Building and deploying Machine Learning models

Abstract

'All models are wrong, but some are useful' - George Box

The main motivation behind this project was to learn to work with data with no context and try and make sense out of it. We are presented with raw data that contains 15 independent features that are used to describe an instance of some observation. Each feature is labeled from 'A' to 'O'. We do not know what each feature means in terms of what the numbers represent. Another challenge was that the dataset itself was large and complex. With no evident correlations between the independent and the target variables. The count of each class label were not roughly equally distributed with more instances of one class label than the others. Furthermore, there was also not much scope to improve the quality of the data since there were not a lot of incosistencies and noise that could be removed in order to make better predictions. For example, the dataset had no missing values, few columns with outliers, and not much multicollinearity.

Overall, I found this project to be very intriguing and it was interesting to explore how a model would take in raw data with no context and try to come up with predictions. I quickly learned that the accuracy would not tend to improve with simple models that would take the entire dataset as a whole and find functions to map the input with the output. It would take effort to find out how exactly what features are being used to describe the targets in the first place. Future scope for this project would include using domain knowledge on the different features to try and understand correlations and dependencies. Also, trying to use certain boosting techniques to try and improve the accuracy of relatively weaker models. Additionally, we could also tune the hyperparameters to change certain fitting characteristics in order to improve model performance.

Overview

Problem Statement: The main aim of the project is to develop a classification model pipeline that can be used to make predictions on out-of-sample data.

Relevant literature:

- *Anupama Jha, Meenu Dave, Supriya Madan*. "Comparison of Binary Class and Multi-Class Classifier Using Different Data Mining Classification Techniques", 2019, Proceedings of International Conference on Advancements in Computing & Management (ICACM) 2019 (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3464211)
- *Salma Begum, Ramazan Aygun*. "Greedy hierarchical binary classifiers for multi-class classification of biological data", 2014, Network Modeling Analysis in Health Informatics and Bioinformatics. (https://www.researchgate.net/publication/271913431_Greedy_hierarchical_binary_classifiers_for_multi-class_classification_of_biological_data)
- *Ana Carolina Lorena, Andréde Carvalho, João M. P. Gama*. "A review on the combination of binary classifiers in multiclass problems", Artificial Intelligence Review, 2009. (https://link.springer.com/article/10.1007s10462-009-9114-9)

Proposed methodology: The data is first cleaned to remove any evident noise and inconsistencies that may hinder performance. Exploratory Data Analysis (EDA) is used to gather any relevant insights that might help in making the right decisions in terms of model selection and feature importance. The next step would be to assess the feature importance and try to reduce the dimensionality of the data. Principal Component Analysis (PCA) is performed on the dataset in order to reduce the data into 2 principal components that can be used to explain the variance and build a working model that can make decent predictions. The main thing to consider apart from just PCA is to convert the given multi-class classification problem into a set of binary classification tasks. That is, instead of building a model that can classify targets as either 1,2 or 3, we build binary classification models that can classify the data as either belonging to class 1 or not class 1, and class2 or not class 2, and class3 or not class 3. This way each model knows what kind of data belongs to each class type and they can then be combined to give us a model which has learned sets of inputs that can make predicitions on new data.

Data Processing

Importing the libraries

In [ ]:
```
!pip install sklearn2pmml
!pip install skl2onnx
!pip install onnxruntime
```

```
Requirement already satisfied: sklearn2pmml in /usr/local/lib/python3.7/dist-packages (0.71.1)
Requirement already satisfied: joblib>=0.13.0 in /usr/local/lib/python3.7/dist-packages (from sklearn
2pmml) (1.0.1)
Requirement already satisfied: sklearn-pandas>=0.0.10 in /usr/local/lib/python3.7/dist-packages (from
sklearn2pmml) (1.8.0)
Requirement already satisfied: scikit-learn>=0.18.0 in /usr/local/lib/python3.7/dist-packages (from s
klearn2pmml) (0.22.2.post1)
Requirement already satisfied: scipy>=0.14 in /usr/local/lib/python3.7/dist-packages (from sklearn-pa
ndas>=0.0.10->sklearn2pmml) (1.4.1)
Requirement already satisfied: numpy>=1.6.1 in /usr/local/lib/python3.7/dist-packages (from sklearn-p
andas>=0.0.10->sklearn2pmml) (1.19.5)
Requirement already satisfied: pandas>=0.11.0 in /usr/local/lib/python3.7/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/python3.7/dist-packages (from pandas>=
0.11.0->sklearn-pandas>=0.0.10->sklearn2pmml) (2018.9)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from python-dateut
il>=2.7.3->pandas>=0.11.0->sklearn-pandas>=0.0.10->sklearn2pmml) (1.15.0)
Collecting skl2onnx
  Using cached https://files.pythonhosted.org/packages/2e/2e/efe7874c6b92ce4dd262b58a2860e9bf50097c68
588114a542b29affca46/skl2onnx-1.8.0-py2.py3-none-any.whl
Requirement already satisfied: scikit-learn>=0.19 in /usr/local/lib/python3.7/dist-packages (from skl
2onnx) (0.22.2.post1)
Requirement already satisfied: protobuf in /usr/local/lib/python3.7/dist-packages (from skl2onnx) (3.
12.4)
Collecting onnxconverter-common<1.9,>=1.6.1
  Using cached https://files.pythonhosted.org/packages/42/f5/82c29029a643dd4de8e0374fe2d5831f50ca5862
3dd1ee41e0b8df8a7d71/onnxconverter_common-1.8.1-py2.py3-none-any.whl
Requirement already satisfied: scipy>=1.0 in /usr/local/lib/python3.7/dist-packages (from skl2onnx)
(1.4.1)
Requirement already satisfied: numpy>=1.15 in /usr/local/lib/python3.7/dist-packages (from skl2onnx)
(1.19.5)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from skl2onnx) (1.15.0)
Collecting onnx>=1.2.1
  Using cached https://files.pythonhosted.org/packages/3f/9b/54c950d3256e27f970a83cd0504efb183a243127
02deed0179453316dbd0/onnx-1.9.0-cp37-cp37m-manylinux2010_x86_64.whl
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-le
arn>=0.19->skl2onnx) (1.0.1)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-packages (from protobuf->s
kl2onnx) (56.0.0)
Requirement already satisfied: typing-extensions>=3.6.2.1 in /usr/local/lib/python3.7/dist-packages
(from onnx>=1.2.1->skl2onnx) (3.7.4.3)
Installing collected packages: onnx, onnxconverter-common, skl2onnx
Successfully installed onnx-1.9.0 onnxconverter-common-1.8.1 skl2onnx-1.8.0
Collecting onnxruntime
  Downloading https://files.pythonhosted.org/packages/0c/f0/666d6e3ceaa276a54e728f9972732e058544cbb6a
3e1a778a8d6f87132c1/onnxruntime-1.7.0-cp37-cp37m-manylinux2014_x86_64.whl (4.1MB)
     |████████████████████████████████| 4.1MB 5.3MB/s
Requirement already satisfied: numpy>=1.16.6 in /usr/local/lib/python3.7/dist-packages (from onnxrunt
ime) (1.19.5)
Requirement already satisfied: protobuf in /usr/local/lib/python3.7/dist-packages (from onnxruntime)
(3.12.4)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-packages (from protobuf->o
nnxruntime) (56.0.0)
Requirement already satisfied: six>=1.9 in /usr/local/lib/python3.7/dist-packages (from protobuf->onn
xruntime) (1.15.0)
Installing collected packages: onnxruntime
Successfully installed onnxruntime-1.7.0
```

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

from sklearn import tree
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.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB


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 import metrics
```

Importing the data

In [ ]:
```
df = pd.read_csv('/content/drive/MyDrive/Datasets/data_public.csv.gz', compression='gzip', header=0, se
p=',', quotechar='"')
df.head()
```

Out[ ]:

	A	B	C	D	E	F	G	H	I	J	K	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.160805	82.873279	127.350084	224.592926	-5
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.711852	-8.356041	23.792402	4.199023	2
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.299219	-6.612401	26.285392	5.911292	6
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.640135	82.560019	157.105143	212.989231	-3
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.300011	89.961688	130.299732	201.795100	-1

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

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

In [ ]:
```
len(df)
```

Out[ ]:
```
1200000
```

A quick glance of our dataset reveals the following :

- We have 15 independent variables (A-O) that are being used to describe which class a particular record(row) belongs to.
- Each row of the data is classified into one of three unique class labels (1,2 and 3)
- We have a total of 1200000 unique instances or records in our dataset.

Our goal is to build a predictive model whose taks is approximating the mapping function from the independent variables and the target class. The main goal is to identify which class/label a new data instance would fall into.

We do this using a Pipeline built from Scikit-Learn. The purpose of the pipeline is to combine the different steps of processing, model-building and model-testing into one operation. It also allows for hypermater tuning in order to improve the accuracy of our results. Our pipeline will consist of the following steps :

- Scaling the data
- Principal Component Analysis (PCA)
- Building the classification model
- Testing its accuracy

In [ ]:
```
## Building a simple pipeline without any preprocessing

