

# Computation of Self-Attention

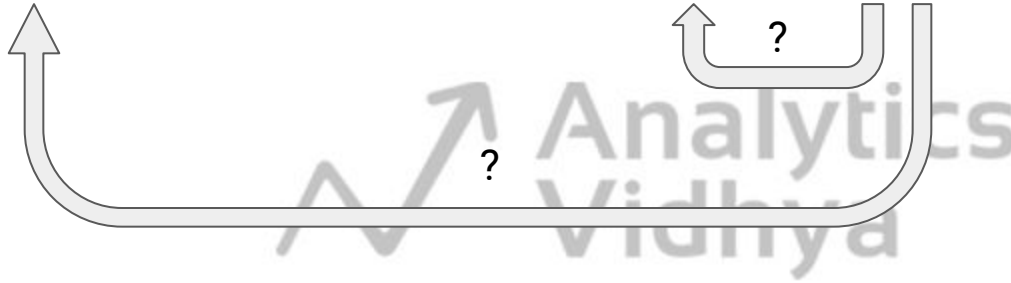
# Intuition behind Self Attention

“The kids were scared of the lions, so they left right away.”



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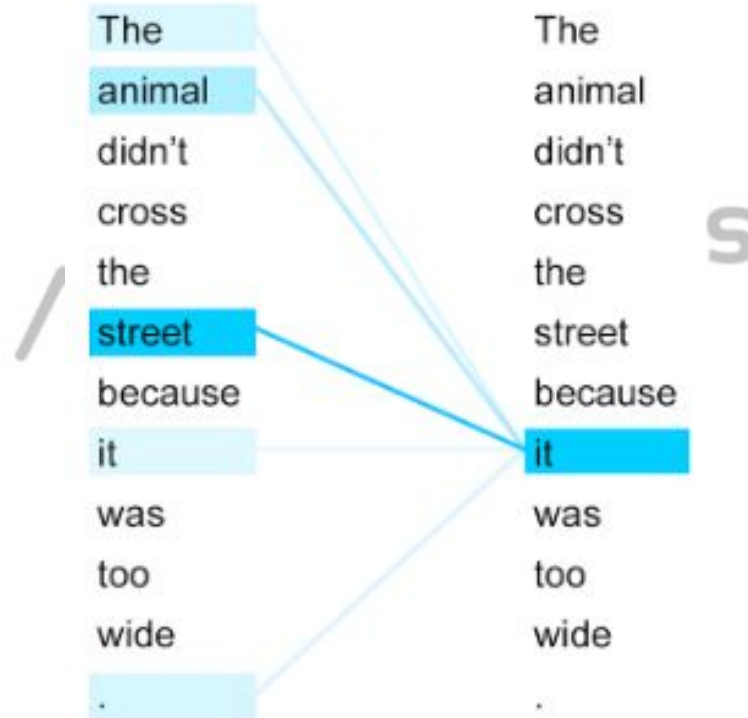


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“The kids were scared of the lions, so they left right away.”

