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

John Canny

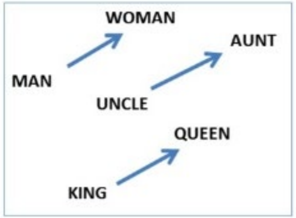
Spring 2020

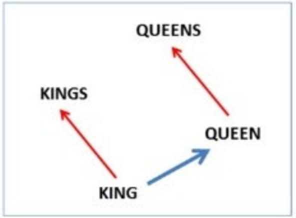
Lecture 13: Translation

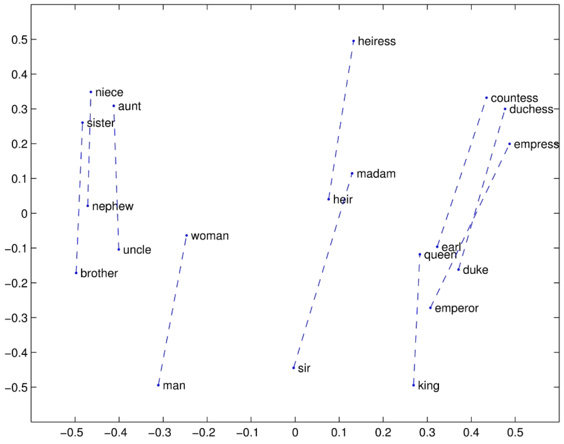
Last Time: Word Embeddings

t-SNE of
word vectors

Relations among
word embeddings

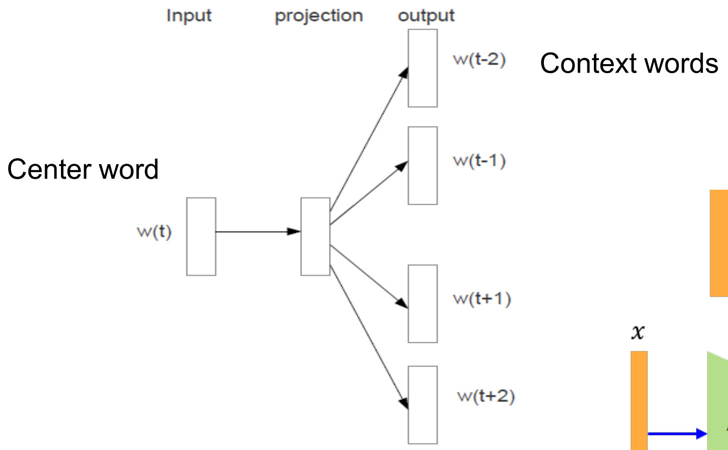




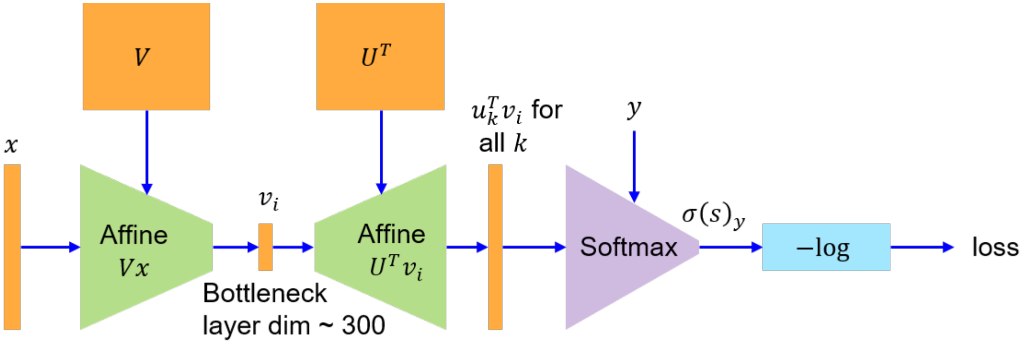


Last Time: Word2vec: Local context

The pairs of center word/context word are called **"skip-grams."** Typical distances are 3-5 word positions. Skip-gram model:



Softmax $p(j|i) = \frac{\exp(u_j^T v_i)}{\sum_{k=1}^{V} \exp(u_k^T v_i)}$



Word2vec as a deep network. Input is (x, y) (center, context) word pairs, x corresponds to word i, and y to word j.

Last Time: GloVe: Word embedding for analogies

Let C_{ij} denote the number of times that word j occurs in the context of word i.
Glove loss is:

$$J(\theta) = \sum_{i,j=1}^{V} f(C_{ij})\left(u_i^T v_j + b_i + \tilde{b}_j - \log C_{ij}\right)^2$$

A sensible choice of $f(.)$ is : $f(x) = \begin{cases} (x/x_{\max})^{\alpha} & \text{if } x < x_{\max} \\ 1 & \text{otherwise} \end{cases}$. typical α = ¾, $x_{\max}$=100

Nearest words to
frog:

1. frogs
2. toad
3. litoria
4. leptodactylidae
5. rana
6. lizard
7. eleutherodactylus

litoria

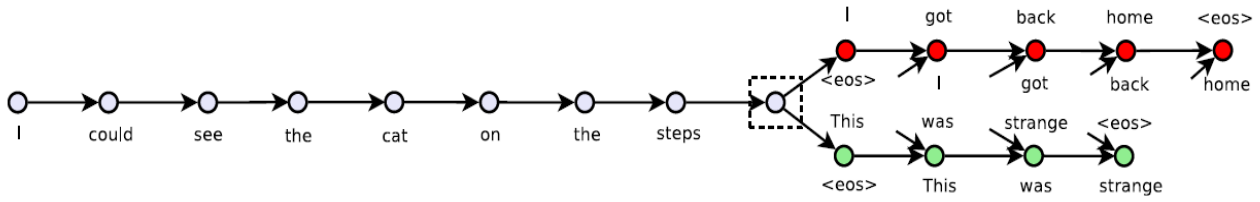
leptodactylidae

rana

eleutherodactylus

Last Time: Skip-Thought Vectors

Skip-thought embeddings use sequence-to-sequence RNNs to predict the next and previous ***sentences***.



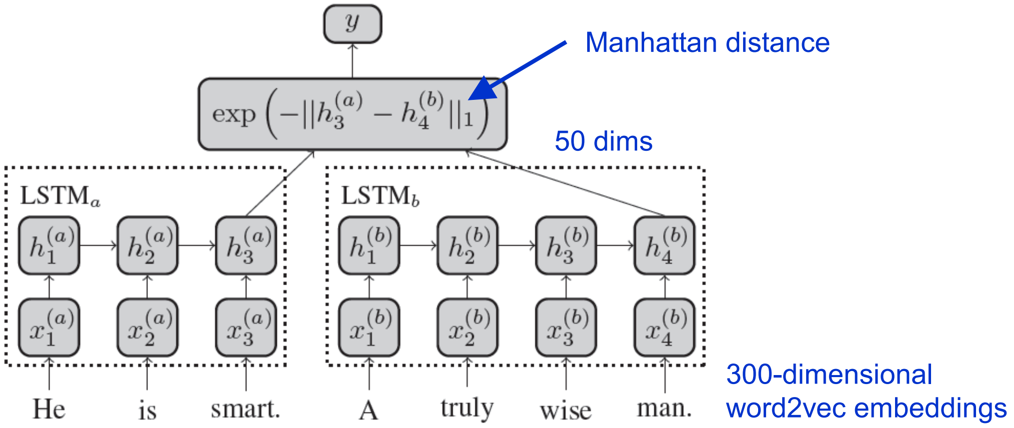
The output state vector of the boundary layer (dotted box) forms the embedding. RNN units are GRU units.

Once the network is trained, we discard the red and green sections of the network, and use the white section to embed new sentences.

From "Skip-Thought Vectors," Ryan Kiros et al., Arxiv 2015.

Last Time: Siamese Networks for Semantic Relatedness

This network is trained on pairs of sentences a, b with a similarity label y.



Parameters are shared between the two networks.

From “Siamese Recurrent Architectures for Learning Sentence Similarity” Jonas Mueller, Aditya Thyagarajan, AAAI-2016

Updates

282A Project checkin this week!

Assignment 2 deadline pushed back until Thursday.

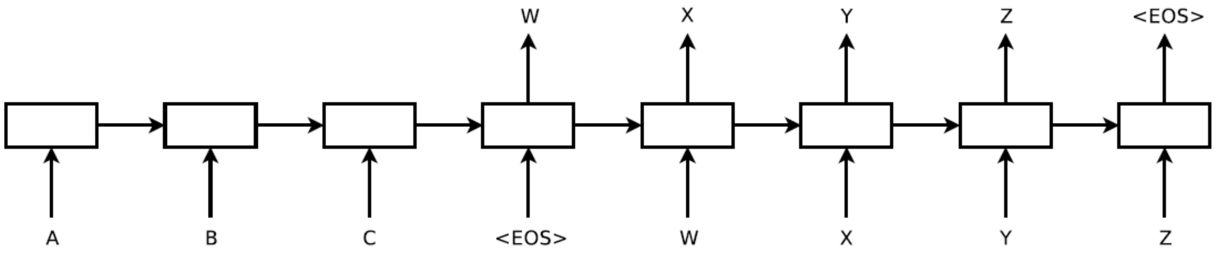
Assignment 3 also out by Thursday.

This Time: Translation

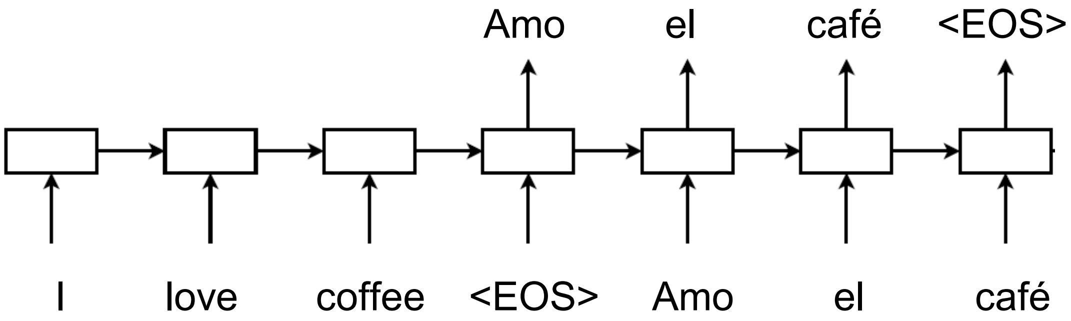
- Sequence-to-sequence translation
- Adding Attention
- Parsing as translation
- Attention only models
- English-to-English translation ?!

Sequence-To-Sequence RNNs

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

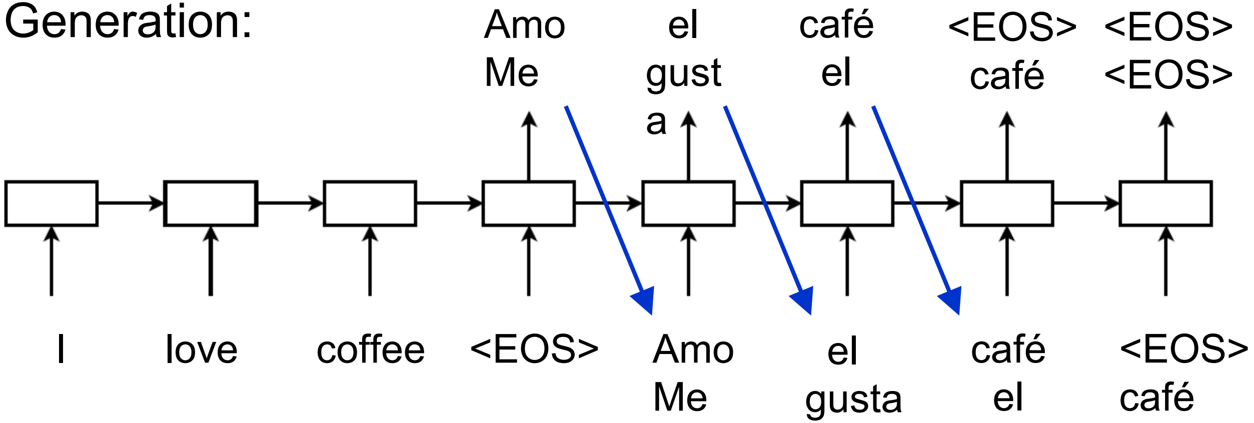


For translation:



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: the the the the the the the.
Reference 1: The cat is on the 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.

