ML-2 PROJECT REPORT

FASNA
11/02/2024

TABLE OF CONTENTS:

TABLE OF FIGURE

TABLES:

Problem 1

Context CNBE, a prominent news channel, is gearing up to provide insightful coverage of recent elections, recognizing the importance of data-driven analysis. A comprehensive survey has been conducted, capturing the perspectives of 1525 voters across various demographic and socio-economic factors. This dataset encompasses 9 variables, offering a rich source of information regarding voters' characteristics and preferences.

Objective The primary objective is to leverage machine learning to build a predictive model capable of forecasting which political party a voter is likely to support. This predictive model, developed based on the provided information, will serve as the foundation for creating an exit poll. The exit poll aims to contribute to the accurate prediction of the overall election outcomes, including determining which party is likely to secure the majority of seats.

Data Description

vote: Party choice: Conservative or Labour

age: in years

economic.cond.national: Assessment of current national economic conditions, 1 to 5.

economic.cond.household: Assessment of current household economic conditions, 1 to 5.

Blair: Assessment of the Labour leader, 1 to 5.

Hague: Assessment of the Conservative leader, 1 to 5.

Europe: an 11-point scale that measures respondents' attitudes toward European integration. High scores represent 'Eurosceptic' sentiment.

political.knowledge: Knowledge of parties' positions on European integration, 0 to 3.

gender: female or male.

Answers:

#import libary

 # Read the Excel file into a DataFrame

	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

Table-1 first 5 rows of the data set

#drop the unnamed column

#columns of the data frame

```
Index(['vote', 'age', 'economic.cond.national', 'economic.cond.household',
       'Blair', 'Hague', 'Europe', 'political.knowledge', 'gender'],
      dtype='object')
```

1.1- Define the problem and perform Exploratory Data Analysis

- Problem definition - Check shape, Data types, and statistical summary - Univariate analysis - Multivariate analysis - Use appropriate visualizations to identify the patterns and insights - Key meaningful observations on individual variables and the relationship between variables

```
#check shape of the data set
(1525, 9)
data set have 1525 rows and 9 columns
#check the data types of data
<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
the data set have 7 integer ,2 object type columns.
```

	age	economic.cond.national	economic.cond.household	Blair	Hague	Europe	political.knowledge
count	1525.000000	1525.000000	1525.000000	1525.000000	1525.000000	1525.000000	1525.000000
mean	54.182295	3.245902	3.140328	3.334426	2.746885	6.728525	1.542295
std	15.711209	0.880969	0.929951	1.174824	1.230703	3.297538	1.083315
min	24.000000	1.000000	1.000000	1.000000	1.000000	1.000000	0.000000
25%	41.000000	3.000000	3.000000	2.000000	2.000000	4.000000	0.000000
50%	53.000000	3.000000	3.000000	4.000000	2.000000	6.000000	2.000000
75	67.00	4.000000	4.000000	4.000	4.000	10.0000	2.000000

%	0000			000	000	00	
max	93.000000	5.000000	5.000000	5.000000	5.000000	11.000000	3.000000

Table-2-statistical summary

#create data frames with numerical data columns and object columns

Univariate analysis

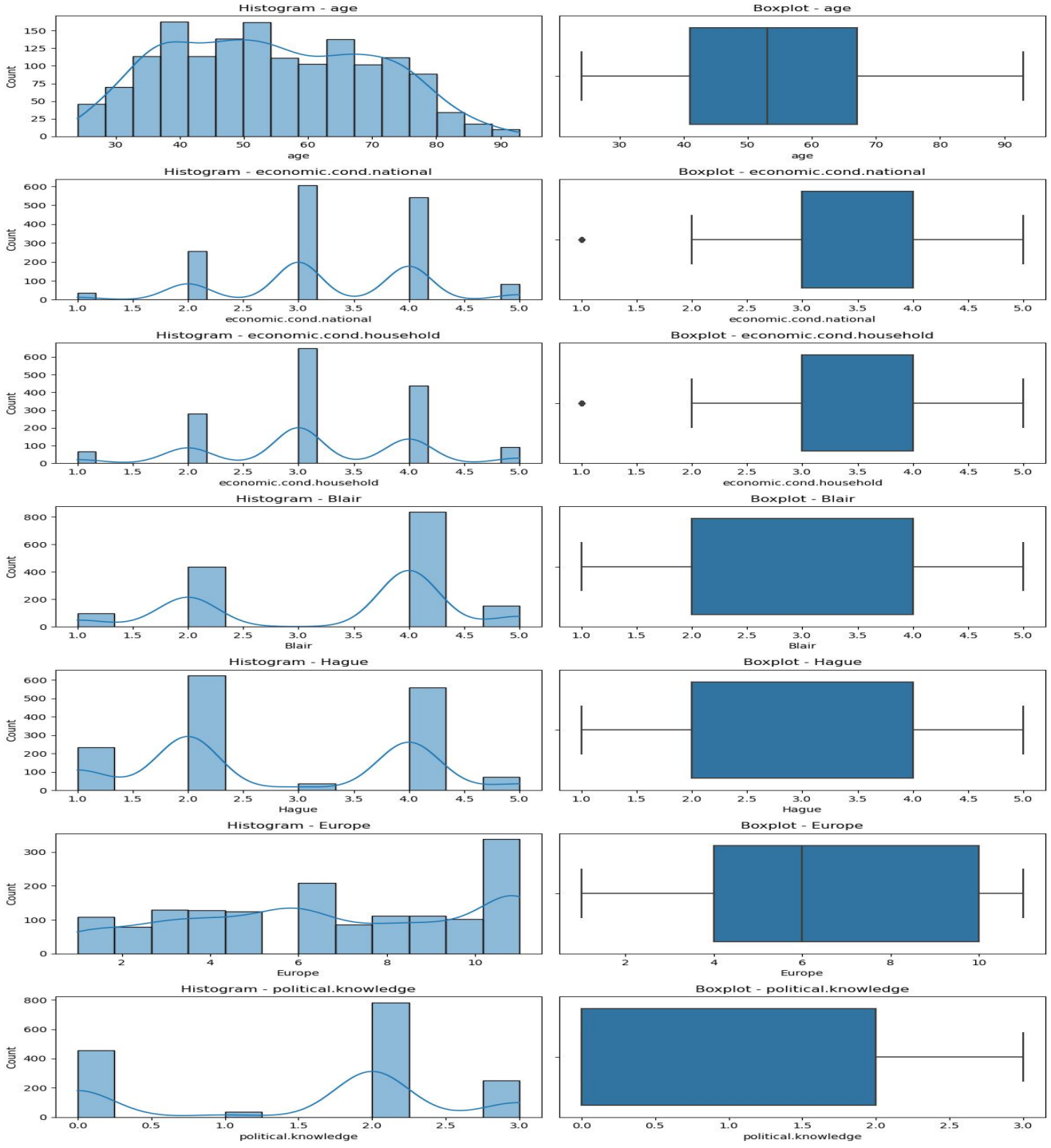


Figure-1 -histogram and boxplot of numerical columns

outliers presents in lower values of 'economic.cond.national ' and 'economic.cond.household' columns.

```
#describe the age column
count    1525.000000
mean       54.182295
std        15.711209
min        24.000000
25%        41.000000
50%        53.000000
75%        67.000000
max        93.000000
Name: age, dtype: float64
the mean of the voters age is 54
# describe economic.cond.national column
count    1525.000000
mean        3.245902
std         0.880969
min         1.000000
25%         3.000000
50%         3.000000
75%         4.000000
max         5.000000
Name: economic.cond.national, dtype: float64
50% of the assessment of current national economic conditions is 3.
# describe economic.cond.household column
count    1525.000000
mean        3.140328
std         0.929951
min         1.000000
25%         3.000000
50%         3.000000
75%         4.000000
max         5.000000
Name: economic.cond.household, dtype: float64
75% of the assessment of current household economic conditions
# describe  Blair column
count    1525.000000
mean        3.334426
std         1.174824
min         1.000000
25%         2.000000
50%         4.000000
75%         4.000000
```

```
max         5.000000
Name: Blair, dtype: float64
mean of the Assessment of the Labour leader is 3
# describe Hauge column
count    1525.000000
mean        2.746885
std         1.230703
min         1.000000
25%         2.000000
50%         2.000000
75%         4.000000
max         5.000000
Name: Hague, dtype: float64
75% of the assessment of the Conservative leader is 4.
## describe Europe column
count    1525.000000
mean        6.728525
std         3.297538
min         1.000000
25%         4.000000
50%         6.000000
75%        10.000000
max        11.000000
Name: Europe, dtype: float64
50% of respondents attitudes toward European integration is 6.728
# describe political.knowledge column
count    1525.000000
mean        1.542295
std         1.083315
min         0.000000
25%         0.000000
50%         2.000000
75%         2.000000
max         3.000000
Name: political.knowledge, dtype: float64
mean of the Knowledge of parties' positions on European integration' is 1.54
#columns of df_cat
Index(['vote', 'gender'], dtype='object')
#countplot of vote
```

