Diyala Journal for Pure Science

Sentiment Analysis for Movie Reviews Based on Four Machine Learning Techniques

Hanaa Mohsin Ahmed and Hanan Rabeea Jaber*

Computer science department – University of Technology – Iraq

hananalbandiwya@gmail.com

Received: 2 August 2019 **Accepted: 5 September 2019**

DOI: https://dx.doi.org/10.24237/djps.16.01.514B

Abstract

The spread of Internet and social media led to be sentiment analysis an open research area. Social media is used so the people can be state their opinions and attitudes on blogs, Tweets, and forums. Sentiment analysis deals with identifying and extracting people's opinions and attitudes from texts on the internet. The classification of the text which is based upon sentiment is differ from topical text classification because it has recognition based on an opinion on a topic. This research studying the ability to apply TF-IDF feature selection approach for sentiment analysis and examines the performance for classification by 4 machine learning methods (naïve Bayes, KNN, J48, and logistic regression) with regard to recall, precision and F1-measure. This research included a comparison between the selected ML methods. The results show the naïve Bayes over performed on other classification methods with precision about 94.0%.

Keywords: Sentiment analysis, movie review dataset, naïve Bayes, J48, k-nearest neighbor, logistic regression.

Diyala Journal for Pure Science

Sentiment Analysis for Movie Reviews Based on Four Machine Learning Techniques

Hanaa Mohsin Ahmed and Hanan Rabeea Jaber

تحليل الشعور لناقدي الافلام بناء على اربع طرق لتعليم الاله

هناء محسن احمد و حنان ربيع جابر

الجامعه التكنولوجيه – قسم علوم الحاسوب

الخلاصة

ادى انتشار الإنترنت و وسائل التواصل الاجتماعي إلى أن يكون تحليل الشعور مجالًا مفتوحًا للبحث. يتم استخدام الوسائط الاجتماعية حتى يتمكن الأشخاص من ذكر آرائهم ومواقفهم على المدونات والتغريدات والاجتماعات. يتعامل تحليل الشعور مع تحديد واستخراج آراء الناس ومواقفهم من النصوص على الإنترنت يختلف تصنيف النص الذي يستند إلى الشعور عن تصنيف النص الموضعي لأنه يحتوي على اعتراف بناءً على رأي بشأن موضوع ما. يدرس هذا البحث القدرة على تطبيق (اسلوب اخيار الميزات (TF-IDF)) لتحليل الشعور ويفحص أداء التصنيف من خلال اربع طرق للتعلم الآلي (النايف بايز، KNN، J48 والانحدار اللوجستي) فيما يتعلق بالدقة والقياس F1. البحث شمل المقارنة بين طرق التعليم الالي المختارة. أظهرت النتائج أن النايف بايز تتغلب على طرق التصنيف الأخرى بدقة حوالي 94.0 ٪.

الكلمات المفتاحية: تحليل الشعور، مجموعة البيانات لناقدي الافلام، النايف بايز و الانحدار اللوجستي، J48, KNN.

Introduction

In the recent years, the attention about sentiment analysis is increased, due to its relationship with the mining of texts and processing of natural languages. The governments, companies, and agents benefit from the massive resources on the internet of opinions like reviews sites and personal blogs where this information is analyzed and exploring opinions. The primary goal of sentiment classification is exploring online texts (review, blog, comment, news, etc.) if they have positive or negative sentiments [1]. Sentiment analysis deals with detection the thoughts, feelings, and opinions. It is used normally to perceive Natural Language Processing (NLP). The basic goal is identifying the thoughts of the people about a specific topic [4] or determining the whole polarity of a text or document. This means SA is utilized for the extraction and retrieval of information from unstructured raw data then introduce them as judgement or assessment and

