Transformers

MUSTAFA HAJIJ

What is attention ?

We like to model every word in the sentence in terms to other words around it.

I really enjoyed the trip to Canada

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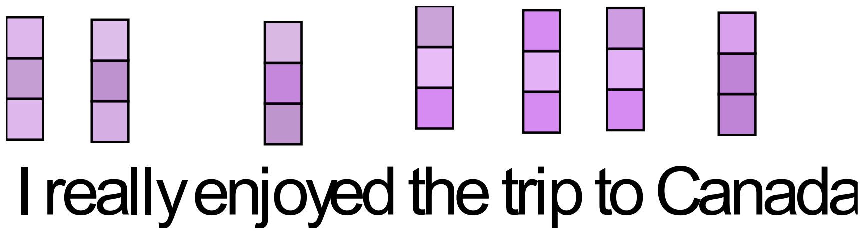
Assume every word has some embedding attached with it



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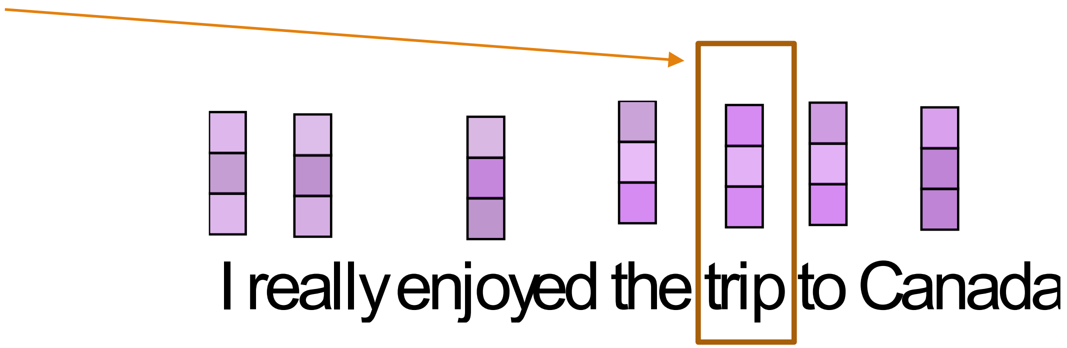
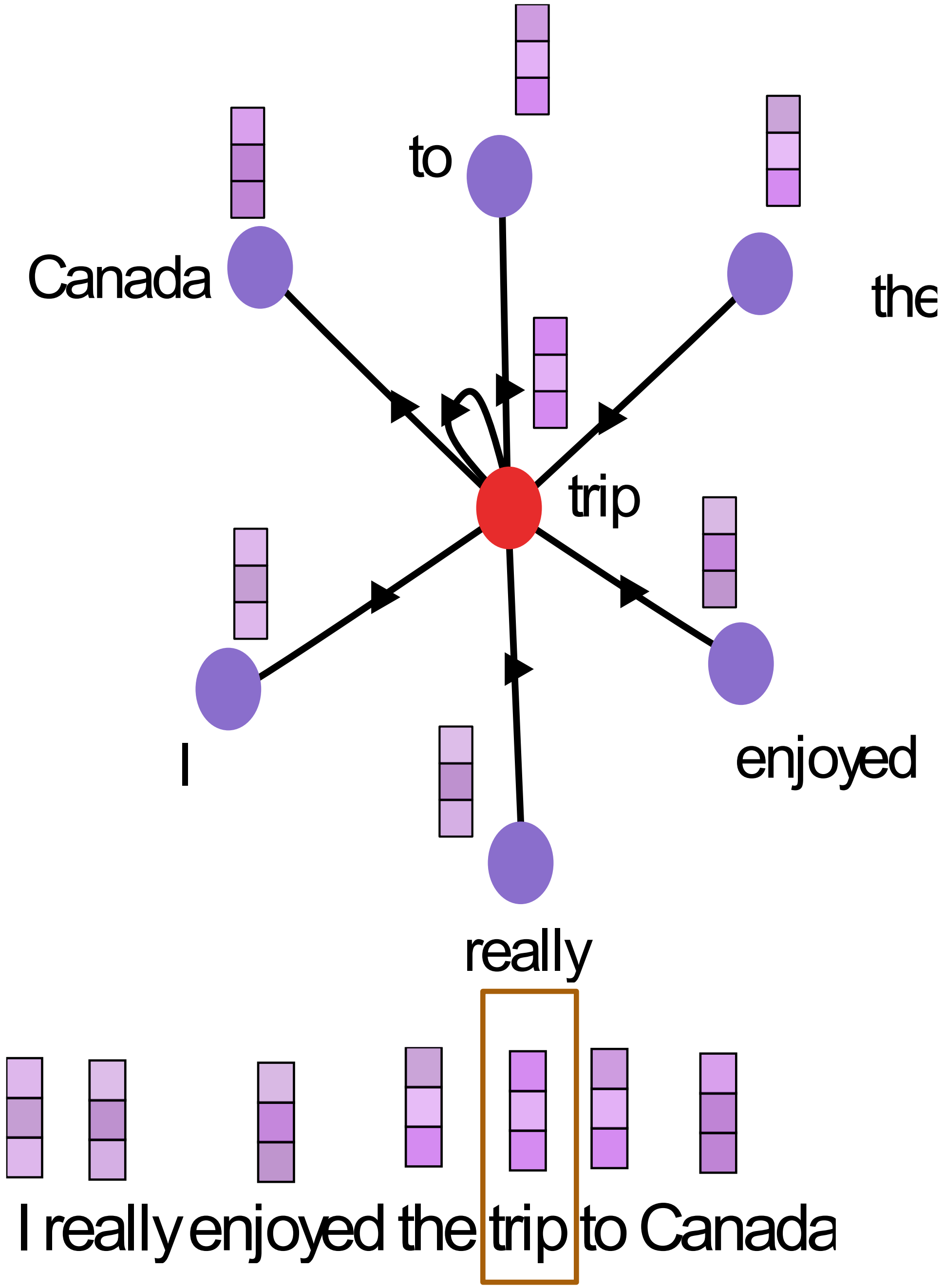
Consider trip to be the target word



