Neural Machine Translation

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Rheinische Friedrich-Wilhelms-Universität Bonn
Seminar: Natural Language Processing

Agenda

- Introduction to Machine Translation

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- Evaluation Metric

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- Statistical Phrase-Based Translation

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- Evaluation Metric
- Statistical Phrase-Based Translation
- Introduction to Deep Learning

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- Statistical Phrase-Based Translation
- Introduction to Deep Learning
- Neural Machine Translation

Machine Translation

In a probabilistic perspective, machine translation can be formulated the problem of finding a target sentence y that maximizes the conditional probability of y from a given source sentence x.

$$arg\, max_y\ p(x|y)$$

Evaluation Metric

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- No one best traget sentence possible.
- Even human translators don't translate to the same target sentence.

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- Depends on modified n-gram precision (or co-occurrence).
- Needs lots of target sentences for better results.

BLEU

- Candidate 1: It is a guide to action which ensures that the military always obey the commands the party.
- Candidate 2: It is to insure the troops forever hearing the activity guidebook that party direct.
- Reference 1: It is a guide to action that ensures that the military will forever heed Party commands.

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- Reference 2: It is the guiding principle which guarantees the military forces always being under the command of the Party.

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- **Clearly candidate 1 is better.**

BLEU

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- Just count the number of N-gram matches.

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- Just count the number of N-gram matches.
- The match could be position-independent.
- Reference could be matched multiple times.
- No need to be linguistically-motivated.

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N-gram Precision : 17

BLEU

Candidate 2: It is to insure the troops forever hearing the activity guidebook that party direct.
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N-gram Precision : 8

BLEU

Issues with N-gram precision Candidate: the the the the the the the.

Reference 1: The cat is on the mat.

Reference 2: There is a cat on the mat.

N-gram Precision : 7 and BLEU : 1

BLEU

Algorithm	Example
Count the max number of times a word occurs in any single reference	Ref 1: The cat is on the mat. Ref 2: There is a cat on the mat. “the” has max count 2
Clip the total count of each candidate word	Unigram count = 7 Clipped unigram count = 2 Total no. of counts = 7
Modified N-gram Precision equal to Clipped count/ Total no. of candidate word	Modified-ngram precision: Clipped count = 2 Total no. of counts =7 Modified-ngram precision = 2/7

N-grams with different Ns are used but 4 is most common metric.

Phrase Based Machine Translation

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- Lots of individual components but the core idea is learning statistical patterns in training data.

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Some of the individual components:

- Sentence alignment: Gale and Church Algorithm based on Dynamic programming.

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- Beam search: For generating target sentence.
- Beam search is a generic algorithm that is used even in the latest NMT systems.

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- Needs one model for each language pair.
- Google avoided the need for combinatorial number of models by always translating to English as intermediate language.
- Thus in practice, the accuracy dropped further.

Introduction to Deep Learning

Machine Learning (Supervised)

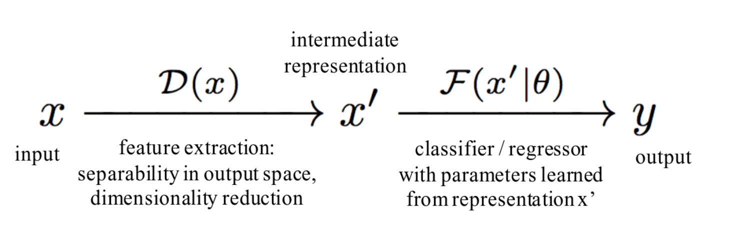

Figure: Traditional Supervised learning

Deep Learning (Supervised)

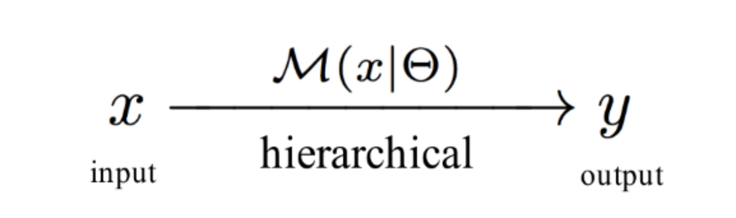

Figure: Deep learning

- Hierarchical representations of features.

