Neural Machine Translation Basics II

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Modelling Translation

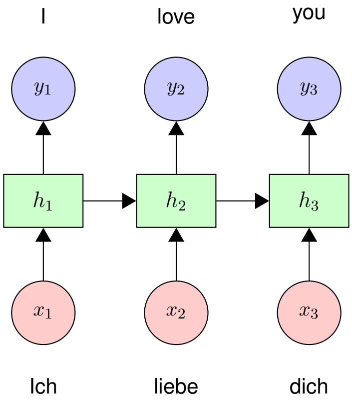
- Suppose that we have:
  - a source sentence S of length m $(x_1, \ldots, x_m)$
  - a target sentence T of length n $(y_1, \ldots, y_n)$
- We can express translation as a probabilistic model

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

- Expanding using the chain rule gives

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

Language Model for Translation?



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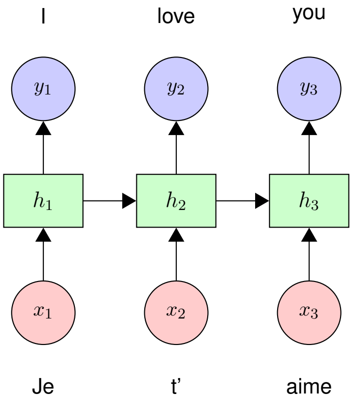

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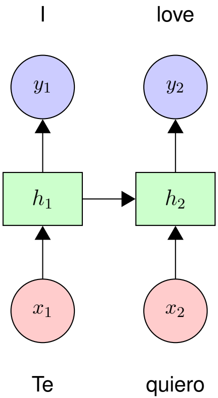

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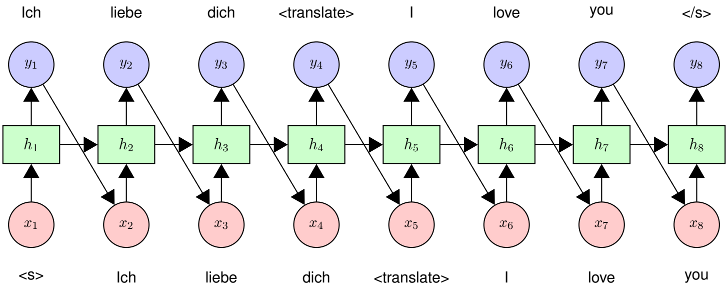

Differences Between Translation and Language Model

- Target-side language model:

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

- Translation model:

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

- We could just treat sentence pair as one long sequence, but:
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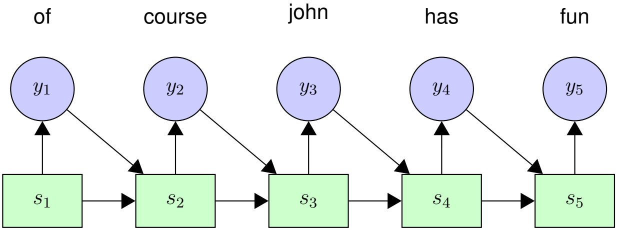
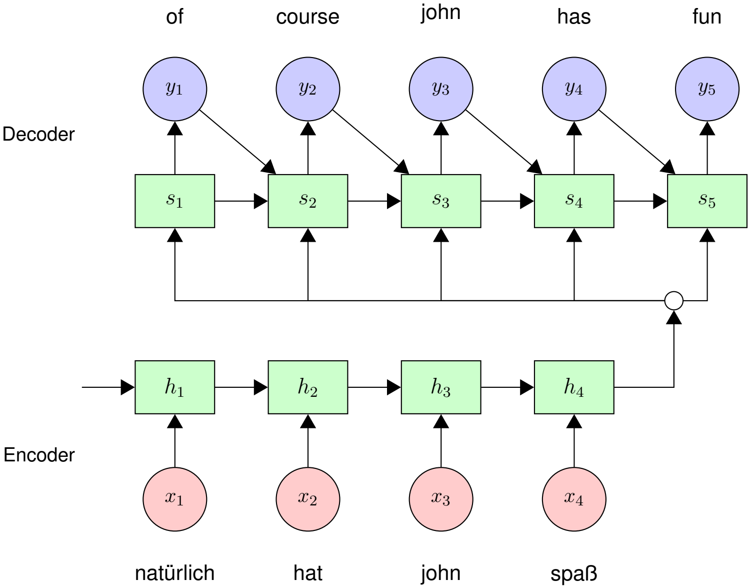
$\rightarrow$ Use separate RNNs for source and target.

