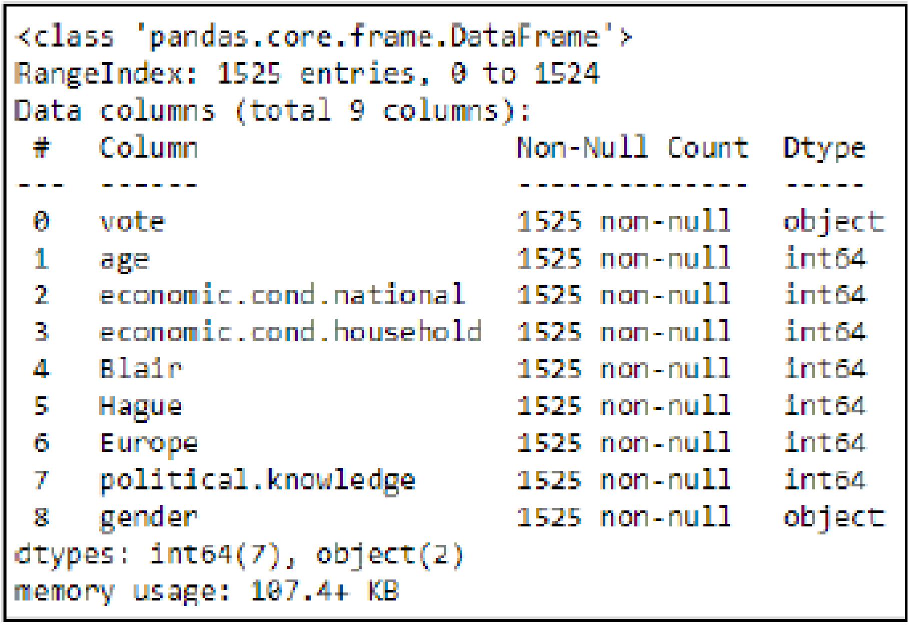
ML 2-COded project by Sowmya Subramaniam -Date:17-03-2024

Problem 1:

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.

1.1 Read the dataset. Do the descriptive statistics and do the null value condition check.



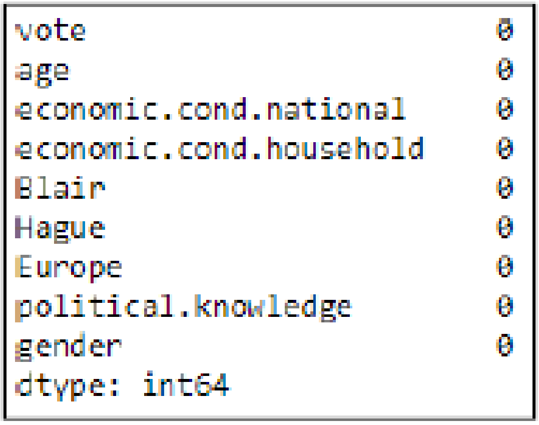
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1525 entries, 0 to 1524
Data columns (total 9 columns):
 #   Column                   Non-Null Count  Dtype 
---  ------                   --------------  ----- 
 0   vote                     1525 non-null   object
 1   age                      1525 non-null   int64 
 2   economic.cond.national   1525 non-null   int64 
 3   economic.cond.household  1525 non-null   int64 
 4   Blair                    1525 non-null   int64 
 5   Hague                    1525 non-null   int64 
 6   Europe                   1525 non-null   int64 
 7   political.knowledge      1525 non-null   int64 
 8   gender                   1525 non-null   object
dtypes: int64(7), object(2)
memory usage: 107.4+ KB
```

<u>Observation:</u>

- We have dropped the 'unnamed' column from the dataset as it is not useful for our study.
- The dataset had 8 duplicated values. So, we are dropped them.

- The data set had 1525 rows and 9 columns. After dropping the duplicate values, there are 1517 rows and 9 columns.
- It has 7 numerical data types and 2 categorical data types.
- There is no null value in any column.

Checking for missing values:



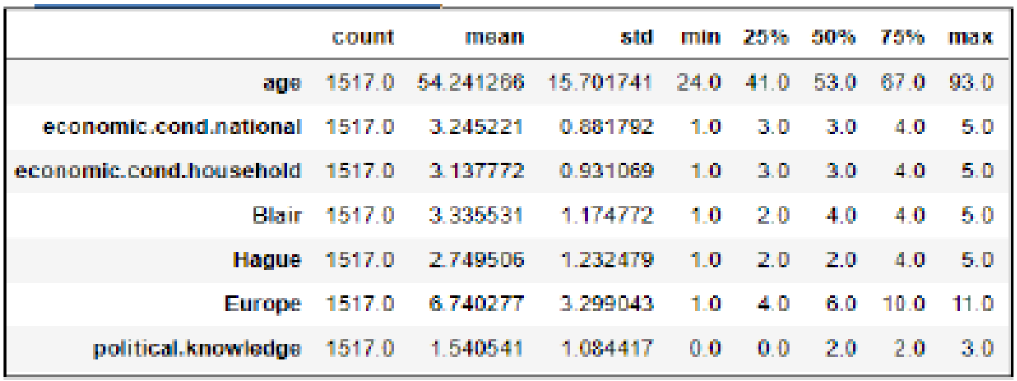
```
vote                       0
age                        0
economic.cond.national     0
economic.cond.household    0
Blair                      0
Hague                      0
Europe                     0
political.knowledge        0
gender                     0
dtype: int64
```

There are no missing values.

Checking for duplicated values:

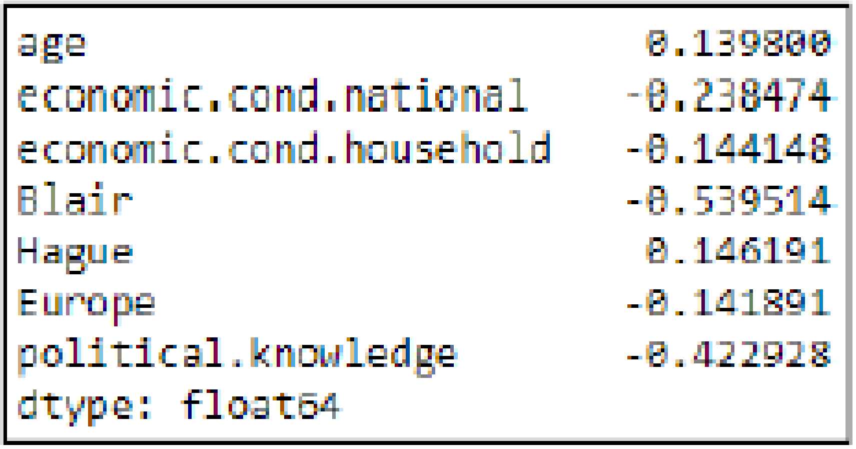
There are 8 duplicated values. So, we are dropping them.

Data description:



	count	mean	std	min	25%	50%	75%	max
age	1517.0	54.241266	15.701741	24.0	41.0	53.0	67.0	93.0
economic.cond.national	1517.0	3.245221	0.881792	1.0	3.0	3.0	4.0	5.0
economic.cond.household	1517.0	3.137772	0.931069	1.0	3.0	3.0	4.0	5.0
Blair	1517.0	3.335531	1.174772	1.0	2.0	4.0	4.0	5.0
Hague	1517.0	2.749506	1.232479	1.0	2.0	2.0	4.0	5.0
Europe	1517.0	6.740277	3.299043	1.0	4.0	6.0	10.0	11.0
political.knowledge	1517.0	1.540541	1.084417	0.0	0.0	2.0	2.0	3.0

Checking the skewness of the data:



```
age                         0.139800
economic.cond.national     -0.238474
economic.cond.household    -0.144148
Blair                      -0.539514
Hague                       0.146191
Europe                     -0.141891
political.knowledge        -0.422928
dtype: float64
```

The rule of thumb of skewness seems to be:

• If the skewness is between -0.5 and 0.5, the data are fairly symmetrical.

• If the skewness is between -1 and – 0.5 or between 0.5 and 1, the data are moderately skewed.

• If the skewness is less than -1 or greater than 1, the data are highly skewed.

Inferences:

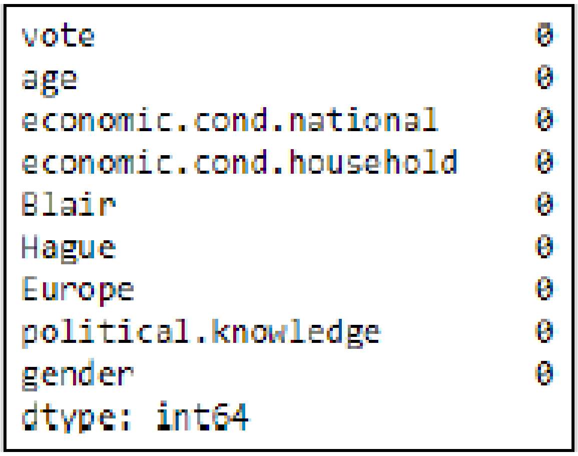
- Here, we can see that there isn't much skewness in the data.
- All the values are between -0.5 and 0.5.
- The value of 'Blair' is a little bit higher than -0.5.

- The data overall, is fairly symmetrical.

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

Exploratory Data Analysis:

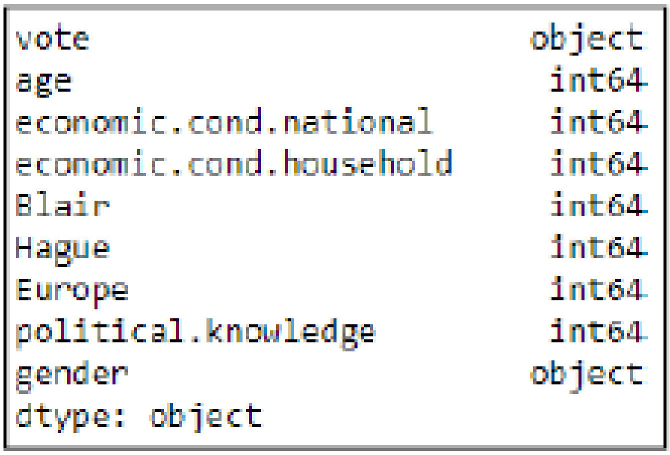
Null value check:



```
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
```

There are no null values present in the data.

Data types:

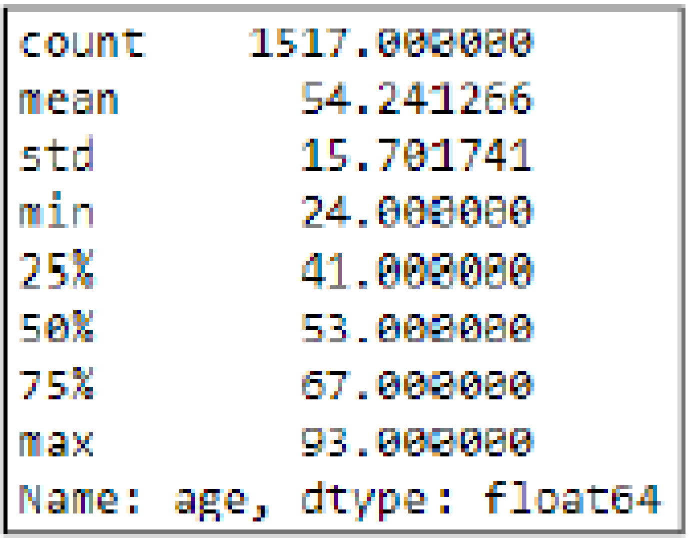


```
vote                        object
age                          int64
economic.cond.national       int64
economic.cond.household      int64
Blair                        int64
Hague                        int64
Europe                       int64
political.knowledge          int64
gender          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

There are 7 numerical and 2 categorical data types in the data.

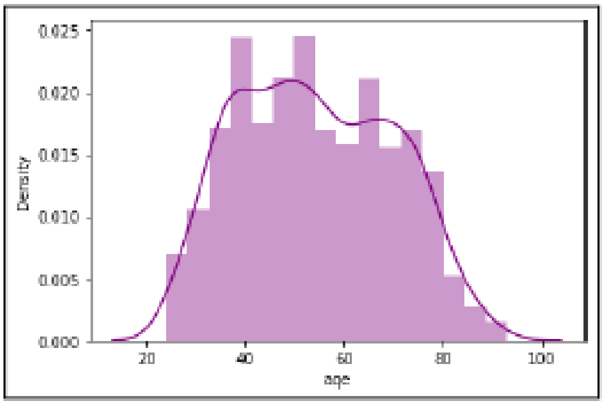
Univariate Analysis:

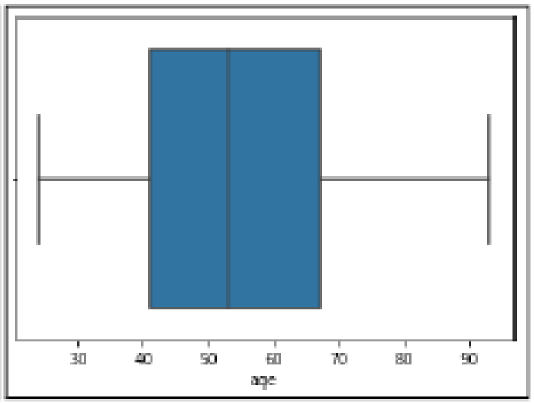
Description of 'age':



```
count    1517.000000
mean       54.241266
std        15.701741
min        24.000000
25%        41.000000
50%        53.000000
75%        67.000000
max        93.000000
Name: age, dtype: float64
```

Histogram and boxplot of 'age':

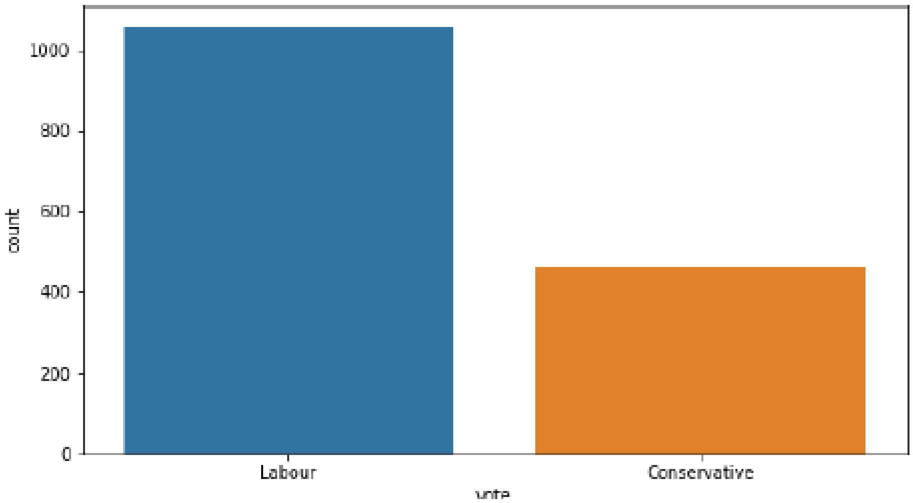


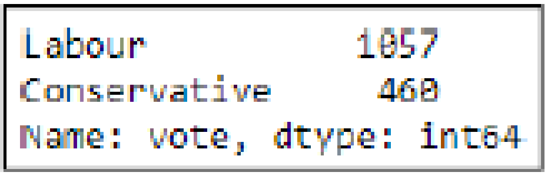


Observation:

- The data is normally distributed.
- Maximum number of people are aged between 40 and 70.
- Outliers are not present.
- The minimum value is 24 and the maximum value is 93.
- The mean value is 54.241266

Count plot of 'vote':





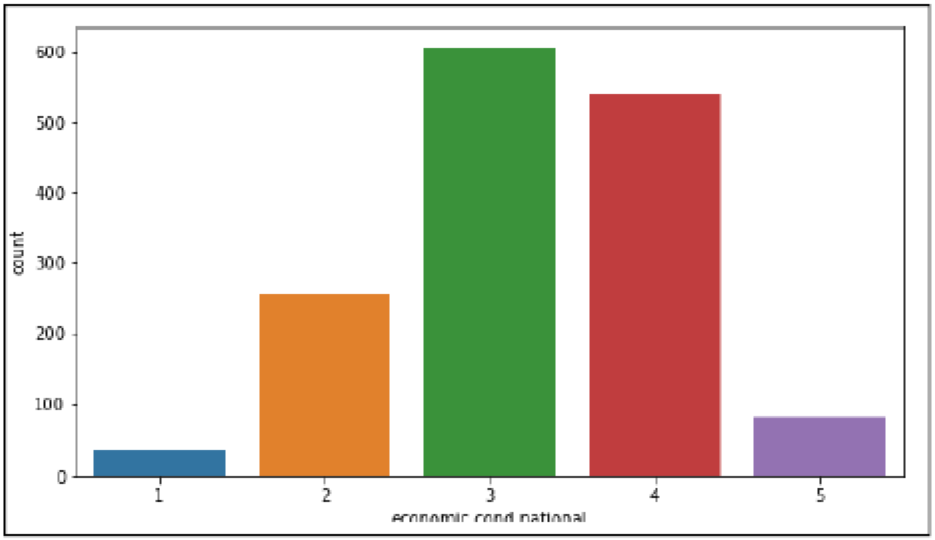
```
Labour          1057
Conservative     460
Name: vote, dtype: int64
```

Observation:

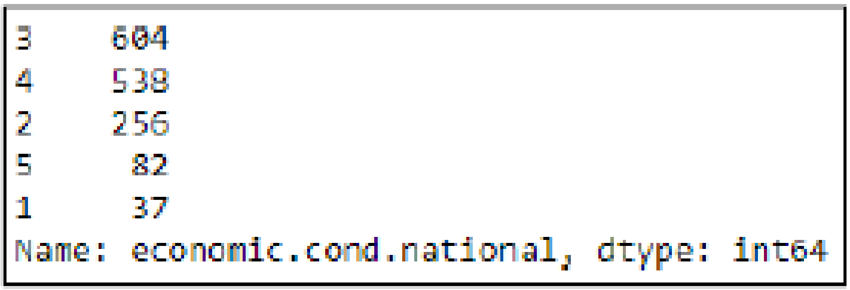
• Labour party has higher number of votes. It has more than double the votes of conservative party.

• Labour party has 1057 votes.

• Conservative party has 460 votes.

