



**Phash 2 : Innovation Sentiment
Analysis Marketing**

Sentiment Analysis

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1. Introduction

Sentiment is an attitude, thought, or judgment prompted by feeling. Sentiment analysis, which is also known as opinion mining, studies people's sentiments towards certain entities. From a user's perspective, people are able to post their own content through various social media, such as forums, micro-blogs, or online social networking sites. From a researcher's perspective, many social media sites release their application programming interfaces (APIs), prompting data collection and analysis by researchers and developers. However, those types of online data have several flaws that potentially hinder the process of sentiment analysis. The first flaw is that since people can freely post their own content, the quality of their opinions cannot be guaranteed. The second flaw is that ground truth of such online data is not always available. A ground truth is more like a tag of a certain opinion, indicating whether the opinion is positive, negative, or neutral.

“It is a quite boring movie..... but the scenes were good enough. ”

The given line is a movie review that states that “it” (the movie) is quite boring but the scenes were good. Understanding such sentiments require multiple tasks.

Hence, SENTIMENTAL ANALYSIS is a kind of text classification based on *Sentimental Orientation* (SO) of opinion they contain.

Sentiment analysis of product reviews has recently become very popular in text mining and computational linguistics research.

- . Firstly, evaluative terms expressing opinions must be extracted from the review.
- . Secondly, the SO, or the polarity, of the opinions must be determined.
- . Thirdly, the opinion strength, or the intensity, of an opinion should also be determined.
- . Finally, the review is classified with respect to sentiment classes, such as Positive and Negative, based on the SO of the opinions it contains.

2. Review of Literature

The most fundamental problem in sentiment analysis is the sentiment polarity categorization, by considering a dataset containing over 5.1 million product reviews from Amazon.com with the products belonging to four categories.

A max-entropy POS tagger is used in order to classify the words of the sentence, an additional python program to speed up the process. The negation words like no, not, and more are included in the adverbs whereas Negation of Adjective and Negation of Verb are specially used to identify the phrases.

The following are the various classification models which are selected for categorization: Naïve Bayesian, Random Forest, Logistic Regression and Support Vector Machine.

For feature selection, Pang and Lee suggested to remove objective sentences by extracting subjective ones. They proposed a text-categorization technique that is able to identify subjective content using minimum cut. Gann et al. selected 6,799 tokens based on Twitter data, where each token is assigned a sentiment score, namely TSI (Total Sentiment Index), featuring itself as a positive token or a negative token. Specifically, a TSI for a certain token is computed as:

$$TSI = \frac{p - \frac{tp}{tn} \times n}{p + \frac{tp}{tn} * n}$$

where p is the number of times a token appears in positive tweets and n is the number of times a token appears in negative tweets is $\frac{tp}{tn}$ the ratio of total

number of positive tweets over total number of negative tweets.

3. Objective of the Project

- ✚ Scrapping product reviews on various websites featuring various products specifically amazon.com.
- ✚ Analyze and categorize review data.
- ✚ Analyze sentiment on dataset from document level (review level).
- ✚ Categorization or classification of opinion sentiment into-
 - . Positive
 - . Negative

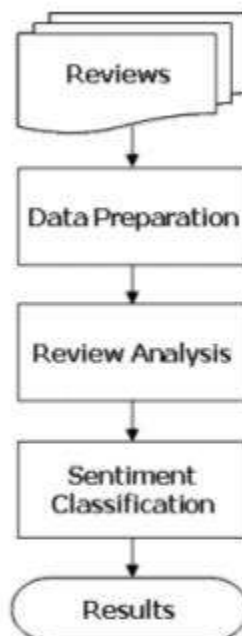


Figure 1: A typical sentiment analysis model.

4.System Design

Hardware Requirements:

- . Core i5/i7 processor
- . At least 8 GB RAM
- . At least 60 GB of Usable Hard Disk Space

Software Requirements:

- . Python 3.x
- . Anaconda Distribution
- . NLTK Toolkit
- . UNIX/LINUX Operating System.

Data Information:

- . The Amazon reviews dataset consists of reviews from amazon. The data span aperiod of 18 years, including ~35 million reviews up to March 2013.
Reviews include product and user information, ratings, and a plaintext review. For more information, please refer to the following paper: J. McAuley and J. Leskovec. Hidden factors and hidden topics: understanding rating dimensions with review text. RecSys, 2013.
- . The Amazon reviews full score dataset is constructed by Xiang Zhang (xiang.zhang@nyu.edu) from the above dataset. It is used as a text classification benchmark in the following paper: Xiang Zhang, Junbo Zhao, Yann LeCun. Character-level Convolutional Networks for Text Classification. Advances in Neural Information Processing Systems 28 (NIPS 2015).
- . The Amazon reviews full score dataset is constructed by randomly taking 200,000 samples for each review score from 1 to 5. In total there are 1,000,000 samples.

Star Level	General Meaning
	I hate it.
	I don't like it.
	It's okay.
	I like it.
	I love it.

Books	reviews (22,507,155 reviews)	metadata (2,370,585 products)	image features
Electronics	reviews (7,824,482 reviews)	metadata (498,196 products)	image features
Movies and TV	reviews (4,607,047 reviews)	metadata (208,321 products)	image features
CDs and Vinyl	reviews (3,749,004 reviews)	metadata (492,799 products)	image features
Clothing, Shoes and Jewelry	reviews (5,748,920 reviews)	metadata (1,503,384 products)	image features
Home and Kitchen	reviews (4,253,926 reviews)	metadata (436,988 products)	image features
Kindle Store	reviews (3,205,467 reviews)	metadata (434,702 products)	image features
Sports and Outdoors	reviews (3,268,695 reviews)	metadata (532,197 products)	image features
Cell Phones and Accessories	reviews (3,447,249 reviews)	metadata (346,793 products)	image features
Health and Personal Care	reviews (2,982,326 reviews)	metadata (263,032 products)	image features
Toys and Games	reviews (2,252,771 reviews)	metadata (336,072 products)	image features
Video Games	reviews (1,324,753 reviews)	metadata (50,953 products)	image features
Tools and Home Improvement	reviews (1,926,047 reviews)	metadata (269,120 products)	image features
Beauty	reviews (2,023,070 reviews)	metadata (259,204 products)	image features
Apps for Android	reviews (2,638,173 reviews)	metadata (61,551 products)	image features
Office Products	reviews (1,243,186 reviews)	metadata (134,838 products)	image features
Pet Supplies	reviews (1,235,316 reviews)	metadata (110,707 products)	image features
Automotive	reviews (1,373,768 reviews)	metadata (331,090 products)	image features
Grocery and Gourmet Food	reviews (1,297,156 reviews)	metadata (171,760 products)	image features
Patio, Lawn and Garden	reviews (993,490 reviews)	metadata (109,094 products)	image features
Baby	reviews (915,446 reviews)	metadata (71,317 products)	image features
Digital Music	reviews (836,006 reviews)	metadata (279,899 products)	image features
Musical Instruments	reviews (500,176 reviews)	metadata (84,901 products)	image features
Amazon Instant Video	reviews (583,933 reviews)	metadata (30,648 products)	image features

