Neural Machine Translation

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Language modeling

autoregressive language modeling

- language modeling: estimate the probability distribution of sentences
- a sentence T of length n is a sequence of tokens $w_1, \ldots, w_n \in [1, \ldots, K]$
- autoregressive decomposition: estimate the probability of each token given its prefix

$$
\begin{aligned}
p(T) &= p(w_1, \ldots, w_n) \\
&= \prod_{i=1}^{n} p(w_i | w_1, \ldots, w_{i-1}) \qquad \text{(chain rule)}
\end{aligned}
$$

Language modeling with neural networks

neural network probability estimator

$$p(w_i = k | w_1, \ldots, w_{i-1}) = f_k(w_1, \ldots, w_{i-1}; \theta)$$

- f is a neural network with parameters θ that computes a vector of K probabilities

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- general structure:

$$f(w_1, \ldots, w_{i-1}) = \text{softmax}(Proj(Seq(Emb(w_1), \ldots, Emb(w_{i-1}))))$$

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

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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

$$\underset{\theta}{\operatorname{argmax}} \sum_{j} \sum_{i=1}^{n^{(j)}} \log p(w_i^{(j)} | w_1^{(j)}, \ldots, w_{i-1}^{(j)})$$

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

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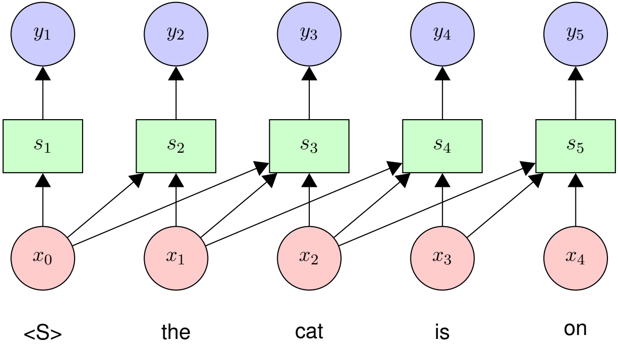
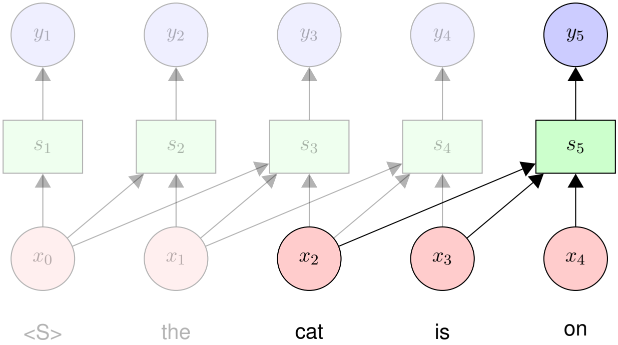
- mini-batch stochastic gradient descent
- adaptive learning rate and momentum (e.g. Adam optimizer)
- other training criteria can be used (e.g. reinforcement learning, GANs)
    - in practice it's hard to do better than MLE

Convolutional language model [Bengio et al., 2003]



