Abstract

- This project lets to know how to perform different models on the dataset.From this project I learnt how a multi class classification can be broken down into binary classification and I also reasearched alot about the tools and pipelines.One more insight which i got from this project is that model being complex is not alone necessary it has to be a perfect fit.Working on a industrial level dataset gave a lot of insights on how class embalances and can be generalized.

Overview

- Problem statement: The objective of this project is to build a model that generalizes well out of sample.
- Proposed methodology: The data is scaled and principal component analysis (PCA) is performed on it. The final classifier uses a decision tree classifier.

In [ ]:
```
!pip install sklearn2pmml
```

```
Collecting sklearn2pmml
  Downloading sklearn2pmml-0.73.5.tar.gz (5.9 MB)
     |████████████████████████████████| 5.9 MB 4.5 MB/s
Requirement already satisfied: joblib>=0.13.0 in /usr/local/lib/pyth
on3.7/dist-packages (from sklearn2pmml) (1.0.1)
Requirement already satisfied: scikit-learn>=0.18.0 in /usr/local/li
b/python3.7/dist-packages (from sklearn2pmml) (0.22.2.post1)
Requirement already satisfied: sklearn-pandas>=0.0.10 in /usr/local/
lib/python3.7/dist-packages (from sklearn2pmml) (1.8.0)
Requirement already satisfied: numpy>=1.11.0 in /usr/local/lib/pytho
n3.7/dist-packages (from scikit-learn>=0.18.0->sklearn2pmml) (1.19.5
)
Requirement already satisfied: scipy>=0.17.0 in /usr/local/lib/pytho
n3.7/dist-packages (from scikit-learn>=0.18.0->sklearn2pmml) (1.4.1)
Requirement already satisfied: pandas>=0.11.0 in /usr/local/lib/pyth
on3.7/dist-packages (from sklearn-pandas>=0.0.10->sklearn2pmml) (1.1
.5)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/
lib/python3.7/dist-packages (from pandas>=0.11.0->sklearn-pandas>=0.
0.10->sklearn2pmml) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python
3.7/dist-packages (from pandas>=0.11.0->sklearn-pandas>=0.0.10->skle
arn2pmml) (2018.9)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/
dist-packages (from python-dateutil>=2.7.3->pandas>=0.11.0->sklearn-
pandas>=0.0.10->sklearn2pmml) (1.15.0)
Building wheels for collected packages: sklearn2pmml
  Building wheel for sklearn2pmml (setup.py) ... done
  Created wheel for sklearn2pmml: filename=sklearn2pmml-0.73.5-py3-n
one-any.whl size=5938302 sha256=35d2298b4b07fc5b3e10e02472ce40c7f38a
cc5dec40b274ace8fdc0ee9eabf5
  Stored in directory: /root/.cache/pip/wheels/bf/7d/76/096fca0396cd
c33f32f97b17c1a3873f2ed0f5fb3e5bf20b73
Successfully built sklearn2pmml
Installing collected packages: sklearn2pmml
Successfully installed sklearn2pmml-0.73.5
```

In [ ]:

```
!pip install skl2onnx
!pip install onnxruntime
```

```
Collecting skl2onnx
  Downloading skl2onnx-1.9.0-py2.py3-none-any.whl (239 kB)
     |████████████████████████████████| 239 kB 5.1 MB/s
Requirement already satisfied: numpy>=1.15 in /usr/local/lib/python3
.7/dist-packages (from skl2onnx) (1.19.5)
Collecting onnxconverter-common>=1.6.1
  Downloading onnxconverter_common-1.8.1-py2.py3-none-any.whl (77 kB
)
     |████████████████████████████████| 77 kB 4.0 MB/s
Requirement already satisfied: scipy>=1.0 in /usr/local/lib/python3.
7/dist-packages (from skl2onnx) (1.4.1)
Requirement already satisfied: scikit-learn>=0.19 in /usr/local/lib/
python3.7/dist-packages (from skl2onnx) (0.22.2.post1)
Collecting onnx>=1.2.1
  Downloading onnx-1.9.0-cp37-cp37m-manylinux2010_x86_64.whl (12.2 M
B)
     |████████████████████████████████| 12.2 MB 12.6 MB/s
Requirement already satisfied: protobuf in /usr/local/lib/python3.7/
dist-packages (from skl2onnx) (3.17.3)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-
packages (from onnx>=1.2.1->skl2onnx) (1.15.0)
Requirement already satisfied: typing-extensions>=3.6.2.1 in /usr/lo
cal/lib/python3.7/dist-packages (from onnx>=1.2.1->skl2onnx) (3.7.4.
3)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python
3.7/dist-packages (from scikit-learn>=0.19->skl2onnx) (1.0.1)
Installing collected packages: onnx, onnxconverter-common, skl2onnx
Successfully installed onnx-1.9.0 onnxconverter-common-1.8.1 skl2onn
x-1.9.0
Collecting onnxruntime
  Downloading onnxruntime-1.8.1-cp37-cp37m-manylinux_2_17_x86_64.man
ylinux2014_x86_64.whl (4.5 MB)
     |████████████████████████████████| 4.5 MB 5.3 MB/s
Requirement already satisfied: flatbuffers in /usr/local/lib/python3
.7/dist-packages (from onnxruntime) (1.12)
Requirement already satisfied: protobuf in /usr/local/lib/python3.7/
dist-packages (from onnxruntime) (3.17.3)
Requirement already satisfied: numpy>=1.16.6 in /usr/local/lib/pytho
n3.7/dist-packages (from onnxruntime) (1.19.5)
Requirement already satisfied: six>=1.9 in /usr/local/lib/python3.7/
dist-packages (from protobuf->onnxruntime) (1.15.0)
Installing collected packages: onnxruntime
Successfully installed onnxruntime-1.8.1
```

In [ ]:
```
!pip install git+https://github.com/WillKoehrsen/feature-selector
```

```
Collecting git+https://github.com/WillKoehrsen/feature-selector
  Cloning https://github.com/WillKoehrsen/feature-selector to /tmp/p
ip-req-build-ayn01vei
```

```
  Running command git clone -q https://github.com/WillKoehrsen/featu
re-selector /tmp/pip-req-build-ayn01vei
Requirement already satisfied: lightgbm>=2.1.1 in /usr/local/lib/pyt
hon3.7/dist-packages (from feature-selector===N-A) (2.2.3)
Requirement already satisfied: matplotlib>=2.1.2 in /usr/local/lib/p
ython3.7/dist-packages (from feature-selector===N-A) (3.2.2)
Requirement already satisfied: seaborn>=0.8.1 in /usr/local/lib/pyth
on3.7/dist-packages (from feature-selector===N-A) (0.11.1)
Requirement already satisfied: numpy>=1.14.5 in /usr/local/lib/pytho
n3.7/dist-packages (from feature-selector===N-A) (1.19.5)
Requirement already satisfied: pandas>=0.23.1 in /usr/local/lib/pyth
on3.7/dist-packages (from feature-selector===N-A) (1.1.5)
Requirement already satisfied: scikit-learn>=0.19.1 in /usr/local/li
b/python3.7/dist-packages (from feature-selector===N-A) (0.22.2.post
1)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dis
t-packages (from lightgbm>=2.1.1->feature-selector===N-A) (1.4.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.
0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=2.1.
2->feature-selector===N-A) (2.4.7)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/li
b/python3.7/dist-packages (from matplotlib>=2.1.2->feature-selector=
==N-A) (2.8.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python
3.7/dist-packages (from matplotlib>=2.1.2->feature-selector===N-A) (
0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/p
ython3.7/dist-packages (from matplotlib>=2.1.2->feature-selector===N
-A) (1.3.1)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-
packages (from cycler>=0.10->matplotlib>=2.1.2->feature-selector===N
-A) (1.15.0)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python
3.7/dist-packages (from pandas>=0.23.1->feature-selector===N-A) (201
8.9)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python
3.7/dist-packages (from scikit-learn>=0.19.1->feature-selector===N-A
) (1.0.1)
Building wheels for collected packages: feature-selector
  Building wheel for feature-selector (setup.py) ... done
  Created wheel for feature-selector: filename=feature_selector-N_A-
py3-none-any.whl size=20733 sha256=c3cdbba85b767f75602e4bd38282f0be7
0e93c416cd4d19de10f7c889bfb1171
  Stored in directory: /tmp/pip-ephem-wheel-cache-o9wdp4so/wheels/01
/6e/ae/7e91c28a7d2cb9f6c7a29ce0e4228ba302698cbbcde457f1cf
  WARNING: Built wheel for feature-selector is invalid: Metadata 1.2
mandates PEP 440 version, but 'N-A' is not
Failed to build feature-selector
Installing collected packages: feature-selector
    Running setup.py install for feature-selector ... done
```

```
  DEPRECATION: feature-selector was installed using the legacy 'setu
p.py install' method, because a wheel could not be built for it. A p
ossible replacement is to fix the wheel build issue reported above.
You can find discussion regarding this at https://github.com/pypa/pi
p/issues/8368.
Successfully installed feature-selector-N-A
```