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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.

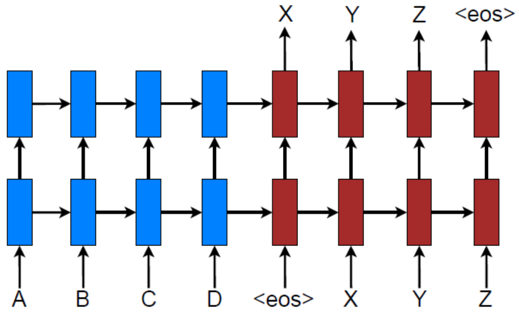
$$\text{BLEU} = \text{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right)$$

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

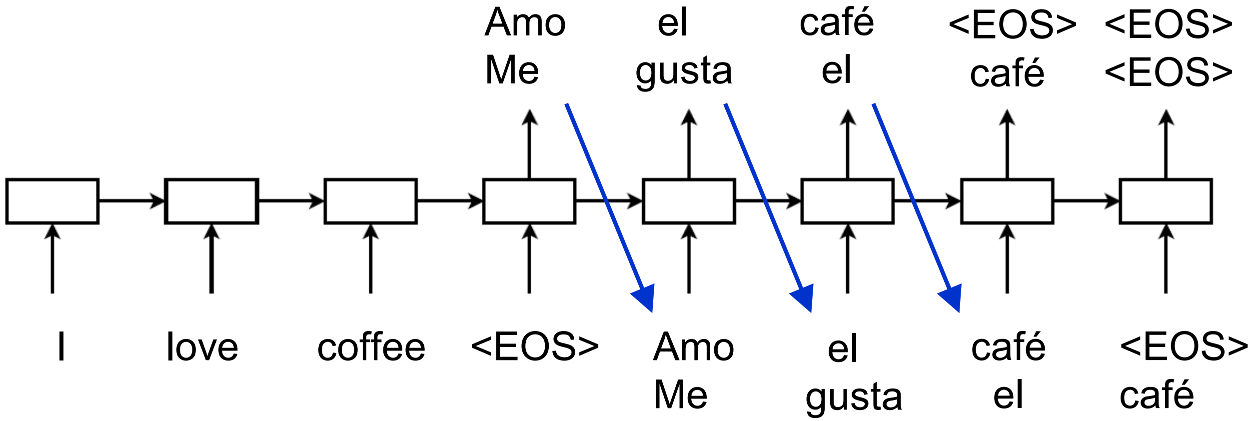
Candidate length c shorter than reference r translation

Sequence-To-Sequence Model Translation

Encoder Decoder



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**

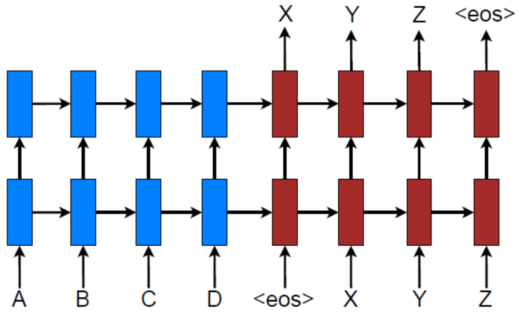
Reversed = reverse the order of the input sentence.

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

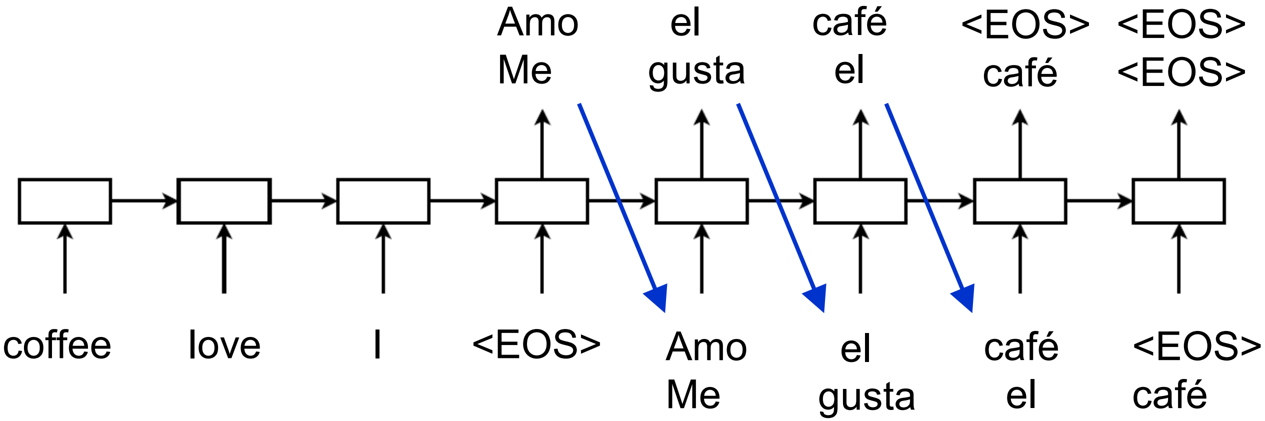
From Sutskeyver et al. “Sequence to Sequence Learning with Neural Networks” 2014.

Sequence-To-Sequence Model Translation

Input sequence reversal



A depth-2 model



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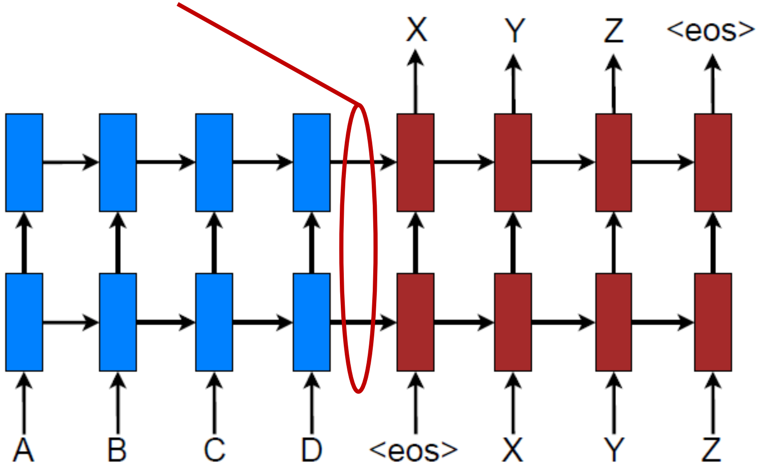
Beam sizes are tiny!!

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.

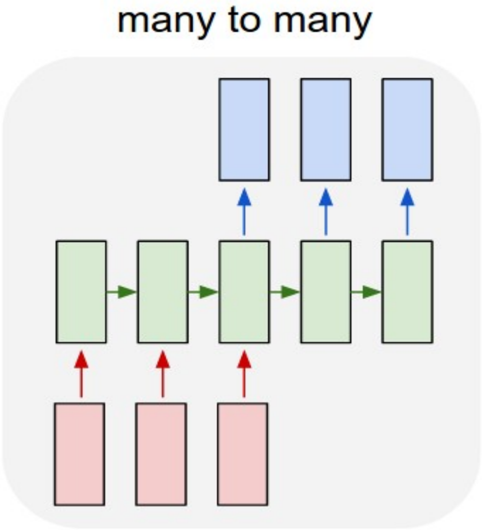


Sentence length varies, but the encoding always has a fixed size.

Soft Attention for Translation

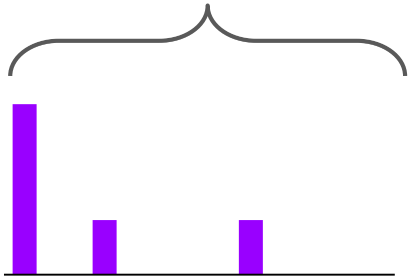
“I love coffee” -> “Me gusta el café”

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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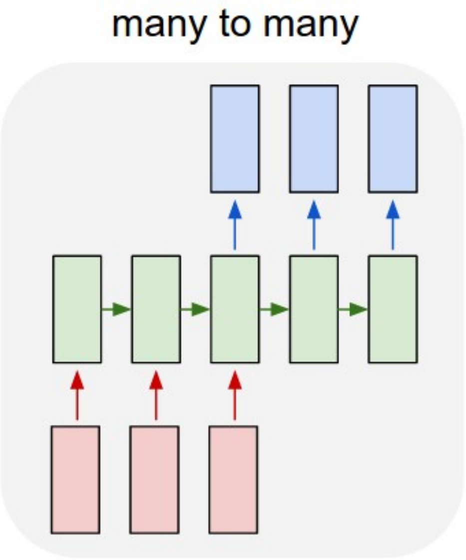

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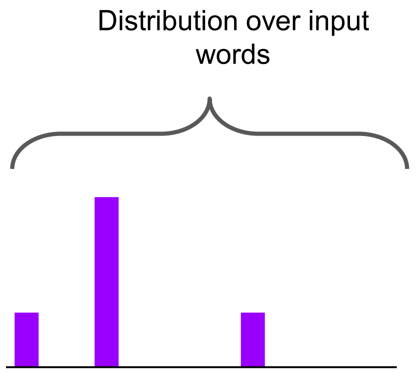

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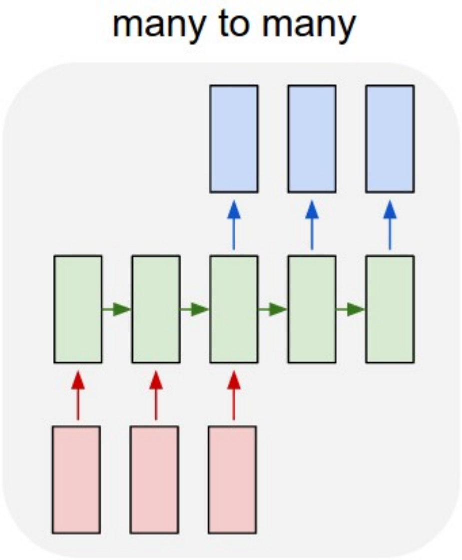

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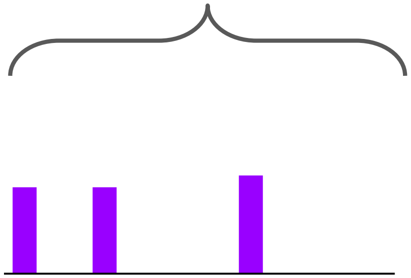

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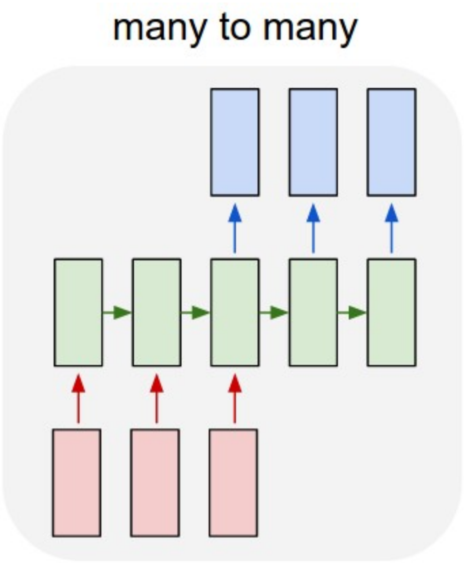

