Deep Learning for Natural Language Processing

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EUROPEAN UNION
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Operational Programme Research,
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Outline

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- NLP tasks learn end-to-end using deep learning — the number-one approach in current research

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- State of the art in POS tagging, parsing, named-entity recognition, machine translation, ...
- Good news: training without almost any linguistic insight
- Bad news: requires enormous amount of training data and really big computational power

What is deep learning?

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- Buzzword for machine learning using neural networks with many layers using back-propagation
- Learning of a real-valued function with millions of parameters that solves a particular problem
- Learning more and more abstract representation of the input data until we reach such a suitable representation for our problem

Neural Networks Basics

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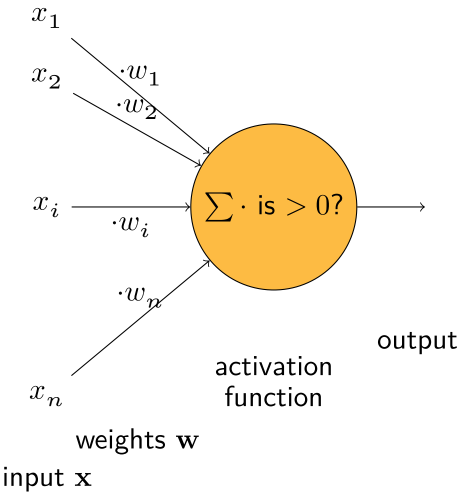
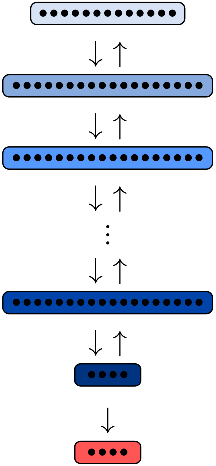

x_1
x_2
x_i
x_n
$\cdot w_1$
$\cdot w_2$
$\cdot w_i$
$\cdot w_n$
$\sum \cdot$ is > 0?
output
activation function
weights $\mathbf{w}$
input $\mathbf{x}$

Neural Network



$$
\begin{array}{ccc}
x & & \uparrow \\
\downarrow & & \\
h_1 = f(W_1 x + b_1) & & \uparrow \\
\downarrow & & \\
h_2 = f(W_2 h_1 + b_2) & & \uparrow \\
\downarrow & & \\
\vdots & & \uparrow \\
\downarrow & & \\
h_n = f(W_n h_{n-1} + b_n) & & \uparrow \\
\downarrow & & \\
o = g(W_o h_n + b_o) & & \frac{\partial E}{\partial W_o} = \frac{\partial E}{\partial o} \cdot \frac{\partial o}{\partial W_o} \\
\downarrow & & \uparrow \\
E = e(o, t) & \rightarrow & \frac{\partial E}{\partial o}
\end{array}
$$

Implementation

Logistic regression:

$$y = \sigma\left(Wx + b\right) \tag{1}$$

Computation graph:

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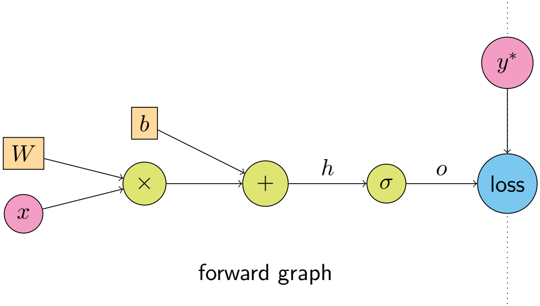

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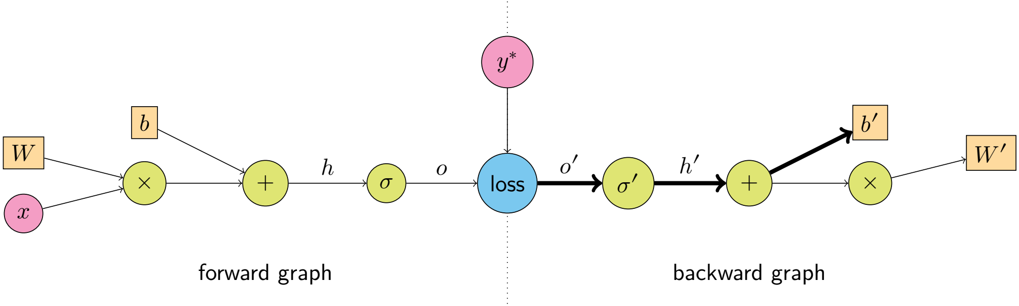

research and prototyping in Python

- graph statically constructed, symbolic computation
- computation happens in a session
- allows graph export and running as a binary

- computations written dynamically as normal procedural code
- easy debugging: inspecting variables at any time of the computation

Representing Words

Language Modeling

- estimate probability of a next word in a text

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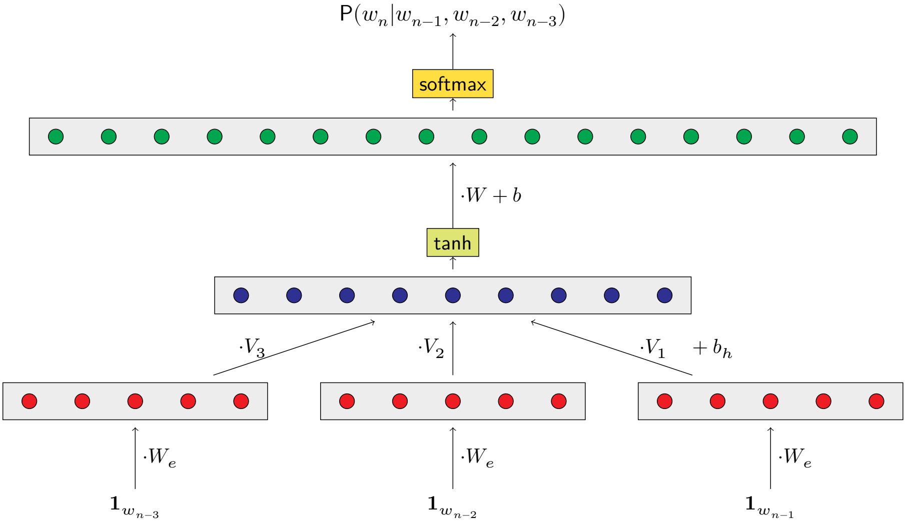
- Let's simulate it with a neural network:

$$\dots \approx F(w_{i-1}, \dots, w_{i-n}|\theta)$$

θ is a set of trainable parameters.

Simple Neural Language Model



Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Jauvin. A neural probabilistic language model. *The Journal of Machine Learning Research*, 3 (Feb):1137–1155, 2003. ISSN 1532-4435

Neural LM: Word Representation

- limited vocabulary (hundred thousands words): indexed set of words

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The first hidden layer is then:

$$h_1 = V_{w_{i-n}} \oplus V_{w_{i-n+1}} \oplus \dots \oplus V_{w_{i-1}}$$

Matrix V is shared for all words.

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Table 7: Word embeddings in the word lookup table of the language model neural network LM1 trained with a dictionary of size 100,000. For each column the queried word is followed by its index in the dictionary (higher means more rare) and its 10 nearest neighbors (using the Euclidean metric, which was chosen arbitrarily).

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- in IR: query expansion by nearest neighbors
- in deep learning models: embeddings initialization speeds up training / allows complex model with less data

Implementation in PyTorch I

```
import torch
import torch.nn as nn

class LanguageModel(nn.Module):
    def __init__(self, vocab_size, embedding_dim, hidden_dim):
        super().__init__()

        self.embedding = nn.Embedding(vocab_size, embedding_dim)
        self.hidden_layer = nn.Linear(3 * embedding_dim, hidden_dim)
        self.output_layer = nn.Linear(hidden_dim, vocab_size)
        self.loss_function = nn.CrossEntropyLoss()

    def forward(self, word_1, word_2, word_3, target=None):
        embedded_1 = self.embedding(word_1)
        embedded_2 = self.embedding(word_2)
        embedded_3 = self.embedding(word_3)
```

Implementation in PyTorch II

```
hidden = torch.tanh(self.hidden_layer(
    torch.cat(embedded_1, embedded_2, embedded_3)))
logits = self.output_layer(hidden)

loss = None
if target is not None:
    loss = self.loss_function(logits, targets)

return logits, loss
```

Implementation in TensorFlow I

```
import tensorfow as tf

input_words = [tf.placeholder(tf.int32, shape=[None]) for _ in range(3)]
target_word = tf.placeholder(tf.int32, shape[None])

embeddings = tf.get_variable(tf.float32, shape=[vocab_size, emb_dim])
embedded_words = tf.concat([tf.nn.embedding_lookup(w) for w in input_words])

hidden_layer = tf.layers.dense(embedded_words, hidden_size, activation=tf.tanh)
output_layer = tf.layers.dense(hidden_layer, vocab_size, activation=None)
output_probabilities = tf.nn.softmax(output_layer)

loss = tf.nn.cross_entropy_with_logits(output_layer, target_words)

optimizer = tf.optimizers.AdamOptimizers()
train_op = optimizer.minimize(loss)
```

Implementation in TensorFlow II

```
session = tf.Session()
# initialize variables
```

Training given batch

```
_, loss_value = session.run([train_op, loss], feed_dict={
    input_words[0]: ..., input_words[1]: ..., input_words[2]: ...,
    target_word: ...
})
```

Inference given batch

```
probs = session.run(output_probabilities, feed_dict={
    input_words[0]: ..., input_words[1]: ..., input_words[2]: ...,
})
```

Representing Sequences

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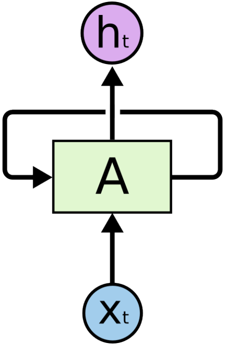
Recurrent Networks

Recurrent Networks (RNNs)

…the default choice for sequence labeling



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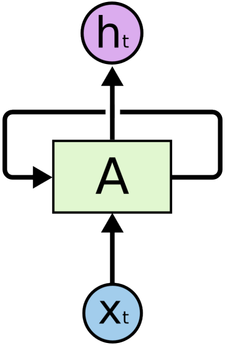

