iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** XI **Month of publication:** November 2021

DOI: https://doi.org/10.22214/ijraset.2021.38859

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue XI Nov 2021- Available at www.ijraset.com

Business Use of Data Science – Churn Prediction

Themaliparambil Naveed Abbas
Undergraduate Student at Delhi University

I. INTRODUCTION

Churn prediction is probably one of the most important applications of data science in the business sector. The thing that makes it popular is that its effect are more tangible to comprehend and it plays a major factor in the overall profits earned by the business.

A. What is Churn Prediction?

Churn quantifies the number of customers who have left your brand by cancelling their subscriptions or stopping paying for your services. This is bad news for any business as it costs five times as much to attract a new customer as it does to keep an existing one. A high customer churn rate will hit your company's finances hard. By leveraging advanced artificial intelligence techniques like machine learning (ML), you will be able to anticipate potential churners who are about to abandon your services.

B. Why is it important?

You probably already have more customer data than you know. By using this data, you are able to identify behaviour patterns of customers who are likely to churn. This knowledge will enable you to segment those customers and take the appropriate measures to win them back.

The simpler way to calculate churn rate is to divide the number of customers lost during a given time interval by the number of active customers at the beginning of the period. For example, if you got 1000 customers and lost 50 last month, then your monthly churn rate is 5 percent.

II. DATA EXPLORATION

I have used the Telecom Customer Churn dataset from kaggle.

A. Important Required Dependencies

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.metrics import accuracy_score, confusion_matrix

from sklearn.model_selection import RandomizedSearchCV

%matplotlib inline
```

B. Loading the Dataset

```
df=pd.read_csv('../input/telco-customer-churn/WA_Fn-UseC_-Telco-Customer-Churn.csv')
df.info()
```

©IJRASET: All Rights are Reserved

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

As we can see there are a total of 20 columns in our data set. Out of these,3 are of numeric data type.

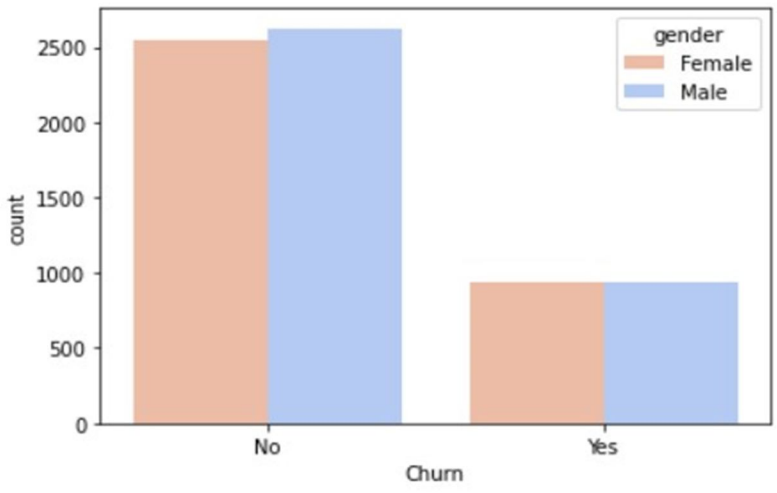
C. Data Visualization

We need to explore the data to find some patterns.

For the columns in the dataset which are non-numerical, we can use a seaborn countplot to plot a graph against the Churn column.

sns.countplot (x='Churn ',data=df,hue='gender',palette="coolwarm_r")

