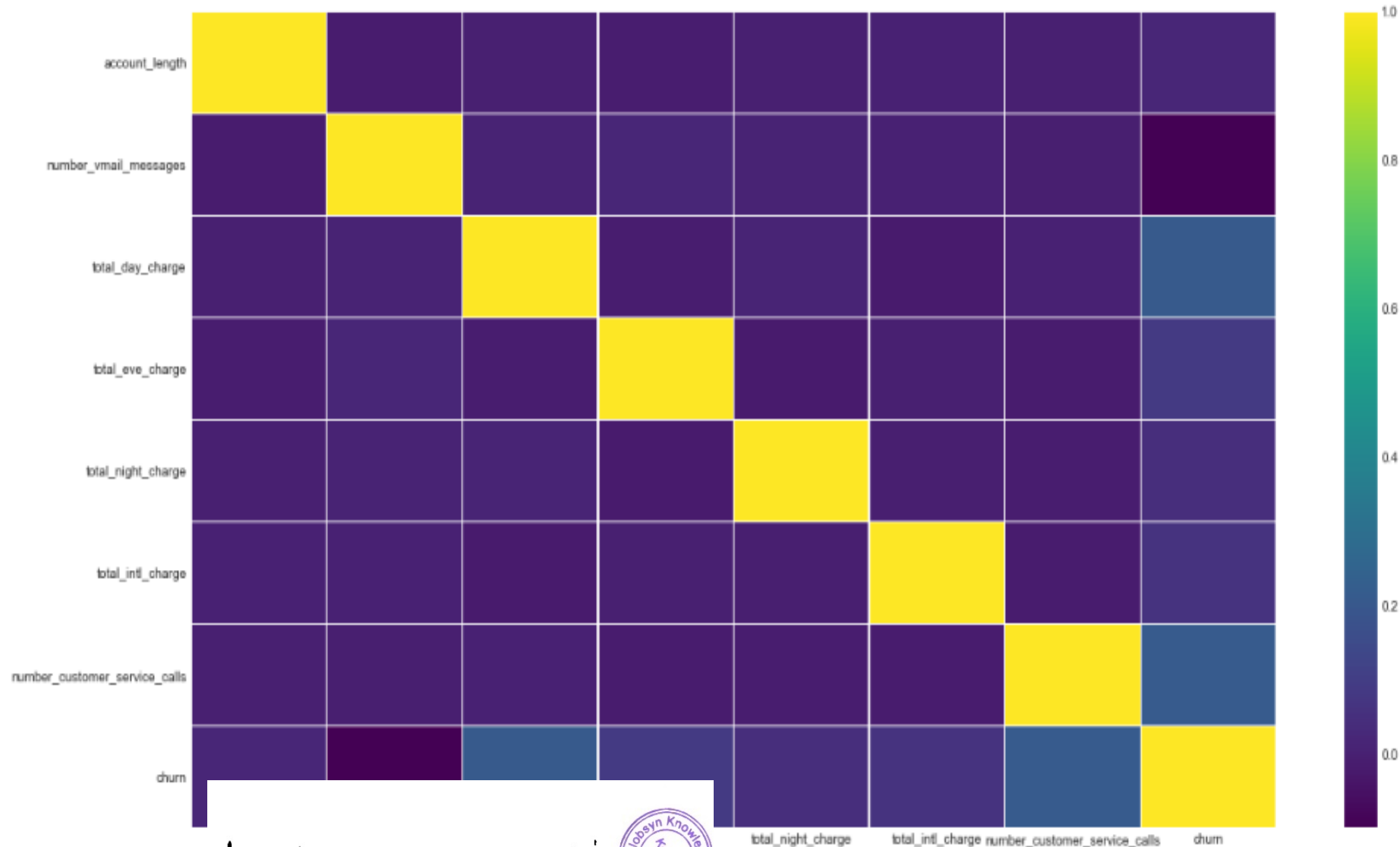
```
In [13]: sns.set_style('whitegrid')
sns.countplot(x='churn',data=ch,palette='RdBu_r')
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0xef077ceb70>
```



