Emotion-Cause Pair Extraction

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Emotion-Cause extraction task has been a active research area for the last few years because of the potential usefulness of the task in knowing the underlying causes for various emotions in the text. But the major disadvantage in this task is that it requires the text to be annotated with the emotion so as to perform cause extraction which is not possible in case of real world applications. To overcome this problem in Emotion-Cause extraction task, a new task Emotion-Cause Pair Extraction has been proposed recently. In this task, given a document all the potential emotion and cause clauses are identified in the first stage and in the second stage the correct pairs of emotion and cause clauses are retrieved. In this project an attempt is made to perform Emotion-Cause pair extraction and show the effectiveness of the task in determining the causes behind the emotions in the text.

ACM Reference Format:
Shripad Anant Bhat. 2020. Emotion-Cause Pair Extraction. 1, 1 (May 2020), 13 pages. https://doi.org/10.1145/1122445.1122456

1 INTRODUCTION

Since the 1960s scientific studies on human emotions have been performed which resulted in the following two theories of emotion: *Discrete Emotion Theory* and *Dimensional Model*. According to Yadollahi et al.(2017), *Discrete Emotion Theory* states that different emotions arise from separate neural systems,while the dimensional model states that a common and interconnected neurophysiological system is responsible for all affective states. There are certain emotions that are prevalent across all the languages, race and culture. Ekman was a theorist who stated that certain emotions are universally recognised and form a set of basic emotions. The model suggested by Ekman et al. (1972) which consists of six emotions(Anger, Disgust, Fear, Joy, Sadness, Surprise) is most commonly used in Computer Science Research.

Emotion analysis in text consist of several tasks such as emotion detection, emotion classification, emotion polarity classification and emotion cause extraction as shown by Yadollahi et al. (2017) by creating a logical taxonomy of various tasks in sentiment analysis. A lot of researchers in the past few years have been focusing on determining the cause behind the emotions in the text. This is due to the fact that such information could be very useful in cases like evaluating the product/service reviews of customers. Determining the causes could help companies in improving their products and services.

Emotion Cause extraction task needs the text to be annotated with an emotion so as to extract the cause. This is not feasible in real world, which limits the applications of Emotion Cause extraction. Hence a new task Emotion Cause Pair extraction has been proposed by Xia et al. (2019).

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Manuscript submitted to ACM

Following example mentioned by Xia et al. (2019) will be used to understand Emotion-Cause pair extraction task. Document is "*Yesterday morning, a policeman visited the old man with the lost money, and told him that the thief was caught. The old man was very happy, and deposited the money in the bank.*". This document consists of following five clauses: [*Yesterday morning*, *a policeman visited the old man with the lost money*, *and told him that the thief was caught*, *The old man was very happy*, *and deposited the money in the bank*]. The fourth clause in document (*The old man was very happy*), contains the emotion "happy". This clause is denoted as **emotion clause**. The reason for "happy" emotion is in the second (*a policeman visited the old man with the lost money*) and third clause (*and told him that the thief was caught*). These two clauses are denoted as **cause clauses**.

In case of Emotion-Cause pair extraction task the desired output after the processing the document example discussed above is [(*The old man was very happy*, *a policeman visited the old man with the lost money*), (*The old man was very happy*, *and told him that the thief was caught*)]. Each emotion clause is paired with its corresponding cause clause and a set of such Emotion-Cause pairs is extracted from the document.

2 RELATED WORK

The Emotion Cause Extraction was first proposed by Lee et al. (2010) as a task to label a sequence of words. A small scale Chinese Emotion-Cause corpus was created in which each word in the text was annotated as emotion or cause or none. Chen et al. (2010) used linguistic patterns both manually generalised patterns and automatically generalised patterns to extract cause expressions. They had proposed that it is most appropriate to define the cause extraction task at clause level instead of word level and used a multi-label approach to detect emotion clauses. Russo et al. (2011) proposed EMOCause which automatically identifies linguistic contexts which contain possible causes of emotions or emotional states from Italian newspaper articles (La Repubblica Corpus). Neviarouskaya et al. (2013) perform automatic extraction of phrases related to causes of emotions using syntactic and dependency parser and rules for the analysis of eight types of the emotion-cause linguistic relations. Lee et al. (2012) analysed Chinese emotion cause corpus, which yielded the identification of seven groups of linguistic cues and two sets of generalized linguistic rules for the detection of emotion causes. They implemented a linguistic rule based method to detect emotion cause in the text.

