

# **Deep Recurrent Neural Network applied to Incomplete Data**

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## Motivation

- Text summarization with incomplete data
- In the real world, data is not always correct or complete
- This work compares the effect that this type of "noisy" data has in models that have been trained with complete/correct data.
- We compare the Long Short-Term Memory (LSTM) model with the Multiple Timescale LSTM in a RNN Encoder-Decoder Framework
- We show that MTLSTM has better performance

## Building dataset

- Term Frequency-Inverse Document Frequency (TF-IDF)
- Goal: to calculate the most relevant (important) words in a given document

$$Tf(d,t) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}}$$

$$N$$

Tf: frequency of appearance d: document; t: # times term t appears in document d

ldf: number of documents term t appears in c: document (corpus); t. # times term t appears in corpus c; log: tweak to avoid giving high scores to very rare words

 $Tf.Idf(c,d,t) = Tf(d,t)Idf(c,t) \qquad \begin{array}{l} \text{Tf.Idf. term frquency-inverse document frequency} \\ \text{$N:$ \# total documents} \end{array}$ 

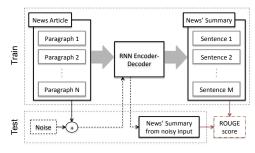
- Two datasets formed of incomplete sentences as input and complete sentences as output
  - 1. Missing relevant (important) words
  - 2. Missing common (non-important)
  - Variants of those dataset by changing the missing words ratio (from 0 to 20%)

## **Evaluation Method**

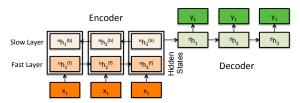
- Recall-Oriented Understudy for Gisting Evaluation (ROUGE), proposed by Lin (2004)
  - ROUGE-N (1 and 2): N-grams between generated and reference sentences
- ROUGE-L: Longest Common Subsequence based statistics
- Package for automatic evaluation of summaries.
- - P-score: precision, # correct positive results / # all positive results returned by the model
  - R-score: recall, # correct positive results / # all relevant samples that should have been classified as positive.
  - F-Score: accuracy, considers both P and R.

## Approach (1/2)

- Noise: missing words
- Compare effect of noise in model trained with complete (correct) data

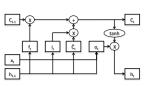


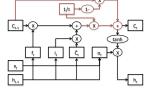
■ Bi-directional LSTM RNN Encoder-Decoder



## Approach (2/2)

- LSTM vs MTLSTM
- MTLSTM: same forget, input and output gates as LSTM + Multiple Timescales which differ depending on the layer. The deeper, the slower it is so as to mimic different levels of
- Model used: taus = {1, 0.9, 0.8}, 256 hidden units, 128 word embedding, 50000 vocabulary, 0.15 learning rate



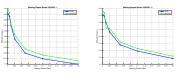


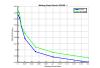
$$\begin{split} f_t &= \sigma(W_{hf}h_{t-1} + W_{xf}x_t + b_f) \\ i_t &= \sigma(W_{hi}h_{t-1} + W_{xi}x_t + b_i) \\ \tilde{C}_t &= tanh(W_{hC}h_{t-1} + W_{xC}x_t + b_C) \\ C_t &= f_tC_{t-1} + it\tilde{C}_t \\ o_t &= \sigma(W_{ho}h_{t-1} + W_{xo}x_t + b_o) \\ h_t &= otanh(C_t) \end{split}$$

$$C'_t = f_t C_{t-1} + i_t \tilde{C}_t$$
 
$$C_t = C'_t \frac{1}{\tau} + C_{t-1} \left(1 - \frac{1}{\tau}\right)$$

## Results

- ROUGE F-Score Degradation Curve





Excerpt of original input

ROUGE-1 0.3164 ROUGE-2 0.1225 ROUGE-3 0.2958

■ Complex Words





ROUGE-2 0.0751

ROUGE-3 0.2519







## Conclusion & Future works

- MTLSTM performs better than LSTM
- Future works
  - Expand results by increasing the missing words ratio
  - Different tuning parameters and model structure (more layers, units per layer)

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