COMP 4446 / 5046
Lecture 7: Models – Transformer

Jonathan K. Kummerfeld

Semester 1, 2025

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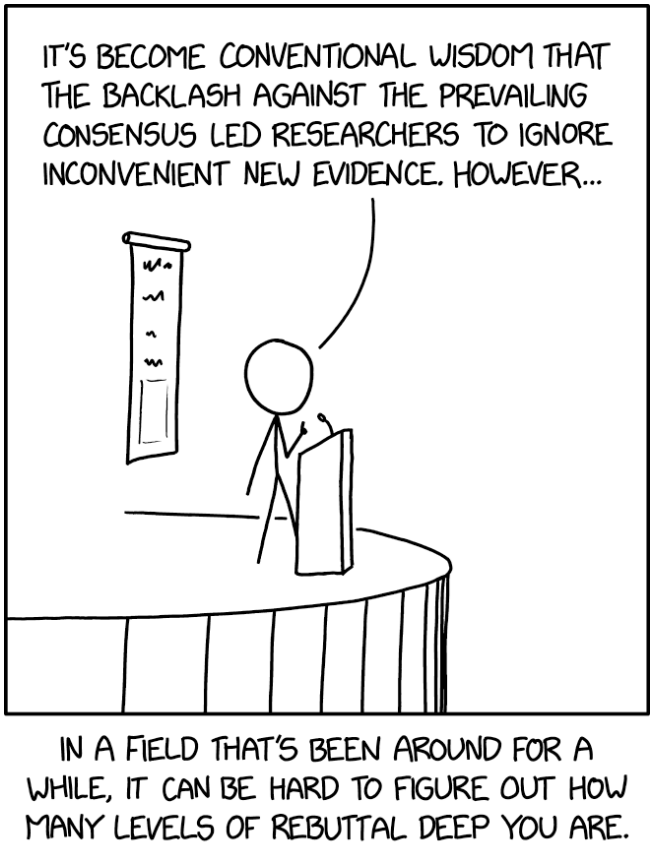
Rebuttals




```
[The mainstream dogma sparked a wave of dogmatic
revisionism, and this revisionist mainstream
dogmatism has now given way to a more rematic
mainvisionist dogstream.]
```

Source: https://xkcd.com/2857/

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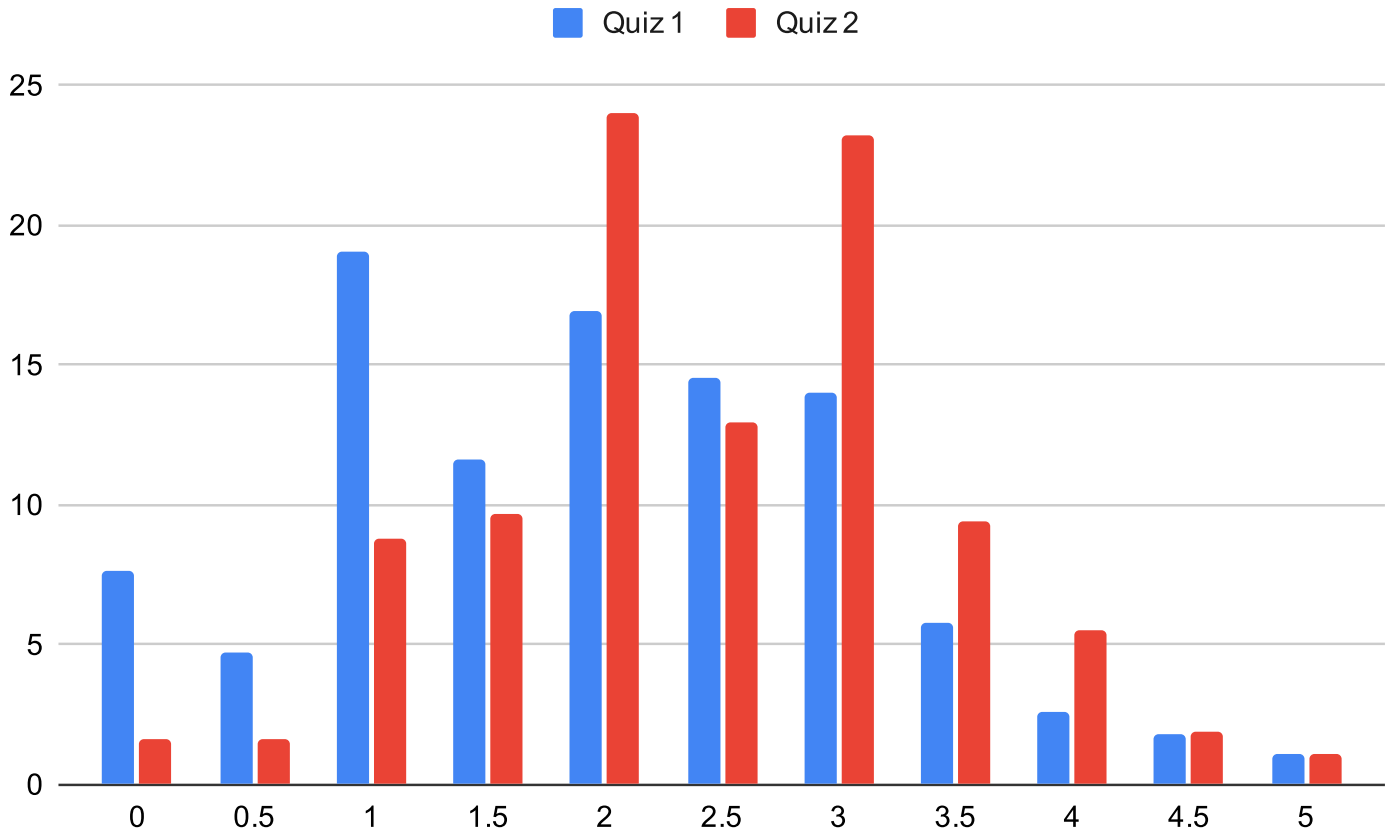
Quiz results - an improvement! But still 22% below 2



To avoid the bugs from this quiz, I will be getting TAs to check them in future (just as exams are reviewed by another academic)

Note: resu ts
credit for t

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Special Consideration Reminder

Short release assignments - No simple extensions

Regular Special Consideration is not processed fast enough

Slip days instead!

For major issues (e.g., broke your arm and can’t type for a month), go through Special Consideration process and a more significant change will be determined

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Office Hours shift

This week Office Hours will be 2-3pm on Tuesday

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Self-Attention

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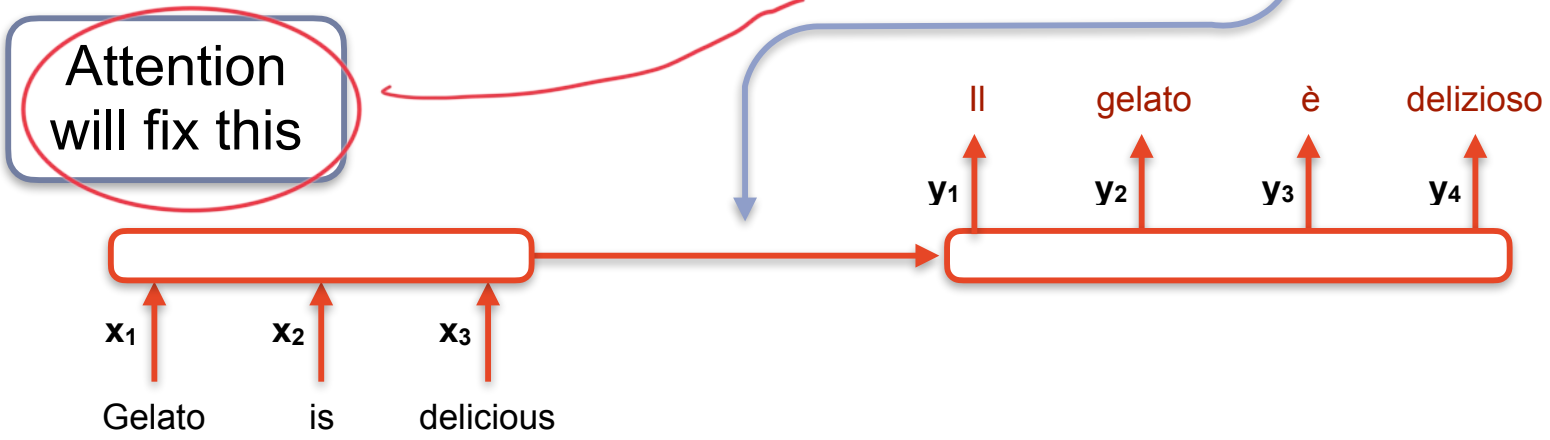
Reminder: Issues with the encoder-decoder

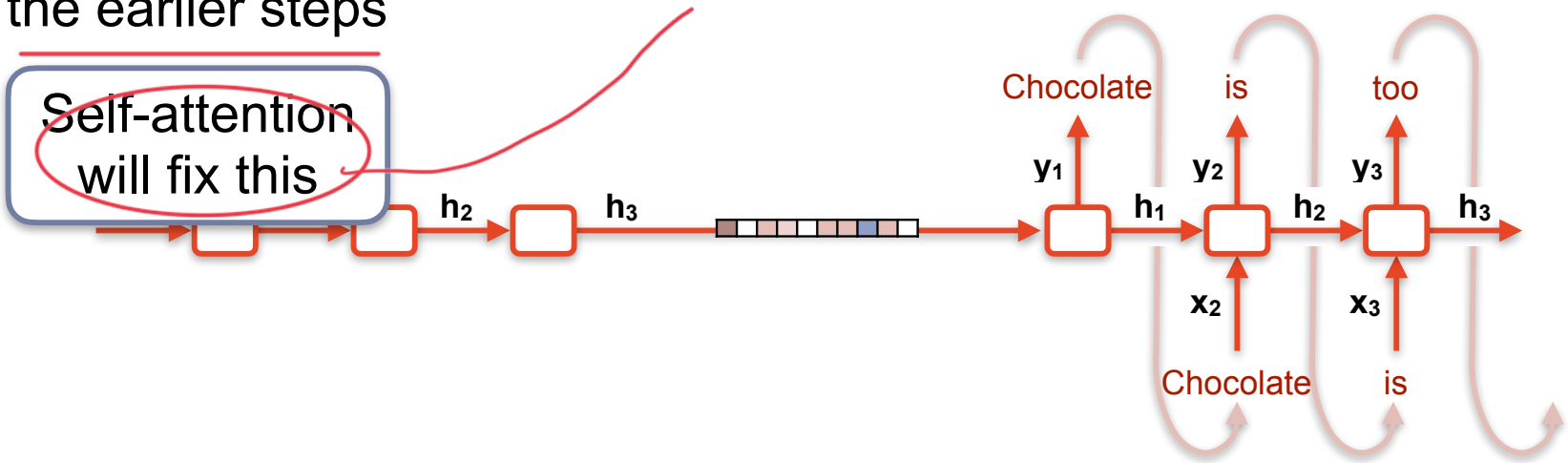
Review

Data loss

Bottleneck - all information has to go through one vector



Hard to parallelise - every step of the calculation depends on the earlier steps



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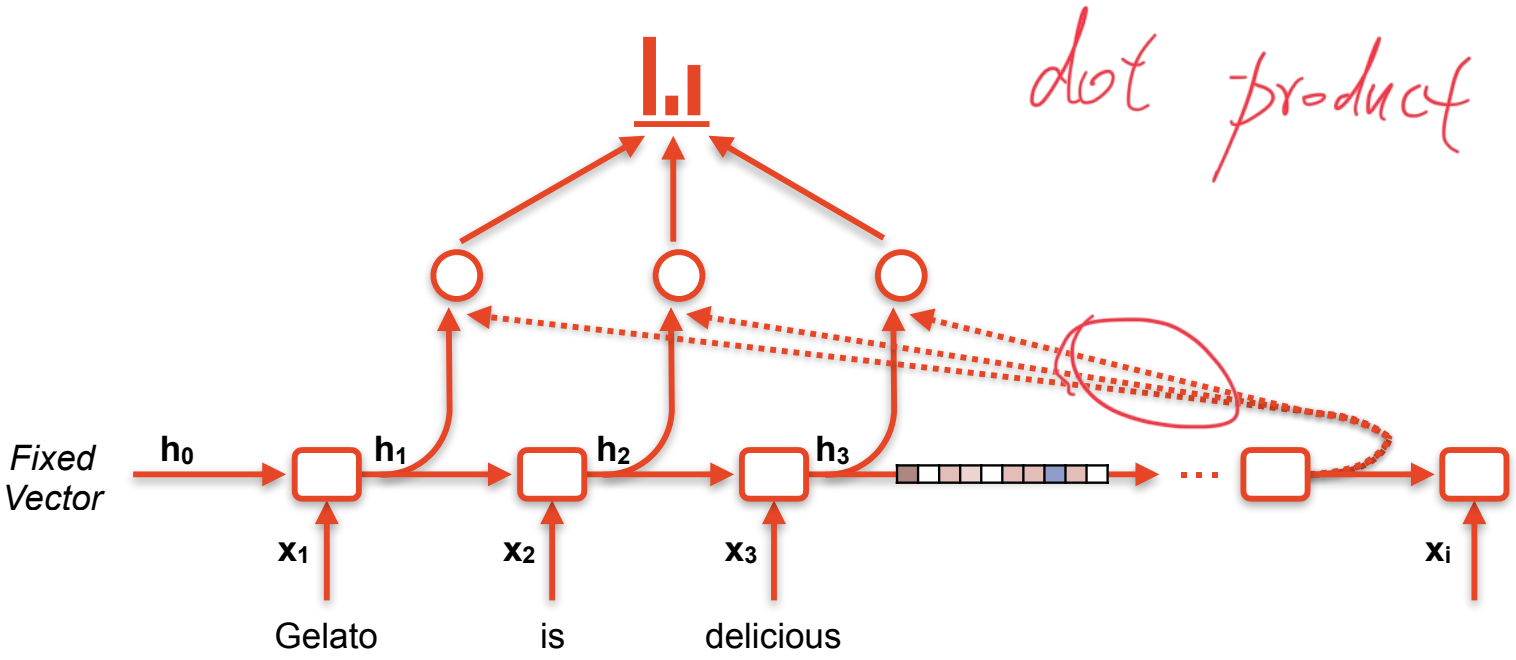
We will solve this with ‘attention’

Give each output step
a representation of the input
that is most useful for that output decision



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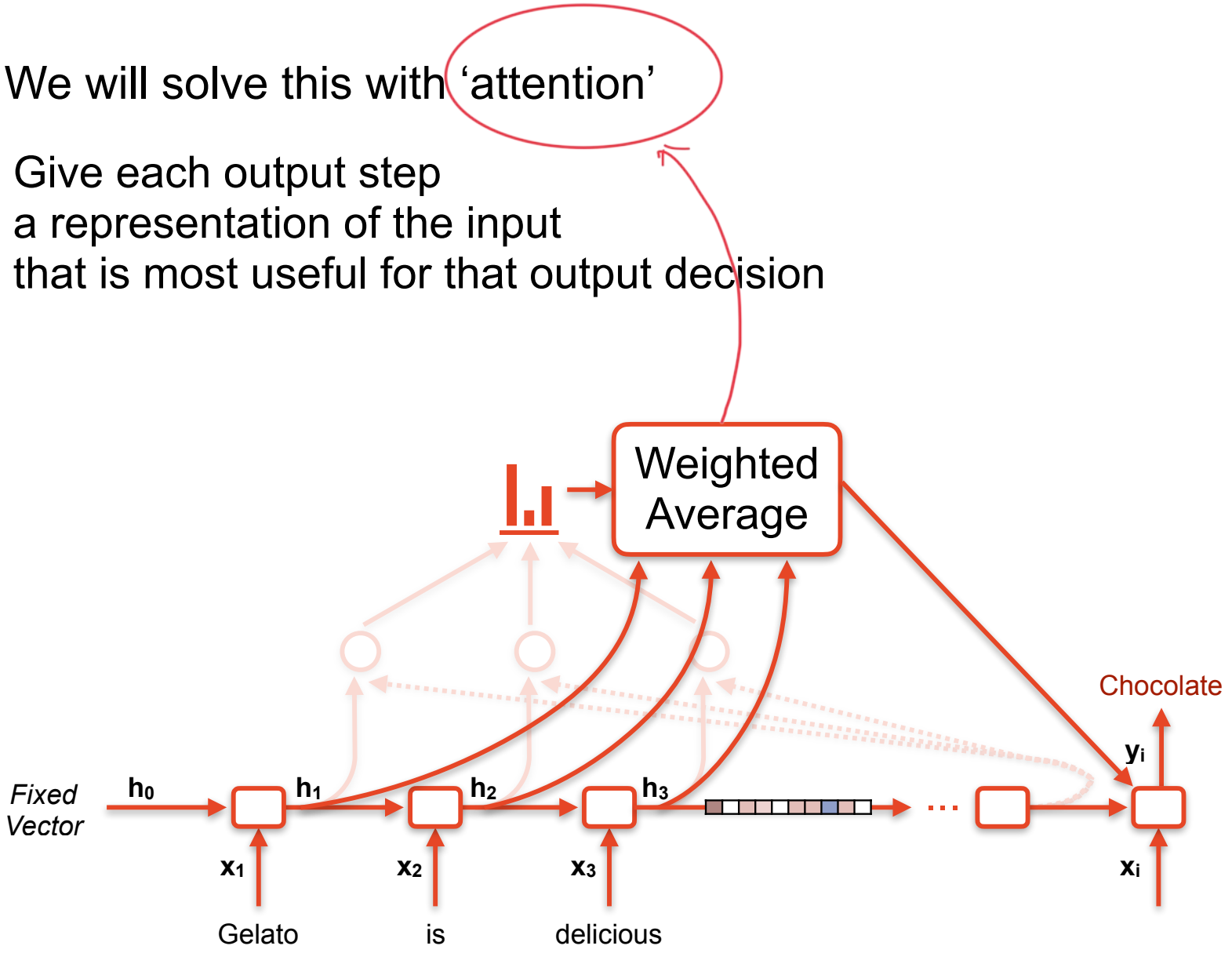

