Adaptive Model for Sentiment Analysis of Social Media Data Using Deep Learning

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Abstract. Due to inception of Web 2.0 and increased dependency and freedom to share views, thoughts, opinions on social media, there is high rise in generation of digitized, opinionated social media data. Online forums, blogs, micro-blogging sites, shopping sites, etc. are inundated with mammoth data. This data from multiple domains needs to be extracted and analyzed in order to get the notion of timely insights, and ongoing trends. Many sectors like industries, academia, government and firms are interested to know the sentiments of people towards launched schemes, sales, products, service, policies, rules, etc. to make decisions. Therefore, inferring ongoing trend of topics and finding associated sentiments from huge scale of social data in an automated manner is the need of the hour. This paper proposes an adaptive model for aspect based sentiment analysis of social media data with deep learning approach. Unlike existing methods, our approach performs the task of aspect modeling and sentiment analysis simultaneously using latent semantic indexing with regularization and long short term memory model respectively. The proposed model does not require feature engineering and it is adaptable to datasets of varied domains.

Keywords: Aspect detection · Deep learning · Sentiment analysis · Regularization

1 Introduction

The domain of artificial intelligence and computer science in which computer systems and natural languages interact with each other to develop automated systems is called Natural Language Processing (NLP). As natural language is characterized by large vocabularies, words with different semantics and varied accent of speakers, it is challenging to design a system having ability to understand, speak and respond to natural language. Paraphrasing from input data, language translation, automated question answering, drawing inference from textual data are some of the major tasks involved in NLP. Being a subfield of NLP, sentiment analysis deals with determining attitude, sentiments, emotions of a speaker or a writer towards stuffs like products, events, issues, services, and their attributes [1].

Due to inception of Web 2.0 and increase in active users of social media, people are accustomed to share their views, opinions on forums, blogs, micro-blogs, social media

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platforms such as Twitter, Facebook, Instagram, Tinder, etc. Due to this, we have mammoth volume of opinionated data created by social media platforms in digital and unstructured form. With reference to recent survey, more than 500 million tweets are sent to Twitter daily [2]. Sentiment analysis is one of the most active research areas in the domain of NLP. It is mostly studied under information retrieval, data/web mining, and text mining domains. Whenever we need to make some decisions, it is common practice to seek the opinions of others. This is also true for organizations to take into account the opinions of end users to launch new products, sale offers, etc. Even the government bodies also need to get idea of citizen's sentiments regarding current policies and upgrade them according to feedback from citizens. Due to all these reasons, automated systems performing sentiment analysis of opinionated text is largely required in multitude of domains.

Figure 1 shows increase in interests among Artificial Intelligence, Natural Language Processing and Deep Learning since past lustrum. Owing to availability of large scale data, powerful GPUs, significant advancements have been done in the past lustrum in the domain of artificial intelligent systems for recognition and analysis of sentiments and emotions. It is forecasted that emotion analysis and opinion mining systems would generate worldwide revenue of $3.8 billion by 2025 [3]. It is anticipated that sectors like customer Experience and services, healthcare, automotive, product research, education and gaming would be contributing for generating the revenues.

Exiting research related to sentiment analysis from opinionated text include supervised and unsupervised methods. Support Vector Machines (SVM), Naïve Bayes, Maximum Entropy are commonly used supervised approaches for sentiment analysis. Dictionary based approaches, syntactical patterns, grammatical analysis are widely adapted in unsupervised settings. On account of this, several survey papers and books have been published in covering all the aspects of sentiment analysis [4–7]. Resurgence of deep learning due to large availability of datasets and cheap processing power has changed the way of solving problems in many fields. With reference to state-of-the-art results obtained using deep learning in Computer Vision [8–11], deep learning has also been applied to natural language processing [12–15].

This paper proposes an adaptive model for sentiment analysis of social media data using deep learning approach. The proposed approach jointly extracts the aspects from opinionated text and simultaneously predicts the sentiments associated with the extracted aspects. The framework encompasses latent semantic indexing approach constrained by regularization and long short term memory model (LSTM) for joint aspect extraction and sentiment analysis respectively. The beauty of proposed approach is that it simultaneously performs aspect extraction and sentiment analysis tasks and it is applicable to work on opinionated text from multiple domains.

The contents of the paper are portrayed as follows. Section 2 deals with related work. Proposed framework is thoroughly explained in Sect. 3. Section 4 gives details of experimentation and results. The paper is concluded in Sect. 5.