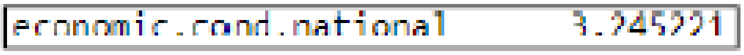


Count plot of 'economic.cond.national':



```
3    604
4    538
2    256
5     82
1     37
Name: economic.cond.national, dtype: int64
```

Mean of 'economic.cond.national':



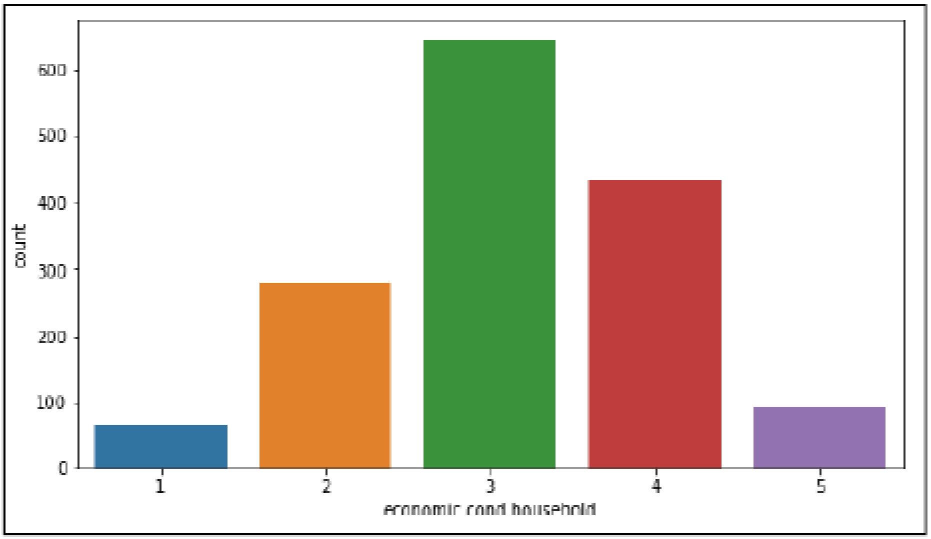
```
economic.cond.national       3.245221
```

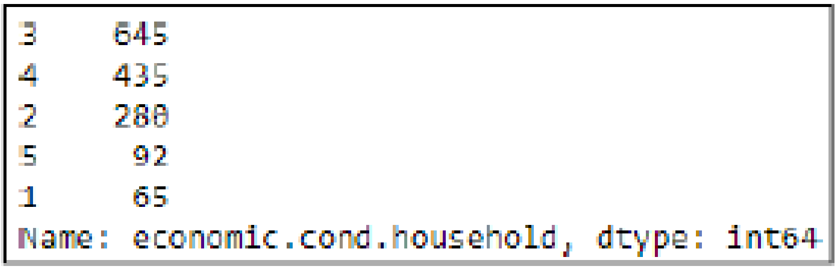
Observation:

- The top 2 variables are 3 and 4.
- 1 has the least value which is 37.
- 3 has the highest value which is 604.

- 3 is slightly higher than the 2nd highest variable 4 whose value is 538.
- The average score of 'economic.cond.national' is 3.245221

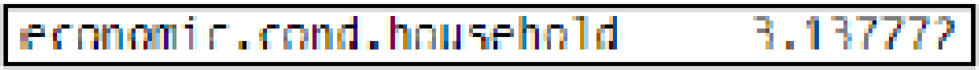
Count plot of 'economic.cond.household':





```
3    645
4    435
2    280
5     92
1     65
Name: economic.cond.household, dtype: int64
```

Mean of 'economic.cond.household':



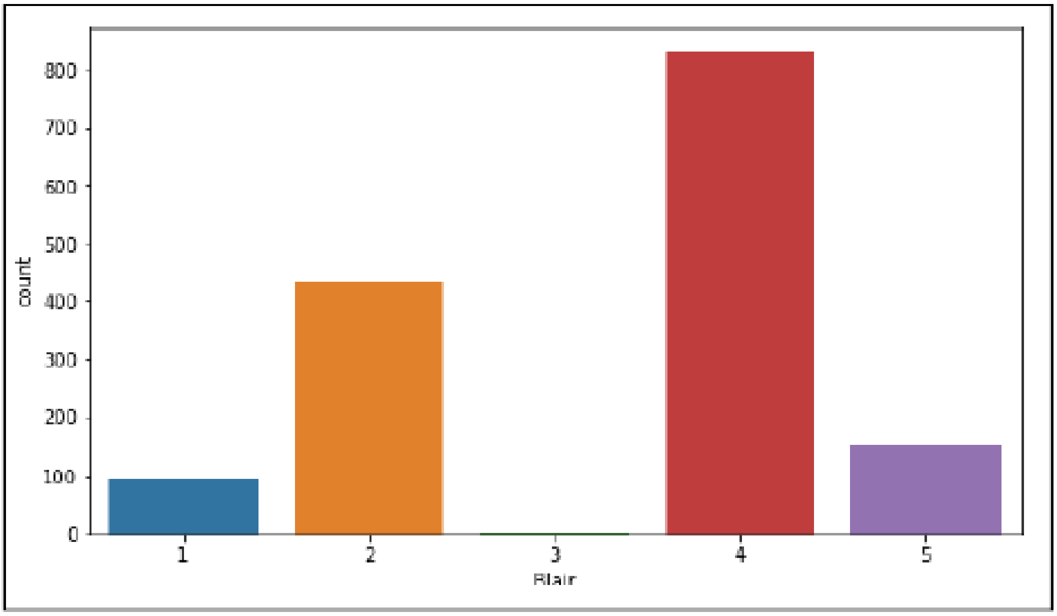
```
economic.cond.household     3.137772
```

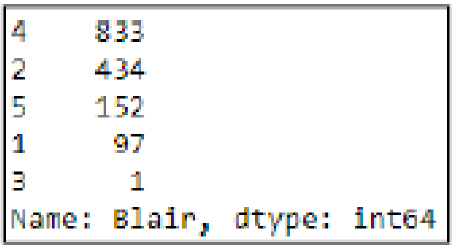
Observation:

- The top 2 variables are 3 and 4.
- 1 has the least value which is 65.

- 3 has the highest value which is 645.
- 3 is moderately higher than the 2nd highest variable 4 whose value is 435.
- The average score of 'economic.cond.household' is 3.137772

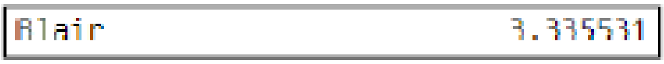
Count plot of 'Blair':





```
4    833
2    434
5    152
1     97
3      1
Name: Blair, dtype: int64
```

Mean of 'Blair':



```
Blair                       3.335531
```

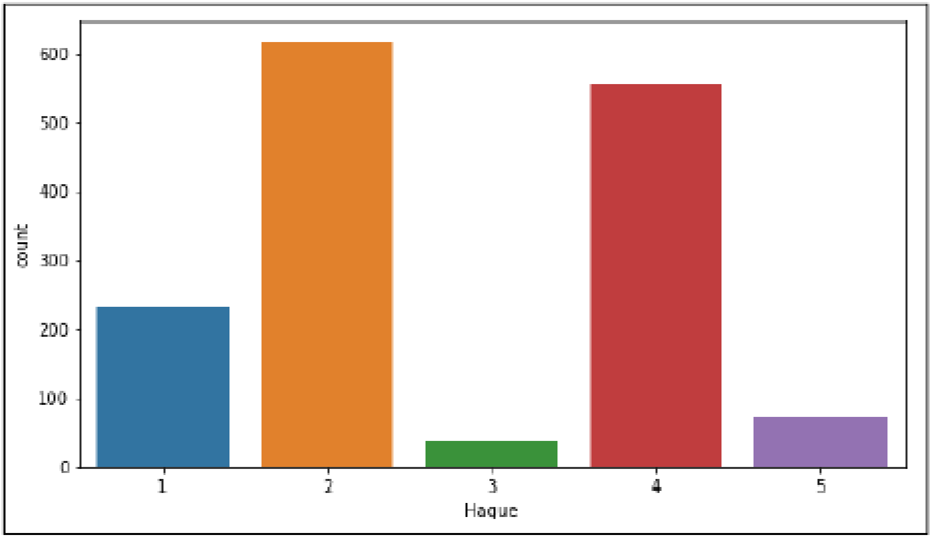
Observation:

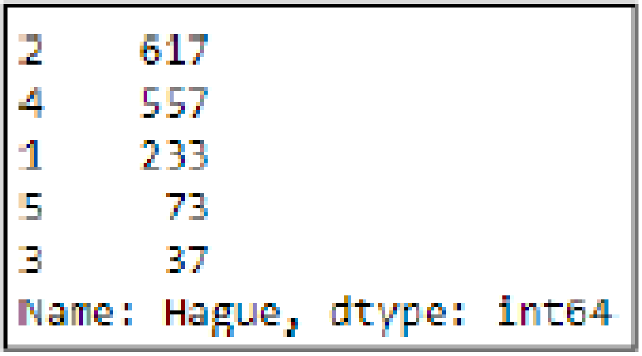
- The top 2 variables are 2 and 4.

- 3 has the least value which is 1.
- 4 has the highest value which is 833.
- 4 is much higher than the 2nd highest variable 2 whose value is 434.

The average score of 'Blair' is 3.335531

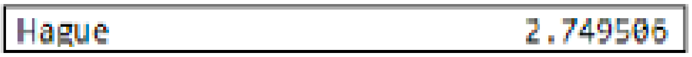
Count plot of 'Hague':





```
2    617
4    557
1    233
5     73
3     37
Name: Hague, dtype: int64
```

Mean of 'Hague':



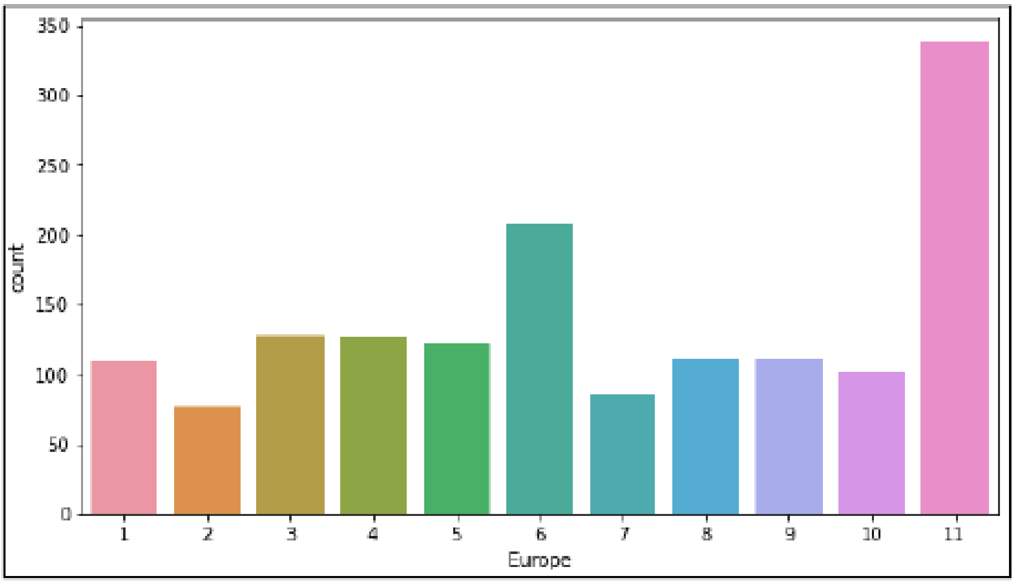
```
Hague                    2.749506
```

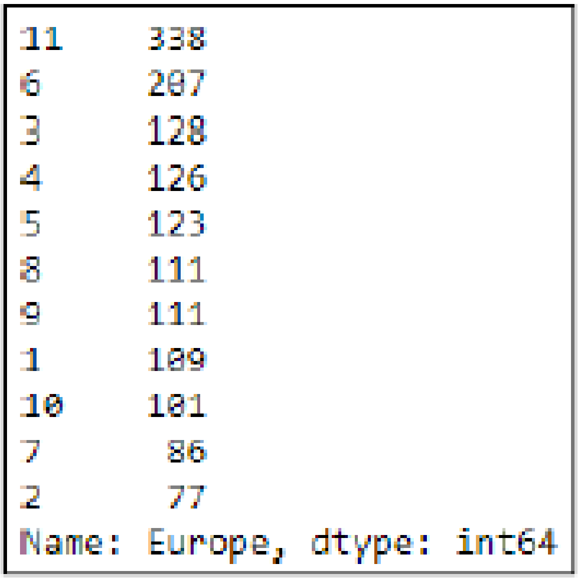
Observation:

The top 2 variables are 2 and 4.

- 3 has the least value which is 37.
- 2 has the highest value which is 617.
  - 2 is slightly higher than the 2nd highest variable 4 whose value is 557.
- The average score of 'Blair' is 2.749506

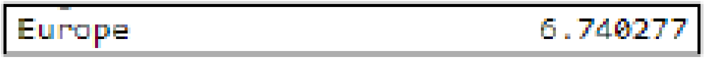
Count plot of 'Europe':





```
11    338
6     207
3     128
4     126
5     123
8     111
9     111
1     109
10    101
7      86
2      77
Name: Europe, dtype: int64
```

Mean of 'Europe':

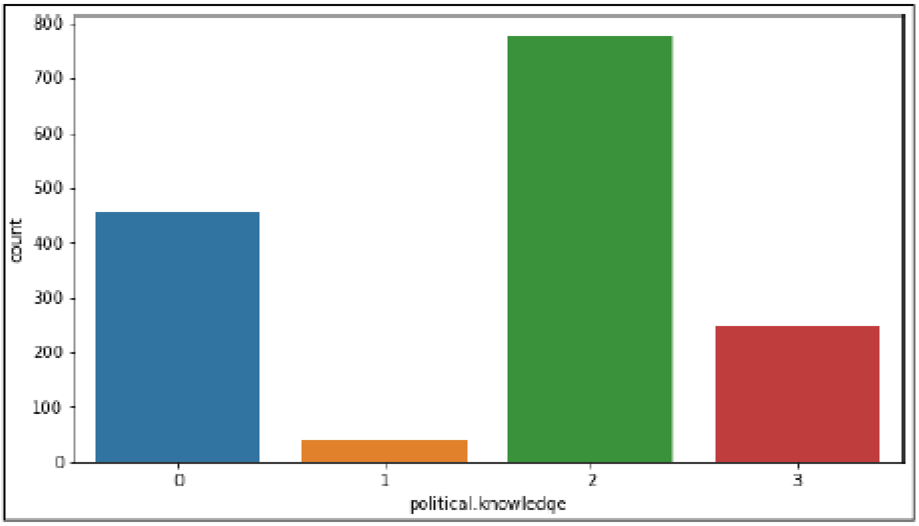


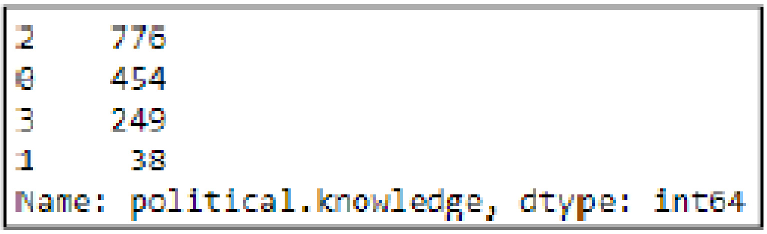
```
Europe                 6.740277
```

Observation:

- The top 2 variables are 11 and 6.
- 2 has the least value which is 77.
- 11 has the highest value which is 338.
- 11 is moderately higher than the 2nd highest variable 6 whose value is 207.
- The average score of 'Europe' is 6.740277

Count plot of 'political.knowledge':





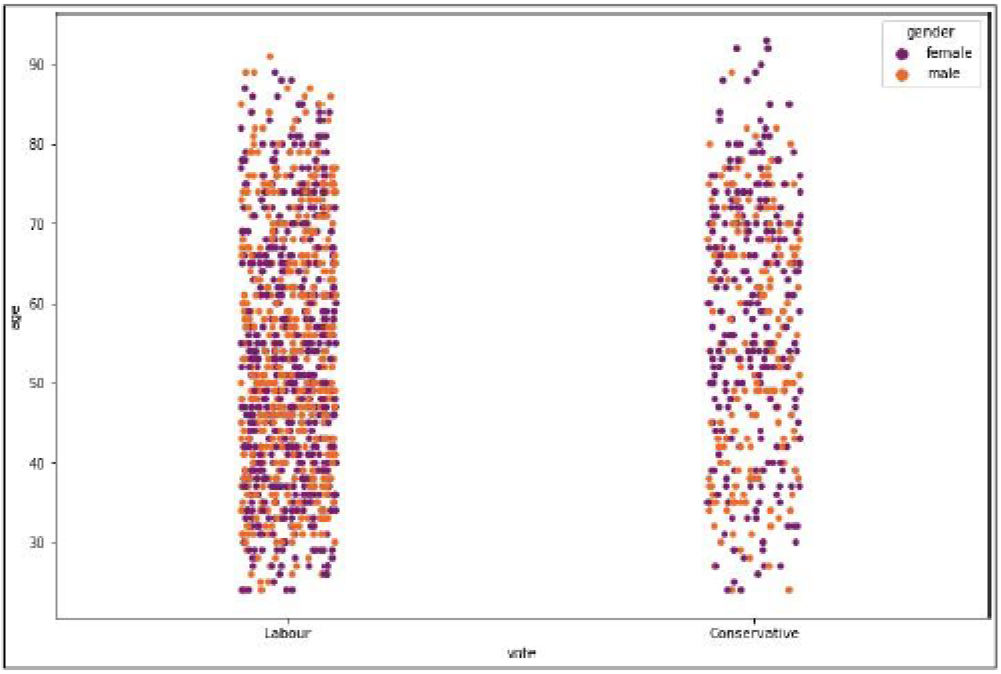
```
2    776
0    454
3    249
1     38
Name: political.knowledge, dtype: int64
```

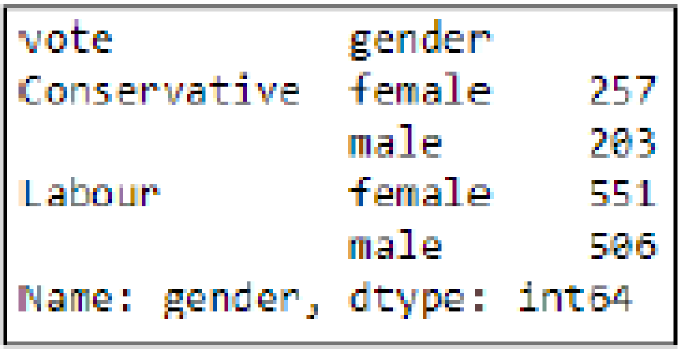
Observation:

- The top 2 variables are 2 and 0
  - 1 has the least value which is 38.
- 2 has the highest value which is 776.
- 2 is much higher than the 2nd highest variable 0 whose value is 454.
- We can see that, 454 out of 1517 people do not have any knowledge of parties' positions on European integration which is 29.93% of the total population.
- The average score of 'Europe' is 6.740277

Bivariate Analysis:

Strip plot of 'vote' and 'age':



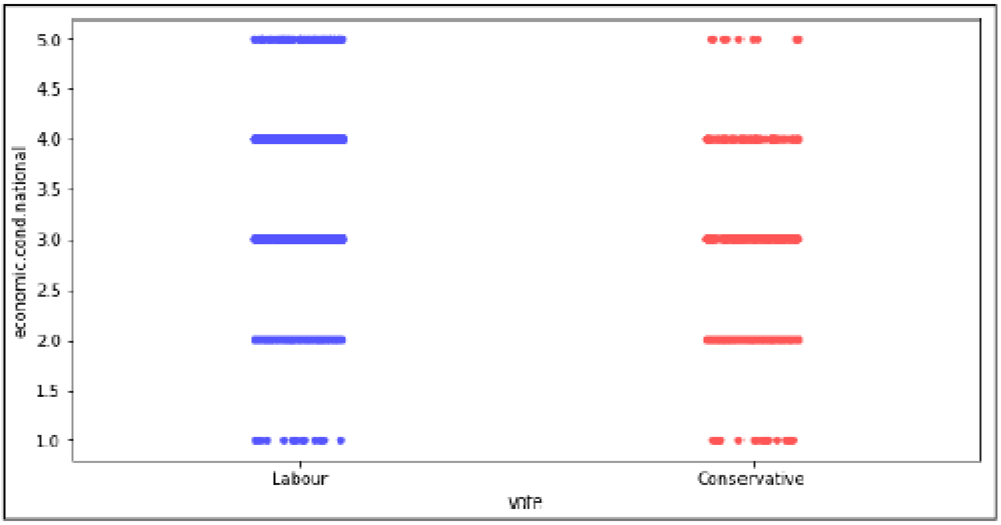


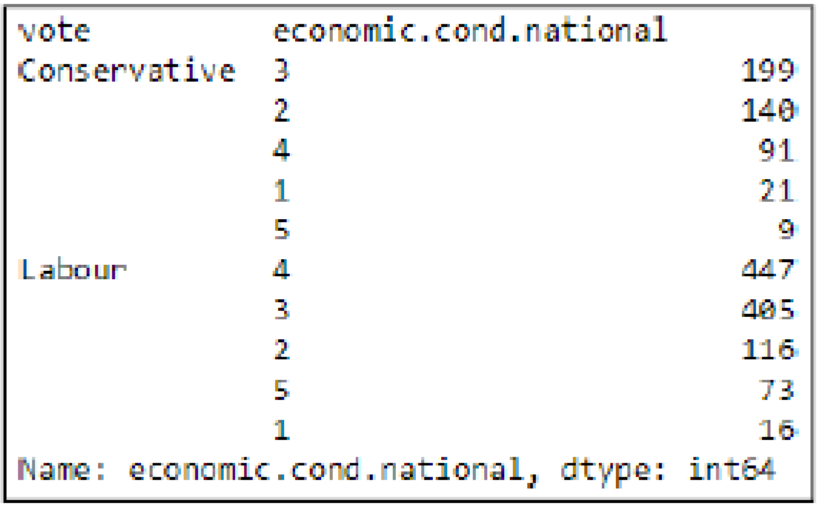
```
vote          gender
Conservative  female    257
              male      203
Labour        female    551
              male      506
Name: gender, dtype: int64
```

Observation:

- We can clearly see that, the labour party has got more votes than the conservative party.
- In every age group, the labour party has got more votes than the conservative party.
- Female votes are considerably higher than the male votes in both parties.
- In both genders, the labour party has got more votes than the conservative party.

