Predicting Virality with Extreme Gradient Boosting on Online News Popularity Data

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Data Science Pipeline (PAPEM-DM):

- [x] Planning
- [x] Acquisition of Data
- [x] Preparation of Data
- [x] Exploration of Data
- [x] Modeling
- [ ] ~~Delivery~~
- [ ] ~~Maintenance~~

PLANNING

> Get the data. Prepare the data. Conduct EDA. Split the data. Prepare data for modeling. Create initital xgboost model. Make predictions on train and test data. Evaluate performance. Tune hyperparameters. Create final xgboost model. Make predictions on train and test data. Evaluate performance. Extract feature importance. - *De Dios (2020)*

ACQUISITION

Before we can get the data, let's first import the packagees that we're going to need.

In [1]:
```
# 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()
```

```
Using `tqdm.autonotebook.tqdm` in notebook mode. Use `tqdm.tqdm` instead to force co
nsole mode (e.g. in jupyter console)
```

In [2]:
```
THRESHOLD = 1400
ALPHA = 0.05
```

Let's read the raw dataset which can be downloaded from the UCI Machine Learning Repository

https://archive.ics.uci.edu/dataset/332/online+news+popularity

In [3]:
```
# Read a csv file
df = pd.read_csv('../data/in/OnlineNewsPopularity.csv')
```

PREPARATION

Let's take a peek and familiarize ourselves with the structure and contents of the dataset.

In [4]:
```
df.head()
df.info()
df.shape
```

Out[4]:

	url	timedelta	n_tokens_title	n_tokens_content	n_u
0	http://mashable.com/2013/01/07/amazon-instant-video-browser/	731.0	12.0	219.0	
1	http://mashable.com/2013/01/07/ap-samsung-sponsored-tweets/	731.0	9.0	255.0	
2	http://mashable.com/2013/01/07/apple-40-billion-app-downloads/	731.0	9.0	211.0	
3	http://mashable.com/2013/01/07/astronaut-notre-dame-bcs/	731.0	9.0	531.0	
4	http://mashable.com/2013/01/07/att-u-verse-apps/	731.0	13.0	1072.0	

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39644 entries, 0 to 39643
Data columns (total 61 columns):
 #   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
 19   kw_min_min                     39644 non-null  float64
 20   kw_max_min                     39644 non-null  float64
 21   kw_avg_min                     39644 non-null  float64
 22   kw_min_max                     39644 non-null  float64
 23   kw_max_max                     39644 non-null  float64
 24   kw_avg_max                     39644 non-null  float64
 25   kw_min_avg                     39644 non-null  float64
 26   kw_max_avg                     39644 non-null  float64
 27   kw_avg_avg                     39644 non-null  float64
 28   self_reference_min_shares      39644 non-null  float64
 29   self_reference_max_shares      39644 non-null  float64
 30   self_reference_avg_sharess     39644 non-null  float64
 31   weekday_is_monday              39644 non-null  float64
 32   weekday_is_tuesday             39644 non-null  float64
 33   weekday_is_wednesday           39644 non-null  float64
 34   weekday_is_thursday            39644 non-null  float64
 35   weekday_is_friday              39644 non-null  float64
 36   weekday_is_saturday            39644 non-null  float64
 37   weekday_is_sunday              39644 non-null  float64
 38   is_weekend                     39644 non-null  float64
 39   LDA_00                         39644 non-null  float64
 40   LDA_01                         39644 non-null  float64
 41   LDA_02                         39644 non-null  float64
 42   LDA_03                         39644 non-null  float64
 43   LDA_04                         39644 non-null  float64
 44   global_subjectivity            39644 non-null  float64
 45   global_sentiment_polarity      39644 non-null  float64
 46   global_rate_positive_words     39644 non-null  float64
 47   global_rate_negative_words     39644 non-null  float64
 48   rate_positive_words            39644 non-null  float64
 49   rate_negative_words            39644 non-null  float64
 50   avg_positive_polarity          39644 non-null  float64
```

```
 51   min_positive_polarity          39644 non-null  float64
 52   max_positive_polarity          39644 non-null  float64
 53   avg_negative_polarity          39644 non-null  float64
 54   min_negative_polarity          39644 non-null  float64
 55   max_negative_polarity          39644 non-null  float64
 56   title_subjectivity             39644 non-null  float64
 57   title_sentiment_polarity       39644 non-null  float64
 58   abs_title_subjectivity         39644 non-null  float64
 59   abs_title_sentiment_polarity   39644 non-null  float64
 60   shares                         39644 non-null  int64
dtypes: float64(59), int64(1), object(1)
memory usage: 18.5+ MB
```

Out[4]: (39644, 61)

Let's see if there's any missing values anywhere.

In [5]:
```
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_perce
                        'num_empty': empty_count, 'empty_percentage': empty_percen
                        'nan_count': nan_count, 'nan_percentage': nan_percentage})
    return dfx

show_missing(df)
```

Out[5]:

	num_missing	missing_percentage	num_empty	empty_perce
url	0	0.0	0	
timedelta	0	0.0	0	
n_tokens_title	0	0.0	0	
n_tokens_content	0	0.0	0	
n_unique_tokens	0	0.0	0	
n_non_stop_words	0	0.0	0	
n_non_stop_unique_tokens	0	0.0	0	
num_hrefs	0	0.0	0	
num_self_hrefs	0	0.0	0	
num_imgs	0	0.0	0	
num_videos	0	0.0	0	
average_token_length	0	0.0	0	
num_keywords	0	0.0	0	
data_channel_is_lifestyle	0	0.0	0	
data_channel_is_entertainment	0	0.0	0	
data_channel_is_bus	0	0.0	0	
data_channel_is_socmed	0	0.0	0	
data_channel_is_tech	0	0.0	0	
data_channel_is_world	0	0.0	0	
kw_min_min	0	0.0	0	
kw_max_min	0	0.0	0	
kw_avg_min	0	0.0	0	
kw_min_max	0	0.0	0	
kw_max_max	0	0.0	0	
kw_avg_max	0	0.0	0	
kw_min_avg	0	0.0	0	
kw_max_avg	0	0.0	0	
kw_avg_avg	0	0.0	0	
self_reference_min_shares	0	0.0	0	
self_reference_max_shares	0	0.0	0	

	num_missing	missing_percentage	num_empty	empty_perce
self_reference_avg_sharess	0	0.0	0	
weekday_is_monday	0	0.0	0	
weekday_is_tuesday	0	0.0	0	
weekday_is_wednesday	0	0.0	0	
weekday_is_thursday	0	0.0	0	
weekday_is_friday	0	0.0	0	
weekday_is_saturday	0	0.0	0	
weekday_is_sunday	0	0.0	0	
is_weekend	0	0.0	0	
LDA_00	0	0.0	0	
LDA_01	0	0.0	0	
LDA_02	0	0.0	0	
LDA_03	0	0.0	0	
LDA_04	0	0.0	0	
global_subjectivity	0	0.0	0	
global_sentiment_polarity	0	0.0	0	
global_rate_positive_words	0	0.0	0	
global_rate_negative_words	0	0.0	0	
rate_positive_words	0	0.0	0	
rate_negative_words	0	0.0	0	
avg_positive_polarity	0	0.0	0	
min_positive_polarity	0	0.0	0	
max_positive_polarity	0	0.0	0	
avg_negative_polarity	0	0.0	0	
min_negative_polarity	0	0.0	0	
max_negative_polarity	0	0.0	0	
title_subjectivity	0	0.0	0	
title_sentiment_polarity	0	0.0	0	
abs_title_subjectivity	0	0.0	0	
abs_title_sentiment_polarity	0	0.0	0	

	num_missing	missing_percentage	num_empty	empty_perce
shares	0	0.0	0	

There is no missing values. However, one of the columns seems mispelled. Let's take a look at the rest of the columns and see if there's anything else that is odd.

In [6]:
```
df.columns
```

Out[6]:
```
Index(['url', ' timedelta', ' 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_length', ' num_keywords', ' 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_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_sharess',
       ' weekday_is_monday', ' weekday_is_tuesday', ' weekday_is_wednesday',
       ' weekday_is_thursday', ' weekday_is_friday', ' weekday_is_saturday',
       ' weekday_is_sunday', ' is_weekend', ' LDA_00', ' LDA_01', ' LDA_02',
       ' LDA_03', ' LDA_04', ' 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', ' shares'],
      dtype='object')
```

The column names are prepended with a space. Let's deal with that.

In [7]:
```
for col in df.columns:
    df = df.rename(columns={col:(col.strip(' '))})

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

Now, let's drop some duplicates if any.

In [8]:
```
df.shape
df = df.drop_duplicates(keep = False)
df.shape
```

Out[8]:
```
(39644, 61)
```

Out[8]:
```
(39644, 61)
```

There are no duplicates after all. This dataset is already [retty clean!

Let's now create our target variable using the threshold of 1400 social media shares.

In [9]:
```
# 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'])
```

Now, we're ready to export our cleaned and prepared dataset.

In [10]:
```
df.to_csv('../data/out/online_news_popularity_clean.csv', index=False)
```

Let's do a little bit of exploration.

EXPLORATION

Let's take a peek!

In [11]:
```
df.head()
```

Out[11]:

	n_tokens_title	n_tokens_content	n_unique_tokens	n_non_stop_words	n_non_stop_unique
0	12.0	219.0	0.663594	1.0	0
1	9.0	255.0	0.604743	1.0	0
2	9.0	211.0	0.575130	1.0	0
3	9.0	531.0	0.503788	1.0	0
4	13.0	1072.0	0.415646	1.0	0

In [12]:
```
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
```

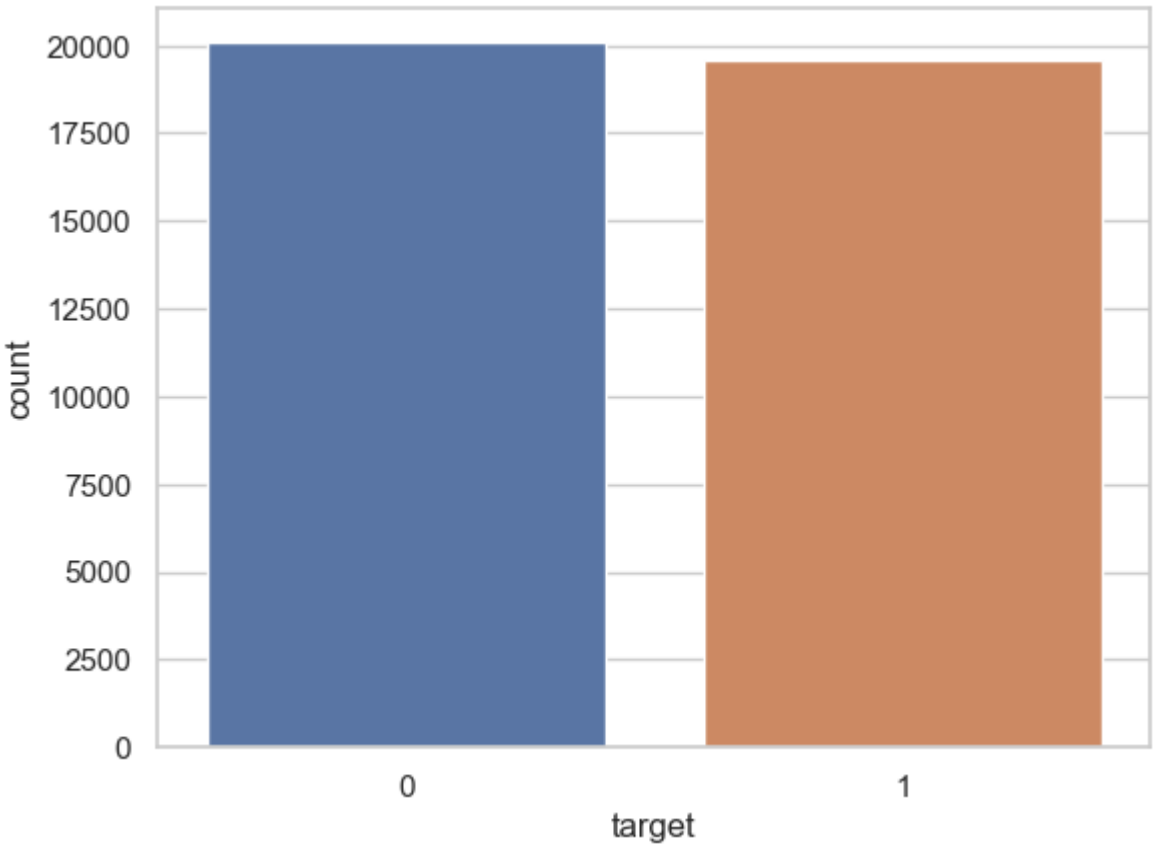
In [13]:
```
df.describe()
```

Out[13]:

	n_tokens_title	n_tokens_content	n_unique_tokens	n_non_stop_words	n_non_stop_un
count	39644.000000	39644.000000	39644.000000	39644.000000	3
mean	10.398749	546.514731	0.548216	0.996469	
std	2.114037	471.107508	3.520708	5.231231	
min	2.000000	0.000000	0.000000	0.000000	
25%	9.000000	246.000000	0.470870	1.000000	
50%	10.000000	409.000000	0.539226	1.000000	
75%	12.000000	716.000000	0.608696	1.000000	
max	23.000000	8474.000000	701.000000	1042.000000	

In [14]:
```
sns.countplot(x='target', data=df)
```

Out[14]:
```
<Axes: xlabel='target', ylabel='count'>
```



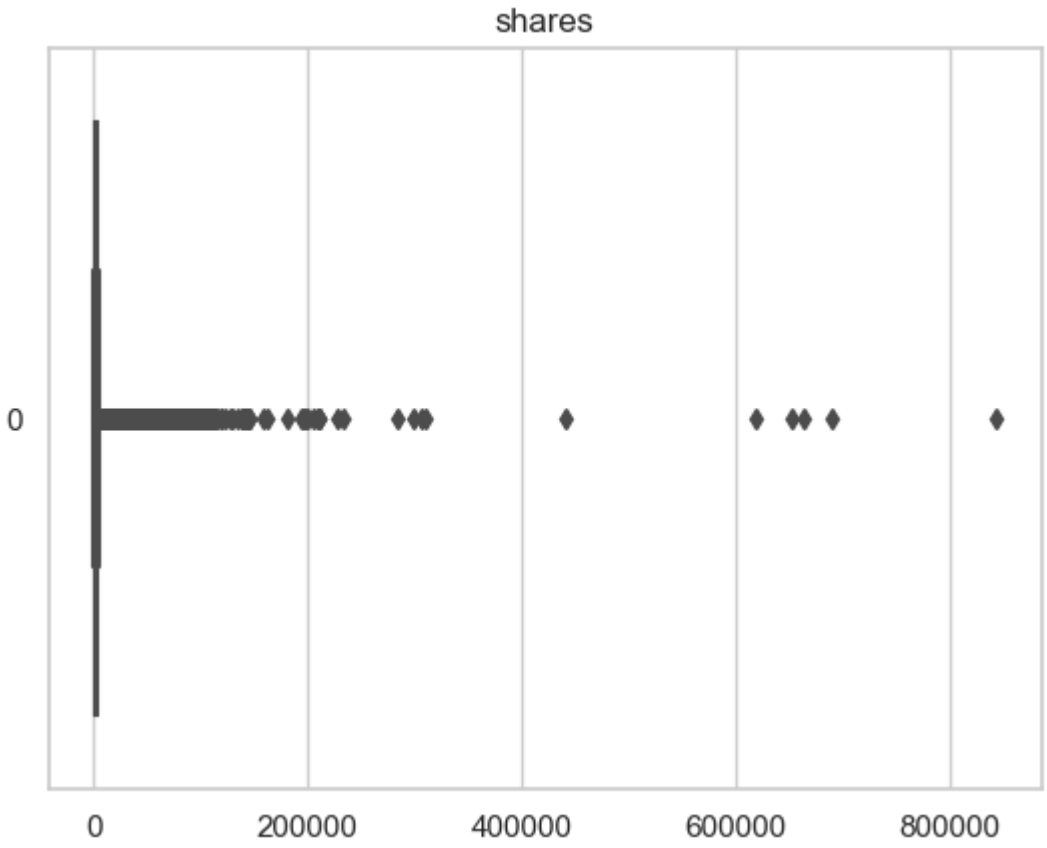
We have do not have an imbalanced dataset.

In [15]:
```
token_cols = ['n_tokens_title', 'n_tokens_content', 'n_unique_tokens', 'n_non_stop_
links_cols = ['num_hrefs', 'num_self_hrefs']
media_cols = ['num_imgs', 'num_videos']
channel_cols = ['data_channel_is_lifestyle', 'data_channel_is_entertainment', 'data
kw_cols = ['kw_min_min', 'kw_max_min', 'kw_avg_min', 'kw_min_max', 'kw_max_max', 'k
self_ref_cols = ['self_reference_min_shares', 'self_reference_max_shares', 'self_re
week_cols = ['weekday_is_monday', 'weekday_is_tuesday', 'weekday_is_wednesday', 'we
topic_cols = ['LDA_00', 'LDA_01', 'LDA_02', 'LDA_03', 'LDA_04']
global_cols = ['global_subjectivity', 'global_sentiment_polarity', 'global_rate_pos
local_cols = ['rate_positive_words', 'rate_negative_words', 'avg_positive_polarity'
title_cols = ['title_subjectivity', 'title_sentiment_polarity', 'abs_title_subjecti

all_columns = ['token_cols', 'links_cols', 'media_cols', 'channel_cols', 'kw_cols',
               'weekday_cols', 'weekend_cols', 'topic_cols', 'global_cols', 'local_
```

In [16]:
```
def viz_box(df, col):
    sns.boxplot(df[col], orient="h")
    plt.title(str(col))
    plt.show()
```

In [17]:
```
viz_box(df, 'shares')
```



We see some outliers. Let's remove them.

In [18]:
```
percentile25 = df['shares'].quantile(0.25)
percentile75 = df['shares'].quantile(0.75)

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

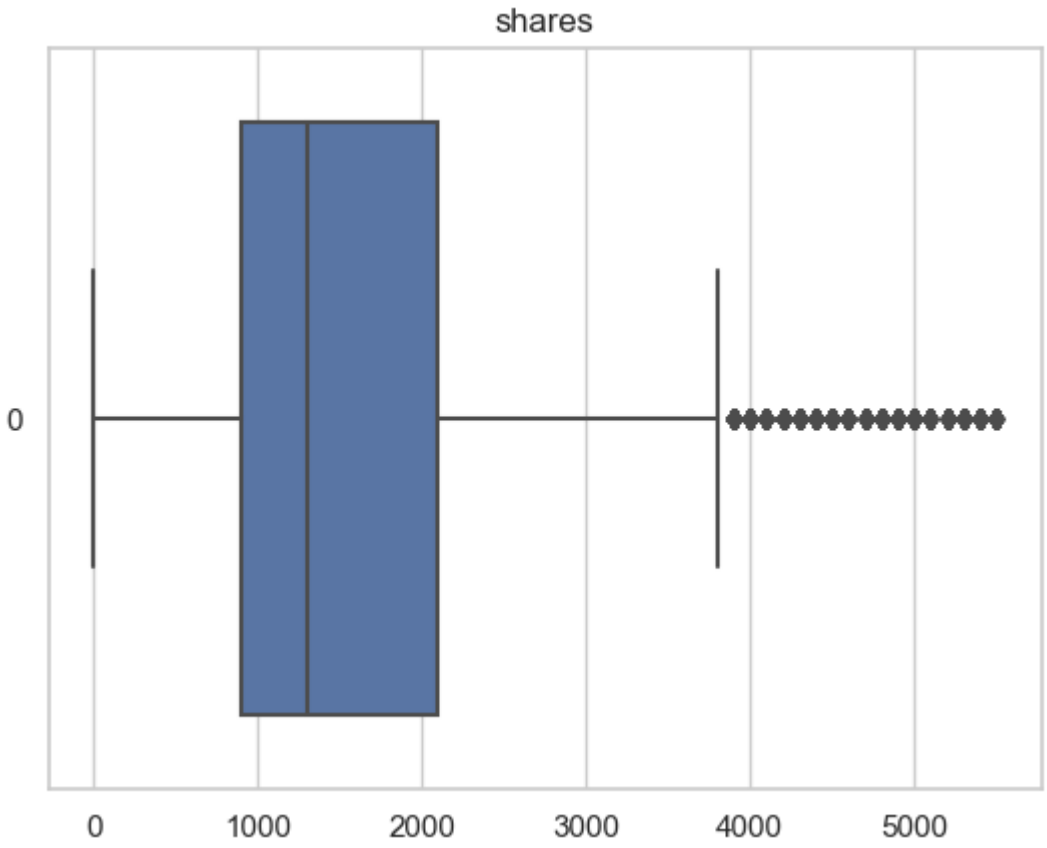
iqr = percentile75 - percentile25

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))
```

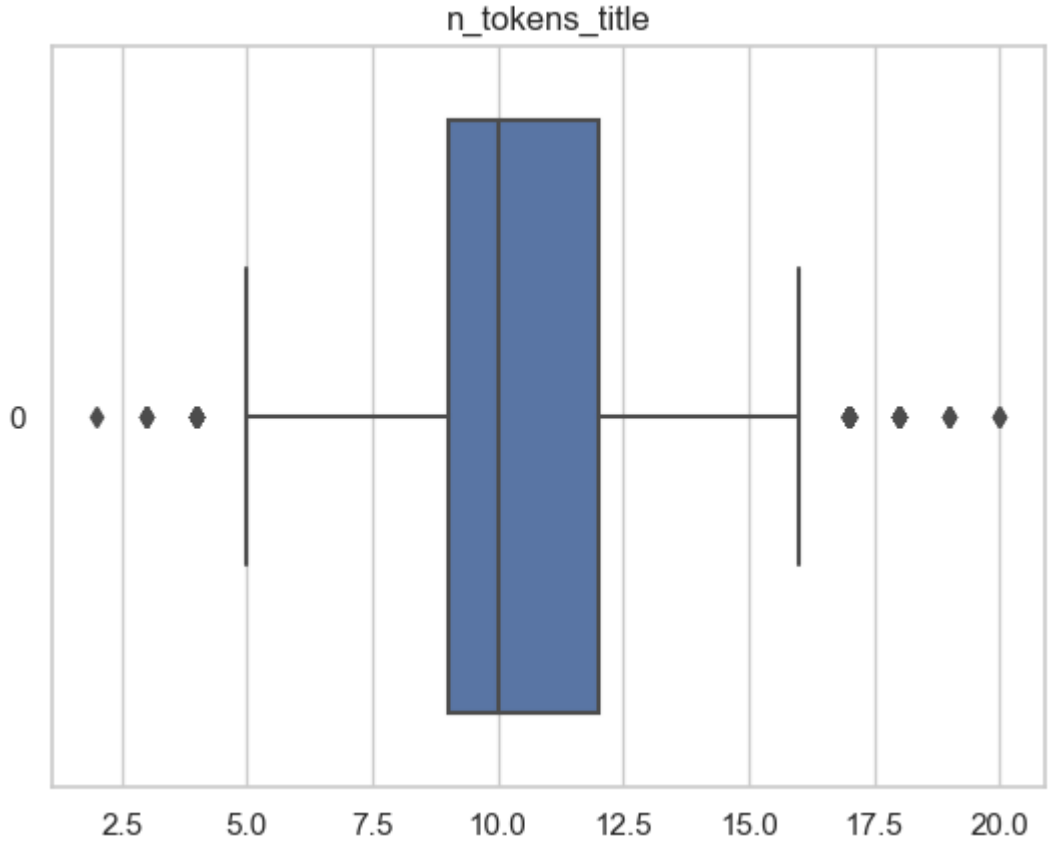
```
75th quartile:  2800.0
25th quartile:  946.0
35103
```

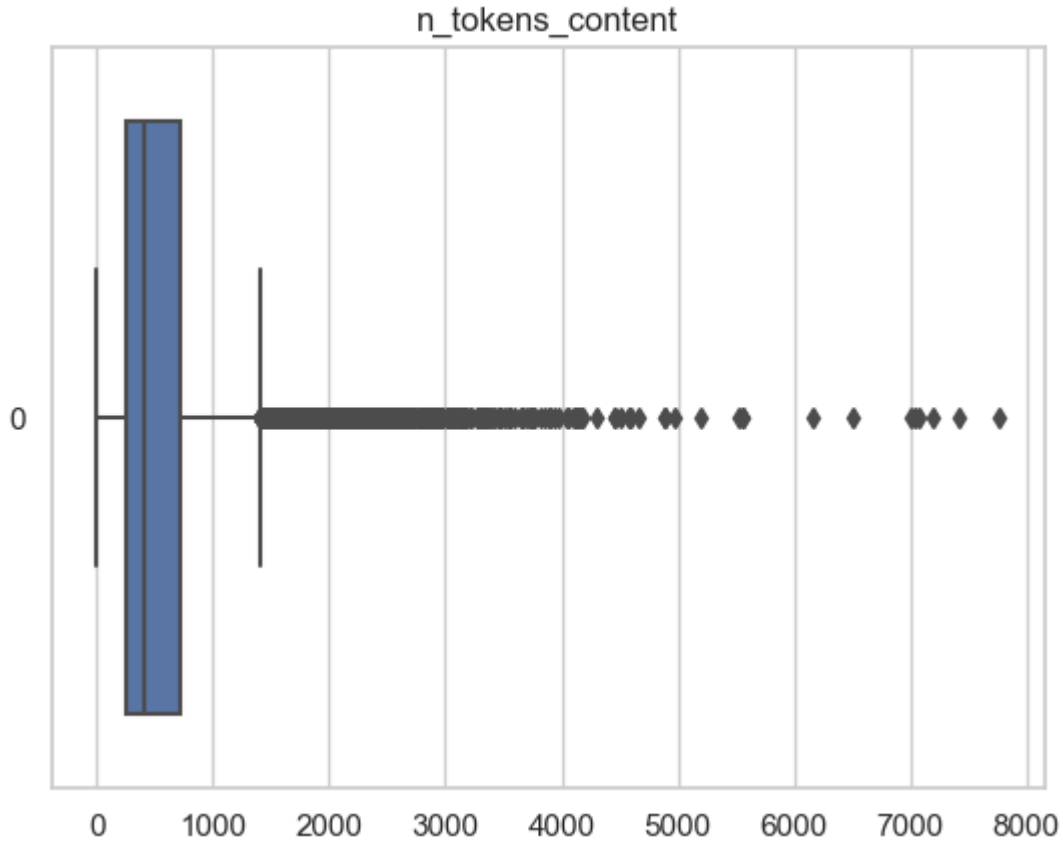
In [19]:
```
viz_box(df, 'shares')
```

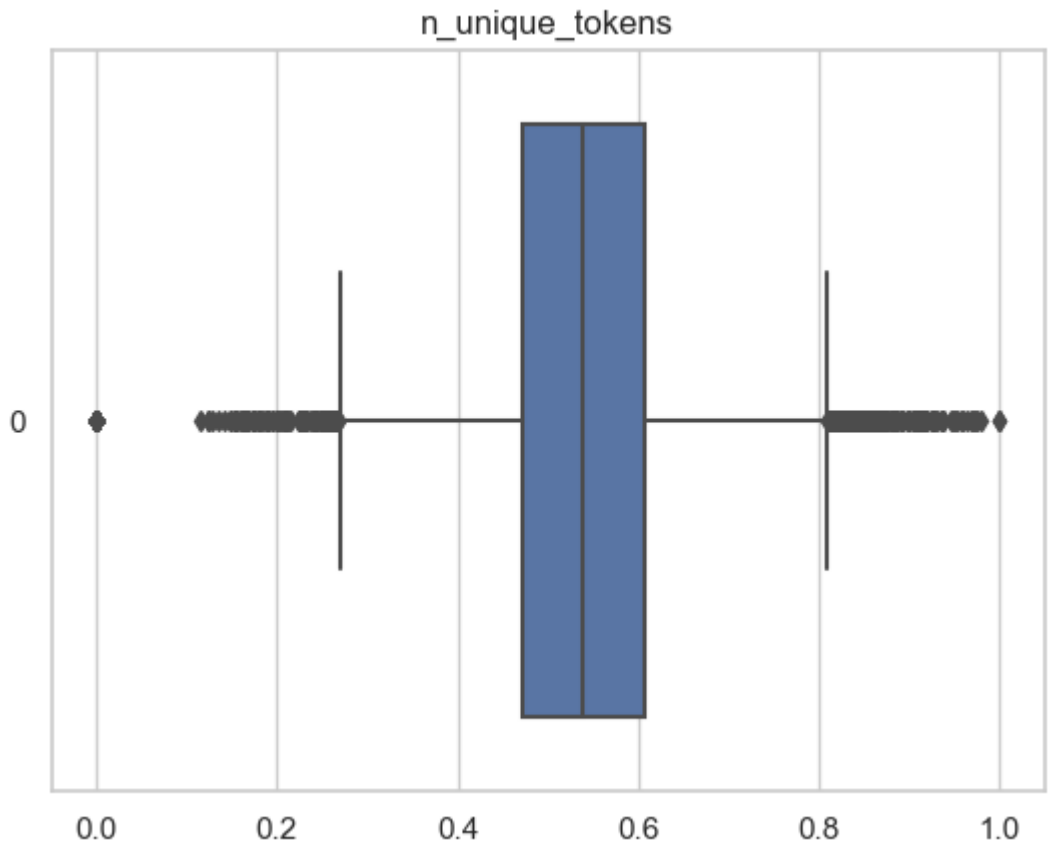


In [20]:
```
continuous_cols = token_cols + links_cols + kw_cols + self_ref_cols + global_cols +
```