Fixed width sliding window of lenth L

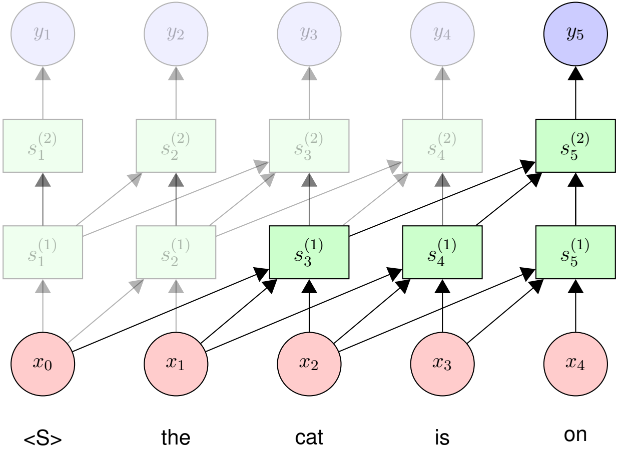
Convolutional language model



Fixed width sliding window of lenth L

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

Convolutional language model



Multiple layers increase both depth and window size

Convolutional language model

pros & cons

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

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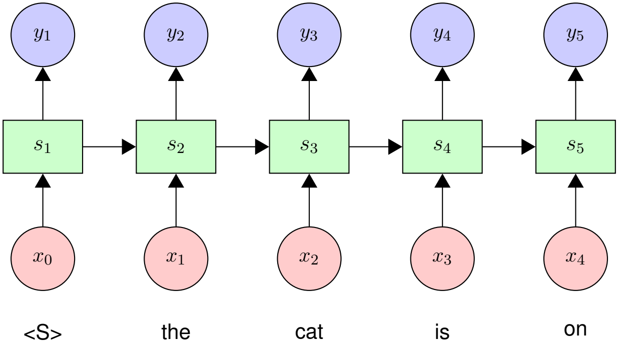
extensions [Bai et al., 2018]

- residual connections
- normalization layers (e.g. batch norm, layer norm)
- dilated convolutions

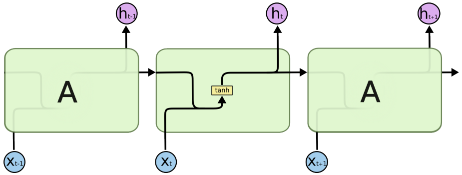
Recurrent language model [Mikolov et al., 2010]



Recurrent decomposition

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

RNN variants



gated units

- alternative to plain RNN
- sigmoid layers σ act as “gates” that control flow of information
- allows passing of information over long time
  $\rightarrow$ avoids vanishing gradient problem
- strong empirical results
- popular variants:
  - Long Short Term Memory (LSTM) (shown)
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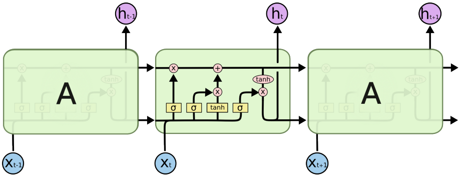

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Recurrent language model

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- pro: can capture long distance dependencies
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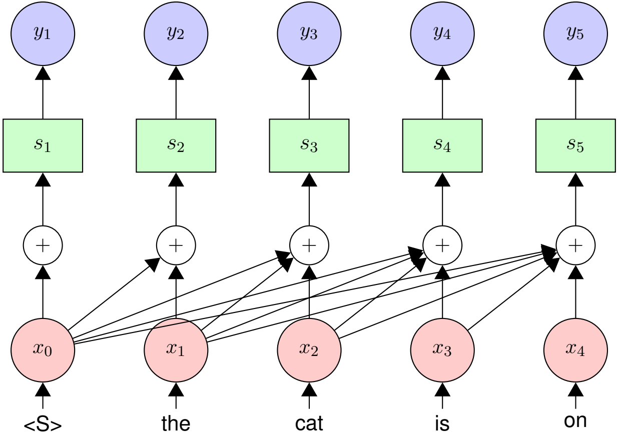
extensions

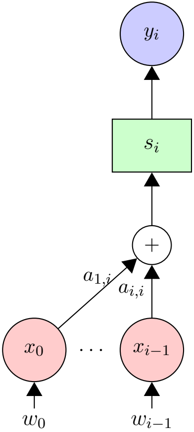
- stacked depth and transition depth [Miceli Barone et al., 2017]
- residual connections
- normalization layers (layer norm)
- etc.

Transformer language model [Vaswani et al., 2017]



Causal self-attention

Transformer language model



causal self-attention

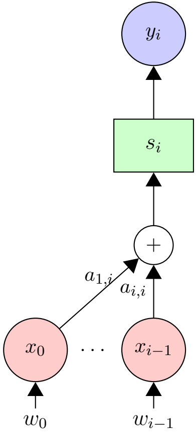
$$e_{j,i} = x_{j-1}^{\dagger} \cdot W^K \cdot W^Q \cdot x_{i-1} \text{ (dot product attention)}$$

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

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

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

Transformer language model



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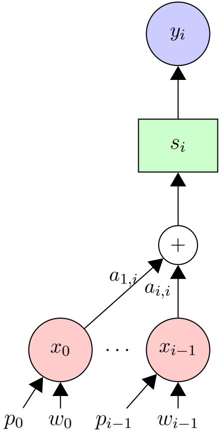

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$x_i = x_i^{word} + x_i^{pos}$

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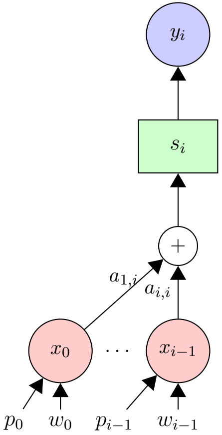

transformer in practice

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

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

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

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

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

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

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

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Transformer language model

pros & cons

- pro: **SOTA on everything**
- pro: can capture long distance dependencies
- pro: training can be parallelized over words
- con: theoretical complexity increases at each step
  - not an issue for single sentences
- con: tricky to train
  - require dropout, learning rate warmup, label smoothing, etc.

