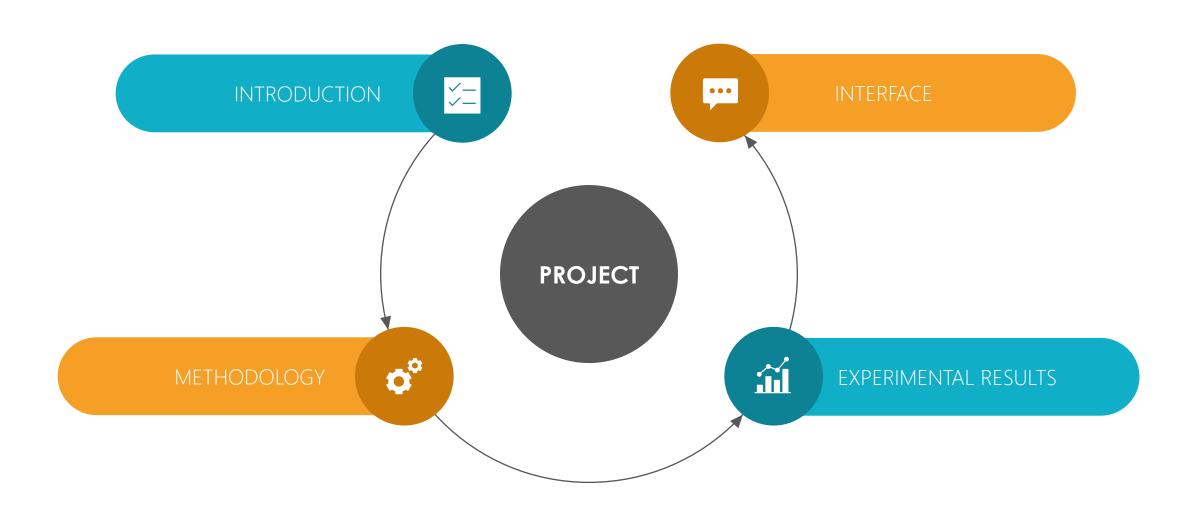
Fake reviews detection on Amazon dataset

Gianmaria Saggini



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Fake reviews detection_



Introduction

User-oriented online reviews serve as the second most reliable source of product information.

80% of customers change their purchasing decisions after reading negative reviews.

87% of customers approve their decisions after reading positive reviews.



60% of reviews for top 10 electronic products on Amazon are fake.

Fake reviews can not only manipulate product rankings, but more widely reduce consumer trust in online reviews.

Methodology



DATASET

Descriptions of the two datasets used.



EXPLORATORY DATA ANALYSIS

Analysis of the features and their distributions.



PREPROCESSING

Text preprocessing: parsing, tokenization, stemming...



FEATURE EXTRACTION

Text vectorization using BoW and TF-IDF.



WORD EMBEDDINGS

Training of Word2Vec model to generate word embeddings of reviews.

Methodology Dataset

Labeled dataset

- 21000 reviews
- Half real, half fake
- Labeled by Amazon
- Used for classification

Features:

Label

Rating

Verified purchase

Product category

Product id

Product title

Review title

Review text

Unlabeled dataset

- Half a billion reviews
- Used for Word2Vec training

Features (only used ones):

