CS60092: INFORMATION RETRIEVAL

Project Report Submitted by:

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PROJECT-6 : Offensive query detection

PROBLEM STATEMENT:

Offensive queries have become an important challenge for all search engine and social marketing applications. Often new socio-political events trigger new searches, which if shown as suggestions can be deemed offensive to the users. Even in social media the comment section became so hateful in some cases. So as an organization, that company has to take care of all those hateful queries and don't let users feel about it. Hence this challenge is of high relevance to many software companies.

Motivation for work:

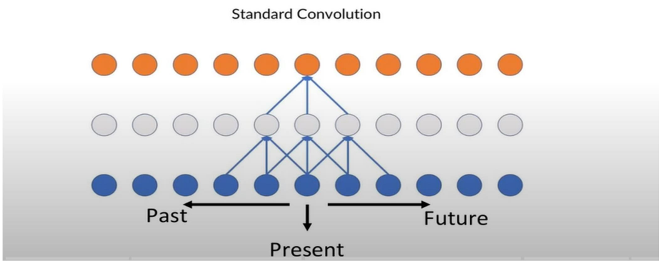
Interested to combine the causal and non-causal model for sentimental analysis:

Causal model: In this model we can look only backward in the sequence in order to predict the sentiment, Example, RNN

Non causal model: In this model we can look only **backward** as well as **forward** in the sequence in order to predict the sentiment, Example CNN

CNN model:

Standard Conv 1d can be for future values in the consideration



RNNmodel:

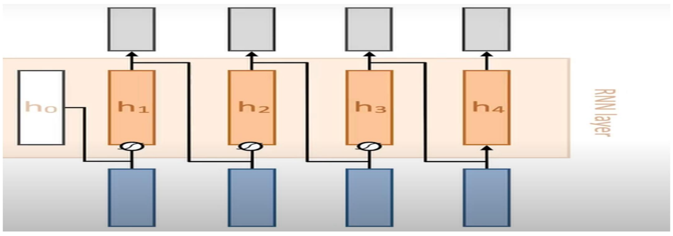


Figure: we can look only backward in the sequence

WHY WE HAVE TAKEN HINGLISH DATASET:

To solve this problem we have taken a Hinglish dataset which means data is a mixup of Hindi and English languages. Hinglish is the most common language and we have to deal with it throughout our country. That's why we picked Hinglish. However the same methodology which we incorporated here can be easily extended to any other language.

THE CHALLENGES IN DATA SET:

We need some Preprocessing of data because we cannot directly extract features from the data given to us. The difficulties we are having are as follows.

- The sentences are not following any grammar both in English and Hindi.
- The words are not exact words, they are slang words.
  Eg. pyar,pyaar,pyaarr
- Very few examples in the data set.

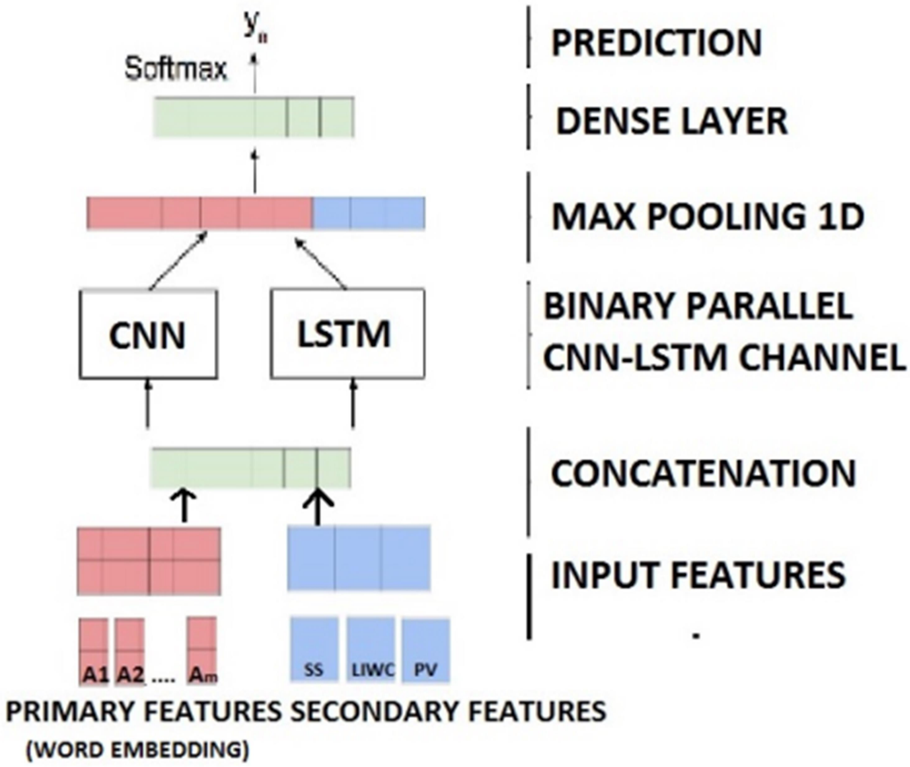
Our model will classify data into categories related to hatefulness by considering all the challenges it is having.