Gui et al. (2014) create a emotion cause corpus using the Chines microblog(Weibo) posts to identify the chracteristics of emotion cause expressions. A rule based method is then used using 25 manually compiled rules for determining the causes of emotions. Li et al. (2014) perform classification of emotions by making use of a triggering causal event of the emotion. They use the emotion corpus created using Chinese microlog posts and perform classification by training a SVR classifier. Gao et al. (2015) proposed a Chinese micro-blog emotion cause detection based on the ECOCC model, focusing on mining factors for eliciting some kinds of emotions. They make use of emotional lexicon with multiple characteristics (e.g., emoticon, punctuation, etc.). Ghazi et al. (2015) automatically build an English dataset annotated with both the emotion and the stimulus using FrameNet’s emotions-directed frame. They build a CRF learner, a sequential learning model to detect the emotion stimulus spans in emotion-bearing sentences. Gui et al. (2016) created an annotated dataset using SINA city news which follows the scheme of W3C Emotion Markup Language. They present a new event-driven emotion cause extraction method using multi-kernel SVMs where a syntactical tree based approach is used to represent events in text. Then, a convolution kernel and linear kernel based multi-kernel SVMs are used to extract emotion causes.

Gui et al. (2017) proposed a question answering approach to emotion cause extraction. They take inspiration from deep memory networks and consider emotion cause identification as reading comprehension task in QA. They make use of convolutional neural networks to extract the features. Xu et al. (2017) proposed an ensemble based approach to emotion cause extraction with event extraction and multi kernel SVMs. Cheng et al. (2017) focus on emotion cause detection in Chinese micro blogs for multiple user structure. They make use of SVM and LSTM to perform the classification task. Chen et al. (2018) proposed a neural network based joint model for emotion classification and emotion cause detection. They make use of LSTM and Attention layers to perform the task. Li et al. (2018) proposed a co-attention based neural network model which make use of the context around emotion word to improve emotion cause detection. Yu et al. (2019) proposed a hierarchical network-based clause selection framework in which the similarity is calculated by considering document features from word's position, different semantic levels (word and phrase), and interaction among clauses.

As discussed earlier the disadvantages of Emotion-Cause extraction limits its applications in real world. Hence Xia et al. (2019) proposed Emotion Cause Pair extraction task which has been implemented[1] in this project using different approaches and the results obtained are analysed.

3 TASK

Emotion Cause Pair Extraction for a given document D which has n clauses is defined as follows:
If the document

$$D = (C_1, C_2, ..., C_n)$$

then the set of emotion-cause pairs are

$$P = (..., (C^e, C^c), ...)$$

where

$$C^e \text{ and } C^c$$

are Emotion Clause and Cause Clause respectively.

4 APPROACH

Emotion Cause Pair Extraction task is addressed with a two stage approach as described below.

- **Step 1: Emotion and Cause Classification**
  In this step two classifiers are used one for Emotion and other for Cause to classify each of the clauses in the document D either as a Emotion Clause or Cause Clause or both or neither of them. At the end of this step we obtain a set of Emotion clauses

  $$EC = (C_1^e, C_2^e, ..., C_i^e)$$

  and a set of Cause clauses

  $$CC = (C_1^c, C_2^c, ..., C_j^c)$$

- **Step 2: Emotion Cause Pair Filtering**
  In this step, first Cartesian product of the set of Emotion Clauses (EC) and Cause Clauses (CC) is performed. Then a filter is trained to eliminate all the Emotion-Cause Pairs which do not have causal relationship.

[1] https://github.com/bhshri/Emotion-Cause-Pair-Extraction

4.1 Step 1: Emotion and Cause Classification

Before performing the classification it is important to have a mathematical representation of the text. In this project, TF-IDF and word2vec proposed by Mikolov et al. (2013) have been used to represent the text. For classification of clauses into emotion or cause clause, following models have been used: Logistic Regression and SVM with rbf kernel.

Apart from these, deep learning models like LSTM proposed by Hochreiter, S et al. (1997) and Attention proposed by Bahdanau et al. (2014) have also been used. Multi task learning models were created using Bi-LSTM and Attention layers and the embedding layer was initialised using word2vec vectors and fine tuned during the process of training. Figure 1 and Figure 2 below show the architecture of deep learning models used for emotion and cause classification. Both the models are multi task learning models which means two classifiers are trained in a single model, one for emotion classification, other for cause classification.

