Amazon Fake Review Detection using various ML Model

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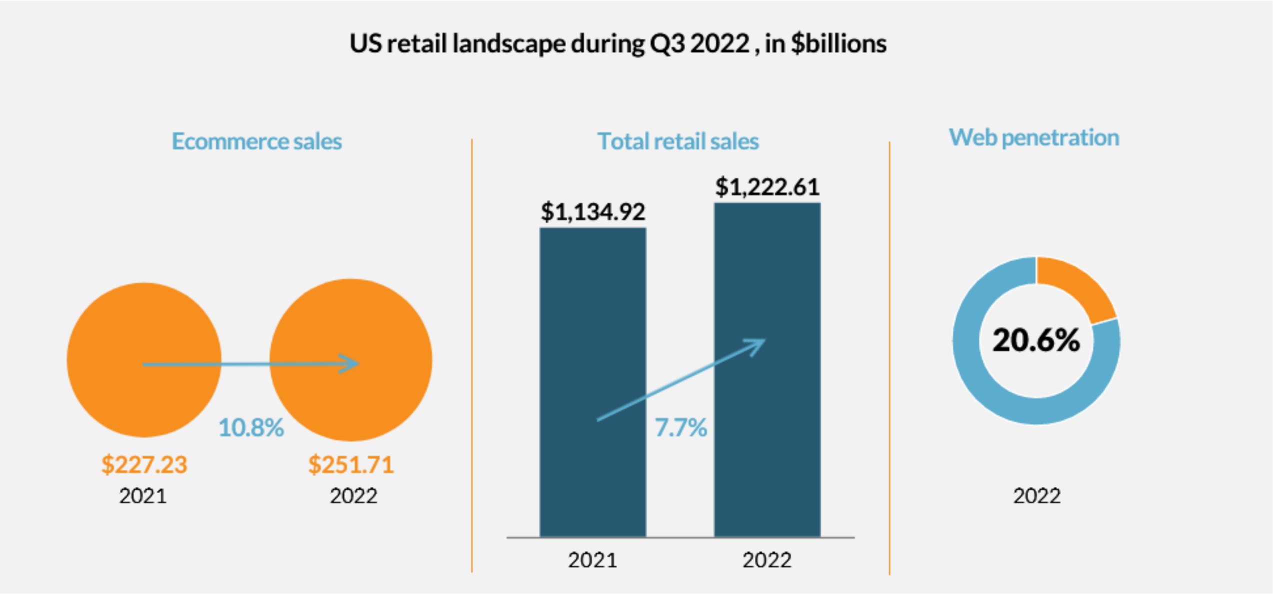
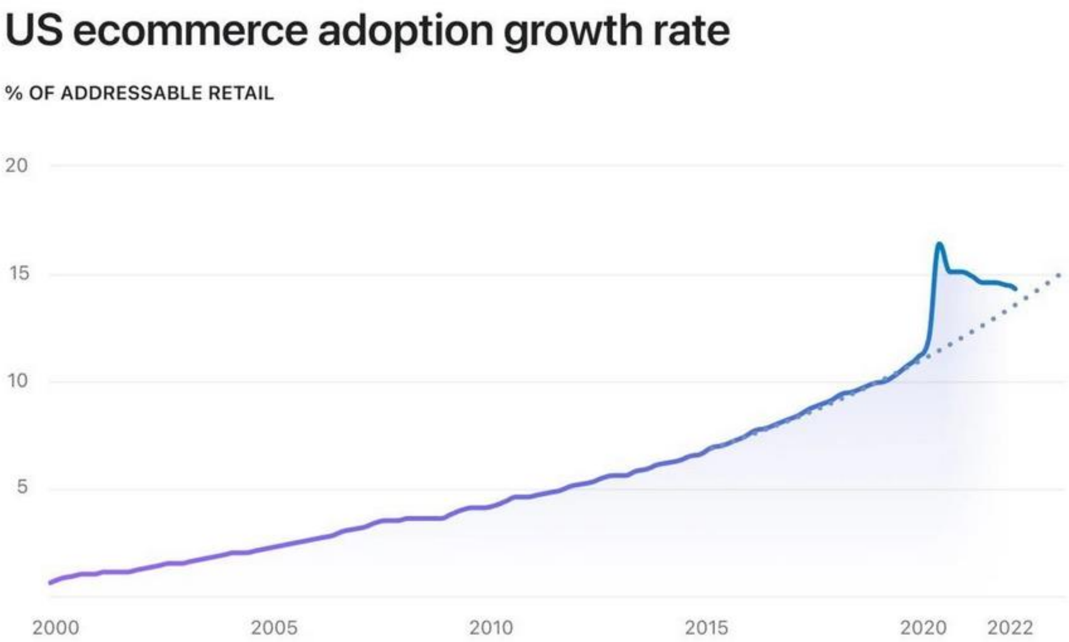
605.744

Ecommerce Growth





U.S. ecommerce grew 10.8% in Q3 2022.

- E-commerce sales accounted for around 14% of retail sales

About Review

Reviews are key to the decision-making process, helping customers to get a better idea about the product

95% of consumers read online reviews before they shop

- 58% say they would pay more for the products of a brand with good reviews.

Related Works

In 2008, Jindal and Liu identified spam by analyzing the number of feedbacks, length of review titles, sorting order by date, positives used repeatedly in content, percentage of negative words, and review evaluation ratings for amazon reviews.

In 2021, Alsubari used Chicago hotel reviews (1600 hotel reviews, 800 fake, 800 real review), and predicted fake reviews with an accuracy of 93% and 95% with a review classifier using machine learning (SVM, Random Forest).