consider any type of emotions [2]. SA mainly has a couple of approaches. The first one is using machine learning (ML) classifiers, which trained on labelled corpus. The first step is building the model, then classifying the text after inputting it into predetermined classes. This approach is referred to as supervised or corpus-based. The other approach is using a list of words, these words are related to their polarities (+1 or −1), where the model determine overall text polarity from the single polarities of words or sentences in the text. This approached is referred to as lexicon-based or unsupervised [3]. The researches about the topic of SA can be classified as document, sentence, and aspect-/feature-levels sentiment analyses. Sentence-level analysis extracts the sentiment or the opinion which is expressed in a sentence while document-level analysis is involved with the whole document a single unit. Both types of analysis cannot discover what particularly people liked and disliked. Aspect-based sentiment analysis engage with approaches which determine entities / aspects in the inputted text concerning what opinion or attitude has been expressed [4]. Moreover, the sentiments that are expressed concerning those entities are determined. For instance, “although the service is not that good, I still love the food”; here, “service” and “food” are the entities about which opinion is stated. If the Aspect-based sentiment analysis method used, the model is determining the entities, then determine the opinions concerning those entities. This method is referred to as feature-level opinion mining as well [5].

Sentiment analysis is used primarily in different fields such as:

a) In the marketing field: The corporations used SA to improve marketing strategies and better understanding to customer opinions about the products. Also, it's possible to identify the responding to the campaigns or product launches, the opinion about the brand and the reasons why customers are reluctant to purchase products [6].

b) In the field of politics, it is utilized to review the political opinions, and discover the consistency and inconsistency of the political statements and actions. Also, it used for the prediction of the election results [6].

c) Sentiment analysis also is used to track and analyze social phenomena, for the spotting of potentially dangerous circumstances and identifying the overall attitude of the blogosphere [6].

d) Healthcare: There are many medical blogs on the internet. These blogs deal with medical information and health-care topics like types of diseases, treatments, and medications. As a result of the health-related experiences and medical histories these blogs provide for both patients and practitioners, sentiment analysis tools must be expanded to use it in the medical fields [7].

e) Decision making - One of the important fields which SA can be used is decision making systems. In the field of financial investment, many news, blogs, articles and tweets on every public company which SA can use them as a huge resource in order to explore the articles discussing companies and overall the sentiments that are related to them as a single score which may be utilized by an automated trading system. An example of this type of systems is Stock Sonar [8].

f) The government agencies can discover general opinion and people's concerns by watching social media, due to its wide use especially in China, where the people can express their opinion about government policies and to expose corruptions and other violations of government officials. Moreover, it considers as a fast and popular way to report any bad attitude in the society [9].

Our contribution in this paper is discovering the efficiency of the four machine learning tools (naïve Bayes (NB), J46, K. Nearest neighbor (KNN), and logistic regression (LR)). NB is a probabilistic classifier which utilizes Bayesian theory with the assumption that characteristics are stand-alone (occurrence of one characteristic does not affect the probability of others). J48 the algorithm is an extension of ID-3 algorithm and can makes a small tree. The method of divide and conquer is used in order to increase the decision trees. KNN constitute one of the popular schemes used for learning task under supervision. This scheme needs only to define the different between two instances. Essentially, KNN classifies a specific input element by

appointing the most usual label among its k-nearest prototypes of the training group based on that different. LR is used to define the output or the result in the case of one or many separated variables. The form of output value may appear in binary form.

Preliminary and methodology

1. Related Works

The concept of SA was first introduced in the year 2003. Several techniques were used for sentiment analysis in history. The following few works are related to this technique:

Rehab M. Duwairi and Islam Qarqaz [10]: They used three of approaches for machine learning which are NB, K-NN, and SVMs, for the purpose of sentiment analysis of Arabic dataset of tweets and Facebook comments. They are using TF-IDT for extract features. The results show the NB achieve precision about 66.205% and KNN achieve precision about 70.97%.

Tripathy, Abinash, Ankit Agrawal, and Santanu Kumar Rath [11]: They used a couple of methods used in machine learning that are NB and SVM, for the purpose of sentiment categorization of movie reviews that comprise of 2000 positive and negative reviews distributed equally and used vectorization (countVectorizer, TF-IDF) for extract features. The results demonstrate that the Naive Bayes method is performing better than SVM. The precision of NB was 0.895%.

