

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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- Neural Machine Translation

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Motivation

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- Why do we need it?
- Do I need to convince that we need 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 .

$$\mathit{arg\,max}_y \, p(x|y)$$

Evaluation Metric

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

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- Needs lots of target sentences for better results.

- 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.
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- **Clearly candidate 1 is better.**

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- Reference could be matched multiple times.
- No need to be linguistically-motivated.

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N-gram Precision : 17

Candidate 2: It is to insure the troops forever hearing the activity guidebook that party direct.

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N-gram Precision : 8

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

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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- Works at the level of phrases instead of words.
- Lots of individual components but the core idea is learning statistical patterns in training data.

Phrase Based Machine Translation

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

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- Sentence alignment: Gale and Church Algorithm based on Dynamic programming.
- Word alignment: Expectation Maximization.
- Phrases generation: Heuristic based complex algorithms.
- Phrase lookup: Statistical matching.
- 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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- Achieved a BLEU score of 28.0 on WMT'14 English-to-French dataset.

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- 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)

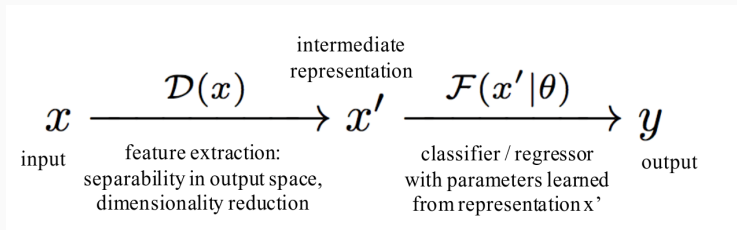


Figure: Traditional Supervised learning

Deep Learning (Supervised)

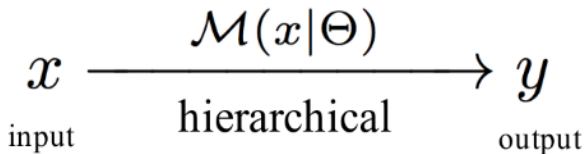


Figure: Deep learning

- Hierarchical representations of features.

Deep Learning (Supervised)

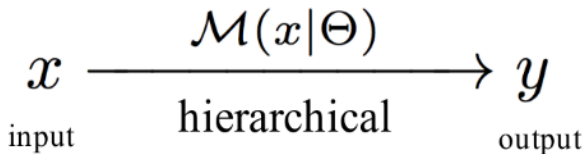


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- Hierarchical representations of features.
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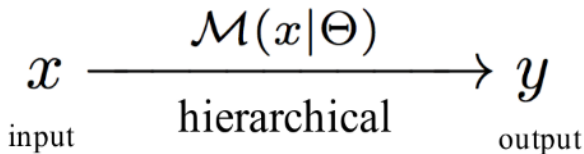


Figure: Deep learning

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

Perceptron

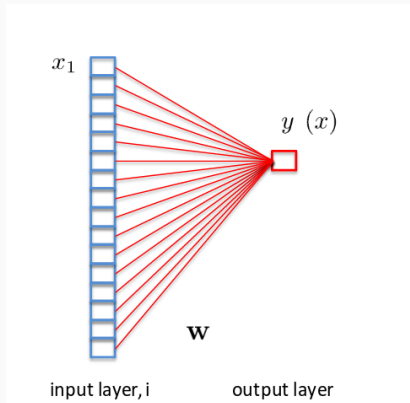


Figure: A perceptron (close to a biological neuron)

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

Logistic Regression

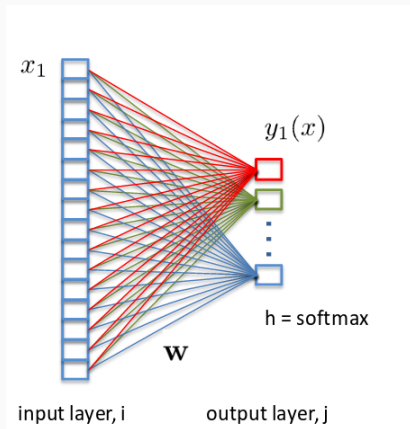


Figure: A perceptron (A collection of perceptrons)

