Machine Learning

Course Project Report (Classification)

(Final Report, Team No: 01)

Title of the project: Online News Popularity

Student 1 : Sarang Galada, sarang.g-25@scds.saiuniversity.edu.in
Student 2 : R Sai Pranav Aadhitya, saipranavaadhitya.r-25@scds.saiuniversity.edu.in

ML Category: Classification

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1. Introduction

The Online News Popularity dataset contains a variety of features about news articles published by digital media platform Mashable over a period of 2 years. The goal here is to predict the popularity of the news article measured through the number of times the article has been shared on social media platforms. Framed as a classification problem, we implement various binary classification models to predict whether a news article is popular or not.

The significance of trying to model the relationship between the numerous features of an article and its popularity is that it helps authors understand what makes news articles popular and thereby equips them with the knowledge to improve their popularity.

- Problem Statement: (Binary Classification)

  Predicting whether news articles are popular or not based on the values of their various features.

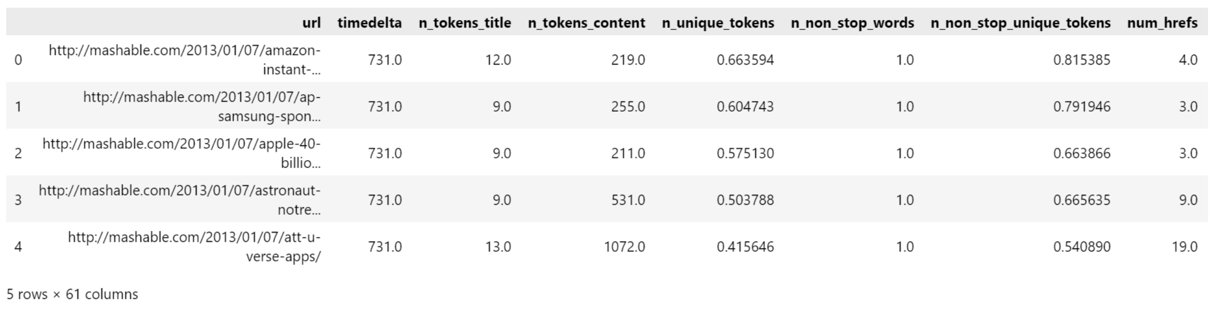
2. Dataset and Features

- Details of the dataset:

This project makes use of the Online News Popularity dataset from University of California, Irvine's Machine Learning Repository, sourced from a Portugal based research team, K. Fernandes et al. The dataset consists of 39,644 rows and 61 columns. The rows represent instances of new articles, while the columns depict various features of the articles - such as number of words, videos, images, hyperlinks in the article, average word length, tags, to name a few. Of these 61 columns, 59 are the input features for our learning model, with the 61st column 'shares', signifying the number of times an article has been shared on social media (measure of popularity) being the target variable we wish to predict. The first column 'url' is simply to identify the url of each article instance in the dataset.

- Exploratory Data Analysis:

Initially, the dataset contains 39,644 rows and 61 columns.



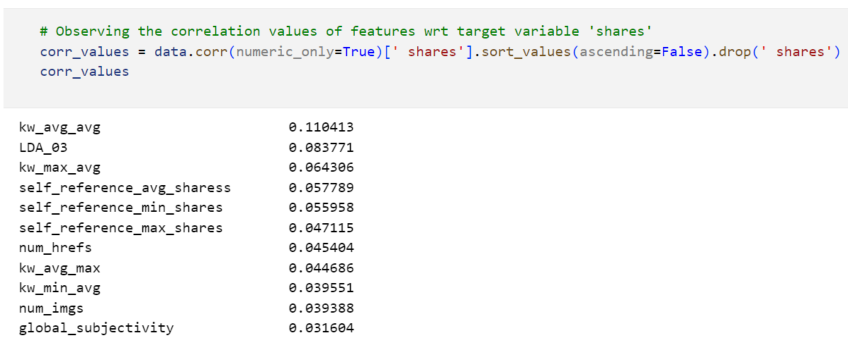
	url	timedelta	n_tokens_title	n_tokens_content	n_unique_tokens	n_non_stop_words	n_non_stop_unique_tokens	num_hrefs
0	http://mashable.com/2013/01/07/amazon-instant-...	731.0	12.0	219.0	0.663594	1.0	0.815385	4.0
1	http://mashable.com/2013/01/07/ap-samsung-spon...	731.0	9.0	255.0	0.604743	1.0	0.791946	3.0
2	http://mashable.com/2013/01/07/apple-40-billio...	731.0	9.0	211.0	0.575130	1.0	0.663866	3.0
3	http://mashable.com/2013/01/07/astronaut-notre...	731.0	9.0	531.0	0.503788	1.0	0.665635	9.0
4	http://mashable.com/2013/01/07/att-u-verse-apps/	731.0	13.0	1072.0	0.415646	1.0	0.540890	19.0

