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Research Article

Sentimental Analysis using Machine Learning and Deep Learning: Performance Measurement, Challenges and Opportunities

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Abstract

Our regular existence has consistently been impacted with the aid of what individuals think. Thoughts and tests of others have consistently inspired our personal sentiments. Web 2.0 has caused extended action in Podcasting, Tagging, Blogging, and Social Networking. As an end result, social media web sites have emerged as one of the structures to raise consumer's opinions and influence the way any commercial enterprise is commercialized. Sentiment analysis is the prediction of feelings in a word, sentence, or corpus of files. It is deliberate to fill in as a software to recognize the mentalities, conclusions, and feelings communicated interior a web point out. This paper reviews at the design of sentiment evaluation, mining the sizeable resources of information for evaluations. The number one goal is to provide a way for studying sentiment rating in social media platforms. Here we discuss diverse methods to perform a computational remedy of sentiments and reviews, diverse supervised or facts-driven techniques to research sentiments like Naïve Bayes, Support Vector Machine, and SentiWordNet technique to Sentiment Analysis. Results classify consumer's belief through social media posts into positive, negative, and neutral.

Keywords: *Podcasting, Tagging, Blogging, and Social Networking, Naïve Bayes, Support Vector Machine*

1. Introduction

Sentiment Analysis is a technique of widespread supposition approximately an entity. We can also use Opinion mining in region of Sentiment Analysis. Opinion is a judgement of an individual with recognize to an element that shifts from every other and tells approximately the decision of the supposition holder. In today's modernized world, social media provides a simpler way for communicating your thoughts.

Sentiment Analysis or opinion mining is the computational investigation of an individual's emotions, evaluations, perspectives, and emotions closer to the entities and their attitude of communication within the context. They are key influencers of human behaviors. Nowadays, we see numerous critiques of social media which are not possible to read by way of buyers since the posts are so scattered. Whenever we want to determine, we regularly rely on others' opinions. Sentiment Analysis performs an essential position inside the decision-making and recommender machine. Decision making consists of choosing whether or not to shop for a particular product or no longer or to make a funding in a certain organization or no longer, while recommender structures encompass recommending movies or meals items, or songs in line with your likes or dislikes on media systems. It facilitates in making it clean as it describes the polarity of the evaluate post so that the man or woman can without problems know whether it is wonderful or terrible without having the trouble of reading the entire sentence and understanding it. Improvement in field of Sentiment Analysis relies on the development of online platforms. We have mined a massive extent of information on public reviews which gives upward push in pursuit of Sentiment Analysis. Sentiment Analysis has won large reputation among multinational corporations. The studies have unfolded from the field of Computer Science to Business Management and Political Science because of the gravity that it holds for enterprise and community as an entire. The approach to sentiment analysis is broadly practiced in enterprises. Basically, Sentiment Analysis is used to extract humans' suppositions from the textual content. Three tiers of Sentiment analysis are report level, sentence stage, and thing stage.

To classify a sentiment various steps are had to be accompanied which can be information collection, facts pre-processing, characteristic extraction, sentiment class, and evaluation. We collect facts from numerous sources which is in uncooked form. The facts need to be in a based shape for sentiment classification, therefore pre-processing of the facts is finished. Next

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step is feature extraction. After this training and testing of data is done and then sentiment classification can be finished easily.

Analysis of sentiments for classification

Sentiment analysis cites to the extraction and identification of raw data using natural language processing and text analysis techniques. It is effectively used in surveying products for marketing purposes. Basic chore of sentiment analysis is clarifying the polarity of the given text which can be done in three steps: Document, Sentence, and Aspect or Feature Level.

A. Document Sentiment Classification Level

The document category classifies a report as exhibiting high quality or dreadful sentiment. It does now not extricate any statistics in the report. This class is generally formulated as a supervised learning hassle with two lessons, high-quality and poor. Supervised Classification inclusive of Naïve Bayes and Support Vector Machine can be put in application without delay. Whereas, Unsupervised Classification tactics can also be used which are specifically based on language styles and sentiment phrases. Lexicon based method also can be used. It focuses on a set of sentiment words or phrases with suitable scores and an aggression scheme to mixture the ratings of the sentiment phrases that seemed within the record to carry out the classification. It is located that Supervised class is area-sensitive, that means that the classifiers which can be trained using a document from one domain, works poorly while examined on every other domain. The cause being, phrases utilized in exclusive domains for expressing evaluations may suggest one-of-a-kind that is positive in a single domain may be poor in any other. To cope with this hassle area adaption or transfer gaining knowledge of strategies have been employed.

