International Journal of Advance Research in Science and Engineering
Volume No. 12, Issue No. 08, August 2023
www.ijarse.com

IJARSE
ISSN 2319 - 8354

REVIEW ON AMAZON TEXT REVIEW SENTIMENT CLASSIFICATION BY MACHINE LEARNING AND DEEP LEARNING

Aditya Partap Singh[1], Ved Parkash[1], Deepak Kumar, Divya[1]

[1]*Computer engineering department, ,State institute of engineering and technology, Nilokheri, Haryana*

Abstract

Used recently developed deep learning architectures to build models for solving various tasks that are related to sentiment analysis. Specifically, we have developed a method of feature representation customized for sentiment analysis. We have built an efficient model for the helpfulness analysis of reviews. We have also designed a model for identification of subjective and objective sentences. We have used all of these approaches together to create a step- by-step framework for the broader purpose of sentiment analysis, and shown its efficacy in comparison to more direct and generalized approaches. Our framework serves as an one- of-its-kind structure which can perform reliable and accurate sentiment analysis. It can be useful for businesses to assess customer feedback and make strategic decisions

Keywords*:* Sentiment, review, deep learning, machine learning, classification, detection

1. INTRODUCTION

The Internet is witnessing an information explosion, owing to the exponential growth in user-generated content each day. The popularity of Web 2.0 and ease of internet access has led to data being available in plenty on almost every topic. This information includes the opinions and reviews of users, consumers and customers of various products and services available all over the world. Data such as movie reviews, product reviews, financial market sentiments, political opinions, etc., are readily available for someone seeking to make an informed decision. In this context, it becomes both necessary and useful to have a mechanism that sifts through the mass of data, analyzes them and also categorizes, quantifies or scores them, in order to aid decision making. This has given rise to the concept of sentiment analysis. Sentiment analysis is the process of analyzing opinions or views expressed in textual form and their overall classification, scoring or quantification. Opinion mining is another term used to mean the same. The primary purpose is to get an idea of people’s general attitude and feelings towards a certain subject [12, 36] [10].

The task of sentiment analysis is particularly significant since users around the world look up such reviews before deciding about purchase of products (e.g., books, electron- ics, clothing and accessories) or avail of services (e.g., movies, restaurants, repair service providers). Similarly, product sellers and service providers consider such reviews as feed- back and utilize them to improve their offerings. The reviews are also taken into account for planning and strategy building regarding future products and services [122].

As per the BrightLocal Local Consumer Review Survey 2020 [5] - 87%

- of consumers refer and read reviews about local businesses
- 79% of users trust online reviews and personal recommendations at a similar level 96% of
- consumers read businesses' responses to reviews
- The top five industries with maximum likelihood of consumers reading reviews are: Restaurants, Hotels, Medical, Automotive, and Clothing stores
- The top five significant review features are: Star rating, Legitimacy, Recency, Sen- timent, and Quantity

These findings highlight the influence of reviews on users, and the importance of review analysis by businesses. Hence, sentiment analysis has become essential in the current social and economic context.

Sentiment analysis deals with massive unstructured data, which is generally sub- jective, vague, and not strictly adherent to language rules. Thus, sentiment analysis becomes a complex task, requiring the contribution of various domains, including data mining, natural language processing, data analytics, computational intelligence, machine learning, etc. At a fundamental level, sentiment analysis is a problem of classification, as it categorizes opinions into broad categories like positive, negative or neutral. But in- depth analysis can lead to exploring finer details and extracting more useful information [96, 122].

Considering the complexity of sentiment analysis and the available variety in data, it is desirable to automate the process to save manpower, get faster output, filter massive unnecessary data to find relevant material, and present the results in necessary formats. The task of sentiment analysis is a broad field that includes various subtasks, like review usefulness analysis, negation handling, spam detection, word sense disambiguation, sub- jectivity detection, and named entity recognition. Sentiment analysis tools are greatly useful for extracting data from various sources, viz. review sites, feedback forums, social networking sites, blogs, and so on, and can also perform detailed analytical operations on it [109].

