04. Transformers

Transformers may not fix all your NLP problems.

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But they are worth some attention.

Source: Ramsri Goutham

CS 1671/2071
Human Language Technologies

Session 16: Transformers part 1

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March 17, 2025

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Course logistics

- I will release the quiz for this week today, will be **due this Thu Mar 20**
- I pushed back the due date for the project progress report, now due next Thu Mar 27. I will release instructions for that early this week
- Homework 3 will be released this week, probably Fri Mar 21. Is due Apr 9

Lecture overview: Transformers part 1

- Self-attention
- Multi-headed attention
- Transformer blocks
- Activity: work through self-attention

Contextual word embeddings

Problem with static embeddings (word2vec)

They are static! The embedding for a word doesn't reflect how its meaning changes in context.

`The chicken didn't cross the road because` **`it`** `was too tired`

What is the meaning represented in the static embedding for "it"?

Slide adapted from Jurafsky and Martin

Contextual Embeddings

- Intuition: a representation of meaning of a word should be different in different contexts!
- **Contextual embedding**: each word has a different vector that expresses different meanings depending on the surrounding words
- How to compute contextual embeddings? **Attention**

Slide adapted from Jurafsky and Martin

Contextual Embeddings

`The chicken didn't cross the road because it`

What should be the properties of "it"?

`The chicken didn't cross the road because it was too` **`tired`**

`The chicken didn't cross the road because it was too` **`wide`**

At this point in the sentence, it's probably referring to either the chicken or the street

Slide adapted from Jurafsky and Martin

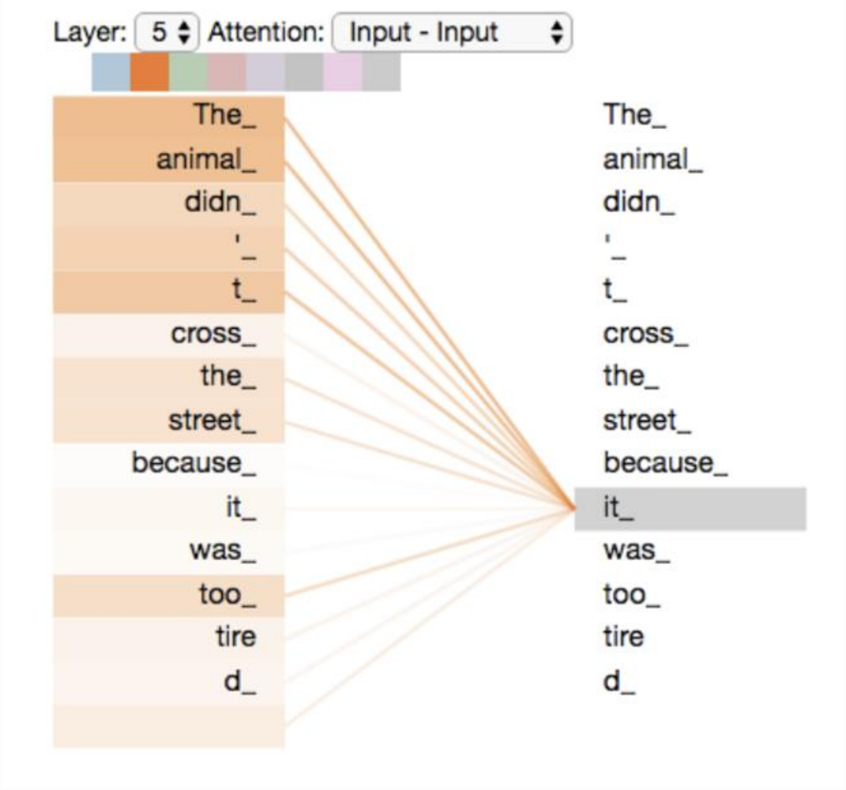
Intuition of attention

- Build up the contextual embedding from a word by selectively integrating information from all the neighboring words
- We say that a word "attends to" some neighboring words more than others

Slide adapted from Jurafsky and Martin

Self-attention

Self-attention illustrated



Source: The Illustrated Transformer

Attention definition

A mechanism for helping compute the embedding for a token by selectively attending to and integrating information from surrounding tokens (at the previous layer).

More formally: a method for doing a weighted sum of vectors.

Slide adapted from Jurafsky and Martin

An actual attention head: slightly more complicated

High-level idea: instead of using vectors (like x_i and x_4) directly, we'll represent 3 separate roles each vector $\mathbf{x}_i$ plays:

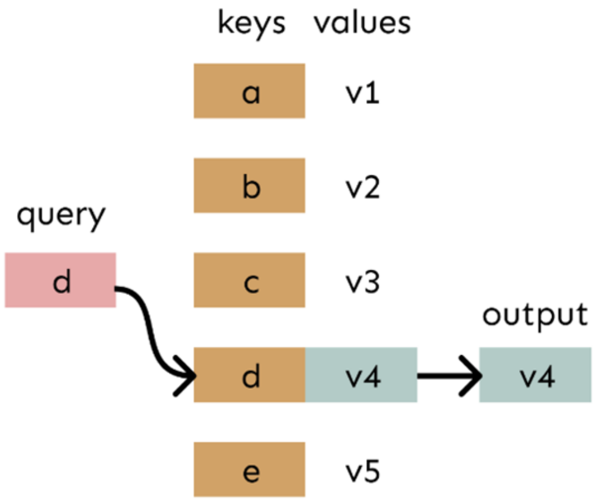
- **query:** As *the current element* being compared to the other inputs.
- **key:** as *an input* that is being compared to the current element to determine a similarity
- **value:** a value of a preceding element that gets weighted and summed

Slide adapted from Jurafsky and Martinc

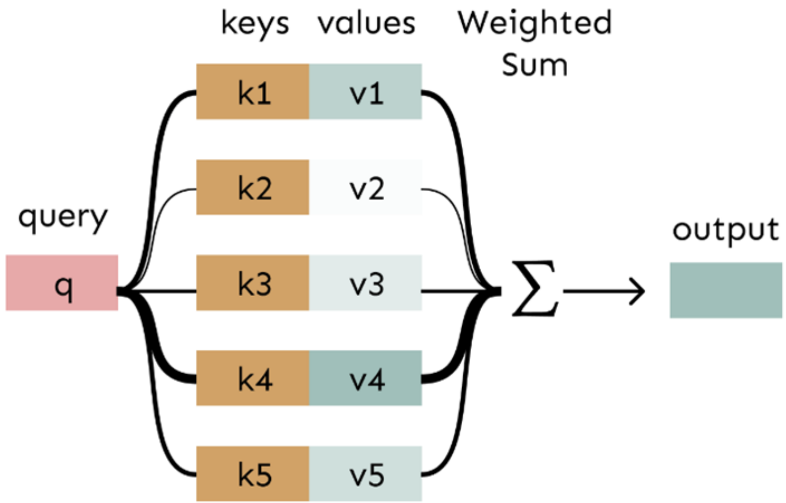
Attention as a soft, averaging lookup table

We can think of **attention** as performing fuzzy lookup in a key-value store.

In a **lookup table**, we have a table of **keys** that map to **values**. The **query** matches one of the keys, returning its value.



In **attention**, the **query** matches all **keys** *softly*, to a weight between 0 and 1. The keys' **values** are multiplied by the weights and summed.



