Social Media & Text Analysis

lecture 9 - Deep Learning for NLP

CSE 5539-0010 Ohio State University

Instructor: Wei Xu

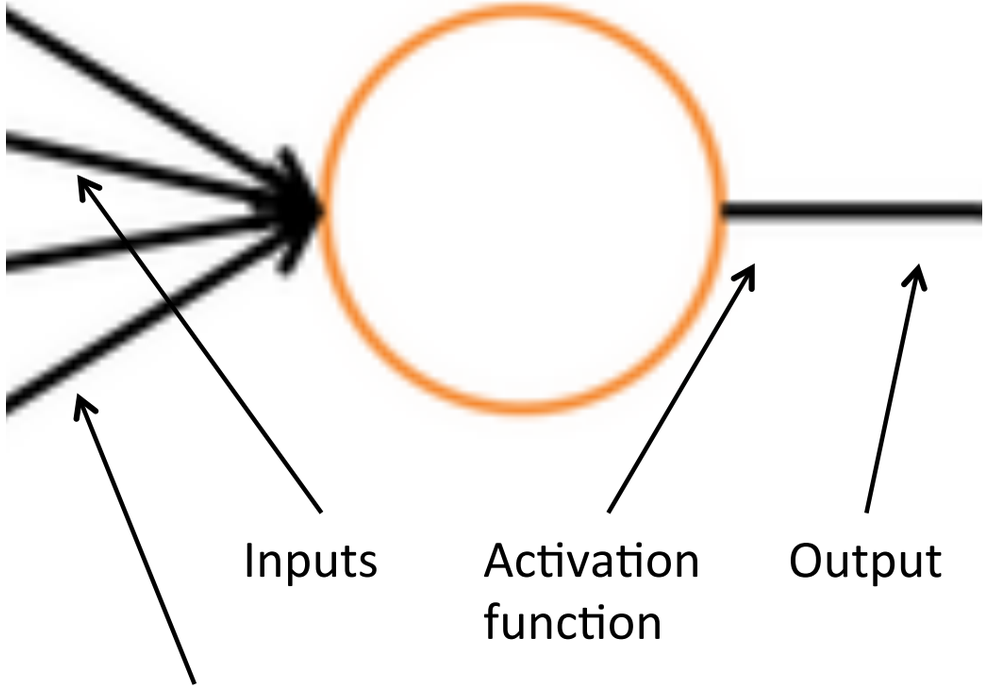
Website: socialmedia-class.org

Many slides are adapted from Richard Socher, Greg Durret, Chris Dyer, Dan Jurafsky, Chris Manning

A Neuron

- If you know Logistic Regression, then you already understand a basic neural network neuron!

A single neuron
A computational unit with *n* (3) inputs
and 1 output
and parameters *W, b*



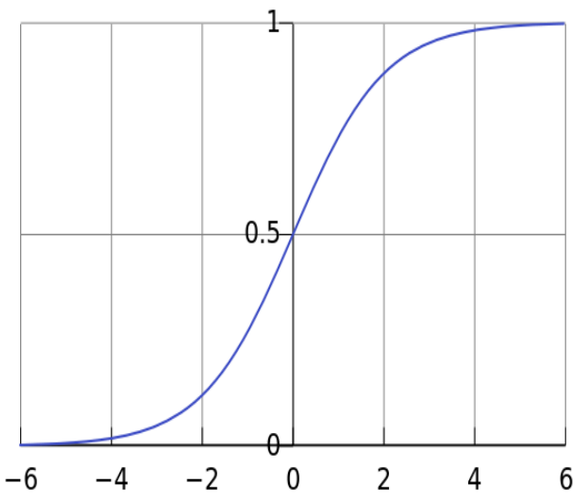
A Neuron

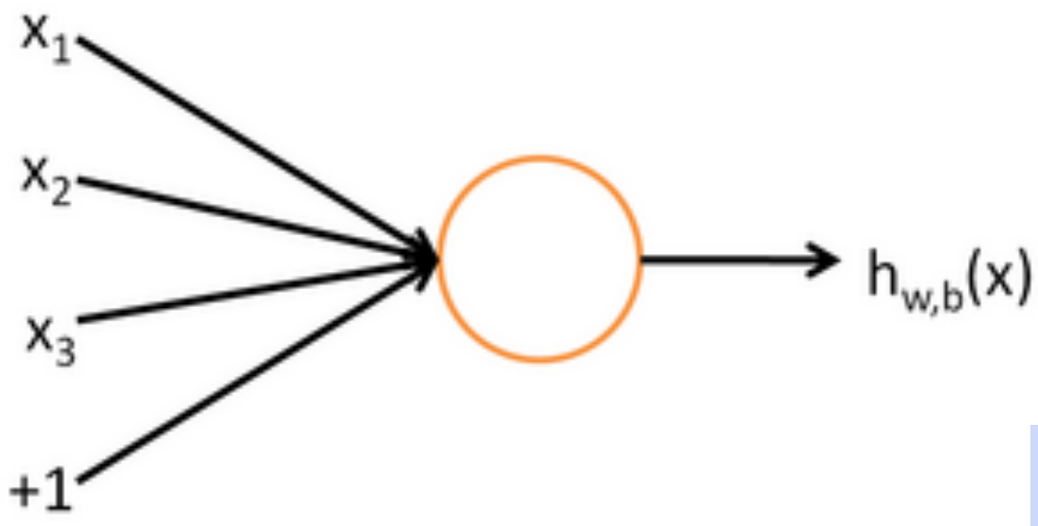
is essentially a binary logistic regression unit

$$h_{w,b}(x) = f(w^{\mathsf{T}}x + b)$$

b: We can have an "always on" feature, which gives a class prior, or separate it out, as a bias term

$$f(z) = \frac{1}{1+e^{-z}}$$



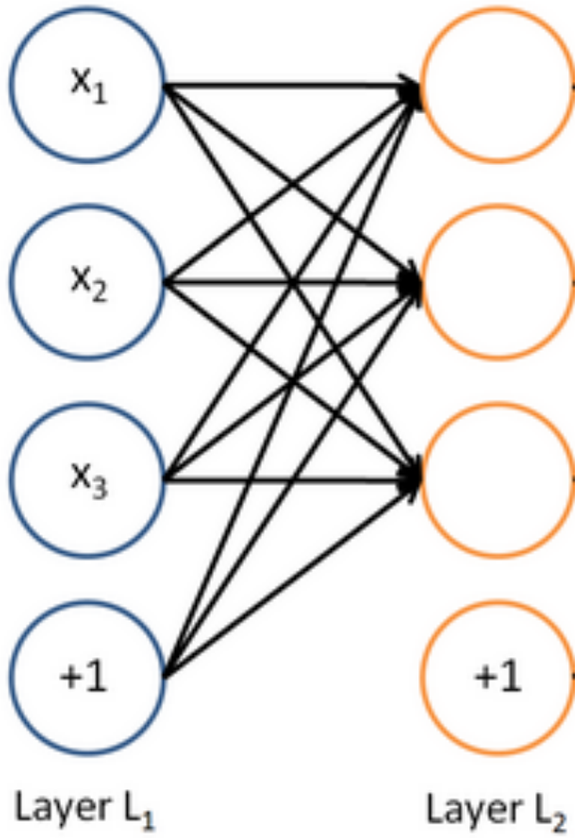


w, *b* are the parameters of this neuron
i.e., this logistic regression model

A Neural Network

= running several logistic regressions at the same time

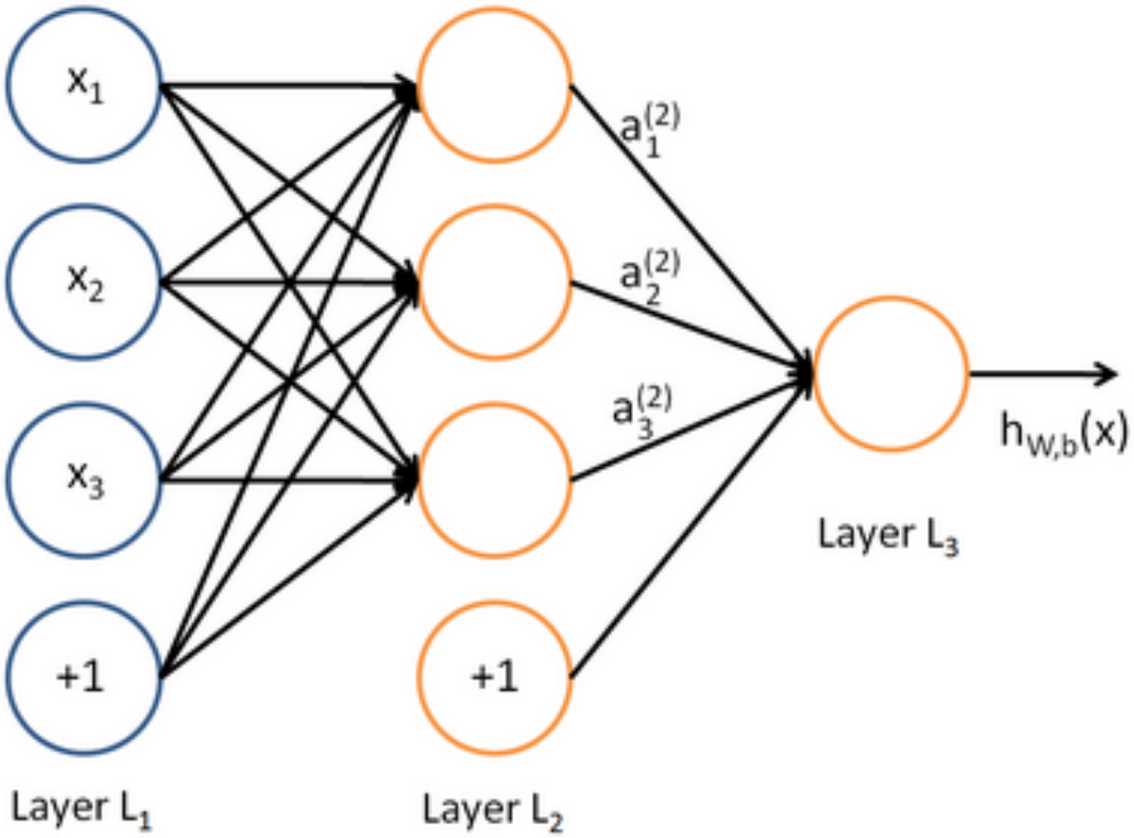
If we feed a vector of inputs through a bunch of logistic regression functions, then we get a vector of outputs …



A Neural Network

= running several logistic regressions at the same time

… which we can feed into another logistic regression function

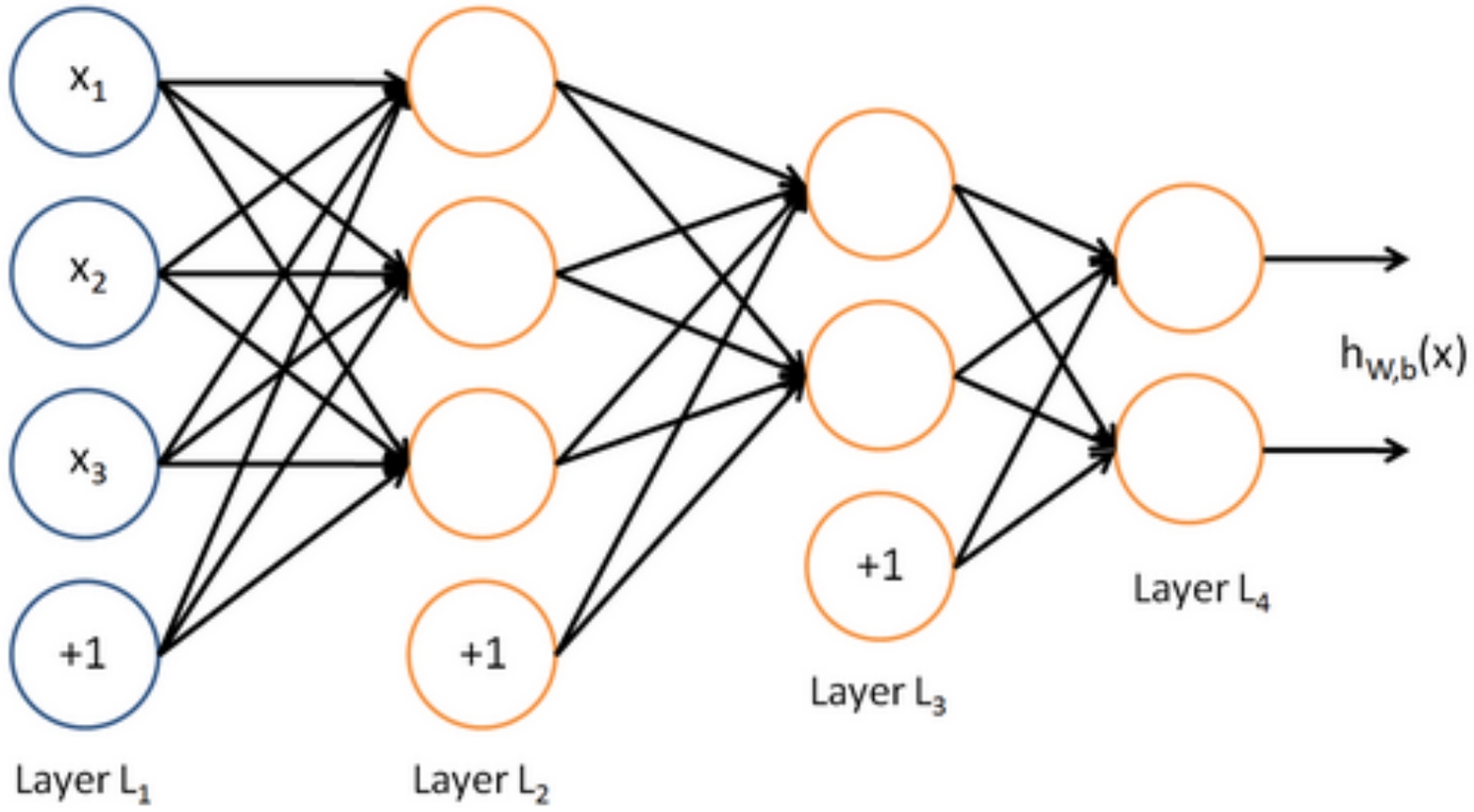


It is the loss function that will direct what the intermediate hidden variables should be, so as to do a good job at predicting the targets for the next layer, etc.

