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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- Statistical Phrase-Based Translation

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- Statistical Phrase-Based Translation
- Introduction to Deep Learning

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

Motivation

- Translation: The process of translating words or text from one language into another (OED).

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- Machine Translation: Translation carried out by a computer (OED).
- Why do we need it?
- Do I need to convince that we need 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.

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

Introduction to Deep Learning

Machine Learning (Supervised)

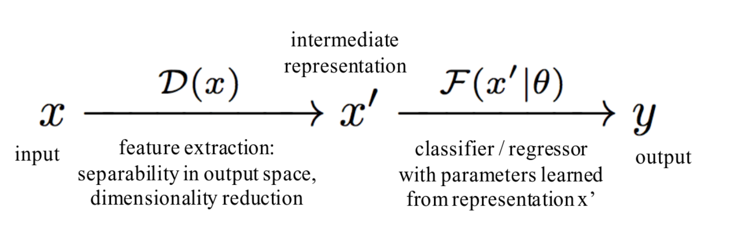

Figure: Traditional Supervised learning

Deep Learning (Supervised)

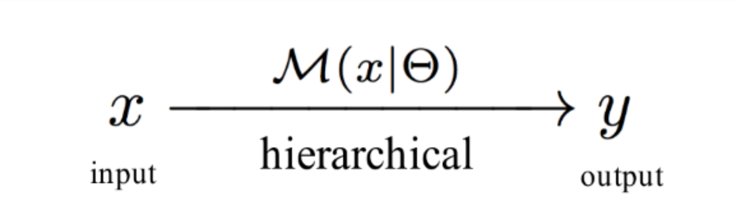

Figure: Deep learning

- Hierarchical representations of features.

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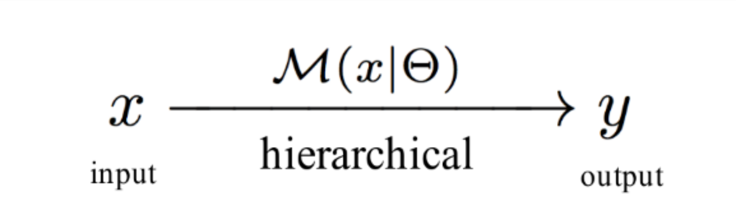

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- Hierarchical representations of features.
- Joint learning of representation.

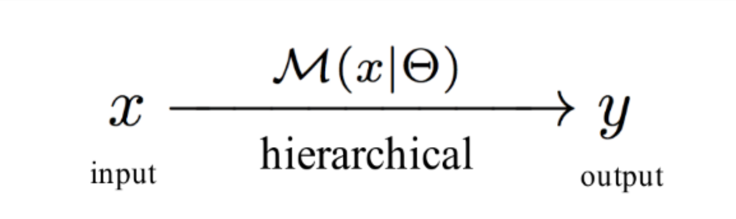


Figure: Deep learning

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

Perceptron

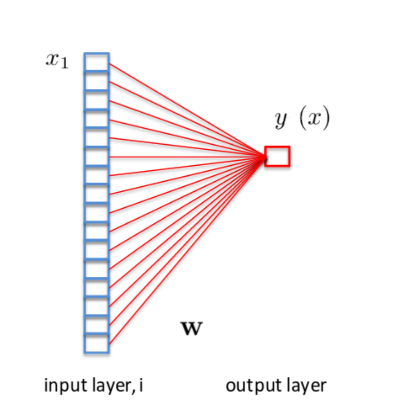


Figure: A perceptron (close to a biological neuron)

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

Logistic Regression

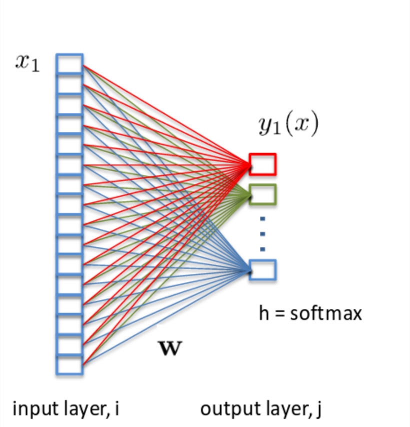


Figure: A perceptron (A collection of perceptrons)