Hussam Hamdan, Patrice Bellot and Frederic Bechet [12]: they used LR for opinion goal Retrieval and analyzing of sentiment polarity, where regression model is used along with positive and negative labels scheme. Various sets of characteristics (syntactic, semantic, lexical, lexicon, and Z score) are extracted. The results of apply LR equals 75.5%.

Suchita V Wawre and Sachin N Deshmukh [13]: They used a couple of approaches for machine learning that are NB and SVM, with an objective of sentiment categorization of movie reviews and used the regular features that assume f1, f2,.., fm be a defined in advance group of m

features which can show up in a document. The results demonstrate that the NB method is performing better than SVM. The accuracy of NB was 65.57%.

Akrivi Krouska, Christos Troussas andMaria Virvou [14]: they used four of approaches for machine learning which are NB, SVM, C 4.5 and KNN for the purpose of discovering the impact of pretreatment procedures on Twitter Sentiment Analysis. The results demonstrate centigramme and 1-to-3-grams make more suitable compared to other representations and naïve Bayes achieve precision about 92.59%, KNN achieve precision about 66.02%.

Sana Alowaidi, Mustafa Saleh, Osama Abulnaja [15]: They used a couple of approaches for ML which are NB and SVMs for purpose of Semantic SA of Arabic Texts. They used BOW and Arabic WordNet (AWN) thought as an external information on the basis of extract features. The practical results refer that a performance of the ATSA model can be enhanced in case of using concept features with comparison of basic BoW impersonation. The precision NB was about 85.99%. [15].

Divyashree N, Santhosh Kumar K L and Jharna Majumdar [16]: They used J48 for Sentimental Analysis of TripAdvisor.in for Reviews of Hotels. They used Clustering PAM Algorithm from data that extracted from CSV files with assistance of J48 algorithm, the resulting data after the clustering process considers a an input to be categorized and the data will associated to the dictionary words, after that, the negative and positive words will be gained from the reviews of hotels on TripAdvisor. Percentage of words gained for positive is 86% and a negative 14%.

Ghosh, Monalisa, and Goutam Sanyal [17]: They used four approaches for machine learning which are (NB, SVM, KNN, and ME) to Rating of performance of multiple classifiers on the basis of the scheme of choosing a group of features for SA of a movie review. Composite feature vector was able to achieve a better performance compared to the unigram feature. the precision of NB about 85.7% with movie review dataset.

Banik, Dolon, Naznin, Shifat, Emran and Md. Abdullah [18]: They used five of approaches for machine learning which are (KNN, NB, SVMs, Neural Network (NN), and LR) to sentiment

analysis of Movie review dataset. There are various prevalent features for Natural Language Processing (NLP) tasks: Word embedding's, Dictionary / Lexicons used to extract features. The results show the NB with precision about 84.99%, KNN with precision about 74% and LR with precision about 70.67%.

2. Tools of proposed system

2.1 preprocessing steps

A. **Tokenization**: this is the operation of break up influx of text content to various words, expression, symbols, or any element have a meaning which called tokens. Tokens are isolated by the path of whitespace characters, like spaces, punctuation symbol or line break [19].

B. Stop Word Filtering: Stop words are frequently used common words like and, are, and this. The stop words do not provide to the knowledge source and they can be removed from the textual data. Challenges in the process of stop word filtering are firstly, difficulty in constructing a list of stop words because of its inconsistency between different textual sources and secondly their high frequency of occurrences pose difficulty in processing the textual data [20].

C. stemming: is an operation which decrease the words to their uninflected basis structures. Occasionally, the stem is unlike the root. Anyway, it is helpful because the associated words normally map to one stem although if the stems are not in authentic root. Stemming is a significant phase in the system of text mining [21].