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

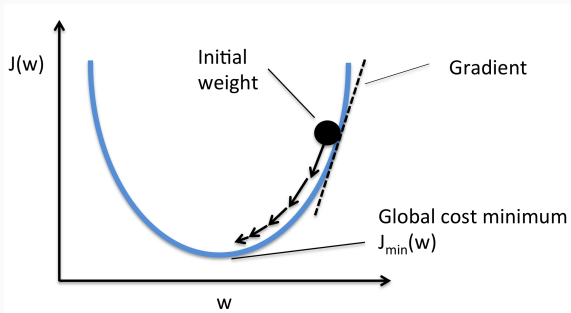


Figure: Update weights in the direction of negative gradient.

Multi Layer Perceptron

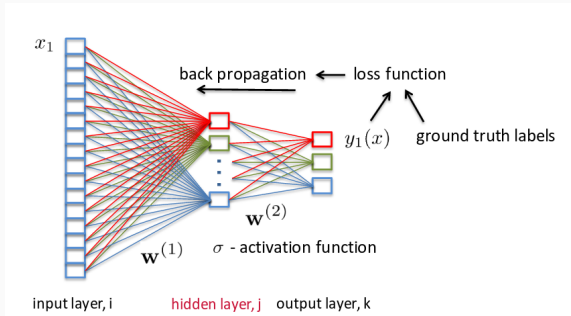


Figure: Multiple layers of perceptron

Learning weights: Same as before but apply chain rule.

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

Deep Neural Networks

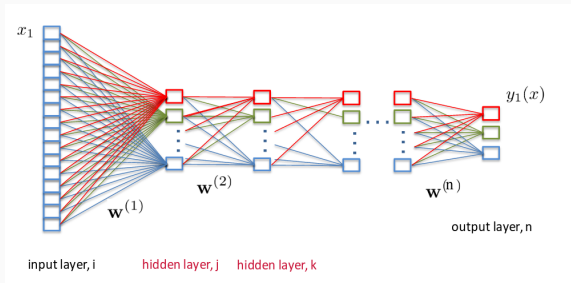


Figure: Deep Neural Networks

- Simply adding layers won't work.

Deep Neural Networks

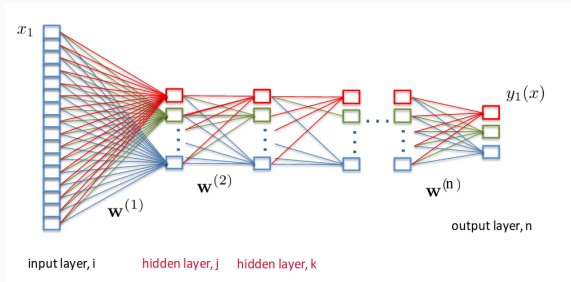


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Deep Neural Networks

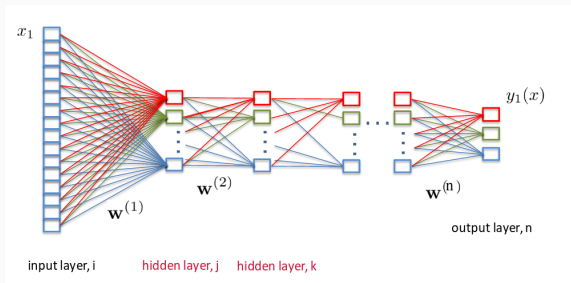


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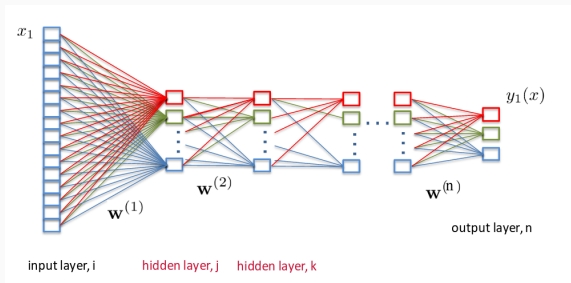


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- Need smart architectures to capture additional priors.
- Two most commonly used architectures are CNNs and RNNs.

