Deep Learning for NLP

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Overview

Previous part

- Supervised machine learning
  - Linear classifiers
    - Logistic regression
    - Softmax regression
  - Deep neural networks
    - Fully-connected
    - Convolutional
- Training algorithms
  - Stochastic gradient descent
  - Stochastic gradient descent with momentum
  - Backpropagation to compute gradient
- Processing text as input
  - Preprocessing
  - Vectorization

Language modeling

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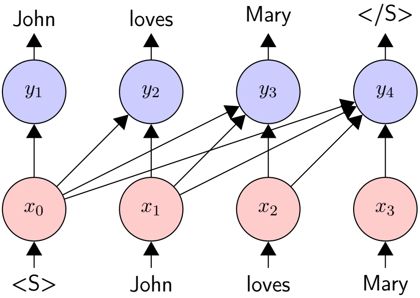
  - Unsupervised machine learning problem or "self-supervised"as they say now
- Autoregressive decomposition: estimate the probability of each token given its prefix

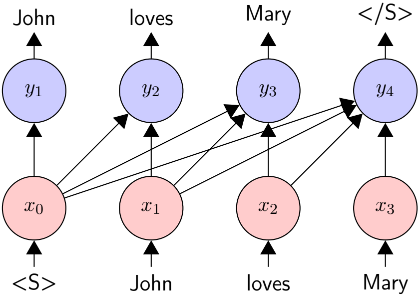
$$p(t_1, \ldots, t_M) = \prod_{i=1}^{M} p(t_i | t_1, \ldots, t_{i-1}) \qquad \text{(chain rule)}$$

Autoregressive Language modeling



- Similar to a sequence tagging task
  - Each position is tagged with the next token
  - Special start-of-sentence and end-of-sentence tokens
  - Causality
    - each position only depends on the past

Autoregressive Language modeling



- Applications
  - Text generation

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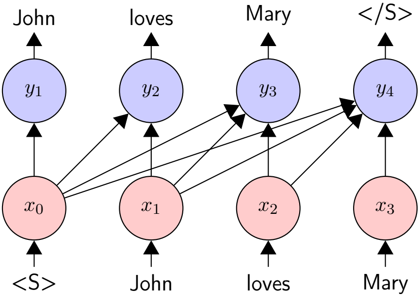

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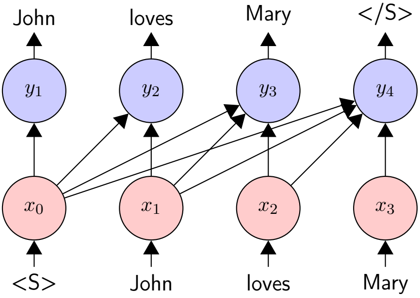

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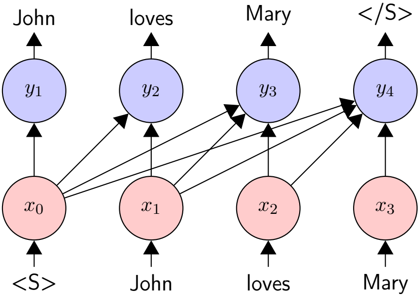

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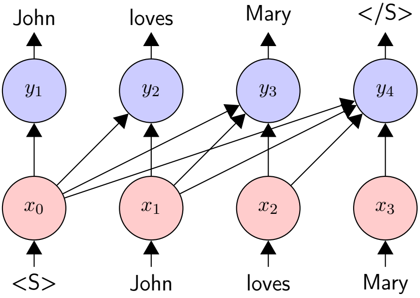

- Applications
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  - Scoring
  - Representation learning (embeddings)

Language modeling with neural networks

- Estimate probabilities with a neural network

$$p(t_i = k | t_1, \ldots, t_{i-1}) = f_k(t_1, \ldots, t_{i-1}; \theta)$$

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- general structure:

$$f(t1, \ldots, t_{i-1}) = \text{softmax}(Proj(Seq(Emb(t_1), \ldots, Emb(t_{i-1}))))$$

  - $Emb(k) = W^{Emb}_{:,k}$: word embeddings $W^{Emb} \in \mathcal{R}^{d \times V}$
  - $Seq(x_1, \ldots, x_{i-1})$: sequence combinator
  - $Proj(s) = W^{Out} \cdot s$: output projection $W^{Out} \in \mathcal{R}^{V \times d}$.

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    - usually $W^{Out} = \text{transpose}(W^{Emb})$ [Press and Wolf, 2017]

Training

- Maximum Likelihood Estimation
  - maximize the log-likelihood of the training set $\{T^{(j)}\}$ under the model

$$\underset{\theta}{\operatorname{argmax}} \sum_{j} \sum_{i=1}^{n^{(j)}} \log p(t_i^{(j)} | t_1^{(j)}, \dots, t_{i-1}^{(j)})$$

  - mini-batch stochastic gradient descent
  - adaptive learning rate and momentum (e.g. RMSProp, Adam)

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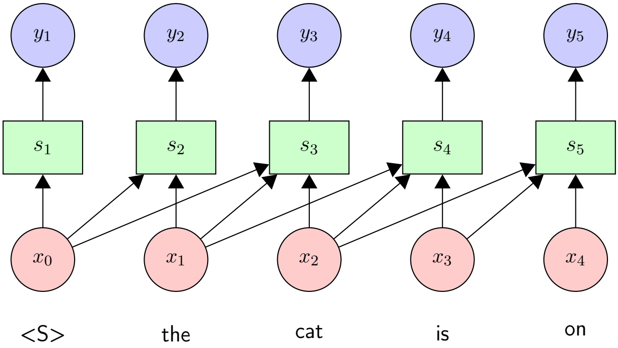
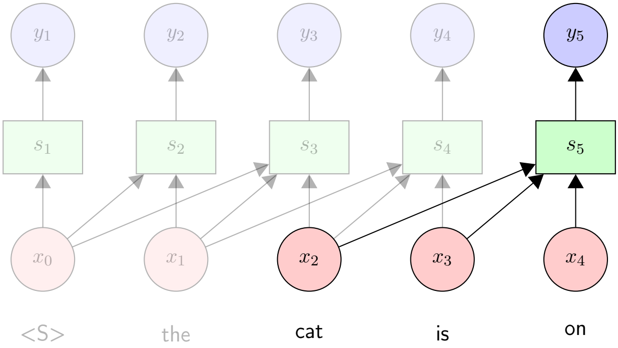
  - mini-batch stochastic gradient descent
  - adaptive learning rate and momentum (e.g. RMSProp, Adam)
  - other training criteria can be used (e.g. reinforcement learning, GANs)
    - in practice it's hard to do better than MLE