D. Normalization: Most of the reviews are in the compound form that is uppercase and lowercase and it needs to convert the whole document into uppercase or lowercase. Case Normalization is the process in which all the characters in a document convert either in the uppercase or lowercase [22].

2.2 TF-IDF feature selection

The result of the process of selecting features is filtering the features which are useful and neglecting the irrelevant ones. This process can assist to decrease the size of the feature set in

order to maintain system efficiency. There are two benefits of this process: the first one is using small feature set for the efficiency of the system where it requires a smaller amount of time to end its run but sustains its precision. The second benefit is the irrelevant features may have a negative effect on the overall performance and the quality of the system and the quality of the resulting model [23].

Term frequency- inverse document frequency (TF-IDF)) TF-IDF is a numerical statistic that detects the significance of a single word for one of the documents in a collection. The Tf - IDF is normally used to scale the data retrieval and text mining. If the TF-IDF value of was high this refers to how many the word is mentioned in a document, but it's conflicting with redundancy of a word in the corpus. This may be useful when several words are more common than others [24].

The mathematical description of tfidf:

$$\mathbf{TF-IDF}(\mathbf{T},\mathbf{D}) = \mathbf{TF}(\mathbf{T},\mathbf{D}) \times \mathbf{IDF}(\mathbf{T}) \quad \textbf{(1)}$$

TF (T, D) represents the frequency of a word, IDF (T) is defined as:

$$\mathbf{IDF}(\mathbf{T}) = \mathbf{Log}\frac{|\mathbf{D}|}{\mathbf{DF}(\mathbf{T})} \quad \textbf{(2)}$$

Where DF (T) represents the number of documents in D which have the word.

|D| is the whole number of documents in a dataset.

2.3 Machine learning classification

a) NB classifier

The naive Bayesian is considered as one of the simplest and popular classifiers. Its model determines the posterior likelihood of a class on the basis of allocation the word in the whole document. Bays theory is used in order to forecast the possibility which a particular group of features belongs to a certain label.

$$\mathbf{P(label|features)} = \frac{\mathbf{p(label)*p(features\ |label)}}{\mathbf{P(features)}} \quad \mathbf{(3)}$$

The initial label likelihood is called P (label), or the likelihood which a haphazard feature set the label. The P feature considers as the initial likelihood where a specific feature group is happened [25].

b) KNN classifier

The kNN can be considered as a famous example of classifier, its techniques are very popular because it's simple and accurate. This classifier can ranks any neighbors documents score among a set of training documents. Moreover, a class labels of the k most similar neighbors is used in kNN classifier. In case of specific d document to be examined, the system is able to find kNN amongst training documents. The likeness score of every document of the nearest neighbor to the examined document has been utilized [26]. The weighted total in kNN classification can be expressed using the following equation:

$$\mathbf{Score(di,d)} = \sum_{\mathbf{dj=k-nn(d)}} \mathbf{sum\ (d,dj)\ \delta(dj,cj)} \quad \mathbf{(4)}$$

K-NN (d) is to the group of K nearest neighbors of the document d. in the case where dj is part of ci, $\boldsymbol{\delta(dj,cj)}$ = 1, or otherwise 0. For a testing document d, it must be a part of the class which has the highest value of the resultant weighted summation. For the purpose of determining $\boldsymbol{sum\ (d,dj)}$,

Euclidean distance has been utilized, due to the fact that it provides the normal way by which humans understand distance in the actual world.

$$\mathbf{D\ euclidean(x,y)} = \sqrt{\sum_{\mathbf{i=1}}^{\mathbf{m}} \mathbf{(xi-yi)^2}} \quad \mathbf{(5)}$$

c) J48 decision tree classifier

J48 is a decision tree-based classifier, and this classifier produces rules in order to forecast the target terms. It can handle big training data-sets more than other classifiers. The word properties

for corpus sentences that are possessed from labeled arf fle of training set are stated in the leaf nodes of decision tree. The function of labels to the word properties of test group progressively produces two different sections of the decision tree. An entropy function is used in this algorithm to examine the classification of terms from the test set [27].