Strip plot of 'vote' and 'economic.cond.national':





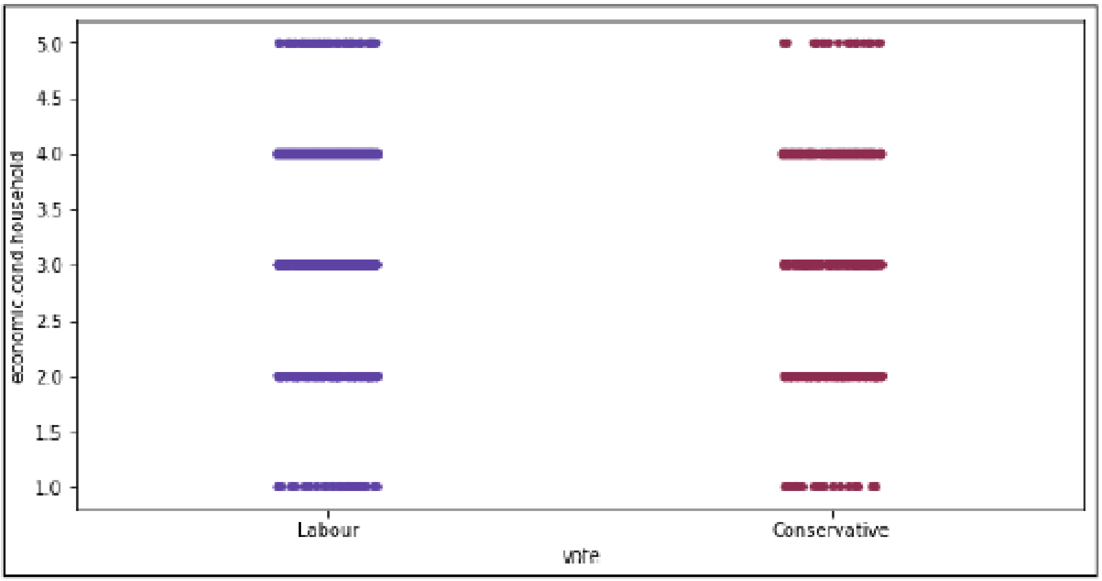
```
vote          economic.cond.national
Conservative  3                         199
              2                         140
              4                          91
              1                          21
              5                           9
Labour        4                         447
              3                         405
              2                         116
              5                          73
              1                          16
Name: economic.cond.national, dtype: int64
```

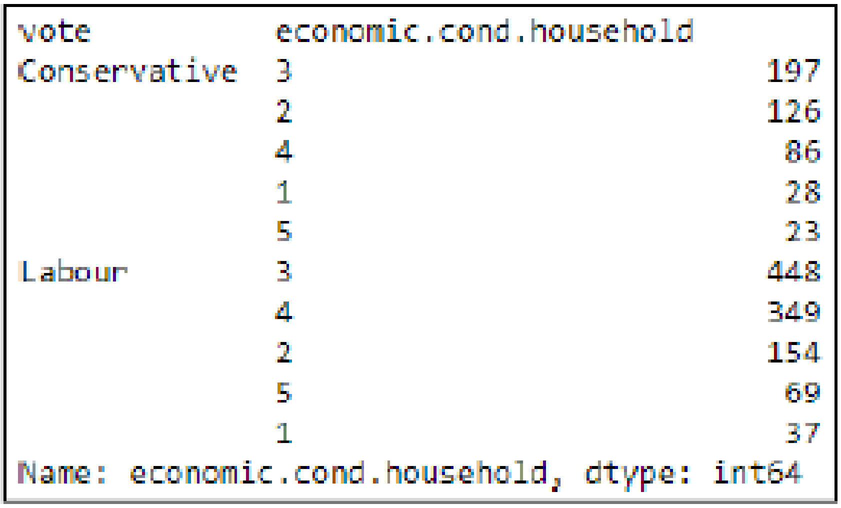
Observation:

- Labour party has higher votes overall.
- Out of 82 people who gave a score of 5, 73 people have voted for the labour party.

- Out of 538 people who gave a score of 4, 447 people have voted for the labour party. This is the highest set of people in the labour party.
- Out of 604 people who gave a score of 3, 405 people have voted for the labour party. This is the 2nd highest set of people in the labour party. The remaining 199 people who have voted for the conservative party is the highest set of people in that party.
- Out of 256 people who gave a score of 2, 116 people have voted for the labour party. 140 people have voted for the conservative party. This is the instance where the conservative party has got more votes than the labour party.
- Out of 37 people who gave a score of 1, 16 people have voted for the labour party. 21 people have voted for the conservative party.
- The score of 3, 4 and 5 have more votes in the labour party.
- The score of 1 and 2 have more votes in the conservative party.

Strip plot of 'vote' and 'economic.cond.household':





```
vote          economic.cond.household
Conservative  3                           197
              2                           126
              4                            86
              1                            28
              5                            23
Labour        3                           448
              4                           349
              2                           154
              5                            69
              1                            37
Name: economic.cond.household, dtype: int64
```

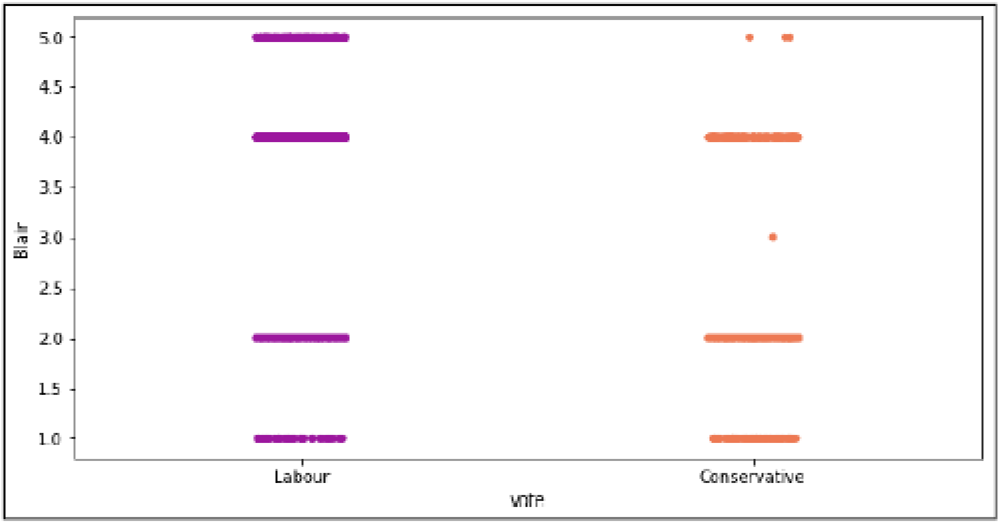
Observation:

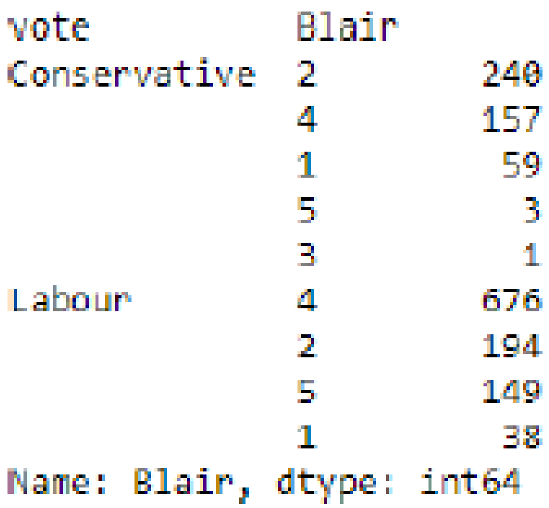
- Labour party has higher votes overall.
- Out of 92 people who gave a score of 5, 69 people have voted for the labour party.
- Out of 435 people who gave a score of 4, 349 people have voted for the labour party. This is the 2nd highest set of people in the labour party.

Out of 645 people who gave a score of 3, 448 people have voted for the labour party. This is the highest set of people in the labour party. The remaining 197 people who have voted for the conservative party is the highest set of people in that party.

- Out of 280 people who gave a score of 2, 154 people have voted for the labour party. 126 people have voted for the conservative party.
- Out of 65 people who gave a score of 1, 37 people have voted for the labour party. 28 people have voted for the conservative party.
- In all the instances, the labour party have more votes than the conservative party.

Strip plot of 'vote' and 'Blair':





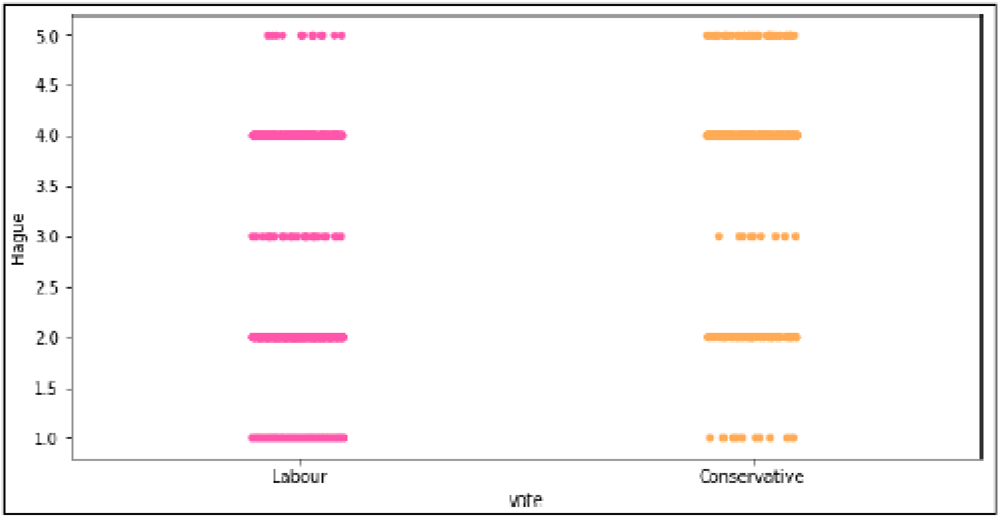
```
vote          Blair
Conservative  2        240
              4        157
              1         59
              5          3
              3          1
Labour        4        676
              2        194
              5        149
              1         38
Name: Blair, dtype: int64
```

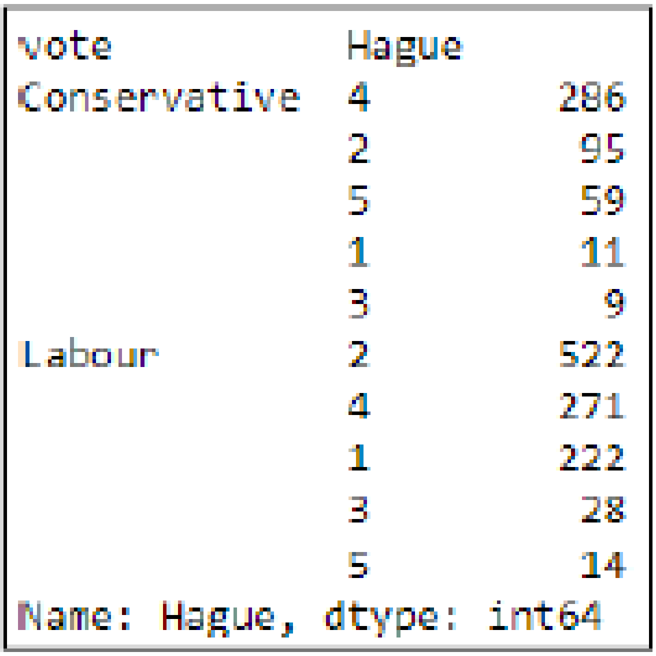
Observation:

- Labour party has higher votes overall.
- Out of 152 people who gave a score of 5, 149 people have voted for the labour party. The remaining 3 people, despite giving a score of 5 to the labour leader, have chosen to vote for the conservative party.

- Out of 833 people who gave a score of 4, 676 people have voted for the labour party. The remaining 157 people, despite giving a score of 4 to the labour leader, have chosen to vote for the conservative party.
- Only 1 person has given a score of 3 and that person has voted for the conservative party.
- Out of 434 people who gave a score of 2, 240 people have voted for the conservative party. The remaining 194 people, despite giving an unsatisfactory score of 2 to the labour leader, have chosen to vote for the labour party.
- Out of 97 people who gave a score of 1, 59 people have voted for the conservative party. The remaining 38 people, despite giving the lowest score of 1 to the labour leader, have chosen to vote for the labour party.
- The score of 4 and 5 have more votes in the labour party.
- The score of 1, 2 and 3 have more votes in the conservative party.

Strip plot of 'vote' and 'Hague':





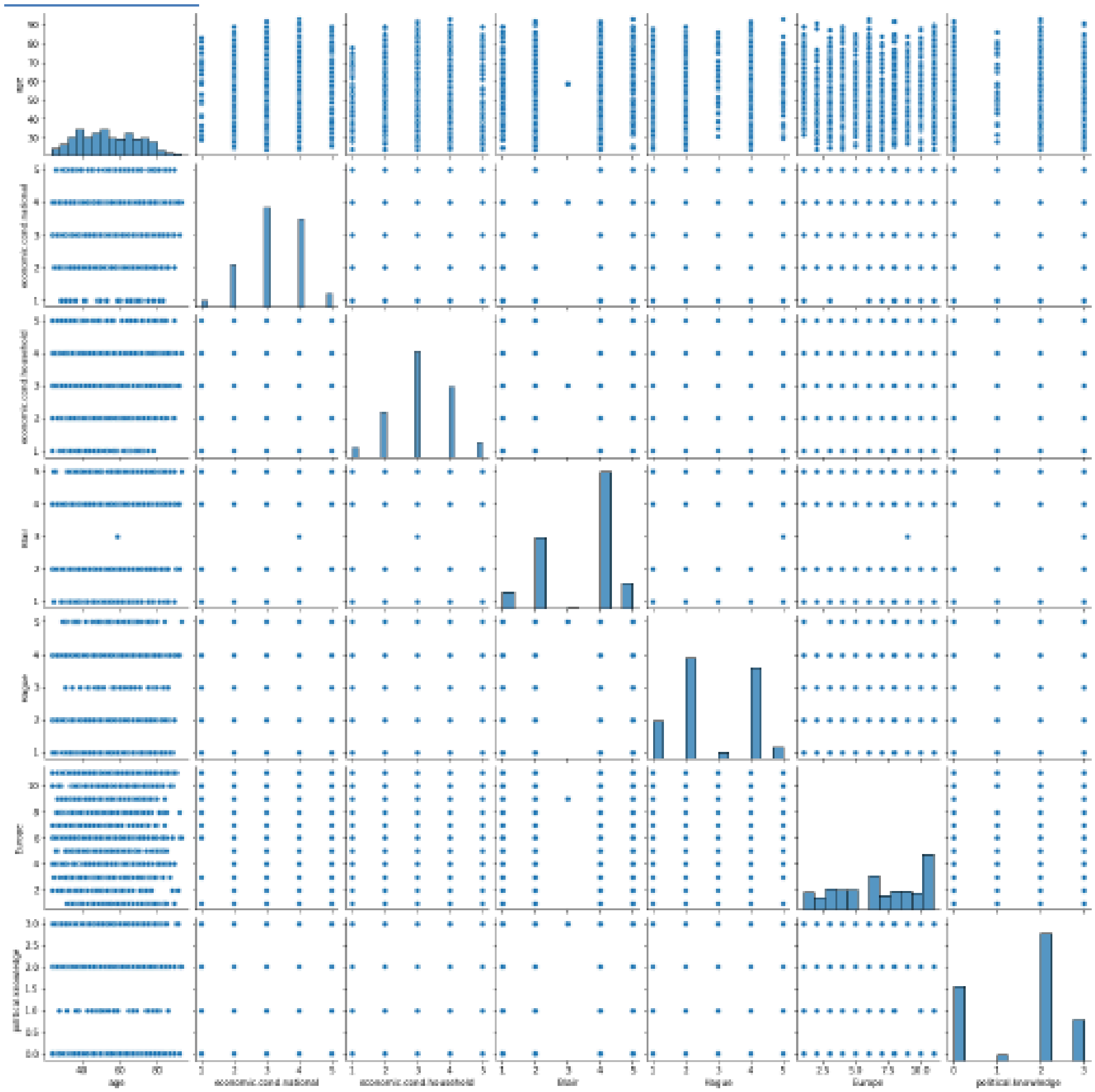
```
vote          Hague
Conservative  4        286
              2         95
              5         59
              1         11
              3          9
Labour        2        522
              4        271
              1        222
              3         28
              5         14
Name: Hague, dtype: int64
```

Observation:

- Labour party has higher votes overall.
- Out of 73 people who gave a score of 5, 59 people have voted for the conservative party. The remaining 14 people, despite giving a score of 5 to the conservative leader, have chosen to vote for the labour party.
- Out of 557 people who gave a score of 4, 286 people have voted for the conservative party. The remaining 271 people, despite giving a score of 4 to the conservative leader, have chosen to vote for the labour party.
- Out of 37 people who gave a score of 3, 28 have voted for the labour party. The remaining 9, despite giving an average score of 3 to the conservative party, have chosen to vote for the conservative party.
- Out of 617 people who gave a score of 2, 522 people have voted for the labour party. The remaining 95 people, despite giving an unsatisfactory score of 2 to the conservative leader, have chosen to vote for the conservative party.

