



Jay Alammar

Visualizing machine learning one concept at a time. @JayAlammar on Twitter. YouTube Channel

## **Artificial Intelligence**

**Creating the Future** 

**Dong-A University** 

Division of Computer Engineering & Artificial Intelligence

## References

### Main

• https://jalammar.github.io/illustrated-transformer/

#### **Transformer**

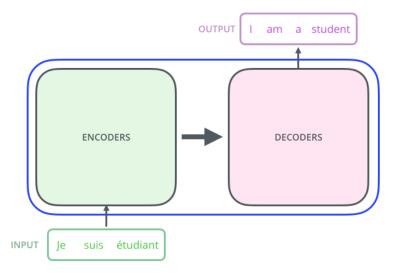
- A model that uses attention to boost the speed with which these models can be trained.
- The Transformers outperforms the Google Neural Machine Translation model in specific tasks.
- The biggest benefit, however, comes from how The Transformer lends itself to parallelization. It is in fact Google Cloud's recommendation to use The Transformer as a reference model to use their <u>Cloud TPU</u> offering.

- A TensorFlow implementation of it is available as a part of the <u>Tensor2Tensor</u> package.
- Harvard's NLP group created <u>a guide annotating the paper with PyTorch implementation</u>.

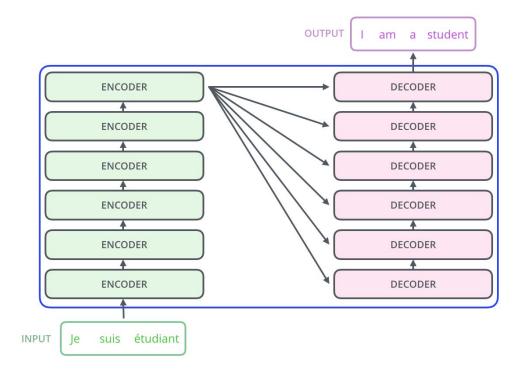
### A High-Level Look

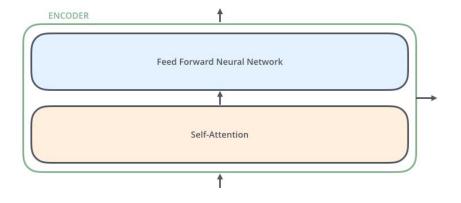
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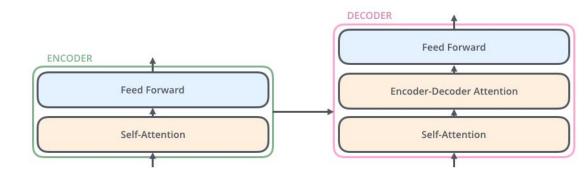




### A High-Level Look



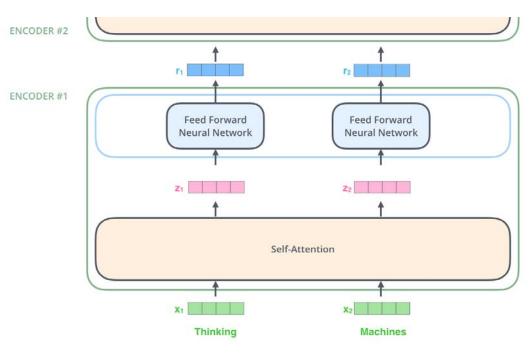




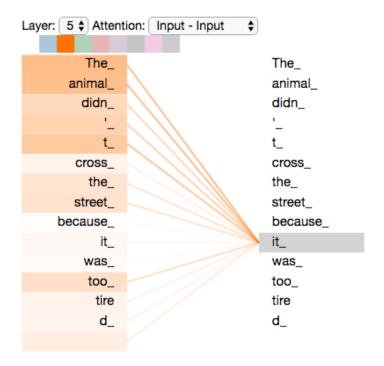
### **Bringing The Tensors Into The Picture**

# **X**1 étudiant Je suis ENCODER A Feed Forward Self-Attention étudiant Je suis

### **Bringing The Tensors Into The Picture**



### Self-Attention at a High Level



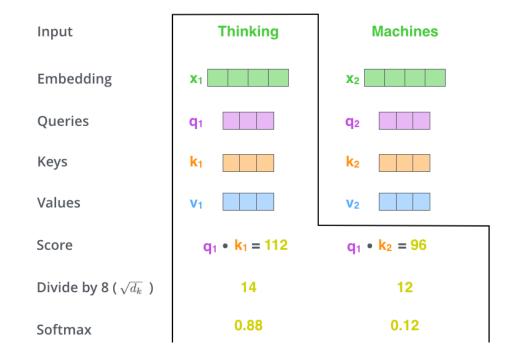
### **Self-Attention in Detail**

Input	Thinking	Machines	
Embedding	X <sub>1</sub>	X <sub>2</sub>	
Queries	<b>q</b> 1	<b>q</b> <sub>2</sub>	Wa
Keys	k <sub>1</sub>	k <sub>2</sub>	Wĸ
Values	V <sub>1</sub>	V <sub>2</sub>	w