B. Sentence Sentiment Classification Level

This is alike report type as a record may get damaged down into sentences. This is a bit tough as records held in a sentence is still less compared to that held in a file. For example, a document containing facts or reviews about an apple can be labeled as high quality or bad but a sentence mentioning that I consume an apple each day does now not offer any information approximately whether or not the apple is ideal or bad or whether consuming its miles fine or negative. For this motive, Sentence Classification needs to encompass one more class that is a neutral elegance (i.e., neither high-quality nor terrible). The strategies which can be used for Document Classification may be clearly applied for Sentence Classification. Some sentence unique procedures are hierarchical sequence getting to know model and deep gaining knowledge of strategies. In sentiment category, exclusive styles of sentences might also need one-of-a-kind varieties of classification. For example, conditional sentences which contains clauses that are dependent on each different and interrogative sentences. Example: If you observe difficult, you will pass the examination expresses no sentiment in the direction of a particular difficulty but the phrase “bypass” expresses a high-quality sentiment. This can be categorized the use of supervised studying because it uses a group of lexical features (i.e., phrases, pos tags, nerve-racking styles, conditional connectives). Another sort of sentence is sarcasm in which the writer or the writer writes something but approach the other component. Sentences inclusive of subjective (specific opinions, appraisals, reviews, allegations, desires, beliefs, suspicions, speculations, or stances) and objective (desirable and undesirable information) are different troubles yet to be solved.

C. Aspect Sentiment Classification Level

Aspect stage or feature degree category classifies the sentiment on person objectives. This isn't always achieved in both record level and sentence level classifications. To classify on the premise of person target one regularly needs to understand the opinion goal or it's miles of confined use. For instance, I am scripting this code in Python language as it does execute properly in C language gives a negative sentiment however does now not inform with which goal the terrible sentiment is related. In element stage classification it's going to inform that high quality opinion in the direction of Python and negative opinion closer to C language. In a nutshell, aspect level type classifies sentiments conveyed on entities, which offers handy information when compared to report sentiment analysis. Supervised gaining knowledge of and lexicon-primarily based procedures can be applied but it nevertheless needs improvement in the approaches of sentiment expressions to make a decision if it covers the prey-word in the sentence or not.

Fig 1. Depicting Process of Sentiment Analysis

Feature extraction

Extracting features from the context is a essential venture in Sentiment Analysis. To enact features in Machine Learning classifiers the text has to transform right into a feature vector. We can do this using numerous vectorization algorithms like TF-IDF (term frequency-inverse document frequency), CountVectorizer, and Word2Vec.

A. Vectorization Algorithms

CountVectorizer

A fundamental vectorizer which takes each token in the dataset and turns it right into a function. It creates a matrix of features. It counts the repetition of each phrase within the record through taking every textual content and assigning it an applicable ID. This multiset of words is given as an enter for classification. It is knows as a scarce dataset which means that every document will consist more than one zeroes for the word that is no-existent inside the corpus.

TF-IDF

It performs vectorization on the word by considering the frequency of the words in a given document. We can use TF-IDF to filter terminating-words in many text files that includes summaries and dialogues. We use it to improve the performance of the occurrence of frequent words by using below mentioned formula:

TF-IDF = TF*IDF

where TF = number of times the term occurred in the text/total number of words in the text,

IDF = total number of documents/number of documents with the word in it.

Word2Vec

Word2Vec additionally is aware of as phrase embedding is one of the strategies of converting the stated group of phrases into vectors or numbers. It preserves text courting within the report by way of appearing certain operations like addition or subtraction. All text within the language are mapped into vector area of the given size.

B. Part of Speech (POS) Tagging

In the English Language, words specially accommodate feelings of an individual. POS tagging enables to locate those tagged words in a dataset. Verbs, adverbs, and adjectives may be appeared as capabilities and irrelevant phrases can be eliminated from the document in order that the size may be decreased.

C. Negation

Whenever a negative word is seen with a positive opinion, negation is used to invert the polarity. For example: “not good restaurant” contains “good” as a positive polarity whereas it also contains “not” as a negative polarity.