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Slide credit: John Hewitt

Parameters: weight matrices for queries, keys and values

- We'll use matrices to project each vector x_i into a representation of its role as query, key, value:

- query: W^Q
- key: W^K
- value: W^V

$$\mathbf{q}_i = \mathbf{x}_i \mathbf{W}^{\mathbf{Q}}; \quad \mathbf{k}_i = \mathbf{x}_i \mathbf{W}^{\mathbf{K}}; \quad \mathbf{v}_i = \mathbf{x}_i \mathbf{W}^{\mathbf{V}}$$

Slide adapted from Jurafsky and Martinc

An Actual Attention Head: slightly more complicated

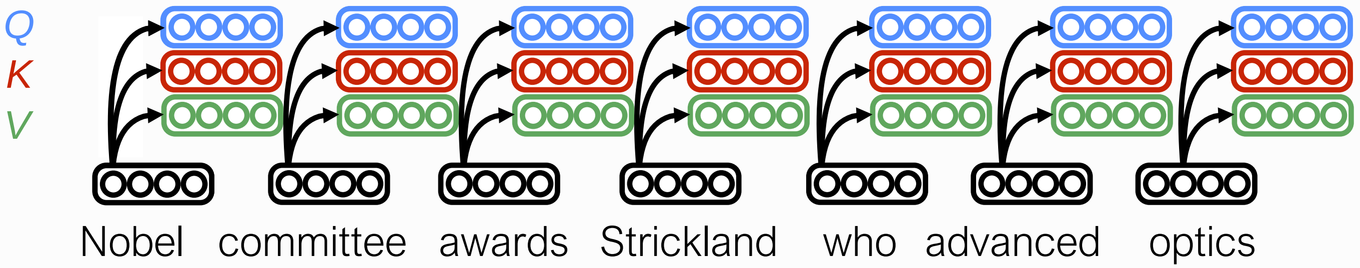
- Given these 3 representation of $\mathbf{x}_i$

$$\mathbf{q}_i = \mathbf{x}_i \mathbf{W}^{\mathbf{Q}}; \quad \mathbf{k}_i = \mathbf{x}_i \mathbf{W}^{\mathbf{K}}; \quad \mathbf{v}_i = \mathbf{x}_i \mathbf{W}^{\mathbf{V}}$$

- To compute the similarity of current element $\mathbf{x}_i$ with some element (for self-attention) $\mathbf{x}_j$
- We'll use dot product between $\mathbf{q}_i$ and $\mathbf{k}_j$.
- And instead of summing up $\mathbf{x}_j$, we'll sum up $\mathbf{v}_j$