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

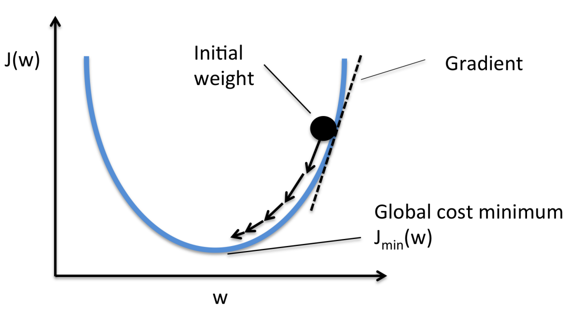


Figure: Update weights in the direction of negative gradient.

Multi Layer Perceptron

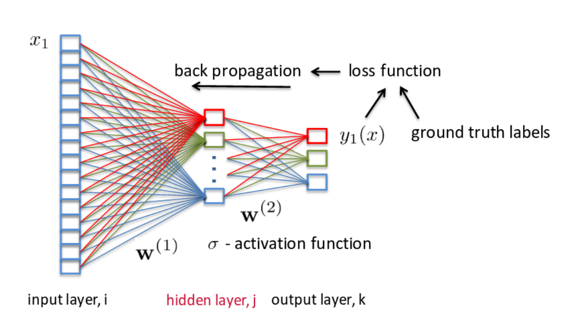


Figure: Multiple layers of perceptron

Learning weights: Same as before but apply chain rule.

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

Deep Neural Networks

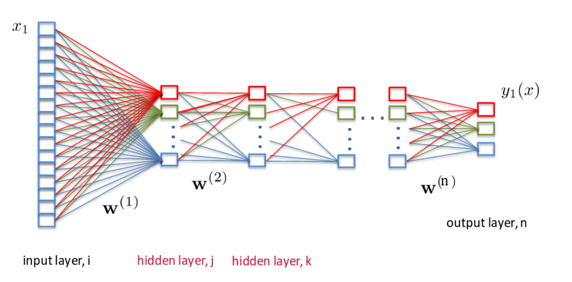
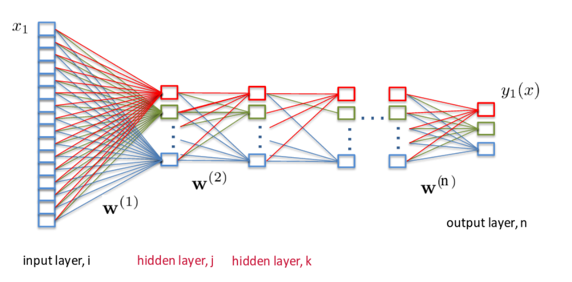


Figure: Deep Neural Networks

- Simply adding layers won't work.

Deep Neural Networks



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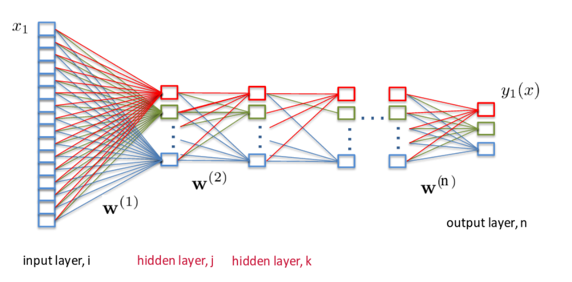
Deep Neural Networks



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- Need smart architectures to capture additional priors.

Deep Neural Networks

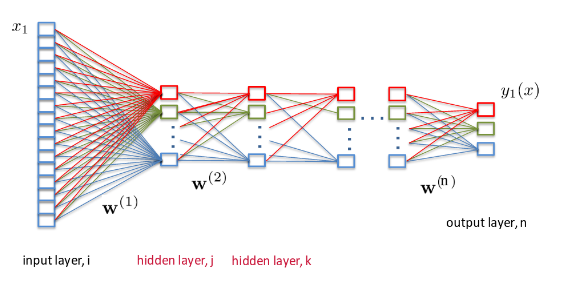


Figure: Deep Neural Networks

- Simply adding layers won't work.
- Too many parameters to train.
- Need smart architectures to capture additional priors.
- Two most commonly used architectures are CNNs and RNNs.

