

Introduction to (Neural) Machine Translation

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unless otherwise stated

Outline

- Statistical Machine Translation
 - Why “classical” SMT fails
- Neural Machine Translation
 - Learning Representations
 - Processing Text
 - Transformer (Self-Attention)
- Some of Training Magic
- Caveats on Interpreting Results

Some slides by Jindřich Helcl, Jindřich Libovický, Tom Kocmi. Many slides based on slides by Rico Sennrich and others.

Further Reading

Slides from my subject here at ÚFAL:

<https://ufal.mff.cuni.cz/courses/npfl1087>

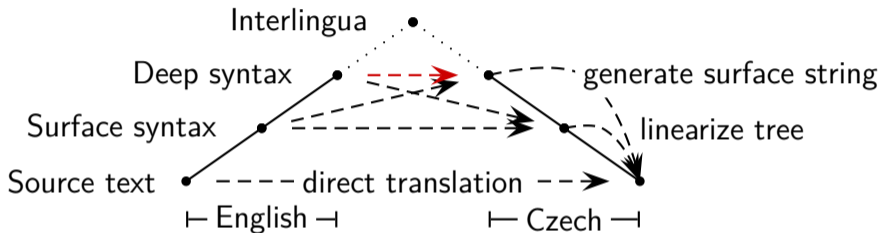
Videlectures & Wiki (everything before neural):

<http://mttalks.ufal.ms.mff.cuni.cz/>

Books and others:

- Philipp Koehn: Neural Machine Translation. Cambridge University Press. June 2020. <http://statmt.org/nmt-book/>
- Philipp Koehn: Statistical Machine Translation. Cambridge University Press, 2009. Slides: <http://statmt.org/book/>
Chapter on NMT: <https://arxiv.org/abs/1709.07809>
- Ondřej Bojar: Čeština a strojový překlad. ÚFAL, 2012.

Approaches to Machine Translation



- The deeper analysis, the easier the **transfer** should be.
- A hypothetical interlingua captures pure meaning.
- Statistical systems learn “automatically” from data.
- Rule-based systems implemented by linguists-programmers.

Until NMT, it was best to combine the approaches.

The Statistical Approach

(Statistical = Information-theoretic.)

- Specify a probabilistic model.
 - = How is the probability mass distributed among possible outputs given observed inputs.
- Specify the training criterion and procedure.
 - = How to learn free parameters from training data.

Notice:

- Linguistics helpful when designing the models:
 - How to divide input into smaller units.
 - Which bits of observations are more informative.

Statistical MT

Given a source (foreign) language sentence $f_1^J = f_1 \dots f_j \dots f_J$,

Produce a target language (English) sentence $e_1^I = e_1 \dots e_j \dots e_I$.

Among all possible target language sentences, choose the sentence with the highest probability:

$$\hat{e}_1^I = \operatorname{argmax}_{I, e_1^I} p(e_1^I | f_1^J) \quad (1)$$

We stick to the e_1^I, f_1^J notation regardless the source and target languages.

Brute-Force MT

Translate only sentences listed in a “translation memory” (TM):

Good morning. = Dobré ráno.
How are you? = Jak se máš?
How are you? = Jak se máte?

$$p(e_1^I | f_1^J) = \begin{cases} 1 & \text{if } e_1^I = f_1^J \text{ seen in the TM} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Any problems with the definition?

Brute-Force MT

Translate only sentences listed in a “translation memory” (TM):

Good morning. = Dobré ráno.
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$$p(e_1^I | f_1^J) = \begin{cases} 1 & \text{if } e_1^I = f_1^J \text{ seen in the TM} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

- Not a probability. There may be f_1^J , s.t. $\sum_{e_1^I} p(e_1^I | f_1^J) > 1$.
⇒ Have to normalize, use $\frac{\text{count}(e_1^I, f_1^J)}{\text{count}(f_1^J)}$ instead of 1.
- Not “smooth”, no generalization:

Good morning. ⇒ Dobré ráno.
Good evening. ⇒ ∅

Old School: Noisy Channel Model

$$\hat{e}_1^I = \operatorname{argmax}_{I, e_1^I} p(e_1^I | f_1^J) = \operatorname{argmax}_{I, e_1^I} p(f_1^J | e_1^I) p(e_1^I) \quad (3)$$

Bayes' law divided the model into components:

$p(f_1^J | e_1^I)$ Translation model ("reversed", $e_1^I \rightarrow f_1^J$)
...is it a likely translation?

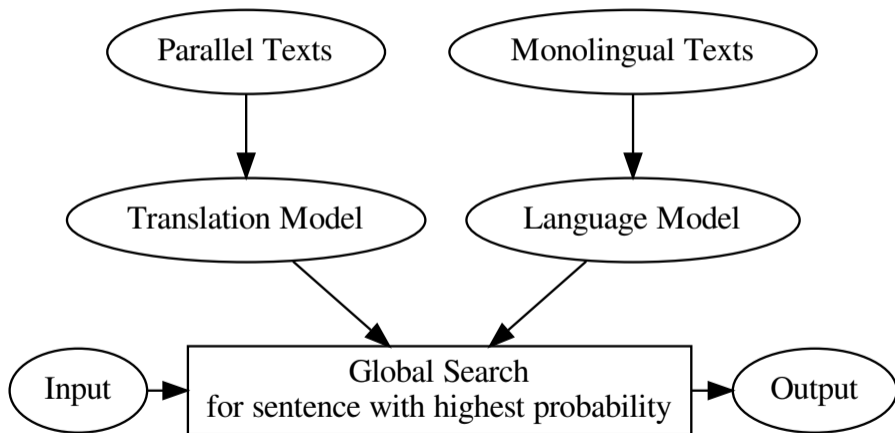
$p(e_1^I)$ Language model (LM)
...is the output a likely sentence of the target language?

- The components can be trained on different sources.

There are far more monolingual data \Rightarrow language model can be more reliable.

... smoothing enabled by a math trick.

Without Equations



Translation Model of Phrase-Based MT

- The key element was **phrase translation probability**:

$$p(\tilde{f}_k | \tilde{e}_k) = \frac{\text{count}(\tilde{f}, \tilde{e})}{\text{count}(\tilde{e})} \quad \dots \text{how often } \tilde{f}_k \text{ served as the translation of } \tilde{e}_k.$$

- The whole source sentence was covered with phrase translations.
- The total translation probability was the product of individual phrase translation probabilities:

$$h_{\text{Phr}}(f_1^J, e_1^I, s_1^K) = \log \prod_{k=1}^K p(\tilde{f}_k | \tilde{e}_k)$$

... **smoothing via decomposition into smaller units.**

Work on Your Data

- CzEng (Czech-English) reached 180M million sentence pairs:
 - 0.6 cs / 0.7 en **gigawords** of genuine parallel text (61M sentpairs)
 - 2.0 cs / 2.3 en **gigawords** of synthetic text (127M sentpairs)

Ver.	S. Pairs	Main Focus	Details in
0.5	0.9M	Sentence alignment, common format	Bojar and Žabokrtský (2006)
0.7	1.0M	Used in WMT06 and WMT07	Bojar et al. (2008)
0.9	8.0M	Automatic annotation up to t-layer	Bojar and Žabokrtský (2009)
–	–	Sentence-level filtering	Bojar et al. (2010)
1.0	15.0M	Improving monolingual annotation through parallel data	Bojar et al. (2012)
1.6	62.5M	Processing tools dockered	Bojar et al. (2016)
1.7	57.1M	Block-level filtering	–
2.0	188.0M	Filtering + Synthetic data	–

From Aligned Documents ...

In my dream , there was a sycamore growing out of the ruins of the sacristy , and I was told that , if I dug at the roots of the sycamore , I would find a hidden treasure . But I ' m not so stupid as to cross an entire desert just because of a recurrent dream . " And they disappeared . The boy stood up shakily , and looked once more at the Pyramids . " It is I who dared to do so , " said the boy . This man looked exactly the same , except that now the roles were reversed . " It is I who dared to do so , " he

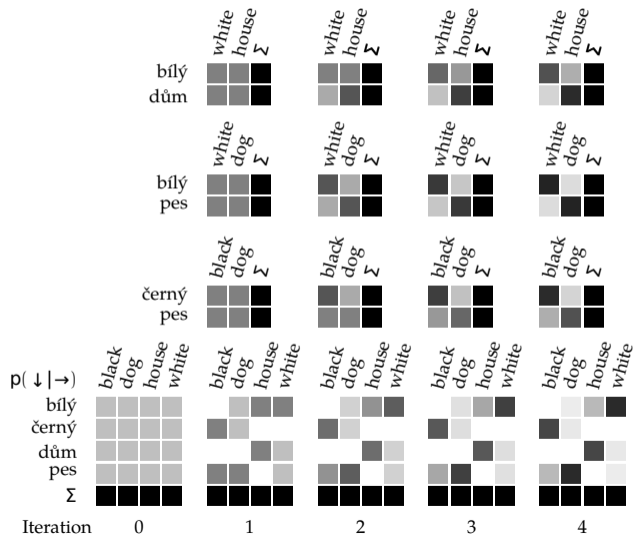
अपने सपने में मुझे एक गुलर का पेड़ दिखाई देता था और मुझे लगता था कि अगर मैं उस गुलर की जड़ें खोद डालूं तो मुझे छिपा हुआ खजाना मिल जाएगा । मगर मैं तुम्हारी तरह इतना बेवकूफ नहीं हूँ कि महज बार - बार आने वाले एक सपने के कारण पूरे रेगिस्तान को पार करूं । वे लोग , उसके बाद वहां से चले गए । लड़का लड़खड़ाता हुआ किसी तरह खड़ा हो गया । <s>एक बार फिर उसने पिरामिडों को देखा । " यह जुर्रत मैंने की थी , " लड़के ने कहा । <s>उसे सेंटियागो मातामोरोस की वह प्रतिमा याद आई जिसमें वह घोड़े पर सवार था और उसके घोड़े के खुशियों में कितने ही नास्तिक कुचले हुए पड़े थे । यह घुड़सवार भी बिलकुल वैसा ही था । यह बात और थी कि इनके किरदार बदले हुए थे । " मैंने ही ऐसा करने का साहस किया था , " लड़के ने दोहराया और अपनी गर्दन तलवार का वार सहने के लिए झुका दी । ' जिंदगी ने भी हमेशा मेरे साथ अच्छा बर्ताव किया । '