A Neural Network

= running several logistic regressions at the same time

Before we know it, we have a multilayer neural network….



f: Activation Function

We have

$$a_1 = f(W_{11}x_1 + W_{12}x_2 + W_{13}x_3 + b_1)$$

$$a_2 = f(W_{21}x_1 + W_{22}x_2 + W_{23}x_3 + b_2)$$

etc.

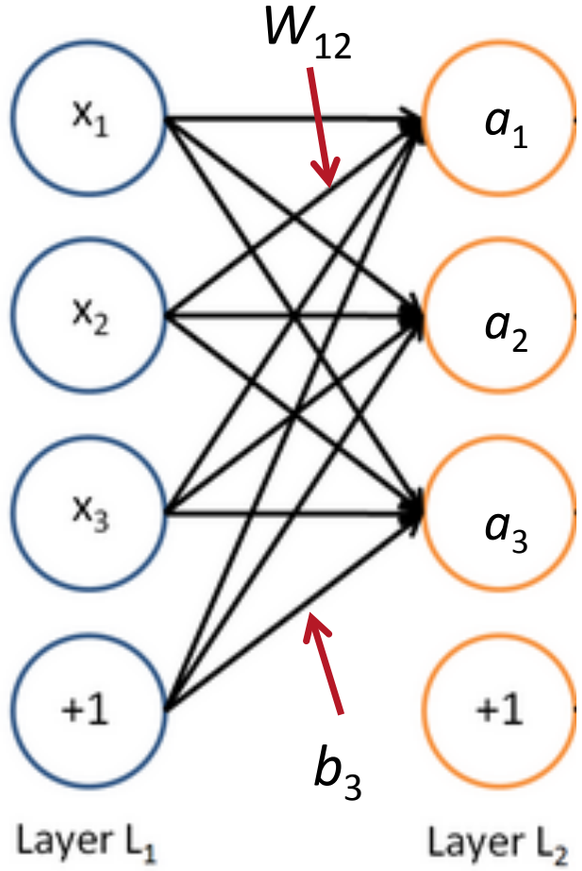
In matrix notation

$$z = Wx + b$$

$$a = f(z)$$

where f is applied element-wise:

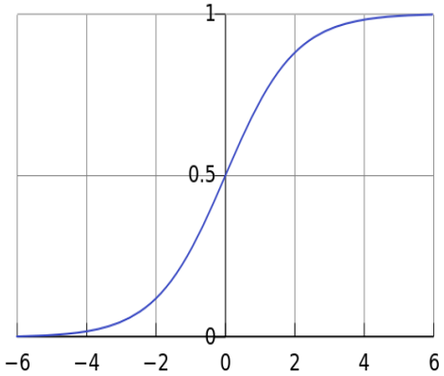
$$f([z_1, z_2, z_3]) = [f(z_1), f(z_2), f(z_3)]$$



Activation Function

logistic ("sigmoid")

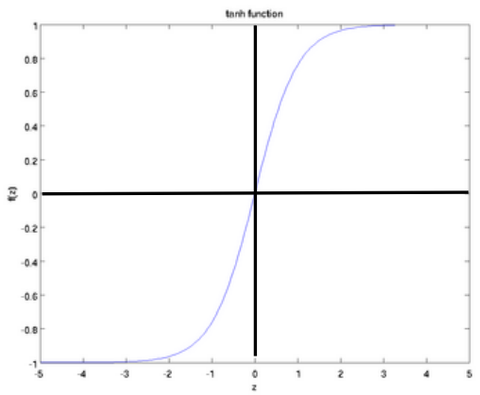
$$f(z) = \frac{1}{1 + \exp(-z)}.$$



$$f'(z) = f(z)(1 - f(z))$$

tanh

$$f(z) = \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}},$$



$$f'(z) = 1 - f(z)^2$$

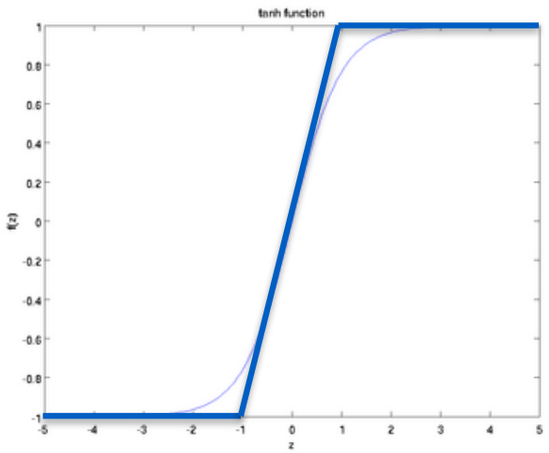
tanh is just a rescaled and shifted sigmoid

$$\tanh(z) = 2\text{logistic}(2z) - 1$$

Activation Function

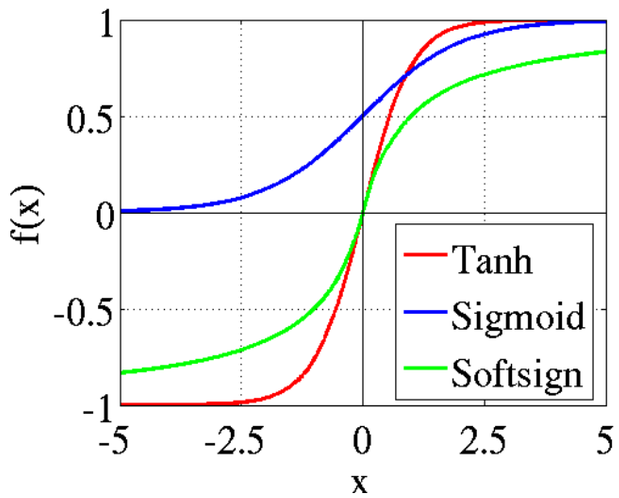
hard tanh

$$\text{HardTanh}(x) = \begin{cases} -1 & \text{if } x < -1 \\ x & \text{if } -1 <= x <= 1 \\ 1 & \text{if } x > 1 \end{cases}$$



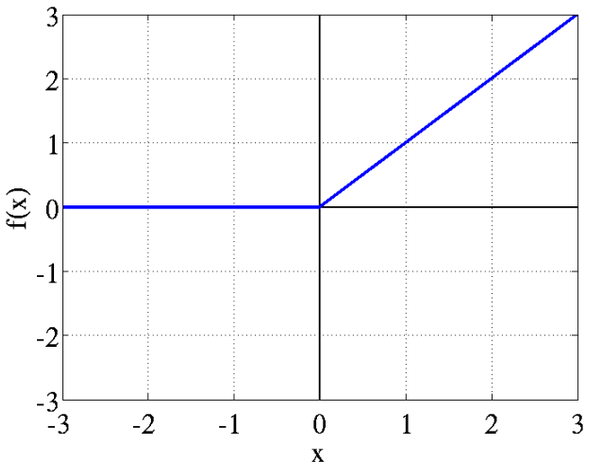
soft sign

$$\text{softsign}(z) = \frac{a}{1+|a|}$$



rectified linear (ReLu)

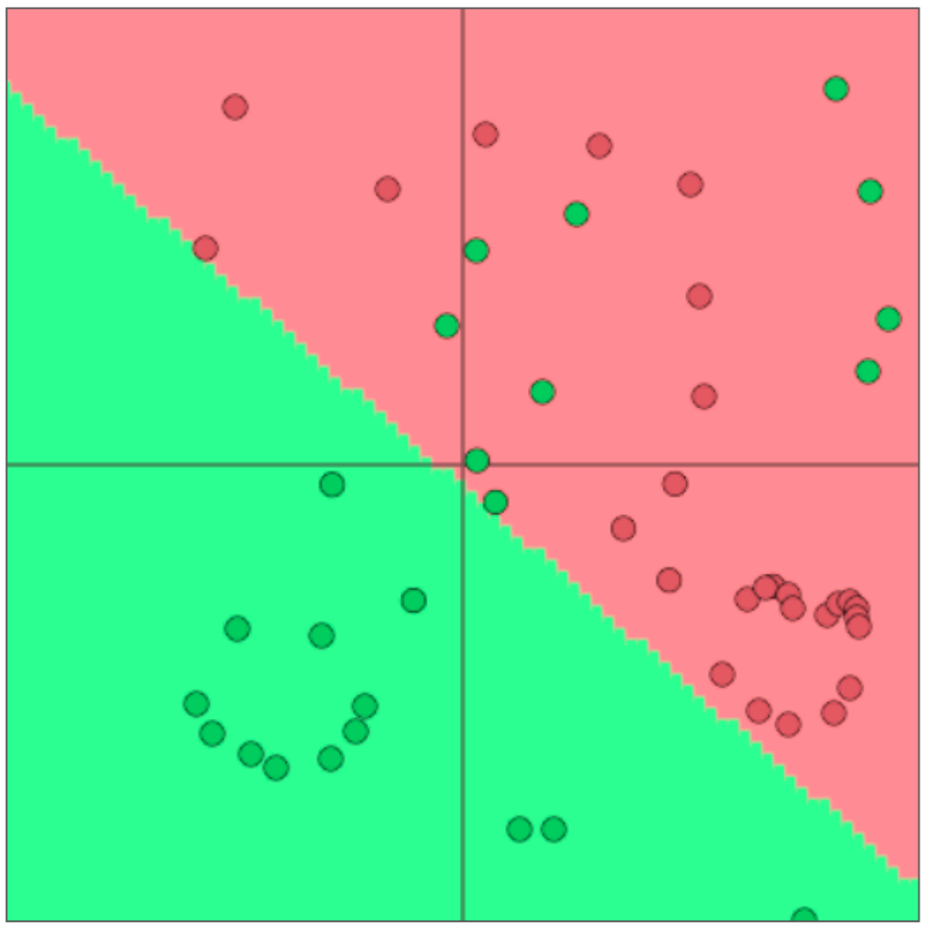
$$\text{rect}(z) = \max(z, 0)$$



- hard tanh similar but computationally cheaper than tanh and saturates hard.
- Glorot and Bengio, *AISTATS* 2011 discuss softsign and rectifier