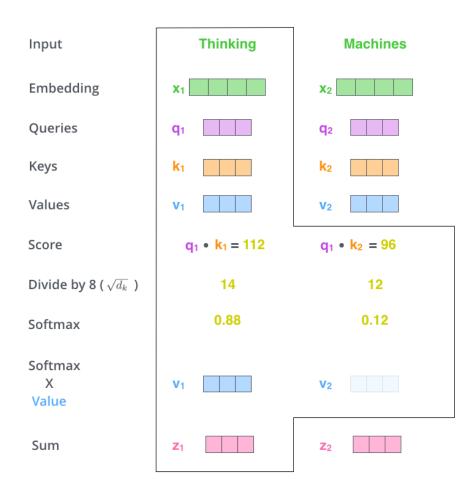
### **Self-Attention in Detail**

#### **Thinking Machines** Input **Embedding** $X_1$ X<sub>2</sub> Queries $q_1$ Keys $k_1$ $k_2$ Values $V_1$ $V_2$ Score $q_1 \cdot k_1 = 112$ $q_1 \cdot k_2 = 96$

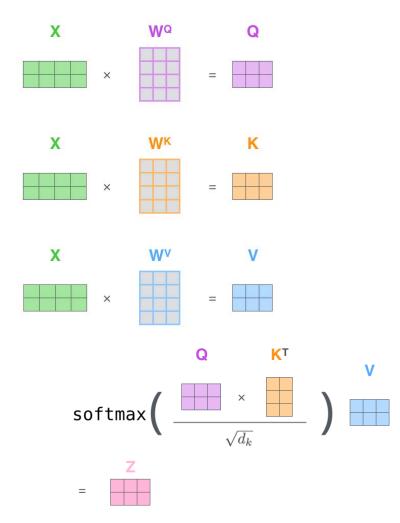
### **Self-Attention in Detail**



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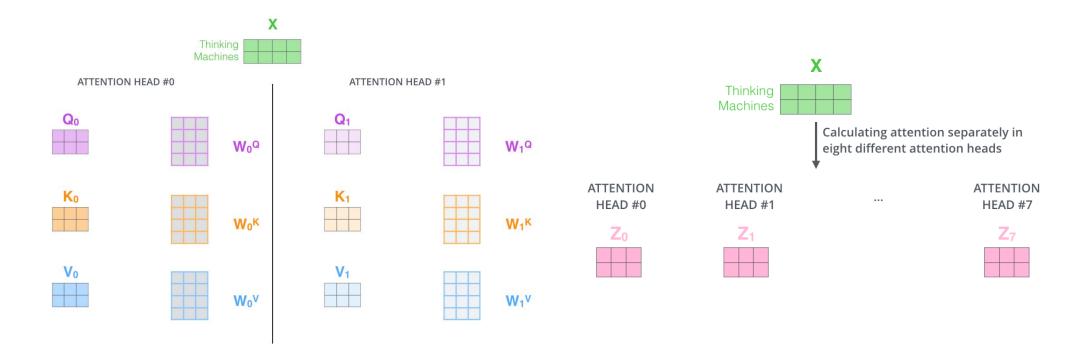


### **Matrix Calculation of Self-Attention**



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### **The Beast With Many Heads**



### **The Beast With Many Heads**



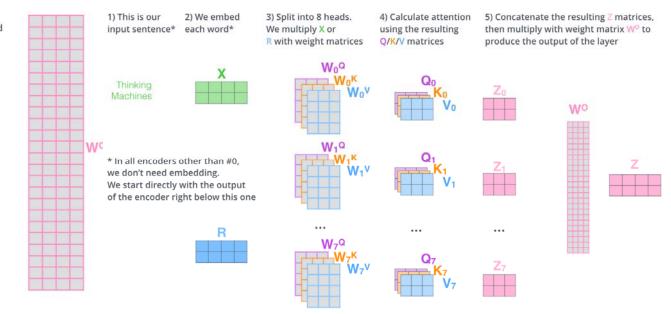


2) Multiply with a weight matrix W<sup>o</sup> that was trained jointly with the model

