An Article Classifier

Know Before You Read

By Carla and Vincent





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For Practitioners & Stakeholders

1. Background

Problem Statement & Objective

Problem Statement

The reasoning behind our problem...

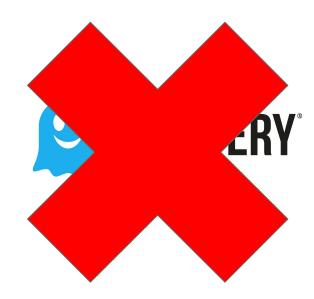
Information Overload





Absence of Tool in the Market





Current Research Without Business Implications

Detecting Promotional Content in Wikipedia

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Abstract

This paper presents an approach for detecting promotional content in Wikipedia. By incorporating stylometric features, including features based on n-gram and PCFG language models, we demonstrate improved accuracy at identifying promotional articles, compared to using only lexical information and metafeatures.

based on both n-grams and Probabilistic Context Free Grammars (PCFGs). We show that using such stylometric features improves over using only shallow lexical and meta-features.

2 Related Work

Anderka et al. (2012) developed a general model for detecting ten of Wikipedia's most frequent quality flaws. One of these flaw types, "Advert", refers to

Bert-Based Promotional Words Detection Classifier Development

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Abstract

From the analysis last semester, we can see the necessity for us to find a way to get rid of advertising and promotion words from our corpora. After manually picking out promotion sentences, we get a list of "blackwords" from video descriptions corpora, which can be used as a dataset in machine learning. In this report, I use the traditional model Word2Vec and the most advanced NLP model "BERT" combining with other machine learning methods to help us picking out the promotion sentences from video descriptions.

Objective

"Provide a convenient method in article classification for web browsers such as Chrome, Firefox, or Safari".

Key Goals

- Build a classifier for promotional articles
- Improve web-browsers capabilities
- Apply text analytics techniques
- Provide a new solution to an existing problem

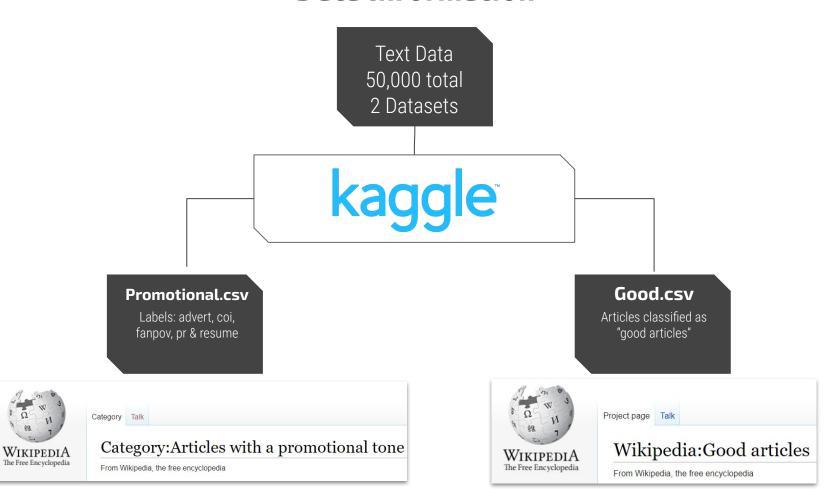




2. Methodology & Results

Data Information, Process, Results & Limitations

Data Information



[]	good	.head()
₽		text url
	0	Nycticebus linglom is a fossil strepsirrhine p https://en.wikipedia.org/wiki/%3F%20Nycticebus
	1	Oryzomys pliocaenicus is a fossil rodent from https://en.wikipedia.org/wiki/%3F%20Oryzomys%2
	2	.hack dt hk is a series of single player actio https://en.wikipedia.org/wiki/.hack%20%28video
	3 T	The You Drive Me Crazy Tour was the second con https://en.wikipedia.org/wiki/%28You%20Drive%2
	4	0 8 4 is the second episode of the first seaso https://en.wikipedia.org/wiki/0-8-4
[]	good	.describe()
₽		text url
	cou	nt 30279 30279
	uniq	ue 30279 30279
	top	Hurricane Joanne was one of four tropical cycl https://en.wikipedia.org/wiki/Bernard%20Waldman
	free	q 1 1