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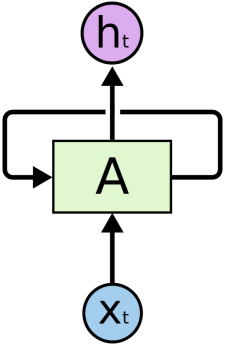
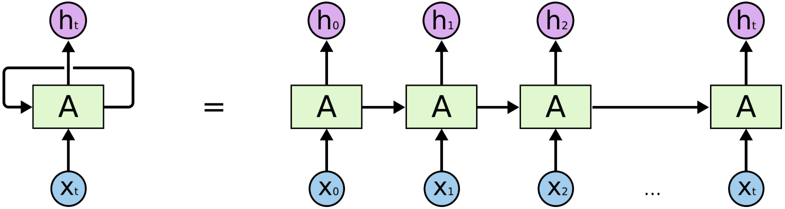


- inputs: $x_{,} \ldots, x_T$
- initial state $h_0 = \mathbf{0}$, a result of previous computation, trainable parameter
- recurrent computation: $h_t = A(h_{t-1}, x_t)$

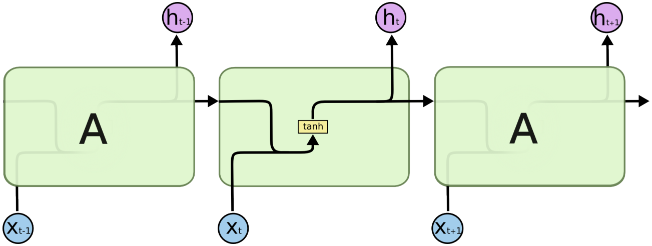
RNN as Imperative Code

```python
def rnn(initial_state, inputs):
  prev_state = initial_state
  for x in inputs:
    new_state, output = rnn_cell(x, prev_state)
    prev_state = new_state
    yield output
```

RNN as a Fancy Image



Vanilla RNN



$$h_t = \tanh\left(W[h_{t-1}; x_t] + b\right)$$

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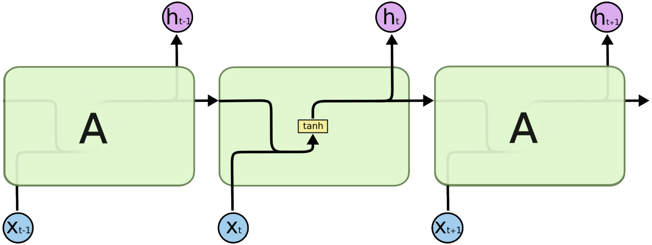

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- cannot propagate long-distance relations

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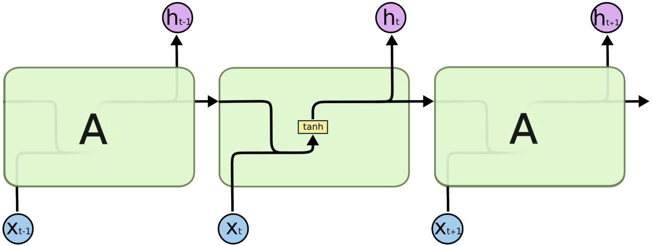
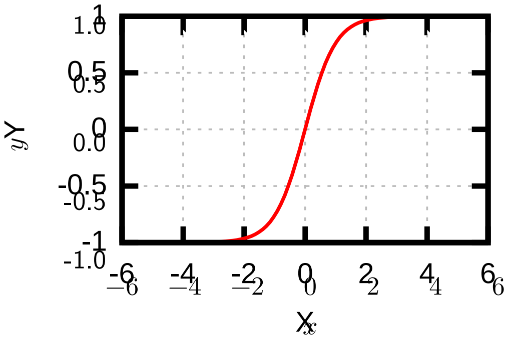


$$h_t = \tanh\left(W[h_{t-1}; x_t] + b\right)$$

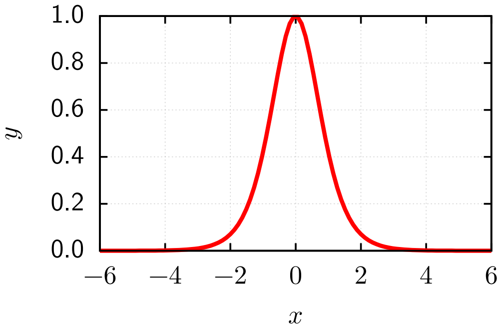
- cannot propagate long-distance relations
- vanishing gradient problem

Vanishing Gradient Problem (1)

$$\tanh x = \frac{1 - e^{-2x}}{1 + e^{-2x}}$$



$$\frac{\mathrm{d}\tanh x}{\mathrm{d}x} = 1 - \tanh^2 x \in (0, 1]$$



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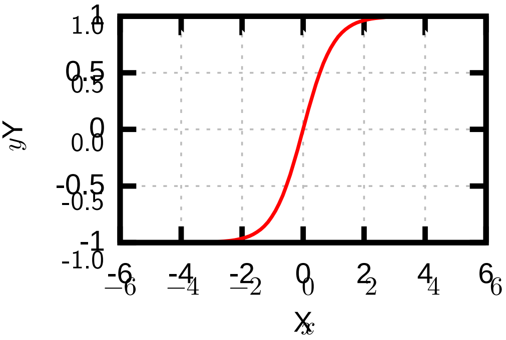
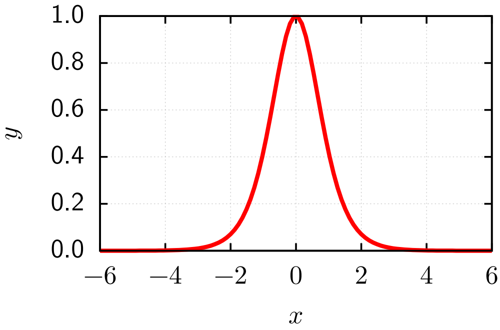
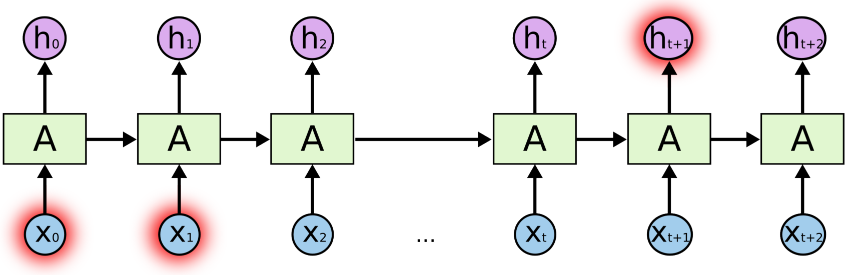




Weight initialized $\sim \mathcal{N}(0, 1)$ to have gradients further from zero.

Vanishing Gradient Problem (2)



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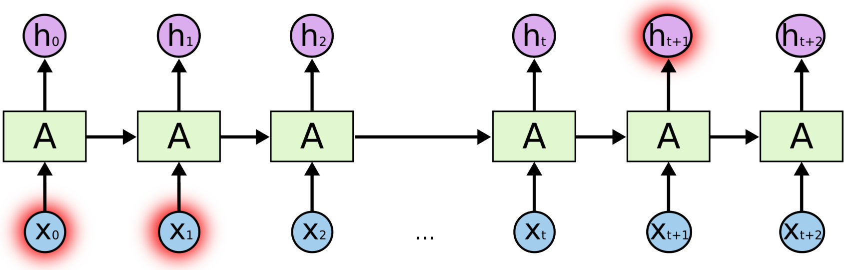

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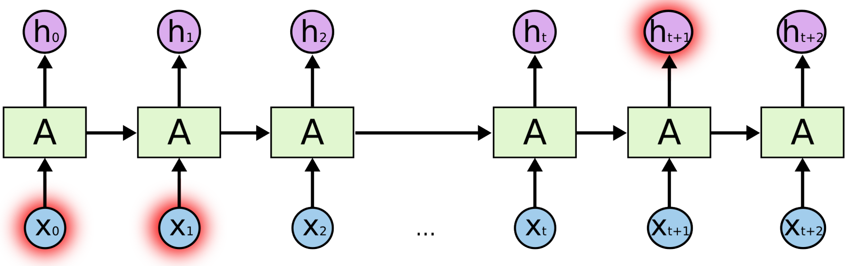
Vanishing Gradient Problem (2)



$$\frac{\partial E_{t+1}}{\partial b} = \frac{\partial E_{t+1}}{\partial h_{t+1}} \cdot \frac{\partial h_{t+1}}{\partial b}$$ (chain rule)

Vanishing Gradient Problem (3)

$$\frac{\partial h_t}{\partial b} =$$

Vanishing Gradient Problem (3)

$$\frac{\partial h_t}{\partial b} = \frac{\partial \tanh \overbrace{(W_h h_{t-1} + W_x x_t + b)}^{= z_t \text{ (activation)}}}{\partial b} \qquad (\tanh' \text{ is derivative of } \tanh)$$

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&= \tanh'(z_t) \cdot \left(\frac{\partial W_h h_{t-1}}{\partial b} + \underbrace{\frac{\partial W_x x_t}{\partial b}}_{=0} + \underbrace{\frac{\partial b}{\partial b}}_{=1} \right)
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&= \underbrace{W_h}_{\sim \mathcal{N}(0,1)} \underbrace{\tanh'(z_t)}_{\in (0;1]} \frac{\partial h_{t-1}}{\partial b} + \tanh'(z_t)
\end{aligned}$$

Long Short-Term Memory Networks

LSTM = Long short-term memory

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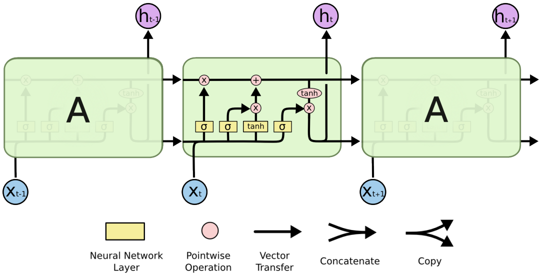

