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ESILV - DIA1

Python for data analysis — 2021

ONLINE NEWS POPULARITY

CONTENTS

CONTEXT

- This dataset summarizes a heterogeneous set of features about articles published by Mashable in a period of two years.
- The goal is to predict the number of shares in social networks (popularity).

THE DATASET

— *The dataset is composed of 61 attributes*

— *It has 39797 instances*

— *It's area is business*

— *Relevant paper :*

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

58 PREDICTIVE ATTRIBUTES

Such as :

- The number of words in the title,
- The number of videos,
- The day of the week it was published on, etc.

2 NON-PREDICTIVE

- The URL
- The timedelta (Days between the article publication and the dataset acquisition)

1 GOAL FIELD

- The number of shares (popularity)

FIRST STEPS

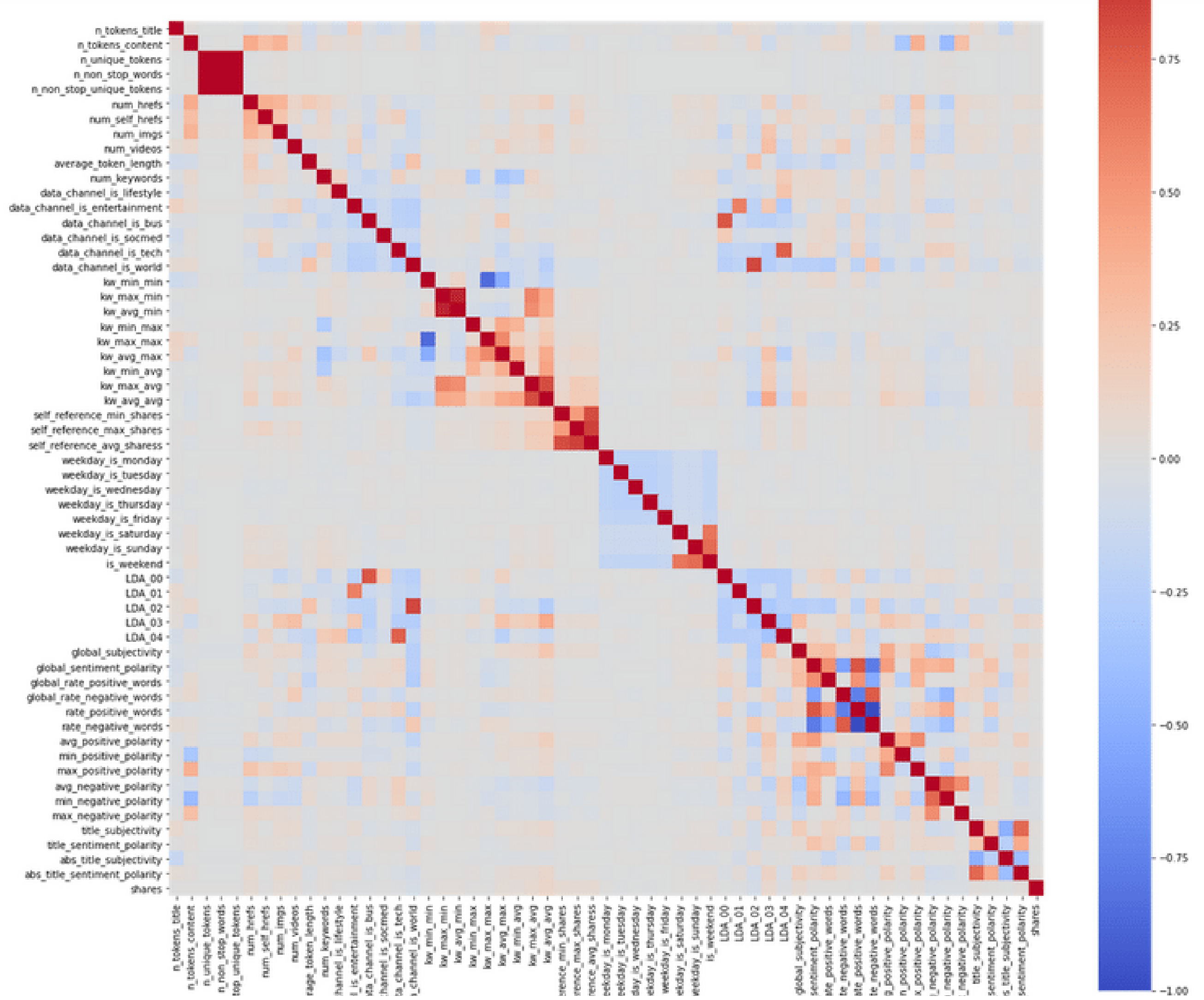
DATA PRE-PROCESSING

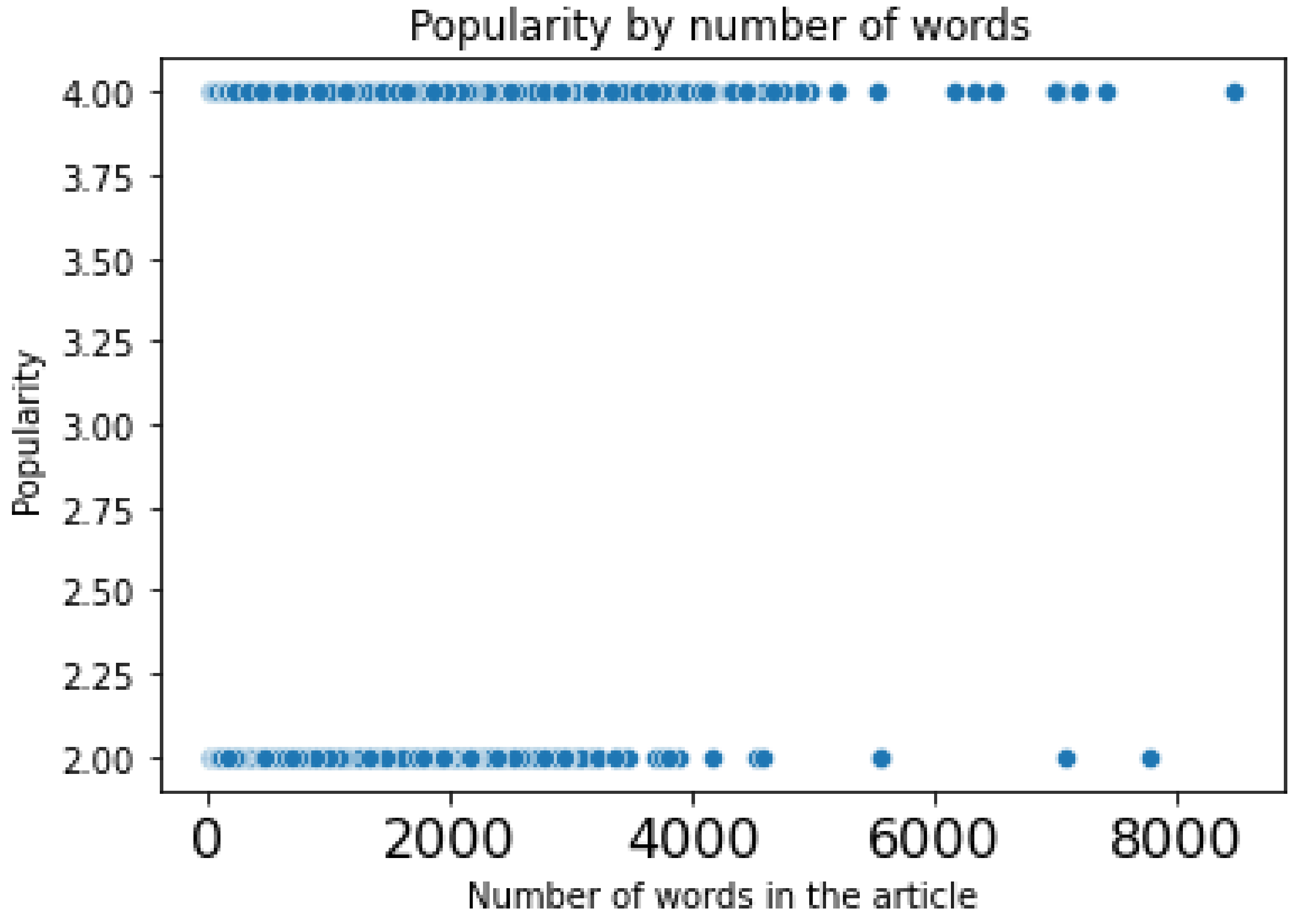
The first step is to clean our data :