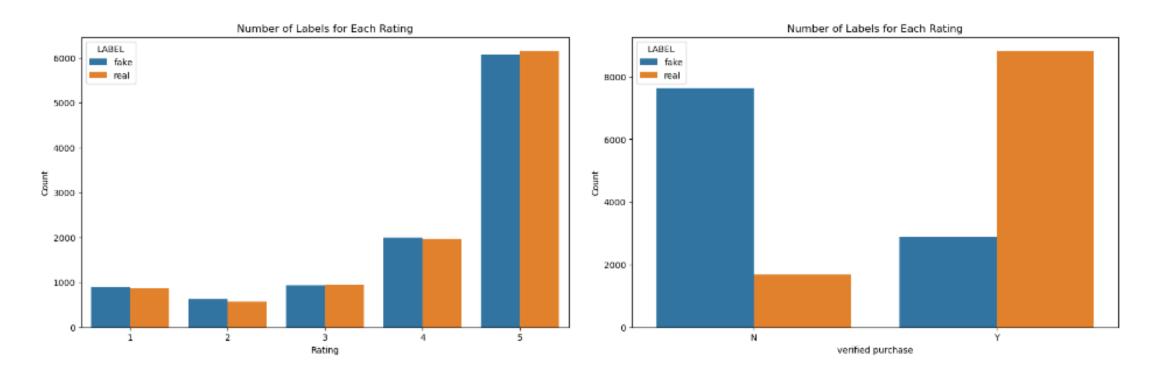
Review text

Timestamp

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Methodology EDA

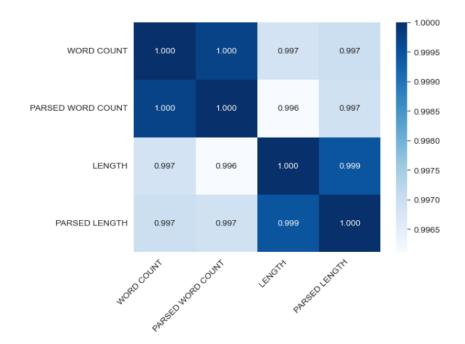
Distribution of fake and real reviews in various attributes:

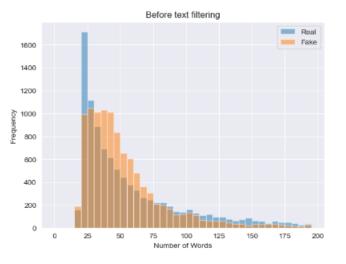


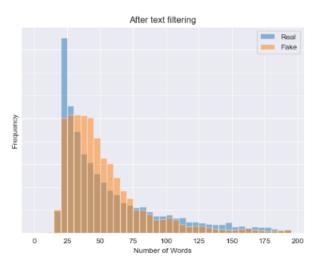
Methodology EDA

Analysis of text related features.

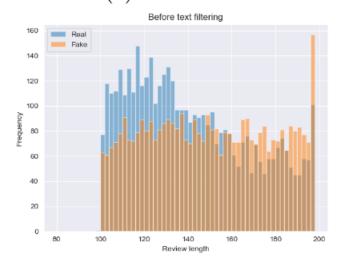
- Number of words (before filtering)
- Number of words (after filtering)
- Text length (before filtering)
- Text length (after filtering)

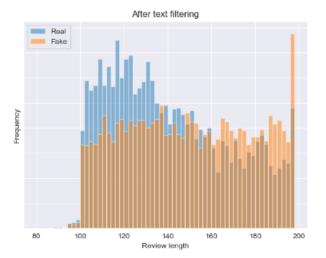




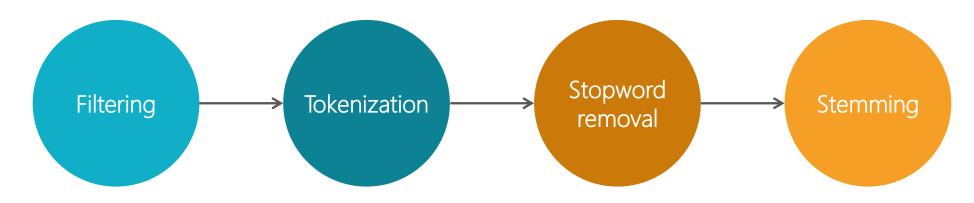


(a) Number of fake and real reviews for ratings.





Methodology Preprocessing



Remove URLs and HTML tags.

Text is converted to lowercase. Text is divided into tokens with only latin letters.

