



Grammar and Product reviews

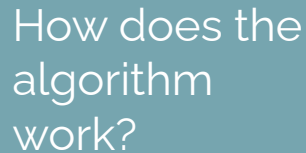
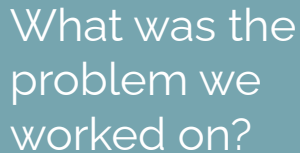
Data Mining

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Introduction



Natural Language Processing (NLP) is ubiquitous and has multiple applications. For example, a few use cases include email classification into spam and ham, chatbots, AI agents, social media analysis, and classifying customer or employee feedback as positive, negative, or neutral.

Despite these many applications of NLP, implementation remains difficult because text data is different from tabular transactional data. Cleaning text data is also difficult because you deal with natural language. This is where text processing is helpful to clean the text corpus and make it ready for further operation.

Preprocessing



It is important to pre-process text before you run the module to extract key phrases from the corpus. The most common pre-processing steps are:

1. Remove stop words: These are unhelpful words like 'the', 'is', 'at'. They are not helpful because the frequency of such stop words is high in the corpus, but they don't help in differentiating the target classes. The removal of stop words also reduces the data size.
2. Detect Sentences: This inserts a sentence boundary mark while performing analysis. The sentence terminator is represented by three pipe characters: |||.
3. Remove punctuation: The rule of thumb is to remove everything that is not in the form of x,y,z.
4. Normalize case to lowercase: Words like 'Clinical' and 'clinical' need to be considered as one word, so they are converted to lowercase.
5. Remove special characters: Non-alphanumeric special characters are replaced with the pipe | character.
6. Expand verb contractions: This is an important feature applied to verb contractions. For example, selecting this option will replace the phrase "wouldn't buy this product" with "would not buy this product".
7. Stemming: The goal of stemming is to reduce the number of inflectional forms of words appearing in the text. This causes words such as "argue," "argued," "arguing," and "argues" to be reduced to their common stem, "argu". This helps decrease the size of the vocabulary space.

Preprocessing

```
stop_words = set(line.strip() for line in open('stopwords.txt'))
exclude = set(string.punctuation)
def docs_preprocessor(docs):
    tokenizer = RegexpTokenizer(r'\w+')
    for idx in range(len(docs)):
        docs[idx] = docs[idx].lower() # Convert to lowercase.
        docs[idx] = tokenizer.tokenize(docs[idx]) # Split into words.
    # Remove numbers, but not words that contain numbers.
    docs = [[token for token in doc if not token.isdigit()] for doc in docs]
    # Remove stop words in documents
    docs = [[token for token in doc if not token in stop_words] for doc in docs]
    # Remove punctuations in documents
    docs = [[token for token in doc if not token in exclude] for doc in docs]
    # Remove words that are only one character.
    docs = [[token for token in doc if len(token) > 2] for doc in docs]

    # Lemmatize all words in documents.
    lemmatizer = WordNetLemmatizer()
    docs = [[lemmatizer.lemmatize(token) for token in doc] for doc in docs]

    return docs
# Perform function on our document
documents = docs_preprocessor(docs)
```

Text cleaning is one of the most challenging areas of natural language processing. In every application of text analytics, such as email classification, sentiment analysis, key phrase extraction, or visualizing text data, you will be required to perform text cleaning.

Statistics

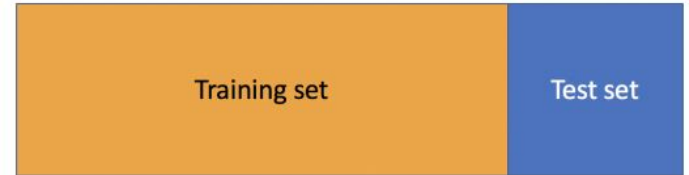
- 25 columns
- 71045 tuples



Most important columns:

- Brand
- Categories
- Reviews-purchase
- Reviews-recommended

Training set 80%
Testing set 20%



<https://www.kaggle.com/datafiniti/grammar-and-online-product-reviews>

Review Purchased and Not Purchased

	Total
RevPurchasedTrue	3682
RevPurchasedFalse	28476

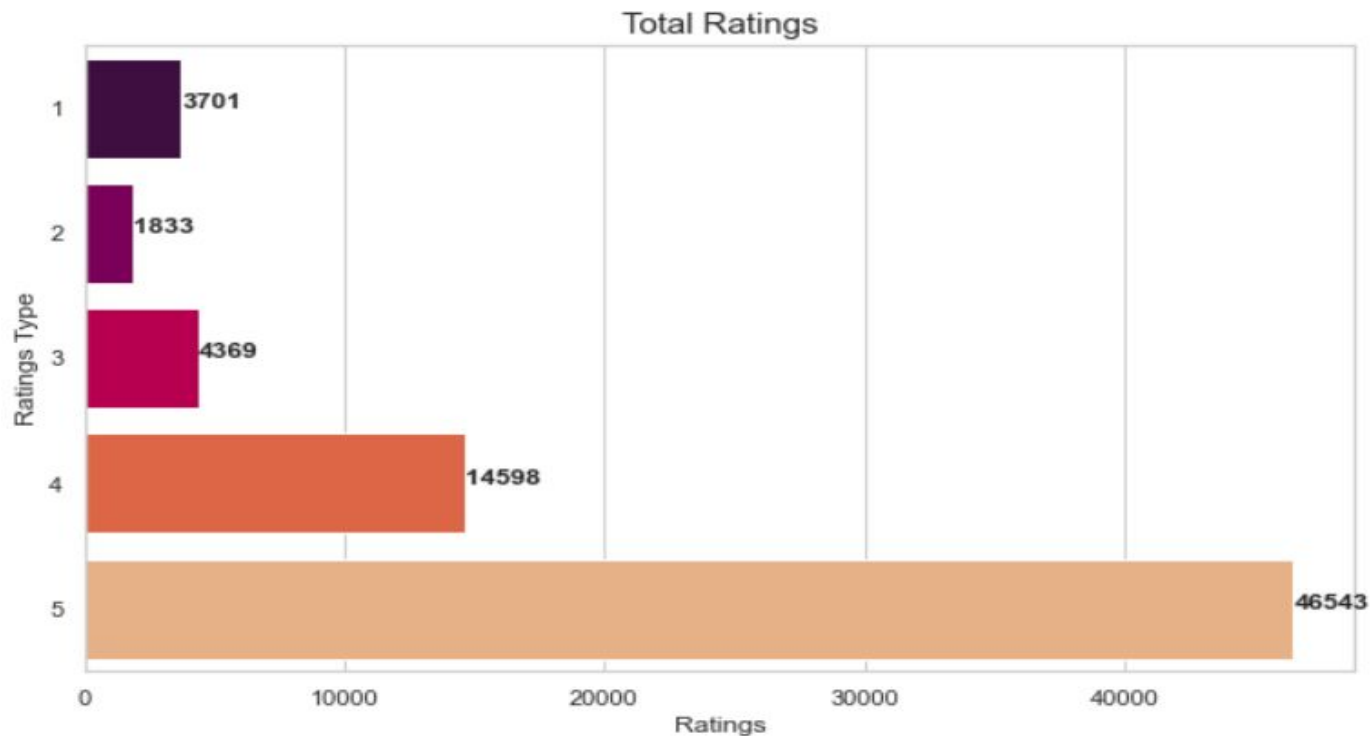


Review Recommended and Not Recommended

	Total
RevRecommended	55587
RevNotRecommended	4842



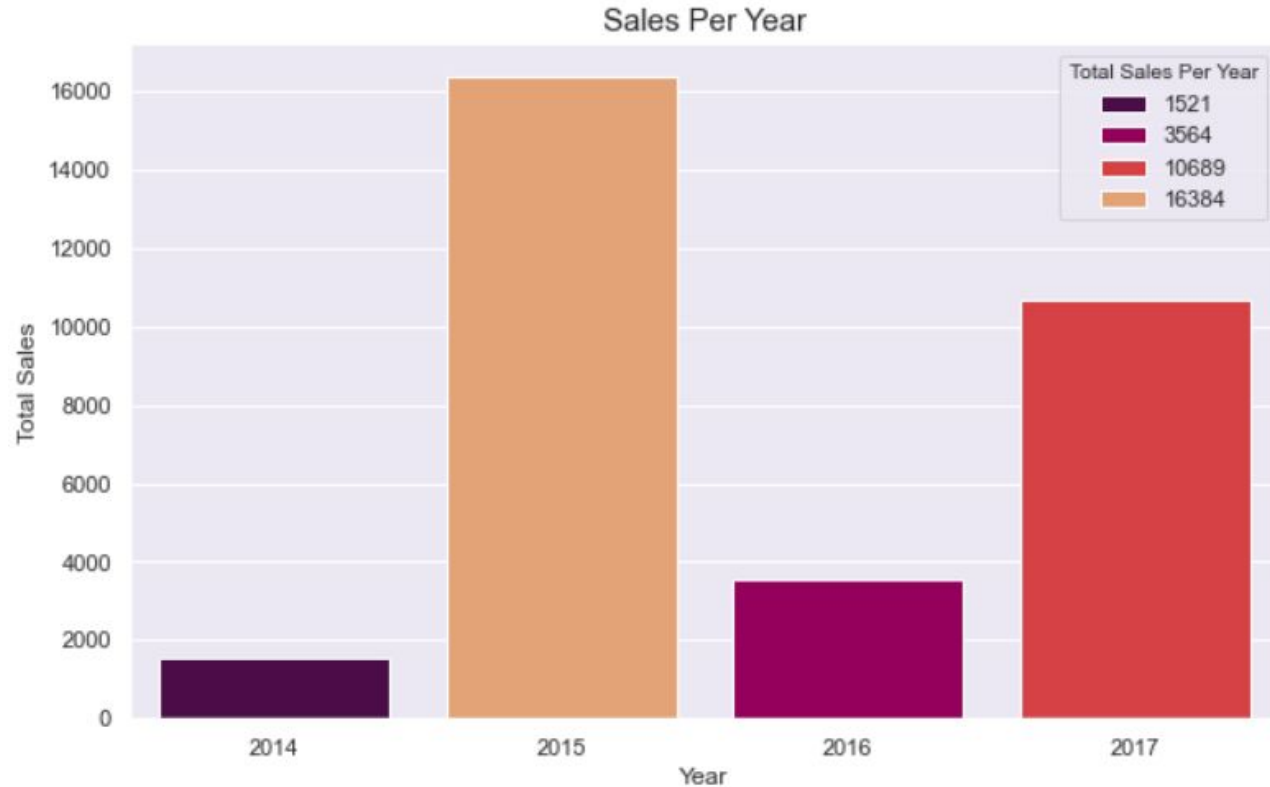
Reviews Rating



Total Sales per Year

Total Sales Per Year

Year	
2014	1521
2015	16384
2016	3564
2017	10689



WordCloud



The first line of code generates the word cloud on the 'reviewText' corpus, while the second to fourth lines of code prints the word cloud.