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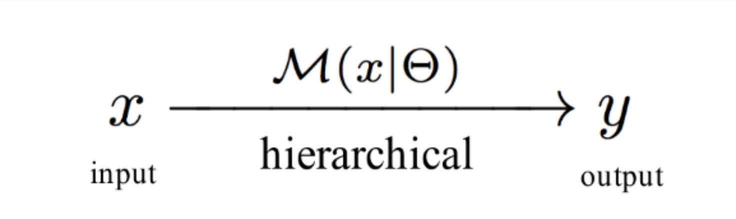

Figure: Deep learning

- Hierarchical representations of features.
- Joint learning of representation.

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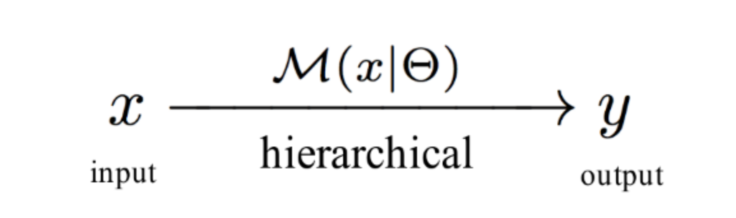


Figure: Deep learning

- Hierarchical representations of features.
- Joint learning of representation.
- Increased levels of abstraction.

Perceptron

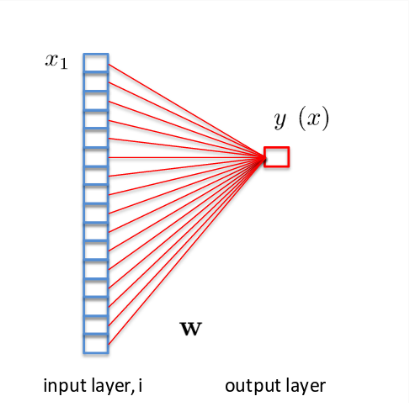


Figure: A Neuron (close to a biological neuron)

$$y(x) = f(W^T x)$$

Logistic Regression

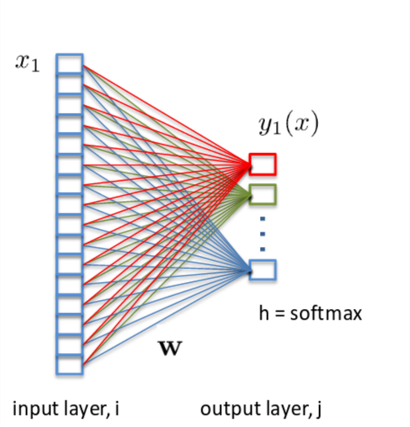


Figure: A perceptron (A collection of perceptrons)

Logistic Regression

Binary classification:

$$P(y=1|x) = h_w(x) = \frac{1}{1+exp(-W^T x)}$$

$$P(y=0|x) = 1 - h_w(x) = 1 - P(y=1|x)$$

Logistic Regression

Cost function:

$$J(w) = -\sum_{i}(y^i log(h_w(x^i)) + (1 - y^i)log(1 - h_w(x^i)))$$

Learning Weights : Gradient Descent

$$\nabla_w J(w) = \frac{\partial J(w)}{\partial w_j} = \sum_{i} x_j^i (h_w(x^i) - y^i)$$

Gradient Descent

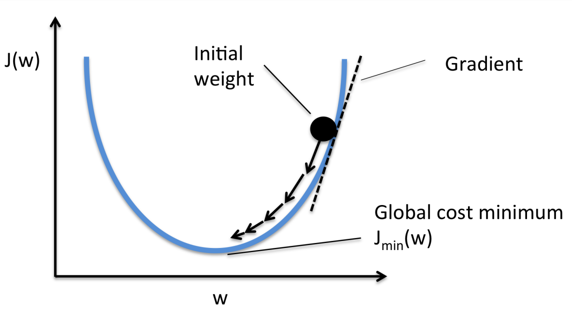


Figure: Update weights in the direction of negative gradient.