5 rows × 61 columns

Apart from the 'url' column which is of type Object and not relevant to our analysis, and the target variable 'shares' which is of type Int64, the remaining 59 input attributes are of type Float64. The data neither contains any missing values nor any duplicate data instances.

The target variable 'shares' has a right-skewed distribution, with a minimum value of 1, a median value of 1400, a mean value of 3395.38 and a maximum of 843300.

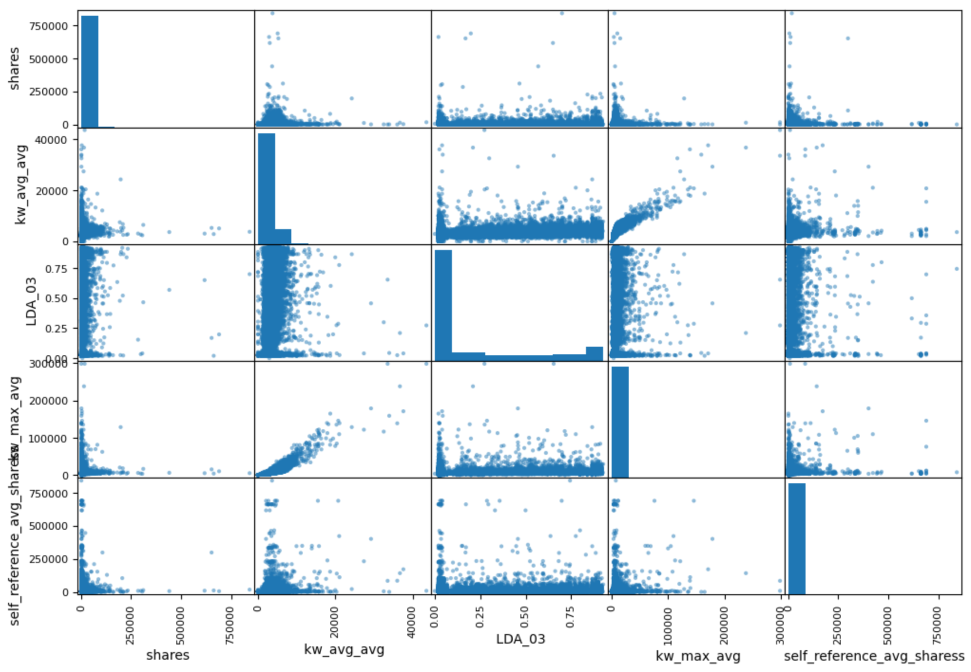
When inspecting the correlation values between the input features and the target variable, we see that apart from '*kw_avg_avg*', which has the highest correlation value of 0.110413, all other features have correlation values below 0.1. This implies that there is very low linear dependence between the attributes and the target variable.



```
# Observing the correlation values of features wrt target variable 'shares'
corr_values = data.corr(numeric_only=True)[' shares'].sort_values(ascending=False).drop(' shares')
corr_values
```

```
kw_avg_avg                       0.110413
LDA_03                           0.083771
kw_max_avg                       0.064306
self_reference_avg_sharess       0.057789
self_reference_min_shares        0.055958
self_reference_max_shares        0.047115
num_hrefs                        0.045404
kw_avg_max                       0.044686
kw_min_avg                       0.039551
num_imgs                         0.039388
global_subjectivity              0.031604
```