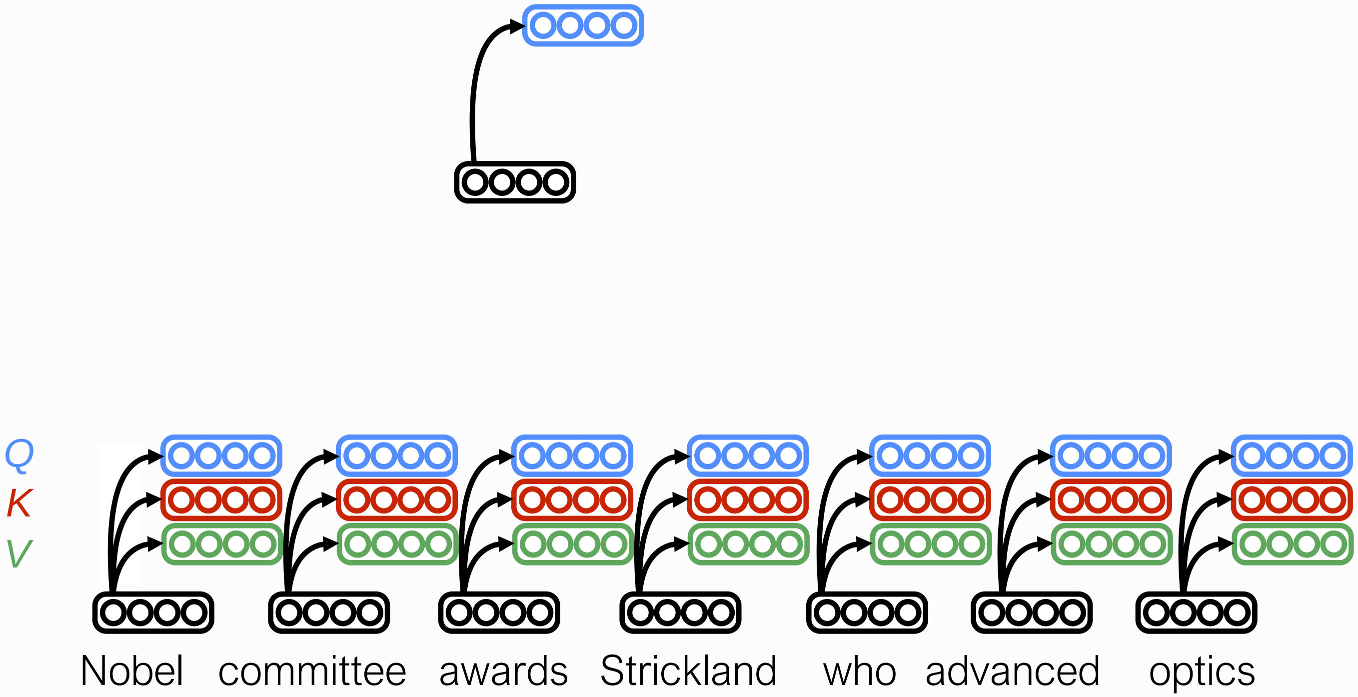
Slide adapted from Jurafsky and Martinc

Transformer self-attention



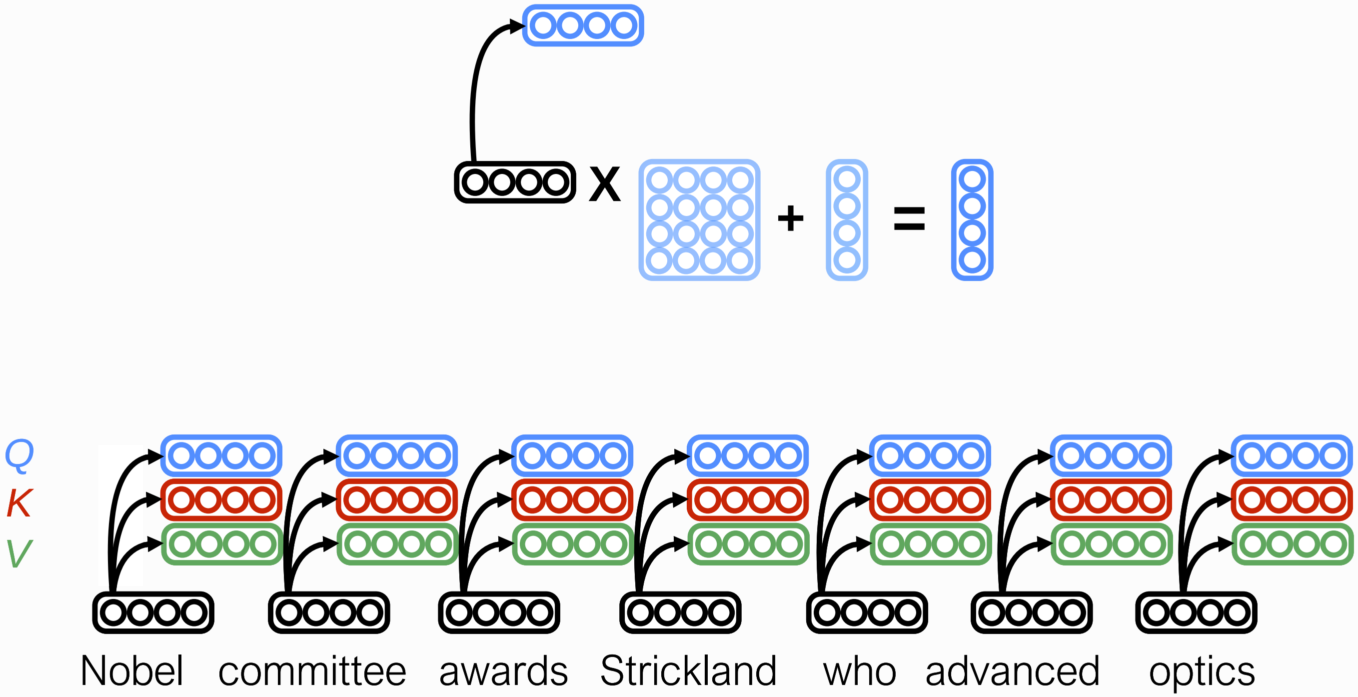
Source: Emma Strubell

Transformer self-attention



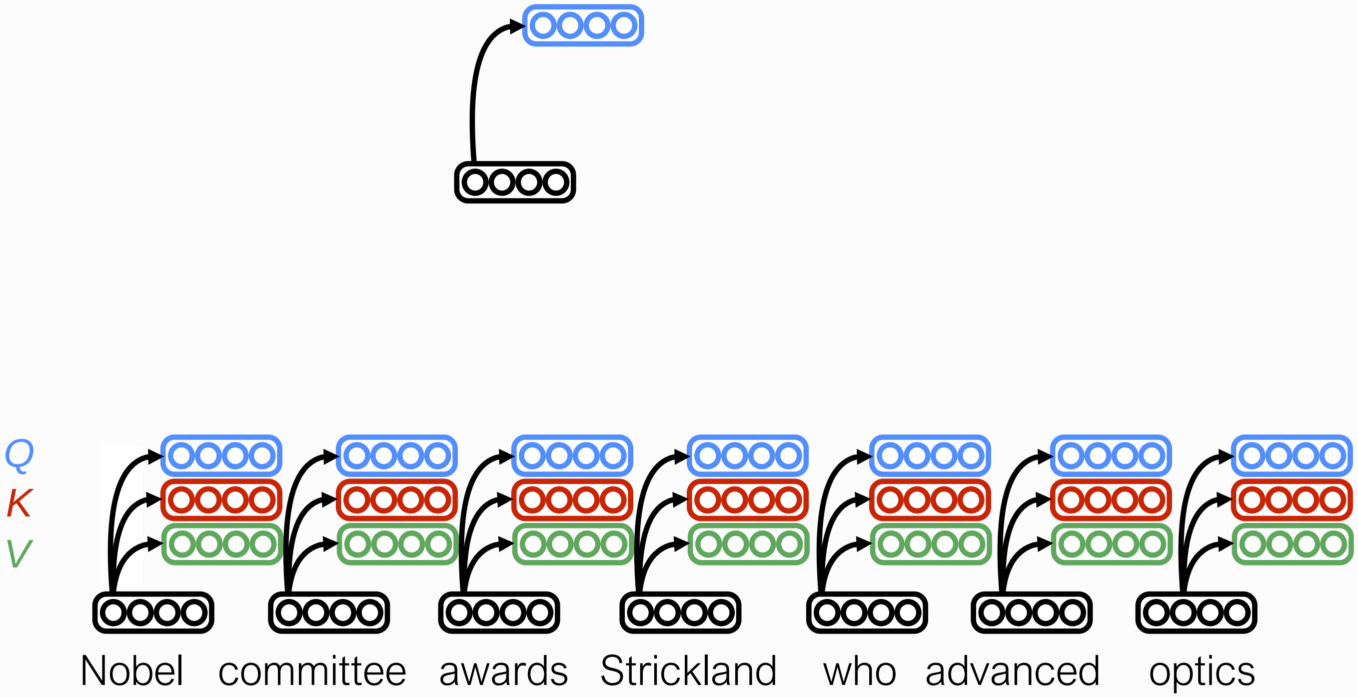
Source: Emma Strubell

Transformer self-attention



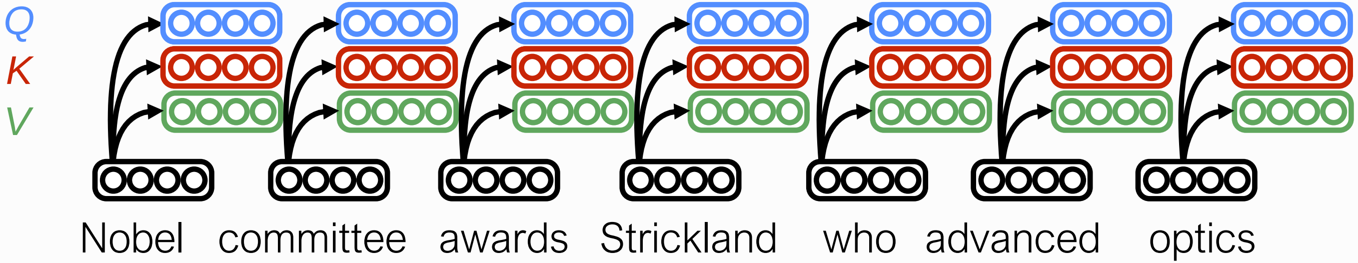
Source: Emma Strubell

