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HDAS: A Hybrid Deep Learning Approach for Aspect based Sentiment Analysis

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ABSTRACT: The observation and analysis of a person's opinion on a specific context out of the reviews given is called sentiment analysis. One of this sentiment analysis is Aspect mining in which sentiment analysis performed on not only the entire product but individual features of the product/ context. The task of aspect mining is really challenging as the features or properties of the product may implicitly present in the text as a feedback given by the user and calculating polarity relative to corresponding properties present in the text is also difficult. From the past few years, several authors proposeda vast number of models to handle these issues. Reverse Document frequency, Term frequency, Lexicon-based approaches are a few of the models from these and reverse document frequency are some of the suggested approaches by the authors. In this article we aim to propose an effective method to analyze the sentiments at aspect level by using Semantic feature extraction, further by using Word to Vector (Word2vec) transform the extracted aspects and finally applying a hybrid deep learning model that comprises of both Support Vector Machines and Convolutional Models for the mining of opinion. SemEval 2016 dataset is used to implement and test the proposed model. Finally, the conclusions were drawn.

Keywords: Aspect Mining, Sentiment Analysis, Opinion mining, Word2vec, Convolutional Neural Networks.

I. Introduction

Sentiment analysis is a very popular task in opinion mining and is used to analyse customer reviews for the product or service. The result of any sentiment analysis is to analyse the review and find out whether the review given by the customer is either positive or negative. Aspect level sentiment predictionfor the customer reviews is still a big challenge: recognizing the inherent relationships between parameters in the semantic meaning of sentences. Profound customer review datasets are available in multiple websites like Yelp, Amazon, SemEval 2017 and IMDB. The early step in the sentiment analysis is the text pre-processing, because the reviews given by the customer might contain lot of noise and to avoid grammatical errors. Most of the works suggested some supervised as well as unsupervised models and few of the researchers proposed lexicon models and a few works recently implemented convolutional network models for text pre-processing. Any Aspect based Sentiment mining contains few steps. They are Extracting Entity, Extracting Aspects and classification of aspect sentiment.

Entity extraction is the task of retrieving the customer's opiniongiven from the customer feedback. Aspect-based sentiment analysis is a text analysis method that split text into aspects

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attributes or of a product's or service's components, and then assigns each one a sentiment level as positive, negative or neutral [8].

$$S= (a_i, b_{ij}, c_{ijkl}, d_k, e_l)$$

where a_i is the entity in consideration b_{ij} is a exacting aspect or feature of the unit d_k is an sentiment holder e_l is the time at which the sentiment is supposed c_{ijkl} is the sentiment about aspect b_{ij} of entity a_i supposed by d_k at time e_l.

Extracting Aspects is the process of identifying features from the product or services from the customer feedbacks. This can be accomplished based on some of the machine learning models either supervised or unsupervised models.

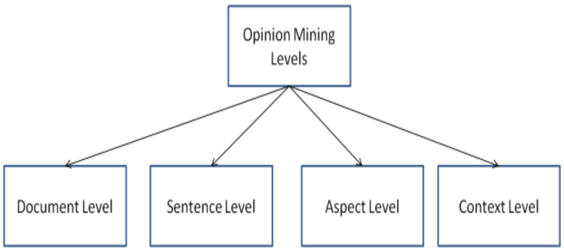

Figure 1: Opinion mining Levels

Aspect based sentiment analysis:

Classification in Aspect-based sentiment analysis can be prepared by performing two tasks:
(1) Aspects recognition.
(2) Sentiment categorization of recognized aspects into positive or negative

Classification of aspects is the classification approach for finding the polarity of the opinion on the aspects that were present in the customer reviews. Most of the authors used SVM, CNN, RNN and other approaches and evaluates through accuracy. Some of the researchers adopt Deep and Hybrid CNN models for various levels.
The motivation of this work is to find the customer opinions out of the customer review text aspect wise. To fulfil this task, a hybrid convolutional neural network based Aspect Mining is introduced to learn a vector-based sentence representation. The proposed model initially learns sentences using convolutional neural networks and semantics of sentences with their relations are adaptively encoded in document representation. When the customer review data contains aspects with less frequency, the proposed models are very effective and yields good accuracies[12]. Customer reviews given for the laptops in SemEval-2016 dataset are considered for the experimental assessment of the proposed model. Experimental results illustrate that the proposed neural network model shownbest presentation over traditional modelsin aspect modelling of sentiment analysis.Accuracy is considered as a performance measure.