Convolutional Neural Networks

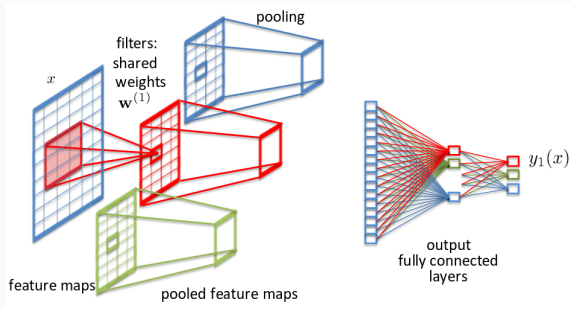


Figure: Convolutional Neural Networks

- Each layers learns a set of convolution kernels.

Convolutional Neural Networks

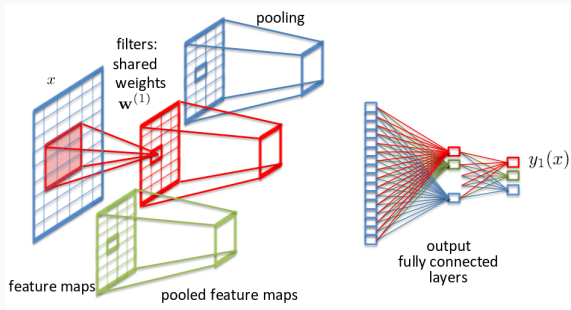


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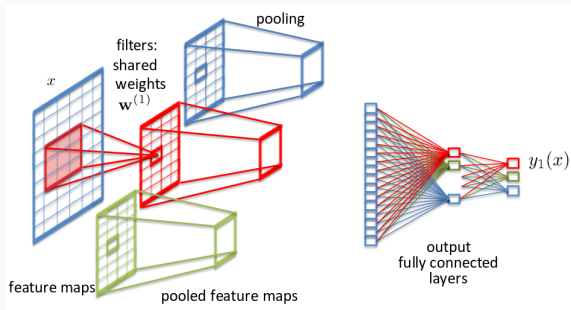


Figure: Convolutional Neural Networks

- 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

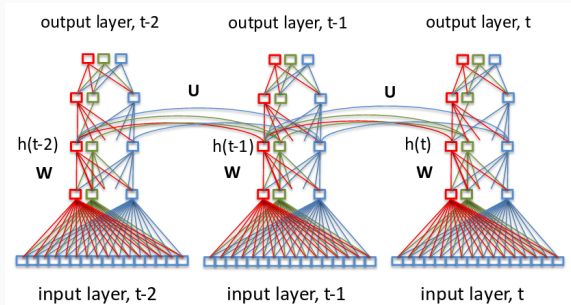


Figure: Recurrent Neural Networks

- Used for predicting sequential data

Recurrent Neural Networks

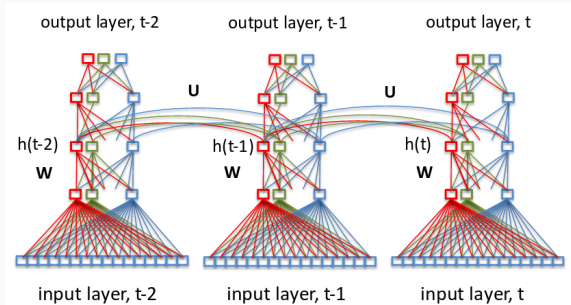


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- Used for predicting sequential data
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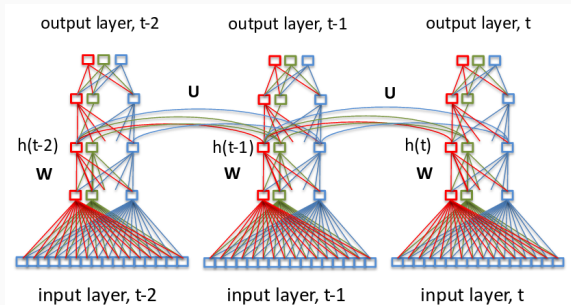