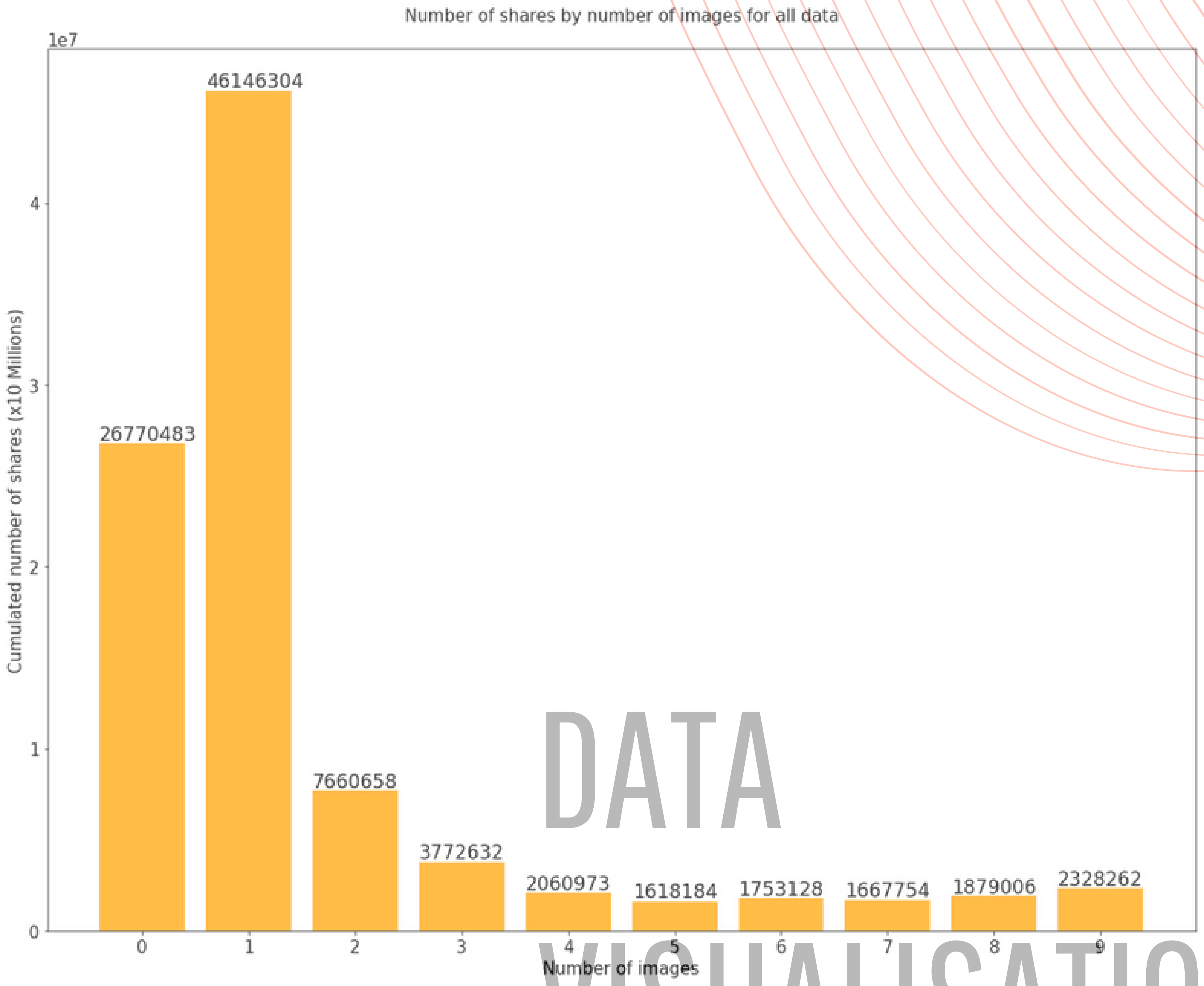
- Deleting empty spaces in attributes' names
- Droping articles containing 0 word
- Droping the non-predictive features
- Droping the duplicates and NA
- Droping a part of highly corelated features ("n_non_stop_unique_tokens","n_non_stop_words","kw_avg_min")

HOW TO INTERPRET THE TARGET

- We tried regression models like linear regression or random forest regression (and others) but the results weren't good (MSE too big, score too low).
- The goal is to predict the popularity : Being able to say the article is popular or not is far more representative than a number without its context. Setting only 2 classes gives us a better accuracy too.
- We tested to set the thresh old value to set the popular/unpopular label with the mean of shares of every articles. => The accuracy was the best among every models we could find on the net but the recall and F1-score were around 0 (the model was able to recognize an article was unpopular very well because it had many of this examples, but sucked when it had to predict that a popular article was popular)
- <u>So finally we choose to set this value to the Median which is 1400</u> and create a popularity column which takes 2 if the article is unpopular, else 4.