... Obtain Aligned Sentences

In my dream , there was a sycamore growing out of the ruins of the sacristry , and I was told that , if I dug at the roots of the sycamore , I would find a hidden treasure . अपने सपने में मुझे एक गुजर का पेड़ दिखाई देता था और मुझे लगता था कि अगर मैं उस गुजर की जड़ें खोद दालूँ तो मुझे थिया हुआ खजाना मिल जाएगा ।
But I ' m not so stupid as to cross an entire desert just because of a recurrent dream . " मगर मैं तुम्हारी तरह इतना बेवकूफ नहीं हूँ कि महज बार - बार आने वाले एक सपने के कारण पूरे शैंगस्तान को घार करूँ ।
And they disappeared . वे लोग , उसके बाद वहाँ से चले गए ।
The boy stood up shakily , and looked once more at the Pyramids . लड़का लड़कपट्टाता हुआ थिची तरह खड़ा हो गया । एक बार फिर उसने पिरामिडों को देखा ।
" It is I who dared to do so , " said the boy . यह धूसरसागर भी थिलकुल बैला ही था ।
This man looked exactly the same , except that now the roles were reversed . यह बात और थी कि इनके किरदार बदले हुए थे ।
" It is I who dared to do so , " he repeated , and he lowered his head to receive a blow from the sword . " मैंने ही ऐसा करने का साहस किया था , " लड़के ने दोहराया और अपनी गर्दन तलवार का धार सहने के लिए झुका दी ।
" Life was good to me , " the man said . " जिंदगी ने भी हमेशा मेरे साथ अच्छा बर्ताव किया । "
" When you appeared in my dream , I felt that all my efforts had been rewarded , because my son ' s poems will be read by men for generations to come . उस आदमी ने कहा , " जब आप मेरे सपने में आए थे , तो मुझे लगा कि मैंने अपने कर्मों का पुरस्कार पा लिया ... मेरे लिए इससे बढ़कर और क्या बात होती कि मेरे बेटे की कविताएँ युग - युगों तक पढ़ी जाएँ ।
I don ' t want anything for myself . नहीं , मुझे अपने लिए कुछ नहीं चाहिए ।
But any father would be proud of the fame achieved by one whom he had cared for as a child , and educated as he grew up . कोई भी बाप उस इंसान की सोहरत खूबकार फूला नहीं समाएगा जिसे उसने अपनी गोद में थिलासा , पढ़ाया - थिलाखाया और पाल - पोसकर बड़ा किया हो ।
" We ' re two very different things . " हम दो अलग - अलग चीजें हैं । "
" That ' s not true , " the boy said . " यह सही नहीं है । " लड़के ने कहा ,
" I learned the alchemist ' s secrets in my travels . " यात्रा के दौरान मैंने कीमिथ्यार के रहस्यों को जाना है ।
I have inside me the winds , the deserts , the oceans , the stars , and everything created in the universe . मेरी भी भीतर सब थिया है — हवा , शैंगस्तान , समुद्र , तारे और वह सब कुछ जो ब्रह्माण्ड ने सृजित किया है ।
We were all made by the same hand , and we have the same soul . हम सबको उसी हाथ ने बनाया और हम सबकी आत्मा भी एक ही है ।
You ' ll learn to love the desert , and you ' ll get to know every one of the fifty thousand palms . तुम्हें शैंगस्तान से प्यार करना आ जाएगा और उन पचास हजार खजूर के पेड़ों में तुम एक - एक को पहचानने लगोगे ।
You ' ll watch them as they grow , demonstrating how the world is always changing . उन्हें बढ़ता हुआ देखकर तुम अनुभव करोगे कि कैसे हर क्षण दुनिया बदलती रहती है ।
And you ' ll get better and better at understanding omens , because the desert is the best teacher there is . तुम शकून पहचानने में बेहतर से बेहतर बनते जाओगे चूँकि इस मामले में शैंगस्तान से बढ़कर कोई अच्छा गुरु नहीं है ।
" Sometime during the second year , you ' ll remember about the treasure . " फिर , थिची बरस , तुमारे साल के दौरान तुमसे खजाने की याद साराएगी ।
The omens will begin insistently to speak of it , and you ' ll try to ignore them . शकून कोरान तुमसे उसके बारे में बताना शुरू कर देगे , मगर तुम उससे अनदेखा करना चाहोगे ।
But you know that I ' m not going to go to Mecca . just as you know that you ' re not going to buy your sheep . " तुम अम्हरा तरह से जानते हो , कि मैं मक्का नहीं जाने वाला हूँ टीक उसी तरह जैसे कि तुम कोई भेड़ - बेड़ नहीं खरीदने वाले हो ! "
" Who told you that ? " asked the boy , startled . " आपसे ऐसा कितने कहा ? " लड़के को आश्चर्य हुआ ।
" Maktub " said the old crystal merchant . " मक्तूब ! " किरस्टल - व्यापारी ने कहा ,
And he gave the boy his blessing . कुछ पल खामेश ख कर , उसने लड़के को भरसूर आशीर्वाद दिया ।
The boy went to his room and packed his belongings . कमरे में जाकर लड़के ने अपने सामान बांधा ।
They filled three sacks . तीन बोरे भर गए ।
As he was leaving , he saw , in the corner of the room , his old shepherd ' s pouch . बाहर जाते हुए उसने कमरे के एक कोने में , अपनी पुरानी थोली देखी ।
" I want to see the greatness of Allah , " the chief said , with respect . " मैं अल्लाह की महानता देखना चाहता हूँ । " बड़े आदर के साथ मुथिया ने कहा ।
" I want to see how a man turns himself into the wind . " " मैं देखना चाहता हूँ कि कैसे कोई अदनी खुद को हवा में बदलता है । "
But he made a mental note of the names of the two men who had expressed their fear . मगर उसने अपने मन में उन दो सेनपतियों के नाम याद कर लिए जिन्होंने उर का इन्हांर किया था ।

Gale and Church (1993) illustrated in MT Talk #7
(https://youtu.be/_4lnyoC3mtQ)

From Sent. Pairs, Learn Word Translations



IBM Model 1 illustrated in Bojar (2012).
 See also MT Talk #8
 (<https://youtu.be/mqyMDLu5JPw>)

1: Align Training Sentences

Nemám žádného psa.

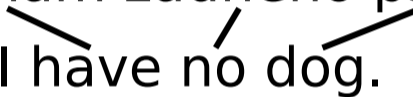
I have no dog.

Viděl kočku.

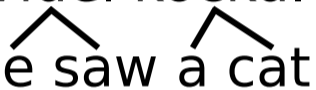
He saw a cat.

2: Align Words

Nemám žádného psa.
I have no dog.



Viděl kočku.
He saw a cat.



3: Extract Phrase Pairs (MTUs)

Nemám žádného psa.
I have no dog.

Viděl kočku.
He saw a cat.

4: New Input

Nemám žádného psa.
I have no dog.

Viděl kočku.
He saw a cat.

New input: Nemám kočku.

4: New Input

Nemám žádného psa.
I have no dog.

Viděl kočku.
He saw a cat.

... I don't have cat.

New input: Nemám kočku.

5: Pick Probable Phrase Pairs (TM)

Nemám žádného psa.
I have no dog.

Viděl kočku.
He saw a cat.

... I don't have cat.

New input:

Nemám kočku.
I have

6: So That n -Grams Probable (LM)

Nemám žádného psa.
I have no dog.

Viděl kočku.
He saw a cat.

... I don't have cat.

New input:

Nemám kočku.
I have a cat.

Meaning Got Reversed!

Nemám žádného psa.
I have no dog.

Viděl kočku.
He saw a cat.

... I don't have cat.

New input:

Nemám kočku.
I have a cat. ❌

What Went Wrong?

$$\hat{e}_1^I = \operatorname{argmax}_{I, e_1^I} p(f_1^J | e_1^I) p(e_1^I) = \operatorname{argmax}_{I, e_1^I} \prod_{(\hat{f}, \hat{e}) \in \text{phrase pairs of } f_1^J, e_1^I} p(\hat{f} | \hat{e}) p(e_1^I) \quad (4)$$

Too strong independence assumptions:

- Language model as a separate unit.
 - $p(e_1^I)$ models the target sentence independently of f_1^J .
- Phrases translated independent of one another.
 - In fact, phrases do depend on each other.
Here “nemám” and “žádného” jointly express one negation.
 - Word alignments ignored that dependence.
But adding it would increase data sparseness.
 - LM was the only means for glueing phrases, but it prefers positive sents.

Redefining $p(e_1^I | f_1^J)$

What if we modelled $p(e_1^I | f_1^J)$ directly, word by word:

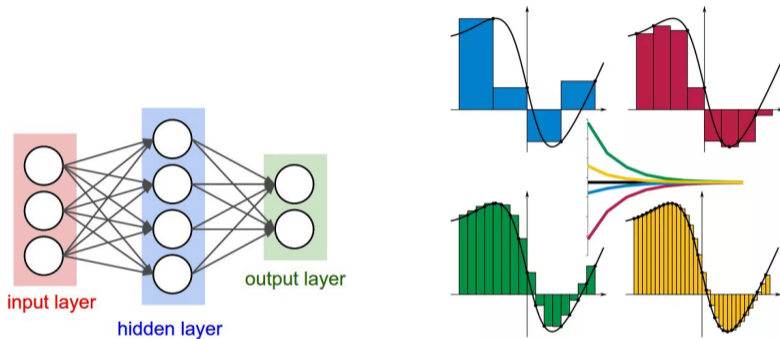
$$\begin{aligned} p(e_1^I | f_1^J) &= p(e_1, e_2, \dots, e_I | f_1^J) \\ &= p(e_1 | f_1^J) \cdot p(e_2 | e_1, f_1^J) \cdot p(e_3 | e_2, e_1, f_1^J) \dots \\ &= \prod_{i=1}^I p(e_i | e_1, \dots, e_{i-1}, f_1^J) \end{aligned} \tag{5}$$

...this is “just a cleverer language model:” $p(e_1^I) = \prod_{i=1}^I p(e_i | e_1, \dots, e_{i-1})$

Main Benefit: All dependencies available.

