Sentiment Classifier Empowered With LSTM Autoencoder

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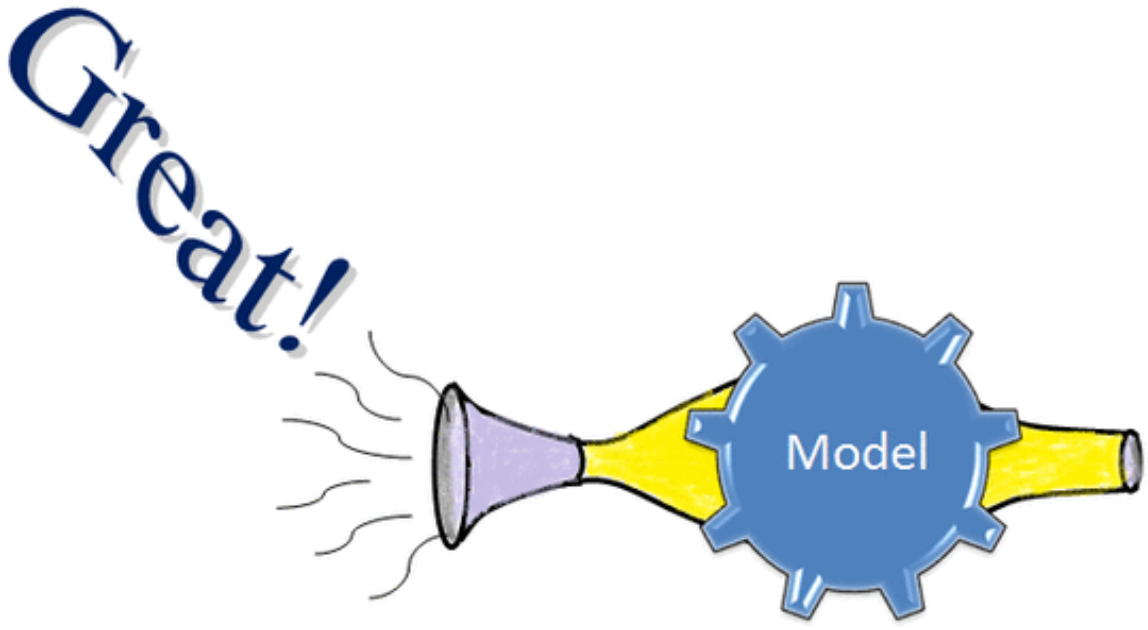
Computer Science Department

RKMVERI

Introduction

Overview of Sentiment Analysis



Description of Amazon Reviews Dataset

- **Source:** Kaggle
- **Features:**
  - Data is in *fastText*[5] format
  - Training dataset: Consists 36 lakh examples,
    Used 2 lakh for training, 1 lakh for validation
    Test dataset: Consists 4 lakh examples,
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  - Multilingual data (Consists of Spanish, French etc. along with English)
    Translated non-English language to English using Google translator [4]
  - Two labels: *__label__1* & *__label__2*
    __label__1 $\Longrightarrow$ 1 & 2 star ratings
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Literature Survey

Probabilistic Modelling

- Multinomial Naive Bayes [8]

RNN framework

- LSTM[12]/GRU[2]
- Bidirectional RNN [11]
- Hierarchical RNN [10]

Transformer-based network

- ELMo[9]
- BERT[3] and its variants

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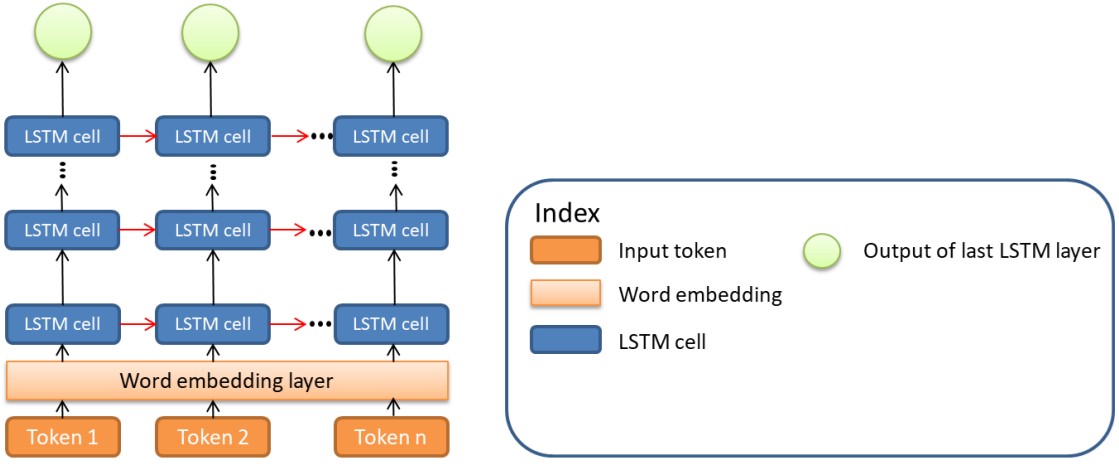
Modelling Approach

