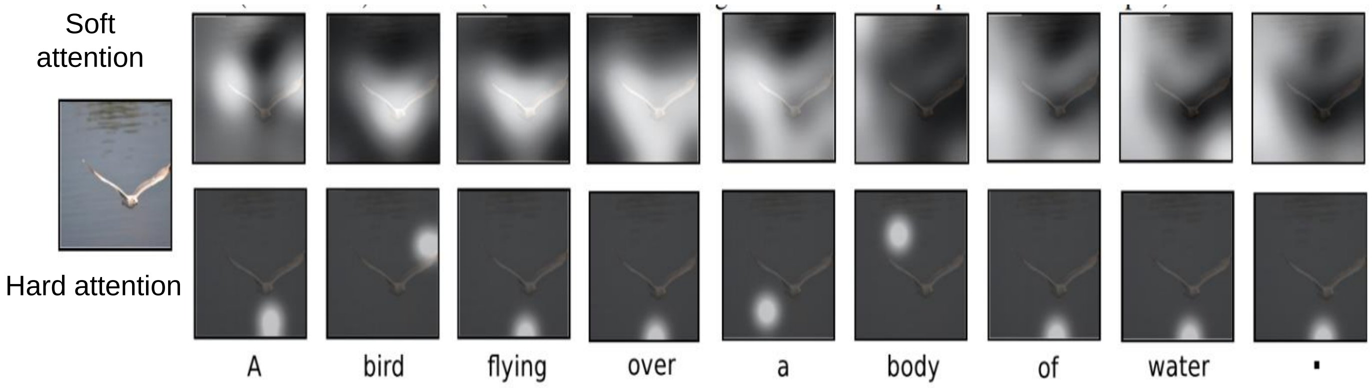
CS182/282A: Designing, Visualizing and Understanding Deep Neural Networks

John Canny

Spring 2019

Lecture 13: Translation

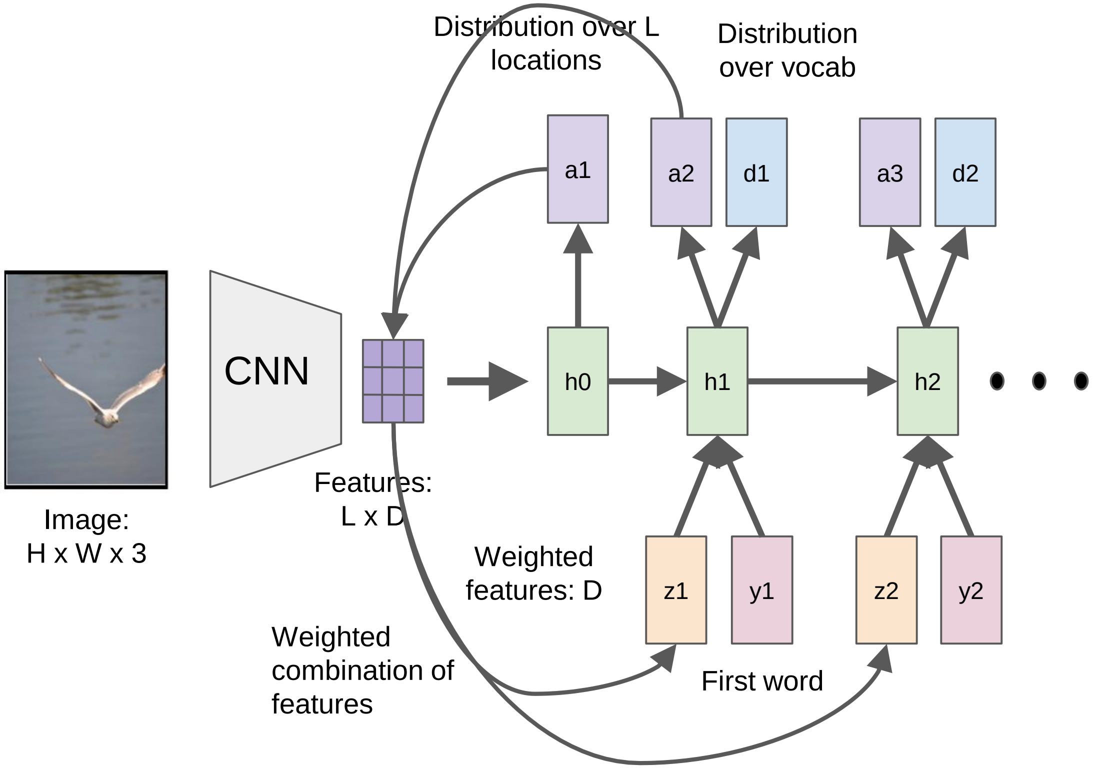
Last Time: Soft vs Hard Attention



Hard attention: Attend to a single input location, can’t use gradient descent, Need **reinforcement learning.**

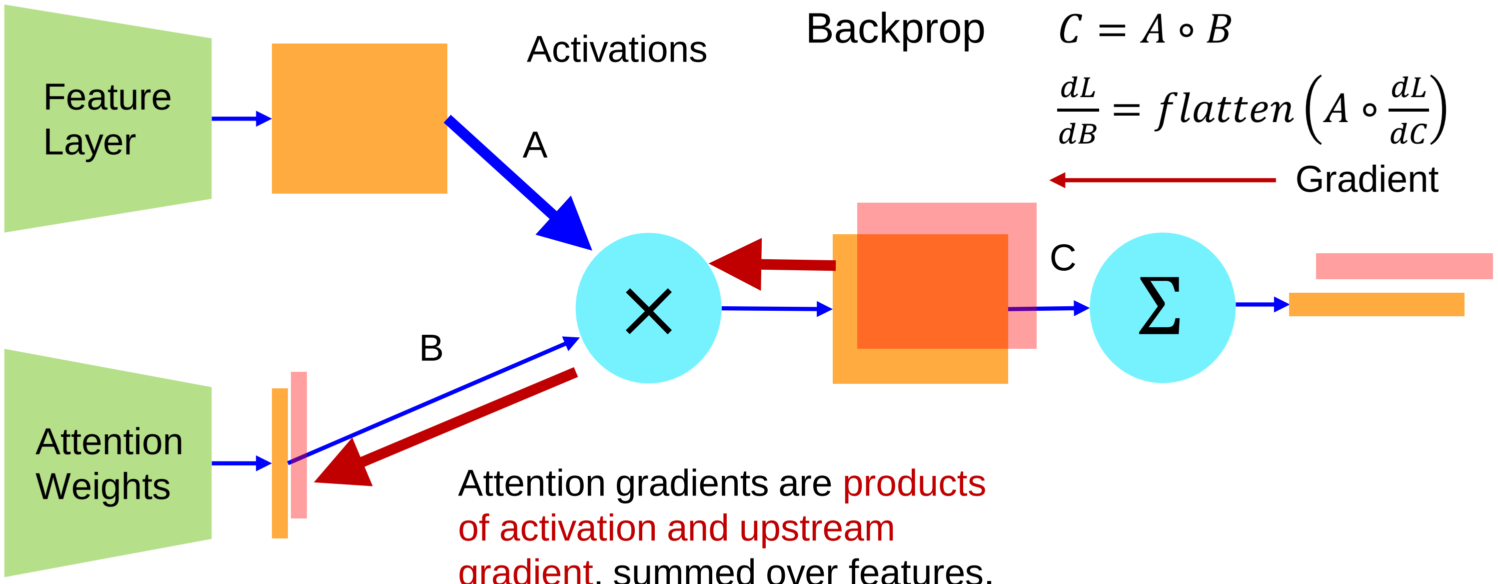
Soft attention: Compute a weighted combination (attention) over some inputs using an attention network. Can use backpropagation to train end-to-end.

Last Time: Recurrent Attention for Captioning



Last Time: Attention Mechanics: Salience

During training, the attention layer receives gradients which are the product of the upstream gradient and the feature layer activations (salience).



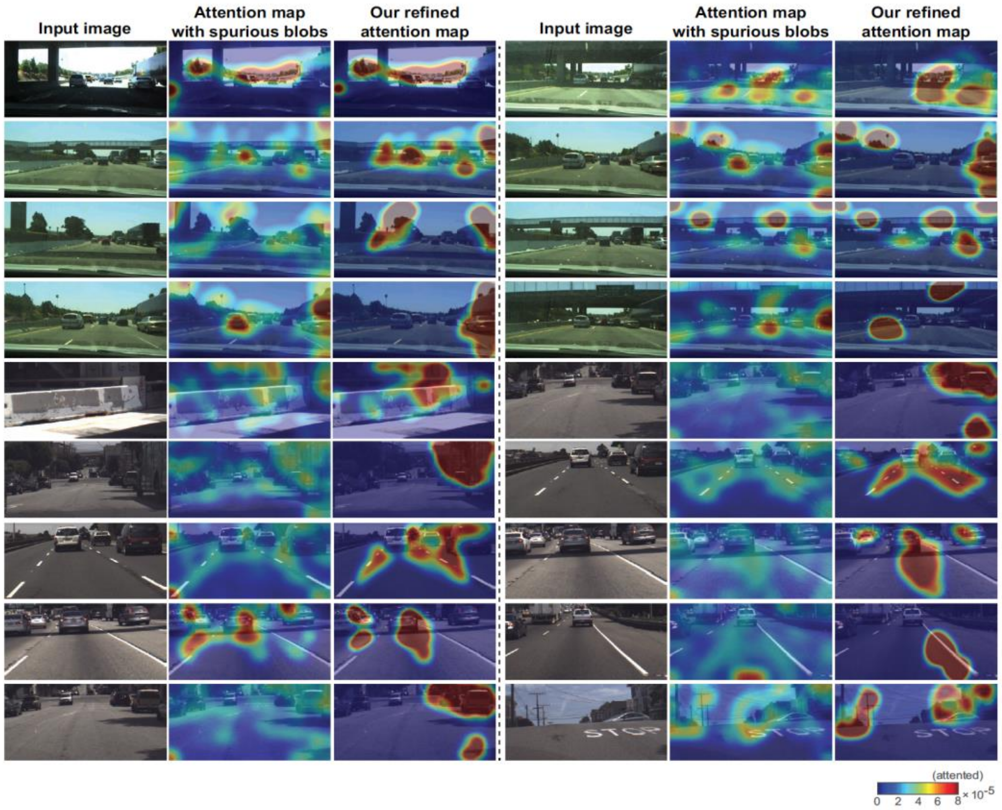
Attention gradients are products of activation and upstream gradient, summed over features.
This is a ***salience*** (importance) signal.

Last Time: Attention and Interpretability

Attention models learn to predict salient (important) inputs.

Attention visualizations help users understand the causes of the network's behavior.

Not every attended region is actually important, but post-processing can remove regions that aren't.



Updates

Project checkin this week!

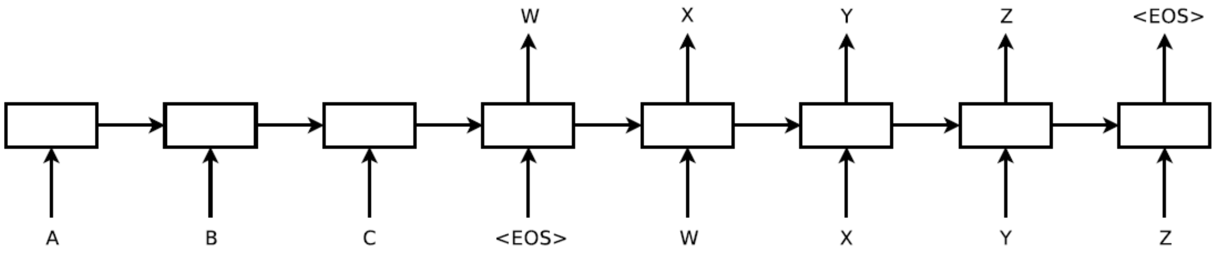
Assignment 3 should be out today.

This Time: Translation

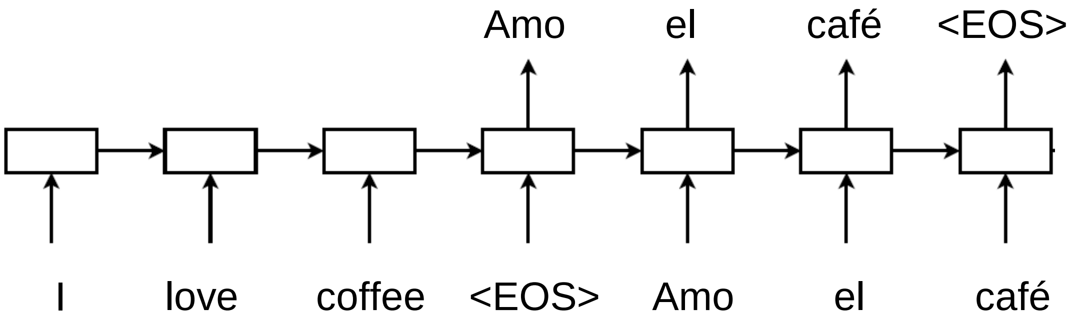
- Sequence-to-sequence translation
- Adding Attention
- Parsing as translation
- Attention only models
- English-to-English translation ?!

