How do ‘Large Language Models’ work?

All of the history, none of the maths

Ali Knott

How we arrived at GPT—some landmarks

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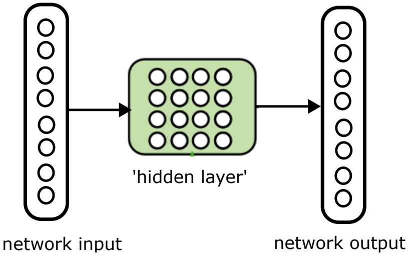
Nowadays, you can be a computational linguist without knowing anything that happened before 2012.

Recap: a basic network for supervised learning

Here's the basic neural network architecture I introduced before.



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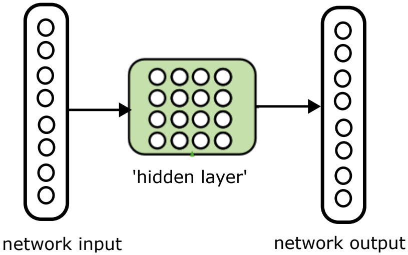

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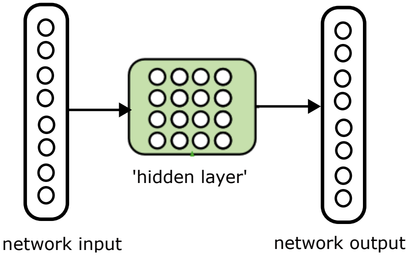

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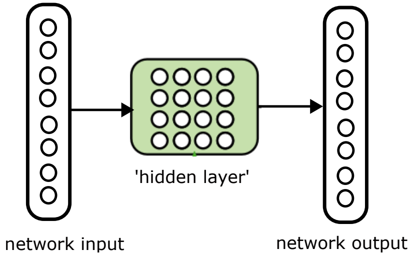

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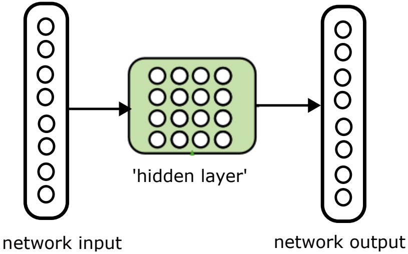

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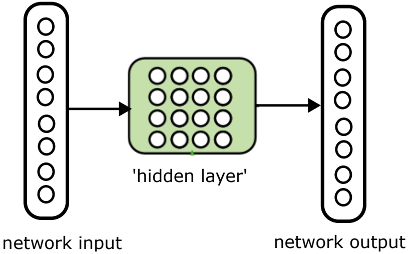

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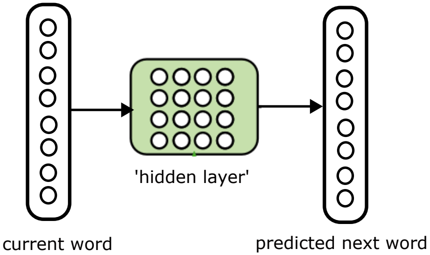

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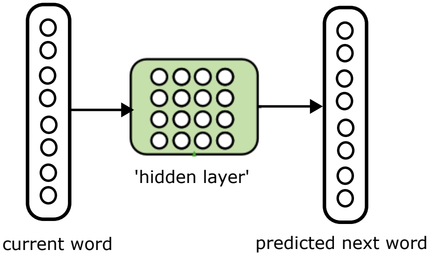
- This network can learn from any sample of language, through 'self-supervision'.



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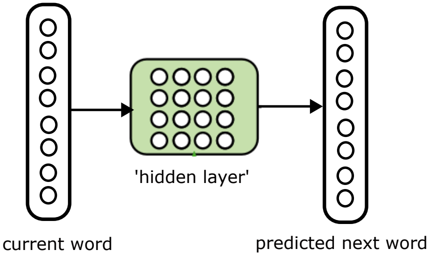

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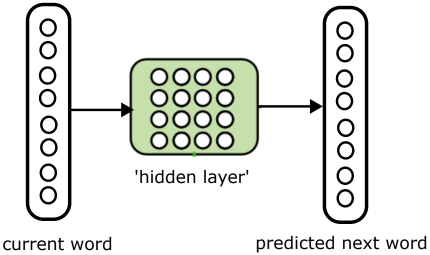

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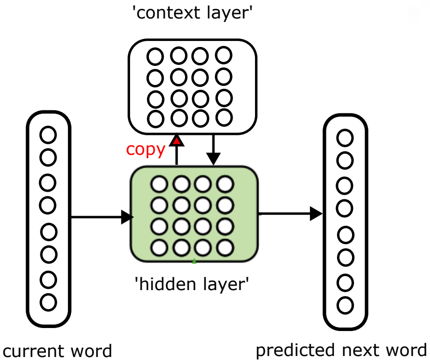

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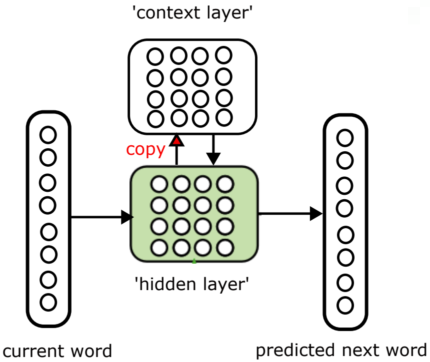

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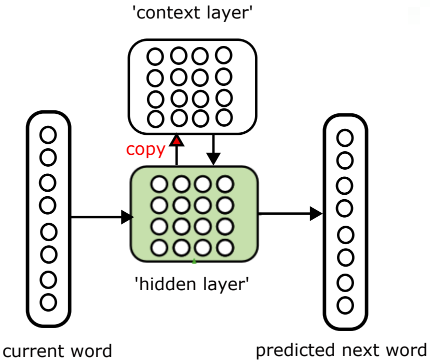

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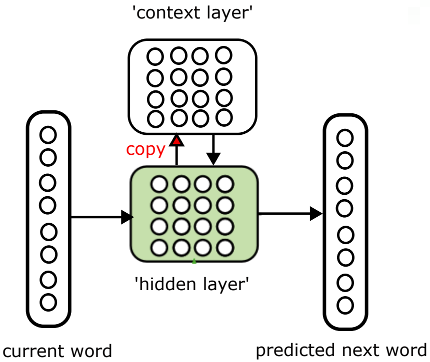

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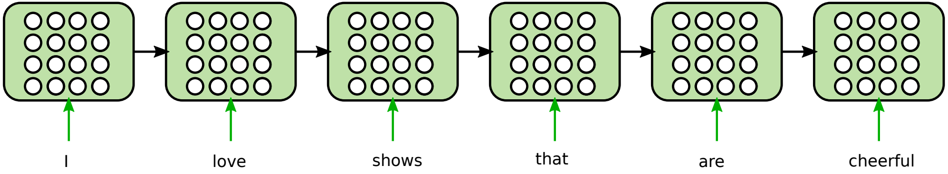

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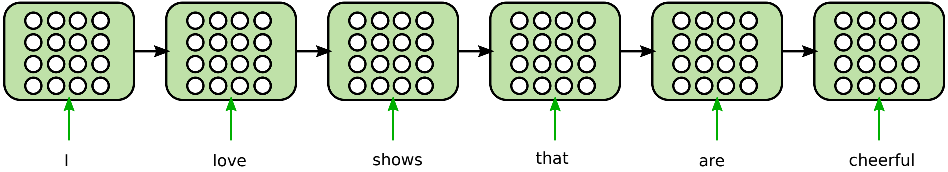

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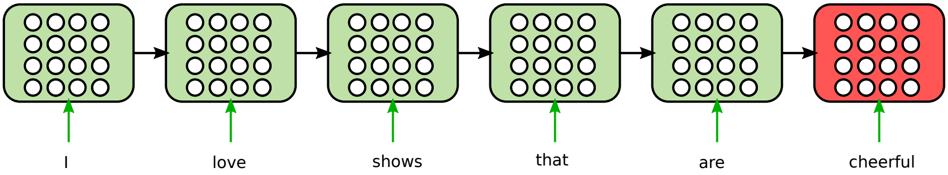

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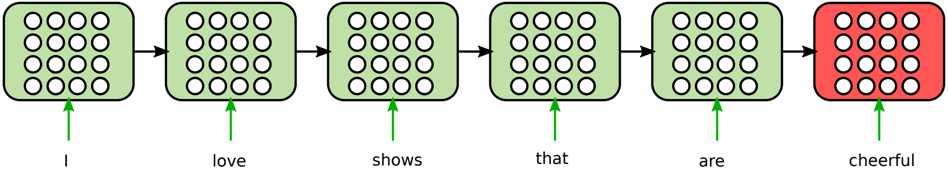

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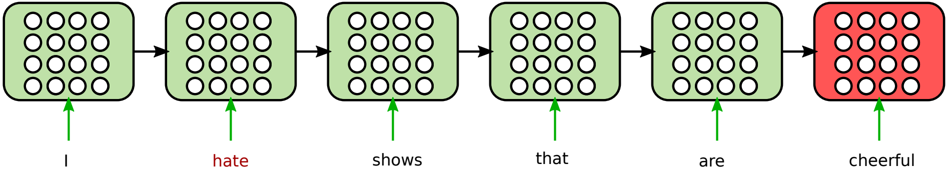

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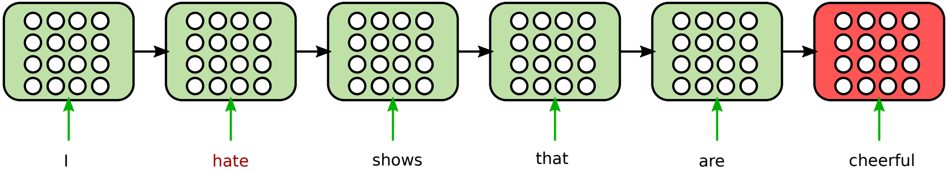

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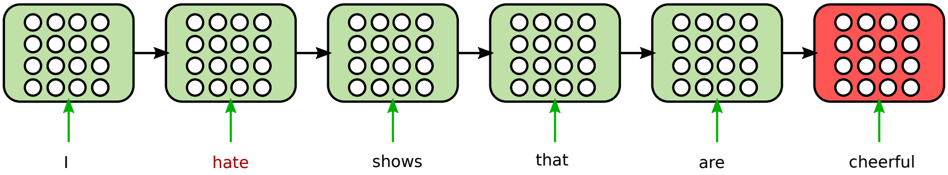

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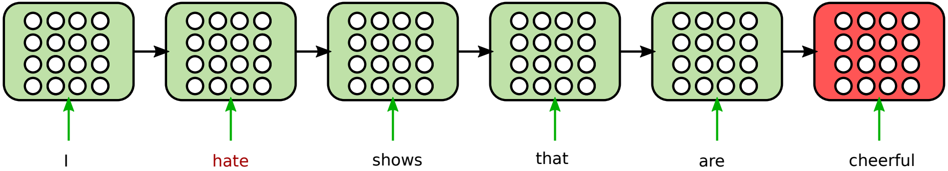
- A recurrent hidden layer creates a 'bottleneck problem'.



Representations of words in neural networks

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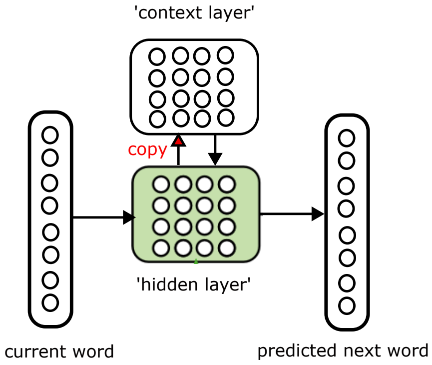

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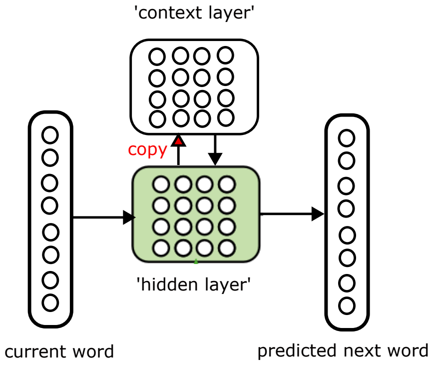

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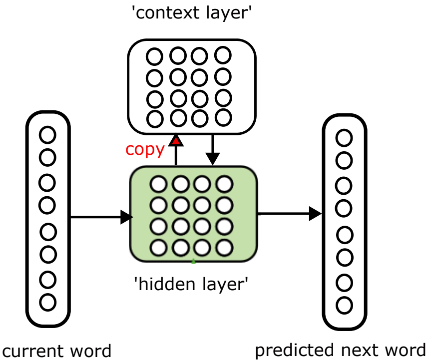

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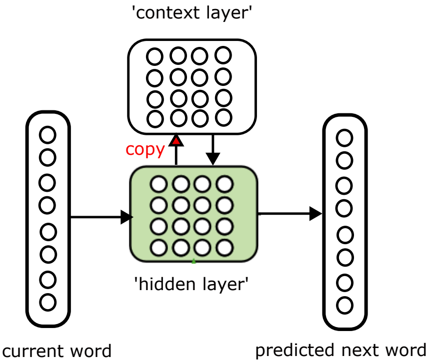