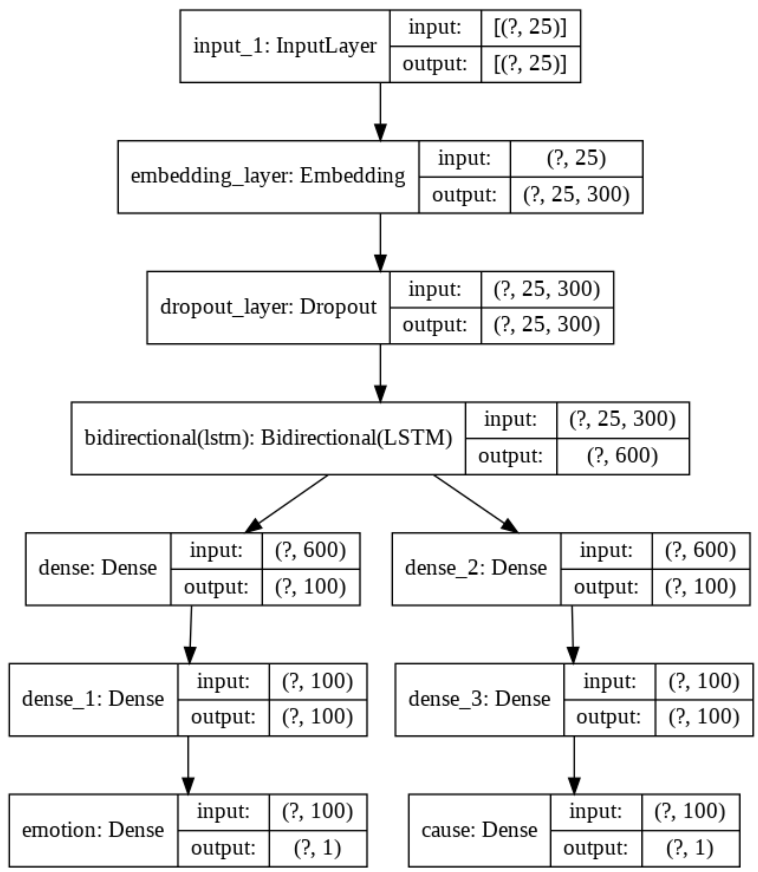

Fig. 1. BI-LSTM MULTI TASK MODEL

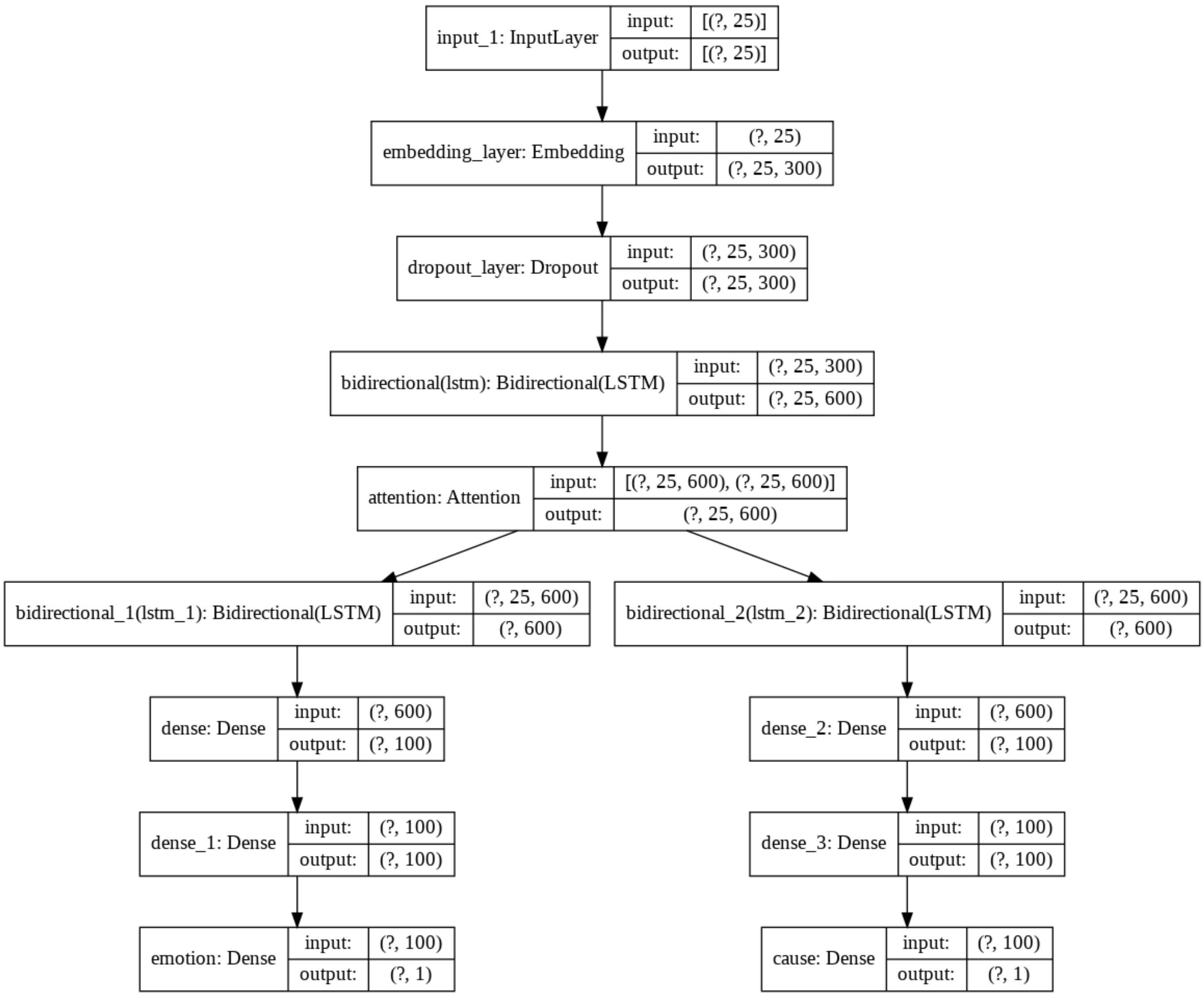

Fig. 2. BI-LSTM + ATTENTION MULTI TASK MODEL

4.2 Step 2: Emotion Cause Pair Filtering

As discussed previously the correct pairs of emotion and cause have to be identified from the Cartesian product of emotion and cause clauses obtained in previous step. Similar to previous step, for text representation TF-IDF and word2vec has been used. Logistic Regression, SVM and XGBoost proposed by Chen at al. (2016) have been used to classifying the emotion cause pairs. The vectors of emotion and cause are concatenated and used as an input to these models. For deep learning models BI-LSTM and Attention layers are used and their architecture is shown in Figure 3 and 4. This step is crucial in ensuring that only the correct emotion cause pairs are identified and the rest are filtered out. This step is more difficult than the previous step as semantic understanding of the emotion and cause pair is required to determine if there is a valid causal relationship between the two clauses.