Soft Attention for Translation

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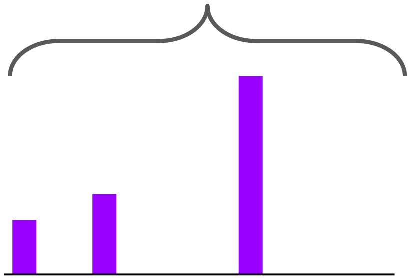
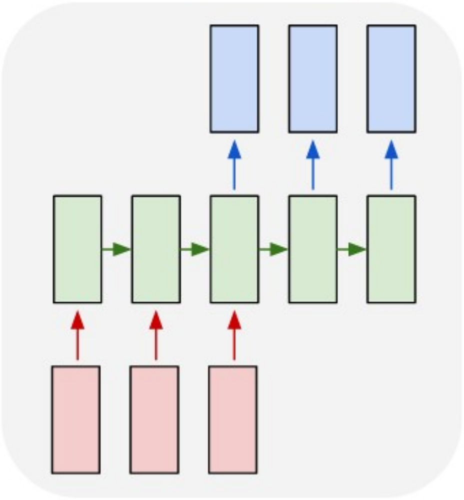


"I love coffee” -> “Me gusta el café”

many to many



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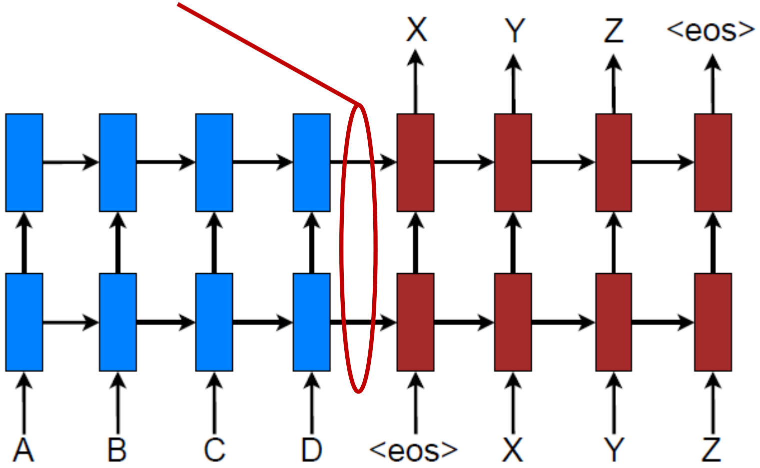
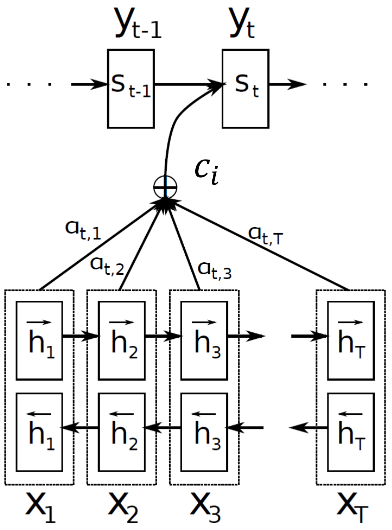


Sentence length varies, but the encoding always has a fixed size.

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})

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

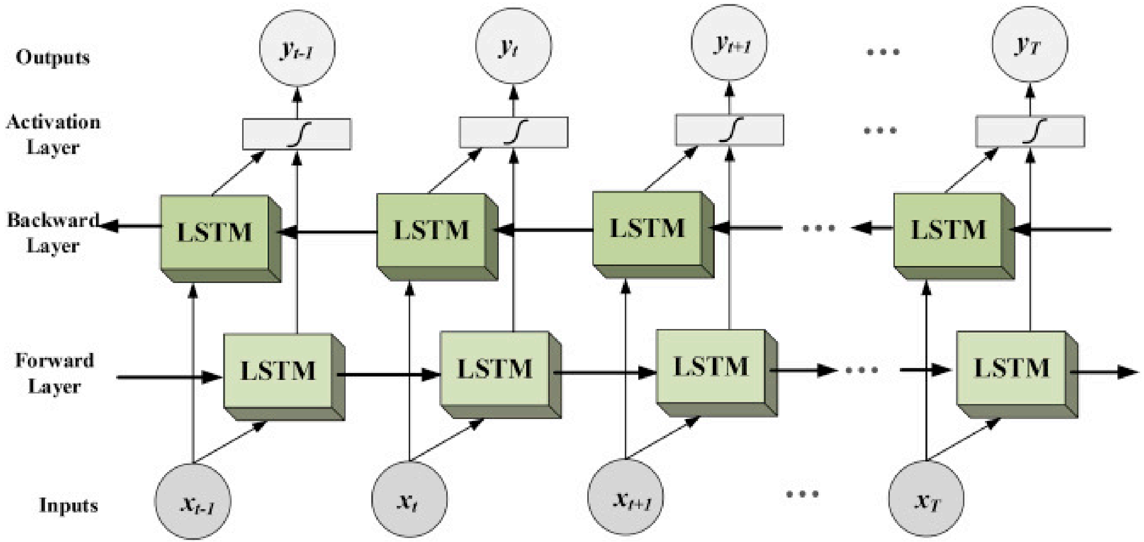
Alignment score (how well do input words near j match output words at position i):

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

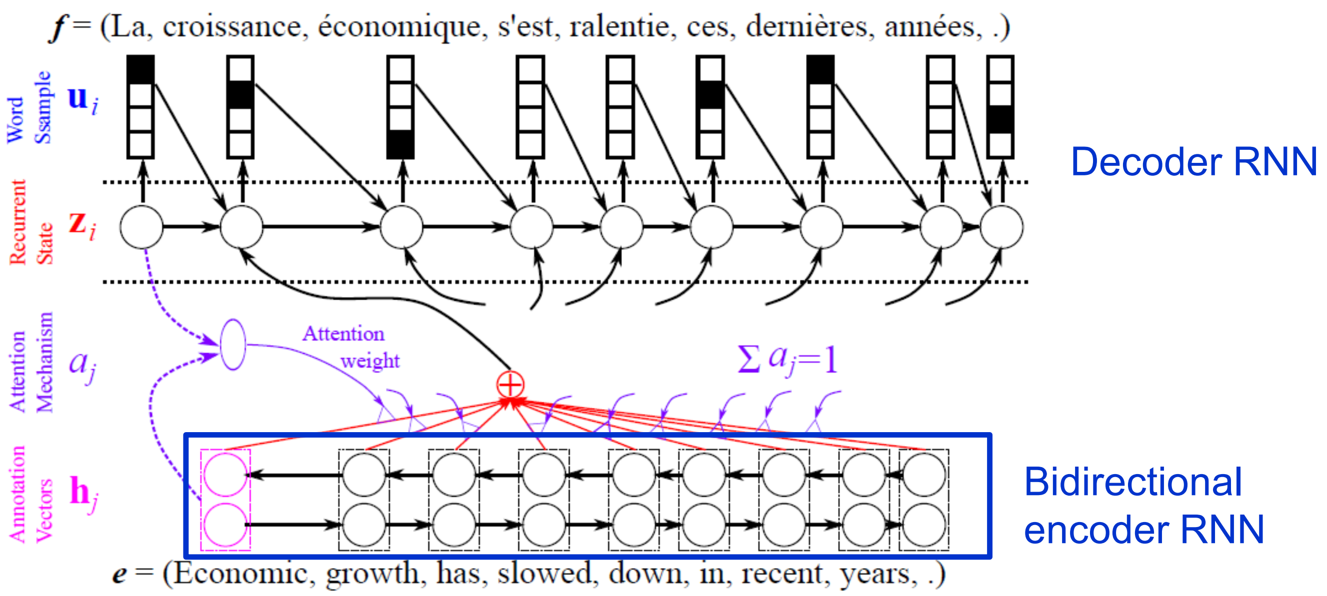
Bahdanau et al, “Neural Machine Translation by Jointly Learning to Align and Translate”, ICLR 2015

Aside: Bidirectional Recurrent Networks:

Implemented with forward and backward rows of units in parallel:

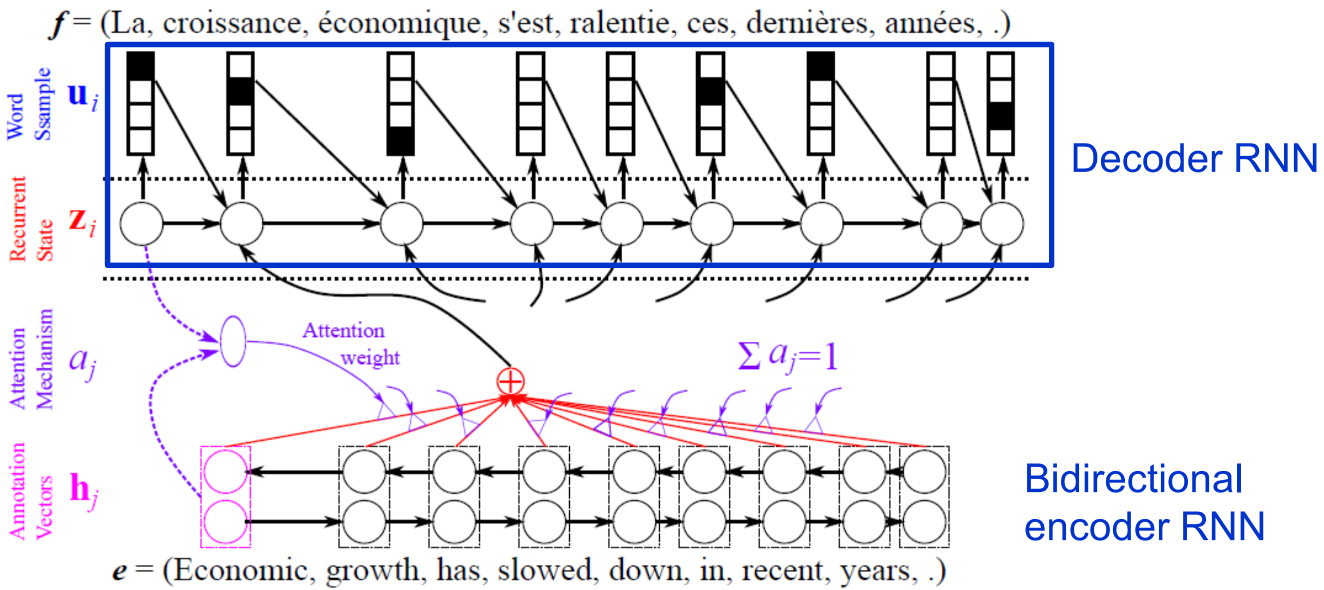


Soft Attention for Translation



From Y. Bengio CVPR 2015 Tutorial

Soft Attention for Translation



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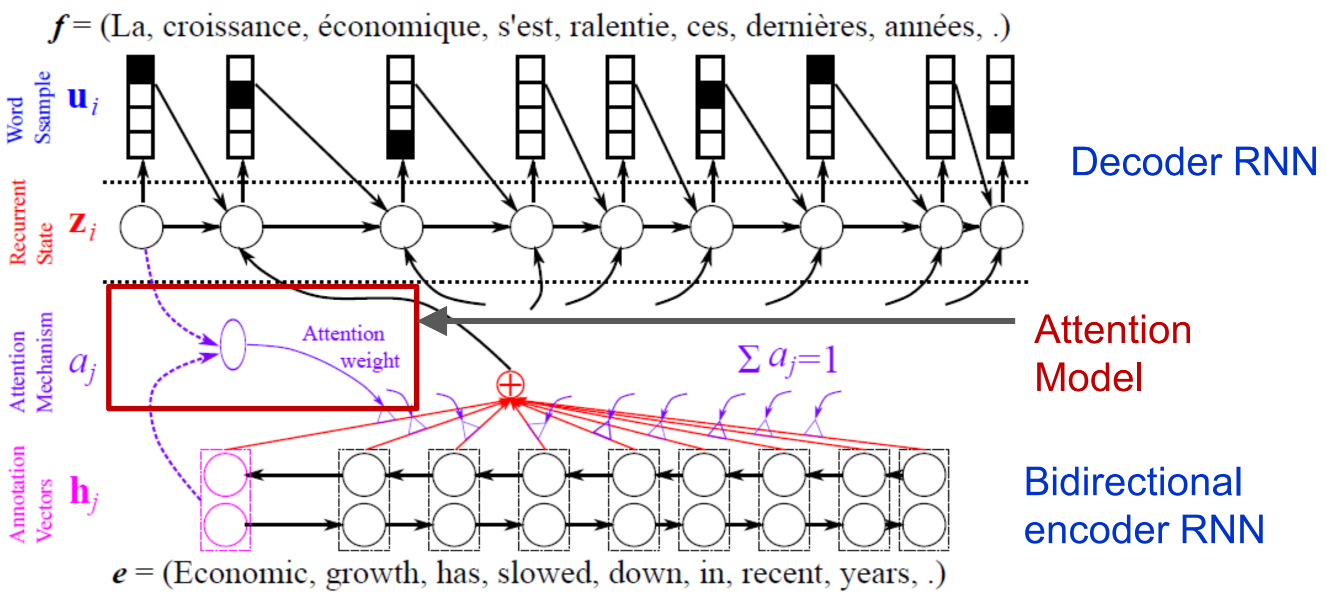