Methods of sentimental analysis

Sentiment Analysis can be completed using system studying-based totally, lexicon-primarily based and hybrid strategies. In the device gaining knowledge of approach, we use a categorized dataset where the polarity of a sentence is already noted. Machine mastering methods are divided into classes, supervised getting to know and unsupervised gaining knowledge of.

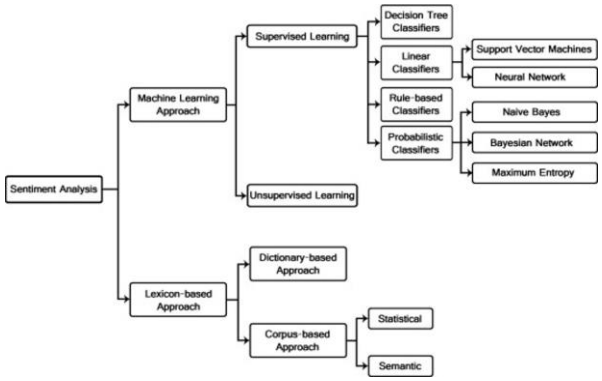


Fig 2. Analytical Approach

A. Supervised Learning

We use this method whenever we've classified statistics available with us for schooling the version. It is done in two stages, training of the version and predicting the output. Records marked with labels is given as an input to the selected model to receive an output. After that take a look at facts is given into the identical model for prediction of the sentiment polarity.

The numerous supervised class algorithms are mentioned below:

Naïve Bayes

Naïve Bayes is a family of simple probabilistic classifiers with strong independent assumptions between the features. Every phrase is considered as an impartial word as it does no longer keep in mind the region of a term. Naïve Bayes is primarily based on Bayes theorem to calculate the probability of every feature which corresponds to a label.

$p(A|B) = p(A) * p(B|A) / p(B)$

where,

p(A) is the prior probability of the label in the dataset,
p(B|A) is the prior probability of a feature related to a label and
p(B) is the prior probability of a feature that is occurred.

Support Vector Machine (SVM)

Support Vector Machine primarily focuses on two-group classification problems. On describing the selection bounds most data factors which form exceptional training SVM specializes in determining

the fine hyperplanes that act as a separator. To keep the maximum distance among guide vectors of various training a hyperplane should be decided on. The Support Vector Machine controls the linear and non-linear classifications based on training and testing datasets.

Decision Tree

A flowchart-like structure depicts a decision tree wherein the internal nodes represent a "test" on an attribute and the leaf nodes represents label of a class. On the premise of a circumstance, a direction is selected. The closing mission is to reach to a leaf node which testifies the internal nodes as "yes" for all attributes. The foremost assignment here is to discover which characteristic to pick out as a root node. It is a superb method for sentiment evaluation because it offers precise results on a huge quantity of records.

B. Unsupervised Learning

We use this strategy when dependability of marked data is troublesome. We face more difficulty in gathering the labeled data than an unlabeled one. The sentences are arranged according to keyword lists of all group. For breaking down space subordinate information, it is simpler to utilize the unsupervised approach. An experiment was performed using unsupervised methodology where posts were bunched into the effective and gloomy polarity groups. It was inferred from this experiment that Spectral clustering outflanks Naïve Bayes and Support Vector Machine.

C. Lexicon-Based Method

Lexicon is cluster of words. In this, focus is on fixed expressions and vocabulary is prized over grammar. It appears to be the perfect method for sentiment analysis. This method uses a lexicon that fits with a phrase to categorize the sentence. There are two class methods underneath the lexicon-based totally technique. They are Dictionary based totally technique and Corpus-based totally method.

D. Dictionary-Based Approach

Dictionary-based sentiment analysis is another approach that measures feelings conveyed in a text for an individual.

In this approach, we select some of the phrases as root phrases which we then use in discovering synonyms and antonyms for expanding the phrase set. Online dictionaries are also used for the same purpose. Root phrases act as opinion phrases which might be critical in a file. Various dictionaries used are WordNet, SentiWordNet, SentiFul, SenticNet. A glossary lexicon may be built using those dictionaries. The improved word list facilitates in enhancing the accuracy of the class undertaking. This method is time-eating.

