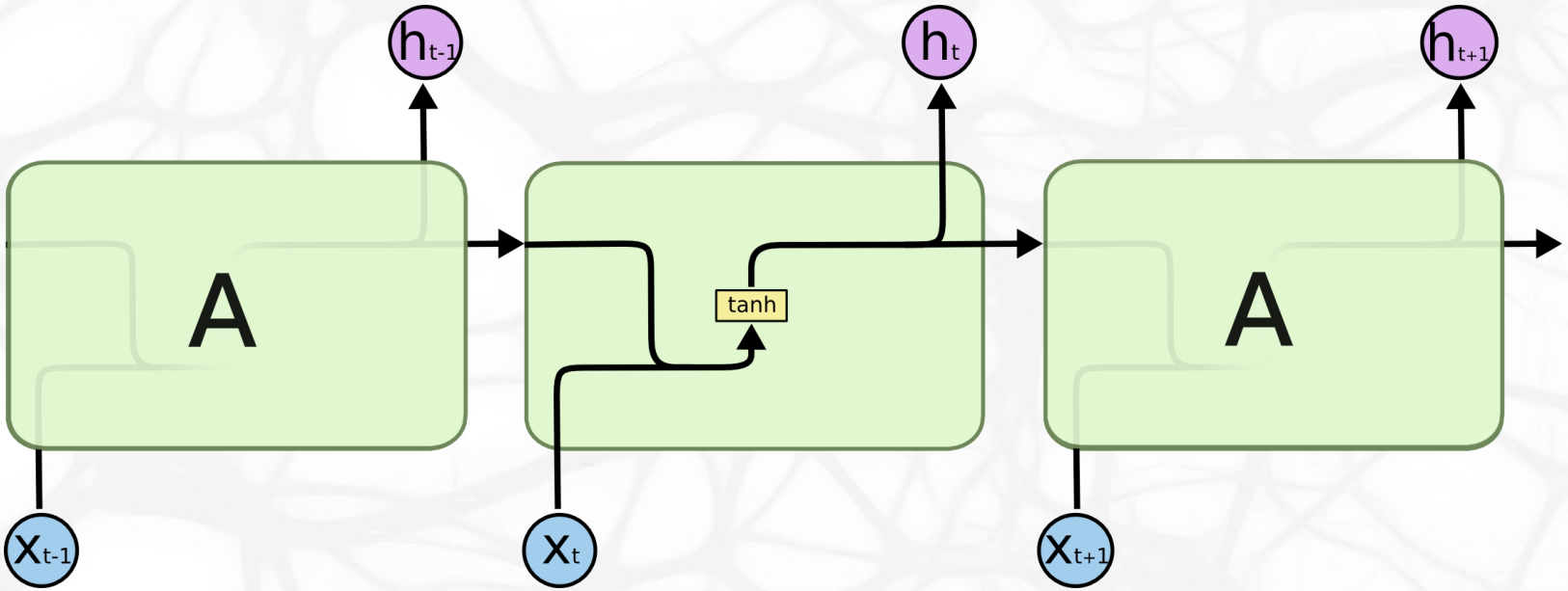
NPFL114, Lecture 09

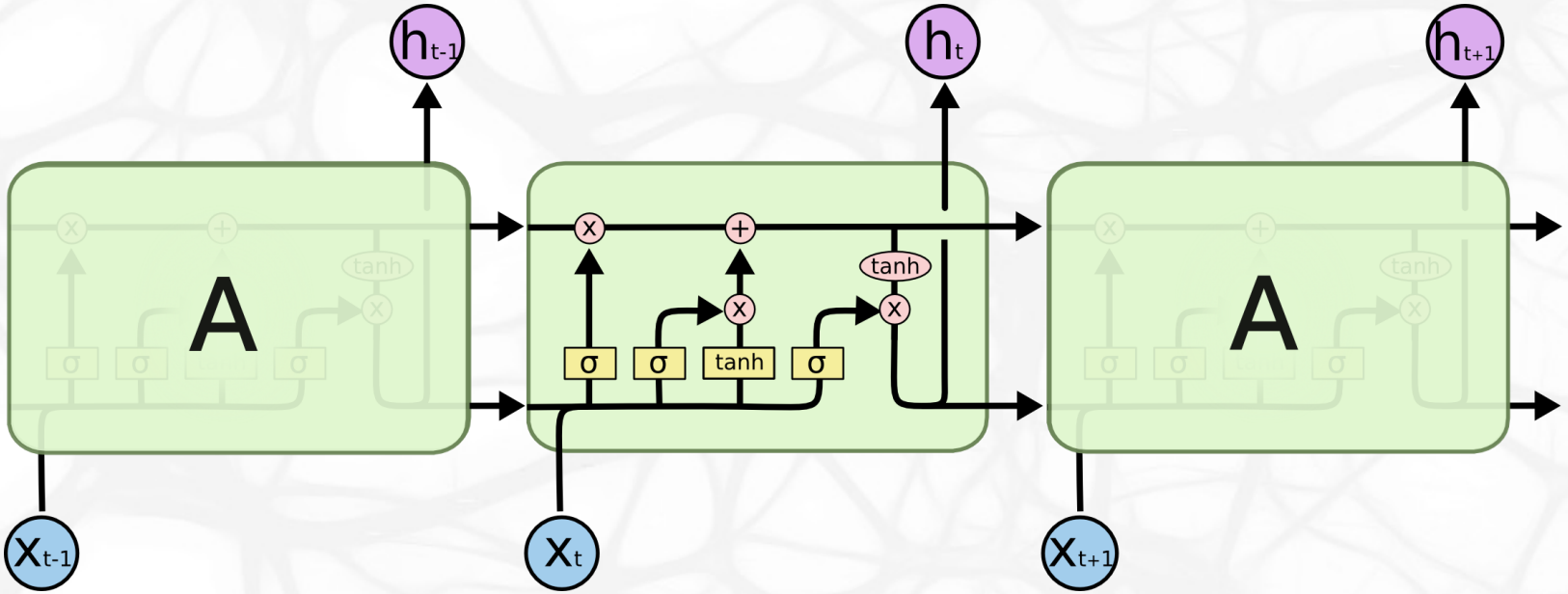
Recurrent Neural Networks III, Machine Translation

Milan Straka

Basic RNN Cell



LSTM Cell



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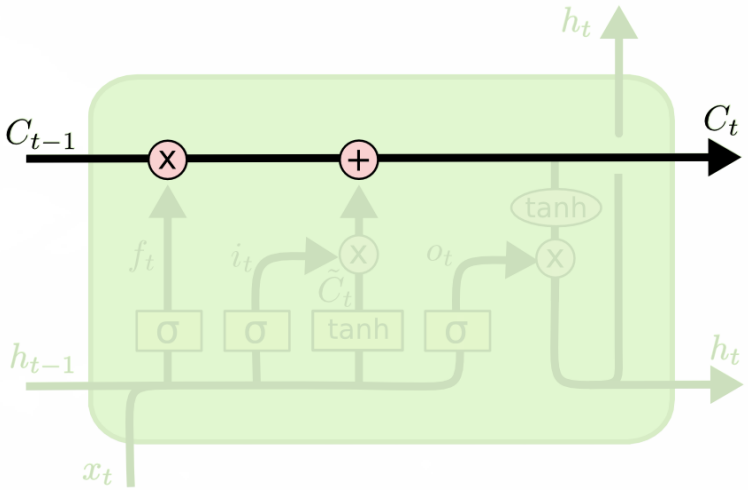

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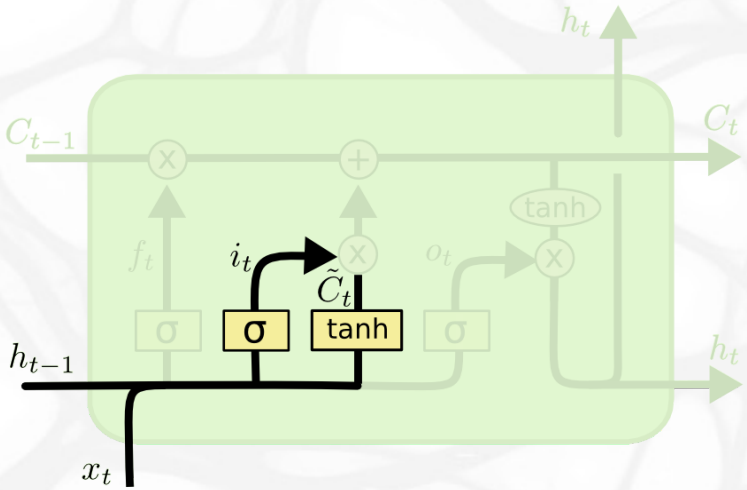

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

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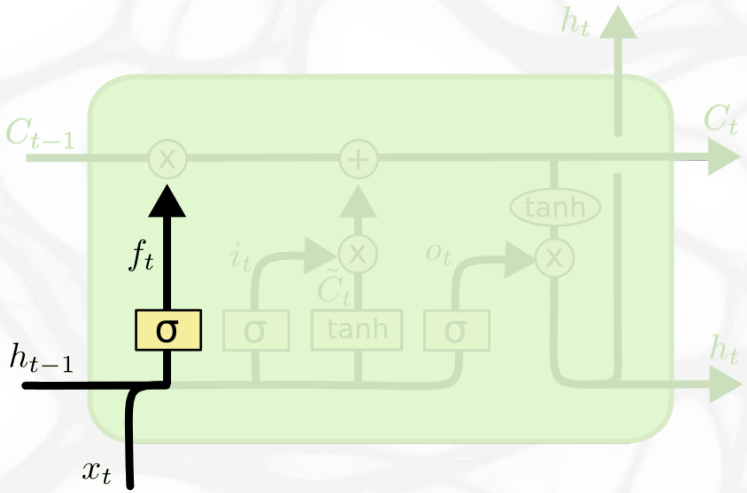

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

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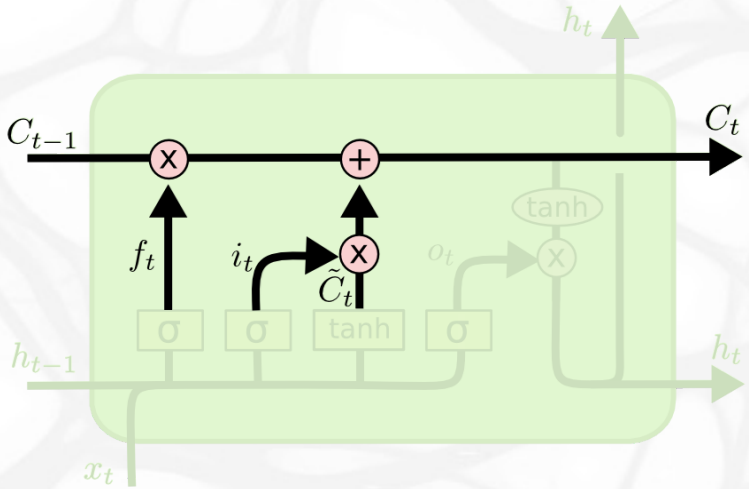
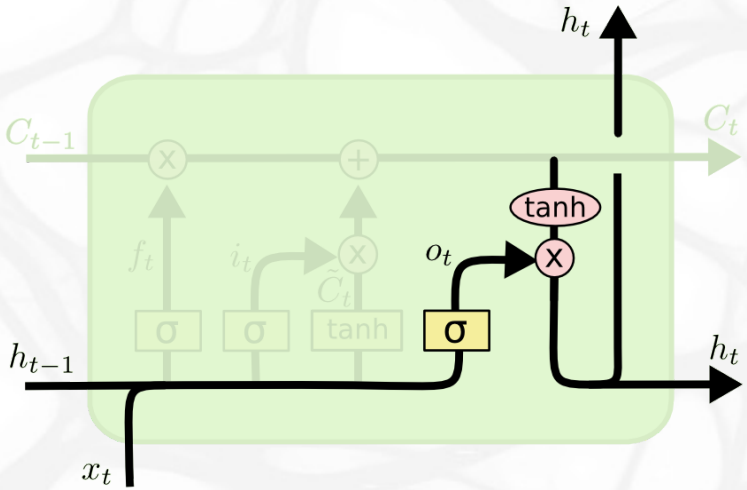


