Predicting Virality with Extreme Gradient Boosting on Online News Popularity Data

Ednalyn C. De Dios

D214

September 11, 2023

Western Governors University

Predicting Virality with Extreme Gradient Boosting on Online News Popularity Data

In this digital age that we're in, understanding the different factors that contribute to the popularity of online news articles is a crucial endeavor for media organizations, marketing professionals, and content creators alike. Boundless amount of data exists and presents a challenge of distilling patterns to uncover hidden insights regarding user behavior. Furthermore, identifying key factors that determine an online news article's popularity has become the holy grail of many, including data scientists. Machine learning techniques like XGBoost help uncover these hidden insights and translate them into actionable nuggets of information that stakeholders can act upon.

XGBoost, which stands for eXtreme Gradient Boosting, is a powerful and versatile machine learning algorithm that has gained popularity in recent years due to its effectiveness in handling a wide range of predictive tasks. Created by Tianqi Chen, XGBoost is "a scalable tree boosting system" (2023) equipped with both sequential and parallel architectures (Suginoo, 2022). A supervised learning algorithm, gradient boosting predicts "a target variable by combining the estimates of a set of simpler, weaker models" (How XGBoost Works, n.d.).

A – Research Question

In this study, eXtreme Gradient Boosting or XGBoost is used to analyze the Online News Popularity Data by Fernandes et al. (2015) and predict the popularity of online news articles. The aim is to construct a model with more than 65% accuracy and an AUC score of above 60%. The secondary goal of this study is to identify which attributes in the available data are key factors driving the number of social media shares. Stakeholders would like to know this information to optimize their content for "going viral." This study will examine the different relationships between different attributes of the data in relation to the designation of whether the online news article is popular or not, as defined by the number of times the article has been shared on social media channels. Thus, the question can then be summarized as follows: Can gradient boosting be constructed based solely on the research data?

The null hypothesis of the research question is that gradient boosting cannot be made from the Online News Popularity dataset. For example, an optimized gradient boosting model using XGBoost fails to achieve an accuracy score of more than 65% nor an AUC score of more than 60%. The alternative hypothesis is that an optimized gradient boosting model can be made from the Online News Popularity dataset. For example, an optimized gradient boosting model using XGBoost achieves an accuracy score of more than 65% with an AUC score of more than 60%.

B – Data Collection

This study uses the "Online News Popularity" dataset which is publicly available from the UC Irvine Machine Learning Repository project (Fernandes et al., 2015). The dataset contains statistics on articles published by Mashable.com. The dataset contains 39,797 records and 61 attributes, of which 58 are predictive, two are non-predictive, and one goal field. The dataset is publicly available to the public and licensed under Creative Commons Attribution 4.0 International (CC BY 4.0). The following table lists the name, type, and description of the attributes that were included in this study.

Field	**Type**	**Description**
url	Categorical	URL of the article
timedelta	Continuous	Days between the article publication and the dataset acquisition

n_tokens_title	Continuous	Number of words in the title
n_tokens_content	Continuous	Number of words in the content
n_unique_tokens	Continuous	Rate of unique words in the content
n_non_stop_words	Continuous	Rate of non-stop words in the content
n_non_stop_unique_tokens	Continuous	Rate of unique non-stop words in the content
num_hrefs	Continuous	Number of links
num_self_hrefs	Continuous	Number of links to other articles published by Mashable
num_imgs	Continuous	Number of images
num_videos	Continuous	Number of videos
average_token_length	Continuous	Average length of the words in the content
num_keywords	Continuous	Number of keywords in the metadata
data_channel_is_lifestyle	Categorical	Is data channel 'Lifestyle'?
data_channel_is_entertainment	Categorical	Is data channel 'Entertainment'?
data_channel_is_bus	Categorical	Is data channel 'Business'?
data_channel_is_socmed	Categorical	Is data channel 'Social Media'?
data_channel_is_tech	Categorical	Is data channel 'Tech'?
data_channel_is_world	Categorical	Is data channel 'World'?
kw_min_min	Continuous	Worst keyword (min. shares)
kw_max_min	Continuous	Worst keyword (max. shares)
kw_avg_min	Continuous	Worst keyword (avg. shares)
kw_min_max	Continuous	Best keyword (min. shares)
kw_max_max	Continuous	Best keyword (max. shares)
kw_avg_max	Continuous	Best keyword (avg. shares)
kw_min_avg	Continuous	Avg. keyword (min. shares)
kw_max_avg	Continuous	Avg. keyword (max. shares)
kw_avg_avg	Continuous	Avg. keyword (avg. shares)
self_reference_min_shares	Continuous	Min. shares of referenced articles in Mashable

self_reference_max_shares	Continuous	Max. shares of referenced articles in Mashable
self_reference_avg_sharess	Continuous	Avg. shares of referenced articles in Mashable
weekday_is_monday	Categorical	Was the article published on a Monday?
weekday_is_tuesday	Categorical	Was the article published on a Tuesday?
weekday_is_wednesday	Categorical	Was the article published on a Wednesday?
weekday_is_thursday	Categorical	Was the article published on a Thursday?
weekday_is_friday	Categorical	Was the article published on a Friday?
weekday_is_saturday	Categorical	Was the article published on a Saturday?
weekday_is_sunday	Categorical	Was the article published on a Sunday?
is_weekend	Categorical	Was the article published on the weekend?
LDA_00	Categorical	Closeness to LDA topic 0
LDA_01	Categorical	Closeness to LDA topic 1
LDA_02	Categorical	Closeness to LDA topic 2
LDA_03	Categorical	Closeness to LDA topic 3
LDA_04	Categorical	Closeness to LDA topic 4
global_subjectivity	Continuous	Text subjectivity
global_sentiment_polarity	Continuous	Text sentiment polarity
global_rate_positive_words	Continuous	Rate of positive words in the content
global_rate_negative_words	Continuous	Rate of negative words in the content
rate_positive_words	Continuous	Rate of positive words among non-neutral tokens
rate_negative_words	Continuous	Rate of negative words among non-neutral tokens
avg_positive_polarity	Continuous	Avg. polarity of positive words
min_positive_polarity	Continuous	Min. polarity of positive words
max_positive_polarity	Continuous	Max. polarity of positive words
avg_negative_polarity	Continuous	Avg. polarity of negative words

min_negative_polarity	Continuous	Min. polarity of negative words
max_negative_polarity	Continuous	Max. polarity of negative words
title_subjectivity	Continuous	Title subjectivity
title_sentiment_polarity	Continuous	Title polarity
abs_title_subjectivity	Continuous	Absolute subjectivity level
abs_title_sentiment_polarity	Continuous	Absolute polarity level
shares	Continuous	Number of shares (target)

There are several advantages with the chosen dataset. There are no missing values, the class distribution is relatively balanced, and the categorical variables have already been encoded into numerical form. However, one observed disadvantage is the sheer size of the dataset. One trial run of the experiment took almost three hours to run hyperparameter tuning. The challenge of long running time was overcome by setting the tree_method to 'gpu_hist' and limiting the range of the parameter search space.

```
# Read a csv file
df = pd.read_csv('../data/in/OnlineNewsPopularity.csv')
```

C – Data Extraction and Preparation

The next phase of the analysis is data preparation. The tool used is Python 3.9.9 and Jupyter Notebook 7.0.2 was used as the interactive development environment. Python was chosen for its versatility and easy-to-learn syntax. Jupyter Notebook was chosen for its markdown capability. One disadvantage of Python is performance while Jupyter makes good code versioning very difficult (Mueller, 2018).

After reading the data into a dataframe, the next step is to check for any missing values.

```
def show_missing(df):
    """
    Takes a dataframe and returns a dataframe with stats
    on missing and null values with their percentages.
    """
    null_count = df.isnull().sum()
    null_percentage = (null_count / df.shape[0]) * 100
    empty_count = pd.Series(((df == ' ') | (df == '')).sum())
    empty_percentage = (empty_count / df.shape[0]) * 100
    nan_count = pd.Series(((df == 'nan') | (df == 'NaN')).sum())
    nan_percentage = (nan_count / df.shape[0]) * 100
    dfx = pd.DataFrame({'num_missing': null_count, 'missing_percentage': null_percentage,
                        'num_empty': empty_count, 'empty_percentage': empty_percentage,
                        'nan_count': nan_count, 'nan_percentage': nan_percentage})
    return dfx

show_missing(df)
```

Next is correcting the column names.

```
for col in df.columns:
    df = df.rename(columns={col:(col.strip(' '))})

df = df.rename(columns={'self_reference_avg_sharess':'self_reference_avg_shares'})
```

Then, duplicates are dropped if any. There weren't any as shown by df.shape before and after the operation.

```
df.shape
df = df.drop_duplicates(keep = False)
df.shape
```

```
(39644, 61)

(39644, 61)
```

The target variable was created by applying a condition on the ‘shares’ variable and designating 1 or 0 depending on the THRESHOLD value. The threshold value for this notebook is 1400.

```
# creates a new column for the new target variable and non-descriptive column
df['target'] = np.where(df['shares'] > THRESHOLD, int(1), int(0))
df = df.drop(columns=['url', 'timedelta'])
```

Finally, the cleaned and prepared dataset is exported using pandas’ to_csv() method.

```
df.to_csv('../data/out/online_news_popularity_clean.csv', index=False)
```

D – Analysis

Once the dataset is prepared, the next step in the analysis is to conduct EDA or explanatory data analysis. The high-levels steps are:

1. Get familiar with the data
2. Review class distribution
3. Get summary statistics
4. Remove outliers
5. Compare the interactions of the variables

```
df.head()
```

	n_tokens_title	n_tokens_content	n_unique_tokens	n_non_stop_words	n_non_stop_unique_tokens	num_hrefs	num_self_hrefs	num_imgs	num_videos	average_token_le
0	12.0	219.0	0.663594	1.0	0.815385	4.0	2.0	1.0	0.0	4.68
1	9.0	255.0	0.604743	1.0	0.791946	3.0	1.0	1.0	0.0	4.91
2	9.0	211.0	0.575130	1.0	0.663866	3.0	1.0	1.0	0.0	4.39
3	9.0	531.0	0.503788	1.0	0.665635	9.0	0.0	1.0	0.0	4.40
4	13.0	1072.0	0.415646	1.0	0.540890	19.0	19.0	20.0	0.0	4.68

