GA PROJECT 3

NLP CLASSIFICATION FOR AD TARGETING

R/CODINGBOOTCAMP VS R/CSMAJOR



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CONTENTS

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

BACKGROUND

There is increased competition in the space for coding bootcamps.











BACKGROUND

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









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



DECLINE IN MARKET SHARE



LOWER MARKETING ROI



POORER LEAD GENERATION

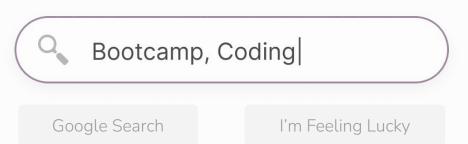


BACKGROUND



- 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.





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





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







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

























EVALUATE























EVALUATE





WORKFLOW

























EVALUATE



WORKFLOW













































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?



Coding Bootcamp

Join

r/codingbootcamp

22.3k

Members



Students of Computer Science!

r/csMajors



153k Members



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	lve 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 dont hink he goes to us 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

Ol. 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]



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EDA



EDA: REMOVING ADDITIONAL STOPWORDS

Coding Bootcamp top 50 words

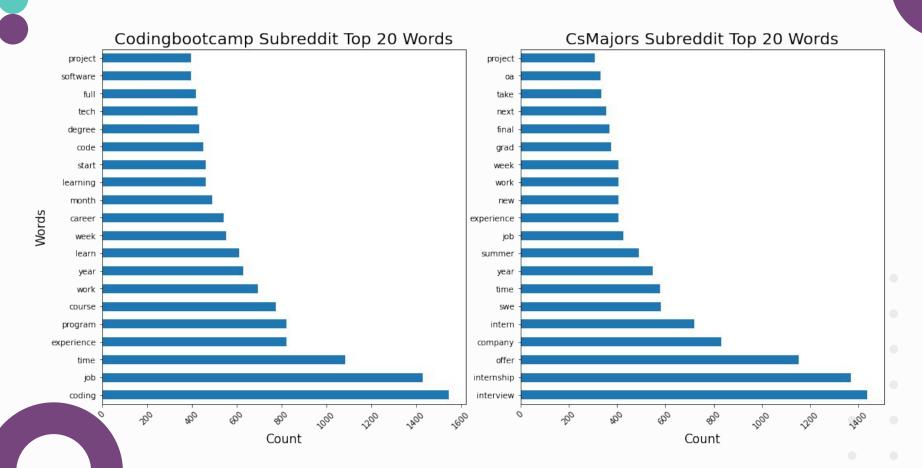
			A PROPERTY OF THE PROPERTY OF	
*	bootcamp	2207	💢 really	566
~	coding	1544	week	554
	job	1427	🗱 help	553
*	would	1238	career	542
***	get	1149	month	491
*	im	1117	ive	483
×	like	1095	need	482
••	time	1083	learning	463
×	know	900	start	462
••	experience	824	💢 make	458
	program	823	code	453
×	camp	788	💢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

CS Majors top 50 words

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



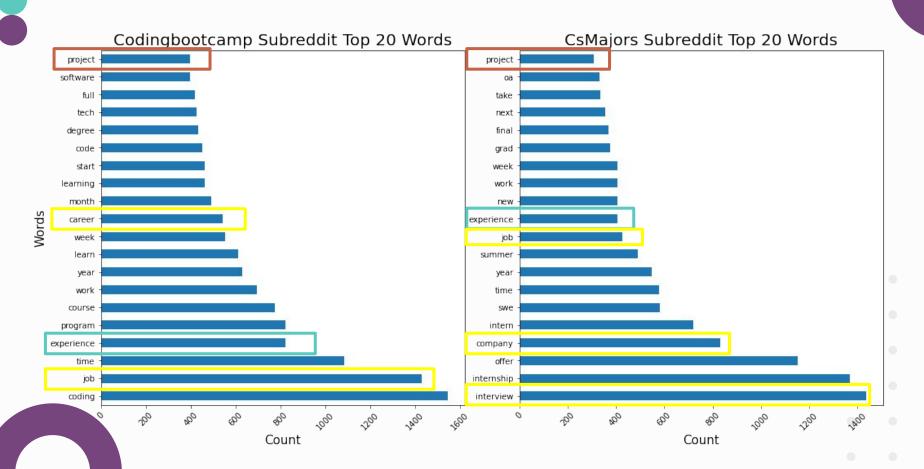
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11111111111