Multi Layer Perceptron

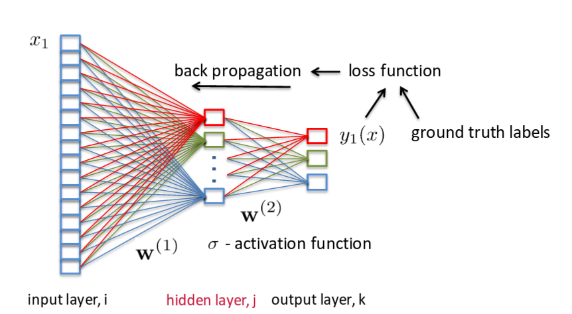


Figure: Multiple layers of perceptron

Learning weights: Same as before but apply chain rule.

$$\frac{\partial x}{\partial y} = \frac{\partial x}{\partial z} * \frac{\partial z}{\partial y}$$

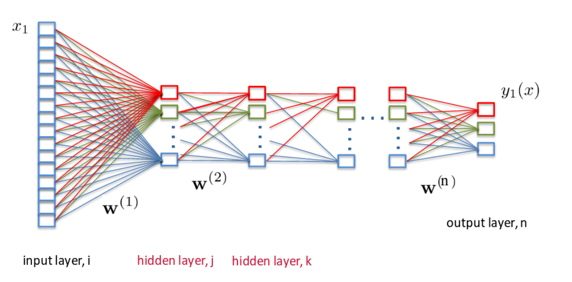
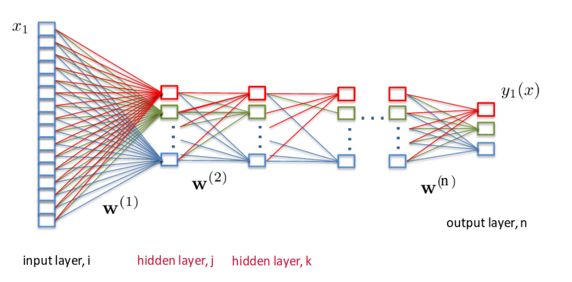


Figure: Deep Neural Networks

- Simply adding layers won't work.

Deep Neural Networks



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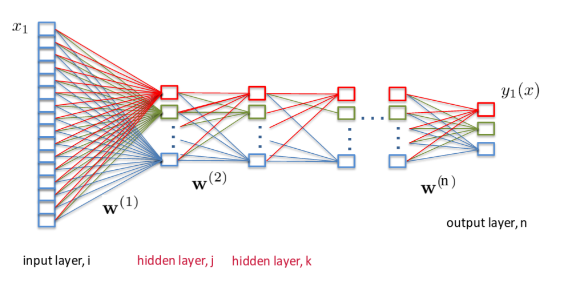

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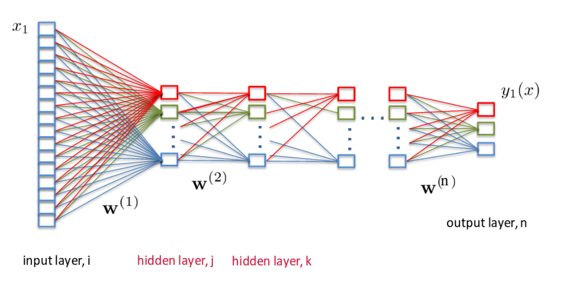

Figure: Deep Neural Networks

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- Too many parameters to train.
- Need smart architectures to capture additional priors.
- Two most commonly used architectures are CNNs and RNNs.

Convolutional Neural Networks

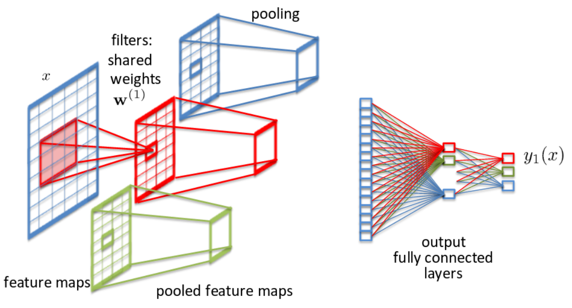
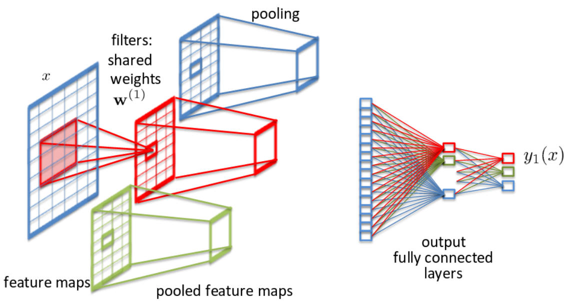


Figure: Convolutional Neural Networks

- Each layers learns a set of convolution kernels.