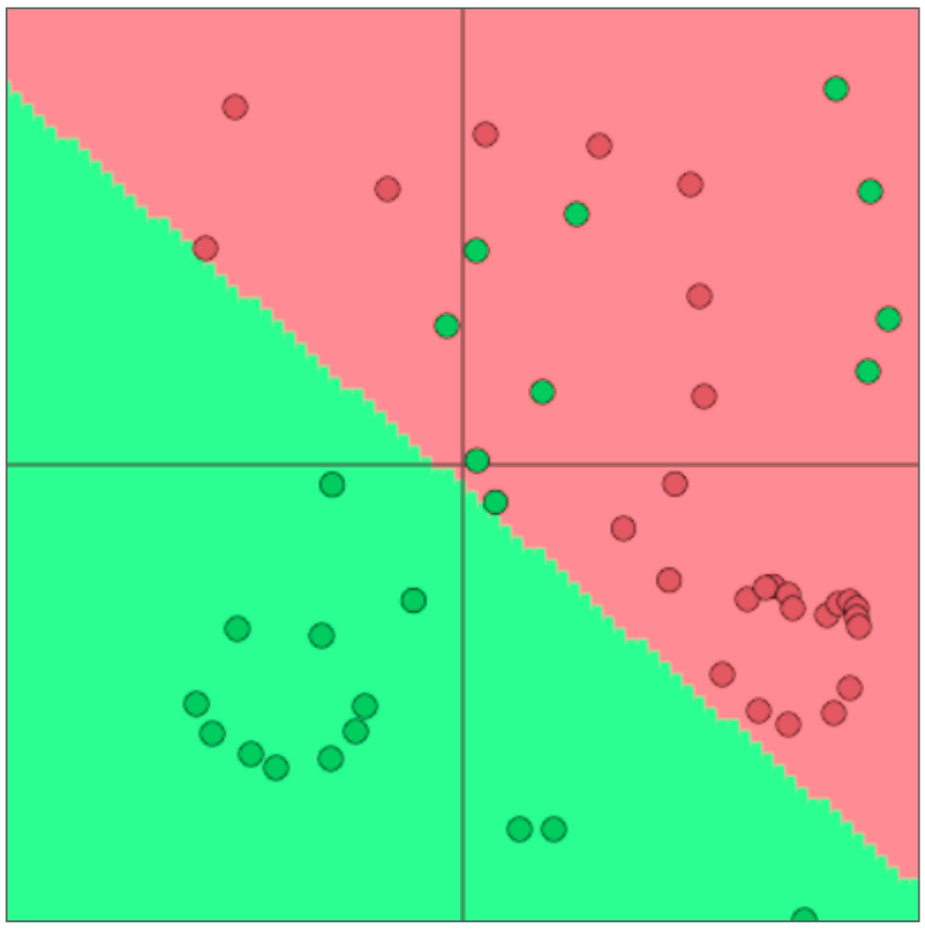
Non-linearity

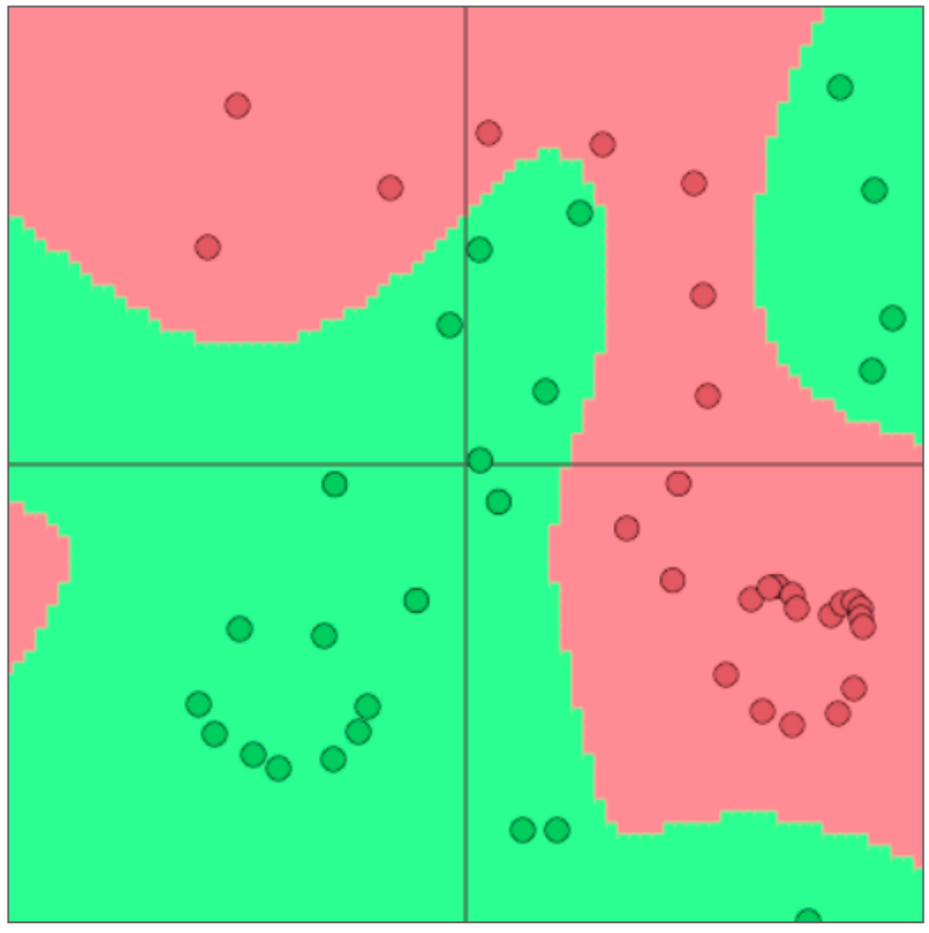
- Logistic (Softmax) Regression only gives linear decision boundaries



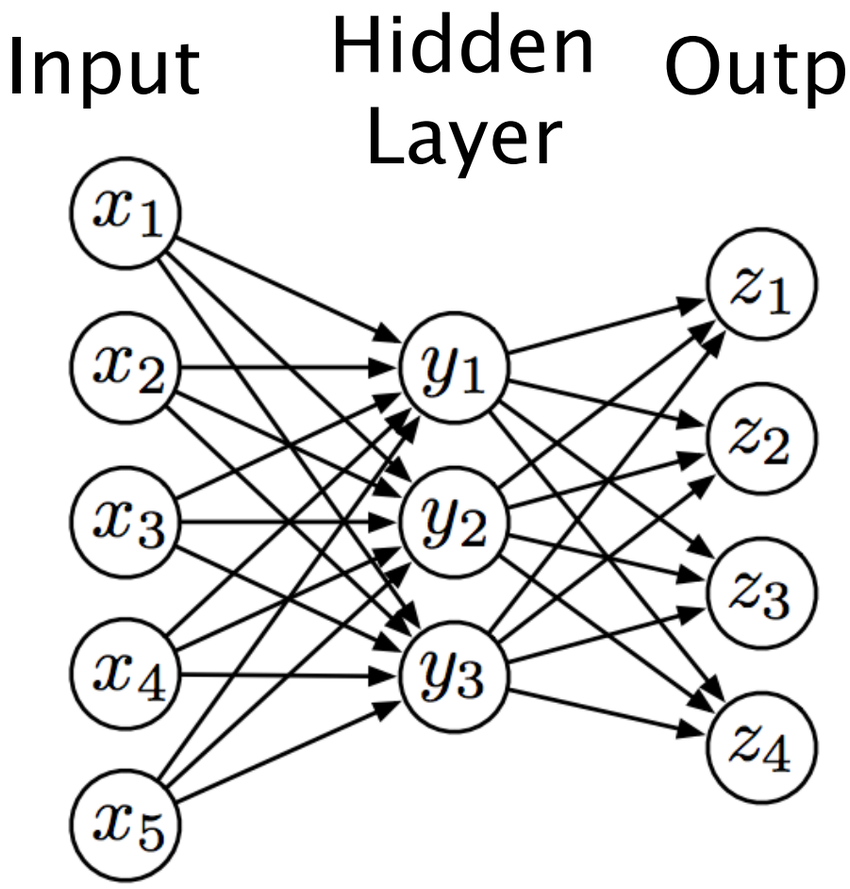
Non-linearity

- Neural networks can learn much more complex functions and nonlinear decision boundaries!





Non-linearity



$$\boldsymbol{y} = g(\mathbf{W}\boldsymbol{x} + \boldsymbol{b})$$

$$\mathbf{z} = g(\mathbf{V}\underbrace{g(\mathbf{W}\mathbf{x} + \mathbf{b})}_{\text{output of first layer}} + \mathbf{c})$$

With no nonlinearity:

$$\mathbf{z} = \mathbf{V}\mathbf{W}\mathbf{x} + \mathbf{V}\mathbf{b} + \mathbf{c}$$

Equivalent to $\mathbf{z} = \mathbf{U}\mathbf{x} + \mathbf{d}$

What about Word2vec (Skip-gram and CBOW)?

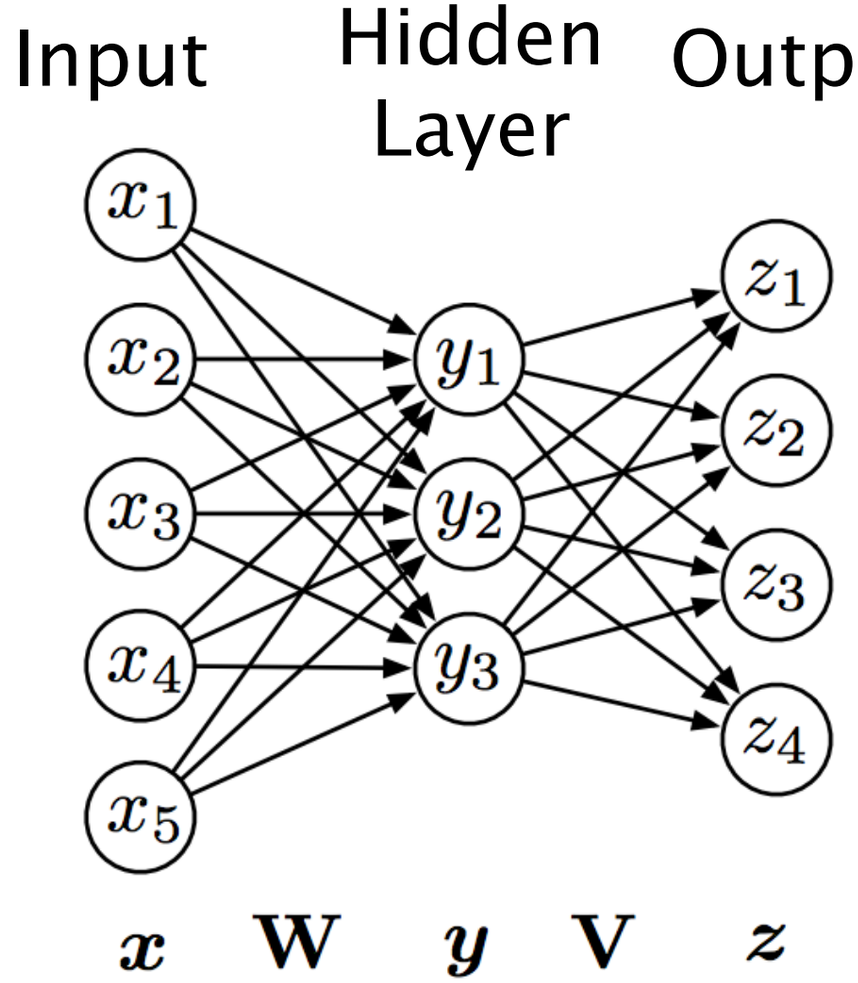
So, what about Word2vec (Skip-gram and CBOW)?

It is not deep learning — but “shallow” neural networks.

It is — in fact — a log-linear model (softmax regression).

So, it is faster over larger dataset yielding better embeddings.

Learning Neural Networks



change in output w.r.t. hidden

$$\frac{dz}{dx} = \frac{dz}{dy} \cdot \frac{dy}{dx}$$

change in hidden w.r.t. input

change in output w.r.t. input

Computing these looks like running this network in reverse (backpropagation)

Strategy for Successful NNs

- Select network structure appropriate for problem
  - Structure: Single words, fixed windows, sentence based, document level; bag of words, recursive vs. recurrent, CNN, …
  - Nonlinearity
- Check for implementation bugs with gradient checks
- Parameter initialization
- Optimization tricks
- Should get close to 100% accuracy/precision/recall/etc… on training data
  - Tune number of iterations on dev data

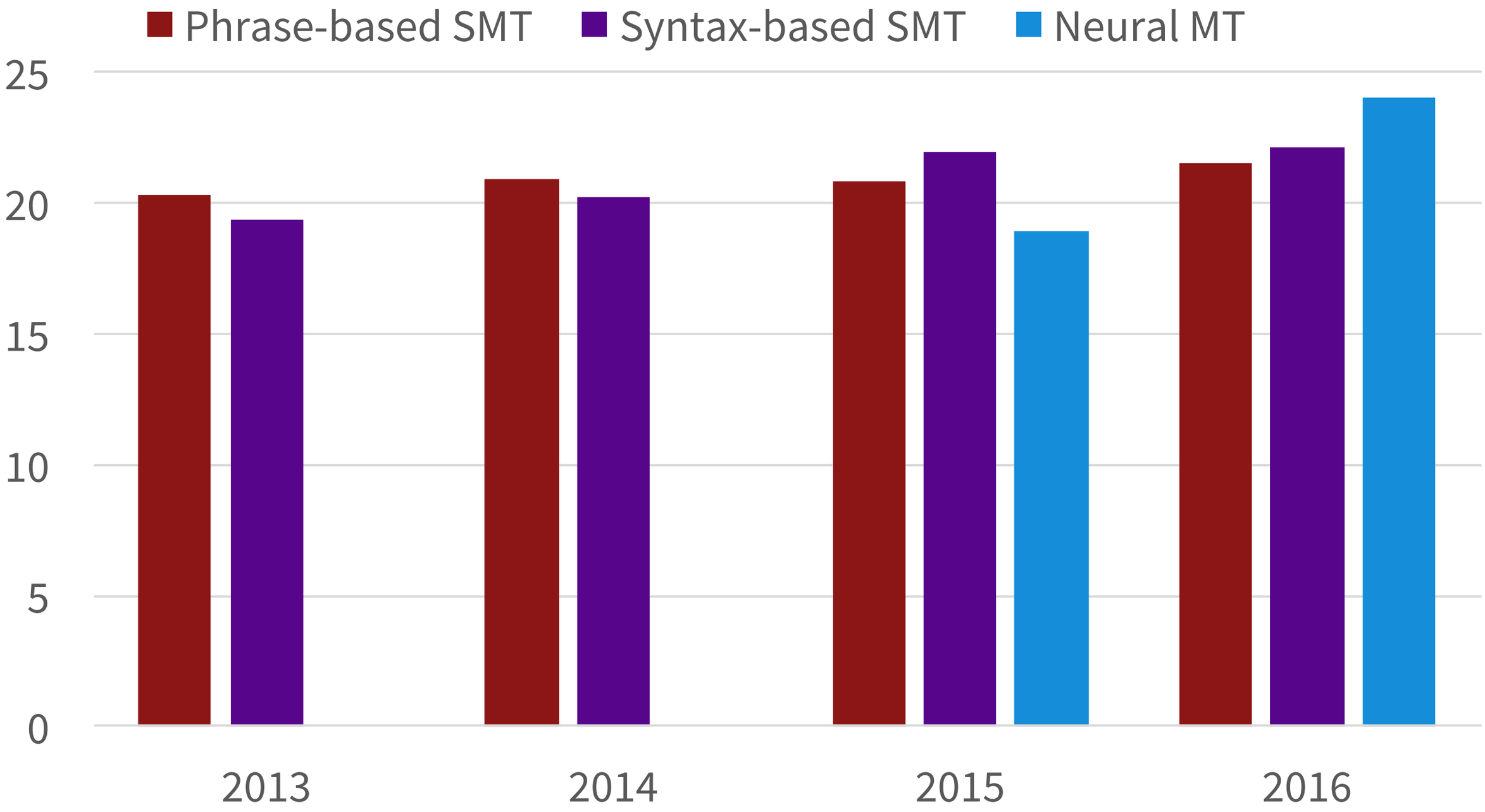
Neural Machine Translation

Neural MT went from a fringe research activity in 2014 to the widely-adopted leading way to do MT in 2016.

Amazing!

Progress in Machine Translation

[Edinburgh En-De WMT newstest2013 Cased BLEU; NMT 2015 from U. Montréal]



From [Sennrich 2016, http://www.meta-net.eu/events/meta-forum-2016/slides/09_sennrich.pdf]

What is Neural MT (NMT)?

