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CHENNAI

TITLE OF THE PROJECT:

Customer Churn Prediction

A Project Report

submitted as part of the course

Real Time Analytics

CSE3069

School of Computer Science and Engineering

VIT Chennai

Winter 2022-2023

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Acknowledgement

Primarily, we would like to thank the almighty for all the blessings he showered over us to complete this project without any flaws. The success and final outcome of this assignment required a lot of guidance and assistance from many people and we are extremely fortunate to have got this all along with the completion of our project.

Whatever we have done is only due to such guidance and assistance by our faculty, Dr. Valarmathi Sudhakar, to whom we are really thankful for giving us an opportunity to do this project. Last but not the least, we are grateful to all our fellow classmates and our friends for the suggestions and support given to us throughout the completion of our project.

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Abstract

The Orange Telecom is a telecommunication service provider (TSP) which traditionally provides telephone, mobile phone networks, modern cloud service systems, mobile data transmission and similar services. The Customer Churn is a crucial activity in rapidly growing and mature competitive telecommunication sector and is one of the greatest importance for a project manager. Due to the high cost of acquiring new customers, customer Churn prediction has emerged as an indispensable part of telecom sectors' strategic decision making and planning process. It is important to forecast customer churn behavior in order to retain those customers that will churn or possible may churn. If Orange Telecom Company doesn't maintain a good customer experience nor meet the demands of the customers then users may cancel their subscriptions anytime. It is highly important to dive deep to Churn problems. Many different factors come into play as to why a particular user may or may not churn.

Churn prediction is big business. It minimizes customer defection by predicting which customers are likely to cancel a subscription to a service. Though originally used within the telecommunications industry, it has become common practice across banks, ISPs, insurance firms, and other verticals. Getting new customers is much more expensive than retaining existing ones. Some studies have shown that it costs six to seven times more to acquire a new customer than to keep an existing one.

The prediction process is heavily data driven and often utilizes advanced machine learning techniques. In this project we will understand the customer behaviors and identify the customers who will cancel their subscription whether in free or paid tier. In this project we will be working on what types of teleservice customer data are typically used we will be performing some preliminary analysis of the data, and generate churn prediction models - all with PySpark and its machine learning frameworks. We will finally encapsulate the differences between Apache Spark framework, Spark-MLlib and ML.

The Orange Telecom's Churn Dataset, consists of customer activity data (features), along with a churn label specifying whether a customer canceled the subscription, will be used to develop predictive models.

The objective of our project is to build an Churn prediction model which can identify Churn customers and non-Churn customers and implementing this model by using Naïve Bayes algorithm, further we will implement the same model with other Machine Learning Algorithms, then compare the results of all the models & we will highlight which algorithm is best to build a best Churn prediction model.

Introduction

Customer churn is one of the pointing issues of today's rapidly developing and competitive Tele-communication industry. The focus of the telecom sector has shifted from acquiring new customer to retaining existing customers because of the associated high cost. The retention of existing customers also leads to improved sales and reduced marketing cost as compared to new customers. These facts have ultimately resulted in customer churn, prediction activity to be an indispensable part of telecom sector's strategic decision making and planning process. Customer retention is one of the main objectives of customer relationship management (CRM). Its importance has led to the development of various tools that support some important tasks in predictive modelling and classification.

Why **C**hurn **I**s **I**mportant: - Customer churn – Shifting from one service provider to next competitor in the market. It is a key challenge in highly competitive markets, which is highly observed in telecommunication sector. Companies make revenue from their customers. This is the basics of every business. If one company is losing their customers whatever the reasons, revenues will be decreased. Churn reasons can be customer experience problems, high prices, low quality and so on. It depends on the business area actually.

From the analysis of various surveys, customer Churn has been broadly classified into three kinds:

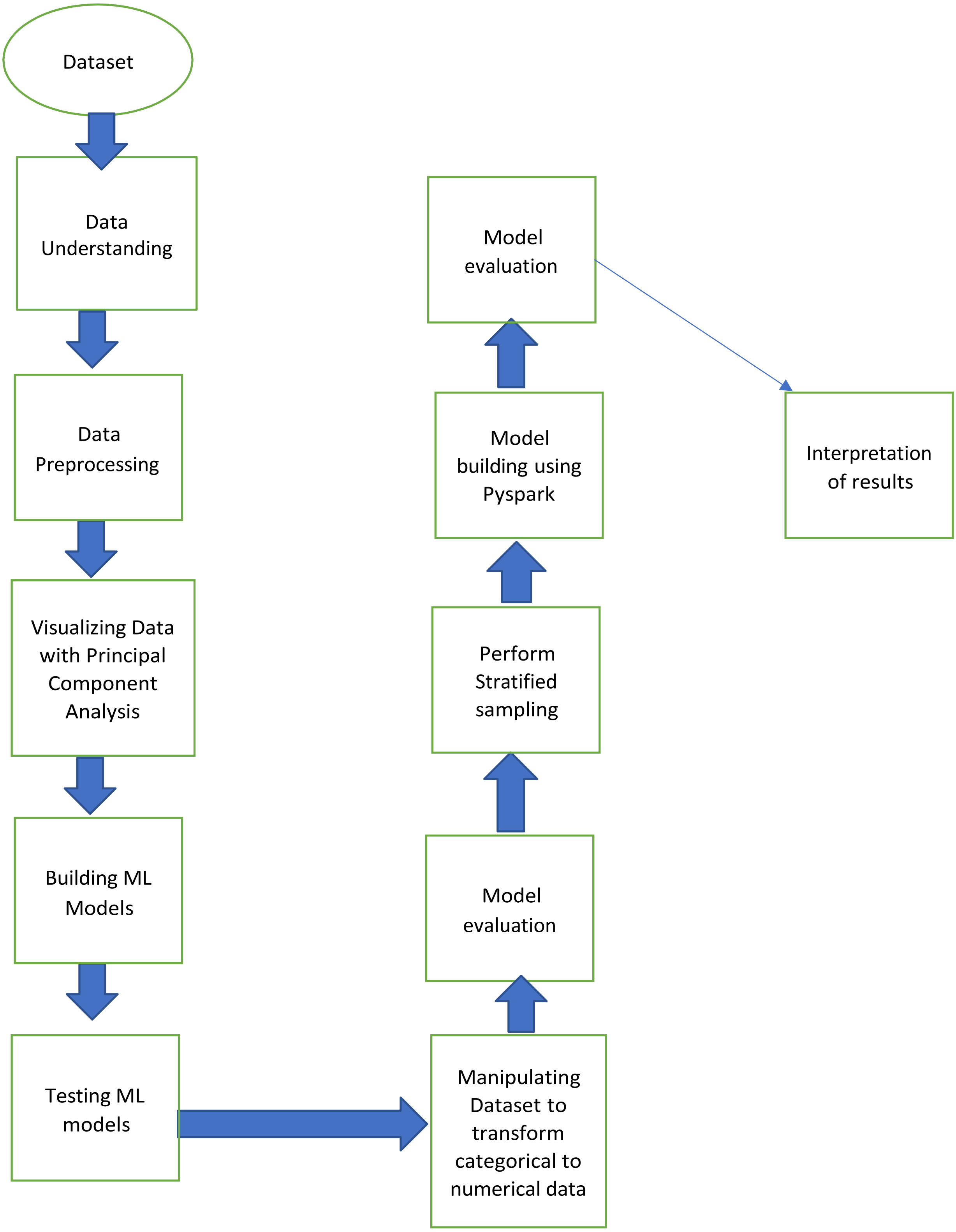
• Active churner (Volunteer): The customers who take the decision to quit the contract and Choose the service or the product of the next provider.

• Passive churner (Non-Volunteer): When the company cease the service to a customer due to some reasons like not paying the money for subscription or if they have identified that the customer is fraud.

• Rotational churner (Silent): The customers who discontinues the usage of service or the products without prior decision or prior knowledge to both company & customer. This generally happens when the customer involuntarily stop using the services or product of a company due to some of the reasons like his busy schedule or unavailability of particular product/service in their dwelling place.

The first two kinds of Churns can be predicted easily with the help of traditional approaches in term of the Boolean class value, but the third type of churn may exist which is difficult to predict because there may have such type of customers who may possibly churns in near future. It should be the goal of the decision maker and marketers to decrease the churn ratio because it is a well-known phenomenon that existing customers are the most valuable assets for companies as compare to acquiring new one

Proposed Model


Dataset
Data Understanding
Data Preprocessing
Visualizing Data with Principal Component Analysis
Building ML Models
Testing ML models
Manipulating Dataset to transform categorical to numerical data
Model evaluation
Perform Stratified sampling
Model building using Pyspark
Model evaluation
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Using Spark MLlib Package

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Using Spark ML Package
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Explanation of Project Components

1. ***Data overview: -*** In this module we start with initial data collection. We have collected Telecom Customer Churn Dataset. We need to understand the dataset clearly in order to decide the objectives & methodologies. The first step of data understanding includes identification of key variables or predicting variables in the dataset. Before working on any dataset, we need to understand the dataset completely because it is highly important to deal with missing values, remove outliers & know the categorical columns & numerical columns.

