



C1A0

Artificial
Intelligence
Exposition

OUR SPONSORS





C1A0
EXPO

State-of-the-art concepts in NLP

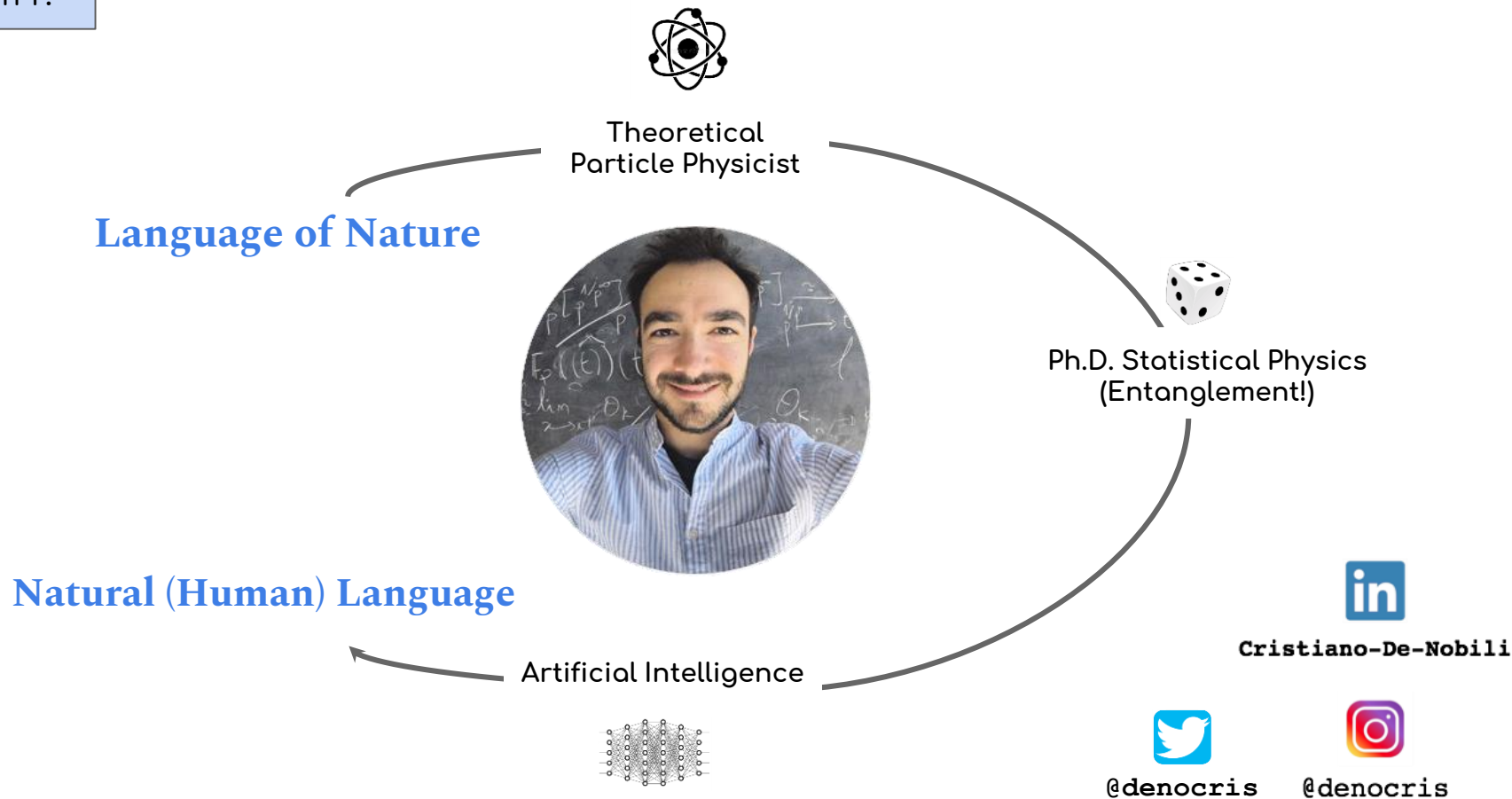
(... and their limits)

Cristiano De Nobili, Ph.D.

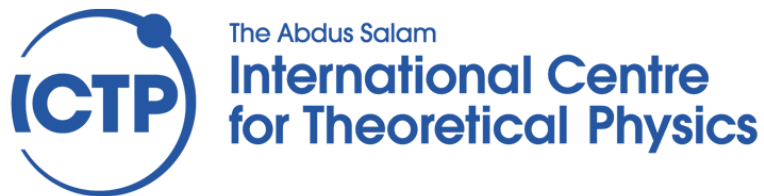
Harman - Samsung &  **AINDO**



Who am I?



Trieste: Sea, Coffee & Science



- Language & Computers: a bird's-eye view
- Recurrent Neural Network (the state-of-the-art till yesterday)
- Auto-encoders and Seq2Seq
- The Attention and Self-Attention Mechanism
- Transformers
- Cool NLP Applications
- Limits: energy and... (we will see later)

Language

Humans do **3** basic things with language that machines also can do, or at least attempt.



We can listen!



... computers can now easily translate
text to voice, ~~handwritten notes to typed text.~~
~~handwritten notes to typed text.~~
handwritten notes to typed text.

Language

But humans also perform a fourth function...



We can understand language(s)!



That's what NLP is trying to
achieve

Language is a hard task for a machine

Dai diamanti non nasce niente, dal letame nascono i fiori.

Una lunga vacanza. Una lunga coda.

“Giulia, sei libera domani alle sei?”

Language is a hard task for a machine

Dai diamanti non

So,
how a machine can understand language?

Una lunga coda.

“Giulia,

Words and Numbers

Words and numbers have always been thought to be at odds. You can be a man of letters or a man of science. There are poets, philosophers & journalist on one side. Scientists & engineers on the other.

But, what is the language of a machine?



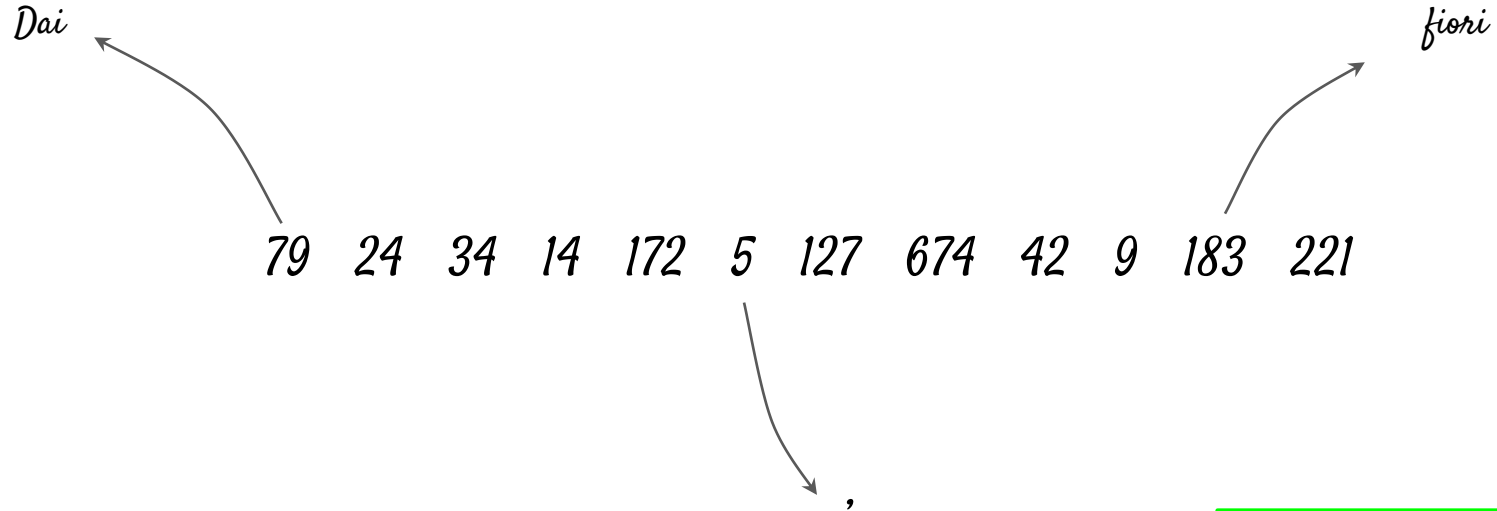
Therefore, thanks to NLP, words and number can become best friends after many centuries!