$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

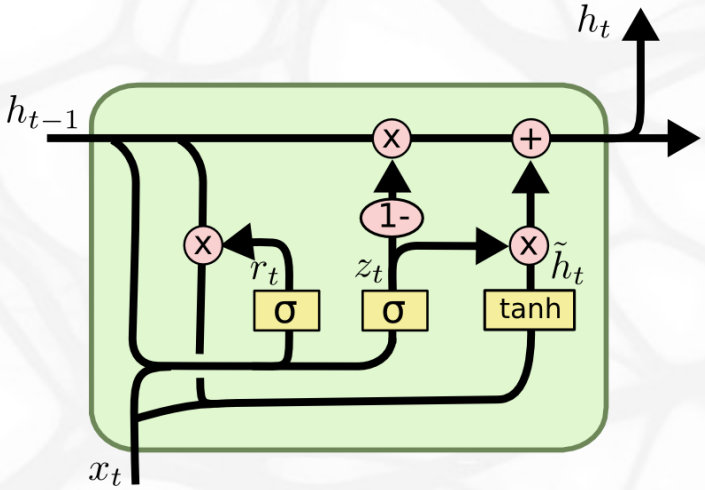
LSTM Cell



$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

GRU Cell



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Highway Networks

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$$\boldsymbol{y} \leftarrow H(\boldsymbol{x}, \boldsymbol{W}_H).$$

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Usually, the gating is defined as

$$T(\boldsymbol{x}, \boldsymbol{W}_T) \leftarrow \sigma(\boldsymbol{W}_T \boldsymbol{x} + \boldsymbol{b}_T).$$

Highway Networks

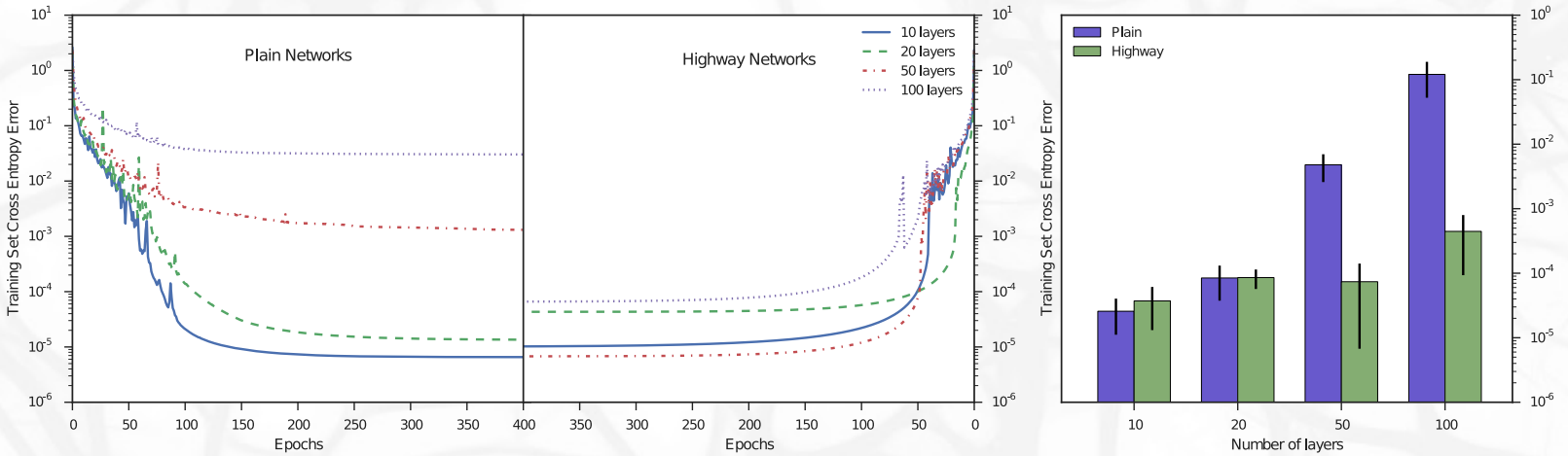
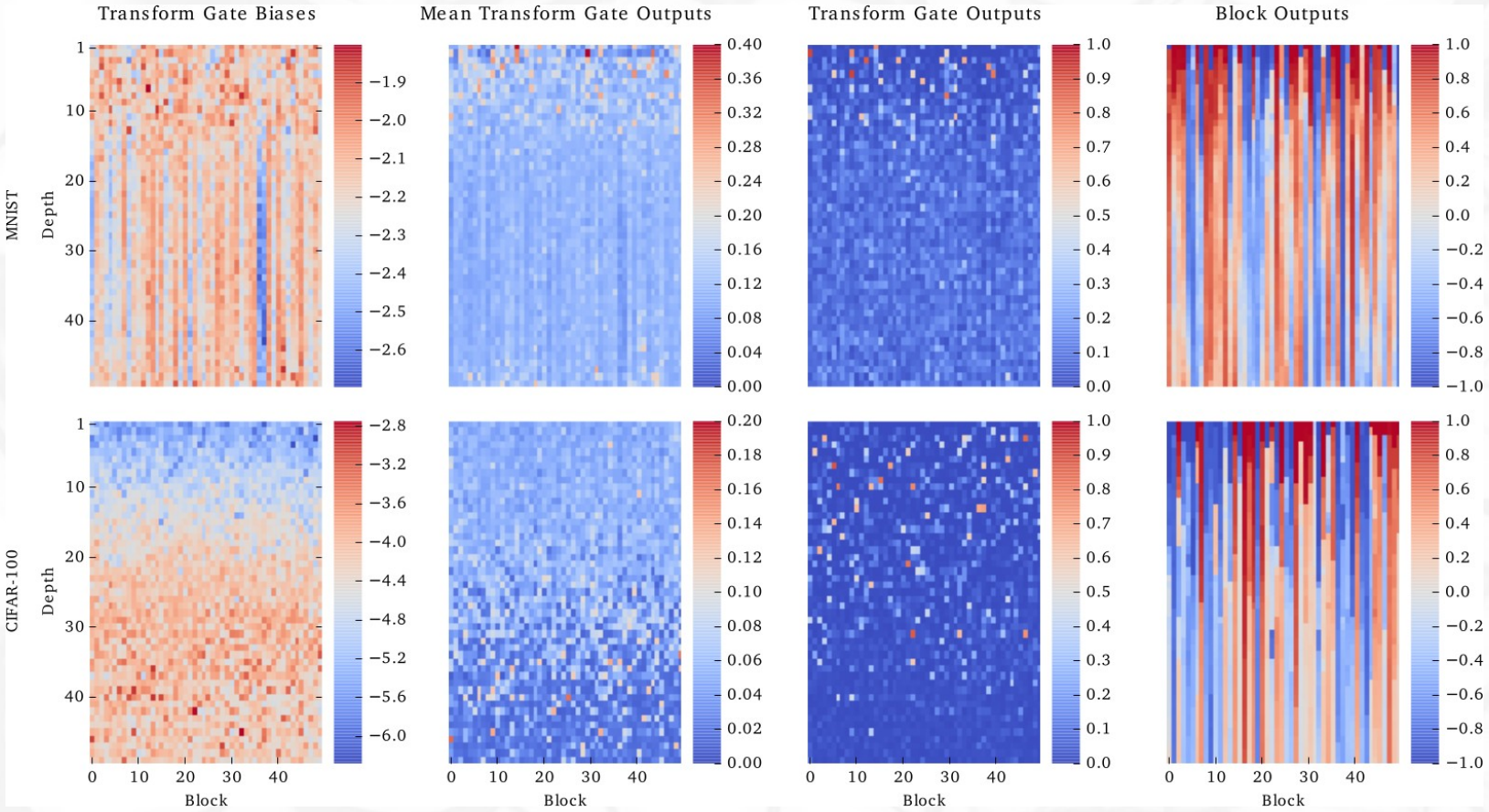


Figure 1: Comparison of optimization of plain networks and highway networks of various depths. *Left:* The training curves for the best hyperparameter settings obtained for each network depth. *Right:* Mean performance of top 10 (out of 100) hyperparameter settings. Plain n tworks become much harder to optimize with increasing depth, while highway networks with up to 100 layers can still be optimized well. Best viewed on screen (larger version included in Supplementary Material).

Highway Networks



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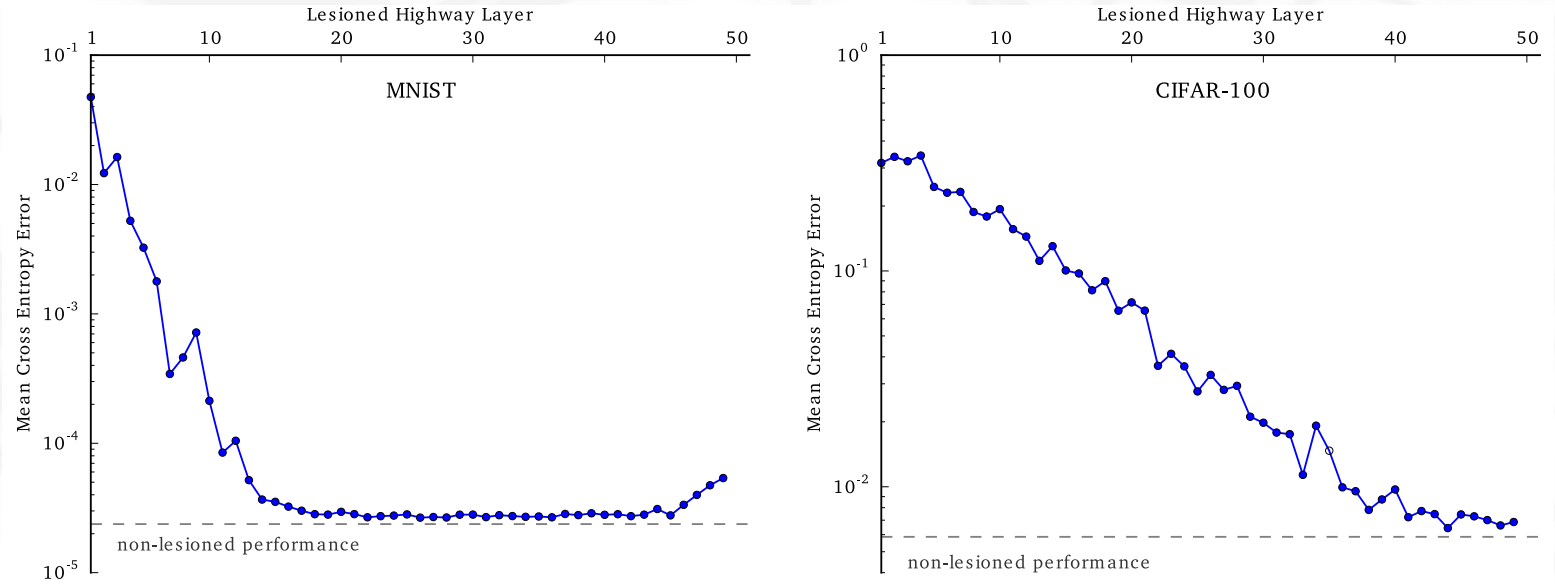
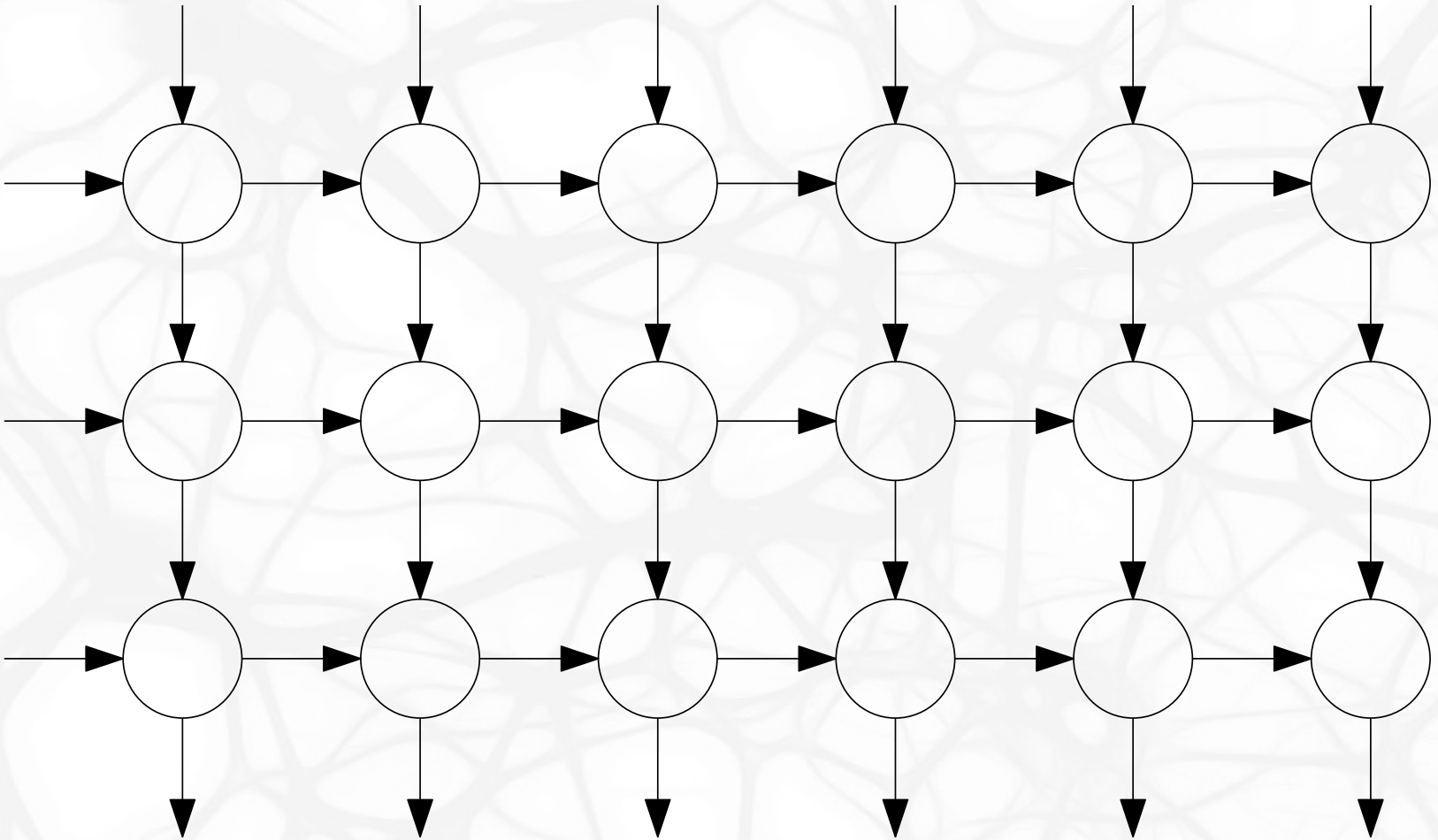