In [ ]:

```
from google.colab import drive
import time
from feature_selector import FeatureSelector
from sklearn.metrics import silhouette_score
from sklearn import metrics
from sklearn import preprocessing
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification
import graphviz
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import classification_report
from sklearn.cluster import KMeans
from sklearn.ensemble import BaggingClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_validate
from mlxtend.feature_selection import ColumnSelector
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
import datetime
from sklearn.datasets import load_iris
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.compose import ColumnTransformer
from skl2onnx.common.data_types import FloatTensorType
from skl2onnx import convert_sklearn

import onnxruntime as rt

from onnx.tools.net_drawer import GetPydotGraph, GetOpNodeProducer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import os
from sklearn.feature_selection import SelectKBest, chi2
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn import tree
```

```python
import graphviz
from sklearn_pandas import DataFrameMapper
from sklearn import decomposition
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import SelectKBest
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
from sklearn.tree import DecisionTreeClassifier
from sklearn.pipeline import Pipeline
from sklearn2pmml.decoration import ContinuousDomain
from sklearn2pmml.pipeline import PMMLPipeline
from sklearn2pmml import sklearn2pmml
from sklearn.externals.six import StringIO
from IPython.display import Image
from sklearn import tree
import sklearn.datasets as datasets
from sklearn.tree import export_graphviz
import graphviz
import math
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/externals/joblib/__in
it__.py:15: FutureWarning: sklearn.externals.joblib is deprecated in
0.21 and will be removed in 0.23. Please import this functionality d
irectly from joblib, which can be installed with: pip install joblib
. If this warning is raised when loading pickled models, you may nee
d to re-serialize those models with scikit-learn 0.21+.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/externals/six.py:31:
FutureWarning: The module is deprecated in version 0.21 and will be
removed in version 0.23 since we've dropped support for Python 2.7.
Please rely on the official version of six (https://pypi.org/project
/six/).
  "(https://pypi.org/project/six/).", FutureWarning)
```

In [ ]:
```python
drive.mount("/content/drive")
```

In [ ]:
```
pmml_df = pd.read_csv("/content/drive/My Drive/data_public.csv.gz", co
mpression='gzip',header=0,sep=',', quotechar='"')
pmml_df.head()
```

Out[ ]:

	A	B	C	D	E	F	G	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.16
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.71
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.29
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.64
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.30

In [ ]:
```
print(len(pmml_df))
print(pmml_df.shape)
```

```
1200000
(1200000, 16)
```

In [ ]:
```
P = pd.DataFrame(data=pmml_df.drop('Class', axis=1))
P.head()
```

Out[ ]:

	A	B	C	D	E	F	G	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.16
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.71
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.29
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.64
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.30

In [ ]:
```
training_labels = list(P.columns)
print(training_labels)
```

```
['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J', 'K', 'L', 'M', 'N
', 'O']
```

In [ ]:
```
q = pd.DataFrame(data=pmml_df['Class'])
q.head()
```

Out[ ]:

	Class
0	2
1	3
2	2
3	2
4	3

In [ ]:
```
P_train, P_test, q_train, q_test = train_test_split(P, q, test_size=0.
20, random_state=97)
```

In [ ]:
```
training_data = pd.concat([P_train,q_train],axis=1)
training_data.head()
print(len(training_data))
```

```
960000
```

Data Processing and Analysis

Checking for Missing Values

- First, I checked for any missing values in the dataset.To Check for the missing values in the dataset there are many ways I choose isnull() method which helps me to find any null values present in the dataset.If yes it returns True or else False.

In [ ]:
```
# Check whether the dataframe contains any missing value
print(training_data.isnull().values.any())
print(len(training_data.columns))
```

```
False
16
```

No missing data was found.So it returned False.

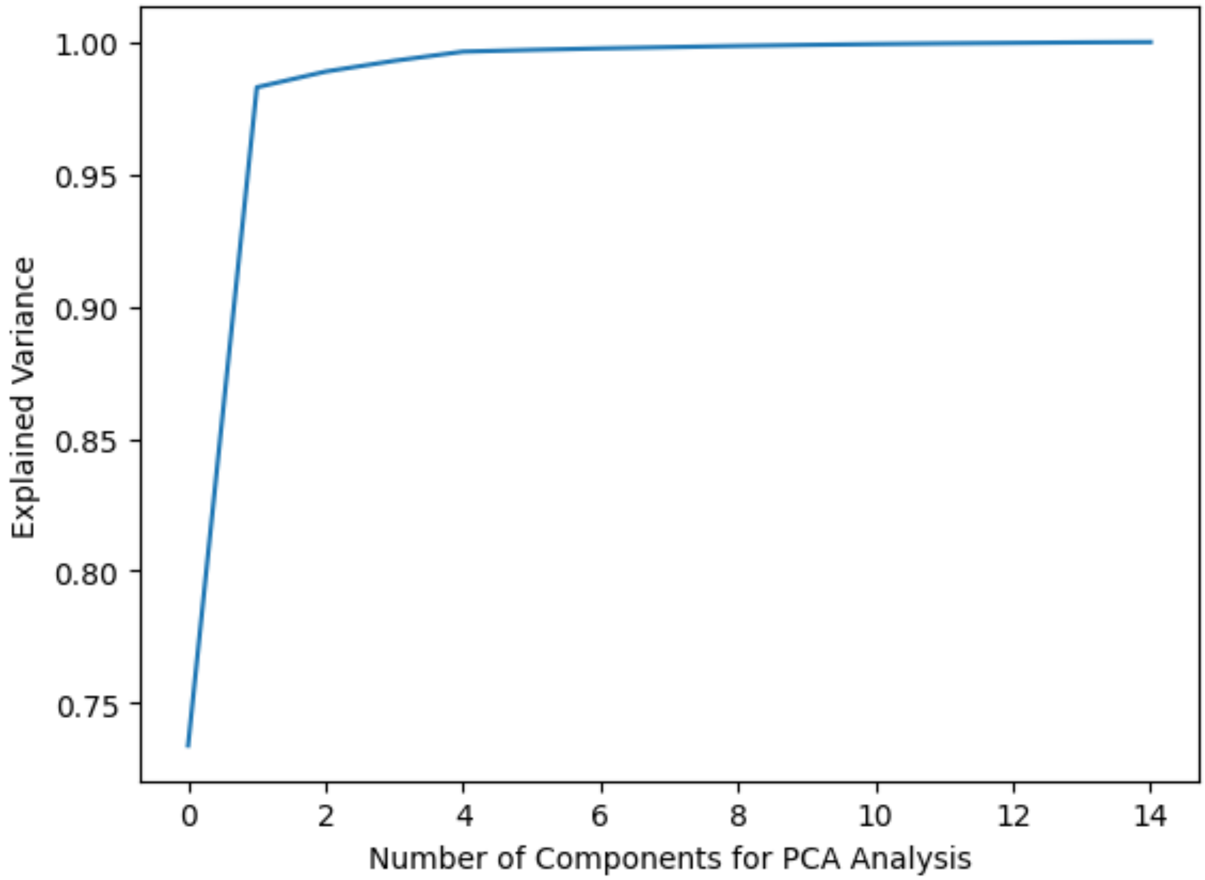
Principal Component Analysis

- Next I am performing principal components to find the optimal number of components in the entire datasets.Before performing PCA I scaled the entire dataset and then performed PCA with n_components on the scaled trained dataset with total number of features and generated a plot.

