Sentiment Analysis on Financial Data Using Neural Networks

<u>Approach 1(For Microblog dataset)</u>

<u>The Head on Approach</u>

This was the very first basic approach. The initial preprocessing was done to remove the urls and clean the data. The data was tokenized using keras tokenizer and corpus of words was formed using all the words in the spans each being given a unique number. Each span was represented corresponding to the unique number in the dictionary and later the input matrix of span was padded with zeros to the maximum length. The maximum length was kept as 25 as the longest span encompassed 25 words.

The second step we took was to use GloVe as choice for word embedding. Each word in the corpus was expressed as 300 dimensional vector using the GloVe (Twitter 42B Tokens).

The last step was to create the Network Structure and train to improve accuracy. Starting with the embedding layer, the network architecture combined of alternate LSTM layers and dense layers two each and finally 'tanh' activation function was used as the output layer.

The network accuracy for training and validation was both ~1.6%, even after tuning all the available hyper parameters (number of layers, number of neurons, activation function, optimizers etc.)

We then procced on taking a research path and referred some papers to take inspiration for network architecture and tried to make some new models as described below with the variation in the referred models.

Approach 2

We have combined hand-engineered lexical, sentiment, and metadata features with the representations learned from deep-learning approaches like Convolutional Neural Networks (CNN) and Bidirectional Gated Recurrent Unit (Bi-GRU).

Analysis of Data

Predicting sentiments of financial data has diverse applications. Positive news has the capability to boost the market by increasing optimism among people. 'Fine-Grained Sentiment Analysis on Financial Microblogs and News' aims at analyzing the polarity of public sentiments from financial data present in newspapers and social media.

Data Distribution

Task	Training	Trial	Test
Subtask-1	1,694	10	799
Subtask-2	1,142	14	491

The dataset is noisy and contains URLs, cashtags, digits, usernames and emoticons. The messages are short with an average number of 13 tokens for the microblog data and 10 tokens for the headlines data.

Feature Engineering

Before extracting the features, the following steps are applied as a part of Data
(a)Converting the text to lowercase
(b)Stemming
(c)Replacing named entities(NE) and digits with common identifiers.
The above-mentioned steps are performed to reduce noise in the data.

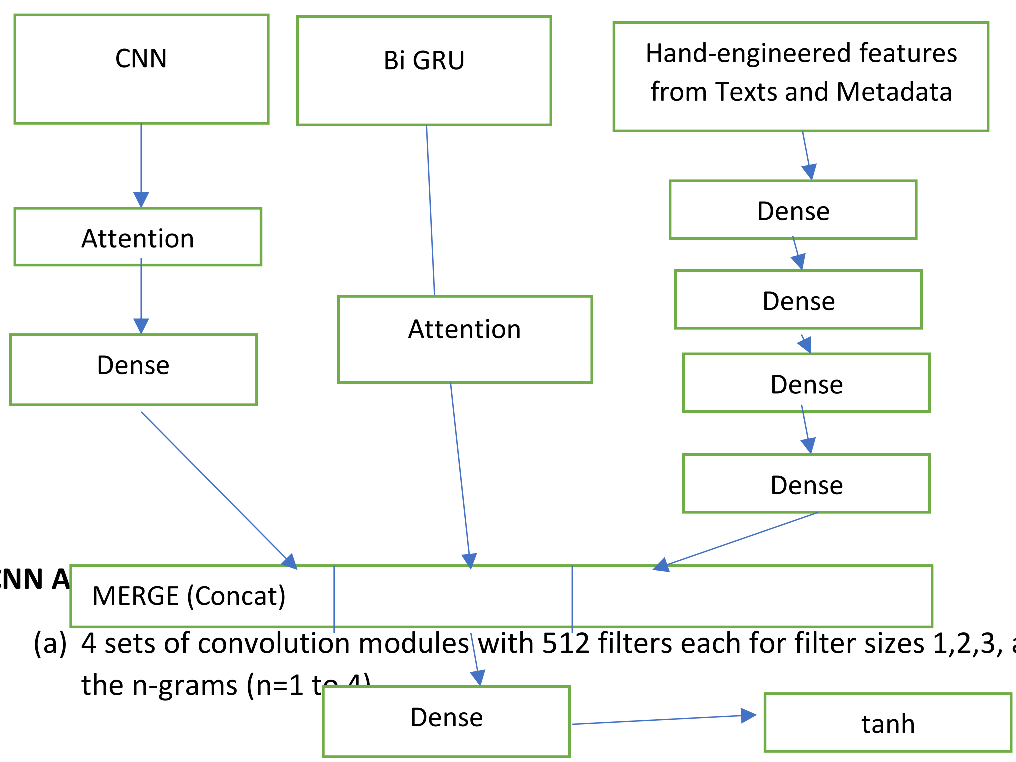
Lexical:
We extracted word n-grams (n=1,2,3) and character n-grams (n=3,4,5) from the messages.