Figure 4: Lesioned training set performance (y-axis) of he best 50-layer highway networks on MNIST (left) and CIFAR-100 (right), as a function of the lesioned layer (x-axis). Evaluated on the full training set while forcefully closing all the transform gates of a single layer at a time. The non-lesioned performance is indicated as a dashed line at the bottom.

Multilayer RNNs



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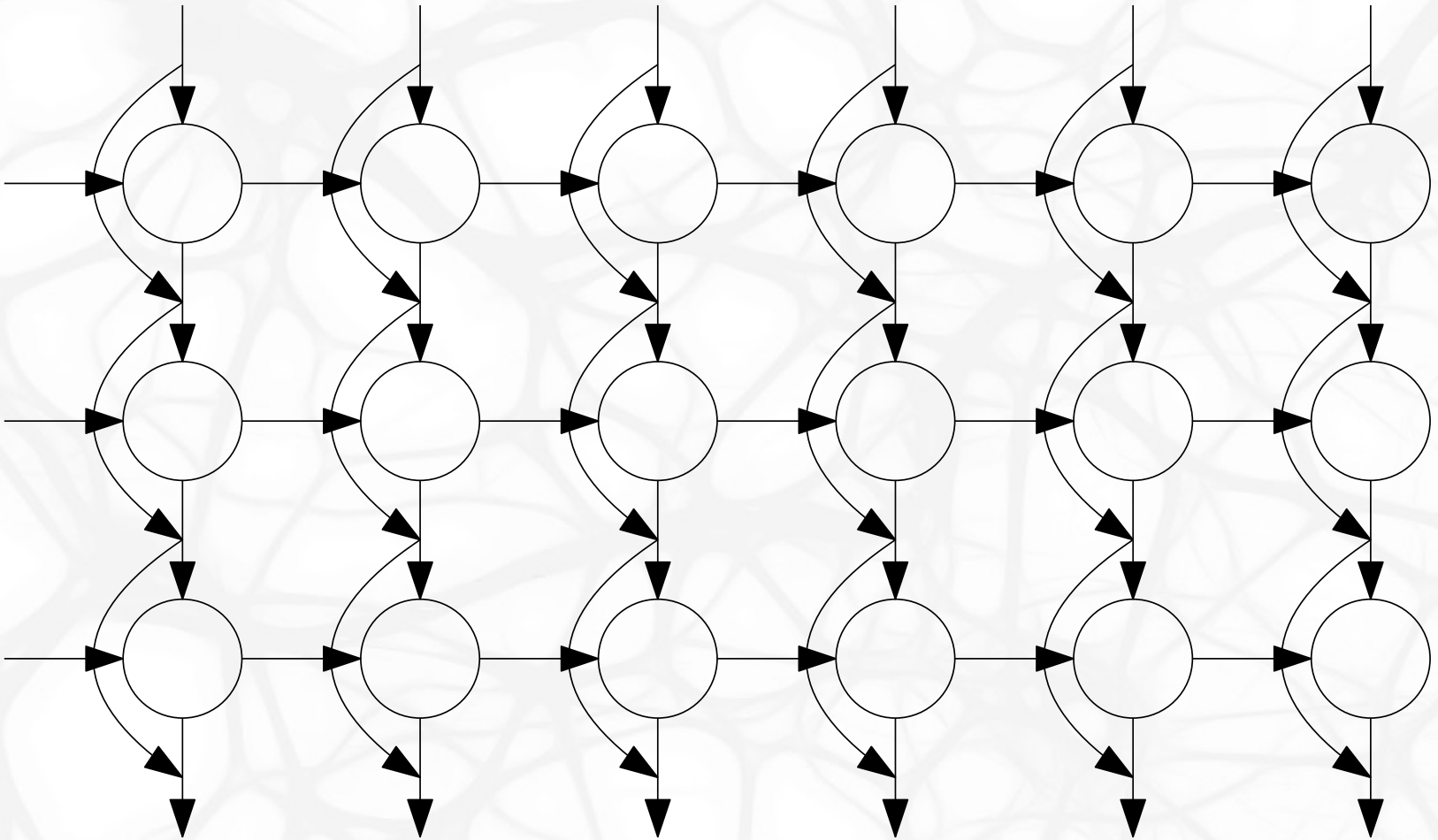
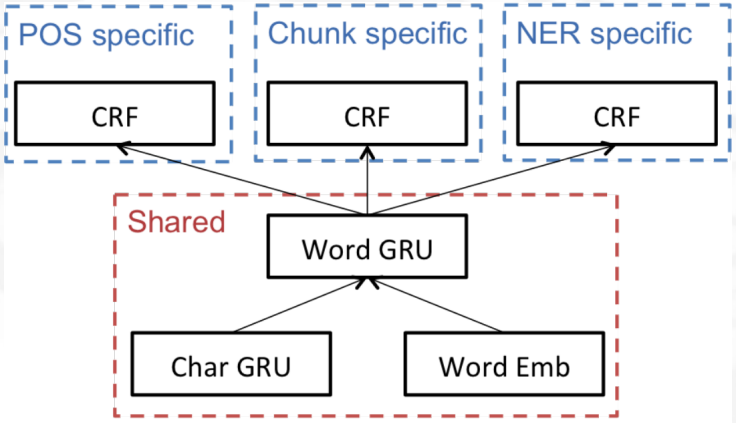
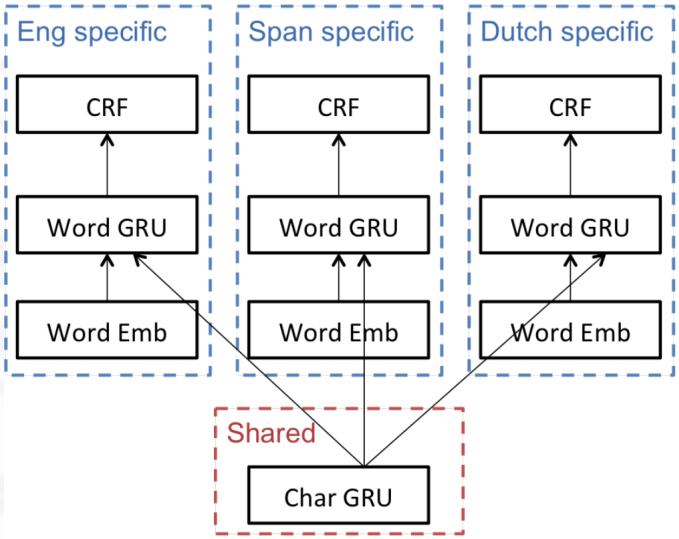


