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Research Article

Aspect-Based Sentiment Analysis for Hotel Reviews Using a Data Augmentation Approach

Yojitha Chilukuri[1*], Ulligaddala Srinivasarao[2]

[1]St. Jude Childrens Cancer Research Hospital, 262 Danny Thomas Place, Memphis, TN 38105, USA
[2]Dept. of CSE GITAM (Deemed to be) UNIVERSITY Hyderabad, India

**Corresponding Author: ulligaddalasrinu@gmail.com*

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Abstract— The amount of user-generated textual material created by social networks, blogs, forums, and e-commerce websites is increasing at an astronomical pace. When it comes to determining the success of a product or service, the opinions of customers are critical. Due to this, interest in FE exams and assessment mining has surged. Angle's put-together feeling examination depends on extracting item qualities from client assessments utilizing subject demonstrating and Latent Dirichlet Allocation (LDA). Because of information sparsity and the non-appearance of co-event designs in short texts, LDA won't be quickly applied to client audits and other short texts. Various methods have been distributed for adapting the latest models like LDA for short. A Pachinko Allocation Model (PAM) is proposed in this paper as a one-of-a-kind methodology for opinion examination because of perspectives. The Pachinko Allocation Model is a new PAM adaptation that extracts product aspects. Data augmentation increases the text data set size for the text classification task. After that, features are extracted using TF-IDF-IC-SDF and TF-IGM methods, and the fine sentiment is extracted utilizing the opinion lexicon. According to the findings of the experiments, PAM is a competitive method for extracting aspects. The outcomes of the trial show that the novel sentiment classification approach is competitive in terms of product extraction. A statistical test has also been conducted.

Keywords— Feature Extraction, PAM, Aspect-based Sentiment Analysis, Topic Modelling.

1. Introduction

As internet apps have been more widely used, the volume of brief messages containing client conclusions in virtual entertainment and client assessments has developed massively. Along these lines, feeling examination and client assessment mining have become unmistakable review themes. Different granularities of sentiment analysis are used. Negative and positive reviews are categorized as such for a quick assessment of user attitude. However, more than SA at this level is required in most circumstances. ABSA should be used for a more comprehensive evaluation. ABSA also collects what users say about product factors, like the polarity of their feelings and preferences.

It's important to note that only the overall sentiment of a text may be discerned by "sentiment analysis" as opposed to "aspect-specific sentiment analysis." Examine the many parts of the written material, then decide the emotion connected with each characteristic. Instead of analyzing a text's overall emotion, an AB approach enables us to link distinct thoughts with different traits or qualities of an item. Sentiment analysis digs deeper into the content of a text to uncover hidden meanings. It's for this reason that the outcomes are more specific. Let's look at the COVID public and social network data. The next step is to examine the many problems and elements of COVID-19 and public opinion on them. Overall, polarity may not be a reliable signal in this situation. Please tell us what you think about this topic. Every business and service-related feedback or opinion must be analyzed similarly. This is partly because unsupervised and semi-supervised algorithms usually make many feedback data.

Singh and colleagues [1] used classic machine-learning techniques to improve sentiment analysis. However, SVM was not included in the comparison, and the One R classification was shown to be superior results. ABSA challenge on Arabic hotel reviews is performed by AL-Smadi et al. [2] utilizing RNN and SVM classifiers, which results in better classification accuracy. Using the firefly optimization approach, Kalarani et al. extract important characteristics for sentiment analysis [3]. SVM and ANN classifiers are used to analyze the retrieved features, and sentiment categorization is tested. The results suggest that ANN beats the SVM classifier by a little margin. The classification model developed by Haghnegahdar et al. is based on an ANN and a whale optimization algorithm [4]. The user's emotional disposition toward an entity or one of its elements has been built up as a long-term sentiment for a long time. The word "affective response" describes the difference between an instantaneous proclamation of an effect and a reaction to an entity or feature that has not evolved. Because they influence marketing choices in distinct ways, these factors (sentiment and emotional response) should be addressed differently. It will take time for consumers to establish a strong sense of loyalty. Thus, long-term marketing techniques will be necessary to cultivate a strong sense of customer loyalty.

Many methods proposed, such as ANN and SVM techniques, are utilized in literature studies and the no-free lunch theory. They are deep recurrent neural networks that are employed for sentiment categorization issues. This research develops an aspect-based sentiment using sentiment analysis and the Pachinko Allocation Model to categorize the sentiment analysis of essential elements of products, services, and quality. Properly selecting neuronal weights in the suggested approach will likely increase the accuracy and performance of sentiment analysis results for product-related services and quality. Comparing the mobile reviews dataset to other sentiment classification methods, such as SVM and artificial neural networks, can yield promising findings (ANN).

The main contribution of the work.

1. New methods for extracting aspects from ABSA are proposed.
2. This paper presents the Pachinko Allocation Model, a new adaption of the PAM for short texts.
3. the suggested PAM could be used in further investigations if the conditions are right.
4. Very little work has been done on aspect-based sentiment classification using the Pachinko Allocation Model.
5. The success rate of this research is higher when extracting aspects from short and lengthy phrases.

