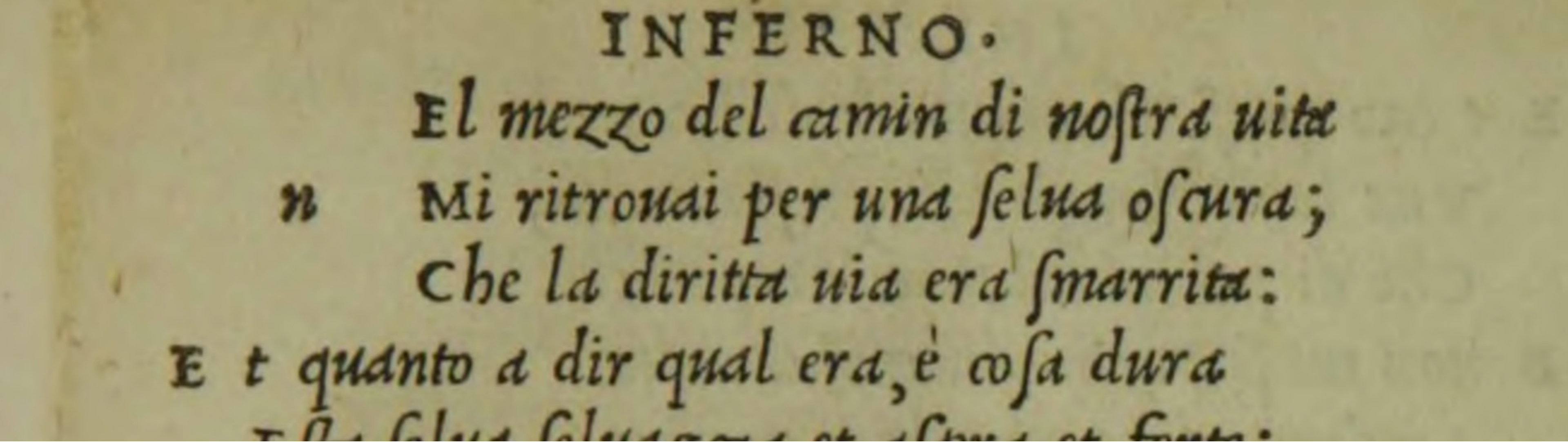

INFERNO.

N El mezzo del camin di noſtra uita

Mi ritrouai per una ſelua oſcura;

Che la diritta uia era ſmarrita:

E t quanto a dir qual era, è coſa dura

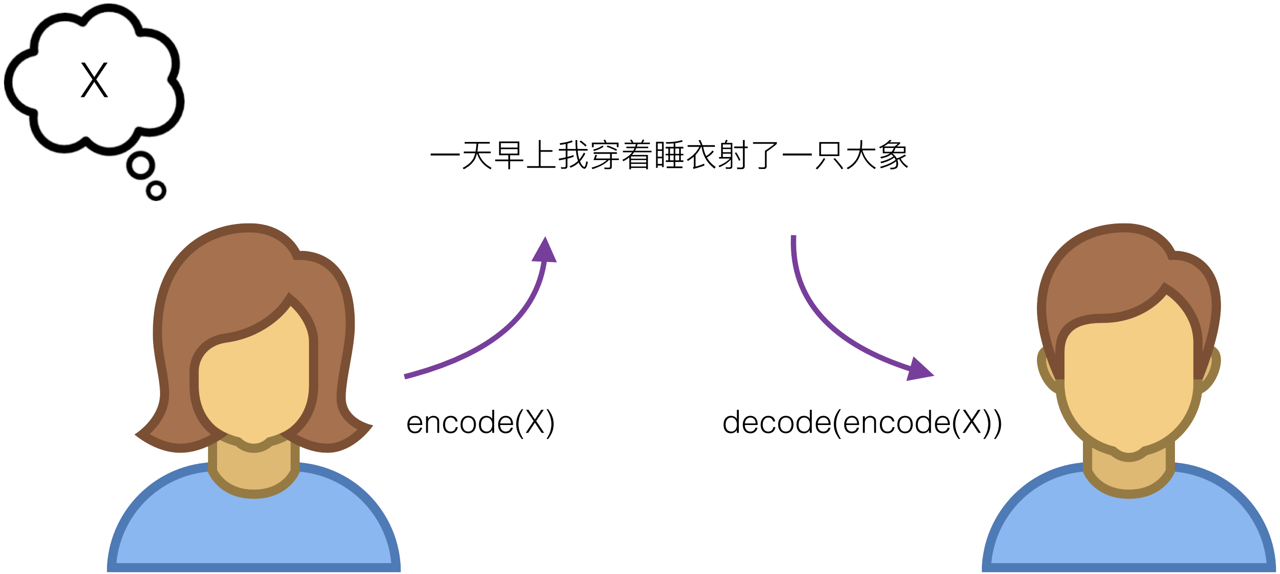
Natural Language Processing

Info 159/259

Lecture 20: Machine Translation (April 6, 2023)

David Bamman, UC Berkeley

Machine Translation

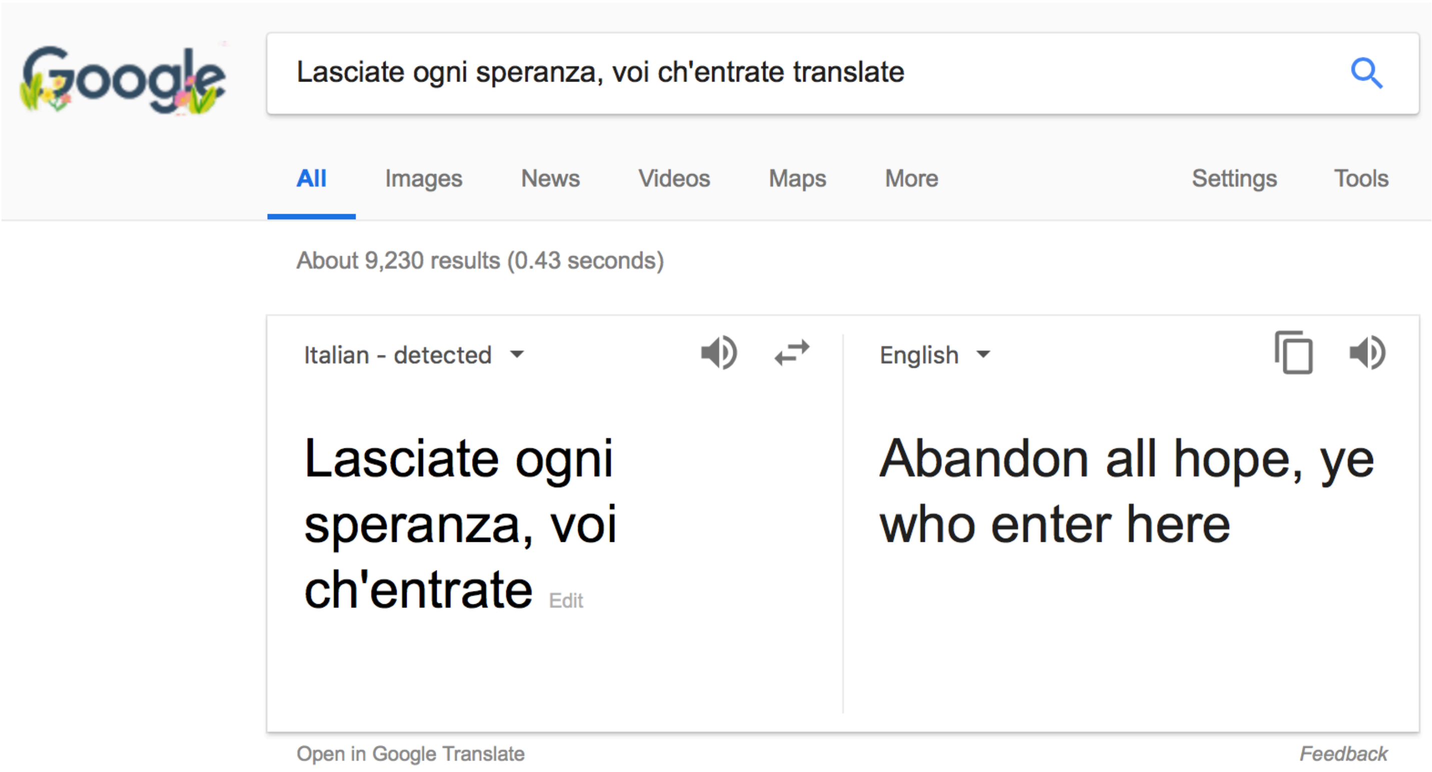


When I look at an article in Russian, I say: 'This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode.'

Weaver 1955

Machine Translation

Task	X	Y
Sentiment analysis	I hate this movie!	negative
POS tagging	I hate this movie!	PRP VB DT NN .
Parsing	I hate this movie!	[tree]
MT	Lasciate ogni speranza, voi ch'entrate	Abandon all hope, you who enter!
Conversational agent	How are you?	I'm great!


Google
Lasciate ogni speranza, voi ch'entrate translate
All
Images
News
Videos
Maps
More
Settings
Tools
About 9,230 results (0.43 seconds)
Italian - detected
English
Lasciate ogni speranza, voi ch'entrate
Edit
Abandon all hope, ye who enter here
Open in Google Translate
Feedback

^ There are many English translations of this famous line. Some examples include

- *All hope abandon, ye who enter here* – Henry Francis Cary (1805–1814)
- *All hope abandon, ye who enter in!* – Henry Wadsworth Longfellow (1882)
- *Leave every hope, ye who enter!* – Charles Eliot Norton (1891)
- *Leave all hope, ye that enter* – Carlyle Okey-Wicksteed (1932)
- *Lay down all hope, you that go in by me.* – Dorothy L. Sayers (1949)
- *Abandon all hope, ye who enter here* – John Ciardi (1954)
- *Abandon every hope, you who enter.* – Charles S. Singleton (1970)
- *No room for hope, when you enter this place* – C. H. Sisson (1980)
- *Abandon every hope, who enter here.* – Allen Mandelbaum (1982)
- *Abandon all hope, you who enter here.* – Robert Pinsky (1993); Robert Hollander (2000)
- *Abandon every hope, all you who enter* – Mark Musa (1995)
- *Abandon every hope, you who enter.* – Robert M. Durling (1996)

Verbatim, the line translates as "Leave (*lasciate*) every (*ogne*) hope (*speranza*), ye (*voi*) that (*ch'*) enter (*intrate*)."

https://en.wikipedia.org/wiki/Inferno_(Dante)#cite_note-18

Data

- Modern machine translation systems are learned from parallel texts: pairs of documents in two languages that have been aligned at the sentence level.

