naharia-qst843-assignment3

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1 Title: Enhancing Logistic Regression Model for Telco Customer Churn Prediction || Assignment 3

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Objective: In this assignment, you will revisit the steps from the notebook 11-Classification-Regression/02-Logistic-Regression-Example.ipynb, applying them to the Telco-Customer-Churn dataset. Your goal is to enhance the logistic regression model using knowledge and examples from the previous three lectures. The data is located in data/Telco-Customer-Churn.csv.

1.1 Customer Churn

Also known as customer attrition, or customer turnover is the loss of clients or customers. Customer churn is a critical metric because it is much less expensive to retain existing customers than it is to acquire new ones.

Companies usually make a distinction between voluntary churn and involuntary churn. In most analyses involuntary churn is excluded.

Predictive analytics uses machine learning to predict the likelihood of a customer churning. These models will identify a small subgroup of potential customers that are at a higher risk of abandoning the company. This empowers the company to focus on the subset of the customers who are most likely to churn and through customer retention marketing programs stop some of that to happen.

1.2 Data

Telco Customer Churn

The data was downloaded from IBM Sample Data Sets: https://www.ibm.com/communities/analytics/watson-analytics-blog/guide-to-sample-datasets/

Each row represents a customer, each column contains customer's attributes described as below:

- **customerID**: Customer ID
- **gender**: Customer gender (female, male)
- **SeniorCitizen**: Whether the customer is a senior citizen or not (1, 0)
- **Partner**: Whether the customer has a partner or not (Yes, No)
- **Dependents**: Whether the customer has dependents or not (Yes, No)
- **tenure**: Number of months the customer has stayed with the company
- **PhoneService**: Whether the customer has a phone service or not (Yes, No)
- **MultipleLines**: Whether the customer has multiple lines or not (Yes, No, No phone service)

- **InternetService**: Customer's internet service provider (DSL, Fiber optic, No)
- **OnlineSecurity**: Whether the customer has online security or not (Yes, No, No internet service)
- **OnlineBackup**: Whether the customer has online backup or not (Yes, No, No internet service)
- **DeviceProtection**: Whether the customer has device protection or not (Yes, No, No internet service)
- **TechSupport**: Whether the customer has tech support or not (Yes, No, No internet service)
- **StreamingTV**: Whether the customer has streaming TV or not (Yes, No, No internet service)
- **StreamingMovies**: Whether the customer has streaming movies or not (Yes, No, No internet service)
- **Contract**: The contract term of the customer (Month-to-month, One year, Two year)
- **PaperlessBilling**: Whether the customer has paperless billing or not (Yes, No)
- **PaymentMethod**: The customer's payment method (Electronic check, Mailed check, Bank transfer (automatic), Credit card (automatic))
- **MonthlyCharges**: The amount charged to the customer monthly
- **TotalCharges**: The total amount charged to the customer
- **Churn**: Whether the customer churned or not (Yes or No)

The data set includes information about:

- Customers who left - the column is called `Churn`
- Services that each customer has signed up for - phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies
- Customer account information - how long they've been a customer, contract, payment method, paperless billing, monthly charges, and total charges
- Demographic info about customers - gender, age range, and if they have partners and dependents

1.3 1. Data Preparation and Logistic Regression Model

Importing Libraries

[150]:
```
from pyspark.ml import Pipeline
from pyspark.ml.feature import VectorAssembler, StringIndexer
from pyspark.ml.classification import LogisticRegression
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder
from pyspark.ml.evaluation import BinaryClassificationEvaluator
from pyspark.mllib.evaluation import MulticlassMetrics
```

[151]:
```
from pyspark.sql import SparkSession

spark = SparkSession.builder \
    .appName("YourAppName") \
    .config("spark.jars.packages", "com.google.cloud.spark:
 ↪spark-bigquery-with-dependencies_2.12:0.21.1") \
    .getOrCreate()
```

[152]:

```python
%matplotlib inline
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from pyspark.sql.functions import *
from pyspark.sql import SparkSession

# the following line gets the bucket name attached to our cluster
bucket = spark._jsc.hadoopConfiguration().get("fs.gs.system.bucket")

# specifying the path to our bucket where the data is located (no need to edit␣
↪this path anymore)
data = "gs://" + bucket + "/data/"
print(data)
```

```
gs://pnqst843/data/
```

Importing data:

[153]:

```python
df = spark.read.format("csv")\
  .option("header", "true")\
  .option("inferschema", True)\
  .load(data + "Telco-Customer-Churn.csv")\
  .coalesce(5)

df = df.drop('customerID')  # Dropping customerID
df.cache()
df.show(5)
df.printSchema()
print("This datasets consists of {} rows.".format(df.count()))
```

```
+------+-------------+-------+----------+------+------------+--------------+----
-----------+--------------+------------+----------------+-----------+-----------
+---------------+--------------+----------------+--------------------+----------
----+------------+-----+
|gender|SeniorCitizen|Partner|Dependents|tenure|PhoneService| MultipleLines|Inte
rnetService|OnlineSecurity|OnlineBackup|DeviceProtection|TechSupport|StreamingTV
|StreamingMovies|      Contract|PaperlessBilling|
PaymentMethod|MonthlyCharges|TotalCharges|Churn|
+------+-------------+-------+----------+------+------------+--------------+----
-----------+--------------+------------+----------------+-----------+-----------
+---------------+--------------+----------------+--------------------+----------
----+------------+-----+
|Female|            0|    Yes|        No|     1|          No|NoPhoneService|
DSL|            No|         Yes|              No|         No|         No|
No|Month_to_month|             Yes|     ElectronicCheck|         29.85|
29.85|   No|
|  Male|            0|     No|        No|    34|         Yes|            No|
```

```
DSL|           Yes|          No|             Yes|         No|         No|
No|       OneYear|             No|         MailedCheck|         56.95|
1889.5|   No|
|  Male|           0|     No|         No|     2|         Yes|            No|
DSL|           Yes|         Yes|              No|         No|         No|
No|Month_to_month|            Yes|         MailedCheck|         53.85|
108.15|  Yes|
|  Male|           0|     No|         No|    45|          No|NoPhoneService|
DSL|           Yes|          No|             Yes|        Yes|         No|
No|       OneYear|             No|BankTransferAutom…|          42.3|
1840.75|   No|
|Female|           0|     No|         No|     2|         Yes|            No|
FiberOptic|            No|          No|              No|         No|         No|
No|Month_to_month|            Yes|     ElectronicCheck|          70.7|
151.65|  Yes|
+------+-------------+-------+----------+------+------------+-------------+----
-----------+-------------+------------+----------------+-----------+-----------
+---------------+-------------+----------------+-------------------+----------
----+-----------+-----+
only showing top 5 rows

root
 |-- gender: string (nullable = true)
 |-- SeniorCitizen: integer (nullable = true)
 |-- Partner: string (nullable = true)
 |-- Dependents: string (nullable = true)
 |-- tenure: integer (nullable = true)
 |-- PhoneService: string (nullable = true)
 |-- MultipleLines: string (nullable = true)
 |-- InternetService: string (nullable = true)
 |-- OnlineSecurity: string (nullable = true)
 |-- OnlineBackup: string (nullable = true)
 |-- DeviceProtection: string (nullable = true)
 |-- TechSupport: string (nullable = true)
 |-- StreamingTV: string (nullable = true)
 |-- StreamingMovies: string (nullable = true)
 |-- Contract: string (nullable = true)
 |-- PaperlessBilling: string (nullable = true)
 |-- PaymentMethod: string (nullable = true)
 |-- MonthlyCharges: double (nullable = true)
 |-- TotalCharges: double (nullable = true)
 |-- Churn: string (nullable = true)
```

```
This datasets consists of 7043 rows.
```

```
23/04/26 15:57:15 WARN CacheManager: Asked to cache already cached data.
```