Encoder-Decoder for Translation

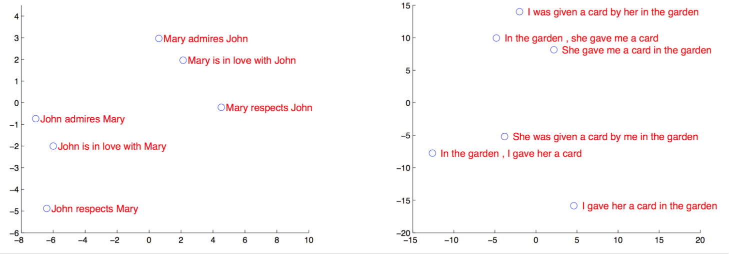


Encoder-Decoder for Translation



Summary vector

- Last encoder hidden-state “summarises” source sentence
- With multilingual training, we can potentially learn language-independent meaning representation

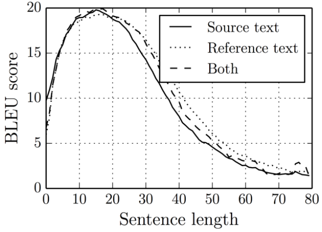


[Sutskever et al., 2014]

Summary vector as information bottleneck

Problem: Sentence Length

- Fixed sized representation degrades as sentence length increases
- Reversing source brings some improvement [Sutskever et al., 2014]



[Cho et al., 2014]

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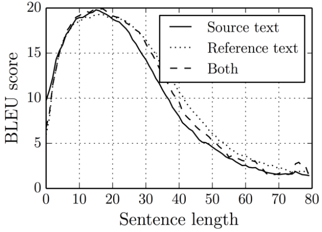
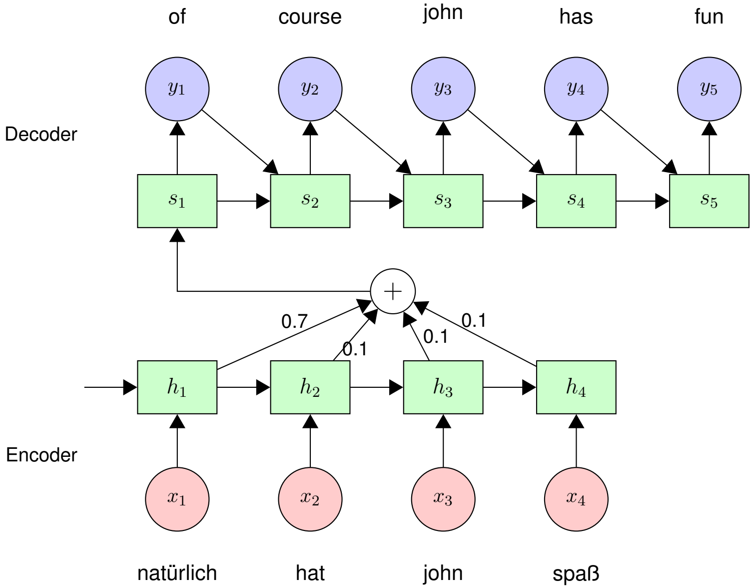


[Cho et al., 2014]

Solution: Attention

- Compute *context vector* as weighted average of source hidden states
- Weights computed by feed-forward network with softmax activation