Main idea

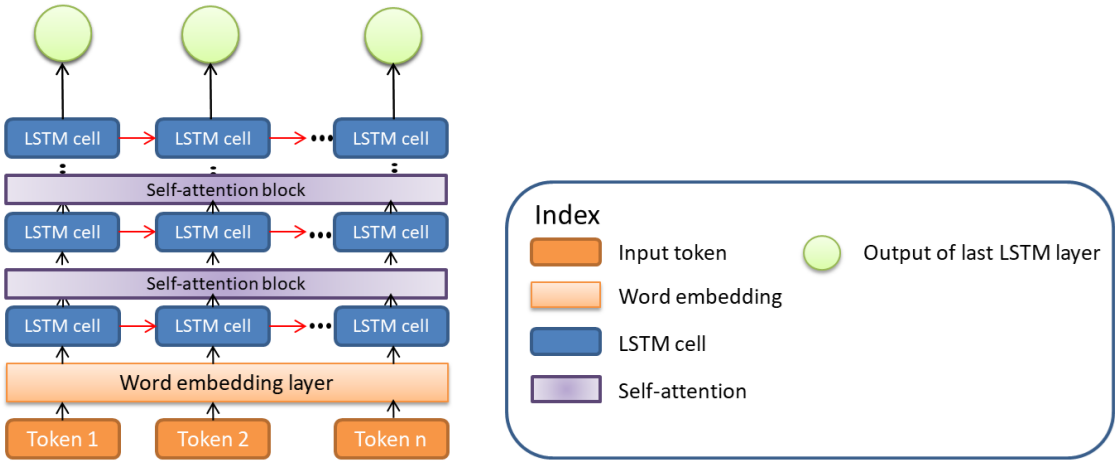
Introducing LSTM autoencoder with LSTM-based classifier network and simultaneously optimizing two objective functions to get better predictions

Modelling Approach



- Encoder: Usual rnn framework with word embedding layer followed by multiple lstm layers — which takes in as input the word tokens and outputs a vector at each time step.

Modelling Approach



- Encoder: Introduced self-attention block in between two LSTM layers to help the encoder learn better.

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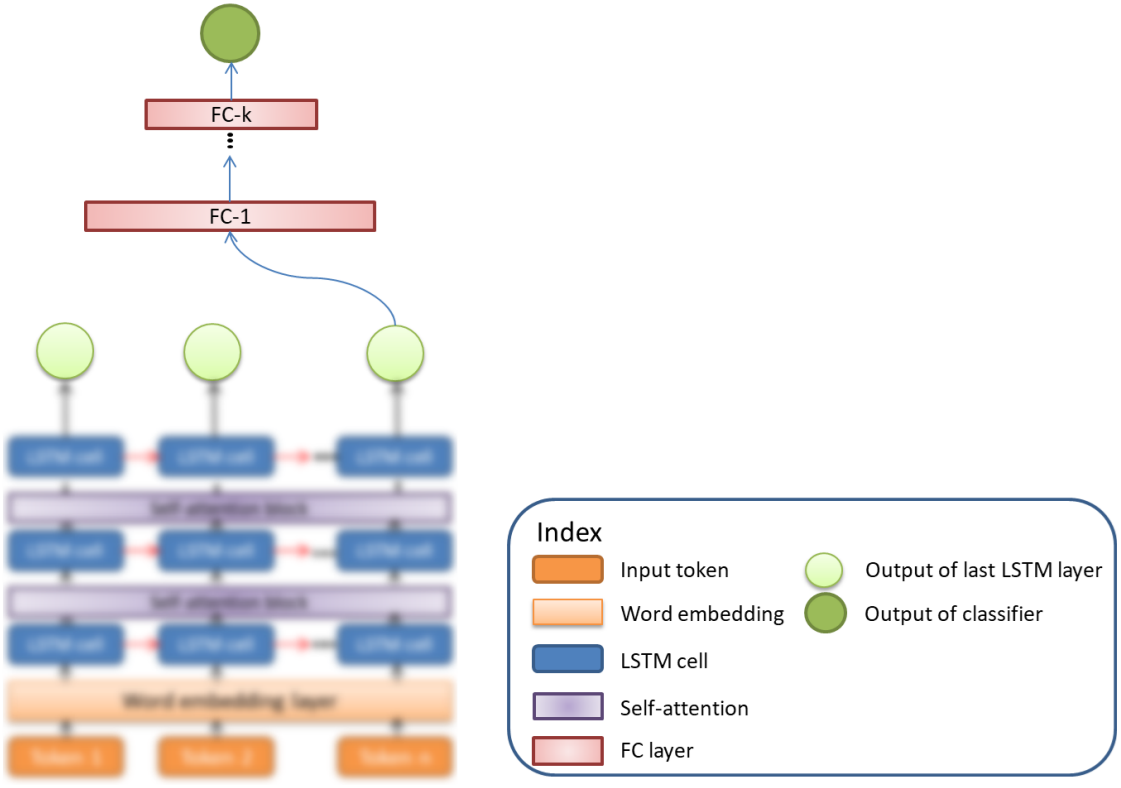
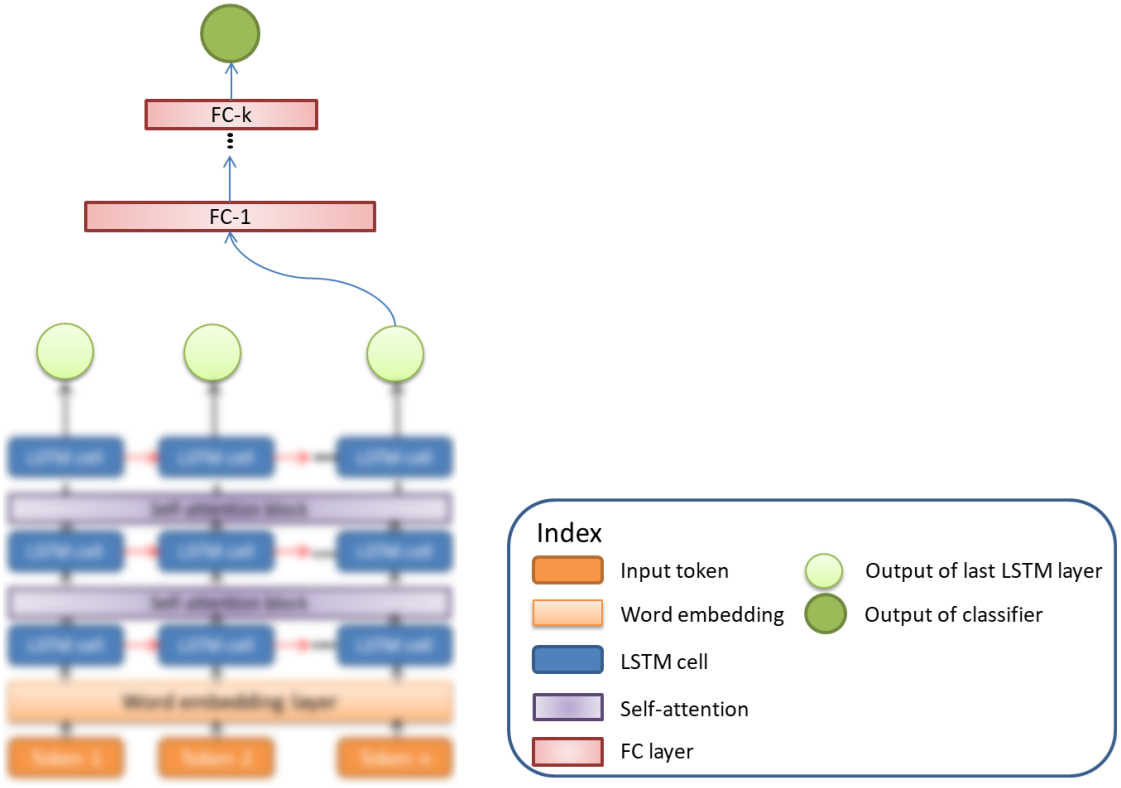


