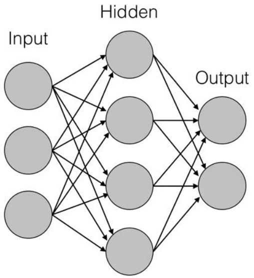
Sequence Modeling: Recurrent and Recursive Networks

Markus Dumke

27th January 2016

Contents

Why RNN's?



- Independence
- Fixed Length

https://www.nervanasys.com/recurrent-neural-networks/

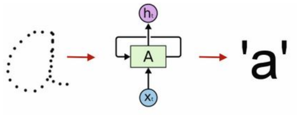
$$g_t(x_t, ..., x_1) = f(x_t, h_{t-1})$$

He went to Germany in 2010.

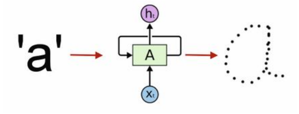
In 2010 he went to Germany.

- sequential data:
  texts, speech, time series
- variable length
- long-term dependencies
- memory

Applications



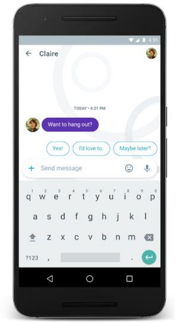
Handwriting recognition



Handwriting generation

https://greydanus.github.io/2016/08/21/handwriting/

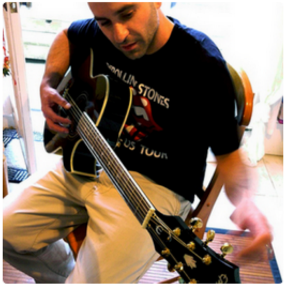
Smart reply



https://research.googleblog.com/2016/05/chat-smarter-with-allo.html

Applications

Image Captioning


"man in black shirt is playing guitar."

Karpathy and Fei-Fei (2015)

Pixel RNNs

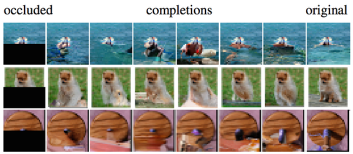


Figure 1. Image completions sampled from a PixelRNN.

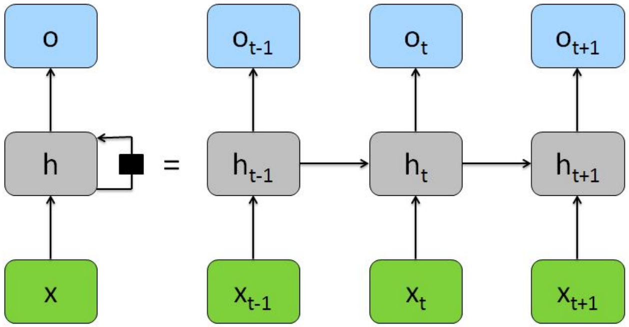
Van den Oord et al. (2016)

Applications

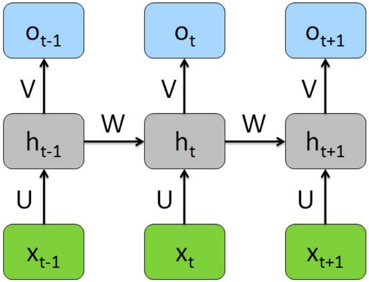
- Machine translation
- Sentiment analysis
- Text summaries
- Speech recognition and generation
- Time series
- Deep Reinforcement Learning