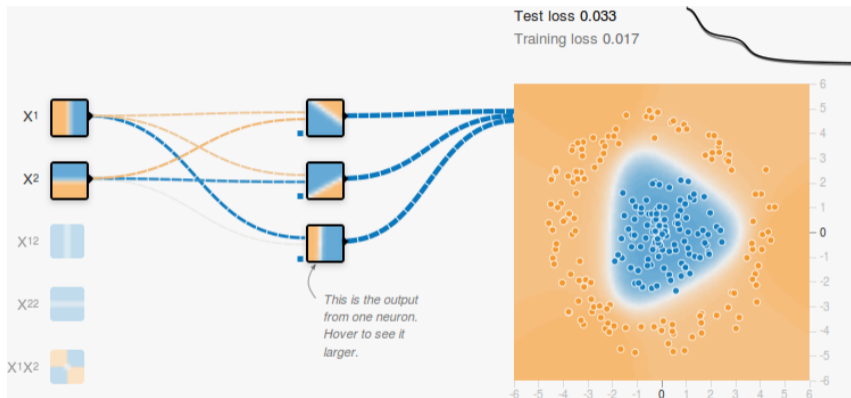
But what technical device can learn this?

NNs: Universal Approximators



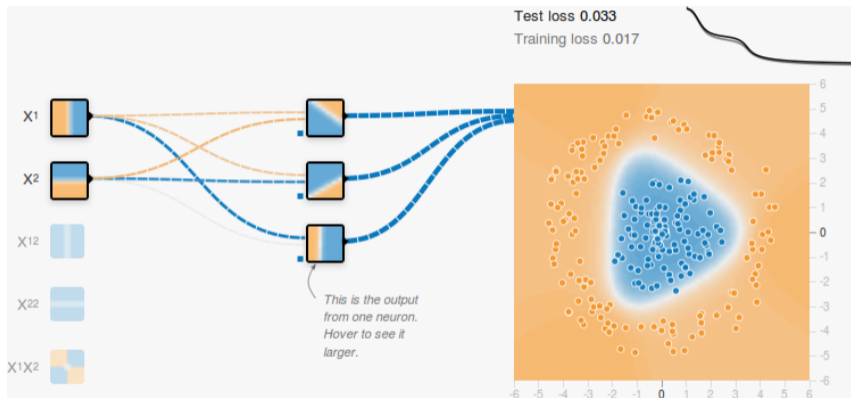
- A neural network with a single hidden layer (possibly huge) can approximate any continuous function to any precision.
- (Nothing claimed about learnability in practice.)

Play with playground.tensorflow.org



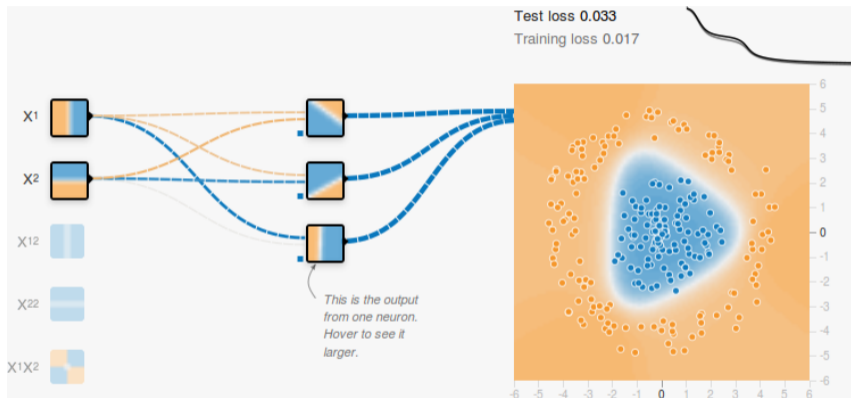
$$\begin{aligned} & -0.43x_1 - 0.89x_2 + 2.0 > 0 \\ \text{and } & -0.67x_1 + 0.89x_2 + 2.1 > 0 \\ \text{and } & 1.4x_1 - 0.067x_2 + 2.3 > 0 \end{aligned}$$

A DL “Program” Is Just a Computation...



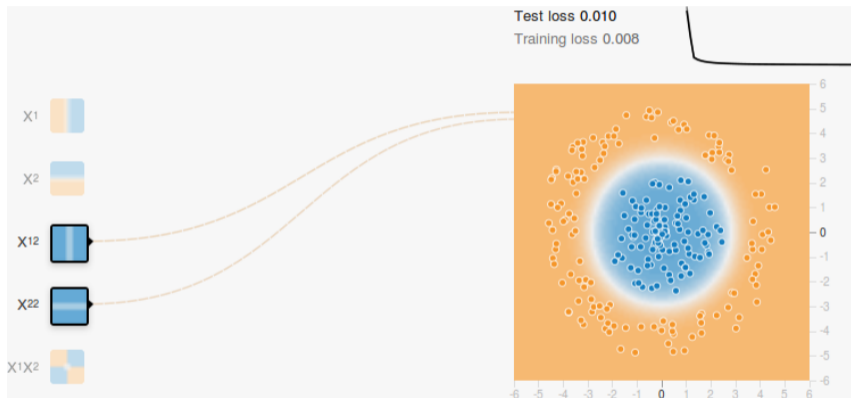
$$\begin{aligned} & \text{In fact: } 1 \tanh(-0.43x_1 - 0.89x_2 + 2.0) \\ & \quad + 1 \tanh(-0.67x_1 + 0.89x_2 + 2.1) \\ & \quad + 1 \tanh(1.4x_1 - 0.067x_2 + 2.3) - \pi/2 > 0 \end{aligned}$$

... with Parameters Guessed Automatically



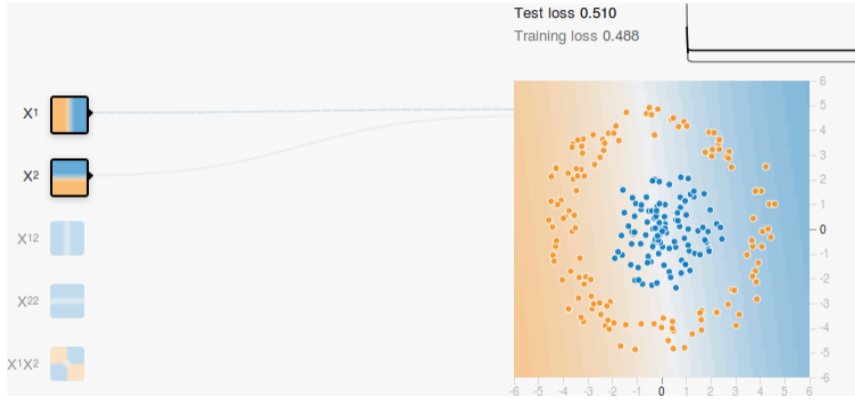
$$\begin{aligned} \text{In fact: } & 1 \tanh(-0.43x_1 - 0.89x_2 + 2.0) \\ & + 1 \tanh(-0.67x_1 + 0.89x_2 + 2.1) \\ & + 1 \tanh(1.4x_1 - 0.067x_2 + 2.3) - \pi/2 > 0 \end{aligned}$$

Perfect Features

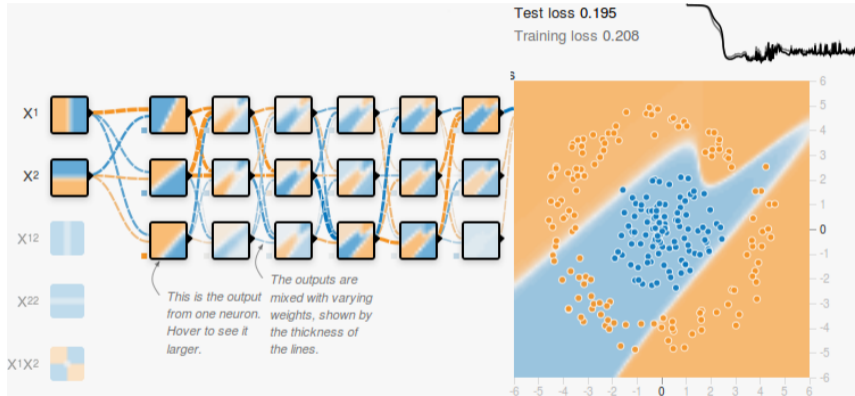


$$1x_1^2 + 1x_2^2 - 1 < 0$$

Bad Features & Low Depth



Too Complex NN Fails to Learn

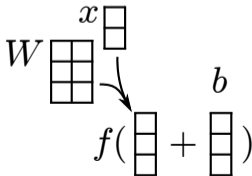


One Fully Connected Layer

- One fully-connected layer converts an input (column) vector x to an output (column) vector h :

$$h = f(Wx + b), \quad (6)$$

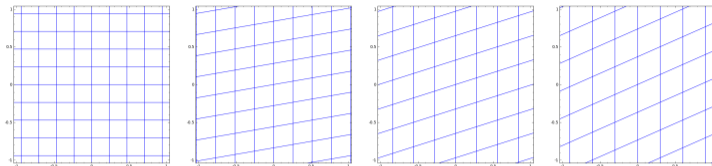
- W is a weight matrix of *input* columns and *output* rows,
- b a bias vector of length of *output*,
- $f(\cdot)$ is a non-linearity applied *usually* elementwise.



