

Differentiating between frugal folks and environmentalist

BACKGROUND

Increased awareness of climate change and its urgency has motivated governments and corporations to adopt greener policies. (e.g. the Straw-Free movement*)

Riding on this wave, there is a growing market for *green* products such as shopping bags, reusable/glass straws, clothes made from recycled waste.





^{*}https://www.nationalgeographic.com/environment/article/news-plastic-drinking-straw-history-ban

PROBLEM STATEMENT

You are an analyst at a social media company which uses targeted advertising on its platform. You have been tasked to create a classification model to identify users who are likely to been keen on green products based on their text based interactions.

STRATEGY

Scrape data from two subreddits to train the classifier

ZeroWaste

where people discuss how to reduce environmental impact through green ideas and minimizing waste

Frugal

where people discuss how to conserve time, money, resources



Reduce waste, Recycle, Reuse, Save



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Save Money



PROBLEM STATEMENT

Goal:

ACCURATELY distinguish green from frugal.

Sensitivity and Overall Accuracy are the primary metrics of success.

CONTENTS

- 1. Data Preparation
- 2. Exploratory Data Analysis
- 3. Analysis
 - Fit Classification Algorithms
 - Assess the errors
 - Tune the models
- 4. Conclusions and Recommendations

DATA PREPARATION

Data Extraction

10,000 text-based reddit posts for each subreddit were scraped using the pushshift API

Data Cleaned

Removed posts that were

- [removed]
- [deleted]
- have no description
- spam(e.g. "Testing", "andfgasg")



EXPLORATORY DATA ANALYSIS

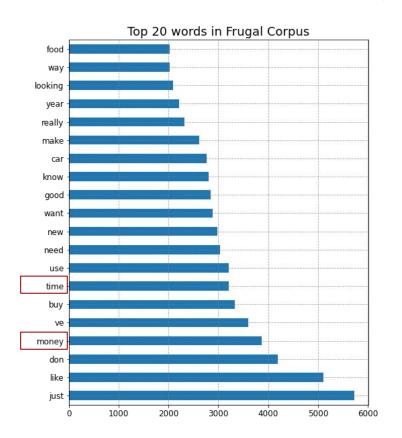
Unigrams (Top 20)

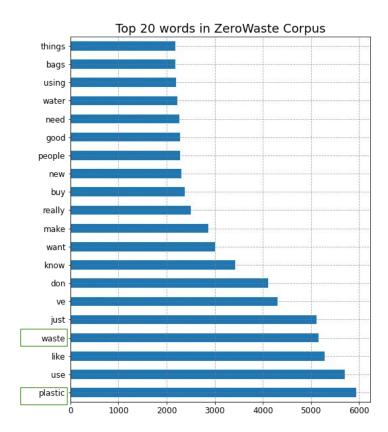
- (Frugal, ZeroWaste) x (CountVectorizer, TfidfVectorizer)

Bigrams (Top 20)

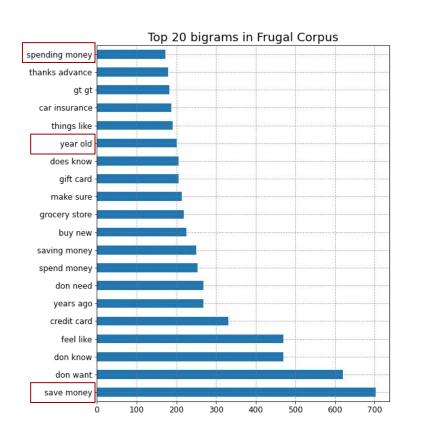
- (Frugal, ZeroWaste) x (CountVectorizer, TfidfVectorizer)

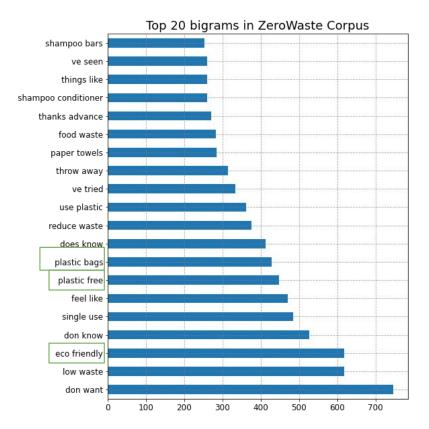
UNIGRAMS





BIGRAMS





ANALYSIS PLAN

Model Exploration (GridSearch)

Combinations of:

- 1. Model
 - K Nearest Neighbor
 - Multinomial Naive Bayes
 - Random Forest
- 2. Vectorizer
 - CountVectorizer
 - o TfidfVectorizer
- 3. Hyper Parameters
 - Max_features
 - Min_df
 - Min_sample_leaf
 - o etc.