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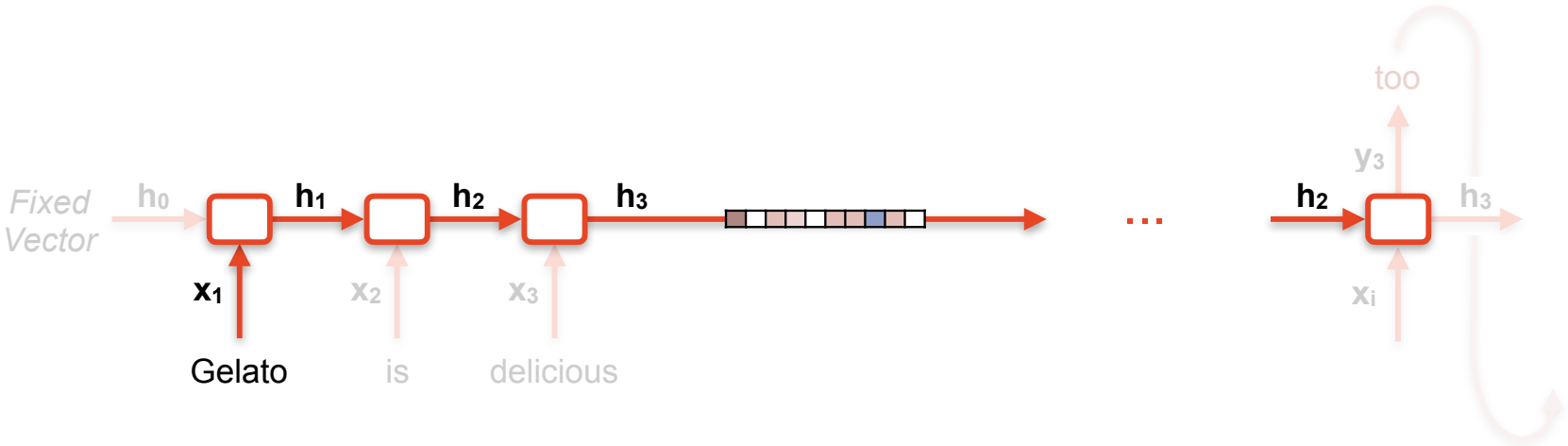
This resolves the bottleneck problem without introducing many extra parameters



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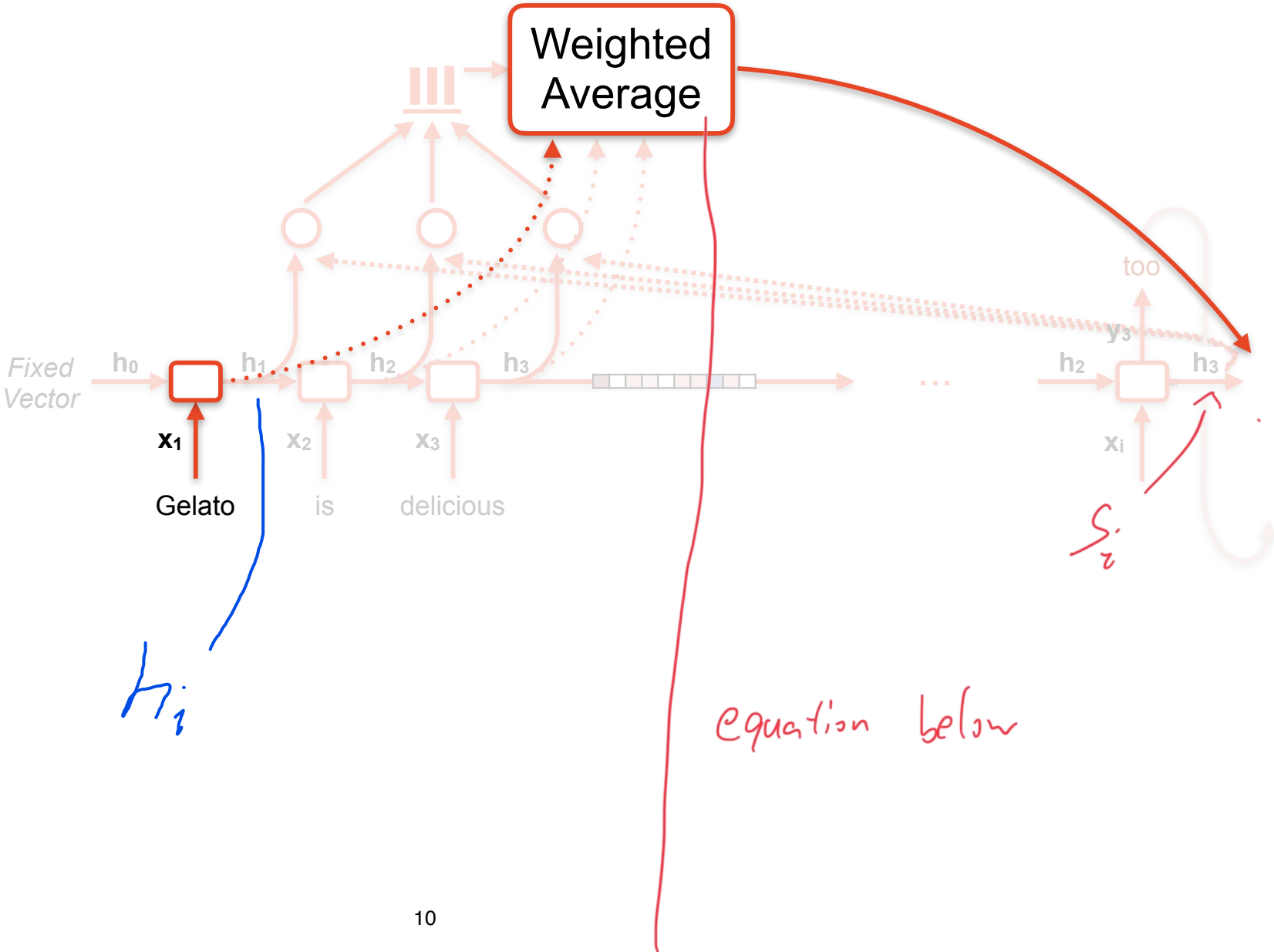

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We will solve this with ‘attention’

Give each output step
a representation of the input
that is most useful for that output decision

Hidden vectors from input $\mathbf{h_1}, \mathbf{h_2}, \mathbf{h_3} \ldots \mathbf{h_N} \in \mathbb{R}^{d_h}$

Hidden vector for current output step $\mathbf{s_i} \in \mathbb{R}^{d_h}$

Calculate attention scores $\mathbf{e_i} = [\mathbf{s_i}^\top \mathbf{h_1}, \mathbf{s_i}^\top \mathbf{h_2}, \mathbf{s_i}^\top \mathbf{h_3}, \ldots \mathbf{s_i}^\top \mathbf{h_N}] \in \mathbb{R}^N$

This is dot product attention

Normalise s $\ldots \text{ax}(\mathbf{e_i}) \in \mathbb{R}^N$

$\alpha_i = \text{softmax}(e_i) \in \mathbb{R}^N$

Calculate weighted average $\mathbf{a_i} = \sum_{j=1}^{N} \alpha_{i,j} \mathbf{h_j} \in \mathbb{R}^{d_h}$

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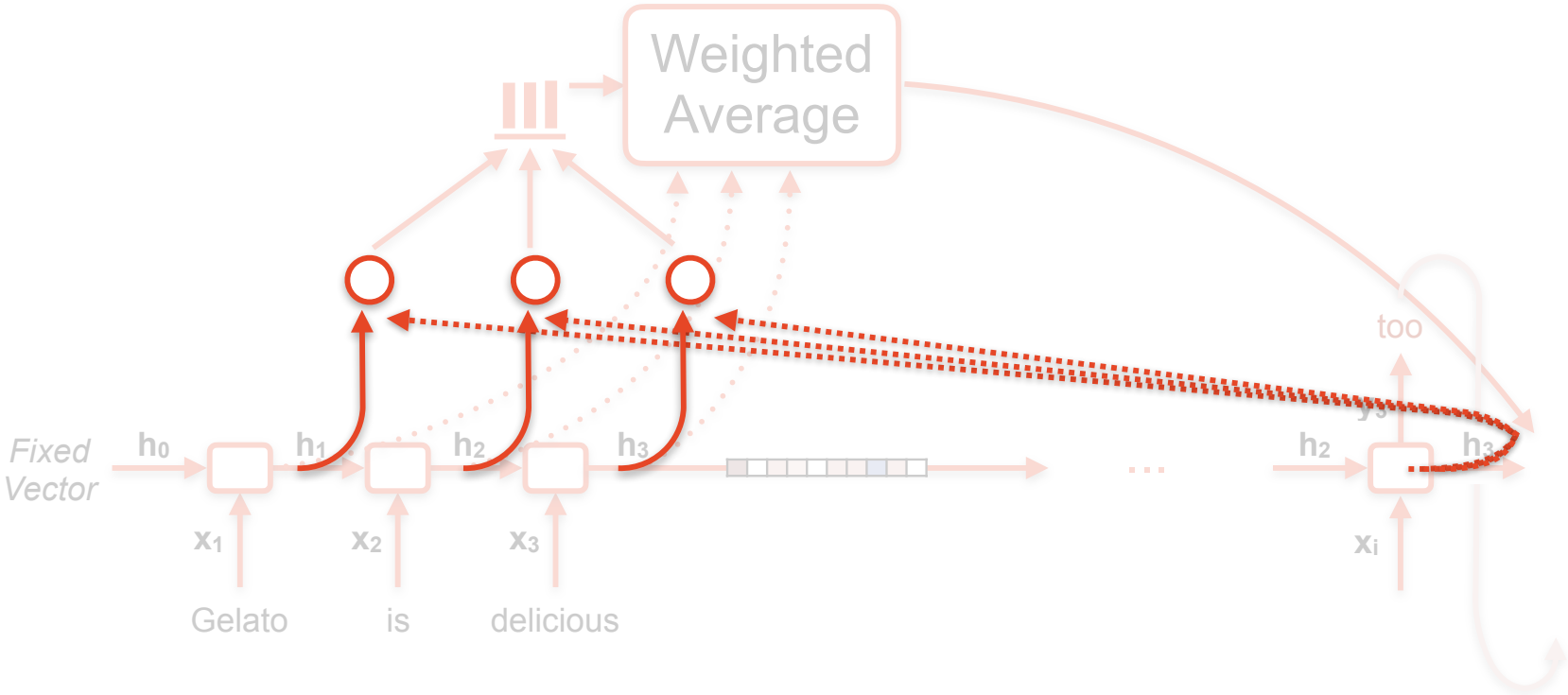

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There are many forms of attention

Dot product attention	$\mathbf{e} = \mathbf{s}^\top \mathbf{h}$	s, h must have same size
Scaled dot product attention	$\mathbf{e} = \frac{\mathbf{s}^\top \mathbf{h}}{\sqrt{d_h}}$	Motivated by statistical properties of dot products
Multiplicative attention / Bilinear attention	$\mathbf{e} = \mathbf{s}^\top \mathbf{W} \mathbf{h}$	s and h can be different sizes
Reduced-rank multiplicative attention	$\mathbf{e} = \mathbf{s}^\top (\mathbf{U}^\top \mathbf{V}) \mathbf{h}$ $= (\mathbf{s}\mathbf{U})^\top (\mathbf{V}\mathbf{h})$	Can improve efficiency
Additive attention / Feedforward attention	$\mathbf{e} = \mathbf{b} \tanh(\mathbf{W}_1 \mathbf{h} + \mathbf{W}_2 \mathbf{s})$	Powerful / Flexible

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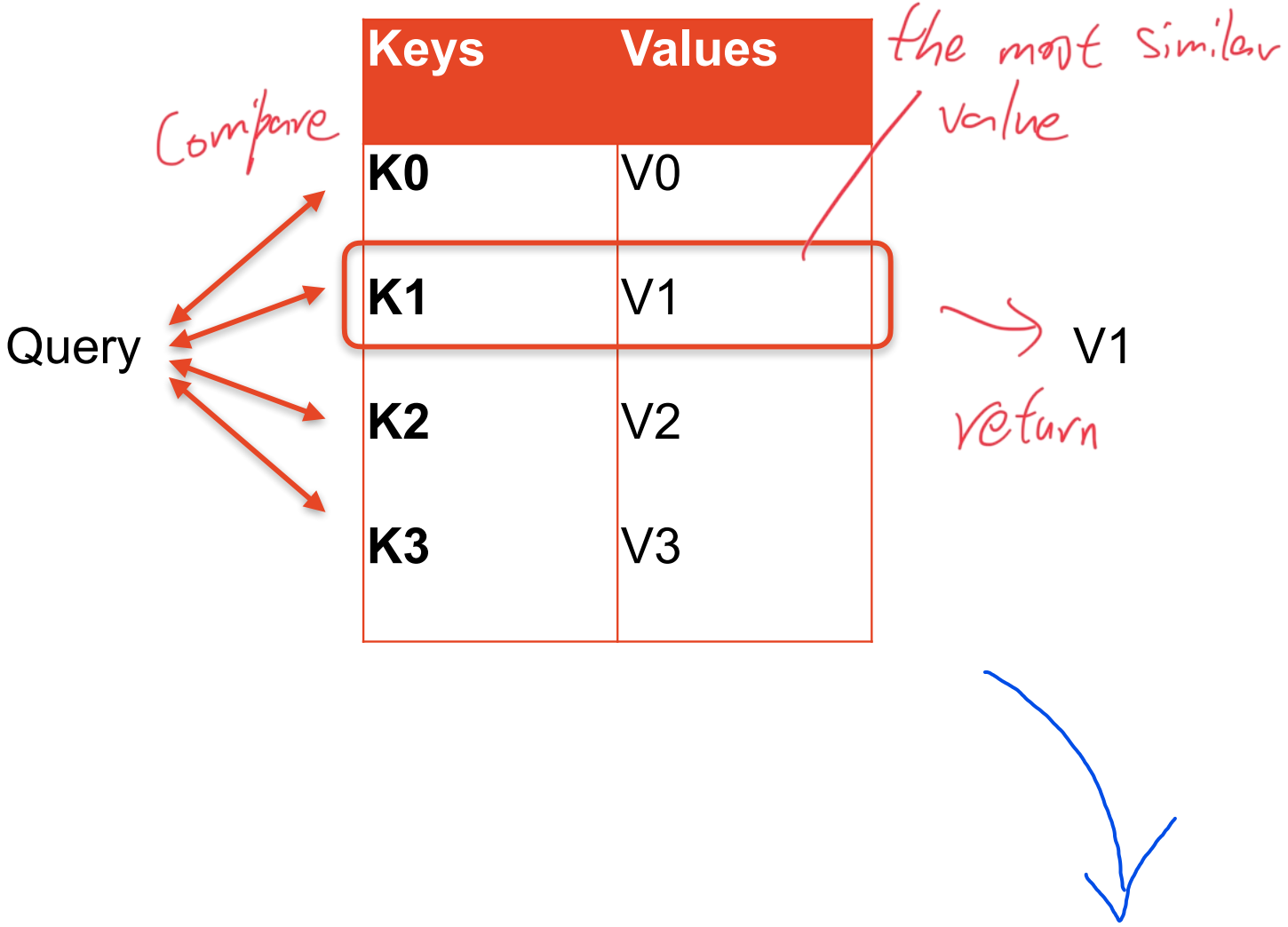
Another way of thinking about attention - looking up values

Consider a lookup table:

One Example

Input

Output



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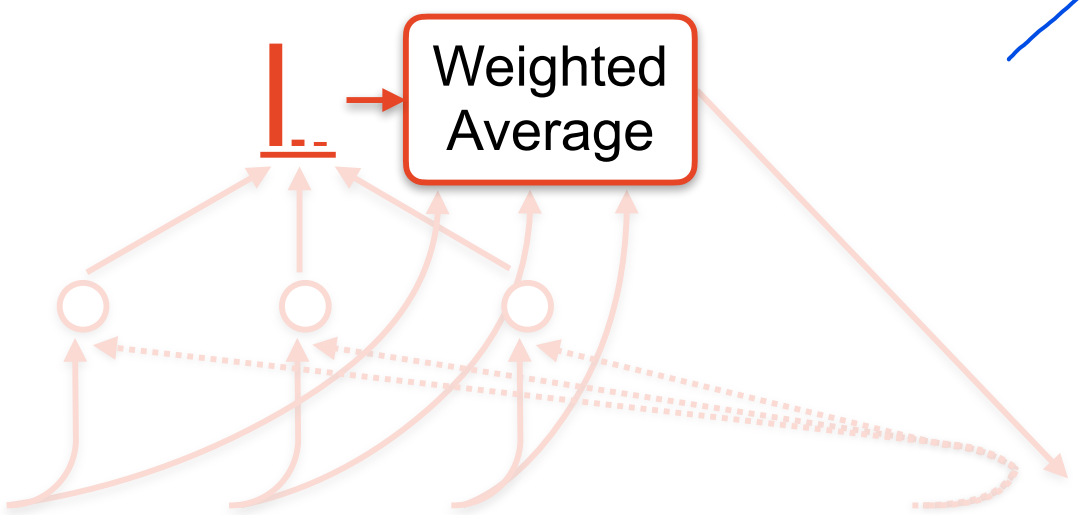

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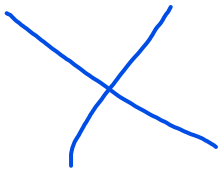

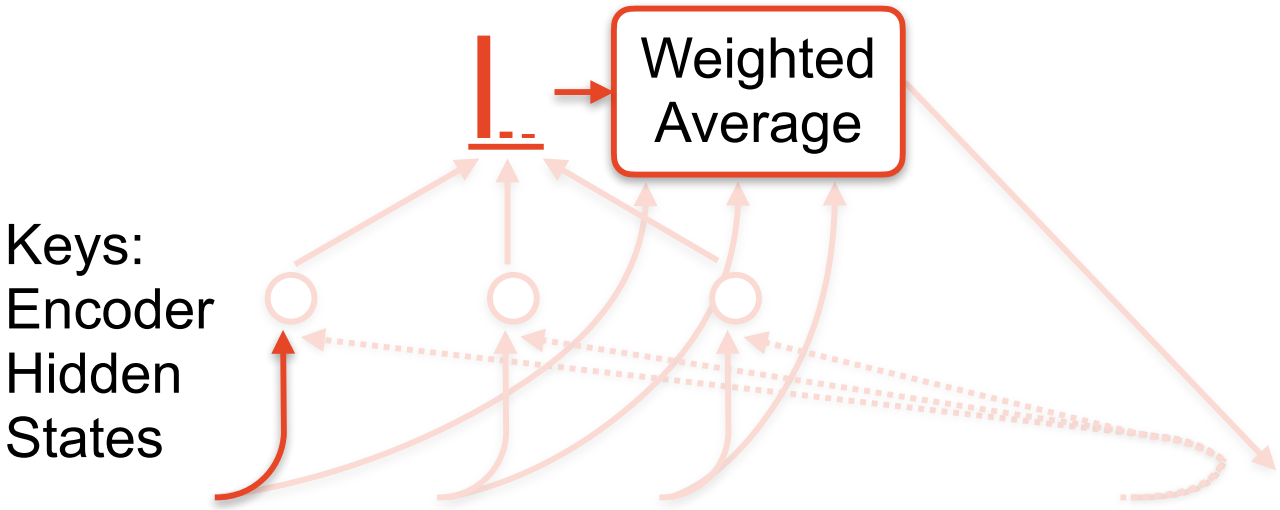

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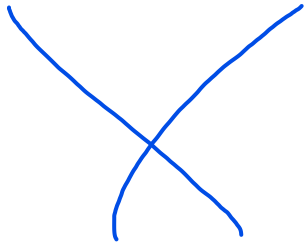