Multitask Learning

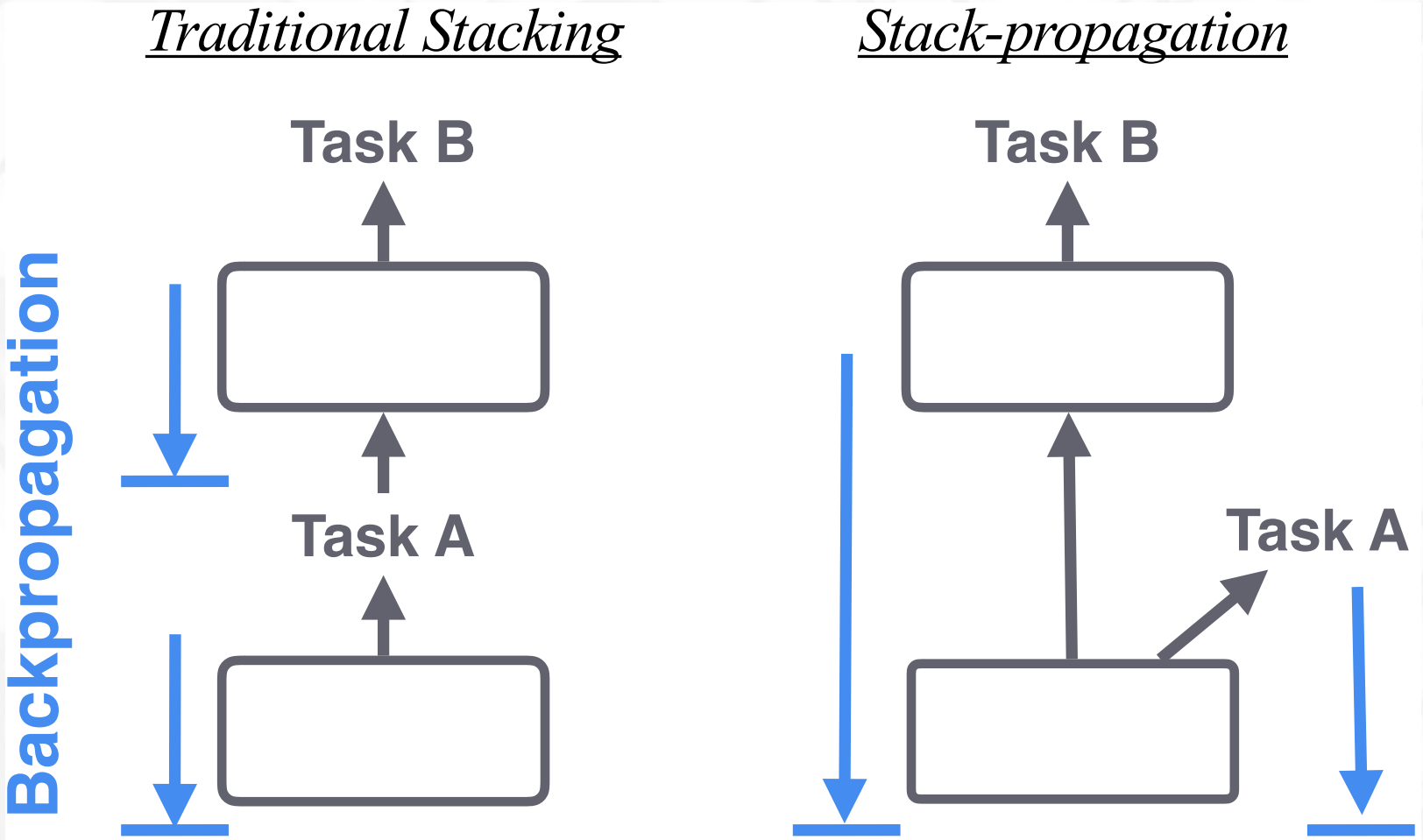


(a) Multi-Task Joint Training



(b) Cross-Lingual Joint Training

Multitask Learning



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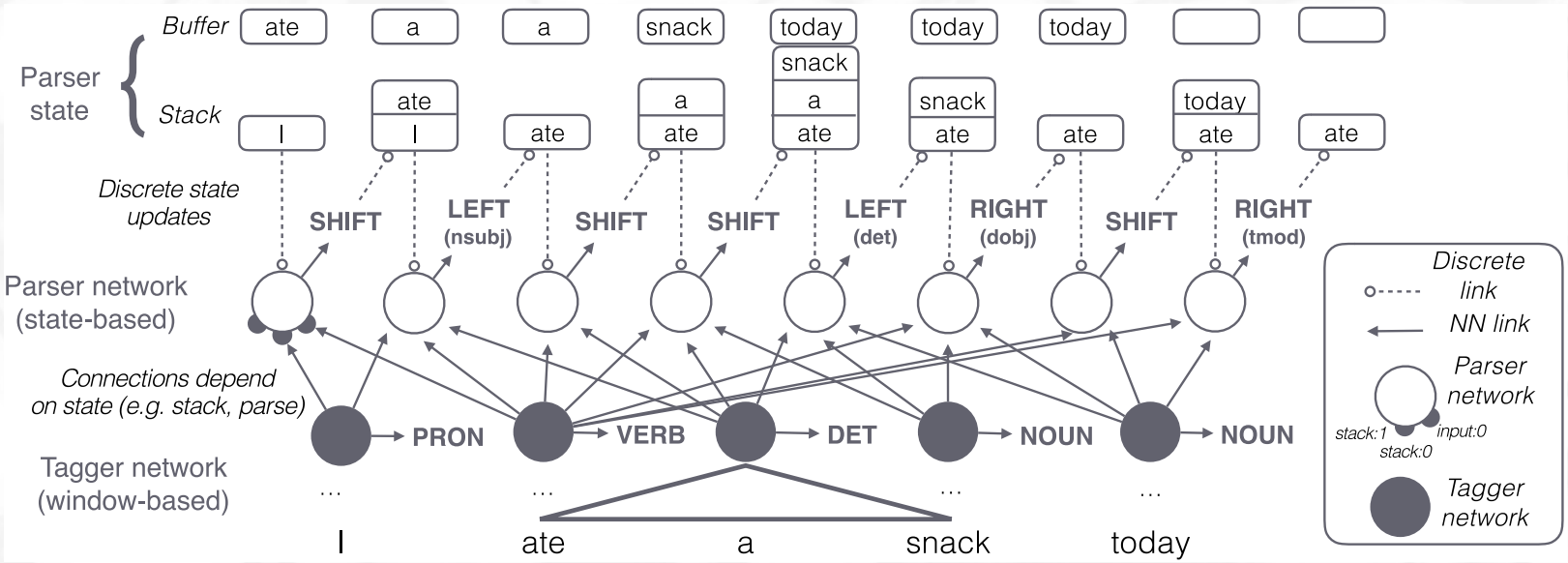

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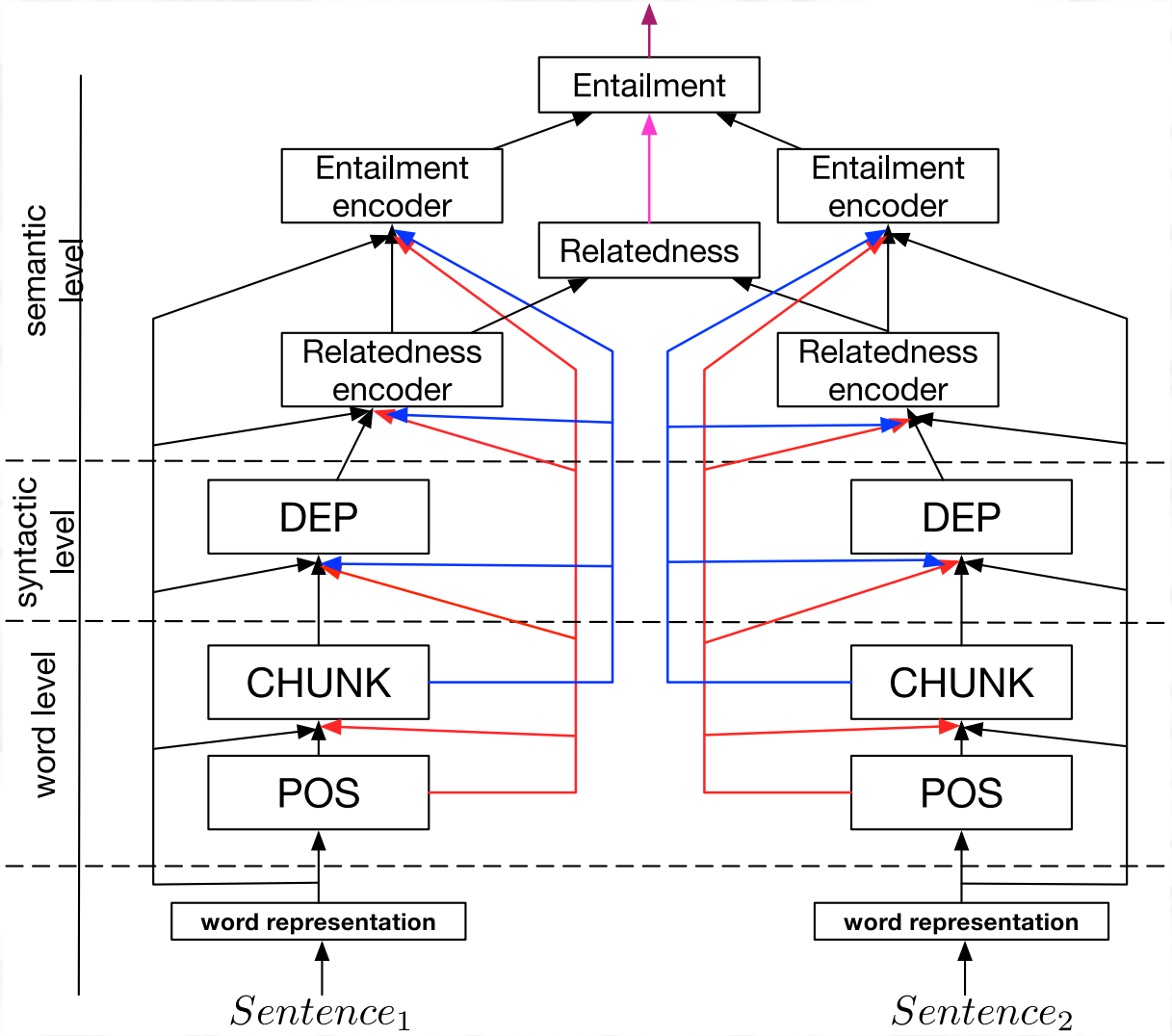

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Dropout

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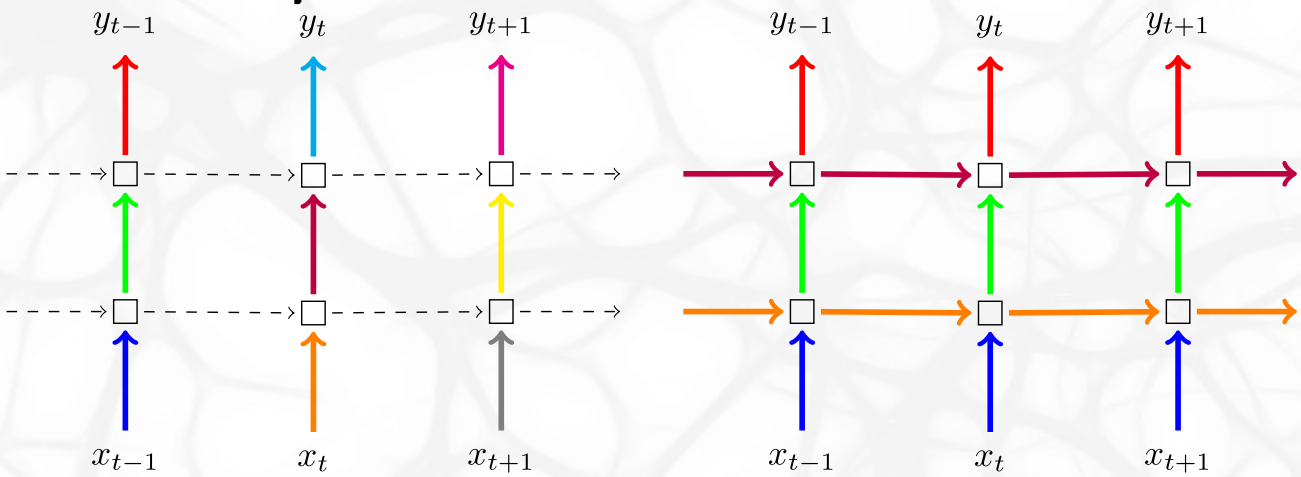
- However, using dropout on the inputs and outputs works well and is used frequently.
  - In case residual connections are present, the output dropout needs to be applied before adding the residual connection.
- Several techniques were designed to allow using dropout on hidden states.
  - Variational Dropout
  - Recurrent Dropout
  - Zoneout

Regularizing RNNs

Variational Dropout



(a) Naive dropout RNN

(b) Variational RNN

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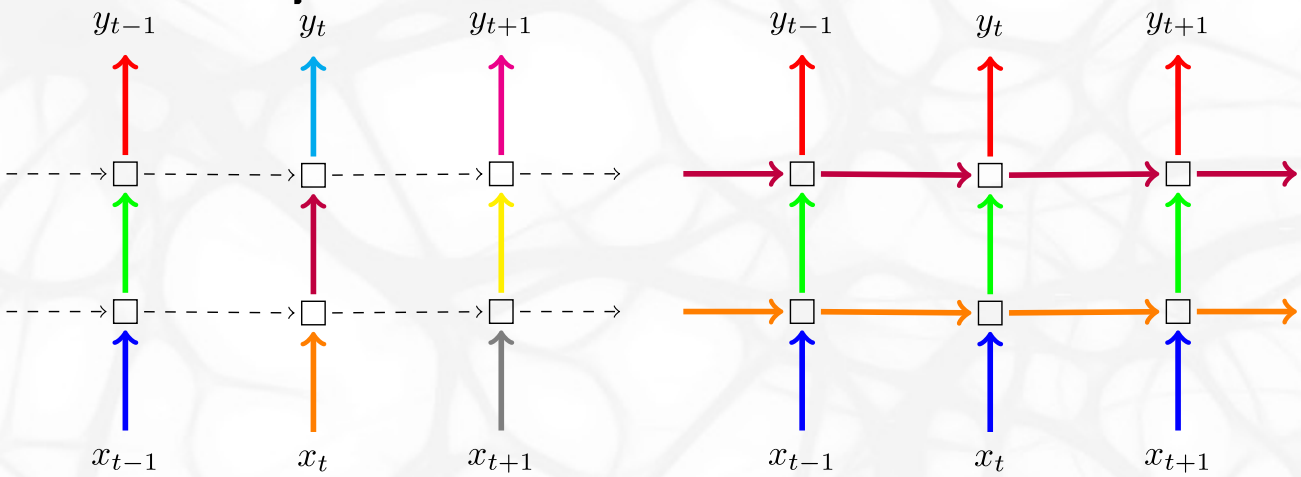
Variational Dropout



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Dropout only candidate states (i.e., values added to the memory cell in LSTM and previous state in GRU).