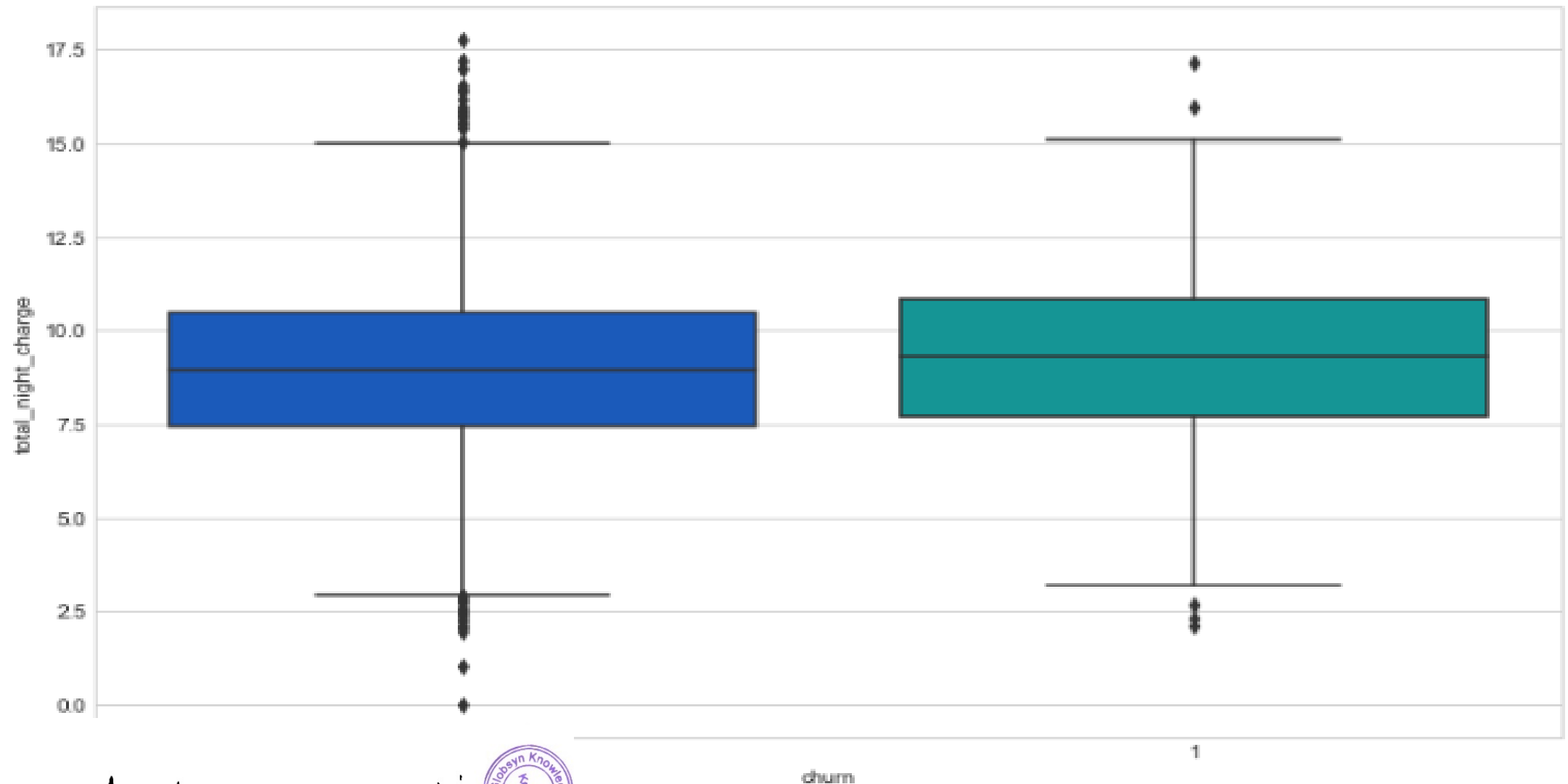

```
In [18]: plt.figure(figsize=(20,10))
sns.heatmap(ch.corr(),cmap="viridis",linewidth=0.3)
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0xef08113666>



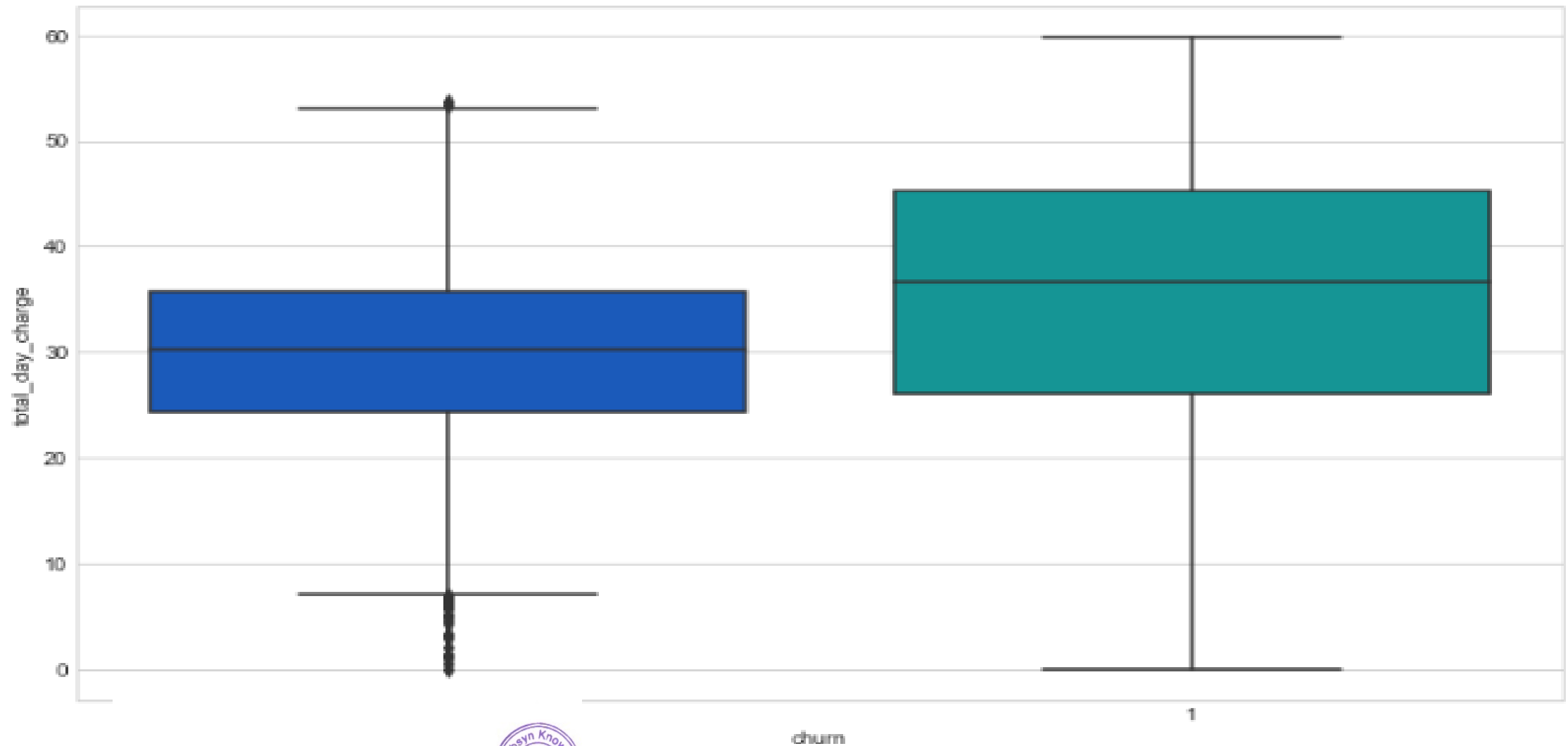
```
In [19]: plt.figure(figsize=(12,7))  
sns.boxplot(x='churn',y='total_night_charge',data=ch,palette='winter')
```