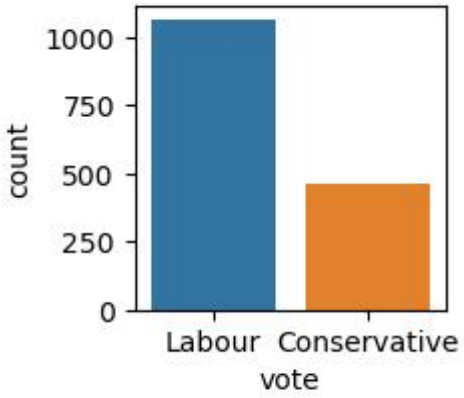


Figure-2-countplot of vote

more voters are labour party choice

#countplot of gender column

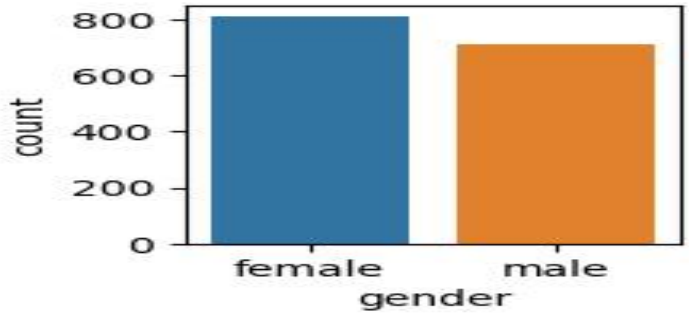


Figure-3-countplot of gender column

more voter are female

multivariate analysis

#plot the correlation map

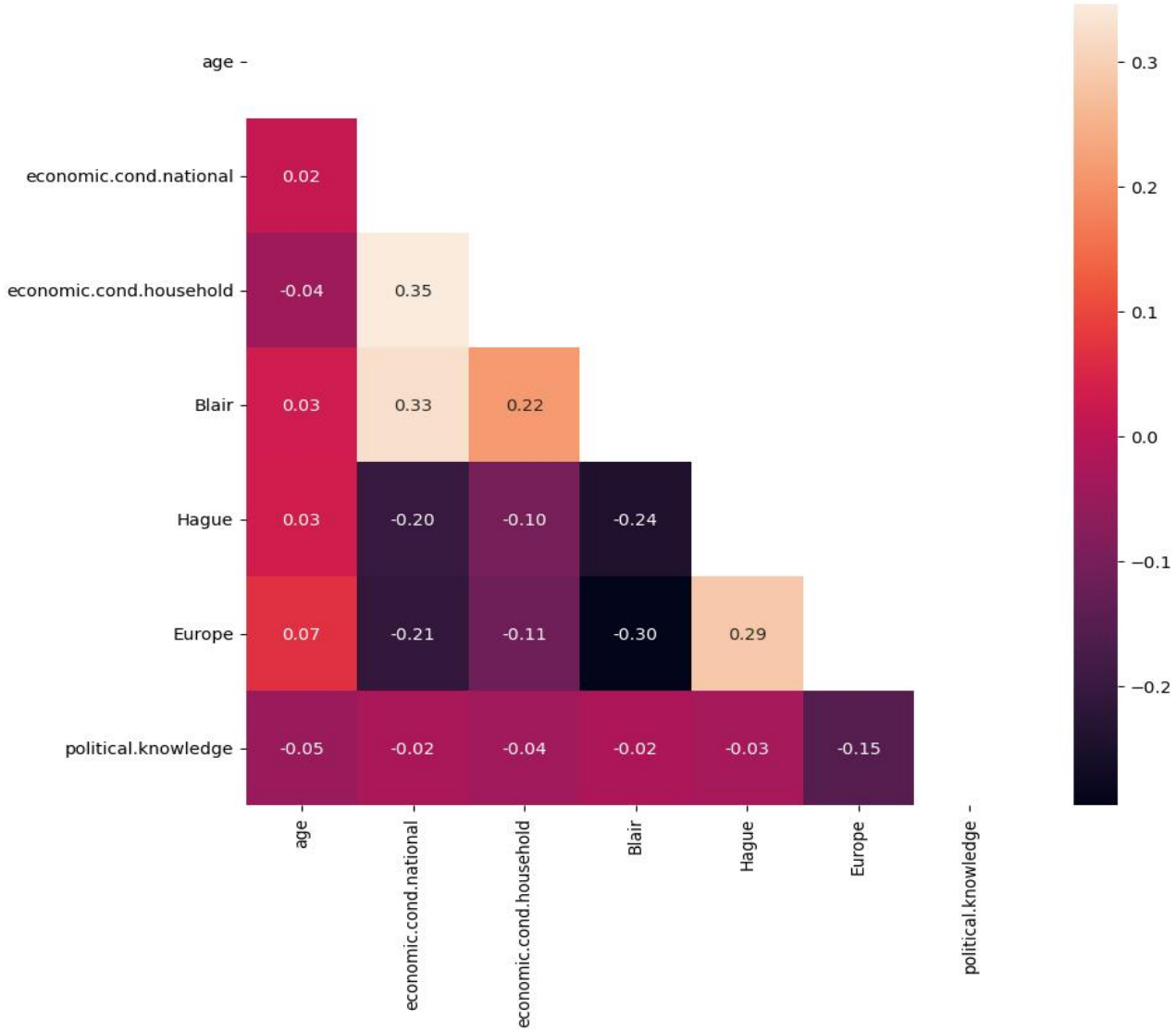


figure-4- *correlation map*

- there is no strong relationship present in between variables
- in this frame highly related one is 'economic.cond.national ' and 'economic.cond.household ' this not huge relationship.

#pair plot

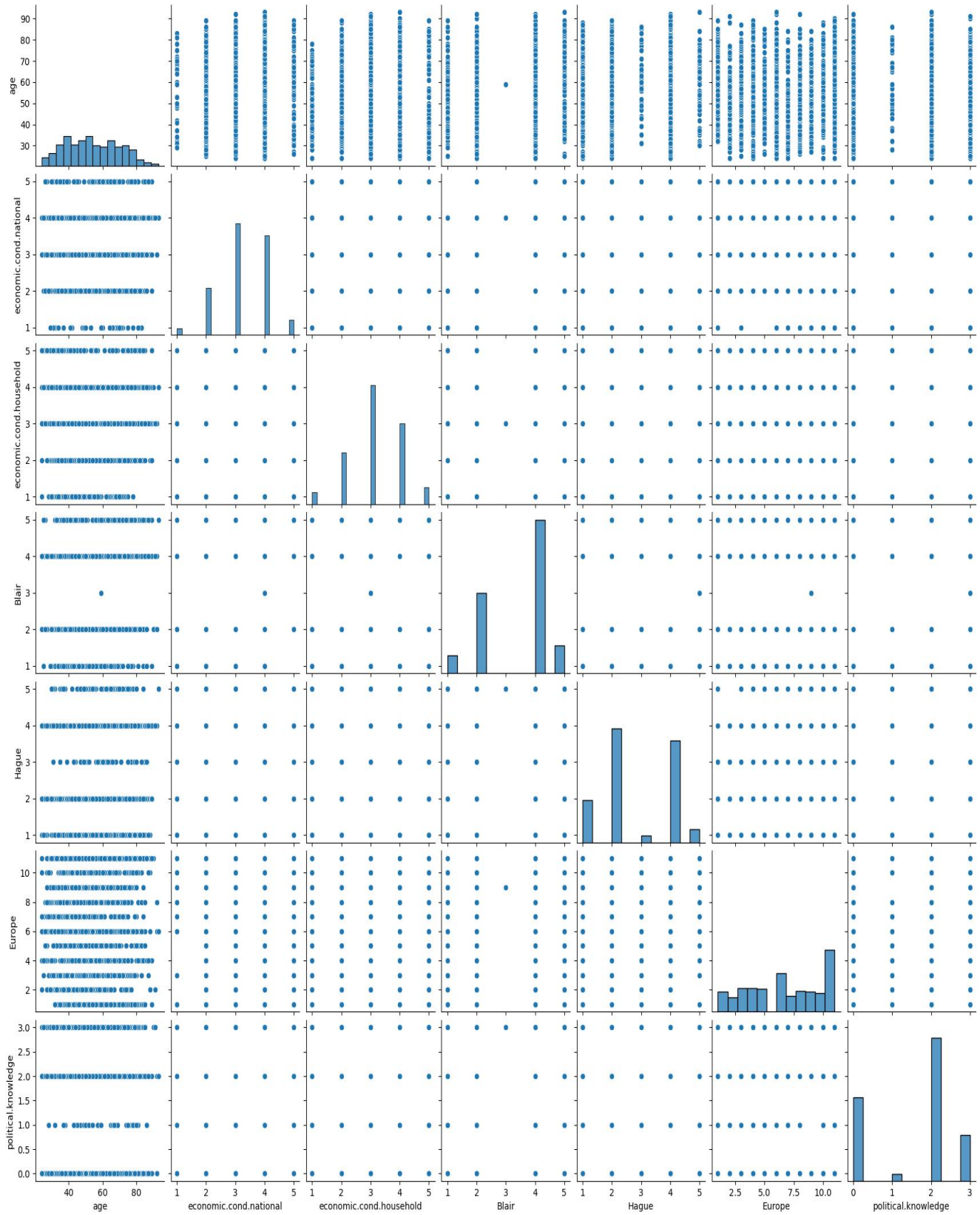


Figure-5-Pair plot-2

#barplot of vote vs age

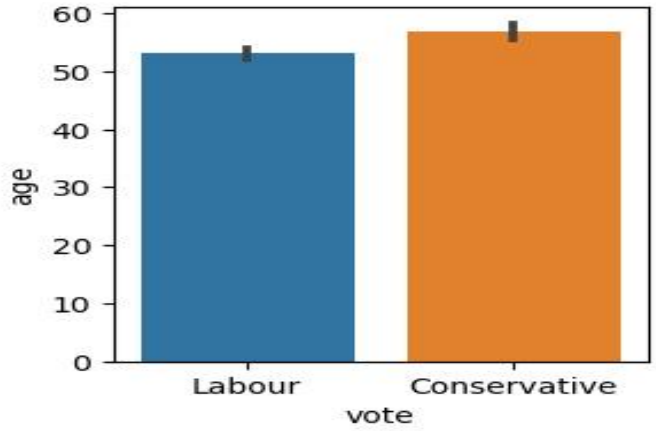


Figure-6-barplot of vote vs age

after 50 age most of voters are select conservative party.