In [ ]:
```
standard_scalar = StandardScaler()
training_df_scaled = standard_scalar.fit_transform(training_data.drop(
'Class', axis=1))
training_df_scaled = pd.DataFrame(training_df_scaled, columns=training
_labels)
print(len(training_df_scaled))
print(training_df_scaled.head(10))
print(training_df_scaled.isnull().values.any())

training_df_scaled = pd.merge(training_data['Class'],training_df_scale
d, left_index=True, right_index=True, how='inner')
print(len(training_df_scaled))
print(training_df_scaled.head(10))
print(training_df_scaled.isnull().values.any())
```

```
960000
          A         B         C  ...         M         N         O
0  1.440950  0.765287  1.458101  ...  0.788554  1.398047  1.413347
1  1.317774  0.528108  1.321870  ...  1.066979  1.476711  1.263338
2 -0.663411  0.429147 -0.662361  ... -0.687958 -0.850573 -0.859964
3 -0.641023 -0.040729 -0.550038  ... -0.503728 -0.851243 -0.858986
4 -0.630074 -0.094215 -0.551774  ... -0.471425 -0.824783 -0.929646
5  1.458450  0.256821  1.356139  ...  1.518827  1.220957  1.347866
6 -0.846250 -1.936970 -1.091371  ... -0.052989 -0.284619  0.110404
7  1.383809  0.958845  1.446394  ...  1.417070  1.392328  1.423425
8 -0.855554 -2.160599 -1.045623  ... -0.315759 -0.284472  0.083560
9 -0.838952 -1.825808 -1.071149  ... -0.322718 -0.461967 -0.041303

[10 rows x 15 columns]
False
768010
        Class         A         B  ...         M         N         O
739135      3 -0.658611  0.228425  ... -0.734685 -0.857980 -0.941281
54118       3  1.356763  0.236029  ...  1.623599  1.415648  1.330797
293468      3 -0.700953  0.254157  ... -0.738406 -0.778306 -0.943118
640194      3 -0.852157 -1.977333  ... -0.316531 -0.113123  0.045479
295311      3 -0.607496  0.035722  ... -0.716740 -0.804954 -0.841795
505214      1 -0.655865  0.451547  ... -0.710435 -0.848495 -0.899821
30934       2  1.381451  0.670002  ...  1.292570  1.144872  1.297473
135046      3 -0.825753 -2.007487  ... -0.177142 -0.283713 -0.075976
951776      2  1.396558  0.773258  ...  1.507046  1.465753  1.568107
836946      3 -0.658029  0.181105  ... -0.902324 -0.816542 -0.901919

[10 rows x 16 columns]
False
```

In [ ]:
```python
pca_n_comp = PCA(n_components=len(training_df_scaled.columns)-1)
pca_n_comp.fit(training_df_scaled.drop('Class', axis=1))
plt.plot(np.cumsum(pca_n_comp.explained_variance_ratio_))
plt.xlabel('Number of Components for PCA Analysis')
plt.ylabel('Explained Variance')
plt.show()
pca_n_comp.explained_variance_ratio_
```



Out[ ]:
```
array([7.33972266e-01, 2.48933297e-01, 5.94149152e-03, 4.07366435e-0
3,
       3.46361345e-03, 6.57919941e-04, 5.61878608e-04, 4.72793000e-0
4,
       4.62247400e-04, 3.82487210e-04, 3.10561061e-04, 2.56399887e-0
4,
       2.01480639e-04, 1.84763545e-04, 1.25136075e-04])
```

The elbow in the above plot occurs at n = 1.So I used 1 principal component for all the pipelines.

In [ ]:
```
training_labels_str = ''.join(map(str, training_labels))
print(training_labels_str)
```

```
ABCDEFGHIJKLMNO
```

Next, I performed a PMML pipeline which includes Standard scaler,PCA and a Decision Tree Classifier.Fitted the pipeline with the p and q train.Calculated the score for the p and q test.

In [ ]:
```
#DecisionTreeClassifier
pipeline = PMMLPipeline([('scaler',StandardScaler()),('pca',PCA(n_comp
onents=1)),('classifier',DecisionTreeClassifier(max_depth=2))])
pipeline.fit(P_train,q_train)
print(pipeline.score(P_test,q_test)) f
```

```
0.4976416666666665
```

The Accuracy of the total dataset is 49.7%.

Feature Removal

> Checking the accuracy of the dataset by dropping each feature

In [ ]:
```
features = 'ABCDEFGHIJKLMNO'
for i in range(0, len(features)):
    pipeline = PMMLPipeline([('scaler',StandardScaler()),('pca',PCA(n_
components=1)),('classifier',DecisionTreeClassifier(max_depth = 2))])
    pipeline.fit(training_data.drop([features[i:i+1]], axis=1),trainin
g_data['Class'])
    results = pipeline.predict(P_test)
    actual = np.concatenate(q_test.values)
    print("Dropped feature:", features[i:i+1], ", Accuracy:", metrics.
accuracy_score(actual, results))
```

```
Dropped feature: A , Accuracy: 0.4976416666666665
Dropped feature: B , Accuracy: 0.4976416666666665
Dropped feature: C , Accuracy: 0.4976416666666665
Dropped feature: D , Accuracy: 0.4976416666666665
Dropped feature: E , Accuracy: 0.4976416666666665
Dropped feature: F , Accuracy: 0.4976416666666665
Dropped feature: G , Accuracy: 0.4976416666666665
Dropped feature: H , Accuracy: 0.4976416666666665
Dropped feature: I , Accuracy: 0.4976416666666665
Dropped feature: J , Accuracy: 0.4976416666666665
Dropped feature: K , Accuracy: 0.4976416666666665
Dropped feature: L , Accuracy: 0.4976416666666665
Dropped feature: M , Accuracy: 0.4976416666666665
Dropped feature: N , Accuracy: 0.4976416666666665
Dropped feature: O , Accuracy: 0.4976416666666665
```

After dropping the each feature in the dataset at once there is no change in the accuracy.We can even check accuracy by dropping two features

In [ ]:
```
to_drop = ['A','B']
pipeline0 = PMMLPipeline([('mapper',DataFrameMapper([(P_train.columns.
drop(to_drop).values,[StandardScaler()])])),('pca',PCA(n_components=1)
),('classifier',DecisionTreeClassifier(max_depth = 2))])
pipeline0.fit(training_data.drop(to_drop, axis=1),training_data['Class
'])
results = pipeline0.predict(P_test.drop(to_drop, axis=1))
actual = np.concatenate(q_test.values)
print('Accuracy:', metrics.accuracy_score(actual, results))
```

```
Accuracy: 0.4976416666666665
```

By dropping two features from dataset there is no change in the accuracy.It is still 49.7% because of which no feature can be dropped neither can be selected as the best feature or the important feature out of 15.So I assume dropping the feature from the dataset doesnt make any sense based on the accuracy.I am gonna perform some more experiments to find the best features.

Binary Classification

- Performing binary classification on the dataset because it is an another way to find three class classification.Choosing class 1 and checking for the accuracy versus classes which are not class 1.

In [ ]:
```
#For class 1 vs not 1
pmml_df_class1=pmml_df.copy(deep=True)
pmml_df_class1.head()
```

Out[ ]:

	A	B	C	D	E	F	G	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.16
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.71
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.29
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.64
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.30

Considering only class 1 values and replacing class 2 and class 3 as 0.

In [ ]:
```
#Making class 2 and class 3 values as 0
pmml_df_class1.loc[(pmml_df_class1['Class']== 2)|(pmml_df_class1['Clas
s']==3),'Class'] = 0
pmml_df_class1.head()
```

Out[ ]:

	A	B	C	D	E	F	G	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.16(
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.71
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.29
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.64(
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.30(

In [ ]:
```
pmml_df_class1['Class'].unique()
```

Out[ ]: array([0, 1])

In [ ]:
```
#Training the values
P_class1 = pd.DataFrame(data=pmml_df_class1.drop('Class', axis=1))
q_class1 = pd.DataFrame(data=pmml_df_class1['Class'],columns=['Class']
)
P_class1_train, P_class1_test, q_class1_train, q_class1_test = train_t
est_split(P_class1,q_class1,test_size=0.2)
train_data = pd.concat([P_class1_train,q_class1_train],axis=1)
train_data.head()
```

Out[ ]:

	A	B	C	D	E	F	G
697976	-37.784934	-10.654496	12.896484	16.375475	-27.292293	-27.990642	3.313893
124109	-32.882887	-8.463958	12.949734	21.512647	-30.915887	-21.083901	3.120177
337632	-37.275441	-20.219862	12.339928	16.686933	-20.581779	-25.722242	2.674869
739151	-64.834974	-58.952422	-36.876284	-116.873617	-19.714555	-135.352202	-57.657791
1114969	-24.707871	-9.747992	4.354934	22.178446	-22.095645	-23.535415	5.105842

In [ ]:
```
#DecisionTreeClassifier
pipeline1_DTC = PMMLPipeline([('scaler',StandardScaler()),('pca',PCA(n
_components=1)),('classifier',DecisionTreeClassifier(max_depth=2))])
pipeline1_DTC.fit(P_class1_train,q_class1_train)
print(pipeline1_DTC.score(P_class1_test,q_class1_test))
```

0.8332541666666666

The accuracy for the class 1 versus not class 1(i.e., class 2 and class 3 considered as 0 class) is 83%.

In [ ]:
```
#RandomForestClassifier
pipeline1_RFC = PMMLPipeline([('scaler',StandardScaler()),('pca',PCA(n_components=1)),('classifier',RandomForestClassifier(max_depth=2))])
pipeline1_RFC.fit(P_class1_train,q_class1_train)
print(pipeline1_RFC.score(P_class1_test,q_class1_test))
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/pipeline.py:354: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
  self._final_estimator.fit(Xt, y, **fit_params)

0.8327375
```

The accuracy for the class 1 versus not class 1(i.e., class 2 and class 3 considered as 0 class) is 83%.

