Machine Learning Assignment : Problem 1: Election Data

JANUARY 23

Machine Learning Assignment
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Problem 1 : Election Data

You are hired by one of the leading news channels CNBE who wants to analyze recent elections. This survey was conducted on 1525 voters with 9 variables. You have to build a model, to predict which party a voter will vote for on the basis of the given information, to create an exit poll that will help in predicting overall win and seats covered by a particular party.

Data Dictionary:

Sr No	Feature	Meaning
1	Vote	Party choice: Conservative or Labour
2	age	in years
3	economic.cond.national	Assessment of current national economic conditions, 1 to 5.
4	economic.cond.household:	Assessment of current household economic conditions, 1 to 5.
5	Blair	Assessment of the Labour leader, 1 to 5.
6	Hague	Assessment of the Conservative leader, 1 to 5.
7	Europe	an 11-point scale that measures respondents' attitudes toward European integration. High scores represent 'Eurosceptic' sentiment.
8	Political knowledge	Knowledge of parties' positions on European integration, 0 to 3.
9	gender	female or male.

Question List:

- **Data Ingestion:** 11 marks

  1.1 Read the dataset. Do the descriptive statistics and do the null value condition check. Write an inference on it. (4 Marks)

  1.2 Perform Univariate and Bivariate Analysis. Do exploratory data analysis. Check for Outliers. (7 Marks)

- **Data Preparation**: 4 marks

  1.3 Encode the data (having string values) for Modelling. Is Scaling necessary here or not? Data Split: Split the data into train and test (70:30). (4 Marks)

- **Modeling**: 22 marks

  1.4 Apply Logistic Regression and LDA (linear discriminant analysis). (4 marks)

  1.5 Apply KNN Model and Naïve Bayes Model. Interpret the results. (4 marks)

  1.6 Model Tuning, Bagging (Random Forest should be applied for Bagging), and Boosting. (7 marks)

  1.7 Performance Metrics: Check the performance of Predictions on Train and Test sets using Accuracy, Confusion Matrix, Plot ROC curve and get ROC_AUC score for each model. Final Model: Compare the models and write inference which model is best/optimized. (7 marks)

- **Inference**: 5 marks

  1.8 Based on these predictions, what are the insights? (5 marks)

Data Ingestion:

1.1 Read the dataset. Do the descriptive statistics and do the null value condition check. Write an inference on it. (4 Marks)

First of all we will import all the necessary libraries like Pandas, Numpy, seaborn, os to set the path,

After setting the path we will import “Election_Data.xlsx” and sheet named as 'Election_Dataset_Two Classes'.

After importing we will read the dataset. By using head and tail command we will see the First 5 rows and last 5 rows of the dataset, we will get basic idea how data actually is.

First 5 rows,

	Unnamed: 0	vote	age	economic.cond.national	economic.cond.household	Blair	Hague	Europe	political.knowledge	gender
0	1	Labour	43	3	3	4	1	2	2	female
1	2	Labour	36	4	4	4	4	5	2	male
2	3	Labour	35	4	4	5	2	3	2	male
3	4	Labour	24	4	2	2	1	4	0	female
4	5	Labour	41	2	2	1	1	6	2	male

Last 5 rows,

	Unnamed: 0	vote	age	economic.cond.national	economic.cond.household	Blair	Hague	Europe	political.knowledge	gender
1520	1521	Conservative	67	5	3	2	4	11	3	male
1521	1522	Conservative	73	2	2	4	4	8	2	male
1522	1523	Labour	37	3	3	5	4	2	2	male
1523	1524	Conservative	61	3	3	1	4	11	2	male
1524	1525	Conservative	74	2	3	2	4	11	0	female

We can see there are 10 columns but the first column we will not consider as this is redundant or of no use, we will remove it further.

Total 9 columns we can see. All seems valid and having significance.

Here All 8 features are Independent variable whereas 9th Feature vote is dependent variable.it is basically Target variable model wants to predict. All features except vote and gender are Numerical. Vote and gender are Nominal Categorical.

Decsription of Data

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
Unnamed: 0	1525	NaN	NaN	NaN	763	440.374	1	382	763	1144	1525
vote	1525	2	Labour	1063	NaN	NaN	NaN	NaN	NaN	NaN	NaN
age	1525	NaN	NaN	NaN	54.1823	15.7112	24	41	53	67	93
economic.cond.national	1525	NaN	NaN	NaN	3.2459	0.880969	1	3	3	4	5
economic.cond.household	1525	NaN	NaN	NaN	3.14033	0.929951	1	3	3	4	5
Blair	1525	NaN	NaN	NaN	3.33443	1.17482	1	2	4	4	5
Hague	1525	NaN	NaN	NaN	2.74689	1.2307	1	2	2	4	5
Europe	1525	NaN	NaN	NaN	6.72852	3.29754	1	4	6	10	11
political.knowledge	1525	NaN	NaN	NaN	1.5423	1.08331	0	0	2	2	3
gender	1525	2	female	812	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In above description we can see mean values and 50% are almost same, mean and median are almost Coherent.

Gender and vote seems to be Categorical Nominal variables, where order is not important aspect

All other variables are Categorical Ordinal Variables, Ratings

All features seems to be somewhat equally distributed around mean.

Information of Data:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1525 entries, 0 to 1524
Data columns (total 10 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Unnamed: 0              1525 non-null   int64
 1   vote                    1525 non-null   object
 2   age                     1525 non-null   int64
 3   economic.cond.national  1525 non-null   int64
 4   economic.cond.household 1525 non-null   int64
 5   Blair                   1525 non-null   int64
 6   Hague                   1525 non-null   int64
 7   Europe                  1525 non-null   int64
 8   political.knowledge     1525 non-null   int64
 9   gender                  1525 non-null   object
dtypes: int64(8), object(2)
memory usage: 119.3+ KB
```

We can see gender and vote are of Object Datatype, we will try to convert it into integer Data type further.

Total 1525 datapoints are there, 1525 different people, No null value can be detected here.

Null value check:

```
Unnamed: 0                0
vote                      0
age                       0
economic.cond.national    0
economic.cond.household   0
Blair                     0
Hague                     0
Europe                    0
political.knowledge       0
gender                    0
dtype: int64
```

No Null values can be seen in dataset.

Lets drop the column Unnamed: 0, which has no significance here.

Check for Duplicates in dataset:

Number of duplicate rows = 8

We will check manually whether these are exact duplicates or partial duplicates.

	vote	age	economic.cond.national	economic.cond.household	Blair	Hague	Europe	political.knowledge	gender
67	Labour	35	4	4	5	2	3	2	male
626	Labour	39	3	4	4	2	5	2	male
870	Labour	38	2	4	2	2	4	3	male
983	Conservative	74	4	3	2	4	8	2	female
1154	Conservative	53	3	4	2	2	6	0	female
1236	Labour	36	3	3	2	2	6	2	female
1244	Labour	29	4	4	4	2	2	2	female
1438	Labour	40	4	3	4	2	2	2	male

These are the 8 rows which are duplicates. Actually this is not even 1% data we can remove it, but if we can see the age is different for each entry hence this can be data of different personalities. We will keep as it is.

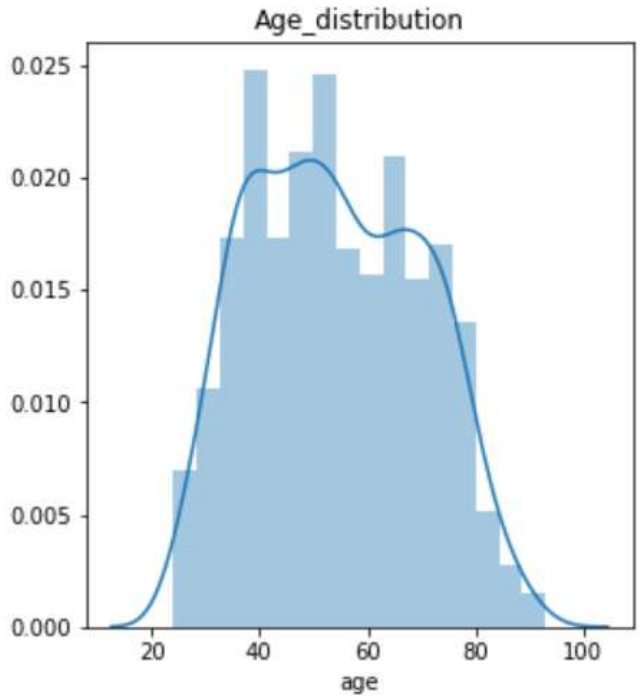
Shape of data:

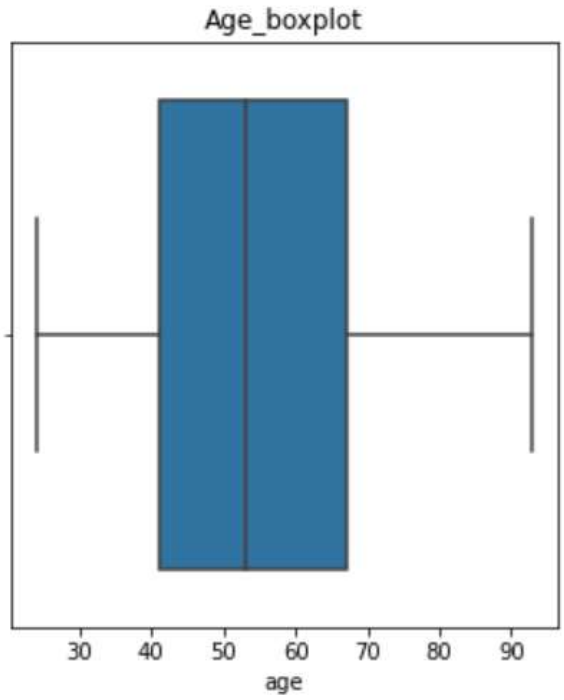
Shape of the dataset is 1525 rows and 9 Columns.

1.2 Perform Univariate and Bivariate Analysis. Do exploratory data analysis. Check for Outliers.

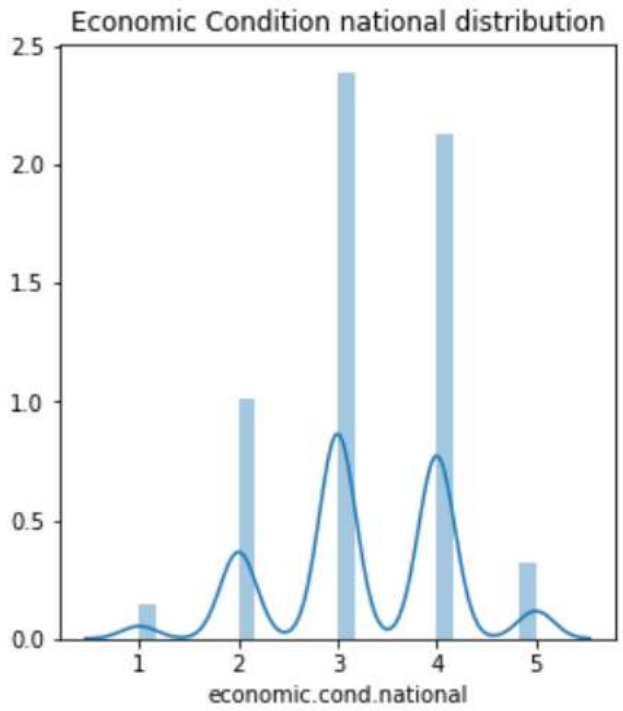
Univariate Analysis:

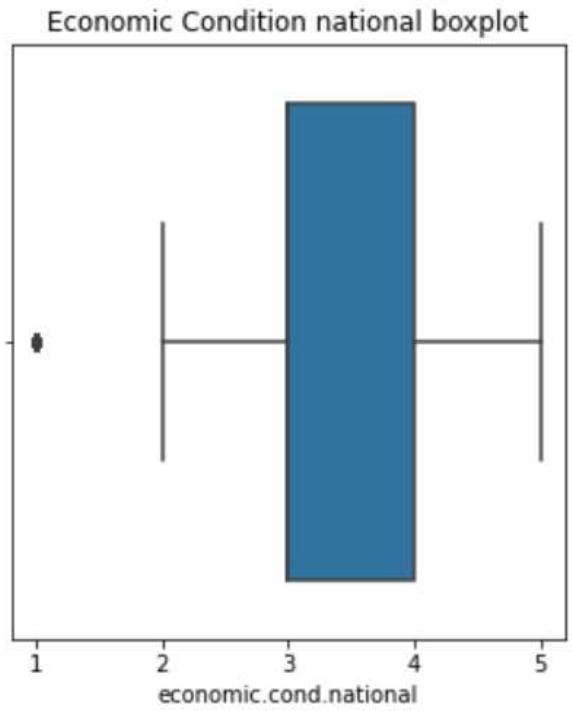
Lets do the univariate analysis, we will check it for each feature separately to get its distribution or any hidden insights.



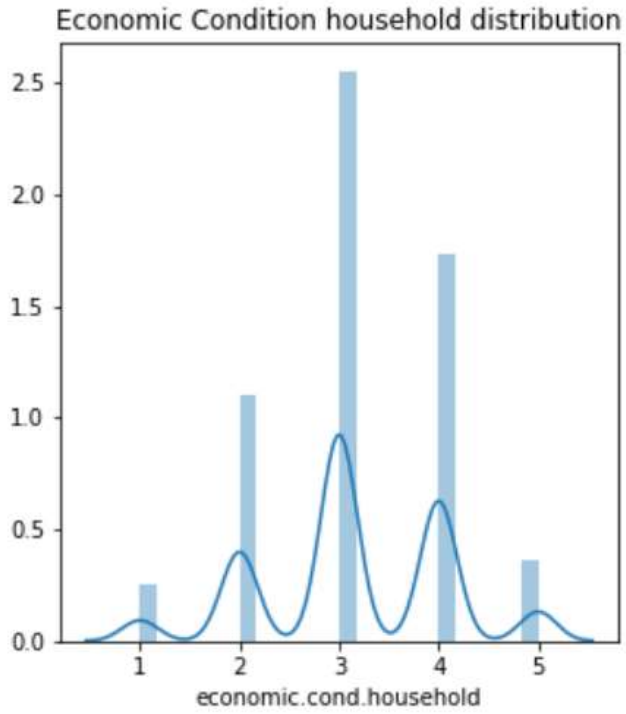


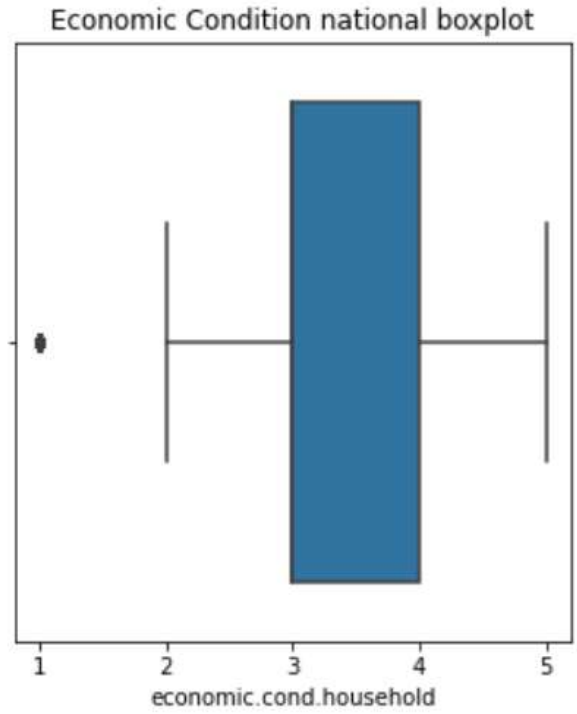
It seems that Age is normally distibuted and not much skewed, all age groups are covered, it has no outliers as well.



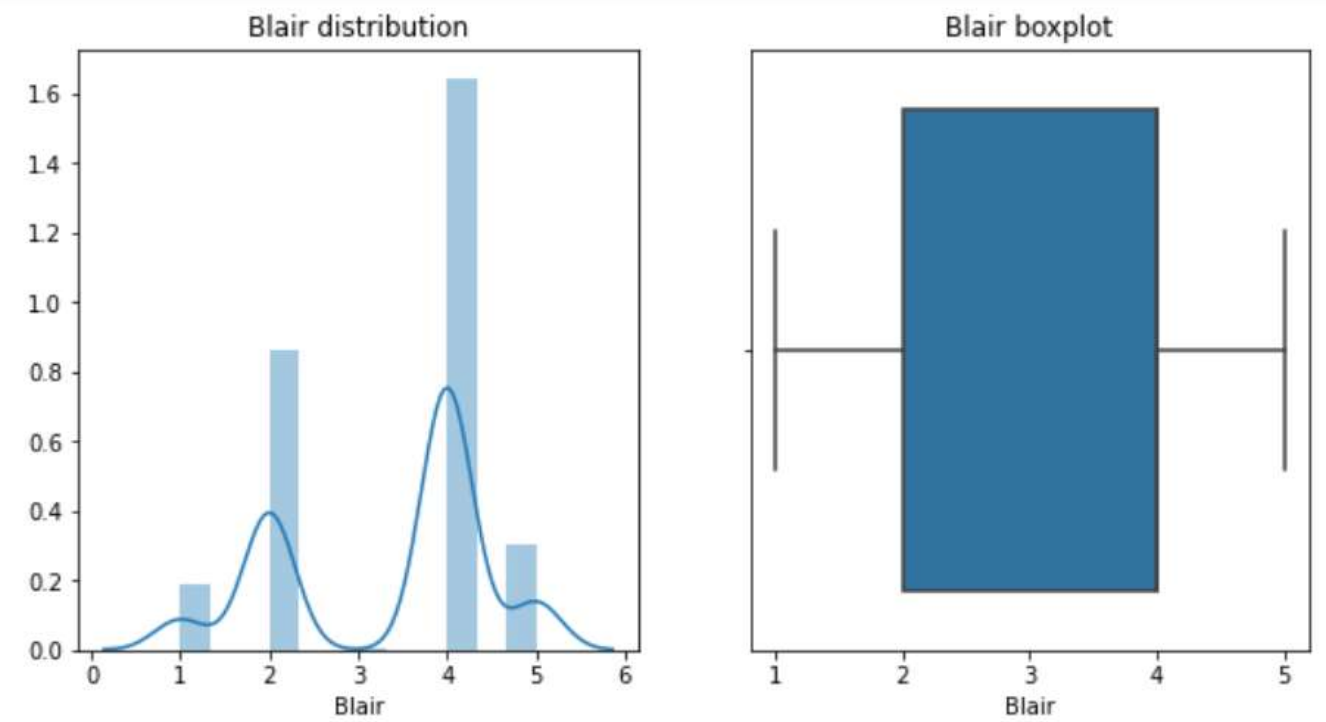


In above plot we can see spikes at almost every rating, but even this is showing most people has given 3 ratings.very less people have given 1 and 5 rating, from this we can say that this particular nation neither have great economical condition nor poor condition.

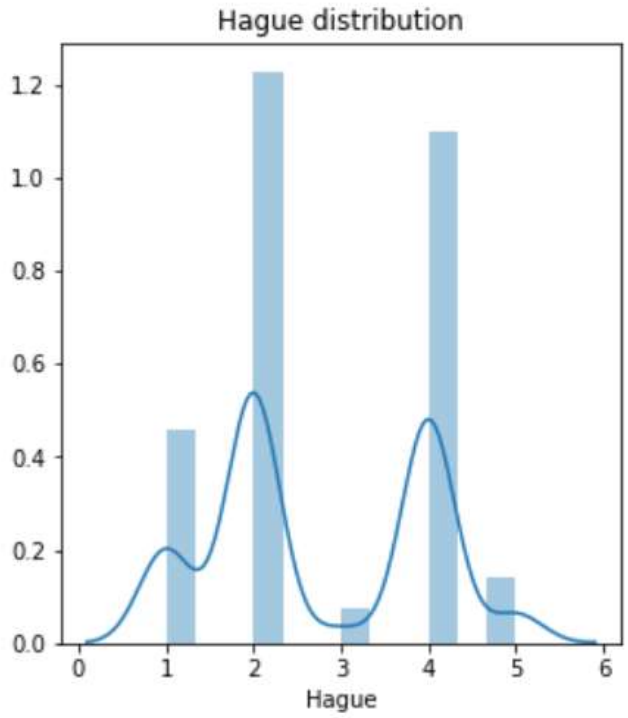


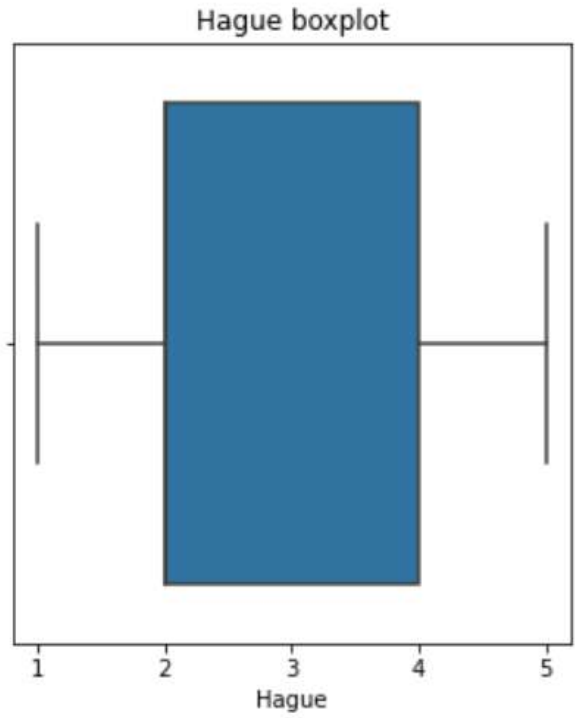


In above plot we can see spikes at almost every rating, but even this is showing most people has given 3 ratings.very less people have given 1 and 5 rating, from this we can say that this particular nation's people neither have great economical condition nor poor condition.

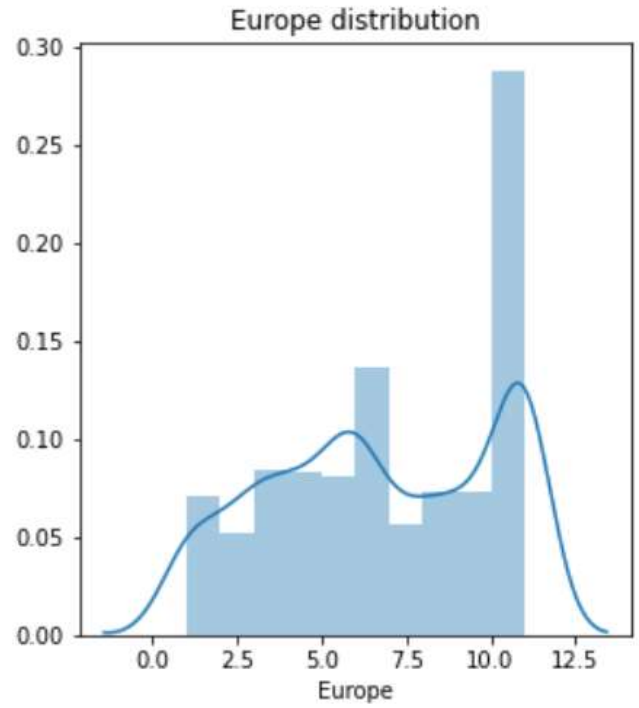


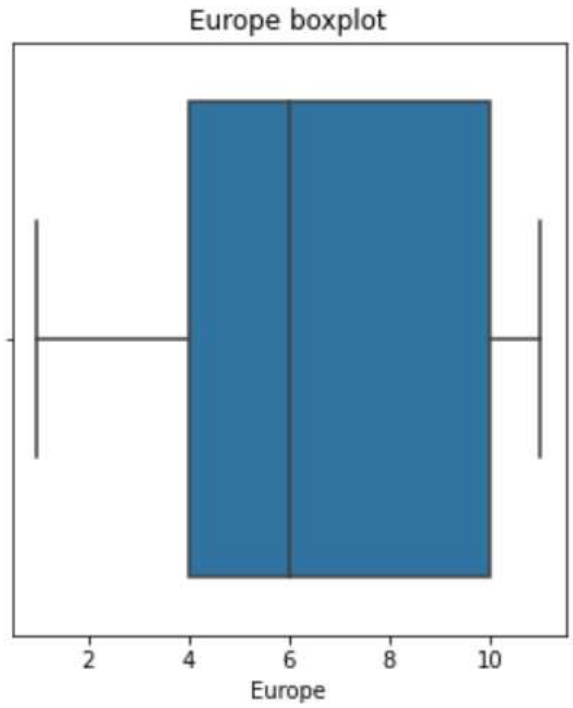
Labour leader Blair has received 2 and 4 score mostly.4 is the highest frequency.



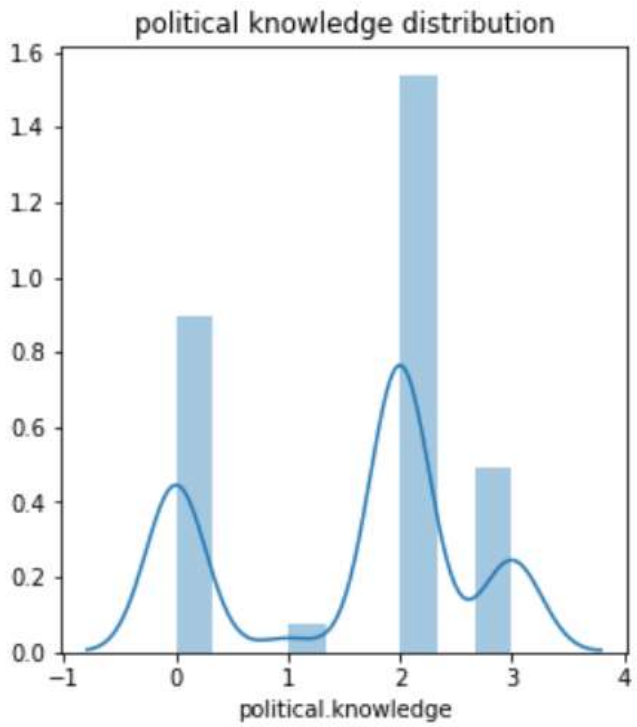


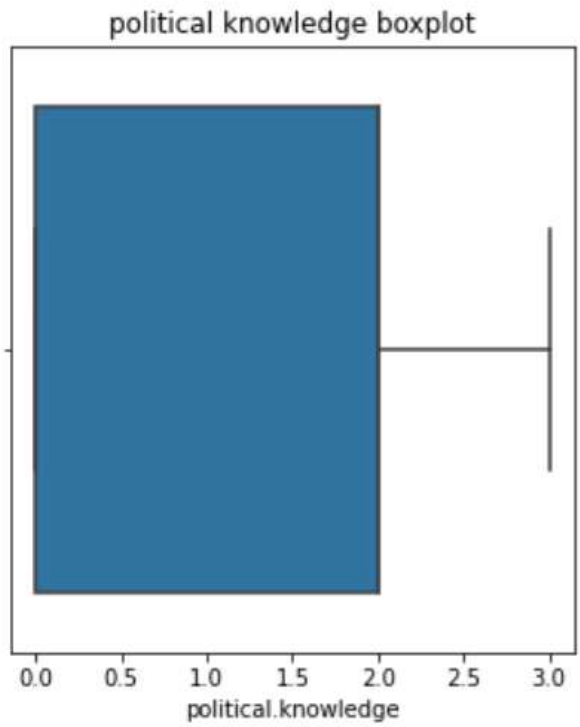
Conservative Party leader Hague has received 2 and 4 score mostly.2 is the highest frequency.





from the Europe plot, the 50% people has rated 4-10 it means they have Eurosceptic sentiment in increasing order.
10 score seems to be have Highest Frequency here, it says that most of the people are against Europe Integration.