$$\textbf{Entropy (Term)} = -\sum_{j=1}^{n} \frac{termj}{term} \log 2 \frac{termj}{term} \quad (6)$$

d) LR classifier

LR might be ordinal, binomial, or multi- nomial. Binomial, otherwise known as binary logistic regression is concerned with cases where the observed result for a dependent variable has two possibilities of types only, "0" and "1" (that can mean, "yes" and "no" or "true" and "false"). A logistic function is utilized for the determination of the correlation between categorically dependent and one or more independent variables [28].

The equation for logistic regression can be seen in Equation.

$$\log_y = \frac{\exp(\alpha * x1 + \beta * x2 + y)}{1 + \exp(\alpha * x1 + \beta * x2 + y)} \quad (7)$$

Where γ is the bias, α and β is the weight, and X1, X2 is the features.

Suggested System

Figure 1. Show the steps of process of sentiment analysis

1. Data collection

For the sake of determining the efficiency of machine learning, algorithms-based sentiment analyzers, used dataset exhibiting different characteristics. Dataset is comprised of movie reviews which are more grammatical and orthographical than other dataset such as tweets that collected from a popular website ("kaggle.com") which presented a large number of movies

from almost all film industries around the world. This dataset is labeled a positive class with 1000 documents and negative class with 1000 documents.

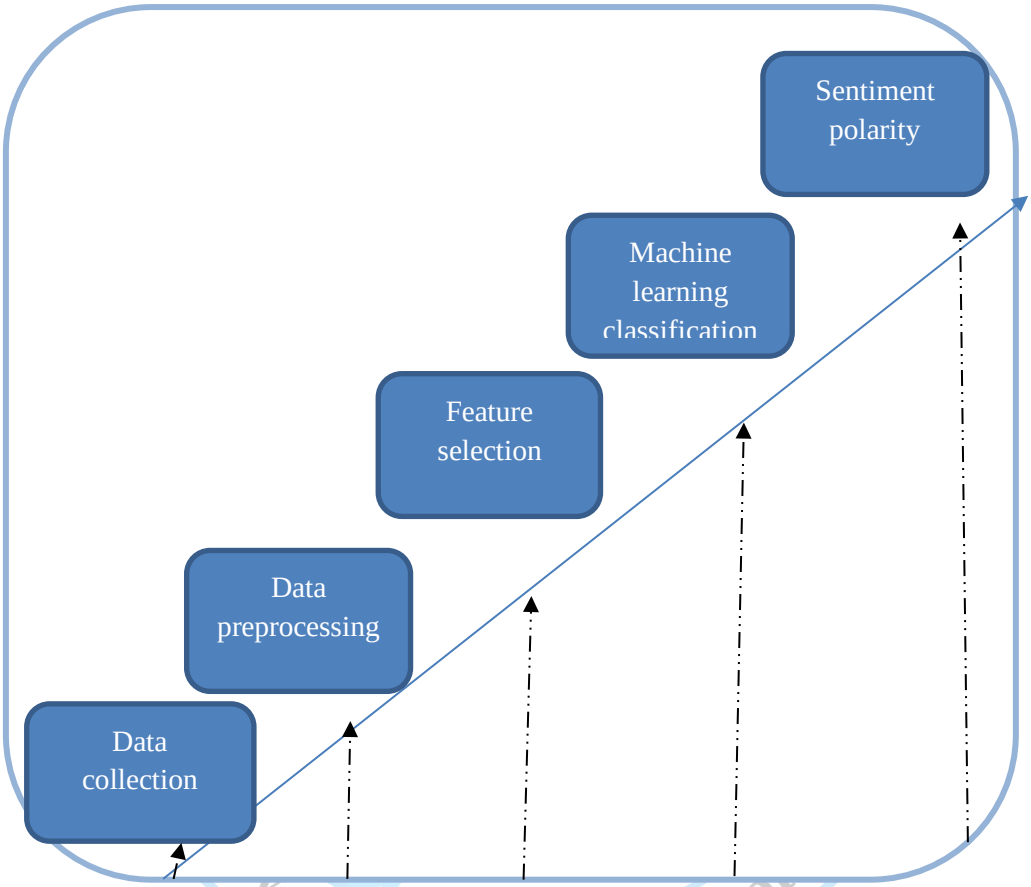

Figure 1: Show the diagram of Sentiment analysis process

2. preprocessing steps

A good Preprocessing step must implement all the following to every movie review to produce better output**:**

