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Cross-Domain Aspect Detection and Categorization using Machine Learning for Aspect-based Opinion Mining

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ABSTRACT

There is an increase in the development of social media and electronic commerce sites day by day. In order to express their opinions about the products purchased user's write comments, messages and reviews. The reviews present in the e-commerce sites are also increasing. Users find difficulty in getting appropriate information about the right topic from this large data. Aspect-based Opinion Mining (ABOM) helps users in this regard. In many real-world applications ABOM is used to get the details about the aspects of entities, where the opinion is expressed for those aspects and entities. One of the key elements of ABOM is Aspect extraction. Unsupervised Machine Learning approach has been used to extract aspects from the reviews as it does not require pre-labelled data. In this regard Latent Dirichlet Allocation (LDA) and Latent Semantic Analysis (LSA) are two most commonly used unsupervised Topic Modeling approaches. The topics are extracted from three different datasets such as Amazon Mobile Reviews, Hotel Reviews and IMDb Movie Reviews using LDA and LSA algorithms. These extracted topics are aspects of our interest. The results of topic modeling algorithms are quite difficult to be interpreted by the common user. The different visualization methods are used to display the results of topic modeling algorithms in an interactive way. Two different multi-class classifiers such as Multinomial Naive Bayes (MNB) and Support Vector Machine (SVM) have been constructed for aspect categorization. These classifiers are evaluated by considering the evaluation measures such as Precision, Recall and F1 score. As a result, SVM classifier has good performance than MNB classifier for aspect categorization task of aspect-based opinion mining.

1. Introduction

The use of social media and e-commerce sites is increasing day by day. The users and organizations are using these for decision making by using the opinions expressed in the form of reviews, comments, discussions in the blogs, forums, etc. The expansion of e-commerce leads to all products being sold on the web. Also there is an increase in the number of customers who are depending on the e-commerce sites. Customers get the complete details about the product which they are interested in from reviews before placing an order. Online sites save the customers precious time and makes customers to buy right product at affordable rate. Online purchase sites allow customers to express their thoughts about the products bought by them, so that they can use it to improve customer satisfaction and shopping experience (Liu 2012).

But the number of reviews present in e-commerce sites will be very high which makes the customers difficult to analyze all the reviews to come to conclusion. Also if a customer goes through less number of reviews then it will be difficult for him/ her to get complete characteristics of products. In the same way, product developer also finds difficulty in improving business strategies and for the right placement of products. Because of this there is a need for product review summarization for both users and organizations (Jawale 2014).

Opinion mining is a branch of Natural Language Processing (NLP) (Palivela 2021) in which we will be performing analysis of sentiments and emotions expressed by the customers (Chintalapudi et al. 2021; Sanjay et al. 2021). In Opinion Mining, analysis of customer opinions is carried out by extracting people's opinions, sentiments, perceptions, and emotions (Liu 2012).

Opinion mining is classified into three categories based on level of granularity: document level, sentence level, and aspect level. Document level opinion mining takes complete document as input and classifies it as positive or negative opinionated (Pang, 2002). Sentence level opinion mining classifies opinionated sentences as positive or negative opinion (Wiebe and Ellen 2005).

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Even though document level and sentence level opinion mining are used in many applications, they still don't provide complete information. If a text is evaluated as positive, then it doesn't mean that every aspect of the entity has positive opinion. Similarly, if a text is evaluated as negative, then it doesn't mean that every aspect of the entity has negative opinion.

ABOM is a fine-grain opinion mining where the aim is to build systems that receive input as a set of texts (e.g. reviews, social media text etc) discussing a particular entity (Hu and Bing 2004; Pathan and Prakash 2021). The systems attempt to detect the main aspects (features) of the entity and estimates the average sentiment based on the opinion in context. The task is decomposed into three stages (Pontiki et al. 2015):

1 Aspect Term Extraction

Aspect term identifies a feature of the entity under discussion. e.g. A review about a mobile phone might mention aspects like battery life, screen resolution etc. Aspect might also be present in the form of a co-reference or be present inherently within the sentence. These are called implicit aspect expressions contrary to explicit expressions where the aspect term is present in the text.

2 Aspect Categorization

Each aspect is assigned as one of the pre-defined categories of attributes related to the entity. For example, the aspect terms alfredo pasta and masala dosa in a restaurant review can be categorized to food, while waiters and staff are categorized to service.

3 Sentiment Polarity Classification

Given an aspect, find the polarity based on subjective context that an opinion about it. The polarity is classified as being positive, negative or neutral.

Aspects are issues on which people express their opinions. Aspects are sometimes known as features, product characteristics, or opinion targets in the field of sentiment analysis. Aspects are vital since the thoughts presented in a statement or reviews are useless unless they are understood. For example, "size" is the element for which an opinion is conveyed in the review line "after using it, I felt the size to be excellent for carrying in a pocket." Aspect detection is also important in opinion mining since its efficacy has a big impact on how well opinion word detection and sentiment orientation identification work. As a result, in this paper we focus on the aspect detection and categorization process of opinion mining.

Aspect detection techniques now available may be divided into two categories: supervised and unsupervised. A collection of pre-labeled training data is required for supervised aspect detection techniques. Although supervised techniques can be useful, gathering enough labelled data is frequently costly and requires a lot of human effort. Because unlabeled data is commonly available, developing a model that works with unlabeled data is useful. Furthermore, due to the diversity and breadth of items and services evaluated on the internet, supervised, domain-specific, or language-dependent models are frequently impractical. As a result, the framework for detecting aspects must be reliable and easily transferrable between domains or languages.

Topic modeling is an unsupervised learning approach that aids users in analysing and comprehending hidden topics in unlabeled text documents (Prem, Rajendran, and Sundarraj 2021). In this paper, we use Unsupervised Topic Modeling algorithms such as LDA and LSA in order to extract topics which are aspects of our interest.

Our research contributions are listed below:

- We have proposed an unsupervised model that handles the key tasks required in a opinion mining system to discover aspects from review phrases using Topic Modeling algorithms such as LDA and LSA.
- Our model does not require labeled training data or extra metadata for aspect extraction.
- We have used different visualization methods are used to display the results of topic modeling algorithms in an interactive way.
- We have compared two machine learning algorithms such as MNB and SVM in order to determine their effectiveness in aspect categorization task of aspect-based opinion mining.
- The evaluation results indicate that SVM classifier has good performance than MNB classifier for aspect categorization task of aspect-based opinion mining.
- The proposed method is easily adaptable to different domains or languages.

This paper is organized as follows: Section 2 highlights the different topic modeling approaches available in the literature for Aspect detection. Section 3 outlines the proposed methodology for the aspect detection and categorization. Section 4 describes the various visualization methods available for the representation of aspects using topic modeling, along with the comparison of SVM and MNB for aspect categorization. In Section 5, we present the Contributions to literature and Implications for practice along with conclusion.

2. Literature Survey

A huge quantity of opinionated text is available from electronic commerce sites and social networking media in the form of reviews, comments, blogs, news portals which has led to the more research on aspect-based opinion mining (Liu 2012).

Aspect extraction is the core steps of opinion mining. If we perform aspect extraction effectively, then the opinion mining system will be very powerful (Türkmen, Ekinci, and Omurca 2016). Hu and Liu (Hu and Liu 2004) explained about the explicit and implicit aspects and performed explicit aspect extraction. They used association rule mining to extract explicit aspects like noun and noun phrases.

Popescu and Etzioni (Popescu and Etzioni 2005) extracted explicit aspects using an unsupervised framework known as OPINE. Pointwise Mutual Information was used in their system to prune aspects space. Wei et al. (Wei et al. 2010) incorporated Semantic Based Refinement to further improve this system. For extraction of explicit aspects and pruning, different methods such as General Inquirer and Co-occurrence-based pruning, Opinion-based infrequent feature identification, Conjunction-based infrequent feature identification rules are used.

Brody (Brody, 2010) used Local LDA method to find aspects. This was an unsupervised method, where Mutual Information was used to find aspect representative words. For example, "card, chicken, table, and so on" are representative words for "meal". For extracting adjectives conjunctions and negations were used. To determine adjective polarities Conjunction graph was used.

Wang (Wang 2010) proposed Co-LDA which is a semi-supervised model, where aspects and sentiments are simultaneously represented. Sentiment LDA and topic LDA are two main elements of this model. Jo and Alice (Jo and Alice 2011) proposed Aspect and Sentiment Unification Model which is an enhancement of Sentence LDA. One of the principles of this model is that words that occur in a same sentence come under same topic. Both aspects and sentiments were represented together and aspect sentiment pairs were obtained.

Xianghua et al. (Xianghua et al. 2013) in their work extracted global topics from Chinese reviews using LDA. For extracting local topics they have used sliding window. Hownet lexicon was used for sentiment polarity assignment. Ding et al. (Ding et al. 2013) proposed Hierarchical Dirichlet Process-LDA (HDP-LDA). Difference between HDP-LDA and LDA is that HDP-LDA automatically finds topic counts. They used lexicon for finding sentiment polarity. Bagheri, Mohamad and Franciska (Bagheri, Mohamad and Franciska 2013) proposed Aspect Detection Model based on LDA (ADMLDA). This model is based on Markov Chain and doesn't consider bag of words. Zheng et al. (Zheng et al. 2014) proposed Appraisal Expression Patterns LDA (AEP-LDA). They used restaurant, hotel, MP3 player and camera reviews and extracted product aspects. This model extracts aspects and sentiments in parallel by assuming that words in the same sentence are under the same topic.