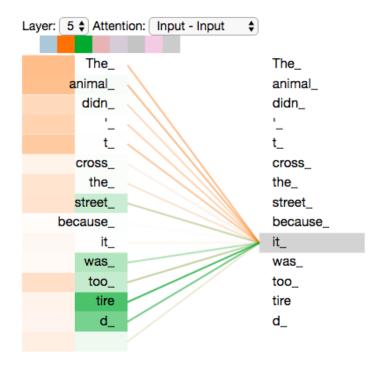
X

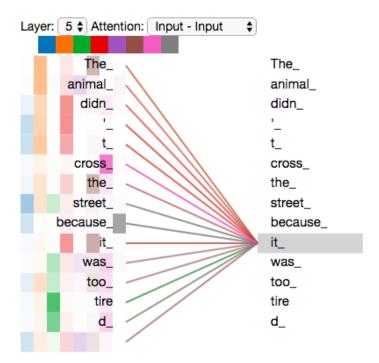
3) The result would be the  ${\mathbb Z}$  matrix that captures information from all the attention heads. We can send this forward to the FFNN



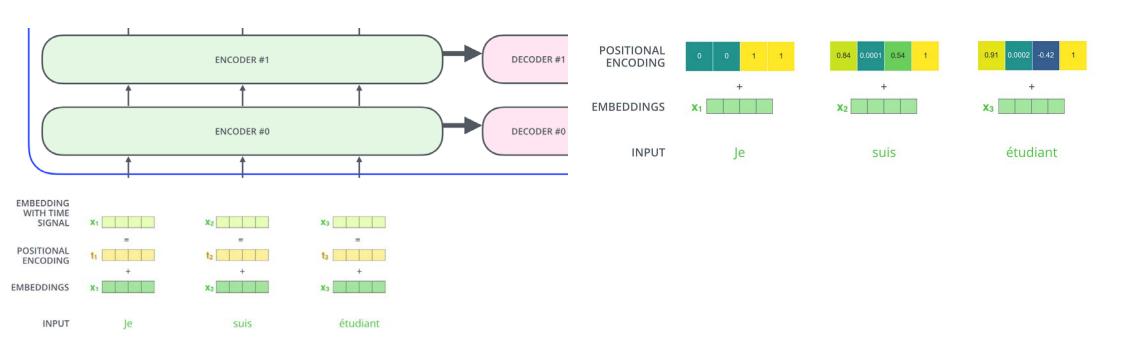


### **The Beast With Many Heads**

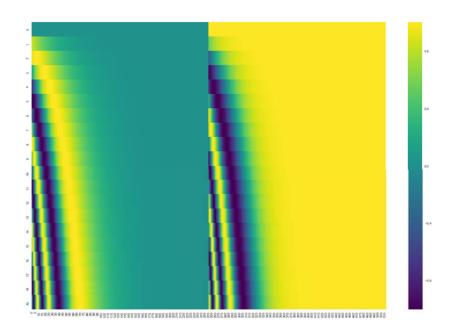


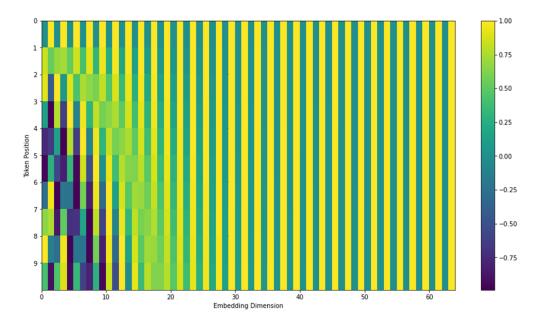


# Representing The Order of The Sequence Using Positional Encoding

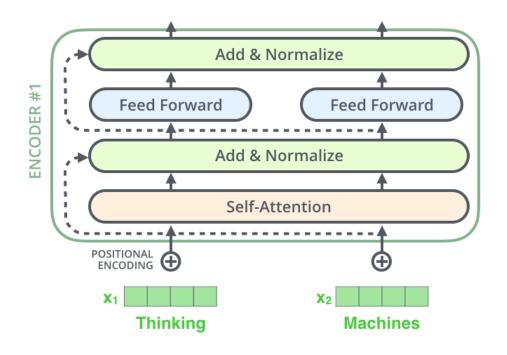


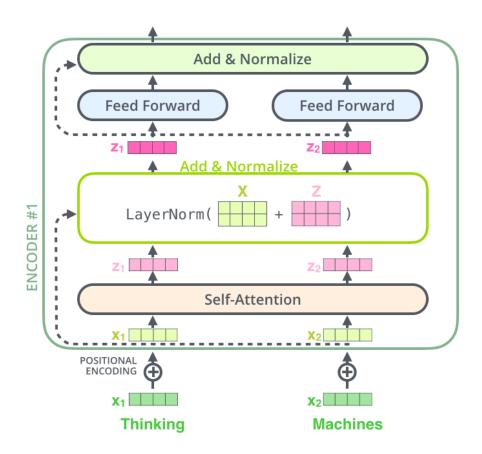
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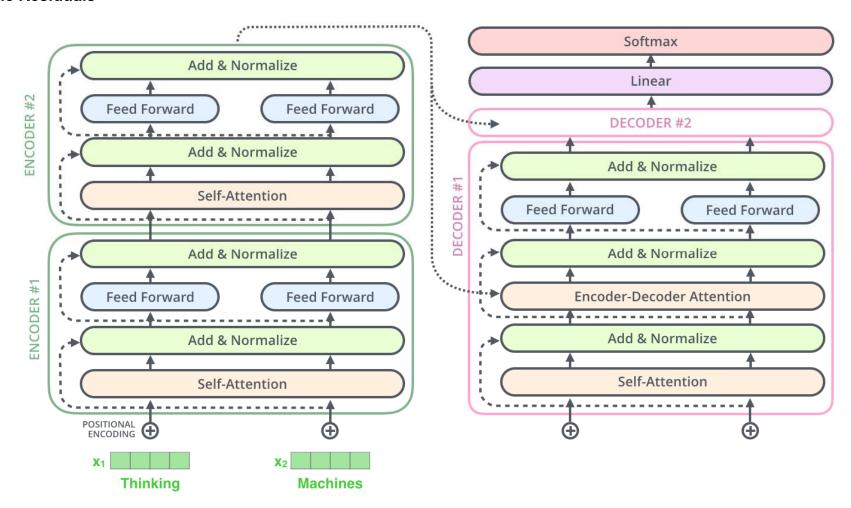


### The Residuals

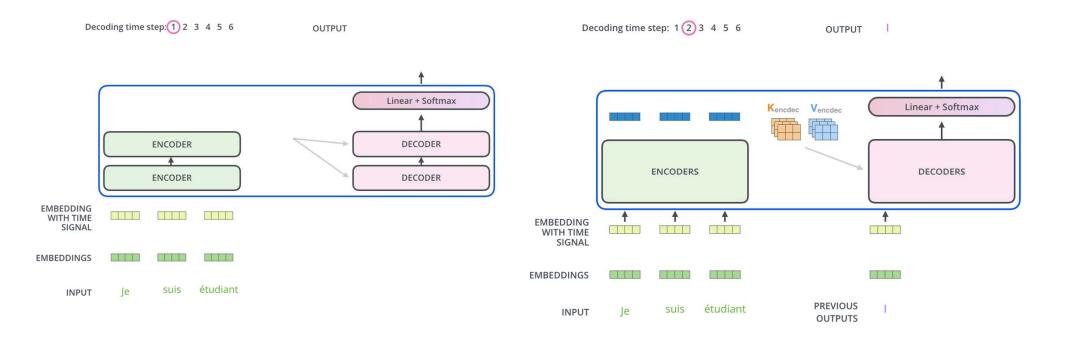