Reprise de la session	Resumption of the session
Je déclare reprise la session du Parlement européen qui avait été interrompue le vendredi 17 décembre dernier et je vous renouvelle tous mes vux en espérant que vous avez passé de bonnes vacances.	I declare resumed the session of the European Parliament adjourned on Friday 17 December 1999, and I would like once again to wish you a happy new year in the hope that you enjoyed a pleasant festive period.
Comme vous avez pu le constater, le grand "bogue de l'an 2000" ne s'est pas produit. En revanche, les citoyens d'un certain nombre de nos pays ont été victimes de catastrophes naturelles qui ont vraiment été terribles.	Although, as you will have seen, the dreaded 'millennium bug' failed to materialise, still the people in a number of countries suffered a series of natural disasters that truly were dreadful.

European Parliament Proceedings Parallel Corpus 1996-2011

http://www.statmt.org/europarl/

Data

- Europarl (proceedings of European parliament, 50M words/language)
  http://www.statmt.org/europarl/

- UN Corpus (United Nations documents, six languages, 300M words/langauge)
  http://www.euromatrixplus.net/multi-un/

- Common crawl (Web documents, long tail of language pairs)

Evaluation

ἄνδρα μοι ἔννεπε, μοῦσα, πολύτροπον

- Tell me Muse, of the man of many ways — Lattimore 1965
- Sing to me of the man, Muse, the man of twists and turns — Fagles 1996
- Tell me about a complicated man — Wilson 2018

Evaluation

- BLEU (Papineni et al. 2002): what fraction of {1-4}-grams in the system translation appear in the reference translations?

$$p_n = \frac{\textbf{Number of ngram tokens in system and reference translations}}{\textbf{Number of ngram tokens in system translation}}$$

$$\textbf{BLEU} = BP \times \exp \frac{1}{N} \sum_{n=1}^{N} \log p_n$$

Hypothesis translation
Appeared calm when he was taken to the American plane, which will to Miami, Florida.

Reference translations
Orejuela appeared sedate as he was led to the American plane which will take him to Miami, Florida.
Orejuela appeared calm while being escorted to the plane that would take him to Miami, Florida.
Orejuela appeared calm as he was being led to the American plane that was to carry him to Miami in Florida.
Orejuela seemed quite calm as he was being led to the American plane that would take him to Miami in Florida.

Appeared
calm
when
he
was
taken
to
the
American

plane
,
which
will
to
Miami
,
Florida
.

$$p_1 = \frac{15}{18} = 0.833$$

Ngrams appearing >1 time in the hypothesis can match up to the max number of times they appear in a single reference — e.g., two commas in hypothesis but one max in any single reference.

Callison-Burch et al. (2006), Re-evaluating the Role of BLEU in Machine Translation Research

Hypothesis translation
Appeared calm when he was taken to the American plane, which will to Miami, Florida.

Reference translations
Orejuela appeared sedate as he was led to the American plane which will take him to Miami, Florida.
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Orejuela seemed quite calm as he was being led to the American plane that would take him to Miami in Florida.

Appeared calm
calm when
when he
he was
was taken
taken to
to the
the American
American plane
plane ,
, which
which will
will to
to Miami
Miami ,
, Florida
Florida .

$$p_2 = \frac{10}{17} = 0.588$$

Callison-Burch et al. (2006), Re-evaluating the Role of BLEU in Machine Translation Research

$$\textbf{BLEU} = BP \times \exp \frac{1}{N} \sum_{n=1}^{N} \log p_n$$

$$p_n = \frac{\textbf{Number of ngram tokens in system and reference translations}}{\textbf{Number of ngram tokens in system translation}}$$

- We could optimize the score by minimizing the denominator (the number of ngrams generated)
- Brevity penalty:

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

- c = length of hypothesis translation
- r = length of the reference translation whose length is the closest to c

Statistical MT

Noisy Channel

	X	Y
ASR	speech signal	transcription
MT	target text	source text
OCR	pixel densities	transcription

$$P(Y \mid X) \propto \underbrace{P(X \mid Y)}_{\text{channel model}} \underbrace{P(Y)}_{\text{source model}}$$

Noisy Channel

This the translation model

This is just a language model for the target language

$$P(Y \mid X) \propto \underbrace{P(X \mid Y)}_{\text{channel model}} \quad \underbrace{P(Y)}_{\text{source model}}$$

- If we're translating from English (X) into French (Y) we assume some true French sentence Y that was "corrupted" into English version X.

Noisy Channel

This the translation model

This is just a language model for the target language

$$P(Y \mid X) \propto \underbrace{P(X \mid Y)}_{\text{channel model}} \quad \underbrace{P(Y)}_{\text{source model}}$$

Estimate this from parallel texts

Estimate this from monolingual data

Statistical MT

The statistical revolution in machine translation (1990) started by exploiting the structure of parallel sentences to learn the translation model.

Lasciate ogni speranza, voi ch'entrate

Abandon all hope, you who enter!

Brown et al. (1990), “A statistical approach to machine translation,” *Computational Linguistics*

Statistical MT

Lasciate ogni speranza, voi ch'entrate

Abandon all hope, you who enter!

mi lasciate in pace

Leave me in peace

Lasciate i monti

Leave the mountains

Statistical MT

Lasciate ogni speranza, voi ch'entrate

Abandon all hope, you who enter!

mi lasciate in pace

Leave me in peace

Lasciate i monti

Leave the mountains

Statistical MT

Italian	English	P(English | Italian)
lasciate	leave	0.67
lasciate	abandon	0.33

Translation table

Italian	English	P(English | Italian)
Voi ch’entrate	you who enter	0.91
Voi ch’entrate	you who are entering	0.09

Phrase translation table

IBM Alignment models

If we had explicit word alignments we could estimate translation tables directly from them.

mi lasciate in pace

Leave me in peace

Lasciate i monti

Leave the mountains

But we don't have word alignments — just sentence alignments!

IBM Alignment models

Unsupervised models for aligning words and phrases in parallel sentences.

mi lasciate in pace

Leave me in peace

Lasciate i monti

Leave the mountains

Brown, Peter F. (1993). "The mathematics of statistical machine translation: Parameter estimation," Computational Linguistics

IBM Alignment models

Model 1	Independent word translation (order doesn’t matter)
Model 2	Word translation + distance between source and target position
Model 3	Word translation + fertility (how many target words a source word can align to)
Model 4	Word translation + relative ordering among target words of same source
Model 5	(Fixes deficiency of model 4)
HMM (Vogel et al. 1996)	Word translation plus relative ordering

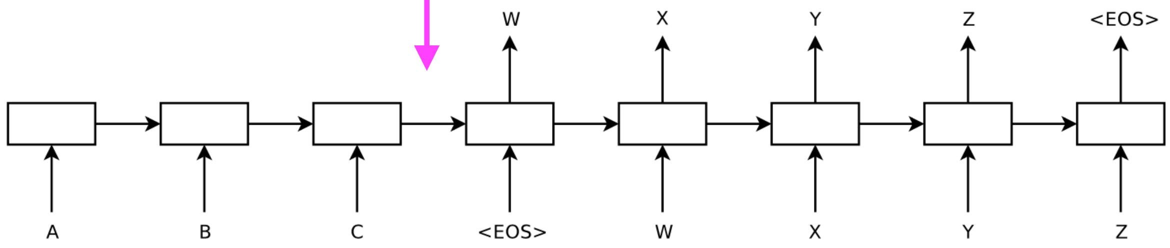
Brown, Peter F. (1993). “The mathematics of statistical machine translation: Parameter estimation,” Computational Linguistics

Neural MT

- Encoder-decoder
- Encoder-decoder + attention
- Transformer (Vaswani et al. 2018)

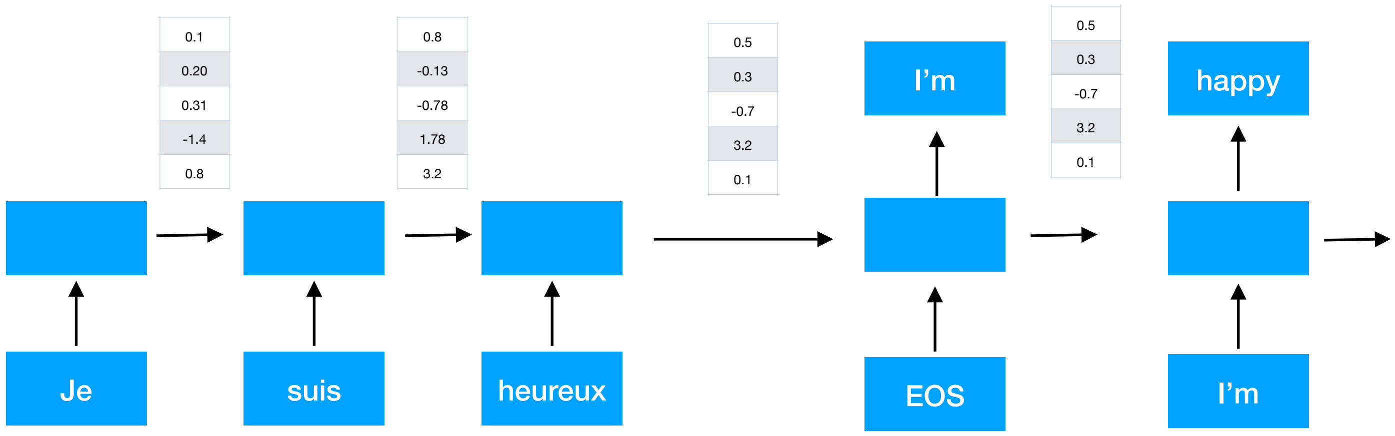
Encoder-decoder framework

K-dimensional vector representing entire context



Condition on word generated in translation

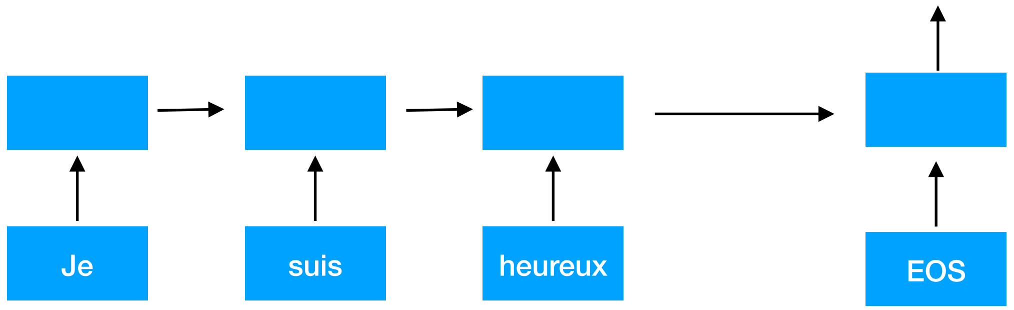
Sutskever et al. (2015);



0.1
0.20
0.31
-1.4
0.8
0.8
-0.13
-0.78
1.78
3.2
0.5
0.3
-0.7
3.2
0.1
I’m
0.5
0.3
-0.7
3.2
0.1
happy
Je
suis
heureux
EOS
I’m

Training

- As in other RNNs, we can train by minimizing the loss between what we predict at each time step and the truth.