   Telecom Customer Churn dataset consists of training set & testing set. The two sets are from the same batch, but have been split by an 80/20 ratio. As more data is often desirable for developing ML models, we will be using the larger set (that is, Churn-80) for training and cross-validation purposes, and the smaller set (that is, Churn-20) for final testing and model performance evaluation.

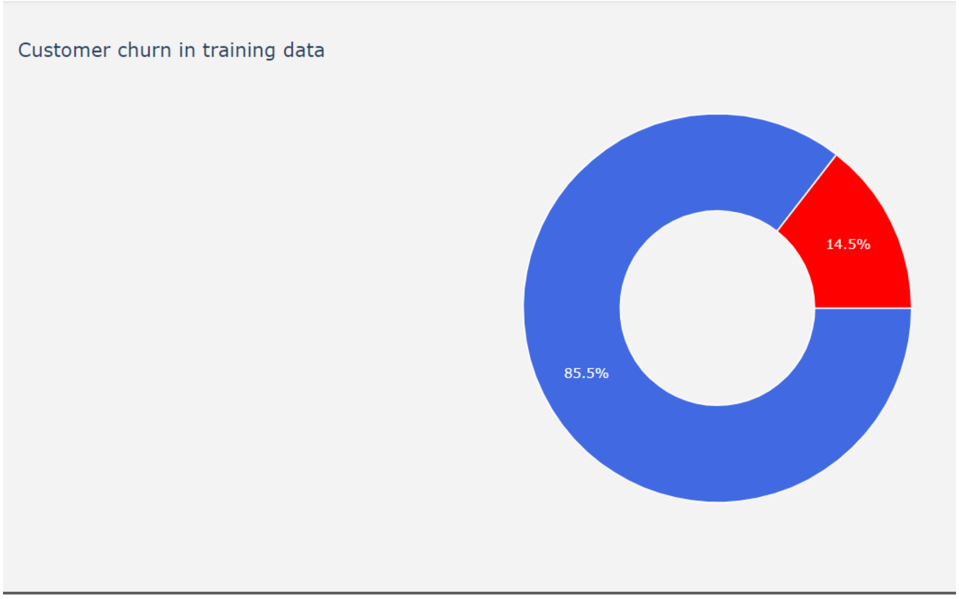
   Results of Data Overview:

```
Overview of the training dataset:

Rows: 2666

Number of features: 20

Features:
['State', 'Account length', 'Area code', 'International plan', 'Voice mail pla
n', 'Number vmail messages', 'Total day minutes', 'Total day calls', 'Total da
y 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']

Missing values: 0

Unique values:
State                       51
Account length             205
Area code                    3
International plan           2
Voice mail plan              2
Number vmail messages       42
Total day minutes         1489
Total day calls            115
Total day charge          1489
Total eve minutes         1442
Total eve calls            120
Total eve charge          1301
Total night minutes       1444
Total night calls          118
Total night charge         885
Total intl minutes         158
Total intl calls            21
Total intl charge         158
Customer service calls     10
Churn                       2
dtype: int64


Overview of the test dataset:

Rows: 667

Number of features: 20

Features:
['State', 'Account length', 'Area code', 'International plan', 'Voice mail pla
n', 'Number vmail messages', 'Total day minutes', 'Total day calls', 'Total da
y 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']

Missing values: 0

Unique values:
State                      51
Account length            179
Area code                   3
International plan          2
Voice mail plan             2
Number vmail messages      37
Total day minutes         562
Total day calls           100
Total day charge          562
Total eve minutes         557
Total eve calls            94
Total eve charge          528
Total night minutes       568
Total night calls          96
Total night charge        453
Total intl minutes        132
Total intl calls           17
Total intl charge         132
Customer service calls      9
Churn                       2
dtype: int64
```

2. **Exploratory Data Analysis: -** We perform Exploratory Data Analysis in order to uncover the underlying structure. The structure of the various data sets determines the trends, patterns, and relationships among them.

   2.1 **Customer Churn in Data:** For Customer Churn Analysis the foremost analysis that we need to do is identify the percentage of churn customers & percentage of non-churn customers in a company. Based on this analysis we can see the distribution of Churn customers of the company in dataset which will help in building an efficient model.