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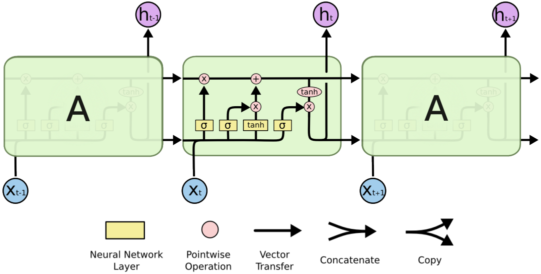

Control the gradient flow by explicitly gating:

LSTM = Long short-term memory

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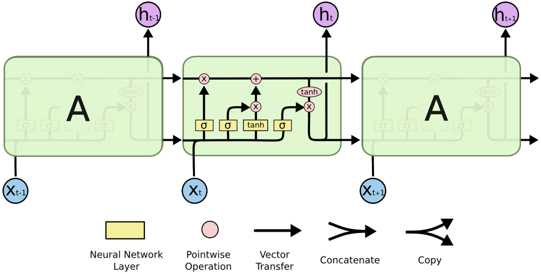

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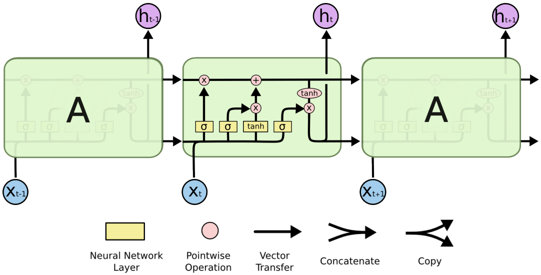

Control the gradient flow by explicitly gating:

- what to use from input,
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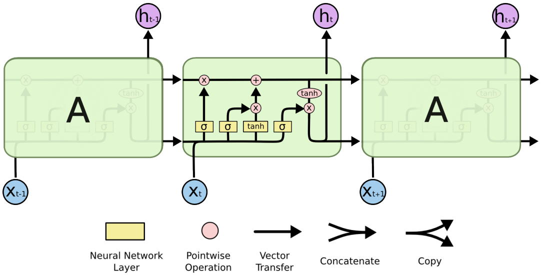
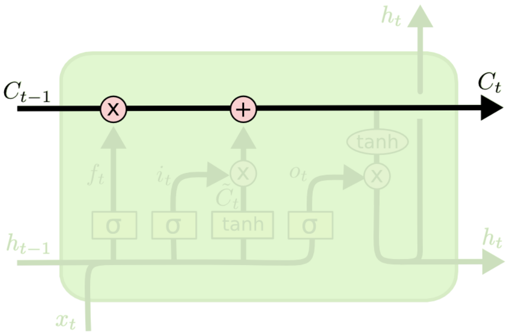


Control the gradient flow by explicitly gating:

- what to use from input,
- what to use from hidden state,
- what to put on output

LSTM: Hidden State

- two types of hidden states



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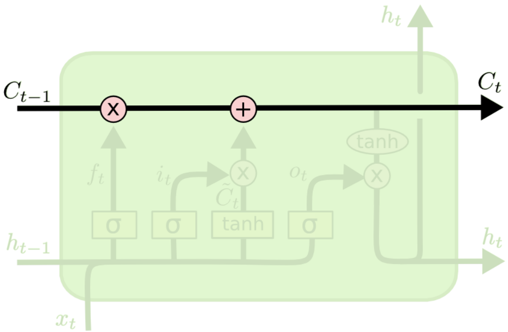
- h_t — "public" hidden state, used an output



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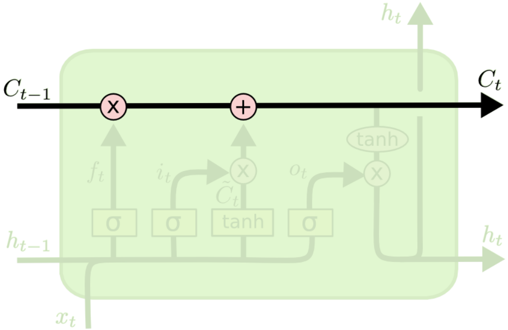
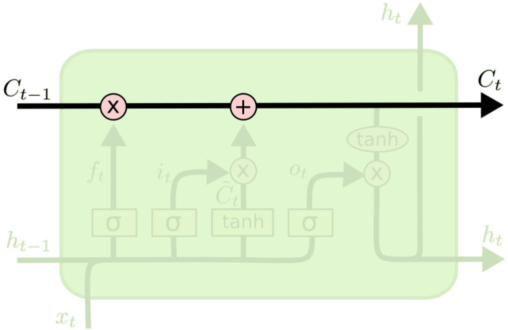
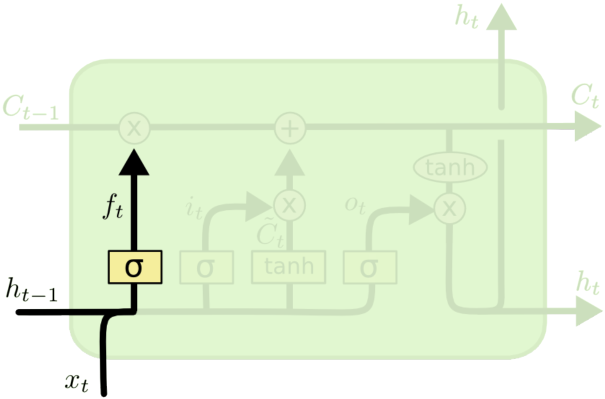


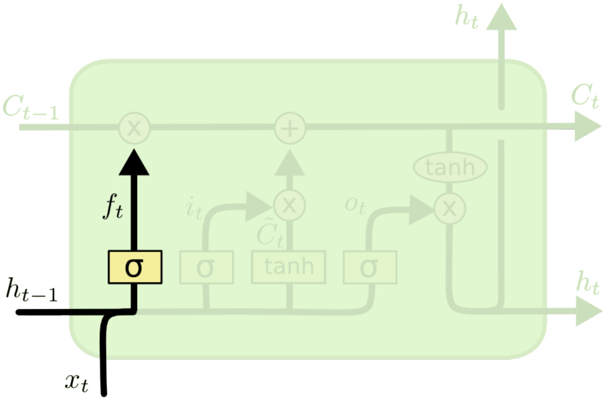
LSTM: Hidden State

- two types of hidden states
- h_t — “public” hidden state, used an output
- c_t — “private” memory, no non-linearities on the way
- direct flow of gradients (without multiplying by ≤ 1 derivatives)





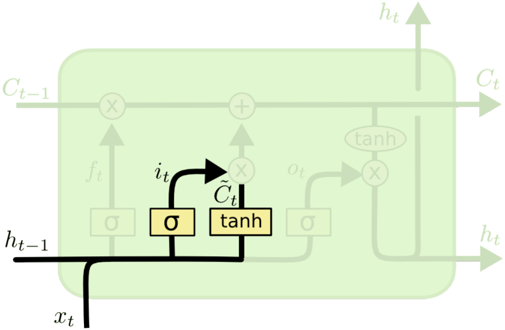
$$f_t = \sigma\left(W_f[h_{t-1}; x_t] + b_f\right)$$



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

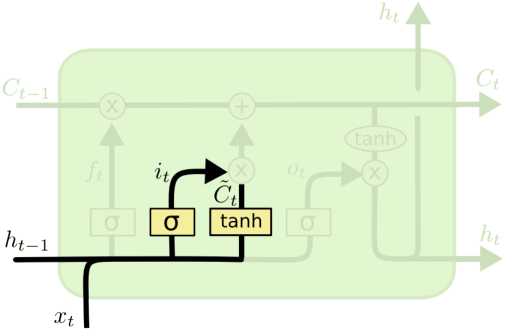
- based on input and previous state, decide what to forget from the memory

LSTM: Input Gate



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

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



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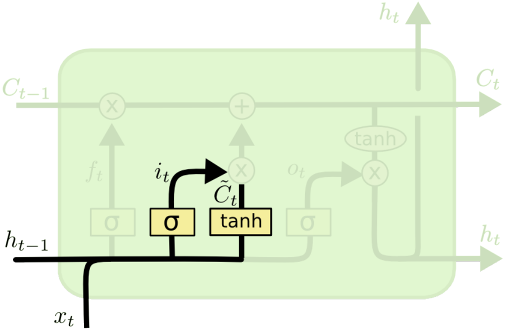

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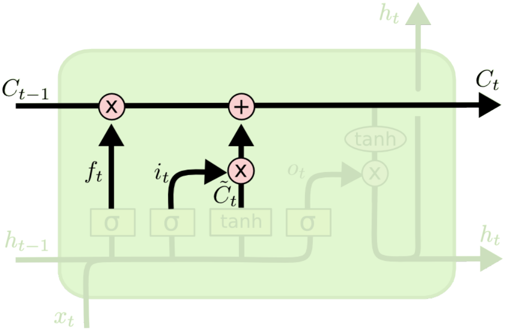
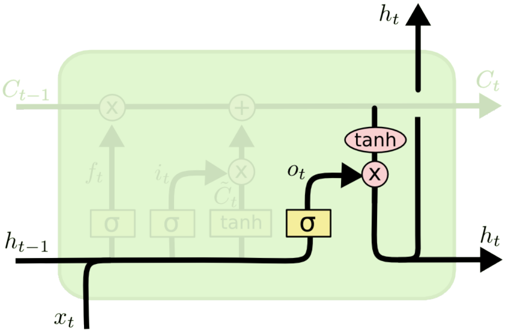
- $\tilde{C}$ — candidate what may want to add to the memory
- i_t — decide how much of the information we want to store

LSTM: Cell State Update



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

LSTM: Output Gate



$$o_t = \sigma\left(W_o \cdot [h_{t-1}; x_t] + b_o\right)$$

$$h_t = o_t \odot \tanh C_t$$

Here we are, LSTM!

$$
\begin{aligned}
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o_t &= \sigma\left(W_o \cdot [h_{t-1};x_t] + b_o\right) \\
\tilde{C}_t &= \tanh\left(W_c \cdot [h_{t-1};x_t] + b_C\right) \\
C_t &= f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \\
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Question How would you implement it efficiently?