Sentiment:
We used SenticNet library as it provides a collection of concept-level opinion lexicons with scores in five dimensions (aptitude, attention, pleasantness, polarity, and sensitivity). Both stemmed and non-stemmed versions of the messages are used to extract concepts from the knowledge base. Concepts are modeled as bag-of-concepts(BOC) and used as binary features.

cashtag	id	sentiment	source	spans	concepts	polarity	attention	pleasantr	aptitude	sensitivity	stemmed_pol	stemmed_atten	stemmed_pleas	stemmed_aptitu	stemmed_sensi	stemmed_concep
$FB	7.20E+17	0.366	twitter	consumers	cautious stance ke	0.177333	0.389667	-0.1	0.419	-0.173333	0.136	0.228	0.02	0.306	-0.14	keep
$LUV	7.20E+17	0.638	twitter	NAMEDEN	entry	0.073	0.066	0	0.154	0	0	0	0	0	0	
$NFLX	5329774	-0.494	stocktwits	Every Reas	every reason	-0.341	0.143	-0.35	-0.2965	0.338	0.078	0.286	-0.09	0.227	-0.18	reason
$DIA	7.20E+17	0.46	twitter	NAMEDEN	high all time need	0.19575	-0.3675	0.08	0.306	0.219	0.19575	-0.3675	0.08	0.306	0.219	high all time need
$PLUG	20091246	0.403	stocktwits	Long setup	long	0.056	0.065	0	0.142	0.039	0.056	0.065	0	0.142	0.039	long
$GMCR	5819749	0	stocktwits	will be a so	today term passive	0.166833	0.0855	0.0258	0.315	0.1628333	0.421	0.2414	0.3646	0.3518	0.0128	today term ad lon
$IBM	7.10E+17	-0.296	twitter	recall	recall	0.483	0.722	0.726	0	0	0	0	0	0	0	
$IOSB	17892972	-0.546	stocktwits	NAMEDEN	deal cash new raisi	0.451167	0.2345	0.4438	0.446	-0.0225	0.46466667	0.5175	0.4435	0.4615	-0.0225	deal cash new wir
$CSTM	7.10E+17	-0.438	twitter	NAMEDENTITY		0	0	0	0	0	0	0	0	0	0	
$PYPL	7.08E+17	0.408	twitter	NAMEDENTITY AppleStores ar		0	0	0	0	0	0.035	0	0.048	0.058	0	liquid
$GOOGL	31971935	-0.398	stocktwits	NAMEDEN	star analyst buy	0.34	-0.24667	0.492	0.212667	0	0.34	-0.246666667	0.492	0.212666667	0	star analyst buy
$ENDP	7.10E+17	-0.349	twitter	Excited big	excited value big	0.124	0.306333	0.3143	0.048	-0.263667	0.1985	0.491	0.0185	0.1115	0.0245	hope big
$XLI	13915103	0.025	stocktwits	NAMEDENTITY		0	0	0	0	0	0	0	0	0	0	
$PCLN	10448993	0.486	stocktwits	NAMEDENTITY		0	0	0	0	0	0	0	0	0	0	
$AA	24886266	0.308	stocktwits	NAMEDEN	going	-0.72	0	-0.66	-0.91	0.585	-0.55	0	-0.78	-0.88	0	go
$AAPL	12793642	-0.372	stocktwits	NAMEDENTITY NAMEDENTITY		0	0	0	0	0	0	0	0	0	0	
$AAPL	9408369	0.461	stocktwits	not guaranteed		0	0	0	0	0	0	0	0	0	0	
$GOLD	7.20E+17	0.408	twitter	Potential o	potential continua	0.312	0.562	0.3355	0.1045	-0.06	0	0	0	0	0	

Word Embeddings: Since word embeddings show semantic information, word vectors trained on Google News has been used to capture the semantic representation of the messages. It has 3M vocabulary entries. We averaged the word vectors of every word in the messages and represented them with a 300-dimensional vector. The words that are not available in the pre-trained vectors vocabulary are skipped.