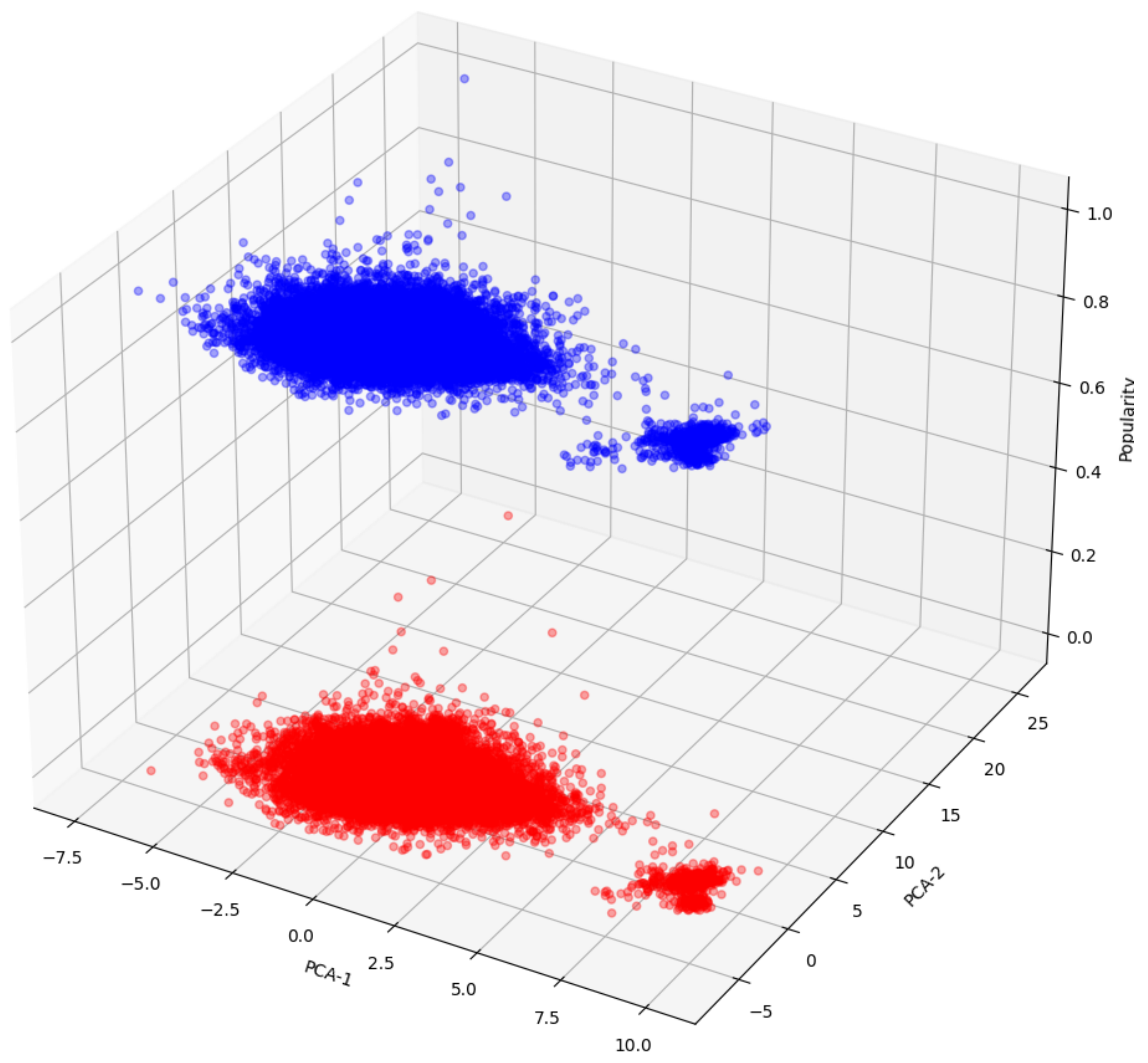
The first column of the following scatter matrix shows this lack of linear dependence.



- Dimensionality Reduction & Data Visualisation:

  We use dimensionality reduction techniques to reduce the number of features in the data from 59 to 2, so that the point cloud can be visualized in 3D when the features are plotted against the target variable 'shares'. In this project, we only implemented Principal Component Analysis (PCA), since t-SNE was very computationally intense even after using PCA to reduce the data first. The below plot shows the distribution of the data points with respect to the 2D PCA features, differentiated by colour based on their class - blue implies 'popular' and red, 'unpopular'.

Visualisation of PCA reduced data in 3D



3. Methods

Following are the various methods used in this project.

3.1 Baseline - Logistic Regression

The logistic regression model calculates the probability that a given input belongs to a particular class, and is the most popular baseline classification approach in machine learning. It is called logistic regression because it is based on the logistic function, a type of sigmoid function, which transforms values to between the range 0 and 1, to indicate the likelihood of a certain combination of features belonging to a particular class. It accomplishes this by mapping the input features to a real-valued output using a linear combination of the features. This linear combination is then transformed using the logistic function to obtain a probability value between 0 and 1.