Transformer self-attention



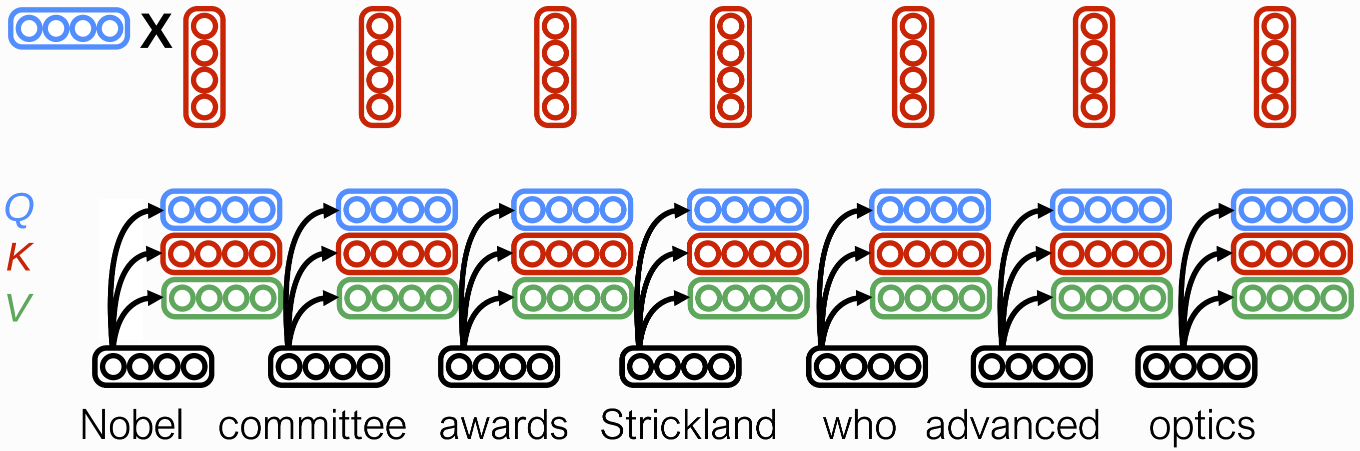
Source: Emma Strubell

Transformer self-attention



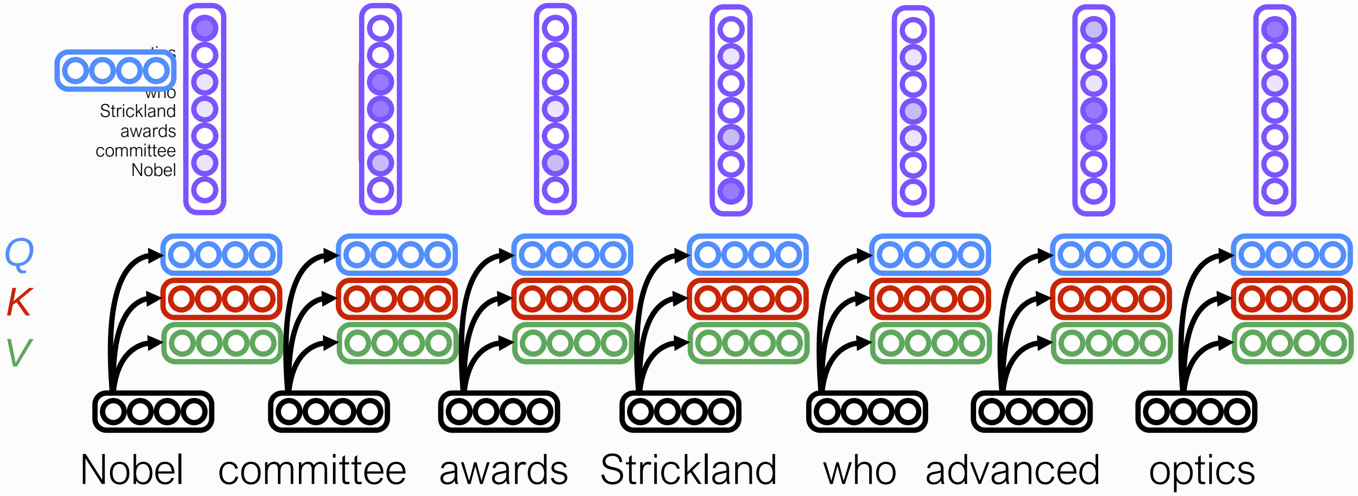
Source: *Emma Strubell*

Transformer self-attention



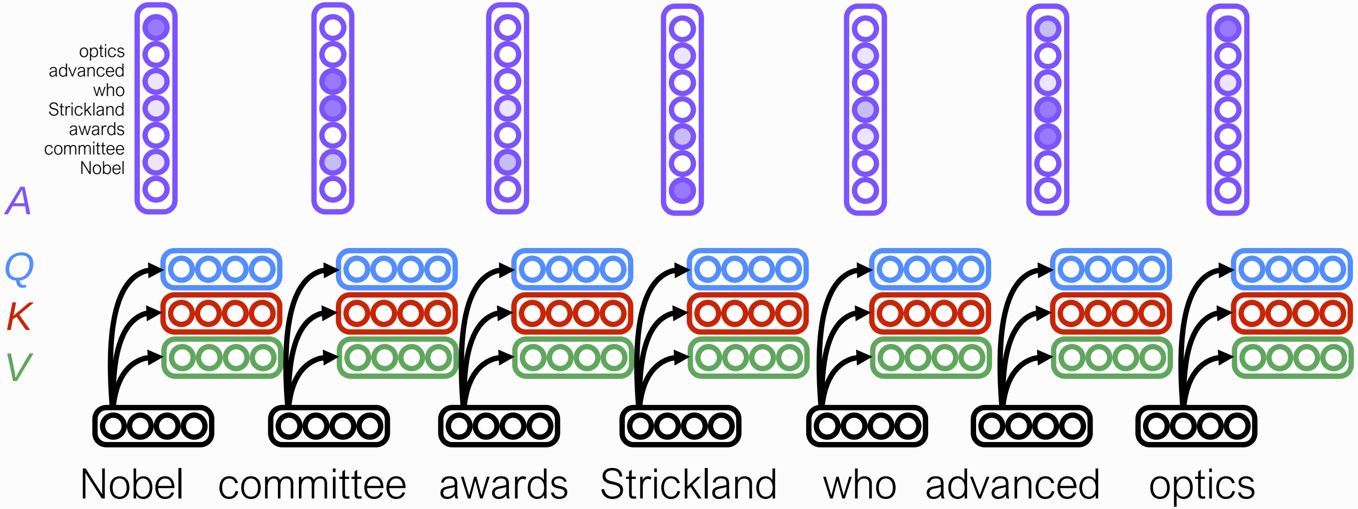
Source: Emma Strubell

Transformer self-attention



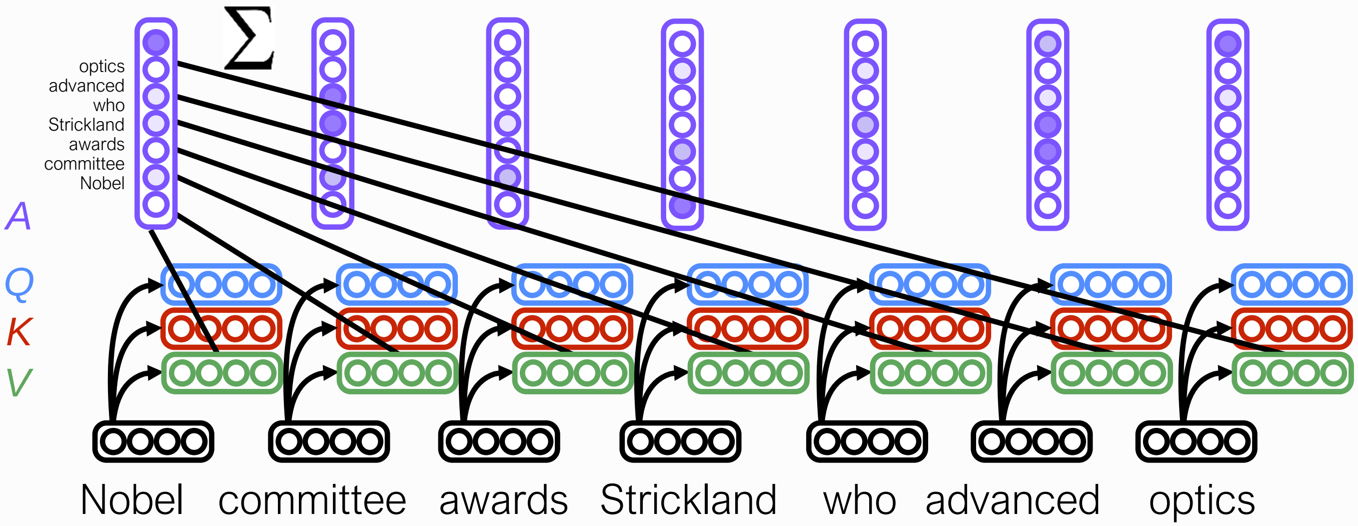
Source: Emma Strubell