Data Format:

The dataset we will use is .json file. The sample of the dataset is given below.

```
{
  "reviewSummary": "Surprisingly delightful",
  "reviewText": "This is a first read filled with unexpected humor and profound insights into the art of politics and policy. In brief, it is sly, wry, and wise. ",
  "reviewRating": "4",
}
```

5. Methodology for Implementation (Formulation/Algorithm)

DATA COLLECTION:

Data which means product reviews collected from amazon.com from May 1996 to July 2014. Each review includes the following information: 1) reviewer ID; 2) product ID; 3) rating; 4) time of the review; 5) helpfulness; 6) review text. Every rating is based on a 5-star scale, resulting all the ratings to be ranged from 1-star to 5-star with no existence of a half-star or a quarter-star.

SENTIMENT SENTENCE EXTRACTION & POS TAGGING:

Tokenization of reviews after removal of STOP words which mean nothing related to sentiment is the basic requirement for POS tagging. After proper removal of STOP words like “am, is, are, the, but” and so on the remaining sentences are converted in tokens. These tokens take part in POS tagging

In natural language processing, part-of-speech (POS) taggers have been developed to classify words based on their parts of speech. For sentiment analysis, a POS tagger is very useful because of the following two reasons: 1) Words like nouns and pronouns usually do not contain any sentiment. It is able to filter out such words with the help of a POS tagger; 2) A POS tagger can also be used to distinguish words that can be used in different parts of speech.

NEGATIVE PHRASE IDENTIFICATION:

Words such as adjectives and verbs are able to convey opposite sentiment with the help of negative prefixes. For instance, consider the following sentence that was found in an electronic device’s review: “The built in speaker also has its uses but so far nothing revolutionary.” The word, “revolutionary” is a positive word according to the list in. However, the phrase “nothing revolutionary” gives more or less negative feelings. Therefore, it is crucial to identify such phrases. In this work, there are two types of phrases have been identified, namely negation-of-adjective (NOA) and negation-of-verb (NOV).

SENTIMENT CLASSIFICATION ALGORITHMS:

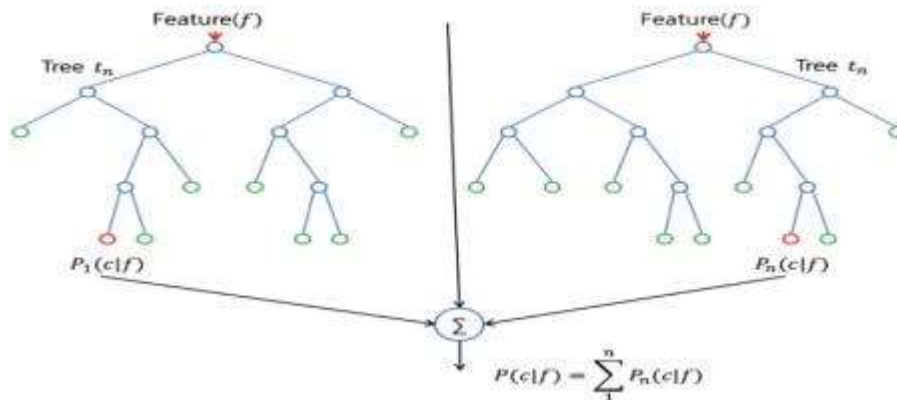
Naïve Bayesian classifier:

The Naïve Bayesian classifier works as follows: Suppose that there exist a set of training data, D , in which each tuple is represented by an n -dimensional feature vector, $X = x_1, x_2, \dots, x_n$, indicating n measurements made on the tuple from n attributes or features. Assume that there are m classes, C_1, C_2, \dots, C_m . Given a tuple X , the classifier will predict that X belongs to C_i if and only if: $P(C_i | X) > P(C_j | X)$, where $i, j \in [1, m]$ and $i \neq j$. $P(C_i | X)$ is computed as:

$$P(C_i | X) = \prod_{k=1}^n P(x_k | C_i)$$

Random forest

The random forest classifier was chosen due to its superior performance over a single decision tree with respect to accuracy. It is essentially an ensemble method based on bagging. The classifier works as follows: Given D , the classifier firstly creates k bootstrap samples of D , with each of the samples denoting as D_i . D_i has the same number of tuples as D that are sampled with replacement from D . By sampling with replacement, it means that some of the original tuples of D may not be included in D_i , whereas others may occur more than once. The classifier then constructs a decision tree based on each D_i . As a result,



a “forest” that consists of k decision trees is formed.

To classify an unknown tuple, X , each tree returns its class prediction counting as one vote. The final decision of X ’s class is assigned to the one that has the most votes.

The decision tree algorithm implemented in scikit-learn is CART (Classification and Regression Trees). CART uses Gini index for its tree induction. For D , the Gini index is computed as:

$$Gini(D) = 1 - \sum_{i=1}^m p_i^2$$

Where p_i is the probability that a tuple in D belongs to class C_i . The Gini index measures the impurity of D . The lower the index value is, the better D was partitioned.

Support vector machine

Support vector machine (SVM) is a method for the classification of both linear and nonlinear data. If the data is linearly separable, the SVM searches for the linear optimal separating hyperplane (the linear kernel), which is a decision boundary that separates data of one class from another. Mathematically, a separating hyper plane can be written as: $W \cdot X + b = 0$, where W is a weight vector and $W = w_1, w_2, \dots, w_n$. X is a training tuple. b is a scalar. In order to optimize the hyperplane, the problem essentially transforms to the minimization of $\|W\|$, which is eventually computed as:

$$\sum_{i=1}^n \alpha_i y_i x_i,$$

where “ α_i ” are numeric parameters, and y_i are labels based on support vectors, X_i .