WORDS <-> NUMBERS

Dai diamanti non nasce niente, dal letame nascono i fiori.

,

WORDS <-> NUMBERS



Yes, but this is just
the first step...

VECTORS

$$\begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \end{bmatrix}$$

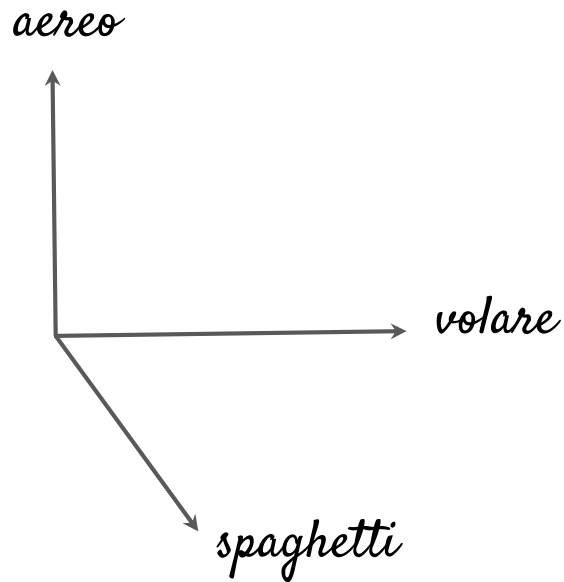
Dai diamanti non nasce niente, dal letame nascono i fiori.

$$\begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}$$

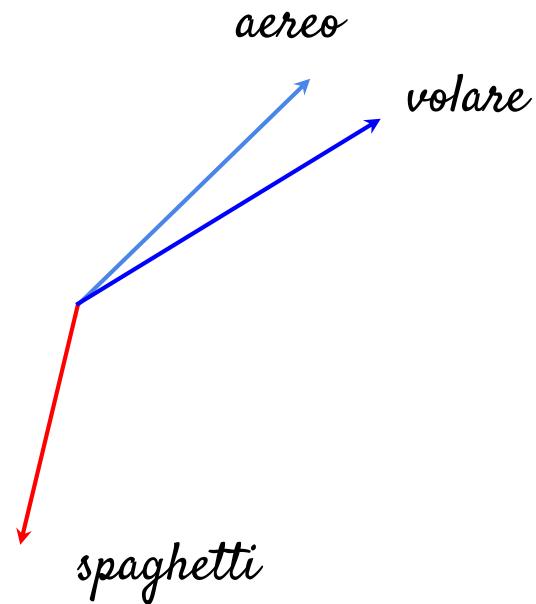
However...

- these are sparse vectors
- ... and orthogonal

DENSE VECTORS



all words are equally distant!



some words are more similar!

(Word2Vec, Glove) arXiv: 1301.3781

DENSE VECTORS

(from discrete to continuous variables)

$$\begin{bmatrix} 0.12 \\ \vdots \\ 0.23 \\ 0.78 \end{bmatrix}$$
$$\begin{bmatrix} 0.55 \\ \vdots \\ 0.17 \\ 0.61 \end{bmatrix}$$

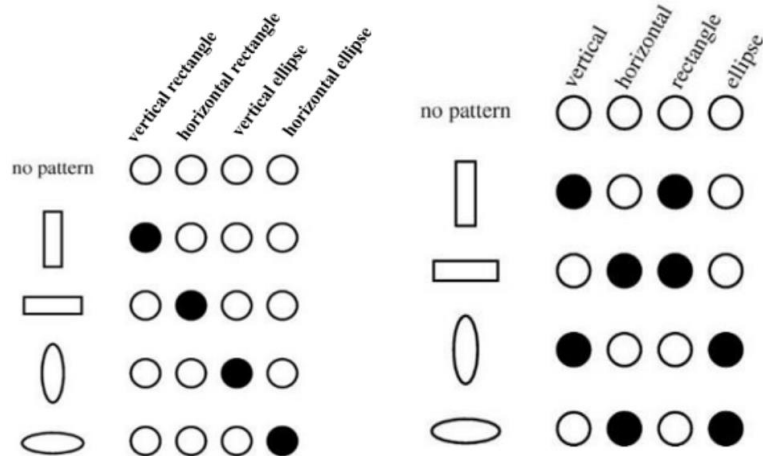
Dai diamanti non nasce niente, dal letame nascono i fiori.

They can encode more complex structures/relations

- syntactics
- semantics and more

$$\begin{bmatrix} 0.67 \\ \vdots \\ 0.42 \\ 0.28 \end{bmatrix}$$

DENSE REPRESENTATIONS: forget for a while about words...



SPARSE

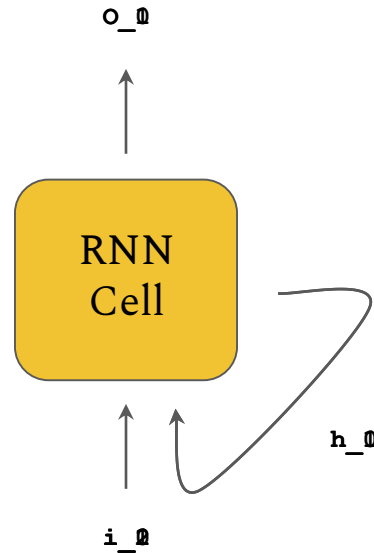
DENSE

$$\bigcirc \approx \text{Vertical} + \text{Horizontal} + \text{Ellipse} = \bullet \bullet \bigcirc \bullet$$

- One concept is represented by more than one dot
- One dot represents more than one concept

RECURRENT NEURAL NETWORKS

(state-of-the-art till yesterday...)



RECURRENT NEURAL NETWORKS

(state-of-the-art till yesterday...)

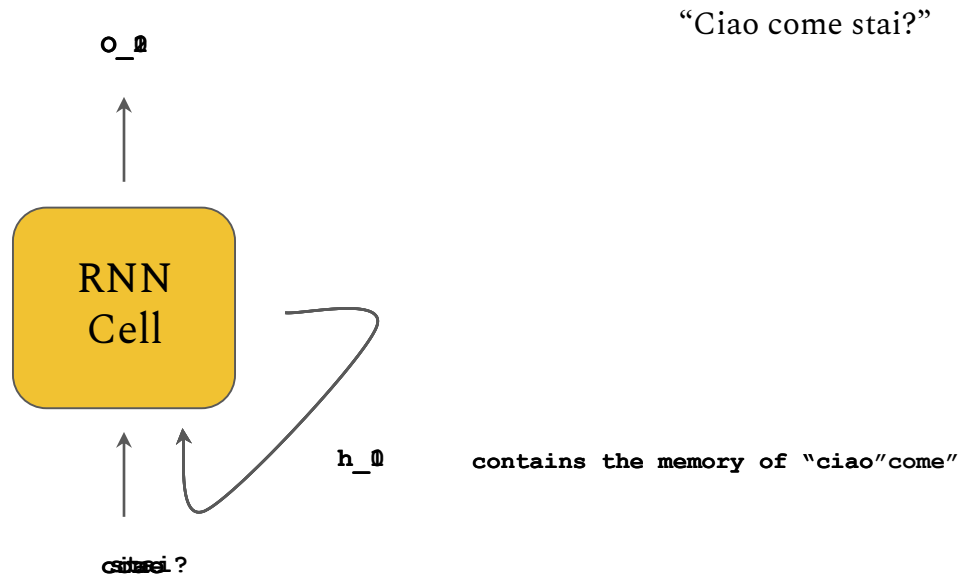
Used for many
NLP tasks!