For the dataset which we have taken we have plotted donutchart using go.pie. In go.Pie , data visualized by the sectors of the pie is set in values. The sector labels are set in labels. The sector colors are set in marker.



We can see that the training dataset of Customer Churn contains 85.5% of customer non-Churn rate & 14.5% of customer Churn rate.

2.2 **Variable Distributions:** In this step we will be trying to understand the distribution of variables present in dataset to determine the most appropriate statistical analyses to use. We have found out that there are 307 samples in the Telecom Customer Churn dataset.

Since the dataset is too big, Let’s consider sample data & try to understand the distribution & relation between the variable through pair plot.

Understandings drawn from the result of pairplot:
Several of the numerical data are very correlated. (Total day minutes and Total day charge), (Total eve minutes and Total eve charge), (Total night minutes and Total night charge) and lastly (Total intl minutes and Total intl charge) are also correlated. We only have to select one of them.

3. **Data Preprocessing:** It's obvious that there are several highly correlated fields. Such correlated data will not be very beneficial for the model training runs, so we are going to remove them. We will do so by dropping one column of each pair of correlated variables along with the State and Area code columns.
   In this Data preprocessing module first, we have removed highly correlated & the columns which doesn't have lot of impact on Churn Variable, then we have assigned the target variable. Separate numerical & categorical Variables.

   3.1 **Statistical Summary**: After Preprocessing the training Churn dataset, we have identified statistical summary & displayed the output in form of "Table". Summary statistics summarize and provide information about the data. It tells you something about the values in your data set. This includes where the mean lies and whether your data is skewed.

   3.2 **Correlation Matrix:** In order to measure the correlation coefficient between two set of variables we have plotted correlation matrix. The results depict that the variables "Voicemail plan" & "Number of voicemail messages" are highly correlated equal to 1.

   3.3 **Visualizing data with Principal Component Analysis:** Visualization is a crucial step to get insights from data. Customer Churn Dataset consists of many dimensions, depicting things in four or five dimensions is impossible because we live in a three-dimensional world and have no idea of how things in such a high dimension would look like. This is where a dimensionality reduction technique such as PCA comes into play.

   PCA in essence is to rearrange the features by their linear combinations. Hence it is called a feature extraction technique. One characteristic of PCA is that the first principal component holds the most information about the dataset. Because PCA is sensitive to the scale, we should normalize each feature by StandardScaler we can see a better result. Here the different classes are more distinctive. So, in Data Preprocessing step we have normalized each feature by StandardScaler.

   3.4 **Binary variable distributions in customer churn (Radar Chart):** Radar Charts are used to compare two or more items or groups on various features or characteristics. Hence, we have visualized Radar chart to compare the rate of Churn & non Churn customers with all the variable present in dataset. We get the result of binary variable distribution in customer churn.

4. **Model Building:** We are aware that as title of project “Customer Churn Analysis” suggests it is a kind of task that can be performed using Machine Learning Models, we have built machine learning models. But what if the size of the data is big. This is when the picture of PySpark comes into the picture.

   Every Telecom Company has massive data that gets generated daily about one particular customer and just imagine we are living in the era of digitalized world, every person living on the earth is a part of any one/two Telecom Companies customer. Thus, massive amounts of data will be generated. In order to find the Churn rate of customers & draw insights like what are the reasons for the customer to leave the services of one particular company to other & few other insights like how to profitise the company. Machine Learning Plays a vital role in this process.

   We are going to dive deep to churn problems with scalable approach for machine learning on big data.

   So, to build & evaluate ML models for Big Data we can implement machine learning in Spark using its MLlib library.

   - Initially as we have considered sample data first, we will build Machine Learning models & evaluate them
   - Next Perform some preprocessing that fits the complete data to implement ML models in PySpark
   - Then Build ML models using PySpark & Evaluate those Models.

- **Model Building without PySpark**

  1.Logistic Regression
  2.Decision tree classifier
  3.Random Forest classifier
  4. Gaussian Naïve Bias
  5.SVC
  6. SVC using rbf Kernel

  Initially We will be defining a function which fits the algorithm to build the model & generate classification report, Accuracy Score & Model Performance plot which consists of Confusion matrix, ROC curve, Feature Importance plot & Threshold for each model build with a particular algorithm.

  As the core problem of our project is classify whether the customer is Churn customer or not, we have built various “Classification models” & generated classification report for each model. So Let’s understand the classification models which we have used & why we have used.