Transformer self-attention



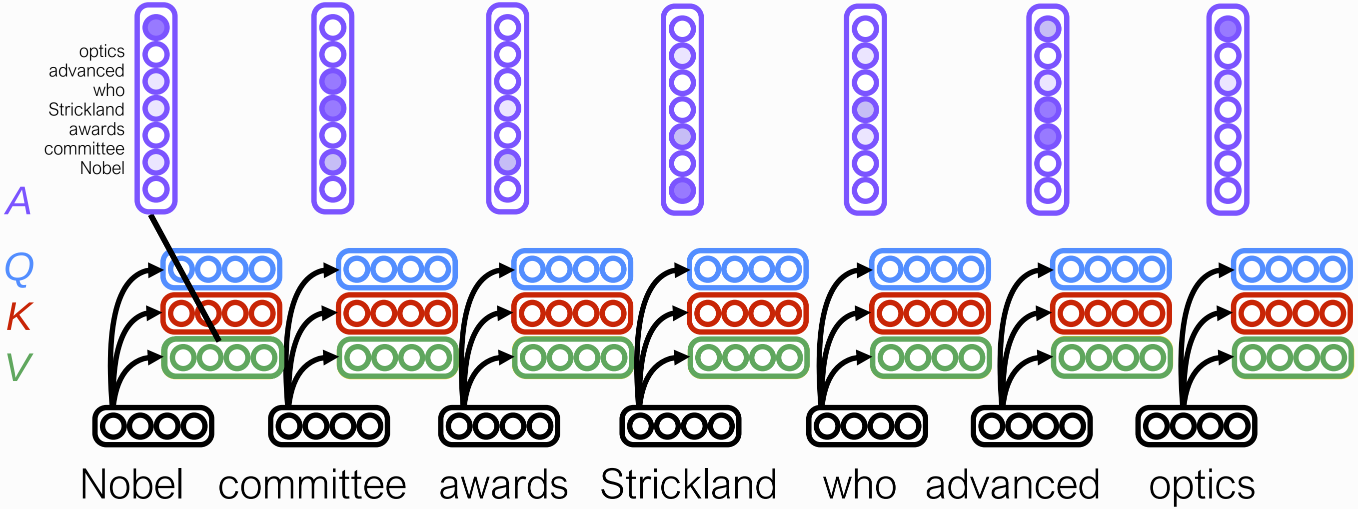
Source: Emma Strubell

Transformer self-attention



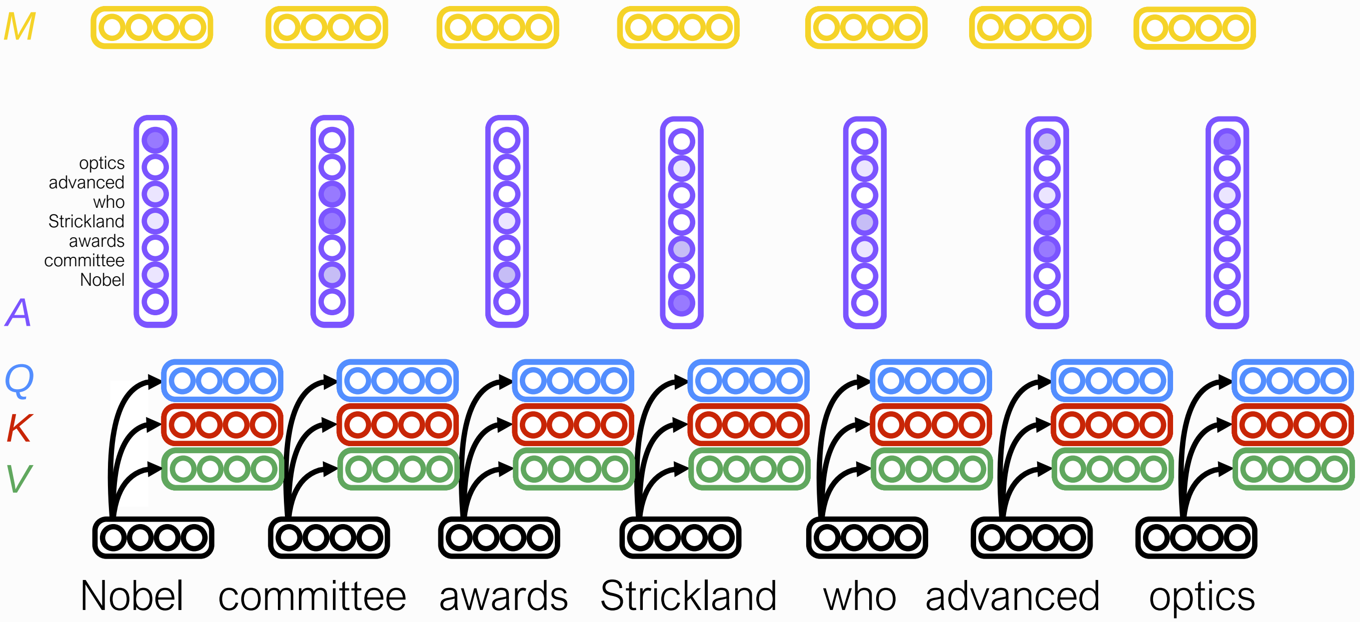
Source: Emma Strubell

Transformer self-attention



Source: Emma Strubell

Transformer self-attention

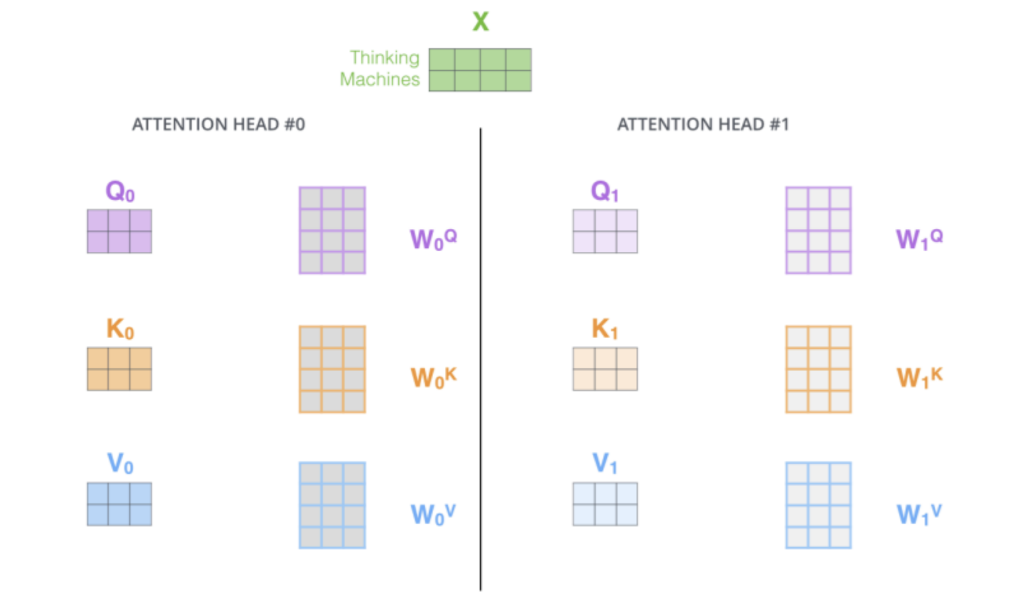


Source: *Emma Strubell*

Multi-headed attention

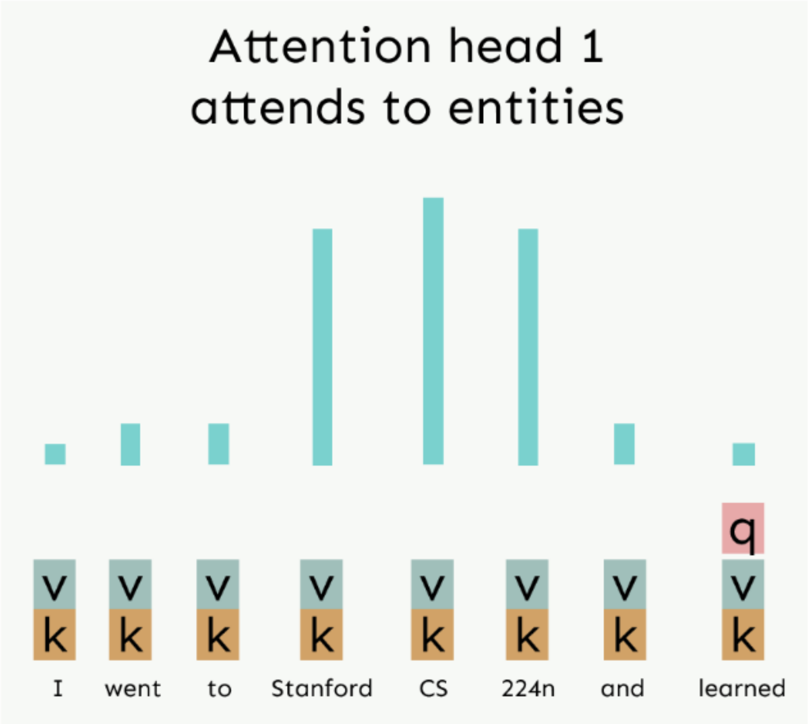