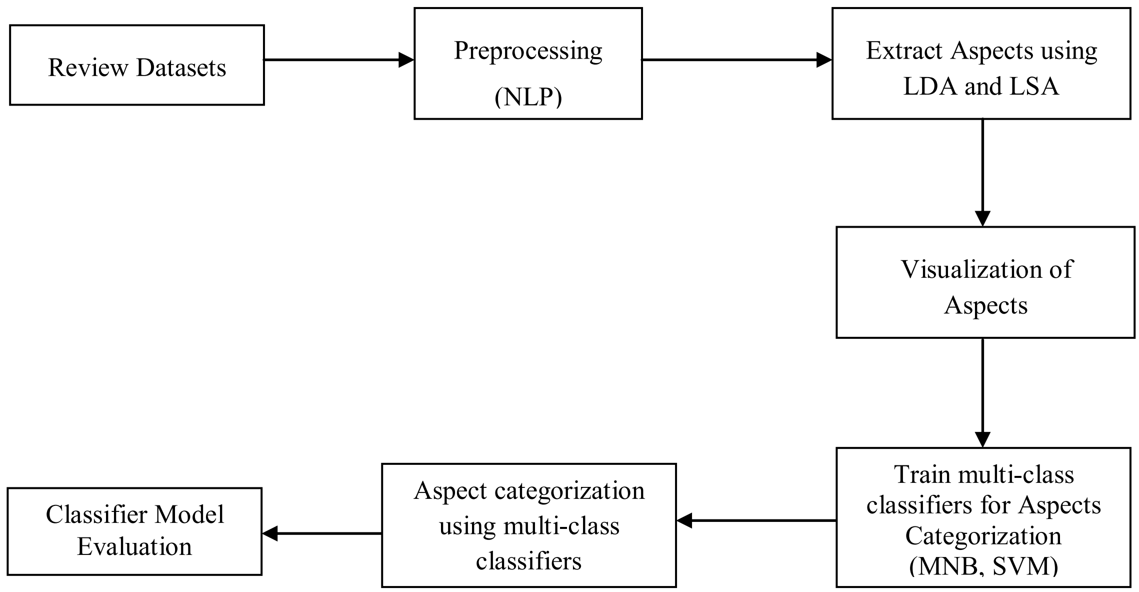


Fig. 1. Methodology of Aspect Extraction using Topic Modeling and Aspect Categorization using multi-class classifiers.

Su et al. (Su et al. 2008) developed a model to represent relation between aspect categories and sentiment groups using Mutual Reinforcement. They used bipartite graph to represent hidden relations. Aspect and sentiment which are in same sentence were connected together. Number of co-occurrence of aspect and sentiment was used to find the connection weight. Zhang, Hua and Wei (Zhang, Hua and Wei 2012) proposed a statistical model based on PMI and frequency based collocation selection to extract explicit aspects. Wang, Hua and Wei (Wang, Hua and Wei 2013) proposed a method for extracting implicit aspects using association rules. For new rule generation five different aspects and sentiment rules were used. PMI and frequency methods were to extract implicit aspects from these new rules.

Bagheri, Mohamad and Franciska (Bagheri, Mohamad and Franciska 2013) proposed a graph based scoring method to extract implicit aspects. In this work Graphs are used to represent relation between explicit aspects and sentiments. Xueke et al. (Xueke et al. 2013) enhanced the LDA model by implementing Joint Aspect/Sentiment Model (JAS). For extracting implicit aspects aspect based sentiments were used. Lau, Chunping and Stephen (Lau, Chunping and Stephen 2014) proposed a model for aspect based sentiment analysis using LDA and fuzzy product ontologies. This model extracts both taxonomic (memory is a hardware) and non-taxonomic (bright flash) relations. Mutual Information was used to represent non-taxonomic relations. Poria et al. (Poria et al. 2015) proposed a model which is rule based method to extract implicit aspects. Explicit aspects and implicit aspect clues (IACs) were used to extract these aspects. Adjectives were considered as IACs and they are mapped to associated aspects category. Xu, Zhang and Wang (Xu, Zhang and Wang 2015) developed a semi-supervised LDA based Explicit Topic Model to extract implicit aspects. The results of this model were fed to SVM to extract implicit aspects.

Table 1 brief about the topic modeling methods used in the literature along with the evaluation measures used and their contribution.

3. Proposed Methodology

Fig. 1 explains in detail various steps involved in performing Aspect Extraction and Aspect Categorization using Topic Modeling and multi-class classifiers on E-commerce sites data.

3.1. Review Datasets

In our proposed work, we have considered three different datasets such as Hotel Reviews, Mobile Reviews and IMDb Movie Reviews. Table 2 describes these review datasets (Pathan and Prakash 2021).

3.2. Preprocessing

Preprocessing steps on these reviews have been performed to produce structured data so that it will be easy for us to extract hidden patterns in the data. The preprocessing steps are:

- Stop-word elimination: Removal of common words which are not useful in aspect extraction. The most common words are numbers, propositions and some of the words which do not contain any useful information.
- Stemming: The root form of words will be formed from given words.
- Lemmatizing: The dictionary form of words will be used.
- Tokenizing: The original sentences will be divided into a number of tokens which helps in aspect extraction.
- And also bigrams and trigrams are considered as a single word.

Fig. 2 shows the algorithm for preprocessing the reviews datasets.

Once the preprocessing is completed, next TF-IDF method is used which is a pre-filtering step. With the help of TF-IDF, based on the occurrence of words, score will be given to a word in a collection of document. This value of score tells how important the word is in a given document.

TF is the ratio of word count in documents to the total words count in all documents. IDF is the logarithmic ratio of total document count in the corpus to the number of documents in which the word appears. If a word occurs in less number of documents then it gives high IDF value and it gives less IDF value if a word occurs in more number of documents. The TF-IDF model is defined in Equations (1) and (2) (Aizawa, 2003):

$$TF = \left(\frac{No.\ of\ occurrences\ of\ word\ in\ documents}{No.\ of\ words\ in\ all\ documents} \right) \tag{1}$$

$$IDF = \log\left(\frac{No.\ of\ documents}{No.\ of\ documents\ with\ word\ occurs} \right) \tag{2}$$

Table 1
Topic Modeling Related Work

Authors	Topic Modeling Method and Evaluation	Description and Result
Chakkarwar and Tamane (2020)	- LDA with bag of words (BoW) model is evaluated. - The topics extracted are visually represented.	- Aims to uncover current trends, subjects, or patterns in research materials in order to provide an overview of various research trends. - The LDA is an excellent topic modelling approach for constructing the context of a document collection, as evidenced by the results.
Sisodia et al. (2020)	- BoW, Term frequency- inverse document frequency (TF-IDF), SVM, Decision trees, Nu-SVC are evaluated in terms of Accuracy, Precision, Recall and F-measure.	- In the collection of individual classifiers, the Nu-support vector classification(Nu-SVC) classifier surpasses all others. - The random forest classifier outperforms the others. - Only two datasets were considered; further datasets of various sizes should be investigated for improved results.
Nugroho et al. (2020)	- LDA, NMF, Task-driven NMF, Plink-LDA, NMjiF are evaluated using Pairwise F-measure and Purity Normalized mutual information (NMI)	- It focuses on a review of ways and explores the aspects that are used to cope with the online social network (OSN) environment's severe sparsity and dynamism. - For comparison, run the algorithms 30 times across both datasets and note the average value of each assessment statistic. - The majority of procedures can attain high purity levels. - Over the other approaches, the NMF and non-negative matrix inter-joint factorization (NMjiF) have the best performance. - The F-measure assessment findings were consistent across all methodologies. - According to all of the assessment measures, NMjiF produces the best outcomes. - Both LDA and NMF concentrate on the same content exploitation of social media postings, as well as the same key aspects (content, social interactions and temporal).
Chen et al. (2019)	- LDA, NMF, KGNMF are evaluated using methods such as Human judgements and PMI Score	- Several themes were put to the test (20,40,60,80 and 100). - The NMF outperforms both NMF and LDA. - The knowledge-guided NMF(KGNMF) model outperforms both NMF and LDA. - The NMF has a larger number of themes than LDA, ranging from 20 to 100.
Ray et al. (2019)	- Latent Semantic Indexing (LSI), LDA, Non-negative matrix factorization (NMF) are evaluated using Topic coherence and perplexity.	- Intended to offer subject modelling methodologies and tools in Hindi. - Discussed a variety of subject modelling methodologies and tools. - The NMF model's coherence findings were somewhat better than the LDA model's. - When compared to other studied topic modelling approaches, the LDA model on the Hindi dataset has a higher perplexity.
Anantharaman et al. (2019)	- LDA, LSA, NMF are evaluated using Precision, Recall, F-measure, Accuracy, Cohen's - Kappa score, Matthewes Correlation Coefficient - and Time taken	- Use BoW and TF-IDF representations to evaluate all topic modelling techniques. - For the 20-newsgroup dataset, we used the Nave Bayes classifier, and for the BBC news and PubMed datasets, we used the random forest classifier. - The findings of the LDA with BoW algorithm on the 20-newsgroup dataset beat those of other topic algorithms. - When compared to BoW, the LDA model performs poorly with TF-IDF. - When compared to the LSA and NMF models, the LDA takes a long time.
Xu et al. (2019)	- LDA is evaluated using Perplexity.	- Intended to assist Chinese film makers in understanding the psychological demands of moviegoers and to offer ideas for improving the quality of Chinese films. - Used a word cloud as a visual representation of high-frequency terms in a text to provide a rudimentary grasp of the text data's fundamental ideas. - The LDA model proposes subjects for a thorough examination of the Douban online review. - Used the perplexity approach to find the optimal number of extracted topics, resulting in a total of 20 extracted topics.
Ahmed Taloba et al. (2018)	- PCA model, Standard SVM, J-48 decision tree, KNN methods are evaluated using Precision, Accuracy, Sensitivity, F-measure	- The goal was to compare how well these approaches performed before and after employing PCA. - When compared to the other classifiers, the RF provides acceptable and greater accuracy. - The RF algorithm performs better, and its performance improves once PCA is used.
Shi et al. (2017)	- Vector space model (VSM), LSI, PLSA, LDA are the different methods studied.	- Examined VSM, LSI, PLSA, and LDA as well as other approaches. - Used a bag-of-words technique to review the key principles of topic modelling. - Discussed the fundamental concepts of topic modelling, including the bag-of-words method, model training, and output. - Gensim, standard topic modelling toolkit, Machine Learning for Language Toolkit (MALLET), and BigARTM were discussed as topic modelling applications, features, and limitations.
Chen et al. (2017)	- NMF, Principal Component analysis (PCA), LDA, KATE are visually represented using t-Distributed stochastic neighbor embedding (TSNE) dimensionality reduction.	- Intended to compare and assess a variety of topic modelling techniques in the context of evaluating a significant number of US Securities and Exchange Commission (SEC) filings by US public banks. - The NMF and LDA algorithms both provide excellent document representation, however the K-Competitive Autoencoder for Text (KATE) produced more intelligible documents with higher accuracy. - In terms of topic representation categorization, the LDA yields the best results.

