# STANCE DETECTION IN FAKE NEWS

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# Why fake news detection?



# INTRODUCTION

- News is a relevant part of our daily life.
- Social media sites are the most accessed and impactful sources of news.
- News from social sites turns viral in a matter of hours.

# MOTIVATION

- Fake News is spread across social media sites.
- Recent US elections demonstrate the influence of fake news on general public opinion and election results.
- Manually impossible to determine the authenticity of all the news on the web.
- Need for an automated mechanism to identify the fake news.

# PROBLEM STATEMENT

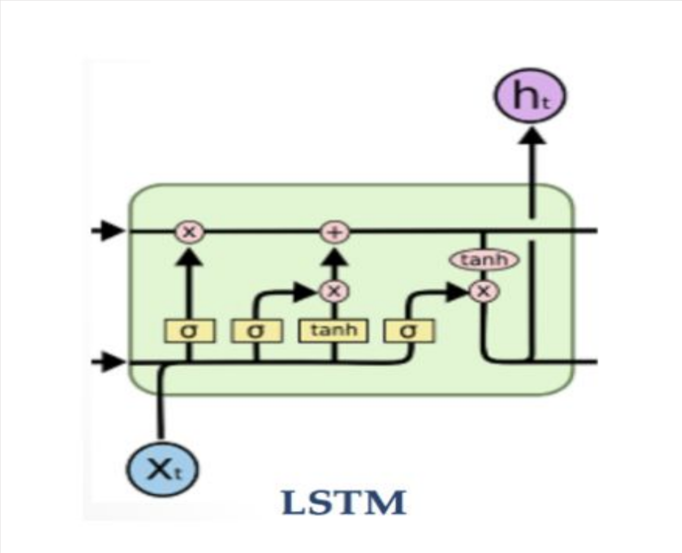
- Fake news detection is a challenging problem.
- Stance detection among news headline - body pairs can significantly help in Fake News detection.
- Fake News Challenge (FNC1) presents a dataset, a collection of news articles with resemblance to real world news for the task of stance detection.
- Aim is to identify whether the article body agrees, disagrees or discusses the news heading or is entirely unrelated.

# PROPOSED SOLUTION

GLoVE embeddings (50 dimensional) for words in news corpus were used with following models :

- Feed-forward neural network:
  Embeddings of headlines and body are averaged separately and concatenated to train the model.
- Long Short Term Memory Model (LSTM):

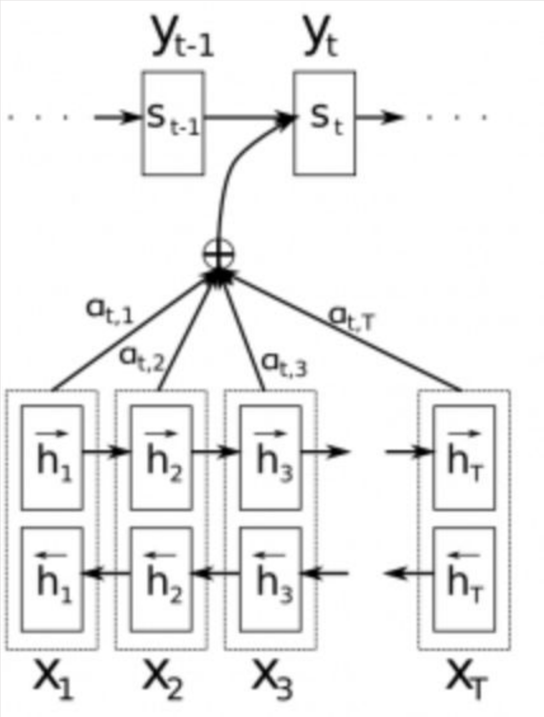
  Since LSTMs are good at capturing long term dependencies, embedded vectors of concatenated header and article are used for training LSTM layers.



# PROPOSED SOLUTION

- LSTM with attention:

- ❑ Attention mechanism is good at learning a summarized context and performs well with large inputs.
- ❑ So attention model is constructed over the first L output states from headlines of the articles.
- ❑ Relevant context is extracted from headlines and articles and so should improve the performance for stance detection.