Fake Review

These reviews produced by persons who have not personally experienced the subjects of the reviews are called spam reviews; spam reviews might also be called fake reviews, non-genuine reviews, or fraudulent reviews.

- Detection of review spam: A survey

Project Idea

Using supervised machine learning technique to train model to detect fake review based on labeled dataset.

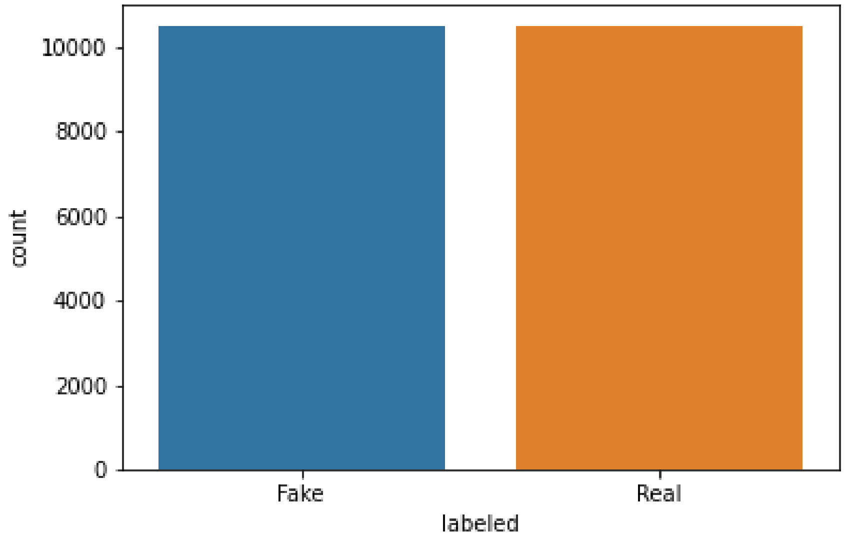
Dataset

Used the dataset from Kaggle and previous research

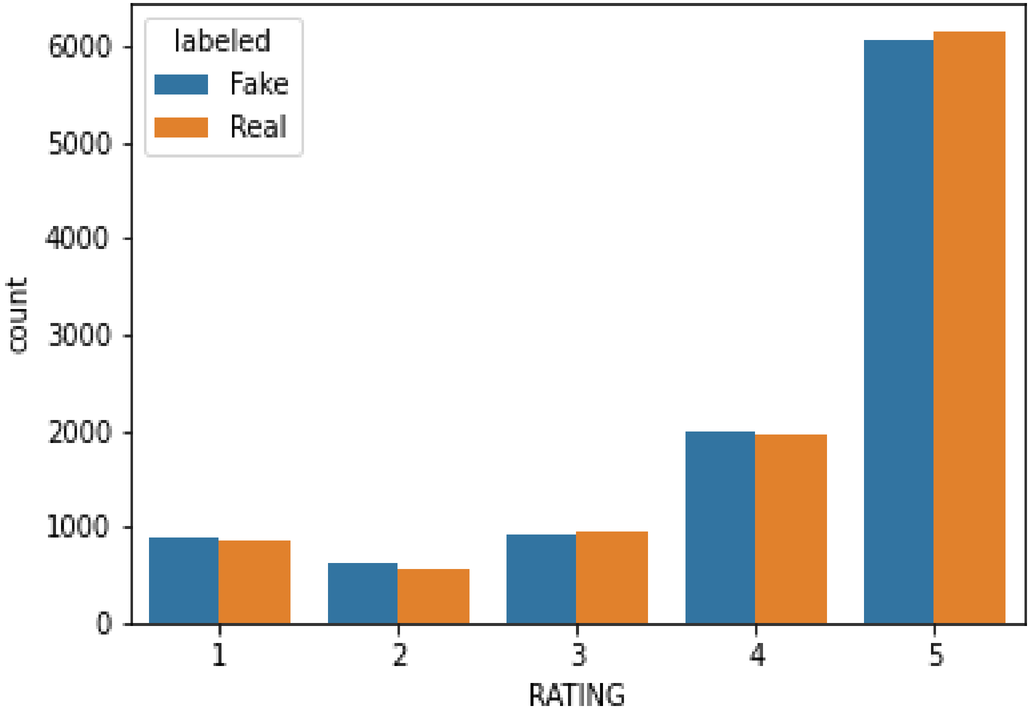
Dataset of 20000 reviews

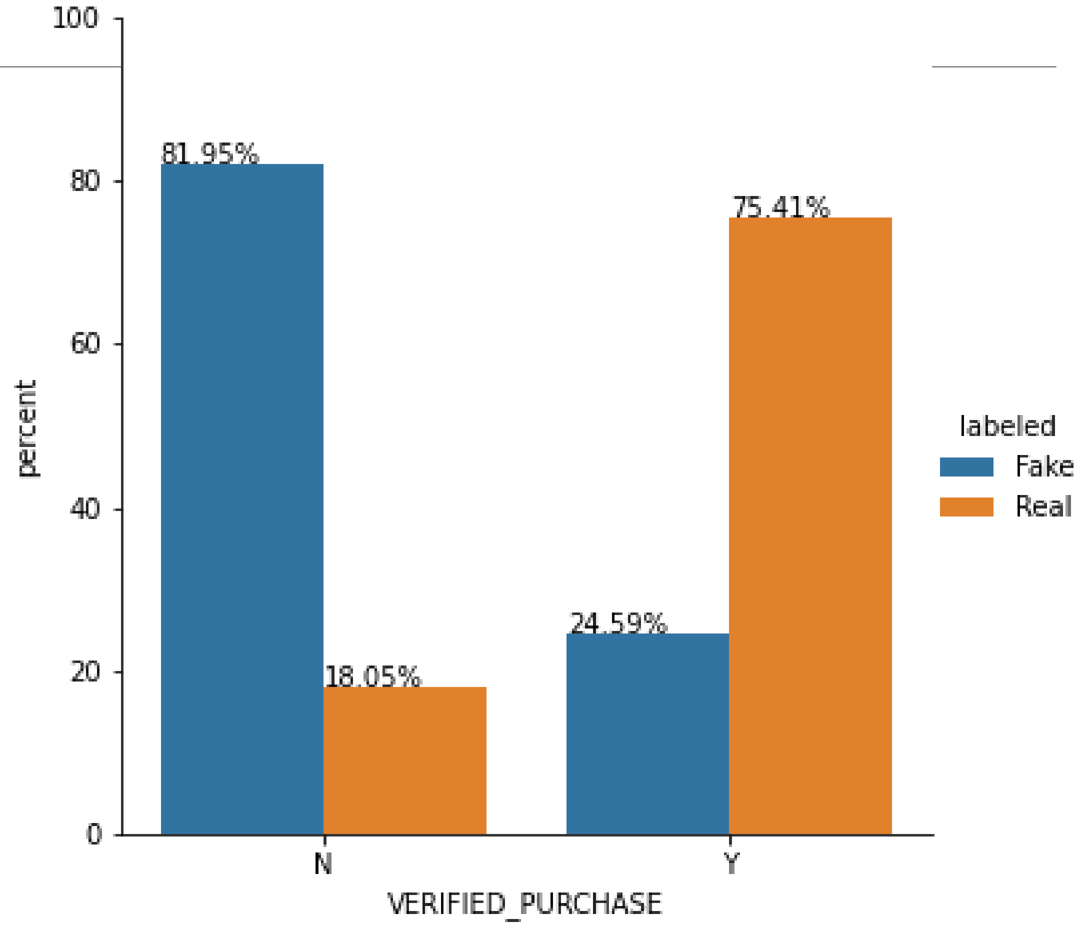
- 10000 fake reviews
- 10000 Real reviews

Reviews about amazon product reviews.