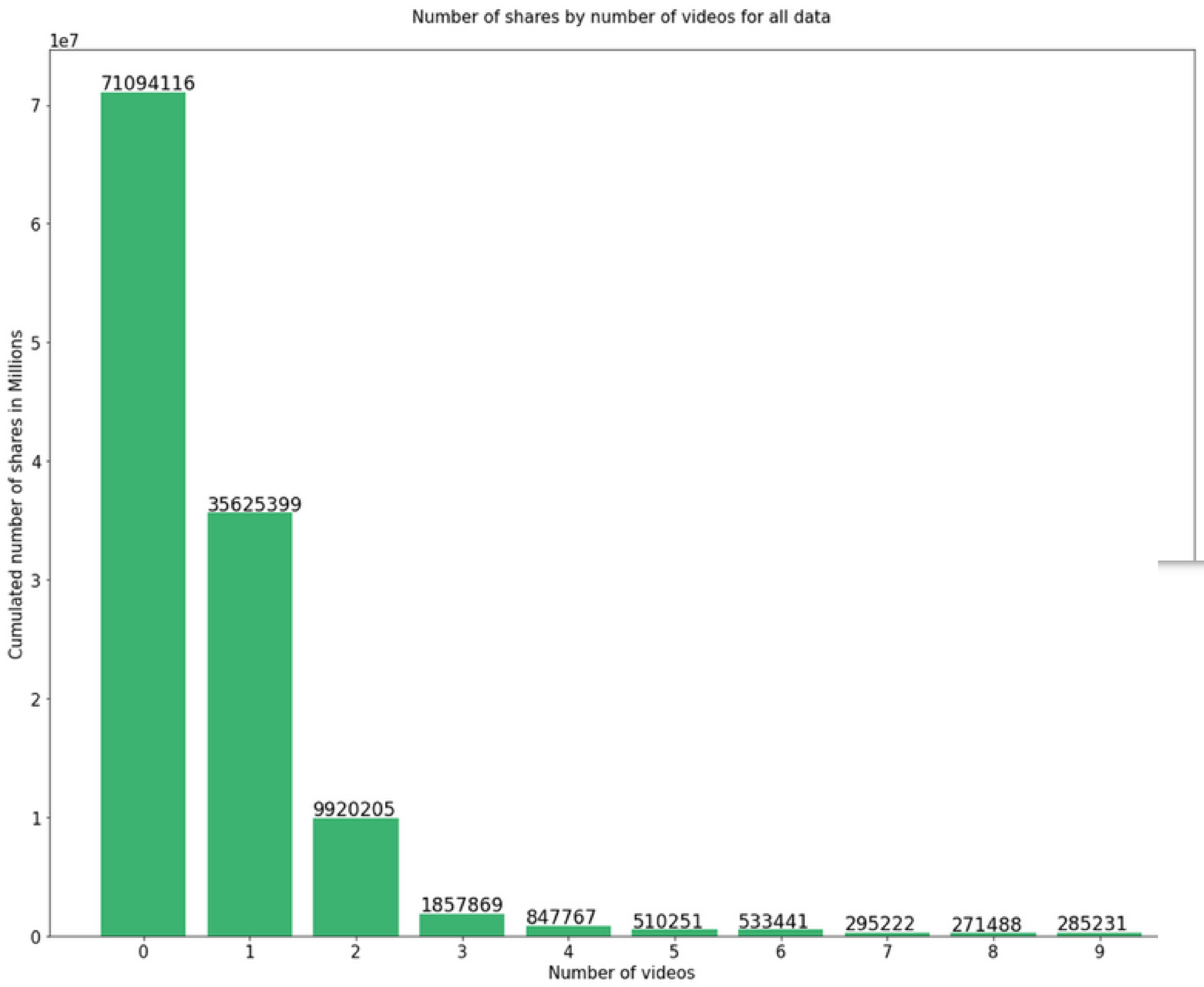


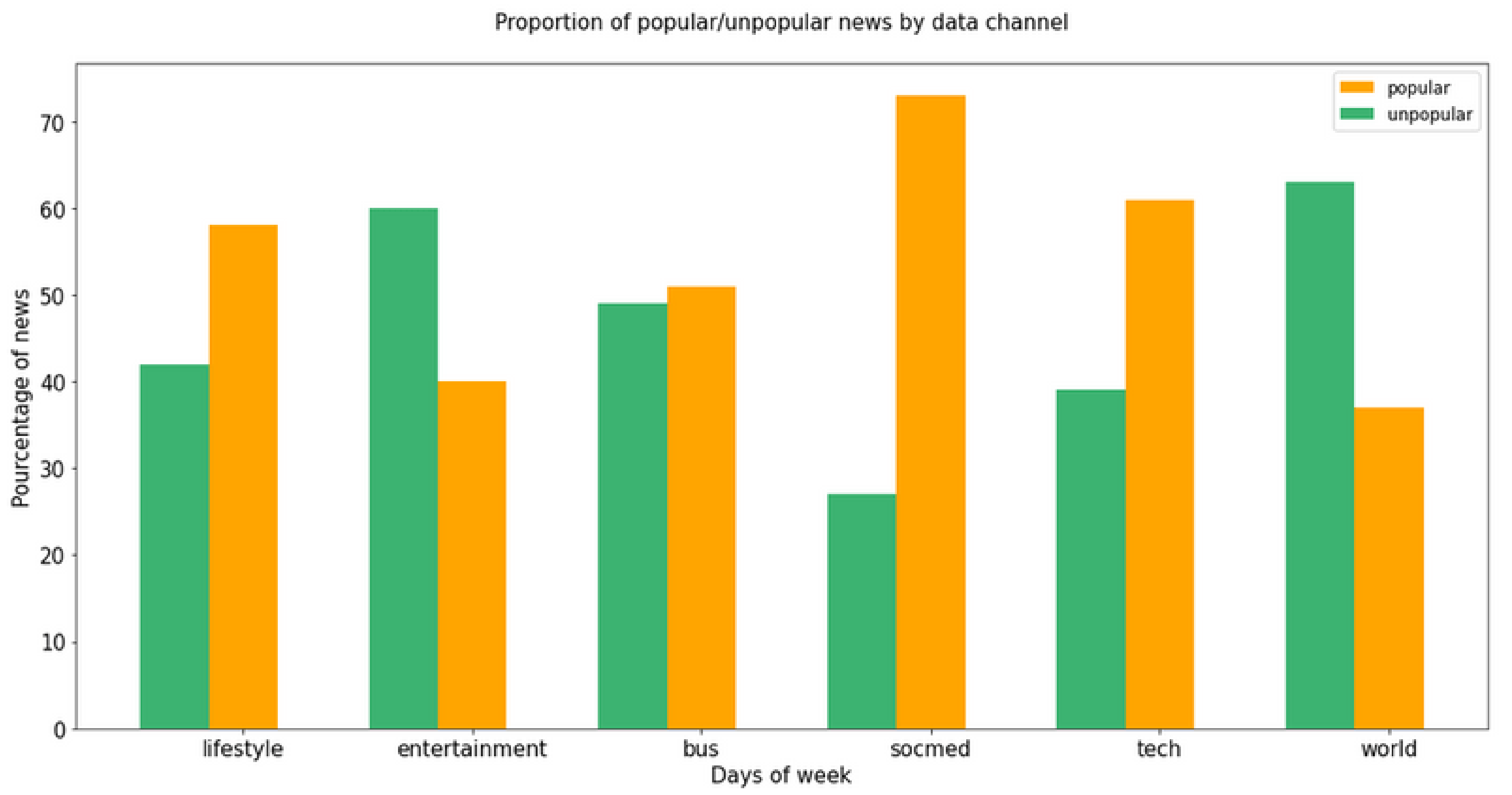


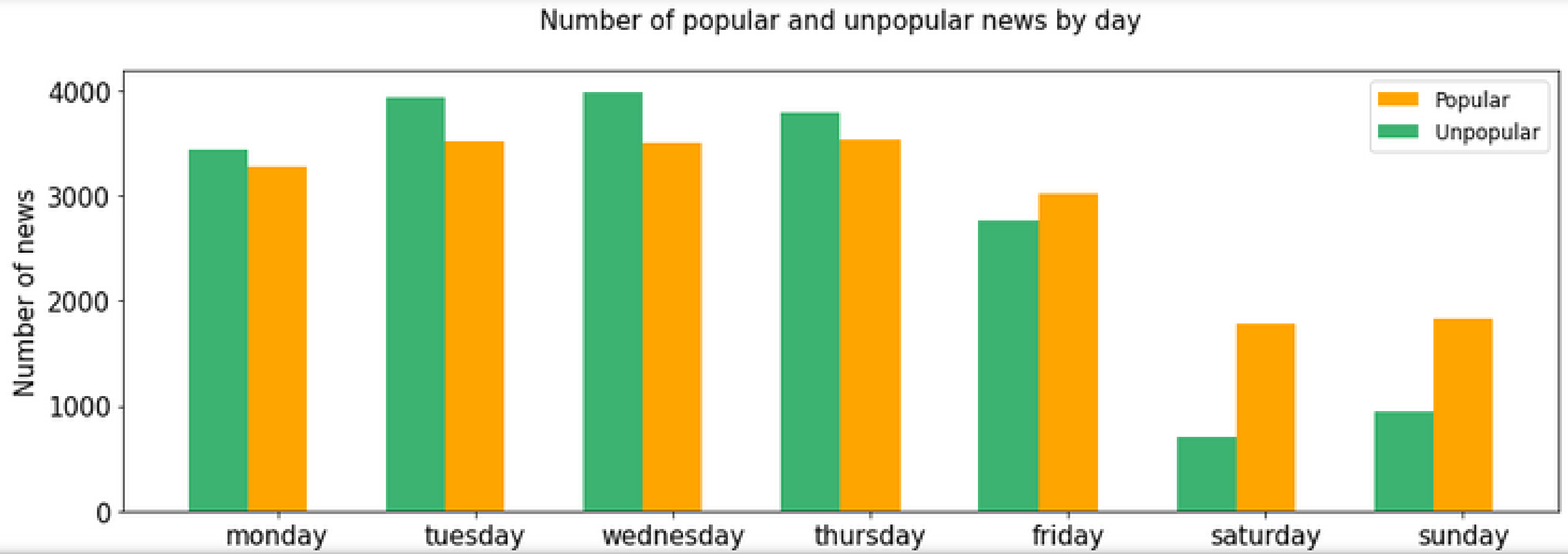


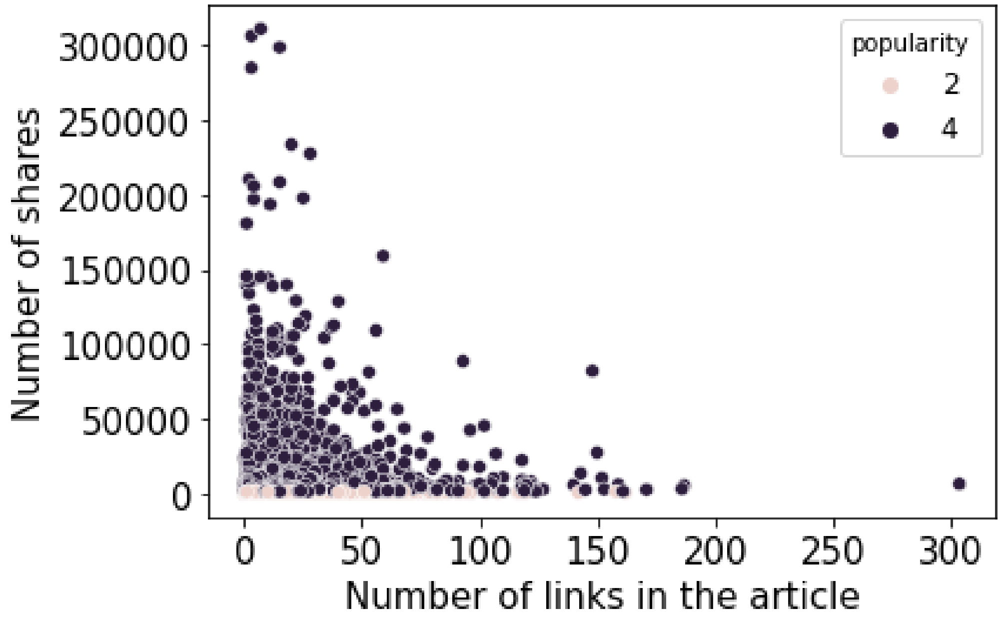
DATA VISUALISATION

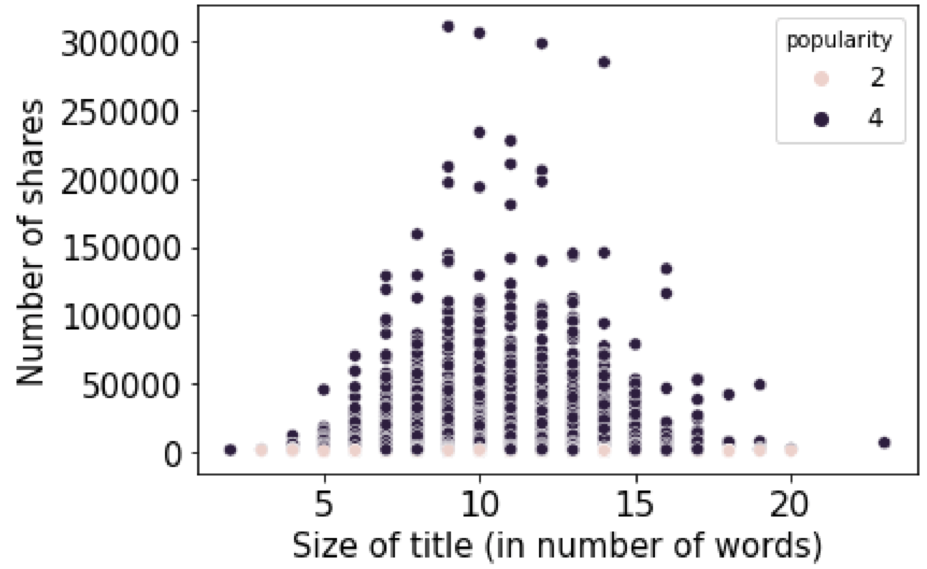
— We tried to demonstrate visually many interesting points in order to better understand the data set and the links with the variable shares


Number of shares by number of videos for all data
1e7
Cumulated number of shares in Millions
71094116
35625399
9920205
1857869
847767
510251
533441
295222
271488
285231
Number of videos


Proportion of popular/unpopular news by data channel
popular
unpopular
Pourcentage of news
lifestyle
entertainment
bus
socmed
tech
world
Days of week


Number of popular and unpopular news by day
Popular
Unpopular
Number of news
monday
tuesday
wednesday
thursday
friday
saturday
sunday


popularity
2
4
Number of shares
Number of links in the article


popularity
2
4
Number of shares
Size of title (in number of words)