“Ciao come stai?”

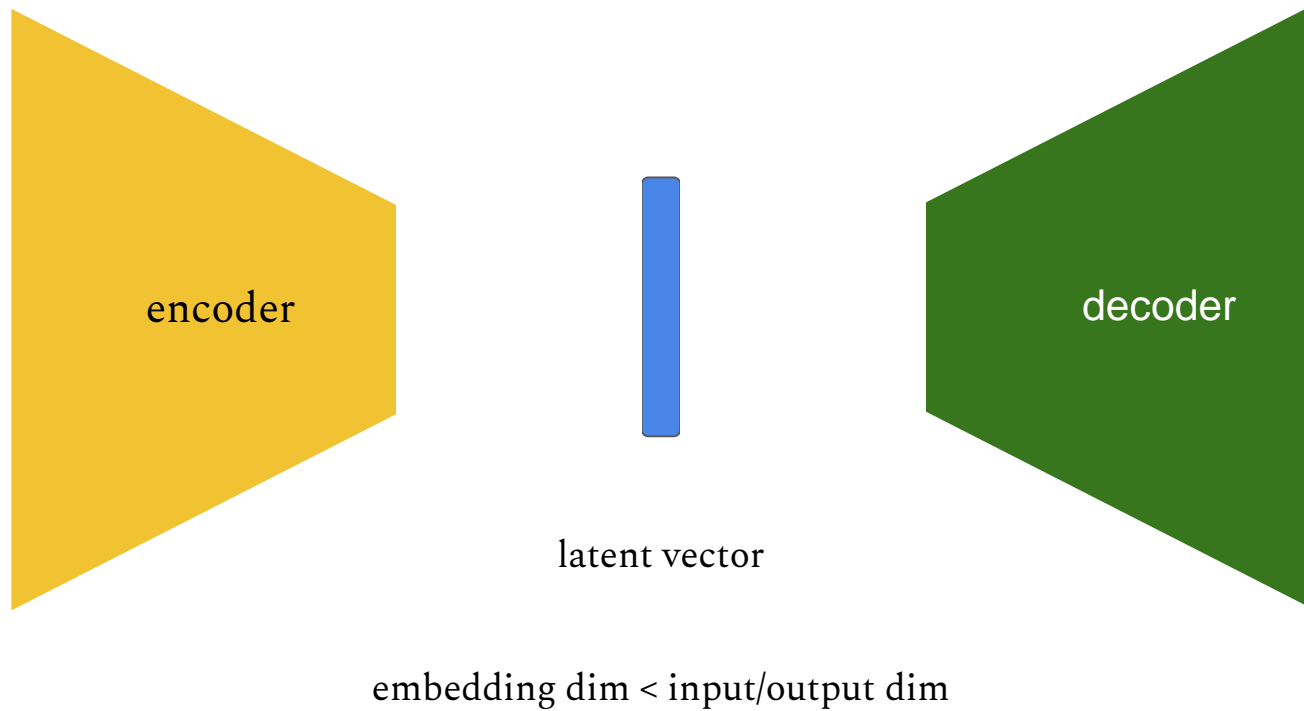


“Hi, how are you?”

We are going to consider translation!