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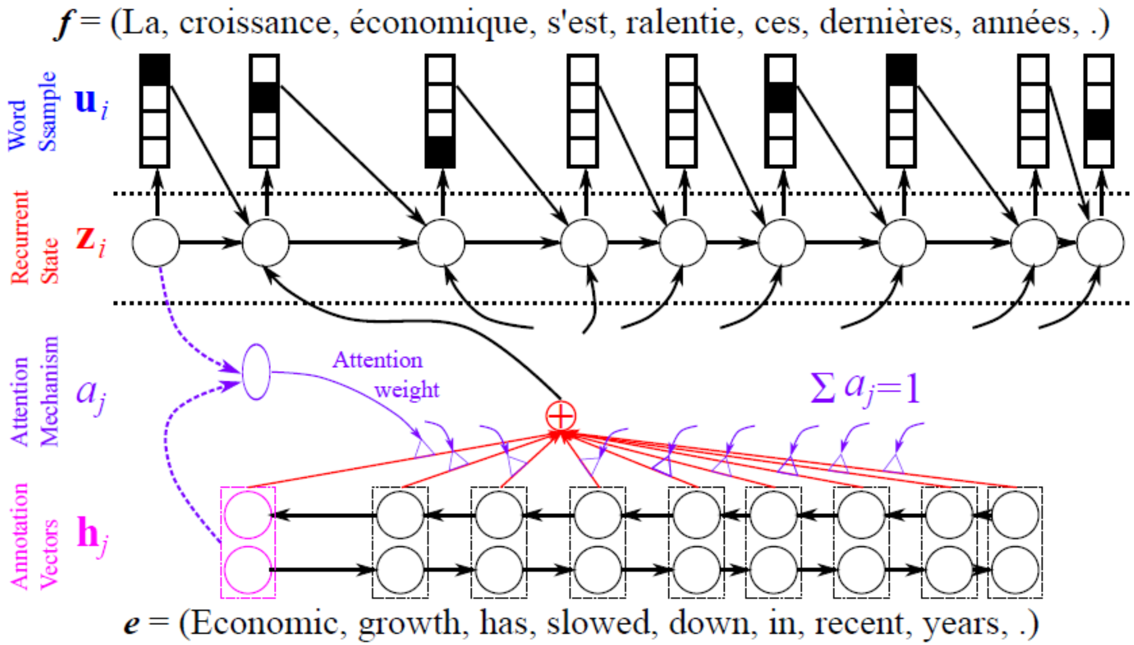
Soft Attention for Translation

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

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



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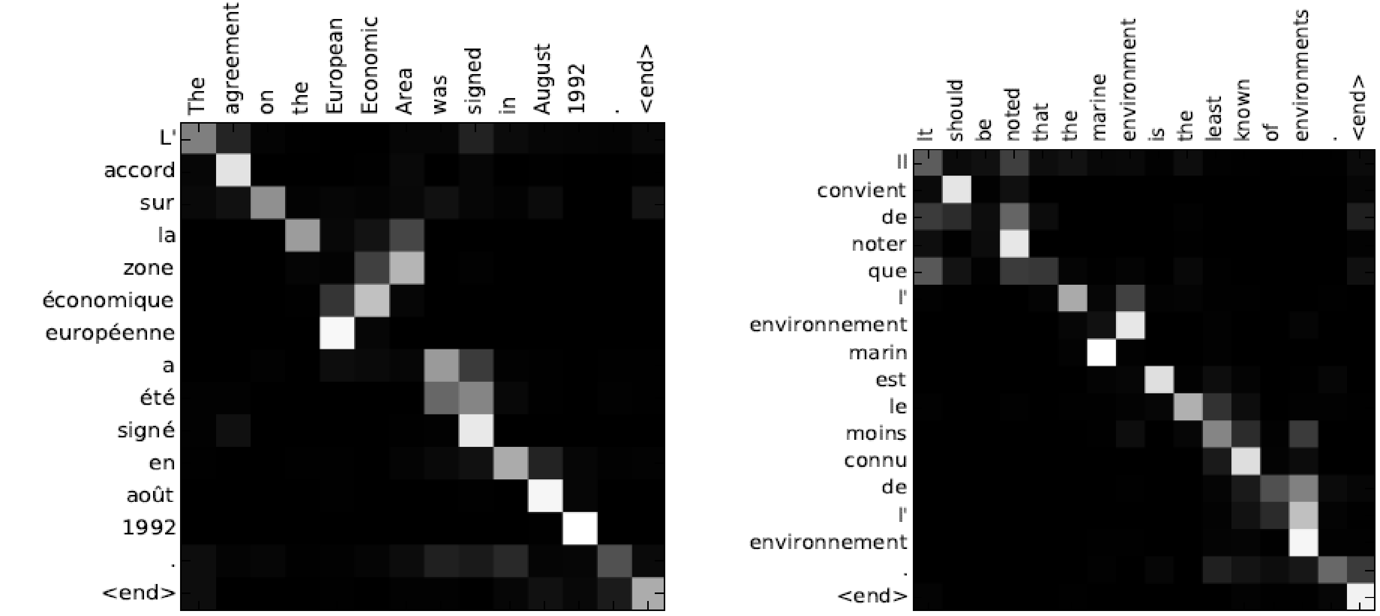


(a) (b)

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

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)**

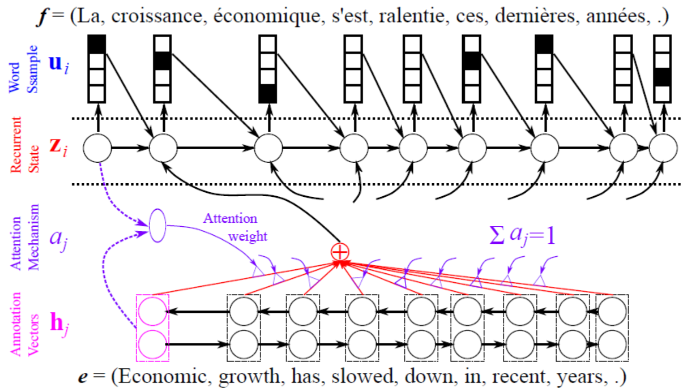
Model	Note
18.3	Neural MT
18.2	JHU, SMT+LM+OSM+Sparse
17.6	CU, Phrase SMT
17.4	U.Edinburgh, Phrase SMT
16.1	U.Edinburgh, Syntactic SMT

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.



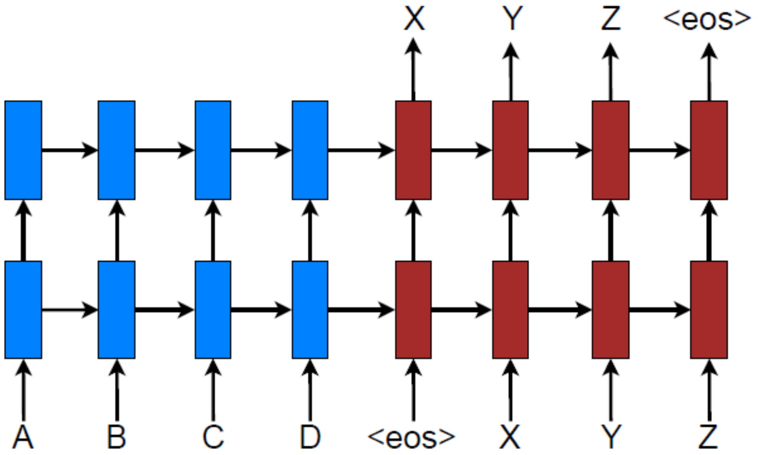
Doesn’t generalize to deeper networks (shown to be Important by Sutskeyver et al.).

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):



Effective Approaches to Attention-based Neural Machine Translation
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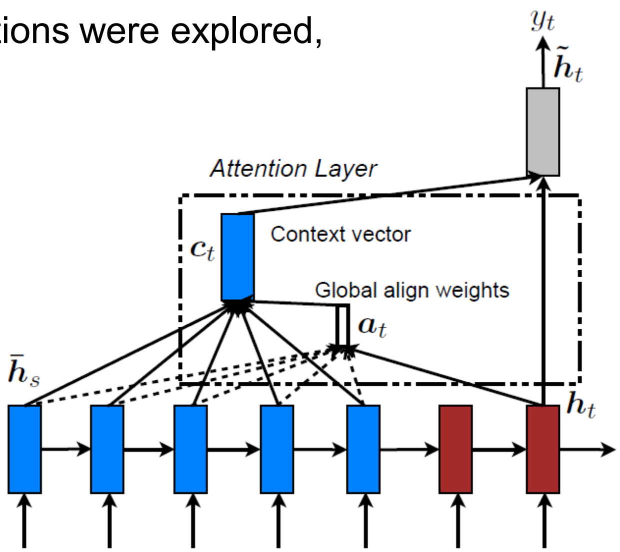
Global Attention Model

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.



Effective Approaches to Attention-based Neural Machine Translation
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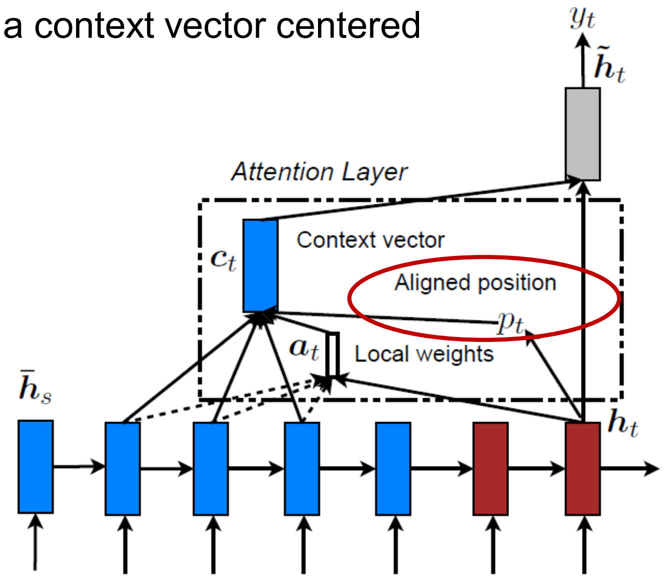
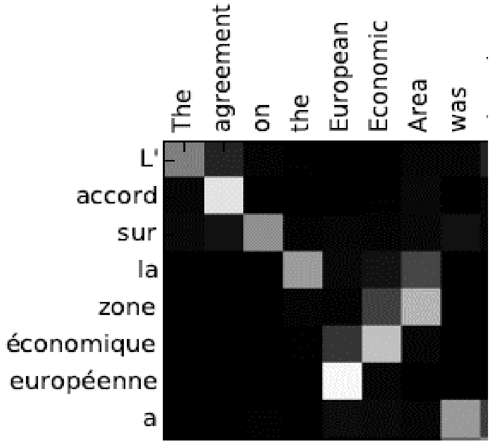
Local Attention Model

- 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**

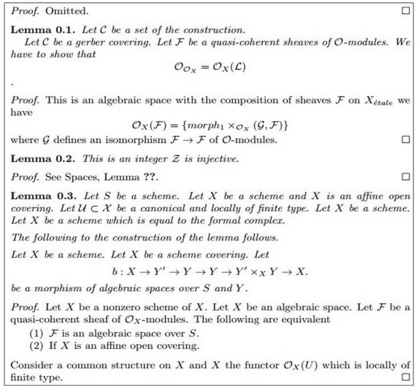
Table 2: **WMT'15 English-German results** – *NIST* BLEU scores of the winning entry in WMT'15 and our best one on newstest2015.

