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ASPECT-BASED SENTIMENT ANALYSIS: A COMPREHENSIVE SURVEY OF TECHNIQUES AND APPLICATIONS

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ABSTRACT:
Identifying the sentiment of particular features or aspects of a service or product is the goal of the NLP subfield known as Aspect-Based Sentiment Analysis (ABSA). ABSA is a challenging task that requires the analysis of multiple aspects in a single text, as well as the identification of the sentiment of each aspect. This study presents a comprehensive summary of ABSA, including its importance, challenges, applications, and recent advances. We review state-of-the-art ABSA models, datasets, and evaluation metrics and comprehensively review their advantages and drawbacks. We also discuss the current trends and future directions in ABSA research.
KEYWORDS: Sentiment Analysis, Aspect-Based Sentiment Analysis, Aspect Extraction, Sentiment classification.

1. INTRODUCTION :

As part of NLP, ABSA seeks to identify the opinion or sentiment of a text regarding specific features or aspects of a product or service. Since social media and Online review platforms have gained significant popularity recently, ABSA has gained much attention.

This survey reviews ABSA techniques and methodologies, including various approaches for aspect extraction, sentiment analysis, and opinion summarization. We also discuss the limitations and challenges of existing techniques, such as dealing with domain-specific language and handling noisy and ambiguous text.

Moreover, we will review the applications of ABSA in various domains, including e-commerce, healthcare, social media, and politics, and examine how ABSA can inform decision-making processes, such as product development, marketing strategies, and public opinion analysis.

We also explore the latest advancements in ABSA, including the techniques, available datasets, evaluation metrics, and applications, highlighting their advantages, limitations, and future directions. In addition, we will discuss the challenges of ABSA and future work. This survey seeks to give a thorough summary of ABSA for NLP applications, aiding researchers and practitioners in its effective utilization. The survey collected 90 articles from reputable publishers such as Elsevier and Springer, using keywords like sentiment analysis and aspect-based sentiment analysis. The majority of the papers considered are from 2016 to date. Figure 1 shows the distribution of articles by year.

2. SENTIMENT ANALYSIS:

Sentiment analysis(SA) is a subfield of NLP that uses statistical techniques and machine learning algorithms to identify and extract the sentiment or opinion from the text. Its primary objective is to categorize text as positive, negative, or neutral by analyzing the expressed sentiment or emotion in the text [1]. The significance of sentiment analysis has risen in recent years, driven by the surge of data generated from social media, online reviews, and customer feedback. It enables businesses and organizations to gain insights into customer or stakeholder attitudes and opinions, facilitating informed decision-making [2]. The SA process involves text pre-processing, feature extraction, sentiment classification, and evaluation. Sentiment analysis has numerous applications in marketing, customer service, political analysis, and social media monitoring, providing valuable insights into people's attitudes and opinions toward products, services, brands, or topics. It is a helpful tool for data-driven decision-making.

Different types of sentiment analysis can be performed depending on the purpose and scope of the study [3]. Here are some common types of sentiment analysis:

- Document-level sentiment analysis: This type looks at a whole piece of writing, like a review or article, to determine the overall feeling conveyed in the text. For example, a report by a columnist on a current issue might have a negative feeling about the government's policy.
- Sentence-level sentiment analysis: This type of analysis involves determining the sentiment for each sentence within a document. This allows for a more granular understanding of the sentiment or opinion expressed in a text. For instance, the following sentence, " not only was the food not fresh but the prices in this restaurant are also very high" expresses negative sentiment.
- Aspect-based sentiment analysis: This type concentrates on particular features or aspects of a service or product, like customer service, quality of the product, or price, and finds out the sentiment related to each aspect. For example, in the comment, " the house is located in a posh locality but is far from school," the aspect of **locality** expresses positive sentiment. In contrast, the aspect of **distance** from school expresses negative sentiment.

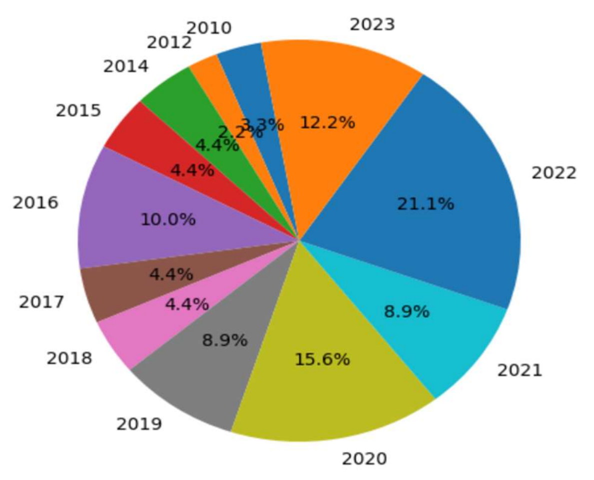

Fig-1: Year-wise distributions of articles pertaining to ABSA

- Entity-level sentiment analysis: This type focuses on specific entities, such as people, companies, or brands, and determines the sentiment expressed about them. For instance, in the sentence 'Google's Bard is a competitive response to chatGPT, ' the entities are **Google**, **Bard**, and **ChatG**PT; the sentence is neutral sentiment.

- Multilingual sentiment analysis: This type is performed on text written in multiple languages. It requires specialized techniques to accurately identify and extract sentiment from text written in different languages. For example, the sentence " ap lo ఈ status ki కారణం వారే" comprises words from English and Telugu. This undermines sentiment analysis at multiple levels, from language identification to sentiment extraction.
- Domain-specific sentiment analysis: This type is tailored to a specific domain, such as healthcare or finance, and uses specialized lexicons and rules to accurately identify sentiment in that domain. For example, the sentence "viral infections are abundant in this locality due to poor sanitary conditions resulting in the spread of Ascaris lumbricoides virus" is a negative sentiment statement of the **health** domain.
- Fine-grained sentiment analysis: This type of sentiment analysis goes beyond simply categorizing sentiment as "Positive," "negative," and "neutral" and instead determines the intensity or polarity of the sentiment conveyed in the text. For example, " I am very disappointed at the customer service in this hotel" may quantify the sentiment as one on a scale of one to five, where one represents the most negative sentiment and five indicates the most positive.

The choice of sentiment analysis type depends on the goals and requirements of the analysis. Different types of sentiment analysis may be used alone or in combination to provide a comprehensive understanding of the sentiment in a text. Table-1 Summarizes various Survey papers on Sentiment Analysis published in the past two years.

Table 1: Survey Papers on sentiment analysis

References	**Challenges**	**Advantages**	**Limitations**	**Future work**
J Cui [4] et al. (2023)	Challenges in fine-grained sentiment analysis, domain adaptation, and integrating multi-modal features	Gives an in-depth view of the evolution of sentiment analysis research and methods.	The study only considered English papers, used specific keywords, and ignored low-frequency keywords.	Expand the scope of research using different literature databases and keywords, and analyze keyword changes over time.
D Kanojia [5] et al. (2023)	Handling unstructured and noisy data and evaluating the efficacy of sentiment analysis models.	Offers insights into the practical applications of sentiment analysis and the obstacles encountered when implementing such applications.	Limited discussion on methods used for sentiment analysis	Further research on evaluating the effectiveness of sentiment analysis techniques in real-world scenarios
Mercha [6] et al. (2023)	Challenges in dealing with multilingual sentiment analysis and selecting appropriate feature	Provides an overview of ML and DL techniques used for sentiment analysis across languages	Limited discussion on the challenges of dealing with noisy and unstructured data	Further research on developing techniques for multilingual sentiment analysis

	representations for different languages			
Wankhade [7] et al. (2022)	Challenges in dealing with sarcasm, irony, and negation in sentiment analysis and selecting appropriate feature representations	Provides a comprehensive overview of sentiment analysis techniques, applications, and challenges	It does not provide an in-depth analysis of specific techniques	The paper focuses more on sentiment analysis applications rather than current research trends
Xiao [8] et al. (2022)	Challenges in integrating multi-modal features and developing techniques for sentiment analysis in non-textual data	Provides an overview of sentiment analysis techniques that utilize multi-modal information	Limited discussion on the challenges of dealing with noisy and unstructured data	Further research on developing techniques for sentiment analysis in non-textual data
Joseph [9] et al. (2022)	Challenges in selecting appropriate neural network architectures and optimizing hyperparameters	Provides an overview of DL techniques used for sentiment analysis	Limited discussion on the challenges of dealing with noisy and unstructured data	Further research on developing techniques for optimizing neural network architectures and hyperparameters

3. ASPECT-BASED SENTIMENT ANALYSIS:

ABSA is a subset of sentiment analysis that concentrates on detecting and examining the sentiment expressed towards particular aspects of a topic, product, or service. In comparison to sentence-level or document-level, ABSA offers a more detailed comprehension of the opinions and attitudes conveyed in the text [10]. The main objective is to extract and categorize a product or service's different aspects or features mentioned in a text and determine the sentiment linked with each specific aspect. For example, a restaurant review may include food quality, service, atmosphere, and price. Identifying and analyzing the sentiment associated with each aspect allows businesses to gain a deeper insight into their strengths and weaknesses.

ABSA involves several steps, including extraction of aspects, classification of sentiment, and aggregation. Aspect extraction consists in recognizing and categorizing the different aspects or features mentioned in the text. Sentiment classification involves determining the sentiment linked to each aspect, such as 'positive', 'negative', or 'neutral'. Aggregation combines the sentiment scores of each aspect to obtain an overall sentiment score for the product or service.

ABSA has numerous applications, including analysis of customer feedback, monitoring of social media, market research, etc. It can provide valuable insights into the specific areas where a product or service excels or needs improvement and help businesses make data-driven decisions based on these insights. Table-2 summarizes various survey papers on sentiment analysis published in recent years.