What is attention ?

Lets put the sentence in a graph
With the target word in the middle
And connect all other words to it as follows:



What is attention ?

Lets put the sentence in a graph
With the target word in the middle
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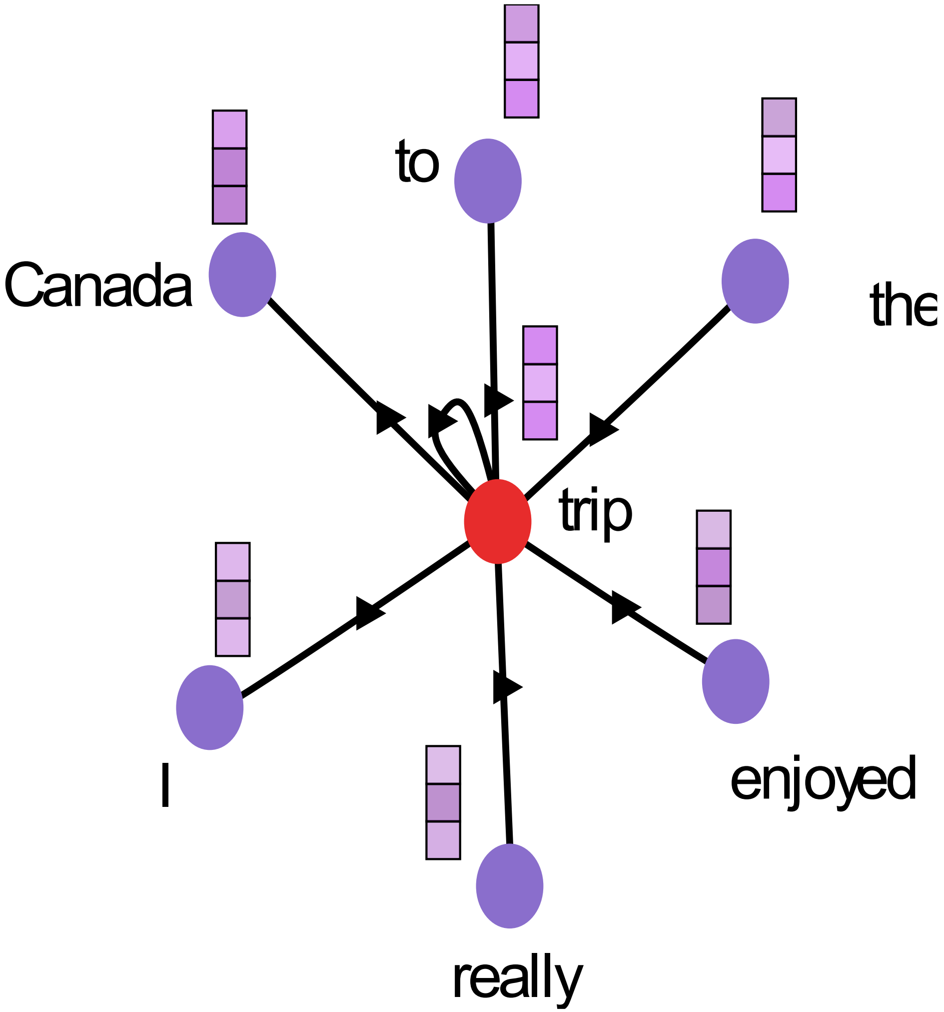
We want to update the vector attached with the 'trip' word in terms of the surrounding words