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

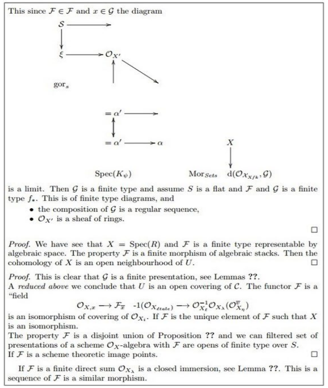
$$b : X \to Y' \to Y \to Y \to Y' \times_X Y \to X.$$

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

$\mathcal{S}$
ξ
$\mathcal{O}_{X'}$
gor_s
$= \alpha'$
$= \alpha'$
α
X
$\mathrm{Spec}(K_\psi)$
Mor_{Sets}
$\mathrm{d}(\mathcal{O}_{X_{X/k}}, \mathcal{G})$

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

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

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 ");
}
```

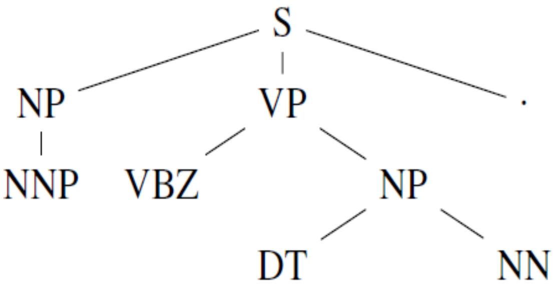
They seem to do well with tree-structured data.

What about natural language parsing?

Parsing

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

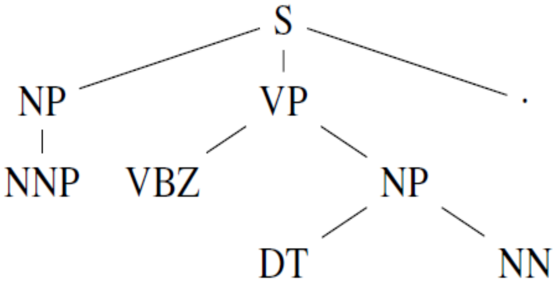
John has a dog . $\rightarrow$



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

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”)

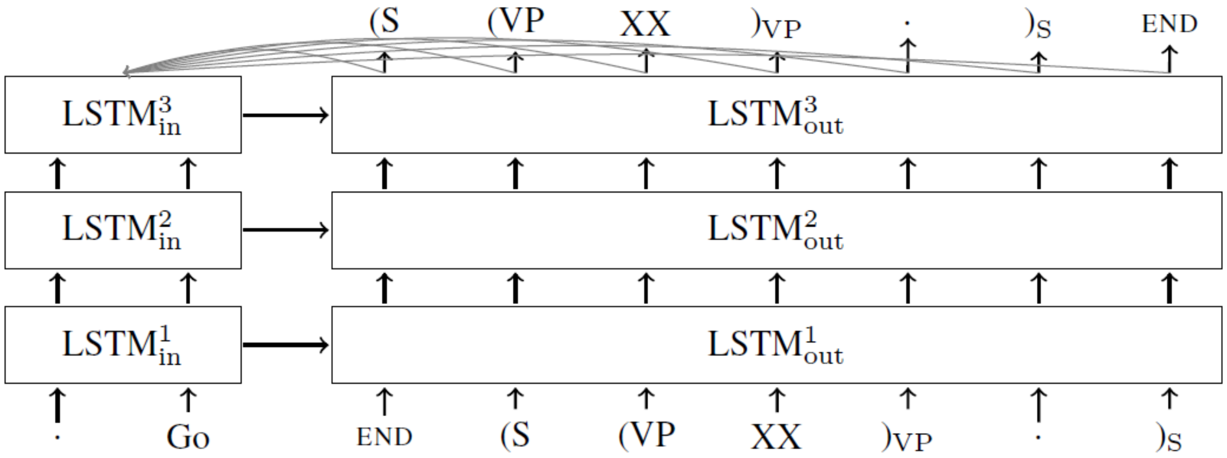
VBZ = Verb, 3rd person, singular (“has”)

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”…)

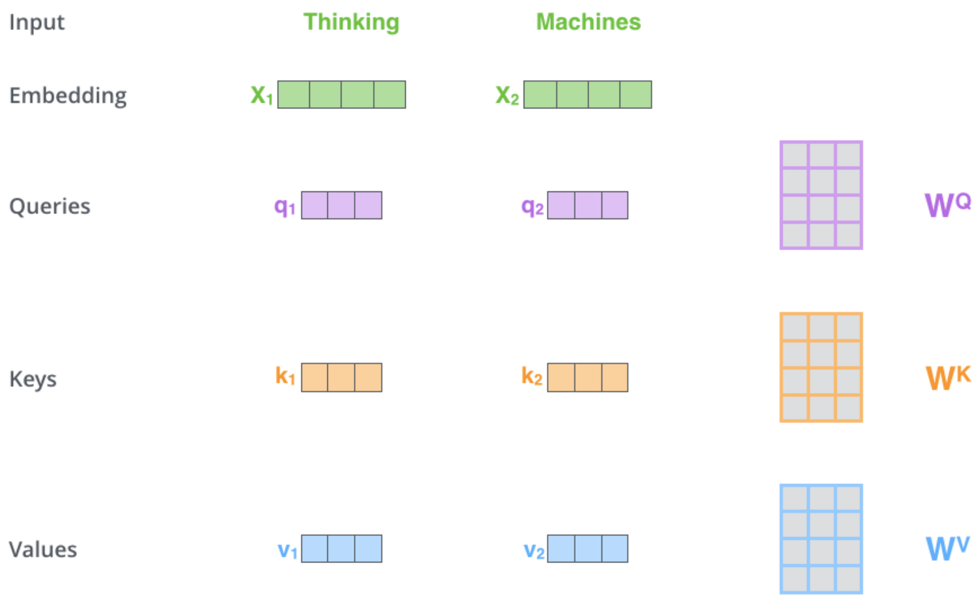
Alternative:

- Convolution – but has other limitations.

The Transformer

"Attention Is All You Need" Vaswani, Shazeer, Parmar, Uszkoreit, Jones, Gomez, Kaiser, Polosukhin 2017

The Transformer uses QKV attention – Query-Key-Value. Idea is that a Query matches different "Keys" and retrieves their "Values".



Embed vectors as queries with W^Q

Embed vectors as keys with W^K

Embed vectors as values with W^V

Figure from "The Illustrated Transformer" – Jay Alamar

The Transformer – matching queries to keys

The Transformer uses QKV attention – Query-Key-Value.

Scores are inner products between a query and various keys.

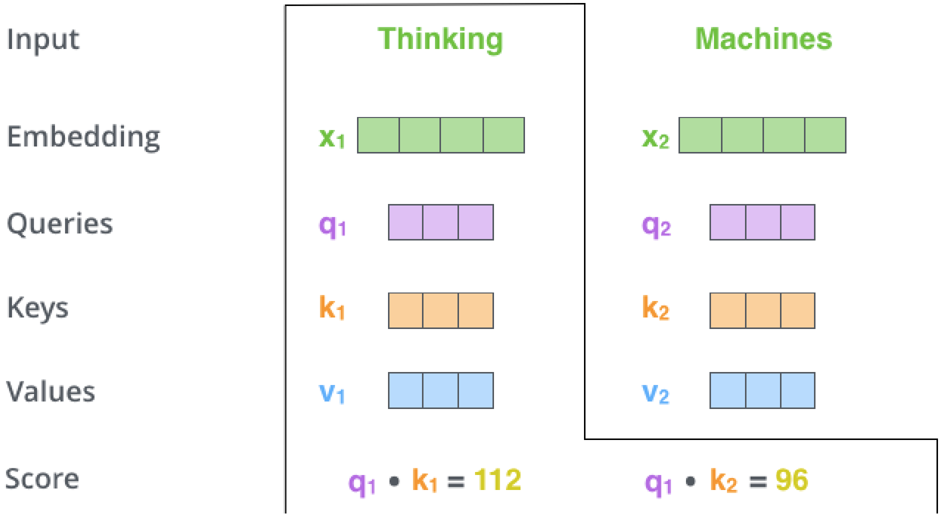


Figure from “The Illustrated Transformer” – Jay Alamar

The Transformer
- Value retrieval

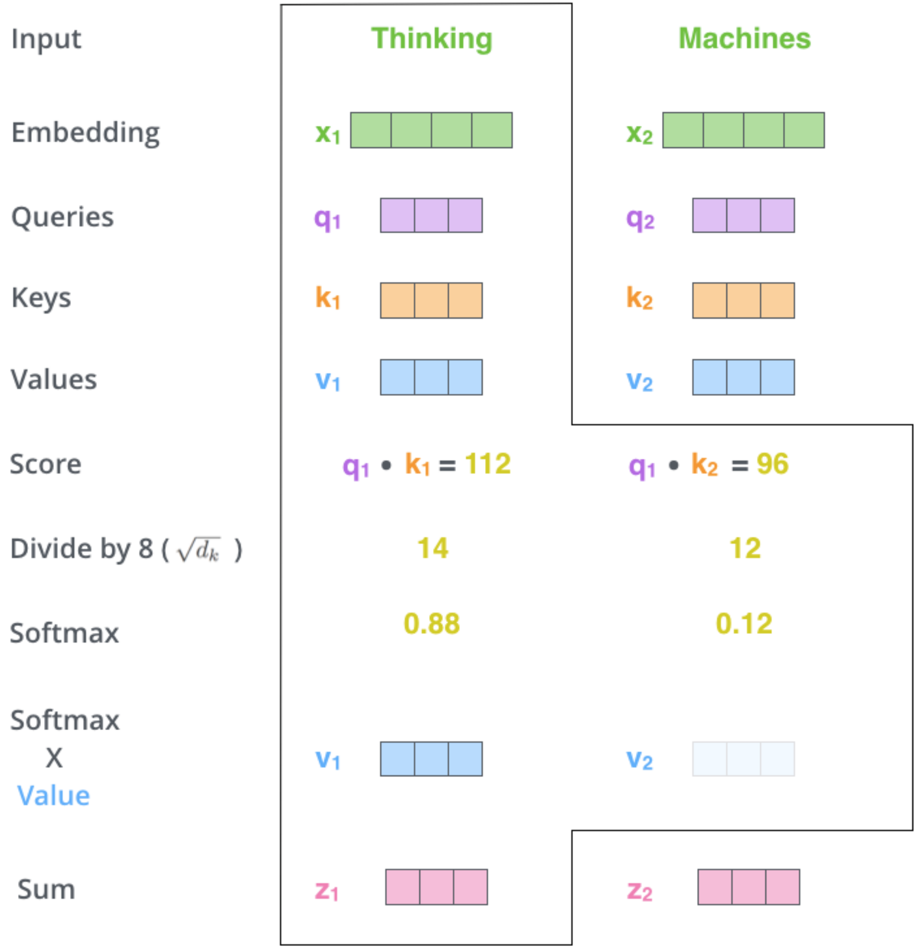