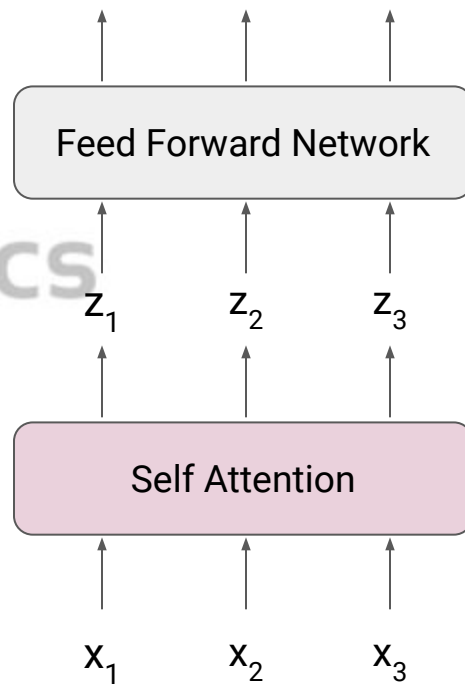


# Self-Attention



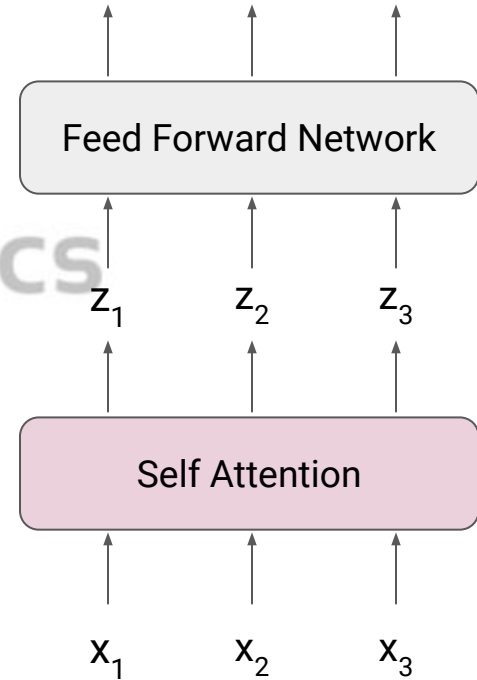
# Self-Attention

- Each encoder or decoder has a self attention layer and a feed forward network



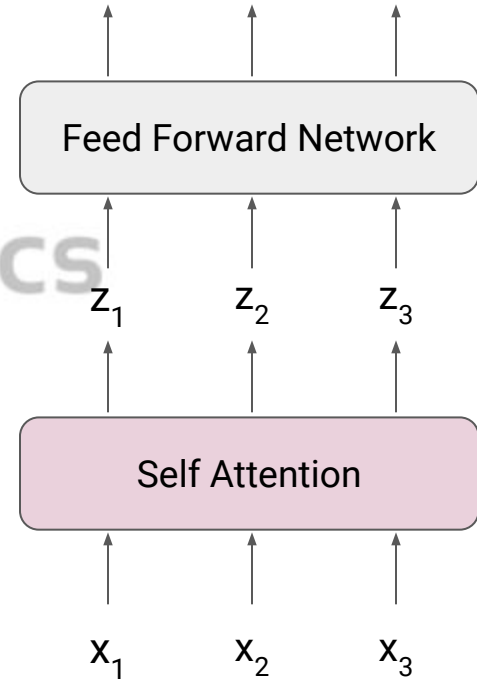
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- Self attention layer encodes a token by incorporating information from other tokens



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- Each encoder or decoder has a self attention layer and a feed forward network
- Self attention layer encodes a token by incorporating information from other tokens
- $x_i$  are the input embeddings and  $z_i$  are the outputs of self attention layer