To assess:

- 1. Accuracy
- 2. Sensitivity

Feature Analysis

To investigate:

- 1. Top performing features
- 2. Wrongly classified posts



Stop Words



MODEL EXPLORATION

		Train			Test		
Model		Accuracy	Sens	Spec	Accuracy	Sens	Spec
Model 1a	KNN with CountVectorizer	0.82	0.81	0.83	0.73	0.72	0.73
Model 1b	KNN with TfidVectorizer	0.87	0.85	0.88	0.81	0.8	0.82
Model 2a	MNB with CountVectorizer	0.90	0.93	0.89	0.88	0.92	0.86
Model 2b	MNB with TfidVectorizer	0.91	0.93	0.89	0.88	0.92	0.86
Model 3a	RandomForest with CountVectorizer	0.92	0.92	0.92	0.89	0.90	0.89
Model 3b	RandomForest with TfidVectorizer	0.95	0.95	0.94	0.89	0.90	0.89

MODEL EXPLORATION

		Train			Test		
Model		Accuracy	Sens	Spec	Accuracy	Sens	Spec
Model 1a	KNN with CountVectorizer	0.82	0.81	0.83	0.73	0.72	0.73
Model 1b	KNN with TfidVectorizer	0.87	0.85	0.88	0.81	0.8	0.82
Model 2a	MNB with CountVectorizer	0.92	0.94	0.90	0.88	0.92	0.86
Model 2b	MNB with TfidVectorizer	0.92	0.94	0.91	0.88	0.92	0.86
Model 3a	RandomForest with CountVectorizer	0.92	0.92	0.92	0.89	0.90	0.89
Model 3b	RandomForest with TfidVectorizer	0.95	0.95	0.94	0.89	0.90	0.89

FEATURE ANALYSIS (TOP PERFORMING FEATURES IN MNB AND RF)

Assess top performing 120 features

Incorporate misleading features as StopWords (Set1)

MNB CVECMNB TVECRF CVECRF TVECityappsproducthiinsurancedeodorantbankrazorshampoo barplastic containersplastic bagsproductstrawsphone plangasbankcompostablemoneycardboardplastic bagscar insurance100015gaszwconditioner60cardboardreducing wastereducingmetal15low wastepill bottlesthrow60ethique300monthlymetal				
insurance deodorant bank razor shampoo bar plastic containers plastic bags product straws phone plan gas bank compostable money cardboard plastic bags car insurance 1000 15 gas zw conditioner 60 cardboard reducing waste reducing metal 15 low waste pill bottles throw 60	MNB CVEC	MNB TVEC	RF CVEC	RF TVEC
shampoo bar plastic containers plastic bags product straws phone plan gas bank compostable money cardboard plastic bags car insurance 1000 15 gas zw conditioner 60 cardboard reducing waste reducing metal 15 low waste pill bottles throw 60	ity	apps	product	hi
straws phone plan gas bank compostable money cardboard plastic bags car insurance 1000 15 gas zw conditioner 60 cardboard reducing waste reducing metal 15 low waste pill bottles throw 60	insurance	deodorant	bank	razor
compostable money cardboard plastic bags car insurance 1000 15 gas zw conditioner 60 cardboard reducing waste reducing metal 15 low waste pill bottles throw 60	shampoo bar	plastic containers	plastic bags	product
car insurance 1000 15 gas zw conditioner 60 cardboard reducing waste reducing metal 15 low waste pill bottles throw 60	straws	phone plan	gas	bank
zw conditioner 60 cardboard reducing waste reducing metal 15 low waste pill bottles throw 60	compostable	money	cardboard	plastic bags
reducing waste reducing metal 15 low waste pill bottles throw 60	car insurance	1000	15	gas
low waste pill bottles throw 60	zw	conditioner	60	cardboard
	reducing waste	reducing	metal	15
ethique 300 monthly metal	low waste	pill bottles	throw	60
	ethique	300	monthly	metal

FEATURE ANALYSIS (TOP WORD COUNT IN WRONGLY CLASSIFIED POSTS)

Assess top 120 features

MNB		RF		
False Negative	False Positive	False Negative	False Positive	
years	people	just	use	
really	clothes	like	just	
waste	way	don	like	
got	food	buy	don	
clothes	using	money	make	
money	ideas	want	ve	
going	does	new	water	
year	products	ve	know	
free	lot	know	buy	
looking	plastic	people	used	

FEATURE ANALYSIS (TOP WORD COUNT IN WRONGLY CLASSIFIED POSTS)

Assess top 120 features

Incorporate misleading features as StopWords (Set2)

M	NB	RF			
False Negative	False Positive	False Negative	False Positive		
years	people	just	use		
really	clothes	like	just		
waste	way	don	like		
got	food	buy	don		
clothes	using	money	make		
money	ideas	want	ve		
going	does	new	water		
year	products	ve	know		
free	lot	know	buy		
looking	plastic	people	used		

MODEL TUNING

	Models	Train			Test		
		Accuracy	Sens	Spec	Accuracy	Sens	Sens
Model 2b	MNB original Stopwords	0.924	0.944	0.909	0.884	0.918	0.860
Model 2b_sw1	MNB Stopwords set1	0.924	0.941	0.910	0.883	0.916	0.859
Model 2b_sw2	MNB Stopwords set2	0.924	0.942	0.909	0.882	0.912	0.860
Model 3b	RF original Stopwords	0.948	0.954	0.943	0.894	0.902	0.888
Model 3b_sw1	RF Stopwords set1	0.948	0.953	0.943	0.894	0.903	0.886
Model 3b_sw2	RF Stopwords set2	0.947	0.952	0.942	0.896	0.905	0.889

CONCLUSIONS AND RECOMMENDATIONS

The best performing model can distinguish between Green users and their close counterparts, the Frugals with an accuracy of 89%. Which means that while it may make errors in advertising 11% of the time it will likely perform much better against more dissimilar audiences.

Base on the current analysis, we would recommend to use the Random Forest model with stop word list 2.

FUTURE DIRECTIONS

- 1) Combine predictions with other behaviours on the social media platform
- 2) Investigate wrongly classified posts in fulltext form
- 3) Refine list of stop words
- 4) Stemming and Lemmatizing

Thank you!