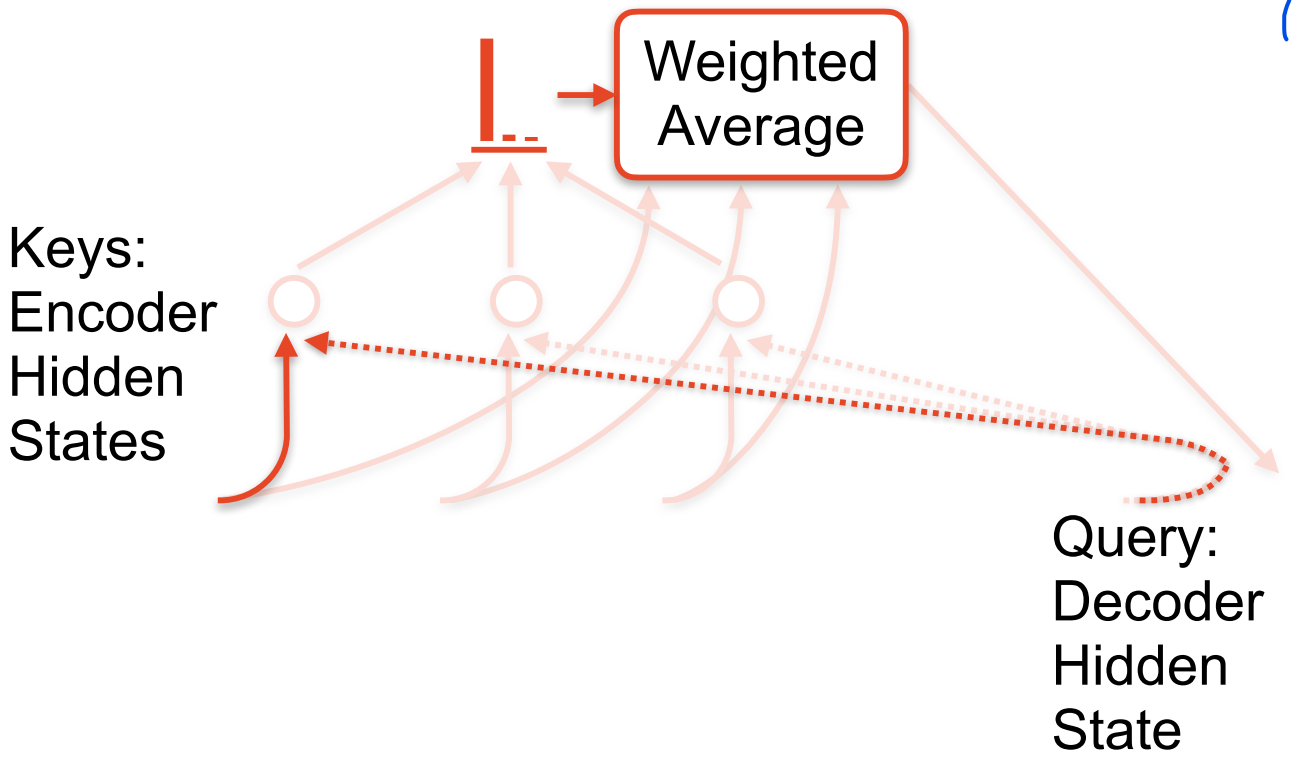

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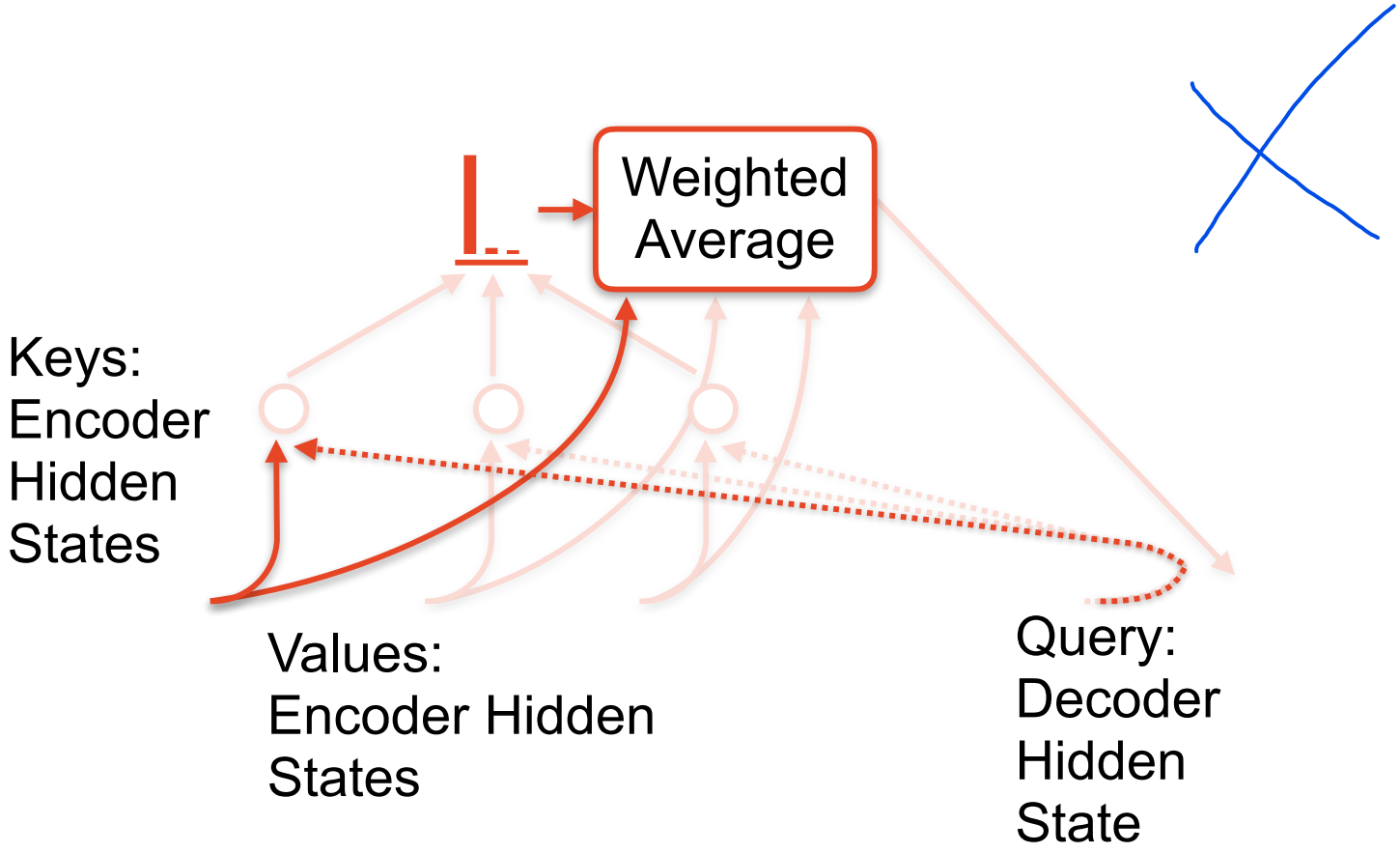

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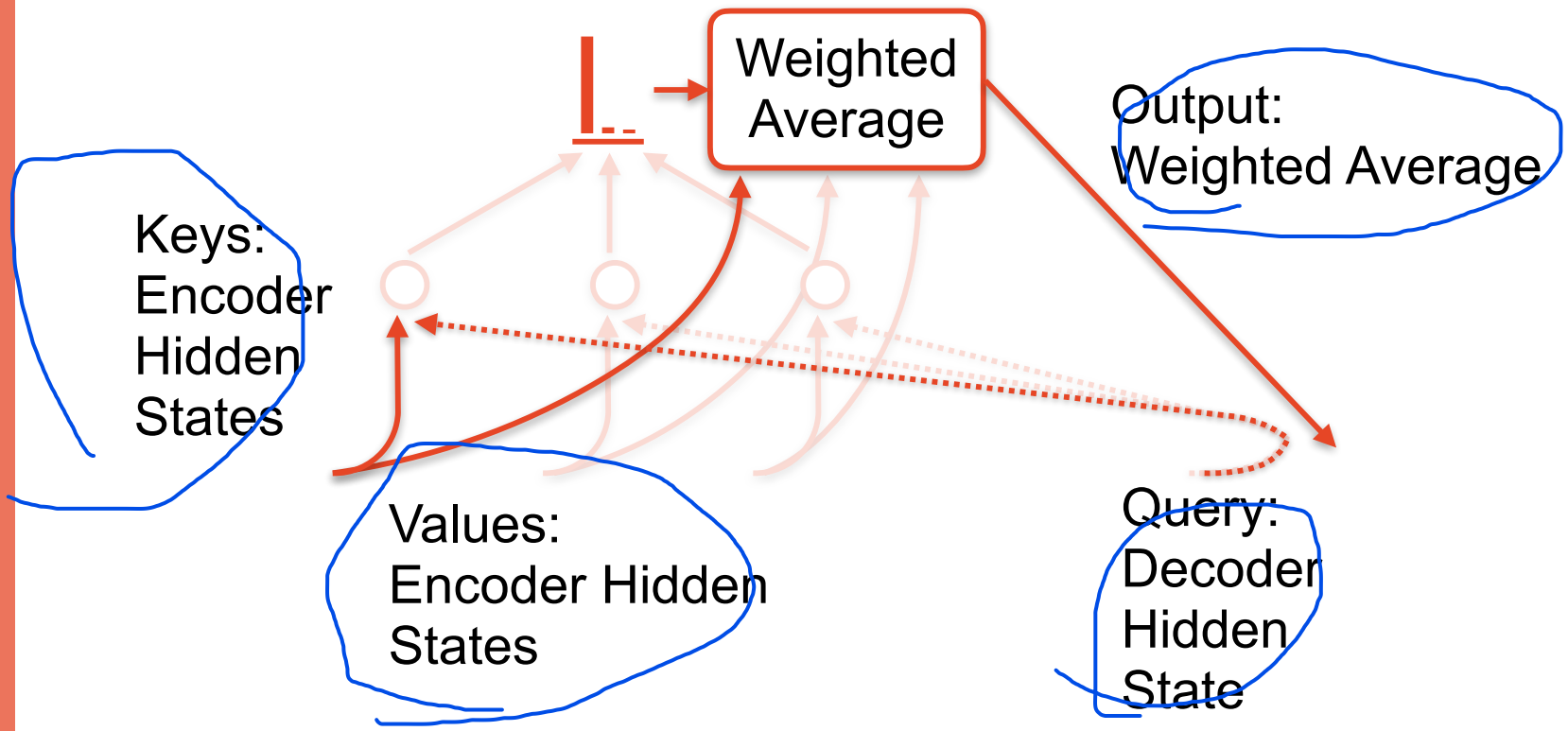

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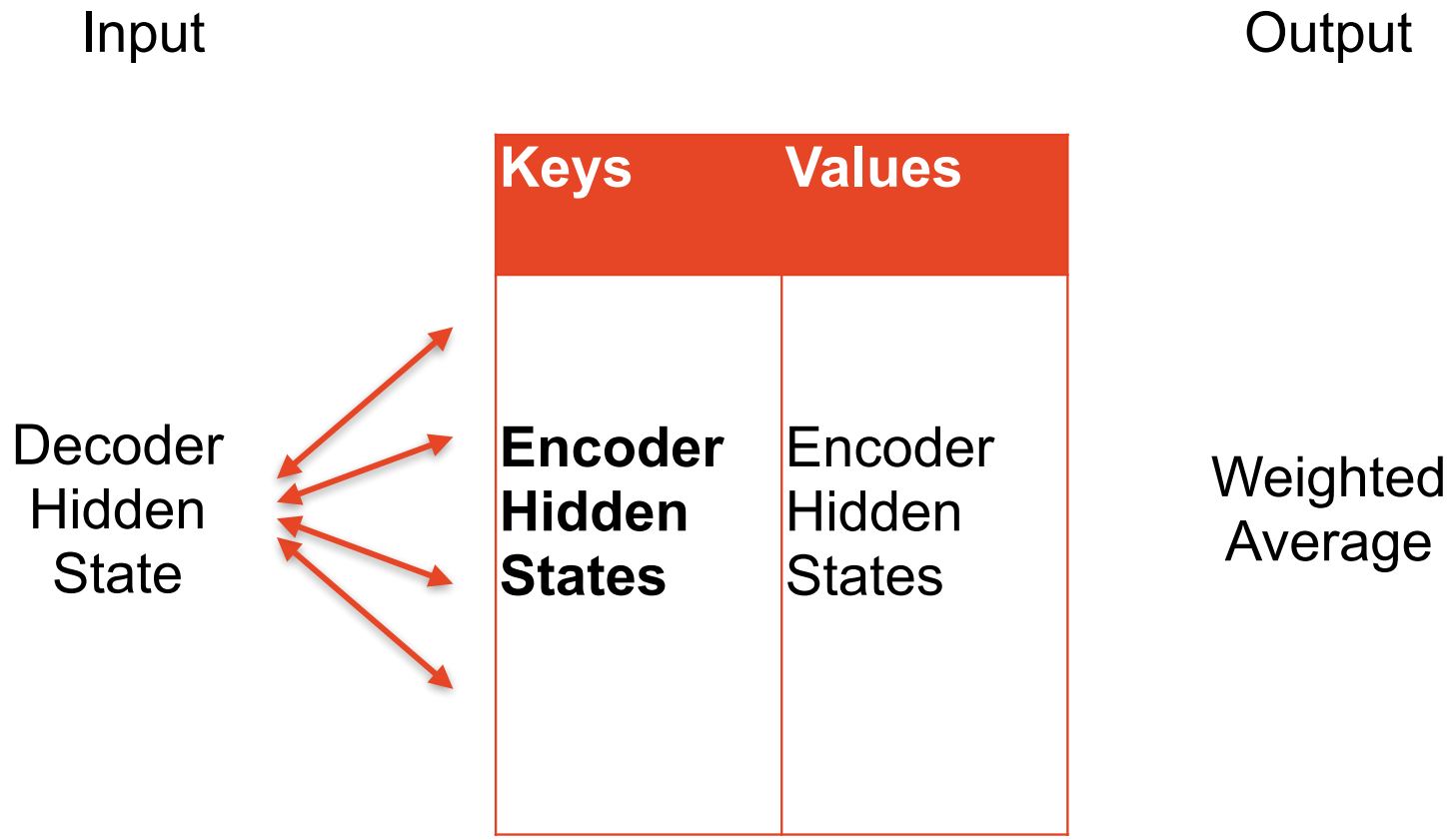

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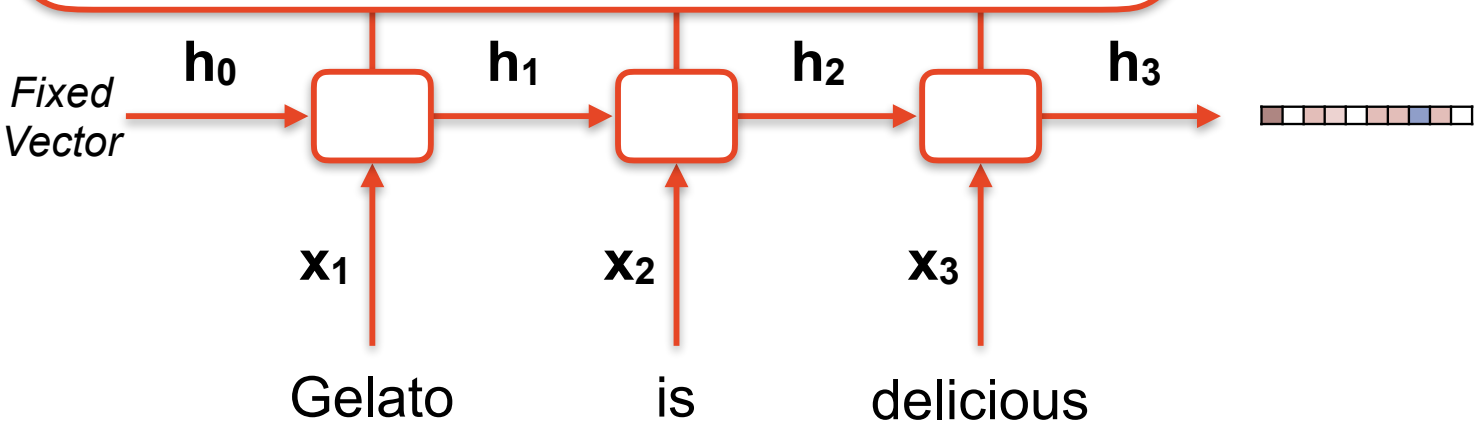
Do we need RNNs?