Encoder-Decoder with Attention



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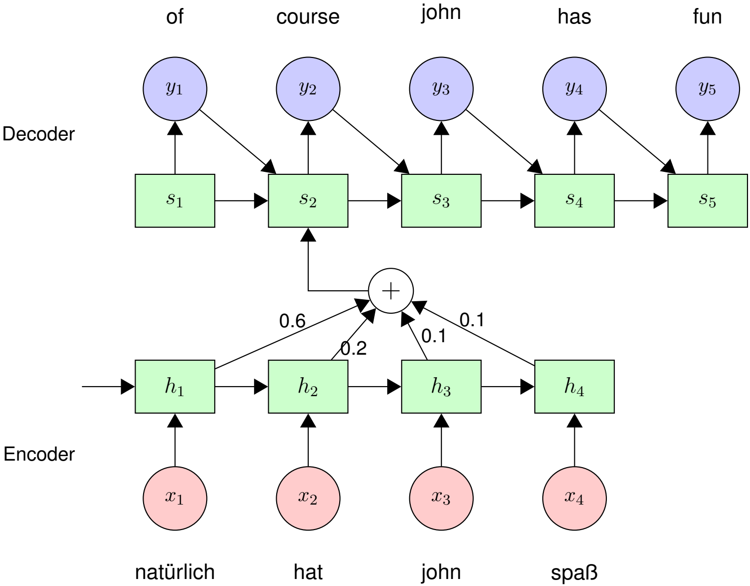

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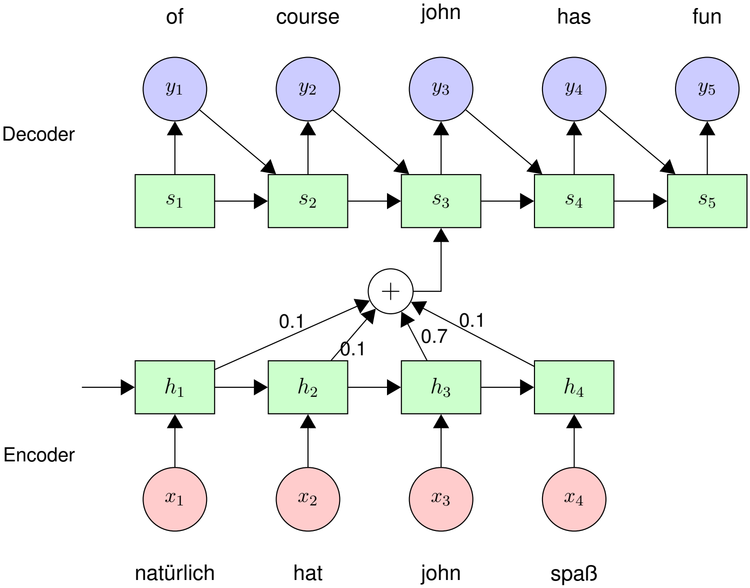

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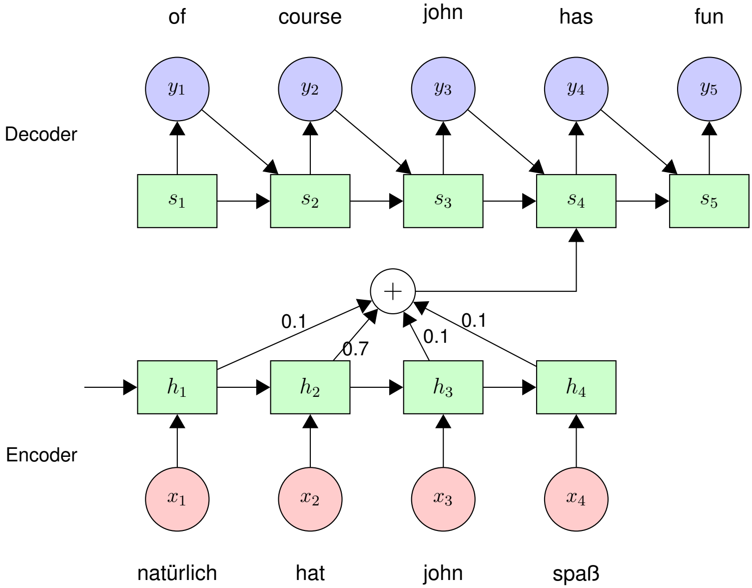

