COLX-531: Neural Machine Translation

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① mute yourself

② You can unmute yourself and ask a question.

③ If you need to leave, you don't have to ask for permission

④ practice common sense / no hard feelings.

⑤ You can stop me anytime.

Attention Is All You Need

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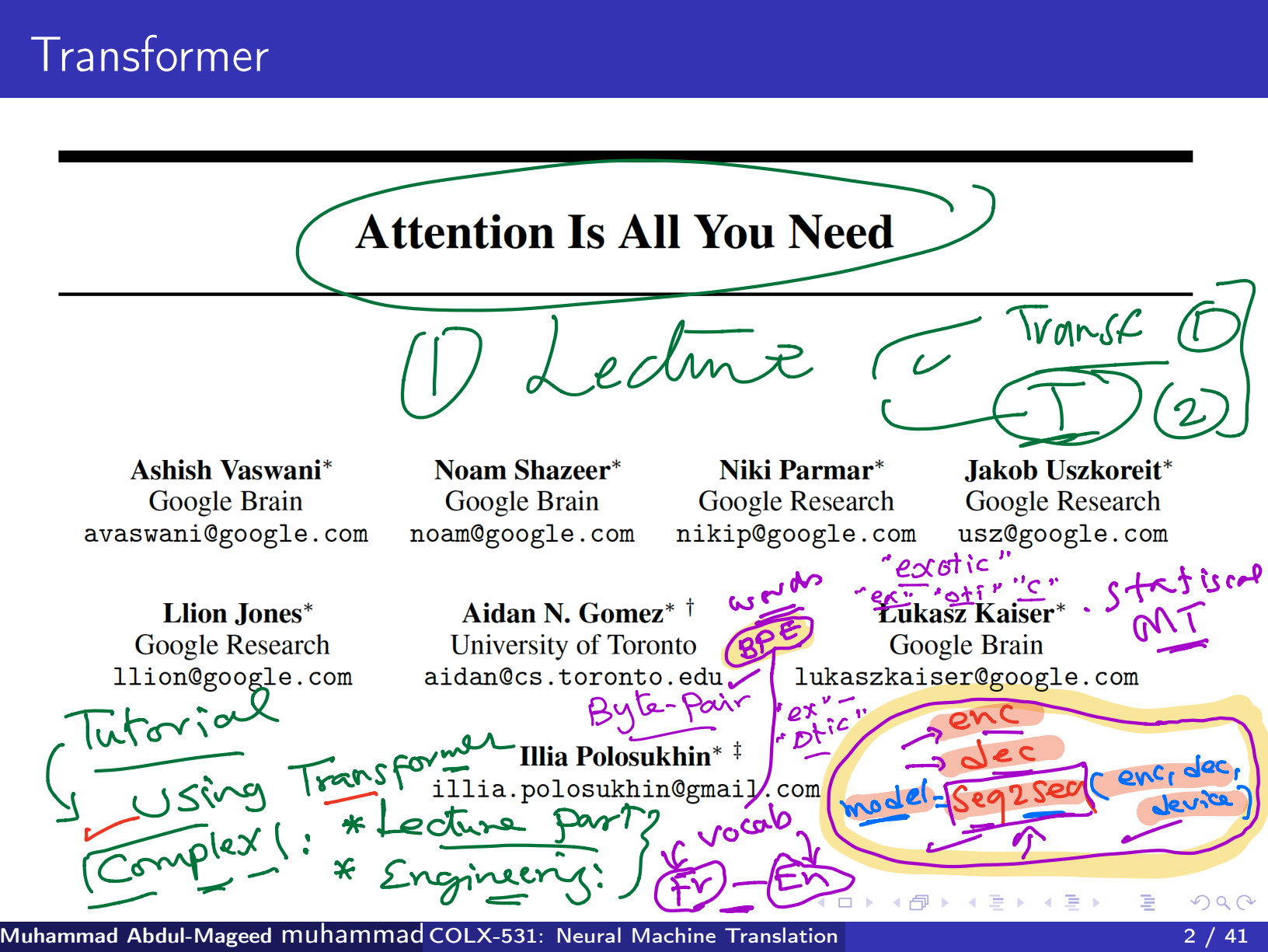


Transformers Motivated

Background

- **Goal:** to reduce sequential computation
- **Extended Neural GPU, ByteNet**, and **ConvS2Sb:** use convnets for computing hidden representations in parallel for all input and output positions.
- Still difficult to learn dependencies between distant positions
- **Transformer:** **Constant number of operations** to relate signals from two arbitrary input or output positions
- This is at the cost of reduced effective resolution due to **averaging attention-weighted positions**
- Counteracted with **Multi-Head Attention**

Self-Attention (*aka* intra-attention)

What is self-attention?

- An attention mechanism that relates different positions of a single sequence in order to compute a representation of the sequence
- Has been successfully applied to **reading comprehension, abstractive summarization, textual entailment**, and **learning task-independent sentence representations**

Self-Attention

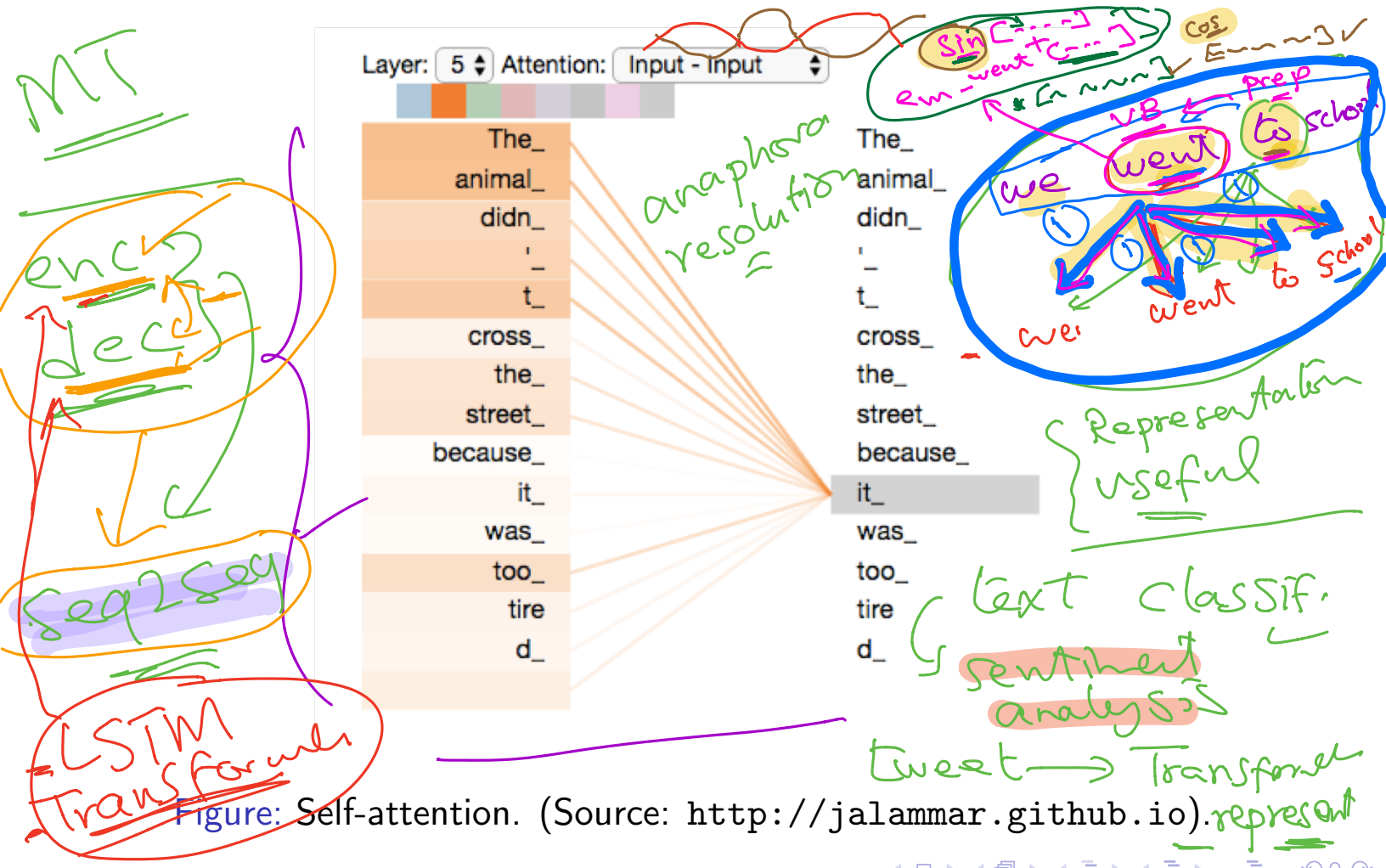


Figure: Self-attention. (Source: `http://jalammar.github.io`).

Transformer Architecture

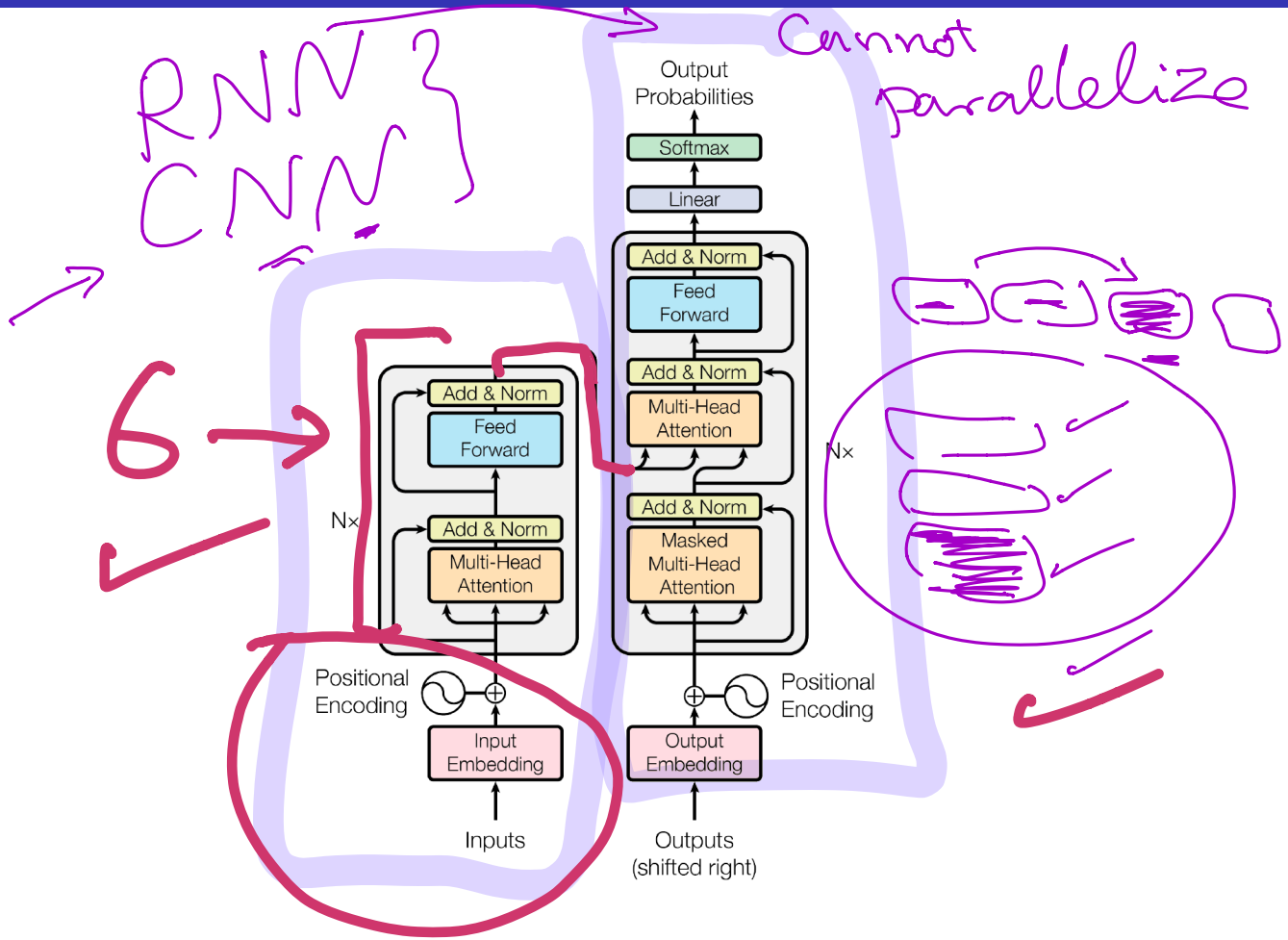


Figure: Transformer: Model Architecture.