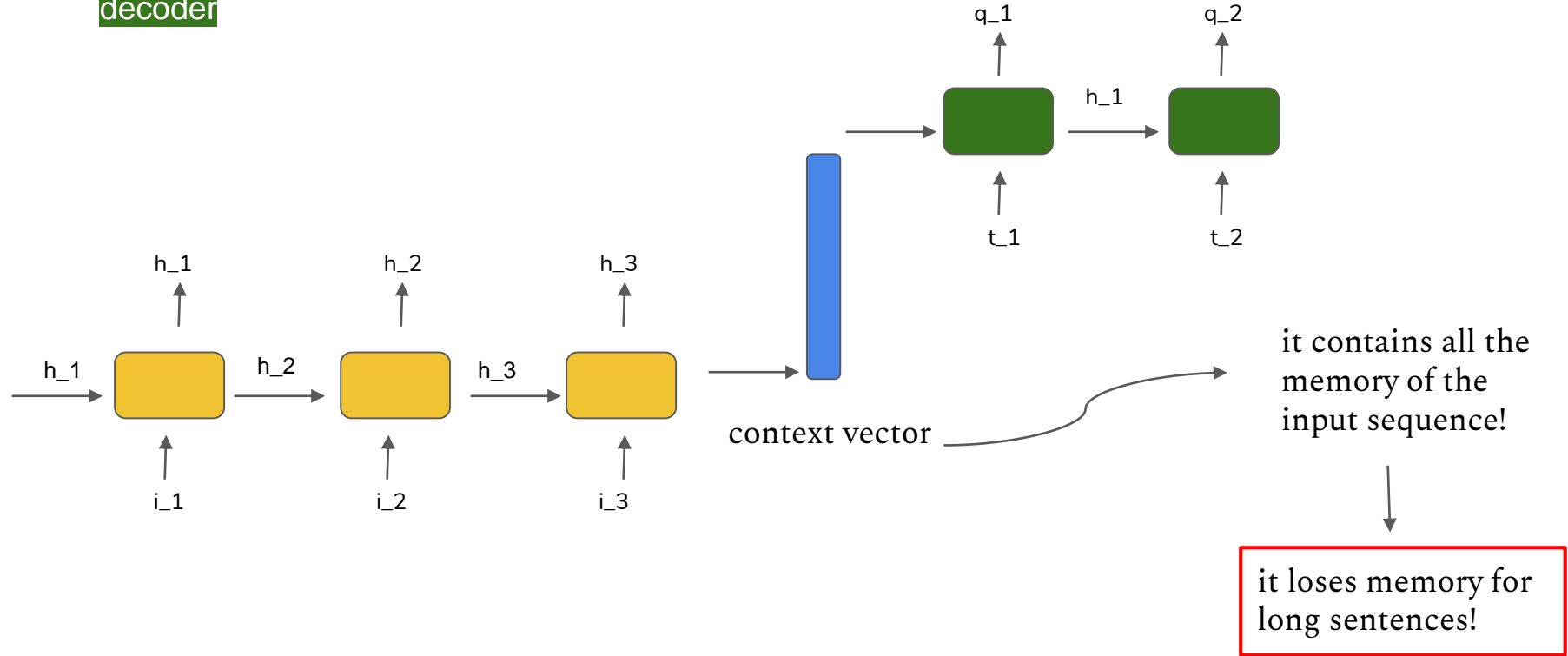
Autoencoders & Seq2Seq



RNN Seq2Seq

encoder

decoder



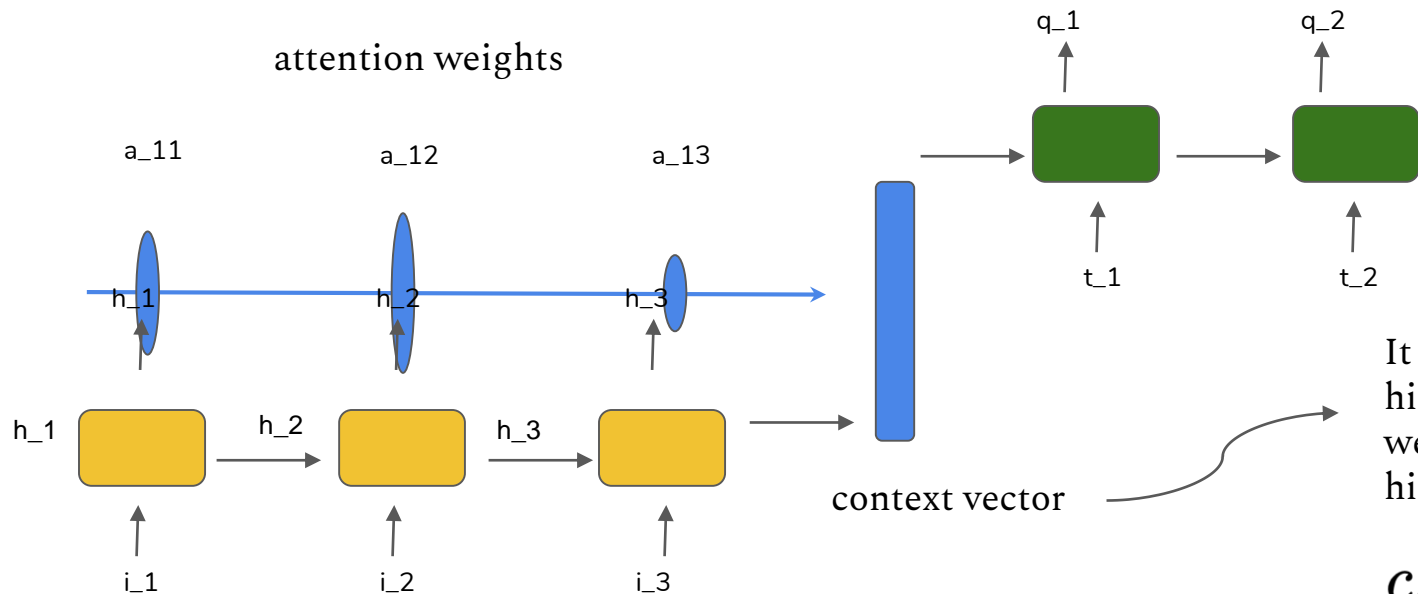
RNN Cons

- they cannot remember/summarize long sequences.
 - they cannot learn long-term dependencies
- they are slow because sequential (not parallelizable)

CNNs solve the first bullet, but
hardly the second.

Attention solves both!

Attention Mechanism



It is not just the last hidden state, but a weighted sum encoder's hidden states!

$$c_j = \sum_i \alpha_{i,j} h_i$$

This is the encoder-decoder attention:

The context vectors enable the decoder to focus on certain parts of the input when predicting its output.

It is computed at each time step j of the decoder

Attention Weights


$$c_j = \sum_i \alpha_{i,j} h_i$$

How are they computed?

How are they learned?

the last
but a
n encoder's
!

$\alpha_{i,j} h_i$

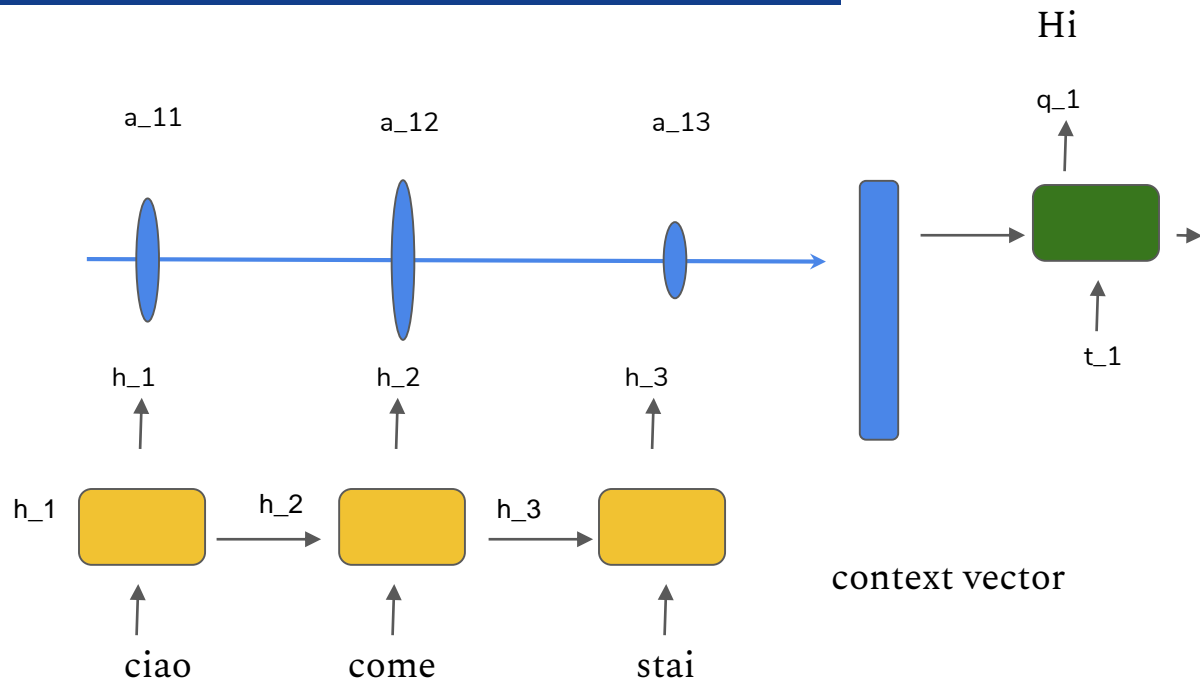
d at each
the decoder

Attention Weights: how are they computed?