a) Tokenization the dataset: The process of breaking a sentence into words, word tokens are delimited by a blank space

b) Remove all the STOP WORDS (Using an exhaustive stop word list- Treating these types of words as a feature in classification would not result in a better outcome. So, these words can be ignored and removed during the preprocessing)

c) Normalizing the dataset- Words are often used with different variations. If these words are reduced to their root words, it will result in efficient performance of the algorithm.

d) Stemming are techniques that are commonly used for normalizing the dataset. For instance, the words: connect, connected, connecting, connection, all the above words can be reduced to the root word "connect".

3 TF-IDF feature selection

TF-IDF algorithm

Provided a collection of documents "D", a word "w", and a specific document d

1-the weight w is computed via the Equation

$$\mathbf{w = f(w, d) * log\ ((|D|/\ f(w, D)\ )} \quad \textbf{(8)}$$

Where f(w, d) or TF is the number of the appearances of "w" in a document "d"

|D| refers to dataset size.

f(w, D) Or IDF represents the number of documents where "w" occurs in D.

2-The output of the TFIDF is a vector that has several terms together with their term weight

4 machine learning classification

There are 4 popular classifiers, which are NB, LR, KNN, and J48, were chosen for the reason of determining the contingent of their performance on the approach of pre-processing which is applied on chosen data-sets.

Table 1: Shows Advantage and Disadvantage of several Machine Learning Methods

Method	Approach	Advantage	Disadvantage
Naïve Bayes	Probabilistic learning algorithm	1. Easy to use and intuitive approach. 2. It features it more accurate and efficiency	1- It normally used if the size of training set is little. 2- A conditional independence should be available among the linguistic features.
KNN Method	Clustering algorithm	1- It established on the reality of the classification of a sample will be like to those near in the space of the vector. 2- It's computationally effective.	1- It require a large amount of storage. 2- It is computationally intensive
J48 method	Decision tree	J48, can be applied on a large amount of data and valuable predictions can be produced	There is matching between the complexity of the run-time of the algorithm with the tree depth. The run-time should be less than the number of attributes.
Logistic regression	Linear regression	1-it is much more robust to correlated features. 2-If two features f1 and f2 are perfectly correlated, regression will simply assign a half the weight to w1 and half to w2. • It is discriminative	Continuous outcomes can not be forecasted by logistic regression, for instance it is not possible to determine the height of influenza patient's fever using logistic regression, due to the continuity of the scale of measurement –temperature

4.1 NB algorithm

Step1: Preparing a table of frequency from the dataset.

Step2: Finding probabilities to create a table of likelihoods.

Step3: Computing the posterior possibility for every one of the classes with the use of the equation of Naive Bayesian.

The final output of projection is a class that has the maximum posterior probability

4.2 J48 decision tree algorithm

The tree can be build using the following basic steps:

a) Be sure that all of the instances are within the same class, then the tree is a leaf and it is labeled with this class.

b) Computing information and information gain for every attribute.

c) Find the most optimal attribute of splitting, and this is related to the current selection criteria

d) Making a decision node which can split on a_best.

e) Recur on the sub-lists that are grained by splitting on a_best, and adding these nodes as children to the node

4.3 KNN clustering algorithm

a) The data should be loaded

b) Initializing the k value

c) For the sake of obtaining the projected class, repeating from 1 to the number of training data points.

d) Determining the space between the testing data and every training data row. Furthermore, Euclidean distance is used as distance measure due to the fact that it's a very famous approach. The other measures which may be utilized are the cosine, Chebyshev, and others.

e) Arranging the computed distance with an ascending order regarding to the values of distance.

f) Obtaining highest k rows from the sorted array

g) Obtaining the most common class of those rows

h) Restore the forecasted class

4.4 LR algorithm

1- Obtain factors which increase the conditional possibility of *G* considering *X* with the use of training data.

