# **Neural Machine Translation**

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Seminar: Natural Language Processing

• Introduction to Machine Translation

- Introduction to Machine Translation
- Statistical Phrase-Based Translation

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- Statistical Phrase-Based Translation
- Introduction to Deep Learning

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- Neural Machine Translation

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

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

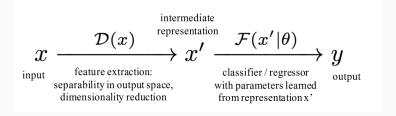
#### **Machine Translation**

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.

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

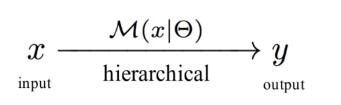
# Introduction to Deep Learning

# Machine Learning (Supervised)



Traditional Supervised learning

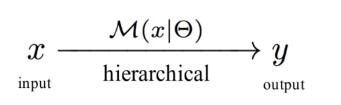
#### Deep Learning (Supervised)



Deep learning

• Hierarchical representations of features.

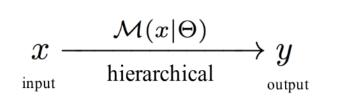
#### Deep Learning (Supervised)



Deep learning

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

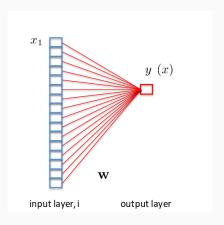
# Deep Learning (Supervised)



Deep learning

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

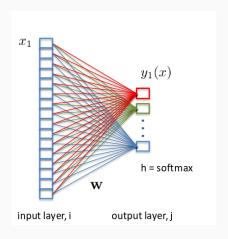
# Perceptron



A perceptron (close to a biological neuron)

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

# **Logistic Regression**



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

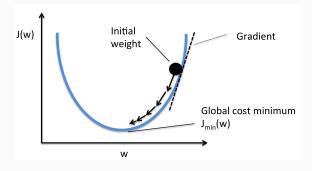
Cost function:

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

Learning Weights: Gradient Descent

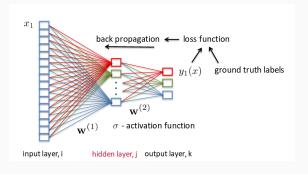
$$\nabla_w J(w) = \frac{\partial J(w)}{\partial w_j} = \sum_i x_j^i (h_w(x^i) - y^i)$$

#### **Gradient Descent**



Update weights in the direction of negative gradient.

# Multi Layer Perceptron

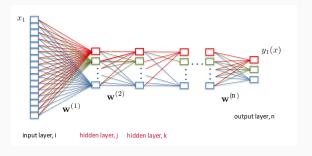


Multiple layers of perceptron

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**



Deep Neural Networks

MLPs with lots of layers (Just a fancy name).

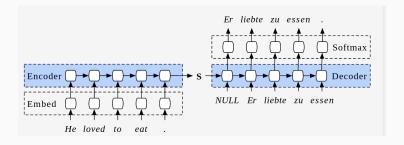
**Neural Machine Translation** 

#### **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.

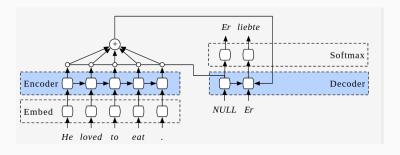
#### NMT - A historic perspective



Encoder-Decoder model for Machine Translation

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

#### Jointly learning to Align and translate



Encoder-Decoder model with context

#### Jointly learning to Align and translate

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

- Encoder and Decoder are multi-layer recurrent neural networks (RNNs).
- 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,  $c = q(\{h_1, \cdots, h_{T_x}\}).$

 $<sup>^1 \</sup>mbox{NEURAL}$  MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE. Dzmitry Bahdanau, KyungHyun Cho, Yoshua Bengio, ICLR, 2015.

#### 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**)

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

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

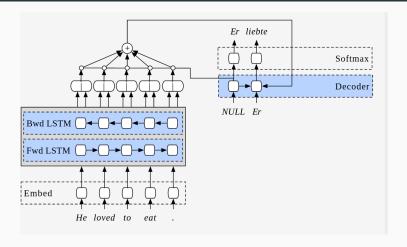
where,

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

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.

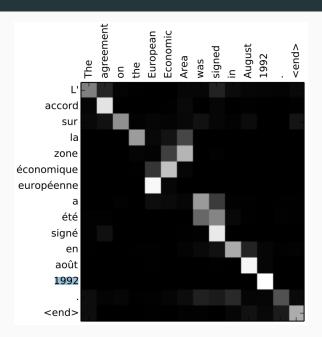
#### **Bi-directional Encoder**



Bi-directional Encoder

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

#### Visualization of the context



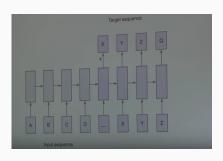
# Seq2Seq Learning

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.
- 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

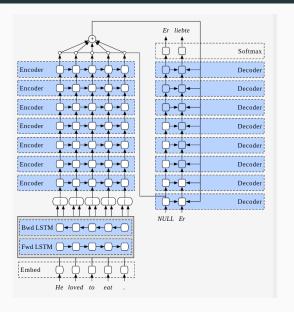


The model

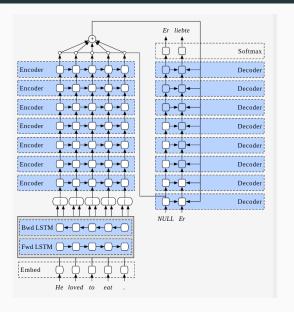
(a) Seq2Seq model

(b) More powerful model

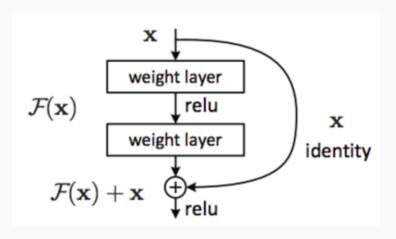
# Google NMT



# Google NMT



# Residual learning



Residual connections enables training of very deep networks.  $^2$ 

<sup>&</sup>lt;sup>2</sup>Deep Residual Learning for Image Recognition. Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. CVPR, 2016.

# Google NMT with Residual connection



#### 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

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