Sequence-To-Sequence RNNs

An input sequence is fed to the left array, output sentence to the right array for training:

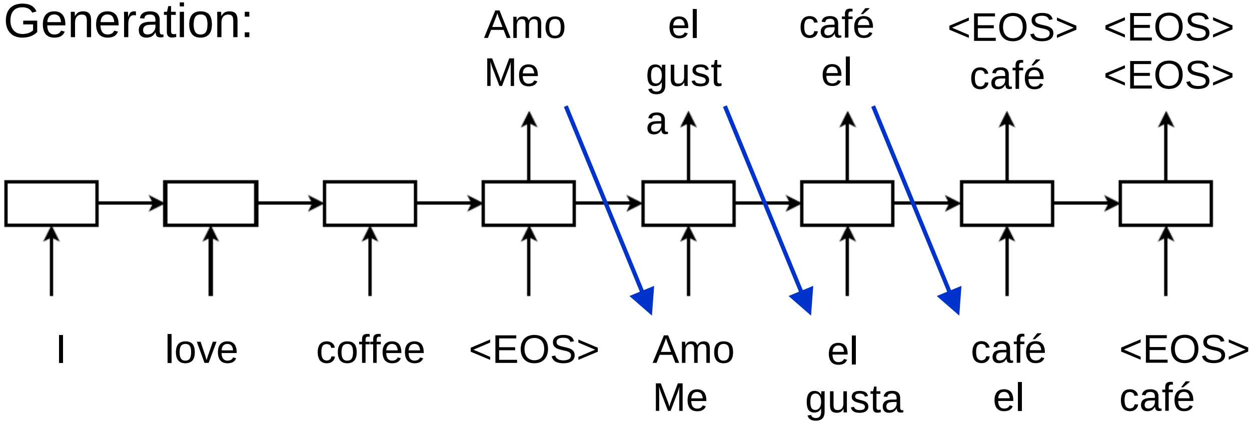


For translation:



Sequence-To-Sequence RNNs

Generation:



Keep an n-best list of partial sentences, along with their partial softmax scores.

Bleu scores for Translation

The goal of bleu scores is to compare machine translations against human-generated translations, allowing for variation.

Consider these translations for a Chinese sentence:

Candidate 1: It is a guide to action which ensures that the military always obeys the commands of the party.

Candidate 2: It is to insure the troops forever hearing the activity guidebook that party direct.

We compare these with several reference sentences and score their similarity.

Bleu Scores for Translation

Candidate 1: It is a guide to action which ensures that the military always obeys the commands of the party.

Candidate 2: It is to insure the troops forever hearing the activity guidebook that party direct.

Reference 1: It is a guide to action that ensures that the military will forever heed Party commands.

Reference 2: It is the guiding principle which guarantees the military forces always being under the command of the Party.

Reference 3: It is the practical guide for the army always to heed the directions of the party.

Bleu Scores for Translation: Candidate Sentence 1

Candidate 1: It is a guide to action which ensures that the military always obeys the commands of the party.

Candidate 2: It is to insure the troops forever hearing the activity guidebook that party direct.

Reference 1: It is a guide to action that ensures that the military will forever heed Party commands.

Reference 2: It is the guiding principle which guarantees the military forces always being under the command of the Party.

Reference 3: It is the practical guide for the army always to heed the directions of the party.

Bleu Scores for Translation: Candidate Sentence 2

Candidate 1: It is a guide to action which ensures that the military always obeys the commands of the party.

Candidate 2: It is to insure the troops forever hearing the activity guidebook that party direct.

Reference 1: It is a guide to action that ensures that the military will forever heed Party commands.

Reference 2: It is the guiding principle which guarantees the military forces always being under the command of the Party.

Reference 3: It is the practical guide for the army always to heed the directions of the party.

Bleu Scores for Translation

Unigram precision:

$$\frac{\text{correct unigrams occuring in reference sentence}}{\text{unigrams occuring in test sentence}}$$

Modified unigram precision: clip counts by maximum occurrence in any reference sentence:

Candidate: <u>the the </u>the the the the the.
Reference 1: <u>The</u> cat is on <u>the</u> mat.
Reference 2: There is a cat on the mat.

Modified precision is 2/7.

Bleu Scores for Translation

Candidate 1: It is a guide to action which ensures that the military always obeys the commands of the party. **unigram precision 17/18**

Candidate 2: It is to insure the troops forever hearing the activity guidebook that party direct. **unigram precision 8/14**

Reference 1: It is a guide to action that ensures that the military will forever heed Party commands.

Reference 2: It is the guiding principle which guarantees the military forces always being under the command of the Party.

Reference 3: It is the practical guide for the army always to heed the directions of the party.

Bleu Scores for Translation

N-gram precision is defined similarly:

$$\frac{\text{correct ngrams occuring in reference sentence}}{\text{ngrams occuring in test sentence}}$$

Modified ngram precision: clip counts by maximum occurrence in any reference sentence.

Unigram scores tend to capture ***adequacy***

Ngram scores tend to capture ***fluency***

Bleu Scores for Translation

Candidate 1: It is a guide to action which ensures that the military always obeys the commands of the party. **bigram precision 10/17**

Candidate 2: It is to insure the troops forever hearing the activity guidebook that party direct. **bigram precision 1/13**

Reference 1: It is a guide to action that ensures that the military will forever heed Party commands.

Reference 2: It is the guiding principle which guarantees the military forces always being under the command of the Party.

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Bleu Scores for Translation

How to combine scores for different n-grams?
Averaging sounds good, but precisions are very different for different n (unigrams have much higher scores).

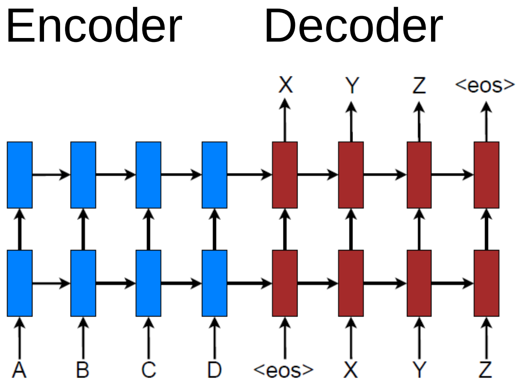
BLEU Score: Take a weighted geometric mean of the n-gram precisions up to some length (usually 4). Add a penalty for too-short predictions.

$$\text{BLEU} = \text{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right)$$

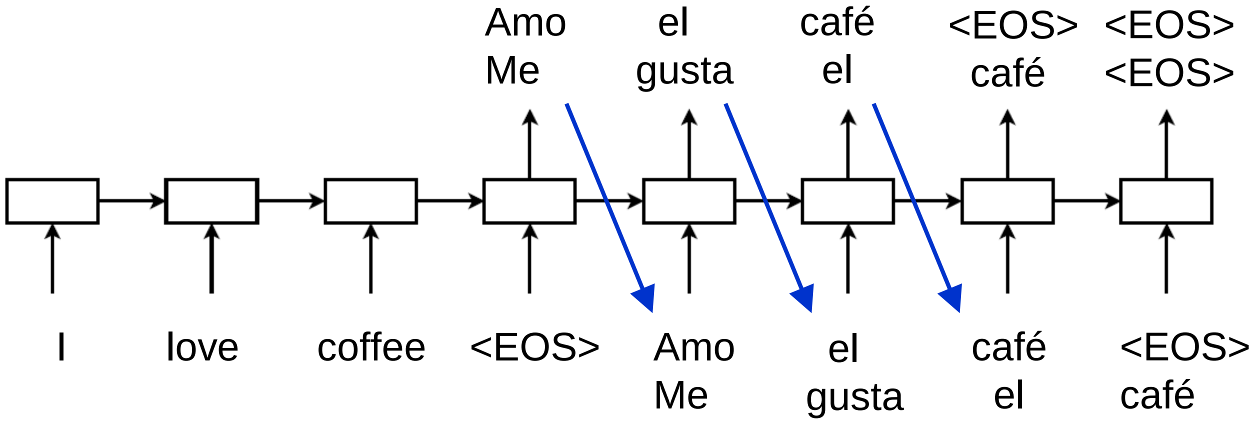
$$\text{BP} = \begin{cases} 1 & \text{if } c > r \\ e^{(1-r/c)} & \text{if } c \leq r \end{cases}$$

Candidate length c shorter than reference r translation

Sequence-To-Sequence Model Translation



A depth-2 model



Beam search
width = 2

Sequence-To-Sequence Model Translation

Raw scores for French-English Translation, depth = 4

Method	test BLEU score (ntst14)
Bahdanau et al. [2]	28.45
Baseline System [29]	33.30
Single forward LSTM, beam size 12	26.17
Single reversed LSTM, beam size 12	30.59
Ensemble of 5 reversed LSTMs, beam size 1	33.00
Ensemble of 2 reversed LSTMs, beam size 12	33.27
Ensemble of 5 reversed LSTMs, beam size 2	34.50
Ensemble of 5 reversed LSTMs, beam size 12	**34.81**

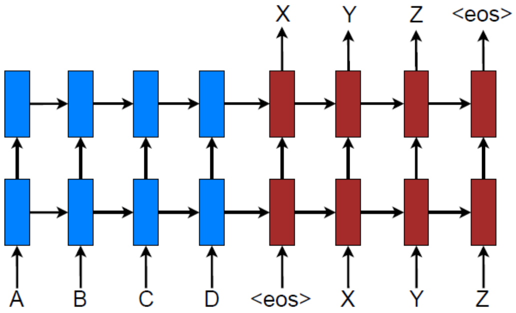
Reversed = reverse the order of the input sentence.

Intuition: the first part of the sentence is the most important, and reversal eases the long-term dependencies from output to input sentence.

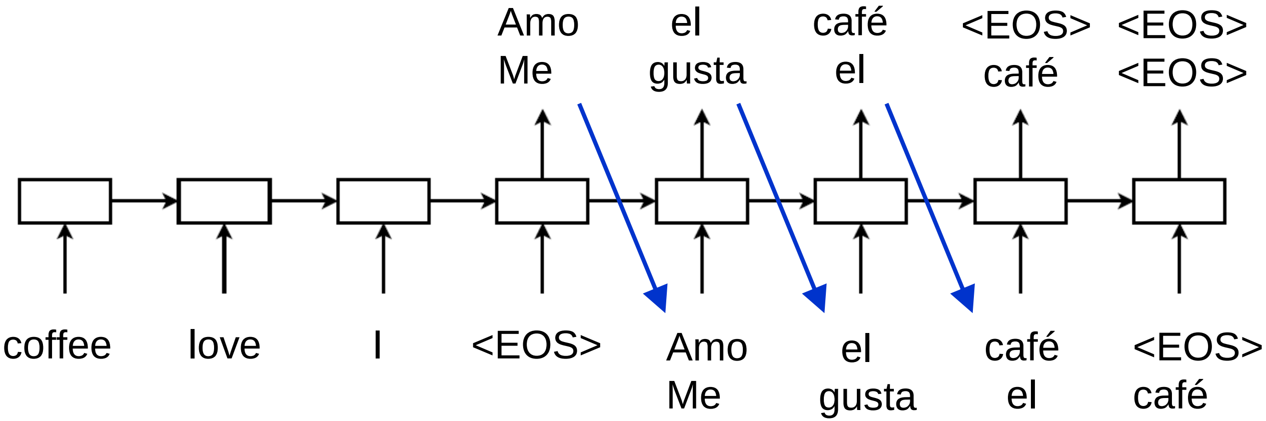
From Sutskeyver et al. “Sequence to Sequence Learning with Neural Networks” 2014.

Sequence-To-Sequence Model Translation

Input sequence reversal



A depth-2 model



Beam search width = 2

Sequence-To-Sequence Model Translation

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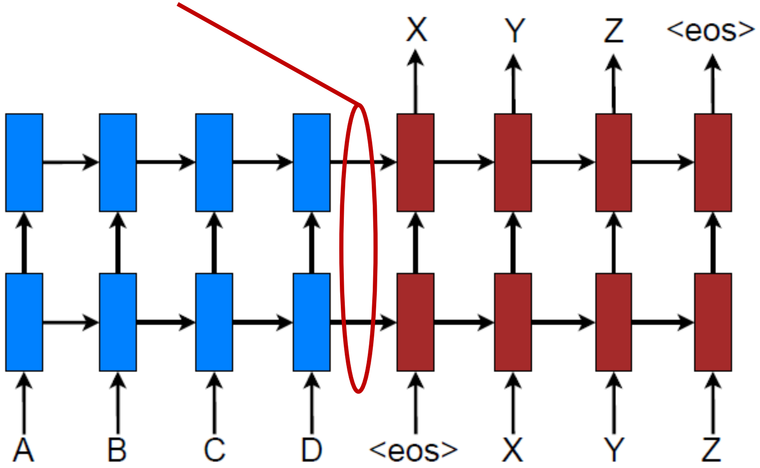
Beam sizes are tiny!!

The model produces state-of-the-art translations with almost no search.

From Sutskeyver et al. “Sequence to Sequence Learning with Neural Networks” 2014.

Sequence-To-Sequence Criticisms

All the information from the source sentence has to pass through the bottleneck at the last unit(s) of the encoder.

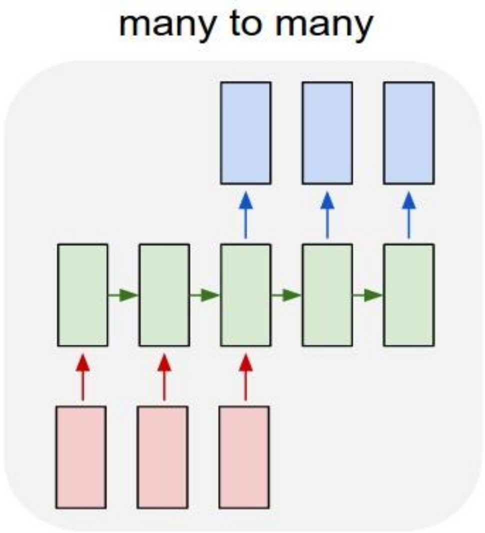


Sentence length varies, but the encoding always has a fixed size.