The proposed work is organized as follows: In section II the associated work in the field of aspect based sentiment analysis is presented. Section III discusses the proposed methodology in detail.Further, the experimental setup, results and consultation are presented in division IV

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and division V respectively. Whereas the conclusions are drawn and future directions are given in division VI.

II. Literature Review:

Duan et.al.[1] have proposed an improved deep hybrid network using CNN and LSTM to improve computational cost as well as accuracy of the model. The authors implemented the model on urban traffic flow prediction.

Akhtar et al. [2] presented a hybrid learning model for the sentiment analysis for the first time in language prediction. The authors have suggested both SVM and CNN for developing hybrid model but they have not performed on aspect mining. The results of the hybrid model are encouraging.

Dos Santos, et al. [3] has suggested a deep CNN model for the sentiment analysis in their work. They have considered twitter data and performed CNN for short text messages. The model utilizes Stanford's Sentiment Tree Book (STTb)and Twitter sentiment corpus (STS corpus). The model adopts a single sentence sentiment prediction model that gives about 85% accuracy.

In one of the study [5] proposed by A. S. Manek, et al., suggested a binary classifier i.e., SVM which was used to find aspect target and adopted semantic and some of the lexical features and gained 94% of accuracy.

Dou [6] worked on user as well as product information and applied a deep memory network. They considered IMDB, Yelp 2013 and Yelp 2014 datasets for the performance evaluation of the model. The objectives of this model are of two fold. First one is LSTM, it is used to learn the representation of a document. As art of the second fold a deep memory network through a several convolutional layer is used for predicting the rating of the review of each document.

NLangp (Toh and Su, 2016) used feed forward neural network to deal with this difficulty. They train feed forward neural network in favour of every entity attribute match up that is a total of 12 classifiers for Restaurant area. A threshold is place for every classifier with outcome of classifier in additional into the set of classes of that sentence if the outcome likelihood of that classifies is generously proportioned than the threshold [9].

Table 1: Application of the various models in the consumer review field.

No	Study	Domain	Dataset & Language	Model	Performance
1	Xiaodi Wang (2020)	Restaurant and laptop sales.	SemEval 2014 for restaurant and laptop sales vals 2015 and 2016 are related to the restaurant	multilevel interactive bidirectional attention network (MI-biGRU)	Accuracy and F1-score of MI-biGRU, at 60% of the data amount
2	Kumar, R.,(2019)	booking.com	hotel reviews	O \ntology-based CNN	88.52%, 94.30%, 85.63% and 86.03% in accuracy, precision, recall and F-measure, respectively.

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3	Liu, N.,(2019)	Chinese datasets, English datasets	camera, car, notebook and phone domains, restaurant and laptop domains form SemEval-2014, SemEval-2015.	LSTM	highest accuracy and macro-F1: 0.71–2.58%, 2.27–4.57%, respectively.
4	Feng et al. (2018)	Mobile phone	PM from Amazon, Jingdong, and Lynx Chinese	Deep CNN + WE + POS + reliant syntactic-(explicit aspects)	Precision: 77.75% Recall: 72.61% F1: 75.09%
5	Xu et al. (2017)	Laptop Restaurant	PM from Yelp English PM from Yelp English	CNN + CRF	Acc: 70.90% (binary, lower than SVM model) Acc: 68.34%
6	Gu et al. (2017)	Smartphone, Shirt	PM from Amazon English PM from Taobao Chinese	Multiple CNNs for each aspect	F1: 72.67 - 83.74% F1: 92.26 - 97.34%
7	Akhtar, Kumar, et al. (2016)	12 personal electronic products	PM (Akhtar, Ekbal, & Bhattacharyya, 2016) Hindi	CNN + SVM	Acc: 65.96% (3-way)
8	Ruder et al. (2016)	Laptop, Mobile Phone, Hotel	SemEval '16 English,Dutch	CNN+ Concatenated vector	F1: 59.83% F1: 45.55% F1: 52.11%
9	Wu et al. (2016)	Smartphone	PM from Amazon,English	Multi-task CNN+word2vec/Wikipedia	Acc: 84.1% (binary)

III. Methodology

This part provides a detailed description of the proposed methodology. The form comprises of two phases. Inthe first phase, the customer review data is pre-processed for the purpose of cleaning of the review data.