# Self-Attention

Embeddings



x



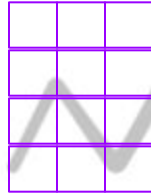
# Self-Attention

Embeddings



$X$

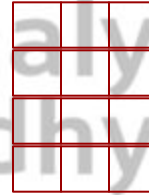
Weight Matrices



$W_q$



$W_k$



$W_v$

# Self Attention Layer

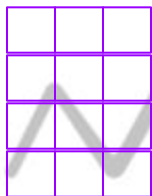
Embeddings

Weight Matrices

Vectors



$x$



$W_q$



$W_k$



$W_v$



Query,  $q$

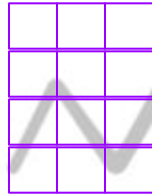
# Self Attention Layer

Embeddings

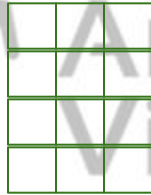


x

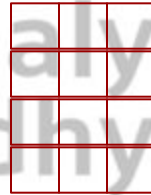
Weight Matrices



$W_q$

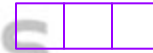


$W_k$



$W_v$

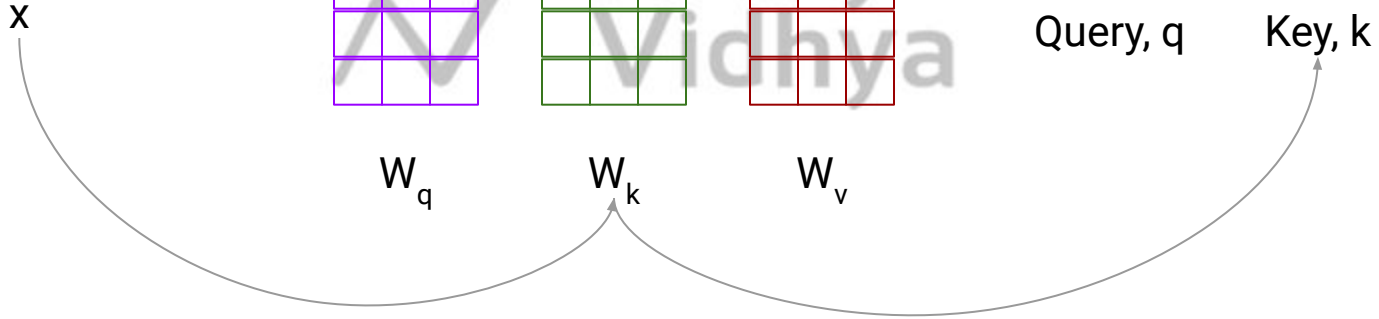
Vectors



Query, q



Key, k



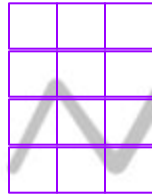
# Self Attention Layer

Embeddings



$x$

Weight Matrices



$W_q$



$W_k$



$W_v$

Vectors



Query,  $q$



Key,  $k$



Value,  $v$

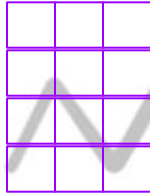
# Self Attention Layer

Embeddings

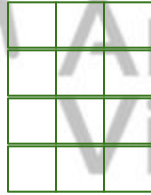


$X$

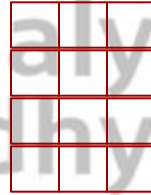
Weight Matrices



$W_q$



$W_k$



$W_v$

Vectors



Query,  $q$

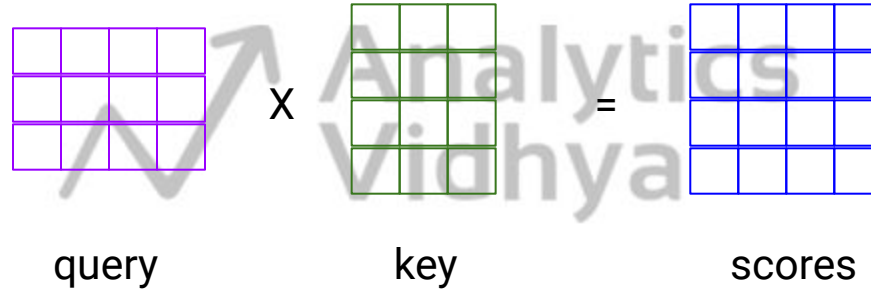


Key,  $k$



Value,  $v$

# Concepts of Query, Key, and Value



# Concepts of Query, Key, and Value

	have	a	nice	day
have	96	23	27	11
a	23	98	35	28
nice	27	35	91	56
day	11	28	56	93

scores



# Self Attention Layer: Computations

Word	q vector	k vector	v vector	score
Action	$q_1$	$k_1$	$v_1$	$q_1 \cdot k_1$
gets		$k_2$	$v_2$	$q_1 \cdot k_2$
results		$k_3$	$v_3$	$q_1 \cdot k_3$

# Self Attention Layer: Computations

Word	q vector	k vector	v vector	score
Action		$k_1$	$v_1$	$q_2 \cdot k_1$
gets	$q_2$	$k_2$	$v_2$	$q_2 \cdot k_2$
results		$k_3$	$v_3$	$q_2 \cdot k_3$

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Word	q vector	k vector	v vector	score
Action		$k_1$	$v_1$	$q_3 \cdot k_1$
gets		$k_2$	$v_2$	$q_3 \cdot k_2$
results	$q_3$	$k_3$	$v_3$	$q_3 \cdot k_3$

# Self Attention Layer: Computations

Word	q vector	k vector	v vector	score	score / 8
Action	$q_1$	$k_1$	$v_1$	$q_1 \cdot k_1$	$q_1 \cdot k_1 / 8$
gets		$k_2$	$v_2$	$q_1 \cdot k_2$	$q_1 \cdot k_2 / 8$
results		$k_3$	$v_3$	$q_1 \cdot k_3$	$q_1 \cdot k_3 / 8$