Soft Attention for Translation

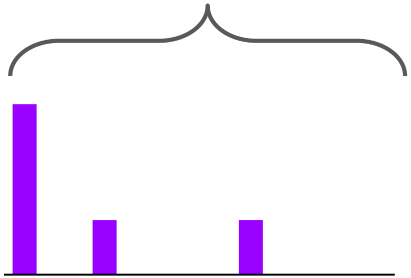
“I love coffee” -> “Me gusta el café”

Bahdanau et al, “Neural Machine Translation by Jointly Learning to Align and Translate”, ICLR 2015



Soft Attention for Translation

Distribution over input words



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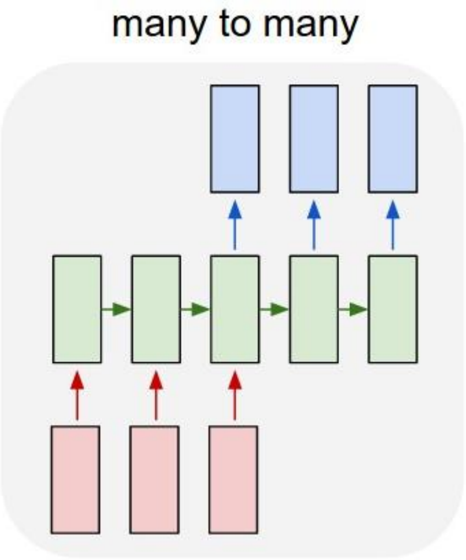

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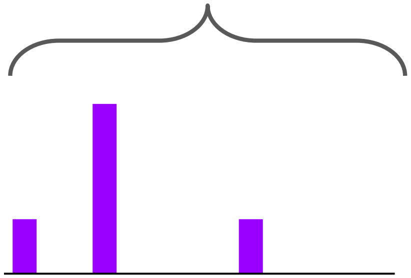

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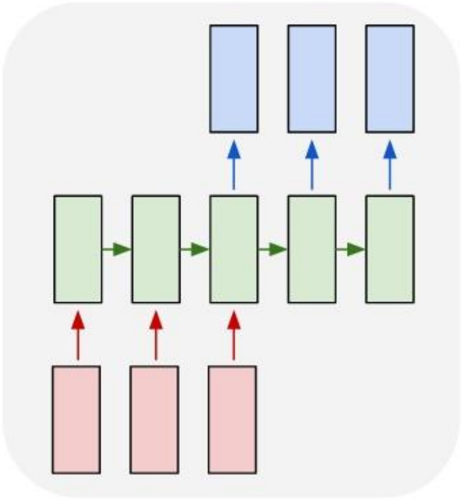
many to many



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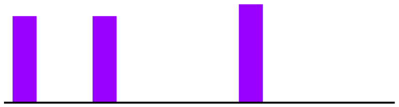
Distribution over input words



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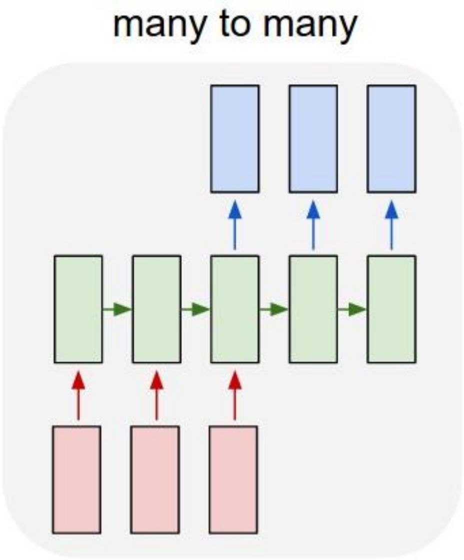

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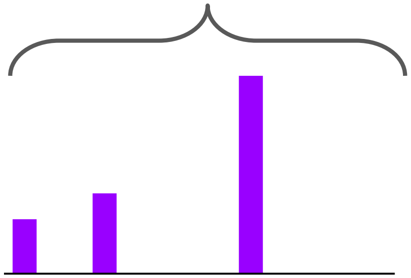

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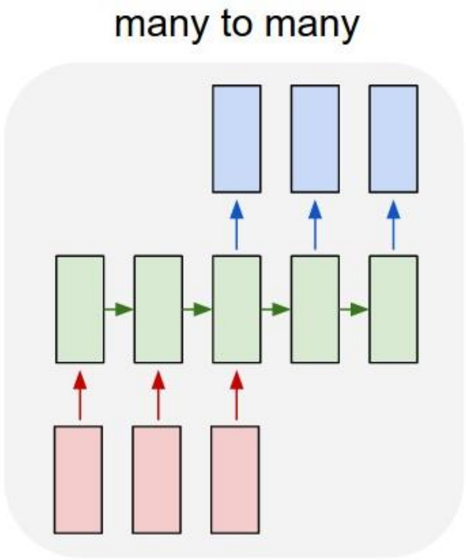

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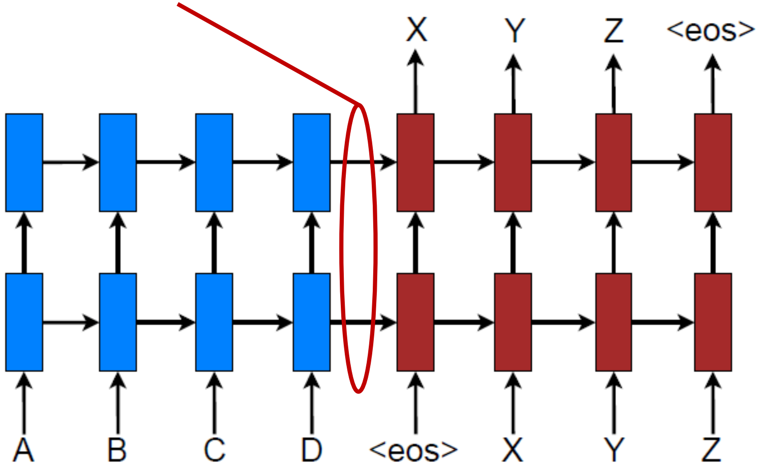
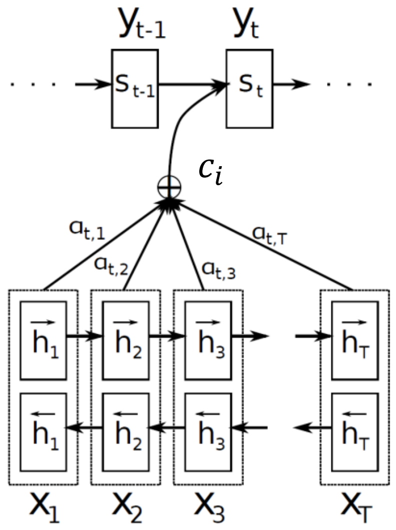


Sentence length varies, but the encoding always has a fixed size.

Soft Attention for Translation – Bahdanau et al. model

For each output word, focus attention on a subset of all input words.

Decoder



Encoder
(bidirectional RNN)

Context vector (input to decoder):

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

Mixture weights (softmax over alignment scores e_{ij})

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}$$

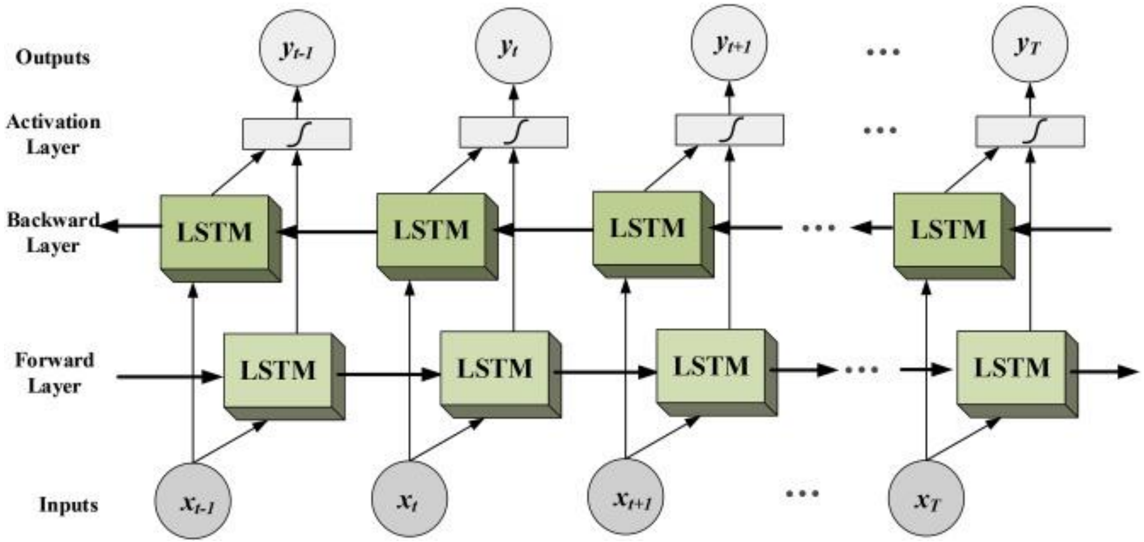
Alignment score (how well do input words near j match output words at position i):

$$e_{ij} = a(s_{i-1}, h_j)$$

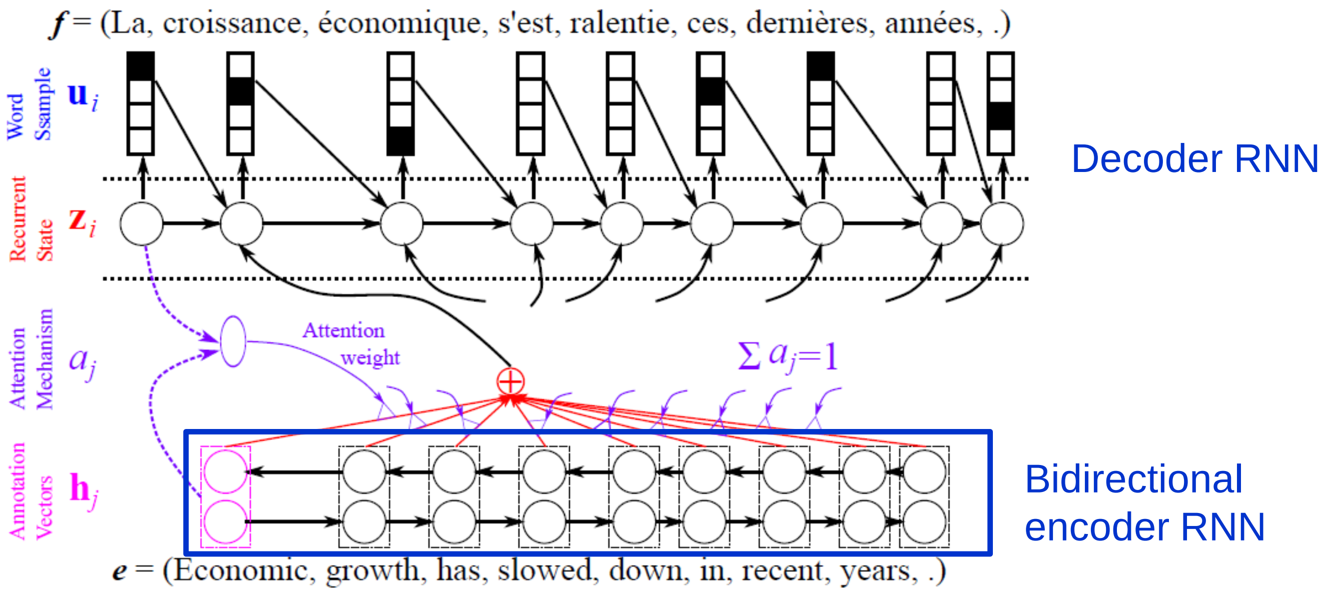
Bahdanau et al, “Neural Machine Translation by Jointly Learning to Align and Translate”, ICLR 2015

Aside: Bidirectional Recurrent Networks:

Implemented with forward and backward rows of units in parallel:

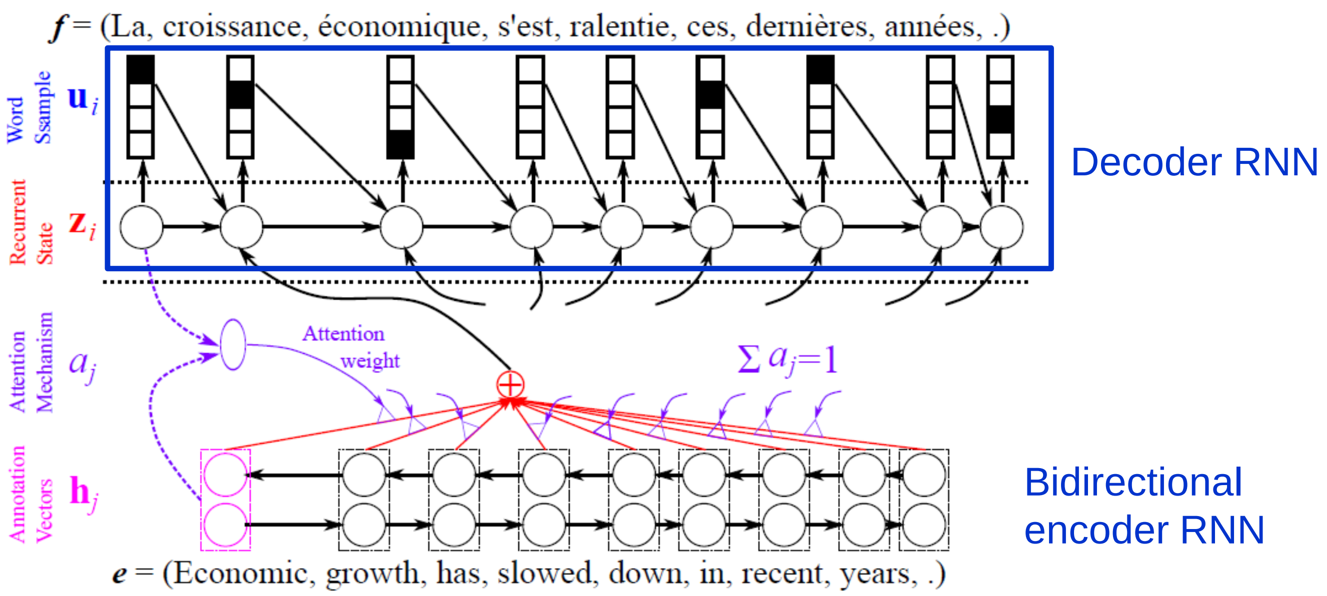


Soft Attention for Translation



From Y. Bengio CVPR 2015 Tutorial

Soft Attention for Translation



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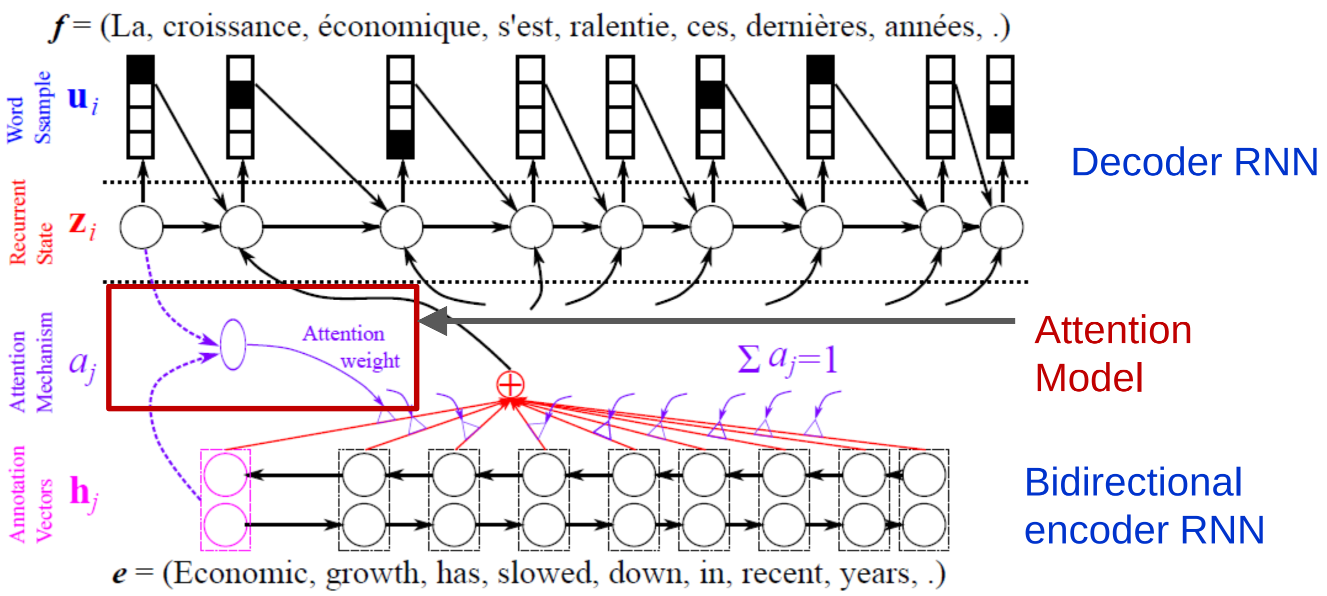

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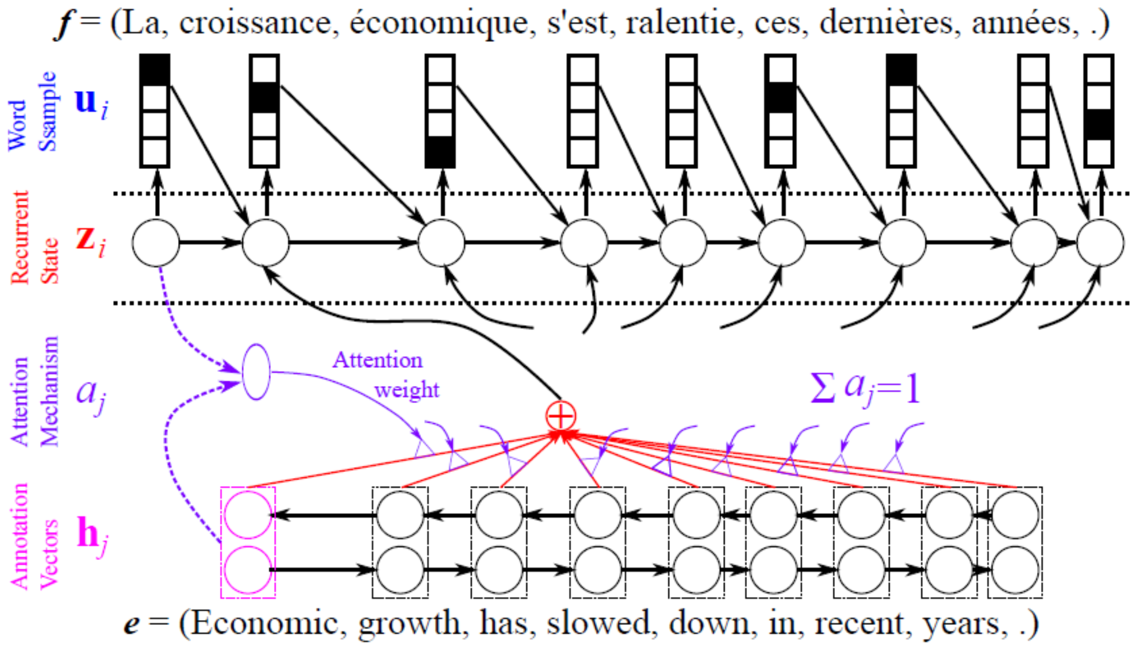
Soft Attention for Translation

$$e_{ij} = a(s_{i-1}, h_j)$$

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}$$



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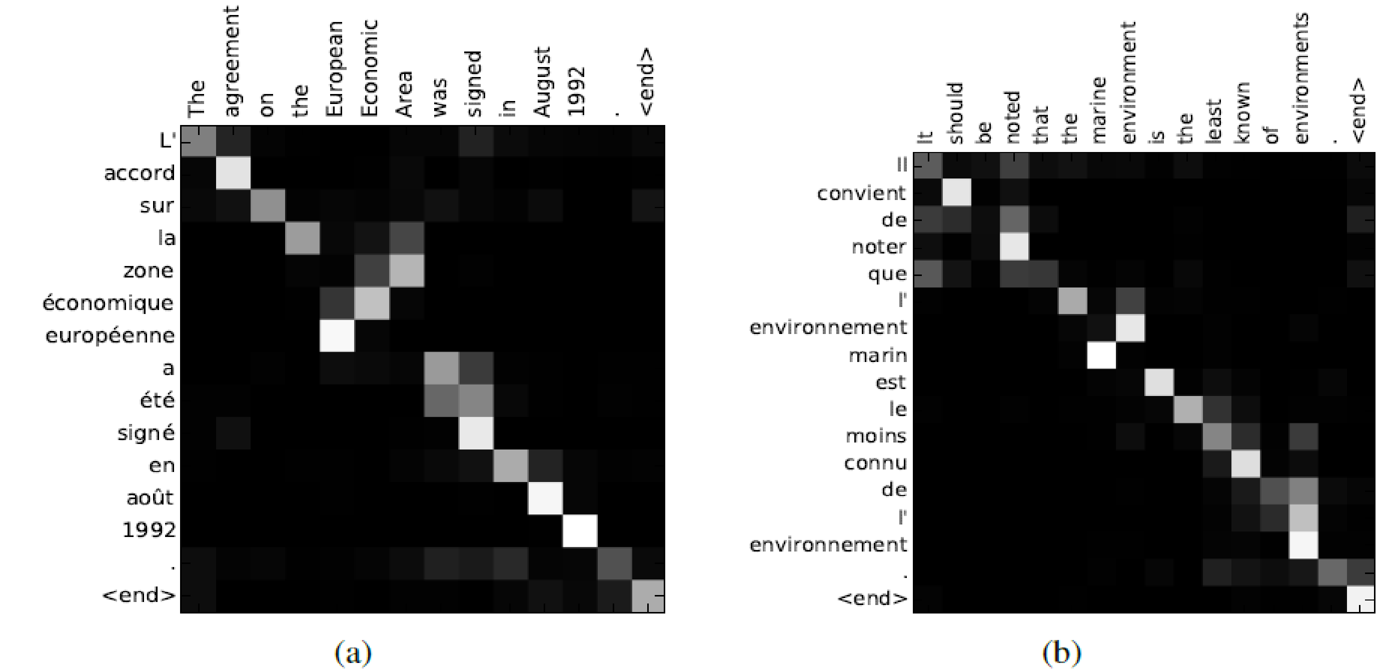

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Soft Attention for Translation

Reached State of the art in one year:

(a) **English→French (WMT-14)**

	NMT(A)	Google	P-SMT
NMT	32.68	30.6*	**37.03•**
+Cand	33.28	–	
+UNK	33.99	32.7°	
+Ens	36.71	**36.9°**	

(b) **English→German (WMT-15)**

Model	Note
24.8	Neural MT
24.0	U.Edinburgh, Syntactic SMT
23.6	LIMSI/KIT
22.8	U.Edinburgh, Phrase SMT
22.7	KIT, Phrase SMT

(c) **English→Czech (WMT-15)**

Model	Note
18.3	Neural MT
18.2	JHU, SMT+LM+OSM+Sparse
17.6	CU, Phrase SMT
17.4	U.Edinburgh, Phrase SMT
16.1	U.Edinburgh, Syntactic SMT

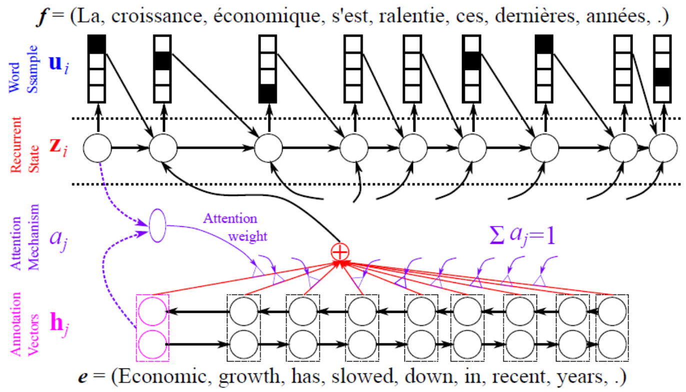
Yoshua Bengio, NIPS RAM workshop 2015

Criticism of Bahdanau et al.

The attention function $a(s_{i-1}, h_j)$ is rather complex (a learned feedforward neural network), yet the attention often seems to be a simple heat map on word similarity:

The data path in Bahdanau et al. is quite complicated: the attention path is another recurrent path between output states.

Doesn't generalize to deeper networks
(shown to be Important by Sutskeyver et al.).

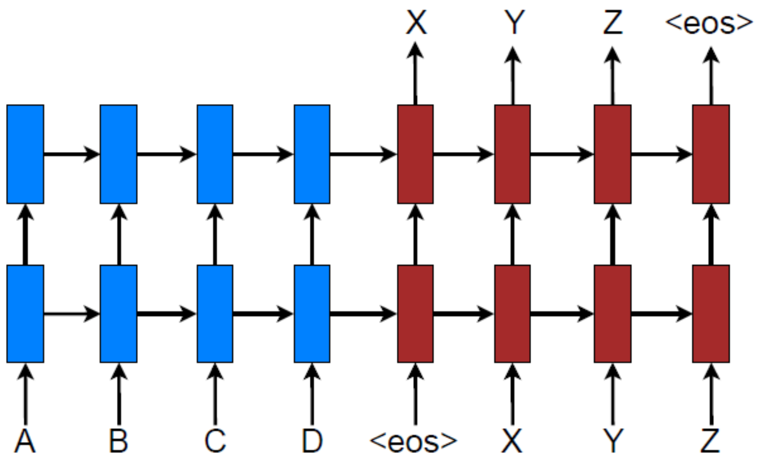


Luong and Manning added several architectural improvements.