Table 2: Papers on Aspect-Based Sentiment Analysis Survey

References	Challenges	Advantages	Limitations	Future Work
Schouten [87] et al. (2016)	Aspect detection, Sentiment analysis, Irony, and sarcasm detection, Standardization of evaluation methodology	Fine-grained sentiment analysis, Improved decision-making, integration of knowledge	Dependency on data quality, Limited scope, language, and cultural differences.	Investigating concept-centric approaches, Developing methods to handle noisy and incomplete data, and detecting and accounting for irony and sarcasm. Investigating the impact of language and cultural differences,
H. Liu [25] et al. (2020)	The domain-dependent study, Aspect-based aspect extraction, Data scarcity	A better understanding of customer sentiment, More efficient market research, and Improved brand reputation management	Limited accuracy, Lack of context, Dependency on data quality	Developing domain-specific sentiment analysis models, Improving aspect extraction accuracy, Addressing data scarcity, Developing models that can understand context, Integrating multiple modalities
A. Nazir [86] et al. (2022)	Aspect extraction, Aspect sentiment analysis, Sentiment evolution Prediction	Improved customer satisfaction, Faster feedback processing, Better decision-making	Dependency on data quality, Limited scope, Limited generalizability	Exploring domain-specific knowledge and ontologies, Investigating the use of multi-task and transfer learning techniques.
Zhu [88] et al. (2022)	Handling Domain-specific language and terms, Data imbalance, Identifying and managing multiple aspects and sentiments	More granular insights into sentiments, Deep learning methods, Applicable to various domains	Depending on data quality, models may need to perform better on specific aspect categories or domains.	Utilizing the constituent and dependency trees for ABSA, Incorporating external knowledge, Addressing data imbalance, and Improving generalizability.
Mihaela [31] et al. (2022)	Handling complex linguistic and syntactic environments, Distinguishing between implicit and explicit	Fine-grained understanding of user sentiments, Deep learning methods,	Dependency on data quality, Models may not perform well on specific aspect categories or domains,	-Developing hybrid methods, Exploring unsupervised learning methods, Improving domain portability, and Developing end-to-end approaches.

	aspects, Dealing with noisy and ambiguous text	Applicable to various domains	Models may not generalize well	

3.1 Importance of aspect-based sentiment analysis:

ABSAis essential for several reasons [10]:

- Granularity: ABSA provides a more granular understanding of the sentiment in the text. Through scrutinizing the sentiment towards particular aspects or features of a product or service, companies can obtain valuable insights into the areas where they excel or require improvement. For example, a hotel chain can analyze feedback on different aspects of their hotel, such as rooms, food, customer service, and location, to identify specific areas for improvement.
- Actionable Insights: The insights obtained from ABSA can assist businesses in making data-driven decisions to enhance their products or services. Businesses can focus on improving those areas by identifying the aspects most important to customers and understanding their sentiments towards them. For example, a clothing brand can use this technique to analyze customer feedback on different aspects of their brand and discover that customers have issues with the speed of delivery and the ease of their returns process. The brand can then improve these areas to provide a better customer experience and increase customer satisfaction.
- Competitive Advantage: ABSA has the potential to provide companies with a competitive edge by allowing them to distinguish themselves from their rivals. By analyzing the sentiment towards specific aspects, businesses can identify the areas where they excel and highlight these strengths in their marketing and advertising. For example, a car manufacturer can use this technique to analyze customer feedback on different aspects of their cars and find out that they excel in safety features. The manufacturer can then use this information to differentiate themselves from their competitors by highlighting their strength in safety features in their marketing and advertising, ultimately improving their market position.
- Customer Satisfaction: ABSA can help businesses improve customer satisfaction by identifying the essential aspects of customers and addressing any issues or concerns they may have. By improving customer satisfaction, businesses can increase customer loyalty and retention. For example, an online retailer can use this technique to analyze customer feedback on different aspects of its service and find out that customers have concerns about delivery speed and customer service. The retailer can then improve these areas to increase customer satisfaction, ultimately raising customer loyalty and retention.
- Brand Reputation: ABSA can helps businesses monitor their brand reputation by analyzing the sentiment towards their brand and identifying any negative sentiment or issues that need to be addressed. By addressing these issues promptly, businesses can maintain a positive brand reputation and avoid potential damage to their brand. For example, a tech company can use this technique to analyze customer feedback on different aspects of their brand and find out that customers have concerns about customer service and value for money. The company can address these issues promptly to maintain a positive brand reputation and avoid potential damage to its brand.

Overall, ABSA is a crucial tool for businesses to attain a more profound comprehension of customer sentiment, detect areas for enhancement, and make data-driven judgments to improve their products or services.

3.2 Challenges in aspect-based sentiment analysis:

ABSA is a challenging task due to several reasons [11], including:

- Aspect Extraction: The first challenge in ABSA is aspect extraction, which provides for recognizing and extracting the aspects or features discussed in the text. This task is difficult, as aspects can be expressed in different forms, including nouns, adjectives, and verbs.
- Contextual Understanding: The context in which an aspect is mentioned can influence the sentiment expressed towards it. For example, the sentiment towards the aspect of "battery life" in a laptop review may differ from that in a smartphone review. Understanding the context is crucial for accurate sentiment analysis.
- Aspect Polarity Ambiguity: An aspect can have multiple polarities, and the sentiment towards it can alter based on the context in which it is referenced. For example, the aspect "price" can have a positive polarity if the product is affordable or a negative polarity if the product is too expensive.
- Data Scarcity: ABSA requires labeled data, including aspect and sentiment annotations. However, obtaining such data can be difficult and expensive, especially for specialized domains.
- Multilingualism: ABSA is challenging in multilingual environments, as aspects and sentiments can be expressed differently in different languages. This requires developing multilingual models that can accurately analyze sentiment in other languages.
- Domain Adaptation: ABSA models trained on a domain may perform poorly on other domains. Hence, it is critical to build domain-specific models or execute domain adaptation to enhance the performance of the ABSA models.

3.3 Applications of ABSA in various domains:

ABSA has various applications across different domains. Following are some examples:

- E-commerce: ABSA is extensively employed in the e-commerce industry to scrutinize customer feedback and reviews of products. Companies can determine which features of their products are most valued by customers and which require improvement. This data can be utilized to enhance product design and optimize marketing strategies.
- Healthcare: ABSA can be utilized in the healthcare industry to scrutinize patient feedback and reviews of healthcare services. The analysis can recognize the areas where healthcare providers excel and where they require enhancement. This data can be employed to improve the quality of healthcare services.
- Social media: ABSA can scrutinize social media posts and comments. This can assist companies in comprehending how their brand is perceived on social media and detecting potential issues that necessitate attention.
- Politics: ABSA can be employed to analyze public sentiment towards political topics and public figures, such as politicians. This can help politicians to understand how their policies are being received and to identify areas where they need to improve.
- Hospitality: ABSA can be used in the hospitality industry to analyze customer feedback and reviews of hotels and restaurants. This can help businesses to improve their services and to provide a better customer experience.
- Finance: ABSA can be used in the finance industry to analyze customer feedback and reviews of financial products and services. This can help financial institutions to identify customer preferences and to design products and services that meet their needs.

3.4 Procedure for aspect-based sentiment analysis:

Yadav [12] et al. outline a general procedure for ABSA as follows:

- Data collection: Collect relevant textual data from varied sources, such as product reviews or social media posts.
- Data pre-processing: Cleanse the gathered data by eliminating Unnecessary data, such as URLs, stop-words, and special characters. This phase may require stemming and lemmatization to normalize the text.
- Aspect extraction: Detect the distinct aspects or features mentioned in the text. This can be achieved through various techniques like rule-based or machine-learning algorithms.
- Sentiment classification: Determines the sentiment of each aspect, such as 'positive', 'negative', or 'neutral'. Various techniques can be employed for this, such as lexicon-based or machine-learning algorithms.
- Aggregation: Combine the sentiment scores of each aspect to obtain an overall sentiment score for the product or service. This can be done using various techniques, such as weighted aggregation or unsupervised methods.
- Evaluation: The ABSA performance can be evaluated using various metrics, including precision, recall, and F1 score.

Figure-2 represents the general procedure for ABSA, and the specific techniques and tools used may vary depending on the dataset and the requirements of the study.

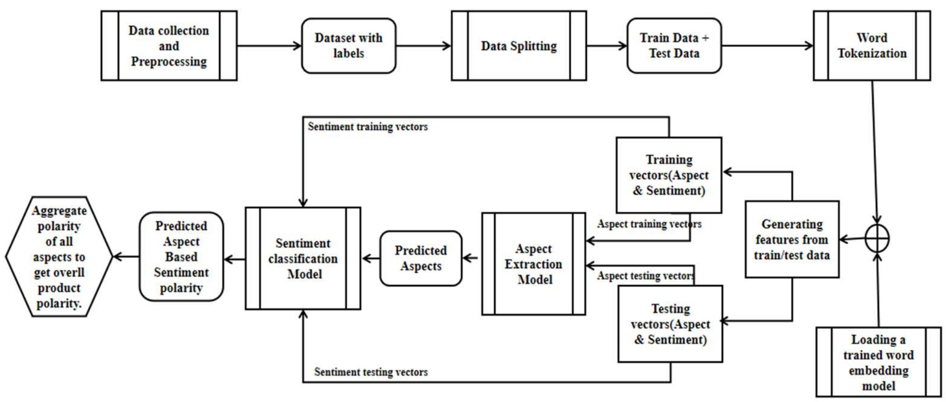

Fig 2: Procedure for Aspect-Based Sentiment Analysis

4. DATA COLLECTION:

Data collection and dataset preparation are critical steps that impact the performance of ABSA models. There are several ways to collect data for ABSA, including manual annotation, crowdsourcing, and semi-automatic techniques such as bootstrapping and active learning. The choice of data collection techniques depends on the available resources and the specific research goals. Pontiki [13] et al. discuss the data collection process for the SemEval-2016 Task 5[61], which focused on the ABSA of restaurant reviews. The authors collected a large dataset comprising 70,790 annotated ABSA tuples, 47,654 sentence level annotations across 8 languages, and 7 domains of restaurant reviews from various sources and annotated them with aspect and sentiment labels.

Datasets:

ABSA is crucial for analyzing customer reviews on products or services as they often contain valuable opinions about different features. However, one of the initial challenges of ABSA was the need for benchmark datasets. In recent years, Pontiki [59] et al. have created publicly available datasets, such as SemEval 2014 task 4, designed explicitly for ABSA. This dataset was expanded to include hotel, laptop, and restaurant reviews in English and later to multiple languages, including Arabic, Russian, Chinese, French, Dutch, Spanish, and Turkish. It encompasses reviews on cameras, laptops, mobile phones, hotels, and restaurants. Dong [74] et al. created a dataset based on Twitter consisting of 6,940 tweets. Maia[75] et al. developed the FiQA dataset, comprising financial microblogs and news headlines samples. Kessler [76] et al. created the ICWSM 2010 JDPA Sentiment corpus encompassing documents on digital devices and automotive. Finally, Toprak [77] et al. established the Darmstadt Service Review Corpus dataset, comprising reviews related to online universities and their services. These datasets provide valuable resources for researchers working on ABSA. Table-3 summarizes various existing datasets in the area of ABSA.