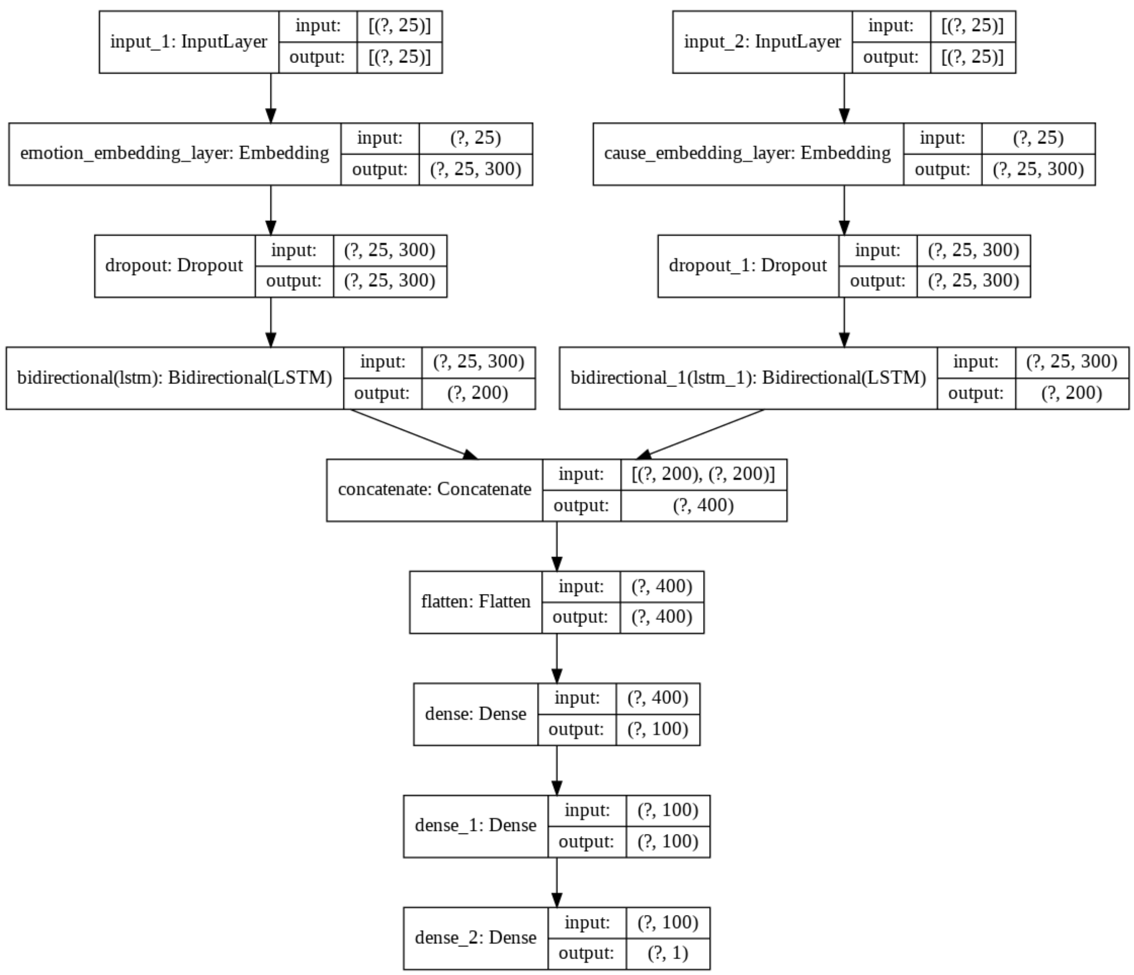

Fig. 3. BI-LSTM PAIR FILTERING MODEL

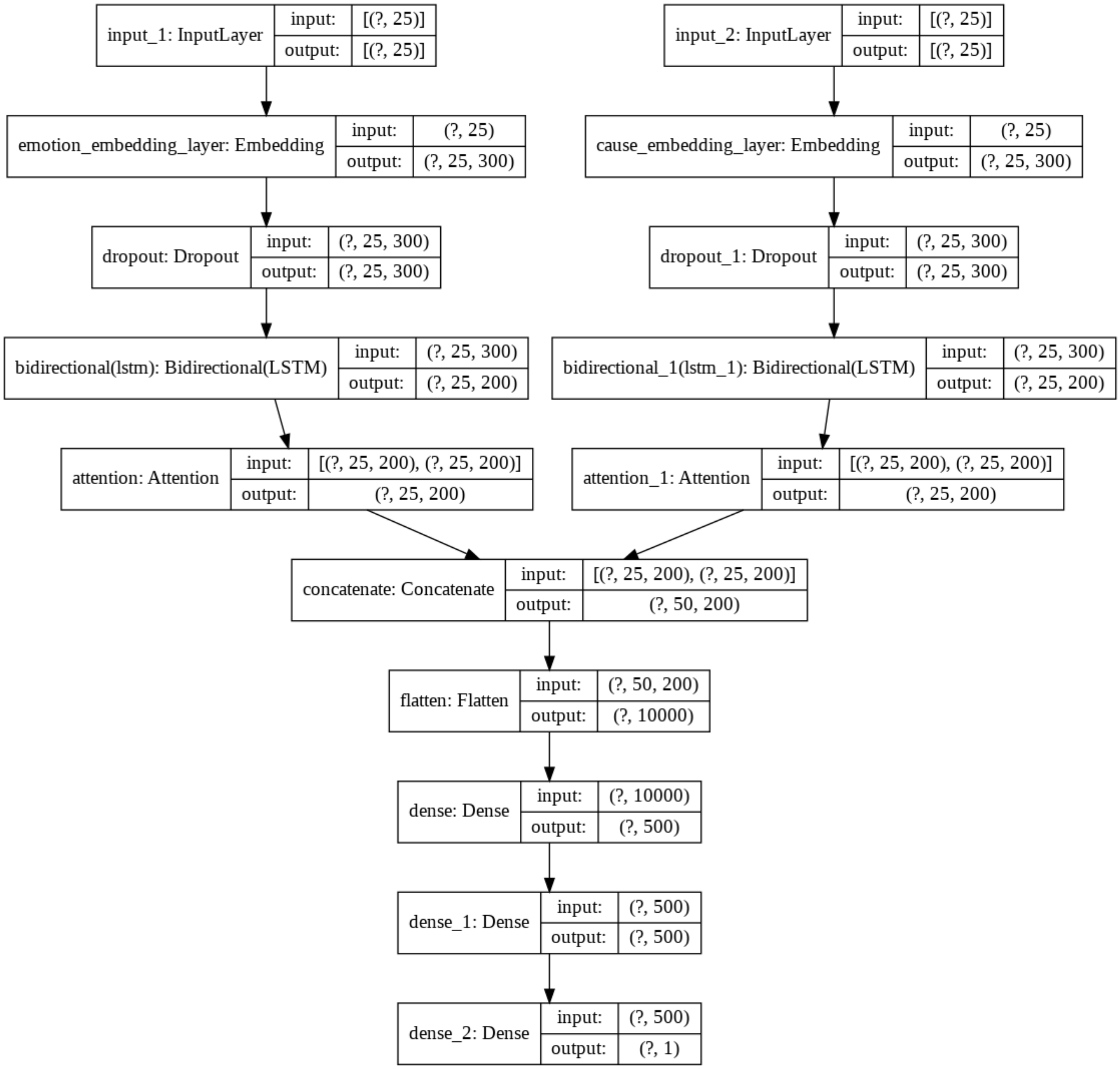

Fig. 4. BI-LSTM + ATTENTION PAIR FILTERING MODEL

5 EXPERIMENTS

5.1 Dataset and Metrics

Since there is no English dataset available for Emotion-Cause Pair Extraction task, the dataset[2] created by Ghazi et al. (2015) using FrameNet's emotion-directed frame for Emotion-Cause Extraction is preprocessed so as to make it suitable for Emotion-Cause Pair extraction. Each of the documents in the dataset is divided into clauses and clauses containing the emotion seed words are annotated as Emotion Clause and clauses containing the <cause>...</cause> XML tag are annotated as Cause Clause. The Dataset has the following emotions: Happy, Anger, Fear, Shame, Sad, Disgust and Surprise. It has 820 sentences and 865 valid Emotion-Cause Pairs. The below table shows the count of different emotions in the dataset.

