Journal of
Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.98549669

A COMPREHENSIVE ANALYSIS OF CROSS DOMAIN ASPECT BASED SENTIMENT ANALYSIS

Teja Yaramasa
Research Scholar, Department of Computer Science and Engineering,
Adikavi Nannaya University, tejayaramasa@gmail.com

Dr. M Kamala Kumari
Associate Professor, Department of Computer Science and Engineering,
Adikavi Nannaya University, kamalamarepalli.aknu@gmail.com

Abstract: The study of sentiment has attracted a lot of interest from experts in text mining and natural language processing. The accuracy of sentiment analysis is being hampered by the paucity of annotated data sets that may be utilized to train a model across all domains. There have been numerous attempts to address this problem and enhance cross-domain sentiment classification. In this article, we offer the findings from a thorough, systematic assessment of the methodologies and methods used in cross-domain sentiment analysis. The computational examination of opinions, assessments, attitudes, and feelings regarding the entities and their properties is known as sentiment analysis. Finding the sentiment polarity of the documents, sentences, or aspects is a fundamental problem of sentiment analysis. Users typically share their thoughts on the goods or services in blog entries, on shopping websites, or on review websites. Such opinion-related contents are abundant and expanding exponentially, making it laborious for the maker to manually classify these items. People also anticipate hearing opinions regarding the entities involved in the elements level procedure. When the destination domain lacks labelled data, the challenge of cross-domain sentiment classification entails adapting a classification model trained on the source domain to the target domain. Because of the issue with feature mismatch, applying a sentiment classifier directly trained in the source domain to the target domain frequently leads to subpar performance. This paper compares various cross-domain sentiment analysis methodologies and obstacles while conducting a quick literature review on the subject.
Keywords: Case-Based Reasoning (CBR), Cross Domain Aspect Based Sentiment Analysis (CDABSA), case-based reasoning (CBR), Dynamic Joint Sentiment-Topic Model (DJST), Joint Sentiment-Topic (JST), Latent Dirichlet Allocation (LDA), Moving-window Attentive Gated Recurrent Units (MAGRU), Natural Language Processing (NLP) Query-by-Committee (QBC), Structured Correspondence Learning (SCL), Spectral Feature Alignment (SFA).

1. INTRODUCTION

The fast expansion of social media has altered how people communicate. People become highly vocal in voicing their thoughts about various topics, including goods, services, public figures, politics, and other topics. The decision-maker will be better able to act concerning their product, services, or policy in accordance with public opinion if they are able to recognize the polarization of this opinion. Every human encounter involves the study of sentiment. We utilize it to assess one another's emotional states or how we will react to a response. However, emotion is not just expressed through spoken communication; it may also be expressed through written material. Therefore, extracting sentiment from text can reveal more about the author's viewpoints and give vital information about what the general public thinks. The computational study of attitudes about subjects, events, goods, entities, and their qualities is called sentiment analysis. People can now express their ideas on a variety of topics thanks to the rapid expansion of web applications including social networks, blogs, forums, and e-commerce sites. For instance, Amazon gathers customer reviews of the goods or services, and users can post their thoughts on any subject on social media sites like Facebook and Twitter, including events, elections, goods or services, and more. Both consumers and manufacturers can benefit from these viewpoints. From client feedback, producers can spot any flaws that need to be fixed in order to boost sales. When buying things from e-commerce sites where one cannot physically see and confirm the quality of the products, customers' opinions of the existing reference about the products are helpful to make decisions.

Classical NLP is at its finest in the context of sentiment categorization, which has numerous real-world applications including the financial sector, corporate communications, and advertising. Since many new venues have emerged in recent years for voicing and displaying one's emotions, the field of Sentiment Analysis (SA) has gained significant traction. It's a method for extracting feelings from individual data elements like sentences, words, and entire paragraphs. The use of sentiment analysis in review analysis has expanded dramatically during the past decade. This is because modern review writing styles are so onerous to decipher. The usage of slang, abbreviations, etc., in review processing presents a new set of challenges. Affective computing includes the field of sentiment analysis, which uses textual analysis to detect and analyze people's emotional states and intentions. In the realms of information retrieval and NLP, sentiment analysis is a core technique. Multimedia content analysis and aggregation are two of the most common uses for text mining technology. In order to extract and examine sentiment features, text analysis forms the basis of sentiment analysis. Text is extracted, processed, analyzed, and polarity is determined as part of the analytical process. To this day, there are two primary schools of thought when it comes to sentiment analysis techniques: those that rely on a lexicon and those that use machine learning. When determining the tone of a piece of writing, the former method refers to an external knowledge source called the sentiment dictionary, which is then used in conjunction with rules and emotion functions to reach a conclusion. In the latter, techniques like machine learning and deep neural networks are used to classify feelings into predetermined categories.

By employing natural language processing methods, researchers in the subject of sentiment analysis analyze user facial expressions in order to assign feelings to the user's input. This region has its own unique flavors according to the cultural standards that prevail there. In addition to considering when the user voiced the emotion or opinion, sentiment analysis also considers the context of the expression. Gathering statements within a time continuum might provide more confidence of the sentiments expressed, as the same user can be under specific circumstances that distort their judgement. In this respect, the social media platform presents both difficulties and possibilities. Having the ability to remain anonymous online is a great freedom, since it allows people to speak their minds without fear of retaliation. In addition, the data can be collected over a specified time period, which can be quite helpful for maintaining uniformity. The information collected in this way can serve as a rock-solid basis for scientific inferences and provides overwhelming support for the researcher's premise. Many industries, including Marketing and others, now choose web-based data collection. Businesses and other organizations place a premium on public and consumer feedback because doing so helps them improve their products and services. Both state and federal governments are interested in hearing citizens' feedback on measures they've already implemented or are considering implementing. Relevant government decision-makers will be able to adapt quickly to shifting economic, social and political conditions with the help of such opinions. In the realm of international politics, it is desirable for every nation to keep tabs on the social media activity of every other nation in order to learn more about what is going on there and how its citizens feel about the events unfolding at home and across the world. Information of this nature is vital to the fields of diplomacy, relations, international and commercial decision making. Individual customers, like corporations, government agencies and organizations, are interested in the views of others before deciding whether or not to purchase goods, use services, or vote for a particular candidate in an election. Companies like Google, YouTube, and Amazon demonstrate how this is done by catering to individual customers' tastes in media. Number of likes, total number of products sold given an age range, etc., are examples of objective metrics that can be crucial in many such sectors. However, fields like psychology and psychiatry lack this luxury because their data is in the form of user-generated text posted across a wide variety of online platforms. This adds a new layer of difficulty because of things like

(a) the usage of different languages on a certain topic.
(b) the use of non-standard words that cannot be located in a dictionary, and
(c) the use of emojis and symbols.

Experts in the field of Natural Language Processing (NLP) as well as those engaged in the study of sentiment analysis try to answer these problems.

2. LITERATURE SURVEY

One area of research in natural language processing that can help with this issue is sentiment analysis. Sentiment analysis examines how people feel about various things, including things like goods, organizations, services, people, issues, events, subjects, and their attributes [1]. The lexicon-based approach and the machine learning method are the two broad categories into which the sentiment analysis technology falls. While machine learning constructs the classifier from labelled datasets, lexicon-based sentiment analysis uses a number of pre-defined opinion terms with their corresponding polarity.

We make our product purchases in accordance with user reviews. However, because there are so many reviews posted on so many different websites, it is exceedingly challenging to manually identify the review papers according to positive or negative emotion. Additionally, individuals are curious about how entities feel at the aspect level. Therefore, it is important to build a sentiment analyzer that automatically determines the sentiment of entity attributes from review papers and categorizes review documents as having a positive or negative sentiment. Numerous activities, including opinion mining [2], market research [3], reviewer summarization [4] [5], and contextual advertising, can benefit from sentiment analysis [6].

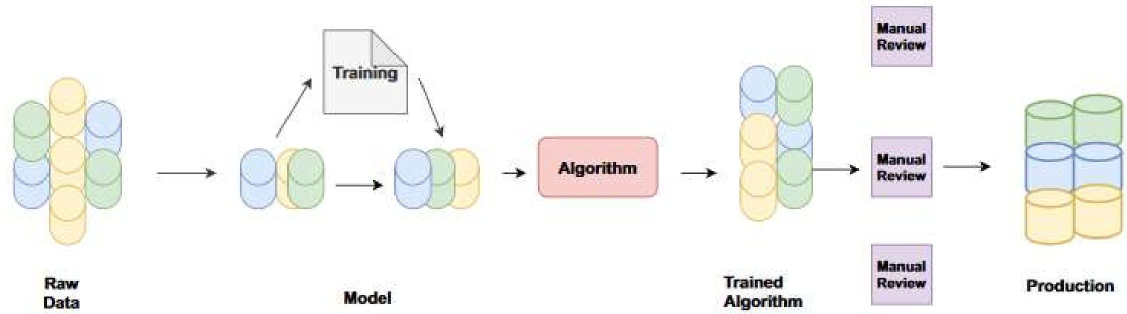


Fig 1: Generally speaking, supervised machine learning categories use sentiment analysis

Numerous reviews and tweets have been evaluated for mood and for predicting major events such as elections [7] and the financial success of movies [8]. In reality, text sentiment analysis is not a novel area of study. Tweets are short blog posts created by Twitter users [9]. Tweets are ideal for sentiment analysis since they allow users to share their opinions and ideas. Reviews can be available on websites like Amazon and Yelp are an evaluation of a specific entity, such as a person, place, or product. Reviews are ideal candidates for sentiment analysis since they are, by their very nature, opinionated. Both reviews and tweets have been heavily utilized for sentiment analysis.