(continued on next page)

Table 1 (*continued*)

Authors	Topic Modeling Method and Evaluation	Description and Result
Mazarura and de Waal (2016)	- LDA, GSDMM are evaluated in terms of Topic Coherence and Topic stability.	- Tried a wide range of themes (10,20,30,40,50 and 100 topics). - As the number of topics in a long text grows, topic coherence diminishes for both the LDA and the Dirichlet multinomial mixture model (GSDMM), indicating a general degradation in the quality of topics identified by both models as the number of topics grows. - The LDA performs marginally better than the GSDMM in terms of coherence values. - The GSDMM is more consistent than the LDA. - On the brief text, the GSDMM is a promising alternative since it has the ability to generate better results than LDA.
Alghamdi and Alfalqi (2015)	- Latent Semantic Analysis(LSA), Probabilistic Latent Semantic Analysis(pLSA), Correlated topic model(CTM) are the different methods that are evaluated.	- -Examined a variety of subject modelling methodologies for their qualities, limits, and theoretical underpinnings. - Evaluated and reviewed a variety of subject modelling application domains and assessment approaches.

Algorithm1. Preprocessing algorithm
Input: Review Datasets
Method:

```
        Extract Review Sentences
        FOR each sentence
            Convert to lowercase
            Remove Numbers
            Remove Stopwords
            Remove Punctuation
            Tokenize Document
            Lemmatize Document
            Identify bigrams and Trigrams
            POS Tagging
        END FOR
```

Output: Preprocessed Reviews

Fig. 2. Preprocessing Algorithm.

Table 2
Review Datasets.

Dataset	Description
Hotel	10000 documents. Fields: This dataset contains ID, name, date, address, categories, Reviewer text and website columns.
Mobile	67986 documents. Fields: This dataset contains asin, name, rating, date, verified, Reviewer text and helpful votes columns.
IMDb Movie	20000 documents. Fields: This dataset contains Reviewer text and label columns.

3.3. Aspect Extraction using LDA and LSA

We implemented the Gensim toolkit, because it contains an NLP package which has efficient implementation of Topic Models such as LDA and LSA. In the next step, the aspects are extracted using LDA and LSA Topic Modeling methods.

Topic Models(TM) are widely used in the field of NLP and Text mining. They assume that each document contains collection of topics and each topic contains words which are distributed probabilistically. A topic model is used to extract topics from given collection of documents (Deerwester et al. 1990). It defines a procedure by which a document is constructed probabilistically. Let us consider that we are creating a new document and D_i is the distribution over the topics. We chose a topic with respect to D_i corresponding to each word in the document. Then we will select a word from the topic. In our work, we are using topic models to extract topics from the collection of documents. Each aspect is a multinomial distribution over words. We can easily group similar words that represent the same or similar aspect under the same aspect. In our work we are using Latent Semantic Analysis (LSA) model and the Latent Dirichlet Allocation (LDA) model to extract aspects and to categorize these aspects using multi-class classifiers.

3.3.1. Latent Semantic Analysis (LSA)

LSA is an unsupervised NLP technique. It uses topics or latent features to generate text data representation (Deerwester et al. 1990). It is used to lessen the features of the text dataset. There are two steps in LSA. In the first step it creates a Document Term Matrix, where a document of length W in the corpus is a vector of word count. Here, W is the total count of words in the dictionary. The corpus is depicted as a Document Term Matrix $D \times W$ with D being document count in the corpus.

Term Frequency- Inverse Document Frequency (TF-IDF) score is placed as the each cell value of the matrix. LSA uses the Singular Value Decomposition (SVD) to represent the documents and terms of this matrix in a reduced dimensionality vector space called latent semantic space (Santosh, Amir and Ch Aswani 2019). Then, it uses the cosine similarity method to find the similar words and documents in the corpus.

3.3.2. Latent Dirichlet Allocation (LDA)

LDA is the extensively used topic modeling technique (Vamshi, Pandey, and Siva 2018). It is Probabilistic topic modeling technique. It assumes that each document is statistical distribution of topics and each topic is statistical distribution of words.

LDA initially performs following steps to model a document:

- Finds the document word count.
- Topic mixture of the document is used to choose predefined set of topics.
- Multinomial distribution of document is used to select a topic.
- Topic's multinomial distribution is used to select a word.

LDA then performs the following steps:

- Each word present in a document is randomly assigned to one of the topics in the beginning.
- Presume that all words are correctly assigned to the topics with the exception of the current one.
- Find proportion of words in document 'd' assigned to topic 't' as $p(t|d)$ and proportion of assignments topic 't' over all documents that belong to word 'w' as $p(w|t)$.
- Assign a new topic to the word based on the probability calculated by multiplying two proportions obtained above.

3.4. Visualization of Aspects

To offer a better understanding of the words in the document collection, the findings of topic modelling approaches can be displayed in visual formats, such as document-topic distribution charts, word-topic distribution charts and pyLDAVis charts.

3.5. Classification using Multi-class classifiers

The two different multi-class classifiers such as MNB and SVM are trained for aspect categorization.

3.6. Model Evaluation

The multi-class classifiers are evaluated using statistical measures such as precision, recall, and F1 score with 50 different topics.

4. Experiment Results

Topic modeling algorithm results are normally depicted as a topic list. In each topic there will be list of words. Each word of topic is given a numerical value which indicates the statistical significance of the word in the topic. In LSA, this value indicates the semantic similarity of the word in the topic and in LDA, this value indicates the probability distribution of words in the topic (Santosh, Amir and Ch Aswani 2019). We have used one of the widely used package called gensim of python to run the models.

LSA Model

LSA results are depicted as a list of words with numerical value which is the semantic similarity of the word in the topic. Figs. 3(a), (b), (c) represents the top 4 topics produced by LSA model for the three different datasets such as Hotel Reviews, Mobile Reviews and IMDb Movie Reviews respectively.

LDA Model

LDA results are depicted as a list of words with numerical value which is the probability distribution of words in the topic. Figs. 4(a), (b), (c) represents the top 4 topics produced by LDA model for the three different datasets such as Hotel Reviews, Mobile Reviews and IMDb Movie Reviews respectively.

Table 3
Aspects extracted for different datasets

Dataset	Extracted Aspects
Hotel Reviews	Food, Price, Service, Ambience, Location.
Mobile Reviews	Price, Picture Quality, Display, Battery, Overall.
IMDb Movie Reviews	Story, Cast, Scene, Music, Director, Overall.

4.1. Visualization of Topic Modeling Results

As we have seen in previous section, the results of topic modeling algorithms are difficult to be interpreted by the common users. Visualization of topic modeling results helps the users to understand them in a better way. The output of topic models shown in above section contains only collection of topic with words occurring in those topics. Word clouds are often used to display the topics produced wherein the word size denotes the importance of the word in the topic. But word clouds are helpful to display only less number of topics. One of the better ways to visualize the results of topic models are document-topic distribution chart and word-topic distribution chart (Santosh, Amir and Ch Aswani 2019) as shown in Figs. 5(a) and 5(b) respectively for Hotel reviews. In these charts documents which are close in space to each other are more semantically similar to each other. The output is produced with the help of Bokeh package. Right hand side chart in figure 5(a) shows the zoomed output of the chosen portion of the Left hand side chart. Similarly, we have displayed the term-topic distribution chart with its zoomed output of selected portion in figure 5(b).

Similarly, we have shown the document-topic distribution charts and word-topic distribution charts in Figs. 6(a)-(b) and 7(a)-(b) for Mobile Reviews and IMDb Movie Reviews respectively.

The visualization of topics can also be shown in a better interactive way. For this purpose we have used pyLDAVis package to display the interactive visual results of LDA model for Hotel reviews as shown in figures 8(a) & (b). In this chart topics are displayed on left hand side and words making up the topics are shown on right hand side. A bubble on the chart indicates the topic. Relevance of the topic is measured by the size of the bubble. If the size of the bubble is large, then it indicates that the topic has more relevance in the corpus. Topics which are less distant on the chart indicate that they are more similar to each other. If we click on any topic, then it will show the representative words forming the topic on the right hand side as shown in figure 8(b). The dispersal of bubbles in all quadrants with very little overlap indicates a strong topic model. We were able to create large bubbles with minimal overlap.

Similarly, we have used pyLDAVis package to display the interactive visual results of LDA model for Mobile reviews and IMDb Movie reviews as shown in figures 9(a)-(b) and figures 10(a)-(b).

4.2. Aspect Extraction Results

The different aspects extracted by LSA and LDA topic models (Pathan and Prakash 2021) are given in the table 3.