```
wordcloud = WordCloud(width=800, height=500, max_words=100, background_color="black", min_word_length=5).generate(reviewText)

plt.axis("off")
plt.imshow(wordcloud, interpolation='bilinear')
plt.show()

wordcloud.to_file("wordcloud.jpeg")
```



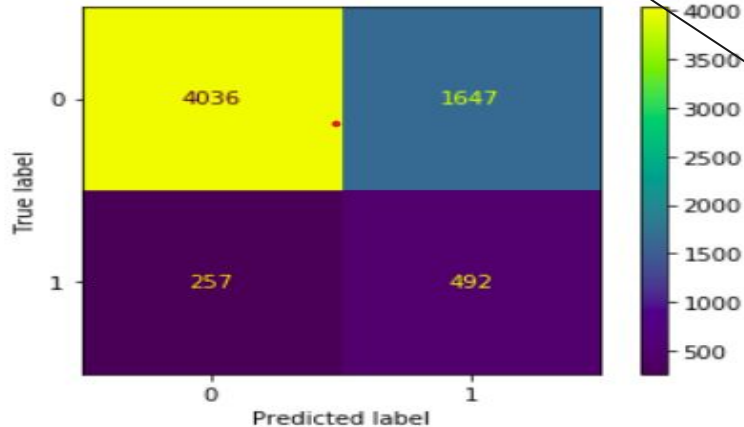
The word cloud displayed here is good, but some of the words are larger than the others. This is because the size of the word in the word cloud is proportional to the frequency of the word inside the corpus. There are various parameters which can be adjusted to change the display of the word cloud, and the list of such parameters can be viewed using the '?WordCloud' command.