Convolutional language model



Fixed width sliding window of lenth L

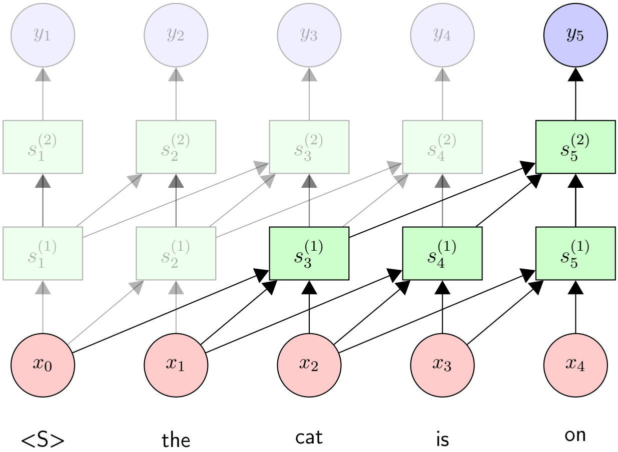
Convolutional language model



Fixed width sliding window of lenth L

$$\begin{aligned} Seq(x_1, \ldots, x_{i-1}) &= Seq(x_{i-L}, \ldots, x_{i-1}) \\ &= \mathrm{ReLU}(b^{conv} + \sum_{j=1}^{L} W^{conv}_{:,:,j} \cdot x_{i-j}) \end{aligned}$$

Convolutional language model



Multiple layers increase both depth and window size

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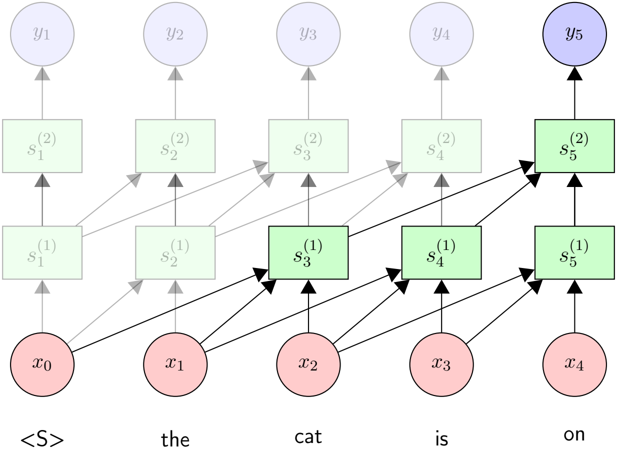

- pro: training can be parallelized over words
- con: strong Markovian independence assumption

Convolutional language model

An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling

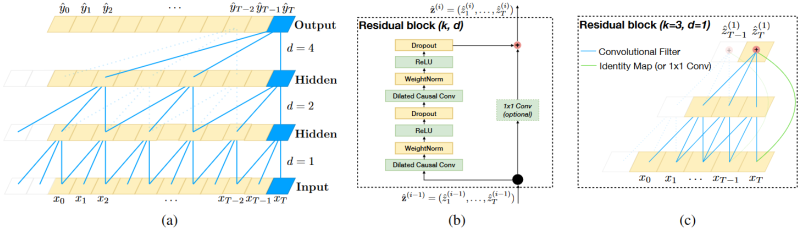

Figure 1. Architectural elements in a TCN. (a) A dilated causal convolution with dilation factors $d = 1, 2, 4$ and filter size $k = 3$. The receptive field is able to cover all values from the input sequence. (b) TCN residual block. An 1x1 convolution is added when residual input and output have different dimensions. (c) An example of residual connection in a TCN. The blue lines are filters in the residual function, and the green lines are identity mappings.

- Extensions [Bai et al., 2018]
  - residual connections
  - dilated convolutions
  - normalization layers
    - weight norm, layer norm, batch norm
  - dropout

Convolutional language model

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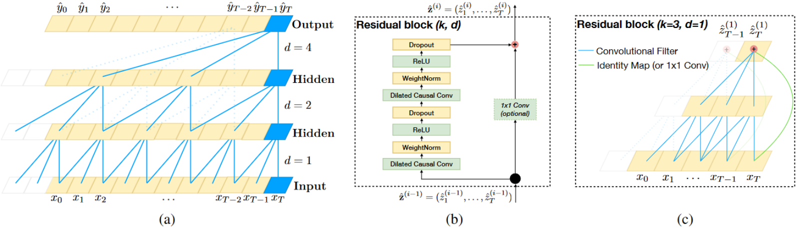

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- Dilated convolutions
  - skip over words

$$\sum_{j=1}^{L} W^{conv}_{:,:,j} \cdot x_{i-(j \cdot D)}$$

  - dilation factor D

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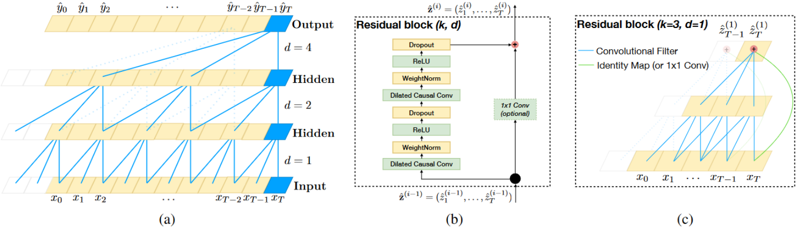

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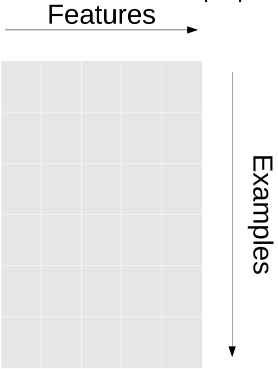
  - dilation factor D
- Increase dilation exponentially over layers

Excursus: normalization

- In a linear model is beneficial to normalize the input
  - Can be done as a preprocessing step



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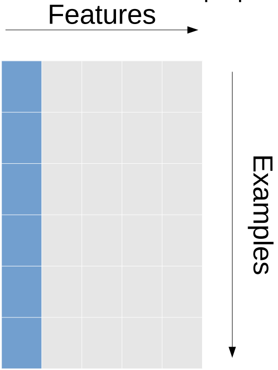
  - 

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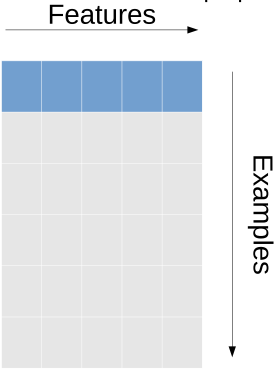
  - 

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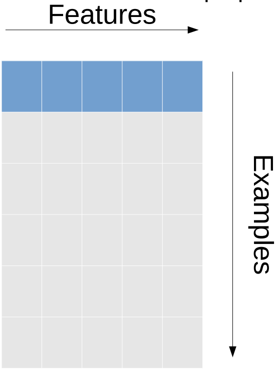
  - 

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  - Training is slow of diverges
  - Poor generalization
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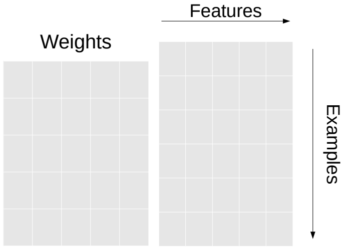
- Solution: normalization layers