4.3. Evaluation of Multi-class Classifiers

The topics are extracted from three different reviews datasets such as Hotel, Mobile and Movie reviews datasets using TM methods, which are clusters of data. Here 50 topics extracted using TM methods are considered. Each topic is assigned aspect name as label. Each TM method has its own advantages and disadvantages. Although, both TM methods performed almost similar with multi-class classifiers, LDA produced good probability of term-topic. This probability varies in the range of

```
LSI Model:
Topic 0:
[('room', 0.4980721303376274), ('hotel', 0.41489311732072365), ('stay', 0.35643882929114795), ('staff', 0.1
6561402565394234), ('good', 0.1595354583825295), ('great', 0.157511016700398), ('time', 0.1453342585999453)
, ('thank', 0.13565661758037673), ('breakfast', 0.11838992666134336), ('clean', 0.11490974804760294)]
Topic 1:
[('room', 0.7450085754608563), ('bed', 0.07968445209722176), ('check', 0.06993405692804879), ('floor', 0.06
008287772852199), ('say', 0.051627893486482924), ('night', 0.05010221907371512), ('small', 0.04960871127723
136), ('bathroom', 0.047922295524382166), ('ask', 0.04736230013693269), ('desk', 0.045365526663068194)]
Topic 2:
[('hotel', 0.8103106574840377), ('walk', 0.04368185977106074), ('parking', 0.04221177956085993), ('area', 0
.03306701838788302), ('book', 0.025979973175890965), ('free', 0.025750700469938752), ('park', 0.02401181840
9992124), ('car', 0.023022799530212197), ('charge', 0.020084830623857648), ('lot', 0.01835392502933504)]
Topic 3:
[('stay', 0.4402658603982729), ('hotel', 0.17177221065009032), ('guest', 0.12243532646281736), ('time', 0.0
9656205684583416), ('night', 0.09641812056516003), ('experience', 0.09290427490010439), ('tell', 0.07868857
344603326), ('say', 0.07681887292329626), ('check', 0.07055704573442989), ('thank', 0.05731147125947919)]
==========
```

(a).Output of LSA model for Hotel Reviews.

```
LSI Model:
Topic 0:
[('phone', 0.8289258949546473), ('use', 0.2061745299288787), ('screen', 0.14487927203523976), ('good', 0.11
949647982792411), ('work', 0.11704248489630999), ('app', 0.10984477609909794), ('battery', 0.10375096094077
844), ('great', 0.09784132931298119), ('camera', 0.09735474982844114), ('time', 0.08617889197547637)]
Topic 1:
[('use', 0.366528412450575), ('screen', 0.3205966220949815), ('app', 0.284313767923871), ('battery', 0.2006
9748356965103), ('camera', 0.18002272744062472), ('good', 0.17579890029492679), ('note', 0.1504109478895307
), ('device', 0.1292478482724789), ('android', 0.10053299500082982), ('really', 0.09464636252777626)]
Topic 2:
[('app', 0.4474669854717508), ('use', 0.40682815177735465), ('work', 0.13458479896938547), ('window', 0.116
8882903213198), ('set', 0.09345522781198409), ('android', 0.06423190340940536), ('store', 0.053279032510734
334), ('lumia', 0.0527207597711758), ('try', 0.05139648226164701), ('contact', 0.05100777548132724)]
Topic 3:
[('screen', 0.2744807784074196), ('phone', 0.18256742467814424), ('camera', 0.12144418109575104), ('app', 0
.10380342334866496), ('picture', 0.059199685534342725), ('feel', 0.04200757775474832), ('light', 0.04160134
325742964), ('video', 0.03638461540485376), ('edge', 0.03495350097273315), ('android', 0.033443512309774825
)]
==========
```

(b).Output of LSA model for Mobile Reviews.

```
LSI Model:
Topic 0:
[('movie', 0.5208083123322077), ('film', 0.5054046502867746), ('good', 0.1861666209776705), ('make', 0.1570
5782501910073), ('time', 0.14309884269244535), ('character', 0.13594404730055867), ('bad', 0.12703705793110
012), ('story', 0.11868377170961064), ('really', 0.11632469608863198), ('watch', 0.11625121868223023)]
Topic 1:
[('film', 0.685202825299709), ('work', 0.024008799975698818), ('man', 0.02199698874973202), ('performance',
 0.02088090304566933), ('character', 0.020558246771187567), ('story', 0.019331762235513035), ('scene', 0.01
882272870877276), ('play', 0.0182086031120522), ('use', 0.016057874398857485), ('set', 0.015574123164347335
)]
Topic 2:
[('character', 0.22292938187104488), ('good', 0.19060566454560648), ('story', 0.1766172205137972), ('time',
 0.16468037153627504), ('play', 0.1307407365423817), ('man', 0.12295105702184221), ('make', 0.1222465778181
6278), ('look', 0.11894130437144118), ('come', 0.11261462624636719), ('know', 0.1122511400354607)]
Topic 3:
[('bad', 0.678242483647358), ('good', 0.34924355802628443), ('really', 0.1613639488474379), ('look', 0.1127
9549303703272), ('guy', 0.09347223198002935), ('thing', 0.08895863934535074), ('watch', 0.08136800659992396
), ('say', 0.0779429434172745), ('think', 0.072592423678806), ('act', 0.07064268981318944)]
==========
```

(c).Output of LSA model for IMDb Movie Reviews.

Fig. 3a. Output of LSA model for Hotel Reviews.
Fig. 3b. Output of LSA model for Mobile Reviews.
Fig. 3c. Output of LSA model for IMDb Movie Reviews.

```
[(0,
  '0.053*"room" + 0.025*"check" + 0.018*"night" + 0.015*"say" + 0.013*"hotel" '
  '+ 0.011*"desk" + 0.011*"work" + 0.011*"lot" + 0.010*"people" + 0.010*"use"'),
 (1,
  '0.062*"stay" + 0.048*"thank" + 0.029*"time" + 0.029*"experience" + '
  '0.020*"guest" + 0.019*"staff" + 0.019*"hotel" + 0.019*"look" + '
  '0.018*"service" + 0.018*"review"'),
 (2,
  '0.026*"hot" + 0.018*"late" + 0.017*"sleep" + 0.015*"overall" + '
  '0.014*"lobby" + 0.013*"amenity" + 0.012*"coffee" + 0.011*"home" + '
  '0.010*"car" + 0.010*"order"'),
 (3,
  '0.046*"room" + 0.039*"hotel" + 0.038*"stay" + 0.028*"breakfast" + '
  '0.025*"great" + 0.021*"clean" + 0.019*"good" + 0.019*"staff" + 0.018*"nice" '
  '+ 0.017*"area"')]
```

(a).Output of LDA model for Hotel Reviews.

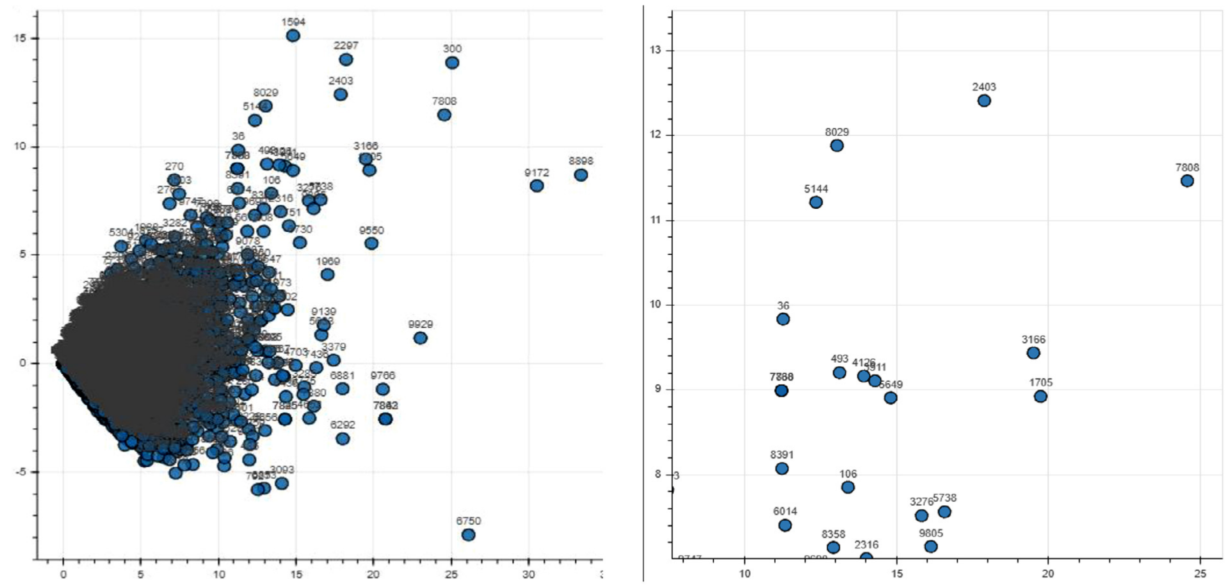
```
[(0,
  '0.184*"phone" + 0.083*"good" + 0.065*"great" + 0.039*"price" + 0.030*"love" '
  '+ 0.026*"say" + 0.025*"buy" + 0.024*"really" + 0.020*"new" + '
  '0.019*"picture"'),
 (1,
  '0.073*"work" + 0.073*"phone" + 0.031*"issue" + 0.020*"update" + '
  '0.016*"problem" + 0.016*"return" + 0.015*"unlock" + 0.015*"experience" + '
  '0.015*"buy" + 0.013*"time"'),
 (2,
  '0.040*"camera" + 0.027*"use" + 0.019*"quality" + 0.018*"feature" + '
  '0.015*"android" + 0.015*"feel" + 0.015*"make" + 0.014*"app" + '
  '0.012*"display" + 0.012*"device"'),
 (3,
  '0.067*"phone" + 0.045*"screen" + 0.030*"battery" + 0.020*"fast" + '
  '0.019*"charge" + 0.017*"use" + 0.016*"day" + 0.015*"thing" + 0.014*"time" + '
  '0.014*"want"')]
```

(b).Output of LDA model for Mobile Reviews.

