GA PROJECT 3

NLP CLASSIFICATION FOR AD TARGETING

R/CODINGBOOTCAMP VS R/CSMAJOR

MARY-ANNE, RIFQI, SHAWN, TING WEI, WEI ZHE

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- Background
- Problem Statement
- Workflow
- Data Cleaning
- EDA
- Modelling
- Limitations/Moving Forward
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BACKGROUND

There is increased competition in the space for coding bootcamps.

HACK REACTOR

le wagon

Vertical Institute

ROCKET ACADEMY

BACKGROUND

There is an increased competition in the space for coding bootcamps.

HACK REACTOR | le wagon | Vertical Institute | ROCKET ACADEMY

If no action is taken, General Assembly may face...

DECLINE IN MARKET SHARE

LOWER MARKETING ROI

POORER LEAD GENERATION

BACKGROUND

GENERAL ASSEMBLY

MARKETING TEAM

- **Better identify the online presence** of a **bootcamp seeker** as opposed to that of a computer science major to aid in targeted advertising.
- Considering the two topics have quite a bit in common, efforts to further segregate the two could yield **better advertising ROI**.

Keywords are an important aspect of digital advertising |

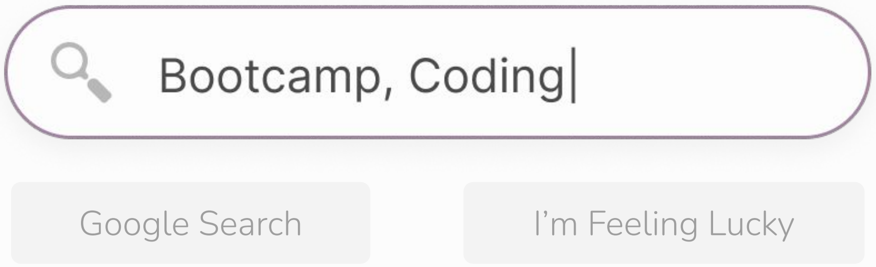
https://www.keywordsrock.com ⋮

Keywords allow for targeted strategies at all levels of the marketing funnel

Keywords guide marketing teams on the sort of advertising content that is required.

E.g. Google ads, one of the most effective platforms for generating leads and sales works well due to its ability to target users with high buying intent based on the keywords they use.

SEO Keywords · Google Ad · General Assembly · Coding Bootcamps

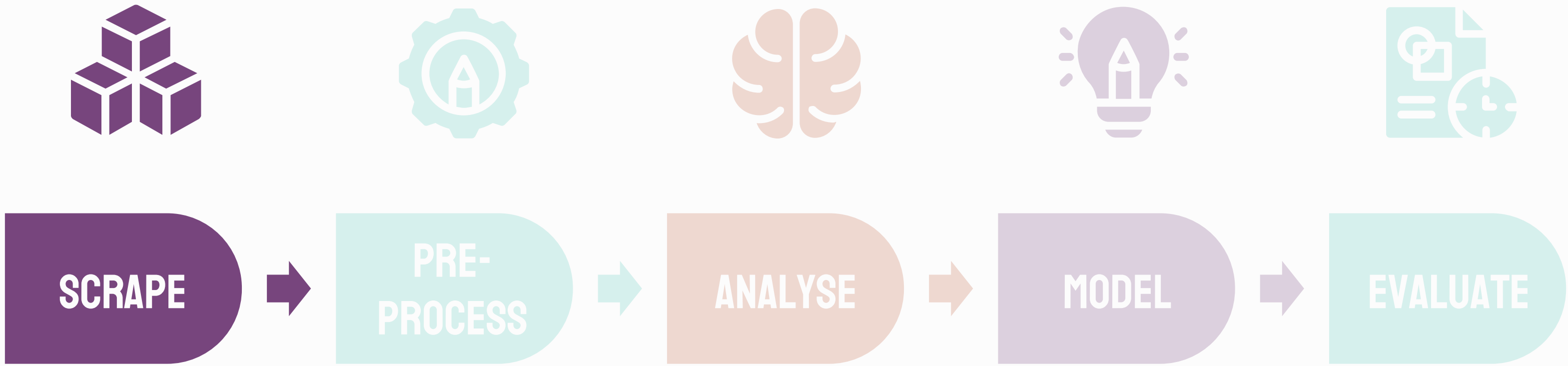


Current classifying model using straightforward **keywords** such as ‘bootcamp’ and ‘coding’ yields around **79% accuracy**.

PROBLEM STATEMENT

Build a model with **>90% accuracy** that helps to identify between **those who are looking for bootcamp style learning** vs computer science majors/prospective students **based on the words they use** online.

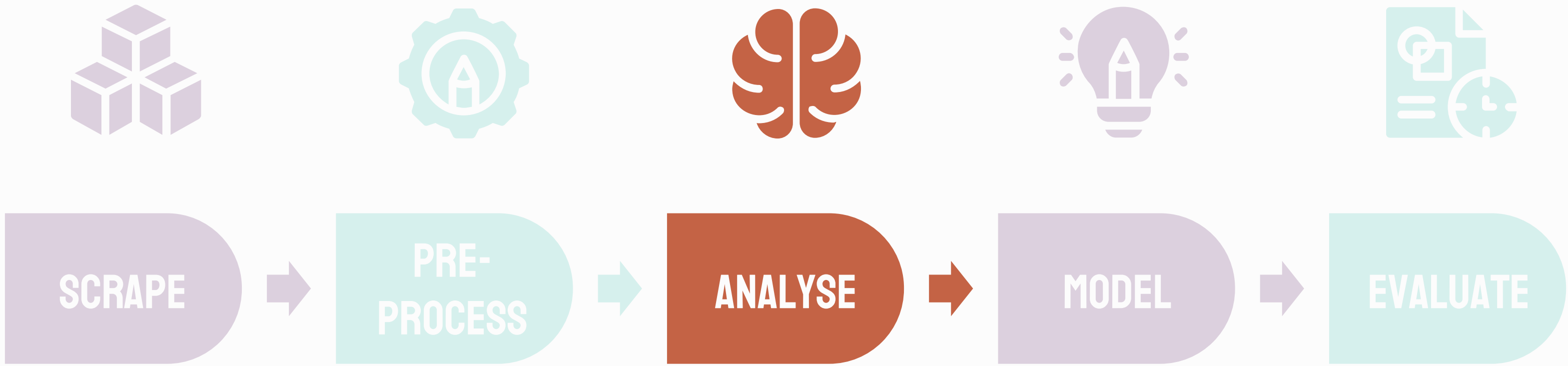
WORKFLOW



WORKFLOW

SCRAPE → PRE-PROCESS → ANALYSE → MODEL → EVALUATE

WORKFLOW



WORKFLOW

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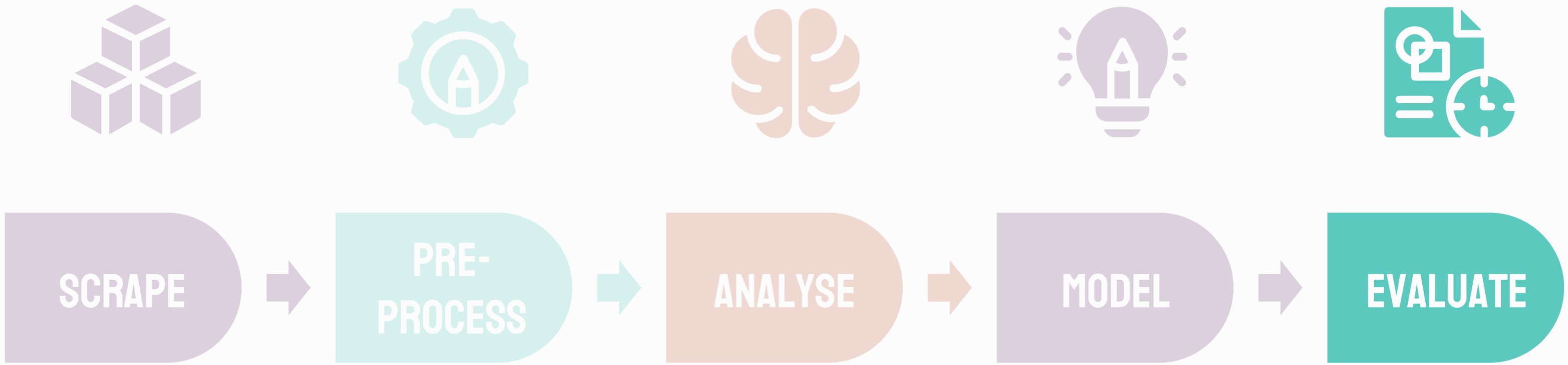
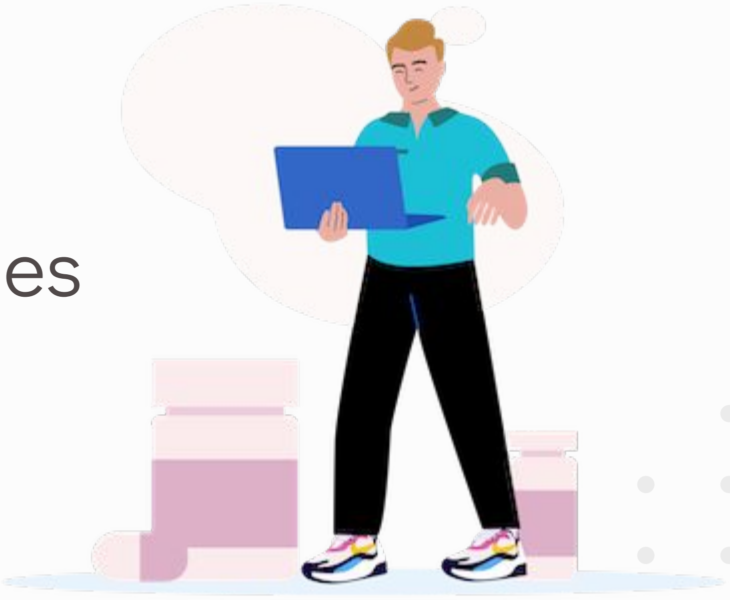


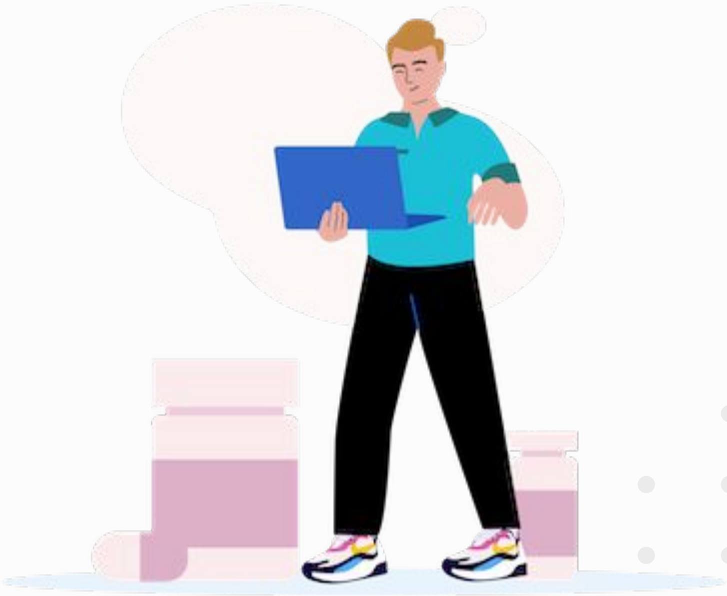
WHAT METHODS ARE WE USING TO CLEAN?