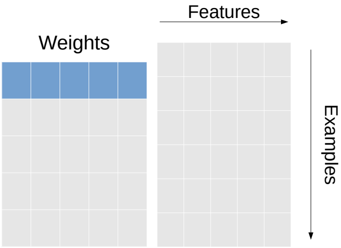
Excursus: normalization



$$z = W \cdot X + b$$

- Base linear layer

Excursus: normalization

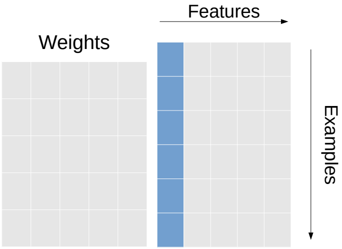


$$z = \hat{W} \cdot X + b$$

$$\hat{W} = g \cdot \text{NormalizeRows}(W)$$

- Weight normalization
  - Normalize the rows of the weight matrix L2 norm equal to 1
  - Multiply by a trainable gain $g \in \mathcal{R}^d$
  - g is initialized to 1

Excursus: normalization



$$z = W \cdot g \cdot \mathsf{NormalizeCols}(X) + b$$

- Batch normalization
  - Normalize the features over a minibatch to mean 0 and sd. 1
  - Multiply by a trainable gain $g \in \mathcal{R}^d$ and add a trainable bias b
  - g is initialized to 1, b is initalized to 0

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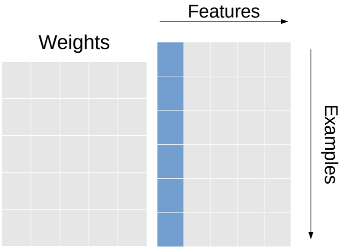

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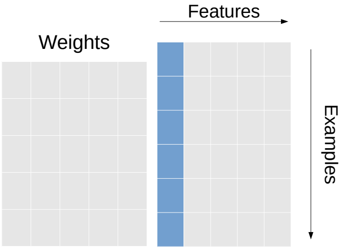

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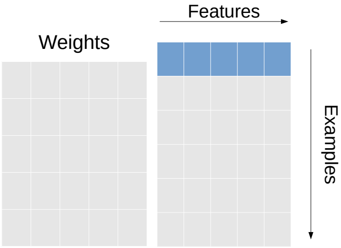

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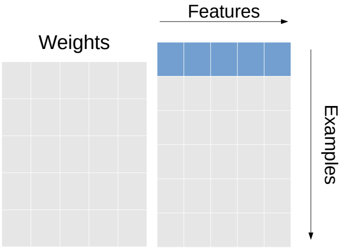

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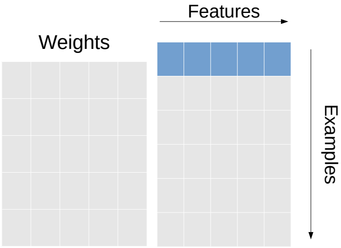

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  - Train and inference are the different
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- Layer normalization
  - Guarantees bounded activations always
  - Non-linear function
  - Train and inference are the same
  - Common in NLP

Excursus: Dropout

- Dropout regularization
- During training
  - Randomly choose activation components with probability p and set them to 0
  - Multiply the other by $1/p$ to keep the mean approx. the same

$$\text{Dropout}(z) = \frac{\text{mask}}{p} \cdot z$$

  - where mask $\in \mathcal{R}^d$, $\text{mask}_j \sim \text{Bernoulli}(1 - p)$
  - Independent over components and examples
  - p is a hyperparameter, usually between 0.1 and 0.5
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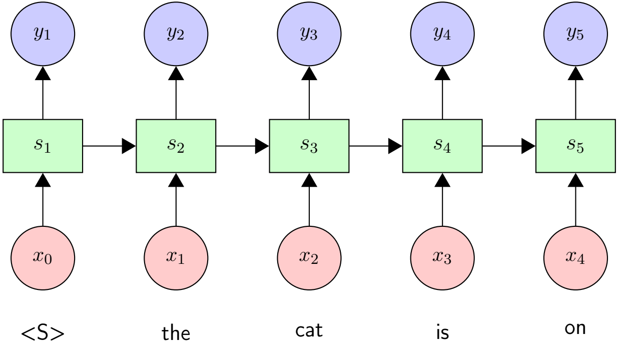
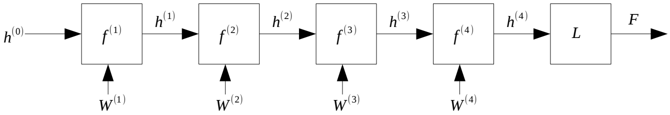
Recurrent language model [Mikolov et al., 2010]



Recurrent decomposition

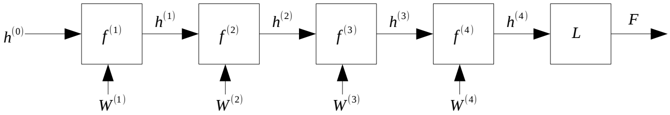
$$
\begin{aligned}
Seq(x_1, \ldots, x_{i-1}) &= \mathsf{RNN}(Seq(x_1, \ldots, x_{i-2}), x_{i-1}) \\
s_0 &= 0 \\
s_i &= \mathsf{RNN}(s_{i-1}, x_{i-1})
\end{aligned}
$$

Backpropagation algorithm



- Forward pass:
  - For k in range $[1, K]$
    - Store in memory $h^{(k-1)}$
    - $h^{(k)} := f^{(k)}(h^{(k-1)}, W^{(k)})$
  - Store in memory $h^{(K)}$
  - Return $L(h^{(K)})$

Backpropagation algorithm



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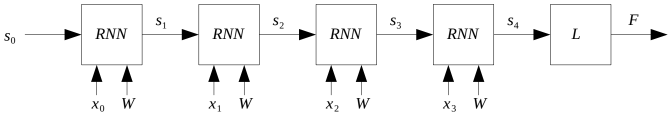
- Backward pass:
  - $h^{(K)} :=$ retrieve from memory
  - adjoint $:= \frac{\mathrm{d}L}{\mathrm{d}h^{(K)}}$
  - For k in range $[K, 1]$
    - $h^{(k-1)} :=$ retrieve from memory
    - $\frac{\mathrm{d}F}{\mathrm{d}W^{(k)}} :=$ adjoint $\cdot \frac{\mathrm{d}}{\mathrm{d}W^{(k)}} f^{(k)}(h^{(k-1)}, W^{(k)})$
    - adjoint $:=$ adjoint $\cdot \frac{\mathrm{d}}{\mathrm{d}h^{(k-1)}} f^{(k)}(h^{(k-1)}, W^{(k)})$
  - Return $\frac{\mathrm{d}F}{\mathrm{d}W^{(k)}}$ for all k

Backpropagation through time



- Forward pass:
  - For k in range $[1, M]$
    - Store in memory s_{k-1}
    - $s_k :=$ RNN(s_k, x_k, W)
  - Store in memory s_M
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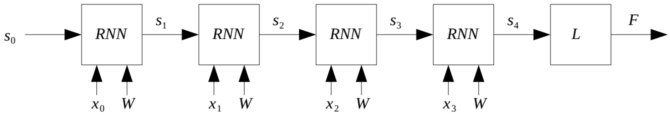

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- Backward pass:
  - $\frac{\mathrm{d}F}{\mathrm{d}W} := 0$
  - $s_M :=$ retrieve from memory
  - adjoint $:= \frac{\mathrm{d}L}{\mathrm{d}s_M}$
  - For k in range $[M, 1]$
    - $s_{k-1} :=$ retrieve from memory
    - $\frac{\mathrm{d}F}{\mathrm{d}W} + =$ adjoint $\cdot \frac{\partial}{\partial W}RNN(s_{k-1}, x_k, W)$
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  - Return $\frac{\mathrm{d}F}{\mathrm{d}W}$

