Reasoning of Reviews based on aspects

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1 Problem Definition

In recent times e-commerce has emerged as a preferred channel for shopping. Almost all the e-commerce platforms facilitate the users to write reviews about the products that they have bought. The user reviews are really helpful for other users planning to buy that product. The sellers of product also get an idea of the customer requirements from the reviews. The users write the reviews in free text form i.e. in an unstructured manner. Also, it is not possible for a potential buyer to read all the reviews for the product. So, over here our objective is to extract the aspects and the opinion about the aspect from the reviews. In this way the review now has some structure associated with it. It is a known fact that different users will give different priorities to the different aspects while making a decision on which product to buy. So, once we obtain the aspects and the opinions from each review of a specific product then we can obtain the overall opinion of the product according to different aspects that the users are generally concerned about.

2 Literature Review

Aspect based sentiment analysis aims to identify the aspects from the text and the sentiment associated with the aspect from a review about a product or a service in general. One of the methods proposed in the very beginning framed this problem as a customer reviews summarization problem and used a rule-based method [1]. Liu [2] discussed approaches like frequent terms, opinion and target relations, supervised classification and topic modelling algorithms. One of the unsupervised techniques proposed for identifying the aspects was the High Adjective Count algorithm (HAC) [3]. This method performs POS tagging followed by counting the adjectives for each noun. Now the nouns having the associated adjectives count above a threshold value are treated as aspects. Also Conditional Random Fields (CRF) have been employed for considering the long term dependencies [2] and it performed better than other supervised models for aspect extraction.

3 Dataset Description

The training dataset consists of 277 user reviews on Laptops. Each review is divided into sentences and so there are a total of 1739 sentences. For each sentence the E#A pairs are given where E is the entity which is being referred to in the sentence and A is the attribute of that entity. One such example is Keyboard#Quality. Polarity also for all such E#A pairs is also give. The 3 possible polarity values are positive, negative and neutral. Similarly the test dataset consists of 173 reviews making up 761 sentences.

4 Baseline Methodology Used

For the subtask of predicting the aspect categories the baseline model uses Support Vector Machine(SVM) with a linear kernel. The set of features is taken as the set of most frequent unigrams in the training dataset. Now a feature vector of length 1000 is made for each sentence. Now for a sentence s in the training set the different categories values are separately taken as the correct labels for the feature vector and the model is trained. Now for each test sentence the feature vector is prepared in a similar manner and the trained model is used to predict the probability values for the different categories. A threshold value of probabilty is used to assign the aspect categories to the test sentence under consideration. For the polarity prediction subtask for each sentence a feature vector is prepared for each sentence is prepared which is composed of the integer value denoting the presence of a particular aspect category. Now the label for the

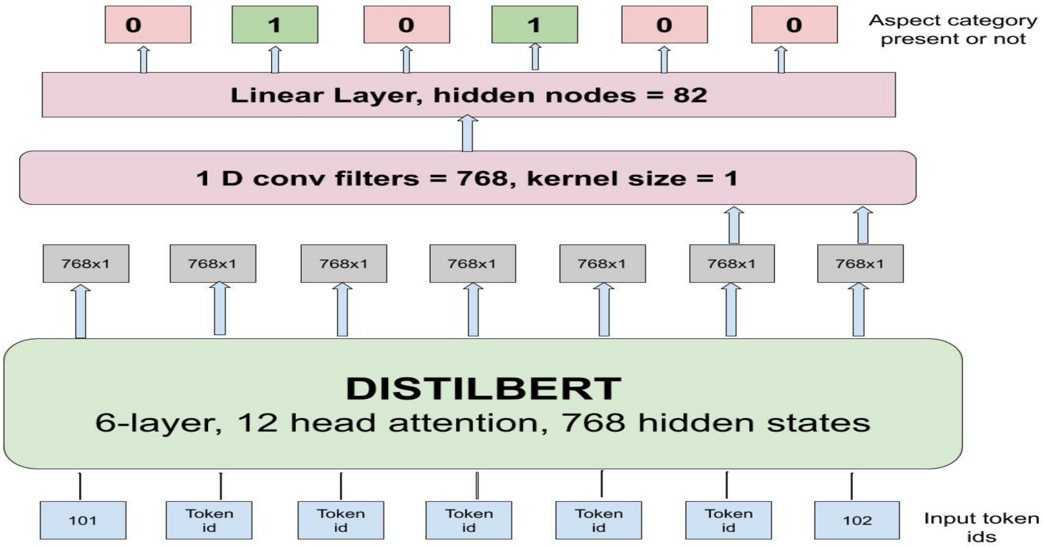

Figure 1: Flow diagram of the methodology used for aspect category classification

feature vector are polarity values assigned to those catgories in that sentence. In this way the model is trained using SVM. Now for each sentence in the test review the polarities are predicted using the trained model. The steps involved in methodology used are :

5 Methodology

The task of analysing reviews for each aspect category is divided into two stage : (i) classification of given aspect categories and, (ii) polarity detection of the aspects present in a given sequence.

5.1 Aspect Category Classification

5.1.1 Problem Formulation

The problem of finding aspect category for a sentence can be seen as a classification problem where each sentence can fall in multi-aspect categories, hence the problem can be referred as one to all classification problem.