#barplot of 'economic.cond.national' vs "vote"

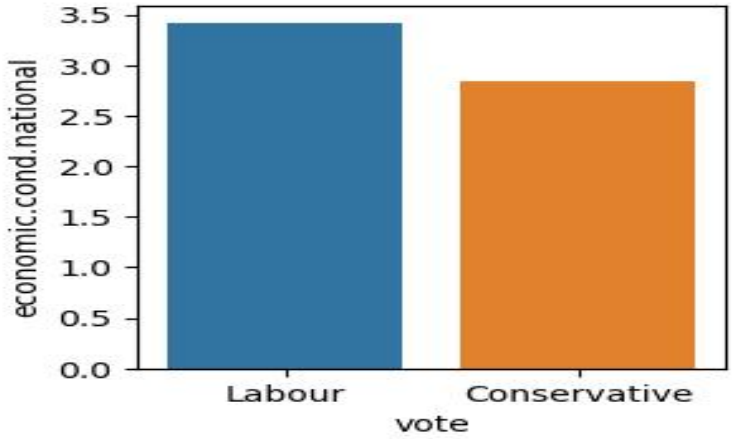


Figure-7-barplot of 'economic.cond.national' vs "vote"

economic condition of the nation is high in labour party choice.

#barplot of 'economic.cond.household" vs "vote"

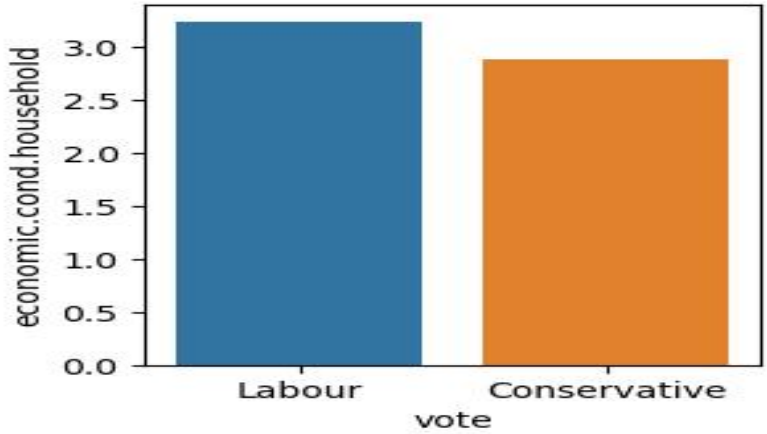


Figure-8-barplot of 'economic.cond.household" vs "vote"

economical condition of household is high in labour party choice

#'Blair' vs "vote"

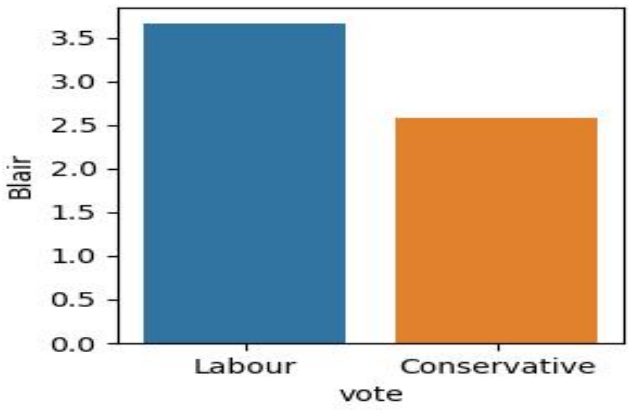


Figure-9-Blair *vs "vote"*

Assessment of the Labour leader is high in labour party choice.

#bar plot of 'Hague'vs "vote"

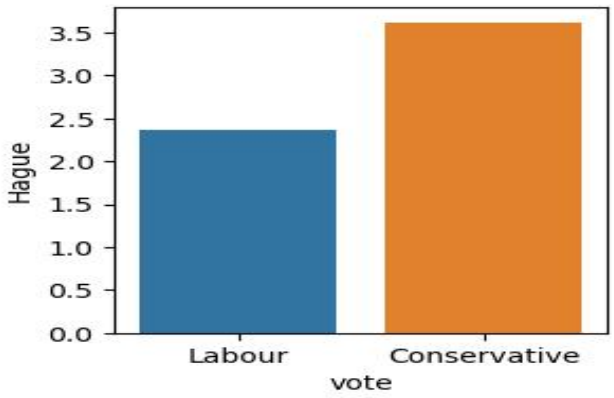


Figure-10-bar plot of 'Hague'vs "vote"

Assessment of the Conservative leader is high in conservative party choice

#barplot of 'Hague' vs "vote"

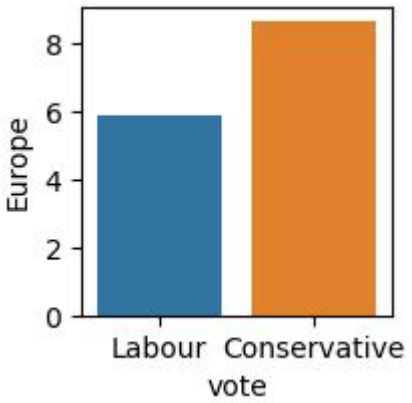


Figure-11-barplot of 'Hague' vs "vote"

attitudes toward European integration is High in conservative party choice.

#barplot of 'political.knowledge'vs"vote"

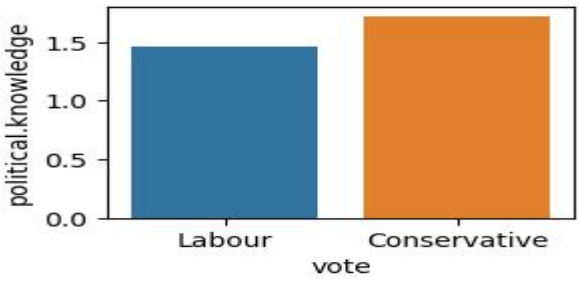


Figure-12-barplot of 'political.knowledge'vs"vote"

political knowledge is high in conservative party voters.

Use appropriate visualizations to identify the patterns and insights - Key meaningful observations on individual variables and the relationship between variables

insights:

Data Overview:

The dataset contains 1525 rows and 9 columns. There are 7 integer type columns and 2 object type columns.

Outliers:

Outliers are present in lower values of 'economic.cond.national' and 'economic.cond.household' columns.

Demographics:

The average age of voters is 54, and there is a shift towards the Conservative party after the age of 50. The dataset has a higher proportion of female voters.

Economic Conditions:

Outliers in lower values of 'economic.cond.national' and 'economic.cond.household' suggest potential economic concerns among some respondents. Labour party voters tend to have higher economic conditions at both the national and household levels.

Leader Assessments:

Voters, on average, rate the Labour leader higher (mean of 3.75) compared to the more polarized assessments of the Conservative leader. There is a correlation between leader assessments and political party choice.

Attitudes Toward European Integration:

Attitudes toward European integration vary widely among respondents. Conservative party supporters tend to have higher scores, reflecting more conservative views on European integration.

Political Knowledge:

On average, voters have a relatively low political knowledge score (mean of 1.54). Conservative party voters show higher political knowledge compared to Labour party voters.

Party Preferences:

The Labour party is more popular among voters in the dataset. After the age of 50, there is a notable shift towards the Conservative party.

Relationships Between Variables:

A moderate relationship exists between 'economic.cond.national' and 'economic.cond.household,' indicating a potential interdependence in how respondents perceive economic conditions. While correlations exist between economic conditions, party choice, and leader assessments, no strong relationships are evident.

Overall Observations:

The dataset portrays a diverse range of opinions and preferences among voters. Economic conditions significantly influence party choice, with Labour party voters favoring higher economic conditions. Age, leader assessments, and attitudes toward European integration contribute to the nuanced landscape of political choices.

Demographics:

The average age of voters is 54, and there is a shift towards the Conservative party after the age of 50. The dataset has a higher proportion of female voters.

Economic Conditions:

Outliers in lower values of 'economic.cond.national' and 'economic.cond.household' suggest potential economic concerns among some respondents. Labour party voters tend to have higher economic conditions at both the national and household levels.

Leader Assessments:

Voters, on average, rate the Labour leader higher (mean of 3.75) compared to the more polarized assessments of the Conservative leader. There is a correlation between leader assessments and political party choice.

Attitudes Toward European Integration:

Attitudes toward European integration vary widely among respondents. Conservative party supporters tend to have higher scores, reflecting more conservative views on European integration.

Political Knowledge:

On average, voters have a relatively low political knowledge score (mean of 1.54). Conservative party voters show higher political knowledge compared to Labour party voters.

Party Preferences:

The Labour party is more popular among voters in the dataset. After the age of 50, there is a notable shift towards the Conservative party.

Relationships Between Variables:

A moderate relationship exists between 'economic.cond.national' and 'economic.cond.household,' indicating a potential interdependence in how respondents perceive economic conditions. While correlations exist between economic conditions, party choice, and leader assessments, no strong relationships are evident.

Overall Observations:

The dataset portrays a diverse range of opinions and preferences among voters. Economic conditions significantly influence party choice, with Labour party voters favoring higher economic conditions. Age, leader assessments, and attitudes toward European integration contribute to the nuanced landscape of political choices.