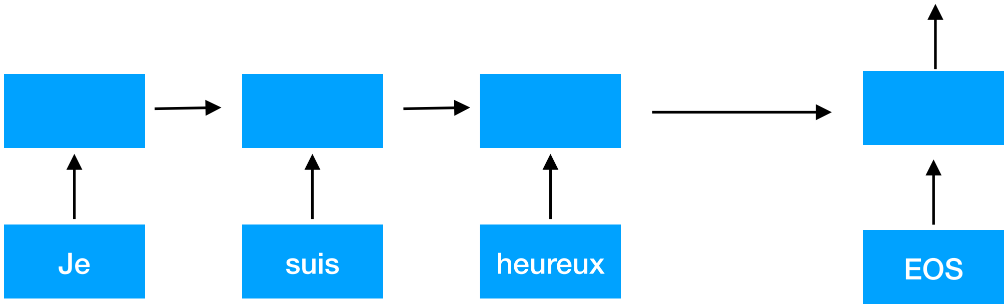
Training

truth

I’m	you	are	the	…
1	0	0	0	0

predicted

I’m	you	are	the	…
0.03	0.05	0.02	0.01	0.009

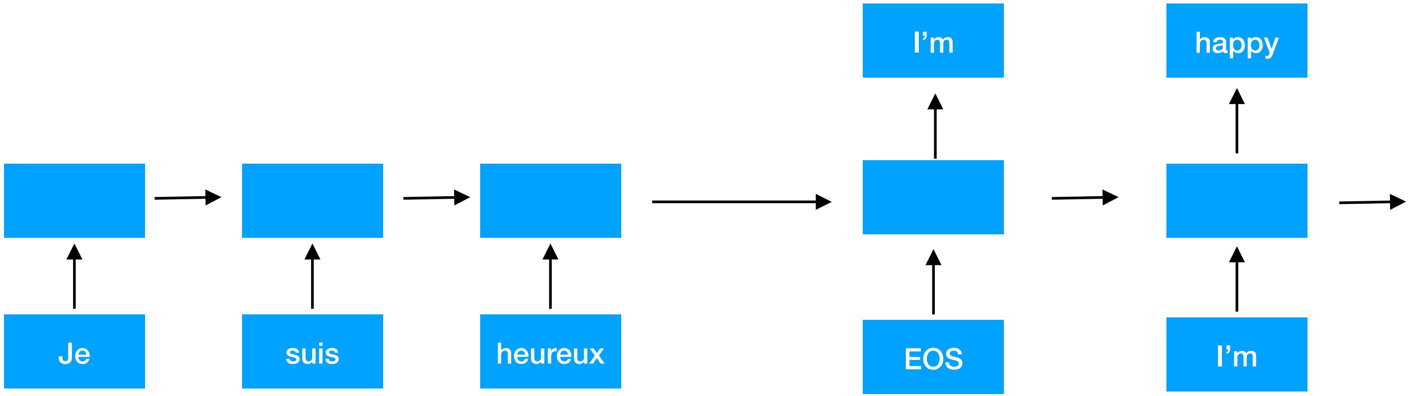


truth

happy	great	bad	ok	…
1	0	0	0	0

predicted

happy	great	bad	ok	…
0.13	0.08	0.01	0.03	0.009

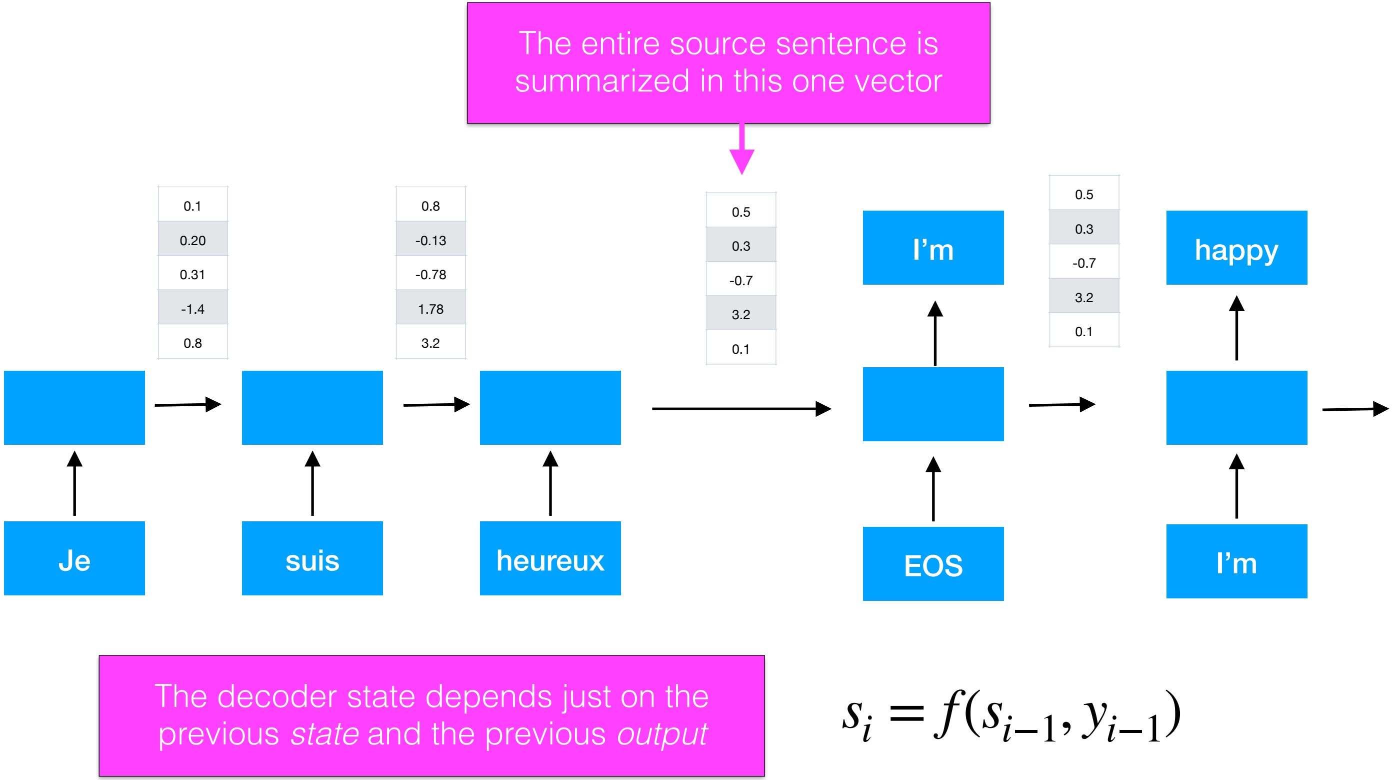


Encoder-decoder

- Sutskever et al. (2014) found better performance when the encoder reads the sentence in backwards, from right to left (increase in BLEU from 25.9 to 30.6)

Sutskever et al. (2014), “Sequence to Sequence Learning with Neural Networks”

Encoder-decoder

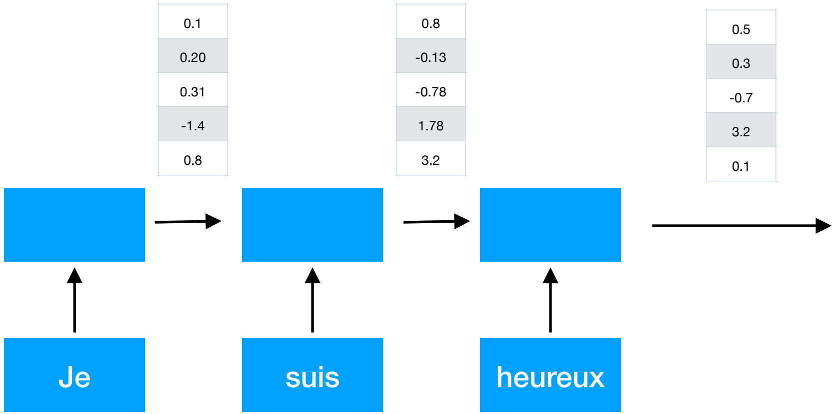


$$s_i = f(s_{i-1}, y_{i-1})$$

Encoder-decoder with attention

The decoder state depends just the previous *state*, the previous *output*, and some *context*