Recall: Basic Encoder Decoder Idea

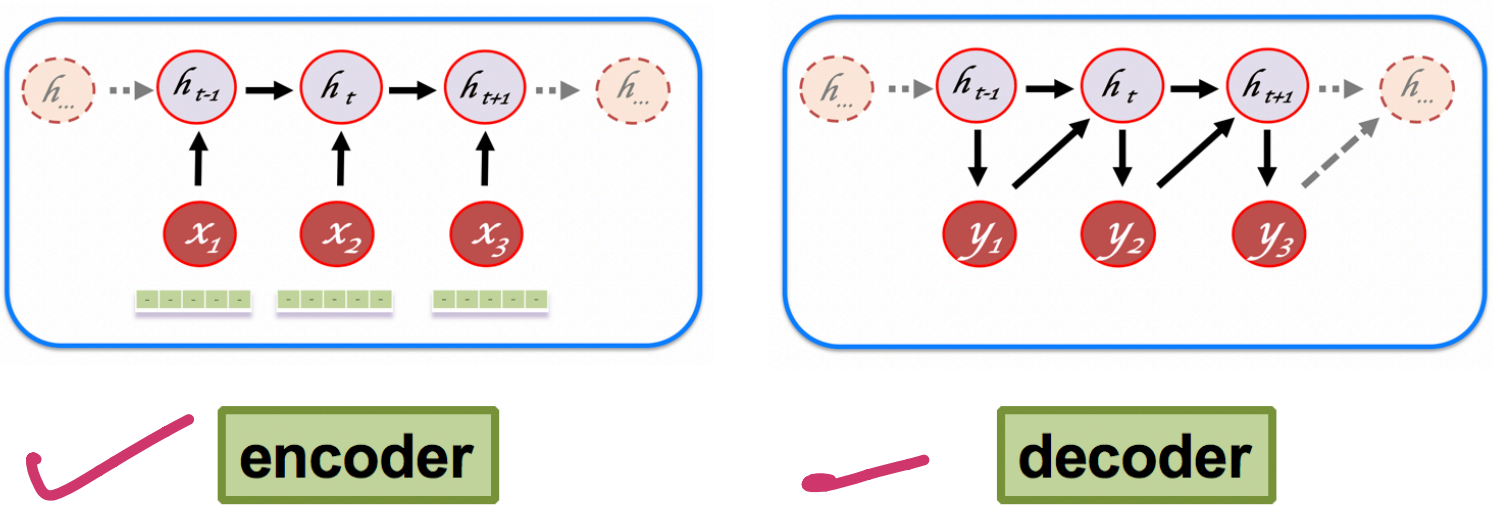


Figure: Transformer has an encoder and a decoder.

Transformer is based on encoder-decoder design

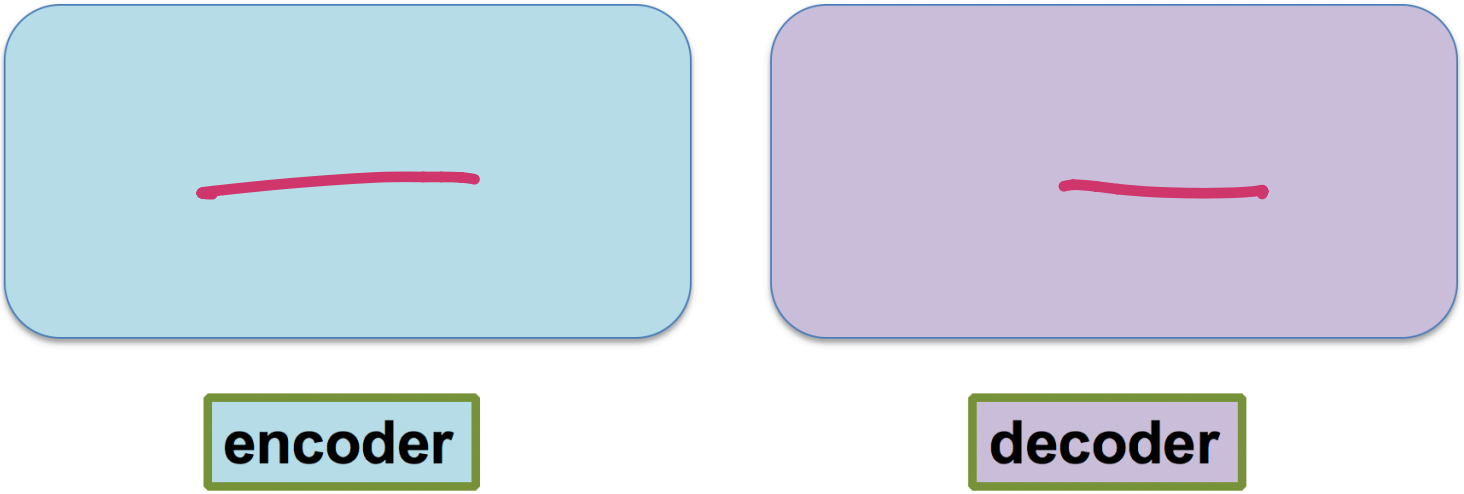


Figure: Transformer has an encoder and a decoder, **each with specialized building blocks**.

Encoder-Decoder

Basic Encoder-Decoder Operations

- **Encoder** maps an input sequence of symbol representations $(x_1, \ldots, x_n)$ to a sequence of continuous representations $\mathbf{z} = (z_1, \ldots, z_n)$.
- Given $\mathbf{z}$, the **decoder** then generates an output sequence $(y_1, \ldots, y_m)$ of symbols one element at a time.
- **Auto-regressive:** At each step the model is auto-regressive, consuming the previously generated symbols as additional input when generating the next.

Input and Output **Embeddings**

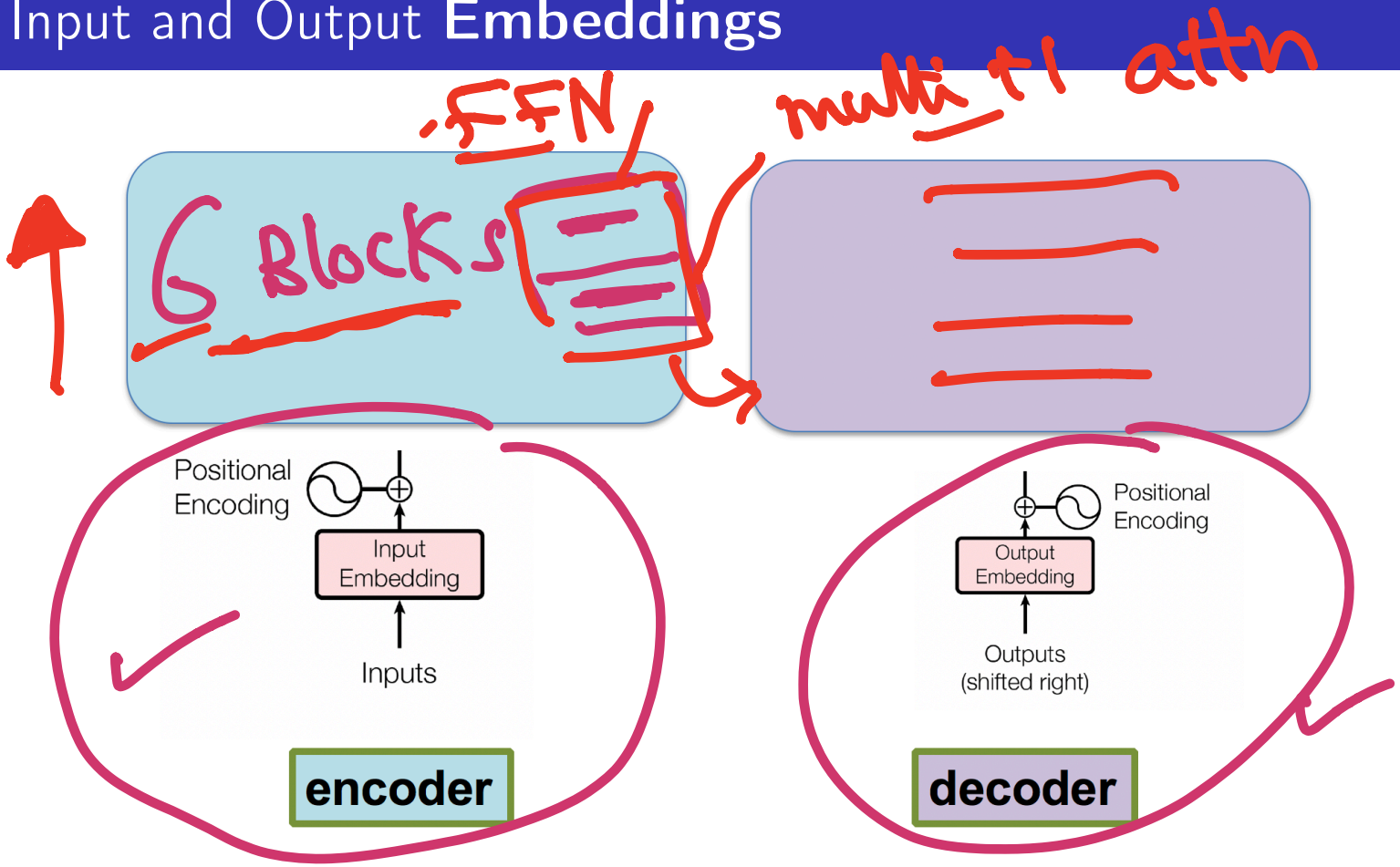


Figure: Embeddings for Encoder and Decoder.