Checking for missing values:

[154]:
```
[(c, df.where(col(c).isNull()).count()) for c in df.columns]
```

[154]:
```
[('gender', 0),
 ('SeniorCitizen', 0),
 ('Partner', 0),
 ('Dependents', 0),
 ('tenure', 0),
 ('PhoneService', 0),
 ('MultipleLines', 0),
 ('InternetService', 0),
 ('OnlineSecurity', 0),
 ('OnlineBackup', 0),
 ('DeviceProtection', 0),
 ('TechSupport', 0),
 ('StreamingTV', 0),
 ('StreamingMovies', 0),
 ('Contract', 0),
 ('PaperlessBilling', 0),
 ('PaymentMethod', 0),
 ('MonthlyCharges', 0),
 ('TotalCharges', 11),
 ('Churn', 0)]
```

From the above output, there are 11 null values in total charges

[155]:
```
pd.options.display.max_columns = None  # do not truncate the middle columns
df.limit(5).toPandas()
```

[155]:
```
   gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  Female              0     Yes         No       1           No
1    Male              0      No         No      34          Yes
2    Male              0      No         No       2          Yes
3    Male              0      No         No      45           No
4  Female              0      No         No       2          Yes

     MultipleLines InternetService OnlineSecurity OnlineBackup  \
0  NoPhoneService             DSL             No          Yes
1               No             DSL            Yes           No
2               No             DSL            Yes          Yes
3  NoPhoneService             DSL            Yes           No
4               No      FiberOptic             No           No

  DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
0               No          No          No              No  Month_to_month
1              Yes          No          No              No         OneYear
2               No          No          No              No  Month_to_month
3              Yes         Yes          No              No         OneYear
```

```
4              No          No          No              No  Month_to_month

  PaperlessBilling          PaymentMethod  MonthlyCharges  TotalCharges Churn
0              Yes        ElectronicCheck           29.85         29.85    No
1               No            MailedCheck           56.95       1889.50    No
2              Yes            MailedCheck           53.85        108.15   Yes
3               No  BankTransferAutomatic           42.30       1840.75    No
4              Yes        ElectronicCheck           70.70        151.65   Yes
```

[156]:
```python
null_totalcharges = df.filter(df['TotalCharges'].isNull())
null_totalcharges.toPandas()
```

[156]:
```
    gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0   Female              0     Yes        Yes       0           No
1     Male              0      No        Yes       0          Yes
2   Female              0     Yes        Yes       0          Yes
3     Male              0     Yes        Yes       0          Yes
4   Female              0     Yes        Yes       0           No
5     Male              0     Yes        Yes       0          Yes
6     Male              0     Yes        Yes       0          Yes
7   Female              0     Yes        Yes       0          Yes
8     Male              0     Yes        Yes       0          Yes
9   Female              0     Yes        Yes       0          Yes
10    Male              0      No        Yes       0          Yes

     MultipleLines InternetService     OnlineSecurity       OnlineBackup  \
0   NoPhoneService             DSL                Yes                 No
1               No              No  NoInternetService  NoInternetService
2               No             DSL                Yes                Yes
3              Yes              No  NoInternetService  NoInternetService
4   NoPhoneService             DSL                Yes                Yes
5               No              No  NoInternetService  NoInternetService
6              Yes              No  NoInternetService  NoInternetService
7               No              No  NoInternetService  NoInternetService
8               No              No  NoInternetService  NoInternetService
9              Yes             DSL                 No                Yes
10             Yes             DSL                Yes                Yes

     DeviceProtection        TechSupport        StreamingTV  \
0                 Yes                Yes                Yes
1   NoInternetService  NoInternetService  NoInternetService
2                 Yes                 No                Yes
3   NoInternetService  NoInternetService  NoInternetService
4                 Yes                Yes                Yes
5   NoInternetService  NoInternetService  NoInternetService
6   NoInternetService  NoInternetService  NoInternetService
7   NoInternetService  NoInternetService  NoInternetService
```

```
8   NoInternetService  NoInternetService  NoInternetService
9                 Yes                Yes                Yes
10                 No                Yes                 No

     StreamingMovies Contract PaperlessBilling          PaymentMethod  \
0                 No  TwoYear              Yes  BankTransferAutomatic
1  NoInternetService  TwoYear               No            MailedCheck
2                Yes  TwoYear               No            MailedCheck
3  NoInternetService  TwoYear               No            MailedCheck
4                 No  TwoYear               No    CreditCardAutomatic
5  NoInternetService  TwoYear               No            MailedCheck
6  NoInternetService  TwoYear               No            MailedCheck
7  NoInternetService  TwoYear               No            MailedCheck
8  NoInternetService  OneYear              Yes            MailedCheck
9                 No  TwoYear               No            MailedCheck
10                No  TwoYear              Yes  BankTransferAutomatic

    MonthlyCharges  TotalCharges Churn
0            52.55           NaN    No
1            20.25           NaN    No
2            80.85           NaN    No
3            25.75           NaN    No
4            56.05           NaN    No
5            19.85           NaN    No
6            25.35           NaN    No
7            20.00           NaN    No
8            19.70           NaN    No
9            73.35           NaN    No
10           61.90           NaN    No
```

[157]:
```
df = df.fillna(0)
```

1.3.1 RFormula

Define an RFormula that uses all of the columns as features and call it `supervised`:

[158]:
```
from pyspark.ml.feature import RFormula

supervised = RFormula(formula="Churn ~ .")
#supervised.fit(df).transform(df).show(2, False)
```

Fit the RFormula transformer and call it `fittedRF`:

[159]:
```
fittedRF = supervised.fit(df)
```

Using `fittedRF` transform our `df` DataFrame. Call this `preparedDF`:

[160]:
```
preparedDF = fittedRF.transform(df)
```

Print the first couple of rows of `preparedDF`, with the truncate option off:

[161]:
```
preparedDF.show(2, truncate=False)
```

```
+------+-------------+-------+----------+------+------------+--------------+----
-----------+--------------+------------+----------------+-----------+-----------
+---------------+--------------+----------------+----------------+--------------+
------------+-----+-------------------------------------------------------------
-----------------------------------------------------------+-----+
|gender|SeniorCitizen|Partner|Dependents|tenure|PhoneService|MultipleLines |Inte
rnetService|OnlineSecurity|OnlineBackup|DeviceProtection|TechSupport|StreamingTV
|StreamingMovies|Contract      |PaperlessBilling|PaymentMethod
|MonthlyCharges|TotalCharges|Churn|features
|label|
+------+-------------+-------+----------+------+------------+--------------+----
-----------+--------------+------------+----------------+-----------+-----------
+---------------+--------------+----------------+----------------+--------------+
------------+-----+-------------------------------------------------------------
-----------------------------------------------------------+-----+
|Female|0            |Yes    |No        |1     |No          |NoPhoneService|DSL
|No            |Yes          |No                |No          |No            |No
|Month_to_month|Yes             |ElectronicCheck|29.85          |29.85        |No
|(30,[3,4,9,10,13,14,16,18,20,22,24,25,28,29],[1.0,1.0,1.0,1.0,1.0,1.0,1.0,1.0,1
.0,1.0,1.0,1.0,29.85,29.85])            |0.0  |
|Male  |0            |No     |No        |34    |Yes         |No              |DSL
|Yes           |No           |Yes               |No          |No            |No
|OneYear       |No              |MailedCheck    |56.95          |1889.5       |No
|(30,[0,2,3,4,5,6,9,11,12,15,16,18,20,26,28,29],[1.0,1.0,1.0,34.0,1.0,1.0,1.0,1.
0,1.0,1.0,1.0,1.0,1.0,1.0,56.95,1889.5])|0.0  |
+------+-------------+-------+----------+------+------------+--------------+----
-----------+--------------+------------+----------------+-----------+-----------
+---------------+--------------+----------------+----------------+--------------+
------------+-----+-------------------------------------------------------------
-----------------------------------------------------------+-----+
only showing top 2 rows
```

Below we will retrieve the name of the columns used to make our feature vector and store them in a pandas DataFrame:

[162]:
```
featureCols = pd.DataFrame(preparedDF.schema["features"].
↪metadata["ml_attr"]["attrs"]["binary"]+
 preparedDF.schema["features"].metadata["ml_attr"]["attrs"]["numeric"]).
↪sort_values("idx")

featureCols = featureCols.set_index('idx')
featureCols.head()
```

```
# binary_features = preparedDF.schema["features"].
↪metadata["ml_attr"]["attrs"]["binary"]
# numeric_features = preparedDF.schema["features"].
↪metadata["ml_attr"]["attrs"]["numeric"]
# all_features = binary_features + numeric_features
# sorted_features = sorted(all_features, key=lambda x: x['idx'])
# featureCols = pd.DataFrame(sorted_features).set_index('idx')
# featureCols.head()
```

[162]:

```
               name
idx
0       gender_Male
1     SeniorCitizen
2        Partner_No
3     Dependents_No
4            tenure
```

Split the transformed data into `train` and `test`. Use a 30% split and a `seed`.

[163]:

```
train, test = preparedDF.randomSplit([0.7, 0.3], seed=42)
```

1.3.2 LogisticRegression

Instantiate an instance of `LogisticRegression`. Call it `lr`:

[164]:

```
from pyspark.ml.classification import LogisticRegression

lr = LogisticRegression()
```

Print the parameters of `lr` to check the default values used. You can always come back to the cell above and change the default values:

[165]:

```
print(lr.explainParams())
```

```
aggregationDepth: suggested depth for treeAggregate (>= 2). (default: 2)
elasticNetParam: the ElasticNet mixing parameter, in range [0, 1]. For alpha =
0, the penalty is an L2 penalty. For alpha = 1, it is an L1 penalty. (default:
0.0)
family: The name of family which is a description of the label distribution to
be used in the model. Supported options: auto, binomial, multinomial (default:
auto)
featuresCol: features column name. (default: features)
fitIntercept: whether to fit an intercept term. (default: True)
labelCol: label column name. (default: label)
lowerBoundsOnCoefficients: The lower bounds on coefficients if fitting under
bound constrained optimization. The bound matrix must be compatible with the
shape (1, number of features) for binomial regression, or (number of classes,
number of features) for multinomial regression. (undefined)
```

```
lowerBoundsOnIntercepts: The lower bounds on intercepts if fitting under bound
constrained optimization. The bounds vector size must beequal with 1 for
binomial regression, or the number oflasses for multinomial regression.
(undefined)
maxBlockSizeInMB: maximum memory in MB for stacking input data into blocks. Data
is stacked within partitions. If more than remaining data size in a partition
then it is adjusted to the data size. Default 0.0 represents choosing optimal
value, depends on specific algorithm. Must be >= 0. (default: 0.0)
maxIter: max number of iterations (>= 0). (default: 100)
predictionCol: prediction column name. (default: prediction)
probabilityCol: Column name for predicted class conditional probabilities. Note:
Not all models output well-calibrated probability estimates! These probabilities
should be treated as confidences, not precise probabilities. (default:
probability)
rawPredictionCol: raw prediction (a.k.a. confidence) column name. (default:
rawPrediction)
regParam: regularization parameter (>= 0). (default: 0.0)
standardization: whether to standardize the training features before fitting the
model. (default: True)
threshold: Threshold in binary classification prediction, in range [0, 1]. If
threshold and thresholds are both set, they must match.e.g. if threshold is p,
then thresholds must be equal to [1-p, p]. (default: 0.5)
thresholds: Thresholds in multi-class classification to adjust the probability
of predicting each class. Array must have length equal to the number of classes,
with values > 0, excepting that at most one value may be 0. The class with
largest value p/t is predicted, where p is the original probability of that
class and t is the class's threshold. (undefined)
tol: the convergence tolerance for iterative algorithms (>= 0). (default: 1e-06)
upperBoundsOnCoefficients: The upper bounds on coefficients if fitting under
bound constrained optimization. The bound matrix must be compatible with the
shape (1, number of features) for binomial regression, or (number of classes,
number of features) for multinomial regression. (undefined)
upperBoundsOnIntercepts: The upper bounds on intercepts if fitting under bound
constrained optimization. The bound vector size must be equal with 1 for
binomial regression, or the number of classes for multinomial regression.
(undefined)
weightCol: weight column name. If this is not set or empty, we treat all
instance weights as 1.0. (undefined)
```

Fit the model on `train` and call it `lrModel`:

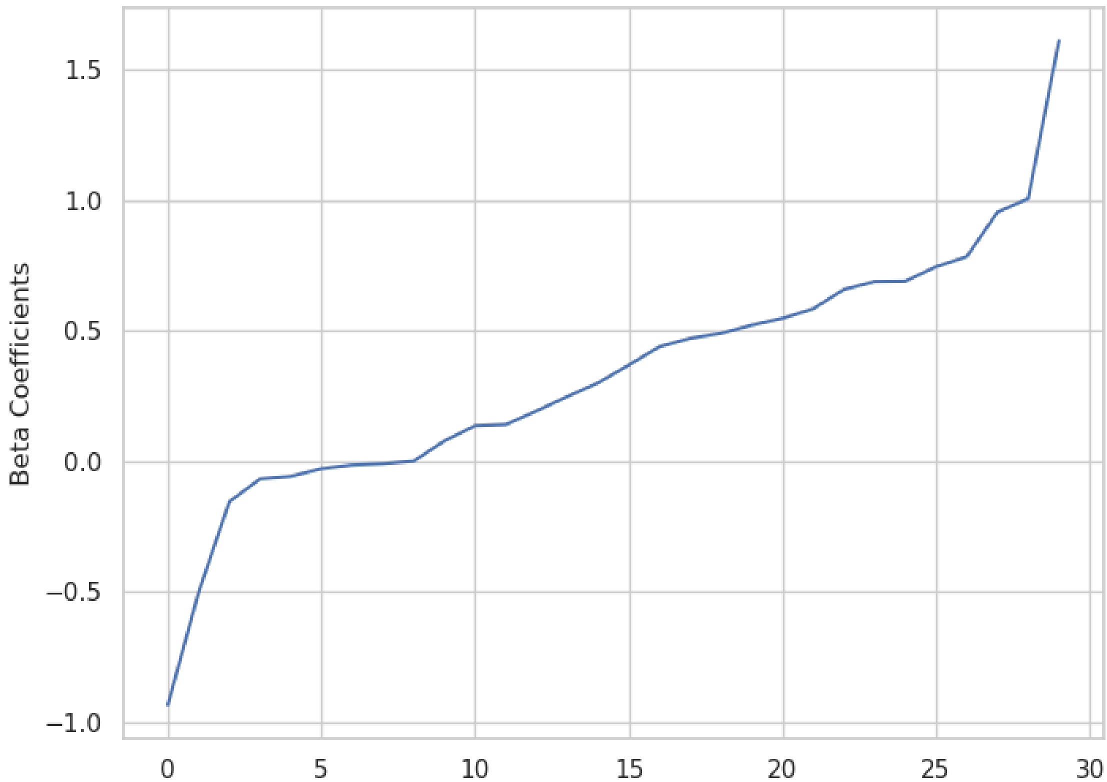
[166]:
```
lrModel = lr.fit(train)
```

Below we plot the coefficients of our model in a sorted fashion:

[167]:
```
plt.rcParams["figure.figsize"] = (8,6)
beta = np.sort(lrModel.coefficients)
plt.plot(beta)
```

```
plt.ylabel('Beta Coefficients')
```

[167]: Text(0, 0.5, 'Beta Coefficients')



1.3.3 Feature importance

We already retrieved the name of the features. Let's join it with the coefficients to identify the ones with bigger absolute value:

[168]:
```
coefsArray = np.array(lrModel.coefficients)  # convert to np.array
coefsDF = pd.DataFrame(coefsArray, columns=['coefs'])  # to pandas

coefsDF = coefsDF.merge(featureCols, left_index=True, right_index=True)  # join␣
 ↪it with featureCols we created above
coefsDF.sort_values('coefs', inplace=True)  # Sort them
coefsDF.head(10)
```

[168]:

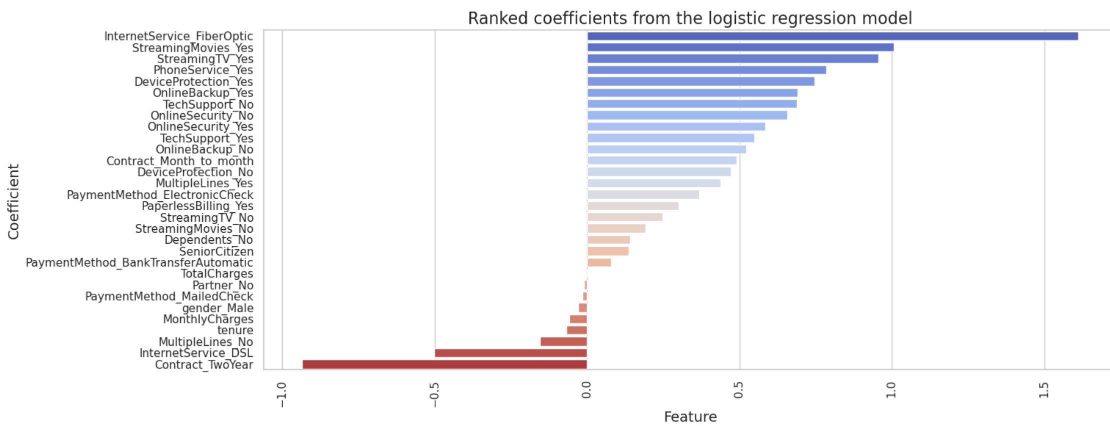
	coefs	name
23	-0.933980	Contract_TwoYear
9	-0.502347	InternetService_DSL
6	-0.155183	MultipleLines_No
4	-0.067761	tenure

```
28 -0.057943                     MonthlyCharges
0  -0.028732                        gender_Male
26 -0.014802           PaymentMethod_MailedCheck
2  -0.009636                         Partner_No
29  0.000387                       TotalCharges
27  0.077996  PaymentMethod_BankTransferAutomatic
```

Plot a Bar Chart

[169]:
```python
import seaborn as sns

# plt.rcParams["figure.figsize"] = (20,3)
# plt.xticks(rotation=90)
# plt.bar(coefsDF.name, coefsDF.coefs)
# plt.title('Ranked coefficients from the logistic regression model')
# plt.show()

sns.set(style="whitegrid")
plt.rcParams["figure.figsize"] = (15, 6)
plt.rcParams["font.size"] = 12
```

[170]:
```python
sorted_coefs = coefsDF.sort_values("coefs", ascending=False)
ax = sns.barplot(x="coefs", y="name", data=sorted_coefs, palette="coolwarm")
ax.set_title('Ranked coefficients from the logistic regression model',␣
 ↪fontsize=16)
ax.set_xlabel("Feature", fontsize=14)
ax.set_ylabel("Coefficient", fontsize=14)
plt.xticks(rotation=90)
plt.show()
```



From our fitted model, `lrModel`, extract the summary and call it `summary`:

[171]:
```python
summary = lrModel.summary
```

From `summary` extract `areaUnderROC`. Note that this AUC is from the `train` dataset and we should pay more attention to the AUC coming from the `test` set:

[172]:
```
print("AUC:", summary.areaUnderROC)
```

```
AUC: 0.8474526767588296
```

From `summary` extract `roc` and convert it to a pandas DataFrame. Call it `roc`:

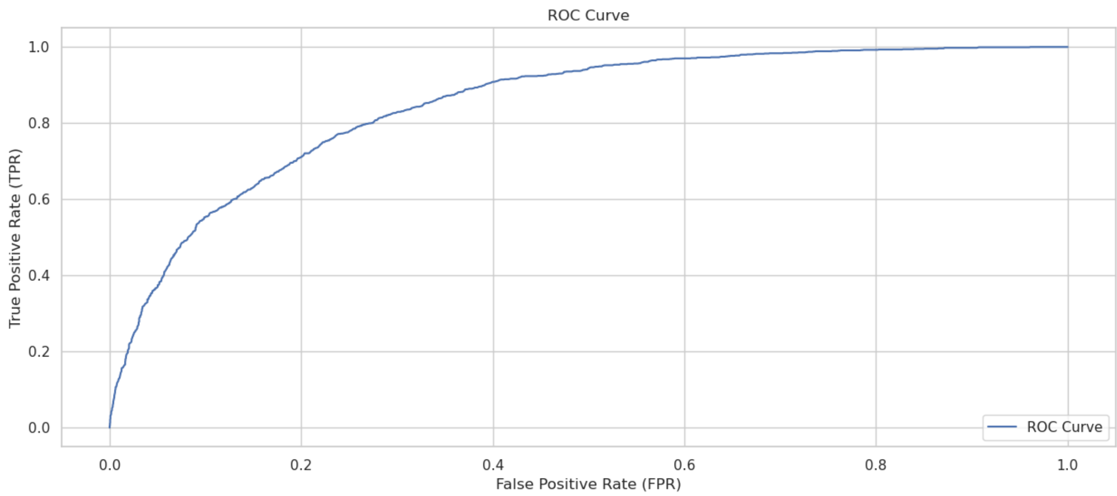
[173]:
```
roc = summary.roc.toPandas()
roc
```