Data Analysis





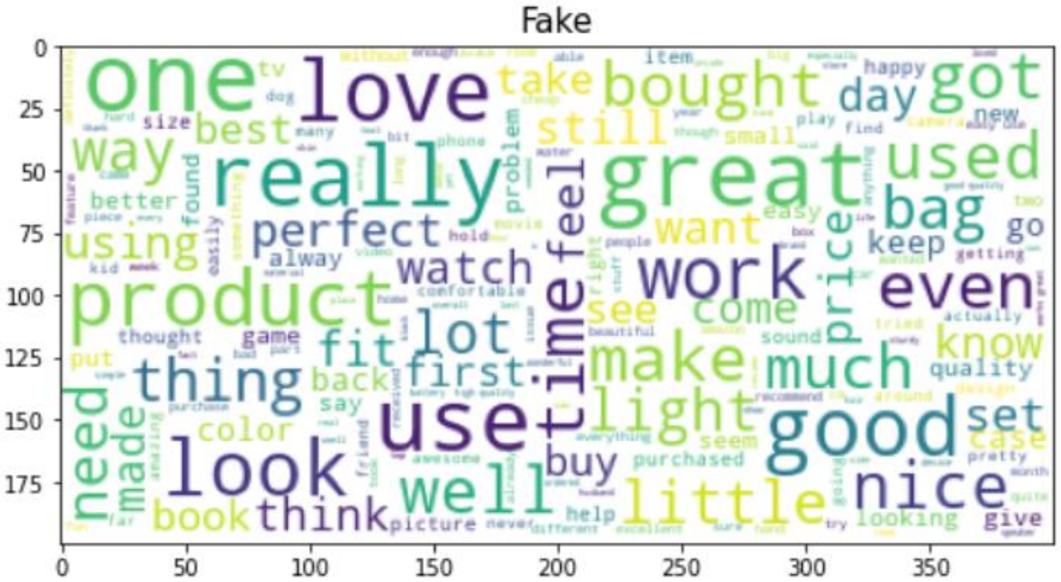
Data Analysis

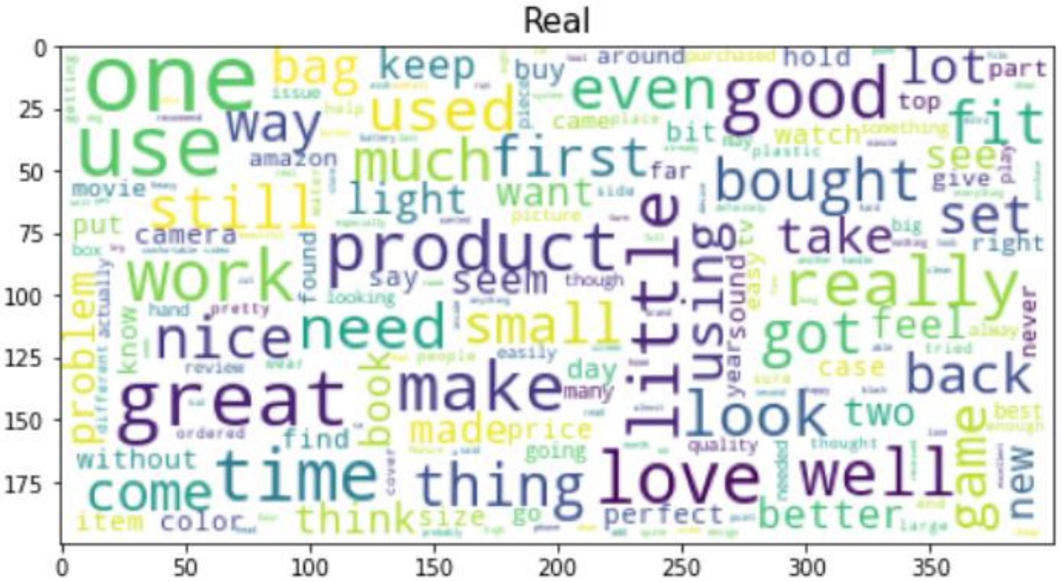
Average Review Title Length

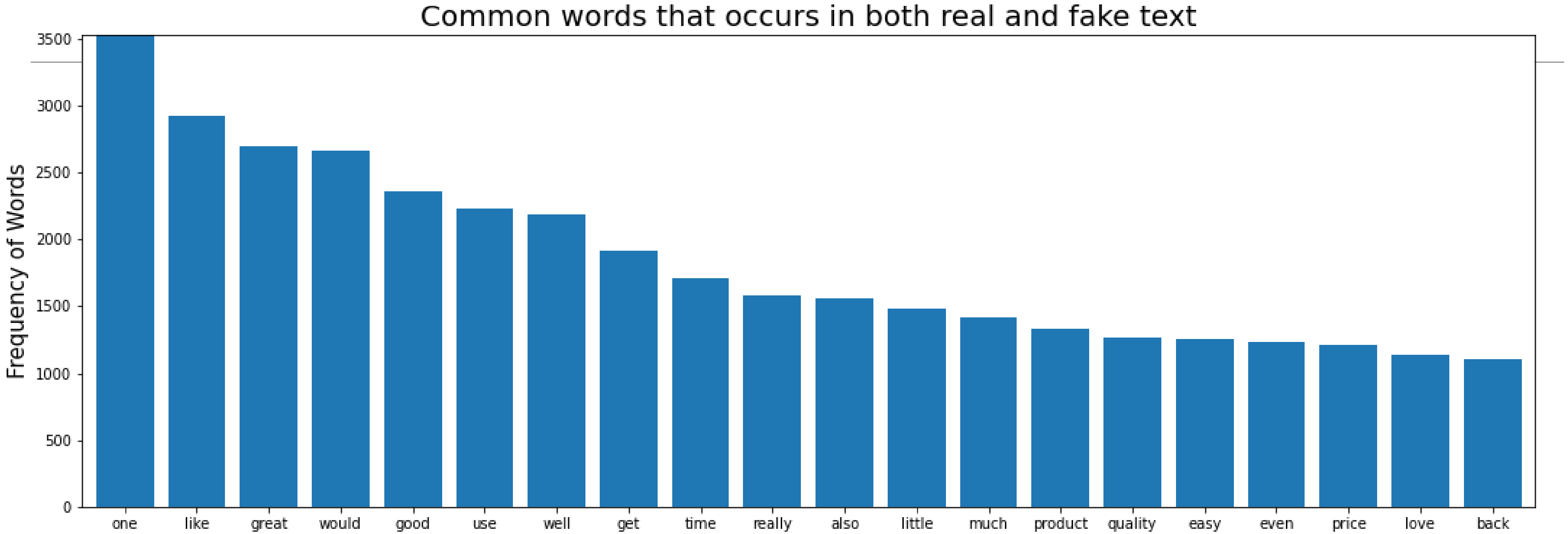
