Project Report Machine Learning Assignment

Assignment by:-

Sweta (1806157) Aparna Juhi (1806181) Smriti Pal (1806191)

Paper

Name: Semantic-Emotion Neural Network for Emotion Recognition

From Text.

Date of publication: August 23, 2019

Paper by: ERDENEBILEG BATBAATAR, MEIJING LI, KEUN HO RYU

Dataset Used

In this assignment we have used daily_dialogue dataset and isear dataset which has been widely used for Emotion Recognition .

Dataset Description:

1. Daily_dialogue dataset:

Each line of the training dialogue file contains a dialogue. A dialogue is a full conversation, like when we talk on phone the whole call is a dialogue.

Each line of the dialogue emotion file contains emotion in the form of numbers, corresponding to each sentence.

Mapping of emotion is as follows:

{ 0: no emotion, 1: anger, 2: disgust, 3: fear, 4: happiness, 5: sadness, 6: surprise}

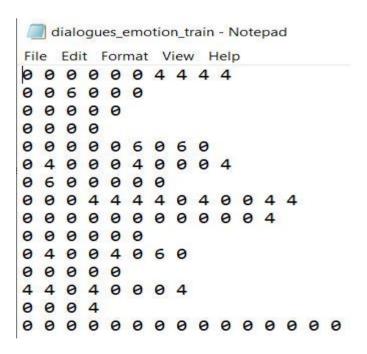
2. Isear dataset :

The dataset contains 2 features.

The first column contains the emotion corresponding to the given text and the second column contains the text .

Daily dialogue dataset:

File Edit Format View Help Say , Jim , how about going for a few beers after dinner ? __eou__ You know that is tempting but is really not g Can you do push-ups ? __eou__ Of course I can . It's a piece of cake ! Believe it or not , I can do 30 push-ups Can you study with the radio on ? __eou__ No , I listen to background music . __eou__ What is the difference ? _ Are you all right ? __eou__ I will be all right soon . I was terrified when I watched them fall from the wire . Hey John , nice skates . Are they new ? __eou__ Yeah , I just got them . I started playing ice hockey in a commu Hey Lydia , what are you reading ? __eou__ I 'm looking at my horoscope for this month ! My outlook is very pos is energetic and loves to socialize . __eou__ Well , you certainly match those criteria , but they ' re so broad Frank 's getting married , do you believe this ? __eou__ Is he really ? __eou__ Yes , he is . He loves the girl I hear you bought a new house in the northern suburbs . __eou_ That 's right , we bought it the same day we ca Hi , Becky , what's up ? __eou__ Not much , except that my mother-in-law is driving me up the wall . __eou__ Wha at her down and told her how we felt about her constant criticizing , and how we welcomed her advice but hoped s How are Zina's new programmers working out ? __eou__ I hate to admit it , but they're good . And fast . The Fili Do you like cooking ? _eou_ Yes . I like cooking very much . I got this hobby when I was 12 years sold . _eou Anyone home ? Jen ! _eou_ I'm in the kitchen ... let yourself in ! _eou_ Wow ! You're really working up a st You look so tan and healthy! __eou__ Thanks . I just got back from summer camp . __eou__ How was it? __eou__ G Diana , do you like the perfume I gave you ? __eou__ It 's good . But to tell you the truth , I don 't wear pe Ah , ah , ah ... __eou__ All right , Bill.Here 's your daily exercise schedule . You are to jog before breakfas Hi Bill , I saw your grandma yesterday . __eou__ Oh where was that ? __eou__ I was running around the track at m I would like to register for a class today . __eou__ No problem , what class would you like to take ? __eou__ I Dad , why are you taping the windows ? __eou__ Honey , a typhoon is coming . __eou__ Really ? Wow , I don't have Hi , my name is Lean , and I'm from Russia . <u>eou</u> Nice to meet you , Lean . My name is Alike . I'm from Japan Can I help you ? <u>eou</u> I hope so . I'm looking for some material for a paper I'm writing , and I'm not quite s Here 's your hot dog and beer . What happened ? Did I miss anything ? __eou__ Yeah , Cal Ripen just hit a home How do you like the pizza here ? __eou__ Perfect . It really hits the spot . __eou__ Do you have a light ? __eou__ Sorry , I don't smoke . __eou__