In [21]:
```
for col in continuous_cols:
    viz_box(df, col)
```


n_tokens_title
0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0


n_tokens_content
0
0
1000
2000
3000
4000
5000
6000
7000
8000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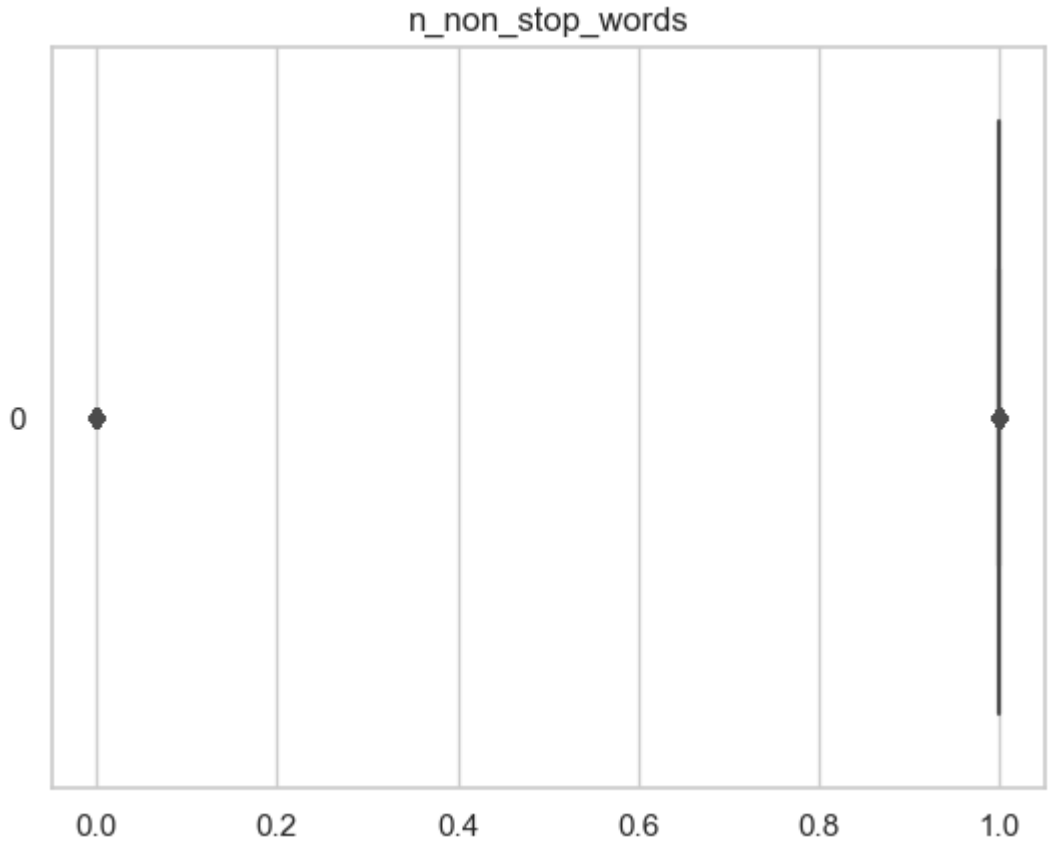
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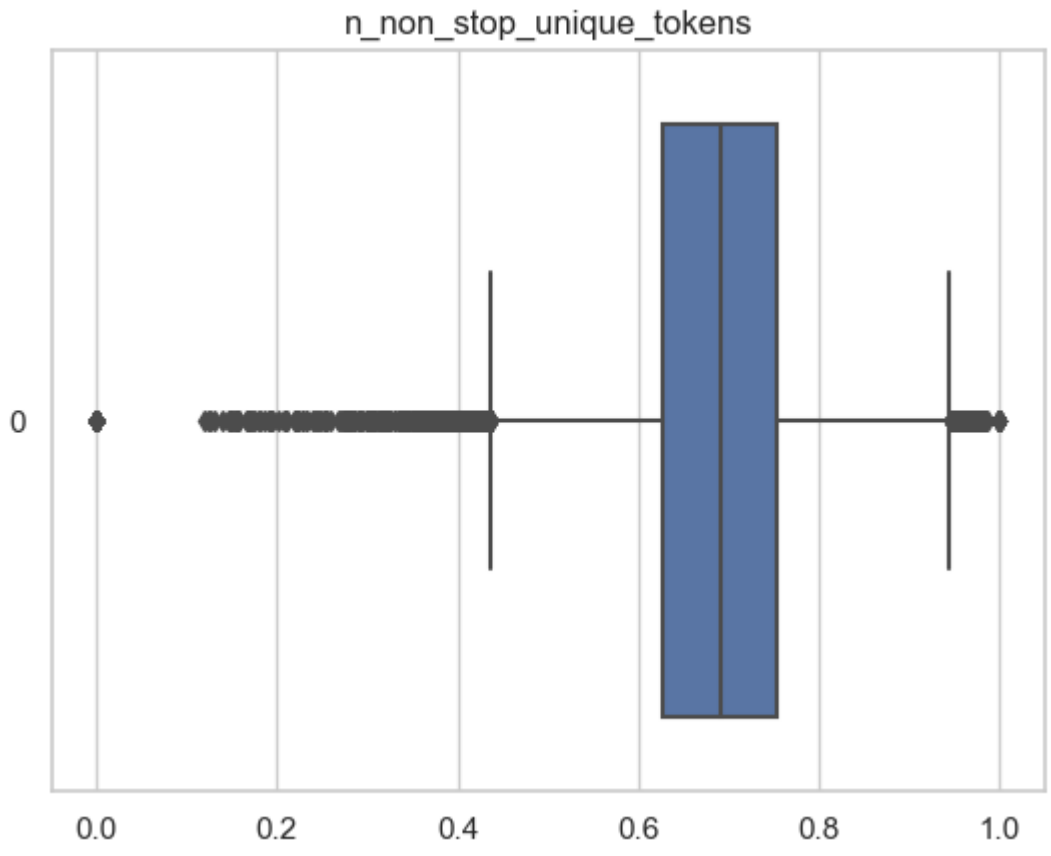
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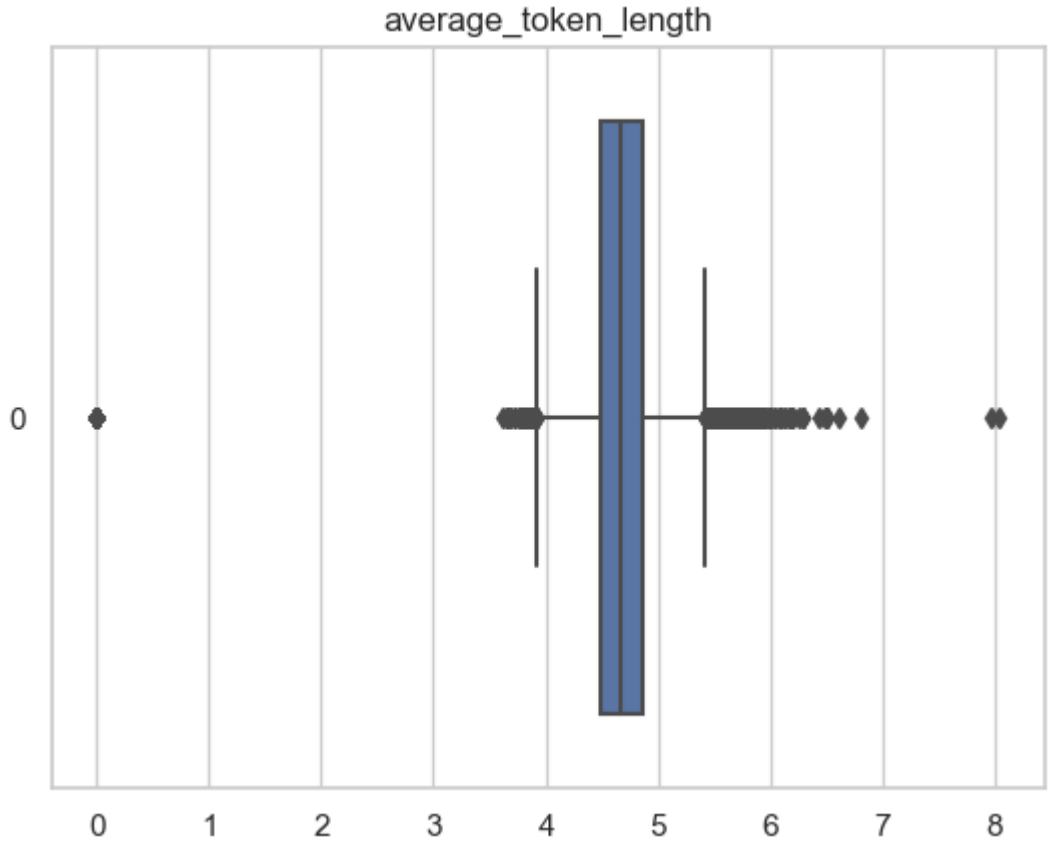
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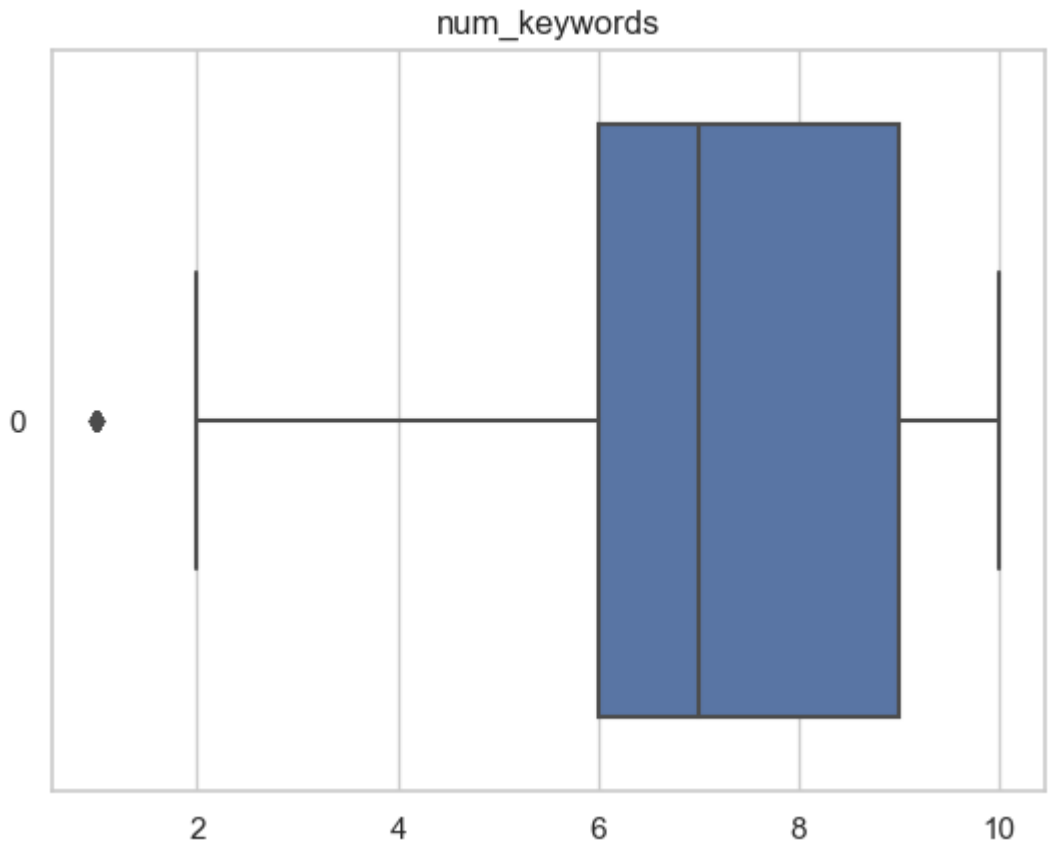
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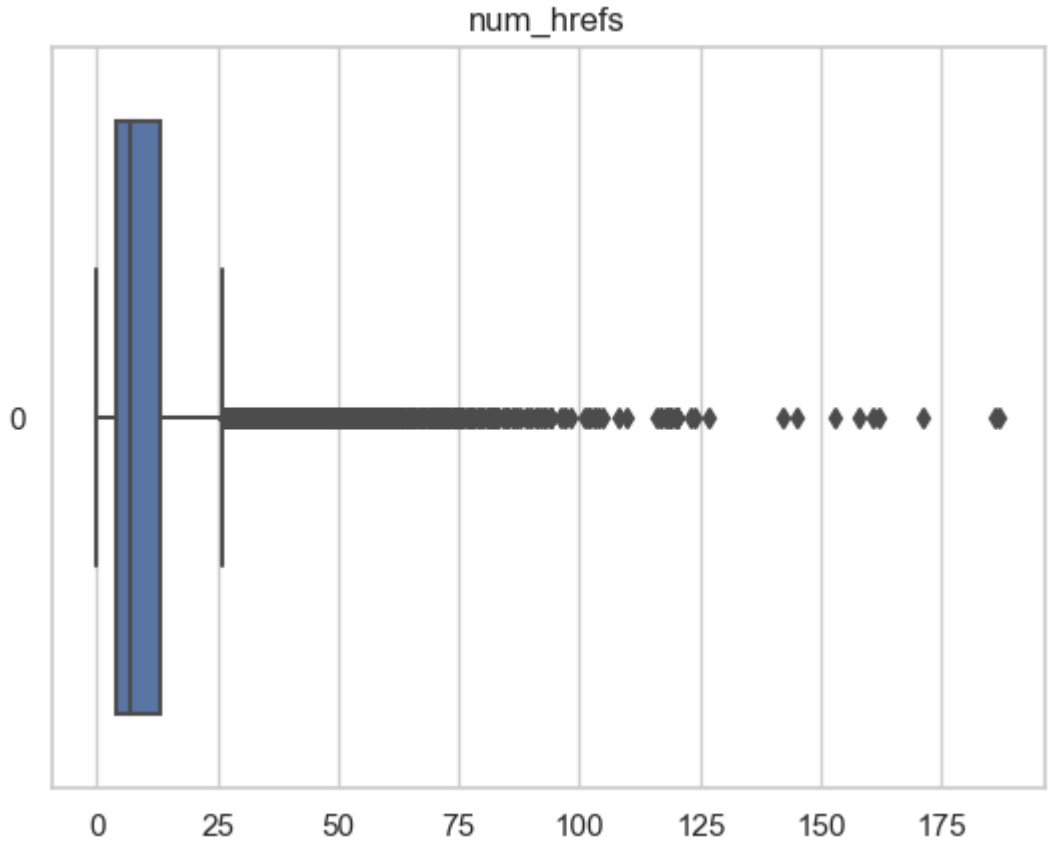
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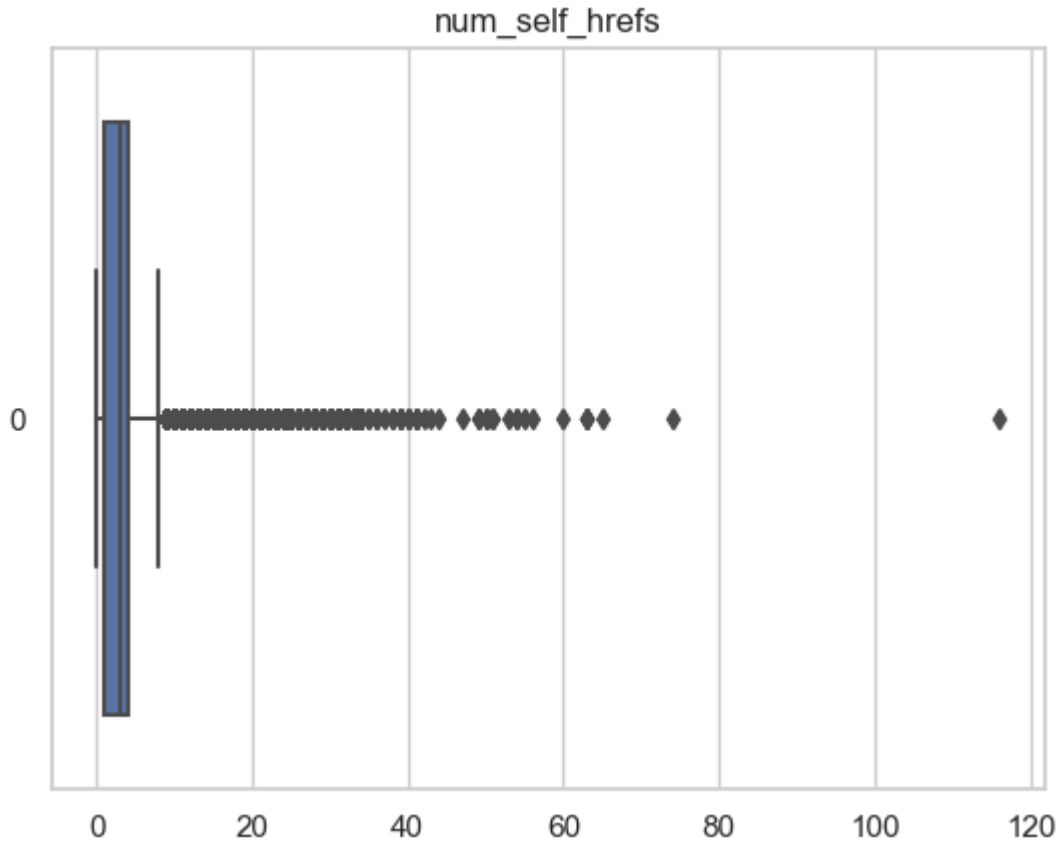
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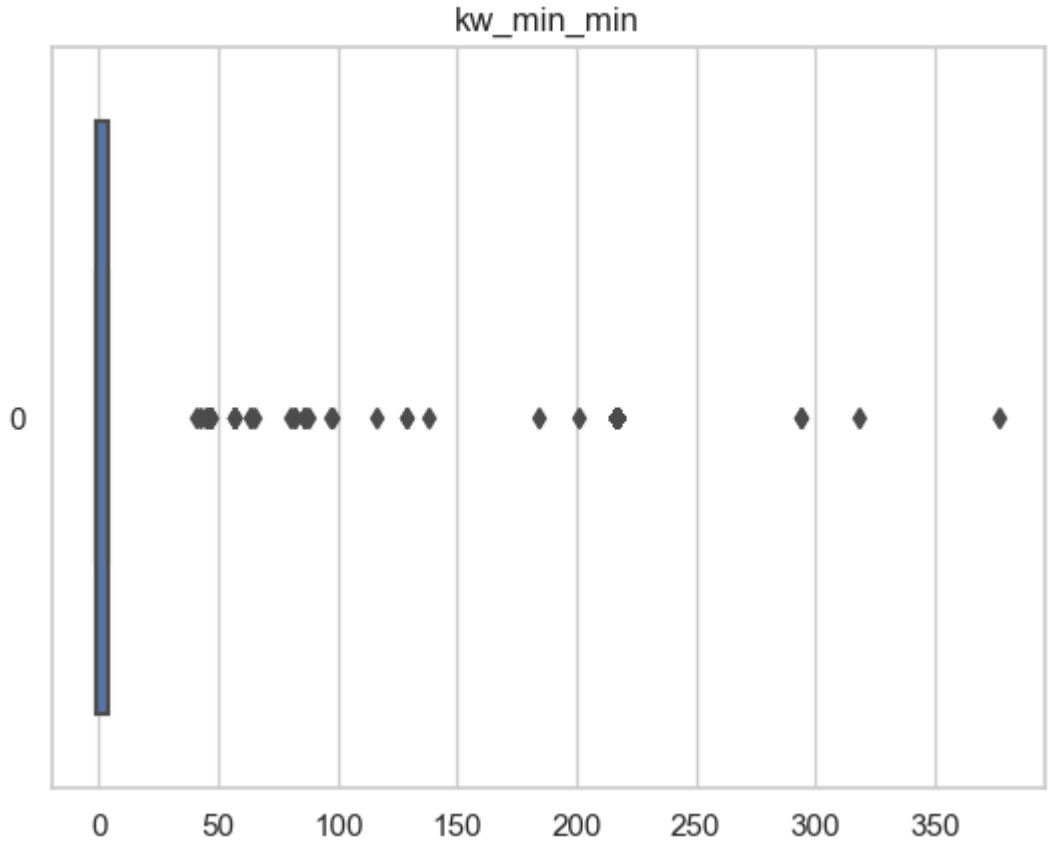
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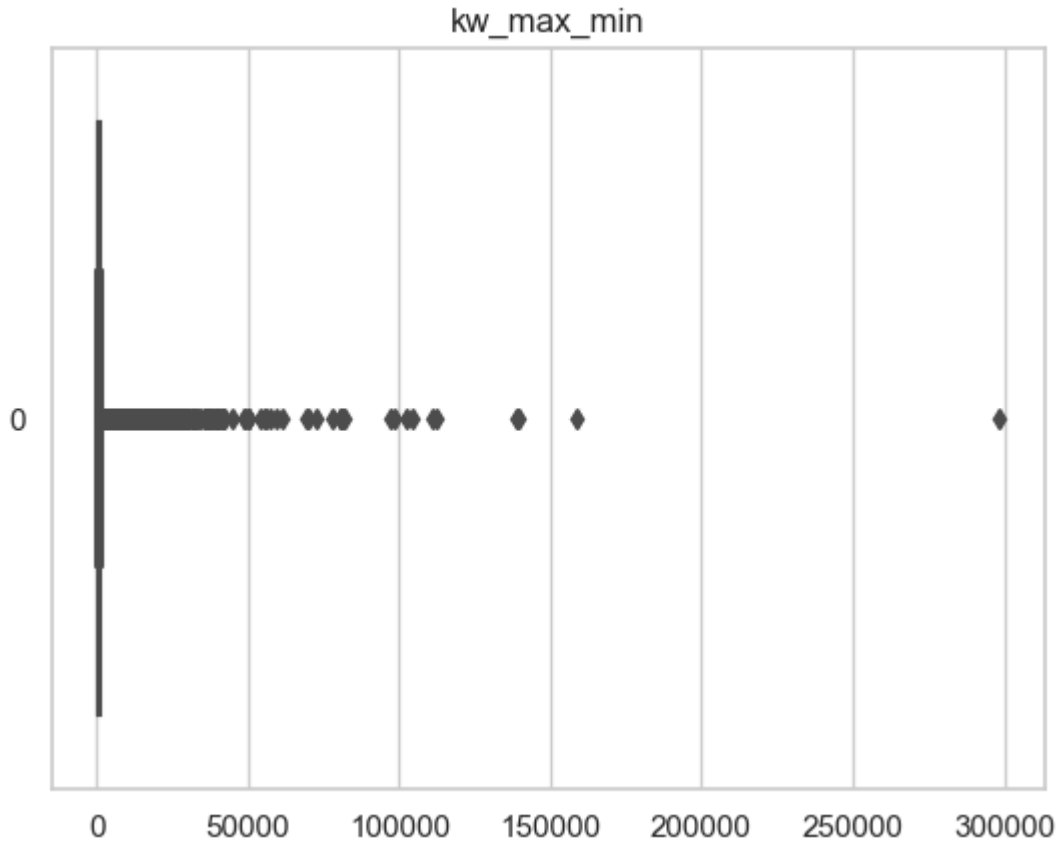
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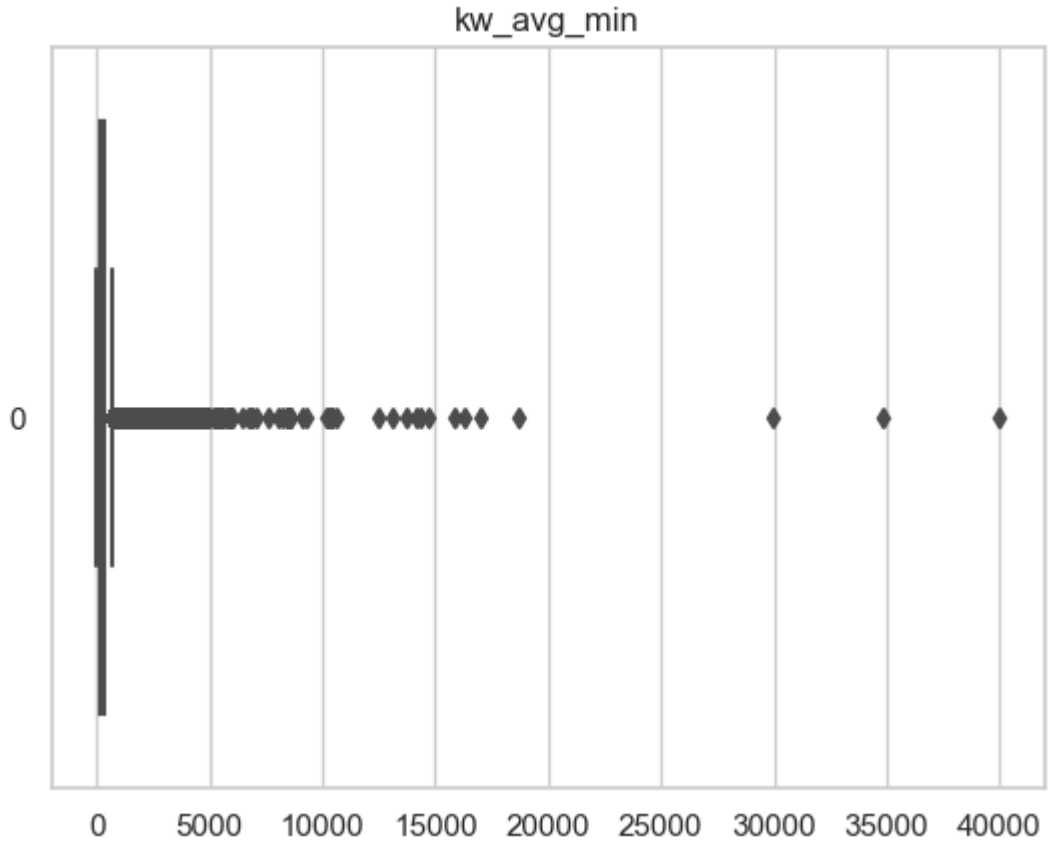
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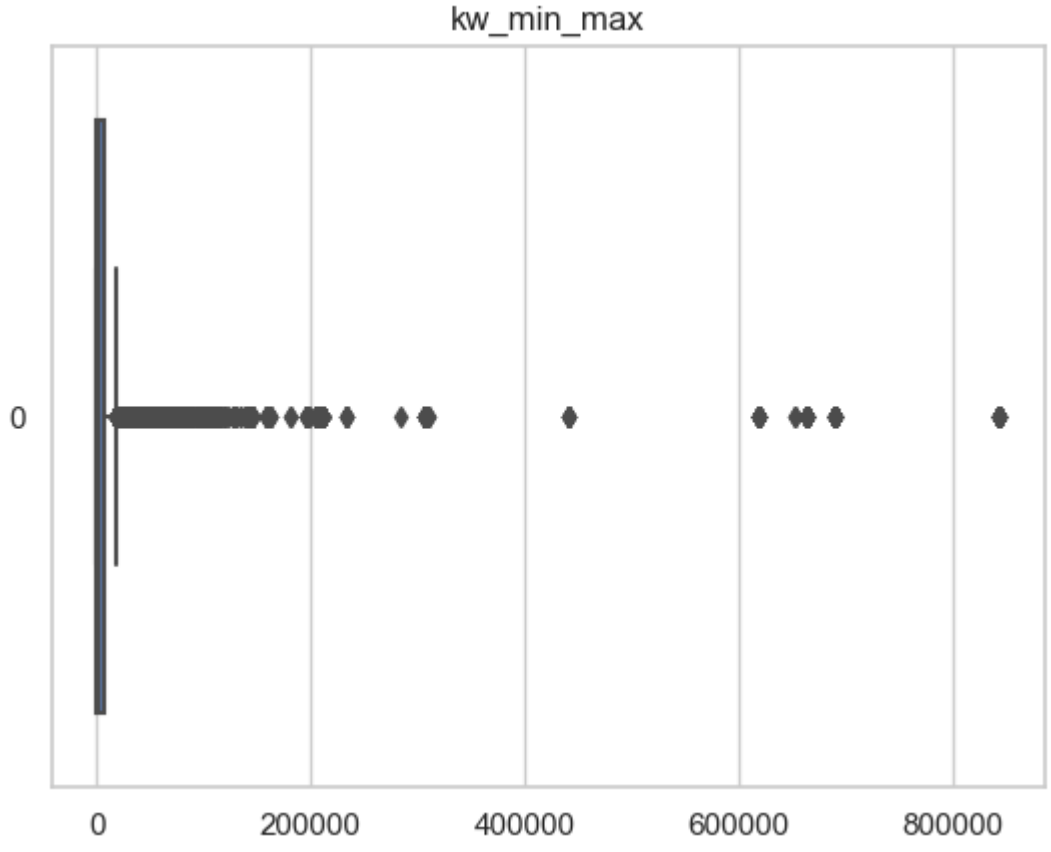
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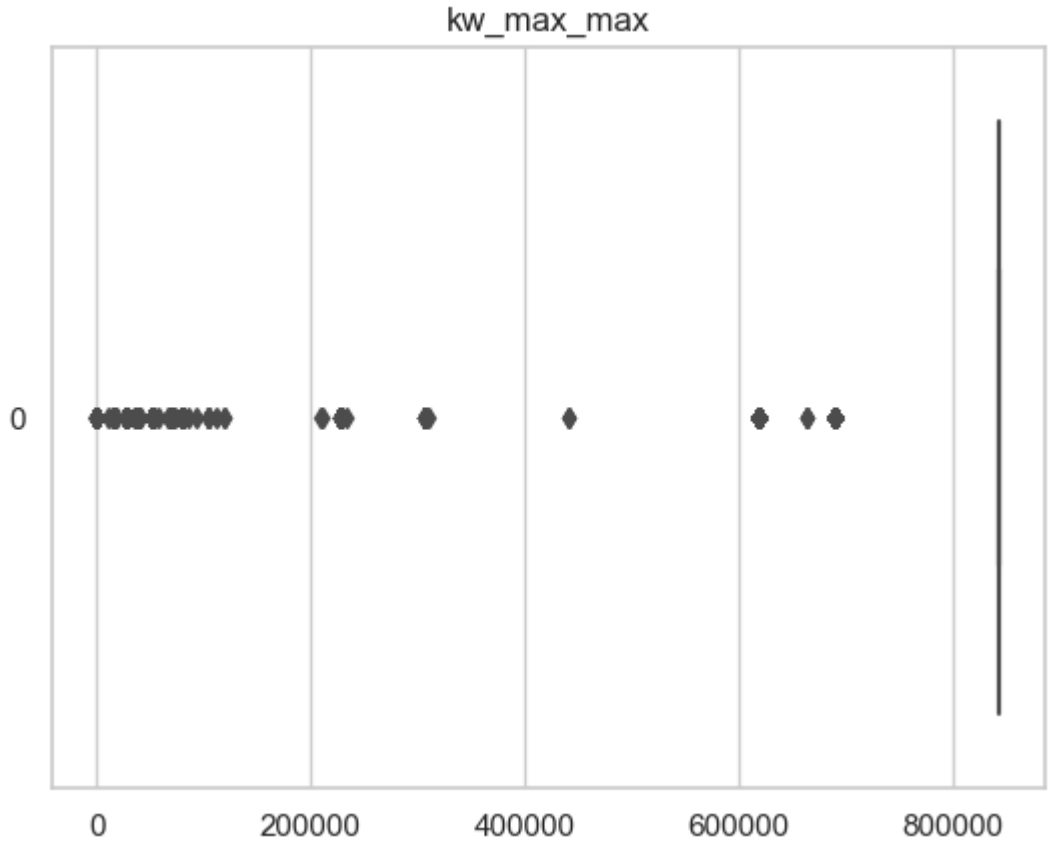
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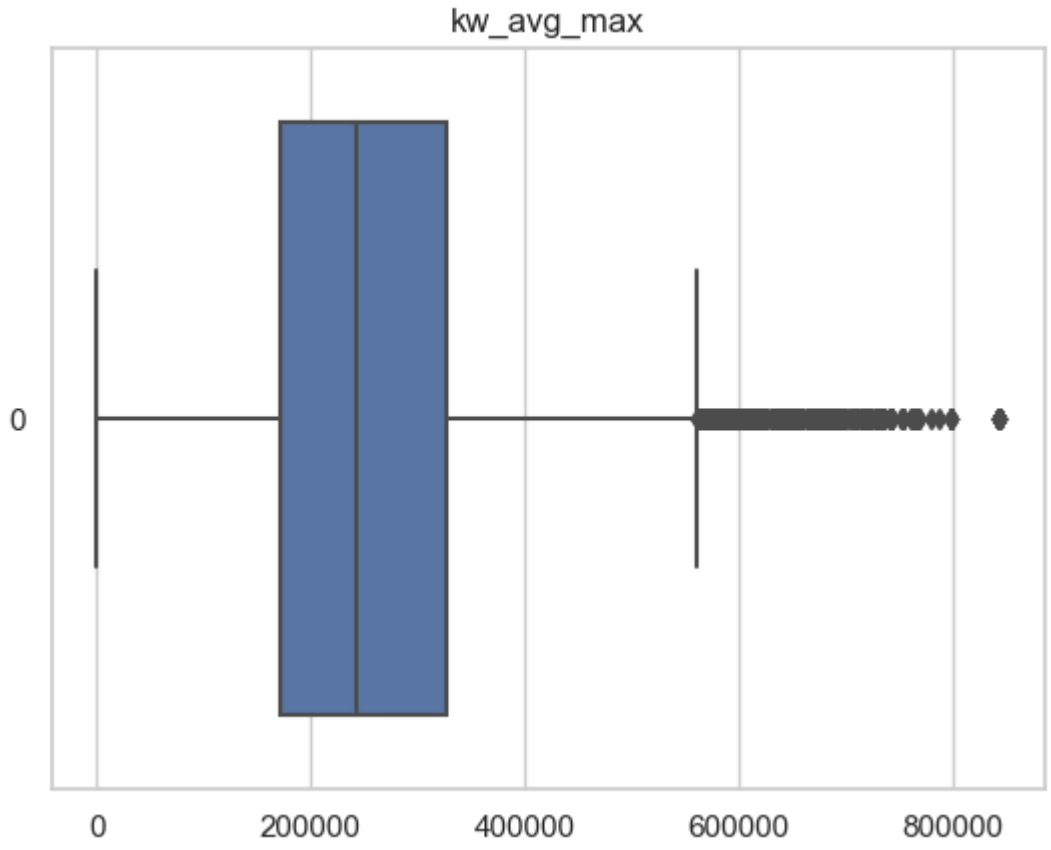
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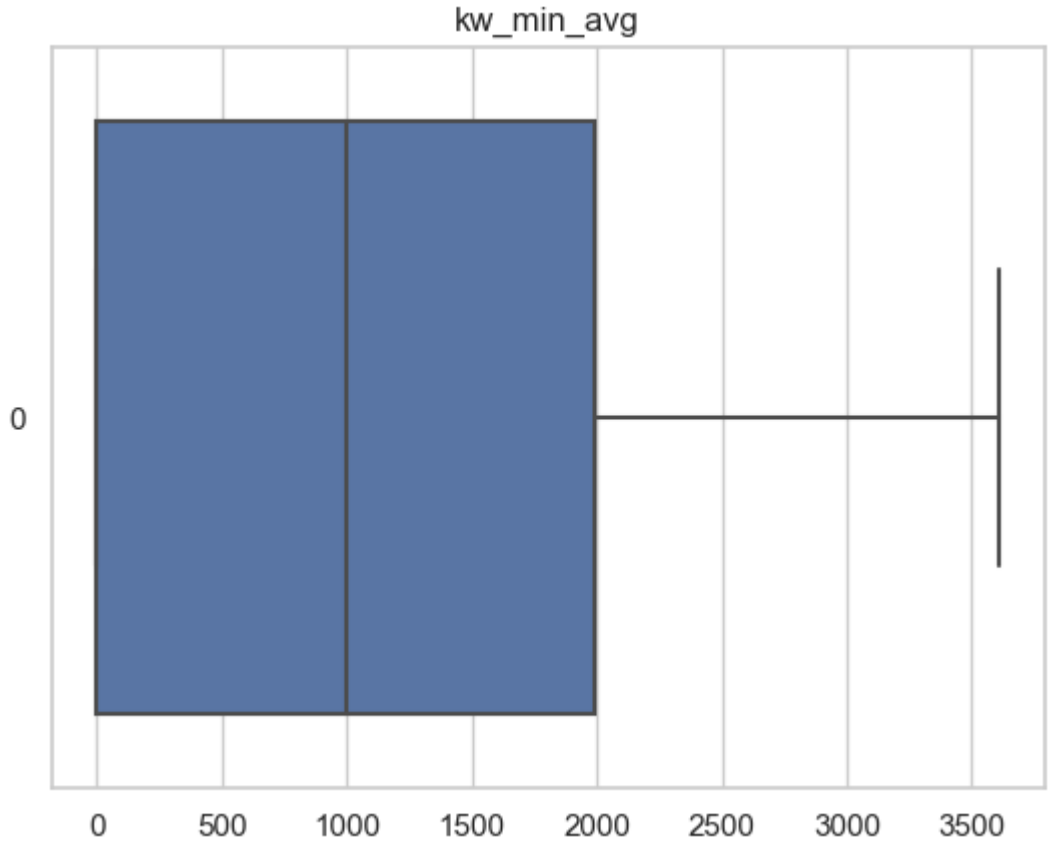
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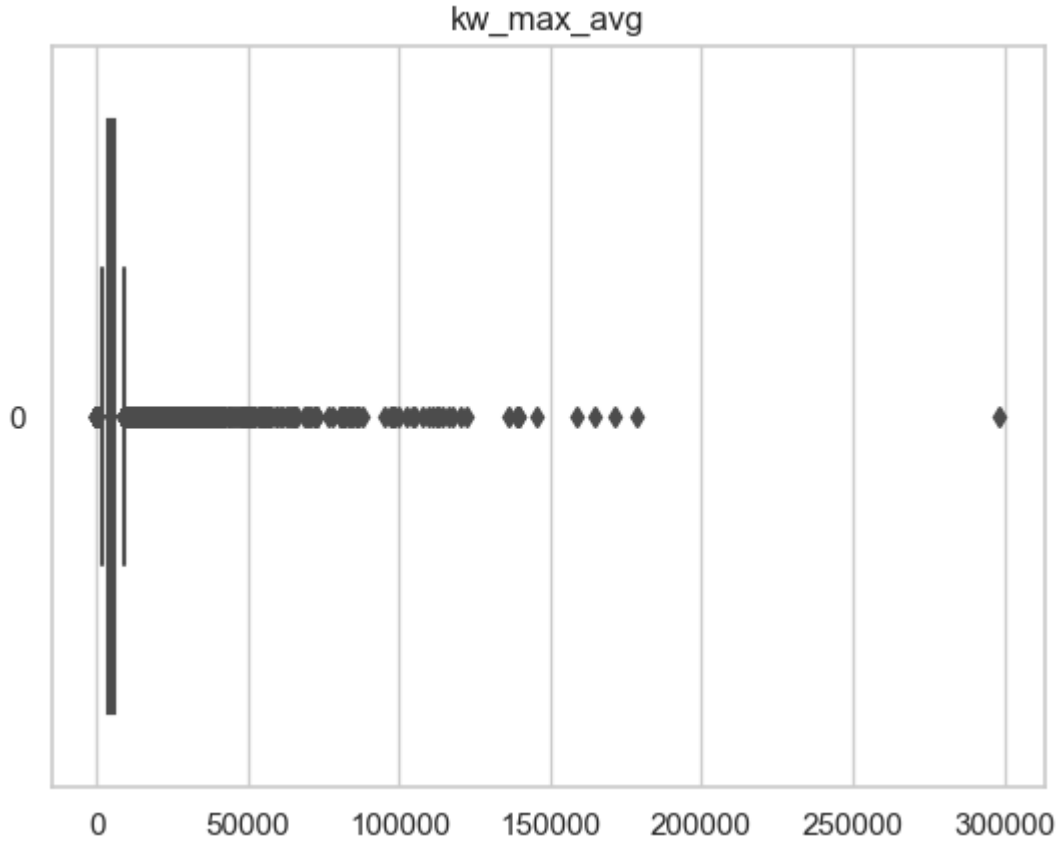
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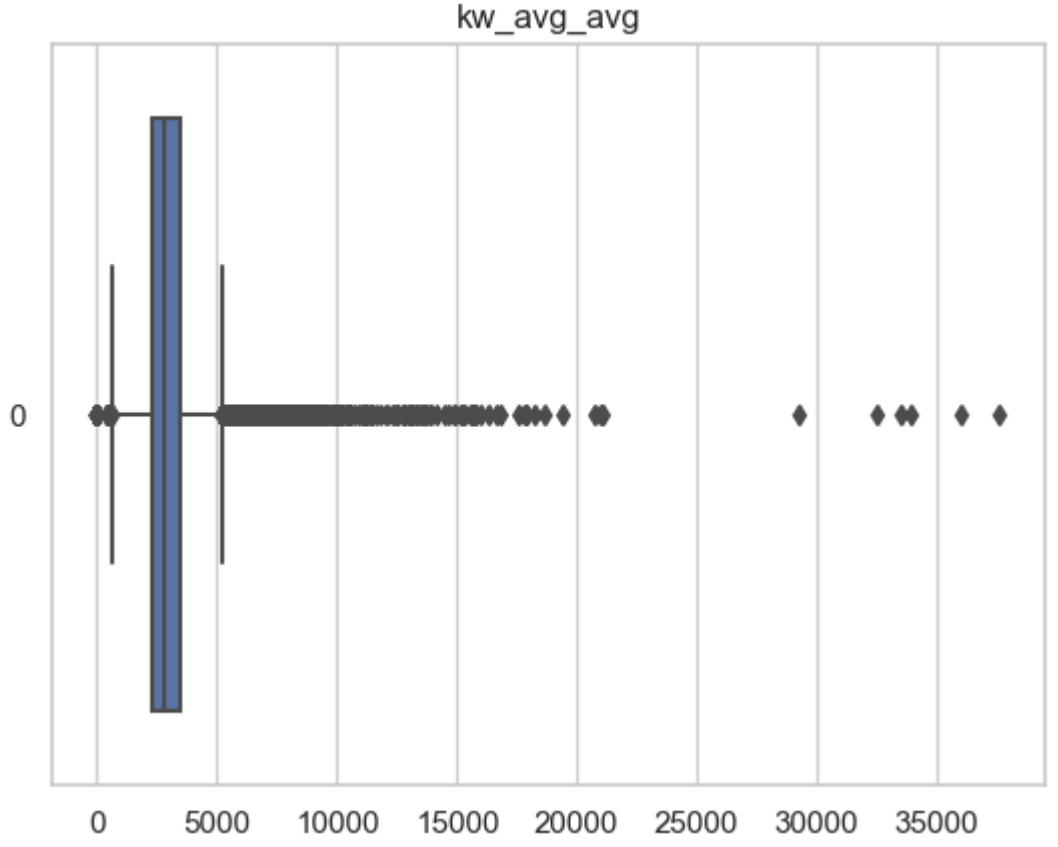
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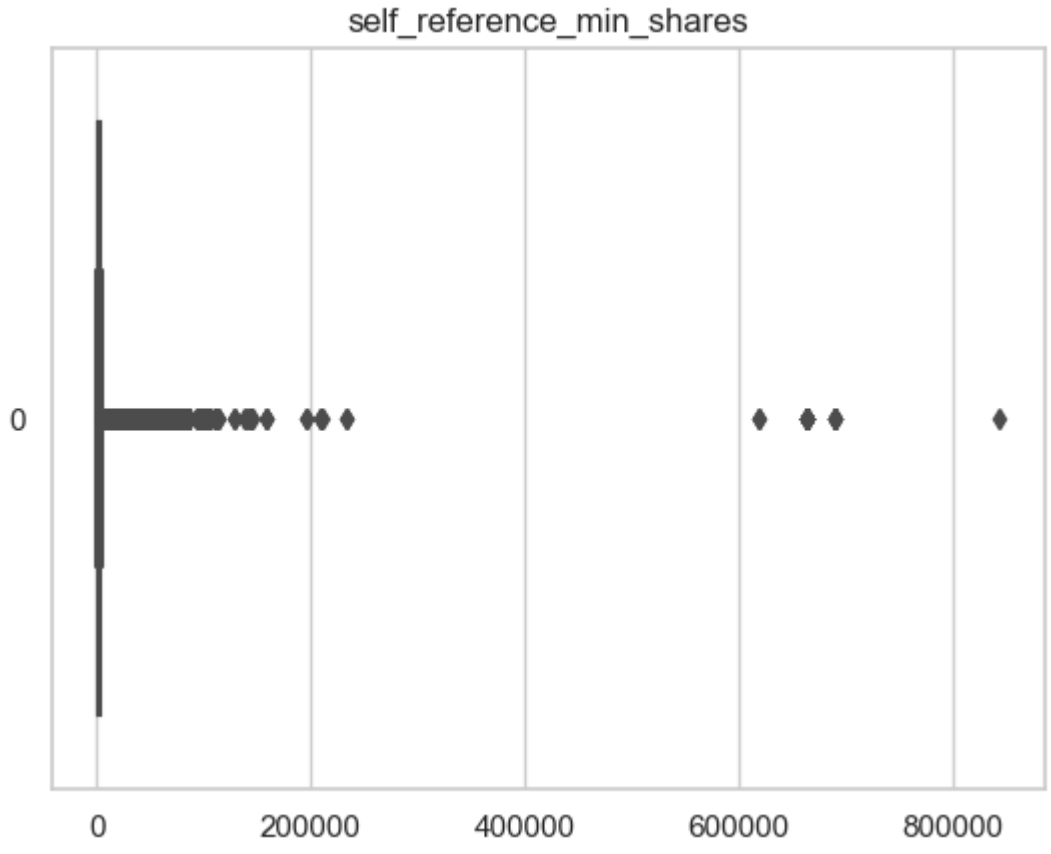
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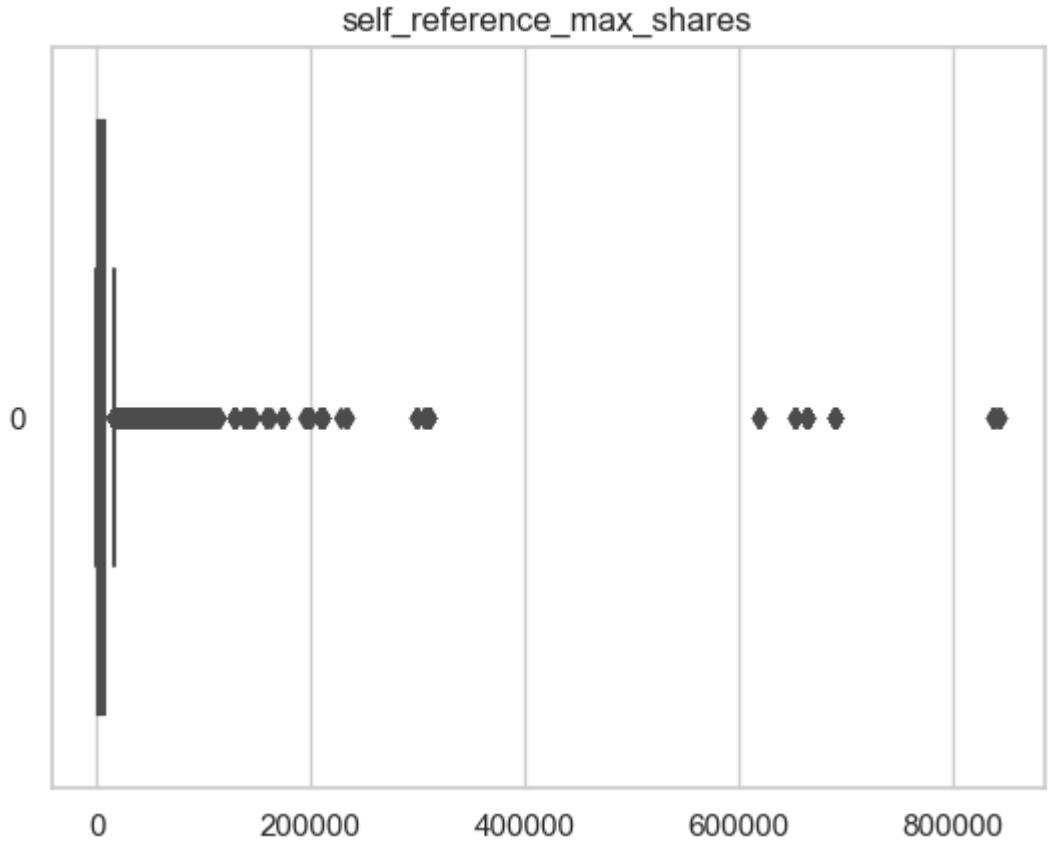
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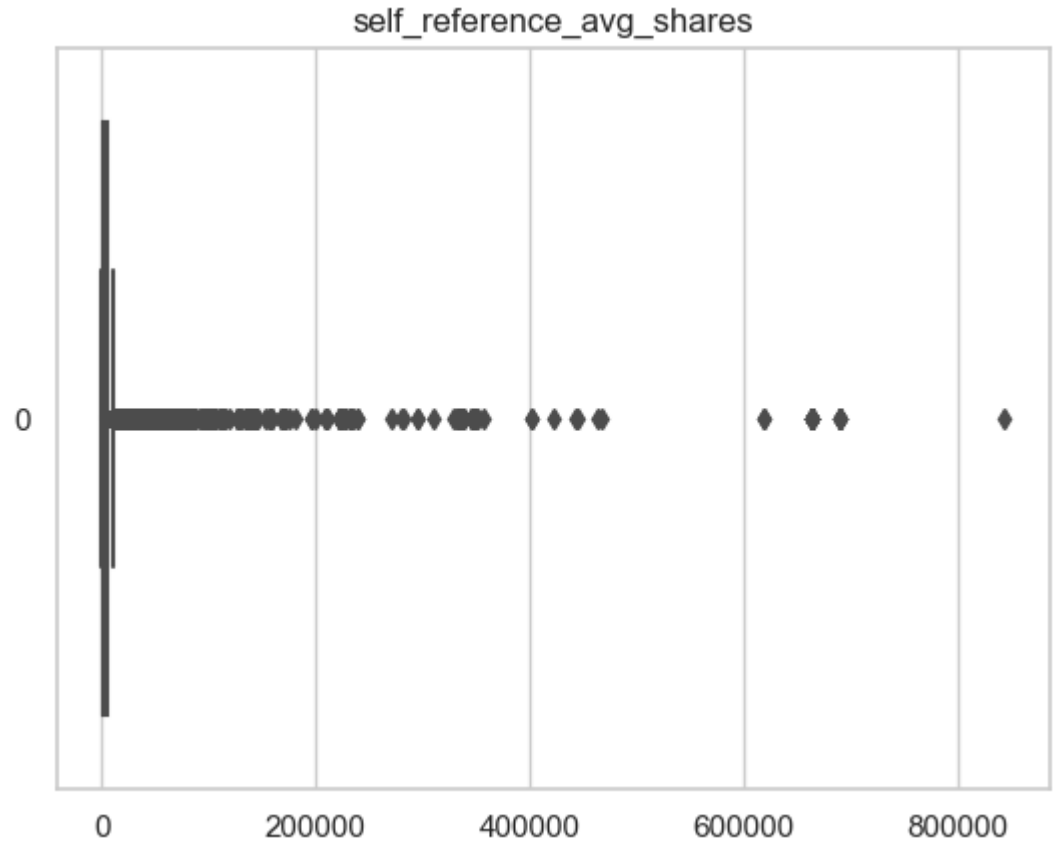
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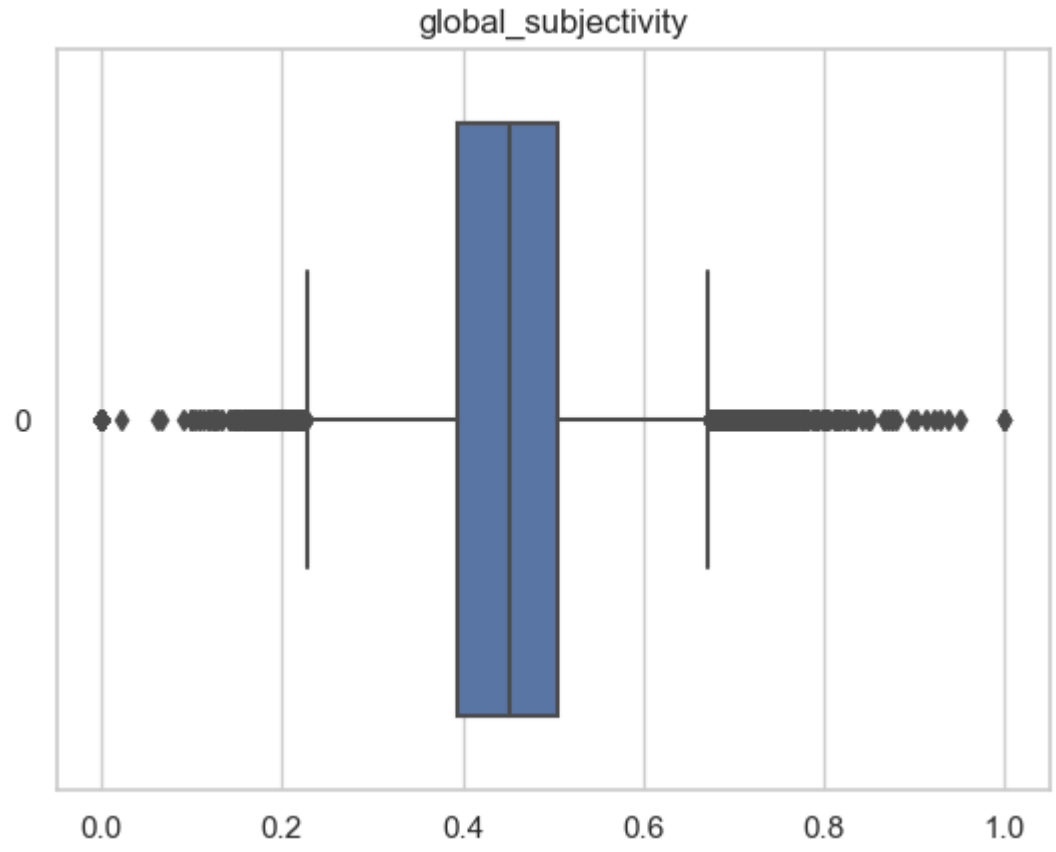
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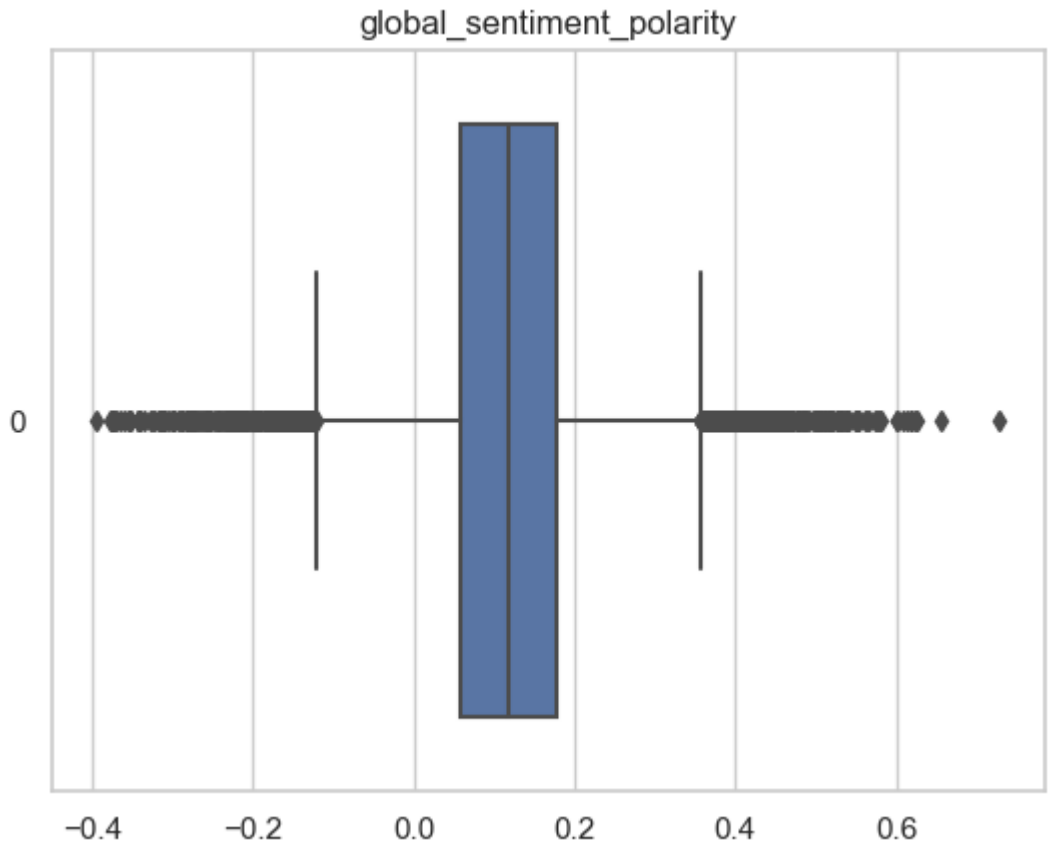
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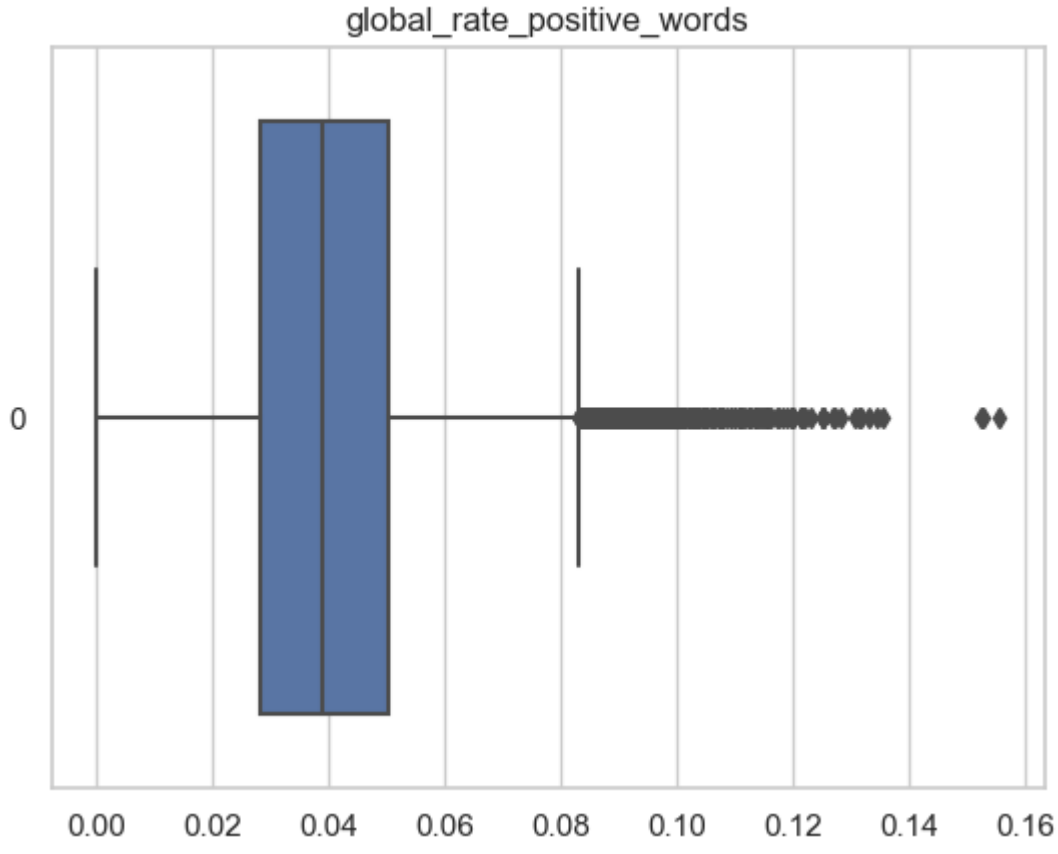
0.6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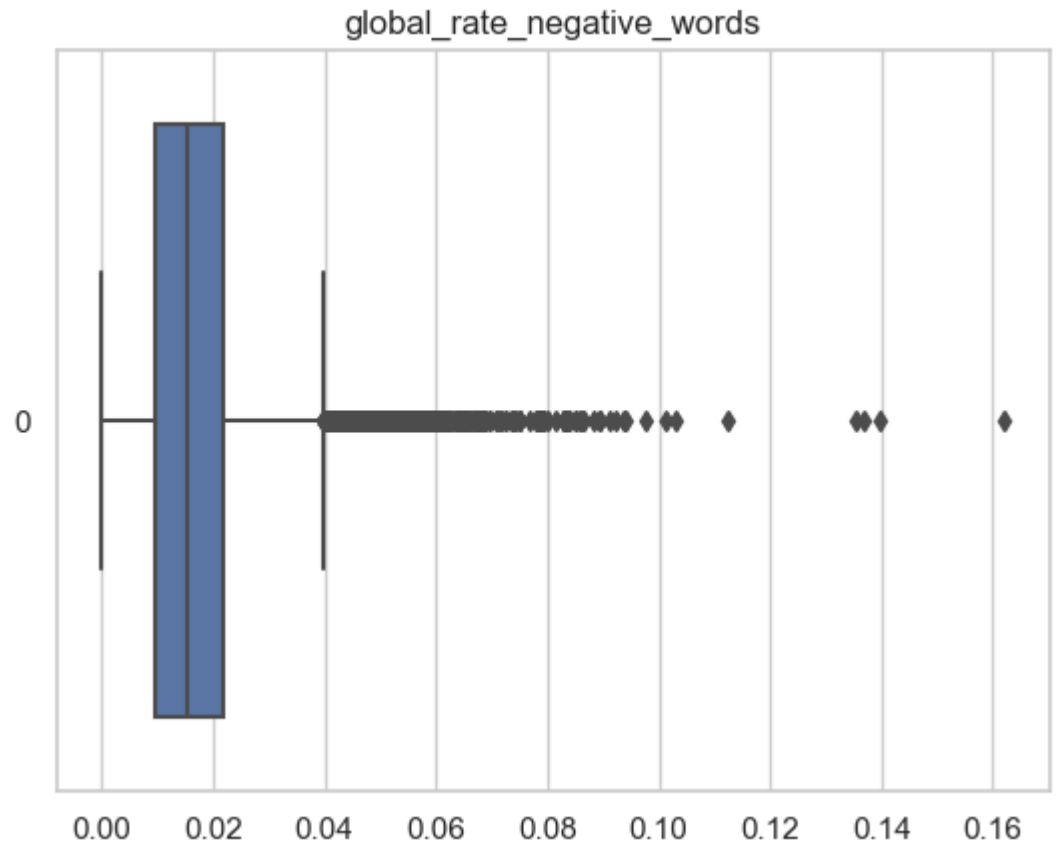
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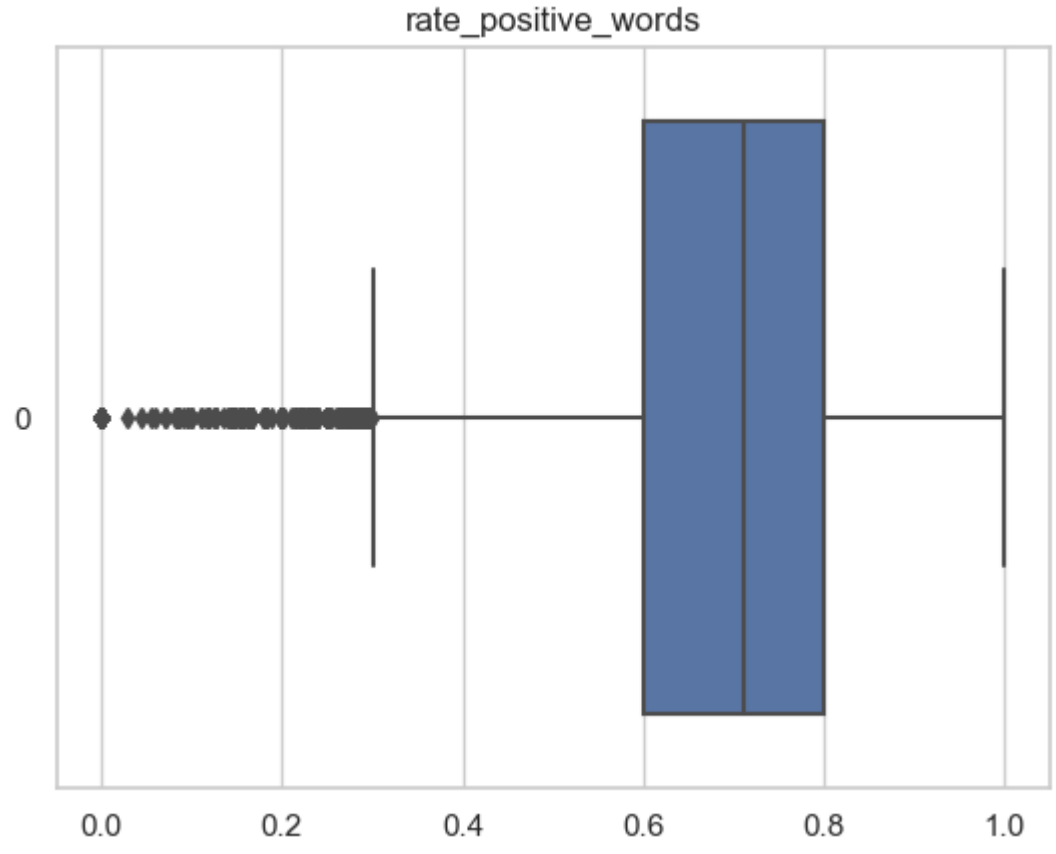
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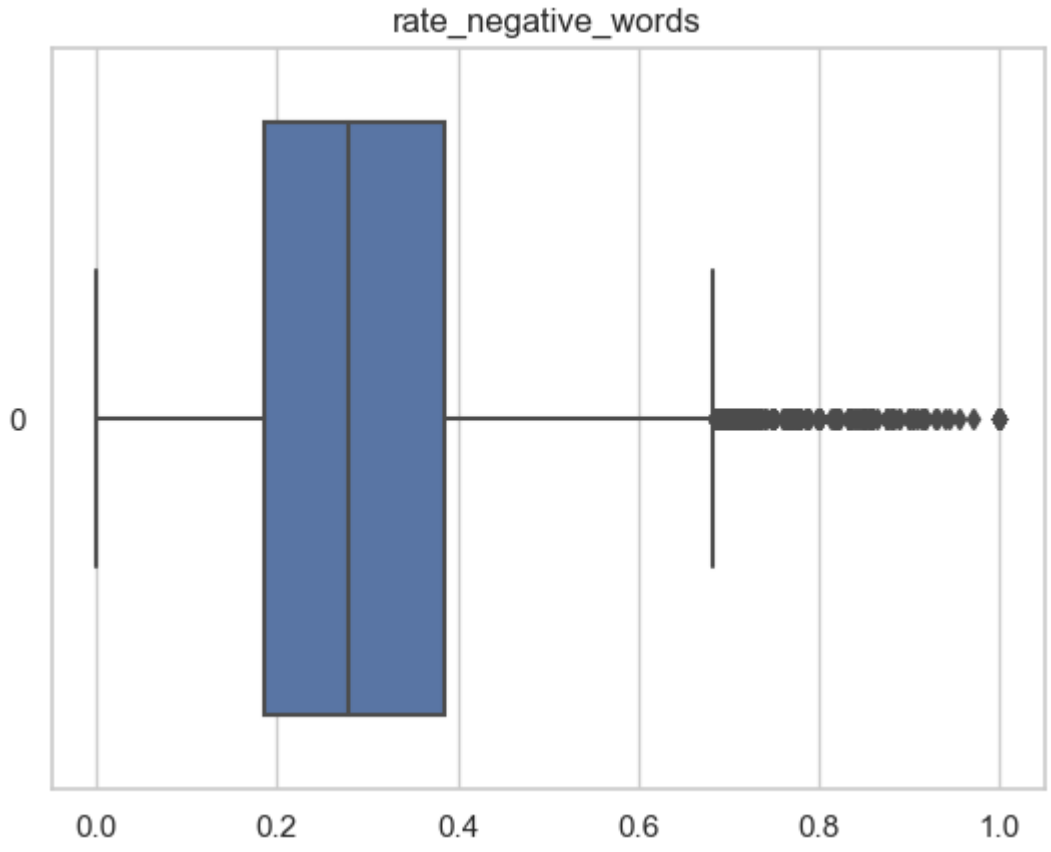
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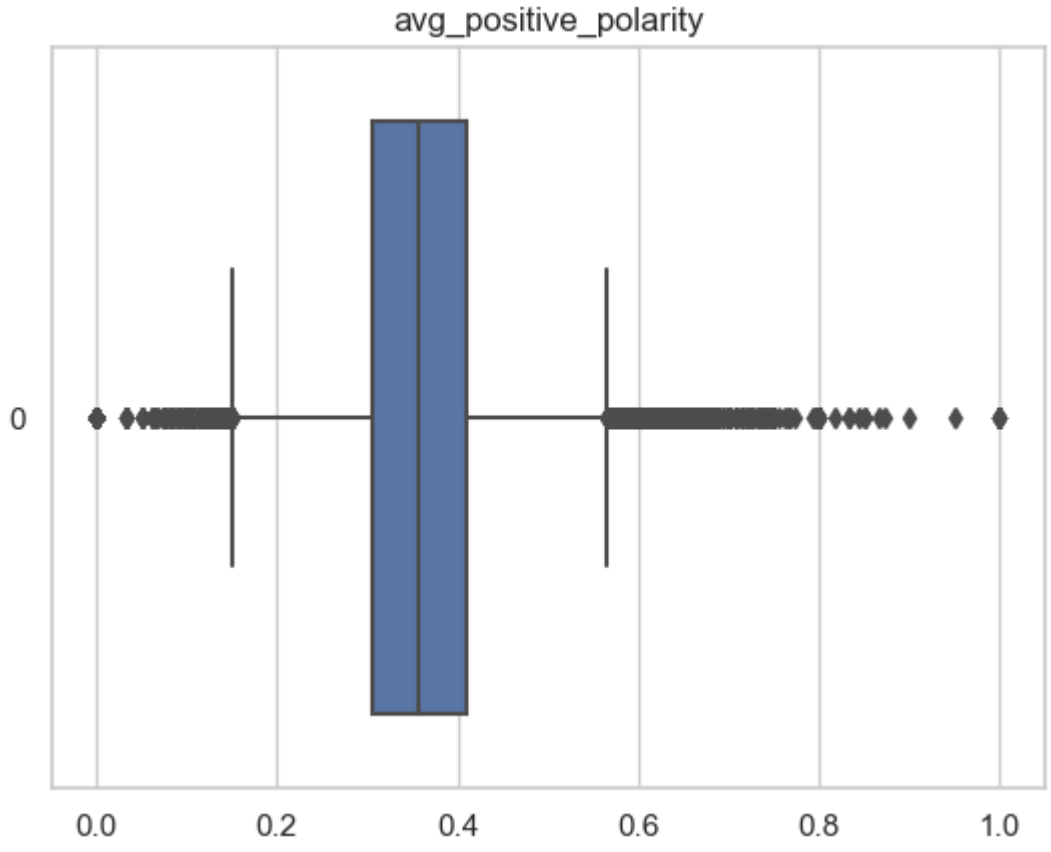
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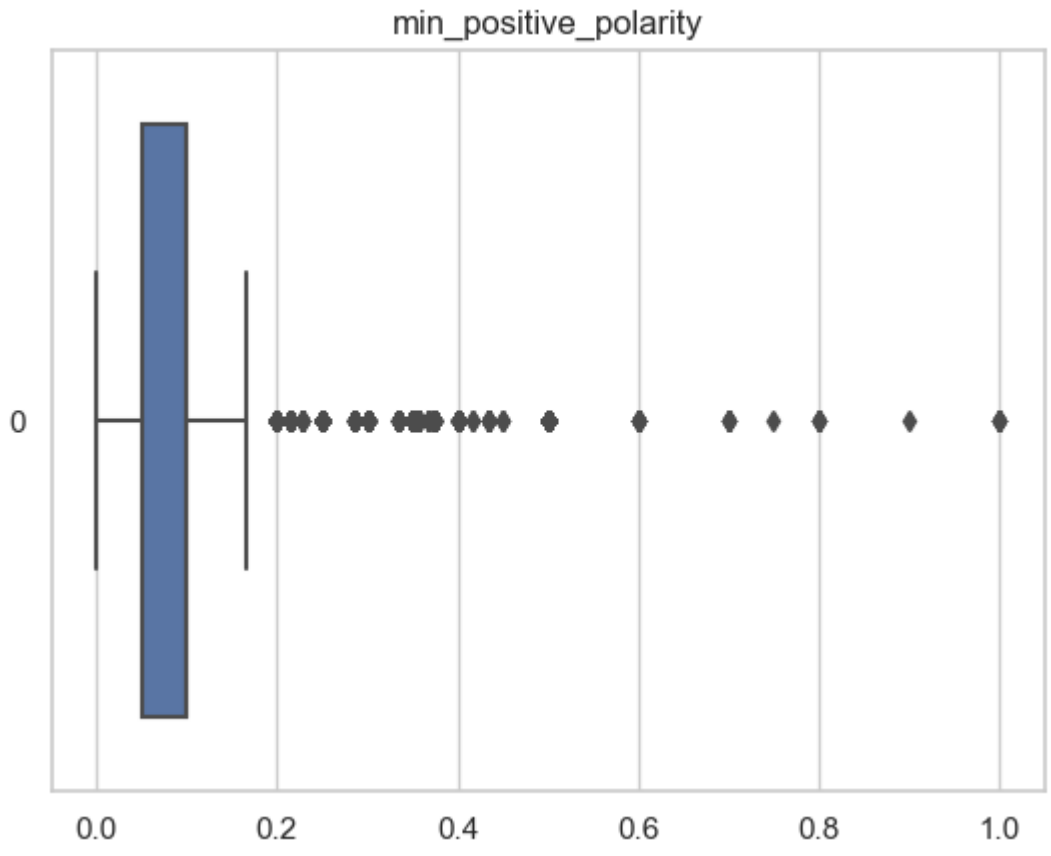
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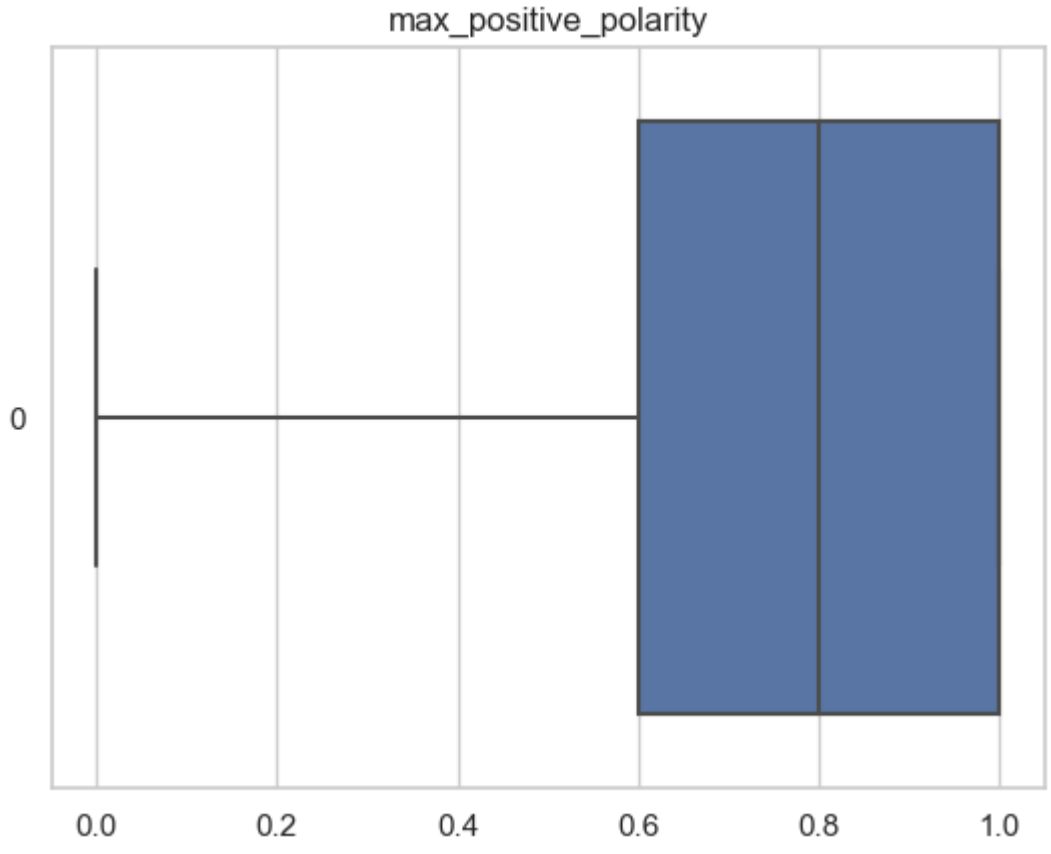
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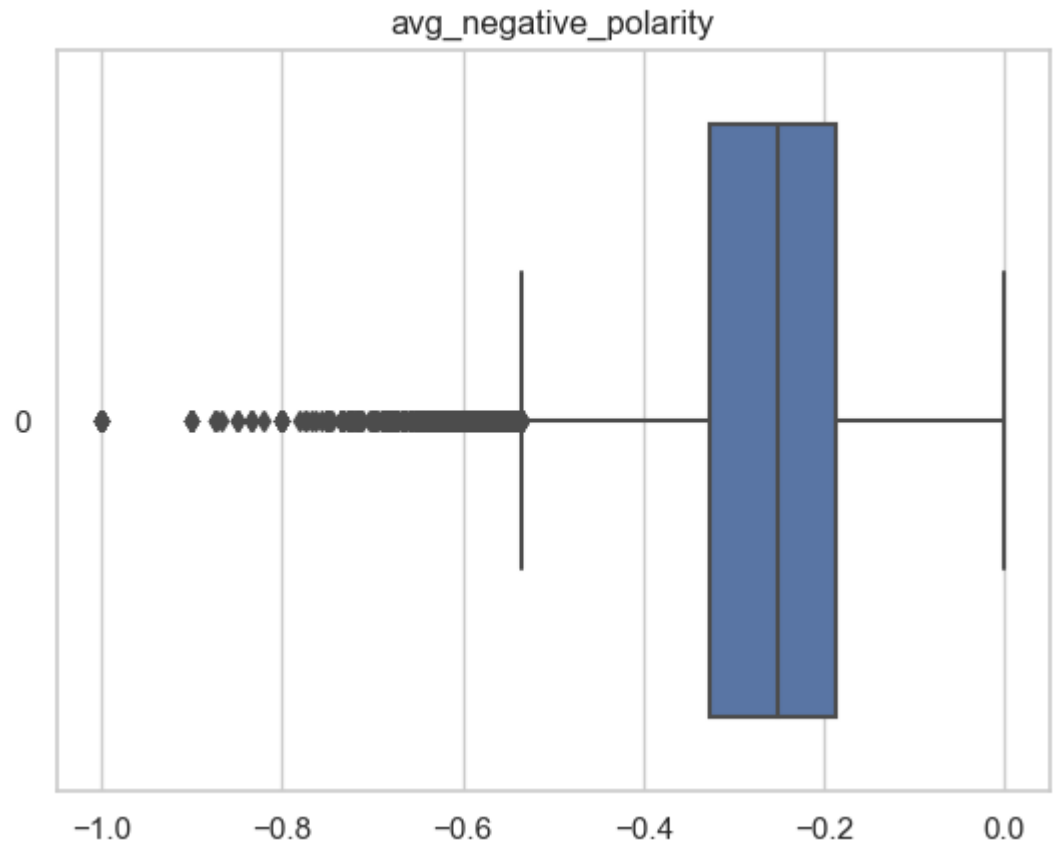
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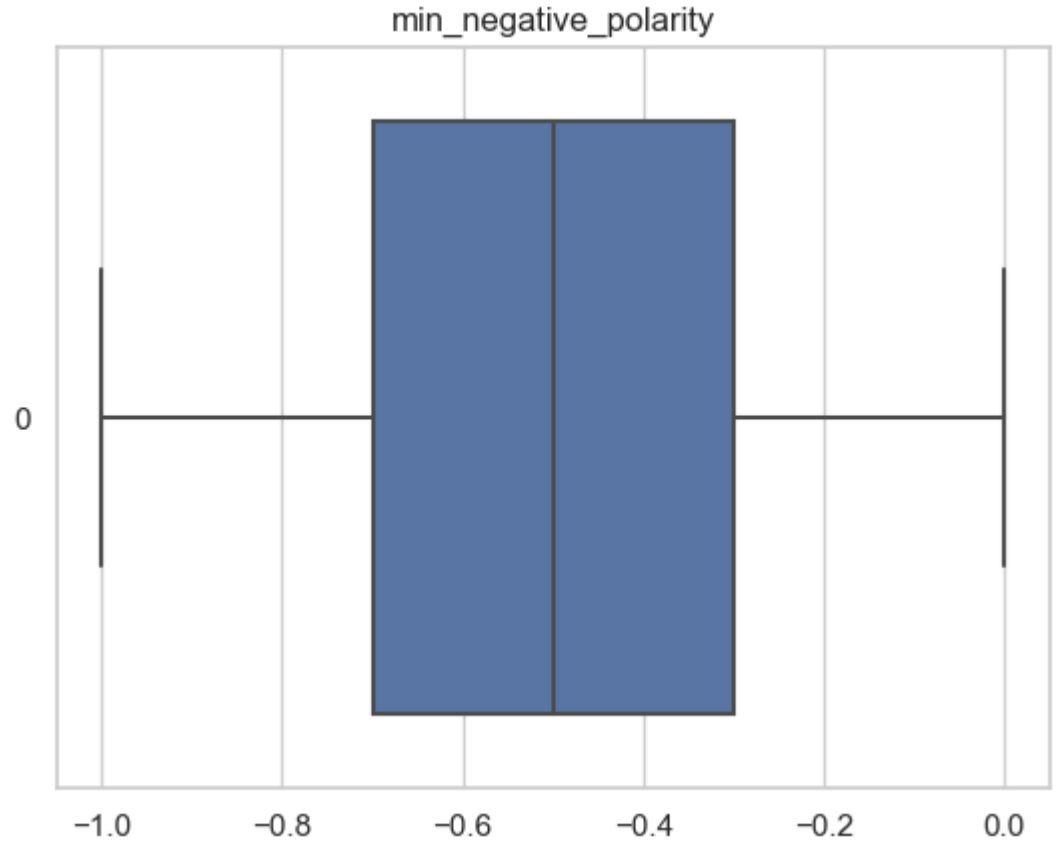
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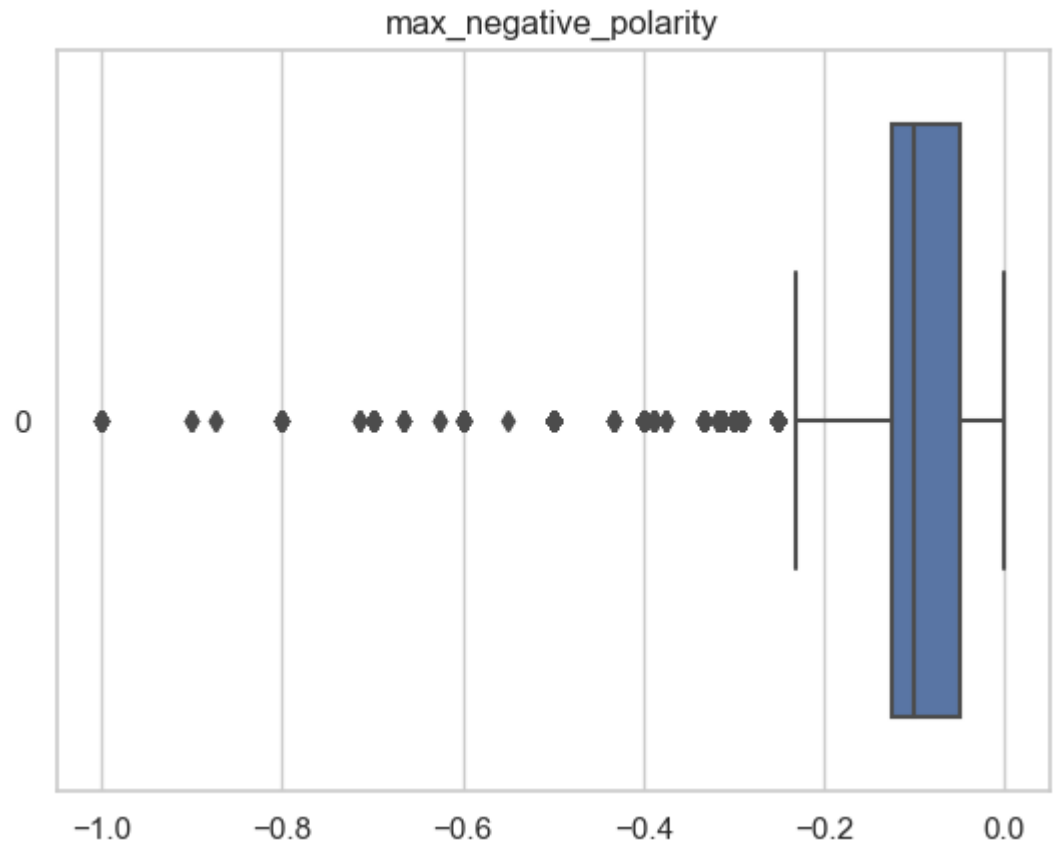
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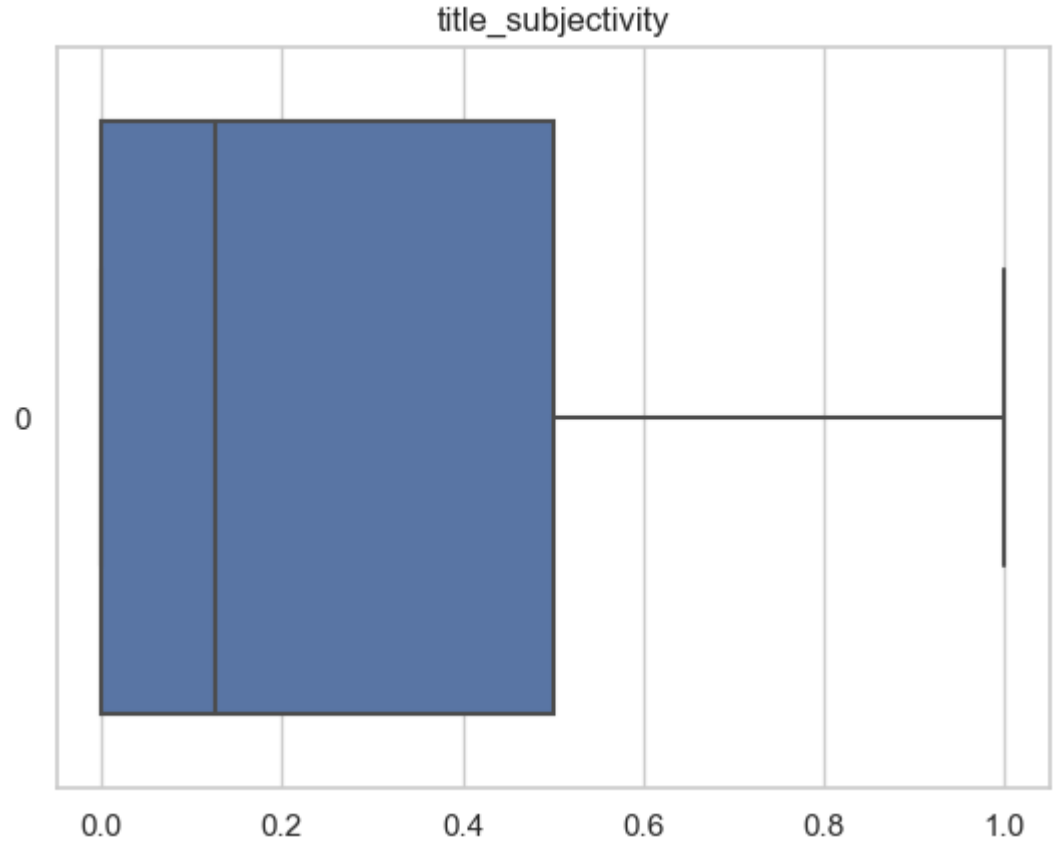
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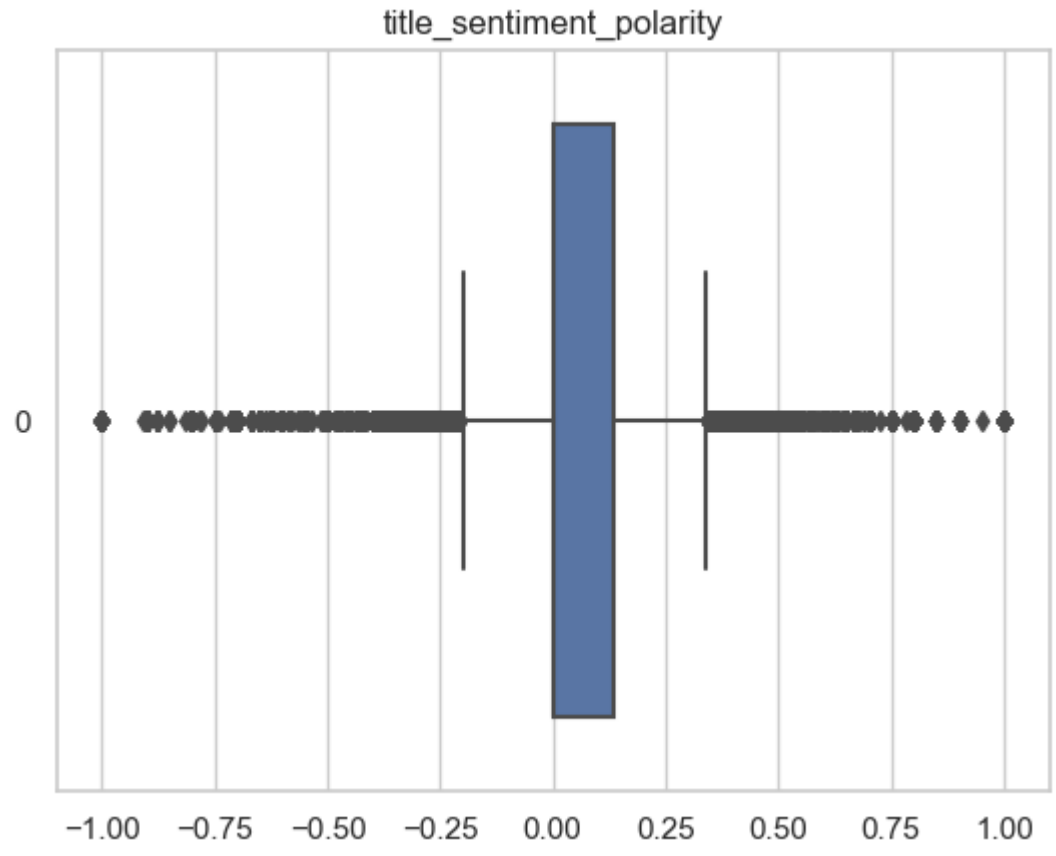
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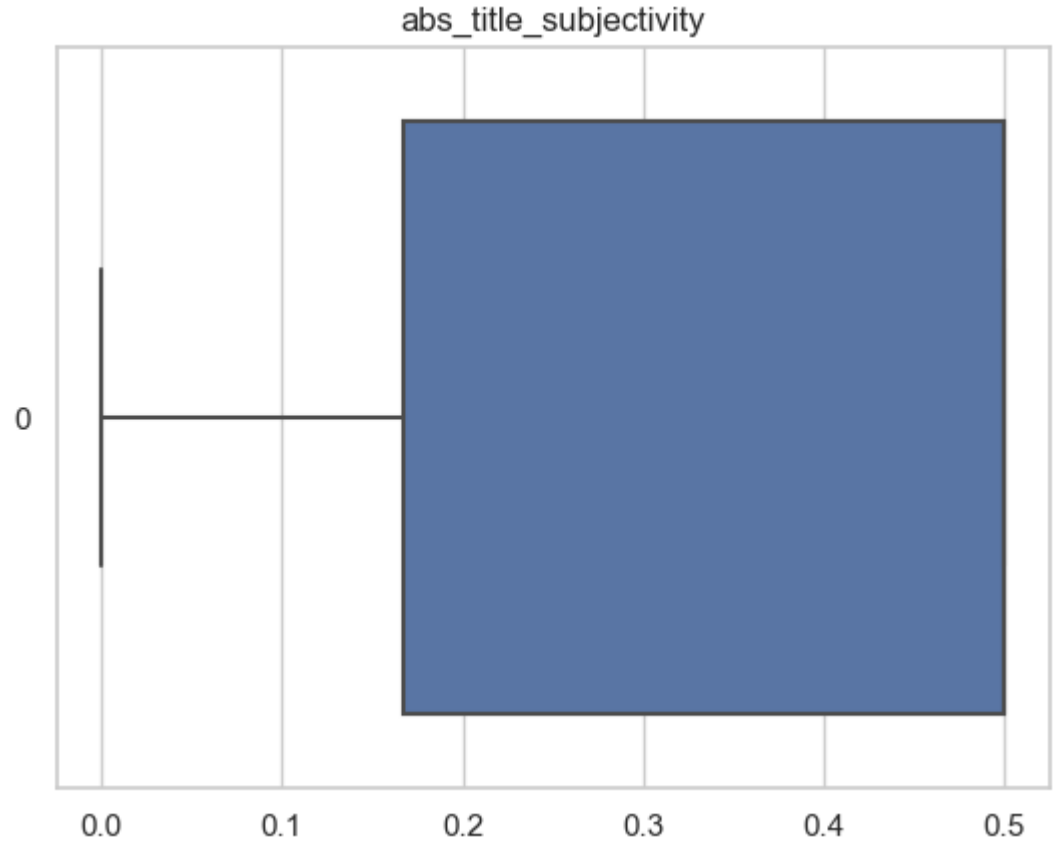
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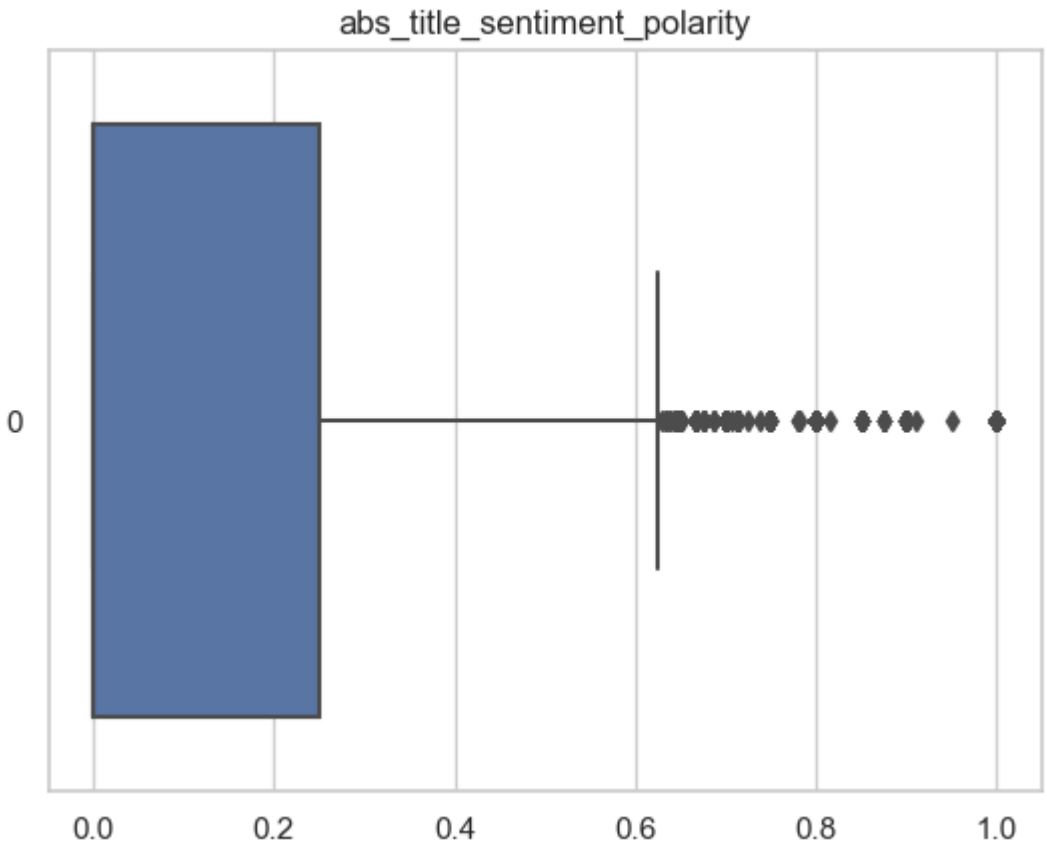