Contents

Recurrent Neural Network



Recurrent Neural Network

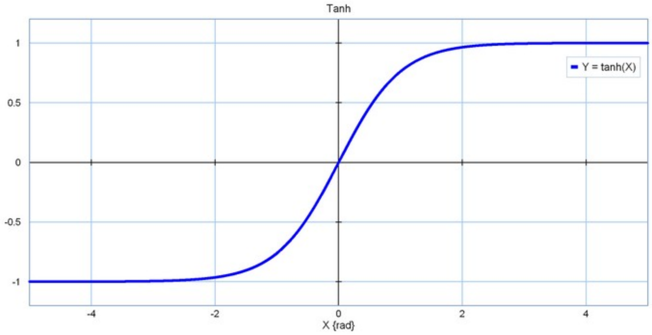


for t = 1 to T:

$$
\begin{aligned}
h_t &= f(b + W\, h_{t-1} + U\, x_t) \\
o_t &= c + V\, h_t \\
\hat{y}_t &= softmax(o_t) \\
&= \frac{exp(o_t^{k'})}{\sum_k exp(o_t^k)} \quad \forall k'
\end{aligned}
$$

Which activation function?

$$f(x) = tanh(x) = \frac{sinh(x)}{cosh(x)} = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$



http://www.20sim.com/webhelp/language_reference_functions_tanh.php

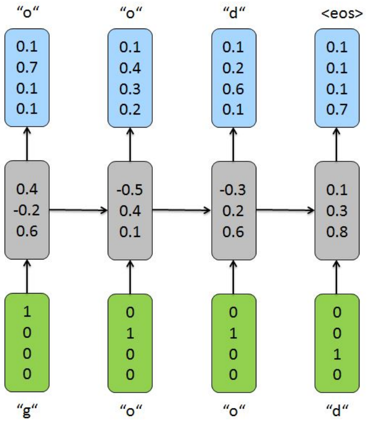
Language Modeling

- Input: word/character encoded as one-hot vector
- Output: Probability distribution over words given previous words

$$\mathrm{P}(\mathrm{y}_1, ..., y_T) = \prod_{i=1}^{T} P(y_i | y_1, ..., y_{i-1})$$

- score sentences with their probabilities

Recurrent Neural Network



$$\underset{n_h\times 1}{h_t} = f(\underset{n_h\times 1}{b} + \underset{n_h\times n_h}{W}\,\underset{n_h\times 1}{h_{t-1}} + \underset{n_h\times n_y}{U}\,\underset{n_y\times 1}{x_t})$$

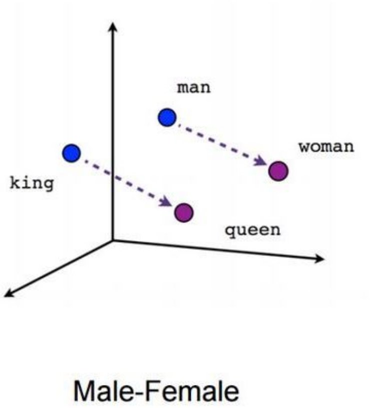
$$\underset{n_y\times 1}{o_t} = \underset{n_y\times 1}{c} + \underset{n_y\times n_h}{V}\,\underset{n_h\times 1}{h_{t-1}}$$

Vocabulary size $n_y > 100000$

Word Embeddings (Word2vec)

- Data sparsity

$$man \rightarrow \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \rightarrow \begin{bmatrix} 0.35 \\ -0.83 \\ \vdots \\ 0.11 \\ 3.2 \end{bmatrix}$$



https://www.tensorflow.org/tutorials/word2vec/

Sampling from an RNN

- Sample from conditional distribution at each time step
- How to generate sequence length?
  - special end symbol
  - Bernoulli random variable
  - integer value τ

Contents

Optimization

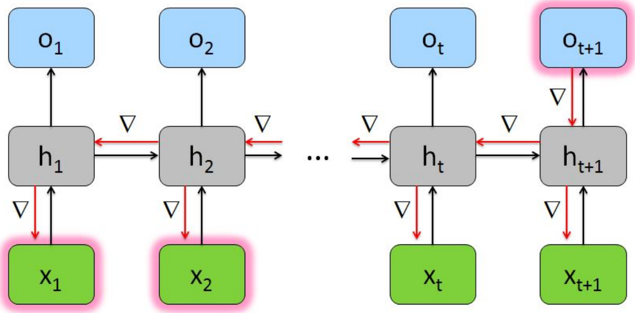
- Forward Propagation:
  - compute hidden states, outputs and loss
  - Loss function, e.g. negative log-likelihood

$$L = \sum_t L_t = \sum_t -log\ p_{model}(y_t \mid x_1, ..., x_t)$$

- Backward Propagation through time (BPTT):
  - compute gradients
- Stochastic Gradient Descent