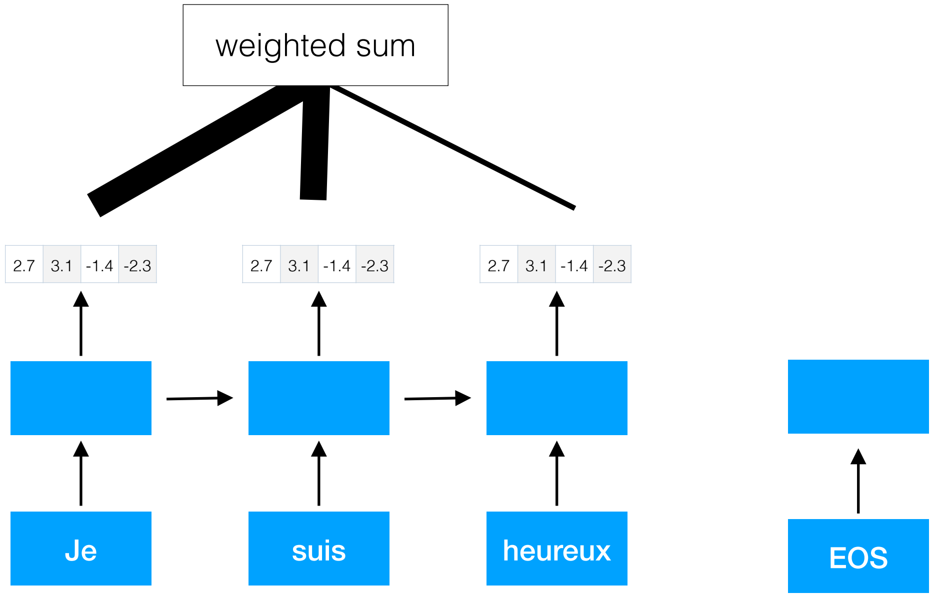
$$s_i = f(s_{i-1}, y_{i-1}, c_i)$$



Encoder-decoder with attention

$$c = h_1a_1 + h_2a_2 + h_3a_3$$

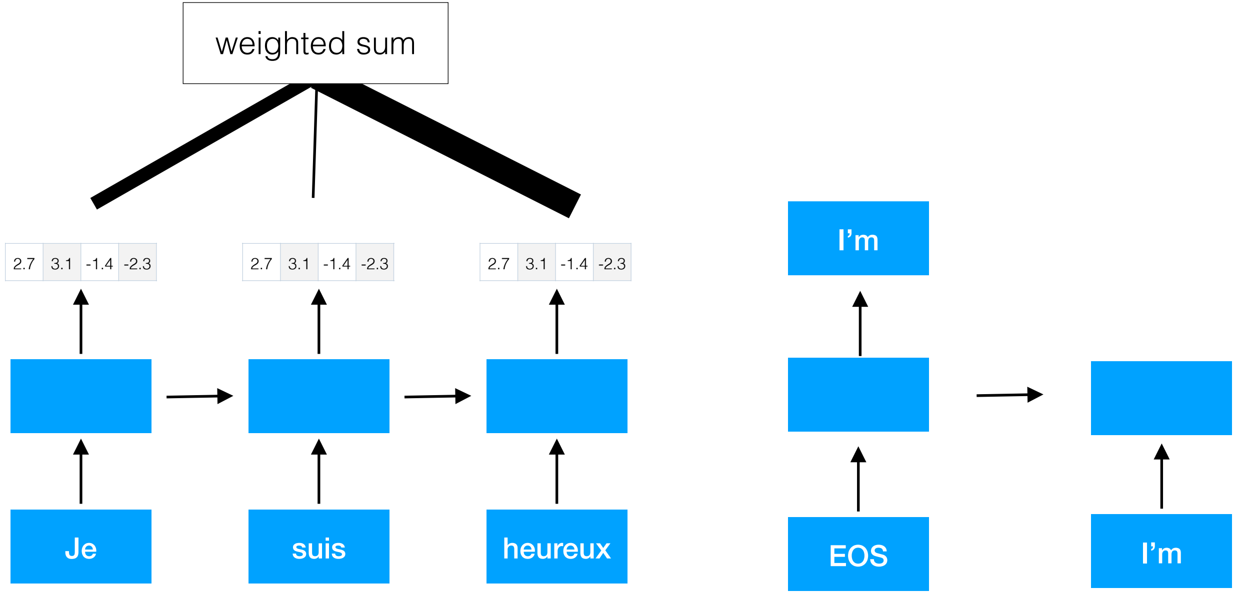
$$s_i = f(s_{i-1}, y_{i-1}, c_i)$$



Encoder-decoder with attention

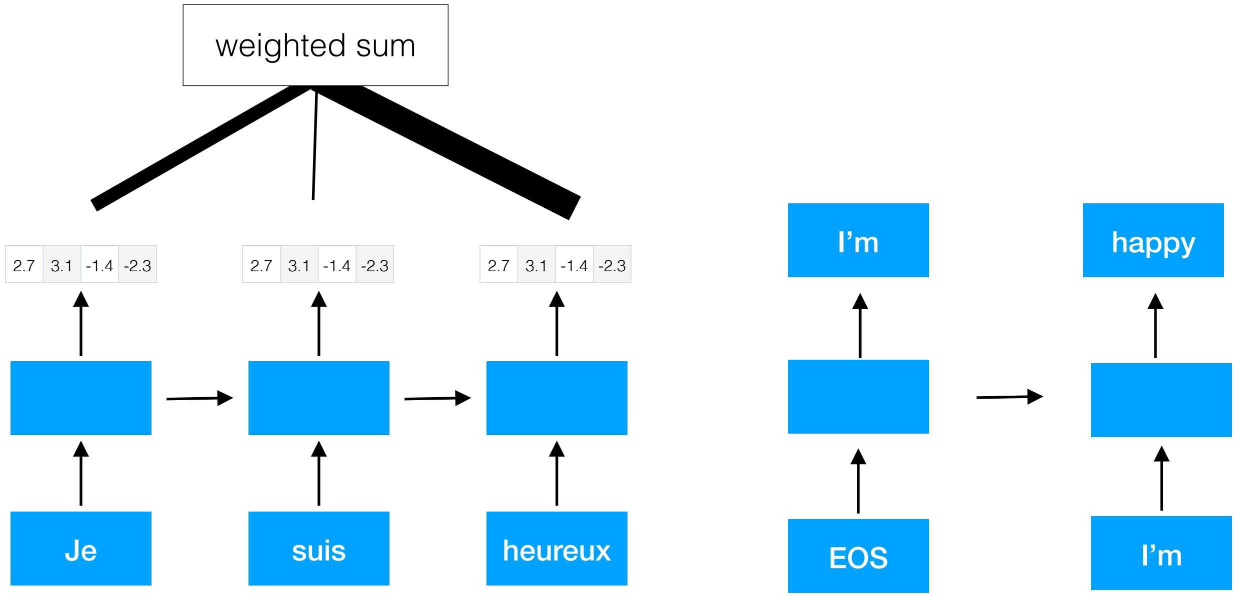
$$c = h_1 a_1 + h_2 a_2 + h_3 a_3$$

$$s_i = f(s_{i-1}, y_{i-1}, c_i)$$



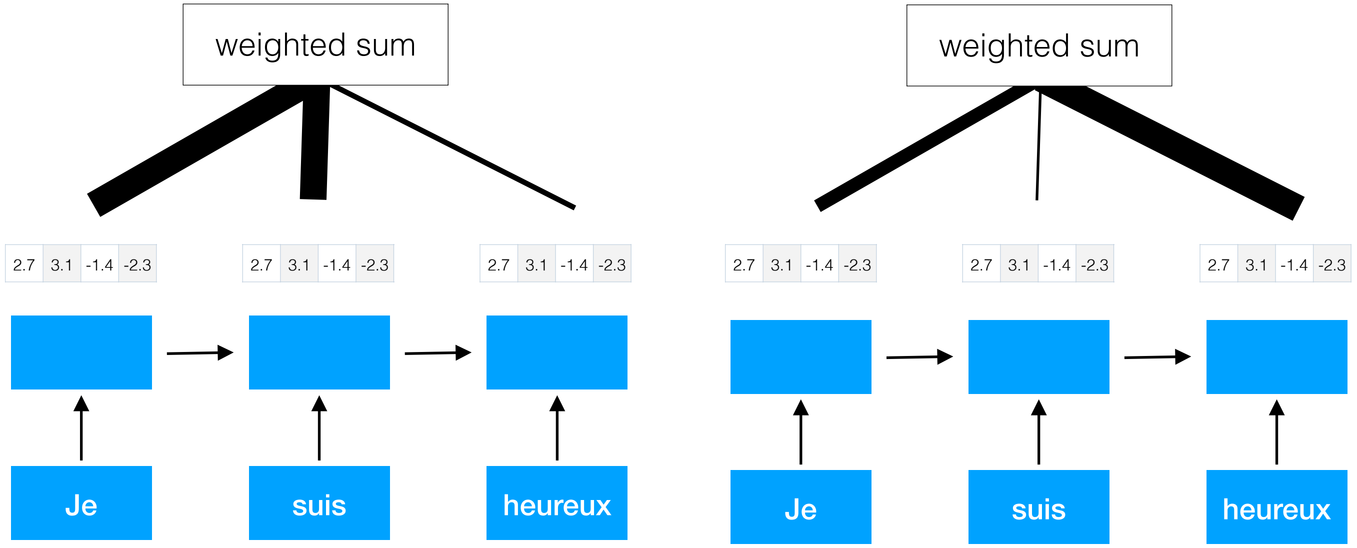
Encoder-decoder with attention

$$c = h_1 a_1 + h_2 a_2 + h_3 a_3$$



Encoder-decoder with attention

- Each time step in the decoder has its own weighted context vector



$$v \in \mathscr{R}^H$$

2.7	3.1	-1.4	-2.3	0.7

With document classification, we parameterized attention with a single vector v to be learned. Attention in an encoder-decoder network is a little different because we're comparing a pair of vectors.

$$r_1 = v^\top x_1 \qquad r_2 = v^\top x_2 \qquad r_3 = v^\top x_3 \qquad r_4 = v^\top x_4 \qquad r_5 = v^\top x_5$$

2.7	3.1	-1.4	-2.3	0.7

2.7	3.1	-1.4	-2.3	0.7

2.7	3.1	-1.4	-2.3	0.7

2.7	3.1	-1.4	-2.3	0.7

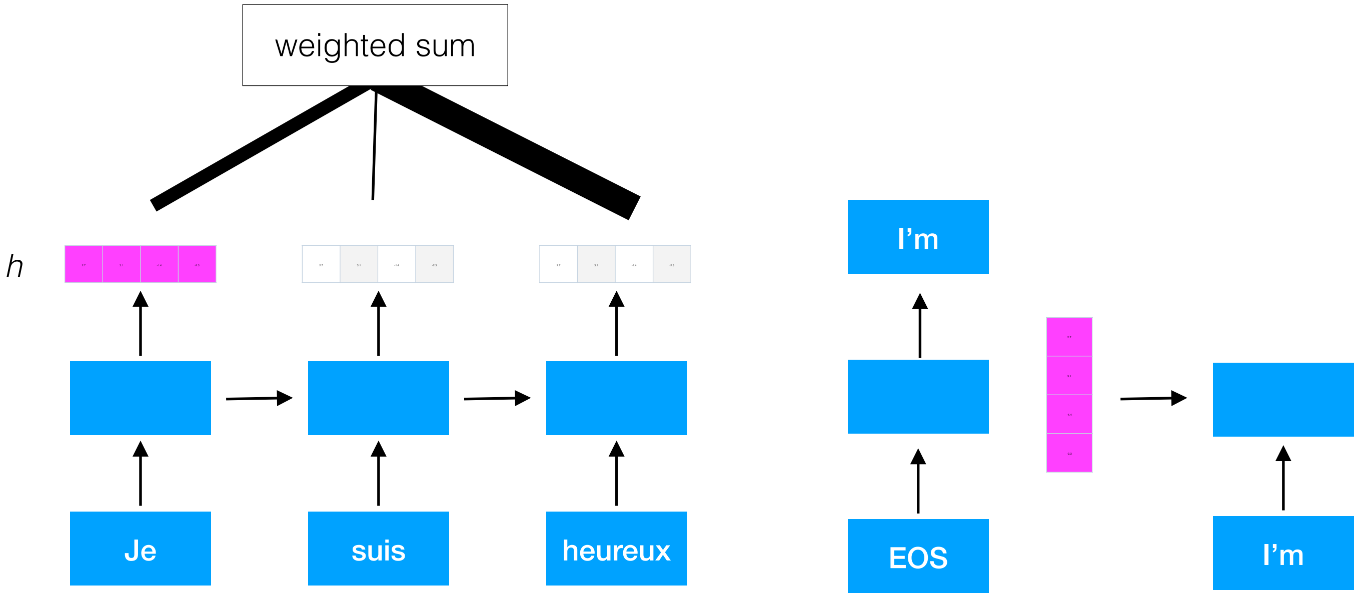
2.7	3.1	-1.4	-2.3	0.7

I loved the movie !

