# Analysis of Methods in Sentiment Analysis for Social Big Data

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***Abstract*—In an era where consumer reviews and big data are becoming more and more prevalent, businesses are finding it more and more important to extract as much meaning from as much data as possible in order to make better informed decisions. Sentiment analysis is a developing sub-field of natural language processing that has close applications to consumer analysis. In this paper, I perform a comprehensive analysis and comparative evaluation between two recent papers proposing novel methods in sentiment analysis using labeled data from Twitter stories. The approaches of the two methods differ in many aspects, but both were proposed with the aim of drawing accurate sentiments from social big data.**

***Index Terms*—Sentiment Analysis, Deep Learning, Attention, CNN, RNN, LSTM**

## I. Introduction

As big data grows more ubiquitous, the tasks of consumer analysis grow more cumbersome. Sentiment analysis aims to draw dominant sentiments from samples of text, providing great value to businesses when trying to understand consumer needs. There have been many proposed and conventional methods in sentiment analysis. In order to gain a general idea of state-of-the-art methods for the analysis of social big data, I compare two recent proposed methods and compare their performance when tested against the social media domain.

Because of limited resources at my disposal (namely, one device for processing data, training models, and evaluation), I was not able to replicate many evaluation methods that the two papers I reference perform. As I will further explain in experiments, I was unable to perform Cross Validation nor train a sufficient amount of epochs for one of the neural networks. In addition, some information needed to fully implement one of the methods was not available on an open-source medium (namely, lexicon features). Hence, I was unable to fully replicate the experimental design.

## II. Related Works

### *A. Improving aspect-based neural sentiment classification with lexicon enhancement, attention regularization and sentiment induction (Bao et al., 2022)*

This paper proposed a novel method, called ATLX (Bao et al., 2022), of aspect-based sentiment analysis which, given parsed aspects to draw sentiments from from text, utilizes an attention layer within the model architecture to pay more attention to the given aspects rather than each individual word. This can provide significant increases in performance when drawing sentiments with multiple sentiment polarities within the same unit of text. However, ATLX assumes that aspects and their embeddings have already been parsed from text and organized which, in practice, can be time consuming and manually cumbersome if not done already or no parser for its specific domain has been built. As will be further explored in experiments, training for each epoch is significantly more time-consuming since the network must process the text along with the aspect embeddings in the attention layer simultaneously.

### *B. Co-LSTM: Convolutional LSTM model for sentiment analysis in social big data (Behera et al., 2021)*

This paper proposed a novel method, called Co-LSTM (Behera et al., 2021), whose main focus was implementing convolutional neural networks (CNNs) and long short-term memory networks (LSTMs) within its model architecture. The paper wanted to utilize the CNNs' high efficacy in local feature selection and LSTMs' high efficacy in sequential analysis of long text to optimize performance when extracting sentiments from the social media domain. The main advantages of Co-LSTM come from its ease of interpretability given its intuitive architecture and its cheap computational cost as no other feature is needed from data other than labels. As will be further explored in experiments, Co-LSTM tends to overfit easily to train data, hindering test performance.

## III. Experiments

The dataset includes 13,680 samples of text from Twitter stories, each labeled with sentiment as either ”positive” or ”negative”. The dataset originally included 24,442 labeled samples as either ”positive”, ”negative”, or ”neutral”. However, Co-LSTM was designed to be trained off of text labeled only ”positive” or ”negative”, so I decided to exclude all ”neutral”-labeled text altogether. For ATLX, the dataset also came with aspect embeddings that will be used for the model's attention layer.

Roughly 30% of samples were set aside as test data. Of train data, 10% were set aside as validation data.

I designed the experiment in Jupyter Notebook, primarily using tools and methods from TensorFlow and Keras to build the architecture of ATLX and Co-LSTM.