Table 3: Various datasets available in the area of ABSA.

Dataset Name	Domain	Language	Dataset Link
SemEval 2014 Task 4 [59]	Restaurants, laptops	English	https:// alt.qcri.org/ semeval2014/ task4/#
SemEval 2015 Task 12[60]	Hotel, restaurant, laptops	English	https://alt.qcri.org/ semeval2015/ task12/#
SemEval 2016 Task 5 [61]	Hotel, restaurant, laptops, mobile, camera	English, Russian, Chinese, Arabic, Dutch, French, Spanish, and Turkish	https://alt.qcri.org/semeval2016/ task5/#
SemEval 2017 Task 5[62]	financial news articles, microblogs	English	https://alt.qcri.org/semeval2017/ task5/#
MAMS[63]	Books, DVDs, musical instruments	English	https://www.cs.jhu.edu/~mdredze/datasets/sentiment/
SentiHood[64]	Restaurants, Hotels, Schools, Hospitals, Shops.	English	https://github.com/LorenzoAgnolucci/BERT_for_ABSA/tree/master/data/ sentihood
Yelp[65]	restaurants, shopping, beauty and spas, nightlife, automotive	English	https://www.yelp.com/dataset
SemEval-2016 Task 5[78], SentiRuEval-2015[79],SentiRuEval-2016[80]	restaurants, automobiles, telecommunication companies, or banks	Russian	https:// github.com/antongolubev5/ Russian-Sentiment- Analysis-Evaluation-Datasets

FiQA ABSA [75]	Financial microblogs and financial news headlines	in English	https://drive.google.com/file/d/1icRTdnu8UcWyDIXtzpsYc2Hm6ACHT-Ch/view
TOWE [67]	restaurant, laptops	English	https:// github.com/NJUNLP/TOWE
ASC-QA [68]	Cosmetics, Electronics	Chinese	https:// github.com/jjwangnlp/ASC-QA
ARTS [69]	restaurant, laptops	English	https:// github.com/zhijing-jin/ARTS_TestSet
ASTE-Data-V2 [70]	restaurant, laptops	English	https:// github.com/xuuuluuu/Position-Aware-Tagging-for-ASTE

5. DATA PRE-PROCESSING:

Pre-processing is an essential stage in ABSA as it guarantees that the input text is in a format that machine learning models can effortlessly scrutinize. Here are some common data pre-processing steps for ABSA:

- Text Cleaning: This step involves removing any irrelevant or noisy information from the text, such as HTML tags, punctuation, and special characters. This can be done using regular expressions or other text-processing libraries. Mohamed [14] et al. present a comparative study of various data cleaning approaches like Stop-word removal, Stemming, and Lemmatization used in sentiment analysis.
- Tokenization: In this stage, the text is divided into individual terms called tokens. Tokenization algorithms like whitespace or word-level tokenization can be utilized for this purpose. Abigail [15] et al. compared four different tokenization methods: whitespace tokenization, punctuation-based tokenization, regular expression-based tokenization, and neural network-based tokenization.
- Stop Word Removal: This step involves removing words that are frequently used that do not hold significant meaning, such as "the", "a", and "is", etc. This can be done using pre-built stop word lists or manually creating a list of stop words. Dhara [16] et al. discussed various stopword identification methods that combine both approaches, such as frequency, list, and hybrid methods. They also reviewed different stopword removal techniques, including simple, conditional, and corpus-specific stopword removal.
- Stemming or Lemmatization: This step includes reducing words to their base form, like transforming "running" to "run". Stemming trims words to their root or stem form by removing suffixes or prefixes. Lemmatization aims to reduce words to their base form or lemma, which is the dictionary form of a word. Divya [17] et al. provide a comparative analysis of lemmatization and stemming in various NLP applications. The decision to use lemmatization or stemming for an NLP task depends on factors such as the text data's nature and the level of accuracy needed.
- Part-of-Speech (POS) Tagging: This step determines the part of speech of every word present in the text, including nouns, verbs, adjectives, and adverbs. This can be done using pre-built POS tagging libraries or training a custom model. Chiche [18] et al. discuss the significance of POS tagging in NLP and its challenges, including word ambiguity and language variability. They then explain the various DL and ML approaches for POS tagging.

These pre-processing steps can decrease unwanted or irrelevant information and enhance the precision or correctness of ABSA models. However, the specific pre-processing steps may vary depending on the dataset and the specific ABSA task.

6. ASPECT EXTRACTION:

Aspect extraction is an NLP task that entails recognizing and extracting particular aspects or characteristics of a product or service: social media posts, customer reviews, and other forms of content generated by users. For example, in a smartphone review, people talk about the camera, battery, screen, and how it works. Extracting aspects is an essential step in opinion mining and sentiment analysis. It enables businesses to understand what customers like and dislike about their products or services and how to improve them. Ruskanda [20] et al. performed a comparative analysis of various rule-based techniques that can be employed for aspect extraction in sentiment analysis. The study evaluates four approaches: the Part-of-Speech (POS), dependency-based, hybrid, and ensemble methods.

Aspect extraction can be performed using various techniques [19], including rule-based and ML methods. Rule-based methods involve defining rules that identify specific patterns or phrases in the text that represent aspects or features. Supervised machine-learning algorithms include training a model on labeled data to predict the relevant aspects or features in the new text. Unsupervised methods involve identifying clusters or topics in the text that represent specific aspects or features.

Recent aspect extraction advancements include deep-learning techniques like neural and capsule networks. These techniques have shown promising results in accurately identifying aspects or features in text, especially in noisy and unstructured data such as social media posts.

Aspect extraction has numerous applications in various industries, including e-commerce, hospitality, healthcare, and more; by comprehending the specific aspects or features that customers appreciate or dislike about their services or products, businesses can make informed decisions based on data to improve customer satisfaction, boost sales, and ultimately enhance their bottom line.

6.1 Rule-based approaches for aspect extraction:

These approaches for aspect extraction rely on pre-defined patterns or rules to identify aspects of the text. These rules or patterns can be based on syntactic or semantic information, such as part-of-speech tags, dependency relations, or domain-specific keywords. Fig-3 represents how rule-based approaches work to extract aspects. Here are some examples of rule-based methods for extracting aspects:

Pattern matching: In this approach, a set of patterns or regular expressions is defined to match specific aspects or features in the text. For example, a pattern like "noun+of+product" can be used to extract aspects that are related to a product, such as "quality of the product" or "price of the product".

Lexicon-based: This approach relies on domain-specific lexicons or dictionaries to identify aspects of the text. The lexicons can contain words or phrases related to specific aspects or features. For example, a lexicon for hotel reviews may have words like "room", "staff", "location", "cleanliness", etc.

Rule-based dependency parsing: In this approach, syntactic dependency relations are used to identify aspects of the text. Dependency parsing is used to extract syntactic relationships between words in a sentence. Rules can be defined to identify specific dependencies that correspond to aspects. For example, a rule can be defined to extract the noun modified by an adjective representing an aspect.

Rule-based approaches have some advantages, such as being relatively simple and transparent, and they can work well in some domains. However, they also have some limitations, such as requiring domain expertise and the inability to capture more complex relationships between aspects and the surrounding context. As a result, they may not be as effective as more advanced machine learning-based approaches in some scenarios. Venugopalan [21] et al. proposed a hierarchical rule-based model with pruning strategies for ABSA, which performs competitively with state-of-the-art methods but needs improvement for multi-term aspect retrieval. Poria [22] et al. present a rule-based approach for aspect extraction using sentence dependency trees and common-sense knowledge, achieving higher detection accuracy than state-of-the-art methods but needing more rules for aspect extraction and extending the scalability of the aspect knowledge base. Toqir [23] et al. proposed a sequential pattern-based rule approach for aspect and opinion extraction using domain-independent opinion lexicons and pruning techniques. This approach surpasses the performance of current state-of-the-art methods. Still, it necessitates the identification of more intricate relationships among aspects and opinions and integration with refined semantic and syntactic relations, as well as other domains.

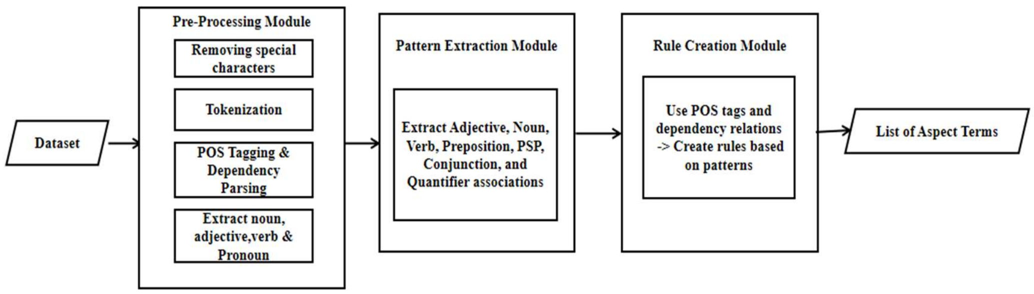

Fig-3: Rule-Based approach for aspect extraction

6.2 Machine learning-based approaches for aspect extraction:

Machine learning can extract essential parts of text using supervised or unsupervised algorithms. Supervised learning uses labeled data, while unsupervised learning does not. Machine learning is good at identifying patterns in complex situations but needs a lot of labeled data and can be computationally intensive. There are popular ML methods for aspect extraction:

6.2.1 Supervised Learning: To identify essential parts of the text, machine learning methods use supervised algorithms that learn from labeled data. These algorithms include SVM, Conditional Random Fields, and Neural Networks. Supervised learning methods can be effective for complex and variable tasks but require large amounts of labeled data and may overfit the training set. Ansari [24] et al. Proposes a supervised model for ABSAusing label spreading, kNN graph sparsification, and transductive SVM, achieving good performance with limited labeled data but is limited to specific domains and needing domain-independent feature sets.