One Layer $\tanh(Wx + b)$, $2D \rightarrow 2D$

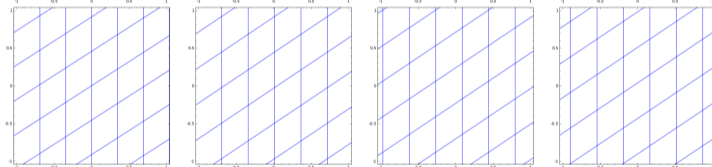
Skew:

W



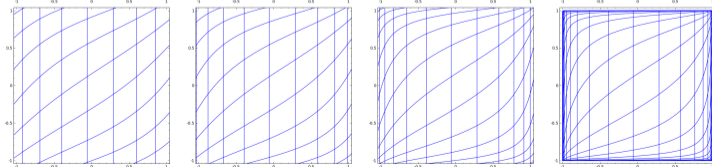
Transpose:

b



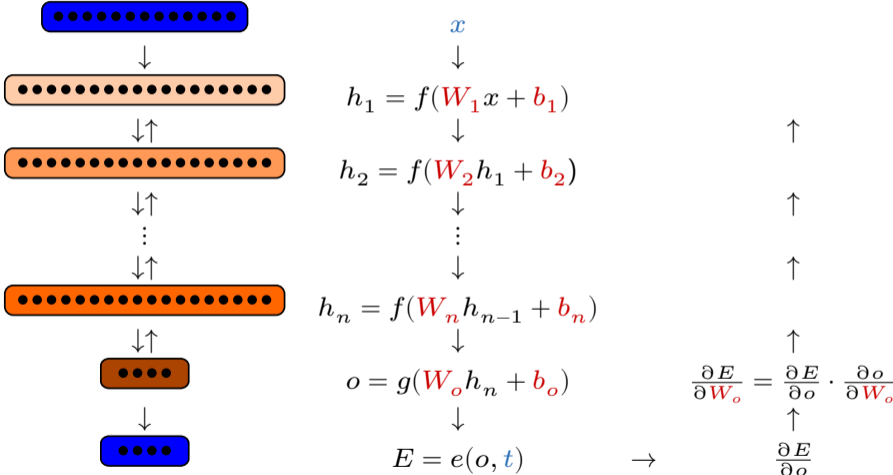
Non-lin.:

\tanh



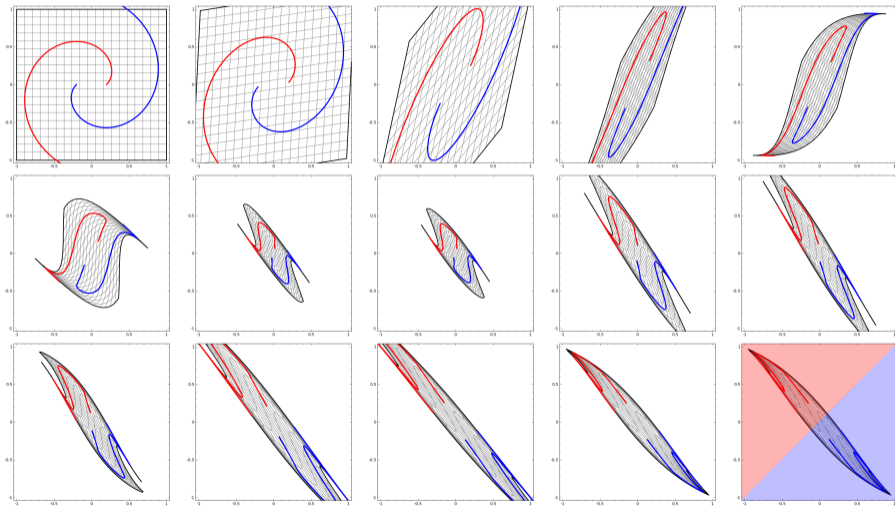
Animation by <http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/>

Feed-Forward Neural Network



blue: Training item (input x , output t), red: Trainable parameters (W_1, b_1, \dots).

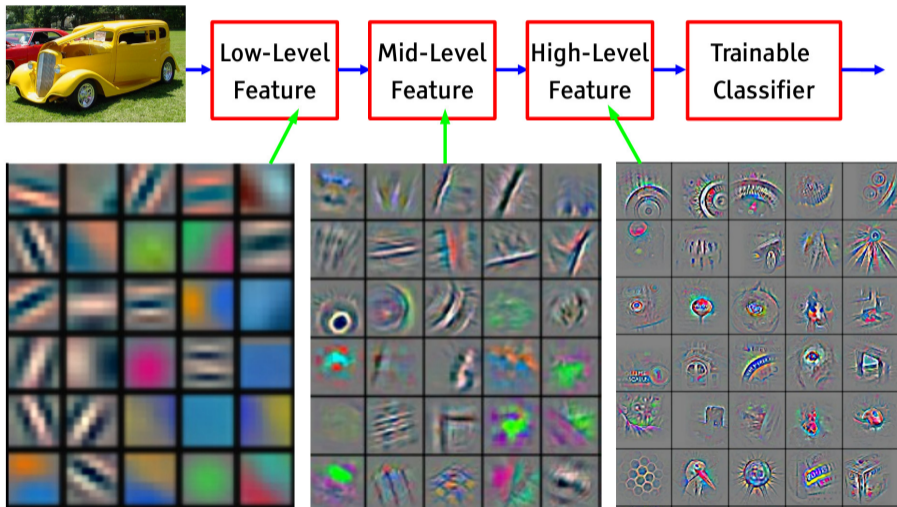
Four Layers, Disentangling Spirals



Animation by <http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/>

Deep NNs for Image Classification

It's **deep** if it has **more than one stage** of non-linear feature transformation



Processing Text with NNs

- Map each word to a vector of 0s and 1s (“1-hot repr.”):

cat \mapsto (0, 0, ..., 0, 1, 0, ..., 0)

- Sentence is then a matrix:

		the	cat	is	on	the	mat
↑	a	0	0	0	0	0	0
	about	0	0	0	0	0	0

	cat	0	1	0	0	0	0

	is	0	0	1	0	0	0

	the	1	0	0	0	1	0

↓	zebra	0	0	0	0	0	0

Processing Text with NNs

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	about	0	0	0	0	0	0

	cat	0	1	0	0	0	0
Vocabulary size:
1.3M English	is	0	0	1	0	0	0
2.2M Czech
	the	1	0	0	0	1	0

↓	zebra	0	0	0	0	0	0

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1.3M English		is	0	0	1	0	0
2.2M Czech	
		the	1	0	0	0	1
	
	↓	zebra	0	0	0	0	0

Main drawback: No relations, all words equally close/far. (Smoothing!)

1: Ensuring Similarity: Word Embeddings

- Idea: Map each word to a dense vector.
- Result: 300–2000 dimensions instead of 1–2M.
 - The dimensions have no clear interpretation.
- The “embedding” is the mapping.
 - Technically, the first layer of NNs for NLP is the matrix that maps 1-hot input to the first layer.
- Embeddings are trained for each particular task.
 - Sentence classification (sentiment analysis, etc.)
 - Neural language modelling.
 - The famous word2vec (Mikolov et al., 2013):
 - CBOW: Predict the word from its four neighbours.
 - Skip-gram: Predict likely neighbours given the word.
 - End-to-end neural MT.

2: Reducing Voc. Size: Sub-Words

- SMT struggled with productive morphology (>1M wordforms).
nejneobhospodařovatelnějšími, Donaudampfschiffahrtsgesellschaftskapitän
- NMT can handle vocabulary of only **only 30–80k** entries.

⇒ Resort to sub-word units.

Orig	český politik svezl migranty
Syllables	čes ký □ po li tik □ sve zl □ mig ran ty
Morphemes	česk ý □ politik □ s vez l □ migrant y
Char Pairs	če sk ý □ po li ti k □ sv ez l □ mi gr an ty
Chars	č e s k ý □ p o l i t i k □ s v e z l □ m i g r a n t y
BPE 30k	český politik s@@ vez@@ l mi@@ granty

BPE (Byte-Pair Encoding, (Sennrich et al., 2016)) or Google's wordpieces (Wu et al., 2016) and Tensor2Tensor's SubwordTextEncoder use n most common substrings (incl. frequent words).

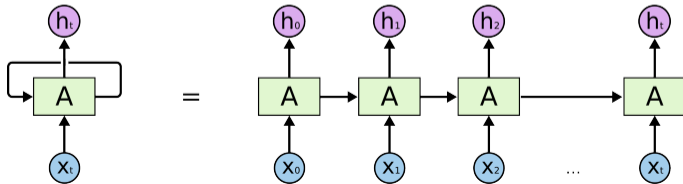
3. Process Variable-Length Sequences: RNN

Variable-length input can be handled by recurrent NNs:

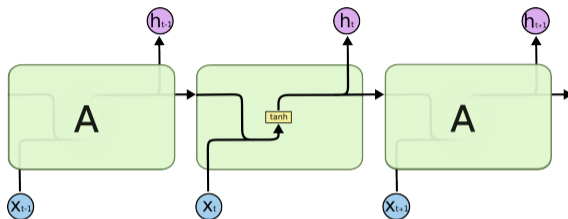
- Processing one input symbol at a time.
 - Initial state $h_0 = (0)$ (or some sentence representation).
 - The **same (trained) transformation A used every time.**

$$h_t = A(h_{t-1}, x_t) \quad (7)$$

- Unroll in time (up to a fixed length limit).



Vanilla RNN



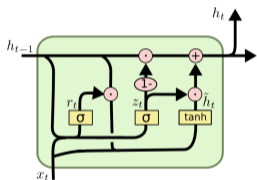
$$h_t = \tanh(W[h_{t-1}; x_t] + b) \quad (8)$$

$[h_{t-1}; x_t]$ is concatenation of h_{t-1} and x_t

- Vanishing gradient problem.
- Non-linear transformation always applied.
 \Rightarrow Type theory: h_t and h_{t-1} live in different vector spaces.

LSTM and GRU Cells for RNN

- LSTM, Long Short-Term Memory Cells (Hochreiter and Schmidhuber, 1997).
- GRU, Gated Recurrent Unit Cells (Chung et al., 2014):



$$z_t = \sigma(W_z[h_{t-1}; x_t] + b_z) \quad (9)$$

$$r_t = \sigma(W_r[h_{t-1}; x_t] + b_r) \quad (10)$$

$$\tilde{h}_t = \tanh(W[r_t \odot h_{t-1}; x_t]) \quad (11)$$

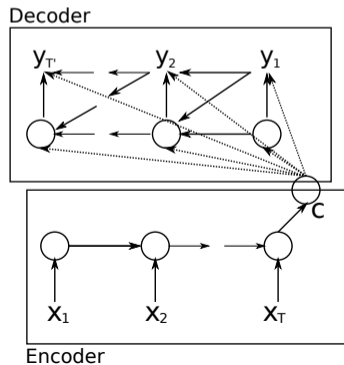
$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (12)$$

- Gates control:
 - what to use from input x_t (GRU: everything),
 - what to use from hidden state h_{t-1} (reset gate r_t),
 - what to put into output (update gate z_t)
- Linear “information highway” preserved.
 - \Rightarrow All states h_t belong to the same vector space.