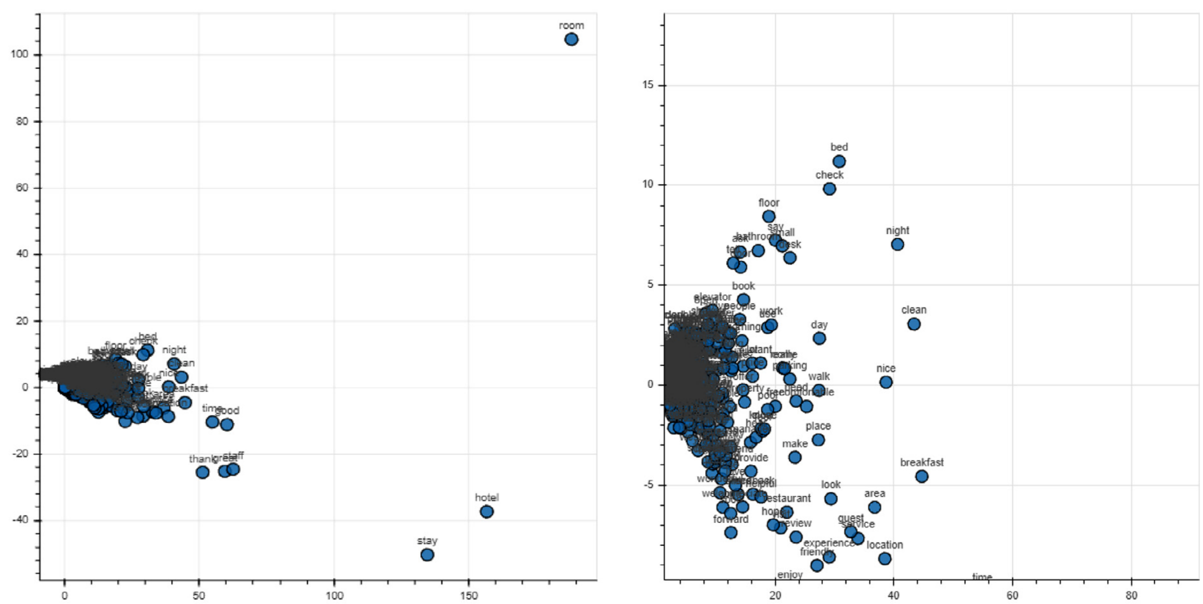
```
[(0,
  '0.019*"play" + 0.017*"life" + 0.016*"love" + 0.016*"man" + 0.015*"story" + '
  '0.014*"great" + 0.013*"woman" + 0.012*"year" + 0.011*"young" + '
  '0.011*"character"'),
 (1,
  '0.102*"film" + 0.015*"scene" + 0.011*"good" + 0.010*"character" + '
  '0.009*"story" + 0.009*"work" + 0.008*"make" + 0.007*"role" + 0.007*"look" + '
  '0.007*"shoot"'),
 (2,
  '0.009*"people" + 0.008*"know" + 0.007*"make" + 0.007*"leave" + 0.007*"live" '
  '+ 0.006*"way" + 0.006*"world" + 0.006*"come" + 0.006*"let" + '
  '0.006*"director"'),
 (3,
  '0.088*"movie" + 0.025*"good" + 0.025*"bad" + 0.021*"really" + 0.020*"watch" '
  '+ 0.018*"think" + 0.016*"time" + 0.013*"make" + 0.013*"say" + 0.011*"look"')]
```

(c).Output of LDA model for IMDb Movie Reviews.

Fig. 4a. Output of LDA model for Hotel Reviews.
Fig. 4b. Output of LDA model for Mobile Reviews.
Fig. 4c. Output of LDA model for IMDb Movie Reviews.



(a).Document-topic distribution chart for Hotel reviews.



(b).Term-topic distribution chart for Hotel Reviews.

Fig. 5a. Document-topic distribution chart for Hotel Reviews.
Fig. 5b. Term-topic distribution chart for Hotel Reviews.

0-1 for both TM methods. LSA method normally produces compact semantic representation of topics by aggregating related words. But, LDA method produces meaningful and legitimate topics compared to LSA for our datasets. If we compare LDA and LSA in terms of run-time, LDA is slower than LSA.

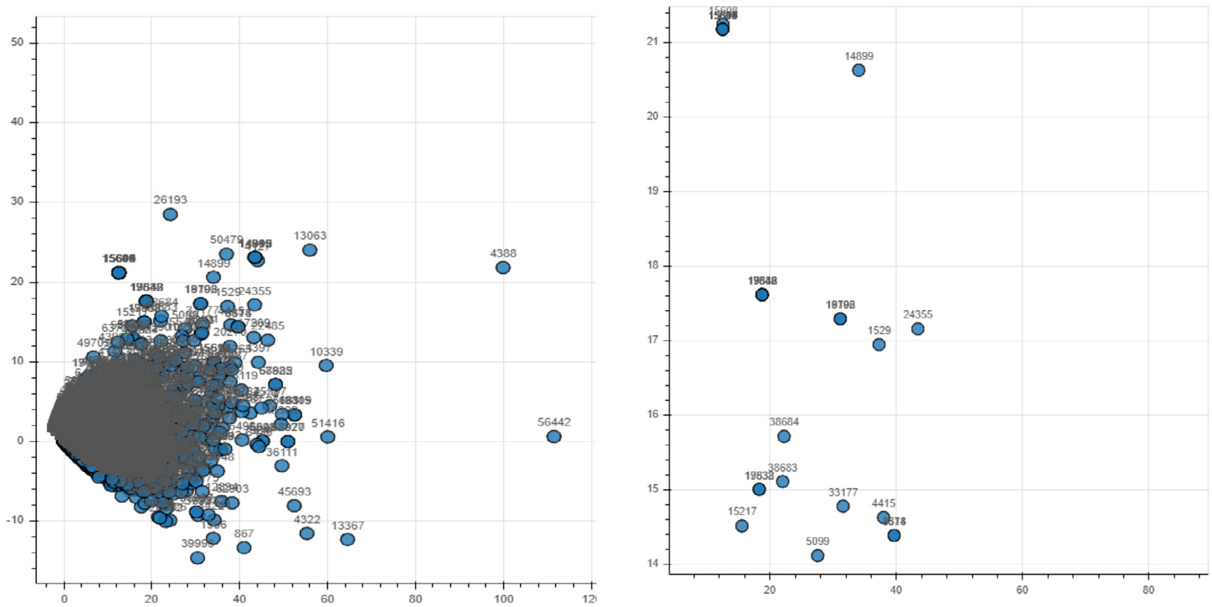
Two different multi-class classifiers such as MNB and SVM are constructed for aspect categorization. These two multi-class classifiers are evaluated using common information retrieval measures such as precision, recall, and F1 score as shown in equations (3)-(5). Precision, recall, and F1 score are defined as follows:

- Precision (P) measures the fraction of retrieved recommended objects to the actual relevant objects.
- Recall (R) measures the fraction of relevant objects among the recommended objects.
- The F1 Score (F) measure is determined by combining precision and recall and it indicates the effectiveness of the retrieval.

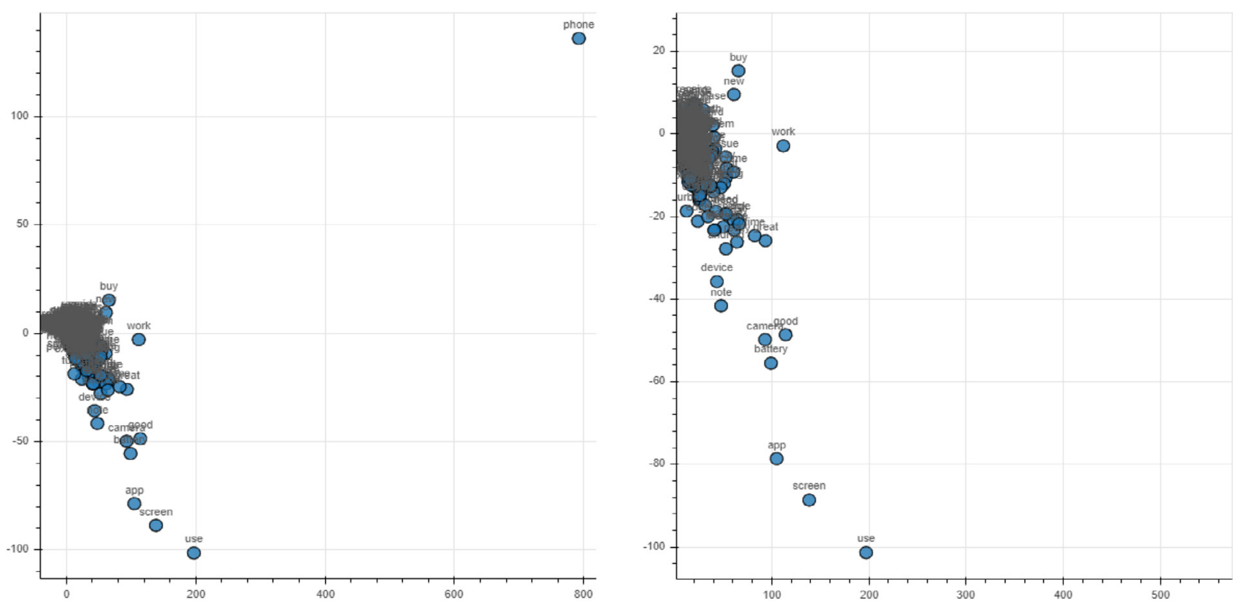
$$Precision = \left(\frac{TP}{TP + FP}\right) \tag{3}$$

$$Recall = \left(\frac{TP}{TP + FN}\right) \tag{4}$$

$$F1\ Score = \left(\frac{2.\ Precision.\ Recall}{Precision + Recall}\right) \tag{5}$$



(a).Document-topic distribution chart for Mobile reviews.