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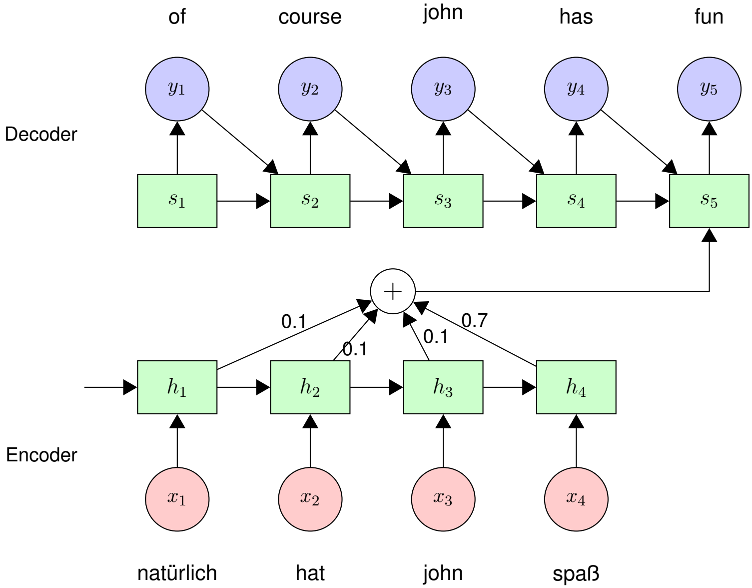


Attentional encoder-decoder: Maths

simplifications of model by [Bahdanau et al., 2015] (for illustration)

- plain RNN instead of GRU
- simpler output layer
- we do not show bias terms
- decoder follows *Look, Update, Generate* strategy [Sennrich et al., 2017]
- Details in `https://github.com/amunmt/amunmt/blob/master/contrib/notebooks/dl4mt.ipynb`

notation

- W, U, E, C, V are weight matrices (of different dimensionality)
  - E one-hot to embedding (e.g. $50000 \cdot 512$)
  - W embedding to hidden (e.g. $512 \cdot 1024$)
  - U hidden to hidden (e.g. $1024 \cdot 1024$)
  - C context (2x hidden) to hidden (e.g. $2048 \cdot 1024$)
  - V_o hidden to one-hot (e.g. $1024 \cdot 50000$)
- separate weight matrices for encoder and decoder (e.g. E_x and E_y)
- input X of length T_x; output Y of length T_y

Attentional encoder-decoder: Maths

encoder

$$\overrightarrow{h}_j = \begin{cases} 0, & \text{, if } j = 0 \\ \tanh(\overrightarrow{W}_x E_x x_j + \overrightarrow{U}_x h_{j-1}) & \text{, if } j > 0 \end{cases}$$

$$\overleftarrow{h}_j = \begin{cases} 0, & \text{, if } j = T_x + 1 \\ \tanh(\overleftarrow{W}_x E_x x_j + \overleftarrow{U}_x h_{j+1}) & \text{, if } j \le T_x \end{cases}$$

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

Attentional encoder-decoder: Maths

decoder

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

$$
t_i = \tanh(U_o s_i + W_o E_y y_{i-1} + C_o c_i)
$$

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

attention model

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

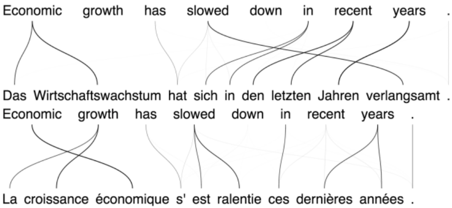
$$
\alpha_{ij} = \text{softmax}(e_{ij})
$$

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

Attention model

attention model

- side effect: we obtain “alignment” between source and target sentence
- 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/

Attention is not alignment

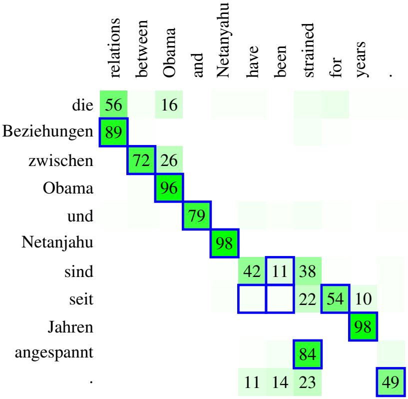


Figure 8: Word alignment for English–German: comparing the attention model states (green boxes with probability in percent if over 10) with alignments obtained from fast-align (blue outlines).

[Koehn and Knowles, 2017]

Attention is not alignment

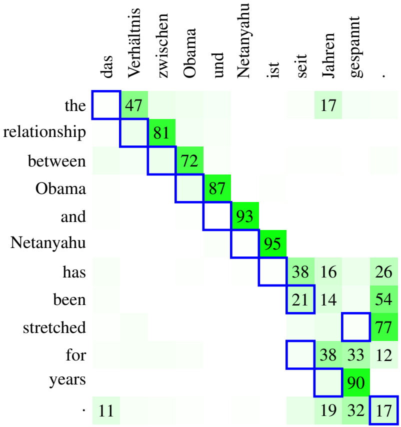


Figure 9: Mismatch between attention states and desired word alignments (German–English).