With the increase in multiplicity of forums of expression, the amount of data generated is massive and heterogeneous. Opinions on various subjects are available on [2, 6] [2] -

- Social media and media sharing sites - With approximately 2.5 billion users active on social media all over the world, it is obvious that the data generated on Facebook, Twitter, LinkedIn, Instagram, YouTube, SoundCloud etc. is rich and voluminous, and a likely place to look for information related to users' opinions and choices.
- Online commerce websites - Many users on popular e-commerce sites like Amazon, Flipkart, eBay, etc. give their feedback and reviews after using a certain product, generally accompanied with a star rating. These opinions can be referred to by a prospective user who is looking for options to buy a product.
- Review sites - Dedicated review websites such as Yelp (Restaurants), TripAdvisor (destinations

and facilities), Rotten Tomatoes and IMDb (Movies), etc. are rich resources of user-generated reviews, ratings and opinions about consumer products and services all over the world.

- Opinion blogs and aggregation sites - Blogging is a popular activity in today's world. Blogs are available about a wide variety of topics like gadgets, current affairs, po- litical issues, travel spots, etc. Aggregation sites such as Tumblr, Reddit, etc. also contain multiple discussions and user generated opinions on a range of topics. These can be analyzed to obtain opinions about the respective content.
- Communication media - Communication mediums like SMS, WhatsApp etc. are also a rich source of information, and can be analyzed for opinions.

These sources have a wide variety of opinions, domains, rating methods, languages used, etc. Hence, collecting, organizing, normalizing and analyzing such data is a major data- intensive task. This needs methods which are up-to-date, fast and adaptable across

multiple domains. This area has seen a spurt in research work during the last decade, and it is still a fascinating and promising field of work, keeping in mind the spread of online activity and networking, and its impact on the markets.

This thesis explores various topics that contribute to the broad task of sentiment analysis. It also attempts to create a framework for a unified and comprehensive approach to sentiment analysis. The framework consists of a sequence of steps that process user- generated data in multiple ways. The resultant data is found to be more suitable for sentiment analysis and gives better performance. The framework applies suitable machine learning and deep learning model combinations at each step to process the data. The aim of the present work is to provide efficient and useful frameworks for sentiment analysis which generate more accurate results and work on a variety of domains.

1.1. Motivation

Online opinions and reviews significantly influence decision making, both by end-users and businesses. Acting as a form of e-Word-of-Mouth, such reviews form the basis on which users decide about purchasing or using a product. On the other hand, based on the reviews of their products, the manufacturers can take strategic decisions on upgrad- ing, replacing or marketing a product, or address issues raised by consumers. Hence, it becomes useful to have a sentiment analysis mechanism which can be beneficial for consumers to perform an informed decision-making, as well as for businesses or manufac- turers to strategize and improve upon the customer experience. There is a lot of existing research in this field, as is seen from the literature. But there is scope for performance improvement, since natural language processing involves many factors which as subjec- tive, contextual and language-specific. Thus, there is a need of newer and better methods to make the task of sentiment analysis more efficient and qualitative.

2. RELATED WORK

Assigning weightage to a review can help the user make a better decision. Knowing the value of opinions not only benefits the users, but also the product or service providers who can pay special attention to the issues raised in such reviews and address them. It adds to the market spread and strategy making process of businesses. For these reasons, e-commerce providers offer guidelines for writing good reviews, and provide options to the users to mark if a particular review was helpful for them or not. This information is also provided to other users for reference. Existing literature divides products or services into broadly three categories - search, experience, and credence goods. For each category, the factors that influence the helpful- ness of reviews are different. Researchers have identified multiple influencing factors, like review depth and extremity, star ratings, reviewer characteristics, etc. [46, 161]. Figure 2.7 displays a detailed review with its star rating taken from Amazon, which 623 people have voted as helpful.

Since the availability of reviews in large numbers and ease of accessibility has only been possible in the last few years, work in the field of review usefulness is recent. Some of the notable research in this field is discussed as follows.