From the perspective of machine learning, determining the emotional tone of a text requires labelled training data from which patterns can be learned to future texts. Training a classifier with labelled data is known as supervised learning. Most supervised learning approaches to sentiment analysis employ the review's emotion as the classifier and the words from the review as attributes. Additional features, such as morphemes, learning requires, and word frequency, can be used, albeit doing so requires more computer resources. When describing genuine feelings, either the positive or negative sentiment label can be used. A classifier sorts through the information to find patterns inside the text, and then makes an opinion about the tone of new examples based on their characteristics. There is a direct correlation between the quality of the training data and the classifier's output. Because of this, training and evaluation data for classifiers are often taken from same domain. However, by utilizing data from a closely comparable domain, a classifier can be trained to correctly classify examples from the specific domain. That's called cross-domain sentiment analysis, and it's really cool.

Sentiment analysis and opinion mining [10, 11] are two well-liked methods for automating the extraction of information from consumer reviews of products and services. The primary goal of examining the polarity of sentiment expressed in textual reviews is to better understand the consumer's perspective on a given topic. Recent research has focused on examining ABSA, as opposed to earlier work on sentiment analysis that attempted, and failed, to obtain the polarity from the complete text evaluation or from the text phrases. [12] [13] [14]

[15]. Features such as picture quality, notebook bulk, and meal prices were among those considered in this case as part of the review analysis. ABSA assignments are seen as more challenging [16] [17] [18] [19] since we have to deal with a challenging question during in the sentiment analysis process.

Although the academic domains of sentiment analysis and opinion mining did not appear until 2003 [20], several articles [21] using different methodologies [8] have been published on the subject ever then. But in recent times, deep learning methods have become synonymous with most cutting-edge approaches. The system proposed in [23], for example, employs a multi - layer perceptron autoencoder as its central component to carry out unsupervised feature extraction from both unlabelled samples. In [24], a neural network composed of convolutional and long short-term memory (LSTM) layers is shown to learn a representation of text by considering the relationships between phrases. As an illustration of the combination of LSTMs with attention processes, consider [25], which employs a hierarchical dynamic interest model to address the article aspect-sentiment rating prediction challenge. LSTMs have also been used for aspect-based sentiment classification. In [26], a plan is proposed for expanding LSTM to include a destination and target-connection. The aim is considered as a new input dimension before being mixed with the others. Even though the current work employs a similar approach, the proposed methodology changes the LSTMs used to bi-directional ones. By feeding word representations into bidirectional LSTMs, [27] achieves aspect-level sentiment categorization without the need for an attention mechanism. The proposed technique has proven to be effective in training the model to zero in on the most pertinent aspects of each sentence. In [28], this functional form is used to suggest an attention-based LSTM technique for ABSA. Although we propose using bidirectional LSTMs, the two media exposure technique only considers text as an additional input.

Using sentiment analysis, we may determine whether a statement, item, or phrase has a positive, negative, or neutral tone. Analysis of the emotional tone of a collection of words or phrases based on its aspects (ABSA). The fundamental technological difficulty with sentiment analysis is that it depends heavily on the domain. In other words, a technique that excels in one area may perform poorly in another. A fresh potential to connect aspects and attitudes across many domains is presented by cross-domain aspect-based sentiment analysis. As a result, the Natural Language Understanding (NLU) capability becomes general and domain-neutral, enabling the models to also analyze the feelings of aspect phrases from many domains. Unsupervised, semi-supervised, and supervised learning are the three primary divisions of aspect-based sentiment analysis methodologies. While semi-supervised learning just needs a few labelled training instances, The labels of the training examples are unavailable for use in unsupervised learning. To develop a model for aspect-based sentiment analysis through supervised learning, we require labelled training data. Although this model works well in the same domain, it might not in others. Because the data distribution in the two domains is different, a model that is developed using training data from one domain (for example, the laptop domain) and testing it on data from a different domain (for example, the restaurant domain), may not perform well.

Most commonly, three to two subtasks make up ABSA**.** For OTE and ACD, neural networks or classifiers [29] with attentions [30][31] were utilized, while for SPC, rule-based

[32], topic modelling [33], and conventional multi label models (such as CRF) [34] were used. For instance, to assist a more thorough collection of aspects, ILWAANet [35] collected characteristics both from data and lexicon using multiple attentions. Cross domain ABSA.

In order to achieve acceptable classification performances, ABSA examines inductive supervised learning methods most frequently, which demand significant human labour during the labelling process [36][37]. Nevertheless, regular data labelling is not practical in real-world settings. Transductive learning is frequently employed to overcome this problem during few labelled data because unlabeled data are simple to gather [38][39][40] Transductive learning uses previously unlabeled material that has been directly classified to enhance classification performance.

DOMAIN EMBEDDINGS FOR SENTIMENT ANALYSIS

The majority of previous studies concentrated on identifying domain-invariant structures to aid in the transfer of domain knowledge in cross-domain ABSA [41]. Taking domain-dependent and property characteristics as orthogonal information, Hu et al. [42] employed a more direct approach to extract domain-invariant features, while Liang et al. [43] used an adversarial multitask learning framework to separate the website embeddings from domain-dependent embeddings. However, in this research, multidomain ABSA numerous models focused on domain-dependent embeddings. For instance, property embeddings [44] were developed and improve the effectiveness of sentence-level sentiment analysis by combining word embeddings and property features. Domain embedding for paragraph domain sentiment analysis was developed by Liu et al. [45] to deal with the problem of unique sentiment phrases for various domains. CD-E2EABSA, in contrast to the current work, focuses on aspect-level sentiment classification and learns domain representation via retraining with a parameter's generation communication rather than an attention mechanism. Furthermore, the multitask learning technique is widely used when a model aims to extract property representations for sentiment analysis. The capacity of the model to perform well and generalize across tasks is enhanced by the multitask learning technique, which enables concurrent learning of several related tasks. The unified model for E2E-ABSA has also been enhanced with an interactive multitask learning network [46], It simultaneously learns to analyze the emotion of documents and the attitudes of individual paragraphs inside those documents. In order to use domain-dependent word embedding in the cross-domain E2E-ABSA task, CD-E2EABSA will use the multitask approach.

The product reviews are initially cleansed to get rid of stop words and special characters. Then, sentiments are determined in order to choose the crucial characteristics that aid in categorizing the good and negative sentiments. Finally, superior decision-making about the polarity of sentiment as positively or negatively was carried out in the acquisition of products.

Both the accuracy and the time required to train the classifier for sentiment classification benefit from this. Several methods for document-level sentiment categorization are investigated in this work, k-Nearest Neighbor, including Naive Bayes, Support Vector Machines, and Decision Trees. Oftentimes, we may not have trained corpora for the specific domains for which we need to categorize the data, hence cross-domain sentiment classification is helpful. Cross-domain processing also saves time and money. With multiple testing datasets from various domains available, sentiment classification can be completed in a fraction of the time it would take with a single dataset, despite the fact that it has low accuracy. Tacit opinion mining for reviews online relies heavily on techniques like aspect-based sentiment analysis. Research has proven that such an end-to-end model may properly evaluate what was once thought of as a group of pipeline activities. The importance of cross-domain ABSA has been brought to the forefront as a result of less labelled resources. It might be challenging to maintain domain-dependent characteristics while searching for domain-invariant features, which is a prerequisite for fine-grained domain adaptation.

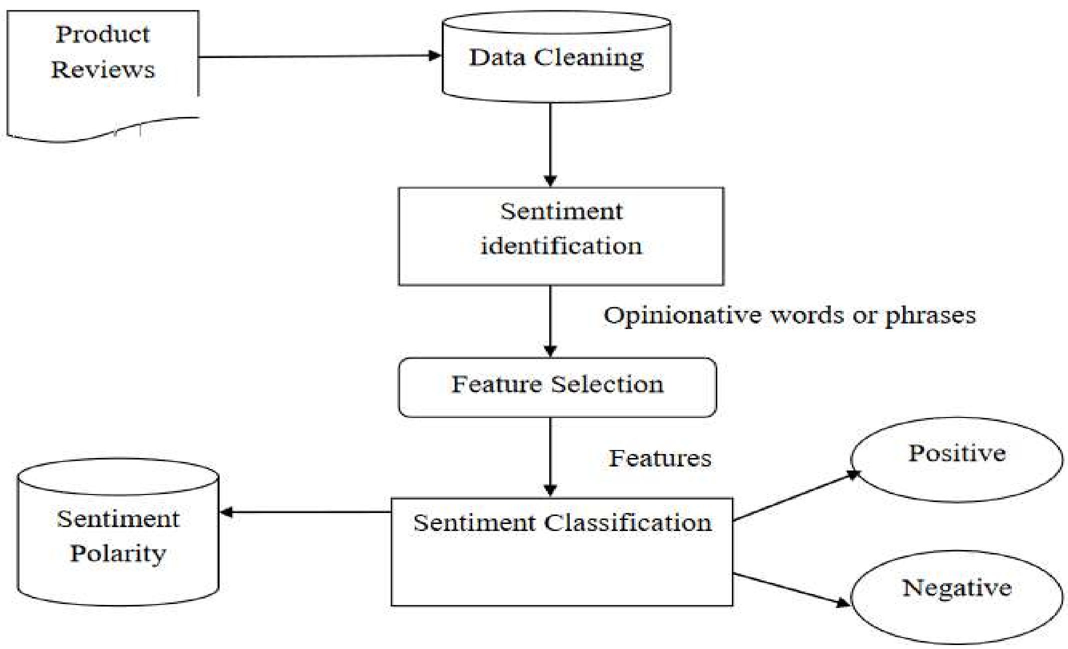


Fig 2: Sentiment Analysis Process

3. TECHNIQUES FOR CROSS DOMAIN SENTIMENT ANALYSIS

Numerous methods have been used in recent years for cross-domain sentiment analysis. In this section, we make an effort to classify these tactics into the following broad categories: Whether a technique uses automatically or manual process developed resources largely determines the resources it employs; other factors include the learning model, the feature representation method and the features it employs sentiment analysis or sentiment classification It is important to note, however, that there is overlap between some of these categories, such that some methods may fit into more than one.