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39644 entries, 0 to 39643
Data columns (total 60 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   n_tokens_title                  39644 non-null  float64
 1   n_tokens_content                39644 non-null  float64
 2   n_unique_tokens                 39644 non-null  float64
 3   n_non_stop_words                39644 non-null  float64
 4   n_non_stop_unique_tokens        39644 non-null  float64
 5   num_hrefs                       39644 non-null  float64
 6   num_self_hrefs                  39644 non-null  float64
 7   num_imgs                        39644 non-null  float64
 8   num_videos                      39644 non-null  float64
 9   average_token_length            39644 non-null  float64
 10  num_keywords                    39644 non-null  float64
 11  data_channel_is_lifestyle       39644 non-null  float64
 12  data_channel_is_entertainment   39644 non-null  float64
 13  data_channel_is_bus             39644 non-null  float64
 14  data_channel_is_socmed          39644 non-null  float64
 15  data_channel_is_tech            39644 non-null  float64
 16  data_channel_is_world          39644 non-null  float64
 17  kw_min_min                      39644 non-null  float64
 18  kw_max_min                      39644 non-null  float64
 19  kw_avg_min                      39644 non-null  float64
```

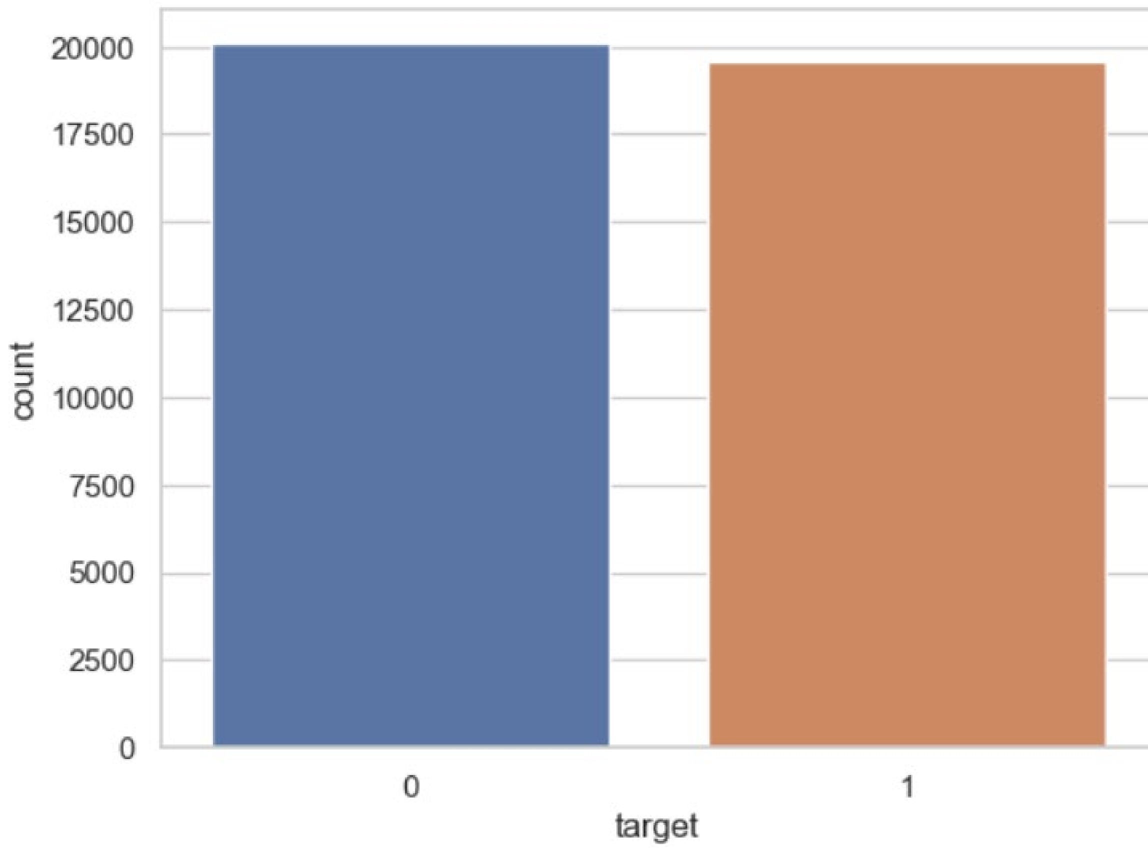
```
 20  kw_min_max                     39644 non-null  float64
 21  kw_max_max                     39644 non-null  float64
 22  kw_avg_max                     39644 non-null  float64
 23  kw_min_avg                     39644 non-null  float64
 24  kw_max_avg                     39644 non-null  float64
 25  kw_avg_avg                     39644 non-null  float64
 26  self_reference_min_shares      39644 non-null  float64
 27  self_reference_max_shares      39644 non-null  float64
 28  self_reference_avg_shares      39644 non-null  float64
 29  weekday_is_monday              39644 non-null  float64
 30  weekday_is_tuesday             39644 non-null  float64
 31  weekday_is_wednesday           39644 non-null  float64
 32  weekday_is_thursday            39644 non-null  float64
 33  weekday_is_friday              39644 non-null  float64
 34  weekday_is_saturday            39644 non-null  float64
 35  weekday_is_sunday              39644 non-null  float64
 36  is_weekend                     39644 non-null  float64
 37  LDA_00                         39644 non-null  float64
 38  LDA_01                         39644 non-null  float64
 39  LDA_02                         39644 non-null  float64
 40  LDA_03                         39644 non-null  float64
 41  LDA_04                         39644 non-null  float64
 42  global_subjectivity            39644 non-null  float64
 43  global_sentiment_polarity      39644 non-null  float64
 44  global_rate_positive_words     39644 non-null  float64
 45  global_rate_negative_words     39644 non-null  float64
 46  rate_positive_words            39644 non-null  float64
 47  rate_negative_words            39644 non-null  float64
 48  avg_positive_polarity          39644 non-null  float64
```

```
 49  min_positive_polarity          39644 non-null  float64
 50  max_positive_polarity          39644 non-null  float64
 51  avg_negative_polarity          39644 non-null  float64
 52  min_negative_polarity          39644 non-null  float64
 53  max_negative_polarity          39644 non-null  float64
 54  title_subjectivity             39644 non-null  float64
 55  title_sentiment_polarity       39644 non-null  float64
 56  abs_title_subjectivity         39644 non-null  float64
 57  abs_title_sentiment_polarity   39644 non-null  float64
 58  shares                         39644 non-null  int64
 59  target                         39644 non-null  int32
dtypes: float64(58), int32(1), int64(1)
memory usage: 18.0 MB
```

As shown in the graph below, the dataset has a relatively balanced class.

```
sns.countplot(x='target', data=df)
```

```
<Axes: xlabel='target', ylabel='count'>
```



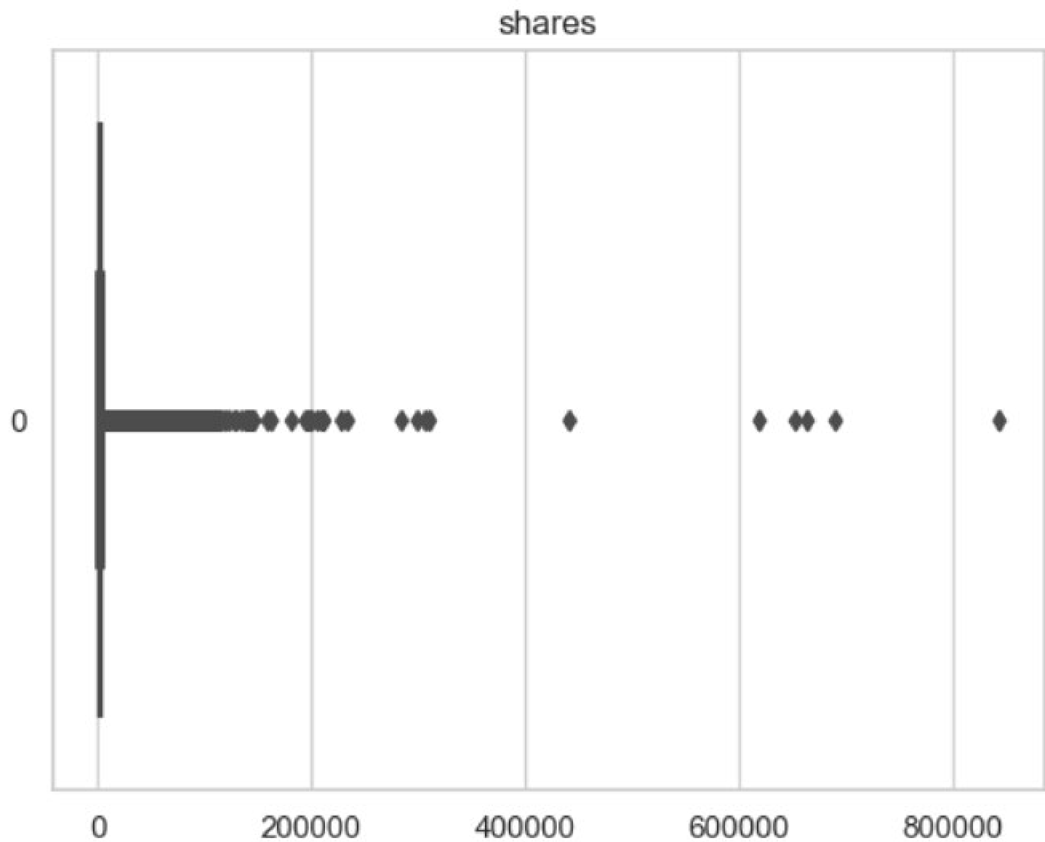

```
df.describe()
```

	n_tokens_title	n_tokens_content	n_unique_tokens	n_non_stop_words	n_non_stop_unique_tokens	num_hrefs	num_self_hrefs	num_imgs	num_videos	avera
count	39644.000000	39644.000000	39644.000000	39644.000000	39644.000000	39644.000000	39644.000000	39644.000000	39644.000000	
mean	10.398749	546.514731	0.548216	0.996469	0.689175	10.883690	3.293638	4.544143	1.249874	
std	2.114037	471.107508	3.520708	5.231231	3.264816	11.332017	3.855141	8.309434	4.107855	
min	2.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	9.000000	246.000000	0.470870	1.000000	0.625739	4.000000	1.000000	1.000000	0.000000	
50%	10.000000	409.000000	0.539226	1.000000	0.690476	8.000000	3.000000	1.000000	0.000000	
75%	12.000000	716.000000	0.608696	1.000000	0.754630	14.000000	4.000000	4.000000	1.000000	
max	23.000000	8474.000000	701.000000	1042.000000	650.000000	304.000000	116.000000	128.000000	91.000000	

Next is to conduct a visual inspection of the boxplot to look for outliers in the dataset.