$$\alpha_{i,j} = h_i^T \cdot q_j$$

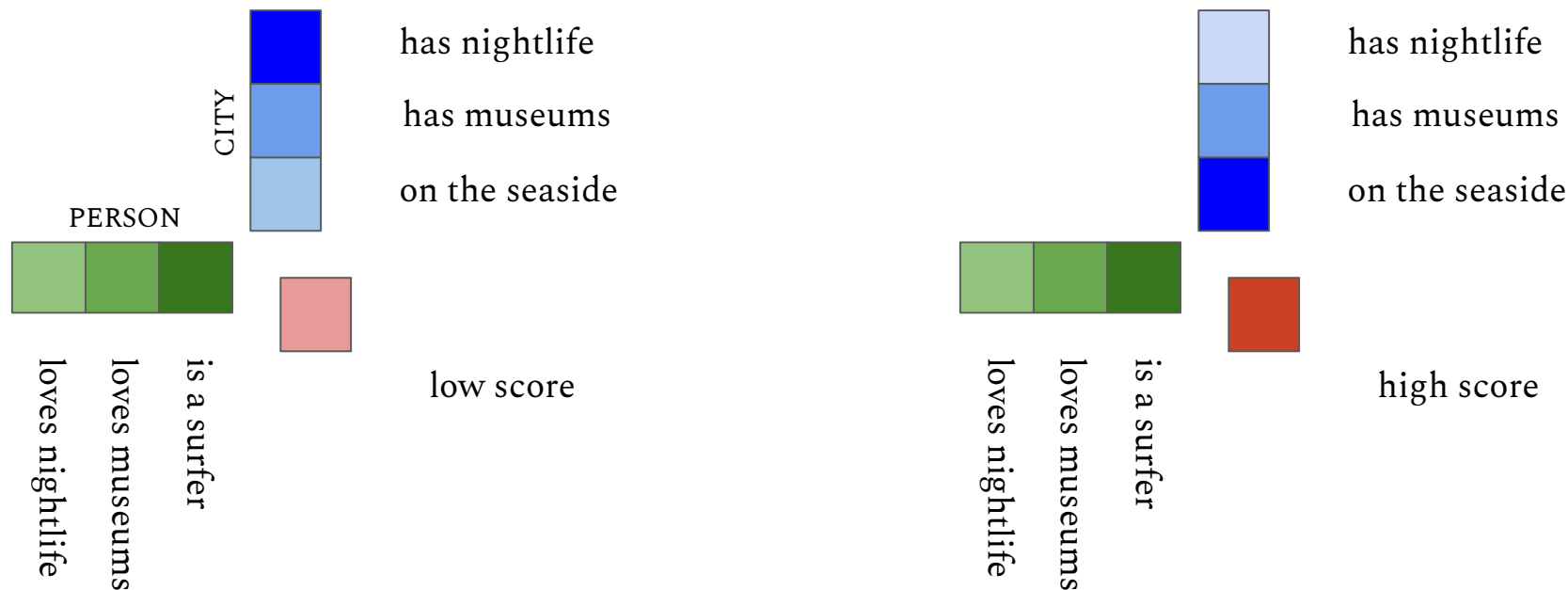
$$c_j = \sum_i \alpha_{i,j} h_i$$

$$c_1 = \alpha_{1,1} h_1 + \alpha_{1,2} h_2 + \alpha_{1,3} h_3$$



$$\alpha_{i,j} = h_i^T \cdot q_j$$

Attention Weights: how are they computed?



We then say that the person “attends” more to the city on the right!

Attention Weights: Alignment

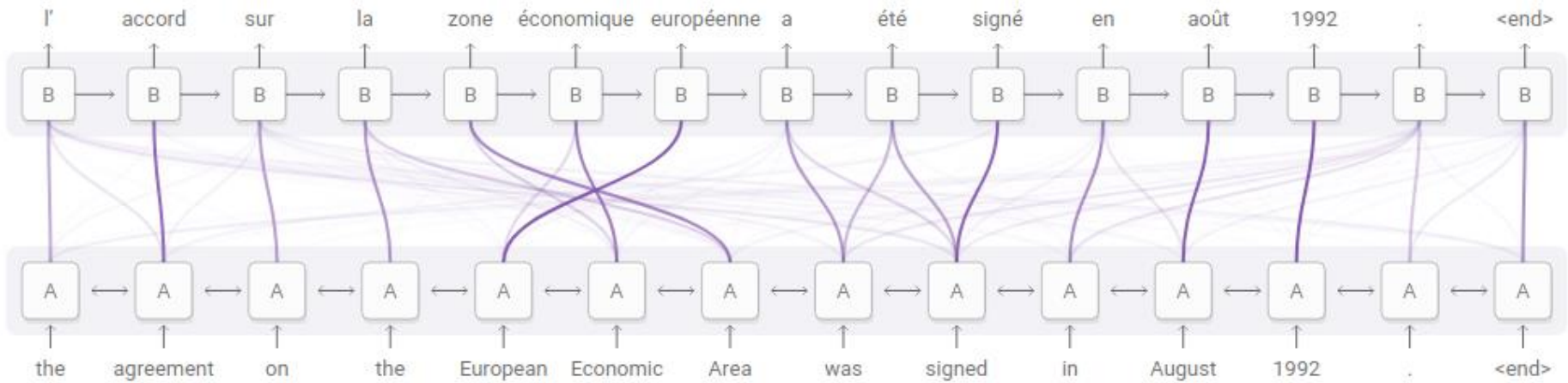
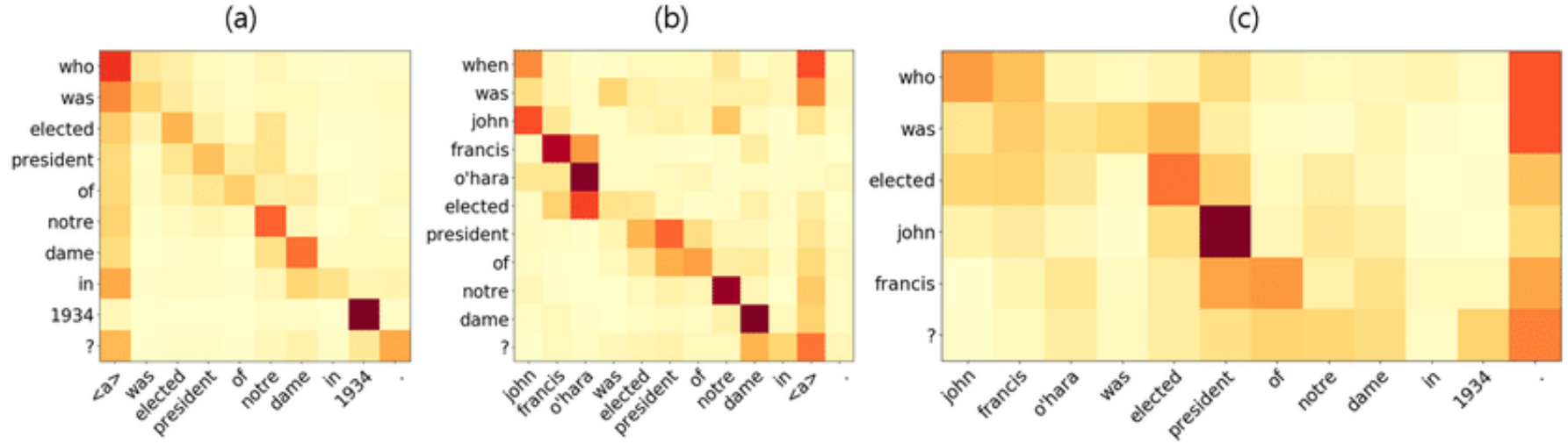


Diagram derived from Fig. 3 of [Bahdanau, et al. 2014](#)

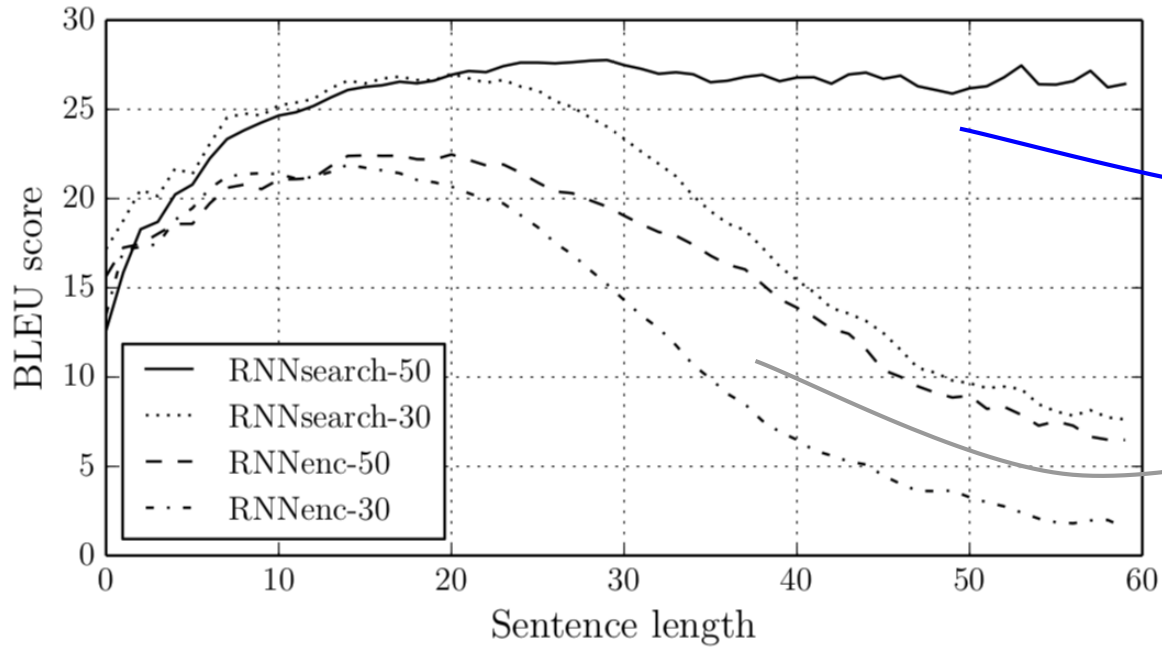
Attention weights measures the alignment between input and output sentences

Attention Matrix



Attention weights measures the alignment between input and output sentences

Attention Matrix



WITH ATTENTION!