Fang et al. [47] conducted a statistical study and found that the usefulness of reviews is dependent upon readability and extremity of reviews, as well as the rating history of the reviewers. A similar kind of study based on regression analysis was done by Racherla and Friske [119] which showed the correlation between reviewer characteristics like identity and expertise, review characteristics like length and extremity, and the type of goods, and their combined influence on the helpfulness of reviews across three categories. Mudambi and Schuff [95] report a study on reviews available on Amazon. They specify that review extremity and length affect the helpfulness, but in varying degrees, depending on the product type. Perceived helpful reviews potentially increase sales, among other benefits. The study also provides guidelines for obtaining more helpful reviews. Qazi et al. [116] also provide an experimental study in the field, and highlight the impact of review length and tone of comparison and suggestion. They suggested two morphological factors, namely the number of concepts present in each review, and the average number of concepts in each sentence, which influence usefulness of reviews. Purnawirawan et al. [115] examine the effect of the ratio of positive to negative reviews, as well as the sequence of review presentation on the usefulness, in which they find that unbalanced review sets are found to be more useful than balanced ones, and order of presentation matter, but only in unbalanced review sets. Choi and Leon [34], Lee et al. [80], Tsai et al. [144], and Malik [91] in their respective works have listed various review characteristics (such as length, readability, rating, etc.), and reviewer characteristics (such as reviewer rank, number of reviews, total votes, etc.) that influence review helpfulness. The effect of emoticons in increasing helpfulness was studied by Huang et al. [62], and the presence of prior reviews and their effect on perceived usefulness was demonstrated by Zhu et al. [160]. The positive impact of similarity between title and content of a review was also highlighted by Zhou et al. [154].

Zuccala et al. [162] introduce a theory of mega citation to represent book reviews as a bibliometric parameter, and implement a Naive Bayes classifier using Laplace correction. Sentences of book reviews are classified as positive, negative or neutral. Two factors, namely writing style and scholarly credibility are considered for classification. They obtain nearly 75% accuracy for scholarly credibility and 64% accuracy for writing style. Lee and Choeh [78] apply a multi-layer perceptron neural network on product reviews from Amazon, to predict review helpfulness using certain textual characteristics and product data. The model generates the relative strength of helpfulness of various determinants, and gives suggestions for better design of review sites.

Ghose and Ipeirotis [51] explore various aspects of review texts and reviewer characteristics, like subjectivity of reviews and review readability, to find proper subsets of features which are equivalent to using all the available features. They experiment on various Random Forest classifiers on a diversified set of product reviews and demonstrate the performances with various feature combinations.

Wei et al. [149] apply a recurrent neural network model for categorizing good and bad product reviews, particularly obtaining good results using LSTM networks. This is one the initial deep learning approaches to review usefulness analysis. Nguy [99] also experiments on different combinations of CNN and LSTM models to perform review usefulness analysis and identify keywords and relevance as more influential factors on usefulness, as compared to readability, length and sentence structure. Singh and Tucker [135] apply machine learn- ing to perform disambiguation of reviews by categorizing them into one of form, function and behavior categories, find the correlation between ratings and product characteristics, and use the results to predict the usefulness. They have experimented on within-product, across-product, within-product-domain and across-product-domains to achieve commend- able results. Krishnamoorthy [74] proposes an effective method that identifies and extracts linguistic features, combines them with metadata, subjectivity and readability related fea- tures, and applies different machine learning models to predict usefulness of reviews using these features. The results are tested individually and in combination, and the efficacy of linguistic features for accurate usefulness prediction are highlighted. It also conducts sensi- tivity analysis to identify the categories of verbs used and their impact on the results. Basiri and Habibi [14] applied convolutional layers with gated recurrent units to predict review helpfulness using content-based, sentiment, semantic and metadata features on Amazon re- view datasets to achieve improved performance over traditional and deep models. Kong et al. [72] combined CNN with TransE to learn semantic information and identify relationships between various entities present in the review. They utilized hand-crafted features based on review, reviewer and product characteristics to improve the proposed model's performance. Du et al. [41] designed a deep neural end-to-end architecture for evaluating the text-rating interaction that enhances the influence of ratings on the review text and their information representation. Their results show higher performance in predicting review usefulness by uti- lizing adaptive rating learning. Qu et al. [117] modeled customer expectations and important review features using an attention-based neural network. The proposed network included multiple attention layers to extract product information and sentiment information. They experimented on Amazon and Yelp datasets and obtained significant improvements using area under the curve (AUC) metric. The best accuracies among these methods range from 80-92%, thereby leaving scope for improvement in the field. Involving sentiment information in review usefulness analysis is also an area where work can be done.

2.1.