X = df.drop(['Class'], axis=1)
y = df['Class']

X_train, X_test, y_train, y_test = train_test_split(X,y,stratify=y, test_size=0.2)

# pipeline steps :
#1. Scaling the data
#2. Pricipal Component Analysis
#3. Building a Decision Tree model
#4. Testing accuracy

pipeline_dt=Pipeline([('scalar',StandardScaler()),
                      ('pca',PCA(n_components=2)),
                      ('dt_classifier',DecisionTreeClassifier(max_depth=3))])

pipeline_dt.fit(X_train, y_train)
pipeline_dt.score(X_test, y_test)     # accuracy
```

Out[ ]:
```
0.4993172603290554
```

Let us try and improve on this model by first preprocessing our data.

Preprocessing our data

What we aim to do from preprocessing the data is check for certain inconsistencies such as missing values in the data, attributes lacking interest, noisy data, outliers, handling categorical values, etc.

We also use Exploratory Data Analysis(EDA), a complement to inferential statistics which looks to describe the dataset using visualizaitons and other key performance statistics and then summarizing it to gather more insights into our data. This will help aid the model building process by helping us understand what the best hyperparameters would be and which model would be best suited for prediction.

We will perform the following steps in order to preprocess our data :

- Exploratory Data Analysis
- Removing duplicates
- Handling missing values
- Outlier treatment
- Normalizing and Scaling
- Encoding categorical variables
- Bivariate analysis
- Splitting the data into train and test sets

In [ ]:
```
## Exploratory Data Analysis

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1200000 entries, 0 to 1199999
Data columns (total 16 columns):
 #   Column  Non-Null Count    Dtype
---  ------  --------------    -----
 0   A       1200000 non-null  float64
 1   B       1200000 non-null  float64
 2   C       1200000 non-null  float64
 3   D       1200000 non-null  float64
 4   E       1200000 non-null  float64
 5   F       1200000 non-null  float64
 6   G       1200000 non-null  float64
 7   H       1200000 non-null  float64
 8   I       1200000 non-null  float64
 9   J       1200000 non-null  float64
 10  K       1200000 non-null  float64
 11  L       1200000 non-null  float64
 12  M       1200000 non-null  float64
 13  N       1200000 non-null  float64
 14  O       1200000 non-null  float64
 15  Class   1200000 non-null  int64
dtypes: float64(15), int64(1)
memory usage: 146.5 MB
```

We notice that all the indpendent variables in our dataset are floating point numbers and our class label is an integer. There is no requirement to handle data points of an unexpected data type.

In [ ]:
```
## checking for missing data

df.isnull().any()
```

Out[ ]:
```
A        False
B        False
C        False
D        False
E        False
F        False
G        False
H        False
I        False
J        False
K        False
L        False
M        False
N        False
O        False
Class    False
dtype: bool
```

We find no missing data present in our dataset. However, to be sure, let us also check if there are any special characters present in the data which may cause discrepencies.

In [ ]:
```
import string
alphabet = string.ascii_letters+string.punctuation

df.columns.str.strip(alphabet).astype(bool).any()
```

Out[ ]:
```
False
```

We can conclude that the data does not contain any missing values or special characters.

In [ ]:
```
## Check for duplicate values
duplicate = df.duplicated()
duplicate.sum()
```

Out[ ]:
```
0
```

There aren't any duplicate values either. So far, so good.

Outliers are data points that don't belong to a particular population. They are abnormal observations that lie beyond the range of the other values in the population.

Identifying outliers using the inter-quartile range(IQR) : The interquartile range (IQR) is a measure of statistical dispersion. We calculate the IQR by finding the difference between the 75th and the 25th percentiles. It is formally written as IQR = Q3 - Q1, where Q3 is the 75th percentile and Q1 is the 25th percentile.

In [ ]:
```
## check for outliers

Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1

((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).sum()
```

Out[ ]:
```
A             0
B        200297
C             0
D        200103
E             0
F             0
G             0
H             0
I             0
J             0
K             0
L        198365
M             0
N             0
O             0
Class         0
dtype: int64
```

We find that the 'B', 'D' and 'L' columns contain outliers in them that need to be treated before proceeding to build the actual model. We can visualize these outliers using boxplots.

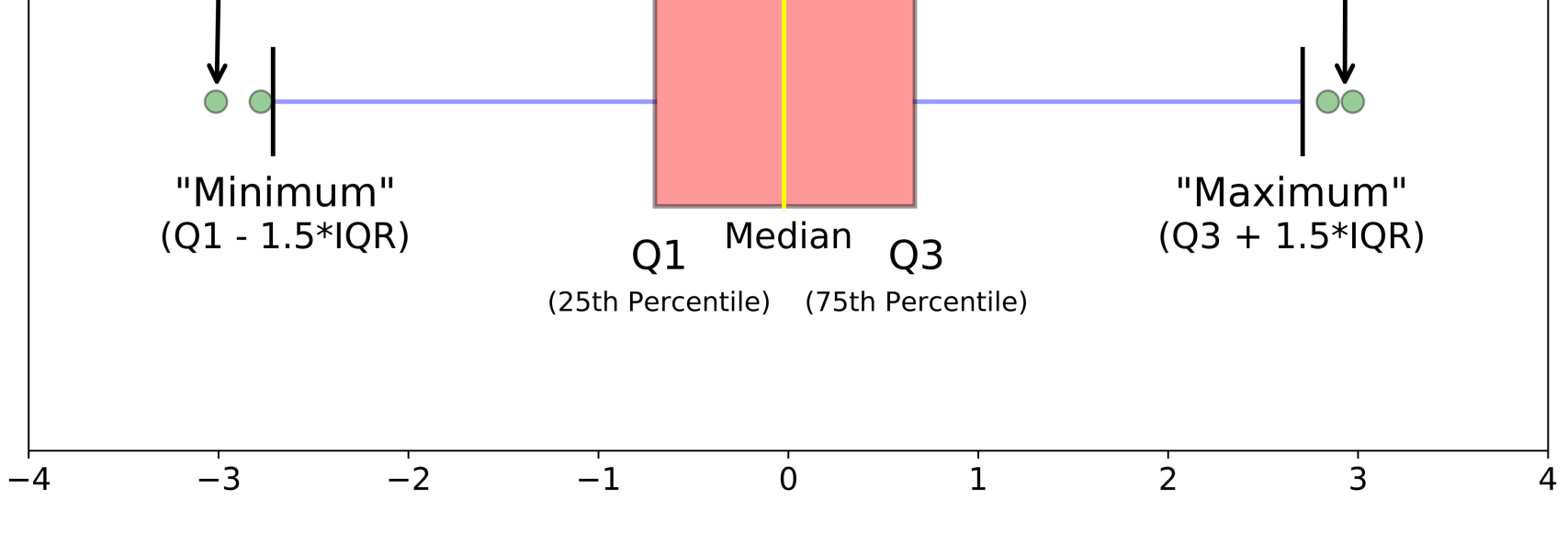
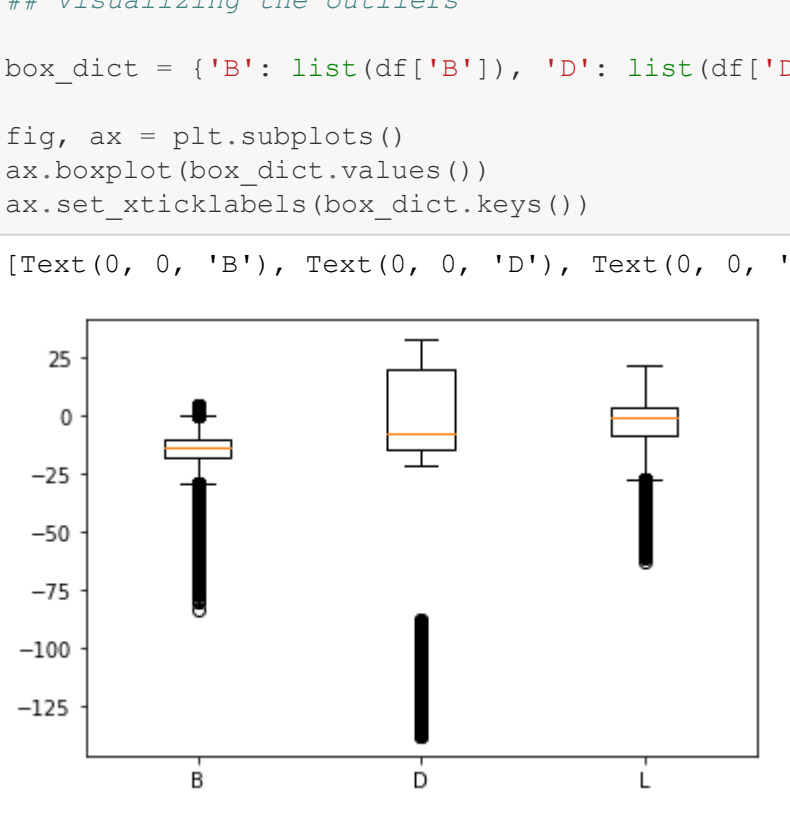


Image source : https://naysan.ca/2020/06/28/interquartile-range-iqr-to-detect-outliers/

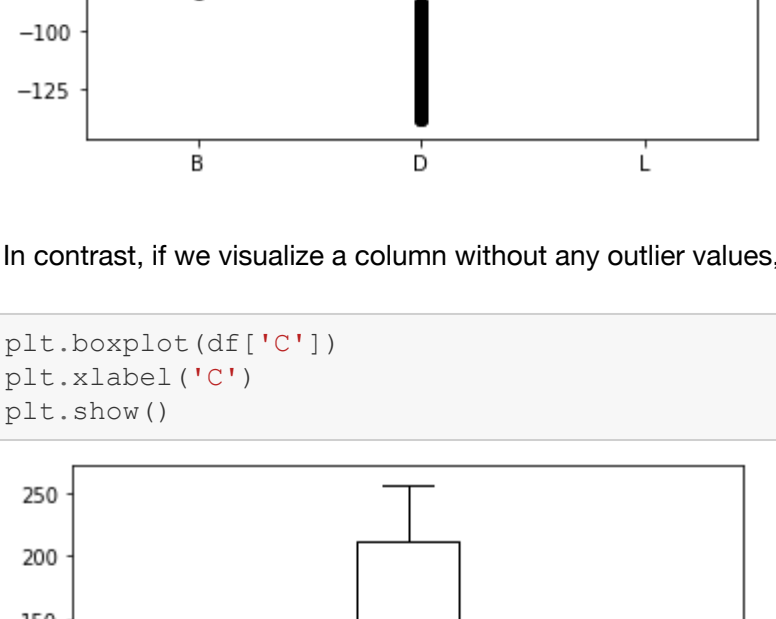
In [ ]:
```
## Visualizing the outliers