EDA: TOP 20 WORDS - SIMILARITIES

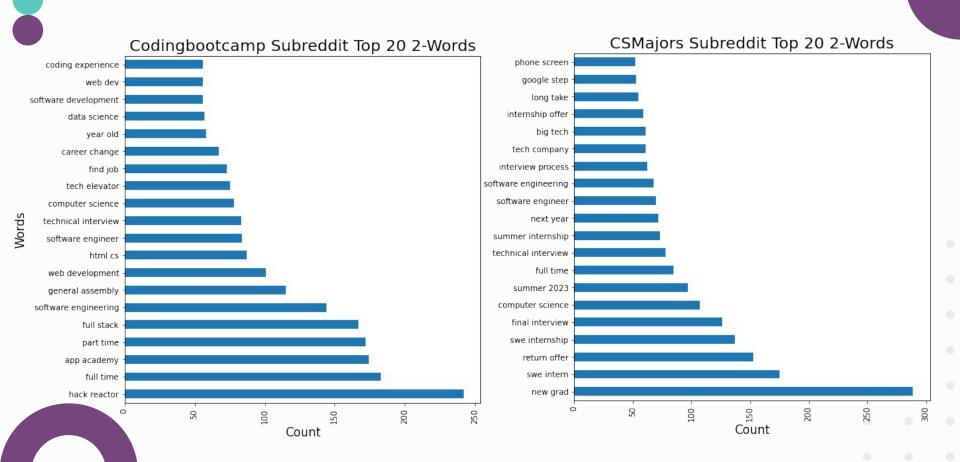
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111111111111