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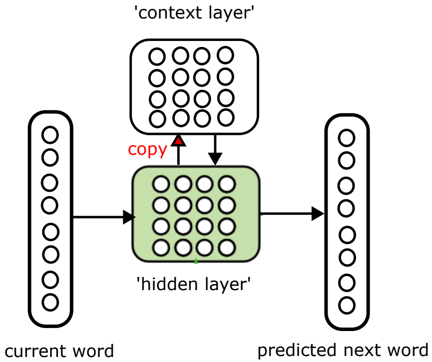

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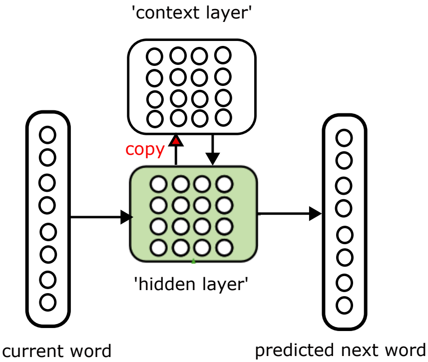

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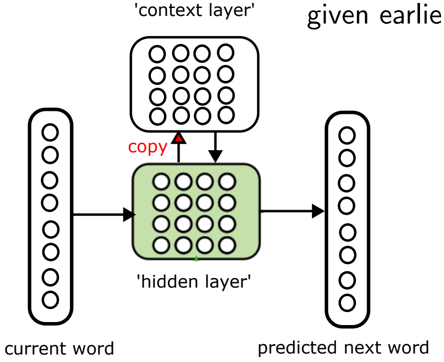

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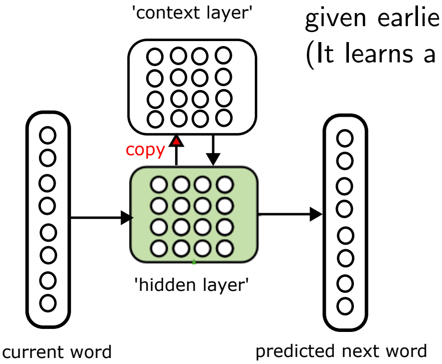
    (It learns a probability model of its training text!)



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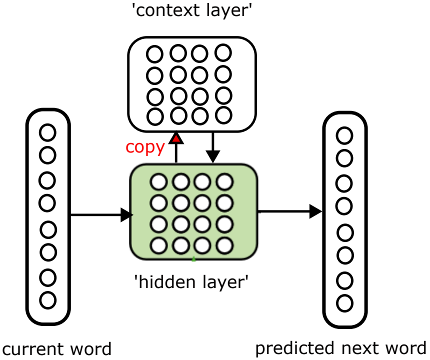

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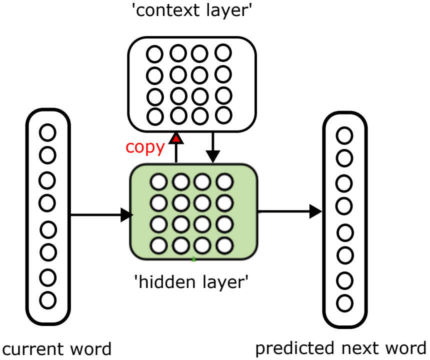

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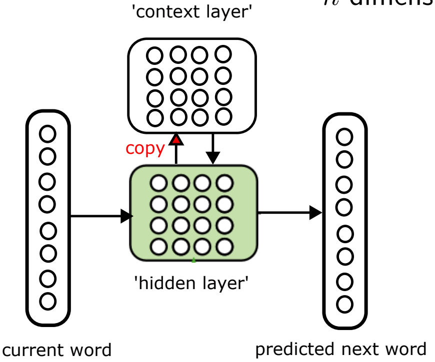
- The answer is to think of the n units in the input layer as holding an 'n-dimensional space' of possible word meanings.



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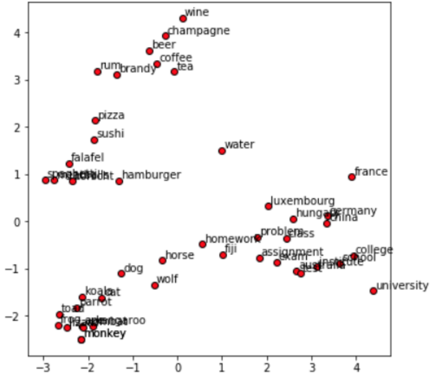

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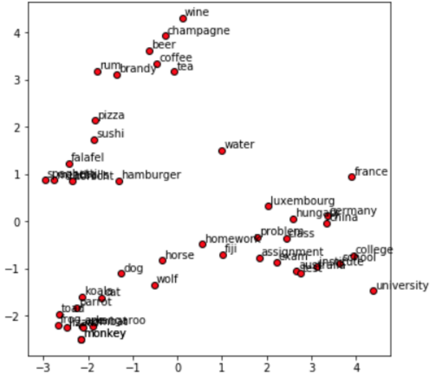

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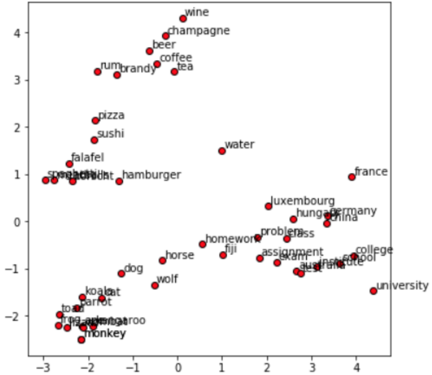
- Again, we want to learn from actual text, using self-supervision. . .



Learning vector-based word representations

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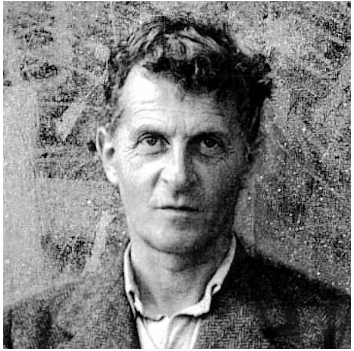

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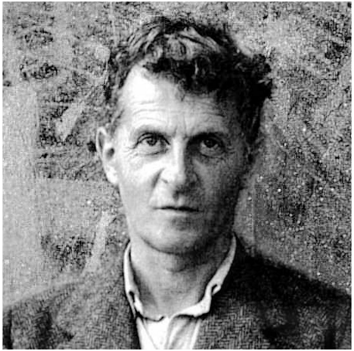

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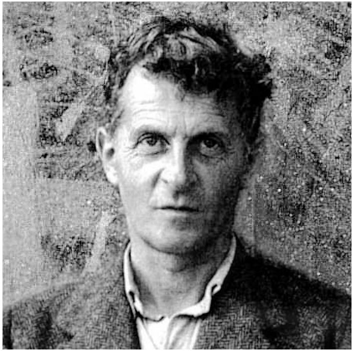
- Different uses of a given word *loosely resemble one another*.



‘Word use’ in a language corpus

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```
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```

‘Word use’ in a language corpus

Aligning uses of words in a corpus makes the point well.