- Out of 233 people who gave a score of 1, 222 people have voted for the labour party. The remaining 11 people, despite giving the lowest score of 1 to the conservative leader, have chosen to vote for the conservative party.
- The score of 4 and 5 have more votes in the conservative party, although in 4, the votes are almost equal in both the parties. Conservative party gets slightly higher.
- The score of 1, 2 and 3 have more votes in the labour party. Still, a significant percentage of people who gave a bad score to the conservative leader still chose to vote for 'Hague'.

Checking pair-wise distribution of the continuous variables:

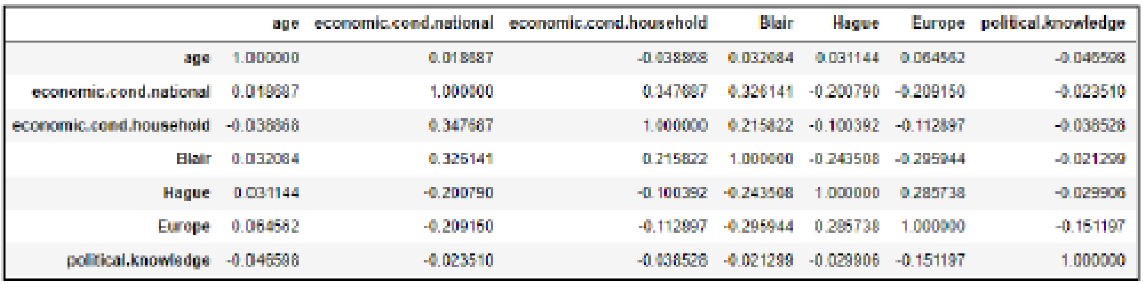


Observation:

- Pair plot is a combination of histograms and scatter plots.
- From the histogram, we can see that, the 'Blair','Europe' and 'political.knowledge' variables are slightly left skewed.
- All other variables seem to be normally distributed.
- From the scatter plots, we can see that, there is mostly no correlation between the variables.

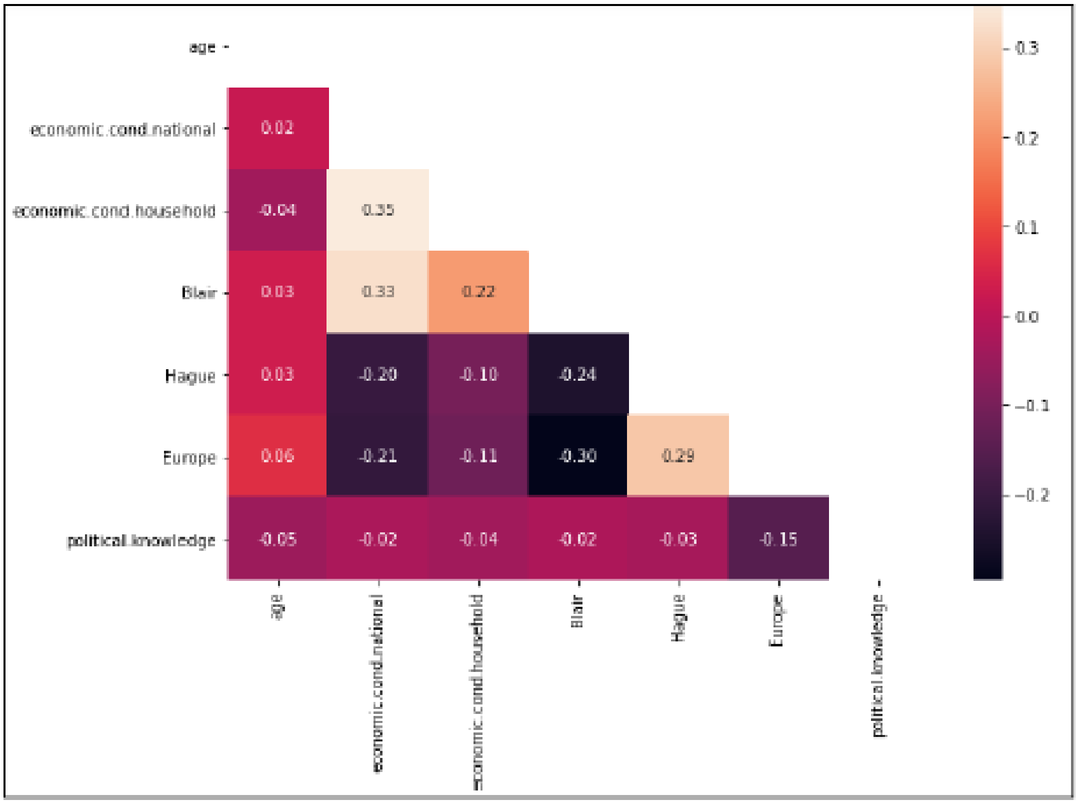
We can use the correlation matrix to view them more clearly.

Correlation matrix is a table which shows the correlation coefficient between variables. Correlation values range from -1 to +1. For values closer to zero, it means that, there is no linear trend between two variables. Values close to 1 means that the correlation is positive.



	age	economic.cond.national	economic.cond.household	Blair	Hague	Europe	political.knowledge
age	1.000000	0.018687	-0.038868	0.032084	0.031144	0.064562	-0.046598
economic.cond.national	0.018687	1.000000	0.347687	0.326141	-0.200790	-0.209150	-0.023510
economic.cond.household	-0.038868	0.347687	1.000000	0.215822	-0.100392	-0.112897	-0.038528
Blair	0.032084	0.326141	0.215822	1.000000	-0.243508	-0.295944	-0.021299
Hague	0.031144	-0.200790	-0.100392	-0.243508	1.000000	0.285738	-0.029906
Europe	0.064562	-0.209150	-0.112897	-0.295944	0.285738	1.000000	-0.151197
political.knowledge	-0.046598	-0.023510	-0.038528	-0.021299	-0.029906	-0.151197	1.000000

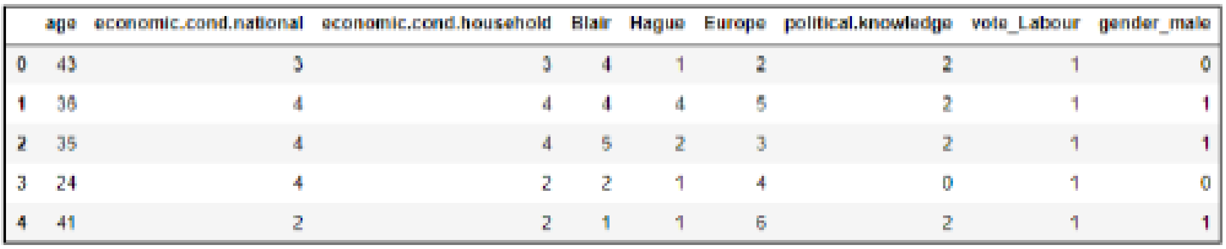
The correlation heat map helps us to visualize the correlation between two variables.



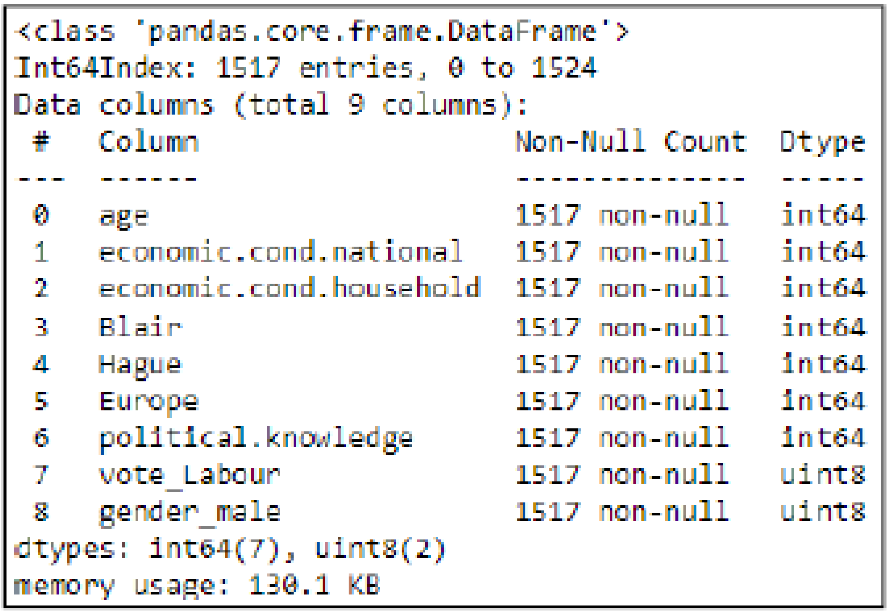
Observation:

- We can see that, mostly there is no correlation in the dataset through this matrix. There are some variables that are moderately positively correlated and some that are slightly negatively correlated.
- ‘economic.cond.national’ with ‘economic.cond.household’ have moderate positive correlation.
- ‘Blair' with 'economic.cond.national' and ‘economic.cond.household’ have moderate positive correlation.
- ‘Europe’ with ‘Hague’ have moderate positive correlation.
- 'Hague' with 'economic.cond.national' and 'Blair' have moderate negative correlation.
- 'Europe' with 'economic.cond.national' and 'Blair' have moderate negative correlation.

1.3 Encode the data



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



```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1517 entries, 0 to 1524
Data columns (total 9 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   age                      1517 non-null   int64
 1   economic.cond.national   1517 non-null   int64
 2   economic.cond.household  1517 non-null   int64
 3   Blair                    1517 non-null   int64
 4   Hague                    1517 non-null   int64
 5   Europe                   1517 non-null   int64
 6   political.knowledge      1517 non-null   int64
 7   vote_Labour              1517 non-null   uint8
 8   gender_male              1517 non-null   uint8
dtypes: int64(7), uint8(2)
memory usage: 130.1 KB
```

Train-test-split:

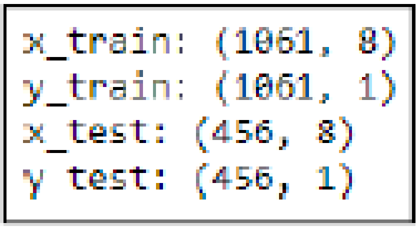
Our model will use all the variables and 'vote_Labour' is the target variable. The train-test split is a technique for evaluating the performance of a machine learning algorithm. The procedure involves taking a dataset and dividing it into two subsets.

- Train Dataset: Used to fit the machine learning model.
- Test Dataset: Used to evaluate the fit machine learning model.

The data is divided into 2 subsets, training and testing set. Earlier, we have extracted the target variable ‘vote_Labour’ in a separate vector for subsets. Random state chosen as 1.

- Training Set: 70percent of data.
- Testing Set: 30 percent of the data.

Train-Test-Split Shape:

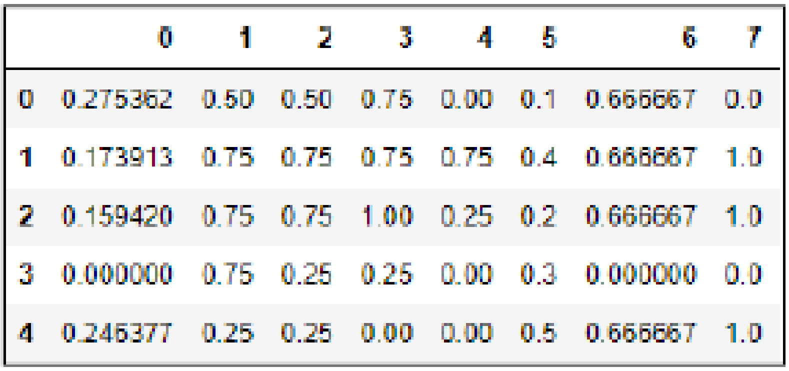


```
x_train: (1061, 8)
y_train: (1061, 1)
x_test: (456, 8)
y test: (456, 1)
```

The dataset contains features highly varying in magnitudes, units and range between the 'age' column and other columns.

- But since, most of the machine learning algorithms use Eucledian distance between two data points in their computations, this is a problem.
- If left alone, these algorithms only take in the magnitude of features neglecting the units.
- The results would vary greatly between different units, 1 km and 1000 metres.
- The features with high magnitudes will weigh in a lot more in the distance calculations than features with low magnitudes.
- To supress this effect, we need to bring all features to the same level of magnitudes. This can be acheived by scaling.
- in this case, we have a lot of encoded, ordinal, categorical and continuous variables. So, we use the minmaxscaler technique to scale the data.

After Scaling



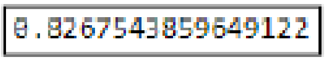
	0	1	2	3	4	5	6	7
0	0.275362	0.50	0.50	0.75	0.00	0.1	0.666667	0.0
1	0.173913	0.75	0.75	0.75	0.75	0.4	0.666667	1.0
2	0.159420	0.75	0.75	1.00	0.25	0.2	0.666667	1.0
3	0.000000	0.75	0.25	0.25	0.00	0.3	0.000000	0.0
4	0.246377	0.25	0.25	0.00	0.00	0.5	0.666667	1.0

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

Logistic Regression Model

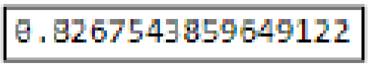
There are no outliers present in the continuous variable 'age'. The remaining variables are categorical in nature. Our model will use all the variables and 'vote_Labour' is the target variable

Accuracy - Train data:



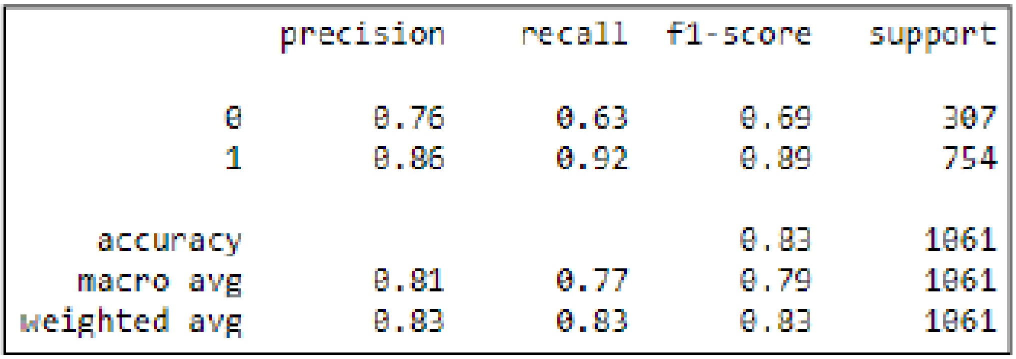
```
0.8267543859649122
```

Accuracy - Test data:



```
0.8267543859649122
```

Classification report - Train data:

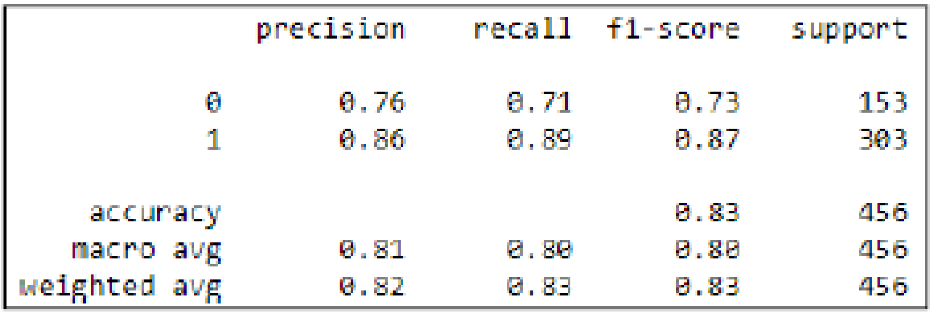


```
              precision    recall  f1-score   support

           0       0.76      0.63      0.69       307
           1       0.86      0.92      0.89       754

    accuracy                           0.83      1061
   macro avg       0.81      0.77      0.79      1061
weighted avg       0.83      0.83      0.83      1061
```

Classification report - Test data:

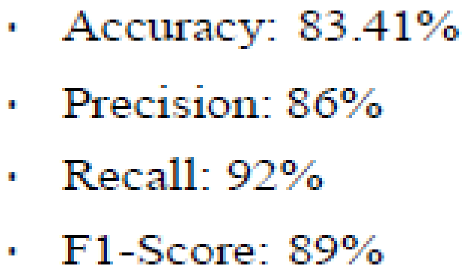


```
              precision    recall  f1-score   support

           0       0.76      0.71      0.73       153
           1       0.86      0.89      0.87       303

    accuracy                           0.83       456
   macro avg       0.81      0.80      0.80       456
weighted avg       0.82      0.83      0.83       456
```

Logistic Regression Model - Observation Train data:



- Accuracy: 83.41%
- Precision: 86%
- Recall: 92%
- F1-Score: 89%

Test data:

Accuracy: 82.68%

- Precision: 86%
- Recall: 89%
- F1-Score: 87%

The model is not over-fitted or under-fitted.

- The error in the test data is slightly higher than the train data, which is absolutely fine because the error margin is low and the error in both train and test data is not too high.
  - Thus, the model is not over-fitted or under-fitted.

Linear Discriminant Analysis Model:

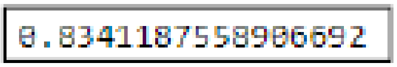
There are no outliers present in the continuous variable 'age'.

The remaining variables are categorical in nature.

Our model will use all the variables and 'vote_Labour' is the target variable.