→				text	advert	coi	fanpov	pr	resume	е	ur
0	0	1 Litre no Nar	mida 1, lit. 1 Litre	of Tears als	0	0	1	0	(0 h	nttps://en.wikipedia.org/wiki/1%20Litre%20no%2.
1	1 1D	ayLater was free,	web based softv	vare that wa	1	1	0	0	(0	https://en.wikipedia.org/wiki/1DayLate
2	2	1E is a privately o	owned IT softwar	e and servic	1	0	0	0	(0	https://en.wikipedia.org/wiki/18
3	3 1Ma	alaysia pronounce	ed One Malaysia	in English a	1	0	0	0	(0	https://en.wikipedia.org/wiki/1Malaysia
4	4 Th	e Jerusalem Bier	nnale, as stated o	on the Bienn	1	0	0	0	(0 h	https://en.wikipedia.org/wiki/1st%20Jerusalem%
→		advert	coi	fanpov		pr	r	esum	е		
÷		advert	coi	fanpov		pr	r	esum	e		
	count		coi 23837.000000	fanpov 23837.000000	23837.0		23837.0				
c	count mean			<u>-</u>			23837.0		0		
r		23837.000000	23837.000000	23837.000000	0.0	00000	23837.0	0000	0		
r	mean	23837.000000 0.793346	23837.000000	23837.000000	0.0	00000 63599	23837.0 0.0 0.2	0000 9221	0 0 8		
r	mean std	23837.000000 0.793346 0.404913	23837.000000 0.089860 0.285988	23837.000000 0.062760 0.242535	0.00 0.24 0.00	00000 63599 44042	23837.0 0.0 0.2 0.0	0000 9221 8932	0 0 8 0		
r	mean std min	23837.000000 0.793346 0.404913 0.000000	23837.000000 0.089860 0.285988 0.000000	23837.000000 0.062760 0.242535 0.000000	0.00 0.24 0.00	00000 63599 44042 00000	23837.0 0.0 0.2 0.0 0.0	00000 9221 8932 0000	0 0 8 0 0 0 0		
r	mean std min 25%	23837.000000 0.793346 0.404913 0.000000 1.000000	23837.000000 0.089860 0.285988 0.000000 0.000000	23837.000000 0.062760 0.242535 0.000000 0.000000	0.00 0.2- 0.00 0.00	00000 63599 44042 00000	23837.0 0.0 0.2 0.0 0.0	00000 92210 89320 00000	0 0 8 8 0 0		

Our Process

Data Cleaning & Exploration

- Data Collection
- Data Preparation

Machine Learning Models

- Sentiment Analysis
- Topic Modelling
- Classification with RF

Results



Data Exploration & Cleaning

Describe Our Data

```
[8] promotional.info()
   <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 23837 entries, 0 to 23836
    Data columns (total 7 columns):
     # Column Non-Null Count Dtype
                23837 non-null object
         advert 23837 non-null int64
                23837 non-null int64
         fanpov 23837 non-null int64
                23837 non-null int64
       resume 23837 non-null int64
                23837 non-null object
    dtypes: int64(5), object(2)
    memory usage: 1.3+ MB
    good.info()
C <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 30279 entries, 0 to 30278
    Data columns (total 2 columns):
     # Column Non-Null Count Dtype
       text 30279 non-null object
                30279 non-null object
    dtypes: object(2)
    memory usage: 473.2+ KB
```

Check for Null Values

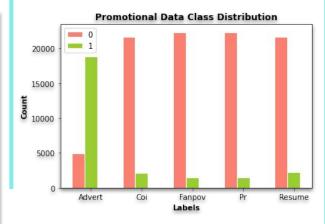
```
[ ] promotional.isnull().sum()

C text    0
    advert    0
    coi    0
    fanpov    0
    pr     0
    resume    0
    url     0
    dtype: int64

[ ] good.isnull().sum()

C text    0
    url     0
    dtype: int64
```