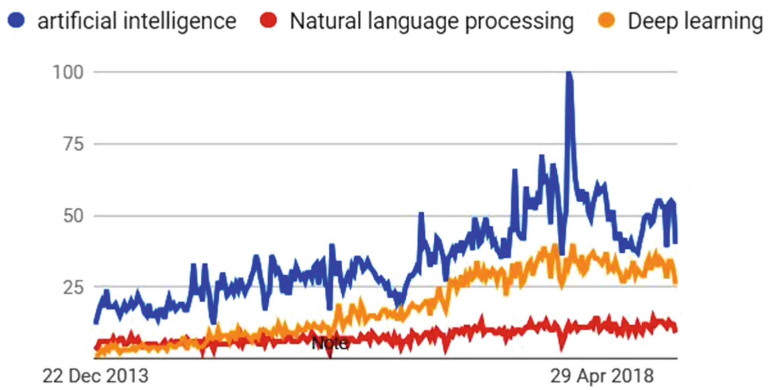

Fig. 1. Proliferation of artificial intelligence, natural language processing, and deep learning over time period from December 2013 to December 2018 (created using Google trends)

2 Related Work

In the era of Digital Universe, every sector such as health, education, business (gaming, product, service), automation industries, customer experience enhancing services are generating big data at large scale. Our previous work thoroughly describes taxonomy and analytics related to big data and also gives solution of how to handle challenges associated big data [16]. Social media data also belongs to category of big data due to its unstructuredness, streaming nature, varied format and huge scale. Inferring the sentiments of people from social media data is widely investigated area since early 2000.

Based on the existing research, sentiment analysis has been carried out at various levels of granularities viz. document [17–19], word [20], aspect [21–23], sense [24], concept [25, 26], sentence [27–29], phrase [23, 30, 31], etc. Considering the scope of the paper, related work has been discussed based on deep learning approaches for aspect based sentiment analysis.

Aspect or feature in a sentence denotes subject itself or attribute of the subject. Aspects can be categorized into explicit and implicit aspects. For instance, the sentence “My phone takes good photos and its battery life is excellent” contain implicit aspect *camera,* and explicit aspect *battery life* of the entity *phone*. The tasks in aspect based sentiment analysis can be divided into aspect extraction and sentiment analysis. These tasks can be carried out in separate manner one after another or both tasks can be jointly executed.

The aspect model proposed in [32] accepts set of word vectors and outputs distribution of probabilities over aspects using two-layered neural network. Sentiment model adapts CNN model from [14] and performs sentence level sentiment classification. Constituency parse tree is proposed to connect sentiments with extracted aspects. Attention based long short term memory model is proposed in [33]. For inferring aspects from sentence using attention mechanism, 2 ways have been proposed. First way is to concatenate aspect vector with hidden representation of sentences for calculating aspect weights. Another way is to append aspect vectors with input word embeddings in the embedding space. This approach extracts only single aspect from a sentence. In [34], problem of aspect extraction is formulated as multi-label classification problem in which probabilities of aspects are outputted. For both tasks, authors used convolutional neural networks (CNNs). For sentiment analysis, they have concatenated aspect embeddings with word embedding. This approach works for multiple languages. Two end-to-end neural models have been proposed in [35] to capture dyadic interaction between aspects and documents. These models, namely, Tensor DyMemNN and Holo DyMemNN are used to guide memory selection operation and capture both symmetric and asymmetric dyadic interactions respectively.

OpiSum model proposed in [36] formulated the problem of aspect extraction as sentence-level aspect mapping task. In this, sentences are mapped to pre-defined aspect categories using cluster of CNNs at first stage. Once the aspects have been mapped to categories, single CNN computes polarity of the aspects in the second stage. Similar to OpiSum model [36], ALA model in [37] maps the aspects to the pre-defined categories in financial domain. To capture the correlation between aspects and context of the text, it uses attention based long short term memory model (LSTM).

For simultaneously extracting the opinion targets and predicting their polarity, token level sequence labeling method based on bidirectional recurrent neural network (RNN) and conditional random field (CRF) is proposed in [38]. This method is designed to work in supervised settings. A supervised joint aspect and sentiment model (SJASM) [39] is a unified framework designed for identification of semantic aspects, aspect-level sentiments from review data and prediction of overall sentiments simultaneously. This framework extends latent dirichlet allocation (LDA) model and uses collapsed Gibbs sampling for inference.

This paper proposes a model for aspect based sentiment analysis in which task of aspect extraction and sentiment analysis is conducted in parallel manner. In addition, proposed model is adaptive in the sense that once it is trained on one dataset, it is adaptable to work on dataset with different domains.

3 Methodology

Figure 2 shows the architecture for joint aspect extraction and sentiment analysis. Review documents pertaining to online reviews are first preprocessed using data cleaning methods. To check whether how much valuable information the collected dataset possess, exploratory data analysis is performed. After this, correspondence analysis has been performed as a generalization of principal component analysis. We analyzed the data using scree plots, heat map, factor score and most contributing variable and confirmed preprocessed documents are good candidates for further aspect detection and sentiment analysis. For representing the input (preprocessed documents), and capturing the correlation of the word with its context, we used 300 dimensional word embedding vectors pre-trained on Google News dataset. This embedding layer acts as input to both aspect detection and sentiment analysis task.

