Opinion Mining through Social Media Analysis

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Task Definition

Our task is to find the public sentiment for a particular topic through social media analysis, mainly twitter. The twitter data is particularly difficult to analyze because of informal language, slang terms and typo ridden nature prevalent on twitter platform. We plan to use this analysis for detecting up to date public reaction to different products.

Motivation

1. People can find the sentiment towards the latest iPhone or a laptop they want to buy.
2. Companies can figure out the latest opinion of their products.
3. This can also be used to track the general sentiment towards Politicians in an electoral race.

Evaluation setup

Training Dataset :
We are using dataset Sentiment140 as our training data. This data has 1.6 million tweets.

The dataset consists of the following features :
0 - the polarity of the tweet (0 = negative, 4 = positive)
1 - the id of the tweet (2087)
2 - the date of the tweet (Sat May 16 23:58:44 UTC 2009)
3 - the query (lyx). If there is no query, then this value is $NO-QUERY$.
4 - the user that tweeted
5 - the text of the tweet

Evaluations :
We split the Sentiment140 dataset into two parts : training and dev dataset.
We are using the accuracy against the dev dataset as our accuracy measure to decide the best model.

Main things accomplished

We started out by using Naive Bayes for sentiment analysis. We tried Unigram features and added PoS Tags later on. The work done in [1] was the motivation behind it.

After that, we moved on to the Neural approach to solving this problem. We tried the following architectures:

- Convolutional Neural Network (CNN)
- Bi-directional LSTM
- Bi-directional LSTM + CNN

The above architectures were used to build an end to end system which takes a raw tweet and gives the sentiment score and label for it. For this system, we first cleaned the data by taking care of urls, usernames, repeated characters, and stop words. After that, we tokenized these tweets. They were then padded to be the size of the maximum sized tweet. Using Keras, they were then converted to embeddings and fed into the architectures described above.

System Description

Layer Type	Output Shape	Param
Embedding	(None, 74, 300)	27000000
Bidirection	(None, 74, 148)	222000
Reshape	(None, 74, 148, 1)	0
Conv2D	(None, 71, 1, 256)	151808
Max Pooling	(None, 1, 1, 256)	0
Flatten	(None, 256)	0
Dropout	(None, 256)	0
Dense	(None, 1)	257

Table 2: LSTM + CNN

Layer Type	Output Shape	Param
Embedding	(None, 74, 300)	27000000
Bidirection	(None, 148)	222000
Dense	(None, 1)	149

Table 3: LSTM

Layer Type	Output Shape	Param
Embedding	(None, 74, 300)	27000000
Reshape	(None, 74, 300, 1)	0
Conv2D	(None, 71, 1, 256)	307456
Max Pooling	(None, 1, 1, 256)	0
Flatten	(None, 256)	0
Dropout	(None, 256)	0
Dense	(None, 1)	257

Table 4: CNN

Key Results & Analysis

Architecture	Epochs	Stop Words	Accuracy
CNN	4	Used	78.10
CNN	4	Not used	80.72
LSTM	4	Used	79.16
LSTM	4	Not used	81.20
LSTM + CNN	4	Used	80.23
LSTM + CNN	4	Not used	81.28
LSTM	6	Not used	81.40
LSTM + CNN	6	Not used	81.58

Importance of Words in context
1. It's Friday - Positive, It's Monday - Negative In this case, the importance given to Friday and Monday are justified and the system correctly classifies the tweets. America beats Pakistan in football - Negative,
2. America beats India in football - Positive. In this case, the importance given to Pakistan and India is not justified and both tweets should ideally

Sarcasm Detection
The model fails to detect the sarcasm in the tweet and sometimes classifies the tweet to have the opposite connotation.

For Example :
Awesome! School on Saturday.
This tweet gets wrongly assigned to the positive sentiment class by our model.

Category	Positive #	Negative #	Sentiment
iPhone	35	15	0.62
Liverpool	36	14	0.71
Trump	32	18	0.56
Avengers	45	5	0.85

Table 1: Sentiment Results

References

[1] Alec Go, Richa Bhayani, and Lei Huang. Twitter sentiment classification using distant supervision. *CS224N Project Report, Stanford*, 1(12), 2009.

[2] Aliaksei Severyn and Alessandro Moschitti. Twitter sentiment analysis with deep convolutional neural networks. In *Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 959–962. ACM, 2015.

Conclusion And Future Work

Neural Network Model give good accuracy in the task of sentiment analysis. With our feature engineering , we get best results for bidirectional LSTM +CNN. The performance can still get affected in cases of Sarcasm Detection

Future Enhancements :
One approach for improving accuracy even further, is applying attention model give biased importance to words according to their importance.