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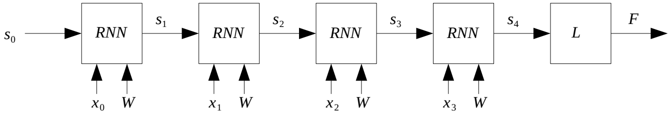

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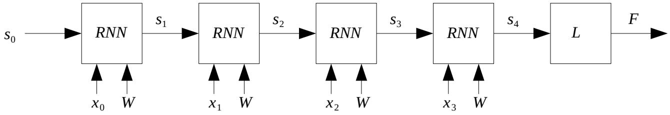
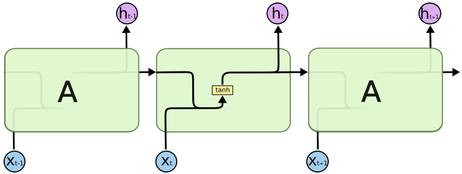


- Deep Learning frameworks handle arbitrary DAGs
- You can freely mix feed-forward and recurrent components
- But beware of memory usage
- Truncated BPTT
  - Split the sequence up to a given maximum length and run the forward and backward passes on the chunks
  - But keep the intermediate state instead of resetting
  - Heuristic approximation, works well in practice

RNN variants



$$\mathsf{RNN}(s_{i-1}, x_{i-1}) = \mathsf{tanh}(W_{\mathsf{state}} \cdot s_{i-1} + W_{\mathsf{in}} \cdot x_{i-1} + b)$$

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  - Simple
  - Very similar to a MLP
  - In theory can compute any arbitrary FSA

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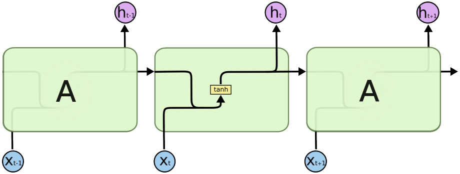

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  - In theory can compute any arbitrary FSA
  - But it's often hard to train
  - Especially on long sequences with long-term dependencies

Christopher Olah http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Why is Elman's RNN hard to train?

- Consider a simplified version
  - No non-linearity
  - Scalar state and input

$$\mathsf{RNN}(s_{i-1}, x_{i-1}) = w \cdot s_{i-1} + x_{i-1}$$

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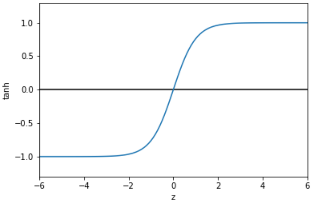

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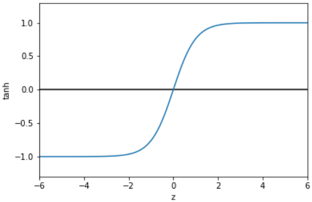

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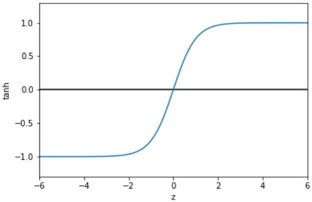

RNN variants

- What about a residual connection?

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$$\tilde{s} = \mathsf{tanh}(W_{\mathsf{state}} \cdot s_{i-1} + W_{\mathsf{in}} \cdot x_{i-1} + b)$$
$$f = \sigma(W^f_{\mathsf{state}} \cdot s_{i-1} + W^f_{\mathsf{in}} \cdot x_{i-1} + b^f)$$
$$\mathsf{RHN}(s_{i-1}, x_{i-1}) = \tilde{s} \cdot (1 - f) + s_{i-1} \cdot f$$

  - $\tilde{s}$: "proposal"gate
  - f: "forget"gate

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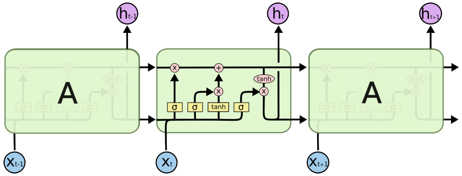
RNN variants



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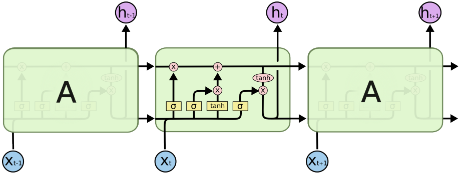

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  - Empirically the strongest
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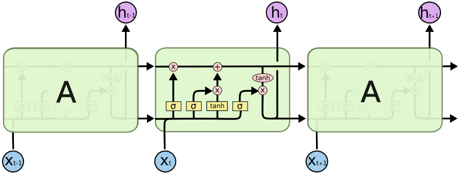

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- TL;DR Use a LSTM, unless you really want a small model

Recurrent language model

- pros & cons
  - pro: can capture long distance dependencies
  - pro: can represent arbitrary FSAs (+ counting)
  - con: inherently sequential even during training
  - con: hidden state can become a bottleneck

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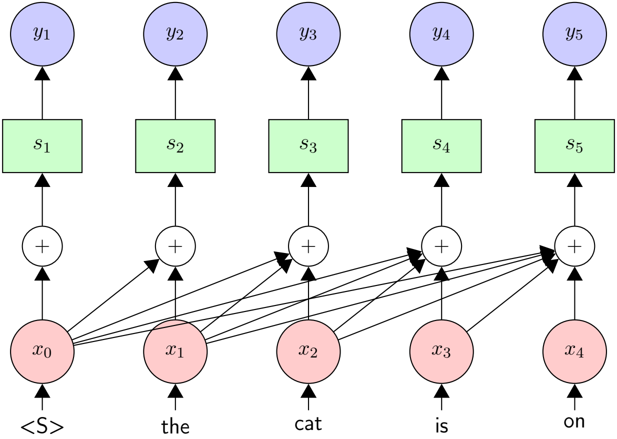
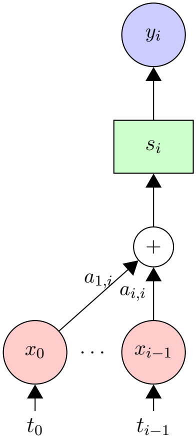
- extensions
  - stacked depth and transition depth [Miceli Barone et al., 2017]
  - residual connections
  - normalization layers (layer norm)
  - dropout
  - etc.