We decided to make only two classes for our output data, since the accompanying research paper had performed their experiments with binary classification, and we wanted to maintain consistency with that. We performed logistic regression on the full training dataset, standardized, and the PCA reduced (20) dataset. Logistic regression on the regular data gave us an accuracy of approximately 0.59, standardized data gave us ~0.655, and the experiment with PCA reduced data gave 0.63728. The observation that logistic regression performs better on standardized and PCA data compared to the regular one becomes quite clear here with respect to our specific dataset.

3.2 Support Vector Machine

- Linear SVM and Kernel SVM

Linear SVC finds the optimal hyperplane by identifying the support vectors that lie closest to the decision boundary. It is different from the SVC class with linear kernel as it uses one-vs-rest classification, while the latter uses the one-vs-one approach. The algorithm aims to maximize the margin, i.e., the distance between the support vectors and the decision boundary, while minimizing classification errors. Although it has multiple hyperparameters, we used only the tolerance and the C parameters, which is the hardness/softness parameter. Finding very little correlation between the input data and the output, we decided to give some room for misclassification, so that a decent score may be achieved. We used LinearSVC on the regular data, standardized data, and the PCA reduced data of 20 features. On the regular data, we got an accuracy score of ~0.535, and obtained scores of ~0.654 and ~0.638 respectively. LinearSVC clearly performed better on standardized and PCA reduced data in our case. On linear kernel SVC, that is, the SVC class with `kernel='linear'`, we received an accuracy of approx. 0.625.

It is to be noted that we used a reduced PCA training set of 20 components to do our kernel SVM experiments, since the size of our data is quite big, and the running time for each SVM was never ending. We halved the size of our training data to accommodate for the computational requirements of running our experiments. LinearSVC class on the other hand was comparatively much faster and gave quick results with all the datasets.

- Polynomial and Radial Basis Function kernels

The Polynomial Kernel SVC works by mapping the original data into a higher-dimensional feature space using a polynomial function. This allows the SVC to find a linear decision boundary in a higher dimension that is linearly separable, and this boundary can be considered equivalent to a polynomial boundary in the original (lower) dimension. The degree of the model is same as the degree of the polynomial function used. Higher degrees can capture more intricate patterns in the data, while lower degrees may result in underfitting. Therefore, the choice of the polynomial degree should be carefully chosen, given the nature of our dataset. Since the number of features were quite high, we chose to go with a degree 3 so that no extreme fitting scenario is achieved, as well as a good enough model is mapped too. The accuracy obtained was approximately 0.648.

The Radial Basis Function is a kernel function that once again maps the data onto higher dimensions by selecting random data points and plotting gaussian distributions over them and comparing the similarity between distributions to classify. Once an appropriate division is discovered based on the given hyperparameters, it brings it back to its original dimensions, but this time with a clear division of classes known. We used `C=2` and `gamma='scale'` as the hyperparameters for training the model after tuning them. The accuracy obtained was ~0.645.

3.3 Decision Tree Classification

Decision trees are a non-parametric machine learning technique used for both classification and regression problems. (Non-parametric implies that they have a variable number of parameters). In both prediction performance as well as computation intensity, Decision Trees are considered superior to the previous techniques used in this project. They work by analysing the features of the data and develop a decision model in the form of a binary tree, using which it makes predictions. The algorithm used to train Decision Trees is the *CART Algorithm*.

The Classification And Regression Tree (CART) Algorithm is a greedy algorithm used to train Decision Trees. It works by recursively splitting the training data into two subsets with respect to a feature and a corresponding threshold, such that the *Gini impurity* of the split is minimised.

The *Gini* value measures the impurity within a node, ie. it captures the ratio of class instances among all training instances within a particular node. It is calculated using the formula:

$$G_i = 1 - \sum_{k=1}^{n} {p_{i,k}}^2$$

3.4 Random Forest Classification

Random Forest classification applies the Ensemble Learning approach of Bagging to a *forest* (ie. collection) of Decision Trees. In Random Forest classification, numerous Classification Trees are trained and the mode value of their predictions is selected, thereby improving prediction accuracy and curtailing overfitting. Random Forest models are considered among the best Machine Learning techniques, as they employ the power of Ensemble Learning on the high performance of Decision Trees.