[Koehn and Knowles, 2017]

Attention model

question: how can model translate correctly, if attention is one-off?

Attention model

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answer: information can also flow along recurrent connections, so there is no guarantee that attention corresponds to alignment

What If You Want Attention to be Alignment-like?

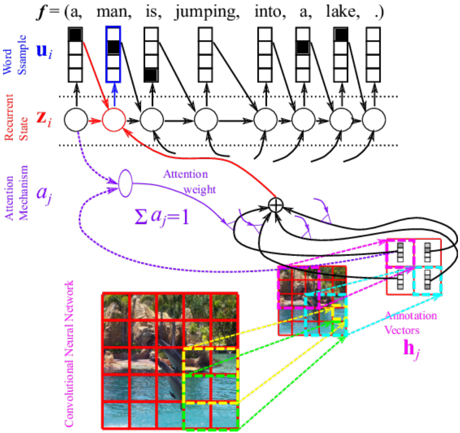
One Solution: Guided Alignment Training [Chen et al., 2016]

1. compute alignment with external tool (IBM models)
2. if multiple source words align to same target words, normalize so that $\sum_j A_{ij} = 1$
3. modify objective function of NMT training:
   - minimize target sentence cross-entropy (as before)
   - minimize divergence between model attention α and external alignment A:

$$H(A, \alpha) = -\frac{1}{T_y} \sum_{i=1}^{T_y} \sum_{j=1}^{T_x} A_{ij} \log \alpha_{ij}$$

Attention model

attention model also works with images:



[Cho et al., 2015]

Attention model

Fig. 5. Examples of the attention-based model attending to the correct object (*white* indicates the attended regions, *underlines* indicated the corresponding word) [22]

[Cho et al., 2015]

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

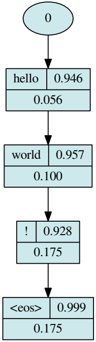
- generate every possible sentence T in target language
- compute score $p(T|S)$ for each
- pick best one

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



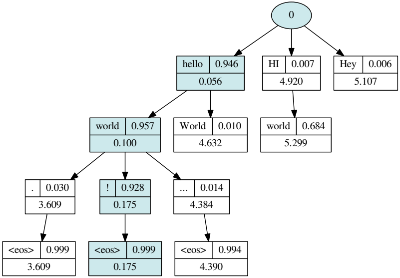
- efficient, but suboptimal

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:

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

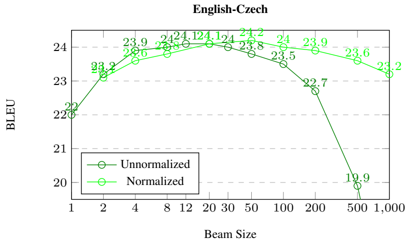


$K = 3$

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

Beam Search in Practice

- translation quality goes down with large beam size (!)
- pruning hypotheses to small beam removes states that are improbable, but have low entropy (label bias)
- models have a bias towards short translation
  $\rightarrow$ cost is often normalized by length
- if model starts copying input, future copying has high probability



[Koehn and Knowles, 2017]

Ensembles

- combine decision of multiple classifiers by voting
- ensemble will reduce error if these conditions are met:
  - base classifiers are accurate
  - base classifiers are diverse (make different errors)

Ensembles in NMT

- vote at each time step to explore same search space
  (better than decoding with one, reranking n-best list with others)
- voting mechanism: typically average (log-)probability

$$\log P(y_i|S, y_{<i}) = \frac{\sum_{m=1}^{M} \log P_m(y_i|S, y_{<i})}{M}$$

- requirements for voting at each time step:
  - same output vocabulary
  - same factorization of Y
  - but: internal network architecture may be different
- we still use reranking in some situations
  example: combine left-to-right decoding and right-to-left decoding

Text Representation

how do we represent text in NMT?