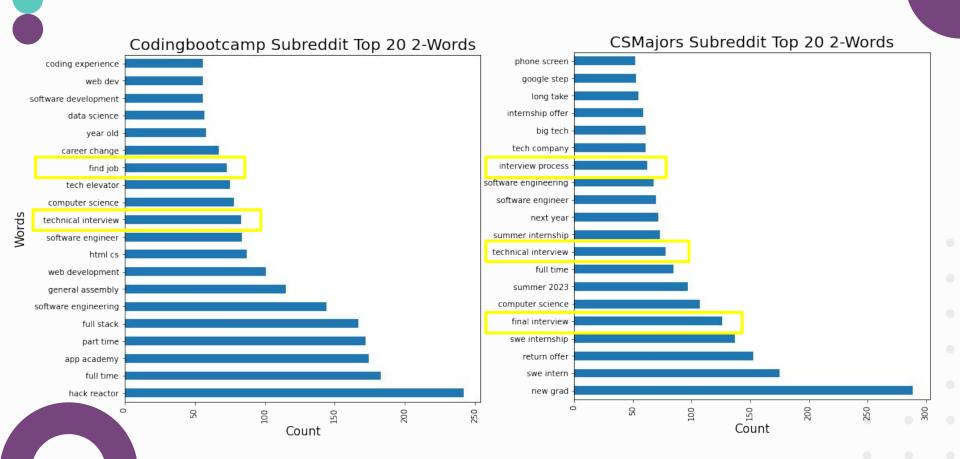
EDA: TOP 20 2-WORDS

////////////

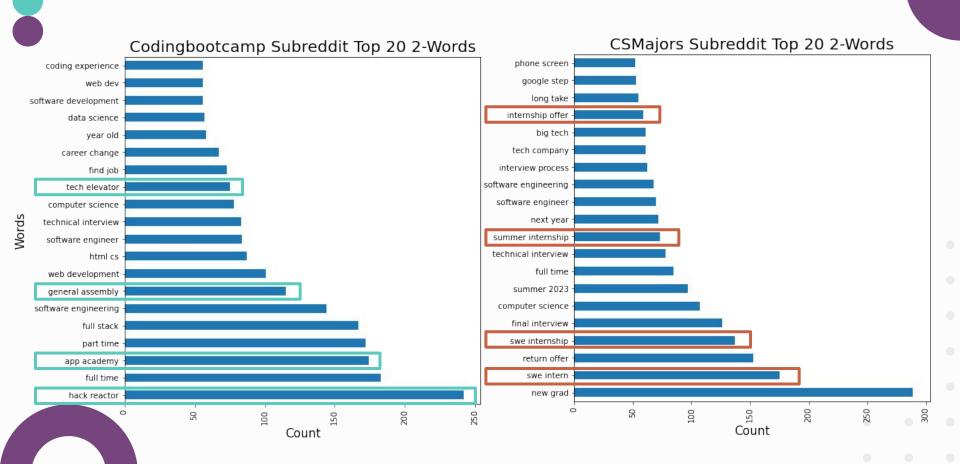


EDA: TOP 20 2-WORDS - SIMILARITIES: CAREER

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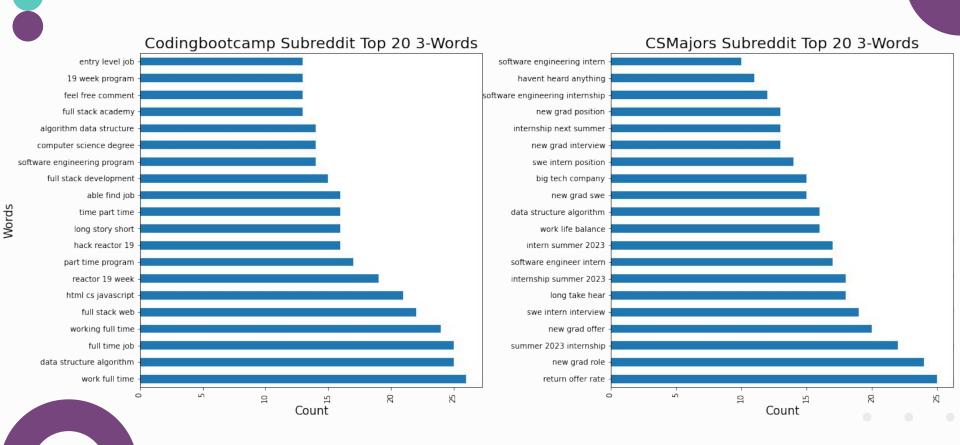