- Fake Review: 2.73
- Real Review: 3.18

Average Review Length

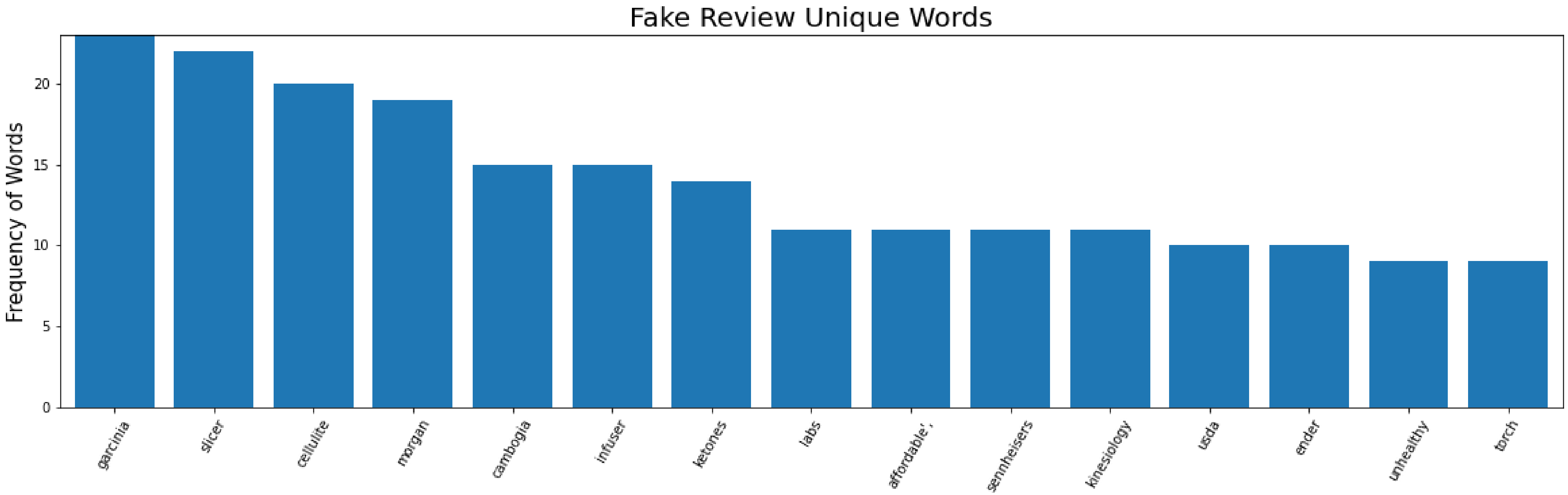
- Fake Review: 28.53
- Real Review: 38.76