In lecture 3:
"How do we handle variable length input?"
"Recurrent Neural Networks (RNNs) address this issue with **context-dependent representations**"

hidden layer

In lecture 6, attention:
"Give each output step
a **representation of the input**
that is most useful for that output decision"

average weight



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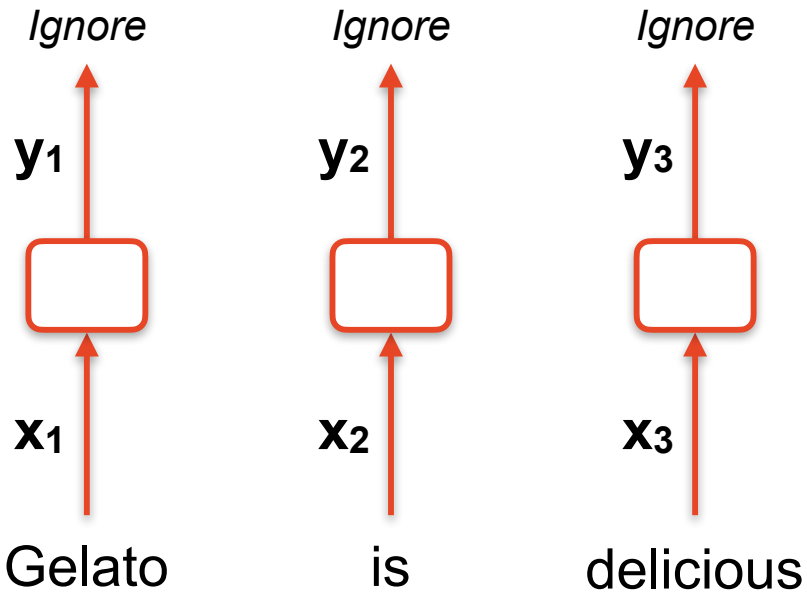
Cut the recurrent edges and use attention instead



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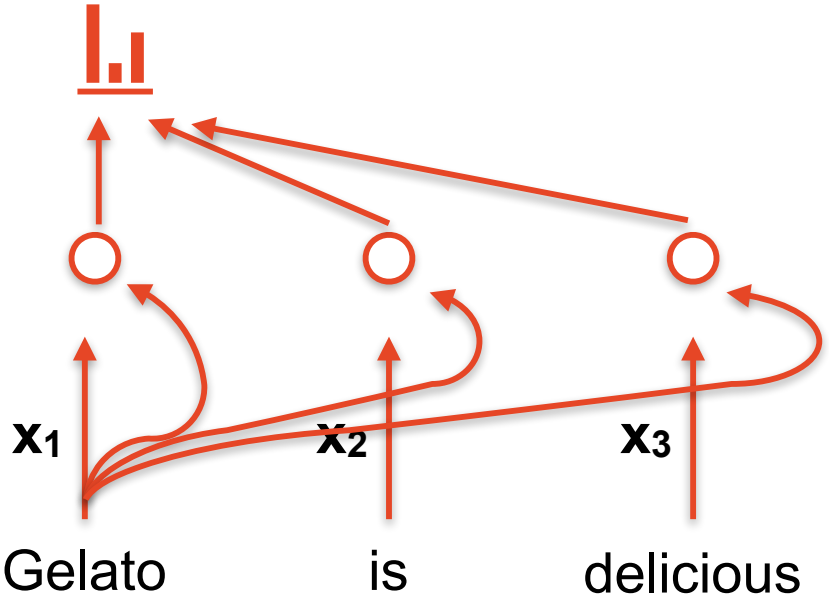

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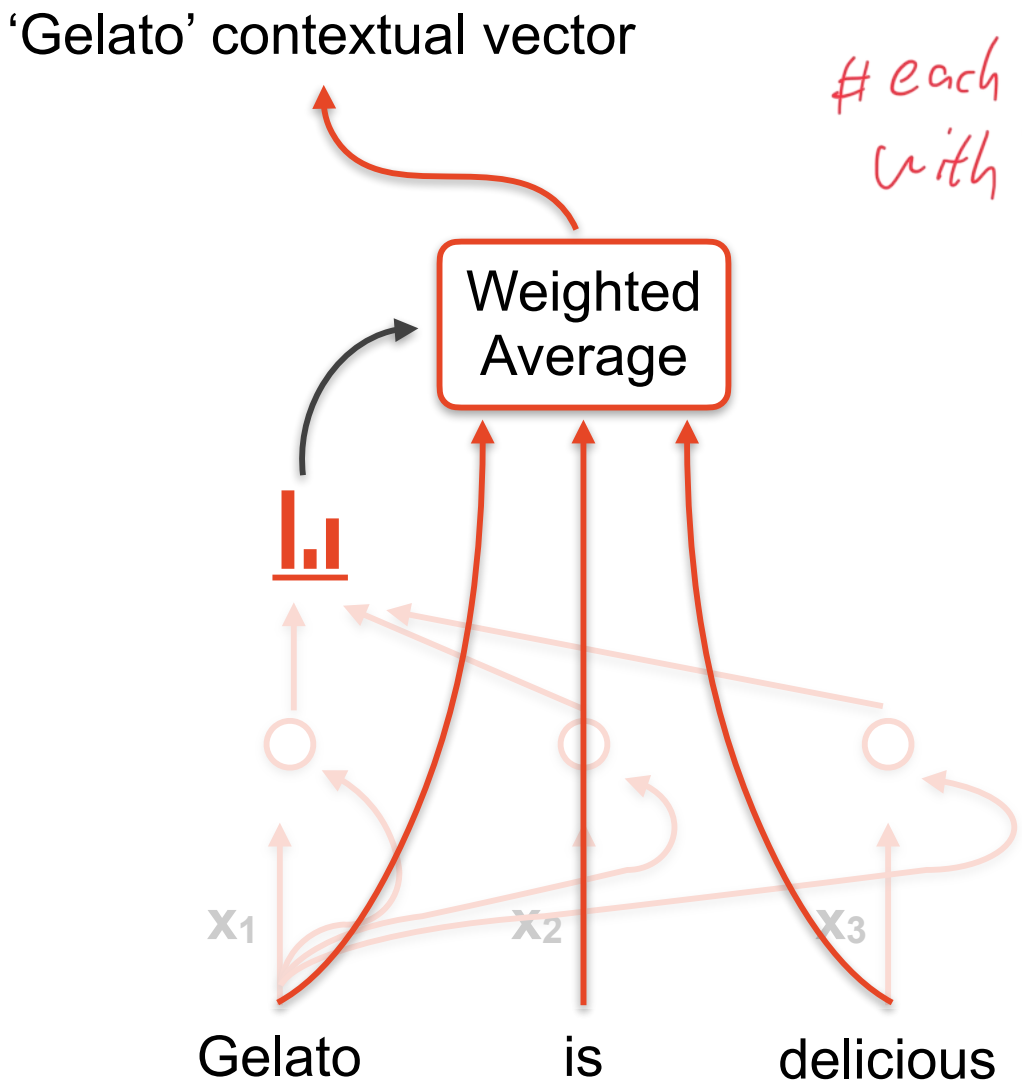

each word compare with 'Gelato'

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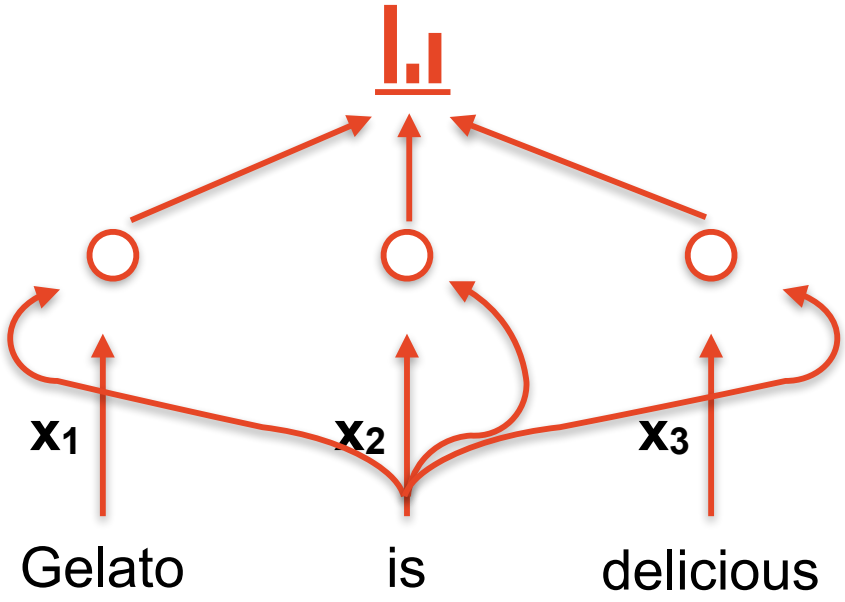

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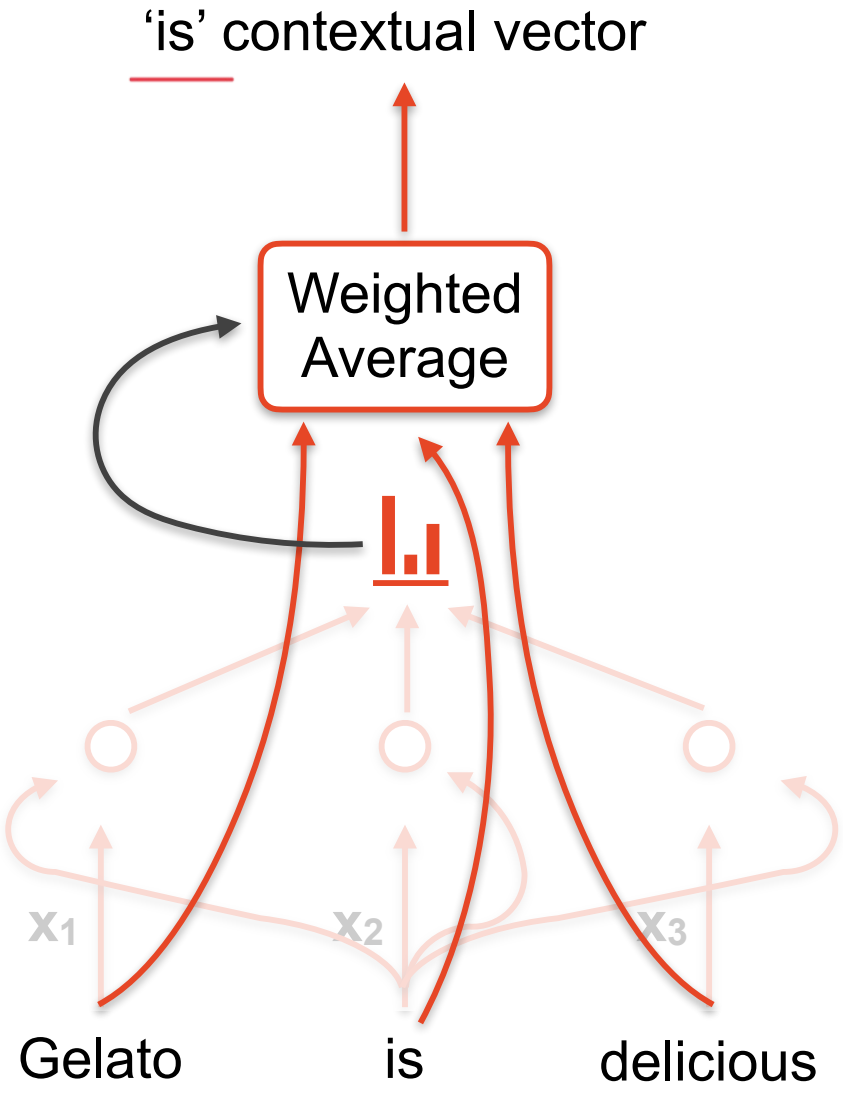

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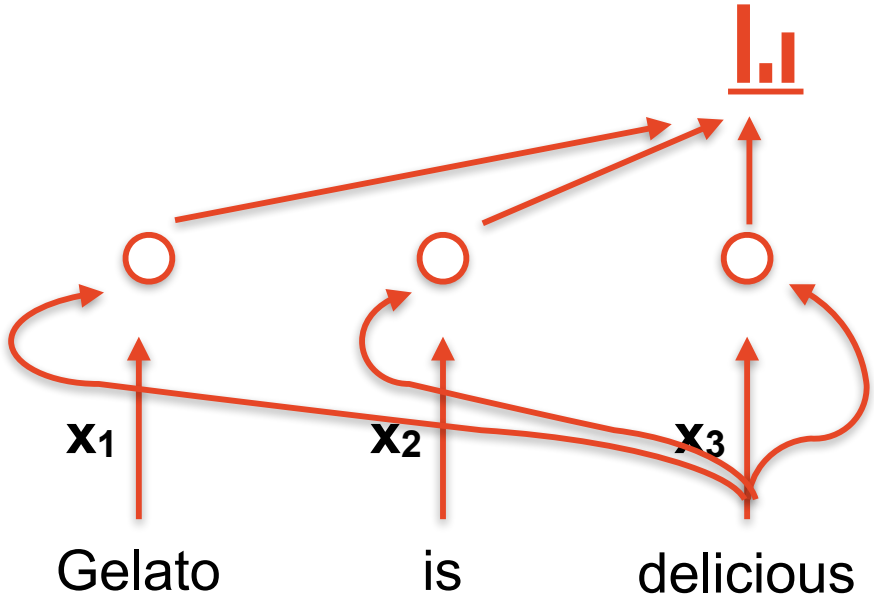

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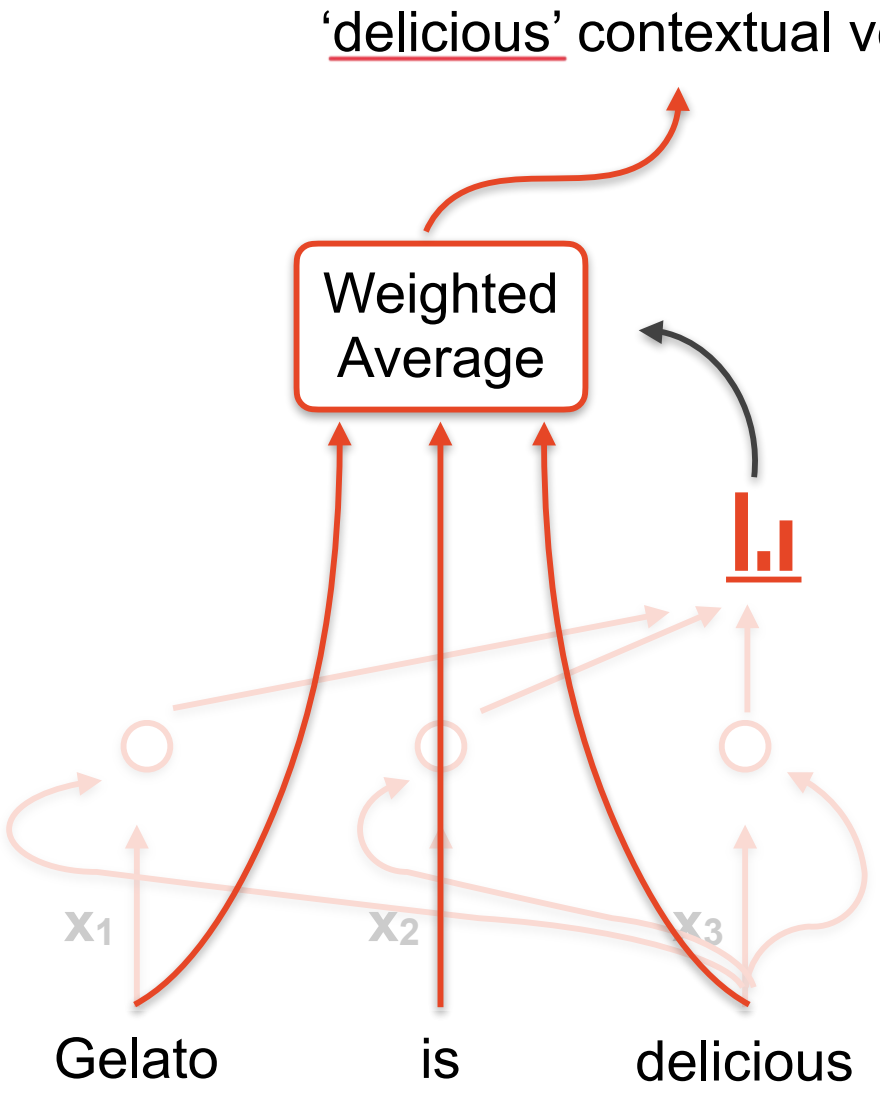

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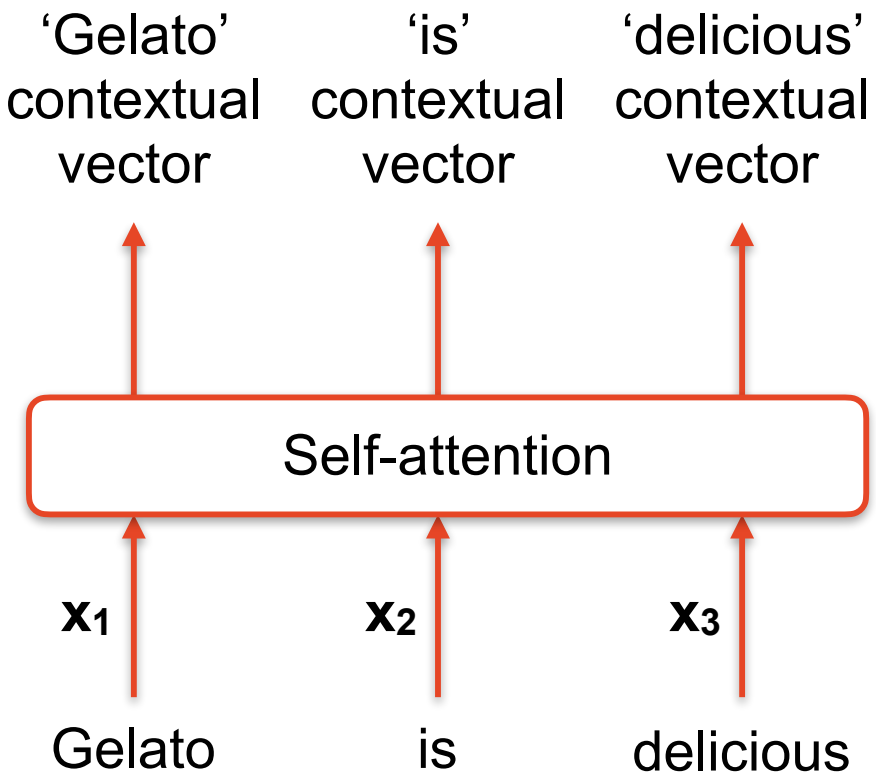
Self-attention gives contextual representations of input



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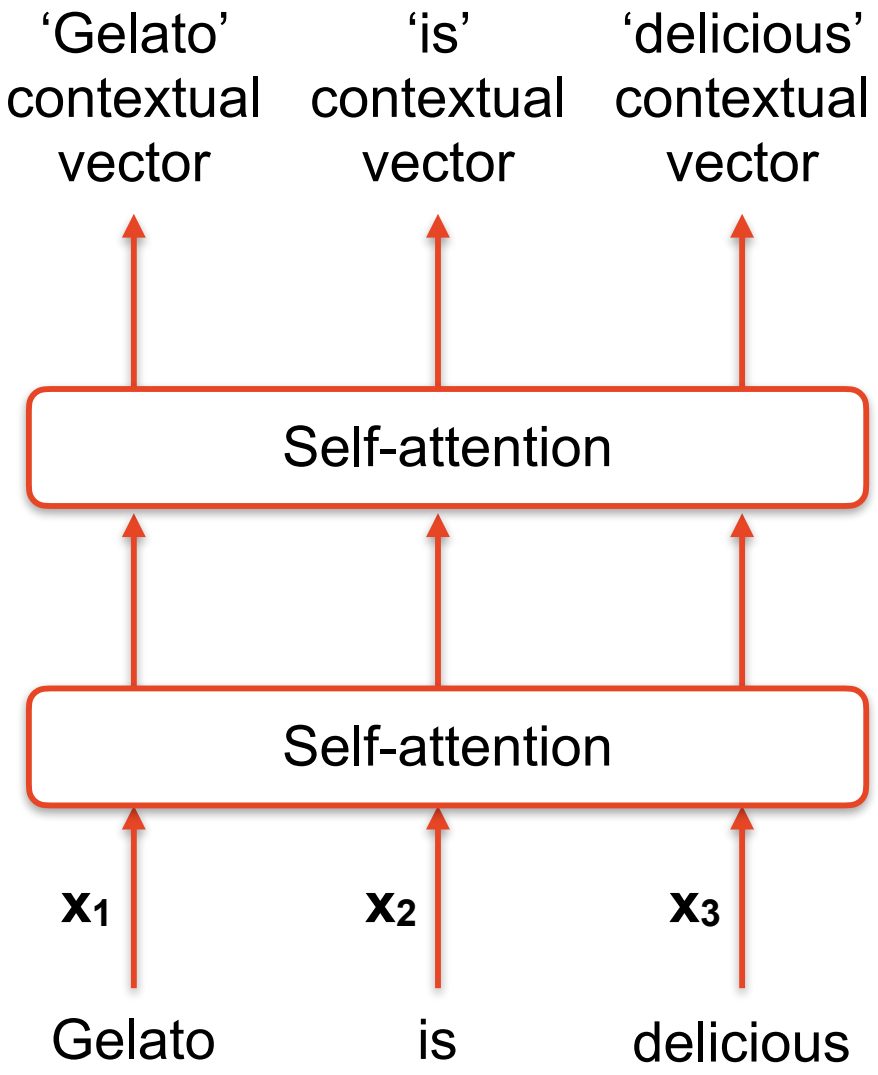