EDA: TOP 20 2-WORDS - DIFFERENCES: SCHOOLS VS INTERNSHIPS

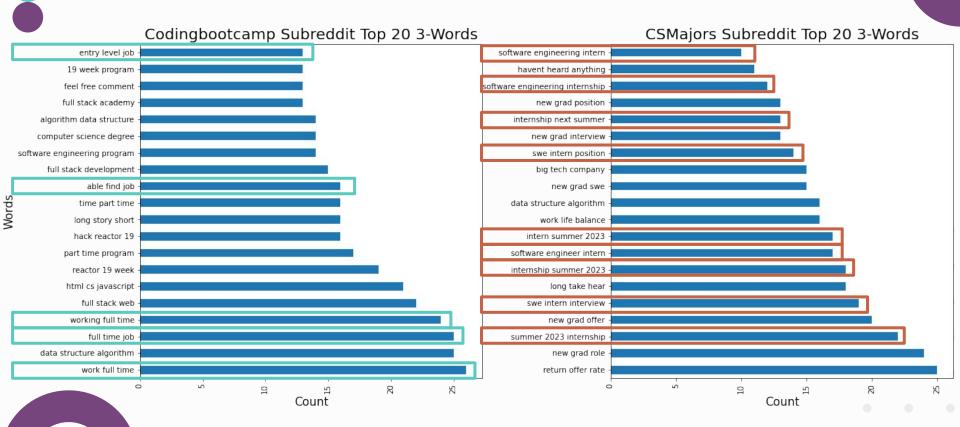


EDA: TOP 20 3-WORDS

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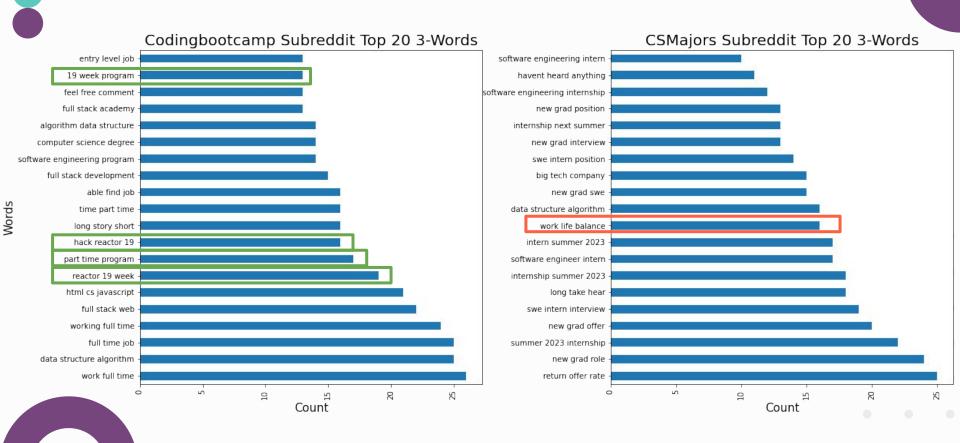






EDA: TOP 20 3-WORDS - DIFFERENCES: TIME VS BALANCE

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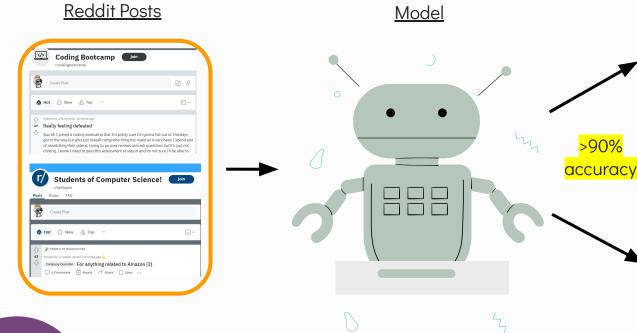
MODELLING





PURPOSE OF MODEL

Bootcamp Style





4 years uni course







Methods used:

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

Models used:

- Bernoulli Naive Bayes
- Multinomial Naive Bayes
- Logistic Regression

Optimization:

Hyperparameter tuning

MODEL SELECTION



VECTORIZATION TYPE	CLASSIFICATION MODEL	TRAIN ACCURACY SCORE	TEST ACCURACY SCORE
Bas	eline	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	0.9 <mark>6193</mark>	0.9 <mark>4231</mark>

^{*}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

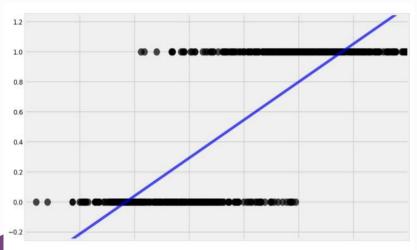
Term	and	but	hate	1	image	language	like	love	natural	processing	python	signal
IDF	0.47712	0.47712	0.4771	0	0.1760913	0.477121	0.1760913	0.477121	0.47712125	0	0.477121	0.477121



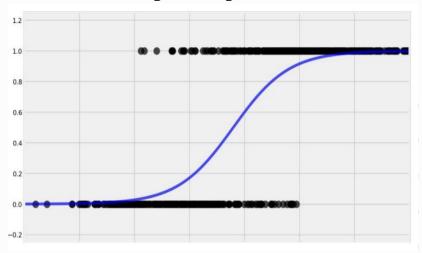
LOGISTIC REGRESSION MODEL

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

Linear Regression



Logistic Regression





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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 •





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BUILDING A CLASSIFICATION MODEL

DATA PREPARATION

Converting text to numerical representation

Methods used:

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- 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		