x_1 x_2 x_3 x_4 x_5

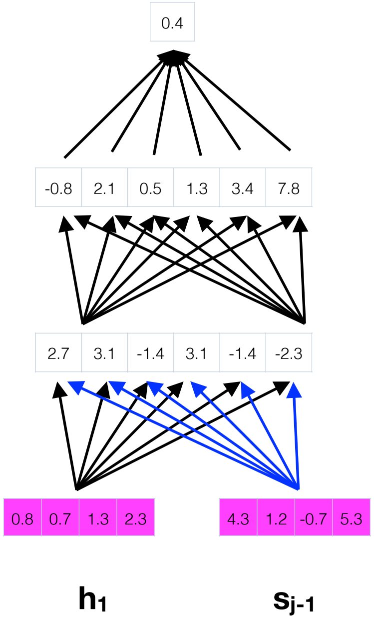
Encoder-decoder with attention

$$c = h_1 a_1 + h_2 a_2 + h_3 a_3 \qquad r_{1,j} = FFNN(h_1, s_{j-1})$$



Feed-forward neural network

The feed-forward network here just takes the two vectors as input as outputs a single scalar. The parameters are all learned using backprop (just like every other parameter).



$W_3 \in \mathbb{R}^6$

$W_2 \in \mathbb{R}^{6\times6}$

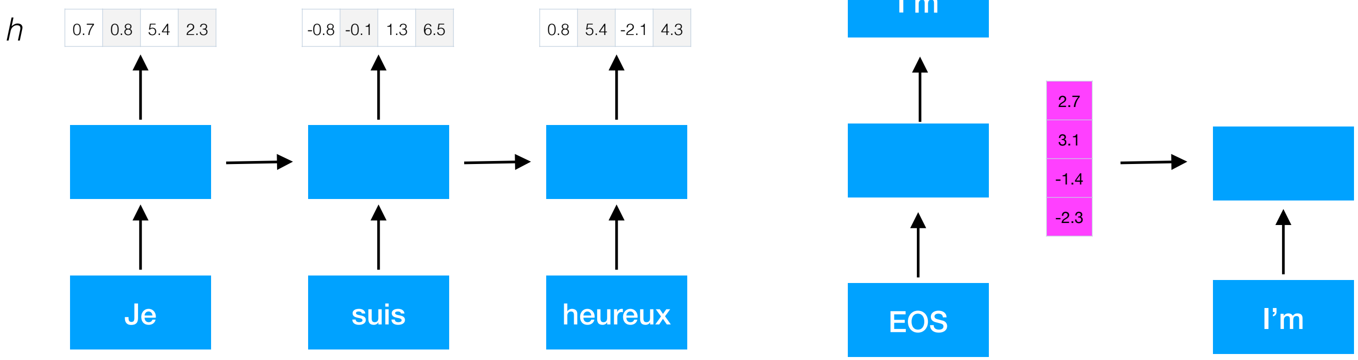
$W_1 \in \mathbb{R}^{4\times6}$

Encoder-decoder with attention

$$a = \text{softmax}(r)$$

$$r = [r_1, r_2, r_3]$$

$r_1 = FFNN(h_1, s_{j-1})$ $r_2 = FFNN(h_2, s_{j-1})$ $r_3 = FFNN(h_3, s_{j-1})$



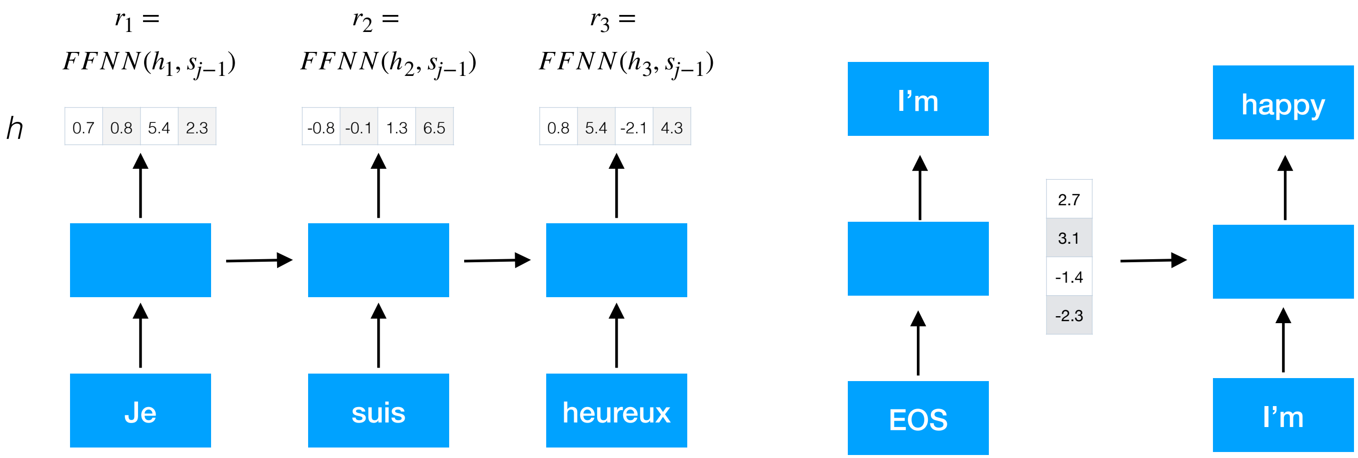
Encoder-decoder with attention

$$c = h_1 a_1 + h_2 a_2 + h_3 a_3$$

$$a = \text{softmax}(r)$$

$$r = [r_1, \ldots, r_5]$$

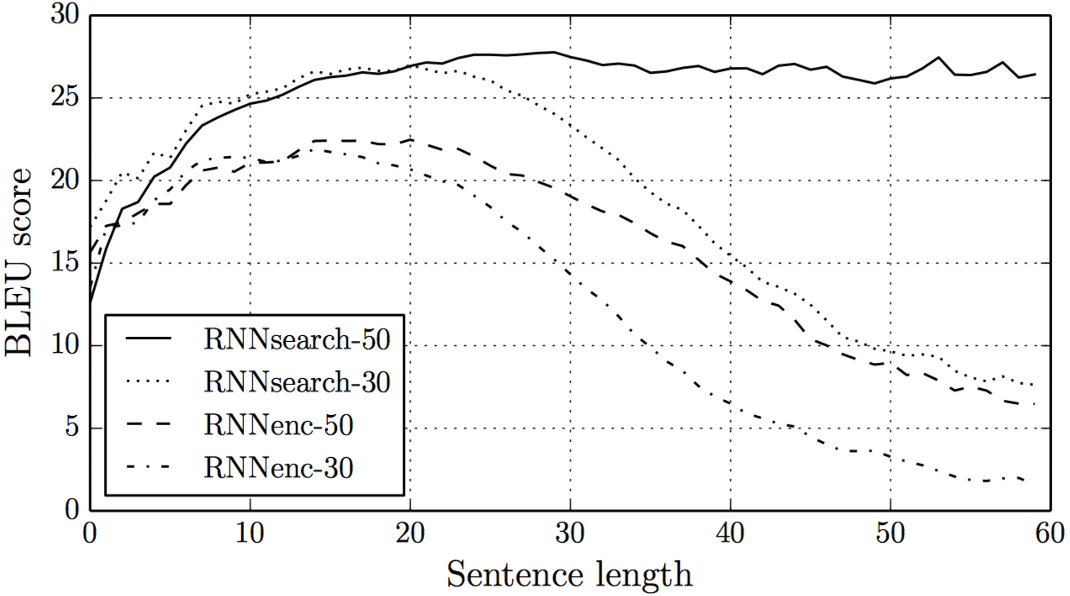
$$s_i = f(s_{i-1}, y_{i-1}, c_i)$$



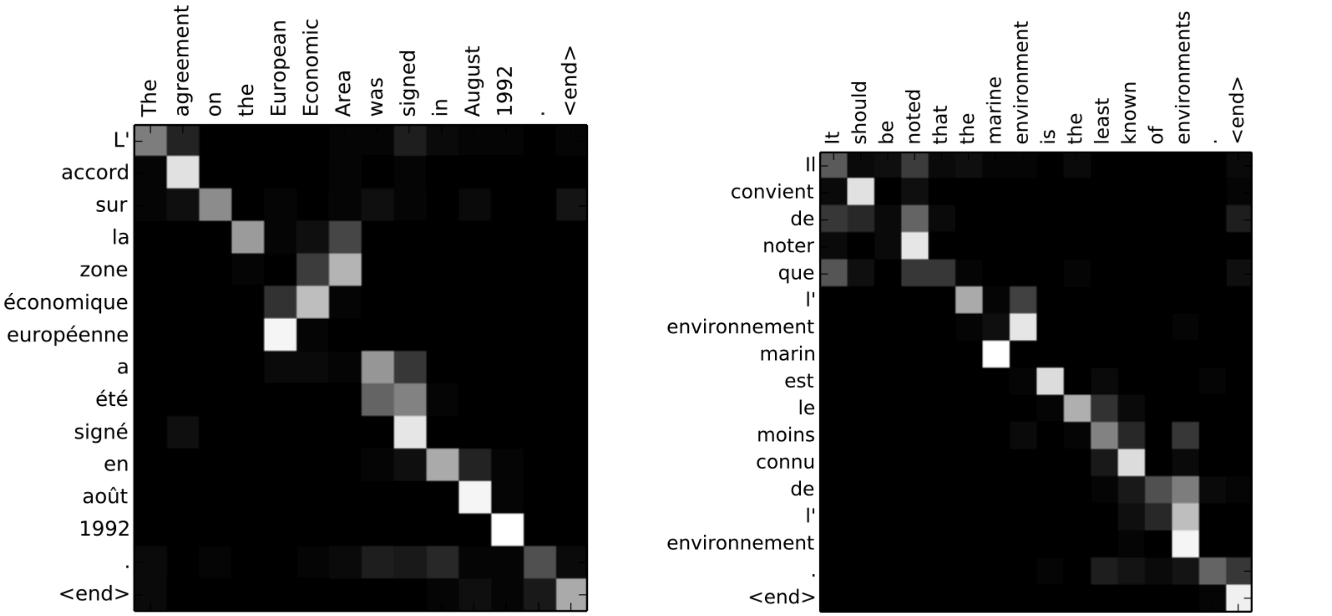
Attention

- For text classification, attention helps decide which words in the text are important for the label.
- For MT, attention changes with each word being generated during decoding. Each subsequent word pays attention to different parts of the input.

