Complex Architectures for Neural Language Modelling

What recent research has to tell us

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Neural Language Models

- Component of almost all Natural Language Processing systems
- Provides a probabilistic score for a piece of text
- Reflects how likely that piece of text is to appear in a given language

Example: Machine Translation

- Source:

  er geht ja nicht nach hause

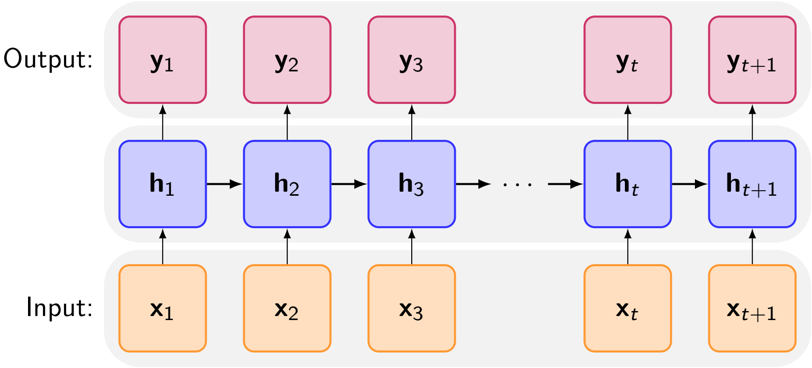
- Candidate translations:

  he is yes not after house

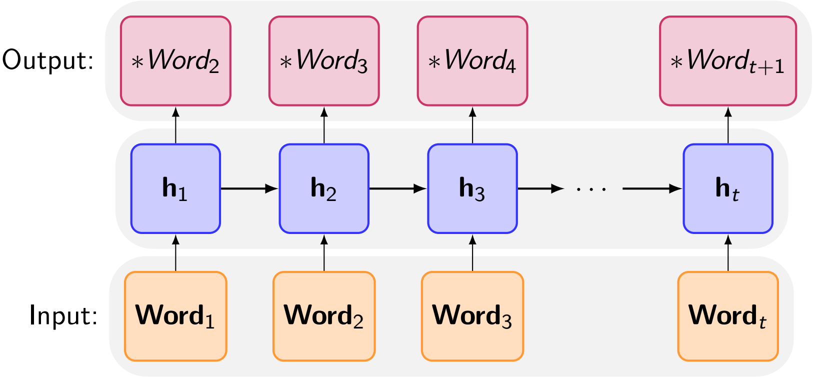
  it are is do not according to home

  – *he does not go home*

Recurrent Neural Network (unrolled through time)



Language Models based on RNNs (Neural Language Models)



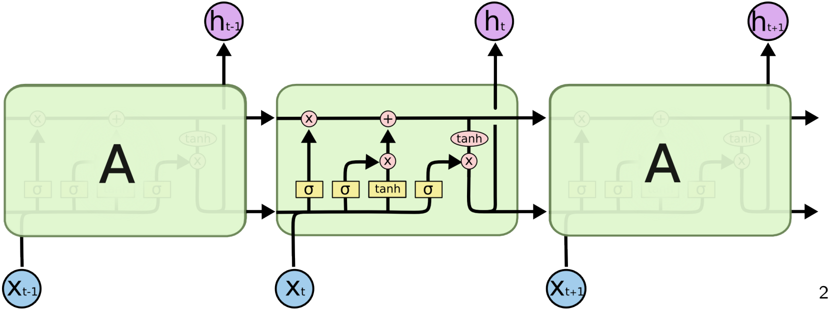
Long Short-Term Memory

LSTM equations[1]