There's a lot of outliers. Thankfully, Xgboost can handle them so we're not going to spend a any more time on outliers.

In [22]:
```
unpopular_df = df[df['shares'] < THRESHOLD ]
popular_df = df[df['shares'] >= THRESHOLD ]
```

Let's see histograms for our continuous variables.

In [23]:
```
popular_df[continuous_cols].hist(figsize=(20,20))
plt.show()
```

Out[23]:
```
array([[<Axes: title={'center': 'n_tokens_title'}>,
        <Axes: title={'center': 'n_tokens_content'}>,
        <Axes: title={'center': 'n_unique_tokens'}>,
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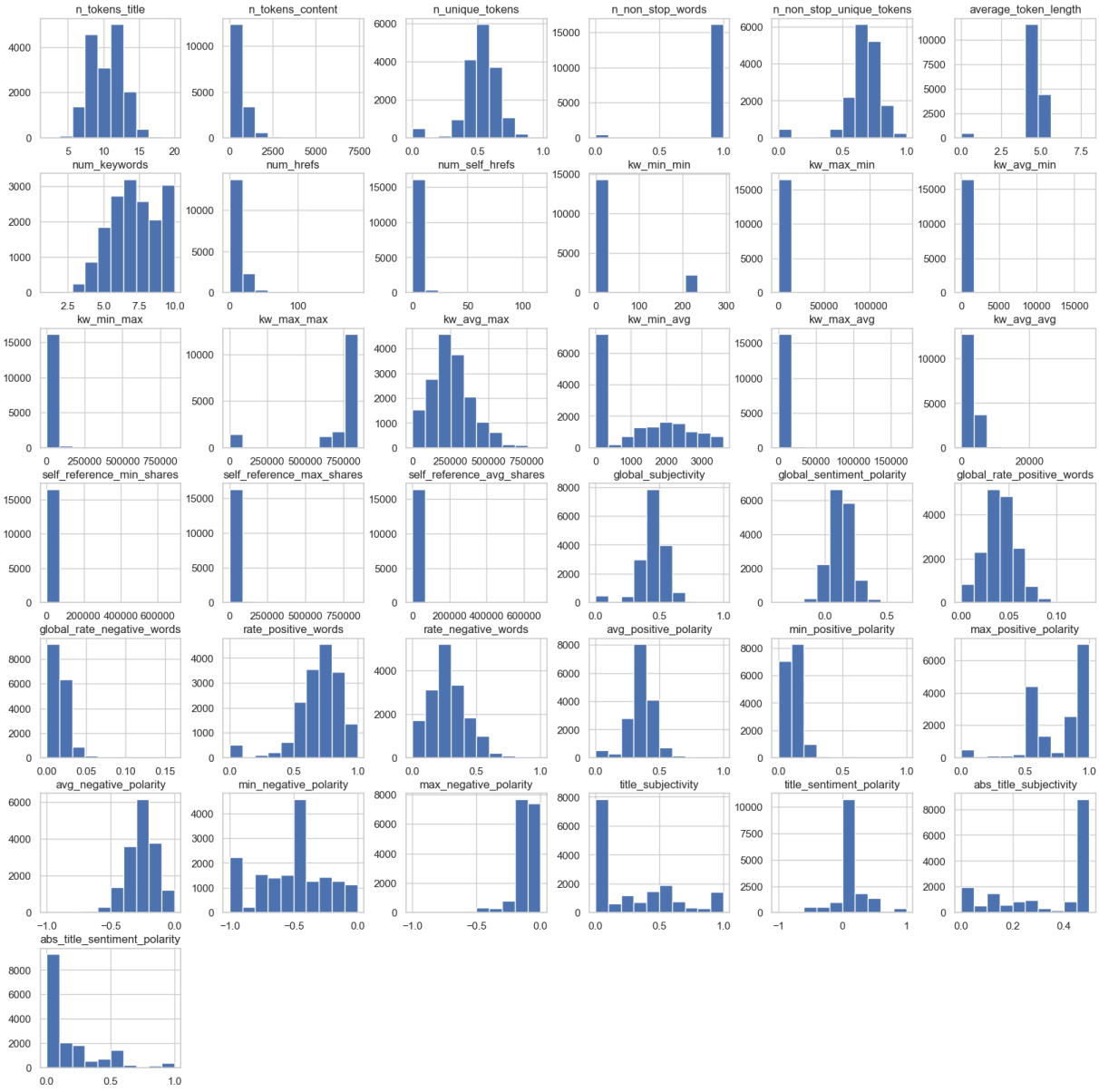

In [24]:
```
unpopular_df[continuous_cols].hist(figsize=(20,20))
plt.show()
```

Out[24]:
```
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        <Axes: title={'center': 'n_tokens_content'}>,
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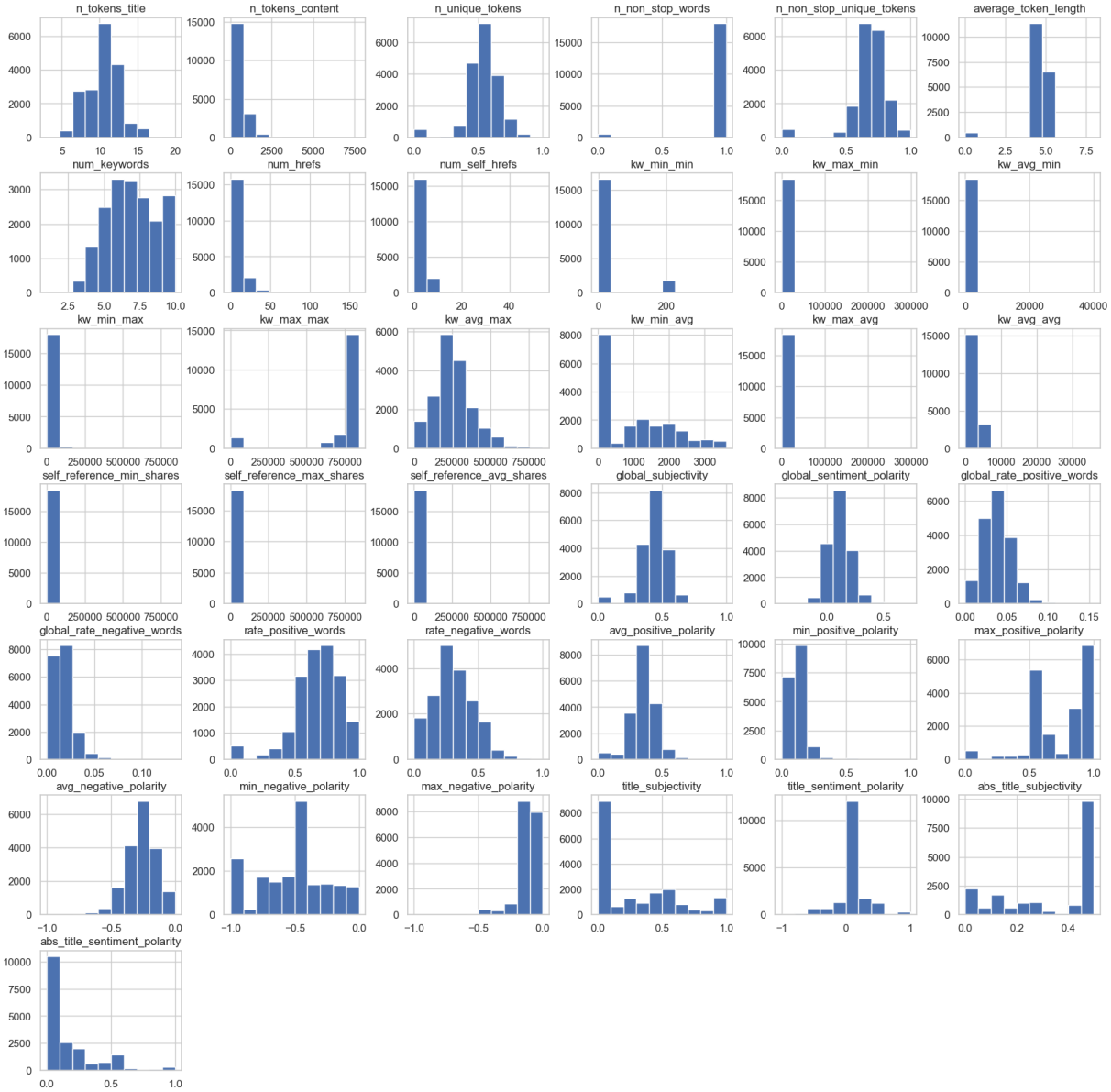
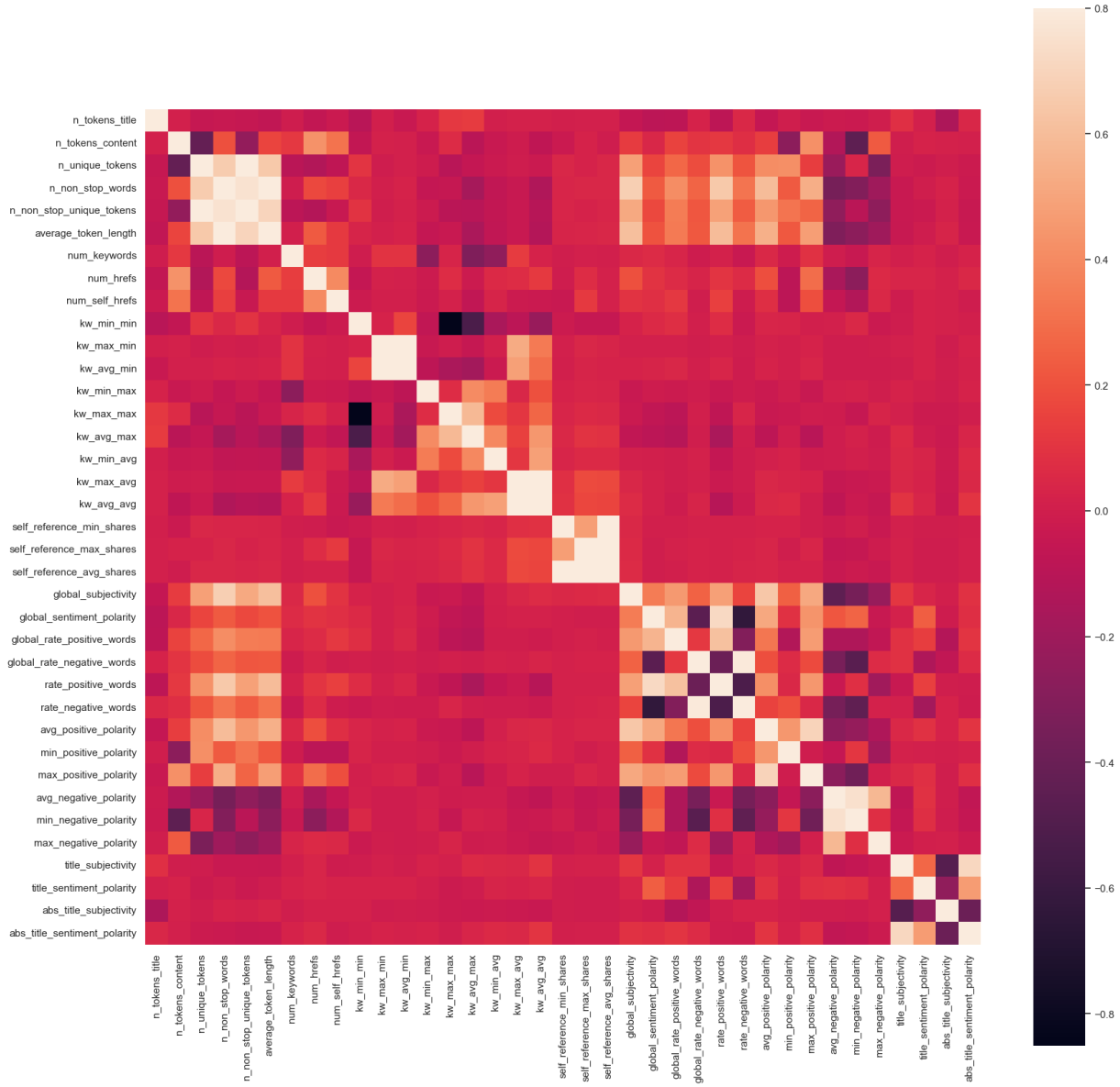
        <Axes: title={'center': 'self_reference_max_shares'}>,
        <Axes: title={'center': 'self_reference_avg_shares'}>,
        <Axes: title={'center': 'global_subjectivity'}>,
        <Axes: title={'center': 'global_sentiment_polarity'}>,
        <Axes: title={'center': 'global_rate_positive_words'}>],
       [<Axes: title={'center': 'global_rate_negative_words'}>,
        <Axes: title={'center': 'rate_positive_words'}>,
        <Axes: title={'center': 'rate_negative_words'}>,
        <Axes: title={'center': 'avg_positive_polarity'}>,
        <Axes: title={'center': 'min_positive_polarity'}>,
        <Axes: title={'center': 'max_positive_polarity'}>],
       [<Axes: title={'center': 'avg_negative_polarity'}>,
        <Axes: title={'center': 'min_negative_polarity'}>,
        <Axes: title={'center': 'max_negative_polarity'}>,
        <Axes: title={'center': 'title_subjectivity'}>,
        <Axes: title={'center': 'title_sentiment_polarity'}>,
        <Axes: title={'center': 'abs_title_subjectivity'}>],
       [<Axes: title={'center': 'abs_title_sentiment_polarity'}>,
        <Axes: >, <Axes: >, <Axes: >, <Axes: >, <Axes: >]], dtype=object)
```



Let's explore correlation between the variables.

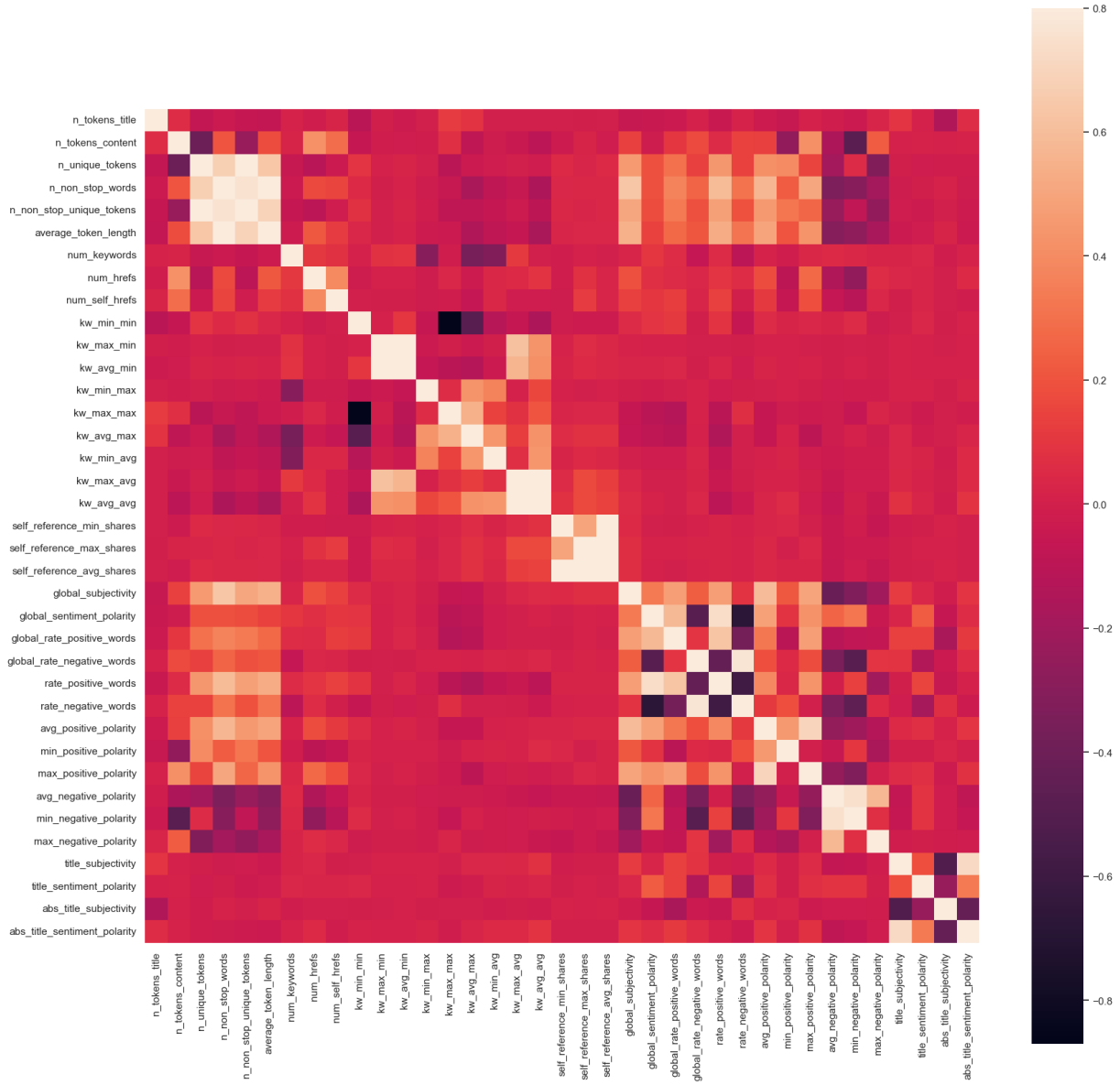
In [25]:
```
corr = popular_df[continuous_cols].corr()
fig = plt.figure(figsize = (20,20))
sns.heatmap(corr, vmax = .8, square = True)
plt.show()
```

Out[25]: <Axes: >



In [26]:
```
corr = unpopular_df[continuous_cols].corr()
fig = plt.figure(figsize = (20,20))
sns.heatmap(corr, vmax = .8, square = True)
plt.show()
```

Out[26]: <Axes: >



In [27]:

```
# Adapted from
# https://stackoverflow.com/questions/10369681/how-to-plot-bar-graphs-with-same-x-c

# 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'

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

Out[27]:
```
<Figure size 1200x500 with 0 Axes>
```

Out[27]:
```
<BarContainer object of 7 artists>
```

Out[27]:
```
<BarContainer object of 7 artists>
```

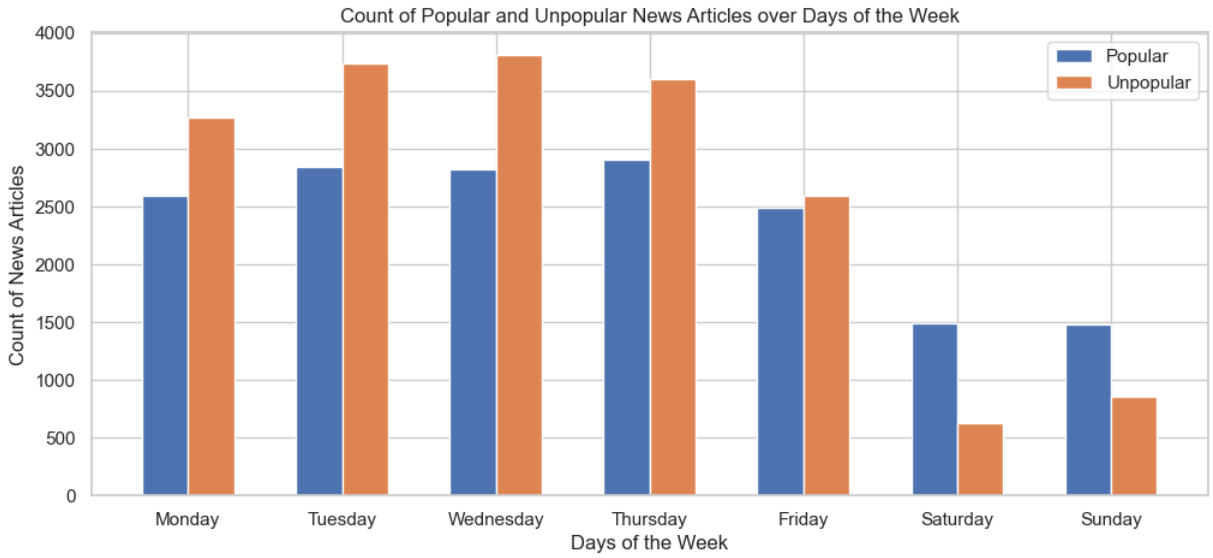
Out[27]:
```
Text(0.5, 0, 'Days of the Week')
```

Out[27]:
```
Text(0, 0.5, 'Count of News Articles')
```

Out[27]:
```
Text(0.5, 1.0, 'Count of Popular and Unpopular News Articles over Days of the Wee
k')
```

Out[27]:
```
([<matplotlib.axis.XTick at 0x1d952d316d0>,
  <matplotlib.axis.XTick at 0x1d952d31f10>,
  <matplotlib.axis.XTick at 0x1d952d37940>,
  <matplotlib.axis.XTick at 0x1d952dab5b0>,
  <matplotlib.axis.XTick at 0x1d952da0c40>,
  <matplotlib.axis.XTick at 0x1d952db2310>,
  <matplotlib.axis.XTick at 0x1d952db2af0>],
 [Text(0.15, 0, 'Monday'),
  Text(1.15, 0, 'Tuesday'),
  Text(2.15, 0, 'Wednesday'),
  Text(3.15, 0, 'Thursday'),
  Text(4.15, 0, 'Friday'),
  Text(5.15, 0, 'Saturday'),
  Text(6.15, 0, 'Sunday')])
```

Out[27]:
```
<matplotlib.legend.Legend at 0x1d952d8d1c0>
```



In [28]:

```
# Adapted from
# https://stackoverflow.com/questions/10369681/how-to-plot-bar-graphs-with-same-x-c

# 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'

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

Out[28]: <Figure size 1200x500 with 0 Axes>

Out[28]: <BarContainer object of 7 artists>

Out[28]: <BarContainer object of 7 artists>

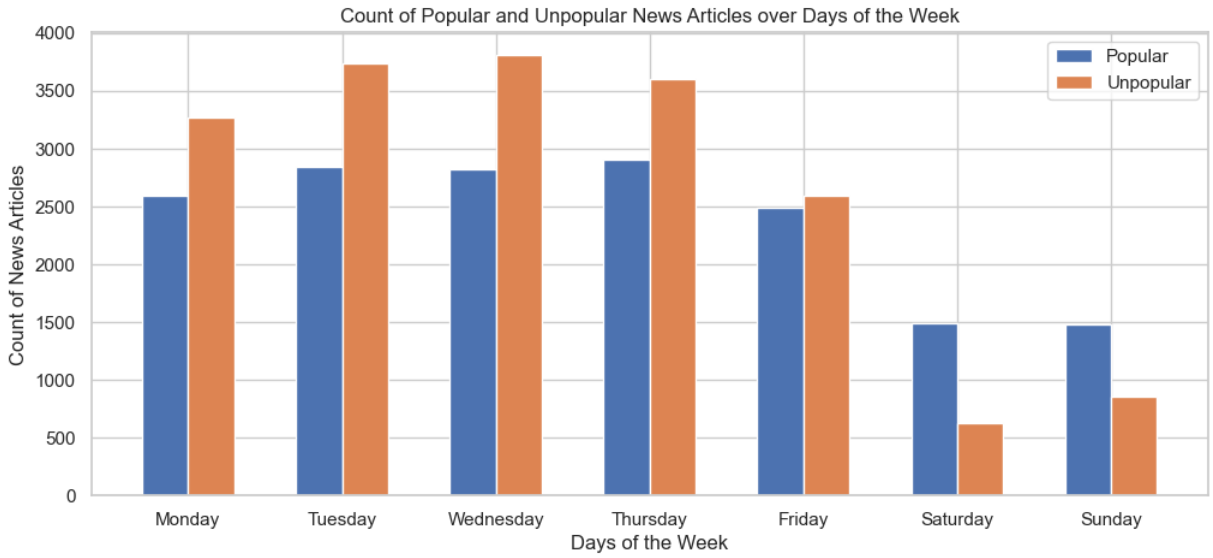
Out[28]: Text(0.5, 0, 'Days of the Week')

Out[28]: Text(0, 0.5, 'Count of News Articles')

Out[28]: Text(0.5, 1.0, 'Count of Popular and Unpopular News Articles over Days of the Week')

Out[28]:
```
([<matplotlib.axis.XTick at 0x1d953063730>,
  <matplotlib.axis.XTick at 0x1d953063700>,
  <matplotlib.axis.XTick at 0x1d953063310>,
  <matplotlib.axis.XTick at 0x1d952dea550>,
  <matplotlib.axis.XTick at 0x1d952e0af40>,
  <matplotlib.axis.XTick at 0x1d952e0f940>,
  <matplotlib.axis.XTick at 0x1d952e0f100>],
 [Text(0.15, 0, 'Monday'),
  Text(1.15, 0, 'Tuesday'),
  Text(2.15, 0, 'Wednesday'),
  Text(3.15, 0, 'Thursday'),
  Text(4.15, 0, 'Friday'),
  Text(5.15, 0, 'Saturday'),
  Text(6.15, 0, 'Sunday')])
```

Out[28]: <matplotlib.legend.Legend at 0x1d95306aeb0>



In [29]:
```
# Adapted from
# https://stackoverflow.com/questions/10369681/how-to-plot-bar-graphs-with-same-x-c

# 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 Medi

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

Out[29]:
```
<Figure size 1200x500 with 0 Axes>
```

Out[29]:
```
<BarContainer object of 6 artists>
```

Out[29]:
```
<BarContainer object of 6 artists>
```

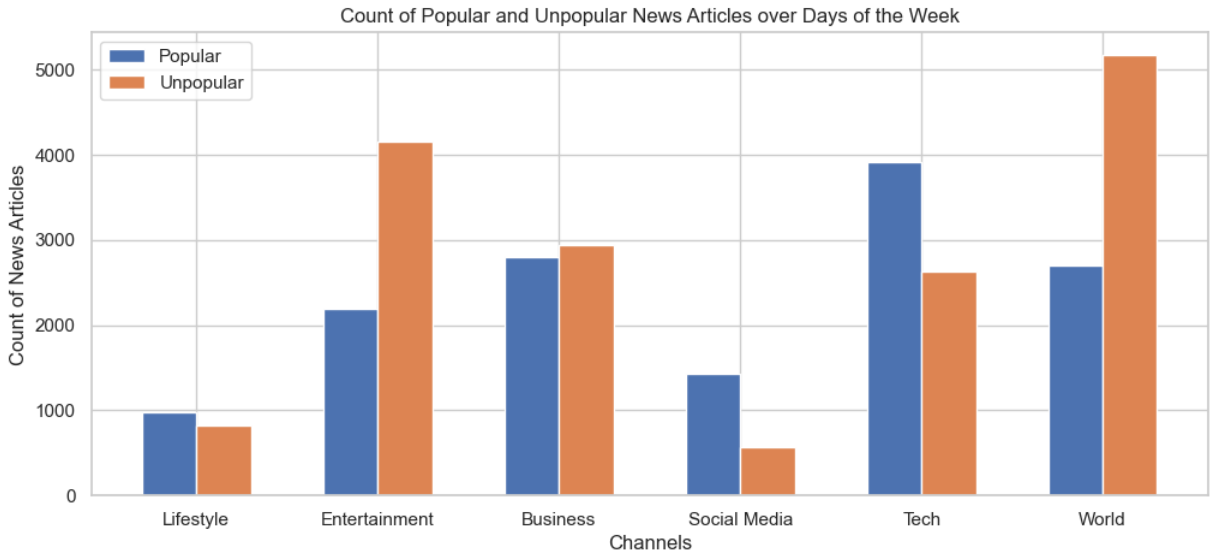
Out[29]:
```
Text(0.5, 0, 'Channels')
```

Out[29]:
```
Text(0, 0.5, 'Count of News Articles')
```

Out[29]:
```
Text(0.5, 1.0, 'Count of Popular and Unpopular News Articles over Days of the Wee
k')
```

Out[29]:
```
([<matplotlib.axis.XTick at 0x1d952e5e160>,
  <matplotlib.axis.XTick at 0x1d952e5e130>,
  <matplotlib.axis.XTick at 0x1d952db9190>,
  <matplotlib.axis.XTick at 0x1d952e47a60>,
  <matplotlib.axis.XTick at 0x1d952ea7ca0>,
  <matplotlib.axis.XTick at 0x1d952ea74c0>],
 [Text(0.15, 0, 'Lifestyle'),
  Text(1.15, 0, 'Entertainment'),
  Text(2.15, 0, 'Business'),
  Text(3.15, 0, 'Social Media'),
  Text(4.15, 0, 'Tech'),
  Text(5.15, 0, 'World')])
```

Out[29]:
```
<matplotlib.legend.Legend at 0x1d952dd9760>
```



In [30]:

```
# Adapted from
# https://stackoverflow.com/questions/10369681/how-to-plot-bar-graphs-with-same-x-c

# 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()
```

Out[30]: <Figure size 1200x500 with 0 Axes>

Out[30]: <BarContainer object of 5 artists>

Out[30]: <BarContainer object of 5 artists>

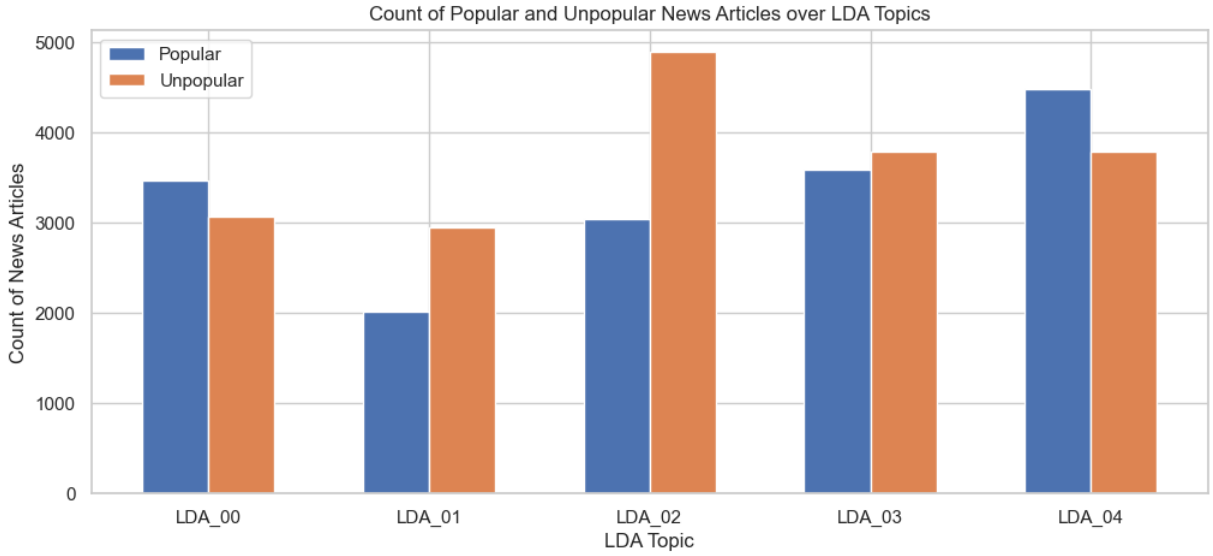
Out[30]: Text(0.5, 0, 'LDA Topic')

Out[30]: Text(0, 0.5, 'Count of News Articles')

Out[30]: Text(0.5, 1.0, 'Count of Popular and Unpopular News Articles over LDA Topics')

Out[30]:
```
([<matplotlib.axis.XTick at 0x1d952ee31c0>,
  <matplotlib.axis.XTick at 0x1d952ee3190>,
  <matplotlib.axis.XTick at 0x1d952e30370>,
  <matplotlib.axis.XTick at 0x1d952f26880>,
  <matplotlib.axis.XTick at 0x1d952f26970>],
 [Text(0.15, 0, 'LDA_00'),
  Text(1.15, 0, 'LDA_01'),
  Text(2.15, 0, 'LDA_02'),
  Text(3.15, 0, 'LDA_03'),
  Text(4.15, 0, 'LDA_04')])
```

Out[30]: <matplotlib.legend.Legend at 0x1d952ee3310>



In [31]:
```
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
1.872477551391861e-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
0.0003501111655936487 - 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
```

In [32]:

```python
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
```

In [33]:
```
final_df = df.drop(columns=['shares'])
```

MODELING

Let's split the data.

In [34]:
```
X = final_df.loc[:, final_df.columns != 'target']
y = final_df.loc[:, final_df.columns == 'target']
```

In [35]:
```
# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
```

Logistics Regression Models

In [36]:
```
logreg0 = LogisticRegression()
logreg0.fit(X_train, y_train)
```

Out[36]:

▾ LogisticRegression

LogisticRegression()

In [37]:
```
print('Accuracy of logistic regression on train set: {:.2f}'.format(logreg0.score(X
print('Accuracy of logistic regression on test set: {:.2f}'.format(logreg0.score(X_
```

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

In [38]:
```
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
```

In [39]:
```
# parameter grid
parameters = {
    'penalty' : ['l1','l2'],
    'C'       : np.logspace(-3,3,7),
    'solver'  : ['newton-cg', 'lbfgs', 'liblinear'],
}
```

In [40]:
```
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)
```

Out[40]:

▸ **GridSearchCV**

▸ **estimator: LogisticRegression**

▸ LogisticRegression

In [41]:
```
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 : 0.6560724692539176
```

In [42]:
```
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(logr
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(logre
```

Out[42]:

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
```

In [43]:
```
y_pred = logreg2.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.65      0.79      0.72      5952
           1       0.63      0.46      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
```

In [44]:
```
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")
```

Out[44]: <Figure size 640x480 with 0 Axes>

Out[44]: [<matplotlib.lines.Line2D at 0x1d9534f8b20>]

Out[44]: [<matplotlib.lines.Line2D at 0x1d9534f8e50>]

Out[44]: (0.0, 1.0)

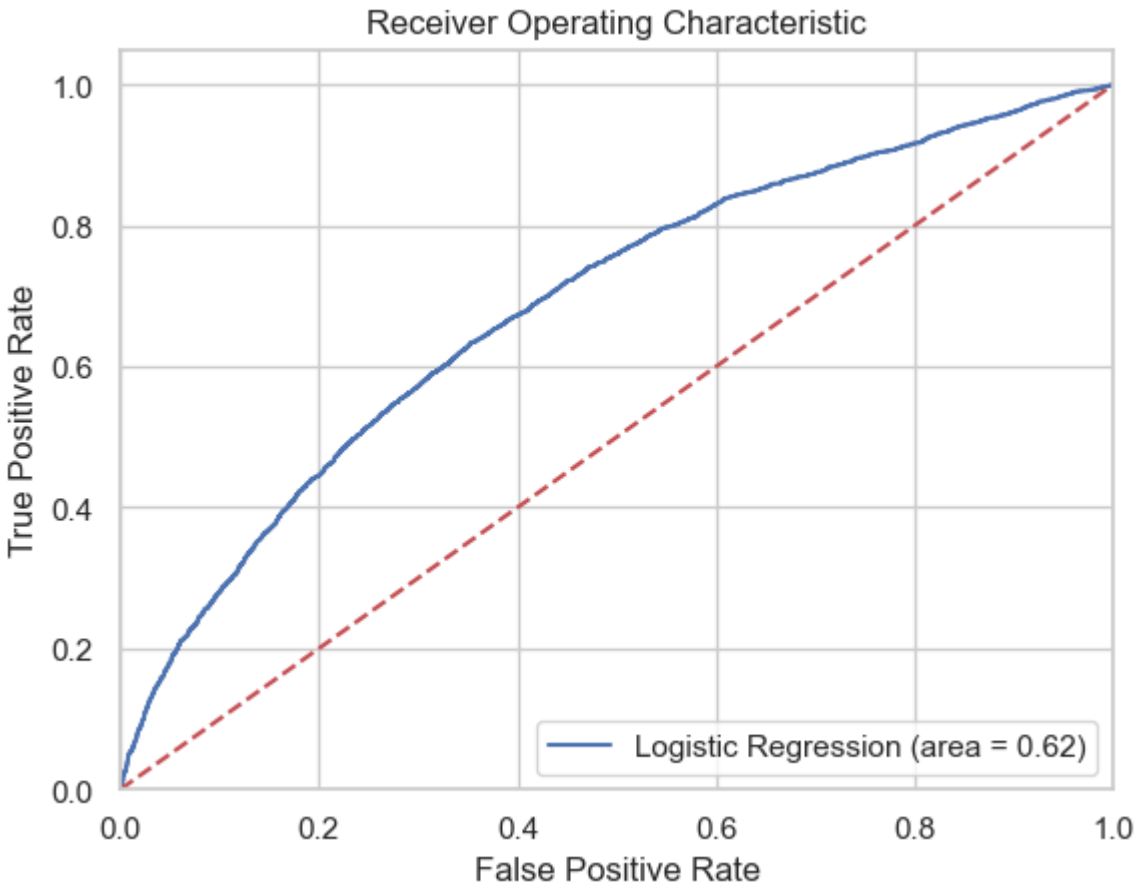
Out[44]: (0.0, 1.05)

Out[44]: Text(0.5, 0, 'False Positive Rate')

Out[44]: Text(0, 0.5, 'True Positive Rate')

Out[44]: Text(0.5, 1.0, 'Receiver Operating Characteristic')

Out[44]: <matplotlib.legend.Legend at 0x1d953098460>



Xgboost Models

In [45]:
```
# initial XGBOOST model
xgb0 = XGBClassifier(tree_method = 'gpu_hist')
xgb0.fit(X_train, y_train)
```

Out[45]:
```
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_typ
e=None,
              interaction_constraints=None, learning_rate=None, max_bin
=None,
```

In [46]:
```
print('Accuracy of xgboost classifier on train set: {:.2f}'.format(xgb0.score(X_tra
print('Accuracy of xgboost classifier classifier on test set: {:.2f}'.format(xgb0.s
```

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

In [47]:
```
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
```

In [48]:
```
pipe = Pipeline([
  ('fs', SelectKBest()),
  ('clf', xgb.XGBClassifier(objective='binary:logistic'))
])
```

In [49]:
```
# 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],
  }
]
```

In [50]:
```
# Define cross validation
kfold = KFold(n_splits=10)
# AUC and accuracy as score
scoring = {'AUC':'roc_auc', 'Accuracy':make_scorer(accuracy_score)}
```

In [51]:
```
# 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
```

In [52]:
```
print('Accuracy of xgboost classifier on train set: {:.2f}'.format(xgb1.score(X_tra
print('Accuracy of xgboost regression classifier on test set: {:.2f}'.format(xgb1.s
```

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

In [53]:
```
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
```

In [54]:
```
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 0x000001D94388B040>}
```

In [55]:
```
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)
```

Out[55]:

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=N
one,
              interaction_constraints=None, learning_rate=0.1, max_bin=
None,
```

In [56]:
```
print('Accuracy of xgboost classifier on train set: {:.2f}'.format(xgb2.score(X_tra
print('Accuracy of xgboost classifier classifier on test set: {:.2f}'.format(xgb2.s
```