Isear dataset

4 A	В	C	D	E	F	G	Н					
joy	[On days when I feel close to my partner and other friends. When I feel at peace with myself and	l also experience a	close conta	ct with peop	le whom I re	gard greatly.]						
fear	Every time I imagine that someone I love or I could contact a serious illness, even death.											
anger	When I had been obviously unjustly treated and had no possibility of elucidating this.											
sadness	When I think about the short time that we live and relate it to the periods of my life when I think that I did not use this short time.											
disgust	At a gathering I found myself involuntarily sitting next to two people who expressed opinions that	At a gathering I found myself involuntarily sitting next to two people who expressed opinions that I considered very low and discriminating.										
shame	When I realized that I was directing the feelings of discontent with myself at my partner and this way was trying to put the blame on him instead of sorting out my own feelings.											
guilt	I feel guilty when when I realize that I consider material things more important than caring for my relatives. I feel very self-centered.											
joy	After my girlfriend had taken her exam we went to her parent's place.											
fear	When, for the first time I realized the meaning of death.											
anger	When a car is overtaking another and I am forced to drive off the road.											
sadness	When I recently thought about the hard work it takes to study, and how one wants to try somethi	ing else. When I re	ead a theore	tical book in	English that	I did not under	stand.					
2 disgust	When I found a bristle in the liver paste tube.											
shame	When I was tired and unmotivated, I shouted at my girlfriend and and brought up negative sides of her character which are actually not so important.											
guilt guilt	When I think that I do not study enough. After the weekend I think that I should have been able to have accomplished something during that time.											
joy	When I pass an examination which I did not think I did well.											
5 fear	When one has arranged to meet someone and that person arrives late, in the meantime one starts	s thinking about al	I that could	have gone wr	ong e.g a tra	affic accident.						
7 anger	When one is unjustly accused of something one has not done.											
sadness	When one's studies seem hopelessly difficult and uninteresting.											
disgust	When one finds out that someone you know is not at all like one had thought, for instance friends	who steal and thi	ngs like that,	quite unwar	ranted.							
shame	When one has been unjust, stupid towards someone else.											
l guilt	When one has neglected or been unjust to a good friend.											
2 joy	Passing an exam I did not expect to pass.											
fear	When I climbed up a tree to pick apples. The angle of the ladder I was on did not enable me to get high enough. This implied that the ladder was not very stable.											
1 anger	Friends who torture animals.											
sadness	[Same as in anger.]											
disgust	Friends who torture animals.											
7 shame	[Same as above - friends who torture animals.]											
guilt	[When excuses are necessary and I get out of doing it myself.]											
joy	When I had my children.											
fear	When my 2 year old son climbed up and sat on the 7th floor balcony with his legs hanging out. He	was holding on tig	ghtly to the u	apper railing o	of the balcor	y but he could	have e					

Data Preprocessing

Word tokenization and Padding: In data preprocessing we have used word tokenizer (Word tokenization is the process of splitting a large sample of text into words). Second thing that we are doing is to pad the tokenized arrays. We know all the sentences will not have an equal number of words but while operating we will need a fixed size of vector. So we have to make them of equal size as here every sentence is made into an array of 20 words where <pad> is used for filling the extra space. It will act like a null word having no meaning.

Global Vectors: We have used Global Vectors(It is an unsupervised learning algorithm developed by Stanford for generating word embeddings by aggregating global word-word co-occurrence matrix from a corpus.) to generate a map from word to vector representation for words.

One-Hot Encoding: One-hot encoding is essentially the representation of categorical variables as binary vectors. In the dataset we used one-hot encoding to convert the emotions in binary vectors.

Model Used

1. BILSTM MODEL

We used bidirectional LSTM to derive the hidden state of each word by summarizing the information from both forward and backward directions. Forward LSTM and backward LSTM are denoted as LSTM reads words from left to right and LSTM in reverse direction.

$$\begin{split} \overrightarrow{h_t} &= \overrightarrow{LSTM} \left(w_t^{sem}, \overrightarrow{h_{t-1}} \right), \quad t \in [1, N] \\ \overleftarrow{h_t} &= \overleftarrow{LSTM} \left(w_t^{sem}, \overleftarrow{h_{t+1}} \right), \quad t \in [1, N] \end{split}$$

We get a representation of each w by concatenating the forward hidden state

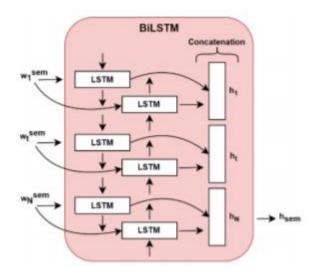
$$h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}]$$

Finally, semantic sequence vector hsem encoded from the last the hidden state is fed into the hidden layer.

$$h_{sem} = h_N$$

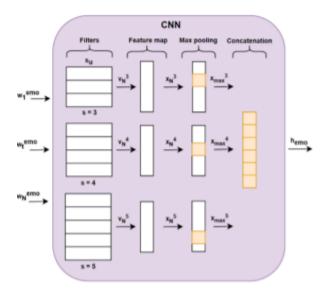
 $g_{sem} = f(w_{sem}h_{sem} + b_{sem})$

BiLSTM Structure



2. CNN MODEL

To better extract emotion features from emotion-based word embeddings, we used CNN to utilize layers with convolving filters that are applied to local features. An architecture of the CNN used in this paper is shown in Figure.