Machine Learning Models:

a. **Logistic Regression-** Logistic regression is a classification algorithm, used when the value of the target variable is categorical in nature. Logistic regression is most commonly used when the data in question has binary output, so when it belongs to one class or another, or is either a 0 or 1. So the classification of customer to one of the classes Churn customer (class=1) or non-Churn customer(class=0).

b. **Decision Tree Classifier-** Decision trees are a powerful and popular tool. They’re commonly used by data analysts to carry out predictive analysis. They’re also a popular tool for machine learning and artificial intelligence, where they’re used as training algorithms for supervised learning i.e., categorizing data based on different tests, such as ‘yes’ or ‘no’ classifiers.

c. **Random Forest Classifier-**Random Forest builds multiple decision trees and merges them together to get a more accurate and stable prediction. One big advantage of random forest is that it can be used for both classification and regression problems, which form the majority of current machine learning systems.

d. **Gaussian Naïve Bias Classifier-** Naive Bayes can be extended to real-valued attributes, most commonly by assuming a Gaussian distribution. This extension of naive Bayes is called Gaussian Naive Bayes**.**

e. **SVC- SVM - Linear Kernel:** SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

   Linear SVM is used for linearly separable data, since our dataset can be classified into two classes by using a single straight line, then such data is termed as linearly separable data, and classifier is used called as Linear SVM classifier.

f. **SVC – RBF (Radial Basis Function) Kernel:** RBF is the default kernel used within the SVM classifier. Since we’re working on a Machine Learning algorithm like Support Vector Machines for non-linear dataset and we can’t seem to figure out the right feature transform or the right kernel to use. In such cases Radial Basis Function (RBF) Kernel is our savior.

RBF Kernel is popular because of its similarity to K-Nearest Neighborhood Algorithm. It has the advantages of K-NN and overcomes the space complexity problem as RBF Kernel Support Vector Machines just needs to store the support vectors during training and not the entire dataset.

❖ Results:

➢ Classification Reports for the build Machine Learning Models:

A classification report is a performance evaluation metric in machine learning. It is used to show the precision, recall, F1 Score, and support of your trained classification model.

To understand the classification report of a machine learning model, you need to know all of the metrics displayed in the report.

Metrics	Definition
Precision	Precision is defined as the ratio of true positive to the sum of true & false positives
Recall	Recall is defined as the ration of true positives to the sum of true positives & false negatives
F1 Score	The F1 is weighted harmonic mean of precision & recall. The closer the value of F1 score is to 1.0, the better the expected performance of the model is.
Support	Support is the number of actual occurrences of the class in the dataset. It doesn't vary

Classification Reports for all the built machine learning models:

Algorithm: Logistic Regression

```
      Classification report:
                     precision    recall f1-score   support

                0       0.87      0.95      0.91       713
                1       0.40      0.18      0.25       121

         accuracy                           0.84       834
        macro avg 0.64      0.57      0.58       834
weighted avg     0.80      0.84      0.82       834

      Accuracy Score:  0.841726618705036
      Area under curve:  0.5677674359301288
```

Algorithm: Decision Tree Classifier

```
      Classification report:
                     precision    recall f1-score   support

                0       0.95      0.96      0.96       713
                1       0.77      0.69      0.73       121

         accuracy                           0.93       834
     macro avg       0.86      0.83      0.84       834
weighted avg       0.92      0.93      0.92       834

      Accuracy Score: 0.9256594724220624
      Area under curve:  0.8295758812142848
```

Algorithm: Random Forest Classifier

```
Classification report:
              precision    recall  f1-score   support

           0       0.94      0.99      0.96       713
           1       0.93      0.62      0.74       121

    accuracy                           0.94       834
   macro avg       0.93      0.81      0.85       834
weighted avg       0.94      0.94      0.93       834

Accuracy Score: 0.9376498800959233
Area under curve: 0.8057097817393623
```

Algorithm: Gaussian NB

```
Classification report:
              precision    recall  f1-score   support

           0       0.90      0.91      0.90       713
           1       0.42      0.40      0.41       121

    accuracy                           0.83       834
   macro avg       0.66      0.65      0.66       834
weighted avg       0.83      0.83      0.83       834

Accuracy Score: 0.8333333333333334
Area under curve: 0.6520637974800922
```