(b).Term-topic distribution chart for Mobile reviews.

Fig. 6a. Document-topic distribution chart for Mobile reviews.
Fig. 6b. Term-topic distribution chart for Mobile reviews.

Table 4
Results of LDA Algorithm with MNB classifier

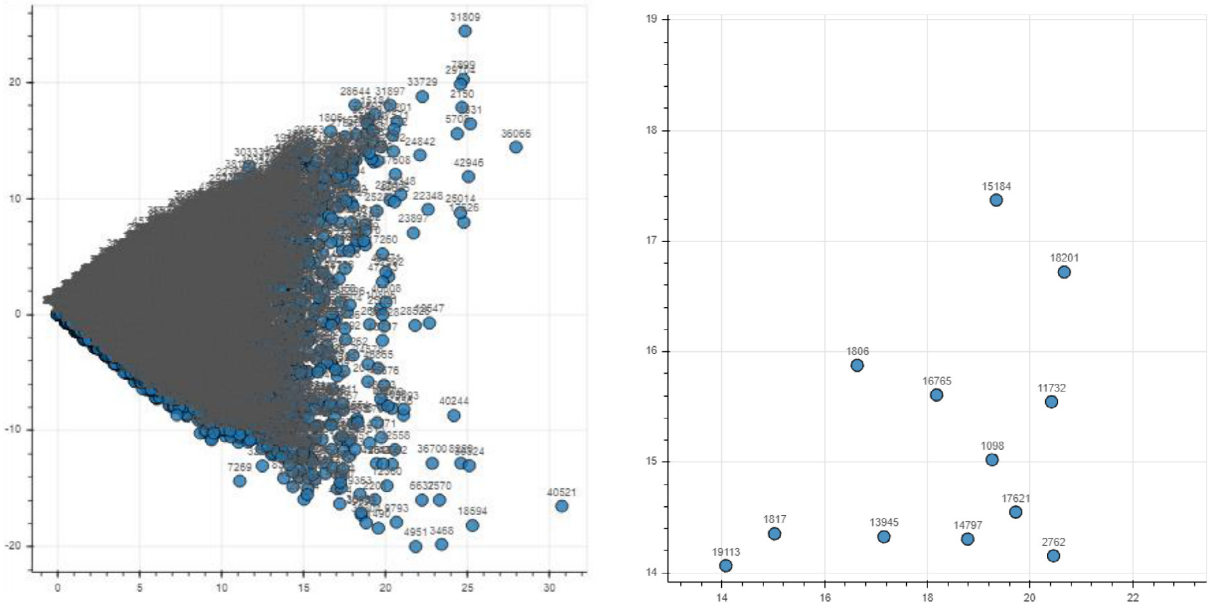
Dataset	Precision	Recall	F1 Score
Hotel Reviews	0.18	0.31	0.23
Mobile Reviews	0.59	0.77	0.67
Movie Reviews	0.15	0.38	0.21
Average	0.31	0.49	0.37

Table 5
Results of LSA Algorithm with MNB classifier

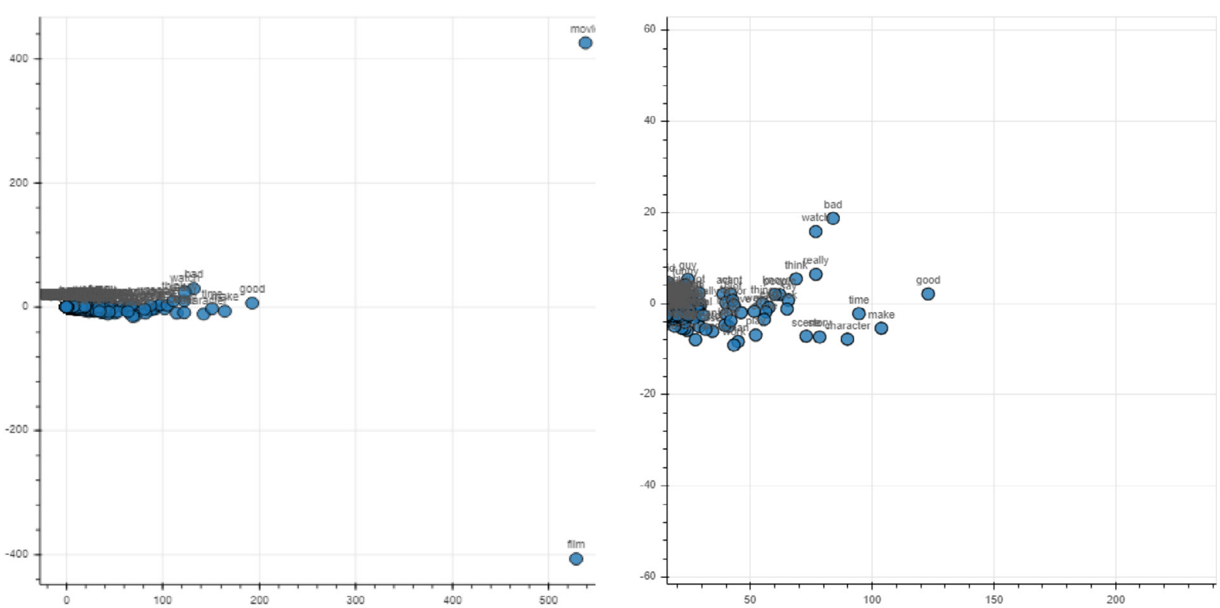
Dataset	Precision	Recall	F1 Score
Hotel Reviews	0.09	0.31	0.14
Mobile Reviews	0.21	0.46	0.29
Movie Reviews	0.06	0.23	0.09
Average	0.12	0.33	0.17

The results of different measures are shown in tables 4, 5, 6, 7. Also the Precision, Recall and F1 Score values of all the three datasets for different multi-class classifiers are aggregated to plot the graph. The aggregated results are shown in the graphs as shown in figures 11 and 12.

Based on the analysis of our results for precision, recall, and F1 Score measures, LDA performs well for our aspect extraction and categorization task than LSA with SVM classifier compared to MNB classifier.



(a).Document-topic distribution for IMDb Movie reviews.



(b).Term-topic distribution chart for IMDb Movie Reviews.

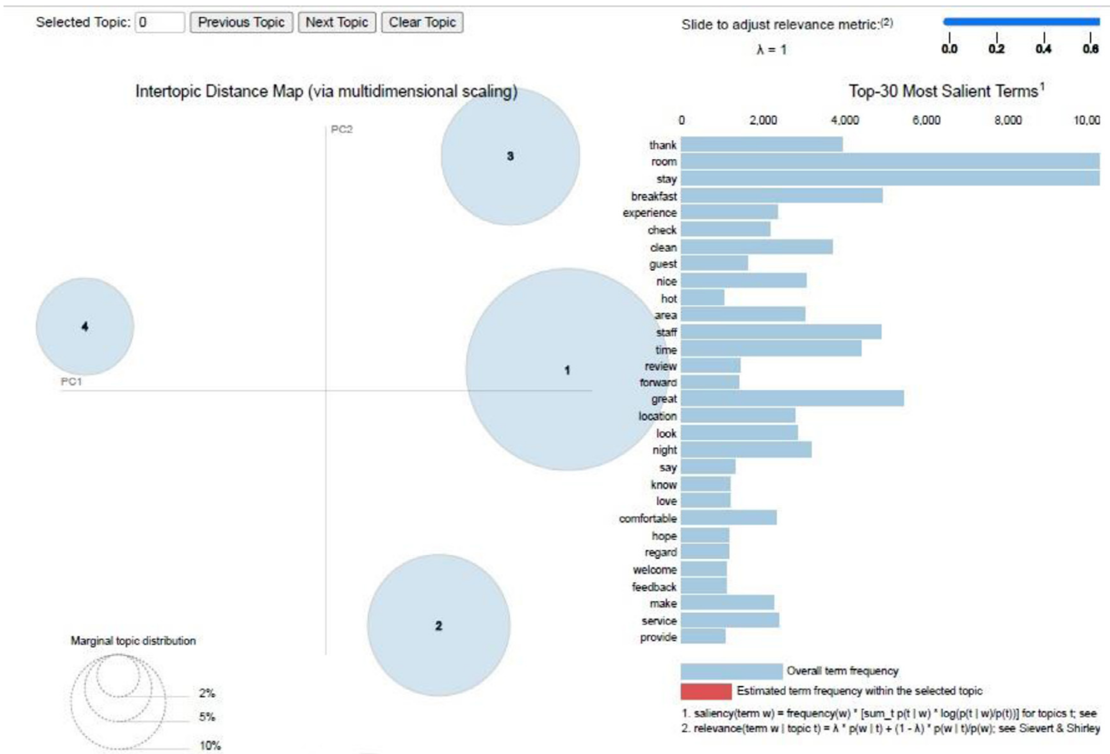
Fig. 7a. Document-topic distribution for IMDb Movie reviews.
Fig. 7b. Term-topic distribution chart for IMDb Movie Reviews.