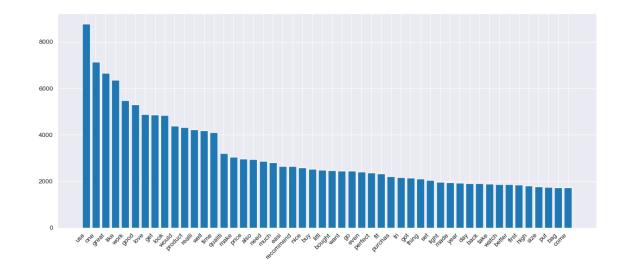
english stopword list.

Remove stopwords with nltk Each token is passedthrough the Snowball Stemmer.



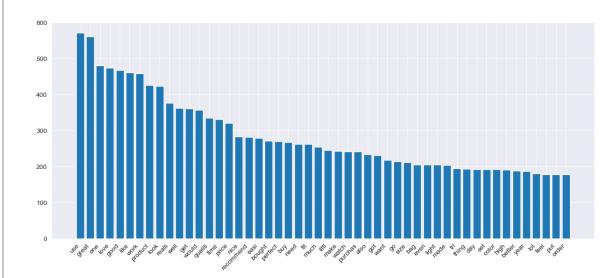
Bag of Words (BoW)

50 most frequent terms in BoW:

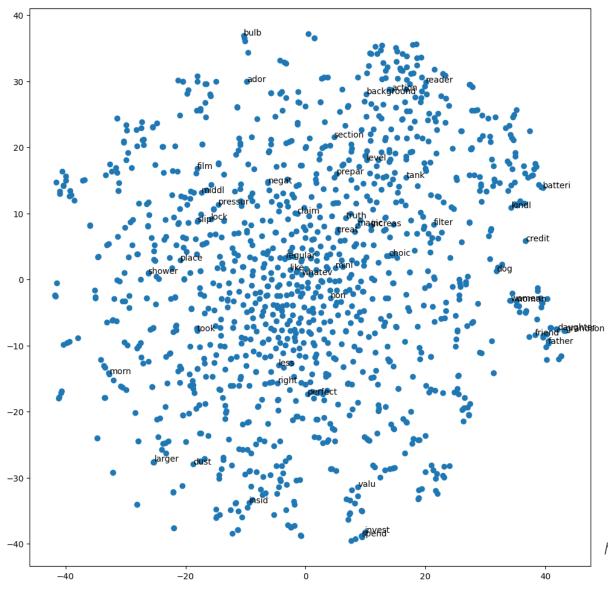


TF-IDF

50 most frequent terms in TF-IDF:



MethodologyWord embeddings



- Skip-Gram variant of Word2Vec model.
- Input: file with a sentence per line.
 To speed up computation, parallelize the work: each line of the file has to be a tokenized sentences.

- Hyperparameters:
 - Window = 5
 - Vector_size = 100
 - Min_count = 700000 and 500000

min_count = 700000

Experimental results

Results

- Random Forest seems to be slightly better than linear SVC.
- TF-IDF has always higher accuracy than Bag of Words.
- As expected, verified purchase plays a fundamental role in the detection of fake reviews.
- Word embeddings 1 (min_count = 700000) doesn't seem to be always better than word embeddings 2 (min_count = 500000).

| Features | Model | Accuracy | F1 score | AUC |
|-------------------|---------------------|------------------------|----------------|--------|
| BoW | RF | 63.81% | 66.04% | 70.17% |
| | SVC | 61.71% | 63.62% | 66.32% |
| BoW+VP | RF | 80.53% | 79.22% | 87.10% |
| | SVC | 79.25% | 78.97% | 84.58% |
| BoW+WE1 | RF | 63.51% | 65.13% | 68.72% |
| | SVC | 62.25% | 64.07% | 66.96% |
| ${ m BoW+WE2}$ | RF | 63.12% | 64.85% | 68.71% |
| | SVC | 62.29% | 64.13% | 67.03% |
| BoW+VP+WE1 | RF | 80.45% | 79.68% | 86.51% |
| | SVC | 78.87% | 78.63% | 84.43% |
| ${ m BoW+VP+WE2}$ | RF | 80.54% | 79.73% | 86.66% |
| | SVC | 78.65% | 78.44% | 84.24% |
| TF-IDF | RF | 64.60% | 65.91% | 70.93% |
| | SVC | 64.17% | 64.37% | 69.58% |
| TF-IDF+VP | RF | 80.68% | 79.36% | 86.94% |
| | SVC | 80.62% | 80.27 % | 86.40% |
| TF-IDF+WE1 | RF | 63.95% | 64.79% | 69.75% |
| | SVC | 64.06% | 64.31% | 69.67% |
| TF-IDF+WE2 | RF | 63.88% | 64.97% | 69.88% |
| | SVC | 64.08% | 64.37% | 69.66% |
| TF-IDF+VP+WE1 | RF | $\boldsymbol{80.75\%}$ | 80.11% | 86.81% |
| | SVC | 80.54% | 80.23% | 86.44% |
| TF-IDF+VP+WE2 | RF | 80.74% | 80.10% | 86.83% |
| | SVC | 80.39% | 80.07% | 86.43% |

