

A Project Report on

**Prediction of Online News Popularity**

Submitted in partial fulfilment for the award of the degree of

**Post Graduate Diploma Management**

In **Business Analytics**

Submitted by

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R19DM054

Under the Guidance of

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**May, 2023**



# Candidate’s Declaration

I, **Vaibhav Tyagi,** hereby declare that I have completed the project work towards **Post Graduate Diploma Management in Business Analytics** at REVA University on the topic entitled **Prediction of Online News Popularity** under the supervision of **Mr. Ratnakar Pandey, Chief Data Scientist and Startup Advisor.** This report embodies the original work done by me in partial fulfilment of the requirements for the award of the degree for the academic year **2023.**

Place: Bengaluru Name of the Student: Vaibhav Tyagi Date:

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# Certificate

This is to Certify that the project work entitled **Prediction of Online News Popularity** carried out by **Vaibhav Tyagi** with **R19DM054,** a bonafide student of REVA University, is submitting the first-year project report in fulfilment for the award of **Post Graduate Diploma Management in Business Analytics** during the academic year **2023**. The Project report has been tested for plagiarism and has passed the plagiarism test with a similarity score of less than 15%. The project report has been approved as it satisfies the academic requirements in respect of the project work prescribed for the said degree.

Signature of the Guide Signature of the Director

Mr. Ratnakar Pandey Dr. Shinu Abhi

Chief Data Scientist and Startup Advisor Director, Corporate Training

External Viva

Names of the Examiners

Place: Bengaluru

Date:

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# Acknowledgment

At the outset, would like to indebt our Mentor Mr. Ratnakar Pandey for his time, valuable input, and guidance. His experience, support, and structured thought process guided me to be on the right track toward the completion of this project.

Heartily thankful to Dr. J.B. Simha our chief mentor for their time-to-time guidance. Extremely gifted and fortunate to have Dr. Shinu Abhi as our academic counselor and director. Her in-depth knowledge and her passion for lucidly delivering the subjects have helped me a lot. Special thanks to her for her guidance towards the entire coursework. Also, thank all the course faculty of the PGDM - BA program for providing me with a strong foundation in various concepts of analytics and machine learning.

Also acknowledge the support provided by Hon’ble Chancellor, Dr. P Shayma Raju, Hon’ble Vice Chancellor, Dr. M. Dhanamjaya, and Registrar, Dr. N Ramesh in all circumstances.

Last, but not the least, I would like to sincerely thank my respective family for giving me the necessary support, space, and time to complete this project. I will certify that the work done by me for conceptualizing and completing this project is original and authentic.

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Dr. Shinu Abhi,

Director, Corporate Training

# List of Abbreviations

|  |  |  |
| --- | --- | --- |
| **Sl. No** | **Abbreviation** | **Long Form** |
| 1 | LR | Logistic Regression |
| 2 | DT | Decision Tree |
| 3 | AUC | Area Under the Curve |
| 4 | RF | Random Forest |
| 5 | URL | Uniform Resource locator |
| 6 | VADER | Valence Aware Dictionary and Sentiment Reasoner |
| 7 | WOM | Word of Mouth |
| 8 | CRISP-DM | Cross-Industry Standard Process for Data Mining |
| 9. | RFECV | Recursive feature elimination with cross-validation |
| 10. | KNN | K-Nearest Neighbours |
| 11. | SVM | Support Vector Machine |
| 12. | NB | Naive Bayes |

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# Abstract

Due to its rapid dissemination and easily accessible attributes, the Internet has supplanted traditional newspapers and periodicals as the major platform for broadcasting public news. Thus, estimating Internet news's rising profile is an increasingly important topic.

Due to Internet and technology advancements, news items and blogs have become increasingly popular. Even while print news isn't entirely gone, more and more individuals choose to check the Internet for the day's events because it's quick, easy, and free. Pew Research found in 2018 that slightly more than 50% of Americans acquire their news in some form online.

Forbes reports that the figure reached 55% in 2019 and is still rising. Using data on Mashable articles from the previous two years, machine learning models that forecast the popularity of an article given a set of features about that article—such as the number of words in the article, time of the week on which the article appeared, and the average sentiment polarity of the article content—have been created. Divide the continuous predictor variable "shares" into two categories before running these models: "Low" popularity for articles with multiple shares below the median share total for all articles, and "High" popularity for articles with numerous shares above or equal to that median total.

Three machine learning models predict the level of popularity of a certain article using the Naive Bayes (NB), Random Forest (RF), and K-Nearest Neighbours (KNN) algorithms. Overall, the accuracy gained from the three models is subpar and is not much improved by the various data processing methods. The models are performed with supervised discretization using Python and the Valence Aware Dictionary and Sentiment Reasoner (VADER) module. The overall performance, however, calculated and achieved by using a Random Forest model with supervised discretization and without "looking" at the test set is 67%.

Keywords: Text Mining, Natural Language Processing, Sentiment Analysis

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# Chapter 1: Introduction

In today's digital age, online news has become an integral part of the day to day lives. With a click of a button, news articles can reach millions of readers worldwide, shaping opinions and influencing conversations. However, not all news stories are created equal when it comes to popularity and engagement. Some articles go viral, generating an avalanche of shares, comments, and views, while others remain largely unnoticed.

The ability to predict the popularity of online news articles has significant implications for content creators, media organizations, and digital marketers alike. By understanding the factors that contribute to an article's success, publishers can optimize their content strategy, enhance audience engagement, and ultimately maximize the reach and impact of their news stories.

The proliferation of smartphones and Internet connectivity has increased the number of news websites covering a wide range of issues, including politics, economics, business, entertainment, technology, fashion, and many more. This will be useful to online news organisations in gauging the interest in their stories before publication.

Academic studies frequently examine how to foresee the proliferation of internet news. User comments augment content analysis on the internet. It turns fame into a contest in which the winners are the days on which the most enticing stories were published. To classify how interesting a piece of internet news is, Support Vector Machine (SVM) is used to employ a ranking.

The work of predicting the popularity of web material still confronts several significant difficulties, even though it has significant effects in many different fields. First, a variety of elements make prediction challenging, such as the popularity of a piece of information can be influenced by its quality or relevance to viewers. Second, it can be challenging to both gather and provide information to the prediction engine about how real-world occurrences relate to the content itself. Finally, predicting intricate social interactions and information cascades at the microscopic level is quite difficult. Fourth, the forecast could also be challenging due to material that is hard to get, such as context from sources outside of the web, regional conditions, and circumstances that have an impact on the population. Last but not least, the prediction could also be challenging depending on network factors like network topology and how different web layer interactions interact.

The era of reading and sharing information and news has gained popularity as it has become part of people’s entertainment nowadays. Hence, predicting the popularity of news before its publication on how news includes different topics about the world and how it will affect an individual in both positive and negative influences plays a crucial role. Samples of 39484 observations from the articles are considered from the Mashable website, which is published between the years 2013 and 2015 on Mashable’s official website (*UCI Machine Learning Repository: Online News Popularity Data Set*, n.d.).

This study challenges the traditional binary job of evaluating popularity as either popular or unpopular and instead employs multiple advanced techniques such as Random Forest, Adaptive Boosting, and SVM. The study also uses real-time rolling windows to operate within. In addition, this study utilizes the well-known news source, Mashable (mashable.com/), which has not been previously examined for popularity forecasting, and compiles a comprehensive dataset covering the last two years, which is a much larger timeframe than what is typically used in literature.

In recent years, the online news sector has grown dramatically, and machine learning algorithms are being used more frequently to analyse huge databases and forecast readership. In this work, a variety of machine learning techniques were employed to predict the recognition of online news based on a collection of variables, including Random Forest, linear regression, and Adaboost. Mashable, a well-known international media and entertainment organisation that offers online news and information, provided the dataset for the study.

The goal of the study was to assist online news organisations in estimating before a story is published how popular it will be. The caliber and applicability of the news to viewers are just two examples of the many variables that might affect how popular internet news is. It might also be difficult to compile and present data regarding how actual events connect to the material itself. Furthermore, it can be challenging to forecast intricate social interactions and information cascades at the microscopic level. 39,484 observations from Mashable's website between 2013 and 2015 were used in the study. Different machine learning algorithms were used to analyse the dataset, and the results were assessed using AUC, F-measure, and precision to identify the accurate algorithm. The simplest model for making predictions was determined to be the Random Forest method, which had a 67% accuracy rate.

The study's overall goal was to offer knowledge on anticipating the popularity of online news and assist online news organisations in making judgments about the news articles they publish. Large datasets and the application of machine learning algorithms can assist improve the quality of online news material while also shedding light on the elements that affect its popularity.

# Chapter 2: Literature Review

There is a growing body of literature on online news popularity prediction, which has evolved from traditional methods such as page views and click-through rates to more sophisticated techniques based on machine learning and natural language processing.

Ananto et al. employed Genetic Algorithms along with Machine Learning Methods to forecast the popularity of online content, as noted by Wicaksono and Supianto in 2018 (Ananto Setyo Wicaksono & Ahmad Afif Supianto, 2018). The Random Forest algorithm's parameters include the number of Decision Trees, minimum sample leaf size, leaf weight percentage, and optimizing the hyperparameter K in the KNN technique. The crossover and mutation rates were both set to 0.5, and the study performed ten iterations. The team used Scikit-learn's evolutionary algorithm search CV with a population size of 50 and a generation number of 1000 to implement this approach. Despite the use of evolutionary algorithms and hyperparameter optimization, the KNN method produced the quickest results, with an accuracy of only 58% in 61 seconds. In comparison, the Random Forest algorithm took 659 seconds and achieved an accuracy of 67%.