```
def viz_box(df, col):
    sns.boxplot(df[col], orient="h")
    plt.title(str(col))
    plt.show()
```

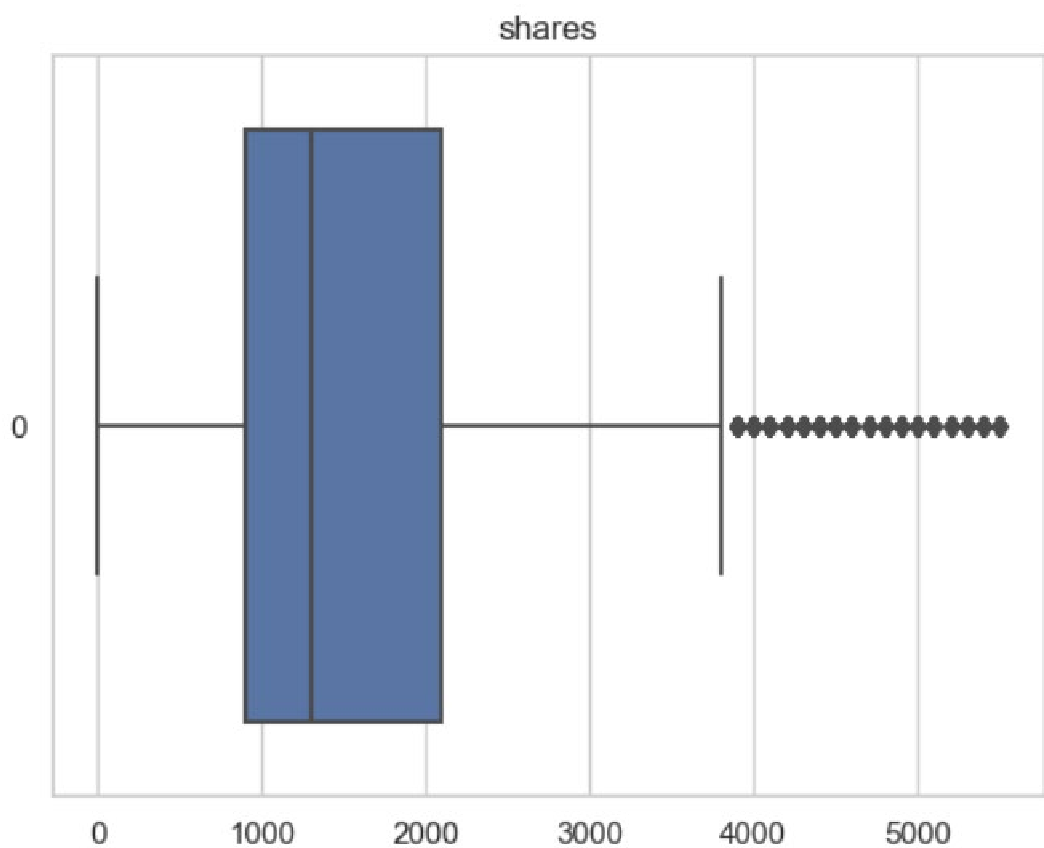
```
viz_box(df, 'shares')
```



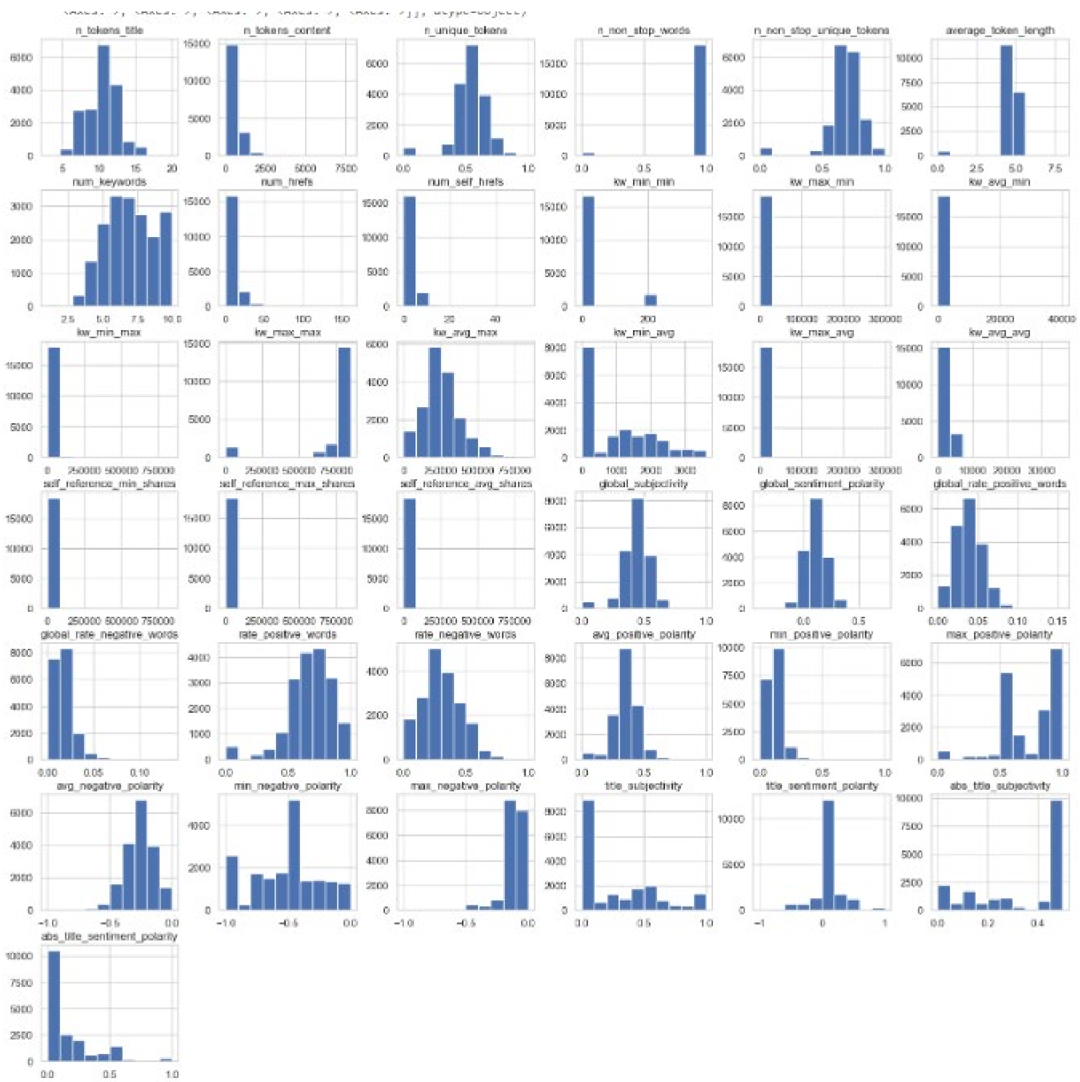
After confirming the existence of outliers visually, the interquartile range or IQR was calculated so that the records outside the lower and upper bound could be removed.

```
percentile25 = df['shares'].quantile(0.25)
percentile75 = df['shares'].quantile(0.75)

print("75th quartile: ", percentile75)
print("25th quartile: ", percentile25)

iqr = percentile75 - percentile25

upper_bound = percentile75 + 1.5 * iqr
lower_bound = percentile25 - 1.5 * iqr

df = df[df['shares'] < upper_bound]
df = df[df['shares'] > lower_bound]
print(len(df))
```

```
viz_box(df, 'shares')
```

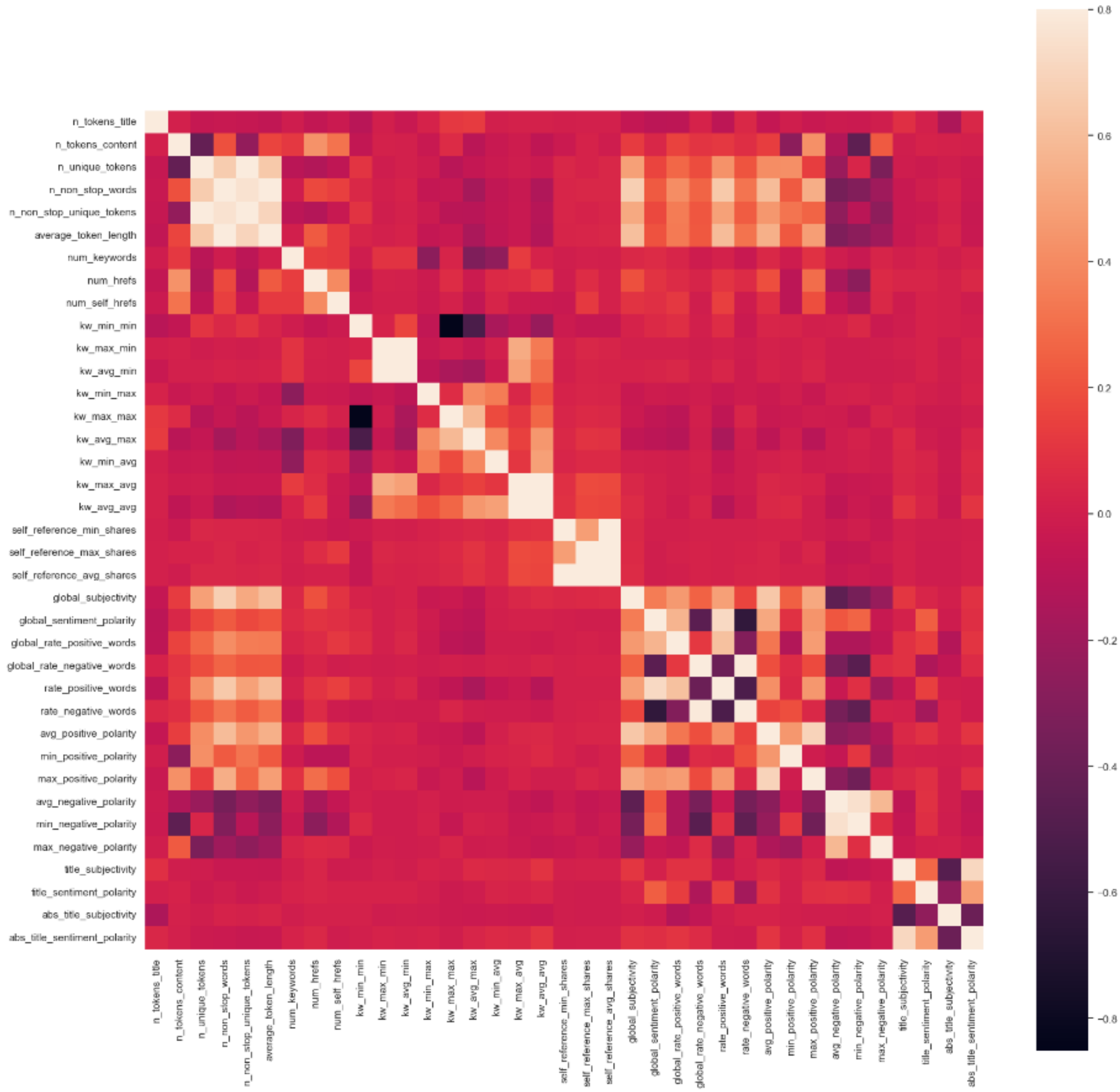


Next is the plotting of histograms for the continuous variables. As shown, the continuous variables are not distributed normally.

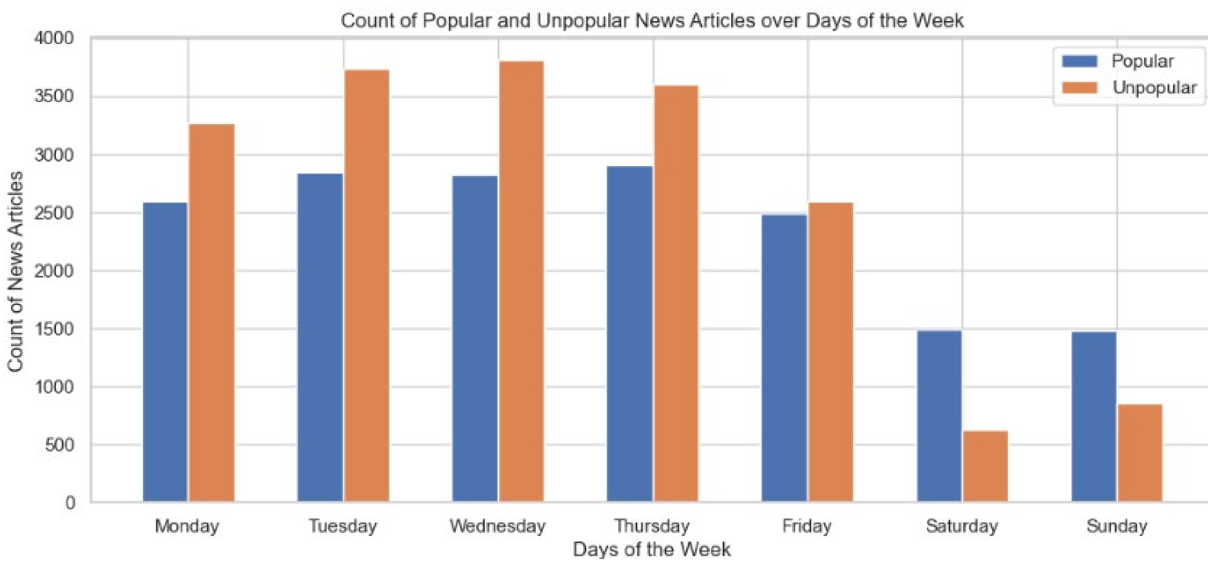


The correlation heatmap shows a few interesting relationships between several variables.

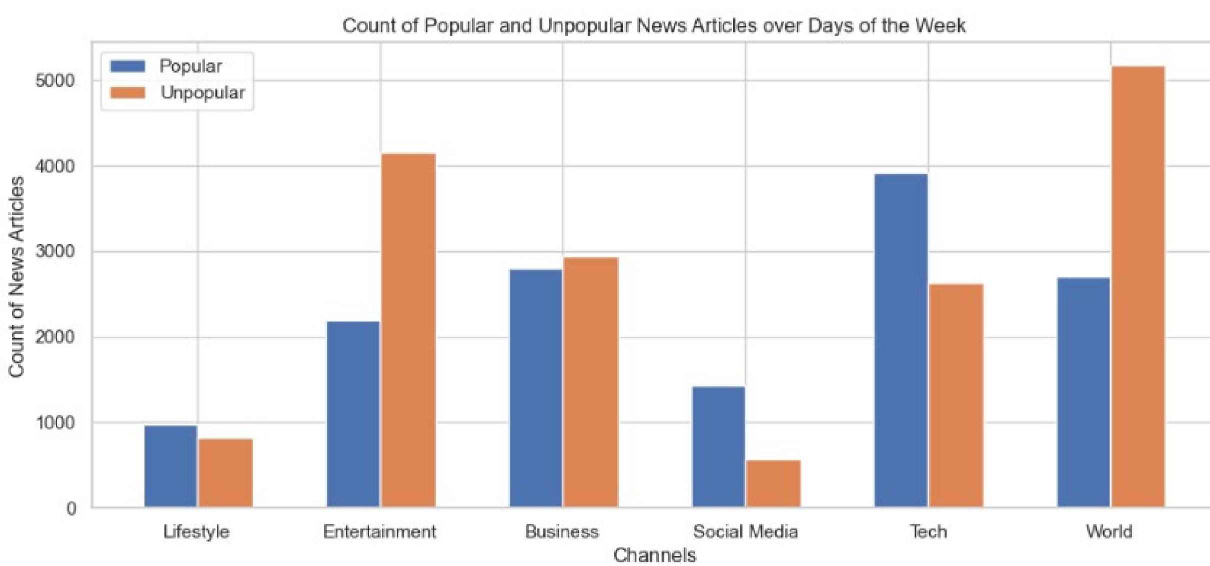
```
corr = popular_df[continuous_cols].corr()
fig = plt.figure(figsize = (20,20))
sns.heatmap(corr, vmax = .8, square = True)
plt.show()
```


n_tokens_title
n_tokens_content
n_unique_tokens
n_non_stop_words
n_non_stop_unique_tokens
average_token_length
num_keywords
num_hrefs
num_self_hrefs
kw_min_min
kw_max_min
kw_avg_min
kw_min_max
kw_max_max
kw_avg_max
kw_min_avg
kw_max_avg
kw_avg_avg
self_reference_min_shares
self_reference_max_shares
self_reference_avg_shares
global_subjectivity
global_sentiment_polarity
global_rate_positive_words
global_rate_negative_words
rate_positive_words
rate_negative_words
avg_positive_polarity
min_positive_polarity
max_positive_polarity
avg_negative_polarity
min_negative_polarity
max_negative_polarity
title_subjectivity
title_sentiment_polarity
abs_title_subjectivity
abs_title_sentiment_polarity
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8

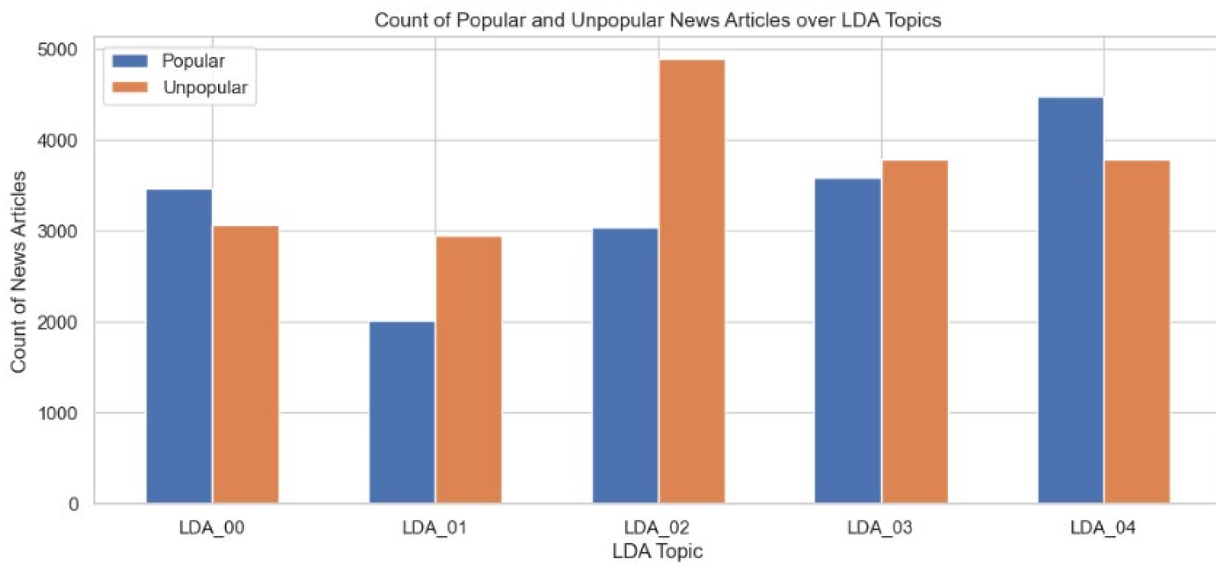
According to the graph below, the weekend is a slow news cycle for both popular and unpopular articles. It is worth noting that articles published during the weekend are more likely to be popular those published during the week.



Evident in the graph below, the topics of Tech, Business, and Entertainment dominate both popular and unpopular articles. Volume wise, the difference between the count of popular and unpopular articles in the World and Entertainment is noteworthy.



Similarly, LDA Topic #2 shows the same imbalance between popular and unpopular articles.



Conducting a T-test revealed more significant differences between the popular and unpopular groups than insignificant ones. In this case, n_non_stop_words, kw_min_max, kw_avg_max, min_negative_polarity, max_negative polarity, and abs_title_subjectivity have insignificant differences in samples.

