Learning Phrase Representations using RNN Encoder-decoder for Statistical Machine Translation

Cho et al. (2014)

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Outline

1. Motivation for choice
2. Preliminary on RNNs
3. GRU vs LSTM
4. Cho's experiments
5. Discussion

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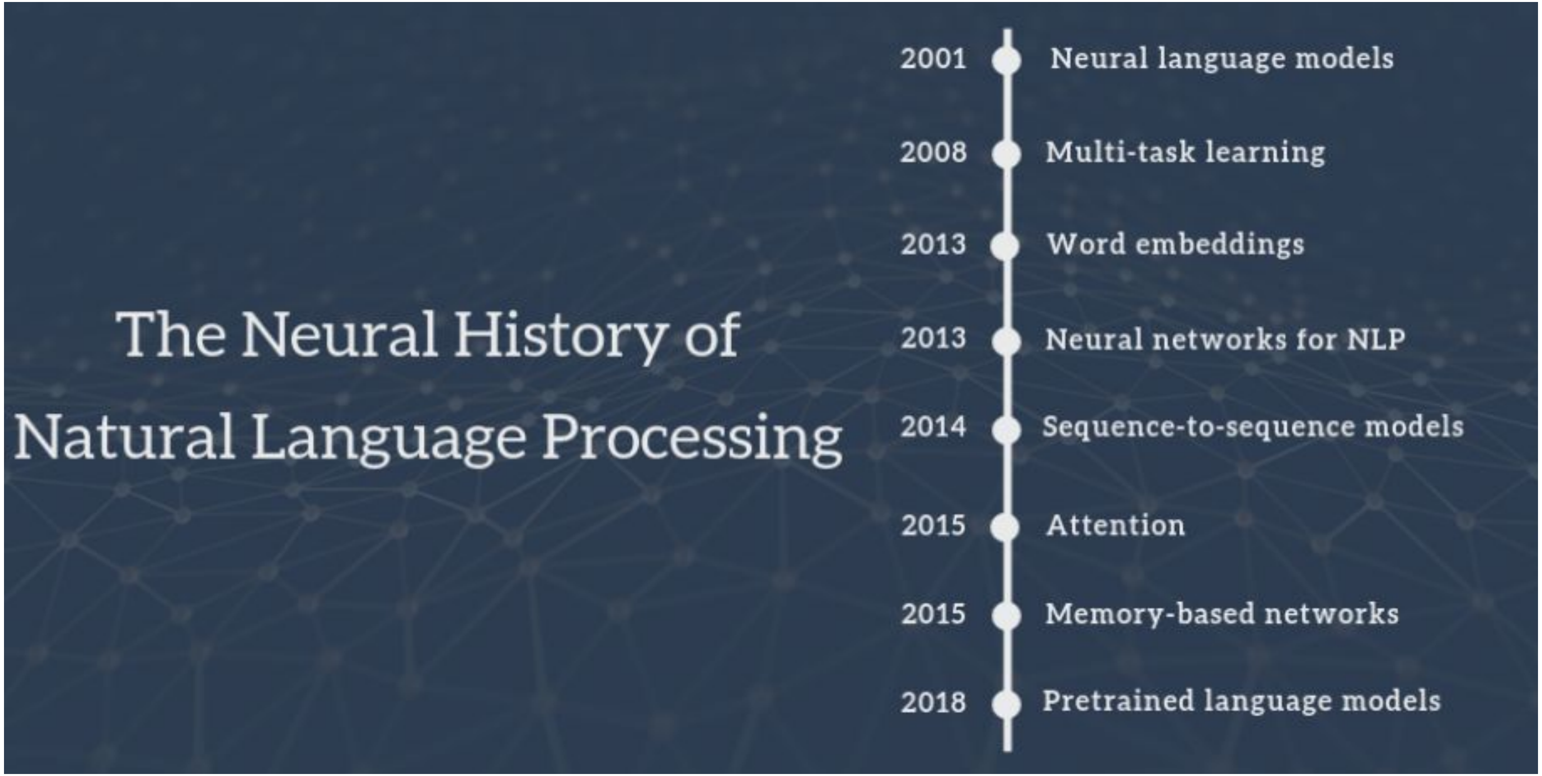
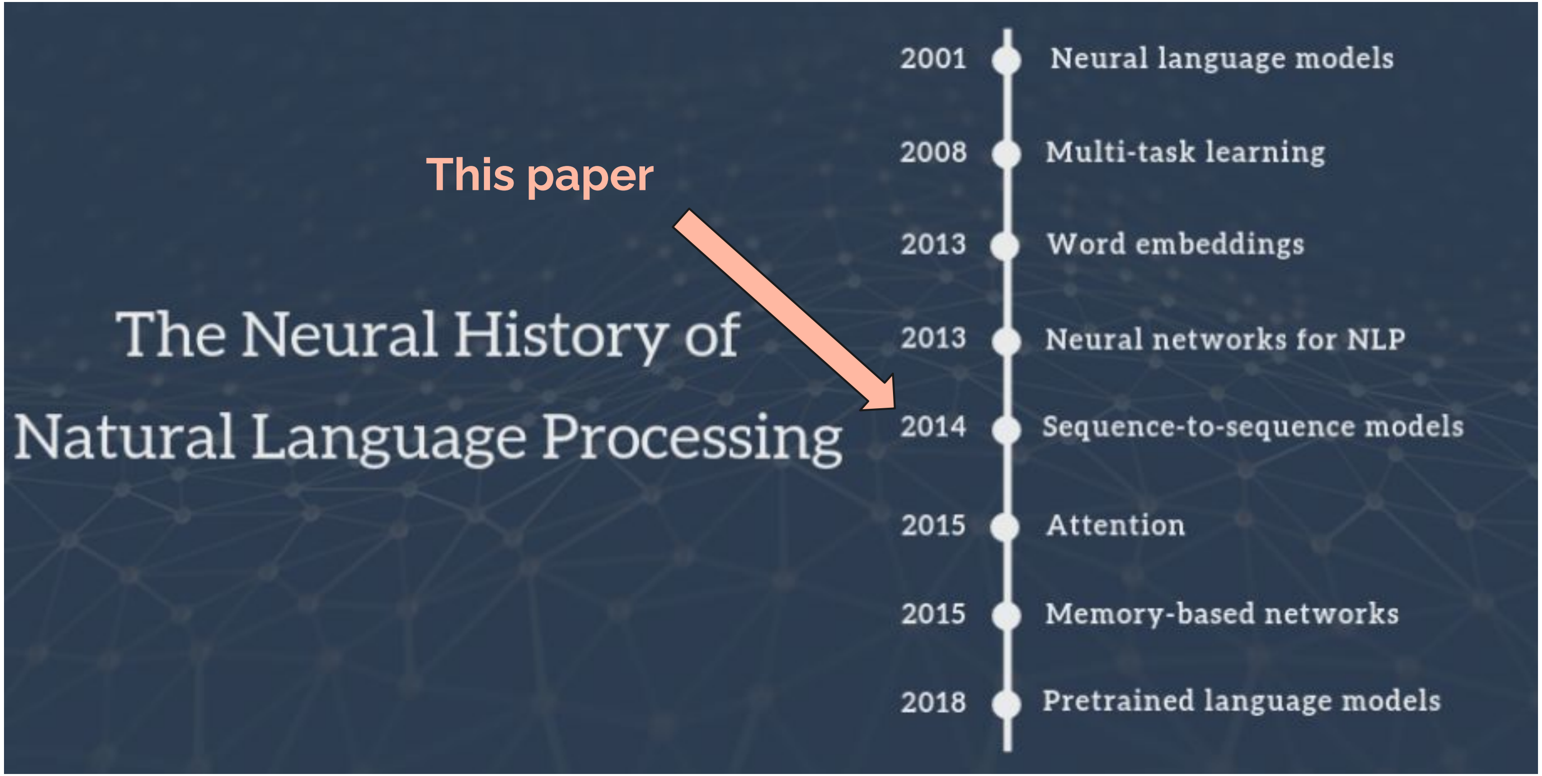
Why this paper?