That is: if $y_i = 1$ then

$$\sum_{i=1}^n w_i x_i \geq 1$$

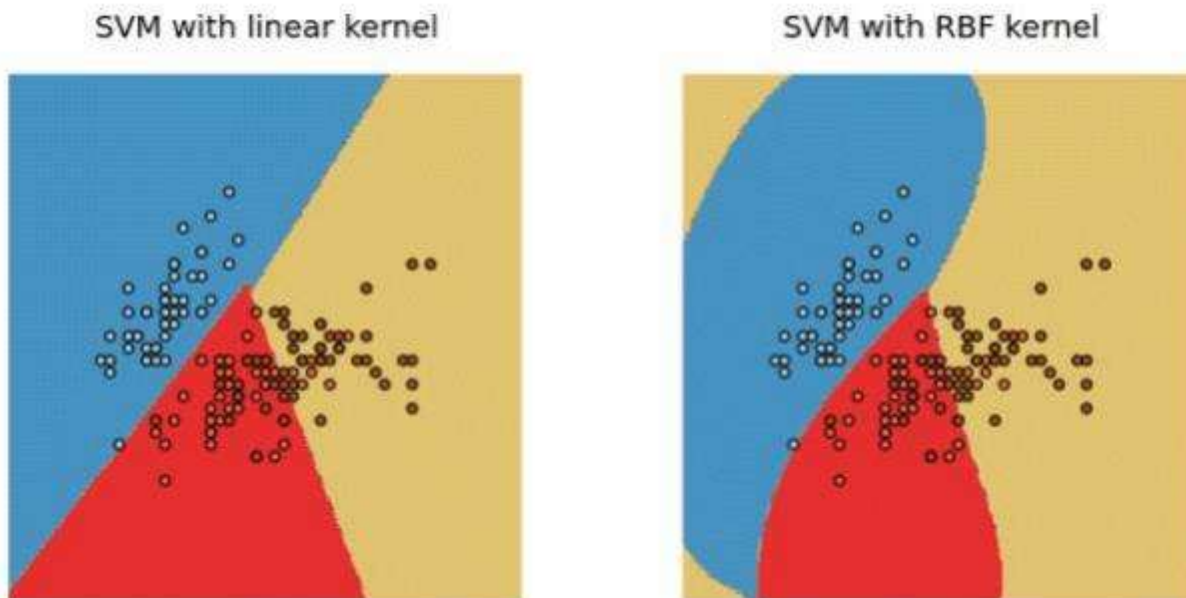
if $y_i = -1$ then

$$\sum_{i=1}^n w_i x_i \leq -1$$

If the data is linearly inseparable, the SVM uses nonlinear mapping to transform the data into a higher dimension. It then solve the problem by finding a linear hyperplane. Functions to perform such transformations are called kernel functions. The kernel function selected for our experiment is the Gaussian Radial Basis Function (RBF):

$$K(X_i, X_j) = e^{-\gamma \|X_i - X_j\|^2 / 2}$$

where X_i are support vectors, X_j are testing tuples, and γ is a free parameter that uses the default value from scikit-learn in our experiment. Figure shows a classification example of SVM based on the linear kernel and the RBF kernel on the next page-



Logistic Regression

Logistic regression predicts the probability of an outcome that can only have two values (i.e. a dichotomy). The prediction is based on the use of one or several predictors (numerical and categorical). A linear regression is not appropriate for predicting the value of a binary variable for two reasons:

- A linear regression will predict values outside the acceptable range (e.g. predicting probabilities outside the range 0 to 1)
- Since the dichotomous experiments can only have one of two possible values for each experiment, the residuals will not be normally distributed about the predicted line.

On the other hand, a logistic regression produces a logistic curve, which is limited to values between 0 and 1. Logistic regression is similar to a linear regression, but the curve is constructed using the natural logarithm of the “odds” of the target variable, rather than the probability. Moreover, the predictors do not have to be normally distributed or have equal variance in each group.

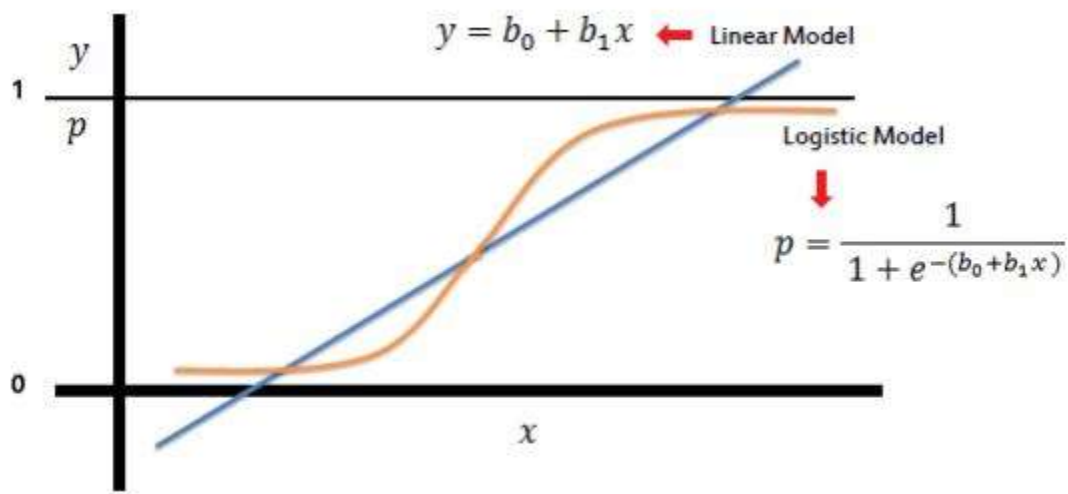
Logistic regression uses [maximum](#) likelihood estimation (MLE) to obtain the model coefficients that relate predictors to the target. After this initial function is estimated, the process is repeated until LL (Log Likelihood) does not change significantly.

$$\beta^1 = \beta^0 + [X^T W X]^{-1} . X^T (y - \mu)$$

β is a vector of the logistic regression coefficients.