[173]:
```
          FPR       TPR
0     0.00000  0.000000
1     0.00000  0.003754
2     0.00027  0.006757
3     0.00027  0.010511
4     0.00054  0.013514
…         …         …
1000  0.99622  1.000000
1001  0.99757  1.000000
1002  0.99892  1.000000
1003  1.00000  1.000000
1004  1.00000  1.000000

[1005 rows x 2 columns]
```

Visualize the `roc` DataFrame:

[174]:
```
%matplotlib inline
import matplotlib.pyplot as plt

plt.plot(roc['FPR'], roc['TPR'], label='ROC Curve')
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.title('ROC Curve')
plt.legend(loc='lower right')
print('Train AUC:', summary.areaUnderROC)
#plt.plot([0, 1], [0, 1], linestyle='--', color='gray') #randomclassifier␣
↪diagonal line
```

```
Train AUC: 0.8474526767588296
```



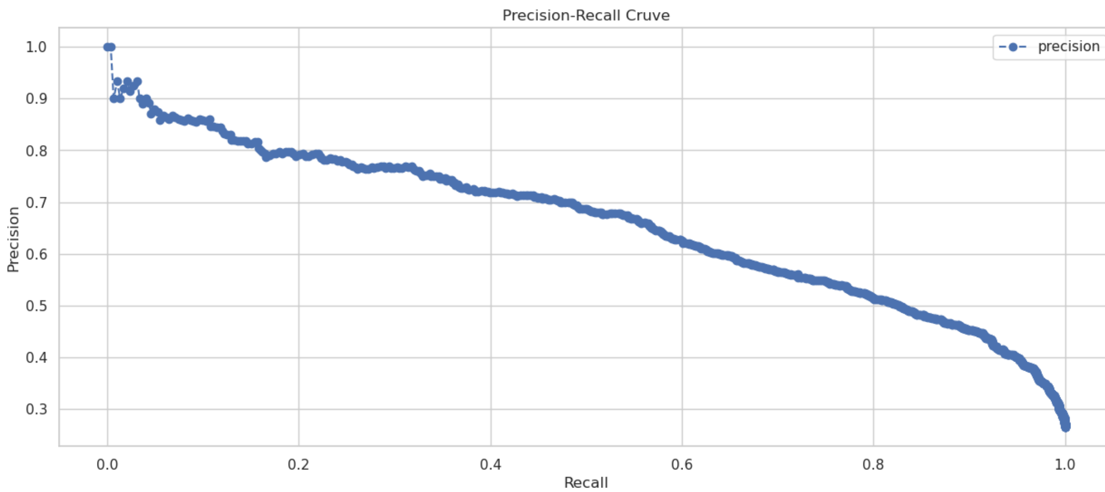
Do the same with `pr` from `summary`:

```
[175]: pr = summary.pr.toPandas()
       pr
```

```
[175]:        recall  precision
       0     0.000000   1.000000
       1     0.003754   1.000000
       2     0.006757   0.900000
       3     0.010511   0.933333
       4     0.013514   0.900000
       …          …          …
       999   1.000000   0.265497
       1000  1.000000   0.265233
       1001  1.000000   0.264969
       1002  1.000000   0.264706
       1003  1.000000   0.264496

       [1004 rows x 2 columns]
```

```
[176]: pr.plot(x='recall', y='precision', style='--o', legend=False)
       plt.xlabel('Recall')
       plt.title('Precision-Recall Cruve')
       plt.ylabel('Precision')
       plt.legend(loc='upper right')
```

```
[176]: <matplotlib.legend.Legend at 0x7f0485e25a20>
```



Our baseline model looks promising. Let's do some predictions on the `test` set.

Pass the `test` set through our trained model. Called the resulting DataFrame `fittedTest`:

[177]:
```
fittedTest = lrModel.transform(test)
```

Print the first few rows of this DataFrame. Only show the following columns: "label", "prediction", "rawPrediction"

[178]:
```
fittedTest.select('label','prediction','rawPrediction').show(6)
```

```
+-----+----------+--------------------+
|label|prediction|       rawPrediction|
+-----+----------+--------------------+
|  0.0|       1.0|[-0.3511581527595...|
|  1.0|       1.0|[-0.2767090139105...|
|  0.0|       0.0|[0.55682764262286...|
|  1.0|       1.0|[-0.2172075913226...|
|  0.0|       0.0|[0.51122949635904...|
|  1.0|       0.0|[0.04185624638468...|
+-----+----------+--------------------+
only showing top 6 rows
```

Make an evaluator from `BinaryClassificationEvaluator` function that calculates AUC. We will use this function to measure our model's performance on the `test` set. Call this evaluator `aucEvaluator`.

Note that this function can be found under the `pyspark.ml.evaluation` module.

[179]:
```
from pyspark.ml.evaluation import BinaryClassificationEvaluator
from pyspark.mllib.evaluation import BinaryClassificationMetrics
aucEvaluator = BinaryClassificationEvaluator(metricName="areaUnderROC")
```

```
#fittedTest
```

Using our `aucEvaluator` find out the AUC on the `test` set:

[180]:
```
auc_test = aucEvaluator.evaluate(fittedTest)
print(f"AUC on test set: {auc_test:.4f}")
```

```
AUC on test set: 0.8500
```

[181]:
```
# fittedTestRDD = fittedTest.select("label", "prediction").rdd
# predictionAndLabels = fittedTestRDD.map(lambda row: (float(row.prediction),␣
↪row.label))
# metrics = BinaryClassificationMetrics(predictionAndLabels)
# auc = metrics.areaUnderROC
# print("Area under ROC = %s" % auc)
```

[182]:
```
print('AUC on Train:', summary.areaUnderROC)
print(f"AUC on test set: {auc_test:.11f}")
```

```
AUC on Train: 0.8474526767588296
AUC on test set: 0.84998036459
```

Q. Are your test and train AUC's within the same range?

Ans. Yes both the AUC - Test & Train are within the same range. Overall, the results suggest that the logistic regression model is a decent classifier for this problem. However, there may still be room for improvement by experimenting with different models, feature engineering, or hyperparameter tuning.

1.4 2. Model Enhancement

a. Explore different options to improve the logistic regression model using knowledge and examples from the previous three lectures.

b. Implement at least two improvements to the model (e.g., feature selection, hyperparameter tuning, or additional feature engineering).