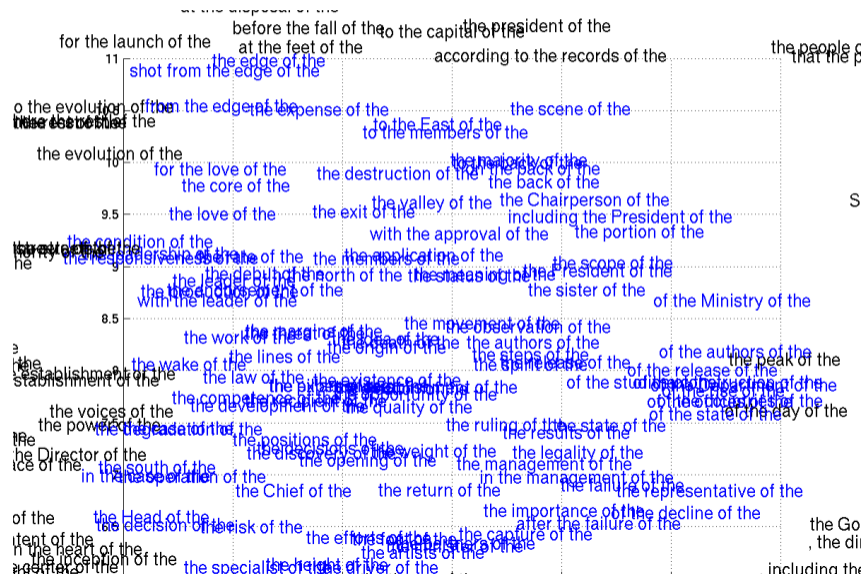
NNs as Translation Model in SMT

Cho et al. (2014) proposed:

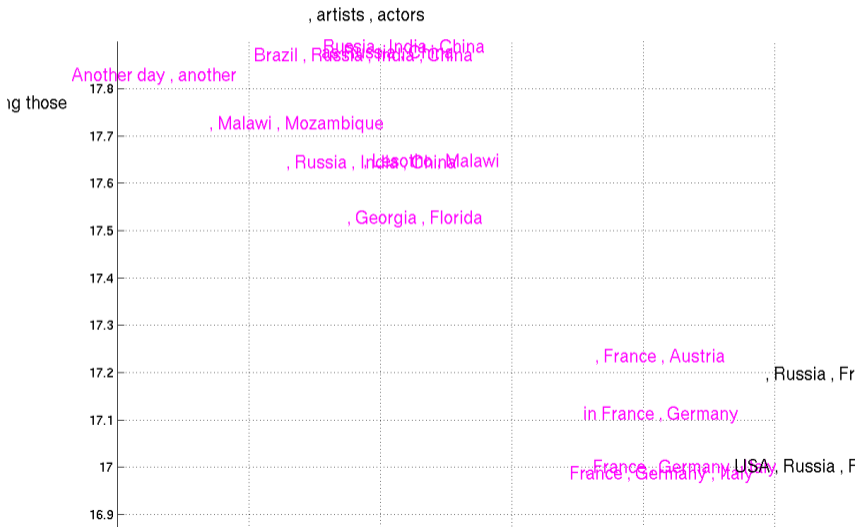
- encoder-decoder architecture and
- GRU unit (name given later by Chung et al. (2014))
- to score variable-length phrase pairs in PBMT.



⇒ Syntactic Similarity (“of the”)

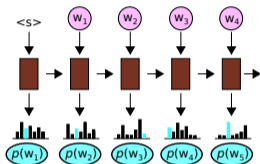


⇒ Semantic Similarity (Countries)

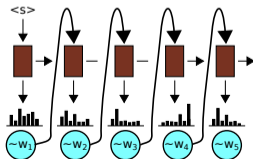


RNN Language Model

- Train RNN as a **classifier for next words** (unlimited history):



- Can be used:
 - To estimate sentence probability / perplexity.
 - To sample from the distribution:

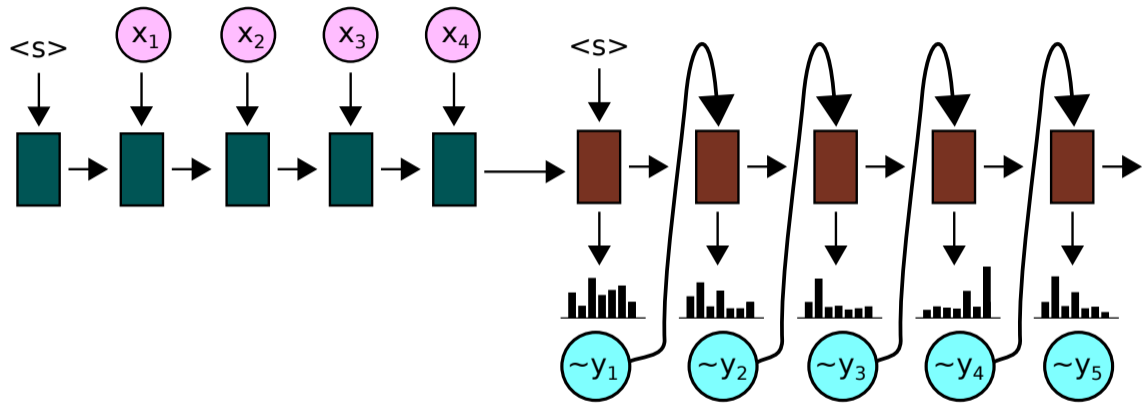


Two Views on RNN LM

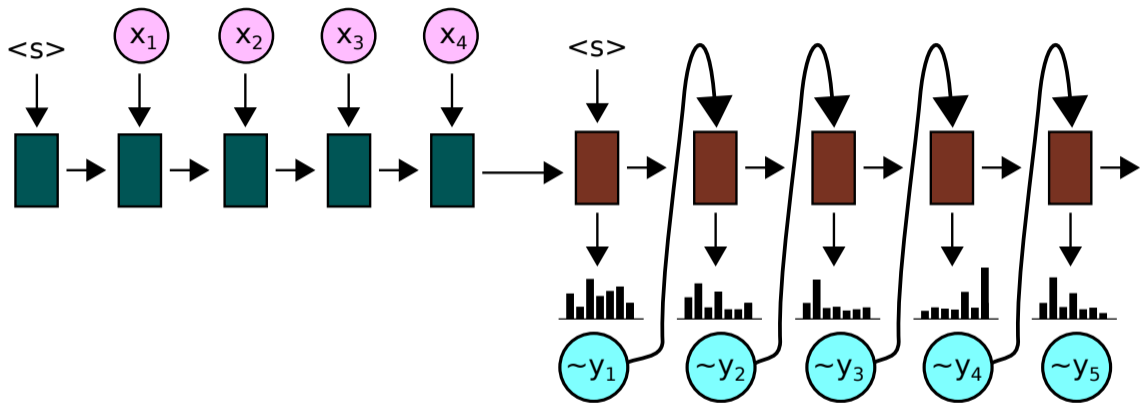
- RNN is a for loop / functional map over sequential data
- all outputs are conditional distributions
 - probabilistic distribution over sequences of words

$$P(w_1, \dots, w_n) = \prod_{i=1}^n P(w_i | w_{i-1}, \dots, w_1)$$

RNN for Translation: Encoder-Decoder



RNN for Translation: Encoder-Decoder



source language input + target language LM

Encoder-Decoder Model – Formal Notation

Data

input tokens (source language) $\mathbf{x} = (x_1, \dots, x_{T_x})$

output tokens (target language) $\mathbf{y} = (y_1, \dots, y_{T_y})$

Encoder-Decoder Model – Formal Notation

Data

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output tokens (target language) $\mathbf{y} = (y_1, \dots, y_{T_y})$

Encoder

initial state $h_0 \equiv \mathbf{0}$

j -th state $h_j = \text{RNN}_{\text{enc}}(h_{j-1}, x_j) = \tanh(U_e h_{j-1} + W_e E_e x_j + b_e)$

final state h_{T_x}

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final state h_{T_x}

Decoder

initial state

$$s_0 = h_{T_x}$$

i -th decoder state

$$s_i = \text{RNN}_{\text{dec}}(s_{i-1}, \hat{y}_{i-1}) = \tanh(U_d s_{i-1} + W_d E_d \hat{y}_{i-1} + b_d)$$

i -th word score

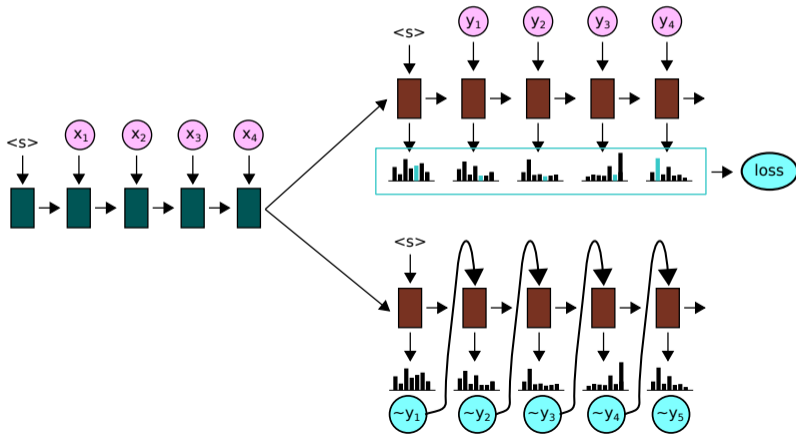
$$t_i = \tanh(U_o s_i + W_o E_d \hat{y}_{i-1} + b_o) \text{ ("output projection")}$$

output

$$\hat{y}_i = \arg \max V_o t_i$$

Implementation: Training vs. Runtime

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



Summary So Far

- Statistical MT chooses the most probable sentence:

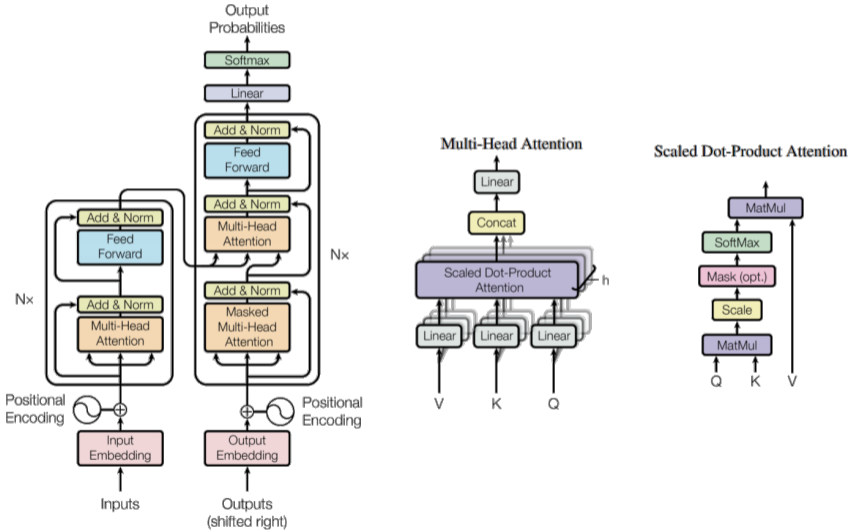
$$\hat{e}_1^I = \operatorname{argmax}_{I, e_1^I} p(e_1^I | f_1^J)$$

- Independence assumptions (LM vs. TM; phrase independence) were harmful.
- Neural MT predicts word by word; “just a clever LM”.

$$p(e_1^I | f_1^J) = \prod_{i=1}^I p(e_i | e_1, \dots, e_{i-1}, f_1^J)$$

- Sub-word units, word embeddings, RNN for variable-length, encoder-decoder.
- We moved from **searching for best minimum translation units** to **representing words and phrases in continuous space** and **relating them to each other**.