Multi-Headed Attention Expands Transformer Models' Ability to Focus on Different Positions

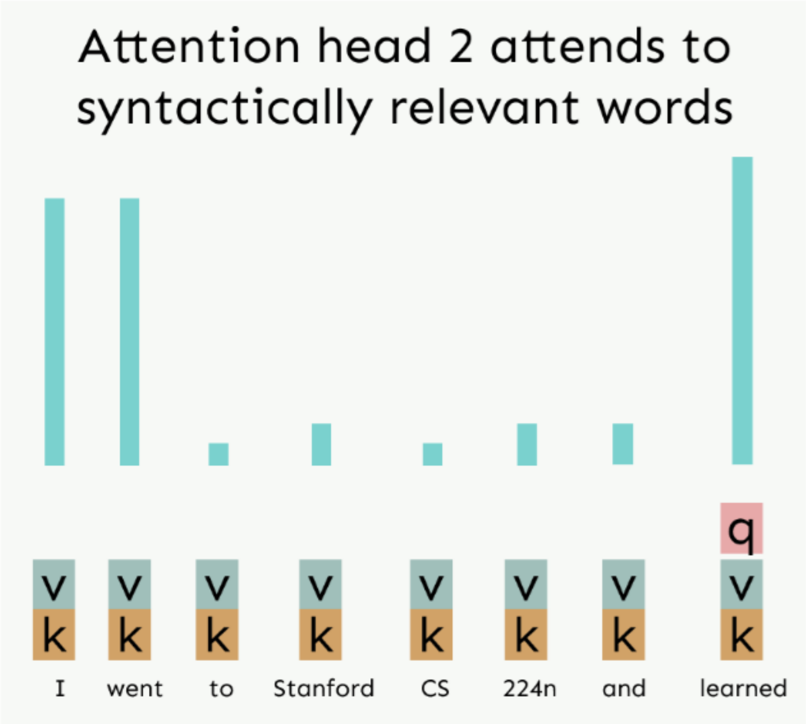
Maintain distinct weight matrices for each attention head—distinct representational subspaces:



Slide credit: *David Mortensen*

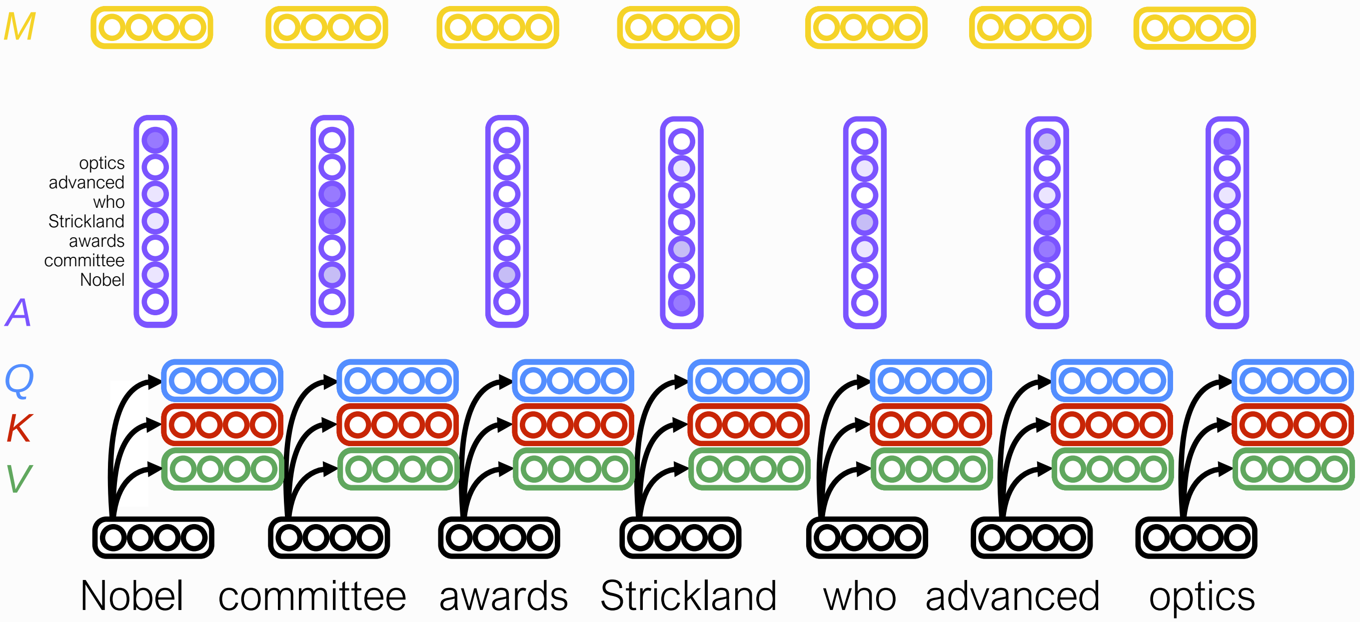
Hypothetical example of multi-headed attention