```python
ttest_same = []
ttest_diff = []

for column in continuous_cols:

    result = stats.ttest_ind(popular_df[column], unpopular_df[column])[1]

    if result > ALPHA:
        interpretation = 'insignificant - SAME'
        ttest_same.append(column)
    else:
        interpretation = 'significant - DIFFERENT'
        ttest_diff.append(column)

    print(result, '-', column, ' - ', interpretation)
```

```
2.2504282720304512e-19 - n_tokens_title  -  significant - DIFFERENT
1.540713115573688e-19 - n_tokens_content  -  significant - DIFFERENT
2.9880436047459157e-20 - n_unique_tokens  -  significant - DIFFERENT
0.1936199104088964 - n_non_stop_words  -  insignificant - SAME
1.3901924209284012e-20 - n_non_stop_unique_tokens  -  significant - DIFFERENT
0.0008373135389349559 - average_token_length  -  significant - DIFFERENT
5.124818509804509e-38 - num_keywords  -  significant - DIFFERENT
2.864037347216668e-48 - num_hrefs  -  significant - DIFFERENT
1.8442399645567025e-18 - num_self_hrefs  -  significant - DIFFERENT
5.950648914047732e-29 - kw_min_min  -  significant - DIFFERENT
5.100318754407514e-05 - kw_max_min  -  significant - DIFFERENT
1.344140676190898e-10 - kw_avg_min  -  significant - DIFFERENT
0.4989833952664203 - kw_min_max  -  insignificant - SAME
4.375358509213268e-17 - kw_max_max  -  significant - DIFFERENT
0.5208306960828408 - kw_avg_max  -  insignificant - SAME
3.159778399488084e-47 - kw_min_avg  -  significant - DIFFERENT
1.7754195612623336e-20 - kw_max_avg  -  significant - DIFFERENT
3.146230642300792e-116 - kw_avg_avg  -  significant - DIFFERENT
4.227667874173408e-14 - self_reference_min_shares  -  significant - DIFFERENT
1.8724775513918610e-21 - self_reference_max_shares  -  significant - DIFFERENT
2.1416561555131787e-22 - self_reference_avg_shares  -  significant - DIFFERENT
8.83025051250046e-30 - global_subjectivity  -  significant - DIFFERENT
4.422571139138585e-50 - global_sentiment_polarity  -  significant - DIFFERENT
8.64088412791597e-36 - global_rate_positive_words  -  significant - DIFFERENT
1.1463628301422673e-10 - global_rate_negative_words  -  significant - DIFFERENT
7.128978169033561e-28 - rate_positive_words  -  significant - DIFFERENT
1.3342228191351876e-47 - rate_negative_words  -  significant - DIFFERENT
1.7680195246297564e-05 - avg_positive_polarity  -  significant - DIFFERENT
2.90326731691146e-10 - min_positive_polarity  -  significant - DIFFERENT
1.2660915642576633e-14 - max_positive_polarity  -  significant - DIFFERENT
0.013479436287143189 - avg_negative_polarity  -  significant - DIFFERENT
0.0838875232392592 - min_negative_polarity  -  insignificant - SAME
0.19100281659526497 - max_negative_polarity  -  insignificant - SAME
0.00035011116559364487 - title_subjectivity  -  significant - DIFFERENT
5.425254469115109e-21 - title_sentiment_polarity  -  significant - DIFFERENT
0.41820000733762275 - abs_title_subjectivity  -  insignificant - SAME
3.015299461334996e-07 - abs_title_sentiment_polarity  -  significant - DIFFERENT
```

Confirming the visual inspection earlier, Shapiro tests indicate that none of the variables are distributed normally.

```
shap_yesn = []
shap_notn = []

for column in continuous_cols:

    stat, result = stats.shapiro(df[column])

    if result > ALPHA:
        interpretation = 'insignificant - NORMAL'
        shap_yesn.append(column)
    else:
        interpretation = 'significant - NOT NORMAL'
        shap_notn.append(column)

    print(result, '-', column, ' - ', interpretation)
```

```
0.0 - n_tokens_title  -  significant - NOT NORMAL
0.0 - n_tokens_content  -  significant - NOT NORMAL
0.0 - n_unique_tokens  -  significant - NOT NORMAL
0.0 - n_non_stop_words  -  significant - NOT NORMAL
0.0 - n_non_stop_unique_tokens  -  significant - NOT NORMAL
0.0 - average_token_length  -  significant - NOT NORMAL
0.0 - num_keywords  -  significant - NOT NORMAL
0.0 - num_hrefs  -  significant - NOT NORMAL
0.0 - num_self_hrefs  -  significant - NOT NORMAL
0.0 - kw_min_min  -  significant - NOT NORMAL
0.0 - kw_max_min  -  significant - NOT NORMAL
0.0 - kw_avg_min  -  significant - NOT NORMAL
0.0 - kw_min_max  -  significant - NOT NORMAL
0.0 - kw_max_max  -  significant - NOT NORMAL
0.0 - kw_avg_max  -  significant - NOT NORMAL
0.0 - kw_min_avg  -  significant - NOT NORMAL
0.0 - kw_max_avg  -  significant - NOT NORMAL
0.0 - kw_avg_avg  -  significant - NOT NORMAL
0.0 - self_reference_min_shares  -  significant - NOT NORMAL
0.0 - self_reference_max_shares  -  significant - NOT NORMAL
0.0 - self_reference_avg_shares  -  significant - NOT NORMAL
0.0 - global_subjectivity  -  significant - NOT NORMAL
8.407790785948902e-45 - global_sentiment_polarity  -  significant - NOT NORMAL
1.401298464324817e-45 - global_rate_positive_words  -  significant - NOT NORMAL
0.0 - global_rate_negative_words  -  significant - NOT NORMAL
0.0 - rate_positive_words  -  significant - NOT NORMAL
0.0 - rate_negative_words  -  significant - NOT NORMAL
0.0 - avg_positive_polarity  -  significant - NOT NORMAL
0.0 - min_positive_polarity  -  significant - NOT NORMAL
0.0 - max_positive_polarity  -  significant - NOT NORMAL
0.0 - avg_negative_polarity  -  significant - NOT NORMAL
0.0 - min_negative_polarity  -  significant - NOT NORMAL
0.0 - max_negative_polarity  -  significant - NOT NORMAL
0.0 - title_subjectivity  -  significant - NOT NORMAL
0.0 - title_sentiment_polarity  -  significant - NOT NORMAL
0.0 - abs_title_subjectivity  -  significant - NOT NORMAL
0.0 - abs_title_sentiment_polarity  -  significant - NOT NORMAL
```

```
final_df = df.drop(columns=['shares'])
```

The exploration of the dataset involved both visual exploration and statistical testing. An advantage of visualization is the ease it provides the reader to grasp the characteristics of the data that is being inspected. In addition, the output of the statistical testing eliminates guesswork by supplying a statistic and p-value. One disadvantage is that visual inspection can only go so far. It does not provide a value up front without extensive coding of matplotlib methods.

These are the steps involved in the modeling part of the analysis:

1. Splitting the dataset into training and test sets
2. Building logistic regression models for reference
3. Building XGBoost classifier models
4. Extracting feature importance based on the best XGBoost model

Let's split the data.