```
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0xef085b5be0>
```



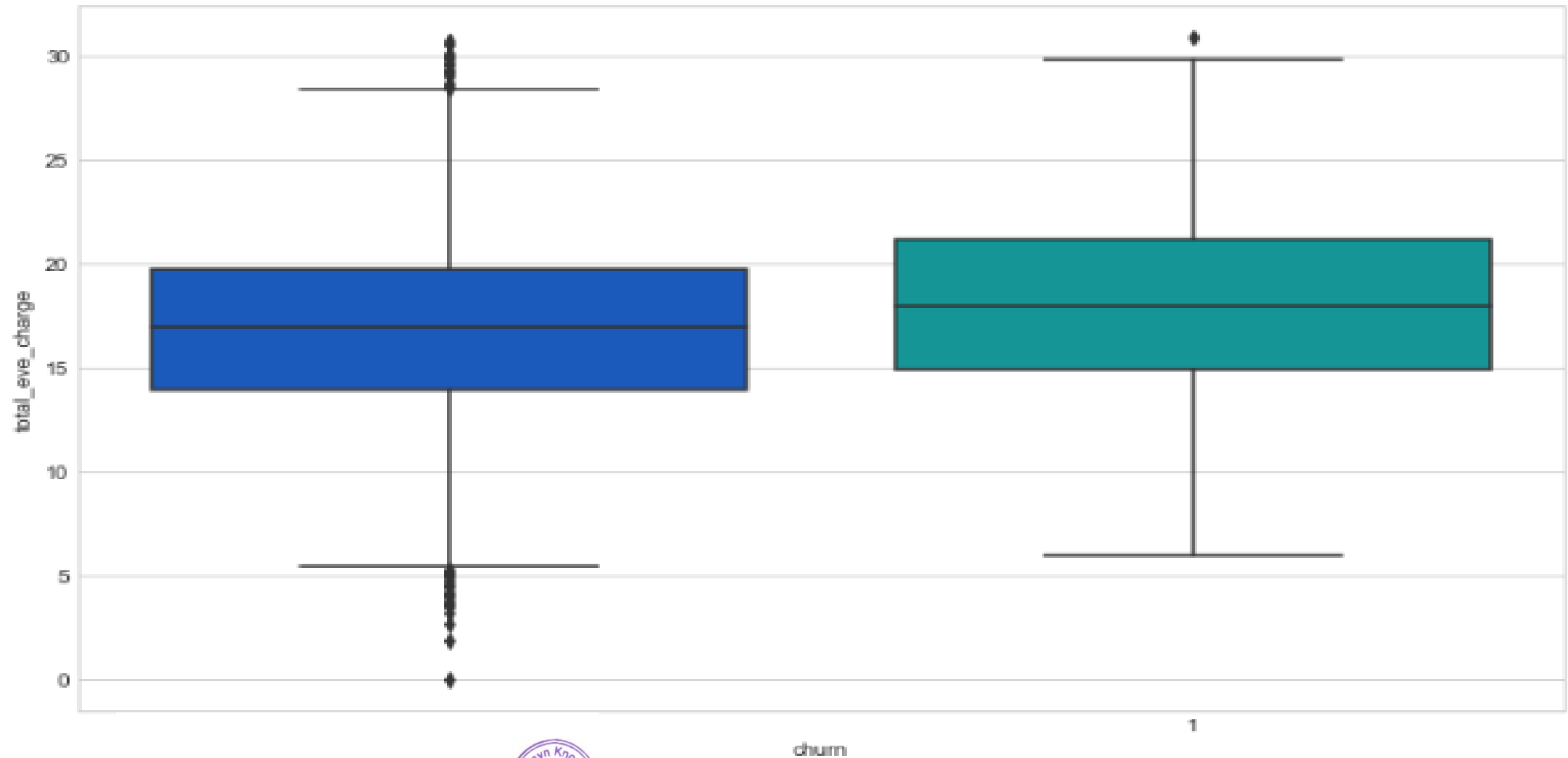
```
In [20]: plt.figure(figsize=(12,7))
sns.boxplot(x='churn',y='total_day_charge',data=ch,palette='winter')
```

```
Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0xef08964940>
```



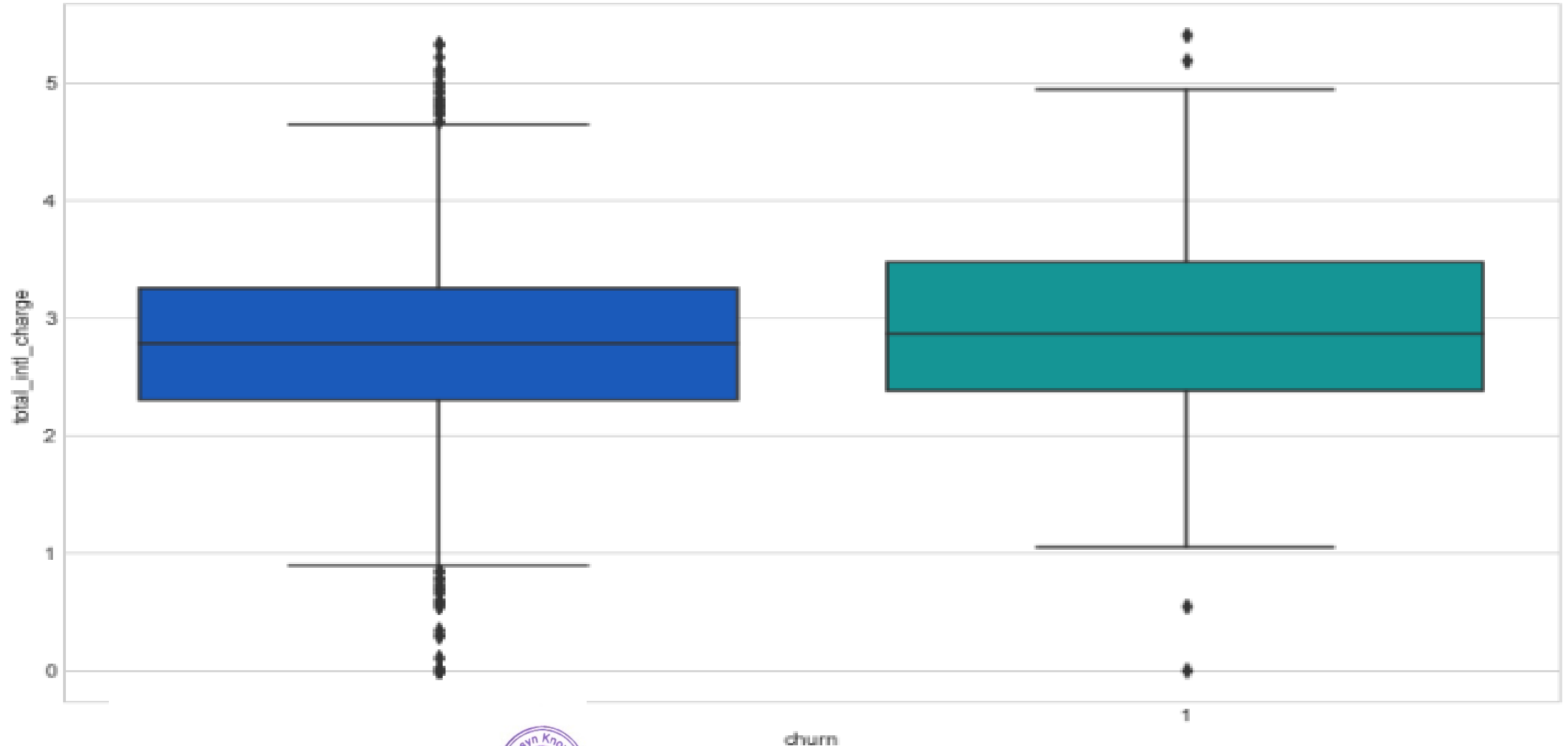
```
In [21]: plt.figure(figsize=(12,7))  
sns.boxplot(x='churn',y='total_eve_charge',data=ch,palette='winter')
```