Hensinger et al. frame it as a competitive setting in which the day's most appealing content wins out. They propose a linear "appeal" function as a solution, which is essentially a bag-of-words model. The parameters of this linear function are learned from pairs of articles that have different levels of popularity while being published on the same day and page. Using a year's worth of data from six distinct sources, an appeal function was trained with the help of Support in Ranking Using Vector Machines (Hensinger et al., 2013).

Rizos et al. employed a framework to predict a variety of news article popularity data, including the number of comments, users, votes, and a contentious Ness score. In three online news post datasets, it is demonstrated how the recommended graph-based characteristics significantly improve the process of identifying contested articles and the prediction of all popularity indices. That is to illustrate the complexity of the two networks of social interaction. In a news-focused Reddit dataset, a method for controversiality prediction that previously employed solely fundamental comment tree traits found a 5% relative improvement (Rizos et al., 2016).

Elisa Shearer presents data from the Pew Research Centre showing that social media platforms are now more popular than print newspapers among Americans, in an article entitled "Social Media Outpaces Print Publications in the U.S. as a News Source,"(Shearer & Eva Matsa, 2018). One in five Americans now regularly gets their news from social media, surpassing the number who read print newspapers (16%). The poll also indicated that 27% of respondents aged 18-29 regularly visit news websites, making them the second most popular news source among this age group. For news, 36% of Millennials and Gen Zers choose social media, whereas 27% prefer news websites, 16% prefer TV, 13% prefer radio, and 2% prefer print. Younger Americans are distinctive because they don't rely on just one platform as their elders did, who relied mostly on television. Between the ages of 18 and 29 and between the ages of 30 and 49, about half of the population regularly uses just one news source.

Namrata Godbole, conducted research titled "Large-Scale Sentiment Analysis for News and Blogs"(Godbole et al., 2007) is create a system that can give entities referenced in news stories and blogs favorable or negative ratings. There are two stages to this system: (1) detecting emotions, and (2) collecting, analysing, and ranking those emotions. During the first stage, views are matched with the appropriate entities, and during the second, sentiments are aggregated and scored. This research looks at the value of various scoring methods for a massive database of news and weblogs. The research also intends to broaden the scope of spatial analysis of news items to include sentiment maps, which can pinpoint areas of the world where people are more likely to have positive or negative feelings about specific topics.

Igor Suciu, Increased Use of Social Media as a Source of News among Americans. More and more people in the United States are reading news articles on social media. It's no secret that the vast majority of Americans don't follow the news by reading newspapers or tuning in to the evening broadcast. As the official newspaper increasingly focuses on local news and sports scores, social media platforms like Facebook and Twitter are becoming increasingly attractive alternatives. A recent study by the Pew Research Centre found that 55% of Americans now "often" or "often" acquire their news from social media, up 8% from the previous year. Up from 20% in 2018, about 30% of respondents said they "frequently" accessed the news. "Knowing that Russians used Facebook to influence a sizable number of political views with their conflict with Ukraine; and despite knowing, it had an impact on the presidential election," Safko said.

Ren and Yang's goal was to find the machine learning model and characteristics to foretell the success of online news. Mashable is a popular news website, and the researchers used data from there to try out 10 different learning algorithms. Each algorithm's efficiency was evaluated and compared to the others. To improve accuracy and minimise the number of features, feature selection techniques were used. According to the findings, Random Forest was the prediction model, with an accuracy of 70% when using the acceptable settings.

A Survey of Social Media Prediction, by Sheng Yu and Subhash Kak (Sheng Yu & Subhash Kak, 2012). Brands are mentioned in about 19% of tweets, however, the vast majority of these posts (almost 80%) are emotionless advertisements. The decision took to research the impact of online communities and widespread e-word-of-mouth (eWOM) on product uptake to predict better for its future popularity. The number of supporters and advocates is staggering. As of 2009, however, 77.9% of user pairings were one-way. This means that just 22.1% of user couples are in committed relationships. As a result, people's inner circles of real friends are tighter and more fundamental. Even if the results of this kind of study are still quite inaccurate, social media has provided new means to gather, extract, and objectively utilise the wisdom of crowds at little cost and with great efficiency.

Tatar et al., How to gauge what will go viral on the web: a survey (Tatar et al., 2014). By filtering out irrelevant content, users can focus their attention, the most valuable commodity in the digital realm, on the data that truly matters to them. In a market where companies are allocating up to 30 percent of their advertising budget online. There is no universally accepted definition of "viral" material online. Increased online activity or presence may be a sign of popularity, whether for an individual or a business. The application of content popularity prediction to the planning of networking solutions is not well documented. However, more scalable content distribution strategies that proactively repeat information in response to user demand may be developed by understanding the dynamics of online content popularity.

The article "Predicting Online News Popularity" (by Benjamin Dornel | Towards Data Science, n.d.) was written by Benjamin Dornel. Determine the factors that contribute to a story's success or failure in the news. The first step is to examine online New York Times stories and make predictions about their popularity using factors like word count, headline length, and abstract length. These are wordless interactive articles. Since this information isn't truly 'Missing At Random' (MAR), Imputation to fill in the gaps is used. Articles with shorter abstracts and headlines (50-130 words) tend to do better. Popular items are more likely to come from the Politics, Games, and Washington news departments, while those from the Sports, Culture, and Podcasts desks tend to be ignored. In comparison to obituaries and straight news reporting, news analysis and interactive articles tend to be more read.

Feras Namous et al., Using machine learning and a variety of data mining methods, Online News Popularity Prediction (Namous et al., 2019) sought to identify the most effective model and feature set for making such predictions. The popular news website Mashable was the source of the data. Precision was used to assess the results, recall, and F-measure, with the latter two metrics compared to determine the efficient option. In addition, results are to be compared to those of other studies using the same dataset. The top prediction models are revealed to be Random Forest and Neural Network, both of which attain an accuracy of 65% with the best-case settings. With an F-measure of around 65%, the valuable performance was achieved by using 0.1 as a learning rate, four hidden layers, and Random Forests or Multilayer Perception. However, combining Bagging or AdaBoost with Random Forests into a hybrid model opens up further room for development.

Koustav Mukherjee, The Future of Newspapers in an Age of Social Media (Mukherjee, n.d.). Multiple studies, from a variety of angles, have examined the impact of social media on the journalism business. People claim to have entered a new era in which ideas can be communicated in as few as 140 characters, thanks to the rapid expansion of social media platforms like Orkut, Twitter, Facebook, and Instagram. Journalists' thoughts on how social media has altered their work and the way they do it are explored in this research. The development of technology has been crucial in the production of these aggregations. Because of the increased competition, established media outlets will strive to uphold their reputations by providing consumers with accurate and engaging news coverage.

Rasmus Kleis Nielsen (Alessio Cornia, Kleis Nielsen, & Antonis Kalogeropoulos, n.d.) examines the difficulties and opportunities facing the news industry in today's increasingly mobile, digital, and social media-driven environment. It's a sign that we're entering a new era characterised by more competition for people's attention as the world becomes increasingly mobile, digital, and social media-centric. The majority of people nowadays acquire their news from digital sources, mostly online and on their mobile devices (especially smartphones) through shared links and recommendations from friends and family. There are 31% "Proactive Participants" who regularly post writings, comment on them, occasionally blog or participate in campaigns, and 48% "Passive Consumers" who might converse with friends and coworkers both online and offline about news, but refrain from participating in more participatory forms of media use such as posting or commenting. This made traditional forms of media such as television and newspapers more challenging to succeed in. Their importance in the newsmaking process remains high, but their influence as news carriers is dwindling.

Arpit Garg, Data Mining and Prediction from Online News Feeds, (Arpit Garg, Online News Feeds, n.d.). The goal of the Online News Feed Prediction System is to compare and contrast various prediction algorithms by analysing their respective implementation methodologies. Media outlets may utilise this strategy to increase readership and revenue. The goal is to figure out how to get there. With LinkedIn as the target, "Topic" transformed into four columns of zeroes and ones, and the remaining parameters were chosen as features, the prediction accuracy was 54.38%. After resegregating "Topic" into bins of 0, 1, 2, 3, and "SentimentTitle" and "SentimentHeadline" into bins of -1, 0, and 1, the testing set's accuracy score was 0.547082797083, or 54.7% for criteria. When switching the criteria to Entropy, the accuracy increases to 54.64 percent. Python is used for the SVM implementation, and a train test split is utilised to split the data (60% to 40%) between the training and testing sets. Facebook is the most well-liked social media platform, followed by LinkedIn, while Google Plus is the least. Headline popularity rankings for Microsoft aside, LinkedIn and Google Plus are quite similar. The popularity rankings are heavily influenced by the social media site through which the news is released.