2. Literature Survey

Several studies on sentiment analysis have been published in the existing study to gather user thoughts. Researchers have been concentrating more on sentiment analysis in recent years. Maharani et al. [5] suggested using NLP and sentence syntactic analysis to extract aspects. They adhered to a set of guidelines based on the word POS tags. Liu et al. [6] created a rule-based strategy for ABSA, in contrast to earlier rule-based techniques. Traditional rule-based procedures start by establishing the rules and then applying them. The optimum set of rules could be derived from the rules already stated. The researchers developed a greedy search technique and simulated-based rule-based models. Liao et al. [7] created ABSA for Chinese Social Media Communications. The aspect words are nodes in the network, and each edge is weighted based on the emotional connection between the two nodes. The graph data structure was combined with these word embeddings. The use of sentiment analysis techniques like word embeddings has increased recently. Rezaeinia et al. [8] proposed that word embeddings in sentiment analysis have improved. The researchers considered all of the POS tags, lexicon-based techniques, word position algorithms, and word embedding algorithms, and they found a higher degree of success. Two approaches for generating sentiment analysis approaches were developed by Mowlaei et al. [9]. There are two methods for analyzing reviews: one uses a genetic algorithm, and the other is based on the frequency of phrases in favorable and unfavorable remarks. Hu and Liu [10] say that they ran trials utilizing reviews of products from several websites and their dataset.

The PDA method can process massive data sets and lengthy documents. Knowing how often a particular term appears in the document using a PDA is essential. PDA is useless for short texts because there aren't enough co-occurrence patterns and data. The study of LDA adaptation for brief texts is a hot topic. Sokhin and Butakov proposed an additive regularisation method for sentiment analysis [11]. Short-term memory-based strategies have lately risen to prominence in the ABSA challenge. PDAs and other Deep Neural Network models are employed to complete the same objective. ICU patients' clinical remarks may have been utilized to construct a mortality prediction model [12] disclosed by Jo et al., according to Liu and Jansson [13], who advise combining PDA, LSTM, and CRF to discover named items from user-generated social media data that are uncommon or new. This model simultaneously trains and learns using an LDA and an LSTM neural network. Pergola et al. [14] suggested an LDA-GRU hybrid model for feature extraction and sentiment categorization of text material. Topic embeddings and internal attention are used to address both the issue and how individuals feel about it.

Ma et al. [15] tended to a consideration model for perspective-level opinion research using installing and wise information. Dieng et al. [16] inserted a subject-to-model, which combines LDA with embedding characteristics, was developed to learn more interpretable subjects. For this, the method of amortized variation inference was recommended. Several neural network-based sentiment analysis methods have been described to demonstrate how hyperparameters impact performance. Various models were built by Bhargava et al. [17]. Xiong et al. [18] proposed a novel model, the Word-pair sentiment-based Topic Model (WSTM), for quick response. In WSTM, aspect and emotion words were both simultaneously simulated. Then, using a sliding window, these word pairs were constructed at each stage of the sliding window and added to their topic model. W2VLDA, a viewpoint extraction and feeling extremity recognizable approach based on client surveys, was introduced by Garca-Páblos et al. [19]. They combined a classifier that maximized entropy with continuous word embeddings and the LDA approach. The method uses datasets from SemEval-2016 task 5 and restaurant and electronic equipment (laptop, digital-slr) ratings discussed in biomedical analysis [20].

3. Background

In this section, explain the background and methodology of the work.

3.1 Pachinko Allocation Model

This section explains the PAM and SWN in great depth. A discrete acyclic graph (DAG) structure is used in the probabilistic Pachinko Allocation Model (PAM) [21] to show and identify sparse topic correlations. Detailed Notation in the Pachinko Allocation Model.

PAM extends the idea of themes to include the distribution of words and subjects. Topic nodes are located on the inside of the DAG, while words are located on the outside. This enables PAM to use any DAG to associate words in V with themes in T. Figure 1 depicts the PAM graphical model. Adapted from text found at [22]**.** Topic models like PAM may be used to generate and index documents like other topic models.

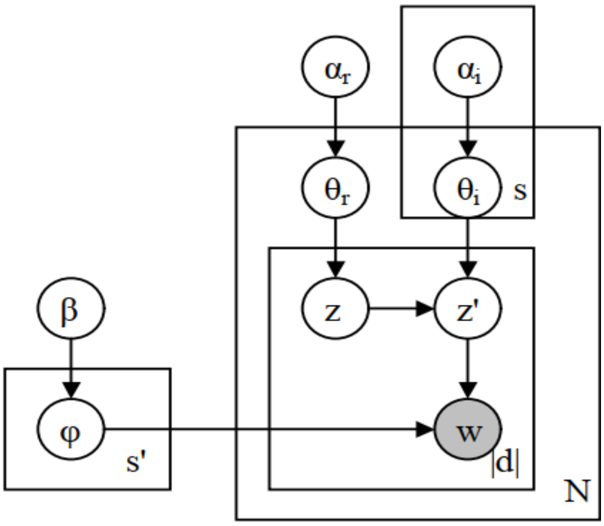

Figure 1: PAM for graphical representation

PAM can be used to create new documents and to search for documents in a database, just like other topic models.
The procedure required to create a document in PAM is as follows:

1. Sample $\theta_{t1}^{(d)}, \theta_{t2}^{(d)}, \ldots\ldots\ldots, \theta_{ts}^{(d)}$ from $g_1(a_1)$, $g_1(a_1)$,.....$g_w(a_s)$, where $\theta_{ti}^{(d)}$ is the multinomial distribution of topics t_i over its children.
2. The topical route is sampled whenever w appears in the text. Since Zw1 is the root and Zw2 through Zw Lw are topic nodes in topics T, the Zw of length Lw is sampled. Zwi is a Zw(i-1) descendant sampled using a multinomial distribution.

The combined likelihood of creating document d is established by

$$P\left(d, z^{(d)}, \theta^{(d)}/\alpha\right) = \prod_{i=1}^{s} P\left(\theta_{ti}^{(d)}/\alpha_i\right) \times \sum_{w} \left(\prod_{i=2}^{Lw} P\left(Z_{wi}/\theta_{ZwLw}^{(d)}\right) P\left(w/\theta_{ZwLw}^{(d)}\right)\right) \qquad (1)$$

The combined likelihood of creating document d is established by

$$\left(\frac{d}{a}\right) = \int \sum_{i=1}^{s} P\left(\theta_{ti}^{(d)}/\alpha_i\right) \times \prod w \sum_{z_w} \left(\prod_{i=2}^{Lw} P\left(Z_{wi}/\theta_{z_{w(i-1)}}^{(d)}\right) P\left(w/\theta_{zwLw}^{(d)}\right)\right) d\theta^{(d)} \qquad (2)$$

Documents are created using the following process: The likelihood of creating a document d is a function. Using PAM for indexing needs an inference approximating the topic's probability of being included. The themes of documents may be inferred using statistical inference methods such as Gibbs sampling.

The paper [23] is a more precise example of Markov and refers to approximation iterative methods. By sampling on variables with lower dimensions, specialized Gibbs sampling simulates a high-dimensional distribution. Each subset's value is reliant on the importance of the others. The sampled values are successfully averaged out to get as near the intended distribution as possible.

Typically, a four-level PAM is used in this situation. Modeling topic correlations with arbitrary DAGs (like PAM) is impossible in this approach. PAM offers a generic framework within which previous models, such as PAM and correlated topic models, may be seen as specific instances. A wide range of model constructions may be shown in Figure 2—source: Source [22].

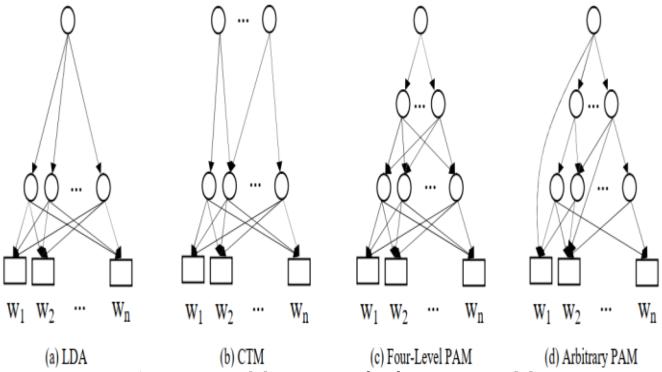

Figure 2: Model structures for four topic models

Look at the sample below to better understand how the arrows in the circles depict the distribution of each rectangle's words about its progeny. This model presents a multinomial across points for each text before delivering words from the subjects. (a) PAM: Each lower-level CTM topic has a multinomial distribution over words, and there is an additional subject with an allocation over them for each pair. (c) A four-level PAM: an arrangement of four levels that includes a root, super-points, sub-themes, and jargon. The subject relationships might be addressed via an inconsistent DAG architecture. (d) PAM: For each subject, there is a distribution of each node's progeny. Additionally, it employs various statistical techniques for topic inference, including Gibbs sampling.

Information discovered by PAM is often scarce, as we've seen in our study. It is particularly appropriate for big datasets with lots of themes, most of which only have modest amounts of vocabulary words. This approach is more effective in inference, training, and testing the models by just considering a restricted selection of topics. As a result, we can explain space and time in simpler terms.