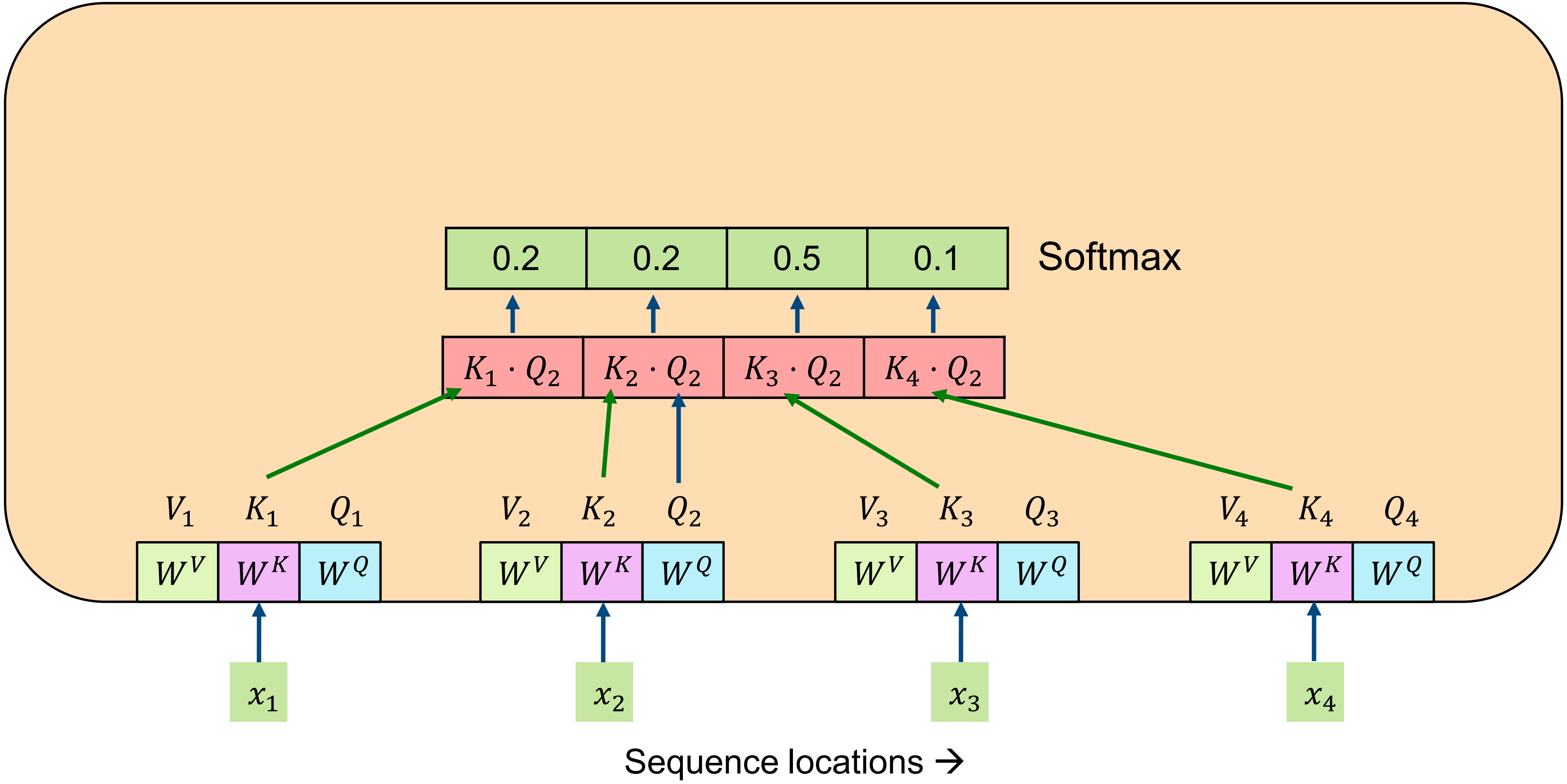
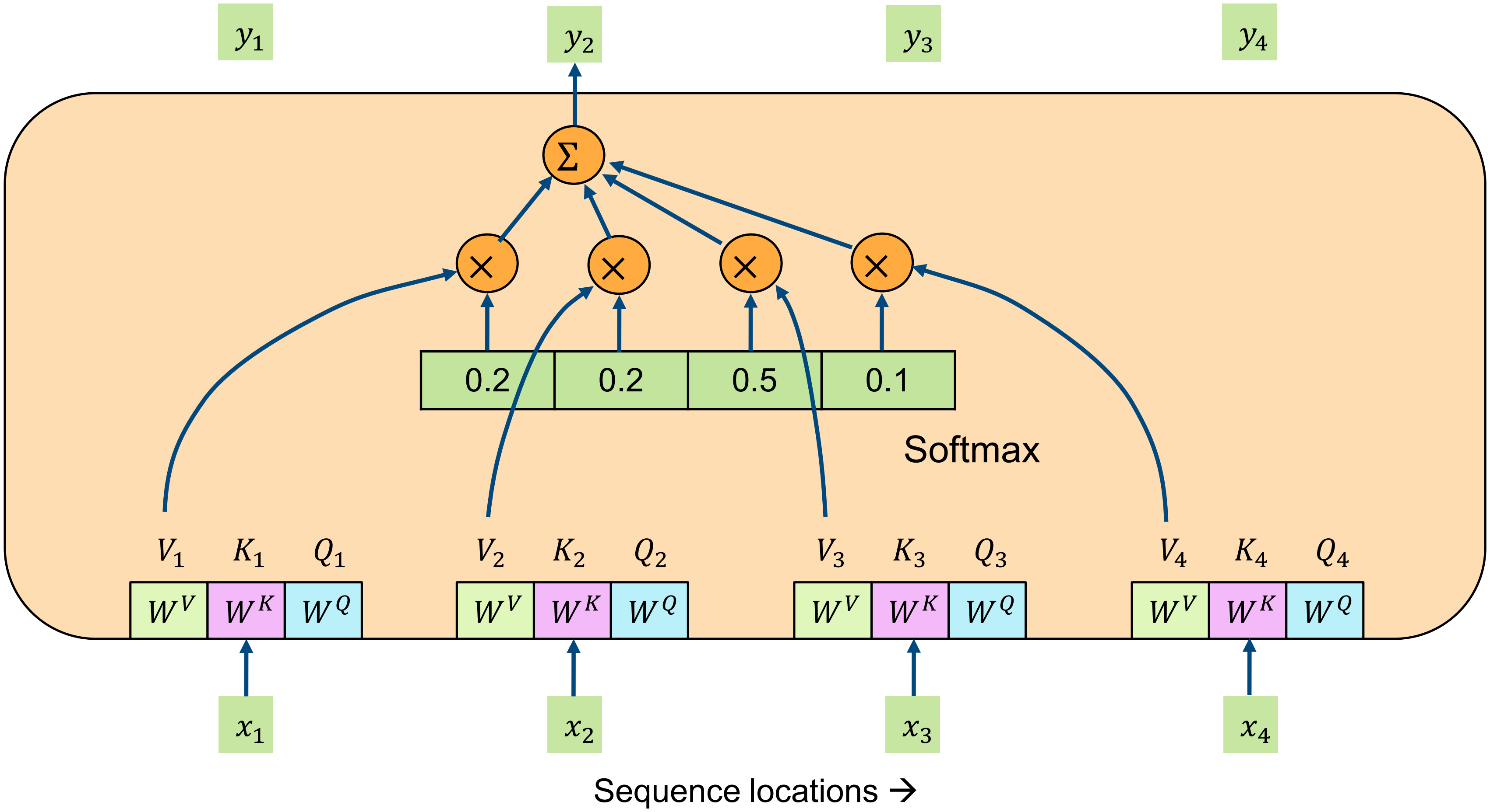


Figure from "The Illustrated Transformer"
– Jay Alamar

The Transformer – Self-Attention Layer



The Transformer – Self-Attention Layer



Attention Implementation with matrices

Transformer networks have extreme parallelism by using *matrices* to hold all the vectors in the network:
Q = matrix of all query vectors (as rows)
K = matrix of all keys (as rows)
V = matrix of all values (as rows)

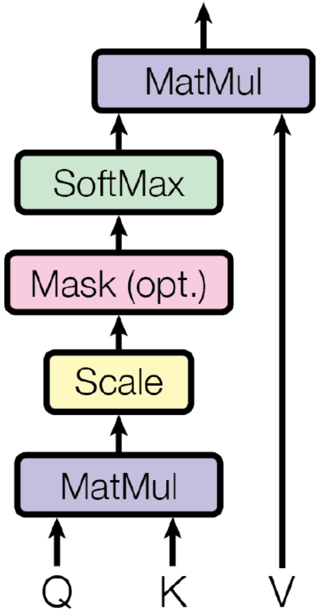
The row index is the position in the sequence.

The entire attention operation can be computed as a *single matrix formula* as:

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

where the softmax is applied across rows (not columns).

Scaled Dot-Product Attention

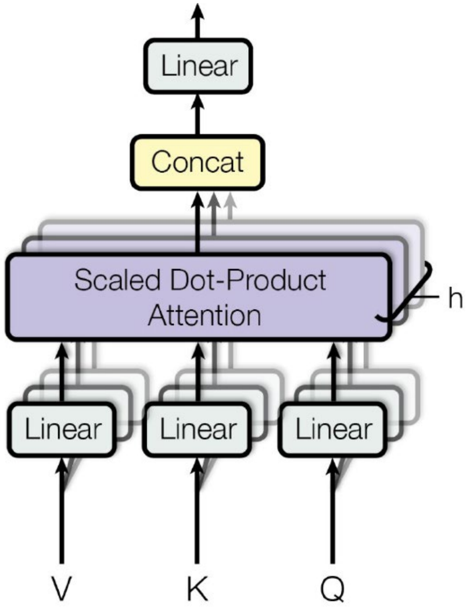


Multi-Headed Attention

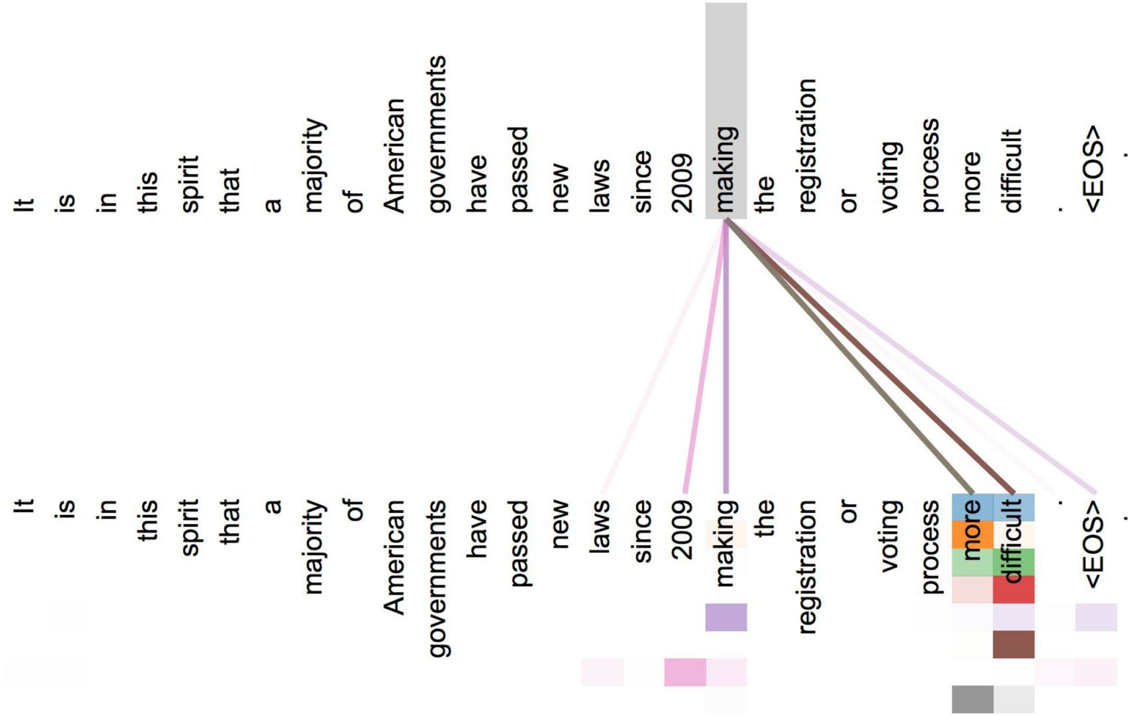
- Standard attention allows each location to attend with a single weight/value embedding to another location.

- We can extend this with “multi-headed” attention by breaking inputs and outputs into ranges, and applying different embeddings for each range.

- The figure to the right shows h heads.

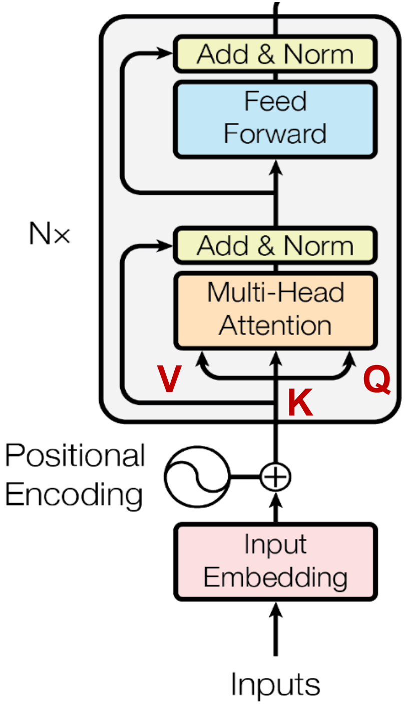


Multi-Headed Attention



Transformer Encoder

- Basic unit shown at right.
- The input is a sequence of symbols at the bottom.
- Because different positions are encoded as matrices, its common not to show the sequence positions.
- Multiple layers can be stacked.



Transformer Encoder

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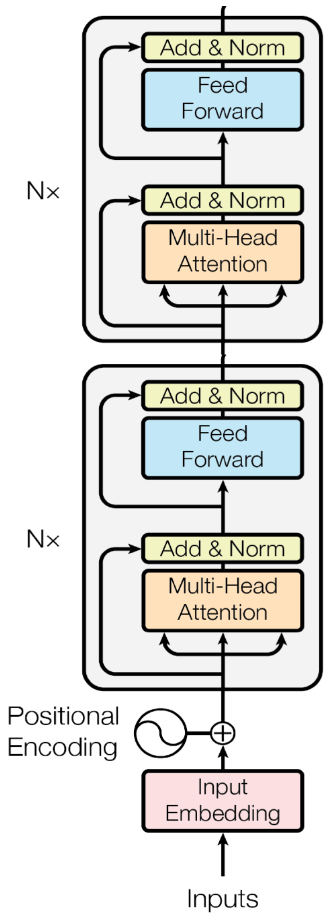
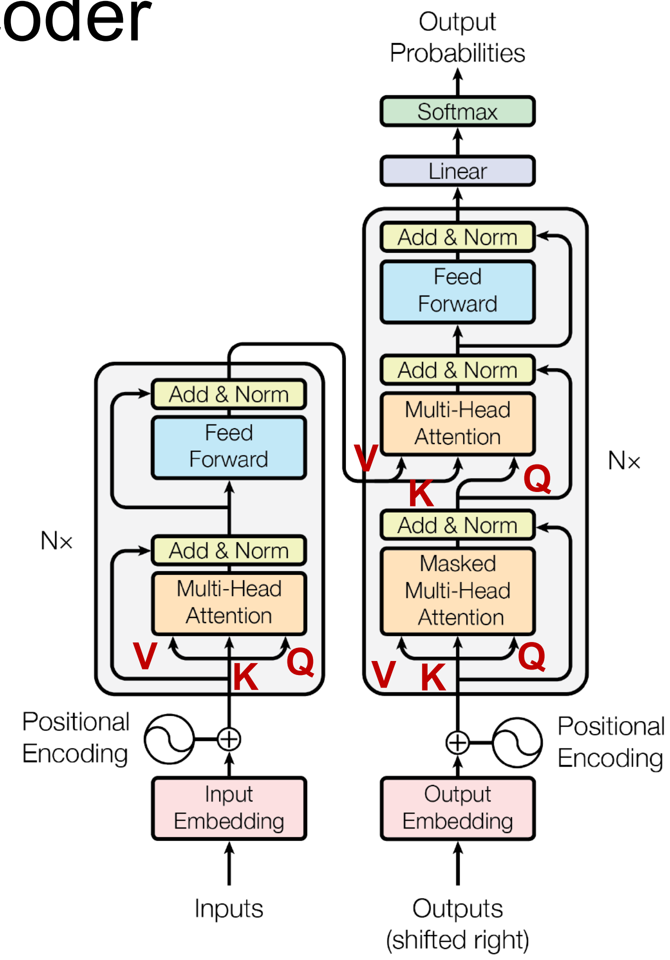
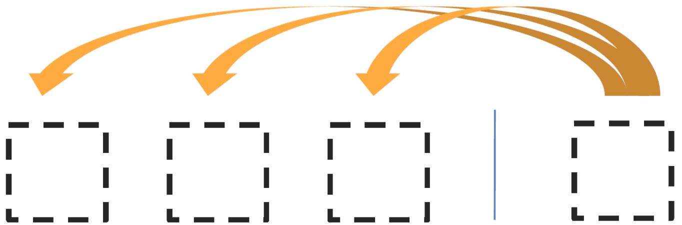


The Transformer Encoder/Decoder

- Basic unit shown at right.
- Now there is both and encoder with self-attention, and a decoder with both masked self-attention and cross-attention.
- In experiments, stacked with N=6.