Metadata:
We used the message sources, cashtags and company names as metadata features.



CNN A

(a) 4 sets of convolution modules with 512 filters each for filter sizes 1,2,3, and 4 to capture the n-grams (n=1 to 4)

(b) On those filters, we apply pooling operation using an attention layer. An attention layer applied on top of a feature map computes the weighted sum.
(c) A dense layer containing 128 neurons were applied on the attention layer to get the final representation for the high-level features produced by the CNN model.

Bi-GRU Architecture

It summarizes the contextual information from both directions of a sequence and provided annotation for the words. The bidirectional GRU contains a forward GRU
of 200 units and another backward GRU of 200 units. We applied an attention layer like CNN on the word annotations to find out the important features and got a vector of 200 dimensions.

MLP Architecture

The extracted features were fed in the input layer and four hidden dense layers having 200, 100, 50, and 10 neurons respectively were used.

The outputs of above three models were concatenated to create a merged layer of size 338. It contained the three types of high-level features. CNN captured the local information, Bi-GRU captured the sequence information and MLP represented the hand-engineered features. We applied a dense layer of 128 neurons on top of this merged layer. The outputs of this layer were passed to the activation layer containing only one neuron having tanh as the activation function(tanh)

Cosine score=0.401

Approach 3 RNN

- **Datasets(loaddataset.py) ---- Data preprocessing**
  1. Load to pandas dataframe and normalize json
  2. Get only required columns
  3. Convert span lists to text
  4. Write index in column
  5. make sentiment score numeric
- **feature engineering------**
  6. transfer word, doc to be vector
  7. pos_features, sentiment_feature, large_features, char_approach
- lexicon library