Encoding Word Position

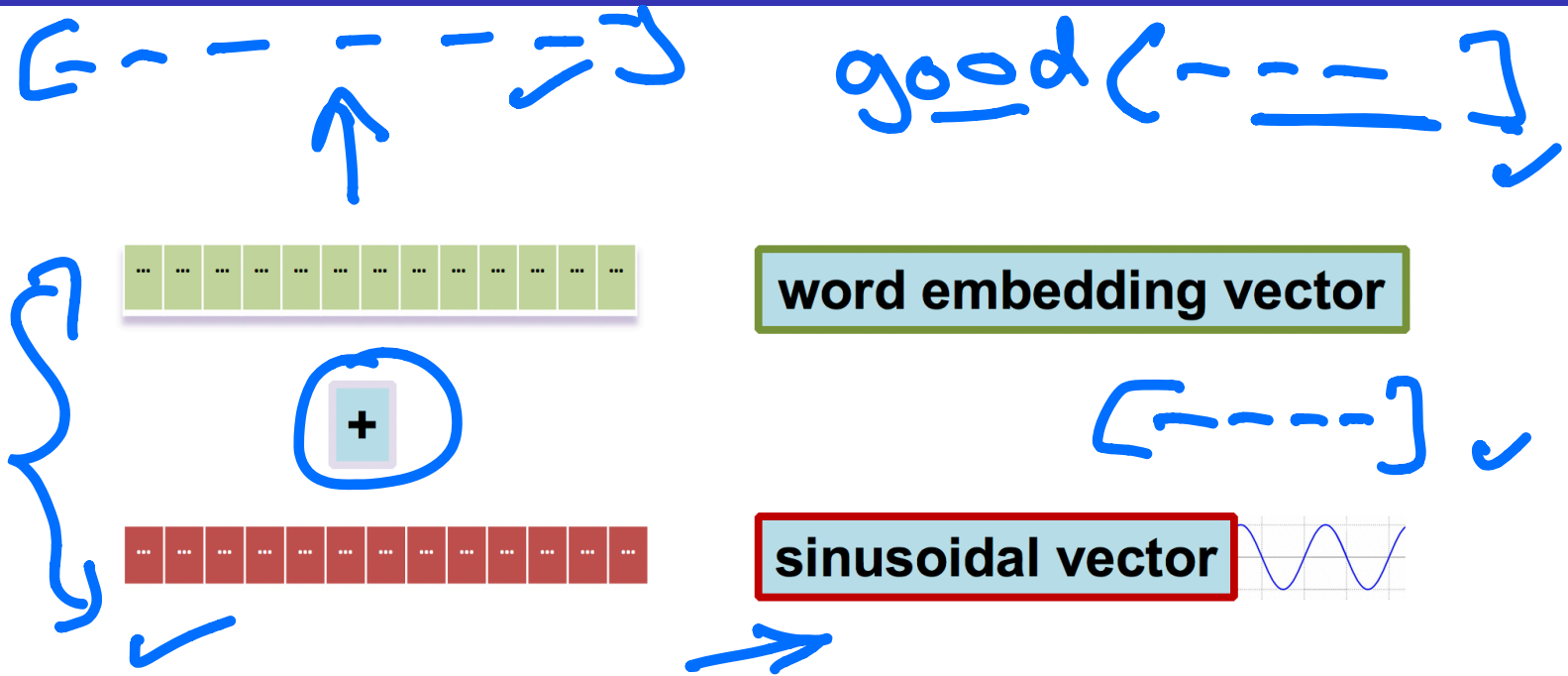


Figure: Simple Addition for encoding word positions

Positional Encoding

Recipe for PE

- **Positional encodings** added to the **input embeddings** at the bottoms of encoder and decoder stacks
- PEs ***have the same dimension*** d_{model} as the embeddings, so the two can be summed:

$PE(pos, 2i) = sin(pos/10000^{2i/d_{model}})$ &
$PE(pos, 2i+1) = cos(pos/10000^{2i/d_{model}})$
where pos is the position and i is the dimension.

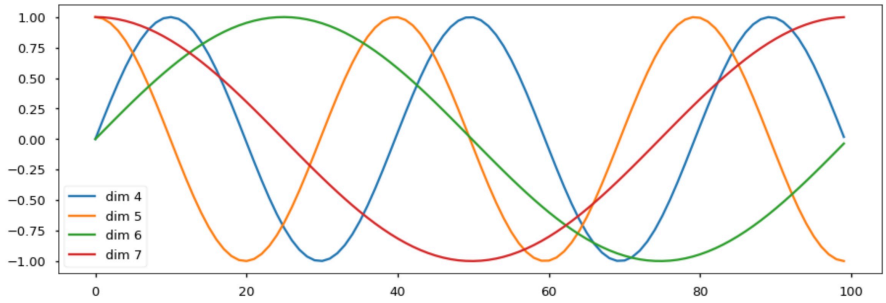


Figure: `https://nlp.seas.harvard.edu/2018/04/03/attention.html`.

Positional Encoding Example

PE Example

- For w at position $pos \in [0, L-1]$, in sequence $s = (w_1 \ldots w_4)$, with 4-dimensional embedding e_w and $d_{model} = 4$:

$$e'_w = e_w + \left[\sin\left(\frac{pos}{10000^0}\right), \cos\left(\frac{pos}{10000^0}\right), \sin\left(\frac{pos}{10000^{2/4}}\right), \cos\left(\frac{pos}{10000^{2/4}}\right) \right]$$

$$= e_w + \left[\sin(pos), \cos(pos), \sin\left(\frac{pos}{100}\right), \cos\left(\frac{pos}{100}\right) \right]$$

where the formula for positional encoding is as follows

$$\mathrm{PE}(pos, 2i) = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right),$$

$$\mathrm{PE}(pos, 2i+1) = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right).$$

with $d_{model} = 512$ (thus $i \in [0, 255]$) in the original paper.

Figure: Source: https://datascience.stackexchange.com/questions/51065/what-is-the-positional-encoding-in-the-transformer-model.

Positional Encoding Illustrated

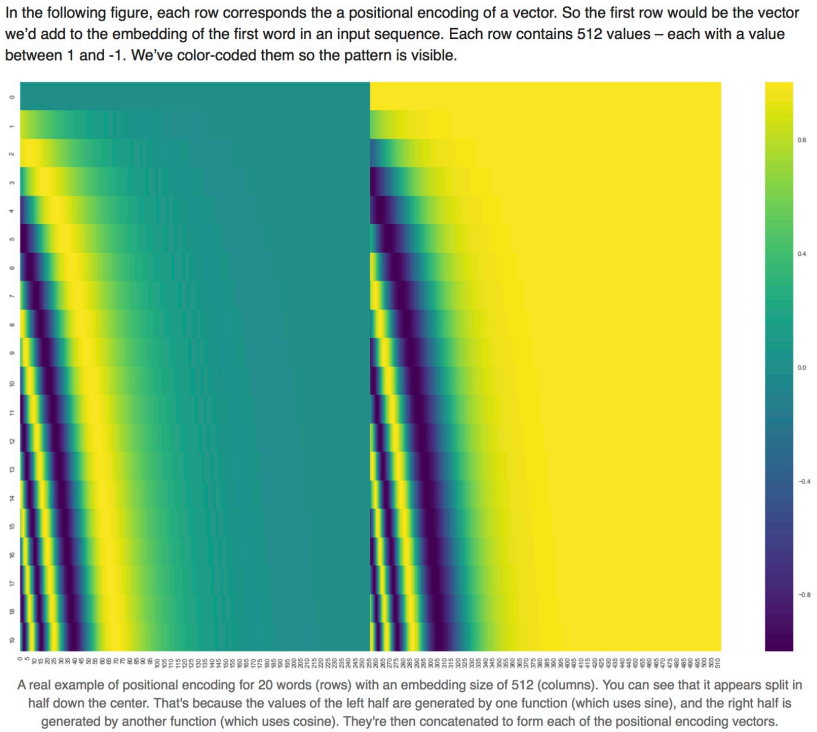
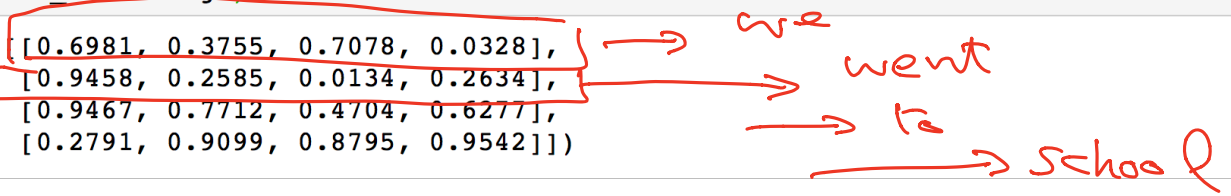


Figure: Source: `http://jalammar.github.io`. This illustration is unfortunately incorrect as it uses `sin` for the first half of the embedding and `cos` for the second half, instead of `sin` for even indices and `cos` for odd indices.

Torch Tensor for Word Embeddings

```
import math
import numpy as np
import torch
import matplotlib.pyplot as plot
#---------------------------------
max_seq_len= 4
d_model= 4
d_embed= 4
"""
Let's create a tensor of word embeddings with 4 dimensions for each word (d_embed),
for 4 words (max_seq_len)
"""
word_embeddings= torch.rand( (max_seq_len, d_embed))
print(word_embeddings)
```

```
tensor([[0.6981, 0.3755, 0.7078, 0.0328],
        [0.9458, 0.2585, 0.0134, 0.2634],
        [0.9467, 0.7712, 0.4704, 0.6277],
        [0.2791, 0.9099, 0.8795, 0.9542]])
```



Tensor for Positions

```
"""
Let's create a tensor of positional encodings, populate by zeros for now.
Each word vector will have a corresponding positional vector within this pe tensor
"""
pe = torch.zeros(max_seq_len, d_embed) # positional encoding
print(pe)
```

```
tensor([[0., 0., 0., 0.],
        [0., 0., 0., 0.],
        [0., 0., 0., 0.],
        [0., 0., 0., 0.]])
```

```
"""
Let's change the positional encodings tensor such that each dimension
is changed by sin or cos, as approbriate
"""
for pos in range(max_seq_len):
    for i in range(0, d_model, 2):
        pe[pos, i] = math.sin(pos / (10000 ** ((2 * i)/d_model))  )
        pe[pos, i + 1] = math.cos(pos / (10000 ** ((2 * i)/d_model))  )
print(pe)
```

```
tensor([[ 0.0000,  1.0000,  0.0000,  1.0000],
        [ 0.8415,  0.5403,  0.0001,  1.0000],
        [ 0.9093, -0.4161,  0.0002,  1.0000],
        [ 0.1411, -0.9900,  0.0003,  1.0000]])
```

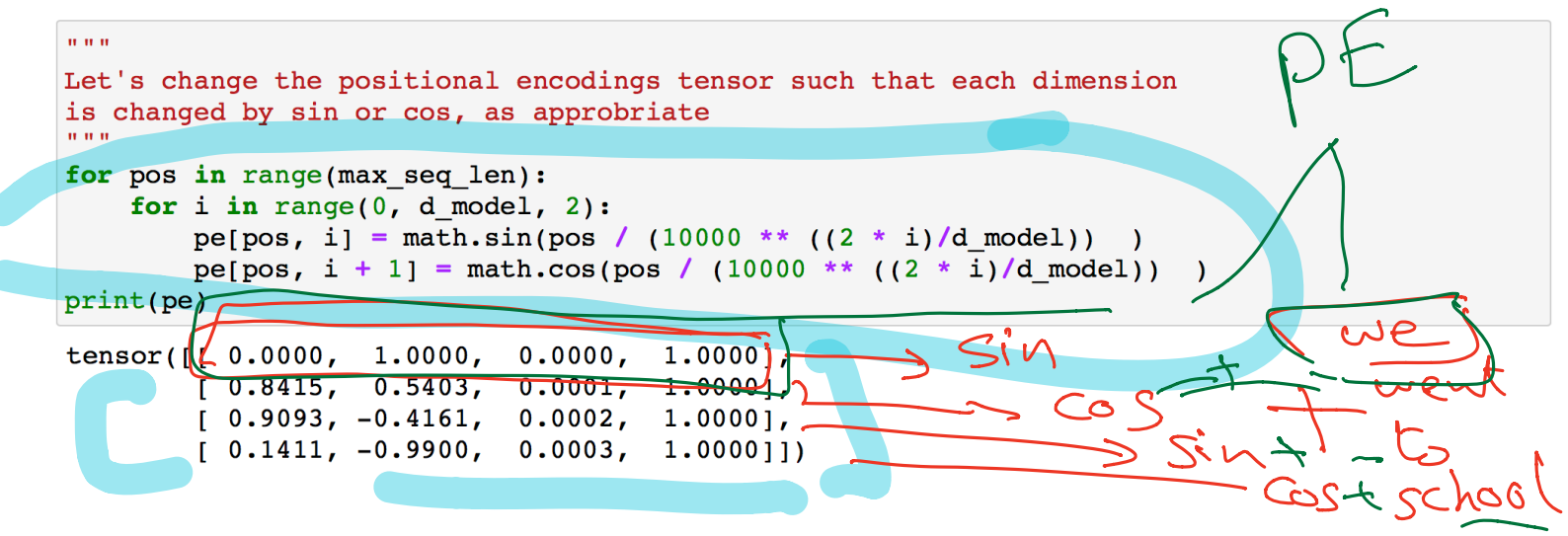


Figure: A tensor for sinusoidal vectors at each position *i* **(sin)** and *i+1* **(cos)**.