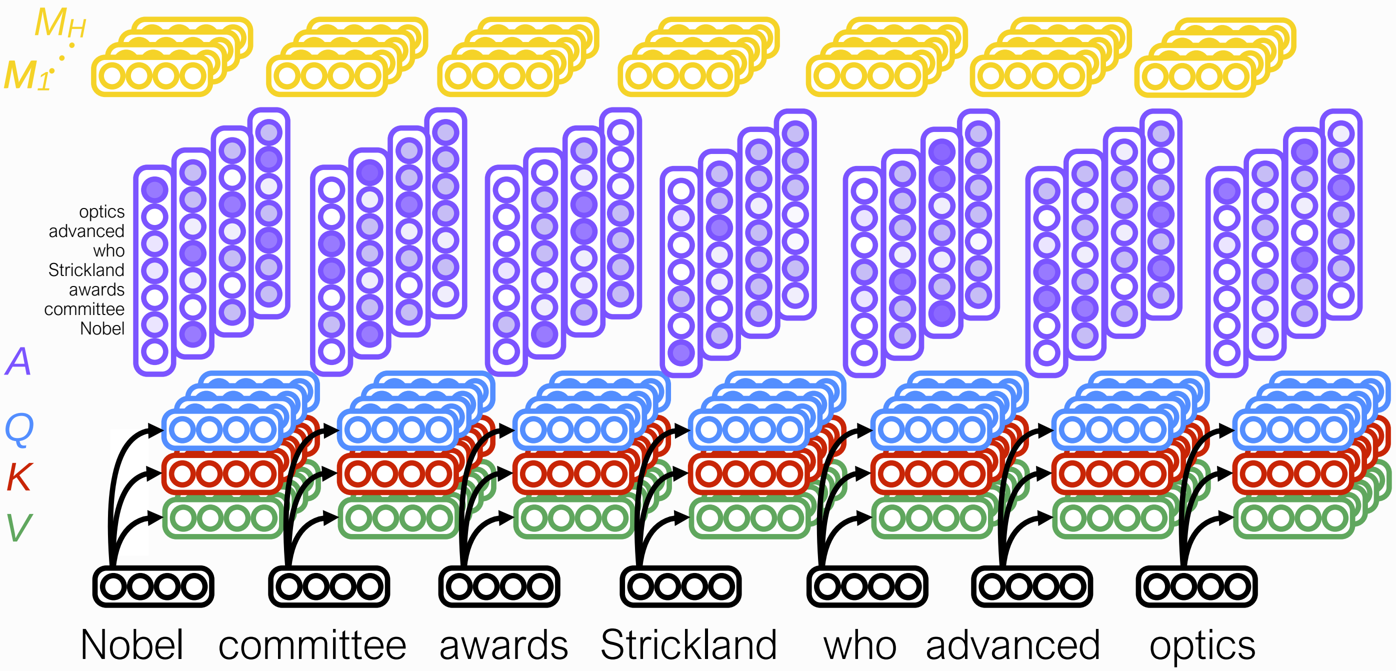
Slide credit: John Hewitt

Transformer self-attention



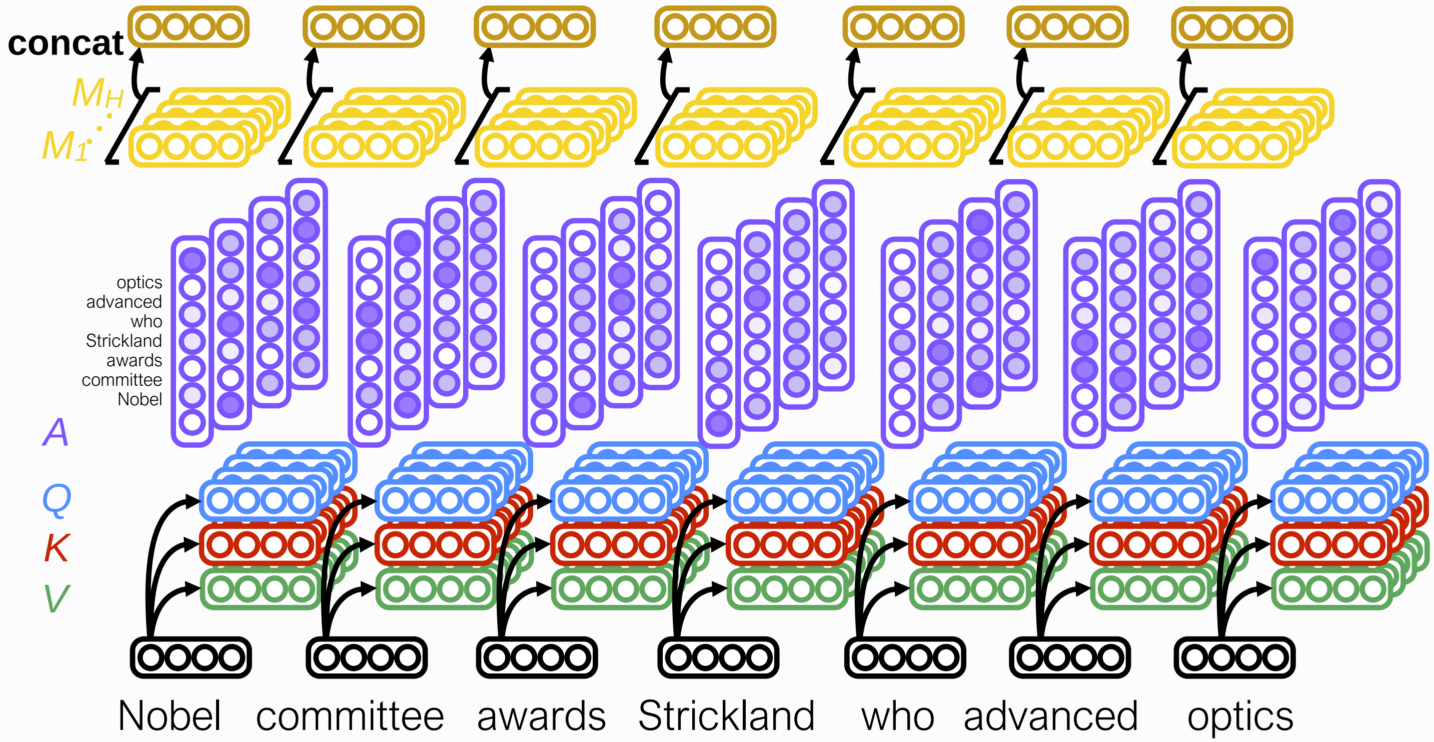
Source: Emma Strubell

Multi-head self-attention



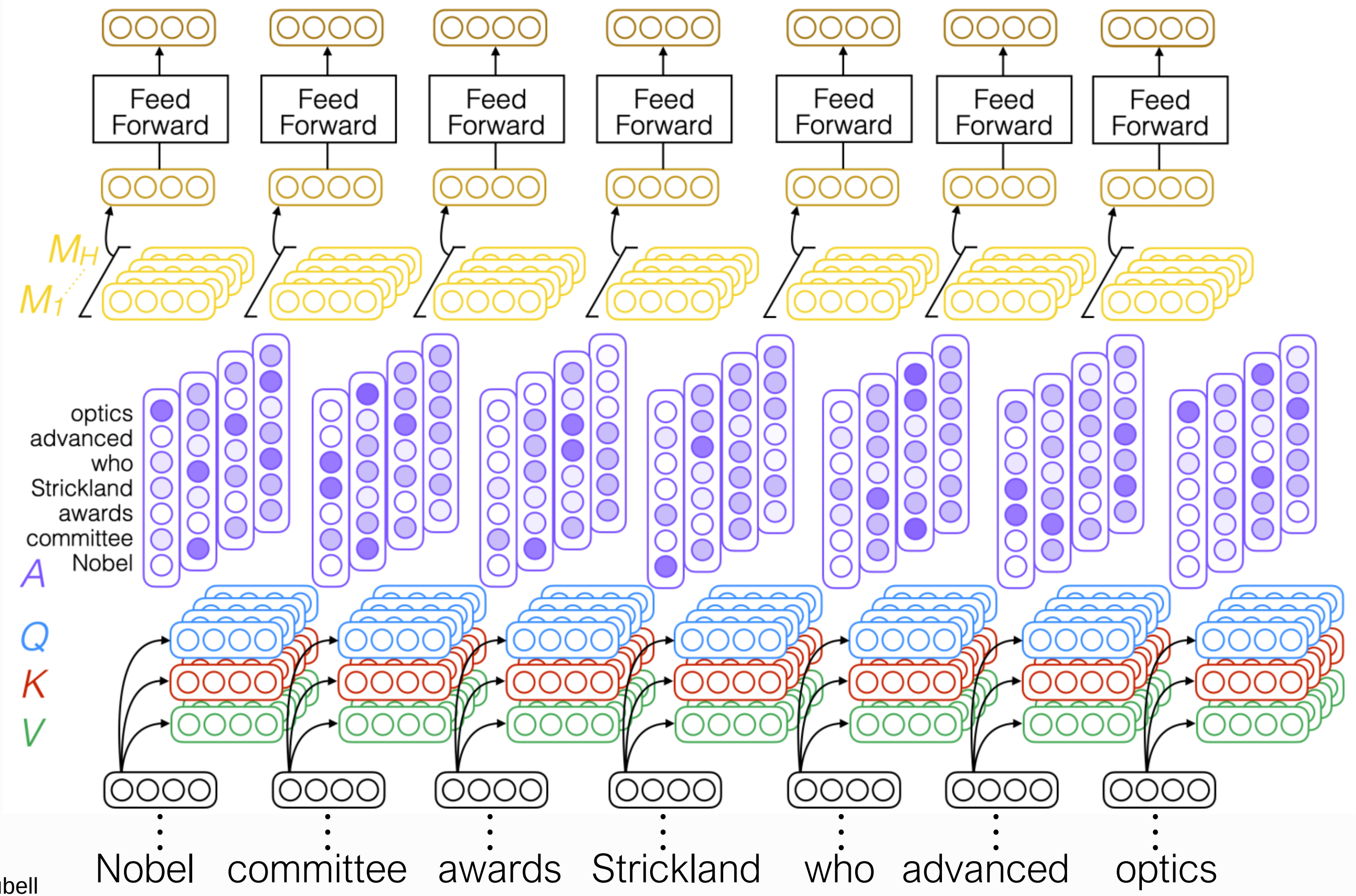
Source: Emma Strubell

Multi-head self-attention



Source: Emma Strubell

Add a feedforward neural transformation for nonlinearity



Source: Emma Strubell

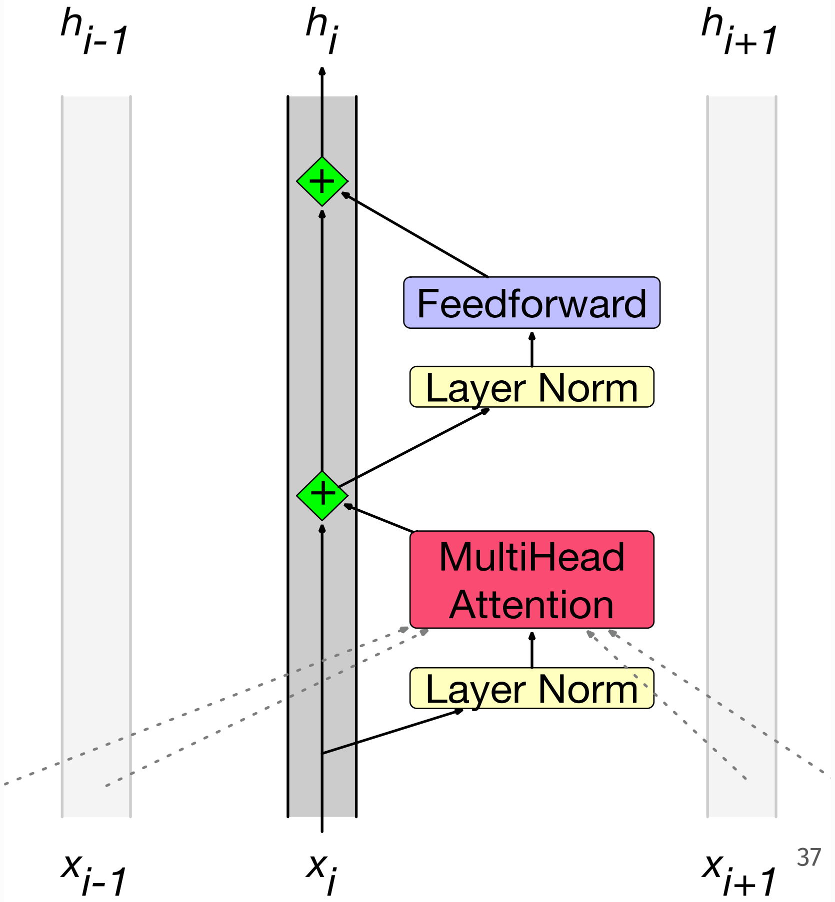
Transformer blocks

Transformer blocks

Each block consists of:

- Self-attention
- Layer normalization and residual connections: tricks to optimize learning
- Feedforward neural network

Output: 1 vector for every input token



Slide adapted from Jurafsky and Martin, John Hewitt

Activity: work through self-attention

Calculate transformed output for one input word

- Example sentence: “we wash our cats” (don’t ask)
- Let’s just calculate the vector output, for one input word: “we”
- High-level points to remember before you get buried in the math:
  - Each token will have an output vector that integrates contextual information from other tokens in the sentence
  - Each token can play a role as a query, key, and value
- Parameters (learned through backpropagation) are assumed given:
  - W^Q, W^K, W^V

Computing Self-Attention, Step One: Compute Key, Query, and Value Vectors

d_x-dimensional embeddings		$d_k \times d_x$-dimensional Weight Matrices		d_k-dimensional vectors	
x_1	$\times$	W^Q	$=$	q_1	queries
x_1	$\times$	W^K	$=$	k_1	keys
x_1	$\times$	W^V	$=$	v_1	values

Slide credit: David Mortensen

Dot product: vector · matrix