Transformer-based pretraining

Credits: Sebastian Ruder



Transformer-based pretraining

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2014- Sequence to sequence

- Sequence-to-sequence → Natural Language Generation (NLG) problems
- DNN architectures and their limitations:
  - Assumes the dimensionality of inputs and outputs are known and fixed

Motivation of Cho et al. (2014)

- Improving Phrase-Based SMT
- RNN allows to model variable-length sequences → as long as length of the sequences is known
    - Sequence to sequence with a neural net called **GRU**
- Concurrent work to Sutskever et al. (2014)

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Preliminary: RNNs

Generalization of feedforward NNs to sequences

We have a variable length sequence $\mathrm{x} = (x_1, \ldots, x_T)$. At each time step t, the hidden state $\mathrm{h}_{\langle t \rangle}$ of the RNN is updated by:

$$\mathrm{h}_{\langle t \rangle} = f\left(\mathrm{h}_{\langle t-1 \rangle}, x_t\right)$$

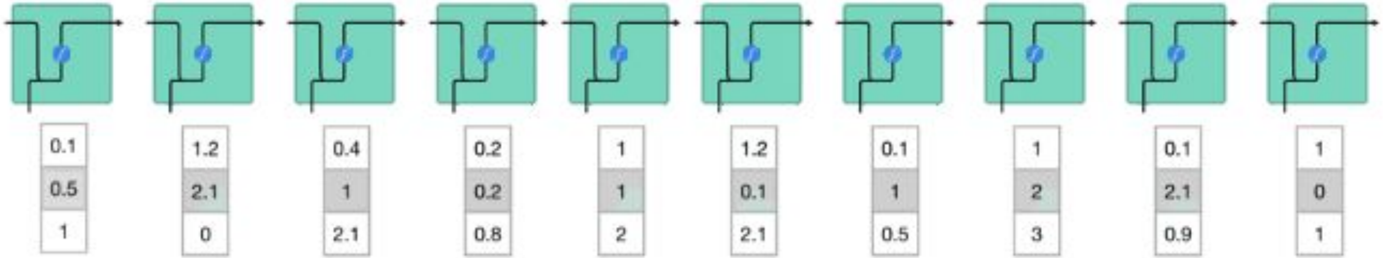
Where f is any non-linear activation function.

Preliminary: RNNs

RNNs can learn a probability distribution over a sequence, by learning to predict the next item in the sequence. Output at timestep t, is a conditional distribution:

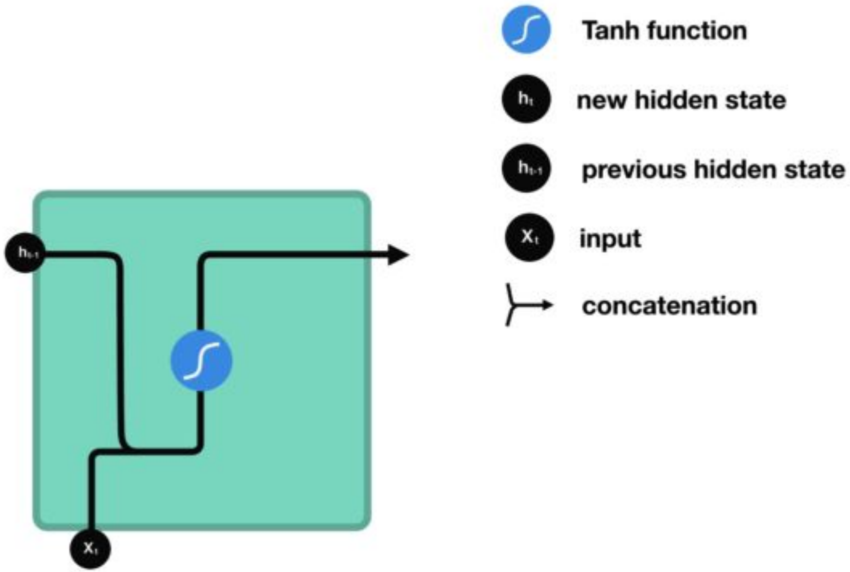
$$p(x_t | x_{t-1}, \ldots, x_1)$$

Preliminary RNNs



Animation credits: Michael Phi

Preliminary RNNs



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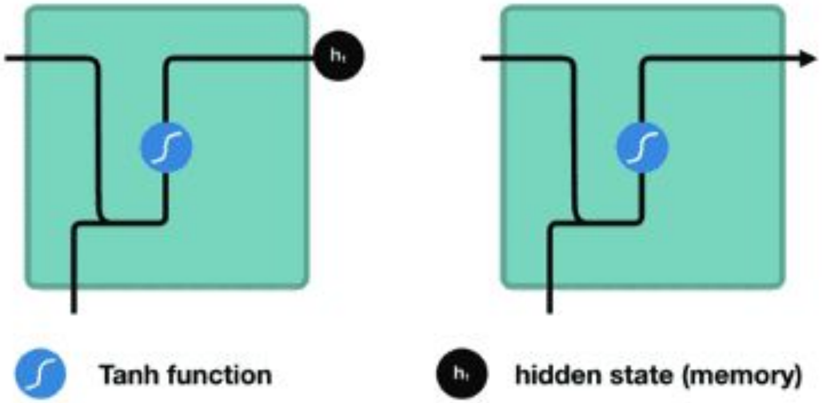
Preliminary RNNs



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Preliminary: RNNs

- Long-term dependencies
- Vanishing/exploding gradients
- Long Short Term Memory (LSTM) networks and Gated Recurrent Units (GRU) help deal with these problems

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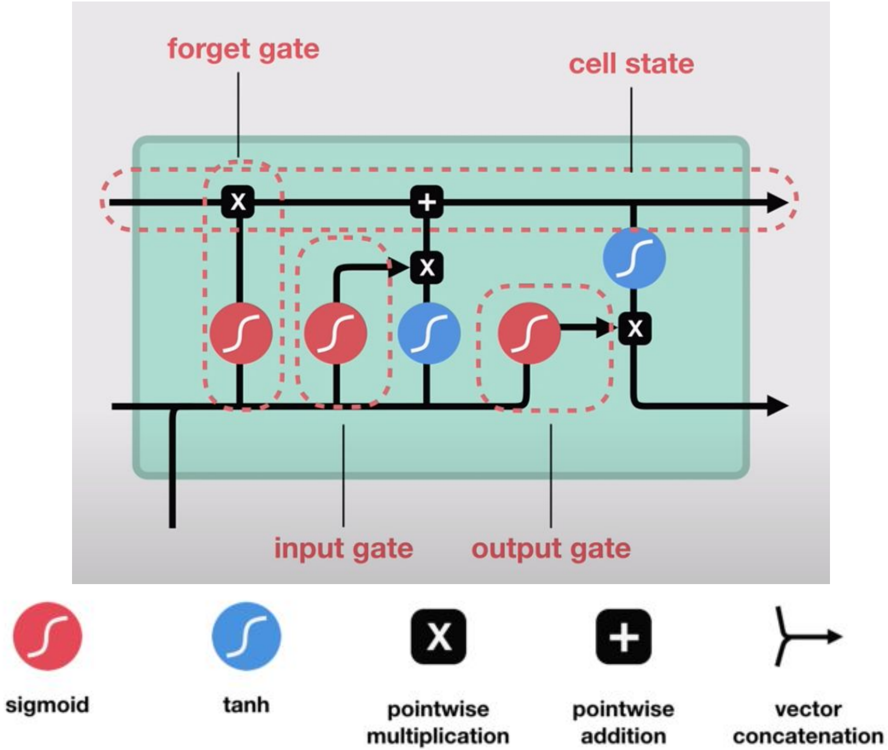
LSTMs

- Gates which can add or remove information
- Forget gate layer
- Input gate layer
- Output layer
- Cell



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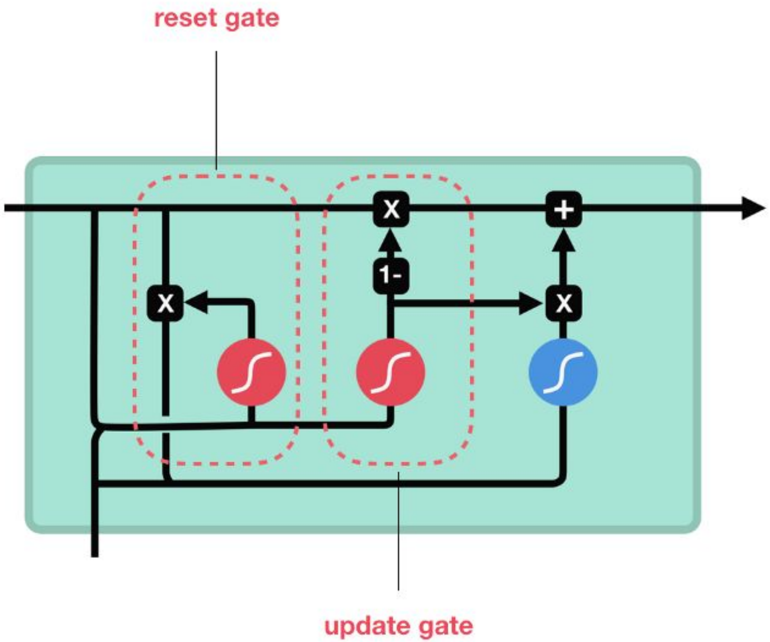
GRU