2- Indicate pk (xi; θ) = Pr (G = k | X = xi; θ).

3-Provided the first input x1, the posterior probability of its class being *g*1 is Pr (G = g1 | X = x1).

4-Because samples in the training data set are independent, the posterior likelihood for *N* samples everyone has class *gi*, *i* = 1, 2... N, given their inputs *x*1, *x*2... xN is:

$\prod_{I=1}^{N}$ PR= (G = gi | X = xi).

Results

In this part, a discussion for the results gained using naïve Bayes, KNN, j 48, and Logistic regression applied to movie review documents are made a comparison of their relative performances on 3 parameters which are: precision, recall and F1-measure, as:

Precision can be defined as how many true positive values from all documents that assigned positive, which is given by

$$\textbf{Precision} = \frac{tp}{tp/fp} \quad (9)$$

Recall is the count of the true positive of the real positive documents, and is represented by the following equation:

$$\textbf{Recall} = \frac{tp}{tp/fn} \quad (10)$$

Lastly, F_measure is a weighted approach of recall and precision, and is calculated using the following equation:

$$\textbf{F\_measure} = \frac{2*precision*recall}{precision+recall} \quad (11)$$

Table 4, display the measures of the efficiency of naive Bayesian, KNN, J48 and logistic regression-based classifiers based on precision, recall and F1-measure.

For example, from dataset movie review

"Films adapted from comic books have had plenty of success"

The results after apply preprocessing step as shown in the following:

"Film adapt comic book plenty success"

The results after applying TF-IDF on movie review example as shown in table (3):

Table 2: TF-IDF Results

	TF-IDF results
film	0.7142290789560615
adapt	2.7806208939370456
comic	7.280635774999012
book	2.1541650878757723
Plenty	2.6736487743848776
success	1.6502599069543555

This values of TF-IDF enter to machine learning algorithms to purpose classification measurements as shown in table 3.

Table 3: Shows Classification measurement of four machine learning methods

Algorithm	Performance Measure (%)	
Naïve Bayes	Precision	94.0
	Recall	96.907
	F1-measure	95.431
KNN	Precision	72.0
	Recall	61.0
	F1-measure	56.0
J48	Precision	65.0
	Recall	65.0
	F1-measure	65.0
Logistic regression	precision	79.0
	Recall	78.0
	F1-measure	78.0

Conclusion and discussion

In the presented study, which is used four ML methods (naive Bayes, J48, KNN, and logistic regression), then TF-IDF method to extract features based on dataset of movie reviews and compare between the results obtained from four machine learning methods. the best thing about the system that it is naïve Bayes classifier for sentiment analysis of movie reviews is best performed than other classifier. J48 methods gave worst results because it does not take all possible possibilities.in future will apply those four machine learning algorithms on the unsupervised method.