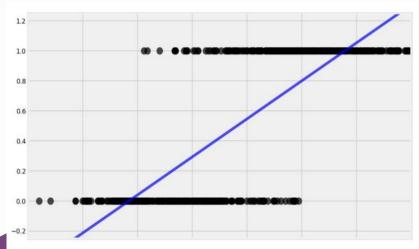




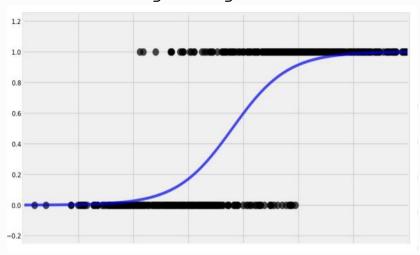
BERNOULLI/ MODEL

- 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%





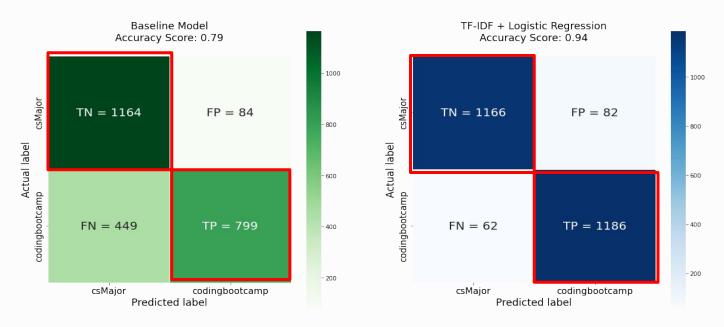


MODEL EVALUATION



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CONFUSION MATRIX - HIGHER ACCURACY FOR MODEL



- TN: $\frac{\text{True}}{\text{True}}$ Negative, TP: $\frac{\text{True}}{\text{True}}$ Positive \rightarrow Predictions are correct, for either classes
- FN: False Negative, FP: False Positive \rightarrow 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**

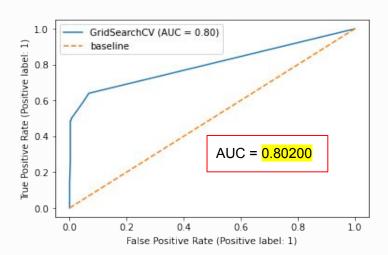
TF-IDF + Logist	ic Regressio	n	
	precision	recall	f1-score
csMajor	0.95	0.93	0.94
codingbootcamp	0.94	0.95	0.94
accuracy			0.94
macro avg	0.94	0.94	0.94
weighted avg	0.94	0.94	0.94

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

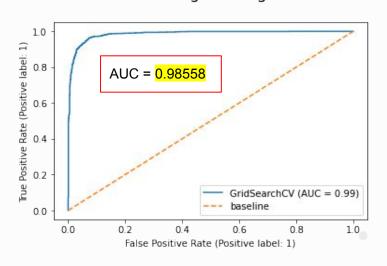


- ROC Receiver Operating Characteristic Curve
- AUC Area Under the Curve

Baseline



TF-IDF + Logistic Regression





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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



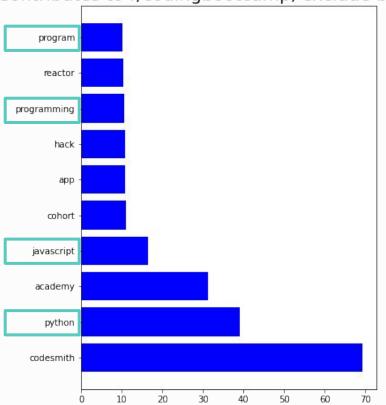






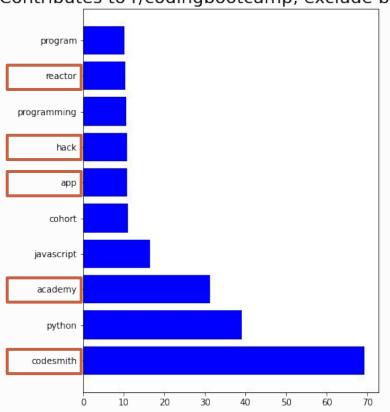


Top 10 Features (Positive: Contributes to r/codingbootcamp, exclude baseline keywords)



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

Top 10 Features (Positive: Contributes to r/codingbootcamp, exclude baseline keywords)



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







SAMPLE PREDICTIONS

Machine Learning App with Flask

Subreddit Post Classifier

This is a demo of a classifier trained using posts from two different subreddits: r/codingbootcamp and r/csMajors.

Enter Your Post Below:

```
Advice on coders camp?

I am thinking to join coders camp. Anyone has any experience with them please lemme know. They gurantee a job with IS. https://www.coderscampus.com/
```

Predict

r/codingbootcamp

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.

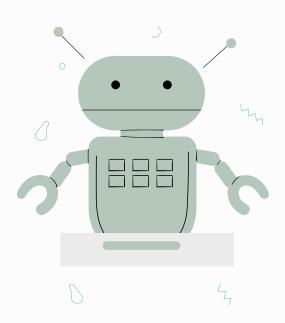
INCREASING VISIBILITY AND RESPONSE

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

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