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

In [57]:
```
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

In [58]:
```
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")
```

Out[58]:
```
<Figure size 640x480 with 0 Axes>
```

Out[58]:
```
[<matplotlib.lines.Line2D at 0x1d9541fd400>]
```

Out[58]:
```
[<matplotlib.lines.Line2D at 0x1d9541fd7f0>]
```

Out[58]:
```
(0.0, 1.0)
```

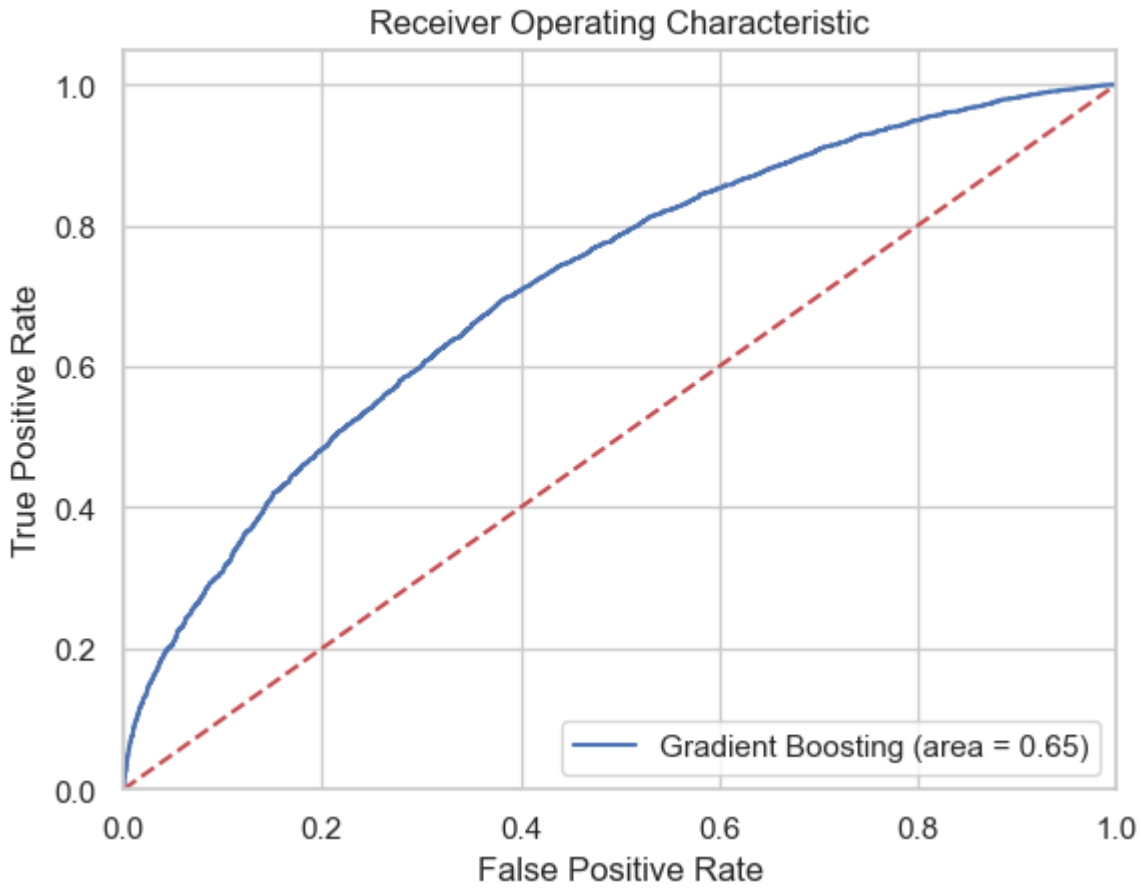
Out[58]:
```
(0.0, 1.05)
```

Out[58]:
```
Text(0.5, 0, 'False Positive Rate')
```

Out[58]:
```
Text(0, 0.5, 'True Positive Rate')
```

Out[58]:
```
Text(0.5, 1.0, 'Receiver Operating Characteristic')
```

Out[58]:
```
<matplotlib.legend.Legend at 0x1d9541a6550>
```



In [59]:
```
#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")
```

Out[59]: [<matplotlib.lines.Line2D at 0x1d900054be0>]

Out[59]: [<matplotlib.lines.Line2D at 0x1d900054f70>]

Out[59]: [<matplotlib.lines.Line2D at 0x1d900064280>]

Out[59]: (0.0, 1.0)

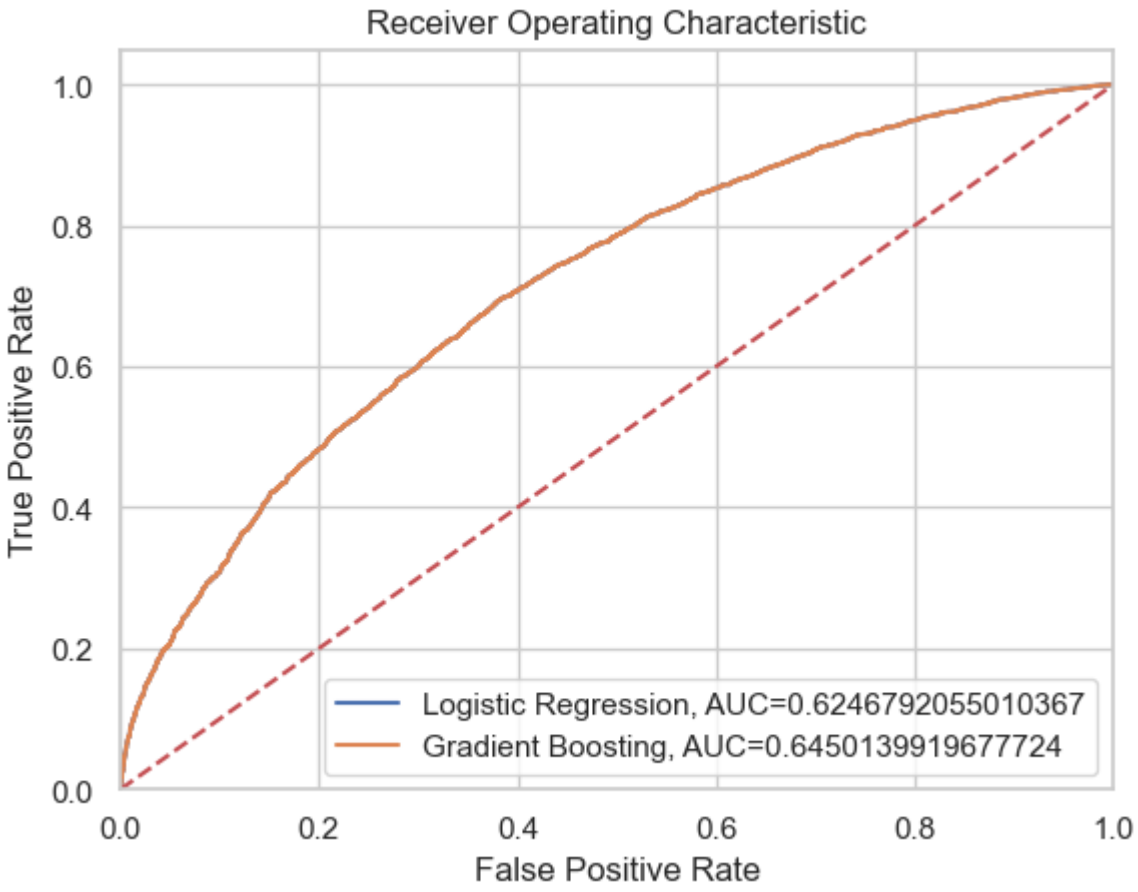
Out[59]: (0.0, 1.05)

Out[59]: Text(0.5, 0, 'False Positive Rate')

Out[59]: Text(0, 0.5, 'True Positive Rate')

Out[59]: Text(0.5, 1.0, 'Receiver Operating Characteristic')

Out[59]: <matplotlib.legend.Legend at 0x1d900054dc0>

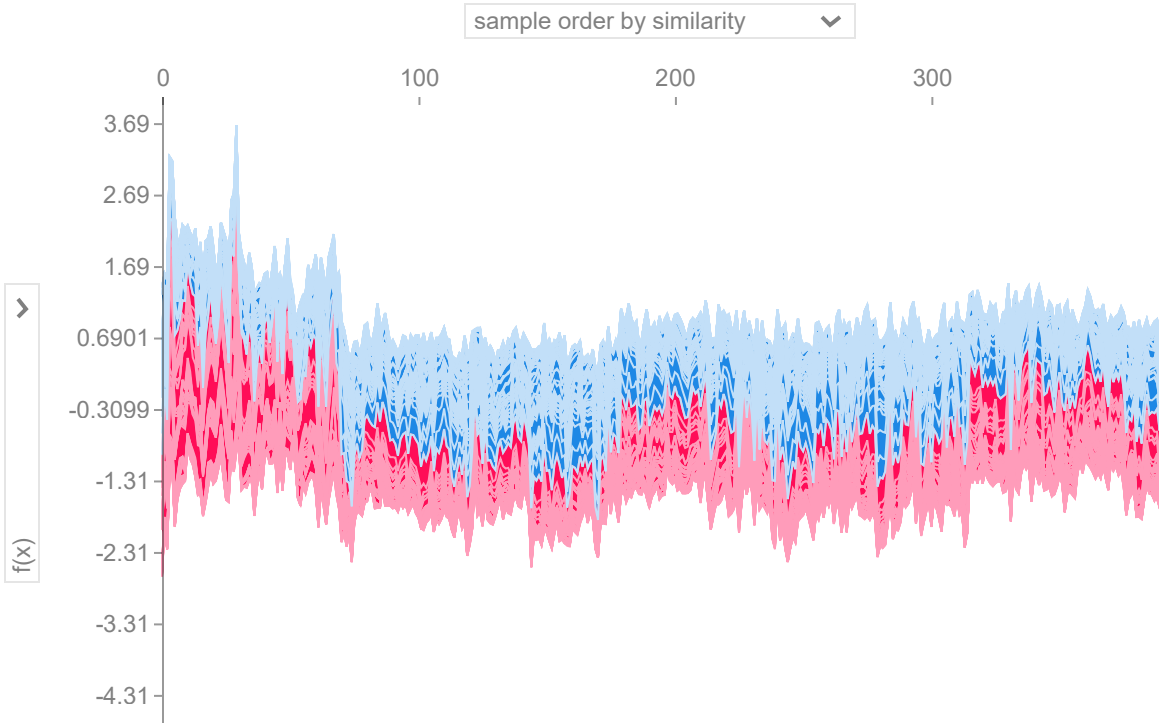


Feature Importance

In [60]:
```
explainer = shap.TreeExplainer(xgb2)
shap_values = explainer.shap_values(X)
```

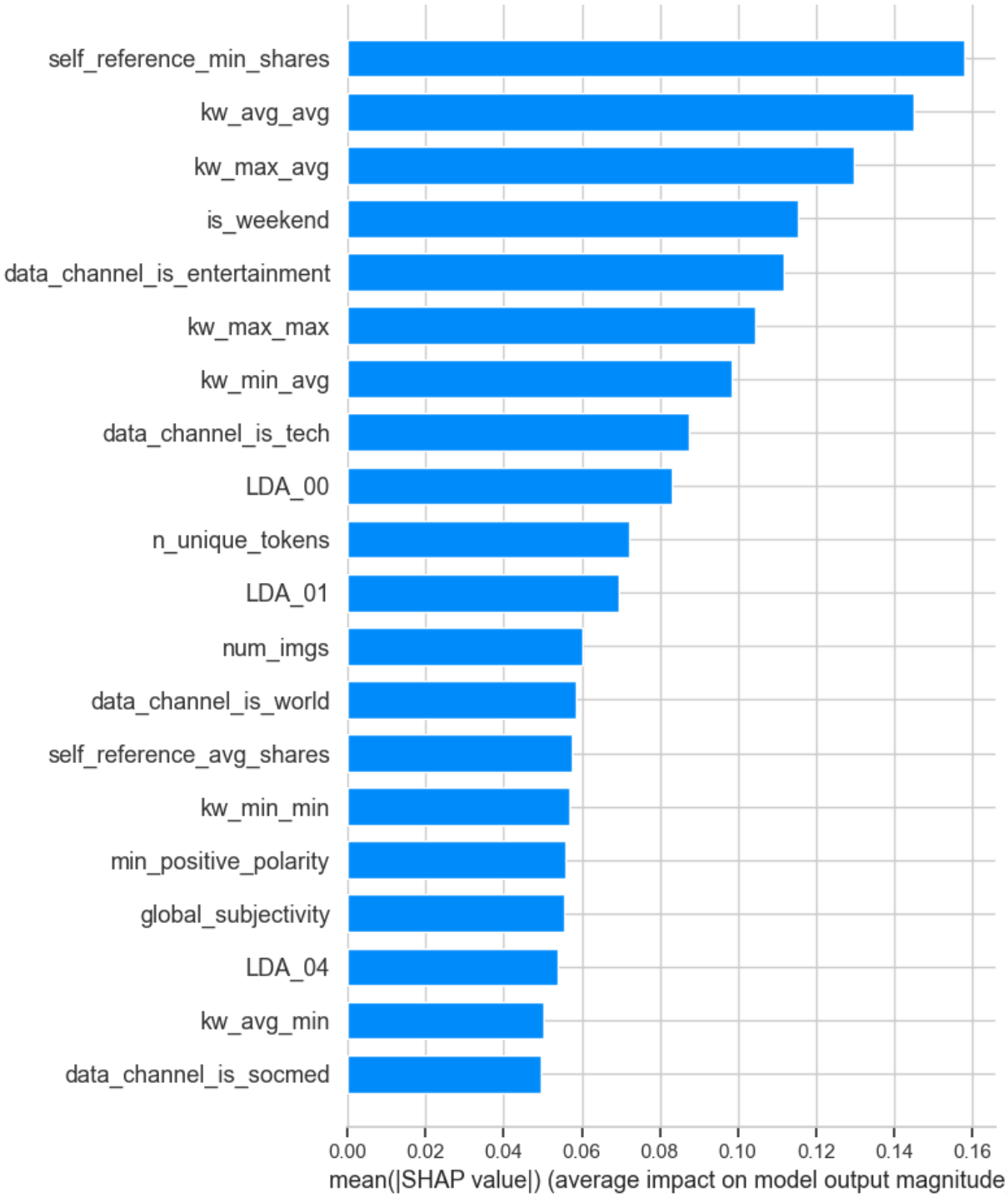
In [61]:
```
shap.force_plot(explainer.expected_value, shap_values[:1000,:], X_train.iloc[:1000,
```

Out[61]:

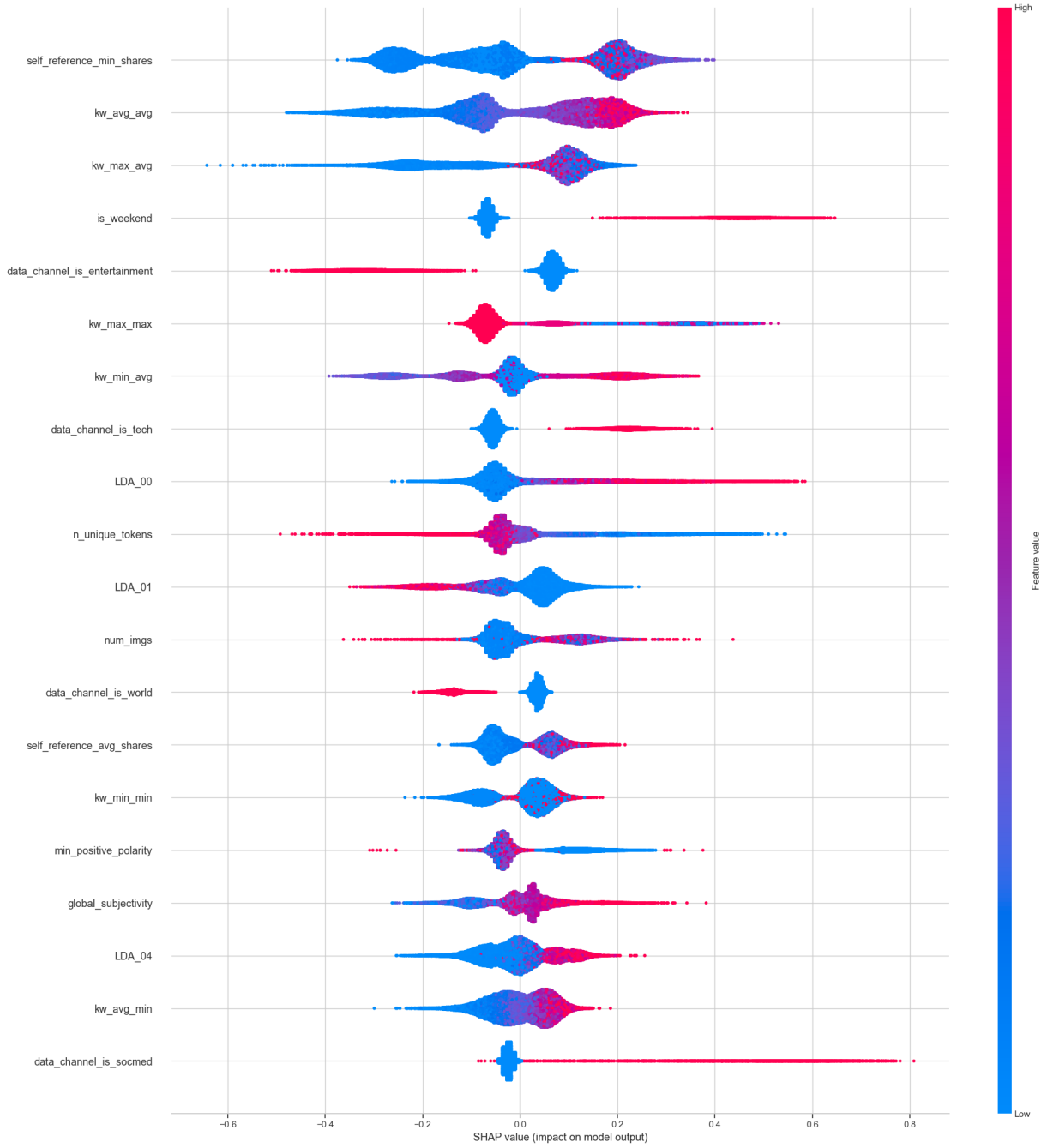


In [62]:
```
plt.figure(figsize = (20,20))
shap.summary_plot(shap_values, X_train, plot_type="bar",)
```

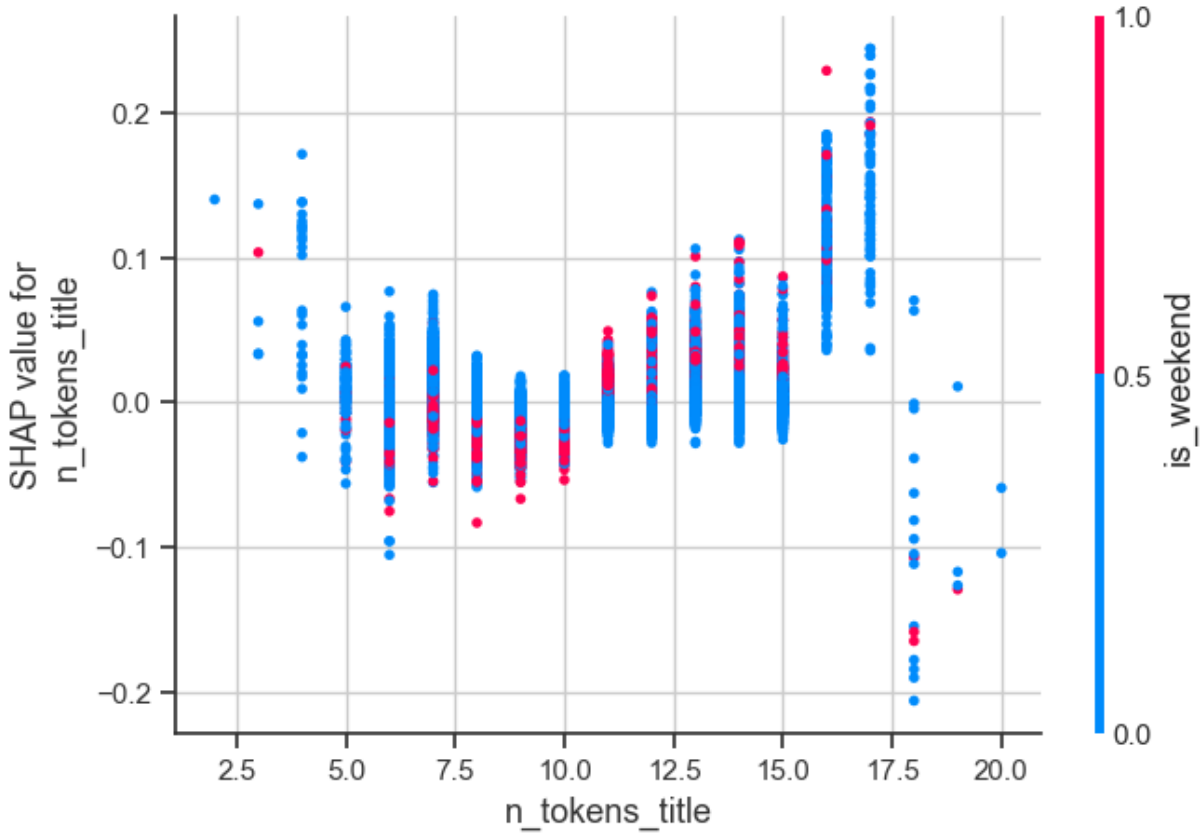
Out[62]:
```
<Figure size 2000x2000 with 0 Axes>
```

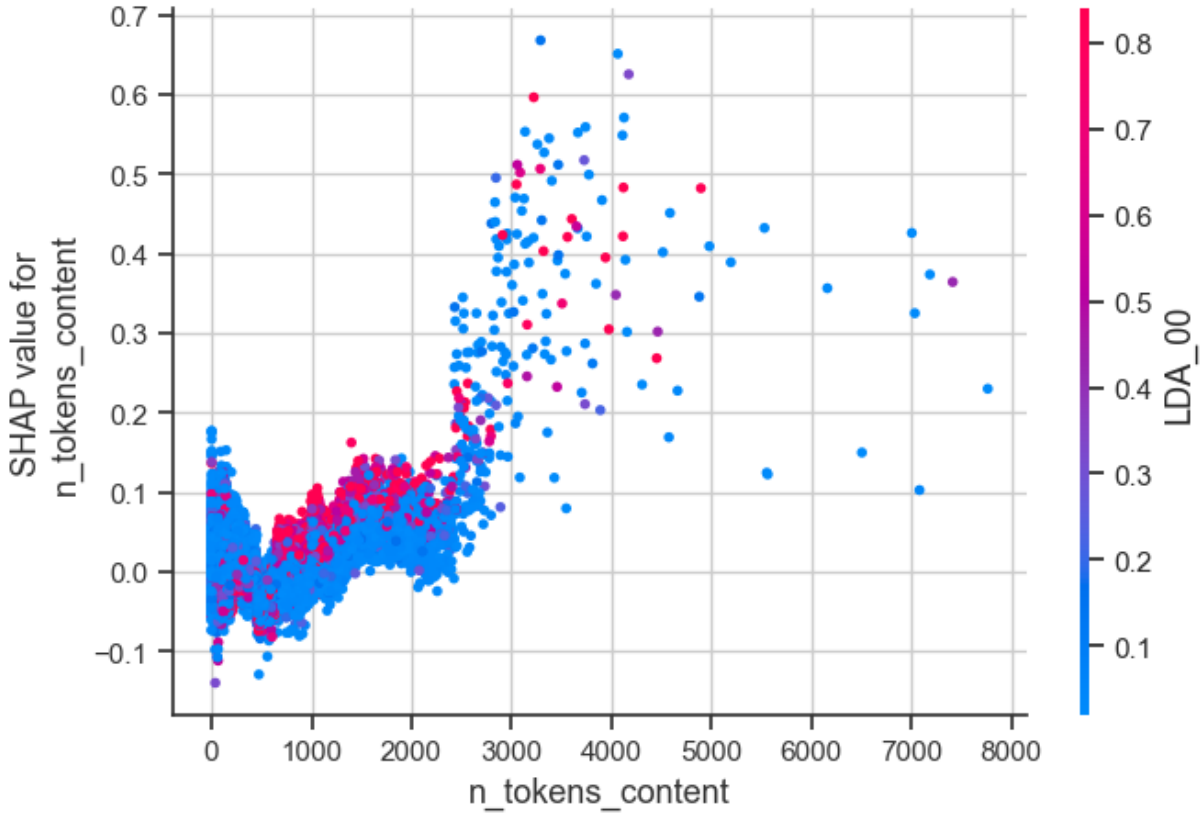


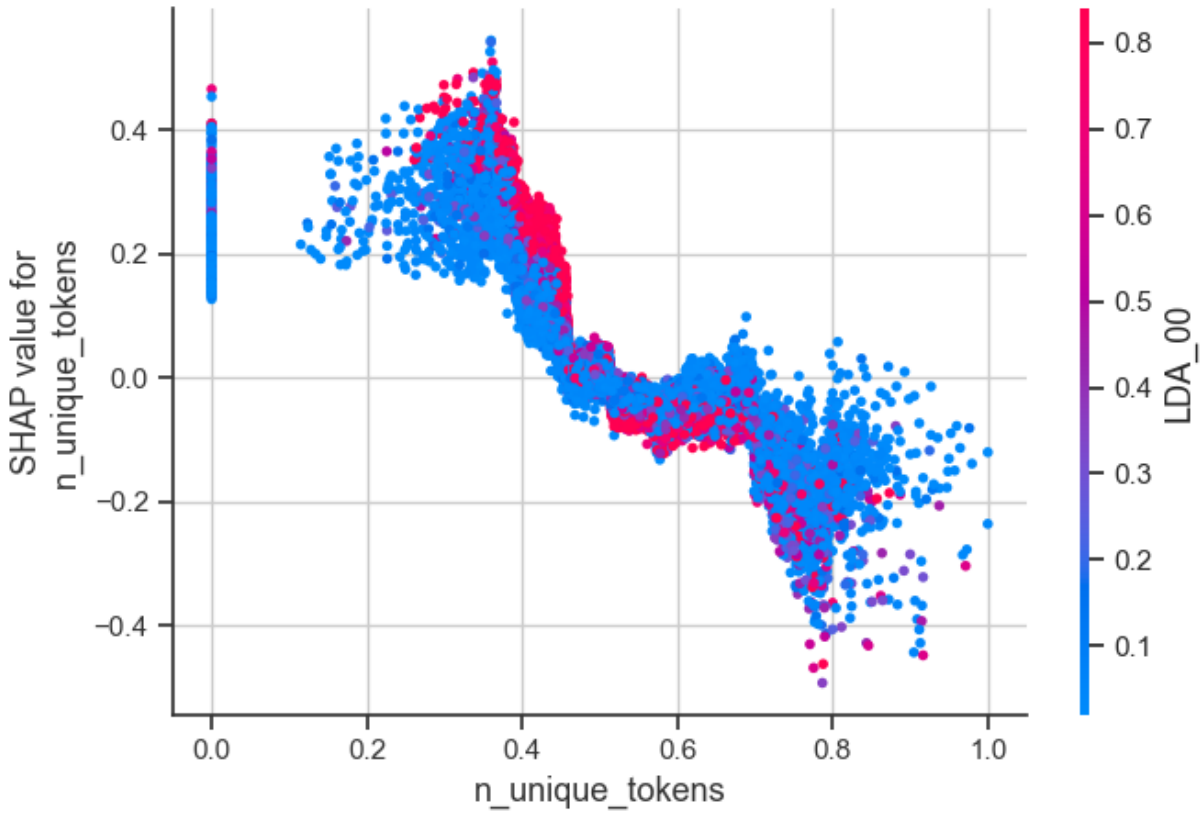
In [63]:
```
shap.summary_plot(shap_values, X, plot_size=(20,20))
```

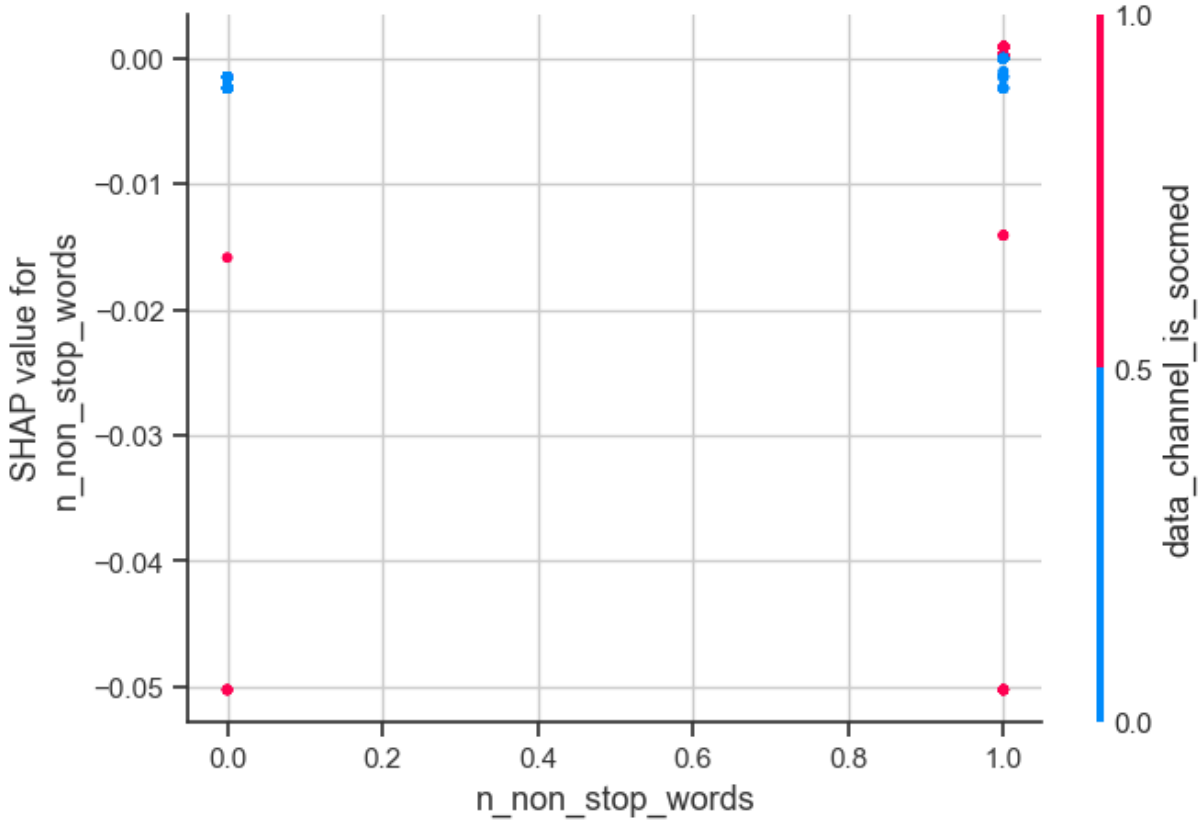


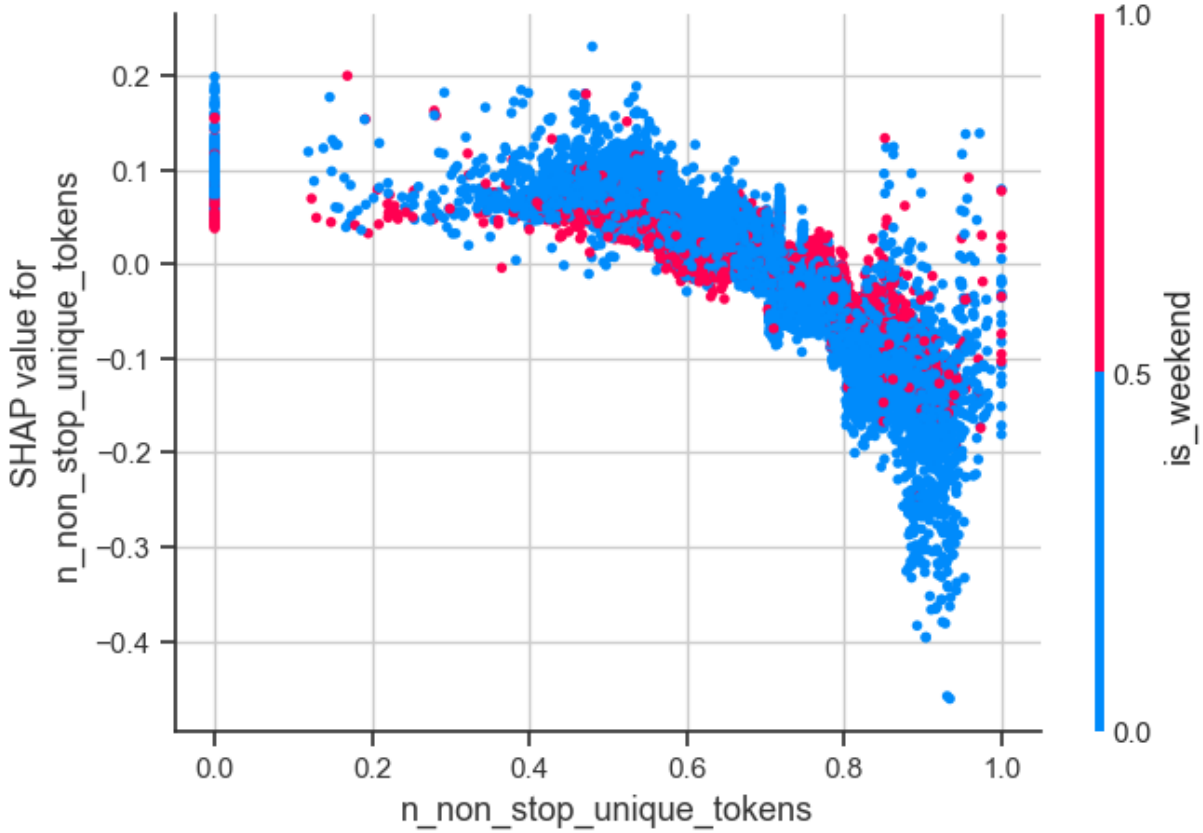
In [64]:
```
for col in X_train.columns:
    shap.dependence_plot(col, shap_values, X)
```

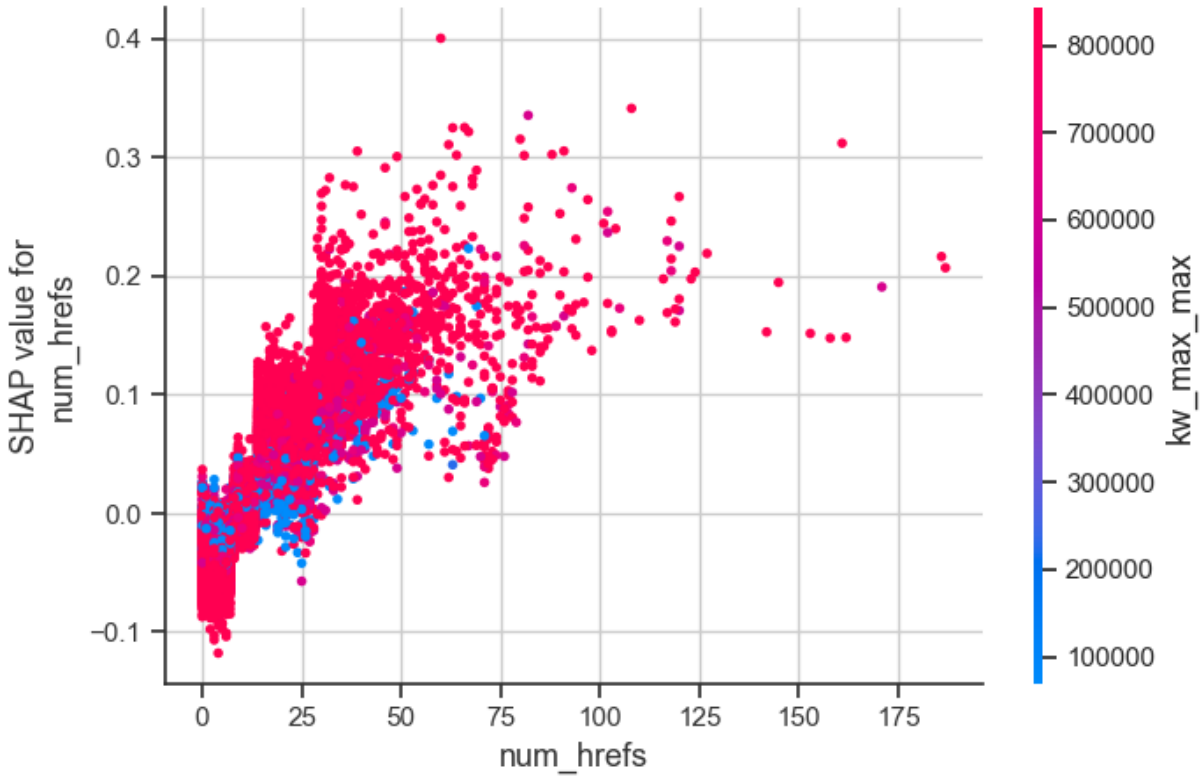

SHAP value for
n_tokens_title
0.2
0.1
0.0
−0.1
−0.2
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
n_tokens_title
1.0
0.5
0.0
is_weekend

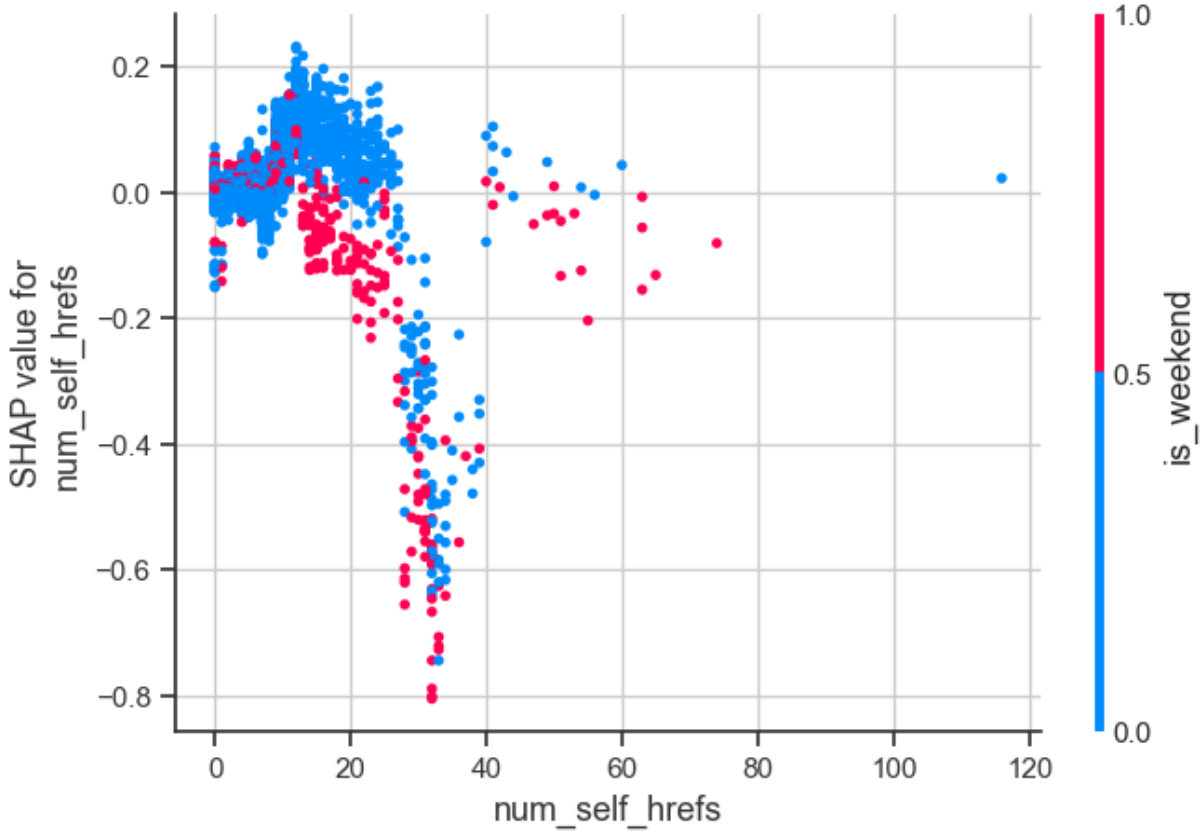

SHAP value for
n_tokens_content
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
−0.1
0
1000
2000
3000
4000
5000
6000
7000
8000
n_tokens_content
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
LDA_00

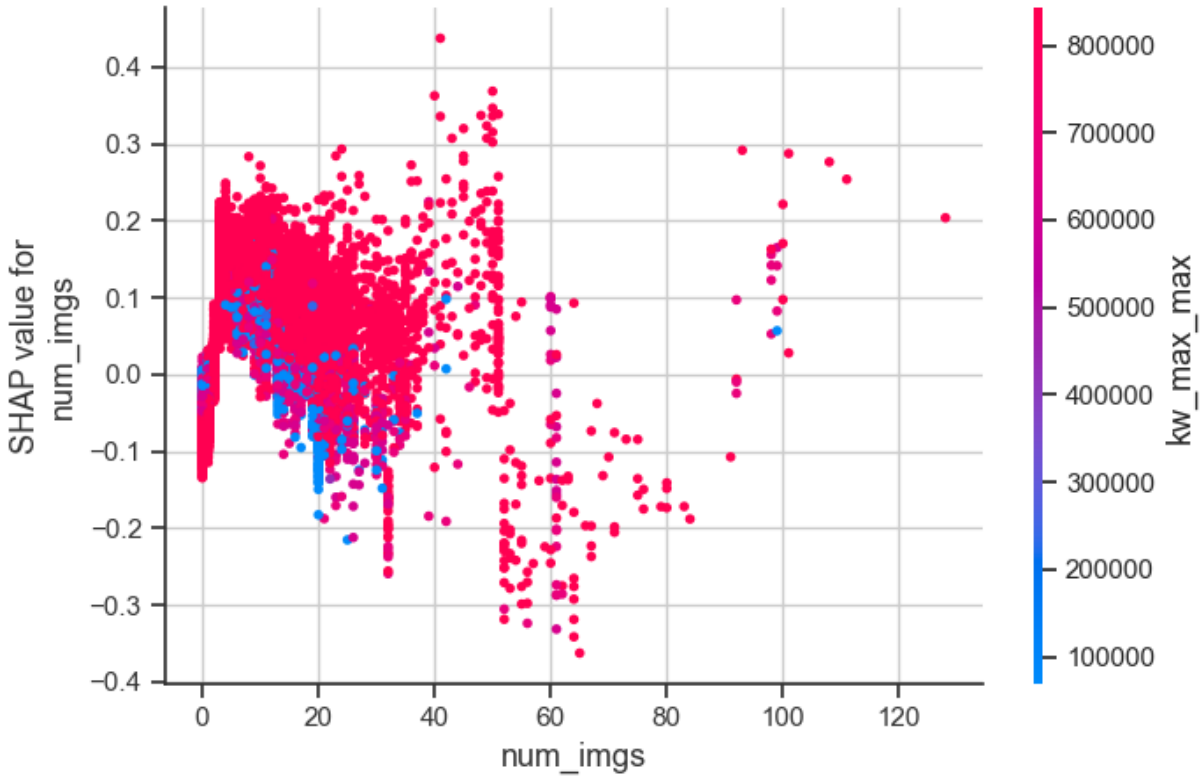

SHAP value for
n_unique_tokens
0.4
0.2
0.0
−0.2
−0.4
0.0
0.2
0.4
0.6
0.8
1.0
n_unique_tokens
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
LDA_00

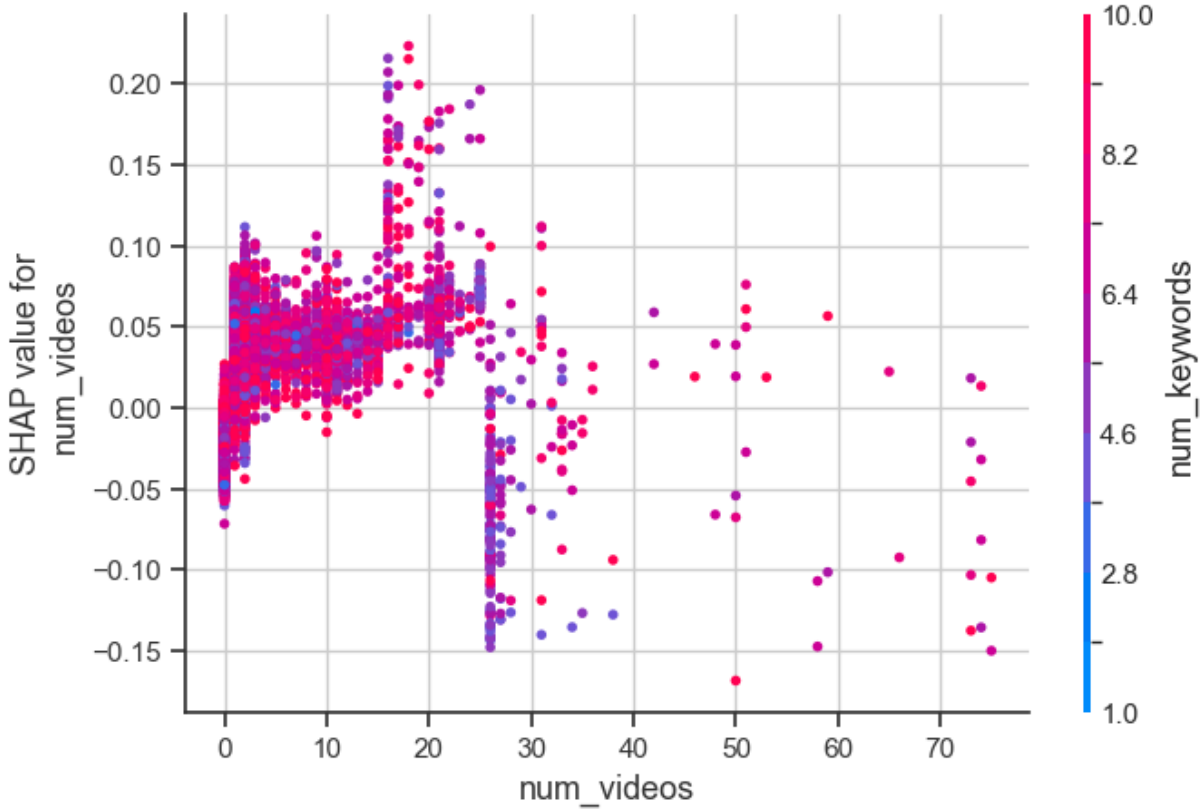

SHAP value for
n_non_stop_words
0.00
−0.01
−0.02
−0.03
−0.04
−0.05
0.0
0.2
0.4
0.6
0.8
1.0
n_non_stop_words
1.0
0.5
0.0
data_channel_is_socmed

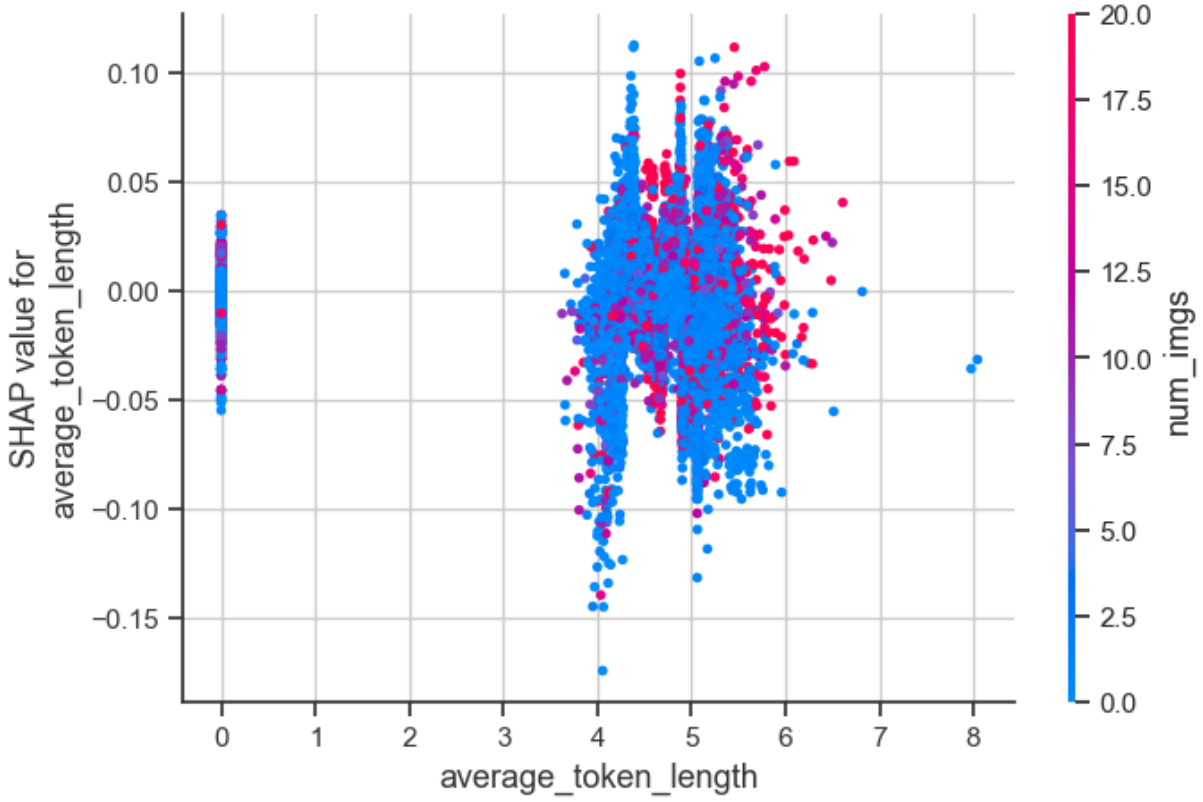

SHAP value for
n_non_stop_unique_tokens
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
0.0
0.2
0.4
0.6
0.8
1.0
n_non_stop_unique_tokens
1.0
0.5
0.0
is_weekend

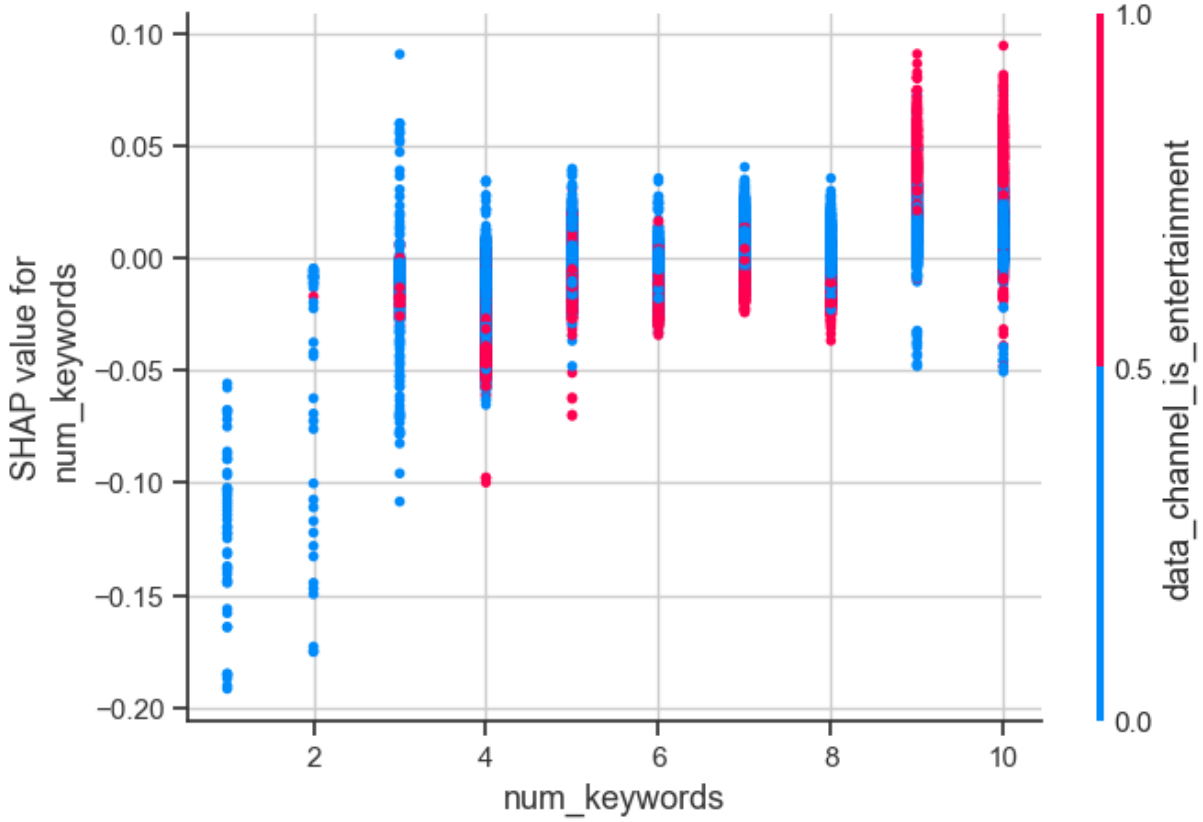

SHAP value for
num_hrefs
0.4
0.3
0.2
0.1
0.0
−0.1
0
25
50
75
100
125
150
175
num_hrefs
800000
700000
600000
500000
400000
300000
200000
100000
kw_max_max

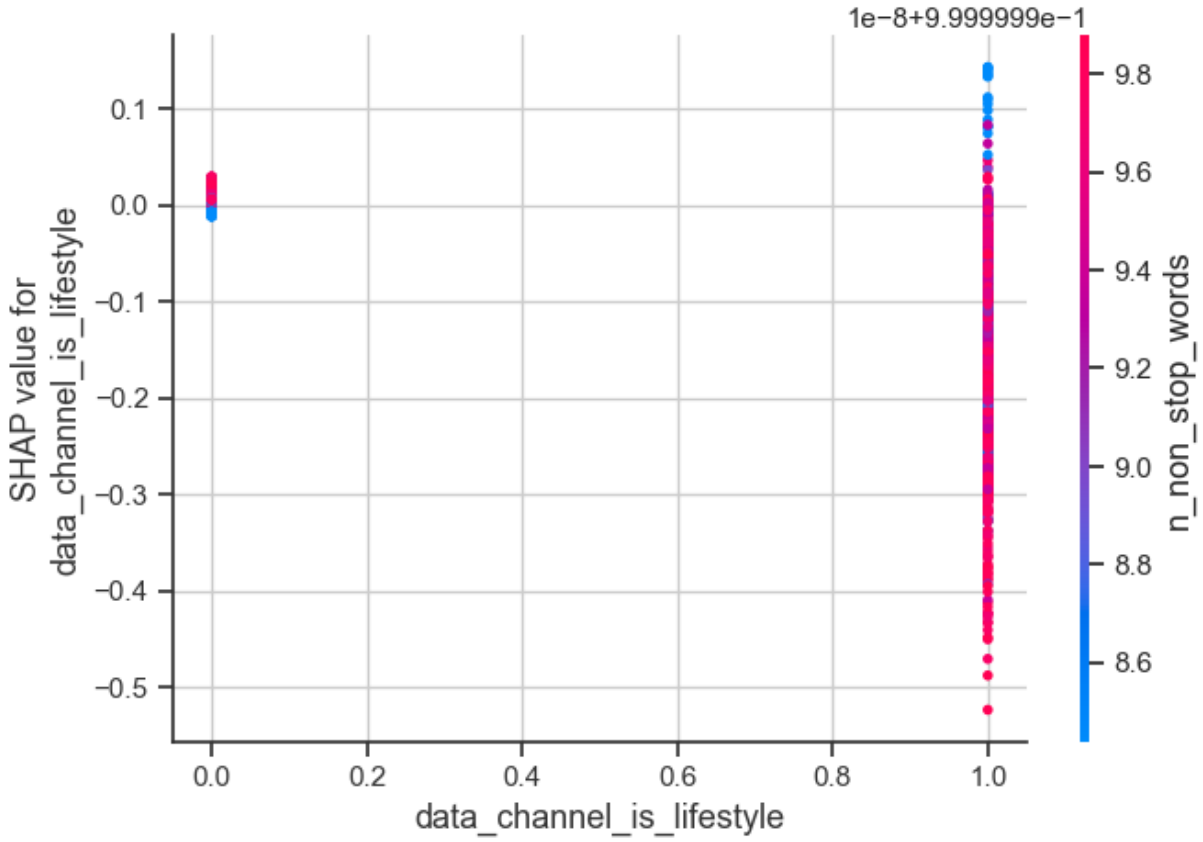

SHAP value for num_self_hrefs
0.2