Almost 25% people has given rating 10 and 11, they posses Eurosceptic sentiment.
1-4 is the rating given by 25% people, they seems to be with European Integration.





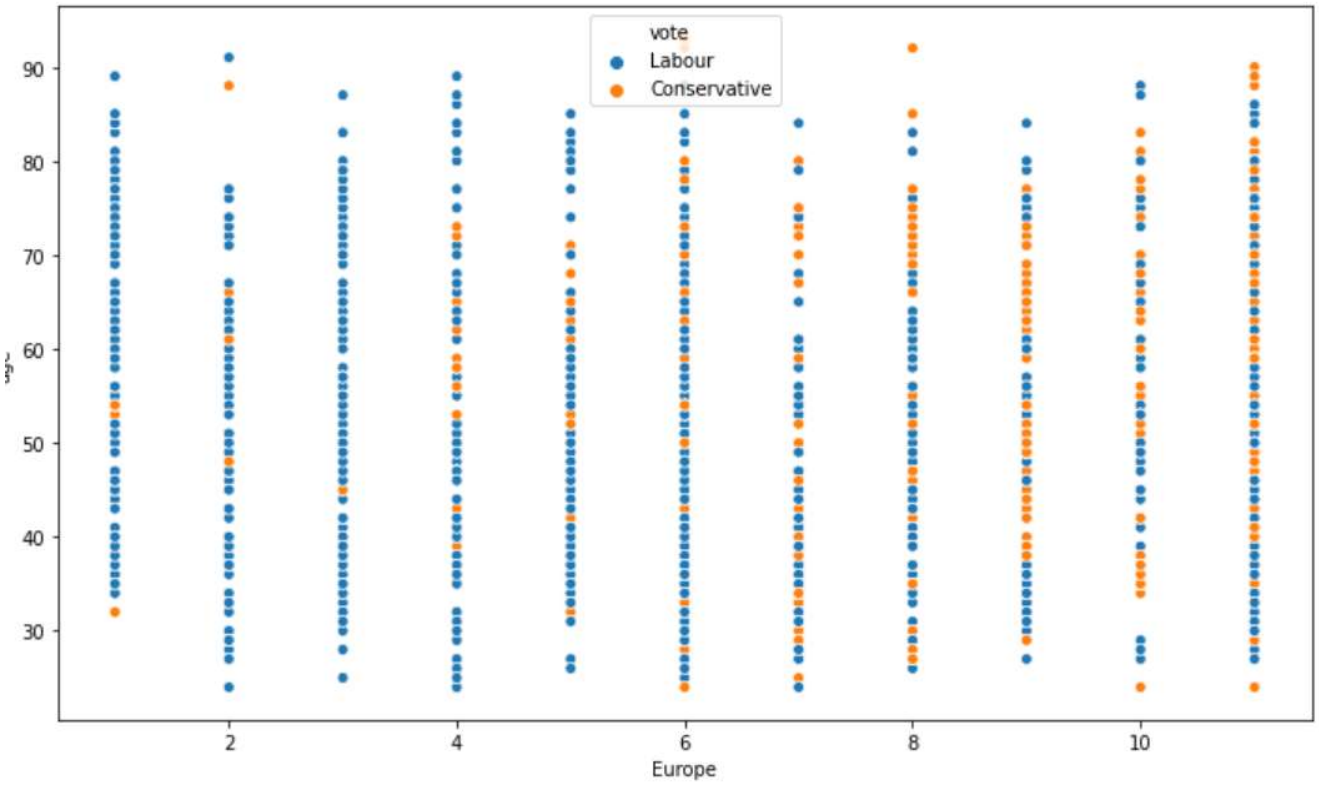
Only around 25% People have average to High political knowledge, 75% people have less Political Knowledge 0,1,2.

Outliers :

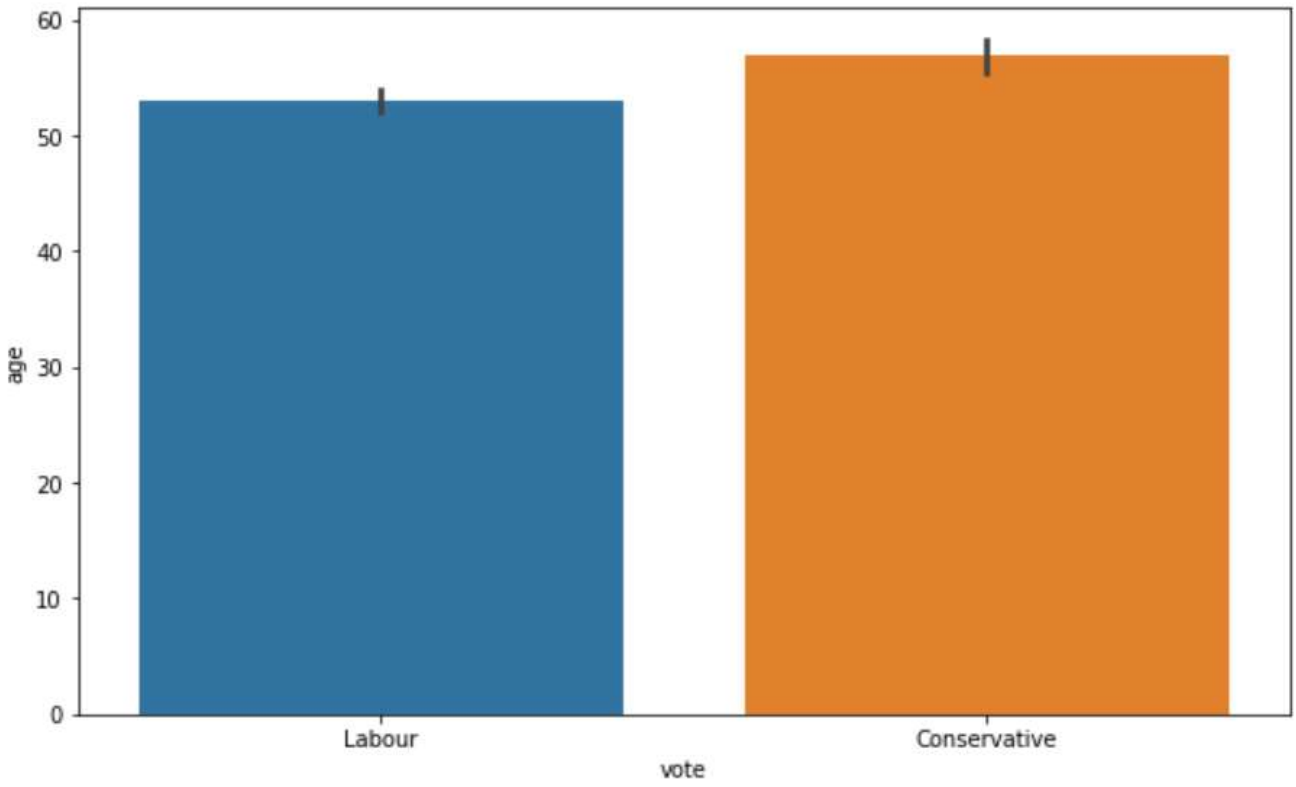
Economic Household conditions and National Household conditions, Rating 1 is outlier as very less number of people has given it. But we will not treat this value as these are valid outliers, we will keep it.

Bivariate Analysis

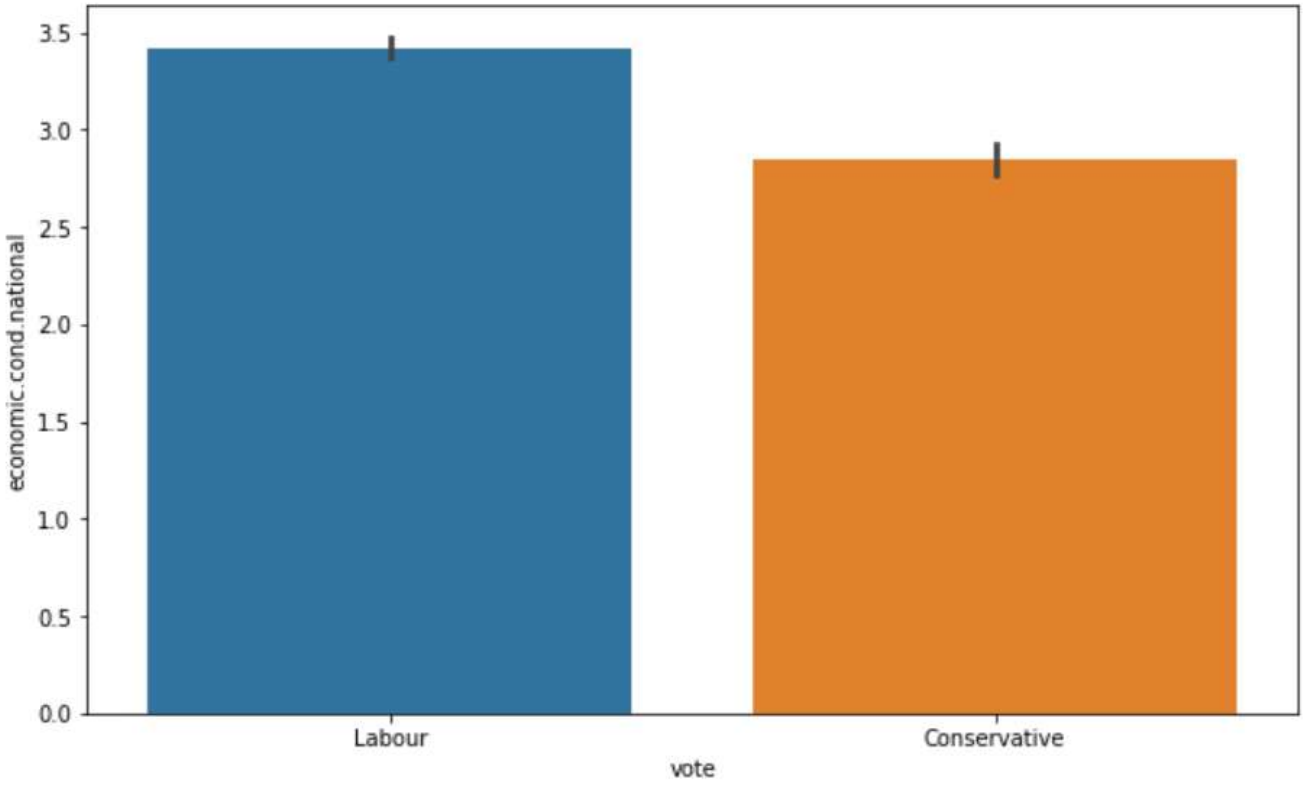
Scatterplot of Europe vs Age



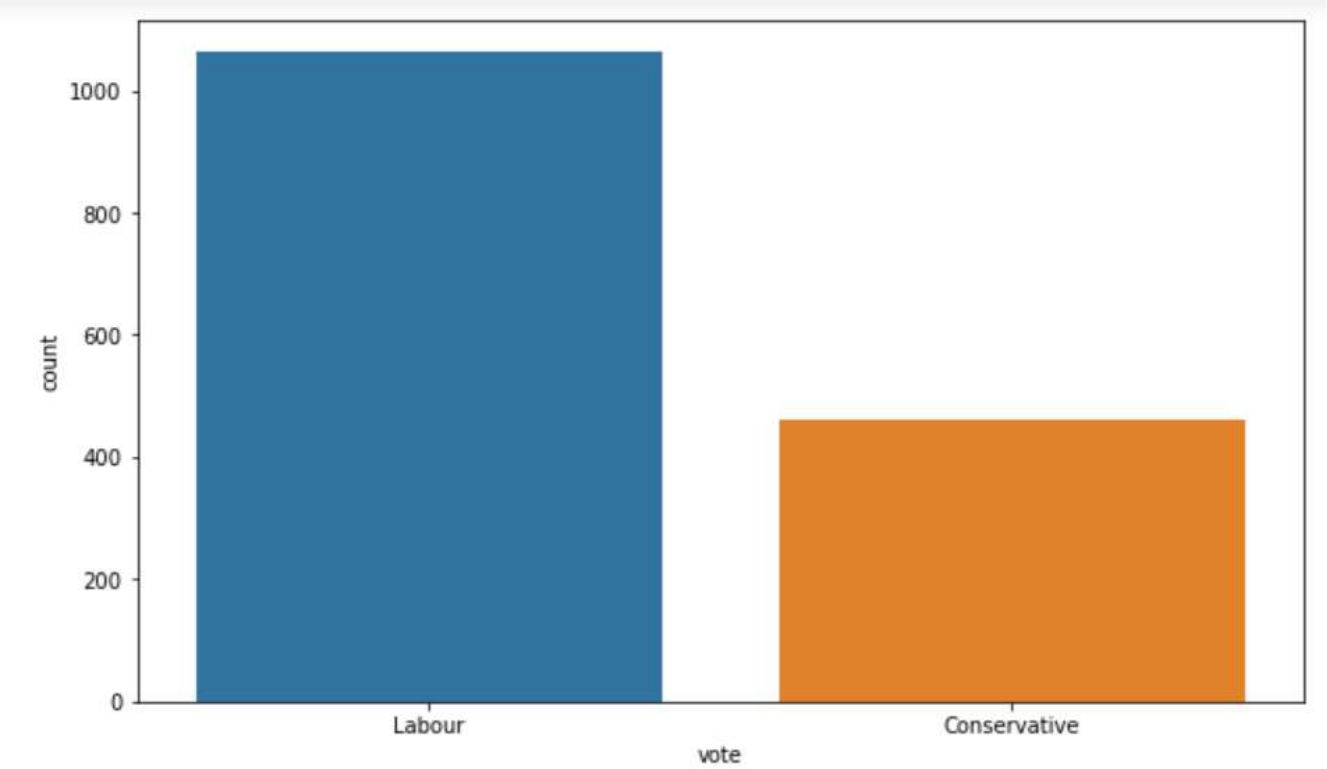
Higher Europe (Eurosceptic) score, it has converted into vote to the Conservative Party. All age group people are voting to both the parties, so it is no more age specific, But Euro Skepticism is playing important role here



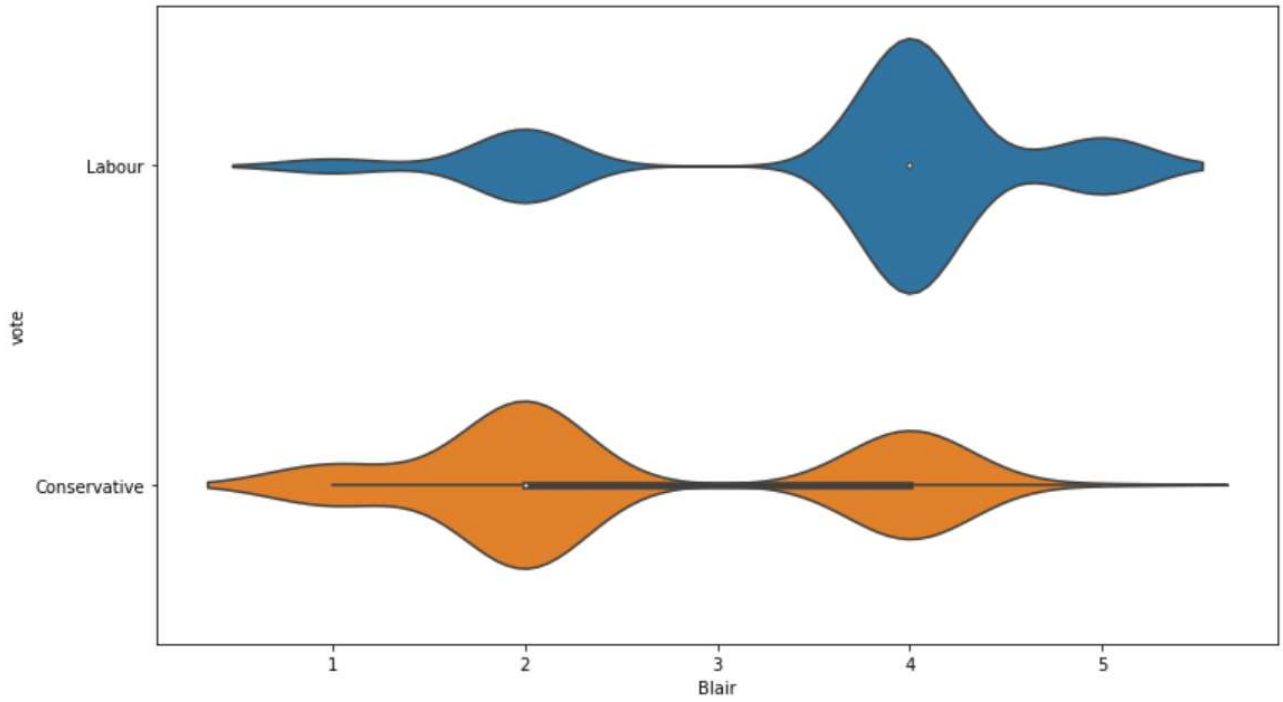
Almost all age groups are voting to Labour and Conservative Party.



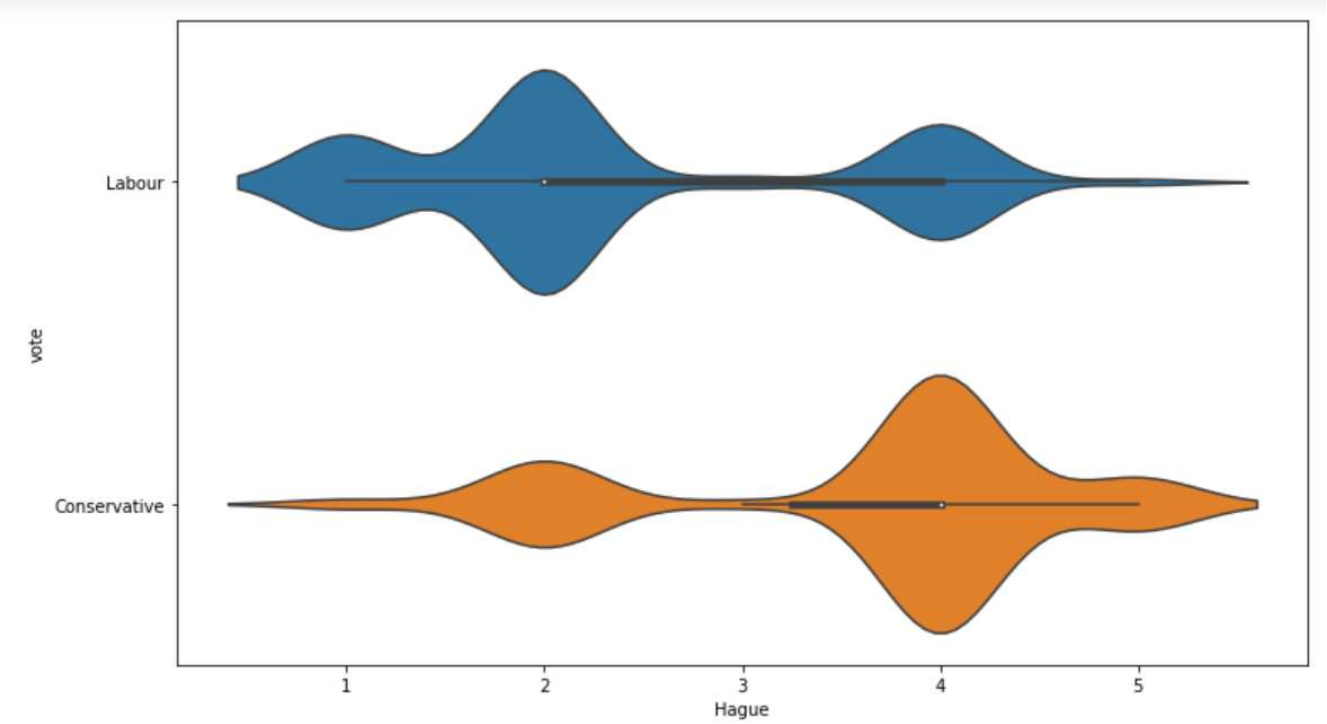
People who are giving good assessment score on National Economic condition are tend to give vote to Labour party, while lesser score turn into vote to Conservative party, this is not the case always happens.



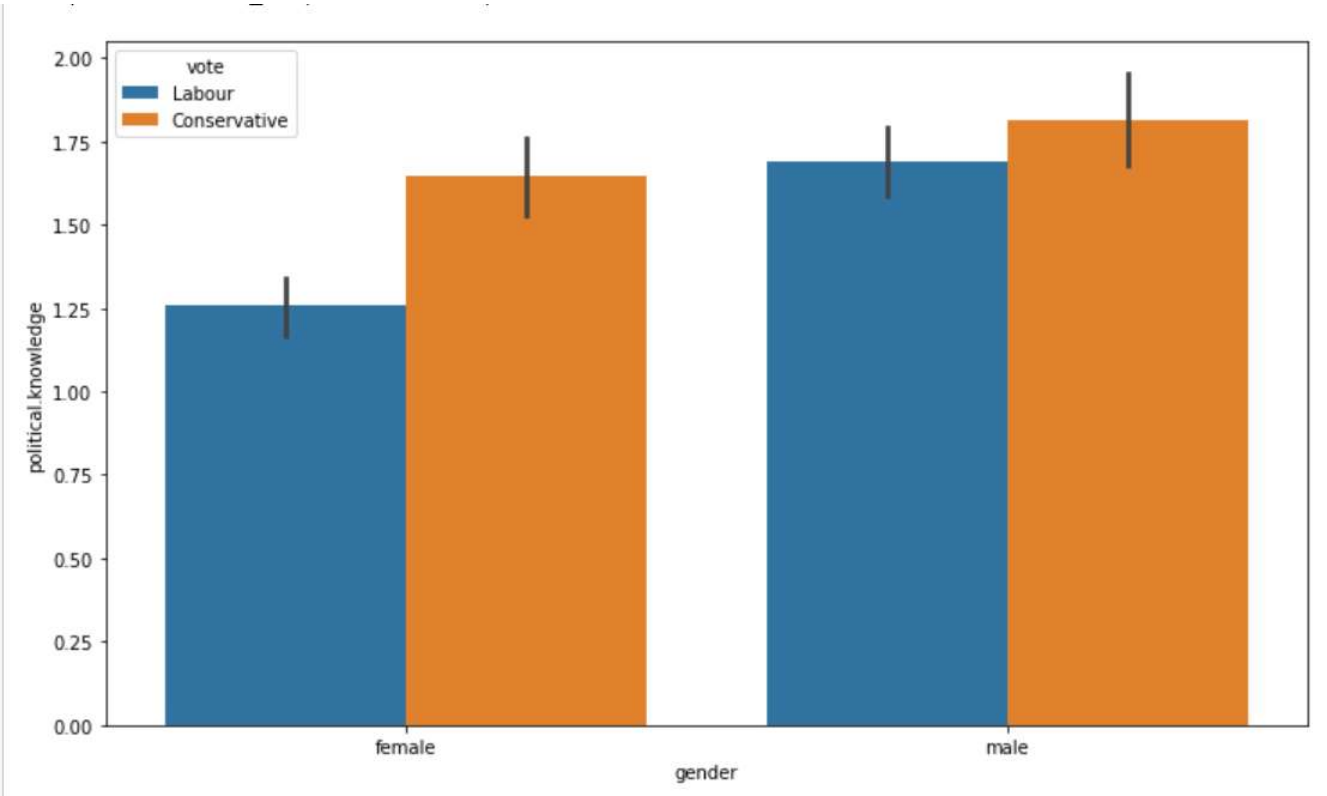
This data has more than 1000 readings who are voting to Labour party while less than 500 who are voting to conservative party it is unbalanced data, might affect to prediction of model.



If person's rating is high to Blair as a party leader, vote will be mostly go into Labour Party's basket. while low Blair score convert the vote into Conservative Party Favor.

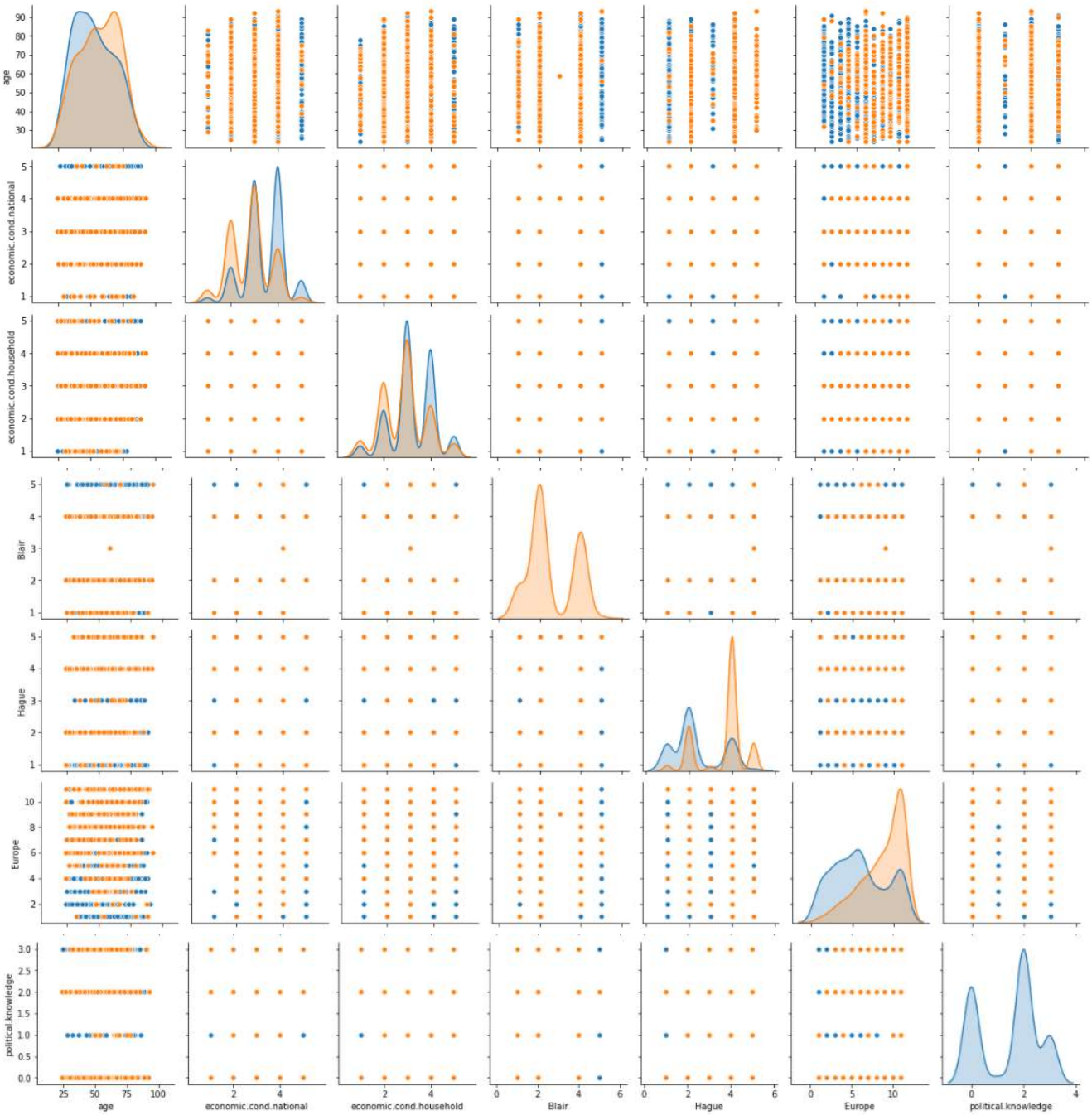


If person's rating is high to Hague as a party leader, vote will be mostly go into Conservative Party's basket. while low Hague score convert the vote into Labour party Favor.

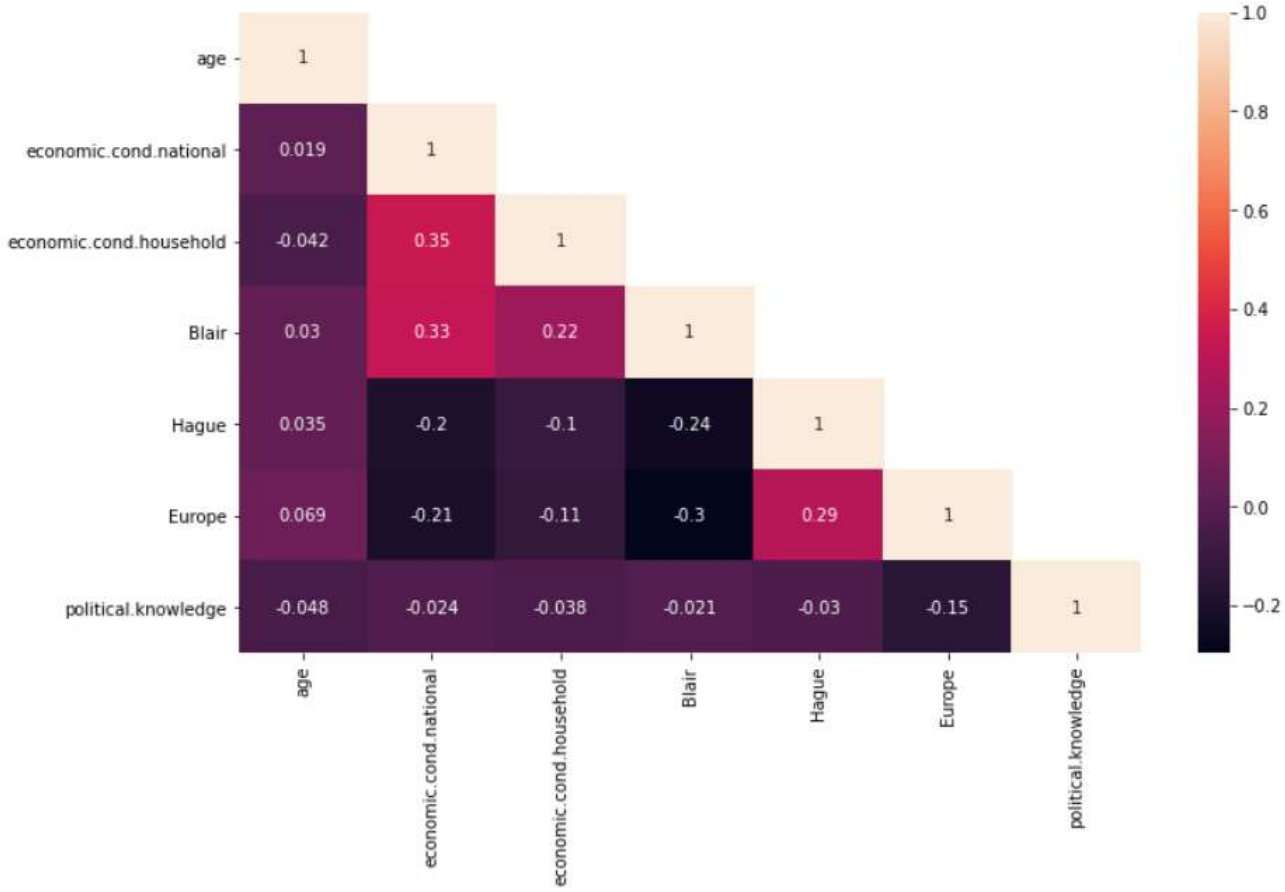


political Knowledge of Males seems to be higher than average knowledge of females. In both cases Higher political Knowledge people are voting to Conservative Party.

Pairplot :



Heatmap for Correlation:



Blair and Economic Household Condition Rating, Economic national Condition rating shows good correlation.
Europe and Blair are inversely related, means if Person is more Eurosceptic there will be less chances he will vote to Blair as a party leader of Labour party
If person is giving good assessment score to Hague he must be with Conservative party and he or she is Highly Eurosceptic.
It is not always true, but people having good political Knowledge are preferring Europe Integration.

Data Preparation:

1.3 Encode the data (having string values) for Modelling. Is Scaling necessary here or not? Data Split: Split the data into train and test (70:30).

We have to encode the features vote and Gender, to feed the data to model.

Here vote and gender are Nominal Categorical variables, we can use one hot encoding to feed data to model.