Transformer language model [Vaswani et al., 2017]



Causal self-attention

Transformer language model



causal self-attention

$$e_{j,i} = x_{j-1}^{\dagger} \cdot W^K \cdot W^Q \cdot x_{i-1} \text{ (dot product attention)}$$

$$a_{j,i} = \underset{j \le i}{\text{softmax}}(e_{j,i})$$

$$c_i = \sum_{j=1}^{i} a_{j,i} W^V \cdot x_{j-1}$$

$$s_i = b^{(2)} + W^{(2)} \cdot \text{ReLU}(b^{(1)} + W^{(1)} \cdot c_i)$$

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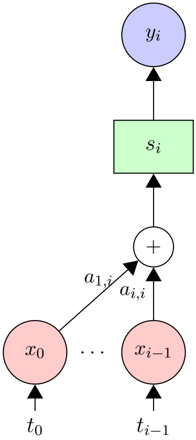

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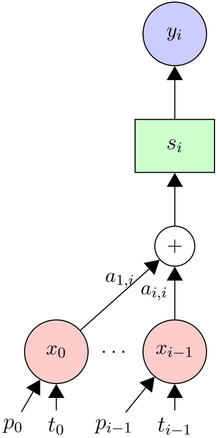

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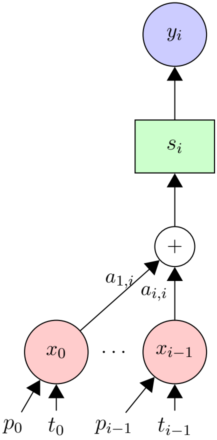
Transformer language model

transformer in practice



$$x_i = x_i^{word} + x_i^{pos} \text{ (position embedding)}$$

$$e_{j,i}^{(h)} = x_{j-1}^{\dagger} \cdot W^{K_h} \cdot W^{Q_h} \cdot x_{i-1}$$

$$a_{j,i}^{(h)} = \operatorname*{softmax}_{j \le i}(e_{j,i}^{(h)})$$

$$c_i^{(h)} = \sum_{j=1}^{i} a_{j,i}^{(h)} W^{V_h} \cdot x_{j-1}$$

$$\widetilde{c}_i = \operatorname*{concat}_{h}(c_i^{(h)}) \text{ (multi-head attention)}$$

$$c_i = \text{layerNorm}(x_i + \widetilde{c}_i) \text{ (residual and layernorm)}$$

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Transformer language model

- pros & cons
  - pro: **SOTA on everything**
  - pro: can capture long distance dependencies
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- extensions
  - Transformer-XL [Dai et al., 2019]
    - recurrent over sentences
  - dynamic convolutions [Wu et al., 2019]
  - etc.

Sequence-to-sequence

- Generate an output sequence based on an input sequence
  - Machine translation
  - Summarization
  - etc., very flexible framework

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  - etc., very flexible framework
- Suppose that we have:
  - a source sentence S of length m $(x_1, \ldots, x_m)$
  - a target sentence T of length n $(y_1, \ldots, y_n)$
- We can express translation as a probabilistic model

$$T^* = \arg\max_T p(T|S)$$

- Expanding using the chain rule gives

$$\begin{aligned} p(T|S) &= p(y_1, \ldots, y_n | x_1, \ldots, x_m) \\ &= \prod_{i=1}^{n} p(y_i | y_1, \ldots, y_{i-1}, x_1, \ldots, x_m) \end{aligned}$$

Differences Between Translation and Language Model

- Target-side language model:

$$p(T) = \prod_{i=1}^{n} p(y_i | y_1, \ldots, y_{i-1})$$

- Translation model:

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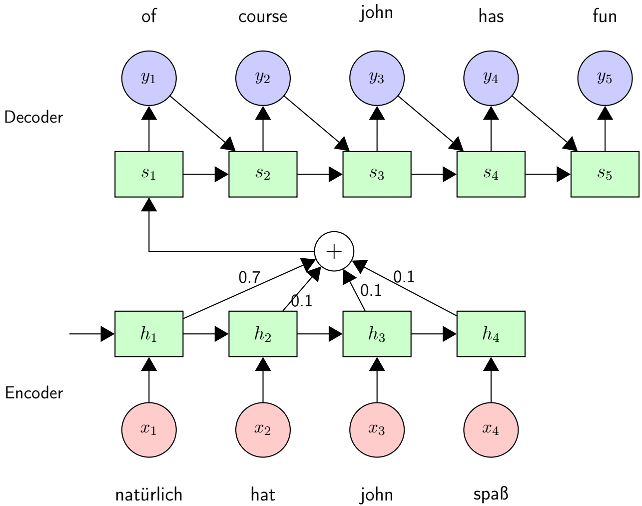
$\rightarrow$ Use separate neural networks for source and target with an attention mechanism

Recurrent Encoder-Decoder with Attention



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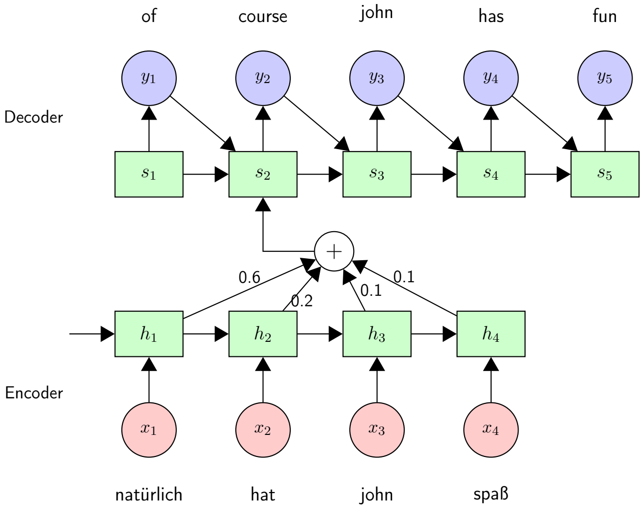

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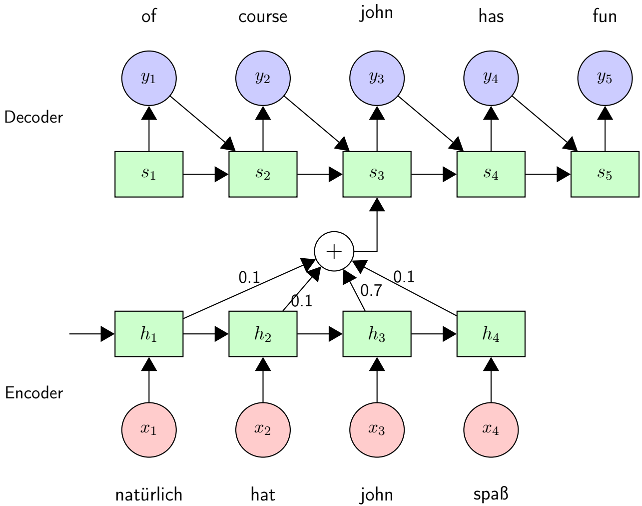

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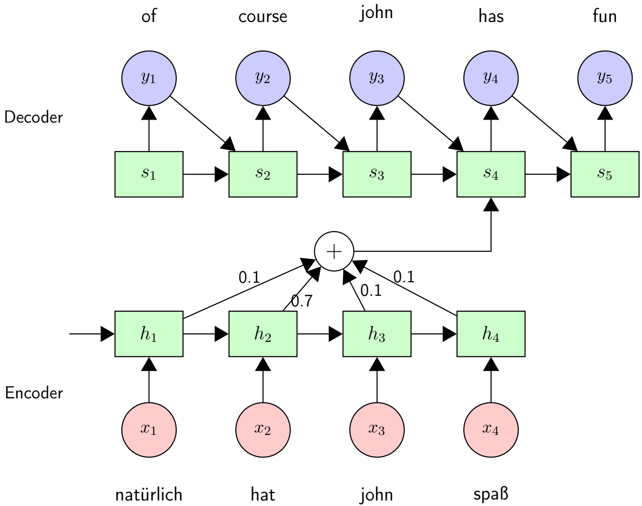