Table 6
Results of LDA Algorithm with SVM classifier

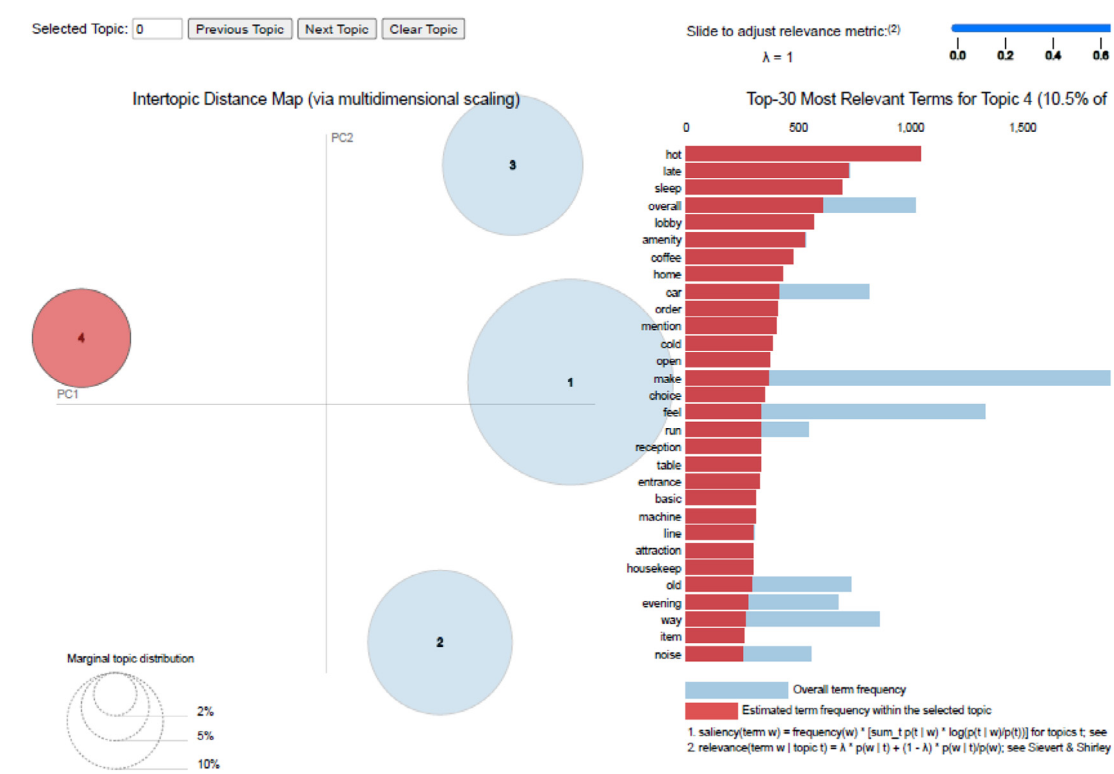
Dataset	Precision	Recall	F1 Score
Hotel Reviews	0.67	0.31	0.36
Mobile Reviews	0.72	0.69	0.7
Movie Reviews	0.57	0.31	0.36
Average	0.65	0.44	0.47

Table 7
Results of LSA Algorithm with SVM classifier

Dataset	Precision	Recall	F1 Score
Hotel Reviews	0.19	0.31	0.23
Mobile Reviews	0.53	0.46	0.46
Movie Reviews	0.33	0.46	0.37
Average	0.35	0.41	0.35



(a)



(b)

Fig. 8. Interactive visual display of LDA model results for Hotel Reviews.

Fig. 9. Interactive visual display of LDA model results for Mobile Reviews.

In one more research paper by Albalawi, Tet Hin and Morad 2020, the results of evaluation for different measures are as shown in table 8. We have done the comparative analysis of our results and their results as shown in figures 13 and 14.

The results of table 8 are plotted as graphs in figures 13 and 14. It is evident from the figures that our results of precision, recall, and F1-score measures for both LDA and LSA models are better compared to the results of paper by Albalawi, Tet Hin and Morad. Also among LDA and LSA, LDA is good algorithm for aspect categorization compared to LSA.

When all three criteria are taken into account, it is clear that both models produced satisfactory results for extracting the aspects, although the LDA model has a higher performance than the LSA with SVM classifier.

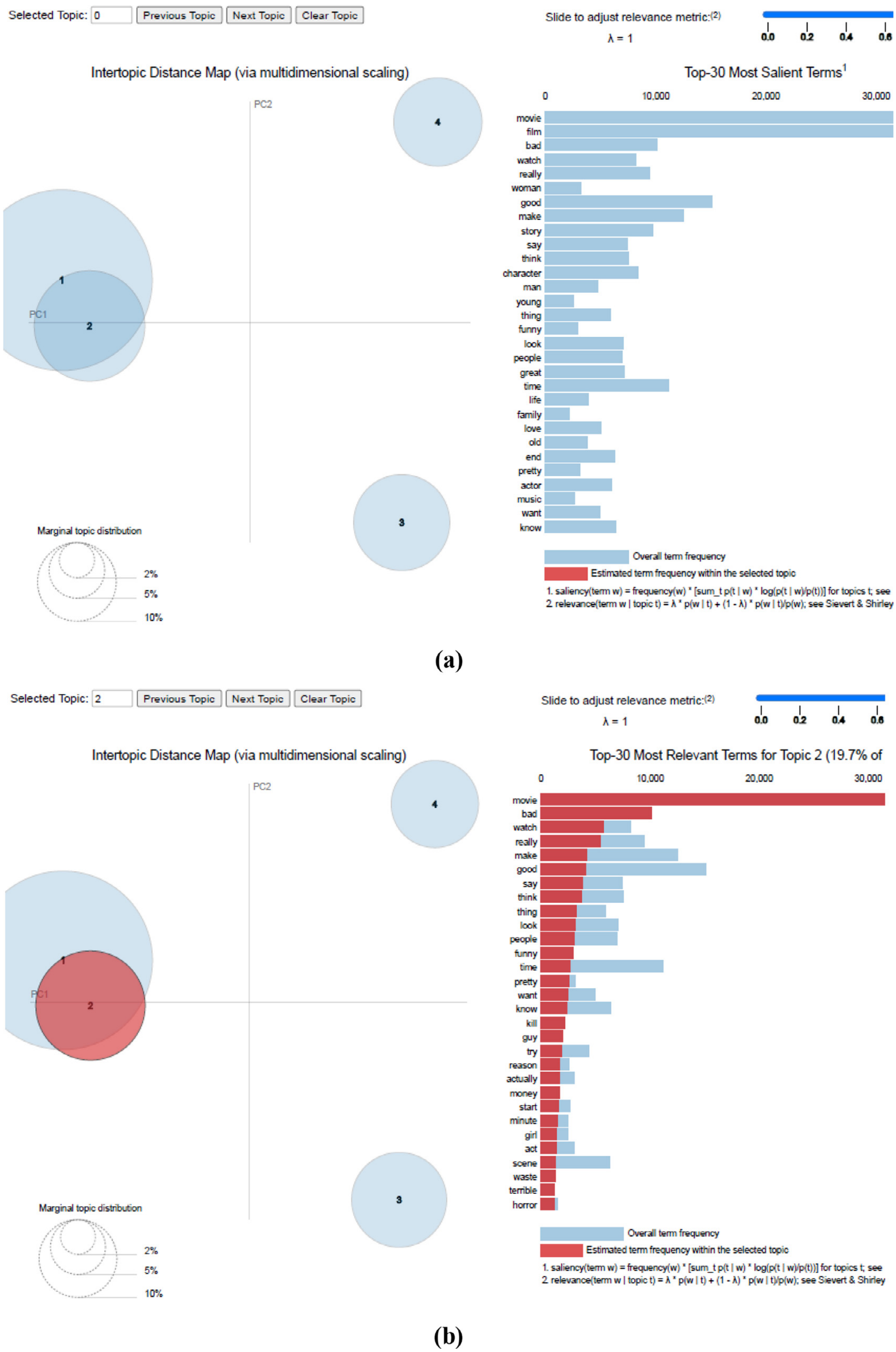


Fig. 10. Interactive visual display of LDA model results for IMDb Movie Reviews.

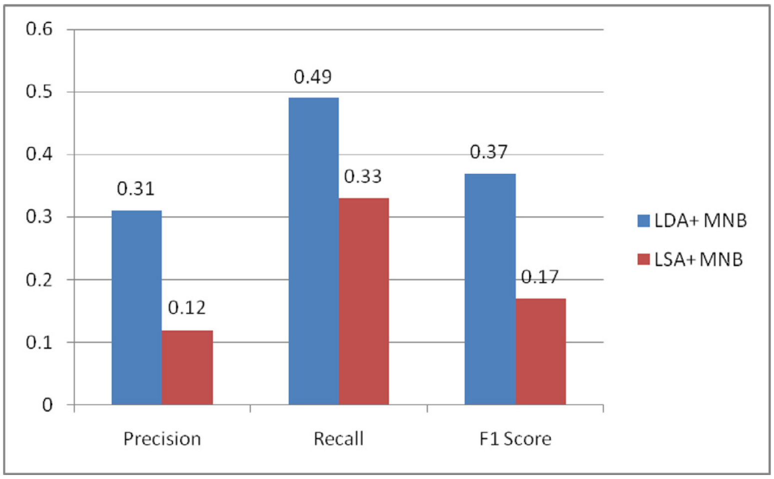


Fig. 11. Results of LDA and LSA with MNB classifier.

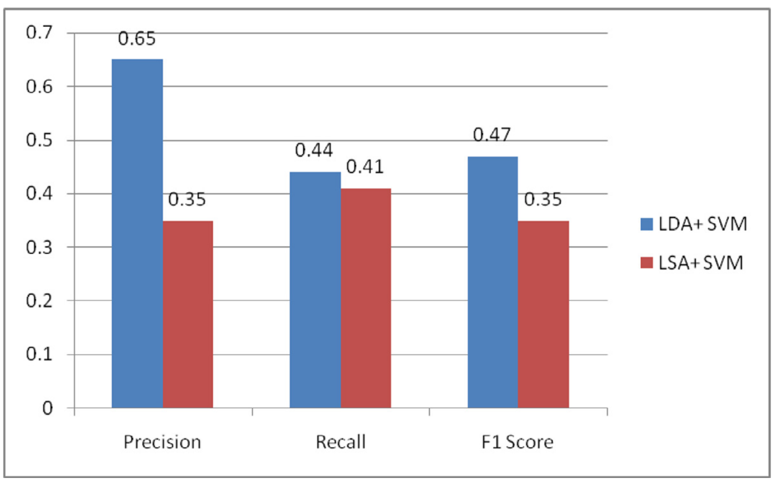


Fig. 12. Results of LDA and LSA with SVM classifier.