- Web Scraping
- Remove Null/Duplicate values
- Remove punctuations



WHAT METHODS ARE WE USING TO CLEAN?

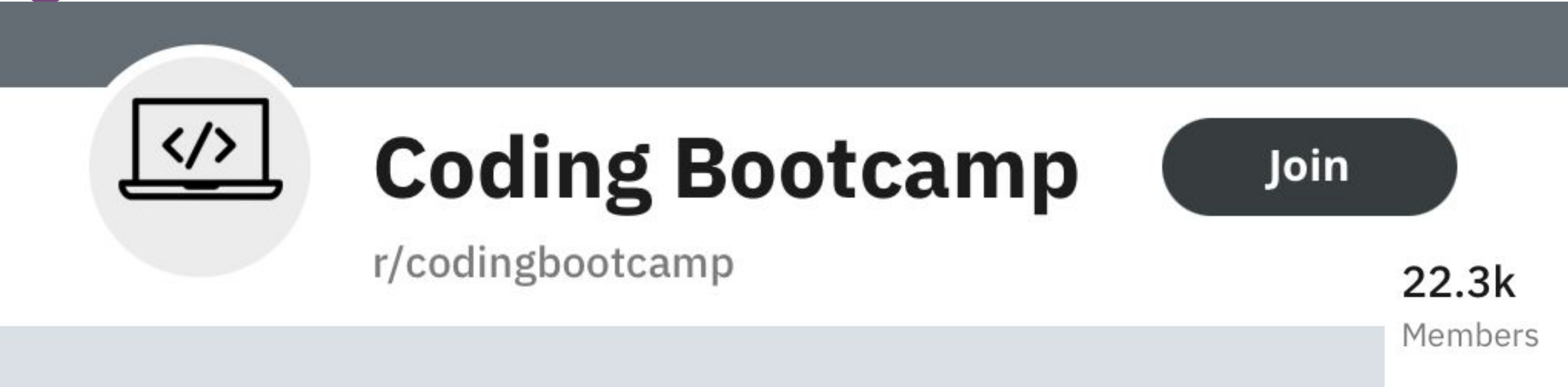
- Tokenization
- Remove stopwords
- Stem / Lemmatize

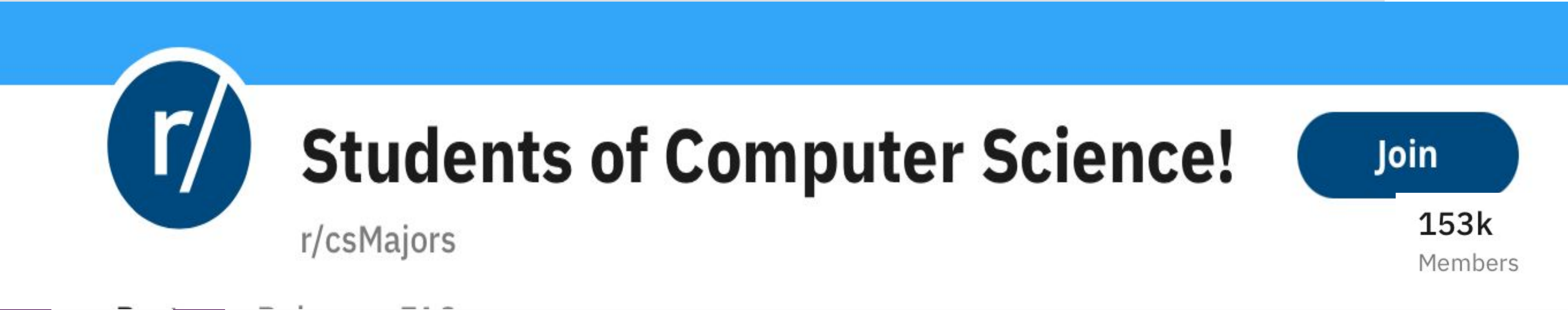


Reddit API vs Pushshift API

- Easier retrieving data
- 5 times greater object limit

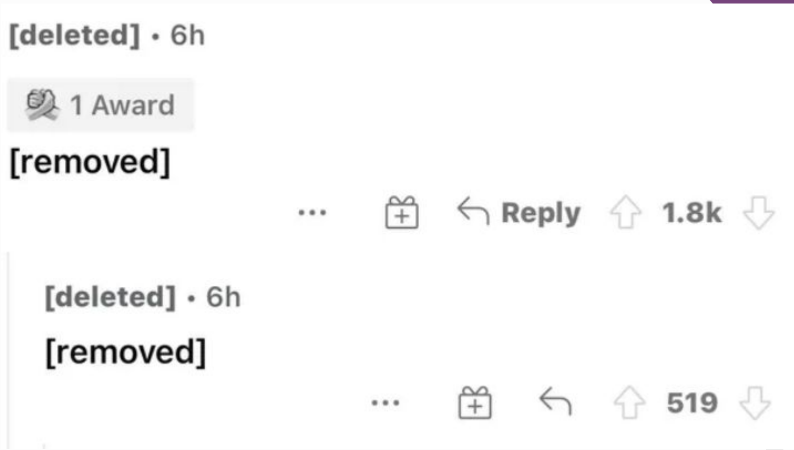
WHERE DO WE SCRAPE FROM?





REMOVED & DELETED

- Removed & Deleted posts are not beneficial to our case



- They are replaced with an empty string

```
# Remove the words [removed] and [deleted] from selftexts
df['selftext'] = df['selftext'].replace('[removed]', '')
df['selftext'] = df['selftext'].replace('[deleted]', '')
```

REMOVE PUNCTUATION & TOKENIZATION

	Removed Punctuation	Tokenization
body_text	body_text_clean	body_text_tokenized
I've been searching for the right words to tha...	Ive been searching for the right words to than...	[ive, been, searching, for, the, right, words,...
Free entry in 2 a wkly comp to win FA Cup fina...	Free entry in 2 a wkly comp to win FA Cup fina...	[free, entry, in, 2, a, wkly, comp, to, win, f...
Nah I don't think he goes to usf, he lives aro...	Nah I dont think he goes to usf he lives aroun...	[nah, i, dont, think, he, goes, to, usf, he, l...
Even my brother is not like to speak with me. ...	Even my brother is not like to speak with me T...	[even, my, brother, is, not, like, to, speak, ...
I HAVE A DATE ON SUNDAY WITH WILL!!	I HAVE A DATE ON SUNDAY WITH WILL	[i, have, a, date, on, sunday, with, will]

LEMMATIZATION

01. What?

02. How?

03. Why?

body_text_stemmed	body_text_lemmatized
[ive, search, right, word, thank, breather, pr...	[ive, searching, right, word, thank, breather,...
[free, entri, 2, wkli, comp, win, fa, cup, fin...	[free, entry, 2, wkly, comp, win, fa, cup, fin...
[nah, dont, think, goe, usf, live, around, tho...	[nah, dont, think, go, usf, life, around, though]
[even, brother, like, speak, treat, like, aid,...	[even, brother, like, speak, treat, like, aid,...
[date, sunday]	[date, sunday]