Convolutional Neural Networks

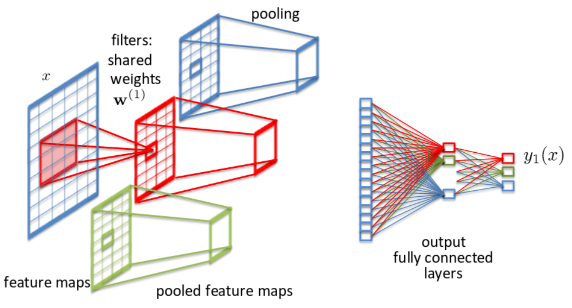
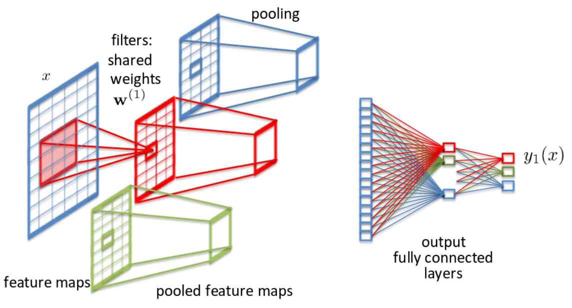


Figure: Convolutional Neural Networks

- Each layers learns a set of convolution kernels.

Convolutional Neural Networks



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- 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.

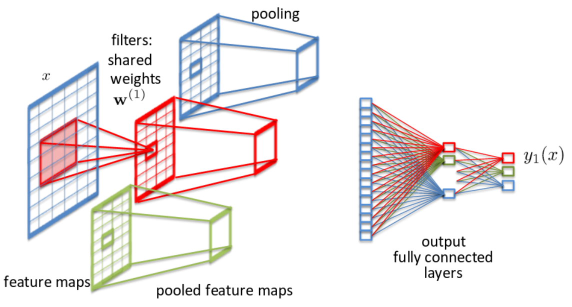


Figure: Convolutional Neural Networks

- 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

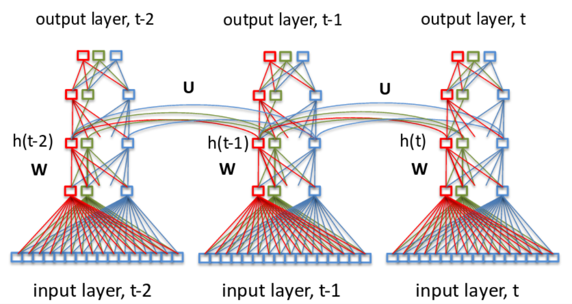
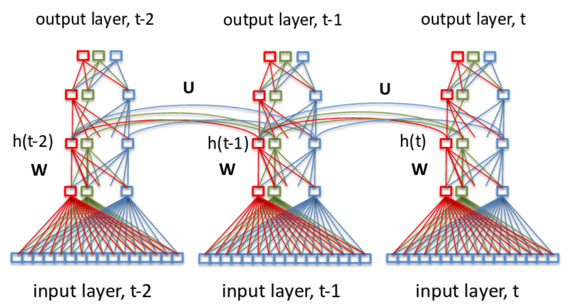


Figure: Recurrent Neural Networks

- Used for predicting sequential data

Recurrent Neural Networks



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- Captures dependences across time frames.

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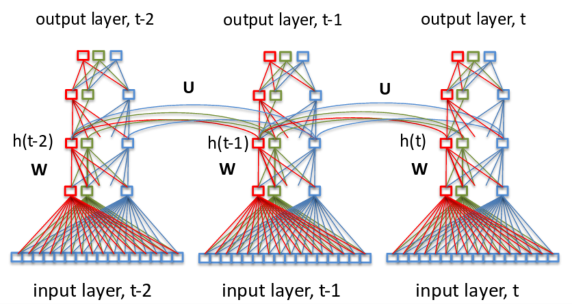
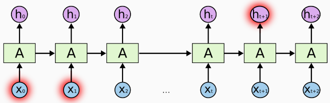