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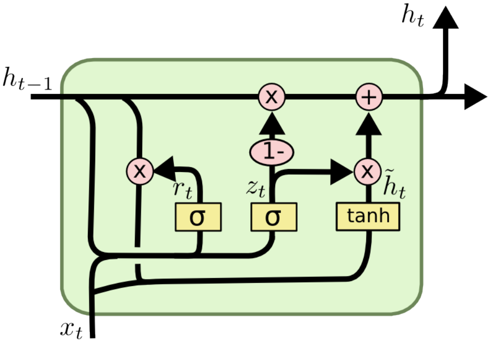
h_t &= o_t \odot \tanh C_t
\end{aligned}
$$

Question How would you implement it efficiently?
Compute all gates in a single matrix multiplication.

Gated Recurrent Units

update gate	$z_t = \sigma(x_t W_z + h_{t-1} U_z + b_z) \in (0,1)$
remember gate	$r_t = \sigma(x_t W_r + h_{t-1} U_r + b_r) \in (0,1)$
candidate hidden state	$\tilde{h}_t = \tanh\left(x_t W_h + (r_t \odot h_{t-1}) U_h\right) \in (-1,1)$
hidden state	$h_t = (1 - z_t) \odot h_{t-1} + z_t \cdot \tilde{h}_t$



LSTM vs. GRU

- GRU is smaller and therefore faster

Junyoung Chung, Çaglar Gülçehre, Kyunghyun Cho, and Yoshua Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. *CoRR*, abs/1412.3555, 2014. ISSN 2331-8422;

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LSTM vs. GRU

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- performance similar, task dependent
- theoretical limitation: GRU accepts regular languages, LSTM can simulate counter machine

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RNN in PyTorch

```
rnn = nn.LSTM(input_dim, hidden_dim=512, num_layers=1,
    bidirectional=True, dropout=0.8)
output, (hidden, cell) = self.rnn(x)
```

https://pytorch.org/docs/stable/nn.html?highlight=lstm#torch.nn.LSTM

RNN in TensorFlow

```
inputs = ... # float tf.Tensor of shape [batch, length, dim]
lengths = ... # int tf.Tensor of shape [batch]

# Cell objects are templates
fw_cell = tf.nn.rnn_cell.LSTMCell(512, name="fw_cell")
bw_cell = tf.nn.rnn_cell.LSTMCell(512, name="bw_cell")

outputs, states = tf.nn.bidirectional_dynamic_rnn(
    cell_fw, cell_bw, inputs, sequence_length=lengths)
```

https://www.tensorflow.org/api_docs/python/tf/nn/bidirectional_dynamic_rnn

Bidirectional Networks

- simple trick to improve performance

Bidirectional Networks

- simple trick to improve performance
- run one RNN forward, second one backward and concatenate outputs

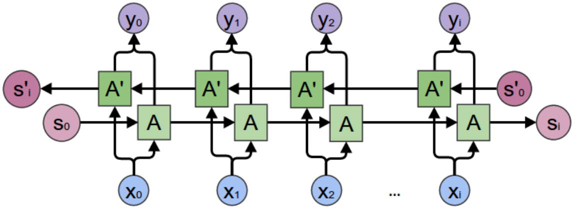

Image from: `http://colah.github.io/posts/2015-09-NN-Types-FP/`

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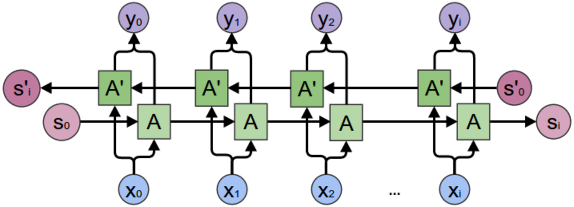

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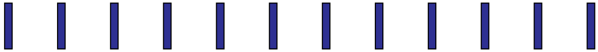
- state of the art in tagging, crucial for neural machine translation

Representing Sequences

Convolutional Networks

1-D Convolution

$\approx$ sliding window over the sequence



embeddings $\mathbf{x} = (x_1, \dots, x_N)$

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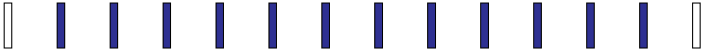


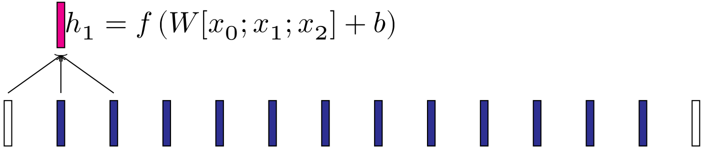
$x_0 = \vec{0}$ embeddings $\mathbf{x} = (x_1, \dots, x_N)$ $x_N = \vec{0}$

pad with 0s if we want to keep sequence length

1-D Convolution

≈ sliding window over the sequence

$h_1 = f\left(W[x_0; x_1; x_2] + b\right)$



$x_0 = \vec{0}$ embeddings $\mathbf{x} = (x_1, \dots, x_N)$ $x_N = \vec{0}$

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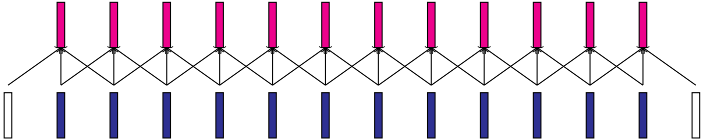
1-D Convolution

$\approx$ sliding window over the sequence

$$h_i = f\left(W\left[x_{i-1}; x_i; x_{i+1}\right] + b\right)$$



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pad with 0s if we want to keep sequence length

1-D Convolution: Pseudocode

```
xs = ... # input sequnce

kernel_size = 3 # window size
filters = 300 # output dimensions
strides=1     # step size

W = trained_parameter(xs.shape[2] * kernel_size, filters)
b = trained_parameter(filters)
window = kernel_size // 2

outputs = []
for i in range(window, xs.shape[1] - window):
    h = np.mul(W, xs[i - window:i + window]) + b
    outputs.append(h)
return np.array(h)
```

1-D Convolution: Frameworks

TensorFlow

```
h = tf.layers.conv1d(x, filters=300 kernel_size=3,
                     strides=1, padding='same')
```

https://www.tensorflow.org/api_docs/python/tf/layers/conv1d

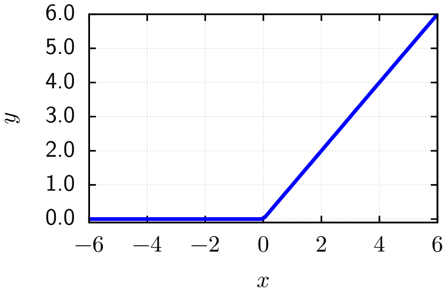
PyTorch

```
conv = nn.Conv1d(in_channels, out_channels=300, kernel_size=3, stride=1,
                 padding=0, dilation=1, groups=1, bias=True)
h = conv(x)
```

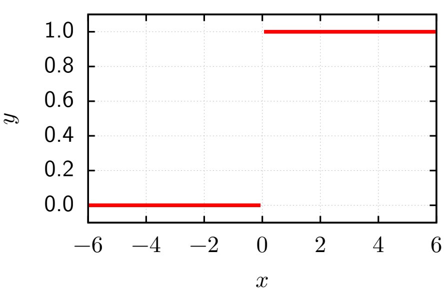
https://pytorch.org/docs/stable/nn.html#torch.nn.Conv1d

Rectified Linear Units

ReLU:



Derivative of ReLU:

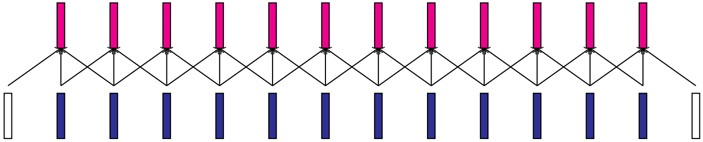


faster, suffer less with vanishing gradient

Vinod Nair and Geoffrey E Hinton. Rectified linear units improve restricted boltzmann machines. In *Proceedings of the 27th International Conference on Machine Learning*, pages 807–814, Haifa, Israel, June 2010. JMLR.org

Residual Connections

$$h_i = f\left(W\left[x_{i-1}; x_i; x_{i+1}\right] + b\right)$$



$x_0 = \vec{0}$ embeddings $\mathbf{x} = (x_1, \ldots, x_N)$ $x_N = \vec{0}$

Allows training deeper networks.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, Las Vegas, NV, USA, June 2016. IEEE Computer Society. ISBN 9781467388511

Residual Connections

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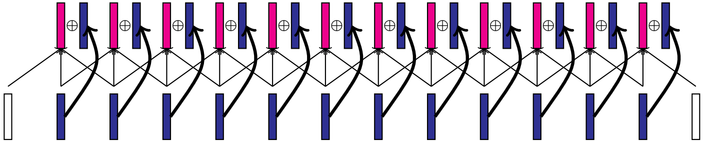

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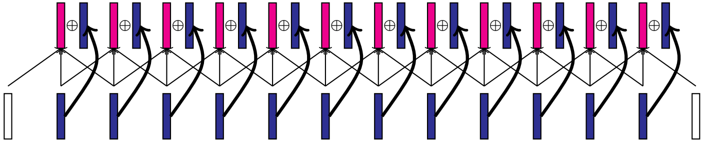

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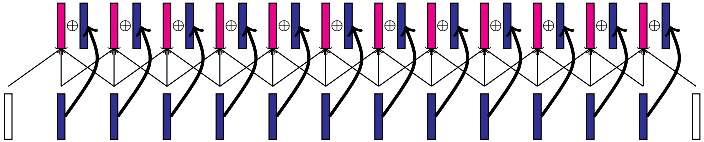

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Why do you think it helps?

Better gradient flow – the same as in RNNs.