Vanishing (and Exploding) Gradient Problem

$$\frac{\partial L}{\partial h_1} = \frac{\partial L}{\partial h_T} \frac{\partial h_T}{\partial h_{T-1}} \cdots \frac{\partial h_2}{\partial h_1}$$

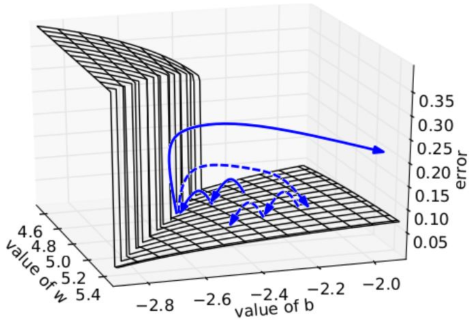


How to deal with exploding gradients?

Gradient Clipping

$$\textit{if}\ ||\nabla W|| > \textit{threshold}:$$

$$\nabla W \leftarrow \frac{\textit{threshold}}{||\nabla W||} \nabla W$$

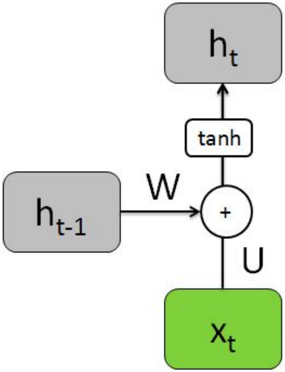


Pascanu, Mikolov and Bengio (2013)

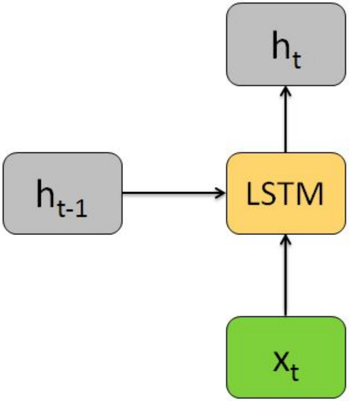
Contents

Vanilla RNN

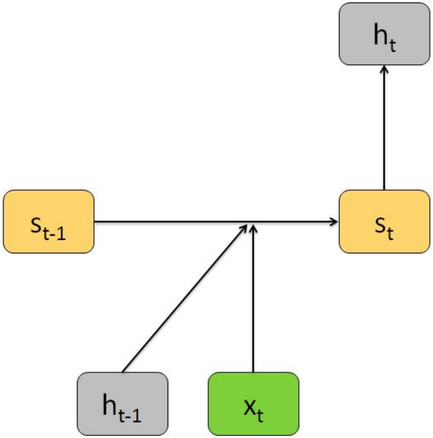
$$h_t = \tanh(b + W\, h_{t-1} + U\, x_t)$$