NO ATTENTION!

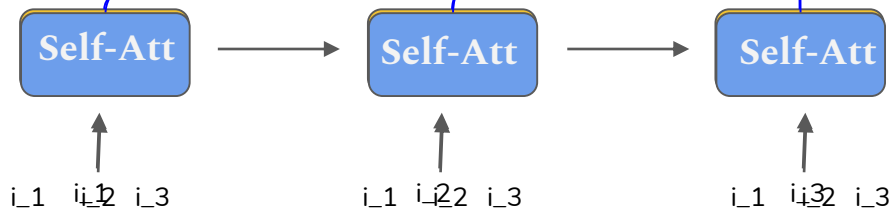
Transformers: Basics

encoder

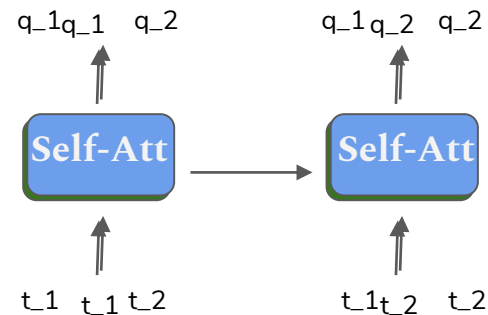
decoder

Attention Is All You Need!

Attention Encoder -Decoder Layer



Parallel!



Attention Is All You Need

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illia.polosukhin@gmail.com

NeurIPS 2017: arXiv:1706.03762

SELF-ATTENTION?

So far we have seen the **encoder-decoder attention**. Together with it, the fundamental operation of any transformer architecture is **self-attention**.

Self-attention is an attention mechanism relating different positions of a single sequence in order to compute a representation of the same sequence.

y_1 y_2 y_3 y_4 y_5

dal *letame* *nascono* *i* *fiori*
 x_1 x_2 x_3 x_4 x_5

SELF-ATTENTION?

$$y_i = \sum_j w_{ij} x_j, \quad w' = x_i^T x_j \quad w_{ij} = \text{softmax}(w'_{ij})$$

$$\mathbf{y}_2 = (\textit{letame} \times \textit{dal}) \times \textit{dal} + \dots$$

<i>dal</i>	<i>letame</i>	<i>nascono</i>	<i>i</i>	<i>fiori</i>
\mathbf{x}_1	\mathbf{x}_2	\mathbf{x}_3	\mathbf{x}_4	\mathbf{x}_5

SELF-ATTENTION?

$$y_i = \sum_j w_{ij} x_j, \quad w' = x_i^T x_j \quad w_{ij} = \text{softmax}(w'_{ij})$$

$$\mathbf{y}_2 = (\text{letame} \times \text{dal}) \times \text{dal} + (\text{letame} \times \text{letame}) \times \text{letame} + \dots$$

dal **letame** nascono i fiori
x_1 x_2 x_3 x_4 x_5

SELF-ATTENTION?

$$y_i = \sum_j w_{ij} x_j, \quad w' = x_i^T x_j \quad w_{ij} = \text{softmax}(w'_{ij})$$

$$\mathbf{y_2} = (\text{letame} \times \text{dal}) \times \text{dal} + (\text{letame} \times \text{letame}) \times \text{letame} + (\text{letame} \times \text{nascono}) \times \text{nascono} +$$

<i>dal</i>	<i>letame</i>	<i>nascono</i>	<i>i</i>	<i>fiori</i>
$\mathbf{x_1}$	$\mathbf{x_2}$	$\mathbf{x_3}$	$\mathbf{x_4}$	$\mathbf{x_5}$

SELF-ATTENTION?

$$y_i = \sum_j w_{ij} x_j, \quad w' = x_i^T x_j \quad w_{ij} = \text{softmax}(w'_{ij})$$

$$\mathbf{y_2} = (\text{letame} \times \text{dal}) \times \text{dal} + (\text{letame} \times \text{letame}) \times \text{letame} + (\text{letame} \times \text{nascono}) \times \text{nascono} + (\text{letame} \times \text{i}) \times \text{i} +$$

<i>dal</i>	<i>letame</i>	<i>nascono</i>	<i>i</i>	<i>fiori</i>
x_1	x_2	x_3	x_4	x_5

SELF-ATTENTION?

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$$\mathbf{y_2} = (\text{letame} \times \text{dal}) \times \text{dal} + (\text{letame} \times \text{letame}) \times \text{letame} + (\text{letame} \times \text{nascono}) \times \text{nascono} + (\text{letame} \times \text{i}) \times \text{i} + (\text{letame} \times \text{fiori}) \times \text{fiori}$$

<i>dal</i>	<i>letame</i>	<i>nascono</i>	<i>i</i>	<i>fiori</i>
x_1	x_2	x_3	x_4	x_5

SELF-ATTENTION LAYER

y_{dal} y_{letame} $y_{nascono}$ y_i y_{fiori}



y_{letame} is a weighted sum over all the embedding vectors in the first sequence, weighted by their (normalized) dot-product with x_{letame}



x_{dal} x_{letame} $x_{nascono}$ x_i x_{fiori}

SELF-ATTENTION LAYER: more detailed

$$y_i = \sum_j w_{ij} x_j, \quad w' = x_i^T x_j \quad w_{ij} = \text{softmax}(w'_{ij})$$

$$\mathbf{y_2} = (\text{letame} \times \text{dal}) \times \text{dal} + (\text{letame} \times \text{letame}) \times \text{letame} + (\text{letame} \times \text{nascono}) \times \text{nascono} + (\text{letame} \times \text{i}) \times \text{i} + (\text{letame} \times \text{fiori}) \times \text{fiori}$$

In self-attention, each input vector (let's say $\mathbf{x_2}$) is used in three different ways in the self attention operation:

- **query:** it is compared to every other vector to establish the weights for its own output $\mathbf{y_2}$
- **key:** it is compared to every other vector to establish the weights for the output of the j -th word $\mathbf{y_j}$
- **value:** it is used as part of the weighted sum to compute each output vector once the weights have been established

SELF-ATTENTION LAYER: more detailed

$$y_i = \sum_j w_{ij} x_j, \quad w' = x_i^T x_j \quad w_{ij} = \text{softmax}(w'_{ij})$$

In the basic self-attention written above, each input vector \mathbf{x}_i must play all three roles.

Its life can be made a bit easier by deriving new vectors for each role (query, key, value), by applying a linear transformation to the original input vector.

$$\mathbf{q}_i = \mathbf{W}_q \mathbf{x}_i \quad \mathbf{k}_i = \mathbf{W}_k \mathbf{x}_i \quad \mathbf{v}_i = \mathbf{W}_v \mathbf{x}_i$$

$$w'_{ij} = \mathbf{q}_i^T \mathbf{k}_j$$

$$w_{ij} = \text{softmax}(w'_{ij})$$

$$\mathbf{y}_i = \sum_j w_{ij} \mathbf{v}_j .$$

*Peter Bloem Blog

SELF-ATTENTION LAYER: more detailed

$$y_i = \sum_j w_{ij} x_j, \quad w' = x_i^T x_j \quad w_{ij} = \text{softmax}(w'_{ij})$$

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$$w'_{ij} = \mathbf{q}_i^T \mathbf{k}_j$$

$$w_{ij} = \text{softmax}(w'_{ij})$$

$$\mathbf{y}_i = \sum_j w_{ij} \mathbf{v}_j$$

- the vector \mathbf{q} encodes the word that is paying attention ('it is querying the other words').
- \mathbf{k} encodes the word to which attention is being paid.