W is a square matrix of order N with elements $n_i \pi_i (1 - \pi_i)$ on the diagonal and zeros everywhere else.

μ is a vector of length N with elements $\mu_i = n_i \pi_i$.



6.Implementation Details

The training of dataset consists of the following steps:

- ✚ **Unpacking of data:** The huge dataset of reviews obtained from amazon.com comes in a .json file format. A small python code has been implemented in order to read the dataset from those files and dump them into a pickle file for easier and fastaccess and object serialization.

```
30 with open(data_file, 'r') as file_handler:
31     for review in file_handler.readlines():
32         df[i] = ast.literal_eval(review)
33         i += 1
34
35 reviews_df = pd.DataFrame.from_dict(df, orient = 'index')
36 reviews_df.to_pickle('reviews_digital_music.pickle')
37
```

Hence initial fetching of data is done in this section using Python File Handlers.

- ✚ **Preparing Data for Sentiment Analysis:**

i) The pickle file is hence loaded in this step and the data besides the one used for sentiment analysis is removed. As shown in our sample dataset in Page 11, there are a lot of columns in the data out of which only rating and text review is what we require. So, the column, “reviewSummary” is dropped from the data file.

ii) After that, the review ratings which are 3 out of 5 are removed as they signify neutral review, and all we are concerned of is positive and negative reviews.

iii) The entire task of preprocessing the review data is handled by this

```
40
47 reviews_df.drop(columns = ['reviewSummary'], inplace = True)
48 reviews_df['reviewRating'] = reviews_df.reviewRating.astype('int')
49
50 reviews_df = reviews_df[reviews_df.reviewRating != 3] # Ignoring 3-star reviews -> neutral
51 reviews_df = reviews_df.assign(sentiment = np.where(reviews_df['reviewRating'] >= 4, 1, 0)) # 1 -> Positive, 0 -> Negati
52
```

utility class- “NltkPreprocessor”.

```
16
17 class NltkPreprocessor:
18
19     def __init__(self, stopwords = None, punct = None, lower = True, strip = True):
20         self.lower = lower
21         self.strip = strip
22         self.stopwords = stopwords or set(sw.words('english'))
23         self.punct = punct or set(string.punctuation)
24         self.lemmatizer = WordNetLemmatizer()
25
26     def tokenize(self, document):
27         tokenized_doc = []
28
29         for sent in sent_tokenize(document):
30             for token, tag in pos_tag(wordpunct_tokenize(sent)):
31                 token = token.lower() if self.lower else token
32                 token = token.strip() if self.strip else token
33                 token = token.strip('_0123456789') if self.strip else token
34                 # token = re.sub(r'\d+', '', token)
35
36                 if token in self.stopwords:
37                     continue
38
39                 if all(char in self.punct for char in token):
40                     continue
41
42                 lemma = self.lemmatize(token, tag)
43                 tokenized_doc.append(lemma)
44
45         return tokenized_doc
46
47     def lemmatize(self, token, tag):
48         tag = {
49             'N': wn.NOUN,
50             'V': wn.VERB,
51             'R': wn.ADV,
52             'J': wn.ADJ
53         }.get(tag[0], wn.NOUN)
54
55         return self.lemmatizer.lemmatize(token, tag)
56
```

iv) The time required to prepare the following data is hence displayed.

```
administrator@administrator-OptiPlex-3040:~/Desktop/sentiment_analysis$
Preprocessing data...
Preprocessing data completed!
Preprocessing time: 0.163 s
```


The time taken to preprocess the data is calculated and displayed



Preprocessing Data: This is a vital part of training the dataset. Here Words present in the file are accessed both as a solo word and also as pair of words. Because, for example the word “bad” means negative but when someone writes “not bad” it refers to as positive. In such cases considering single word for training data will work otherwise. So words in pairs are checked to find the occurrence to modifiers before

any adjective which if present which might provide a different meaning to the outlook.

```
69 X = reviews_df_preprocessed.iloc[:, -1].values
70 y = reviews_df_preprocessed.iloc[:, -2].values
71
72 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)
73
```

 **Training Data/ Evaluation:** The main chunk of code that does the whole evaluation of sentimental analysis based on the preprocessed data is apart of this. The following are the steps followed:

```
103 pipeline = Pipeline([
104     ('vect', TfidfVectorizer(ngram_range = (1,2), stop_words = 'english', sublinear_tf = True)),
105     ('chi', SelectKBest(score_func = chi2, k = 50000)),
106     ('clf', LinearSVC(C = 1.0, penalty = 'l1', max_iter = 3000, dual = False, class_weight='balanced'))
107 ])
108
109 model = pipeline.fit(X_train, y_train)
```

i) The Accuracy, Precision, Recall, and Evaluation time is calculated and displayed.

ii) Navie Bayes, Logistic Regression, Linear SVM and Random forest classifiers are applied on the dataset for evaluation of sentiments.

iii) Prediction of test data is done and Confusion Matrix of prediction is displayed.

iv) Total positive and negative reviews are counted.

v) A review like sentence is taken as input on the console and if positive the console gives 1 as output and 0 for negative input.

7. Results and Sample Output

The ultimate outcome of this Training of Public reviews dataset is that, the machine is capable of judging whether an entered sentence bears positive response or negative response.

Precision (also called [positive](#) predictive value) is the fraction of relevant instances among the retrieved instances, while **Recall** (also known as [sensitivity](#)) is the fraction of relevant instances that have been retrieved over the total amount of relevant instances. Both precision and recall are therefore based on an understanding [and](#) measure of relevance.

$$\text{precision} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|}$$

$$\text{recall} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{relevant documents}\}|}$$

F1 score (also **F-score** or **F-measure**) is a measure of a test's accuracy. It considers both the [precision](#) and the [recall](#) of the test to compute the score: p is the number of correct positive results divided by the number of all positive results returned by the classifier, and r is the number of correct positive results divided by the number of all relevant samples (all samples that should have been identified as positive). The F1 score is the harmonic average of the [precision](#) and recall, where an F1 score reaches its best value at 1 (perfect precision and recall) and worst at 0.

$$F_1 = \frac{2}{\frac{1}{\text{recall}} + \frac{1}{\text{precision}}} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

In statistics, a **receiver operating characteristic curve**, i.e. **ROC curve**, is a [graphical](#) plot that illustrates the diagnostic ability of a [binary](#) classifier system as its discrimination threshold is varied. The [Total](#) Operating Characteristic (TOC) expands on the idea of ROC by showing the total information in the two-by-two [contingency](#) table for each threshold. ROC gives only two bits of relative information for each threshold, thus the TOC gives strictly more information than the ROC.