count	tweets
0	@saud5683 @Mutayyab420 @shivang598 @Ranask35 @milkygaay @Aapaawaambaa @thetanmay @INCIndia Haa jaise tum bhi abhi p\xe2\x80\xa6 https://t.co/wZmXZPIMTD
2	Banti hai empowered woman, feminism pe gyan pelti hai aur din bhar roti rehti hai. Pahle rona band kar madarchod!
2	RT @kim_jong_korea: @updatingwait @Acutereply Ab usko chhod mjse bat kr tera baap aa gya hai ab to ldki ko beech me q la ra hai Madarchod t\xe2\x80\xa6
2	@InviSibleSold @mabkhan86 @dridadahn Punjab in madarchodon ko Khila raha hai, nokrian day raha hai aur yeh imran ma\xe2\x80\xa6 https://t.co/fxaRgyKZXF
2	RT @MrMonsterSaid: Agar koi bole ki ja ke chill maar to madarchod ki gand maar lene ka.
1	@InviSibleSold @mabkhan86 @dridadahn Main jutt Punjabi hoon aur paka N league. Madarchod Imran ki Punjab say nafrat clear hai.
2	@adn_merry To Bhosdike tere Baap ka kya ja raha hai? tu Apna Ghar dekh na Madarchod
2	@updatingwait @Acutereply SUNNY LEONE BANA KE CHODEGE\nTERI MAA KO\nSAMJH ME AAYA \nMADARCHOD NEEM KA PATTA KADVA HAI\xe2\x80\xa6 https://t.co/tsrMfs26rp
2	@akramtyagi @BSF_India @rajnathsingh @Uppolice @moradabadpolice @myogiadityanath Pata nahi aise sanghi kutte ko bha\xe2\x80\xa6 https://t.co/n2PLeOgW0v
1	RT @AnshKSpeaks: Screw the law of the land. If I find this chutiya Madarchod Mulla I will Lynch him, murder him, cut into millions of pieces and Ha\xe2\x80\xa6

Figure: HOT DATASET

Related work:

The model with CNN and LSTM combination has already been implemented in this paper. The major component are described in this figure given below



Our contribution:

We have Analyzed performance on hot data set for the following model on RNN, CNN, RNNandCNN combination, LSTM and CNN combination.

Added the self-attention layer in the LSTM and its combination Analyzed the performance of this model. Fine tuning the models using variable learning rate, changes in the hidden layer to improve accuracy.

Techniques and methodology:

Data Pre-processing: The first pre-processing step was the removal of punctuations, URLs, user mentions {@mentions} and numbers {0-9}. Hash tags and emoticons were suitably converted by their textual counterparts along with conversion of all tweets into lower case.