3.2. Parameter Estimation

Note that the Dirichlet parameters are assumed to be specified in the Gibbs sampling equation. While latent Dirichlet allocation might yield reasonable results with a fundamental uniform Dirichlet, we should get familiar with these boundaries for PAM's super-themes since they catch unmistakable relationships among sub-points. A decent Dirichlet estimate is expected for the root. We could use either the highest probability or the most extreme deduced gauge to find. Hence, these methodologies have no closed-structure answers; therefore, instead of iterative methods, we use moment matching to approximate them [22]. The following principles govern the updating of parameters throughout each round of Gibbs sampling.

$$Mean_{ij} = \frac{1}{N_i} \times \sum_d \frac{n_{ij}^{(d)}}{n_i^{(d)}}$$

$$Vari_{ij} = \frac{1}{N_i} \times \sum_d \left(\frac{n_{ij}^{(d)}}{n_i^{(d)}} - mean_{ij}\right)^2 \quad (4)$$

$$m_{ij} = \frac{mean_{ij} \times (1 - mean_{ij})}{var_{ij}} - 1 \quad (5)$$

$$\propto_{ij} = \frac{mean_{ij}}{Exp\left(\frac{\sum_j log(m_{ij})}{s' - 1}\right)} \quad (6)$$

3.3 SentiwordNet

For feeling arrangement and assessment mining, we have created SENTIWORDNET 3.0, a superior linguistic [24]. It is a refreshed rendition of SENTIWORDNET 1.0, a lexical asset made open for study by the public and now licensed to over 300 research organizations across the globe for usage in a broad range of projects and research areas. All WORDNET synsets have been annotated according to the categories of "positive," "negative," and "neutral" to produce SENTIWORDNET. For each synset, three number scores (Pos, Neg, and neut) are assigned to represent the degree of positivity, negativity, and "objectivity" (i.e. neutral) of the phrases in the synsets. Because of this, multiple meanings of the exact phrase might have wildly divergent connotations. Synsets each have scores ranging from -0.75, 0.0, and 1.0; their total is 1.0. A synset might have nonzero scores in each of the three classifications, showing that the related words have some of each of the three viewpoints' connected attributes to some degree, as demonstrated by the synset.

4. Proposed method

During the design and development of ABSA, we evaluated all the difficulties that need to be addressed. The first problem is that the same product attribute might be conveyed differently. No matter how many distinct words and phrases are used, the system should be able to put them together under a single heading.

PAM-based online reviews are the core focus of this object, which aims to build an almost aspect-based sentiment analysis approach to their development. The dataset under consideration examines the pre-processing task, a collection of tokenized words that have been formed. A separate database is maintained for sentiment analysis of tokenized sentences. PAM is applied to a bag of tokenized terms to produce subject word distribution. These fundamental elements were recognized and cataloged using POS criteria and likelihood values. These aspects are graded by their probability distribution value about the subject. To better organize them, domain experts have divided them into distinct groups. The aspect categorization is aided by adding domain-specific terms as extended aspects terms. Figure 3 Workflow of the proposed model architecture of the model.

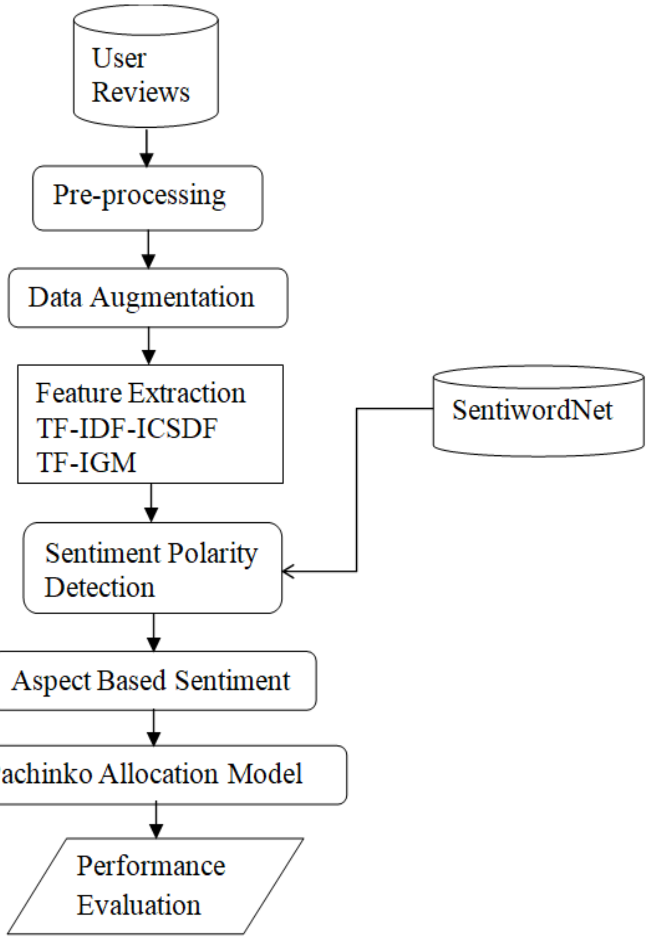

Figure 3: Outline of proposed method

Aspect categories are now used to analyze review sentences for sentiment analysis. Each phrase is associated with a specific aspect map and the emotion values that go along with that aspect map. Each facet category's sentiment is calculated. We used the SWN lexicon, a sentiment vocabulary used to classify and evaluate different types of sentiments. Each phrase's sentiment score is combined to get the average sentiment score for a given topic.