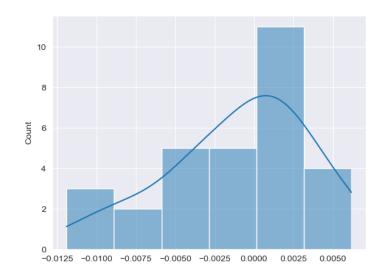
Experimental resultsStatistical comparison

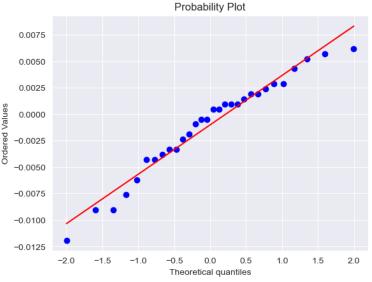
Comparison between RandomForest trained with TF-IDF+VP+WE1 and TF-IDF+VP.

- To have more data, I performed three 10-fold crossvalidations.
- Differences between paired observations are skewed, so I opted for a Wilcoxon signed-rank test.

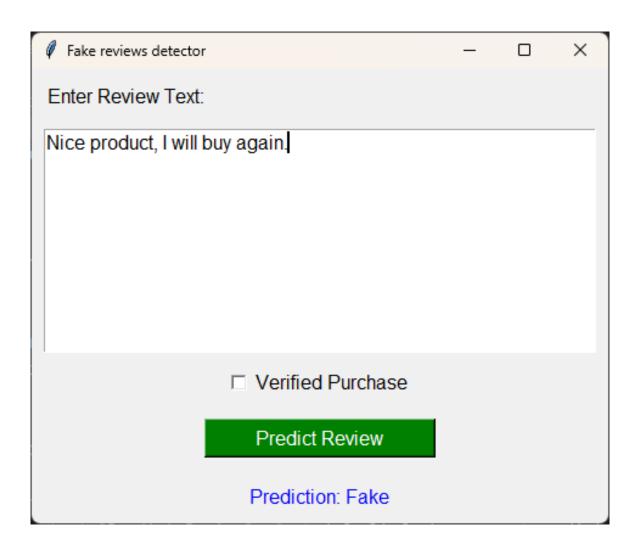
Wilcoxon p-value: 0.44







Interface



References

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Fake review detection in e-Commerce platforms using aspect-based sentiment analysis Journal of Business Research, Volume 167, 2023, 114143, ISSN 0148-2963, https://doi.org/10.1016/j.jbusres.2023.114143

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Journal of Business Research, Volume 149, 2022, Pages 884-900, ISSN 0148-2963, https://doi.org/10.1016/j.jbusres.2022.05.081

Hajek, P., Barushka, A. & Munk, M.

Fake consumer review detection using deep neural networks integrating word embeddings and emotion mining.

Neural Comput & Applic 32, 17259–17274 (2020). https://doi.org/10.1007/s00521-020-04757-2

Datasets:

- https://www.kaggle.com/datasets/lievgarcia/amazon-reviews
- https://cseweb.ucsd.edu/~jmcauley/datasets.html#amazon_reviews