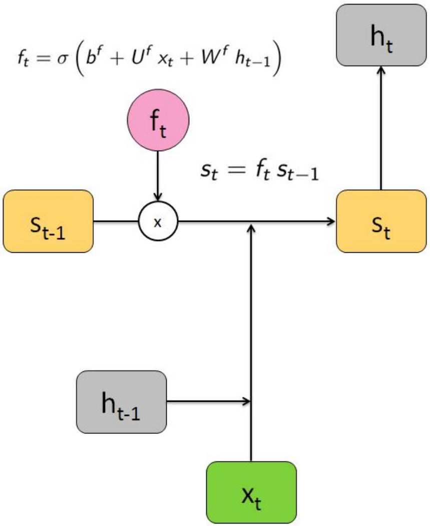
LSTM



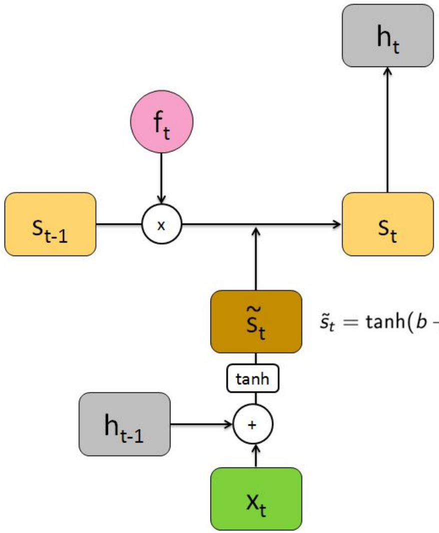
LSTM



LSTM

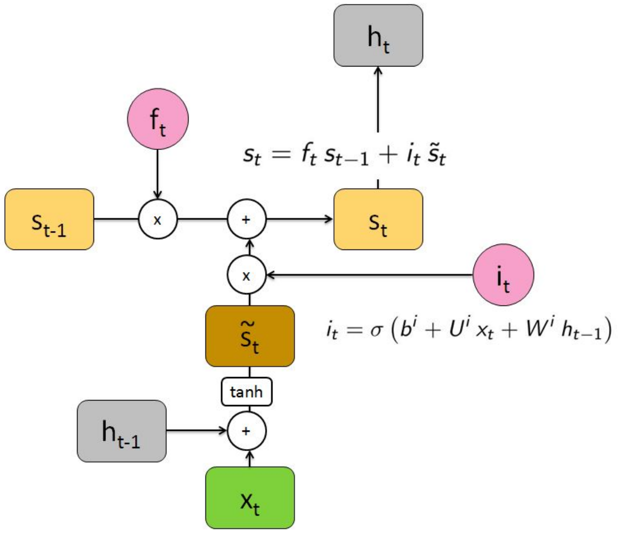


LSTM



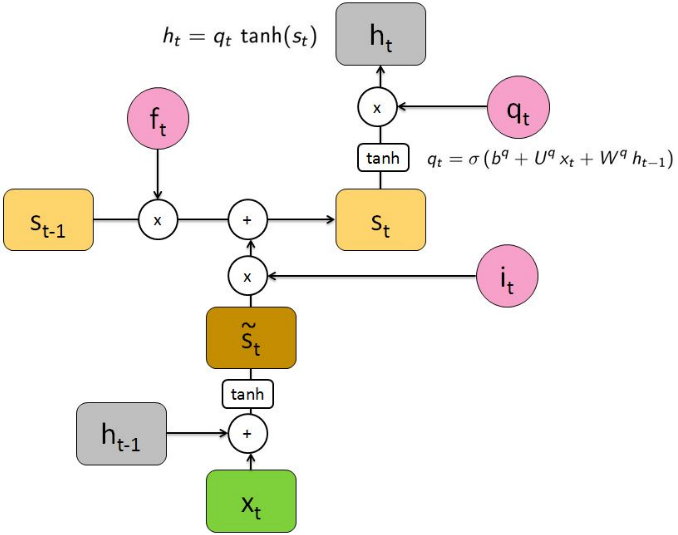
$$\tilde{s}_t = \tanh(b + W\,h_{t-1} + U\,x_t)$$

LSTM



h_t
f_t
$s_t = f_t\, s_{t-1} + i_t\, \tilde{s}_t$
s_{t-1}
x
+
s_t
x
i_t
$\tilde{s}_t$
$i_t = \sigma\left(b^i + U^i\, x_t + W^i\, h_{t-1}\right)$
tanh
h_{t-1}
+
x_t

