Text Sequence Generation and Classification, model or inference

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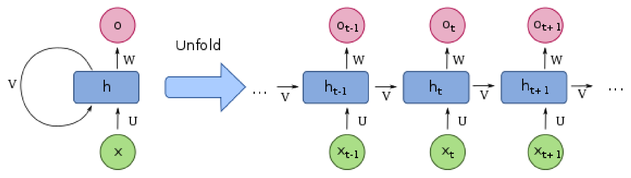
Introduction

- Hidden Markov Models used to be the go-to probabilistic tool to model 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.
- RNN enable to track longer range dependencies while staying tractable by leveraging the simple idea of sharing parameters across the model [3]. Concretely this means adding loops to the hidden units of the neural network.
- RNNs have been used in diverse domains for generating sequences such as music and text [4].
- Despite the aforementionned features, RNN suffer from the fact that the influence of some input 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 [2]. On the other hand the very existence of some monolithic notion of "interpretability" has been recently questionned, see [6] for a philosophical overview and the interesting blog post by Jacob Andreas on the blur between a model and an inference procedure in RNNs.[1]

RNN



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

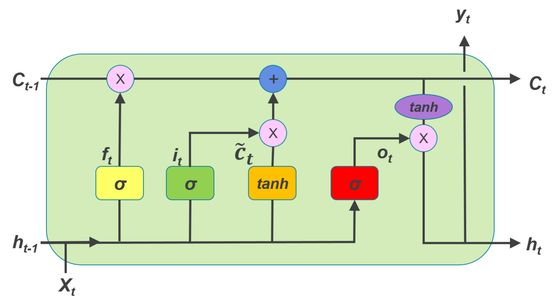
Where U, V and W are weights matrix and the vectors b are bias parameters.
Consider the gradient of $o_{t+\delta}$ with respect to h_t.
Applying the chain rule according to the graph above we get:

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

Thus, as δ grows, the gradient grows exponentially with V. If V is small or large than the gradient will either vanish or explode. A myriad of solutions exist such as regularization through weight noise, the LSTM architecture tries to tackle this issue on a higher level than regularization.

LSTM: architecture and its application to sequence generation

The LSTM model has been introduced primarily to solve the vanishing and exploding gradients problem. This model is a RNN in which we replaced every hidden nodes by a *memory cell*.



Intuitively, RNN have *long-term memory* in the form of matrix weights, they change during the training encoding general knowledge about the data. RNN 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 provides storage for those memories. We now describe components of the cell following.[5]

- Gates (f_t, i_t, o_t): They are sigmoidal units that takes activation from the input x_t and the output of the hidden layer from previous state h_{t-1}. Note that f_t multiply the value of the previous cell c_{t-1}. The term *gate* stands for the literal meaning in the sense that if f_t is close to 0, then the gate is *closed* and the flow from the previous cell is cut off. If f_t is closed to 1 then all flow is passed through. The output to the hidden layer is $h_t = o_t \odot \tanh(c_t)$ where $\odot$ denote the pointwise multiplication.
- Cell state ($c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$): Cell state maintains information on the input. Also refered as the internal state, c_t has a self-connected edges with a fixed unit weight. This constant weight implies that the error can flow across time without vanishing or exploding.

Our implementation

For the implementation section of this project, we gathered text data that we found around the internet to train a sequence classifier and generate text sequences. The training of the classifier consist of identifying from which corpus between Harry Potter, Lord of the rings, some random quotes and Shakespeare, the sequence corresponds to. Further to this, we trained one model per sequence type for the text generation. Finally, we verified that our generated sequences were well classified by our classifier. The parameters we used for the models are shown in the table below.

Before doing any sort or training, we had to do a bit of preprocessing on the data. First, we tokenized each corpus in sequences of 50 tokens. Then, we removed every capital letters to standardize the text. We built up a dictionary of every tokens ($\approx 60k$) in the datasets, this is our input space. Next, encode each token in a 256 dimensions vector with en embedding layer. We then feed the encoded vectors to our LSTMs with a hidden/cell state of 512 dimensions. The output dimension is 4 for the classifier and $\approx 60k$ for the text genetation.

For the generation of sequences, we initialize our LSTM with a random word drawn from our dictionary. Next, we feed back the prediction in the network until we reach the desired sequence length. We generated 1000 sequences (250 per models) and used our classifier on them. A few examples of generated sequences are shown above. With no surprise, we scored 98% on the classification task, which confirms that our sequences are at least probable.

Results

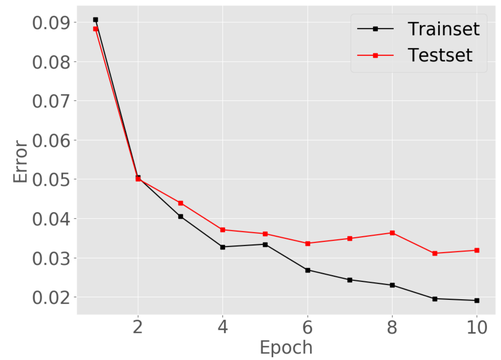


Figure: Classification error on train/test set.

Training trough minimization of the cross-entropy loss, which is equivalent to *perplexity*. The standard metric for language modeling[4].

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

- " 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 .

References

[1] Jacob Andreas. *A neural network is a monference, not a model*. Blog. 2016. URL: `http://blog.jacobandreas.net/monference.html`.

[2] Mathias Berglund et al. "Bidirectional Recurrent Neural Networks as Generative Models - Reconstructing Gaps in Time Series". In: *CoRR* abs/1504.01575 (2015). arXiv: `1504.01575`. URL: `http://arxiv.org/abs/1504.01575`.

[3] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep Learning*. The MIT Press, 2016. ISBN: 0262035618, 9780262035613.

[4] Alex Graves. "Generating Sequences With Recurrent Neural Networks". In: *CoRR* abs/1308.0850 (2013). arXiv: `1308.0850`. URL: `http://arxiv.org/abs/1308.0850`.

[5] Zachary Chase Lipton. "A Critical Review of Recurrent Neural Networks for Sequence Learning". In: *CoRR* abs/1506.00019 (2015). arXiv: `1506.00019`. URL: `http://arxiv.org/abs/1506.00019`.

[6] Zachary Chase Lipton. "The Mythos of Model Interpretability". In: *CoRR* abs/1606.03490 (2016). arXiv: `1606.03490`. URL: `http://arxiv.org/abs/1606.03490`.