K.S.NagaHaritha (Predicting Online News Popularity, n.d.). There has been a rise in interest in finding ways to forecast the reach of online news stories. Logistic Regression (LR) is a machine learning technique used to estimate the probability of an outcome involving a categorical dependent variable. There are just two possible values for the dependent variable in LR: 1 (yes, success, etc.) or 0 (no, failure, etc.). To prioritise challenging circumstances, the *AdaBoostclassifier* ensemble classifier first updates the weights of several copies of the fitted classifier on the original dataset. *Sklearn()* provides a tool called *AdaBoostClassifier*. There is a customizable limit on the size of the boosted ensemble of estimators. It is well-accepted that remodels are low-bias, high-variance models. Training and testing RF takes significantly longer when 500 trees are used in the forest, but this setup yields superior results in terms of ACCURACY, F1-SCORE and Area Under the Curve (AUC).

Overall, the literature on online news popularity prediction highlights the importance of considering multiple factors and features, leveraging machine learning and deep learning techniques, and adapting to the dynamic and heterogeneous nature of online news content and user behavior. These studies represent a subset of the extensive research on online news popularity prediction. They highlight the use of social media data, content analysis, machine learning techniques, and deep learning models to forecast the popularity of news articles. Researchers continue to explore new methodologies and approaches to enhance prediction accuracy and develop practical applications for news organizations.

# Chapter 3: Problem Statement

The problem statement for online news prediction can be defined as follows:

Given a dataset of online news articles or headlines, the task is to develop a predictive model that can accurately forecast the popularity, engagement, or sentiment of upcoming news articles. The objective is to enable news publishers, media organizations, or content creators to make informed decisions about content strategy, timing, and audience targeting*.*

The challenges to address in this problem include:

. 1) Predictive Accuracy

2) Sentiment Analysis

3) Data Variety and Volume

4) Real-time Prediction

5) Ethical Considerations

1. Predictive Accuracy: The model should take into account various factors such as the content of the article, timing of publication, historical trends, and external events that may impact reader interest to develop a model that can accurately forecast the popularity.
2. Sentiment Analysis: Analyzing the sentiment of news articles is important for understanding how readers perceive the content.
3. Data Variety and Volume: The model should be able to handle a large volume of news articles, headlines, or related textual data from various sources and languages. It should also be able to handle different formats like plain text, HTML, or structured data.
4. Real-time Prediction: To be effective, the prediction model should provide real-time or near real-time predictions, allowing news publishers to respond quickly and optimize their publishing strategy based on the predicted outcomes.

By addressing these challenges and developing a robust online news prediction model, it can empower news publishers and content creators to optimize their content strategy, improve reader engagement, and make data-driven decisions in the ever-evolving landscape of online news.

# Chapter 4: Objectives of the Study

The objective of online news popularity prediction is to forecast the level of popularity or engagement that a news article or story will generate in the online environment. By analyzing various factors and patterns, such as content features, social media activity, user behavior, and temporal aspects, the goal is to estimate the potential reach and impact of a news item before it is published or shortly after it appears online.

The prediction of online news popularity can serve several purposes:

1. Content optimization: By understanding what factors contribute to increased popularity, they can tailor their content to align with audience interests, preferences, and trends. This will help news organizations and content creators make informed decisions about the type of content they produce.
2. Audience engagement: To anticipate the level of interest, a story will generate and design engagement strategies, such as interactive features, social media campaigns, or personalized recommendations, to enhance audience participation and interaction.
3. Monetization opportunities: Predicting popularity can help news organizations identify potential monetization opportunities by estimating the traffic and user engagement that a news item may generate.

Overall, the objective of online news popularity prediction is to leverage data-driven approaches to estimate the potential success of news articles, optimize content production and distribution strategies, and enhance audience engagement and monetization in the online news ecosystem.

# Chapter 5: Project Methodology

When conducting a project on online news popularity prediction, Need to follow a systematic methodology that involves several key steps. Here is a general outline of a project methodology for online news popularity prediction to solve the business objective, the traditional Cross Industry Standard Process for Data Mining (CRISP-DM) methodology is used which involves the following tasks.

**Data Exploration and Visualization**

There are thousands of articles in the dataset, all of which were pulled from the online news website Mashable for 3 years. The UCI Machine Learning Repository is where it is retrieved from (K. Fernandes et al., 2015).

TABLE 5.1: List of predictive attributes of the dataset

|  |  |  |  |
| --- | --- | --- | --- |
| **#** | **Column** | **Non-Null count** | **Dtype** |
| 0 | URL | 39644 non-null | Object |
| 1 | timedelta | 39644 non-null | float64 |
| 2 | n\_tokens\_title | 39644 non-null | float64 |
| 3 | n\_tokens\_content | 39644 non-null | float64 |
| 4 | n\_unique\_tokens | 39644 non-null | float64 |
| 5 | n\_non\_stop\_words | 39644 non-null | float64 |
| 6 | n\_non\_stop\_unique\_tokens | 39644 non-null | float64 |
| 7 | num\_hrefs | 39644 non-null | float64 |
| 8 | num\_self\_hrefs | 39644 non-null | float64 |
| 9 | num\_imgs | 39644 non-null | float64 |
| 10 | num\_videos | 39644 non-null | float64 |
| 11 | average\_token\_length | 39644 non-null | float64 |
| 12 | num\_keywords | 39644 non-null | float64 |
| 13 | data\_channel\_is\_lifestyle | 39644 non-null | float64 |
| 14 | data\_channel\_is\_entertainment | 39644 non-null | float64 |
| 15 | data\_channel\_is\_bus | 39644 non-null | float64 |
| 16 | data\_channel\_is\_socmed | 39644 non-null | float64 |
| 17 | data\_channel\_is\_tech | 39644 non-null | float64 |
| 18 | data\_channel\_is\_world | 39644 non-null | float64 |

Earlier, the dataset was pre-processed. For instance, a one-hot encoding strategy was used for the categorical characteristics, such as the day of publication and article type, while a log transformation was applied to the skewed features, such as the number of words in the article.

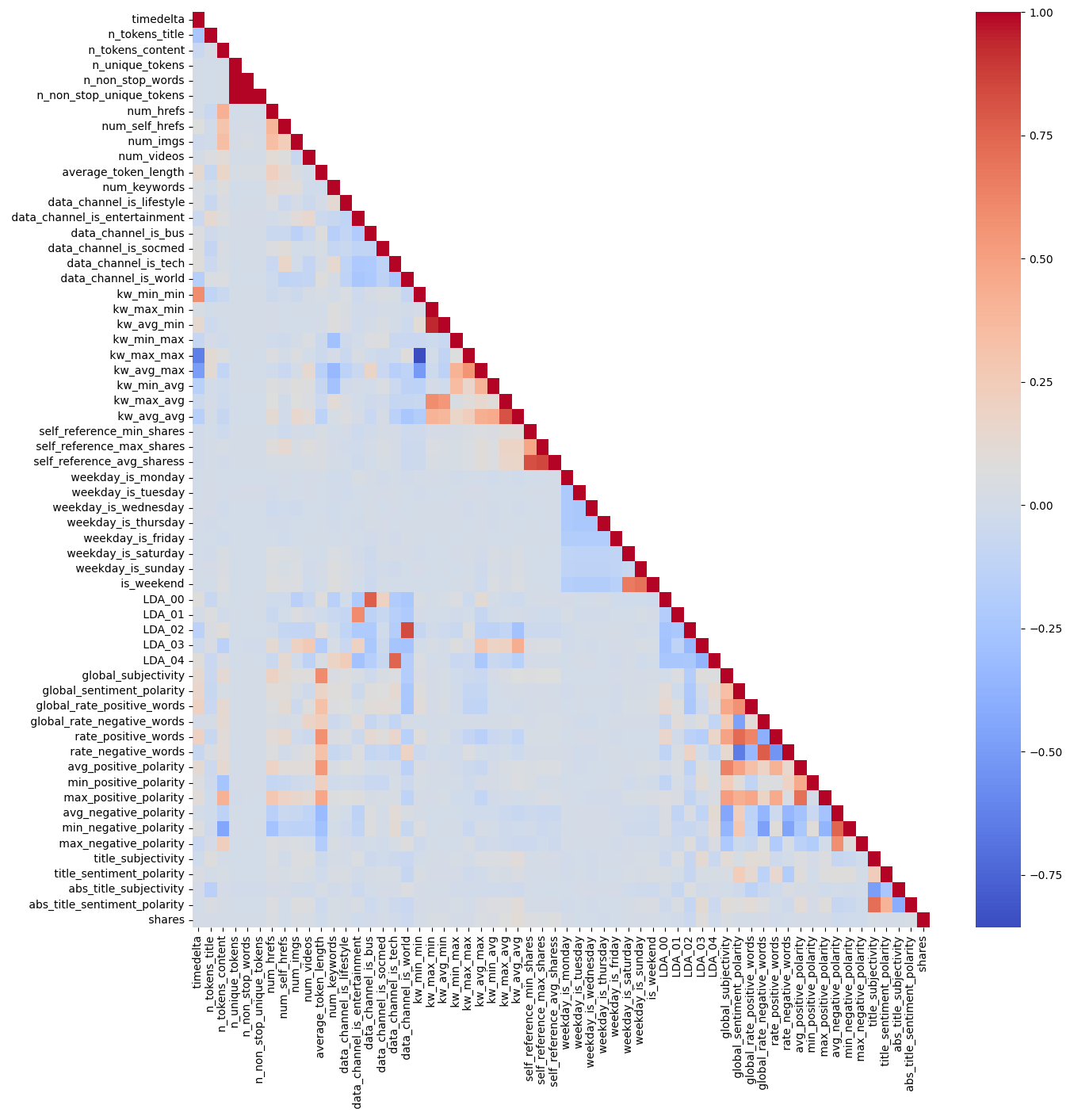


Fig. 5.1: Heatmap of a correlation matrix

**Data Pre-processing**

Preliminary work on the data has been completed as a first step. A one-hot encoding approach was used to modify categorical information like publication day and article category, while a log transformation was used to skewed features like the number of words in the article. To ensure that each feature is given equal weight during supervised learning, the dataset is further pre-processed by normalising the numerical features to the interval [0, 1]. To make the continuous target characteristic into a boolean label, choose its median as the threshold.