EDA

EDA : REMOVING ADDITIONAL STOPWORDS

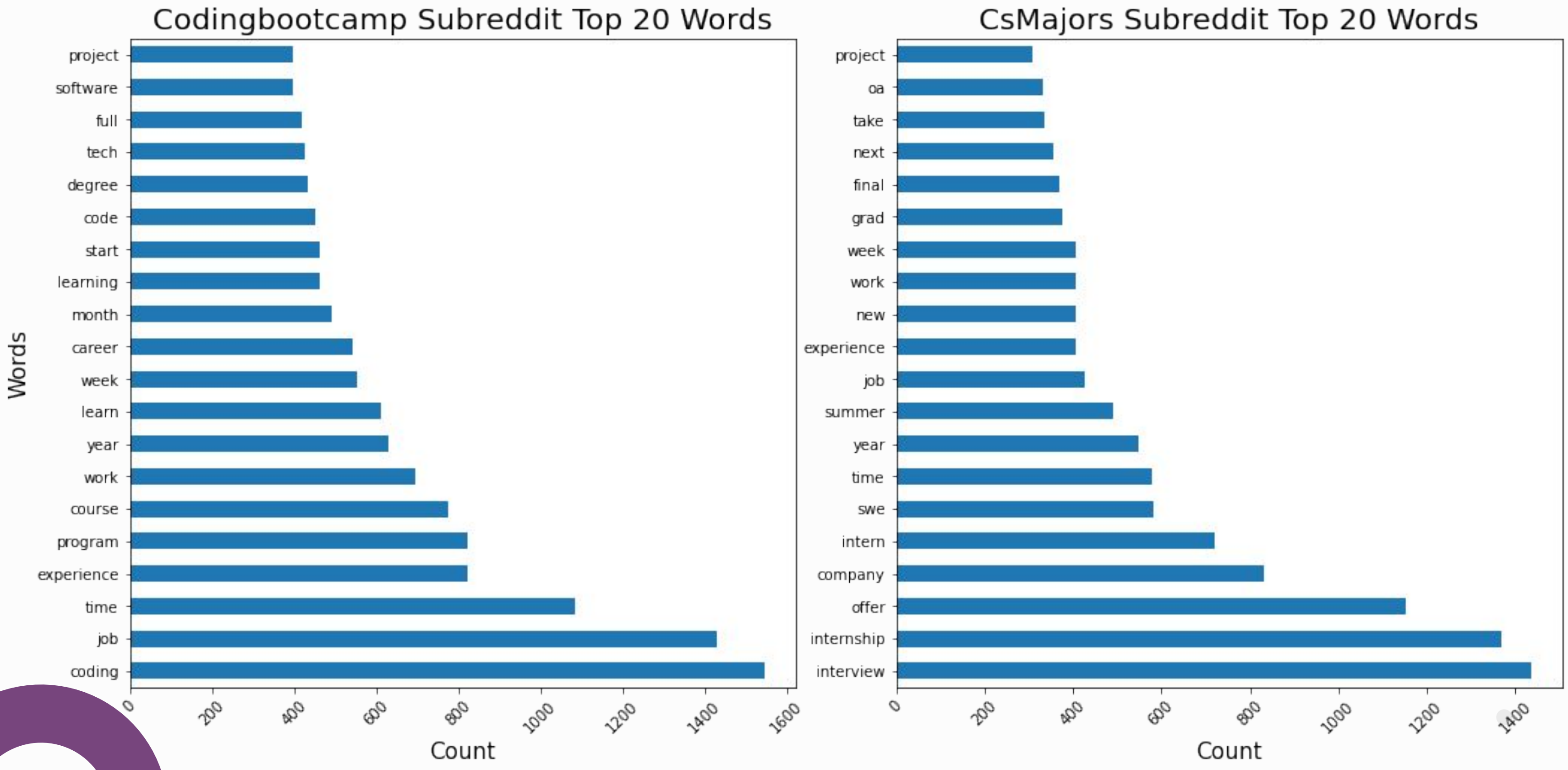
Coding Bootcamp top 50 words

bootcamp	2207
coding	1544
job	1427
would	1238
get	1149
im	1117
like	1095
time	1083
know	900
experience	824
program	823
camp	788
course	774
want	756
anyone	738
one	720
boot	710
work	697
looking	658
bootcamps	633
year	629
good	618
learn	610
also	574
people	571
really	566
week	554
help	553
career	542
month	491
ive	483
need	482
learning	463
start	462
make	458
code	453
dont	450
question	437
degree	432
go	431
tech	428
full	418
going	398
software	397
project	396
lot	395
academy	381
much	376
take	374
feel	368

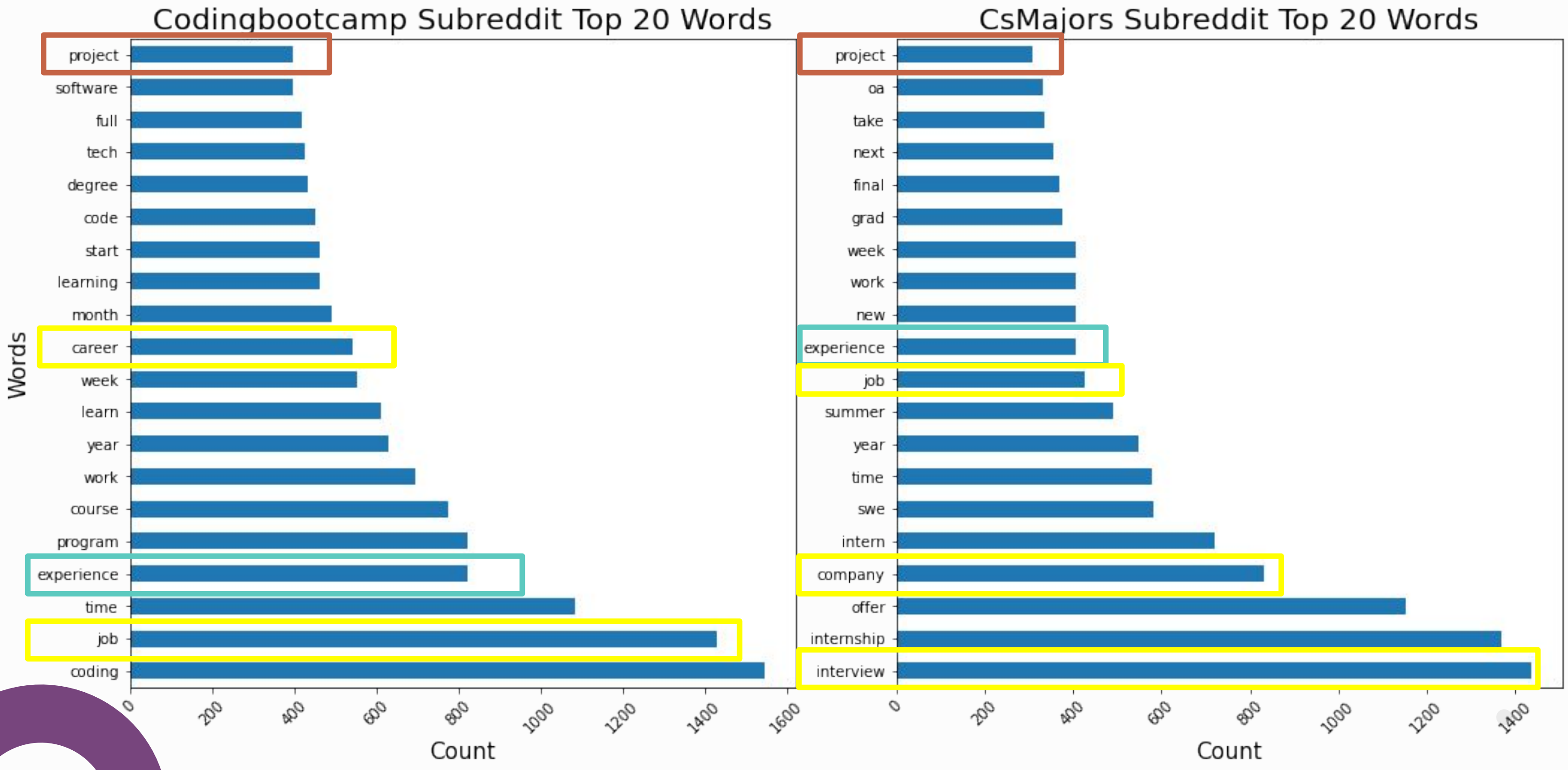
CS Majors top 50 words

interview	1435
internship	1368
offer	1152
company	832
would	831
anyone	812
im	808
get	758
like	736
intern	720
know	650
got	635
question	614
one	590
swe	582
time	578
year	547
summer	492
also	434
job	427
round	425
experience	407
work	406
new	406
week	405
really	404
view	398
back	390
want	383
grad	375
final	369
good	368
next	356
take	336
oa	331
people	321
dont	314
first	313
recruiter	307
project	307
think	299
still	292
tech	292
resume	291
school	284
even	283
getting	278
much	278
feel	275
class	275