- J R Firth (1956): ‘You shall know a word by the company it keeps’.

```
 pierced, elongated into a CUP, and terminated by the phosph
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Start off by placing each word at a random point in the n-dimensional space.

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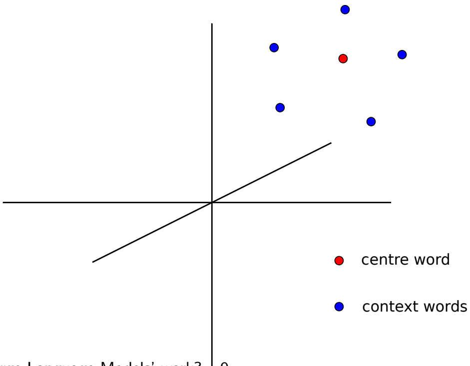

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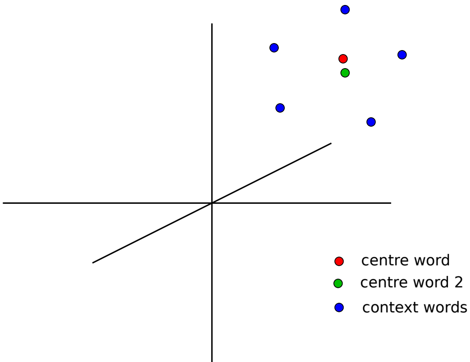

Putting language models to work

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We can use our network-based language models to learn these tasks.

Sequence-to-Sequence language models

A sequence-to-sequence (Seq2Seq) language model is trained on a corpus of input/output text pairs.

Input text	Output text
My name is Ali	Ko Ali taku ingoa
Where do you live	Ko wai tō kainga inaianei
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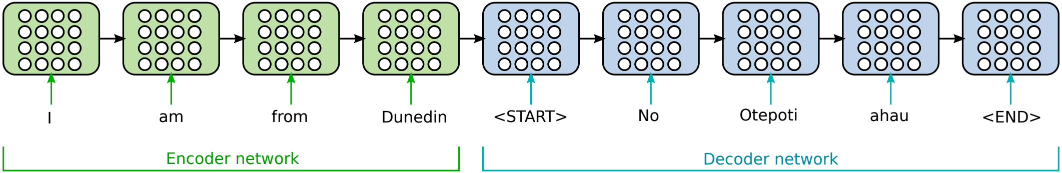

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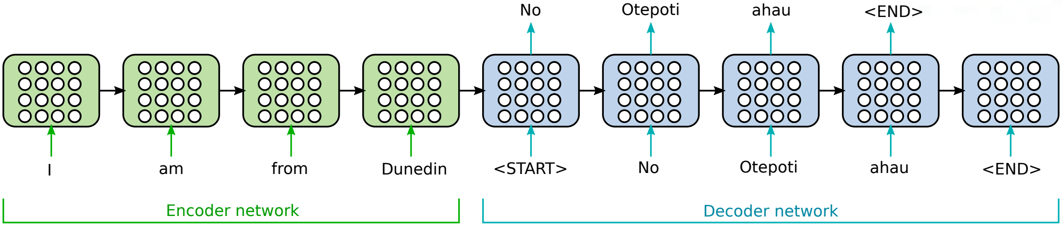

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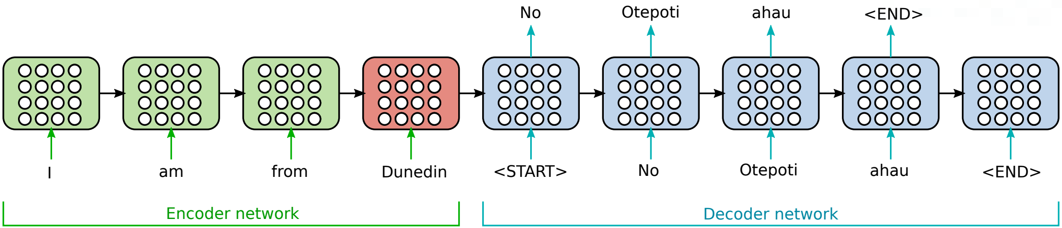

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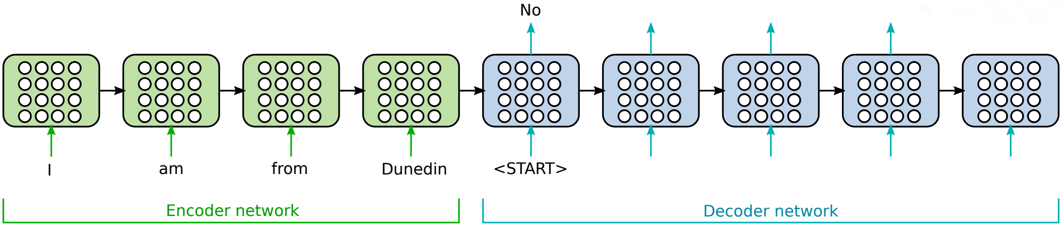

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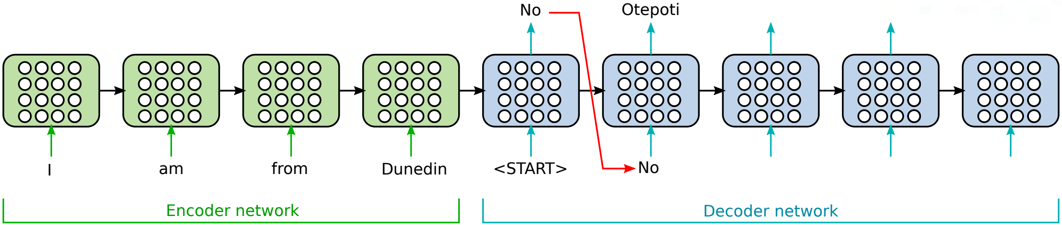

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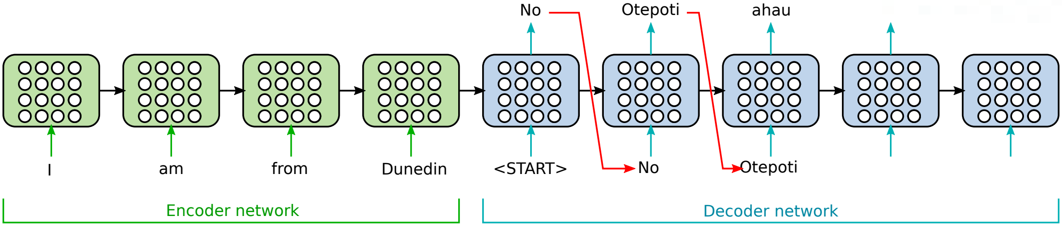

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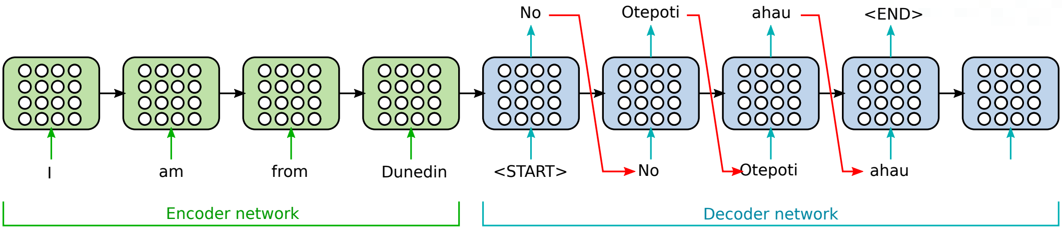

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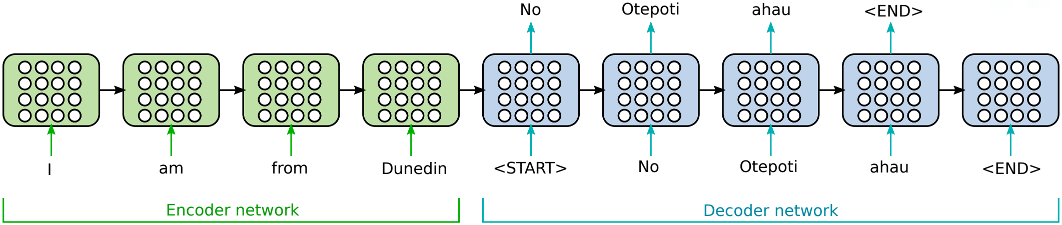
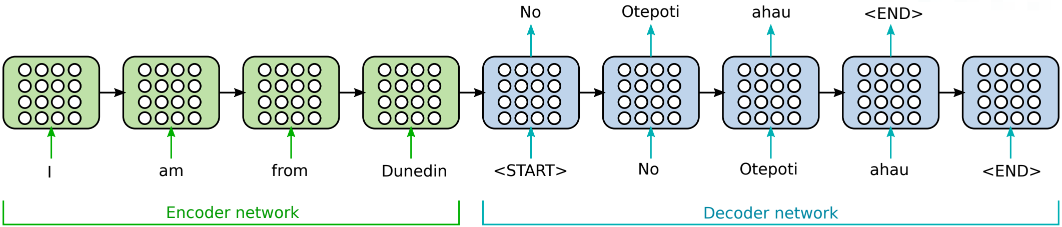


Sequence-to-Sequence language models

A regular RNN network learns a language model:

$$p(w_{i+1}|w_{i-D} \ldots w_D)$$



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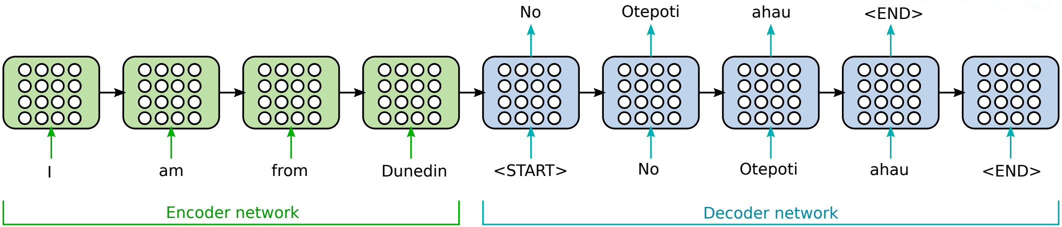