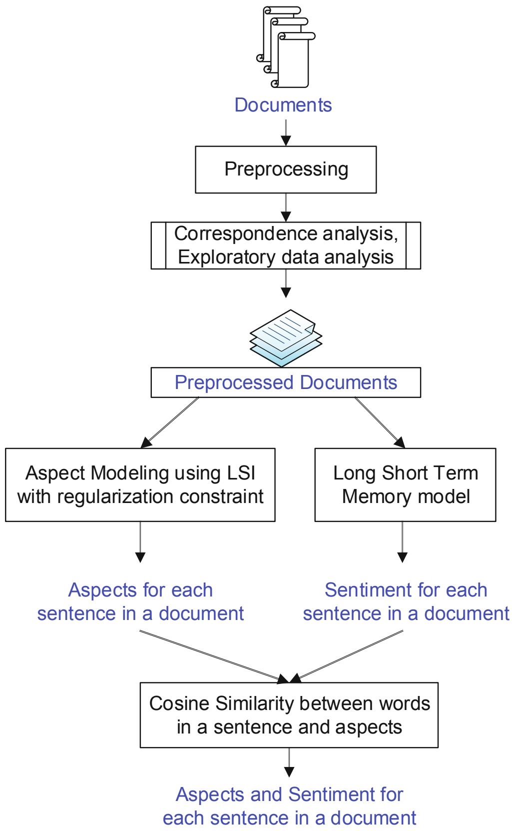

Fig. 2. Architecture for joint aspect extraction and sentiment analysis

For aspect detection, we used latent semantic indexing model with regularization constraint. This model is implemented by designing dense network of feed forward network layers. To capture the long term dependency in the sentences, we applied long short term memory model instead of recurrent neural networks. LSTM performs sentiment analysis for each sentence in a document and outputs probability of sentiments over two classes, namely, positive and negative. After simultaneous operation of LSI model with regularization and LSTM model, cosine similarity among words in a sentence and extracted aspects is calculated. Then sentiments of each aspect is aggregated and shown as aggregated sentiment for each aspect in the dataset.

4 Experimentation Details

For checking the effectiveness of the proposed approach, we applied our model on Restaurant reviews dataset. We performed data preprocessing (data cleaning, stop word removal) using packages in R language. The complete model is developed in TensorFlow using Python. For training and executing the model, Google cloud platform's NVIDIA Tesla K80 GPU has been used.

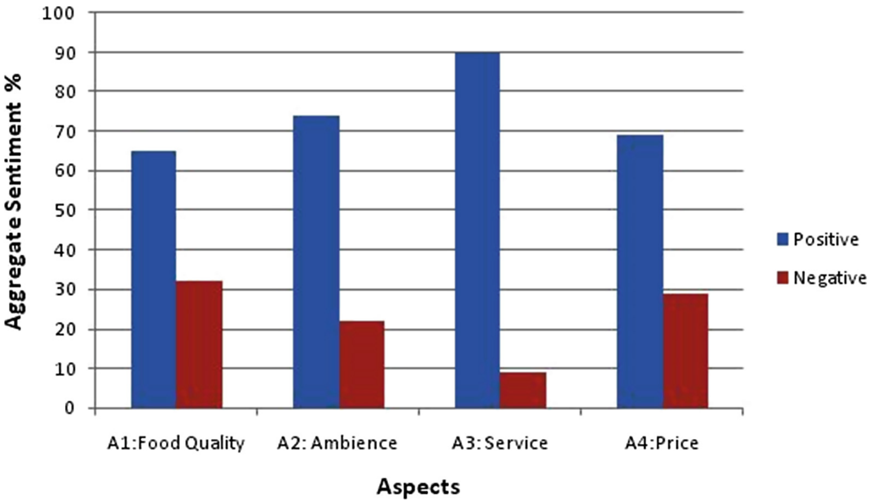

Fig. 3. Aggregated sentiments for each detected aspect

The task of aspect extraction and sentiment analysis is carried simultaneously using latent semantic indexing method constrained by regularization and LSTM model respectively. For restaurant dataset, we extracted 4 aspects as *food quality*, *ambience*, *service*, and *price*. Simultaneously, LSTM calculated sentiments of sentences. Figure 3 shows the aggregated sentiments in percentage for each aspect detected.

5 Conclusion

We have proposed an adaptive model for simultaneous aspect extraction and sentiment analysis tasks. Results show that our approach performs well for aspect detection and sentiment analysis. Currently a model - latent semantic indexing with regularization supports to work on batch dataset. We will check the accuracy of the aspect extraction and sentiment analysis model by comparing the proposed method against baseline approach. The next aim is to apply our model on streaming data by modifying exiting model to support online and incremental learning, and to infer trend of aspects (topics) and associated sentiments over time.

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