2.1.1. 3 Subjectivity detection

Any text that comes under analysis can be either factual, i.e., expressing facts and information, or opinionated, i.e. expressing views and opinions. It is necessary to iden- tify such opinionated statements, as they are relevant for opinion mining tasks. This process is known as subjectivity detection, which is a prerequisite of sentiment analysis. A subjective statement is that which expresses an emotion or feeling, which may or may not be an opinion, even though opinionated statements are generally subjective. Some- times, even objective statements can carry opinions. Once an opinionated statement is discovered, sentiment analysis is performed on it, for classifying its opinion as positive or negative. Deeper study is required to find out the type of opinion expressed in the statement. Hence, subjectivity detection and sentiment classification are complementary processes [7, 30] [5].

Reviews and articles generally contain a combination of objective (factual) and subjective (opinionated) statements. Objective sentences provide only facts and not opinions.

Hence, they are neutral and irrelevant to sentiment analysis. The subjective statements include the user's views towards the product/service under consideration, thus affecting the sentiment analysis results [29]. As an example, the sentence "The mobile has a 6GB RAM and a 5.2inch display with quad-core processor." in a mobile phone review is an objective sentence. Contrarily, the sentence "Great product, fast processor, best phone in this price segment." is subjective and thereby more helpful for readers. Subjectivity detection aids in removing objective parts from given text. The parts that remain are entirely subjective, and useful for further analysis. Subjectivity detection as a preceding step can reduce the amount of data for analysis without impacting the final outputs. Furthermore, presence of neutral content can dilute the detection results. Thus, identification and filtering of such content with the help of subjectivity detection can improve the final results [35, 132].

The field of subjectivity detection has relatively less literature as compared to most other natural language processing fields. Major work in the area is mentioned. Wiebe and Riloff

[150] have designed rule-based subjectivity classifiers, trained on un-annotated data to learn extraction patterns, that gave performance comparable to existing classifiers on world press articles. In another work, Xuan et al. [151] have assessed the syntactic text structures to discover syntax-based patterns involving various parts of speech. These patterns are able to extract informative linguistic features, which gave significant results on movie reviews, taken in combination with traditional features. Bravo-Marquez et al. [21] have presented a feature- representation technique that avoids sparsity and gives improved accuracy in subjectivity detection on Twitter data.

Keshavarz and Abadeh [68] have used a genetic algorithm-based method to build a sub- jectivity lexicon MHSubLex. It is used for subjectivity detection on three Twitter datasets. Multilingual [12] and cross-lingual [9] subjectivity detection has also seen some interest. Lin et al. [82] have performed sentence-level subjectivity detection by applying a hierarchi- cal Bayesian model that is based on latent Dirichlet Allocation (sub-jLDA). The technique is weakly supervised and uses a limited number of linguistic clues. Its results on multi- perspective question answering (MPQA) corpus are competitive with techniques based on larger training sets. Kamal [66] has experimented with four different supervised classifiers using linguistic characteristics like term frequencies, opinion seed word, negation, etc., to characterize unigrams. Feature-opinion pairs are also mined from product reviews using these characteristics. Esuli and Sebastiani [45] have employed a semi-supervised approach involving textual definitions that gives state-of-the-art performance as well as a baseline for subjectivity determination.

Wang and Manning [148] have used Naive Bayes based classifiers with fast dropout for subjectivity detection on various datasets to obtain high accuracy on movie reviews. Kim

[69] has utilized pre-trained word embeddings for various sentence-based subjectivity clas- sification using CNN and achieved 93% accuracy by multichannel CNN. Chaturvedi et al.

[28] have extracted network patterns of concepts and words from text through dynamic Gaussian Bayesian networks to pre-train CNN and obtained 5-10% accuracy improvements compared to standard approaches on MPQA and movie reviews. Further, Chaturvedi et al.

[31] have also implemented an extreme learning framework which includes Bayesian networks for building interconnections. They modelled temporal features using fuzzy recurrent net- work. Their experiments on various datasets prove the model's ability of portability to other languages and domains. Rustamov [128] has also approached sentence-level subjectivity de- tection, building a hybrid model of Fuzzy Control system, Adaptive neuro-fuzzy inference system, and Hidden Markov model. He has used pruned inverse document frequency (IDF) weighting function to detect features, and has obtained higher accuracy than individual classifiers. As observed, there is limited work in this field, especially using deep learning. The few works that exist show good performance by deep learning-based architectures, in the range of 87-96%. This shows the potential of applying more deep learning variants for this task, which can possibly obtain better results and extract contextual information.