```
df_data=pd.get_dummies(data=df, drop_first=True)
```

We will use get dummies function to convert data into 0's and 1's.

vote_labour=1 ; Vote has been given to Labour Party.

vote_labour=0 ; Vote has been given to Conservative Party.

gender_male=0; Female

gender_male=1; male

After Scaling, the first 5 rows,

age	economic.cond.national	economic.cond.household	Blair	Hague	Europe	political.knowledge	vote_Labour	gender_male
43	3	3	4	1	2	2	1	0
36	4	4	4	4	5	2	1	1
35	4	4	5	2	3	2	1	1
24	4	2	2	1	4	0	1	0
41	2	2	1	1	6	2	1	1

All features are having different ranges and different scales like somewhere it is 1-11, 0-4 etc.

We will do scaling for KNN only.

Algorithm	Problem Type	Features might need scaling?
KNN	Either	Yes
Linear regression	Regression	No (unless regularized)
Logistic regression	Classification	No (unless regularized)
Naive Bayes	Classification	No
Decision trees	Either	No
Random Forests	Either	No
AdaBoost	Either	No
Neural networks	Either	Yes

Data Split

Split the data into train and test (70:30).

We will calculate vif to see if there any issue of Multicollinearity or not.

```
age VIF =  1.03
economic.cond.national VIF =  1.28
economic.cond.household VIF =  1.16
Blair VIF =  1.34
Hague VIF =  1.32
Europe VIF =  1.28
political.knowledge VIF =  1.09
vote_Labour VIF =  1.67
gender_male VIF =  1.03
```

All Vif score is less than 4 hence no issue of Multi-collinearity.
Lets copy all the predictor variables into X dataframe. And copy target into the y dataframe.

Split X and y into training and test set in 70:30 ratio.

We have created 4 variables here, X_train, X_test, y_train, y_test.

We will check the distribution percentage for target variable in train and test data.

Train target variable:

```
1  y_train.value_counts(1)
```

```
1    0.697282
0    0.302718
Name: vote_Labour, dtype: float64
```

Test Target variable:

```
1  y_test.value_counts(1)
```

```
1    0.696507
0    0.303493
Name: vote_Labour, dtype: float64
```

Almost 70-30 is the distribution of vote is achieved, as original dataset is also contains 70:30 Labour: Conservative distribution.

Modeling:

1.4 Apply Logistic Regression and LDA (linear discriminant analysis). (4 marks)

Apply Logistic Regression :

First we will create Logistic Regression and then we will fit it on train data **X_train, y_train.**

We will use solver as 'newton-cg' with 10,000 iterations.

```
LogisticRegression(max_iter=10000, n_jobs=2, penalty='none', solver='newton-cg',
                   verbose=True)
```

Predicting on Training and Test dataset

```
ytrain_predict = model.predict(X_train)
ytest_predict = model.predict(X_test)
```

Getting the probabilities:

```
ytest_predict_prob=model.predict_proba(X_test)
pd.DataFrame(ytest_predict_prob).head()
```

First 5 rows of Predicted probabilities.

	0	1
0	0.244205	0.755795
1	0.077634	0.922366
2	0.060125	0.939875
3	0.233158	0.766842
4	0.022498	0.977502

Apply Linear Discriminant Analysis:

Build LDA model

We will create LDA classifier and then we will fit it on training data *X_train, y_train.*

```
clf = LinearDiscriminantAnalysis()
model=clf.fit(X_train,y_train)
```

Then we will predict the values on train and test data *X_train , X_test.*
With a cut off value 0.5

1.5 Apply KNN Model and Naïve Bayes Model. Interpret the results.

Apply KNN Model:

Here we have to note one thing is data is not scaled, and KNN algorithm is sensitive to this kind of data, so we will scale the data using *Z-score* before feeding to the model.

We will import zscore from scipy.stats

After applying z score to the data, and after scaling all the dependent variables,

Data is converted from -1 to +1.

	age	economic.cond.national	economic.cond.household	Blair	Hague	Europe	political.knowledge	gender_male
0	-0.711973	-0.279218	-0.150948	0.566716	-1.419886	-1.434426	0.422643	-0.937059
1	-1.157661	0.856268	0.924730	0.566716	1.018544	-0.524358	0.422643	1.067169
2	-1.221331	0.856268	0.924730	1.418187	-0.607076	-1.131070	0.422643	1.067169
3	-1.921698	0.856268	-1.226625	-1.136225	-1.419886	-0.827714	-1.424148	-0.937059
4	-0.839313	-1.414704	-1.226625	-1.987695	-1.419886	-0.221002	0.422643	1.067169

From *sklearn.neighbors* we will import *KNeighborsClassifier.*

then we will create KNeighborsClassifier()

then we will fit it on train data x_train and y_train.

Apply Naïve Bayes Model:

From sklearn.naive_bayes we will import GaussianNB

Then we will create Naïve Bayes model and fit it on (X_train, y_train).

```
1 NB_model = GaussianNB()
2 NB_model.fit(X_train, y_train)
```

```
GaussianNB()
```

1.6 Model Tuning, Bagging (Random Forest should be applied for Bagging), and Boosting. (7 marks)

Apply Random Forest:

For Bagging we will use Random Forest algorithm as Suggested.

First we will import RandomForestClassifier from sklearn.ensemble.

Then we will create Random forest Classifier with n_estimators as 100.

n_estimators : This is the number of trees we want to build before taking the maximum voting of predictions. Higher number of trees gives better performance.

Then we will fit the model on (X_train, y_train) dataset.

```
from sklearn.ensemble import AdaBoostClassifier

ADB_model = AdaBoostClassifier(n_estimators=100,random_state=1)
ADB_model.fit(X_train,y_train)
```

Apply Bagging

Here we will create Bagging Classifier, Where we will select trees as 100, and base Estimator as Classification and Regression tree.

Then we will fit the model on train data

```
from sklearn.ensemble import BaggingClassifier
Bagging_model=BaggingClassifier(base_estimator=cart,n_estimators=100,random_state=1)
Bagging_model.fit(X_train, y_train)
```

```
BaggingClassifier(base_estimator=DecisionTreeClassifier(), n_estimators=100,
                  random_state=1)
```

Apply Ada boost

First we will import AdaBoostClassifier from sklearn.ensemble library.

Then we will create Ada boost model.

Then we will fit the model on (X_train, y_train) dataset.

```
1  from sklearn.ensemble import AdaBoostClassifier
2
3  ADB_model = AdaBoostClassifier(n_estimators=100,random_state=1)
4  ADB_model.fit(X_train,y_train)
```

```
AdaBoostClassifier(n_estimators=100, random_state=1)
```

Note: Model Tunning is Discussed after Question no. 7

1.7 Performance Metrics: Check the performance of Predictions on Train and Test sets using Accuracy, Confusion Matrix, Plot ROC curve and get ROC_AUC score for each model. Final Model: Compare the models and write inference which model is best/optimized. (7 marks)

So far we have created and trained the models Logistic Regression, LDA, Naive Bayes, KNN, Random Forest, Ada boost on Training data set. Now we will check Performance of all of them.

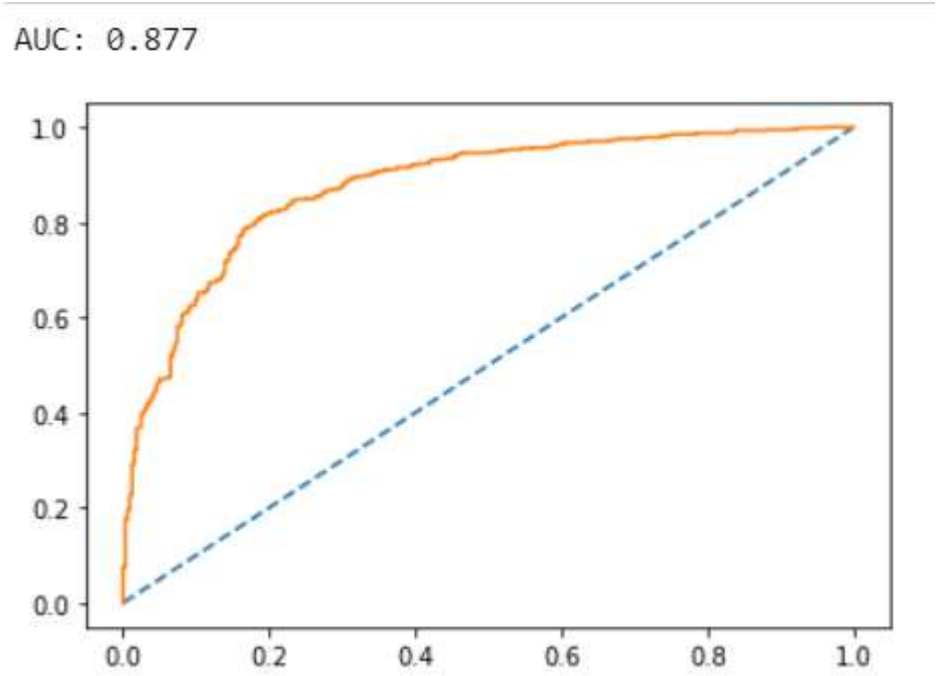
1. Logistic Regression

Accuracy and AUC-ROC:

On Train data:

83% is the Accuracy on train data.

AUC and ROC curve for training data:

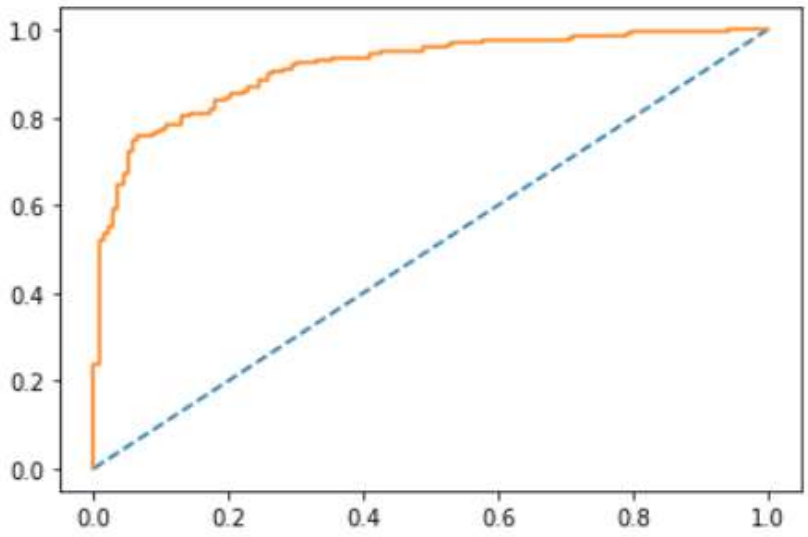


On Test data:

84.93% is the Accuracy on train data.

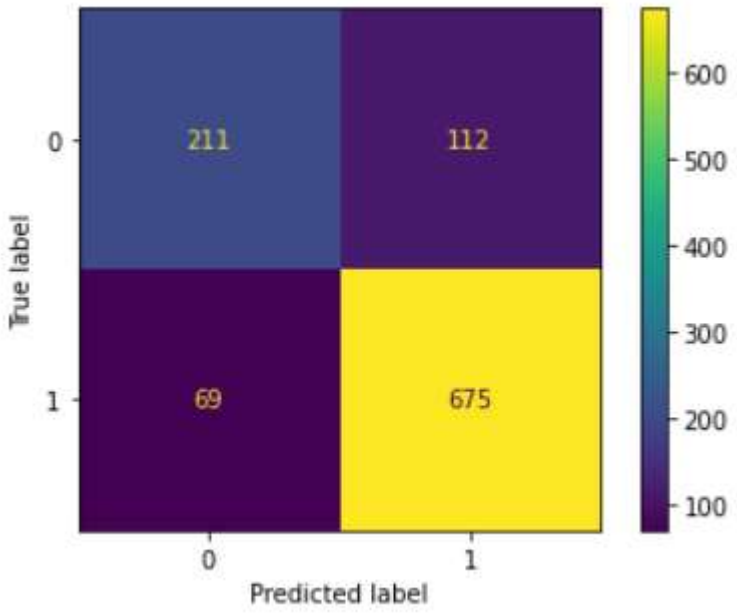
AUC and ROC curve for training data:

```
AUC: 0.914
```

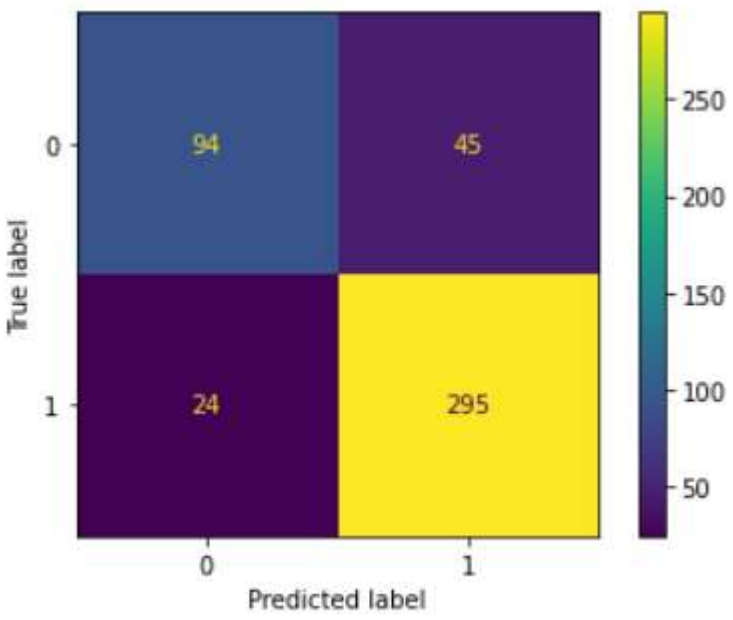


Confusion Matrix

On Train data



On Test Data : Confusion Matrix,



Classification Report

On Train data:

	precision	recall	f1-score	support
0	0.75	0.65	0.70	323
1	0.86	0.91	0.88	744
accuracy			0.83	1067
macro avg	0.81	0.78	0.79	1067
weighted avg	0.83	0.83	0.83	1067

```
lr_train_precision  0.86
lr_train_recall  0.91
lr_train_f1  0.88
```

On Test Data ,

	precision	recall	f1-score	support
0	0.80	0.68	0.73	139
1	0.87	0.92	0.90	319
accuracy			0.85	458
macro avg	0.83	0.80	0.81	458
weighted avg	0.85	0.85	0.85	458

```
lr_test_precision  0.87
lr_test_recall  0.92
lr_test_f1  0.9
```

We can see both 0's and 1's are equally Important here, Because vote to both leaders matter to us. Logistic Regression has performed really well no overfitting issue can be Observed here.

Precision, recall and f1 score to predict 0, is 75%, 65% , 70% on Train data.

It has 83%-84% Accuracy on test data, while f1 score is also 88-90%.

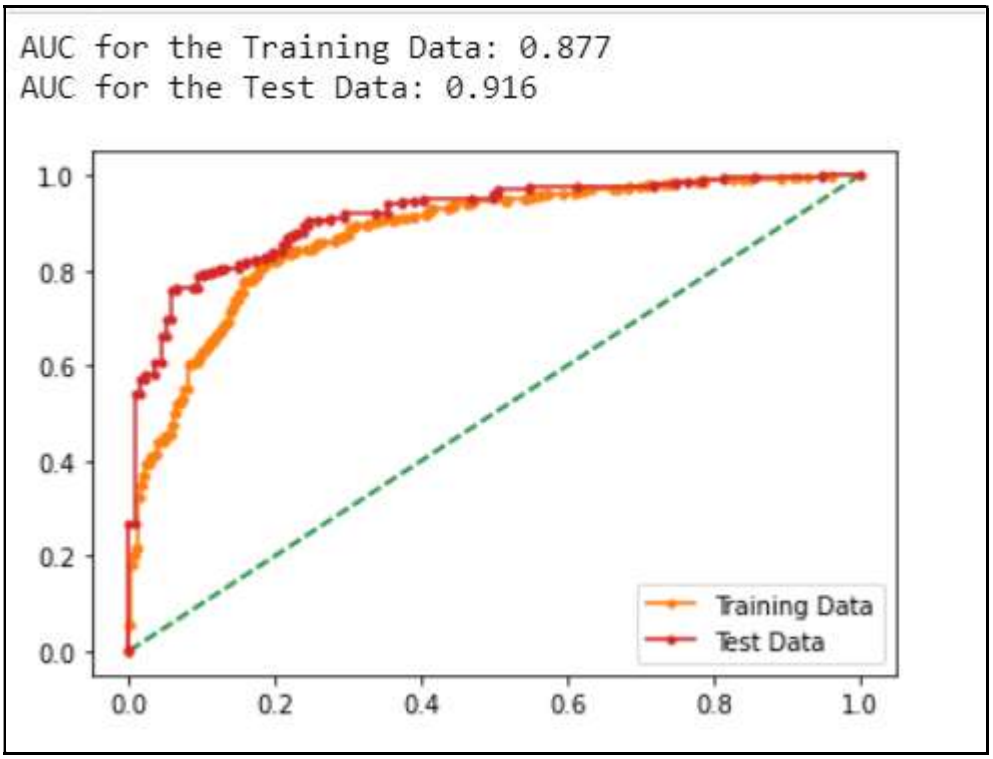
2. Linear Discriminant Analysis

Accuracy and AUC-ROC:

On Train and Test data:

83% and 85% is the Accuracy on train data and test data respectively.

AUC and ROC curve for training and test data:



Confusion Matrix for LDA:

Classification Report for LDA:

Classification Report of the training data:

	precision	recall	f1-score	support
0	0.74	0.67	0.70	323
1	0.86	0.90	0.88	744
accuracy			0.83	1067
macro avg	0.80	0.78	0.79	1067
weighted avg	0.83	0.83	0.83	1067

Classification Report of the test data:

	precision	recall	f1-score	support
0	0.79	0.71	0.75	139
1	0.88	0.92	0.90	319
accuracy			0.85	458
macro avg	0.83	0.81	0.82	458
weighted avg	0.85	0.85	0.85	458

LDA has also performed really well no overfitting issue can be Observed here. On Test data and train data only + - 2% is the difference.

To Predict 0, the precision, recall and f1 score has fallen as compare to Predict 1.

It has 83%-85% Accuracy, while f1 score is also 88-90%.

3. K Nearest Neighbour

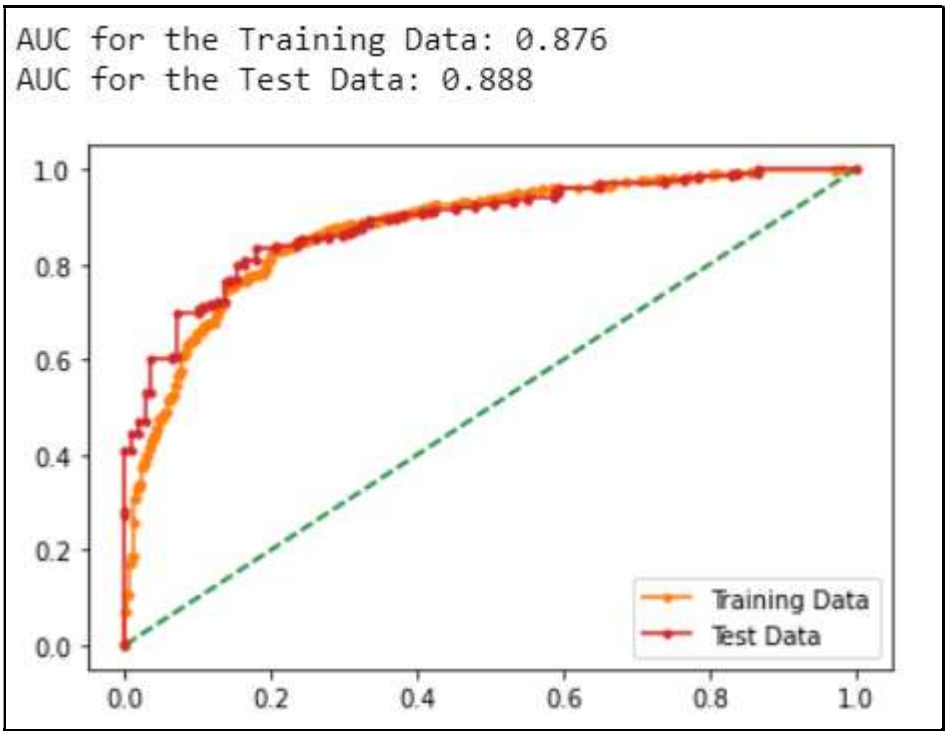
Accuracy and AUC-ROC:

On Train data:

87% is the Accuracy on train data.

82% is the Accuracy on test data.

AUC and ROC curve for and test data:



Confusion Matrix for KNN:

Classification Report for KNN :

Classification report for training data:

	precision	recall	f1-score	support
0	0.81	0.75	0.78	351
1	0.89	0.92	0.91	792
accuracy			0.87	1143
macro avg	0.85	0.83	0.84	1143
weighted avg	0.87	0.87	0.87	1143

Classification report for test data:

	precision	recall	f1-score	support
0	0.69	0.73	0.71	111
1	0.89	0.86	0.87	271
accuracy			0.82	382
macro avg	0.79	0.80	0.79	382
weighted avg	0.83	0.82	0.83	382

Here in KNN we can see The value is little lower in case of Test Data

Accuracy and f1 score, but again even this model will perform well,

We need to Hyperparameter tuning to improve performance.

It is Predicting 1 with Higher f1 score but it is showing poor performance to Predict 0.

4. Naive Bayes Algorithm

Accuracy and AUC-ROC:

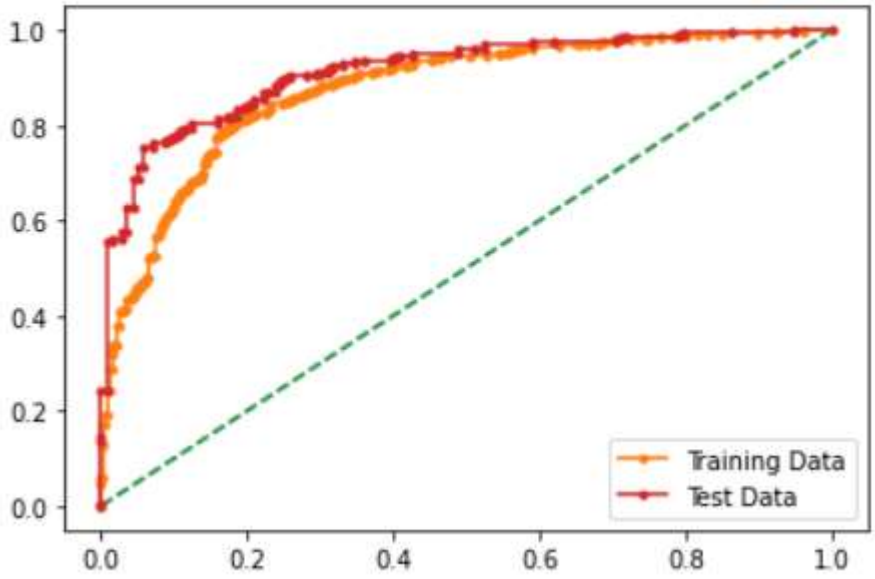
On Train data:

82% is the Accuracy on train data.

84% is the Accuracy on test data.

AUC and ROC curve for train and test data:

```
AUC for the Training Data: 0.876
AUC for the Test Data: 0.915
```



Confusion Matrix :

Classification Report for Naïve Bayes Algorithm:

On Train data:

```
0.8219306466729147
[[223 100]
 [ 90 654]]
              precision    recall  f1-score   support

           0       0.71      0.69      0.70       323
           1       0.87      0.88      0.87       744

    accuracy                           0.82      1067
   macro avg       0.79      0.78      0.79      1067
weighted avg       0.82      0.82      0.82      1067
```

On Test Data:

```
0.8471615720524017
[[101  38]
 [ 32 287]]
              precision    recall  f1-score   support

           0       0.76      0.73      0.74       139
           1       0.88      0.90      0.89       319

    accuracy                           0.85       458
   macro avg       0.82      0.81      0.82       458
weighted avg       0.85      0.85      0.85       458
```

We need Hyperparameter tuning to improve performance.

It is Predicting 1 with Higher f1 score but it is showing poor performance to Predict 0.

5. Random Forest

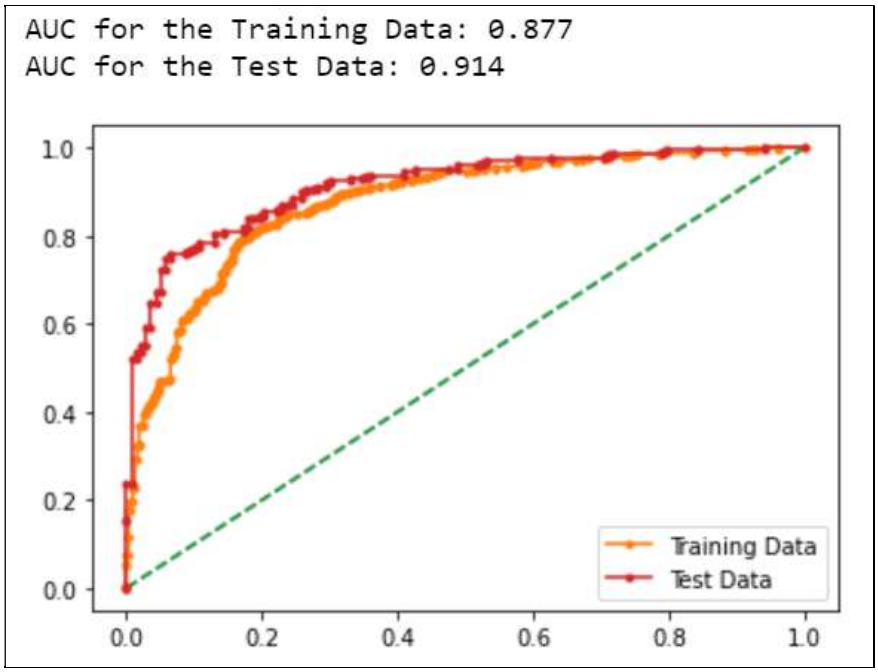
Accuracy and AUC-ROC:

On Train-test data:

100% is the Accuracy on train data.

85% is the Accuracy on test data.

AUC and ROC curve for train and test data:



Confusion Matrix for Random Forest :

Classification Report for Random Forest:

On Train Data:

```
0.9990627928772259
[[322   1]
 [  0 744]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       323
           1       1.00      1.00      1.00       744

    accuracy                           1.00      1067
   macro avg       1.00      1.00      1.00      1067
weighted avg       1.00      1.00      1.00      1067
```

On Test Data:

```
0.8493449781659389
[[ 94  45]
 [ 24 295]]
              precision    recall  f1-score   support