- 1-hot encoding
  - lookup of word embedding for input
  - probability distribution over vocabulary for output
- large vocabularies
  - increase network size
  - decrease training and decoding speed
- typical network vocabulary size: 10 000–100 000 symbols

vocabulary		representation of "cat" 1-hot vector	representation of "cat" embedding
0 1 2 . 1024	the cat is . mat	$\begin{bmatrix} 0 \\ 1 \\ 0 \\ . \\ 0 \end{bmatrix}$	$\begin{bmatrix} 0.1 \\ 0.3 \\ 0.7 \\ 0.5 \end{bmatrix}$

Problem

translation is open-vocabulary problem

- many training corpora contain millions of word types
- productive word formation processes (compounding; derivation) allow formation and understanding of unseen words
- names, numbers are morphologically simple, but open word classes

Non-Solution: Ignore Rare Words

- replace out-of-vocabulary words with UNK
- a vocabulary of 50 000 words covers 95% of text

this gets you 95% of the way...
... if you only care about automatic metrics

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why 95% is not enough

rare outcomes have high self-information

source	The **indoor temperature** is very pleasant.	
reference	Das **Raumklima** ist sehr angenehm.	
[Bahdanau et al., 2015]	Die **UNK** ist sehr angenehm.	✗
[Jean et al., 2015]	Die **Innenpool** ist sehr angenehm.	✗
[**Sennrich**, Haddow, Birch, ACL 2016]	Die **Innen+ temperatur** ist sehr angenehm.	✓

Solution 1: Back-off Models

back-off models [Jean et al., 2015, Luong et al., 2015]

- replace rare words with UNK at training time
- when system produces UNK, align UNK to source word, and translate this with back-off method

source	The **indoor temperature** is very pleasant.	
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[Bahdanau et al., 2015]	Die **UNK** ist sehr angenehm.	✗
[Jean et al., 2015]	Die **Innenpool** ist sehr angenehm.	✗

limitations

- compounds: hard to model 1-to-many relationships
- morphology: hard to predict inflection with back-off dictionary
- names: if alphabets differ, we need transliteration
- alignment: attention model unreliable

Solution 2: Subword Models

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.

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

our experiments [Sennrich et al., 2016]

- after preliminary experiments, we propose:
  - character n-grams (with shortlist of unsegmented words)
  - segmentation via *byte pair encoding* (BPE)

Byte pair encoding for word segmentation

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> w e r</w> n s t</w> i d

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es

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vocabulary:
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es **est</w>**

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

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

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</w>	$\rightarrow$	est</w>
l o	$\rightarrow$	lo

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'l o w **es** t</w>'

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

Byte pair encoding for word segmentation

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e s	→	es
es t</w>	→	**est</w>**
l o	→	lo

Byte pair encoding for word segmentation

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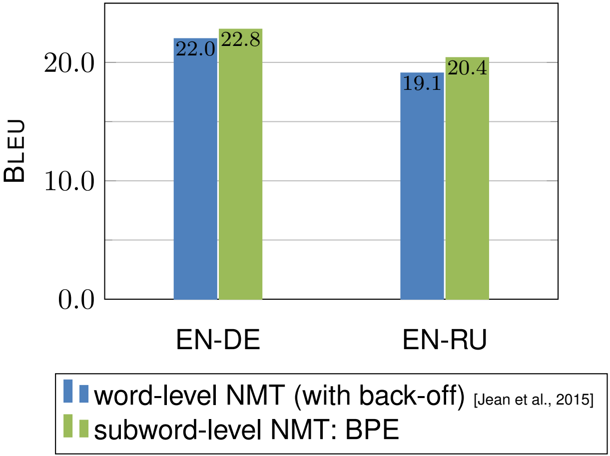
l o	→	**lo**

Subword NMT: Translation Quality



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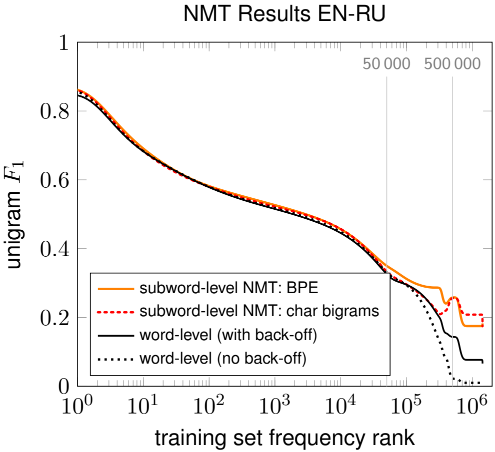