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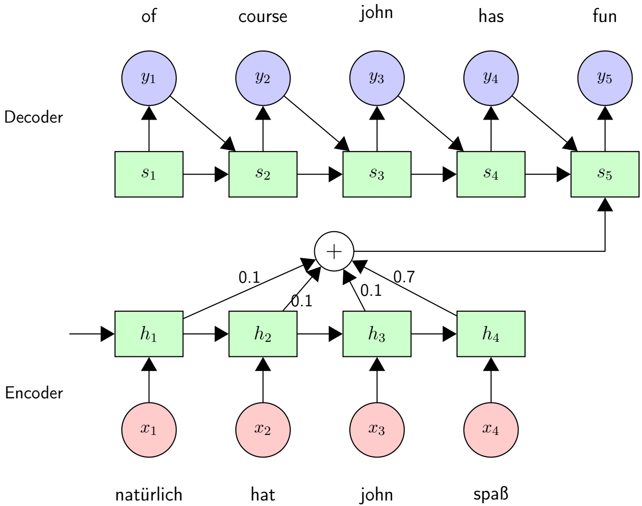


Recurrent Attentional encoder-decoder

encoder

$$\overrightarrow{h}_j = \begin{cases} 0, & \text{, if } j = 0 \\ \mathsf{RNN}(h_{j-1}, x_j) & \text{, if } j > 0 \end{cases}$$

$$\overleftarrow{h}_j = \begin{cases} 0, & \text{, if } j = T_x + 1 \\ \mathsf{RNN}(h_{j+1}, x_j) & \text{, if } j \leq T_x \end{cases}$$

$$h_j = (\overrightarrow{h}_j, \overleftarrow{h}_j)$$

Recurrent Attentional encoder-decoder

decoder

$$s_i = \begin{cases} \mathsf{tanh}(W_s \overleftarrow{h}_i), & \text{, if } i = 0 \\ \mathsf{RNN}(s_{i-1}, y_{i-1}, c_i) & \text{, if } i > 0 \end{cases}$$

$$t_i = \mathsf{tanh}(U_o s_i + W^{out} E_y y_{i-1} + C_o c_i)$$

$$y_i = \mathsf{softmax}(V_o t_i)$$

cross-attention

$$e_{i,j} = h_j^\dagger \cdot W^K \cdot W^Q \cdot s_{i-1}$$

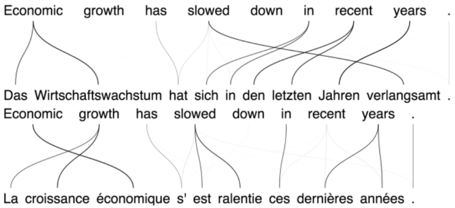
$$a_{i,j} = \underset{j}{\mathsf{softmax}}(e_{i,j})$$

$$c_i = \sum_{j=1}^{T_x} a_{i,j} W^V \cdot h_j$$

Attention model

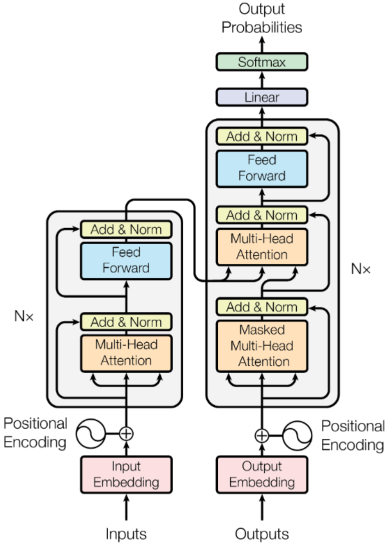
attention model

- side effect: we obtain alignment between source and target sentence
- information can also flow along recurrent connections, so there is no guarantee that attention corresponds to alignment
- applications:
  - visualisation
  - replace unknown words with back-off dictionary [Jean et al., 2015]
  - ...



Kyunghyun Cho http://devblogs.nvidia.com/parallelforall/introduction-neural-machine-translation-gpus-part-3/

Transformer encoder-decoder [Vaswani et al., 2017]



attention is all you need

- acausal self-attention in encoder
- causal self-attention in decoder
- cross-attention between encoder and decoder

Application of Encoder-Decoder Model

Scoring (a translation)

p(La, croissance, économique, s'est, ralentie, ces, dernières, années, . | Economic, growth, has, slowed, down, in, recent, year, .) = ?

Decoding (a source sentence)

Generate the most probable translation of a source sentence

$$y^* = \mathrm{argmax}_y\, p(y|\text{Economic, growth, has, slowed, down, in, recent, year, .})$$

Decoding

exact search

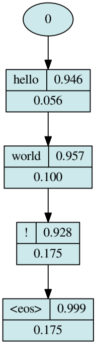
- generate every possible sentence T in target language
- compute score $p(T|S)$ for each
- pick best one

- intractable: $|\text{vocab}|^N$ translations for output length N
  $\rightarrow$ we need approximative search strategy

Decoding

approximative search/1: **greedy search**

- at each time step, compute probability distribution $P(y_i|S, y_{<i})$
- select y_i according to some heuristic:
  - sampling: sample from $P(y_i|S, y_{<i})$
  - greedy search: pick $\mathrm{argmax}_y\, p(y_i|S, y_{<i})$
- continue until we generate *<eos>*



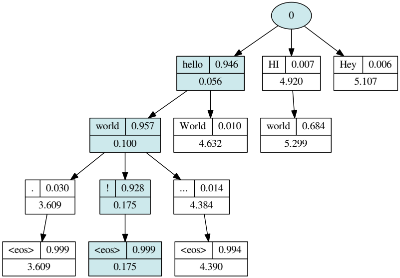
- efficient, but suboptimal

Decoding

approximative search/2: beam search

- maintain list of K hypotheses (beam)
- at each time step, expand each hypothesis k: $p(y_i^k|S, y_{<i}^k)$
- select K hypotheses with highest total probability:

$$\prod_i p(y_i^k|S, y_{<i}^k)$$



$K = 3$

- relatively efficient . . . beam expansion parallelisable
- currently default search strategy in neural machine translation
- small beam ($K \approx 10$) offers good speed-quality trade-off

Subwords for NLP: Motivation

Real text is an open-vocabulary

- compounding and other productive morphological processes
  - they charge a carry-on bag fee.
  - sie erheben eine Hand|gepäck|gebühr.
- names
  - Obama(English; German)
  - Обама (Russian)
  - オバマ (o-ba-ma) (Japanese)
- technical terms, numbers, etc.