Attention is All You Need (Vaswani et al., 2017)



Transformer Detailed Walkthroughs

Transformer Illustrated:

- <http://jalammr.github.io/illustrated-transformer/>
Amazingly simple description! (I am reusing the pictures.)

Transformer paper annotated with PyTorch code:

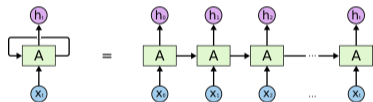
- <http://nlp.seas.harvard.edu/2018/04/03/attention.html>
- PyTorch by examples:
<https://github.com/jcjohnson/pytorch-examples>

Summary at Medium:

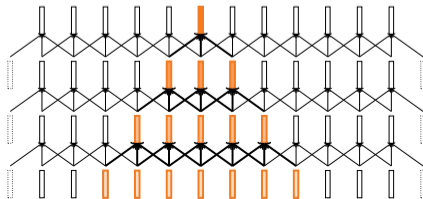
- <https://medium.com/@adityathiruvengadam/transformer-architecture-attention-is-all-you-need-aecc>

Self-Attention Motivation

- Sequences of arbitrary length n need to be processed.
- Information gets lost over too many processing steps.
- RNNs make the (time-unrolled) network as deep as n .



- CNNs allow to trade kernel size k and depth for a target “receptive field”:



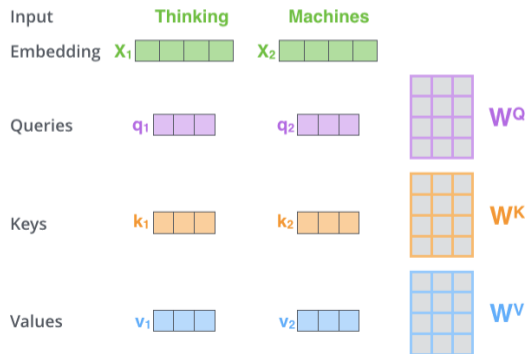
Self-Attention

- Goal: **Aggregate** arbitrary-length input to fixed-size vector.
Allow **data-driven, trainable** aggregation.

Self-Attention

- Goal: **Aggregate** arbitrary-length input to fixed-size vector.
Allow **data-driven, trainable** aggregation.

Given the sequence of inputs x_1, \dots, x_n :



- Create three “**views**” of them: queries, keys, values.
- Using trained matrices W^Q, W^K, W^V .

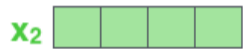
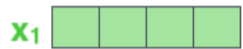
Match All Queries with All Keys

Input

Thinking

Machines

Embedding



Queries



Keys



Values



Score

$q_1 \cdot k_1 = 112$

$q_1 \cdot k_2 = 96$

Normalize Scores

Input

Embedding

Values

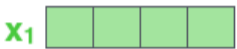
Score

Divide by 8 ($\sqrt{d_k}$)

Softmax

Thinking

Machines



$q_1 \cdot k_1 = 112$

$q_1 \cdot k_2 = 96$

14

12

0.88

0.12

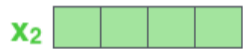
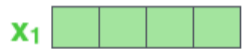
Aggregate Values Accordingly

Input

Thinking

Machines

Embedding



Values



Softmax

0.88

0.12

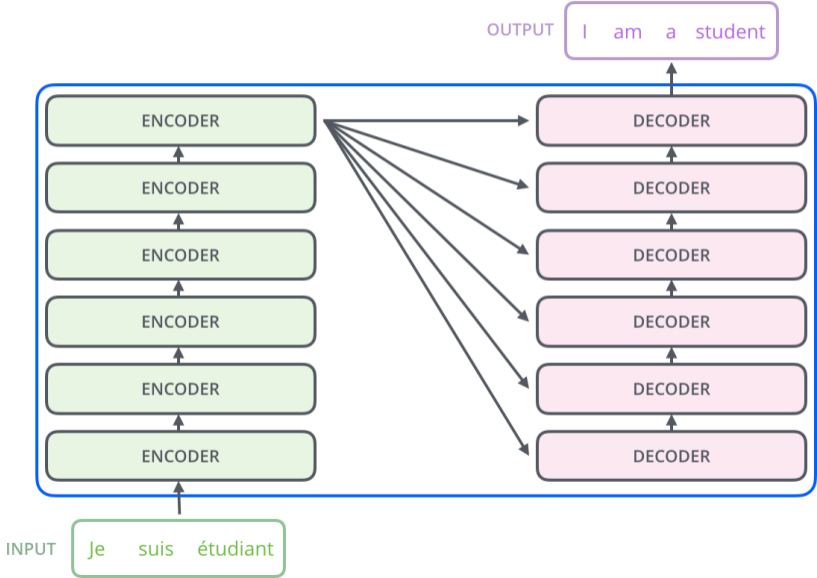
Softmax X Value



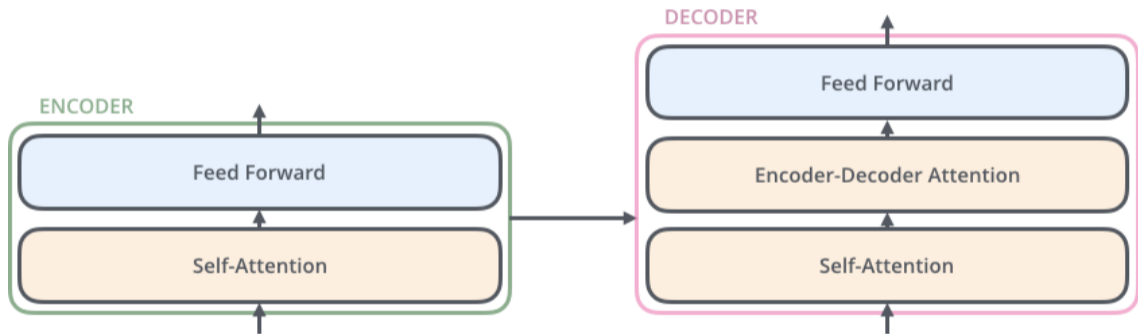
Sum



Transformer = 6 Layers Enc + 6 Dec



Composition of One Layer

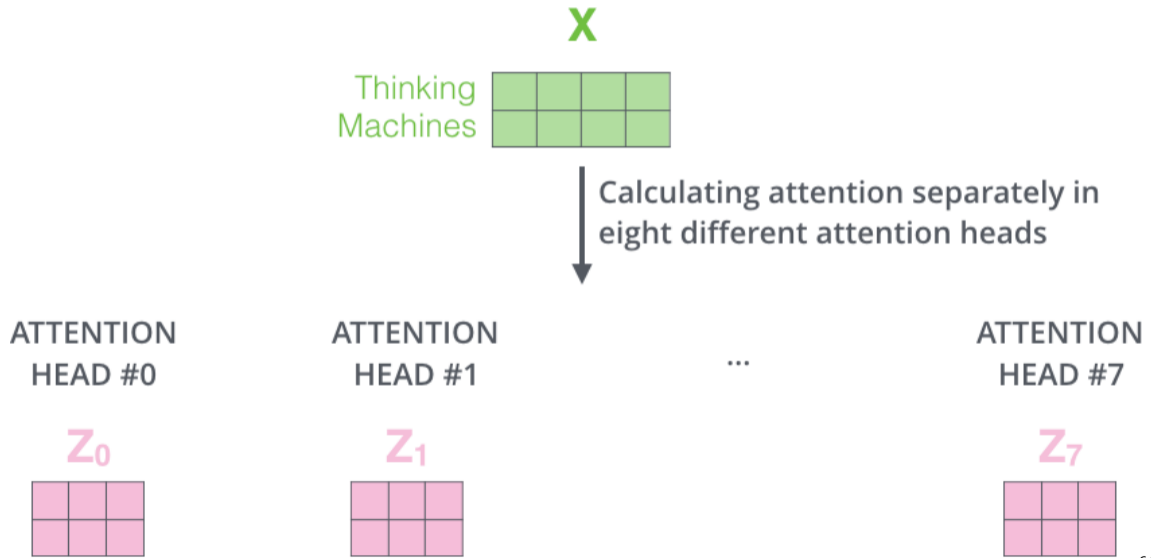


Self-Attention in Transformer

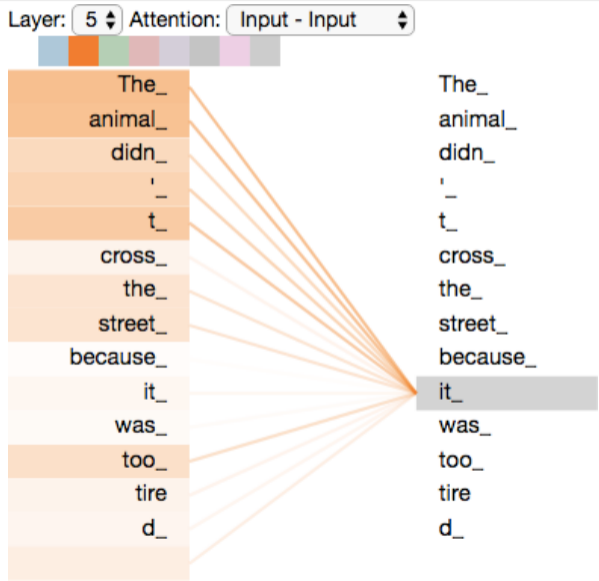
Three uses of multi-head attention in Transformer

- Encoder-Decoder Attention:
 - Q : previous decoder layers; $K = V$: outputs of encoder
 - \Rightarrow Decoder positions attend to all positions of the input.
- Encoder Self-Attention:
 - $Q = K = V$: outputs of the previous layer of the encoder
 - \Rightarrow Encoder positions attend to all positions of previous layer.
- Decoder Self-Attention:
 - $Q = K = V$: outputs of the previous decoder layer.
 - Masking used to prevent depending on future outputs.
 - \Rightarrow Decoder attends to all its previous outputs.