Better performance on long sentences

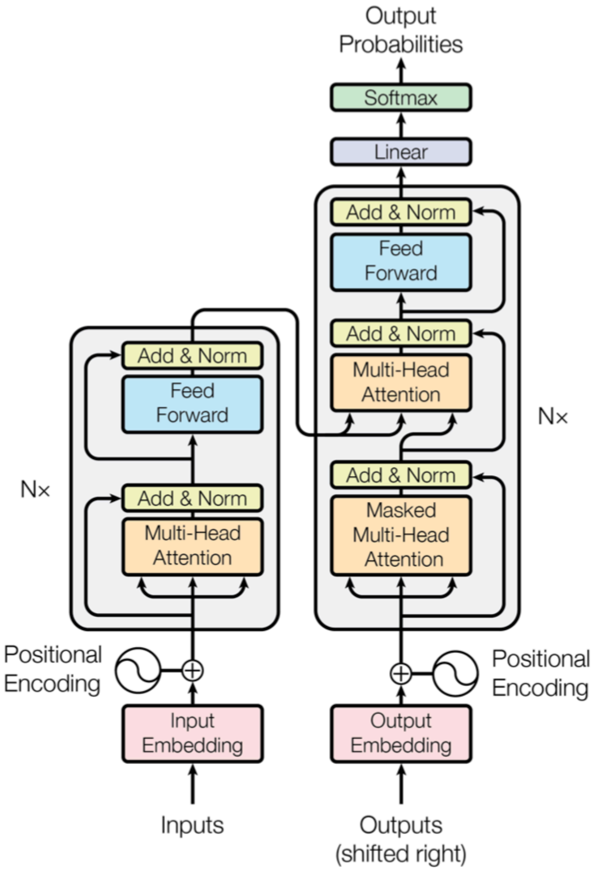


Bahdanau et al. (2016), “Neural Machine Translation by Jointly Learning to Align and Translate”



Bahdanau et al. (2016), “Neural Machine Translation by Jointly Learning to Align and Translate”

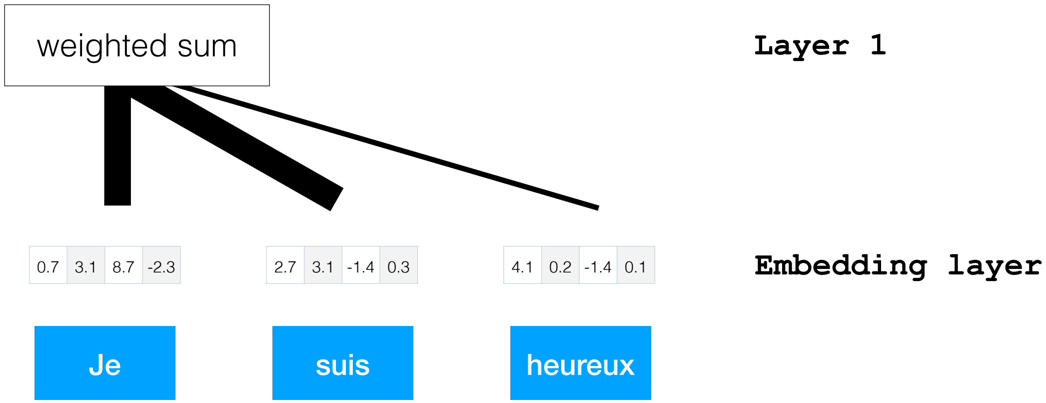
- Transformer network (Vaswani et al. 2017).



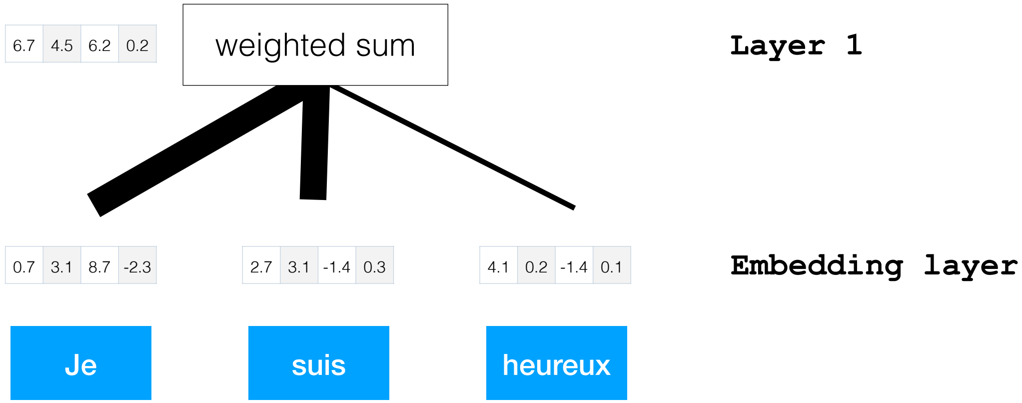
Self-attention

- Multiple layers of representations for an input sequence; each layer attends over the representations in the previous layer.