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extensions

- Transformer-XL [Dai et al., 2019]
  - recurrent over sentences
- dynamic convolutions [Wu et al., 2019]
- etc.

Modelling Translation

- 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:

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

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    - We do not care about $p(S)$
    - We may want different vocabulary, network architecture for source text

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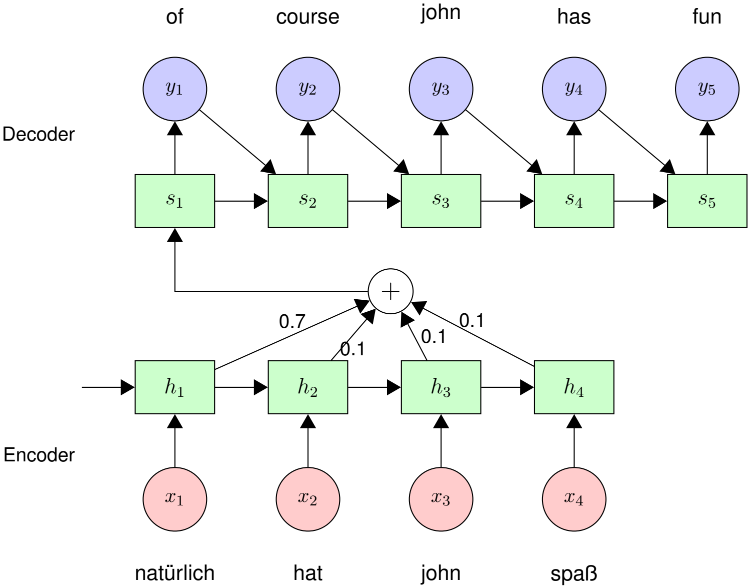
$\rightarrow$ Use separate neural networks for source and target with an attention mechanism

Recurrent Encoder-Decoder with Attention



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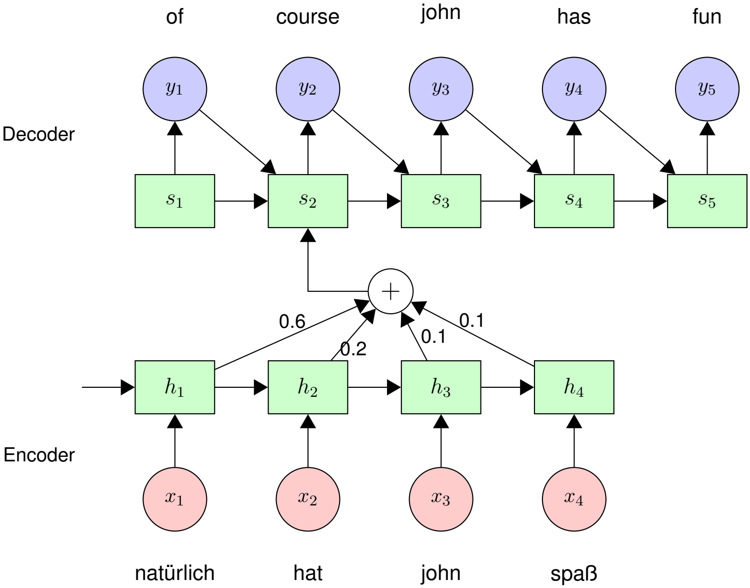