An input for a CNN is represented as a Zemo matrix and the CNN is fed by emotion word vectors. Then the word embedding vectors are concatenated as the feature vector v of the sequence.

$$v = w_1^{emo} \oplus \dots w_t^{emo} \dots \oplus w_N^{emo}$$

In the first convolution layer, convolution calculation is performed using multiple filters with variable window sizes and generate a local emotion feature vector xi for each possible word window size. Each convolution operation generates a new context local feature vector given below in a word window s.

$$x_i^s = f(W \cdot v_{i:i+s-1} + b)$$

The convolution filter generates a local feature mapping vector for each possible word window in the input sequence, which is followed by the completion of the convolution operation to generate a new vector that can be expressed as:

$$x^{s} = [x_{1}^{s}, \dots, x_{i}^{s}, \dots, x_{N-s+1}^{s}]$$

Max pooling operation is employed on the new feature vector generated by the convolution layer. Max pooling mapped the vector to a fixed length vector. The max pooling selects the top number of features corresponding to multiple hidden layers so that the most important emotion feature information can be retained.

$$x_{max}^{s} = \max\{x_1^{s}, \dots, x_i^{s}, \dots, x_{N-s+1}^{s}\}$$

All vectors which are output from the max-pooling layer are concatenated into a single feature vector hemo.

$$h_{emo} = [x_{max}^s], \quad s \in [s_{min}, s_{max}]$$

Finally, the emotion sequence vector hemo is fed into the hidden layer.

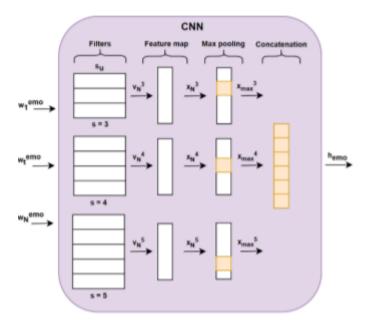
$$g_{emo} = f \left(w_{emo} h_{emo} + b_{emo} \right)$$

where gemo is the output of the emotion encoder, wemo and bemo are parameters of the non-linear f activation function.

3. SENN MODEL

SENN model for emotion recognition from text and the structure is shown in Figure . It consists of two sub-networks: 1) BiLSTM network for semantic encoder between words and 2) CNN network foremotion encoder. The outputs of the sub-networks are used to recognize emotions from the text. Both of the two subnetworks are fed by the same sequence of N words and each word is transformed to a d dimensional word vector.

SENN Structure



EVALUATION MEASURES

For evaluating the SENN model, an exact matching criterion was used to examine three different result types. False negative (FN) and False positives (FP) are incorrect negative and positive predictions. True positives (TP) results corresponded to correct positive predictions, which are actual correct predictions. The evaluation is based on the performance measures precision (P), recall (R) and F-score (F1). Recall denotes the percentage of correctly labelled positive results overall positive cases and is calculated as:

$$R = \frac{TP}{TP + FN}$$

$$P = \frac{TP}{TP + FP}$$

$$F1 = \frac{2 \times P \times R}{P + R}$$

Training

BILSTM MODEL

- Firstly, the dimension of input is converted into 3-Dimension so that it can pass to the LSTM layer.
- Sequential model is used here on which the first layer is of BiLSTM .
- In between the layers, we have used the Dropout layer to prevent overfitting.
- The optimizer used is Adaptive Moment Estimation(Adam).
- The loss function categorical cross entropy (for multi-class classification).
- Batch Size = 128 and Epochs = 20

CNN MODEL

- Sequential model is used here on which the first layer is CNN.
- Conv1D is used with filters =128 ,kernel size=3 and activation = relu.
- In between the layers, we have used the Dropout layer to prevent overfitting.
- MaxPooling1D with pool_size=2.
- The optimizer used is Adaptive Moment Estimation(Adam) .
- The loss function categorical cross entropy (for multi-class classification).

SENN Model

- Applying both BiLSTM and CNN models together.
- Conv1D is used with filters =256 ,kernel size=3 and activation = relu.
- BiLSTM with layers=512.
- The optimizer used is Adaptive Moment Estimation(Adam).
- The loss function categorical cross entropy (for multi-class classification).
- Batch Size = 128 and Epochs = 20

Result

Confusion matrix obtained:

1.Daily_dialogue

[[5	918	29	4	3	290	28	49]
[83	27	0	0	2	1	5]
[35	3	9	0	0	0	0]
[12	1	0	4	0	0	0]
[:	533	3	1	0	474	0	8]
[84	1	0	0	0	17	0]
[60	0	0	0	8	0	48]]

2.lsear

Visualising Data in Percentage

1.Daily_dialogue

<matplotlib.axes._subplots.AxesSubplot at 0x7ff64db91f60>



2. Isear

<matplotlib.axes._subplots.AxesSubplot at 0x7fdb6b4f0a20> o -10.55% 0.66% 0.00% 1.32% 0.13% 0.13% 1.45% -0.12 H - 2.51% 6.60% 1.06% 0.66% 0.40% 0.40% 1.85% -0.10 N - 2.24% 0.92% 7.78% 0.53% 0.26% 0.13% 0.79% -0.08m - 3.69% 0.40% 0.53% 7.65% 0.53% 0.26% 1.85% -0.06 ▼ -1.45% 0.00% 0.40% 0.00% 12.80% 0.26% 0.53% -0.04m - 3.43% 0.40% 0.40% 1.19% 1.85% 6.86% 0.92% -0.02 φ - 2.11% 0.53% 0.66% 2.11% 0.66% 0.26%

5

6

-0.00

Model accuracy on test data

i

2

3

- 1.Daily_dialogue-83.94%
- 2.lsear-62.66%

ò