Convolutional neural networks (CNNs) are related to "normal" neural networks that are that they are of hidden layers consisting of neurons with "capable" parameters. These neurons collect inputs, execute a dot product, and then pursue it with a non-linearity. The whole network articulates the mapping connecting raw image pixels with their class counts. Traditionally, the Softmax function is the classifier used at the very preceding layer of this network.

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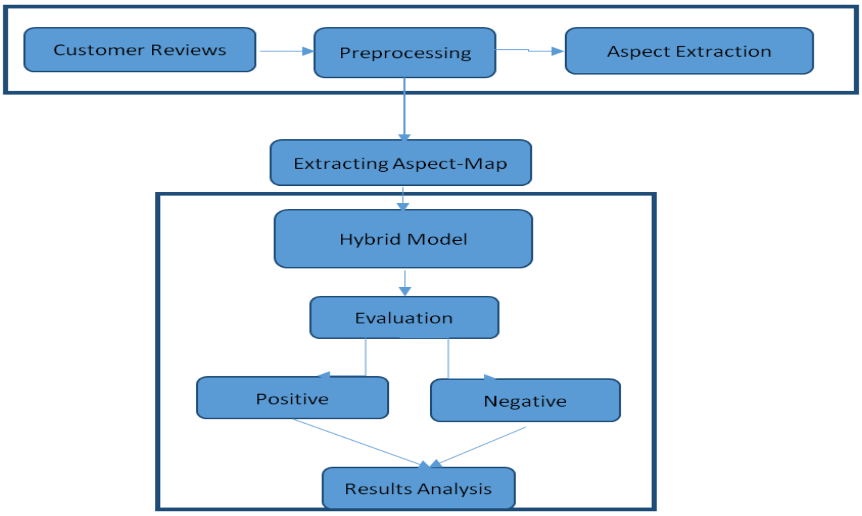

Figure 1: Proposed Methodology

The proposed methodology comprises of three phases. In the phase one customer review data is pre-processed and aspects/featureare extracted. Where as in the phase two, each feature is mapped with its corresponding sentiment expression. The aspect-map targets to extract an aspect and sentiment pair to indicate the sentiment of the reviewwhich is appropriate to a specified aspect. However, Training might not be possible in a straight line to retrieve the aspect-map due to the training set containsdetails of aspects and itsrelevant polarities of the sentiment for the review. But it doesn't provide any details about any relevant. Due to this, Aspect-Map extraction need to learn relevant words using supervised approach. The structure of the CNN model for the Aspect-Map is described below.

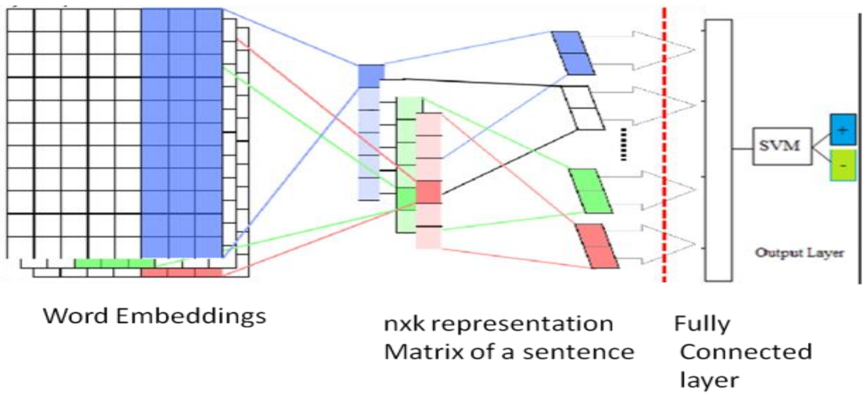

Figure 2. CNN based aspectmap extraction model Architecture

In the phase three, a hybrid learning model is implemented that comprises of multiple levels. The training set will be trained by two classification models namely CNN and SVM that yield the polarities of the training datasets.