3.1 SEML: A Semi-Supervised Multi-Task Learning Framework for Aspect-Based Sentiment Analysis

Aspect Sentiment Classification (ASC) and Aspect Mining (AM), two sub-tasks of ABSA, are intended to extract the words characterizing the aspects of an evaluated entity and assess the expressed sentiments on those aspects. The highest performance has lately been attained by supervised deep sequence learning models since AM and ASC may be defined as a sequence labelling problem to predict the aspect or emotion labels of each word in the review. These supervised models typically only complete one of the two sub-tasks, which restricts their usefulness and necessitates a large number of labelled reviews that are expensive or unavailable. In order to do this, the technique suggests a SEmi-supervised Mega Learning framework for ABSA (referred to as SEML). Three essential traits define SEML. (1) In a unified end-to-end architecture, SEML uses Cross-View Training (CVT) to enable tractor trailer sequence learning over a small number of labelled reviews and a large set of unprocessed reviews from the same domain. (2) By using three stacked bidirectional recurrent neural layers to learn the representations of reviews and feeding the various representations obtained from different levels into CVT, AM, and ASC, respectively, SEML solves the two sub-tasks simultaneously. (3) To improve representation learning and prediction accuracy, SEML creates a unit of MAGRU for the three recurrent neural layers. This is done because nearby contexts within a moving-window in a review can offer crucial semantic information for the prediction task in ABSA.

Four elements make up the SEML framework: representation learning, AM, ASC, and CVT. Our methodology uses deep recurrent neural networks (RNNs) as the fundamental architecture to construct the common contextualized representation learning component for both the AM and ASC sub-tasks since RNNs can naturally represent the sequential information. The shared memory is specifically built using three stacked recurrent neural layers using MAGRU, which extends GRU with a moving-window learning algorithm to encode local semantic significances.

$$S_i^t = Softmax\,(U_a.\tanh(W_a^1 h_i + W_a^2 x_t))$$

Gate $z_t = \sigma(U_z x_t + W_z h_{t-1})$

Reset gate $r_t = \sigma(U_r x_t + W_r h_{t-1})$

Activation function tanh

$h_t = \tanh\,(U_h x_t + W_r(r_t * h_{t-1}))$

Attention gate a_t=ReLU $(\sum_{i=t-N}^{t-1} s_i^t h_i)$

$h_t = (1 - z_t)* h_{t-1} + z_t * h_t + a_t$

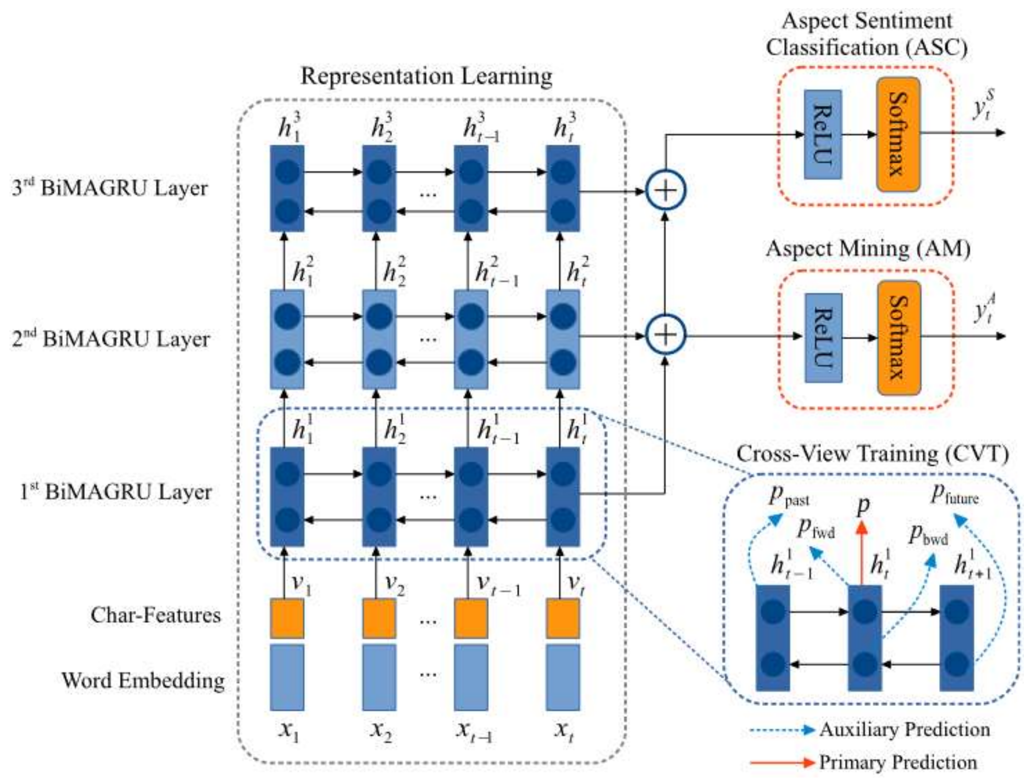


Fig 3 : SEML Architecture

Prediction modules

$P(y_t^A|x_t) = Softmax\ (U_p^A.\text{ReLU}\ (W_p^A(h_t^1 \oplus\ h_t^2\ ))+b^4$

Primary prediction module

$$L_{SUP}^k = \frac{1}{|D_l^k|}\sum_{x_i y_i \epsilon D_l^k} CE(y_t, p(y_t^k\ |x_t)|\ k\ \epsilon\ \{A, S\}$$

Kullback-Leibler (KL)

$$L_{CVT} = \frac{1}{|D_u|}\sum_{x_i \epsilon D_u}\sum_k\sum_j KL\ (p(y_i^k|x_i), p_j\ (y_i^k|x_i))$$

Stochastic gradient descent:

$$L = L_{SUP}^A + L_{SUP}^S + L_{CVT}$$

In ABSA, the two linked subtasks, AM and ASC, are jointly learnt from beginning to conclusion. Additionally, using three stacked and bidirectional neural layers with MAGRU, SEML produces the shared representations of reviews. MAGRU extends GRU with the moving-window long short - term memory to capture significant surrounding semantic contexts. In order to enhance representation learning in a unified end-to-end architecture, SEML also uses CVT to train supplementary prediction modules on unlabeled reviews. Final results show that SEML strongly outperforms existing models, even on much smaller labelled training datasets, for the AM and ASC sub-tasks as well as the whole ABSA over four datasets from the SemEval workshops.

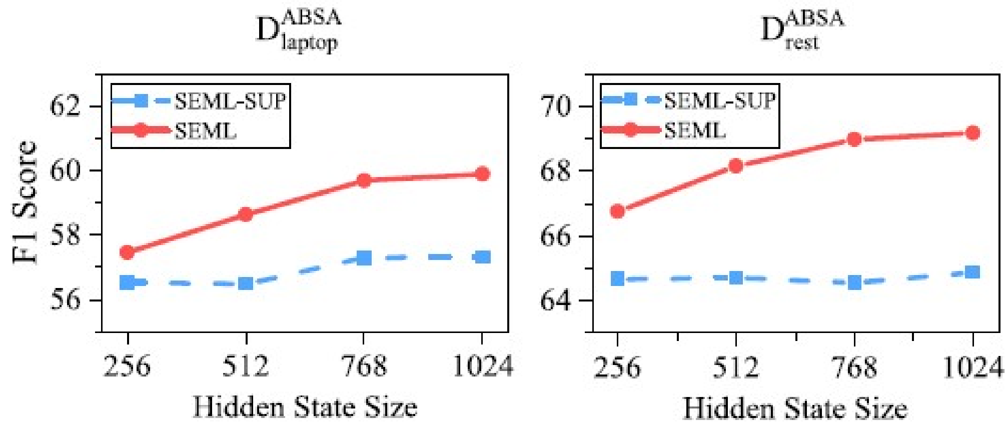


Fig 4: obtained outputs

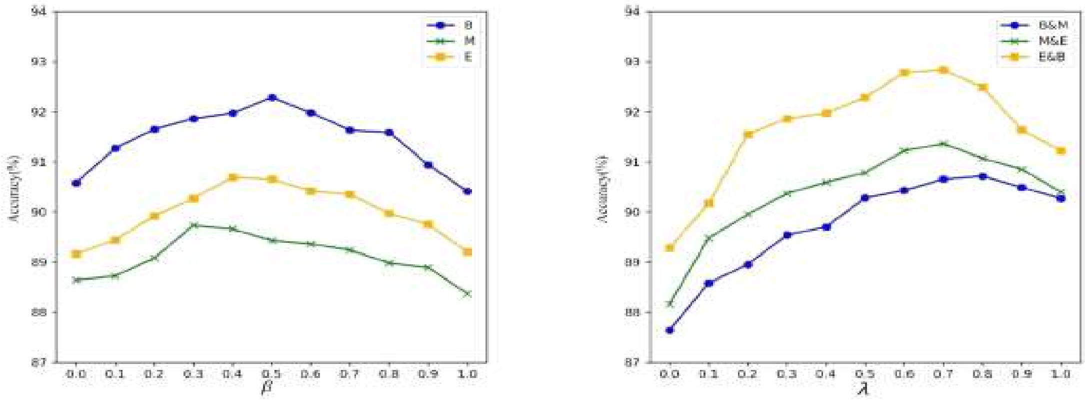
3.2 CDS aware word embeddings for review sentiment analysis