LSTM


$h_t = q_t \tanh(s_t)$
h_t
f_t
q_t
x
tanh
$q_t = \sigma(b^q + U^q x_t + W^q h_{t-1})$
s_{t-1}
x
+
s_t
x
i_t
$\tilde{s}_t$
tanh
h_{t-1}
+
x_t

LSTM in R (mxnet)

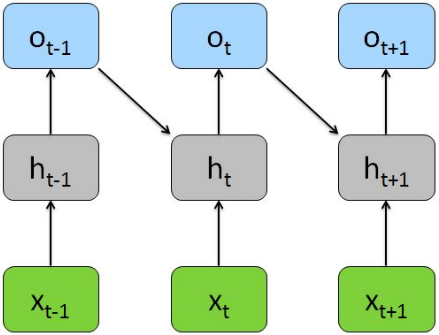
```r
model <- mx.lstm(X.train, X.val,
                 ctx = mx.cpu(),
                 num.round = 100,
                 update.period = 1,
                 num.lstm.layer = 1,
                 seq.len = 32,
                 num.hidden = 16,
                 num.embed = 16,
                 num.label = 100,
                 batch.size = 32,
                 input.size = 100,
                 initializer = mx.init.uniform(0.1),
                 learning.rate = 0.1,
                 wd = 0.00001,
                 clip_gradient = 1)
```

Generating Text

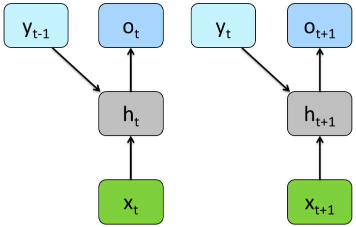
```
infer.model <- mx.lstm.inference(num.lstm.layer=num.lstm.layer,
                                 input.size=vocab,
                                 num.hidden=num.hidden,
                                 num.embed=num.embed,
                                 num.label=vocab,
                                 arg.params=model\text{\$}arg.
                                      params,
                                 ctx=mx.cpu())

mx.lstm.forward(infer.model, input, FALSE)
```

