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Research Article

Aspect Based Opinion Mining Using Global Vectors And Recurrent Connection

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ABSTRACT

Aspect level based opinion mining is the key technique to extract multiple objective information from the text documents written in natural languages. This process helps various businesses to gain actionable sights to further improve their business. The recent abrupt in usage of internet has given the chance to the customer to report good and bad aspects of their consumption. These online posts of a customer on any platform impacts the business as well as market so, the task of aspect level based opinion mining has become of great importance. This article proposes a deep learning based generic method for opinion mining of online customer text reviews from the HotelRec dataset. The proposed method adopts a GloVe word embedding to extract the features from the natural text. The extracted features are then fed to the recurrently connected gated recurrent unit cell for classifying a review into one overall rating and eight key aspect level sub-ratings. This study has compared various state- of-the-art text embedding techniques to extract the features from the textual reviews. The performance obtained from the proposed method has outperformed the existing state-of-the-art methods in this regard.

Keywords: Opinion mining, Aspect level, Hotel reviews, Deep learning

1 Introduction

Opinion mining has emerged as a crucial area of research due to the widespread availability of opinion-rich content on the internet [15]. The ability to analyze opinions expressed in social media posts, product reviews, news articles, and other textual data sources has significant implications for businesses, governments, and individuals. Opinion mining techniques enable organizations to gauge public sentiment towards their products, services, or policies, and to make data-driven decisions accordingly. The hospitality industry thrives on providing exceptional guest experiences, making customer feedback invaluable for identifying areas of improvement and maintaining competitive advantage. With the rise of online review platforms and social media, guest opinions are more accessible than ever before. Opinion mining offers hospitality businesses the opportunity to analyze this vast trove of data to gain actionable insights into guest preferences, sentiments, and trends.

Opinion mining enables hotels, restaurants, and other hospitality establishments to monitor and manage their online reputation by analyzing guest reviews and social media mentions. Positive opinions can be leveraged for marketing and promotional purposes, while negative feedback can prompt proactive measures to address issues and mitigate reputational damage. A hospitality business analyze customer feedback to identify recurring themes, trends, and pain points to do strategic decision-making and service improvements. These improvements may include enhancing amenities, refining dining options, or optimizing check-in processes, opinion mining provides valuable insights for optimizing the guest experience. A single opinion may be used to analyze different aspects of the current business. This requirement has led to the need of a automatic aspect based opinion mining system. Hitherto, various opinion mining systems are developed for either primary tasks or subtasks [16]. The primary tasks solves opinion categorization problems at the document, phrase, and aspect levels [19]. However, the subtask covers challenges related to multi-model and multi-domain opinion categorization. These existing studies can be further grouped in two broad categories—machine learning (ML) and deep learning (DL). The ML based techniques [3, 9–11, 14, 17] have to extract the significant discriminating features prior to the classifier, whereas the DL based approaches [1, 12] focused on learning the complex pattern hidden inside the features.

The ML based approaches have used text embedding techniques such as one-hot encoding [8], TF-IDF [7], Word2Vec, and FastText [18] for extracting the features. The one hot encoding generates a vector (V_w) of size equal to the unique number of total words available in the dataset. Due to this vector size, a sparse matrix of size V_w × number of documents (D) has been developed. If either D or V_w is increasing, then the size of sparse matrix will also be increased which ultimately increase the computational cost of classifier as well as reduces performance. This problem has been solved by TF-IDF word embedding technique. This approach computes the mathematical significance of each word in each customer review. The higher TF-IDF score implies that the word has been frequently used in a document as well as least commonly used in other documents of the corpus. This 4

strategy was applicable to reduce the computational power but lacks in capturing the semantic context of the customer feedback as it ignores the ordering of the word. The Word2Vec word embedding technique uses a complete corpus of the unique words to create a single value. This real number value captures the linguistic context of any word but it fails to capture the sequential context of the words in a customer review. The extracted features either using handcrafted features or word embeddings have been fed to the ML classifiers. The most prominent classifier like support vector machine (SVM) [17, 20] and naive Bayes [5] have provided significant performance but lacks in providing the sequential relationship of words. This allows the customer to post a negative sarcasm on social media and system considers it as a positive feedback. This challenge can be solved by a classifier which can preserve a long sequence to understand the actual context in a customer review.