Algorithm: SVC

```
Classification report:
              precision    recall  f1-score   support

           0       0.85      1.00      0.92       713
           1       0.00      0.00      0.00       121

    accuracy                           0.85       834
   macro avg       0.43      0.50      0.46       834
weighted avg       0.73      0.85      0.79       834

Accuracy Score: 0.854916067146283
Area under curve: 0.5
```

Algorithm: SVC-RBF Kernel

```
Classification report:
              precision    recall  f1-score   support

           0       0.94      0.97      0.95       713
           1       0.77      0.63      0.69       121

    accuracy                           0.92       834
   macro avg       0.85      0.80      0.82       834
weighted avg       0.91      0.92      0.92       834

Accuracy Score: 0.9184652278177458
Area under curve: 0.7979205545187951
```

Model Performance Report Over Training Dataset

Models	Accuracy	Recall	Precision	F1 - Score	ROC_AUC	Kappa metric
Logistic Regression	0.8417	0.1818	0.4	0.25	0.5678	0.1752
Decision Tree	0.9257	0.6942	0.7706	0.7304	0.8296	0.6875
Random Forest	0.9376	0.6198	0.9259	0.7426	0.8057	0.7087
Naïve Bayes	0.8333	0.3967	0.4211	0.4085	0.6521	0.3116
SVM (linear)	0.8449	0.0	0.0	0.0	0.5	0.0
SVM (rbf)	0.9185	0.6281	0.7677	0.6909	0.7979	0.6445

ROC_auc: "Area Under the Curve" (AUC) of "Receiver Characteristic Operator" (ROC). AUC-ROC curve helps us visualize how well our machine learning classifier is performing. Although it works for only binary classification problems, we can even extend it to evaluate multi-class classification problems too.

The Receiver Operator Characteristic (ROC) curve is an evaluation metric for binary classification problems. It is a probability curve that plots the TPR against FPR at various threshold values and essentially separates the 'signal' from the 'noise'. The Area Under the Curve (AUC) is the measure of the ability of a classifier to distinguish between classes and is used as a summary of the ROC curve.

The higher the AUC, the better the performance of the model at distinguishing between the positive and negative classes.

Kappa Metric: The Kappa Statistic or Cohen's* Kappa is a statistical measure of inter-rater reliability for categorical variables. "A Kappa Value of .70 Indicates good reliability". The kappa coefficient measures the agreement between classification and truth values. A kappa value of 1 represents perfect agreement, while a value of 0 represents no agreement.

❖ Manipulating the Dataset: -

While we are in the process of manipulating the datasets, let's transform the categorical data into numeric as required by the machine learning routines, using a simple user-defined function that maps Yes/True and No/False to 1 and 0, respectively. All these tasks will be done using the following get data function.

Using RDD (map ()) transformation PySpark map (map ())to apply the transformation function (lambda) on every element of RDD/DataFrame and returns a new RDD & then built Decision tree for data frame of 2 rows & 7n nodes

<u>Result of Decision Tree Classifier after transforming the data:</u>

```
The two first rows of the training data RDD:
[LabeledPoint(0.0,
[117.0,0.0,0.0,0.0,184.5,97.0,351.6,80.0,215.8,90.0,8.7,4.0,1.0]),
LabeledPoint(1.0,
[65.0,0.0,0.0,0.0,129.1,137.0,228.5,83.0,208.8,111.0,12.7,6.0,4.0])]
==========================
DecisionTreeModel classifier of depth 2 with 7 nodes
 If (feature 4 <= 265.0)
  If (feature 12 <= 3.5)
   Predict: 0.0
  Else (feature 12 > 3.5)
   Predict: 1.0
 Else (feature 4 > 265.0)
  If (feature 2 in {1.0})
   Predict: 0.0
  Else (feature 2 not in {1.0})
   Predict: 1.0
```

❖ Model Evaluation

Result for Decision Tree Model Evaluation

```
Confusion Matrix
 [[530.  29.]
 [ 55. 44.]]
Precision of True     0.6027397260273972
Precision of False    0.905982905982906
Weighted Precision      0.8603581722206031
Recall of True       0.4444444444444444
Recall of False      0.9481216457960644
Weighted Recall        0.8723404255319148
FMeasure of True       0.5116279069767442
FMeasure of False      0.9265734265734266
Weighted fMeasure     0.8641424137465702
Accuracy             0.8723404255319149
```