- Classifier: Feed-forward neural network with multiple fully connected layers — which takes in as input the output of last LSTM layer and outputs the probability of a particular example being in a particular class.

Modelling Approach



- Classifier: Usually the last time step output of encoder is taken as input.

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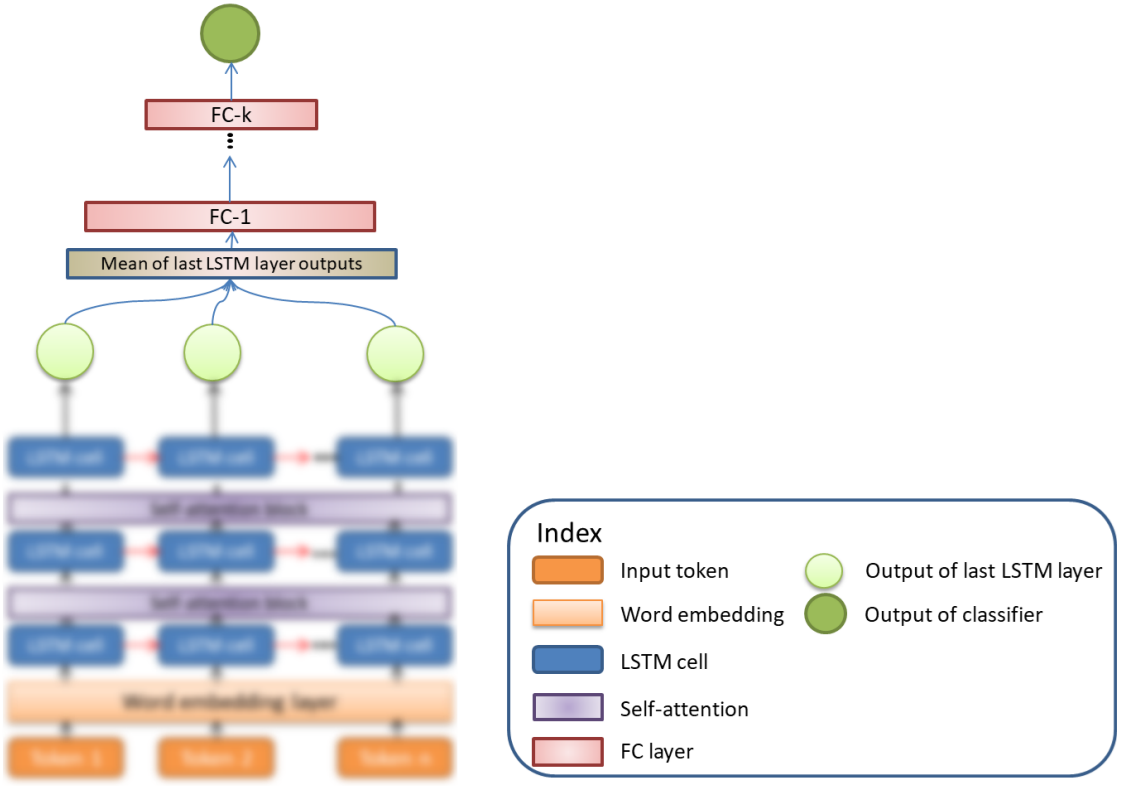
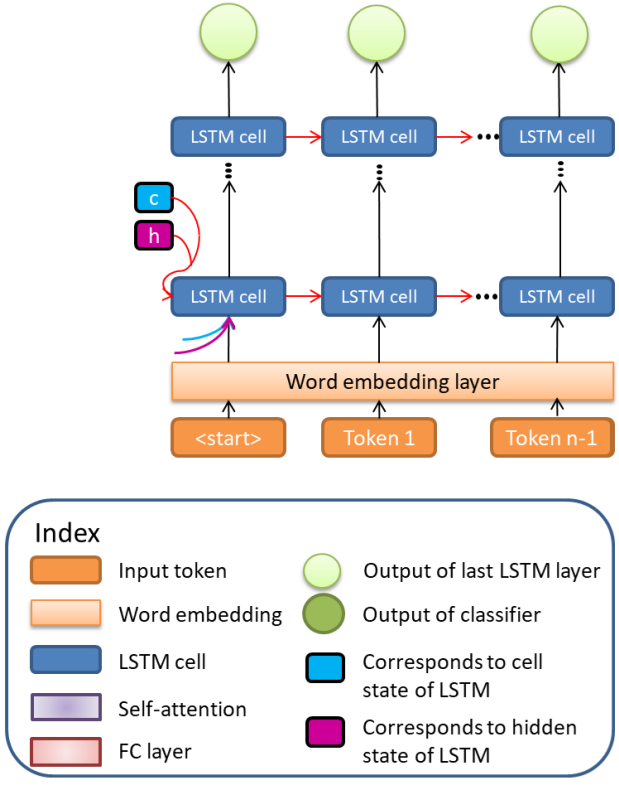


- Classifier: To account for information loss average of all time-step output has been taken as input to classifier.