CLASSIFICATION

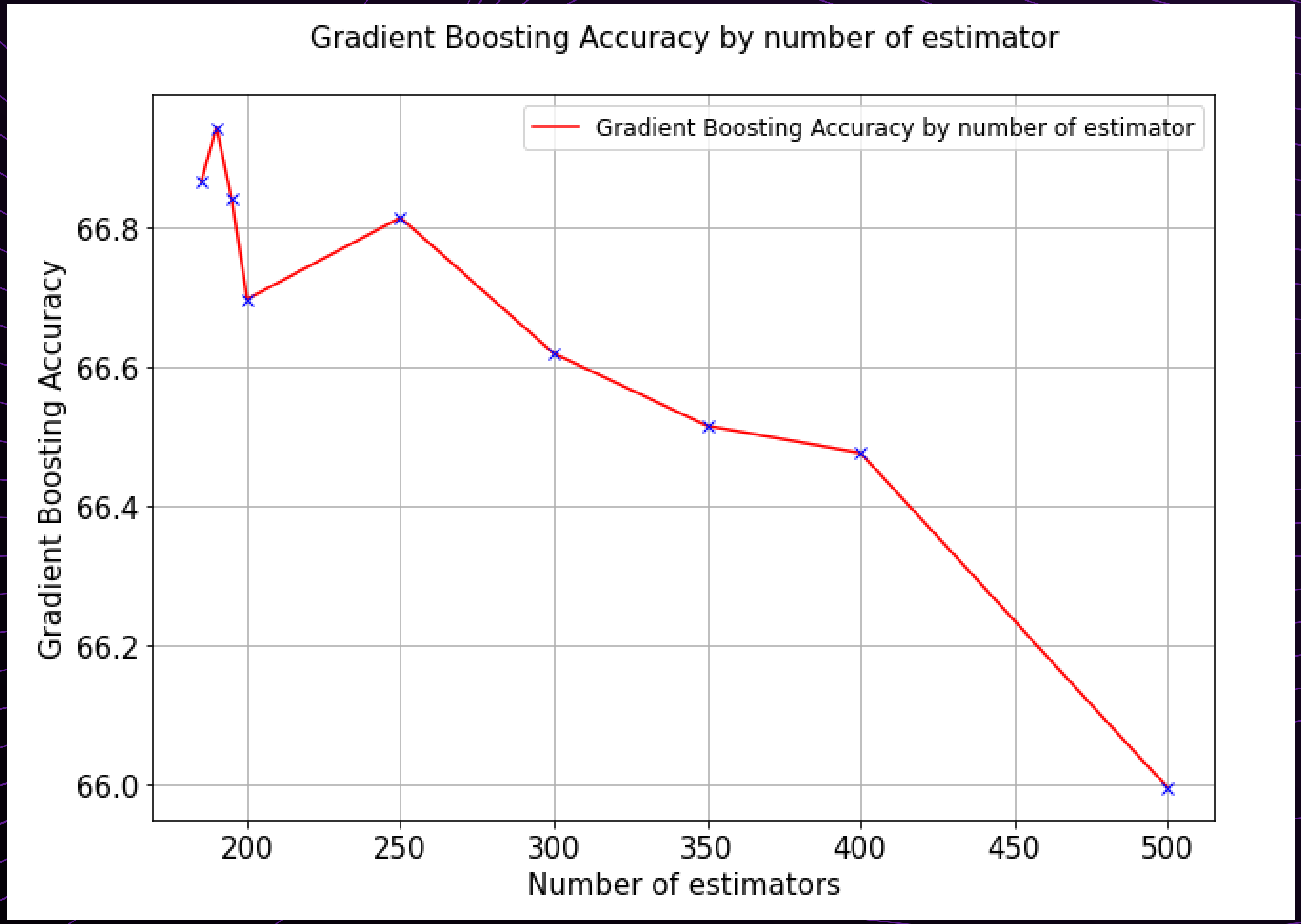
67% →

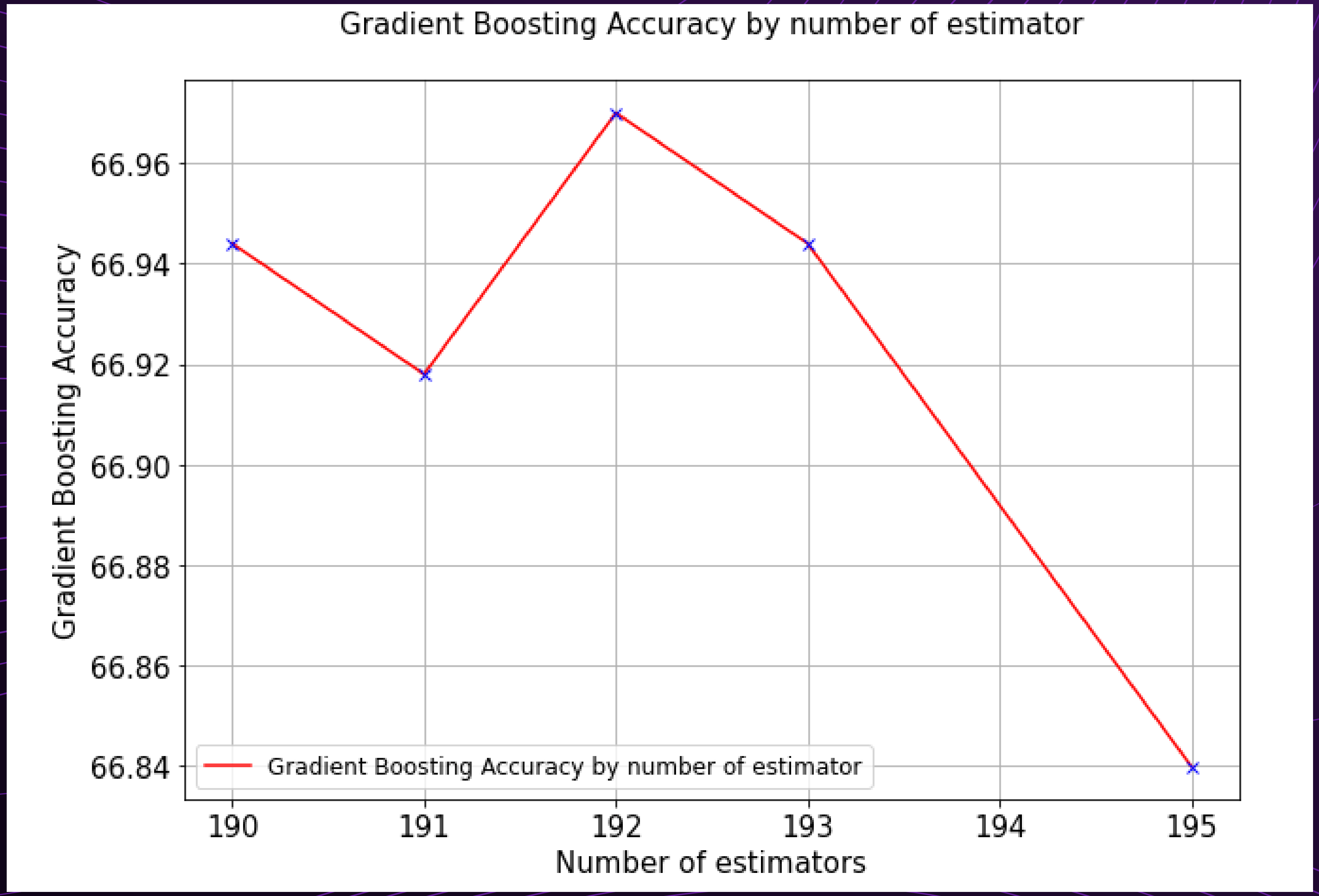
— We tried : Gradient Boosting, Random Forest, Ada Boost, Bagging, Logistic Regression, Naive bayes and KNN,
and tuned them to obtain the best accuracy possible. We don't forget to look at other metrics like recall, precision, F1-score, AUC... We also scaled the data with a robust and a standard scaler when the models needed it.

— 67% of accuracy is the best result we obtained using Gradient Boosting Classification with the threshold set to 1400. The recall and F1-score are good in this case (so is the precision and AUC).