Adding Embeddings and Positions for **PE**

```
"""
Let's retrieve positional encoding at index 3
and also embedding vector for index 3.
"""
pe3= pe[2] # Positional encoding at index 3.
w3_embed = word_embeddings[2] # Embedding for word 3
#-----------------------------------------------------------
print("\n-- Positional encoding for w in position 3:\n\n", pe3)
print("\n-- Embedding vector for w in position 3:\n\n", w3_embed)
```

```
-- Positional encoding for w in position 3:

 tensor([ 0.9093, -0.4161,  0.0002,  1.0000])

-- Embedding vector for w in position 3:

 tensor([0.9467, 0.7712, 0.4704, 0.6277])
```

```
# We simply add the two vectors
print("\n-- Embedding vector and positional encoding added:\n\n", word_embedding + pe3)
```

```
-- Embedding vector and positional encoding added:

 tensor([1.7087, 0.0290, 0.2876, 1.9235], dtype=torch.float64)
```

Figure: Encoding for w3 is by adding its embed and sinusoidal pos vectors.

Encoder Blocks (6 Identical Blocks)

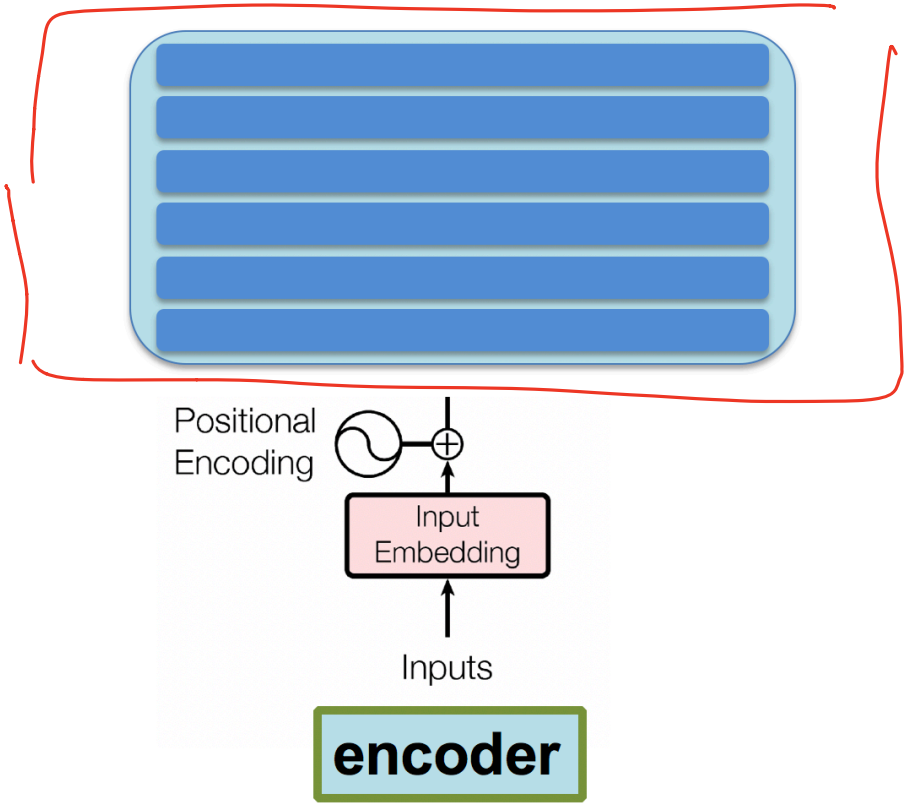


Figure: Encoder's 6 identical blocks.

An Encoder Block

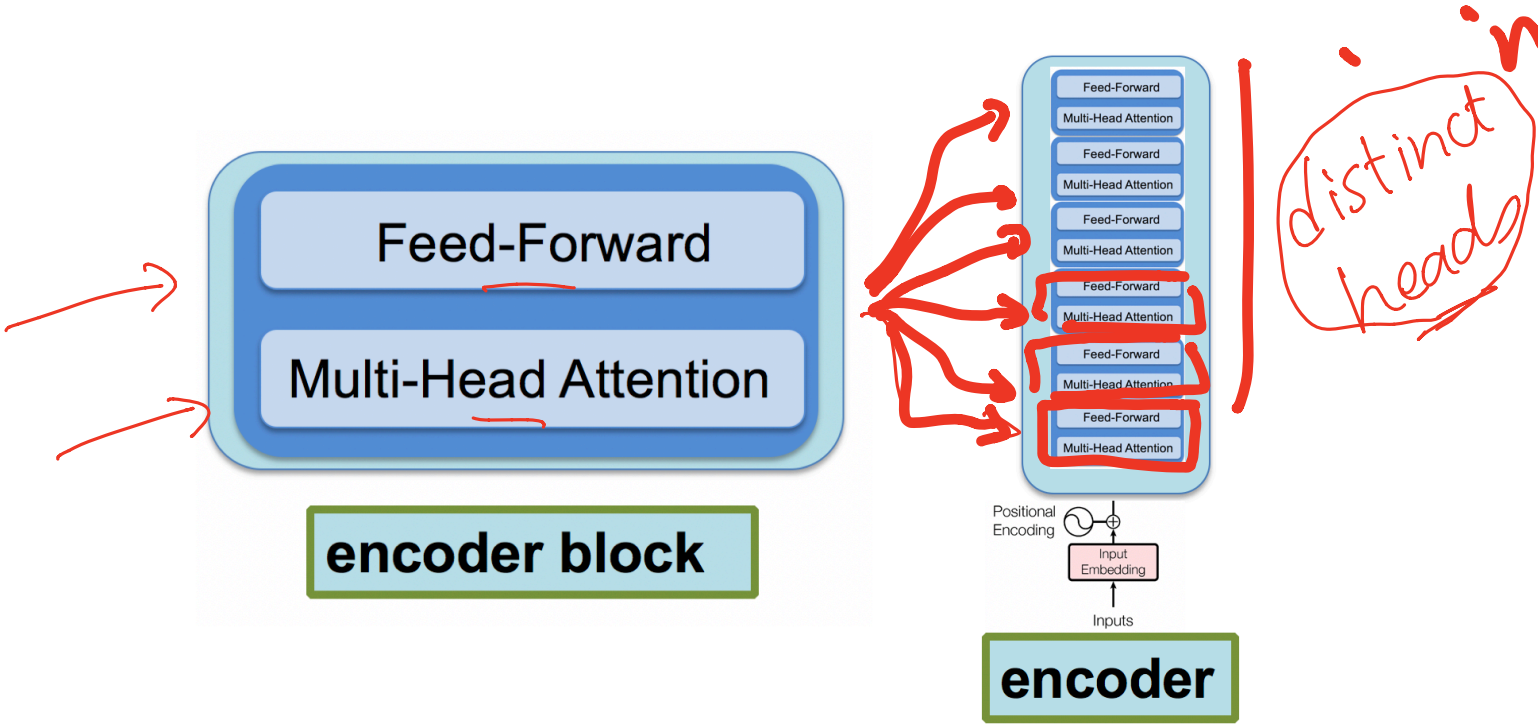


Figure: Each encoder block has two sub-layers, a multi-head attention and a feed-forward.

Self-Attention

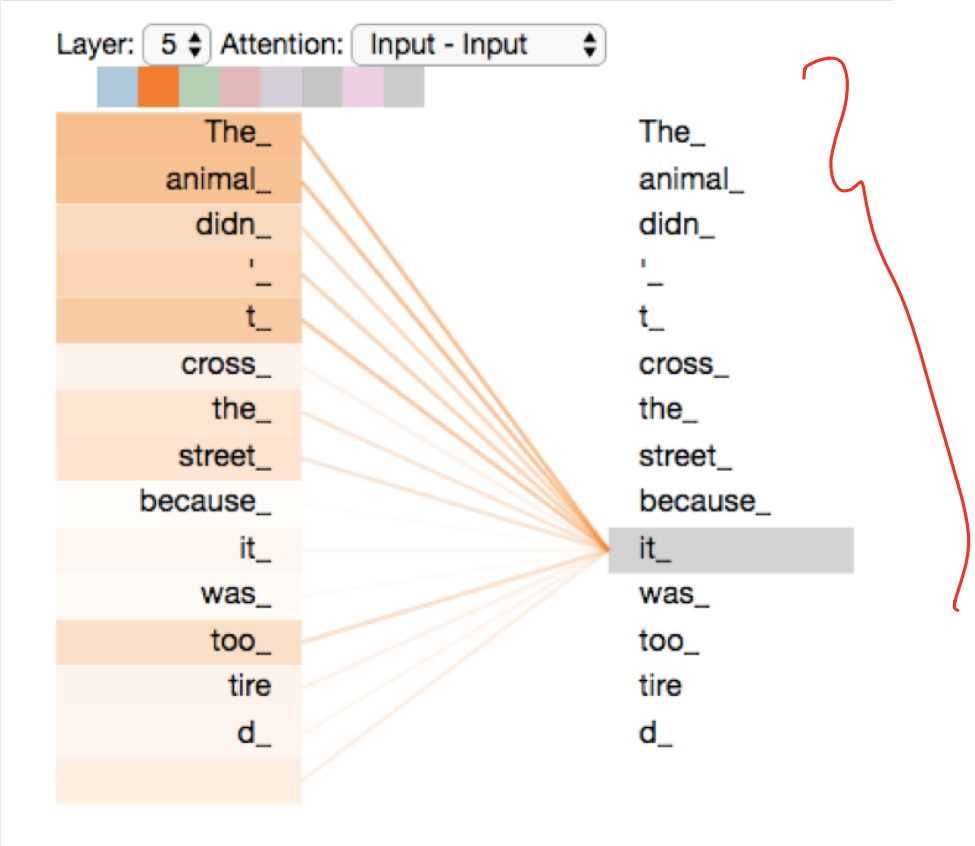
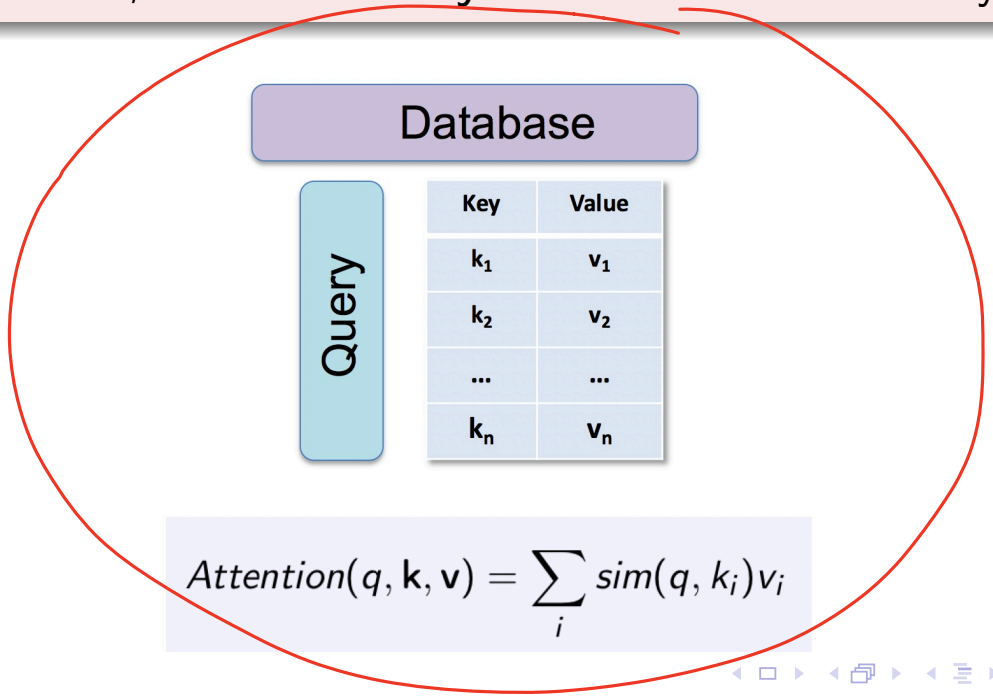


Figure: Self-attention. (Source: `http://jalammar.github.io`).