$$
\begin{aligned}
\widetilde{\mathbf{c}}_t =& tanh(\mathbf{W}\mathbf{x}_t + \mathbf{W}\mathbf{h}_{(t-1)} + \mathbf{b}) \\
\mathbf{i}_t =& \sigma(\mathbf{W}_{ii}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{(t-1)} + \mathbf{b}_i) \\
\mathbf{f}_t =& \sigma(\mathbf{W}_{if}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{h}_{(t-1)} + \mathbf{b}_f) \\
\mathbf{c}_t =& \mathbf{f}_t \times \mathbf{c}_{(t-1)} + \mathbf{i}_t \times \widetilde{\mathbf{c}}_\mathbf{t} \\
\mathbf{o}_t =& \sigma(\mathbf{W}_{io}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{(t-1)} + \mathbf{b}_o) \\
\mathbf{h}_t =& \mathbf{o}_t \times \tanh(\mathbf{c}_t)
\end{aligned}
$$

[1] Gers, F. A., Schmidhuber, J. A., and Cummins, F. A. (2000). Learning to forget: Continual prediction with lstm. *Neural Comput.*, 12(10):2451–2471

LSTMs



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[2] http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Complex Architectures

- Recurrent Memory Network (Tran et al., 2016)
- Long Short-Term *Memory-Network* (LSTMN) (Cheng et al., 2016)
- *N*-Gram Recurrent Neural Network (Daniluk et al., 2017)
- Attentive Language Model (Salton et al., 2017)

- What all this architectures have in common?
  - Complex models
  - Require additional computer power
  - Difficult to optimise
  - **Minor improvements over baselines**

What Recent Research has to Tell us

Press and Wolf (2016)[3] - Embeddings Weights

- Embeddings learned by the NLM are similar to *word2vec*, *GloVe*, etc
- Using these embeddings in the final linear transformation helps in regularizing the embeddings themselves
- Applying variational dropout to input weights is better than regular dropout
  - Note: the authors refer to *Variational dropout* as *Bayesian dropout*
- Results on PennTree Bank:

Model	Params	Valid. Set	Test Set
Large LSTM	66M	82.2	78.4
Large LSTM + VD + WT	**66M**	**75.8**	**73.2**

[3] Press, O. and Wolf, L. (2016). Using the output embedding to improve language models. *arXiv*

Melis et al. (2017)[5] - Hyperparameter search

- There is a lot of hyperparameters in a NLM
- Fine-tuning those hyperparameters makes a huge difference!
  - Also demonstrated by Howard and Ruder (2018)[4] within text classification context

- Results on PennTree Bank:

Model	Params	Valid. Set	Test Set
Large LSTM + VD + WT	66M	75.8	73.2
Fine-tuned LSTM	**24M**	**60.9**	**58.3**

[4] Howard, J. and Ruder, S. (2018). Universal language model fine-tuning for text classification. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 328–339

[5] Melis, G., Dyer, C., and Blunsom, P. (2017). On the state of the art of evaluation in neural language models. *ICLR'2018*, abs/1707.05589

Merity et al. (2017)[6] - Weight Dropping

- Drop Connect Wan et al. (2013) to recurrent weights → Weight Dropping
- Averaged Stochastic Gradient Descent (ASGD) variant → Non-monotonically Triggered ASGD (NT-ASGD)
- Pointer network Merity et al. (2016) (evaluation only)

- Results on PennTree Bank:

Model	**Params**	**Valid. Set**	**Test Set**
Fine-tuned LSTM	24M	60.9	58.3
AWD + WT + Pointer	**24M**	**53.9**	**52.8**

[6] Merity, S., Keskar, N. S., and Socher, R. (2017). Regularizing and Optimizing LSTM Language Models. *arXiv*

Krause et al. (2018)[7] - Dynamic Evaluation

- Update weights during evaluation based on parts of the sequence
- Reset to initial weights at the end of evaluation

- Results on PennTree Bank:

Model	Params	Valid. Set	Test Set
AWD + WT + Pointer	24M	53.9	52.8
AWD + WT + Dynamic	**24M**	**51.6**	**51.1**