Emotion	**happy**	**sad**	**surprise**	**disgust**	**anger**	**fear**	**shame**
Count	211	107	53	38	199	144	68

Table 1. Count of different emotions in the datatset

Precision, Recall and F1 Score will be used to evaluate the task. Precision is the ratio of the number of *correct pairs* to the number of *proposed pairs*. Recall is the ratio of the number of *correct pairs* to the number of *annotated pairs*. *Annotated pairs* refers to the actual emotion cause pairs present in the dataset. *Proposed pairs* refers to the emotion-cause pairs that were identified by the Emotion-Cause extraction model as valid pairs. *Correct pairs* refers to intersection of *Proposed pairs* and the *Annotated pairs*. F1 score is calculated as usual as the harmonic mean of Precision and Recall.

5.2 Experimental settings

The entire dataset is divided into Train Data (72%), Validation Data (8%) and Test Data (20%) by ensuring the distribution of all the emotions in train,validation and test data is the same. For emotion and cause classification and emotion cause pair filtering with Word2Vec, skipgram model was trained using the text from the dataset for 70 iterations and dimension of the vectors generated is 100. In all the statistical machine learning models (Logistic Regression, SVM, XGBoost) 7 fold cross validation is used to tune the hyperparameters.

For the deep learning models the embedding layer uses pretrained word2vec vectors of 300 dimension. Dropout layer of rate 0.8 is applied for the embedding layer. Batch size of 32 and Adam optimizer of rate 0.005 with binary cross entropy loss is used train the models. The hidden size of the Bi-LSTM layers is set to 300.

5.3 Evaluation and Analysis of Results

Each of the models were trained and tested with 5 randomised train test splits of the dataset and the mean of the scores is reported. Table 1 shows the scores obtained for Step 1 of the task that is Emotion and Cause classification and Table 2 shows the scores obtained for Step 2 of the task that is Emotion-Cause Pair filtering.

Figure 5 shows the t-SNE (Maaten et al. (2008)) plot of TF-IDF clause vectors to be classified in emotion clause, cause clause or none of them. Most of the cause clauses are present in the dense region in the centre of the plot while most the emotion clauses are sparsely spread near the dense cluster of cause clauses. This helps in understanding the high F1 score of 0.93 obtained for classification using TF-IDF vectors. Similarly Figure 6 shows t-SNE plot of word2vec clause

[2]http://www.site.uottawa.ca/ diana/resources/emotion_stimulus_data/

vectors. Small clusters of emotion and cause clauses can be observed in this plot. Most clusters of emotion clauses are present in the top and right region of the plot and to some extent separate from the cause clauses that explains the F1 score of 0.92 obtained. Figure 7 shows the t-SNE plot of TF-IDF emotion-cause pair vectors. It an be observed from the plot that both valid/invalid pairs are having similar distribution and it is difficult to separate them. Hence the F1 score obtained for emotion-cause pair filtering using TF-IDF representation is close to 0. Figure 8 shows t-SNE plot of word2vec emotion-cause pair vectors. Small clusters of valid pairs can be seen mostly in the upper region of the plot. This could possibly explain the better results obtained from word2vec as compared to TF-IDF. Also it is known that word2vec has more semantic understanding of the text as compared to TF-IDF and semantic understanding is very crucial to determine whether the emotion and cause show causal relationship.

Classification Type	**Emotion**			**Cause**		
Method	Precision	Recall	F1 score	Precision	Recall	F1 score
TF-IDF + Logistic Regression	0.92825	0.92689	0.92756	0.93051	0.92929	0.92989
TF-IDF + SVM(RBF kernel)	0.93553	0.93406	0.93479	0.93553	0.93406	0.93479
word2vec + Logistic Regression	0.92453	0.92390	0.92498	0.92453	0.92391	0.92421
word2vec + SVM(RBF kernel)	0.92518	0.92381	0.92449	0.92358	0.92390	0.92373
Bi-LSTM	0.95640	0.95562	0.95600	0.95749	0.95681	0.95714
Bi-LSTM + Attention	0.94888	0.94780	0.94833	0.95094	0.95020	0.95056