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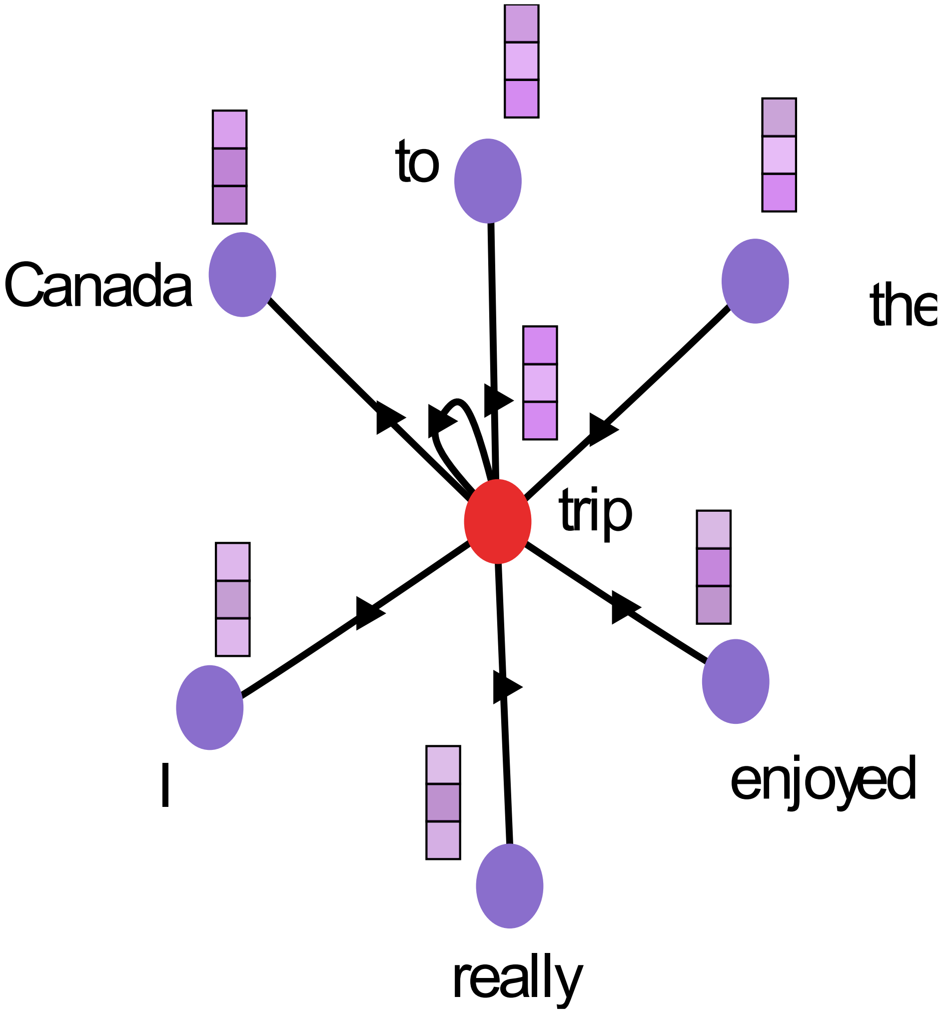