Conditional Random Fields (CRFs): CRFs are a probability-based model for predicting structured outputs based on input data. They are commonly used in NLP, computer vision, and other fields that require structured prediction. Mathematically, a CRF is defined as follows:

CRF defines a probability distribution over an output sequence (Y) based on an input sequence (X). The input sequence comprises observations x1, x2, ..., xN, and their corresponding labels are y1, y2, ..., yN.

$$\mathbf{P(\frac{Y}{X}) = \frac{1}{Z(x)} \prod_{i=1}^{N} exp\ (\sum_{k=1}^{K} \lambda_k f_k(y_i, y_{i-1}, x_i))}$$

Where K is the number of features used to model the output sequence, λ_k is the weight parameter for feature k, f_k is a feature function that maps a label sequence and input sequence to a scalar value, and Z(X) is a normalization constant that ensures the probabilities sum up to one over all possible output sequences. Rubtsova [82] et al. describes an aspect extraction system based on a CRF algorithm with morphological features, tested on two domains, showing high precision comparable to SentiRuEval, with planned future work including adding statistical information and improving recall without reducing accuracy.

Support Vector Machines (SVMs): SVMs are ML models that can be used for both classification and regression tasks in supervised learning. In aspect extraction, SVMs can be trained to identify and extract relevant aspects of a service or product from a given text. SVMs work by identifying a hyperplane that effectively separates the data points of different classes while maximizing the distance (margin) between the hyperplane and the nearest data points. SVM can be expressed as:

$$f(x) = \text{sign}(wx + b)$$

Where x is the input feature vector, w is the weight vector that determines the orientation and slope of the hyperplane, b is the bias term that shifts the hyperplane along the axis, and sign is the sign function that assigns a label (+1 or -1) to the predicted class. In SVMs, the objective is to discover the optimal hyperplane that can effectively divide the input data points into two categories (positive and negative) based on their feature values. The model learns the weights w and bias b from the training data and applies them to predict the class label of a new data point based on its feature values. SVMs can be a powerful tool for aspect extraction, as they can effectively separate the relevant aspects from the non-relevant ones by learning a discriminative boundary between them. However, SVMs can also be sensitive to the choice of hyperparameters and the balance of positive and negative samples, which requires careful tuning and pre-processing of the data. Nadheesh [83] et al. proposed a one-vs-rest SVM classifier with new features and a pre-processing pipeline for aspect extraction on SemEval-2016 Task 5 dataset, outperforming previous results with future work on deep learning techniques and hybrid classifiers.

6.2.2 Unsupervised Learning:

These methods do not require labeled data and learn to identify relevant aspects based on their frequency, co-occurrence, or other statistical properties. Unsupervised learning algorithms for aspect extraction include Non-negative Matrix Factorization (NMF), Latent Dirichlet Allocation (LDA), and Clustering. Unsupervised learning methods can be effective for exploratory analysis or data mining tasks but may need more interpretability and require manual evaluation and refinement. Danny [26] et al. suggest using reference words and clustering, which outperforms deep learning methods but is limited to single-word aspects and needs improvement for reference word selection with hierarchical data. Benarafa [27] et al. present an unsupervised model for implicit aspect identification using KNN with WordNet semantic relations, which improves performance but needs investigation of the impact of WordNet synonym semantic relations and application to other machine learning classifiers. Chauhan [28] et al. proposed an unsupervised BERT-based attention model for aspect extraction, which captures inter-sentence dependencies, incorporates conceptual information, handles grammatically incorrect sentences, and detects domain-irrelevant aspects but requires a pre-trained language model and may not perform well in significantly different domains. Azizkhan [30] et al. suggest using topic modeling algorithms for aspect extraction, which is domain-independent and more efficient in real-time but needs more precision and recall for aspect recognition and is unsuitable for all domains.

Latent Dirichlet Allocation: LDA is an unsupervised ML technique commonly used for topic modeling, text analysis, and aspect extraction, whereby each document is modeled as a combination of topics. A topic represents a probability distribution over a collection of words, and each word is generated from one of the topics with a certain probability. LDA can be expressed as:

$$P(w,d) = \sum \theta_d \sum \varphi_k \, P(w|\theta_d,\varphi_k) \, P(\theta_d|\alpha) \, P(\varphi_k|\beta)$$

Where w is a word in document d, θ_d is the topic distribution for document d, φ_k is the word distribution for topic k, and $P(w|\theta_d,\varphi_k)$ is the probability of word w given topic k. Document d, $P(\theta_d|\alpha)$ is the probability of topic distribution θ_d given hyperparameter α, $P(\varphi_k|\beta)$ is the probability of word distribution φ_k given hyperparameter β. LDA is a technique that tries to identify the main topics in a text based on the words used. It randomly assigns topics to terms and then refines them until it finds a stable set of topics. This can identify different product or service aspects mentioned in the text. The words most likely to be associated with each topic can be extracted as crucial terms for each aspect. LDA can identify implicit aspects not explicitly mentioned in the text and handle multiple aspects and their relationships. Mohammadreza [84] et al. proposed the Enriched Latent Dirichlet Allocation method for aspect extraction. This involves integrating co-occurrence relationships as prior knowledge into LDA topic models, is language-independent, and generates prior knowledge automatically, with potential limitations in incorrect ability and complex datasets.

Non-negative Matrix Factorization (NMF):

NMF is an unsupervised ML algorithm used for dimensionality reduction and data clustering, which can also be applied for aspect extraction. It involves breaking down a non-negative matrix into two low-rank non-negative matrices to approximate the original matrix by their product. NMF can be expressed as:

$$\mathbf{V \approx WH}$$

V is the input data matrix, W is the basis matrix with non-negative columns, and H is the coefficient matrix with non-negative rows. NMF is a mathematical algorithm that finds a way to represent input data as a combination of non-negative basis vectors. Each vector represents a specific feature, and each coefficient represents its importance. It is commonly used for aspect extraction. NMF can identify patterns and handle overlapping or correlated aspects but requires manual tuning and may produce inconsistent results for some data. It is also used in other fields like image processing and bioinformatics. Qiannan[85] et al. propose an NMF method for implicit aspect extraction that utilizes semantic regularities and does not rely on rule-based methods.

Clustering: Clustering is an unsupervised technique for grouping similar data points into clusters, which can also be applied for aspect extraction. The idea behind clustering is to partition the data points into clusters based on their similarity or dissimilarity so that the data points belonging to the same cluster are more comparable to those assigned to other clusters. Clustering can be expressed as:

$$\mathbf{C = argmin \sum_{i=1}^{k} \sum x \text{ in } C_i \, d(x, c_i)^2}$$

Where C is the set of clusters, a number of clusters denoted by k, C_i is the i-th cluster, data point is represented by x, c_i is the centroid or representative of the i-th cluster, $\mathbf{d(x, c_i)}$ is the distance or dissimilarity between x and c_i. Clustering is a method of grouping data points based on similarity to minimize the within-cluster variance and maximize the between-cluster conflict. The algorithm randomly assigns data points to clusters and updates the assignments and centroids iteratively until the clustering is optimized. Clustering can be applied to aspect extraction by representing data points as feature vectors and interpreting the resulting clusters as aspect groups. Each cluster's most frequent words or phrases can be extracted as aspect terms. Clustering can identify diverse aspects and handle partially labeled or noisy data. Nazir [86] et al. propose a clustering approach for simultaneous feature and aspect extraction from online reviews that outperforms state-of-the-art methods, does not require seed terms, and plans to leverage domain knowledge for improved aspect selection in future work.

6.2.3 Semi-supervised Learning: These methods do not require fully annotated data for training. Semi-supervised methods leverage a less amount of labeled data and a more significant amount of unlabeled data to learn representations that can be used for aspect extraction. On the other hand, unsupervised methods do not require labeled data and can automatically discover aspects of text using clustering or topic modeling techniques.

6.2.4 Hybrid Approach: A hybrid approach in machine learning combines multiple techniques to improve the system's accuracy, efficiency, or robustness. Ensemble learning is a typical hybrid approach that integrates various models to make final predictions. Hybrid methods can be customized and optimized for specific tasks but may require more resources and expertise. Ganpat [29] et al. present a hybrid unsupervised approach combining linguistic rules and deep-learning techniques for aspect term extraction, outperforming recent and baseline techniques and reducing the cost of manual annotations but relying on linguistic rules and needing improvement for aspect co-referencing between multi-sentence reviews.

6.3 Deep-learning based approaches for aspect extraction:

Deep-learning (DL) techniques have been widely used in aspect extraction, attaining the best-performing results in many cases. Figure-4 illustrates the contrast between traditional ML and DL methods for feature extraction, which form the basis for the classifier's operation. Some standard DL methods used in aspect extraction are:

Convolutional Neural Networks (CNNs): CNNs are a type of DL algorithm used for signal and image processing, which can also be applied for text analysis, including aspect extraction and ABSA.

The basic idea behind CNNs is to learn local and hierarchical representations of the input data by applying multiple convolution and pooling layers to extract features at different resolutions and scales. The simple CNN model can be expressed as:

$$\mathbf{y = f(W_2 \cdot max(0, W_1 \cdot x + b_1) + b_2)}$$

Where input data is represented by x, such as a sentence or a document, W_1 and W_2 are the weighted matrices of the convolution and pooling layers, b_1 and b_2 are biased vectors of the convolution and pooling layers, max(0, z) is the ReLU activation function that sets negative values to zero, f(z) is the output function, such as a softmax function for classification.

CNNs learn important features in input data by convolving filters and pooling the outputs. They are trained on labeled datasets and can be adapted to new tasks. For aspect extraction and ABSA, input is represented as embeddings, and output is aspect or sentiment labels. CNNs can learn local and context-dependent features and capture interactions between aspects and sentiments. Hu Xu1 [34] et al. propose a model using DE-CNN for aspect term extraction, outperforming state-of-the-art without additional supervision and with a simple yet effective approach but with potential errors in inconsistent labeling and unseen aspects in test data and max pooling losing word positions.