One of the fundamental tasks in natural language processing is learning low-dimensional word vector representations from a huge corpus (NLP). The current universal word embedding model ignores the sentiment information found in the words and instead learns word vectors primarily through grammatical and semantic information from the context [47]. Despite modelling the reviews' sentiment data, some systems do not take certain words from other domains into account. If the generic word vector is used directly to the review sentiment analysis task in a scenario where the emotion fluctuates, this will unavoidably alter the performance of the sentiment classification. This study introduces a cross-domain sentiment aware embeddings learning model that can simultaneously capture sentiment data and domain relevance in order to address this issue. It also extends the continuous bag-of-words (CBoW) word vector model**.** The CDSAWED model is the extended version. Let P and Q represent the two domains. For each word w in the domain P, CDSAWED first trains the word vector p. The word vector of each word in domain Q can then be learned using [48].

$$\mathbf{X}= \begin{cases} 0, with\ p\ probability \\ \frac{x}{1-p}\ , otherwise \end{cases}$$

$$\boldsymbol{X} = \frac{1}{N}\sum_{i=1}^{N} x_i,\ p(w_i|C_i, X) = \frac{exp\ (V_{w_i}^{T}\ (UC_t+\frac{1}{N}UX)}{\sum_{w\epsilon\ V_{ocab}} exp(V_w^T\left(\ (UC_t+\frac{1}{N}UX)\right)}\ ,$$

$$loss_{predict} = -\sum\nolimits_{d}^{D} \sum_{k=[0,1]} f_k^{g}\ (t).\log\ (\ f_k^{pred}(t))$$



(a) sentiment weight β **(b)** domain transfer scaling factor λ

Fig 5 : Effects of various hyperparameter values on performance

---

Algorithm 1 Training Algorithm of CDSAWE_S

Input: Training corpus with sentiment labels

Output: Sentiment word embeddings W_s

Randomly initialize the embedding matrix W_s;

Create vocabulary V, and tokenize the corpus;

Make training batch B;

for training sample r in B **do**

  for context window w in r **do**

    Use Eq. (1) and Eq. (2) to compute context representation $\tilde{X}$;

    Use Eq. (4) and Eq. (5) to compute the loss of the modified CBoW model;

    Make sentiment prediction $f_k^{pred}(t)$ by using context representation $\tilde{X}$;

    Compute the loss of the sentiment prediction;

    Use Eq. (7) to compute the loss of the model;

  end for

end for

Optimize the model by the backpropagation algorithm;

This research contrasts the CDSAWE word embedding model with a number of widely used word embedding learning models in order to assess the validity of the proposed model. This study suggests that, among these, the learning rate be set to 1.0, the context window size to be 3, the batch size to be 64, and the probability p of the corruption strategy to be empirically selected to be 0.8 for the CDSAWE model to be optimized by the AdaGrad optimizer. We run the experiments with TensorFlow and speed up neural network training with an Nvidia Geforce GTX 950 GPU.

To develop cross-domain sentiment-aware word vectors for user review sentiment analysis tasks, this work primarily offers an enhanced word embedding model, CDSAWE, which extends the CBoW model. The CDSAWE model estimates the domain relevance of the words to acquire cross-domain information after first supervising learning through contextual sentiment information to incorporate sentiment information into the word embeddings. In this study, the CDSAWE model and other popular word vector models are evaluated using the sentiment classification task of user review data. The experimental findings demonstrate that the proposed model can integrate data from different domains since it combines domain and sentiment information, and it performs better at sentiment classification on review data from other domains.

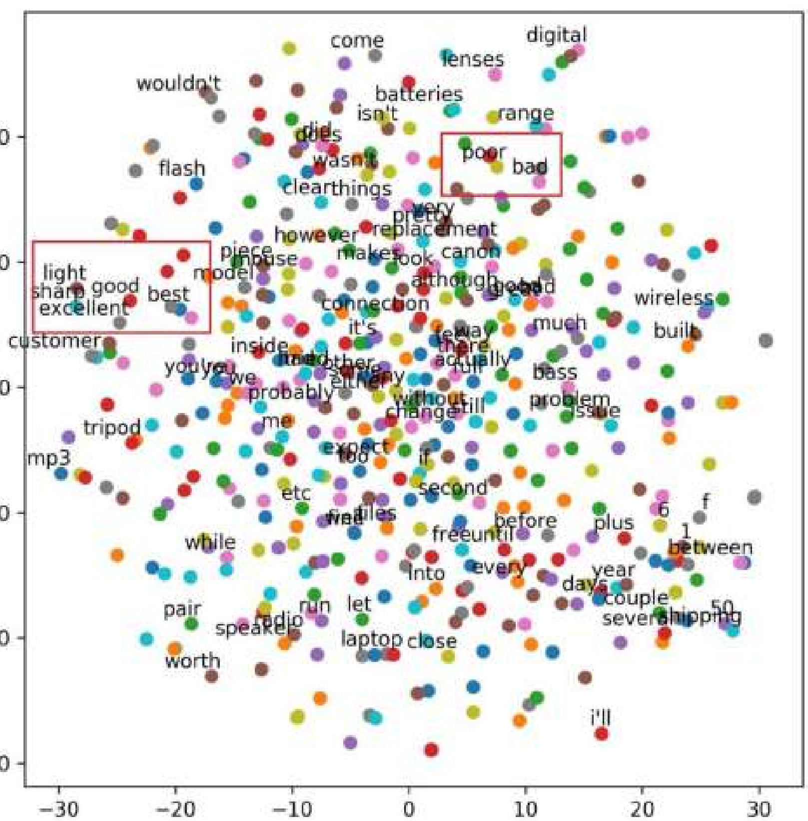


Fig 6: Visualization of the word embedding space

3.3 Cross-Domain Sentiment Encoding through Stochastic Word Embedding

A bag-of-words vector called as a document [49] $x = [x_1, x_2, x_3, \dots \dots \dots \dots .. x_n]^t$ can be used to directly gather the raw data for each review, where xt represents how many times the tth word appears in this text, and n represents the total number of words in the vocabulary. Cross-domain sentiment classification works by using labelled reviews from of the source domain to train a sentiment classifier. The classifier is then expected to provide enough classification performance for reviews in the target domain. To accomplish this, it is essential to acquire robust representations (also known as features) for reviews in both domains, which will allow the classifier to be transferred between domains without suffering a significant performance hit [50].

$$L_i = \begin{cases} +1, & if\ a_{I_i} > 0 \\ -1, & if\ a_{I_i} < 0 \\ 0, & otherwise \end{cases}$$

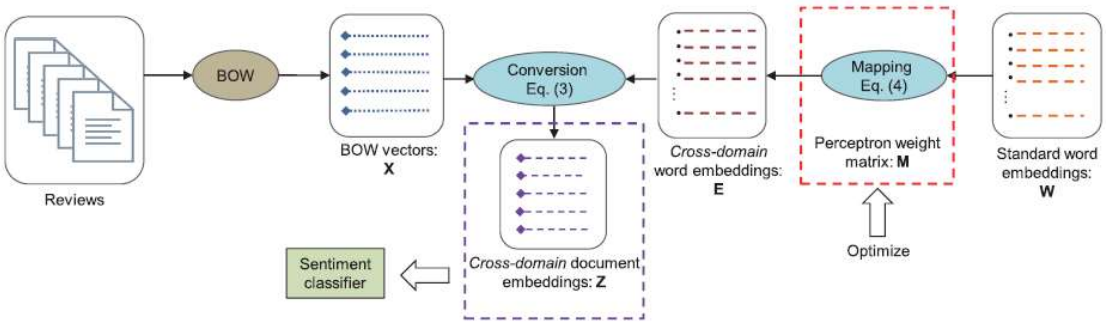


Fig 7: BOW, which stands for "bag-of-words," is the general framework of the proposed cross-domain sentiment classification model.

where I_i stands for the bag-of-words vector's ith pivot location. The amount Li = 1 indicates a positive correlation between this pivot and the review sentiment, whereas Li = -1 indicates a negative correlation and Li = 0 indicates no contribution to sentiment discrimination.

$$r_{ij}^{p} = \max(0, L_i, L_j)$$

Algorithm:
Input: Bag of word matrix X
Output : Weight matrix M, perceptron
Model Parameters: Θ_k , Θ_c , K as perplexity, k parameter for neighbour, α weight relevance , β_1, λ, β_2 balancing parameters μ regularization parameter.
Optimization parameters: N_t iteration number, scheduled momentum ξ(t), ξ, τ, δ *are the learning parameters*
Word selection : pivot and domain
Initialization : M set $\Delta_0^M = 0\ for\ t = 1\ to\ N_t$ do
Gradient $\frac{\partial L}{\partial M}$ is calculated
Mapping matrix is updated

$$\Delta_t^M = \xi(t)\,\Delta_{t-1}^M - \boldsymbol{\eta}\frac{\partial L}{\partial M}, M_{t+1} = M_t + \Delta_t^M$$

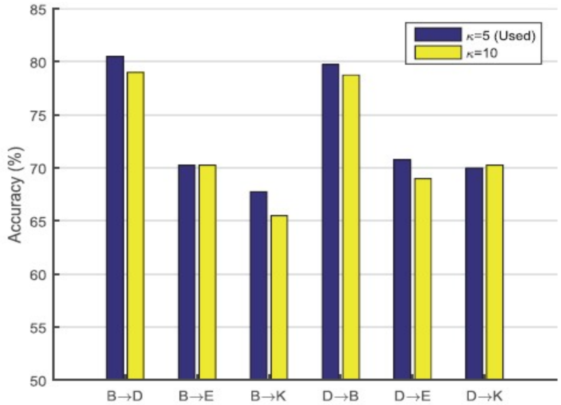


Fig 8: CrossWord performance demonstration for six sample DAT B problems using the two neighbour settings of k = 5 and k = 10.