Table 2. Experimental Results for Emotion and Cause Classification

Method	Precision	Recall	F1 score
TF-IDF + Logistic Regression	1	0.041	0.07877
TF-IDF + XGBoost	0.6	0.008	0.0157
word2vec + Logistic Regression	1	0.3930	0.5642
word2vec + XGBoost	1	0.4473	0.6181
word2vec + SVM(RBF kernel)	1	0.57452	0.7297
Bi-LSTM	1	0.60572	0.7544
Bi-LSTM + Attention	1	0.67352	0.8049

Table 3. Experimental Results for Emotion-Cause Pair Filtering

Significance testing was performed using Kolmogorov-Smirnov test to compare the results of the models. In case of emotion and cause classification it can be seen from Table 2 that there is no improvement by using word2vec vectors instead of TF-IDF vectors. Bi-LSTM model which uses pretrained word2vec vectors is the best model for emotion and cause classification with 10% significance level. Using Attention along with Bi-LSTM did not improve the F1 score.

For emotion-cause pair filtering it can be observed from Table 3 that TF-IDF representation is giving the worst results with F1 score close to 0, which means it is not suitable for tasks in which causal relationships have to be determined. Word2Vec representation with SVM (RBF kernel) gives promising results. Bi-LSTM + Attention is the best model with significance level of 1%.

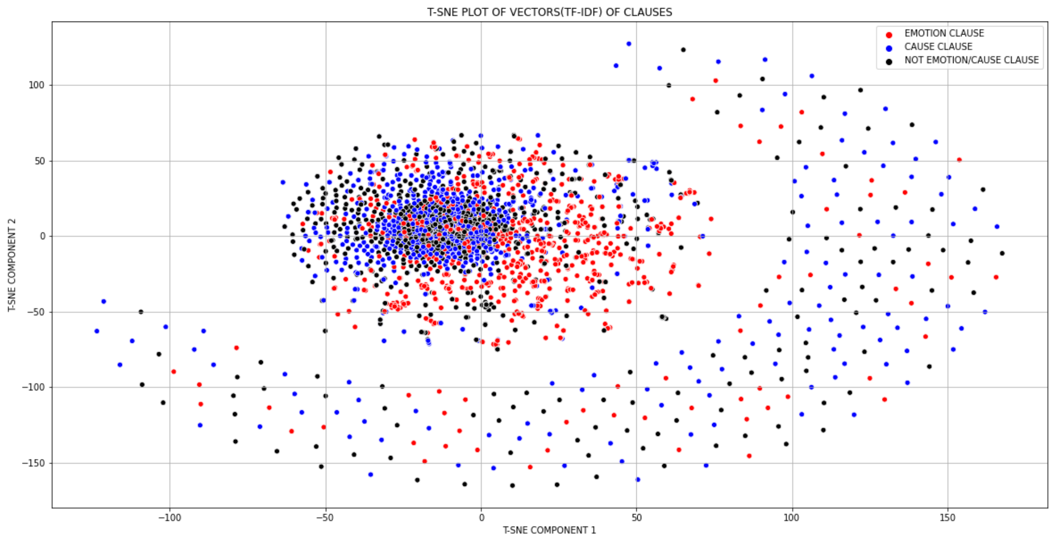

Fig. 5. t-SNE plot of Clause vectors(TF-IDF)

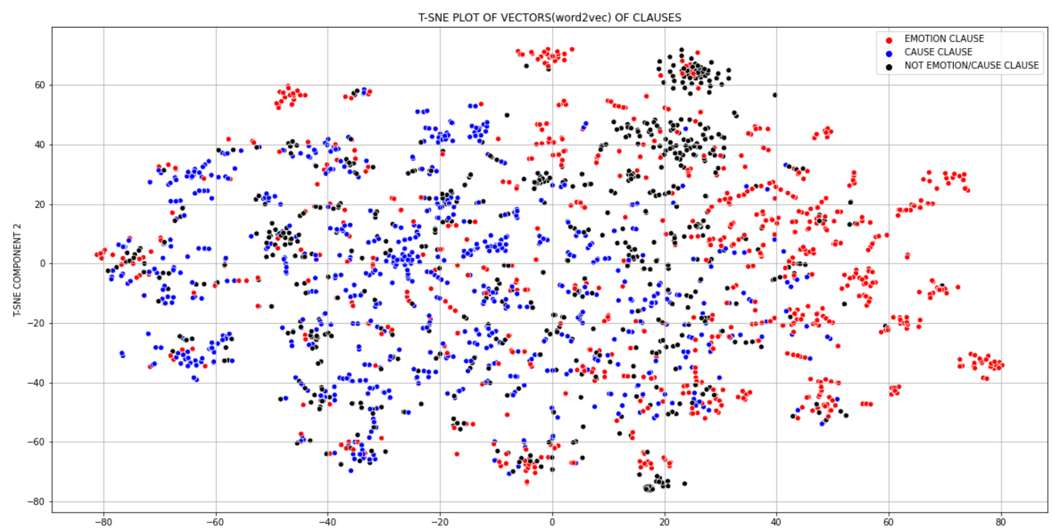

Fig. 6. t-SNE plot of Clause vectors(word2vec)