```
<AxesSubplot:xlabel='Churn', ylabel='count'>
```

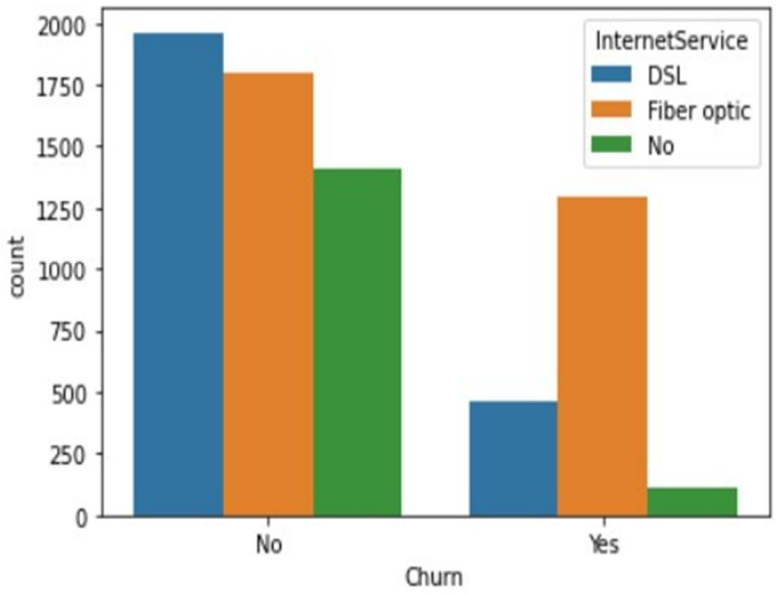


From the above graph we can see that gender is not a contributing factor for customer churn in this dataset as the number of both the genders, that have or haven't churned are almost the same.

©IJRASET: All Rights are Reserved

sns.countplot(x='Churn',data=df, hue='InternetService')

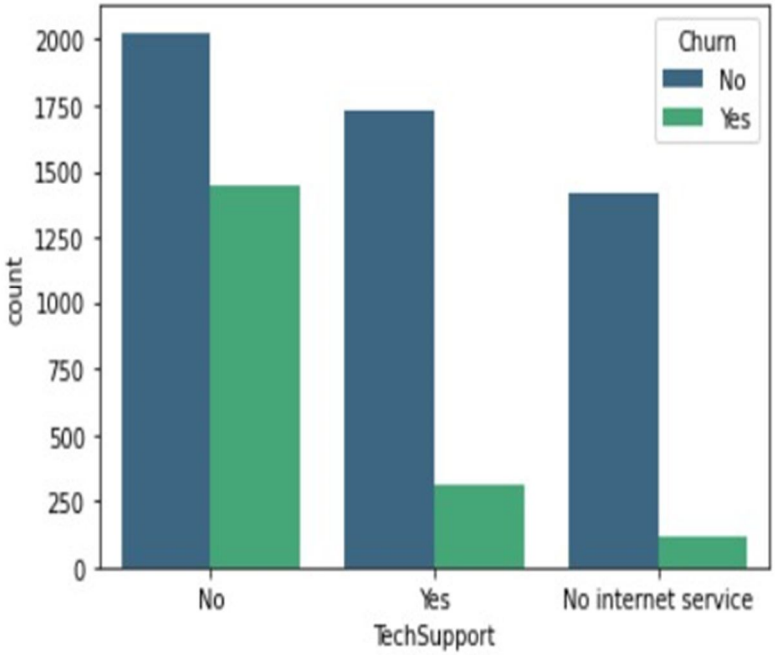
```
<AxesSubplot:xlabel='Churn', ylabel='count'>
```



We can see that people using Fiber-optic services have a higher churn percentage. This shows that the company needs to improve their Fiber-optic service.

sns.countplot(x='TechSupport',data=df, hue='Churn',palette='viridis')

```
<AxesSubplot:xlabel='TechSupport', ylabel='count'>
```



Those customers who don't have tech support have churned more, which is pretty self-explanatory. This also highlights the fact that the tech support provided by the company is up to the mark.

©IJRASET: All Rights are Reserved

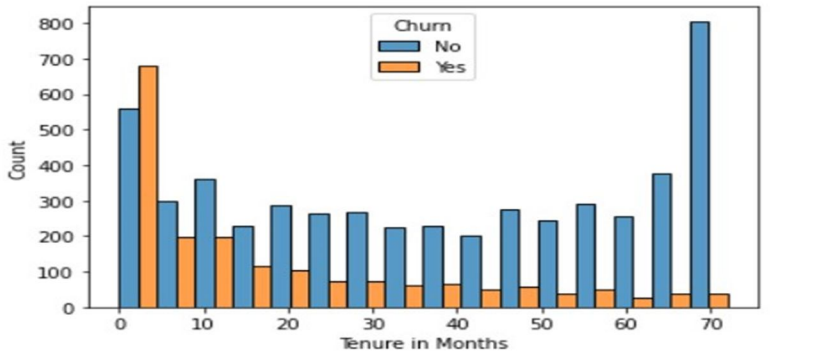
D. Tackling Numeric Data

Now let's look at some numerical value to see how to tackle them.

ax=sns.histplot(x='tenure',hue='Churn',data=df,multiple='dodge')

ax.set(xlabel="Tenure in months",ylabel="Count")

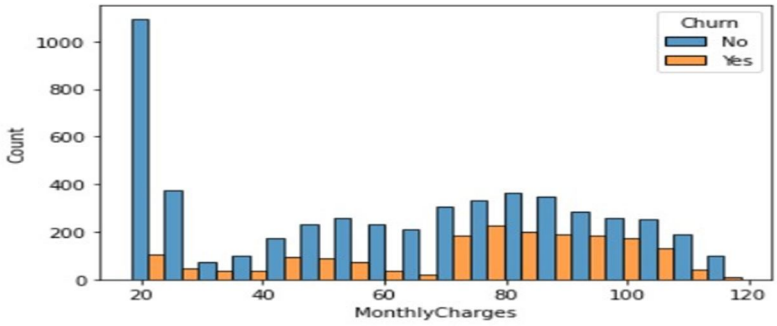
```
[Text(0.5, 0, 'Tenure in Months'), Text(0, 0.5, 'Count')]
```



The churn amount is higher in the initial 5 months, which is usually the time when the new customer try out the service and decide whether to continue or cancel. This pretty much can be attributed to the uncertainly in the customer's mind.

sns.histplot(x='MonthlyCharges',hue='Churn',data=df,multiple='dodge')