Neural Machine Translation is the approach of modeling the **entire** MT process via **one** big artificial neural network*

*But sometimes we compromise this goal a little

The three big wins of Neural MT

1. **End-to-end training**

   All parameters are simultaneously optimized to minimize a loss function on the network's output

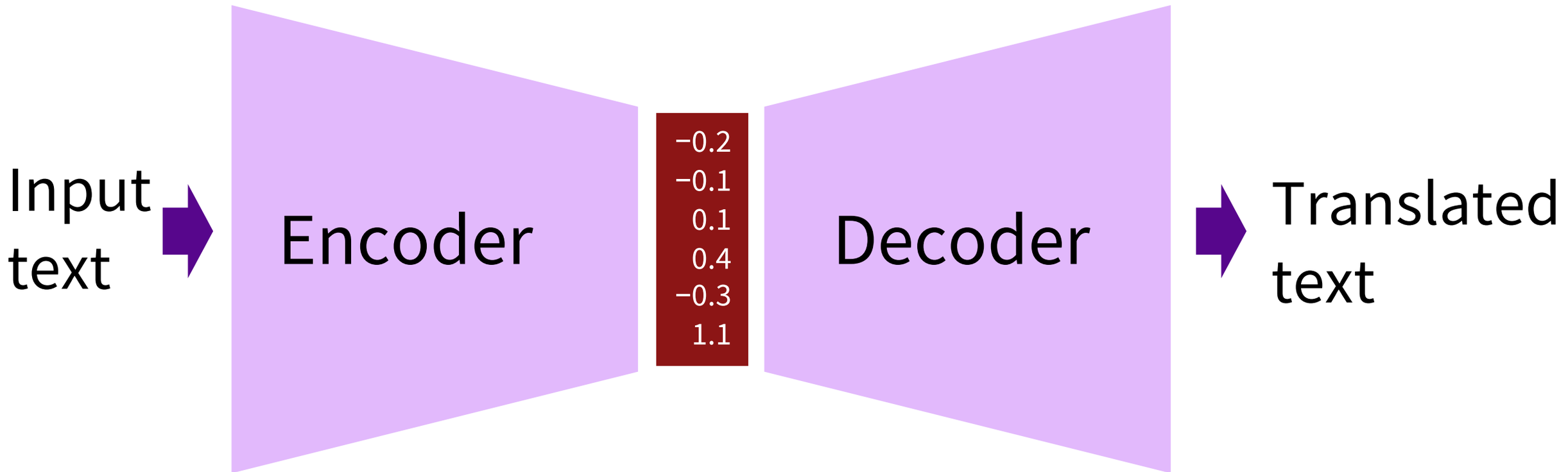
2. **Distributed representations share strength**

   Better exploitation of word and phrase similarities

3. **Better exploitation of context**

   NMT can use a much bigger context – both source and partial target text – to translate more accurately

Neural encoder-decoder architectures



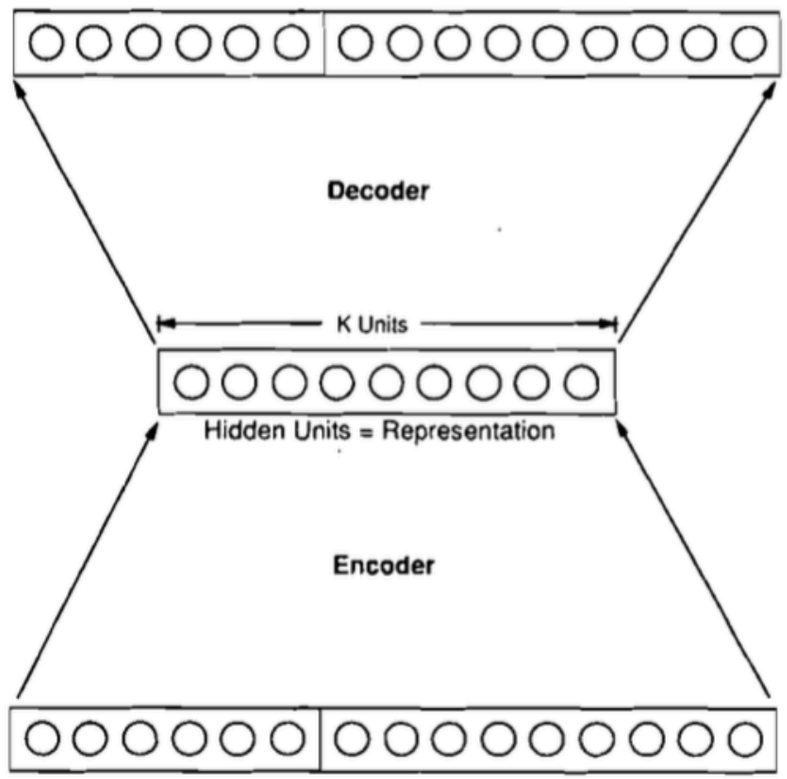
Neural MT: The Bronze Age

[Allen 1987 IEEE 1st ICNN]

3310 En-Es pairs constructed on 31 En, 40 Es words, max 10/11 word sentence; 33 used as test set

The grandfather offered the little girl a book ➔
El abuelo le ofrecio un libro a la nina pequena

Binary encoding of words – 50 inputs, 66 outputs; 1 or 3 hidden 150-unit layers. Ave WER: 1.3 words



Several Studies on Natural Language and Back-Propagation

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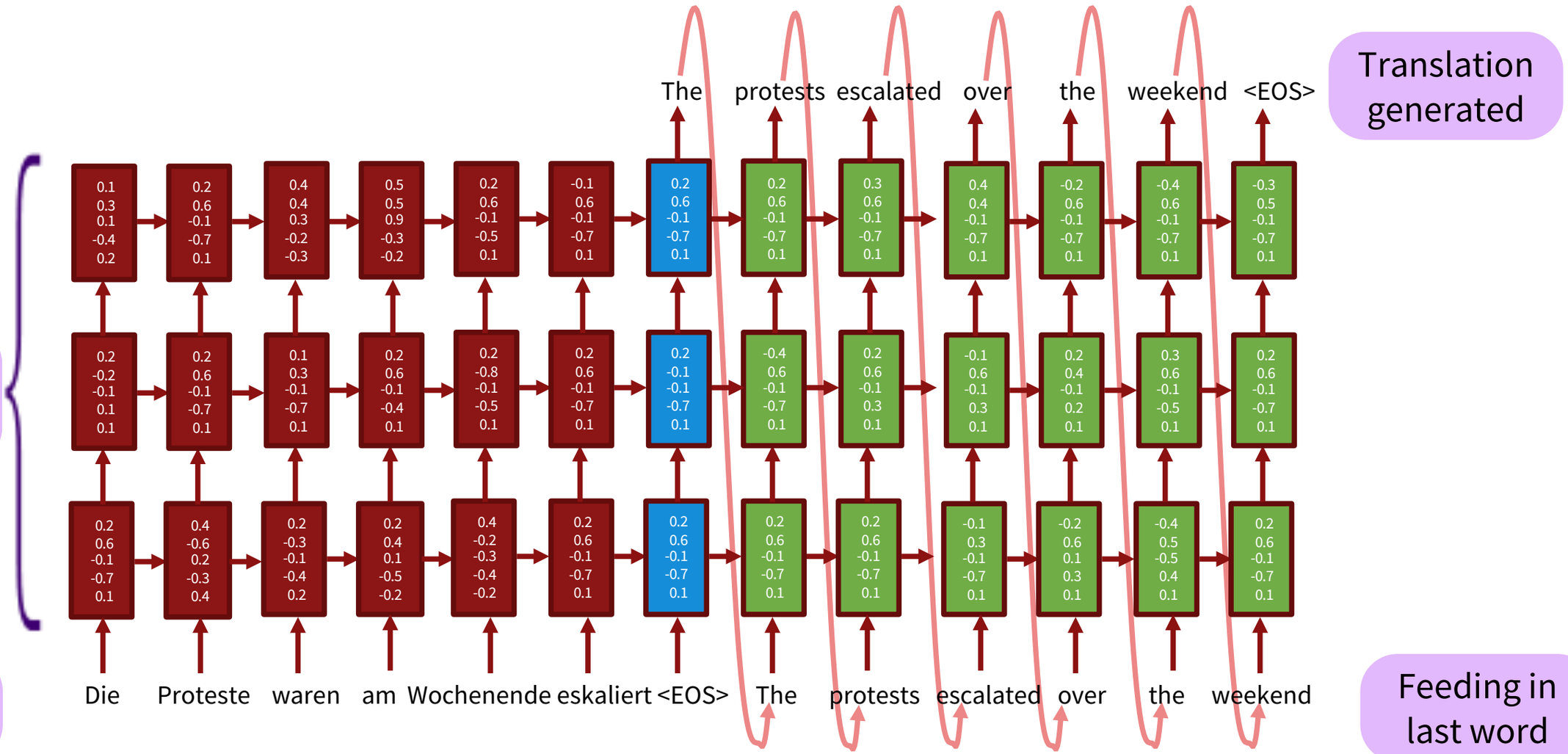
Recent developments in neural algorithms provide a new approach to natural language processing. Two sets of brief studies show how networks may be developed for processing simple demonstratives and analogies. Two longer studies consider pronoun reference and natural language translation. Taken together, the studies provide additional support for the applicability of these algorithms to natural language processing.

Modern Sequence Models for NMT

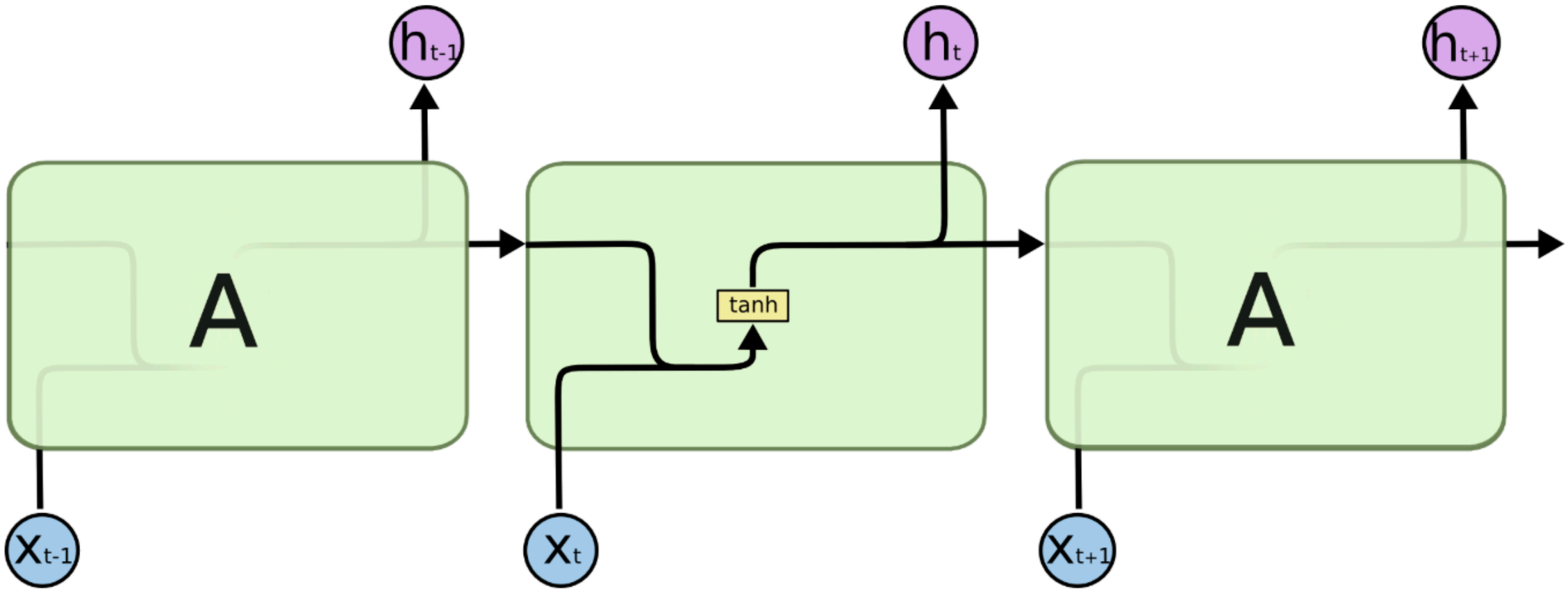
[Sutskever et al. 2014, Bahdanau et al. 2014, et seq.]

following [Jordan 1986] and more closely [Elman 1990]



A deep recurrent neural network

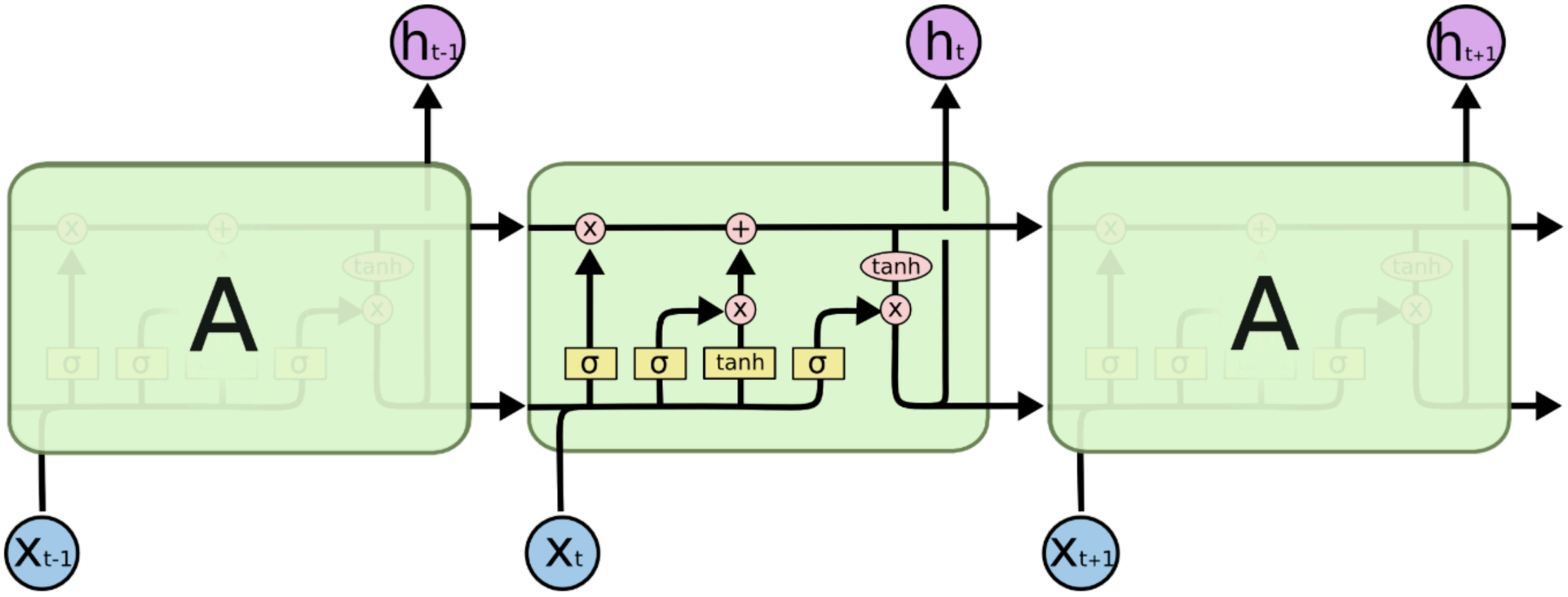
Recurrent Neural Networks (RNN)



The repeating module in a standard RNN contains a single layer.