... but neural architectures require a small token vocabulary

Subword units

segmentation algorithms: wishlist

- **open-vocabulary seq-to-seq**: encode *all* words through small vocabulary
- encoding generalizes to unseen words
- small text size
- good translation quality

Byte pair encoding for word segmentation [Sennrich et al., 2016]

bottom-up character merging

- starting point: character-level representation
  → computationally expensive
- compress representation based on information theory
  → byte pair encoding [Gage, 1994]
- repeatedly replace most frequent symbol pair ('A','B') with 'AB'
- hyperparameter: when to stop
  → controls vocabulary size

word	freq
'l o w </w>'	5
'l o w e r </w>'	2
'n e w e s t </w>'	6
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vocabulary:
l o w </w> e r n s t i d

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vocabulary:
l o w </w> e r n s t i d
es est est</w> **lo**

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Byte pair encoding for word segmentation

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- open-vocabulary:
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  $\rightarrow$ trade-off between text length and vocabulary size

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e s	$\rightarrow$	es
es t	$\rightarrow$	est
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lo w	→	**low**

Byte pair encoding for word segmentation

Applications

- Some form of BPE is used in most neural NLP architectures
- Extensions usually add stochasticity
  - Sentencepiece [Kudo, 2018]
  - BPE-Dropout [Provilkov et al., 2019]

Limitations of supervised learning

- For most tasks, annotated data is scarce
  - High quality data annotation is expensive
  - Data annotated by crowdsourcing or scraped from the web is noisy
- Even high quality annotated data can be out-of-domain
  - Sampling bias
  - Distribution shift over time
  - Different topics, styles, dialects, etc.

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- Non-annotated data
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  - Easier to find in-domain datasets

Semi-supervised learning

- Solution: learn from both unannotated and annotated data

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"When we're learning to see, nobody's telling us what the right answers are—we just look. Every so often, your mother says 'that's a dog,' but that's very little information. You'd be lucky if you got a few bits of information—even one bit per second—that way. The brain's visual system requires 10^{14} connections. And you only live for 10^9 seconds. So it's no use learning one bit per second. You need more like 10^5 bits per second. And there's only one place you can get that much information—from the input itself." - Geoffrey Hinton

Semi-supervised learning

- Mix unannotated and annotated data
  - Computationally expensive
- Or learn an unsupervised model on unannotated data, then transfer to a supervised task
  - Amortizes the cost of learning the unsupervised model
  - Can be more robust

Representation learning

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- For each supervised task
  - Learn a task model ("head") that takes the encoded data as input $f(h(x;\theta);\phi)$

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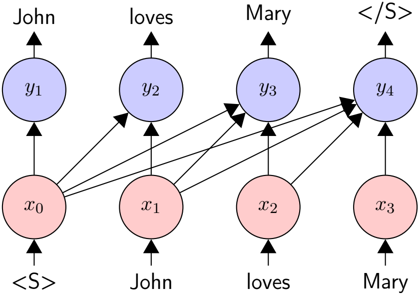
  - Either keep the encoder parameters θ fixed
    - Fast
    - Small memory consumption
    - Less risk of overfitting
  - Or finetune θ alongside ϕ
    - Potentially better quality, assuming no overfitting
    - Many forward and backward passes through the encoder

Masked language models



- Recall the autoregressive decomposition

$$p(t_1, \ldots, t_M) = \prod_{i=1}^{M} p(t_i | t_1, \ldots, t_{i-1})$$

  - Based on the chain rule of probability

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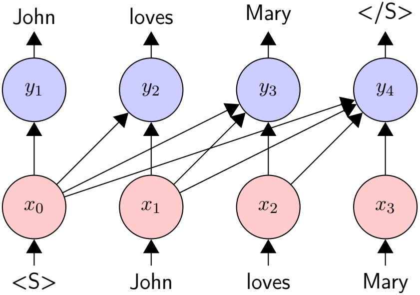

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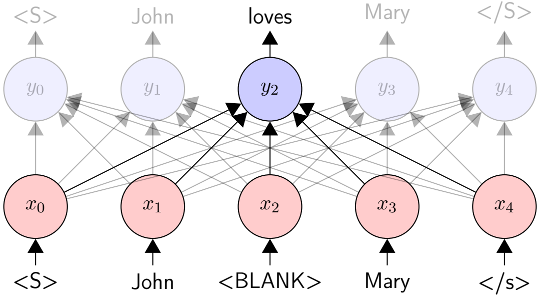
  - But the joint probability can be decomposed in other ways

Masked language models

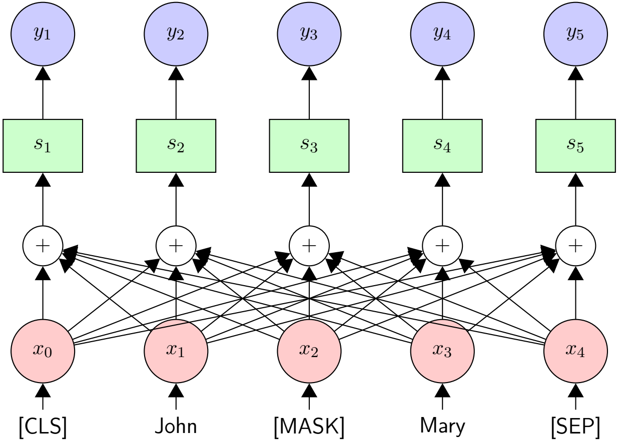


- Gap prediction

$$p(t_1, \dots, t_M) = p(t_i | t_1, \dots, t_{i-1}, t_{i+1}, \dots, t_M) \cdot \\ \cdot\, p(t_1, \dots, t_{i-1}, t_{i+1}, \dots, t_M)$$

  - No closed form for the joint probability
  - But representation learning we don't care

BERT [Devlin et al., 2018]



- Transformer encoder trained on the MLM objective

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- Transformer encoder
  - Very large and deep
  - Sub-word tokenization (wordpiece)
  - Trainable position embeddings
- (Approximate) Masked LM training
  - For each example in each training step randomly choose 15% of tokens as target tokens
  - For each target token
    - Mask with 80% prob.
    - Randomly substitute with 10% prob.
    - Leave the same with 10% prob.
  - Training loss
    $-\sum_{i \in \text{targets}} \log p(t_i | t'_1, \ldots, t_M)$

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  - Turns out not to be very important

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- BERT is actually trained on sentence pairs
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- BERT is pretrained on a large English corpus (BookCorpus + Wikipedia)
- Versions of BERT in other languages or multilingual also exist

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- Task
  - Tagging: subword representations
  - Sentence classification: [CLS] representation
  - Sentence pair classification: [CLS] and [SEP] representation
- Use as fixed representations or finetune on the supervised task
- Supervised head: linear model or shallow MLP

Pretrained representation learning models

- BERT-like
  - RoBERTa
  - ALBERT
  - DistilBERT
  - CamemBERT
    - French
  - XLM
    - Cross-lingual

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    - French
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    - Cross-lingual
- Autoregressive
  - ELMo
  - GPT, GPT-2
  - Transformer-XL
  - XLNet
    - Can be used in autoregressive mode or bidirectional mode
    - Trained on permutations

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  - "**He <MASK> vase. <SEP> The cat <MASK> table.** "→ "**The cat jumped on the table. <SEP> He knocked over the vase.**"
- The intuition is that the model learns the syntax and semantics of language while maintaining a predominantly copying behavior
- Pretrained models
  - BART, mBART
  - MASS
  - T5

Word embeddings

- Transformer-based LMs produce highly informative **contextual** representations
- The representation of each token depends on how it relates to all the other tokens
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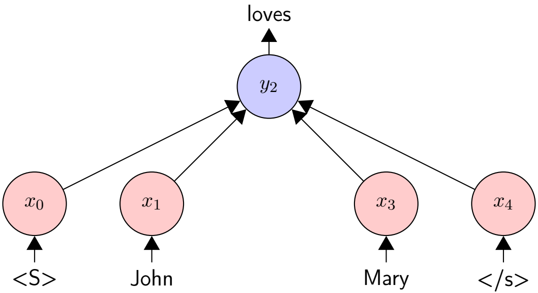
- For analysis
  - Relations between words
  - How words change over time
  - or over domains