```
X = final_df.loc[:, final_df.columns != 'target']
y = final_df.loc[:, final_df.columns == 'target']
```

```
# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=493)
```

Logistics Regression Models

```
logreg0 = LogisticRegression()
logreg0.fit(X_train, y_train)
```

```
▸ LogisticRegression
```

```
print('Accuracy of logistic regression classifier on train set: {:.2f}'.format(logreg0.score(X_train, y_train)))
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(logreg0.score(X_test, y_test)))
```

```
Accuracy of logistic regression classifier on train set: 0.59
Accuracy of logistic regression classifier on test set: 0.59
```

```
y_pred = logreg0.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.60      0.84      0.70      5952
           1       0.56      0.26      0.35      4579

    accuracy                           0.59     10531
   macro avg       0.58      0.55      0.52     10531
weighted avg       0.58      0.59      0.55     10531
```

After splitting the data and building the initial logistic regression model, GridSearchCV was utilized to determine the ideal parameters that maximize the accuracy of the logistic regression model.

```
# parameter grid
parameters = {
    'penalty' : ['l1','l2'],
    'C'       : np.logspace(-3,3,7),
    'solver'  : ['newton-cg', 'lbfgs', 'liblinear'],
}
```

```
logreg1 = LogisticRegression()
clf = GridSearchCV(logreg1,                    # model
                   param_grid = parameters,   # hyperparameters
                   scoring='accuracy',        # metric for scoring
                   cv=10)                     # number of folds

clf.fit(X_train,y_train)
```

```
▸ GridSearchCV
▸ estimator: LogisticRegression
  ▸ LogisticRegression
```

```
print("Tuned Hyperparameters :", clf.best_params_)
print("Logistic Regression) Accuracy :",clf.best_score_)
```

```
Tuned Hyperparameters : {'C': 10.0, 'penalty': 'l1', 'solver': 'liblinear'}
Logistic Regression) Accuracy : 0.6561539190098994
```

In the following code, the final logistic regression model is built using the best parameters given by grid search. The accuracy of the final logistic regression model is 0.65, a value that is relatively close to 0.64 which is the accuracy of the training set. This means that the model generalizes well.

```
logreg2 = LogisticRegression(C = 10,
                             penalty = 'l1',
                             solver = 'liblinear')
logreg2.fit(X_train,y_train)

print('Accuracy of logistic regression classifier on train set: {:.2f}'.format(logreg2.score(X_train, y_train)))
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(logreg2.score(X_test, y_test)))
```

```
LogisticRegression
LogisticRegression(C=10, penalty='l1', solver='liblinear')
```

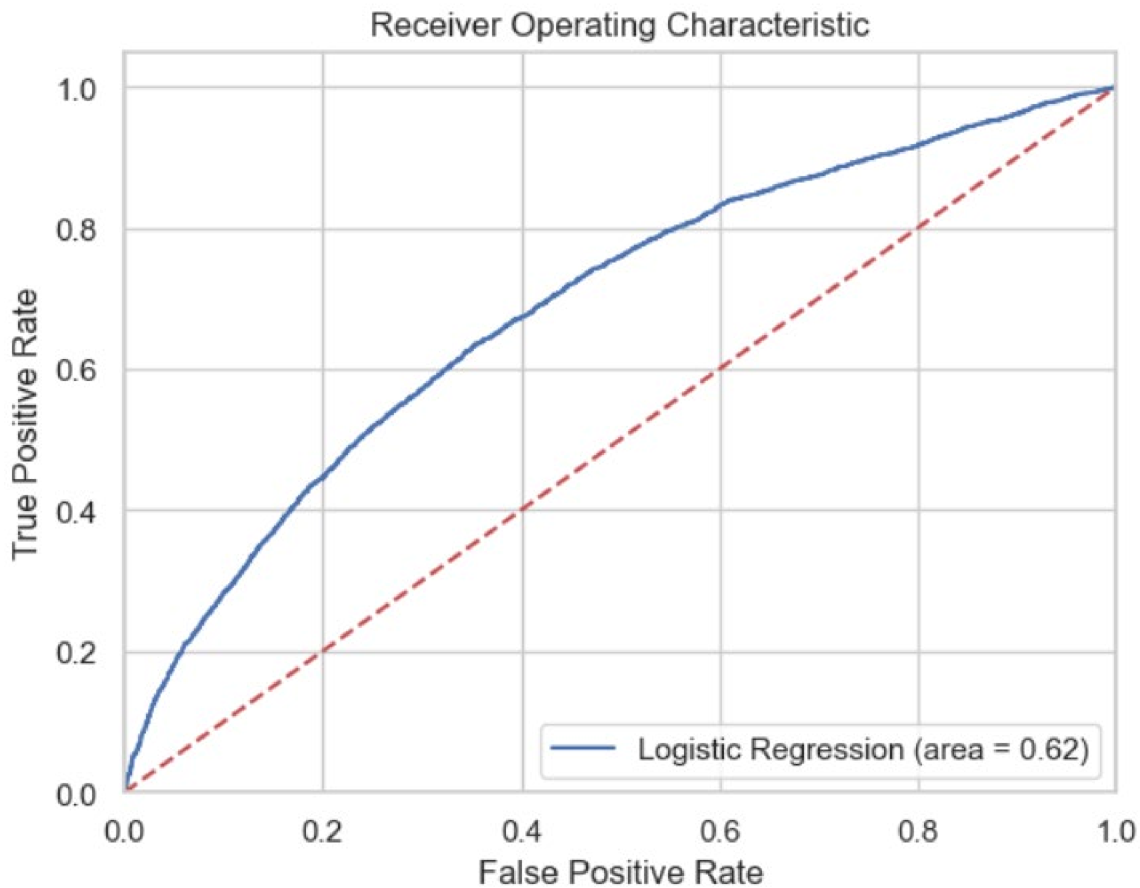
```
Accuracy of logistic regression classifier on train set: 0.66
Accuracy of logistic regression classifier on test set: 0.65
```

```
y_pred = logreg2.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.65      0.80      0.72      5952
           1       0.63      0.45      0.53      4579

    accuracy                           0.65     10531
   macro avg       0.64      0.62      0.62     10531
weighted avg       0.64      0.65      0.64     10531
```

Below, the area-under-the-curve (AUC) score was calculated using the test set and the receiver operating characteristic ROC was plotted. This graph will be used later to compare against the final XGBoost model.

```
logreg_roc_auc = roc_auc_score(y_test, logreg2.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg2.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logreg_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
```



The ROC curve is larger than the unskilled (0.50) line which signifies that the model is slightly a little bit better at predicting an event than flipping a standard coin.

The initial XGBoost model that was trained had an accuracy of 0.90 on the training set and 0.64 on the test set. The initial model did not generalize well and it perhaps overfitted.

Xgboost Models

```
# initial XGBOOST model
xgb0 = XGBClassifier(tree_method = 'gpu_hist')
xgb0.fit(X_train, y_train)
```

```
XGBClassifier

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
```

```
print('Accuracy of xgboost classifier on train set: {:.2f}'.format(xgb0.score(X_train, y_train)))
print('Accuracy of xgboost regression classifier on test set: {:.2f}'.format(xgb0.score(X_test, y_test)))
```

```
Accuracy of xgboost classifier on train set: 0.90
Accuracy of xgboost regression classifier on test set: 0.64
```

```
y_pred = xgb0.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.66      0.75      0.70      5952
           1       0.61      0.50      0.55      4579

    accuracy                           0.64     10531
   macro avg       0.64      0.63      0.63     10531
weighted avg       0.64      0.64      0.64     10531
```

To remedy overfitting, we created a pipeline that utilized grid search again to determine the best parameter for XGBoost.

```
pipe = Pipeline([
  ('fs', SelectKBest()),
  ('clf', xgb.XGBClassifier(objective='binary:logistic'))
])
```

```
# Define our search space for grid search
search_space = [
  {
    'clf__n_estimators': [100, 200],
    'clf__learning_rate': [0.1, 0.01],
    'clf__max_depth': [3, 4, 5],
    'clf__colsample_bytree': [0.1, 0.2],
    'clf__gamma': [0],
    'clf__tree_method': ['gpu_hist'],
    'fs__score_func': [f_classif],
    'fs__k': [10],
  }
]
```

```
# Define cross validation
kfold = KFold(n_splits=10)
# AUC and accuracy as score
scoring = {'AUC':'roc_auc', 'Accuracy':make_scorer(accuracy_score)}
```

```
# Define grid search
grid = GridSearchCV(
  pipe,
  param_grid=search_space,
  cv=kfold,
  scoring=scoring,
  refit='AUC',
  verbose=1,
  n_jobs=-1
)
# Fit grid search
xgb1 = grid.fit(X_train, y_train)
```

```
Fitting 10 folds for each of 24 candidates, totalling 240 fits
```

This time around, the accuracy is 0.69 on the train set and 0.67 on the test set. Although the accuracy is not stellar, the model generalized well and did not overfit.

```
print('Accuracy of xgboost classifier on train set: {:.2f}'.format(xgb1.score(X_train, y_train)))
print('Accuracy of xgboost regression classifier on test set: {:.2f}'.format(xgb1.score(X_test, y_test)))
```

```
Accuracy of xgboost classifier on train set: 0.69
Accuracy of xgboost regression classifier on test set: 0.67
```

```
y_pred = xgb1.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.65      0.80      0.71      5952
           1       0.62      0.43      0.51      4579

    accuracy                           0.64     10531
   macro avg       0.64      0.62      0.61     10531
weighted avg       0.64      0.64      0.63     10531
```

```
print(xgb1.best_params_)
```

```
{'clf__colsample_bytree': 0.2, 'clf__gamma': 0, 'clf__learning_rate': 0.1, 'clf__max_depth': 3, 'clf__n_estimators': 200, 'clf__tree_method': 'gpu_hist',
'fs__k': 10, 'fs__score_func': <function f_classif at 0x00000275C3F0C040>}
```

The best parameters were used in the final XGBoost model.