The activation function is the factor that adds non-linearity to the data elegant throughout the neural network. Throughout these functions, networks can compile abstractions about the data [10]. The activation functions experienced in this effort are Rectext Linear Unit (ReLU) and Linear.

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Word embeddings are the form of illustration of the data used in this effort. They plan words to low-dimensional vectors. In this work, Word2Vec is exploited.

Filters are the basics of a CNN that relate convolution operations on the data. The dimension of the filters is straight related with the quantity of weights of the neural network. The generously proportioned the filter is, the better the quantity of weights to be trained. The filter sizes can be understood as n-grams, that is, a filter of n lines. It works convolution greater than n words.

Feature Maps are accountable for recognizing diverse characteristics at hand in the data. Each map is connected with a known feature of the input data. In computer vision systems, these recognize attributes like nose, eyes and mouth. Likewise, they be able to recognize characteristics such as verb tense, kind, along with plural in NLP associated tasks.

Pooling is a process used to make simpler the information conveyed at the outcome of a feature map. The information can be distorted by averaging the values of a map or by the greatest value of the map. In this effort we examine the force of both the max along with averaging pooling.

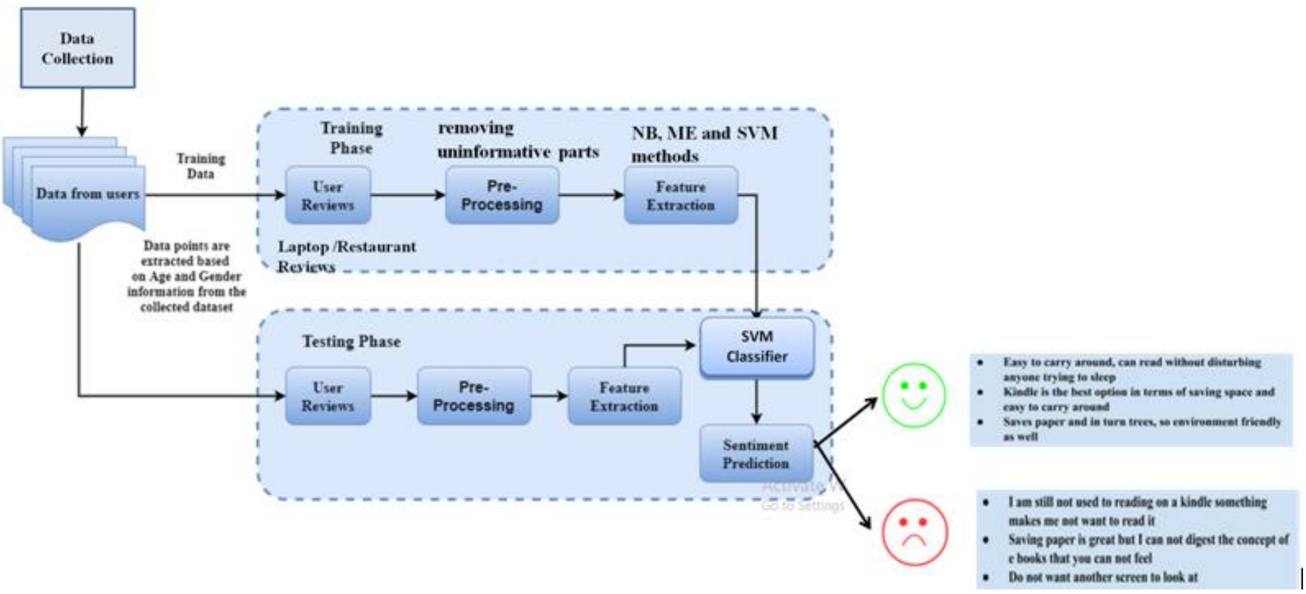

Figure 3: Hybrid model for Aspect Mining based Sentiment Analysis

IV Experimental setup:

The proposed methodology is implemented using python in google colabs. The data set used to implement the proposed model is extracted for SemEval-2016 Laptop reviews. The total number reviews in training and testing sets are 277 and 173 respectively. This data set contains total 1739 sentences training and 761 sentences in test sets. SemEval 2016 English (Laptops) dataset is used to implement. Given an opinionated manuscript about a target entity, here laptop and the goal is to recognize all the opinion tuples with the subsequent types of information:

- **Aspect Category Recognition**. The task is to recognize every entity E and characteristic A two of a kind towards which an opinion is articulated in the known text. E and A should be selected from predefined catalogs of entity types (e.g. LAPTOP,

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MOUSE, SOFTWARE) and characteristic labels (e.g. DESIGN, QUALITY, PRICE). The E, A catalogs for each field are described in the relevant annotation strategy documents.

- **Opinion Target idiom (OTI)**. The job is to mine the OTI, i.e., the linguistic appearance used in the known text to refer to the assessment entity E of each E#A pair. The OTI is defined by its initial and conclusion offsets. When there is no open state of the entity, the place takes the rate “NULL”. This place will be required only for meticulous datasets or domains.

- **Sentiment Divergence**. every identified E#A, OTE tuple has to be allocated one of the subsequent divergence labels: positive, negative, or neutral (slightly positive or slightly negative sentiment).

The observations should be assigned at the sentence point taking also into version the context of the evaluation, since properly identifying the E, A pairs of a sentence and their divergences often requires investigative a wider part or the complete review. Below are two examples of the predictable output for a given assessment from the laptops and the restaurants domains correspondingly:

Review id:LPT1 (Laptop)
S1:The So called laptop Runs to Slow and I hate it! → {LAPTOP#OPERATION_PERFORMANCE, negative}, {LAPTOP#GENERAL, negative}
S2:Do not buy it! → {LAPTOP#GENERAL, negative}
S3:It is the worst laptop ever. → {LAPTOP#GENERAL, negative}

Review id:LPT1 (Laptop)
"The So called laptop Runs to Slow and I hate it! Do not buy it! It is the worst laptop ever."

a system should return the following opinion tuples:

{LAPTOP#OPERATION_PERFORMANCE, negative}
{LAPTOP#GENERAL, negative}

First, the laptop review sentences be conceded through a pre-processing phase. At this phase, a flow of tokens was produced from sentences and stop words be separated. English laptop review sentences from SemEval-2016 Task5 were united to train the word2vec form [11]. The characteristic A of an E#A pair can be allocated the similar labels as in the laptops field, with the difference that “PORTABILITY” is incorporated in the “DESIGN & FEATURES” tag .Hence there are 8 possible labels: GENERAL,PRICE,QUALITY, 17 OPERATION_PERFORMANCE,USABILITY,DESIGN_FEATURES including PORTABILITY),CONNECTIVITY ,and MISCELLANEOUS.

Word Vectors:

A word2vec representation was trained on laptop review sentences. Effectual training of proposed model relied on the regulation of dissimilar hyper parameters for example context window, min word count. These factors can extremely weight the eminence of word vectors. Five parameters be used to manage the training of the word2vec representation and their finest values were selected by hit and test.

V Result and discussions:

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This part presents the results of the proposed model and also provides its description. The figure 4 presents the distribution of each aspect for both training and testing datasets. It is observed that the distribution of the aspects among both training and testing datasets is nearly equal.

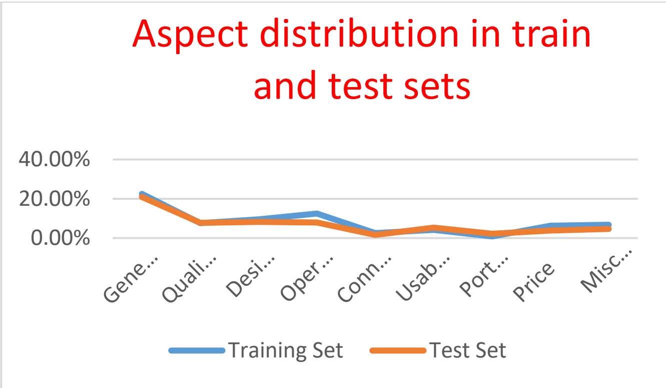

Figure 4: Distribution of Aspects in train and test sets

The distribution of the polarity i.e., positivity, negativity and neutral values for training and testing sets are presented in the Figure 5.