In the same way, the emotion score is determined for each of the other aspects. Using the average sentiment score, we can determine the sentiment strength of a particular aspect in the review data. Hand-annotated data is used to assess accuracy.

As shown in Figure 3, the suggested procedure's flow diagram above Table 1 shows the algorithm for the proposed method. Table 2: Algorithm for methodology.

Table 1: Proposed algorithm steps

Input: Review Data
Output: Reviews per aspect category in sentiment
Step 1: Input review corpus
Step 2: Pre-processing the data using Tokens, Stop word and PoS Tagging
Step 3: Data augmentation is by replacing words
Step 4: Feature Extraction Methods (TF-IDF-ICSDF, TF-IGM)
Step 5: Apply Sentiment Lexicon Algorithm
Step 6: Categorize aspects into various groups
Step 7: Apply the Pachinko Allocation Model for topic-word probability
Step 8: Aspect probability values

4.1 Data pre-processing
Text pre-processing is a three-step process that includes the following: 1. tokenization. Second, stop words should be eliminated through three morphological investigations (POS tagging, lemmatization, and determination of roots and suffixes of words). NLP tools are used to correct types and perform morphological analysis tasks.

4.2 Data augmentation with random word replacement
Data Augmentation aims to generate extra, synthetic training data in settings with insufficient training data. Data augmentation includes basic strategies like rules-based procedures and learnable generation-based methods, which all ensure the authenticity of the supplemented data [25]. It's important to note that the augmented data must be deemed a part of the same distribution as the original data for Data Augmentation approaches to work correctly. For example, machine translation and text categorization use the same label and similar meanings as the original data. To increase the generalizability of the following approaches, validity requires diverse supplemented data. This is the outcome of the extensive set of improved data. Various ways and augmentation effects are associated with multiple types of diversity. DA approaches are divided into three categories: paraphrasing, noising, and sampling, depending on the variety of their enhanced data. Based on correct and restricted sentence alterations, paraphrase-based approaches provide augmented data semantically similar to the original data. The enriched data convey a lot of the same information. To ensure validity, noise-based approaches introduce either discrete or continuous noise. Model robustness may be improved using these techniques. Sample-based approaches master data distributions and collect new points from within by carefully selecting sampling sites. Methods that use artificial heuristics and trained models produce more data that is more diverse and is better suited for tasks that come after.

4.3 Feature Extraction Methods
This part suggests a two-term weighting strategy called TF-IDF-ICSDF and TF-IGM to effectively communicate the ability of terms to differentiate to the vector space model. TF-IDF-ICSDF and TF-IGM are the names of these two weighing systems, respectively. They contain term frequency components from the weighting schemes "TF-IDF-ICSDF," "TF-IGM," and "TF-IGM." The research was conducted for these reasons, even though the general term weighting concerns were recognized in subsection 4.3.1 below, where the suggested weighting method and schemes are discussed in detail.

4.3.1 TF-IDF-IC-SDF
Inverse Class Space Density Frequency (IC-SDF) is a suggested strategy in the Jain research in which TF-IDF information is included as a second collection frequency component [26]. IC-SDF accounts for the distribution of inter-class documents to calculate weighting values for each term. Calculated using the TF-IDF-IC-SDF term weighting system, this term's weighting value is as follows: According to the equation above, class-specific data values (ti in this case) and the number of texts in class j are used.

$$W_{TF.IDF.ICSDF}(t_i) = TF(t_i, d_k) * \left(1 + log\left(\frac{D}{d(t_i)}\right)\right) * \left(1 + log\left(\frac{C}{\sum_{j=1}^{C} \frac{df_{ij}}{D_j}}\right)\right) \quad (7)$$

TF-IDF-IC-SDF is supervised learning because it uses information about the class of terms and gives each word a weighting score.

4.3.2 TF-IGM
This new supervised term weighting strategy combines the TF and Inverse Gravity Moment (IGM) information of terms as the collection frequency factor, and it is one of the most recently suggested ones. IGM is a statistical model modified for term weighting purposes (Chen et al., [27]). There are a few ways to compute inter-class distributions, and the IGM approach is one of the most commonly used. According to Eq. (8) (TF-IGM weighting computation).

$$W_{TF.IGM}(t_i) = TF(t_i, d_k) * \left(1 + \propto * \frac{f_{i1}}{\sum_{r=1}^{C} f_{ir} * r}\right) \quad (8)$$

The word frequency of the phrase t_i is expressed in this equation by the constant f_{ir}. Sorting documents by frequency and then by rank (r = 1,2, 3..., C) is the basis of the IGM weighting approach. The F_{ir} thus displays documents of class in which the phrase "t_i" appears the most often. Also included in this equation is the balance parameter, with a defined range of values of 5.0–9.0. It is also stated in the linked research that the anticipated value is 7.0.