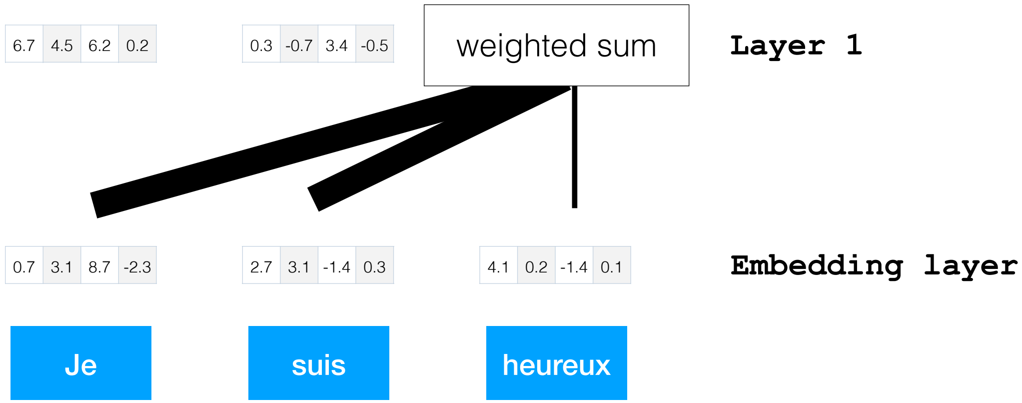
Self-attention



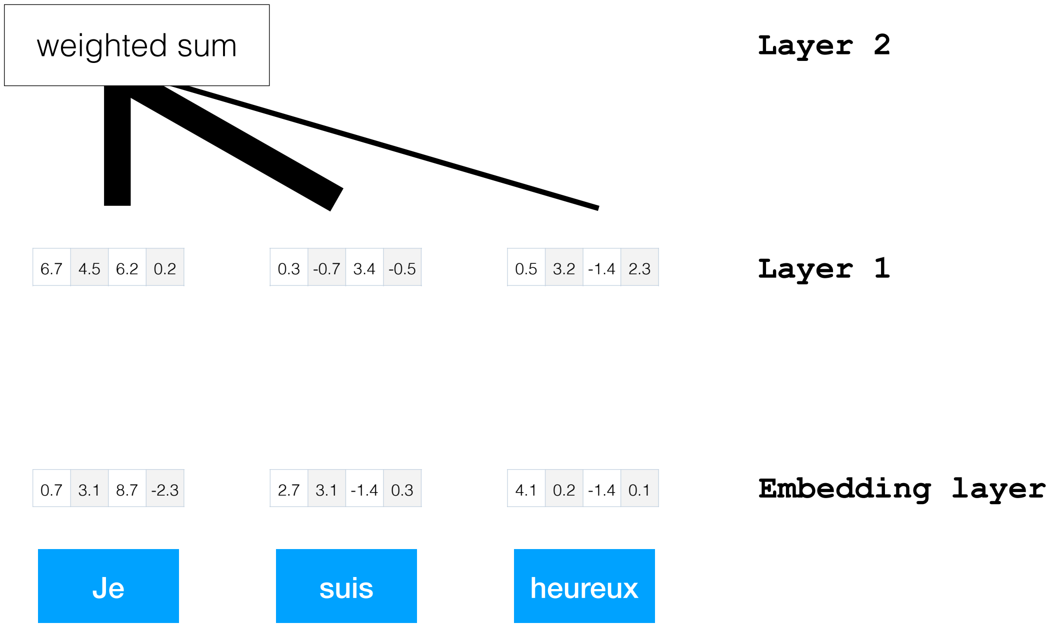
Self-attention



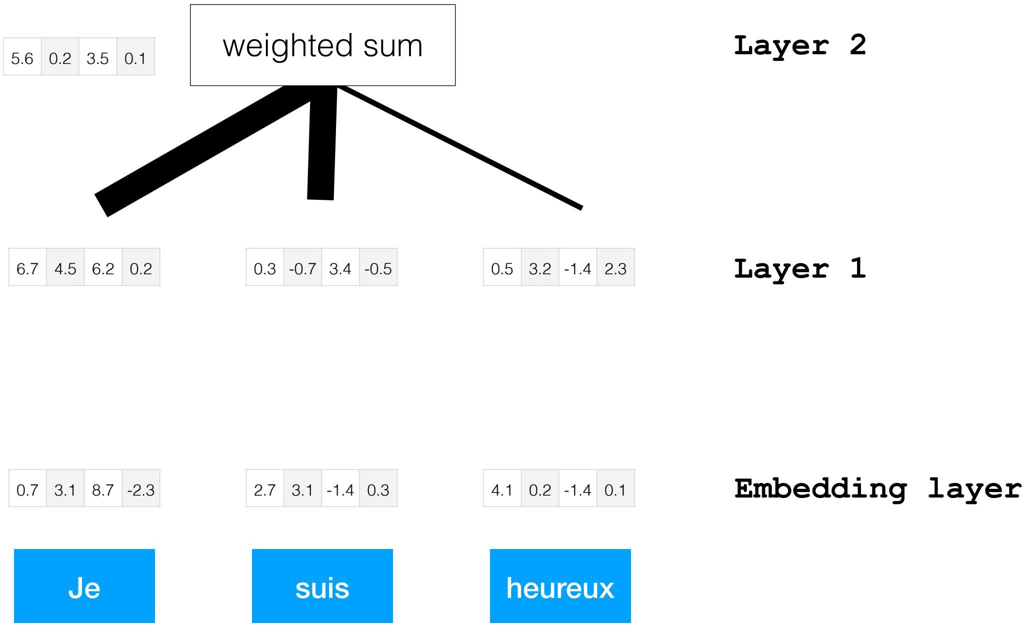
Self-attention



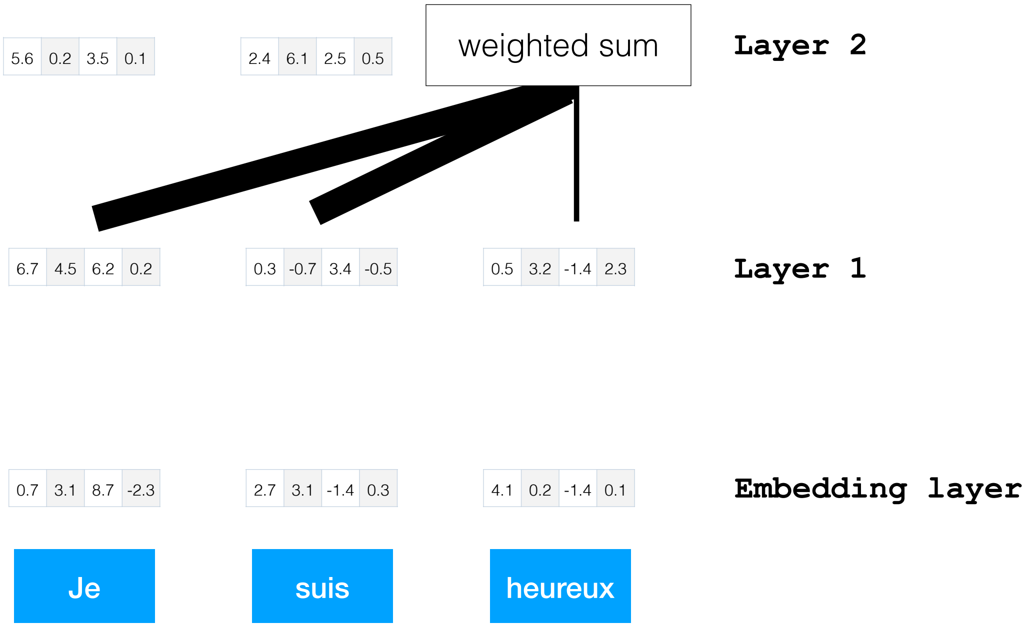
Self-attention



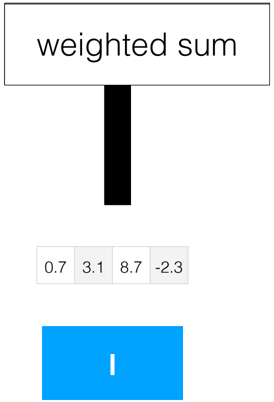
Self-attention



Self-attention

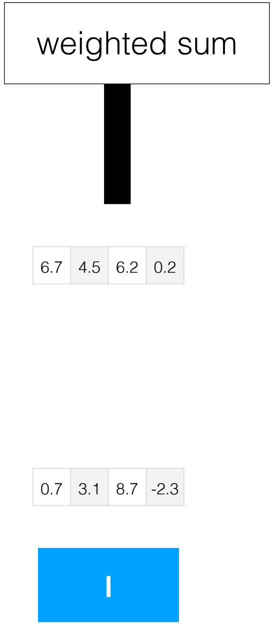


Self-attention



- In the *decoder*, self-attention can only attend over words to the left of the position (since the right ones haven't been generated yet).

Self-attention



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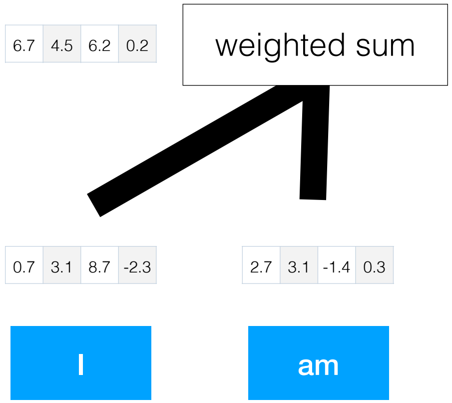
Self-attention



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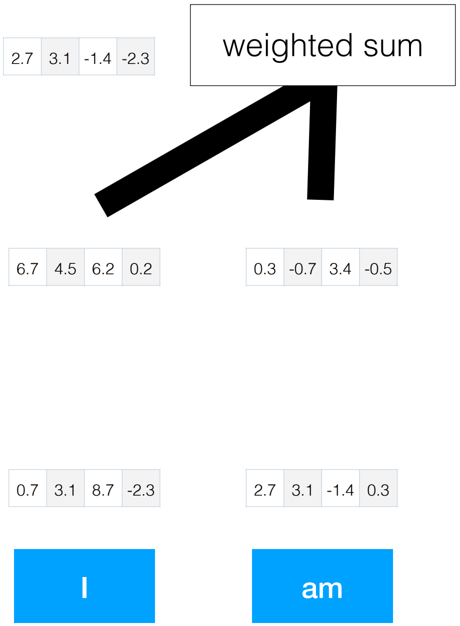
Self-attention

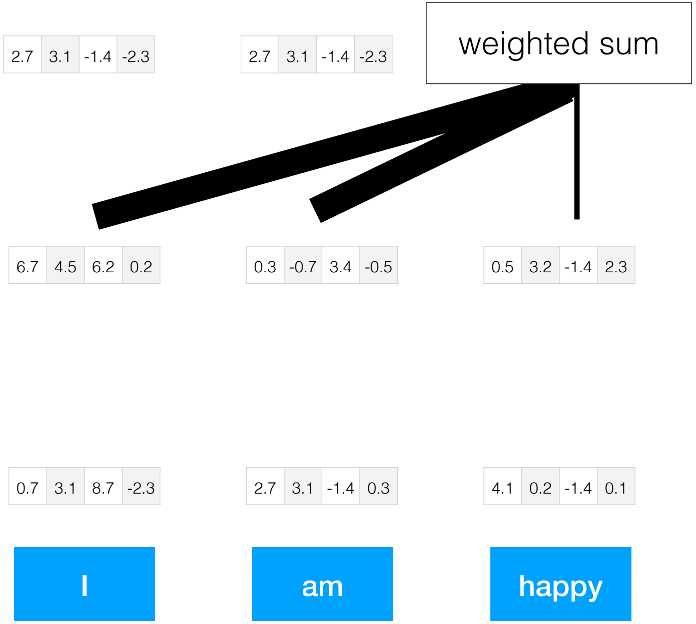


- In the decoder, self-attention can only attend over words to the left of the position (since the right ones haven't been generated yet).

Self-attention

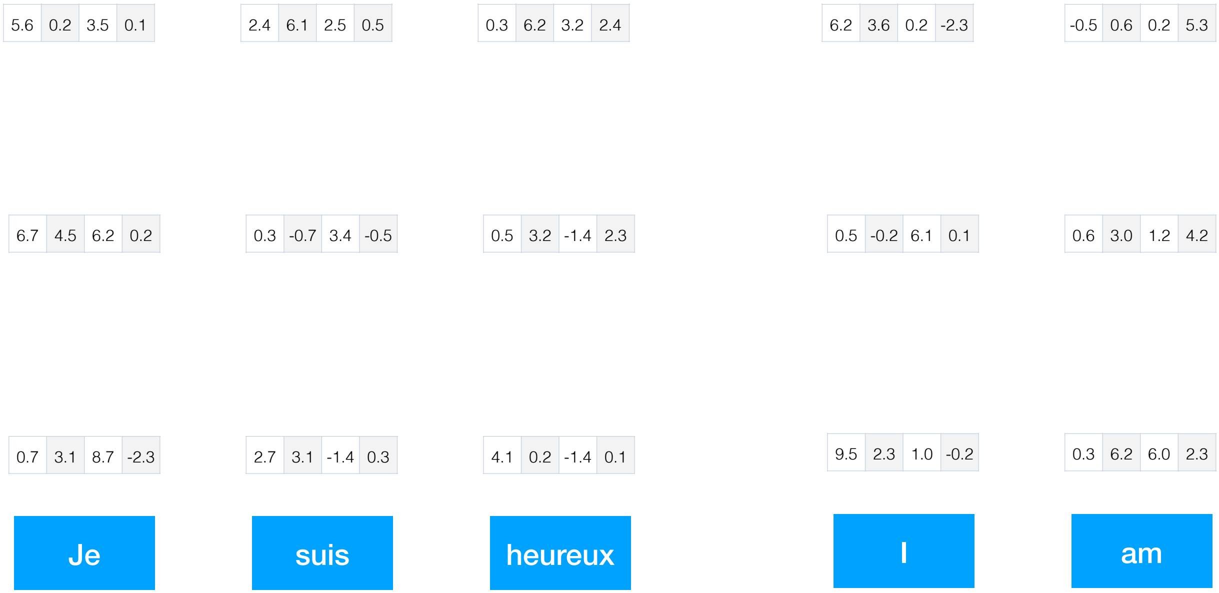
- In the decoder, self-attention can only attend over words to the left of the position (since the right ones haven't been generated yet).