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Using equations, here is what we have done

self attention

Initial word vectors $\mathbf{x_i} \in \mathbb{R}^d$

current word

Do dot product to get attention scores $e_{ij} = \mathbf{x_i}^\top \mathbf{x_j}$

$\mathbf{x_i}$ is the query

$\mathbf{x_j}$ is the key

Softmax to get a distribution $\alpha_{ij} = \text{softmax}(e_{ij})$

all words include self

Weighted average $\mathbf{o_i} = \sum_j \alpha_{ij} \mathbf{x}_j$

$\mathbf{x_j}$ is the value

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Using equations, here is what we have done

Initial word vectors

$$\mathbf{x}_i \in \mathbb{R}^d$$

Transform into query, keys, and values

$$\mathbf{q_i} = Q\mathbf{x_i}$$
$$\mathbf{k_i} = K\mathbf{x_i}$$
$$\mathbf{v_i} = V\mathbf{x_i}$$

Q, K, and V are learned matrices

Do dot product to get attention scores

$$e_{ij} = \mathbf{q_i}^\top \mathbf{k_j}$$

Softmax to get a distribution

$$\alpha_{ij} = \text{softmax}(e_{ij})$$

Weighted average

$$\mathbf{o_i} = \sum_j \alpha_{ij}\mathbf{v_j}$$

(above is linear)

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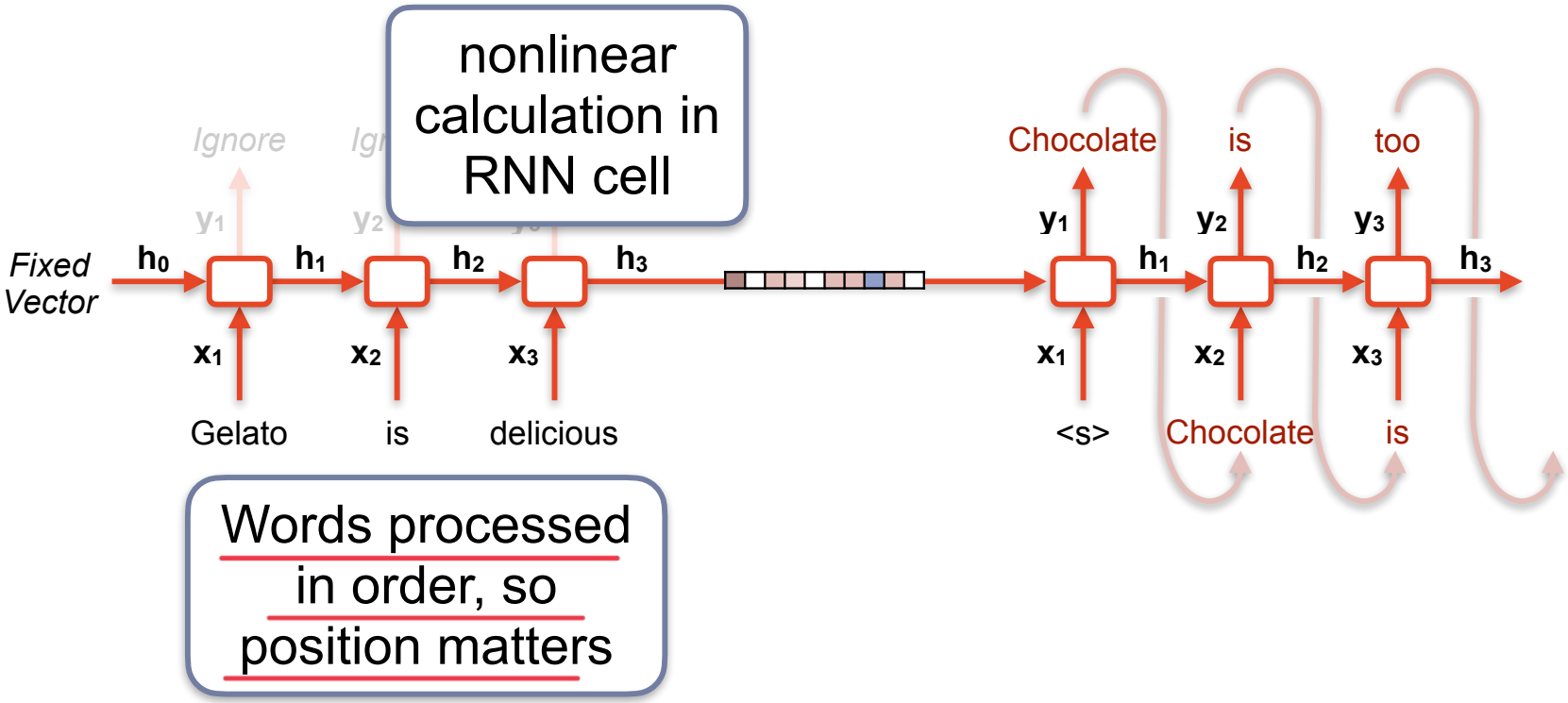
To recover all benefits of the RNN we need nonlinearities and position representation



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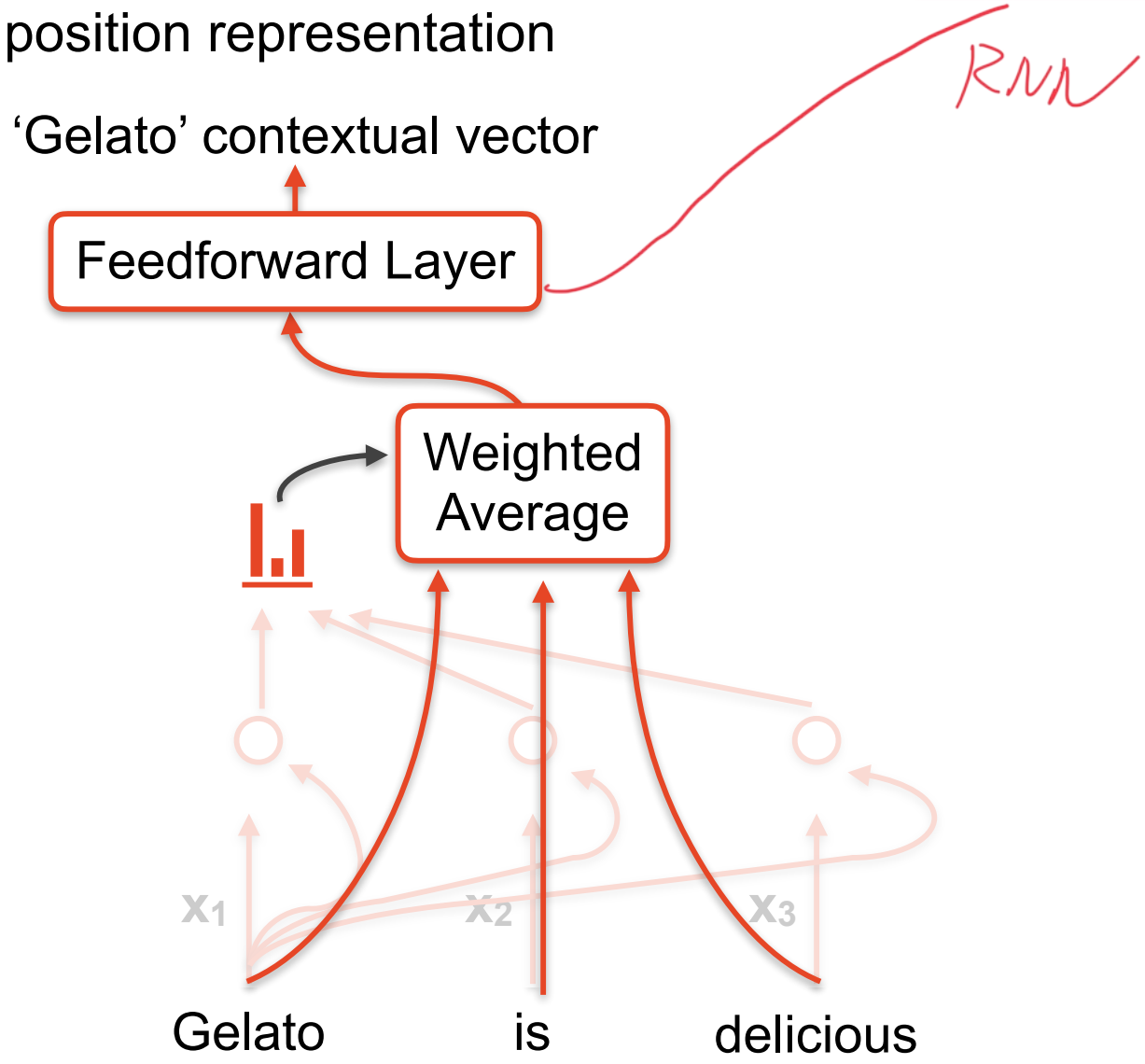

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To recover all benefits of the RNN we need **nonlinearities** and position representation

Initial word vectors $\mathbf{x}_i \in \mathbb{R}^d$

Transform into query, keys, and values

$$\mathbf{q_i} = Q\mathbf{x_i}$$
$$\mathbf{k_i} = K\mathbf{x_i}$$
$$\mathbf{v_i} = V\mathbf{x_i}$$

Do dot product to get attention scores $e_{ij} = \mathbf{q_i}^\top \mathbf{k_j}$

Softmax to get a distribution $\alpha_{ij} = \text{softmax}(e_{ij})$

Weighted average $\mathbf{t_i} = \sum_j \alpha_{ij} \mathbf{v_j}$

Feedforward layer $\mathbf{o_i} = W_2 \text{ReLU}(W_1 \mathbf{t_i} + \mathbf{b_1}) + \mathbf{b_2}$

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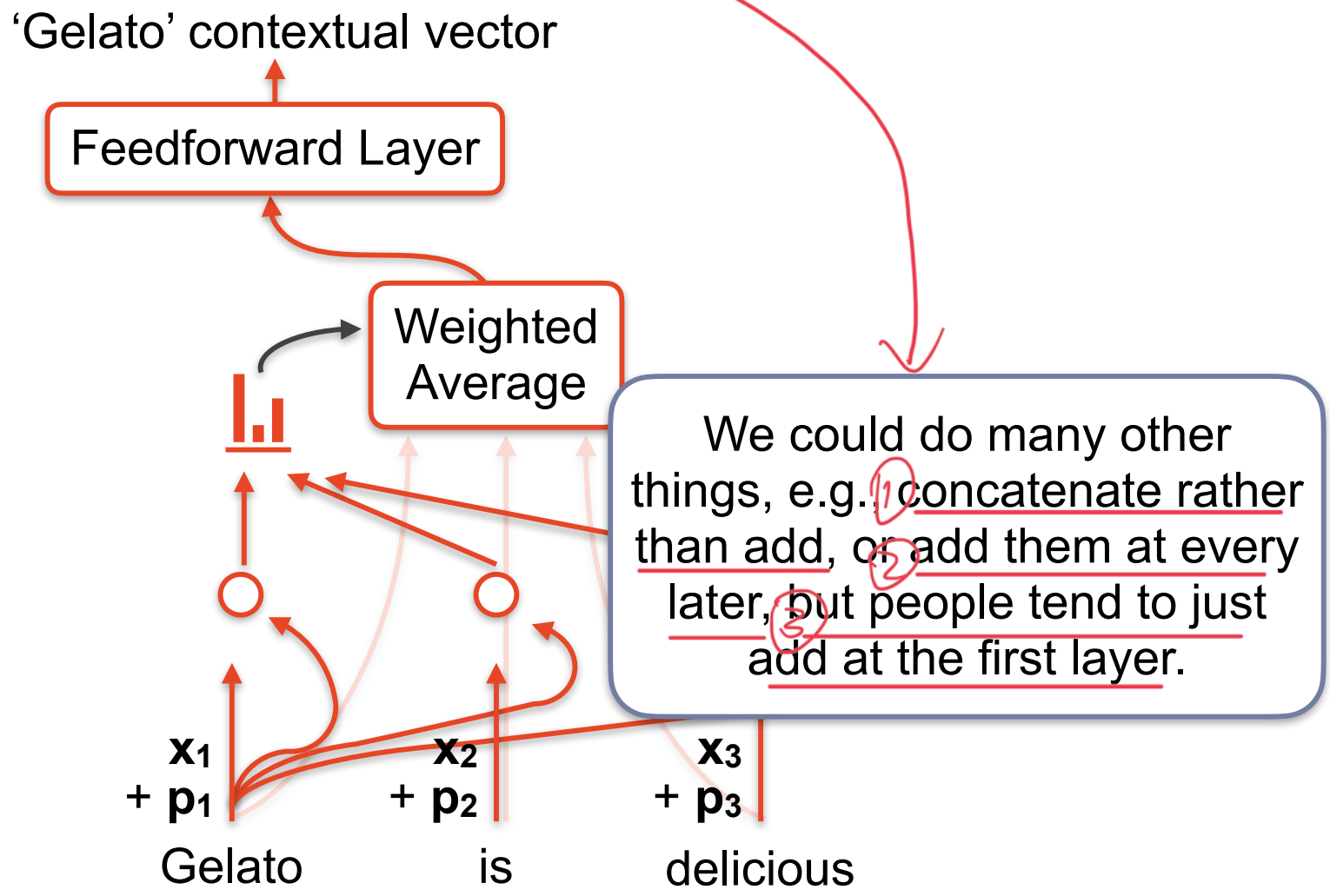
To recover all benefits of the RNN we need nonlinearities and **position representation**



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To recover all benefits of the RNN we need nonlinearities and **position representation**

Original without position

Initial word vectors	$\mathbf{x}_i \in \mathbb{R}^d$
Transform into query, keys, and values	$\mathbf{q_i} = Q\tilde{\mathbf{x}}_\mathbf{i}$ $\mathbf{k_i} = K\tilde{\mathbf{x}}_\mathbf{i}$ $\mathbf{v_i} = V\tilde{\mathbf{x}}_\mathbf{i}$
Do dot product to get attention scores	$e_{ij} = \mathbf{q_i}^\top \mathbf{k_j}$
Softmax to get a distribution	$\alpha_{ij} = \text{softmax}(e_{ij})$
Weighted average	$\mathbf{t_i} = \sum_j \alpha_{ij}\mathbf{v_j}$
Feedforward layer	$\mathbf{o_i} = W_2\text{ReLU}(W_1\mathbf{t_i} + \mathbf{b_1}) + \mathbf{b_2}$

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To recover all benefits of the RNN we need nonlinearities and **position representation**

Initial word vectors with positions

$$\tilde{\mathbf{x}}_i = \mathbf{x_i} + \mathbf{p_i}$$

Transform into query, keys, and values

$$\mathbf{q_i} = Q\tilde{\mathbf{x}}_\mathbf{i}$$

$$\mathbf{k_i} = K\tilde{\mathbf{x}}_\mathbf{i}$$

$$\mathbf{v_i} = V\tilde{\mathbf{x}}_\mathbf{i}$$

Do dot product to get attention scores

$$e_{ij} = \mathbf{q_i}^\top \mathbf{k_j}$$

Softmax to get a distribution

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Weighted average

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Feedforward layer

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To recover all benefits of the RNN we need nonlinearities and **position representation**

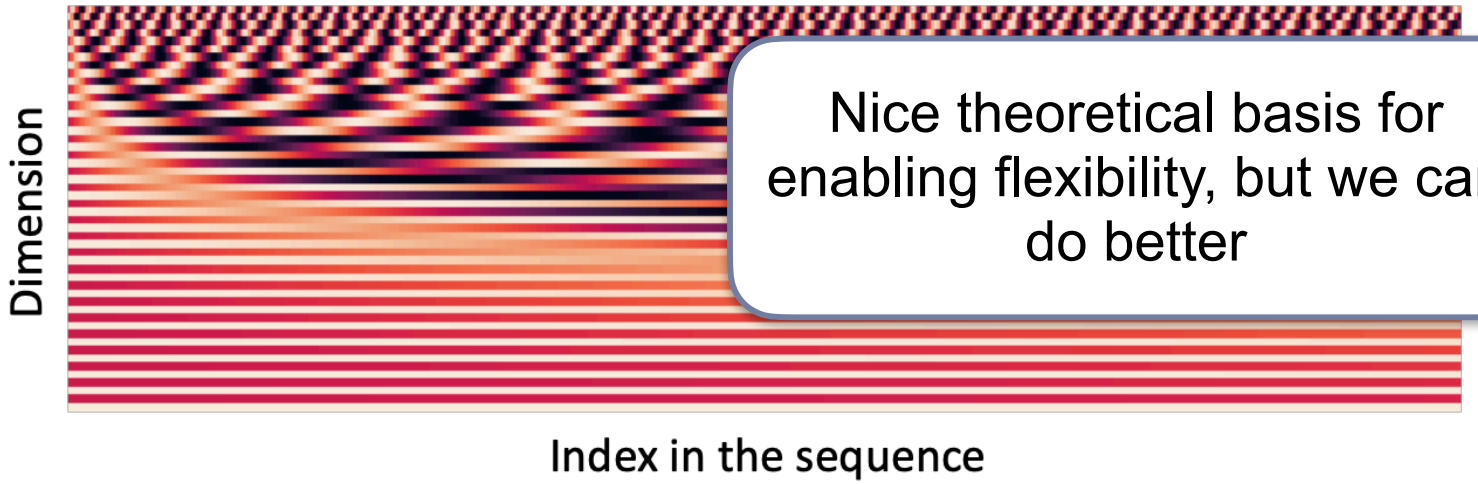
What is $\mathbf{p}_i$?

First idea:

$$\boldsymbol{p}_i = \begin{pmatrix} \sin(i/10000^{2*1/d}) \\ \cos(i/10000^{2*1/d}) \\ \vdots \\ \sin(i/10000^{2*\frac{d}{2}/d}) \\ \cos(i/10000^{2*\frac{d}{2}/d}) \end{pmatrix}$$

at top change quickly

at bottom change slowly



Nice theoretical basis for enabling flexibility, but we can do better

Stanford CS224 lectures

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To recover all benefits of the RNN we need nonlinearities and **position representation**

What is $\mathbf{p}_i$?

Next idea:

1) Learned values - for each position, learn a vector

problem

Note: can't generalise to sequences longer than those seen in training!

