Classifying Reddit Posts

LifeProTips & UnethicalLifeProTips

Presentation by Alexis Lim

What is a Life Pro Tip?

What is a Life Pro Tip?

79.4k

Posted by u/hdpe125 22 hours ago

LPT: If you liked a song by an artist but did not find the other tracks by the artist to your liking, look up the producer and see his other works. Producers have a lot of say in how the final product turns out.

Arts & Culture

1 21 1 16 5 1 1 6 12 12 11

1.8k Comments Give Award Share Save Hide Report 89% Upvoted

What is a Life Pro Tip?

r/LifeProTips

Tips that improve your life in one way or another.

18.4m
Members

18.1k
Online

Created 25 Oct 2010

What is a Life Pro Tip?

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Unethical Life Pro Tips
r/UnethicalLifeProTips

r/IllegalLifeProTips
r/IllegalLifeProTips

Shitty Life Pro Tips
r/ShittyLifeProTips

LPT vs ULPT

r/LifeProTips

Tips that improve your life in one way or another.

18.4m Members

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Created 25 Oct 2010

r/UnethicalLifeProTips

An Unethical Life Pro Tip (or ULPT) is a tip that improves your life in a meaningful way, perhaps at the expense of others and/or with questionable legality. Due to their nature, do not actually follow any of these tips–they're just for fun. Share your best tips you've picked up throughout your life, and learn from others!

1.1m Members

249 looking for unethical tips

Created 1 Mar 2016

ULPT example

r/UnethicalLifeProTips · Posted by u/gotBooched 1 month ago

ULPT: if you're stuck on an annoying call, put your phone on airplane mode instead of just hanging up. The other person will see "call failed" instead of "call ended"

Electronics

3 1 1 1 2

846 Comments Give Award Share Save Hide Report 93% Upvoted

The problem statement

How can we qualify what exactly makes a pro tip **unethical**?

Using a **classification model,** are we able to accurately predict posts for the two subreddits? We want to investigate:

- If we can **quantify** what is ‘unethical’ or anti-social behaviour (according to Reddit!)
- If we can **identify** significant differences between the two subreddits’ posts, given that they are both about protips

The process

01 Getting the data from Reddit

02 Processing our data

03 Exploratory data analysis

04 Modeling & tuning

05 Interpretation & conclusions

Getting data from Reddit

Two ways of getting data:

- **Webscraping,** using .json format on Reddit
    - Structured like a python dictionary and easy to parse
    - Relies on Reddit URL, depending on subreddit can be difficult to get posts
    - Can’t access comments
- PRAW: The Python Reddit API Wrapper
    - Slightly more steps, have to create an account on Reddit to retrieve the data, and different structure
    - Can access more things like comments, posts sorted by top etc.!

Features of interest

79.4k

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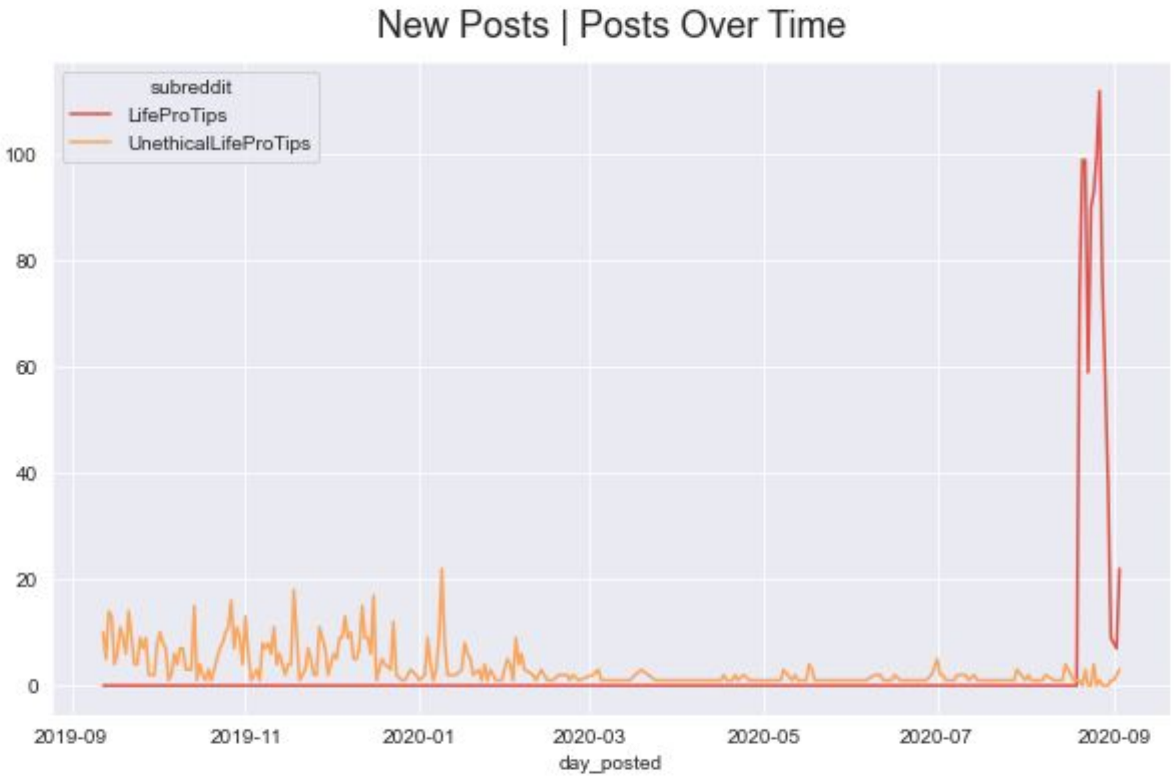
Features of interest