Convolutional Neural Networks



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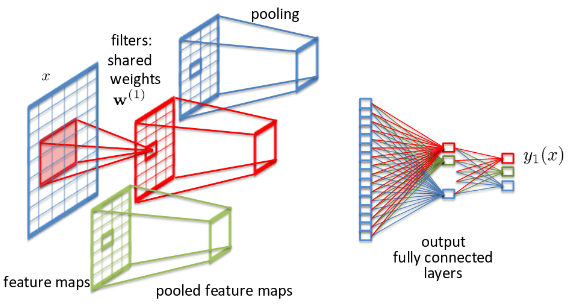


Figure: Convolutional Neural Networks

- Each layers learns a set of convolution kernels.
- Captures a very important prior –smoothness prior– known to computer vision community for a very long time.
- Much less number of parameters.

Recurrent Neural Networks

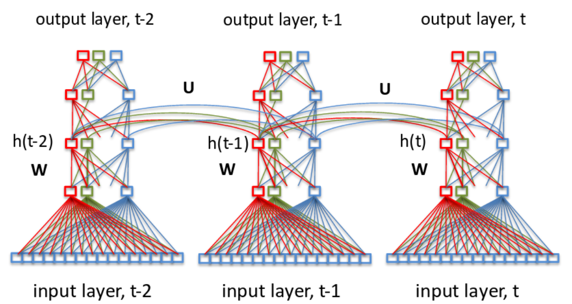
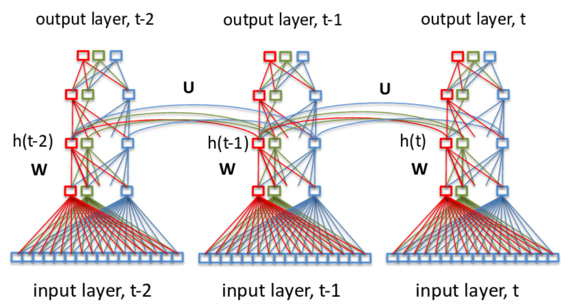


Figure: Recurrent Neural Networks

- Used for predicting sequential data

Recurrent Neural Networks



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- Used for predicting sequential data
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Recurrent Neural Networks

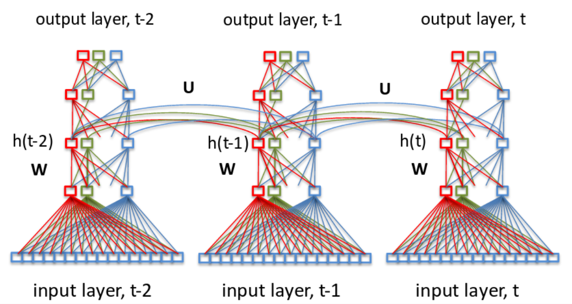


Figure: Recurrent Neural Networks

- Used for predicting sequential data
- Captures dependences across time frames.
- Usually harder to train (Vanishing Gradients).

LSTM

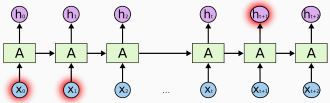


Figure: Recurrent Neural Networks

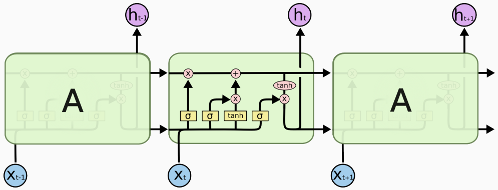
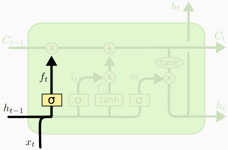


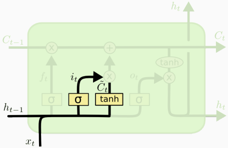
Figure: Long Short Term Memory

LSTM



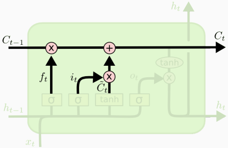
$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

Figure: LSTM Forget gate



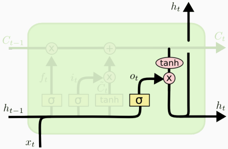
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

Figure: LSTM new content



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

Figure: LSTM Add gate



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

Figure: LSTM Output Gate

Neural Machine Translation

Neural Machine Translation

$$arg\, max_y \; p(y|x)$$

In Neural Machine Translation, a parameterized model (a neural network) is trained to maximize the conditional probability of the sentence pairs given parallel training corpus.