To check the above obtained results and comparing them with those that will be obtained using our new “printAllMetrics” function, We have displayed the confusion matrix that is used to compute all the variables of our new function:

```
+-----+--------------+-----+
|label|predictedLabel|count|
+-----+--------------+-----+
|  1.0|          1.0     |     44|
|  0.0|          1.0     |     31|
|  1.0|          0.0     |     53|
|  0.0|          0.0   |     530|
+-----+--------------+-----+


=========================================
Precision of True     0.6075949367088608
Precision of False    0.919104991394148
** Avg Precision      0.8742664229167203
Recall of True       0.5052631578947369
Recall of False      0.9451327433628318
** Avg Recall        0.8818181818181818
F1 of True          0.5517241379310346
F1 of False         0.9319371727748691
** Avg F1           0.8772095389715899
** Accuracy         0.8818181818181818
```

We have built a new model using the evenly distributed data set and see how it performs. The result displaying the Performance of this model.

```
Confusion Matrix
 [[90. 16.]
 [28. 77.]]
Precision of True     0.8279569892473119
Precision of False    0.7627118644067796
Weighted Precision    0.7951798175264757
Recall of True        0.7333333333333333
Recall of False       0.8490566037735849
Weighted Recall       0.7914691943127963
FMeasure of True      0.7777777777777777
FMeasure of False     0.8035714285714285
Weighted fMeasure     0.7907357255698487
Accuracy              0.7914691943127962
===========================
Precision of True      0.6111111111111112
Precision of False     0.7627118644067796
** Avg Precision       0.6974738353246271
Recall of True         0.7333333333333333
Recall of False        0.6474820143884892
** Avg Recall          0.6844262295081968
F1 of True             0.6666666666666666
F1 of False            0.7003891050583657
** Avg F1              0.6858774000127574
** Accuracy            0.6844262295081968
```

➔ With these new recall values, we can see that the stratified data was helpful in building a less biased model, which will ultimately provide more generalized and robust predictions.

❖ Model Building with PySpark

Let's define a “get_dummy” function that transforms a given classical dataframe to a new other one composed of dense vectors reliable to be running with Spark ML.

Once the required function is ready, let's define the needed numericCols list by removing the Churn column and transforming the datasets:

We can see that the test dataset contains 667 samples.

Model Evaluation Result for K-fold Cross Validation

Classifier name	UnderROC train	underROC test	Accuracy train	Accuracy test	F1 train	Wprecision train	Wprecision test	Wrecall train	Wrecall test
LR	0.594	0.579	0.863	0.858	0.863	0.835	0.824	0.863	0.8858
NB	0.608	0.622	0.629	0.622	0.629	0.800	0.809	0.629	0.622
SVC	0.500	0.500	0.855	0.858	0.855	0.731	0.735	0.855	0.858
DT	0.858	0.881	0.950	0.961	0.950	0.949	0.961	0.950	0.961
RF	0.806	0.799	0.941	0.942	0.941	0.943	0.944	0.941	0.942

Metrics computed using the stratified data (stratified CV data) for the training step:

Classifier name	UnderROC train	underROC test	Accuracy train	Accuracy test	F1 train	Wprecision train	Wprecision test	Wrecall train	Wrecall test
LR	0.763	0.774	0.763	0.778	0.763	0.763	0.870	0.763	0.778
NB	0.602	0.600	0.602	0.585	0.602	0.602	0.801	0.602	0.585
SVC	0.741	0.759	0.741	0.760	0.741	0.741	0.864	0.741	0.760
DT	0.893	0.887	0.894	0.904	0.894	0.899	0.925	0.894	0.904
RF	0.885	0.874	0.885	0.867	0.885	0.886	0.913	0.885	0.867

Model Evaluation Result for each Model built with PySpark

Naïve Bayes Classifier:

```
Weighted Precision   0.6024474355396268
Weighted Recall      0.6020304568527919
F1            0.6020378401496147
Accuracy          0.6020304568527919
============================
Precision of True     0.590818363273453
Precision of False    0.6136363636363636
** Avg Precision      0.6024474355396268
Recall of True       0.6128364389233955
Recall of False      0.5916334661354582
** Avg Recall        0.6020304568527919
F1 of True          0.6016260162601627
F1 of False         0.6024340770791075
** Avg F1           0.6020378401496148
** Accuracy          0.6020304568527919
```

Decision Tree Classifier:

```
Weighted Precision    0.8986643743022468
Weighted Recall       0.8944162436548224
F1               0.8940123670588299
Accuracy           0.8944162436548223
=========================
Precision of True     0.9396751740139211
Precision of False    0.8592057761732852
**Avg Precision      0.8986643743022469
Recall of True       0.8385093167701864
Recall of False      0.9482071713147411
**Avg Recall        0.8944162436548223
F1 of True         0.886214442013129
F1 of False         0.9015151515151516
**Avg F1           0.8940123670588299
**Accuracy         0.8944162436548223
```