3.5 AdaBoost Classification

Boosting is another popular Ensemble Learning technique that combines numerous ‘weak’ learners (predictors) to form a strong learner. It is considered the best performing machine learning technique. Unlike in Bagging, where we independently run several predictors and take their aggregate, in Boosting predictors are trained sequentially such that each predictor compensates for the shortcomings of the previous. So, as a whole the model makes very good predictions, despite each individual learner having poor performance.

In AdaBoost (short for Adaptive Boosting), the model adapts sequentially based on every weak learner’s performance. It does so by modifying every new learner to correct the errors of its predecessor. This is done by assigning weights according to the magnitude of the error in predicting.

3.6 GradientBoosting

Gradient Boosting is a more generalised form of AdaBoost that can work with any loss function, not just the exponential loss function used by AdaBoost. This makes it more flexible and robust to outliers. In specific, Gradient Boosting trains every subsequent weak learner with the residual error of the previous learner. Instead of associating weights to data points, it identifies weaknesses using gradients.

3.7 Hyperparameter Tuning

Majority of models we use in Machine Learning experiments have hyperparameters - parameters set by us that control the model's performance but are external to it, ie. not determined by it. There are systematic ways in Machine Learning to tune these hyperparameters, leading to the best possible performance for the given model. Grid Search and Randomised Search are two such methods.

In Grid Search, a grid containing the hyperparameters interested to tune and a range of values for each is specified by the user. The algorithm tries every combination of the hyperparameter values and selects the optimal combination - usually measured by the Cross-validated R^2 score.

Randomised Search is a variation of Grid Search where random combinations of hyperparameter values are selected from within the grid. This reduces the computation overhead which Grid Search undergoes, although Grid Search is more exhaustive.

4. Experiments & Results

4.1 Protocol

- Data Splitting:

  The data was split into 80% training and 20% testing, maintaining a random seed value of 42 throughout all experiments for reproducibility. To be able to meet the computational requirements of all the experiments, we halved the size of our Training data such that it now has 15,857 rows from the previous 31,715.

- Data Preprocessing.

  - Data cleaning:

    The dataset was searched for missing values and duplicates, which were dropped if found. In the case of this dataset, there were no missing values or duplicates..

  - Feature Scaling - Standardization:

    In addition to experimenting with the regular data, we were interested in reducing the error further by applying standard scaling. We hence scaled the values of X, and applied the fit functions on the scaled dataset. We observed that this indeed did affect the results in a large way - There was observed a consistent increase in the accuracy scores of the experiments run when compared (wherever comparable), with the training done on the regular data.

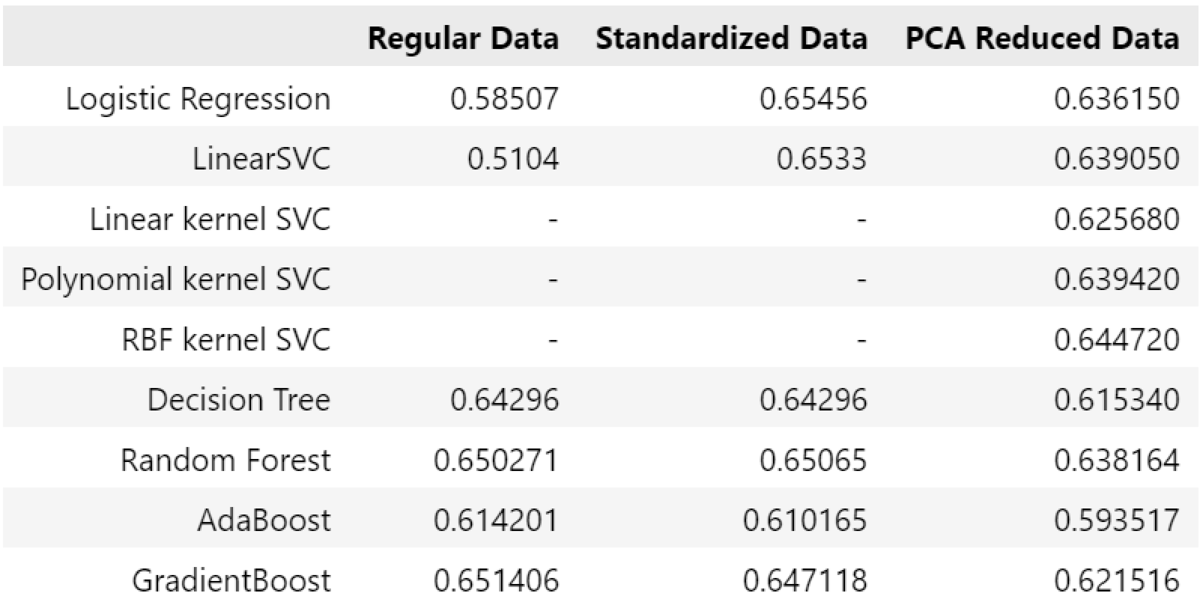
  - Dimensionality Reduction - Principal Component Analysis (PCA):