NMT - A historic perspective

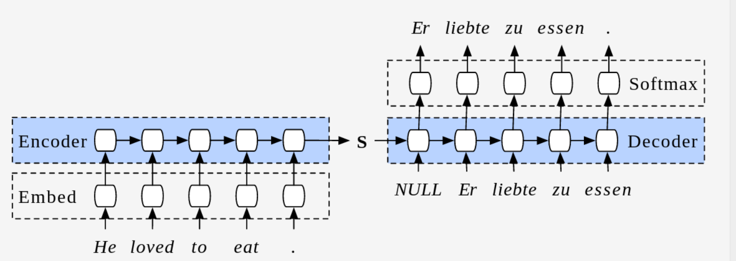


Figure: Encoder-Decoder model for Machine Translation

- Fixed size encodings.

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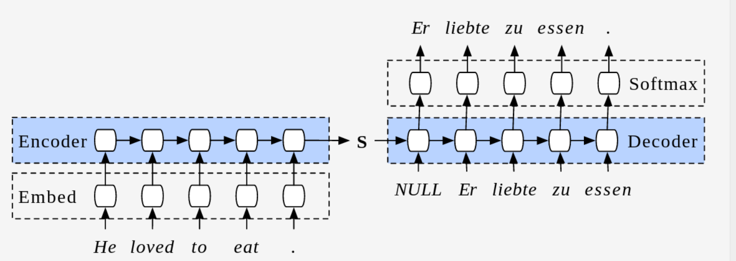

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- Fixed size encodings.
- Each language typically required an Encoder and Decoder.

Jointly learning to Align and translate

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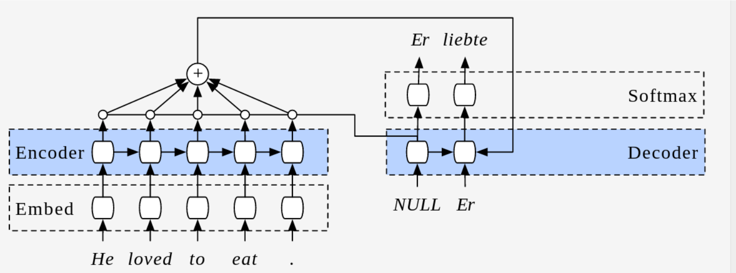

Figure: Encoder-Decoder model with context

Jointly learning to Align and translate

For a input sentence, $X = (x_1, \cdots, x_{T_x})$. The NMT[1] system consists of,

- Encoder and Decoder are multi-layer recurrent neural networks (RNNs).

[1] NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE. Dzmitry Bahdanau, KyungHyun Cho, Yoshua Bengio, ICLR, 2015.

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- Encoder RNN, at each input step t, generates hidden state, $h_t = f(x_t, h_{t-1})$.
- Context vector encodes the input sequence as, $c = q(\{h_1, \cdots, h_{T_x}\})$.

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Jointly learning to Align and translate

- The decoder is trained to predict the next work y_t given the context vector c and all previously predicted words $\{y_1, \cdots, y_{t-1}\}$

$$p(y) = \prod_{t=1}^{T} p(y_t | \{y_1, \cdots, y_{t-1}\}, c)$$

- With RNN, each conditional probability is modeled as,

$$p(y_t | \{y_1, \cdots, y_{t-1}\}, c) = g(y_{t-1}, s_t, c)$$

where s_t is the hidden state of the RNN.