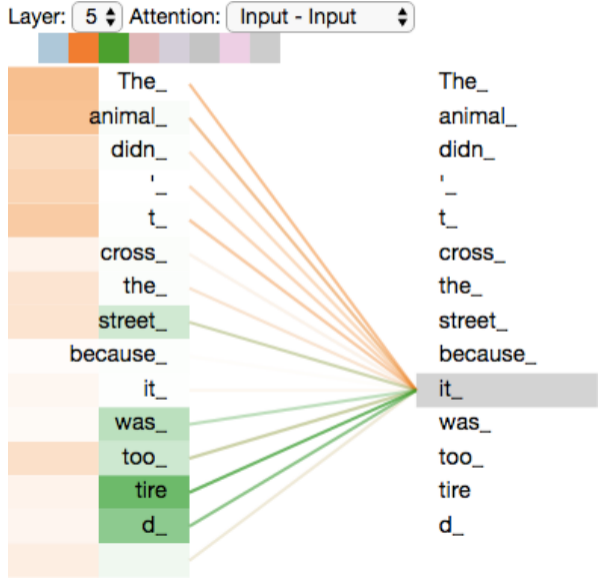
Multi-Head Attention



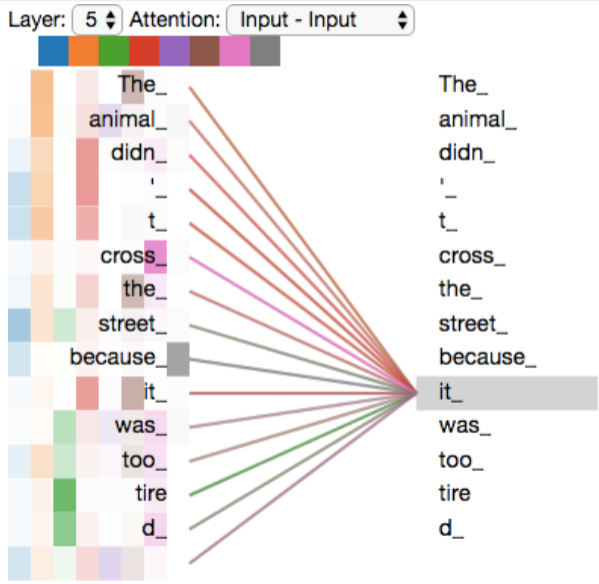
Self-Attention at Enc Layer #5: 1 Head



Self-Attention at Enc Layer #5: 2 Heads



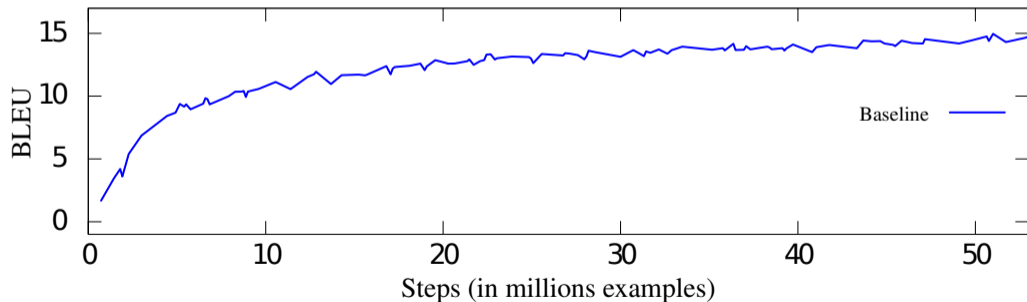
Self-Attention at Enc Layer #5: 8 Heads



Some of Training Magic

Curriculum vs. Catastrophic Forgetting

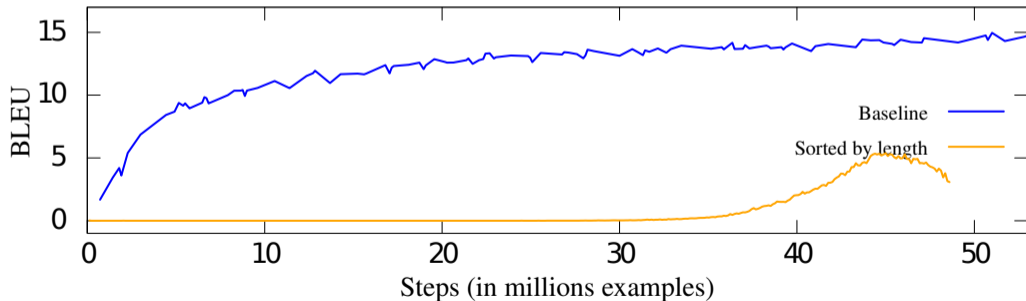
- Kocmi and Bojar (2017) explore curriculum learning:
 - Start with simpler sentences first, add complex ones later.



For further important insights about sentence length overfitting, see Variš and Bojar (2021).

Curriculum vs. Catastrophic Forgetting

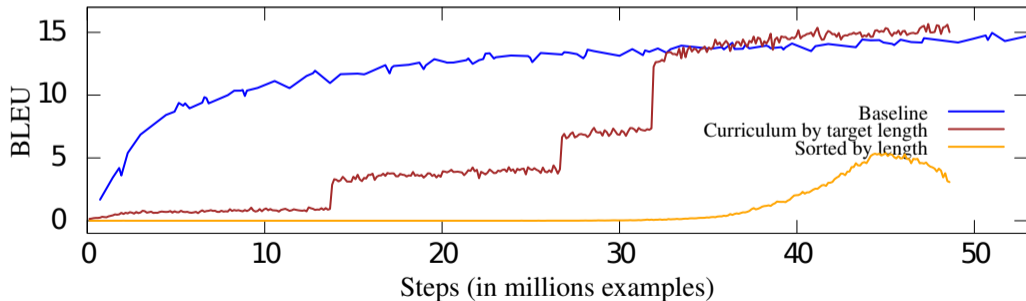
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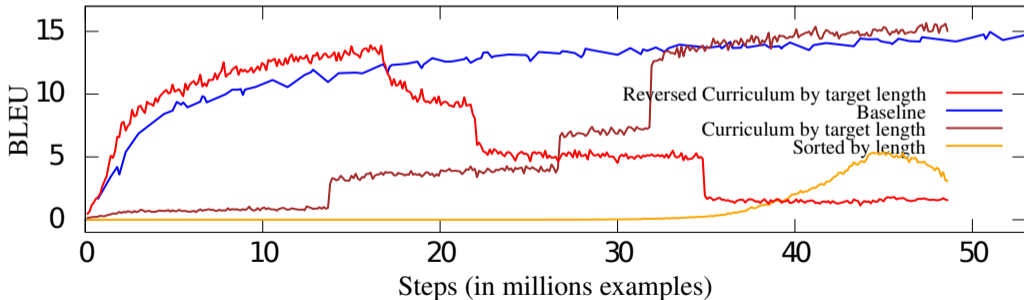
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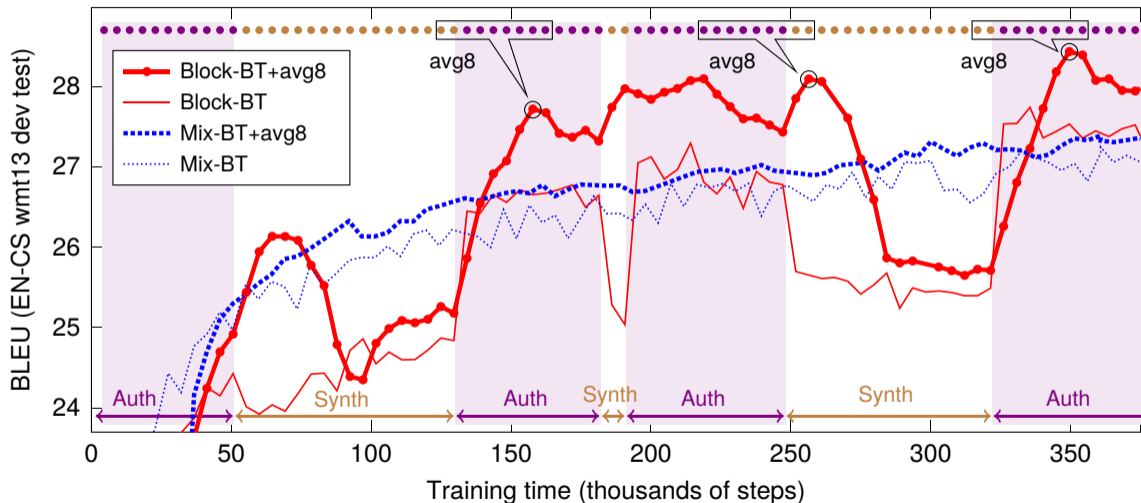
Curriculum vs. Catastrophic Forgetting

- Kocmi and Bojar (2017) explore curriculum learning:
 - Start with simpler sentences first, add complex ones later.
- When “simpler” means “shorter”:
 - Clear jumps in score as bins of longer sentences are allowed.
 - Reversed curriculum *unlearns* to produce long sentences.



For further important insights about sentence length overfitting, see Variš and Bojar (2021).

Block-Backtranslation



See Popel et al. (2020) for more details.

Machine Translation Surpassing Humans (1/2)

- WMT 2018 English-to-Czech news translation results:

	Ave. %	Ave. z	System
1	84.4	0.667	CUNI-TRANSFORMER
2	79.8	0.521	UEDIN
	78.6	0.483	Professional Translation
4	68.1	0.128	ONLINE-B
5	59.4	-0.178	ONLINE-A
6	54.1	-0.354	ONLINE-G

Machine Translation Surpassing Humans (1/2)

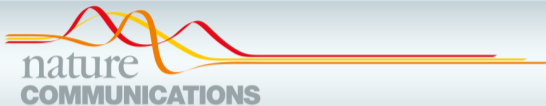
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Caveats:

- Humans translated whole documents, MT individual segments.
 - Evaluation was done for *individual segments*.