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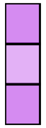
We want to update the vector 
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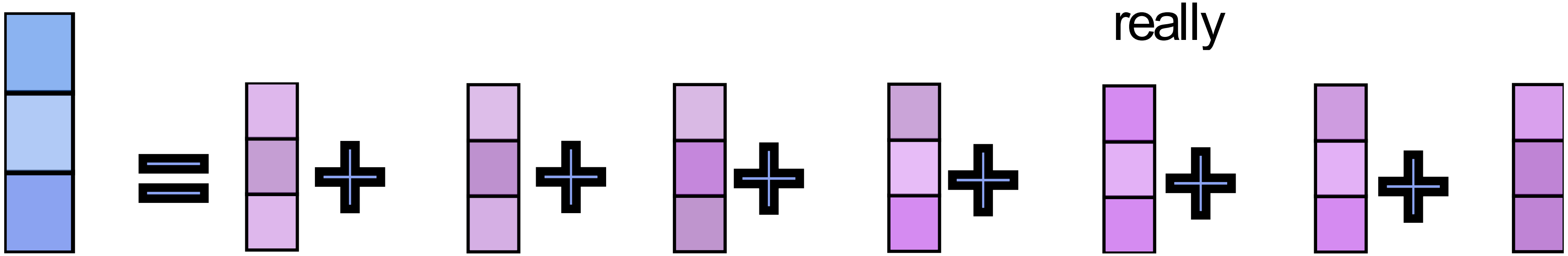
in terms of the surrounding words

First attempt



Updated rep of ‘trip’

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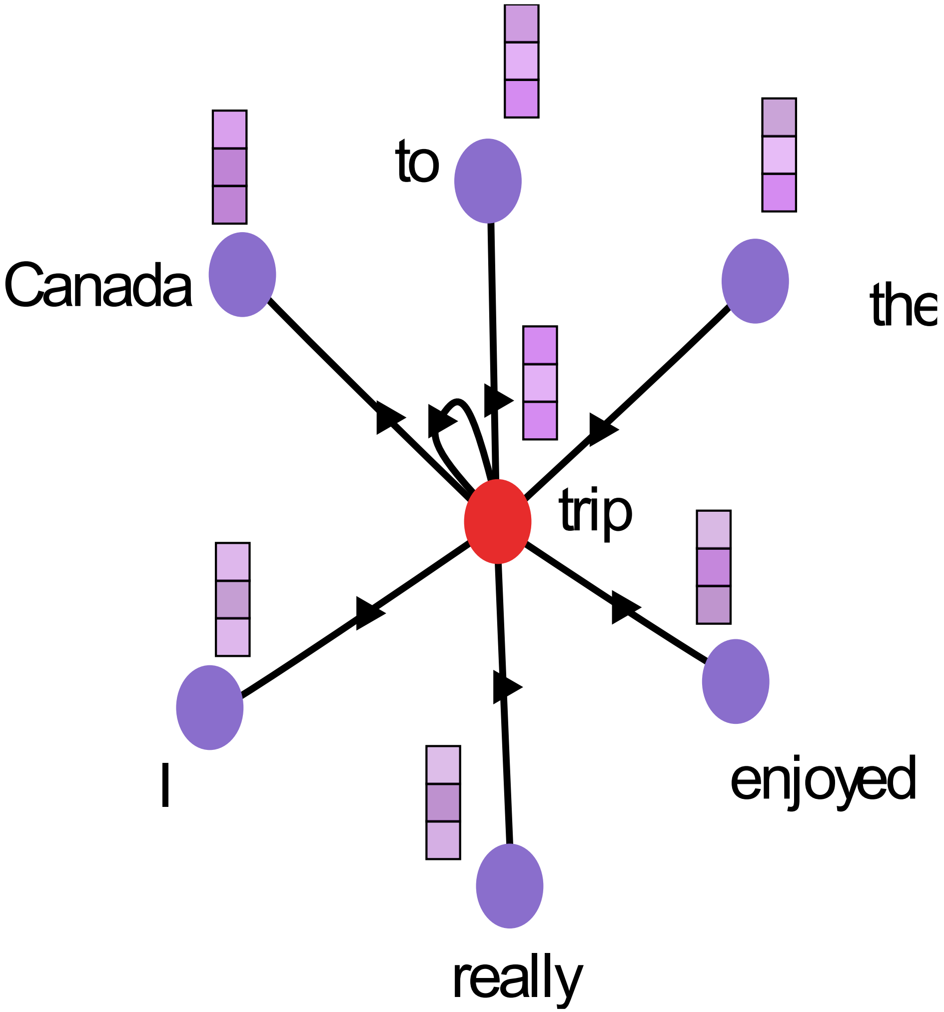
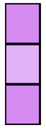