1.4.1 Feature Engineering

Creating number of opted services & MonthlyCharges/TotalCharges giving us the rate

[183]:
```
services = ['PhoneService','MultipleLines','InternetService',
            'OnlineSecurity','OnlineBackup','DeviceProtection','TechSupport',
            'StreamingTV','StreamingMovies']
```

[184]:
```
from pyspark.sql.functions import col, expr
num_of_services_expr = " + ".join([f"CAST(({c} = 'Yes') as INT)" for c in␣
↪services])
```

[185]:
```
df = df.withColumn('numofservices', expr(num_of_services_expr))
```

[186]:
```
#data = df.cache()
df = df.withColumn('charge_ratio', round(col('MonthlyCharges') /
 ↪col('TotalCharges'),2))
df.limit(2).toPandas()
```

[186]:
```
   gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  Female              0     Yes         No       1           No
1    Male              0      No         No      34          Yes

     MultipleLines InternetService OnlineSecurity OnlineBackup  \
0  NoPhoneService             DSL             No          Yes
1              No             DSL            Yes           No

  DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
0               No          No          No              No  Month_to_month
1              Yes          No          No              No         OneYear

  PaperlessBilling    PaymentMethod  MonthlyCharges  TotalCharges Churn  \
0              Yes  ElectronicCheck           29.85         29.85    No
1               No      MailedCheck           56.95       1889.50    No

   numofservices  charge_ratio
0              1          1.00
1              3          0.03
```

[187]:
```
[(c, df.where(col(c).isNull()).count()) for c in df.columns]
```

[187]:
```
[('gender', 0),
 ('SeniorCitizen', 0),
 ('Partner', 0),
 ('Dependents', 0),
 ('tenure', 0),
 ('PhoneService', 0),
 ('MultipleLines', 0),
 ('InternetService', 0),
 ('OnlineSecurity', 0),
 ('OnlineBackup', 0),
 ('DeviceProtection', 0),
 ('TechSupport', 0),
 ('StreamingTV', 0),
 ('StreamingMovies', 0),
 ('Contract', 0),
 ('PaperlessBilling', 0),
 ('PaymentMethod', 0),
 ('MonthlyCharges', 0),
 ('TotalCharges', 0),
 ('Churn', 0),
```

```
 ('numofservices', 0),
 ('charge_ratio', 11)]
```

[188]:
```
df = df.fillna(0)
```

[189]:
```
rformula = RFormula(formula="Churn ~ . + numofservices + charge_ratio",␣
 ↪featuresCol="features", labelCol="label")

fittedRF = rformula.fit(df)
preparedDF = fittedRF.transform(df)
train, test = preparedDF.randomSplit([0.7, 0.3], seed=42)
lrModel = lr.fit(train)

fittedTest = lrModel.transform(test)
testAUC = aucEvaluator.evaluate(fittedTest)

print(f"AUC on test set with new features: {testAUC:.4f}")
```

```
AUC on test set with new features: 0.8579
```

[190]:
```
df.limit(10).toPandas()
```

[190]:
```
   gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  Female              0     Yes         No       1           No
1    Male              0      No         No      34          Yes
2    Male              0      No         No       2          Yes
3    Male              0      No         No      45           No
4  Female              0      No         No       2          Yes
5  Female              0      No         No       8          Yes
6    Male              0      No        Yes      22          Yes
7  Female              0      No         No      10           No
8  Female              0     Yes         No      28          Yes
9    Male              0      No        Yes      62          Yes

     MultipleLines InternetService OnlineSecurity OnlineBackup  \
0  NoPhoneService             DSL             No          Yes
1              No             DSL            Yes           No
2              No             DSL            Yes          Yes
3  NoPhoneService             DSL            Yes           No
4              No      FiberOptic             No           No
5             Yes      FiberOptic             No           No
6             Yes      FiberOptic             No          Yes
7  NoPhoneService             DSL            Yes           No
8             Yes      FiberOptic             No           No
9              No             DSL            Yes          Yes

  DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
```

```
0              No          No          No               No  Month_to_month
1             Yes          No          No               No         OneYear
2              No          No          No               No  Month_to_month
3             Yes         Yes          No               No         OneYear
4              No          No          No               No  Month_to_month
5             Yes          No         Yes              Yes  Month_to_month
6              No          No         Yes               No  Month_to_month
7              No          No          No               No  Month_to_month
8             Yes         Yes         Yes              Yes  Month_to_month
9              No          No          No               No         OneYear

  PaperlessBilling          PaymentMethod  MonthlyCharges  TotalCharges Churn  \
0              Yes        ElectronicCheck           29.85         29.85    No
1               No            MailedCheck           56.95       1889.50    No
2              Yes            MailedCheck           53.85        108.15   Yes
3               No  BankTransferAutomatic           42.30       1840.75    No
4              Yes        ElectronicCheck           70.70        151.65   Yes
5              Yes        ElectronicCheck           99.65        820.50   Yes
6              Yes    CreditCardAutomatic           89.10       1949.40    No
7               No            MailedCheck           29.75        301.90    No
8              Yes        ElectronicCheck          104.80       3046.05   Yes
9               No  BankTransferAutomatic           56.15       3487.95    No

   numofservices  charge_ratio
0              1          1.00
1              3          0.03
2              3          0.50
3              3          0.02
4              1          0.47
5              5          0.12
6              4          0.05
7              1          0.10
8              6          0.03
9              3          0.02
```

1.4.2 Hyperparameter tuning using Grid Search and Cross-Validation

[191]:
```python
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder

paramGrid = ParamGridBuilder() \
    .addGrid(lr.regParam, [0.0, 0.1, 0.01]) \
    .addGrid(lr.elasticNetParam, [0.0, 0.5, 1.0]) \
    .addGrid(lr.maxIter, [10, 50, 100]) \
    .build()

crossval = CrossValidator(estimator=lr,
                          estimatorParamMaps=paramGrid,
```

```
                              evaluator=BinaryClassificationEvaluator(),
                              numFolds=3)


cvModel = crossval.fit(train)

fittedTest = cvModel.transform(test)

auc_test = aucEvaluator.evaluate(fittedTest)

print(f"Test AUC: {auc_test:.4f}")
```

```
Test AUC: 0.8593
```

1.4.3 OneHotEncoding & RandomForestClassifier

[122]:
```
from pyspark.ml.feature import StringIndexer, OneHotEncoder
from pyspark.ml import Pipeline

dfv = df.cache()
categorical_columns = [
    "gender", "Partner", "Dependents", "PhoneService", "MultipleLines",␣
↪"InternetService", "OnlineSecurity",
    "OnlineBackup", "DeviceProtection", "TechSupport", "StreamingTV",␣
↪"StreamingMovies", "Contract",
    "PaperlessBilling", "PaymentMethod"
]

# Apply StringIndexer transformation
indexers = [StringIndexer(inputCol=column, outputCol=column+"_index").fit(df)␣
↪for column in categorical_columns]
pipeline_indexers = Pipeline(stages=indexers)
df_indexed = pipeline_indexers.fit(dfv).transform(dfv)

churn_indexer = StringIndexer(inputCol="Churn", outputCol="Churn_index")
df_transformed = churn_indexer.fit(df_transformed).transform(df_transformed)

# Apply OneHotEncoder transformation
encoders = [OneHotEncoder(inputCol=column+"_index", outputCol=column+"_Vec")␣
↪for column in categorical_columns]
pipeline_encoders = Pipeline(stages=encoders)
df_transformed = pipeline_encoders.fit(df_indexed).transform(df_indexed)
```

```
23/04/26 14:14:43 WARN CacheManager: Asked to cache already cached data.
```

[124]:
```
churn_indexer = StringIndexer(inputCol="Churn", outputCol="Churn_index")
df_transformed = churn_indexer.fit(df_transformed).transform(df_transformed)
```

