**TopicRNN: A Recurrent Neural Network with Long-Range Semantic Dependency**

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**Summary and Contributions**

- Neural network-based language models have achieved state of the art results on many NLP tasks.
- One difficulty is to capture long-range dependencies.
- We use latent topics to capture semantic and RNNS to capture syntax in a simple and end-to-end trainable architecture: TopicRNN.
- More specifically, we use topic features learned by an encoder as additional bias to the softmax layer of an RNN.
- We use a binary switching variable determined by hidden layer vectors to decide whether to predict a stop word or not.
- TopicRNN is trained using the Adam algorithm on the evidence lower-bound.
- TopicRNN shows better generalization abilities on the Penn Treebank and achieves SOTA-comparable sentiment classification error rate on the IMDB.

**Language Modeling**

A language model is a distribution over a sequence of words:

\[ p(w_1, ..., w_T) = \prod_{t=1}^{T} p(w_t | w_{1:t-1}). \]

- RNN-based language models [3] define the conditional probability of each word \( w_t \) given all the previous words \( w_{1:t-1} \) through their hidden state via a softmax.
- However, RNNS face difficulties remembering very long-range dependencies.
- Modeling long-range dependencies in language is a research challenge.
- The intuition below motivates our work in this area.

**Intuition: Syntax is local, semantic is global**

“The U.S. presidential race isn’t only drawing attention and controversy in the United States—it’s being closely watched across the globe. But what does the rest of the world think about a campaign that has already thrown up one surprise after another? CNN asked 10 journalists for their take on the race so far, and what their country might be hoping for in America’s next President.”

**Figure 1:** The unrolled TopicRNN architecture. \( x \)’s are words in the document. \( h_t \) is the state of the RNN at time step \( t \). \( x_{t-1} \)’s are stop word indicators, \( \theta \) is the latent representation of the input document and is unshaded by convention.

**Figure 2:** The TopicRNN model architecture in its compact form: stacked LSTM of 200 units each (112.4 vs 115.9).

**Table 1:** Five Topics from the TopicRNN Model. More results can be found on the paper.

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**Table 2:** Test perplexity on the Penn TreeBank for different number of hidden units. 1 TopicGRU with 100 units performs better than 2 stacked LSTM of 200 units each (112.4 vs 115.9).

<table>
<thead>
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<th>Hidden Units</th>
<th>Test perplexity</th>
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**References**