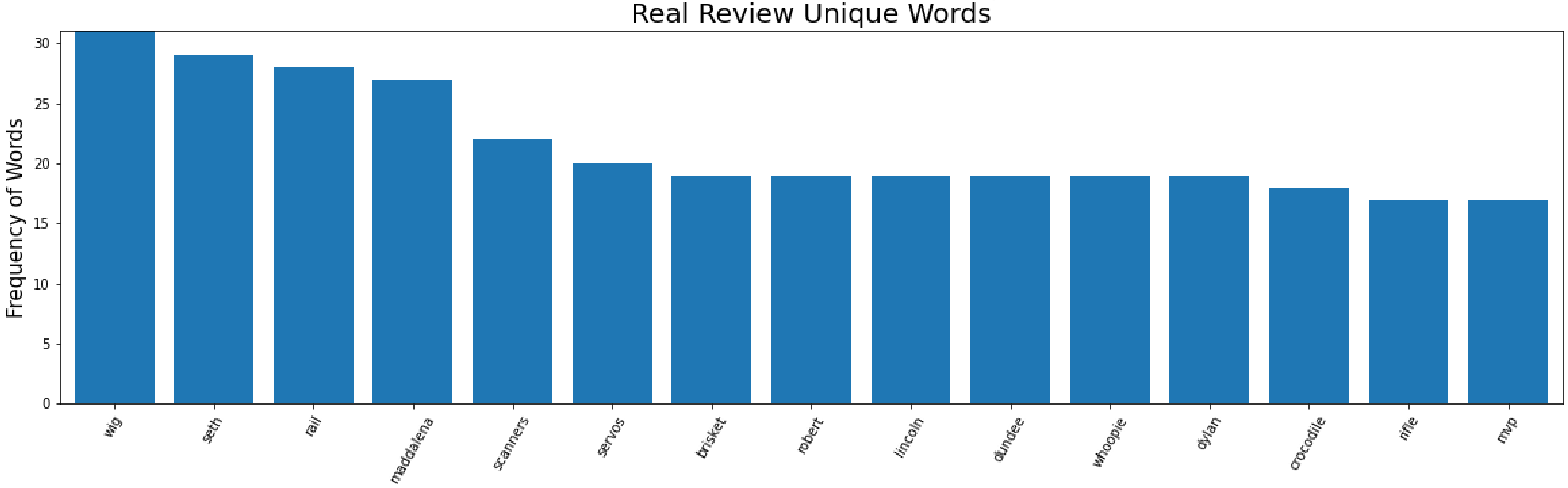

Fake
0
25
50
75
100
125
150
175
0
50
100
150
200
250
300
350
one
love
bought
got
take
day
really
great
used
way
best
still
bag
using
perfect
want
go
keep
product
work
even
watch
price
lot
see
come
fit
time
feel
make
much
know
thing
first
light
set
need
made
use
good
case
look
buy
well
little
nice
book
think
give


Real
0
25
50
75
100
125
150
175
0
50
100
150
200
250
300
350
one
bag
keep
even
good
lot
use
used
way
fit
much
first
bought
still
light
want
set
product
take
work
little
really
using
need
small
nice
got
great
make
back
problem
look
two
time
thing
love
well
game
come
think
perfect
better
new