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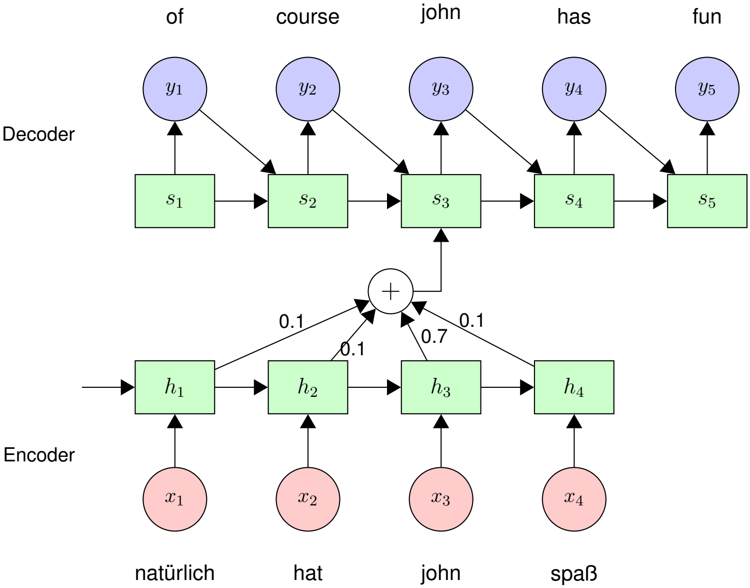

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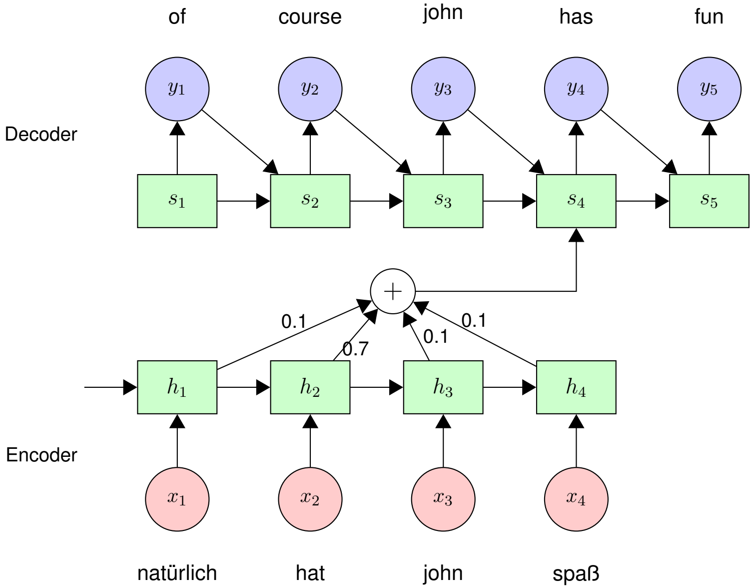

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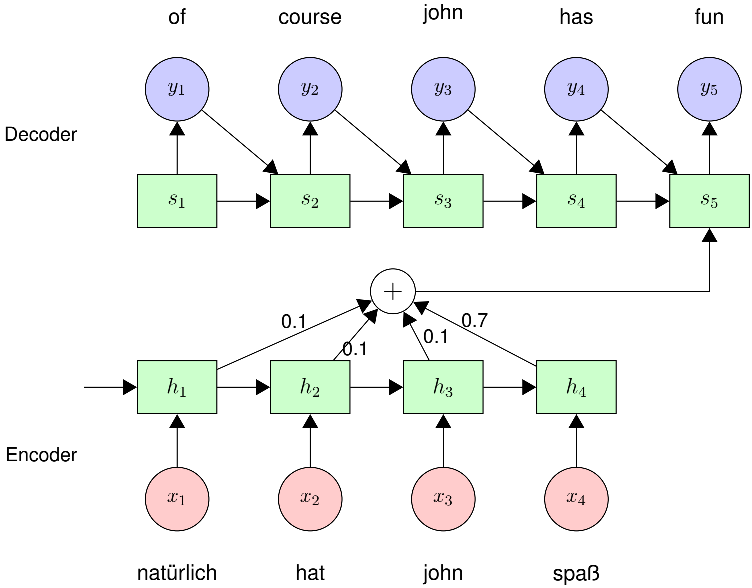


Recurrent Attentional encoder-decoder: Maths

encoder

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

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

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

Recurrent Attentional encoder-decoder: Maths

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

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

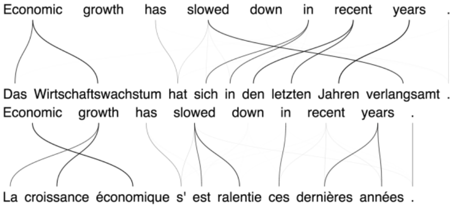
$$a_{i,j} = \mathsf{softmax}_j(e_{i,j})$$