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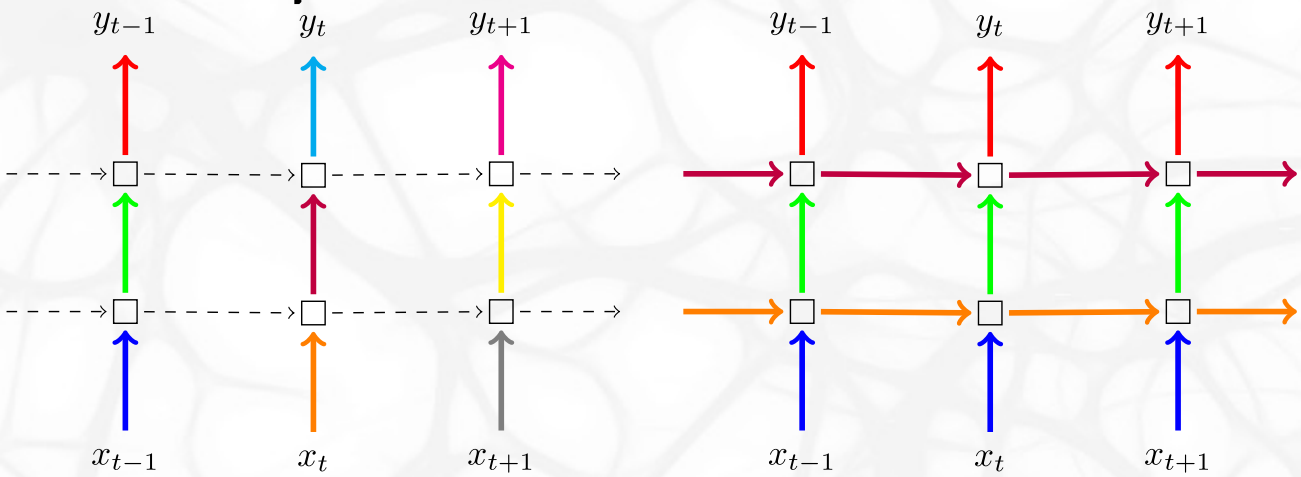

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Randomly preserve hidden activations instead of dropping them.

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Batch Normalization

Very fragile and sensitive to proper initialization (there were papers with negative results until people managed to make it work).

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Layer Normalization

Much more stable than batch normalization.

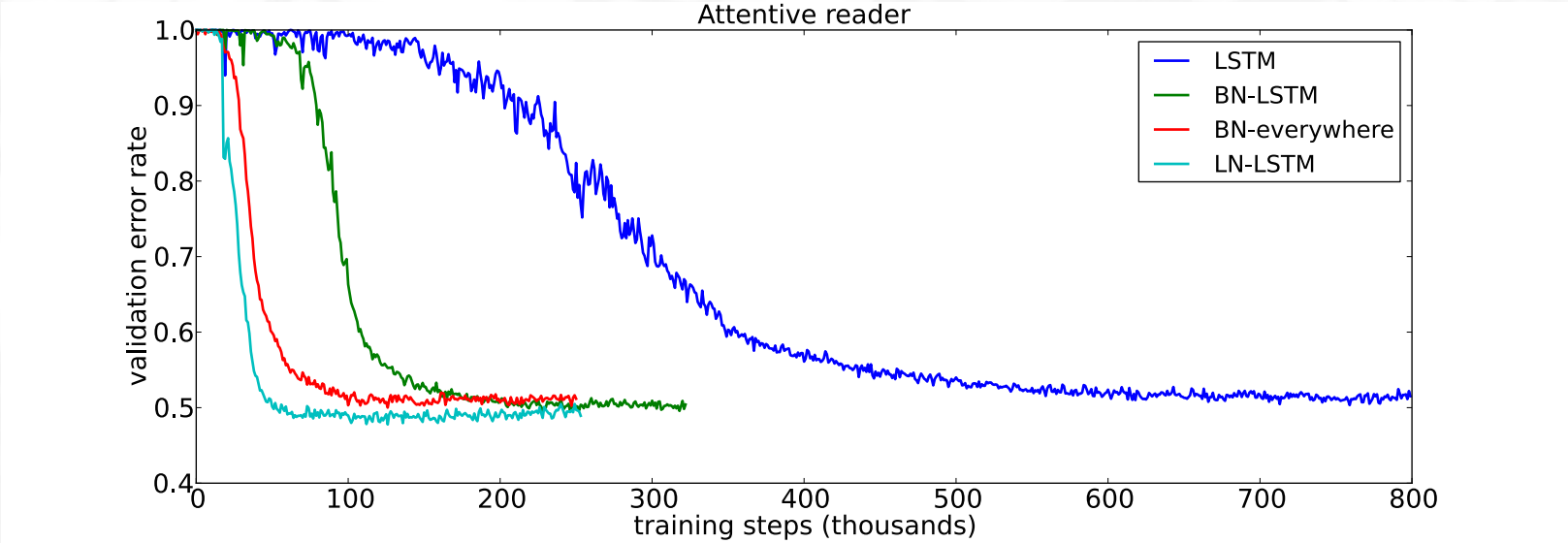

Figure 2: Validation curves for the attentive reader model. BN results are taken from [Cooijmans et al., 2016].

TF Layers and Variable Creation

When tf.layers.Dense or tf.nn.rnn_cell.{GRU,...}Cell is constructed, no variables are yet created (one of the reasons is that the size of the input is not known at that time).

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If no variable scope is defined during variable instantiation, a unique one is generated; otherwise, it is respected. This causes problems during tf.nn.[bidirectional_]dynamic_rnn, which opens a fixed scope if None is passed. Therefore, the safest approach is to always provide a unique scope for tf.nn.[bidirectional_]dynamic_rnn.

Refreshing Word Embeddings

Recall that instead of one-hot encoding, distributed representation of words is preferred.

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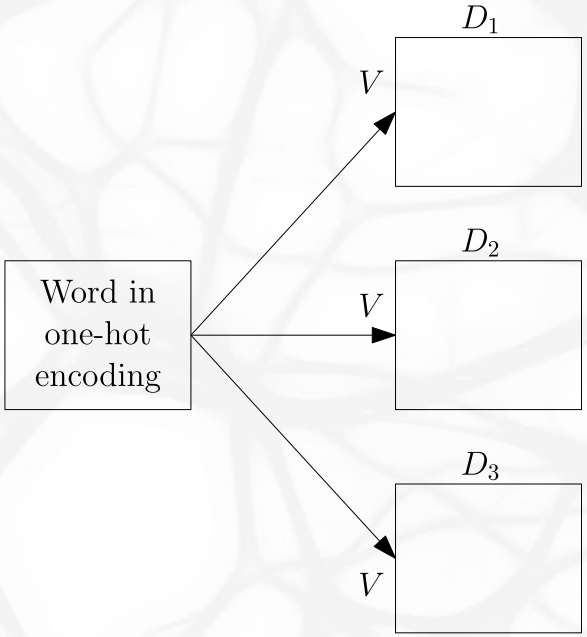

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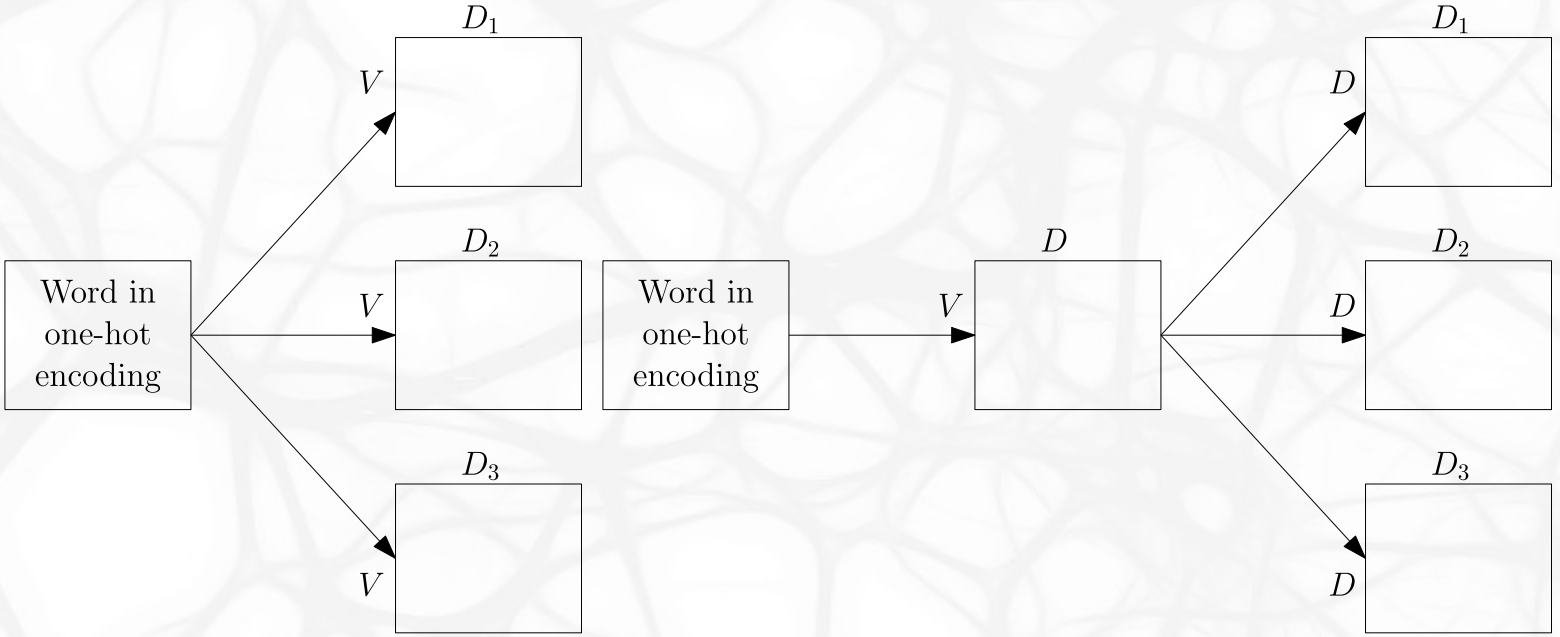

Sequence-to-Sequence Architecture

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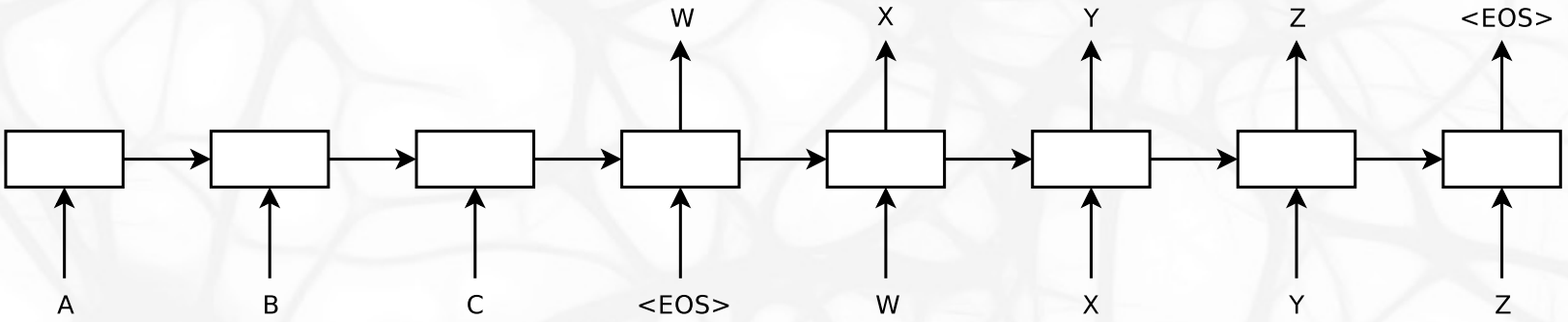