- Cho et al. (2014) introduced GRUs → inspired by LSTMs but computationally less expensive
- Reset gate
- Update gate



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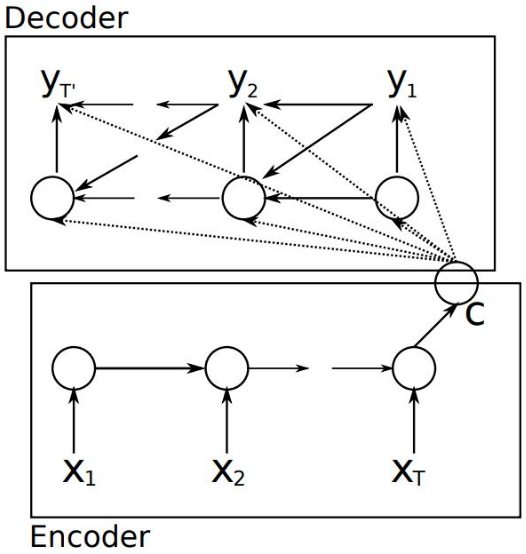
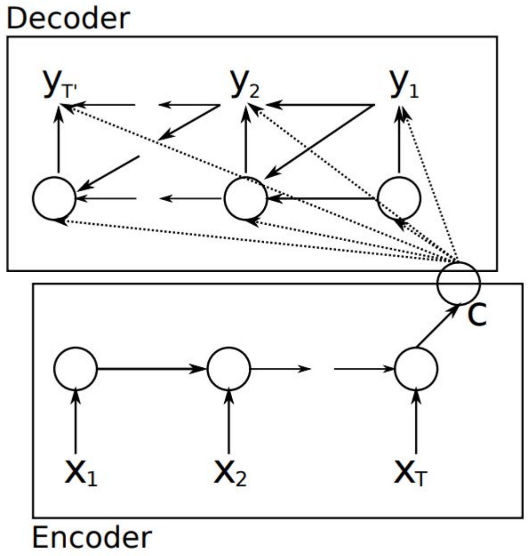
RNN Encoder-Decoder



One RNN encodes a sequence into a fixed-length vector, another RNN decodes the vector into symbols.

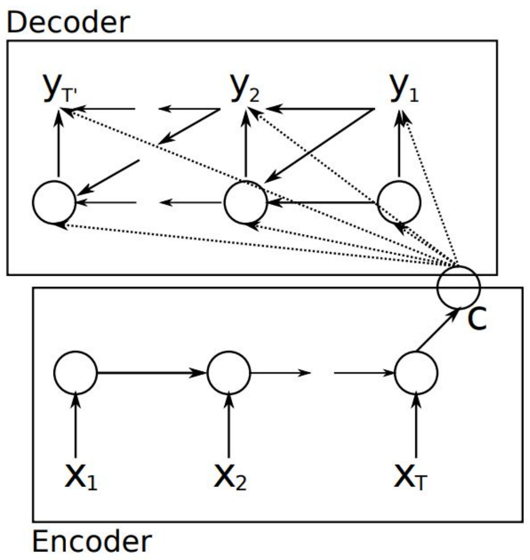
RNN Encoder-Decoder



One RNN encodes a sequence into a fixed-length vector, another RNN decodes the vector into symbols.

The internal states of the encoder are fed into the decoder. This is the initial state of the decoder.

RNN Encoder-Decoder



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Sutskever et al. (2014) uses LSTMs…

Cho et al. (2014) introduces the GRU...