Machine Translation Surpassing Humans (2/2)










ARTICLE



<https://doi.org/10.1038/s41467-020-18073-9>

OPEN

Transforming machine translation: a deep learning system reaches news translation quality comparable to human professionals

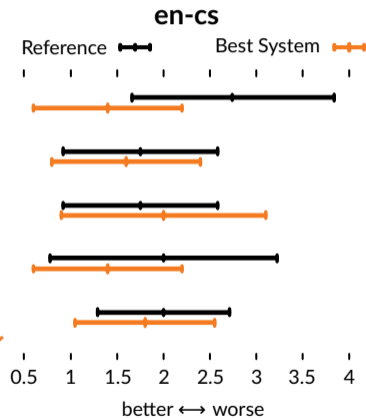
Martin Popel ^{1,5✉}, Marketa Tomkova ^{2,5}, Jakub Tomek ^{3,5}, Łukasz Kaiser ⁴, Jakob Uszkoreit ⁴, Ondřej Bojar ¹ & Zdeněk Žabokrtský ¹

MT of Full Documents: Audit Reports

Manual evaluation by domain experts, scoring in categories:

1. Language Resources – Spelling and Morphology
2. Vocabulary – Adequacy of Terms Used
3. Vocabulary – Clarity of the Text in Terms of Used Words
4. Syntax and Word Order
5. Coherence and Overall Understanding of the Text

plotted as average rank for better comparability



MT of Full Documents: Agreements Input

Supplement No. 1 to the agreement on the sublease the apartment, of 13th May 2016
On the day, month and year written below Marta Burešová, pers. no. 695604/3017
Address: Radimova 8, Prague 6, 169 00 as the tenant on the one hand (Hereinafter referred to as "the tenant") and Karolína Černá, pers. no. 136205/891 Address: Alfrédova 13, Praha 4, 142 00 As a lessee on the other (Hereinafter referred to as "the lessee") collectively also referred to as "the Contracting parties" have agreed on this Supplement No. 1 to the Agreement on the sublease the apartment, of 13th May 2016 (hereinafter referred to as the "Supplement No. 1")

I. Introductory Provisions

On 13th May 2016, the tenant and the lessee closed the Agreement on the sublease of the apartment, under which the tenant let the lessee use the apartment No. 4 (area 49 m²) of size 1+1/L in the ground floor of the house in Prague 4, Alfrédova 13, ...

MT of Full Documents: Agreements Output

Dodatek č. 1 ke smlouvě o podnájmu bytu ze dne 13. května 2016

V den, měsíc a rok níže napsané Marta Burešová, pers. no.

695604/3017 Adresa: Radimova 8, Praha 6, 169 00 jako nájemce na jedné straně (dále jen “nájemce”) a Karolína Černá, pers. no.

136205/891 Adresa: Alfrédova 13, Praha 4, 142 00 jako nájemce na straně druhé (dále jen “nájemce”) společně označované také jako “smluvní strany” se dohodly na tomto dodatku č. 1 ke smlouvě o podnájmu, dále jen “nájemní smlouva”, dále jen “13. května 2016”).

I. Úvodní ustanovení

Dne 13. května 2016 nájemce a nájemce uzavřeli smlouvu o dalším pronájmu bytu, podle níž nájemce pronajímá nájemci byt č. 4 (plocha 49 m²) o velikosti 1+1/I v přízemí domu v Praze 4, Alfrédova 13, ...

MT of Full Documents: Agreements Output

Dodatek č. 1 ke smlouvě o podnájmu bytu ze dne 13. května 2016

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"smluvní strany" se dohodly na tomto dodatku č. 1 ke smlouvě o podnájmu, dále jen "**nájemní smlouva**", dále jen "13. května 2016").

I. Úvodní ustanovení

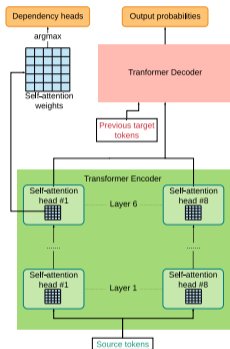
Dne 13. května 2016 **nájemce a nájemce** uzavřeli smlouvu o dalším pronájmu bytu, podle níž **nájemce pronajímá nájemci** byt č. 4

(plocha 49 m²) o velikosti 1+1/I v přízemí domu v Praze 4, Alfrédova

13

Caveats on Interpreting Results

“Modeling Source Syntax Helps NMT” (1/2)

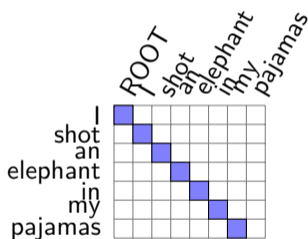


	BLEU	UAS
Baseline	36.66	–
Parse from layer 0	36.60	82.85
Parse from layer 1	38.01	90.78
Parse from layer 2	37.87	91.18
Parse from layer 3	37.67	91.43
Parse from layer 4	37.60	91.56
Parse from layer 5	37.67	91.46

- Forcing one Trafo head to provide dependency tree helps BLEU.

“Modeling Source Syntax Helps NMT” (1/2)

I shot an elephant in my pajamas



	BLEU	UAS
Baseline	36.66	–
Parse from layer 0	38.14	99.96
Parse from layer 1	38.06	99.99
Parse from layer 2	37.85	99.98
Parse from layer 3	37.70	99.98
Parse from layer 4	37.47	99.96
Parse from layer 5	37.54	99.95

- Forcing one Trafo head to provide dependency tree helps BLEU.
- Forcing one Trafo head to provide linear tree helps more.

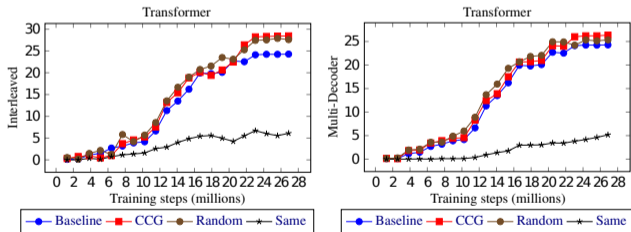
Pham, Macháček, Bojar. Promoting the Knowledge of Source Syntax in Transformer NMT Is Not Needed. CyS, 2019.

“Modeling Target Syntax Helps NMT”

- Alternating output words and CCG tags helps. (Nadejde et al. 2017)

Tgt: NP Obama ((S[*dcl*]\NP)/PP)/NP receives NP Net+ an+ yahu PP/NP in NP/N the N capital (

- We tried the same with: (RNN or Transformer; interleaved or multi-decoder)
 - correct CCG tags, ● random tags, ★ a single dummy tag.

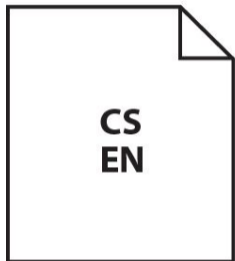


- Except ★ single dummy tag, both improve over the ● baseline.

Kondratuyk, Cardenas, Bojar. Replacing Linguists with Dummies: A Serious Need for Trivial Baselines in Multi-Task Neural Machine Translation. PBML 2019.

Transfer Learning (TL)

Parent corpus



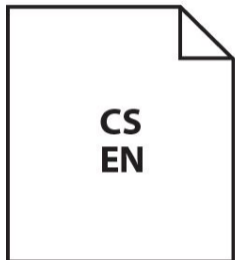
Child corpus



See Kocmi and Bojar (2018) for more details.

Transfer Learning (TL)

Parent corpus



Child corpus



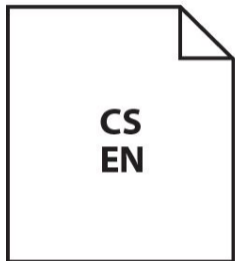
Balanced vocabulary



See Kocmi and Bojar (2018) for more details.

Transfer Learning (TL)

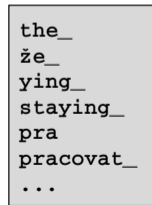
Parent corpus



Child
corpus



Balanced
vocabulary



See Kocmi and Bojar (2018) for more details.

“TL Exploits Language Similarity”

Child model: Slovak

Parent model	Corpus size difference	Direction	Baseline (BLEU)	Transfer (BLEU)	Δ (BLEU)
Czech	9x	from English	16.13	17.75	1.62 *
Czech	9x	to English	19.19	22.42	3.23 *

* statistically significant

See Kocmi and Bojar (2018) for more details.

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Child model: Estonian

Parent model	Corpus size difference	Direction	Baseline (BLEU)	Transfer (BLEU)	Δ (BLEU)
Finnish	3.5x	from English	17.03	19.74	2.71 *
Russian	16x	from English	17.03	20.09	3.06 *
Czech	50x	from English	17.03	20.41	3.38 *
Finnish	3.5x	to English	21.74	24.18	2.44 *
Russian	16x	to English	21.74	23.54	1.80 *

* statistically significant

See Kocmi and Bojar (2018) for more details.

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“TL Exploits Language Similarity”

Child model: Slovak

Parent model	Corpus size difference	Direction	Baseline (BLEU)	Transfer (BLEU)	Δ (BLEU)
Related	9x	from English	16.13	17.75	1.62 *
Related	9x	to English	19.19	22.42	3.23 *

Child model: Estonian

Parent model	Corpus size difference	Direction	Baseline (BLEU)	Transfer (BLEU)	Δ (BLEU)
Related	3.5x	from English	17.03	19.74	2.71 *
Cyrillic	16x	from English	17.03	20.09	3.06 *
Biggest	50x	from English	17.03	20.41	3.38 *
Related	3.5x	to English	21.74	24.18	2.44 *
Cyrillic	16x	to English	21.74	23.54	1.80 *

* statistically significant

See Kocmi and Bojar (2018) for more details.

Summary

- Given all the data we had for SMT, given big GPUs, given all the training tricks, and given a few weeks of training time, Transformer can reach
(average) quality comparable to (sloppy) humans.
- Intuition **why** something works is often wrong.
 - Use trivial baselines to exclude misinterpretations; read more here:



Kocmi Tom, Macháček Dominik, Bojar Ondřej (2021). **The Reality of Multi-Lingual Machine Translation**. ISBN 978-80-88132-11-0.
<https://ufal.mff.cuni.cz/books/2021-kocmi>

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