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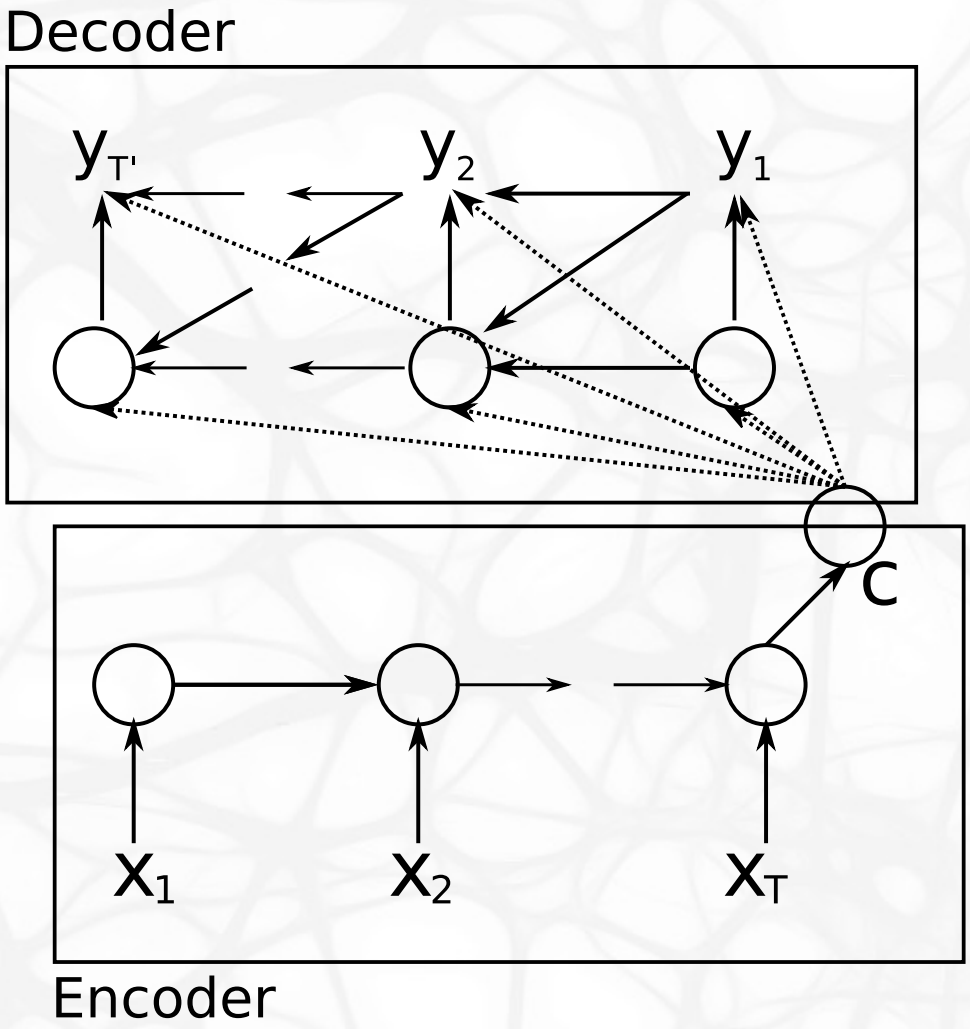

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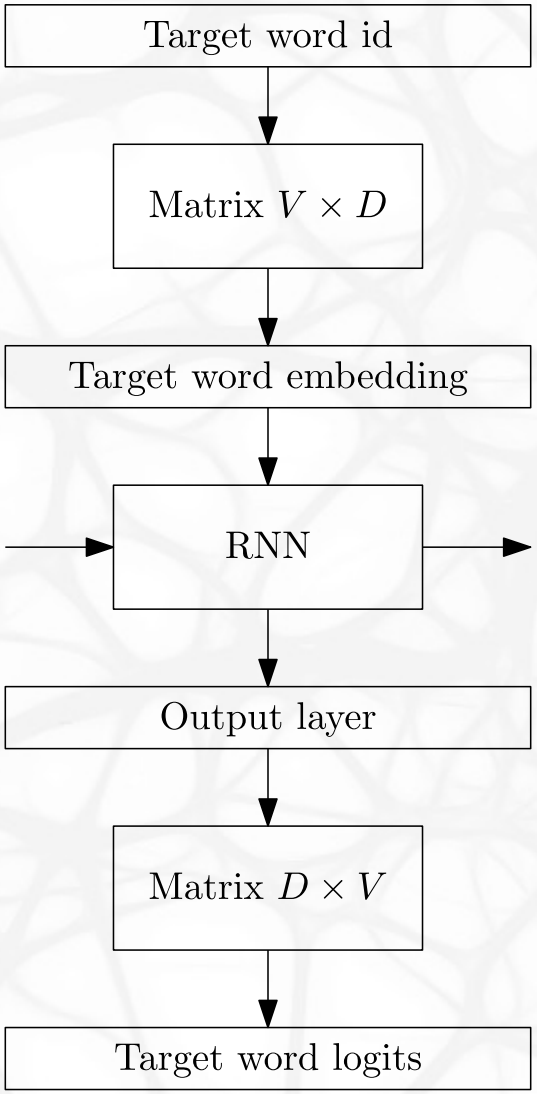
Inference

During inference, the network processes its own predictions.

Usually, the generated logits are processed by an $\arg\max$, the chosen word embedded and used as next input.

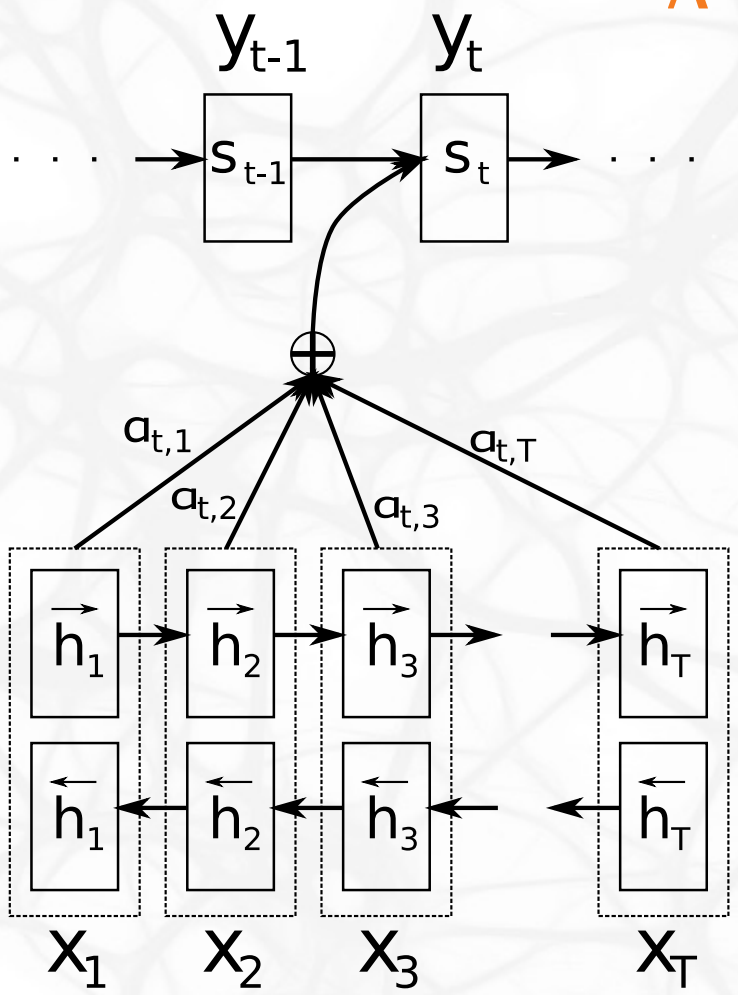
Tying Word Embeddings



Attention

As another input during decoding, we add *context vector* c_i:

$$\boldsymbol{s}_i = f(\boldsymbol{s}_{i-1}, \boldsymbol{y}_{i-1}, \boldsymbol{c}_i).$$



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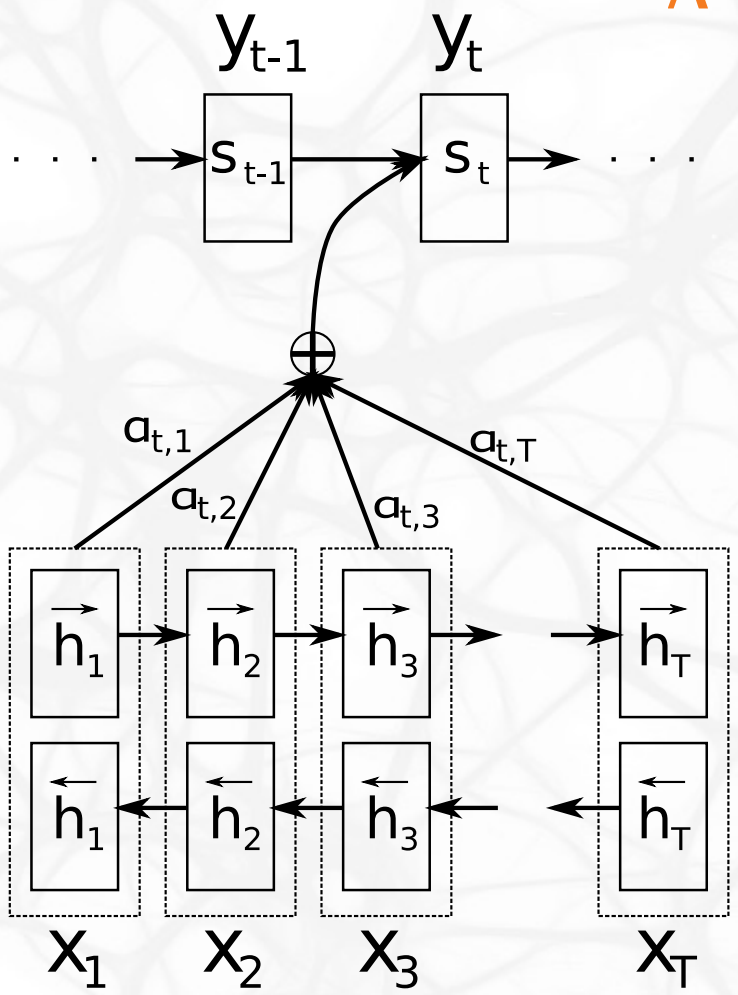