We have used word embedding representations of Glove, mapping of Hindi words with Corresponding English meaning in order to used glove

Use of classifier model such as RNN, CNN, LSTM and there combinations, attention layer with all these combinations.

Architecture:

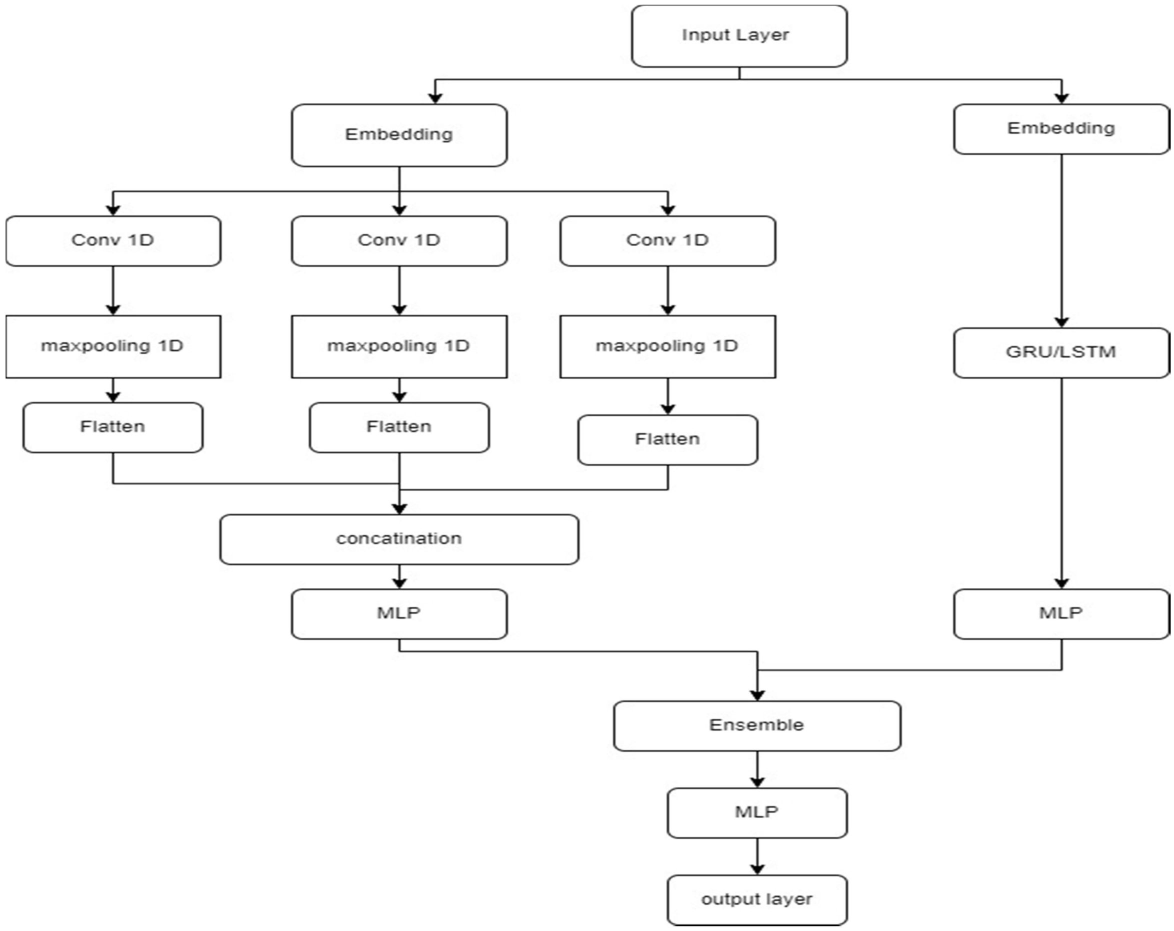


FIGURE: CNN+RNN/LSTM Architecture followed

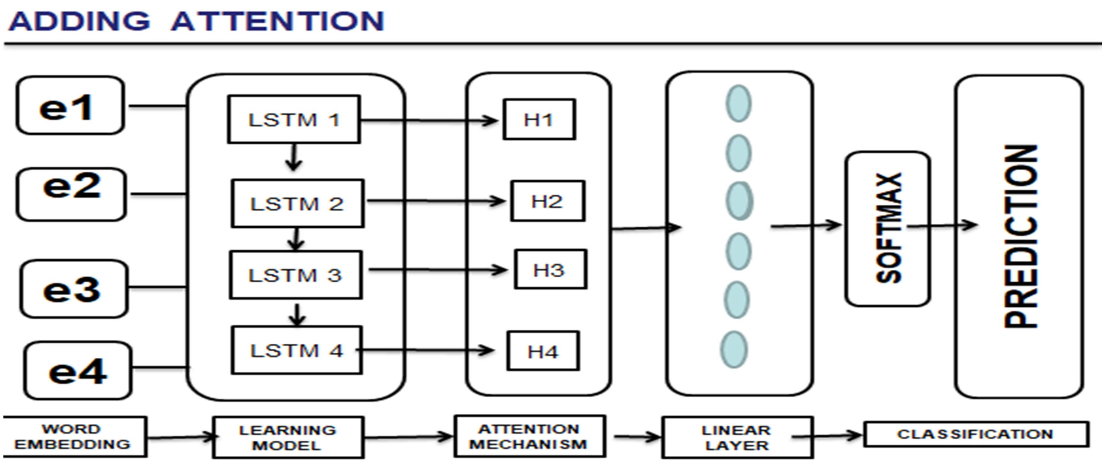


Figure: Our model Architecture

Results and conclusions:

RNN model:

```
Accuracy of the Model on Train Data : 96.73684210526315
Accuracy of the Model on Validation Data : 80.66666666666666
CLASS  : 0                         RECALL : 0.85   PRECISION : 0.78
CLASS  : 1                         RECALL : 0.43   PRECISION : 0.58
CLASS  : 2                         RECALL : 0.89   PRECISION : 0.90
F1 Score :0.74
Accuracy of the Model on Test Data : 83.15789473684211
```

LSTM model:

```
Accuracy of the Model on Train Data : 89.89473684210526
Accuracy of the Model on Validation Data : 71.66666666666667
CLASS  : 0                         RECALL : 0.74   PRECISION : 0.72
CLASS  : 1                         RECALL : 0.15   PRECISION : 0.19
CLASS  : 2                         RECALL : 0.85   PRECISION : 0.83
F1 Score :0.58