box_dict = {'B': list(df['B']), 'D': list(df['D']), 'L':list(df['L'])}

fig, ax = plt.subplots()
ax.boxplot(box_dict.values())
ax.set_xticklabels(box_dict.keys())
```

Out[ ]:
```
[Text(0, 0, 'B'), Text(0, 0, 'D'), Text(0, 0, 'L')]
```



In contrast, if we visualize a column without any outlier values, we get:

In [ ]:
```
plt.boxplot(df['C'])
plt.xlabel('C')
plt.show()
```



In [ ]:
```
## Dropping rows with ouliers

len(df)    # Initial lengths
```

Out[ ]:
```
1200000
```

In [ ]:
```
from scipy import stats
df = df[(np.abs(stats.zscore(df)) < 3).all(axis=1)]

len(df)      # Length after dropping rows that are outliers
```

Out[ ]:
```
1193716
```

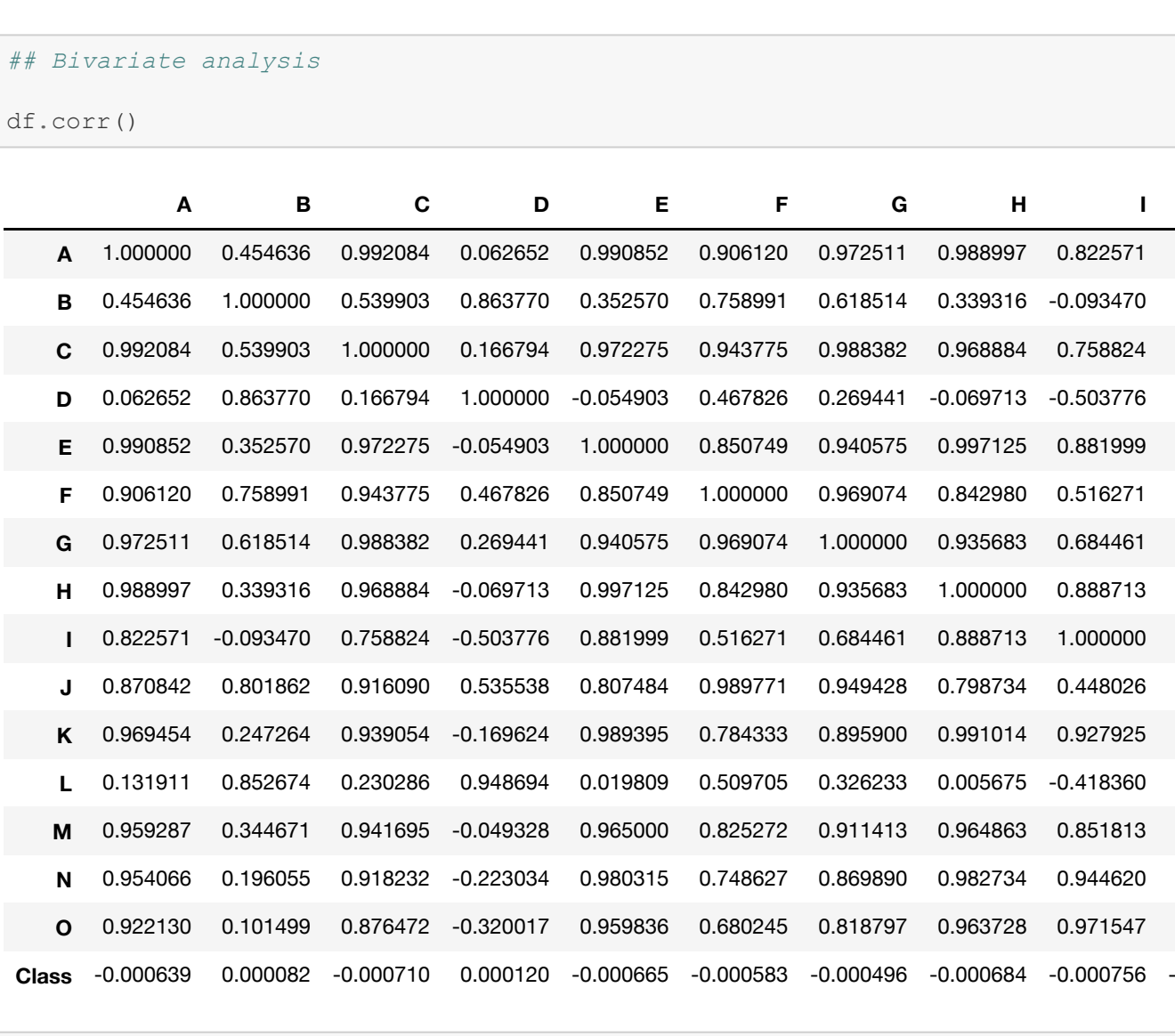
Let us now explore if there is any correlation between our variables that might help with feature extraction.

In [ ]:
```
## Bivariate analysis

df.corr()
```

Out[ ]:

	A	B	C	D	E	F	G	H	I	J	K	L	
A	1.000000	0.454636	0.992084	0.062652	0.990852	0.906120	0.972511	0.988997	0.822571	0.870842	0.969454	0.131911	
B	0.454636	1.000000	0.539903	0.863770	0.352570	0.758991	0.618514	0.339316	-0.093470	0.801862	0.247264	0.852674	
C	0.992084	0.539903	1.000000	0.166794	0.972275	0.943775	0.988382	0.968884	0.758824	0.916090	0.939054	0.230286	
D	0.062652	0.863770	0.166794	1.000000	-0.054903	0.467826	0.269441	-0.069713	-0.503776	0.535538	-0.169624	0.948694	-
E	0.990852	0.352570	0.972275	-0.054903	1.000000	0.850749	0.940575	0.997125	0.881999	0.807484	0.989395	0.019809	
F	0.906120	0.758991	0.943775	0.467826	0.850749	1.000000	0.969074	0.842980	0.516271	0.989771	0.784333	0.509705	
G	0.972511	0.618514	0.988382	0.269441	0.940575	0.969074	1.000000	0.935683	0.684461	0.949428	0.895900	0.326233	
H	0.988997	0.339316	0.968884	-0.069713	0.997125	0.842980	0.935683	1.000000	0.888713	0.798734	0.991014	0.005675	
I	0.822571	-0.093470	0.758824	-0.503776	0.881999	0.516271	0.684461	0.888713	1.000000	0.448026	0.927925	-0.418360	
J	0.870842	0.801862	0.916090	0.535538	0.807484	0.989771	0.949428	0.798734	0.448026	1.000000	0.733811	0.571380	
K	0.969454	0.247264	0.939054	-0.169624	0.989395	0.784333	0.895900	0.991014	0.927925	0.733811	1.000000	-0.090594	
L	0.131911	0.852674	0.230286	0.948694	0.019809	0.509705	0.326233	0.005675	-0.418360	0.571380	-0.090594	1.000000	
M	0.959287	0.344671	0.941695	-0.049328	0.965000	0.825272	0.911413	0.964863	0.851813	0.783634	0.957007	0.022680	
N	0.954066	0.196055	0.918232	-0.223034	0.980315	0.748627	0.869890	0.982734	0.944620	0.694936	0.992229	-0.142388	
O	0.922130	0.101499	0.876472	-0.320017	0.959836	0.680245	0.818797	0.963728	0.971547	0.620983	0.983320	-0.236721	
Class	-0.000639	0.000082	-0.000710	0.000120	-0.000665	-0.000583	-0.000496	-0.000684	-0.000756	-0.000373	-0.000705	0.000080	-

In [ ]:
```
## Visualizing correlation

plt.figure(figsize=(12,10))
cor = df.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```



We notice a lot of correlations between the features themselves but no visible correlation between any of the features and the target variable.