Figure 1: Keras architecture of ATLX

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 1099, 100)         65812700

 dropout (Dropout)           (None, 1099, 100)         0

 bidirectional (Bidirectiona  (None, 1099, 128)        84480
 l)

 dropout_1 (Dropout)         (None, 1099, 128)         0

 bidirectional_1 (Bidirectio  (None, 1099, 128)        98816
 nal)

 dropout_2 (Dropout)         (None, 1099, 128)         0

 attention (Attention)       (None, 1099, 128)         1227

 dropout_3 (Dropout)         (None, 1099, 128)         0

 flatten (Flatten)           (None, 140672)            0

 dense (Dense)               (None, 2)                 281346

 activation (Activation)     (None, 2)                 0

=================================================================
Total params: 66,278,569
Trainable params: 465,869
Non-trainable params: 65,812,700
```

Figure 2: Keras arhictecture of Co-LSTM

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_1 (Embedding)     (None, 1099, 100)         65812700

 conv1d (Conv1D)             (None, 1092, 32)          25632

 max_pooling1d (MaxPooling1D  (None, 546, 32)          0
 )

 lstm_1 (LSTM)               (None, 546, 64)           24832

 lstm_2 (LSTM)               (None, 546, 64)           33024

 flatten_1 (Flatten)         (None, 34944)             0

 dense_1 (Dense)             (None, 64)                2236480

 dense_2 (Dense)             (None, 2)                 130

 activation_1 (Activation)   (None, 2)                 0

=================================================================
Total params: 68,132,798
Trainable params: 68,132,798
Non-trainable params: 0
```

After all pre-processing and model construction, training was performed with 25 training epochs for each model. Training accuracy and loss (both train and validation loss) were recorded. For ATLX, each epoch took roughly 20 minutes (see introduction for computational challenges) while for Co-LSTM, each epoch took roughly 5 minutes.