Examples

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)

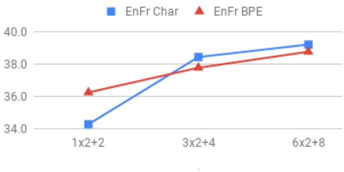
Subword Models: Variants

- morphologically motivated subword units [Sánchez-Cartagena and Toral, 2016, Tamchyna et al., 2017, Huck et al., 2017, Pinnis et al., 2017]
- probabilistic segmentation and sampling [Kudo, 2018]

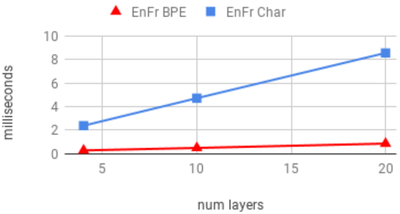
Solution 3: Character-level Models

- advantages:
  - (mostly) open-vocabulary
  - no heuristic or language-specific segmentation
  - neural network can learn from raw character sequences
- drawbacks:
  - increasing sequence length slows training/decoding
    (reported x2–x8 increase in training time)
  - memory requirement: trade-off between embedding matrix size and sequence length
- active research on specialized architectures [Ling et al., 2015, Luong and Manning, 2016, Chung et al., 2016, Lee et al., 2016]

Character-level NMT: Current Results (as of 5 days ago: August 29 2018)



For deep LSTMs, char-level systems can achieve higher BLEU than BPE



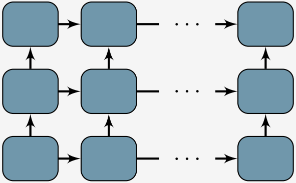
...but training time (per sentence) is 8x higher

[Cherry et al., 2018]

Deep Networks

- increasing model depth often increases model performance
- example: stack RNN:

$$
\begin{aligned}
h_{i,1} &= g(U_1 h_{i-1,1} + W_1 E_x x_i) \\
h_{i,2} &= g(U_2 h_{i-1,2} + W_2 h_{i,1}) \\
h_{i,3} &= g(U_3 h_{i-1,3} + W_3 h_{i,2})
\end{aligned}
$$



Deep Networks

- often necessary to combat vanishing gradient:
  residual connections between layers:

$$
\begin{aligned}
h_{i,1} &= g(U_1 h_{i-1,1} + W_1 E_x x_i) \\
h_{i,2} &= g(U_2 h_{i-1,2} + W_2 h_{i,1}) + \mathbf{h_{i,1}} \\
h_{i,3} &= g(U_3 h_{i-1,3} + W_3 h_{i,2}) + \mathbf{h_{i,2}}
\end{aligned}
$$

Layer Normalization

- if input distribution to NN layer changes, parameters need to adapt to this **covariate shift**
- especially bad: RNN state grows/shrinks as we go through sequence
- normalization of layers reduces shift, and improves training stability
- re-center and re-scale each layer $\mathbf{a}$ (with H units)
- two bias parameters, $\mathbf{g}$ and $\mathbf{b}$, restore original representation power

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

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

$$\mathbf{h} = \left[\frac{\mathbf{g}}{\sigma} \odot (\mathbf{a} - \mu) + \mathbf{b}\right]$$

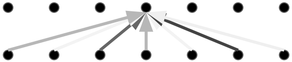
Layer Normalization and Deep Models: Results from UEDIN@WMT17

system	CS→EN 2017	DE→EN 2017	LV→EN 2017	RU→EN 2017	TR→EN 2017	ZH→EN 2017
baseline	27.5	32.0	16.4	31.3	19.7	21.7
+layer normalization	28.2	32.1	17.0	32.3	18.8	22.5
+deep model	28.9	33.5	16.6	32.7	20.6	22.9

- layer normalization and deep models generally improve quality
- layer normalization also speeds up convergence when training (fewer updates needed)

Attention Is All You Need [Vaswani et al., 2017]

- main criticism of recurrent architecture:
  recurrent computations cannot be parallelized
- core idea: instead of recurrence, use attention mechanism to condition hidden states on context
  $\rightarrow$ self-attention
- specifically, attend over previous layer of deep network



https://nlp.stanford.edu/seminar/details/lkaiser.pdf

Attention Is All You Need [Vaswani et al., 2017]