Recurrent Neural Networks (RNNs): RNNs are a class of ANN that has the ability to capture temporal or sequential information in the input data, which is particularly useful for text data where the definition and usage of a term within a given context can depend on the previous words or sentences. At the core of RNNs is the concept of processing input tokens one by one, and at each time step, the hidden state is updated by considering both the previous hidden state and the current input. The RNN can be expressed as:

$$\mathbf{h_t = f(W_x h * x_t + W_{hh} * h_{t-1})}$$

Where h_t is the hidden state at time t, x_t is the input token at time t, $W_x h$ and W_{hh} are the weight matrices that connect the input and hidden layers, f is the activation function that introduces non-linearity to the model. RNNs map input tokens to a hidden state that captures context. They can be combined with other layers to extract aspects/sentiments from the text. For ABSA, RNNs classify aspect sentiment based on context. They need extensive labeled data and tuning and may need help with gradients and overfitting.

Long Short-Term Memory Networks (LSTMs): It is a type of RNN often used in NLP. LSTM learns a sequence of representations of input data, where each representation captures context and dependencies from the previous ones. The LSTM can be expressed as:

$$\mathbf{i_t = sigmoid(W_i\,[h_{\{t-1\}}, x_t] + b_i)}\ ,$$
$$\mathbf{f_t = sigmoid(W_f\,[h_{\{t-1\}}, x_t] + b_f)}\ ,$$
$$\mathbf{o_t = sigmoid(W_o\,[h_{\{t-1\}}, x_t] + b_o)},$$
$$\mathbf{g_t = tanh(W_g\,[h_{\{t-1\}}, x_t] + b_g)},$$
$$\mathbf{c_t = f_t * c_{\{t-1\}} + i_t * g_t},$$
$$\mathbf{h_t = o_t * tanh(c_t)}$$

Where at time t the input is x_t, $h_{\{t-1\}}$ is the hidden state at time t-1, i_t is the input gate, f_t is forget gate, o_t is output gates, the cell state is c_t, the candidate cell state is g_t, W_i, W_f, W_o, W_g are the weight matrices for each gate, b_i, b_f, b_o, and b_g are the bias vectors for each gate, tanh, and sigmoid are activation functions. LSTM selectively updates cell and hidden states based on input, previous state, and forget gate to learn relevant information from input sequences. The output gate controls relevance, and the cell state preserves long-term dependencies. For aspect extraction and ABSA, input sequences can be represented as word embeddings, with output interpreted as aspect terms or sentiment labels. LSTM can model complex dependencies and long-range contexts and handle variable-length inputs and outputs. Widhianto [32] et al. proposed a DL model using CNN and LSTM for aspect extraction in restaurant reviews of Indonesian, outperforming traditional methods but facing challenges with out-of-vocabulary words and imbalanced data distribution. Rodrigues [33] et al. present a model using POS-AttWD-BLSTM-CRF for aspect-based sentiment analysis, requiring minimal feature engineering and achieving promising results compared to state-of-the-art but with potential limitations in the automatic selection of relevant POS tags and lack of manual selection.

Transformer models: Transformer models, such as BERT and RoBERTa, have been successful in aspect extraction. These models are trained on existing data to understand the contextual relationships between words within a sentence. Fine-tuning a pre-trained model on annotated data or using the model as a feature extractor and training a separate classifier on top of the extracted features are two common approaches for transformer models in aspect extraction. Overall, transformer models have shown great promise in aspect extraction and are likely to play a significant role in future research. Entony [35] et al. present a DILBERT model for aspect extraction in Amazon laptop reviews and Yelp restaurant reviews, outperforming state-of-the-art with a fraction of the unlabeled data but not discussing its application to other tasks besides aspect extraction or its effectiveness across different languages.

7. SENTIMENT CLASSIFICATION:

Sentiment classification determines a given text's polarity (positive, negative, or neutral). Here are some common sentiment classification techniques:

- **Rule-Based Systems:** Rule-based sentiment analysis maps specific words or patterns to sentiment polarities (positive/negative). For example, "good" is positive, while "bad" is negative. Rule-based systems are simple but struggle with complex text. Vashishtha [36] et al. proposed a fuzzy rule-based method for sentiment analysis of Twitter posts. It uses multiple lexicons and NLP techniques to classify positive, negative, or neutral posts. The approach can handle vague and ambiguous language and work with any lexicon and dataset. VADER lexicon is useful for micro-blogging sites.

- **Lexicon-Based Methods:** Lexicon-based sentiment analysis uses pre-built sentiment lexicons or dictionaries to assign sentiment polarities to words. To calculate the sentiment score of a text, the polarity scores of the individual words in the text are summed up. This method is more accurate than rule-based systems but may require domain-specific sentiment lexicons to improve accuracy. Farah [37]et al. propose an N-gram approach with existing lexicons to classify sentiment across multiple datasets. Future work suggests the use of DL methods and advanced feature selection techniques. Hota [38] et al. analyze Twitter sentiment during the COVID-19 pandemic using a lexicon and VADER-based approach, focusing on improving performance for the hardest-hit countries in future work. Machová [39] et al. introduce an automated method for lexicon labeling using particle swarm optimization to improve opinion classification in Slovak language reviews. Future work includes extending the approach to different domains and potential applications in emotion analysis and recognizing antisocial behavior.

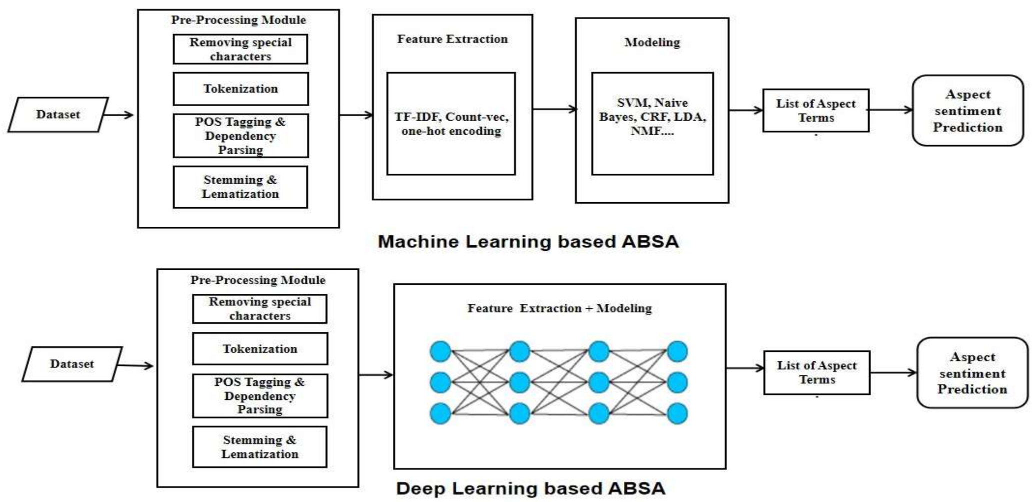

Fig-4: Difference between Machine learning & Deep learning Approaches

- **Machine Learning Algorithms:** This approach entails training a machine learning model on a dataset of labeled texts and their associated sentiment polarities. Standard ML algorithms used for sentiment classification include SVM, Naive Bayes, Decision Trees, etc... ML algorithms are highly accurate and can be trained on large datasets but may require significant computational resources not to be interpretable. Kamal [40] et al. evaluate the performance of different classifiers on COVID-19-related tweets, suggesting a comparative analysis of ML-based classifiers. Saranya [41] et al. proposed an ML-based sentiment analysis method using Random Forest on Twitter data, with future work exploring TF-IDF and deep intelligent wordnet lemmatize. Sinha [42] et al. investigate the effectiveness of various ML algorithms for sentiment analysis on tweets and movie reviews, with future work exploring the use of these techniques on text-based data. Benrouba [43] et al. propose a solution for filtering emotionally harmful content on Twitter using the Twitter API and Natural Language API, with future work exploring the use of this approach on other social media platforms. Michele [44] et al. proposed a financial market-adapted BERT model for sentiment analysis on COVID-19-related news articles, with future work exploring the impact of news sentiment on financial markets. Huwail [45] et al. compared the performance of neural network-based ML methods and topic models for sentiment analysis on consumer reviews, with future work exploring the use of these techniques for diagnostics and predictions.
- **Deep Learning Methods:** These methods use neural networks with multiple layers to learn and classify sentiments. Despite the significant data and computational requirements for training, these methods can attain a high level of accuracy in sentiment classification. Popular DL models for sentiment

classification include CNNs, RNNs, LSTM, and Transformer models. Kaur [46] et al. propose an LSTM model for sentiment analysis on online reviews, with future work exploring consumer review summarization and making the model language independent. Padma [47] et al. proposed a bimodal sentiment analysis approach using the MOUD dataset, with future work exploring integrating nonverbal communication methods to increase accuracy. Kim [48] et al. present a CNN model for sentiment analysis on movie reviews, with future work exploring the application of the model to other classification tasks. Amit Kumar [49] et al. proposes a CNN and Word2Vec model for sentiment analysis on short sentences, with future work focusing on improving DL methods for longer sentences. Lu Chen [50] et al. proposes a modified Tree-LSTM model for sentiment analysis on complex sequential data, with future work exploring other deep learning algorithms and architectures. Tabinda [51] et al. propose a BERT-based CBRNN model for sentiment analysis on social media reviews. Future work will apply the model to other resource-poor languages and multi-class classification. Leeja [52] et al. propose a BERT, ROBERT, and ALBERT model for sentiment analysis on the IMDB dataset, with future work building a generalized hybrid model. Kian[53] et al. propose an ensemble hybrid DL model for sentiment analysis on multiple datasets. Future work will explore alternative data augmentation techniques and apply the model to other sentiment analysis tasks and domains. Abayomi [54]et al. propose combining BERT with CNN, RNN, and BiLSTM for sentiment analysis on tweets. Future work explores sentiment analysis on non-online data and other transformer models like RoBERTa.

- **Hybrid methods:** combine the above techniques, where different methods are used at various stages of the sentiment classification process. An example of a hybrid approach could be using a combination of a rule-based system and ML techniques to identify words and phrases that express sentiment. Kathuria [55] et al. proposed a hybrid approach combining lexicon and ML techniques to analyze students' feedback for teaching improvement. Future work will extend the approach to other domains and datasets. Zainuddin [56] et al. propose a hybrid approach with feature selection using PCA, LSA, and RP for ABSA on the STC dataset. Future work will investigate the approach's effectiveness on other social media platforms. Saha [57] et al. proposed a hybrid model with BiLSTM and CNN for sentiment analysis of Bangla News comments, achieving an accuracy of 89.89% and extending the approach to other domains and languages with future work. Ramaswamy [58] et al. proposed a hybrid model combining an external database and LSTM with CNN and attention mechanisms for aspect-level sentiment analysis on five online datasets. Future work will enhance the ensemble application for five-way sentiment classification.