Query, Key, and Value

Intuition

- Retrieving from a database, we issue a **query (q)** to identify a **key (k)** that has a similarity, based on a value (v), to q.
- To do **backpropagation** on the output, we will not just want one similarity value, but a **similarity distribution** over all keys.



MT Example of Query, Key, and Value

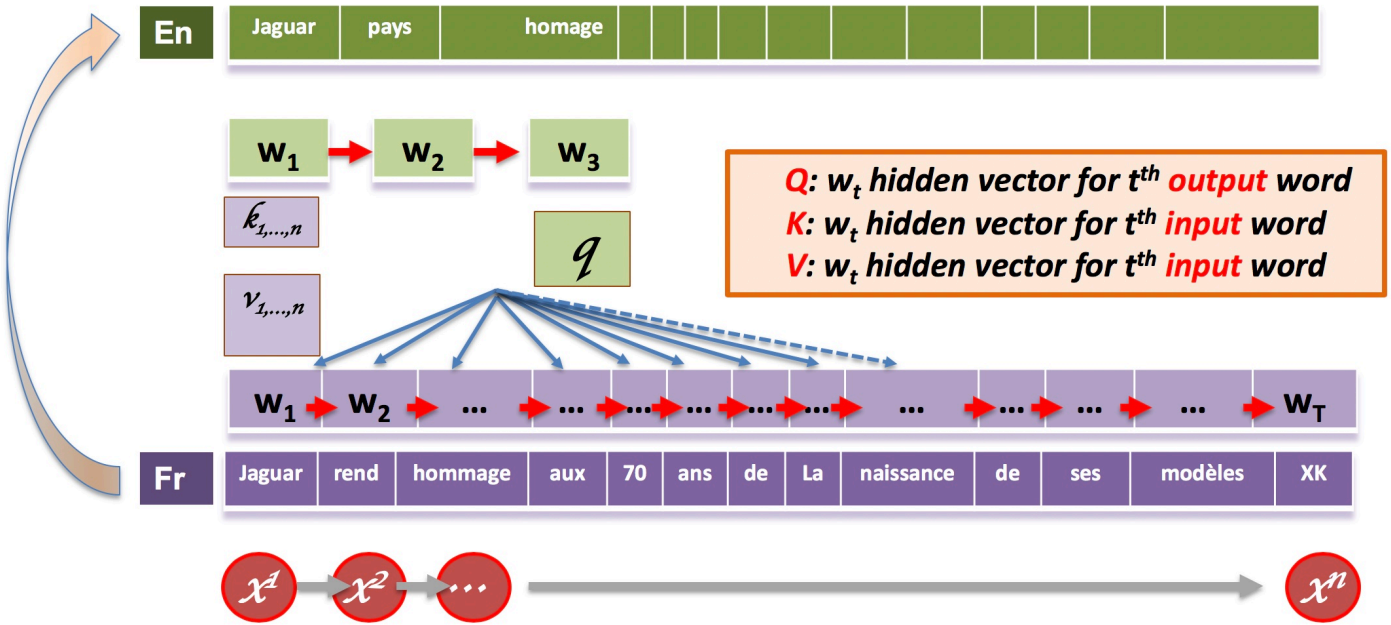


Figure: q, k, and v in MT.

Self-Attention in Transformer with q, k, v

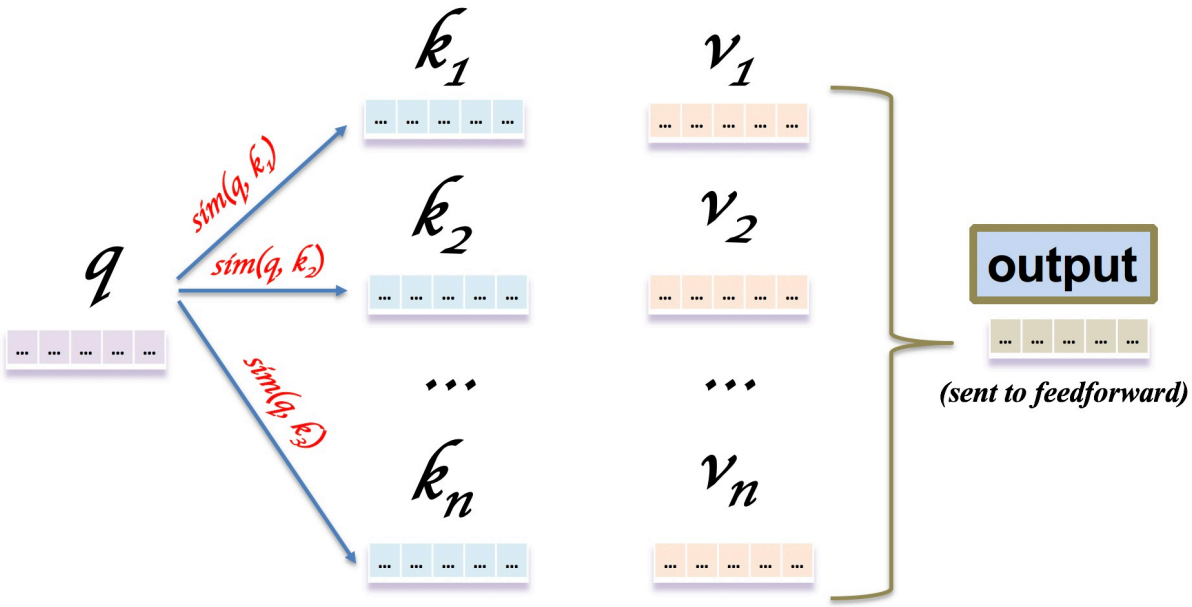


Figure: Mapping a **query** and a set of **key-value** pairs to an output. **Similarity s** will be based on **dot product**. Well, *scaled dot product*...

Z weighted sum of $\sum_i \text{softmax}(\text{sim}(q, k_i))v_i$

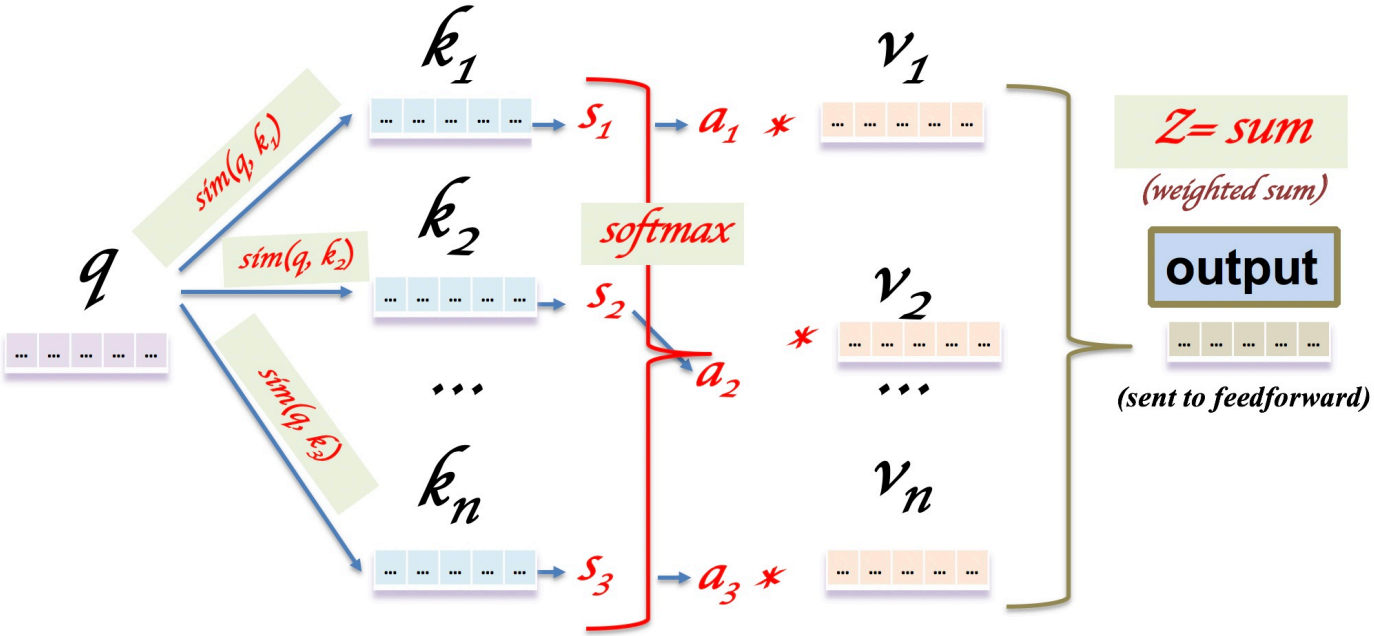


Figure: s=sim(q, k_i). $\alpha = softmax(s)$. $z = \sum_i a_i v_i$

Self-Attention Illustrated: Query "the"

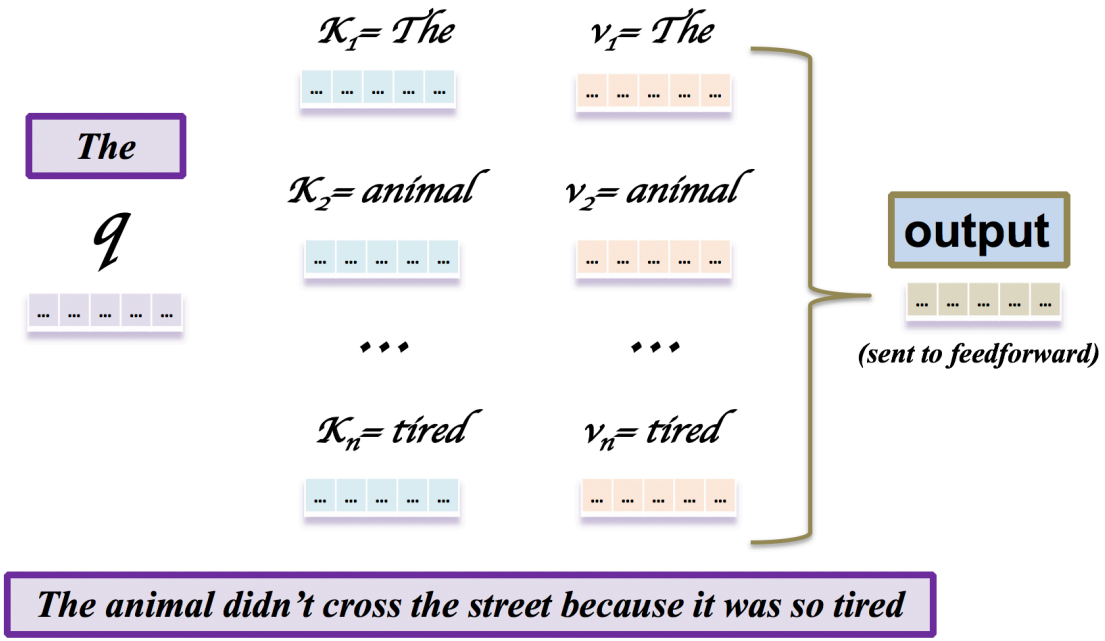


Figure: Mapping the **query** "the" and a set of **key-value** pairs to an output.