# PROPOSED SOLUTION

- LSTM with Attention equations:

$$\mathbf{M} = \tanh(\mathbf{W}^y\mathbf{Y} + \mathbf{W}^h\mathbf{h}_N \otimes \mathbf{e}_L) \qquad \mathbf{M} \in \mathbb{R}^{k\times L}$$

$$\alpha = \mathrm{softmax}(\mathbf{w}^T\mathbf{M}) \qquad \alpha \in \mathbb{R}^L$$

$$\mathbf{r} = \mathbf{Y}\alpha^T \qquad \mathbf{r} \in \mathbb{R}^k$$

$$\mathbf{h}^* = \tanh(\mathbf{W}^p\mathbf{r} + \mathbf{W}^x\mathbf{h}_N) \qquad \mathbf{h}^* \in \mathbb{R}^k$$

- Attention mechanism presented in Rocktaschel et al. https://arxiv.org/pdf/1509.06664.pdf

# Evaluation

- FNC dataset is divided into training set (60%), development set (20%) and test set(20%).
- Since data is skewed, ‘Computation Score’ for the algorithm is computed for [HEADLINE, BODY TEXT] pair as follow:

❑ 0.25 increment in score for a correct prediction of unrelated pair
❑ 0.25 increment in score for a correct prediction of related pair.
❑ 0.75 increment in score if pair is correctly predicted as agrees, disagrees or discusses.