We want to update the vector 
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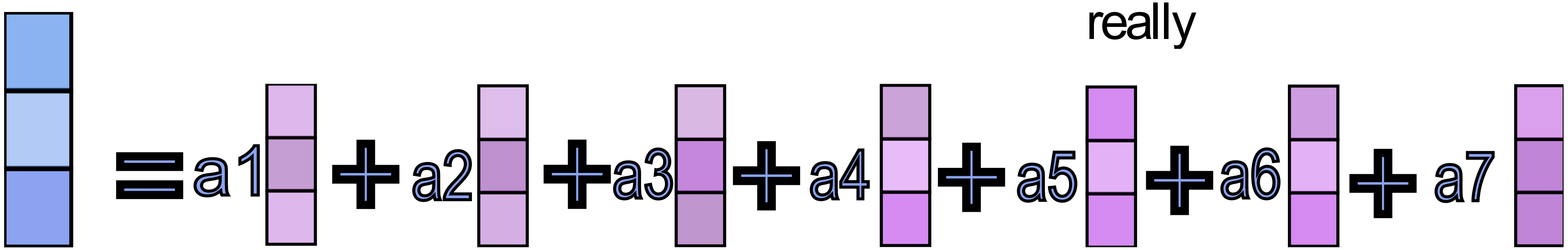
A better rep