Source: Colah's Blog

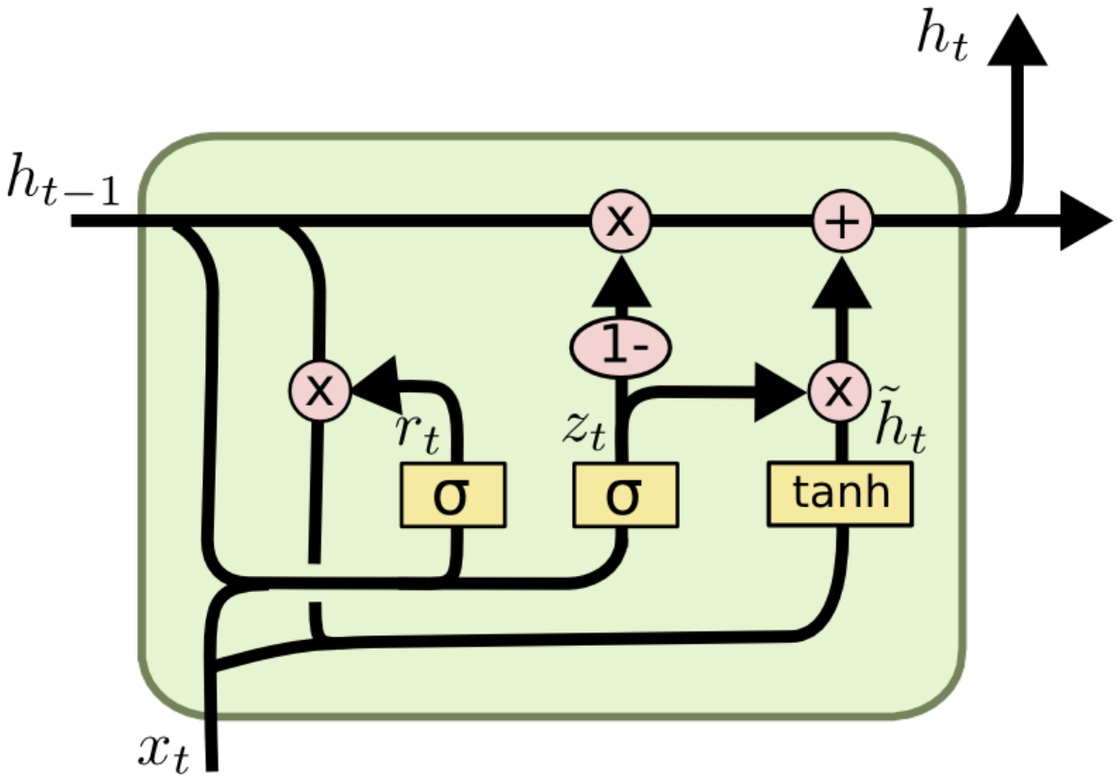
Long Short-Term Memory Networks (LSTM)



The repeating module in an LSTM contains four interacting layers.

Source: Colah's Blog

Long Short-Term Memory Networks (LSTM)

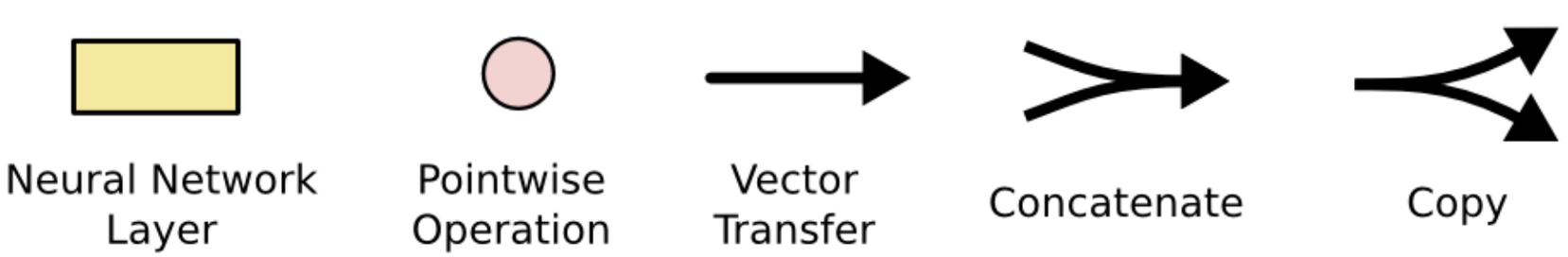


$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

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

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

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



Source: Colah's Blog

Data-Driven Conversation

- **Twitter:** ~ 500 Million Public SMS-Style Conversations ***per Month***
- **Goal:** Learn conversational agents directly from massive volumes of data.

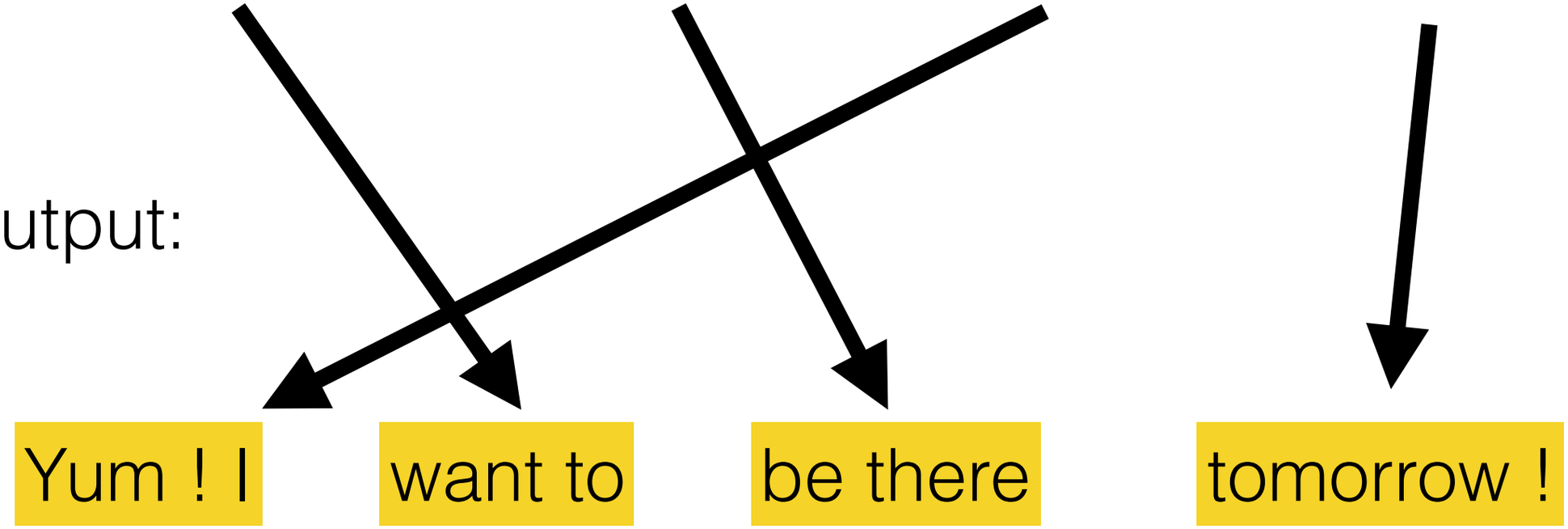
[Ritter, Cherry, Dolan EMNLP 2011]

Noisy Channel Model

Input:

Who wants to come over for dinner tomorrow?

Output:



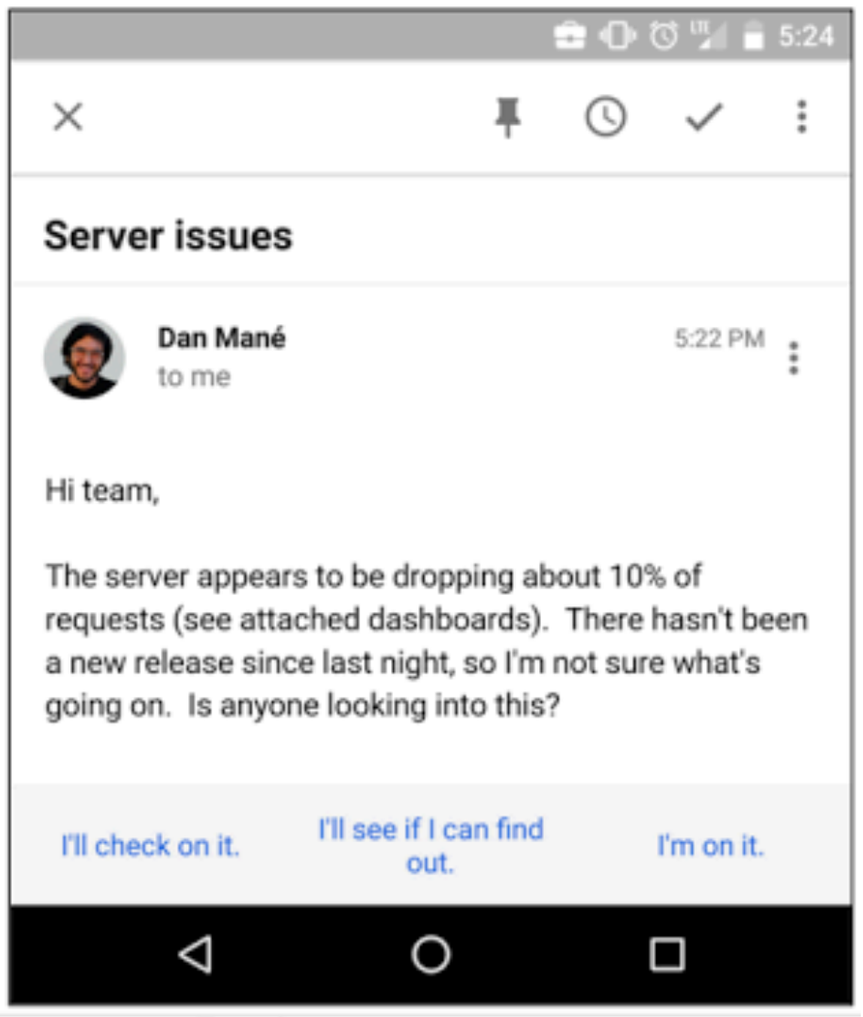
Neural Conversation

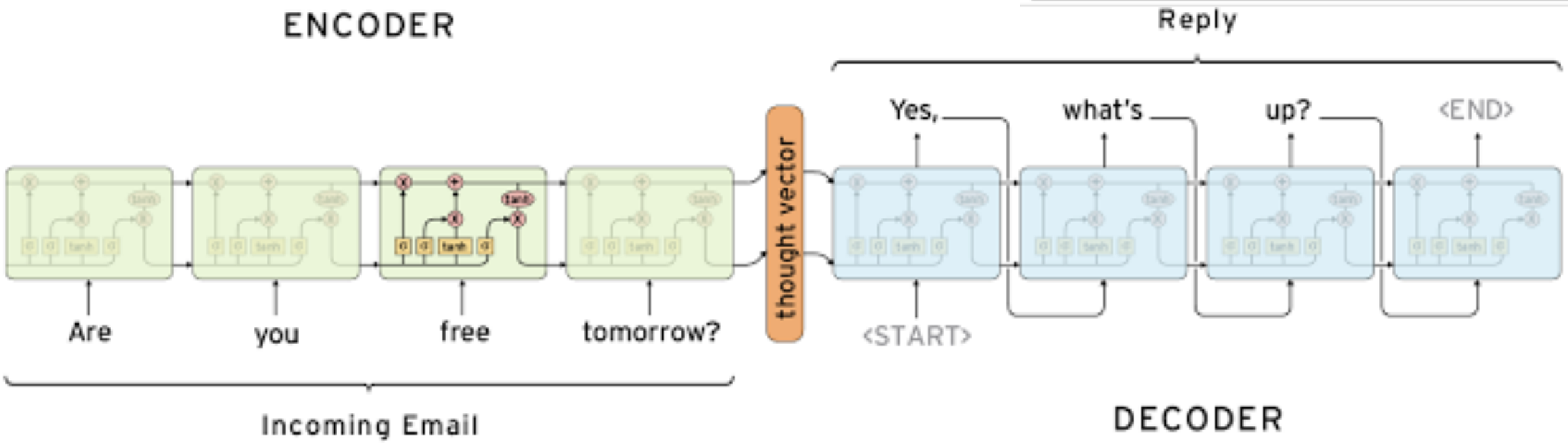
Google Research Blog

Computer, respond to this email.