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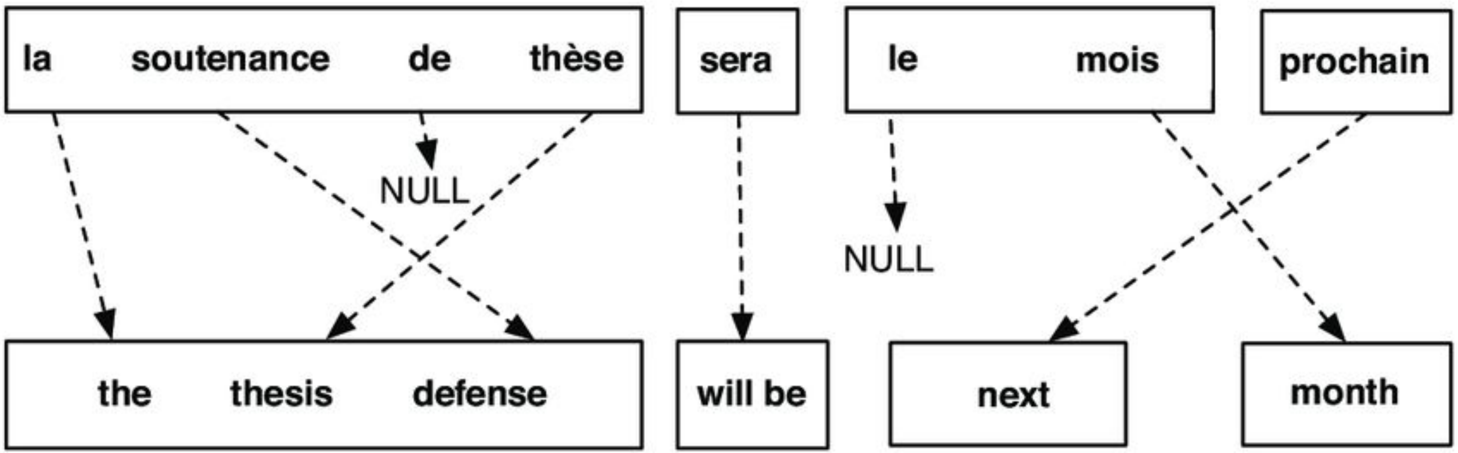
Experiments: Phrase-based Statistical Machine Translation



Experiments: Phrase-based Statistical Machine Translation

English	$\phi(\bar{e}\|\bar{f})$	English	$\phi(\bar{e}\|\bar{f})$
the proposal	0.6227	the suggestions	0.0114
's proposal	0.1068	the proposed	0.0114
a proposal	0.0341	the motion	0.0091
the idea	0.0250	the idea of	0.0091
this proposal	0.0227	the proposal ,	0.0068
proposal	0.0205	its proposal	0.0068
of the proposal	0.0159	it	0.0068
the proposals	0.0159	...	...

Rescoring Phrase Pairs

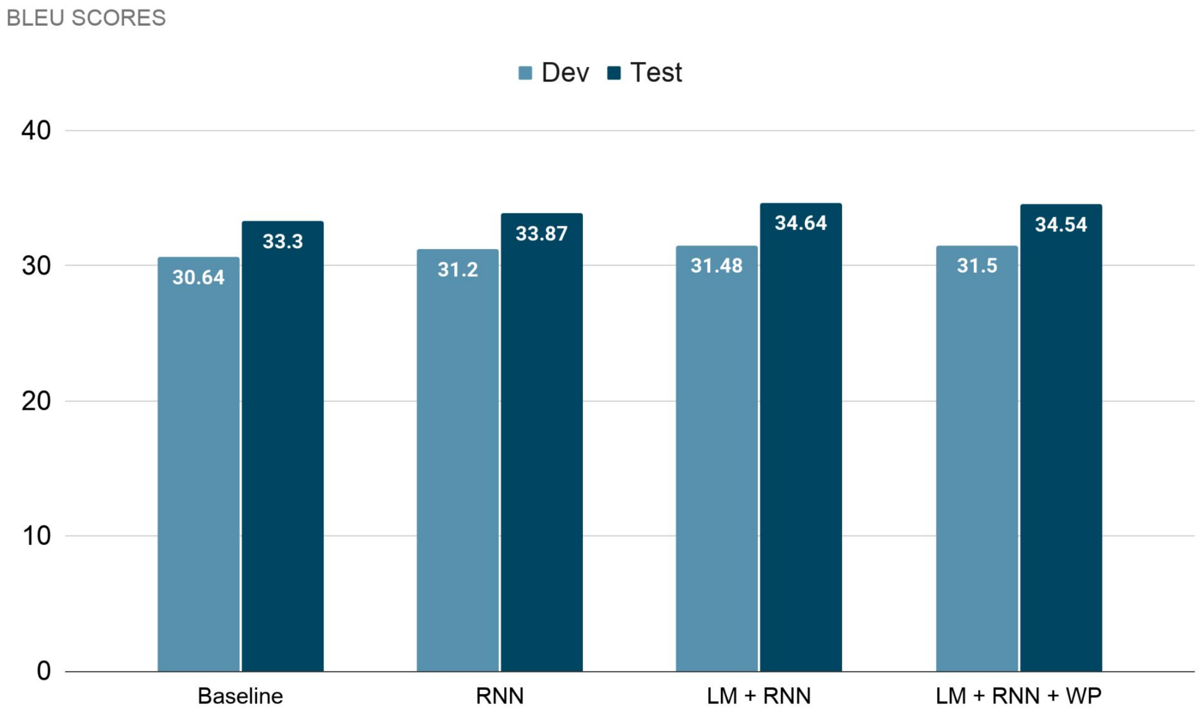
1. Train RNN encoder-decoder on a table of phrase pairs