```
xgb2 = XGBClassifier(colsample_bytree=.2,
                     gamma=0,
                     learning_rate=0.1,
                     max_depth=4,
                     n_estimators=200,
                     tree_method = 'gpu_hist'
                    )
xgb2.fit(X_train, y_train)
```

```
XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.2, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=0, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=4, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=200, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
```

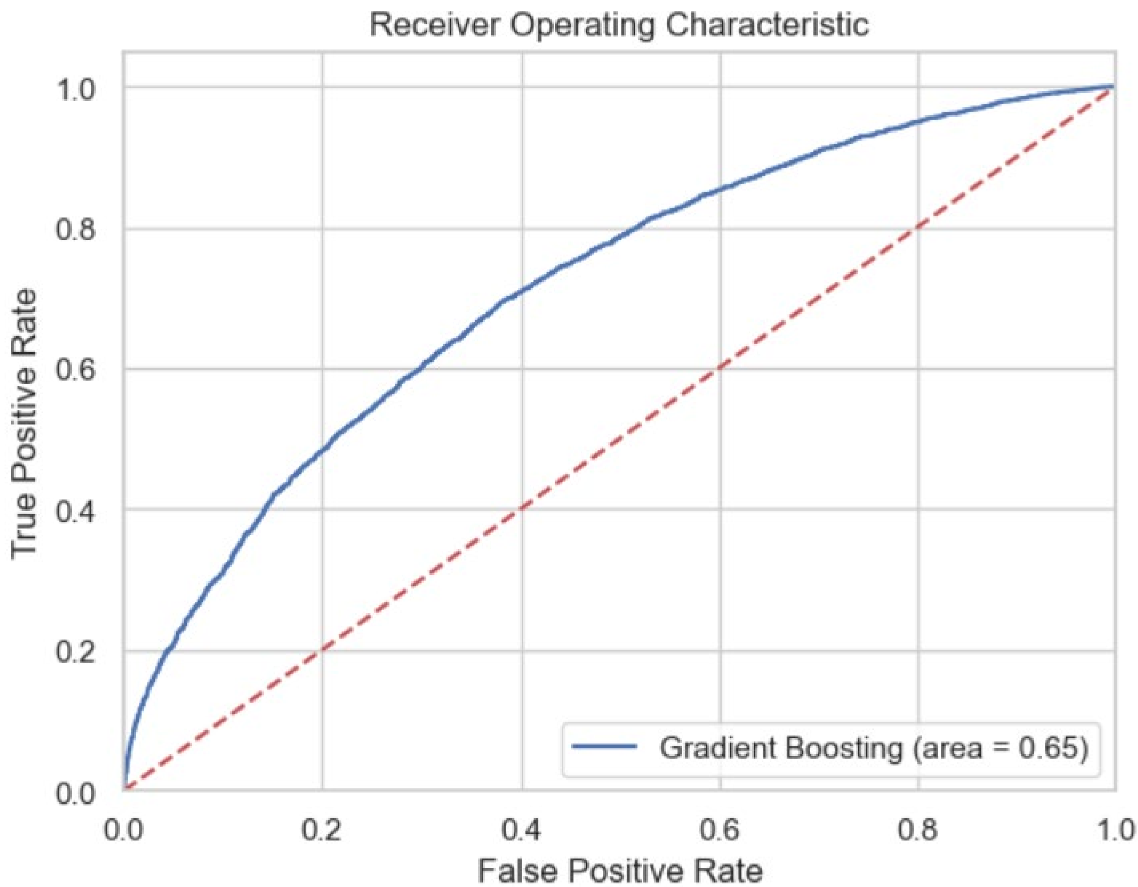
```
print('Accuracy of xgboost classifier on train set: {:.2f}'.format(xgb2.score(X_train, y_train)))
print('Accuracy of xgboost regression classifier on test set: {:.2f}'.format(xgb2.score(X_test, y_test)))
```

```
Accuracy of xgboost classifier on train set: 0.73
Accuracy of xgboost regression classifier on test set: 0.66
```

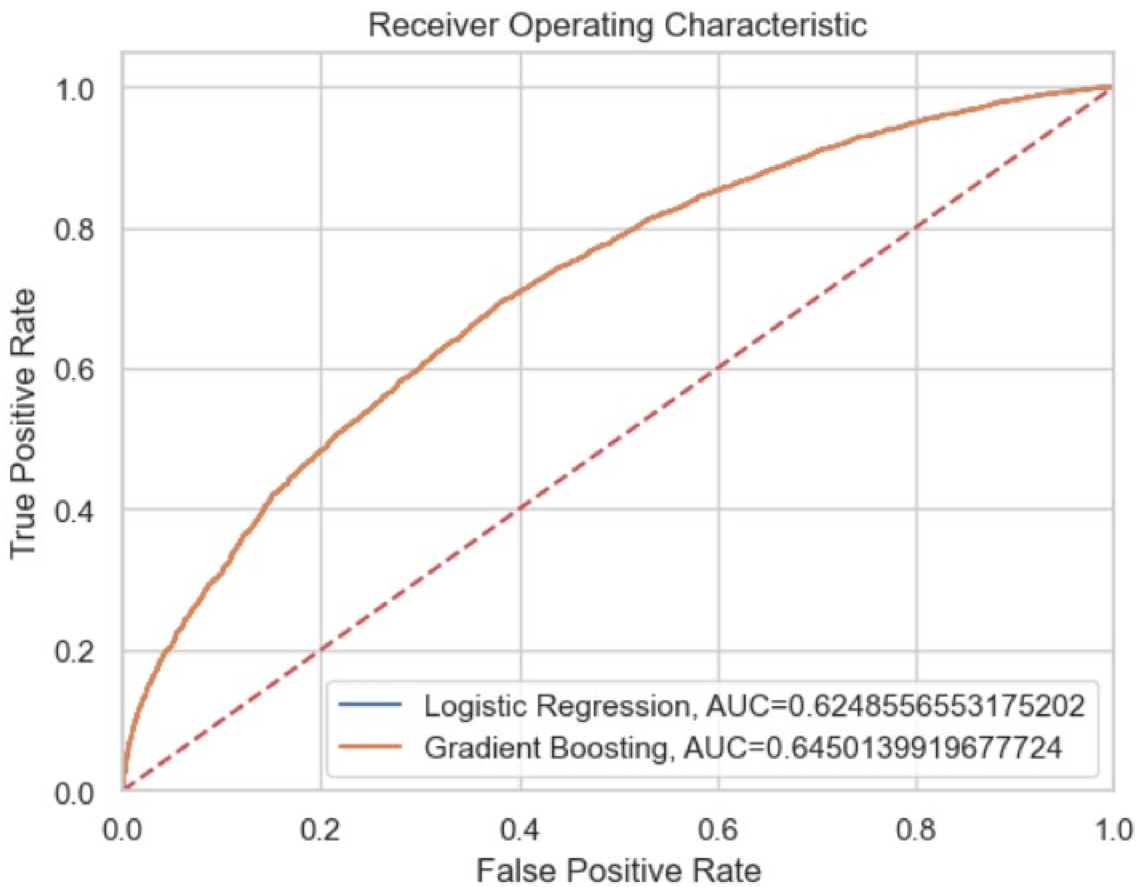
```
y_pred = xgb2.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.67      0.79      0.72      5952
           1       0.64      0.50      0.57      4579

    accuracy                           0.66     10531
   macro avg       0.66      0.65      0.65     10531
weighted avg       0.66      0.66      0.66     10531
```

The final XGBoost model sports an accuracy of 0.73 on the train set and 0.66 on the test set. The AUC was calculated and ROC plotted.



When the best logistic regression model and the best XGBoost were plotted together, there was no indication that the two models were different at all. However, the AUC says otherwise. Nevertheless, XGBoost saw an improvement over logistic regression by one point in accuracy and two points in AUC score.

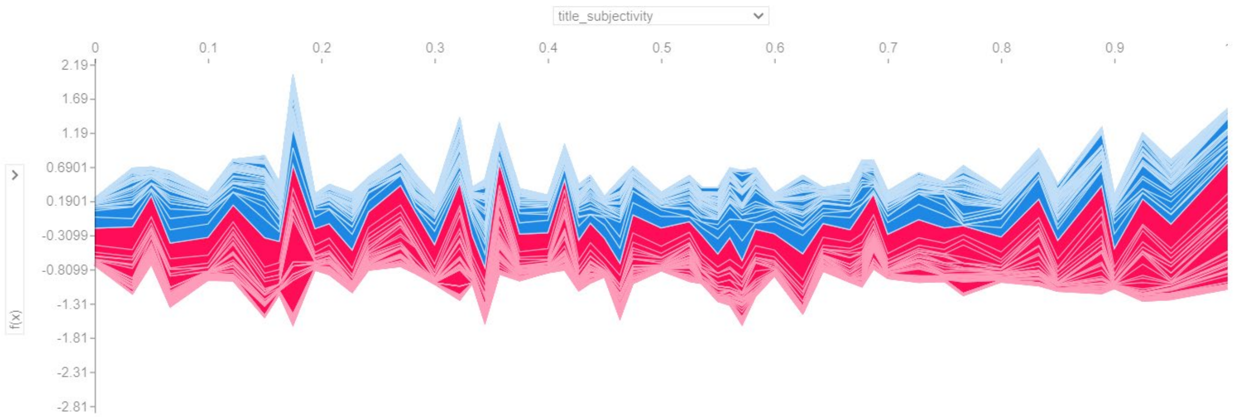


Now, feature importance will be extracted to determine the factors that contribute to an online news article's popularity. For this purpose, the author decided to use the SHAP package to extract feature importance because those ranked by XGBoost were inconsistent. In "Interpretable Machine Learning with XGBoost," Lundberg found that "feature importance orderings are very different for each of the three options provided by XGBoost" (2018). Therefore, SHAP method will be used to extract feature importance.

Feature Importance

```
explainer = shap.TreeExplainer(xgb2)
shap_values = explainer.shap_values(X)
```