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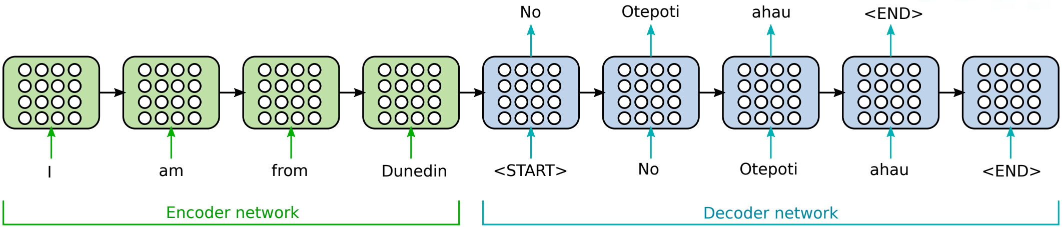

Attention (Bahdanau, Cho and Bengio, 2014)

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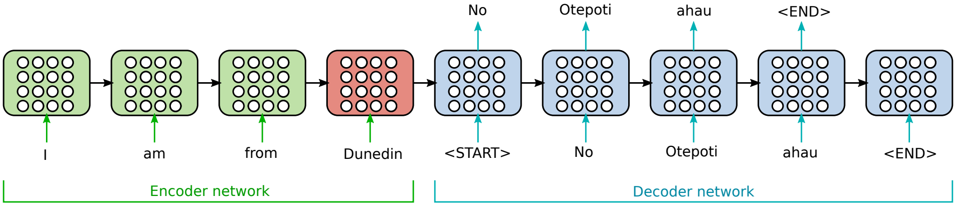
The Seq2Seq model just described still suffers from the ‘bottleneck problem’:



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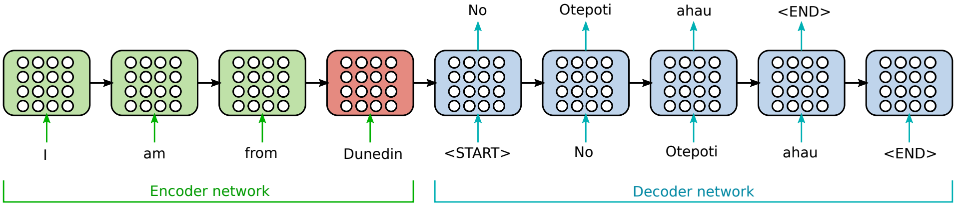

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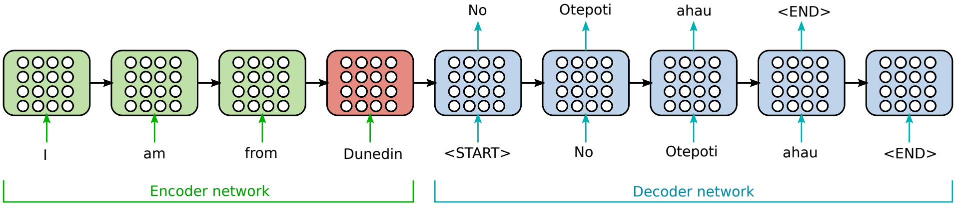
- The attention mechanism radically changed that.



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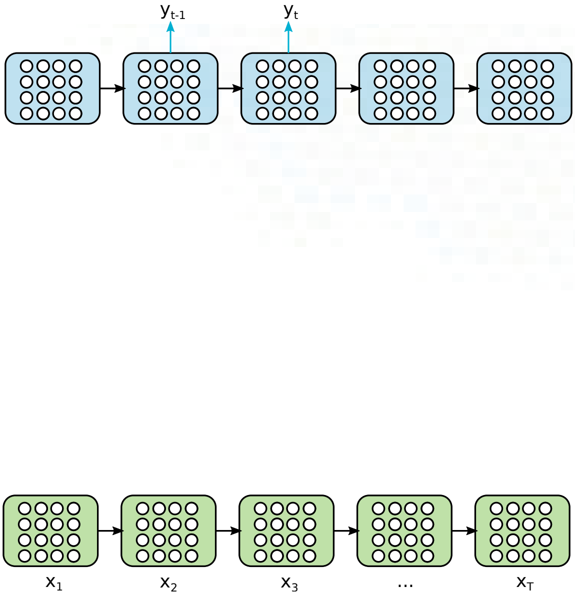

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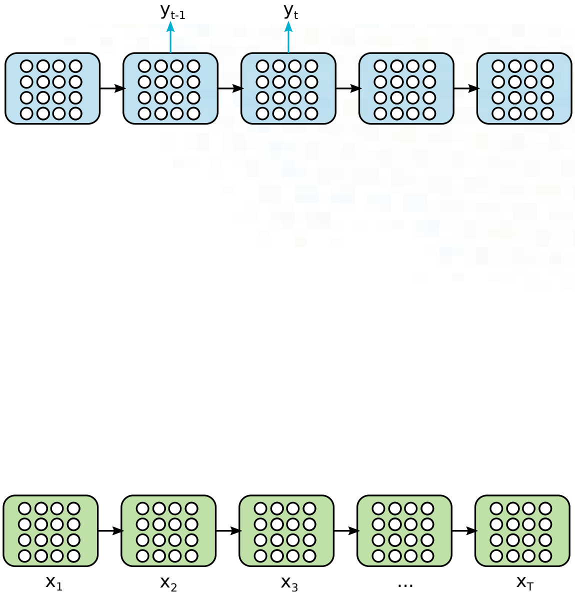

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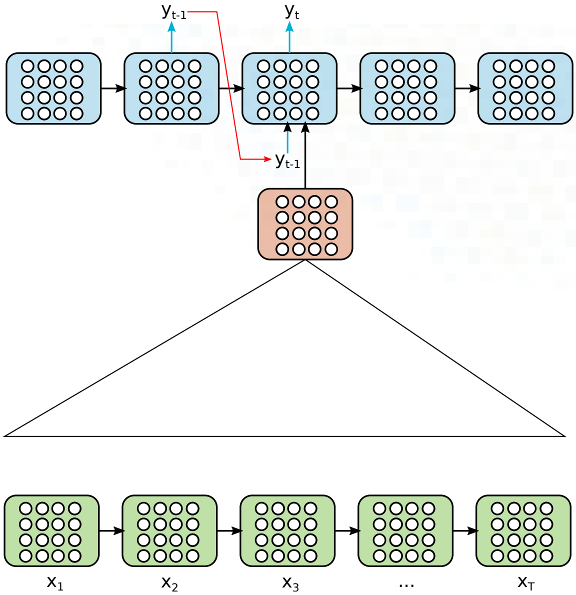

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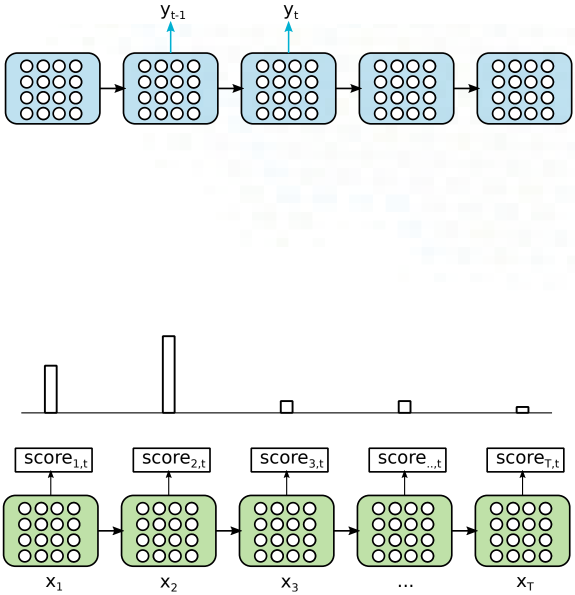

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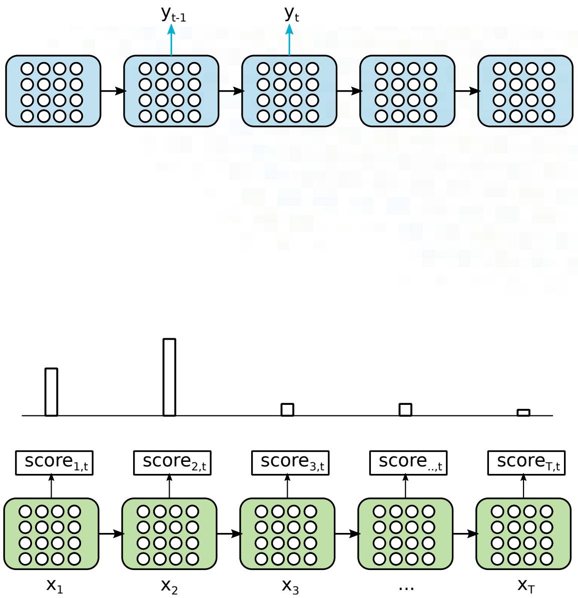
The decoder can now 'pay attention' to different parts of the encoded text at different times.



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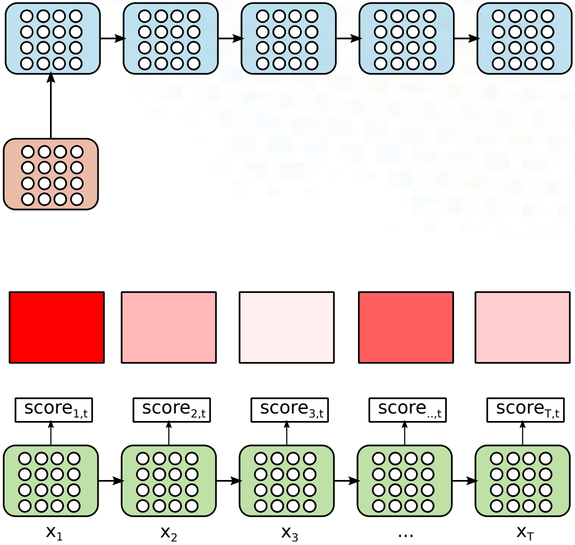

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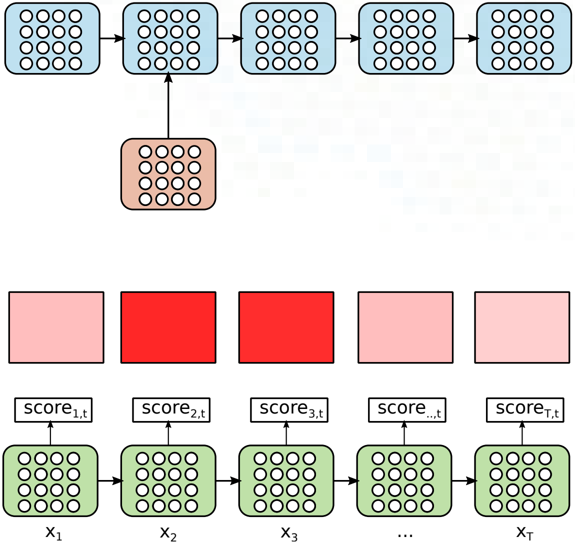

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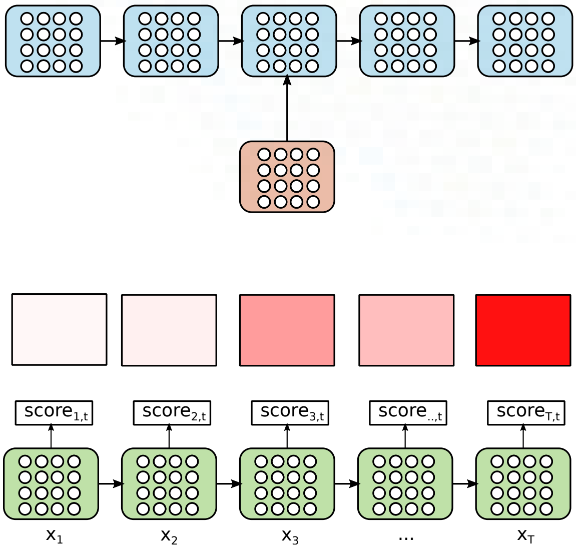

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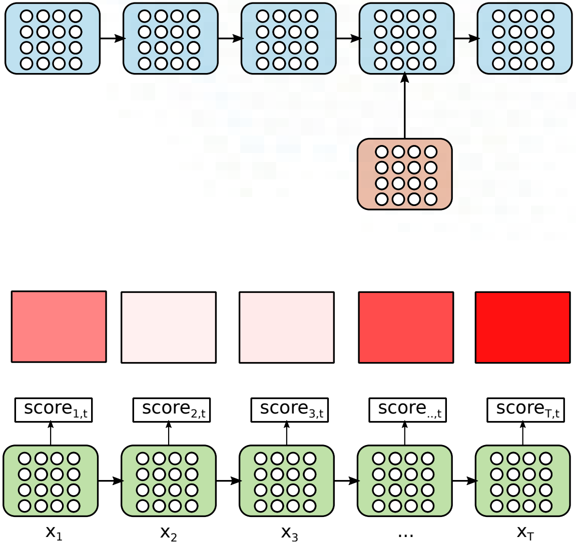

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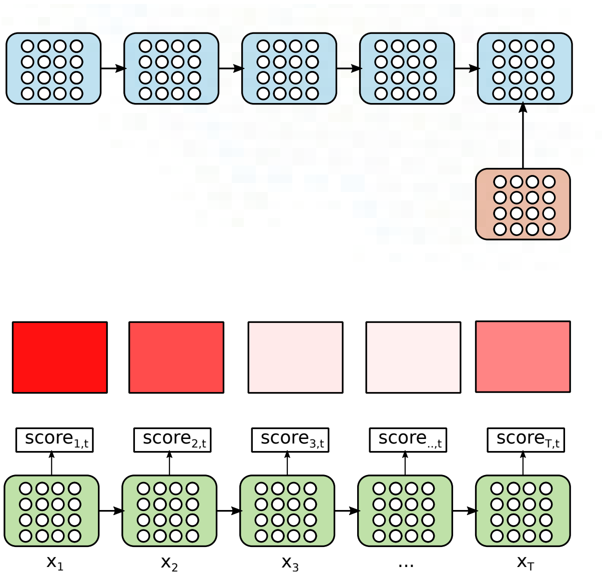

Attention and word alignment

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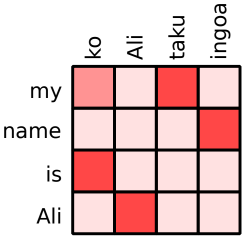
We often use an alignment chart to visualise this.



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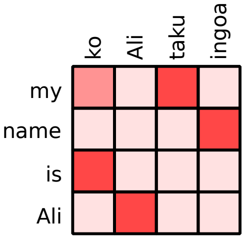