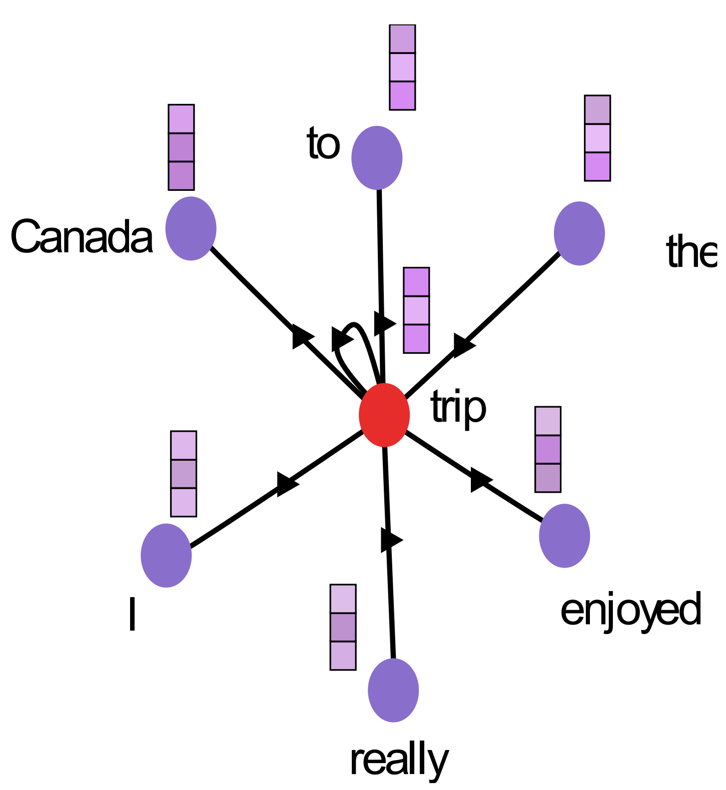


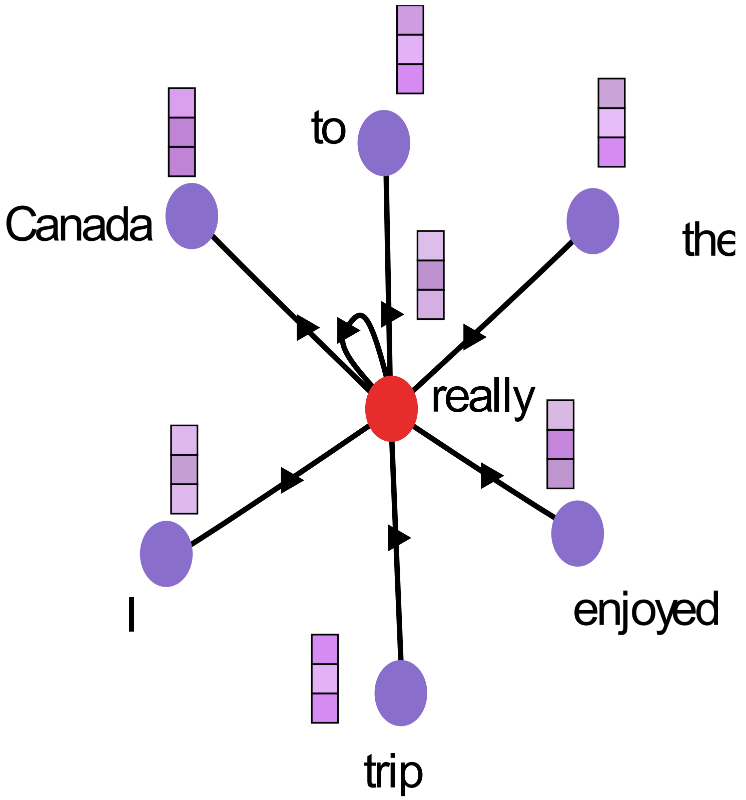
Updated rep of 'trip'

Where $\boldsymbol{a1} + \boldsymbol{a2} + \boldsymbol{a3} + \boldsymbol{a4} + \boldsymbol{a5} + \boldsymbol{a6} + \boldsymbol{a7} = \mathbf{1}$ **and** $\mathbf{0} \leq \boldsymbol{a_i} \leq \mathbf{1}$

What is attention ?

Repeat this for every word in the sentence





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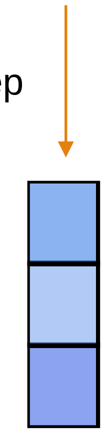
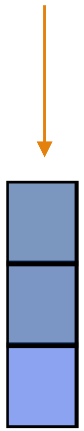
Gives the updated rep

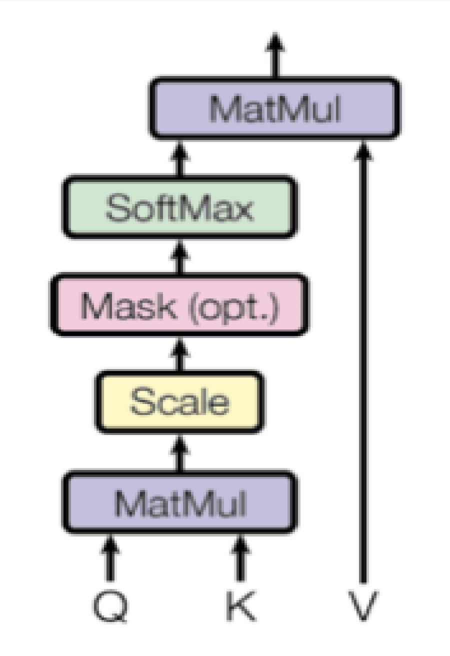




We obtain a 7X7 matrix of attention coefficients representing the attention of every word to every other word and 7 updated reps for the words.

The details

The transformer model, each attention unit learns three weight matrices: **query weights (W_Q), key weights (W_K), and value weights (W_V).**



Scaled dot-product attention
Taken from "Attention Is All You Need"

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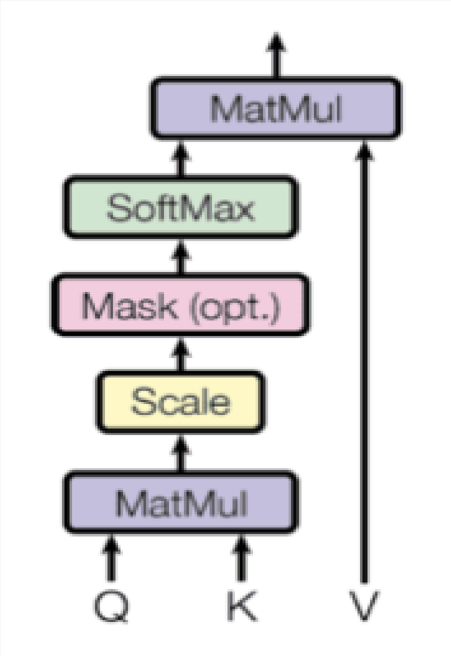
The transformer model, each attention unit learns three weight matrices: **query weights (W_Q), key weights (W_K), and value weights (W_V).**