Model: RNN MODEL

Grid research for finding the best parameters for model

AdamOptimizer

batch_size = 187

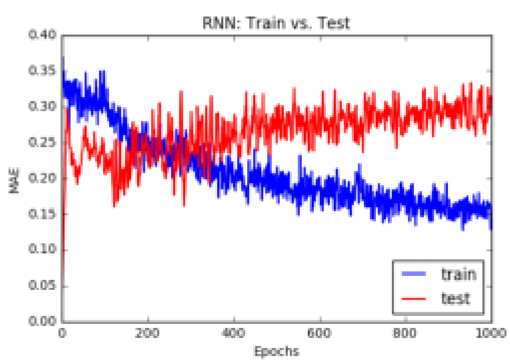
p_dropout = 0.51

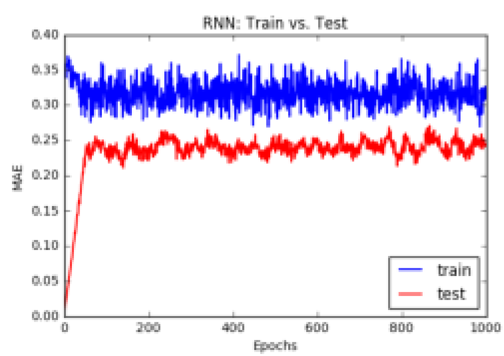
p_layer_count = 15

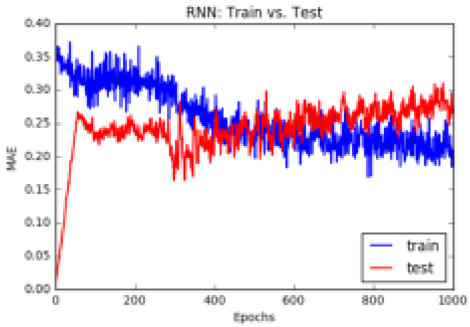
p_num_layers = 8

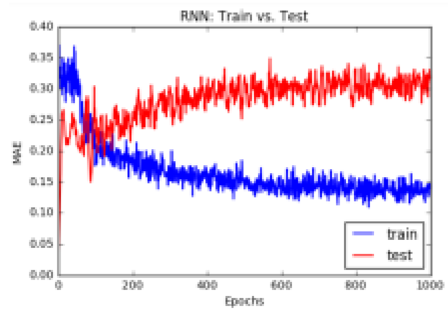
epochs = 1000

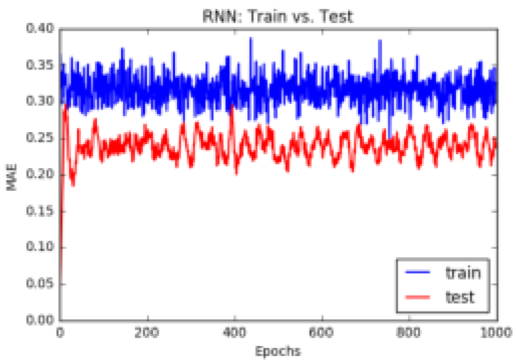
- **test vs train error for different features:**

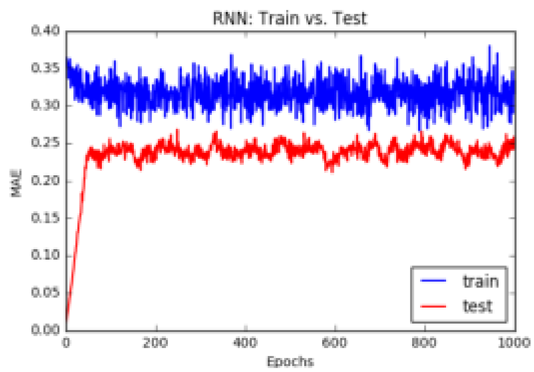








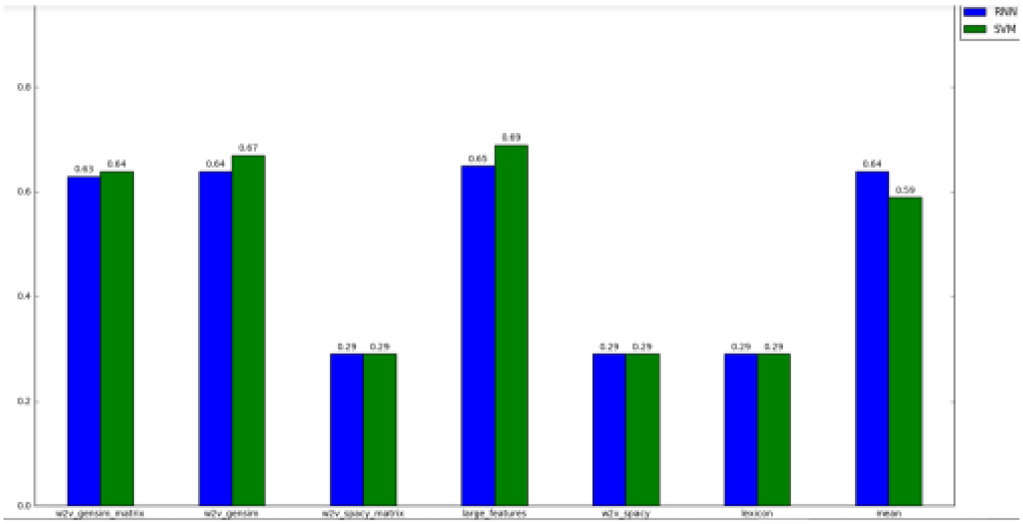




- **Using Kfold CV Training data cross-validation, split to 5 folder, here is the performance for each folder only using the training data to test the model :**