Figure: Recurrent Neural Networks

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

LSTM

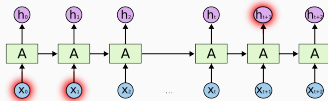


Figure: Recurrent Neural Networks

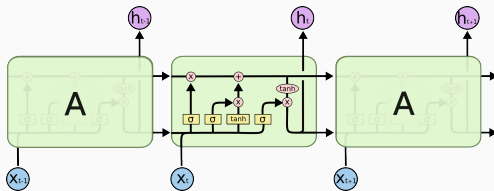
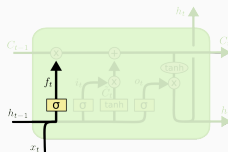
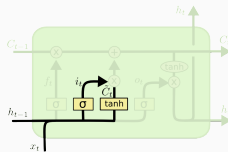


Figure: Long Short Term Memory



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

Figure: LSTM Forget gate

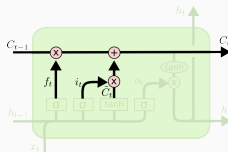


$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

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

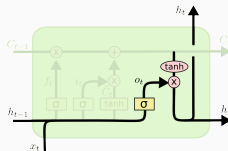
Figure: LSTM new content

LSTM



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

Figure: LSTM Add gate



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

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

Figure: LSTM Output Gate

Neural Machine Translation

$$\mathop{arg\,max}_y p(x|y)$$

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

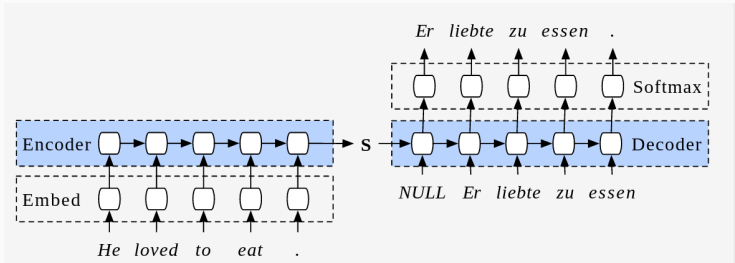


Figure: Encoder-Decoder model for Machine Translation

- Fixed size encodings.

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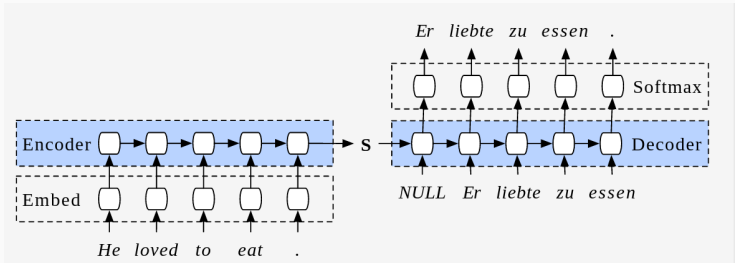


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- Fixed size encodings.
- Each language typically required an Encoder and Decoder.

Jointly learning to Align and translate

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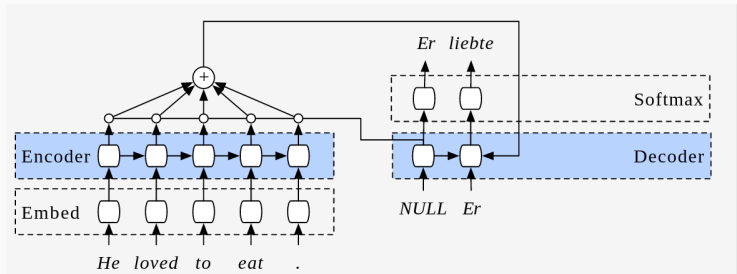


Figure: Encoder-Decoder model with context

Jointly learning to Align and translate

For a input sentence, $X = (x_1, \dots, x_{T_x})$. The NMT¹ system consists of,

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

¹NEURAL 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,
 $c = q(\{h_1, \dots, h_{T_x}\})$.