	subreddit	selftext	score	title	upvote_ratio	created_utc	id	fullname	num_comments
0	LifeProTips	I had a phone interview scheduled this morning...	165153	LPT: keep your mouth shut, and don't volunteer...	0.96	1.582156e+09	f6jt5e	t3_f6jt5e	4973
1	LifeProTips	NaN	131334	LPT: If you want a smarter kid, teach your chi...	0.92	1.585245e+09	fpfwra	t3_fpfwra	3103
2	LifeProTips	I just found this quote online and wanted to s...	107877	LPT: Just because you did something wrong in t...	0.94	1.588878e+09	gfcq4g	t3_gfcq4g	2036

Target Variable Y

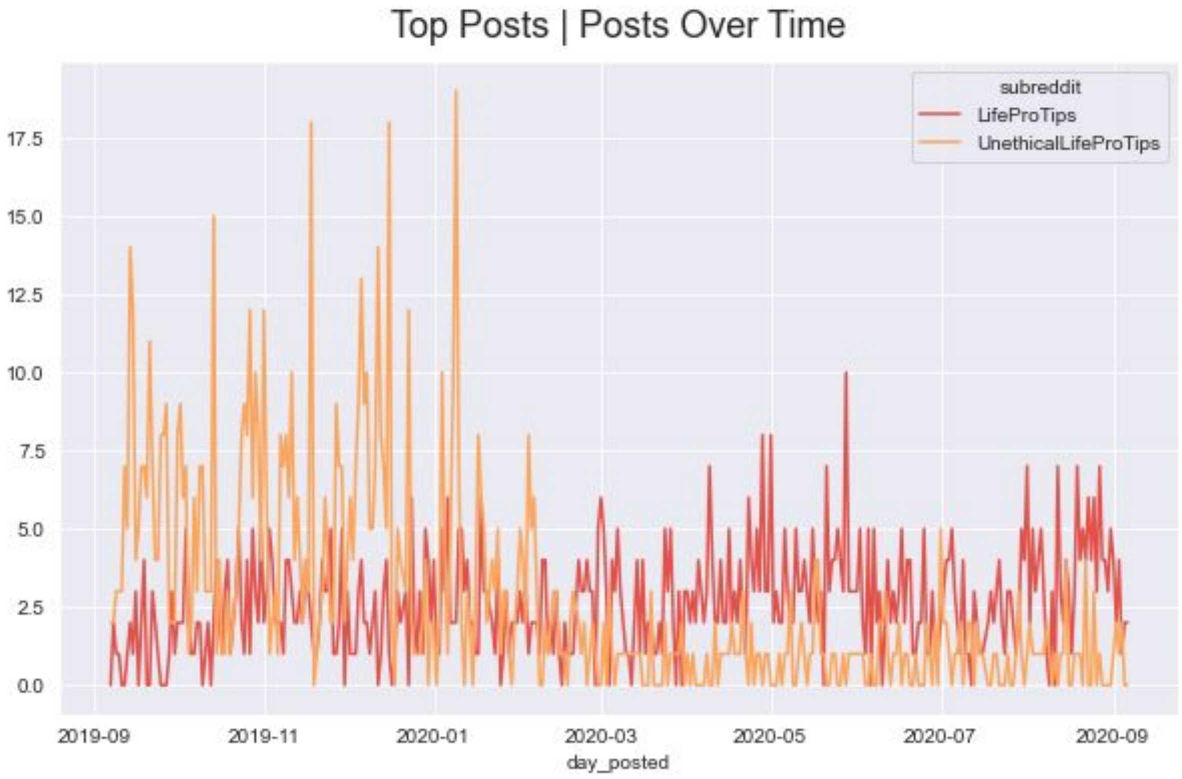
Predictive Data for X

Scraping from new posts versus top posts



The LPT subreddit is much more active than the ULPT subreddit

Scraping from new posts versus top posts



Taking **the top 1000 posts for the past year** gives us a better representation

Removing duplicates

To remove duplicates, we searched for duplicates in the post title and selftext.

	subreddit	selftext	score	title	upvote_ratio	created_utc	id	fullname	num_comments	total_awards_received	author
7	LifeProTips		97685	LPT If you ever forget your WiFi password or y...	0.95	1.568801e+09	d5vknk	t3_d5vknk	2908	13	None
733	LifeProTips	Edit: Wow 2 silver! My first time, thanks kind...	3627	LPT If you ever forget your WiFi password or y...	0.96	1.575529e+09	e6dlbm	t3_e6dlbm	270	2	slackftw

Creating new features

- **Target variable:** Mapping ULPT posts to the positive class and LPT posts to the negative class

```
master_df_top['subreddit_cat'] = master_df_top['subreddit'].map(
                                  {'LifeProTips': 0, 'UnethicalLifeProTips': 1})
```

- **Time:** Converting timestamp to EST and extracting day, hours, etc.

```
master_df_top['timestamp'] = master_df_top['created_utc'].apply(lambda x: datetime.fromtimestamp(x))
master_df_top['timestamp'] = master_df_top['timestamp'].dt.tz_localize('UTC')
master_df_top['timestamp'] = master_df_top['timestamp'].dt.tz_convert('US/Eastern')
```

- **Text:** Combining our title and selftext variables

```
master_df_top['selftext'] = master_df_top['selftext'].fillna("")
master_df_top['all_text'] = master_df_top['title'] + " " +  master_df_top['selftext']
```

Preparing our text for analysis

LPT: When a friend is upset, ask them one simple question before saying anything else: 'Do you want to talk about it or do you want to be distracted from it?' This is honestly one of the best thin...

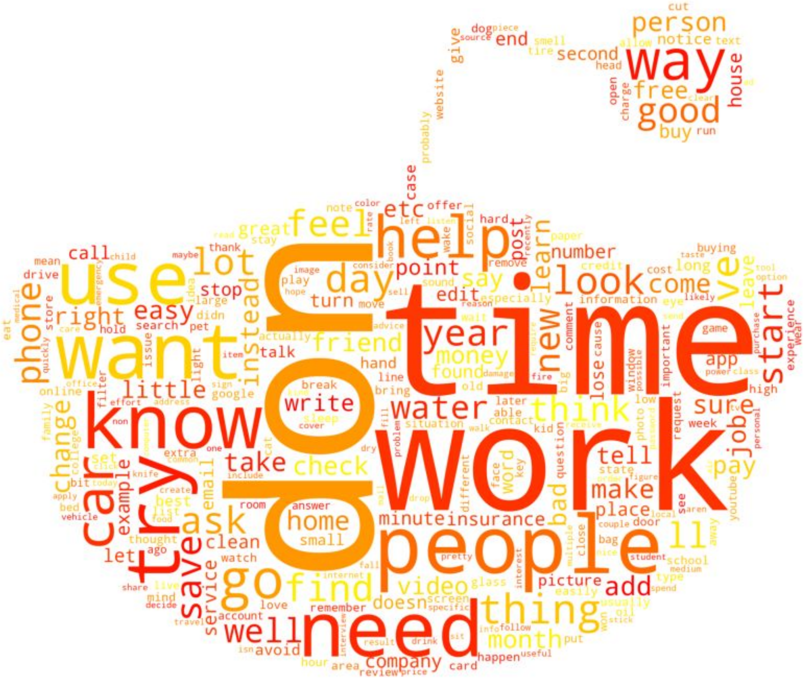
Lowercase, removal of numbers and punctuation