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To recover all benefits of the RNN we need nonlinearities and **position dependent representation**

Rotary Positional Embeddings

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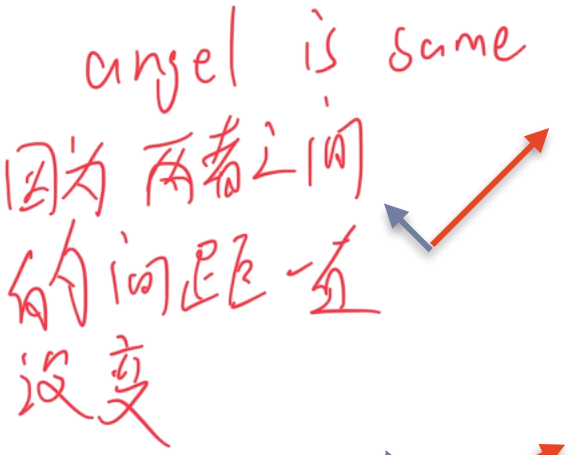
To recover all benefits of the RNN we need nonlinearities and **position dependent representation**

Rotary Positional Embeddings



This chocolate is delicious

I think chocolate is delicious

Most people know chocolate is delicious

Cosine similarity remains the same for two words the same distance apart!

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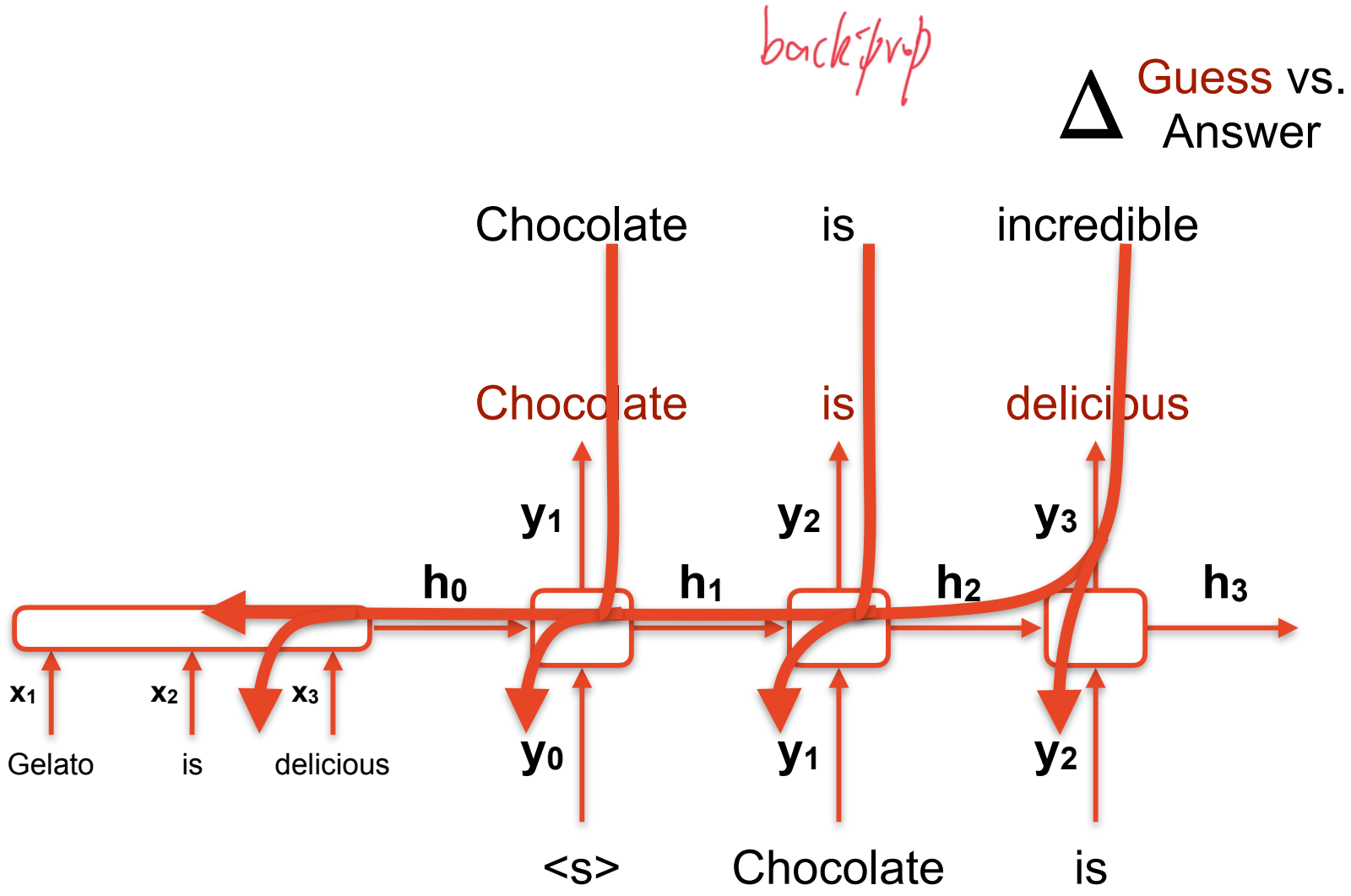
Training needs to account for what is known at each step



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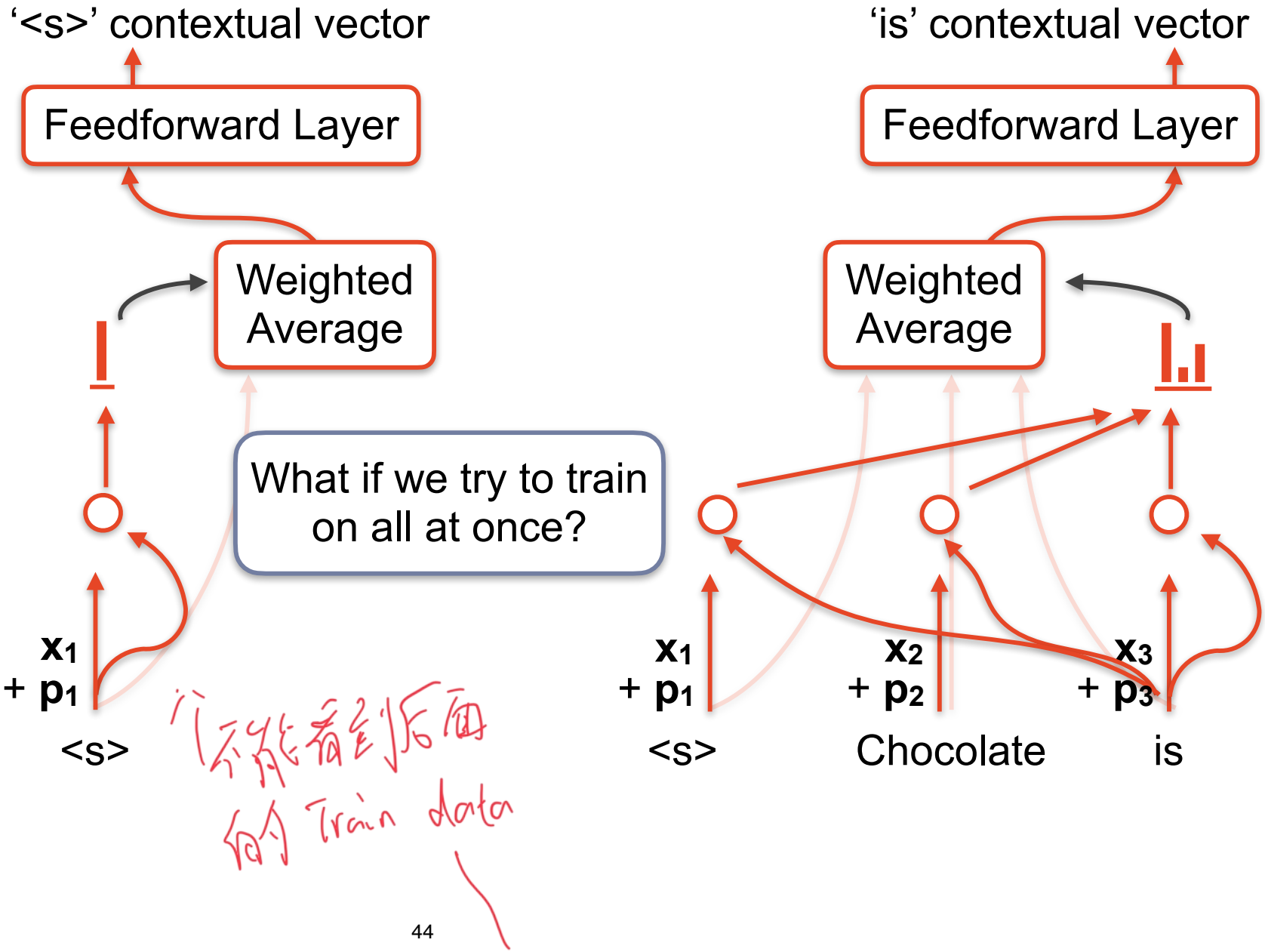

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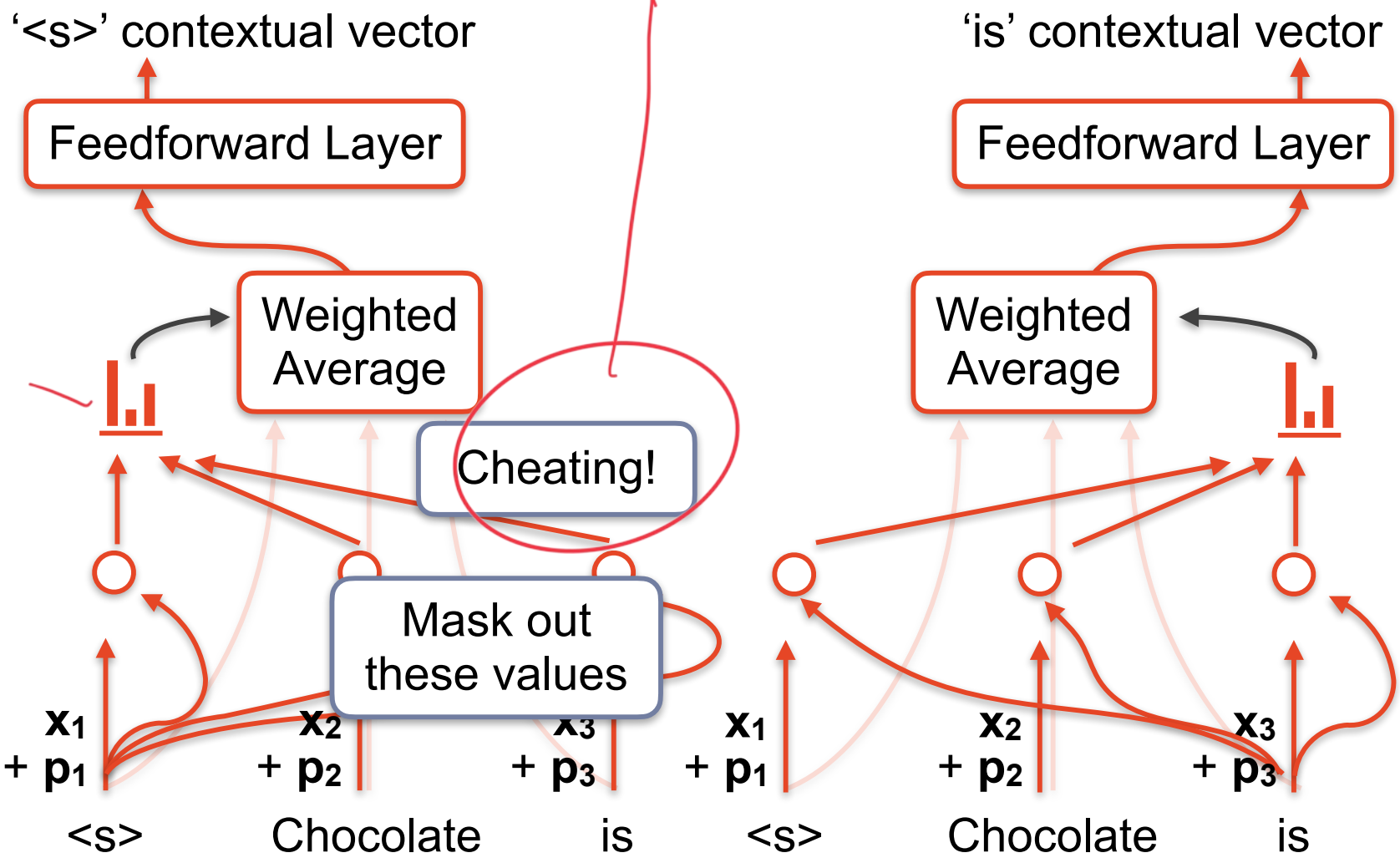

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Training needs to account for what is known at each step

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$$\mathbf{k_i} = K\tilde{\mathbf{x}}_\mathbf{i}$$
$$\mathbf{v_i} = V\tilde{\mathbf{x}}_\mathbf{i}$$

Do dot product to get attention scores

$$e_{ij} = \mathbf{q_i}^\top \mathbf{k_j}$$

Training:

$$e_{ij} = \begin{cases} \mathbf{q_i}^\top \mathbf{k_j}, j \leq i \\ -\infty, j > i \end{cases}$$

Softmax to get a distribution

bar chart in Gradescope

$$\alpha_{ij} = \text{softmax}(e_{ij})$$

Weighted average

$$\mathbf{t_i} = \sum_j \alpha_{ij} \mathbf{v_j}$$

Feedforward layer

$$\mathbf{o_i} = W_2 \text{ReLU}(W_1 \mathbf{t_i} + \mathbf{b_1}) + \mathbf{b_2}$$

3 minute Break - stretch and visit Menti

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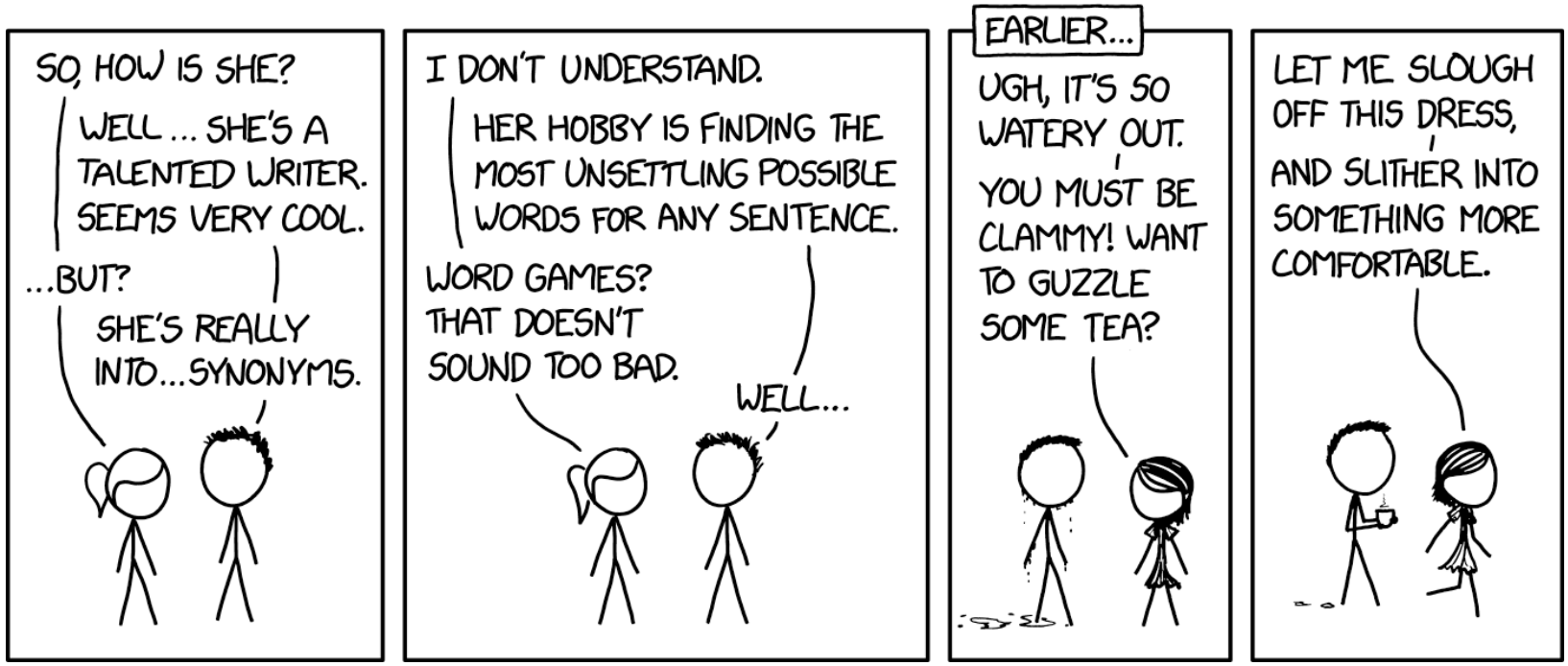
Synonym Date



[We need some grub to munch—I'll go slouch over to the kitchen.]