Convolutional neural networks. CNNs represent complex versions of artificial neural net- works (ANNs), with neurons organized in the dimensions of height, width and depth. Typ- ical CNNs consist of convolutional, max pooling and flattening layers. These are followed by a fully connected network, which is the same as a standard ANN. These layers perform stepwise dimensionality reduction, while simultaneously representing higher level features with each consecutive layer. This enables them to not only identify data, but also relate it to its surrounding context, thereby increasing accuracy of classification. Although originally designed for image processing in higher dimensions, CNNs are increasingly being applied to NLP applications, including sentiment analysis [75, 104]. CNNs led the way for the popular- ity of deep learning by providing an error rate of 16% on an image classification challenge, which halved the previous best error rate of 28%.

CNNs can identify patterns hidden in the data at various levels of abstraction, and are also independent of position or orientation. By combining several layers, significant patterns can be derived and understood. The initial layer, which is generally the con- volution layer, applies mathematical functions as filters on the input. The number of dimensions in the filter depends on the dimensions of the input, which is 1 in case of text data. The filter applied consists of a set of learnable parameters, also known as a kernel. The kernel slides over sections of the input and performs dot product operations. These operations generate a feature map from the important parts of the input. The convolution layer implements three main ideas -

- Sparse interaction - Convolution layers use a kernel smaller than the input size, which generates fewer parameters representing only significant information. This is in contrast to a standard neural network, where all input units are linked directly to all output units. Thus, less memory is utilized and statistical efficiency is increased.
- Shared parameters - Convolution filters use the same sets of weights on different por- tions of the input, which refers to parameter sharing. The random nature of weights in a neural network

generates different weights in different stages, which is modified by convolu- tion layers to retain important features in various sections of the input.

- Representation equivariance - Since the parameters are shared, translational varia- tions in the input will be reflected as similar variations in the output. This is known as representation equivariance.

The feature map generated by convolutional layer is provided to the pooling layer. This layer reduces the feature map size by calculating representative values. It applies mathe- matical functions on a neighborhood, such as weighted average, L2 norm, etc. Max pooling is the most commonly used function, which selects the maximum value present in a neigh- borhood. The feature map is now replaced by a smaller map which contains only the pooled values. This helps in further reducing the size of the representation. It also identifies higher level features by this process. Based on the model design and input data structure, several pairings of convolutional and pooling layers can be sequentially connected.

The convolutional and pooling layer pairs are followed by a fully connected neural network that performs the final classification. This layer receives the information generated by the previous set of layers in the form of reduced representative data as input.

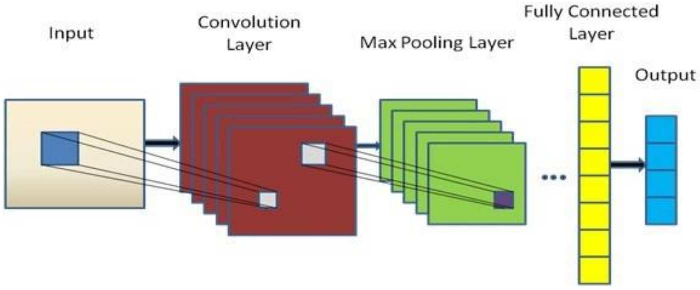

Figure 1: Architecture of a CNN

structure of this layer is like a regular neural network with all connections, and matrix multiplication takes place to generate the final output. The general architecture of a CNN is given in figure 2.8 [104].

Recurrent neural networks. RNNs are neural networks augmented to understand and re- member sequential data. This enables them to take care of dependencies over a longer range, thereby providing enhanced functionality to existing models for applicability to more domains. Dialogue systems, text processing, surgery, self-driven cars, etc. are some of the areas benefited by the ability of RNNs to use a memory component. RNNs are use- ful when contextual information affects the results of classifications or predictions. Some models of RNNs include Long-Short Term Memory (LSTM), Bi-directional RNN (BRNN), Neural Turing Machine, Gated recurrent Unit (GRU), etc. The number of time-steps before the current step that the RNN remembers, can be adjusted and used according to problem context. RNNs have found special applications in NLP, like text prediction and generation, trans- lation, image captioning, etc. [3, 83] [3]. Figure 2.9 displays the standard architecture of recurrent neural networks [3].