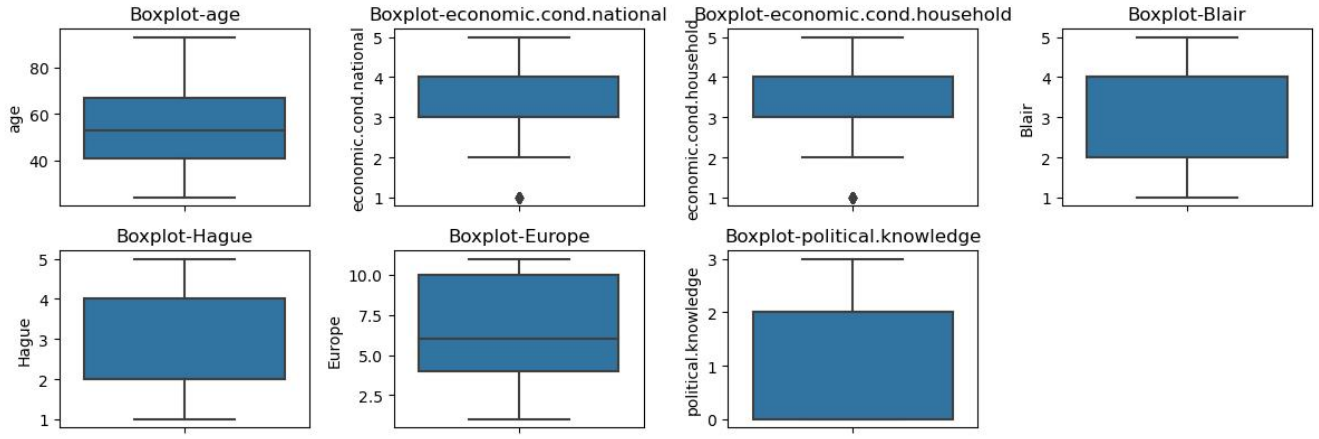
1.2-Data Pre-processing

Prepare the data for modelling: - Outlier Detection(treat, if needed)) - Encode the data - Data split - Scale the data (and state your reasons for scaling the features)

```
#check 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

no missing values in the data set



#Figure-13-checking outliers using boxplot

outliers are present in the lower values of 'economic.cond.national', 'economic.cond.household''economic.cond.national', 'economic.cond.household'.

#remove outliers

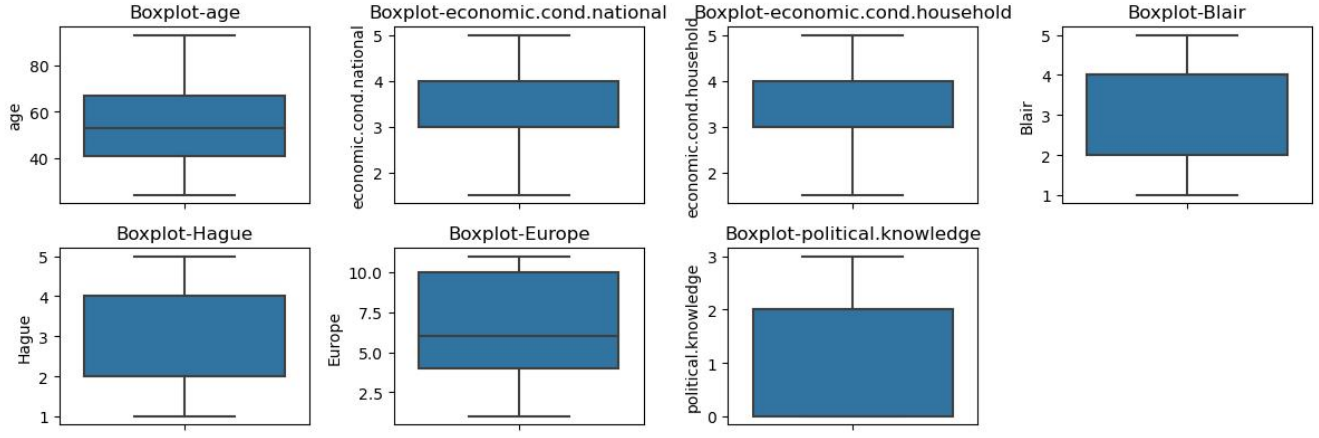


Figure-14-checking outliers using boxplot after treatment

Encode the data

#converting all obect columns to categorical column

colum: vote

['Labour', 'Conservative']
Categories (2, object): ['Conservative', 'Labour']
[1 0]

colum: gender
['female', 'male']
Categories (2, object): ['female', 'male']
[0 1]

```
#create new data frame
#copy the df_cat to new data frame
# merging new dataframe and numerical data frame
# columns of new data  frame
Index(['vote', 'gender', 'age', 'economic.cond.national',
       'economic.cond.household', 'Blair', 'Hague', 'Europe',
       'political.knowledge'],
```

	vote	gender	age	economic.cond.national	economic.cond.household	Blair	Hague	Europe	political.knowledge
0	1	0	43.0	3.0	3.0	4.0	1.0	2.0	2.0
1	1	1	36.0	4.0	4.0	4.0	4.0	5.0	2.0
2	1	1	35.0	4.0	4.0	5.0	2.0	3.0	2.0
3	1	0	24.0	4.0	2.0	2.0	1.0	4.0	0.0
4	1	1	41.0	2.0	2.0	1.0	1.0	6.0	2.0

Table-3-first 5 rows of new data frame

Data split

Scale the data (and state your reasons for scaling the features)