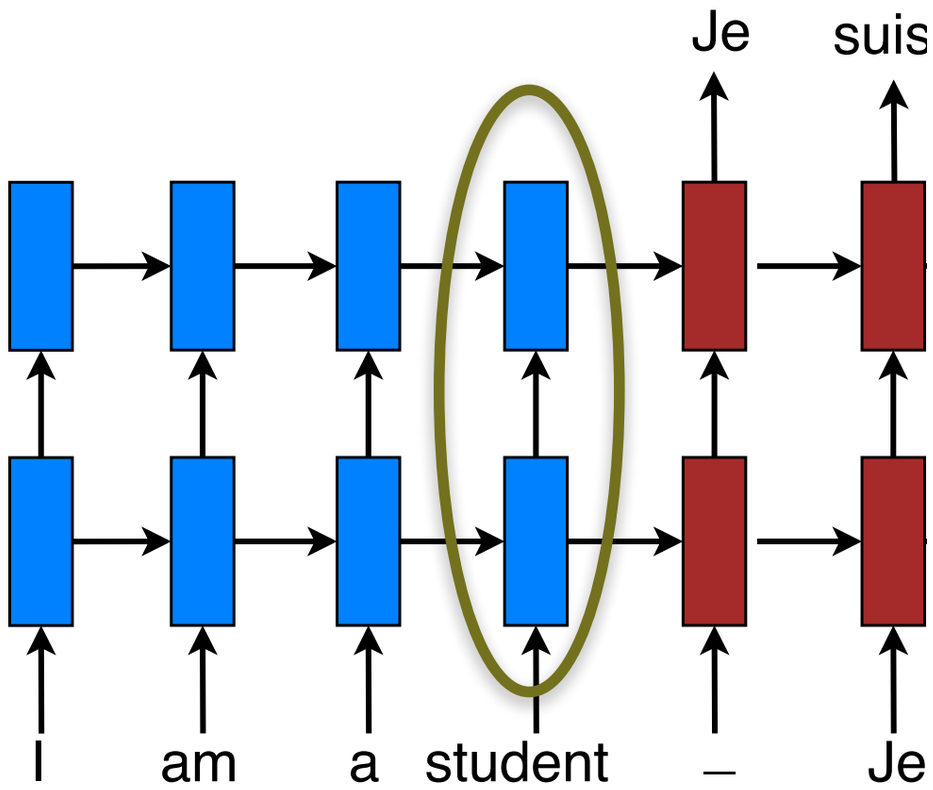
Tuesday, November 03, 2015

Posted by Greg Corrado*, Senior Research Scientist





Vanilla seq2seq & long sentences

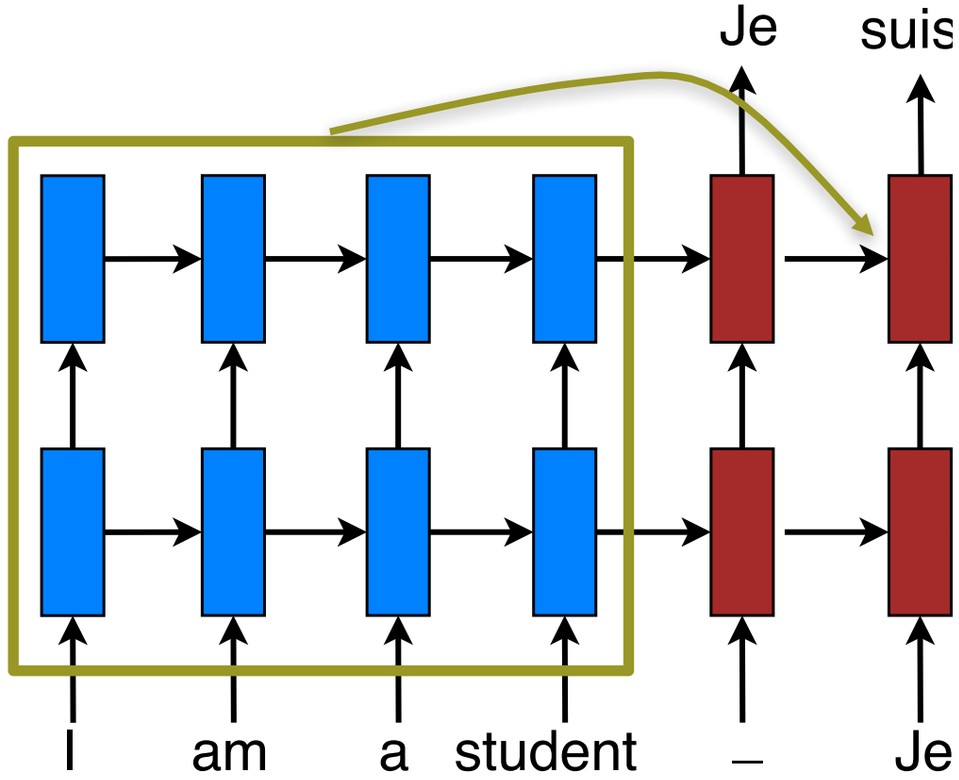


Problem: fixed-dimensional representations

Attention Mechanism

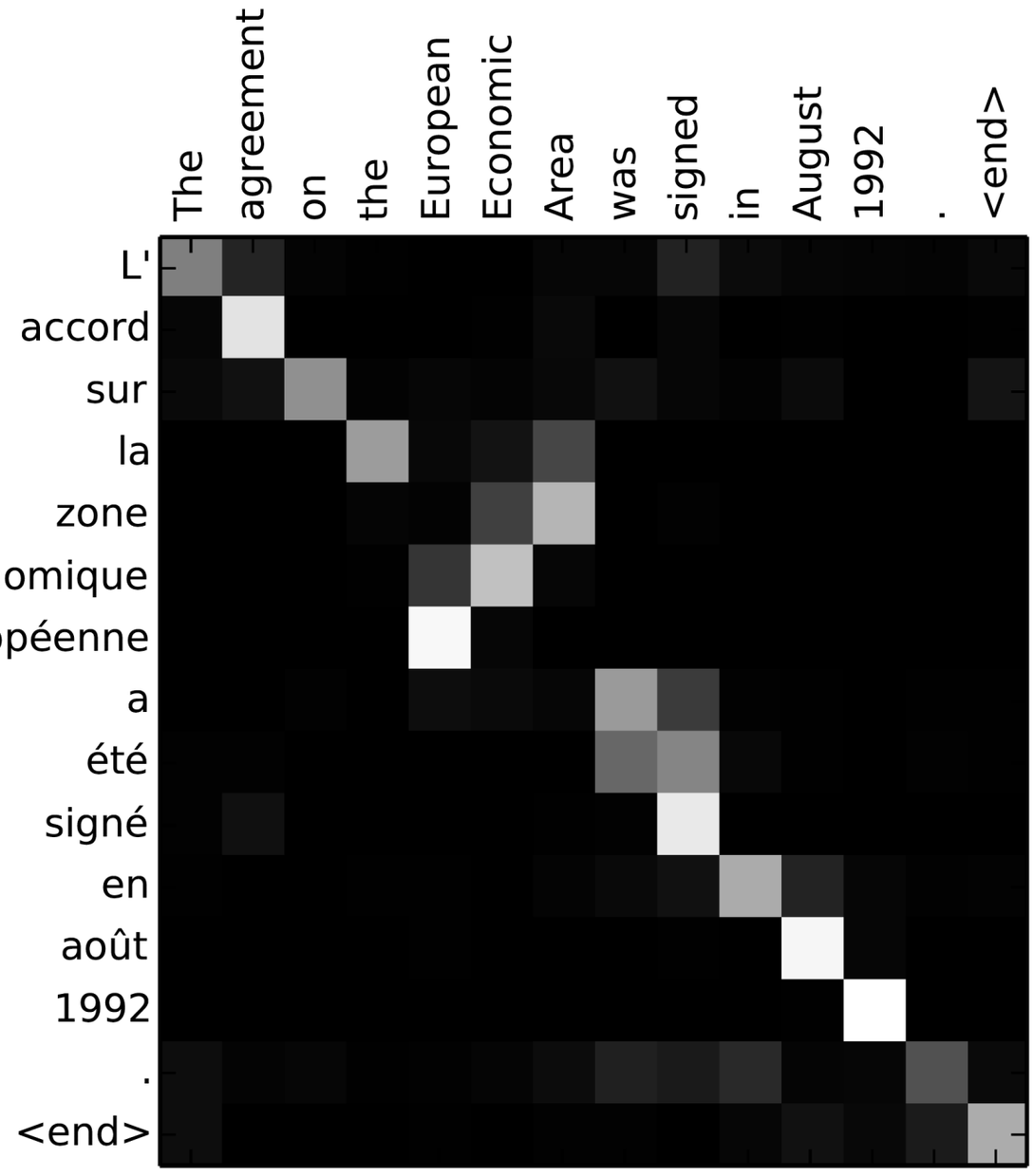
Started in computer vision! [Larochelle & Hinton, 2010], [Denil, Bazzani, Larochelle, Freitas, 2012]

Pool of source states



- Solution: random access memory
  - Retrieve as needed.

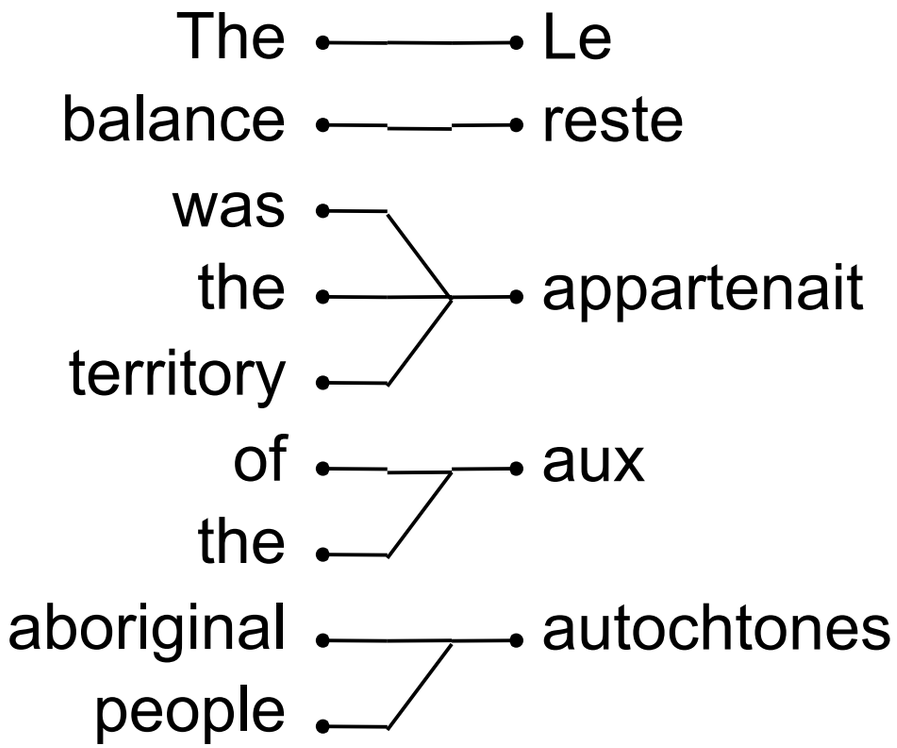
Learning both translation & alignment

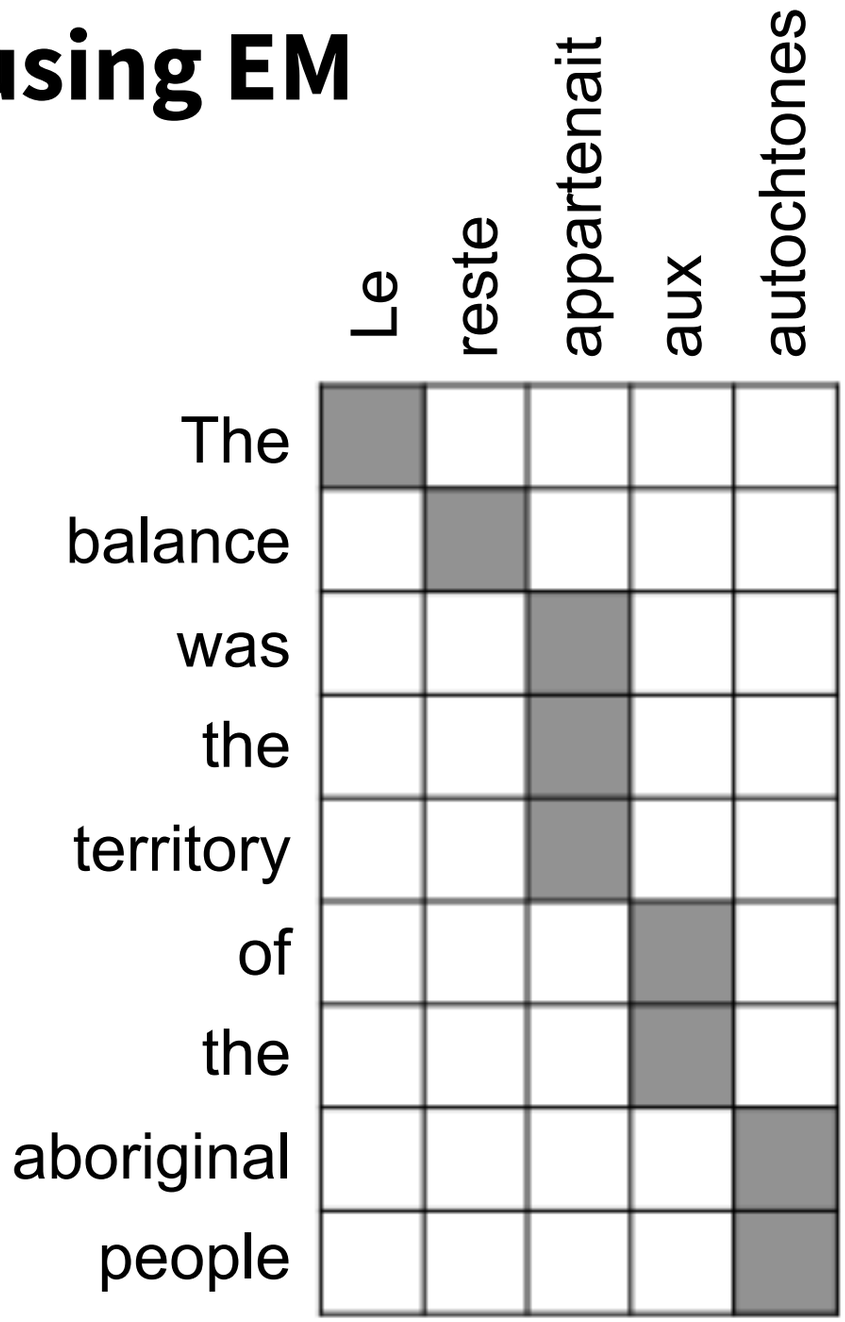


Dzmitry Bahdanau, KyungHuyn Cho, and Yoshua Bengio. ***Neural Machine Translation by Jointly Learning to Translate and Align****. ICLR'15.*