A Seq2Seq model using attention learns alignments by itself.

Transformers

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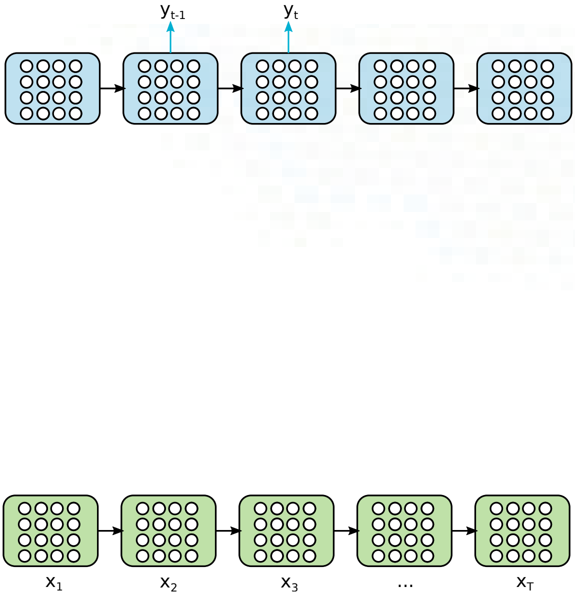
- It avoids *one* bottleneck problem.



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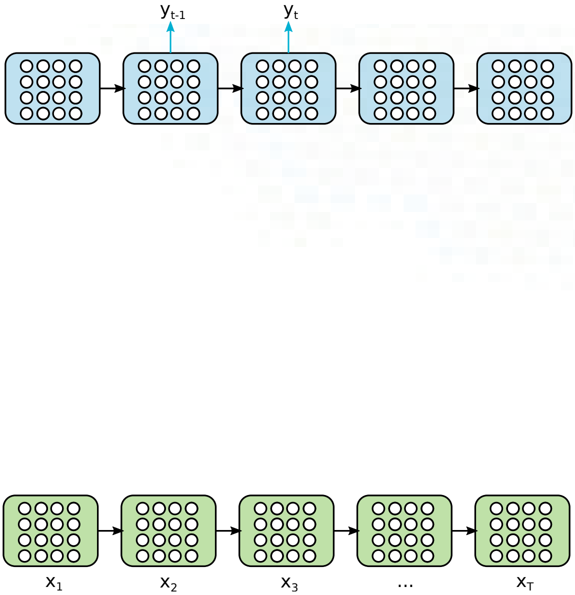

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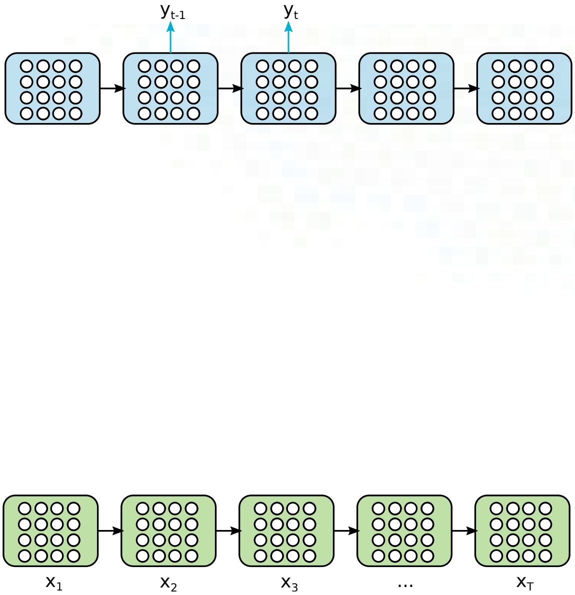
- Google's 'transformer' model replaced each of these with a self-attention mechanism.



Using attention to represent an input sentence

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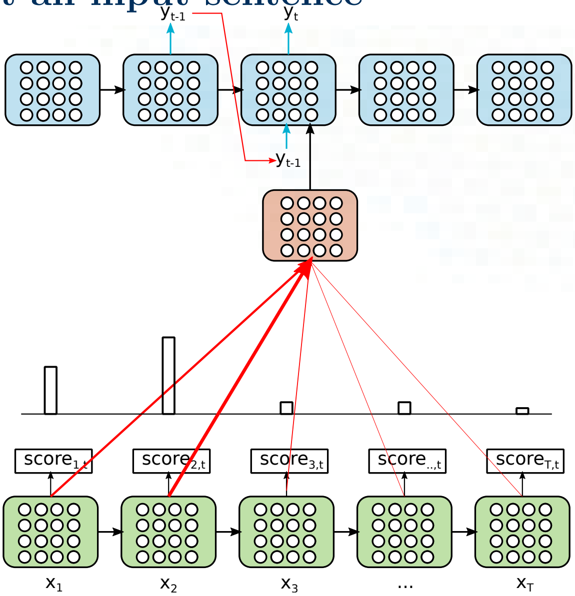

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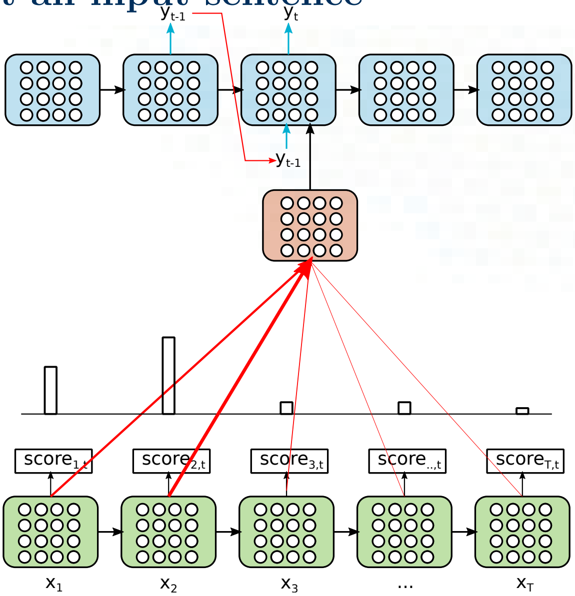

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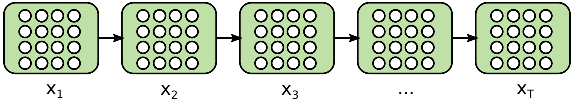

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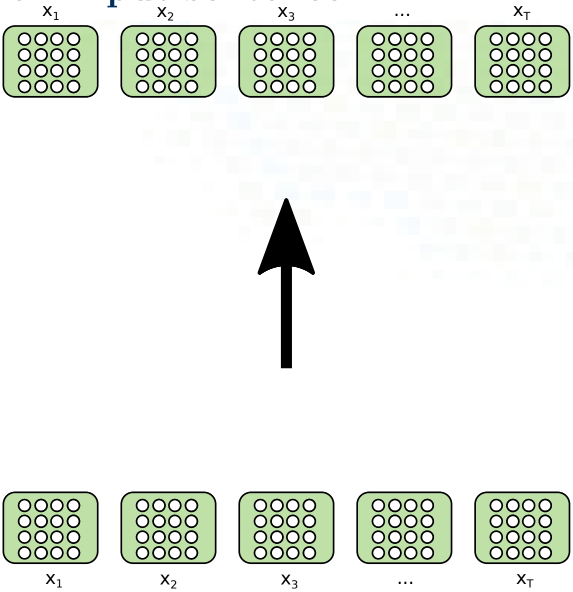

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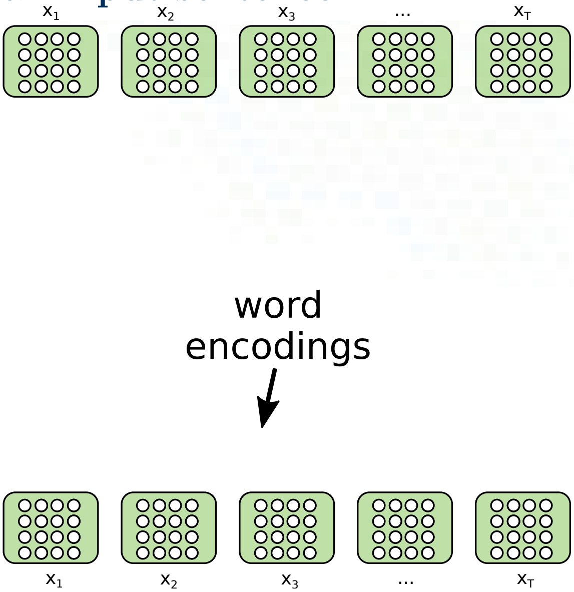

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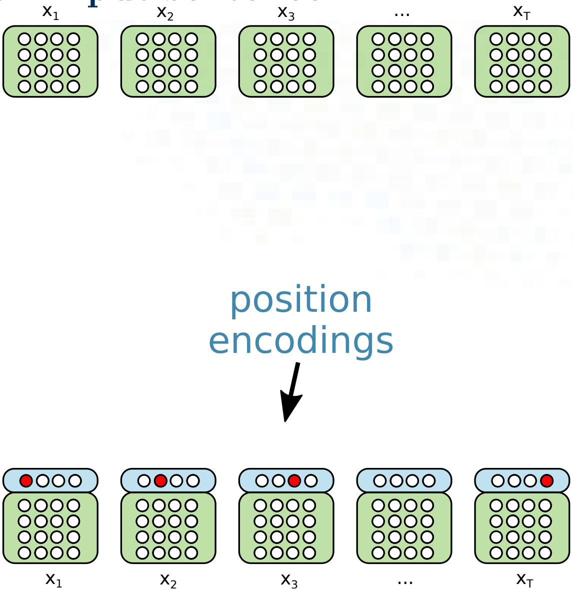

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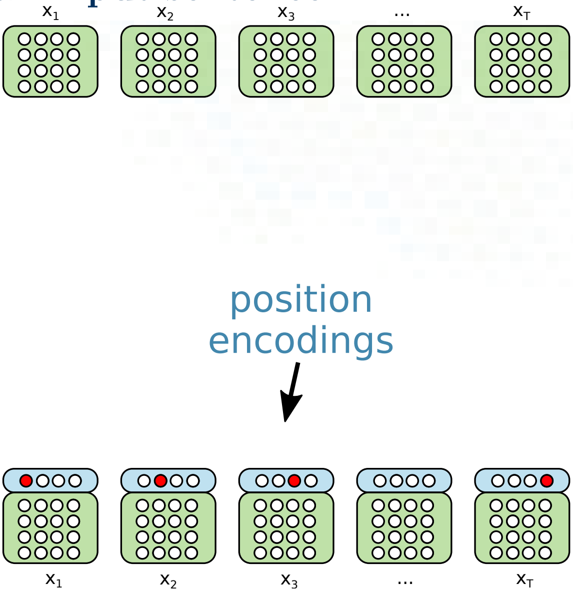

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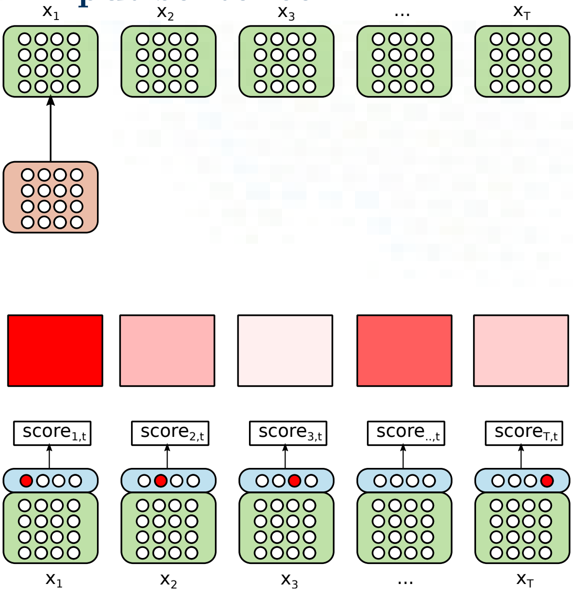

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- We do this by building an attention network that learns to map the input sentence *onto itself*.
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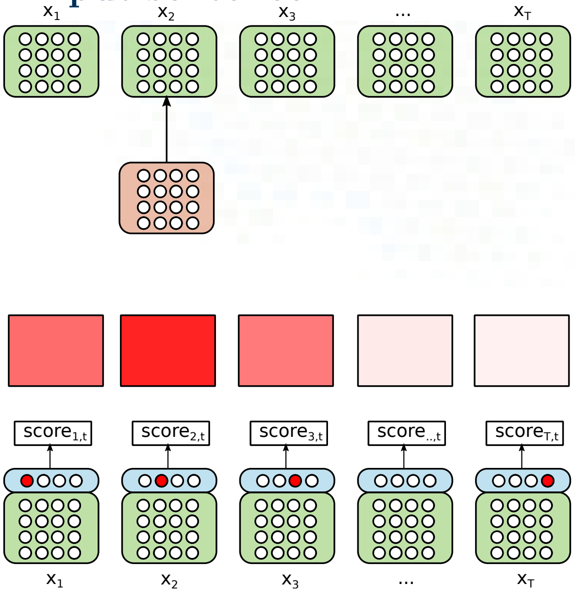

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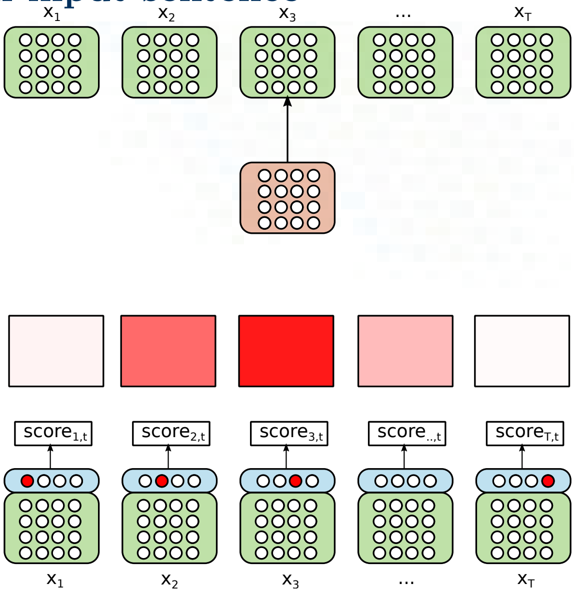

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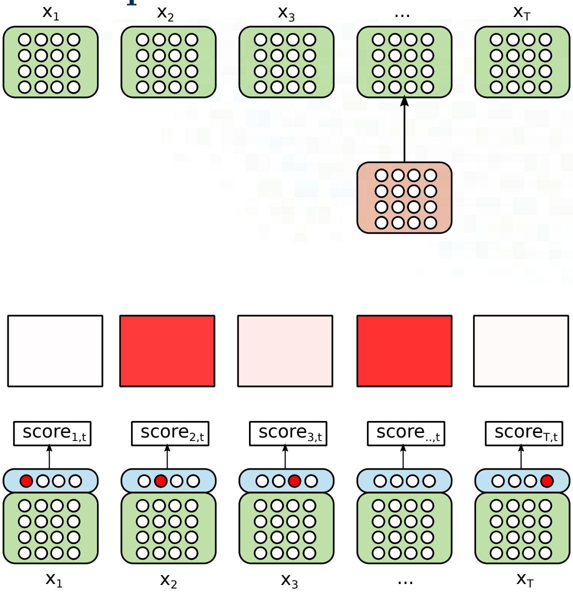

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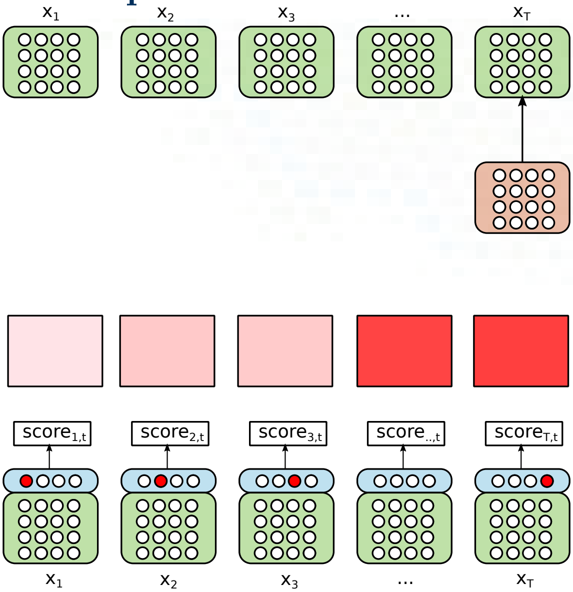