Context Vector

The context vector for a input sentence i, is computed as a weighted sum of hidden states of the encoder (also known as **annotations**)

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j$$

$$\alpha_{ij} = \frac{exp(e_{ij})}{\sum_{k=1}^{T_x} exp(e_{ik})}$$

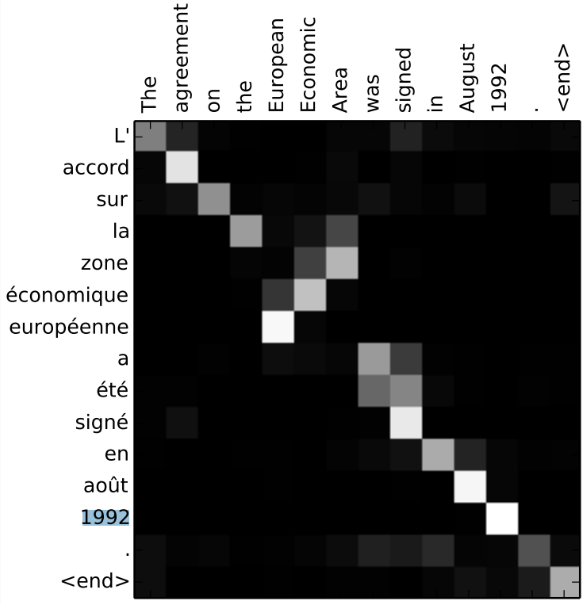
where,

$$e_{ij} = a(s_{i-1}, h_j)$$

is the alignment model that scores how well the inputs around the j and the output at the position i match.

A feedforward neural network is used as the alignment model and is **jointly trained** with all the NMT system as a whole.

Visualization of the context



Bi-directional Encoder

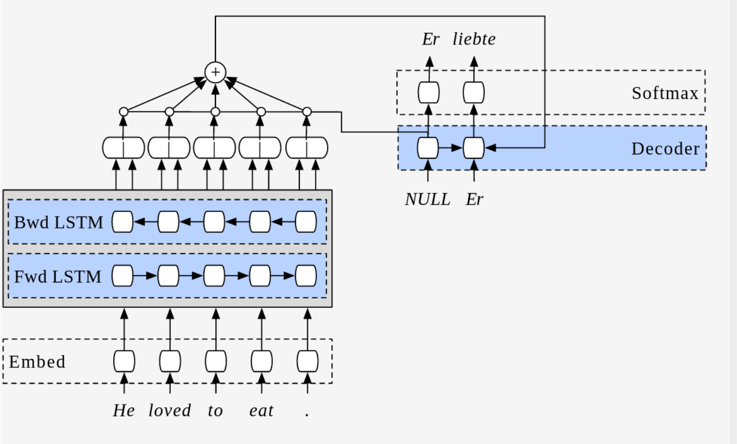


Figure: Bi-directional Encoder

- Recurrent connection in both directions.

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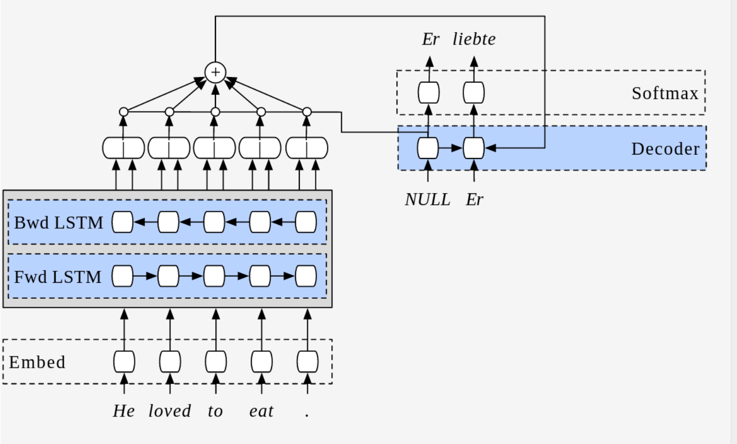

Figure: Bi-directional Encoder

- Recurrent connection in both directions.
- Two independent states, updated independently.

Error Function and training details

- Standard maximum-likelyhood:

$$\mathbb{O}_{ML}(\Theta) = \sum_{i=1}^{N} logP_{\Theta}(Y^{*(i)}|X^{(i)})$$

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- Optimizer-SGD.
- Minibatch of 80 sentences.
- BLEU comparable to PBMT.

Seq2Seq Learning

Seq2Seq Learning

Machine Translation is can treated as a special case of a more generic sequence to sequence modeling.