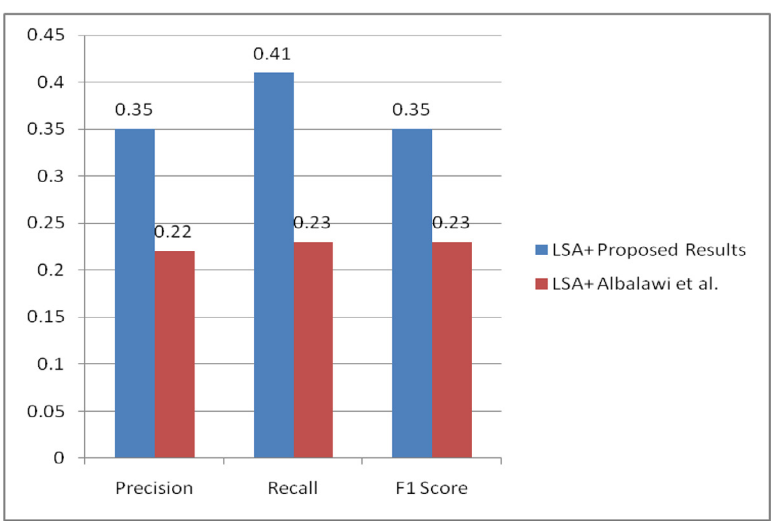


Fig. 13. Results of LSA Algorithm.

5. Discussion

The extraction of polarities pertaining to certain aspects included in the examined texts is one of the most significant study directions in opinion mining. Particularly when documents come from unidentified domains, the identification of such features may be crucial. In fact, while it is possible to train domain-specific models in certain settings to enhance the performance of aspects extraction algorithms, in others applying unsupervised approaches to make such algorithms more efficient and domain-independent in a real-time environment is the best option. The necessity to use aspect-based analysis findings to launch actions based on these facts is also becoming more and more apparent. Due to this, solutions enabling both an efficient analysis of user-generated material and an effective and simple method of showing gathered data

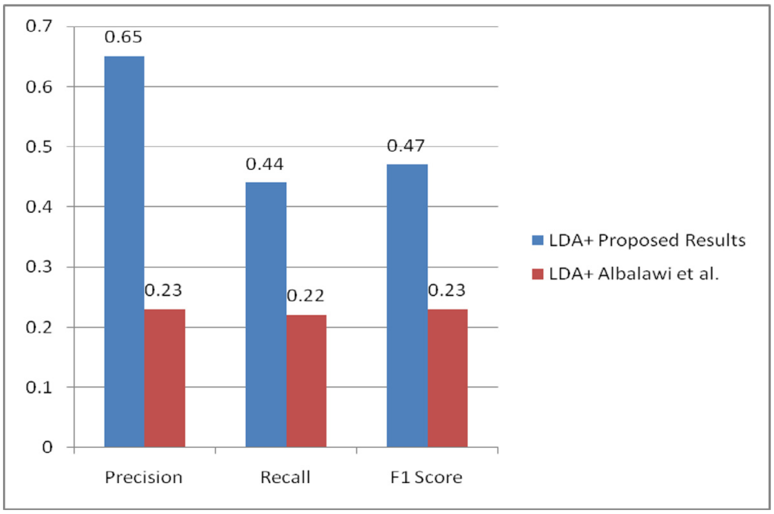


Fig. 14. Results of LDA Algorithm.

Table 8
Results of LDA and LSA Algorithms

Authors	Method	Precision	Recall	F1 Score
Proposed results	LSA	0.35	0.41	0.35
	LDA	0.65	0.44	0.47
Albalawi, Tet Hin and Morad 2020	LSA	0.22	0.23	0.23
	LDA	0.23	0.22	0.23

were required. Based on these observations, in this section contribution to the literature and practical implications of this work are presented.

5.1. Contribution to literature

The identification of the aspects, and the computation of the polarities are the two major steps involved in the aspect-based opinion mining. The former calls for distinct approaches, but the latter may be easily accommodated by employing opinion-based dictionaries. Numerous theories described in Section 2 and given in the literature suggested supervised models for extracting elements from text. Unfortunately, using a supervised technique conflicts with what is needed in the actual world. First, annotated datasets with aspect annotations for every conceivable domain are necessary for the development of a model. These datasets are no longer accessible outside of a select few domains. Second, statements from multiple of these domains may be found in a single text. Consequently, it is not practical to utilise only one model.

In light of these difficulties, the development of methodologies that can deliver efficient aspect extraction, polarity computation, and data visualisation procedures is of interest for situations where it is necessary to provide dashboards showing a real-time summary of opinion-based data-streams containing documents from unknown-at-the-outset domains. In a real-time environment, the adoption of an open information extraction approach may be appropriate. In this case, the system must effectively harvest and analyse data from every conceivable source.

The aim of this work is to provide a framework of support for opinions based on the three foundations listed below:

- The creation of a scalable platform that can process a large number of opinion-based documents in real-time,
- The design and creation of an open information extraction method to support the detection of aspects within texts,
- and the creation of a data visualization interface to facilitate easy access to the processed data.

In order to establish this work as a cutting-edge platform for the real-time administration of complicated opinion-based documents, the novel component of this solution relies on the integration of these three pillars.

One of the goals of the proposed system is to assist various user types (managers, purchasers, consumers, etc.) with a multifaceted study of the qualities of items. In fact, the biggest problem with evaluating a product using a single measure (such as total document polarity) is that it prevents consumers from getting results that are catered to their particular requirements. Customers of an online store, for instance, can be more concerned with a laptop's battery life than with its general quality. If customers are unable to rate the specific battery life element, they do not yet have the option of getting this sort of information directly from reviews.

The ease with which the domain of the studied text may be identified is another crucial factor linked to this case. It should be feasible to create domain-specific models for enabling the extraction of the aspects in this situation by assuming that a training set is available. This approach, however, conflicts with two real-world scenarios: (i) finding annotated datasets for all potential domains is challenging, and (ii) it is conceivable for words to belong to many domains inside a single document, making the use of domain-specific models impractical. In order to address these problems, we have provided an unsupervised approach based on natural language processing techniques that don't rely on domain-specific knowledge.

5.2. Practical Implications

One thing that has to be brought up is the possibility of privacy infringement while using programmes that collect information about users' preferences. We believe that, in the minds of many people, having one's public blog checked by a coffee company for favourable mentions of its product is one thing, and having one's cell phone conversations checked by the ruling party of one's own country for disparaging remarks about public officials is quite another. However, even if we focus only on the ostensibly innocent field of business intelligence, some concerns surrounding the possibility of manipulation do surface. Since they cannot control user-generated information, businesses already engage in controlling online impressions as part of routine public relations activities. However, they can focus on it carefully. They can even affect it often and even to a significant degree. There are more than twice as many businesses using social media monitoring tools that actively participate in customer dialogues as those that do not. In an effort to affect public opinion, dispel rumours, get customer input, reward loyalty, test out new concepts, or for any number of other reasons, over a third of all businesses (39%) regularly participate in online discussions with consumers.

Additionally, other apparently less severe techniques of manipulation have been proposed. For instance, one group of writers states in their analysis of the strategic ramifications for a business of providing online customer reviews that "if the seller is able to pick the time to give consumer reviews at the individual product level, it may not necessarily be optimum to supply consumer evaluations at a very early stage of new product launch, even if such reviews are accessible"[46], excerpt from the July 2004 working-paper version, and others have developed a manufacturer-oriented system that ranks evaluations "according to their predicted influence on sales", adding that they might not be the ones that are thought to be the most useful to users[47].

Opinion mining tools make it possible for users to consult a large number of strangers; yet, this also makes it more difficult for users to gauge the reliability of the persons (or "people") they are consulting. Therefore, opinion-mining systems can possibly make it simpler for users to be mislead by hostile actors, a concern that such systems' creators may want to avoid. On the other hand, an information-access system that is (perhaps unjustly) seen to be susceptible to manipulation is unlikely to be extensively utilised; as a result, developers of such systems may want to take precautions to make it challenging to "game the system".

6. Conclusion

The objective of this paper is to provide directions for researchers in the domain of Aspect-based Opinion Mining. There are two stages to aspect-based opinion mining. In the first phase of aspect and opinion extraction, an entity's aspects as well as its words are extracted. The polarity of the extracted opinion words is decided in the second step, which is the sentiment lexicon phase. Aspect extraction involves identifying the aspects from the opinionated content. These factors may be explicit or implicit. For the purpose of identifying features in reviews, a model was put out in this work. Domain dependence and the requirement for labelled data are two significant bottlenecks that this methodology can handle. For mining elements from reviews, we put up a variety of strategies. We utilised the information about word relationships in a review and the impact of an opinion word in identifying an aspect.

Three different reviews datasets such as Hotel, Mobile and Movie reviews datasets are used in this work for the evaluation of the proposed method. We have compared two of the most often used unsupervised topic modelling methods, LDA and LSA. They can both automatically extract topics from reviews, but they represent the texts in different ways. We have tested both the models on the same datasets. Our aim was to figure out which one would work best for these three datasets. And the results of our experiments revealed that both models perform effectively in the process of aspect extraction, with LDA having somewhat good performance than LSA. The extracted aspects are then categorized using two multi-class classifiers such as MNB and SVM. It is important to note that using LDA improves the categorization of topics into aspects with SVM classifier compared to the MNB classifier. Based on these insights we have proposed an unsupervised model that handles the key tasks required in a opinion mining system to discover aspects from review phrases using Topic Modeling algorithms such as LDA and LSA. The proposed method is easily adaptable to different domains or languages.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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