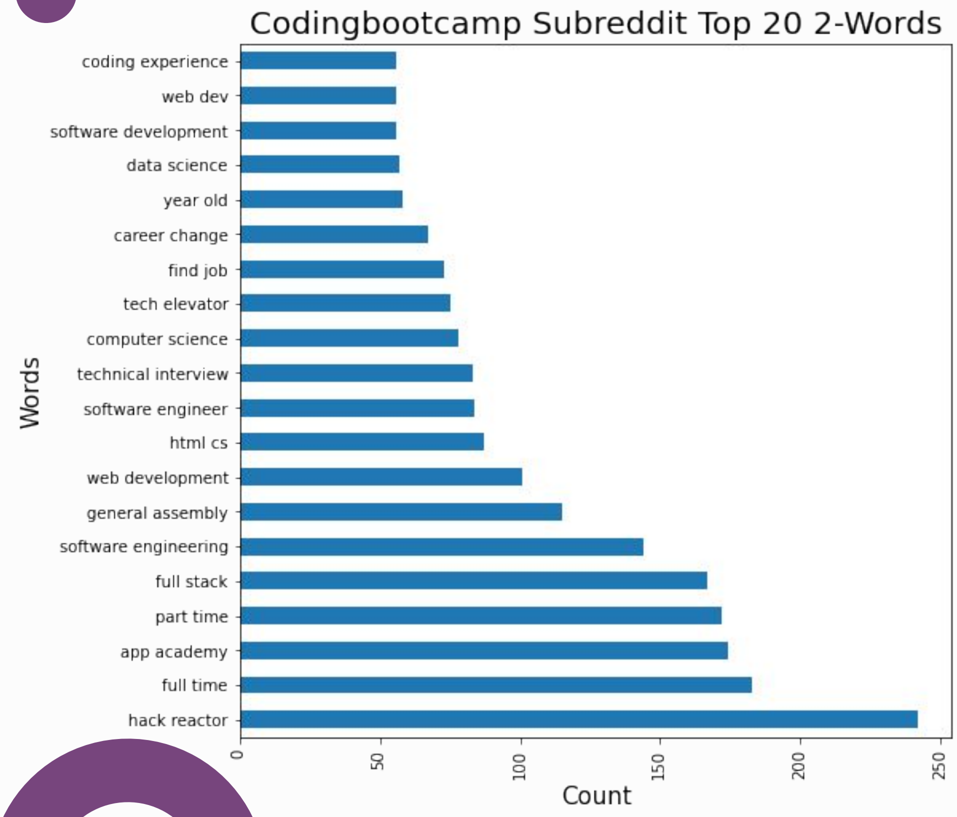
EDA : TOP 20 WORDS

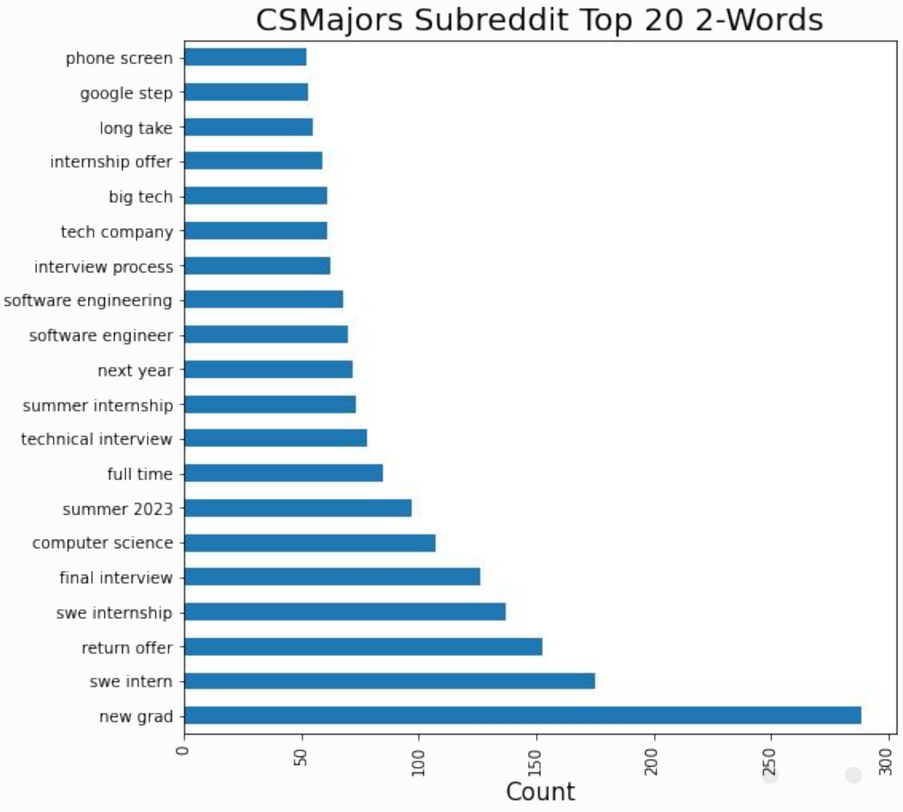


EDA : TOP 20 WORDS - SIMILARITIES

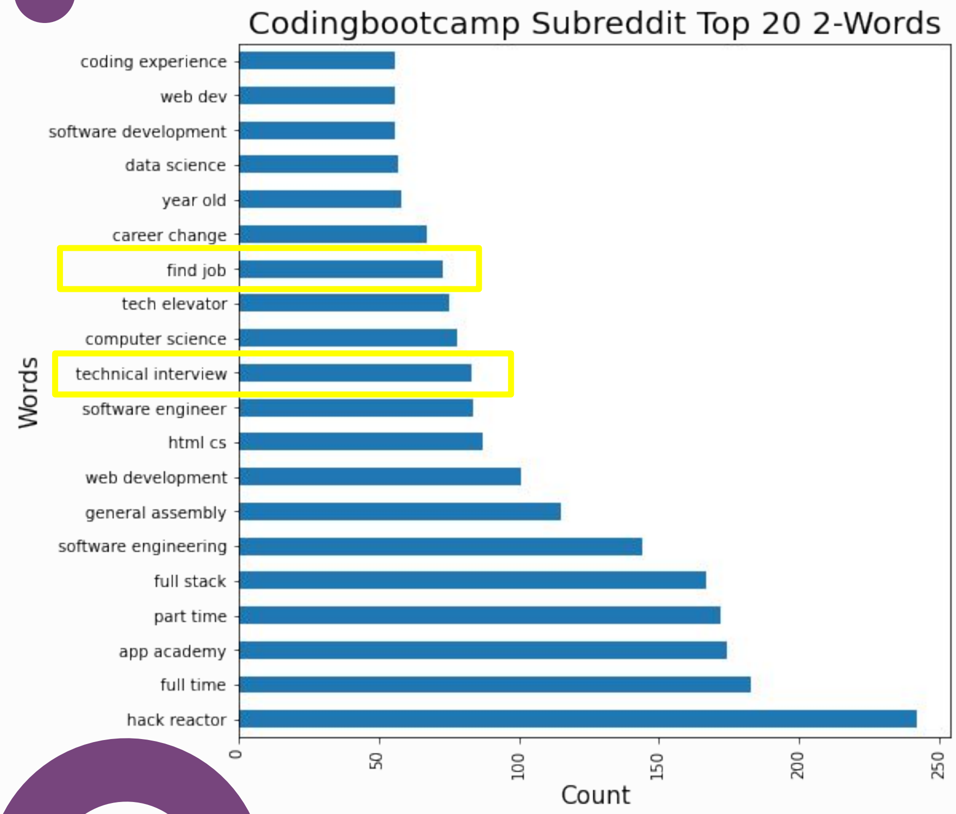


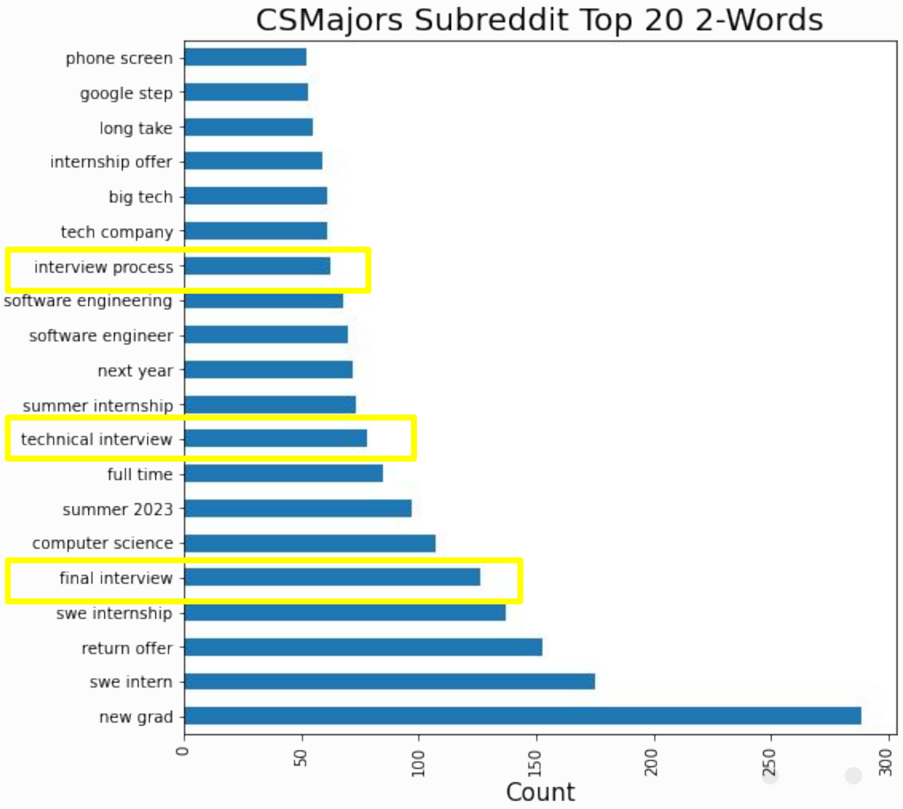
EDA : TOP 20 2-WORDS



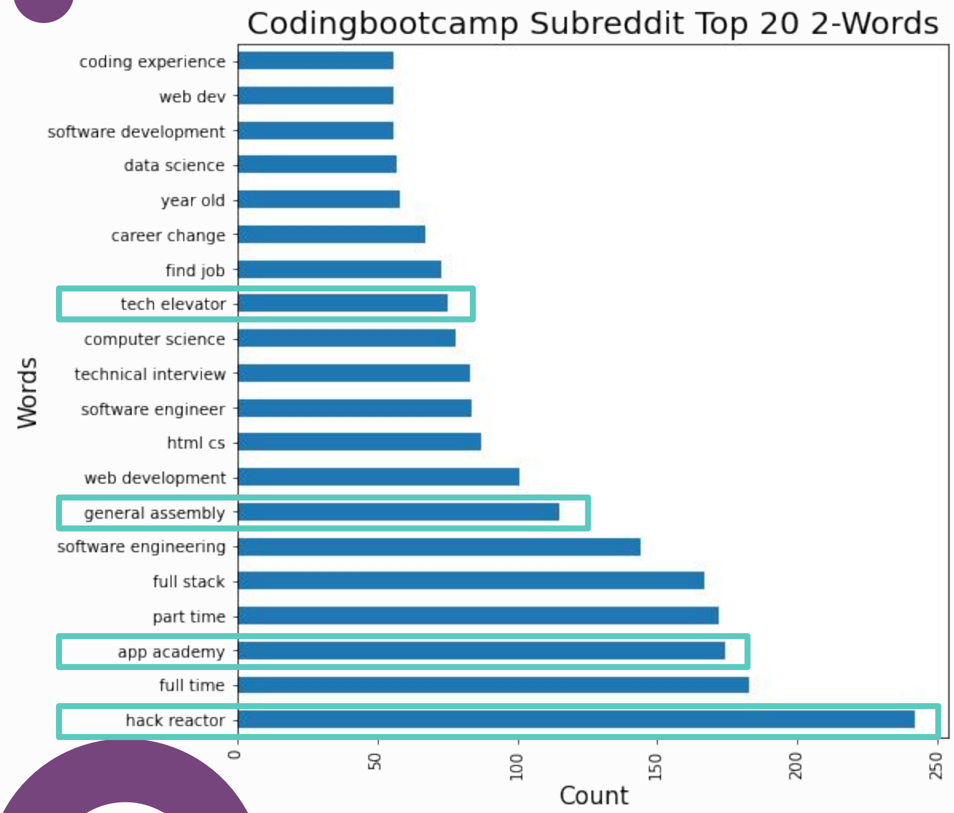


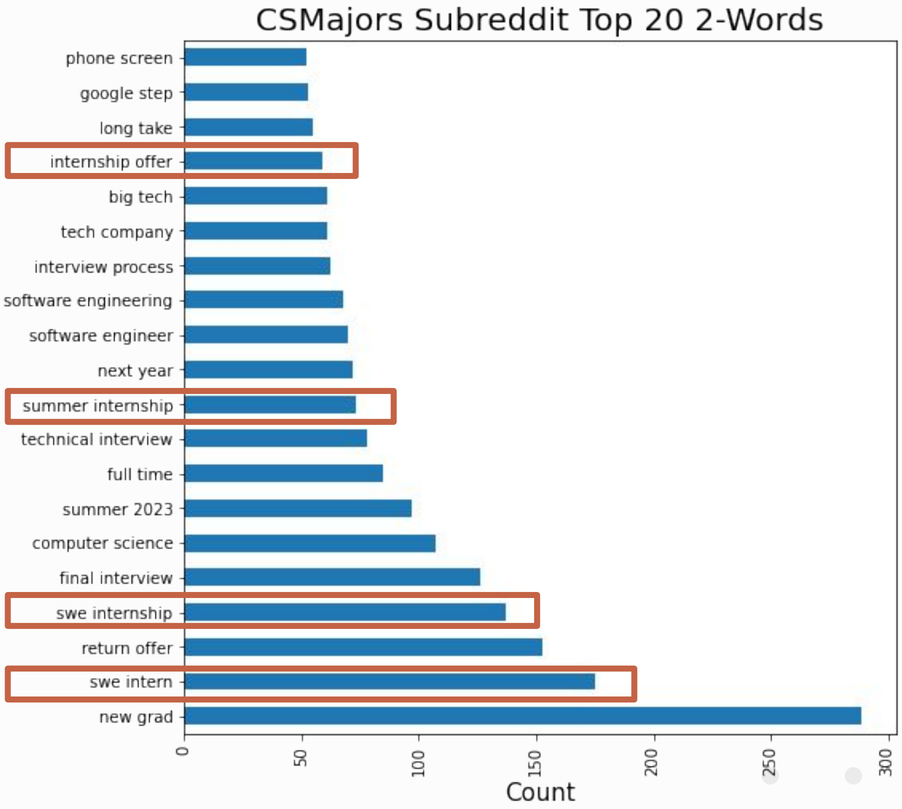
EDA : TOP 20 2-WORDS - SIMILARITIES: CAREER