           0       0.80      0.68      0.73       139
           1       0.87      0.92      0.90       319

    accuracy                           0.85       458
   macro avg       0.83      0.80      0.81       458
weighted avg       0.85      0.85      0.85       458
```

Random Forest is Clearly a overfitting one, as almost all metrics has reduced on test data.

6. Bagging

Accuracy and AUC-ROC:

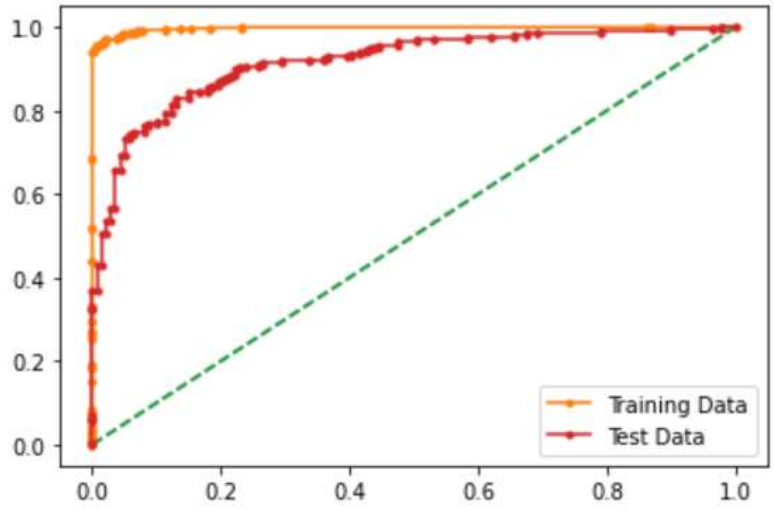
On Train-test data:

99.7% is the Accuracy on train data.

91.8% is the Accuracy on test data.

AUC and ROC curve for train and test data:

```
AUC for the Training Data: 0.997
AUC for the Test Data: 0.918
```



Confusion Matrix for Bagging :

Classification Report for Bagging:

On Train Data,

```
0.971883786316776
[[298  25]
 [  5 739]]
              precision    recall  f1-score   support

           0       0.98      0.92      0.95       323
           1       0.97      0.99      0.98       744

    accuracy                           0.97      1067
   macro avg       0.98      0.96      0.97      1067
weighted avg       0.97      0.97      0.97      1067
```

On Test data,

```
0.8427947598253275
[[ 93  46]
 [ 26 293]]
              precision    recall  f1-score   support

           0       0.78      0.67      0.72       139
           1       0.86      0.92      0.89       319

    accuracy                           0.84       458
   macro avg       0.82      0.79      0.81       458
weighted avg       0.84      0.84      0.84       458
```

Model has stability in predicting 1 while Predicting 0, Bagging Model is Overfitting.

7. Ada Boost

Accuracy and AUC-ROC:

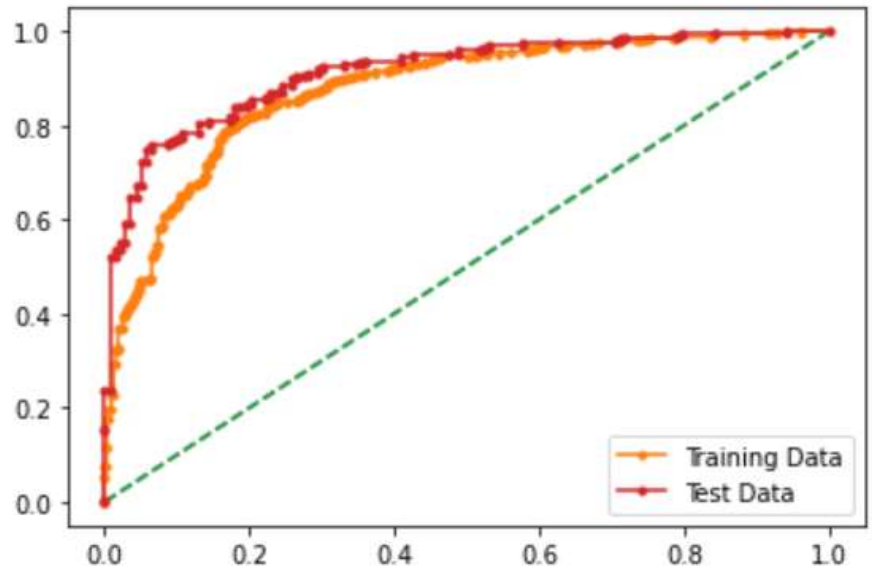
On Train-test data:

84.5% is the Accuracy on train data.

83.62% is the Accuracy on test data.

AUC and ROC curve for train and test data:

```
AUC for the Training Data: 0.877
AUC for the Test Data: 0.914
```



Confusion Matrix for Ada Boost:

Classification Report for Ada Boost:

On Train Data,

```
0.8444236176194939
[[227  96]
 [ 70 674]]
              precision    recall  f1-score   support

           0       0.76      0.70      0.73       323
           1       0.88      0.91      0.89       744

    accuracy                           0.84      1067
   macro avg       0.82      0.80      0.81      1067
weighted avg       0.84      0.84      0.84      1067
```

On Test Data,

```
0.8362445414847162
[[ 94  45]
 [ 30 289]]
              precision    recall  f1-score   support

           0       0.76      0.68      0.71       139
           1       0.87      0.91      0.89       319

    accuracy                           0.84       458
   macro avg       0.81      0.79      0.80       458
weighted avg       0.83      0.84      0.83       458
```

Model is Performing well as compare to other models.

All Model Comparison by its performance metrics:

	Logit Train	Logit Test	LDA Train	LDA Test	KNN Train	KNN Test	Naive Bayes Train	Naive Bayes Test	RF Train	RF Test	Ada Boost Train	Ada Boost Test	Ada Boost Train_0	Ada Boost Test_0
Accuracy	0.83	0.85	0.83	0.84	0.87	0.71	0.82	0.85	1.00	0.85	0.84	0.84	0.84	0.84
AUC	0.88	0.91	0.88	0.91	0.88	0.89	0.88	0.91	0.88	0.91	0.90	0.91	0.90	0.91
Recall	0.91	0.92	0.90	0.91	0.92	0.86	0.88	0.90	1.00	0.92	0.70	0.91	0.70	0.68
Precision	0.86	0.87	0.86	0.87	0.89	0.89	0.87	0.88	1.00	0.87	0.76	0.87	0.76	0.76
F1 Score	0.88	0.90	0.88	0.89	0.91	0.87	0.87	0.89	1.00	0.90	0.73	0.89	0.73	0.71

Now the Train data seems to be unbalanced, like 30-70% Conservative Party and Labour party votes, so we will use SMOTE oversampling method on train data here to balance the Data.

Naive Bayes with SMOTE

Performance metrics for Naive Bayes with SMOTE:

On Train Data :

```
0.8131720430107527
[[595 149]
 [129 615]]
              precision    recall  f1-score   support

           0       0.82      0.80      0.81       744
           1       0.80      0.83      0.82       744

    accuracy                           0.81      1488
   macro avg       0.81      0.81      0.81      1488
weighted avg       0.81      0.81      0.81      1488
```

On Test Data:

```
0.8427947598253275
[[109  30]
 [ 42 277]]
              precision    recall  f1-score   support

           0       0.72      0.78      0.75       139
           1       0.90      0.87      0.88       319

    accuracy                           0.84       458
   macro avg       0.81      0.83      0.82       458
weighted avg       0.85      0.84      0.84       458
```

Model is overfitting here, so we will see what happens with SMOTE and Ada Boost, Linear Regression.

SMOTE with Ada Boost:

Classification Report:

On Train Data,

```
0.8145161290322581
[[601 143]
 [133 611]]
              precision    recall  f1-score   support

           0       0.82      0.81      0.81       744
           1       0.81      0.82      0.82       744

    accuracy                           0.81      1488
   macro avg       0.81      0.81      0.81      1488
weighted avg       0.81      0.81      0.81      1488
```

On Test Data,

```
0.8362445414847162
[[110  29]
 [ 46 273]]
              precision    recall  f1-score   support

           0       0.71      0.79      0.75       139
           1       0.90      0.86      0.88       319

    accuracy                           0.84       458
   macro avg       0.80      0.82      0.81       458
weighted avg       0.84      0.84      0.84       458
```

This is again Overfitting/Underfitting issue while predicting 0's and 1.

SMOTE with Logistic Regression:

Classification Report:

On Train Data,

```
0.821236559139785
[[611 133]
 [133 611]]
              precision    recall  f1-score   support

           0       0.82      0.82      0.82       744
           1       0.82      0.82      0.82       744

    accuracy                           0.82      1488
   macro avg       0.82      0.82      0.82      1488
weighted avg       0.82      0.82      0.82      1488
```

On Test Data,

```
0.8362445414847162
[[114  25]
 [ 50 269]]
              precision    recall  f1-score   support

           0       0.70      0.82      0.75       139
           1       0.91      0.84      0.88       319

    accuracy                           0.84       458
   macro avg       0.81      0.83      0.82       458
weighted avg       0.85      0.84      0.84       458
```

Not exactly but Logistic Regression seems much stable as Compare to other models, after applying SMOTE-balanced data.

Model Tunning :

Now we will use Model tunning for various Algorithms to check whether the performance is Improving or not by changing its hyperparameters.

For Naive Bayes Model, will use K-fold validation how model performs on Limited dataset.

```
Cross Validation Score: [0.82242991 0.8411215  0.81308411 0.81308411 0.81308411 0.82242991
 0.79439252 0.87735849 0.81132075 0.81132075] [0.82242991 0.8411215  0.81308411 0.81308411 0.81308411 0.82242991
 0.79439252 0.87735849 0.81132075 0.81132075]
Average Score: 0.8219626168224299
```

Average Score is 0.82, which is good score, it is performing well.

Lets check using GRID search, for KNN

```
params = {'n_neighbors':[2,4,6,8,10,12,14,16,18],
          'algorithm': ['auto','ball_tree','kd_tree','brute'],
          'leaf_size':list(range(1,30)),
          'p':[1,2],
          'metric':['minkowski','euclidean','manhattan','chebyshev', 'mahanalobis']}
```

We are here using different distance metrics, P value is

When p = 1, this is equivalent to using manhattan_distance

P=2,Power parameter for the Minkowski metric.

We are selecting leaf size from 1 to 30, to get the optimal value.

Before fitting the data, we are scaling train data by using z score

Scaled data:

age	economic.cond.national	economic.cond.household	Blair	Hague	Europe	political.knowledge	gender_male
0.497751	-0.279218	-0.150948	-1.136225	1.831354	0.385710	-1.424148	1.067169
-0.902983	-0.279218	0.924730	0.566716	-1.419886	-1.131070	1.346038	1.067169
-0.138946	-1.414704	-0.150948	-1.136225	1.831354	1.295778	0.422643	-0.937059
-0.457295	-0.279218	-0.150948	0.566716	-0.607076	-0.827714	-1.424148	-0.937059
-0.202616	-0.279218	-1.226625	0.566716	-0.607076	-1.434426	0.422643	-0.937059
...	...	...	...	...	...	...	...
0.816100	0.856268	-0.150948	1.418187	-0.607076	-1.434426	0.422643	1.067169
-1.730689	1.991754	2.000408	-1.136225	-1.419886	-0.827714	1.346038	1.067169
-1.285001	0.856268	2.000408	0.566716	1.018544	0.082354	0.422643	-0.937059
-1.157661	0.856268	0.924730	0.566716	-0.607076	0.082354	0.422643	-0.937059
-1.412340	-1.414704	-1.226625	0.566716	1.018544	-0.524358	1.346038	1.067169

The values set for algorithm,

```
GridSearchCV(estimator=KNeighborsClassifier(),
             param_grid={'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute'],
                         'leaf_size': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,
                                       13, 14, 15, 16, 17, 18, 19, 20, 21, 22,
                                       23, 24, 25, 26, 27, 28, 29],
                         'metric': ['minkowski', 'euclidean', 'manhattan',
                                    'chebyshev', 'mahanalobis'],
                         'n_neighbors': [2, 4, 6, 8, 10, 12, 14, 16, 18],
                         'p': [1, 2]},
             verbose=1)
```

These are the best Parameters for KNN:

```
{'algorithm': 'auto',
 'leaf_size': 1,
 'metric': 'minkowski',
 'n_neighbors': 16,
 'p': 2}
```

Train and Test Accuracy for KNN after Grid Search CV.

```
Train Accuracy is :0.8433945756780402

Test Accuracy is :0.8272251308900523
```

It is almost same as earlier.

Lets check using GRID search, for Logistic Regression and Random Forest

We will import Pipeline from sklearn.pipeline library.

In this we will create two Classifier – Logistic Regression and Random Forest will see the best performing model with its best Parameters.

```
{'classifier': LogisticRegression(C=11.288378916846883, solver='liblinear'),
 'classifier__C': 11.288378916846883,
 'classifier__penalty': 'l2',
 'classifier__solver': 'liblinear'}
```

Logistic Regression Classiofier is giving best results,with Solver Liblinear
With Classifier Penalty as Ridge.

```
Train Accuracy is :0.8294283036551078

Test Accuracy is :0.8493449781659389
```

Classification Report:

Classification report for Train set:

	precision	recall	f1-score	support
0	0.75	0.65	0.70	323
1	0.86	0.91	0.88	744
accuracy			0.83	1067
macro avg	0.80	0.78	0.79	1067
weighted avg	0.83	0.83	0.83	1067

Classification report for Test set:

	precision	recall	f1-score	support
0	0.80	0.68	0.73	139
1	0.87	0.92	0.90	319
accuracy			0.85	458
macro avg	0.83	0.80	0.81	458
weighted avg	0.85	0.85	0.85	458

The Logistic Regression is Performing well on Test data and Train data, it seems to be stable. It is predicting 0 and 1 clearly.
It has low scores while predicting 0 but for 1 Precision, Recall and F1 is good on both train and test data.
Prediction of 0 i.e vote to conservative Party, prediction is little tougher as there is very less data points conveying vote to Conservative Party. This can be minimized if we ask for more data.

If we check the first 10 votes, It is clearly, mentioning the vote to Labour party.

```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1], dtype=uint8)
```

First 400 votes,

```
{0: 96, 1: 304}
```

Here out of 400, 96 votes are to the Conservative party and 304 votes are to the Labour party so clearly it is indicating the Labour party will win.
Again there are some assumptions and data limits we have, so as of now this is the scenario.

1.8 Based on these predictions, what are the insights?

Summary:

In this Case study we have to decide strategy or plan or we have to predict which party will win election, To which party particular person will vote. What are the deciding factors to win election that we are studying here. Survey is Conducted on 1525 different people, where features like Age, whether person is Eurosceptic with ratings, Assessment to both leaders Hague and Blair. Person is having political Knowledge or not. what is public opinion on Household and national economy, their gender is also taken into consideration, so it seems we have sufficient features to evaluate result.

Steps Performed and Insights:

To predict results, we have started with Exploratory data Analysis where we got some hidden insights by looking at Dataset, by using univariate analysis, Multivariate analysis. Null value, Outlier detection. From EDA we have drawn below mentioned Insights:

Assesment to leader Blair and Economic Household Condition Rating, Economic national Condition rating shows good correlation.

Europscepticism score and Blair Assesment score are inversly related, means if Person is more Eurosceptic there will be less chances he will vote to Blair as a party leader of Labour party.

If person is giving good assesment score to Hague he must be with Conservative party and he or she is Highly Eurosceptic.

It is not always true, but people having good political Knowledge are preferring Europe Integration.

Modelling

As the target variable here is Categorcal i.e Conservative and Labour, we can use Logistic Regression, LDA, KNN, Naive Bayes, RF, Bagging, Boosting.

After all this we have created a Final Classification report where all performance metrics are mentioned.

We have used all mentioned Algorithms. If we check the Target Variable we have almost 70% data of Labour Party and 30 % Conservative Party. We have built all algorithms on this data first, after this we have used SMOTE technique of Oversampling to balance Imbalanced data. We can see in the Classification report that Accuracy, Precision has been dropped.

After all this to do Model tunning we have used Gridsearch CV, K fold cross validation to Improve performance of Existing Base models.

Results:

To get the crystal clear picture, we need more data points to avoid Imbalance data issue. but from this data, we can say that to win the election one must be with vision Europe integration, as this vision has helped labour party.

The Model Logistic Regression has good score and seems to be very stable model in this Scenario. If we predict on Test Data, The labour Party seems to be get Higher number of Votes as compare to Conservative Party. Again the question arises here does this sample represent the whole nation, any bias in the data, like from Particular region data is collected where Labour Party has higher influence. There are less votes to Conservative party, but again it needs more data to predict correct results. But as of now this data tells us that Labour party will win this elections.

In this particular project, we are going to work on the inaugural corpora from the nltk in Python. We will be looking at the following speeches of the Presidents of the United States of America:

President Franklin D. Roosevelt in 1941 President John F. Kennedy in 1961 President Richard Nixon in 1973 (Hint: use .words(), .raw(), .sent() for extracting counts)

Questions:

2.1 Find the number of characters, words, and sentences for the mentioned documents. – 3 Marks
2.1.1 : Number of characters, words, and sentences for Franklin D. Roosevelt
2.1.2 : Number of characters, words, and sentences for John F. Kennedy
2.1.3 : Number of characters, words, and sentences for Richard Nixon

2.2 Remove all the stopwords from all three speeches. – 3 Marks
2.2.1 : Remove all the stopwords from Speech Franklin D. Roosevelt
2.2.2 : Remove all the stopwords from Speech John F. Kennedy
2.2.3 : Remove all the stopwords from Speech Richard Nixon

2.3 Which word occurs the most number of times in his inaugural address for each president? Mention the top three words.(after removing the stopwords) – 3 Marks
2.3.1 : Word occurs the most in speech Franklin D. Roosevelt
2.3.2 : Word occurs the most in speech John F. Kennedy
2.3.3 : Word occurs the most in speech Richard Nixon

2.4 Plot the word cloud of each of the speeches of the variable. (after removing the stopwords) – 3 Marks [refer to the End-to-End Case Study done in the Mentored Learning Session]
2.4.1 : WordCloud for Franklin D. Roosevelt
2.4.2 : WordCloud for John F. Kennedy
2.4.3 : WordCloud for Richard Nixon

Code Snippet to extract the three speeches:

" import nltk nltk.download('inaugural') from nltk.corpus import inaugural inaugural.fileids() inaugural.raw('1941-Roosevelt.txt') inaugural.raw('1961-Kennedy.txt') inaugural.raw('1973-Nixon.txt') "

2.1 Find the number of characters, words, and sentences for the mentioned documents.

2.1.1 : Number of characters, words, and sentences for Franklin D. Roosevelt.
2.1.2 : Number of characters, words, and sentences for John F. Kennedy
2.1.3 : Number of characters, words, and sentences for Richard Nixon

2.1.1 : Number of characters, words, and sentences for Franklin D. Roosevelt.

First download the inaugural and import the text files "1941-Roosevelt.txt", "1961-Kennedy.txt"." 1973-Nixon.txt".
And do the analysis.