Furthermore, let us look at some of the summary statistics for the dataset.

In [ ]:
```
df.describe()
```

Out[ ]:

	0	1	2	3	4	5	6	7	8
count	1.193716e+06	1.193716e+06	1.193716e+06	1.193716e+06	1.193716e+06	1.193716e+06	1.193716e+06	1.193716e+06	1.193716e+06
mean	-8.682936e-02	-1.179830e-01	1.744621e-01	2.945297e-02	-6.603729e-02	-1.804881e-01	4.078992e-02	-3.276651e-02	4.305327e-02
std	3.718887e-01	7.764584e-02	1.956824e-01	2.400391e-01	2.344030e-01	2.511771e-01	1.533557e-01	2.977592e-01	1.324322e-01
min	-5.641228e-01	-3.467873e-01	-2.451355e-01	-5.426783e-01	-4.212605e-01	-5.797971e-01	-2.662464e-01	-4.687216e-01	-2.141106e-01
25%	-3.831722e-01	-1.837829e-01	8.731156e-02	-2.710167e-02	-2.757621e-01	-3.426897e-01	-3.819777e-02	-2.977815e-01	-8.606633e-02
50%	-2.715352e-01	-1.390441e-01	1.530571e-01	1.379041e-01	-1.884983e-01	-2.808178e-01	1.744693e-02	-2.055153e-01	-2.241985e-02
75%	4.222780e-01	-2.420942e-02	3.935976e-01	2.214873e-01	2.382795e-01	1.451724e-01	2.135965e-01	3.549691e-01	1.629290e-01
max	4.915968e-01	4.438030e-02	4.694679e-01	3.580803e-01	2.932855e-01	2.255647e-01	3.066592e-01	4.235634e-01	2.972185e-01

Pricipal Compnent Analysis

Principal Component Analysis, or PCA, is a dimensionality-reduction method that is often used to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller one that still contains most of the information in the large set.

Reducing the number of variables of a data set naturally comes at the expense of accuracy, but the trick in dimensionality reduction is to trade a little accuracy for simplicity. Because smaller data sets are easier to explore and visualize and make analyzing data much easier and faster for machine learning algorithms without extraneous variables to process.

SOURCE : https://builtin.com/data-science/step-step-explanation-principal-component-analysis

In [ ]:
```
df_original = pd.read_csv('/content/drive/MyDrive/Datasets/data_public.csv.gz')
df_copy = df_original.copy()
```

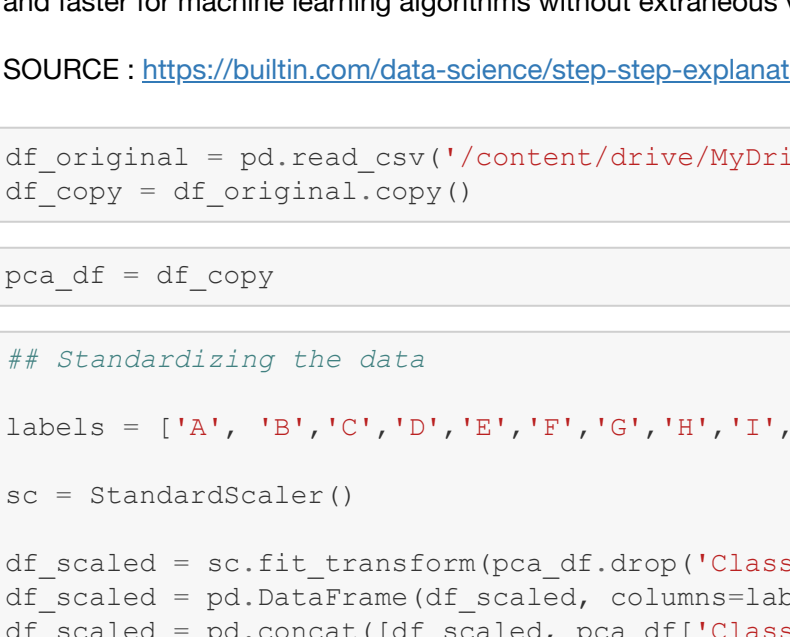
In [ ]:
```
pca_df = df_copy
```

In [ ]:
```
## Standardizing the data

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

sc = StandardScaler()

df_scaled = sc.fit_transform(pca_df.drop('Class', axis=1))
df_scaled = pd.DataFrame(df_scaled, columns=labels)
df_scaled = pd.concat([df_scaled, pca_df['Class']], axis=1)
df_scaled.head()
```

Out[ ]:

	A	B	C	D	E	F	G	H	I	J	K	L	
0	1.398333	0.457892	1.386800	-0.043941	1.518831	1.136805	1.499176	1.421937	1.182621	1.123217	1.531100	0.048383	1.542
1	-0.686316	0.320671	-0.589262	0.764323	-0.755534	-0.166762	-0.477999	-0.820431	-0.980689	-0.222670	-0.792750	0.613532	-0.949
2	-0.695429	-0.109594	-0.480605	0.710940	-0.759987	-0.177913	-0.520931	-0.739075	-0.939343	-0.190270	-0.774695	0.830704	-0.815
3	1.322591	0.902156	1.378256	0.077838	1.336854	1.249231	1.157837	1.416902	1.175193	1.509929	1.408750	0.200674	1.499
4	1.376193	0.441525	1.263438	0.005832	1.503497	1.331041	1.259054	1.529661	1.350708	1.161552	1.290718	0.332113	1.518

In [ ]:
```
## Elbow plot to decide optimal number of pricipal components

pca = decomposition.PCA(n_components=15)
pca.fit(df_scaled.drop(['Class'], axis=1))

plt.plot(np.cumsum(pca.explained_variance_ratio_))

plt.xlabel('Number of components')
plt.ylabel('Explained Variance')
plt.show()
```



Based on the elbow plot above, we notice that PCA reveals that the optimal number of components that can explain most of the variance in the data is 1. Hence for all our models, we will set the number of principal components to be 1.

In [ ]:
```
labels = ['A', 'B','C','D','E','F','G','H','I','J','K','L','M','N','O']
X = pd.DataFrame(data=df_copy.drop('Class', axis=1),
columns=labels)
y = pd.DataFrame(data=df_copy['Class'],
columns=['Class'])
X_train, X_test, y_train, y_test = train_test_split(X,
y,
test_size=0.3)
training_data = pd.concat([X_train,
y_train],
axis=1)
training_data.head()
```

Out[ ]:

	A	B	C	D	E	F	G	H	I	J	
1072504	-33.490647	-14.661206	11.747871	22.346489	-27.721191	-32.512465	1.824240	-21.259593	-2.589216	26.955136	6.3
713041	232.502535	-16.856704	205.474510	-14.107232	136.581658	83.115921	123.487581	199.993118	92.758674	118.742837	211.8
450874	-57.255765	-54.097917	-47.377616	-110.555513	-5.144220	-127.730494	-54.644947	-16.453346	54.164936	-93.148273	51.8
979023	-38.155386	-17.266492	14.639302	17.939150	-23.693301	-26.303813	1.091643	-23.316217	-4.596005	24.001450	-3.1
410123	-64.632650	-42.713574	-43.565149	-120.293119	-14.512706	-118.812219	-54.989279	-8.047951	42.408857	-87.328656	37.8

We then try a brute force method to detect which features hinder the accuracy of our results the most. Based on this, we can decide which features to remove and which features to keep. We loop over all the features and test the accuracy of the model on each feature and decide which one to drop based on the accuracies obtained.