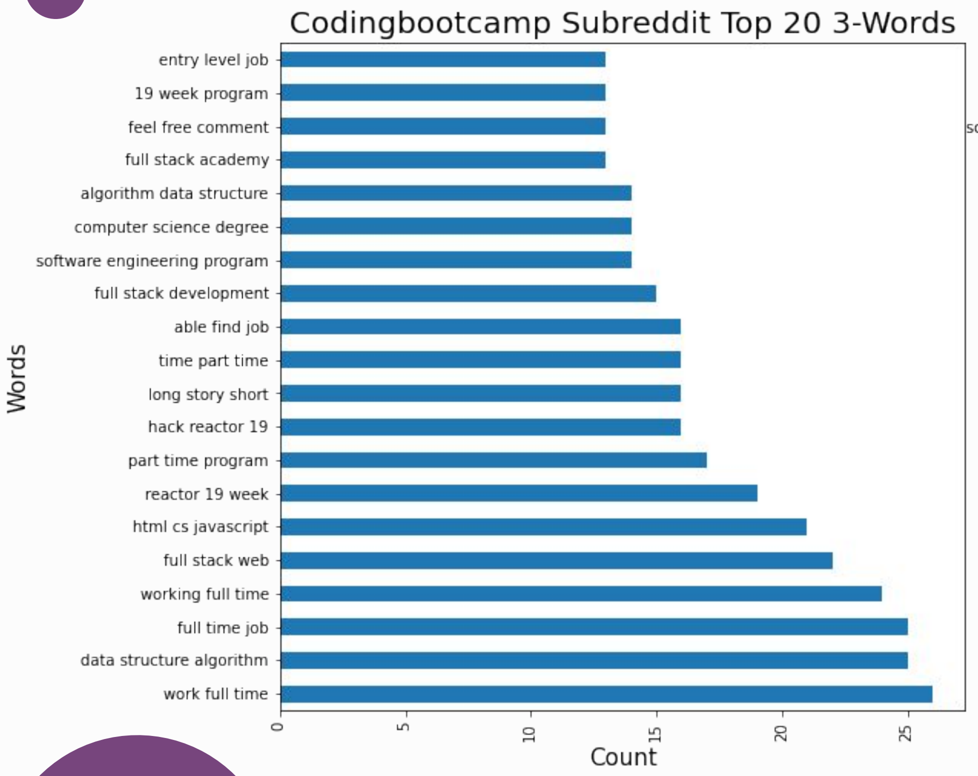


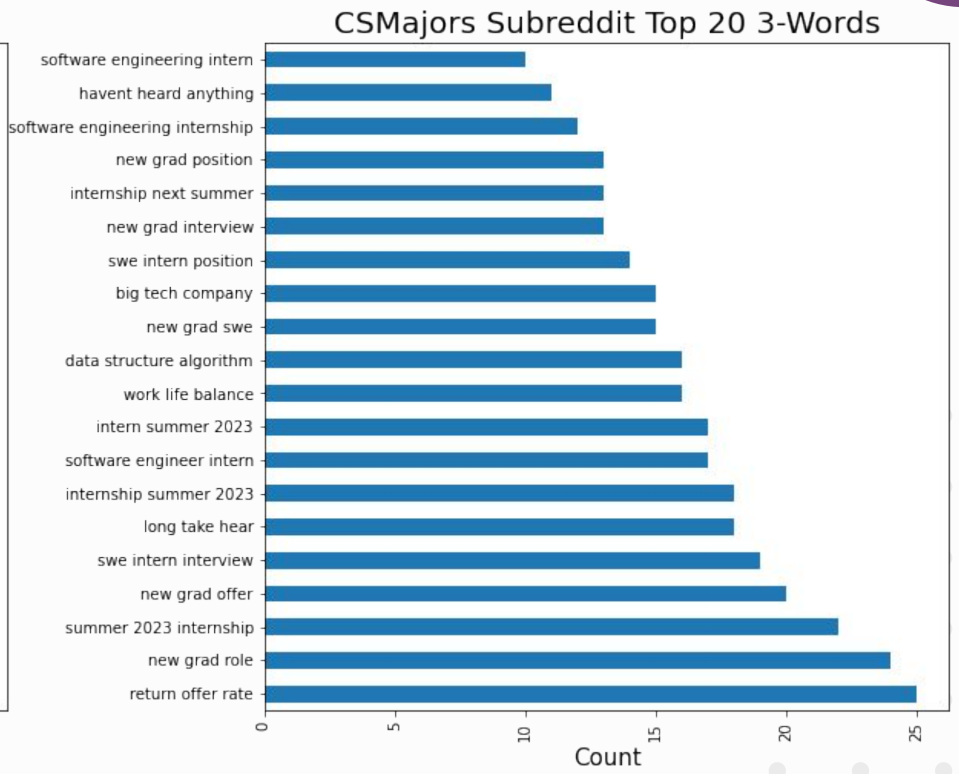
EDA : TOP 20 2-WORDS - DIFFERENCES: SCHOOLS VS INTERNSHIPS



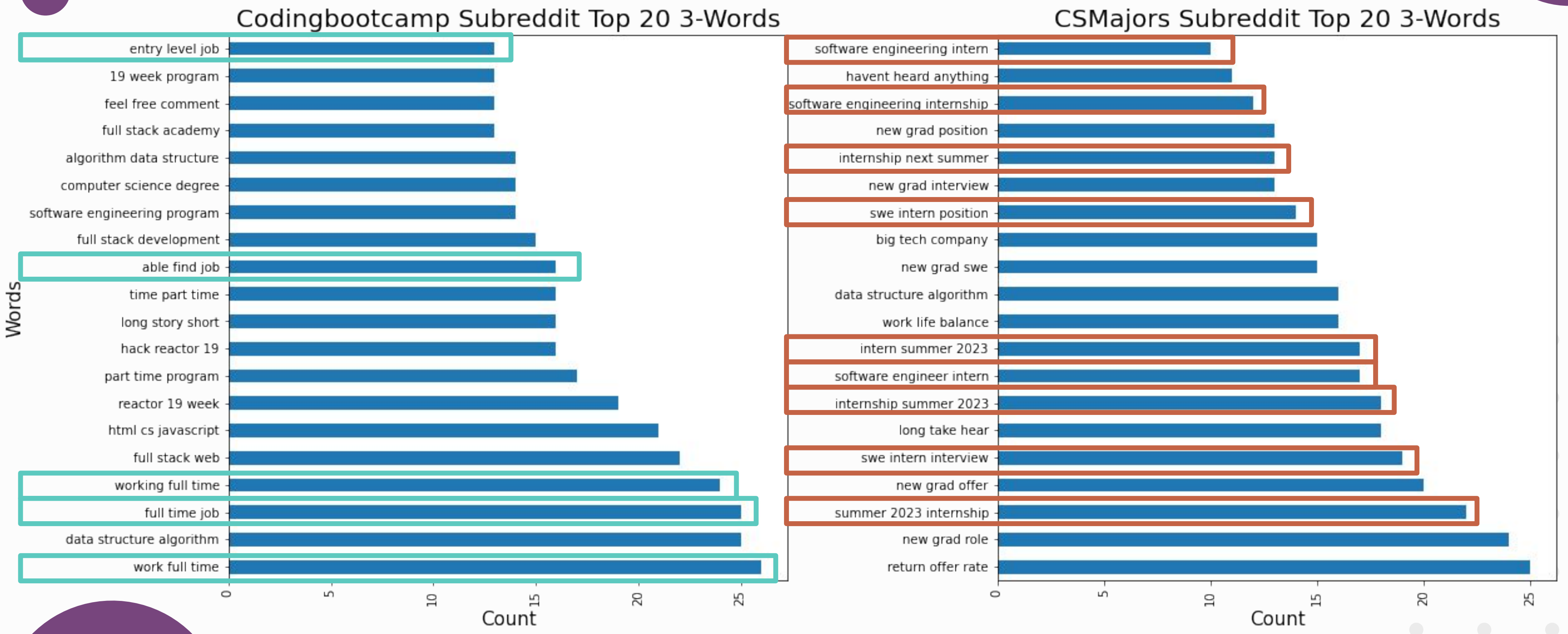


EDA : TOP 20 3-WORDS

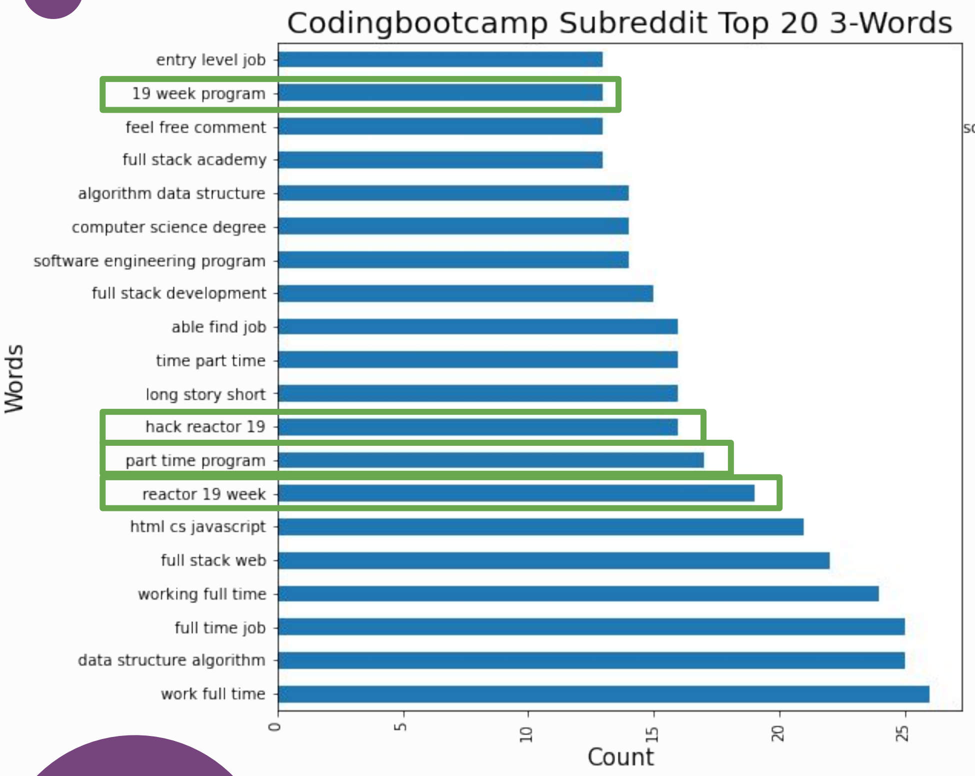


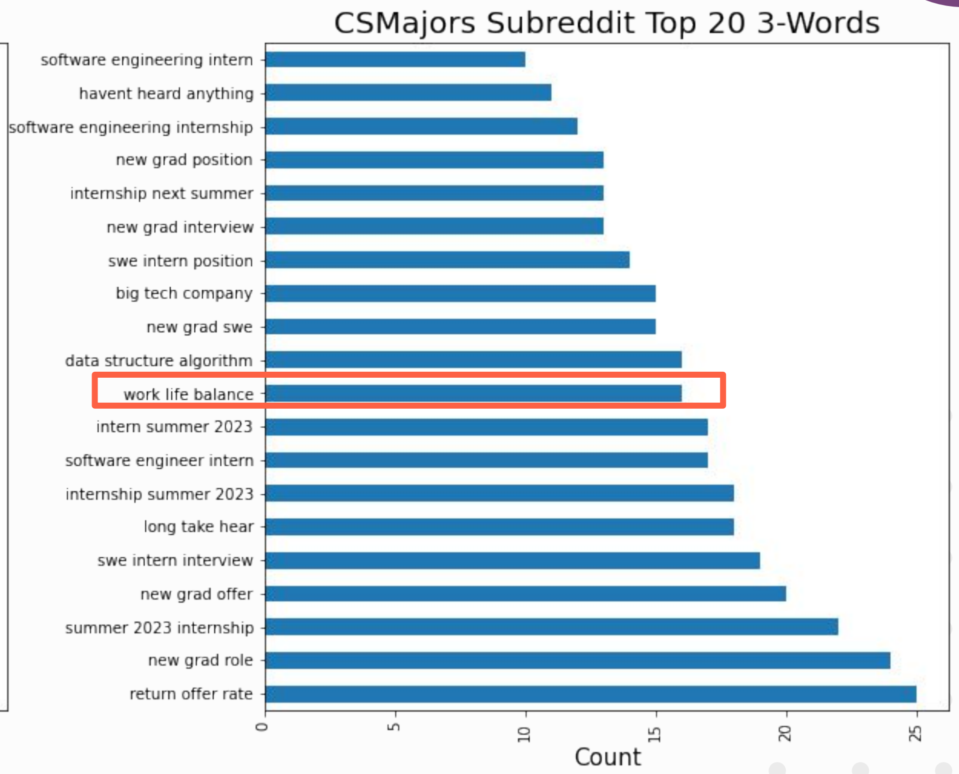


EDA : TOP 20 3-WORDS - DIFFERENCES: FULL TIME JOB VS INTERNSHIP



EDA : TOP 20 3-WORDS - DIFFERENCES: TIME VS BALANCE

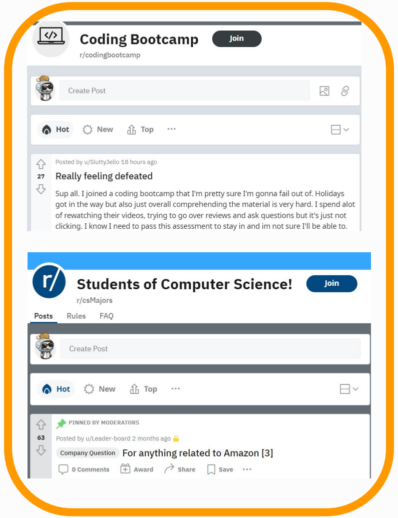




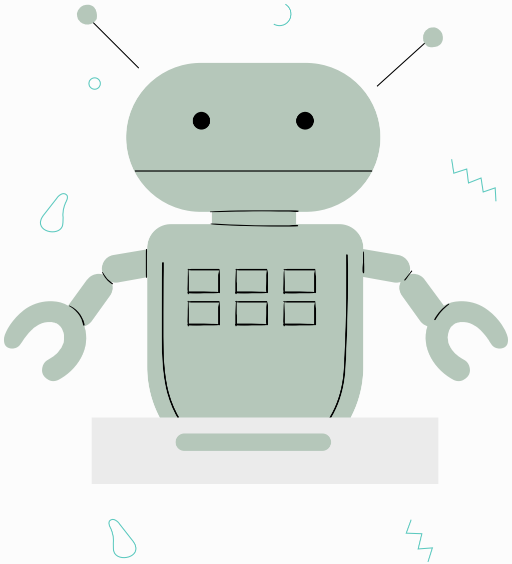
MODELLING

PURPOSE OF MODEL

Reddit Posts



Model



>90% accuracy

Bootcamp Style

4 years uni course

BUILDING A CLASSIFICATION MODEL

DATA PREPARATION

Converting text to numerical representation

Methods used:

- Countvectorizer
- N-grams
- TF-IDF (Term Frequency-Inverse Document Frequency)

MODEL OPERATION

Classification model selection

Models used:

- Bernoulli Naive Bayes
- Multinomial Naive Bayes
- Logistic Regression

MODEL OPTIMIZATION

Improving model accuracy

Optimization:

- Hyperparameter tuning

MODEL SELECTION

VECTORIZATION TYPE	CLASSIFICATION MODEL	TRAIN ACCURACY SCORE	TEST ACCURACY SCORE
Baseline		0.78039	0.78646
Countvectorizer	Bernoulli Naive Bayes	0.84611	0.84215
Countvectorizer	Multinomial Naive Bayes	0.93214	0.93149
Countvectorizer	Logistic Regression	0.98678	0.93429
N-Gram*	Bernoulli Naive Bayes	0.90435	0.86057
N-Gram*	Multinomial Naive Bayes	0.98464	0.90545
N-Gram*	Logistic Regression	0.94416	0.875
TF-IDF	Bernoulli Naive Bayes	0.95698	0.92548
TF-IDF	Multinomial Naive Bayes	0.95431	0.92748