The current work has proposed a Deep Learning based approach for aspect based opinion mining. The proposed method has deployed Global Vectors for word representation (GloVe) [13] for word embedding. This embedding has solved the problem of matrix sparsity and capture the sequential information of the words in a customer review. The size of each review using GloVe technique has been reduced to 1 × 50 × 200, where '50' is the embedding size of a word and '200' is the size of a review. This matrix has been fed to the recurrently connected Gated Recurrent Unit (GRU) cell. The GRU classifier has captured the sequential and temporal features hidden inside the customer review. The significant contributions of the proposed study are as follows:

1. All the customer reviews are pre-processed based upon natural language processing (NLP) techniques.
2. The pre-processed textual content has been passed through GloVe word embedding technique to generate the feature matrix of size 1 × 50 × 200.
3. The generated feature matrix has been fed to the recurrently connected GRU classifier to capture the temporal and sequential information.
4. Results obtained from the proposed method have outperformed the existing works in this regard.
   The rest of the paper has been organized as follows: The Section 2 describes the dataset and Section 3 elaborates the proposed method. Section 4 provides the result and discussion of the experimental work, whereas Section 5 concludes this work.

2 Dataset statistics

The proposed study has used HotelRec dataset [2] developed by TripAdvisor company. This organization has one of the largest online travelling website with respect to the daily usage. There are almost 1.4 million worldwide properties listed on this website. The experiments in this work have been carried out on 4.5 million out of 50 million customer reviews from this dataset. Each review has 8 different aspect based ratings and 1 overall rating varied in the range of 1 to 5. The generated dataset has polarity with respect to the overall rating. Almost 81.2% customer review samples either belong to 4 or 5 rating.

The overall distribution of samples in comparison to the overall ratings is presented in Fig. 1.

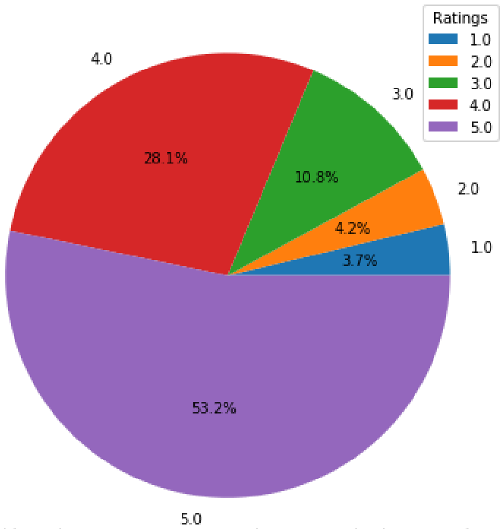

Fig. 1 Data distribution among various opinion values of the dataset.

3 Methodology

A customer provides his feedback in natural language and in unstructured for- mat on online platform. This feedback may often include noises such as special symbols, HTML tags, abbreviations or short text, numeric or mathematical values, etc. A pre-processing technique based on NLP has been deployed to remove these noises from each customer review. The pre-processing technique included removal of HTML tags, stop words, and special characters. Each char- acter of every review has been converted into lower case to remove redundancy and lemmatization has been applied to remove different verb forms. Thereafter, the features have been extracted using GloVe word embedding technique and passed through a recurrently connected classifier (GRU). These two modules are explained in the following sections.

3.1 GloVe

The GloVe word embedding technique has used unsupervised approach to generate a vector for each word present in the corpus. This has been achieved by creating a co-occurrence matrix for the words in the dataset. The entry value in this matrix shows the occurrence of a word (O_w) in the context of another word within a pre-defined window size (W_s). A mathematical function been developed to capture the relationship between any two O_w on 6 the basis of their co-occurrence probabilities. To do so, stochastic gradient descent (SGD) optimization technique has been used to minimize the difference between the dot-product of two vectors and logarithm of their respective co-occurrence probability. This mathematics reflects the cooccurrence of words in W_s within a customer feedback. The

representation of each word in a vector of real numbers of size '100' has been used in the present work. These representations have captured semantic relationship of words within W_s range in a customer feed- back. This has overcome the challenges posed by one-hot encoding, TF-IDF, and Word2Vec embedding techniques (discussed in Section 1). The GloVe technique provides the vector of size 1 × 50 for each word in the corpus. A feature matrix of size 1 × 50 × 200 has been generated for each customer review. The generated vectors have been used as features to be further fed to the classifier.