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Jointly learning to Align and translate

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

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

- With RNN, each conditional probability is modeled as,

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

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**)

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

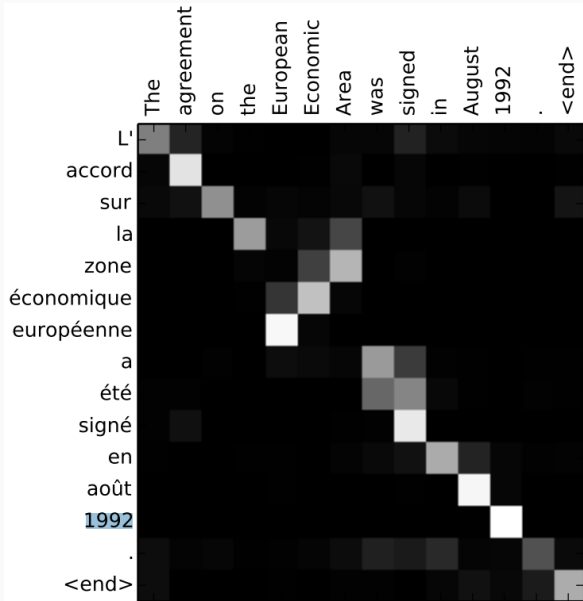
where,

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

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

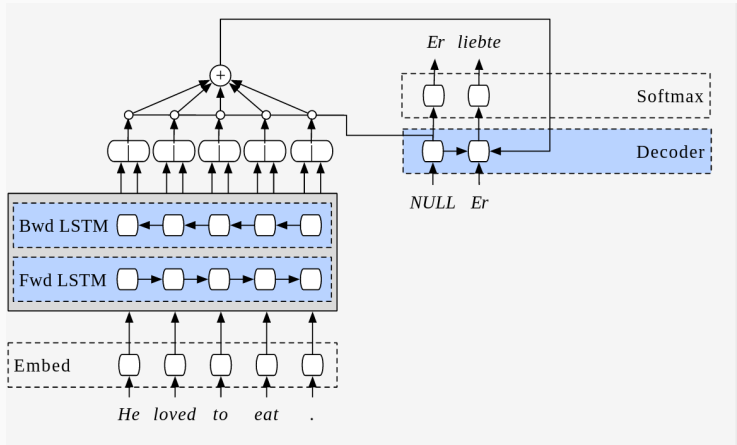


Figure: Bi-directional Encoder

- Recurrent connection in both directions.

Bi-directional Encoder

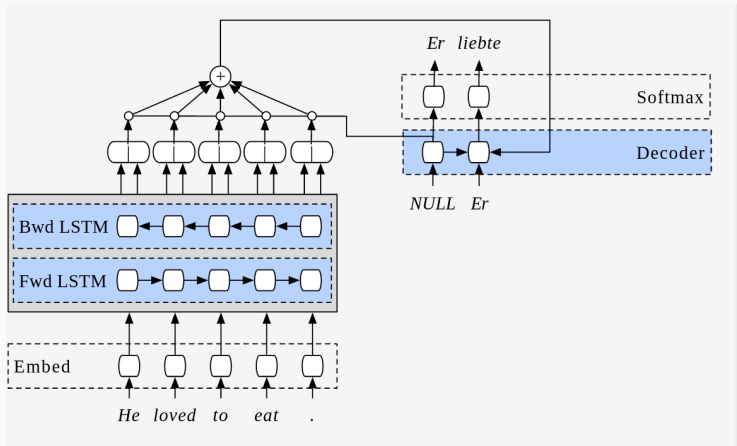


Figure: Bi-directional Encoder

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

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.

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

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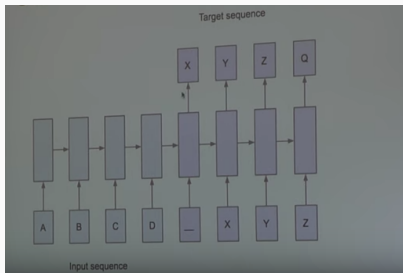
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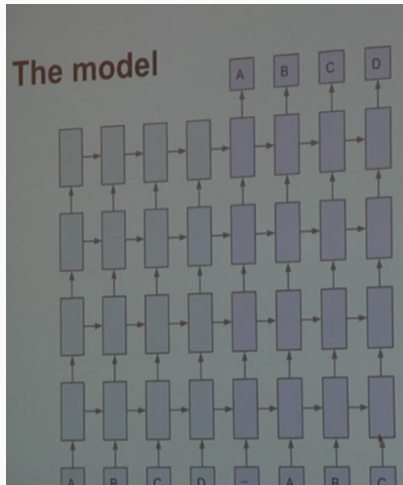
1. Idea is simple: Throw more power at the network.
2. Deep LSTM layers.
3. No special handling for Machine translation.
4. Trained with SGD.