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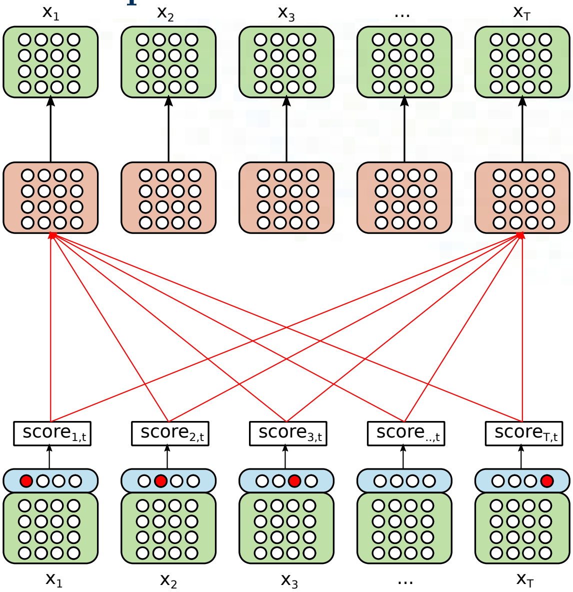

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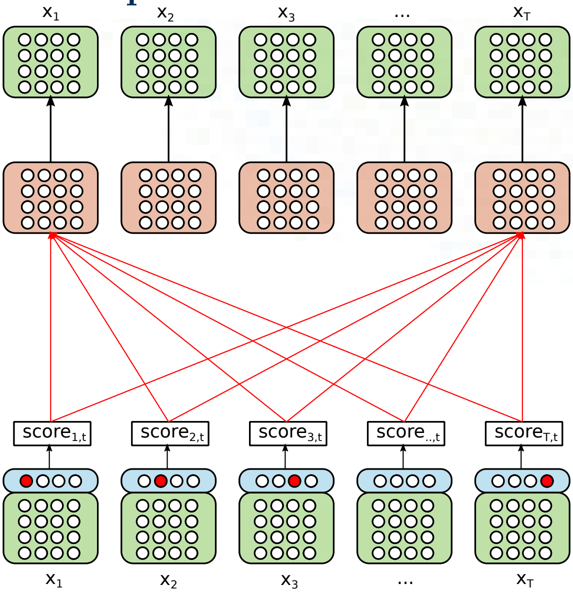

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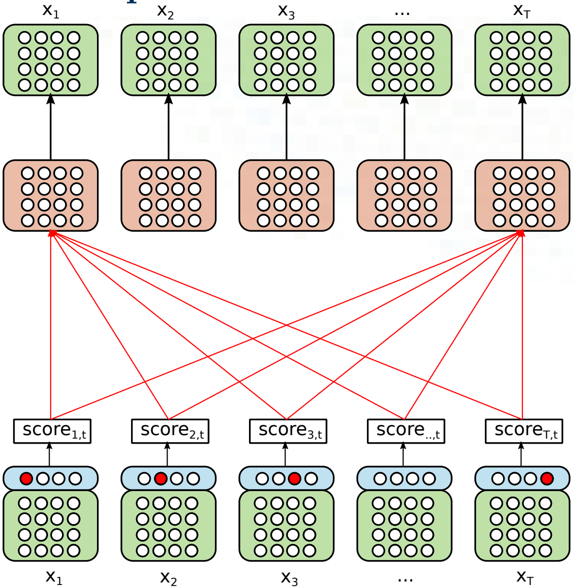
The network is basically an *autoencoder*—but without recurrent connections.



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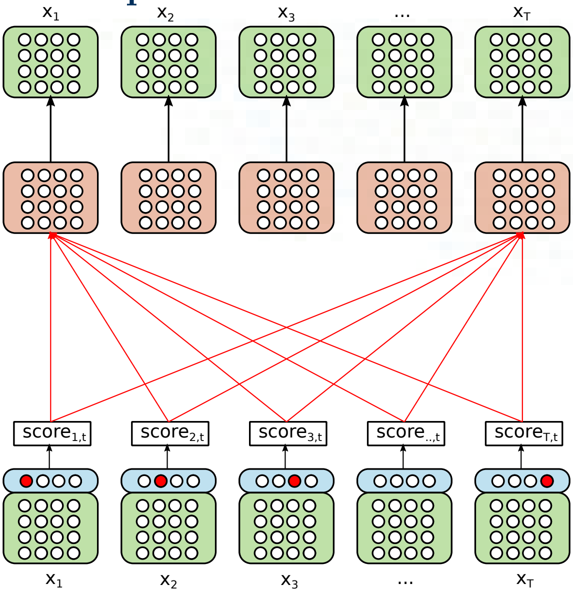
The new representation of each input word is then passed through a feed-forward layer, to allow the network to learn richer representations.



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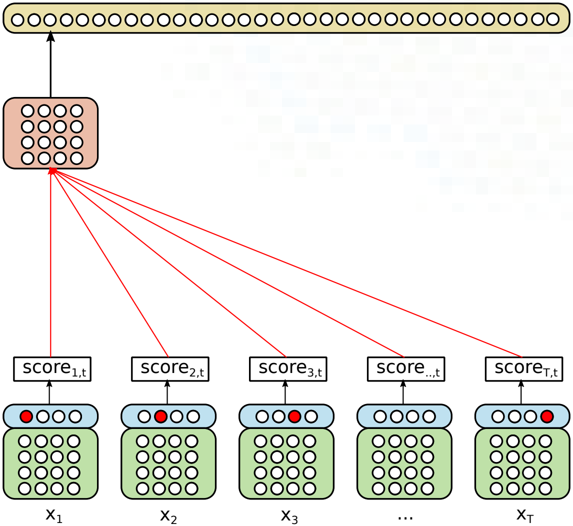

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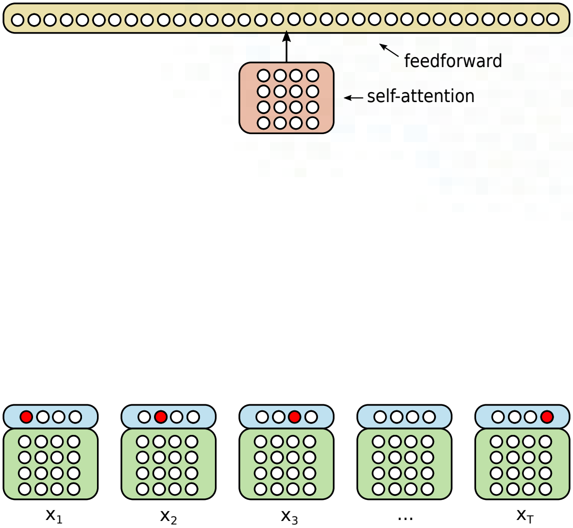

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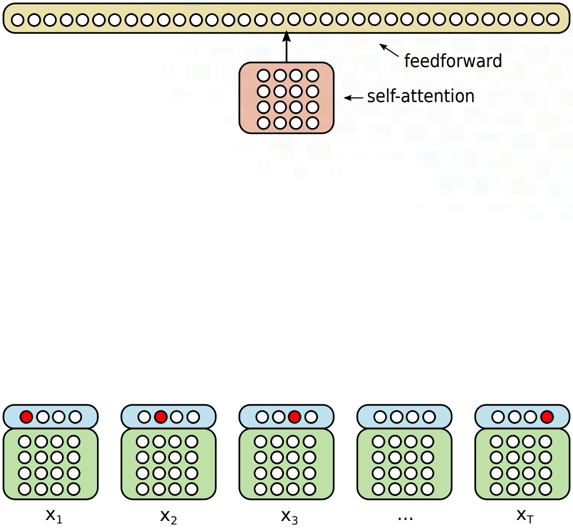
And then this pattern of self-attention and feed-forward is repeated 6 times.



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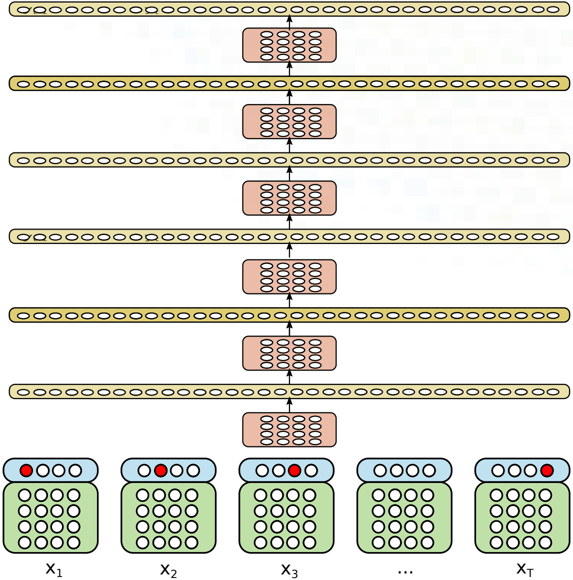

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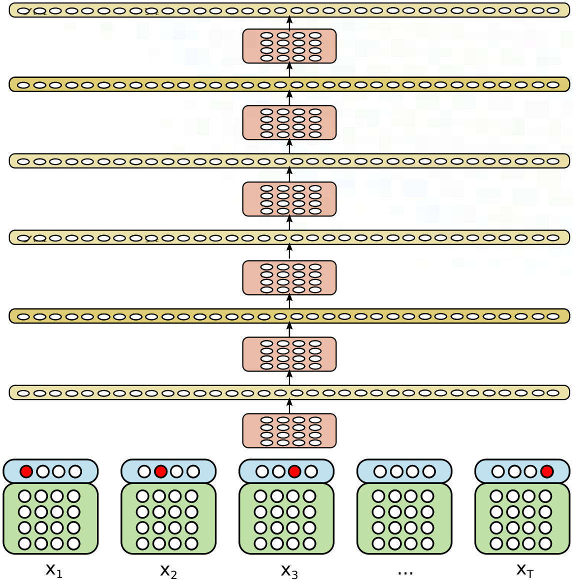

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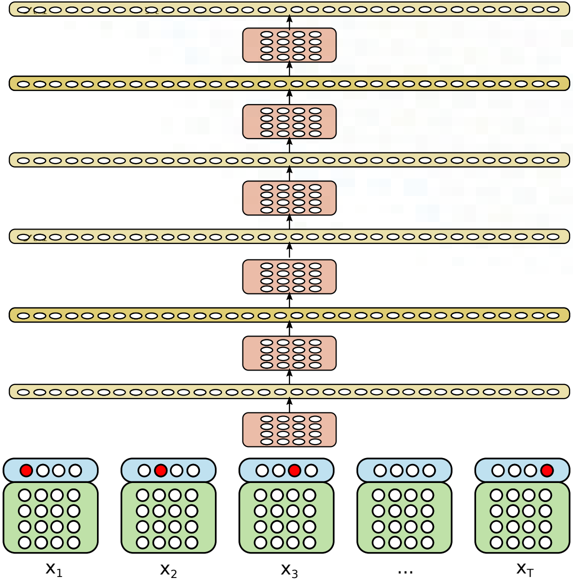

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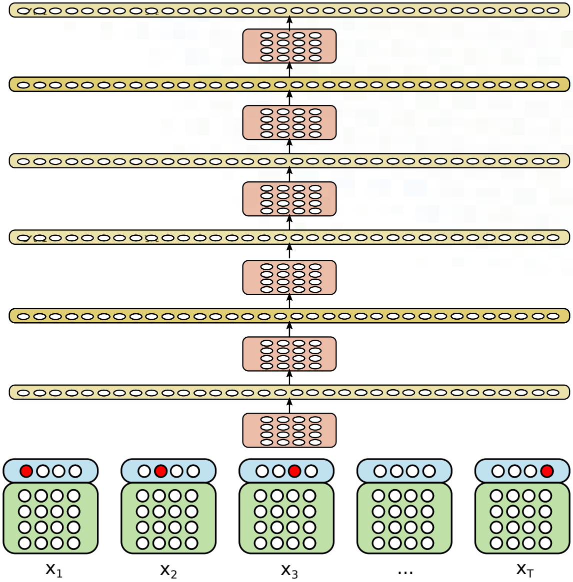

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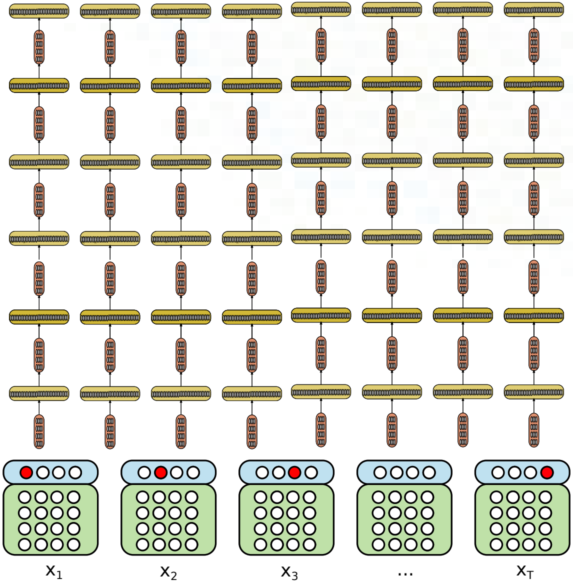

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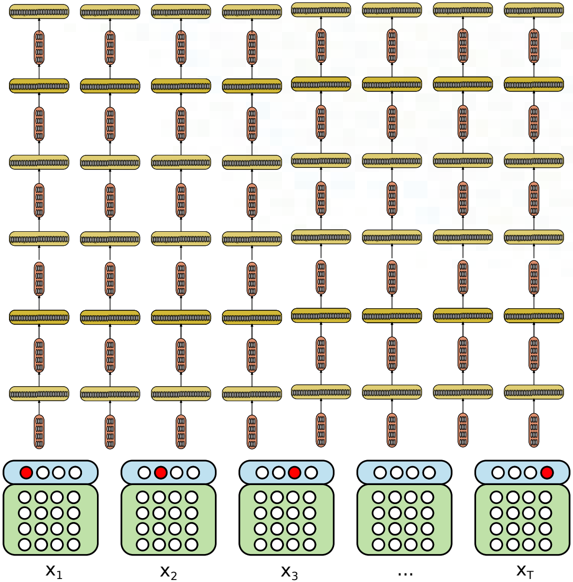

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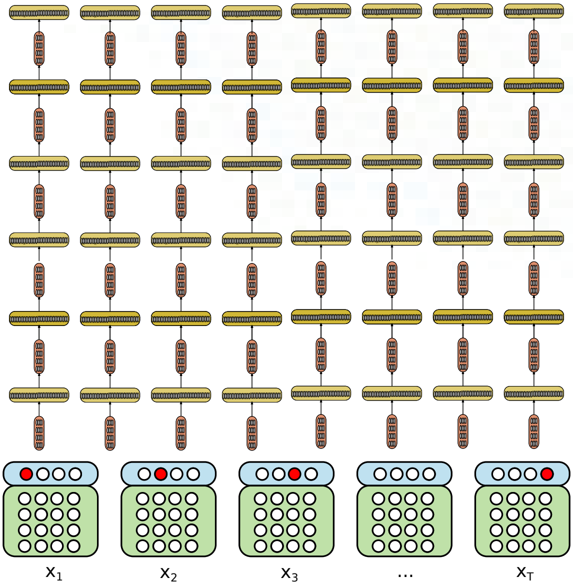
Each attentional system is associated with its own ‘key’.



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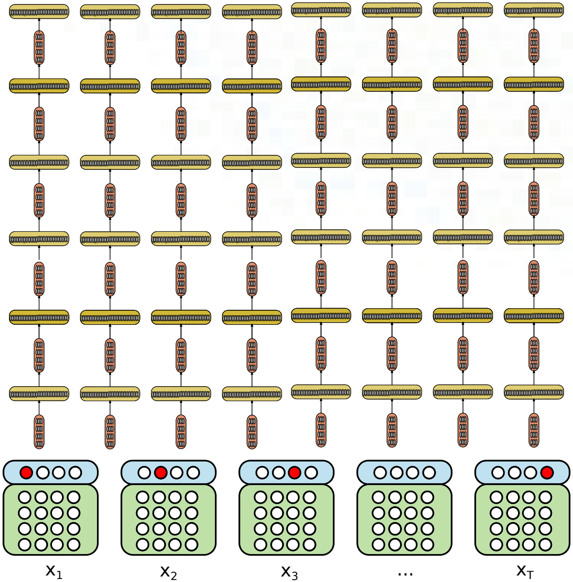
- Recall the 'query'/'key'/'value' notation mentioned earlier...