For every token i, the input word embedding x_i is multiplied by these weight matrices to generate

- a query vector $(\boldsymbol{q_i} = \boldsymbol{x_i} * \boldsymbol{W_Q})$,
- a key vector $(\boldsymbol{k_i} = \boldsymbol{x_i} * \boldsymbol{W_K})$,
- and a value vector $(\boldsymbol{v_i} = \boldsymbol{x_i} * \boldsymbol{W_V})$



Scaled dot-product attention
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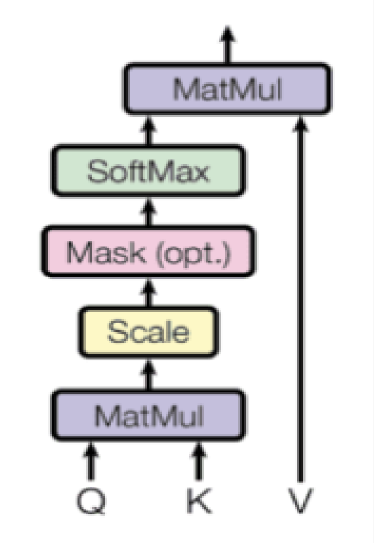
The details

We define three matrices: $Q, K, and\ V$. Each row of these matrices corresponds to a vector q_i, k_i, and v_i respectively.

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



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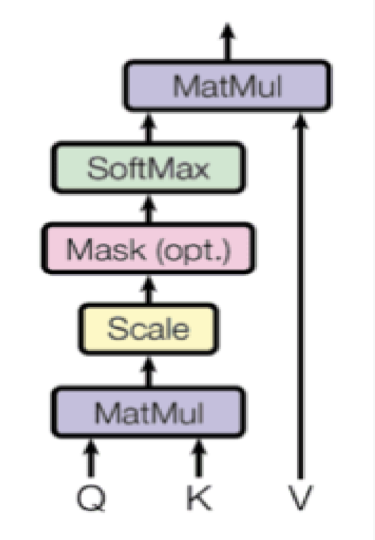

Scaled dot-product attention
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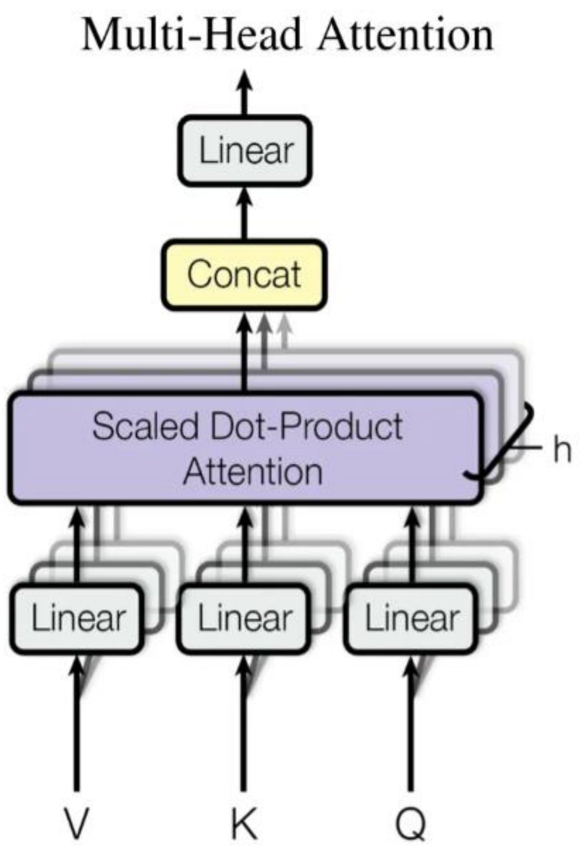
- The attention weights a in the transformer model are determined by the influence of each word in the sequence (represented by Q) on all other words in the sequence (represented by K).

- The SoftMax function is applied to these weights to ensure they form a distribution between 0 and 1.
- These weights are then used to scale the corresponding word vectors in V, which are the same vectors as Q for the encoder and decoder, but different for the module that combines encoder and decoder inputs.

Multihead attention



$$\text{MultiheadedAttention}(Q, K, V) = \text{Concat}_{i \in [\#heads]}(\text{Attention}(XW_i^Q, XW_i^K, XW_i^V))W^O$$

Refs