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

Attention model

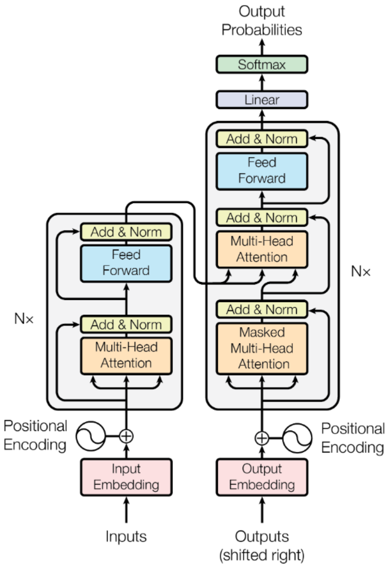
attention model

- 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

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

Decoding

exact search

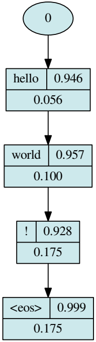
- generate every possible sentence T in target language
- compute score $p(T|S)$ for each
- pick best one

- 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 $\operatorname{argmax}_y p(y_i|S, y_{<i})$
- continue until we generate *<eos>*



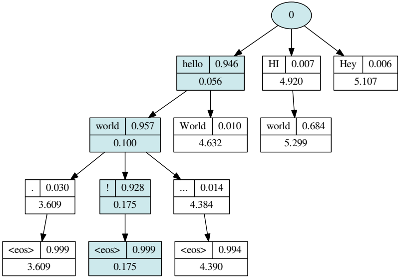
- efficient, but suboptimal

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

Advanced NMT [Sennrich et al., 2016a]

In order to achieve high quality NMT benefits from specific techniques. For instance:

- Subword models to allow translation of rare/unknown words
  $\rightarrow$ since networks have small, fixed vocabulary
- Back-translated monolingual data as additional training data
  $\rightarrow$ allows us to make use of extensive monolingual resources
- Dropout
  $\rightarrow$ Improves generalisation performance with small training data
- Virtual mini-batching
  $\rightarrow$ Improves generalization by tuning gradient noise

Subwords for NMT: Motivation

MT is an open-vocabulary problem

- 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 MT architectures have small and fixed vocabulary

Subword units

segmentation algorithms: wishlist

- **open-vocabulary NMT**: 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., 2016c]

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
'w i d e s t </w>'	3

vocabulary:
l o w </w> e r n s t i d

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es

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

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word	freq
'**low** </w>'	5
'**low** e r </w>'	2
'n e w est</w>'	6
'w i d est</w>'	3

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

Byte pair encoding for word segmentation

why BPE?

- open-vocabulary:
  operations learned on training set can be applied to unknown words
- compression of frequent character sequences improves efficiency
  $\rightarrow$ trade-off between text length and vocabulary size

'l o w e s t </w>'

e s	$\rightarrow$	es
es t	$\rightarrow$	est
est </w>	$\rightarrow$	est</w>
l o	$\rightarrow$	lo
lo w	$\rightarrow$	low

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est </w>	$\rightarrow$	est</w>
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lo w	$\rightarrow$	low

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

'l o w **est** </w>'

e s	$\rightarrow$	es
es t	$\rightarrow$	**est**
est </w>	$\rightarrow$	est</w>
l o	$\rightarrow$	lo
lo w	$\rightarrow$	low

Byte pair encoding for word segmentation

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Evaluation: data and methods