0.0
−0.2
−0.4
−0.6
−0.8
0
20
40
60
80
100
120
num_self_hrefs
1.0
0.5
0.0
is_weekend

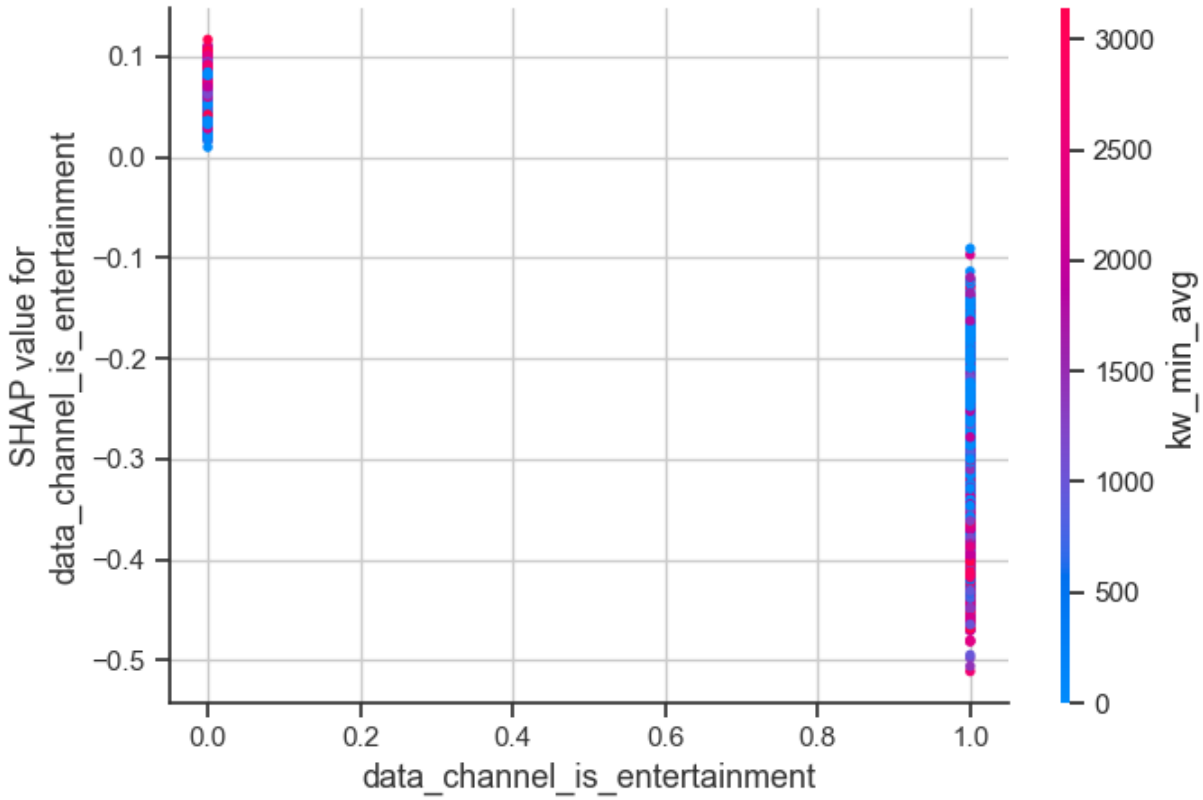

SHAP value for num_imgs
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
0
20
40
60
80
100
120
num_imgs
800000
700000
600000
500000
400000
300000
200000
100000
kw_max_max

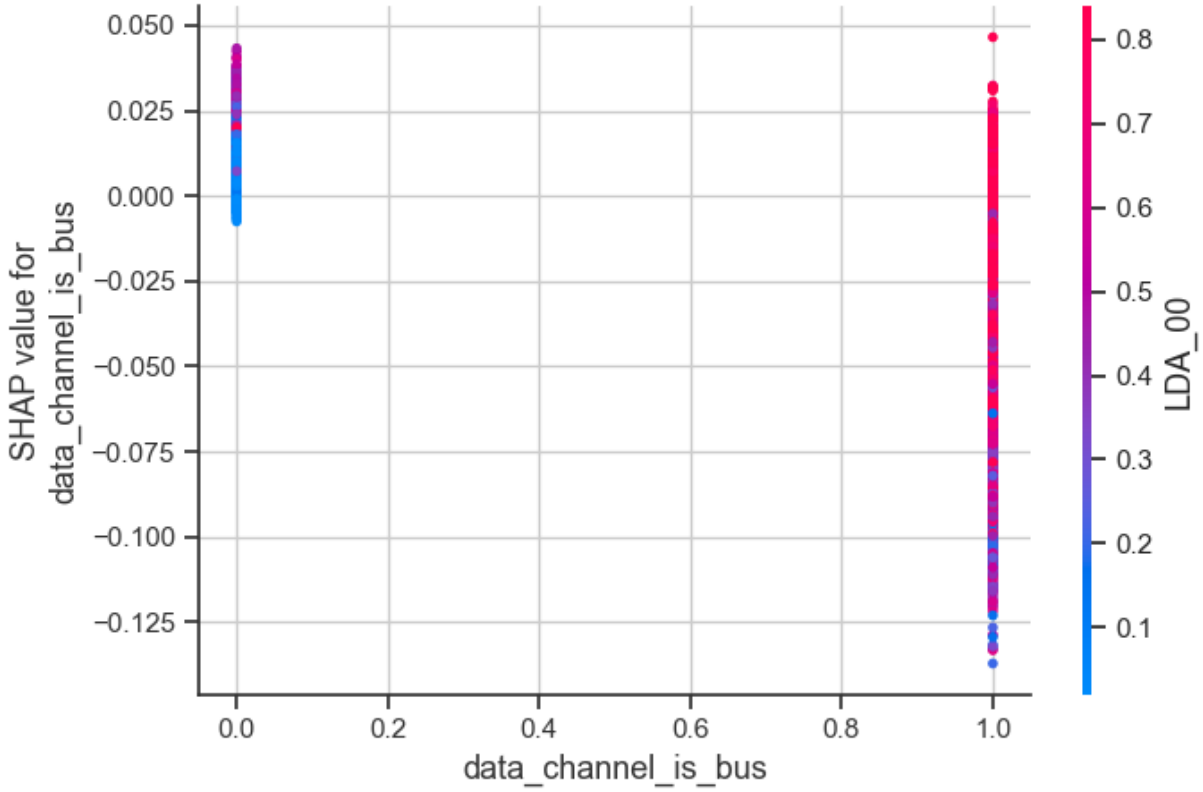

SHAP value for
num_videos
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
0
10
20
30
40
50
60
70
num_videos
num_keywords
10.0
8.2
6.4
4.6
2.8
1.0

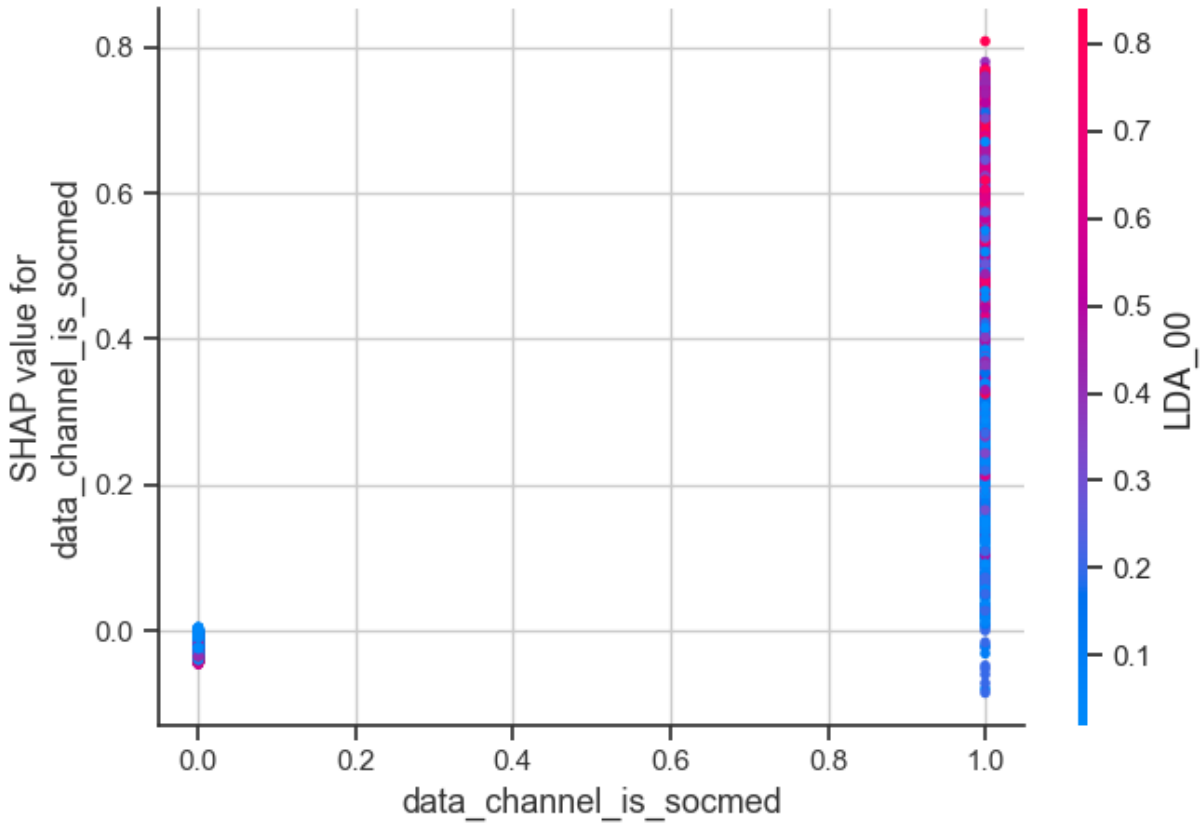

SHAP value for
average_token_length
0.10
0.05
0.00
−0.05
−0.10
−0.15
0
1
2
3
4
5
6
7
8
average_token_length
num_imgs
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0

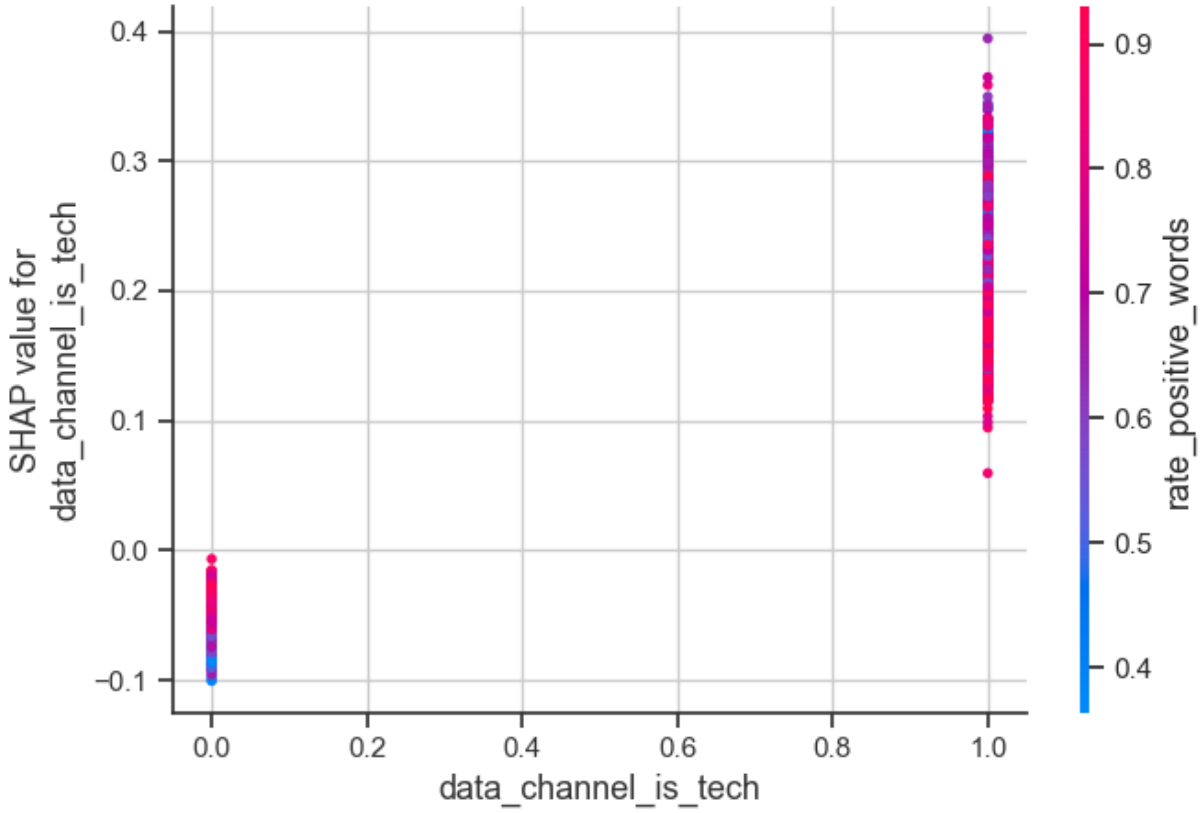

SHAP value for
num_keywords
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
2
4
6
8
10
num_keywords
1.0
0.5
0.0
data_channel_is_entertainment

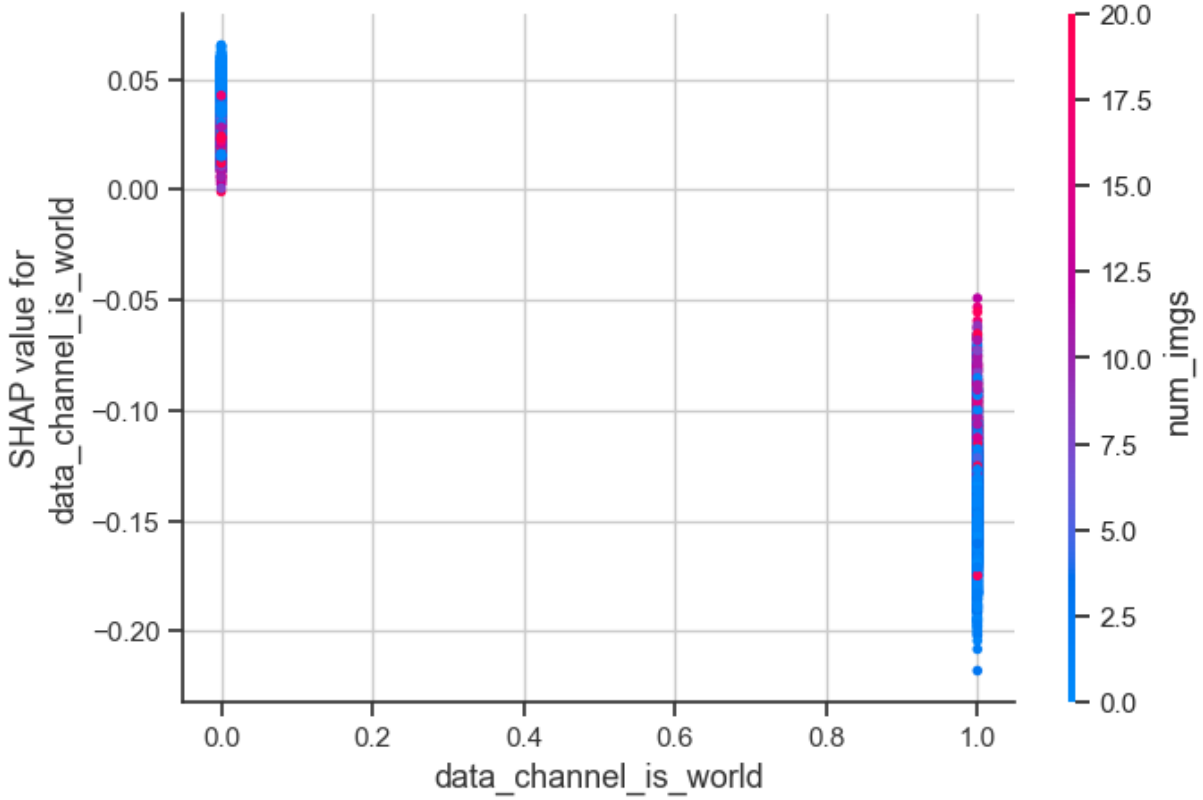

1e−8+9.999999e−1
SHAP value for
data_channel_is_lifestyle
0.1
0.0
−0.1
−0.2
−0.3
−0.4
−0.5
0.0
0.2
0.4
0.6
0.8
1.0
data_channel_is_lifestyle
9.8
9.6
9.4
9.2
9.0
8.8
8.6
n_non_stop_words

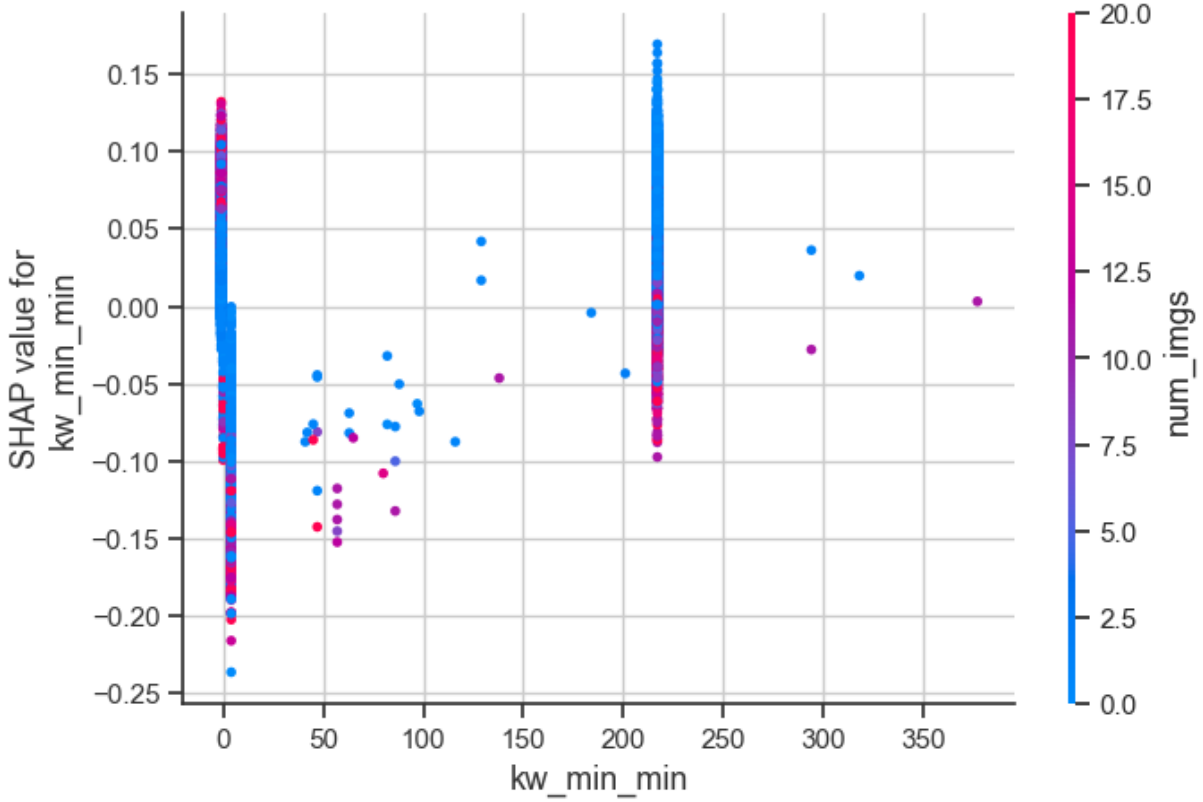

SHAP value for
data_channel_is_entertainment
0.1
0.0
−0.1
−0.2
−0.3
−0.4
−0.5
0.0
0.2
0.4
0.6
0.8
1.0
data_channel_is_entertainment
kw_min_avg
3000
2500
2000
1500
1000
500
0

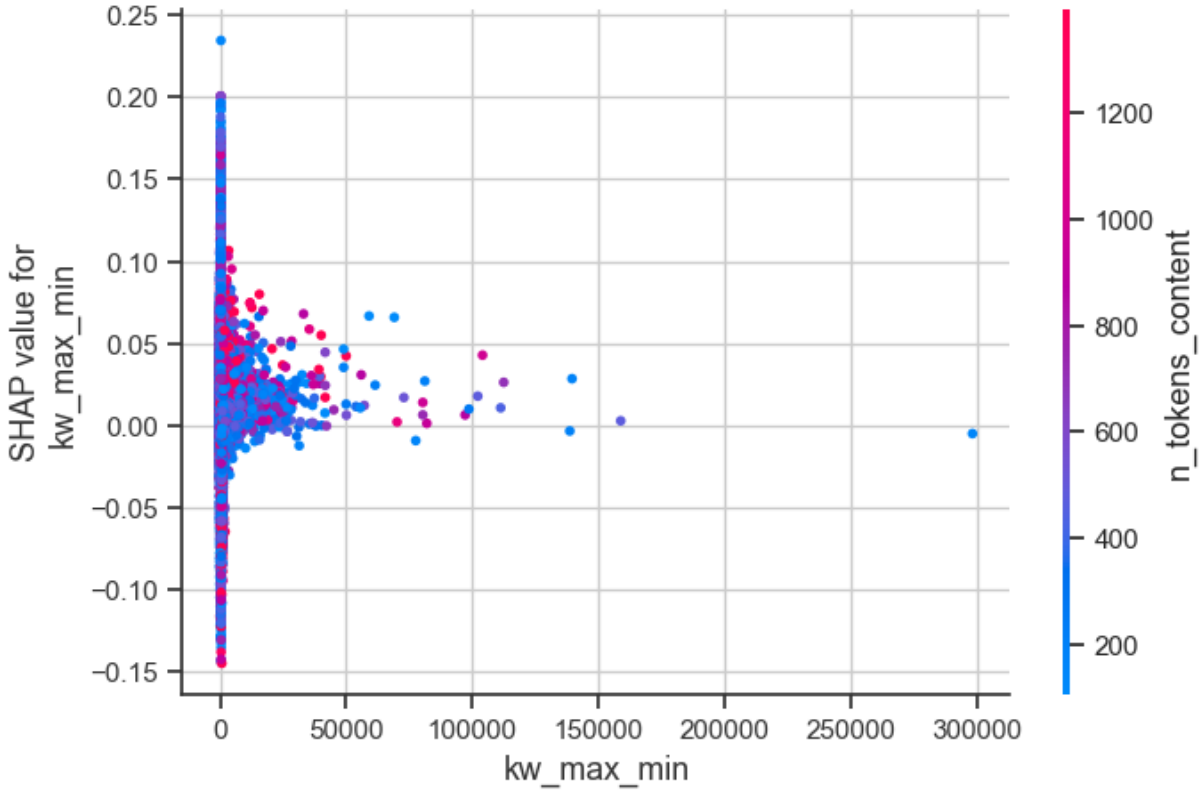

SHAP value for
data_channel_is_bus
0.050
0.025
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
0.0
0.2
0.4
0.6
0.8
1.0
data_channel_is_bus
LDA_00
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1

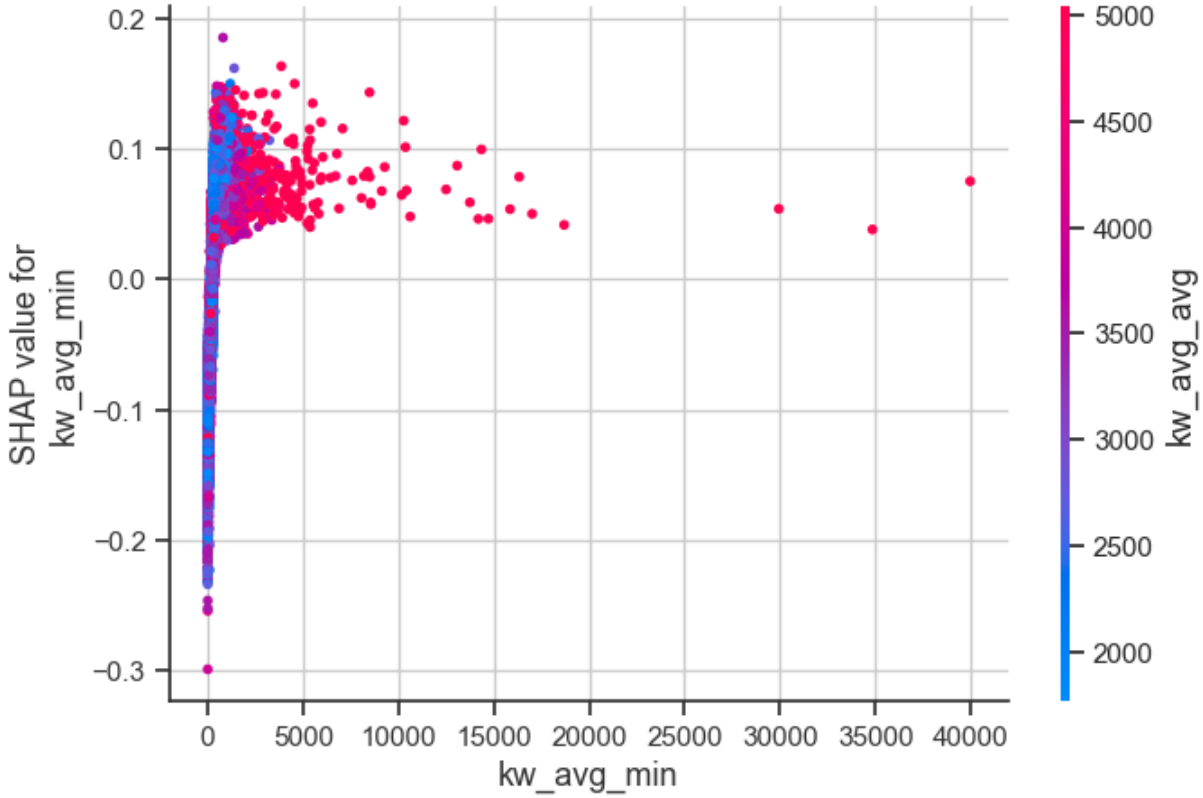

SHAP value for
data_channel_is_socmed
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
data_channel_is_socmed
LDA_00
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1

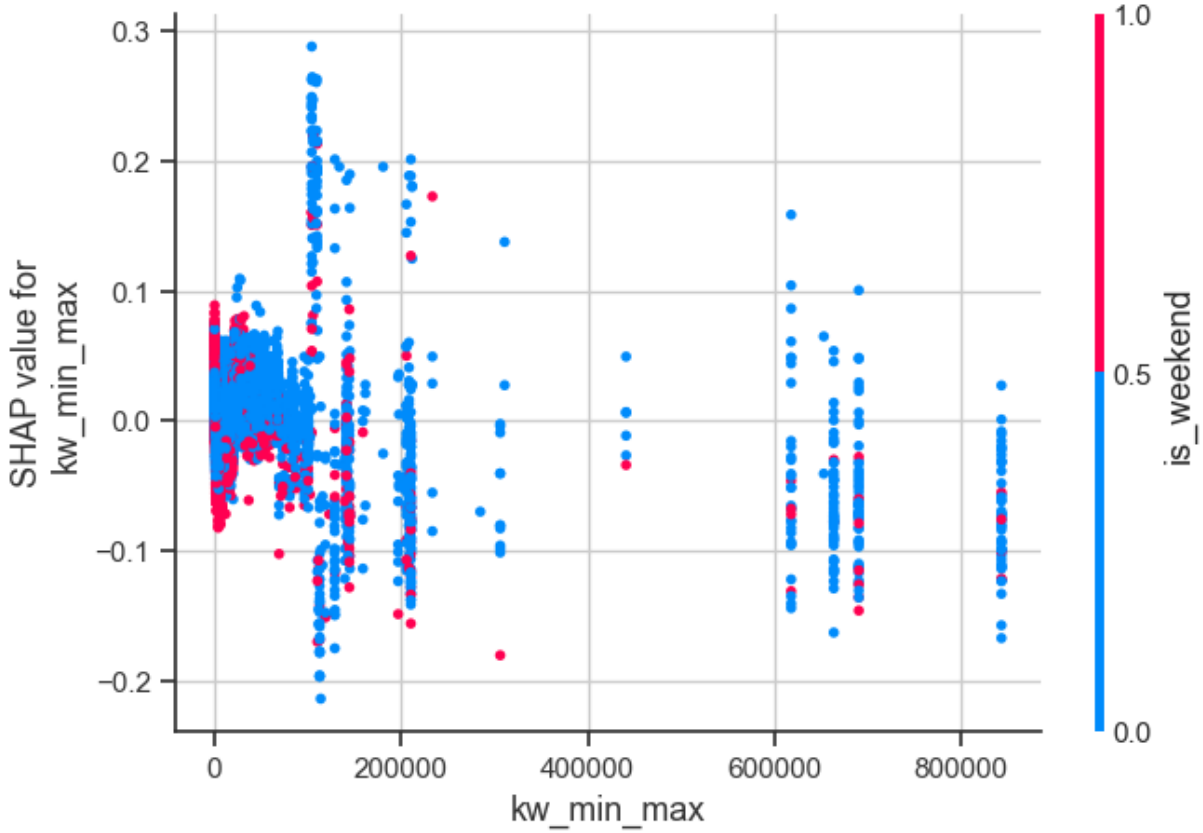

SHAP value for
data_channel_is_tech
0.4
0.3
0.2
0.1
0.0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
data_channel_is_tech
rate_positive_words
0.9
0.8
0.7
0.6
0.5
0.4

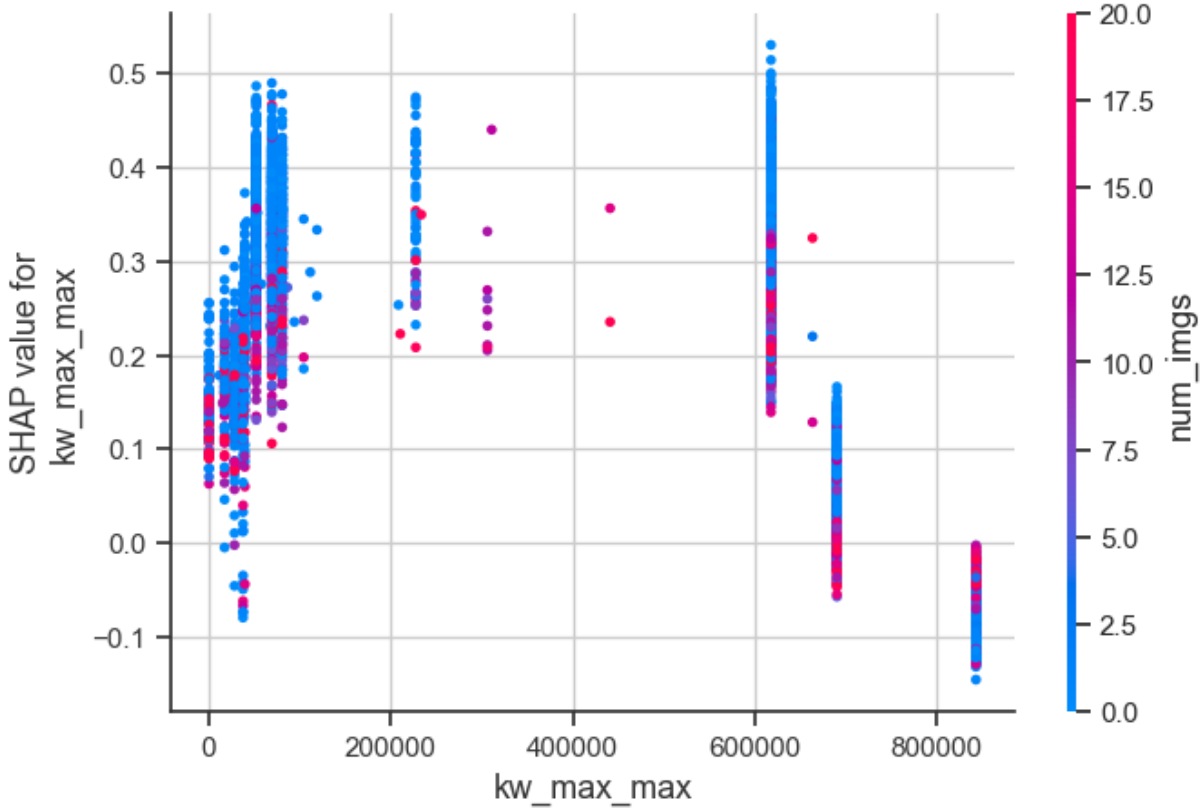

SHAP value for
data_channel_is_world
0.05
0.00
−0.05
−0.10
−0.15
−0.20
0.0
0.2
0.4
0.6
0.8
1.0
data_channel_is_world
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
num_imgs

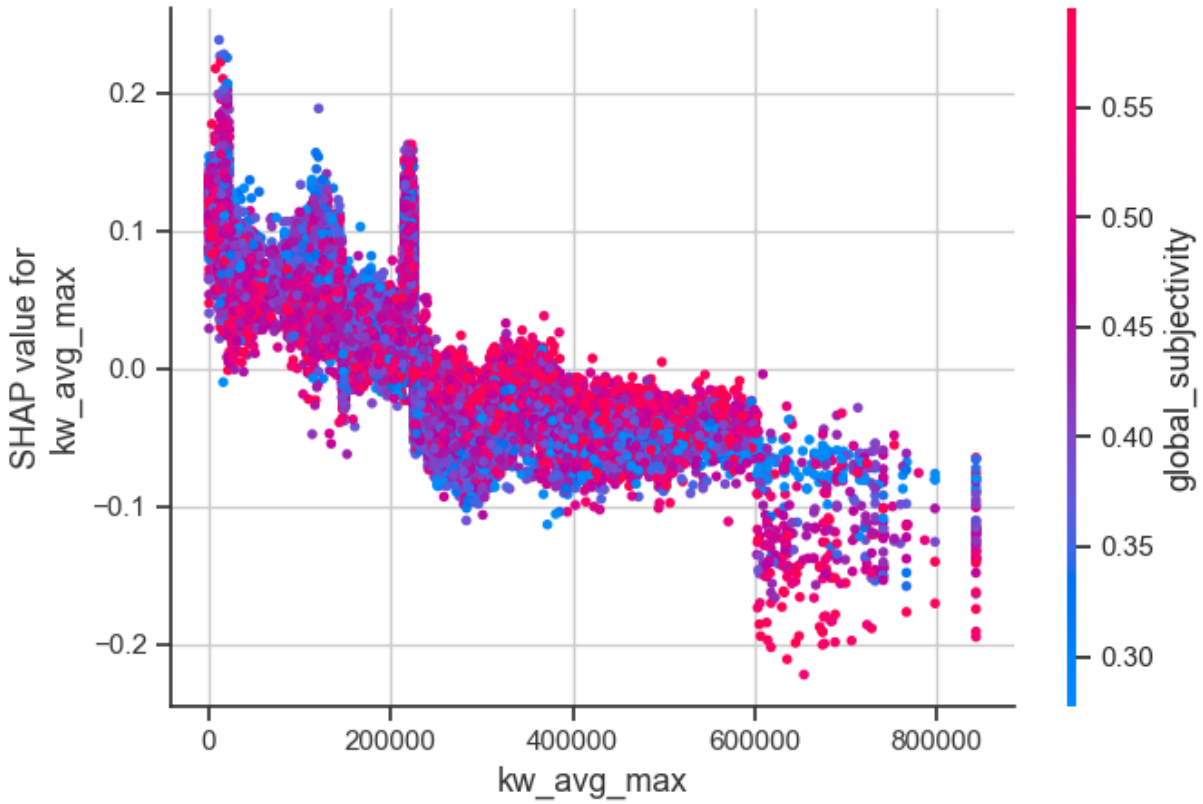

SHAP value for
kw_min_min
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
−0.25
0
50
100
150
200
250
300
350
kw_min_min
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
num_imgs

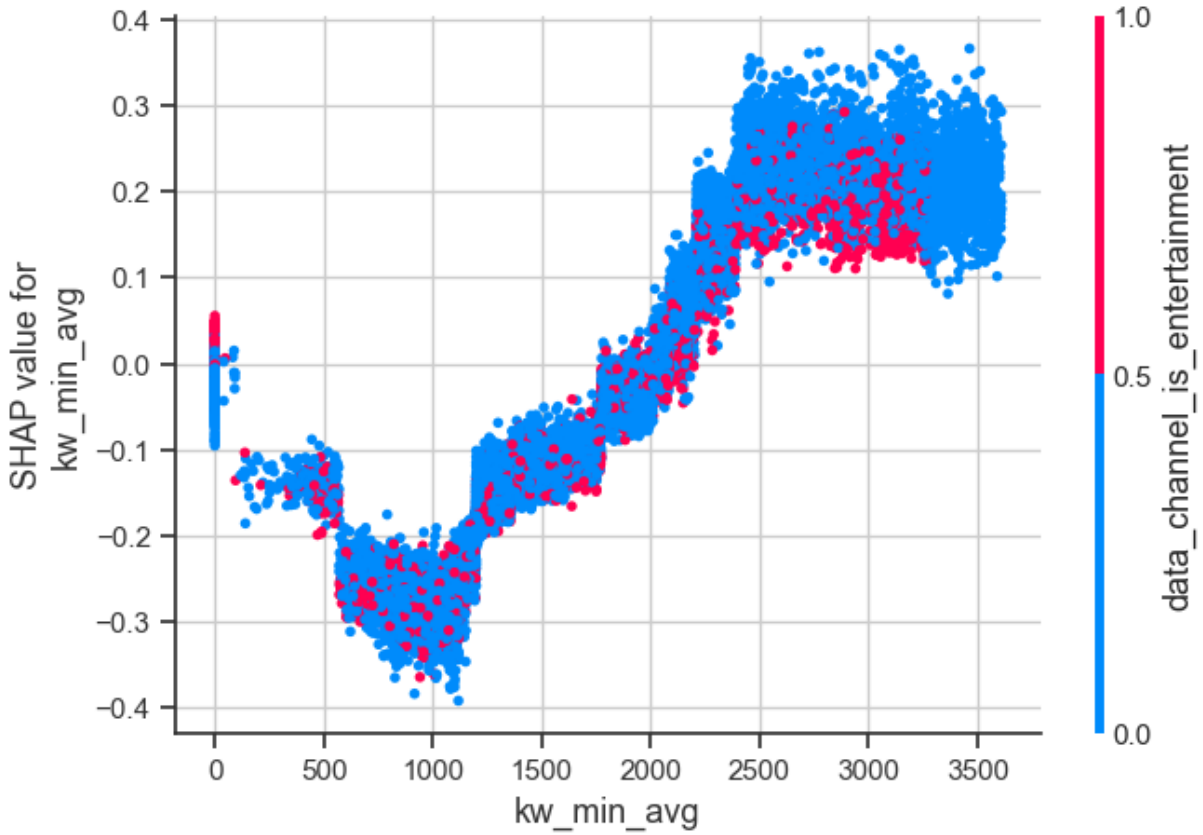

SHAP value for
kw_max_min
0.25
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
0
50000
100000
150000
200000
250000
300000
kw_max_min
n_tokens_content
1200
1000
800
600
400
200

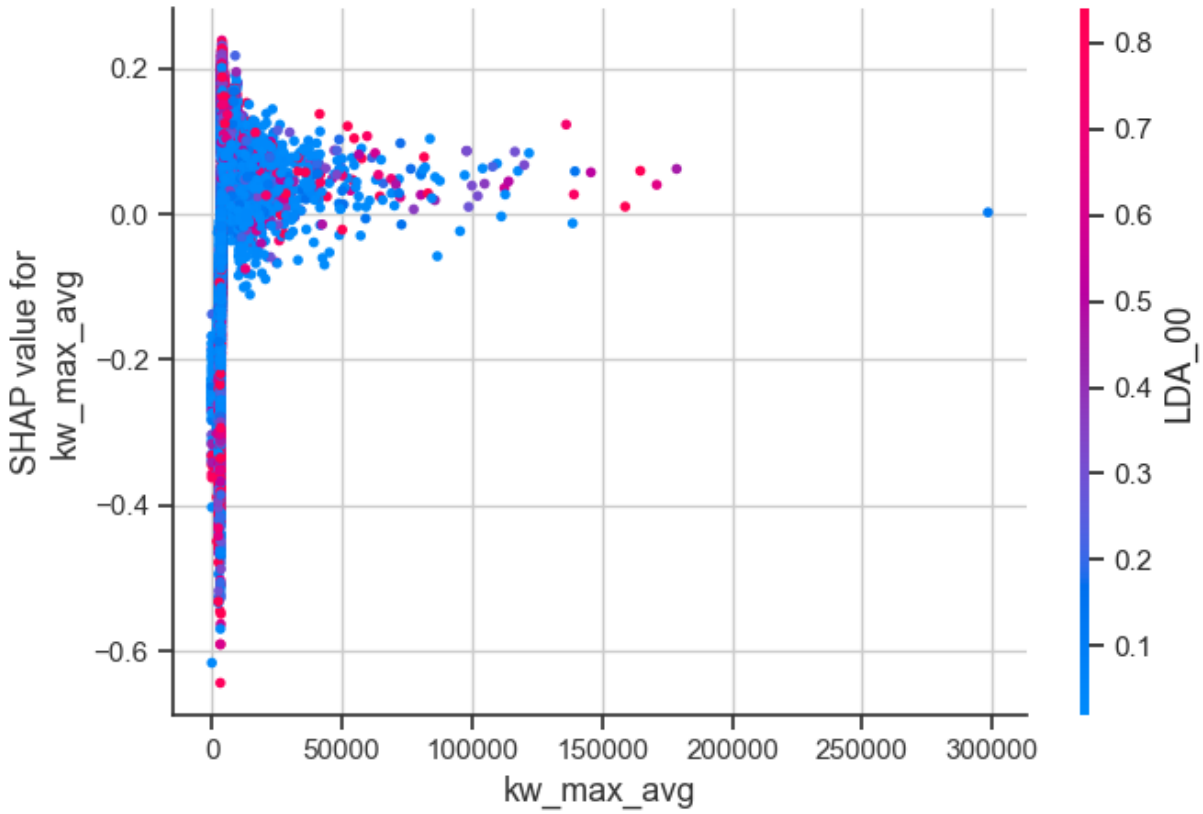

SHAP value for
kw_avg_min
0.2
0.1
0.0
−0.1
−0.2
−0.3
0
5000
10000
15000
20000
25000
30000
35000
40000
kw_avg_min
kw_avg_avg
5000
4500
4000
3500
3000
2500
2000

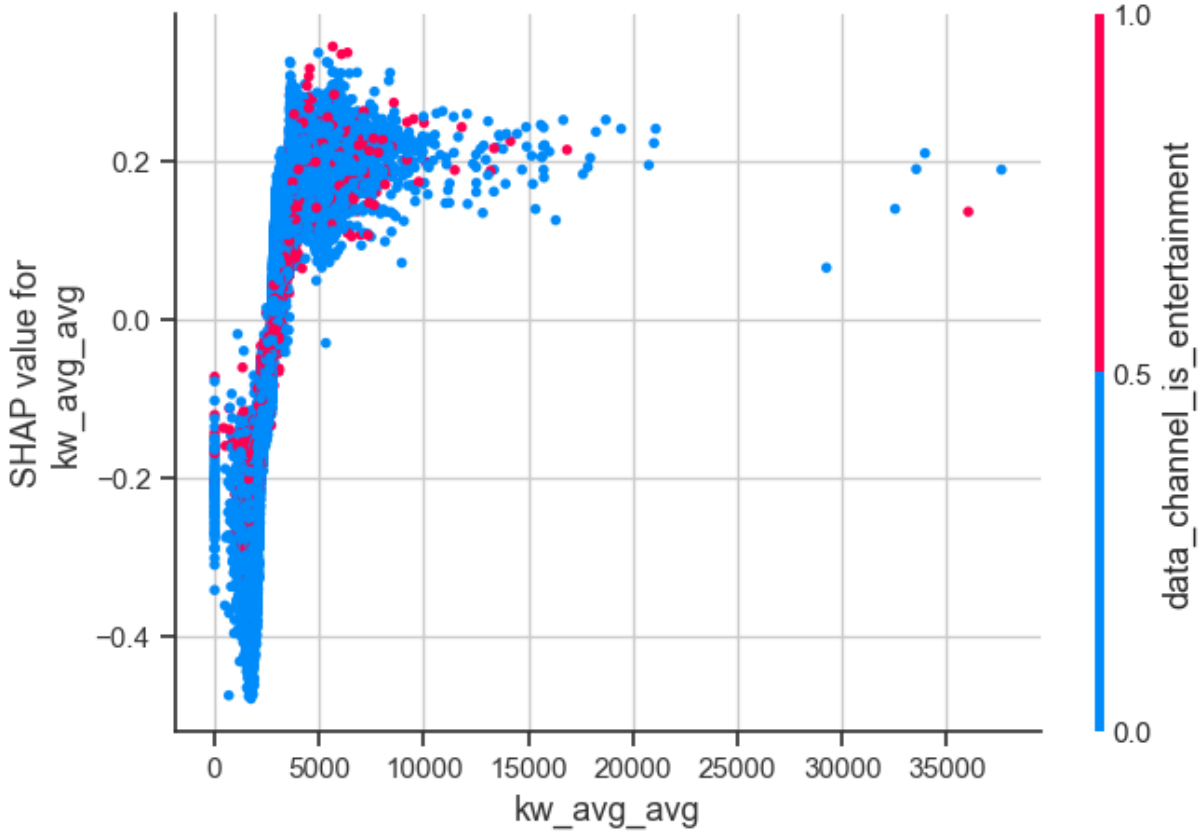

SHAP value for
kw_min_max
0.3
0.2
0.1
0.0
−0.1
−0.2
0
200000
400000
600000
800000
kw_min_max
1.0
0.5
0.0
is_weekend

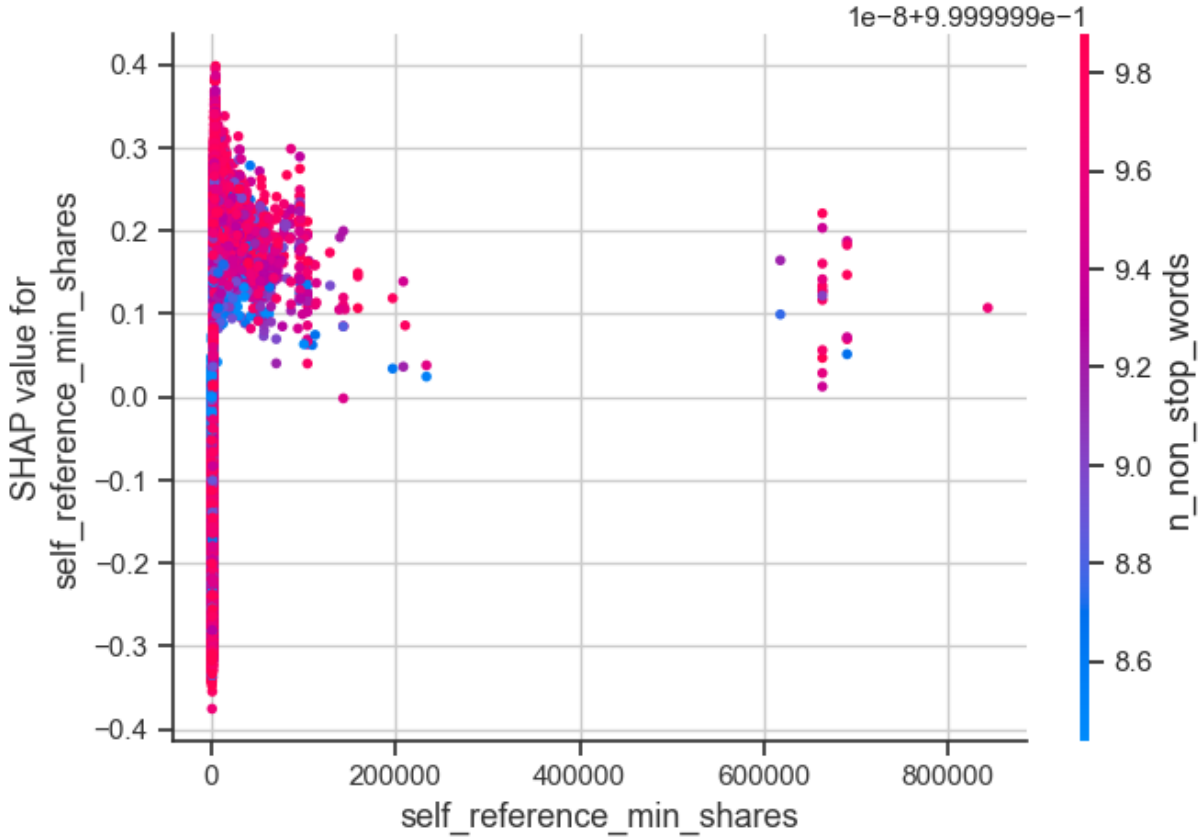

SHAP value for
kw_max_max
0.5
0.4
0.3
0.2
0.1
0.0
−0.1
0
200000
400000
600000
800000
kw_max_max
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
num_imgs

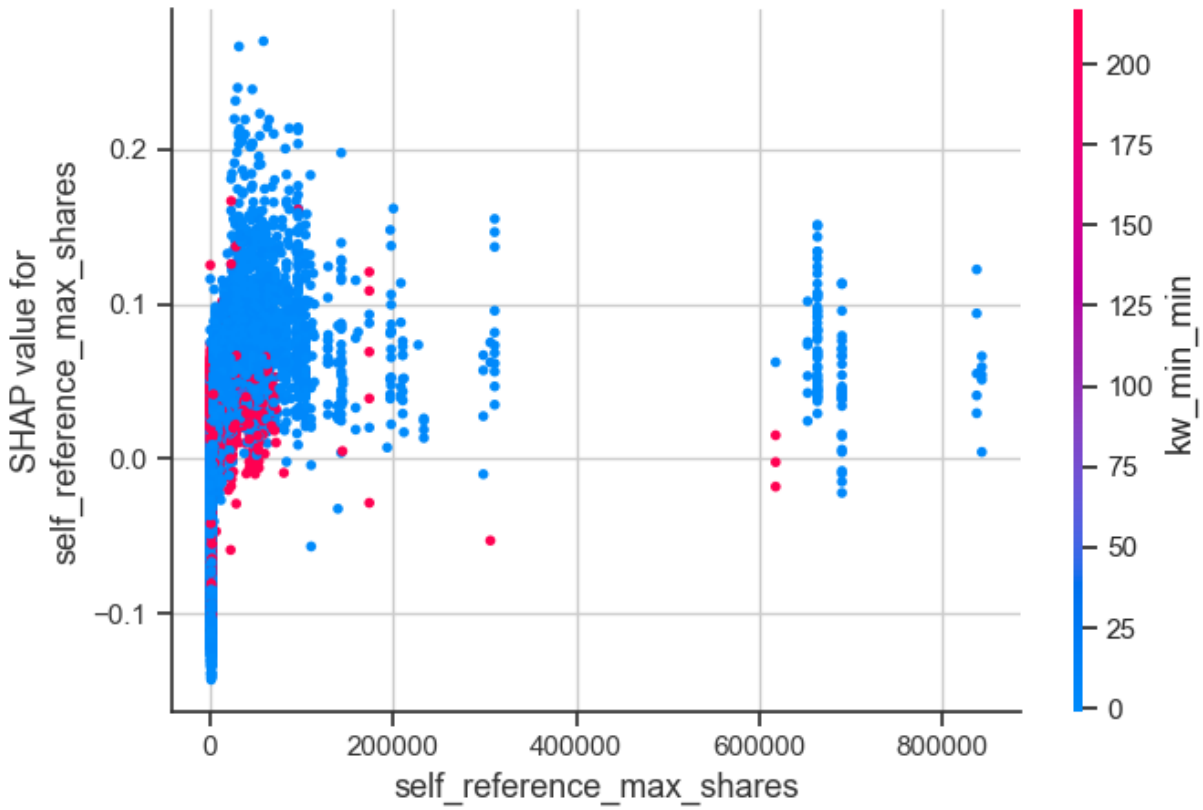

SHAP value for
kw_avg_max
0.2
0.1
0.0
−0.1
−0.2
0
200000
400000
600000
800000
kw_avg_max
0.55
0.50
0.45
0.40
0.35