```
<AxesSubplot:xlabel='MonthlyCharges', ylabel='Count'>
```



We cannot see a definite pattern in this, but we can conclude that those who have monthly charges as high as 100 dollars have chosen not to churn. This indicates that the company has done well to retain high paying customers. Similarly, we can evaluate the other parameters as well and draw meaningful conclusions as to how the company should improve customer retention.

E. Data Preparation

We need to make sure that the data is in the right form to be used for prediction. Machine Learning models do not work well with categorical inputs. So, we convert the categorical variables in our data set to numerical values by using one-hot encoding.

df_copy=pd.get_dummies(df_copy,drop_first=True)

df_copy.head()

SeniorCitizen	Partner	Dependents	tenure	PhoneService	PaperlessBilling	MonthlyCharges	TotalCharges	Churn	gender_Male	...	TechSupport_Yes	StreamingTV_No internet service
0	1	0	1	0	1	29.85	29.85	0	0	...	0	0
0	0	0	34	1	0	56.95	1889.50	0	1	...	0	0
0	0	0	2	1	1	53.85	108.15	1	1	...	0	0
0	0	0	45	0	0	42.30	1840.75	0	1	...	1	0
0	0	0	2	1	1	70.70	151.65	1	0	...	0	0

The drop_first parameter helps in reducing the number of columns and hence prevents co-relation between the variables. Hence, it is set to True.

©IJRASET: All Rights are Reserved

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue XI Nov 2021- Available at www.ijraset.com

F. Scaling

Scaling data is important to increase prediction accuracy.

```
from sklearn.preprocessing import  MinMaxScaler
features= X.columns.values
scaler=MinMaxScaler(feature_range=(0,1))
scaler.fit(X)
X= pd.DataFrame(scaler.transform(X))
X.columns=features
X.head()
```

SeniorCitizen	Partner	Dependents	tenure	PhoneService	PaperlessBilling	MonthlyCharges	TotalCharges	gender_Male	MultipleLines_No phone service	...	TechSupport_Yes
0.0	1.0	0.0	0.013889	0.0	1.0	0.115423	0.001275	0.0	1.0	...	0.0
0.0	0.0	0.0	0.472222	1.0	0.0	0.385075	0.215867	1.0	0.0	...	0.0
0.0	0.0	0.0	0.027778	1.0	1.0	0.354229	0.010310	1.0	0.0	...	0.0
0.0	0.0	0.0	0.625000	0.0	0.0	0.239303	0.210241	1.0	1.0	...	1.0
0.0	0.0	0.0	0.027778	1.0	1.0	0.521891	0.015330	0.0	0.0	...	0.0

III. PREDICTION

First of all, let's split the data into 2 datasets;
Training and testing.

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test=train_test_split(X,y, test_size=0,3, random_state=41)
```

Now we can start with different algorithms for prediction.

A. Logistic Regression

```
from sklearn.linear_model import LogisticRegression
logreg=LogisticRegression()
logreg.fit(X_train,y_train)
prediction_logreg=logreg.predict(X_test)
print(accuracy_score(y_test,prediction_logreg))
```

Accuracy Score LogReg:0.7950780880265026

B. Random Forest using Random CV

```
From sklearn.ensemble import RandomForestClassifier
rf_c=RandomForestClassifier()

param_grid={'n_estimators':[int(x) for x in np.linspace(start=200,stop=1200,num=11)]
            'max_features':['auto','sqrt'],
            'max_depth':[int(x) for x in np.linspace(start=10,stop=100,num=11)],
            'min_samples_leaf':[1,2,3,5],
            'min_samples_split':[2,5,10,15]}

random_cv=RandomSearchCV(rf_c,param_grid,cv=3,verbose=2,random_state=42)
random_cv.fit(X_train,y_train)
best_random=random_cv.best_estimator_
prediction_cv=best_random.predict(X_test)
print(accuracy_score(y_test,prediction_cv))
```

Accuracy Score RF:0.8021769995267393

©IJRASET: All Rights are Reserved

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue XI Nov 2021- Available at www.ijraset.com

C. XGBoost

```
from xgboost import XGBClassifier
xgb_model=XGBClassifier()
xgb_model.fit(X_train,y_train)
prediction_xgb=xgb_model.predict(X_test)
print(accuracy_score(y_test,prediction_xgb))
```

Accuracy Score XGB:0.7875059157595835

From the above accuracy scores, we see that Random Forest clearly outperforms Logistic Regression and XGBoost. By using RandomCV, the accuracy is further improved.