Figure: Recurrent Neural Networks

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

LSTM



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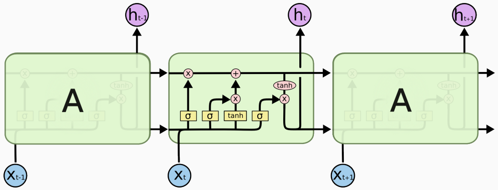
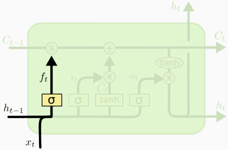


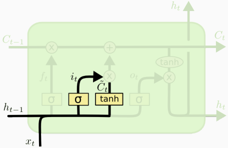
Figure: Long Short Term Memory

LSTM



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

Figure: LSTM Forget gate

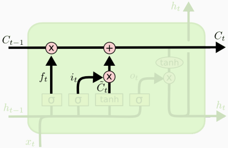


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

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

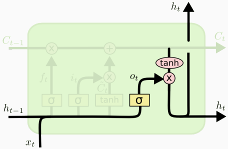
Figure: LSTM new content

LSTM



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

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

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

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

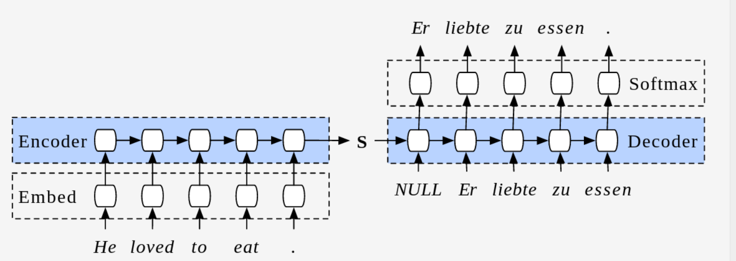


Figure: Encoder-Decoder model for Machine Translation

- Fixed size encodings.

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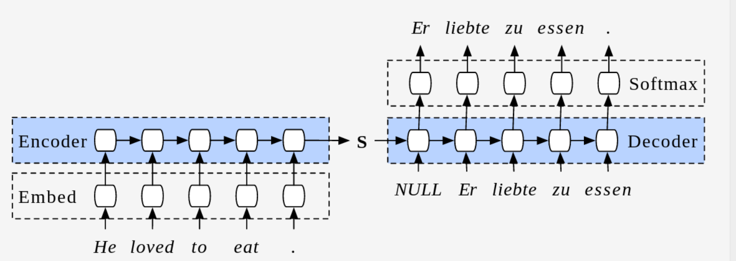

Figure: Encoder-Decoder model for Machine Translation

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

Jointly learning to Align and translate

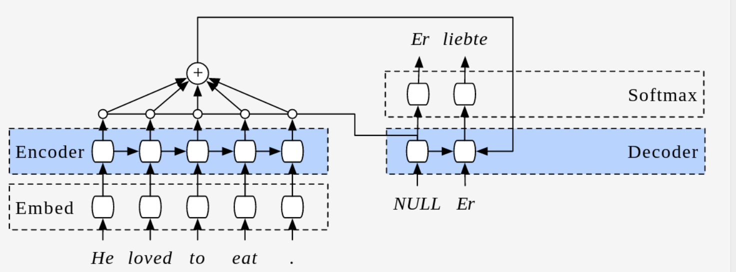

Figure: Encoder-Decoder model with context

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, $h_t = f(x_t, h_{t-1})$.

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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**)