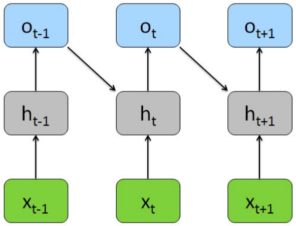
RNN with output recurrence



Teacher Forcing

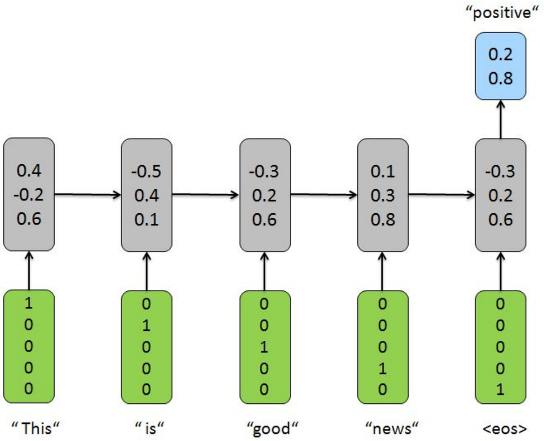


At train time

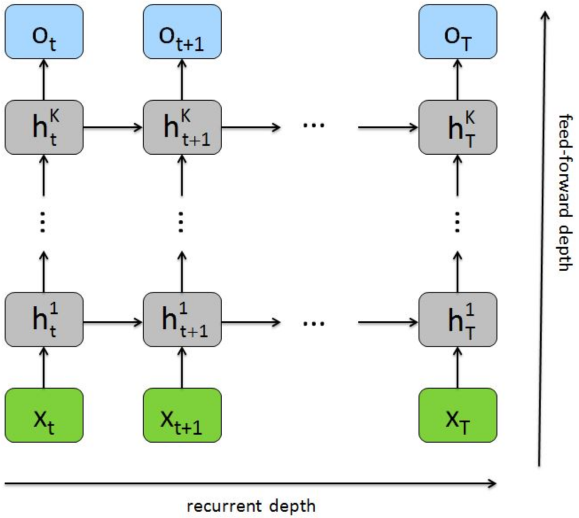


At test time

One-output RNN

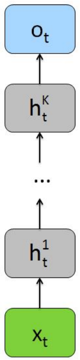


Deep RNNs

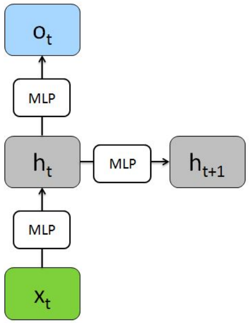


o_t
o_{t+1}
o_T
h_t^K
h_{t+1}^K
...
h_T^K
h_t^1
h_{t+1}^1
...
h_T^1
x_t
x_{t+1}
x_T
recurrent depth
feed-forward depth