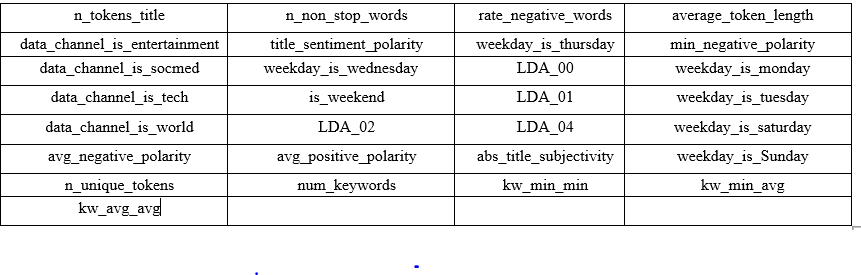
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Fig. 5.2: RFECV for logistic regression estimator: cross-validation score versus feature selection

There are 58 features in the dataset, thus it makes sense to do a feature selection to lower the data noise and speed up the algorithm's execution time, as illustrated in Fig. 5.2.

TABLE 5.2: 29 FEATURES SELECTED USING RFECV WITH LOGISTIC REGRESSION ESTIMATOR



Selecting the most important characteristics for a classifier may be automated with the help of a technique called Recursive characteristics Elimination with Cross-Validation (RFECV). A useful function, *REFCV()*, is available in *Sklearn*.

Table 5.2 demonstrates that a logistic regression estimator is required for *RFECV*. correlation between the cross-validation score and the proportion of features chosen When more than 29 elements are present, the score decreases. From the original set of 58 features, the *RFECV* algorithm picks the 29 most relevant ones. Table 5.2 details the selected 29 characteristics.

The relationship between the cross-validation score and the number of chosen characteristics is seen in Fig. 5.3. The 56 characteristics chosen for *RF* by *RFECV* are nearly all of the features available in the dataset. ‘n\_non\_stop\_words’ and 'data\_channel\_is\_ lifestyle' are the only two characteristics that are not considered by *RFECV* while evaluating *RF*.

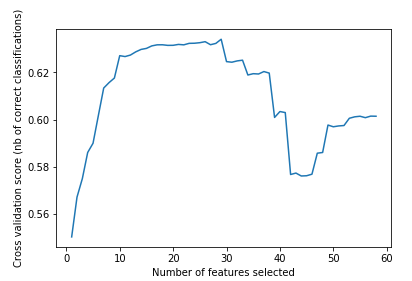


Fig. 5.3: The number of features chosen by RFECV with the RF estimator plotted against the cross-validation score.

Lastly, run *RFECV* with Adaboost estimator on the following features:-

TABLE 5.3: FEATURES SELECTED USING RFECV WITH ADABOOST ESTIMATOR

|  |  |  |  |
| --- | --- | --- | --- |
| n\_unique\_tokens | num\_hrefs | num\_self\_hrefs | num\_imgs |
| num\_videos | num\_keywords | data\_channel\_is\_socmed | data\_channel\_is\_tech |
| kw\_max\_min | data\_channel\_isworld | data\_channel\_is\_entertainment | kw\_avg\_max |
| kw\_max\_max | kw\_min\_max | kw\_min\_avg | kw\_max\_avg |
| self\_reference\_avg\_sharess | kw\_avg\_avg | self\_reference\_min\_shares | LDA\_01 |
| global\_subjectivity | is\_weekend | global\_rate\_positive\_word | avg\_positive\_polarity |
| weekday\_is\_Friday | title\_subjectivity | rate\_negative\_words | LDA\_00 |

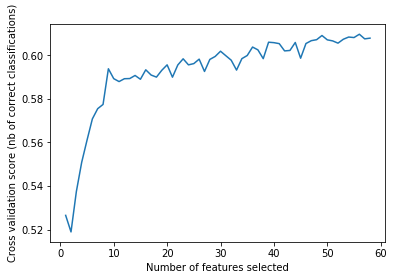


Fig. 5.4: RFECV with Adaboost estimator cross-validation score vs feature selection size.

The cross-validation score vs the number of features chosen is plotted in Fig. 5.4. The optimal value for "Number of features selected" appears to be 18. Therefore, out of a total of 58 characteristics, the *RFECV* algorithm only uses the top 18.

TABLE 5.4: 18 FEATURES SELECTED USING RFECV WITH ADABOOST ESTIMATOR.

| Feature selected using RFECV | | | |
| --- | --- | --- | --- |
| n\_non\_stop\_unique\_tokens | num\_self\_hrefs | num\_imgs | num\_videos |
| data\_channel\_is\_entertainment | num\_keywords | kw\_avg\_min | kw\_min\_min |
| data\_channel\_is\_socmed | kw\_min\_max | kw\_max\_max | kw\_max\_avg |
| global\_sentiment\_polarity | kw\_avg\_avg | self\_reference\_min\_shares | self\_reference\_max\_shares |
| global\_subjectivity | kw\_min\_avg |  |  |

As shown in Table 5.4, the selected 18 features are listed. Now will going to implement the classification algorithms using these selected features.

**Implementation**

Each method randomly divided the dataset with its own chosen characteristics into a training set and a testing set before deployment. The sklearn functions *LogisticRegression()*, *Random-ForestClassifier()* and *AdaBoostClassifier()*, respectively, implement logistic regression, RF and Adaboost.