- 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.



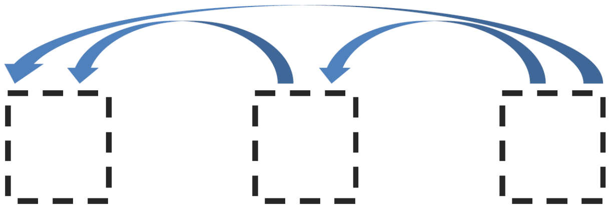
Attention Types in Transformer Networks



We saw this in Bahdanau and Luong models

Encoder-Decoder Attention

Encoder Self-Attention



MaskedDecoder Self-Attention

image from Lukas Kaiser, Stanford NLP seminar

Attention in Transformer Networks

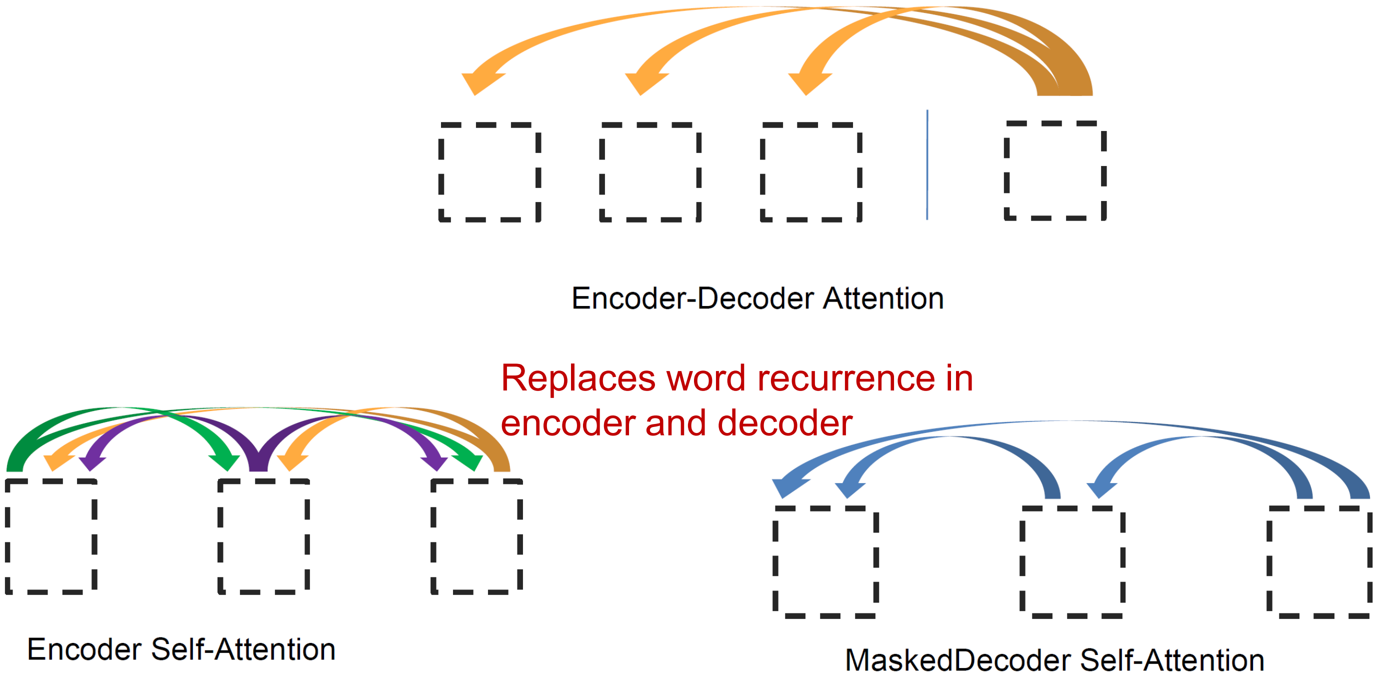
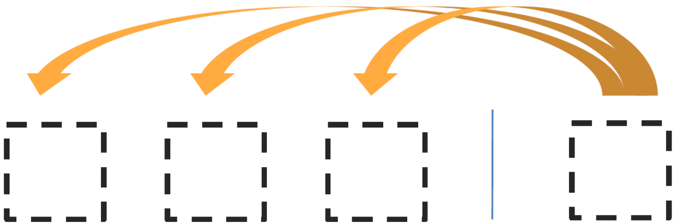


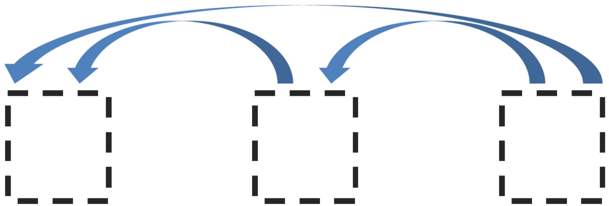
image from Lukas Kaiser, Stanford NLP seminar

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 Efficiency

Compared to a recurrent network, how many steps does it take to compute a forward training pass in a transformer network compared to a recurrent network on a sequence of length n?

Transformer / RNN:

A. $O(n)$ / $O(n)$

B. $O(n)$ / $O(n^2)$

C. $O(1)$ / $O(n)$

D. $O(1)$ / $O(1)$

Oops!

Compared to a recurrent network, how many steps does it take to compute a forward training pass in a transformer network compared to a recurrent network on a sequence of length n?

Transformer / RNN:

A. $O(n)$ / $O(n)$

No the transformer forward pass is only a series of matrix operations on matrices whose number of rows is the sequence length $O(1)$.

Try Again

Continue

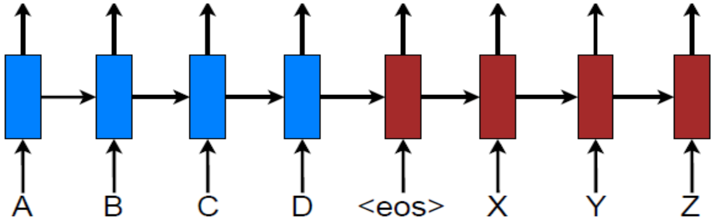
Oops!

Compared to a recurrent network, how many steps does it take to compute a forward training pass in a transformer network compared to a recurrent network on a sequence of length n?

Transformer / RNN:

B. $O(n)$ / $O(n^2)$

No the transformer forward pass is only a series of matrix operations on matrices whose number of rows is the sequence length $O(1)$, and the recurrent network effort is linear because of the recurrent (horizontal) connections:



Try Again

Continue

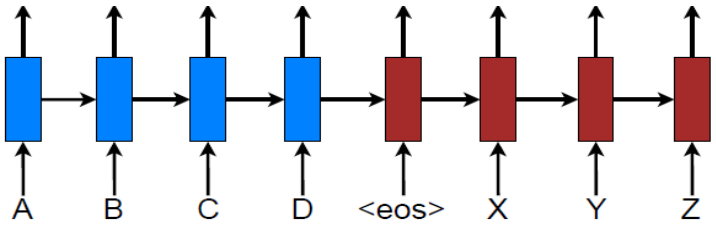
Correct!