Stopwords Removal

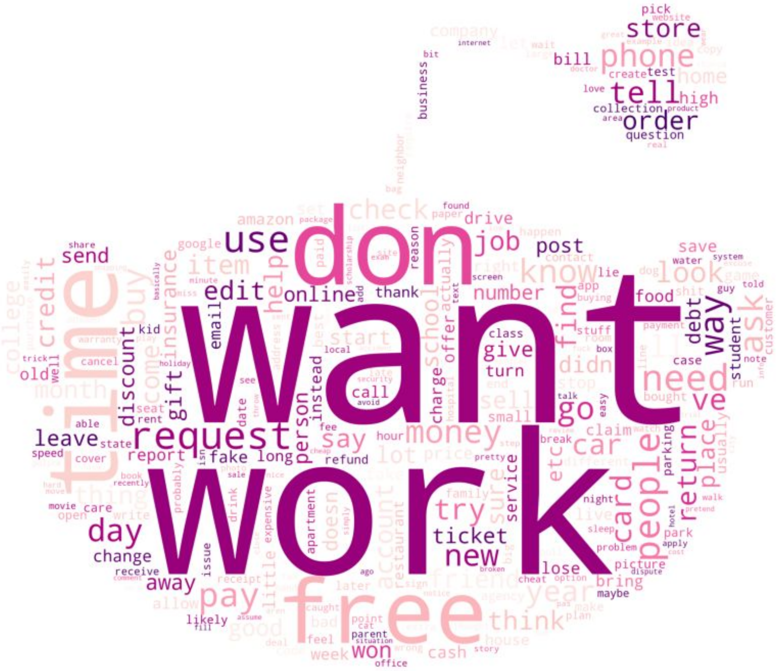
Lemmatization

friend upset ask simple question say want talk want distract honestly best thing upset friend use time people respond people come need vent comfort follow want advice want listen time need let out...