Accuracy of the Model on Test Data : 73.78947368421052
```

CNN model:

```
Accuracy of the Model on Train Data : 99.89473684210526
Accuracy of the Model on Validation Data : 83.66666666666667
CLASS  : 0                         RECALL : 0.84   PRECISION : 0.83
CLASS  : 1                         RECALL : 0.45   PRECISION : 0.69
CLASS  : 2                         RECALL : 0.93   PRECISION : 0.89
F1 Score :0.77
Accuracy of the Model on Test Data : 86.10526315789474
```

RNN+CNN model:

```
Accuracy of the Model on Train Data : 100.0
Accuracy of the Model on Validation Data : 83.66666666666667
CLASS  : 0                      RECALL : 0.83   PRECISION : 0.76
CLASS  : 1                      RECALL : 0.38   PRECISION : 0.70
CLASS  : 2                      RECALL : 0.92   PRECISION : 0.89
F1 Score :0.74
Accuracy of the Model on Test Data : 82.73684210526315
```

LSTM+CNN model:

```
Accuracy of the Model on Train Data : 99.89473684210526
Accuracy of the Model on Validation Data : 84.0
CLASS  : 0                      RECALL : 0.83   PRECISION : 0.79
CLASS  : 1                      RECALL : 0.36   PRECISION : 0.62
CLASS  : 2                      RECALL : 0.92   PRECISION : 0.89
F1 Score :0.73
Accuracy of the Model on Test Data : 83.57894736842105
```