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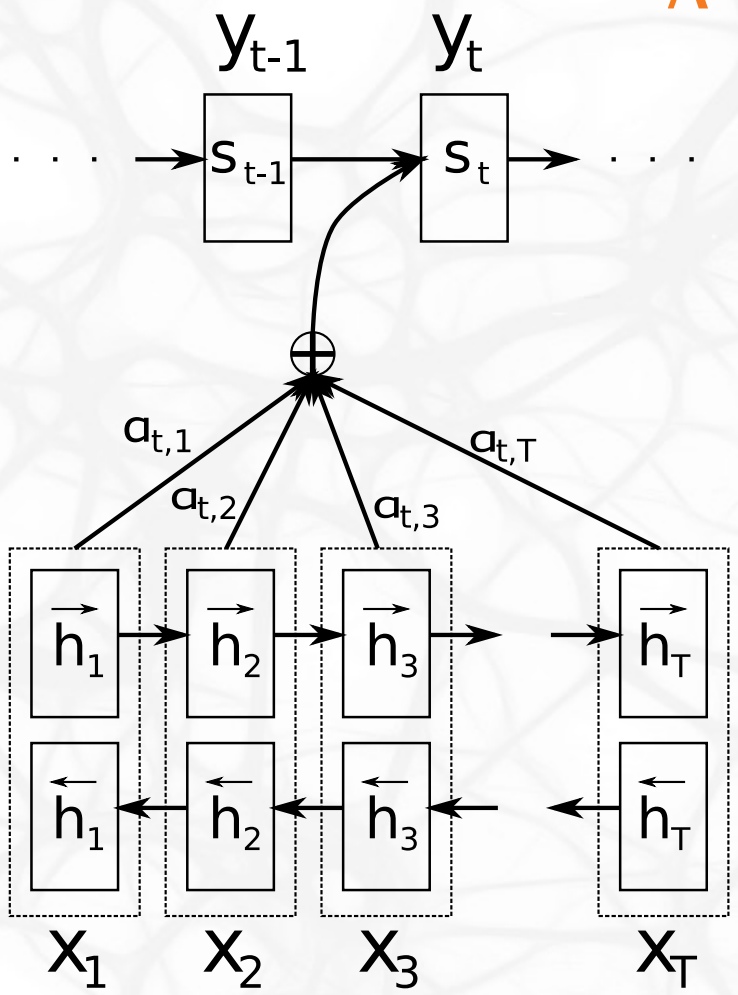
The weights α_{ij} are softmax of e_{ij} over j, $\boldsymbol{\alpha}_i = \mathrm{softmax}(\boldsymbol{e}_i)$, with e_{ij} being

$$e_{ij} = \boldsymbol{v}^\top \tanh(\boldsymbol{V}\boldsymbol{h}_j + \boldsymbol{W}\boldsymbol{s}_{i-1} + \boldsymbol{b}).$$



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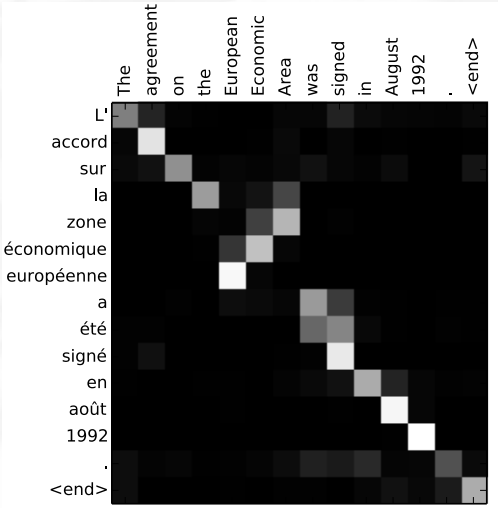
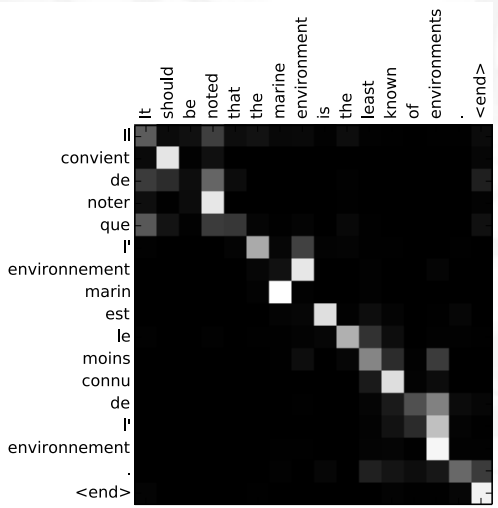


(a)



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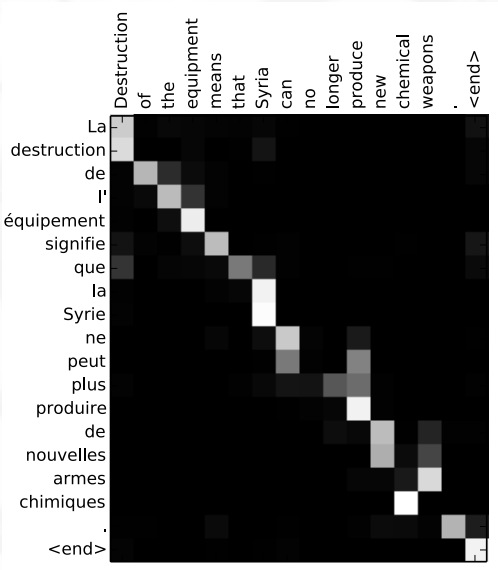
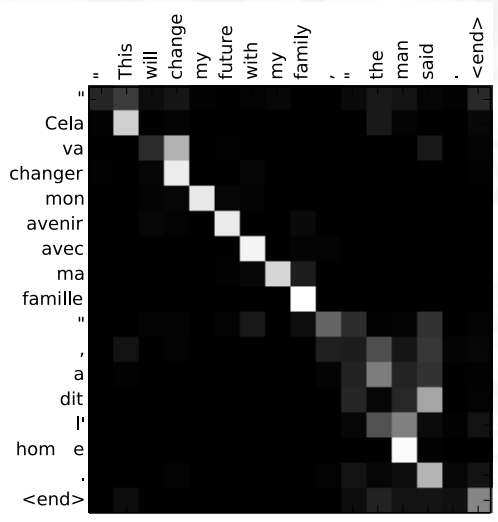


(c)



(d)

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  Considering a dictionary with words *low, lowest, newer, wider*:

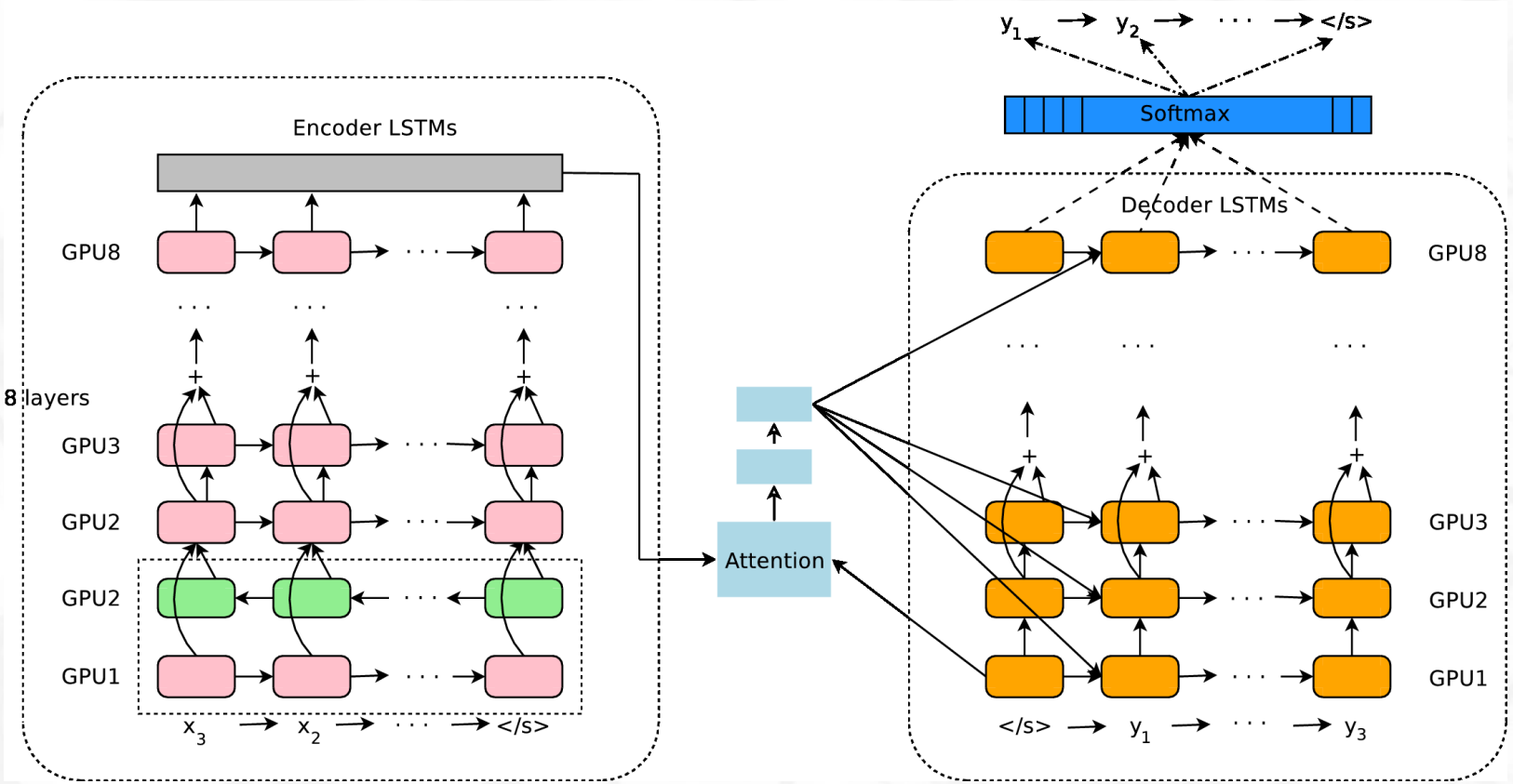
$$r \ \cdot \rightarrow r\cdot$$
$$l \ \ o \rightarrow lo$$
$$lo \ \ w \rightarrow low$$
$$e \ \ r\cdot \rightarrow er\cdot$$

Subword Units

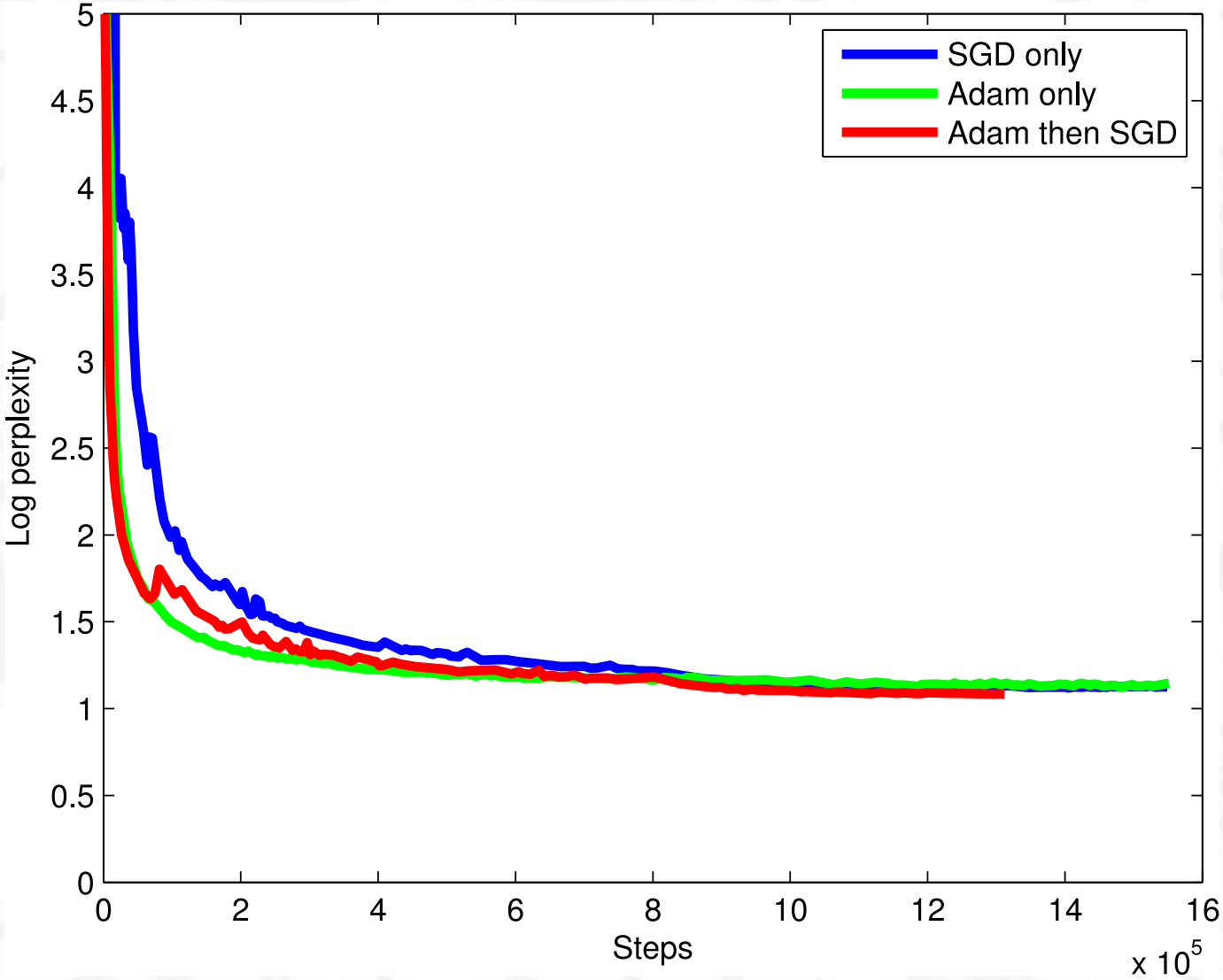
- Wordpieces – Similar heuristic of joining two neighboring symbols (maximizing likelihood under unigram language model).