Wordcloud

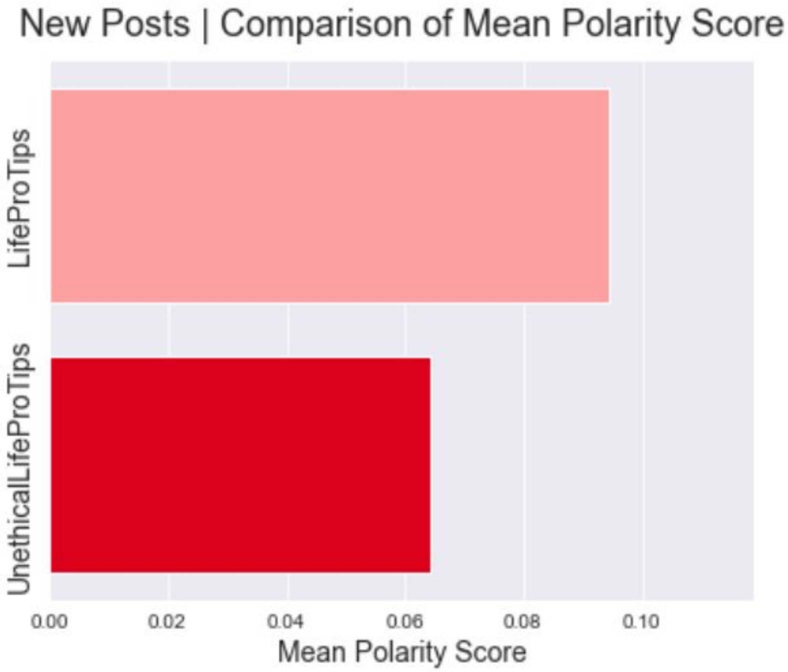


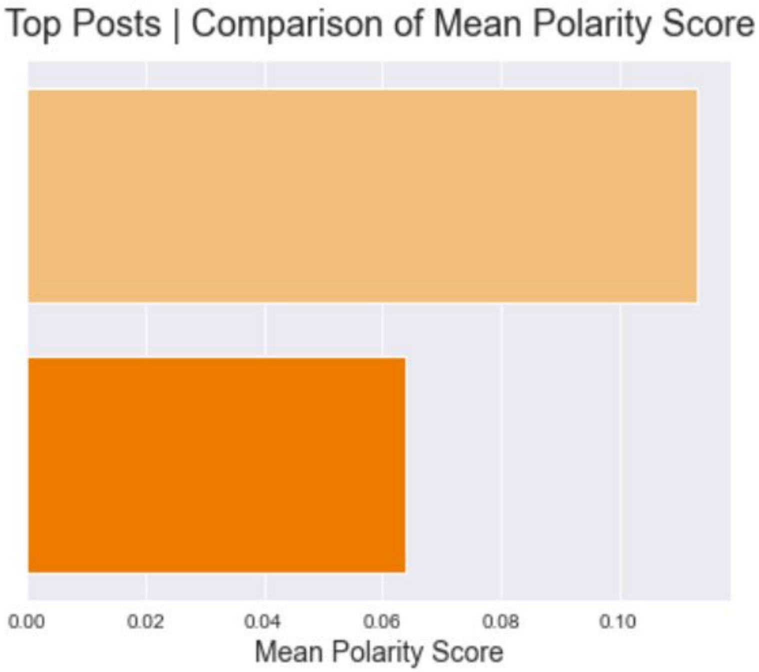
LPT Posts



ULPT Posts

Polarity: positive versus negative sentiment





Vectorizing and modeling

Word vectorization techniques

Count vectorization

TF-IDF vectorization

Modeling techniques

Multinomial Naive Bayes

Logistic Regression

Support Vector Model

7 models were tested, including a voting classifier combining the 3 models.

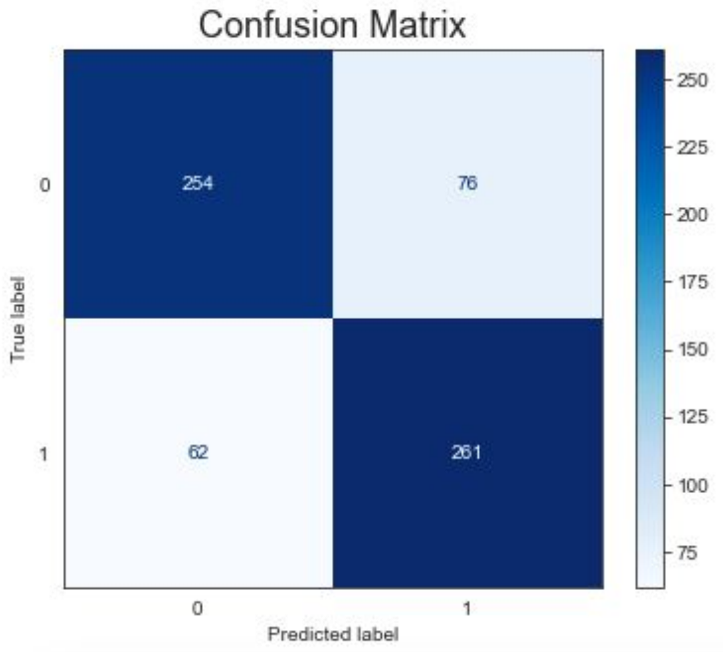