CLASSIFICATION - CONTINUED

AN EXAMPLE OF HOW WE TUNED THE MODELS

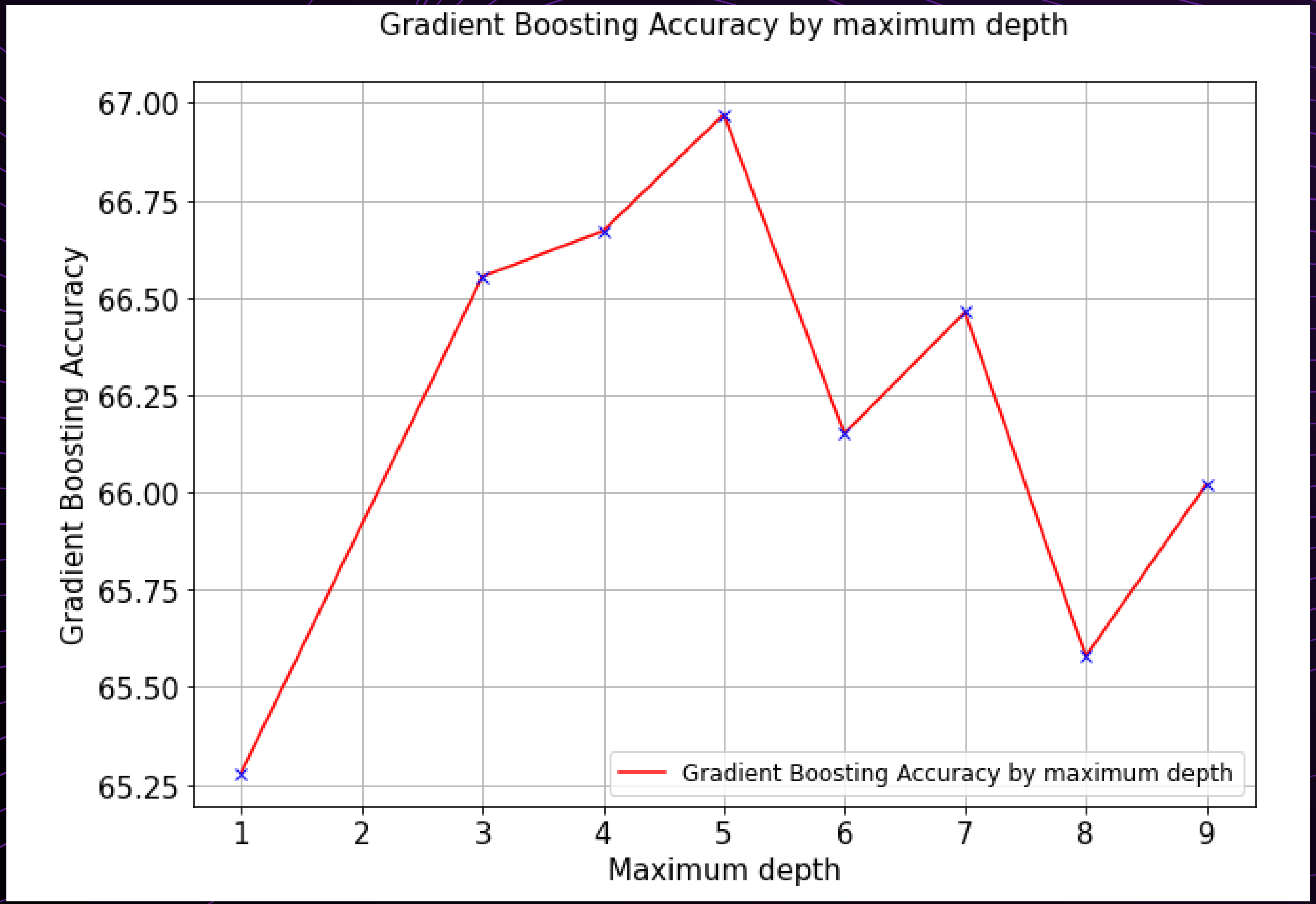




We try to find the best number of estimators for the model to have the best accuracy

CLASSIFICATION - CONTINUED 2

AN EXAMPLE OF HOW WE TUNED THE MODELS

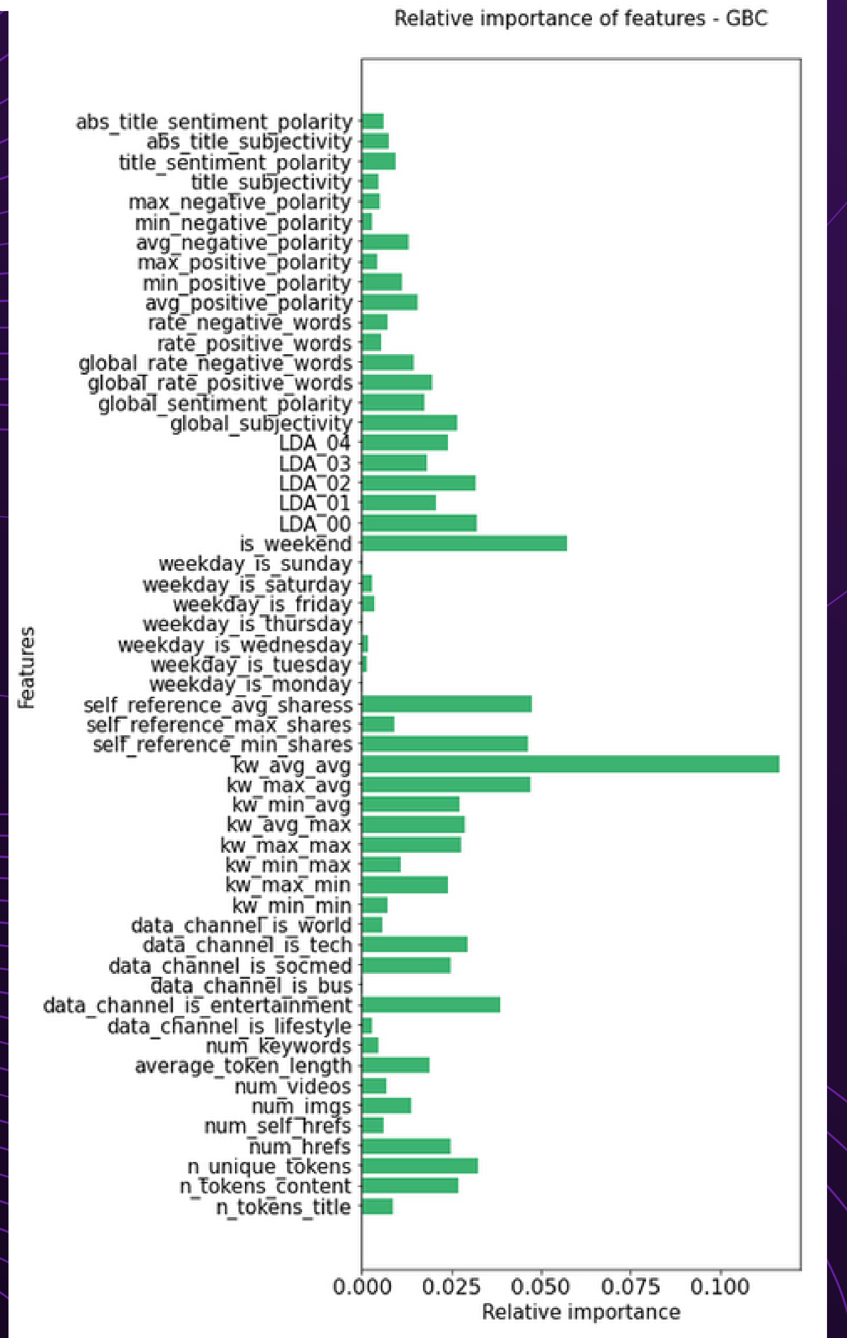


Then we try to find the best maximum depth using the number of estimators we just found

```
Gradient Boosting Classifier Accuracy : 0.6696997270245678
Gradient Boosting Classifier AUC : 0.666770523586857
Gradient Boosting Classifier Recall : 0.7113930226884606
Gradient Boosting Classifier Precision : 0.682264857276556
Gradient Boosting Classifier F1-score : 0.6965245431744894
```