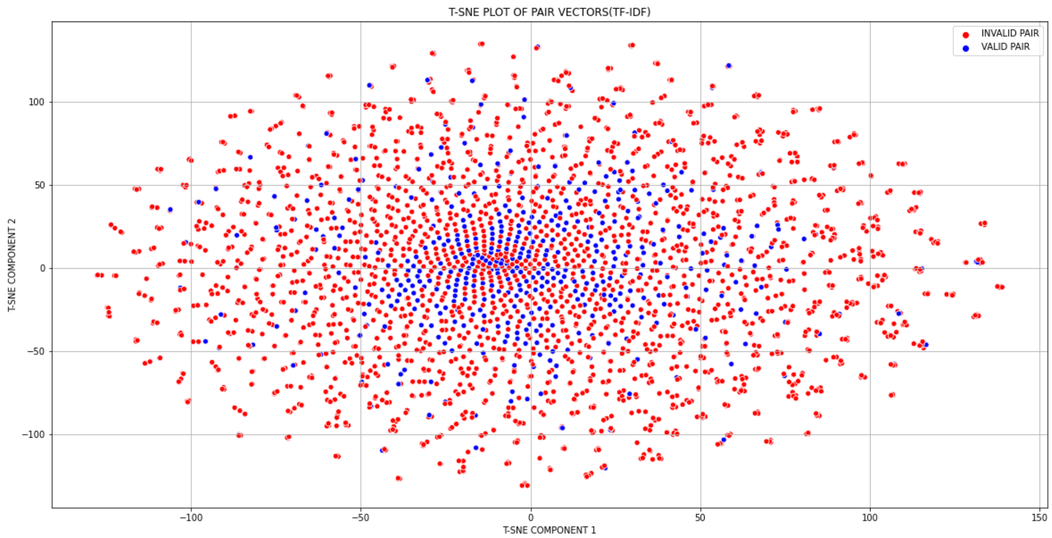

Fig. 7. t-SNE plot of emotion-cause pair vectors(TF-IDF)

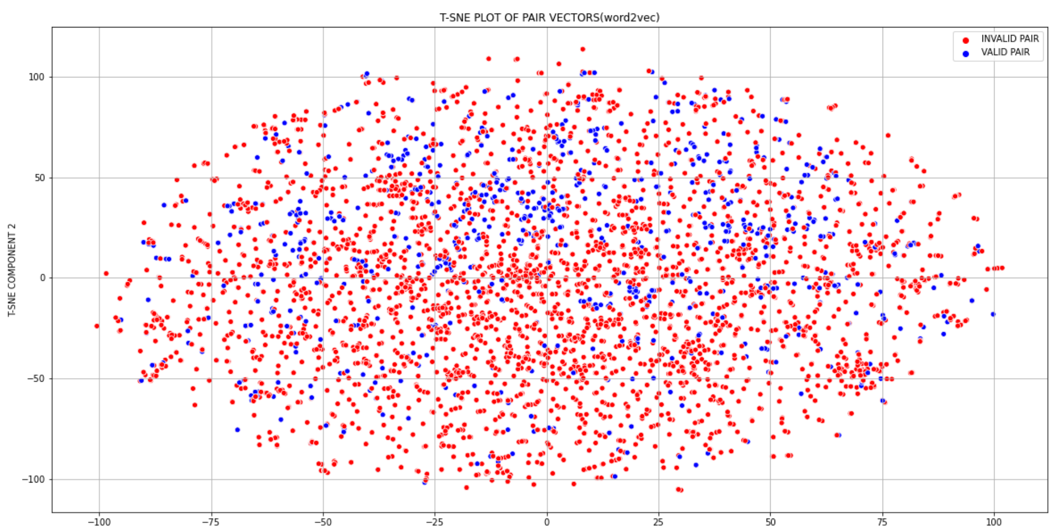

Fig. 8. t-SNE plot of emotion-cause pair vectors(word2vec)

6 CONCLUSION AND FUTURE WORK

In this project, Emotion-Cause Pair extraction task which is more realistic as compared to Emotion Cause extraction was implemented by using 2 step approach. The combination of Bi-LSTM model for Emotion/Cause Classification and Bi-LSTM + Attention gives the best results beating the second best model by approximately 5%. Hence it can concluded that Attention could be useful in modeling causal relationships in the text.

The 2 step approach used has a disadvantage that the Cartesian product applied on the emotion clauses and cause clauses obtained from step 1 could exponentially increase the number of possible emotion cause pairs out which only a small percentage would be valid. Hence in future, attempts could me made to perform this task in a single step.

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