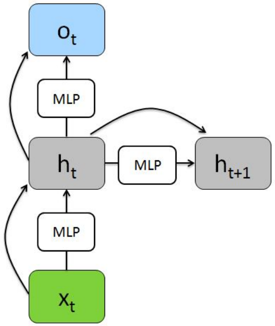
Deep RNNs



Stacked layers

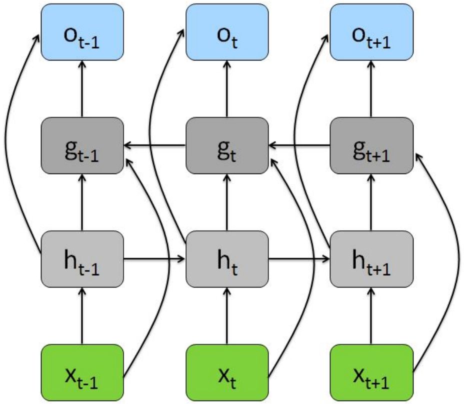


Deep computations

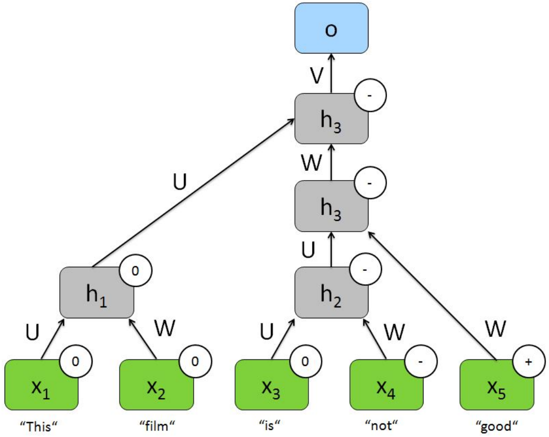


Skip connections

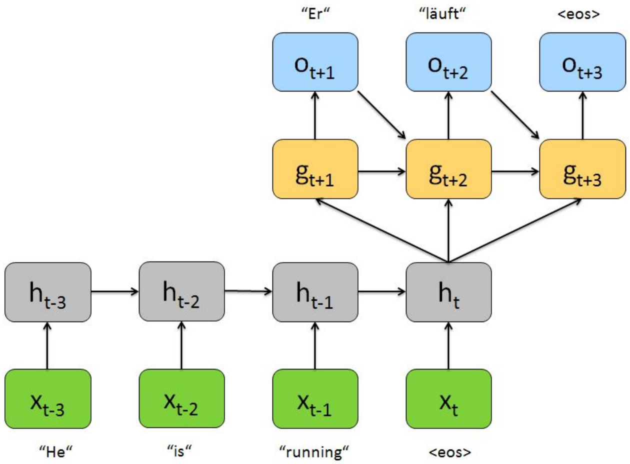
Bidirectional RNN



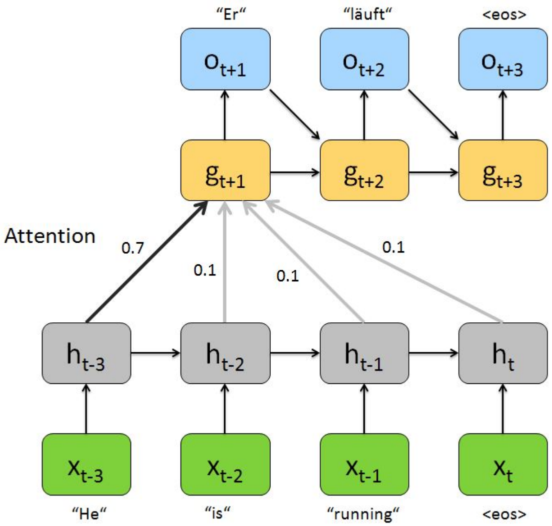
Recursive Neural Network



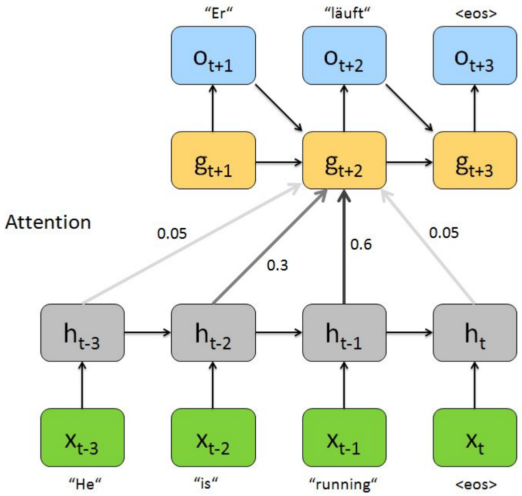
Encoder-Decoder Network



Attention


"Er"
"läuft"
<eos>
o_{t+1}
o_{t+2}
o_{t+3}
g_{t+1}
g_{t+2}
g_{t+3}
Attention
0.7
0.1
0.1
0.1
h_{t-3}
h_{t-2}
h_{t-1}
h_t
x_{t-3}
x_{t-2}
x_{t-1}
x_t
"He"
"is"
"running"
<eos>

Attention



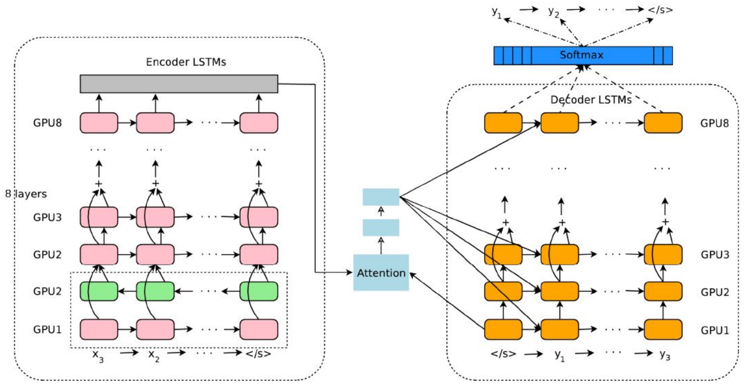
"Er"
"läuft"
<eos>
o_{t+1}
o_{t+2}
o_{t+3}
g_{t+1}
g_{t+2}
g_{t+3}
Attention
0.05
0.3
0.6
0.05
h_{t-3}
h_{t-2}
h_{t-1}
h_t
x_{t-3}
x_{t-2}
x_{t-1}
x_t
"He"
"is"
"running"
<eos>