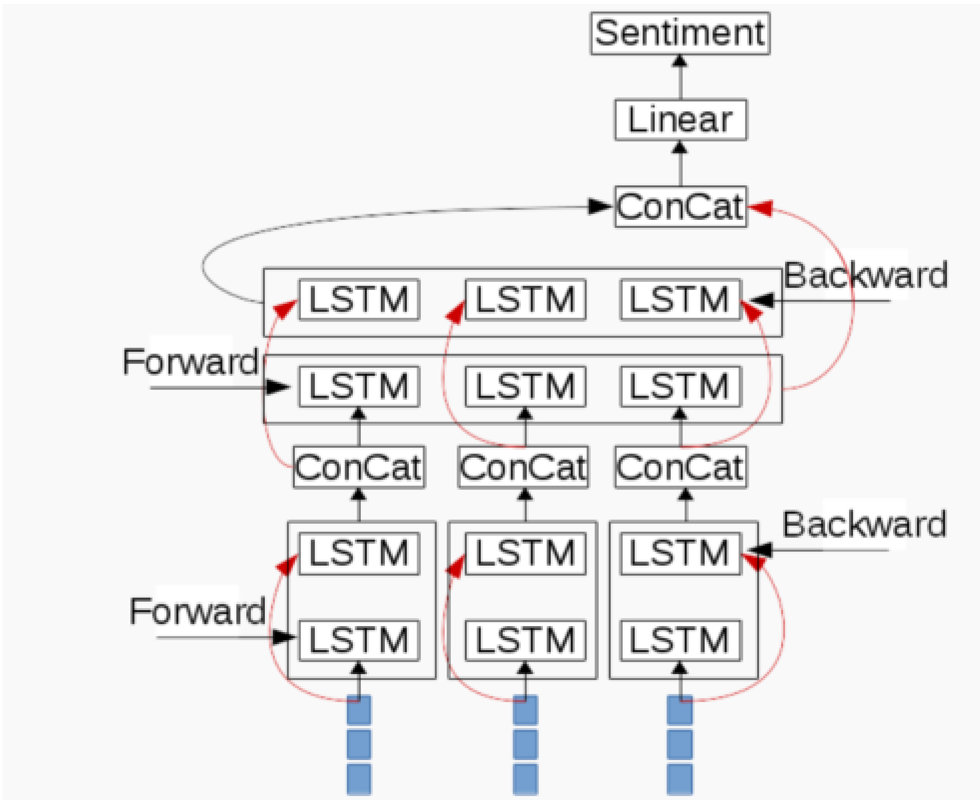
```
1. fold:SVR_w2v_gensim_matrix [[ 0.62116764]] SVR_w2v_gensim [[ 0.68102718]] SVR_w2v_spacy_matrix [[ 0.35890401]] SVR
_large_features [[ 0.68010666]] SVR_w2v_spacy [[ 0.35890401]] SVR_lexicon [[ 0.35866669]] SVR_mean [[ 0.61888199]] RN
N3_w2v_gensim_matrix [[ 0.64227225]] RNN3_w2v_gensim [[ 0.66171637]] RNN3_w2v_spacy_matrix [[ 0.35890401]] RNN3_large
_features [[ 0.66975493]] RNN3_w2v_spacy [[ 0.35890401]] RNN3_lexicon [[ 0.35890416]] RNN3_mean [[ 0.67144422]]


2. fold:SVR_w2v_gensim_matrix [[ 0.61958669]] SVR_w2v_gensim [[ 0.66647377]] SVR_w2v_spacy_matrix [[ 0.31434925]] SVR
_large_features [[ 0.66563883]] SVR_w2v_spacy [[ 0.31434925]] SVR_lexicon [[ 0.31390237]] SVR_mean [[ 0.6049875]] RNN
3_w2v_gensim_matrix [[ 0.58748905]] RNN3_w2v_gensim [[ 0.60609605]] RNN3_w2v_spacy_matrix [[ 0.31434925]] RNN3_large_
features [[ 0.60901205]] RNN3_w2v_spacy [[ 0.31434925]] RNN3_lexicon [[ 0.31435335]] RNN3_mean [[ 0.63866041]]
3. fold:SVR_w2v_gensim_matrix [[ 0.64262701]] SVR_w2v_gensim [[ 0.674]] SVR_w2v_spacy_matrix [[ 0.21010146]] SVR_larg
e_features [[ 0.70149187]] SVR_w2v_spacy [[ 0.21010146]] SVR_lexicon [[ 0.2115608]] SVR_mean [[ 0.54825379]] RNN3_w2v
_gensim_matrix [[ 0.65314751]] RNN3_w2v_gensim [[ 0.66884125]] RNN3_w2v_spacy_matrix [[ 0.21010146]] RNN3_large_featu
res [[ 0.6867044]] RNN3_w2v_spacy [[ 0.21010146]] RNN3_lexicon [[ 0.21013641]] RNN3_mean [[ 0.6180668]]
4. fold:SVR_w2v_gensim_matrix [[ 0.64546054]] SVR_w2v_gensim [[ 0.65729577]] SVR_w2v_spacy_matrix [[ 0.27646883]] SVR
_large_features [[ 0.70166514]] SVR_w2v_spacy [[ 0.27646883]] SVR_lexicon [[ 0.27602476]] SVR_mean [[ 0.58599418]] RN
N3_w2v_gensim_matrix [[ 0.61723103]] RNN3_w2v_gensim [[ 0.63800334]] RNN3_w2v_spacy_matrix [[ 0.27646883]] RNN3_large
_features [[ 0.63608327]] RNN3_w2v_spacy [[ 0.27646883]] RNN3_lexicon [[ 0.27647416]] RNN3_mean [[ 0.6445974]]
5. fold:SVR_w2v_gensim_matrix [[ 0.66833879]] SVR_w2v_gensim [[ 0.67515288]] SVR_w2v_spacy_matrix [[ 0.28344222]] SVR
_large_features [[ 0.70480254]] SVR_w2v_spacy [[ 0.28344222]] SVR_lexicon [[ 0.28376079]] SVR_mean [[ 0.597269]] RNN3
_w2v_gensim_matrix [[ 0.65521527]] RNN3_w2v_gensim [[ 0.62193237]] RNN3_w2v_spacy_matrix [[ 0.28344222]] RNN3_large_f
eatures [[ 0.64804446]] RNN3_w2v_spacy [[ 0.28344222]] RNN3_lexicon [[ 0.28344368]] RNN3_mean [[ 0.63894646]]
```