- A key is a vector (initialised randomly), that is multiplied by each word encoding to create the 'query' posed to the set of input word vectors.



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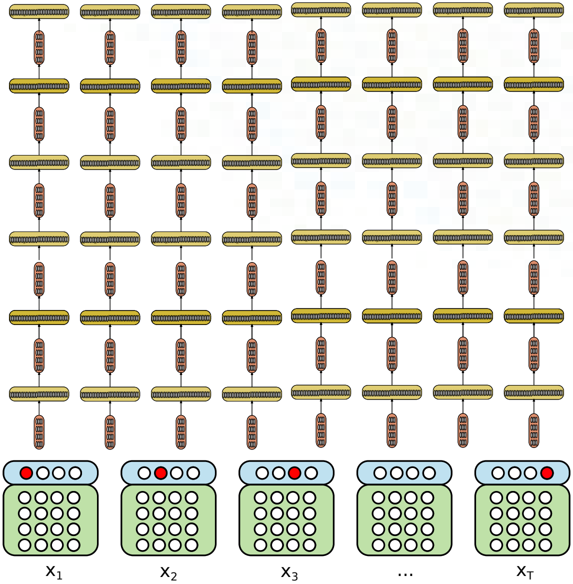
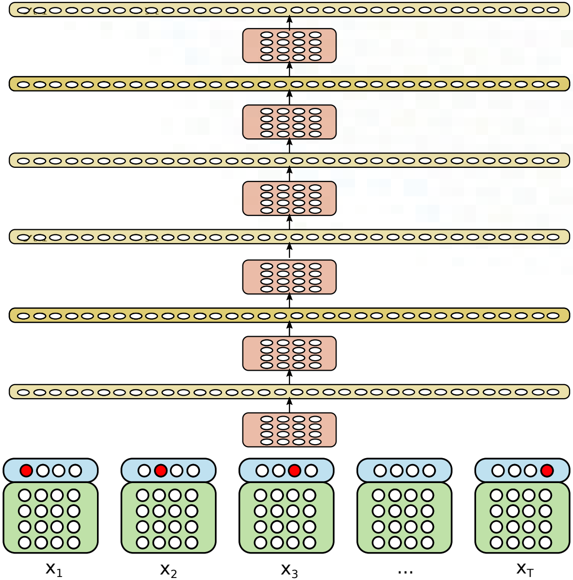
- Each feedforward layer acts like a dedicated 'key' for the next layer. (Whose value is learned through backpropagation.)



Let's have just one head!

...to keep things manageable!



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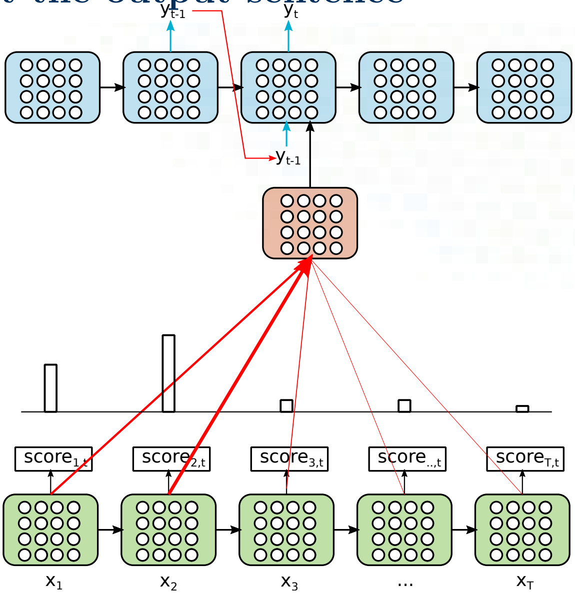
We can use a self-attention mechanism to represent the output sentence too.

- That is, the *decoder* can use self-attention.



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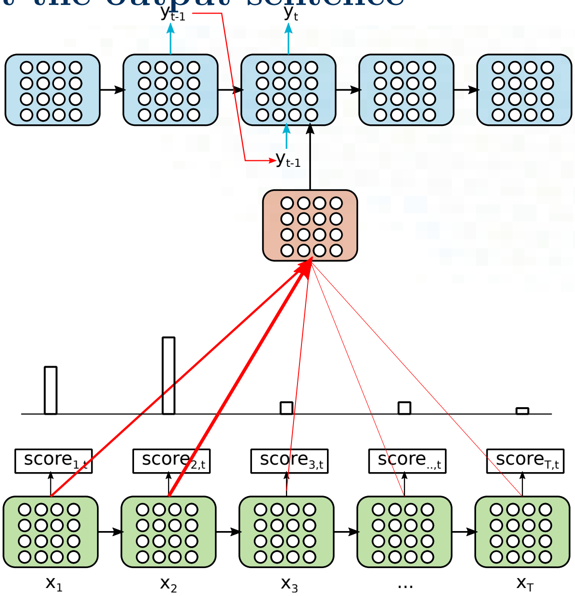

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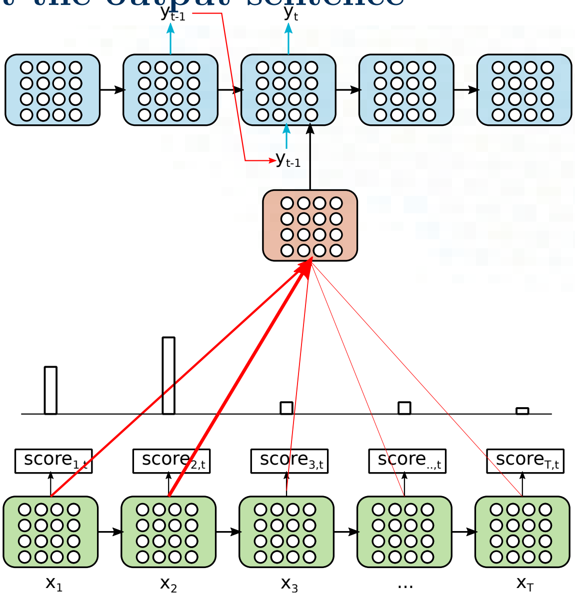
We can use a self-attention mechanism to represent the words produced so far (and their importance).



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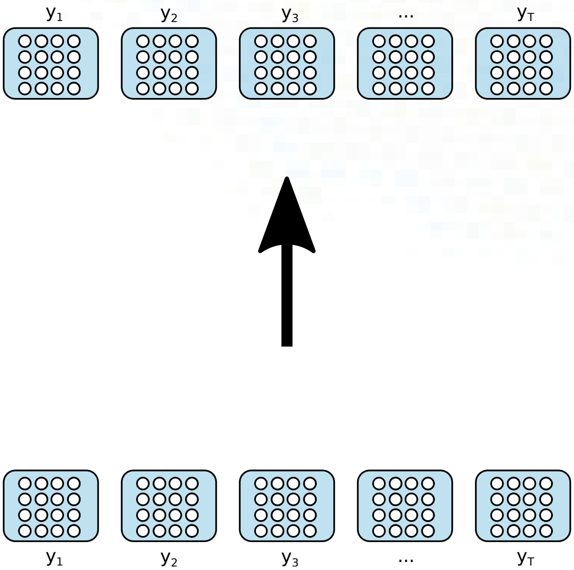

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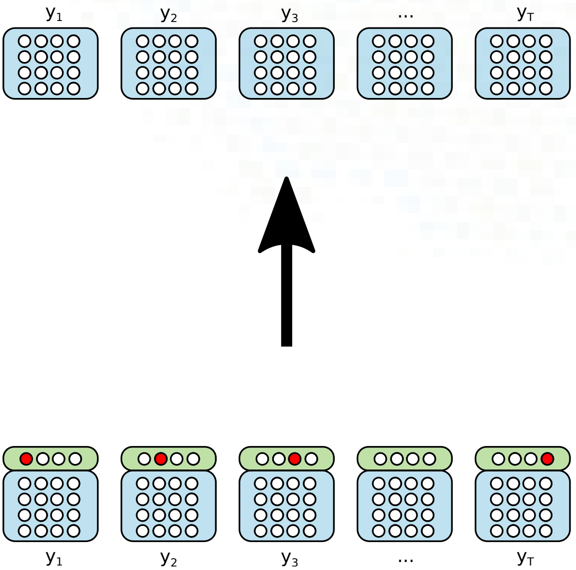

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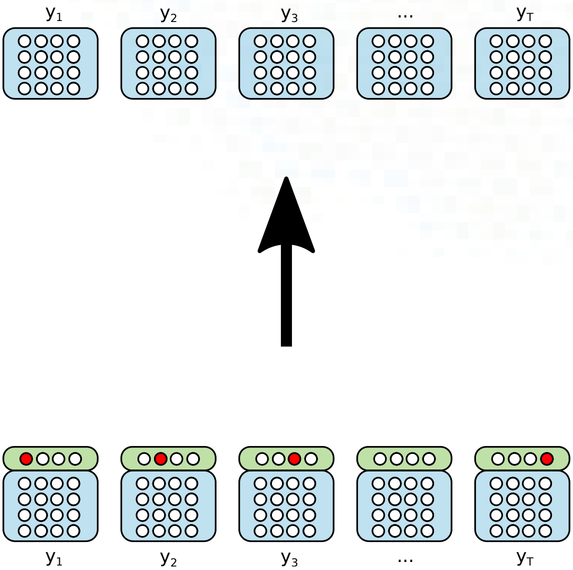

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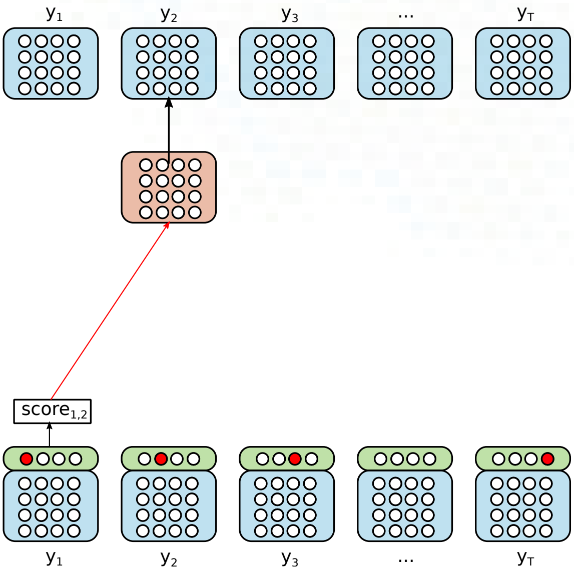

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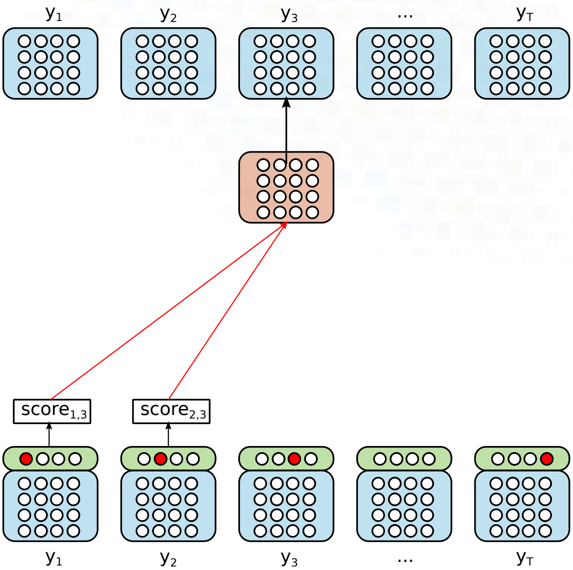

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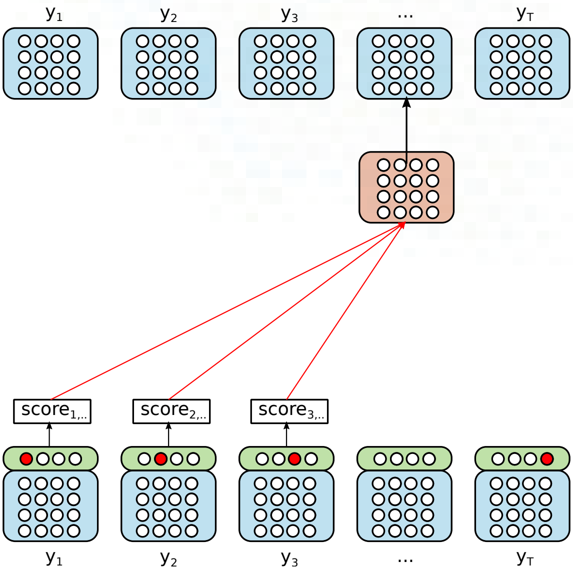

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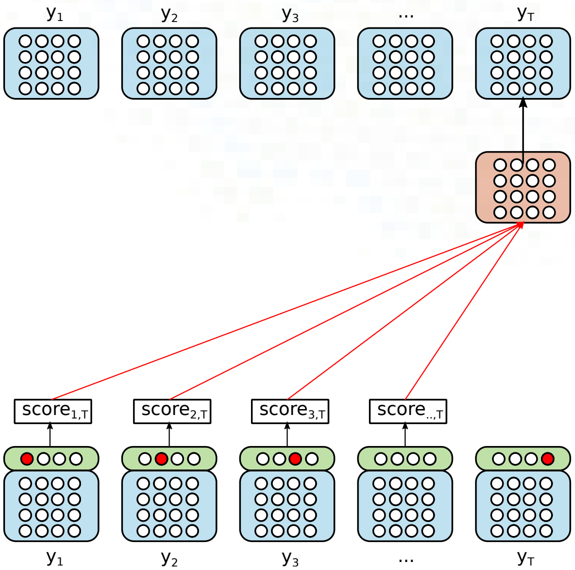

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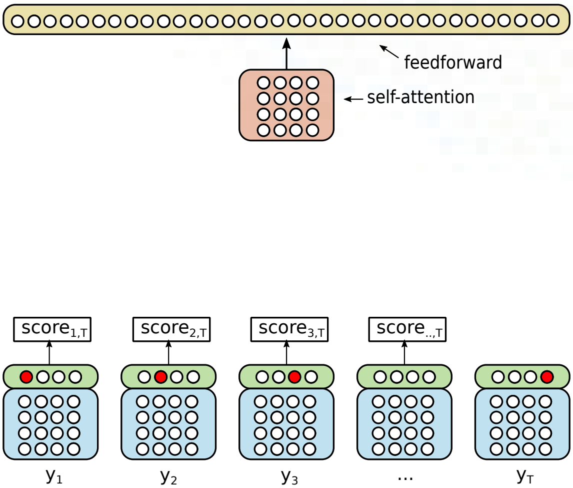

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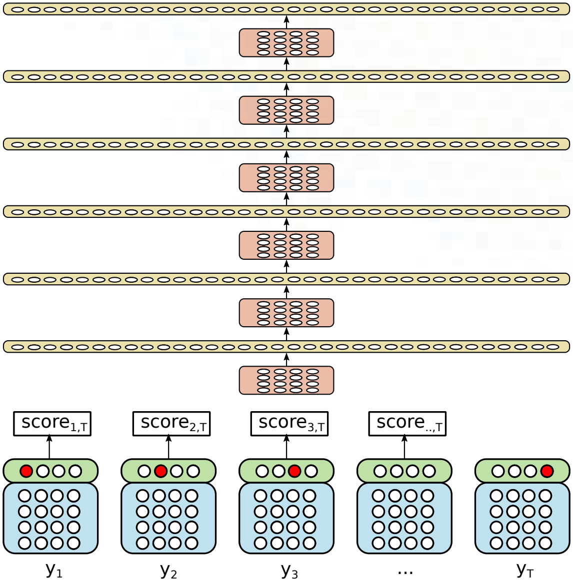

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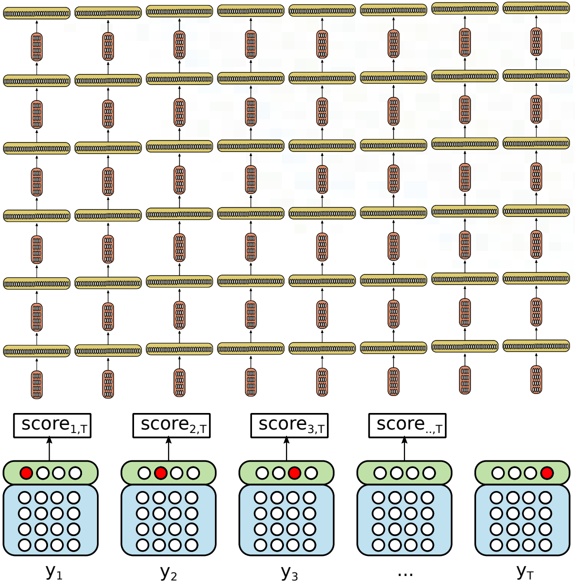