2. Scores are used as input for SMT model
   a. Possible to replace the phrase table with the RNN encoder-decoder
   b. Cho et al. do not try this for computational reasons

3. Use the WMT'14 data

4. Compare RNN encoder-decoder phrase scoring, with SMT + LM
   a. Baseline configuration
   b. Baseline + RNN
   c. Baseline + CSLM + RNN
   d. Baseline + CSLM + RNN + Word penalty

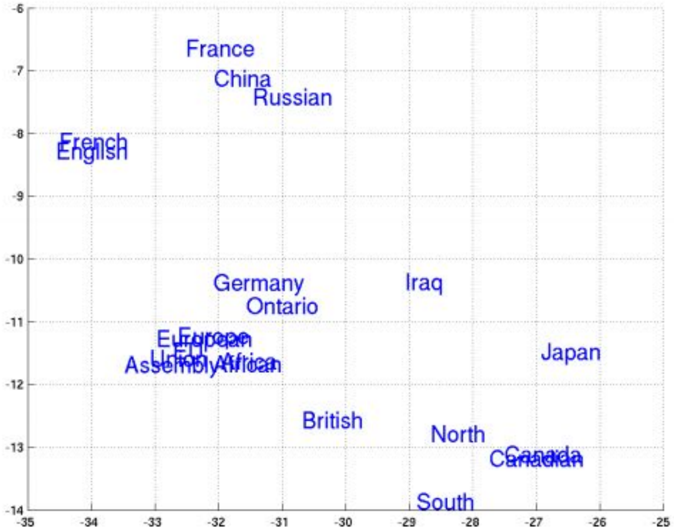
Results


BLEU SCORES
Dev
Test
40
30
20
10
0
30.64
33.3
31.2
33.87
31.48
34.64
31.5
34.54
Baseline
RNN
LM + RNN
LM + RNN + WP

Interesting properties of trained model

- Well known by now:
  - Naturally create a continuous-space representation of a phrase
  - Semantically similar words are clustered together
  - Encoder-decoder captures both semantic and syntactic properties

Extensions: [On the properties of NMT: Encoder-Decoder Approaches]()



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Relation to newer methods

- Attention mechanisms
- RNNs are no longer the standard architecture in NLP → Transformer-based models are now the *de-facto* architecture in NLP
- Transformer-based models can process input sequences of variable length without recurrence → highly parallelizable

References and group discussion

Sequence to Sequence Learning with Neural Networks. Sutskever et al. (2014)

On the properties of NMT: Encoder-Decoder Approaches

Attention is all you need

Papers

Neural Language modeling:
A Neural Probabilistic Language Model (2001)

Multitask learning:
A Unified Architecture for Natural Language Processing: Deep Neural Networks with Multitask Learning (2008)

Word Embeddings:
Natural language processing (almost) from scratch (2011)
Distributed Representations of Words and Phrases and their Compositionality (2013)
Glove: Global vectors for word representation (2014)

Attention:
Neural Machine Translation by Jointly Learning to Align and Translate (2016)