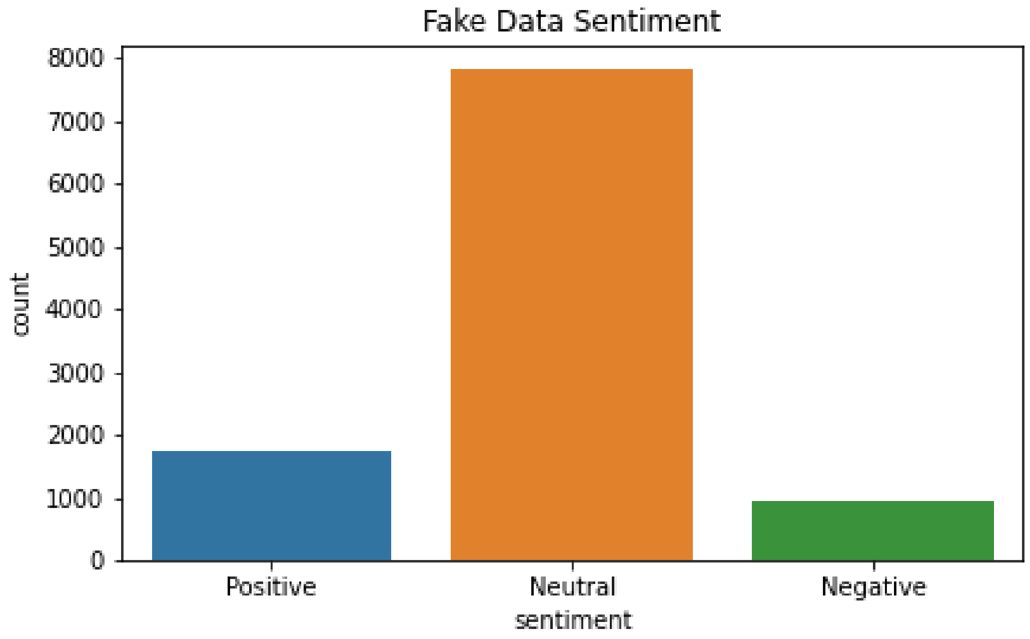


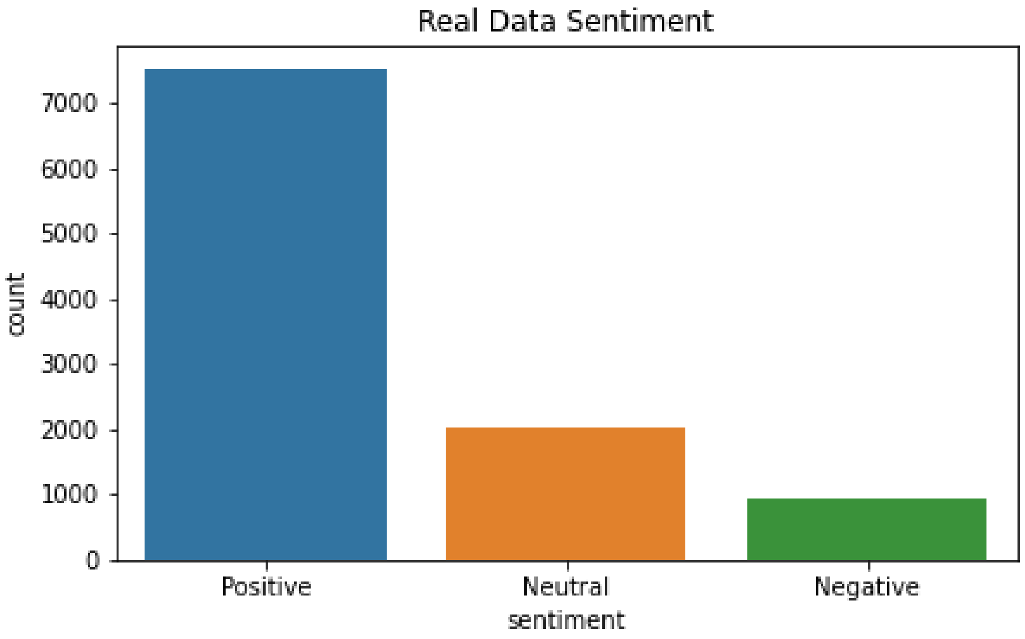
Common words that occurs in both real and fake text

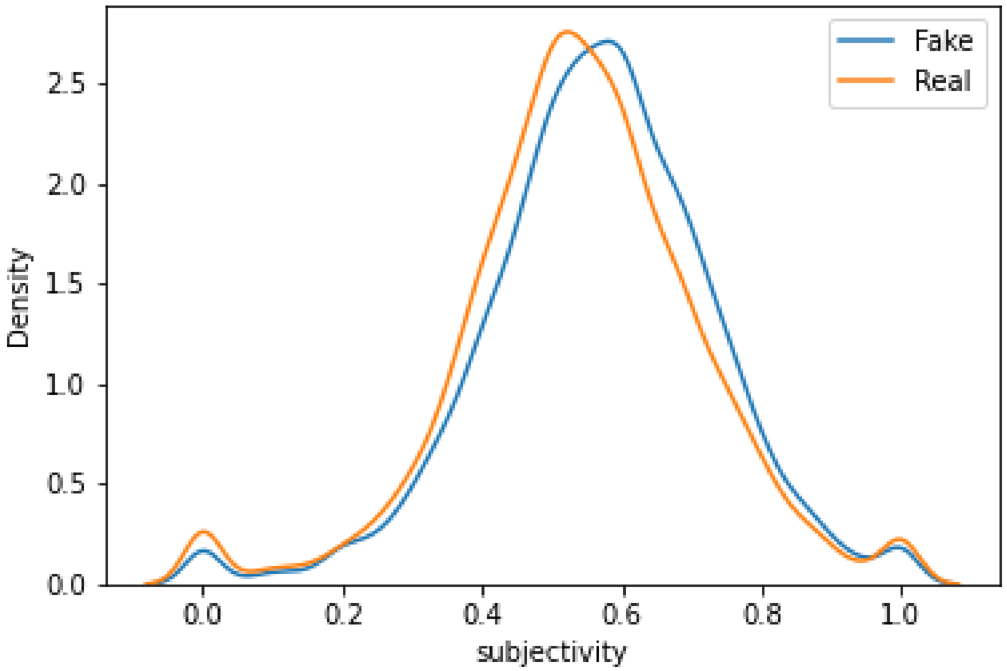

Fake Review Unique Words
Frequency of Words
0
5
10
15
20
garcinia
slicer
cellulite
morgan
cambogia
infuser
ketones
labs
affordable',
sennheisers
kinesiology
usda
ender
unhealthy
torch