Continuous bag of words [Mikolov et al., 2013]



- Log-bilinear model with fixed window L

$$
\begin{aligned}
p(t_i | t_1, \ldots, t_{i-1}, t_{i+1}, \ldots, t_M) &\approx p(t_i | t_{i-L}, \ldots, t_{i-1}, t_{i+1}, \ldots, t_{i+L}) \\
&= \mathsf{softmax}_i(W^{Out} \cdot s)
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$$
s = \sum_{j \neq i}^{[-L, L]} W^{Emb}_{:, t_j}
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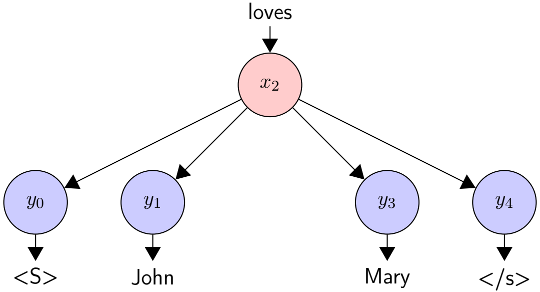
$$

  - Output is $W^{Emb}_{:,t_i}$, not s
  - W^{Emb} and W^{Out} are not tied
  - $-\log \mathsf{softmax}_i(W^{Out} \cdot s)$ is approximated by Negative Sampling
    - Contrastive loss similar to NCE

Skipgram [Mikolov et al., 2013]



- Predict context from central word in a fixed window L

$$p(t_j|t_i) = \text{softmax}_j(W^{Out} \cdot W^{Emb}_{:,t_i})$$
$$|i - j| \leq L$$

- Also with approximated by Negative Sampling

Word embeddings

- CBOW and Skipgram are implemented in word2vec
- fastText [Joulin et al., 2016] is also based on Skipgram, extended with character n-gram features
- GloVe [Pennington et al., 2014] is based on matrix factorization
  - In practice, similar to Skipgram [Levy and Goldberg, 2014]
- Word embeddings can be also extracted from the parameters of recurrent language models or machine translation models

What do word embeddings encode?

- Syntactic similarity
  "to" $\approx$ **"from"**, **"in"**, **"on"**, ...
- Semantic similarity
  "one" $\approx$ **"two"**, **"three"**, **"four"**, ...
  "Paris" $\approx$ **"London"**, **"Rome"**, **"Berlin"**, ...
- Analogies
  "Paris" - "France" $+$ **"UK"** $\approx$ **"London"**
  "king" - "man" $+$ **"woman"** $\approx$ **"queen"**

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  "king" - **"man"** + **"woman"** $\approx$ **"queen"**
  "doctor" - **"man"** + **"woman"** $\approx$ **"nurse"**
  - Word Embeddings learn stereotypes

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- Find a mapping between embeddings trained on different corpora
  - Same language or different languages
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- Given word embedding matrices W^X and W^Y

$$\text{argmax}_{P,\theta} \sum_{i<V} ||W^Y_{:,i} - F(W^X_{:,P(i)}; \theta)||$$

- Find a permutation over the indices P and the parameter θ of a mapping function F that minimize the distance

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  - Usually $F(\cdot;\theta)$ is parametrized as an orthogonal matrix Θ s.t. $\Theta^T \cdot \Theta = I$
  - Isometry assumption
    "king" - "man" + "woman" $\approx$ "queen"
    "König" - "Mann" + "Frau " $\approx$ "Königin"
  - Orthogonal transformations preserve angles

Aligning word embeddings [Ruder et al., 2019]

$$\text{argmax}_{P,\Theta} \sum_{i<V} ||W^Y_{:,i} - \Theta \cdot W^X_{:,P(i)};||$$

1. Initialize permutation P from a seed dictionary
2. Repeat until convergence
   2.1 Find best orthogonal mapping Θ using the Orthogonal Procrustes method
   2.2 Find best permutation P

Orthogonal Procrustes method

$$\text{argmax}_{\Theta} ||\Theta \cdot A - B||$$

- Solution: $\Theta = U \cdot V^T$
- where $B \cdot A^T = U \cdot S \cdot V^T$
  - Singular value decomposition

Open problems in Deep Learning

- Deep Learning revolutionized NLP and other fields
- Nevertheless, Deep Learning is no silver bullet
  - Out-of-distribution fragility
  - Adversarial examples
  - Fairness
  - Explainability

Out-of-distribution fragility

- Deep Learning models are very sensitive to distribution shift between training and inference
- In NLP a common form of distribution shift is word usage
  - E.g. Wikipedia vs. Twitter
  - Europarl vs. Opensubtitles

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- In NLP a common form of distribution shift is word usage
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- But even when word usage is similar deep learning models can struggle due to lack of compositionality

Compositionality

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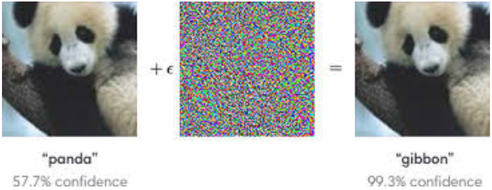
- Deep Learning models can be fooled to make very incorrect predictions when the inputs are perturbed adversarially



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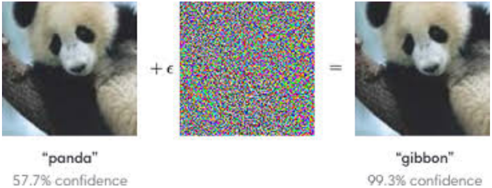

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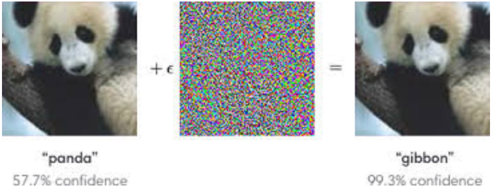

- Adversarial perturbations don't need to be precise
  - Adversary transfer across models
  - Physical adversaries
    - [Eykholt et al., 2018]

Figure 1: The left image shows real graffiti on a Stop sign, something that most humans would not think is suspicious. The right image shows our a physical perturbation applied to a Stop sign. We design our perturbations to mimic graffiti,

Adversarial examples

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  - HotFlip: White-Box Adversarial Examples for Text Classification [Ebrahimi et al., 2017]
  - Universal Adversarial Triggers for Attacking and Analyzing NLP [Wallace et al., 2019]
  - Is BERT Really Robust? A Strong Baseline for Natural Language Attackon Text Classification and Entailment [Jin et al., 2019]

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  - Credit scoring
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  - Even if the data is accurate, if the model is not perfect it will make errors. What does it mean to err fairly?
- Different definition of fairness are mutually exclusive [Kleinberg et al., 2016]

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- The European Union GDPR defines a "right to explanation and appeal"for any automated decision that significantly affects the interests of an EU citizen.
- Similar laws exist in the US for credit scoring

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