Compared to a recurrent network, how many steps does it take to compute a forward training pass in a transformer network compared to a recurrent network on a sequence of length n?

Transformer / RNN:

C. $O(1)$ / $O(n)$

The transformer forward pass is a series of matrix operations on matrices whose number of rows is the sequence length $O(1)$, and the recurrent network effort is linear because of the recurrent (horizontal) connections:



Try Again

Continue

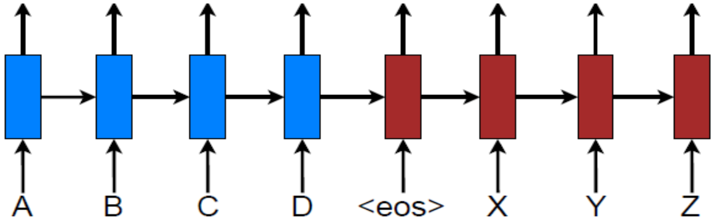
Oops!

Compared to a recurrent network, how many steps does it take to compute a forward training pass in a transformer network compared to a recurrent network on a sequence of length n?

Transformer / RNN:

D. $O(1)$ / $O(1)$

No the recurrent network effort is linear because of the recurrent (horizontal) connections:



Try Again

Continue

Position encoding

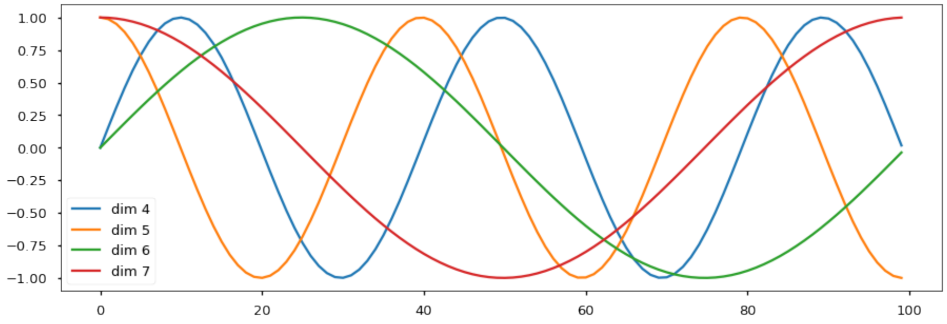
Every cell in the transformer has the same “view” of the data below. Its important to break this symmetry so different cells do different things. Spatial encoding is usually used:

The encoding vector has the same dimension as the model.

Its components are all sinusoidal functions of position.

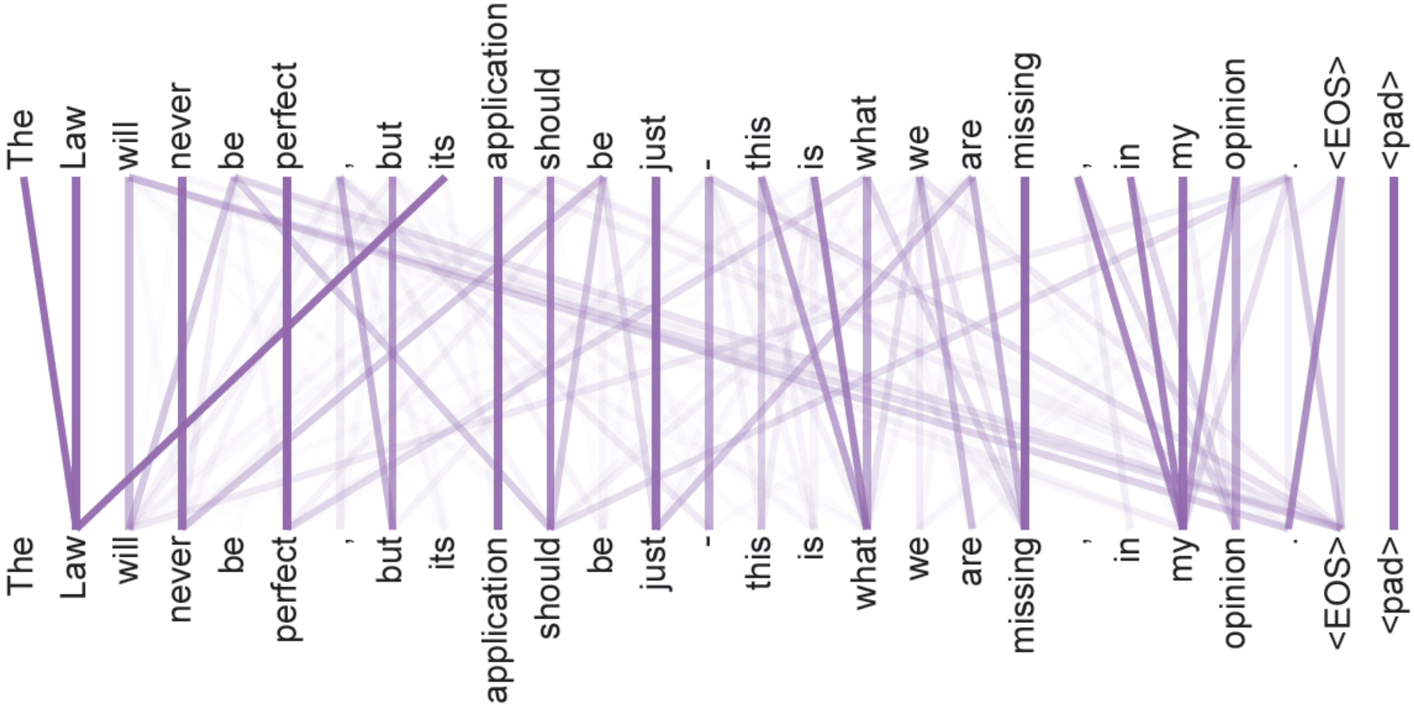
The periods of the sinusoids form a geometric series.

position
vector
values



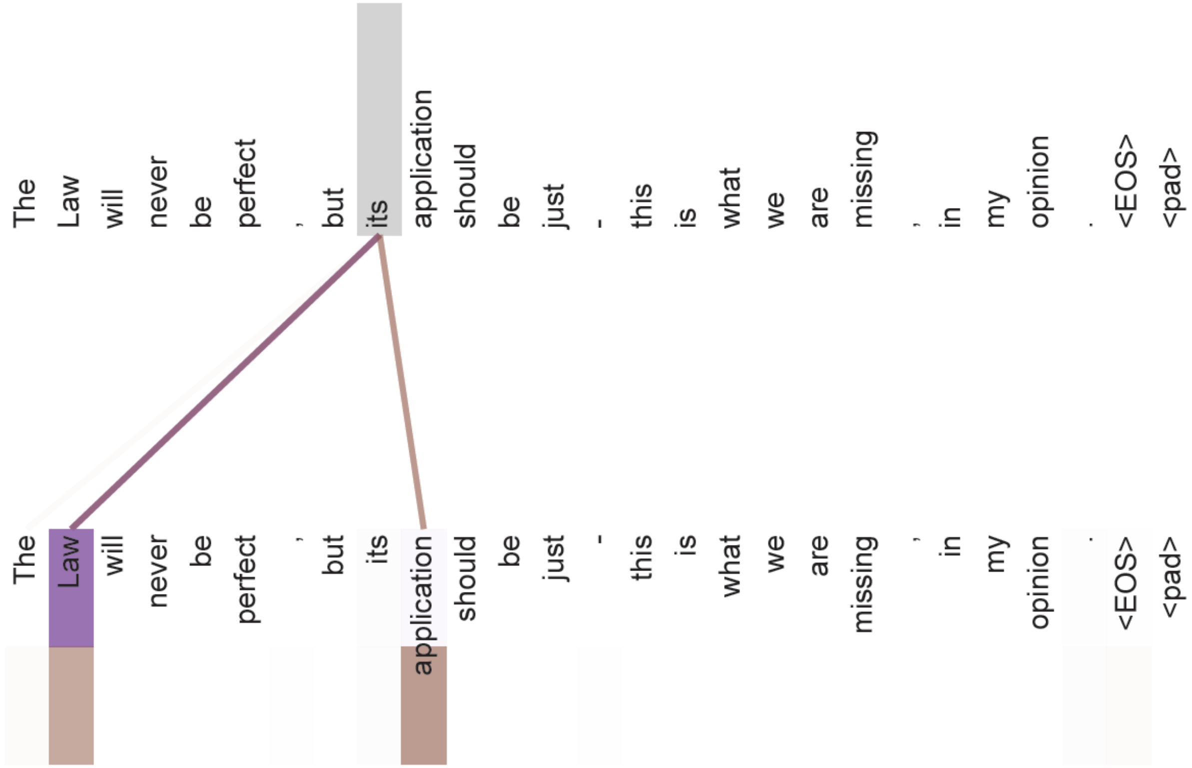
Position in the input

Multi-Headed Attention



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

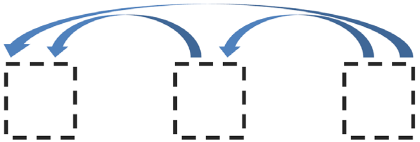
Summarization: M >> N

$O(MN)$

Encoder-Decoder Attention

$O(M^2)$

Encoder Self-Attention



$O(N^2)$

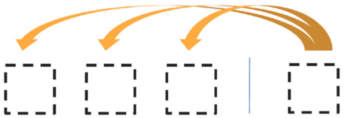
MaskedDecoder Self-Attention

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.

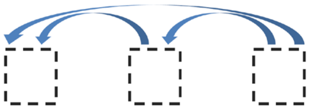


$O(MN)$

Encoder-Decoder Attention

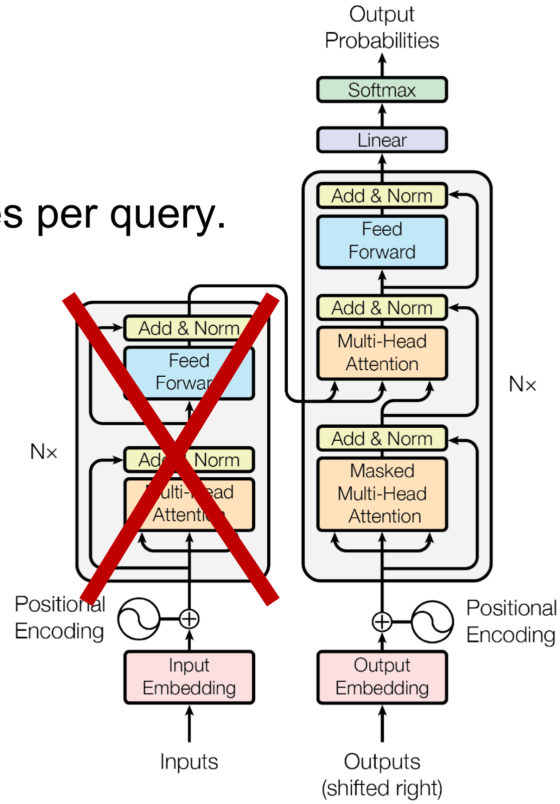
$O(M^2)$

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

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.