The choice of sentiment classification technique depends on the text data's nature, the desired accuracy level, and available resources. By accurately classifying sentiment, businesses can gain valuable insights into customer opinions and feedback, helping them make informed decisions to improve products and services. Table-4 summarize research papers from this paper on different methods for aspect extraction and sentiment classification in ABSA.

Table 4: Research Papers on Different Methods for Aspect Extraction and Sentiment Classification in ABSA.

	Rule-based method	**Lexicon based**	**Machine learning based**	**Deep learning**	**Hybrid**
Aspect extraction	[20],[21], [22],[23]	-	[24], [25], [81], [82], [83], [26], [27], [28],	[32], [33], [34], [35]	-

			[30], [31], [84], [85], [86], [29]		
Sentiment classification	[36]	[37],[38], [39]	[40], [41], [42], [43], [44], [45]	[46], [47], [48], [49], [50], [51], [52], [53], [54]	[56],[57], [58]

8. AGGREGATION:

Aggregation in ABSA combines sentiment scores or polarities for individual aspects or features of a product or service to derive a sentiment score for the entire text. Aggregation aims to provide a more informative and meaningful representation of the sentiment expressed in the text, considering the opinions expressed for each aspect. Pavlopoulos [66] et al. proposed a decomposition approach for aspect aggregation at multiple granularities in ABSA using agglomerative clustering and WordNet-based similarity measures with a novel sense pruning mechanism. Future work could explore more advanced semantic similarity measures and incorporate domain knowledge for better performance.

There are several methods for aggregating sentiment scores in ABSA, including:

- Average aggregation: In this method, the sentiment scores for all aspects are averaged to derive a comprehensive sentiment score for the entire text. This method assumes that all aspects are equally important, and their sentiment scores contribute equally to the overall sentiment score.
- Weighted average aggregation: This method is similar to the average aggregation, but it considers the relative importance of each aspect by assigning weights to them. The weights can be based on the frequency of the text's aspect, the aspect's significance to the product or service, or other factors.
- Majority voting aggregation: In this method, the sentiment score for each aspect is classified into positive, neutral, or negative. The overall sentiment score for the text is then determined by taking the majority sentiment class among all aspects.
- Best aspect aggregation: In this method, the aspect with the highest sentiment score is selected as the representative aspect for the entire text. The sentiment score of the chosen aspect is then used as the overall sentiment score for the text.

Aggregation is a critical step in ABSA as it provides a more comprehensive and informative view of the sentiment expressed in the text. However, it is essential to note that the choice of aggregation method can affect the accuracy of the sentiment analysis results. Therefore, it is necessary to carefully evaluate and select the appropriate aggregation method based on the specific needs and characteristics of the text and the application domain.

9. EVALUATION METRICS & RESULTS:

In ABSA, various metrics are employed to assess the performance of sentiment analysis models. Here are some metrics that are frequently utilized with their formulas:

- Accuracy: It determines the percentage of instances correctly classified by a model. Accuracy is computed by dividing the number of correct predictions by the total number of predictions made by the model.

$$\mathbf{Accuracy} = \frac{(\mathbf{TP} + \mathbf{TN})}{(\mathbf{TP} + \mathbf{FP} + \mathbf{TN} + \mathbf{FN})}$$

Where TP=True Positives, TN=True Negatives, FP=False Positives, FN= False Negatives

- Precision: Precision measures the proportion of true positives among all predicted positives. It is calculated as the number of true positive predictions divided by the total number of predicted positive instances.

$$\textbf{Precision} = \frac{\textbf{TP}}{(\textbf{TP} + \textbf{FP})}$$

- Recall: Recall measures the proportion of true positives among all actual positives. It is computed as the number of true positive predictions divided by the total number of positive instances.

$$\textbf{Recall} = \frac{\textbf{TP}}{(\textbf{TP} + \textbf{FN})}$$

- F1-score: F1 score is a measure that combines both precision and recall, offering a balanced evaluation of model performance. It is calculated as two times the product of precision and recall divided by the sum of precision and recall, resulting in a harmonic mean.

$$\textbf{F1} - \textbf{score} = \frac{\textbf{2}(\textbf{Precision} * \textbf{Recall})}{(\textbf{Precision} + \textbf{Recall})}$$

Note that the above metrics can be adapted to ABSA by considering the sentiment predictions for each aspect or entity separately. For example, precision, recall, and F1-score can be calculated for each aspect and averaged across all aspects to obtain a global performance measure. Table-5 summarizes results and performance metrics from some recent papers on ABSA.

Table 5: Results and Performance metrics from some recent papers on ABSA.

Aspect Extraction:			
References	**Model used**	**Dataset**	**Results**
Venugopalan [21] et al.	Rule-based Approach	SemEval 2014 (restaurant and laptop domains)	Restaurant: Precision:53.0, recall: 81.9, F1-Score: 64 Laptop: Precision:45.5, Recall:68.7, F1-Score: 55
Toqir [23] et al.	Rule-based approach	Online Customer Reviews	Precision: 87, Recall:92
Liu [25] et al.	supervised	SemEval Restaurant Review, Yelp, and Kaggle Datasets	Precision: 76.49, Recall: 80.47 F1-Score: 78.43
Suarez [26] et al.	unsupervised	SemEval 2015 Dataset	Precision: 95.3, Recall: 67.4 F1-Score: 78.9
Ganpat [29] et al.	unsupervised	SemEval-16 dataset	Laptop:Precision:63.23, Recall:74.57, F1-Score: 68.43 Restaurant:Precision:81.02, Recall:77.09, F1-Score: 79.01
Zschornack [33] et al.	Deep learning model	SemEval 2014 , SemEval 2016	Restaurant(2014): Precision:89.81, Recall:86.00, F1-Score:87.75 Restaurant(2016): Precision:73.05, Recall:73.15, F1-Score:73.04

Hu Xu1 [34] et al.	Deep learning model	SemEval-2014-laptop, SemEval-2016-restaurant	Laptop: F1- Score:81.59, Restaurant: F1-Score: 74.37
Sentiment Classification:			
Saranya [41] et al.	supervised	Twitter dataset	Precision:89.92 , Recall: is 89.92 , F1-Score: is 89.92
Kaur [46] et al.	Deep learning model	SemEval-2014 restaurant reviews dataset, Sentiment140, and STS-Gold datasets	Precession: 97.1, Recall: 96.9, F1-Score:96.7 Accuracy - 95.9.
Padma [47] et al.	Deep learning model	MOUD dataset	Accuracy: 84.1, F1- Score: 84.1
Tabinda [51] et al.	Deep learning model	reviews of Airline [71], reviews of Self-driving cars [72], reviews of the US presidential election [73], IMDB	Precision: 96, Recall: 91, F1-Score: 94, Accuracy: 90
Zainuddin [56] et al.	Hybrid model	STC dataset comprises four distinct categories: Microsoft, Google, Apple, and Twitter.	Accuracy: 76.55, Precision: 77.9, Recall: 76.6, F1-Score: 76

10. CONCLUSION:

In this survey paper, we have provided a comprehensive overview of ABSA, a subfield of NLP that aims to identify the sentiment of specific features or aspects of a service or product. We have discussed the importance of ABSA, its challenges, and its applications in various domains. We have also presented a step-by-step procedure for ABSA and reviewed recent models and datasets, highlighting their advantages, limitations, and future directions.

Our analysis of existing ABSA models and datasets suggests that significant progress has been made in developing accurate and efficient models for ABSA. However, there is still a need for improvement in the interpretability of models, domain adaptation, and handling of implicit sentiment. Future research in ABSA should address these challenges and develop models that can handle the complexity and variability of real-world text.

Overall, we hope this survey paper is a valuable resource for researchers, practitioners, and students in sentiment analysis and related areas. We strongly encourage continued research in the area of ABSA and associated fields, as this can significantly impact how we comprehend and analyze customer opinions and preferences.

11. REFERENCES:

[1] Bing Liu. 2012. "Sentiment analysis and opinion mining. Synthesis Lectures on Human Language Technologies" Springer Cham, (2012), 1–167.

[2] Sánchez-Rada JF, Iglesias CA (2019) “Social context in sentiment analysis: formal definition, an overview of current trends and framework for comparison.” Inf Fusion 52:344–356,elsevier.

[3] Mayur Wankhade1,2 · Annavarapu Chandra Sekhara Rao1,2 · Chaitanya Kulkarni1,2(2022) “A survey on sentiment analysis methods, applications, and challenges”, Artificial Intelligence Review, 55:5731–5780-Springer.

[4] J Cui, Z Wang, SB Ho, E Cambria. 2023 “Survey on sentiment analysis: evolution of research methods and topics” - Artificial Intelligence Review, 2023 - Springer

[5] D Kanojia, A Joshi. 2023 “Applications and Challenges of Sentiment Analysis in Real-life Scenarios”- arXiv:2301.09912, 2023 - arxiv.org

[6] EM Mercha, H Benbrahim .2023 “Machine Learning and Deep Learning for sentiment analysis across languages: A survey”- Neurocomputing, 2023 - Elsevier.

[7] M Wankhade, ACS Rao, C Kulkarni. 2022.”A survey on sentiment analysis methods, applications, and challenges” - Artificial Intelligence Review, 2022 - Springer.

[8] J. Xiao and X. Luo, "A Survey of Sentiment Analysis Based on Multi-Modal Information," *2022 IEEE Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC)*, Dalian, China, 2022, pp. 712-715, doi: 10.1109/IPEC54454.2022.9777333.

[9] J Joseph, S Vineetha, NV Sobhana.2022.”A survey on deep learning based sentiment analysis “ Proceedings, 2022 - Elsevier.

[10] G Brauwers, F Frasincar . 2022. “A survey on aspect-based sentiment classification” - ACM Computing Surveys, 2022 - dl.acm.org

[11] W. Zhang, X. Li, Y. Deng, L. Bing, and W. Lam, "A Survey on Aspect-Based Sentiment Analysis: Tasks, Methods, and Challenges," in *IEEE Transactions on Knowledge and Data Engineering*, doi: 10.1109/TKDE.2022.3230975.