```
Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0xef0778ce10>
```



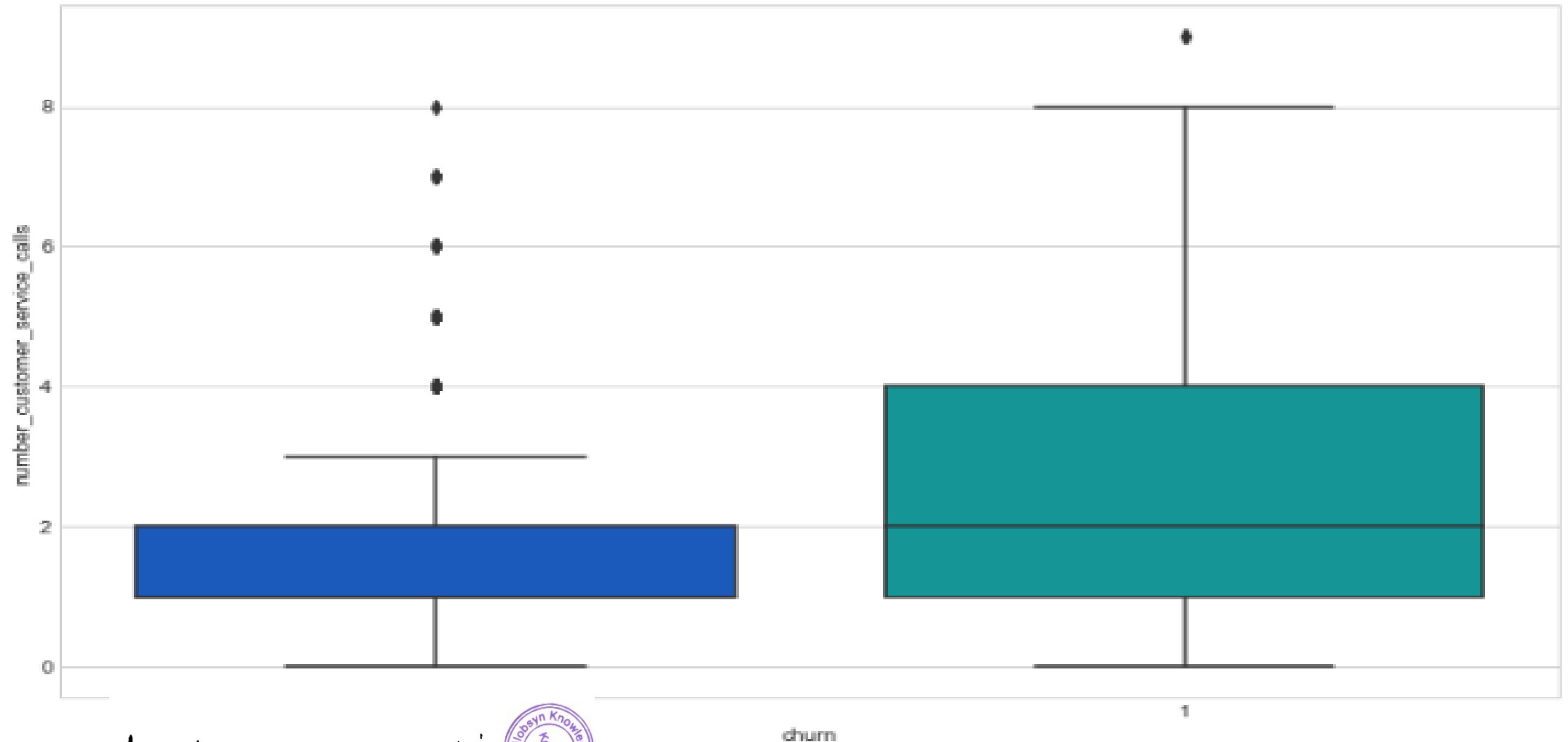

```
In [22]: plt.figure(figsize=(12,7))  
sns.boxplot(x='churn',y='total_intl_charge',data=ch,palette='winter')
```

```
Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0xef0894cef0>
```



```
In [23]: plt.figure(figsize=(12,7))  
sns.boxplot(x='churn',y='number_customer_service_calls',data=ch,palette='winter')
```

```
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0xef0816ada0>
```



Logistic Regression

```
In [24]: ch.drop('account_length',axis=1,inplace=True)
```

```
In [25]: ch.head()
```

```
Out[25]:
```

	number_vmail_messages	total_day_charge	total_eve_charge	total_night_charge	total_intl_charge	number_customer_service_calls	churn
0	25	45.07	16.78	11.01	2.70	1	0
1	26	27.47	16.62	11.45	3.70	1	0
2	0	41.38	10.30	7.32	3.29	0	0
3	0	50.90	5.26	8.86	1.78	2	0
4	0	28.34	12.61	8.41	2.73	3	0

```
In [26]: x=ch[['number_vmail_messages','total_day_charge','total_eve_charge','total_night_charge','total_intl_charge','number_customer_service_calls']]  
y=ch['churn']
```

```
In [27]: from sklearn.model_selection import train_test_split
```

```
In [28]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=101)
```

```
In [29]: from sklearn.linear_model import LogisticRegression
```

```
In [30]: logmodel=Log
```

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```
In [31]: logmodel.fit(x_train,y_train)
```

```
Out[31]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                             intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                             penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                             verbose=0, warm_start=False)
```

```
In [32]: predictions = logmodel.predict(x_test)
```

```
In [33]: from sklearn.metrics import classification_report
```

```
In [34]: print(classification_report(y_test,predictions))
```

	precision	recall	f1-score	support
0	0.87	1.00	0.93	1297
1	0.76	0.06	0.12	203
avg / total	0.86	0.87	0.82	1500

```
In [35]: from sklearn.metrics import confusion_matrix
```

```
In [36]: print(confusion_matrix(y_test,predictions))
```

```
[[1293   4]
 [ 190  13]]
```

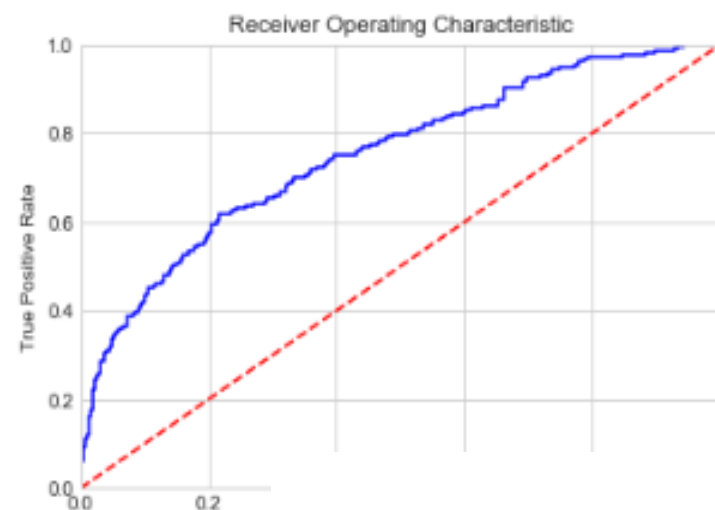
```
In [37]: acc_log=accuracy_score(y_test,predictions)
print("Accuracy of Logistic Regression : ",acc_log)
```

Accuracy 0.666666666667

```
In [43]: from sklearn.metrics import confusion_matrix
features = ch.drop(["churn"], axis=1).columns
probs = logmodel.predict_proba(x_test[features])
get_ipython().magic('matplotlib inline')
confusion_matrix = pd.DataFrame(confusion_matrix(y_test, predictions), columns=["Predicted False", "Predicted True"], index=["Actual False", "Actual True"])
display(confusion_matrix)

# Calculate the fpr and tpr for all thresholds of the classification
fpr, tpr, threshold = roc_curve(y_test, probs[:,1])
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b')
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

	Predicted False	Predicted True
Actual False	1293	4
Actual True	190	13



KNN!