For every model - vectorizer combination:

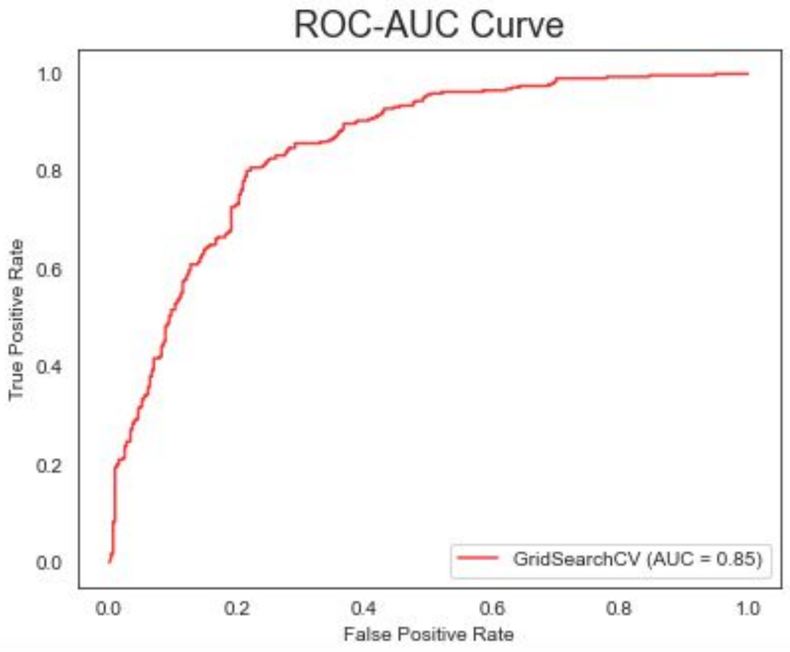
```
For cvec, nb:
Best score: 0.774
Train score: 0.9
Test score: 0.789
Best parameters: {'cvec__max_features': 3000, 'cvec__ngram_range': (1, 2), 'nb__alpha': 1.0, 'nb__fit_prior': True}

ROC-AUC Score: 0.849

True Negatives: 254
False Positives: 76
False Negatives: 62
True Positives: 261
Specificity (Positive Detection Rate): 0.808
Sensitivity (Negative Detection Rate): 0.77
```