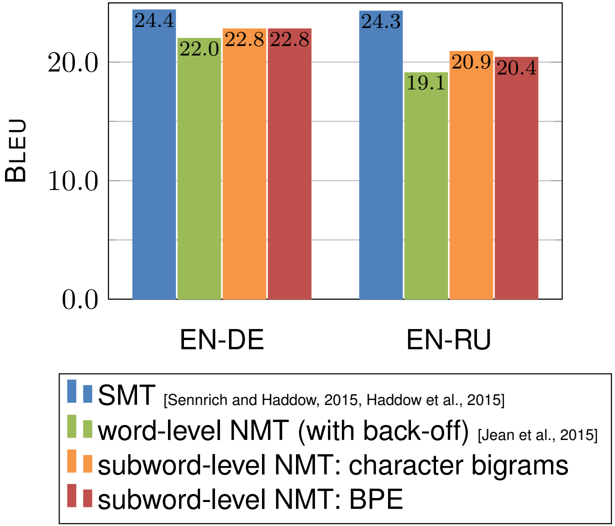
data

- WMT 15 English→German and English→Russian

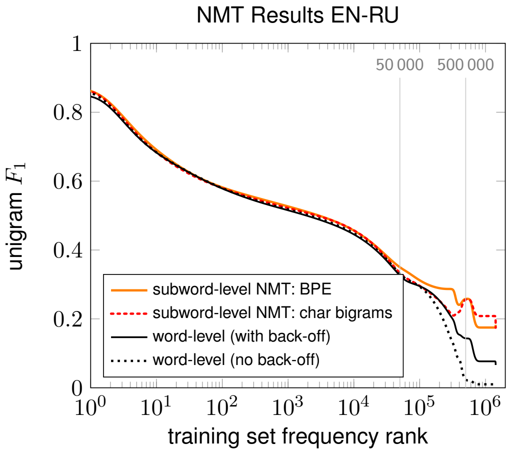
model

- attentional encoder–decoder neural network
- parameters and settings as in [Bahdanau et al, 2014]

Subword NMT: Translation Quality



Subword NMT: Translation Quality



Examples

system	sentence
source	health research institutes
reference	Gesundheitsforschungsinstitute
word-level (with back-off)	Forschungsinstitute
character bigrams	Fo|rs|ch|un|gs|in|st|it|ut|io|ne|n
BPE	Gesundheits|forsch|ungsin|stitute
source	rakfisk
reference	ракфиска (rakfiska)
word-level (with back-off)	rakfisk → UNK → rakfisk
character bigrams	ra|kf|is|k → ра|кф|ис|к (ra|kf|is|k)
BPE	rak|f|isk → рак|ф|иска (rak|f|iska)

BPE in practice

- Use **Joint** BPE for same script languages
  - Just concatenate source and target, then train
  - Named-entities are split consistently

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BPE in practice

- Use **Joint** BPE for same script languages
  - Just concatenate source and target, then train
  - Named-entities are split consistently
- merge operations: 30,000 - 80,000
- for low resource, frequency threshold: 10 [Sennrich and Zhang, 2019]
- Transliterate when scripts are different
- E.g. ISO-9 transliteration for Russian:
  - transliterate Russian corpus into Latin script
  - learn BPE operations on concatenation of English and transliterated Russian corpus
  - transliterate BPE operations into Cyrillic
  - for Russian, apply both Cyrillic and Latin BPE operations
    $\rightarrow$ concatenate BPE files

Code available: `https://github.com/rsennrich/subword-nmt`

Monolingual Data in NMT

Why Monolingual Data for NMT?

- more training data
- more appropriate training data (domain adaptation)

Monolingual Data in NMT

encoder-decoder already conditions on previous target words

$\Downarrow$

no architecture change required to learn from monolingual data

Monolingual Training Instances

Output prediction

- $p(y_i)$ is a function of hidden state s_i, previous output y_{i-1}, and source context vector c_i
- only difference to monolingual RNN: c_i

Problem

we have no source context c_i for monolingual training instances

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Problem

we have no source context c_i for monolingual training instances

Solution: Backtranslation [Sennrich et al., 2016b]

1. train a system in the **reverse** direction (Tgt$\rightarrow$Src)
2. translate target-language data to create a syntetic source Src'
3. flip the direction of the syntetic parallel corpus: Src'$\rightarrow$Tgt
4. merge with the true parallel data and train a Src$\rightarrow$Tgt system

Monolingual Training Instances

Backtranslation

- 1-1 mix of parallel and monolingual training instances
  - oversample parallel data if needed
- randomly sample from back-translated data
- training does not distinguish between real and synthetic parallel data

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Backtranslation

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  - oversample parallel data if needed
- randomly sample from back-translated data
- training does not distinguish between real and synthetic parallel data
  - actually, it's better if it does [Caswell et al., 2019]

Why is monolingual data helpful?

- Domain adaptation effect
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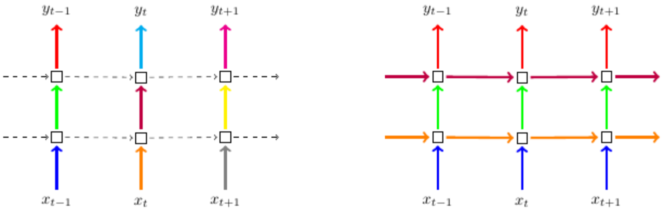
- Improves fluency

Why is monolingual data helpful?