When using normalized units, the area under the curve (often referred to as simply the AUC) is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one (assuming 'positive' ranks higher than 'negative'). This can be seen as follows: the area under the curve is given by (the integral boundaries are reversed as large T has a lower value on the x-axis).

$$A = \int_{-\infty}^{\infty} \text{TPR}(T) \text{FPR}'(T) dT = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} I(T' > T) f_1(T') f_0(T) dT' dT = P(X_1 > X_0)$$

The machine evaluates the accuracy of training the data along with precision Recall and F1

The Confusion matrix of evaluation is calculated.

It is thus capable of judging an externally written review as positive or negative.

A positive review will be marked as [1], and a negative review will be hence marked as [0].

Results obtained using Hold-out Strategy(Train-Test split) [values rounded upto 2 decimal places].

Name of classifier	F1	Accuracy	Precision	Recall	ROC AUC
Multinomial NB	85.25%	85.31%	85.56%	84.95%	85.31%
Logistic Regression	88.12%	88.05%	87.54%	88.72%	88.05%
Linear SVC	88.12%	88.11%	87.59%	88.80%	88.11%
Random Forest	82.43%	81.82%	79.74%	85.30%	81.83%

The Confusion Matrix Format is as follows:

True Negative	False Positive
False Negative	True Positive

The Confusion Matrix of Each Classifier are as follows:

68556	11470
12032	67942

Classifier 1: Multinomial NB

69928	10098
9023	70951

Classifier 2: Logistic Regression

69963	10063
8955	17019

Classifier 3: Liner SVC

62695	17331
11749	68225

Classifier 4: Random Forest

The following are the images of such sample output after successful dataset training using the classifiers:

```
pranits@MacBook-Air:~/sentiment-analysis$ python3 sentiment_analyzer.py
Holdout Strategy...
Splitting data using Train-Test split...
Splitting data completed!
Splitting time: 0.281 s

Training data... Classifier MNB
Training data completed!
Training time: 183.1 s

Training data... Classifier LR
Training data completed!
Training time: 217.264 s

Training data... Classifier SVM
Training data completed!
Training time: 204.815 s

Training data... Classifier RF
Training data completed!
Training time: 759.166 s

Predicting Test data... Classifier MNB
Prediction completed!
Prediction time: 28.198 s

Predicting Test data... Classifier LR
Prediction completed!
Prediction time: 27.813 s

Predicting Test data... Classifier SVM
Prediction completed!
Prediction time: 27.175 s

Predicting Test data... Classifier RF
Prediction completed!
Prediction time: 35.286 s

Evaluating results... Classifier MNB
Results evaluated!
Evaluation time: 0.34 s

Evaluating results... Classifier LR
Results evaluated!
Evaluation time: 0.325 s

Evaluating results... Classifier SVM
Results evaluated!
Evaluation time: 0.318 s

Evaluating results... Classifier RF
Results evaluated!
```

```
Evaluating results... Classifier MNB
Results evaluated!
Evaluation time: 0.34 s

Evaluating results... Classifier LR
Results evaluated!
Evaluation time: 0.325 s

Evaluating results... Classifier SVM
Results evaluated!
Evaluation time: 0.318 s

Evaluating results... Classifier RF
Results evaluated!
Evaluation time: 0.313 s

Evaluation metrics of classifier MNB
Accuracy: 0.8531125
Precision: 0.8555635090237861
Recall: 0.8495513841868354
F1: 0.852546647708782
ROC AUC: 0.853113429223356
Confusion Matrix: [[66598 13470]
 [12832 67942]]
Evaluation metrics of classifier LR
Accuracy: 0.88849375
Precision: 0.8754887853769685
Recall: 0.8871738321454473
F1: 0.8812529887834772
ROC AUC: 0.8804893286711317
Confusion Matrix: [[69528 10098]
 [ 9853 70551]]
Evaluation metrics of classifier SVM
Accuracy: 0.8811375
Precision: 0.8758338752545855
Recall: 0.888061884852578
F1: 0.8818164648797936
ROC AUC: 0.8811397368783848
Confusion Matrix: [[69963 10063]
 [ 8555 70819]]
Evaluation metrics of classifier RF
Accuracy: 0.811825
Precision: 0.7974380224367666
Recall: 0.8530897941701852
F1: 0.8243218751887875
ROC AUC: 0.8182613192413517
Confusion Matrix: [[62995 17331]
 [11749 68225]]

Total number of observations: 100000
Positives in observation: 79274
Negatives in observation: 20726
Majority class is: 50.016749999999994
pranits@MacBook-Air:~/sentiment-analysis$
```

```

administrator@administrator-OptiPlex-3040:~/Desktop/sentiment_analysis$ python3 sentiment_analyzer.py
Preprocessing data...
Preprocessing data completed!
Preprocessing time: 0.131 s

Training data...
Training data completed!
Training time: 244.431 s

Predicting Test data...
Prediction completed!
Prediction time: 11.46 s

Evaluating results...
Accuracy: 0.94855693988754
Precision: 0.983433383243815
Recall: 0.9613014112497147
f1: 0.9722414612616284
Results evaluated!
Evaluation time: 0.084 s

Confusion matrix: [[ 7575  2412]
 [ 5764 143182]]

Total number of observations: 158933
Positives in observation: 148946
Negatives in observation: 9987
Majority class is: 93.7162200424078%
Worst product ever
[0]