LSTM belongs to the family of Recurrent Neural Networks (RNNs). LSTMs perform long term memory retention using some special hidden units. LSTMs consist of the forget gate layer, the input gate layer

IJARSE
ISSN 2319 - 8354

(combination of an update unit and an addition unit), and the output gate layer.

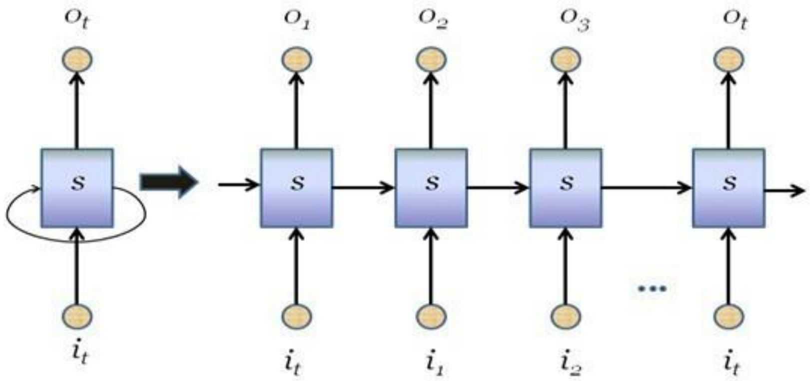

Figure 2: Architecture of a RNN

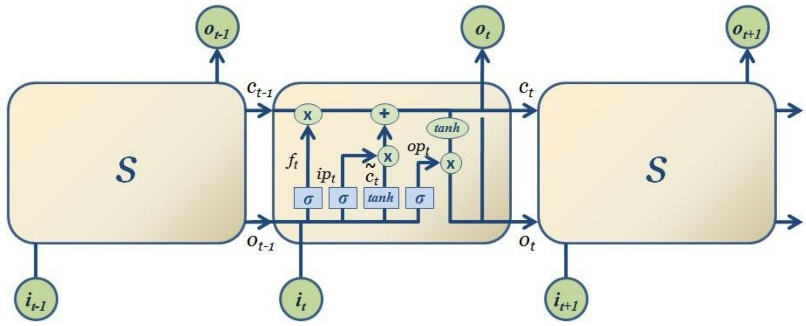

Figure 3: 0: Architecture of a LSTM

Each repeated unit contains these layers. The cell state, which is a memory cell and accumulator, is connected to these layers. It conducts information throughout the model. Gates are present as connection points to the cell state, and control the data to be added and modified. The information to be withheld is decided by the forget gate, and the updated values and additional candidates are provided by the input gate layer. Sections of internal memory state to be given to the output is determined by the output gate. The general architecture of a LSTM is given in figure 2.10 [56].

For a single unit of LSTM, at a given time step t, taking in_t as the input gate, f_t as the forget gate, op_t as the output gate, c_t as the internal cell state and o_t as the hidden state (i.e., output of that particular unit), the working of the unit is given by the equations that follow.

$in_t = \sigma(W_{in} i_t + U_{in} o_{t-1} + b_{in})$

(

2.1) $f_t = \sigma(W_f\ i_t + U_f\ o_{t-1} + b_f)$

(

2.2) $opt = \sigma(W_{op} i_t + U_{op} o_{t-1} + b_{op})$ (2.3)

$\tilde{c}_t = \tanh(W_c i_t + U_c o_{t-1} + b_c)$ (2.4) $c_t = f_t\ 0\ c_{t-1} + in_t\ 0\ \tilde{c}_t$ (2.5) $o_t = op_t\ 0\ \tanh(c_t)$ (2.6)

W, U represent the analogous weight vectors, and b stands for the analogous bias vectors. $\tilde{c}_t$ is the candidate vector which is combined with the input gate to obtain the cell state c_t. 0 represents

International Journal of Advance Research in Science and Engineering
Volume No. 12, Issue No. 08, August 2023
www.ijarse.com
IJARSE
ISSN 2319 - 8354

element to element multiplication. σ is the logistic sigmoid function.