Figure 3: ATLX training loss

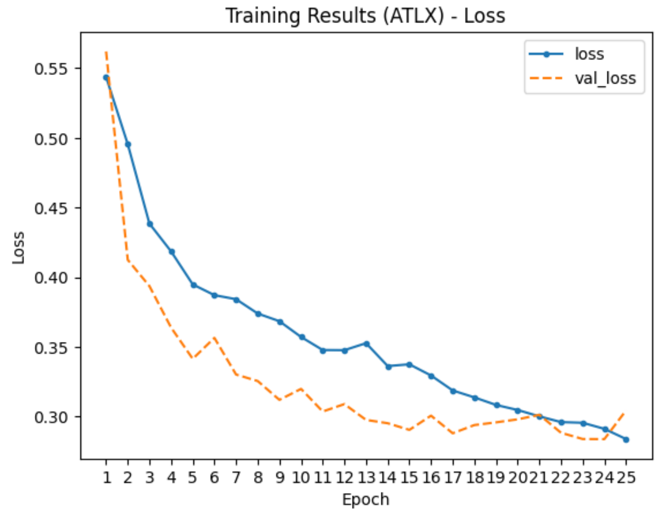



Figure 4: ATLX training accuracy

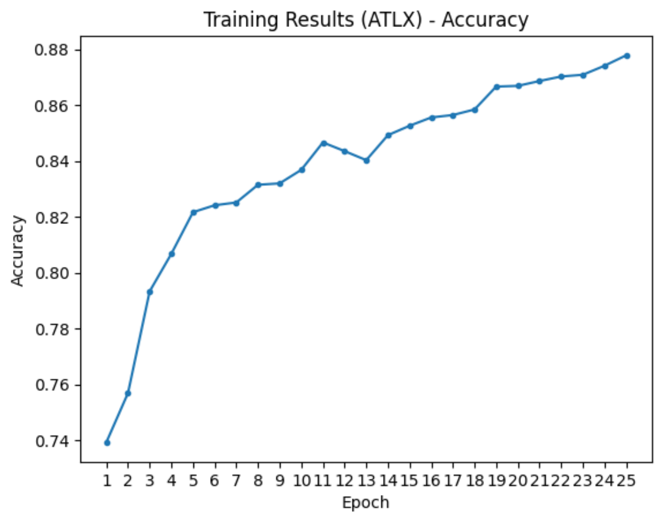



Figure 5: Co-LSTM training loss

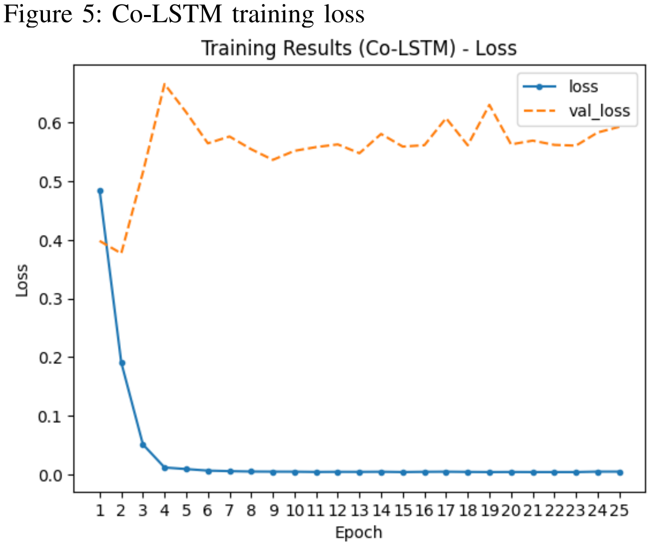
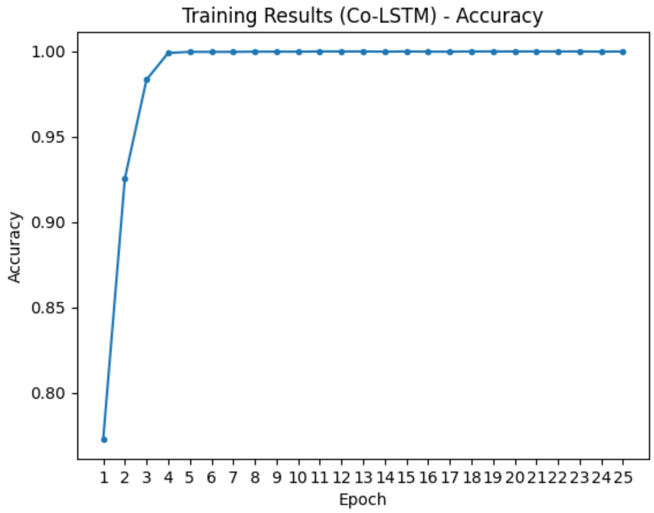


Figure 6: Co-LSTM training accuracy




Figures 3-4 suggest that further training could yield higher training accuracy and lower loss for ATLX, possibly indicating underfitting. Otherwise, ATLX yielded good training behavior (no clear indication of overfitting). Figure 5 strongly suggests overfitting as validation loss stayed at a high range while training loss rapidly converged for Co-LSTM. Figure 6 supports the notion of Figure 5 as training accuracy quickly converged.

ATLX yielded test accuracy of $84\%$. Co-LSTM yielded test accuracy of $81\%$.

## IV. Conclusions

With higher performance and indication of underfitting as opposed to overfitting, ATLX clearly outperforms Co-LSTM in this experiment.

This result suggests that when extracting sentiments from the social media domain, providing emphasis on important aspects improves model accuracy and can be worthwhile to develop methods to parse aspects from text before training if feasible. This experiment suggests in higher confidence that focusing on aspects is more important than feature selection and sequence of words when analyzing sentiments.

Among the social media domain, Twitter stories only represent a subset. Different patterns when posting might be evident when extracting data from other social media platforms which may call for different model architectures for different platforms.

Model reproducibility was not supported in this experiment. Due to the lack of computational resources, Cross Validation was not able to be performed as did the papers proposing ATLX (Bao et al., 2022) and Co-LSTM (Behera et al., 2021).

## References

[1] Bao, L., Lambert, P., Badia, T. (2022). Improving aspect-based neural sentiment classification with lexicon enhancement, attention regularization and sentiment induction. Natural Language Engineering, 1-30.

[2] Behera, R. K., Jena, M., Rath, S. K., Misra, S. (2021). Co-LSTM: Convolutional LSTM model for sentiment analysis in Social Big Data. Information Processing Management, 58(1), 102435.