Self-Attention Illustrated: Query "animal"

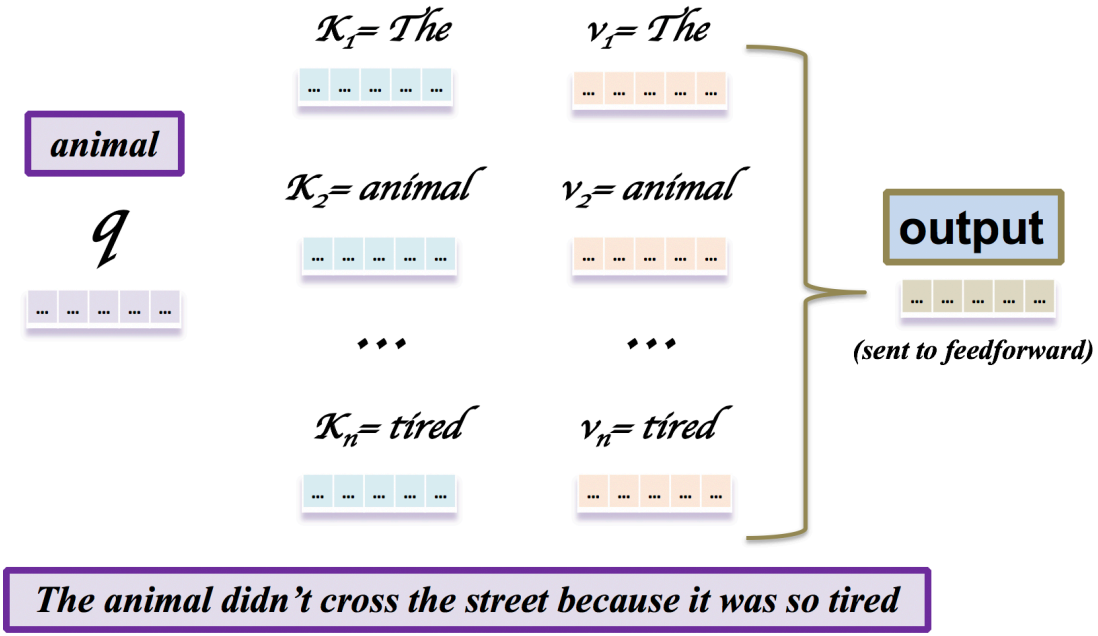


Figure: Mapping the **query** "animal" and a set of **key-value** pairs to an output.

Self-Attention Illustrated: Query "tired"

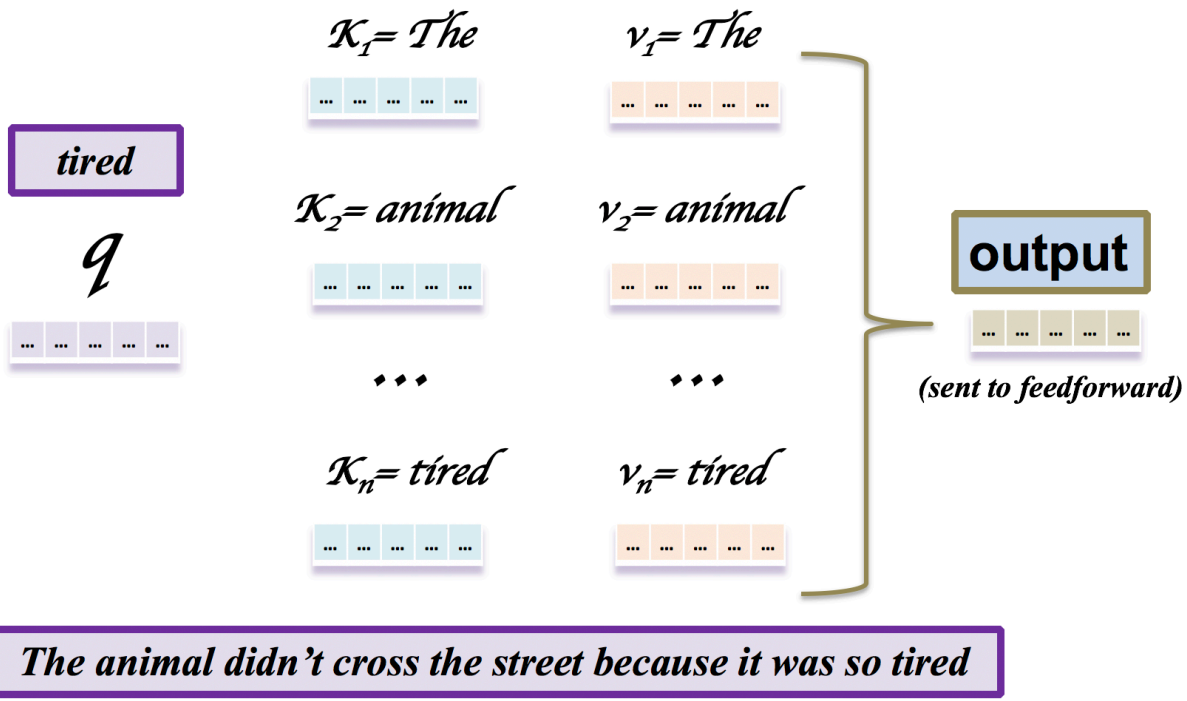


Figure: Mapping the **query** "tired" and a set of **key-value** pairs to an output.

Self-Attention Illustrated: All-Queries Overview'

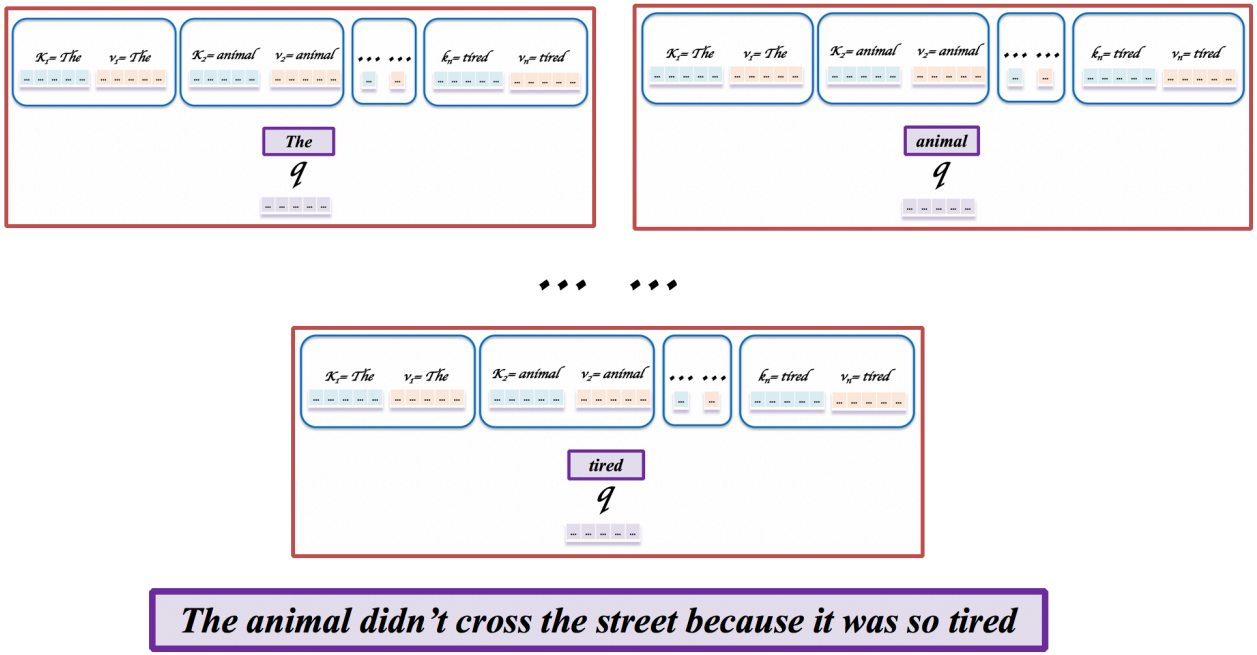


Figure: Mapping all **queries** and a set of **key-value** pairs to an output.

Scaled Dot-Product Attention

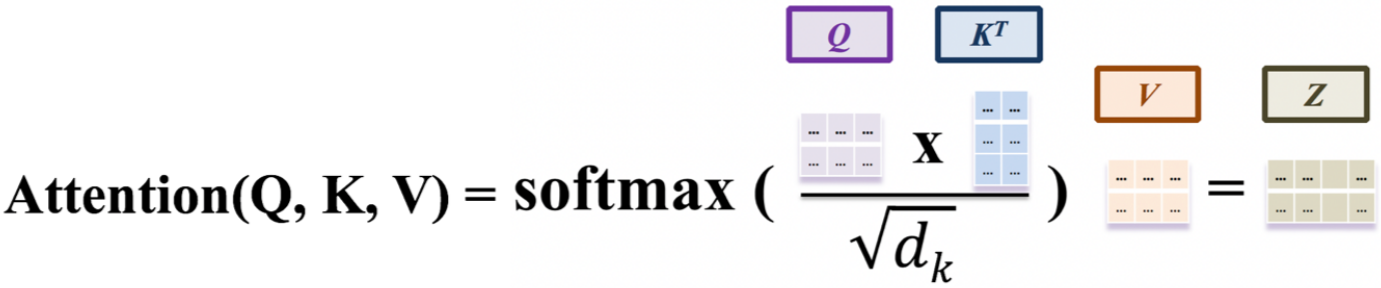


Figure: **Scaled dot-product attention** in the Transformer.

Scaled Dot-Product Attention: Paper Illustration

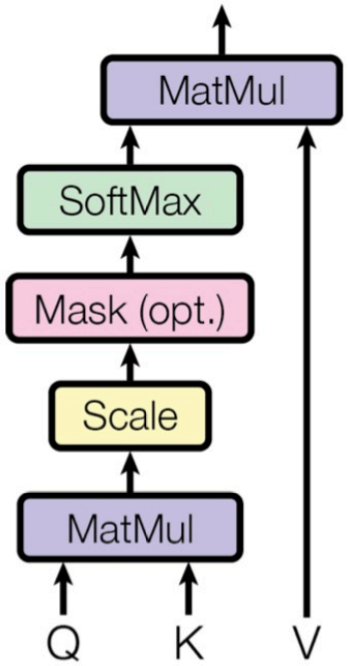


Figure: **Scaled dot-product attention**

Linear Projections of Query, Key, and Value (for Multi-Head Attention)

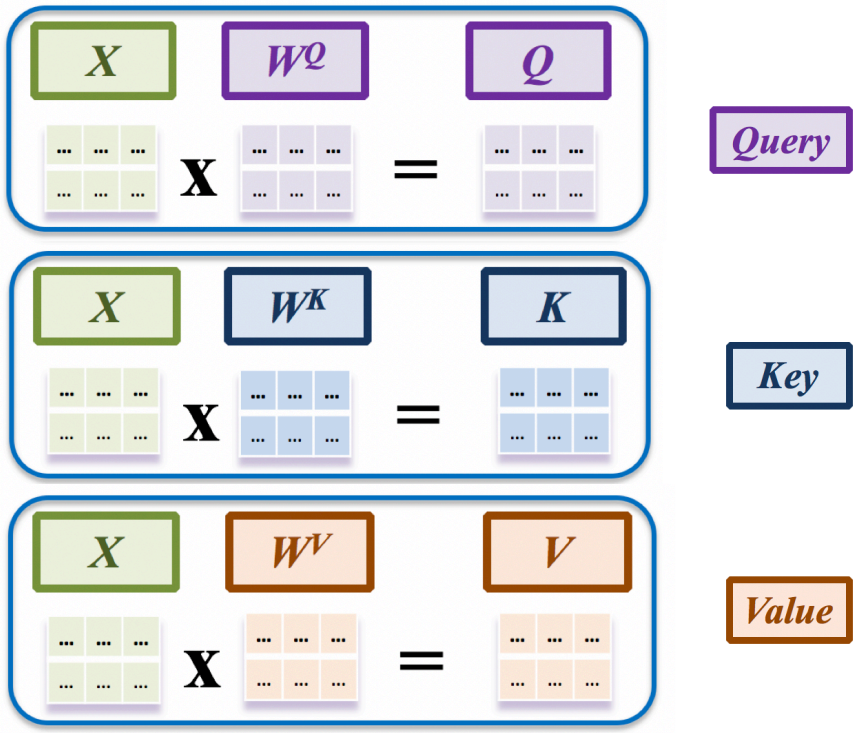


Figure: Linear projections of Q, K, and V. **W** matrixes are learned linear projections.