For every model - vectorizer combination:





Initial testing results

	Model Name	GS Best Score	Train Score	Test Score	ROC-AUC Score	Specificity	Sensitivity
0	cvec_nb	0.774	0.900	0.789	0.849	0.808	0.770
1	tvec_nb	0.779	0.906	0.789	0.864	0.811	0.767
2	cvec_lr	0.758	0.987	0.784	0.867	0.799	0.770
3	tvec_lr	0.776	0.917	0.790	0.876	0.777	0.803
4	cvec_svm	0.743	0.927	0.766	0.856	0.811	0.727
5	tvec_svm	0.784	0.995	0.793	0.886	0.783	0.818
6	tvec_vote	0.777	0.954	0.804	0.878	0.783	0.797

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Highest accuracy score and high ROC-AUC score, but lower specificity

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Highest specificity but lower accuracy scores.

Selecting a model

	Model Name	GS Best Score	Train Score	Test Score	ROC-AUC Score	Specificity	Sensitivity
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Further tuning - adding stopwords

Predictive feature overlap

Consider words that feature heavily for both classes e.g. ‘work’, ‘people’

```
['want', 'work', 'use', 'don', 'need', 'like', 'get', 'way', 'time', 'peo
ple', 'll', 'ask', 'look', 'day', 'try', 'know']
```

Misclassified data word counts

Consider words that appear the most in our misclassified posts

Feature importance

Positive class - ULPT

Ranking of feature importance

Word features

-5.4161	want
-5.4835	request
-5.5212	free
-5.6137	work
-5.7430	use
-5.7728	don
-5.8102	need
-5.8577	buy
-5.8709	like
-5.8805	car
-5.9331	card
-5.9334	get
-5.9475	pay
-5.9688	phone
-5.9718	way
-6.0008	time
-6.0052	people
-6.0662	money
-6.0686	return
-6.0691	new
-6.1274	ll
-6.1342	ask
-6.1811	look
-6.2121	day
-6.2226	tell
-6.2239	gift
-6.2628	check
-6.2822	item
-6.2959	try
-6.2984	know

Negative class - LPT

-5.4442	people
-5.4794	don
-5.6798	time
-5.7143	like
-5.7239	help
-5.7942	work
-5.8272	ask
-5.8431	know
-5.8456	thing
-5.8459	day
-5.8808	edit
-5.9320	feel
-5.9387	need
-5.9894	get
-6.0098	good
-6.0457	way
-6.0461	try
-6.0481	want
-6.0681	go
-6.0796	person
-6.1079	ll
-6.1363	well
-6.1462	ve
-6.1788	think
-6.1867	look
-6.2025	start
-6.2256	use
-6.2304	lot
-6.2355	instead
-6.3108	say

Misclassified posts word count

Positive class - ULPT

	wordcount
want	51
don	48
people	47
ve	43
like	42
work	41
time	32
try	31
m	30
help	29
ask	26
tell	23
job	22
know	21
get	20

Negative class - LPT

	wordcount
car	99
don	59
engine	53
check	49
want	49
use	45
like	45
money	44
look	44
need	43
fuel	41
buy	40
edit	39
work	38
good	38