References

1. A. M. Shoukry, Arabic Sentence-level sentiment analysis, M. Sc. Thesis, university of American, Cairo, Egypt, (2013
2. D. Georgiou, A. MacFarlane, Extracting sentiment from healthcare survey data: An evaluation of sentiment analysis tools, In: Science and Information Conference (SAI 2015), 2015, London, UK, pp. 352-361.
3. N. Abdulla, N. Ahmed, M. Shehab, M. Al-Ayyoub, International Journal of Information Technology, 9(3), 55-71(2014).
4. B. Liu, Synthesis lectures on human language technologies, 5 (1), 1-167 (2012).
5. B. Agarwal, N. Mittal, Machine Learning Approach for Sentiment Analysis. In: Prominent Feature Extraction for Sentiment Analysis, Socio-Affective Computing (Springer, Cham, 2016), pp. 21-45.
6. A. D'Andrea F. Ferri, P. Grifoni, T. Guzzo, International Journal of Computer Applications, 125 (3), 26-33 (2015).
7. R. M. Duwairi, R. Marji, N. Sha'ban, S. Rushaidat, Sentiment analysis in Arabic tweets, In: 5th International Conference on Information and Communication Systems (ICICS, 2014), 2014 Irbid, Jordan.
8. H. V. Thakkar, Twitter Sentiment Analysis using Hybrid Naive Bayes, PhD Thesis, sardar vallabhbhai national institute of technology, surat, (2013).

9. B. Liu, Sentiment analysis: Mining opinions, sentiments, and emotions, University of Illinois, (springer, New York, 2015), pp. 1-384.

10. R. M. Duwairi, I.Qarqaz, Arabic sentiment analysis using supervised classification, In: International Conference on Future Internet of Things and Cloud (2014) 2014, Barcelona, Spain, pp.1-10.

11. A. Tripathy, A. Agrawal, S. K. Rath, Classification of Sentimental Reviews Using Machine Learning Techniques, In: 3rd International Conference on Recent Trends in Computing (ICRTC-2015), 2015, pp. 821-829.

12. H. Hamdan, P. Bellot, F. Bechet, Lsislif: Crf and logistic regression for opinion target extraction and sentiment polarity analysis, In: 9th international workshop on semantic evaluation (SemEval), 2015, pp. (753-758).

13. S. V. Wawre, S. N. Deshmukh, International Journal of Science and Research, 5 (4), 819-821 (2016).

14. A. Krouska, C. Troussas, M. Virvou, The effect of preprocessing techniques on Twitter sentiment analysis, In: 7th International Conference on Information, Intelligence, Systems & Applications, Greece, 2016.

15. S. Alowaidi, M. Saleh, O. Abulnaja, International Journal of Advanced Computer Science and Applications, 8 (2), 256-262 (2017).

16. N. Divyashree, k. Kumar, J. Majumdar, International Research Journal of Engineering and Technology, 4 (11), (2017).

17. M. Ghosh and G. Sanyal, Applied Computational Intelligence and Soft Computing Journal, 2018, 1-12 (2018).

18. M. A. Al Emran, Sentimental Analysis, M. Sc. Thesis, United International University, Dhaka, Bangladesh (2019).

19. M. R. Bhagat, Sentiment Analysis using an ensemble of Feature Selection Algorithms, M.Sc. Thesis, San Jose State University, California, State University (2018).

20. R. Lourdusamy, International Journal of Computer Sciences and Engineering, 6 (3), pp. 2347-2693, (2018).

21. V. Srividhya, R. Anitha, International journal of computer science and application, 47 (11), pp. 49-51(2010).

22. J. Muhammad, S. Kamal, International Journal of advanced computer science and Applications, 9 (10) pp.78-85 (2018).

23. A. Rayner, Computational Science and Technology Journal, 488, pp.464 (2018).

24. S. Vijayarani, J. Ilamathi2, International Journal of Computer Science & Communication Networks, 5 (1), pp. 7-16 (2015).

25. M. Walaa, A. Hassan, H. Korashy. Ain Shams engineering journal, 5 (4), pp.1093-1113 (2014).

26. H. Alshalabi, S.Tiun, N.Omar, M.Albared, Experiments on the use of feature selection and machine learning methods in automatic Malay text categorization, In: 4th International Conference on Electrical Engineering and Informatics, 2013, Malaysia, pp.748-754.

27. S. Jaspreet, G. Singh, R. Singh, Journal of Human-centric Computing and Information Sciences, 7 (1), PP.32 (2017).

28. G. Sai, M. Kumar, R. Manikandan, International Journal of Pure and Applied Mathematics, 118 (20), pp. 2347-2693 (2018).