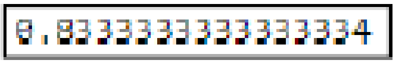
Validness of the model:

Accuracy - Train data:

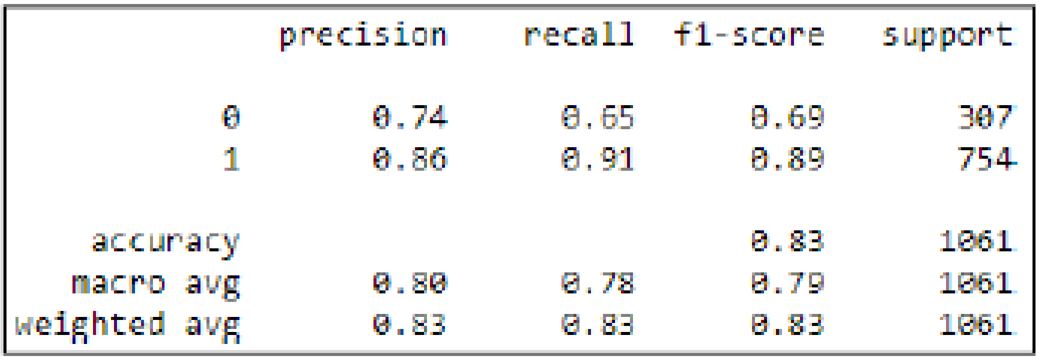


```
0.8341187558906692
```

Accuracy - Test data:



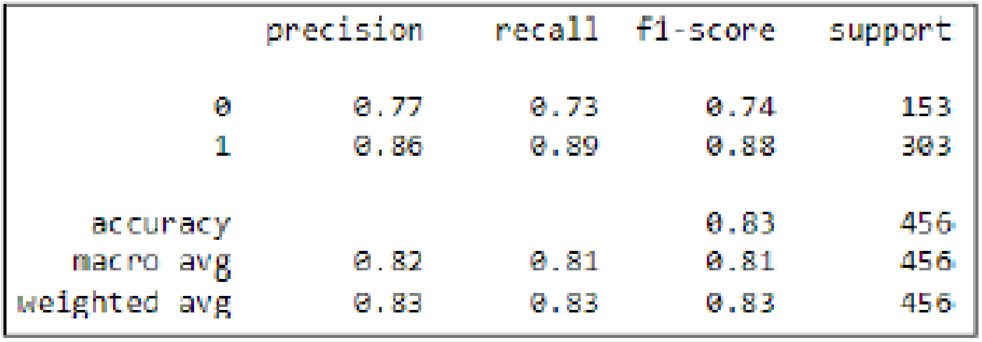
```
0.8333333333333334
```



```
              precision    recall  f1-score   support

           0       0.74      0.65      0.69       307
           1       0.86      0.91      0.89       754

    accuracy                           0.83      1061
   macro avg       0.80      0.78      0.79      1061
weighted avg       0.83      0.83      0.83      1061
```



```
              precision    recall  f1-score   support

           0       0.77      0.73      0.74       153
           1       0.86      0.89      0.88       303

    accuracy                           0.83       456
   macro avg       0.82      0.81      0.81       456
weighted avg       0.83      0.83      0.83       456
```

Linear Discriminant Analysis Model - Observation Train data:

- Accuracy: 83.41%
- Precision: 86%
- Recall: 91%
- F1-Score: 89%

Test data:

- Accuracy: 83.33%
- Precision: 86%
- Recall: 89%
- F1-Score: 88%

Validness of the model:

- The model is not over-fitted or under-fitted.

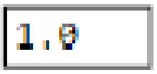
- The error in the test data is slightly higher than the train data, which is absolutely fine because the error margin is low and the error in both train and test data is not too high. Thus, the model is not over-fitted or under-fitted.

1.5 Apply KNN Model and Naïve Bayes Model

K-Nearest Neighbor Model:

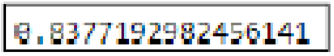
There are no outliers present in the continuous variable 'age'. The remaining variables are categorical in nature. Our model will use all the variables and 'vote_Labour' is the target variable. We take K value as 7.

Accuracy - Train data:



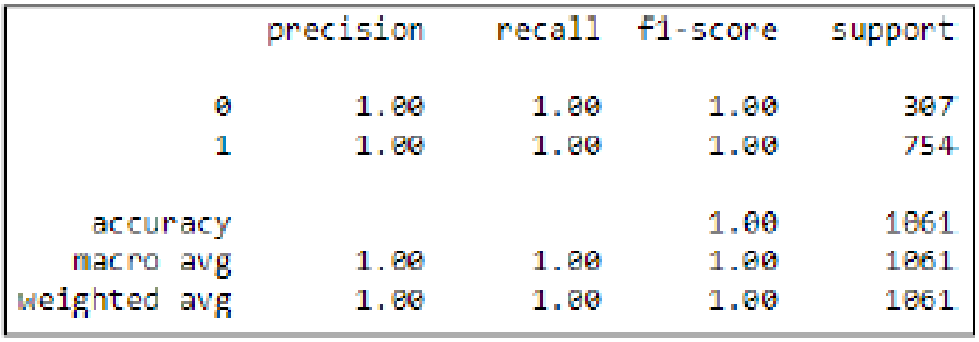
```
1.0
```

Accuracy - Test data:



```
0.8377192982456141
```

Classification report - Train data:

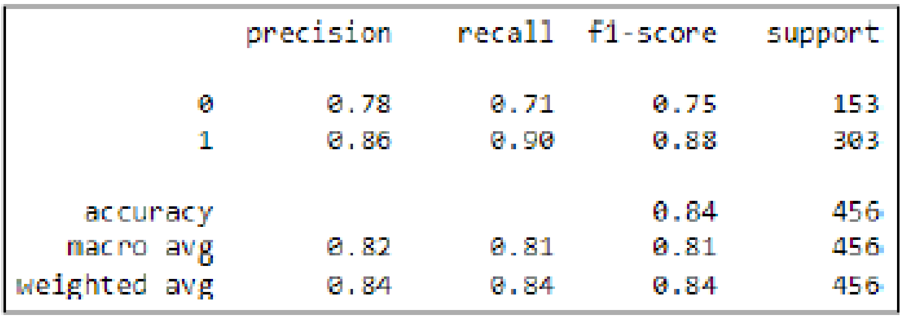


```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       307
           1       1.00      1.00      1.00       754

    accuracy                           1.00      1061
   macro avg       1.00      1.00      1.00      1061
weighted avg       1.00      1.00      1.00      1061
```

Classification report - Test data:



```
              precision    recall  f1-score   support

           0       0.78      0.71      0.75       153
           1       0.86      0.90      0.88       303

    accuracy                           0.84       456
   macro avg       0.82      0.81      0.81       456
weighted avg       0.84      0.84      0.84       456
```

K-Nearest Neighbor Model - Observation Train data:

- Accuracy: 100%
- Precision: 100%
- Recall: 100%
- F1-Score: 100%

Test data:

- Accuracy: 83.77%
- Precision: 86%
- Recall: 90%
- F1-Score: 88%

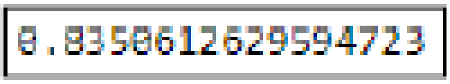
Validness of the model:

- The model is over-fitted.
- As we can see, the train data has a 100% accuracy and test data has 84% accuracy. The difference is more than 10%. So, we can infer that the KNN model is over-fitted.

Naïve Bayes Model:

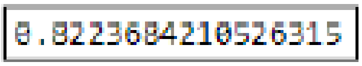
There are no outliers present in the continuous variable 'age'. The remaining variables are categorical in nature. Our model will use all the variables and 'vote_Labour' is the target variable.

Accuracy - Train data:



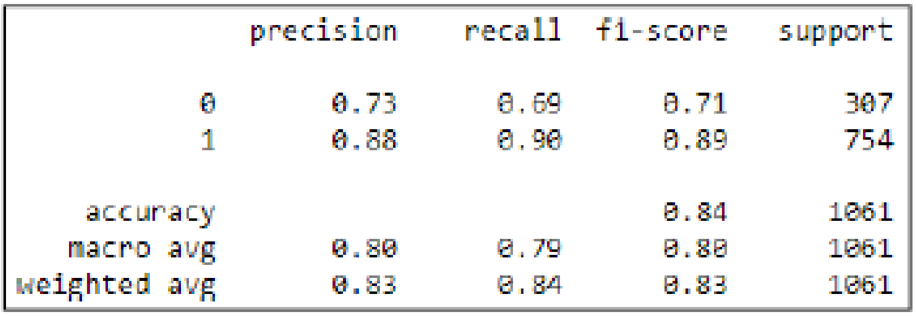
```
0.8350612629594723
```

Accuracy - Test data:



```
0.8223684210526315
```

Classification report - Train data:

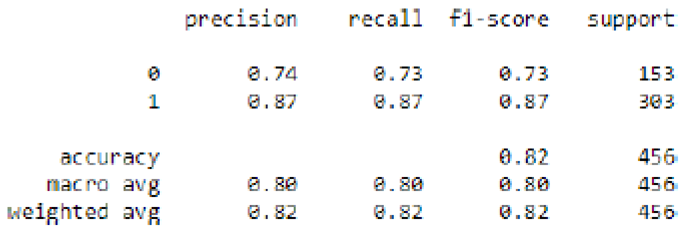


```
              precision    recall  f1-score   support

           0       0.73      0.69      0.71       307
           1       0.88      0.90      0.89       754

    accuracy                           0.84      1061
   macro avg       0.80      0.79      0.80      1061
weighted avg       0.83      0.84      0.83      1061
```

Classification report - Test data:



```
              precision    recall  f1-score   support

           0       0.74      0.73      0.73       153
           1       0.87      0.87      0.87       303

    accuracy                           0.82       456
   macro avg       0.80      0.80      0.80       456
weighted avg       0.82      0.82      0.82       456
```

Naïve Bayes Model - Observation Train data:

- Accuracy: 83.51%
- Precision: 88%
- Recall: 90%
- F1-Score: 89%

Test data:

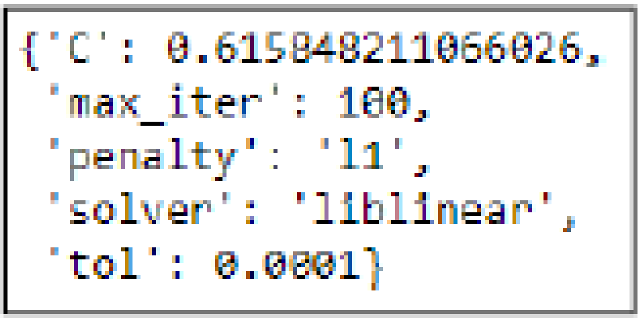
- Accuracy: 82.24%
- Precision: 87%
- Recall: 87%
- F1-Score: 87%

Validness of the model:

- The model is not over-fitted or under-fitted.
- The error in the test data is slightly higher than the train data, which is absolutely fine because the error margin is low and the error in both train and test data is not too high. Thus, the model is not over-fitted or under-fitted.

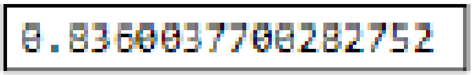
Logistic Regression Model Tuning:

Best parameters



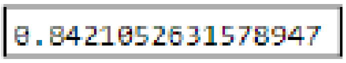
```
{'C': 0.615848211066026,
 'max_iter': 100,
 'penalty': 'l1',
 'solver': 'liblinear',
 'tol': 0.0001}
```

Accuracy - Train data:

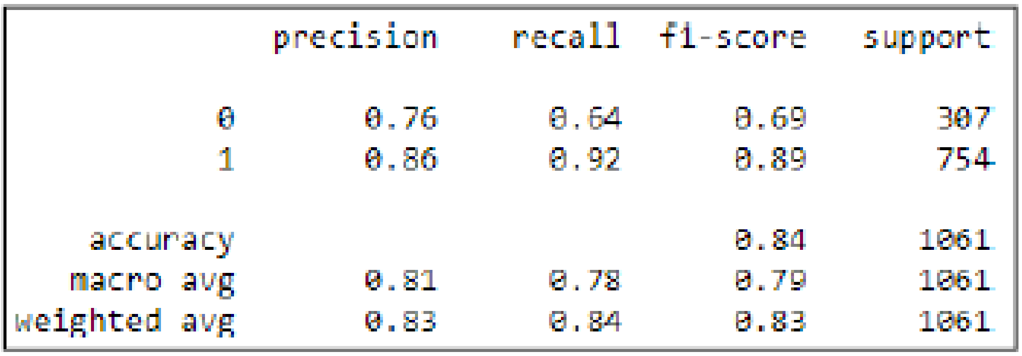


```
0.8360037700282752
```

Accuracy - Test data:



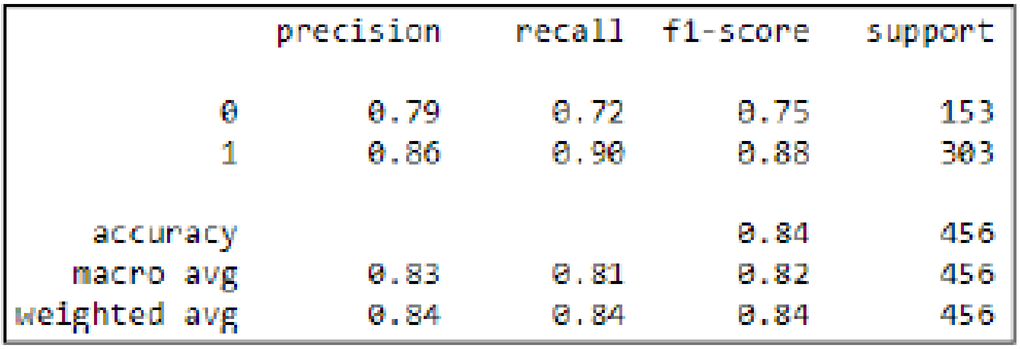
```
0.8421052631578947
```



```
              precision    recall  f1-score   support

           0       0.76      0.64      0.69       307
           1       0.86      0.92      0.89       754

    accuracy                           0.84      1061
   macro avg       0.81      0.78      0.79      1061
weighted avg       0.83      0.84      0.83      1061
```



```
              precision    recall  f1-score   support

           0       0.79      0.72      0.75       153
           1       0.86      0.90      0.88       303

    accuracy                           0.84       456
   macro avg       0.83      0.81      0.82       456
weighted avg       0.84      0.84      0.84       456
```

Logistic Regression Model Tuned - Observation

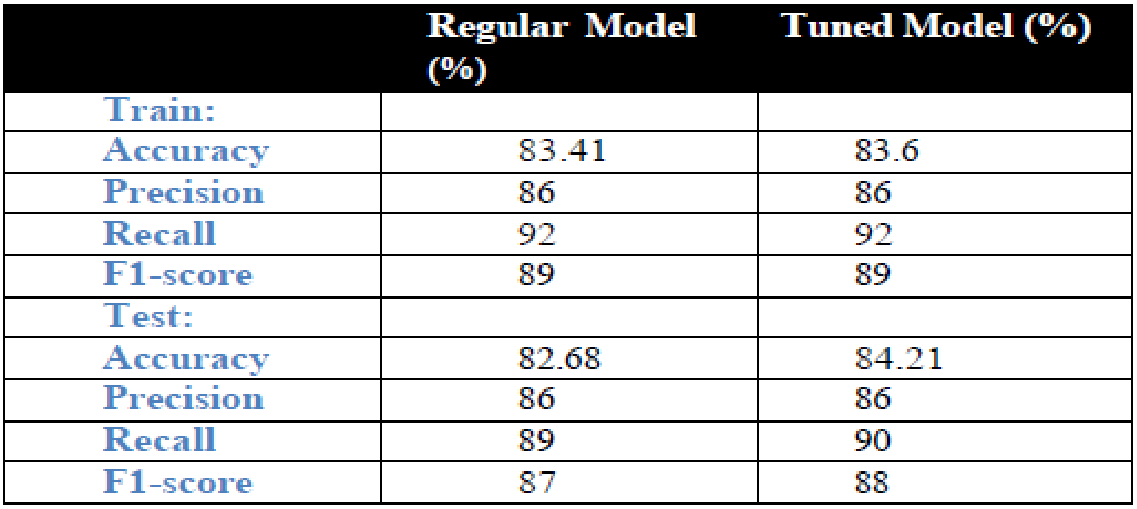
Train data:

- Accuracy: 83.6%
- Precision: 86%
- Recall: 92%
- F1-Score: 89%

Test data:

- Accuracy: 84.21%
- Precision: 86%
- Recall: 90%
- F1-Score: 88%

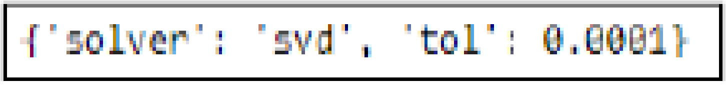
Comparison on performance of both regular and tuned logistic regression models:



	Regular Model (%)	Tuned Model (%)
Train:		
Accuracy	83.41	83.6
Precision	86	86
Recall	92	92
F1-score	89	89
Test:		
Accuracy	82.68	84.21
Precision	86	86
Recall	89	90
F1-score	87	88

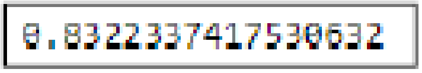
- As we can see from the above tabular comparison, there is not much difference between the performance regular LR model and tuned LR model.
- The values are high overall and there is no over-fitting or under-fitting. Therefore both models are equally good models.

Linear Discriminant Analysis Model Tuning: Best parameters:



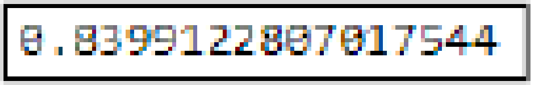
```
{'solver': 'svd', 'tol': 0.0001}
```

Accuracy - Train data:

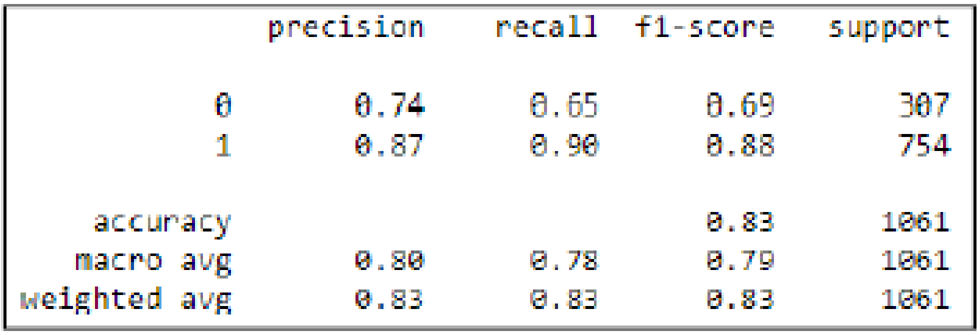


```
0.8322337417530632
```

Accuracy - Test data:



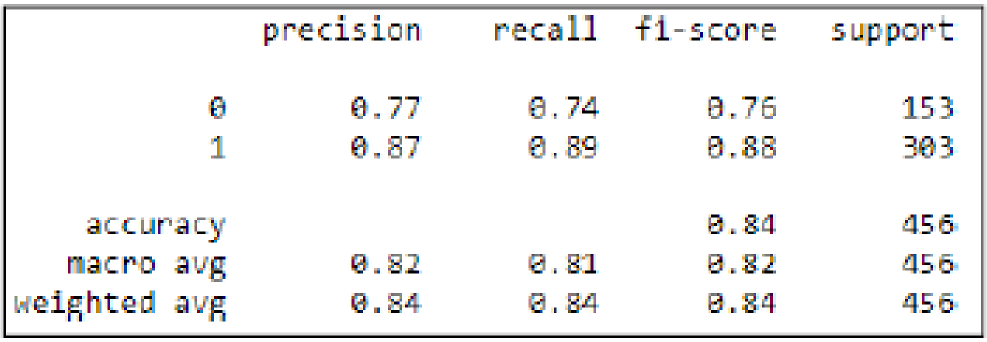
```
0.8399122807017544
```



```
              precision    recall  f1-score   support

           0       0.74      0.65      0.69       307
           1       0.87      0.90      0.88       754

    accuracy                           0.83      1061
   macro avg       0.80      0.78      0.79      1061
weighted avg       0.83      0.83      0.83      1061
```



```
              precision    recall  f1-score   support

           0       0.77      0.74      0.76       153
           1       0.87      0.89      0.88       303

    accuracy                           0.84       456
   macro avg       0.82      0.81      0.82       456
weighted avg       0.84      0.84      0.84       456
```