Effective Approaches to Attention-based Neural Machine Translation
Minh-Thang Luong, Hieu Pham, Christopher D. Manning, EMNLP 15

Luong, Pham and Manning 2015

Stacked LSTM with arbitrary depth (c.f. bidirectional flat encoder in Bahdanau et al):



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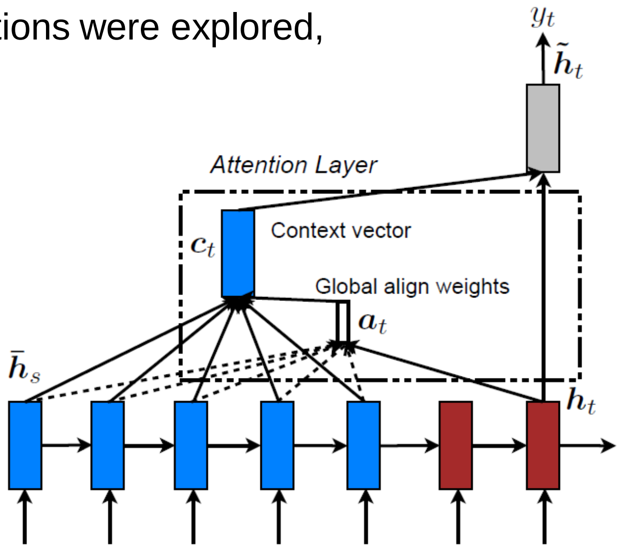
Global Attention Model

Global attention model is similar but simpler than Bahdanau’s. It sits above the encoder/decoder and is not itself recurrent.

Different word matching functions were explored, some yielding better results.



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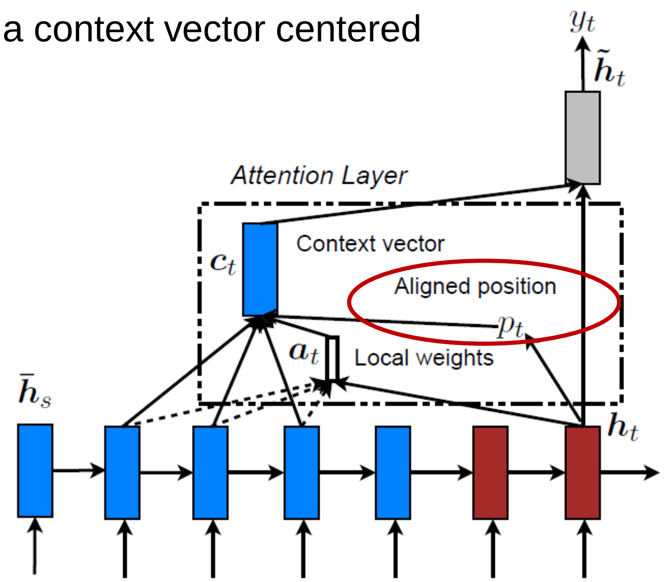
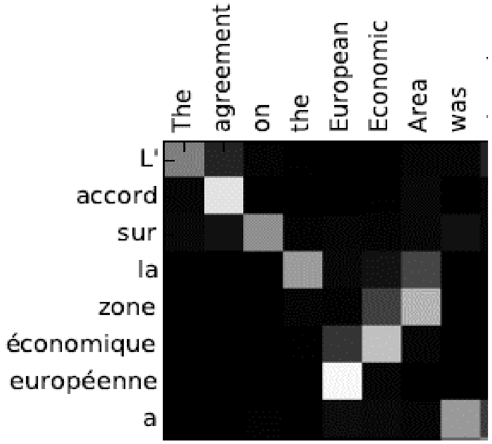
Local Attention Model

- Compute a best aligned position p_t first
- Then compute a context vector centered at that position





Effective Approaches to Attention-based Neural Machine Translation
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Luong, Pham and Manning's Translation System (2015):

System	BLEU
Top – *NMT + 5-gram rerank* (Montreal)	24.9
Our ensemble 8 models + unk replace	**25.9**

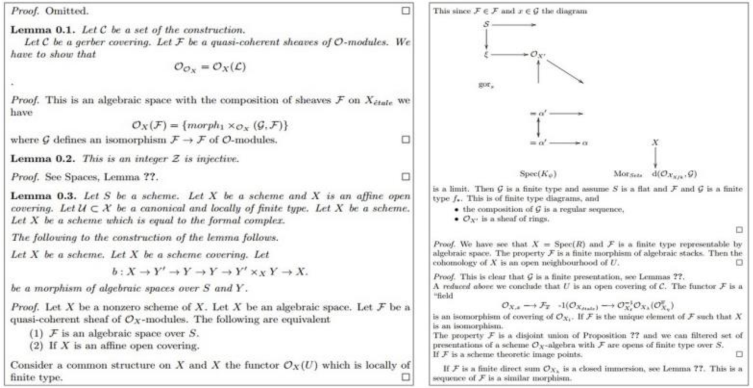
Table 2: **WMT'15 English-German results** – *NIST* BLEU scores of the winning entry in WMT'15 and our best one on newstest2015.

System	Ppl.	BLEU
WMT'15 systems		
SOTA – *phrase-based* (Edinburgh)		**29.2**
NMT + 5-gram rerank (MILA)		27.6
Our NMT systems		
Base (reverse)	14.3	16.9
+ global (*location*)	12.7	19.1 (+*2.2*)
+ global (*location*) + feed	10.9	20.1 (+*1.0*)
+ global (*dot*) + drop + feed	9.7	22.8 (+*2.7*)
+ global (*dot*) + drop + feed + unk		24.9 (+*2.1*)

Table 3: **WMT'15 German-English results** –

Parsing

Recall (Lecture 10) RNNs ability to generate Latex, C code:



Proof. Omitted.

Lemma 0.1. *Let $\mathcal{C}$ be a set of the construction.*

Let $\mathcal{C}$ be a gerber covering. Let $\mathcal{F}$ be a quasi-coherent sheaves of $\mathcal{O}$-modules. We have to show that

$$\mathcal{O}_{\mathcal{O}_X} = \mathcal{O}_X(\mathcal{L})$$

Proof. This is an algebraic space with the composition of sheaves $\mathcal{F}$ on $X_{\acute{e}tale}$ we have

$$\mathcal{O}_X(\mathcal{F}) = \{morph_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

where $\mathcal{G}$ defines an isomorphism $\mathcal{F} \to \mathcal{F}$ of $\mathcal{O}$-modules.

Lemma 0.2. *This is an integer $\mathcal{Z}$ is injective.*

Proof. See Spaces, Lemma ??.

Lemma 0.3. *Let S be a scheme. Let X be a scheme and X is an affine open covering. Let $\mathcal{U} \subset \mathcal{X}$ be a canonical and locally of finite type. Let X be a scheme. Let X be a scheme which is equal to the formal complex.*

The following to the construction of the lemma follows.

Let X be a scheme. Let X be a scheme covering. Let

$$b : X \to Y' \to Y \to Y \to Y' \times_X Y \to X.$$

be a morphism of algebraic spaces over S and Y.

Proof. Let X be a nonzero scheme of X. Let X be an algebraic space. Let $\mathcal{F}$ be a quasi-coherent sheaf of $\mathcal{O}_X$-modules. The following are equivalent

(1) $\mathcal{F}$ is an algebraic space over S.
(2) If X is an affine open covering.

Consider a common structure on X and X the functor $\mathcal{O}_X(U)$ which is locally of finite type.

This since $\mathcal{F} \in \mathcal{F}$ and $x \in \mathcal{G}$ the diagram

is a limit. Then $\mathcal{G}$ is a finite type and assume S is a flat and $\mathcal{F}$ and $\mathcal{G}$ is a finite type f_*. This is of finite type diagrams, and

- the composition of $\mathcal{G}$ is a regular sequence,
- $\mathcal{O}_{X'}$ is a sheaf of rings.

Proof. We have see that $X = \mathrm{Spec}(R)$ and $\mathcal{F}$ is a finite type representable by algebraic space. The property $\mathcal{F}$ is a finite morphism of algebraic stacks. Then the cohomology of X is an open neighbourhood of U.

Proof. This is clear that $\mathcal{G}$ is a finite presentation, see Lemmas ??.

A *reduced above* we conclude that U is an open covering of $\mathcal{C}$. The functor $\mathcal{F}$ is a "field

$$\mathcal{O}_{X,x} \longrightarrow \mathcal{F}_{\bar{x}} \ \text{-}1(\mathcal{O}_{X_{\acute{e}tale}}) \longrightarrow \mathcal{O}_{X_\ell}^{-1}\mathcal{O}_{X_\lambda}(\mathcal{O}_{X_\eta}^{\overline{\ell}})$$

is an isomorphism of covering of $\mathcal{O}_{X_i}$. If $\mathcal{F}$ is the unique element of $\mathcal{F}$ such that X is an isomorphism.

The property $\mathcal{F}$ is a disjoint union of Proposition ?? and we can filtered set of presentations of a scheme $\mathcal{O}_X$-algebra with $\mathcal{F}$ are opens of finite type over S.

If $\mathcal{F}$ is a scheme theoretic image points.

If $\mathcal{F}$ is a finite direct sum $\mathcal{O}_{X_\lambda}$ is a closed immersion, see Lemma ??. This is a sequence of $\mathcal{F}$ is a similar morphism.

```c
static void do_command(struct seq_file *m, void *v)
{
  int column = 32 << (cmd[2] & 0x80);
  if (state)
    cmd = (int)(int_state ^ (in_8(&ch->ch_flags) & Cmd) ? 2 : 1);
  else
    seq = 1;
  for (i = 0; i < 16; i++) {
    if (k & (1 << 1))
      pipe = (in_use & UMXTHREAD_UNCCA) +
        ((count & 0x00000000fffffff8) & 0x000000f) << 8;
    if (count == 0)
      sub(pid, ppc_md.kexec_handle, 0x20000000);
    pipe_set_bytes(i, 0);
  }
  /* Free our user pages pointer to place camera if all dash */
  subsystem_info = &of_changes[PAGE_SIZE];
  rek_controls(offset, idx, &soffset);
  /* Now we want to deliberately put it to device */
  control_check_polarity(&context, val, 0);
  for (i = 0; i < COUNTER; i++)
    seq_puts(s, "policy ");
}
```

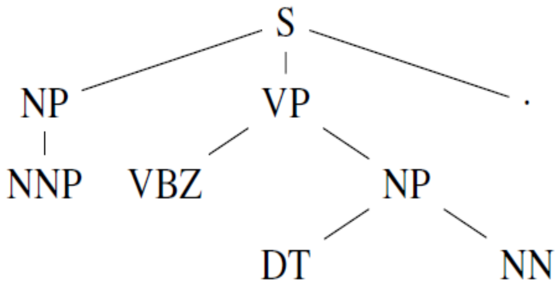
They seem to do well with tree-structured data.

What about natural language parsing?

Parsing

Sequence models generate linear structures, but these can easily encode trees by “closing parens” (prefix tree notation):

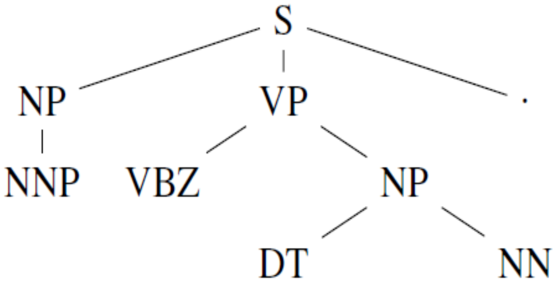
John has a dog . $\rightarrow$



John has a dog . $\rightarrow$ (S (NP NNP $)_{\mathrm{NP}}$ (VP VBZ (NP DT NN $)_{\mathrm{NP}}$ $)_{\mathrm{VP}}$. $)_{\mathrm{S}}$

Parsing Cheat Sheet

John has a dog . $\rightarrow$



John has a dog . $\rightarrow$ (S (NP NNP $)_{NP}$ (VP VBZ (NP DT NN $)_{NP}$ $)_{VP}$. $)_{S}$

S = Sentence

NP = Noun Phrase

VP = Verb Phrase

NNP = Proper Noun ("John")

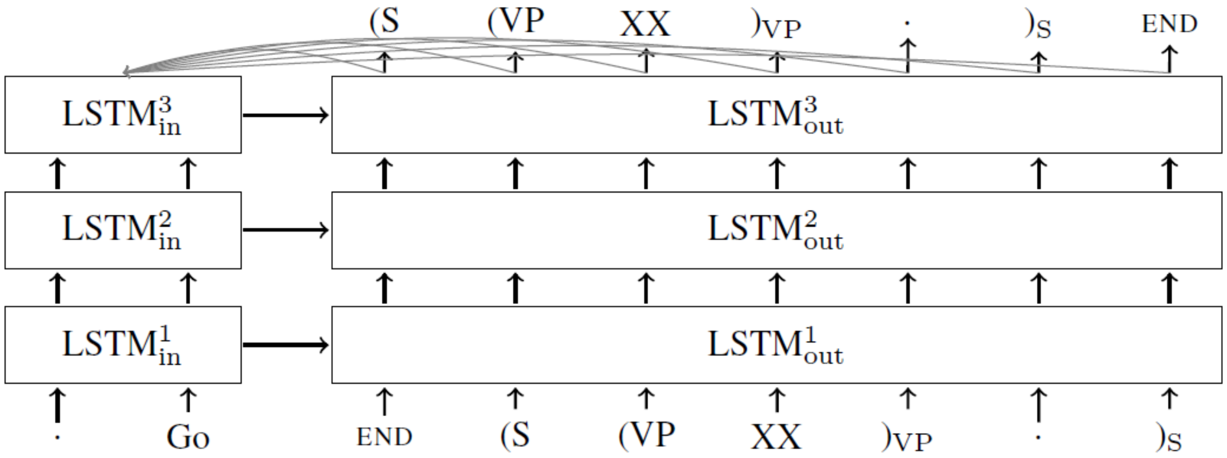
VBZ = Verb, 3rd person, singular ("has")

DT = Determiner ("a")

NN = Noun, singular ("dog")

A Sequence-To-Sequence Parser

The model is a depth-3 sequence-to-sequence predictor, augmented with the attention model of Bahdanau 2014.