*Peter Bloem Blog

SELF-ATTENTION

$$y_i = \sum_j w_{ij} x_j, \quad w' =$$

In the basic self-attention written above, ϵ

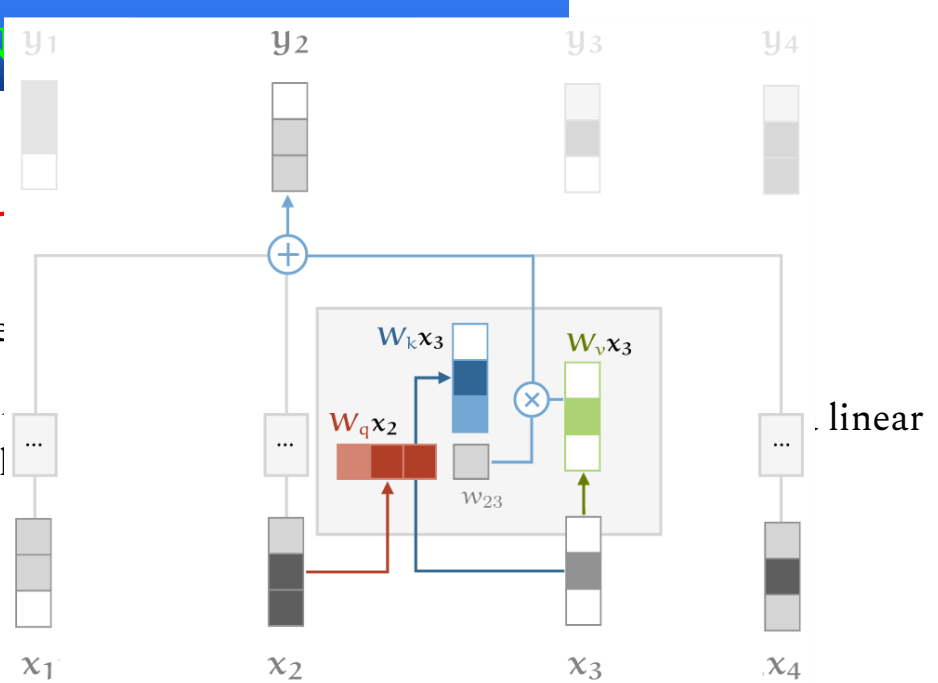
Its life can be made a bit easier by deriving new vector transformation to the

$$\mathbf{q}_i = \mathbf{W}_q \mathbf{x}_i \quad \mathbf{k}_i = \mathbf{W}_k \mathbf{x}_i \quad \mathbf{v}_i = \mathbf{W}_v \mathbf{x}_i$$

$$w'_{ij} = \mathbf{q}_i^T \mathbf{k}_j$$

$$w_{ij} = \text{softmax}(w'_{ij})$$

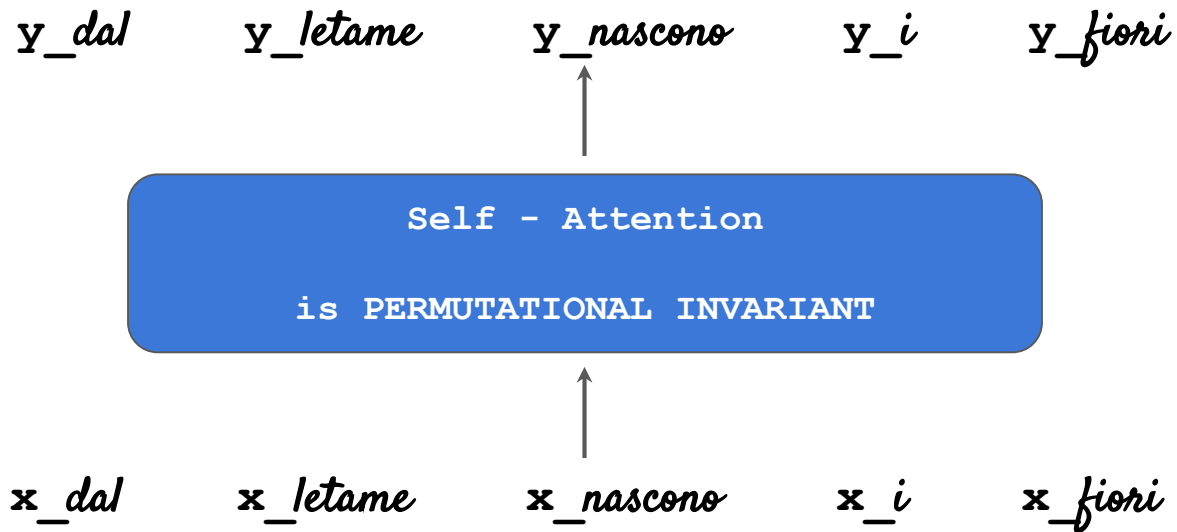
$$\mathbf{y}_i = \sum_j w_{ij} \mathbf{v}_j$$



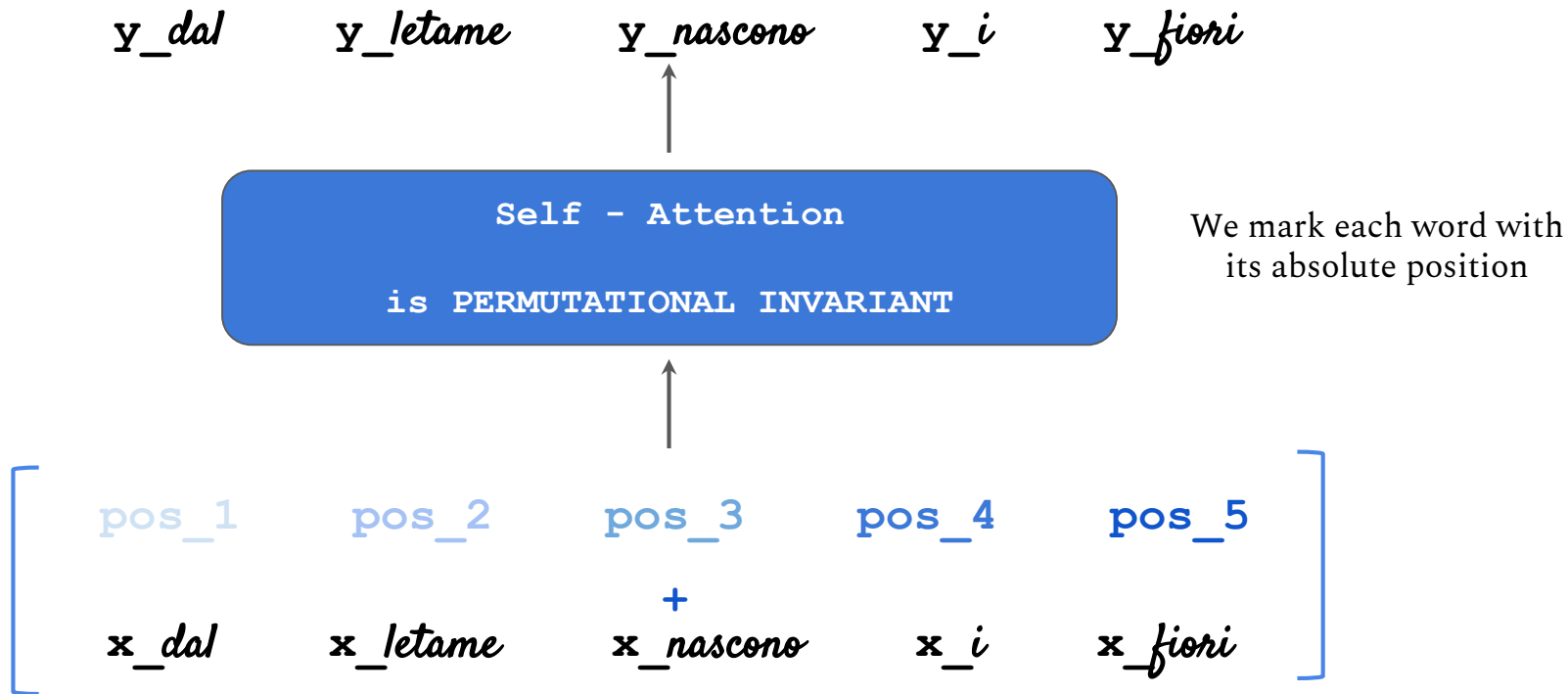
- the vector **q** encodes the word that is paying attention ('it is querying the other words').
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*Peter Bloem Blog