TF-IDF	Logistic Regression	0.96193	0.94231

*Only the best train-test result between Bi-Gram & Tri-Gram for the model is shown.

TERM FREQUENCY-INVERSE DOCUMENT FREQUENCY (TF-IDF)

- Vectorization method that penalizes terms that occur multiple times across different documents.

Text 1	i love natural language processing but i hate python
Text 2	i like image processing
Text 3	i like signal processing and image processing

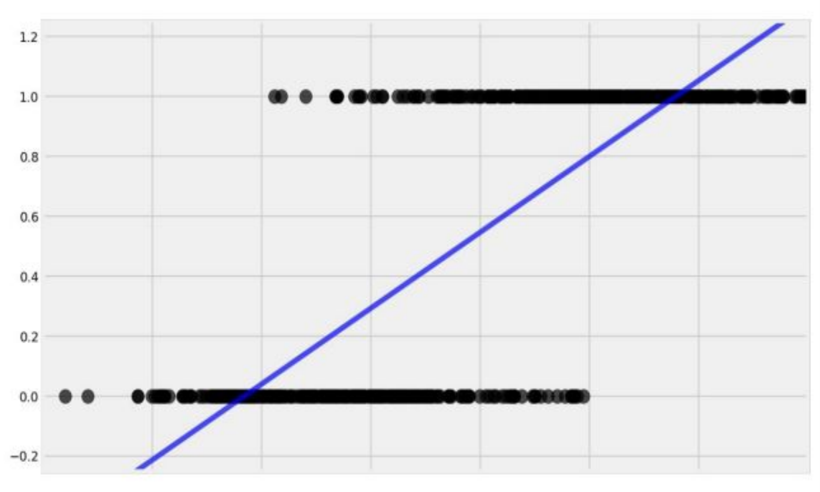
	and	but	hate	i	image	language	like	love	natural	processing	python	signal
Text 1	0	1	1	2	0	1	0	1	1	1	1	0
Text 2	0	0	0	1	1	0	1	0	0	1	0	0
Text 3	1	0	0	1	1	0	1	0	0	2	0	1

Term	and	but	hate	i	image	language	like	love	natural	processing	python	signal
IDF	0.47712	0.47712	0.4771	0	0.1760913	0.477121	0.1760913	0.477121	0.47712125	0	0.477121	0.477121

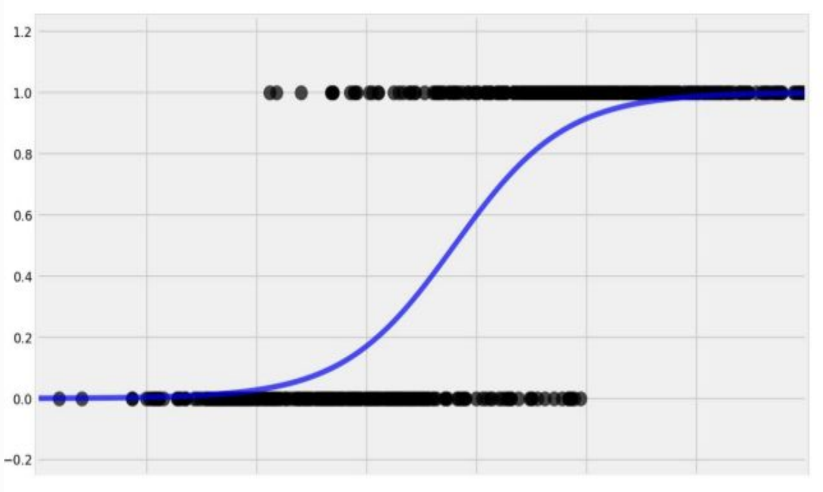
LOGISTIC REGRESSION MODEL

- Logistic regression “bends” our best fit line, to match the range or set of values.
- Useful in predicting binary outcomes.

Linear Regression



Logistic Regression



BUILDING A CLASSIFICATION MODEL

DATA PREPARATION

Converting text to numerical representation

Methods used:

- Countvectorizer
- N-grams
- TF-IDF (Term Frequency-Inverse Document Frequency)

Countvectorizer

Sentence: The Three Musketeers

	The	Three	Musketeers
Sentence	1	1	1

BUILDING A CLASSIFICATION MODEL

DATA PREPARATION

Converting text to numerical representation

Methods used:

- Countvectorizer
- N-grams
- TF-IDF (Term Frequency-Inverse Document Frequency)