E. Corpus-Based approach

In this technique, we identify the marking of a phrase and additionally the orientation of the text. Here, new individual words are generated using a list of root words from a file using syntactic sample of listed phrases. This method similarly works within the following methods:

a. Statistical primarily based technique
b. Semantic-based method

Comparing different technique for analysis

In this field of Sentiment Analysis, a number of researchers have performed various works using various techniques. The comparison of their techniques is shown in the table below.

Results Discussion

A. Amazon Dataset

The implementation of the proposed method yielded the following results with the Amazon's dataset :

Bag of Words was used for feature extraction, the accuracy obtained was 90.63% with Logistic regression model, 90.69% with Naive Bayes model, 73.28% with Random Forest model, 87.03% with SVM, 77.04% with kNn model, and 82.73% with decision tree model as can be seen below:-

	LR	NB	RF	SVM	kNn	DT
Accuracy (in %)	90.63	90.69	73.28	87.03	77.04	82.73

The above results were obtained using a very basic approach of extracting features along with only ML models. It can be observed that except Logistic Regression and Naïve Bayes, none of the ML models give high accuracies.

On the other hand when feature extraction was done using Word2vec and Tf-Idf , better results were given by all the classifiers.

B. Flipkart Dataset

The implementation of the proposed method yielded the following results with the Flipkart dataset :

When Tf-idf was used for feature extraction, the accuracy obtained was 96.7% with Logistic regression model, 96.56% with Naive Bayes model, 96.44% with SVM, and 95.68% with decision tree model as can be seen below:-

	LR	NB	RF	SVM	DT	kNn
Accuracy (in %)	96.7	96.56	96.56	96.44	95.68	96.57

The deep learning model of LSTM also gave good results mainly because of the vast vocabulary. It gave an accuracy of 97.4% on the validation data and 99% on the training data.

Random Forest Algorithm

```
In [42]: rfc = RFC(n_estimators=10, criterion='entropy', max_depth=10, min_samples_split=5, bootstrap='true', random_state=None)

         rfc_cv = f.model_cv(rfc, embeddings_positive ,y)
         f.df_model_cv(rfc_cv, embeddings_names, results_names)
```

Out[42]:

	test_acc	f1	precision	recall
BOW	0.9656	0.982499	0.965600	1.000000
TFIDF	0.9656	0.982499	0.965600	1.000000
Word2Vec	0.9678	0.983678	0.968952	0.998654

k-nearest neighbour

```
In [45]: knn = knc(n_neighbors=15, weights='distance')

         knn_cv = f.model_cv(knn, embeddings_positive ,y)
         f.df_model_cv(knn_cv, embeddings_names, results_names)
```

Out[45]:

	test_acc	f1	precision	recall
BOW	0.9656	0.982499	0.965600	1.000000
TFIDF	0.9657	0.982549	0.965597	1.000000
Word2Vec	0.9689	0.984103	0.971638	0.996883

Decision Tree

```
In [46]: dtc = DecisionTreeClassifier(random_state=9, min_samples_split=5)

         dtc_cv = f.model_cv(dtc, embeddings_positive ,y)
         f.df_model_cv(dtc_cv, embeddings_names, results_names)
```

Out[46]:

	test_acc	f1	precision	recall
BOW	0.9603	0.979504	0.976543	0.982498
TFIDF	0.9568	0.977677	0.975571	0.979806
Word2Vec	0.9393	0.968410	0.973327	0.963545

Logistic regression

```
In [47]: logreg = LogisticRegression(max_iter=500, random_state=9, n_jobs=-1)

         logreg_cv = f.model_cv(logreg, embeddings, y)
         f.df_model_cv(logreg_cv, embeddings_names, results_names)
```

Out[47]:

	test_acc	f1	precision	recall
BOW	0.9739	0.986612	0.977540	0.995858
TFIDF	0.9666	0.982996	0.966754	0.999793
Word2Vec	0.9669	0.983047	0.972342	0.993993

SGD Classifier

```
In [48]: sgd = SGDClassifier(random_state=9, n_jobs=-1)

         sgd_cv = f.model_cv(sgd, embeddings, y)
         f.df_model_cv(sgd_cv, embeddings_names, results_names)
```

Out[48]:

	test_acc	f1	precision	recall
BOW	0.9680	0.983493	0.979862	0.987158
TFIDF	0.9716	0.985484	0.972953	0.998343
Word2Vec	0.9653	0.982271	0.969349	0.995547

```
In [49]: sgd_log = SGDClassifier(loss='log', penalty='elasticnet', random_state=9, n_jobs=-1)

         sgd_log_cv = f.model_cv(sgd_log, embeddings, y)
         f.df_model_cv(sgd_log_cv, embeddings_names, results_names)
```