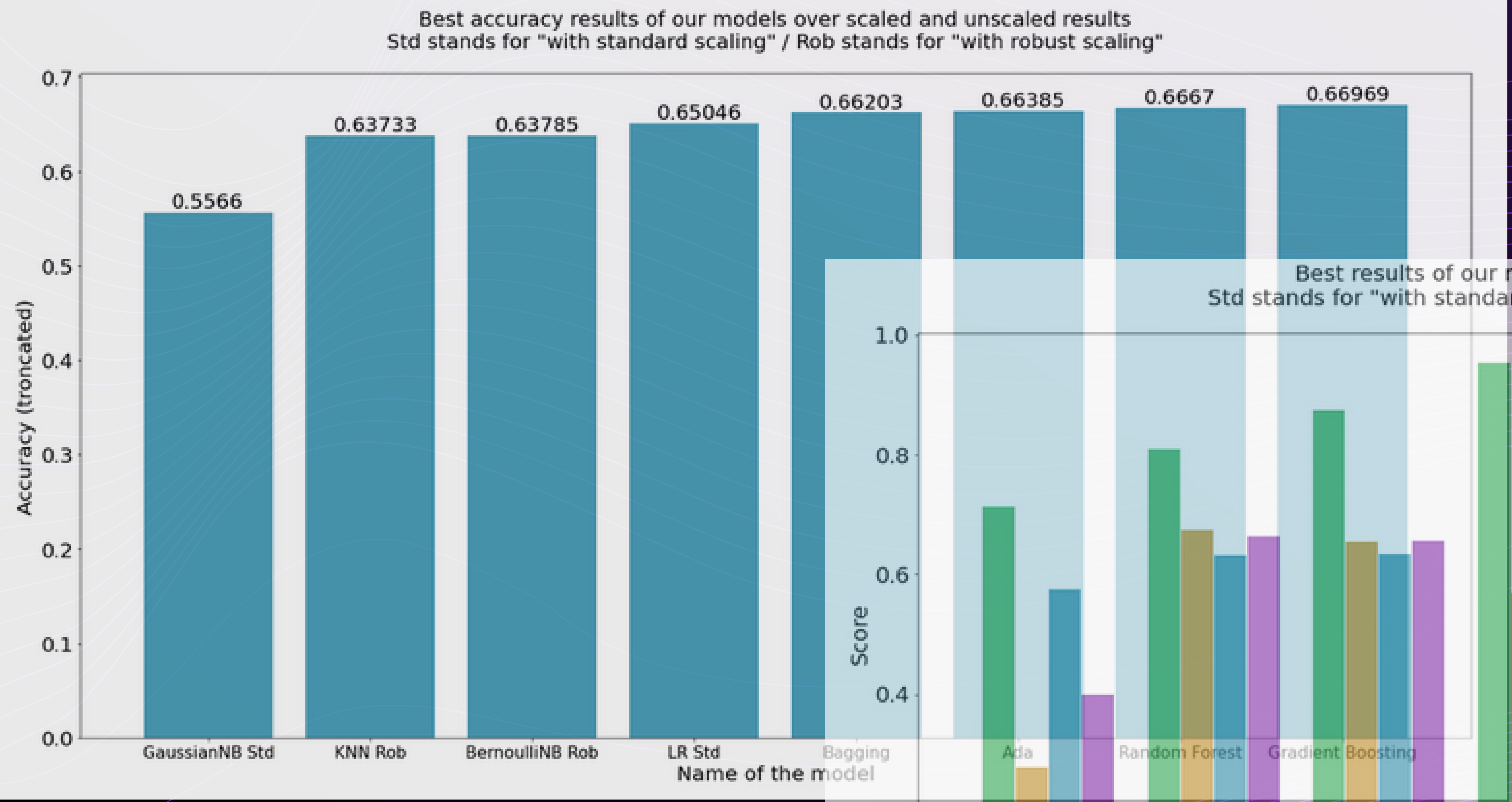
We print the scores using our metrics.

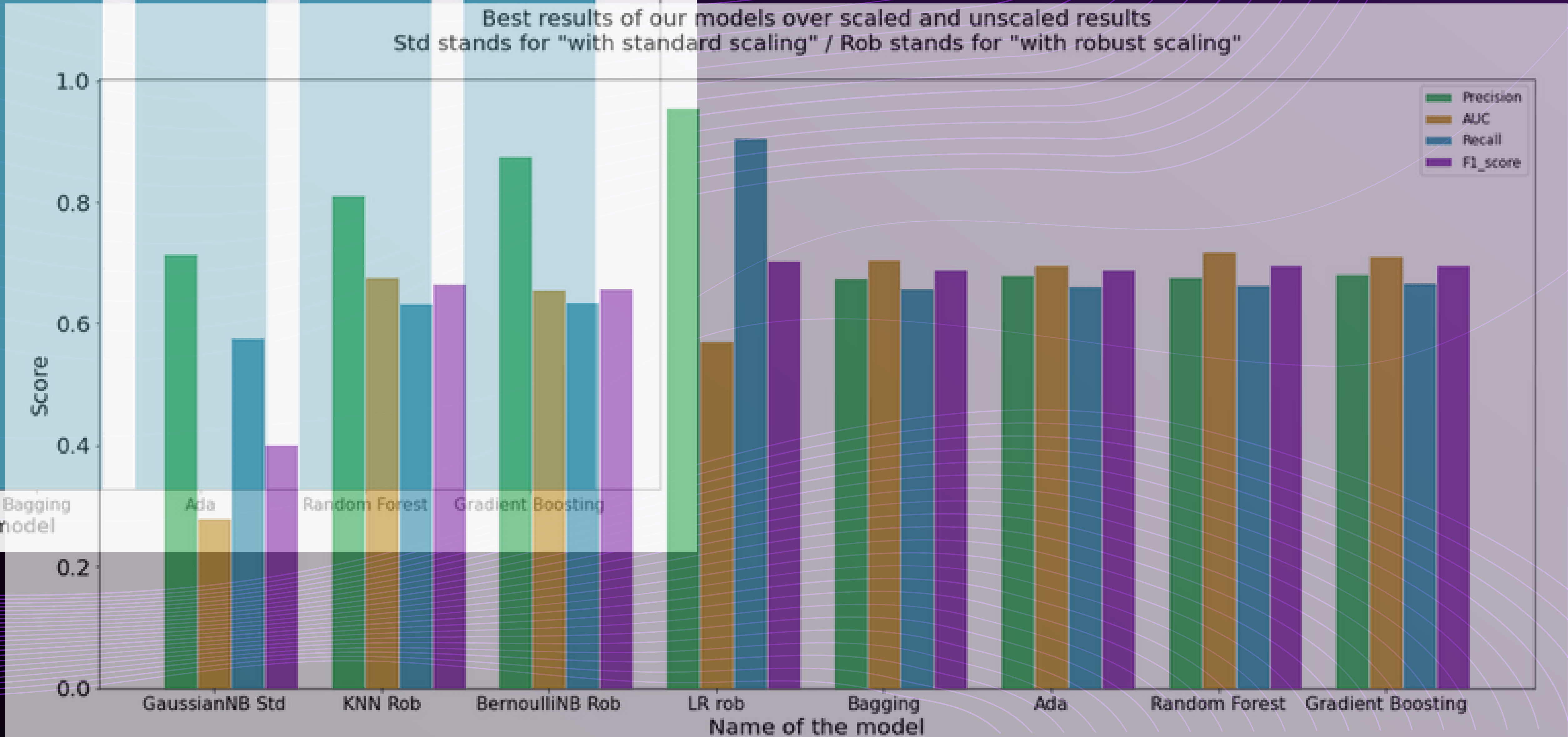
Then we look at the importance of each parameter the model found.