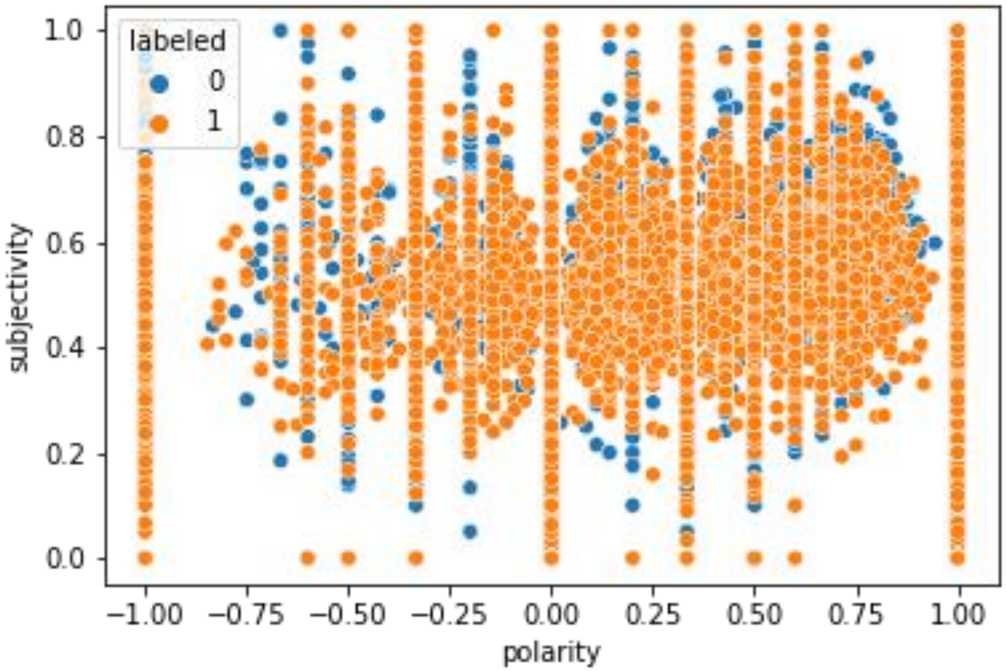

Real Review Unique Words
Frequency of Words
0
5
10
15
20
25
30
wig
seth
rail
maddalena
scanners
servos
brisket
robert
lincoln
dundee
whoopie
dylan
crocodile
rifle
mvp

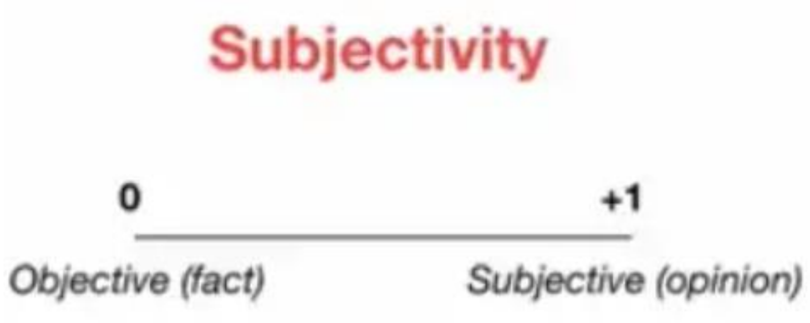
Sentiment Analysis











Subjectivity

0 +1

Objective (fact) Subjective (opinion)

Polarity

-1 +1

Negative Positive

Steps

Dataset

Data Processing

Feature Extraction (TF-IDF)