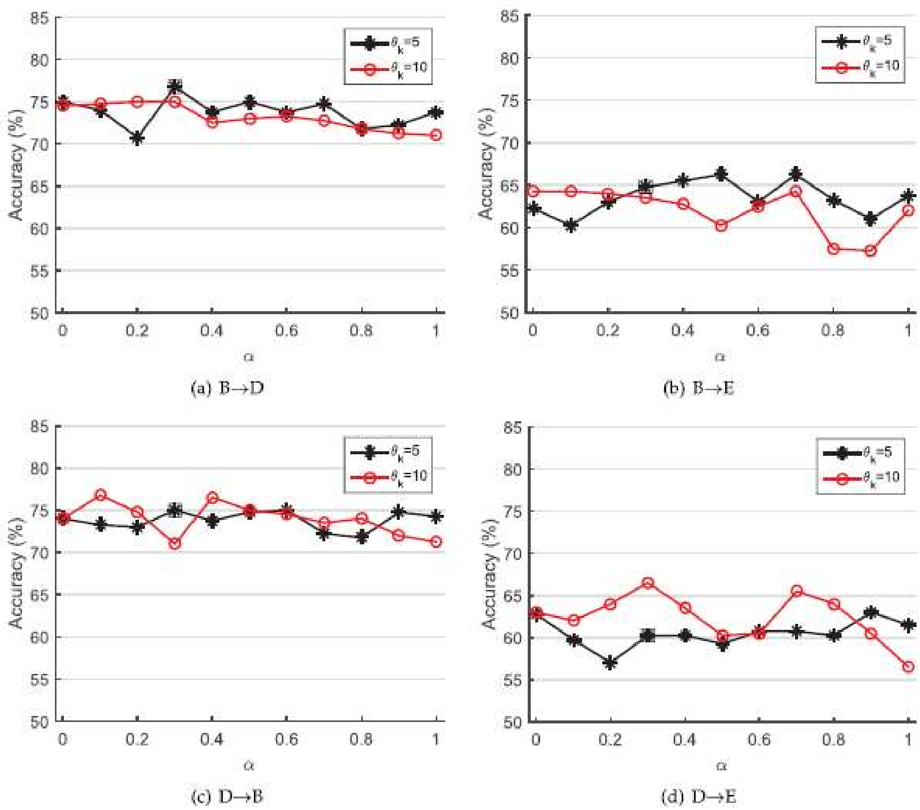


Fig 9: CrossWord performance changes when α ϵ [0,1], measured with the settings $\theta_k =$ 5 5 and uk 14 10, are changed.

Between the source and target feature spaces, the suggested technique successfully aligns them. To build a reliable sentiment classifier that can be applied across domains, low-dimensional document embedding vectors generated from the resulting embedding vectors are sufficient. Between the pivot and domain-specific terms, as well as between the labelled reviews in the source domain and the unlabeled reviews in both domains, CrossWord provides a more precise modelling of the probabilistic similarity relationships. Furthermore, it offers a more precise preservation of the intended similarity structures in the embedding space, which is accomplished by using the stochastic neighbour embedding technique.

3.4 JOINT SENTIMENT TOPIC MODEL

A probabilistic modelling framework founded on Latent Dirichlet Allocation is the JST model developed by [51]. (LDA) Labeled corpora are necessary in order to train the classifiers in a number of machine learning practices for sentiment classification. The JST model, in comparison, is completely unsupervised. The authors' research on polarity-bearing subjects served as the foundation for the JST model, which they used to expand the initial feature space. The domain-independent polarity terms serve as the foundation for learning in the JST paradigm. The JST model was created to concurrently detect an emotion and a topic from text and is an improvement of the LDA model. Discriminative classifiers are employed in the JST model to look for a bounding box that maximizes a certain measure of class separation. Sequential sampling is used to calculate the posterior distribution for each parameter (known as Gibbs sampling). Different terms that display a similar attitude can be grouped together using the JST approach. The characteristics for cross-domain categorization are selected and enhanced using information gain criteria. The JST model was further improved by [52], which led to the development of the DJST. As its name suggests, the DJST approach can be used to monitor and recognize shifting topics and attitudes throughout time.

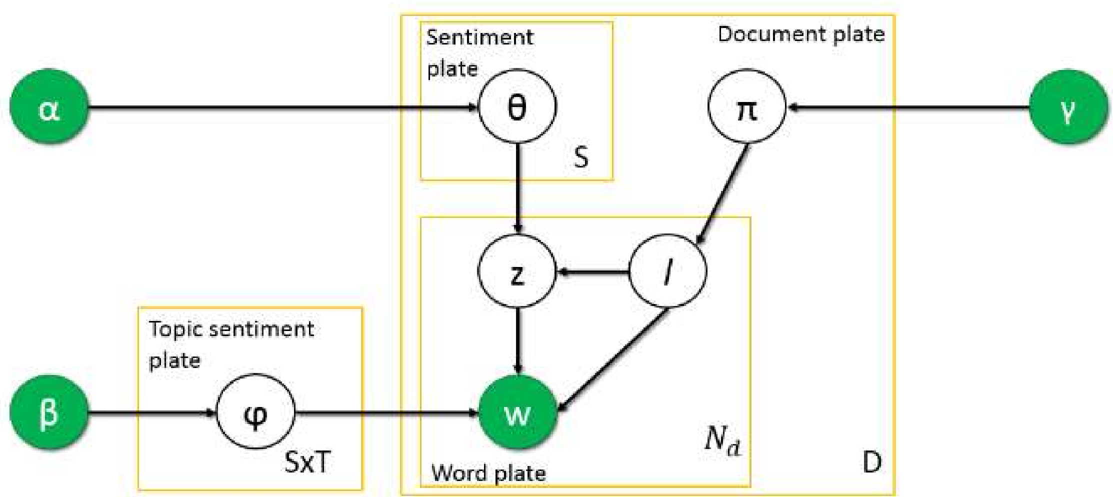


Fig 10:Joint Sentiment Topic model

Consider a corpus of D documents, indicated by C = d_1, d_2, , d_D. Each document in the corpus is a sequence of Nd words, denoted by d = (w_1, w_2, , w_{Nd}), and each word in the document is an item from a vocabulary index with V different terms, denoted by 1, 2, , , V. Let S and T represent the quantity of unique subject and sentiment labels, respectively.

3.5 CASE BASE REASONING

[53] suggested the SCL algorithm as a technique for figuring out the features of various domains. In essence, the algorithm transforms the target domain into the source domain. A

ssuccessful binary classifier is the goal of the authors' work, which states: " Together, a distribution D on X and a labeled function f: X [0,1] form a domain. They used hypothetical distance measures centered on diverging to calculate the distance of two populations, one in the source domain and one in the target domain, in order to build the model. Additionally, by modelling their relationships with pivot features, features from several domains were found. The pivot function is predominantly helpful in semi-supervised machine learning, it should be mentioned. The non-pivot features and comparable pivot features are associated in the SCL method. The classifier is then trained using a discriminative learner. It is vital to be talented to model and apply associations between characteristics in many provinces because the SCL technique does not employ labelled training data in testing. The next year, [54], who created the Structured Interpersonal Learning-Mutual Information, or SCI-MI model.

Input: *D,L,f(L,d)*
Output : CB
Where
D -> Out of domain documents for training
L-> available sentiment lexicons
F(L,d) -> unsupervised sentiment classifier docuemnts
CB← {}
for all d documents in D do
S← {}
For all L in L_i D do
Predictions are made using f(L_i, d)
For correct prediction S ←S U L_i
For S <> {} then
CB← CB U (x(d),S)

$$S_{adj}\ (w) = S(w) * (1 - \sqrt{freq(w)}$$

Where

$S(w), freq(w)$ $are\ the\ \ term\ score\ and\ term\ frequency\ of\ source\ lexicon$

Table 1: Class frequency distribution and fraction of cases dropped

Case base	Size	Pos. %	Neg. %	Discarded %
Books	9683	53.3	46.7	27.8
Electronics	9592	53.6	46.4	28.2
Film	9614	54.1	45.9	28.6
Music	6173	52.6	47.4	25.1
Hotels	11516	53.5	46.5	7.8
Apparel	11002	53.4	46.6	28.9

All lexicons received from the resolution of the single adjacent case are used when k = 1, but for larger values of k, the most often returned lexicons are chosen based on a rating of all solutions. Predictions using fewer lexicons, rather than an average of many, tend to do better in rankings when k is larger.