LDA Model Tuned - Observation

Train data:

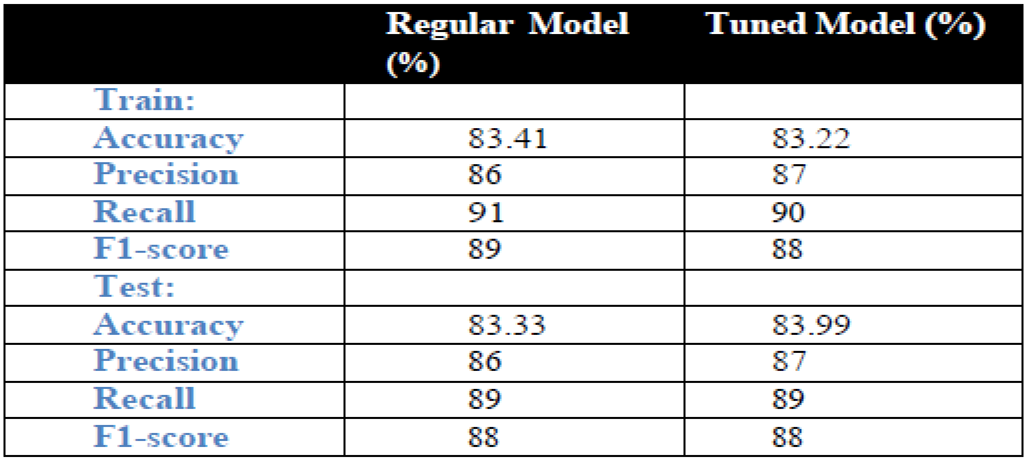
- Accuracy: 83.22%
- Precision: 87%
- Recall: 90%
- F1-Score: 88%

Test data:

- Accuracy: 83.99%

- Precision: 87%
- Recall: 89%
- F1-Score: 88%

Comparison on performance of both regular and tuned LDA models:

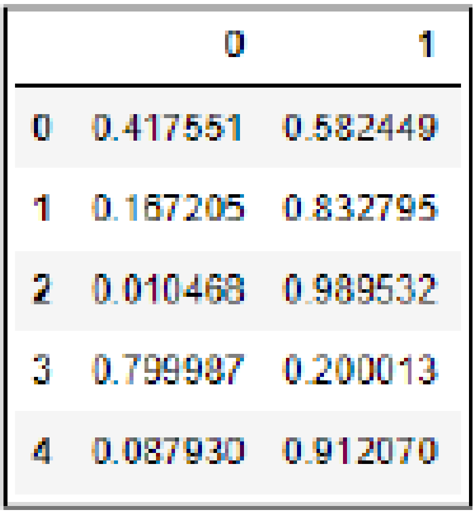


	Regular Model (%)	Tuned Model (%)
Train:		
Accuracy	83.41	83.22
Precision	86	87
Recall	91	90
F1-score	89	88
Test:		
Accuracy	83.33	83.99
Precision	86	87
Recall	89	89
F1-score	88	88

- As we can see from the above tabular comparison, there is not much difference between the performance of regular LDA model and tuned LDA model.
- The values are high overall and there is no over-fitting or under-fitting. Therefore both models are equally good models.

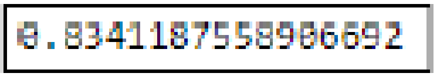
1.6 :Performance Metrics: Check the performance of Predictions on Train and Test sets using Accuracy, Confusion Matrix, Plot ROC curve and get ROC_AUC score for each model.

Logistic Regression Model - Regular:
Predicted Class and probs:



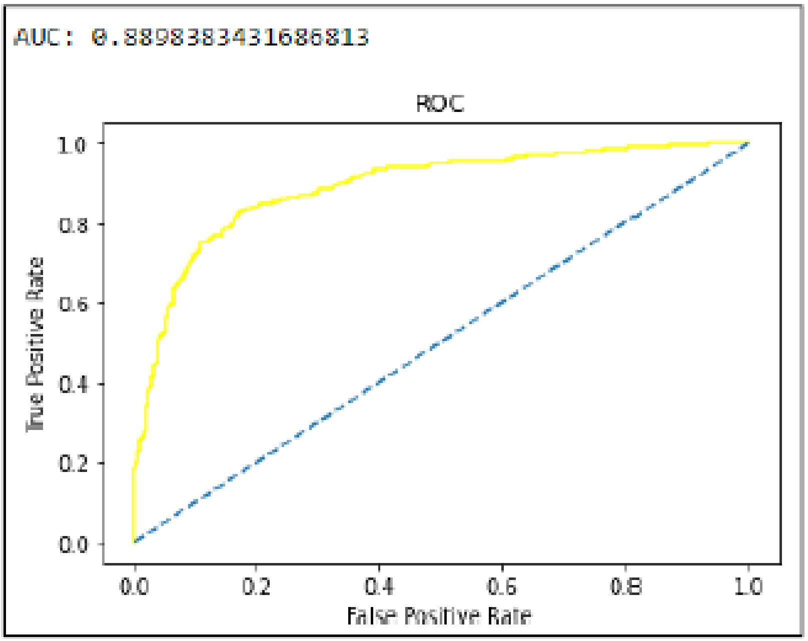
	0	1
0	0.417551	0.582449
1	0.167205	0.832795
2	0.010468	0.989532
3	0.799987	0.200013
4	0.087930	0.912070

Accuracy - Train:



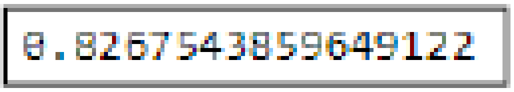
```
0.8341187558906692
```

ROC and AUC - Train:



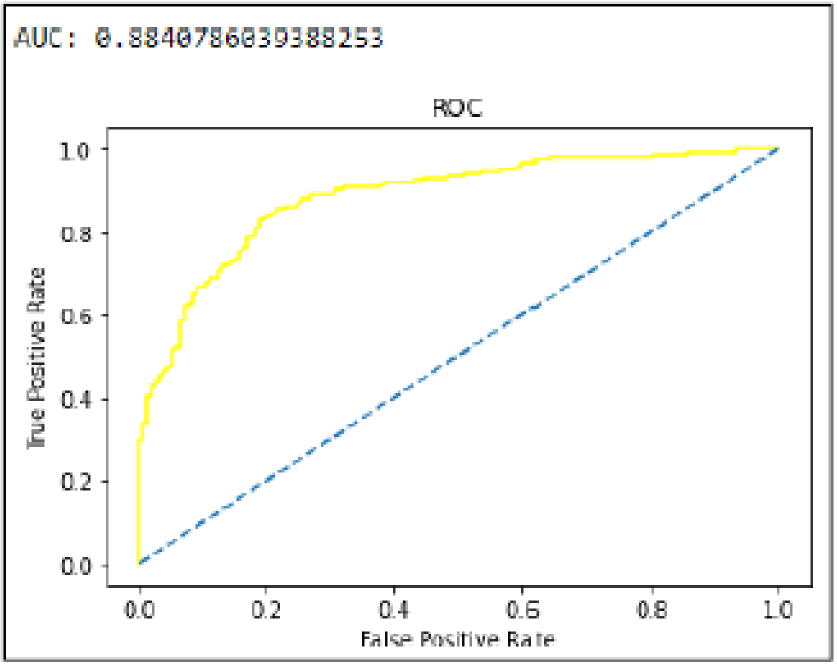
```
AUC: 0.8898383431686813
```

Accuracy - Test:



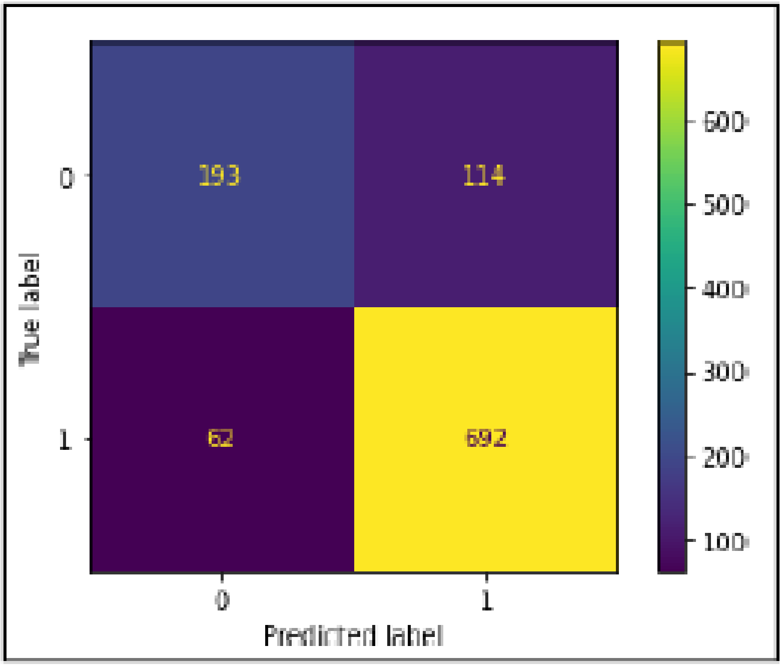
```
0.8267543859649122
```

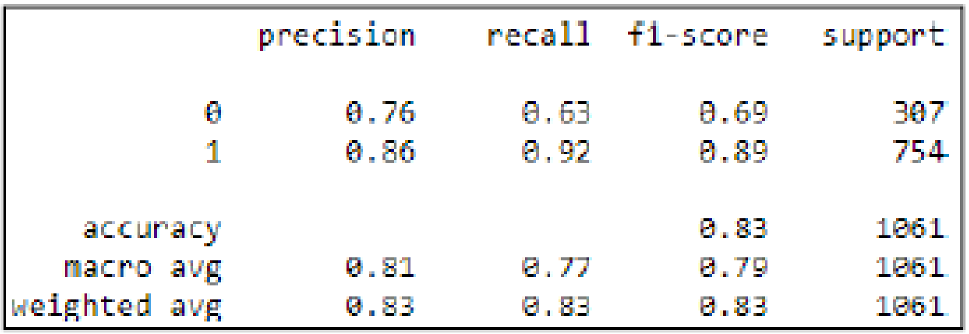
ROC and AUC - Test:



```
AUC: 0.8840786039388253
```

Confusion matrix - Train:



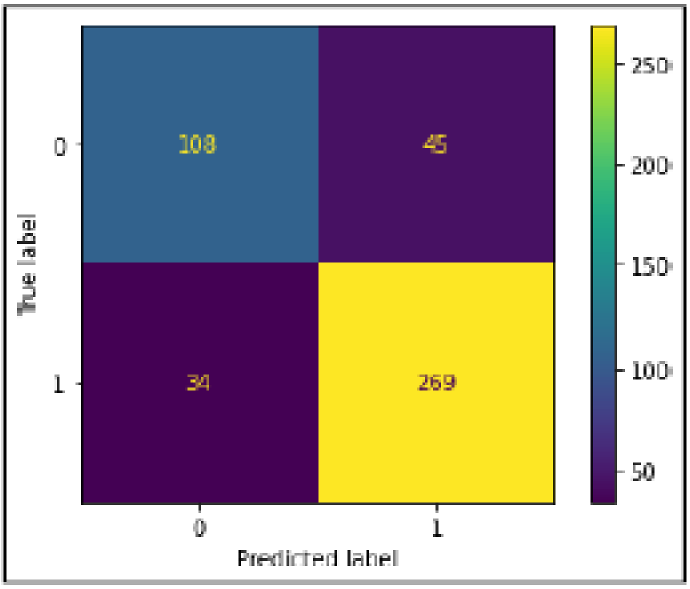


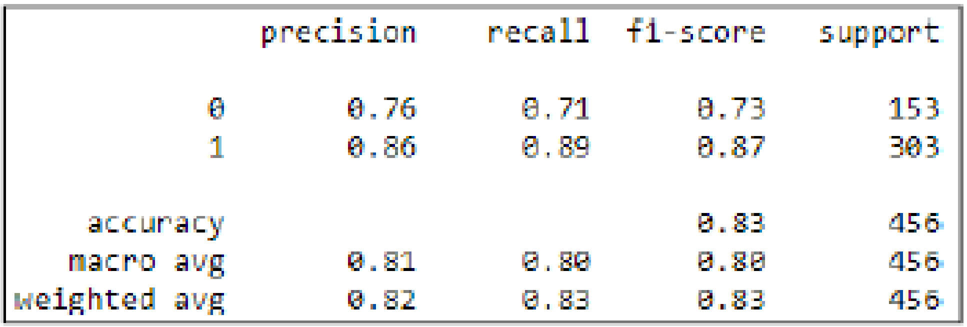
```
              precision    recall  f1-score   support

           0       0.76      0.63      0.69       307
           1       0.86      0.92      0.89       754

    accuracy                           0.83      1061
   macro avg       0.81      0.77      0.79      1061
weighted avg       0.83      0.83      0.83      1061
```

Confusion matrix - Test::





```
              precision    recall  f1-score   support

           0       0.76      0.71      0.73       153
           1       0.86      0.89      0.87       303

    accuracy                           0.83       456
   macro avg       0.81      0.80      0.80       456
weighted avg       0.82      0.83      0.83       456
```

Observation:

Train data:

- Accuracy: 83.41%
- Precision: 86%
- Recall: 92%
- F1-Score: 89%

AUC: 88.98%

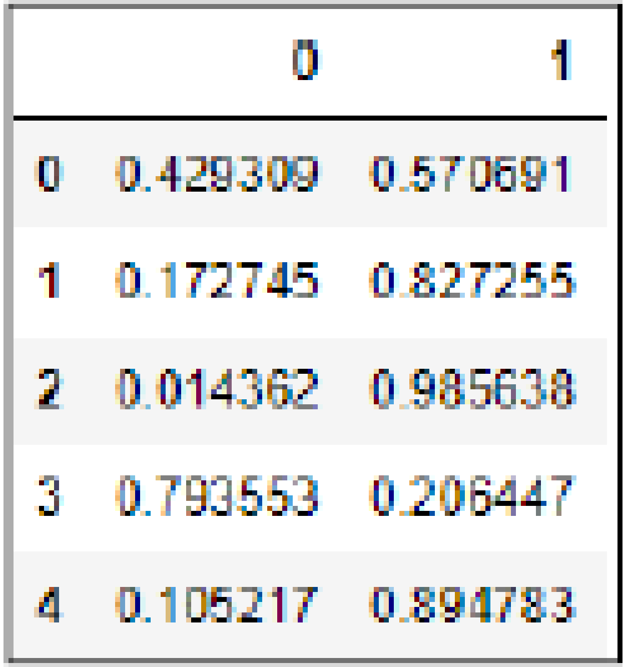
Test data:

- Accuracy: 82.68%
- Precision: 86%

- Recall: 89%
- F1-Score: 87%
- AUC: 88.4%

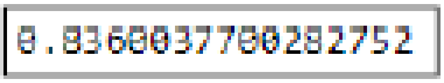
The model is not over-fitted or under-fitted. It is a good model.

Logistic Regression Model - Tuned: Predicted Class and probs



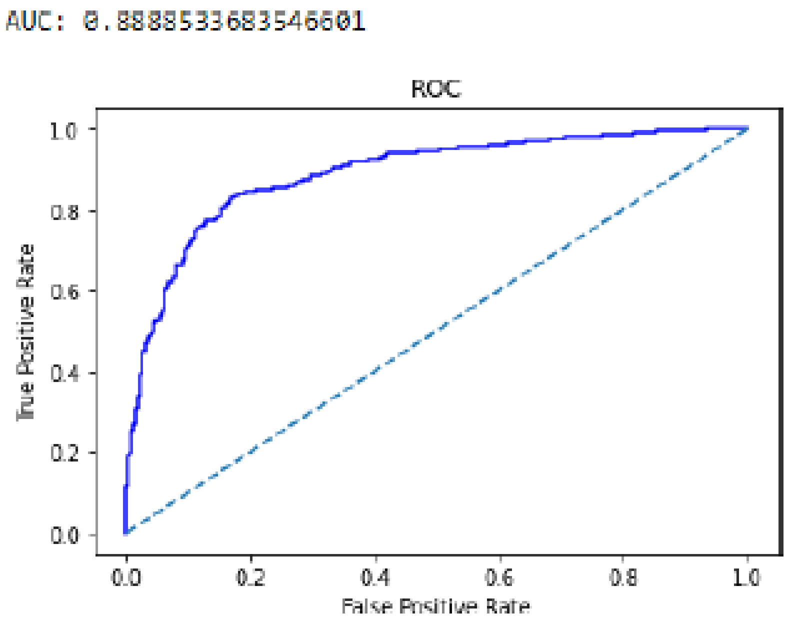
	0	1
0	0.429309	0.570691
1	0.172745	0.827255
2	0.014362	0.985638
3	0.793553	0.206447
4	0.105217	0.894783

Accuracy - Train:



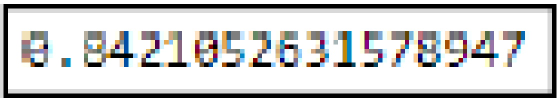
```
0.8360037700282752
```

ROC and AUC - Train:



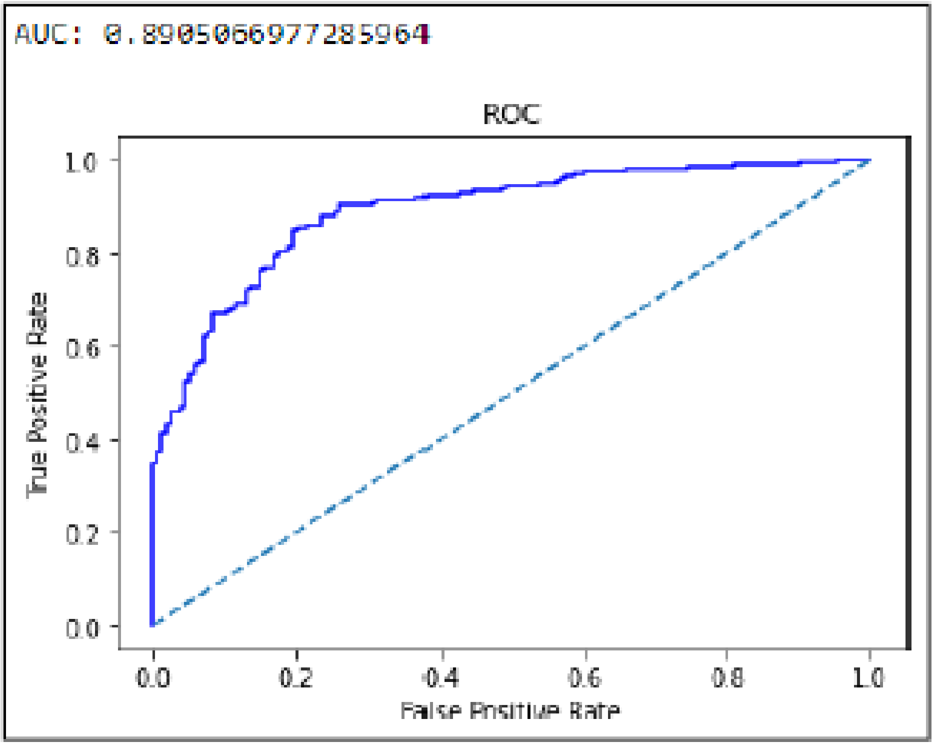
```
AUC: 0.8888533683546601
```

Accuracy - Test:



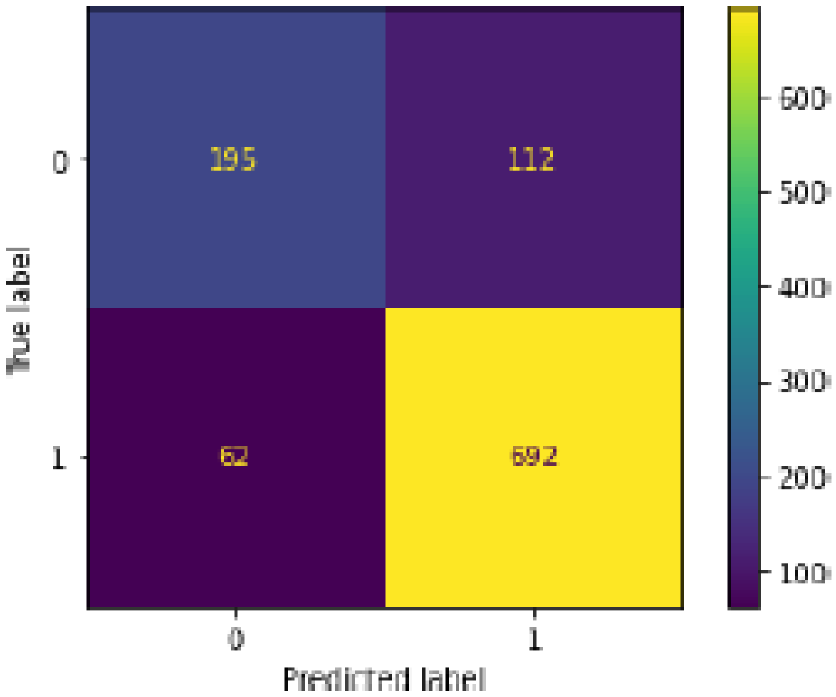
```
0.8421052631578947
```

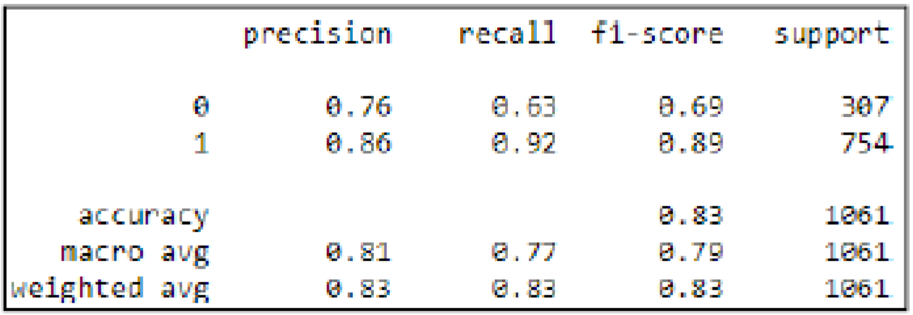
ROC and AUC - Test:



```
AUC: 0.8905066977285964
```

Confusion matrix - Train:

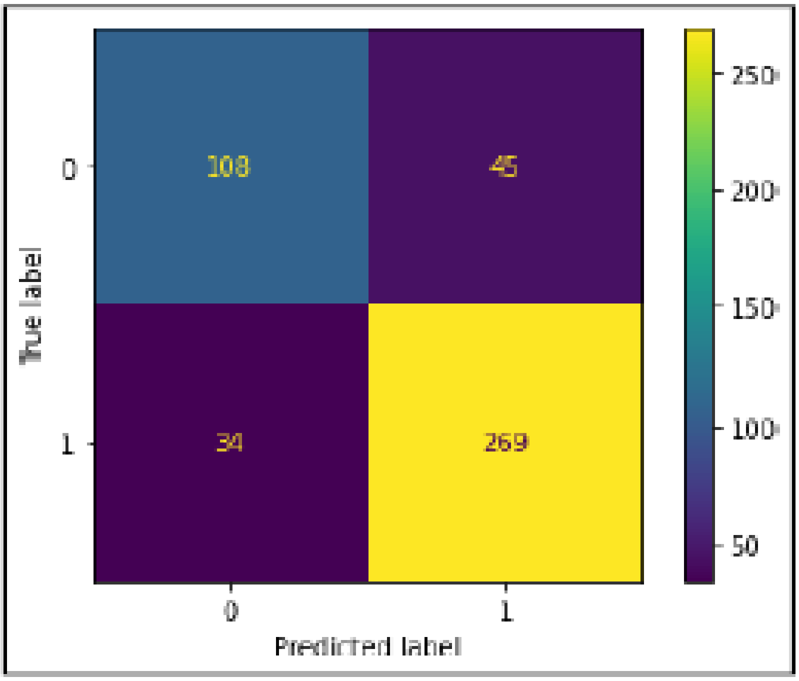




```
              precision    recall  f1-score   support

           0       0.76      0.63      0.69       307
           1       0.86      0.92      0.89       754

    accuracy                           0.83      1061
   macro avg       0.81      0.77      0.79      1061
weighted avg       0.83      0.83      0.83      1061
```



Observation: Train data:

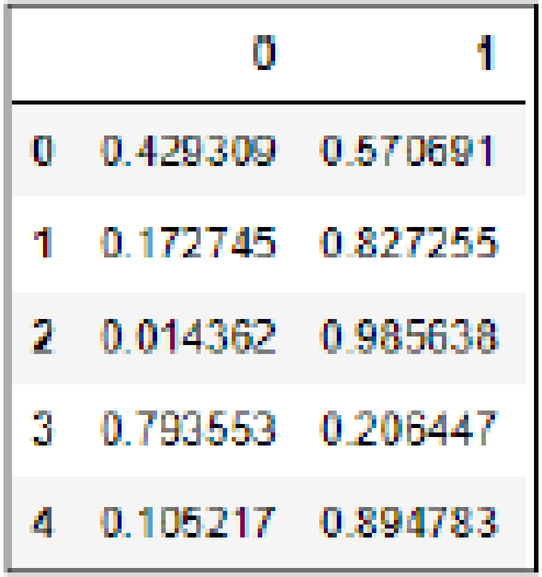
- Accuracy: 83.41%
- Precision: 86%
- Recall: 92%
- F1-Score: 89%
- AUC: 88.98%

Test data:

- Accuracy: 82.68%
- Precision: 86%
- Recall: 89%
- F1-Score: 87%
- AUC: 88.4%

The model is not over-fitted or under-fitted. It is a good model.

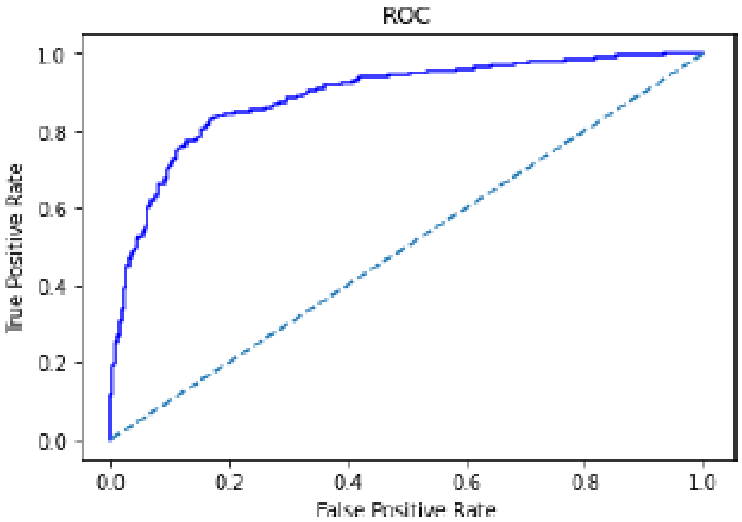
Logistic Regression Model - Tuned: Predicted Class and probs:

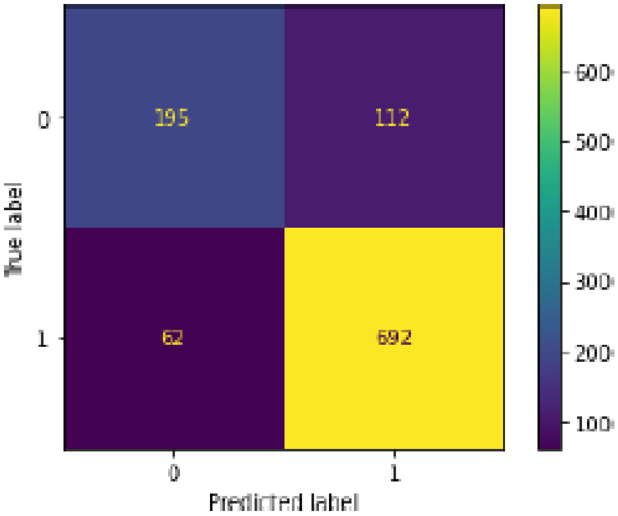


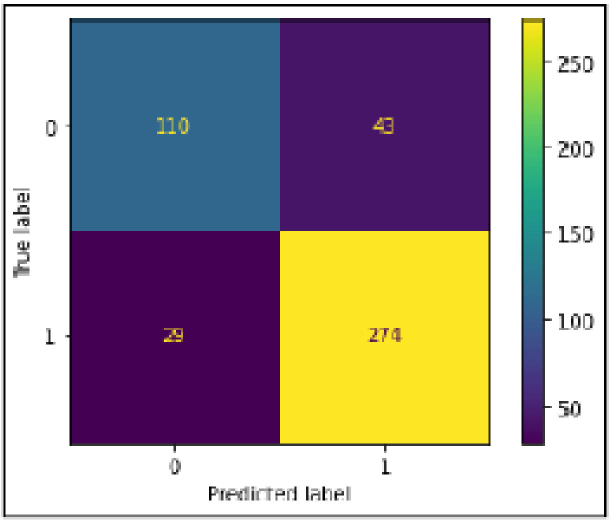
	0	1
0	0.429309	0.570691
1	0.172745	0.827255
2	0.014362	0.985638
3	0.793553	0.206447
4	0.105217	0.894783

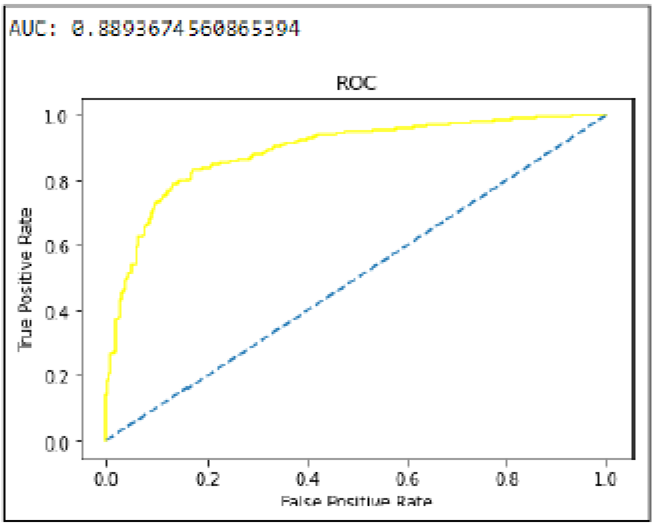
ROC and AUC - Train:

```
AUC: 0.8888533683546601
```

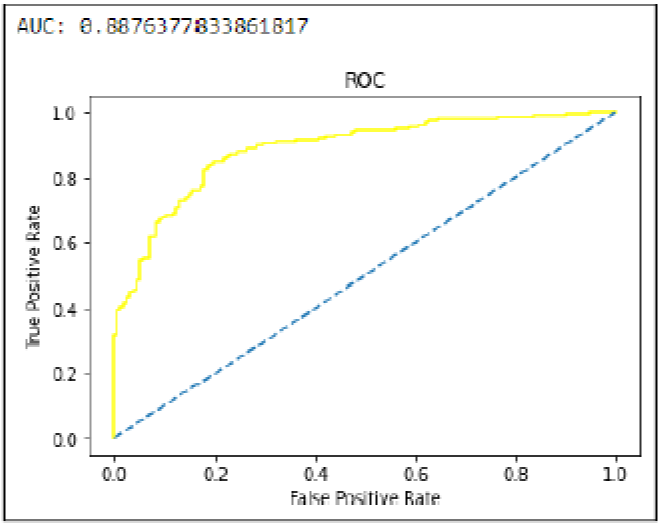



195
112
62
692
0
1
True label
0
1
Predicted label
600
500
400
300
200
100


110
43
29
274
0
1
True label
0
1
Predicted label
250
200
150
100
50



```
AUC: 0.8893674560865394
```

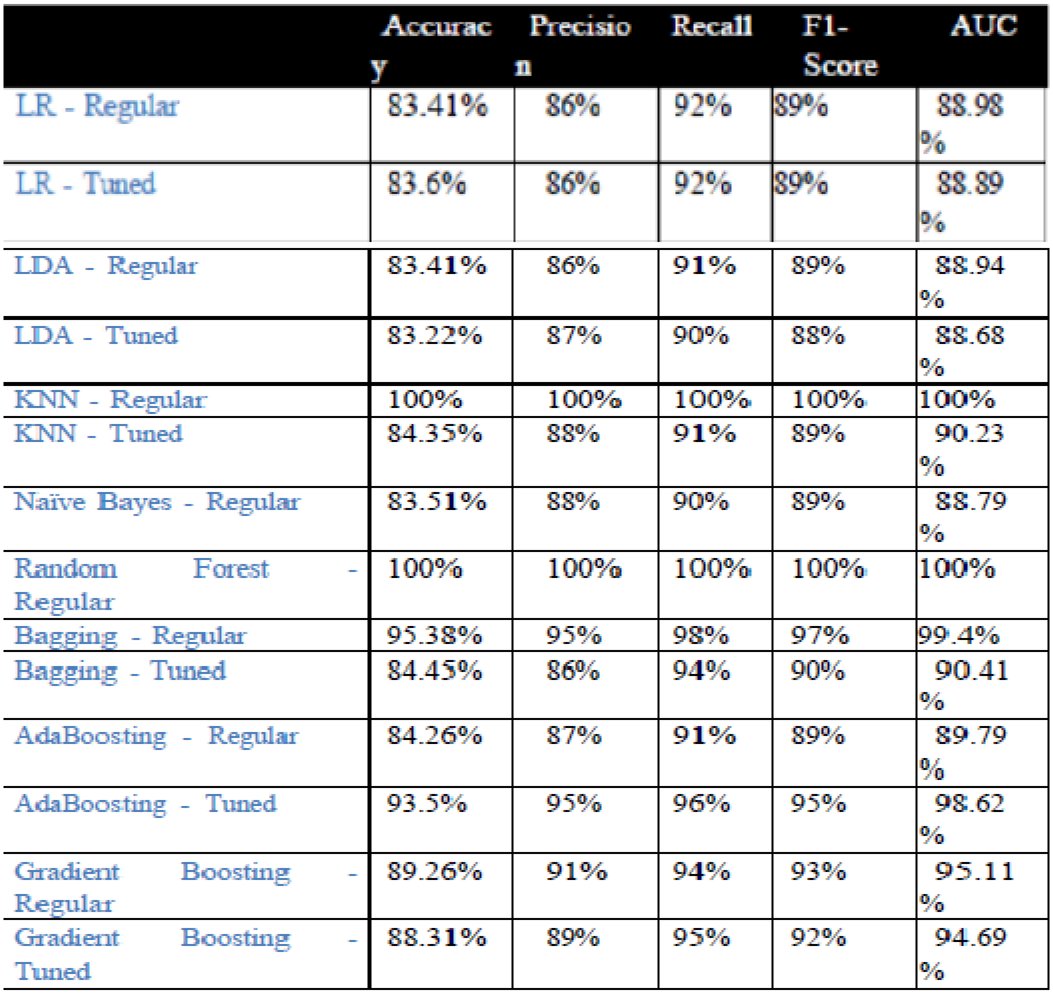


```
AUC: 0.8876377833861817
```

Comparison between the regular LDA model and tuned LDA model

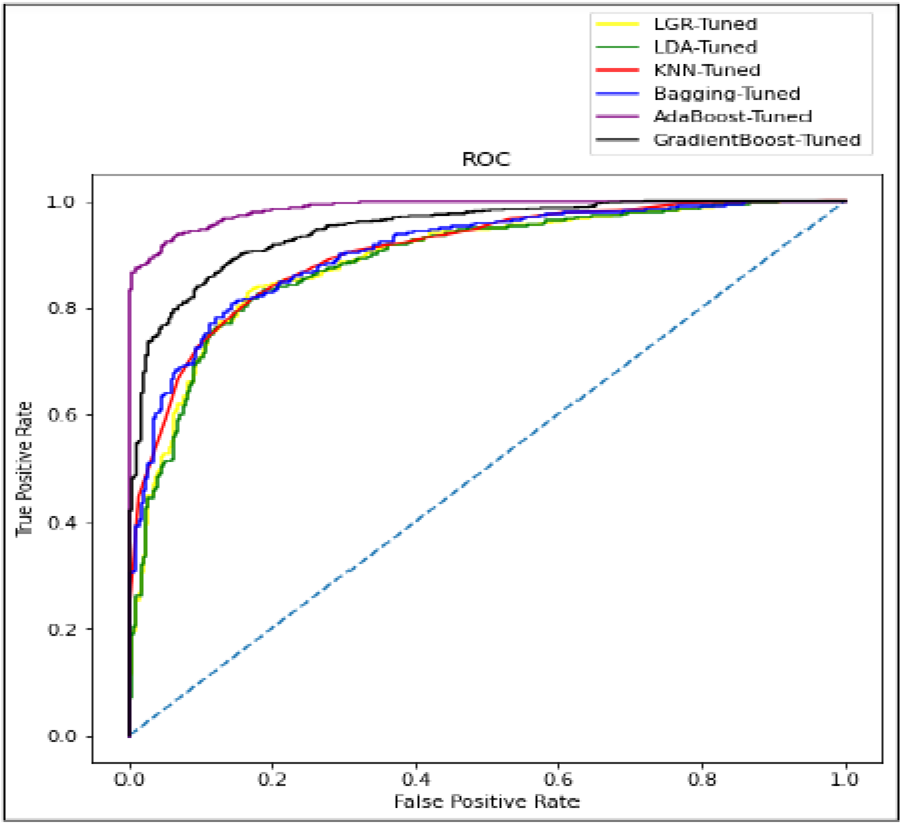
- There is not much difference between the performance of regular LDA model and tuned LDA model.
- The values are high overall and there is no over-fitting or under-fitting.
- Therefore both models are equally good models.