Naive Bayes Algorithm

Results from Naive Bayes

	precision	recall	f1-score	support
0	0.9401	0.7102	0.8091	5683
1	0.2300	0.6569	0.3407	749
accuracy			0.7040	6432
macro avg	0.5851	0.6835	0.5749	6432
weighted avg	0.8574	0.7040	0.7546	6432

NB accuracy: 0.7039800995024875



We use Bayes' theorem to find which label is most likely, given the attributes observed in the feature vector, and given how often the different labels occur in the data.

The Naive Bayes classifier can be an extremely powerful one, and it often results in very robust models.

It's called Naive because the different X variables, that is, the different features in our dataset are considered to be independent.

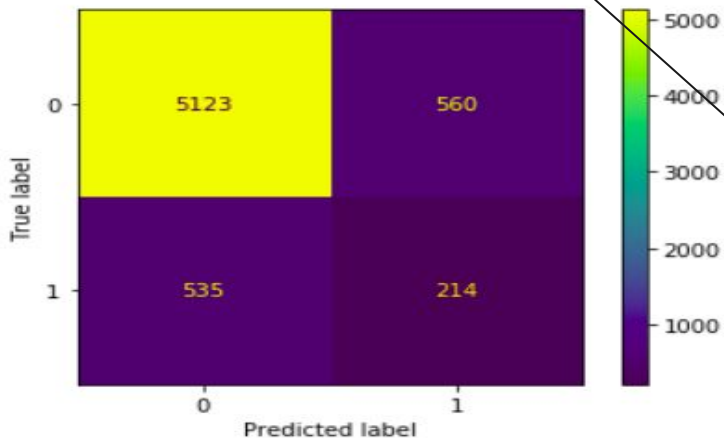
This model performed decently well, and its accuracy on the test data was around 70%.

Decision tree algorithm

Results from Decision Tree

	precision	recall	f1-score	support
0	0.9054	0.9015	0.9034	5683
1	0.2765	0.2857	0.2810	749
accuracy			0.8298	6432
macro avg	0.5910	0.5936	0.5922	6432
weighted avg	0.8322	0.8298	0.8310	6432

DT accuracy: 0.8297574626865671



The decision tree is a popular and widely used machine learning model for classification problems.

You can build and train a decision tree for classification models in scikit-learn using the decision tree classifier.

We have fit a decision tree on our training data using the CART(Classification and Regression Tree) algorithm.

A decision tree splits your underlying data into subsets where every subset contains points that is consider similar. The data is repeatedly split into subsets to form a tree structure, and the shape of the tree depends on the constraints that you specify.

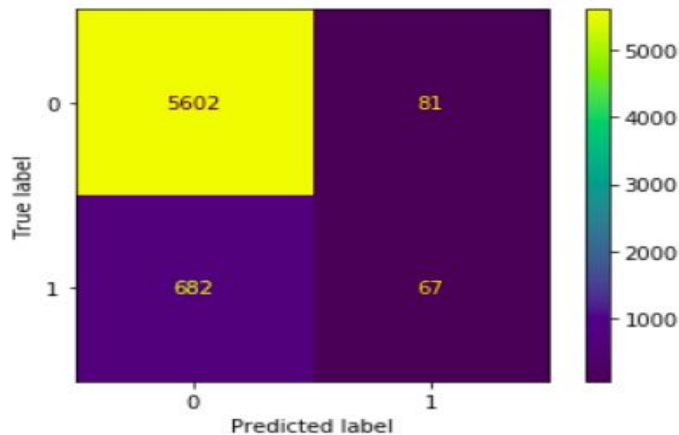
Here you can see that even though on test data, the model accuracy is 82%, which is around what we got with other models, on training data it's clearly overfitted, so it's not really a very good model.