```
#split data
```

we are not going to scale the data for logistic regression,LDA and Naive Baye's model as it is not necessary.

But in case of KNN it is necessary to scale the data,as it a distance based algorithm (typically based on Euclidean distance).scalling te data gives similar weightage to all the variables.

1-3-Model Building

- Metrics of Choice (Justify the evaluation metrics) - Model Building (KNN, Naive bayes, Bagging, Boosting).

1-4-Model Performance evaluation

- Check the confusion matrix and classification metrics for all the models (for both train and test dataset) - ROC-AUC score and plot the curve - Comment on all the model performance

ANSWERS:

############ Metrics of Choice (Justify the evaluation metrics)

here dealing with a classification problem like predicting political party choices

Accuracy:

Accuracy is a common metric that measures the overall correctness of predictions. It is suitable when the classes are balanced, and there is no significant class imbalance in the dataset.

Precision and Recall:

Justification: Precision and recall provide insights into the model's ability to make correct positive predictions and capture all actual positive instances, respectively. In the context of predicting political party choices, both precision and recall are essential. For example: Precision: To measure the accuracy of positive predictions, especially important for avoiding false positives when reporting party choices. Recall: To assess the ability of the model to identify all instances of a particular party choice, important for avoiding false negatives.

F1-Score:

Justification: The F1-Score is the harmonic mean of precision and recall. It is useful when there is an imbalance between classes and you want to balance the trade-off between false positives and false negatives.

Area Under the ROC Curve (AUC-ROC):

Justification: AUC-ROC evaluates the model's ability to distinguish between different classes. It is suitable when there is a need to understand the model's

performance across different probability thresholds. Useful for binary classification problems.

Confusion Matrix:

Justification: The confusion matrix provides a detailed breakdown of true positives, true negatives, false positives, and false negatives. It is valuable for understanding the types of errors the model makes

Model Building (KNN, Naive bayes, Bagging, Boosting).

KNN MODEL

scaling is necessary in KNN MODEL.

	gender	age	economic.cond.national	economic.cond.household	Blair	Hague	Europe	political.knowledge
0	-0.937059	-0.711973	-0.302622	-0.182644	0.566716	-1.419886	-1.434426	0.422643
1	1.067169	-1.157661	0.870182	0.947305	0.566716	1.018544	-0.524358	0.422643
2	1.067169	-1.221331	0.870182	0.947305	1.418187	-0.607076	-1.131070	0.422643
3	-0.937059	-1.921698	0.870182	-1.312594	-1.136225	-1.419886	-0.827714	-1.424148
4	1.067169	-0.839313	-1.475425	-1.312594	-1.987695	-1.419886	-0.221002	0.422643

Table-4-*scaled data*

#split data using scaled data
#build a KNN model and fit
#predict the test,train data
#print accuracy ,classification report,confusion method of train

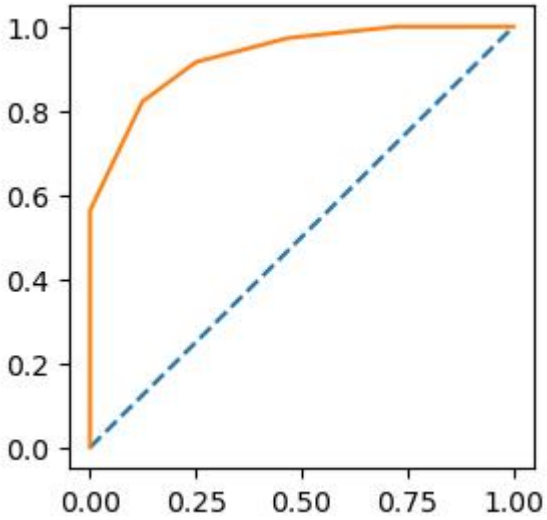
evaluation of train

accuracy: 0.8641049671977507

	precision	recall	f1-score	support

0	0.80	0.75	0.77	332
1	0.89	0.92	0.90	735
accuracy			0.86	1067
macro avg	0.85	0.83	0.84	1067
weighted avg	0.86	0.86	0.86	1067

[[249 83]
[62 673]]
AUC:0.930



 # figure-15-plot the roc curve for the model train

#print accuracy ,classification report,confusion method of train
evaluation of test
accuracy: 0.8187772925764192

	precision	recall	f1-score	support
0	0.67	0.70	0.69	130
1	0.88	0.87	0.87	328
accuracy			0.82	458
macro avg	0.78	0.78	0.78	458
weighted avg	0.82	0.82	0.82	458

[[91 39]
[44 284]]
 # calculate AUC of test
AUC:0.869

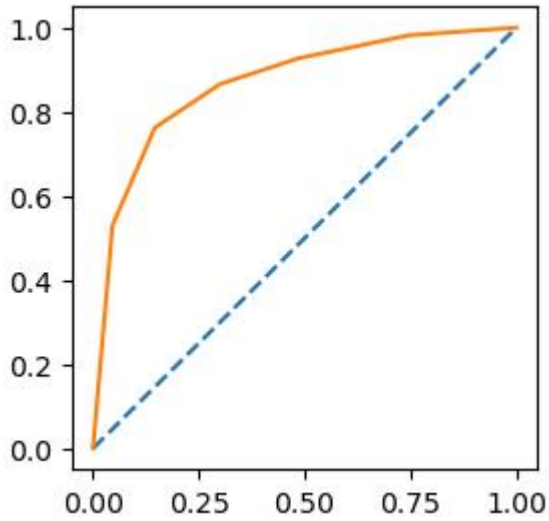


figure-16-plot the roc curve for the modeL test

Summary:

The KNN model performs well on both the training and test sets, showcasing its ability to generalize to unseen data.

The model demonstrates balanced precision and recall for both classes, suggesting a good trade-off between false positives and false negatives.

The AUC scores for both training and test sets are relatively high, indicating strong discriminatory power.

The slight drop in performance on the test set compared to the training set is expected but is not substantial, indicating good generalization.

Overall, the KNN model appears to be a robust classifier for the given task.

Naive bayes

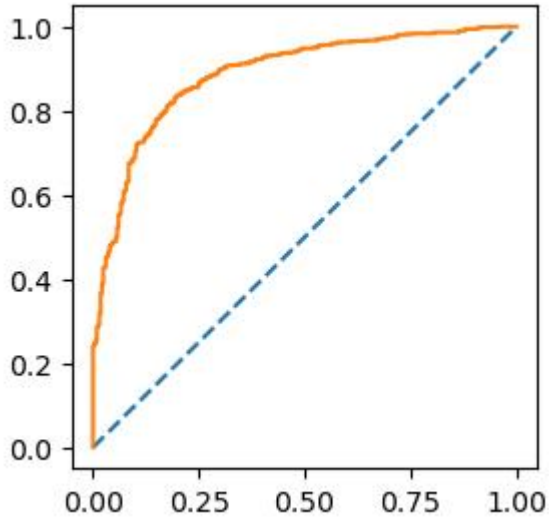
```
#split data using x,y(not using scaled data)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.30, rand¶om_state=1)
```

Training Set Evaluation:
Accuracy: 0.8322399250234301
[[240 92]
[87 648]]

	precision	recall	f1-score	support
0	0.73	0.72	0.73	332
1	0.88	0.88	0.88	735
accuracy			0.83	1067

macro avg	0.80	0.80	0.80	1067
weighted avg	0.83	0.83	0.83	1067

AUC:0.887



#figure-17- plot the roc curve for the model train

Test Set Evaluation:
Accuracy: 0.8384279475982532
[[91 39]
 [35 293]]

	precision	recall	f1-score	support
0	0.72	0.70	0.71	130
1	0.88	0.89	0.89	328
accuracy			0.84	458
macro avg	0.80	0.80	0.80	458
weighted avg	0.84	0.84	0.84	458

AUC:0.890

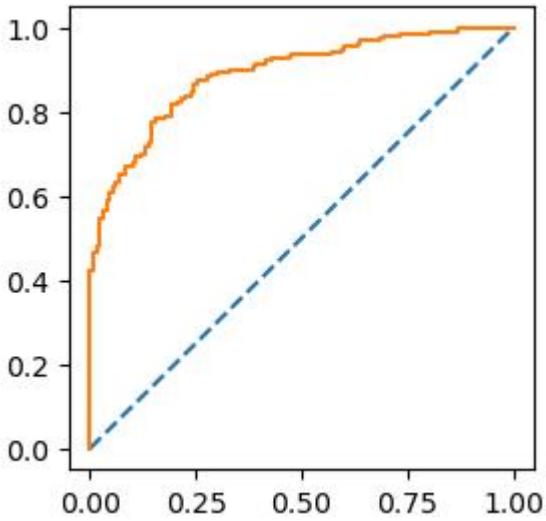


figure-18- plot the roc curve for the model test

Summary:

The Naive Bayes model performs well on both the training and test sets, demonstrating its ability to generalize to unseen data.

The model shows a good balance between precision and recall for both classes, suggesting a good trade-off between false positives and false negatives.

The AUC scores for both training and test sets are relatively high, indicating strong discriminatory power.

The slight drop in performance on the test set compared to the training set is expected but is not substantial, indicating good generalization.

Overall, the Naive Bayes model appears to be a robust classifier for the given task.

Bagging

Performance Matrix on train data set

Accuracy:0.9812558575445174
[[327 5]
[15 720]]

	precision	recall	f1-score	support
0	0.96	0.98	0.97	332
1	0.99	0.98	0.99	735
accuracy			0.98	1067
macro avg	0.97	0.98	0.98	1067

weighted avg 0.98 0.98 0.98 1067

AUC:0.998

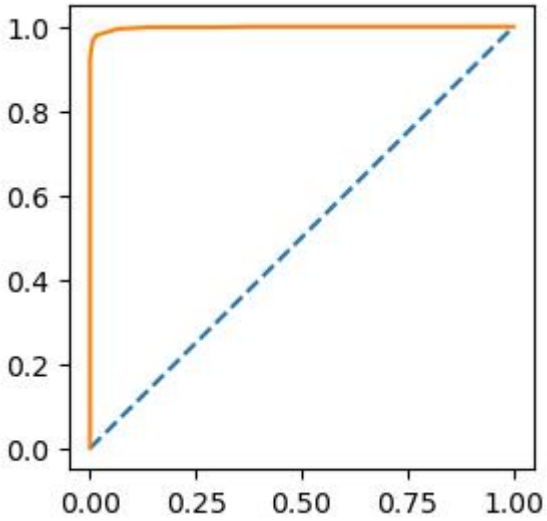


figure-19- plot the roc curve for the model train

Performance Matrix on test data set

Accuracy:0.8100436681222707

[[90 40]
[47 281]]

	precision	recall	f1-score	support
0	0.66	0.69	0.67	130
1	0.88	0.86	0.87	328
accuracy			0.81	458
macro avg	0.77	0.77	0.77	458
weighted avg	0.81	0.81	0.81	458

AUC:0.863

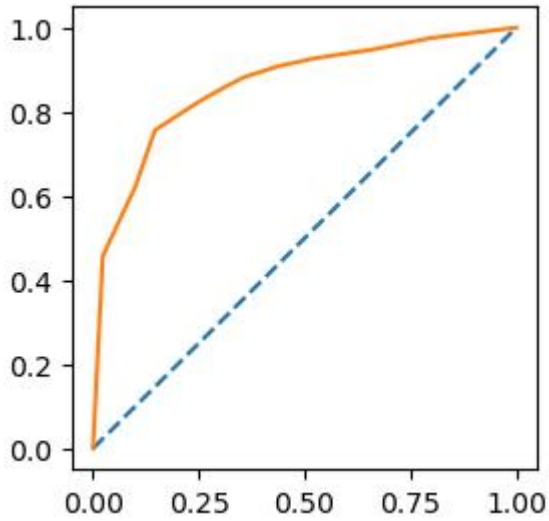


Figure-20-# plot the roc curve for the model test

Summary:

- The Bagging classifier with Decision Tree base classifiers performed exceptionally well on the training dataset, achieving high accuracy and AUC.

- The model generalizes reasonably well to the test dataset, with a slightly lower accuracy and AUC compared to the training dataset.

- The model exhibits good precision, recall, and F1-score values for both classes, indicating balanced performance in classification.

- Overall, the Bagging classifier demonstrates robust performance in both training and test datasets, making it a reliable choice for classification tasks.

- However, there might be room for further optimization or exploration of hyper parameters to improve generalization performance further.

Ada Boost

 # Define the base estimator (you can use DecisionTreeClassifier or any other classifier)
 # Create AdaBoostClassifier
Performance Matrix on train data set

Accuracy:0.9990627928772259
[[332 0]
[1 734]]

	precision	recall	f1-score	support
0	1.00	1.00	1.00	332
1	1.00	1.00	1.00	735

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

 # calculate AUC of train

AUC:1.000

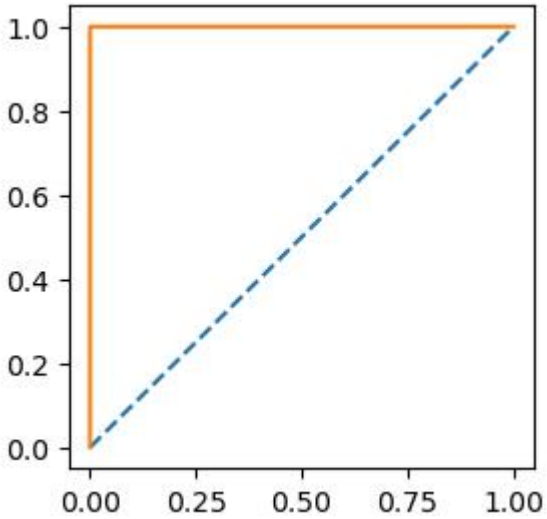


Figure-21-# plot the roc curve for the model train

Performance Matrix on test data set

Accuracy:0.7663755458515283

[[85 45]
 [62 266]]

	precision	recall	f1-score	support
0	0.58	0.65	0.61	130
1	0.86	0.81	0.83	328
accuracy			0.77	458
macro avg	0.72	0.73	0.72	458
weighted avg	0.78	0.77	0.77	458

 # calculate AUC of test

 # plot the roc curve for the model

AUC:0.783

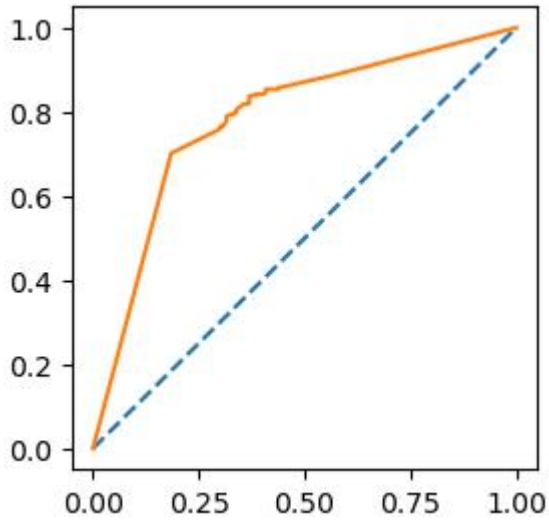


Figure-22-# plot the roc curve for the model test

The model demonstrated excellent performance on the training dataset, achieving near-perfect accuracy and AUC.

However, there is a noticeable drop in performance on the test dataset, indicating potential overfitting on the training data or difficulty in generalizing to unseen data.

1-5 Model Performance improvement

- Improve the model performance of bagging and boosting models by tuning the model - Comment on the model performance improvement on training and test data

ANSWER:

Tuning the Model of BAGGING:

To enhance the bagging model, hyperparameters such as the number of base learners (n_estimators) and the maximum depth of the base learners (max_depth) can be tuned. Adjusting these parameters can impact the model's ability to capture complex patterns and reduce overfitting.

 # Define the hyperparameters to tune

 # Initialize GridSearchCV for hyperparameter tuning

 # Fit the GridSearchCV to the training data

 # Get the best parameters
 # Initialize the Bagging model with the best parameters
 # Fit the best Bagging model on the training data

Best Parameters: {'max_features': 1.0, 'max_samples': 0.7, 'n_estimators': 50}