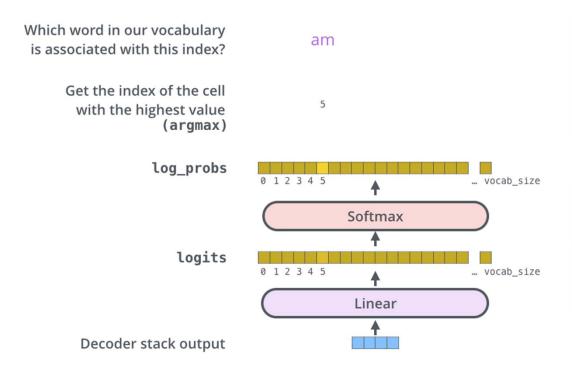
### The Residuals



### **The Decoder Side**



### **The Final Linear and Softmax Layer**



### **Recap Of Training**

#### **Output Vocabulary**

WORD	a	am	ı	thanks	student	<eos></eos>
INDEX	0	1	2	3	4	5

#### **Output Vocabulary**

WORD	a	am	1	thanks	student	<eos></eos>
INDEX	0	1	2	3	4	5

#### One-hot encoding of the word "am"

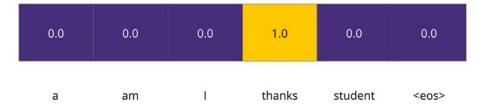
0.0	1.0	0.0	0.0	0.0	0.0
-----	-----	-----	-----	-----	-----

#### **The Loss Function**

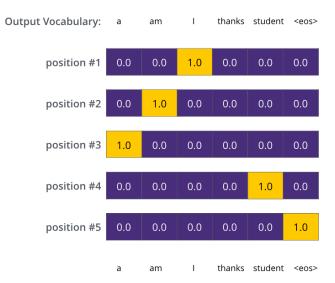
#### **Untrained Model Output**



#### Correct and desired output



### **Target Model Outputs**



#### **Trained Model Outputs**