Modelling Approach



- Decoder: RNN framework with word embedding layer followed by multiple LSTM layers, initiated with <start> token in the first time step.

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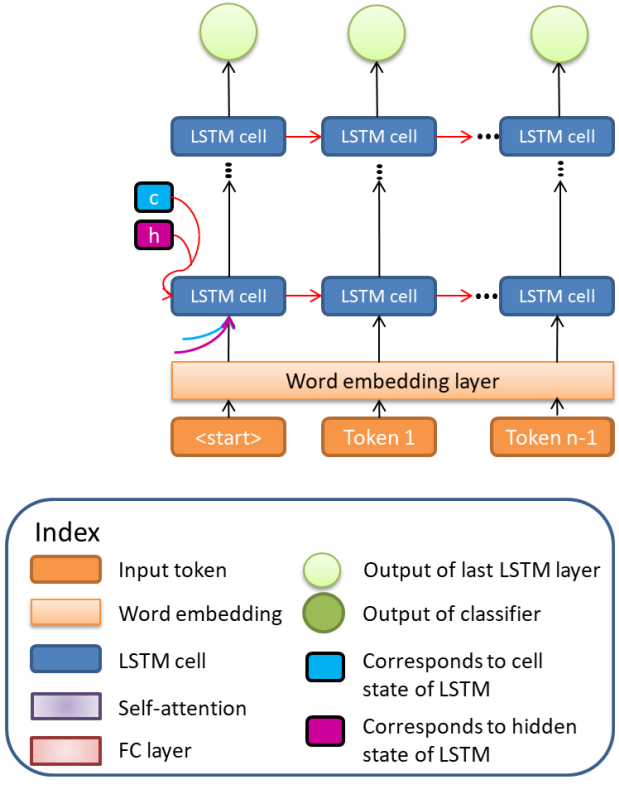

- Decoder: Three inputs to initial LSTM layer — embedded token, context vectors coming from two attention [1] modules where cell state / hidden state of decoder LSTM cells acts as query and outputs of last LSTM layer of encoder act as keys/values.

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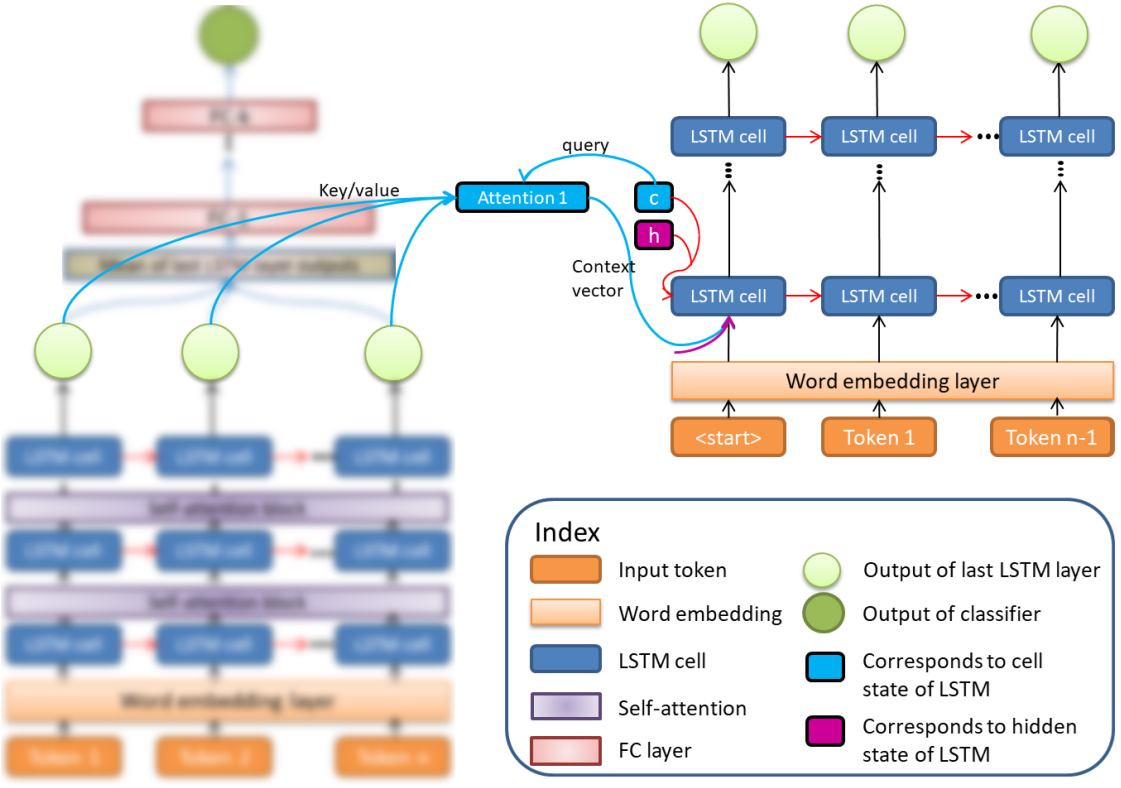