5.1.2 Methodology Used

The train set comprises a total of 81 aspect categories making the task challenging. For extracting the semantics of each word in a given sentence, DistilBert fine tuned features are used. However, to notice the presence of an aspect in the given sentence, we care about the semantic of the entire sentence instead of the semantic of each word. To achieve this, we utilize only two lowermost features coming out of the DistilBert model, which are fed to the one-dimensional convolutional layer of window size half the incoming features. Finally, the hidden layer is applied, output of which gives the probability of being a sentence in a particular aspect. For doing so, sigmoid activation is used.

At test time, if the value coming out of a threshold taken as 0.2 the sentence is said to have the corresponding aspect category.

The model is optimized using Adadelta optimzer at 1.0 learning rate with constant epsilon 1e-06 and value of rho 0.95 for about 10 epochs. Binary cross-entropy loss function is applied to find out multiple aspect categories for a sentence, where 1 denotes the presence of a particular aspect category.

5.2 Polarity detection for each aspect

5.2.1 Problem Formulation

The task is to detect the polarity of each present aspect category in the sentence for instance, given a sentence : 'I don't use my laptop in a way though that needs a long battery life so it's perfect for me' and corresponding aspect category : "Battery#OperationPerformance" the task is to find the polarity of the given aspect category which is 'positive' in this case. The problem can be seen as a polarity classification problem of the present aspect, where the presence of aspects can be seen as a prior given along with an additional or background class indicating absence of aspect. All together, the output following this task is a class for each aspect category where class 0 - is taken as absence

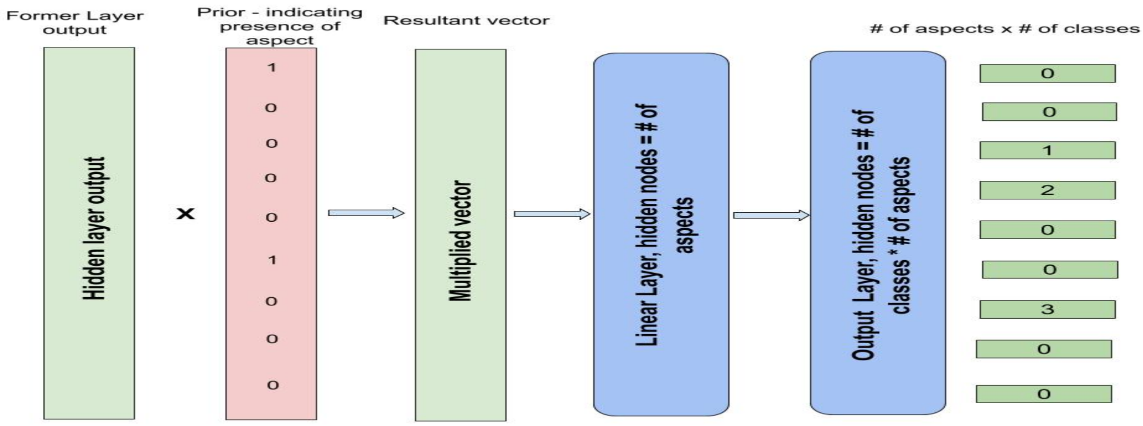

Figure 2: Flow diagram of the methodology used for polarity detection

of aspect category in the sentence, class 1, class 2 class 3 - taken as presence of the aspect category along with the polarity positive, negative and neutral respectively.

5.2.2 Methodology Used

The former layers of the model used for the mentioned problem statement utilizes the same layer structure as used in task 1. The only difference is that now the output of the hidden layer is not followed by the sigmoid activation function instead the output of the hidden layer is multiplied with the binary vector of size of total number of aspect categories indicating the presence of an aspect category in the given sentence. This is done to give the model a prior of presence of corresponding aspect category.
The multiplied vector is then fed to a hidden layer of hidden neurons equal to number of aspect categories which is finally passed to the output layer resulting in a 4 sized vector for each aspect category for a single sentence i.e if there are c number of aspect categories, the size of the output for a single sentence would be (c x 4).

The model is optimized using Adadelta optimzer at 1.0 learning rate with constant epsilon 1e-06 and value of rho 0.95 for about 10 epochs. Muti-class cross entropy is used for each vector for a particular aspect.

Figure 1 and Figure 2 shows the overview of the methodologies used for above tasks.

While training the models for both the tasks, dropout layer with probability rate 0.1 is employed after extracting DistilBert features.

6 Results

As both the two tasks mentioned fall into the classification problem, the metrics used for evaluation is accuracy and macro F1-Score.

6.1 Aspect Category Classification

The results on the train and test set are summarized in Table 1. In addition, F1-score for top-5 classes on test dataset is shown in Table 2.

Dataset	**Accuracy**	**F1-score**
Train data	1.00	0.99
Test data	0.99	0.80

Table 1: Results obtained for Aspect category classification.

Aspect Category	**F1-score**
LAPTOP#GENERAL	0.71
GRAPHICS#GENERAL	1.0
OS#GENERAL	0.69
LAPTOP#PERFORMANCE	0.72
BATTERY#PERFORMANCE	0.74

Table 2: F1 score for some aspects on test data

6.2 Polarity Detection for each aspect

The results on train and test data for this task are summarized in Table 3. As this is a classification problem metrics of evaluation used for this task is also accuracy and macro F1-score.

Dataset	Accuracy	F1-score
Train data	0.99	0.57
Test data	0.99	0.49

Table 3: Results for polarity detection

7 Future Work

As both the models proposed in the project can be used for detecting the sentiment of a particular aspect in a review. As the dataset used is limited to only laptops, if enough dataset is provided for different products, the pipeline suggested can be used for product recommendation system based on given aspects for a product.

8 References

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