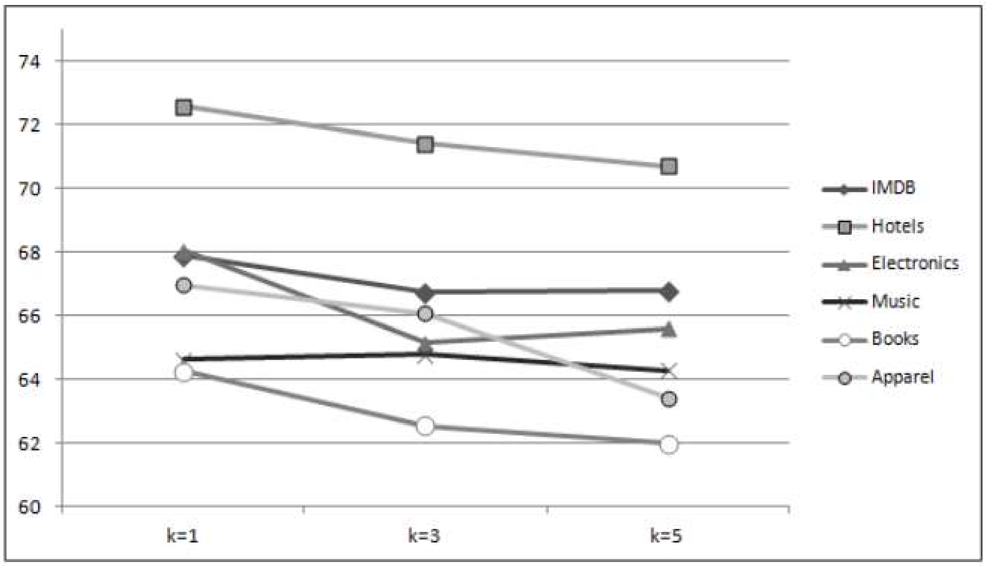


Fig 11: Accuracies for variable k

3.6 SPECTRAL FEATURE ALIGNMENT

Words from many domains can be aligned into a coherent cluster for a certain domain using the SFA method, which was proposed as a way to make advantage of knowledge of copyright terms. The SFA method conducts a number of tasks in order to successfully classify sentiment, including identifying the source and destination domains, constructing a bipartite network, co-clustering and aligning data, and identifying generic and domain-specific characteristics are all examples of this. Once can use a bipartite graph to show how both domain-specific and generic terms fall into distinct groups to decrease any mismatch between the source and destination domains. Then, this cluster used to teach a classifier how to classify sentiment. The domain-specific terms are compiled by the suggested SFA algorithm coming from the target and source domains into express the use of give groups and domain-independent terms as a means of aiding in this procedure. As a result, the distance between the words that are exclusive to each of the two areas decreased. Additionally, the algorithm trains the sentiment classifier in the intended field.

Let
l be the domain independent features to be selected
k be the largest number of sets
I be the information criterion between domains and features

$$I(X^i; D) = \sum_{d \epsilon D} \sum_{x\ \epsilon X^i\ x \neq 0} p(x,d) log_2 \frac{p(x,d)}{p(x)p(d)}$$

D is a domain variable

X^i $specific\ feature\ non-zero\ values$

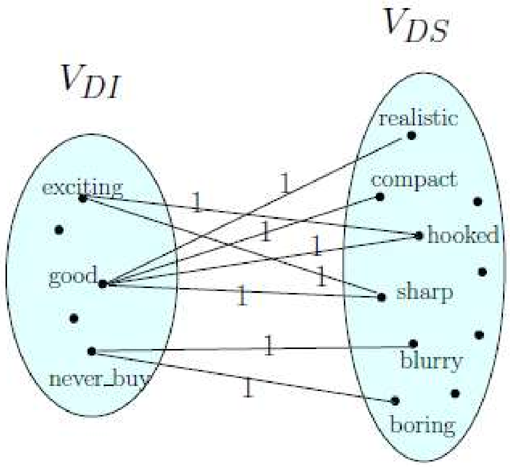


Fig 12: Domain-specific and -general characteristics illustrated as a bipartite graph

Input : Source domain labeled data and unlabeled target domain

$$D_{src} = \{(x_{src1}, y_{src1})\}_{i=1}^{n_{src}} \quad , \quad D_{tar} = \{x_{tarj}\}_{j=1}^{n_{tar}}$$

Output : adaptive classifier $f: X \to Y$

Domain Specific Features $\phi_{DI} = \begin{bmatrix} \phi_{DI}(x_{src}) \\ \phi_{DI}(x_{tar}) \end{bmatrix}$ *and* $\phi_{DS} = \begin{bmatrix} \phi_{DS}(x_{src}) \\ \phi_{DS}(x_{tar}) \end{bmatrix}$

For the weight matrix for DI-word and DS-word is $M \in \mathbb{R}^{(m-l)*l}$

$The\ affinity\ matrix\ is\ given\ as$ $A = \begin{bmatrix} 0 & M \\ M^T & 0 \end{bmatrix}$

The classifier f is given as = $\{(x_{src1}, \gamma\varphi\,(\phi_{DS}\,(x_{src1},))\,(y_{src1})\}_{i=1}^{n_{src}}$

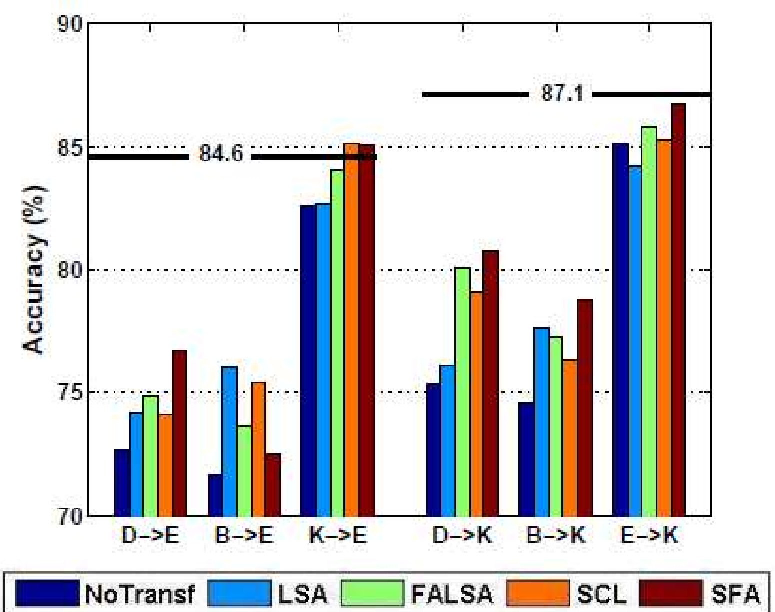


Fig 13: Accuracy comparison from the obtained results

The accuracy obtained from the proposed approach is more when compared with the existing methods.

4. CHALLENGES IN CROSS DOMAIN SENTIMENT ANALYSIS

The fundamental technological difficulty with sentiment classification is that it depends heavily on the domain. In many other words, a technique that excels in one area may perform poorly in another. This problem is particularly difficult since cross-domain categorization using machine learning works best with tagged texts and is therefore very domain-sensitive. The degree of similarity between training and test data impacts how well machine learning algorithm’s function, which suggests that source-target domain combinations have a significant impact on cross-domain sentiment analysis outcomes. Sentiment analysis performance suffers significantly when the sentiment scale is supplemented by two or even more sentiment classes. A significant decline in performance is unacceptable, even though interclass distinction is anticipated to be more difficult than binary classification. Additionally, for evaluations that are not fully binary, a discrepancy among review ratings with review content also affects performance.

Table 2: Challenges faced during cross domain sentiment analysis

CHALLENGE	DESCRIPTION
FEATURE DIVERGENCE	Classifiers that have been received training on data that contains lots of source-specific features are prone to feature divergence, which is also known as feature mismatch or website mismatch, because of the gap between the classifier's understanding and the property features being classified. For this reason, it's possible that domain Y won't appreciate your abilities to provide results in domain X.
POLARITY DIVERGENCE	Each feature has a polarity, and the source as well as the target may have different polarities. domain. In domain A, "easy" might be good while in domain B, it might be negative. Independent features suffer from the polarity divergence issue.
POLYSEMY	When the definition of a term changes, that is polysemy, both the destination and source subdomains change as a result of the the domain's particular setting. This makes testing more challenging. The veracity with which the features are depicted.
SPARSITY	Whenever the target domain contains, the sparsity problem occurs phrases or words that are absent or little used in the domain of origin.

5. CONTRIBUTION OF SENTIMENT ANALYSIS USING VARIOUS APPROACHES ON VARIOUS DATASETS

Table 3: contribution from different others on sentiment analysis—-CHANGE TABLE NAME

Author	Methodology	Dataset	Findings
[55]	CNN	SemEval 2016 workshop	Analysis of Twitter sentiment using user behavior data to identify features
[56]	Tree-LSTM and Discourse-LSTM	Food reviews and the Internet Movie Database (Amazon)	Sentiment analysis that uses the notion of rhetorical structure and aims to increase accuracy
[57]	CNN	IMDB and Movie reviews	AdaBoost + Boosted Post-processing for Sentiment Analysis to learn more about the impact of different filter lengths on the final text polarity.
[58]	CNN, RNN	Twitter	Sentiment analysis using domain-specific word embedding and recent recurrent variants
[59]	CNN, GRU, LSTM	Social networking networks and the SemEval workshop	Comparisons based upon sentiment analysis and aspect extraction are presented as an overview of sentiment classification using deep learning.
[60]	Coattention-LSTM, MemNet	SemEval 2014, Twitter	Sentiment analysis based on specific topics and topics in context
[61]	CNN, LSTM	SemEval 2017	Aspect-based sentiment analysis utilising a combined classification of aspect and polarity. A method for resolving two classification

			issues based on aspect sentiment analysis.
[62]	CNN	SemEval 2016	Polarity and aspect co-classification for use in aspect-based sentiment analysis. A technique based on aspect sentiment classification for fixing two different categorization problems.
[63]	LRNN-ASR, FULL-LRNN-ASR	Tripadvisor	Sentiment analysis relies on many aspects to provide depth to the input's understanding
[64]	CNN, LSTM, doc2vec	StockTwits	Improve StockTwits' sentiment analysis performance with deep learning.
[65]	DNN, CNN	social network sites, Twitter	Feature abstraction through sentiment analysis of weather-related tweets
[66]	CNN, RNN, DNN, LSTM,	Social network sites	Deep learning for sentiment investigation: a literature review covering topics including word embedding, emotion analysis, sarcasm detection, and multimodal data.
[67]	CNN, DNN, RNN	Social network sites	Deep learning has been used to improve upon previous methods for a variety of sentiment analysis jobs. There are a number of terms in this area, including "sentiment analysis," "opinion mining," and "sentiment classification and extraction."