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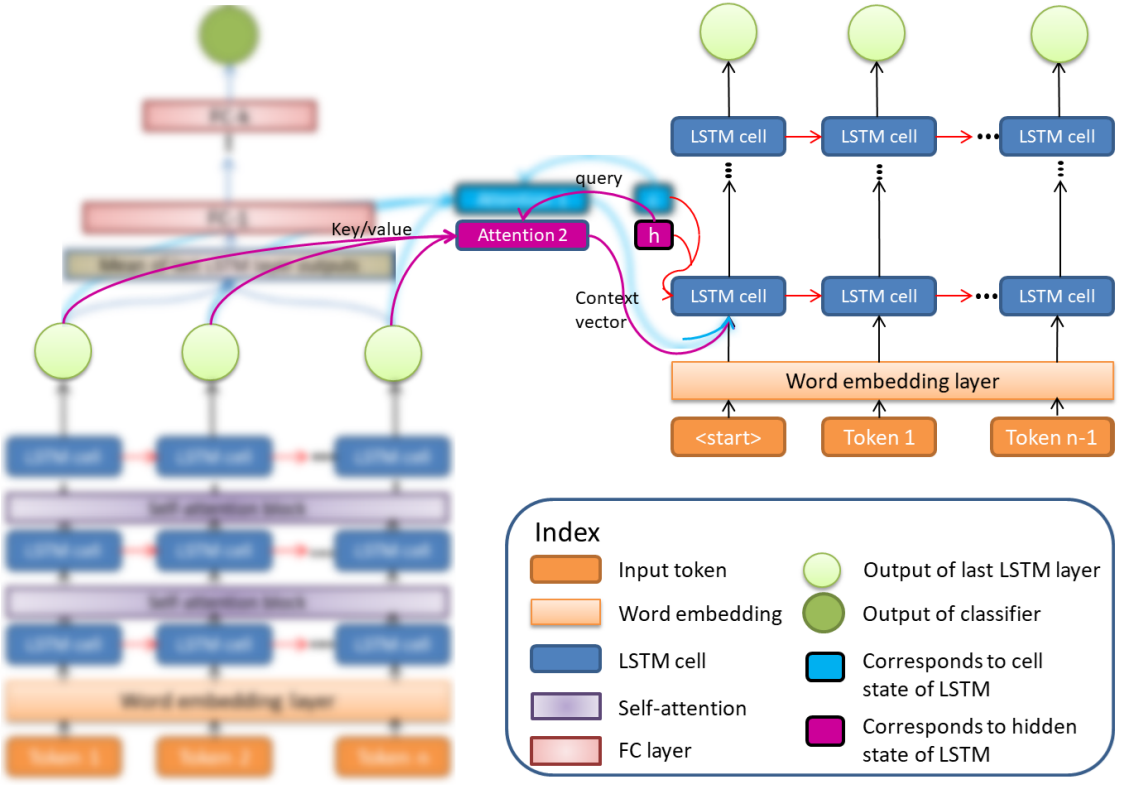

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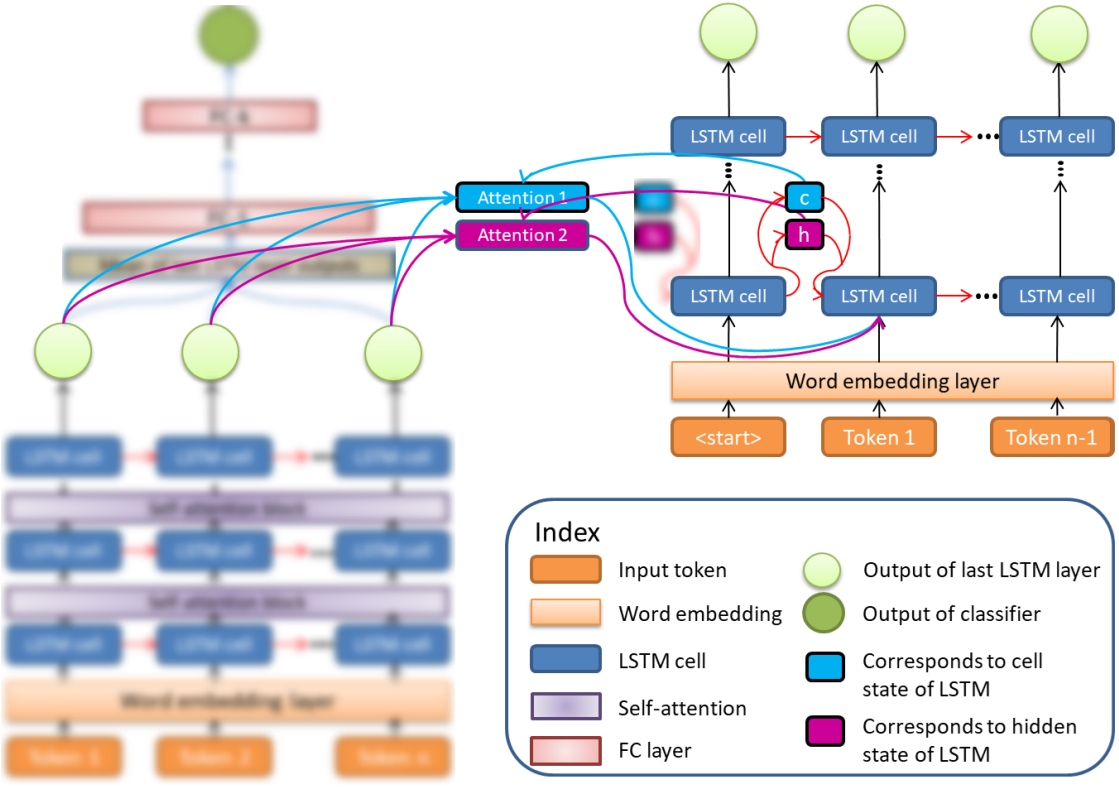