[12] Yadav, K., Kumar, N., Reddy, P. K., & Gadekallu, T. R. (2021). A comprehensive survey on aspect-based sentiment analysis. International Journal of Engineering Systems Modelling and Simulation, 12(4), 279.

[13] Pontiki et al. (2016)."Semeval-2016 Task 5: Aspect Based Sentiment Analysis" Proceedings of SemEval-2016, pages 19–30, San Diego, California, June 16-17, 2016. c 2016 Association for Computational Linguistics.

[14] H. Mohamed Zakir, Vinila Jinny. (2020) ” A Comparative Study on Data Cleaning Approaches in Sentiment Analysis”.Advances in Communication Systems and Networks (pp.421-431). DOI:10.1007/978-981-15-3992-3_35.-Springer

[15] Abigail Rai, Samarjeet Borah.(2021)-”Study of Various Methods for Tokenization”.DOI:10.1007/978-981-15-6198-6_18 In book: Applications of Internet of Things (pp.193-200).-Springer

[16] Dhara J. Ladani; Nikita P. Desai.(2020)-”Stopword Identification and Removal Techniques on TC and IR applications: A Survey”-IEEE-2020 6th ICCCS.

[17] Divya Khyani and Siddhartha B S.(2021)-"An Interpretation of Lemmatization and Stemming in Natural Language Processing"-Journal of University of Shanghai for Science and Technology 22(10):350-357.

[18] Chiche, A., Yitagesu, B. Part of speech tagging: a systematic review of deep learning and machine learning approaches. J Big Data 9, 10 (2022).

[19] Toqir A. Rana, Yu-N Cheah- (2016) Aspect extraction in sentiment analysis: comparative analysis and survey DO - 10.1007/s10462-016-9472-z - Artificial Intelligence Review ER.

[20] F. Z. Ruskanda, D. H. Widyantoro, and A. Purwarianti, "Comparative Study on Language Rule-Based Methods for Aspect Extraction in Sentiment Analysis," *2018 International Conference on Asian Language Processing (IALP)*, Bandung, Indonesia, 2018, pp. 56-61.

[21] M Venugopalan, D Gupta-(2020) "An unsupervised hierarchical rule-based model for aspect term extraction augmented with pruning strategies"-Procedia Computer Science, 2020 - Elsevier

[22] Poria S, Cambria E, Ku LW, Gui C, Gelbukh A. A rule-based approach to aspect extraction from product reviews. In Proceedings of the second workshop on natural language processing for social media (SocialNLP) 2014 Aug (pp. 28-37).

[23] Toqir A. Rana, Yu-N Cheah, A two-fold rule-based model for aspect extraction, Expert Systems with Applications, Volume 89, 2017, Pages 273-285, ISSN 0957-4174.

[24] Gunjan Ansari, Chandni Saxena, Tanvir Ahmad, M.N. Doja, Aspect Term Extraction using Graph-based Semi-Supervised Learning, Procedia Computer Science, Volume 167, 2020, Pages 2080-2090, ISSN 1877-0509.

[25] H. Liu, I. Chatterjee, M. Zhou, X. S. Lu, and A. Abusorrah, "Aspect-Based Sentiment Analysis: A Survey of Deep Learning Methods," in IEEE Transactions on Computational Social Systems, vol. 7, no. 6, pp. 1358-1375, Dec. 2020, doi: 10.1109/TCSS.2020.3033302.

[26] Danny Suarez Vargas, Lucas R. C. Pessutto, and Viviane Pereira Moreira."Simple Unsupervised Similarity-Based Aspect Extraction".arXiv:2008.10820v1 [cs.CL] 25 Aug 2020.

[27] Benarafa, H., Benkhalifa, M. & Akhloufi, M. WordNet Semantic Relations Based Enhancement of KNN Model for Implicit Aspect Identification in Sentiment Analysis. Int J Comput Intell Syst 16, 3 (2023).

[28] Chauhan, G.S., Meena, Y.K., Gopalani, D. et al. A mixed unsupervised method for aspect extraction using BERT. Multimed Tools Appl 81, 31881–31906 (2022).

[29] Ganpat Singh Chauhan, Yogesh Kumar Meena, Dinesh Gopalani, Ravi Nahta,"A two-step hybrid unsupervised model with attention mechanism for aspect extraction, Expert Systems with Applications", Volume 161,2020,113673, ISSN 0957-4174.

[30] Azizkhan F Pathan, Chetana Prakash, Unsupervised Aspect Extraction Algorithm for opinion mining using topic modeling, Global Transitions Proceedings, Volume 2, Issue 2, 2021, Pages 492-499, ISSN 2666-285X.

[31] Maria Mihaela Truşcă, Flavius Frasincar,2022, a survey on aspect detection for aspect-based sentiment analysis, Artificial Intelligence Review,-Springer.

[32] R. A. Widhianto and A. Romadhony, "Aspect Term Extraction Using Deep Learning-Based Approach on Indonesian Restaurant Reviews," *2021 9th International Conference on Information and Communication Technology (ICoICT)*, Yogyakarta, Indonesia, 2021, pp. 202-206.

[33] Zschornack Rodrigues Saraiva F, Linhares Coelho da Silva T, Fernandes de Macêdo JA. Aspect Term Extraction Using Deep Learning Model with Minimal Feature Engineering. Advanced Information Systems Engineering. 2020 May 9;12127:185–98. doi: 10.1007/978-3-030-49435-3_12. PMCID: PMC7266433.

[34] Hu Xu1 , Bing Liu1 , Lei Shu1, and Philip S. Yu1,2."Double Embeddings and CNN-based Sequence Labeling for Aspect Extraction".arXiv:1805.04601v1 [cs.CL] 11 May 2018.

[35] Entony Lekhtman, Yftah Ziser, Roi Reichart."DILBERT: Customized Pre-Training for Domain Adaptation with Category Shift, with an Application to Aspect Extraction".arXiv:2109.00571v1 [cs.CL] 1 Sep 2021.

[36] Srishti Vashishtha, Seba Susan, Fuzzy rule-based unsupervised sentiment analysis from social media posts, Expert Systems with Applications, Volume 138, 2019, 112834, ISSN 0957-4174.

[37] Farah, H.A., Kakisim, A.G. (2023). Enhancing Lexicon-Based Sentiment Analysis Using n-gram Approach. In: Smart Applications with Advanced Machine Learning and Human-Centred Problem Design. ICAIAME 2021. Engineering Cyber-Physical Systems and Critical Infrastructures, vol 1. Springer, Cham.

[38] Hota HS, Sharma DK, Verma N. Lexicon-based sentiment analysis using Twitter data: a case of COVID-19 outbreak in India and abroad. Data Science for COVID-19. 2021:275–95. doi: 10.1016/B978-0-12-824536-1.00015-0. Epub 2021 May 21. PMCID: PMC8989068.

[39] Machová, K.; Mikula, M.; Gao, X.; Mach, M. Lexicon-based Sentiment Analysis Using the Particle Swarm Optimization. *Electronics* 2020, *9*, 1317.

[40] Kamal Gulati;S. Saravana Kumar;Raja Sarath Kumar Boddu;Ketan Sarvakar;Dilip Kumar Sharma;M.Z.M. Nomani; (2022). Comparative analysis of machine learning-based classification models using sentiment classification of tweets related to COVID-19 pandemic. Materials Today: Proceedings, (), –. doi:10.1016/j.matpr.2021.04.364 .

[41] Saranya, S.; Usha, G.,"A Machine Learning-Based Technique with IntelligentWordNet Lemmatize for Twitter Sentiment Analysis", Intelligent Automation & Soft Computing. 2023, Vol. 36 Issue 1, p339-352. 14p.

[42] Sinha, A., Chakma, K. (2022). A Comparative Analysis of Machine Learning Based Sentiment Analysis. In: Sk, A.A., Turki, T., Ghosh, T.K., Joardar, S., Barman, S. (eds) Artificial Intelligence. ISAI 2022. Communications in Computer and Information Science, vol 1695. Springer, Cham.

[43] Benrouba, F., Boudour, R. Emotional sentiment analysis of social media content for mental health safety. Soc. Netw. Anal. Min. 13, 17 (2023).

[44] Michele Costola, Oliver Hinz, Michael Nofer, Loriana Pelizzon, Machine learning sentiment analysis, COVID-19 news and stock market reactions, Research in International Business and Finance, Volume 64, 2023, 101881, ISSN 0275-5319.

[45] Huwail J. Alantari, Imran S. Currim, Yiting Deng, Sameer Singh," An empirical comparison of machine learning methods for text-based sentiment analysis of online consumer reviews", International Journal of Research in Marketing, Volume 39, Issue 1, 2022, Pages 1-19, ISSN 0167-8116.

[46] Kaur, G., Sharma, A. A deep learning-based model using a hybrid feature extraction approach for consumer sentiment analysis. J Big Data 10, 5 (2023).

[47] Padma, Sreevidya & Murthy, O.V. & Veni, S.. (2020). Sentiment analysis by deep learning approaches. TELKOMNIKA (Telecommunication Computing Electronics and Control). 18. 752. 10.12928/telkomnika.v18i2.13912.

[48] Kim, Hannah & Jeong, Young-Seob. (2019). Sentiment Classification Using Convolutional Neural Networks. Applied Sciences (Switzerland). 9. 10.3390/app9112347.

[49] Amit Kumar Sharmaa,∗ , Sandeep Chaurasiaa , Devesh Kumar Srivastavaa." Sentimental Short Sentences Classification by Using CNN Deep Learning Model with Fine Tuned Word2Vec", International Conference on Computational Intelligence and Data Science (ICCIDS 2019), Procedia Computer Science 167 (2020) 1139–1147.

[50] Lu Chen1∗ , Justin Martineau2 , Doreen Cheng2 , Amit Sheth1, Clustering for Simultaneous Extraction of Aspects and Features from Reviews,Proceedings of NAACL-HLT 2016, pages 789–799, San Diego, California, June 12-17, 2016. c 2016 Association for Computational Linguistics.

[51] Sayyida Tabinda Kokab, Sohail Asghar, Shehneela Naz, Transformer-based deep learning models for the sentiment analysis of social media data, Array, Volume 14, 2022, 100157, ISSN 2590-0056, https://doi.org/10.1016/j.array.2022.100157.