In [ ]:
```
features = 'ABCDEFGHIJKLMNO'
for i in range(0, len(features)):
    pipeline = PMMLPipeline([('scaler',StandardScaler()),('pca',PCA(n_components=1)),('classifier',DecisionTreeClassifier(max_depth = 3))])
    pipeline.fit(train_data.drop([features[i:i+1]], axis=1),train_data['Class'])
    results = pipeline.predict(P_class1_test)
    actual = np.concatenate(q_class1_test.values)
    print("Dropped feature:", features[i:i+1], ", Accuracy:", metrics.accuracy_score(actual, results))
```

```
Dropped feature: A , Accuracy: 0.8327125
Dropped feature: B , Accuracy: 0.8327125
Dropped feature: C , Accuracy: 0.8327125
Dropped feature: D , Accuracy: 0.8327125
Dropped feature: E , Accuracy: 0.8327125
Dropped feature: F , Accuracy: 0.8327125
Dropped feature: G , Accuracy: 0.8327125
Dropped feature: H , Accuracy: 0.8327125
Dropped feature: I , Accuracy: 0.8327125
Dropped feature: J , Accuracy: 0.8327125
Dropped feature: K , Accuracy: 0.8327125
Dropped feature: L , Accuracy: 0.8327125
Dropped feature: M , Accuracy: 0.8327125
Dropped feature: N , Accuracy: 0.8327125
Dropped feature: O , Accuracy: 0.8327125
```

By dropping each feature the accuracy also getting the same accuracy as 83%

Now considering the dataset with class 2 and 3 which are 0's.

In [ ]:
```
#Considering class which is not 1
pmml_df_class_not1=pd.DataFrame(data=pmml_df_class1[pmml_df_class1["Cl
ass"]==0])
pmml_df_class_not1.head()
```

Out[ ]:

	A	B	C	D	E	F	G	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.16(
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.71
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.29
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.64(
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.30(

In [ ]:
```
P_class_not1 = pd.DataFrame(data=pmml_df_class_not1.drop('Class', axis
=1))
q_class_not1 = pd.DataFrame(data=pmml_df_class_not1['Class'],columns=[
'Class'])
P_class_not1_train, P_class_not1_test, q_class_not1_train, q_class_not
1_test = train_test_split(P_class_not1,q_class_not1,test_size=0.2)
train_data = pd.concat([P_class_not1_train,q_class_not1_train],axis=1)
train_data.head()
```

Out[ ]:

	A	B	C	D	E	F	G
556753	-36.532190	-18.415576	13.933149	20.687396	-23.433974	-22.105896	2.726087
478801	236.302382	-13.434130	225.457638	-13.842231	138.902776	92.860630	154.281306
911203	-29.944374	-20.631123	4.713876	19.780079	-28.114404	-19.559039	1.585056
1130124	231.006474	-12.044842	212.464184	-12.269698	127.891824	93.639251	118.917273
340727	234.342600	-6.553826	218.764204	-15.853706	130.032273	72.301271	117.434405

In [ ]:
```
#DecisionTreeClassifier
pipelinenot1_DTC = PMMLPipeline([('scaler',StandardScaler()),('pca',PC
A(n_components=1)),('classifier',DecisionTreeClassifier(max_depth=2))]
)
pipelinenot1_DTC.fit(P_class_not1_train,q_class_not1_train)
print(pipelinenot1_DTC.score(P_class_not1_test,q_class_not1_test))
```

```
1.0
```

Accuracy is 100% for predicting the not class 1 i.e., predicting class 2 and class 3

In [ ]:
```
#RandomForestClassifier
pipelinenot1_RFC = PMMLPipeline([('scaler',StandardScaler()),('pca',PC
A(n_components=1)),('classifier',RandomForestClassifier(max_depth=2))]
)
pipelinenot1_RFC.fit(P_class_not1_train,q_class_not1_train)
print(pipelinenot1_RFC.score(P_class_not1_test,q_class_not1_test))
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/pipeline.py:354: Data
ConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples,), for example
using ravel().
  self._final_estimator.fit(Xt, y, **fit_params)
```

```
1.0
```

In [ ]:
```
pmml_df_class23=pmml_df.copy(deep=True)
```

Performing another experiment considering the dataset with only class 2 and class 3

In [ ]:
```
#DataFrame having only class 2 and class 3
pmml_df_class23=pd.DataFrame(data=pmml_df_class23[pmml_df_class23['Cla
ss'].isin([2,3])])
pmml_df_class23.head()
```

Out[ ]:

	A	B	C	D	E	F	G	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.16
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.71
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.29
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.64
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.30

In [ ]:
```
P_class23 = pd.DataFrame(data=pmml_df_class23.drop('Class', axis=1))
q_class23 = pd.DataFrame(data=pmml_df_class23['Class'],columns=['Class
'])
P_class23_train, P_class23_test, q_class23_train, q_class23_test = tra
in_test_split(P_class23,q_class23,test_size=0.2)
train_data23 = pd.concat([P_class23_train,q_class23_train],axis=1)
train_data23.head()
```

Out[ ]:

	A	B	C	D	E	F	G
81617	-25.224550	-6.547884	7.472777	18.269460	-19.696754	-25.542844	4.911291
1160214	-58.540670	-43.411420	-41.180938	-103.508191	-12.673971	-111.638547	-50.357752
29431	-65.128285	-51.037292	-34.991781	-111.275781	-17.320240	-118.622786	-56.653306
930900	-30.556244	-11.204953	6.398578	15.831198	-23.720791	-26.210826	-4.516622
736001	-36.658258	-13.567695	12.632246	19.155808	-25.053527	-23.099226	0.772185

In [ ]:
```
#DecisionTreeClassifier
pipeline23_DTC = PMMLPipeline([('scaler',StandardScaler()),('pca',PCA(
n_components=1)),('classifier',DecisionTreeClassifier(max_depth=2))])
pipeline23_DTC.fit(P_class23_train,q_class23_train)
print(pipeline23_DTC.score(P_class23_test,q_class23_test))
```

```
0.5985590144098559
```

The accuracy for class 2 and class 3 is 59.8%

In [ ]:
```
#For class 2 vs not 2
pmml_df_class2=pmml_df.copy(deep=True)
pmml_df_class2.head()
```

Out[ ]:

	A	B	C	D	E	F	G	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.16
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.71
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.29
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.64
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.30

In [ ]:
```
#Making class 1 and class 3 as 0
pmml_df_class2.loc[(pmml_df_class2['Class']== 1)|(pmml_df_class2['Clas
s']==3),'Class'] = 0
pmml_df_class2.head()
```

Out[ ]:

	A	B	C	D	E	F	G	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.16(
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.71
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.29
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.64(
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.30(

In [ ]:
```
pmml_df_class2['Class'].unique()
```

Out[ ]: array([2, 0])

In [ ]:
```
P_class2 = pd.DataFrame(data=pmml_df_class2.drop('Class', axis=1))
q_class2 = pd.DataFrame(data=pmml_df_class2['Class'],columns=['Class']
)
P_class2_train, P_class2_test, q_class2_train, q_class2_test = train_t
est_split(P_class2,q_class2,test_size=0.2)
train_data = pd.concat([P_class2_train,q_class2_train],axis=1)
train_data.head()
```

Out[ ]:

	A	B	C	D	E	F	G
389762	-21.458930	-13.928468	18.673353	15.807145	-30.521109	-21.101329	0.376187
965199	-29.336786	-17.339083	8.475791	15.713220	-27.983630	-17.351626	-4.953228
189740	-41.862384	-20.422528	11.051082	16.502030	-24.192677	-30.560059	1.200254
1139054	-30.176969	-12.648999	12.694092	20.265177	-18.707140	-24.045240	-5.983972
752992	-61.743326	-37.588624	-43.002446	-115.623661	-13.910972	-115.495916	-49.932937

In [ ]:
```
#DecisionTreeClassifier
pipeline2_DTC = PMMLPipeline([('scaler',StandardScaler()),('pca',PCA(n
_components=1)),('classifier',DecisionTreeClassifier(max_depth=2))])
pipeline2_DTC.fit(P_class2_train,q_class2_train)
print(pipeline2_DTC.score(P_class2_test,q_class2_test))
```

```
0.5002333333333333
```

Accuracy is 50% for the class 2 vs class not 2

In [ ]:
```
#Considering class which is not 2
pmml_df_class_not2=pd.DataFrame(data=pmml_df_class2[pmml_df_class2["Cl
ass"]==0])
pmml_df_class_not2.head()
```

Out[ ]:

	A	B	C	D	E	F	G	
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.7
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.3
7	-28.620633	-16.324678	6.614499	19.866385	-23.119998	-22.328572	1.477065	-26.3
8	-41.092898	-11.525839	12.027010	18.670988	-19.612979	-25.918632	5.266337	-25.9
11	-23.413125	-11.119531	16.910592	18.915184	-25.170026	-28.504337	-2.371616	-26.5

In [ ]:
```
P_class_not2 = pd.DataFrame(data=pmml_df_class_not2.drop('Class', axis
=1))
q_class_not2 = pd.DataFrame(data=pmml_df_class_not2['Class'],columns=[
'Class'])
P_class_not2_train, P_class_not2_test, q_class_not2_train, q_class_not
2_test = train_test_split(P_class_not2,q_class_not2,test_size=0.2)
train_data = pd.concat([P_class_not2_train,q_class_not2_train],axis=1)
train_data.head()
```

Out[ ]:

	A	B	C	D	E	F	G
917867	243.731881	-11.791695	218.015605	-12.797492	134.405109	79.845192	109.650469
759593	-28.521637	-11.260527	11.576526	19.915964	-29.233474	-34.576794	-2.600087
589860	-30.887197	-13.063882	12.776899	22.100048	-27.986933	-26.696003	0.633287
251929	-61.067763	-55.121973	-38.586391	-122.287227	-16.780508	-129.268062	-53.175375
1100621	230.629386	-13.437945	203.011721	-14.391886	128.420820	75.251105	130.007438

In [ ]:
```
#DecisionTreeClassifier
pipelinenot2_DTC = PMMLPipeline([('scaler',StandardScaler()),('pca',PC
A(n_components=1)),('classifier',DecisionTreeClassifier(max_depth=2))]
)
pipelinenot2_DTC.fit(P_class_not2_train,q_class_not2_train)
print(pipelinenot2_DTC.score(P_class_not2_test,q_class_not2_test))
```

```
1.0
```

Accuracy is 100% for predicting the not class 2 i.e., predicting class 1 and class 3

In [ ]:
```
#for class 3
pmml_df_class3=pmml_df.copy(deep=True)
pmml_df_class3.head()
```

Out[ ]:

	A	B	C	D	E	F	G	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.16(
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.71
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.29
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.64(
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.30(

In [ ]:
```
#Making class 1 and class 2 as 0
pmml_df_class3.loc[(pmml_df_class3['Class']== 1)|(pmml_df_class3['Clas
s']==2),'Class'] = 0
pmml_df_class3.head()
```

Out[ ]:

	A	B	C	D	E	F	G	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.16(
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.71
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.29
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.64(
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.30(

In [ ]:
```
pmml_df_class3['Class'].unique()
```

Out[ ]:
```
array([0, 3])
```

In [ ]:
```
P_class3 = pd.DataFrame(data=pmml_df_class3.drop('Class', axis=1))
q_class3 = pd.DataFrame(data=pmml_df_class3['Class'],columns=['Class']
)
P_class3_train, P_class3_test, q_class3_train, q_class3_test = train_t
est_split(P_class3,q_class3,test_size=0.2)
train_data = pd.concat([P_class3_train,q_class3_train],axis=1)
train_data.head()
```

Out[ ]:

	A	B	C	D	E	F	G
1033366	-60.133682	-43.430670	-49.806981	-113.777514	-16.842012	-129.068125	-49.881357
727615	-30.267534	-9.818834	7.436916	22.201498	-22.728165	-21.874823	7.204273
391944	-41.660698	-6.723186	3.551023	21.122214	-26.671501	-26.559982	2.419869
521548	232.913570	-9.873323	215.310070	-12.561418	121.886035	91.612366	111.354136
51953	238.233658	-10.847341	227.223472	-16.177012	134.089662	101.286068	131.808229

In [ ]:
```
#DecisionTreeClassifier
pipeline3_DTC = PMMLPipeline([('scaler',StandardScaler()),('pca',PCA(n
_components=1)),('classifier',DecisionTreeClassifier(max_depth=2))],(P
MMLPipeline([('scaler',StandardScaler()),('pca',PCA(n_components=1)),(
'classifier',LogisticRegression())])))
pipeline3_DTC.fit(P_class3_train,q_class3_train)
print(pipeline3_DTC.score(P_class3_test,q_class3_test))
```

```
0.666625
```

Accuracy is 66.6% for the class 3 vs class not 3

In [ ]:
```
#For class not 3
pmml_df_class_not3=pd.DataFrame(data=pmml_df_class3[pmml_df_class3["Cl
ass"]==0])
pmml_df_class_not3.head()
```

Out[ ]:

	A	B	C	D	E	F	G	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.16
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.29
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.64
5	235.027198	-16.081132	213.391582	-12.934912	122.413766	80.222540	125.240412	185.69
6	-35.819795	-16.688245	5.738227	17.570011	-31.523595	-20.625764	0.077354	-28.94

In [ ]:
```
P_class_not3 = pd.DataFrame(data=pmml_df_class_not3.drop('Class', axis
=1))
q_class_not3 = pd.DataFrame(data=pmml_df_class_not3['Class'],columns=[
'Class'])
P_class_not3_train, P_class_not3_test, q_class_not3_train, q_class_not
3_test = train_test_split(P_class_not3,q_class_not3,test_size=0.2)
train_data = pd.concat([P_class_not3_train,q_class_not3_train],axis=1)
train_data.head()
```

Out[ ]:

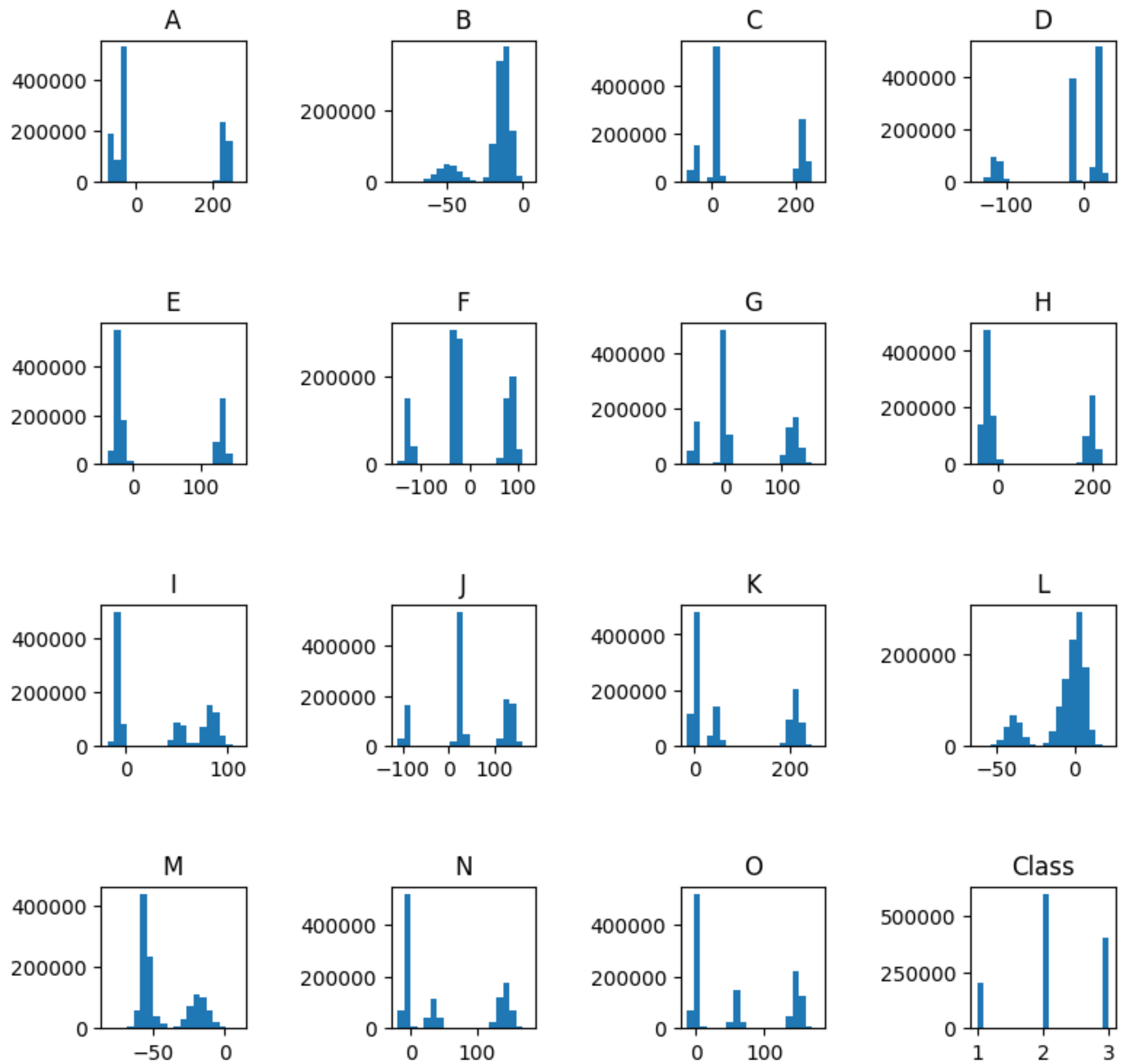
	A	B	C	D	E	F	G
556869	246.453600	-10.075202	213.645825	-14.319736	127.856225	94.027566	120.599359
826515	-36.822987	-16.001259	12.044076	18.387325	-16.476069	-24.673835	4.107730
721367	231.097007	-5.770599	229.597593	-10.696815	139.076048	75.090313	141.084106
592217	-64.198927	-59.922691	-31.873235	-120.188204	-14.169334	-125.845818	-51.060236
926333	-38.677890	-14.220124	14.428087	18.134781	-22.353655	-25.462723	3.508433