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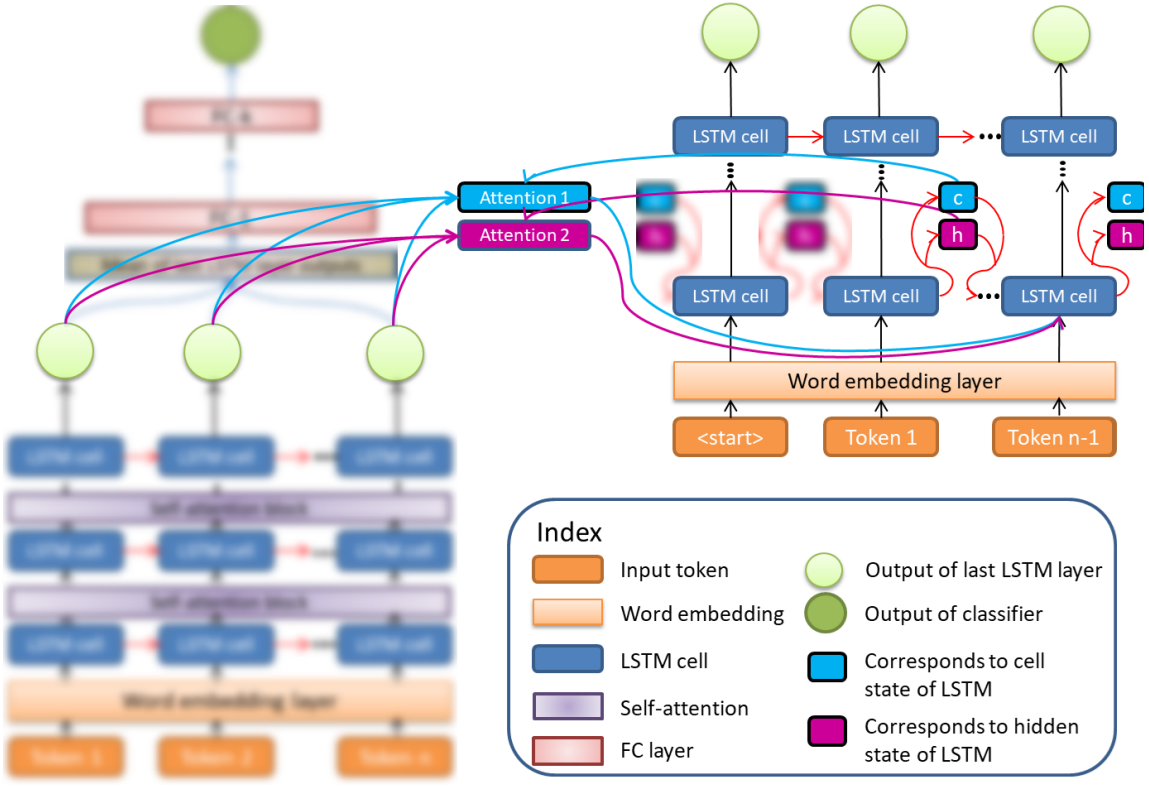

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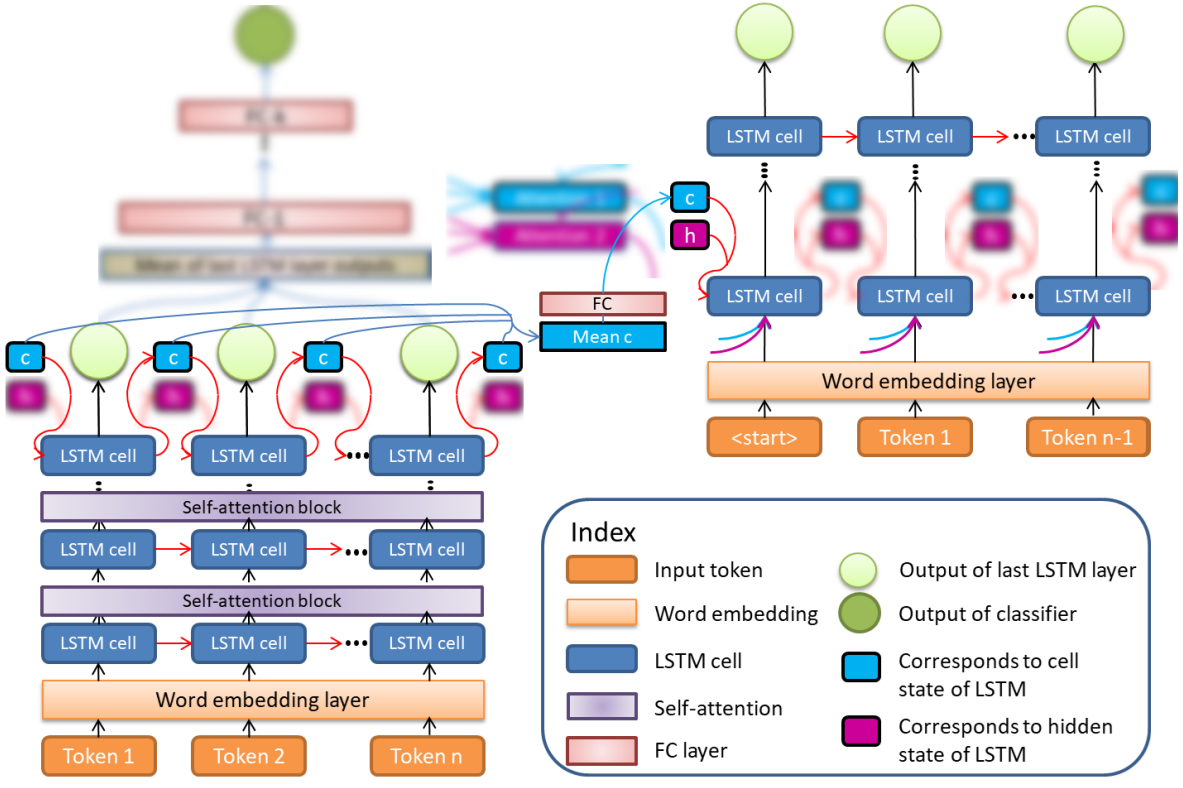