Usually quite little subword units are used (32k-64k), often generated on the union of the two vocabularies (the so-called *joint BPE* or *shared wordpieces*).

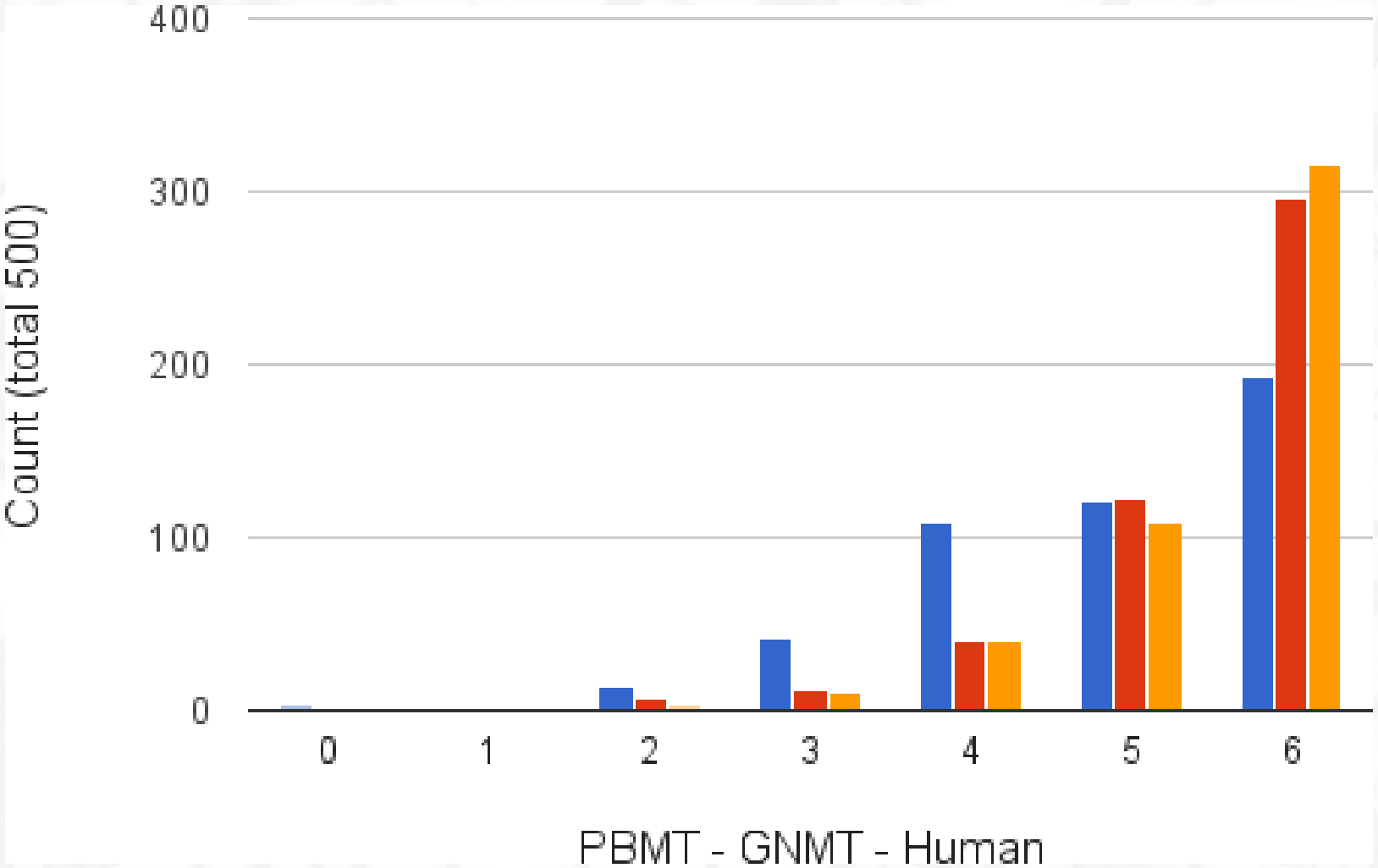
Google NMT


Encoder LSTMs
GPU8
8 layers
GPU3
GPU2
GPU2
GPU1
x3
x2
</s>
Attention
y1
y2
</s>
Softmax
Decoder LSTMs
GPU8
GPU3
GPU2
GPU1
</s>
y1
y3

Google NMT


SGD only
Adam only
Adam then SGD
Log perplexity
Steps
x 10^5
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
0
2
4
6
8
10
12
14
16

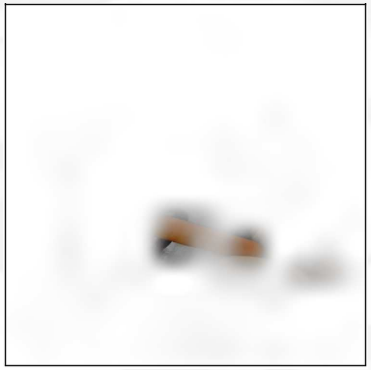
Google NMT



Beyond one Language Pair

Fig. 5. A selection of evaluation results, grouped by human rating.

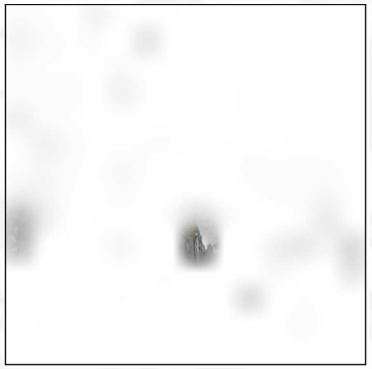
Beyond one Language Pair



What vegetable is the dog chewing on?
MCB: carrot
GT: carrot

What kind of dog is this?
MCB: husky
GT: husky

What kind of flooring does the room have?
MCB: carpet
GT: carpet



What color is the traffic light?
MCB: green
GT: green

Is this an urban area?
MCB: yes
GT: yes

Where are the buildings?
MCB: in background
GT: on left

Multilingual Translation

Many attempts at multilingual translation.

- Individual encoders and decoders, shared attention.
- Shared encoders and decoders.

Attention is All You Need

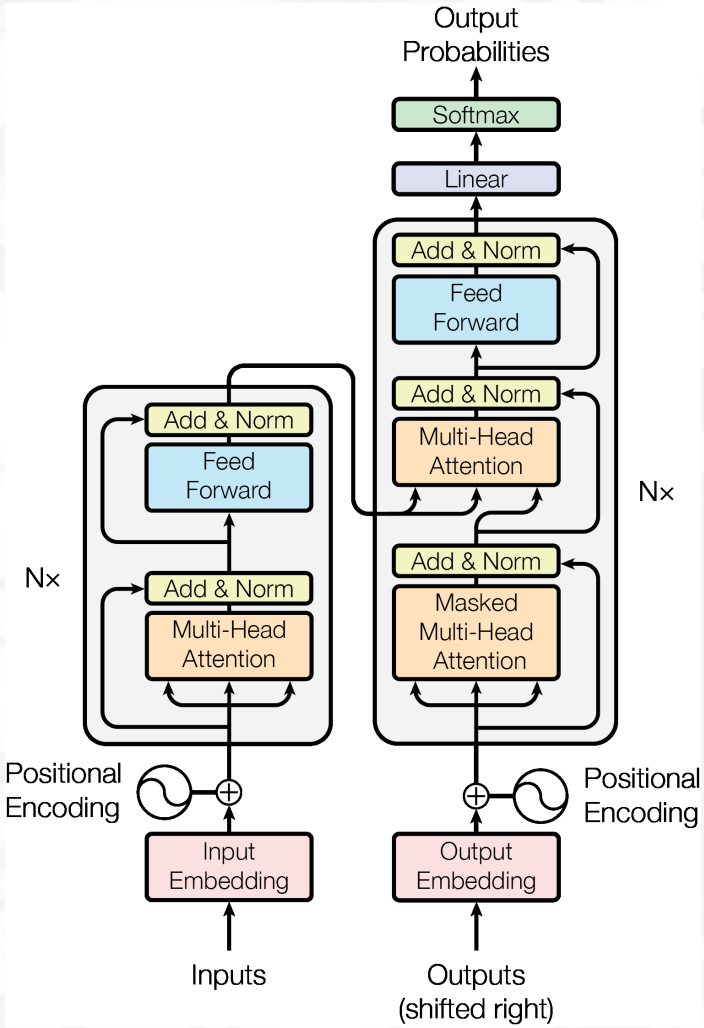


Figure 1: The Transformer - model architecture.

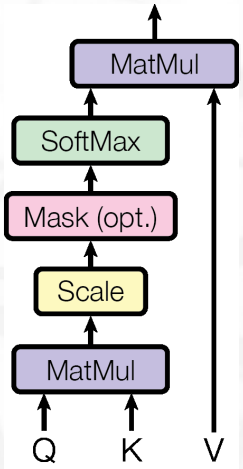
Attention is All You Need

The attention module is defined as:

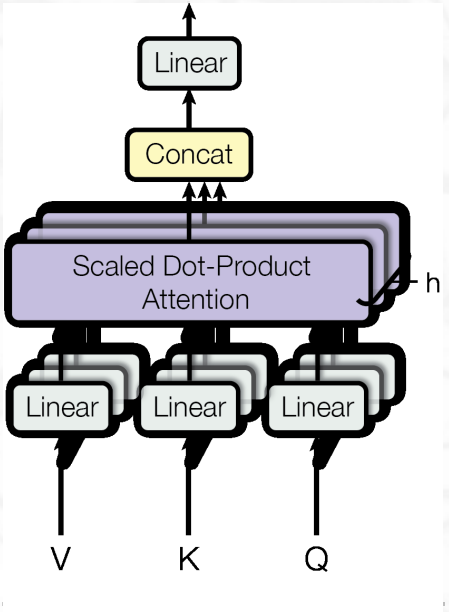
$$\text{Attention}(\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V}) = \text{softmax}\left(\frac{\boldsymbol{Q}\boldsymbol{K}^\top}{\sqrt{d_k}}\right)\boldsymbol{V}.$$

Multihead attention is used in practice.

Scaled Dot-Product Attention



Multi-Head Attention



Positional Embeddings

We need to encode positional information (which was implicit in RNNs).

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- Learned embeddings for every position.

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- Learned embeddings for every position.
- Sinusoids of different frequencies:

$$\mathrm{PE}_{(pos,2i)} = \sin\left(pos/10000^{2i/d}\right)$$
$$\mathrm{PE}_{(pos,2i+1)} = \cos\left(pos/10000^{2i/d}\right)$$

This choice of functions should allow the model to attend to relative positions, since for any fixed k, PE_{pos+k} is a linear function of PE_{pos}.

Why Attention

Table 1: Maximum path lengths, per-layer complexity and minimum number of sequential operations for different layer types. n is the sequence length, d is the representation dimension, k is the kernel size of convolutions and r the size of the neighborhood in restricted self-attention.

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

Transformers Results

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	**$3.3 \cdot 10^{18}$**	
Transformer (big)	**28.4**	**41.8**	$2.3 \cdot 10^{19}$	