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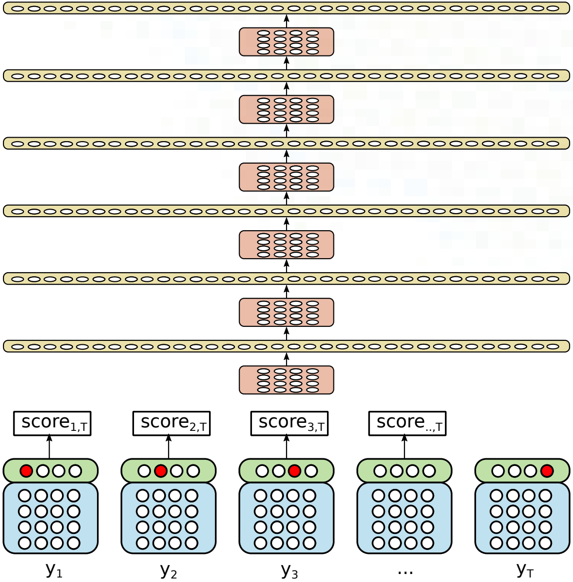
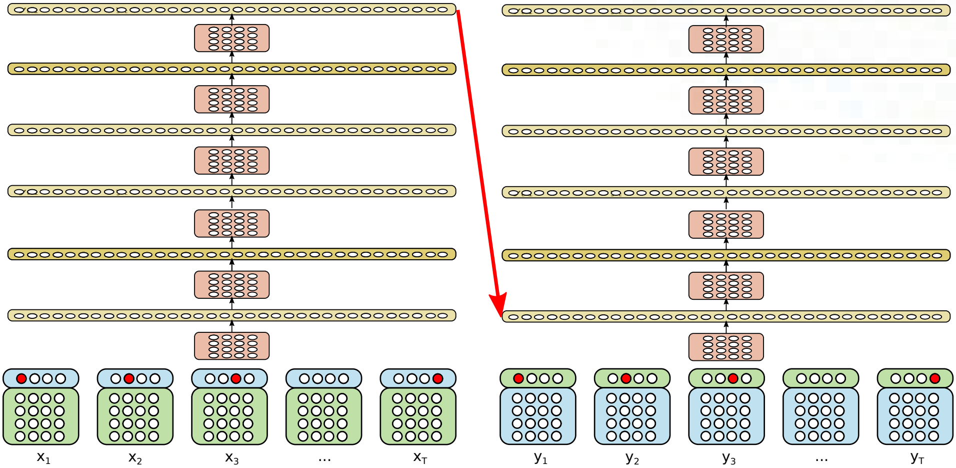
- But let's ignore that!



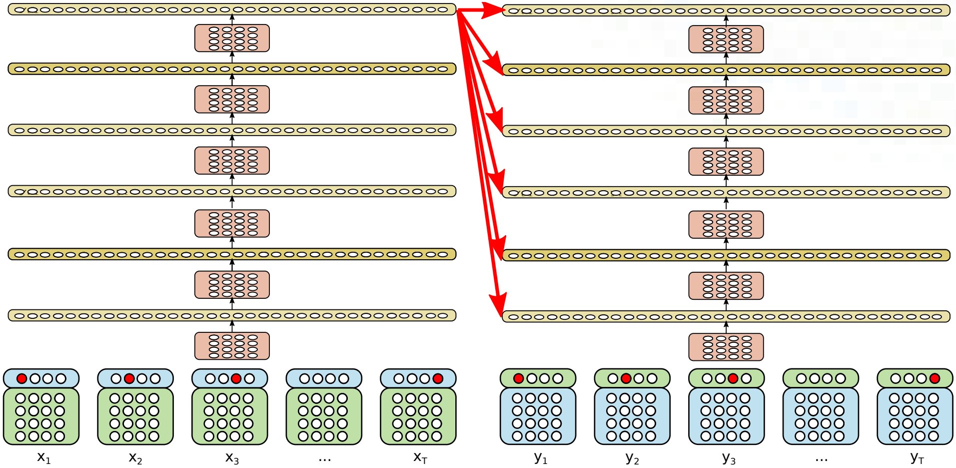
The complete transformer

The encoder and decoder networks are linked with an attentional mechanism, as before.



The complete transformer

Actually, this link uses residual connections ('skip connections') to each decoder layer.



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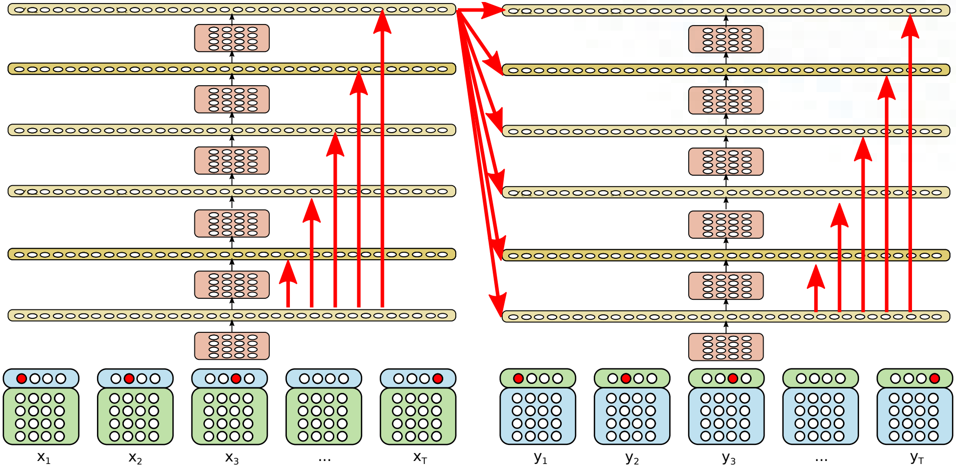
Actually, residual connections are used within each encoder and decoder layer too.



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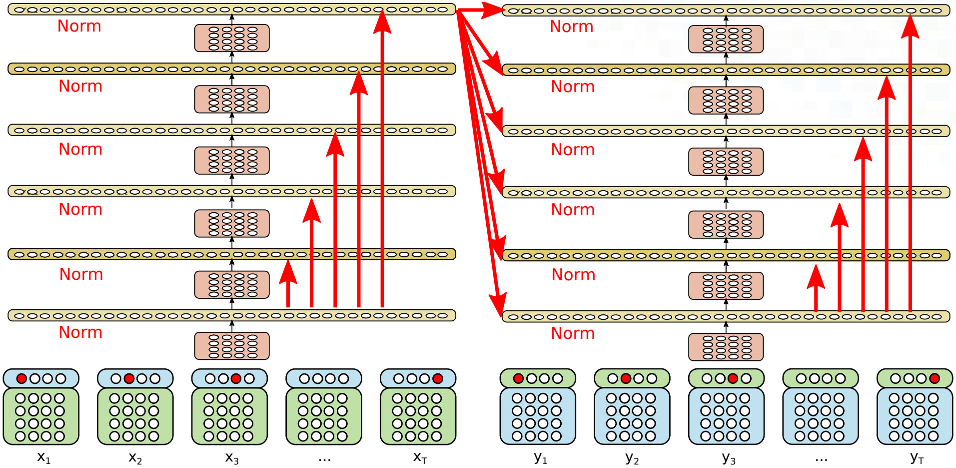

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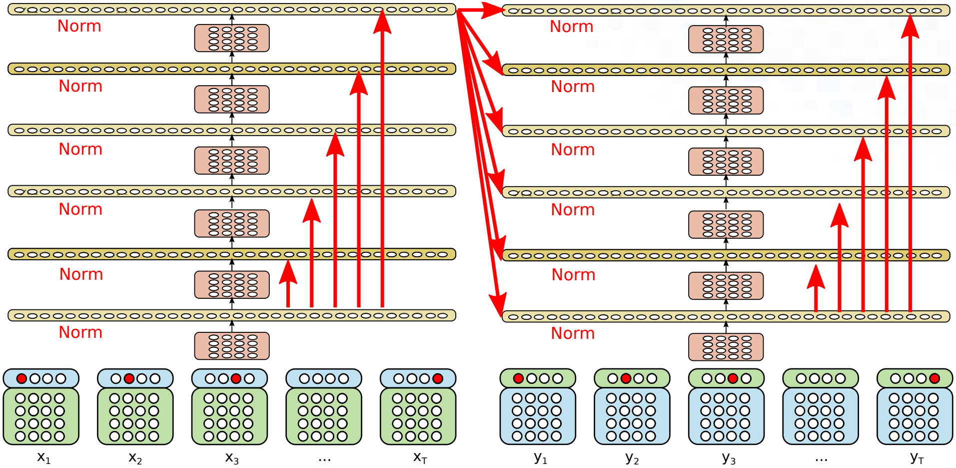
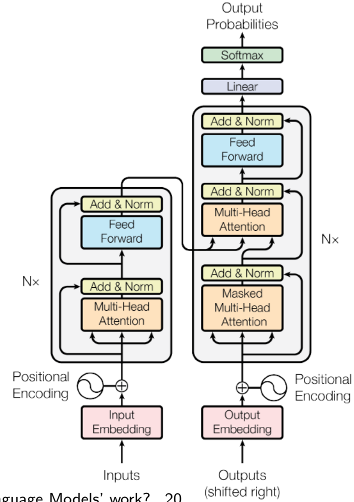


‘Attention is all you need’

Here’s the diagram from the orginal transformer paper (Vaswani *et al.*, 2017).



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After the success of transformers, a number of 'large, fine-tunable, general-purpose' language models were developed, that have since been very influential.

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- In its architecture, it's just the *decoder* portion of Vaswani *et al.*'s transformer.

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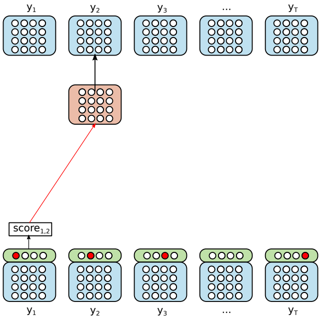

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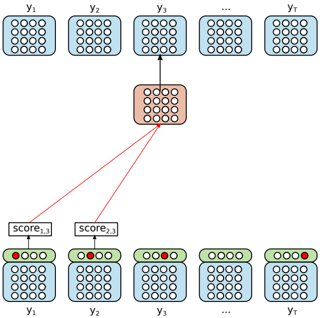

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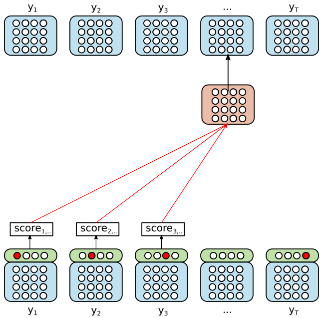

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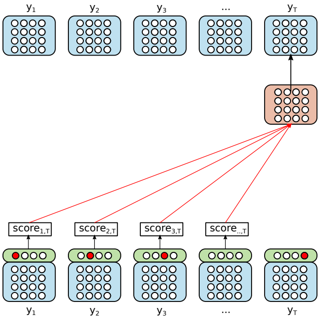

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Next seminar, Simon will be doing a practical course on 'prompt engineering'!