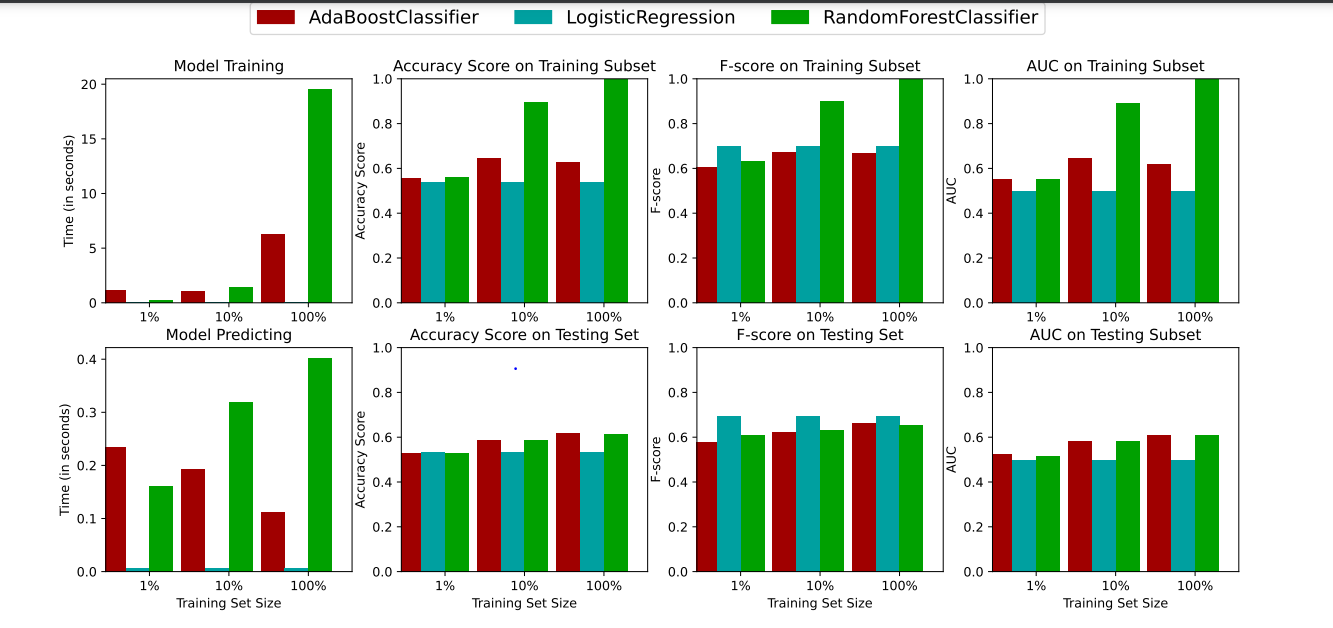


Fig. 5.5: Performance of three classifiers under default parameter setting

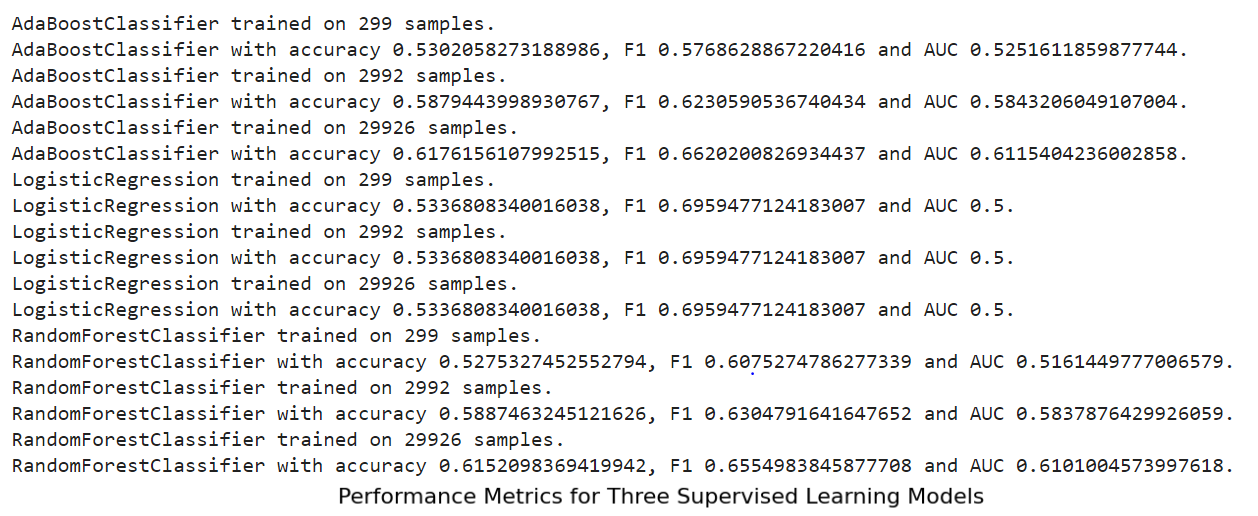


Fig. 5.6: Evaluation of three classifiers under default parameter setting.

Model hyperparameters are used as default values. The default hyperparameters for logistic regression are "C = 1.0", "n estimators = 10", "learning rate = 1.0", and "n estimators = 50" for Adaboost. In the next section, parameters need to be refined.

As shown in Fig. 5.5 and 5.6, demonstrate the performance and evaluation of the three classification methods using the chosen characteristics for each algorithm.

TABLE 5.5: METRICS SCORE OF THREE CLASSIFIERS UNDER DEFAULT HYPERPARAMETERS.

|  |  |  |  |
| --- | --- | --- | --- |
| **Classifier** | **Accuracy** | **F1-score** | **AUC** |
| **Logistic**  **Regression** | 0.533 | 0.6959 | 0.5 |
| **RF** | 0.615 | 0.655 | 0.61 |
| **Adaboost** | 0.6176 | 0.6832 | 0.6513 |

Table 5.5 summarises the accuracy, F1-score, and *AUC* measures. While Adaboost performs exceptionally across the board with the default parameter settings, RF outperforms logistic regression in *AUC* and F1-score, while logistic regression outperforms RF in accuracy. In terms of how quickly models can be trained and evaluated, logistic regression and RF both outperform Adaboost.

**Using some other models**

The provided results show the performance of three different classifiers, Gaussian Naive Bayes, Support Vector Classifier (SVC), and K-Nearest Neighbors (KNN), trained on three different sample sizes of 299, 2992, and 29926 samples.

For all classifiers and sample sizes, the accuracy is around 0.53, which means that the models are correctly classifying approximately 53% of the instances. However, an accuracy score alone may not be sufficient to evaluate the performance of a classifier, especially when the classes are imbalanced, and one class dominates the other.

That's where other evaluation metrics like the F1 score and AUC come into play. The F1 score takes into account both precision and recall and is a better metric to use when there is an imbalance in the classes. In this case, the F1 score is around 0.66-0.70, which means that the models are not able to distinguish between the positive and negative classes effectively.

Moreover, the AUC score is another metric to evaluate the performance of a classifier, which measures the ability of the classifier to distinguish between the positive and negative classes. An AUC score of 0.5 suggests that the classifier is not able to distinguish between the two classes and is performing no better than random guessing.

A screenshot of a graph

Description automatically generated with low confidence

Fig. 5.7: Performance metrics for three supervised learning refined hyperparameters

Therefore, based on the provided results, it appears that the classifiers are not performing well in classifying the instances. Improving the performance may require using different classifiers, exploring different feature engineering techniques, or increasing the sample size to obtain more representative data.

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Description automatically generated

Fig. 5.8: Evaluation metrics for three supervised learning refined hyperparameters

As shown in Table 5.5, the three metrics scores are summarized. Compared with the metrics in Table 5.4, the metrics of logistic regression and Adaboost are just slightly improved, but the metrics of random forest are significantly improved after tuning by grid search.

Overall, this methodology follows a data-driven and iterative approach to online news popularity prediction, combining various techniques and tools from machine learning, deep learning, and natural language processing. It emphasizes the importance of data quality, feature engineering, model selection and tuning, and continuous monitoring and improvement.

# Chapter 6: Business Understanding

Journalists, advertisers, content providers, etc. value news articles published online as a useful resource. Online news portals have taken over as the main news source with the advent of cell phones and the Internet. The key to reaching a large audience is not just how many people read the content, but also how many people share it on social networking sites like Facebook, LinkedIn, Twitter, etc. The number of shares is a well-known indicator of how popular the news is, which affects how much money is made through ads. As noted in the research, the main difficulty in forecasting the popularity of a blog post is that it heavily depends on human conduct.

The rise of the internet and social media has significantly impacted the way people consume news and information. With the increasing accessibility of cell phones and the internet, online news portals have become the primary source of news for many people. As a result, journalists, advertisers, content providers, and other stakeholders in the media industry place a high value on news articles published online.

One crucial aspect of online news articles is the number of shares they receive on social media platforms like Facebook, LinkedIn, Twitter, and others. The number of shares is an essential indicator of how popular an article is, which ultimately impacts the revenue generated through advertising. The more shares an article gets, the higher the chances of it reaching a larger audience, thereby increasing the chances of generating more revenue through ads.

However, predicting the popularity of an article is not an easy task as it heavily depends on human behavior. The behavior of individuals on social media, including their preferences and interests, significantly influences the popularity of news articles. Therefore, accurately forecasting the popularity of a blog post requires understanding the complex interactions between human behavior and online content.

Predicting the popularity of a news article or blog post is challenging because it is influenced by various factors, including the quality and relevance of the content, the timeliness of the topic, the writing style, the format of the article, and the target audience. Additionally, human behavior plays a critical role in determining whether an article becomes popular or not. Factors such as emotions, personal preferences, opinions, social networks, and cultural influences affect whether people share and engage with the content on social media platforms.

As a result, developing an effective tool to predict the popularity of an article online requires analyzing multiple characteristics and factors, including text analytics, sentiment analysis, machine learning algorithms, and social media metrics. This tool can help journalists, advertisers, content providers, and other professionals to understand the potential impact of their content, optimize their marketing strategies, and increase their revenue.

The media industry is facing the challenge of accurately predicting the popularity of news articles and blog posts in the online space. This is crucial because the number of shares an article receives on social media platforms directly impacts the revenue generated through advertising. Therefore, developing an effective tool to forecast the popularity of an article online can help businesses optimize their marketing strategies, increase their reach, and generate more revenue. The tool must take into account various factors that affect the popularity of an article, including text analytics, sentiment analysis, machine learning algorithms, and social media metrics. By analyzing these factors, businesses can gain valuable insights into their target audience's preferences and interests, optimize their content marketing strategies, and create more engaging and relevant content that drives more shares and engagement.

Furthermore, understanding the complex interactions between human behavior and online content is essential for accurately forecasting the popularity of an article. Therefore, businesses must continuously refine and update their forecasting tools to keep up with the latest trends and changes in human behavior on social media platforms. Overall, developing an effective tool to predict the popularity of an article online can help businesses in the media industry stay ahead of the competition, increase their revenue, and provide more value to their target audience.

# Chapter 7: Data Understanding

The well-known characteristics, such as the number of keywords and the blog post’s genre, were simple to comprehend. The main challenge was the inability to initially comprehend the analytics information provided in the data set, such as LDA, polarity, and subjectivity, which necessitated additional knowledge of text mining techniques, which was briefly inferred from "Large scale sentiment analysis for news and blogs." When the data were thoroughly examined, it became clear that the news might either be unimportant and shared by no more than one person, or it may be viral and shared by more than half a million individuals. So, while determining the following steps, the diversity of the data was also an important consideration.