In [ ]:
```
##* CODE REFERENCED FROM VICTORIA BELOTTI  *

features = 'ABCDEFGHIJKLMNO'

for i in range(0, len(features)):

  pipeline = PMMLPipeline([
                          ('mapper', DataFrameMapper([
                                                      (X_train.columns.drop([features[i:i+1]]).values,
                                                       [StandardScaler()])])),
                          ('pca', PCA(n_components=1)),
                          ('classifier', DecisionTreeClassifier(max_depth=12))
                          ])
  pipeline.fit(training_data.drop([features[i:i+1]], axis=1), training_data['Class'])

  results = pipeline.predict(X_test)
  acutal = np.concatenate(y_test.values)
  print('Dropped feature:', features[i:i+1], ", Accuracy:", metrics.accuracy_score(acutal, results))
```

```
Dropped feature: A , Accuracy: 0.49895555555555554
Dropped feature: B , Accuracy: 0.498969444444444447
Dropped feature: C , Accuracy: 0.4988666666666667
Dropped feature: D , Accuracy: 0.498919444444444447
Dropped feature: E , Accuracy: 0.498794444444444443
Dropped feature: F , Accuracy: 0.498875
Dropped feature: G , Accuracy: 0.4989527777777778
Dropped feature: H , Accuracy: 0.499044444444444446
Dropped feature: I , Accuracy: 0.498697222222222224
Dropped feature: J , Accuracy: 0.4989777777777778
Dropped feature: K , Accuracy: 0.498969444444444447
Dropped feature: L , Accuracy: 0.498933333333333334
Dropped feature: M , Accuracy: 0.49895
Dropped feature: N , Accuracy: 0.499019444444444446
Dropped feature: O , Accuracy: 0.49875555555555556
```

We notice that the above method does not really help us make decisions on feature importance since all features seem to be giving us more or less the same accuracy.

I was curious as to how the performance of the model would change if I were to increase the number of principal components to 2 instead of 1. My main thought process was that if two components are sufficient to explain the variance ratio of the dataset, then we can test its performance on the model.

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

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

## Separating out the target variable

X = pca_df.loc[:, features].values
y = pca_df.loc[:, ['Class']].values

# Standardizing
X = StandardScaler().fit_transform(X)
```

In [ ]:
```
## Implementing PCA

from sklearn.decomposition import PCA

pca = PCA(n_components=2)

principalComps = pca.fit_transform(X)

principalDf = pd.DataFrame(data = principalComps, columns=['p1', 'p2'])
```

In [ ]:
```
principalDf.head()
```

Out[ ]:

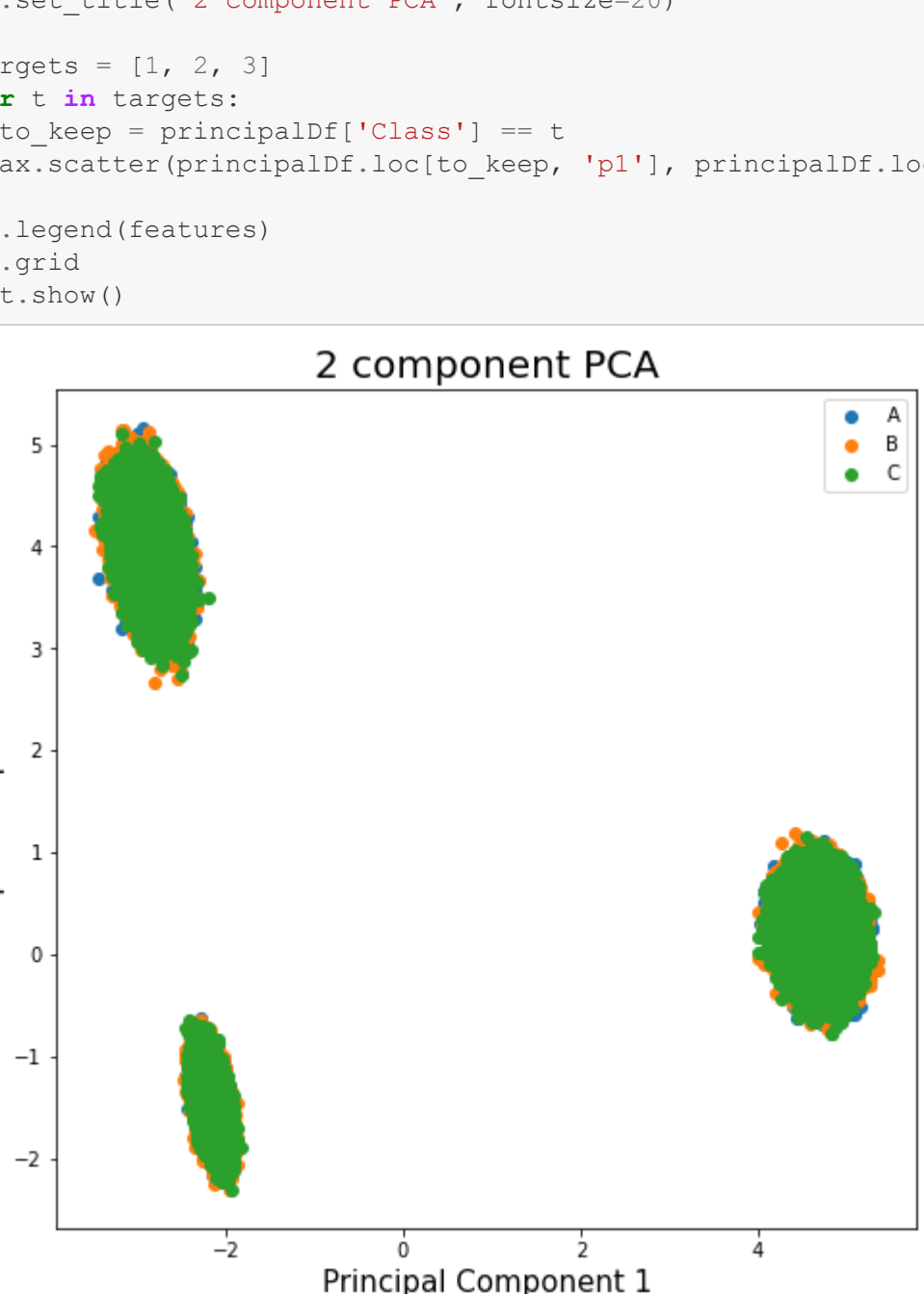
	p1	p2
0	4.799926	0.360278
1	-2.262345	-1.525723
2	-2.193845	-1.387110
3	4.721129	-0.118250
4	4.749759	0.201256

In [ ]:
```
principalDf = pd.concat([principalDf, pca_df[['Class']]], axis=1)
principalDf.head()
```

Out[ ]:

	p1	p2	Class
0	4.799926	0.360278	2
1	-2.262345	-1.525723	3
2	-2.193845	-1.387110	2
3	4.721129	-0.118250	2
4	4.749759	0.201256	3

In [ ]:
```
## visualize pca

fig = plt.figure(figsize=(8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize=15)
ax.set_ylabel('Principal Component 2', fontsize=15)
ax.set_title('2 component PCA', fontsize=20)

targets = [1, 2, 3]
for t in targets:
  to_keep = principalDf['Class'] == t
  ax.scatter(principalDf.loc[to_keep, 'p1'], principalDf.loc[to_keep, 'p2'])

ax.legend(features)
ax.grid
plt.show()
```



In [ ]:
```
pca.explained_variance_ratio_
```

Out[ ]:
```
array([0.73386468, 0.24903022])
```

In [ ]:
```
sum(pca.explained_variance_ratio_)
```

Out[ ]:
```
0.9828949000184242
```

We find something interesting here.

Taking two principal components, we notice that they are able to explain 98.2% of the variance. We can therefore consider n=2 principal components to be optimal in explaining the variance ratio as well.

The next task I tried was to come up with the most optimal features using another technique. I figured using similarity between features would be an efficient way to go. And so I tried to select the 5 most similar features based on their similarities. Sklear's SelectKBest function helps us do just that using the Chi Square Distance.

```
from sklearn.feature_selection import SelectKBest, chi2
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
X_scaled = scaler.fit(X).transform(X)
X_scaled
```

```
array([[0.89073462, 0.80987235, 0.8779829 , ..., 0.72740866, 0.82026832,
        0.85913693],
       [0.10258527, 0.78723745, 0.21941259, ..., 0.24100718, 0.04457839,
        0.07310273],
       [0.09913998, 0.71626466, 0.2556253 , ..., 0.26721914, 0.07971828,
        0.0609862 ],
       ...,
       [0.86894928, 0.75106377, 0.86598024, ..., 0.72631794, 0.8528543 ,
        0.81182299],
       [0.04370846, 0.46993384, 0.05424333, ..., 0.24168541, 0.27271645,
        0.34996566],
       [0.94234337, 0.87639288, 0.86258877, ..., 0.61200446, 0.75515142,
        0.79526219]])
```

```
print(X_scaled[0])    # for reference
```

```
[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]
```

```
from sklearn.feature_selection import SelectKBest, chi2

X_new = SelectKBest(chi2, k=5).fit_transform(X_scaled, y)
X_new
```

```
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]])
```

```
print(X_new[0])
```

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

If we compare the above result with the first row of the scaled data, we can map the column names as : ACDHI

Therefore, based on the selecting features on distance similarity, we have come up with the 5 best features to choose for our model : [A, C, D, H, I]. Let us try to build our pipeline using these new features only.