RNN
SVM
0.0
0.2
0.4
0.6
0.8
0.63
0.64
0.64
0.67
0.29
0.29
0.65
0.69
0.29
0.29
0.29
0.29
0.64
0.59
w2v_gensim_matrix
w2v_gensim
w2v_spacy_matrix
large_features
w2v_spacy
lexicon
mean

Approach 4(For Headlines dataset)

Preprocessing and Additional data used



1.Lower cased

2.Tokenised using unitok package

Word2Vec – This was created using Gensim

BLSTM Sentence Representation:

1)Sentences are fixed length.

2)All words are represented as vectors.

We created two different Bidirectional Long Short-Term Memory using the Python Keras library with tensor flow backend. We choose an LSTM model as it solves the vanishing gradients problem of Recurrent Neural Networks. We used a bidirectional model as it allows us to capture information that came before and after instead of just before, thereby allowing us to capture more relevant context within the model (similar to using Bi-GRU in the first approach) A

BLSTM is two LSTMs one going forward through the tokens the other in reverse order and in our models concatenating the resulting output vectors together at each time step.

Both BLSTM models have the following similar properties:

(1) Minimised the Mean Square Error (MSE) loss using RMSprop with a mini batch size of 32.

(2) The output activation function is linear.

The main difference between the two models is the use of drop out and when they stop training over the data (epoch).

Standard Model(SLSTM)

- Drop out 0f 0.2 between layers and connections
- 25 times trained over the data (epoch of 25)

Early Stopping LSTM(ELSTM)

- Drop out of 0.5 between layers only
- Early stopping used to determine the epoch.

Cosine Score of SLSTM=0.41

Cosine Score of ELSTM=0.412

In ELSTM, the epoch is not fixed, it uses early stopping with a patience of 10. This model is expected to generalize better than the standard one due to the higher drop out and that the epoch is based on early stopping which relies on a validation set to know when to halt training.

Advantages of LSTMS:

a) Good at learning sequential data
b) Able to learn long term dependencies.

Conclusion:

Our model of choice was BLSTM with early stopping variation as it was the model giving us the maximum accuracy which was ~40%.

Acknowledgement

This report is based on the work by Sudipta Kar and Andrew Moore.

https://github.com/apmoore1/semeval/blob/master/paper/lancaster-semeval-2017.pdf

http://www.aclweb.org/anthology/S17-2150

http://www.aclweb.org/anthology/S17-2154