In [ ]:
```
#DecisionTreeClassifier
pipelinenot3_DTC = PMMLPipeline([('scaler',StandardScaler()),('pca',PC
A(n_components=1)),('classifier',DecisionTreeClassifier(max_depth=2))]
)
pipelinenot3_DTC.fit(P_class_not3_train,q_class_not3_train)
print(pipelinenot3_DTC.score(P_class_not3_test,q_class_not3_test))
```

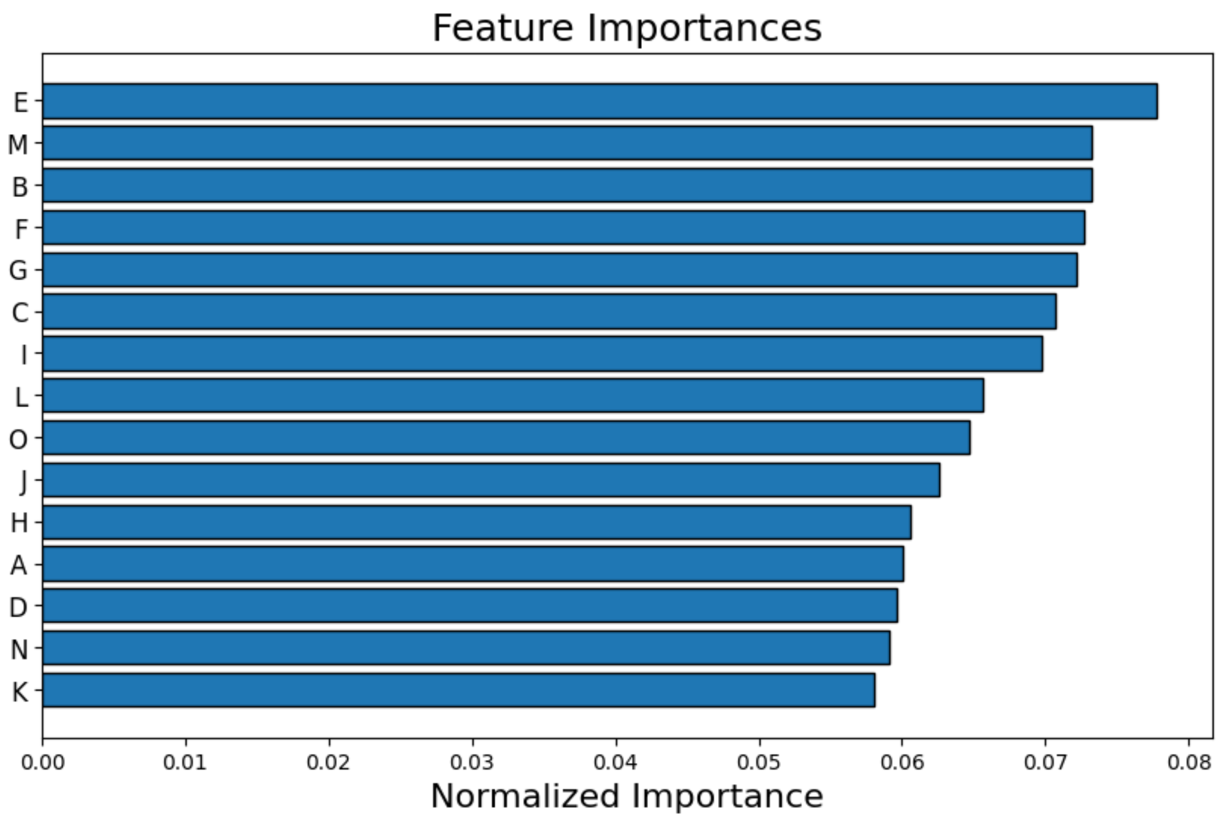
```
1.0
```

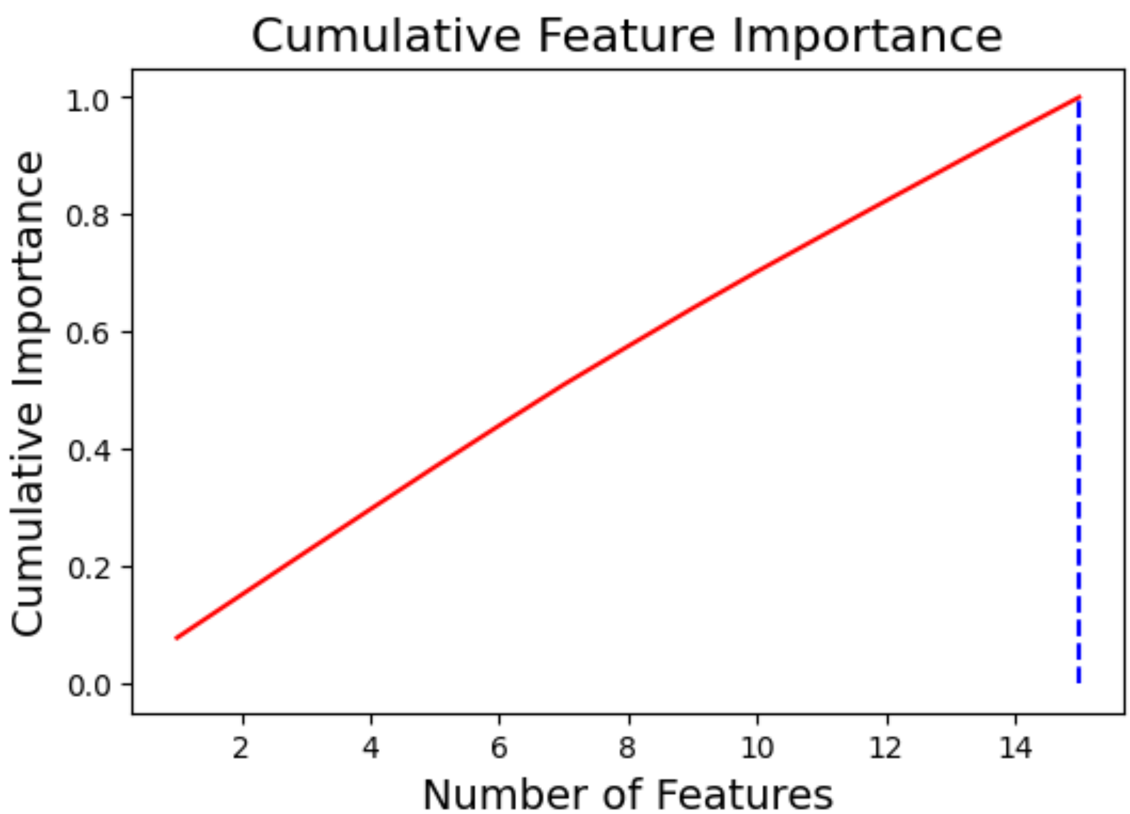
Accuracy is 100% for predicting the not class 3 i.e., predicting class 1 and class 2

In [ ]:
```
fig = plt.figure()
for i in range(1,16):
    fig.add_subplot(4,4,i)
    plt.hist(pmml_df[features[i-1:i]], bins=20)
    plt.title(features[i-1:i])
fig.add_subplot(4,4,16)
plt.hist(pmml_df['Class'], bins=20)
plt.title('Class')
fig.subplots_adjust(hspace=1, wspace=1)
fig.set_figheight(9)
fig.set_figwidth(9)
```



In [ ]:
```
zero_importance_features = fs.ops['zero_importance']
fs.plot_feature_importances(threshold = 0.97, plot_n = 15)
```






```
15 features required for 0.97 of cumulative importance
```

From the above plot of feature importance it is clear that all the features in the dataset have the equal importance.Dropping a feature with the high correlation or keeping the feature with high correlation gives the same accuracy.