```

```

administrator@administrator-OptiPlex-3040:~/Desktop/sentiment_analysis$ python3 sentiment_analyzer.py
Preprocessing data...
Preprocessing data completed!
Preprocessing time: 0.163 s

Training data...
Training data completed!
Training time: 239.406 s

Predicting Test data...
Prediction completed!
Prediction time: 11.402 s

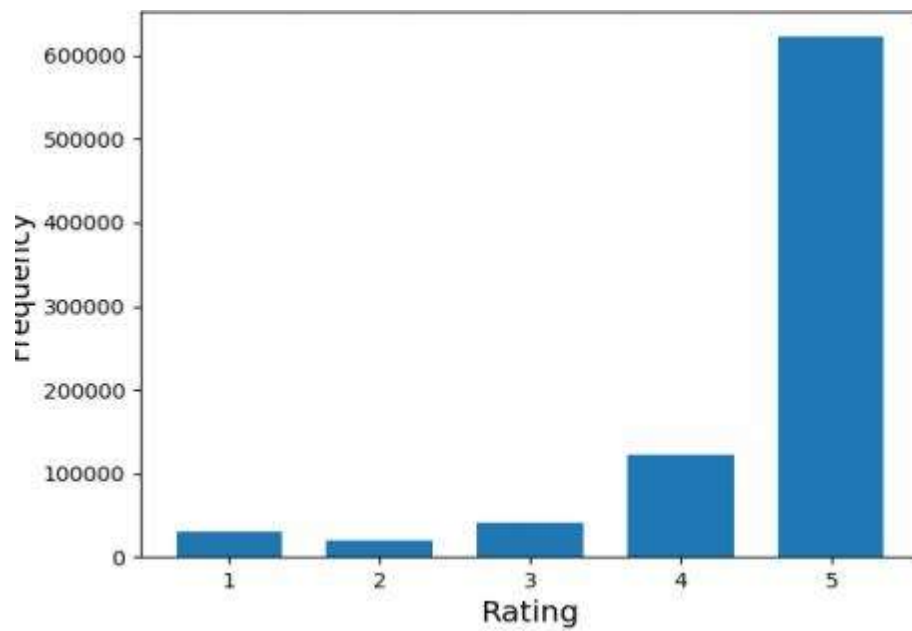
Evaluating results...
Accuracy: 0.9486261506420944
Precision: 0.983467838868093
Recall: 0.9613416943053187
f1: 0.9722789017488227
Results evaluated!
Evaluation time: 0.086 s

Confusion matrix: [[ 7580  2407]
 [ 5758 143188]]

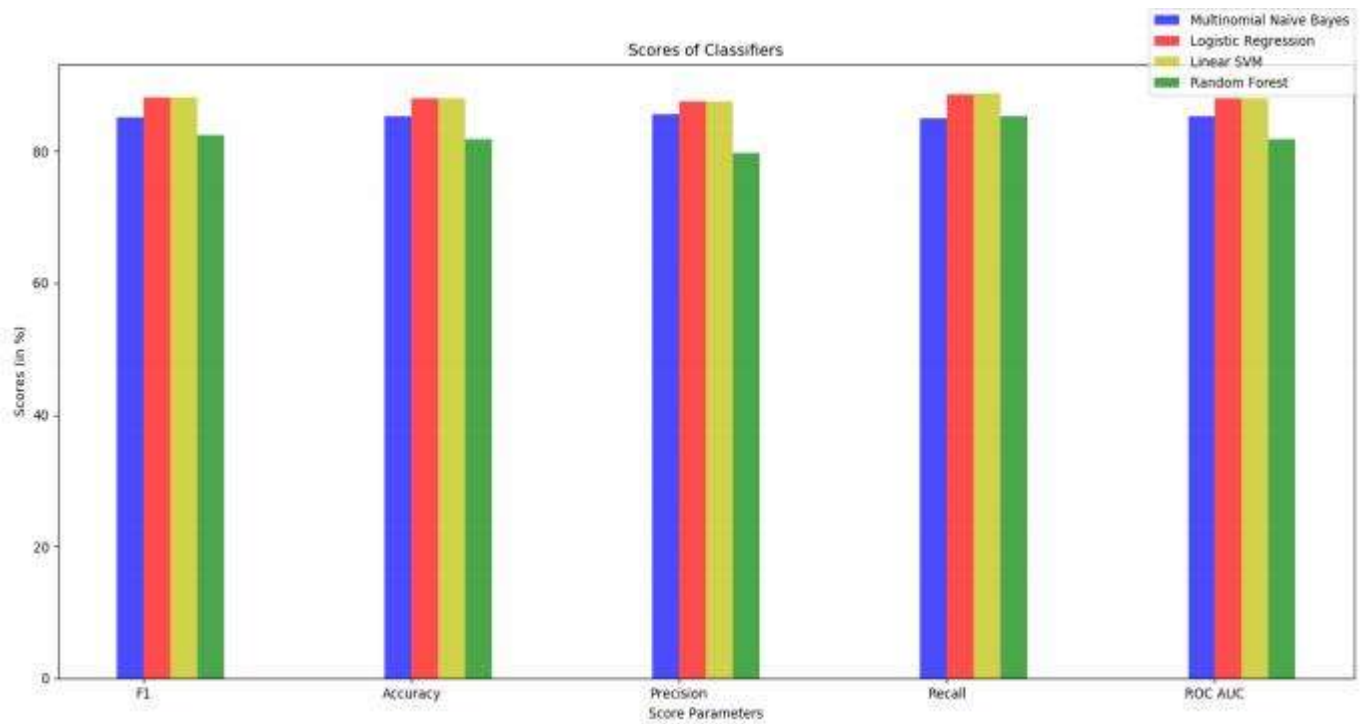
Total number of observations: 158933
Positives in observation: 148946
Negatives in observation: 9987
Majority class is: 93.7162200424078%
not a good product
[1]

```

The Bar Graph showing the Frequency of Ratings in the dataset



This Bar graph shows the score of each classifier after successful training. The parameters be: F₁ Score, Accuracy, Precision, Recall and Roc-Auc.



8. Conclusion

Sentiment analysis deals with the classification of texts based on the sentiments they contain. This article focuses on atypical sentiment analysis model consisting of three core steps, namely data preparation, review analysis and sentiment classification, and describes representative techniques involved in those steps.

Sentiment analysis is an emerging research area in text mining and computational linguistics, and has attracted considerable research attention in the past few years.

Future research shall explore sophisticated methods for opinion and product feature extraction, as well as new classification models that can address the ordered labels property in rating inference. Applications that utilize results from sentiment analysis is also expected to emerge in the near future.