LSTMs retain information only from preceding words. It is also possible to obtain in- formation from subsequent words, by using bidirectional architecture. Bidirectional LSTMs use two hidden layers to process the data in forward as well as backward directions, and the final output combines both layers. The standard architecture of a bidirectional LSTM is given in figure 2.11 [56].

In a bidirectional LSTM, the forward hidden state $\overrightarrow{o}_t$ and the backward hidden state $\overleftarrow{o}_t$ are calculated. Overall output out_t is calculated using the equation out_t =

$$W_{\overrightarrow{o}} \overrightarrow{o}_t + W_{\overleftarrow{o}} \overleftarrow{o}_t + b_o \qquad (2.7)$$

Attention networks. Attention networks can address the long-range dependency problems in LSTMs. They increase the capability to retain connections between words far apart within a sentence.
They can also attach weightage to input words and use them to generate context vectors. This helps to prioritize specific parts of a sentence [118]. Attention networks have been shown to considerably improve performance of various models that use LSTM and its variants [129]. Bahdanau et al. [11] designed the first attention model, as illustrated in Figure 2.12. It includes an encoder implemented by a bidirectional RNN. It creates annotations to represent the input words and produces a set of states. Each state carries certain information regarding the sentence, obtained by focusing on a specific phrase and its neighboring parts. Thus, it
puts attention on words throughout a sentence by keeping track of them over states.
A feed-forward neural network undergoes training using the encoder states in combi- na- tion with the present decoder state. In this process, the last encoder state is considered as the initial present decoder state. The neural network learns to represent attention by gener- ating differential values. The encoder state values are passed through a softmax function to

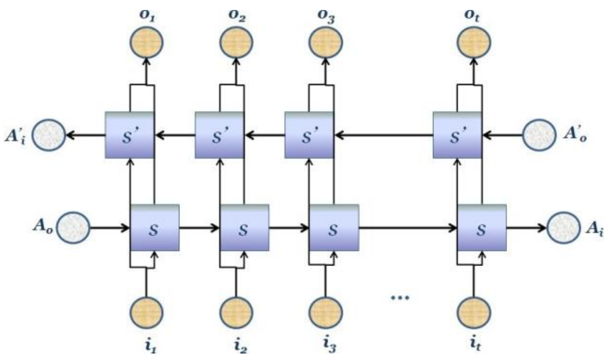

Figure 4: 1: Architecture of a bidirectional LSTM

generate attention weights. These weights are utilized to calculate a vector that represents the input sentence. This vector is called the context vector. Such a method of state-based vector generation distinguishes the attention network from RNN since RNN uses only the last form to generate a fixed context vector.

A gated recurrent unit (GRU) forms the decoder. It utilizes the context vector combined with the output generated in the preceding time step (the task performed during the last instant) for predicting the upcoming word. This becomes the present state of the decoder. Together with the encoder states, this present state is applied to again train the feed-forward neural network. The scores of encoder state for the subsequent time step are generated. The whole process is repeated until an "END" token is generated by the decoder. This means that the entire sentence is generated [4].

3. CONCLUSION

Our framework serves as an one-of-its-kind structure which can perform reliable and accurate sentiment analysis. It can be useful for businesses to assess customer feedback and make strategic decisions. It can also be useful to customers to understand general views and opinions about products and services, and decide on purchase or avail of the same. All of the models proposed by us provide solutions in real-time, once they are trained on a sufficient amount of data. Thus, they can be practically utilized in decision-making by users and businesses. The models designed by us in this thesis can also form the basis of future