4.3.3 Sentiment Lexicon
Based on the separate reviews generated by Algorithm 1, we are now ready for ABSA. For this, SWN is used as a sentiment lexicon. Every thought is analyzed using a category-specific sentiment analysis to determine its overall sentiment. Negative and positive feelings are kept distinct in the database. It's the same in every review. We looked at how people felt about a broad range of topics and how strong that feeling was for each one. The same method was used to

acquire sentiment ratings for each category. SWN, a sentiment-scoring tool that works with Synsets, is used for this purpose. The sentiment score is calculated by adding the sentiment values to each synset in a sentence.

Sentiment may be expressed as 0 (neutral) and 3 (positive). The synset's emotion is positive if the positive value is more significant than the negative value.' Similarly, the emotion is considered negative when the negative number exceeds the positive amount. To be neutral, there must be an equal amount of negative and positive. When calculating a sentence's emotion score, you add up the feelings expressed by each synset. Strongly favorable emotion is 0.75, whereas negative sentiment is 0.25.

5. Experimental results and analysis

The following details of the proposed aspect-based sentiment categorization model were attained on a computer: The system comes pre-installed with Python 3.7, Windows 10 64-bit, and 8 GB of RAM.

Two datasets from two different fields are being analyzed. Yelp's hotel reviews2 and unlocked mobile reviews from Amazon have been selected. Both datasets can be accessed for free on Kaggle. One is mobile, which includes 9716 reviews of HTC smartphones, while the Hotel dataset consists of 7897 reviews of hotels.

Table 2: Dataset statistics

Name of Dataset	Total
Hotel Reviews	7897
Mobile Reviews	9716

Table 2 displays the complete dataset. Table 3 shows the aspect-based different types of probabilities. Figure 4 illustrates the word cloud for both datasets, which depicts the most frequently occurring words. Application of PAM to the mobile domain yields the results shown in Table 5, which shows the probability of word lists.

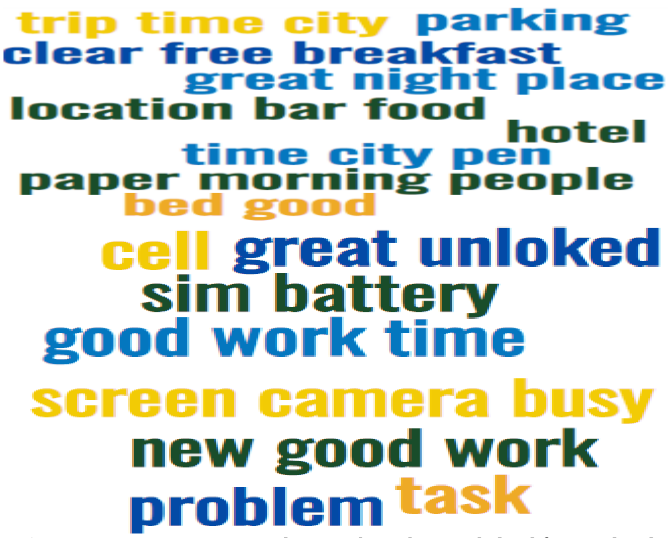

Figure 4: Frequent terms visualization through a word cloud for Hotel and Mobile dataset

Table 3: Top Aspects Extracted from the PAM Model

Aspect	Probability
Wifi	0.005
Battery	0.017
Service	0.019
Network	0.004
Screen	0.024
New	0.013
Charger	0.021

According to the SWN lexicon, 40% of mobile and hotel reviews had positive emotion, 32% had negative sentiment, and 28% had neutral sentiment. Negative sentiment in mobile and hotel review data is shown as a circle in Figure 5. As tagged reviews are not considered, 100 reviews for each domain are picked and manually labelled in terms of sentiment to test the correctness of the proposed ABSA algorithm. An equal amount of positive and negative feedback was collected for each of the twenty different aspect categories. This dataset was used to evaluate the new algorithm's efficiency. Tables 4 and 5 show the scores for each type of emotion calculated from the test data.