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

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

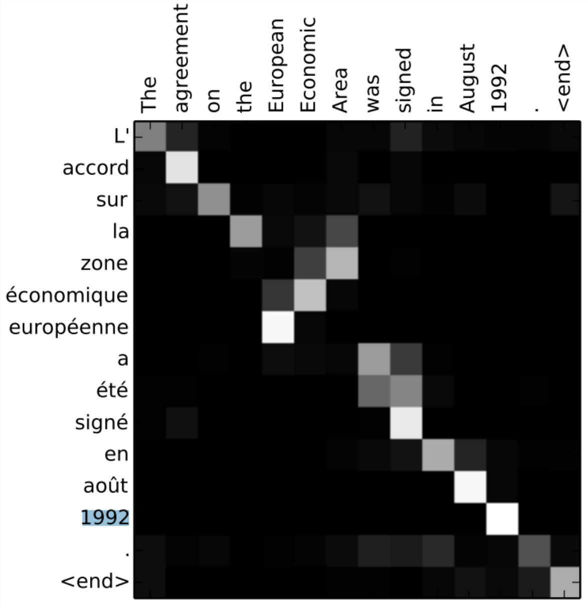
where,

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

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

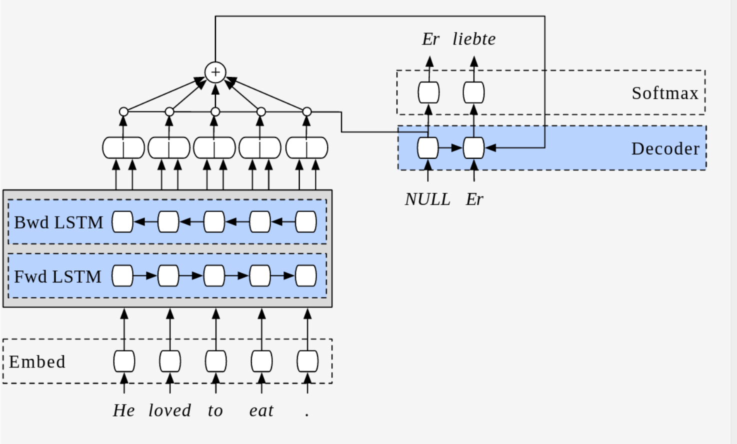


Figure: Bi-directional Encoder

- Recurrent connection in both directions.

Bi-directional Encoder

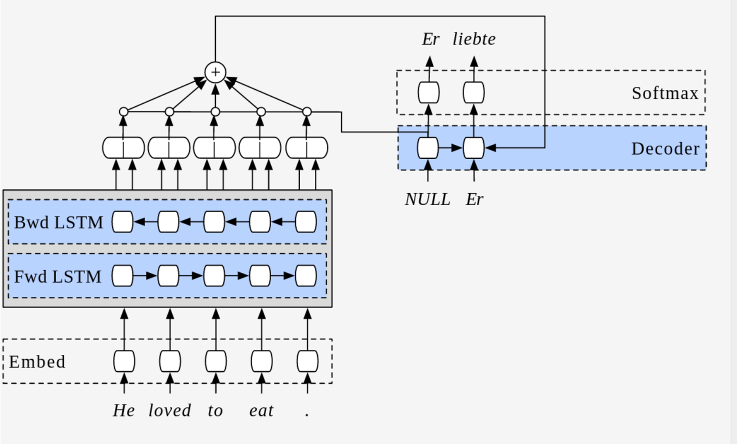


Figure: Bi-directional Encoder

- 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.

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

Seq2Seq Learning

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2. Deep LSTM layers.

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3. No special handling for Machine translation.

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

Seq2Seq Learning

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.
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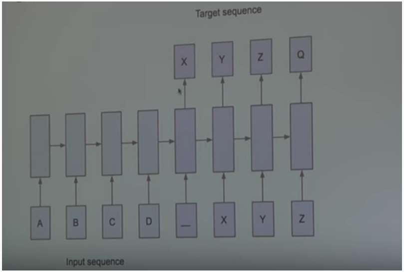
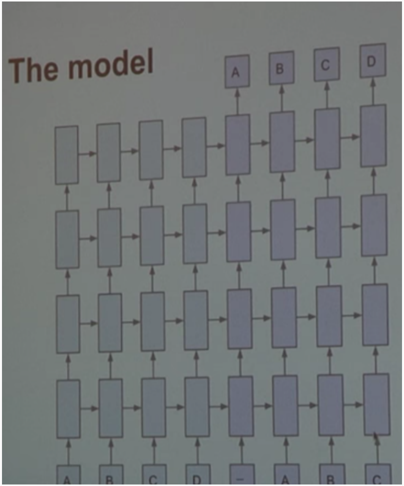
3. No special handling for Machine translation.
4. Trained with SGD.