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Residual Connections: Numerical Stability

Numerically unstable, we need activation to be in similar scale $\Rightarrow$ layer normalization.
Activation before non-linearity is normalized:

$$\overline{a}_i = \frac{g_i}{\sigma_i}\left(a_i - \mu_i\right)$$

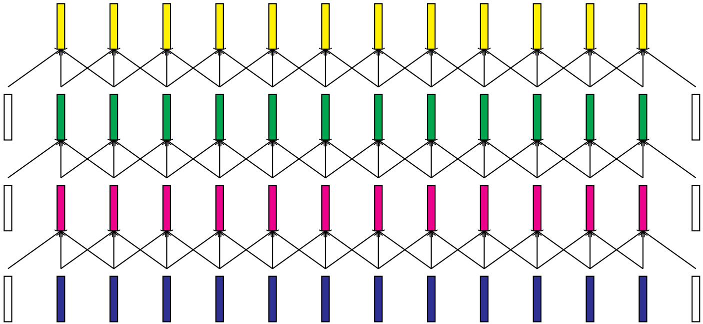
…g is a trainable parameter, μ, σ estimated from data.

$$\mu = \frac{1}{H}\sum_{i=1}^{H} a_i$$

$$\sigma = \sqrt{\frac{1}{H}\sum_{i=1}^{H}(a_i - \mu)^2}$$

Lei Jimmy Ba, Ryan Kiros, and Geoffrey E Hinton. Layer normalization. *CoRR*, abs/1607.06450, 2016. ISSN 2331-8422

Receptive Field



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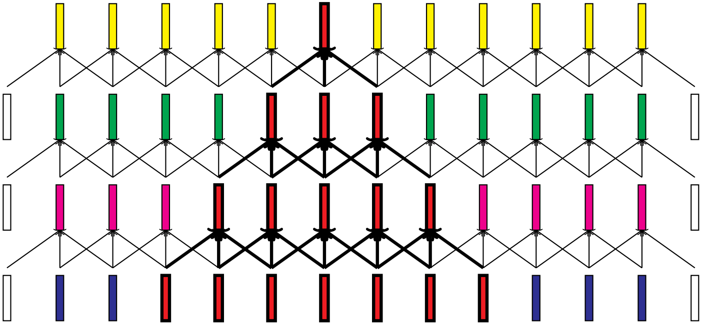
Can be enlarged by dilated convolutions.



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Convolutional architectures

$+$

- extremely computationally efficient

$-$

- limited context
- by default no aware of n-gram order

- max-pooling over the hidden states $=$ element-wise maximum over sequence

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- extremely computationally efficient

$-$

- limited context
- by default no aware of n-gram order

- max-pooling over the hidden states $=$ element-wise maximum over sequence
- can be understood as an $\exists$ operator over the feature extractors

Representing Sequences

Self-attentive Networks

Self-attentive Networks

- In some layers: states are linear combination of previous layer states

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems 30*, pages 6000–6010, Long Beach, CA, USA, December 2017. Curran Associates, Inc

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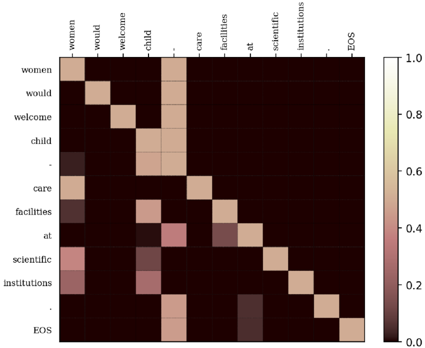

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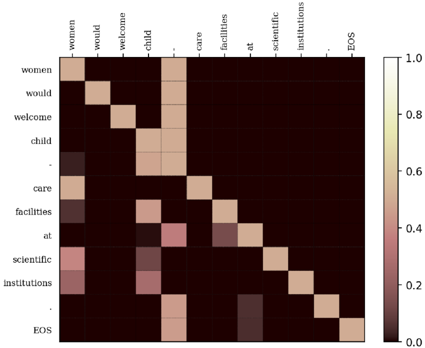

- similarity matrix between all pairs of states
- $O(n^2)$ memory, $O(1)$ time (when paralelized)
- next layer: sum by rows

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems 30*, pages 6000–6010, Long Beach, CA, USA, December 2017. Curran Associates, Inc

Multi-head scaled dot-product attention

Single-head setup

$$\text{Attn}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d}}\right) V$$

$$h_{i+1} = \sum \text{softmax}\left(\frac{h_i h_i^\top}{\sqrt{d}}\right)$$

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$$\mathrm{Multihead}(Q, V) = (H_1 \oplus \cdots \oplus H_h)W^O$$
$$H_i = \mathrm{Attn}(QW_i^Q, VW_i^K, VW_i^V)$$

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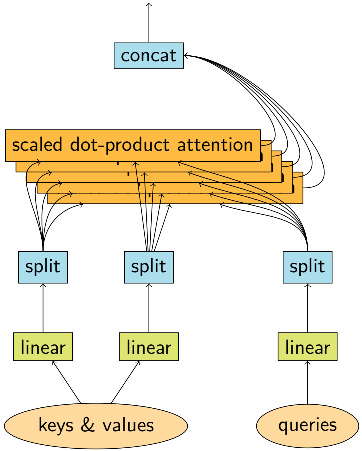


Dot-Product Attention in PyTorch

```python
def attention(query, key, value, mask=None):
    d_k = query.size(-1)
    scores = torch.matmul(query, key.transpose(-2, -1)) \
             / math.sqrt(d_k)
    p_attn = F.softmax(scores, dim = -1)
    return torch.matmul(p_attn, value), p_attn
```

Dot-Product Attention in TensorFlow

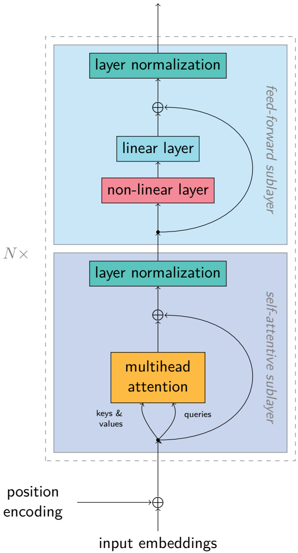
```
def scaled_dot_product(self, queries, keys, values):
    o1 = tf.matmul(queries, keys, transpose_b=True)
    o2 = o1 / (dim**0.5)

    o3 = tf.nn.softmax(o2)
    return tf.matmul(o3, values)
```

Position Encoding

Model is not aware of the position in the sequence.

$$\text{pos}(i) = \begin{cases} \sin\left(\frac{t}{10^4}^{\frac{i}{d}}\right), & \text{if } i \mod 2 = 0 \\ \cos\left(\frac{t}{10^4}^{\frac{i-1}{d}}\right), & \text{otherwise} \end{cases}$$

Stacking self-attentive Layers



- several layers (original paper 6)

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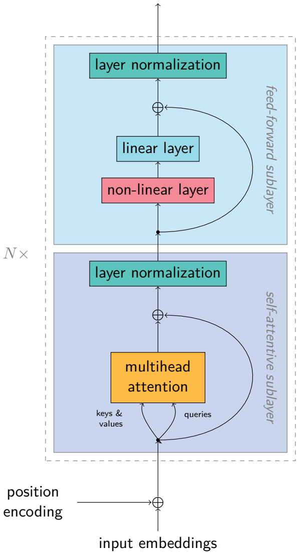

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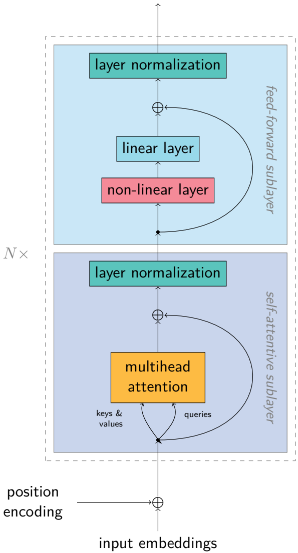

- several layers (original paper 6)
- each layer: 2 sub-layers: self-attention and feed-forward layer
- everything inter-connected with residual connections

Architectures Comparison

	computation	sequential operations	memory
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n \cdot d)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(n \cdot d)$
Self-attentive	$O(n^2 \cdot d)$	$O(1)$	$O(n^2 \cdot d)$

d model dimension, n sequence length, k convolutional kernel

Classification and Labeling

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Sequence Classification

- tasks like sentiment analysis, genre classification

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- need to get one vector from sequence $\rightarrow$ average or max pooling

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- tasks like sentiment analysis, genre classification
- need to get one vector from sequence $\rightarrow$ average or max pooling
- optionally hidden layers, at the end softmax for probability distribution over classes

Softmax & Cross-Entropy

Output layer with softmax (with parameters W, b):

$$P_y = \mathrm{softmax}(\mathbf{x}) = \mathsf{P}(y = j \mid \mathbf{x}) = \frac{\exp \mathbf{x}^\top W + b}{\sum \exp \mathbf{x}^\top W + b}$$

Softmax & Cross-Entropy

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Network error = cross-entropy between estimated distribution and one-hot ground-truth distribution $T = \mathbf{1}(y^*)$:

$$\begin{aligned} L(P_y, y^*) = H(P, T) &= -\mathbb{E}_{i\sim T} \log P(i) \\ &= -\sum_i T(i) \log P(i) \\ &= -\log P(y^*) \end{aligned}$$

Derivative of Cross-Entropy

Let $l = \mathbf{x}^\top W + b$, l_{y^*} corresponds to the correct one.

$$\begin{aligned}\frac{\partial L(P_y, y^*)}{\partial l} &= -\frac{\partial}{\partial l} \log \frac{\exp l_{y^*}}{\sum_j \exp l_j} = -\frac{\partial}{\partial l} l_{y^*} - \log \sum \exp l \\ &= \mathbf{1}_{y^*} + \frac{\partial}{\partial l} - \log \sum \exp l = \mathbf{1}_{y^*} - \frac{\sum \mathbf{1}_{y^*} \exp l}{\sum \exp l} = \\ &= \mathbf{1}_{y^*} - P_y(y^*)\end{aligned}$$

Interpretation: Reinforce the correct logit, suppress the rest.