```
Accuracy train:0.979381443298969
[[319  13]
 [  9 726]]
              precision    recall  f1-score   support

           0       0.97      0.96      0.97       332
           1       0.98      0.99      0.99       735

    accuracy                           0.98      1067
   macro avg       0.98      0.97      0.98      1067
weighted avg       0.98      0.98      0.98      1067

Accuracy test:0.8144104803493449
[[ 89  41]
 [ 44 284]]
              precision    recall  f1-score   support

           0       0.67      0.68      0.68       130
           1       0.87      0.87      0.87       328

    accuracy                           0.81       458
   macro avg       0.77      0.78      0.77       458
weighted avg       0.82      0.81      0.82       458
```

```
# calculate AUC of train
# plot the roc curve for the model
AUC of train:0.998
```

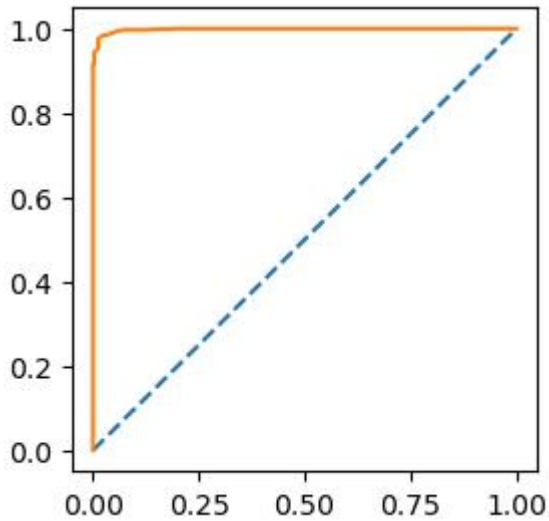


Figure-23- plot the roc curve for the model of train

AUC of test:0.877

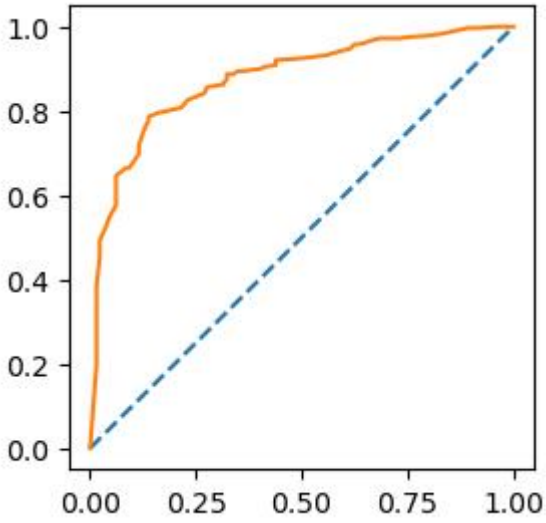


Figure-24- plot the roc curve for the model of test

- After tuning, the Bagging model's performance remained consistent on the training data while showing slight improvements in accuracy and AUC on the test data.
- Both models exhibit robust performance, with the tuned Bagging model showing slightly better performance metrics on the test dataset.
- The tuning process likely involved adjusting hyperparameters like the maximum number of features, maximum number of samples, and the number of estimators.
- Overall, the tuned Bagging model presents a reliable classifier with improved generalization ability compared to the original model.

Tuning the Model of ADA BOOSTING

Hyperparameters like the number of base learners (n_estimators) and the learning rate (learning_rate) can be tuned to optimize the AdaBoost model.

```
# Define the parameter grid to search

# Create GridSearchCV
# Fit the model to the training data
# Get the best parameters
# Print the best parameters
# Get the best model
# Predictions on the training set
# Performance metrics on the training set
```

Best Parameters: {'base_estimator__max_depth': 1, 'learning_rate': 0.1, 'n_estimators': 150}
Training Set Evaluation:
0.8397375820056232

[[223 109]
 [62 673]]

	precision	recall	f1-score	support
0	0.78	0.67	0.72	332
1	0.86	0.92	0.89	735
accuracy			0.84	1067
macro avg	0.82	0.79	0.81	1067
weighted avg	0.84	0.84	0.84	1067

Test Set Evaluation:
0.8296943231441049
[[86 44]
 [34 294]]

	precision	recall	f1-score	support
0	0.72	0.66	0.69	130
1	0.87	0.90	0.88	328
accuracy			0.83	458
macro avg	0.79	0.78	0.79	458
weighted avg	0.83	0.83	0.83	458

 # calculate AUC of train
AUC:0.905

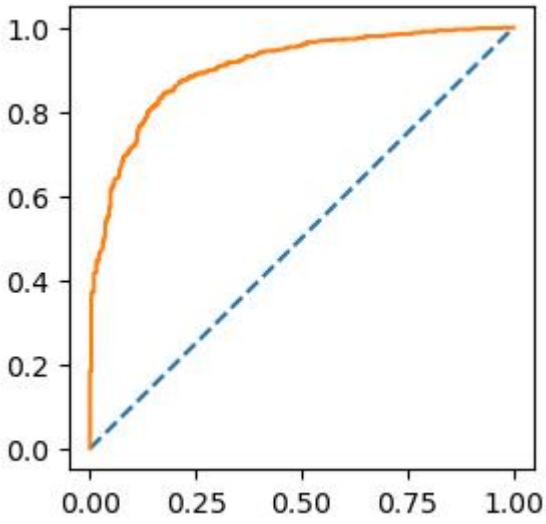


Figure-25- plot the roc curve for the model train

 # calculate AUC of test
AUC:0.888

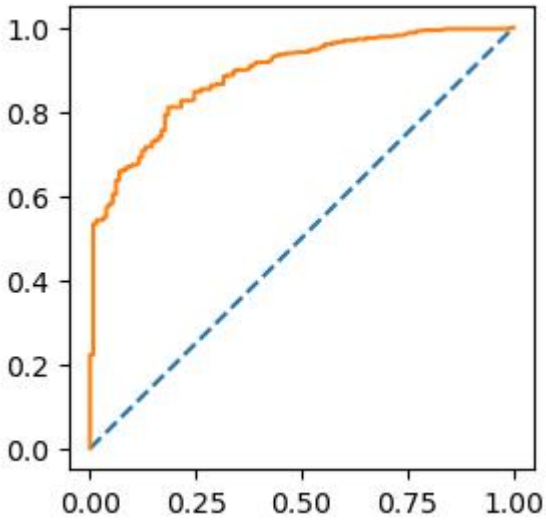


Figure-26- plot the roc curve for the model test

The original AdaBoost model demonstrated signs of overfitting, with a significant drop in performance between training and test datasets.

By tuning the AdaBoost model with 150 estimators and adjusting parameters like the base learner's maximum depth and learning rate, the model's overfitting was reduced.

The tuned AdaBoost model achieved a more balanced performance between training and test datasets, with improved accuracy and AUC on both.

While the original model showed higher accuracy on the training data, it struggled with generalization to unseen data. In contrast, the tuned model demonstrates better generalization ability, making it more reliable for real-world applications.

1.6-Final Model Selection

- Compare all the model built so far - Select the final model with the proper justification - Check the most important features in the final model and draw inferences.

To compare the models built so far-

KNN Model:

Accuracy: 83.84% (Test set) AUC: 0.890 (Test set) No information provided regarding overfitting, precision, recall, or F1-score on the training set.

Naive Bayes Model:

Accuracy: 83.84% (Test set) AUC: 0.890 (Test set) No information provided regarding overfitting, precision, recall, or F1-score on the training set.

Bagging Model:

Accuracy: 81.44% (Test set) AUC: 0.877 (Test set) Potential overfitting: Accuracy on the training set is significantly higher (97.94%) than on the test set. High precision, recall, and F1-score on the training set.

AdaBoost Model:

Accuracy: 82.97% (Test set) AUC: 0.888 (Test set) Potential overfitting: Accuracy on the training set is higher (83.97%) than on the test set. Balanced precision, recall, and F1-score on both the training and test sets.

Justification for Final Model Selection:

Based on the provided evaluation results and considering the balance between model performance and potential overfitting, the AdaBoost model seems to be the most suitable choice. Here's why:

The AdaBoost model demonstrates a relatively high accuracy (82.97%) and AUC (0.888) on the test set, indicating good predictive performance. The AdaBoost model shows a balanced performance in terms of precision, recall, and F1-score on both the training and test sets, suggesting good generalization capability. While there is a slight drop in accuracy from the training set to the test set, the magnitude of this drop is smaller compared to the Bagging model, indicating potentially less overfitting. The Bagging model exhibits a significantly higher accuracy on the training set (97.94%), suggesting a higher risk of overfitting compared to the AdaBoost model. Therefore, considering both performance metrics and potential overfitting, the AdaBoost model appears to be the most suitable final model among the ones evaluated.