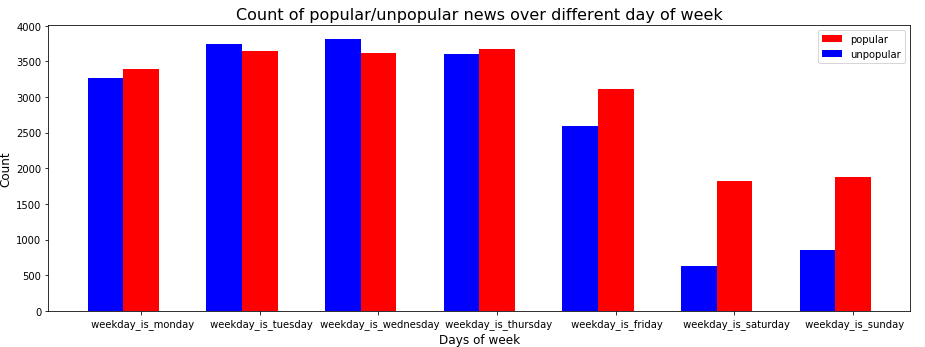


Fig. 7.1: Count of popular/unpopular news over different days of a week

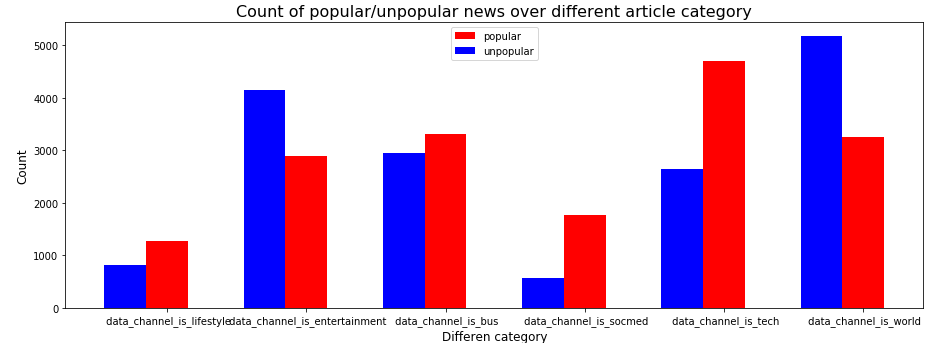


Fig. 7.2: Count of popular/unpopular news over different article categories

As shown in Fig. 7.1, several features, such as the day of the week and the article category, seem to be important. A graph showing the number of days of the week that particular news stories were the most/least popular. The potential readership of content published over the weekend is higher. This makes sense, as it's probable that weekend readers will spend more time than usual perusing the news online. In Fig. 7.2, a scatter plot showing the number of positive and negative news stories across all article types. While the proportion of popular news to unpopular news is much larger in the category of technology ("data channel is tech") and the opposite is true in the categories of the world ("data channel is the world"), social media ("data channel is socmed (social media)"), and entertainment ("data channel is entertainment"). This might indicate that Mashable's audience is more interested in technology and social media than in global and entertainment news.

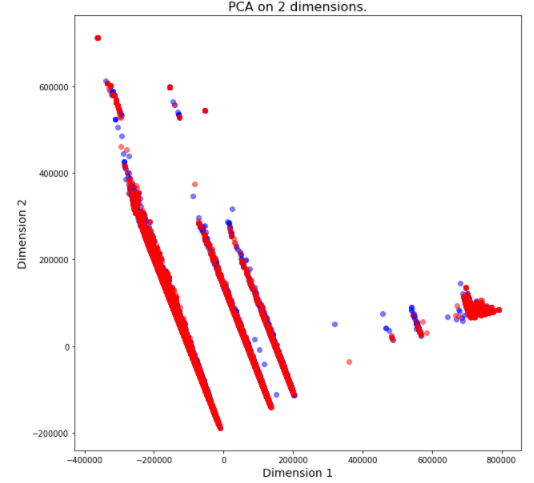


Fig. 7.3: Data projected on the first two principle Components.

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Fig. 7.4: Data projected on the first three Principle components (Red: popular; Blue: unpopular)

To better understand the information, Principal Component Analysis (PCA) will be used. Fig. 7.3 illustrates how to map a data point into the first two and third components. PCA space does not allow for linear separation of the dataset. Red indicates high popularity and blue indicates low popularity for the data projected on the first two principal components, as illustrated in Fig. 7.3 and 7.4.

The objective of the data analysis is to predict the popularity of news articles based on various characteristics and factors. The dataset contains news articles published on Mashable, an online news portal, and includes features such as the number of shares, the article category, the day of the week when the article was published, and text analytics metrics such as LDA, polarity, and subjectivity.

The data analysis revealed that predicting the popularity of an article is challenging and depends on various factors such as the quality and relevance of the content, the writing style, the format of the article, and the target audience. Additionally, human behavior plays a critical role in determining whether an article becomes popular or not. The behavior of individuals on social media, including their preferences and interests, significantly influences the popularity of news articles.

The data analysis also revealed that certain features such as the day of the week when the article was published and the article category are relevant in predicting the popularity of an article. Articles published over the weekends have a higher potential to be popular, as people tend to spend more time browsing news online during weekends. The category of technology and social media has a higher proportion of popular news, while the category of world and entertainment has a higher proportion of unpopular news.

PCA was performed to visualize the data and revealed that the dataset is not linearly separable in PCA space. The data projection on the first two and three principal components showed that popular and unpopular news articles are scattered across the space and do not have a distinct separation.

In addition to the features mentioned above, the analysis also includes the use of text mining techniques, such as LDA, polarity, and subjectivity, to gain a better understanding of the data. The LDA technique was used to identify the topics discussed in the news articles, while the polarity and subjectivity analysis helped to determine the sentiment and tone of the articles.

One of the main challenges in analyzing the data was the diversity of the news articles, which ranged from unimportant to viral. This required careful consideration of the various features and factors that could influence the popularity of the articles.

Two significant features that were found to have an impact on the popularity of the news articles were the day of the week and the article category. As shown in Fig. 7.1, articles published over the weekends had a higher potential to be popular, likely due to people spending more time browsing news online on their days off. Additionally, in the category of technology and social media, the proportion of popular news was much larger than the unpopular ones, while in the categories of world and entertainment, the proportion of unpopular news was higher than popular ones. This suggests that Mashable readers prefer news related to technology and social media over news related to the world and entertainment.

To visualize the data, PCA was performed, as shown in Fig. 7.3 and 7.4. The data points were projected onto the first two and three principal components, respectively, and colored based on their popularity. It was found that the dataset was not linearly separable in PCA space, indicating that other techniques might be needed to improve the accuracy of popularity prediction.

Overall, the analysis highlights the importance of considering various features and factors when predicting the popularity of news articles. By leveraging text mining techniques and other data analysis tools, journalists, advertisers, content providers, and other professionals can gain insights into the potential impact of their content and optimize their marketing strategies to increase revenue.

# Chapter 8: Data Preparation

The data Cleaning Dataset has been thoroughly checked using various summarizing techniques for identifying 1. Inconsistent data 2. Inappropriate data 3. Missing data. It’s observed that all the data types i.e., the variable types are consistent.