```
The numbers of characters in Roosevelt 1941 speech is: 7571
The numbers of words in Roosevelt 1941 speech is: 1536
The numbers of sentences in Roosevelt 1941 speech is: 68
```

2.1.2 : Number of characters, words, and sentences for John F. Kennedy

```
The numbers of characters in 1961-Kennedy speech is: 7618
The numbers of words in 1961-Kennedy speech is: 1546
The numbers of sentences in 1961-Kennedy speech is: 52
```

2.1.3 : Number of characters, words, and sentences for Richard Nixon

```
The numbers of characters in 1973-Nixon speech is: 9991
The numbers of words in 1973-Nixon speech is: 2028
The numbers of sentences in 1973-Nixon speech is: 69
```

2.2 Remove all the stopwords from all three speeches.

2.2.1 : Remove all the stopwords from Speech Franklin D. Roosevelt
2.2.2 : Remove all the stopwords from Speech John F. Kennedy
2.2.3 : Remove all the stopwords from Speech Richard Nixon

2.2.1 : Remove all the stopwords from Speech Franklin D. Roosevelt

Download stopwoprds from nltk.

After removing all the stopwords from Speech Franklin D. Roosevelt

national day inauguration since people renewed sense dedication united states washington day task people create weld together n
ation lincoln day task people preserve nation disruption within day task people save nation institutions disruption without us
come time midst swift happenings pause moment take stock recall place history rediscover may risk real peril inaction lives nat
ions determined count years lifetime human spirit life man three score years ten little little less life nation fullness measur
e live men doubt men believe democracy form government frame life limited measured kind mystical artificial fate unexplained re
ason tyranny slavery become surging wave future freedom ebbing tide americans know true eight years ago life republic seemed fr
ozen fatalistic terror proved true midst shock acted acted quickly boldly decisively later years living years fruitful years pe
ople democracy brought us greater security hope better understanding life ideals measured material things vital present future
experience democracy successfully survived crisis home put away many evil things built new structures enduring lines maintained
fact democracy action taken within three way framework constitution united states coordinate branches government continue freel
y function bill rights remains inviolate freedom elections wholly maintained prophets downfall american democracy seen dire pre
dictions come naught democracy dying know seen revive grow know die built unhampered initiative individual men women joined tog
ether common enterprise enterprise undertaken carried free expression free majority know democracy alone forms government enlis
ts full force men enlightened know democracy alone constructed unlimited civilization capable infinite progress improvement hum
an life know look surface sense still spreading every continent humane advanced end unconquerable forms human society nation li
ke person body body must fed clothed housed invigorated rested manner measures objectives time nation like person mind mind mus
t kept informed alert must know understands hopes needs neighbors nations live within narrowing circle world nation like person
something deeper something permanent something larger sum parts something matters future calls forth sacred guarding present th
ing find difficult even impossible hit upon single simple word yet understand spirit faith america product centuries born multi
tudes came many lands high degree mostly plain people sought early late find freedom freely democratic aspiration mere recent p
hase human history human history permeated ancient life early peoples blazed anew middle ages written magna charta americas imp
act irresistible america new world tongues peoples continent new found land came believed could create upon continent new life
life new freedom vitality written mayflower compact declaration independence constitution united states gettysburg address firs
t came carry longings spirit millions followed stock sprang moved forward constantly consistently toward ideal gained stature c
larity generation hopes republic forever tolerate either undeserved poverty self serving wealth know still far go must greatly
build security opportunity knowledge every citizen measure justified resources capacity land enough achieve purposes alone enou
gh clothe feed body nation instruct inform mind also spirit three greatest spirit without body mind men know nation could live
spirit america killed even though nation body mind constricted alien world lived america know would perished spirit faith speak
s us daily lives ways often unnoticed seem obvious speaks us capital nation speaks us processes governing sovereignties states
speaks us counties cities towns villages speaks us nations hemisphere across seas enslaved well free sometimes fail hear heed v
oices freedom us privilege freedom old old story destiny america proclaimed words prophecy spoken first president first inaugur
al words almost directed would seem year preservation sacred fire liberty destiny republican model government justly considered
deeply finally staked experiment intrusted hands american people lose sacred fire let smothered doubt fear shall reject destiny
washington strove valiantly triumphantly establish preservation spirit faith nation furnish highest justification every sacrifi
ce may make cause national defense face great perils never encountered strong purpose protect perpetuate integrity democracy mu
ster spirit america faith america retreat content stand still americans go forward service country god

2.2.2 : Remove all the stopwords from Speech John F. Kennedy

```
vice president johnson mr speaker mr chief justice president eisenhower vice president nixon president truman reverend clergy f
ellow citizens observe today victory party celebration freedom symbolizing end well beginning signifying renewal well change sw
orn almighty god solemn oath forebears l prescribed nearly century three quarters ago world different man holds mortal hands po
wer abolish forms human poverty forms human life yet revolutionary beliefs forebears fought still issue around globe belief rig
hts man come generosity state hand god dare forget today heirs first revolution let word go forth time place friend foe alike t
orch passed new generation americans born century tempered war disciplined hard bitter peace proud ancient heritage unwilling w
itness permit slow undoing human rights nation always committed committed today home around world let every nation know whether
wishes us well ill shall pay price bear burden meet hardship support friend oppose foe order assure survival success liberty mu
ch pledge old allies whose cultural spiritual origins share pledge loyalty faithful friends united little host cooperative vent
ures divided little dare meet powerful challenge odds split asunder new states welcome ranks free pledge word one form colonial
control shall passed away merely replaced far iron tyranny shall always expect find supporting view shall always hope find stro
ngly supporting freedom remember past foolishly sought power riding back tiger ended inside peoples huts villages across globe
struggling break bonds mass misery pledge best efforts help help whatever period required communists may seek votes right free
society help many poor save rich sister republics south border offer special pledge convert good words good deeds new alliance
progress assist free men free governments casting chains poverty peaceful revolution hope become prey hostile powers let neighb
ors know shall join oppose aggression subversion anywhere americas let every power know hemisphere intends remain master house
world assembly sovereign states united nations last best hope age instruments war far outpaced instruments peace renew pledge s
upport prevent becoming merely forum invective strengthen shield new weak enlarge area writ may run finally nations would make
adversary offer pledge request sides begin anew quest peace dark powers destruction unleashed science engulf humanity planned a
ccidental self destruction dare tempt weakness arms sufficient beyond doubt certain beyond doubt never employed neither two gre
at powerful groups nations take comfort present course sides overburdened cost modern weapons rightly alarmed steady spread dea
dly atom yet racing alter uncertain balance terror stays hand mankind final war let us begin anew remembering sides civility si
gn weakness sincerity always subject proof let us never negotiate fear let us never fear negotiate let sides explore problems u
nite us instead belaboring problems divide us let sides first time formulate serious precise proposals inspection control arms
bring absolute power destroy nations absolute control nations let sides seek invoke wonders science instead terrors together le
t us explore stars conquer deserts eradicate disease tap ocean depths encourage arts commerce let sides unite heed corners eart
h command isaiah undo heavy burdens let oppressed go free beachhead cooperation may push back jungle suspicion let sides join c
reating new endeavor new balance power new world law strong weak secure peace preserved finished first days finished first days
life administration even perhaps lifetime planet let us begin hands fellow citizens mine rest final success failure course sinc
e country founded generation americans summoned give testimony national loyalty graves young americans answered call service su
rround globe trumpet summons us call bear arms though arms need call battle though embattled call bear burden long twilight str
uggle year year rejoicing hope patient tribulation struggle common enemies man tyranny poverty disease war forge enemies grand
global alliance north south east west assure fruitful life mankind join historic effort long history world generations granted
role defending freedom hour maximum danger shrink responsibility welcome believe us would exchange places people generation ene
rgy faith devotion bring endeavor light country serve glow fire truly light world fellow americans ask country ask country fell
ow citizens world ask america together freedom man finally whether citizens america citizens world ask us high standards streng
th sacrifice ask good conscience sure reward history final judge deeds let us go forth lead land love asking blessing help know
ing earth god work must truly
```

2.2.3 : Remove all the stopwords from Speech Richard Nixon.

mr vice president mr speaker mr chief justice senator cook mrs eisenhower fellow citizens great good country share together met four years ago america bleak spirit depressed prospect seemingly endless war abroad destructive conflict home meet today stand threshold new era peace world central question us shall use peace let us resolve era enter postwar periods often time retreat i solation leads stagnation home invites new danger abroad let us resolve become time great responsibilities greatly borne renew spirit promise america enter third century nation past year saw far reaching results new policies peace continuing revitalize t raditional friendships missions peking moscow able establish base new durable pattern relationships among nations world america bold initiatives long remembered year greatest progress since end world war ii toward lasting peace world peace seek world flim sy peace merely interlude wars peace endure generations come important understand necessity limitations america role maintainin g peace unless america work preserve peace peace unless america work preserve freedom freedom let us clearly understand new nat ure america role result new policies adopted past four years shall respect treaty commitments shall support vigorously principl e country right impose rule another force shall continue era negotiation work limitation nuclear arms reduce danger confrontati on great powers shall share defending peace freedom world shall expect others share time passed america make every nation confl ict make every nation future responsibility presume tell people nations manage affairs respect right nation determine future al so recognize responsibility nation secure future america role indispensable preserving world peace nation role indispensable pr eserving peace together rest world let us resolve move forward beginnings made let us continue bring walls hostility divided wo rld long build place bridges understanding despite profound differences systems government people world friends let us build st ructure peace world weak safe strong respects right live different system would influence others strength ideas force arms let us accept high responsibility burden gladly gladly chance build peace noblest endeavor nation engage gladly also act greatly me eting responsibilities abroad remain great nation remain great nation act greatly meeting challenges home chance today ever his tory make life better america ensure better education better health better housing better transportation cleaner environment re store respect law make communities livable insure god given right every american full equal opportunity range needs great reach opportunities great let us bold determination meet needs new ways building structure peace abroad required turning away old pol icies failed building new era progress home requires turning away old policies failed abroad shift old policies new retreat res ponsibilities better way peace home shift old policies new retreat responsibilities better way progress abroad home key new res ponsibilities lies placing division responsibility lived long consequences attempting gather power responsibility washington ab road home time come turn away condescending policies paternalism washington knows best person expected act responsibly responsi bility human nature let us encourage individuals home nations abroad decide let us locate responsibility places let us measure others today offer promise purely governmental solution every problem lived long false promise trusting much government asked d eliver leads inflated expectations reduced individual effort disappointment frustration erode confidence government people gove rnment must learn take less people people let us remember america built government people welfare work shirking responsibility seeking responsibility lives let us ask government challenges face together let us ask government help help national government great vital role play pledge government act act boldly lead boldly important role every one us must play individual member comm unity day forward let us make solemn commitment heart bear responsibility part live ideals together see dawn new age progress a

merica together celebrate th anniversary nation proud fulfillment promise world america longest difficult war comes end let us learn debate differences civility decency let us reach one precious quality government provide new level respect rights feeling s one another new level respect individual human dignity cherished birthright every american else time come us renew faith amer ica recent years faith challenged children taught ashamed country ashamed parents ashamed america record home role world every turn beset find everything wrong america little right confident judgment history remarkable times privileged live america recor d century unparalleled world history responsibility generosity creativity progress let us proud system produced provided freedo m abundance widely shared system history world let us proud four wars engaged century including one bringing end fought selfish advantage help others resist aggression let us proud bold new initiatives steadfastness peace honor made break toward creating world world known structure peace last merely time generations come embarking today era presents challenges great nation genera tion ever faced shall answer god history conscience way use years stand place hallowed history think others stood think dreams america think recognized needed help far beyond order make dreams come true today ask prayers years ahead may god help making d ecisions right america pray help together may worthy challenge let us pledge together make next four years best four years amer ica history th birthday america young vital began bright beacon hope world let us go forward confident hope strong faith one an other sustained faith god created us striving always serve purpose

2.3 Which word occurs the most number of times in his inaugural address for each president? Mention the top three words.(after removing the stopwords)

2.3.1 : Word occurs the most in speech Franklin D. Roosevelt
2.3.2 : Word occurs the most in speech John F. Kennedy
2.3.3 : Word occurs the most in speech Richard Nixon

2.3.1 : Word occurs the most in speech Franklin D. Roosevelt

Nation

```
## Stemming Using Lemmatizer -  Stem the words to its root word
from nltk import WordNetLemmatizer
lt = nltk.WordNetLemmatizer()
texts = [lt.lemmatize(i) for i in stopped_tokens]
```

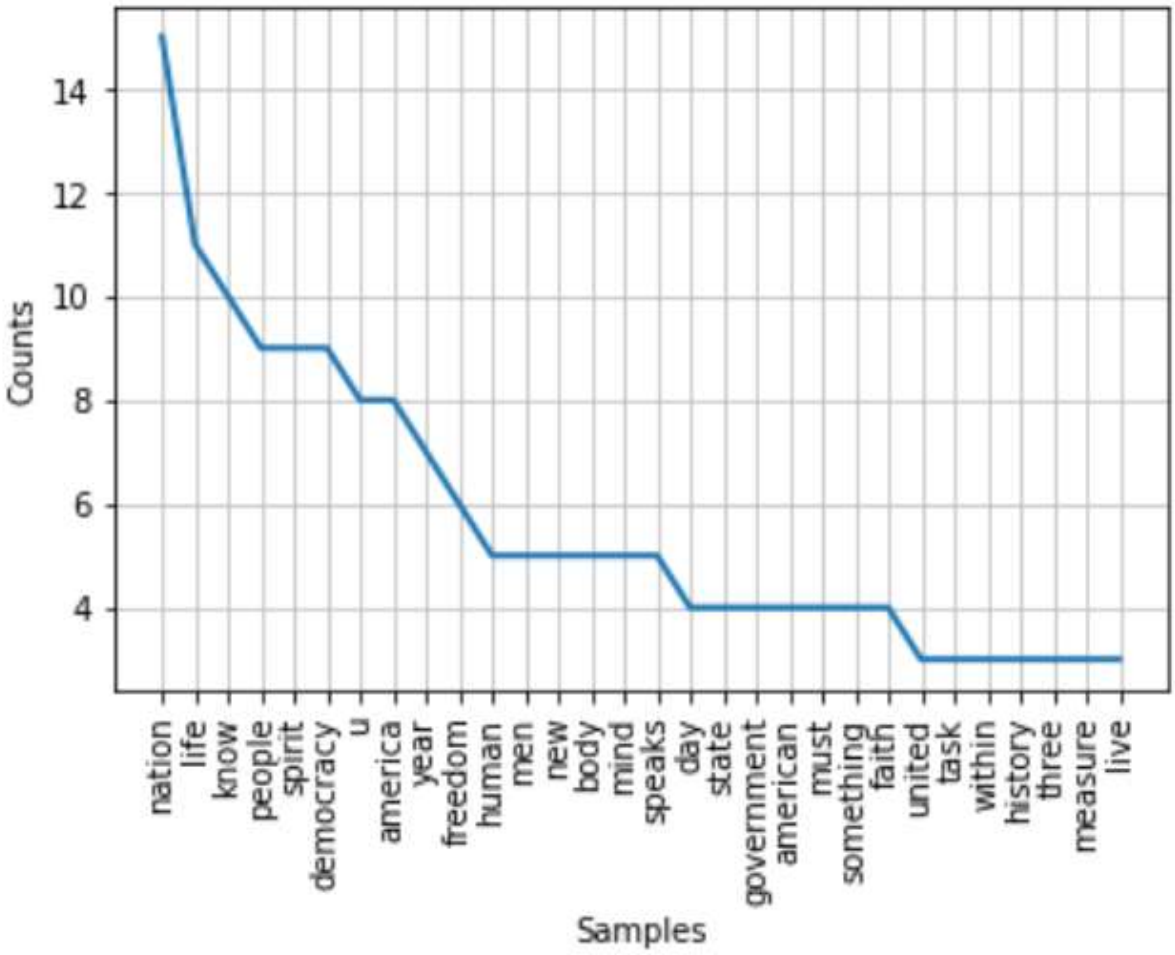
```
## Stemming Using Lemmatizer -  Stem the words to its root word
from nltk import WordNetLemmatizer
lt = nltk.WordNetLemmatizer()
texts = [lt.lemmatize(i) for i in stopped_tokens]## Top 10 frequency occuring words
Roosevelt_10 = nltk.FreqDist(texts).most_common(10)
Roosevelt_10

# Word which is used the most
Roosevelt_1 = nltk.FreqDist(texts).most_common(1)
Roosevelt_1

```

```
[('nation', 15)]
```

```
print('The word which used mostly in Roosevelt speech is nation.')
```

```
The word which used mostly in Roosevelt speech is nation.
```

Frequency plot:



2.3.2 : Word occurs the most in speech John F. Kennedy

Let