Data Splitting

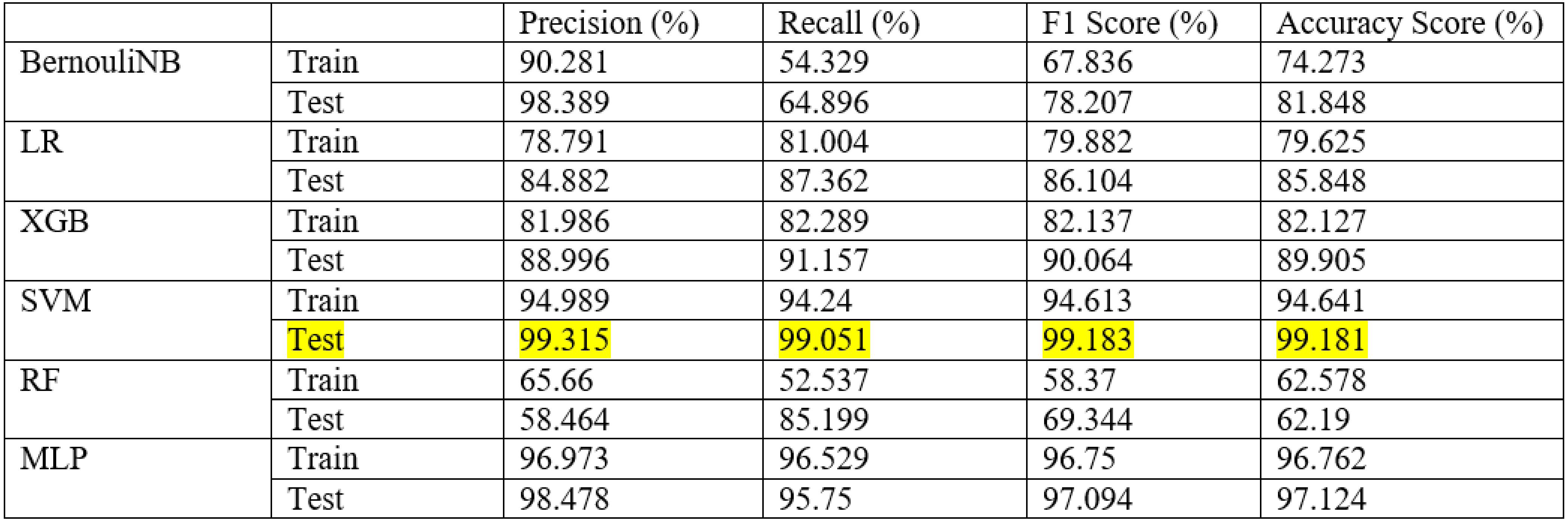
Supervised Machine Learning Techniques

Performance Evaluation

Machine Learning Models

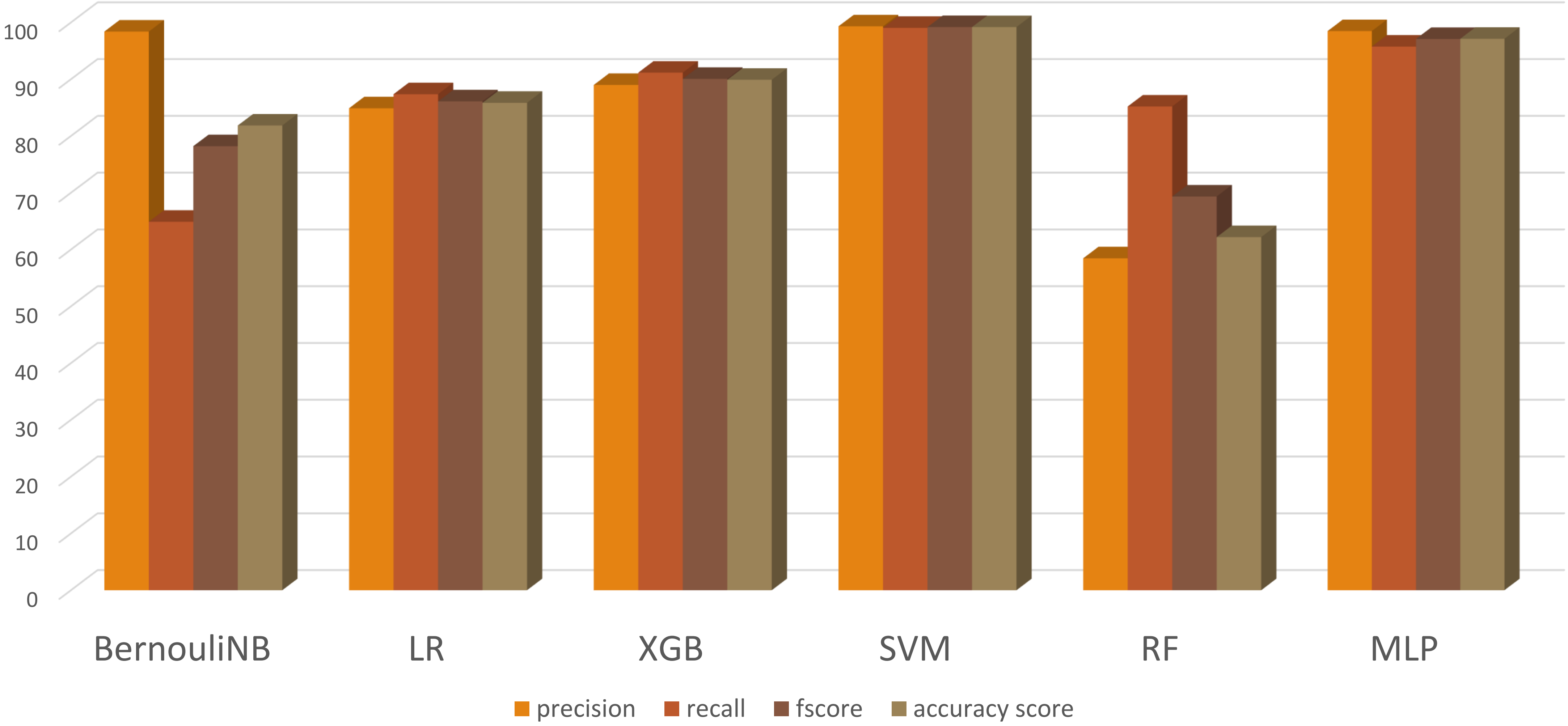
1. Naïve Bayes Classifier
2. Logistic Regression
3. XGBoost Classifier
4. Support Vector Machine
5. Random Forest Classifier
6. Multi-layer Perceptron classifier (MLP)

Experiment Result



		Precision (%)	Recall (%)	F1 Score (%)	Accuracy Score (%)
BernouliNB	Train	90.281	54.329	67.836	74.273
	Test	98.389	64.896	78.207	81.848
LR	Train	78.791	81.004	79.882	79.625
	Test	84.882	87.362	86.104	85.848
XGB	Train	81.986	82.289	82.137	82.127
	Test	88.996	91.157	90.064	89.905
SVM	Train	94.989	94.24	94.613	94.641
	Test	99.315	99.051	99.183	99.181
RF	Train	65.66	52.537	58.37	62.578
	Test	58.464	85.199	69.344	62.19
MLP	Train	96.973	96.529	96.75	96.762
	Test	98.478	95.75	97.094	97.124

ML Classification Results



Conclusion

SVM

- Text Categorization with Support Vector Machines: Learning with Many Relevant Features - Thorsten Joachims

Future Plans / Works

- Larger dataset
- Testing new models

Reference

1. Heydari, A., Tavakoli, M. A., Salim, N., & Heydari, Z. (2015). Detection of review spam: A survey. Expert Systems with Applications, 42(7), 3634-3642.

2. Jindal, N., & Liu, B. (2008). Opinion spam and analysis. Proceedings of the 2008 International Conference on Web Search and Data Mining, Palo Alto, California, USA, ACM, 219-230.

3. Alsubari, Saleh & Deshmukh, Sachin & Alqarni, Ahmed & Alsharif, Nizar & Aldhyani, Theyazn & Fawaz, Waselallah & Alsaade, & Khalaf, Osamah. (2021). Data Analytics for the Identification of Fake Reviews Using Supervised Learning. Computers, Materials and Continua. 70. 10.32604/cmc.2022.019625.

4. Joachims, Thorsten. “Text Categorization with Support Vector Machines: Learning with Many Relevant Features.” European Conference on Machine Learning (1998).

Thanks