Boosting Algorithm

Results from Boosting

	precision	recall	f1-score	support
0	0.8915	0.9857	0.9362	5683
1	0.4527	0.0895	0.1494	749
accuracy			0.8814	6432
macro avg	0.6721	0.5376	0.5428	6432
weighted avg	0.8404	0.8814	0.8446	6432

AdaBoost accuracy: 0.8813743781094527



In Boosting, multiple models are trained sequentially and each model learns from the errors of its predecessors. In this guide, we will implement one boosting techniques of AdaBoost.

AdaBoost, short for 'Adaptive Boosting', is the first practical boosting algorithm proposed by Freund and Schapire in 1996. It focuses on classification problems and aims to convert a set of weak classifiers into a strong one.

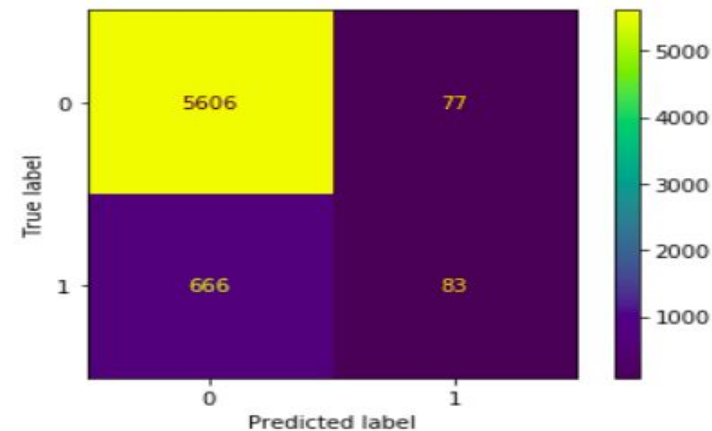
The accuracy of the AdaBoost Classifier ensemble is 88%, which is higher than the other models.

Random Forest Algorithm

Results from Random Forest

	precision	recall	f1-score	support
0	0.8938	0.9865	0.9379	5683
1	0.5188	0.1108	0.1826	749
accuracy			0.8845	6432
macro avg	0.7063	0.5486	0.5602	6432
weighted avg	0.8501	0.8845	0.8499	6432

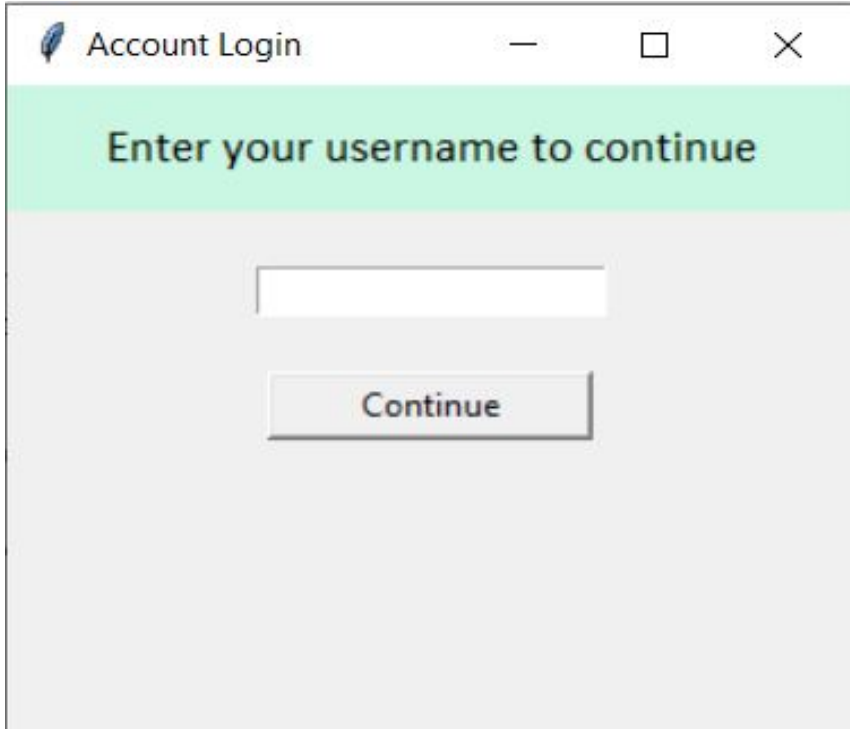
Random Forest accuracy: 0.8844838308457711



Random Forest is an extension of bagged decision trees, where the samples of the training dataset are taken with replacement. The trees are constructed with the objective of reducing the correlation between the individual decision trees. In scikit-learn, a random forest model is constructed by using the Random Forest Classifier class.