    Principal Component Analysis, or PCA, reduces the features of the data by finding their directions of maximum variance and projecting the data along those directions, thus preserving information of the original attributes and also reducing the size of the dataset for better computations and visualizations. In our case, we reduced our dataset from 59 features to 20 features, so that all experiments could handle the size computationally. Similar to the results obtained with standardization, wherever comparable, the accuracy scores showed a general increase in relation to the scores obtained when the training was done on the regular data.

4.2 Results

<u>Classification Accuracy</u>

Table of Classification Accuracy scores for all the Machine Learning experiments conducted in this project



	Regular Data	Standardized Data	PCA Reduced Data
Logistic Regression	0.58507	0.65456	0.636150
LinearSVC	0.5104	0.6533	0.639050
Linear kernel SVC	-	-	0.625680
Polynomial kernel SVC	-	-	0.639420
RBF kernel SVC	-	-	0.644720
Decision Tree	0.64296	0.64296	0.615340
Random Forest	0.650271	0.65065	0.638164
AdaBoost	0.614201	0.610165	0.593517
GradientBoost	0.651406	0.647118	0.621516

<u>Note</u>: The SVC model from Scikit-Learn couldn't fit the regular dataset or standardised dataset in a short time frame due to their having a large number of features, hence experiments were not conducted for those.

Cross Validation Scores

5-fold Cross-validated weighted F1-scores of all experiments conducted in this project

	Regular Data	Standardized Data	PCA Reduced Data
Logistic Regression	0.59376 +/- 0.01425	0.65394 +/- 0.00577	0.63381 +/- 0.00168
LinearSVC	0.4078 +/- 0.06238	0.65408 +/- 0.00588	0.63532 +/- 0.00326
Linear kernel SVC	0	0	0.62283 +/- 0.00237
Polynomial kernel SVC	0	0	0.63955 +/- 0.00486
RBF kernel SVC	0	0	0.64892 +/- 0.00596
Decision Tree	0.64028 +/- 0.00744	0.64028 +/- 0.00744	0.61597 +/- 0.00456
Random Forest	0.65733 +/- 0.00784	0.65739 +/- 0.00765	0.63 +/- 0.00637
AdaBoost	0.62375 +/- 0.00616	0.62305 +/- 0.00955	0.59776 +/- 0.00475
GradientBoost	0.65349 +/- 0.00636	0.65784 +/- 0.00417	0.62908 +/- 0.00533

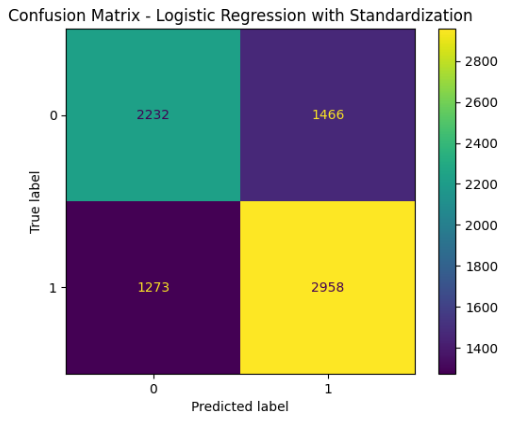
Hyperparameter Tuning Results

(GridSearchCV)