```
new_df = df_copy[['A', 'C', 'D', 'H', 'I', 'Class']]
new_df.head()
```

	A	C	D	H	I	Class
0	231.420023	217.624839	-15.611916	198.160805	82.873279	2
1	-38.019270	9.583547	22.293822	-33.711852	-8.356041	3
2	-39.197085	21.023083	19.790280	-25.299219	-6.612401	2
3	221.630408	216.725322	-9.900781	197.640135	82.560019	2
4	228.558412	204.637218	-13.277704	209.300011	89.961688	3

```
X_new = new_df.drop(['Class'], axis=1)
y_new = new_df['Class']

X_new_train, X_new_test, y_new_train, y_new_test = train_test_split(X_new, y_new, stratify=y, test_size
=0.2)
```

```
## Decision Tree Pipeline

pipeline_dt_new = Pipeline([('scalar',StandardScaler()),
                     ('pca',PCA(n_components=2)),
                     ('dt_classifier',DecisionTreeClassifier(max_depth=3))])

pipeline_dt.fit(X_new_train, y_new_train)
pipeline_dt.score(X_new_test, y_new_test)
```

```
0.4993208333333333
```

Unfortunately, we do not notice any improvements in accuracy using the K-Best distance similarity metric to reduce the number of features to the most important features.

My next approach was to try different model pipelines on the data and see if I can receive a better accuracy. The models I tried were :

- Logistic Regression
- Decision Tree Classifier
- Random Forest Classifier
- Naive-Bayes Classifier

```
## Creating pipelines for the different classifiers

## Logistic Regression

pipeline_lr=Pipeline([('scalar1',StandardScaler()),
                     ('pca1',PCA(n_components=2)),
                     ('lr_classifier',LogisticRegression(random_state=10))])

pipeline_lr.fit(X_train, y_train)
score = pipeline_lr.score(X_test, y_test)
pred = pipeline_lr.predict(X_test)
acc = metrics.accuracy_score(y_test, pred)
print('Classification report:')
print(metrics.classification_report(y_test, pred))
print('Accuracy score: ', acc)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:760: DataConversionWarning: A colu
mn-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), f
or example using ravel().
  y = column_or_1d(y, warn=True)
Score : 0.4991777777777778
Classification report:
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1272: UndefinedMetricWarnin
g: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
              precision    recall  f1-score   support

           1       0.00      0.00      0.00     59804
           2       0.50      1.00      0.67    179704
           3       0.00      0.00      0.00    120492

    accuracy                           0.50    360000
   macro avg       0.17      0.33      0.22    360000
weighted avg       0.25      0.50      0.33    360000

Accuracy:  0.4991777777777778
```

```
## Decision Tree

pipeline_dt=Pipeline([('scalar2',StandardScaler()),
                     ('pca2',PCA(n_components=2)),
                     ('dt_classifier',DecisionTreeClassifier(max_depth=3, random_state=0))])

pipeline_dt.fit(X_train, y_train)
score2 = pipeline_dt.score(X_test, y_test)
pred2 = pipeline_dt.predict(X_test)
acc2 = metrics.accuracy_score(y_test, pred2)
print('Classification report:')
print(metrics.classification_report(y_test, pred2))
print('Accuracy score: ', acc2)
```

```
Classification report:
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1272: UndefinedMetricWarnin
g: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
              precision    recall  f1-score   support

           1       0.00      0.00      0.00     59804
           2       0.50      1.00      0.67    179704
           3       0.25      0.00      0.00    120492

    accuracy                           0.50    360000
   macro avg       0.25      0.33      0.22    360000
weighted avg       0.33      0.50      0.33    360000

Accuracy score:  0.49917222222222224
```

```
## Random Forest

pipeline_rf = Pipeline([('scalar3',StandardScaler()),
                     ('pca3',PCA(n_components=2)),
                     ('rf_classifier',RandomForestClassifier(max_depth=5, n_estimators=5))])

pipeline_rf.fit(X_train, y_train)
score3 = pipeline_rf.score(X_test, y_test)
pred3 = pipeline_rf.predict(X_test)
acc3 = metrics.accuracy_score(y_test, pred3)
print('Classification report:')
print(metrics.classification_report(y_test, pred3))
print('Accuracy score: ', acc3)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/pipeline.py:354: DataConversionWarning: A column-vecto
r y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for exampl
e using ravel().
  self._final_estimator.fit(Xt, y, **fit_params)
Classification report:
              precision    recall  f1-score   support

           1       0.12      0.00      0.00     59804
           2       0.50      1.00      0.67    179704
           3       0.33      0.00      0.00    120492

    accuracy                           0.50    360000
   macro avg       0.32      0.33      0.22    360000
weighted avg       0.38      0.50      0.33    360000

Accuracy score:  0.4991388888888889
```

```
## Naive Bayes Classifier

pipeline_nb=Pipeline([('scalar4',StandardScaler()),
                     ('pca4',PCA(n_components=2)),
                     ('nb_classifier',GaussianNB())])

pipeline_nb.fit(X_train, y_train)
score4 = pipeline_nb.score(X_test, y_test)
pred4 = pipeline_nb.predict(X_test)
acc4 = metrics.accuracy_score(y_test, pred4)
print('Classification report:')
print(metrics.classification_report(y_test, pred4))
print('Accuracy score: ', acc4)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/naive_bayes.py:206: DataConversionWarning: A column-ve
ctor y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for ex
ample using ravel().
  y = column_or_1d(y, warn=True)
Classification report:
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1272: UndefinedMetricWarnin
g: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
              precision    recall  f1-score   support

           1       0.00      0.00      0.00     59804
           2       0.50      1.00      0.67    179704
           3       0.00      0.00      0.00    120492

    accuracy                           0.50    360000
   macro avg       0.17      0.33      0.22    360000
weighted avg       0.25      0.50      0.33    360000

Accuracy score:  0.4991777777777778
```

We note that changing the model gives us very similar results. This is probably due to the fact that there were no evident correlations to learn between the features and the target varaible and hence changing the type of learning function or the shape of the line of fit would not necessarily improve the model.

Treating the multi-class classification problem as several binary classification problems

The next thing I tried was to split the multi-calss classification procedure into steps of binary classifications. Implying to train a model to learn to classify instances to 'Class A' and 'Not Class A' instead of 'Class A', 'Class B', and 'Class C'. Similarly for 'Class B'/'Class C' and 'not Class B/not Class C'.

Model 1 : [1, not 1]
Model 2 : [2, not 2]
Model 3 : [3, not 3]

Let us first try to build a model that can classify instances into 'Class 1' and 'not Class 1'

```
df_copy.loc[(df_copy['Class'] == 2) | (df_copy['Class'] == 3), 'Class' ] = 0
```

```
df_copy.head()
```

	A	B	C	D	E	F	G	H	I	J	K	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.160805	82.873279	127.350084	224.592926	-5
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.711852	-8.356041	23.792402	4.199023	2
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.299219	-6.612401	26.285392	5.911292	6
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.640135	82.560019	157.105143	212.989231	-3
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.300011	89.961688	130.299732	201.795100	-1

```
df_1 = df_copy
```

```
df_1['Class'].unique()
```

```
array([0, 1])
```

```
X1 = df_1.drop(['Class'], axis=1)
y1 = df_1['Class']
```

```
X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, stratify=y, test_size=0.2)

pipeline_rf1 = Pipeline([('scaler',StandardScaler()),
                     ('pca',PCA(n_components=2)),
                     ('rf_classifier',RandomForestClassifier(max_depth=5))])

pipeline_rf1.fit(X_train1, y_train1)
pipeline_rf1.score(X_test1, y_test1)
```

```
0.8333416666666666
```

We see a better perfromance in the model pipeline when we train it on a single target class by considering the other two classes as a single entity (In this case, 1 and not 1.

Let us now try and model for classes 2 and 3.