Transformer architecture

- stack of N self-attention layers
- self-attention in decoder is *masked*
- decoder also attends to encoder states
- *Add & Norm*: residual connection and layer normalization
- RNN can learn to count raw text
  Transformer needs *positional encoding*

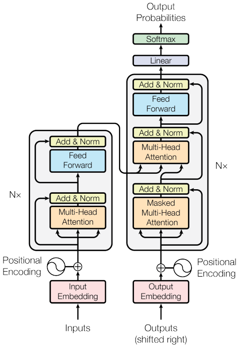


Figure 1: The Transformer - model architecture.

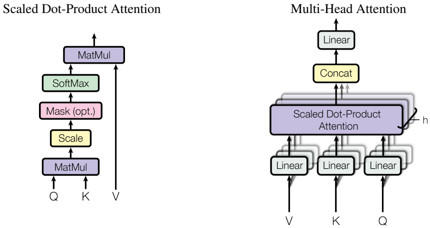
[Vaswani et al., 2017]

Multi-Head Attention

- basic attention mechanism in AIAYN: Scaled Dot-Product Attention

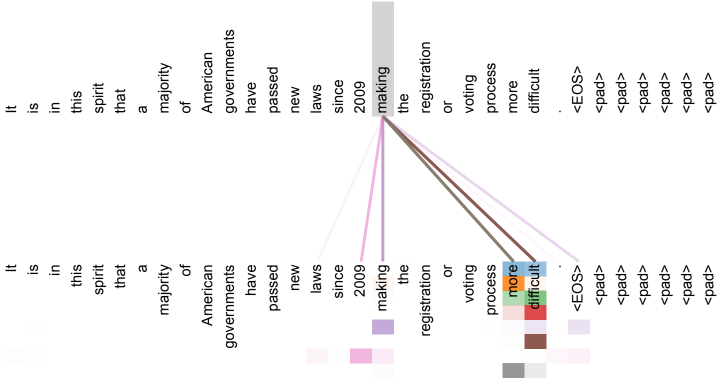
$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

- query Q is decoder/encoder state (for attention/self-attention)
- key K and value V are encoder hidden states
- multi-head attention: use h parallel attention mechanisms with low-dimensional, learned projections of Q, K, and V



Multi-Head Attention

motivation for multi-head attention:
different heads can attend to different states



Comparison

empirical comparison difficult

- some components could be mix-and-matched
  - choice of attention mechanism
  - choice of positional encoding
  - hyperparameters and training tricks
- different test sets and/or evaluation scripts

Comparison

SOCKEYE [Hieber et al., 2017] (EN-DE; newstest2017)

system	BLEU
deep LSTM	25.6
Convolutional	24.6
Transformer	**27.5**

[Chen et al., 2018] (EN-DE; newstest2014)

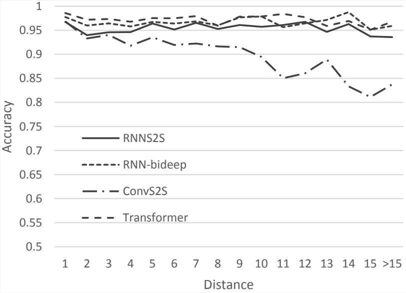
system	BLEU
GNMT (RNN)	24.7
Transformer	27.9
RNMT+ (RNN)	**28.5**

Why Self-Attention?

- our understanding of neural networks lags behind empirical progress
- there are some theoretical arguments why architectures work well... (e.g. self-attention reduces distance in network between words)
- ...but these are very speculative

Targeted Evaluation [Tang et al., 2018]

- quality of long-distance agreement is similar between GRU and Transformer
- strength of Transformer: better word sense disambiguation



Further Reading

- primary literature:
  - Sutskever, Vinyals, Le (2014): Sequence to Sequence Learning with Neural Networks.
  - Bahdanau, Cho, Bengio (2014): Neural Machine Translation by Jointly Learning to Align and Translate.
  - Vaswani et al. (2017): Attention Is All You Need
- secondary literature:
  - Koehn (2017): Neural Machine Translation.
  - Neubig (2017): Neural Machine Translation and Sequence-to-sequence Models: A Tutorial
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