0.30
global_subjectivity

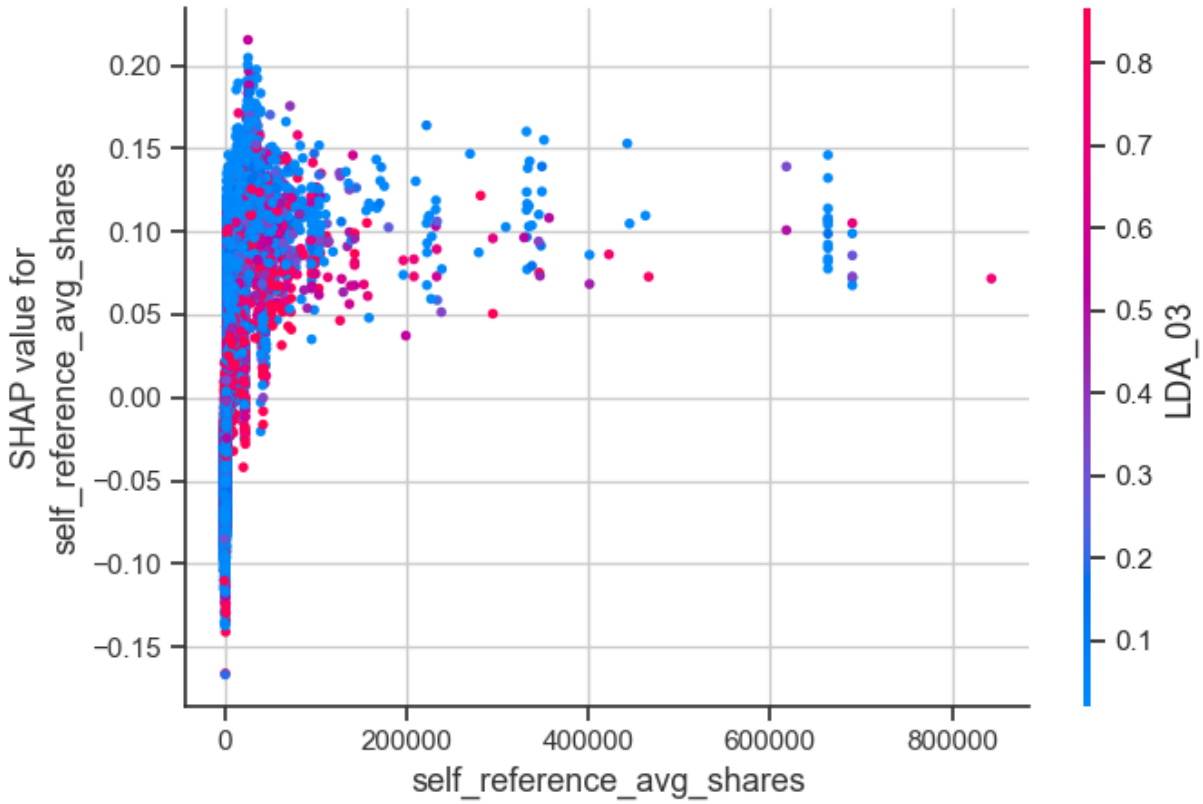

SHAP value for
kw_min_avg
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
0
500
1000
1500
2000
2500
3000
3500
kw_min_avg
1.0
0.5
0.0
data_channel_is_entertainment

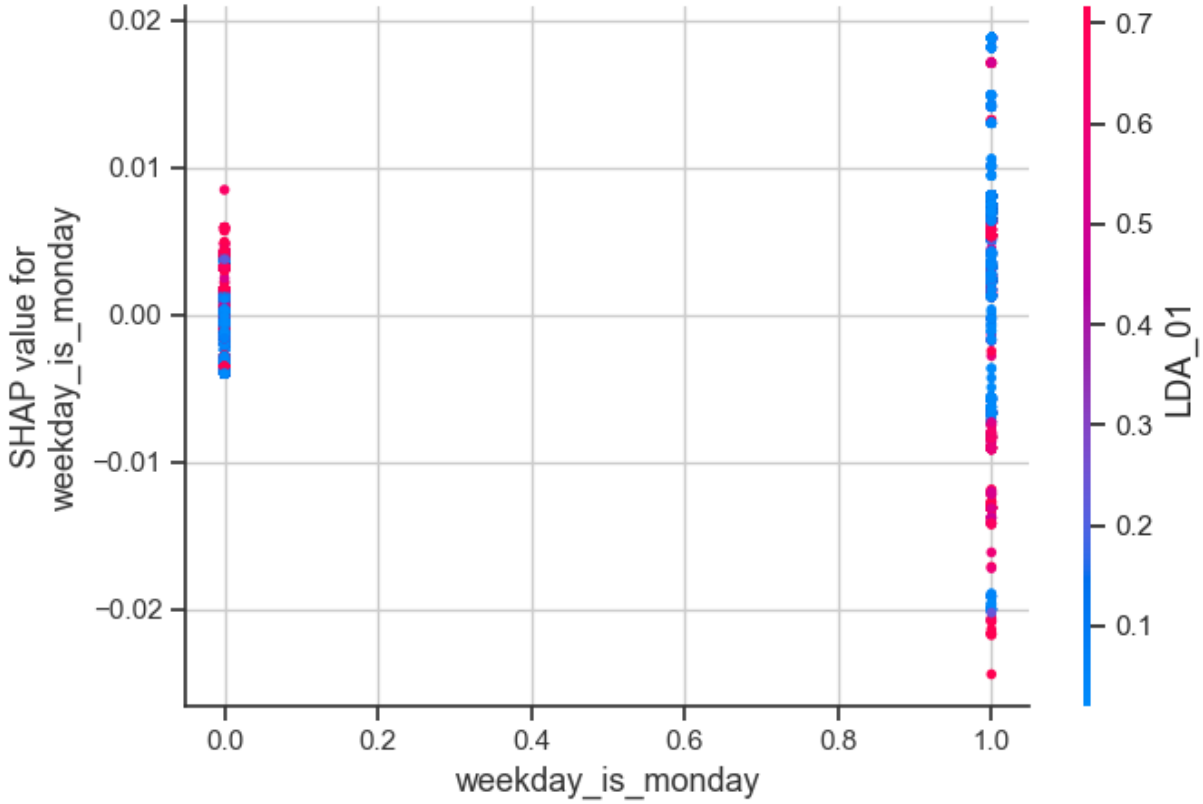

SHAP value for
kw_max_avg
0.2
0.0
−0.2
−0.4
−0.6
0
50000
100000
150000
200000
250000
300000
kw_max_avg
LDA_00
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1

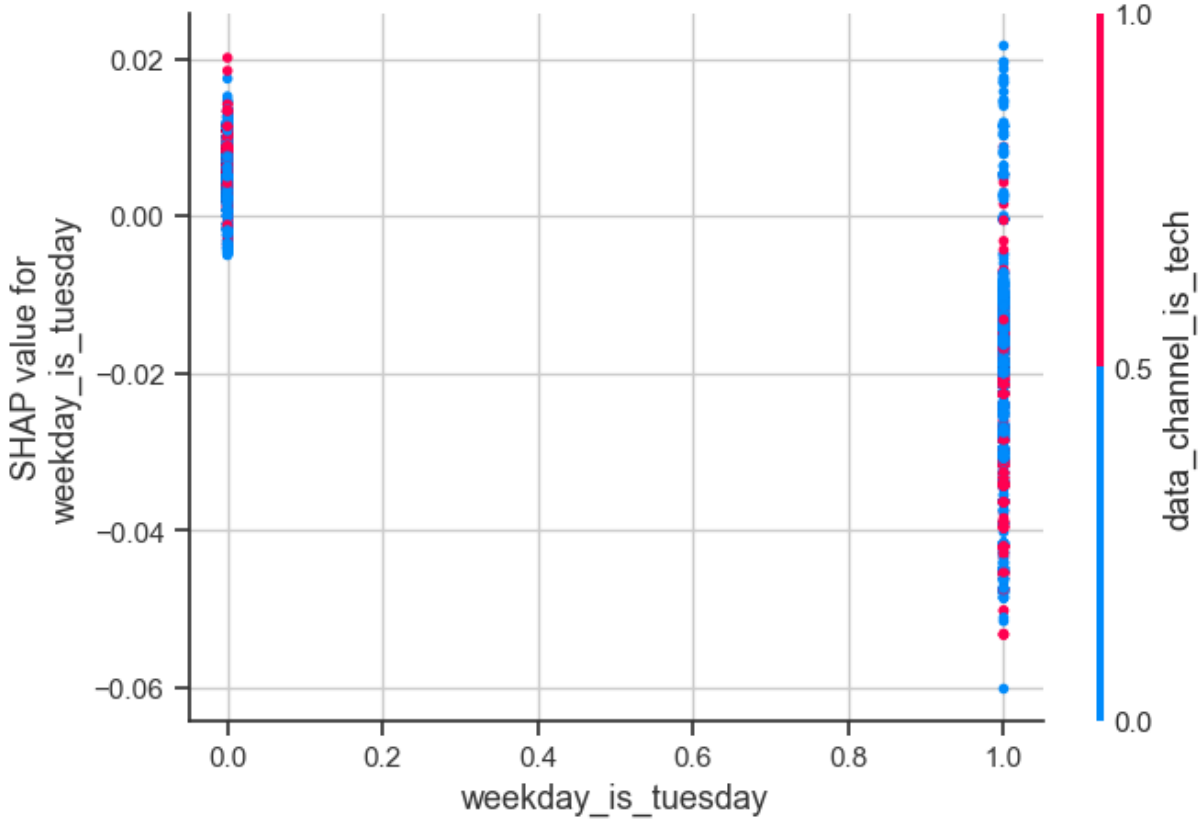

SHAP value for
kw_avg_avg
0.2
0.0
−0.2
−0.4
0
5000
10000
15000
20000
25000
30000
35000
kw_avg_avg
data_channel_is_entertainment
1.0
0.5
0.0

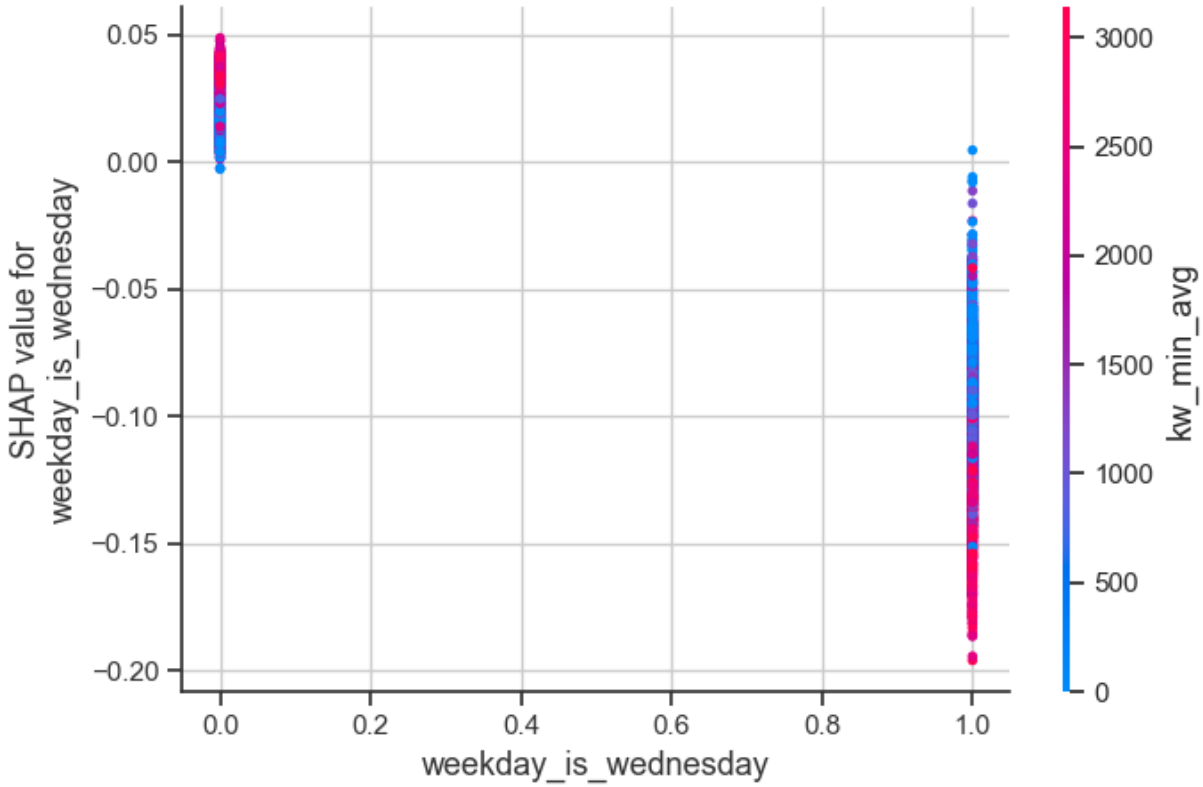

1e−8+9.999999e−1
SHAP value for
self_reference_min_shares
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
0
200000
400000
600000
800000
self_reference_min_shares
9.8
9.6
9.4
9.2
9.0
8.8
8.6
n_non_stop_words

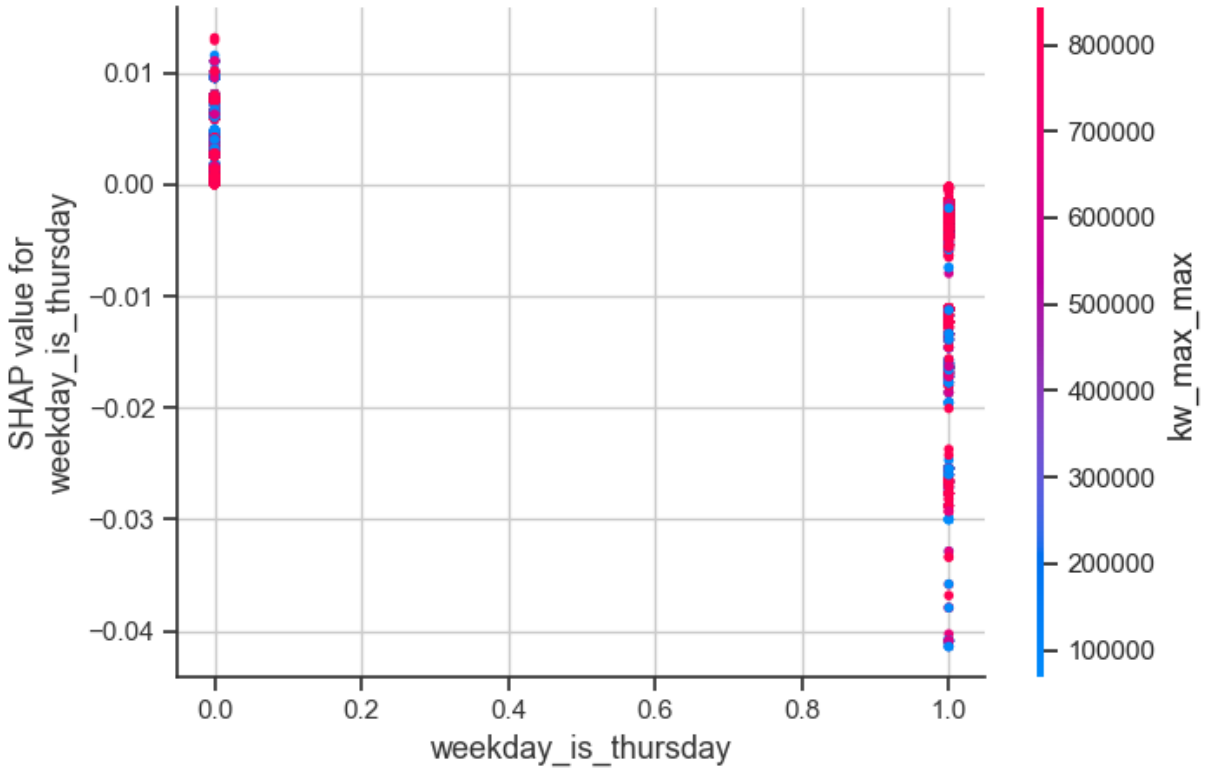

SHAP value for
self_reference_max_shares
0.2
0.1
0.0
−0.1
0
200000
400000
600000
800000
self_reference_max_shares
200
175
150
125
100
75
50
25
0
kw_min_min

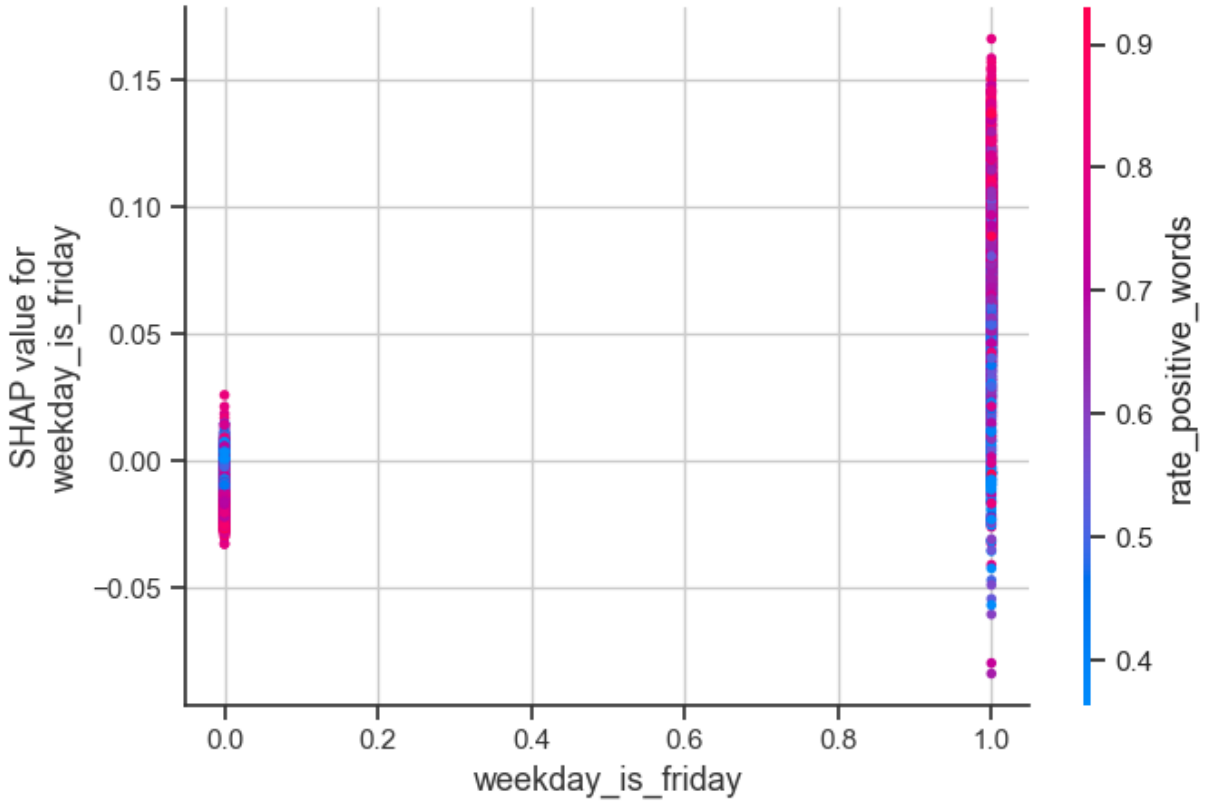

SHAP value for
self_reference_avg_shares
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
0
200000
400000
600000
800000
self_reference_avg_shares
LDA_03
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1

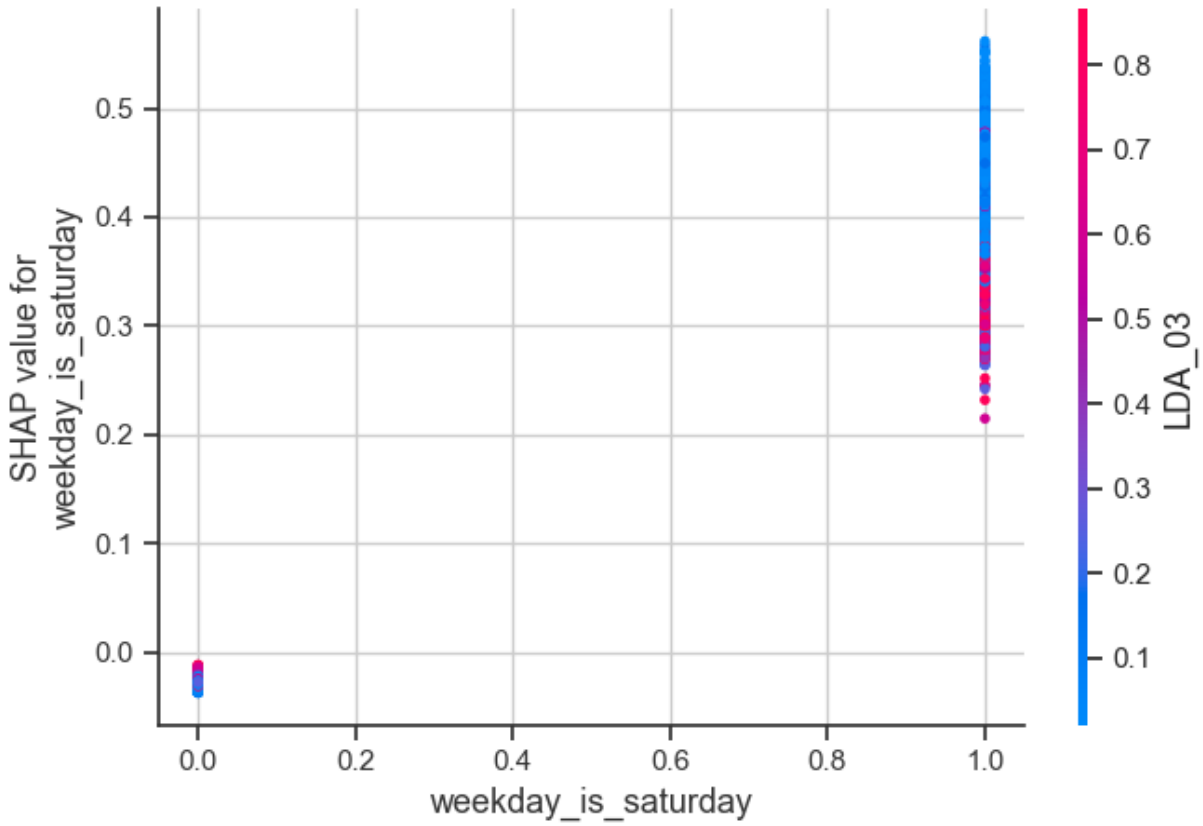

SHAP value for
weekday_is_monday
0.02
0.01
0.00
−0.01
−0.02
0.0
0.2
0.4
0.6
0.8
1.0
weekday_is_monday
LDA_01
0.7
0.6
0.5
0.4
0.3
0.2
0.1

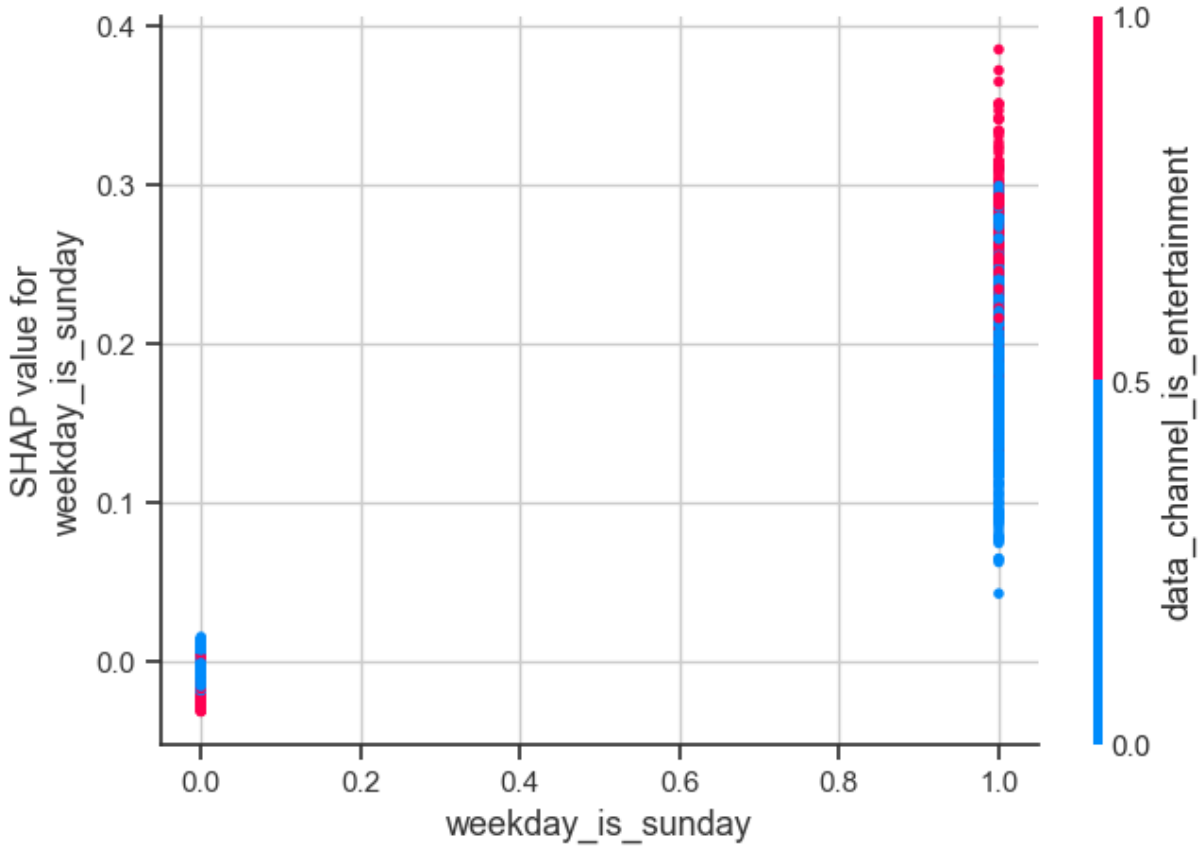

SHAP value for
weekday_is_tuesday
0.02
0.00
−0.02
−0.04
−0.06
0.0
0.2
0.4
0.6
0.8
1.0
weekday_is_tuesday
data_channel_is_tech
1.0
0.5
0.0

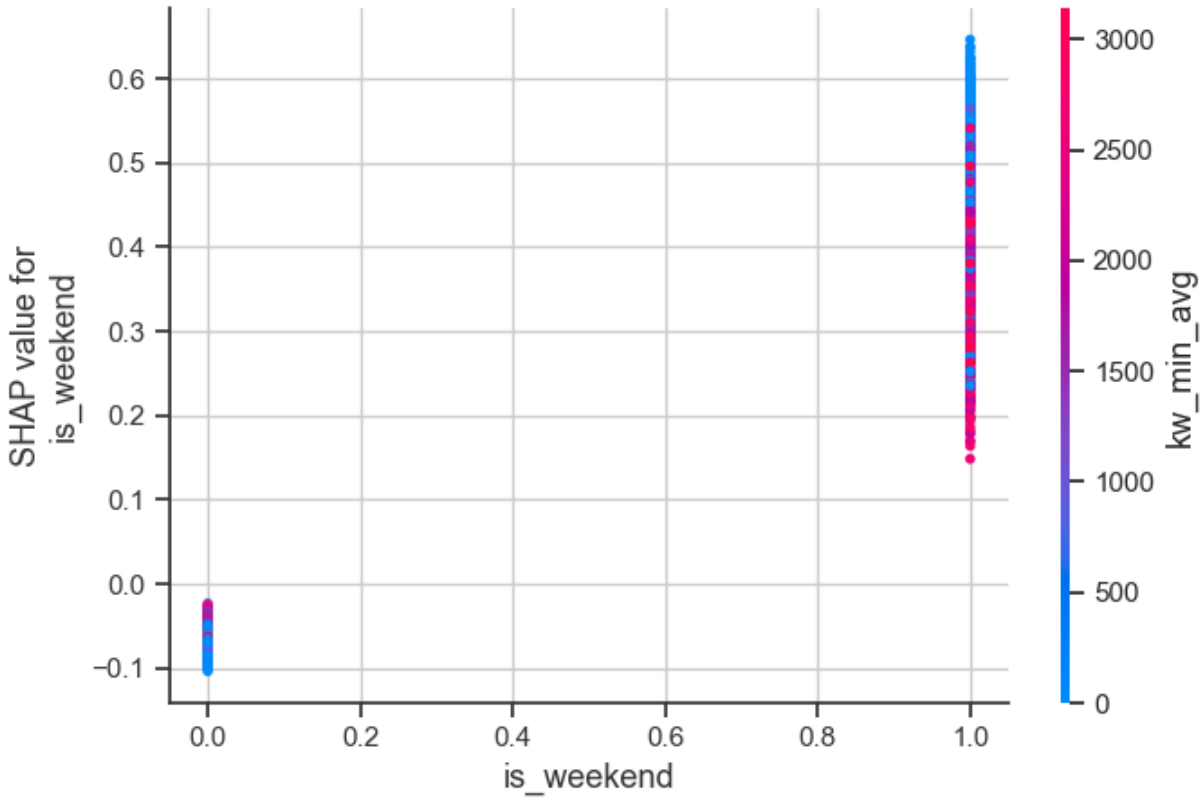

SHAP value for
weekday_is_wednesday
0.05
0.00
−0.05
−0.10
−0.15
−0.20
0.0
0.2
0.4
0.6
0.8
1.0
weekday_is_wednesday
kw_min_avg
3000
2500
2000
1500
1000
500
0

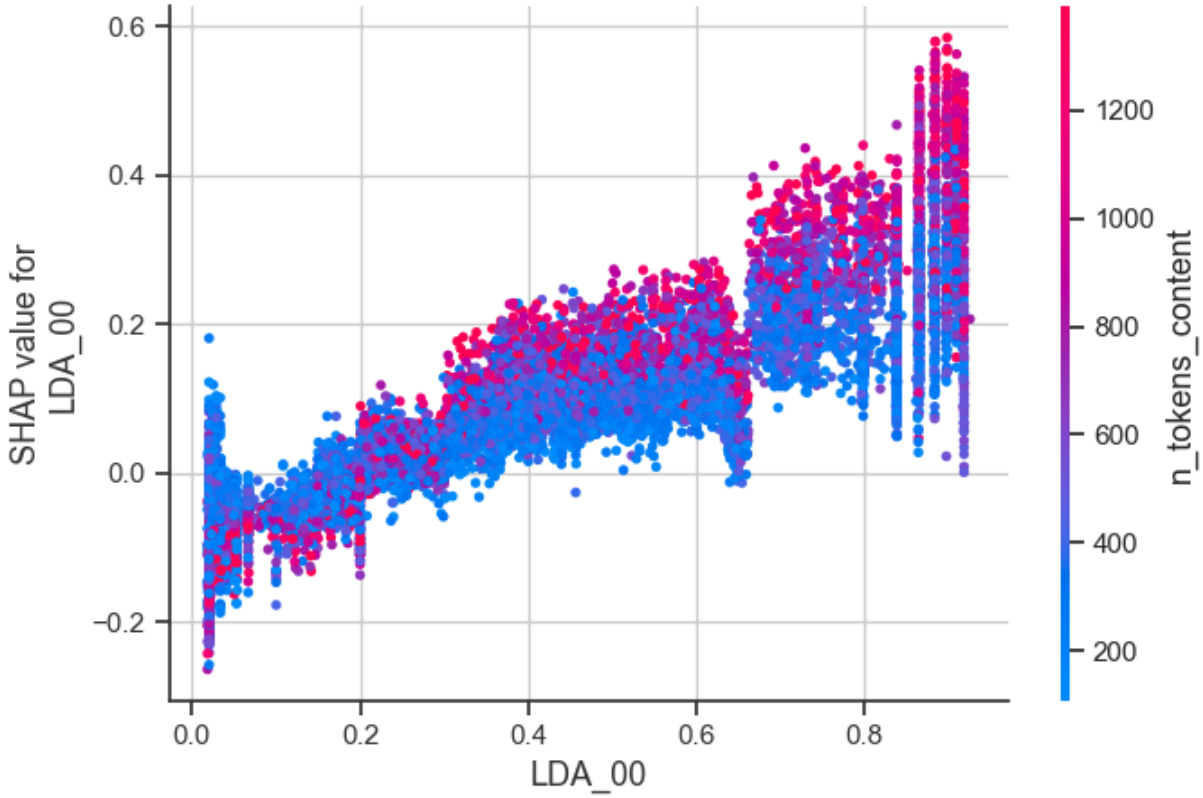

SHAP value for
weekday_is_thursday
0.01
0.00
−0.01
−0.02
−0.03
−0.04
0.0
0.2
0.4
0.6
0.8
1.0
weekday_is_thursday
800000
700000
600000
500000
400000
300000
200000
100000
kw_max_max

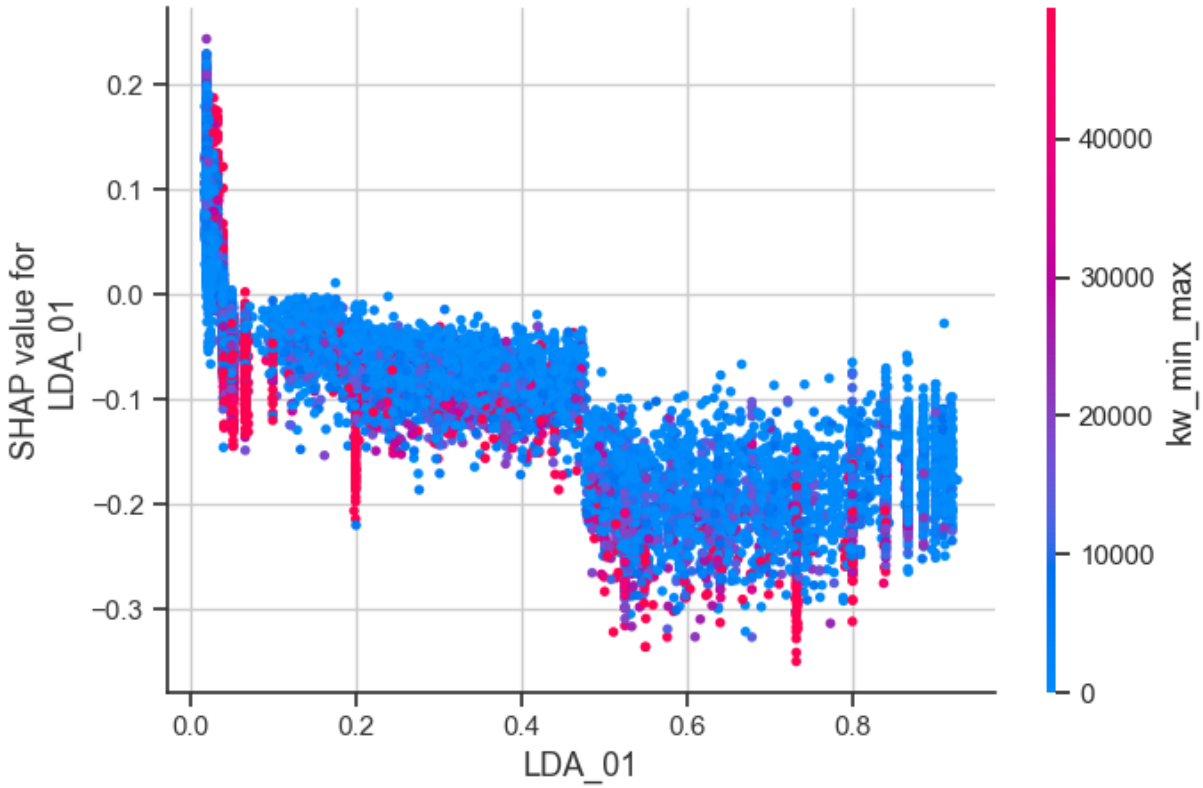

SHAP value for
weekday_is_friday
0.15
0.10
0.05
0.00
−0.05
0.0
0.2
0.4
0.6
0.8
1.0
weekday_is_friday
0.9
0.8
0.7
0.6
0.5
0.4
rate_positive_words

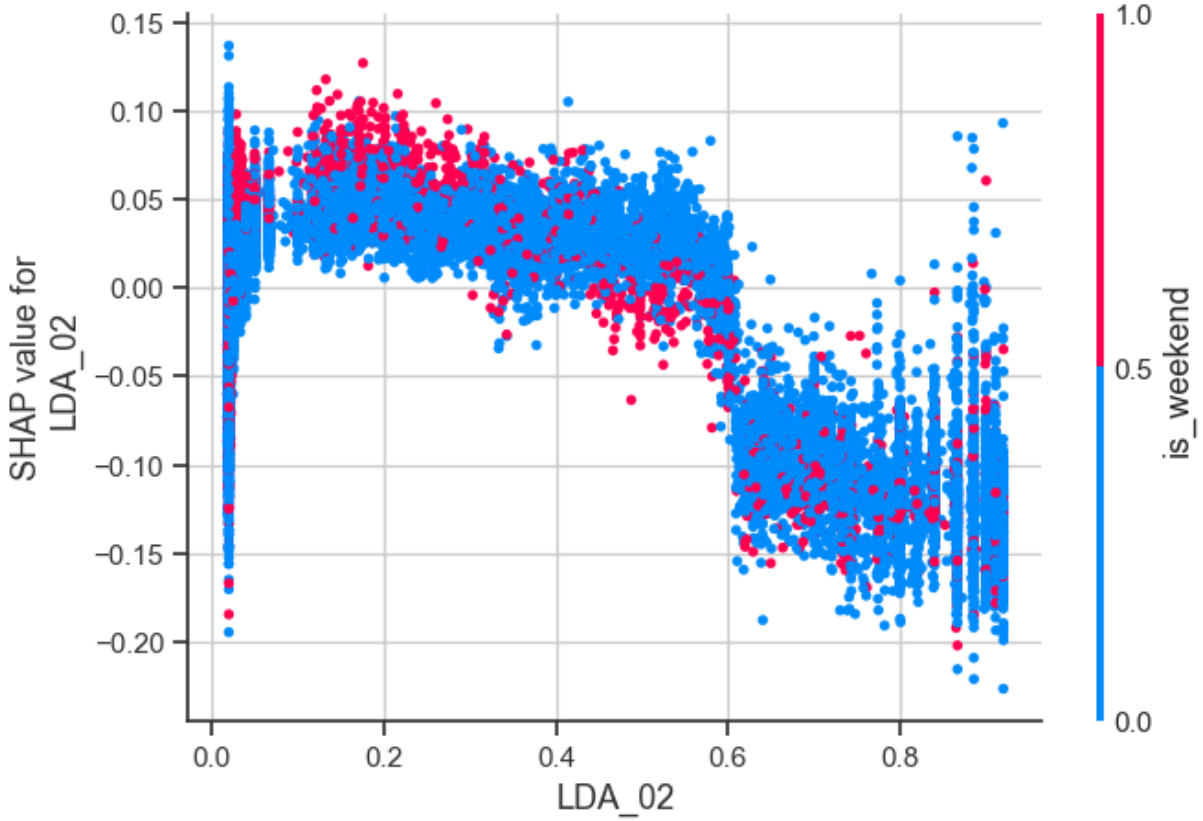

SHAP value for
weekday_is_saturday
0.0
0.1
0.2
0.3
0.4
0.5
0.0
0.2
0.4
0.6
0.8
1.0
weekday_is_saturday
LDA_03
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8

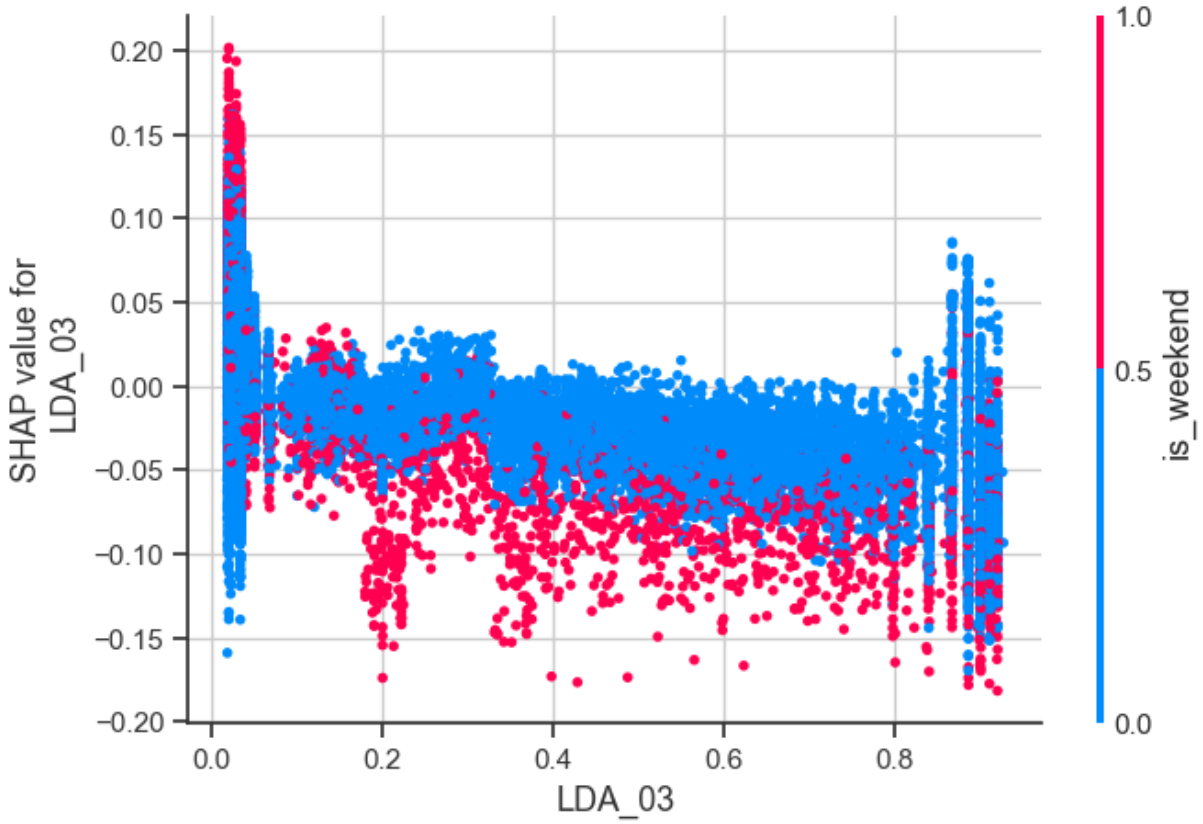

SHAP value for
weekday_is_sunday
0.0
0.1
0.2
0.3
0.4
0.0
0.2
0.4
0.6
0.8
1.0
weekday_is_sunday
data_channel_is_entertainment
0.0
0.5
1.0

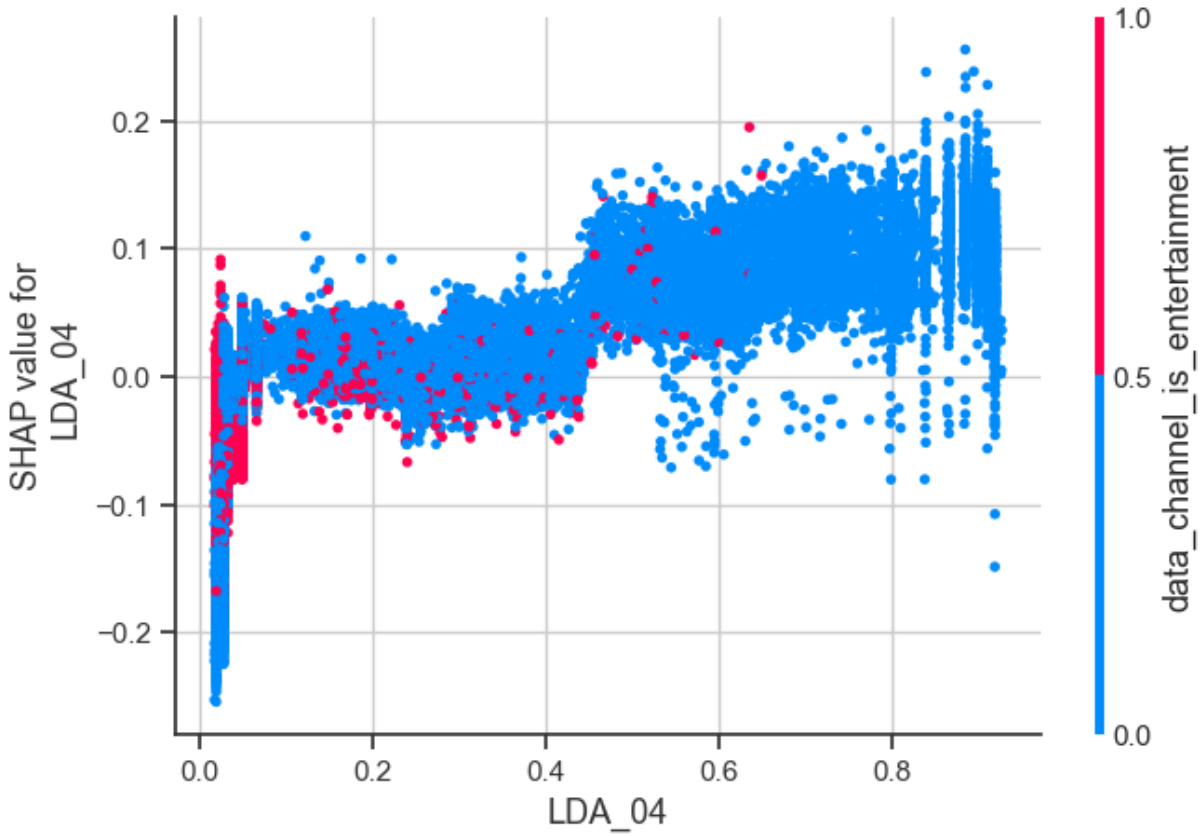

SHAP value for
is_weekend
0.6
0.5
0.4
0.3
0.2
0.1
0.0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
is_weekend
3000
2500
2000
1500
1000
500
0
kw_min_avg

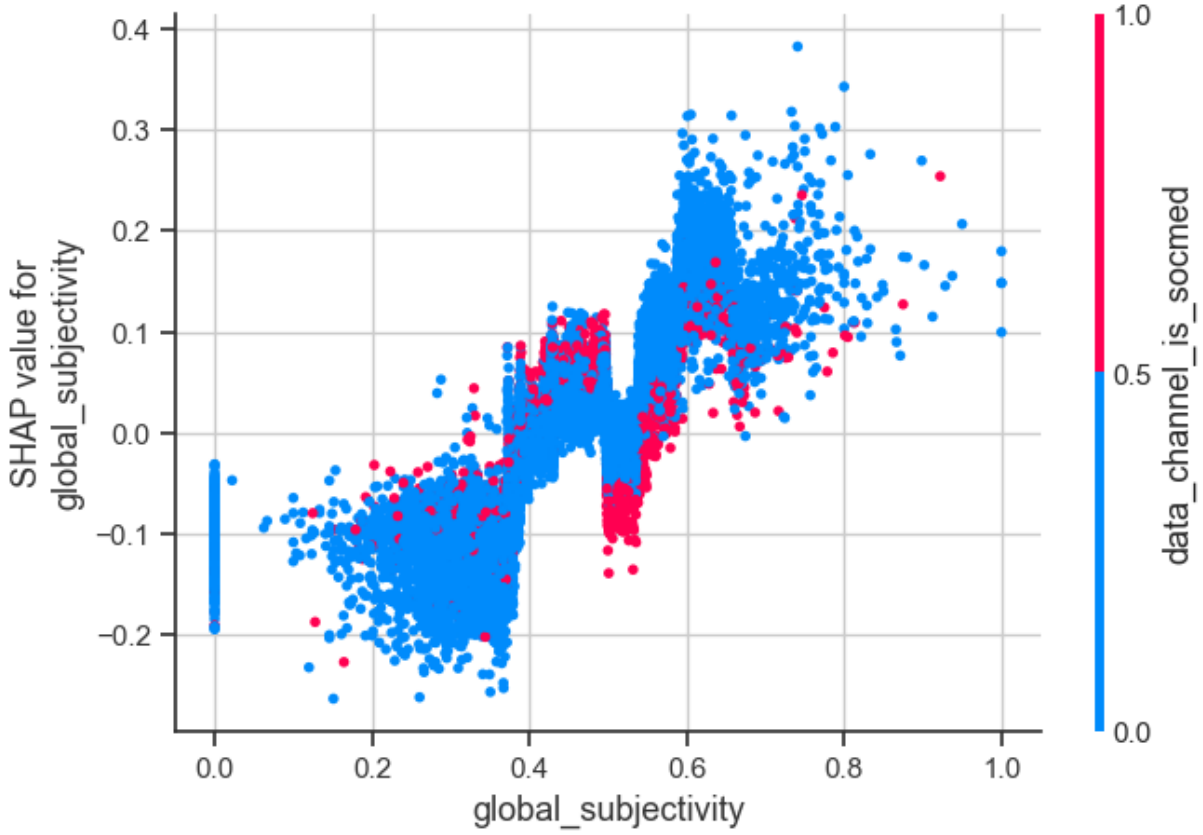

SHAP value for
LDA_00
0.6
0.4
0.2
0.0
−0.2
0.0
0.2
0.4
0.6
0.8
LDA_00
1200
1000
800
600
400
200
n_tokens_content

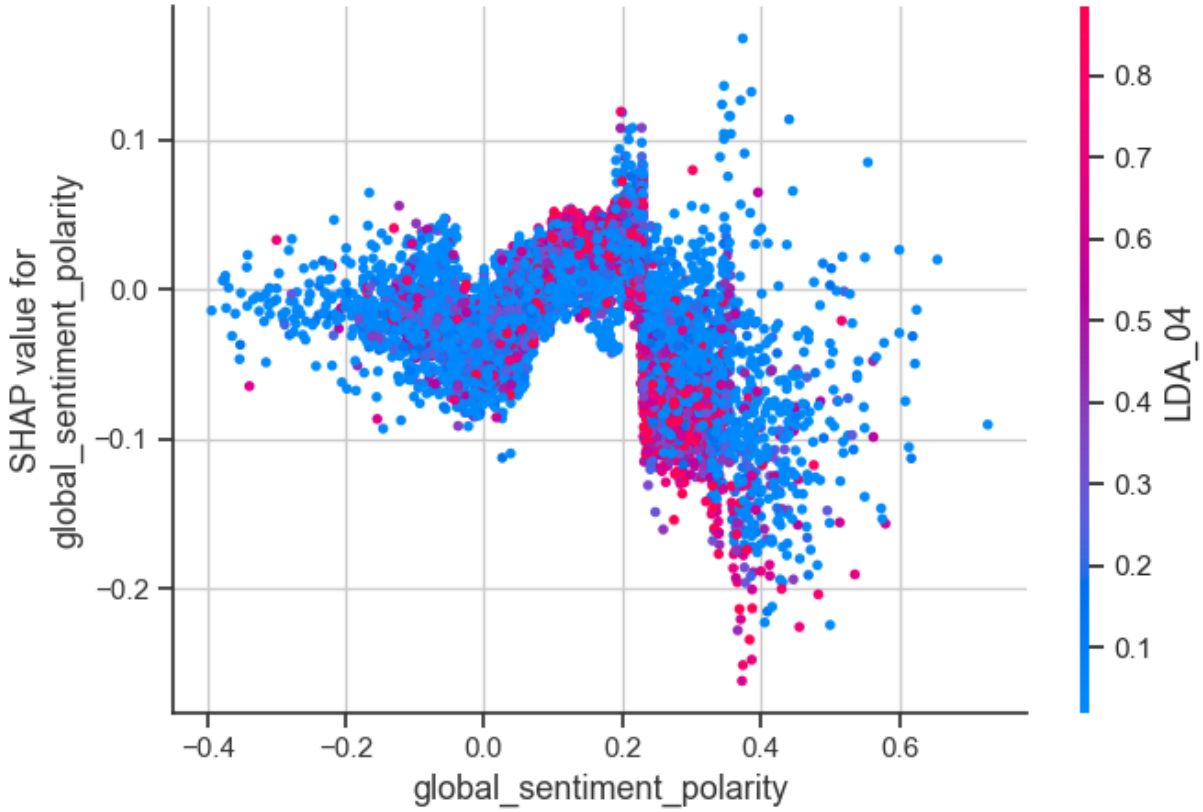

SHAP value for
LDA_01
0.2
0.1
0.0
−0.1
−0.2
−0.3
0.0
0.2
0.4
0.6
0.8
LDA_01
40000
30000
20000
10000
0
kw_min_max

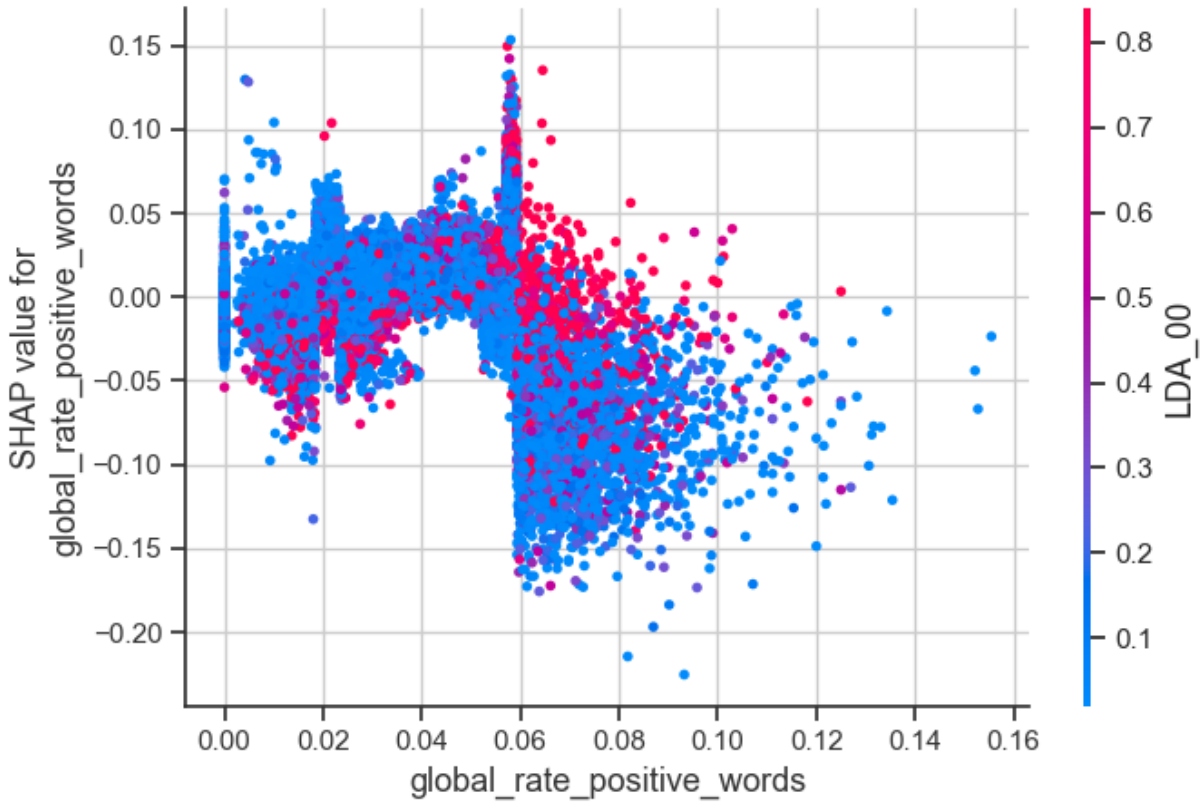

SHAP value for
LDA_02
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
0.0
0.2
0.4
0.6
0.8
LDA_02
1.0
0.5
0.0
is_weekend

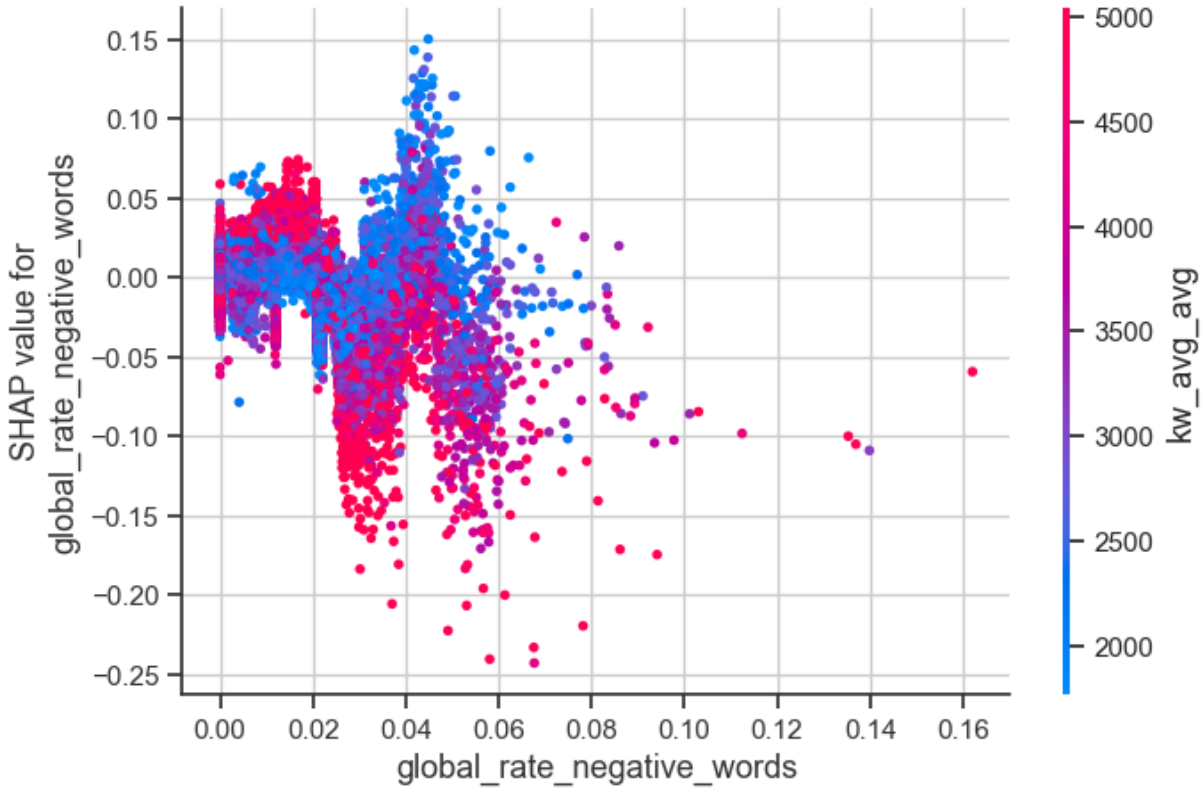

SHAP value for