[68]	CNN, DNN, RNN, DBN	Social network sites	Information extraction and classification from social media's unstructured information, including one with a description of sentiment analysis via deep learning algorithms.
[69]	CNN, lexicon, DNN, hybrid, RNN	Social network sites	Research on how deep learning-based sentiment analysis stacks up against conventional methods. Issues with domain dependence, feature extraction, false and spam review sentiment polarity, a large lexicon, negation, and ambivalent terms.
[70]	RNN	Amazon	Emotional data mining for online recommendation systems. By sifting through all the reviews and then generating a score based on them, this feature might suggest nearby establishments to the user.
[71]	CNN, RNN, LSTM	Financial tweets	Financial market sentiment analysis using ABSA

6. CONCLUSION AND FUTURE SCOPE

Over the years, researchers in the fields of text mining including natural language processing have paid a good amount of attention to sentiment classification. However, the effectiveness of sentiment analysis is being hampered by the scarcity of labelled data that can be utilized to train models for all domains. No research aimed at fixing this issue and bettering cross-domain sentiment classification has been found. We conducted a thorough literature analysis to identify the key cross-domain difficulties and approaches in order to support researchers in their work. Cross-domain sentiment analysis's reliability has improved significantly since the last time we looked at it, despite the fact that there is no perfect solution, which will open the door for future improvements. The majority of cross-domain sentiment analysis techniques rely on the parallelism between the target and source domains. An incorrect assumption is made about the similarities between the features of the source and target domains during the investigation, but because there are few similarities, the procedures produce subpar results with less precision. Additionally, while training various classification models utilizing labelled datasets, more precise results can be found. Since manually labelling a dataset is expensive and time-consuming, numerous strategies have been used by various studies over the past few years. It introduces the attention mechanism, which automatically and without human involvement captures pivot features. Based on that attentive network, it is suggested that only domain independent and domain-specific or pivot whole-part linkages receive higher word attention, which chooses significant sentiment from the entire article dynamically. As a follow-up to this research, a unified performance review approach might be created to analyze various methods.

Researchers may choose to follow a number of promising research avenues in the upcoming years. The first route that merits consideration is multi-view learning, which combines a few semi-supervised techniques to take use of different perspectives on the same input data. The second is about using models that can extract features from datasets across several source domains that are independent of a given domain. A further course of action would be to create models that can employ a subjectivity lexicon that is independent of a particular domain rather than spreading polarity in the opposite direction from source to target. The last requirement includes, feature transfer and novel word embeddings approaches for modelling can be developed. Furthermore, the use of deep learning techniques, as well as disparate feature spaces and a variety of data sources, should be examined. Last but not least, there is a trend toward integrating word embedding methods with deep brain learning, which, based on the results so far reported, appears to promise promising outcomes. Novel models that combine embeddings with deep neural learning are worth investigating, developing, and deploying.

Declaration

The authors have no conflicts of interest to declare that are relevant to the content of this article

REFERENCES

[1] B. Liu, “Sentiment analysis and opinion mining,” Synthesis lectures on human language technologies, vol. 5, no. 1, pp. 1–167, 2012.

[2] Jinbo Zhu, Huihen Wang, Muhua Zhu, Tsou, BK & Ma, M 2011, ‘Aspect-Based Opinion Polling from Customer Reviews’, IEEE Transaction on Affective Computing, vol. 2, no. 1, pp. 37-49.

[3] Hu, M & Liu, B 2004, ‘Mining and Summarizing Customer Reviews’, in Proceedings of 10th ACM SIG KDD International Conference on Knowledge Discovery and Data mining, pp. 168-177.

[4] Lu ,Y, Zhai, C & Sundaresan, N 2009, ‘Rated Aspect Summarization of Short Comments’, in Proceedings of the 18th Conference on World Wide Web, pp.131-140.

[5] Titov Ivan & Mcdonald Ryan 2008, ‘A Joint Model of Text and Aspect Ratings for Sentiment Summarization’, in Proceedings of the Conference ACL-08: HLT, Columbus, Ohio, USA, Association for Computational Linguistics, pp. 308-316.

[6] Fan, TK & Chang, CH 2010, ‘Sentiment-Oriented Contextual Advertising’, Knowledge and Information Systems, vol. 23, no. 3, pp. 321–344.

[7] H. Wang, D. Can, A. Kazemzadeh, F. Bar, and S. Narayanan, “A system for real-time twitter sentiment analysis of 2012 us presidential election cycle,” in Proceedings of the

ACL 2012 System Demonstrations. Association for Computational Linguistics, 2012, pp. 115–120.

[8] C. Meador and J. Gluck, "Analyzing the relationship between tweets, box-office performance and stocks," Methods, 2009.

[9] (2015, Jun.) Twitter usage statistics. [Online]. Available: http://www.internetlivestats.com/twitter-statistics//

[10] Liu, B. (2012). Sentiment analysis and opinion mining. Synthesis lectures on human language technologies, 5, 1–167.

[11] Cambria, E. (2016). Affective computing and sentiment analysis. IEEE Intelligent Systems, 31, 102–107

[12] Breck, E., & Cardie, C. (2017). Opinion mining and sentiment analysis. In The Oxford Handbook of Computational Linguistics. (2nd ed.).

[13] Feldman, R. (2013). Techniques and applications for sentiment analysis. Communications of the ACM, 56 , 82–89.

[14] Lau, R. Y., Li, C., & Liao, S. S. (2014). Social analytics: learning fuzzy product ontologies for aspect-oriented sentiment analysis. Decision Support Systems,65, 80–94.

[15] Schouten, K., & Frasincar, F. (2016). Survey on aspect-level sentiment analysis. IEEE Transactions on Knowledge and Data Engineering, 28, 813–830.

[16] Akhtar, M. S., Gupta, D., Ekbal, A., & Bhattacharyya, P. (2017). Feature selection and ensemble construction: A two-step method for aspect-based sentiment analysis. Knowledge-Based Systems, 125, 116–135.

[17] Mukherjee, A., & Liu, B. (2012). Aspect extraction through semi-supervised modeling. In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Long Papers-Volume 1 (pp. 339–348). Association for Computational Linguistics.

[18] Wang, T., Cai, Y., Leung, H.-f., Lau, R. Y., Li, Q., & Min, H. (2014). Product aspect extraction supervised with online domain knowledge. Knowledge-Based Systems, 71, 86–100.

[19] Matsuno, I. P., Rossi, R. G., Marcacini, R. M., & Rezende, S. O. (2017). Aspect based sentiment analysis using semi-supervised learning in bipartite heterogeneous networks. Journal of Information and Data Management, 7, 141–154.

[20] Dave, K., Lawrence, S., Pennock, D.M.: Mining the peanut gallery: opinion extraction and semantic classification of product reviews. In: Proceedings of the 12th International Conference on World Wide Web. WWW 2003, pp. 519–528. ACM, New York (2003). https://doi.org/10.1145/775152.775226.

[21] Ravi, K., Ravi, V.: A survey on opinion mining and sentiment analysis: tasks, approaches and applications. Knowl.-Based Syst. 89, 14–46 (2015). https://doi.org/10.1016/j.knosys.2015.06.015. http://www.sciencedirect .com /science/article/pii/S0950705115002336

[22] Liu, B.: Sentiment Analysis and Opinion Mining. Morgan & Claypool Publishers, San Rafael (2012)

[23] Glorot, X., Bordes, A., Bengio, Y.: Domain adaptation for large-scale sentiment classification: a deep learning approach. In: Proceedings of the 28th International

Conference on International Conference on Machine Learning. ICML 2011, pp. 513–520. Omnipress, USA (2011), http://dl.acm.org/citation.cfm ?id=3104482. 3104547

[24] Ruder, S., Ghaffari, P., Breslin, J.G.: A hierarchical model of reviews for aspect-based sentiment analysis. arXiv preprint arXiv:1609.02745 (2016)

[25] Tang, D., Qin, B., Feng, X., Liu, T.: Effective LSTMs for target-dependent sentiment classification. arXiv preprint arXiv:1512.01100 (2015)

[26] Tang, D., Qin, B., Liu, T.: Document modeling with gated recurrent neural network for sentiment classification. In: Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, pp. 1422–1432 (2015).

[27] Wang, Y., Huang, M., Zhao, L., et al.: Attention-based LSTM for aspect-level sentiment classification. In: Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pp. 606–615 (2016).

[28] Yang, M., Tu, W., Wang, J., Xu, F., Chen, X.: Attention based LSTM for target dependent sentiment classification (2017). https://aaai.org/ocs/index.php/AAAI/AAAI17/paper/view/14151.

[32] S. Poria, E. Cambria, and A. Gelbukh, "Aspect extraction for opinion mining with a deep convolutional neural network," *Knowledge-Based Systems*, vol. 108, pp. 42–49, 2016.

[30] D. Ma, S. Li, X. Zhang, and H. Wang, "Interactive attention networks for aspect-level sentiment classification," 2017, https://arxiv.org/abs/1709.00893.