Word alignments

Phrase-based SMT aligned words in a preprocessing-step, usually using EM



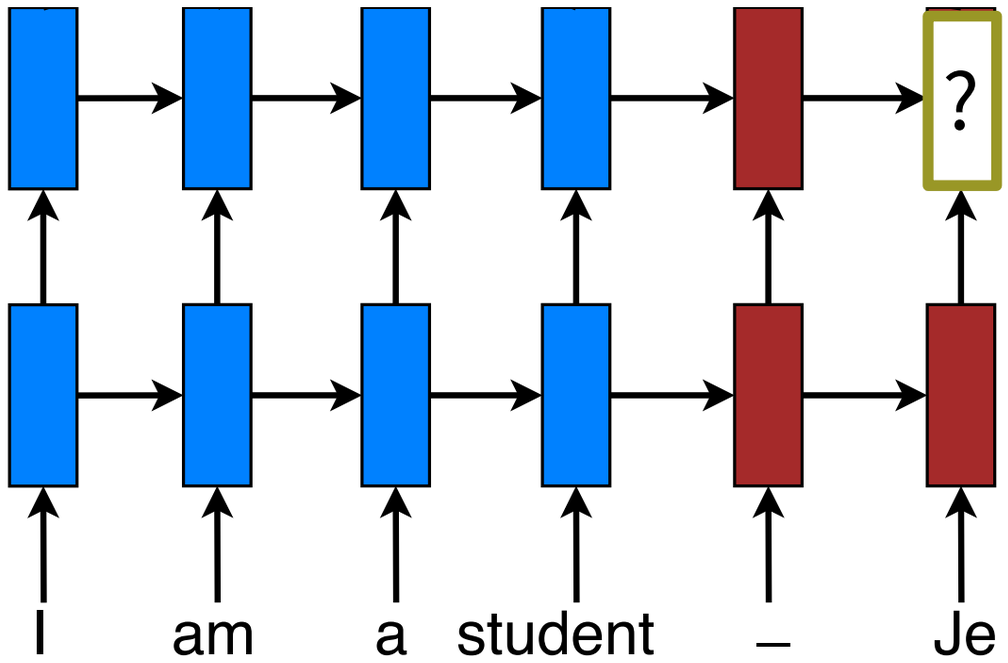


➜ Models of attention

[Bahdanau et al. 2014; ICLR 2015]

Part 3b later

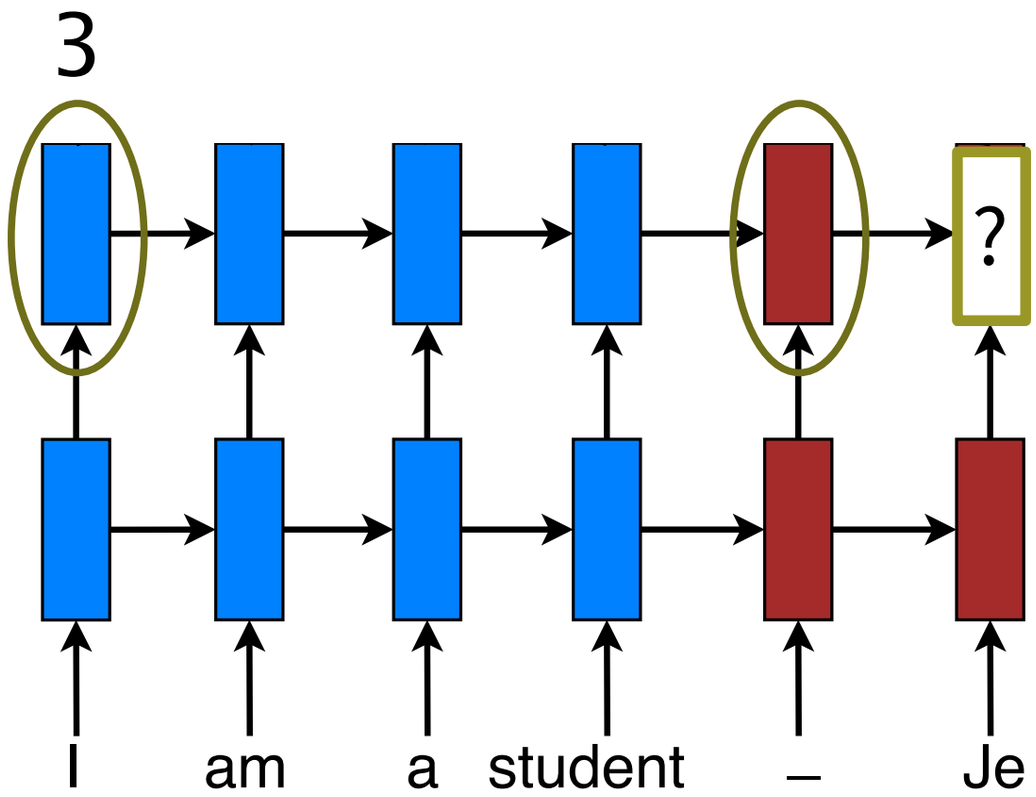
Attention Mechanism



Simplified version of (Bahdanau et al., 2015)

Attention Mechanism – *Scoring*

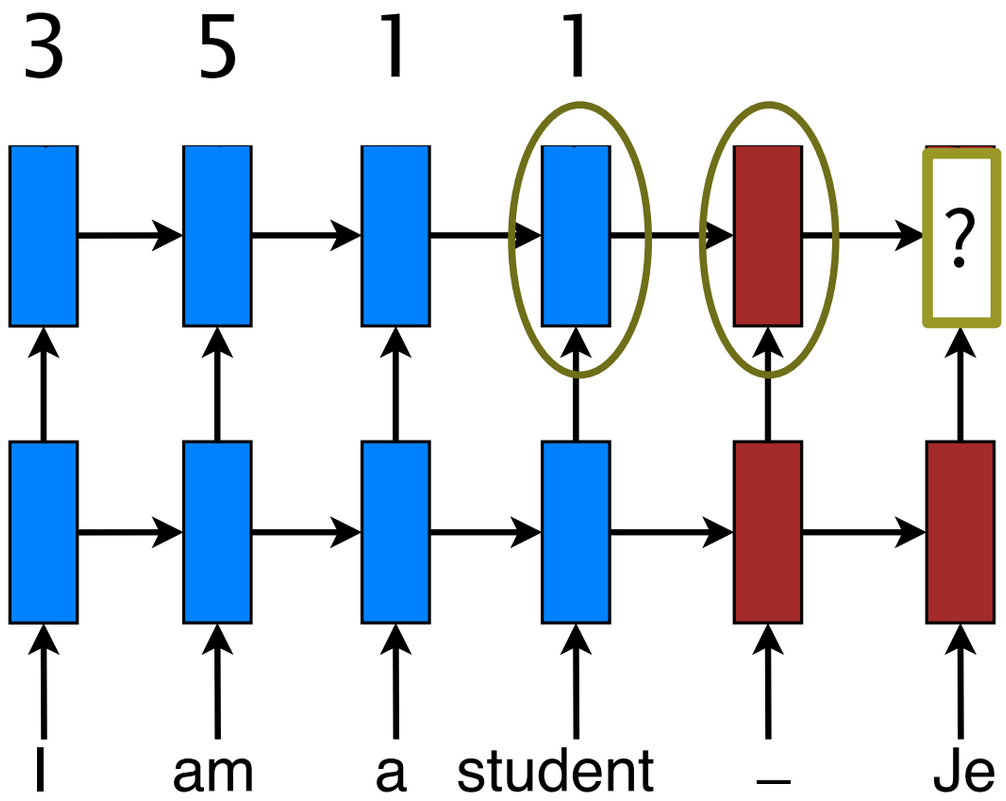
$$\text{score}(\boldsymbol{h}_{t-1}, \bar{\boldsymbol{h}}_s)$$



- Compare target and source hidden states.

Attention Mechanism – *Scoring*

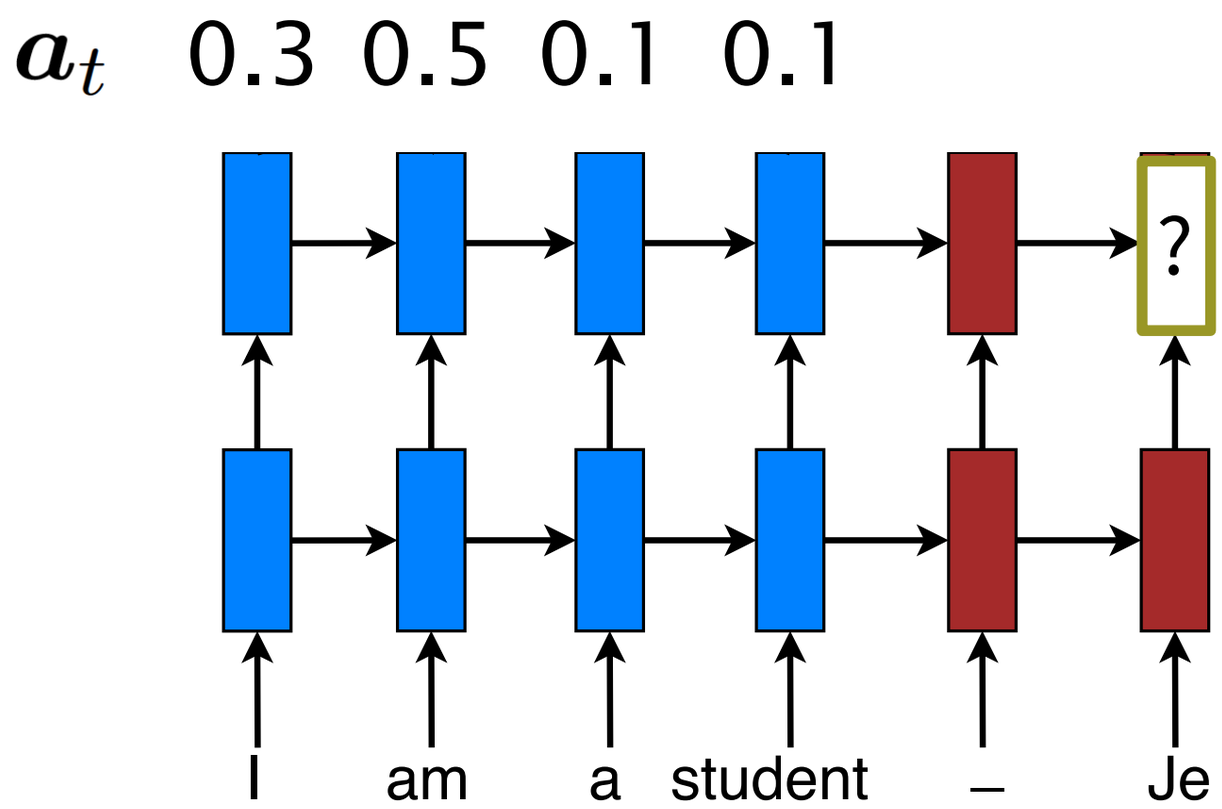
$$\text{score}(\boldsymbol{h}_{t-1}, \bar{\boldsymbol{h}}_s)$$



- Compare target and source hidden states.

Attention Mechanism – *Normalization*

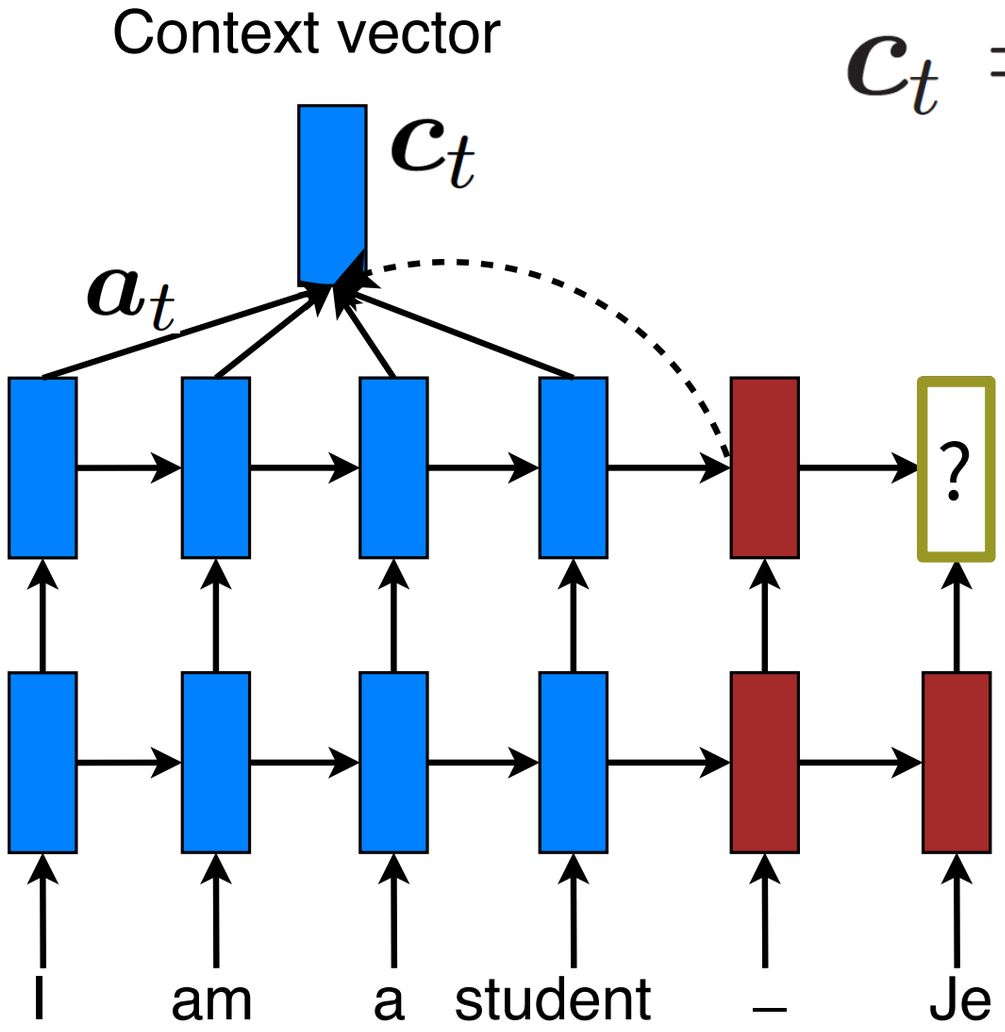
$$\boldsymbol{a}_t(s) = \frac{\mathrm{e}^{\mathrm{score}(s)}}{\sum_{s'} \mathrm{e}^{\mathrm{score}(s')}}$$



- Convert into alignment weights.