[125]:
```
df_transformed.limit(9).toPandas()
```

[125]:
```
   gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  Female              0     Yes         No       1           No
1    Male              0      No         No      34          Yes
2    Male              0      No         No       2          Yes
3    Male              0      No         No      45           No
4  Female              0      No         No       2          Yes
5  Female              0      No         No       8          Yes
6    Male              0      No        Yes      22          Yes
7  Female              0      No         No      10           No
8  Female              0     Yes         No      28          Yes

    MultipleLines InternetService OnlineSecurity OnlineBackup  \
0  NoPhoneService             DSL             No          Yes
1              No             DSL            Yes           No
2              No             DSL            Yes          Yes
3  NoPhoneService             DSL            Yes           No
4              No      FiberOptic             No           No
5             Yes      FiberOptic             No           No
6             Yes      FiberOptic             No          Yes
7  NoPhoneService             DSL            Yes           No
8             Yes      FiberOptic             No           No

  DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
0               No          No          No              No  Month_to_month
1              Yes          No          No              No         OneYear
2               No          No          No              No  Month_to_month
3              Yes         Yes          No              No         OneYear
4               No          No          No              No  Month_to_month
5              Yes          No         Yes             Yes  Month_to_month
6               No          No         Yes              No  Month_to_month
7               No          No          No              No  Month_to_month
8              Yes         Yes         Yes             Yes  Month_to_month

  PaperlessBilling           PaymentMethod  MonthlyCharges  TotalCharges Churn  \
0              Yes         ElectronicCheck           29.85         29.85    No
1               No             MailedCheck           56.95       1889.50    No
2              Yes             MailedCheck           53.85        108.15   Yes
3               No  BankTransferAutomatic           42.30       1840.75    No
4              Yes         ElectronicCheck           70.70        151.65   Yes
5              Yes         ElectronicCheck           99.65        820.50   Yes
6              Yes    CreditCardAutomatic           89.10       1949.40    No
7               No             MailedCheck           29.75        301.90    No
8              Yes         ElectronicCheck          104.80       3046.05   Yes

   numofservices  charge_ratio  gender_index  Partner_index  Dependents_index  \
```

```
0            1        1.00           1.0           1.0              0.0
1            3        0.03           0.0           0.0              0.0
2            3        0.50           0.0           0.0              0.0
3            3        0.02           0.0           0.0              0.0
4            1        0.47           1.0           0.0              0.0
5            5        0.12           1.0           0.0              0.0
6            4        0.05           0.0           0.0              1.0
7            1        0.10           1.0           0.0              0.0
8            6        0.03           1.0           1.0              0.0

  PhoneService_index  MultipleLines_index  InternetService_index  \
0                1.0                  2.0                    1.0
1                0.0                  0.0                    1.0
2                0.0                  0.0                    1.0
3                1.0                  2.0                    1.0
4                0.0                  0.0                    0.0
5                0.0                  1.0                    0.0
6                0.0                  1.0                    0.0
7                1.0                  2.0                    1.0
8                0.0                  1.0                    0.0

  OnlineSecurity_index  OnlineBackup_index  DeviceProtection_index  \
0                  0.0                 1.0                     0.0
1                  1.0                 0.0                     1.0
2                  1.0                 1.0                     0.0
3                  1.0                 0.0                     1.0
4                  0.0                 0.0                     0.0
5                  0.0                 0.0                     1.0
6                  0.0                 1.0                     0.0
7                  1.0                 0.0                     0.0
8                  0.0                 0.0                     1.0

  TechSupport_index  StreamingTV_index  StreamingMovies_index  \
0               0.0                0.0                    0.0
1               0.0                0.0                    0.0
2               0.0                0.0                    0.0
3               1.0                0.0                    0.0
4               0.0                0.0                    0.0
5               0.0                1.0                    1.0
6               0.0                1.0                    0.0
7               0.0                0.0                    0.0
8               1.0                1.0                    1.0

  Contract_index  PaperlessBilling_index  PaymentMethod_index gender_Vec  \
0            0.0                     0.0                  0.0      (0.0)
1            2.0                     1.0                  1.0      (1.0)
2            0.0                     0.0                  1.0      (1.0)
```

```
3            2.0                    1.0               2.0      (1.0)
4            0.0                    0.0               0.0      (0.0)
5            0.0                    0.0               0.0      (0.0)
6            0.0                    0.0               3.0      (1.0)
7            0.0                    1.0               1.0      (0.0)
8            0.0                    0.0               0.0      (0.0)

  Partner_Vec Dependents_Vec PhoneService_Vec MultipleLines_Vec  \
0       (0.0)          (1.0)            (0.0)        (0.0, 0.0)
1       (1.0)          (1.0)            (1.0)        (1.0, 0.0)
2       (1.0)          (1.0)            (1.0)        (1.0, 0.0)
3       (1.0)          (1.0)            (0.0)        (0.0, 0.0)
4       (1.0)          (1.0)            (1.0)        (1.0, 0.0)
5       (1.0)          (1.0)            (1.0)        (0.0, 1.0)
6       (1.0)          (0.0)            (1.0)        (0.0, 1.0)
7       (1.0)          (1.0)            (0.0)        (0.0, 0.0)
8       (0.0)          (1.0)            (1.0)        (0.0, 1.0)

  InternetService_Vec OnlineSecurity_Vec OnlineBackup_Vec  \
0          (0.0, 1.0)         (1.0, 0.0)       (0.0, 1.0)
1          (0.0, 1.0)         (0.0, 1.0)       (1.0, 0.0)
2          (0.0, 1.0)         (0.0, 1.0)       (0.0, 1.0)
3          (0.0, 1.0)         (0.0, 1.0)       (1.0, 0.0)
4          (1.0, 0.0)         (1.0, 0.0)       (1.0, 0.0)
5          (1.0, 0.0)         (1.0, 0.0)       (1.0, 0.0)
6          (1.0, 0.0)         (1.0, 0.0)       (0.0, 1.0)
7          (0.0, 1.0)         (0.0, 1.0)       (1.0, 0.0)
8          (1.0, 0.0)         (1.0, 0.0)       (1.0, 0.0)

  DeviceProtection_Vec TechSupport_Vec StreamingTV_Vec StreamingMovies_Vec  \
0           (1.0, 0.0)      (1.0, 0.0)      (1.0, 0.0)          (1.0, 0.0)
1           (0.0, 1.0)      (1.0, 0.0)      (1.0, 0.0)          (1.0, 0.0)
2           (1.0, 0.0)      (1.0, 0.0)      (1.0, 0.0)          (1.0, 0.0)
3           (0.0, 1.0)      (0.0, 1.0)      (1.0, 0.0)          (1.0, 0.0)
4           (1.0, 0.0)      (1.0, 0.0)      (1.0, 0.0)          (1.0, 0.0)
5           (0.0, 1.0)      (1.0, 0.0)      (0.0, 1.0)          (0.0, 1.0)
6           (1.0, 0.0)      (1.0, 0.0)      (0.0, 1.0)          (1.0, 0.0)
7           (1.0, 0.0)      (1.0, 0.0)      (1.0, 0.0)          (1.0, 0.0)
8           (0.0, 1.0)      (0.0, 1.0)      (0.0, 1.0)          (0.0, 1.0)

  Contract_Vec PaperlessBilling_Vec PaymentMethod_Vec  Churn_index
0   (1.0, 0.0)                (1.0)   (1.0, 0.0, 0.0)          0.0
1   (0.0, 0.0)                (0.0)   (0.0, 1.0, 0.0)          0.0
2   (1.0, 0.0)                (1.0)   (0.0, 1.0, 0.0)          1.0
3   (0.0, 0.0)                (0.0)   (0.0, 0.0, 1.0)          0.0
4   (1.0, 0.0)                (1.0)   (1.0, 0.0, 0.0)          1.0
5   (1.0, 0.0)                (1.0)   (1.0, 0.0, 0.0)          1.0
```

```
6   (1.0, 0.0)                  (1.0)   (0.0, 0.0, 0.0)         0.0
7   (1.0, 0.0)                  (0.0)   (0.0, 1.0, 0.0)         0.0
8   (1.0, 0.0)                  (1.0)   (1.0, 0.0, 0.0)         1.0
```