1. Idea is simple: Throw more power at the network.

$$p(y_1, \cdots, y_T | x_1, \cdots, x_T) = \prod_{t=1}^{T} p(y_t | v, y_1, \cdots, y_{t-1})$$

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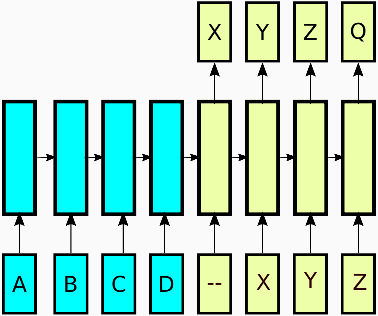
4. Trained with SGD.

$$p(y_1, \cdots, y_T | x_1, \cdots, x_T) = \prod_{t=1}^{T} p(y_t | v, y_1, \cdots, y_{t-1})$$

Seq2Seq Learning



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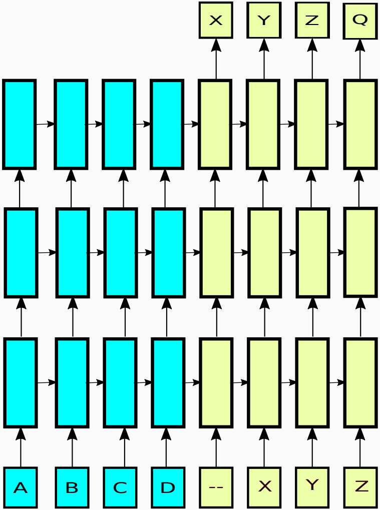

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- Not just a research idea but already serves billions of queries a day.

Residual learning

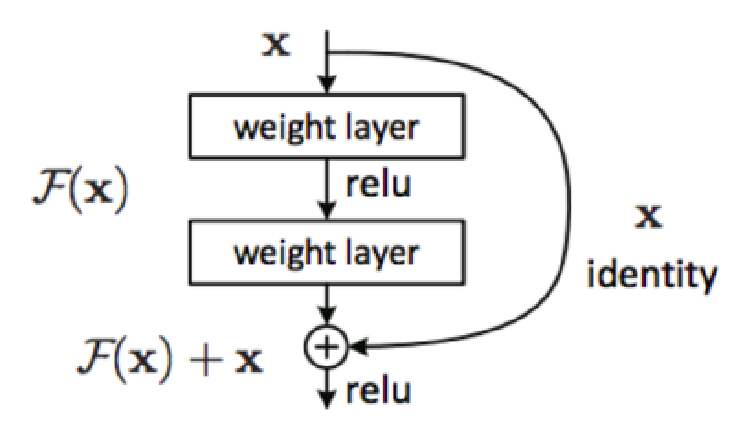

Figure: Residual networks

Residual connections enables training of very deep networks.[2]

[2] Deep Residual Learning for Image Recognition. Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. CVPR, 2016.

Google NMT with Residual connection

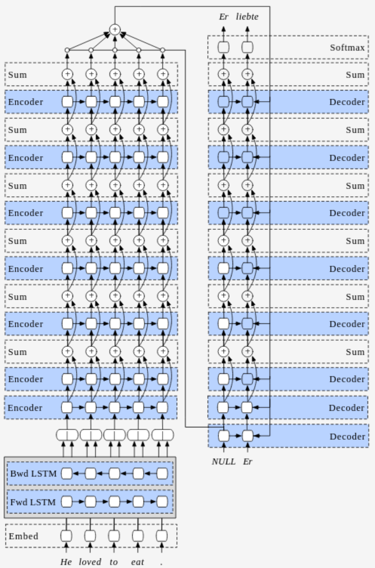

Figure: GNMT with residual connections.

Google NMT

Error function

- Standard maximum-likelyhood:

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- Refined error function aiming to maximize BLEU:

$$\mathbb{O}_{ML}(\Theta) = \sum_{i=1}^{N} \sum_{Y=\mathbb{Y}}^{N} logP_{\Theta}(Y^{*(i)}|X^{(i)})r(Y, Y^{*(i)})$$

where $r(\Delta)$ is per-sentence score computed as an expectation over all Y upto certain-length.

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- One giant model that runs all Google translate queries.

Conclusion

Neural Machine Translation systems,

- Are State-of-the-art in machine translation.
- Greatly benefited from the neural network research by other communities.
- Used in production by companies like Google, Microsoft, Facebook, etc.

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- "Attention Is All You Need"arxiv preprint from Google threw away all LSTMS, Residual connections, etc., but managed to achieve BLEU score of 41.0 with only feedforward connections and attention.