In [ ]:
```
#Performing correlation for the complete dataset
pmml_df.corr('pearson')
```

Out[ ]:

	A	B	C	D	E	F	G	H
A	1.000000	0.455949	0.991999	0.071330	0.990703	0.905353	0.972223	0.988807
B	0.455949	1.000000	0.541742	0.865856	0.352946	0.760708	0.620607	0.339549
C	0.991999	0.541742	1.000000	0.176224	0.971805	0.943482	0.988351	0.968342
D	0.071330	0.865856	0.176224	1.000000	-0.047459	0.477183	0.279248	-0.062451
E	0.990703	0.352946	0.971805	-0.047459	1.000000	0.849129	0.939705	0.997116
F	0.905353	0.760708	0.943482	0.477183	0.849129	1.000000	0.969055	0.841227
G	0.972223	0.620607	0.988351	0.279248	0.939705	0.969055	1.000000	0.934714
H	0.988807	0.339549	0.968342	-0.062451	0.997116	0.841227	0.934714	1.000000
I	0.818399	-0.098558	0.753474	-0.502643	0.879142	0.508345	0.678043	0.886017
J	0.870016	0.803246	0.915784	0.544357	0.805749	0.989868	0.949429	0.796856
K	0.968827	0.246429	0.937868	-0.163679	0.989217	0.781534	0.894114	0.990875
L	0.139619	0.854635	0.238723	0.949485	0.026319	0.518117	0.335039	0.012005
M	0.958931	0.345030	0.941040	-0.042057	0.964769	0.823551	0.910385	0.964627
N	0.953081	0.194578	0.916578	-0.217856	0.979925	0.745156	0.867546	0.982403
O	0.920322	0.098805	0.873800	-0.316241	0.958885	0.675416	0.815281	0.962873
Class	-0.000620	0.000138	-0.000686	0.000150	-0.000649	-0.000540	-0.000472	-0.000670

From the correlation of the total dataset features A,C,E,H,K,N have the correlation nearly 100%

In [ ]:
```
#Training the dataset with the features A C E H K N
labels = ['A','C','E','H','K','N']
X_total = pd.DataFrame(data=pmml_df.drop('Class', axis=1),columns=labe
ls)
y_total = pd.DataFrame(data=pmml_df['Class'],columns=['Class'])
X_total_train, X_total_test, y_total_train, y_total_test = train_test_
split(X_total,y_total,test_size=0.2)
train_total_data = pd.concat([X_total_train,y_total_train],axis=1)
train_total_data.head()
```

Out[ ]:

	A	C	E	H	K	N	Class
512016	230.112441	224.960377	124.450080	208.680709	206.293291	134.148450	2
1052460	-63.987924	-44.613475	-17.520819	-10.606659	50.504001	40.533964	2
914029	-37.996257	12.750275	-23.663272	-22.725101	-0.931928	-13.166034	2
29378	-34.474782	15.025885	-26.595210	-28.362149	1.302834	-8.530303	2
76450	-40.234858	14.958358	-26.016517	-26.860865	3.498730	-0.461116	3

In [ ]:
```
#Calculating the accuracy for the dataset considering only the best fe
atures from the correlation of total dataset
to_keep_total = ['A','C','E','H','K','N']
pipeline_total = PMMLPipeline([('mapper',DataFrameMapper([(X_total_tra
in[to_keep_total].columns,[StandardScaler()])])),('pca',PCA(n_componen
ts=1)),('classifier',RandomForestClassifier(max_depth=2,n_estimators=1
0))])
pipeline_total.fit(train_total_data,train_total_data['Class'])
results = pipeline_total.predict(X_total_test)
actual = np.concatenate(y_total_test.values)
print('Accuracy:',metrics.accuracy_score(actual, results))
```

```
Accuracy: 0.49925416666666667
```

Performing MinMaxscaling and kbest on the entire dataset to get the best features from the dataset

In [ ]:
```
#Taking the complete dataset
df_class1 = pmml_df.copy(deep=True)
df_class1.head()
```

Out[ ]:

	A	B	C	D	E	F	G	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.16(
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.71
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.29
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.64(
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.30(

In [ ]:
```
df_class1['Class'].unique()
```

Out[ ]:
```
array([2, 3, 1])
```

In [ ]:
```
X_class123 = df_class1.drop(['Class'], axis=1)
y_class123 = df_class1['Class']
```

In [ ]:
```
from sklearn.preprocessing import MinMaxScaler
#Performing MinMaxScaler
scaler = MinMaxScaler()
X_class123_scaled = scaler.fit(X_class123).transform(X_class123)
X_class123_scaled
```

Out[ ]:
```
array([[0.89073462, 0.80987235, 0.8779829 , ..., 0.72740866, 0.82026
832,
        0.85913693],
       [0.10258527, 0.78723745, 0.21941259, ..., 0.24100718, 0.04457
839,
        0.07310273],
       [0.09913998, 0.71626466, 0.2556253 , ..., 0.26721914, 0.07971
828,
        0.0609862 ],
       ...,
       [0.86894928, 0.75106377, 0.86598024, ..., 0.72631794, 0.85285
43 ,
        0.81182299],
       [0.04370846, 0.46993384, 0.05424333, ..., 0.24168541, 0.27271
645,
        0.34996566],
       [0.94234337, 0.87639288, 0.86258877, ..., 0.61200446, 0.75515
142,
        0.79526219]])
```

In [ ]:
```
print(X_class123_scaled[0])
```

```
[0.89073462 0.80987235 0.8779829  0.71654357 0.90861604 0.83052713
 0.8518387  0.87368383 0.78048193 0.83263085 0.87148368 0.6727923
 0.72740866 0.82026832 0.85913693]
```

In [ ]:
```
from sklearn.feature_selection import SelectKBest, chi2
#Performing KBest feature selection
fs = SelectKBest(chi2, k=5).fit_transform(X_class123_scaled, y_class12
3)
fs
```

Out[ ]:
```
array([[0.89073462, 0.8779829 , 0.71654357, 0.87368383, 0.78048193],
       [0.10258527, 0.21941259, 0.93923052, 0.03176728, 0.07591281],
       [0.09913998, 0.2556253 , 0.92452282, 0.06231308, 0.08937904],
       ...,
       [0.86894928, 0.86598024, 0.73817325, 0.88009701, 0.76335731],
       [0.04370846, 0.05424333, 0.08953574, 0.11858609, 0.56500229],
       [0.94234337, 0.86258877, 0.71981219, 0.86702489, 0.79852367]]
)
```

In [ ]:
```
print(fs[0])
```

```
[0.89073462 0.8779829  0.71654357 0.87368383 0.78048193]
```

After scaling the dataset using the MinMaxScalar and using the kbest for selecting the features.I am getting A , C , D , H , I features.

In [ ]:
```
#Training the dataset with the features A C D H I
labels = ['A','C','D','H','I']
X10 = pd.DataFrame(data=df_class1.drop('Class', axis=1),columns=labels
)
y10 = pd.DataFrame(data=df_class1['Class'],columns=['Class'])
X10_train, X10_test, y10_train, y10_test = train_test_split(X10,y10,te
st_size=0.2)
train10_data = pd.concat([X10_train,y10_train],axis=1)
train10_data.head()
```

Out[ ]:

	A	C	D	H	I	Class
845083	233.731660	215.821624	-12.304190	192.338994	88.054537	3
944495	-25.174129	11.070344	15.243019	-28.600797	-8.885604	2
993722	-30.358624	11.183767	19.055807	-28.003526	-9.399976	3
204702	-38.872679	8.783887	17.836025	-18.870303	-6.800224	2
1176883	-37.594810	5.615331	23.948040	-26.408375	-9.639009	2

In [ ]:
```
#Calculating the accuracy for the dataset considering only the KBest f
eatures
to_keep10 = ['A','C','D','H','I']
pipeline10 = PMMLPipeline([('mapper',DataFrameMapper([(X10_train[to_ke
ep10].columns,[StandardScaler()])])),('pca',PCA(n_components=1)),('cla
ssifier',RandomForestClassifier(max_depth=2,n_estimators=10))])
pipeline10.fit(train10_data,train10_data['Class'])
results = pipeline10.predict(X10_test)
actual = np.concatenate(y10_test.values)
print('Accuracy:',metrics.accuracy_score(actual, results))
```

```
Accuracy: 0.49964166666666665
```

In [ ]:
```
#Finding the correlation for the dataset which are containing best fea
tures
train10_data.corr()
```

Out[ ]:

	A	C	D	H	I	Class
A	1.000000	0.991992	0.071745	0.988791	0.818106	-0.000721
C	0.991992	1.000000	0.176698	0.968298	0.753094	-0.000771
D	0.071745	0.176698	1.000000	-0.062152	-0.502739	0.000406
H	0.988791	0.968298	-0.062152	1.000000	0.885833	-0.000776
I	0.818106	0.753094	-0.502739	0.885833	1.000000	-0.000925
Class	-0.000721	-0.000771	0.000406	-0.000776	-0.000925	1.000000

Considering the correlation for the dataset with the KBest features my assumptions are A,C,H have the correlation nearly 100% considering the correlation between the features.