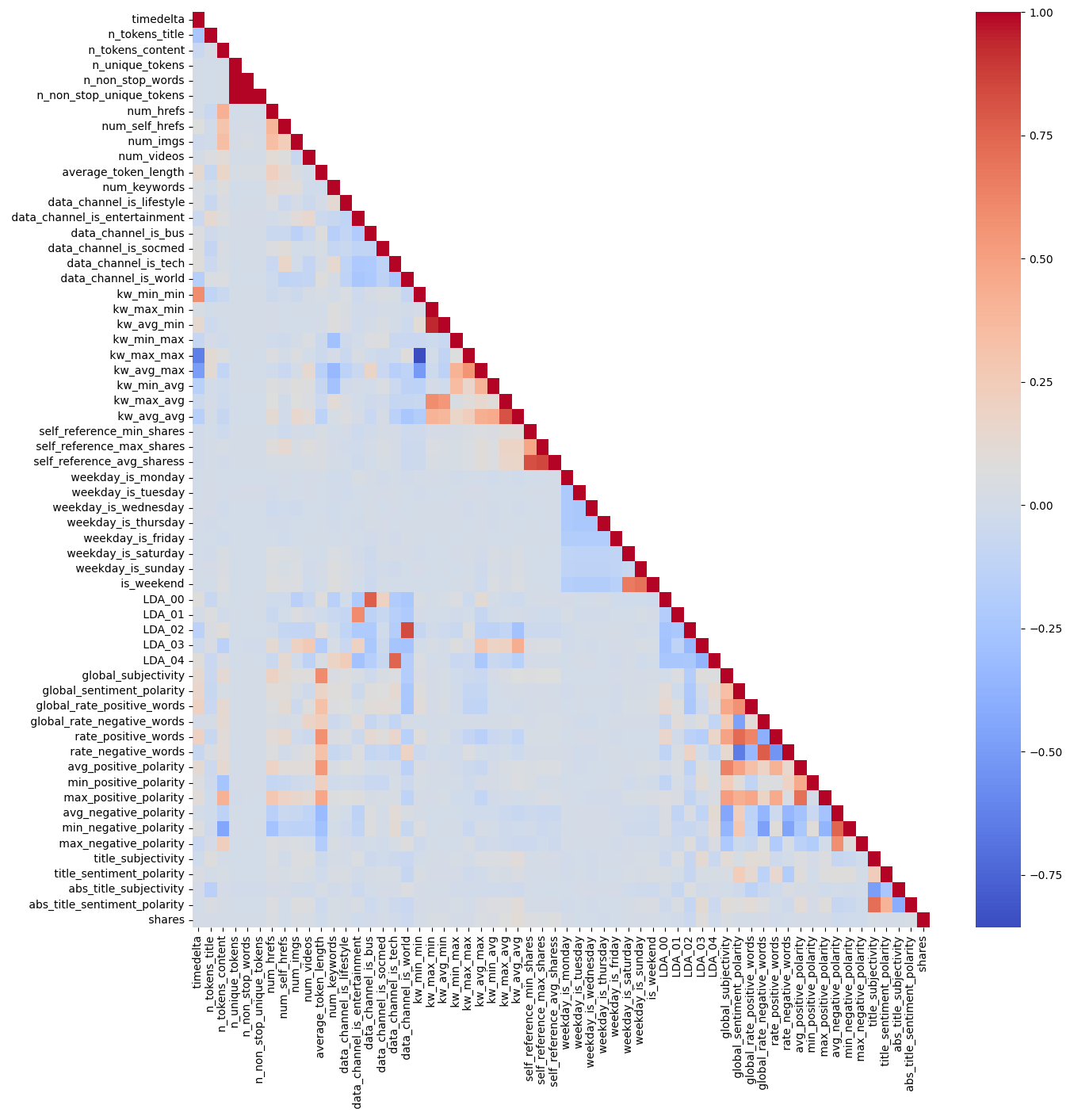


Fig. 8.1: Correlation between default features

Numeric fields are filled with only numeric values and there are no irrelevant negative values. While exploring the data summary of the input variables few irrelevant values in the n\_tokens\_content attribute are found. The value for n\_tokens\_content is 0 for a few records. With the business understanding, the number of words in the news content can never be 0. Upon checking the news post on the website with the URL provided in the dataset, it’s observed that the rows with value 0 for n\_tokens\_content are misleading and irrelevant data. So, it is excluded and considered missing data.

As shown in Fig. 8.1, Applied a cluster map to examine the correlation among variables. This seems that some of them have a high correlation. However, correlated information between features is limited. Distribution of weekdays showed that the numbers of shares are highest during the middle of the week and decreased during the weekends; Tuesdays, Wednesdays, and Thursdays are higher than the rest of the days. After some analysis, it is observed that a weekend article has less opportunity to be shared as an article.

# Chapter 9: Modeling

In the previous section of the report, it was identified the dependent variables after cleaning the data by eliminating outliers and extraneous information. The correlation matrix is constructed to reveal the associations between the dependent variables and the dependent variable of interest. Considering the heatmap of feature correlation and found that the majority of the characteristics are independent of one another. In addition, there are over 1400 possible values for the target variable, making accurate prediction difficult. To determine which of several popularity tiers (most popular, most popular, least popular, viral, etc.) a given post falls into, the target variable is binned. A regression model was applied to the problem space and data before the target variable was binned into categories.

Then, explore the relationship between the target (number of shares) and some selected features:

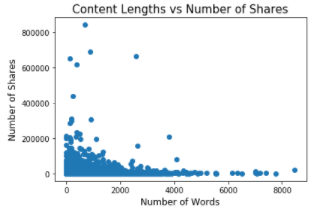


Fig. 9.1: Content length vs Number of shares.

As shown in Fig. 9.1, the Comparison is between several words in the content vs of several shares. It is showing that if the content is big, then there is less chance of sharing whereas if the content size is a short number of users will read and share the news.

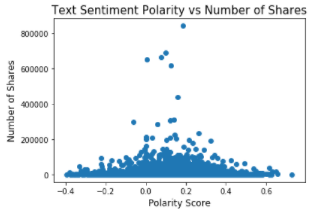


Fig. 9.2: Text sentiment popularity vs Number of shares

As shown in Fig. 9.2, If the content is having sentiments, that will attract the users and will allow users to share also. Initially, regression models were used to predict the number of shares of a piece of news. All features except for news URL and timedelta were included in the model. *StandardScaler()* was applied to numerical features.

TABLE 9.1: REGRESSION MODEL ERROR COMPARISON

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **R2** | **Mean Absolute Error** | **Median Absolute Error** |
| **LassoCV** | 0.021390 | 3039.425129 | 1675.728808 |
| **RidgeCV** | 0.019512 | 3053.470410 | 1662.516891 |
| **RandomForestRegressor** | -0.070401 | 3456.761696 | 1584.380000 |

Regression models produced substantial median absolute errors, as shown in Table 9.1, suggesting that classification models might be better suited to this issue. The model includes all features except the news URL and the timedelta. The numerical characteristics were scaled using *StandardScaler()*. Each categorisation algorithm was given its pipeline.

Choosing the threshold -- Mean (3395) or Median (1400)

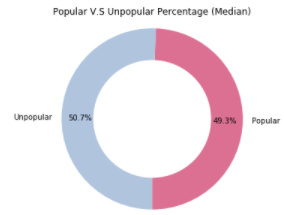
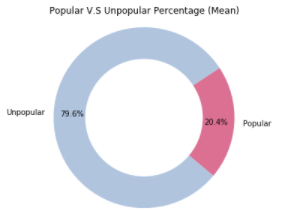
 

Fig. 9.3: Comparisons of popular vs unpopular percentages in Mean and Median

As shown in Fig. 9.3, If the mean number of shares (3395) is used as the threshold, the popular and unpopular classes would be imbalanced. Additionally, the large range of several shares would make the mean not appropriate to divide the news into two classes. Therefore, decided to choose the median number of shares (1400) as the threshold. *LogisticRegressionCV*, *KNeighborsClassifier*, *Naive Bayes* (*GaussianNB*), and *RandomForestClassifier* are the classifiers utilised in this study.

TABLE 9.2: CLASSIFIER COMPARISON BETWEEN FOUR MODELS

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **accuracy** | **precision** | **recall** | **f1 score** |
| **LogisticRegressionCV** | 0.641569 | 0.644345 | 0.620777 | 0.641405 |
| **KNeighborsClassifier** | 0.595788 | 0.606519 | 0.529337 | 0.593988 |
| **GaussianNB** | 0.533611 | 0.672938 | 0.118110 | 0.437456 |
| **RandomForestClassifier** | 0.663640 | 0.666842 | 0.644653 | 0.663509 |

As shown in Table 9.2, the calculation is made on the basis of equations used for accuracy on basis of equation (9.1), precision is calculated on the basis of equation (9.2),

recall is calculated based on equation (9.3) and F1 score is calculated on basis of equation (9.4). Accuracy is 67% using equation (9.1) with a 0.67 F1 Score using equation (9.4) which shows better results for the Random Forest classifier among all the models.

(9.1)

(9.2)

(9.3)

(9.4)

- F1-score is used when False Negatives and False Positives are crucial

- F1-score is a better metric when there are imbalanced classes

The logistic regression model predicts the two-category results with a balanced accuracy of 64% using equation (9.1). The accuracy curve for different cut-offs is as below, so to maximize the accuracy the threshold limit is chosen as 0.5.

News articles include results from text mining and sentiment analysis and tried to create a Naive Bayes Classifier for this data set. The observed accuracy and f-score are not that satisfactory. So, concluded that the Naive Bayes Model does not fit the data set as expected. The failure can be attributed to the naive assumption about class conditional independence. It is possible that the features in the data set are not independent.

The random forest model is built with the same set of input variables, testing set, and training set which was used for logistic regression to understand the accuracy of the models. The random forest model is initially set with 500 trees and 7 splits. Later, confirming the right model, the number of trees, and the number of splits will be tuned to find the optimized results. Using the F1 score, Random Forest Classifier is the suitable model.

# Chapter 10: Model Evaluation

The article's headline may benefit from some sentimental examination. The capacity to use unstructured data for meaningful insights is crucial for managing a successful article using emotional data.

To determine whether an author is being subjective or objective, or even positive or negative, as seen in Fig. 10.1, sentimental analysis employs Natural Language Processing algorithms.

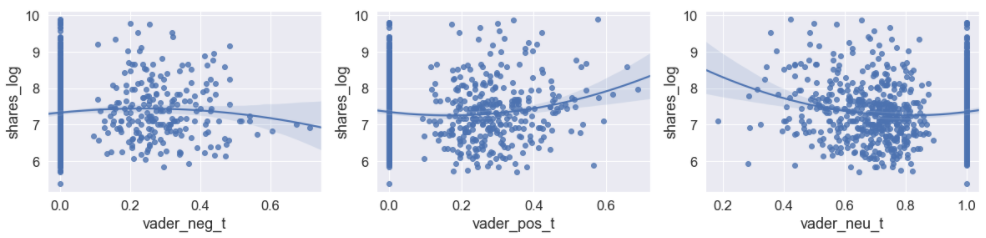


Fig. 10.1: Comparison of subjective information using Sentimental analysis in Positive, Negative, and neutral

As shown in Fig. 10.1, shows the comparison of subjective information using Sentimental analysis in Positive, Negative, and neutral which highlights, that data having positive and neutral sentiments will be viewed more and shared.

Surprisingly, there is a positive correlation between social shares of news stories and a score positive in the title: Between 20-40% shown in Fig. 10.2 of those who score positive in the title are shared. (Note - the logarithmic scale for social shares).