Appendix

Code:

Loading the dataset:

```
import json
import pickle

import numpy as np

from matplotlib import pyplot as plt
from textblob import TextBlob

# fileHandler = open('datasets/reviews_digital_music.json', 'r')
# reviewDatas = fileHandler.read().split('\n')

# reviewText = []
# reviewRating = []

# for review in reviewDatas:
#     if review == "":
#         continue
#     r = json.loads(review)
#     reviewText.append(r['reviewText'])
#     reviewRating.append(r['overall'])

# fileHandler.close()

# saveReviewText = open('review_text.pkl', 'wb')
# saveReviewRating = open('review_rating.pkl', 'wb')
# pickle.dump(reviewText, saveReviewText)
# pickle.dump(reviewRating, saveReviewRating)
reviewTextFile = open('review_text.pkl', 'rb')
```

```

reviewRatingFile = open('review_rating.pkl', 'rb')
reviewText = pickle.load(reviewTextFile)

reviewRating = pickle.load(reviewRatingFile)
# print(len(reviewText))

# print(reviewText[0])
# print(reviewRating[0])
# ratings = np.array(reviewRating)

plt.hist(ratings, bins=np.arange(ratings.min(), ratings.max()+2)-0.5,rwidth=0.7)
plt.xlabel('Rating', fontsize=14)

plt.ylabel('Frequency', fontsize=14)
plt.title('Histogram of Ratings', fontsize=18)
plt.show()

lang = {}
i = 0

for review in reviewText:
    tb = TextBlob(review)
    l = tb.detect_language()

    if l != 'en':

        lang.setdefault(l, [])
        lang[l].append(i)

        print(i, l)

    i += 1
print(lang)

```

Scrapping data:

```

from selenium import webdriver

from selenium.webdriver.chrome.options import Options
from bs4 import BeautifulSoup

import openpyxl

class Review():
    def __init__(self):

```

```

        self.rating=""
        self.info=""

        self.review=""
def scrape():
    options = Options()
    options.add_argument("--headless") # Runs Chrome in headless mode.
    options.add_argument('--no-sandbox') # # Bypass OS security model
    options.add_argument('start-maximized')
    options.add_argument('disable-infobars')
    options.add_argument("--disable-extensions")
    driver=webdriver.Chrome(executable_path=r'C:\chromedriver\chromedriver.exe')
    url='https://www.amazon.com/Moto-PLUS-5th-Generation-Exclusive/product-reviews/B0785NN142/ref=cm_cr_ar_p_d_paging_btm_2?ie=UTF8&reviewerType=all_reviews&pageNumber=5'
    driver.get(url)

    soup=BeautifulSoup(driver.page_source,'lxml')
    ul=soup.find_all('div',class_='a-section review')

    review_list=[]
    for d in ul:
        a=d.find('div',class_='a-row')
        sib=a.findNextSibling()

        b=d.find('div',class_='a-row a-spacing-medium review-data')
        "print sib.text"
        new_r=Review()
        new_r.rating=a.text
        new_r.info=sib.text
        new_r.review=b.text

        review_list.append(new_r)
    driver.quit()

    return review_list
def main():

```

```

m = scrape()
i=1

for r in m:

    book = openpyxl.load_workbook('Sample.xlsx')
    sheet = book.get_sheet_by_name('Sample Sheet')
    sheet.cell(row=i, column=1).value = r.rating

    sheet.cell(row=i, column=1).alignment = openpyxl.styles.Alignment(horizontal='center',
vertical='center', wrap_text=True)

    sheet.cell(row=i, column=3).value = r.info

    sheet.cell(row=i, column=3).alignment = openpyxl.styles.Alignment(horizontal='center',
vertical='center', wrap_text=True)

    sheet.cell(row=i, column=5).value = r.review.encode('utf-8')

    sheet.cell(row=i, column=5).alignment = openpyxl.styles.Alignment(horizontal='center',
vertical='center', wrap_text=True)

    book.save('Sample.xlsx')
    i=i+1

if __name__ == '__main__':
    main()

```

Preprocessing Data:

```

import string

from nltk.corpus import stopwords as sw
from nltk.corpus import wordnet as wn
from nltk import wordpunct_tokenize

from nltk import sent_tokenize
from nltk import WordNetLemmatizer
from nltk import pos_tag

class NltkPreprocessor:

    def __init__(self, stopwords = None, punct = None, lower = True, strip = True):
        self.lower = lower

        self.strip = strip

        self.stopwords = stopwords or set(sw.words('english'))

```

```

self.punct = punct or set(string.punctuation)
self.lemmatizer = WordNetLemmatizer()

def tokenize(self, document):
    tokenized_doc = []

    for sent in sent_tokenize(document):
        for token, tag in pos_tag(wordpunct_tokenize(sent)):
            token = token.lower() if self.lower else token
            token = token.strip() if self.strip else token
            token = token.strip('_0123456789') if self.strip else token
            # token = re.sub(r'\d+', '', token)

            if token in self.stopwords:
                continue

            if all(char in self.punct for char in token):
                continue

            lemma = self.lemmatize(token, tag)
            tokenized_doc.append(lemma)

    return tokenized_doc

def lemmatize(self, token, tag):
    tag = {
        'N': wn.NOUN,
        'V': wn.VERB,
        'R': wn.ADV,
        'J': wn.ADJ
    }.get(tag[0], wn.NOUN)
    return self.lemmatizer.lemmatize(token, tag)

