LSTM for Text Generation and Classsification

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Abstract

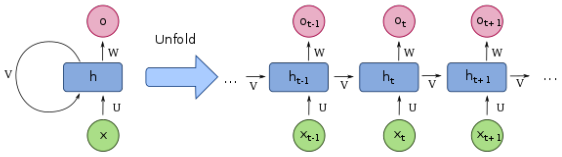
In the context of our project for the IFT6269-A2018 we have investigated the different available models for the generation and classification of natural text data. While we were initially interested in fully probabilistic models such as Hidden Markov Models (HMM), a quick review of the contemporary literature on the topic of pattern recognition on sequences made it clear that neural networks (NN) provided the better toolset. In the end we implemented two Long Short-Term Memory networks, for generation and classification respectively which we trained on subsequences of some corpora of prose fiction. Despite the rather coarse nature of our implementation the generators were able to produce legible and decently structured text which reflected the material used for training; in the style of the writing for example. The classifier reported excellent metrics however there are several interesting questions as to what overfitting consists of when classifying prose fiction. The most obvious is the one of proper nouns, but others such as temporal markers are more subtle. The solutions to be decided with some context of the intent of the task, so as to be the answer to a well-defined question.

1. Introduction

Hidden Markov Models used to be the go-to probabilistic tool to reason about sequential data; the Markov assumption however proves to often be unreasonably strong. Adding links to form higher order chains is not a scalable solution as the computationnal complexity grows exponentially in the order of the chain. Recurrent Neural Networks (RNN) constitute a family of neural network architectures specialized to process sequential data which can forfeit Markovian assumptions while remaining tractable. RNNs can track longer range dependencies while staying tractable by leveraging the simple idea of sharing parameters across the model (**?**). Concretely this means adding loops to the hidden units of the neural network. RNNs have been successfully used in diverse domains for generating sequences such as music and text (**?**). Despite the aforementionned features, naive RNNs suffer from the fact that the influence of some input to the hidden layer either decays or blows up exponentially in time, a phenomenon reffered to in the literature as the *vanishing gradient problem*. The cost of abandonning probabilistic models such as the HMM in favor of neural networks is the loss of a fully probabilistic interpretation. There has recently been an increased interest into finding reasonable probabilistic interpretaions to RNNs, see for example (**?**). On the other hand the very existence of some monolithic notion of "interpretability" has been recently questionned, see (**?**) for a philosophically inclined take on the question.

2. Neural Networks Archicture

2.1. RNN and the Vanishing Gradient



$$h_t = \sigma(Ux_t + Vh_{(t-1)} + b_h) \quad o_t = \text{softmax}(Wh_t + b_o)$$

Where U, V and W are weights matrix and the vectors b are bias parameters. Consider the gradient of $o_{t+\delta}$ with respect to h_t. Applying the chain rule according to the graph above we get:

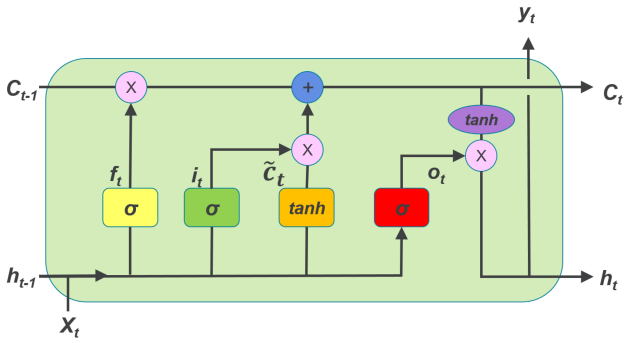
$$\nabla_{h_t} o_{t+\delta} = \left(\prod_{k=t+1}^{t+\delta} V^T \text{diag}(1 - h_k^2) \right) \nabla_{h_{t+\delta}} o_{t+\delta}.$$

Thus, as δ grows, the gradient grows exponentially with V. If V is small or large then the gradient will either vanish or explode. A myriad of solutions exist such as regularization through weight noise, the Long Short Term Memory

architecture tries to tackle this issue on a higher level than regularization.