```
In [45]: from sklearn.preprocessing import StandardScaler
```

```
In [46]: scaler = StandardScaler()
```

```
In [47]: scaler.fit(ch.drop('churn',axis=1))
```

```
Out[47]: StandardScaler(copy=True, with_mean=True, with_std=True)
```

```
In [48]: scaled_features = scaler.transform(ch.drop('churn',axis=1))
```

```
In [49]: ch_feat = pd.DataFrame(scaled_features,columns=ch.columns[:-1])  
ch_feat.head()
```

```
Out[49]:
```

	number_vmail_messages	total_day_charge	total_eve_charge	total_night_charge	total_intl_charge	number_customer_service_calls
0	1.273145	1.574074	-0.063849	0.876286	-0.095509	-0.436676
1	1.346973	-0.347082	-0.101089	1.069818	1.245982	-0.436676
2	-0.572549	1.171286	-1.572084	-0.746737	0.695971	-1.202236
3	-0.572549	2.210457	-2.745155	-0.069377	-1.329681	0.328885
4	-0.572549	-0.252115	-1.034426	-0.267307	-0.055264	1.094445

```
In [50]: from sklearn.model_selection import train_test_split
```

```
In [51]: X_train, X_test, y_train, y_test = train_test_split(scaled_features,ch['churn'],test_size=0.30)
```

```
In [52]: from sklearn.ensemble import RandomForestClassifier
```

```
In [53]: knn = KNeighborsClassifier(n_neighbors=1)
```

```
In [54]: knn.fit(X_train,y_train)
```

```
Out[54]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',  
                             metric_params=None, n_jobs=1, n_neighbors=1, p=2,  
                             weights='uniform')
```

```
In [55]: pred = knn.predict(X_test)
```

```
In [56]: from sklearn.metrics import classification_report,confusion_matrix
```

```
In [57]: print(confusion_matrix(y_test,pred))
```

```
[[1197   99]  
 [  84 120]]
```

```
In [58]: print(classification_report(y_test,pred))
```

	precision	recall	f1-score	support
0	0.93	0.92	0.93	1296
1	0.55	0.59	0.57	204
avg / total	0.88	0.88	0.88	1500

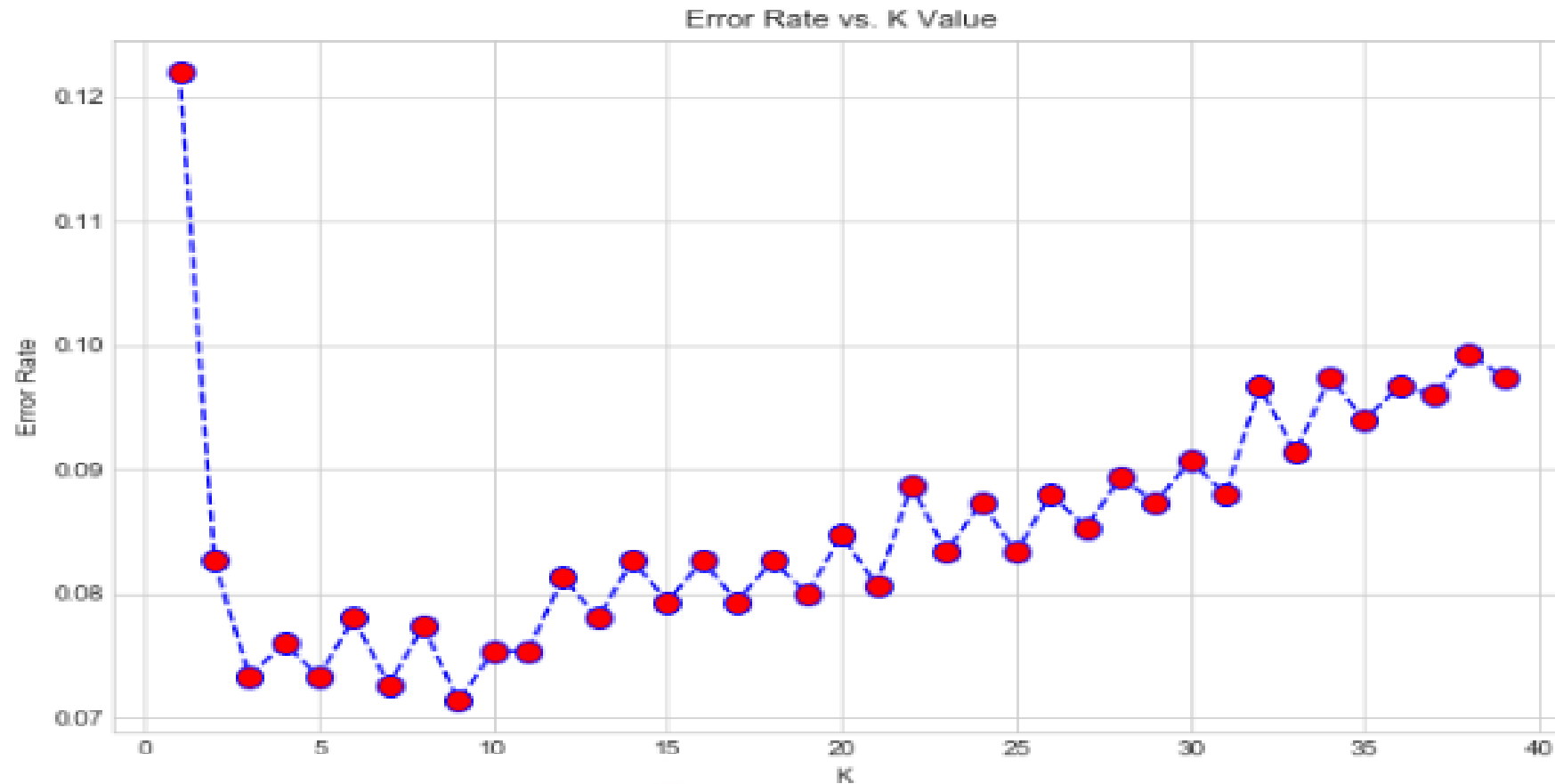
```
In [59]: error_rate = []
```