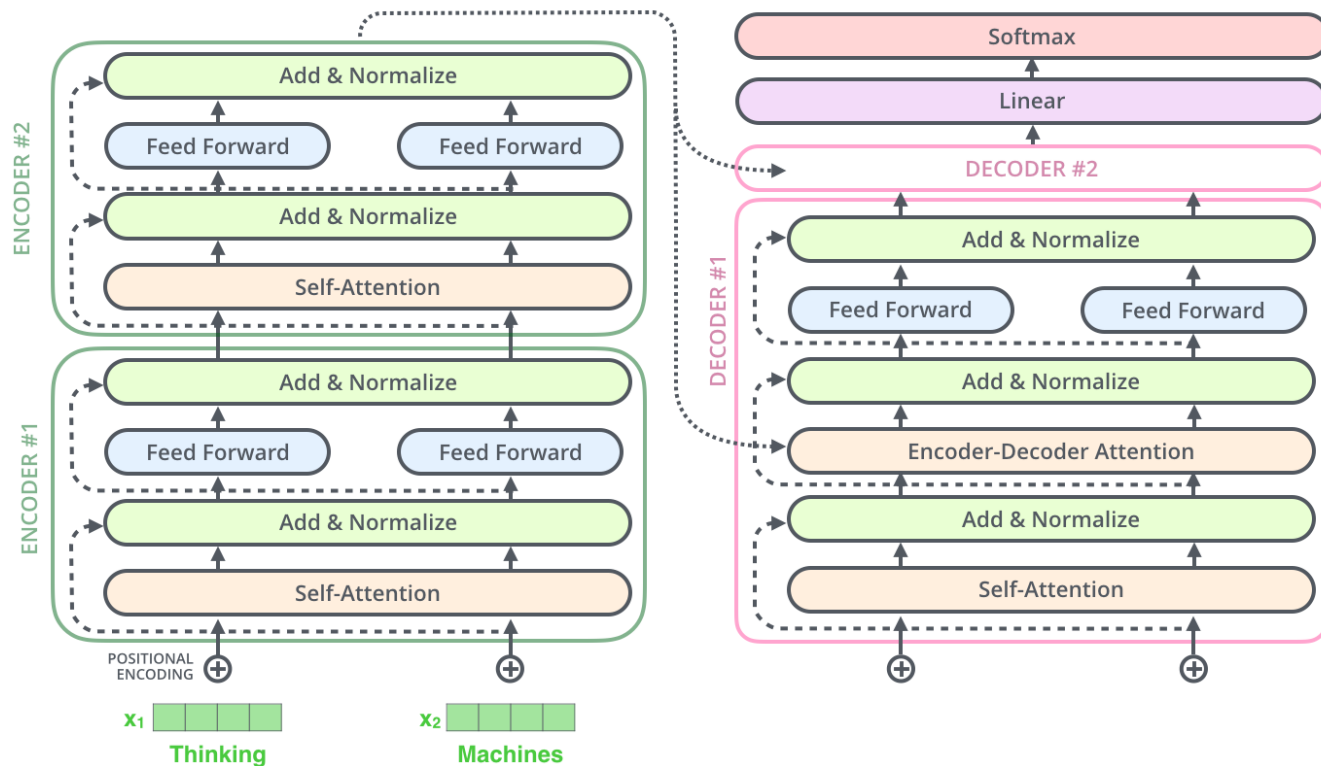
Positional Encoding



Positional Encoding



Transformers



NLP popular models



arXiv:1810.04805



"Language Models are Unsupervised Multitask Learners"



Write With Transformer |

transformer.huggingface.co

All of them are based on Transformers!

Applications

- spell checker
- auto-completion
- machine translation
- word sense disambiguation
- chat bots & virtual assistants
- sentiment analysis & social media marketing
- summarizing text
- text classification
- sentiment analysis
- ...

Machine translation is a huge application for NLP that allows us to overcome barriers to communicating



Start-up based in Budapest. They developed a technology leveraging AI (computer vision + NLP) that is able to recognize and translate sign language.





Aircraft Maintenance: NLP helps mechanics synthesize information from enormous aircraft manuals. It can also find meaning in the descriptions of problems reported verbally or handwritten from pilots.

Neurodegenerative Disease



Neurodegenerative diseases causing dementia are known to affect a person's speech and language. NLP is used to identify those defects.

Predicting probable Alzheimer's disease using linguistic deficits and biomarkers, Orimaye et al. (2017)
A new diagnostic approach for the identification of patients with neurodegenerative cognitive complaints, Al-Hameed et al. (2019)

Genomics



Transcription, the biological process through which DNA is transcribed into RNA, is heavily regulated by DNA-binding transcription factors. Transformers are used for the transcription factor binding site prediction task.

An Attention-Based Model for Transcription Factor Binding Site Prediction, Gunjan Baid (Berkeley, Thesis)

LIMIT #1: Efficiency



90 x 10⁹ neurons
firing 10³ time/s
each 10⁴ connections

2 x 10⁹ Mflops (ops/s)

Energy

20 watt

Serial + Massively Parallel



10⁹ operations/s
5 x 10⁹ transistors/cpu

8 x 10⁹ Mflops (ops/s)

Energy

2.5 x 10⁷ watt

Mostly Serial

LIMIT #1: Efficiency



90×10^9 neurons
firing 10^3 times
each 10^4 connections

2×10^9 Mflops

Energy

20 watt

Green AI

Roy Schwartz*[◇] Jesse Dodge*^{◇★} Noah A. Smith^{◇♡} Oren Etzioni[◇]

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[★]Carnegie Mellon University, Pittsburgh, Pennsylvania, USA

[♡]University of Washington, Seattle, Washington, USA

July 2019

aiXiv:1907.10597

operations/s
transistors/cpu

Flops (ops/s)

energy

2.5×10^7 watt

Serial + Massively Parallel

Mostly Serial

LIMIT #2

I do not know how to define this limit...

...è di finezze che si distingue una persona di spessore.

Quell'uomo era così onesto che anche il caffè lo prendeva corretto.

Non contare sulle altre persone, la somma potrebbe essere zero.

Un'errore è corretto per coerenza.

LIMIT #2

*Siamo fatti di sorrisi e silenzi,
sorrisi e silenzi.
I primi vincono,
i secondi passano.*

Will AI be able to generate it?



Cristiano-De-Nobili

Thanks



@denocris



@denocris

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15-16

Novembre 2019

Genova

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