Sequence Labeling

- assign value / probability distribution to every token in a sequence

Lab next time: i/y spelling as sequence labeling

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Lab next time: i/y spelling as sequence labeling

Generating Sequences

Sequence-to-sequence Learning

- target sequence is of different length than source

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- non-trivial ($=$ not monotonic) correspondence of source and target

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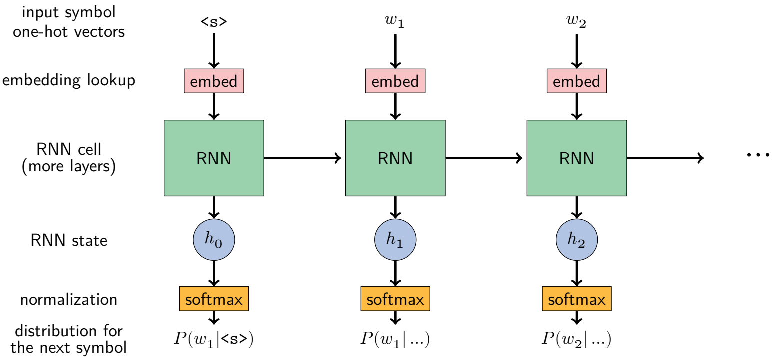
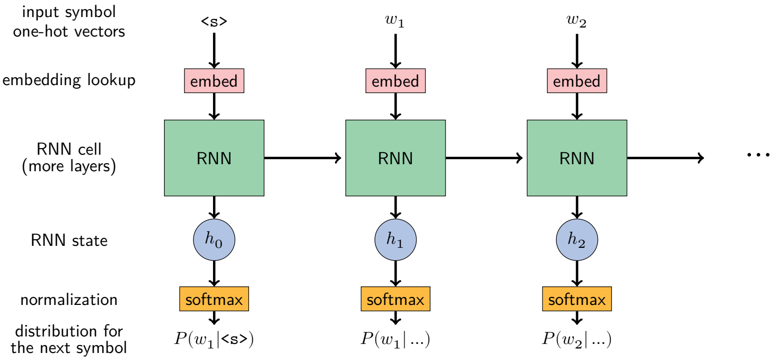
- target sequence is of different length than source
- non-trivial (= not monotonic) correspondence of source and target
- tasks like: machine translation, text summarization, image captioning

Neural Language Model



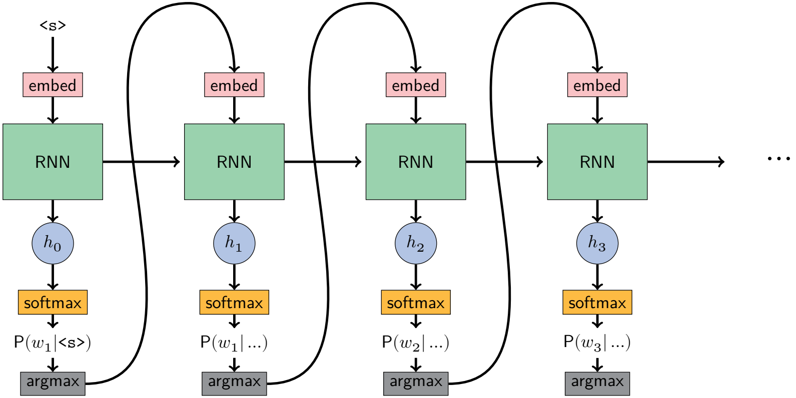
- estimate probability of a sentence using the chain rule

Neural Language Model



- estimate probability of a sentence using the chain rule
- output distributions can be used for sampling

Sampling from a LM



Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In *Advances in Neural Information Processing Systems 27*, pages 3104–3112, Montreal, Canada, December 2014. Curran Associates, Inc

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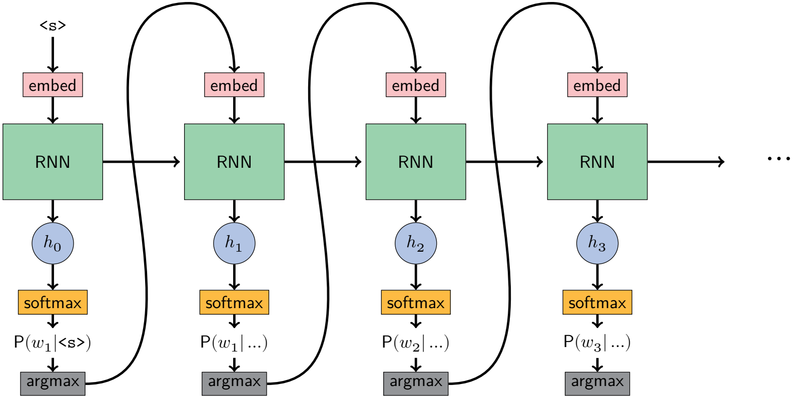

when conditioned on input → autoregressive decoder

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Autoregressive Decoding: Pseudocode

```
last_w = "<s>"
while last_w != "</s>":
    last_w_embeding = target_embeddings[last_w]
    state, dec_output = dec_cell(state,
                                 last_w_embeding)
    logits = output_projection(dec_output)
    last_w = np.argmax(logits)
    yield last_w
```

Architectures in the Decoder

- RNN – original sequence-to-sequence learning (2015)

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- RNN – original sequence-to-sequence learning (2015)
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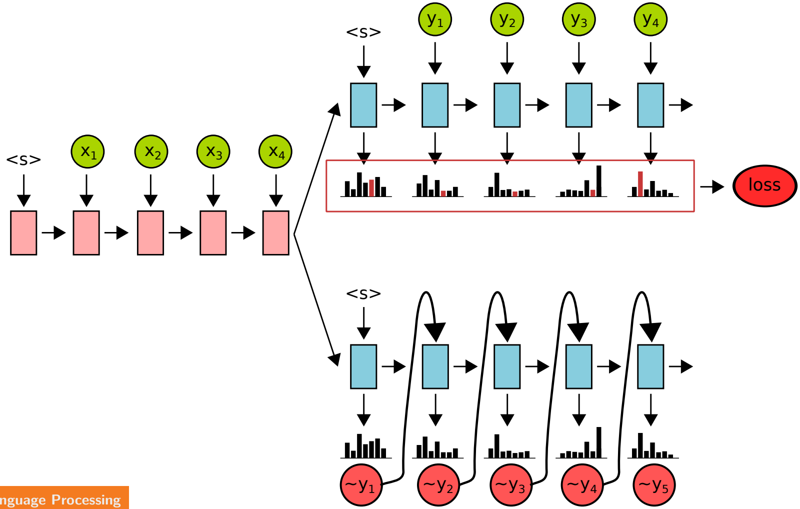
- CNN – convolution sequence-to-sequence by Facebook (2017)
- Self-attention (so called Transformer) by Google (2017)

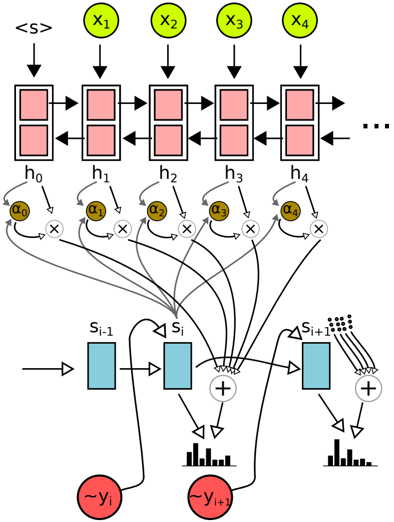
More on the topic in the MT class.

Implementation: Runtime vs. training

runtime: $\hat{y}_j$ (decoded) $\times$ **training:** y_j (ground truth)



Attention Model



Attention Model in Equations (1)

Inputs:

decoder state s_i

encoder states $h_j = \left[\overrightarrow{h_j}; \overleftarrow{h_j}\right] \quad \forall i = 1 \ldots T_x$

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. *CoRR*, abs/1409.0473, 2014. ISSN 2331-8422

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Attention energies:

$$e_{ij} = v_a^\top \tanh\left(W_a s_{i-1} + U_a h_j + b_a\right)$$

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Context vector:

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

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. *CoRR*, abs/1409.0473, 2014. ISSN 2331-8422

Attention Model in Equations (2)

Output projection:

$$t_i = \mathrm{MLP}\left(U_o s_{i-1} + V_o E y_{i-1} + C_o c_i + b_o\right)$$

...attention is mixed with the hidden state

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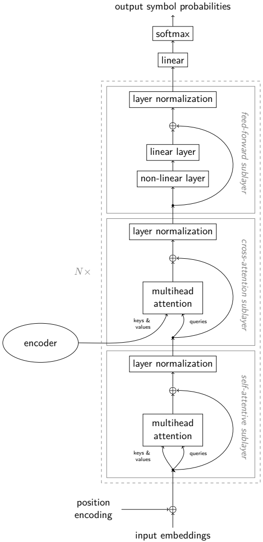
Output distribution:

$$p\left(y_i = k | s_i, y_{i-1}, c_i\right) \propto \exp\left(W_o t_i\right)_k + b_k$$

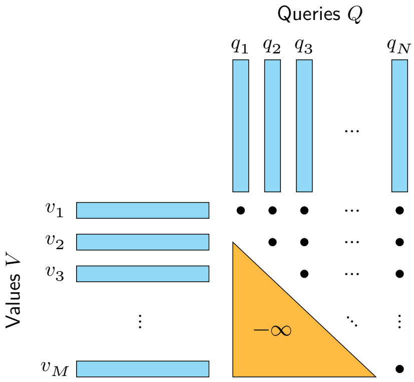
Transformer Decoder



- similar to encoder, additional layer with attention to the encoder
- in every steps self-attention over complete history $\Rightarrow O(n^2)$ complexity