Grammar as a Foreign Language Oriol Vinyals, Google, Lukasz Kaiser, Terry Koo, Slav Petrov, Ilya Sutskever, Geoffrey Hinton, NIPS 2015

"Neural machine translation by jointly learning to align and translate." Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. arXiv 2014.

A Sequence-To-Sequence Parser

Chronology:

- First tried training a basic sequence-to-sequence model on human-annotated training treebanks. **Poor results.**
- Then training on parse trees **generated by the Berkeley Parser**, achieved similar performance (90.5 F1 score) to it.
- Next added the attention model, trained **on human treebank data**, also achieved 90.5 F1.
- Finally, created a synthetic dataset of **high-confidence parse trees** (agreed on by two parsers). Achieved a new state-of-the-art of 92.5 F1 score (WSJ dataset).

F1 is a widely-used accuracy measure that combines precision and recall

A Sequence-To-Sequence Parser

Quick Training Details:

- Depth = 3, layer dimension = 256.
- **Dropout** between layers 1 and 2, and 2 and 3.
- **No Part-Of-Speech tags!!** Improved by F1 1 point by leaving them out.
- Input reversing.

Attention-only Translation Models

Problems with recurrent networks:

- Sequential training and inference: time grows in proportion to sentence length. Hard to parallelize.
- Long-range dependencies have to be remembered across many single time steps.
- Tricky to learn hierarchical structures (“car”, “blue car”, “into the blue car”…)

Alternative:

- Convolution – but has other limitations.

Self-Attention

Information flows from within the same subnetwork (either encoder or decoder). Convolution applies fixed transform weights. Self-attention applies variable weights (but typically not transformations):

image from Lukas Kaiser, Stanford NLP seminar

Self-Attention "Transformers"

- Constant path length between any two positions.
- Variable receptive field (or the whole input sequence).
- Supports hierarchical information flow by stacking self-attention layers.
- Trivial to parallelize.
- Attention weighting controls information propagation.

- **Can replace word-based recurrence entirely.**

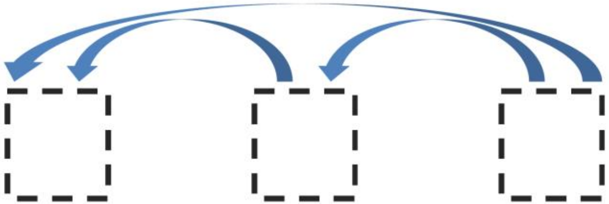
Vaswani et al. "Attention is all you need", arXiv 2017

Attention in Transformer Networks

Encoder-Decoder Attention

We saw this in Bahdanau and Luong models

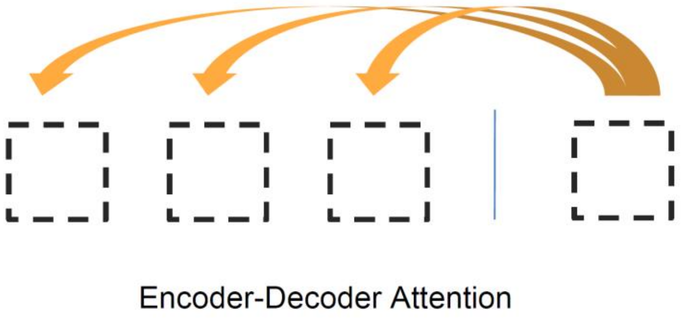
Encoder Self-Attention



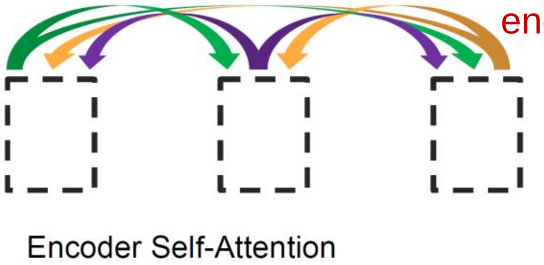
MaskedDecoder Self-Attention

image from Lukas Kaiser, Stanford NLP seminar

Attention in Transformer Networks



Replaces word recurrence in
encoder and decoder



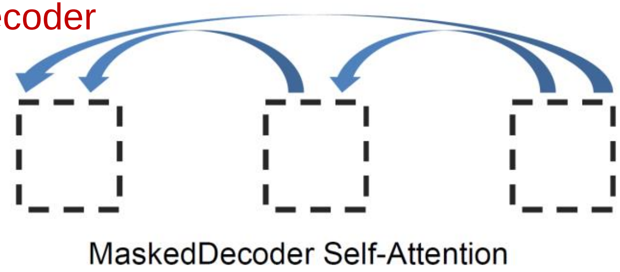
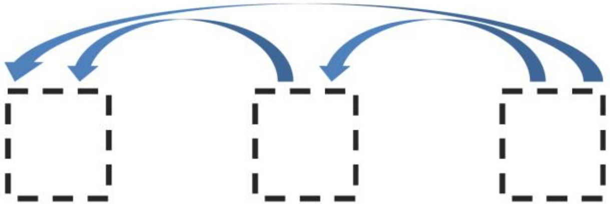


image from Lukas Kaiser, Stanford NLP seminar

Attention in Transformer Networks

Encoder-Decoder Attention

Encoder Self-Attention



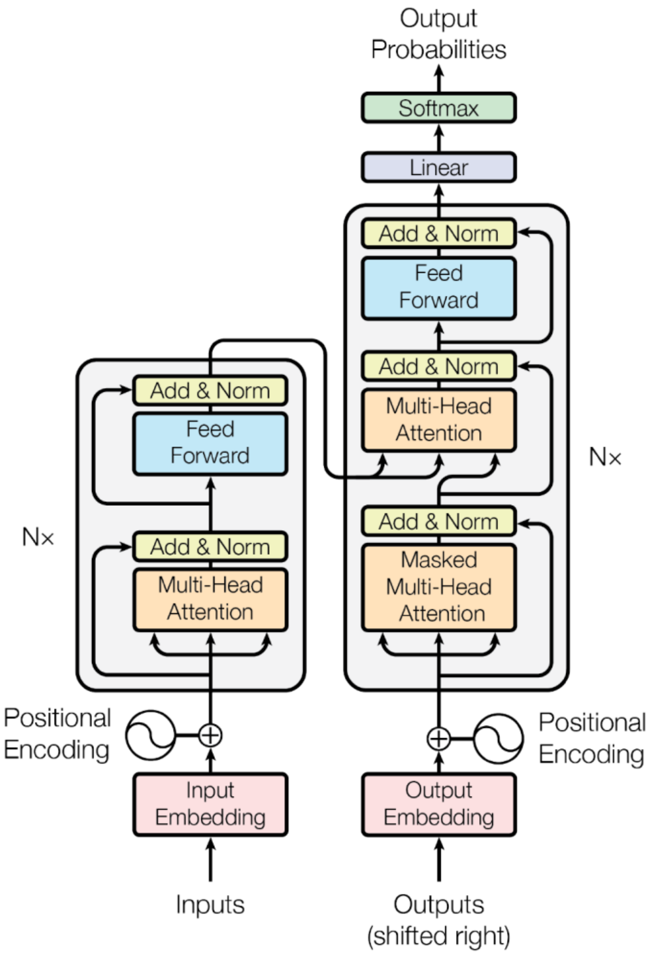
MaskedDecoder Self-Attention

Masking limits attention to earlier units: y_i depends only on y_j for $j < i$.

image from Lukas Kaiser, Stanford NLP seminar

The Transformer

- Basic unit shown at right.
- In experiments, stacked with N=6.
- Output words fed back as input, shifted right. Can use beam search as before.
- Inputs and outputs are embedded in vector spaces of fixed dimension.
- Positional encoding: when words are combined through attention, their location is lost. Positional encoding adds it back.



Attention Implementation

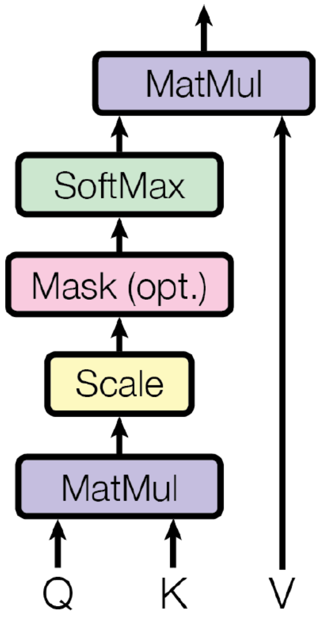
- Attention is modeled as a key-value store:
  Q = query vector
  K = key
  V = value

Encoder-decoder layer: the queries come from the previous decoder layer, and the memory keys and values come from the output of the encoder. (Similar to Bahdanau).

Self-attention layer: all of the keys, values and queries come from the output of the previous layer in the encoder.

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

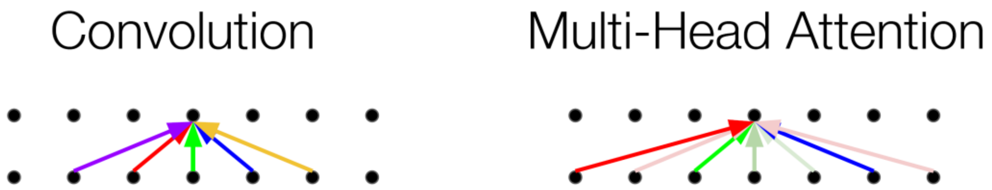
Scaled Dot-Product Attention

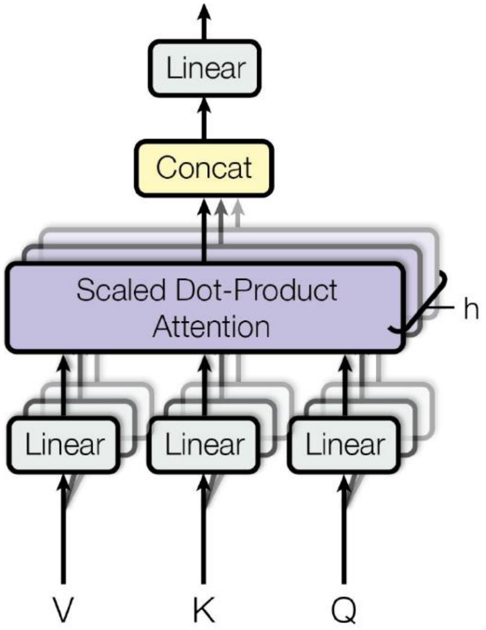


Multi-Headed Attention

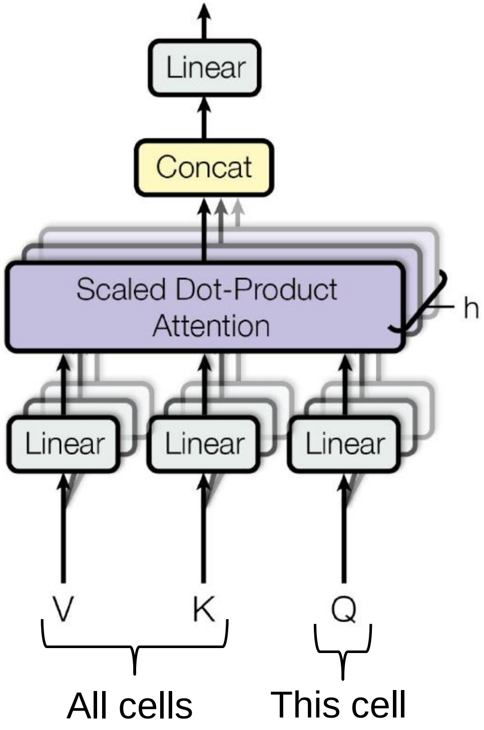
- Simple attention blends the results of all the attended-to inputs. It doesn't allow a per-input transformation, as convolution does.