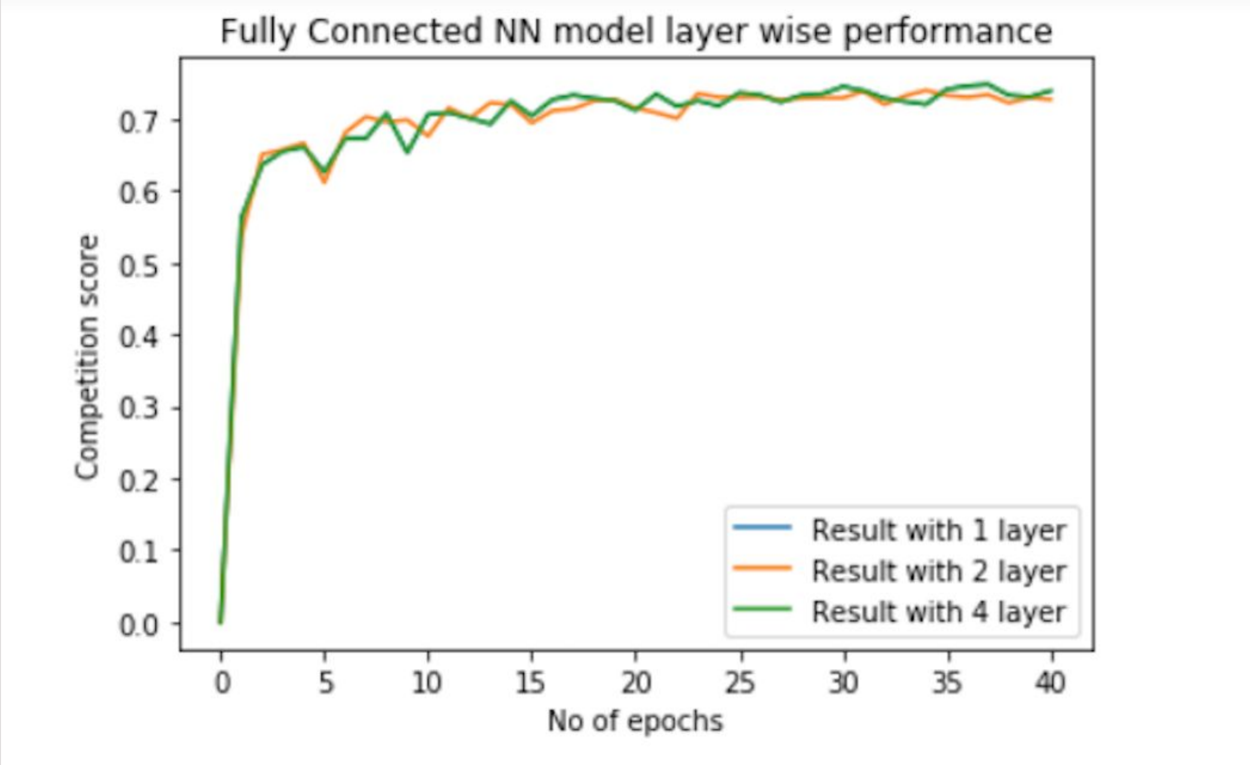
# RESULTS

- Table for competition scores and F1 scores obtained from each of the three models: Feed-forward network, LSTM, LSTM with attention for the four classes: Agrees, Disagrees, Discuss, Unrelated are shown below:

| Models | Competition Score | Agrees | Disagrees | Discuss | Unrelated |
|---|---|---|---|---|---|
| Feed-forward network | 0.7458 | 0.631502 | 0.4637931 | 0.806563 | 0.965368 |
| LSTM | 0.781332 | 0.783748 | 0.561194 | 0.89695 | 0.9687995 |
| LSTM with attention | 0.79501 | 0.833917 | 0.72327 | 0.91811 | 0.97327 |