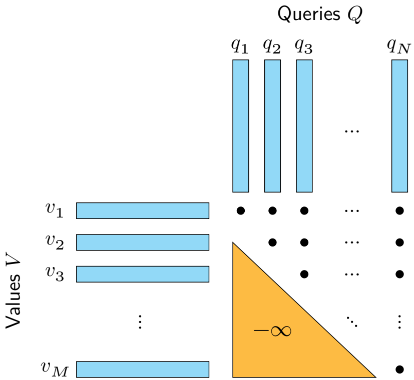
Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems 30*, pages 6000–6010, Long Beach, CA, USA, December 2017. Curran Associates, Inc

Transfomer Decoder: Non-autoregressive training



- analogical to encoder

Transfomer Decoder: Non-autoregressive training



- analogical to encoder
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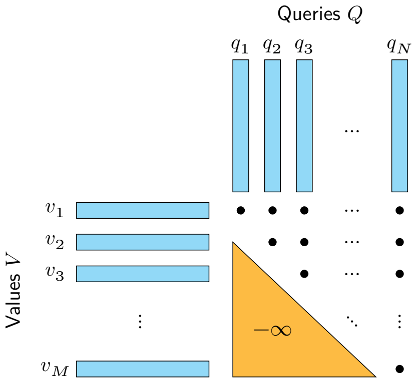

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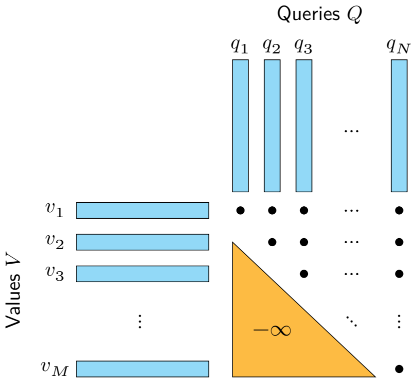

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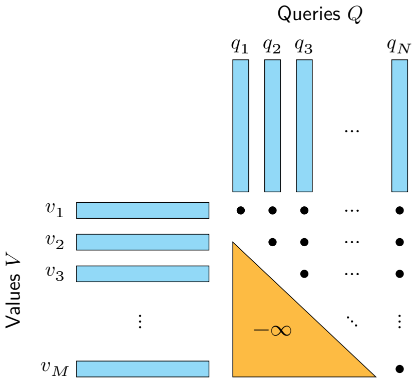

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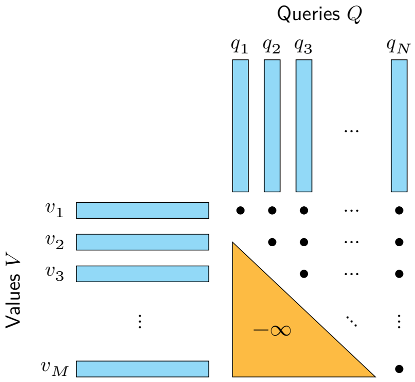
Question 1: What if the matrix was diagonal?

Transfomer Decoder: Non-autoregressive training



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Question 1: What if the matrix was diagonal?
Question 2: How such a matrix look like for convolutional architecture?

Pre-training Representations

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- representations that emerge in models seem to carry a lot of information about the language

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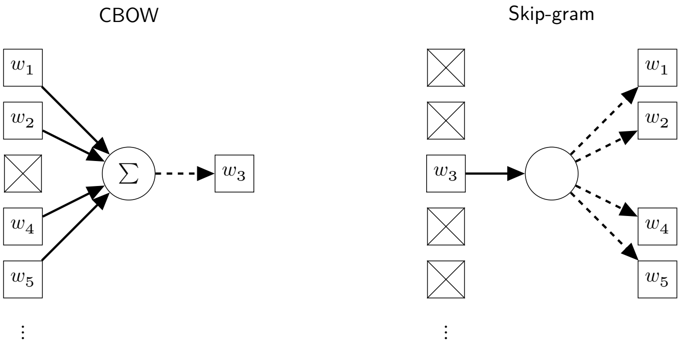
- representations that emerge in models seem to carry a lot of information about the language
- representations pre-trained on large data can be re-used on tasks with smaller training data

Pre-training Representations

Word2Vec

- way to learn word embeddings without training the complete LM



Tomáš Mikolov, Wen-tau Yih, and Geoffrey Zweig. Linguistic regularities in continuous space word representations. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 746–751, Atlanta, GA, USA, June 2013. Association for Computational Linguistics

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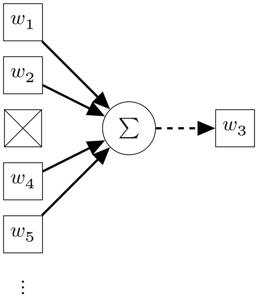
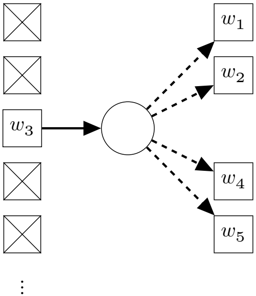
CBOW



Skip-gram



- CBOW: minimize cross-entropy of the middle word of a sliding windows

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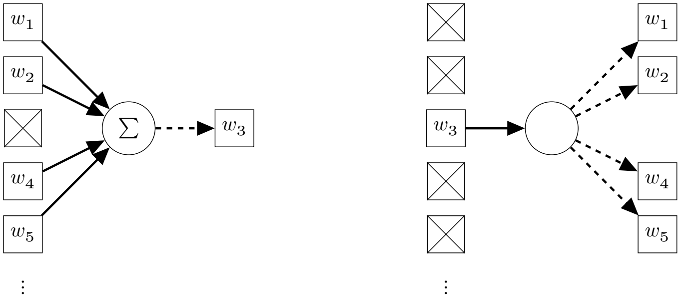
CBOW Skip-gram



- CBOW: minimize cross-entropy of the middle word of a sliding windows
- skip-gram: minimize cross-entropy of a bag of words around a word (LM other way round)

Tomáš Mikolov, Wen-tau Yih, and Geoffrey Zweig. Linguistic regularities in continuous space word representations. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 746–751, Atlanta, GA, USA, June 2013. Association for Computational Linguistics

Word2Vec: sampling

1.	[All human beings] are born free and equal in dignity …	→	(All, humans) (All, beings)
2.	[All human beings are] born free and equal in dignity …	→	(human, All) (human, beings) (human, are)
3.	[All human beings are born] free and equal in dignity …	→	(beings, All) (beings, human) (beings, are) (beings, born)
4.	All [human beings are born free] and equal in dignity …	→	(are, human) (are, beings) (are, born) (are, free)

Word2Vec: Formulas

- Training objective:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{j\sim(-c,c)}\log p(w_{t+c}|w_t)$$

Equations 1, 2. Tomáš Mikolov, Wen-tau Yih, and Geoffrey Zweig. Linguistic regularities in continuous space word representations. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 746–751, Atlanta, GA, USA, June 2013. Association for Computational Linguistics

Word2Vec: Formulas

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- Probability estimation:

$$p(w_O|w_I) = \frac{\exp\left({V'}_{w_O}^{\top} V_{w_I}\right)}{\sum_w \exp\left({V'}_{w}^{\top} V_{w_i}\right)}$$

where V is input (embedding) matrix, V' output matrix

Equations 1, 2. Tomáš Mikolov, Wen-tau Yih, and Geoffrey Zweig. Linguistic regularities in continuous space word representations. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 746–751, Atlanta, GA, USA, June 2013. Association for Computational Linguistics

Word2Vec: Training using Negative Sampling

The summation in denominator is slow, use noise contrastive estimation:

$$\log \sigma \left({V'}^{\top}_{w_O} V_{w_I} \right) + \sum_{i=1}^{k} E_{w_i \sim P_n(w)} \left[\log \sigma \left(-{V'}^{\top}_{w_i} V_{w_I} \right) \right]$$

Equations 1, 3. Tomáš Mikolov, Wen-tau Yih, and Geoffrey Zweig. Linguistic regularities in continuous space word representations. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 746–751, Atlanta, GA, USA, June 2013. Association for Computational Linguistics

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Main idea: classify independently by logistic regression the positive and few sampled negative examples.

Equations 1, 3. Tomáš Mikolov, Wen-tau Yih, and Geoffrey Zweig. Linguistic regularities in continuous space word representations. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 746–751, Atlanta, GA, USA, June 2013. Association for Computational Linguistics

Word2Vec: Vector Arithmetics

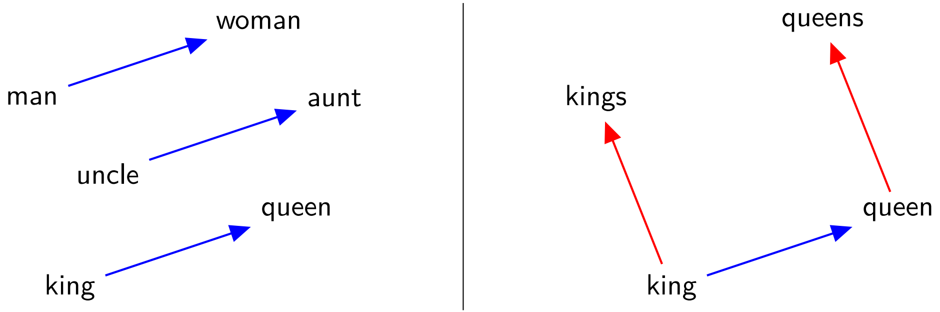

Image originally from Tomáš Mikolov, Wen-tau Yih, and Geoffrey Zweig. Linguistic regularities in continuous space word representations. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 746–751, Atlanta, GA, USA, June 2013. Association for Computational Linguistics

Few More Notes on Embeddings

- many method for pre-trained words embeddings (most popluar GloVe)

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- many method for pre-trained words embeddings (most popluar GloVe)
- embeddings capturing character-level properties
- multilingual embeddings

Training models

FastText – Word2Vec model implementation by Facebook

`https://github.com/facebookresearch/fastText`

```
./fasttext skipgram -input data.txt -output model
```

Pre-training Representations

ELMo

What is ELMo?

- pre-trained large language model

Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 2227–2237, New Orleans, LA, USA, June 2018. Association for Computational Linguistics

What is ELMo?

- pre-trained large language model
- "nothing special" – combines all known tricks, trained on extremely large data

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What is ELMo?