Comparison of train data of all models in a structured tabular manner:



	Accuracy	Precision	Recall	F1-Score	AUC
LR - Regular	83.41%	86%	92%	89%	88.98%
LR - Tuned	83.6%	86%	92%	89%	88.89%
LDA - Regular	83.41%	86%	91%	89%	88.94%
LDA - Tuned	83.22%	87%	90%	88%	88.68%
KNN - Regular	100%	100%	100%	100%	100%
KNN - Tuned	84.35%	88%	91%	89%	90.23%
Naïve Bayes - Regular	83.51%	88%	90%	89%	88.79%
Random Forest - Regular	100%	100%	100%	100%	100%
Bagging - Regular	95.38%	95%	98%	97%	99.4%
Bagging - Tuned	84.45%	86%	94%	90%	90.41%
AdaBoosting - Regular	84.26%	87%	91%	89%	89.79%
AdaBoosting - Tuned	93.5%	95%	96%	95%	98.62%
Gradient Boosting - Regular	89.26%	91%	94%	93%	95.11%
Gradient Boosting - Tuned	88.31%	89%	95%	92%	94.69%

Comparing the AUC, ROC curve on the train data of all the tuned models:



All the tuned models have high values and every model is good. But as we can see, the most consistent tuned model in both train and test data is the Gradient Boost model.

- The tuned gradient boost model performs the best with 88.31% accuracy score in train and 87.28% accuracy score in test. Also it has the best AUC score of 94% in both train and test data which is the highest of all the models.
- It also has a precision score of 88% and recall of 94% which is also the highest of all the models. So, we conclude that Gradient Boost Tuned model is the best/optimized model.

Insights:

- Labour party has more than double the votes of conservative party.
- Most number of people have given a score of 3 and 4 for the national economic condition and the average score is 3.245221

- Most number of people have given a score of 3 and 4 for the household economic condition and the average score is 3.137772
- Blair has higher number of votes than Hague and the scores are much better for Blair than for Hague.
- The average score of Blair is 3.335531 and the average score of Hague is 2.749506. So, here we can see that, Blair has a better score.
- On a scale of 0 to 3, about 30% of the total population has zero knowledge about politics/parties.
- People who gave a low score of 1 to a certain party, still decided to vote for the same party instead of voting for the other party. This can be because of lack of political knowledge among the people.
- People who have higher Eurosceptic sentiment, has voted for the conservative party and lower the Eurosceptic sentiment, higher the votes for Labour party.
- Out of 454 people who gave a score of 0 for political knowledge, 360 people have voted for the labour party and 94 people have voted for the conservative party.
- All models performed well on training data set as well as test dat set. The tuned models have performed better than the regular models.
- There is no over-fitting in any model except Random Forest and Bagging regular models.
    - Gradient Boosting model tuned is the best/optimized model.

Business recommendations:

- Hyper-parameters tuning is an import aspect of model building. There are limitations to this as to process these combinations, huge amount of processing power is required. But if tuning can be done with many sets of parameters, we might get even better results.
- Gathering more data will also help in training the models and thus improving the predictive powers.

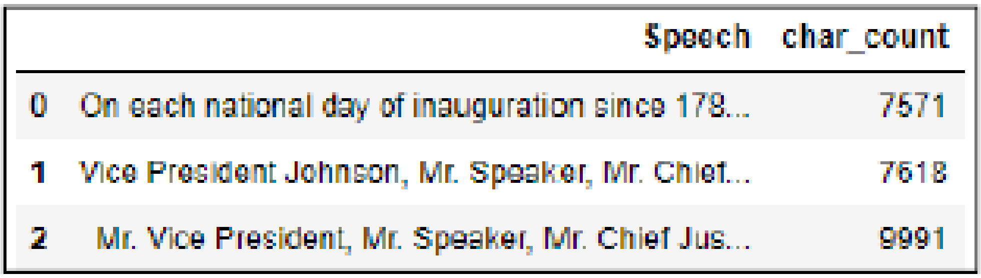
- We can also create a function in which all the models predict the outcome in sequence. This will helps in better understanding and the probability of what the outcome will be.
- Using Gradient Boosting model without scaling for predicting the outcome as it has the best optimized performance.

____–

PROBLEM 2

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

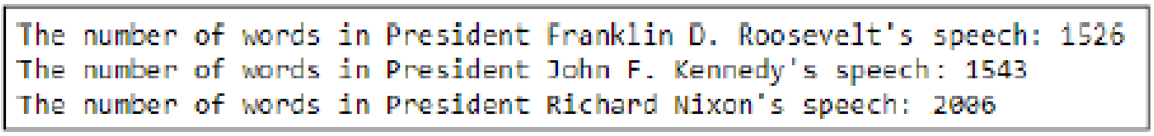
Number of characters:



	Speech	char_count
0	On each national day of inauguration since 178...	7571
1	Vice President Johnson, Mr. Speaker, Mr. Chief...	7618
2	Mr. Vice President, Mr. Speaker, Mr. Chief Jus...	9991

President Franklin D. Roosevelt's speech have 7571 characters (including spaces).

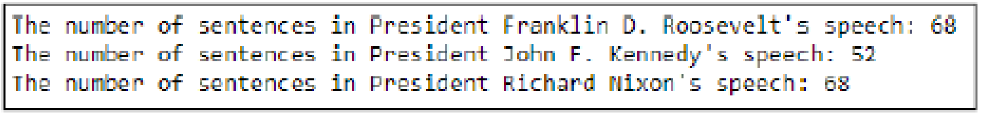
- President John F. Kennedy's speech have 7618 characters (including spaces).
- President Richard Nixon's speech have 9991 characters (including spaces).



```
The number of words in President Franklin D. Roosevelt's speech: 1526
The number of words in President John F. Kennedy's speech: 1543
The number of words in President Richard Nixon's speech: 2006
```

- There are 1526 words in President Franklin D. Roosevelt's speech.
- There are 1543 words in President John F. Kennedy's speech.
- There are 2006 words in President Richard Nixon's speech.

Number of Sentences

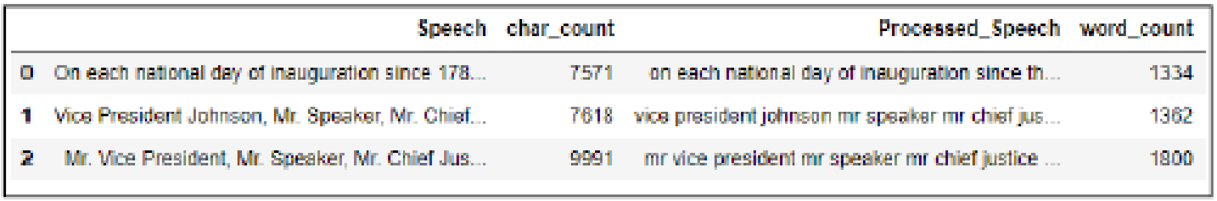


```
The number of sentences in President Franklin D. Roosevelt's speech: 68
The number of sentences in President John F. Kennedy's speech: 52
The number of sentences in President Richard Nixon's speech: 68
```

- There are 68 sentences in President Franklin D. Roosevelt's speech.
- There are 52 sentences in President John F. Kennedy's speech.
- There are 68 sentences in President Richard Nixon's speech.

<u>2.2 Remove all the stop-words from all three speeches.</u>

Before, removing the stop-words, we have changed all the letters to lowercase and we have removed special characters.
Word count before the removal of stop-words:

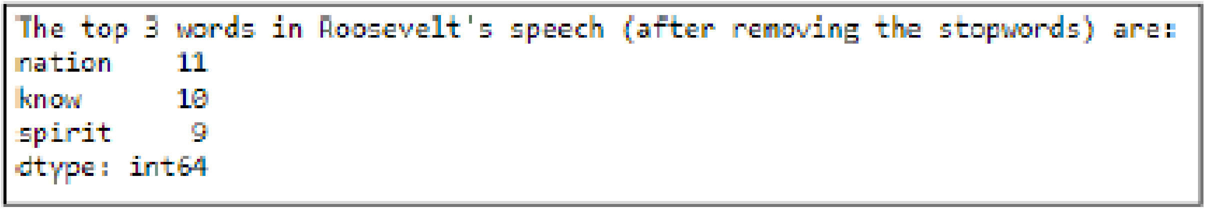


	Speech	char_count	Processed_Speech	word_count
0	On each national day of inauguration since 178...	7571	on each national day of inauguration since th...	1334
1	Vice President Johnson, Mr. Speaker, Mr. Chief...	7618	vice president johnson mr speaker mr chief jus...	1362
2	Mr. Vice President, Mr. Speaker, Mr. Chief Jus...	9991	mr vice president mr speaker mr chief justice ...	1800

Before the removal of stop-words,
- President Franklin D. Roosevelt's speech have 1334 words.
- President John F. Kennedy's speech have 1362 words.
- President Richard Nixon's speech have 1800 words

After the removal of stop-words,
- President Franklin D. Roosevelt's speech have 623 words.
- President John F. Kennedy's speech have 693 words.
- President Richard Nixon's speech have 831 words.

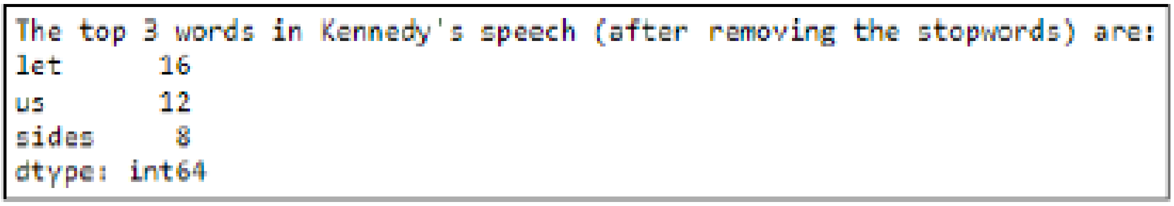
2.3) Which word occurs the most number of times in his inaugural address for each president? Mention the top three words. (after removing the stop-words)



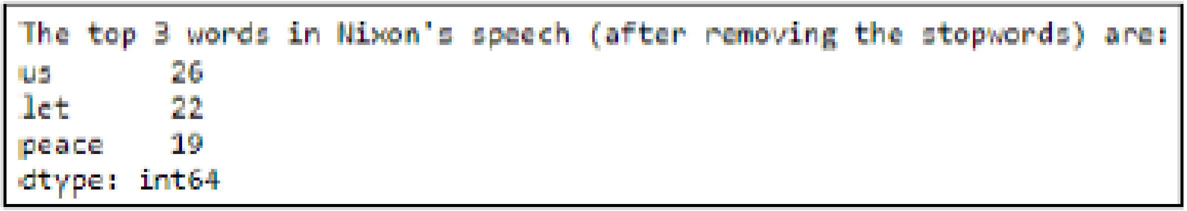
```
The top 3 words in Roosevelt's speech (after removing the stopwords) are:
nation    11
know      10
spirit     9
dtype: int64
```

The top 3 words are,

- nation - 11
- know - 10
- spirit - 9



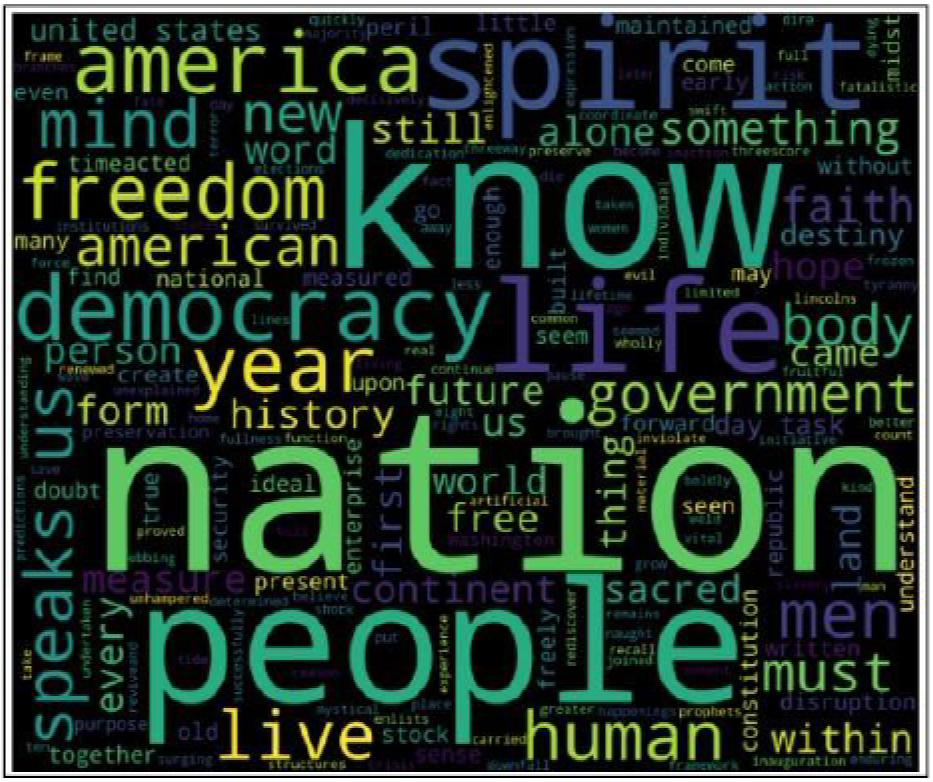
```
The top 3 words in Kennedy's speech (after removing the stopwords) are:
let      16
us       12
sides     8
dtype: int64
```



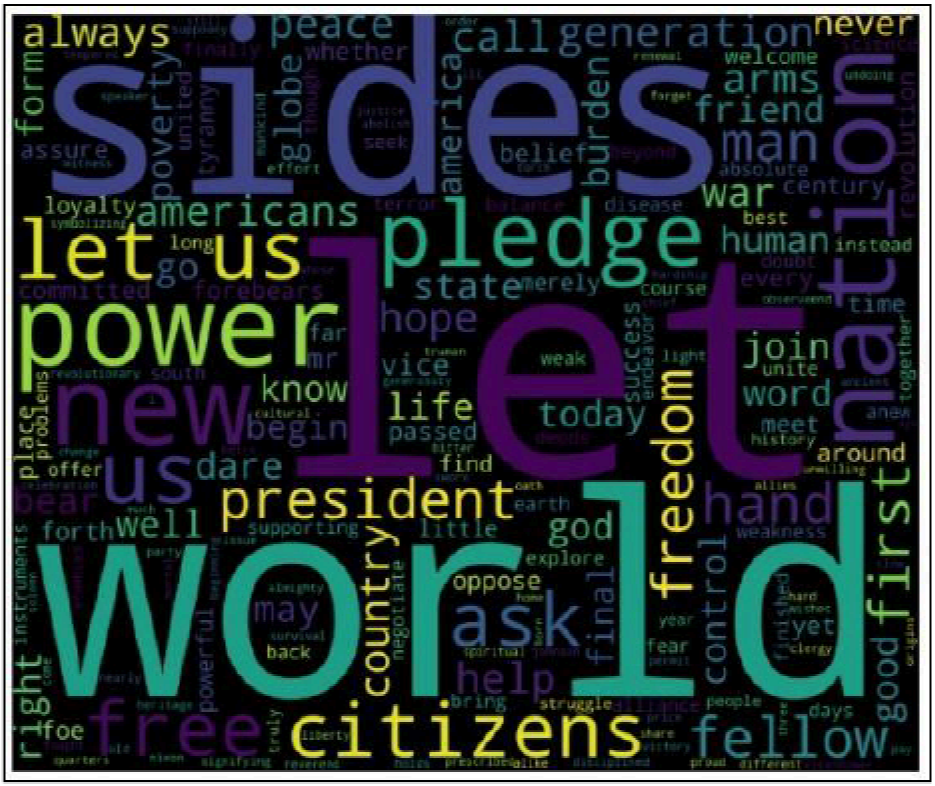
```
The top 3 words in Nixon's speech (after removing the stopwords) are:
us        26
let       22
peace     19
dtype: int64
```

2.4) Plot the word cloud of each of the three speeches. (after removing the stop-words)

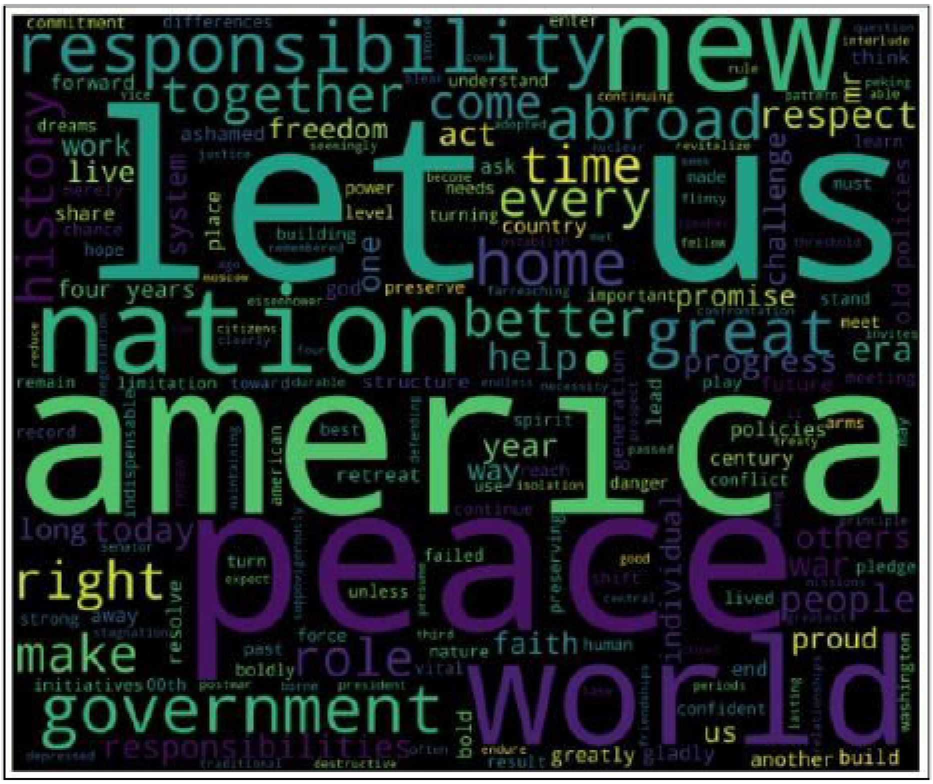
Word cloud of Roosevelt's speech:



Word cloud of Kennedy's speech:



Word cloud of Nixon's speech:


commitment
differences
enter
question
interlude
responsibility
new
think
forward
understand
rule
peking
able
mr
together
come
abroad
respect
dreams
ashamed
freedom
act
revitalize
learn
work
live
time
every
history
system
power
needs
made
must
share
level
turning
chance
hope
building
country
home
challenge
fellow
threshold
old policies
let us
four years
god
preserve
important
promise
stand
nation
better
great
meet
reduce
citizens
clearly
help
progress
era
remain
limitation
toward
durable
structure
future
meeting
one
america
record
spirit
arms
treaty
policies
best
year
century
lead
generation
indispensable
way
reach
retreat
american
danger
conflict
use
isolation
continue
long
today
others
senator
individual
peace
war
right
pledge
turn
good
expect
failed
people
strong
away
unless
preserving
resolve
make
role
faith
force
third
proud
nature
human
past
boldly
washington
end
initiatives
200th
vital
president
confident
government
world
us
responsibilities
bold
gladly
another
build
greatly
result
endure
depressed
destructive