[31] Y. Wang, M. Huang, X. Zhu, and Li Zhao, "Attention-based lstm for aspect-level sentiment classification," in Paper Presented at the Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, Austin, TX, USA, November 2016.

[29] M. S. Akhtar, D. Gupta, A. Ekbal, and P. Bhattacharyya, "Feature selection and ensemble construction: a two-step method for aspect based sentiment analysis," Knowledge-Based Systems, vol. 125, pp. 116–135, 2017.

[33] A. Weichselbraun, S. Gindl, F. Fischer, S. Vakulenko, and A. Scharl, "Aspect-based extraction and analysis of affective knowledge from social media streams," IEEE Intelligent Systems, vol. 32, no. 3, pp. 80–88, 2017.

[34] C. Brun, J. Perez, and C. Roux, "Xrce at semeval-2016 task 5: feedbacked ensemble modeling on syntactico-semantic knowledge for aspect based sentiment analysis," in Paper presented at the Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016), San Diego, CA, USA, June 2016.

[35] H.-T. Nguyen, L.-M. Nguyen, and Nguyen Le-Minh, "Ilwaanet: an interactive lexicon-aware word-aspect attention network for aspect-level sentiment classification on social networking," Expert Systems with Applications, vol. 146, Article ID 113065, 2020.

[36] Rana, T. A., & Cheah, Y.-N. (2017). A two-fold rule-based model for aspect extraction. Expert Systems with Applications, 89 , 273–285.

[37] Schouten, K., & Frasincar, F. (2016). Survey on aspect-level sentiment analysis. IEEE Transactions on Knowledge and Data Engineering, 28 , 813–830.

[38] Kong, X., Ng, M. K., & Zhou, Z.-H. (2013). Transductive multilabel learning via label set propagation. IEEE Transactions on Knowledge and Data Engineering, 25 , 704–719.

[39] Chapelle, O., Schölkopf, B., & Zien, A. (Eds.) (2006). Semi-Supervised Learning. MIT Press.

[40] Belkin, M., Niyogi, P., & Sindhwani, V. (2006). Manifold regularization: A geometric framework for learning from labeled and unlabeled examples. Journal of Machine Learning Research, 7 , 2399–2434.

[41] Z. Li, Y. Zhang, W. Ying, Y. Wu, and Q. Yang, "End-to-End adversarial memory network for cross-domain sentiment classification," in Paper presented at the IJCAI, Sydney, Australia, August 2017.

[42] M. Hu, Y. Wu, and S. Zhao, "Domain-invariant feature distillation for cross-domain sentiment classification," 2019, https://arxiv.org/abs/1908.09122.

[43] Y. Liang, F. Meng, and J. Zhang, "An iterative knowledge transfer network with routing for aspect-based sentiment analysis," 2020, https://arxiv.org/abs/2004.01935.

[44] Y. Cai and X. Wan, "Multi-domain sentiment classification based on domain-aware embedding and attention," in Paper presented at the IJCAI, Macao, China, August 2019.

[45] Qi Liu, Y. Zhang, and J. Liu, "Learning domain representation for multi-domain sentiment classification," in Paper presented at the Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, New Orleans, LA, USA, June 2018.

[46] R. He, W. Sun Lee, Ng Hwee Tou, and D. Dahlmeier, "An interactive multi-task learning network for end-to-end aspect-based sentiment analysis," 2019, https://arxiv.org/abs/1906.06906.

[47] Almuhareb A, Alsanie W (2019) Arabic word segmentation with long short-term memory neural networks and word embedding. IEEE Access 7:12879–12887.

[48] Le A, Clanuwat T, Kitamoto A (2019) A human-inspired recognition system for pre-modern japanese historical documents. IEEE Access 7:84163–84169

[49] E. Cambria, "Affective computing and sentiment analysis," IEEE Intelligent Systems vol. 31, no. 2, pp. 102–107, Mar./Apr. 2016.

[50] J. Yu and J. Jiang, "Learning sentence embeddings with auxiliary tasks for cross-domain sentiment classification," in Proc. Conf. Empirical Methods Natural Lang. Process., 2016, pp. 236–246.

[51] He, C. Lin, and H. Alani, ''Automatically extracting polarity-bearing topics for cross-domain sentiment classification,'' in Proc. 49th Annual Meeting, Jun. 2011, pp. 123–131.

[52] Y. He, C. Lin, W. Gao, and K.-F. Wong, ''Dynamic joint sentiment-topic model,'' ACM Trans. Intelligent Syst. Technol., vol. 5, no. 1, p. 6, 2013.

[55] C. Lin, Y. Lee, C. Yu, and H. Chen, ''Exploring ensemble of models in taxonomy-based cross-domain sentiment classification,'' in Proc. 23rd ACM Int. Conf. Conf. Inf. Know. Manage. -(CIKM), 2014, pp. 1279–1288.

[56] S. J. Pan, X. Ni, J.-T. Sun, Q. Yang, and Z. Chen, ''Cross-domain sentiment classification via spectral feature alignment,'' in Proc. 19th Int. Conf. World Wide Web, vol. 10. 2010, p. 751.

[53]. J. Blitzer, R. McDonald, and F. Pereira, ''Domain adaptation with structural correspondence learning,'' in Proc. Conf. Empirical Methods Natural Lang. Process., 2006, pp. 120–128.

[54] J. Blitzer, M. Dredze, and F. Pereira, ''Biographies, bollywood, boom-boxes and blenders: Domain adaptation for sentiment classification,'' in Proc. ACL, vol. 7. 2007, pp. 440–447.

[55]. Alharbi, A.S.M.; de Doncker, E. Twitter sentiment analysis with a deep neural network: An enhanced approach using user behavioral information. Cogn. Syst. Res. 2019, 54, 50–61. [CrossRef]

[56]. Kraus, M.; Feuerriegel, S. Sentiment analysis based on rhetorical structure theory: Learning deep neural networks from discourse trees. Expert Syst. Appl. 2019, 118, 65–79. [CrossRef].

[57]. Gao, Y.; Rong, W.; Shen, Y.; Xiong, Z. Convolutional neural network based sentiment analysis using Adaboost combination. In Proceedings of the 2016 International Joint Conference on Neural Networks (IJCNN), Vancouver, BC, Canada, 24–29 July 2016; pp. 1333–1338.

[58]. Abid, F.; Alam, M.; Yasir, M.; Li, C.J. Sentiment analysis through recurrent variants latterly on convolutional neural network of Twitter. Future Gener. Comput. Syst. 2019, 95, 292–308. [CrossRef].

[59]. Do, H.H.; Prasad, P.; Maag, A.; Alsadoon, A.J. Deep Learning for Aspect-Based Sentiment Analysis: A Comparative Review. Expert Syst. Appl. 2019, 118, 272–299. [CrossRef].

[60]. Yang, C.; Zhang, H.; Jiang, B.; Li, K.J. Aspect-based sentiment analysis with alternating coattention networks. Inf. Process. Manag. 2019, 56, 463–478. [CrossRef].

[61]. ang, D.; Zhang, M. Deep Learning in Sentiment Analysis. In Deep Learning in Natural Language Processing; Springer: Berlin, Germany, 2018; pp. 219–253.

[62]. Zhang, Z.; Zou, Y.; Gan, C. Textual sentiment analysis via three different attention convolutional neural networks and cross-modality consistent regression. Neurocomputing 2018, 275, 1407–1415. [CrossRef]

[63]. Pham, D.-H.; Le, A.-C. Learning multiple layers of knowledge representation for aspect based sentiment analysis. Data Knowl. Eng. 2018, 114, 26–39. [CrossRef].

[64]. Sohangir, S.; Wang, D.; Pomeranets, A.; Khoshgoftaar, T.M. Big Data: Deep Learning for financial sentiment analysis. J. Big Data 2018, 5, 3. [CrossRef].

[65]. Qian, J.; Niu, Z.; Shi, C. Sentiment Analysis Model on Weather Related Tweets with Deep Neural Network. In Proceedings of the 2018 10th International Conference on Machine Learning and Computing, Macau, China, 26–28 February 2018; pp. 31–35.

[66]. Zhang, L.; Wang, S.; Liu, B. Deep learning for sentiment analysis: A survey. WIREs Data Min. Knowl. Discov.2018, 8, e1253. [CrossRef.

[67]. Tang, D.; Zhang, M. Deep Learning in Sentiment Analysis. In Deep Learning in Natural Language Processing; Springer: Berlin, Germany, 2018; pp. 219–253.

[68]. Ain, Q.T.; Ali, M.; Riaz, A.; Noureen, A.; Kamran, M.; Hayat, B.; Rehman, A. Sentiment analysis using deep learning techniques: A review. Int. J. Adv. Comput. Sci. Appl. 2017, 8, 424.

[69]. Bhavitha, B.; Rodrigues, A.P.; Chiplunkar, N.N. Comparative study of machine learning techniques in sentimental analysis. In Proceedings of the 2017 International Conference on Inventive Communication and Computational Technologies (ICICCT), Coimbatore, India, 10–11 March 2017; pp. 216–221.

[70]. Preethi, G.; Krishna, P.V.; Obaidat, M.S.; Saritha, V.; Yenduri, S. Application of deep learning to sentiment analysis for recommender system on cloud. In Proceedings of the 2017 International Conference on Computer, Information and Telecommunication Systems (CITS), Dalian, China, 21–23 July 2017; pp. 93–97.

[71]. Jangid, H.; Singhal, S.; Shah, R.R.; Zimmermann, R. Aspect-Based Financial Sentiment Analysis using Deep Learning. In Proceedings of the Companion of the The Web Conference 2018 on The Web Conference, Lyon, France, 23–27 April 2018; pp. 1961–1966.