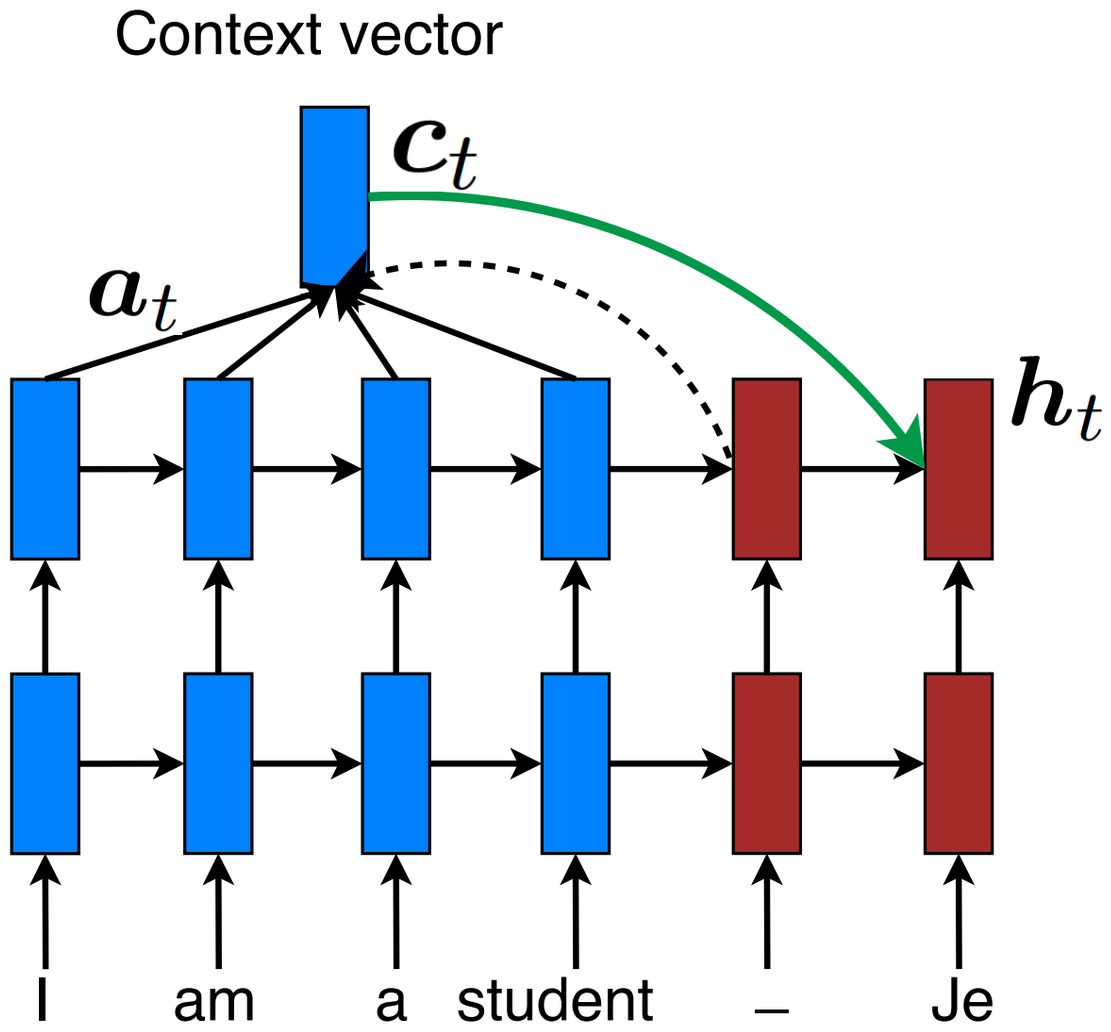
Attention Mechanism – *Context*

$$\boldsymbol{c}_t = \sum_s \boldsymbol{a}_t(s)\bar{\boldsymbol{h}}_s$$



- Build context vector: weighted average.

Attention Mechanism – *Hidden State*

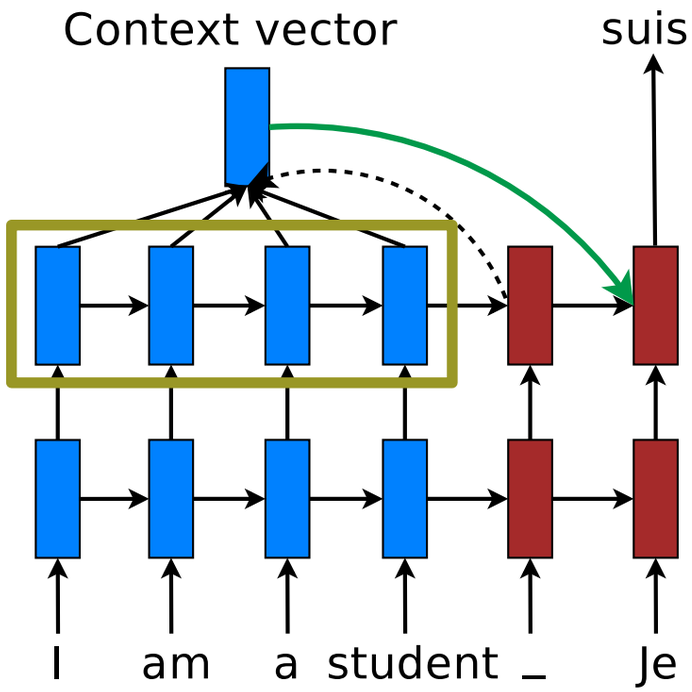


- Compute the next hidden state.

Attention Mechanisms+



- Simplified mechanism & more functions:



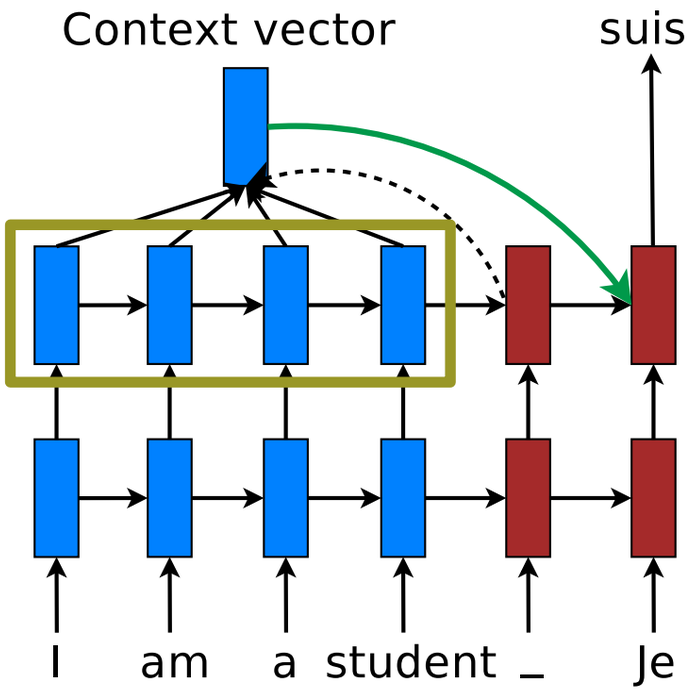
$$\text{score}(\boldsymbol{h}_t, \bar{\boldsymbol{h}}_s) = \begin{cases} \boldsymbol{h}_t^\top \bar{\boldsymbol{h}}_s \\ \boldsymbol{h}_t^\top \boldsymbol{W_a} \bar{\boldsymbol{h}}_s \\ \boldsymbol{v}_a^\top \tanh\left(\boldsymbol{W_a}[\boldsymbol{h}_t; \bar{\boldsymbol{h}}_s]\right) \end{cases}$$

Thang Luong, Hieu Pham, and Chris Manning. ***Effective Approaches to Attention-based Neural Machine Translation****. EMNLP'15.*

Attention Mechanisms+



- Simplified mechanism & more functions:



Bilinear form: well-adopted.

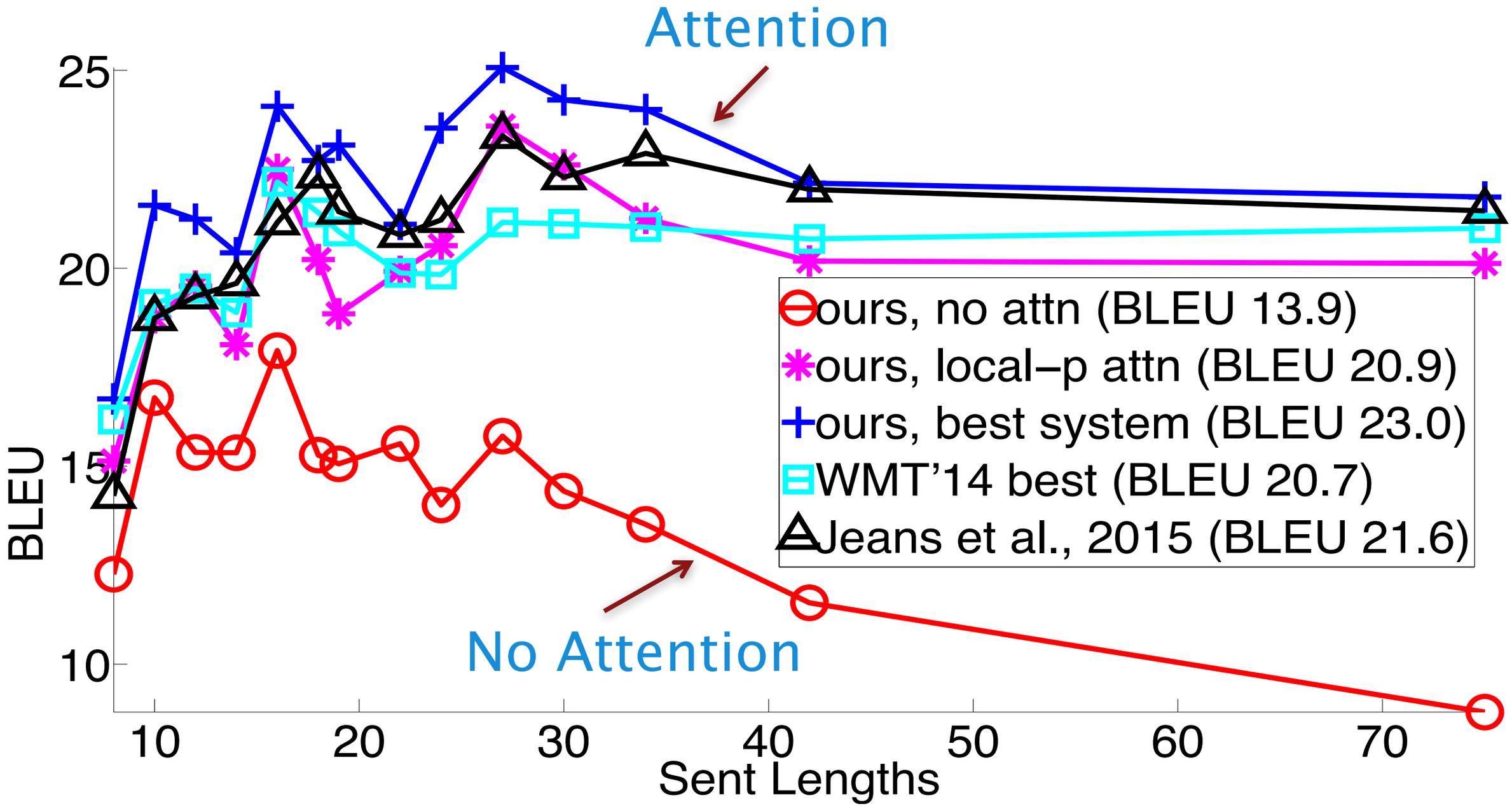
$$\text{score}(\boldsymbol{h}_t, \bar{\boldsymbol{h}}_s) = \begin{cases} \boldsymbol{h}_t^\top \bar{\boldsymbol{h}}_s \\ \boldsymbol{h}_t^\top \boldsymbol{W}_{\boldsymbol{a}} \bar{\boldsymbol{h}}_s \\ \boldsymbol{v}_a^\top \tanh\left(\boldsymbol{W}_{\boldsymbol{a}}[\boldsymbol{h}_t; \bar{\boldsymbol{h}}_s]\right) \end{cases}$$

GitHub, Inc. [US] https://github.com/harvardnlp/seq2seq-attn

Sequence-to-Sequence Learning with Attentional Neural Networks

The attention model is from Effective Approaches to Attention-based Neural Machine Translation, Luong et al. EMNLP 2015. We use the *global-general-attention* model with the *input-feeding* approach from the paper. Input-feeding is optional and can be turned off.

Better Translation of Long Sentences



Neural Network Toolkits

★ **PyTorch**: http://pytorch.org/

- Facebook AI Research and many others

- **Tensorflow**: https://www.tensorflow.org/
  - By Google, actively maintained, bindings for many languages

- **DyNet**: https://github.com/clab/dynet
  - CMU and other individual researchers, dynamic structures that change for every training instance
- **Caffe**: http://caffe.berkeleyvision.org/
  - UC Berkeley, for vision
- **Theano**: http://deeplearning.net/software/theano
  - University of Montreal, less and less maintained