Multi-Head Attention

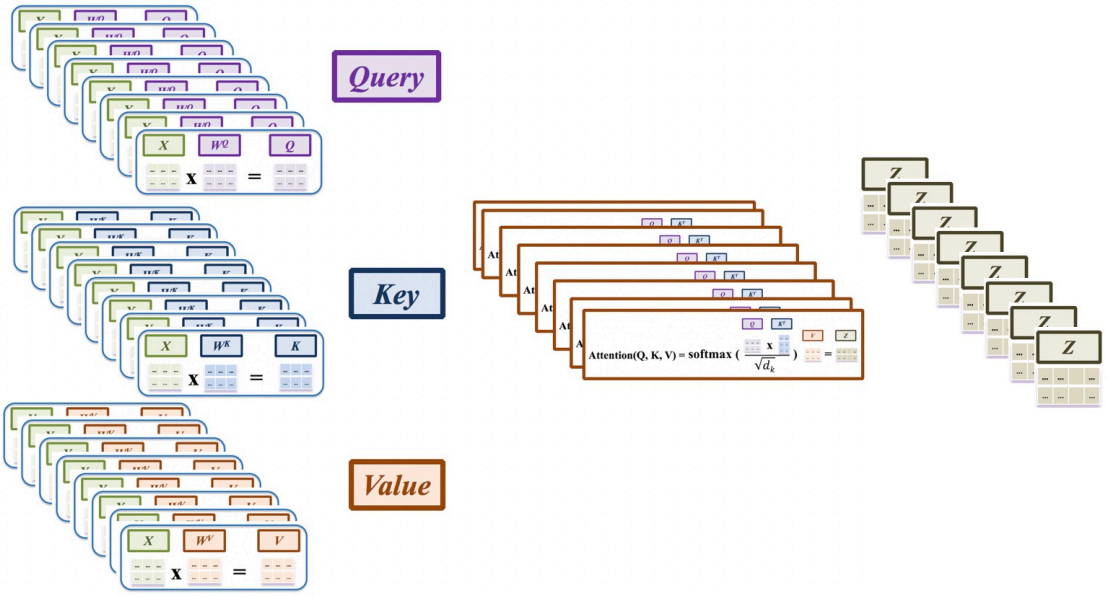


Figure: Multi-Head Attention with 8 attention heads.

Multi-Head Attention in Paper

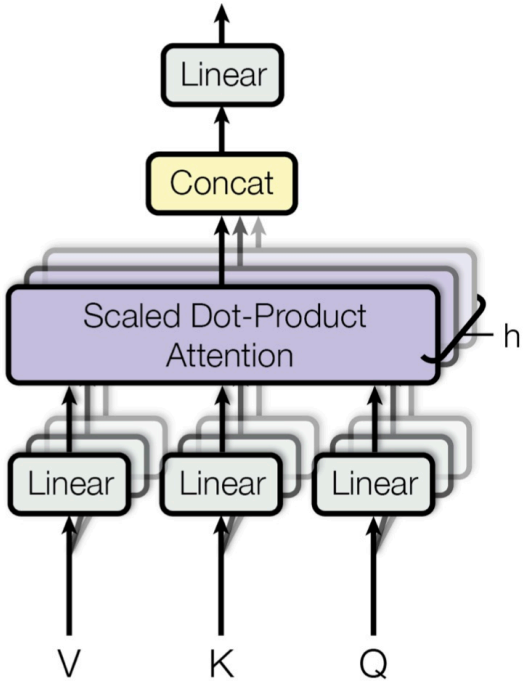
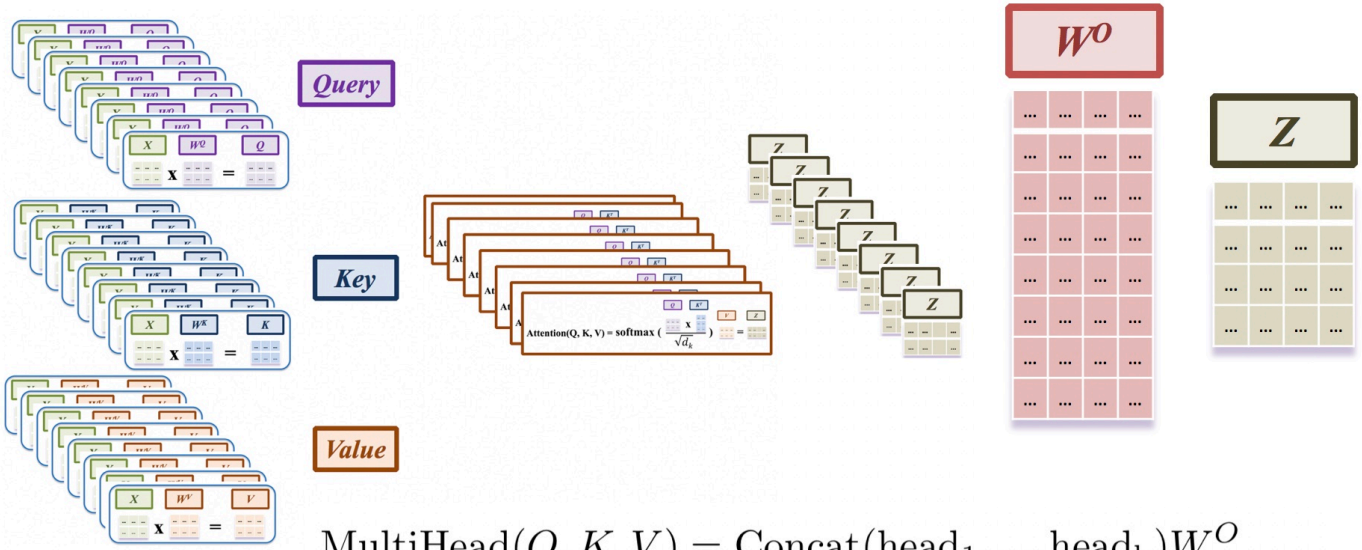


Figure: **Multi-Head Attention**

Multi-Head Attention: Output Concatenation

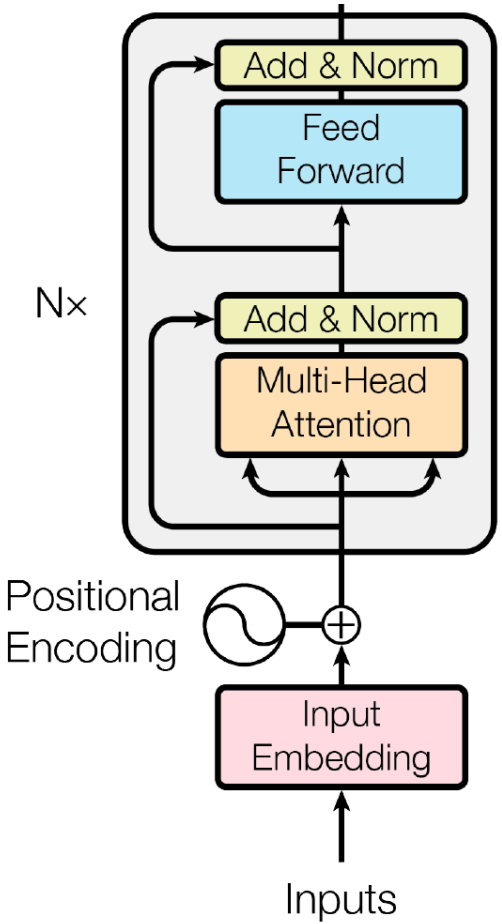


$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_\text{h})W^O$$

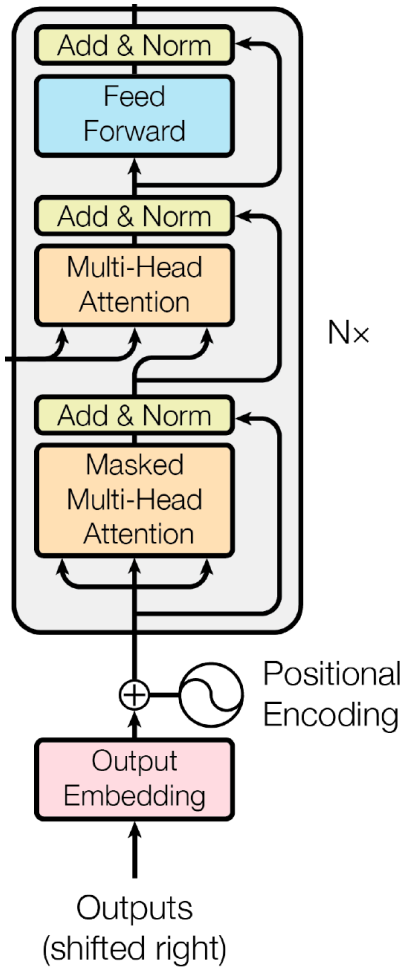
$$\text{where head}_\text{i} = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

Figure: Output of attention heads are concatenated and projected to a linear layer.

Detailed Encoder Block



Detailed Decoder Block



Masked Attention

1: Attention

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

2: Masked Attention

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

Masking Matrix M

M is a matrix of 0's (in lower triangular) and $-\infty$ (in upper triangular)

Masked Attention II

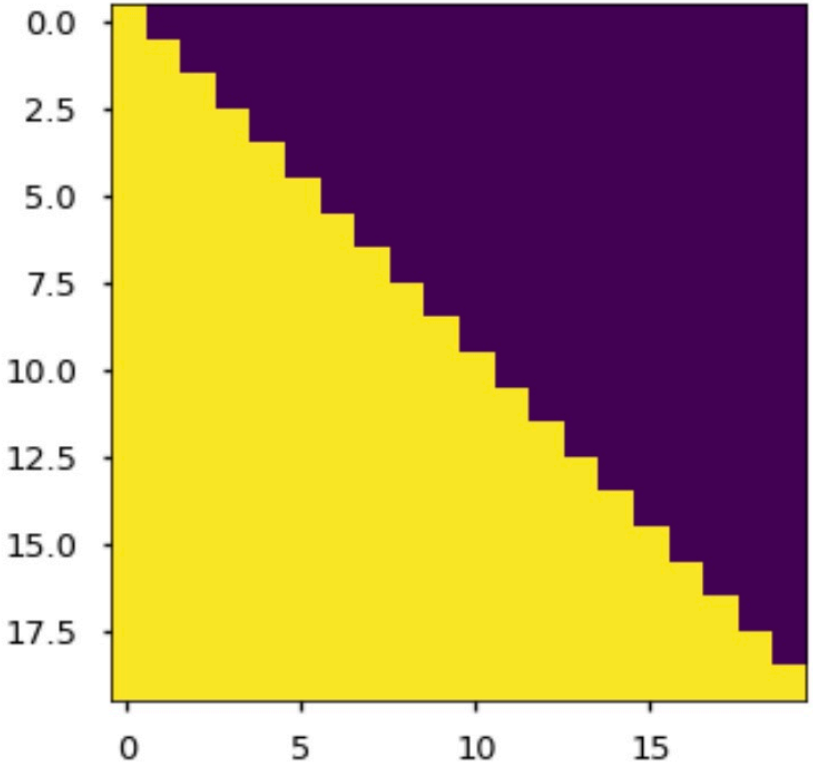


Figure: Masking in Transformer. (Source: `https://nlp.seas.harvard.edu/2018/04/03/attention.html`).