```


Sentiment Analysis:

```
import ast
import numpy asnp
import pandas aspd
import re

from nltk.corpus import stopwords
from nltk.stem import SnowballStemmer
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import SelectKBest, chi2, SelectPercentile, f_classif
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.pipeline import Pipeline

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score,
confusion_matrix

from sklearn.svm import LinearSVC
# from textblob import TextBlob

from time import time

def getInitialData(data_file):
    print('Fetching initial data...')
    t = time()

    i = 0
    df = {}
    with open(data_file, 'r') as file_handler:
        for review in file_handler.readlines():
            df[i] = ast.literal_eval(review)
            i += 1

    reviews_df = pd.DataFrame.from_dict(df, orient = 'index')
    reviews_df.to_pickle('reviews_digital_music.pickle')
```

```

print('Fetching data completed!')
print('Fetching time: ', round(time()-t, 3), 's\n')

# def filterLanguage(text):
#     text_blob = TextBlob(text)
#     return text_blob.detect_language()

def prepareData(reviews_df):
    print('Preparing data...')
    t = time()

    reviews_df.rename(columns = {"overall" : "reviewRating"}, inplace=True)

    reviews_df.drop(columns = ['reviewerID', 'asin', 'reviewerName', 'helpful', 'summary',
'unixReviewTime', 'reviewTime'], inplace = True)

    reviews_df = reviews_df[reviews_df.reviewRating != 3.0] # Ignoring 3-star reviews -> neutral
    reviews_df = reviews_df.assign(sentiment = np.where(reviews_df['reviewRating'] >= 4.0, 1, 0)) # 1
-> Positive, 0 -> Negative

    stemmer = SnowballStemmer('english')
    stop_words = stopwords.words('english')

    # print(len(reviews_df.reviewText))
    # filterLanguage = lambda text: TextBlob(text).detect_language()
    # reviews_df = reviews_df[reviews_df['reviewText'].apply(filterLanguage) == 'en']
    # print(len(reviews_df.reviewText))

    reviews_df = reviews_df.assign(cleaned = reviews_df['reviewText'].apply(lambda text: '
'.join([stemmer.stem(w) for w in re.sub('[^a-z]+|(quot)+' , ' ', text.lower()).split() if w not in stop_words])))
    reviews_df.to_pickle('reviews_digital_music_preprocessed.pickle')

```

```

print('Preparing data completed!')
print('Preparing time: ', round(time()-t, 3), 's\n')

def preprocessData(reviews_df_preprocessed):
    print('Preprocessing data...')
    t = time()

    X = reviews_df_preprocessed.iloc[:, -1].values
    y = reviews_df_preprocessed.iloc[:, -2].values

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)

    print('Preprocessing data completed!')
    print('Preprocessing time: ', round(time()-t, 3), 's\n')

    return X_train, X_test, y_train, y_test

def evaluate(y_test, prediction):
    print('Evaluating results...')
    t = time()

    print('Accuracy: {}'.format(accuracy_score(y_test, prediction)))
    print('Precision: {}'.format(precision_score(y_test, prediction)))
    print('Recall: {}'.format(recall_score(y_test, prediction)))
    print('f1: {}'.format(f1_score(y_test, prediction)))

    print('Results evaluated!')
    print('Evaluation time: ', round(time()-t, 3), 's\n')

# getInitialData('datasets/reviews_digital_music.json')
# reviews_df = pd.read_pickle('reviews_digital_music.pickle')

```

```

# prepareData(reviews_df)
reviews_df_preprocessed = pd.read_pickle('reviews_digital_music_preprocessed.pickle')
# print(reviews_df_preprocessed.isnull().values.sum()) # Check for any null values

X_train, X_test, y_train, y_test = preprocessData(reviews_df_preprocessed)

print('Training data...')
t = time()

pipeline = Pipeline([
    ('vect', TfidfVectorizer(ngram_range = (1,2), stop_words = 'english',
sublinear_tf = True)),
    ('chi', SelectKBest(score_func = chi2, k = 50000)),
    ('clf', LinearSVC(C = 1.0, penalty = 'l1', max_iter = 3000, dual = False,
class_weight = 'balanced'))
])

model = pipeline.fit(X_train, y_train)

print('Training data completed!')
print('Training time: ', round(time()-t, 3), 's\n')

print('Predicting Test data...')
t = time()

prediction = model.predict(X_test)

print('Prediction completed!')
print('Prediction time: ', round(time()-t, 3), 's\n')

evaluate(y_test, prediction)

print('Confusion matrix: {}'.format(confusion_matrix(y_test, prediction)))

```

```

print()
l = (y_test == 0).sum() + (y_test == 1).sum()
s = y_test.sum()

print('Total number of observations: ' + str(l))
print('Positives in observation: ' + str(s))

print('Negatives in observation: ' + str(l - s))
print('Majority class is: ' + str(s / l * 100) + '%')

```

Graph Plotting Code:

```

import numpy asnp
import matplotlib.pyplot asplt
from matplotlib.ticker import MaxNLocator
from collections import namedtuple

n_groups = 5

score_MNB = (85.25, 85.31, 85.56, 84.95, 85.31)
score_LR = (88.12, 88.05, 87.54, 88.72, 88.05)
score_L SVC=(88.12, 88.11, 87.59, 88.80, 88.11)
score_RF=(82.43, 81.82, 79.74, 85.30, 81.83)

#n1=(score_MNB[0], score_LR[0], score_L SVC[0], score_RF[0])
#n2=(score_MNB[1], score_LR[1], score_L SVC[1], score_RF[1])
#n3=(score_MNB[2], score_LR[2], score_L SVC[2], score_RF[2])
#n4=(score_MNB[3], score_LR[3], score_L SVC[3], score_RF[3])
#n5=(score_MNB[4], score_LR[4], score_L SVC[4], score_RF[4])

fig, ax = plt.subplots()

index = np.arange(n_groups)
bar_width = 0.1

opacity = 0.7

error_config = {'ecolor': '0.3'}

rects1 = ax.bar(index,score_MNB, bar_width,
                alpha=opacity, color='b',

```

```

        error_kw=error_config,
        label='Multinomial Naive Bayes')
z=index + bar_width

rects2 = ax.bar(z, score_LR, bar_width,
               alpha=opacity, color='r',
               error_kw=error_config,
               label='Logistic Regression')
z=z+ bar_width

rects3 = ax.bar(z, score_LSVC, bar_width,
               alpha=opacity, color='y',
               error_kw=error_config,
               label='Linear SVM')
z=z+ bar_width

rects4 = ax.bar(z, score_RF, bar_width,
               alpha=opacity, color='g',
               error_kw=error_config,
               label='Random Forest')

ax.set_xlabel('Score Parameters')
ax.set_ylabel('Scores (in %)')
ax.set_title('Scores of Classifiers')
ax.set_xticks(index + bar_width / 2)
ax.set_xticklabels(('F1', 'Accuracy', 'Precision', 'Recall', 'ROC AUC'))
ax.legend(bbox_to_anchor=(1, 1.02), loc=5, borderaxespad=0)

fig.tight_layout()
plt.show()

```

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