```
for i in range(1,40):  
    knn = KNeighborsClassifier(n_neighbors=i)  
    knn.fit(X_train,y_train)  
    pred_  
    error
```

```
test))
```

```
In [60]: plt.figure(figsize=(10,6))
plt.plot(range(1,40),error_rate,color='blue', linestyle='dashed', marker='o',
         markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

Out[60]: Text(0,0.5,'Error Rate')



```
In [61]: knn = KNeighborsClassifier(n_neighbors=1)

knn.fit(X_train,y_train)
pred = knn.predict(X_test)

print('WITH K=1')
print('\n')
print(confusion_matrix(y_test,pred))
print('\n')
print(classification_report(y_test,pred))
```

WITH K=1

```
[[1197   99]
 [  84 120]]
```

	precision	recall	f1-score	support
0	0.93	0.92	0.93	1296
1	0.55	0.59	0.57	204
avg		.88	0.88	1500

```
In [62]: knn = KNeighborsClassifier(n_neighbors=8)

knn.fit(X_train,y_train)
pred = knn.predict(X_test)

print('WITH K=1')
print('\n')

print(confusion_matrix(y_test,pred))
print('\n')
print(classification_report(y_test,pred))
acc_knn=accuracy_score(y_test,pred)
print("Accuracy of KNN classifier : ",acc_knn)
```

WITH K=1

```
[[1294   2]
 [ 114  90]]
```

	precision	recall	f1-score	support
0	0.92	1.00	0.96	1296
1	0.98	0.44	0.61	204
avg / total	0.93	0.92	0.91	1500

Accuracy

0.9666666666666666

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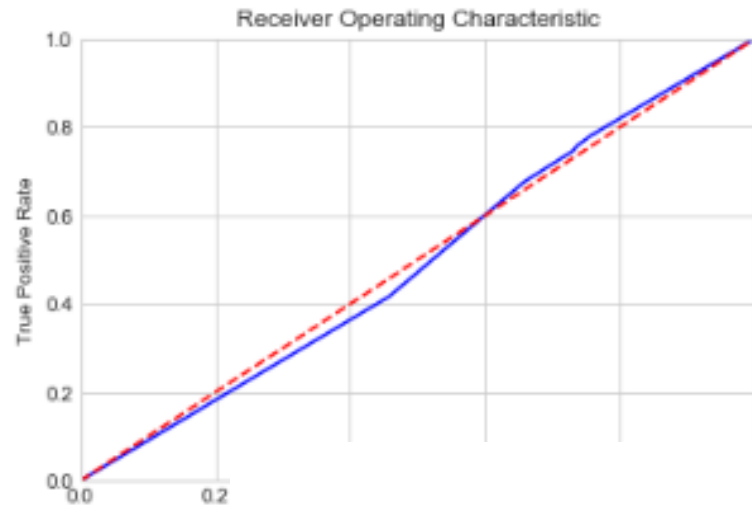


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```
In [86]: from sklearn.metrics import confusion_matrix
features = ch.drop(["churn"], axis=1).columns
probs = knn.predict_proba(x_test[features])
get_ipython().magic('matplotlib inline')
confusion_matrix = pd.DataFrame(confusion_matrix(y_test, pred), columns=["Predicted False", "Predicted True"], index=["Actual False", "Actual True"])
display(confusion_matrix)

# Calculate the fpr and tpr for all thresholds of the classification
fpr, tpr, threshold = roc_curve(y_test, probs[:,1])
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b')
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

	Predicted False	Predicted True
Actual False	1294	2
Actual True	114	90



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Naive Bayse

```
In [64]: #Import Library of Gaussian Naive Bayes model
from sklearn.naive_bayes import GaussianNB
```

```
In [65]: x1=np.array(ch1['account_length'].head(5000)).reshape(-1,1)
x2=np.array(ch1['number_vmail_messages'].head(5000)).reshape(-1,1)
x3=np.array(ch1['total_day_charge'].head(5000)).reshape(-1,1)
x4=np.array(ch1['total_eve_charge'].head(5000)).reshape(-1,1)
x5=np.array(ch1['total_night_charge'].head(5000)).reshape(-1,1)
x6=np.array(ch1['total_intl_charge'].head(5000)).reshape(-1,1)
x7=np.array(ch1['number_customer_service_calls'].head(5000)).reshape(-1,1)

y1=np.array(ch1["churn"].head(5000))
```

```
In [66]: df=ch1[ch1["churn"]==False]
df.head(5)
```

```
Out[66]:
```

	account_length	number_vmail_messages	total_day_charge	total_eve_charge	total_night_charge	total_intl_charge	number_customer_service_calls	churn
0	128	25	45.07	16.78	11.01	2.70	1	0
1	107	26	27.47	16.62	11.45	3.70	1	0
2	137	0	41.38	10.30	7.32	3.29	0	0
3	84	0	50.90	5.26	8.86	1.78	2	0
4				12.61	8.41	2.73	3	0

```
In [67]: model=GaussianNB()
model.fit(x1,y1)

x10=np.array(df['account_length'].tail(4293)).reshape(-1,1)
x11=np.array(df['number_vmail_messages'].tail(4293)).reshape(-1,1)
x12=np.array(df['total_day_charge'].tail(4293)).reshape(-1,1)
x13=np.array(df['total_eve_charge'].tail(4293)).reshape(-1,1)
x14=np.array(df['total_night_charge'].tail(4293)).reshape(-1,1)
x15=np.array(df['total_intl_charge'].tail(4293)).reshape(-1,1)
x16=np.array(df['number_customer_service_calls'].tail(4293)).reshape(-1,1)
predicted1=(model.predict(x10))
print(predicted1)

model.fit(x2,y1)
predicted2=(model.predict(x11))
print(predicted2)

model.fit(x3,y1)
predicted3=(model.predict(x12))
print(predicted3)

model.fit(x4,y1)
predicted4=(model.predict(x13))
print(predicted4)

model.fit(x5,y1)
predicted5=(model.predict(x14))
print(predicted5)

model.fit(x6,y1)
predicted6=(model.predict(x15))
print(predicted6)

model.fit(x7,y1)
predicted7=(model.predict(x16))
print(predicted7)
```

```
[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
[0 0 0 ... 0 0 0]
```