```
df_original.head()
```

	A	B	C	D	E	F	G	H	I	J	K	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.160805	82.873279	127.350084	224.592926	-5
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.711852	-8.356041	23.792402	4.199023	2
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.299219	-6.612401	26.285392	5.911292	6
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.640135	82.560019	157.105143	212.989231	-3
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.300011	89.961688	130.299732	201.795100	-1

```
df_2 = df_original.copy()
```

```
df_2.loc[(df_2['Class'] == 1) | (df_2['Class'] == 3), 'Class' ] = 0
```

```
df_2.head()
```

	A	B	C	D	E	F	G	H	I	J	K	
0	231.420023	-12.210984	217.624839	-15.611916	140.047185	76.904999	131.591871	198.160805	82.873279	127.350084	224.592926	-5
1	-38.019270	-14.195695	9.583547	22.293822	-25.578283	-18.373955	-0.094457	-33.711852	-8.356041	23.792402	4.199023	2
2	-39.197085	-20.418850	21.023083	19.790280	-25.902587	-19.189004	-2.953836	-25.299219	-6.612401	26.285392	5.911292	6
3	221.630408	-5.785352	216.725322	-9.900781	126.795177	85.122288	108.857593	197.640135	82.560019	157.105143	212.989231	-3
4	228.558412	-12.447710	204.637218	-13.277704	138.930529	91.101870	115.598954	209.300011	89.961688	130.299732	201.795100	-1

```
df_2['Class'].unique()
```

```
array([2, 0])
```

```
X2 = df_2.drop(['Class'], axis=1)
y2 = df_2['Class']
```

```
X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2, stratify=y, test_size=0.2)

pipeline_rf2 = Pipeline([('scaler',StandardScaler()),
                     ('pca',PCA(n_components=2)),
                     ('rf_classifier',RandomForestClassifier(max_depth=5))])

pipeline_rf2.fit(X_train2, y_train2)
pipeline_rf2.score(X_test2, y_test2)
```

```
0.499975
```

```
df_3 = df_original.copy()
df_3.loc[(df_3['Class'] == 1) | (df_3['Class'] == 2), 'Class' ] = 0
df_3['Class'].unique()
```

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

```
X3 = df_3.drop(['Class'], axis=1)
y3 = df_3['Class']
```

```
X_train3, X_test3, y_train3, y_test3 = train_test_split(X3, y3, stratify=y, test_size=0.2)

pipeline_rf3 = Pipeline([('scaler',StandardScaler()),
                     ('pca',PCA(n_components=2)),
                     ('rf_classifier',RandomForestClassifier(max_depth=5))])

pipeline_rf3.fit(X_train3, y_train3)
pipeline_rf3.score(X_test3, y_test3)
```

```
0.6660166666666667
```

As we can see, training binary classifiers on our data seems to improve the accuracy to a certain extent.

Model accuracies :

- 1 and not 1 : 83.33%
- 2 and not 2 : 49.99%
- 3 and not 3 : 66.6%

Let us now combine these pipelines into a single model pipeline that can hopefully fit the entire dataset. We use sklearn's VotingClassifier to combine multiple models.

```
from sklearn.ensemble import VotingClassifier

vclf = VotingClassifier(estimators = [('rf1', pipeline_rf1), ('rf2', pipeline_rf2), ('rf3', pipeline_rf
3)], voting='hard')
```

```
vclf.fit(X_train, y_train)
vclf.score(X_test, y_test)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/preprocessing/_label.py:235: 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().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.7/dist-packages/sklearn/preprocessing/_label.py:268: 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().
  y = column_or_1d(y, warn=True)
0.4991777777777778
```

```
pipeline_vclf = Pipeline([('scaler',StandardScaler()),
                     ('pca',PCA(n_components=2)),
                     ('vclf_classifier',VotingClassifier(estimators=[('rf1', pipeline_rf1), ('rf2', pip
eline_rf2), ('rf3', pipeline_rf3)], voting='hard'))])

pipeline_vclf.fit(X_train, y_train)
pipeline_vclf.score(X_test, y_test)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/preprocessing/_label.py:235: 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().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.7/dist-packages/sklearn/preprocessing/_label.py:268: 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().
  y = column_or_1d(y, warn=True)
0.4991777777777778
```

Now, my hypotesis was that considering the fact that most of the instances in our main dataset are classified into class 2, we could create two binary classification models : one that classifies instances for just targets 'class 2' and 'not class 2' and another model that classifies 'class 1' and 'class 3'. And then combining these two models to make predictions on our main dataset could help create a working model.

```
## Model to classify 1 and 3

df_13 = df_original.copy()
df_13.drop(df_13[df_13['Class'] == 2].index, inplace=True)
df_13['Class'].unique()
```

```
array([3, 1])
```

```
len(df_13)
```

```
600772
```

```
X13 = df_13.drop(['Class'], axis=1)
y13 = df_13['Class']
```

```
X_train13, X_test13, y_train13, y_test13 = train_test_split(X13, y13, test_size=0.2)
```

```
X_train13, X_test13, y_train13, y_test13 = train_test_split(X13, y13,test_size=0.2)

pipeline_rf13 = Pipeline([('scaler',StandardScaler()),
                     ('pca',PCA(n_components=2)),
                     ('rf_classifier',RandomForestClassifier(max_depth=5))])

pipeline_rf13.fit(X_train13, y_train13)
pipeline_rf13.score(X_test13, y_test13)
```

```
0.6686613124713912
```

Now, we combine this model with the one that was able to classify class 2 alone and model the train dataset.

```
pipeline_vclf = Pipeline([('scaler',StandardScaler()),
                     ('pca',PCA(n_components=2)),
                     ('vclf_classifier',VotingClassifier(estimators=[('rf13', pipeline_rf13), ('rf2', p
ipeline_rf2)], voting='hard'))])

pipeline_vclf.fit(X_train, y_train)
pipeline_vclf.score(X_test, y_test)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/preprocessing/_label.py:235: 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().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.7/dist-packages/sklearn/preprocessing/_label.py:268: 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().
  y = column_or_1d(y, warn=True)
0.4991777777777778
```

We notice the same accuracy as before.

Finally, I tried to combine the models that can classify [Class 2, Class 3], [Class 2, Class 1] and [Class 1 and Class3]

```
## Class 1 and Class 2

df_12 = df_original.copy()
df_12.drop(df_12[df_12['Class'] == 3].index, inplace=True)
df_12['Class'].unique()
```

```
array([2, 1])
```

```
X12 = df_12.drop(['Class'], axis=1)
y12 = df_12['Class']
```

```
X_train12, X_test12, y_train12, y_test12 = train_test_split(X12, y12, test_size=0.2)
```

```
X_train12, X_test12, y_train12, y_test12 = train_test_split(X12, y12,test_size=0.2)

pipeline_rf12 = Pipeline([('scaler',StandardScaler()),
                     ('pca',PCA(n_components=2)),
                     ('rf_classifier',RandomForestClassifier(max_depth=5))])

pipeline_rf12.fit(X_train12, y_train12)
pipeline_rf12.score(X_test12, y_test12)
```

```
0.7499499512024224
```

```
## Class 2 and 3

df_23 = df_original.copy()
df_23.drop(df_23[df_23['Class'] == 1].index, inplace=True)
df_23['Class'].unique()
```

```
array([2, 3])
```

```
X23 = df_23.drop(['Class'], axis=1)
y23 = df_23['Class']
```

```
X_train23, X_test23, y_train23, y_test23 = train_test_split(X23, y23, test_size=0.2)
```

```
X_train23, X_test23, y_train23, y_test23 = train_test_split(X23, y23,test_size=0.2)

pipeline_rf23 = Pipeline([('scaler',StandardScaler()),
                     ('pca',PCA(n_components=2)),
                     ('rf_classifier',RandomForestClassifier(max_depth=5))])

pipeline_rf23.fit(X_train23, y_train23)
pipeline_rf23.score(X_test23, y_test23)
```

```
0.5996990030099699
```

Now we combine the three models.

Final Model

```
pipeline_vclf123 = Pipeline([('scaler',StandardScaler()),
                     ('pca',PCA(n_components=2)),
                     ('vclf_classifier',VotingClassifier(estimators=[('rf13', pipeline_rf13), ('rf12',
pipeline_rf12), ('rf23', pipeline_rf23)], voting='hard'))])

pipeline_vclf.fit(X_train, y_train)
pipeline_vclf.score(X_test, y_test)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/preprocessing/_label.py:235: 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().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.7/dist-packages/sklearn/preprocessing/_label.py:268: 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().
  y = column_or_1d(y, warn=True)
0.4991777777777778
```

This is the final model that we will use to make predictions.

ONNX

```
from skl2onnx import  convert_sklearn
from skl2onnx.common.data_types import FloatTensorType

onnx_model_path = '/content/drive/MyDrive/Datasets/AkhilSrinath_final_model.onnx'

num_features = 15
initial_type = [('float_input', FloatTensorType([None, num_features]))]
onx = convert_sklearn(pipeline_vclf123, initial_types=initial_type)
with open(onnx_model_path, 'wb') as f:
  f.write(onx.SerializeToString())
```

```
---------------------------------------------------------------------------
RuntimeError                              Traceback (most recent call last)
/usr/local/lib/python3.7/dist-packages/skl2onnx/_parse.py in parse_sklearn(scope, model, inputs, cust
om_parsers, final_types)
    518             outputs = _parse_sklearn(
--> 519                 scope.temp(), model, inputs, custom_parsers=custom_parsers)
    520         except RuntimeError:

/usr/local/lib/python3.7/dist-packages/skl2onnx/_parse.py in _parse_sklearn(scope, model, inputs, cus
tom_parsers, final_types)
    486         outputs = sklearn_parsers_map[tmodel](scope, model, inputs,
--> 487                                               custom_parsers=custom_parsers)
    488     elif isinstance(model, pipeline.Pipeline):

/usr/local/lib/python3.7/dist-packages/skl2onnx/_parse.py in _parse_sklearn_pipeline(scope, model, in
puts, custom_parsers)
    195         inputs = _parse_sklearn(scope, step[1], inputs,
--> 196                                 custom_parsers=custom_parsers)
    197     return inputs

/usr/local/lib/python3.7/dist-packages/skl2onnx/_parse.py in _parse_sklearn(scope, model, inputs, cus
tom_parsers, final_types)
    486         outputs = sklearn_parsers_map[tmodel](scope, model, inputs,
--> 487                                               custom_parsers=custom_parsers)
    488     elif isinstance(model, pipeline.Pipeline):

/usr/local/lib/python3.7/dist-packages/skl2onnx/_parse.py in _parse_sklearn_classifier(scope, model,
 inputs, custom_parsers)
    350         this_operator = scope.declare_local_operator('SklearnZipMap')
--> 351         classes = get_label_classes(scope, model)
    352 

/usr/local/lib/python3.7/dist-packages/skl2onnx/common/utils_classifier.py in get_label_classes(scop
e, op, node_names)
     44             "No known ways to retrieve the number of classes for class %r."
---> 45             "" % type(op))
     46     return classes

RuntimeError: No known ways to retrieve the number of classes for class <class 'sklearn.ensemble._vot
ing.VotingClassifier'>.