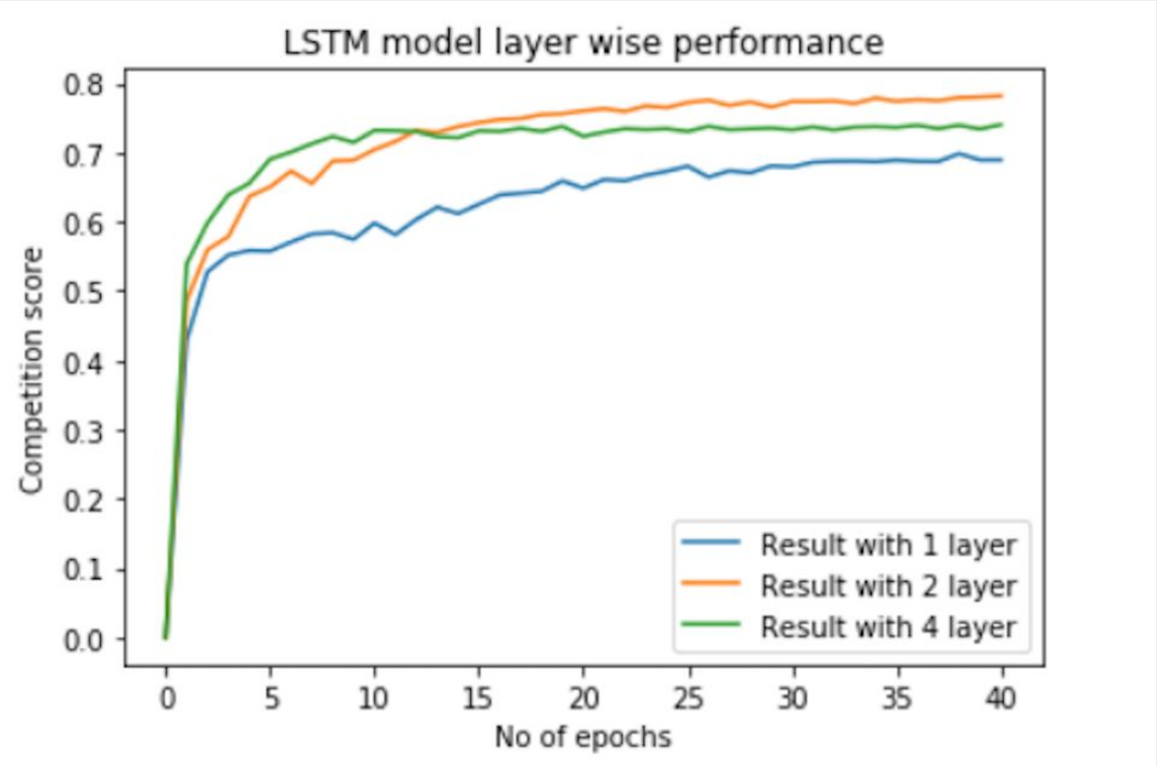
# RESULTS

- Competition scores with varying number of hidden layers



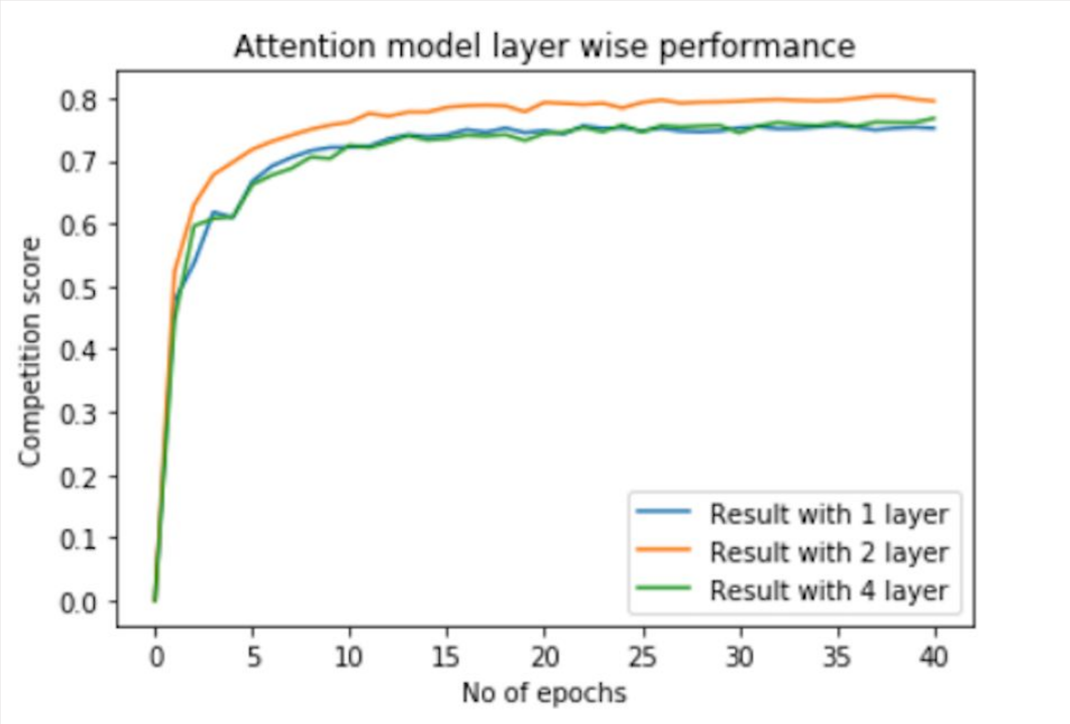
# RESULTS

- Competition Scores with LSTM layers.



# RESULTS

- Competition scores for LSTM with attention.



# DISCUSSION

- Nice performance was observed with 40 epochs and 2 hidden layers in the above models.

- Attention model outperforms basic LSTM model and feed forward Neural Network.

- Score didn’t improve further with 4 LSTM layers, maybe cause of limited data and less number of epochs for training.

# DISCUSSION

- Score improves till sequence length of 100 tokens. Beyond that score show no improvement.

- Long sequences are difficult to learn from for LSTM models with limited layers.

- Examples for “disagrees” labels were less and basic neural network and LSTM performed poorly with them. LSTM with attention was able to show significant improvement in identifying headline-body pairs that disagrees.

# FUTURE WORK

- Bidirectional LSTM model is widely used for providing more insights from context learned by traversing from the forward and reverse direction.

- Bidirectional LSTM with attention can be tried to determine if there is any significant improvement in performance by learning context from upcoming words.

# THANK YOU!