CLASSIFICATION - CONTINUED 3

RESULTS





CLASSIFICATION - CONTINUED 4

BONUS

```
df2 = df.iloc[:,:56]
liste = list()
for x in df2['shares']:
    if x >= 3355 :
        liste.append(4)
    else:
        liste.append(2)
df2["popularity2"] = liste
```

As you can see, setting the threshold value to 3355 on a random forest classifier gives us an amazing accuracy of 80.3%. But recall and F1-score are very bad.

```
clf = RandomForestClassifier(n_estimators = 150, max_depth=15, random_state=0, bootstrap = True, n_jobs=-1)
clf.fit(X2_train, Y2_train)
Y2_pred = clf.predict(X2_test)
```

```
Random Forest Classifier Accuracy : 0.8029377356037957
Random Forest Classifier AUC : 0.5178392258754849
Random Forest Classifier Recall : 0.04218040233614536
Random Forest Classifier Precision : 0.6190476190476191
Random Forest Classifier F1-score : 0.0789793438639125
```

API

— Our API takes 3 inputs : A title, a text, and a categorie It then uses our model and gives you a prediction whether it will be popular or not.

WE TRAINED THE MODEL ON THIS PARAMETERS =>

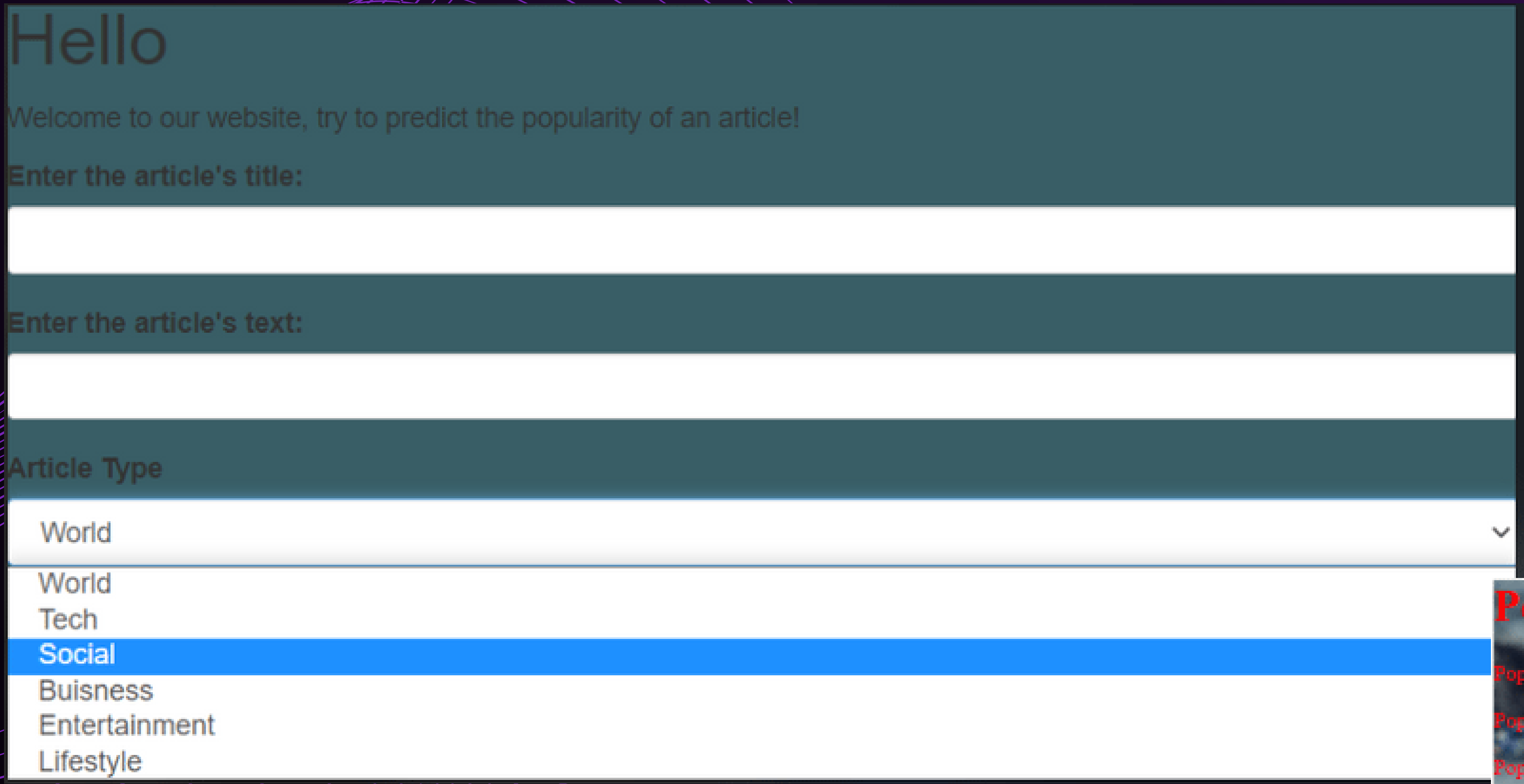
It's accuracy is 59.3%

'n_tokens_title',
'n_tokens_content',
'n_unique_tokens',
'average_token_length',
'n_non_stop_unique_tokens',
'num_hrefs',
'global_subjectivity',
'avg_positive_polarity',
'global_sentiment_polarity', 'data_channel_is_world',
"data_channel_is_tech", "data_channel_is_socmed",
"data_channel_is_bus",
"data_channel_is_entertainment",
"data_channel_is_lifestyle

```
def tokenizetext(text):
    return word_tokenize(text)
def words(text):
    l = [word for word in word_tokenize(text) if word.isalpha()]
    return l
def unique_words(text):
    return list(set(words(text)))
def rate_uni_words(text):
    uni_words = len(unique_words(text))/len(words(text))
    return uni_words
def avglengthtoken(text):
    w = words(text)
    sum = 0
    for item in w:
        sum+=len(item)
    avglen = sum/len(w)
    return avglen
def n_non_stop_unique_tokens(text):
    uw = unique_words(text)
    n_uw = [item for item in uw if item not in stopwords]
    w = words(text)
    n_w = [item for item in w if item not in stopwords]
    rate_nsut = len(n_uw)/len(n_w)
    return rate_nsut
def numlinks(article):
    return len(BeautifulSoup(article).findAll('link'))
def get_subjectivity(a_text):
    return a_text.sentiment.subjectivity
def get_polarity(a_text):
    return a_text.sentiment.polarity
def word_polarity(words):
    pos_words = []
    ppos_words = [] # polarity of pos words
    neg_words = []
    pneg_words = [] # polarity of negative words
    neu_words = []
```

And we created the functions that allows us to create every values corresponding to this parameters with only 3 inputs which are : a title, a text and a categorie.

API



Hello
Welcome to our website, try to predict the popularity of an article!
Enter the article's title:
Enter the article's text:
Article Type
World
World
Tech
Social
Buisness
Entertainment
Lifestyle

Unpopular
Unpopular
Unpopular
Unpopular
Unpopular
Unpopular
Unpopular
Unpopular
Unpopular
Unpopular
Unpopular
Unpopular
Unpopular
Unpopular

Popular
Popular
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Popular

CONCLUSION

We found that articles containing :

- Less than 4500 words
- 1 image (or 0)
- 0 video (or 1)
- Between 0 and 40 links
- Posted on week-end
- The categorie social media, tech or lifestyle
- Title between 6 and 16 characters

Tend to be more popular than the others

The accuracy alone isn't an accurate metric as we saw with the case of the threshold of the popularity set to 3355 shares. It gave us an amazing accuracy but very poor recall and F1-score.
We think that a 2 class classification suits the best this dataset but more data could also helps for regression or multiclass classification.

We could get a better accuracy by getting more data but also using deep learning and neural networks. We found on the net someone getting a 98% accuracy using Keras.
A better features selection might bring less biais since we didn't really tested that out.

Popularity might change with people and with time, so we think that the articles liked and popular today might not be the same as the one at the time of the dataset (2013-2015).
A new dataset with actual data might increase the performance of the API.