2.2. LSTM Architecture

To go from a RNN to a LSTM we replace hidden units with components known as *memory cells*. Our presentation and notation follows (**?**).



Intuitively, RNNs have *long-term memory* in the form of matrix weights, they change during the training; encoding through training some general knowledge about the data. They also have *short-term memory* in the form of activation passing from each node to successive ones. The memory cell introduced in the LSTM model formalizes those notions and provides a framework to control their impact on the internal representation of the network.

- f_t, i_t, o_t: Respectively forget, input and output gates.
  - Sigmoidal units activated through x_t (current input) and h_{t-1} (past hidden unit output)
  - f_t controls the recursive flow
  - i_t and o_t control the input and output flow respectively
  - $h_t = o_t \odot \tanh(c_t)$ where $\odot$ denotes element wise multiplication.
- $c_t = \mathbf{f_t} \odot \mathbf{c_{t-1}} + i_t \odot \tilde{c}_t$: The cell which has a self-connected edge with a fixed unit weight, thereby delegating control of recursion to the gate

3. Implementation

Four text sequences (referred to as datasets later on) were used for training: excerpts from Shakespeare' plays, books of the Harry Potter and Lord of the Ring series and a list of popular quotes. All in English and ASCII encoded. Punctuation and structure was left unprocessed. Each dataset was split in sequences of 50 tokens (i.e. "words") and a dictionnary was built from the complete input ($\approx 60k$ unique tokens), defining the input space for the networks. Vector encoding of this space was used through an embedding layer mapping the words to a real vector space of dimension 256. Available embeddings such as *word2vec* and *glove* were initally used but proved to be more cumbersome than our own trained version. Five LSTM networks were trained with the above, Four *generators* and a *classifier*. Training was achieved at "word" level (strings tokenized by whitespace). Character level had been previsously envisionned for the rest of the project as it is more flexible and can *learn new words and structural information*(**?**) for the generators). Despite this we kept the training at word level for multiple reasons, the primary one being robustness towards unicode characters which might vary between versions of the text available and the second one being speed of convergence.

To generate the sequences the trained models were initialized with a random word drawn from the dictionary and the most likely next word was fed back in the network until the desired sequence length was reached. 1000 sequences (250 per model) were generated. The classifier was then used to automatically estimate which dataset (or model, equivalently) was used for its generation, thereby giving us some "metric" of the quality of the data; expecting data generated from the Shakespeare trained model to consistenly differ from the data "generated by Harry Potter".

4. Empirical Results

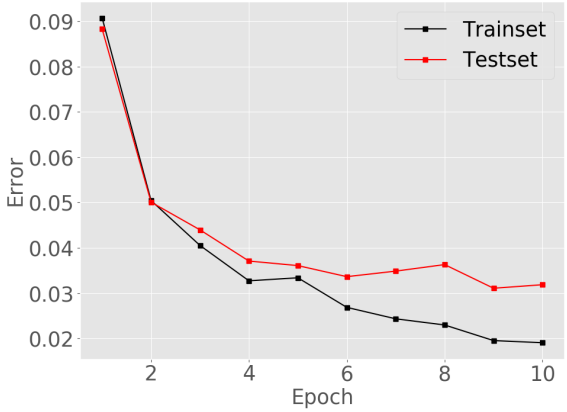


Figure 1. Classification error on train/test set.

Training trough minimization of the cross-entropy loss, which is equivalent to *perplexity*; the standard metric for language modeling (**?**).

Dataset	BPC	Perplexity
Harry Potter	1.00	33
LOTR	1.02	35
Random quotes	1.10	45
Shakespeare	0.94	26

Examples of generated quotes:

- “ well , we ’ ll do it with a wand , ” said hermione . “ really ? ” said harry , looking at each other .
- what looked about this way , the black citadel , was far from the darkness , the ring was heard , but the sea big was big , and a great ring was in his battle .
- failure is a beginning of love and a family which comes from god .
- ” that now my mind shall screens his music , ” ” and i to give thee my vulgar heaven , ” ” i am your brother .

5. Conclusion and Further Work

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6. Citations and References