# Self Attention Layer: Computations

Word	q vector	k vector	v vector	score	score / 8	Softmax
Action	$q_1$	$k_1$	$v_1$	$q_1 \cdot k_1$	$q_1 \cdot k_1 / 8$	$x_{11}$
gets		$k_2$	$v_2$	$q_1 \cdot k_2$	$q_1 \cdot k_2 / 8$	$x_{12}$
results		$k_3$	$v_3$	$q_1 \cdot k_3$	$q_1 \cdot k_3 / 8$	$x_{13}$

# Self Attention Layer: Computations

Word	q vector	k vector	v vector	score	score / 8	Softmax	Softmax * v	Sum
Action	$q_1$	$k_1$	$v_1$	$q_1 \cdot k_1$	$q_1 \cdot k_1 / 8$	$x_{11}$	$x_{11} * v_1$	$z_1$
gets		$k_2$	$v_2$	$q_1 \cdot k_2$	$q_1 \cdot k_2 / 8$	$x_{12}$	$x_{12} * v_2$	
results		$k_3$	$v_3$	$q_1 \cdot k_3$	$q_1 \cdot k_3 / 8$	$x_{13}$	$x_{13} * v_3$	

# Self Attention Layer: Computations

Word	q vector	k vector	v vector	score	score / 8	Softmax	Softmax * v	Sum <sup>#</sup>
Action		$k_1$	$v_1$	$q_2 \cdot k_1$	$q_2 \cdot k_1 / 8$	$x_{21}$	$x_{21} * v_1$	
gets	$q_2$	$k_2$	$v_2$	$q_2 \cdot k_2$	$q_2 \cdot k_2 / 8$	$x_{22}$	$x_{22} * v_2$	$z_2$
results		$k_3$	$v_3$	$q_2 \cdot k_3$	$q_2 \cdot k_3 / 8$	$x_{23}$	$x_{23} * v_3$	

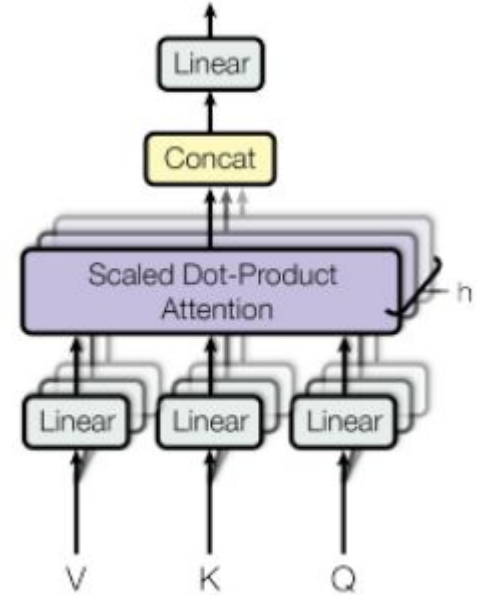
# Self Attention Layer: Computations

Word	q vector	k vector	v vector	score	score / 8	Softmax	Softmax * v	Sum <sup>#</sup>
Action		$k_1$	$v_1$	$q_3 \cdot k_1$	$q_3 \cdot k_1 / 8$	$x_{31}$	$x_{31} * v_1$	
gets		$k_2$	$v_2$	$q_3 \cdot k_2$	$q_3 \cdot k_2 / 8$	$x_{32}$	$x_{32} * v_2$	
results	$q_3$	$k_3$	$v_3$	$q_3 \cdot k_3$	$q_3 \cdot k_3 / 8$	$x_{33}$	$x_{33} * v_3$	$z_3$



# Multi-headed Self-Attention

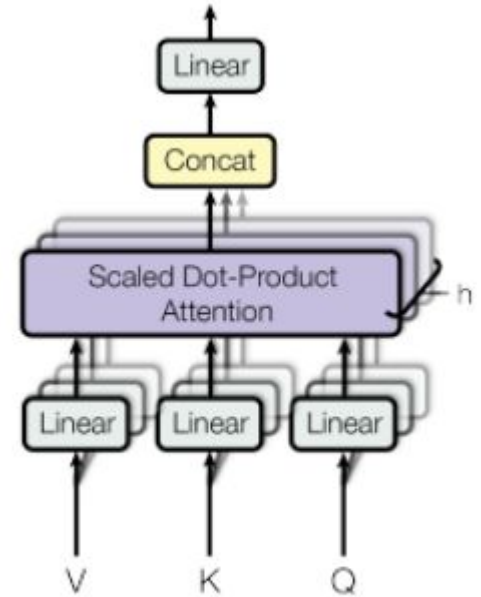
- Multiple sets of  $W_q$ ,  $W_k$ ,  $W_v$  and query, key and value vectors..