Source: https://xkcd.com/2352/

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Transformer

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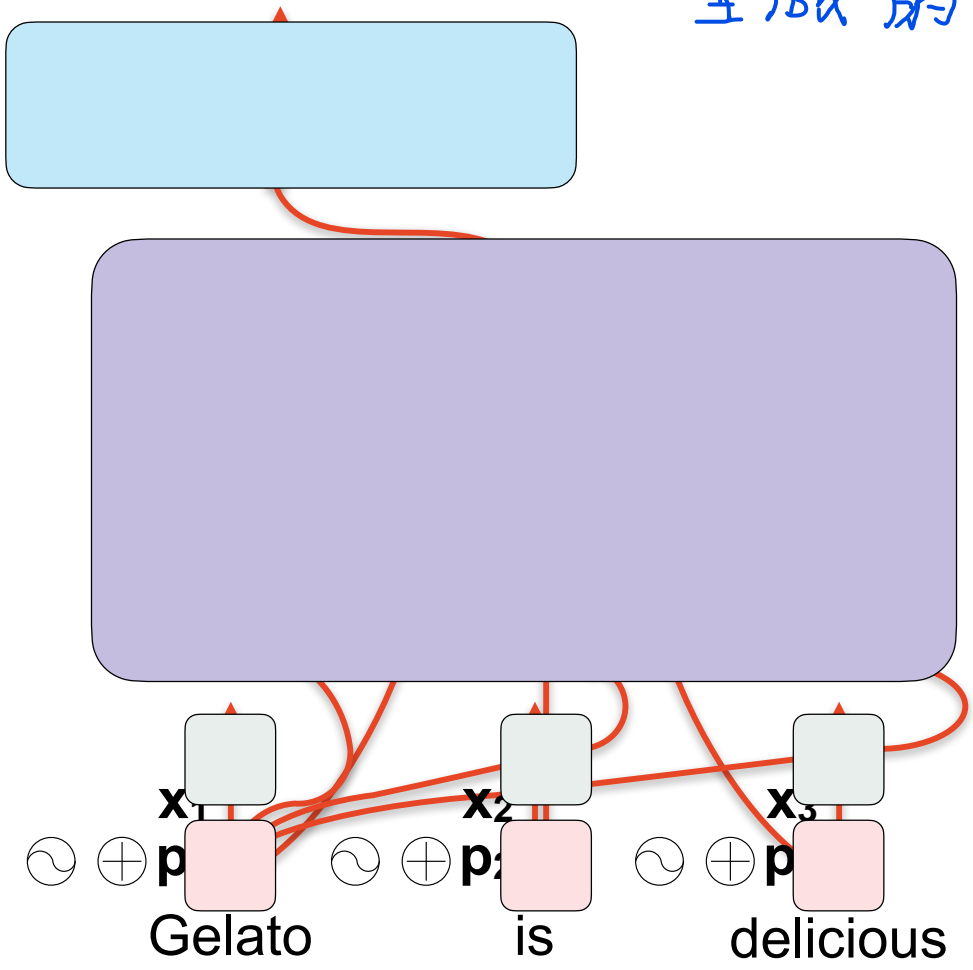
Going from Self-Attention to the Transformer

用box表示之前在self-attention里做的

‘Gelato’ contextual vector



Feed Forward

$$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$$

⊕ Element-wise sum

Attention:

$$\text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Linear transform

Look up vector

Position as vector

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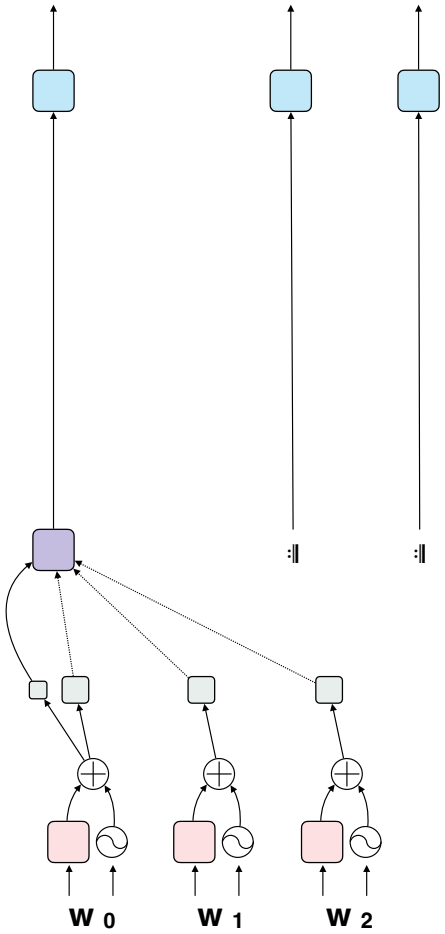
Going from Self-Attention to the Transformer



Feed Forward

$$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$$

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Linear transform

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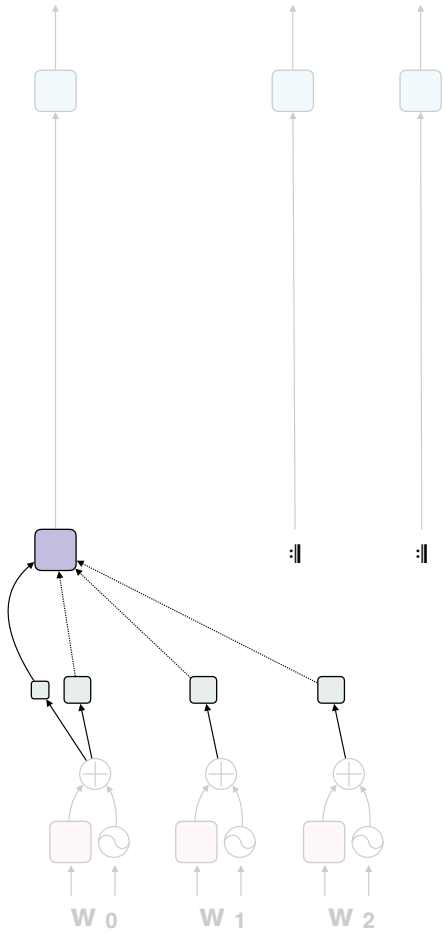
Going from Self-Attention to the Transformer: Multi-Head Attention



Feed Forward

$$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$$

⊕ Element-wise sum

Attention:

$$\text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Linear transform

Look up vector

Position as vector

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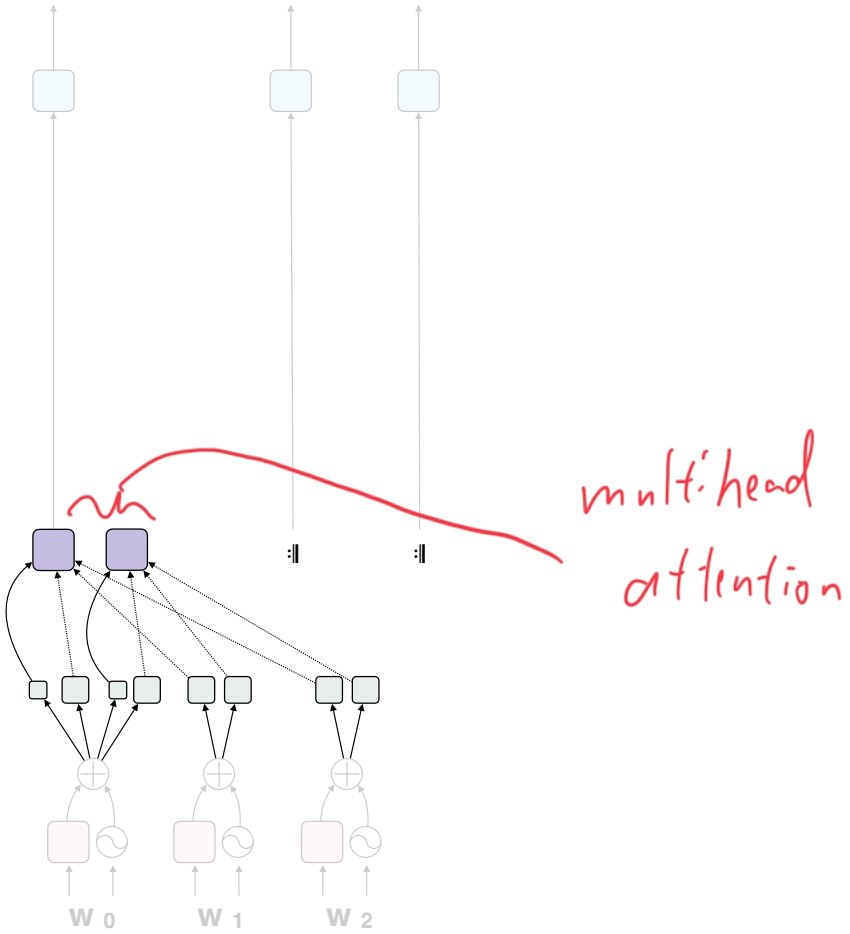
Going from Self-Attention to the Transformer: Multi-Head Attention



Feed Forward

$$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$$

⊕ Element-wise sum

Attention:

$$\text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Linear transform

Look up vector

Position as vector

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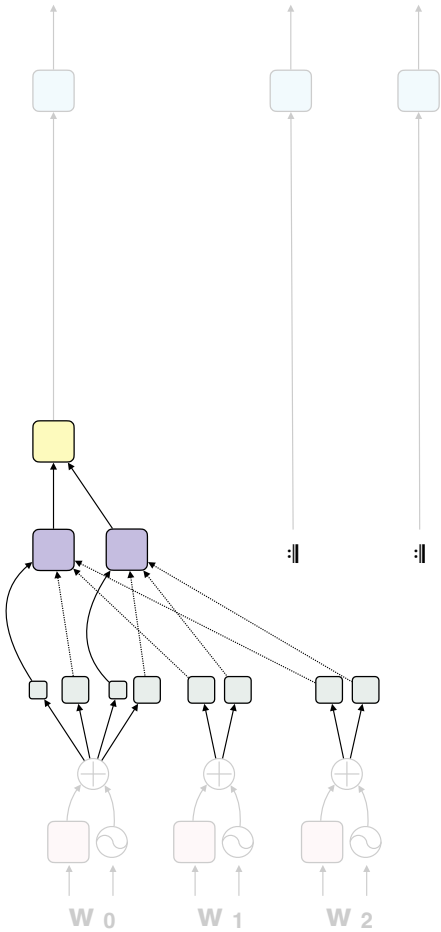
Going from Self-Attention to the Transformer: Multi-Head Attention



Feed Forward

$$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$$

⊕ Element-wise sum

Concatenate

Attention:

$$\text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Linear transform

Look up vector

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Why do multi-head attention?

Attention is more than just a dot product here

Attention Head 1
(Entity focused)

Attention Head 2
(Syntax focused)

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Why do scaled dot-product attention?

Attention:

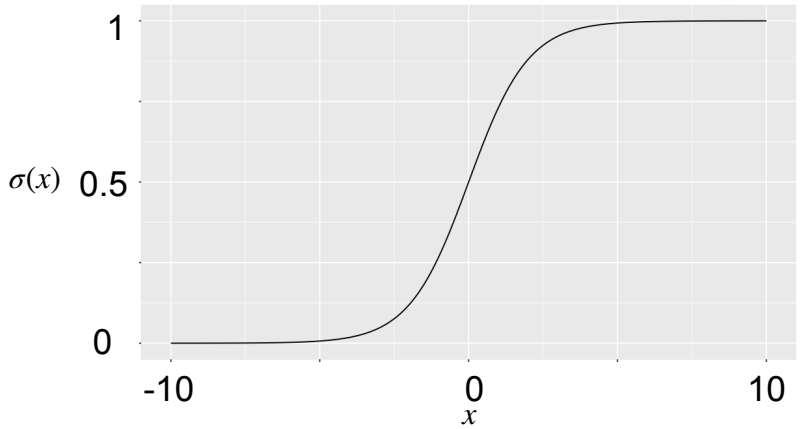
$$\text{softmax}\left(\frac{\mathbf{Q}\mathbf{V}^\top}{\sqrt{\mathbf{d_k}}}\right)\mathbf{V}$$

Can avoid

If we increase dimensionality, dot products become larger:

[1, 2] . [2, 3] = 8
[1, 2, 1] . [2, 3, 4] = 12
[1, 2, 1, 1] . [2, 3, 4, 8] = 20

Larger dot products mean smaller gradients after softmax:



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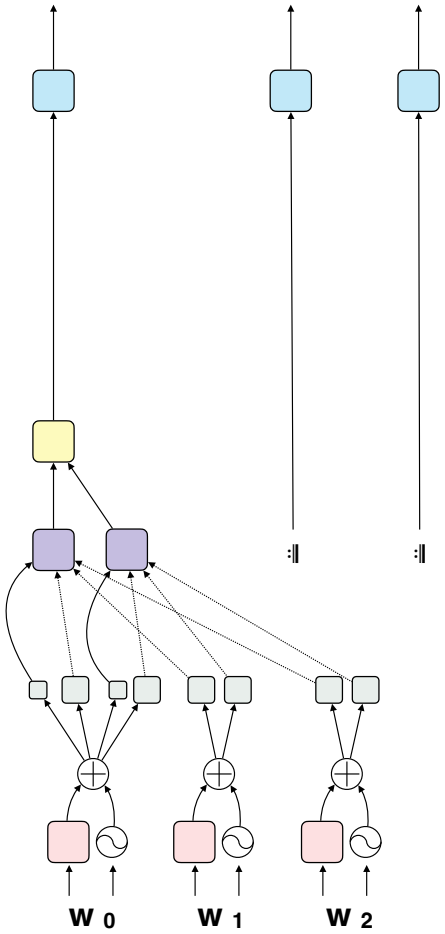
Going from Self-Attention to the Transformer: Multi-Head Attention, Residuals



Feed Forward

$$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$$

⊕ Element-wise sum

Concatenate

Attention:

$$\text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Linear transform

Look up vector

Position as vector

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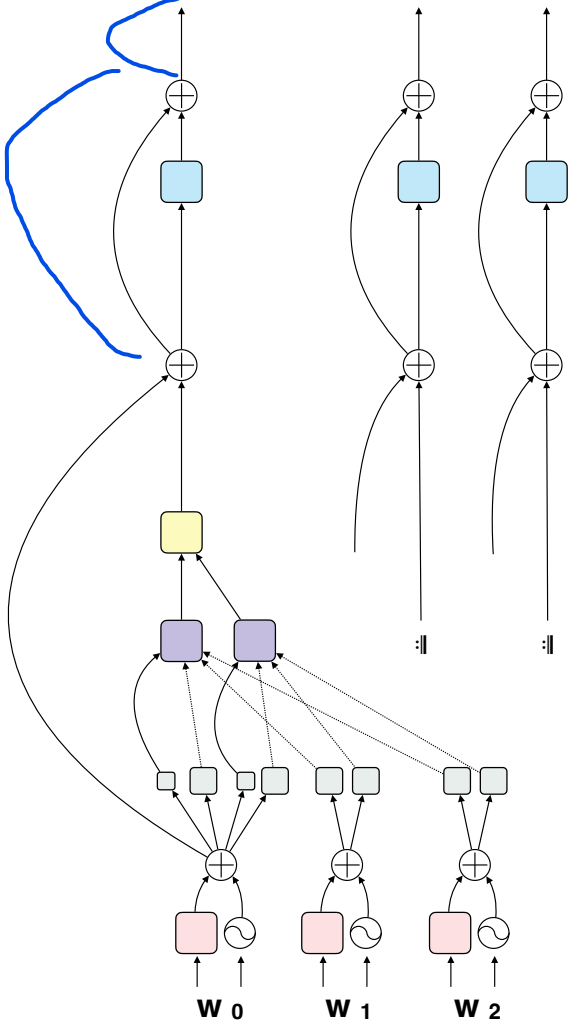
Going from Self-Attention to the Transformer: Multi-Head Attention, Residuals



Feed Forward

$$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$$

⊕ Element-wise sum

Concatenate

Attention:

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Linear transform

Look up vector

Position as vector

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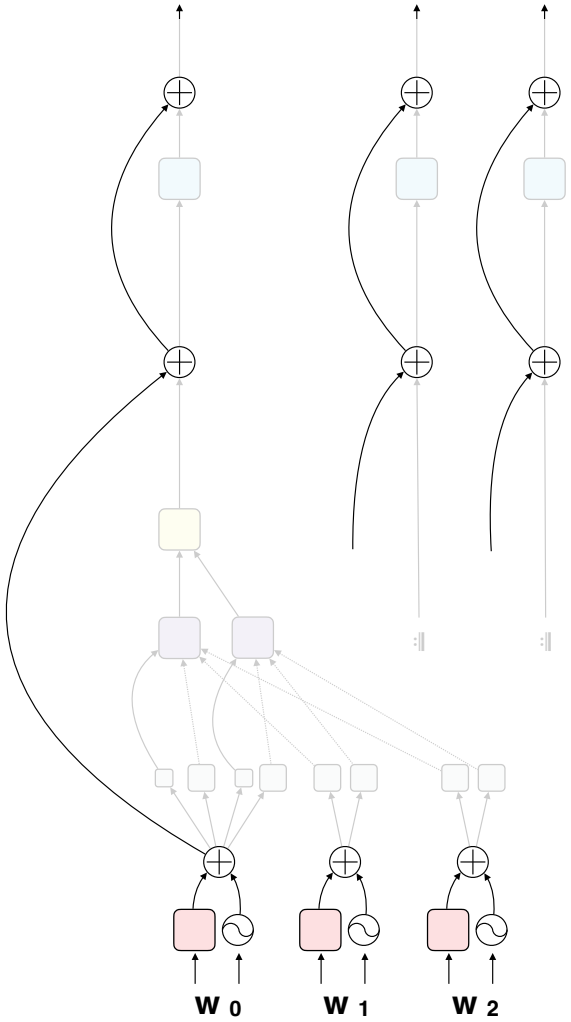
Going from Self-Attention to the Transformer: Multi-Head Attention, Residuals



Feed Forward

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⊕ Element-wise sum

Concatenate

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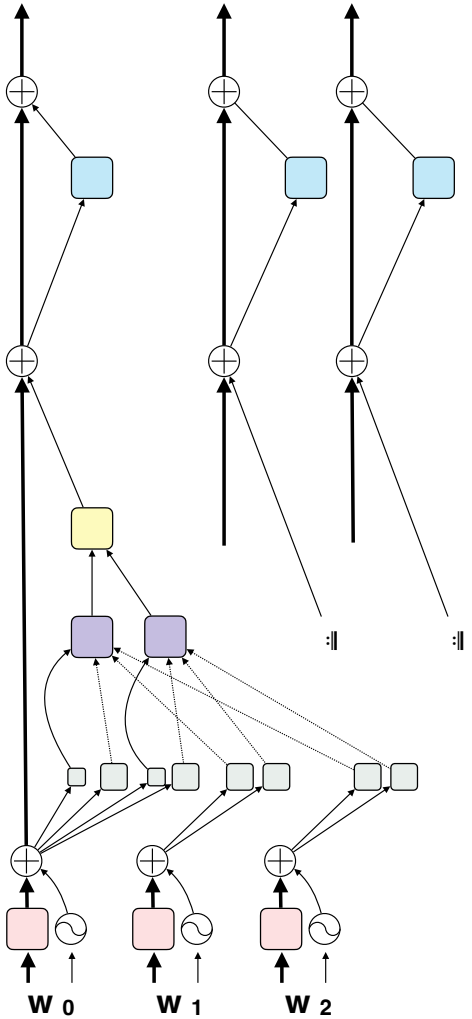
Going from Self-Attention to the Transformer: Multi-Head Attention, Residuals



Feed Forward

$$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$$

⊕ Element-wise sum

Concatenate

Attention:

$$\text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Linear transform

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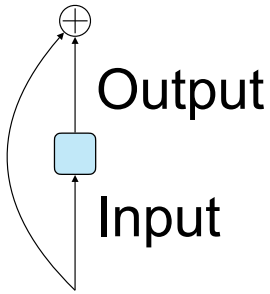
What is a residual?

Originally from Computer Vision.
Taking the output of some calculation and adding the input to it:

means



Why?

- Gradient passes back easily (no non-linearity on the edge we added!)
- Encourages our model to capture something close to the identity function
- Frees up the model to use the weights to capture stuff other than the identity function

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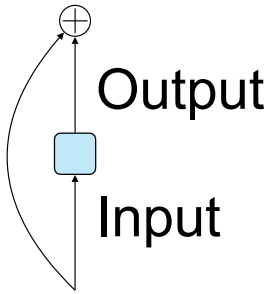
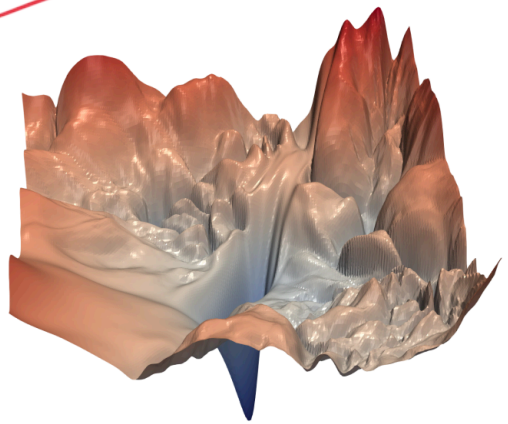
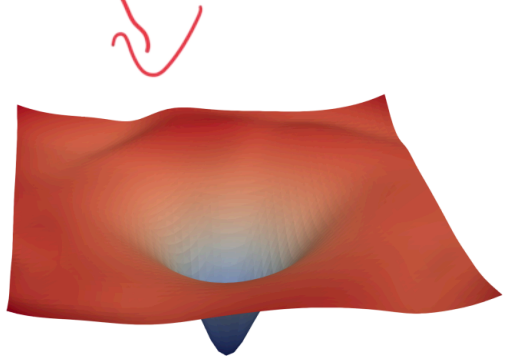


Smooth gradients.