Attention layer in LSTM:

```
Accuracy of the Model on Train Data : 98.57894736842105
Accuracy of the Model on Validation Data : 76.33333333333333
CLASS  : 0                      RECALL : 0.74   PRECISION : 0.83
CLASS  : 1                      RECALL : 0.43   PRECISION : 0.26
CLASS  : 2                      RECALL : 0.87   PRECISION : 0.89
F1 Score :0.67
Accuracy of the Model on Test Data : 78.3157894736842
```

Attention layer in LSTM+CNN model:

```
Accuracy of the Model on Train Data : 99.89473684210526
Accuracy of the Model on Validation Data : 83.33333333333334
CLASS  : 0                      RECALL : 0.85   PRECISION : 0.77
CLASS  : 1                      RECALL : 0.44   PRECISION : 0.67
CLASS  : 2                      RECALL : 0.88   PRECISION : 0.89
F1 Score :0.75
Accuracy of the Model on Test Data : 82.84210526315789
```

Comparison of models:

MODEL	TEST ACCURACY	F1 SCORE
LSTM Model	73.78%	0.58
RNN Model	83.15%	0.74
CNN Model	86.11%	0.77
RNN+CNN Model	82.73%	0.74
LSTM+CNN Model	83.57%	0.73
LSTM with Attention	78.31%	0.67
LSTM with Attention +CNN	82.84%	0.75

Conclusion and future work:

We have added attention layer in the LSTM and its combination with CNN and we have observed the improvement of accuracy on test data sets.

So far we have found the offensiveness of a given query by using multiple models like CNN,RNN, LSTM ,attention with and combinations among them. But we haven't focused on the kind of offensiveness and the target situation/person/purpose etc. and our natural human language is so general and diverse such that sometimes the sentences may seem not offensive but actually they are. So we generally train our models with plain text but not the context. So without knowing the context it is impossible to find out the offensiveness of the statement sometimes.

So it will be an interesting challenge for us to build new machine learning and deep learning models in such a way that our model can predict the situation/context from the given data.

REFERENCES:

https://arxiv.org/pdf/2010.12472.pdf

https://medium.com/hackernoon/fighting-for-acceptance-on-social-media-tackling-offensive-tweets-in-hinglish-ad10e0eef2b9

https://medium.com/geekculture/recap-of-how-to-implement-lstm-in-pytorch-e17ec11b061e

http://emnlp2014.org/papers/pdf/EMNLP2014181.pdf

https://medium.com/analytics-vidhya/pytorch-for-deep-learning-lstm-for-sequence-data-d0708fdf5717

https://aclanthology.org/W18-3504.pdf

https://aclanthology.org/W18-5118.pdf

INDIVIDUAL CONTRIBUTION:

NAME: Subham Kumar Das
ROLLNO: 21CS60R28
CONTRIBUTION:

- **Written Driver code for models**
- **DATA PREPROCESSING in code**
- **Word embedding in code**
- **Addition attention layer in LSTM in the code**
- **Participation in ppt making**

NAME: Rahul Mehta
ROLLNO: 21CS60R31
CONTRIBUTION:

- **Implementation of RNN,CNN,LSTM and there combinations in code**
- **Fine-tuning all the models**
- **Plotting the graphs**
- **Calculation of f1_score and confusion matrix**
- **Participated in report writing**

NAME: Sudarshaan Kashyap Das
ROLLNO: 21CS60R02
CONTRIBUTION:

- **Implementation of attention layer in combination of CNN and LSTM in the code**
- **Participated in discussion with team members regarding implementation techniques and discussed the methodologies in research papers**

NAME: Vamsikrishna pilli

ROLLNO: 21CS60R51

CONTRIBUTION:

- **Read various research papers and understand the project flow in a clear manner.**
- **Participated in discussion with team members regarding implementation techniques and discussed the methodologies in research papers.**
- **Made the report work**