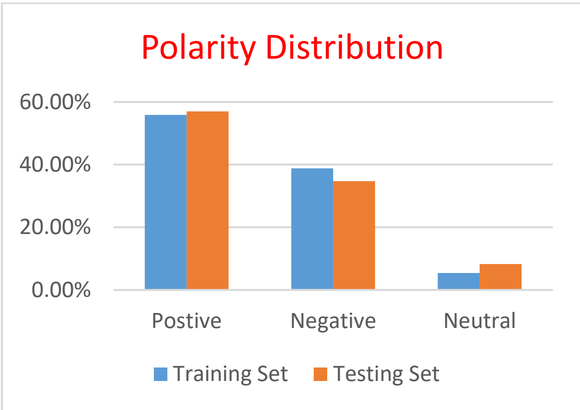

Figure 5: Distribution of polarity for both training and testing datasets.

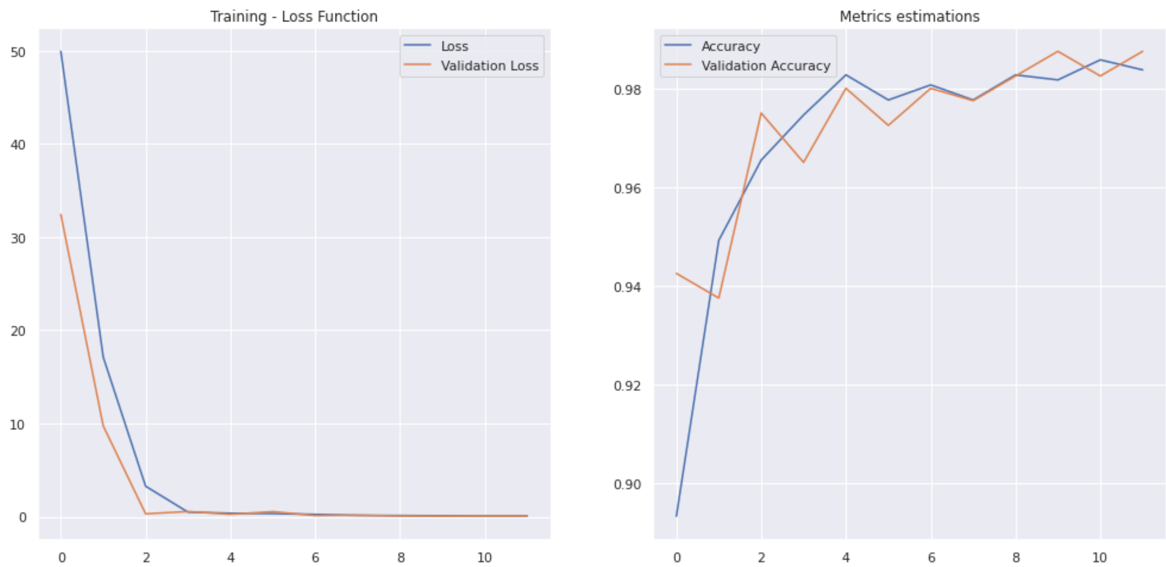

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Figure 6: The loss function and accuracy of both training and test sets for SemEval-2016 Laptop dataset

The classifier loss and accuracies of the HDAS model is presented in Figure 6 for both training and testing sets. The final accuracies for Training set is 98.56% and the testing set is 99.2%. The loss of the training model is 0.04% and for testing model is 0.052% for both training and testing sets respectively.

VI. Conclusion:

In this paper a two stage CNN model is proposed and implemented for aspect based sentimental analysis. Extracting proper aspects from the customer reviews is the major task in aspect mining. Whereas the customer reviews are further analysed for their aspect polarity. In the proposed model. The proposed representation consists of two CNNs, where one CNN approach is used for mining an aspect map for a known text and a target aspect and the other is for classifying the sentiment partition of the text based on the extracted aspect map. To model is implemented and tested on the text-level SemEval 2016 ABSA tasks; the projected model attains good performance when compared to other.

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