- pre-trained large language model
- “nothing special” – combines all known tricks, trained on extremely large data
- improves almost all NLP tasks

Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 2227–2237, New Orleans, LA, USA, June 2018. Association for Computational Linguistics

What is ELMo?

- pre-trained large language model
- "nothing special" – combines all known tricks, trained on extremely large data
- improves almost all NLP tasks
- published in June 2018

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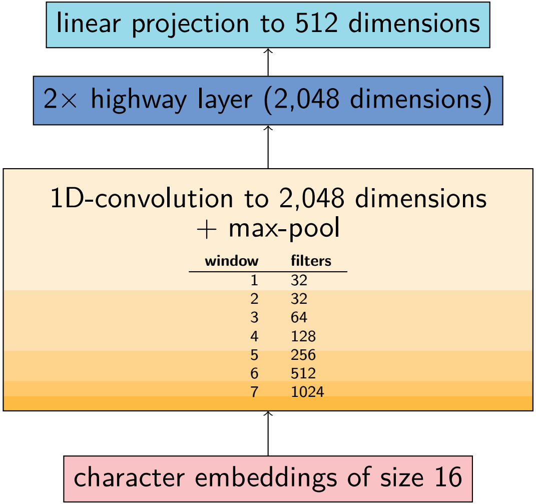
ELMo Architecture: Input



- input tokenized, treated on character level

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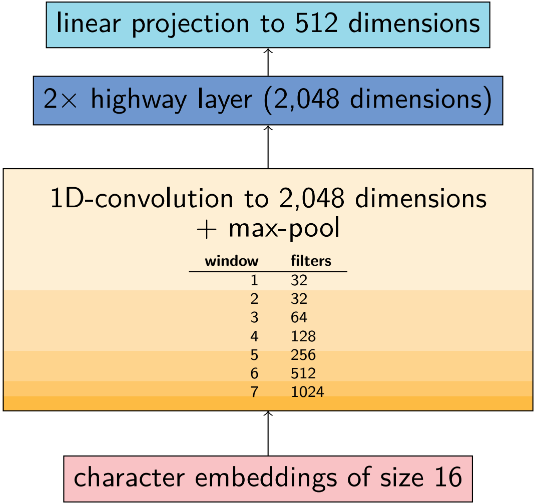

window	filters
1	32
2	32
3	64
4	128
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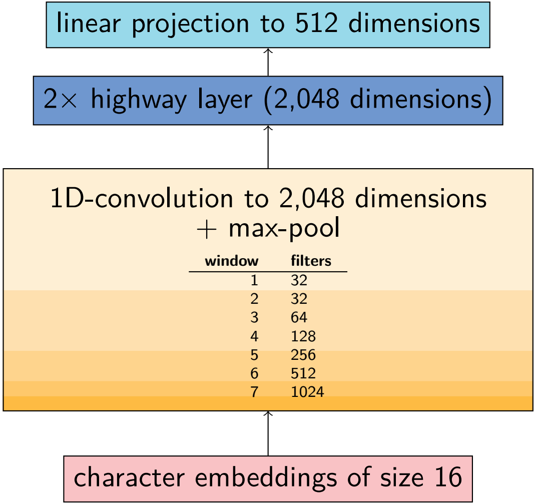

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- input tokenized, treated on character level
- 2,048 n-gram filters + max-pooling ($\sim$ soft search for learned n-grams)
- 2 highway layers:

$$g^{l+1} = \sigma\left(W_g h^l + b_g\right)$$
$$h^{l+1} = (1 - g^{l+1}) \odot h^l +$$
$$g^{l+1} \odot \mathrm{ReLu}\left(W h^l + b\right)$$

contain gates that contol if projection is needed

ELMo Architecture: Language Models

- token representations input for 2 language models: forward and backward

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Learned layer combination for downstream tasks:

$$\text{ELMo}_k^{\text{task}} = \gamma^{\text{task}} \sum_{\text{layer}\, L} s_L^{\text{task}} h_k^{(L)}$$

γ^{task}, s_L^{task} trainable parameters.

Task where ELMo helps

Answer Span Selection
Find an answer to a question in a unstructured text.

Semantic Role Labeling
Detect *who* did *what* to *whom* in sentences.

Natural Language Inference
Decide whether two sentences are in agreement, contradict each other, or have nothing to do with each other.

Named Entity Recognition
Detect and classify names people, locations, organization, numbers with units, email addresses, URLs, phone numbers …

Coreference Resolution
Detect what entities pronouns refer to.

Semantic Similarity
Measure how similar meaning two sentences have. (Think of clustering similar question on StackOverflow or detecting plagiarism.)

Improvements by Elmo

Task	Previous SOTA		Our baseline	ELMo + baseline	Increase (absolute/ relative)
SQuAD	Liu et al. (2017)	84.4	81.1	85.8	4.7 / 24.9%
SNLI	Chen et al. (2017)	88.6	88.0	88.7 ± 0.17	0.7 / 5.8%
SRL	He et al. (2017)	81.7	81.4	84.6	3.2 / 17.2%
Coref	Lee et al. (2017)	67.2	67.2	70.4	3.2 / 9.8%
NER	Peters et al. (2017)	91.93 ± 0.19	90.15	92.22 ± 0.10	2.06 / 21%
SST-5	McCann et al. (2017)	53.7	51.4	54.7 ± 0.5	3.3 / 6.8%

How to use it

- implemetned in AllenNLP framework (uses PyTorch)

```
from allennlp.modules.elmo import Elmo,
    batch_to_ids

options_file = ...
weight_file = ...

elmo = Elmo(options_file, weight_file, 2,
          dropout=0)

sentences = [['First', 'sentence', '.'],
             ['Another', '.']]
character_ids = batch_to_ids(sentences)

embeddings = elmo(character_ids)
```

https://github.com/allenai/allennlp/blob/master/tutorials/how_to/elmo.md

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AllenNLP

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- pre-trained English models available

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Pre-training Representations

BERT

What is BERT

- another way of pretraining sentence representations

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805, 2018. ISSN 2331-8422

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- another way of pretraining sentence representations
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- done by Google, published in November 2018

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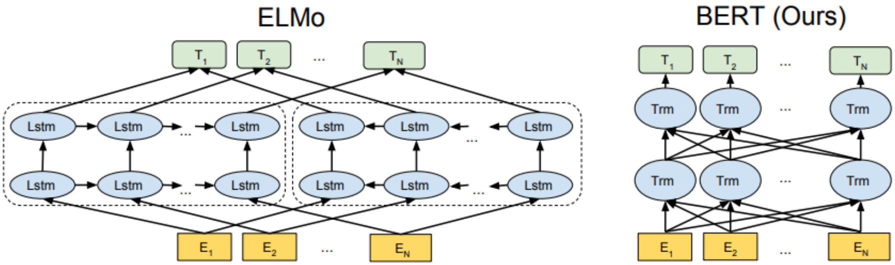
Achitecture Comparison



Masked Language Model

All	human	being	are	born	free	and	equal	in	dignity	and	rights

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1. Randomly sample a word → free

Masked Language Model

All	human	being	are	born	`MASK`	and	equal	in	dignity	and	rights

1. Randomly sample a word $\rightarrow$ free
2. With 80% change replace with special `MASK` token.

Masked Language Model

All	human	being	are	born	hairy	and	equal	in	dignity	and	rights

1. Randomly sample a word → free
2. With 80% change replace with special `MASK` token.
3. With 10% change replace with random token → hairy

Masked Language Model

All	human	being	are	born	free	and	equal	in	dignity	and	rights

1. Randomly sample a word → free
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Masked Language Model

All	human	being	are	born	free	and	equal	in	dignity	and	rights

1. Randomly sample a word → free
2. With 80% change replace with special `MASK` token.
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Then a classifier should predict the missing/replaced word free

Additional Objective: Next Sentence Prediction

- trained in the multi-task learning setup

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- secondary objective: next sentences prediction
- decide for a pair of consecuitve sentences whether they follow each other

Performance of BERT

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	Average
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**91.1**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**81.9**

Table 1: GLUE Test results, scored by the GLUE evaluation server. The number below each task denotes the number of training examples. The "Average" column is slightly different than the official GLUE score, since we exclude the problematic WNLI set. OpenAI GPT = (L=12, H=768, A=12); $\text{BERT}_{\text{BASE}}$ = (L=12, H=768, A=12); $\text{BERT}_{\text{LARGE}}$ = (L=24, H=1024, A=16). BERT and OpenAI GPT are single-model, single task. All results obtained from https://gluebenchmark.com/leaderboard and https://blog.openai.com/language-unsupervised/.

System	Dev		Test	
	EM	F1	EM	F1
Leaderboard (Oct 8th, 2018)				
Human	-	-	82.3	91.2
#1 Ensemble - nlnet	-	-	86.0	91.7
#2 Ensemble - QANet	-	-	84.5	90.5
#1 Single - nlnet	-	-	83.5	90.1
#2 Single - QANet	-	-	82.5	89.3
Published				
BiDAF+ELMo (Single)	-	85.8	-	-
R.M. Reader (Single)	78.9	86.3	79.5	86.6
R.M. Reader (Ensemble)	81.2	87.9	82.3	88.5
Ours				
$\text{BERT}_{\text{BASE}}$ (Single)	80.8	88.5	-	-
$\text{BERT}_{\text{LARGE}}$ (Single)	84.1	90.9	-	-
$\text{BERT}_{\text{LARGE}}$ (Ensemble)	85.8	91.8	-	-
$\text{BERT}_{\text{LARGE}}$ (Sgl.+TriviaQA)	**84.2**	**91.1**	**85.1**	**91.8**
$\text{BERT}_{\text{LARGE}}$ (Ens.+TriviaQA)	**86.2**	**92.2**	**87.4**	**93.2**

Tables 1 and 2. Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805, 2018. ISSN 2331-8422

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http://ufal.cz/courses/npfl124

Summary

1. Discrete symbols → continuous representation with trained embeddings
2. Architectures to get suitable representation: recurrent, convolutional, self-attentive
3. Output: classification, sequence labeling, autoregressive decoding
4. Representations pretrained on large data helps on downstream tasks

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