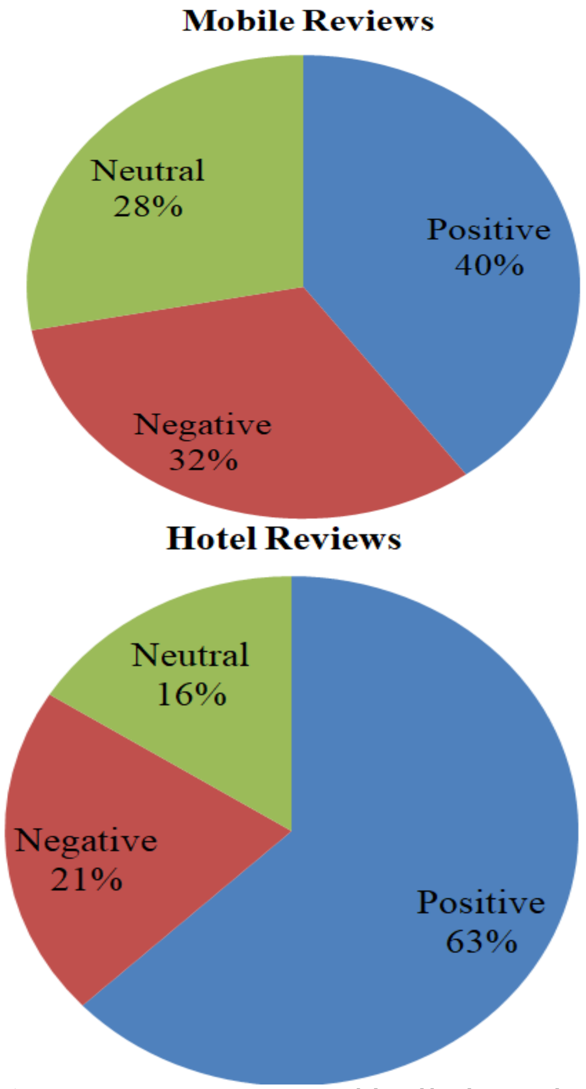

Figure 5: Categorization sentiment in mobile and hotel reviews data

For this study, an overall ABSA average value will be calculated by averaging the scores for each category. Tables 4 and 5 evaluate the performance of ANN, SVM (support vector machine), LDA, and Random Forest to determine the best method for mobile and hotel review sentiment evaluations (Positive, Negative, and Neutral), respectively. The suggested viewpoint-based opinion categorization model's presentation is evaluated using quality norms like accuracy, review, and exactness. The proposed technique beats all previous approaches, including the traditional ANN, support vector machine (SVM), LDA, and random forest. The performance metrics are represented by Accuracy (P), Precision (P), and Recall (R).

Table 4: Comparison of Positive, negative, and neutral reviews for mobile data

Method	Dataset	Sentiment	A (%)	P (%)	R (%)
PAM	Mobile reviews	Positive	97.09	96.18	98.46
		Negative	86.17	86.19	87.43
		Neutral	81.14	80.29	83.37
ANN		Positive	89.19	89.14	87.13
		Negative	83.07	83.21	85.71
		Neutral	81.51	81.59	83.74
SVM		Positive	79.09	79.01	79.46
		Negative	73.14	72.19	72.81
		Neutral	76.05	75.12	75.97
LDA		Positive	87.45	88.71	89.09
		Negative	81.24	82.19	83.76
		Neutral	75.08	72.91	72.81
Random Forest		Positive	71.19	72.57	73.87
		Negative	78.41	78.09	76.86
		Neutral	75.07	73.67	78.09

Table 5: Comparison of Positive, negative, and neutral reviews for hotel reviews

Method	Dataset	Sentiment	A(%)	P (%)	R (%)
PAM	Hotel reviews	Positive	95.11	96.51	93.36
		Negative	85.21	86.39	83.13
		Neutral	80.15	82.12	79.37
ANN		Positive	82.21	84.54	80.34
		Negative	82.17	83.21	80.81
		Neutral	81.01	82.79	81.45
SVM		Positive	78.09	79.01	77.56
		Negative	70.19	71.24	69.51
		Neutral	74.25	75.42	72.47
LDA		Positive	88.25	89.31	86.91
		Negative	83.24	85.79	80.86
		Neutral	77.58	78.11	75.14
Random Forest		Positive	76.11	77.27	74.71
		Negative	79.12	80.29	77.16
		Neutral	77.77	78.09	75.01

The effectiveness of the classifier is assessed using precision measurements. A more excellent precision score means the data is categorized more accurately and has fewer false positives. Recall measures are used to evaluate a classifier's thoroughness or sensitivity. The data is classified with fewer false negatives when the recall value is larger.