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

Seq2Seq Learning



(a) Seq2Seq model



(b) More powerful model

Seq2Seq Learning

- 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

Seq2Seq Learning

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

Seq2Seq Learning

Architecture details:

- 4 LSTM layers.

Seq2Seq Learning

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- 1000 LSTM cells in each layer.

Seq2Seq Learning

Architecture details:

- 4 LSTM layers.
- 1000 LSTM cells in each layer.
- 1000 dimensional word embeddings.

Google NMT

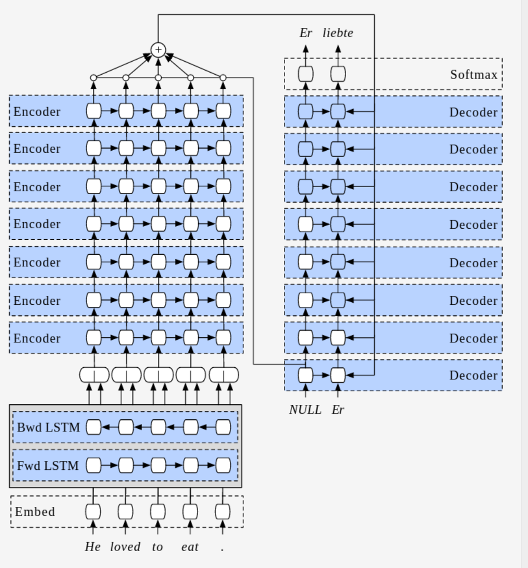

Figure: Simple Encoder-Decoder but more deeper as in Seq2Seq, and Context

Residual learning

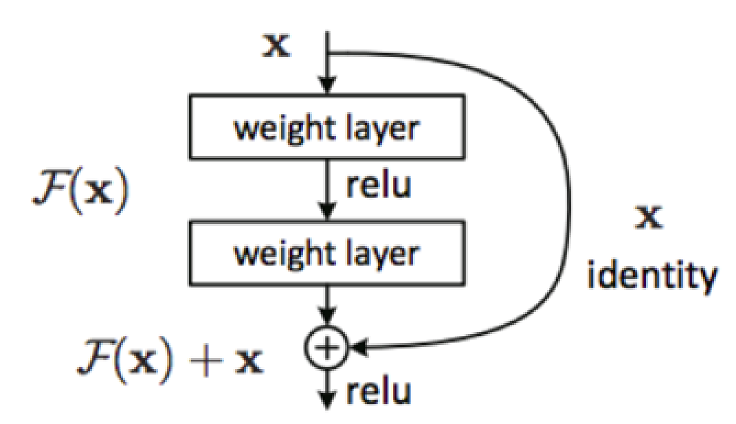

Figure: Residual networks

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

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

Google NMT with Residual connection

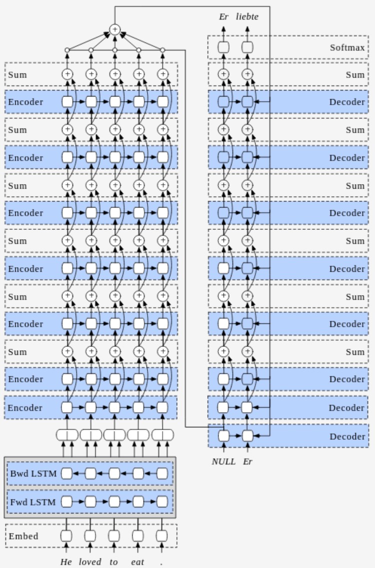

Figure: GNMT with residual connections.

Google NMT

Google NMY properties

- One Encoder and one Decoder for all the languages.

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- The input language are encoded usign word3vec for all languages.
- One additional token (¡$_{EN_{>,<_{FR_{>,<_{DE_{>,<_{ES_{>)indicationgthetargetlanguage.}}}}}}}}$
- One gaint 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.
- In production by companies like Google, Microsoft, Facebook, etc.

Referencee

http://liris.cnrs.fr/natalia.neverova/nslides/presentation$_{s}oftshake_{1}51022_{n}ovide$