Self-attention



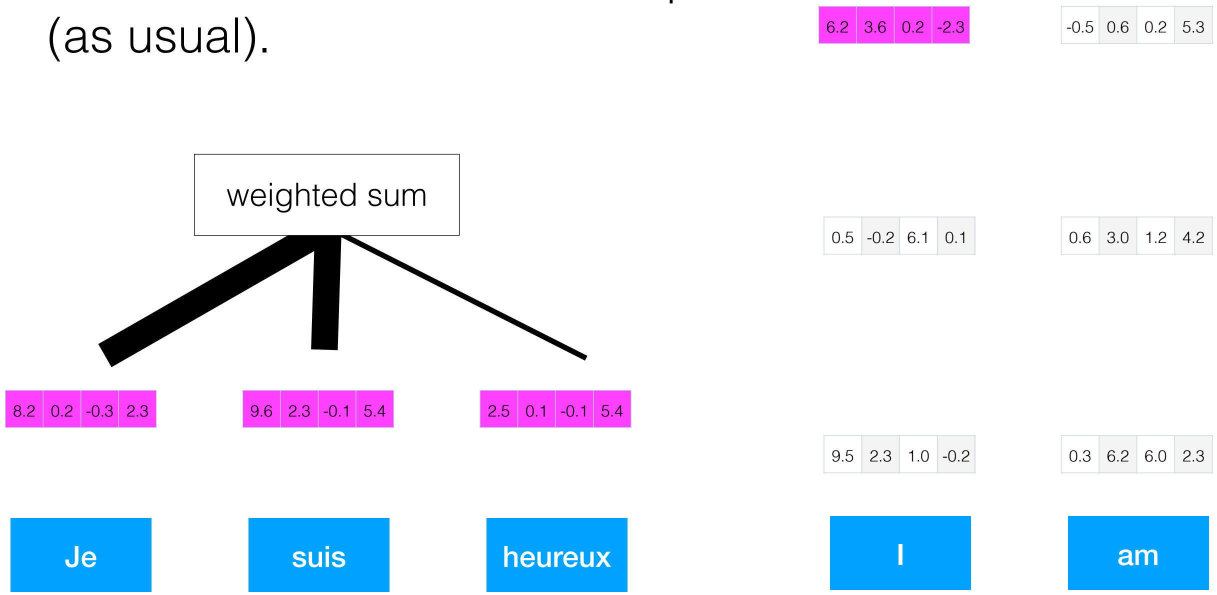
- In the decoder, self-attention can only attend over words to the left of the position (since the right ones haven't been generated yet).

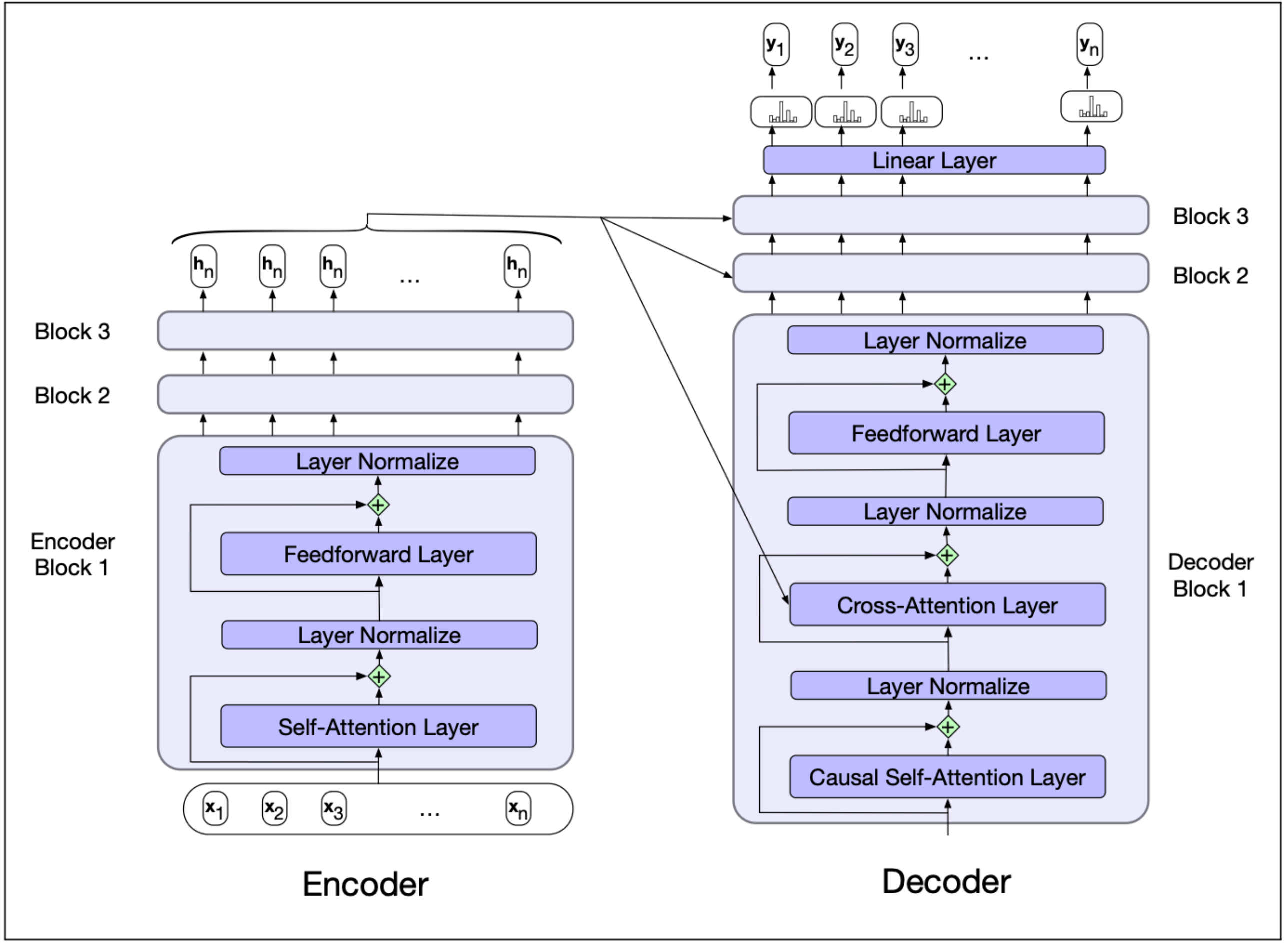
Encoder-decoder cross-attention



Encoder-decoder cross-attention

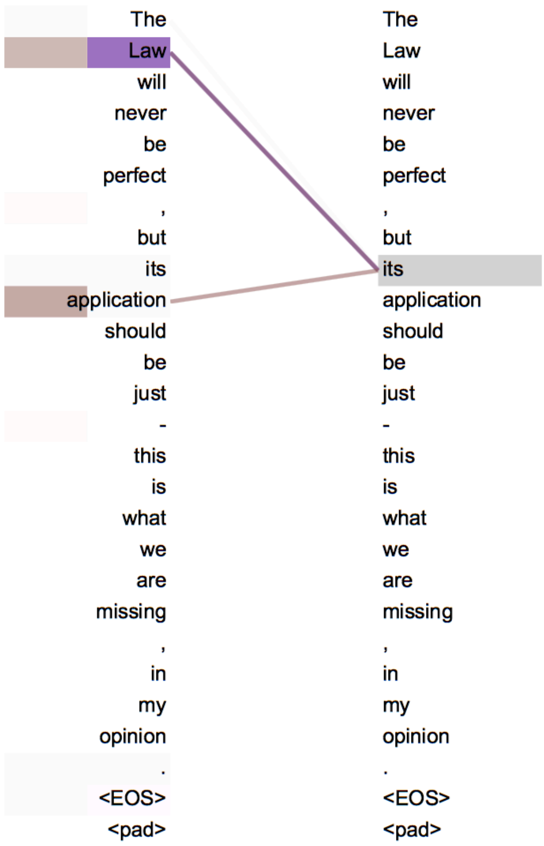
- Each layer in the decoder attends over the encoder output (as usual).





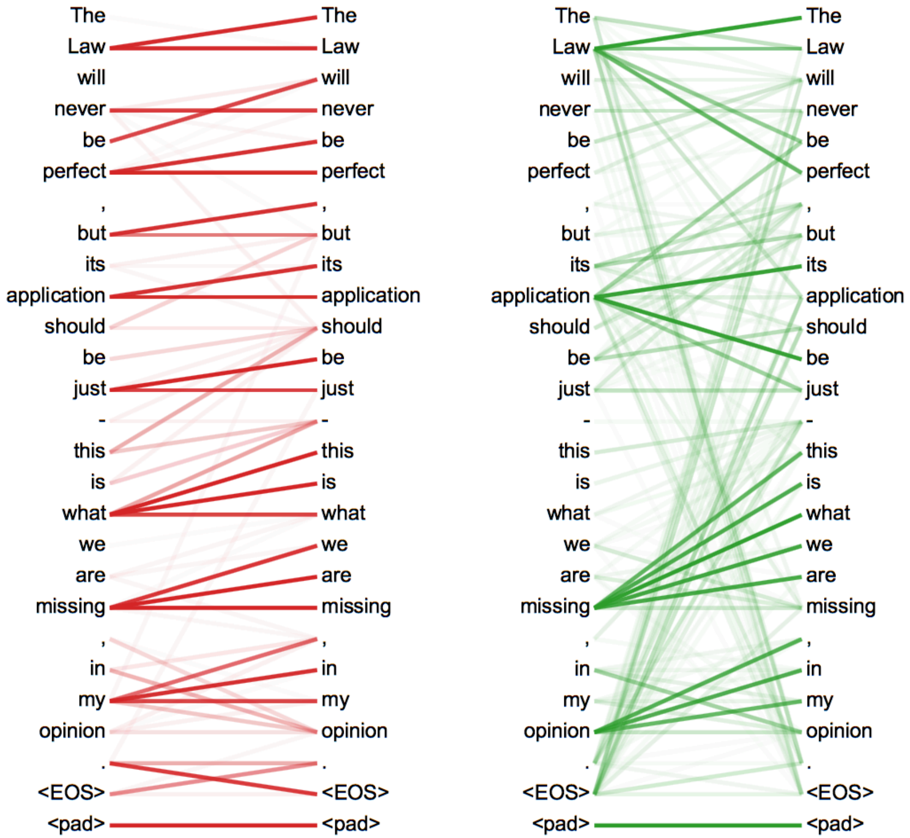
SLP3 fig. 10.6; https://web.stanford.edu/~jurafsky/slp3/13.pdf

- Self-attention captures structure in the input (like coreference)



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

- Multiple heads capture different structure.



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

Model	BLEU	
	EN-DE	EN-FR
ByteNet [18]	23.75	
Deep-Att + PosUnk [39]		39.2
GNMT + RL [38]	24.6	39.92
ConvS2S [9]	25.16	40.46
MoE [32]	26.03	40.56
Deep-Att + PosUnk Ensemble [39]		40.4
GNMT + RL Ensemble [38]	26.30	41.16
ConvS2S Ensemble [9]	26.36	**41.29**
Transformer (base model)	27.3	38.1
Transformer (big)	**28.4**	**41.8**