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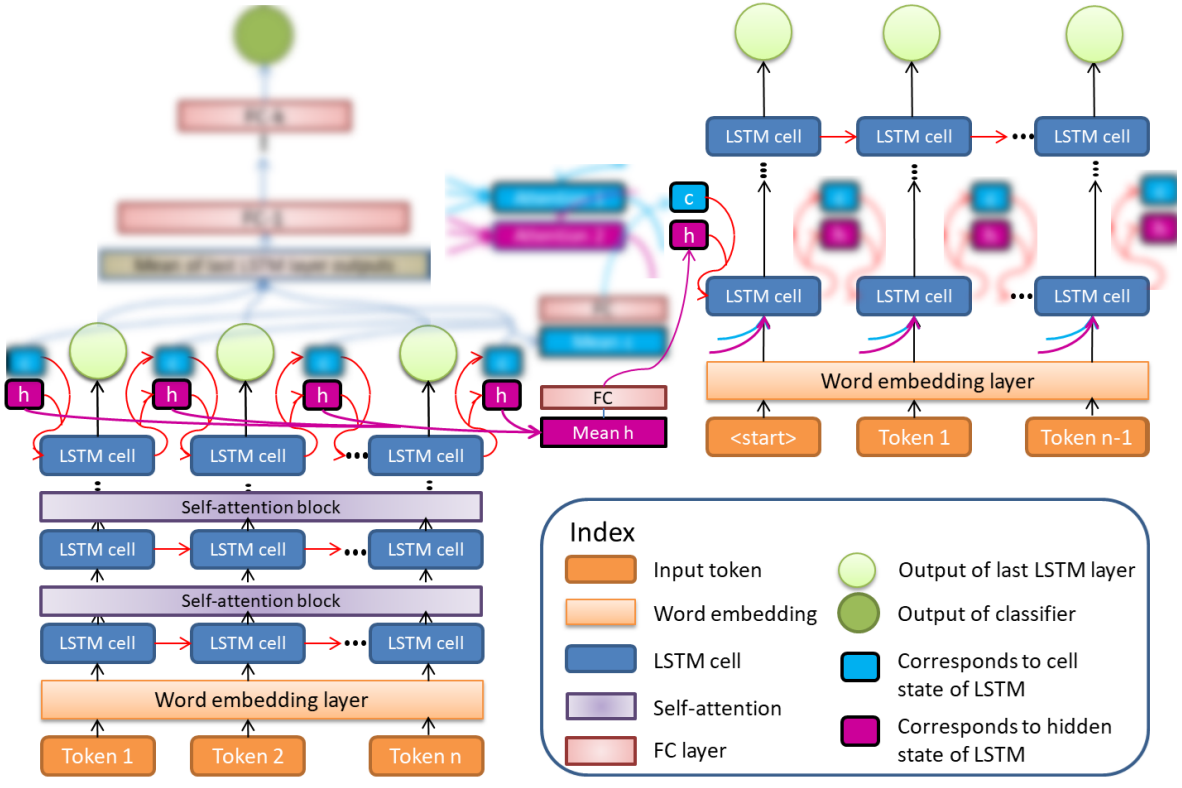

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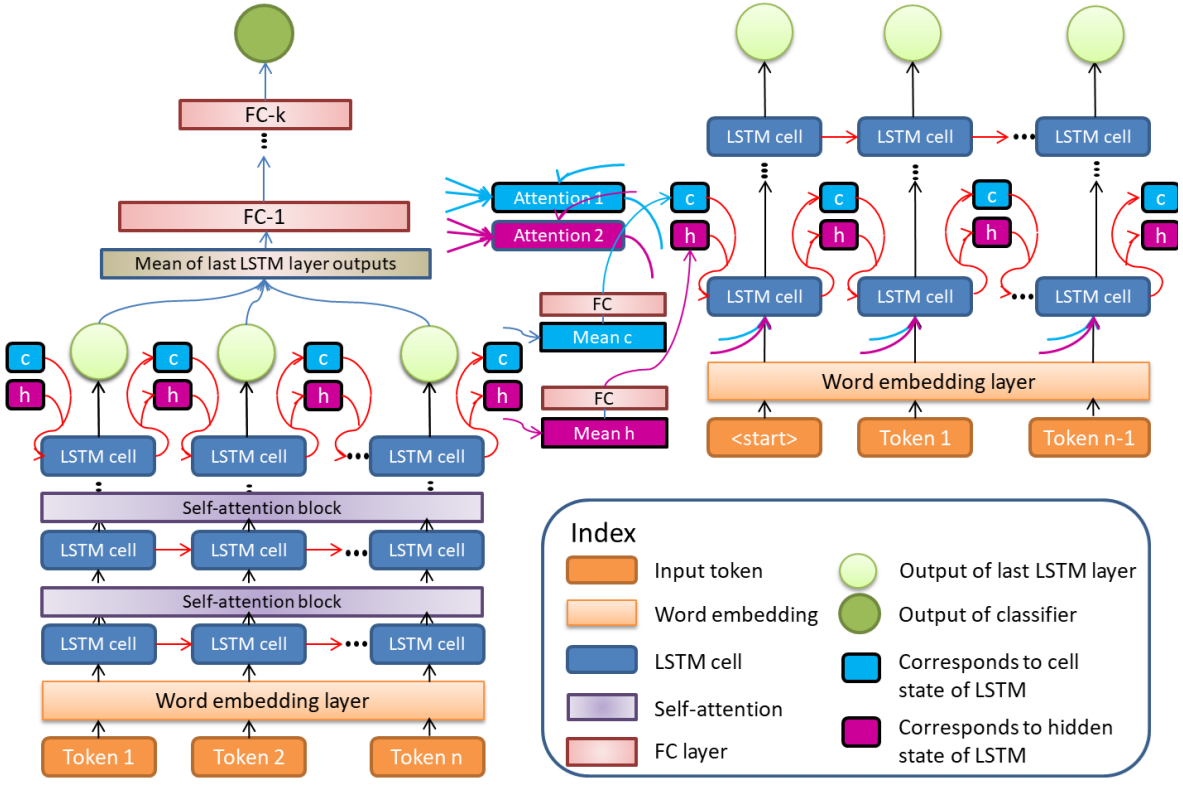