3.2 Opinion classification

The feature set obtained after the GloVe word embedding has been fed to GRU classifier. Since the recurrent neural network (RNN) suffers from vanishing gradient [4] and LSTM cell is computationally expensive, so the present work has used GRU cell to capture long sequential information. Each cell of GRU is expressed as follows:

$$G_r = \sigma(WM_r[h_{t-1}, ip_t] + Bias_r) \quad (1)$$

$$G_u = \sigma(WM_u[h_{t-1}, ip_t] + Bias_u) \quad (2)$$

$$i = G_r \circ h_{t-1} \quad (3)$$

$$\tilde{h}_t = \phi(WM_{\tilde{h}}[x_t, i] + Bias_{\tilde{h}}) \quad (4)$$

$$h_t = [G_u \circ \tilde{h}_{t-1}] + [(1 - G_u) \circ \tilde{h}_t] \quad (5)$$

where, G_* denotes the GRU cell gates (r: reset, u: update), WM_* are the weight matrices, ip_t is the input feature vector at any timestamp t, h_t is one type of hidden state of GRU, $h\tilde{}t$ is another type of additional hidden state, $Bias_*$ are the biases at different gates to provide nonlinearity, ϕ and σ notation denote the hyperbolic tangent and sigmoid activation function respectively, and $\circ$ is the element-wise product operator. Each GRU cell has two gates—G_r determines the magnitude of past learning to forget and G_u determines the magnitude of past learning to move forward. Each customer review has been passed through GRU layer in 64 timestamps as proposed method has 64 GRU cells in classification layer.

4 Results and Discussion

The experiments have been carried out on HotelRec dataset (as mentioned in Section 2). The dataset has been divided in two sets— train set and test set in
the ratio of 8:2. The performance of the proposed method has been evaluated in terms of *precision*, *recall*, *accuracy*, and *F1-score* metrics. These metrics are defined as follows:

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN} \tag{9}$$

The experimental results have been computed using these metrics are presented in Fig. 2. An experiment has been carried out with another embedding (Word2Vec) technique and classifier (ensemble learning classifier) combination. The result obtained using this experiment is presented in Table 1. Similarly, the proposed method has been evaluated against existing works in this regard in Table 1. It has been found that the proposed method has outperformed ensemble learning method.

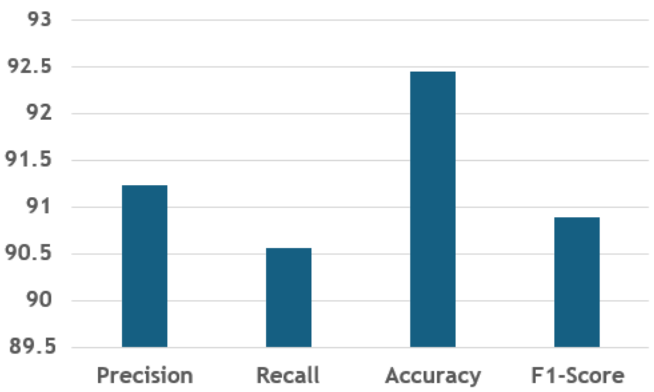

Fig. 2 A comparison of performance using various evaluation metrics.

Table 1 Comparison of the opinion mining performances with a few existing works in this regard

Study	Feature	Classifier	F1measure
Prasad et al. [15]	TF-IDF	Ensemble Learning	88.90
Present work	Word2Vec	LSTM	89.59
Proposed	**GloVe**	**GRU**	**90.36**

5 Conclusion and Future Work

This work has proposed a DL based approach to find the 9 different aspect based opinions from a customer review. The approach has extracted features using GloVe word embedding followed by a recurrently connected GRU classifier. The selection of GloVe word embedding has reduced the matrix sparsity problem and preserve the sequential context of words. On the other hand, GRU classifier has prevented vanishing gradient and reduces the computational complexity while capturing the long term sequential information in the extracted features. All these facts have led to the improvement in performance of the proposed method in comparison to the existing method (may be seen in Table 1). However, the performance of the proposed method has not surpassed the benchmark results of opinion mining in other domains. An attempt will be made in future to improve the performance of the opinion mining in hospitality industry by incorporating attention mechanism along with the recurrent connections.

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