```
shap.force_plot(explainer.expected_value, shap_values[:1000,:], X_train.iloc[:1000,:])
```

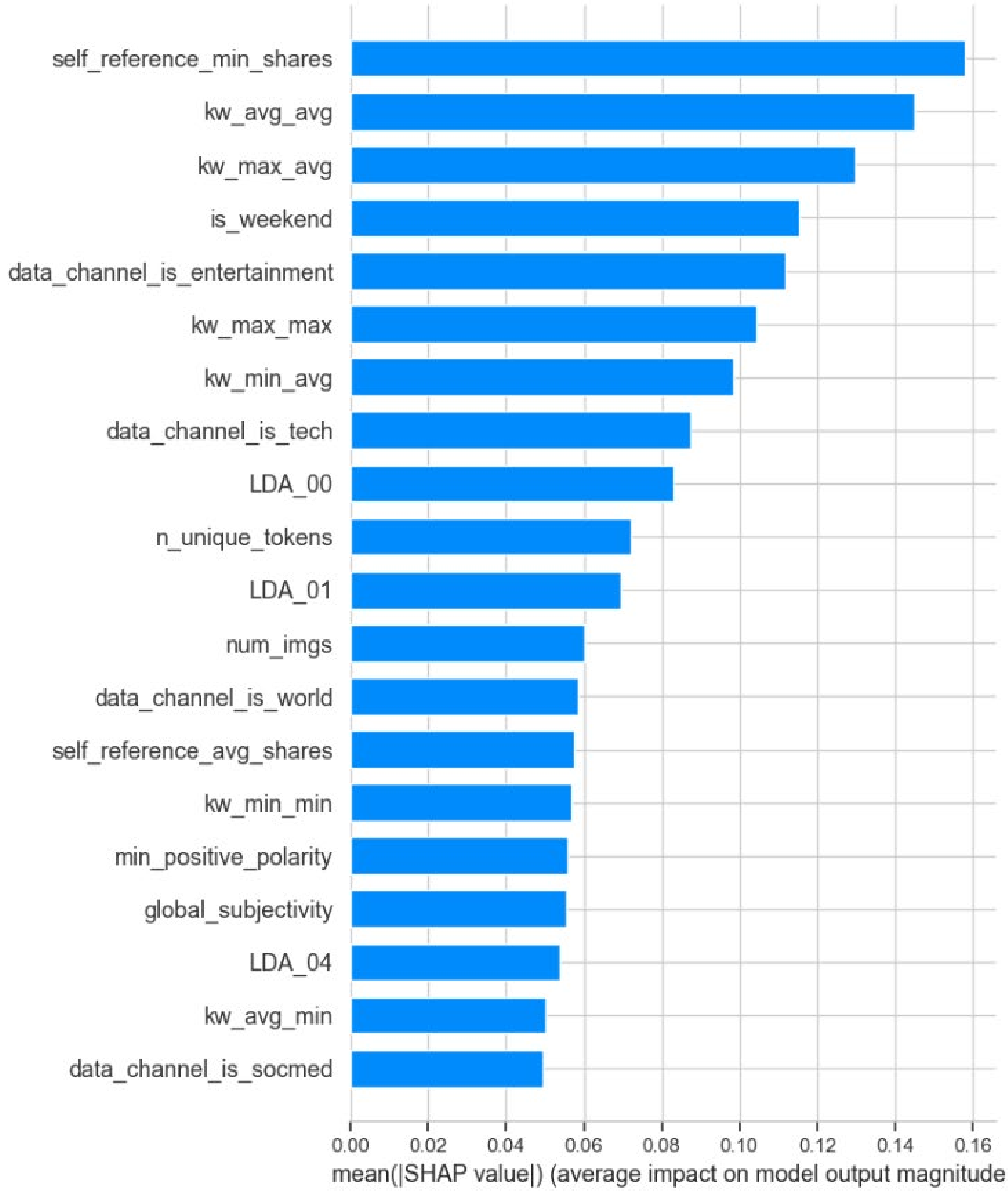


Above, we use the shap package to extract feature importance. Below, the shap package helps in extracting the most important features of our dataset. In relation to the final XGBoost model, the most important features are:

1. self_reference_min_shares
2. kw_avg_avg
3. kw_max_avg
4. is_weekend
5. data_channel_is_entertainment

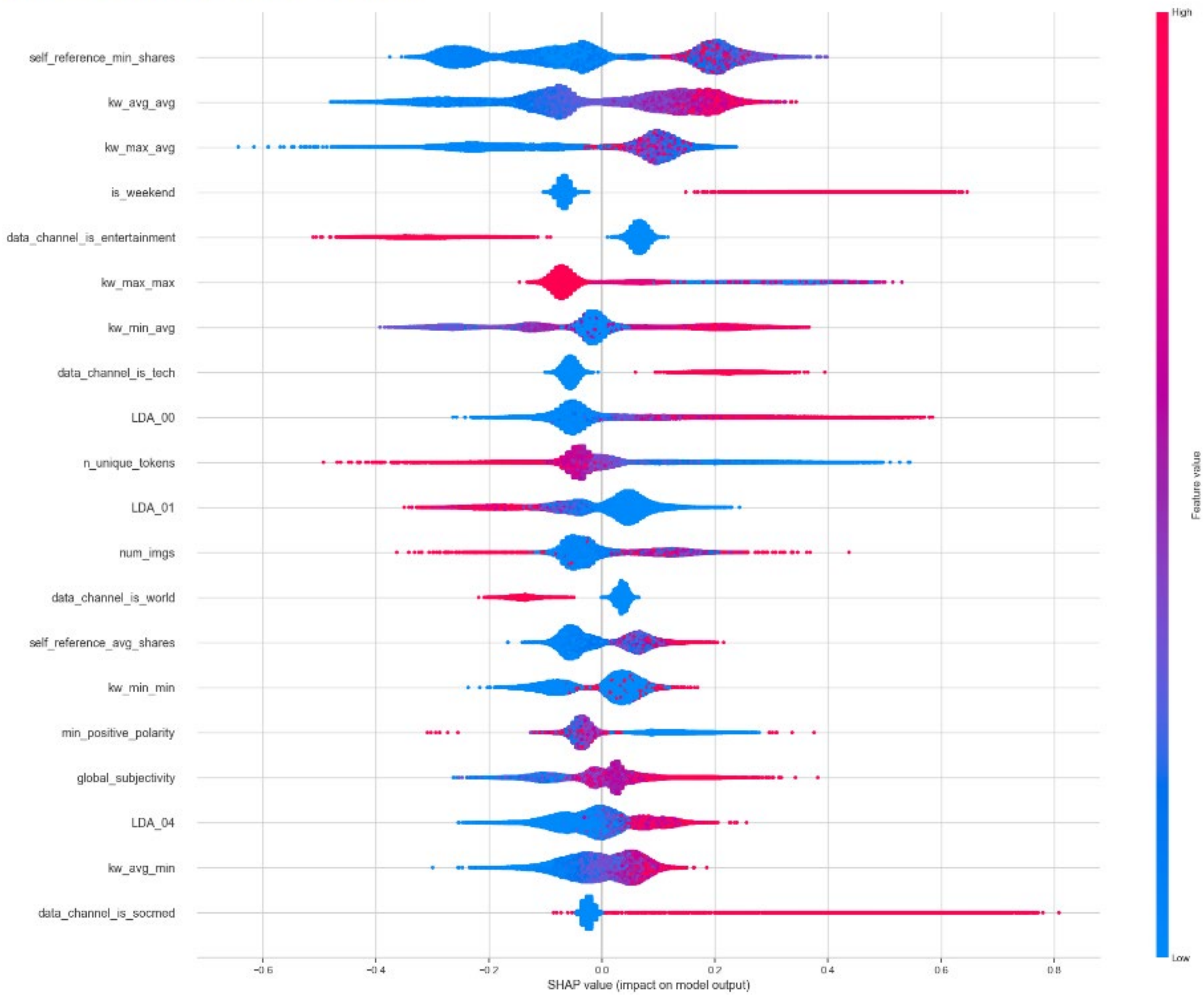
```
plt.figure(figsize = (20,20))
shap.summary_plot(shap_values, X_train, plot_type="bar",)
```

```
<Figure size 2000x2000 with 0 Axes>
```



In the graph below, every article has one dot on each row. The x position of the dot is the impact of that feature on the model's prediction for the article, and the color of the dot represents the value of that feature for the article. Dots that do not fit on the row pile up to show density (Lundberg, 2018).

```
shap.summary_plot(shap_values, X, plot_size=(20,15))
```



E – Data Summary and Implications

The research question of this study is "Can gradient boosting be constructed based solely on the research data?" Based on the analysis using XGBoost, a gradient boosting model can be made from the Online News Popularity dataset with an accuracy of more than 65% and an AUC score of more than 60%. Some variables seem to have a stronger influence on the target variable as shown in the listing of mean SHAP values.

One limitation of this study is that the original dataset only included articles from one website (Mashable.com). The prevalence of popular articles in tech, business, and entertainment reflects the niched demographic of Mashable's distribution. A sample containing articles from all sorts of publications would make a better dataset that could generalize better in predicting previously unseen articles.

Based on this study, one recommendation that can be made is to pay particular attention to the kind of articles that are published during the weekend. Even though the number of articles published on the weekend is less than those published during the week, the study shows that articles published during the weekend are more likely to be popular than not. This phenomenon surely warrants more investigation to determine the reason why.

The author of this study submits the following recommendation as course of actions for future studies:

- Use of XGBoost regression to predict the number of social media shares instead of using a threshold value
- Clustering the articles based on channels or topic

Initially converting the number of social media shares into the categorical number of 0 or 1 presented the possibility of information loss. Predicting the number of social media shares could possibly yield better results. In addition, leveraging clustering algorithms could also yield more insights about the different segments within the publication's reader base.

F – Sources

- Chen, Tianqi. (n.d.). Tianqi Chen. Retrieved August 31, 2023, from https://tqchen.com.
- Fernandes, Kelwin, Vinagre, Pedro, Cortez, Paulo, and Sernadela, Pedro. (2015). Online News Popularity. UCI Machine Learning Repository. https://doi.org/10.24432/C5NS3V
- How XGBoost Works. (n.d.). Amazon Sagemaker. Retrieved August 31, 2023, from https://docs.aws.amazon.com/sagemaker/latest/dg/xgboost-HowItWorks.html
- Lundberg, Scott. (2018, April 17). Interpretable Machine Learning with XGBoost. Towards Data Science. Retrieved from https://towardsdatascience.com/interpretable-machine-learning-with-xgboost-9ec80d148d27.
- Mueller, Alex. (2018, March 24). 5 reasons why jupyter notebooks suck. Towards Data Science. Retrieved September 1, 2023, from https://towardsdatascience.com/5-reasons-why-jupyter-notebooks-suck-4dc201e27086
- Suginoo, Michio. (2022, October 20). XGBoost: its Genealogy, its Architectural Features, and its Innovation. Towards Data Science. Retrieved August 31, 2023, from https://towardsdatascience.com/xgboost-its-genealogy-its-architectural-features-and-its-innovation-bf32b15b45d2.
- Uddin, Md. Taufeeq (2018). Predicting the Popularity of Online News from Content Metadata. Retrieved August 29, 2023, from

https://github.com/krishnakartik1/onlineNewsPopularity/blob/master/Paper2/Predicting%20the%20Popularity%20of%20Online%20News%20from%20Content%20Metadata.pdf

G – Appendix

```
# setting the random seed for reproducibility
import random
random.seed(493)

# for manipulating dataframes
import pandas as pd
import numpy as np

# for statistical testing
from scipy import stats

# for modeling
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.model_selection import KFold
from sklearn import metrics
import statsmodels.api as sm
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.metrics import accuracy_score
from sklearn.metrics import make_scorer
import xgboost as xgb
from xgboost import XGBClassifier
import shap
```

```
# for visualizations
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="whitegrid")

# to print out all the outputs
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

# set display options
import warnings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
pd.set_option('display.max_colwidth', None)

# print the JS visualization code to the notebook
shap.initjs()

THRESHOLD = 1400
ALPHA = 0.05

# Read a csv file
df = pd.read_csv('../data/in/OnlineNewsPopularity.csv')

df.head()
df.info()
df.shape

def show_missing(df):
    """
    Takes a dataframe and returns a dataframe with stats
    on missing and null values with their percentages.
    """
```

```
    null_count = df.isnull().sum()
    null_percentage = (null_count / df.shape[0]) * 100
    empty_count = pd.Series(((df == ' ') | (df == '')).sum())
    empty_percentage = (empty_count / df.shape[0]) * 100
    nan_count = pd.Series(((df == 'nan') | (df == 'NaN')).sum())
    nan_percentage = (nan_count / df.shape[0]) * 100
    dfx = pd.DataFrame({'num_missing': null_count, 'missing_percentage': null_percentage,
                        'num_empty': empty_count, 'empty_percentage': empty_percentage,
                        'nan_count': nan_count, 'nan_percentage': nan_percentage})
    return dfx

show_missing(df)
df.columns

for col in df.columns:
    df = df.rename(columns={col:(col.strip(' '))})

df = df.rename(columns={'self_reference_avg_sharess':'self_reference_avg_shares'})

df.shape
df = df.drop_duplicates(keep = False)
df.shape

# creates a new column for the new target variable and non-descriptive column
df['target'] = np.where(df['shares'] > 1400, int(1), int(0))
df = df.drop(columns=['url', 'timedelta'])

df.to_csv('../data/out/online_news_popularity_clean.csv', index=False)

df.head()
df.info()
df.describe()

sns.countplot(x='target', data=df)
```

```
token_cols = ['n_tokens_title', 'n_tokens_content', 'n_unique_tokens', 'n_non_stop_words',
'n_non_stop_unique_tokens', 'average_token_length', 'num_keywords']
links_cols = ['num_hrefs', 'num_self_hrefs']
media_cols = ['num_imgs', 'num_videos']
channel_cols = ['data_channel_is_lifestyle', 'data_channel_is_entertainment',
'data_channel_is_bus', 'data_channel_is_socmed', 'data_channel_is_tech', 'data_channel_is_world']
kw_cols = ['kw_min_min', 'kw_max_min', 'kw_avg_min', 'kw_min_max', 'kw_max_max', 'kw_avg_max',
'kw_min_avg', 'kw_max_avg', 'kw_avg_avg']
self_ref_cols = ['self_reference_min_shares', 'self_reference_max_shares',
'self_reference_avg_shares']
week_cols = ['weekday_is_monday', 'weekday_is_tuesday', 'weekday_is_wednesday',
'weekday_is_thursday', 'weekday_is_friday', 'weekday_is_saturday', 'weekday_is_sunday']
topic_cols = ['LDA_00', 'LDA_01', 'LDA_02', 'LDA_03', 'LDA_04']
global_cols = ['global_subjectivity', 'global_sentiment_polarity', 'global_rate_positive_words',
'global_rate_negative_words']
local_cols = ['rate_positive_words', 'rate_negative_words', 'avg_positive_polarity',
'min_positive_polarity', 'max_positive_polarity', 'avg_negative_polarity', 'min_negative_polarity',
'max_negative_polarity']
title_cols = ['title_subjectivity', 'title_sentiment_polarity', 'abs_title_subjectivity',
'abs_title_sentiment_polarity']

all_columns = ['token_cols', 'links_cols', 'media_cols', 'channel_cols', 'kw_cols',
'self_ref_cols',
               'weekday_cols', 'weekend_cols', 'topic_cols', 'global_cols', 'local_cols',
'title_cols']

def viz_box(df, col):
    sns.boxplot(df[col], orient="h")
    plt.title(str(col))
    plt.show()

viz_box(df, 'shares')

percentile25 = df['shares'].quantile(0.25)
percentile75 = df['shares'].quantile(0.75)
```