Overall architecture

Modelling Approach

Choice of hyperparameters:

- Number of LSTM layers in encoder is greater than that of decoder: Good reconstruction with weaker decoder requires the later layers of encoder to learn something really meaningful. [13]
- SELU activation [6] in classifier: Does away with the need of batch normalization, resulting in fewer parameters and less training time.
- AdamW optimizer [7]: Variant of Adam, but known to generalize well than Adam.
- Dropout of 20% throughout the network: Acts as regularizer and also stabilizes the training process.

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Training Scheme:

Training is conducted in two phases in every epoch.

1. Phase 1: Train autoencoder with cross-entropy loss averaged over all time-steps but masking out the padded tokens.
2. Phase 2: Train encoder and classifier together with binary cross-entropy loss.

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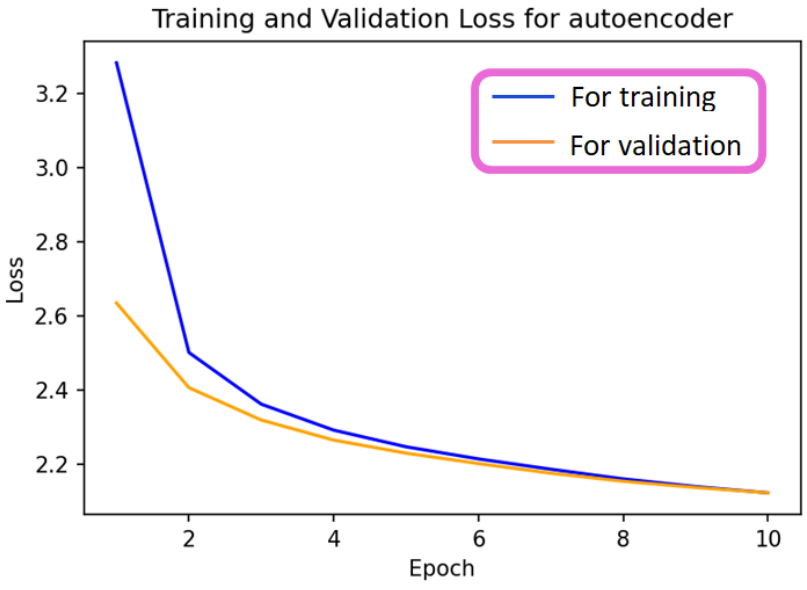
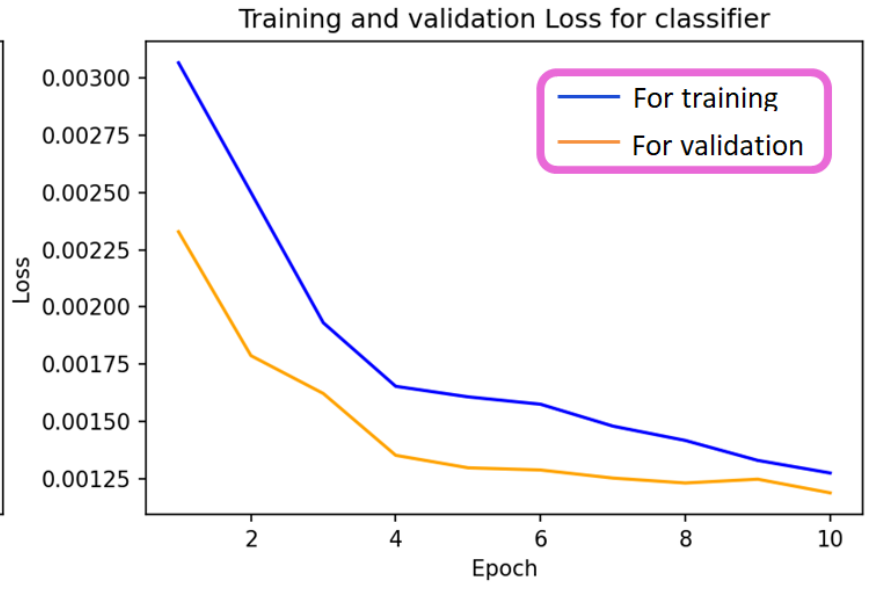
Result

Training and validation loss





Test results

Accuracy: 90.5215%, Precision: 91.1331%, Recall: 89.7154%

Future Work

- Checking if weak decoder helps encoder in gaining better encoded representation of a sequence.
- Checking the performance of the model by tweaking some hyperparameters (for example, changing number of LSTM layers, replacing SELU with other activation functions like SERLU or DELU etc.)
- Trying out bidirectional LSTM layers
- Modifying Attention mechanisms to improve performance

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References


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THANK YOU