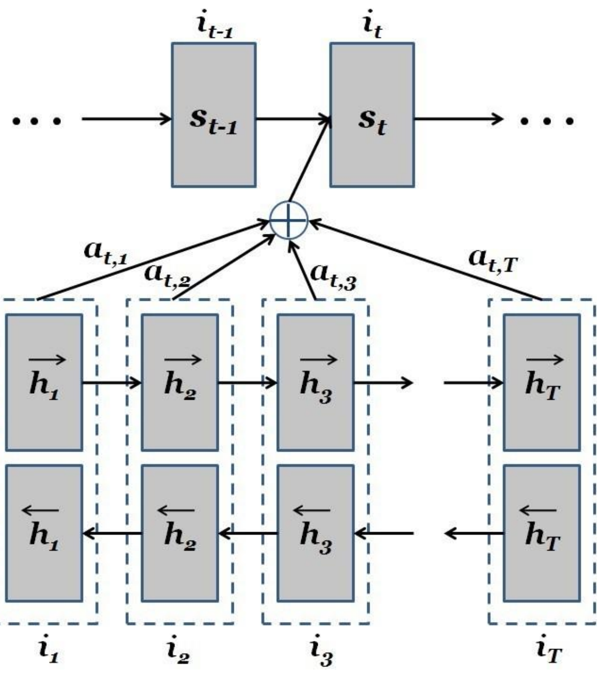

Figure 5: 2: Architecture of attention network

research and development in the area of sentiment analysis in particular, as well as natural language processing in general.

References

[1] [link].
URL https://jmcauley.ucsd.edu/data/amazon/

[2] [link].

URL https://blog.neongoldfish.com/uncategorized/are-blogs-a-reliable-source-of-information

[3] [link].

URL https://www.analyticsvidhya.com/blog/2017/12/introduction-to-recurrent-neural-networks/

[4] [link].

URL https://towardsdatascience.com/intuitive-understanding-of-attention-mechanism-in-deep- learning-6c9482aecf4f

[5] Sentence subjectivity detection with weakly-supervised learning, AFNLP (2011) 1153–1161. [6] (2013). [link].

URL https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit?usp=sharing [7] (2014). [link].

URL https://www.kaggle.com/datasets/rajathmc/bag-of-words-meets-bags-of-popcorn- [8] (2018). [link].

URL https://www.yelp.com/dataset

[9] I. Amini, S. Karimi, A. Shakery, Cross-lingual subjectivity detection for re- source lean languages, Proceedings of the Tenth Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis (2019) 81–90.

[10] E. Aydogan, M. A. Akcayol, A comprehensive survey for sentiment analysis tasks using machine learning techniques, International Symposium on INnovations in Intelligent SysTems and Applications (INISTA) (2016) 1–7.

[11] D. Bahdanau, K. Cho, Y. Bengio (2014).

[12] C. Banea, R. Mihalcea, J. Wiebe, Sense-level subjectivity in a multilingual setting, Computer Speech & Language 28 (2014) 7–19.

[13] L. Barbosa, J. Feng, Robust sentiment detection on twitter from biased and noisy data, Coling 2010: Posters (2010) 36–44.

[14] M. E. Basiri, S. Habibi, Review helpfulness prediction using convolutional neural networks and gated recurrent units, 2020 6th International Conference on Web Research (ICWR) (2020) 191–196.

[15] M. E. Basiri, S. Nemati, M. Abdar, E. Cambria, U. R. Acharya, Abcdm: An attention-based bidirectional cnn-rnn deep model for sentiment analysis, Future Gen- eration Computer Systems 115 (2021) 279–294.

[16] Y. Bengio, A. Courville, P. Vincent, Representation learning: A review and new perspectives, IEEE Trans. Pattern Anal. Mach. Intell 35 (2013) 1798–1828.

[17] Y. Bengio, I. Goodfellow, A. Courville, Deep learning, Vol. 1, MIT press, Massachusetts, USA, 2017.

[18] A. K. Bhunia, A. Konwer, A. K. Bhunia, A. Bhowmick, P. P. Roy, U. Pal, Script identification in natural scene image and video frames using an attention based convolutional-lstm network, Pattern Recognition 85 (2019) 172–184.

[19] J. Bjerva, N. Bhutani, B. Golahn, W. C. Tan, Augenstein, I, Subjqa: A dataset for subjectivity and

review comprehension, Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (2020).

[20] M. M. Bradley, P. J. Lang, Affective norms for english words (anew): Instruction manual and affective ratings, Technical report C-1, the center for research in psychophysiology âĂę (1999).

[21] F. Bravo-Marquez, M. Mendoza, B. Poblete (2014).

[22] E. Cambria, D. Das, S. Bandyopadhyay, A. Feraco (2017)

[23] E. Cambria, B. Schuller, Y. Xia, C. Havasi, New avenues in opinion mining and sentiment analysis, IEEE Intelligent systems 28 (2013) 15–21.