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```
In [68]: y2=ch["churn"].head(4293)
print("For Account Length\n",classification_report(y2,predicted1))
print("number_vmail_messages\n",classification_report(y2,predicted2))
print("total_day_charge\n",classification_report(y2,predicted3))
print("total_eve_charge\n",classification_report(y2,predicted4))
print("total_night_charge\n",classification_report(y2,predicted5))
print("total_intl_charge\n",classification_report(y2,predicted6))
print("number_customer_service_calls\n",classification_report(y2,predicted7))
```

For Account Length

	precision	recall	f1-score	support
0	0.86	1.00	0.92	3677
1	0.00	0.00	0.00	616
avg / total	0.73	0.86	0.79	4293

number_vmail_messages

	precision	recall	f1-score	support
0	0.86	1.00	0.92	3677
1	0.00	0.00	0.00	616
avg / total	0.73	0.86	0.79	4293

total_day_charge

	precision	recall	f1-score	support
0	0.86	1.00	0.92	3677
1	0.00	0.00	0.00	616
avg / total	0.73	0.86	0.79	4293

total_eve_charge				
	precision	recall	f1-score	support
0	0.86	1.00	0.92	3677
1	0.00	0.00	0.00	616
avg / total	0.73	0.86	0.79	4293

total_night_charge				
	precision	recall	f1-score	support
0	0.86	1.00	0.92	3677
1	0.00	0.00	0.00	616
avg / total	0.73	0.86	0.79	4293

total_intl_charge				
	precision	recall	f1-score	support
0	0.86	1.00	0.92	3677
1	0.00	0.00	0.00	616
avg / total	0.73	0.86	0.79	4293

number_customer_service_calls				
	precision	recall	f1-score	support
0	0.86	0.99	0.92	3677
1	0.14	0.01	0.02	616
avg / total	0.75	0.85	0.79	4293

In [69]:

```
acc_nb=accuracy_score(y2,predicted1)
print("Accuracy of Naive Bayse Classifier : ",acc_nb)
```

Accu

r : 0.8565105986489634

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Random Forest

```
In [61]: features = ch.drop(["churn"], axis=1).columns
```

```
In [62]: x_train, x_test = train_test_split(ch, test_size=0.25)
```

```
In [63]: # Set up our RandomForestClassifier instance and fit to data  
clf = RandomForestClassifier(n_estimators=30)  
clf.fit(x_train[features], x_train["churn"])
```

```
# Make predictions  
predictions = clf.predict(x_test[features])  
probs = clf.predict_proba(x_test[features])  
display(predictions)
```

```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

```
In [64]: score = clf.score(x_test[features], x_test["churn"])  
print("Accuracy: ", score)
```

Accur

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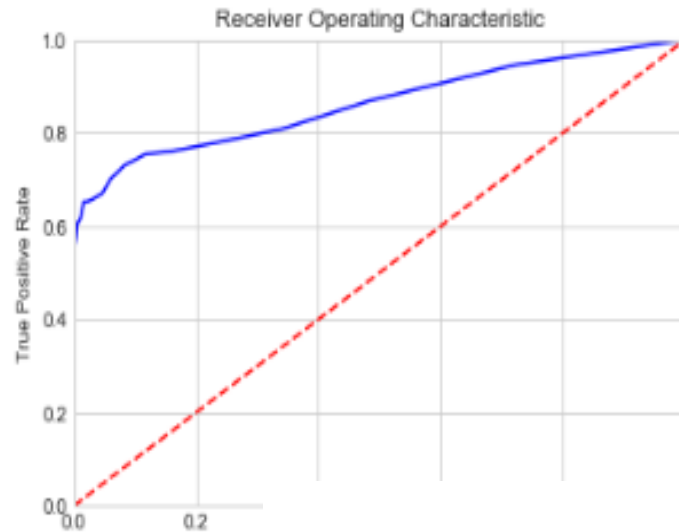


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```
In [65]: get_ipython().magic('matplotlib inline')
confusion_matrix = pd.DataFrame(confusion_matrix(x_test["churn"], predictions), columns=["Predicted False", "Predicted True"], index=["Actual False", "Actual True"])
display(confusion_matrix)

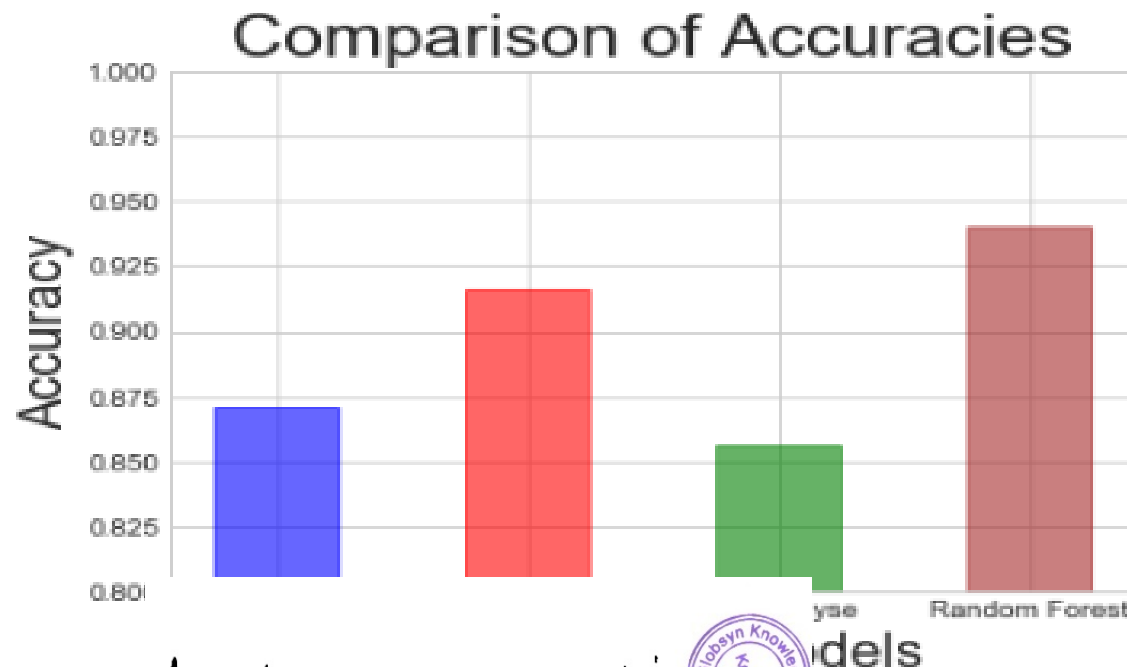
# Calculate the fpr and tpr for all thresholds of the classification
fpr, tpr, threshold = roc_curve(x_test["churn"], probs[:,1])
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b')
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