Let's see the confusion matrix of Random Forest

```
print(confusion_matrix(y_test,prediction_cv))
```

```
Confusion Matrix:
[[1410  144]
 [ 274  285]]
```

It shows that our model needs to improve the False Negative classifications.

IV. CONCLUSION

We went through the various tasks involved in churn prediction in this article. It is important to note that finding patterns in Exploratory Data Analysis (EDA) is as important as the final prediction itself.

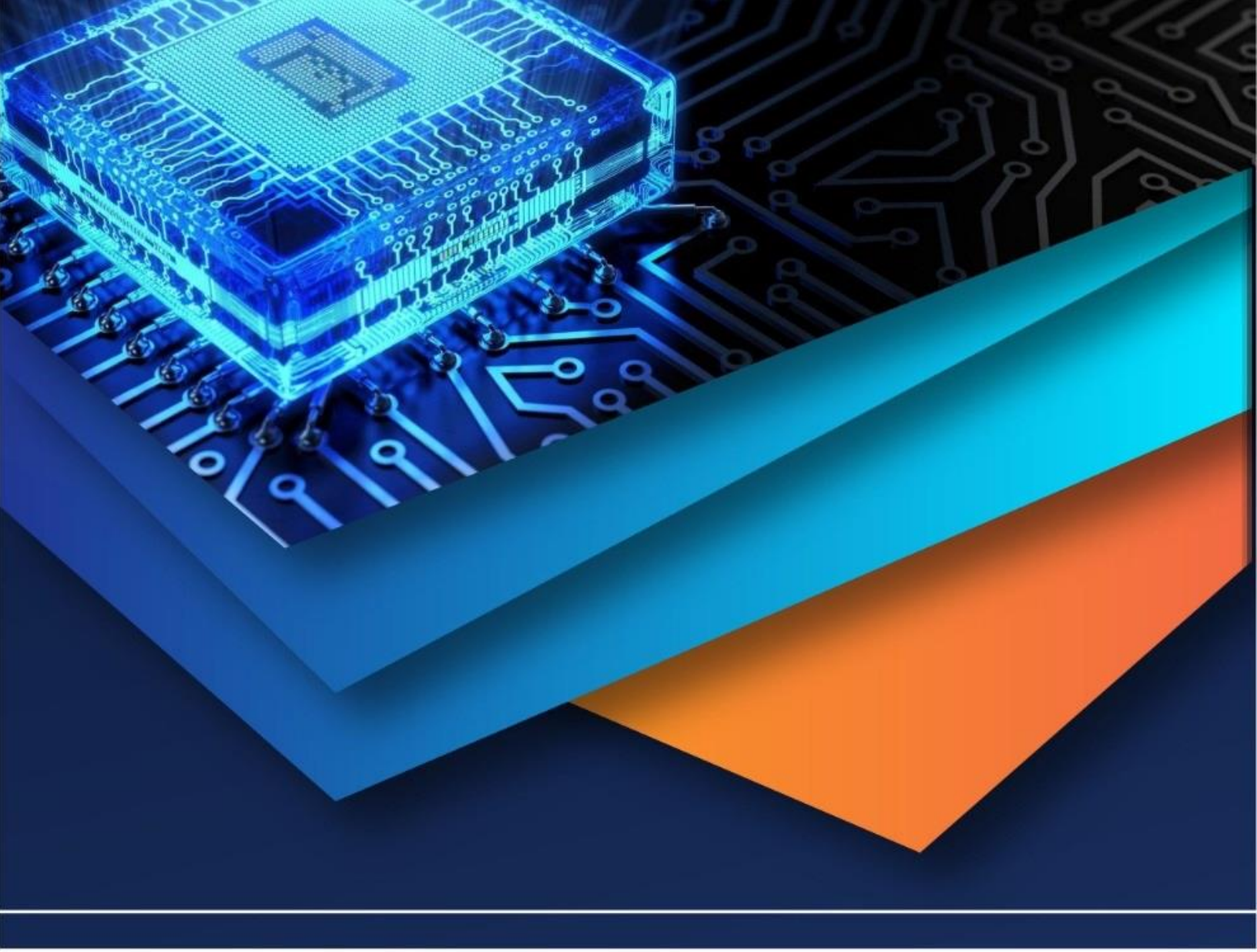
A Churn prediction task remains unfinished if the data patterns are not found in EDA. Most people can do the prediction part but struggle with data visualization and conveying the findings in an interesting way.

This skill is not only limited to Churn prediction but will also help you in the solving of the usual data science problems.

REFERENCES

[1] Soham Naik (August,2021) Example of Churn Prediction from the given dataset.
[2] Telecom Customer Dataset from kaggle.

©IJRASET: All Rights are Reserved



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)