```
# Create a DataFrame to display feature importances
# Sort the DataFrame by importance in descending order
# Display the top features
```

```
                Feature  Importance
4                 Blair    0.200000
5                 Hague    0.200000
1                   age    0.173333
6                Europe    0.160000
2  economic.cond.national    0.106667
```

Hague (Political Leader): 20%

Blair (Political Leader): 20%

Age: 17%

Europe (Geographical Factor): 16%

Economic Condition (National): 10%

Interpretation:

Political Leaders (Hague and Blair):

The model gives the highest importance to features related to political leaders, specifically "Hague" and "Blair." This suggests that public sentiment or opinions about these political figures significantly influence the model's predictions.

Geographical Factor (Europe):

The "Europe" feature is also considered important, indicating that sentiments or opinions related to European affairs play a role in the model's decision-making.

Demographic Factor (Age):

"Age" is a feature with moderate importance, suggesting that the age of individuals has some influence on the model's predictions.

Economic Condition (National):

The "Economic Condition (National)" feature has a relatively lower importance but still contributes to the model's decision-making, indicating that national economic sentiments play a role.

Recommendations:

Political Leaders:

Public sentiment towards political leaders, especially Hague and Blair, seems to be crucial. Monitoring and understanding public opinions about these figures could be valuable.

Geopolitical Considerations:

The model highlights the importance of considering geopolitical factors, particularly sentiments related to Europe. Events or issues related to Europe may impact the predictions.

Demographic Insights:

Age appears to have some influence. Analyzing the preferences or opinions of different age groups might provide additional insights.

Economic Sentiments:

While economic conditions have a lower importance, staying aware of national economic sentiments could still be relevant for understanding model predictions.

1-7 Actionable Insights & Recommendations

- Compare all four models - Conclude with the key takeaways for the business

K-Nearest Neighbors (KNN):

Training Set Accuracy: 86.4%

Testing Set Accuracy: 81.8%

AUC (Test): 86.9%

Comments: Balanced performance, but a slight indication of overfitting.

Naive Bayes:

Training Set Accuracy: 83.22%

Testing Set Accuracy: 83.8%

AUC (Test): 89.0%

Comments: Balanced performance, particularly good AUC on the test set.

Bagging (Decision Tree base):

Training Set Accuracy: 97.9%

Testing Set Accuracy: 81.4%

AUC (Test): 87.7%

Comments: Potential overfitting indicated by the large difference between training and testing accuracies.

AdaBoost:

Training Set Accuracy: 83.9%

Testing Set Accuracy: 82.9%

AUC (Test): 88.8%

Comments: Balanced performance, good AUC on the test set, and less prone to overfitting compared to Bagging.

Key Takeaways:

Model Performance:

Naive Bayes and AdaBoost demonstrate balanced performance on both training and testing sets.

KNN shows balanced performance but with a slight indication of overfitting. Bagging exhibits potential overfitting, as suggested by the large difference between training and testing accuracies.

Discriminative Power:

AdaBoost stands out with the highest AUC on the test set (89.3%), indicating strong discrimination between positive and negative instances. Naive Bayes also shows excellent AUC (89.0%).

Overfitting Concerns:

Bagging, with a high training accuracy, raises concerns about potential overfitting, while AdaBoost is less prone to this issue.

Interpretability:

Naive Bayes is known for its simplicity and interpretability, making it easy to understand and explain.

Insights:

Political Leaders Influence:

Public sentiment towards political leaders, especially figures like Hague and Blair, has a substantial impact on the model's predictions. Continuous monitoring of public opinions about political leaders can provide valuable insights into potential shifts in sentiment that may affect the business environment.

Geopolitical Considerations:

The model highlights the importance of geopolitical factors, specifically sentiments related to Europe. Events or issues related to Europe may significantly impact customer sentiments and influence their preferences.

Demographic Factor:

Age plays a moderate role in the model's decision-making process. Understanding the preferences or opinions of different age groups can provide additional insights into customer behavior.

Economic Sentiments:

While economic conditions have a lower importance, they still contribute to the model's decision-making. Staying aware of national economic sentiments can be relevant for understanding shifts in consumer behavior.

Business Recommendations:

Public Opinion Monitoring:

Establish a system for continuous monitoring of public opinions about key political figures. Utilize social media listening tools, surveys, or sentiment analysis to stay informed about changing sentiments.

Geopolitical Risk Assessment:

Stay informed about geopolitical events, especially those related to Europe. Conduct regular risk assessments to anticipate and manage potential impacts on customer sentiments and market dynamics.

Targeted Marketing Strategies:

Tailor marketing strategies based on age demographics. Understand the preferences and needs of different age groups to create targeted and effective campaigns.

Adaptability and Agility:

Maintain an adaptable business strategy that can quickly respond to changing circumstances. Regularly update and refine the model as new data becomes available to ensure its accuracy and relevance over time.

Collaboration with Stakeholders:

Foster collaboration with political analysts, economists, and other experts to gain deeper insights into factors influencing public opinion and economic conditions.

Customer Engagement Initiatives:

Engage with customers to gather feedback and understand their concerns. Implement initiatives that address customer sentiments and contribute positively to public perceptions.

Educational Campaigns:

If economic conditions play a role, consider implementing educational campaigns to inform customers about relevant economic factors, fostering a better understanding of the business environment.

Problem 2

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 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') "

ANSWERS

Importing the necessary libraries along with the standard import

2-1-Exploratory Data Analysis

-Problem Definition - Find the number of Character, words & sentences in all three speeches

#read data set

	Name	Speech
0	Roosevelt	On each national day of inauguration since 178...
1	Kennedy	Vice President Johnson, Mr. Speaker, Mr. Chief...
2	Nixon	Mr. Vice President, Mr. Speaker, Mr. Chief Jus...

Table-5- head of the data set

#how no.of words in all 3 speeches

	Name	Speech	no.of_words
0	Roosevelt	On each national day of inauguration since 178...	1323
1	Kennedy	Vice President Johnson, Mr. Speaker, Mr. Chief...	1364
2	Nixon	Mr. Vice President, Mr. Speaker, Mr. Chief Jus...	1769

Table-6-dataset with no.of words column

#how many no.of characters

	Name	Speech	no.of_words	no.of_char
0	Roosevelt	On each national day of inauguration since 178...	1323	7651
1	Kennedy	Vice President Johnson, Mr. Speaker, Mr. Chief...	1364	7673
2	Nixon	Mr. Vice President, Mr. Speaker, Mr. Chief Jus...	1769	10106

Table-7-dataset with no.of character column

#how many no.of sentances

	Name	Speech	no.of_words	no.of_char	no.of_sen
0	Roosevelt	On each national day of inauguration since 178...	1323	7651	69
1	Kennedy	Vice President Johnson, Mr. Speaker, Mr. Chief...	1364	7673	56
2	Nixon	Mr. Vice President, Mr. Speaker, Mr. Chief Jus...	1769	10106	70

Table-8-dataset with no.of sentances column

2-2 - Text cleaning

- Stopword removal - Stemming - find the 3 most common words used in all three speeches

```
#converting lowercase
#stop word removal
0    national day inauguration since 1789, people r...
1    vice president johnson, mr. speaker, mr. chief...
2    mr. vice president, mr. speaker, mr. chief jus...
Name: Speech, dtype: object
#  Stemming
# Remove numeric characters from the 'Speech' column
#remove punctuation
0    nation day inaugur sinc  peopl renew sens dedi...
1    vice presid johnson mr speaker mr chief justic...
2    mr vice president mr speaker mr chief justice ...
Name: Speech, dtype: object
# replace \n\n by " "
```

	Name	Speech	no.of_words	no.of_char	no.of_sen
0	Roosevelt	nation day inaugur sinc peopl renew sens dedi...	1323	7651	69
1	Kennedy	vice presid johnson mr speaker mr chief justic...	1364	7673	56
2	Nixon	mr vice president mr speaker mr chief justice ...	1769	10106	70

Table-9-After cleaning process data set

```
# find the 3 most common words used in all three speeches
```

find the 3 most common words used in all three speeches

```
# find the 10 most common words used in  Roosevelt speech
nation     16
know       10
us          8
life        8
spirit      8
america     7
year        6
speak       5
mind        5
men         5
dtype: int64
# find the 10 most common words used in kennedy speech
us        11
let       11
```

```
power      8
side       7
new        7
pledg      7
world      6
nation     6
ask        6
shall      5
dtype: int64
# find the 10 most common words in Nixon speech

:

america    19
new        15
nation     14
world      12
peac       11
great       9
make        8
respons     8
polici      7
everi       7
dtype: int64
#remove unwanted words "us","let","mr"