During handling of the above exception, another exception occurred:

RuntimeError                              Traceback (most recent call last)
<ipython-input-137-5b4706d96fca> in <module>()
      6 num_features = 15
      7 initial_type = [('float_input', FloatTensorType([None, num_features]))]
----> 8 onx = convert_sklearn(pipeline_vclf123, initial_types=initial_type)
      9 with open(onnx_model_path, 'wb') as f:
     10   f.write(onx.SerializeToString())

/usr/local/lib/python3.7/dist-packages/skl2onnx/convert.py in convert_sklearn(model, name, initial_ty
pes, doc_string, target_opset, custom_conversion_functions, custom_shape_calculators, custom_parsers,
 options, intermediate, white_op, black_op, final_types, dtype)
    151         custom_shape_calculators, custom_parsers, options=options,
    152         white_op=white_op, black_op=black_op,
--> 153         final_types=final_types)
    154 
    155     # Infer variable shapes

/usr/local/lib/python3.7/dist-packages/skl2onnx/_parse.py in parse_sklearn_model(model, initial_type
s, target_opset, custom_conversion_functions, custom_shape_calculators, custom_parsers, options, whit
e_op, black_op, final_types)
    623     outputs = parse_sklearn(scope, model, inputs,
    624                             custom_parsers=custom_parsers,
--> 625                             final_types=final_types)
    626 
    627     # The object raw_model_container is a part of the topology we're

/usr/local/lib/python3.7/dist-packages/skl2onnx/_parse.py in parse_sklearn(scope, model, inputs, cust
om_parsers, final_types)
    520         except RuntimeError:
    521             return _parse_sklearn(
--> 522                 scope, model, inputs, custom_parsers=custom_parsers)
    523 
    524         reserved = []

/usr/local/lib/python3.7/dist-packages/skl2onnx/_parse.py in _parse_sklearn(scope, model, inputs, cus
tom_parsers, final_types)
    485     elif tmodel in sklearn_parsers_map:
    486         outputs = sklearn_parsers_map[tmodel](scope, model, inputs,
--> 487                                               custom_parsers=custom_parsers)
    488     elif isinstance(model, pipeline.Pipeline):
    489         parser = sklearn_parsers_map[pipeline.Pipeline]

/usr/local/lib/python3.7/dist-packages/skl2onnx/_parse.py in _parse_sklearn_pipeline(scope, model, in
puts, custom_parsers)
    194     for step in model.steps:
    195         inputs = _parse_sklearn(scope, step[1], inputs,
--> 196                                 custom_parsers=custom_parsers)
    197     return inputs
    198 

/usr/local/lib/python3.7/dist-packages/skl2onnx/_parse.py in _parse_sklearn(scope, model, inputs, cus
tom_parsers, final_types)
    485     elif tmodel in sklearn_parsers_map:
    486         outputs = sklearn_parsers_map[tmodel](scope, model, inputs,
--> 487                                               custom_parsers=custom_parsers)
    488     elif isinstance(model, pipeline.Pipeline):
    489         parser = sklearn_parsers_map[pipeline.Pipeline]

/usr/local/lib/python3.7/dist-packages/skl2onnx/_parse.py in _parse_sklearn_classifier(scope, model,
 inputs, custom_parsers)
    349     else:
    350         this_operator = scope.declare_local_operator('SklearnZipMap')
--> 351         classes = get_label_classes(scope, model)
    352 
    353     this_operator.inputs = probability_tensor

/usr/local/lib/python3.7/dist-packages/skl2onnx/common/utils_classifier.py in get_label_classes(scop
e, op, node_names)
     43         raise RuntimeError(
     44             "No known ways to retrieve the number of classes for class %r."
---> 45             "" % type(op))
     46     return classes
     47 

RuntimeError: No known ways to retrieve the number of classes for class <class 'sklearn.ensemble._vot
ing.VotingClassifier'>.
```

We observe that ONNX is having troubles converting the VotingClassifier model from sklearn. Hence, we use the RandomForestClassifier that we built initially to create the onnx file that can make predictions on our out-of-sample data.

Creating .onnx file

```
from skl2onnx import  convert_sklearn
from skl2onnx.common.data_types import FloatTensorType

onnx_model_path = '/content/drive/MyDrive/Datasets/AkhilSrinath_final_model.onnx'

num_features = 15
initial_type = [('float_input', FloatTensorType([None, num_features]))]
onx = convert_sklearn(pipeline_rf, initial_types=initial_type)
with open(onnx_model_path, 'wb') as f:
  f.write(onx.SerializeToString())
```

Compute predictions with ONNX runtime

```
import onnxruntime as rt
import numpy

sess = rt.InferenceSession(onnx_model_path)
input_name = sess.get_inputs()[0].name
label_name = sess.get_outputs()[0].name

pred_onx = sess.run(None, {input_name: X_test.values.astype(np.float32)})[0]
print(pred_onx)
```

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

As we can see, the .onnx file is able to make predictions on out-of-sample data.

Conclusion

In this project, we attempted various procedures to study the data and find patterns that would help in identifying ways to model the data and classify instances. The best method that we were able to find was to try and convert the multi-class classification problem into a set of binary classification problems. We found that when the model was trained on each independent target class while treating the other two class types as a single entity, the model showed better accuracy. For example, when the model was trained on classifying target class 1 while combining the other two class labels as "not 1", we were able to achieve and accuracy of 83%. However, this model can only learn how to classify class label 1. Similarly, we built binary classification models that were able to classify other combinations of class labels. So, we can conclude that a positive result from the project is that we were able to develop pretty accurate binary classification models that can predict class labels of one type seperately as either 'Class 1' or 'not Class 1' and 'Class 2' or 'not Class 2' and 'Class 3' or 'not Class 3'. However, the major caveat is that when we attempt to combine the binary classification models, the model accuracy drops down to 49%. This allows scope to research on how to effectively combine the binary models into a single model that has learned from its constituent models and can eventually make decent predictions on out-of-sample data.

Data Sources

- Scikit-Learn Pipelines : https://medium.com/vickdata/a-simple-guide-to-scikit-learn-pipelines-4ac0d974bdcf
- Outlier detection and treatment : https://towardsdatascience.com/ways-to-detect-and-remove-the-outliers-404d16608dba
- PCA : https://builtin.com/data-science/step-step-explanation-principal-component-analysis
- Notebook by Victoria Belotti (Blackboard)
- Combining models using VotingClassifier : https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.VotingClassifier.html#sklearn.ensemble.VotingClassifier

Source Code

- https://pandas.pydata.org/
- http://scikit-learn.org/stable/modules/generated/sklearn.pipeline.Pipeline.html
- https://scikit-learn.org/
- http://scikit-learn.org/stable/modules/ensemble.html
- https://stackoverflow.com/questions/21506128/best-way-to-combine-probabilistic-classifiers-in-scikit-learn

Bibliography

- *Anupama Jha, Meenu Dave, Supriya Madan*. "Comparison of Binary Class and Multi-Class Classifier Using Different Data Mining Classification Techniques", 2019, Proceedings of International Conference on Advancements in Computing & Management (ICACM) 2019 (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3464211)
- *Salma Begum, Ramazan Aygun*. "Greedy hierarchical binary classifiers for multi-class classification of biological data", 2014, Network Modeling Analysis in Health Informatics and Bioinformatics. (https://www.researchgate.net/publication/271913431_Greedy_hierarchical_binary_classifiers_for_multi-class_classification_of_biological_data)
- *Ana Carolina Lorena, Andréde Carvalho, João M. P. Gama*. "A review on the combination of binary classifiers in multiclass problems", Artificial Intelligence Review, 2009. (https://link.springer.com/article/10.1007/