[52] Leeja Mathew1*, Bindu V R2, Efficient Transformer Based Sentiment Classification Models, Informatica 46 (2022) 175–184 175.

[53] Kian Long Tan, Chin Poo Lee, Kian Ming Lim, And Kalaiarasi Sonai Muthu Anbananthen,"Sentiment Analysis With Ensemble Hybrid Deep Learning Model", Digital Object Identifier 10.1109/ACCESS.2022.3210182.

[54] Abayomi Bello, Sin-Chun Ng, and Man-Fai Leung ," A BERT Framework to Sentiment Analysis of Tweets", 2023, *23*(1), 506.

[55] Kathuria, A., Gupta, A. & Singla, R.K. AOH-Senti: Aspect-Oriented Hybrid Approach to Sentiment Analysis of Students' Feedback. SN COMPUT. SCI. 4, 152 (2023).

[56] Zainuddin, N., Selamat, A. & Ibrahim, R. Hybrid sentiment classification on Twitter aspect-based sentiment analysis. Appl Intell 48, 1218–1232 (2018).

[57] U. Saha, M. S. Mahmud, A. Chakrobortty, M. T. Akter, M. R. Islam and A. A. Marouf, "Sentiment Classification in Bengali News Comments using a hybrid approach with Glove," *2022 6th International Conference on Trends in Electronics and Informatics (ICOEI)*, Tirunelveli, India, 2022, pp. 01-08.

[58] Ramaswamy, S.L., Chinnappan, J. Recog Net-LSTM+CNN: a hybrid network with attention mechanism for aspect categorization and sentiment classification. J Intell Inf Syst 58, 379–404 (2022).

[59] Maria Pontiki, Dimitris Galanis, John Pavlopoulos, Harris Papageorgiou, Ion Androutsopoulos, and Suresh Manandhar. 2014. SemEval-2014 Task 4: Aspect Based Sentiment Analysis. In Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014), pages 27–35, Dublin, Ireland. Association for Computational Linguistics.

[60] Maria Pontiki, Dimitris Galanis, Haris Papageorgiou, Suresh Manandhar, and Ion Androutsopoulos. 2015. SemEval-2015 Task 12: Aspect Based Sentiment Analysis. In Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015), pages 486–495, Denver, Colorado. Association for Computational Linguistics.

[61] Maria Pontiki, Dimitris Galanis, Haris Papageorgiou, Ion Androutsopoulos, Suresh Manandhar, Mohammad AL-Smadi, Mahmoud Al-Ayyoub, Yanyan Zhao, Bing Qin, Orphée De Clercq, Véronique Hoste, Marianna Apidianaki, Xavier Tannier, Natalia Loukachevitch, Evgeniy Kotelnikov, Nuria Bel, Salud María Jiménez-Zafra, and Gülşen Eryiğit. 2016. SemEval-2016 Task 5: Aspect Based Sentiment Analysis. In Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016), pages 19–30, San Diego, California. Association for Computational Linguistics.

[62] Keith Cortis, André Freitas, Tobias Daudert, Manuela Huerlimann, Manel Zarrouk, Siegfried Handschuh, and Brian Davis. 2017. SemEval-2017 Task 5: Fine-Grained Sentiment Analysis on Financial Microblogs and News. In Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017), pages 519–535, Vancouver, Canada. Association for Computational Linguistics.

[63] Qingnan Jiang, Lei Chen, Ruifeng Xu, Xiang Ao, and Min Yang. 2019. A Challenge Dataset and Effective Models for Aspect-Based Sentiment Analysis. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 6280–6285, Hong Kong, China. Association for Computational Linguistics.

[64] Marzieh Saeidi, Guillaume Bouchard, Maria Liakata, and Sebastian Riedel. 2016. SentiHood: Targeted Aspect Based Sentiment Analysis Dataset for Urban Neighbourhoods. In Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers, pages 1546–1556, Osaka, Japan. The COLING 2016 Organizing Committee.

[65] Asghar, Nabiha. (2016). Yelp Dataset Challenge: Review Rating Prediction.

[66] Pavlopoulos, John & Androutsopoulos, Ion. (2014). Multi-Granular Aspect Aggregation in Aspect-Based Sentiment Analysis. 14th Conference of the European Chapter of the Association for Computational Linguistics 2014, EACL 2014. 78-87. 10.3115/v1/E14-1009.

[67] Z. Fan, Z. Wu, X. Dai, S. Huang, and J. Chen, "Target oriented opinion words extraction with target-fused neural sequence labeling," in NAACL-HLT, 2019, pp. 2509–2518.

[68] J. Wang, C. Sun, S. Li, X. Liu, L. Si, M. Zhang, and G. Zhou, "Aspect sentiment classification towards question-answering with reinforced bidirectional attention network," in ACL, 2019, pp. 3548–3557.

[69] X. Xing, Z. Jin, D. Jin, B. Wang, Q. Zhang, and X. Huang, "Tasty burgers, soggy fries: Probing aspect robustness in aspect-based sentiment analysis," in EMNLP, 2020, pp. 3594–3605.

[70] L. Xu, H. Li, W. Lu, and L. Bing, "Position-aware tagging for aspect sentiment triplet extraction," in EMNLP, 2020, pp. 2339–2349.

[71] Wan Y., Gao Q. An ensemble sentiment classification system of Twitter data for airline services analysis, 2015 IEEE international conference on data mining workshop, IEEE (2015), pp. 1318-1325.

[72] Chen L.C., Barron J.T., Papandreou G., Murphy K., Yuille A.L. Semantic image segmentation with task-specific edge detection using cnns and a discriminatively trained domain transform ,Proceedings of the IEEE conference on computer vision and pattern recognition (2016), pp. 4545-4554.

[73] Bifet A., Frank E.Sentiment knowledge discovery in twitter streaming data,International conference on discovery science, Springer (2010), pp. 1-15.

[74] Li Dong, Furu Wei, Chuanqi Tan, Duyu Tang, Ming Zhou, and Ke Xu. 2014. Adaptive Recursive Neural Network for Target-dependent Twitter Sentiment Classification. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 49–54, Baltimore, Maryland. Association for Computational Linguistics.

[75] Macedo Maia, Siegfried Handschuh, André Freitas, Brian Davis, Ross McDermott, Manel Zarrouk, and Alexandra Balahur. 2018. WWW'18 Open Challenge: Financial Opinion Mining and Question Answering. In *WWW '18 Companion: The 2018 Web Conference Companion, April 23–27, 2018, Lyon, France*. ACM, New York, NY, USA, 2 pages.

[76] Kessler, Jason & Eckert, Miriam & Clark, Lyndsie & Nicolov, Nicolas. (2010). The ICWSM 2010 JDPA Sentiment Corpus for the Automotive Domain.

[77] Cigdem Toprak, Niklas Jakob, and Iryna Gurevych. 2010,*Darmstadt Service Review* Corpora

[78] Pontiki M, Galanis D, Papageorgiou H, Androutsopoulos I, Manandhar S, AL-Smadi M, Al-Ayyoub M, Zhao Y, Qin B, De Clercq O, Hoste V, Apidianaki M, Tannier X, Loukachevitch N, Kotelnikov E, Bel N, Jiménez-Zafra SM, Eryigit G. 2016. SemEval-2016 task 5: aspect based sentiment analysis. In: Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016). San Diego, California: Association for Computational Linguistics, 19–30

[79] Lukashevich N, Rubtsova YV. 2016. Sentirueval-2016: overcoming time gap and data sparsity in tweet sentiment analysis. In: Computational Linguistics and Intellectual Technologies: Proceedings of the International Conference "Dialogue" 2016. Russian State University for the Humanities, 416–426.

[80] Loukachevitch N, Blinov P, Kotelnikov E, Rubtsova Y, Ivanov V, Tutubalina E. 2015. SentiRuEval: testing object-oriented sentiment analysis systems in Russian. In: Computational Linguistics and Intellectual Technologies: Proceedings of the International Conference “Dialogue” 2015. Vol. 2. Russian State University for the Humanities, 3–13.

[81] Charles Sutton and Andrew McCallum, An Introduction to Conditional Random Fields,Foundations and TrendsR in Machine Learning Vol. 4, No. 4 (2011) 267–373 c 2012 C. Sutton and A. McCallum DOI: 10.1561/2200000013.

[82] Rubtsova, Y., Koshelnikov, S. (2015). Aspect Extraction from Reviews Using Conditional Random Fields. In: Klinov, P., Mouromtsev, D. (eds) Knowledge Engineering and Semantic Web. KESW 2015. Communications in Computer and Information Science, vol 518. Springer, Cham.

[83] Nadheesh Jihan, Yasas Senarath, Dulanjaya Tennekoon, Mithila Wickramarathne, and Surangika Ranathunga, Multi-Domain Aspect Extraction using Support Vector Machines, The 2017 Conference on Computational Linguistics and Speech Processing ROCLING 2017, pp. 308-322.

[84] Mohammadreza Shams, Ahmad Baraani-Dastjerdi, Enriched LDA (ELDA): Combination of latent Dirichlet allocation with word co-occurrence analysis for aspect extraction, Expert Systems with Applications, Volume 80, 2017, Pages 136-146, ISSN 0957-4174.

[85] Xu, Qiannan & Zhu, Li & Dai, Tao & Guo, Lei & Cao, Sisi. (2020). Non-negative matrix factorization for implicit aspect identification. Journal of Ambient Intelligence and Humanized Computing. 11. 10.1007/s12652-019-01328-9.

[86] A. Nazir, Y. Rao, L. Wu and L. Sun, "Issues and Challenges of Aspect-based Sentiment Analysis: A Comprehensive Survey," in IEEE Transactions on Affective Computing, vol. 13, no. 2, pp. 845-863, 1 April-June 2022, doi: 10.1109/TAFFC.2020.2970399.

[87] K. Schouten and F. Frasincar, "Survey on Aspect-Level Sentiment Analysis," in IEEE Transactions on Knowledge and Data Engineering, vol. 28, no. 3, pp. 813-830, 1 March 2016, doi: 10.1109/TKDE.2015.2485209.

[88] Zhu L, Xu M, Bao Y, Xu Y, Kong X. Deep learning for aspect-based sentiment analysis: a review. PeerJ Comput Sci. 2022 Jul 19;8:e1044. doi: 10.7717/peerj-cs.1044. PMID: 36092006; PMCID: PMC9454971.