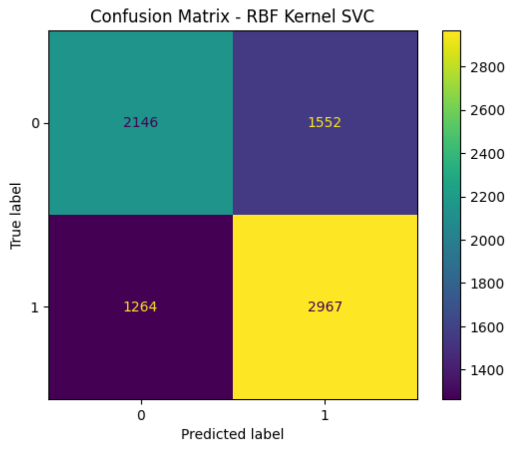
	Regular Data	Standardized Data	PCA Reduced Data
Logistic Regression	-	-	-
LinearSVC	-	0.655232	-
Linear kernel SVC	-	-	-
Polynomial kernel SVC	-	-	-
RBF kernel SVC	-	-	-
Decision Tree	-	-	-
Random Forest	-	0.66633	-
AdaBoost	-	0.650817	-
GradientBoost	-	0.670493	-

<u>Confusion Matrices & Classification Reports</u>

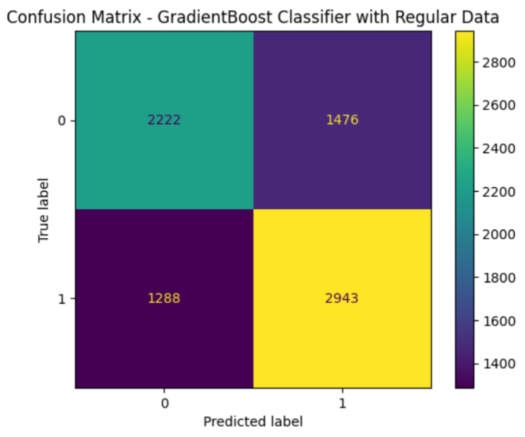
Confusion Matrices & Classification Reports for select experiments



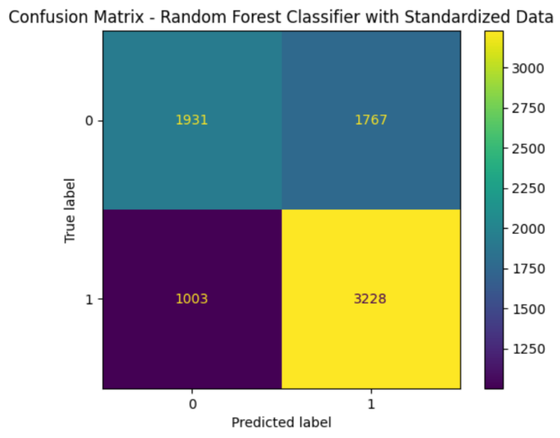
```
              precision    recall  f1-score   support

           0       0.64      0.60      0.62      3698
           1       0.67      0.70      0.68      4231

    accuracy                           0.65      7929
   macro avg       0.65      0.65      0.65      7929
weighted avg       0.65      0.65      0.65      7929
```



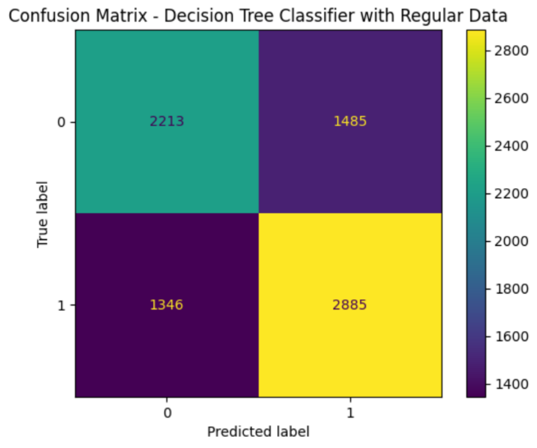
```
              precision    recall  f1-score   support

           0       0.63      0.58      0.60      3698
           1       0.66      0.70      0.68      4231

    accuracy                           0.64      7929
   macro avg       0.64      0.64      0.64      7929
weighted avg       0.64      0.64      0.64      7929
```