- Domain adaptation effect
- Reduces over-fitting
- Improves fluency

- Additional techniques: copied monolingual data [Currey et al., 2017]
    - improves named entities accuracy

Dropout



[Gal, 2015]

- Dropout (randomly zeroing activations in training) prevents overfitting
- For RNNs repeat mask across timesteps [Gal, 2015]
- Necessary for English↔Romanian (0.6M sentences)
- Masks of 0.1-0.2 provide gain of 4-5 BLEU

Multi-lingual NMT

Why multilinguality?

- NMT models are usually trained on language pairs
- If we have N languages this implies N^2 models
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Multi-lingual translation

- single model for multiple languages pairs
- we'd like to transfer training information between pairs
    - ideally, zero-shot translation

Multi-lingual NMT

Multi-lingual NMT techniques

- universal models
- direct pivoting
- backtranslation pivoting

Universal models [Ha et al., 2016]

model trained on multiple language pairs

- NMT models easily support multiple source languages
  - e.g. we want De→En and Fr→En
  - just mix the training corpora

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- for multiple target languages append a tag
  - on the source side [Ha et al., 2016, Johnson et al., 2017]
  - or on the target side with forced decoding [Firat et al., 2016]

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pros & cons

- pro: works well on related languages
- pro: can be finetuned on parallel data
- con: inefficient for distant languages and/or different scripts
  - transliteration might help
- con: training set balancing issues

Direct pivoting

concatenate two models

- often one language (e.g. En) is strongly over-represented in the training data
- use it as a **pivot** language
    - e.g. we want Cs$\rightarrow$Zh
    - train Cs$\rightarrow$En and En$\rightarrow$Zh and concatenate them

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  - train Cs$\rightarrow$En and En$\rightarrow$Zh and concatenate them

pros & cons

- pro: models can be optimized separately
- pro: allows language-specific pre- and post-processing
- pro: no negative interference between distant languages pairs
- con: can't use parallel data
- con: final system is more cumbersome

Backtranslation pivoting [Bawden et al., 2019]

pivot during training using backtraslations

- Example
  - we want En→Gu
  - we have little En↔Gu data, but plenty of En↔Hi and Hi↔Gu

1. train Hi→En
2. translate the Hi side of the the Hi↔Gu corpus to synthetic En'
3. pair back the original Gu to En' and flip it around to obtain En'↔Gu
4. merge with the true parallel data and train En→Gu

Backtranslation pivoting [Bawden et al., 2019]

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pros & cons

- pro: can use parallel and monolingual data
- pro: no negative interference between distant languages pairs
- pro: simple final system
- con: more complicated training

Backtranslation pivoting [Bawden et al., 2019]

pivot during training using backtraslations

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WMT 2019

- we used this setup for the Edinburgh's submission to WMT 2019
- + transliteration of Hi to Gu and semi-supervised training
- human evaluation results
  - En→Gu: first place
  - Gu→En: second place

Getting Started: Do it Yourself

- sample files and instructions for training NMT model
  `https://github.com/EdinburghNLP/wmt17-scripts`
  `https://github.com/EdinburghNLP/wmt17-transformer-scripts`
- pre-trained models to test decoding (and for further experiments)
  `http://statmt.org/rsennrich/wmt16_systems/`

(A small selection of) Resources

NMT tools

- Nematus (TensorFlow) `https://github.com/EdinburghNLP/nematus`
- Marian (C++/CUDA) `https://github.com/marian-nmt/marian-dev`
- Tensor2Tensor (TensorFlow) `https://github.com/tensorflow/tensor2tensor`
- Fairseq (PyTorch) `https://github.com/pytorch/fairseq`
- XLM (PyTorch) `https://github.com/facebookresearch/XLM`
- ...and many more `https://github.com/jonsafari/nmt-list`

Further Reading

secondary literature

- lecture notes by Kyunghyun Cho: [Cho, 2015]
- chapter on *Neural Network Models* in “Statistical Machine Translation” by Philipp Koehn http://mt-class.org/jhu/assets/papers/neural-network-models.pdf
- tutorial on sequence-to-sequence models by Graham Neubig
  https://arxiv.org/abs/1703.01619
- The Illustrated Transformer http://jalammar.github.io/illustrated-transformer/

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Questions

Thank you!

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