The accuracy of the Random Forest Classifier ensemble is 88.44%, a significant improvement over the other models.

Prototype Description



Account Login

Enter your username to continue

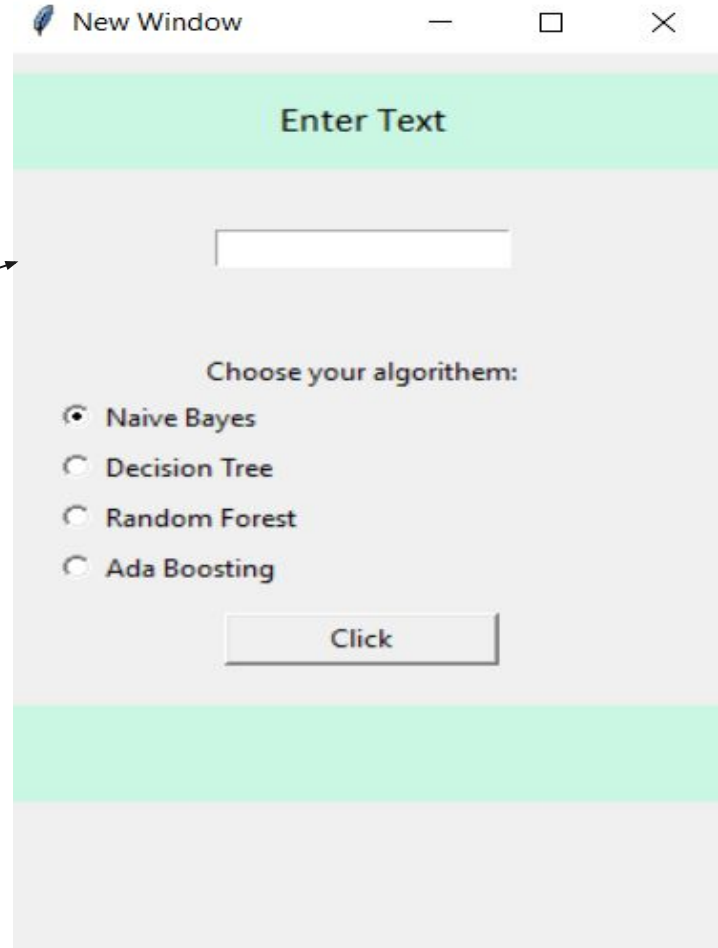
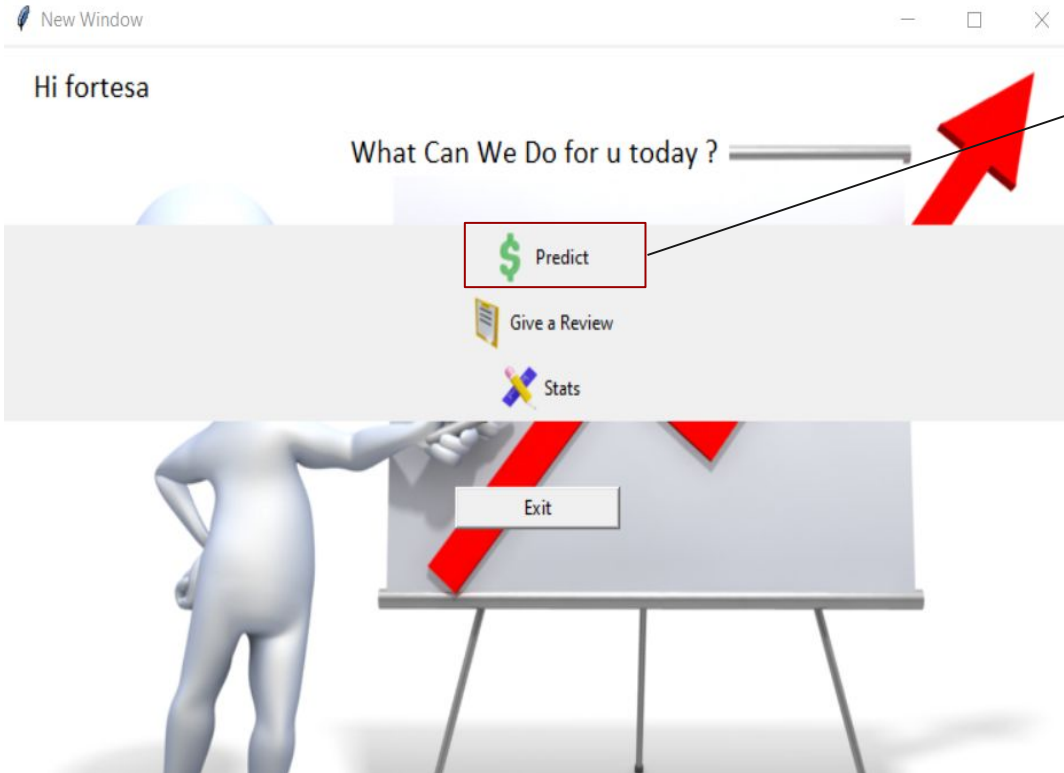
Continue