Bi-gram

Sentence: The Three Musketeers

	The Three	Three Musketeers
Sentence	1	1

Tri-gram

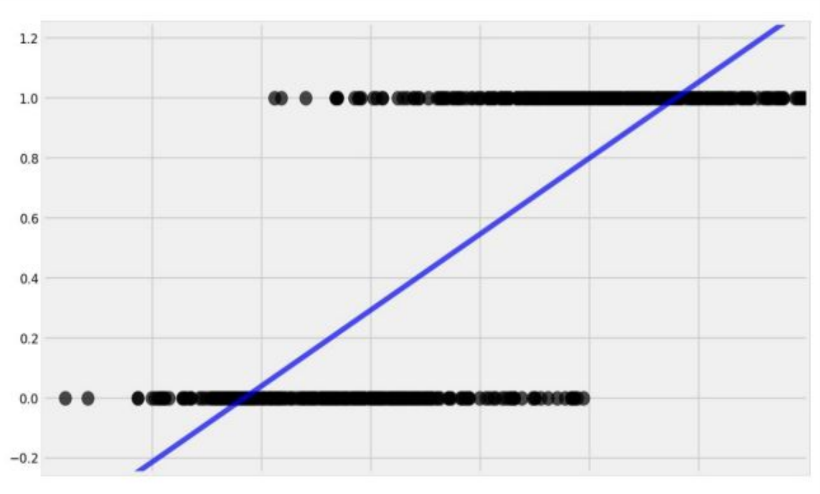
Sentence: The Three Musketeers

	The Three Musketeers
Sentence	1

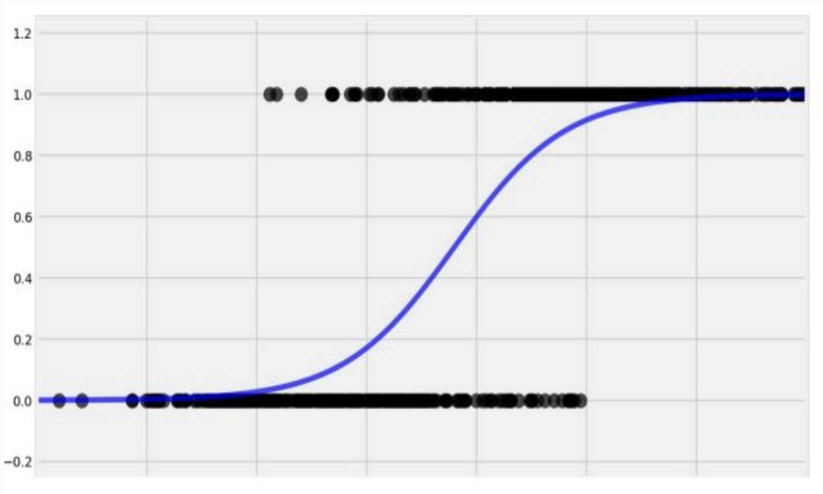
BERNOULLI/ MODEL

- Logistic regression “bends” our best fit line, to match the range or set of values.
- Useful in predicting binary outcomes.

Linear Regression



Logistic Regression

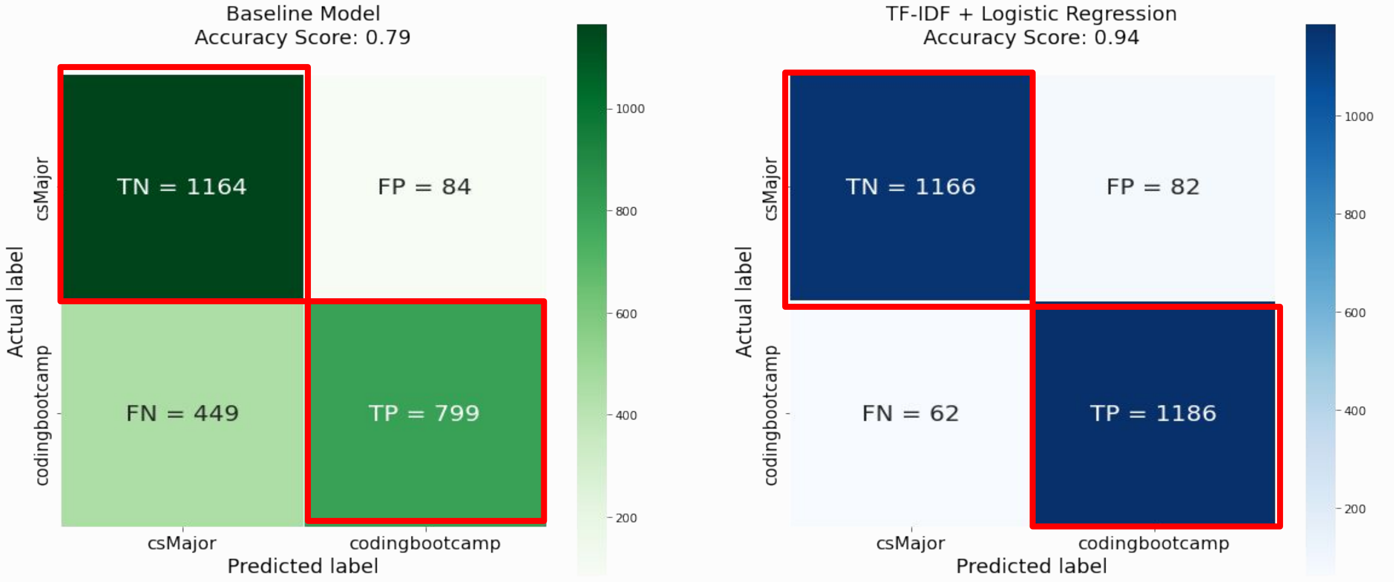


MODEL OPTIMIZATION

VECTORIZATION + MODEL TYPE	PARAMETERS OPTIMIZED	IMPROVEMENT
TF-IDF + Logistic Regression	max features min_df max_df lg_solver	~0.04%

MODEL EVALUATION

CONFUSION MATRIX - HIGHER ACCURACY FOR MODEL



- TN: True Negative, TP: True Positive → Predictions are correct, for either classes
- FN: False Negative, FP: False Positive → Predictions are wrong, for either classes
- Positive class: codingbootcamp, Negative class: csMajor.
- Accuracy = True Predictions / Total Predictions.

CLASSIFICATION REPORT - HIGHER FI-SCORE

BASELINE

Baseline

	precision	recall	f1-score
csMajor	0.72	0.93	0.81
codingbootcamp	0.90	0.64	0.75
accuracy			0.79
macro avg	0.81	0.79	0.78
weighted avg	0.81	0.79	0.78

TF-IDF + LOGISTIC REGRESSION

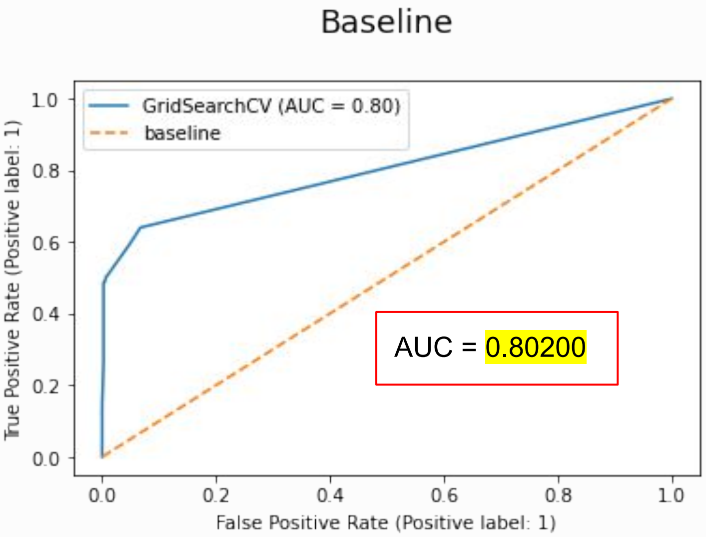
TF-IDF + Logistic Regression

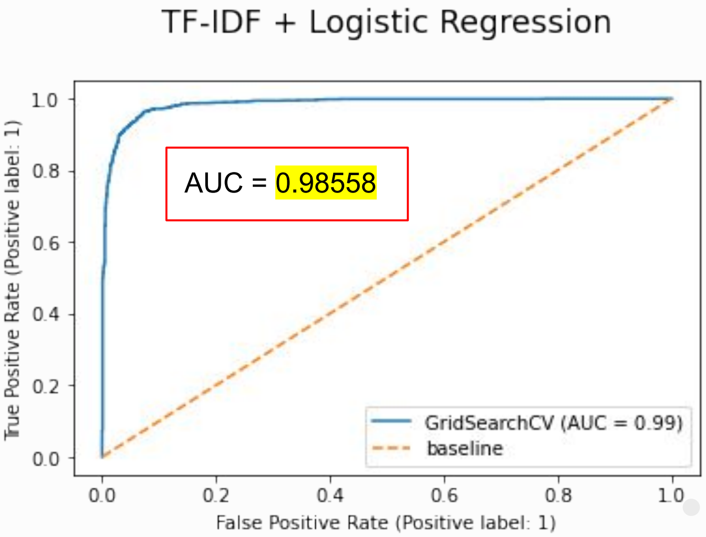
	precision	recall	f1-score
csMajor	0.95	0.93	0.94
codingbootcamp	0.94	0.95	0.94
accuracy			0.94
macro avg	0.94	0.94	0.94
weighted avg	0.94	0.94	0.94

- Precision = TP / (TP + FP)
- Recall = TP / (TP + FN)
- F1-Score = Weighted Average of Precision and Recall
  - Offers a better overall measure of performance

ROC CURVE - HIGHER AUC SCORE

- ROC - Receiver Operating Characteristic Curve
- AUC - Area Under the Curve





Higher AUC score → Better differentiation between categories

MOVING FORWARD

TIME & RESOURCES

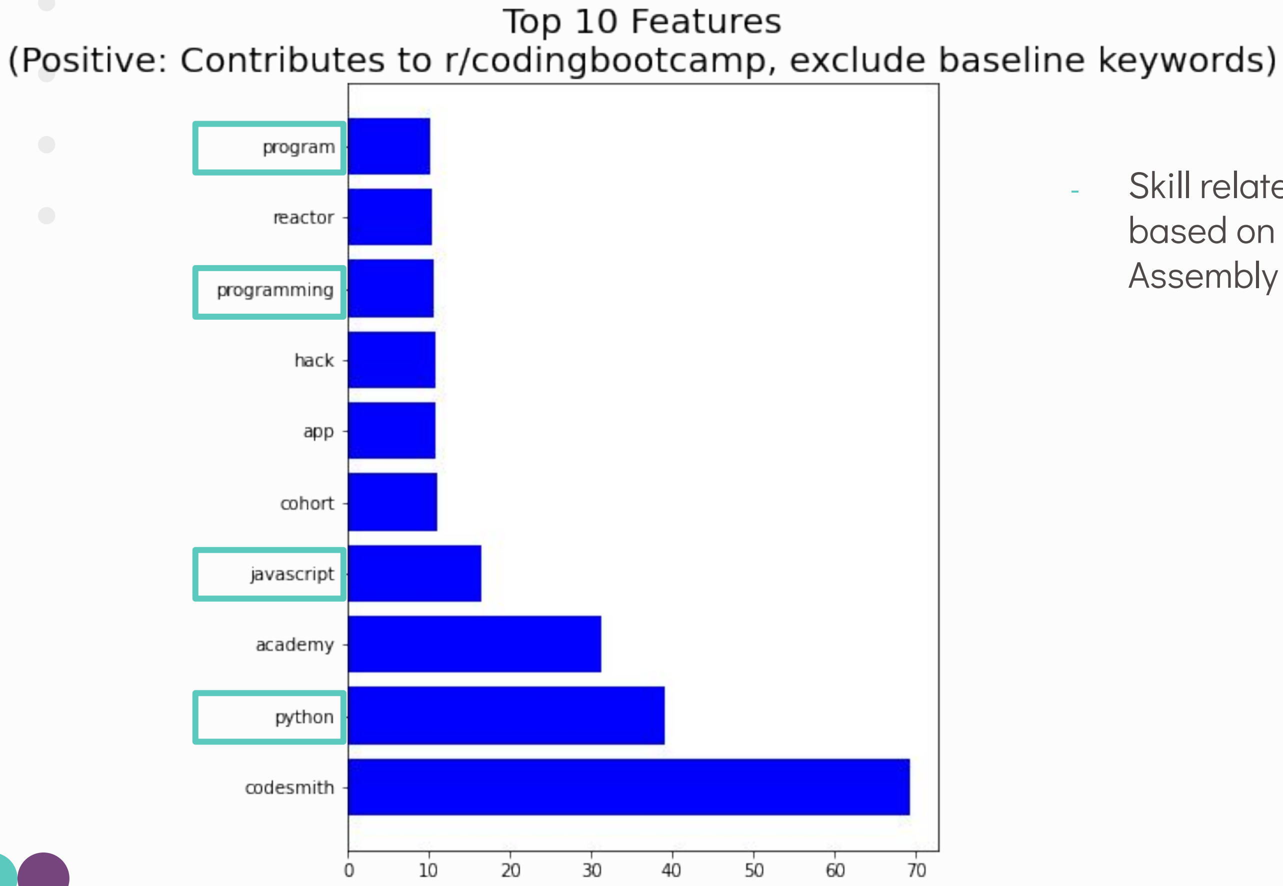
Gather more data to train the model, using information from various platforms