Logistic Regression Classifier

```
Weighted Precision    0.7634563788643671
Weighted Recall       0.7634517766497462
F1                  0.7633902874489755
Accuracy             0.7634517766497462
==========================
Precision of True     0.7637130801687764
Precision of False    0.7632093933463796
** Avg Precision      0.763456378864367
Recall of True       0.7494824016563147
Recall of False      0.7768924302788844
** Avg Recall        0.7634517766497462
F1 of True          0.7565308254963428
F1 of False         0.769990128331688
** Avg F1           0.7633902874489755
** Accuracy          0.7634517766497462
```

Linear SVC

```
Weighted Precision    0.7411923065395787
Weighted Recall       0.7411167512690355
F1                  0.7411354330068094
Accuracy             0.7411167512690355
============================
Precision of True     0.7336065573770492
Precision of False    0.7484909456740443
** Avg Precision      0.7411923065395787
Recall of True       0.7412008281573499
Recall of False      0.7410358565737052
```

```
** Avg Recall       0.7411167512690355
F1 of True          0.7373841400617919
F1 of False         0.7447447447447447
** Avg F1           0.7411354330068094
** Accuracy         0.7411167512690355
```

Random forest classifier

```
Weighted Precision    0.8857688739323354
Weighted Recall       0.8852791878172589
F1                    0.8851936902420627
Accuracy              0.8852791878172589
================================
Precision of True     0.8987068965517241
Precision of False    0.8733205374280231
** Avg Precision      0.8857688739323354
Recall of True        0.8633540372670807
Recall of False       0.9063745019920318
** Avg Recall         0.8852791878172589
F1 of True            0.8806758183738119
F1 of False           0.8895405669599217
** Avg F1             0.8851936902420628
** Accuracy           0.8852791878172589
```

The Result we have obtained for the best fit model is the count of Churn customers & count of non-Churn customers. Prediction Using Decision tree model for the testing dataset which we have given as the input.

```
+-----+-----+
|Churn|count|
+-----+-----+
|  0.0| 2850|
|  1.0|  483|
+-----+-----+
```

❖ Conclusion

Customer Churn is one of the major problems which the telecom sector is facing nowadays. It is essential to recognize possible customer churn so that the losses can be avoided. In order to maintain a loyal base of customer the service providers in telecom sector aims to retain customers with themselves.

In this project, we have walked through a complete end-to-end machine learning project using the Telco customer Churn dataset. We started by cleaning the data and analyzing it with visualization. Then, to be able to build a machine learning model, we transformed the categorical data into numeric variables (feature engineering). After transforming the data, we tried 6 different machine learning algorithms using default parameters.

PySpark is a great language for data scientists to learn because it enables scalable analysis and ML pipelines. If we’re already familiar with Python and Pandas, then much of your knowledge can be applied to Spark. To sum it up, we have learned how to build a machine learning application using PySpark.

The Decision tree, Random Forest and Gradient-boosted tree are the more efficient classifiers. However, the best model created according to the cross-validation process seems to be the Decision tree. Indeed, the different metrics obtained by using this classifier are higher as well as very close to each other comparing to those of the other classifiers. An explication on how to compute all the different metrics excepting both area under ROC and area under PR is given in a function called printAllMetrics.

Thus, we can conclude that the big data analytics with machine learning techniques have proven to be accurate and effective to predicts customer churn in nearby future.

❖ References:

Ahmad, A.M., Jafar, A, Aljoumaa, K. (2019). Customer churn prediction in telecom using machine learning in big data platform. Journal of Big Data, 6(28), pp. 1-24

https://www.analyticsvidhya.com/blog/2021/08/churn-prediction-commercial-use-of-data-science/#:~:text=So%2C%20Churn%20Prediction%20is%20essentially,costlier%20than%20retaining%20old%20ones.

https://spark.apache.org/docs/latest/api/python/#:~:text=PySpark%20is%20an%20interface%20for,data%20in%20a%20distributed%20environment.

https://towardsdatascience.com/all-machine-learning-models-explained-in-6-minutes-9fe30ff6776a

https://medium.com/analytics-vidhya/machine-learning-in-pyspark-part-4-5813e831922f

https://scikit-learn.org/stable/modules/generated/sklearn.metrics.classification_report.html