Residual Learning

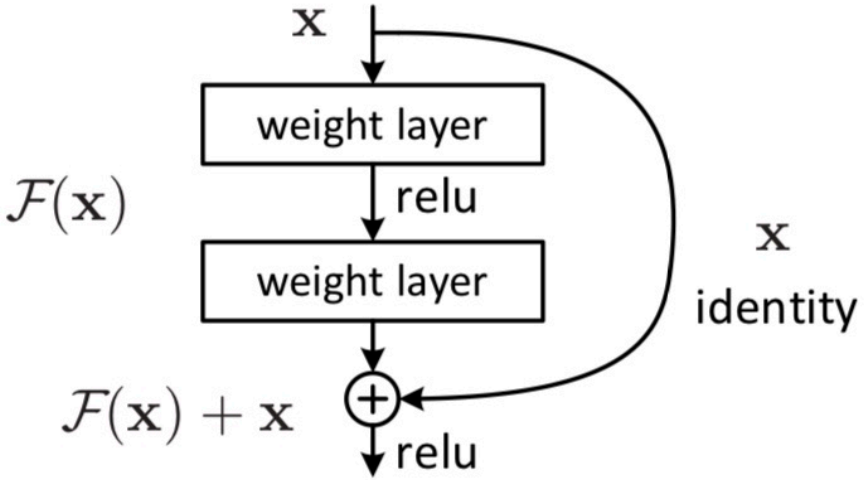


Figure 2. Residual learning: a building block.

Figure: Source: He et al. ("Deep Residual Learning for Image Recognition", 2016)
http://openaccess.thecvf.com/content_cvpr_2016/papers/He_Deep_Residual_Learning_CVPR_2016_paper.pdf

Whole Transformer Architecture

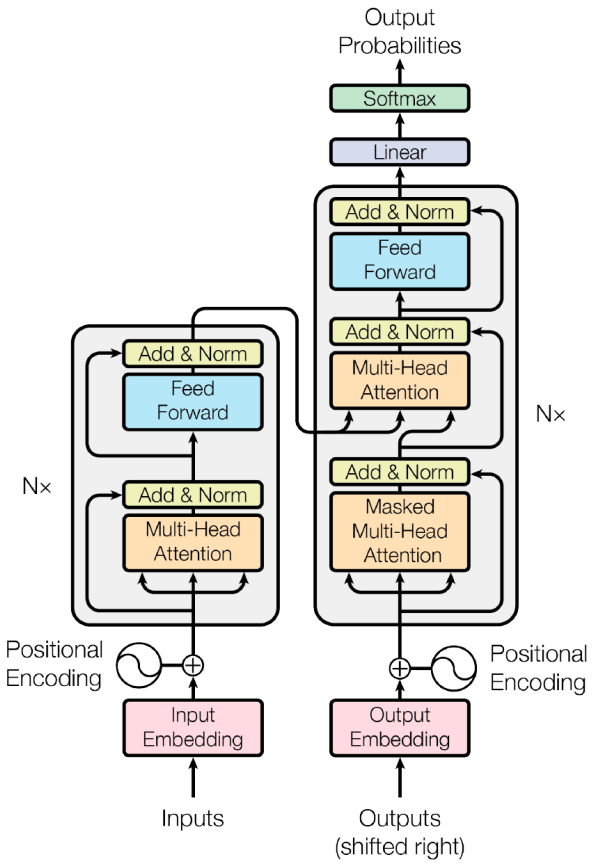
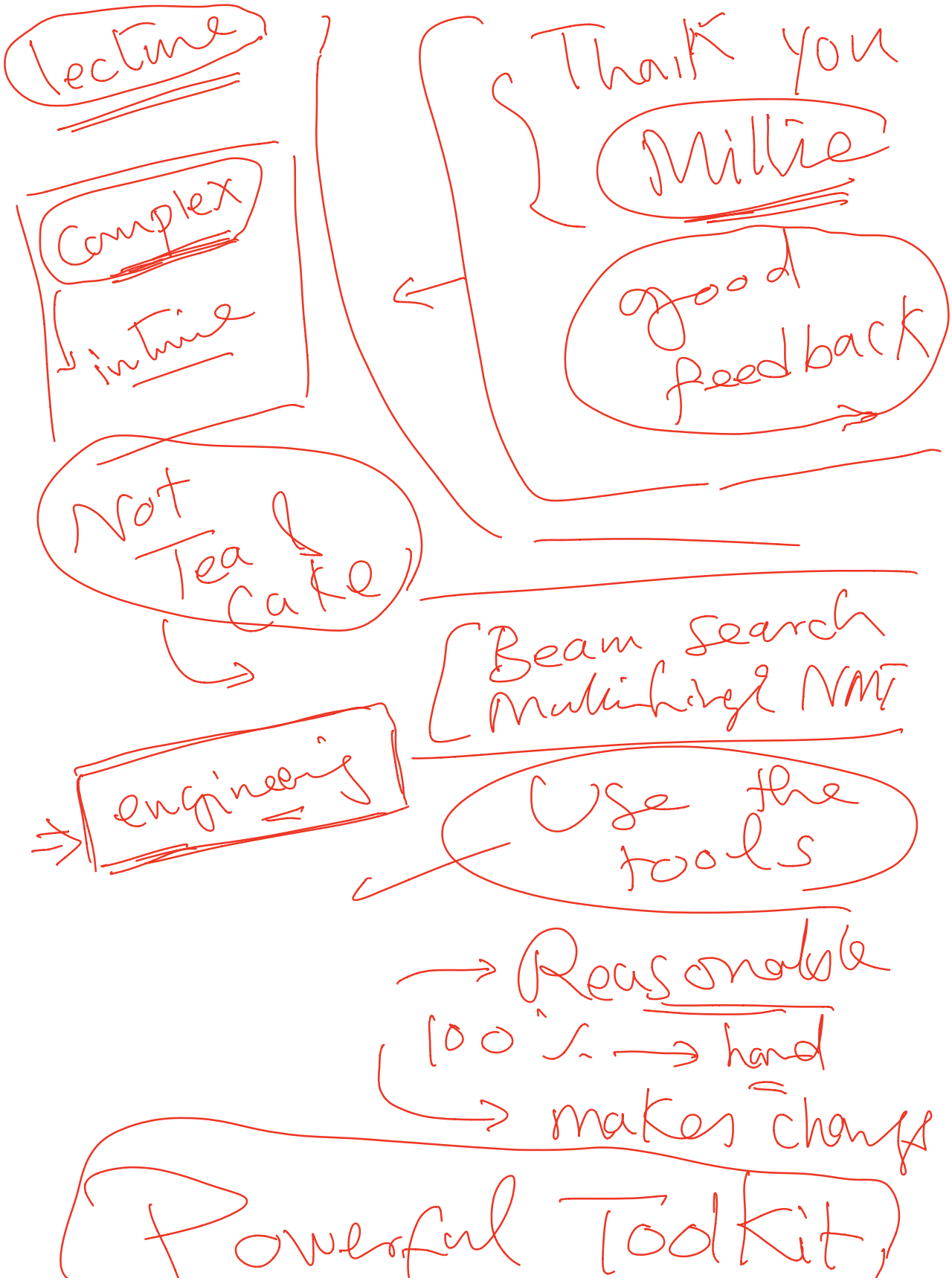


Figure: Transformer: Model Architecture.

Application of Attention in the Transformer

Attention in Transformer

1. **Encoder self-attention layers:** In a self-attention layer all of the keys, values and queries come from the same place, in this case, the output of the previous layer in the encoder.
2. In "**encoder-decoder attention**" **layers:** queries come from the previous decoder layer, and the memory keys and values come from the output of the encoder.
3. **Decoder self-attention layers:** Each position in the decoder attends to all positions in the decoder up to and including that position.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Complex
intuition
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Thank you
Millie
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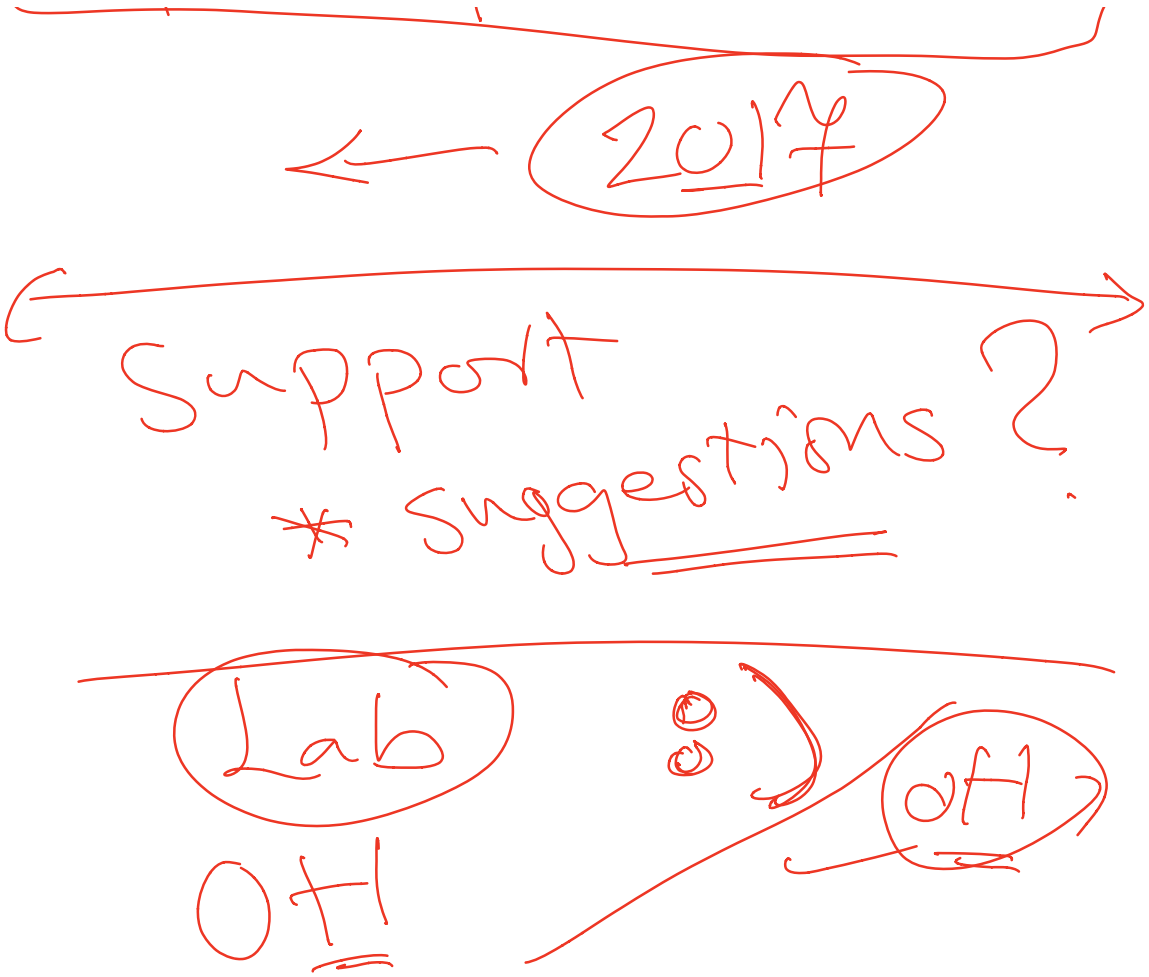
feedback
Beam search
Use the
tools
Reasonable
100% → hand
makes change
Powerful Toolkit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