```
## Stemming Using Lemmatizer -  Stem the words to its root word
from nltk import WordNetLemmatizer
lt = nltk.WordNetLemmatizer()
texts2 = [lt.lemmatize(i) for i in stopped_tokens]## Top 10 frequency occuring words
Kennedy_10 = nltk.FreqDist(texts2).most_common(10)
Kennedy_10
Kennedy_1 = nltk.FreqDist(texts2).most_common(1)
Kennedy_1
```

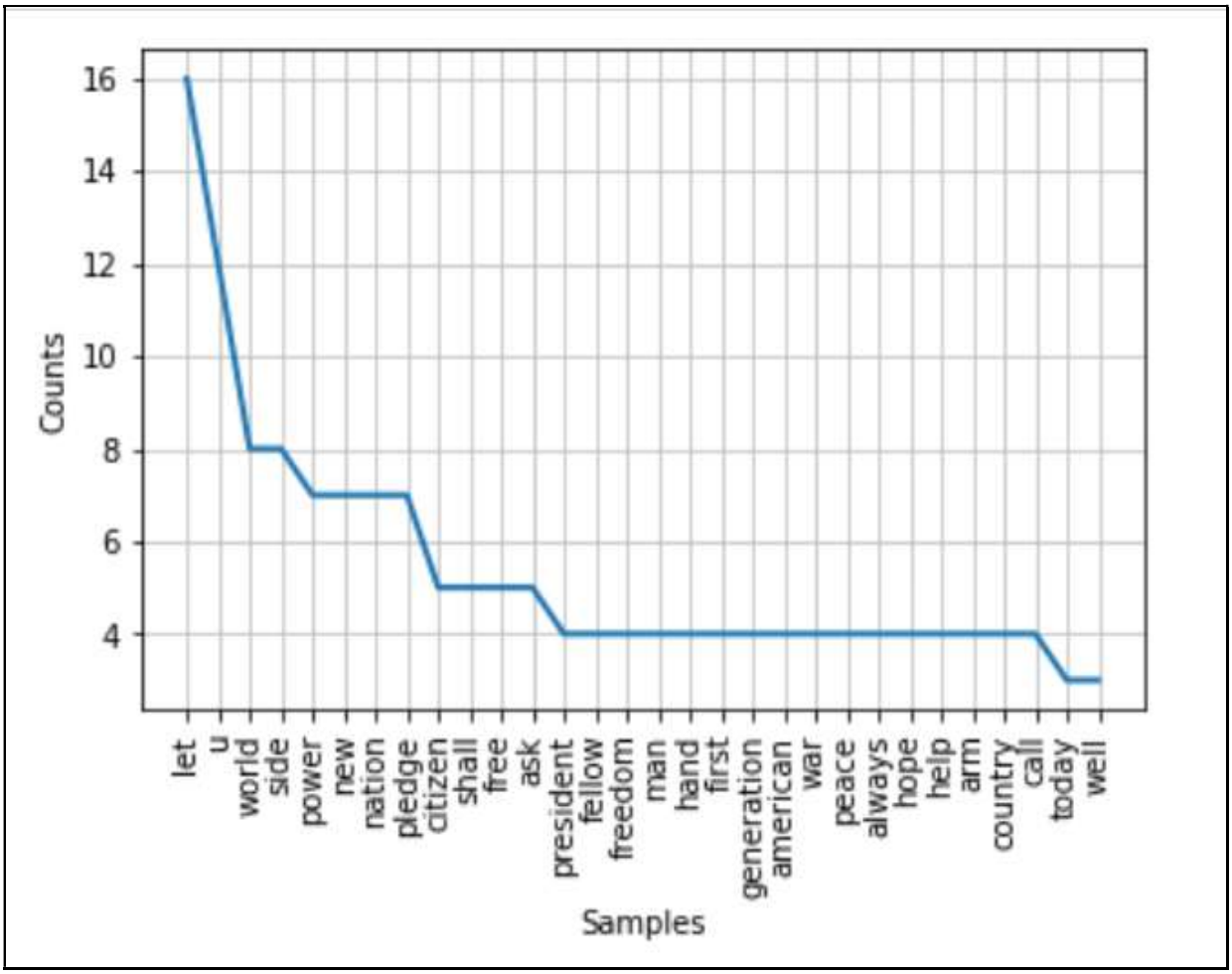
```
[('let', 16)]
```

```
print('The word which is Occurred most in John F. Kennedy Speech is let')
```

```
The word which is Occurred most in John F. Kennedy Speech is let
```

Here if we additionally remove some words, world is the most used words.

Frequency plot:



2.3.3 : Word occurs the most in speech Richard Nixon

u (Before removing user-defined stopwords like let and u)

america (After removing user-defined stopwords like let and u)

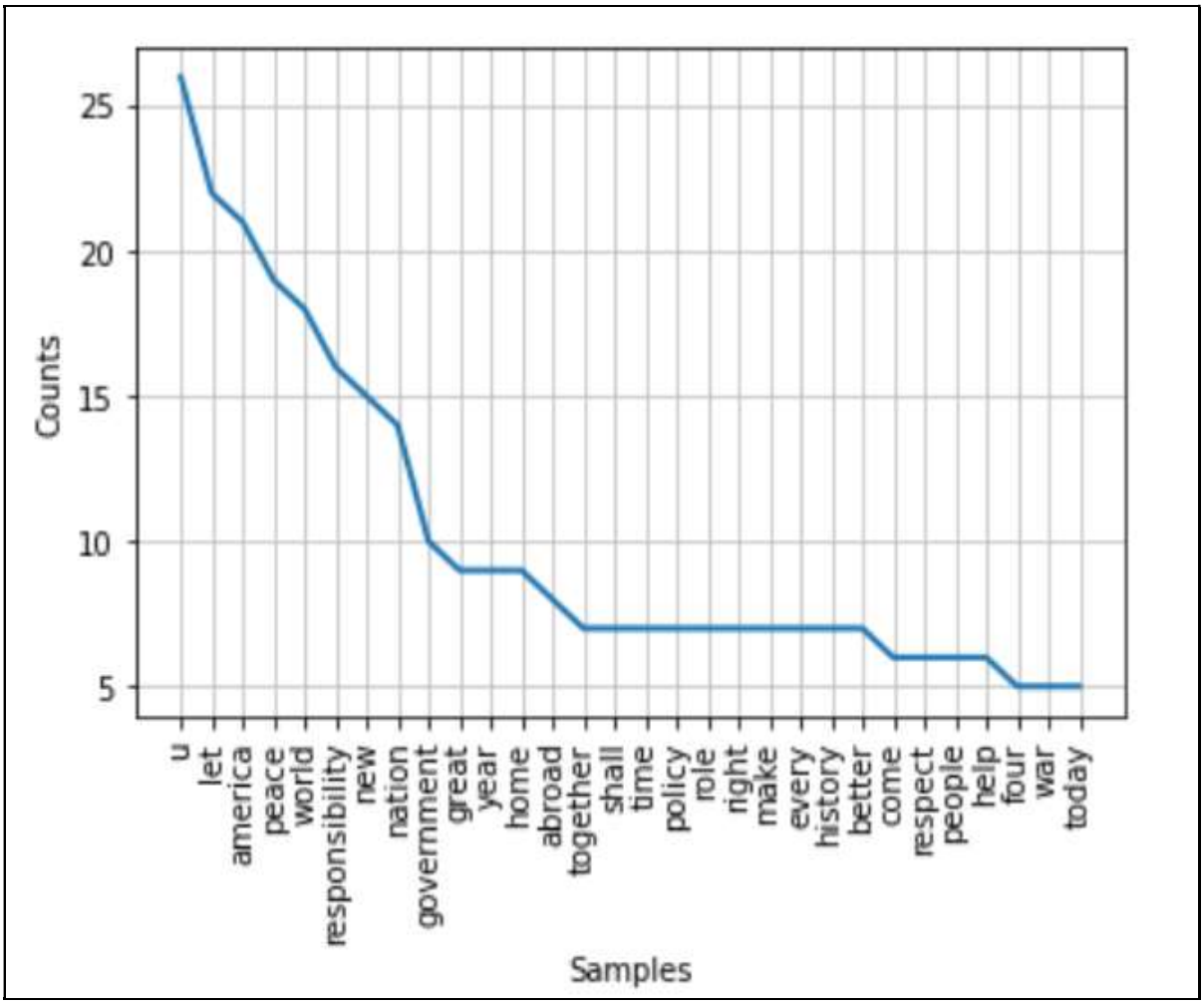
```
## Stemming Using Lemmatizer -  Stem the words to its root word
from nltk import WordNetLemmatizer
lt = nltk.WordNetLemmatizer()
texts3 = [lt.lemmatize(i) for i in stopped_tokens3]## Top 10 frequency occuring words
Nixon_10 = nltk.FreqDist(texts3).most_common(10)
Nixon_10
Nixon_1 = nltk.FreqDist(texts3).most_common(1)
Nixon_1
```

```
[('u', 26)]
```

```
print('Before removing stopwords The word which is Occurred most in Nixon Speech is u')
print('After removing stopwords The word which is Occurred most in Nixon Speech is america')
```

```
Before removing stopwords The word which is Occurred most in Nixon Speech is u
After removing stopwords The word which is Occurred most in Nixon Speech is america
```

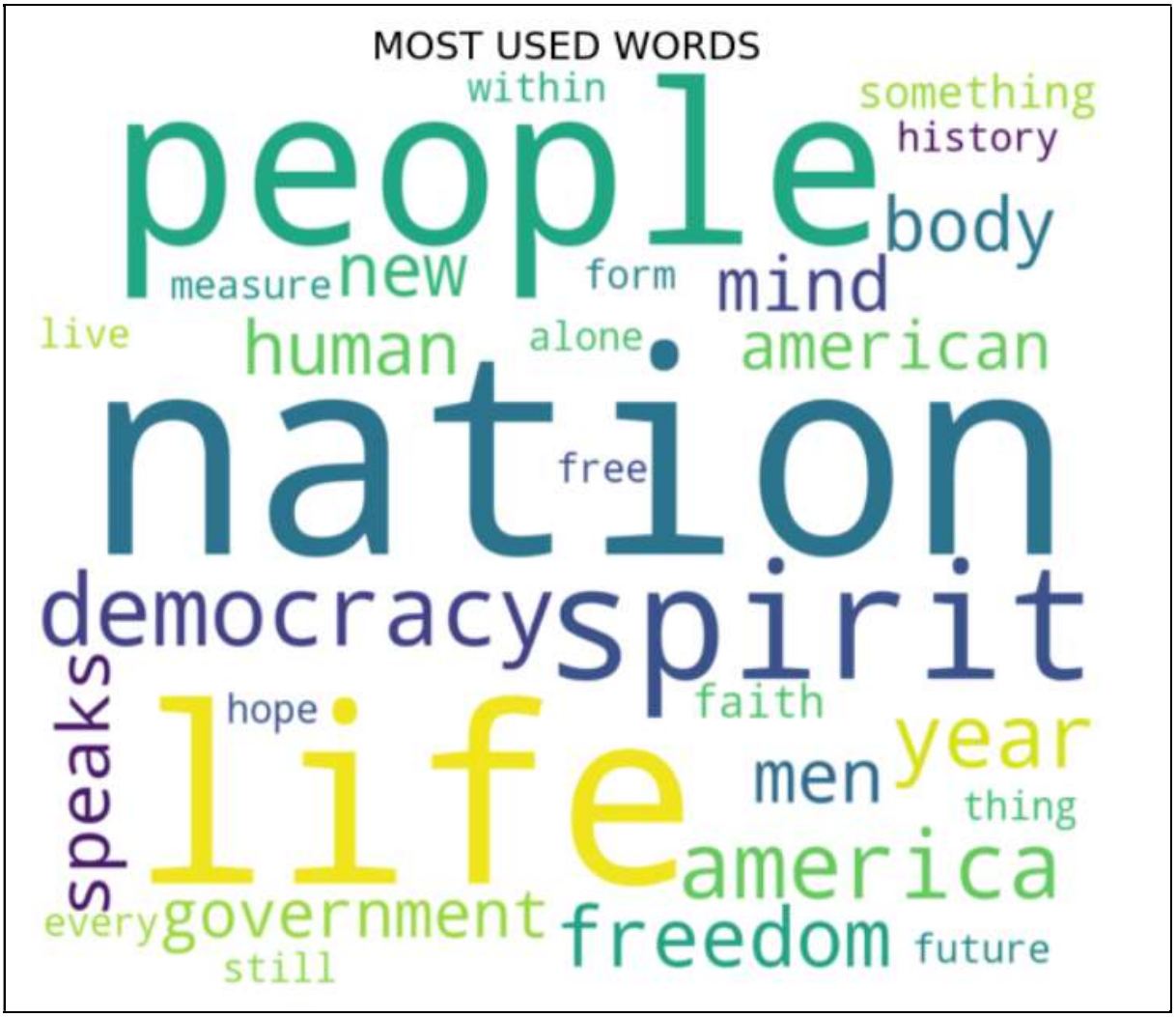
Frequency plot:


Counts
25
20
15
10
5
u
let
america
peace
world
responsibility
new
nation
government
great
year
home
abroad
together
shall
time
policy
role
right
make
every
history
better
come
respect
people
help
four
war
today
Samples

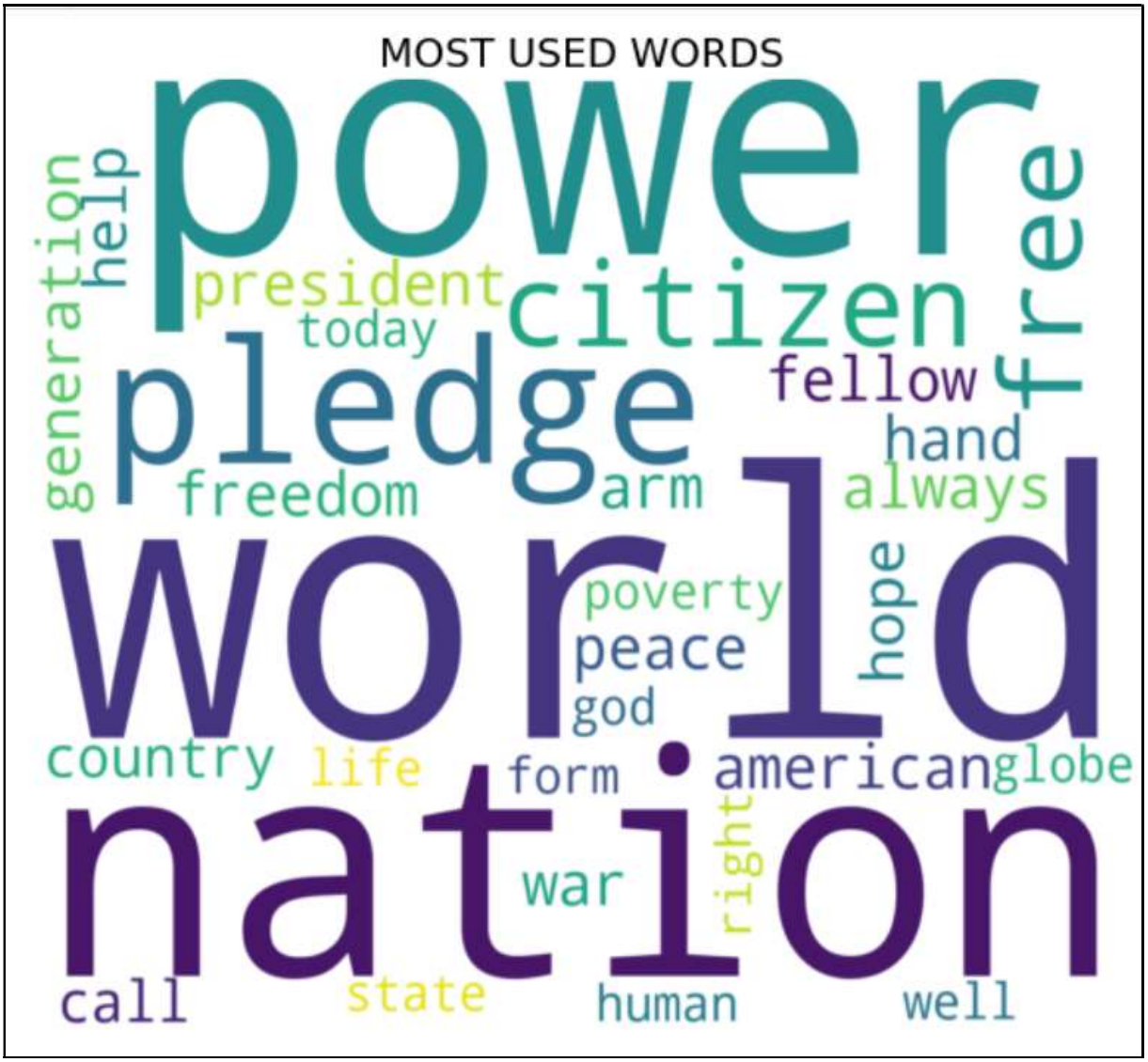
2.4 Plot the word cloud of each of the speeches of the variable. (after removing the stopwords)

2.4.1 : WordCloud for Franklin D. Roosevelt
2.4.2 : WordCloud for John F. Kennedy
2.4.3 : WordCloud for Richard Nix

2.4.1 : WordCloud for Franklin D. Roosevelt



2.4.2 : WordCloud for John F. Kennedy



2.4.3 : WordCloud for Richard Nixon