#the most 3 words used in Roosevelt's speech
nation    16
know      10
life       8
dtype: int64
## #the most 3 words used in kennedy's speech
power    8
new      7
pledg    7
dtype: int64
# #the most 3 words used in Nixon's speech
america    19
new        15
nation     14
dtype: int64
```

2-3- Plot Word cloud of all three speeches

- Show the most common words used in all three speeches in the form of word clouds

Word Cloud for Roosevelt Speech

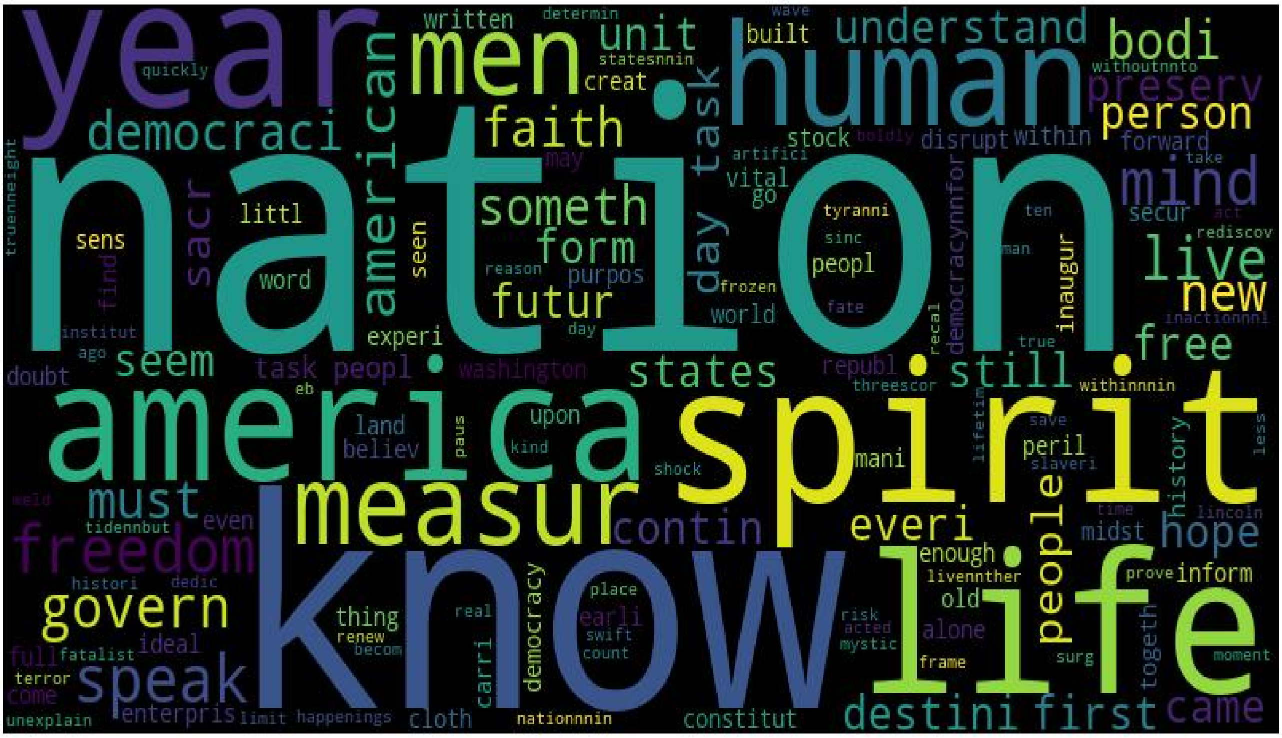


Figure-27-Word Cloud for Roosevelt speech

Word Cloud for Kennedy Speech

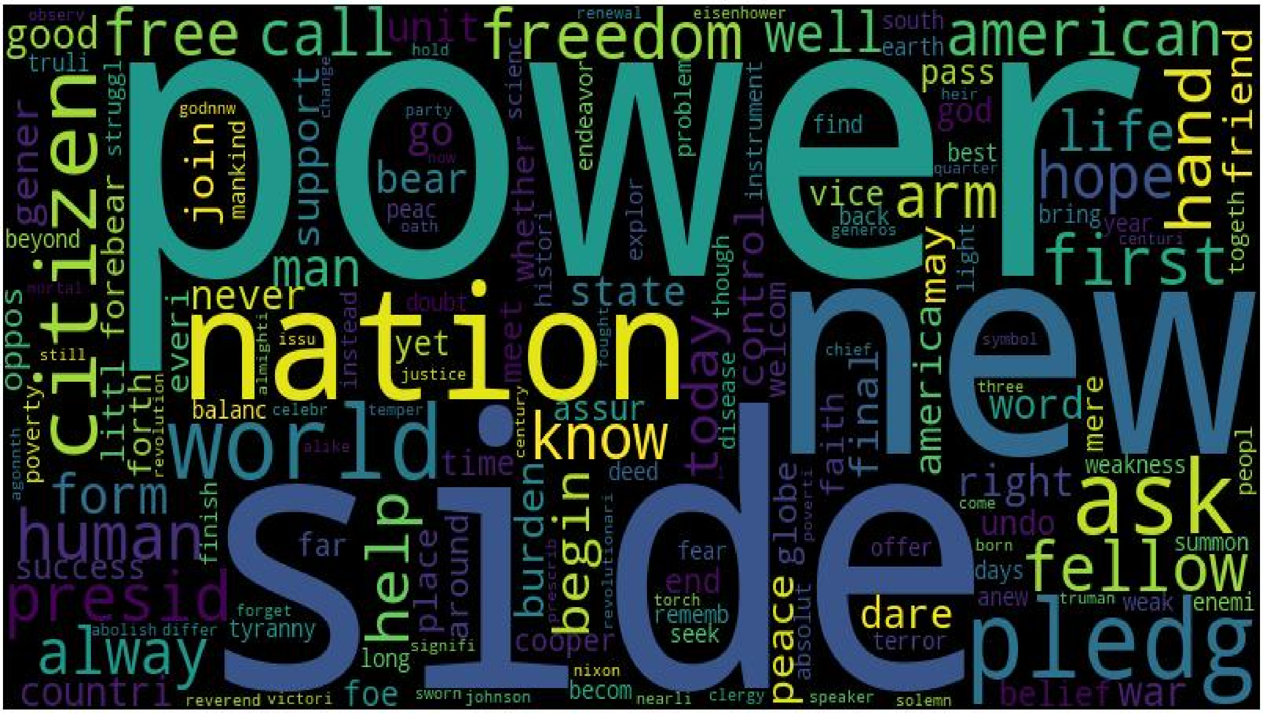


Figure-28-Word Cloud for Kennedy speech

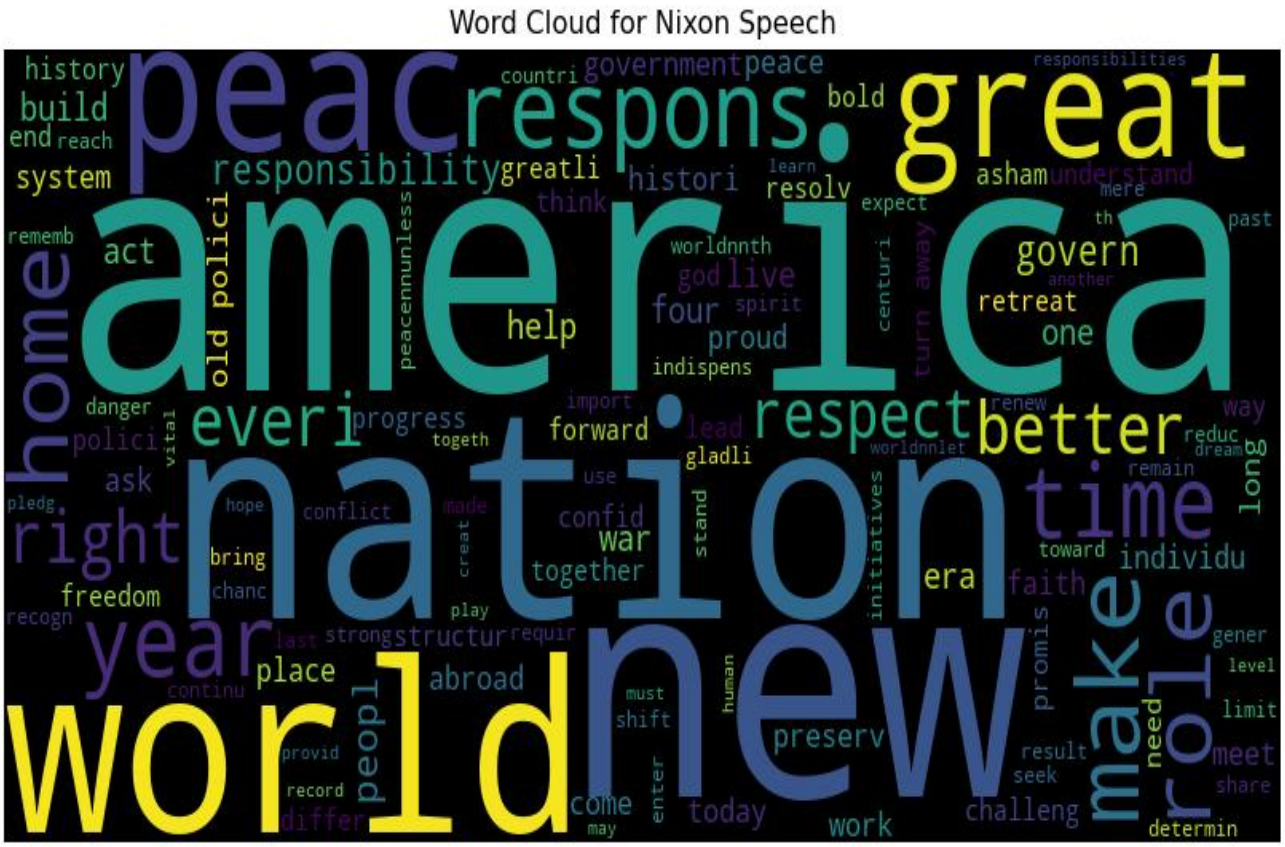


Figure-29-Word Cloud for Nixon's speech