WEB LINGO

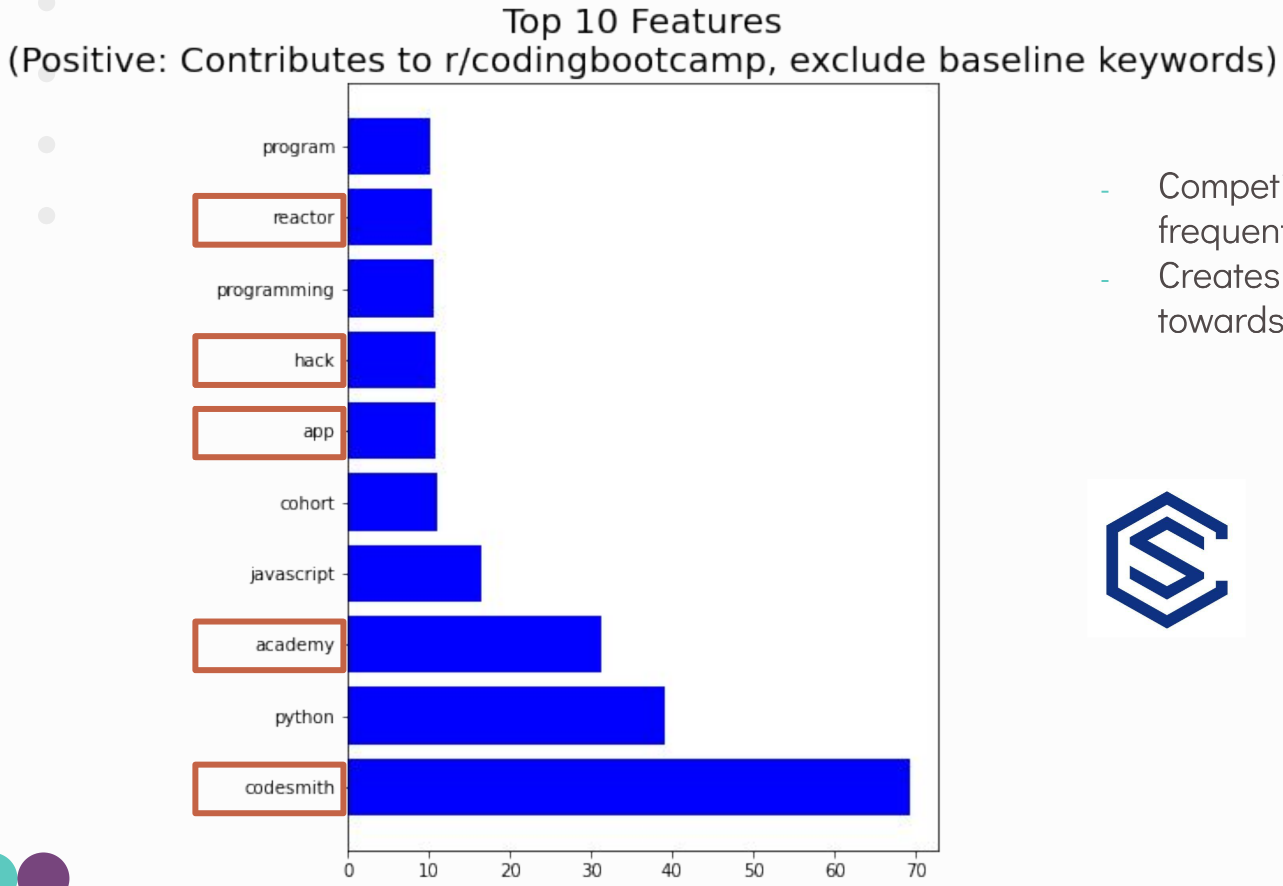
Train the model to better understand acronyms and abbreviations being used

SENTIMENT ANALYSIS

Expand the model to understand the sentiments behind the posts

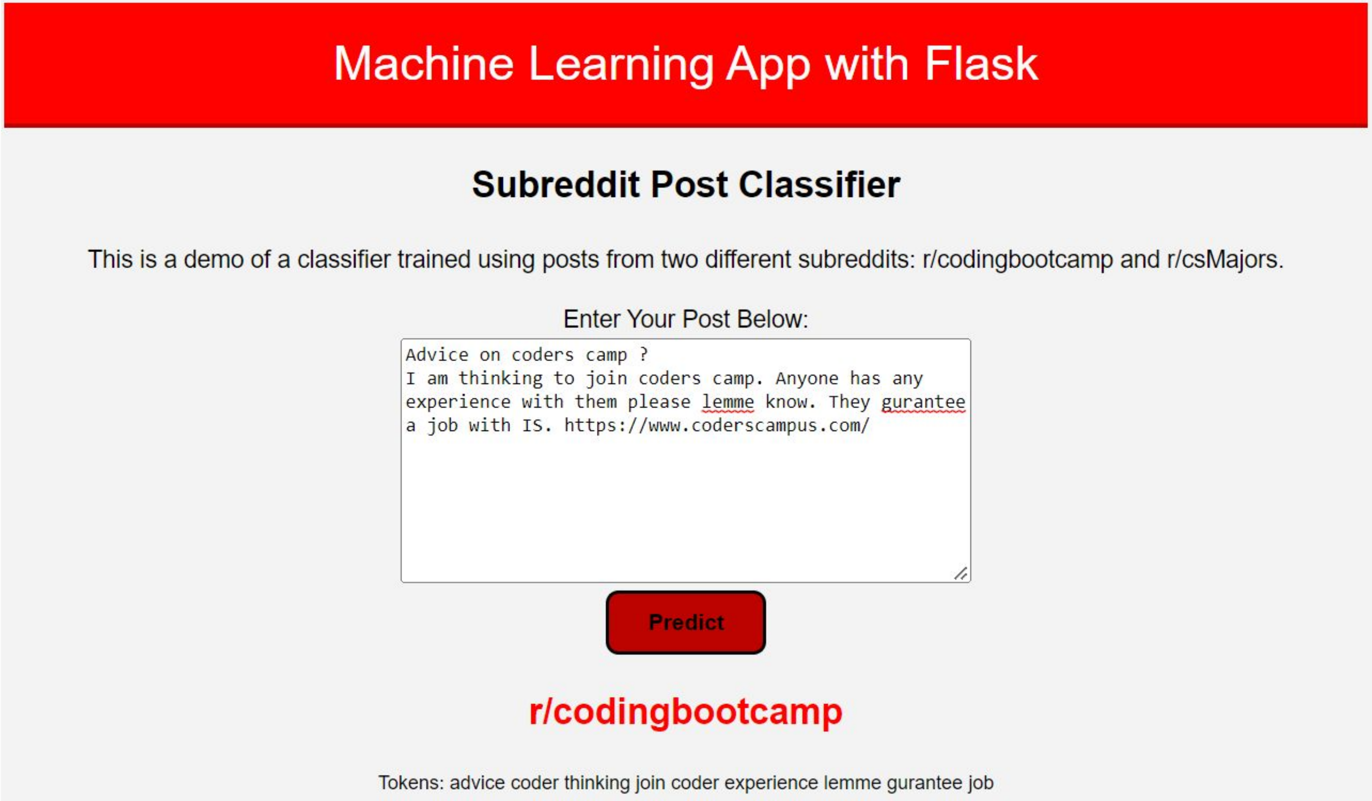


- Skill related features that we can focus on based on courses offered at General Assembly



- Competitors are mentioned more frequently on Reddit
- Creates opportunity for GA to market towards these users

SAMPLE PREDICTIONS



RECOMMENDATIONS

KEYWORDS

Features produced by our model will allow the team to better identify suitable posts to engage with.

AUTOMATION

Deployment of the model to automatically scan our social media interactions.

MARKETING

Boost marketing across channels to increase visibility compared with our competitors.

CONCLUSION

01.

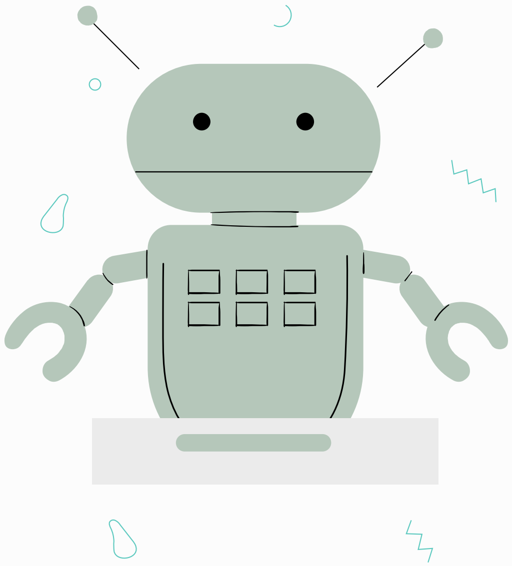
INCREASING VISIBILITY AND RESPONSE

GA needs to stand out from our competitors and speed is also essential in being able to act before our competitors.

02.

SEGMENTING AND TARGETING THE RIGHT AUDIENCE

Maximise our marketing ROI and increase our conversion rate.



THANK YOU