LDA_03
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
0.0
0.2
0.4
0.6
0.8
LDA_03
1.0
0.5
0.0
is_weekend

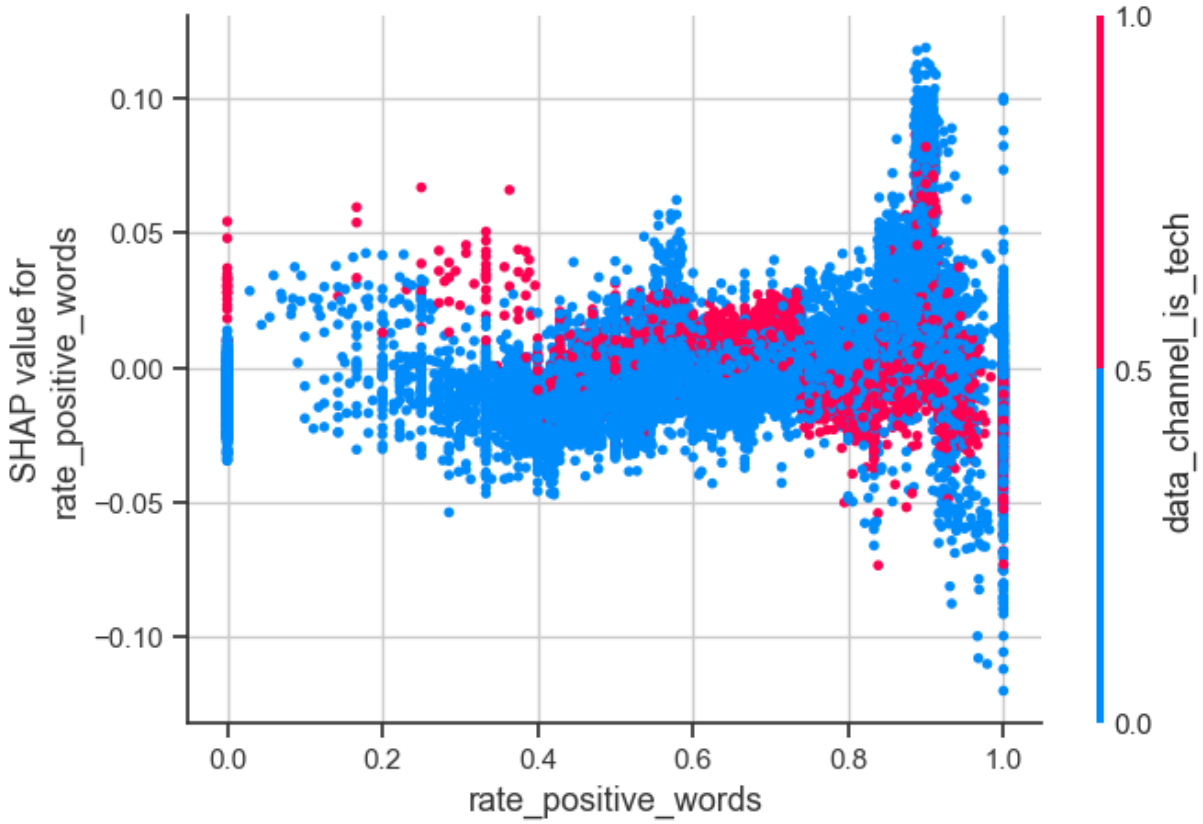

SHAP value for
LDA_04
0.2
0.1
0.0
−0.1
−0.2
0.0
0.2
0.4
0.6
0.8
LDA_04
1.0
0.5
0.0
data_channel_is_entertainment

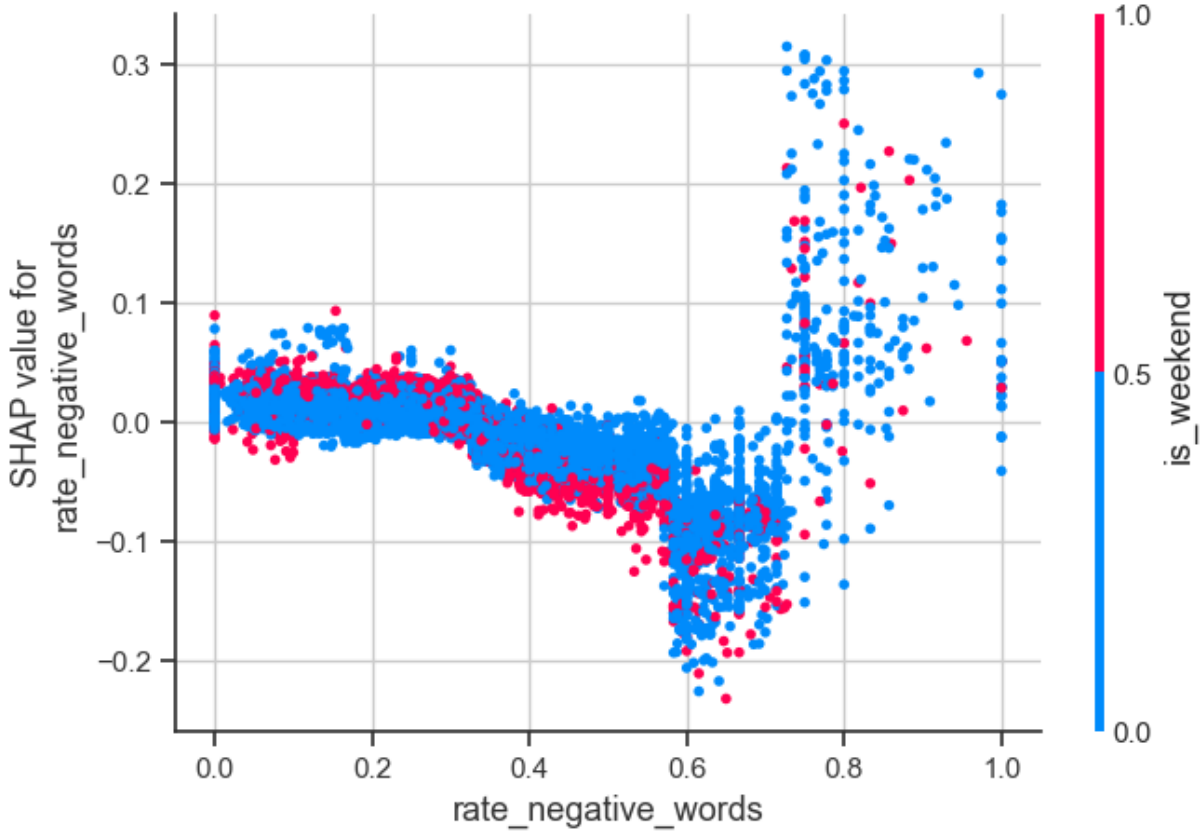

SHAP value for global_subjectivity
global_subjectivity
data_channel_is_socmed
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.0
0.5
0.0

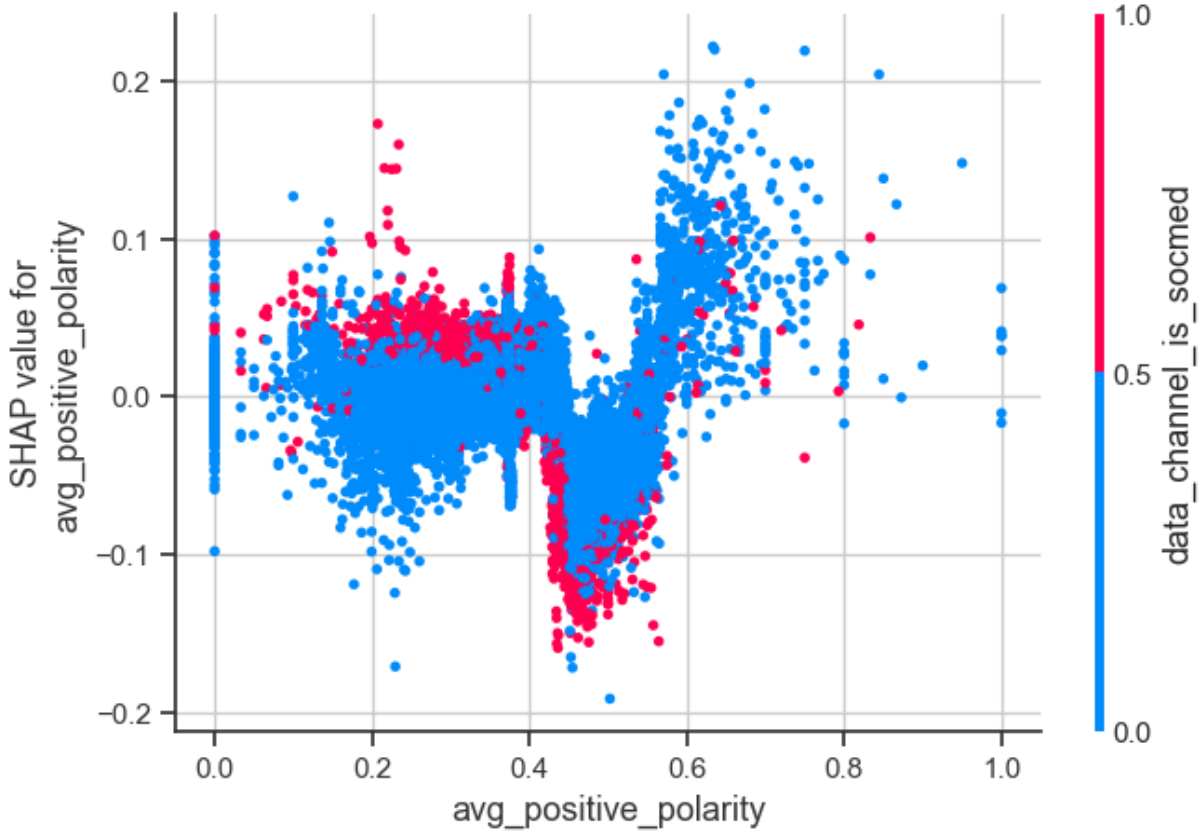

SHAP value for global_sentiment_polarity
global_sentiment_polarity
LDA_04
0.1
0.0
−0.1
−0.2
−0.4
−0.2
0.0
0.2
0.4
0.6
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1

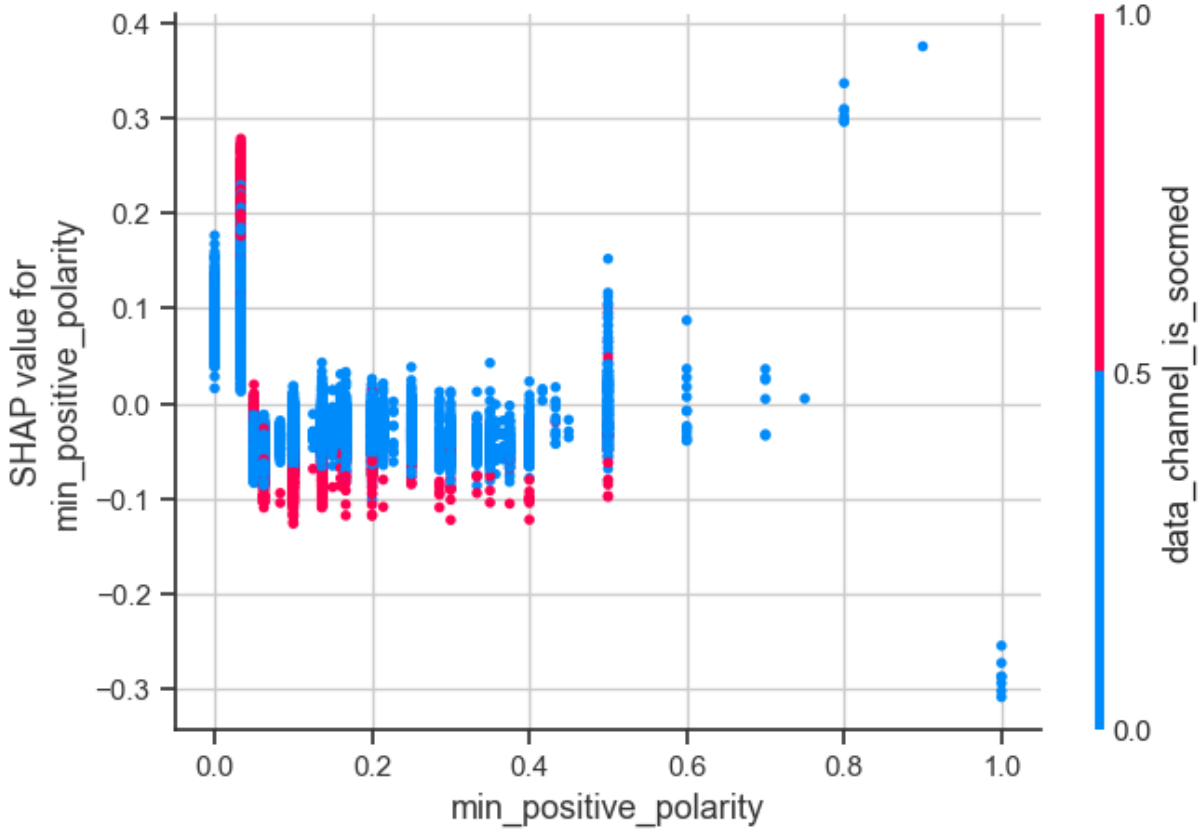

SHAP value for
global_rate_positive_words
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
global_rate_positive_words
LDA_00
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1

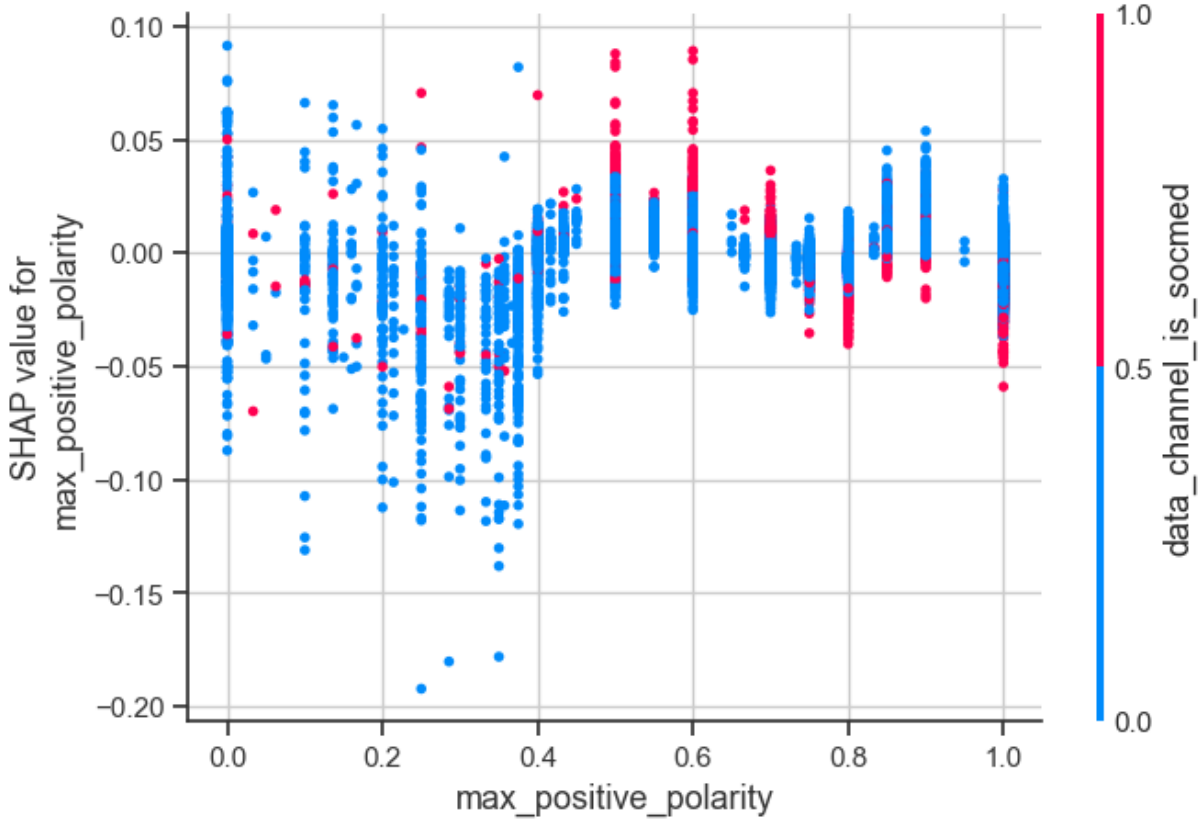

SHAP value for
global_rate_negative_words
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
−0.25
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
global_rate_negative_words
kw_avg_avg
5000
4500
4000
3500
3000
2500
2000

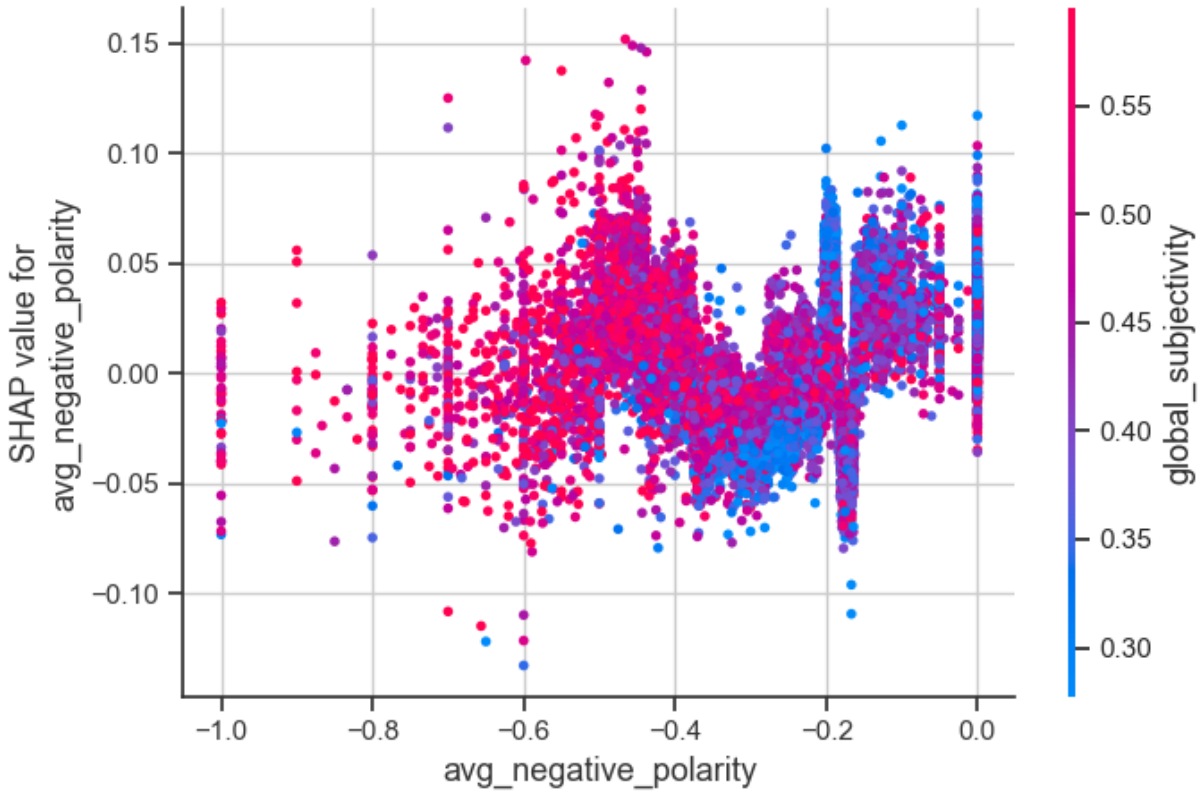

SHAP value for
rate_positive_words
0.10
0.05
0.00
−0.05
−0.10
0.0
0.2
0.4
0.6
0.8
1.0
rate_positive_words
1.0
0.5
0.0
data_channel_is_tech

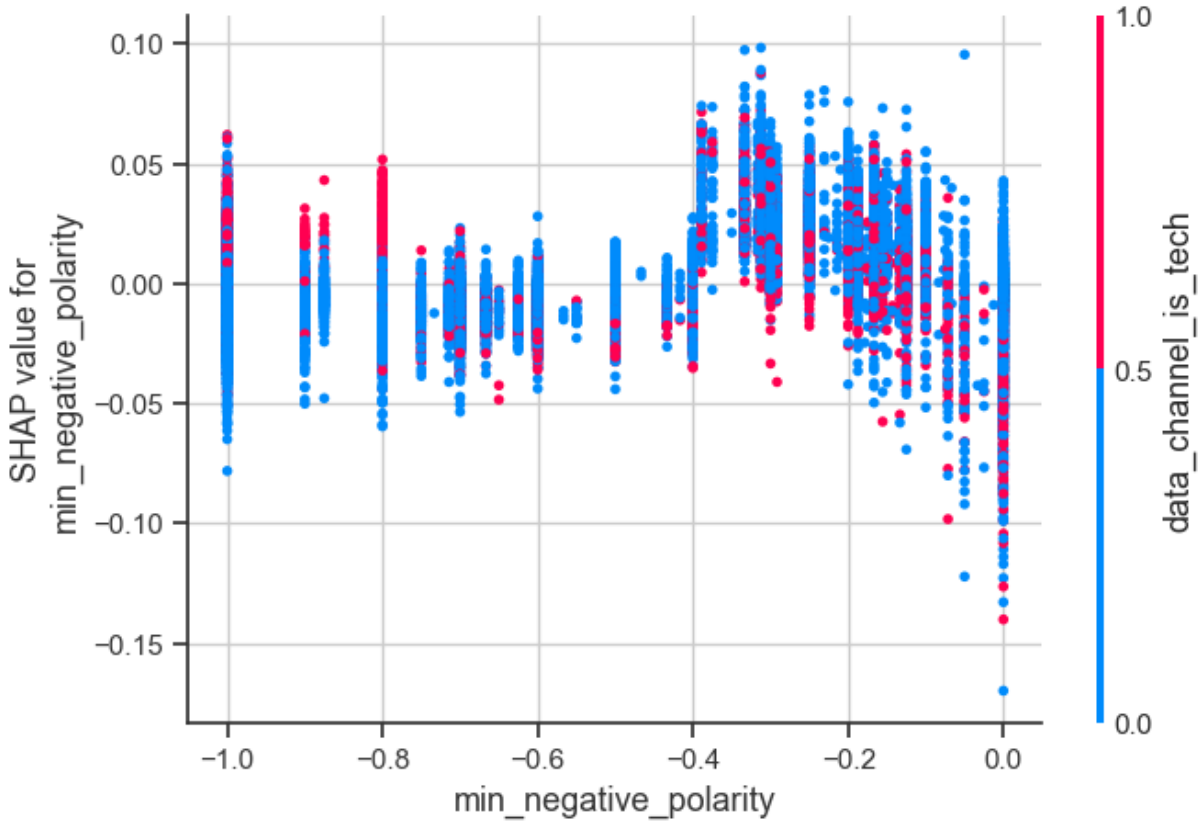

SHAP value for
rate_negative_words
0.3
0.2
0.1
0.0
−0.1
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
rate_negative_words
1.0
0.5
0.0
is_weekend

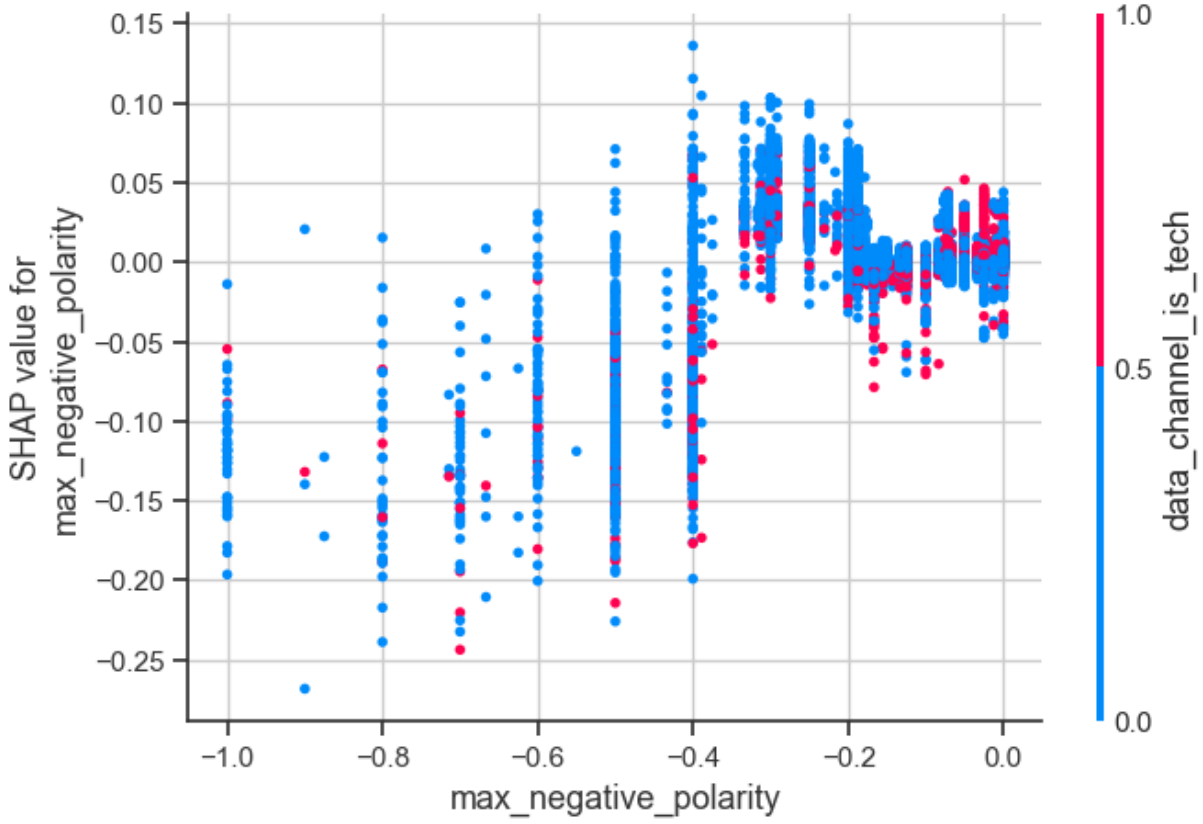

SHAP value for
avg_positive_polarity
0.2
0.1
0.0
−0.1
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
avg_positive_polarity
1.0
0.5
0.0
data_channel_is_socmed

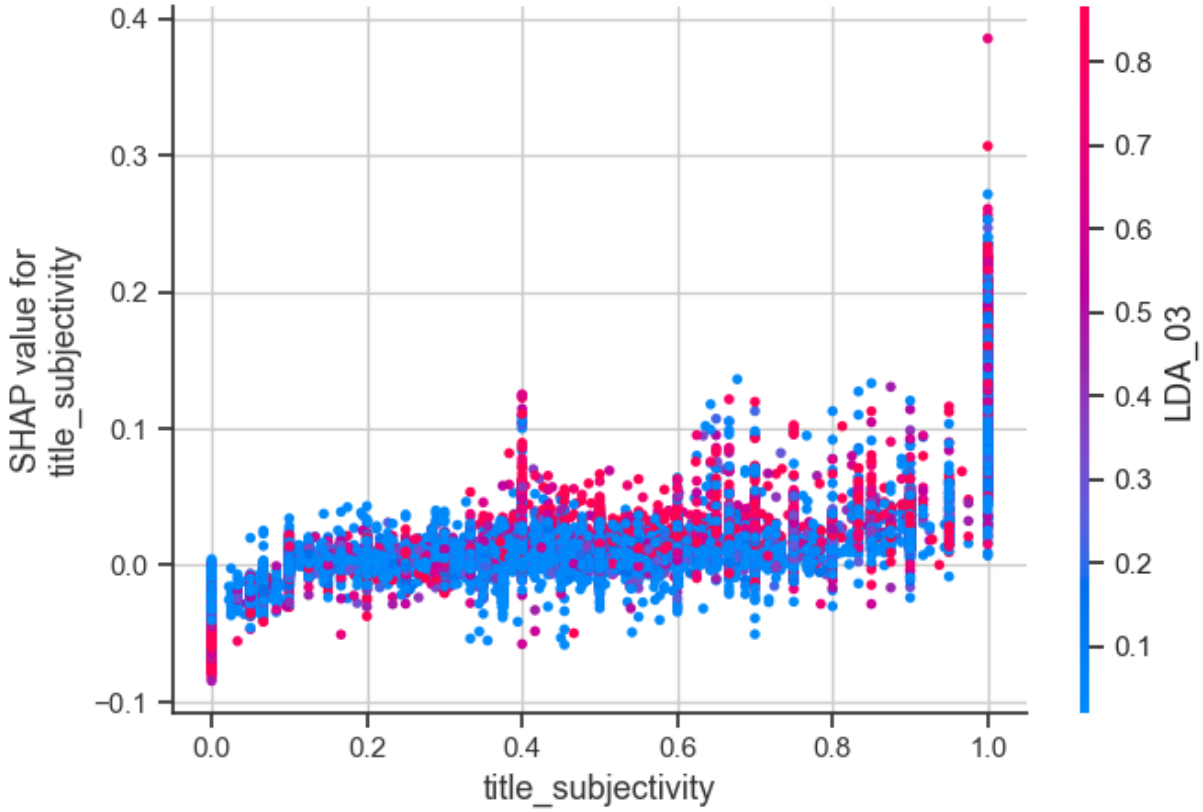

SHAP value for
min_positive_polarity
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
0.0
0.2
0.4
0.6
0.8
1.0
min_positive_polarity
1.0
0.5
0.0
data_channel_is_socmed

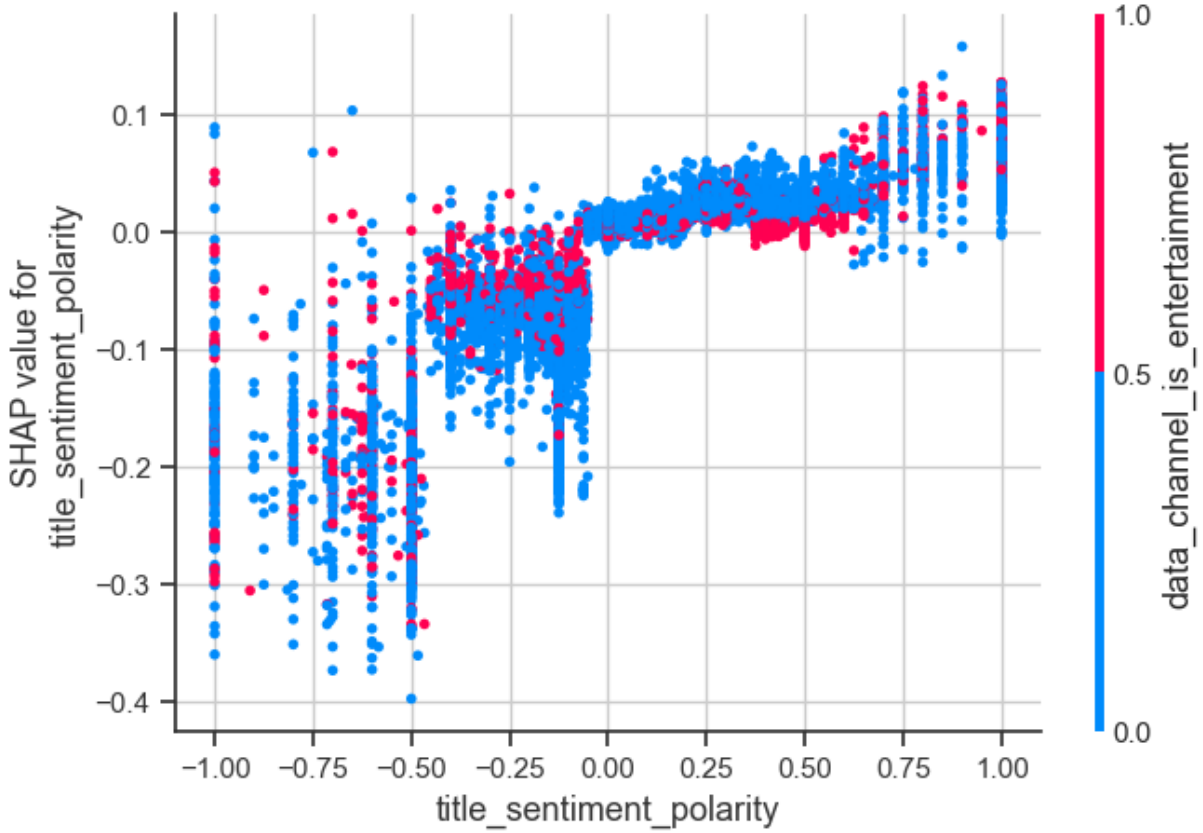

SHAP value for
max_positive_polarity
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
0.0
0.2
0.4
0.6
0.8
1.0
max_positive_polarity
1.0
0.5
0.0
data_channel_is_socmed

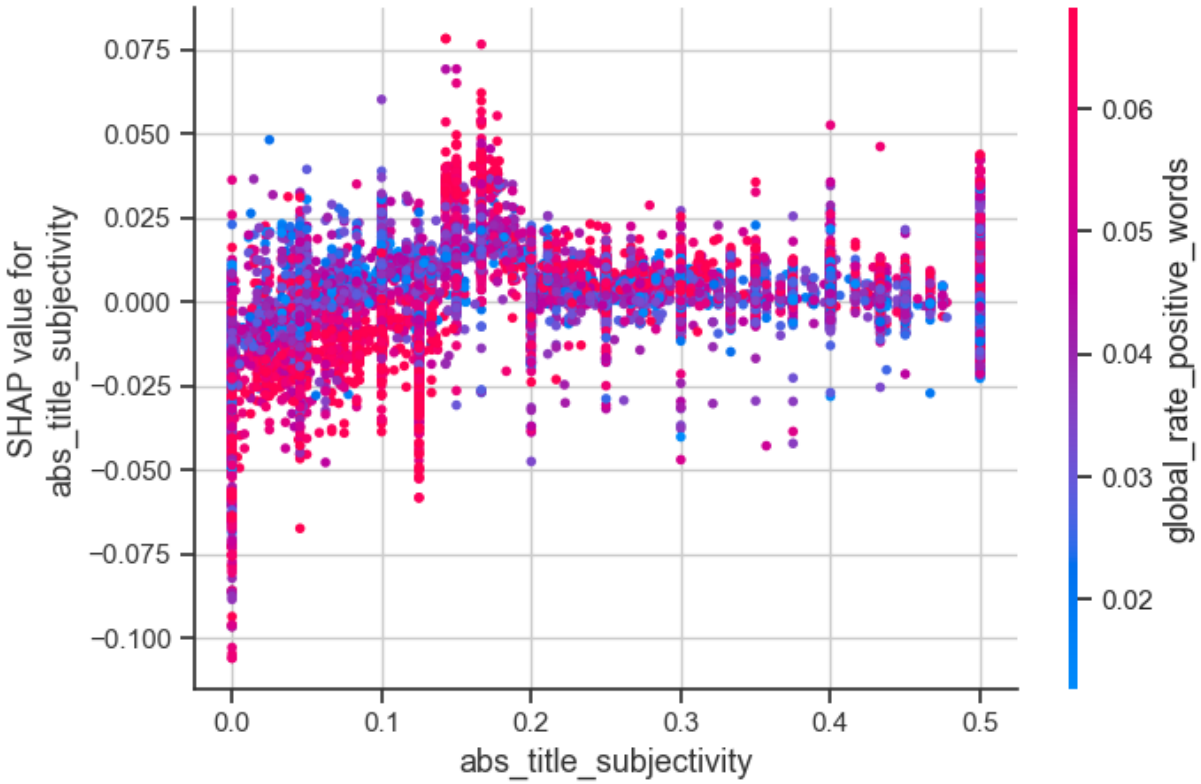

SHAP value for
avg_negative_polarity
0.15
0.10
0.05
0.00
−0.05
−0.10
−1.0
−0.8
−0.6
−0.4
−0.2
0.0
avg_negative_polarity
0.55
0.50
0.45
0.40
0.35
0.30
global_subjectivity

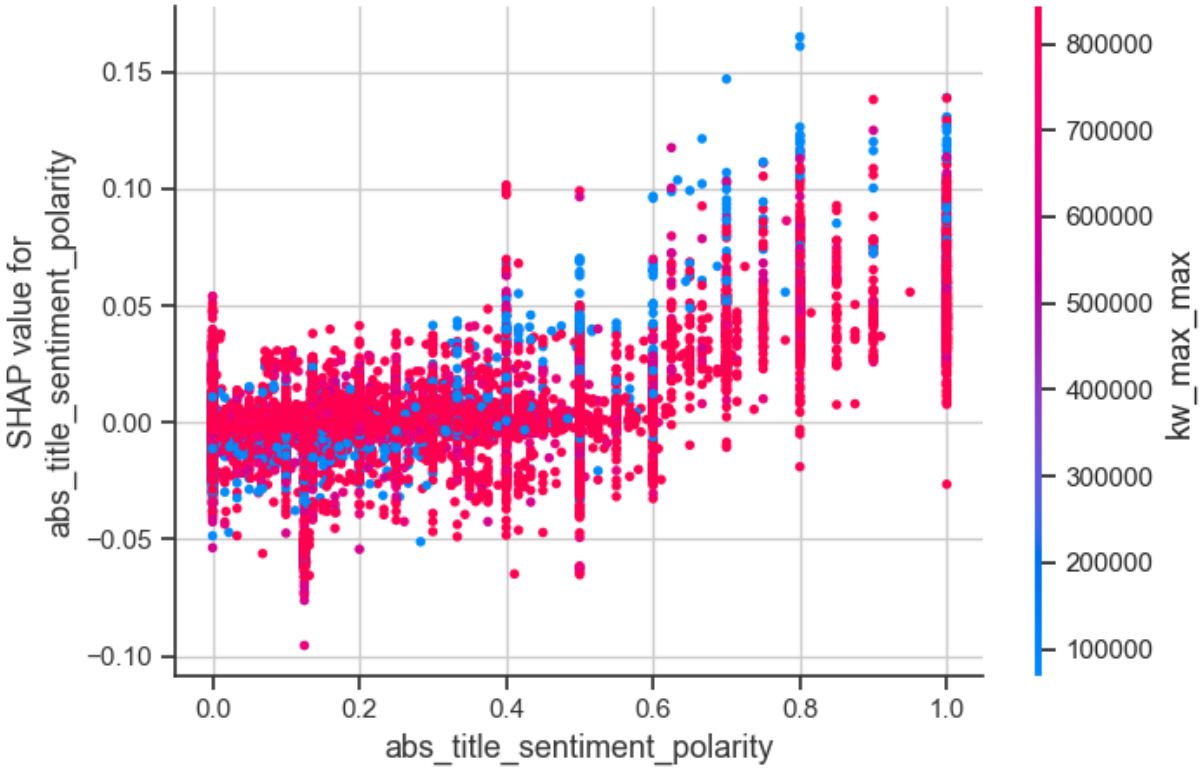

SHAP value for
min_negative_polarity
0.10
0.05
0.00
−0.05
−0.10
−0.15
−1.0
−0.8
−0.6
−0.4
−0.2
0.0
min_negative_polarity
1.0
0.5
0.0
data_channel_is_tech


SHAP value for
max_negative_polarity
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
−0.25
−1.0
−0.8
−0.6
−0.4
−0.2
0.0
max_negative_polarity
1.0
0.5
0.0
data_channel_is_tech


SHAP value for
title_subjectivity
0.4
0.3
0.2
0.1
0.0
−0.1
0.0
0.2
0.4
0.6
0.8
1.0
title_subjectivity
LDA_03
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1


SHAP value for
title_sentiment_polarity
0.1
0.0
−0.1
−0.2
−0.3
−0.4
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
title_sentiment_polarity
data_channel_is_entertainment
1.0
0.5
0.0





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- Fernandes, Kelwin, Vinagre, Pedro, Cortez, Paulo, and Sernadela, Pedro. (2015). Online News Popularity. UCI Machine Learning Repository. https://doi.org/10.24432/C5NS3V.

In [65]:
```
print('Successful run!')
```

```
Successful run!
```