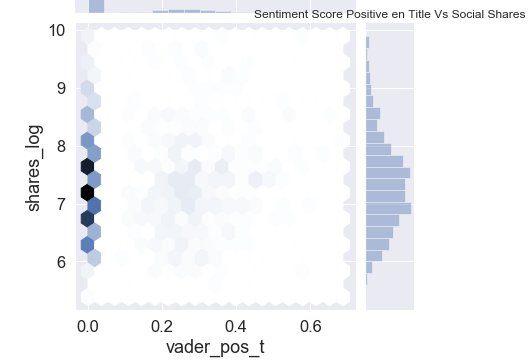


Fig. 10.2: Correlation between sentiment score positive on title vs social shares

As shown in Fig. 10.2, Here’s a correlation between positive sentiments and the number of shares.

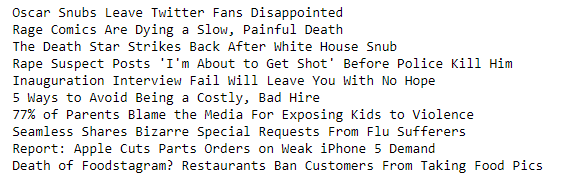


Fig. 10.3: Top 10 Negative features by VADER score

As shown in Fig. 10.3, Using the VADER library, here’s a ranking of the 10 titles with negative scores by the number of social shares of those articles. Abusing language and violent words like kill reflect negative phrases.

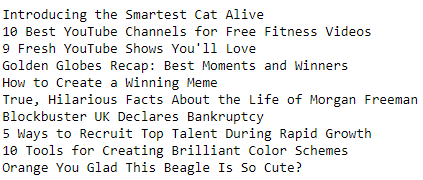


Fig. 10.4: Top 10 Positive features by VADER score

As shown in Fig. 10.4, here’s a ranking of the 10 titles with negative scores by the number of social shares of those articles. 4 records include numbers. Also, one of them has a video. It seems that strong visuals and including numbers in the title create the biggest impact to share.

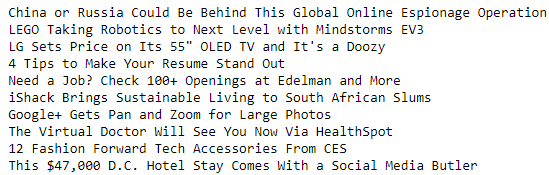


Fig. 10.5: Top 10 Neutral features by VADER

As shown in Fig. 10.5, the ranking of the 10 titles with neutral scores by the number of social shares of those articles. This section generally offers products, job offers, and news related to that is reflected.



Fig. 10.6: The word cloud shows that specific keywords may be more informative and technological

The word cloud as shown in Fig. 10.6 shows that specific words should be more informative, descriptive, and technological. This suggests that the influencing factors that result in the title of an article being popular and experiencing the highest volume of media sharing are ones that: have the placement of a single number in the title, contain strong visual imagery such as videos, and convoy positive messaging.

# Chapter 11: Analysis and Results

The favourable performance is also given by the RF model as shown in Table 11.1, which achieves a 0.67 of 10 accuracy score, and 0.67 for the F1 score. The metrics of the RF model are an accuracy of 0.663 and an F1-score of 0.663. By comparison, the accuracy and F1 score are all better than the benchmark model. So obtained model achieves comparable performance to the benchmark model and it is significant enough to solve the popular news classification problem.

TABLE 11.1: RF MODEL FOR NEWS CLASSIFICATION

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **accuracy** | **precision** | **recall** | **f1 score** |
| **LogisticRegressionCV** | 0.641569 | 0.644345 | 0.620777 | 0.641405 |
| **KNeighborsClassifier** | 0.595788 | 0.606519 | 0.529337 | 0.593988 |
| **GaussianNB** | 0.533611 | 0.672938 | 0.118110 | 0.437456 |
| **RandomForestClassifier** | 0.663640 | 0.666842 | 0.644653 | 0.663509 |

**Sentimental Analysis**

Sentiment analysis is a technique used to determine the sentiment or emotional tone expressed in a piece of text. It is commonly used in various applications, including online news prediction. VADER is one of the popular sentiment analysis tools used to analyze the sentiment of text data.

When it comes to online news prediction, sentiment analysis can be applied to analyze the sentiment of news articles or headlines. By using sentiment analysis techniques, it becomes possible to predict the sentiment of online news articles before they are published or analyze the sentiment of existing articles to gain insights.

Vader, specifically, is a rule-based sentiment analysis tool that uses a combination of lexical and grammatical heuristics to determine the sentiment of a given text. It incorporates a pre-trained sentiment lexicon that consists of words and their corresponding sentiment scores, capturing both the polarity (positive or negative) and intensity of sentiment. Vader considers not only individual words but also contextual information, punctuation, and capitalization to provide more accurate sentiment analysis results. It assigns sentiment scores to the input text, indicating the degree of positivity, negativity, and neutrality. These scores can be used to determine the overall sentiment of a text or compare sentiments across different pieces of text.

In the context of online news prediction, Vader can be employed to analyze the sentiment of news articles or headlines and predict the sentiment of upcoming articles. By monitoring sentiment trends over time, it may be possible to identify patterns, predict the popularity or impact of news articles, or detect potential biases in news reporting.

However, it's important to note that sentiment analysis, including the use of tools like Vader, is not a perfect science. It can have limitations and may not always accurately capture the nuances and complexities of human sentiment. Therefore, it's crucial to apply sentiment analysis as a part of a broader analysis framework and consider other factors when making predictions or drawing conclusions about online news.

# Chapter 12: Conclusions and Future Scope

For this project, initially tried to predict the number of shares of a piece of news with regression models. Fit three algorithms, Lasso, Ridge, and Random Forest Regressor, and found that the Median Absolute Error (MedAE) was around 1600, which is high considering that some news only has a few hundred shares.

Treated this problem as classification and used the median number of shares (1400) as a threshold to divide the news into two classes, popular and unpopular. Fit four algorithms, Logistic Regression, K-Nearest Neighbours, Gaussian Naive Bayes, and Random Forest Classifier, and found that Random Forest Classifier has a favorable performance using the F1 score.

Now tuned the hyperparameters of the random forest classifier based on cross-validation scores since grid/random search was too slow for this dataset. In final model had an F1 score of 0.66 and an accuracy of 66% for the test data.

The business problem was to predict the reach/popularity of the news article. After multiple levels of cleaning and pre-processing the data are stabilized for model building. Since the linear model could not produce better results because of the variance in the data, various numbers of bins are used, and classification algorithms are applied. Upon analyzing various models, the suited random forest model is fine-tuned. Though 2 categories classification provides better and more relevant results, it assumes popularity as a definitive output rather than a ranking methodology. In the next steps, instead of categorizing the news article, a ranking mechanism can be built using the bag of words and other text mining, and clustering methodologies. The ranking methodology can be improved over the period using reinforcement learning by adding the words from popular articles to the bag of words.

**Future Enhancements**

The field of online news popularity prediction is continuously evolving, driven by advancements in technology and data analysis. Here are some potential future enhancements for online news popularity prediction:

Incorporation of multimodal data: Currently, most online news popularity prediction models focus on text-based features. Future enhancements can involve incorporating additional data modalities such as images, videos, and audio to capture a more comprehensive understanding of news articles. This can provide richer context and improve the accuracy of popularity predictions.

**Integration of user-generated content:** User-generated content, including comments, reviews, and discussions, can provide valuable insights into news article popularity. Future enhancements can involve leveraging sentiment analysis and topic modeling techniques on user-generated content to capture user opinions and incorporate them into the popularity prediction models.

**Real-time prediction:** Real-time prediction of news popularity can be highly valuable for news organizations. Future enhancements can focus on developing models that can make accurate predictions as soon as news articles are published or shortly thereafter. This would enable news organizations to adapt their promotion and distribution strategies promptly.

**Dynamic modeling of temporal patterns:** News popularity is influenced by temporal dynamics, including time of day, day of the week, and seasonality. Future enhancements can involve developing dynamic models that capture the changing patterns of popularity over time. This would enable more accurate predictions by considering the temporal context.

**Incorporation of external factors:** Online news popularity can be influenced by various external factors, such as social events, public sentiment, and trending topics. Future enhancements can involve integrating external data sources and incorporating these factors into the prediction models. This would provide a more holistic view of news popularity and enable organizations to respond to emerging trends.

**Explainable AI:** As popularity prediction models become more complex, there is a growing need for explainability. Future enhancements can focus on developing models that provide interpretable explanations for their predictions. This would enable news organizations to understand the factors contributing to popularity and make informed decisions based on the model's insights.

Personalization and context-aware prediction: Future enhancements can involve developing prediction models that consider individual user preferences and context. By leveraging personalized data, such as browsing history, user profiles, and location, models can provide tailored predictions that align with user interests and current context.

**Integration with recommendation systems:** Online news popularity prediction can be integrated with recommendation systems to provide a seamless user experience. Future enhancements can involve combining popularity prediction with collaborative filtering, content-based filtering, or hybrid recommendation algorithms. This would enable news organizations to deliver personalized news recommendations based on predicted popularity.

By exploring these future enhancements, online news popularity prediction can become more accurate, dynamic, and context-aware, leading to improved content strategies, audience engagement, and business outcomes for news organizations.

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# Appendix

## Plagiarism Report[[1]](#footnote-1)

**Plagiarism Report** with below 15% Similarly index to be attached in the annexure. The title page and last pages with the similarity index report are attached.

## Github Link

<https://github.com/VaibhavRevaBA06/Online_News_Popularity>

1. [↑](#footnote-ref-1)