Multi-Head Attention

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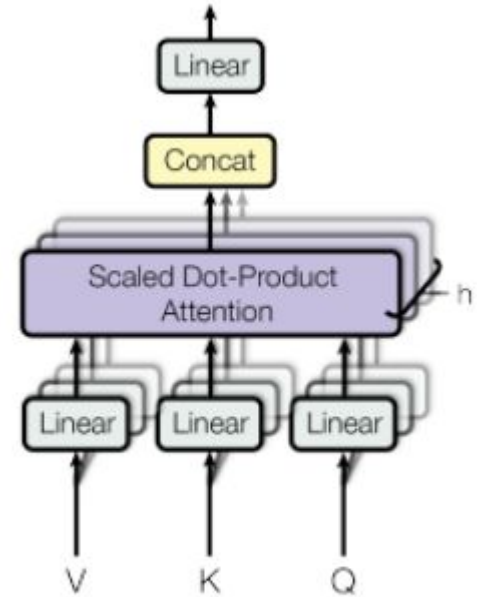
- Multiple sets of  $W_q$ ,  $W_k$ ,  $W_v$  and query, key and value vectors.
- Transformer uses 8 self-attention heads.



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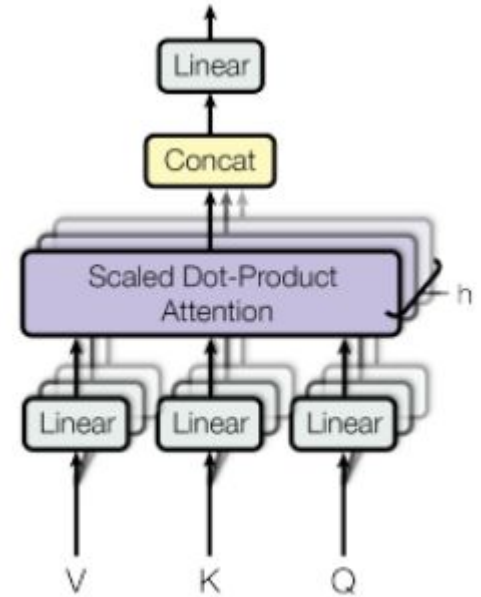
- Multiple sets of  $W_q$ ,  $W_k$ ,  $W_v$  and query, key and value vectors.
- Transformer uses 8 self-attention heads.
- Each head represents the input embeddings into a different representation space.



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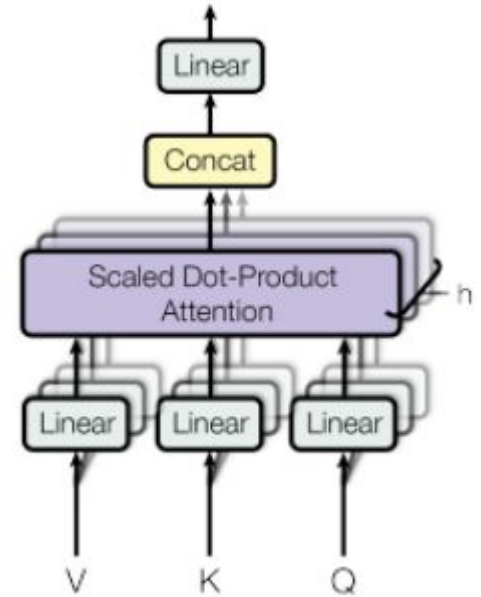
- Multiple sets of  $W_q$ ,  $W_k$ ,  $W_v$  and query, key and value vectors.
- Transformer uses 8 self-attention heads.
- Each head represents the input embeddings into a different representation space.
- $(q_0, k_0, v_0), (q_1, k_1, v_1), (q_2, k_2, v_2), \dots, (q_7, k_7, v_7)$



Multi-Head Attention

# Multi-headed Self-Attention

- Each head produces a Z-score matrix ( $Z_0, Z_1, Z_2, \dots, Z_7$ )
- These Z matrices are concatenated and multiplied with another weight matrix  $W$  to arrive at the final  $Z_f$  matrix.



Multi-Head Attention



Thank You