[127]:
```
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.classification import RandomForestClassifier
from pyspark.ml.evaluation import BinaryClassificationEvaluator

assembler = VectorAssembler(
    inputCols=[column+"_Vec" for column in categorical_columns] + ["tenure",␣
 ↪"MonthlyCharges", "TotalCharges", "numofservices", "charge_ratio"],
    outputCol="features"
)
df_assembled = assembler.transform(df_transformed)


train, test = df_assembled.randomSplit([0.8, 0.2], seed=42)
rf = RandomForestClassifier(labelCol="Churn_index", featuresCol="features",␣
 ↪numTrees=100)
model = rf.fit(train)


predictions = model.transform(test)
evaluator = BinaryClassificationEvaluator(labelCol="Churn_index",␣
 ↪rawPredictionCol="rawPrediction", metricName="areaUnderROC")
auc = evaluator.evaluate(predictions)
print("Area Under ROC Curve: ", auc)
```

```
Area Under ROC Curve:  0.8440139671275291
```

1.5 3. Next Steps

Provide a list of additional suggestions to further enhance the model or feature engineering techniques to try.

Discuss the potential impact of these suggestions on the model's performance.

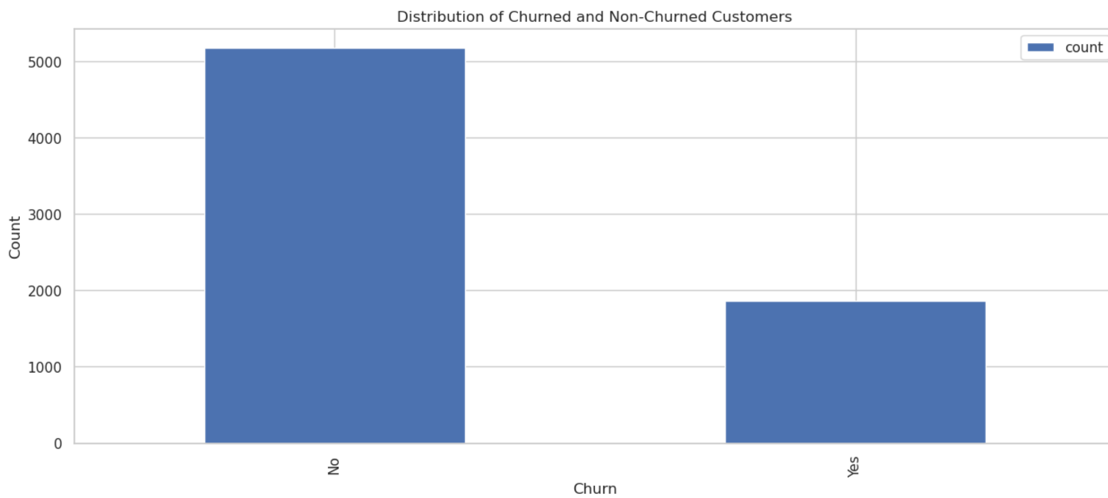
1. Feature scaling: We can perform scaling on the numeric columns using StandardScaler on ['tenure', 'MonthlyCharges', 'TotalCharges'], resulting in similar range of values and improved performance of the models.

2. Feature Engineering: We can create a new column for overall revenue. This can be done by multiplying tenure with monthlycharges. 2.1 As a feature engineering technique, we can create a new column to calculate the overall revenue by multiplying tenure with monthlycharges. Additionally, we can perform an in-depth analysis of the relationship between tenure and contract to gain insights into customer churn. For example, we can explore the correlation between 'year to year contract' and 'tenure $<$ 10 months' to identify customers who are less likely to churn. Conversely, we can focus on customers who have been on a 'year to year' contract & tenure $>$ 10 months or more as they may be more likely to churn.

3. Feature selection: We can also use techniques such as correlation analysis, forward/backward selection, and LASSO regularization to identify and remove redundant or irrelevant features that may negatively impact the model's performance.

4. Resampling Techniques: From the below graph we can see that the dataset is imbalanced, having majority as not churning (NO > 5000). Therefore, oversampling the minority and undersampling the majority can help improve the model's performance. (Note: Oversamplying -> can also lead to -> Overfitting & Undersampling -> to -> Underfitting)

[142]:
```python
# 4.  Point
churn_count = df.groupBy('Churn').count().toPandas()
churn_count.plot(kind='bar', x='Churn', y='count')
plt.title('Distribution of Churned and Non-Churned Customers')
plt.xlabel('Churn')
plt.ylabel('Count')
plt.show()
```



1.6 4. Final Model Evaluation

Report your best model with its AUC on the test and train sets.

[192]:
```python
# Best Model with AUC on train and test sets.
train_auc = aucEvaluator.evaluate(cvModel.transform(train)) #train
print(f"Train AUC: {train_auc:.4f}")

# AUC on test set
test_auc = aucEvaluator.evaluate(cvModel.transform(test)) #test
print(f"Test AUC: {test_auc:.4f}")
```

```
Train AUC: 0.8498
Test AUC: 0.8593
```

From the above the best model achieved so far is from hyper-parameter tuning having AUC (train): 0.8498 and AUC (test) : 0.8593 - explaining the model's ability to interpret positive and negative instances.

1.7 5. Notebook Organization

References: 1. https://github.com/soltaniehha/Big-Data-Analytics-for-Business : for lecture notes & .ipynb notebook and previous lecture concept implementation 2. https://www.w3schools.com/python/matplotlib_pyplot.asp : Used for better graph learning opportunity and practice. 3. notebook 11-Classification-Regression/02-Logistic-Regression-Example.ipynb

[204]:
```
# bm = cvModel.bestModel.summary
# print(bm)
# bestModelroc = bm.roc.toPandas()
# bestModelroc
# %matplotlib inline
# import matplotlib.pyplot as plt

# plt.plot(bestModelroc['FPR'], bestModelroc['TPR'], label='ROC Curve')
# plt.xlabel('False Positive Rate (FPR)')
# plt.ylabel('True Positive Rate (TPR)')
# plt.title('ROC Curve')
# plt.legend(loc='lower right')
# #print('Train AUC:', summary.areaUnderROC)
# bestModelpr = bm.pr.toPandas()
# bestModelpr
# bestModelpr.plot(x='recall', y='precision', style='--o', legend=False)
# plt.xlabel('Recall')
# plt.title('Precision-Recall Cruve')
# plt.ylabel('Precision')
# plt.legend(loc='upper right')
```