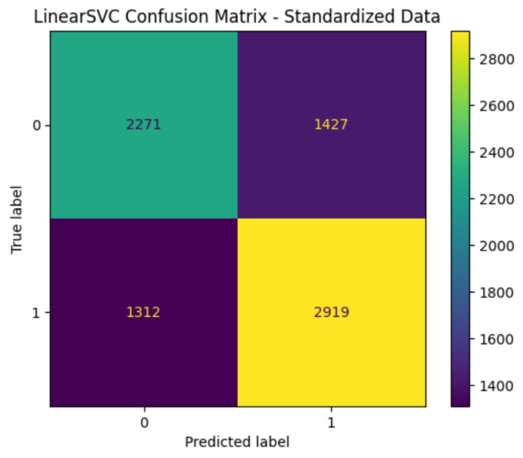
```
              precision    recall  f1-score   support

           0       0.63      0.60      0.62      3698
           1       0.67      0.70      0.68      4231

    accuracy                           0.65      7929
   macro avg       0.65      0.65      0.65      7929
weighted avg       0.65      0.65      0.65      7929
```



```
              precision    recall  f1-score   support

           0       0.66      0.52      0.58      3698
           1       0.65      0.76      0.70      4231

    accuracy                           0.65      7929
   macro avg       0.65      0.64      0.64      7929
weighted avg       0.65      0.65      0.64      7929
```



```
              precision    recall  f1-score   support

           0       0.62      0.60      0.61      3698
           1       0.66      0.68      0.67      4231

    accuracy                           0.64      7929
   macro avg       0.64      0.64      0.64      7929
weighted avg       0.64      0.64      0.64      7929
```



```
              precision    recall  f1-score   support

           0       0.63      0.61      0.62      3698
           1       0.67      0.69      0.68      4231

    accuracy                           0.65      7929
   macro avg       0.65      0.65      0.65      7929
weighted avg       0.65      0.65      0.65      7929
```

5. Discussion

When judging based on Cross-validated F1-scores, the GradientBoost model gave the best score of 0.65784 on standardised data. Random Forest was marginally lower, with a score of 0.65739 on regular and standardised data. LinearSVC and the baseline Logistic Regression were similarly very close, with scores 0.65403 and 0.65394 respectively. What is interesting is that when it came to Classification Accuracy scores, the order of performance of these four models was reversed, although the differences were still in 2nd or 3rd decimal places. RBF kernel SVM came next with a CV score of 0.64892, followed by 0.64028 for Decision Trees and the remaining models.

The greatest impact of standardisation was seen with the LinearSVC model, with the score shooting from 0.4078 to 0.65403. Logistic Regression also showed a significant improvement similarly. Since Decision Trees are indifferent to standardisation, the performance on regular as well as standardised data was identical. The ensemble methods - Random Forest, AdaBoost & GradientBoost experiments - showed only a very minor increment in scores for standardised data.

The PCA data yielded scores slightly lower than that of the standardised data, probably due to the drastic reduction in dimensions of the dataset employed for it. When considering the PCA data alone, the RBF and Polynomial kernel Support Vector Classifiers gave the best scores of 0.64892 and 0.64035 respectively.

6. Conclusion

Considering the Cross-validated weighted F1-score as our primary performance metric, the GradientBoost model was the best performer in our experiments. Equally comparable were the Random Forest, LinearSVC and even baseline Logistic Regression model. It was surprising to see that the baseline was on par with the other advanced models used.

However, as noted in the *Discussion* section, The RBF and Polynomial kernel Support Vector Classifiers performed best on the PCA reduced data. Extrapolating these results on the PCA reduced data, one could argue that the RBF and Polynomial kernel SVCs may be the best performing among the ML models used in this project for the given dataset. But since we did not run experiments for these two models on the regular and standardised data, we cannot conclude this. Nevertheless, based on the experiments we conducted, the difference in performance between the various models employed is marginal and all performed relatively good.

The reasonable capability of these ML models to predict our target variable 'Popularity' shows that a media article's popularity can indeed be determined by its various features and attributes, such as those part of the dataset used in this project.

7. References

[1] K. Fernandes, P. Vinagre and P. Cortez. 'A Proactive Intelligent Decision Support System for Predicting the Popularity of Online News'. Proceedings of the 17th EPIA 2015 - Portuguese Conference on Artificial Intelligence, September, Coimbra, Portugal.

[2] UCI Machine Learning Repository: Online News Popularity

[3] What and why behind fit_transform() and transform() in scikit-learn!

[4] When and why to standardize a variable

[5] Scikit-Learn - DecisionTreeClassifier

[6] Scikit-Learn - RandomForestClassifier

[7] Do Decision Trees need Feature Scaling?

[8] Max_depth or Max_leaf_nodes in Random Forest?

[9] Depth-first vs. best-first search: new results

[10] Adaboost vs Gradient Boosting - Data Science Stack Exchange