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A Comprehensive Survey for Aspect-based Sentiment Classification

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***Abstract*— With the rapid development of information technology, Internet review texts have also become an important source for people to find reference information for decision-making. It is very necessary to conduct sentiment analysis on these texts. Aspect-based sentiment analysis can calculate opinions, sentiments, evaluations and attitudes in the text, and realize automatic sentiment recognition. The focus of this survey is aspect-level sentiment analysis based on deep learning, and its purpose is to determine the sentiment polarity of the aspects mentioned in the document. The current research work still lacks the systematic classification of existing methods. This is the gap that our investigation aims to fill. In this article, an in-depth overview of the current state-of-the-art deep learning-based methods is presented to show the tremendous progress that has been made in this research direction. First, a comprehensive review of the latest research results of ABSA based on deep learning. Then, pointed out the future research directions in this field, which will be helpful for researchers.**

***Index Terms*— Deep learning, Aspect Based Sentiment Analysis, Neural Networks**

I. Introduction

Today, with the rapidly growing volume of user-generated text on the web, the interest in analyzing and understanding the users' opinions has arisen. Sentiment Analysis (SA) is the computational investigation and identification of human tendencies and opinions expressed in textual documents. Sentiment Analysis can be divided into three levels, namely the document level, the sentence level, and the aspect level [1]. The document-level sentiment analysis comes with an assumption that the whole document only contains opinions about one topic. Obviously, this is not reasonable in many cases. The sentence-level sentiment analysis similarly assumes that only one topic is expressed in one sentence. However, it is often the case that one sentence contains multiple topics or that the opinions are opposite within the same sentence. For both the document-level and the sentence-level sentiment analysis, the decided sentiment polarities are based on the whole document/sentence rather than the topics given in the document/sentence. In contrast, aspect-level sentiment analysis aims to judge the sentiment polarity expressed for each aspect being discussed. This allows for a more detailed analysis that makes use of more information given by the review/tweet. A more thorough analysis, therefore, requires investigation at entity and aspect level to identify entities and related aspects and classify sentiments associated with these entities and aspects. Examples of entities include products, services, topics, issues, persons, organizations or events, which usually have several aspects. Furthermore, as an entity is the hierarchy of all aspects, it is also a general aspect. For the purpose of this paper, ABSA signifies sentiment analysis at entity or aspect level.

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II. ASPECT-BASED SENTIMENT ANALYSIS

Aspect based sentiment analysis is a fundamental task in sentiment analysis research field [2], which includes several key sub-tasks: aspect extraction, opinion identification and ASC. Some previous studies have tried to solve these subtasks jointly, dedicating most of the research work in dealing with an individual sub-task. In this study, we focus on deep learning methods for solving ASC problem. Different from document-level and sentence-level sentiment classification, ASC considers both the sentiment and the target information, as a sentiment always has a target. As mentioned above, a target is usually an entity or an aspect of an entity. For simplicity, both entity and aspect are usually called aspect. Given a sentence and an aspect, ASC aims to infer the sentiment polarity/orientation of the sentence towards the given aspect.

Traditional methods for ASC are mostly traditional machine learning models based on lexicons and syntactic features. The performance of such models is highly dependent on the quality of the hand-crafted features which is labor intensive. Therefore, recent research has turned its attention to developing end-to-end deep neural network models. To provide insight into the large number of proposed deep learning based methods for ASC, a categorization is made based the types of employed deep learning techniques, dividing all approaches into the following categories: convolutional neural network (CNN), recursive neural network (RecNN), recurrent neural network (RNN) and memory network.

Deep neural networks are good examples of deep learning. Deep neural networks are types of artificial neural networks which include a significant number of layers of "neurons" or connected processors, activated either by sensors from the environment or by the weighted computations from previous neurons. For deep learning, as for machine learning approaches in general, datasets are often divided into three components: training, validation and test datasets, conforming to general machine learning principles. CNN is proved effective for achieving sentiment classification accuracy, [3] along with many other NLP tasks such as relation classification and information retrieval. Li et al. [4]

utilized CNN layer for extracting salient features from the transformed word representations originated from a bidirectional RNN. They adopted a proximity strategy that accurately located the sentiment indicators by scaling the input of CNN layer with positional relevance between word and target. The technique demonstrated its capability by handling both general and target-sensitive sentiment.

Aspect-level SA classifies sentiments by learning separate representation for each data object. NN models get clear presentation of words, adding more information at the word-level, by measuring and identifying the semantic and syntactic relatedness between different data objects. The implementation of Bi-LSTM with character-level embeddings have performed clear representation of non-vocabulary words, and thus contributed in the acquisition of good sentiment information. For instance, Ma et al. [5] learned and pointed out non-vocabulary words through a hierarchical multi-layer Bi-GRU. The model produced target labels appropriately and thus made good prediction for sentiment labels. Pham combined feed-forward NN, containing representation learning techniques of word embeddings, with compositional vector model for capturing semantic-information and richer-knowledge representations. The designed NN utilized existing aspect-rating and higher-aspect representation layer to produce compositional sentiments.

Although, RNN and CNN both significantly process out relevant information from one step to another through gated mechanisms and convolutional procedures for improved sentiment classification. But with the longer-input sequences, sometimes it becomes difficult for a NN to keep the context of hidden vectors. Here, attention mechanism helps to mitigate long-sequence issue by encoding the most relevant information of the input sequences. It combines with neural word embeddings to capture the key parts of the sentence, which helps to explicitly combine the explicit and implicit knowledge and produces good sentiment information. For instance, He et al. [6] utilized attention-based LSTM that was trained on aspect-level data for capturing domain-specific sentiment words. They hypothesized that domain-knowledge could be fully exploited to achieve additional knowledge from documents, that were from similar domain, by using two transfer-learning methods, i.e., pre-training and multi-task learning, as these two tasks are highly related semantically. Moreover, Hu utilized aggregated-sentiments and negation-specific words as attentions for capturing the semantic components from data to form sentence representation.

Next, they incorporated the hierarchical structure of word, sentence and document representations into one-target-class label for final sentiment prediction. they adopted an autoencoder trained with a neural-attention-based sentiment classifier for learning aspect embeddings those were semantically related (meaningful). Further, they exploited a local-attention mechanism to create a weighted combination of aspect embeddings for a given target by averaging the target and context information. The adopted autoencoder provided good target representation with a high accuracy on the predicted sentiment.

Another category of network architecture are memory networks that provide an explicit context representation for every input word in the sequence. Memory networks, like attention mechanisms, also mitigate the issue of learning long-range dependencies in sequential data, and also draw relationships between different data objects for improved sentiment performance. For instance, Tang et al. [7] employed an external memory which contained multiple-layers, where each layer acted as an attention mechanism, for learning significance of each context word. They considered aspect terms as a query and utilized contextual information for continuous text representation. The computed features of last layer were considered for sentiment classification. Moreover, Zhu and Qian [8] performed the interactions between two memories, i.e., deep memory network and auxiliary memory, for learning the context of each input word and for explicitly generating connections between aspects and terms. They considered each memory as attention, and the result of auxiliary memory fed to the main memory for final sentiment classification.

III. FUTURE RESEARCH

In the future, researchers could explore the effectiveness of using the position prediction for other neural networks, for example, using sequence labeling to develop the position prediction part into an aspect extraction model. It is also worth analyzing and comparing with different approaches with the position information for aspect-based sentiment analysis. Exploring to solve the task of aspect-based sentiment analysis with other optimization algorithms is an exciting direction to do.

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