Contents

Machine Translation

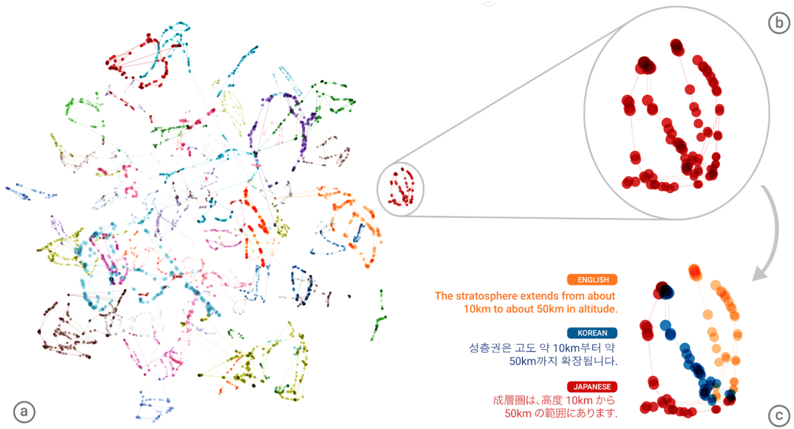
- last decades: phrase-based systems
- neural networks as part of phrase-based systems
- Encoder-decoder RNNs:
  - Sutskever et al. (2014), Bahdanau et al. (2015)
- Google's Neural Machine Translation (September/November 2016)

Google's Neural Machine Translation System



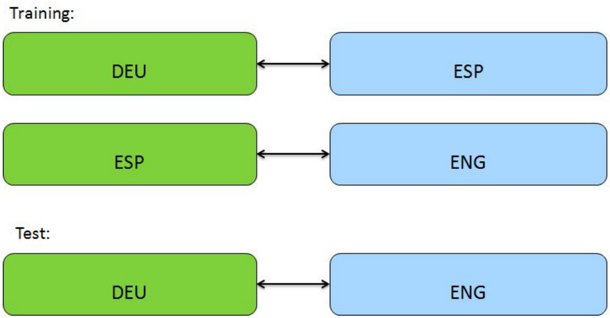
Wu et al. (2016): Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation

Language Embeddings



Johnson et al. (2016): Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation

Zero-shot Translation



Details Machine Translation

Main challenges:

- speed
- handling of rare words
- not translating all words (coverage)

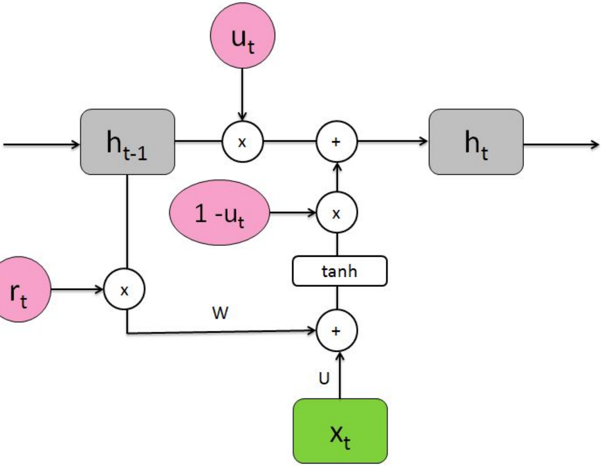
Solutions:

- GPU training
- sub-word units (wordpieces)
- coverage penalty
- length-normalization

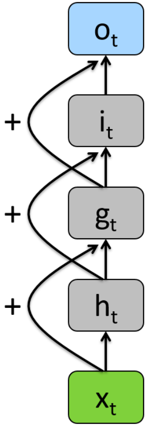
How to deal with vanishing gradients?

- Regularization $\nabla_{h_t} L \approx (\nabla_{h_t} L) \frac{\partial h_t}{\partial h_{t-1}}$
- skip-connections over time
- Leaky units $\mu = \alpha\, \mu_{t-1} + (1-\alpha)\, \nu_t$
- remove short-term connections
- Explicit Memory
- **LSTM**, GRU and other gated RNNs

GRU



Residual Networks (Res-Nets)



- training of very deep models possible
- like an ensemble of shallow architectures