```
print("75th quartile: ", percentile75)
print("25th quartile: ", percentile25)

iqr = percentile75 - percentile25

upper_bound = percentile75 + 1.5 * iqr
lower_bound = percentile25 - 1.5 * iqr

df = df[df['shares'] < upper_bound]
df = df[df['shares'] > lower_bound]
print(len(df))

viz_box(df, 'shares')

continuous_cols = token_cols + links_cols + kw_cols + self_ref_cols + global_cols + local_cols +
title_cols

for col in continuous_cols:
    viz_box(df, col)

unpopular_df = df[df['shares'] < THRESHOLD ]
popular_df = df[df['shares'] >= THRESHOLD ]

popular_df[continuous_cols].hist(figsize=(20,20))
plt.show()

unpopular_df[continuous_cols].hist(figsize=(20,20))
plt.show()

corr = popular_df[continuous_cols].corr()
fig = plt.figure(figsize = (20,20))
sns.heatmap(corr, vmax = .8, square = True)
plt.show()
```

```
corr = unpopular_df[continuous_cols].corr()
fig = plt.figure(figsize = (20,20))
sns.heatmap(corr, vmax = .8, square = True)
plt.show()

# Adapted from
# https://stackoverflow.com/questions/10369681/how-to-plot-bar-graphs-with-same-x-coordinates-side-
by-side-dodged

# Numbers of pairs of bars you want
N = 7

# Data on X-axis

# Specify the values of blue bars (height)
popular_week = popular_df[week_cols].sum().values
# Specify the values of orange bars (height)
unpopular_week = unpopular_df[week_cols].sum().values

# Position of bars on x-axis
ind = np.arange(N)

# Figure size
plt.figure(figsize=(12,5))

# Width of a bar
width = 0.3

# Plotting
plt.bar(ind, popular_week , width, label='Popular')
plt.bar(ind + width, unpopular_week, width, label='Unpopular')

plt.xlabel('Days of the Week')
plt.ylabel('Count of News Articles')
plt.title('Count of Popular and Unpopular News Articles over Days of the Week')
```

```
# xticks()
# First argument - A list of positions at which ticks should be placed
# Second argument -  A list of labels to place at the given locations
plt.xticks(ind + width / 2, ('Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday',
'Sunday'))

# Finding the best position for legends and putting it
plt.legend(loc='best')
plt.show()

# Adapted from
# https://stackoverflow.com/questions/10369681/how-to-plot-bar-graphs-with-same-x-coordinates-side-
by-side-dodged

# Numbers of pairs of bars you want
N = 7

# Data on X-axis

# Specify the values of blue bars (height)
popular_week = popular_df[week_cols].sum().values
# Specify the values of orange bars (height)
unpopular_week = unpopular_df[week_cols].sum().values

# Position of bars on x-axis
ind = np.arange(N)

# Figure size
plt.figure(figsize=(12,5))

# Width of a bar
width = 0.3

# Plotting
```

```
plt.bar(ind, popular_week , width, label='Popular')
plt.bar(ind + width, unpopular_week, width, label='Unpopular')

plt.xlabel('Days of the Week')
plt.ylabel('Count of News Articles')
plt.title('Count of Popular and Unpopular News Articles over Days of the Week')

# xticks()
# First argument - A list of positions at which ticks should be placed
# Second argument -  A list of labels to place at the given locations
plt.xticks(ind + width / 2, ('Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday',
'Sunday'))

# Finding the best position for legends and putting it
plt.legend(loc='best')
plt.show()

# Adapted from
# https://stackoverflow.com/questions/10369681/how-to-plot-bar-graphs-with-same-x-coordinates-side-
by-side-dodged

# Numbers of pairs of bars you want
N = 6

# Data on X-axis

# Specify the values of blue bars (height)
popular_week = popular_df[channel_cols].sum().values
# Specify the values of orange bars (height)
unpopular_week = unpopular_df[channel_cols].sum().values

# Position of bars on x-axis
ind = np.arange(N)

# Figure size
```

```
plt.figure(figsize=(12,5))

# Width of a bar
width = 0.3

# Plotting
plt.bar(ind, popular_week , width, label='Popular')
plt.bar(ind + width, unpopular_week, width, label='Unpopular')

plt.xlabel('Channels')
plt.ylabel('Count of News Articles')
plt.title('Count of Popular and Unpopular News Articles over Days of the Week')

# xticks()
# First argument - A list of positions at which ticks should be placed
# Second argument -  A list of labels to place at the given locations
plt.xticks(ind + width / 2, ('Lifestyle', 'Entertainment', 'Business', 'Social Media', 'Tech',
'World'))

# Finding the best position for legends and putting it
plt.legend(loc='best')
plt.show()

# Adapted from
# https://stackoverflow.com/questions/10369681/how-to-plot-bar-graphs-with-same-x-coordinates-side-
by-side-dodged

# Numbers of pairs of bars you want
N = 5

# Data on X-axis

# Specify the values of blue bars (height)
popular_week = popular_df[topic_cols].sum().values
# Specify the values of orange bars (height)
```

```
unpopular_week = unpopular_df[topic_cols].sum().values

# Position of bars on x-axis
ind = np.arange(N)

# Figure size
plt.figure(figsize=(12,5))

# Width of a bar
width = 0.3

# Plotting
plt.bar(ind, popular_week , width, label='Popular')
plt.bar(ind + width, unpopular_week, width, label='Unpopular')

plt.xlabel('LDA Topic')
plt.ylabel('Count of News Articles')
plt.title('Count of Popular and Unpopular News Articles over LDA Topics')

# xticks()
# First argument - A list of positions at which ticks should be placed
# Second argument -  A list of labels to place at the given locations
plt.xticks(ind + width / 2, ('LDA_00', 'LDA_01', 'LDA_02', 'LDA_03', 'LDA_04'))

# Finding the best position for legends and putting it
plt.legend(loc='best')
plt.show()

ttest_same = []
ttest_diff = []

for column in continuous_cols:

    result = stats.ttest_ind(popular_df[column], unpopular_df[column])[1]
```

```
    if result > ALPHA:
        interpretation = 'insignificant - SAME'
        ttest_same.append(column)
    else:
        interpretation = 'significant - DIFFERENT'
        ttest_diff.append(column)

    print(result, '-', column, ' - ', interpretation)

shap_yesn = []
shap_notn = []

for column in continuous_cols:

    stat, result = stats.shapiro(df[column])

    if result > ALPHA:
        interpretation = 'insignificant - NORMAL'
        shap_yesn.append(column)
    else:
        interpretation = 'significant - NOT NORMAL'
        shap_notn.append(column)

    print(result, '-', column, ' - ', interpretation)

final_df = df.drop(columns=['shares'])

X = final_df.loc[:, final_df.columns != 'target']
y = final_df.loc[:, final_df.columns == 'target']

# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=493)

logreg0 = LogisticRegression()
logreg0.fit(X_train, y_train)
```

```
print('Accuracy of logistic regression on train set: {:.2f}'.format(logreg0.score(X_train,
y_train)))
print('Accuracy of logistic regression on test set: {:.2f}'.format(logreg0.score(X_test, y_test)))

y_pred = logreg0.predict(X_test)
print(classification_report(y_test, y_pred))

# parameter grid
parameters = {
    'penalty' : ['l1','l2'],
    'C'       : np.logspace(-3,3,7),
    'solver'  : ['newton-cg', 'lbfgs', 'liblinear'],
}

logreg1 = LogisticRegression()
clf = GridSearchCV(logreg1,                    # model
                   param_grid = parameters,   # hyperparameters
                   scoring='accuracy',        # metric for scoring
                   cv=10)                     # number of folds

clf.fit(X_train,y_train)

print("Tuned Hyperparameters :", clf.best_params_)
print("Logistic Regression) Accuracy :",clf.best_score_)

logreg2 = LogisticRegression(C = 10,
                            penalty = 'l1',
                            solver = 'liblinear')
logreg2.fit(X_train,y_train)

print('Accuracy of logistic regression classifier on train set:
{:.2f}'.format(logreg2.score(X_train, y_train)))
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(logreg2.score(X_test,
y_test)))
```

```
y_pred = logreg2.predict(X_test)
print(classification_report(y_test, y_pred))

logreg_roc_auc = roc_auc_score(y_test, logreg2.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg2.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logreg_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")

# initial XGBOOST model
xgb0 = XGBClassifier(tree_method = 'gpu_hist')
xgb0.fit(X_train, y_train)

print('Accuracy of xgboost classifier on train set: {:.2f}'.format(xgb0.score(X_train, y_train)))
print('Accuracy of xgboost classifier classifier on test set: {:.2f}'.format(xgb0.score(X_test,
y_test)))

y_pred = xgb0.predict(X_test)
print(classification_report(y_test, y_pred))

pipe = Pipeline([
  ('fs', SelectKBest()),
  ('clf', xgb.XGBClassifier(objective='binary:logistic'))
])

# Define our search space for grid search
search_space = [
  {
```

```
    'clf__n_estimators': [100, 200],
    'clf__learning_rate': [0.1, 0.01],
    'clf__max_depth': [3, 4, 5],
    'clf__colsample_bytree': [0.1, 0.2],
    'clf__gamma': [0],
    'clf__tree_method': ['gpu_hist'],
    'fs__score_func': [f_classif],
    'fs__k': [10],
  }
]

# Define cross validation
kfold = KFold(n_splits=10)
# AUC and accuracy as score
scoring = {'AUC':'roc_auc', 'Accuracy':make_scorer(accuracy_score)}

# Define grid search
grid = GridSearchCV(
  pipe,
  param_grid=search_space,
  cv=kfold,
  scoring=scoring,
  refit='AUC',
  verbose=1,
  n_jobs=-1
)
# Fit grid search
xgb1 = grid.fit(X_train, y_train)

print('Accuracy of xgboost classifier on train set: {:.2f}'.format(xgb1.score(X_train, y_train)))
print('Accuracy of xgboost regression classifier on test set: {:.2f}'.format(xgb1.score(X_test,
y_test)))

y_pred = xgb1.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
print(xgb1.best_params_)

xgb2 = XGBClassifier(colsample_bytree=.2,
                     gamma=0,
                     learning_rate=0.1,
                     max_depth=4,
                     n_estimators=200,
                     tree_method = 'gpu_hist'
                    )
xgb2.fit(X_train, y_train)

print('Accuracy of xgboost classifier on train set: {:.2f}'.format(xgb2.score(X_train, y_train)))
print('Accuracy of xgboost classifier classifier on test set: {:.2f}'.format(xgb2.score(X_test,
y_test)))

y_pred = xgb2.predict(X_test)
print(classification_report(y_test, y_pred))

xgbc_roc_auc = roc_auc_score(y_test, xgb2.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, xgb2.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Gradient Boosting (area = %0.2f)' % xgbc_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")

#set up plotting area
plt.figure(0).clf()
plt.plot(fpr,tpr,label="Logistic Regression, AUC=" + str(logreg_roc_auc))
plt.plot(fpr,tpr,label="Gradient Boosting, AUC=" + str(xgbc_roc_auc))
```

```
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")

explainer = shap.TreeExplainer(xgb2)
shap_values = explainer.shap_values(X)

shap.force_plot(explainer.expected_value, shap_values[:1000,:], X_train.iloc[:1000,:])

plt.figure(figsize = (20,20))
shap.summary_plot(shap_values, X_train, plot_type="bar",)

shap.summary_plot(shap_values, X, plot_size=(20,20))

for col in X_train.columns:
    shap.dependence_plot(col, shap_values, X)

print('Successful run!')
```