Out[49]:

	test_acc	f1	precision	recall
BOW	0.9729	0.986084	0.978004	0.994304
TFIDF	0.9682	0.983792	0.968587	0.999482
Word2Vec	0.9663	0.982737	0.972234	0.993475

Multinomial Naive Bayes

```
In [40]: naive = MultinomialNB()

         naive_cv = f.model_cv(naive, embeddings_positive, y)
         f.df_model_cv(naive_cv, embeddings_names, results_names)
```

Out[40]:

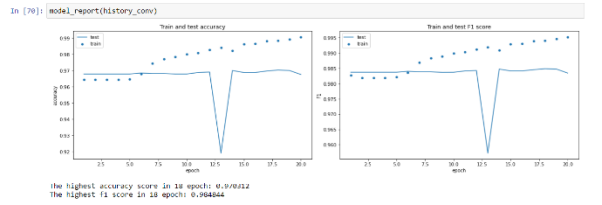
	test_acc	f1	precision	recall
BOW	0.9689	0.984025	0.976163	0.992026
TFIDF	0.9656	0.982499	0.965600	1.000000
Word2Vec	0.9656	0.982499	0.965600	1.000000

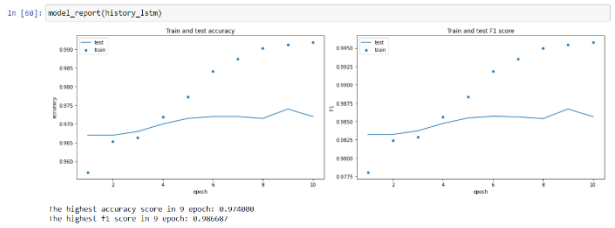
Support Vector Machine

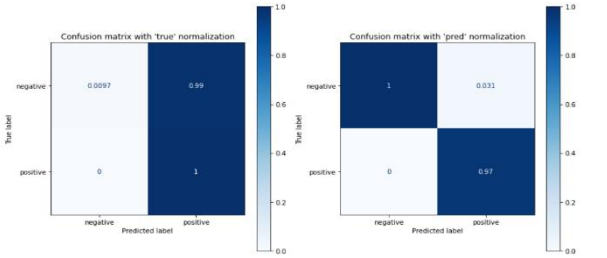
```
In [41]: svc = SVC(C=100, kernel="linear")

         svc_cv = f.model_cv(svc, embeddings_positive ,y)
         f.df_model_cv(svc_cv, embeddings_names, results_names)
```

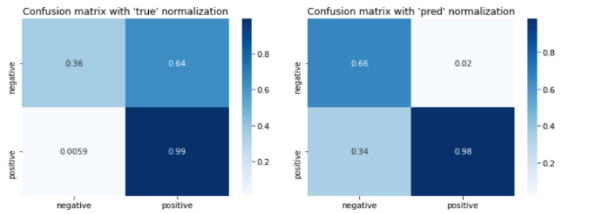
Out[41]:

	test_acc	f1	precision	recall
BOW	0.9578	0.978108	0.979839	0.976387
TFIDF	0.9644	0.981612	0.979089	0.984155
Word2Vec	0.9654	0.982361	0.967374	0.997825









Conclusion

Our paper aims at identifying sentiments through product reviews on Amazon, Facebook and other social and business media forum using various NLP and machine learning techniques. Individuals openly explicit their views here. By reading these opinions you can still extract statistics approximately their place of interest and may do the improvement. This project does a comparative analysis of the various proposed models to find the best model among the proposed models. The project was implemented on Jupyter using Python language and the highest accuracy was given when feature extraction was done using **TF-IDF** with **Logistic Regression** model. After careful study of all the papers it was concluded that expansion in feature selection and classification models are an open area for research. Focal point of exploration can be mix of AI strategies and assessment dictionary technique to improve exactness of conclusion order and versatile ability to assortment of areas and various dialects. Sentiment analysis can be conducted on conversational texts as nicely. For conversational texts, a talk dataset may be taken and evaluation may be finished. Owing to various issues and new openings sentiment analysis nonetheless is a place of new studies and researches.

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