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

Seq2Seq Learning



(a) Seq2Seq model



(b) More powerful model

- Trained in WMT English to French dataset with 12M sentences consisting of 348M French words and 304M English words.

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- Used 160,000 of the most frequent words for the source language and 80,000 of the most frequent words for the target language

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- Used 160,000 of the most frequent words for the source language and 80,000 of the most frequent words for the target language
- Every out-of-vocabulary word was replaced with a special “UNK” token

Architecture details:

- 4 LSTM layers.

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- Achieved BLEU score of 33.3 on WMT'14 English-to-French dataset.

Google NMT

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- Also, adds almost all the nice ideas in Deep learning research in the last few years.
- Not just a research idea but already serves billions of queries a day.

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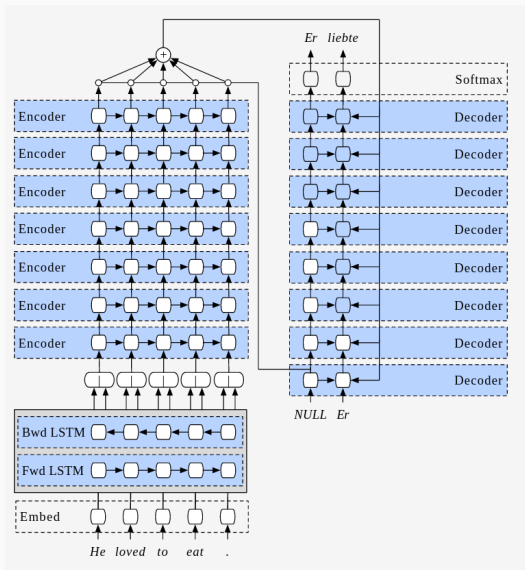


Figure: Simple Encoder-Decoder but more deeper as in Seq2Seq, and Context

Residual learning

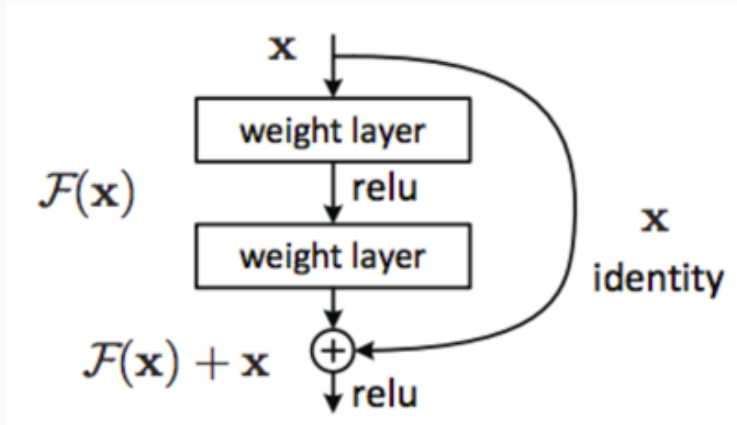


Figure: Residual networks
Residual connections enables training of very deep networks.²

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

Google NMT with Residual connection

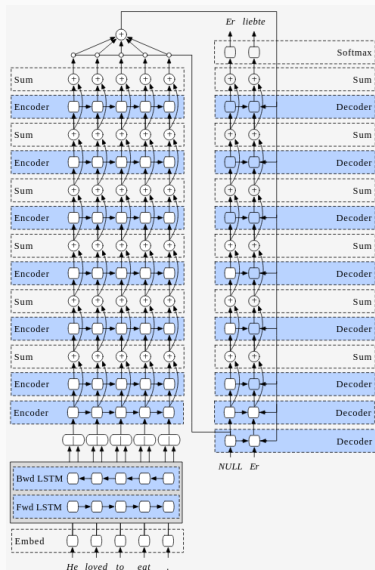


Figure: GNMT with residual connections.

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- One giant model that runs all Google translate queries.

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**.