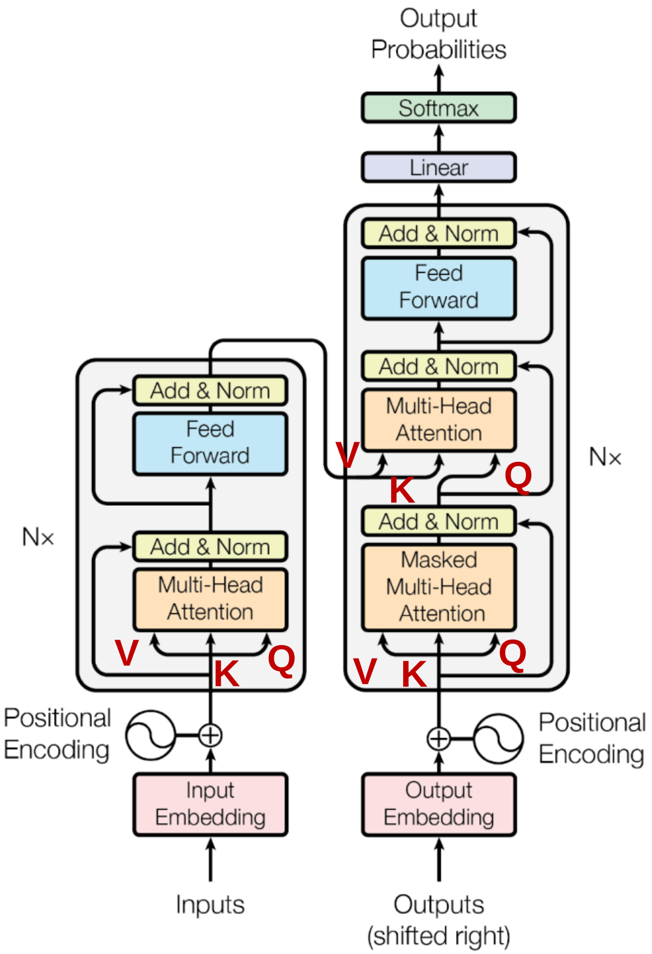
- The solution is to use "multi-headed attention":





The Transformer





Position encoding

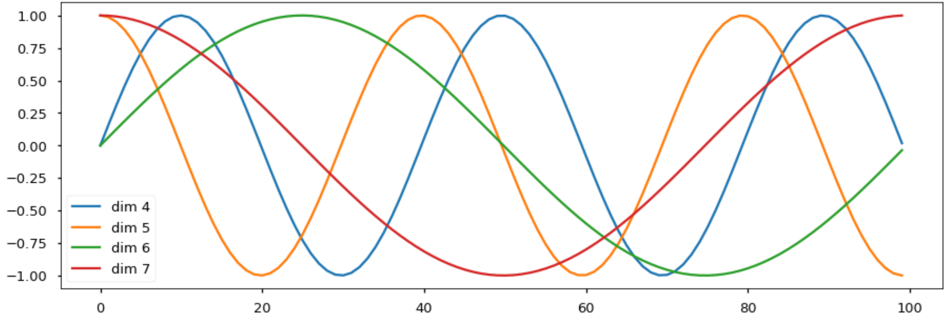
Every cell in the transformer has the same “view” of the data below. Its important to break this symmetry so different cells do different things. Spatial encoding is usually used:

The encoding vector has the same dimension as the model.

Its components are all sinusoidal functions of position.

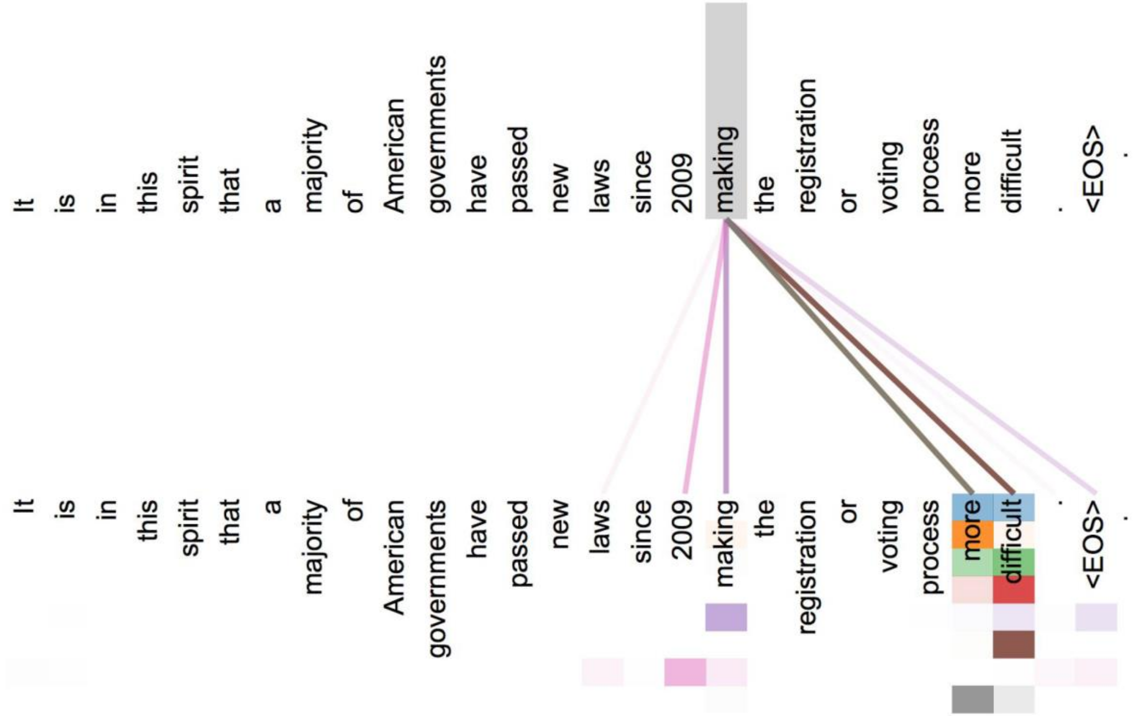
The periods of the sinusoids form a geometric series.

position
vector
values

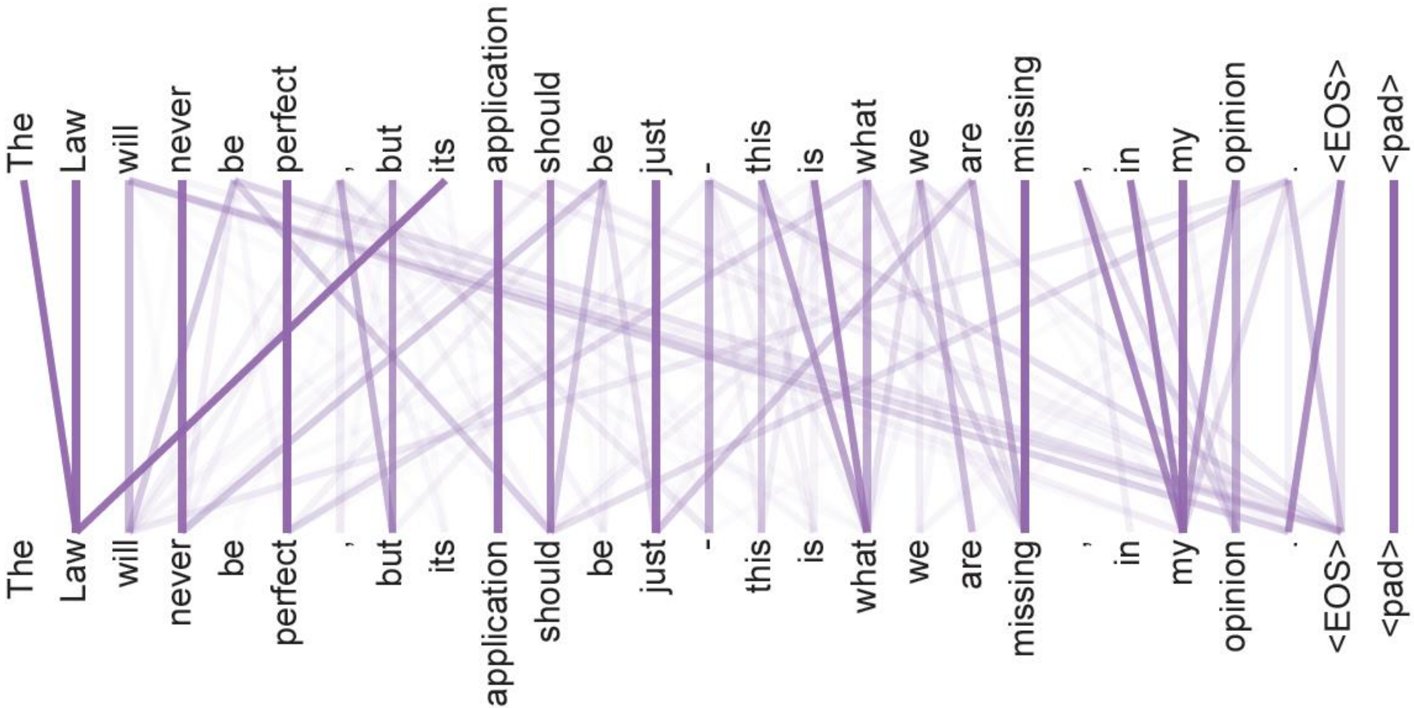


Position in the input

Multi-Headed Attention

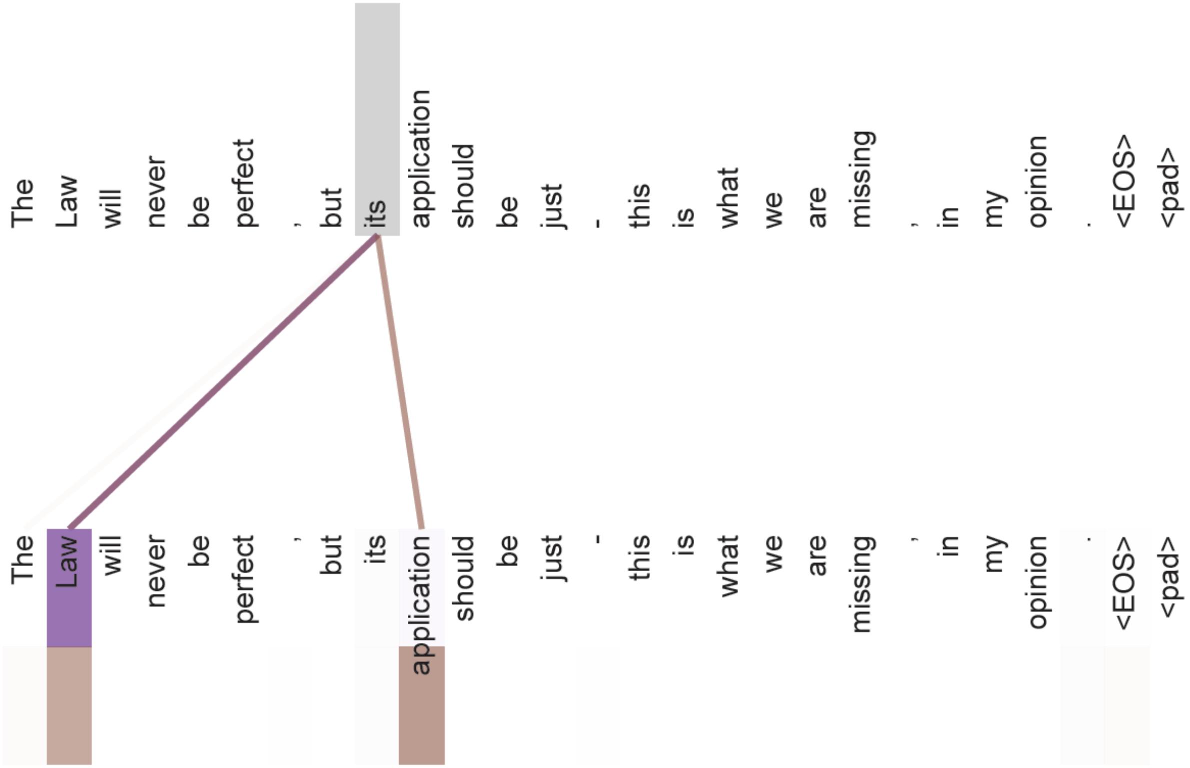


Multi-Headed Attention



Anaphora (pronoun or article) resolution

Multi-Headed Attention



Anaphora (pronoun or article) resolution

Transformer Results

Machine Translation Results: WMT-14

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [17]	23.75			
Deep-Att + PosUnk [37]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [36]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [31]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [37]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [36]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.0**	$2.3 \cdot 10^{19}$	

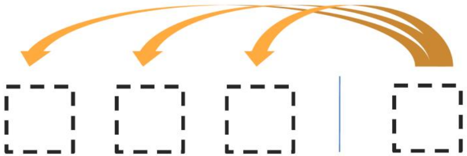
English-to-English Translation ?!

Yes, it does make sense. a.k.a. summarization.

Liu et al, “GENERATING WIKIPEDIA BY SUMMARIZING LONG SEQUENCES” arXiv 2018

M = input length, N = output length

Summarization: M >> N

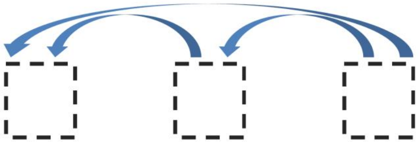


$O(MN)$

Encoder-Decoder Attention

$O(M^2)$

Encoder Self-Attention



$O(N^2)$

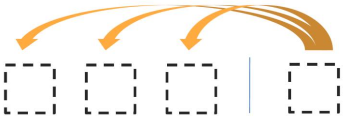
MaskedDecoder Self-Attention

Large-scale Summarization (Wikipedia)

Like translation, but we completely remove the encoder.

Source data (large!):

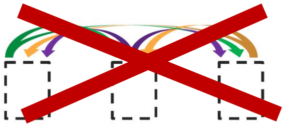
- The references for a Wikipedia article.
- Web search using article section titles, ~ 10 web pages per query.