Final Model: Training and Validation

> I have created a final pipeline with the column selector having A,C,H features which i got it from the correlation which is performed on using the KBest method

In [ ]:
```
final_pipeline= Pipeline(steps=[('scaler',StandardScaler()), ('pca',PC
A(n_components=1)), ('classifier',DecisionTreeClassifier(max_depth=3))
])
final_df_model= final_pipeline.fit(P_train, q_train)
print(final_df_model.score(P_test,q_test))
```

```
0.49755
```

ONNX Runtime

In [ ]:
```
num_featurex=15
```

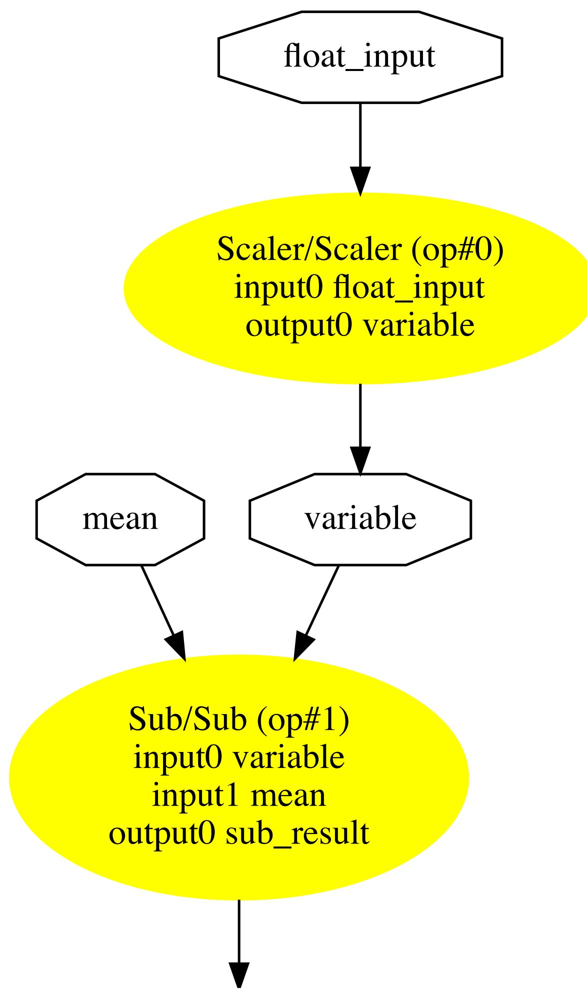
In [ ]:
```
onnx_model_path='/content/drive/My Drive/AmruthamLakshmiHimaja_final_m
odel.onnx'
in_types = [('float_input', FloatTensorType([None, num_featurex]))]
model_onnx = convert_sklearn(final_pipeline,initial_types=in_types)
with open(onnx_model_path, "wb") as f:
    f.write(model_onnx.SerializeToString())
```

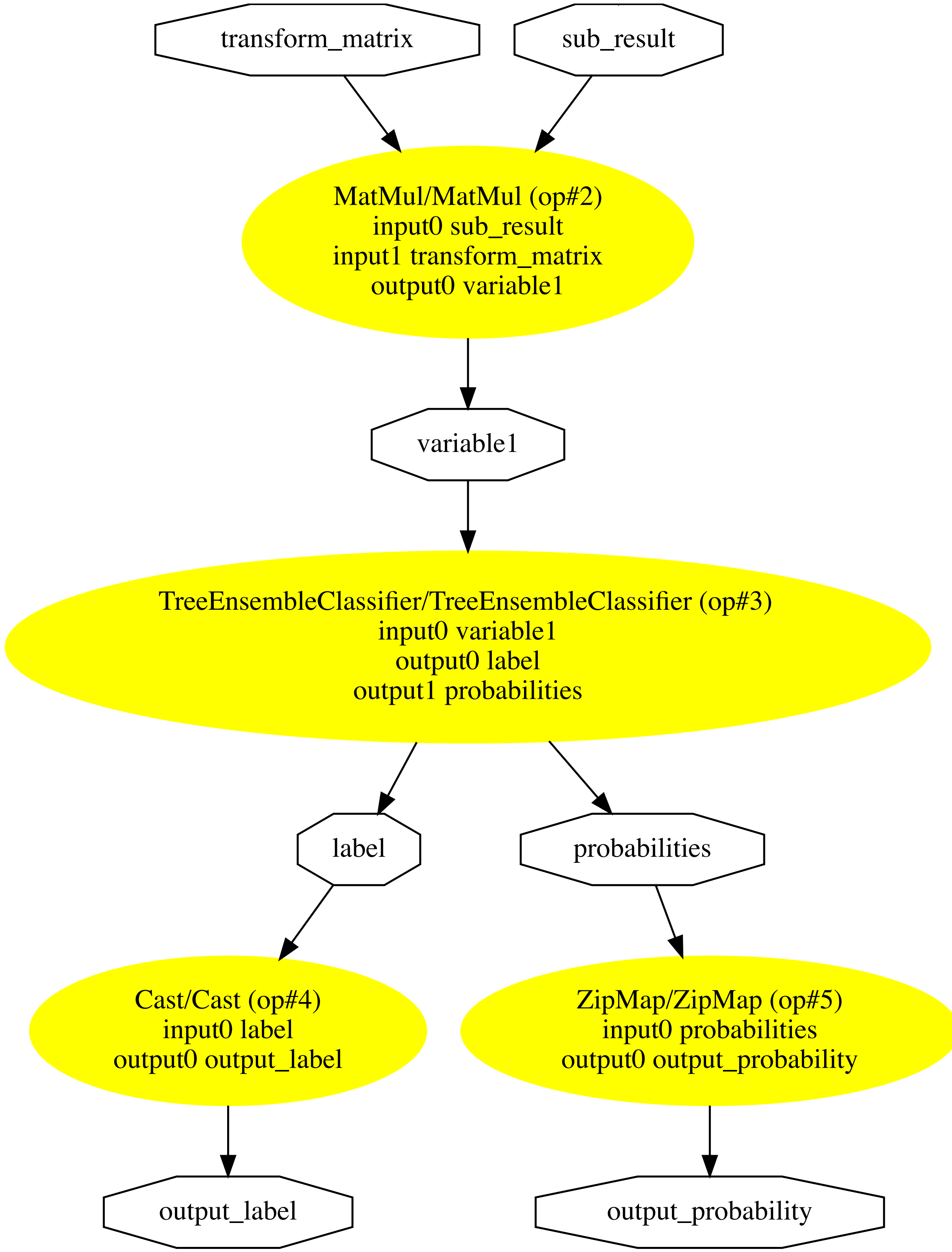
In [ ]:
```
import onnxruntime as rt
session_onnx = rt.InferenceSession(onnx_model_path)
input_name=session_onnx.get_inputs()[0].name
label_name=session_onnx.get_inputs()[0].name
predict_onnx = session_onnx.run(None, {input_name: P_test.values.astyp
e(np.float32)})[0]
print("predict", predict_onnx)
```

```
predict [2 2 2 ... 2 2 2]
```

In [ ]:
```
py_graph = GetPydotGraph(model_onnx.graph,name=model_onnx.graph.name,r
ankdir="TB",node_producer=GetOpNodeProducer("docstring",color="yellow"
,fillcolor="yellow",style="filled"))
graphviz.Source(py_graph)
```

Out[ ]:




transform_matrix
sub_result
MatMul/MatMul (op#2)
input0 sub_result
input1 transform_matrix
output0 variable1
variable1
TreeEnsembleClassifier/TreeEnsembleClassifier (op#3)
input0 variable1
output0 label
output1 probabilities
label
probabilities
Cast/Cast (op#4)
input0 label
output0 output_label
ZipMap/ZipMap (op#5)
input0 probabilities
output0 output_probability
output_label
output_probability

References

- https://machinelearningmastery.com/handle-missing-data-python/ (https://machinelearningmastery.com/handle-missing-data-python/)
- https://lukesingham.com/whos-going-to-leave-next/ (https://lukesingham.com/whos-going-to-leave-next/)
- https://github.com/WillKoehrsen/feature-selector/blob/master/feature_selector/feature_selector.py (https://github.com/WillKoehrsen/feature-selector/blob/master/feature_selector/feature_selector.py)
- https://www.analyticsvidhya.com/blog/2018/08/dimensionality-reduction-techniques-python/ (https://www.analyticsvidhya.com/blog/2018/08/dimensionality-reduction-techniques-python/)