$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} ax + by + cz \\ dx + ey + fz \\ gx + hy + iz \end{bmatrix}$$

Computing Self-Attention, Step One: Compute Key, Query, and Value Vectors

d_x-dimensional embeddings	$d_k \times d_x$-dimensional Weight Matrices	d_k-dimensional vectors	
x_1 = [3, 0, 1, -0.5] x_1 $\times$	$W^Q = \begin{bmatrix} 1.5 & 1 & 2 \\ 3 & -2 & 5 \\ 1 & 2 & -2 \\ 9 & 4 & 2 \end{bmatrix}$ $=$	q_1	queries
x_1 = [3, 0, 1, -0.5] x_1 $\times$	$W^K = \begin{bmatrix} 1 & 0.5 & 2 \\ -2 & 0.5 & 3 \\ .5 & 2 & -3 \\ 5 & 3 & 2 \end{bmatrix}$ $=$	k_1	keys
x_1 = [3, 0, 1, -0.5] x_1 $\times$	W^V $=$	v_1	values

$\boxed{\text{Find } q_1 \text{ and } k_1}$

Slide credit: David Mortensen

Computing Self-Attention, Step Two: Weighted Sum of Value Vectors

	We	wash	our	cats
	x_1	x_2	x_3	x_4
query-key dot product	$q_1 \cdot k_1 =$	$q_1 \cdot k_2 =$	$q_1 \cdot k_3 =$	$q_1 \cdot k_4 =$
divide by $\sqrt{d_k}$ Assume $d_k = 64$				
softmax				
$\times$ value	$\times\, v_1$	$\times\, v_2$	$\times\, v_3$	$\times\, v_4$
sum	z_1			

$k_2 = [3, 4, 3]$
$k_3 = [5, 2, 3]$
$k_4 = [3, 2, 1]$

$v_1 = [1, 0.5, -1]$
$v_2 = [4, 5, -2]$
$v_3 = [-3, 2, 2]$
$v_4 = [1, 1, 6]$

Slide credit: David Mortensen

Wrapping up

- Transformers are a high-performing NLP architecture based on self-attention
- Transformer blocks perfom a number of transformations on vectors for input tokens, including integrating information from the surrounding tokens (self-attention)
- Transformer blocks produce one output vector per each input token, which is contextual, i.e. varies depending on what words surround the token
- Self-attention computation is easily parallelizable

Questions?