Final model

	Model Name	GS Best Score	Train Score	Test Score	ROC-AUC Score	Specificity	Sensitivity
0	cvec_nb	0.774	0.900000	0.789000	0.849	0.808	0.770
1	tvec_nb	0.779	0.906000	0.789000	0.864	0.811	0.767
2	cvec_lr	0.758	0.987000	0.784000	0.867	0.799	0.770
3	tvec_lr	0.776	0.917000	0.790000	0.876	0.777	0.803
4	cvec_svm	0.743	0.927000	0.766000	0.856	0.811	0.727
5	tvec_svm	0.784	0.995000	0.793000	0.886	0.783	0.818
6	tvec_vote	0.777	0.954000	0.804000	0.878	0.783	0.797
7	tvec_nb_new	NA	0.906344	0.790199	0.865	0.811	0.770

Feature importances

Positive class - ULPT

-8.4200	action	-5.4161	want
-8.4200	add list	-5.4835	request
-8.4200	allergy	-5.5212	free
-8.4200	animation	-5.6137	work
-8.4200	applicant	-5.7430	use
-8.4200	apply job	-5.7728	don
-8.4200	appreciation	-5.8102	need
-8.4200	area rug	-5.8577	buy
-8.4200	art	-5.8709	like
-8.4200	assist	-5.8805	car
-8.4200	attitude	-5.9331	card
-8.4200	automatically	-5.9334	get
-8.4200	backwards	-5.9475	pay
-8.4200	bath	-5.9688	phone
-8.4200	bbt	-5.9718	way
-8.4200	behavior	-6.0008	time
-8.4200	beneficiary	-6.0052	people
-8.4200	bike	-6.0662	money
-8.4200	blade	-6.0686	return
-8.4200	braid	-6.0691	new
-8.4200	braid gray	-6.1274	ll
-8.4200	brain	-6.1342	ask
-8.4200	bread	-6.1811	look
-8.4200	breath	-6.2121	day
-8.4200	breathe	-6.2226	tell
-8.4200	breathing	-6.2239	gift
-8.4200	cam	-6.2628	check
-8.4200	capture	-6.2822	item
-8.4200	cellular	-6.2959	try
-8.4200	change mind	-6.2984	know

Negative class - LPT

-8.4995	admin	-5.4442	people
-8.4995	advance	-5.4794	don
-8.4995	airpods	-5.6798	time
-8.4995	anniversary	-5.7143	like
-8.4995	asshole	-5.7239	help
-8.4995	believable	-5.7942	work
-8.4995	borrow	-5.8272	ask
-8.4995	buy new	-5.8431	know
-8.4995	cancellation	-5.8456	thing
-8.4995	cancellation fee	-5.8459	day
-8.4995	cheat	-5.8808	edit
-8.4995	club	-5.9320	feel
-8.4995	controller	-5.9387	need
-8.4995	craigslist	-5.9894	get
-8.4995	despite	-6.0098	good
-8.4995	donor	-6.0457	way
-8.4995	felon	-6.0461	try
-8.4995	free trial	-6.0481	want
-8.4995	furniture store	-6.0681	go
-8.4995	haircut	-6.0796	person
-8.4995	hallway	-6.1079	ll
-8.4995	hassle	-6.1363	well
-8.4995	immigrant	-6.1462	ve
-8.4995	leftover	-6.1788	think
-8.4995	ll pay	-6.1867	look
-8.4995	parking	-6.2025	start
-8.4995	parking lot	-6.2256	use
-8.4995	pop	-6.2304	lot
-8.4995	radio	-6.2355	instead
-8.4995	reservation	-6.3108	say

What features are most predictive?

Both classes

```
Overlap in Features
******************
want know
don buy
need help
go
web
tie
ask
listen
```

ULPT class

```
Features for ULPT
******************
reply
free trial
usps
busy
card
care
payment
personal information
resume
new account
moment
lock
```

LPT class

```
Features for LPT
******************
help
know
thin
dealership
edit
feel guilty
gotten
good way
perform
wife
vehicle
thing people
```

Conclusions

- **Definitive overlap** between our two subreddits: especially things to do with work or people.
- There seems to be a greater focus on **purchases and 'gaming' the system**, in our ULPT posts.
- We don’t get a strong sense of anti-social behaviour or a clear “unethical” definition - maybe a different subreddit will be better to determine this.
- We have to note that our data may be:
    - Biased to this context and group of people
    - Unreliable as it is user-generated (but it is moderated and using top posts helps to counter this)

Potential extensions

- **Further refine NLP** by optimizing custom set of stopwords, part-of-speech analysis

- **Expand our dataset** with comments, sample posts across a period of time etc.

- **Investigate other trends** for Reddit posts: Score, upvote ratio, whether it reaches r/all

Thank you!