[7] Krause, B., Kahembwe, E., Murray, I., and Renals, S. (2018). Dynamic evaluation of neural sequence models. In *Proceedings of the 35th International Conference on Machine Learning*

Yang et al. (2018)[8] - Mixture of Softmaxes

- Replace softmax with a *Mixture of Softmaxes*, *i.e.*, a set of softmaxes are applied to different parts of the prediction vector
- Each part of the prediction vector has its own *mixture weight*
- In the authors' words words:
  - "MoS computes K Softmax distributions and uses a weighted average of them as the next-token probability distribution"

- Results on PennTree Bank:

Model	Params	Valid. Set	Test Set
AWD + WT + Dynamic	24M	51.6	51.1
AWD + WT + MoS + Dynamic	**24M**	**48.3**	**47.6**

[8] Yang, Z., Dai, Z., Salakhutdinov, R., and Cohen, W. W. (2018). Breaking the softmax bottleneck: A high-rank RNN language model.
ICLR'2018

What all these models have in common?

- Tricks to reuse parameters
- Use of dropout on recurrent connections
- Include prior information about the sequences on test/eval. time
- **Great improvement over initial baselines**

- **Use of standard LSTM units!**

Khandelwal et al. (2018)[9] - Use of context by NLMs with LSTM units

- NLMs have an effective context size of about 200 tokens on average
- Infrequent words need more context than frequent words
- Content words matter more than function words
- Local word order only matters for the most recent 20 tokens
- LSTM units can regenerate words seen in nearby context
- Caches help words that can be copied from long-range context the most

[9] Khandelwal, U., He, H., Qi, P., and Jurafsky, D. (2018). Sharp nearby, fuzzy far away: How neural language models use context. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics*, pages 284–294

Mahalunkar and Kelleher, (2018)[10] - MI decay of datasets

- Analysis of Mutual Information (MI) of long-distance dependencies:
  - The decay of that MI in benchmark language model datasets is a power-log decay
- Why not explore this information to help the LM to recover the MI from context?

[10] *To appear*

Salton et al., (2018)[12] - Recurrent residual connections

- We revisit recurrent residual connections Wang and Tian (2016)[11]
- Although these are preliminary results, our results are competitive with the SOTA models when not considering dynamic evaluation methods
- We are now:
  - conducting ablation studies similar to Khandelwal et al. (2018) to understand exactly where the model is improving
  - finetuning hyperparameters and analysing the use of dynamic evaluation methods
- Results on PennTree Bank (without dynamic evaluation methods):

Model	Params	Valid. Set	Test Set
AWD + WT	24M	60.0	57.3
AWD + WT + MoS	24M	56.5	54.4
AWD + WT + RIT†	24M	58.7	54.0

†Ours

[11] Wang, Y. and Tian, F. (2016). Recurrent residual learning for sequence classification. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 938–943. Association for Computational Linguistics

[12] *To appear*

Conclusions

Summary of Published Results

Model	Params	Valid. Set	Test Set
Medium LSTM†	16M	86.2	82.7
Large LSTM†	66M	82.2	78.4
Large LSTM + VD + WT‡	66M	75.8	73.2
Fine-tuned LSTM$^{\diamond}$	24M	60.9	58.3
AWD + WT + Pointer$^{\pm}$	24M	53.9	52.8
AWD + WT + Dynamic§	24M	51.6	51.1
AWD + WT + MoS + Dynamic$^{\mp}$	24M	**48.3**	**47.6**

$\dagger$Zaremba et al. (2015)
$\ddagger$Press and Wolf (2016)
$\diamond$ Melis et al. (2017)
$\pm$ Merity et al. (2017)
$\S$ Krause et al. (2018)
$\mp$ Yang et al. (2018)

Conclusions

- If you do not have a good infrastructure to run complex models, you are better of using carefully tuned standard LSTMs
- In fact, until the next breakthrough, we are all better of using carefully tuned standard LSTMs with some type of caching mechanism after training.

Thank you!

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