Our GUI Form

Prediction

Statistics

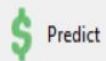
GUI Form



New Window

Hi fortessa

What Can We Do for u today ?



Predict



Give a Review



Stats

Exit

New Window

Review Purchased / Not Purchased

Review Recommended / Not Recommended

Total Ratings

Total Sales Per Brand

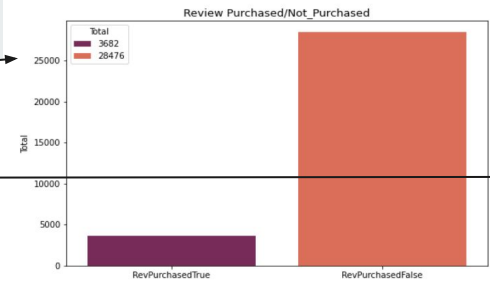
Total Sold And Recommended

Sales Per Year

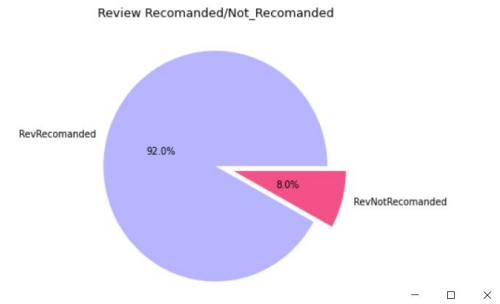
Sales Per Month Separated by years

Recommendations Per Year

Review Purchased / Not Purchased



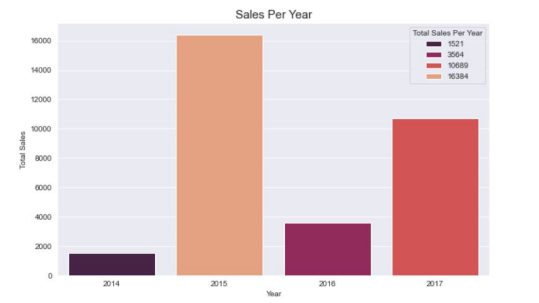
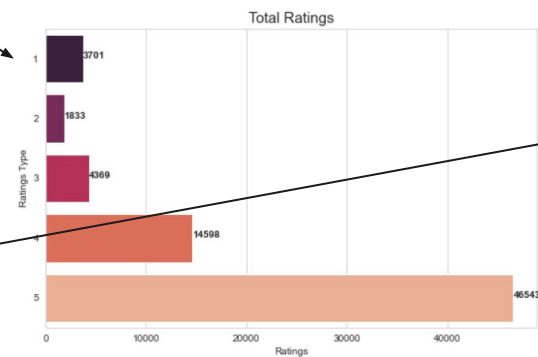
Review Recommended / Not Recommended



Total Ratings

tk

Total Sales Per Brand



Total Sold And Recommended

Sales Per Year

Sales Per Month Separated by years

tk

Recommendations Per Year