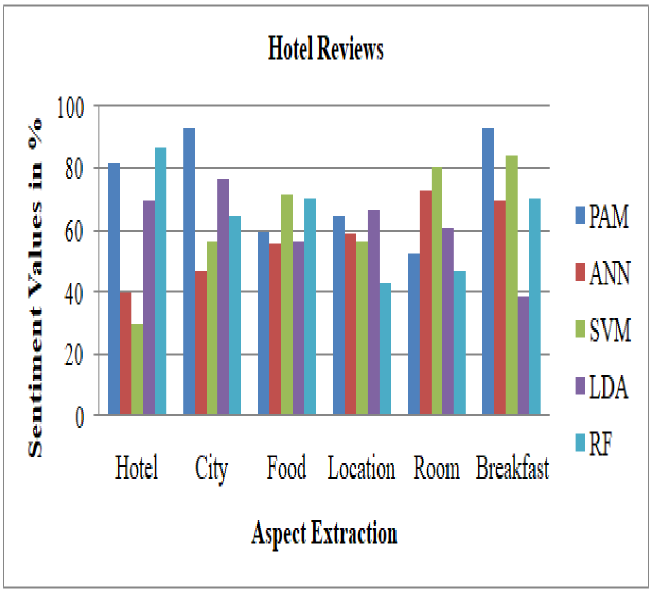

Figure 6: Aspect Sentiment Scores for hotel reviews

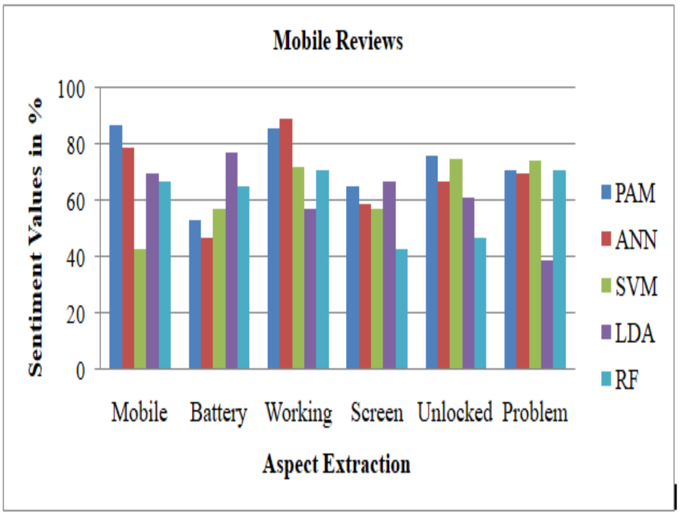

Figure 7: Aspect Sentiment Scores for Mobile Reviews

The classification algorithm's accuracy is assessed using precision. A high precision number increases the accuracy of data classification. Recall is used to gauge the accuracy of the classifier. When the recall is higher, there is a higher likelihood that the data will have fewer false negatives. The trial results were compared to current ANN, SVM (support vector machine), LDA, and Random Forest classifiers for precision, recall, and accuracy. Graphs illustrating the results are shown in Figures 6 and 7.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{9}$$

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

$$Recall = \frac{TP}{TP + FN} \tag{11}$$

Table 6: Comparison between proposed and existing methods by t-test validation

Proposed Method		P-value	H-value
		4.35e-19	2
Existing Methods	ANN	3.26e-07	2
	SVM	2.47e-o4	2
	LDA	3.96e-57	2
	Random Forest	2.67e-14	2

The analysis results above are encouraging for all mobile items in the proposed work. The t-test statistical test was employed to evaluate and compare the proposed strategy with other approaches. The testing has revealed statistically significant benefits for the new strategy over the existing ones. The results of the t-test are presented numerically in Table 6. The H value above shows that the false hypothesis can be ruled out at a 5% level of certainty. Zero indicates that the information could be more crucial. Additionally, if H has a value of "2," the knowledge is essential. It proves that the proposal method is more likely to work than alternative methods.

6. Conclusions

A strategy for extracting aspects for sentiment analysis using a PAM model is provided here. There is no need for annotated training data with the PAM technique. As a resource, a sentiment dictionary is required. This approach involves preparing datasets utilizing unstructured review data, such as tweets and SWN sentiment labeling. The method can be used for several review data types by making minor adjustments to the original. AM is an excellent approach to extracting product attributes from data, as evidenced by experiments reviewing cell phones. PAM outperformed all other works utilizing internet restaurant reviews to compare the literature. PAM outperformed the rest of the topic modeling in terms of aspect extraction. In recent years, deep learning and word embedding techniques have become popular. PAM has, therefore, been contrasted with studies in the literature that use deep learning and word embeddings for aspect extraction. The suggested course of action has been enhanced. First and foremost, the method for segmenting phrases needs to be improved. You can enhance the sentence segmentation or use different algorithms. The precision with which words are subdivided determines the overall efficacy of the proposed strategy. A statistical test has also been performed. H1 in this test has a value of "0," but H2 has a value of "2," indicating that the test's outcomes are statistically significant. A group may be used to create LDA topics in the future. The future scope of this study applies a transfer learning model to extract more aspects of the content.

Data Availability

The data supporting this study's findings are available on request from the corresponding author.

Conflict of Interest

The authors declare no potential conflict of interest.

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Authors' Contributions

All Authors contribute equally to the development and presentation of this manuscript.

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AUTHORS PROFILE

Yojitha Chilukuri received her B.Tech in Computer Science and Engineering from JNTU KAKINADA, Andhra Pradesh, in 2015 and her Master's in Computer Science from the University of Illinois, Springfield, IL, in 2016. She is a software developer at St. Jude Children's Research Hospital, Memphis, TN, and is a senior UI developer in the USA. Her areas of interest are Data Science, Data Mining, Text Mining, Sentiment Analysis, Information Retrieval, Machine Learning, and Deep Learning. She is working as a reviewer for several publishers like Elsevier, Springer, etc.

Dr. U. Srinivasarao received his B.Tech and M.Tech Degree in Computer Science and Engineering from JNTU KAKINADA, Andhra Pradesh, in 2015 and 2017, respectively, and Ph.D. in Computer Science & Engineering at the National Institute of Technology (NIT) Raipur, Chhattisgarh, in 2022. Currently, he works as an Assistant Professor in the Department of CSE at GITAM (Deemed to be) UNIVERSITY, Hyderabad. His areas of interest are Data Science, Data Mining, Text Mining, Sentiment Analysis, Information Retrieval, Machine Learning, and Deep Learning. He is working as a reviewer for several publishers like Elsevier, Springer, IEEE, etc.