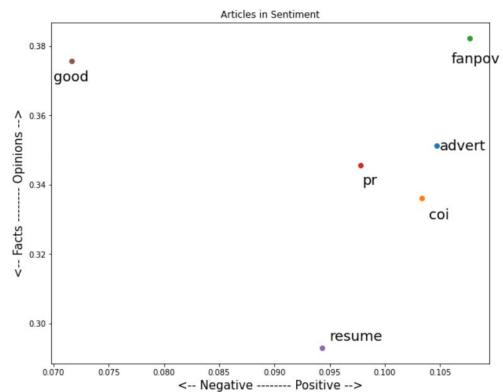
Check Class Distribution



Machine Learning Models

Sentiment Analysis, Topic Modelling & Classification

Sentiment Analysis



- Good articles usually are thought to be more fact-based and neutral in wording
- Promotional articles are more positive
- Resume-like articles are more negative

Topic Modeling Process

- 1. Tokenization of texts
- 2. Remove Stopwords, Create Bigrams & Lemmatization
- 3. LDA Model
- 4. Coherence score
- 5. Wordcloud Visualizations



Promotional Articles







Topic 0: Science/Robotic

Topic 1: Sports

Topic 2: Military

Topic 3: History

Topic 4: Power Supplies

Topic 5: Business

Topic 6: Releases

Topic 7: Society

Topic 8: Results

Good Articles

sav

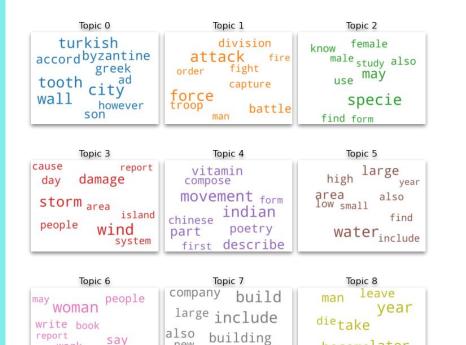
case

work

child

new

city year



becomelater

time

day

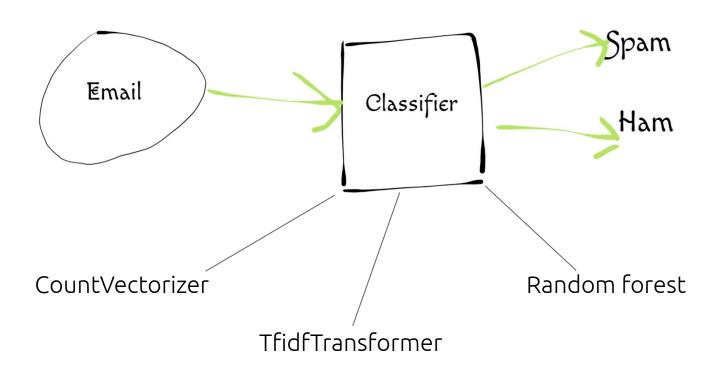
return

```
Topic 0: Culture
Topic 1: War
Topic 2: Science
Topic 3: Weather Conditions
Topic 4: Cultural Movements
Topic 5: Lands
Topic 6: Books
```

Topic 7: Companies

Topic 8: Historical Events

Classifier



Advantages

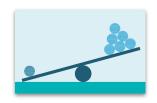


Easy Input Useful Classifications



Accuracy Score: 0.81 Resume: Advertisement

Limitations



Imbalanced Data

Most Promotional are Advertisements



Black-Box Model

Which Decision Tree? How to Tune?

3. Recommendations & Implications

For Practitioners & Stakeholders

CEO of Web Browsers / Director of Quality

- Complexity of articles on the web
- Create a web-browser extension
- Increase customer satisfaction/product quality
- Attract new users





- Improve interest in text analytics
- Develop attractive articles
- Realize people's need of useful information

Marketing Analysts

Websites' Owners / Administrators

- Avoid using articles that are misleading
- Implement this tool in their own articles
- Recognize user's real needs



Credits

Team Members: Vincent Chen, Carla M. Fera



Prof. Nohel Zaman

All faculty members & classmates!!

Thanks!

Does anyone have any questions?