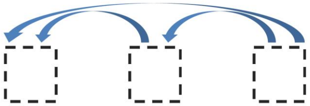
$O(MN)$

Encoder-Decoder Attention

$O(M^2)$

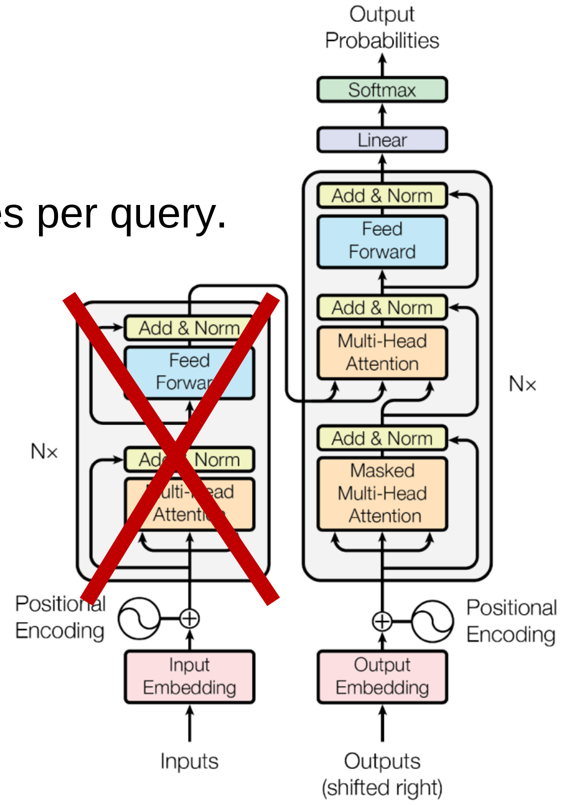


Encoder Self-Attention



$O(N^2)$

MaskedDecoder Self-Attention



Large-scale Summarization

Results:

Model	Test perplexity	ROUGE-L
seq2seq-attention, $L = 500$	5.04952	12.7
Transformer-ED, $L = 500$	2.46645	34.2
Transformer-D, $L = 4000$	2.22216	33.6
Transformer-DMCA, no MoE-layer, $L = 11000$	2.05159	36.2
Transformer-DMCA, MoE-128, $L = 11000$	1.92871	37.9
Transformer-DMCA, MoE-256, $L = 7500$	1.90325	38.8

L = input window length.
ED = encoder-decoder.
D = decoder only.
DMCA = a memory compression technique (strided convolution).
MoE = mixture of experts layer.

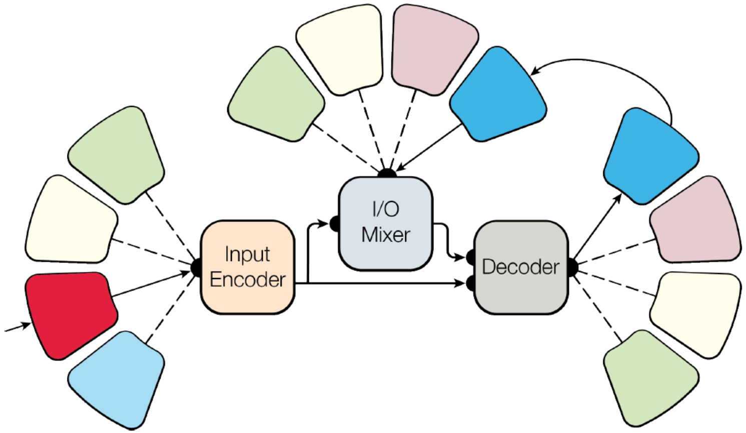
Liu et al, “GENERATING WIKIPEDIA BY SUMMARIZING LONG SEQUENCES” arXiv 2018

Other Transformer-Based Systems

In “One Model to Learn Them All”, Kaiser et al:

Train a shared transformer-based model on these tasks:

(1) WSJ speech corpus [7]
(2) ImageNet dataset [23]
(3) COCO image captioning dataset [14]
(4) WSJ parsing dataset [17]
(5) WMT English-German translation corpus
(6) The reverse of the above: German-English translation.
(7) WMT English-French translation corpus
(8) The reverse of the above: German-French translation.



Other Transformer-Based Systems: BERT

BERT = Bidirectional Encoding Representations from Transformers

Pretrain a single language model on a large corpus, fine-tune one output layer for various NLP tasks.

Gives state-of-the-art performance on 11 tasks, including the “GLUE” benchmark

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

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, Jacob Devlin et al. 2018.

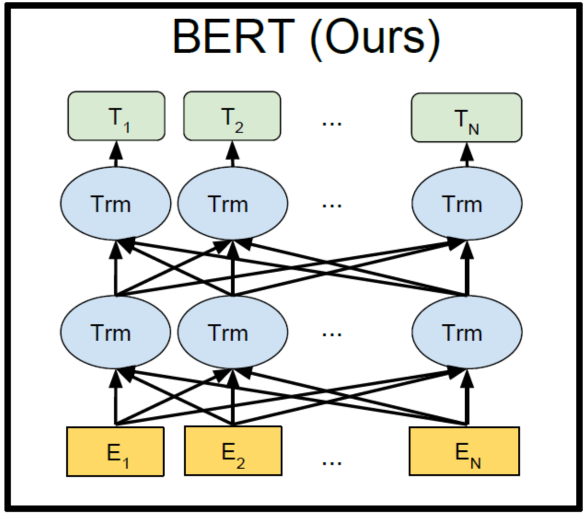
Other Transformer-Based Systems: BERT

Train on a large dataset: Books Corpus (800M words) + Wikipedia (2.5B words)

As the name suggests, BERT uses bidirectional attention.

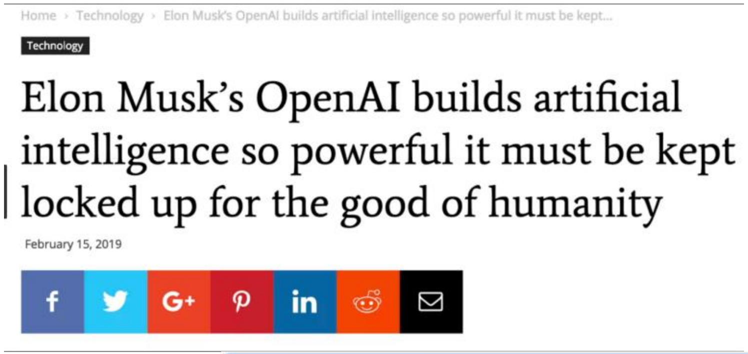
Its trained with two losses:

- Delete a random word (15%) and predict it.
- Predict the next sentence from the current one.



BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, Jacob Devlin et al. 2018.

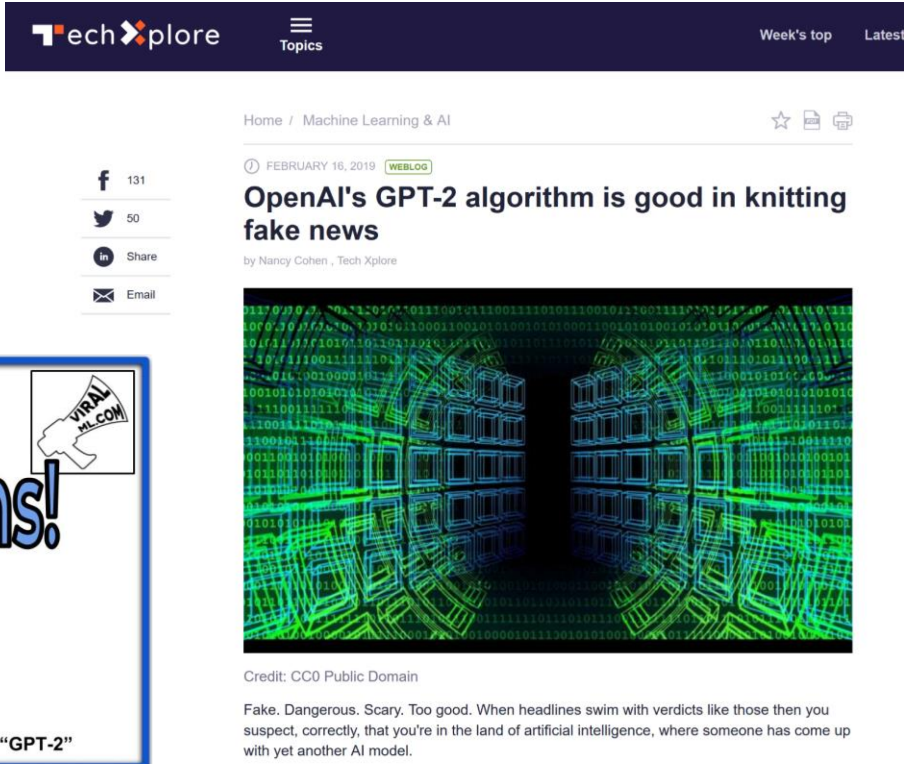
Other Transformer-Based Systems: GPT and GPT2


Home › Technology › Elon Musk's OpenAI builds artificial intelligence so powerful it must be kept...

Technology

Elon Musk's OpenAI builds artificial intelligence so powerful it must be kept locked up for the good of humanity

February 15, 2019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FEBRUARY 16, 2019 WEBLOG

OpenAI's GPT-2 algorithm is good in knitting fake news

by Nancy Cohen , Tech Xplore

Credit: CC0 Public Domain

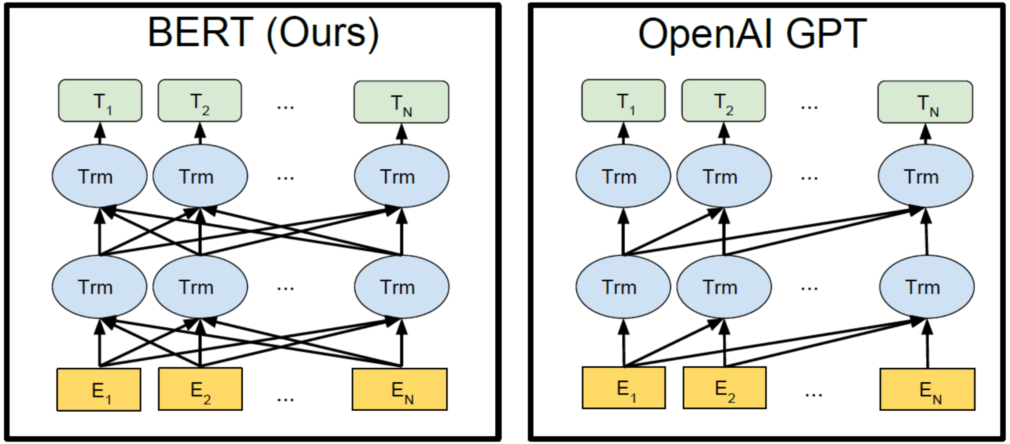
Fake. Dangerous. Scary. Too good. When headlines swim with verdicts like those then you suspect, correctly, that you're in the land of artificial intelligence, where someone has come up with yet another AI model.

Other Transformer-Based Systems: GPT and GPT2

OpenAI develop an even simpler transformer based model with even more parameters, trained it on even more data, and achieved new levels of performance on more tasks.

GPT = Generative Pre-Training

GPT doesn't require fine-tuning any more, only adaptation of inputs.



Improving Language Understanding by Generative Pre-Training, Radford et al. 2018

Language Models are Unsupervised Multitask Learners, Radford et al. 2019

Other Transformer-Based Systems: GPT and GPT2

GPT2 is trained on a web crawl (WebText) of 8 million web pages (40GB of text).
The GPT2 model has 1.5 billion parameters, in 48 layers and 1,600 model dimensions.

DATASET	METRIC	OUR RESULT	PREVIOUS RECORD	HUMAN
Winograd Schema Challenge	accuracy (+)	**70.70%**	63.7%	92%+
LAMBADA	accuracy (+)	**63.24%**	59.23%	95%+
LAMBADA	perplexity (-)	**8.6**	99	~1-2
Children's Book Test Common Nouns (validation accuracy)	accuracy (+)	**93.30%**	85.7%	96%
Children's Book Test Named Entities (validation accuracy)	accuracy (+)	**89.05%**	82.3%	92%
Penn Tree Bank	perplexity (-)	**35.76**	46.54	unknown
WikiText-2	perplexity (-)	**18.34**	39.14	unknown
enwik8	bits per character (-)	**0.93**	0.99	unknown
text8	bits per character (-)	**0.98**	1.08	unknown
WikiText-103	perplexity (-)	**17.48**	18.3	unknown

GPT-2 achieves state-of-the-art on Winograd Schema, LAMBADA, and other language modeling tasks.

SYSTEM PROMPT (HUMAN-WRITTEN)

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

MODEL COMPLETION (MACHINE-WRITTEN, 10 TRIES)

The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Pérez and the others then ventured further into the valley. "By the time we reached the top of one peak, the water looked blue, with some crystals on top," said Pérez.

Pérez and his friends were astonished to see the unicorn herd. These creatures could be seen from the air without having to move too much to see them – they were so close they could touch their horns.

While examining these bizarre creatures the scientists discovered that the creatures also spoke some fairly regular English. Pérez stated, "We can see, for example, that they have a common 'language,' something like a dialect or dialectic."

Dr. Pérez believes that the unicorns may have originated in Argentina, where the animals were believed to be descendants of a lost race of people who lived there before the arrival of humans in those parts of South America.

While their origins are still unclear, some believe that perhaps the creatures were created when a human and a unicorn met each other in a time before human civilization. According to Pérez, "In South America, such incidents seem to be quite common."

However, Pérez also pointed out that it is likely that the only way of knowing for sure if unicorns are indeed the descendants of a lost alien race is through DNA. "But they seem to be able to communicate in English quite well, which I believe is a sign of evolution, or at least a change in social organization," said the scientist.

Translation Takeaways

- Sequence-to-sequence translation

  - Input reversal
  - Narrow beam search

- Adding Attention

  - Compare latent states of encoder/decoder (Bahdanau).
  - Simplify and avoid more recurrence (Luong).

Translation Takeaways

- Parsing as translation:

  - Translation models can solve many "transduction" tasks.

- Attention only models:

  - Self-attention replaces recurrence, improves performance.
  - Use depth to model hierarchical structure.
  - Multi-headed attention allows interpretation of inputs.