	Predicted False	Predicted True
Actual False	1079	4
Actual True	71	96



Comparison of Accuracy

```
In [66]: mod_compare=['Logistic Regression','K Neighbors','Naive Bayse','Random Forest']
acc=[acc_log,acc_knn,acc_nb,score]
barlist=plt.bar(mod_compare,acc,width=0.5,alpha=0.6)
plt.ylim([0.8,1.0])
barlist[0].set_color('blue')
barlist[1].set_color('red')
barlist[2].set_color('green')
barlist[3].set_color('brown')
plt.xlabel('Classification Models',fontsize=20)
plt.ylabel('Accuracy',fontsize=20)
plt.title('Comparison of Accuracies',fontsize=25)
plt.show();
```



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Decision Tree

```
In [122]: from sklearn.tree import DecisionTreeClassifier
```

```
In [168]: #dtree = DecisionTreeClassifier()  
dtree = DecisionTreeClassifier(criterion = "entropy", random_state = 100,  
                               max_depth=3, min_samples_leaf=5)
```

```
In [169]: X=ch[['number_vmail_messages','total_day_charge','total_eve_charge','total_night_charge','total_intl_charge','number_customer_service_calls']]  
#X=ch[['number_vmail_messages']]  
y=ch['churn']  
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)  
dtree.fit(X_train,y_train)
```

```
Out[169]: DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=3,  
                                max_features=None, max_leaf_nodes=None,  
                                min_impurity_decrease=0.0, min_impurity_split=None,  
                                min_samples_leaf=5, min_samples_split=2,  
                                min_weight_fraction_leaf=0.0, presort=False, random_state=100,  
                                splitter='best')
```

```
In [170]: from IPython.display import Image  
from sklearn.externals.six import StringIO  
from sklearn.tree import export_graphviz  
  
features = list(ch.columns[1:])  
features
```

```
Out[170]: ['total_day_charge',  
           'total_eve_charge',  
           'total_night_charge',  
           'total_intl_charge',  
           'number_customer_service_calls',  
           'churn']
```

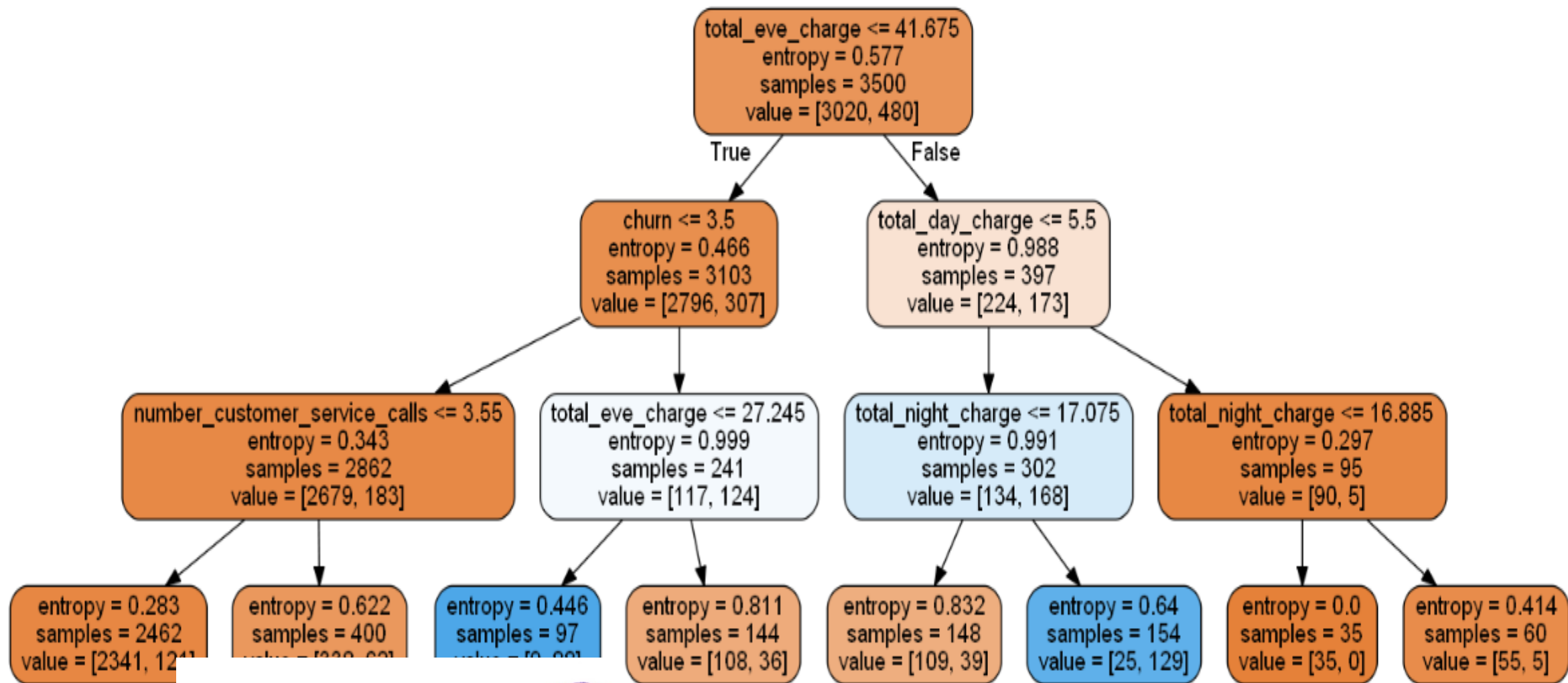
```

In [171]: import pydot
dot_data = StringIO()
export_graphviz(dtree, out_file=dot_data, feature_names=features, filled=True, rounded=True)

graph = pydot.graph_from_dot_data(dot_data.getvalue())
Image(graph[0].create_png())

```

Out[171]:



Future Scope of Improvements

Based on the EDA and models, an increase in the below variables increases the probability of customer churn:

Number of customer service calls

Total day charge

Total evening charge

Total international charge

Total night charge

Additionally, an increase in number of voice mail messages decreases the probability of customer churn. These insights from the discriminant model can help the business formulate strategies to reduce customer churn. Here's what I would recommend to the business based on what we've learned: First, customer issues should be resolved within the first or second call, as repeated calls to customer service causes customer churn. Second, there should be an organized escalation procedure for issues not resolved within two calls. Lastly, the provider should offer more attractive plans that reduce the cost of day, evening, and international calls based on usage.

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Certificate

This is to certify that Mr [*Karan Patadia*] of [*The Heritage Academy*], registration number: [*162131010047*], has successfully completed a project on [*Predicting Customer Churn*] using [*Machine Learning with Python*] under the guidance of Mr [*Anubhav Chaturvedi*].


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This is to certify that Mr [*Rupam Aich*] of *The* [*The Heritage Academy*], registration number: [*162131010080*], has successfully completed a project on [*Predicting Customer Churn*] using [*Machine Learning with Python*] under the guidance of Mr [*Anubhav Chaturvedi*].

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