No residuals



Residuals

Li, et. Al. (NeurIPS 2018)

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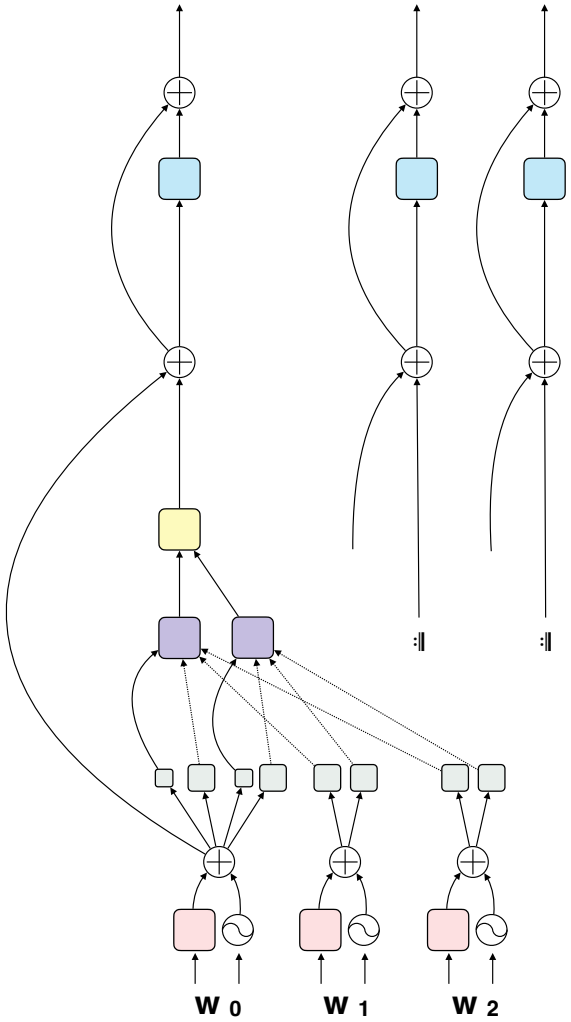
Going from Self-Attention to the Transformer: Multi-Head Attention, Residuals, and Layer Normalization



Feed Forward

$$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$$

⊕ Element-wise sum

Concatenate

Attention:

$$\text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Linear transform

Look up vector

Position as vector

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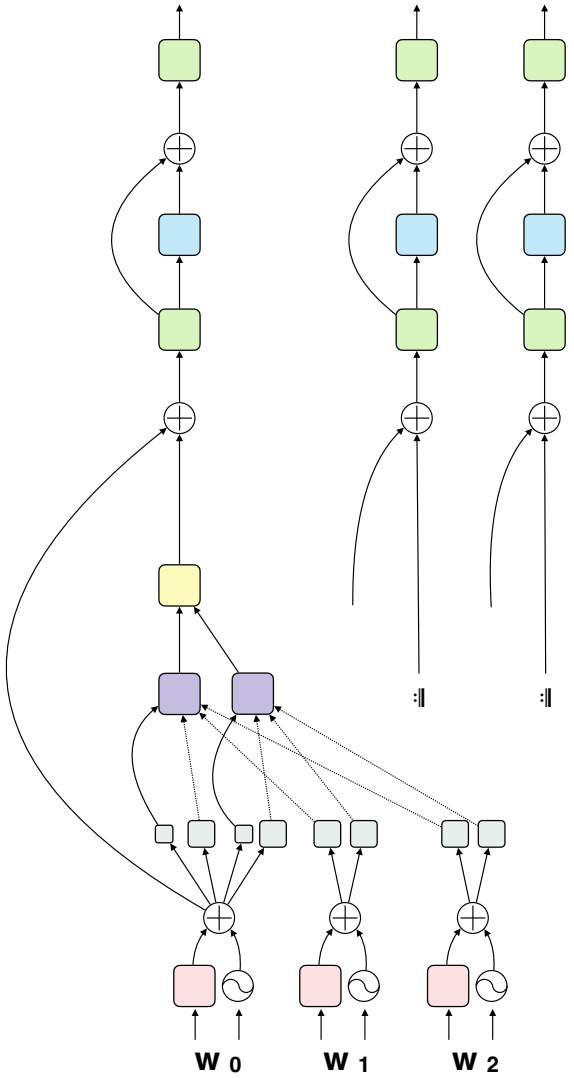
Going from Self-Attention to the Transformer: Multi-Head Attention, Residuals, and Layer Normalization



Feed Forward

$$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$$

Layer Norm

⊕ Element-wise sum

Concatenate

Attention:

$$\text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Linear transform

Look up vector

Position as vector

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Layer Normalization shifts values in a way that improves training

Take a vector $x \in \mathbb{R}^d$

Calculate the mean and standard deviation of the vector's values

$$\mu = \sum_{j=1}^{d} x_j$$

$$\sigma = \sqrt{\frac{1}{d} \sum_{j=1}^{d} (x_j - \mu)^2}$$

Define two learned weight vectors (or set them to 1 and 0)

$\gamma \in \mathbb{R}^d$ $\beta \in \mathbb{R}^d$

Rescale the vector

$$\text{output} = \frac{x - \mu}{\sqrt{\sigma + \epsilon}} * \gamma + \beta$$

to square root

A small value to prevent division by zero

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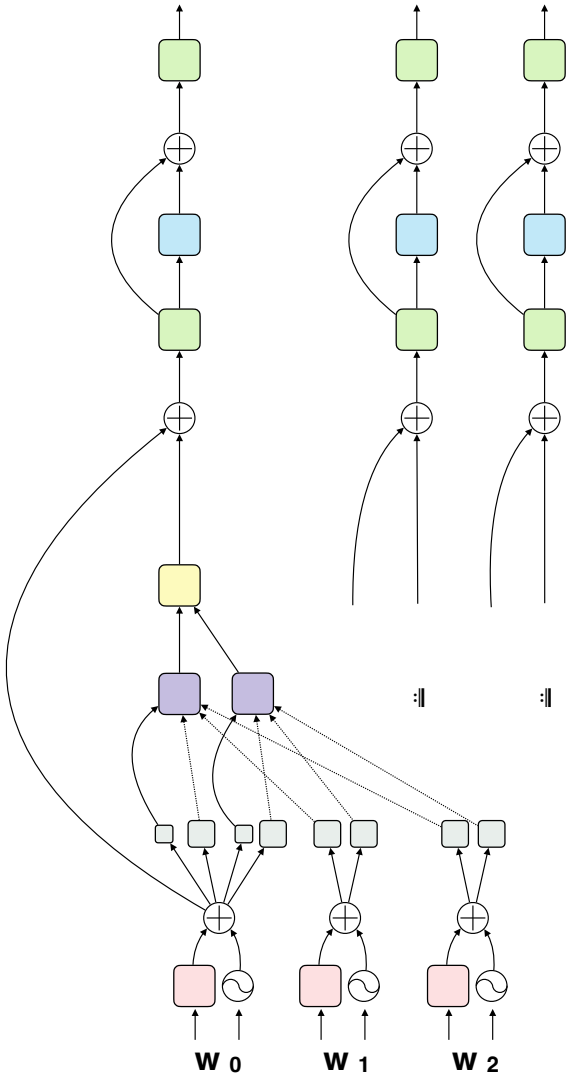
Going from Self-Attention to the Transformer: Multi-Head Attention, Residuals, and Layer Normalization



Feed Forward

$$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$$

Layer Norm

⊕ Element-wise sum

Concatenate

Attention:

$$\text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

Linear transform

Look up vector

Position as vector

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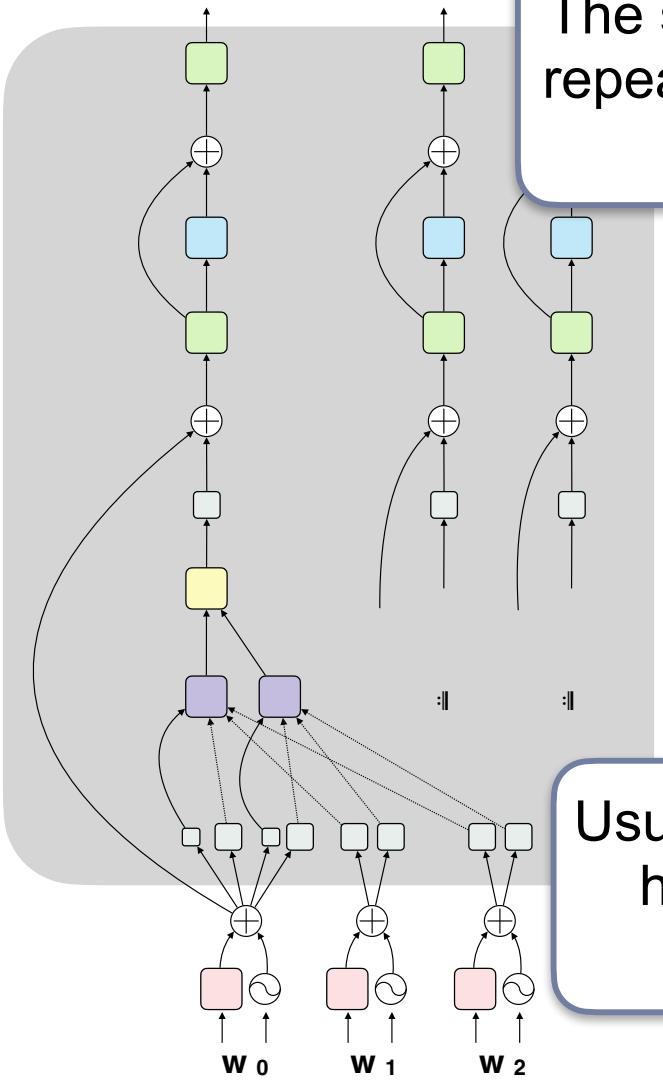
This is the Transformer encoder! (Almost)



The shaded area is repeated in a stack, 6 times

Usually more than 2 heads (original paper had 8)

Feed Forward
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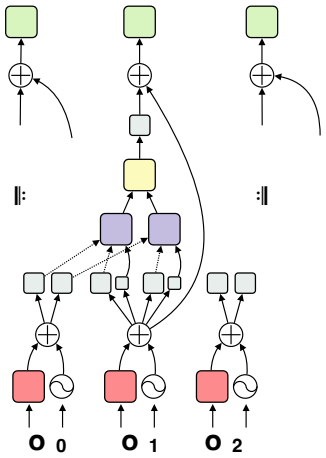
What about the decoder?

Start the same as the encoder, except attention does not apply to the future



Softmax

Feed Forward

$$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$$

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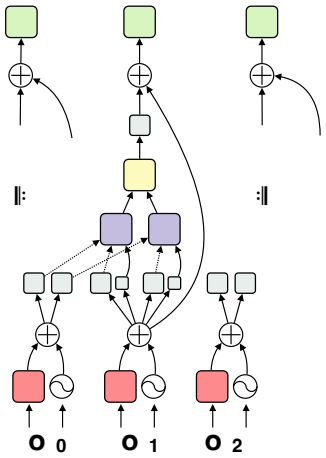
What about the decoder?

Provide encoder state using attention, also multi-head



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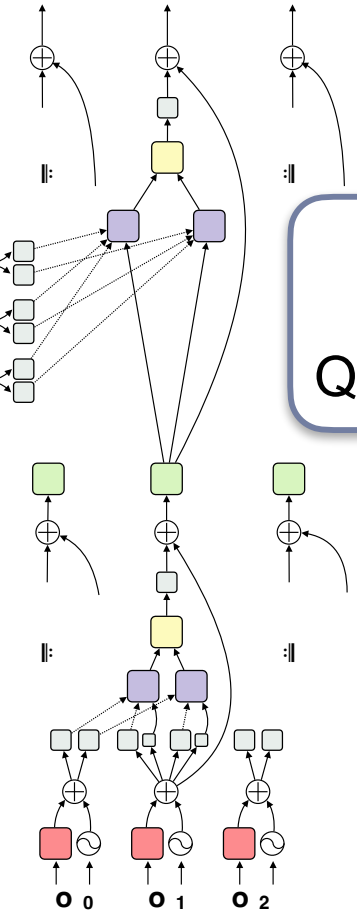
What about the decoder?

Provide encoder state using attention, also multi-head

Called ‘cross attention’ to distinguish it from ‘self attention’

Encoder

Input text



decoder

K and V come from encoder
Q comes from decoder

Softmax

Feed Forward

$$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$$

Layer Norm

Attention:

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Position as vector

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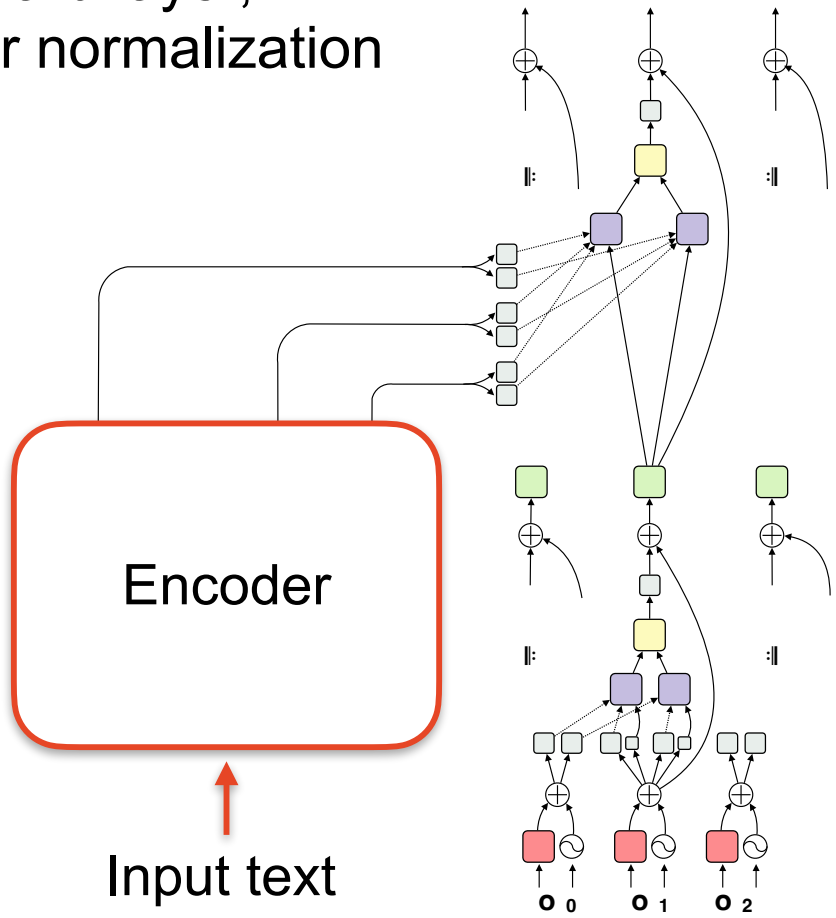
What about the decoder?

Add another feed forward layer, with layer normalization



Softmax

Feed Forward

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⊕ Element-wise sum

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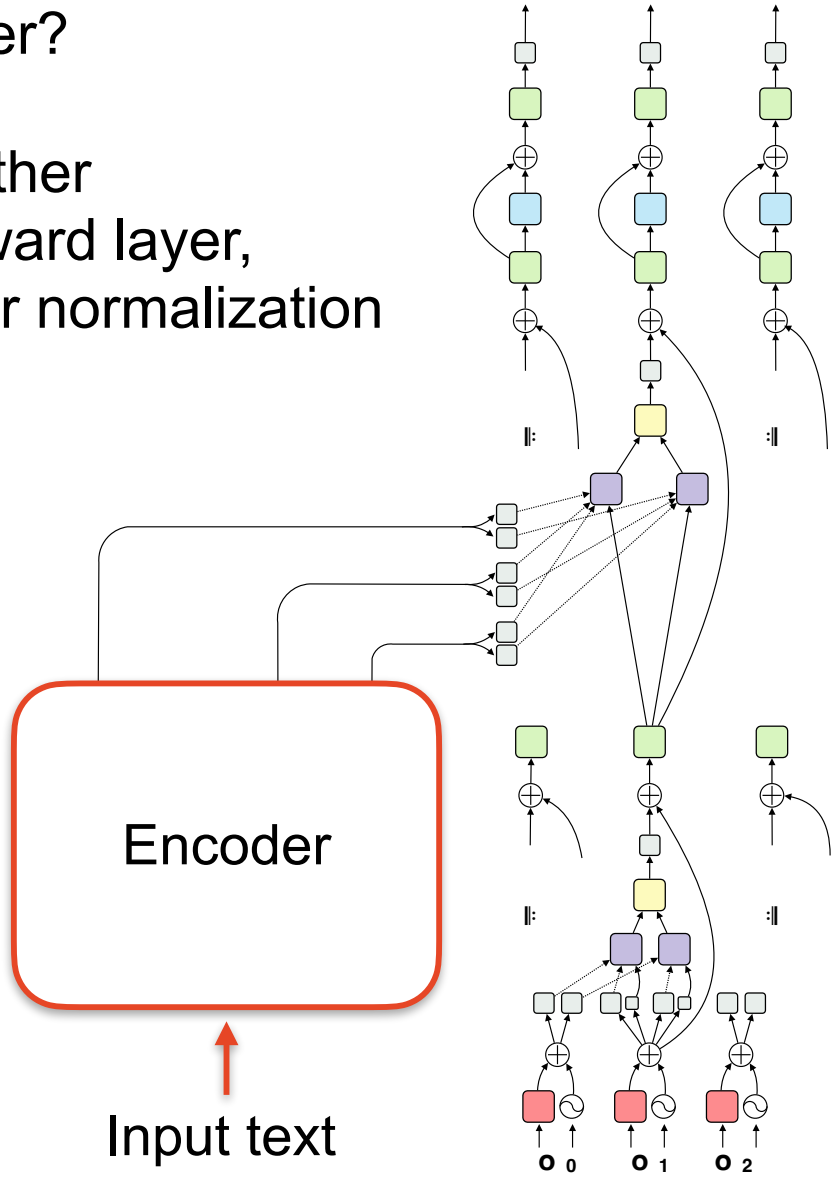

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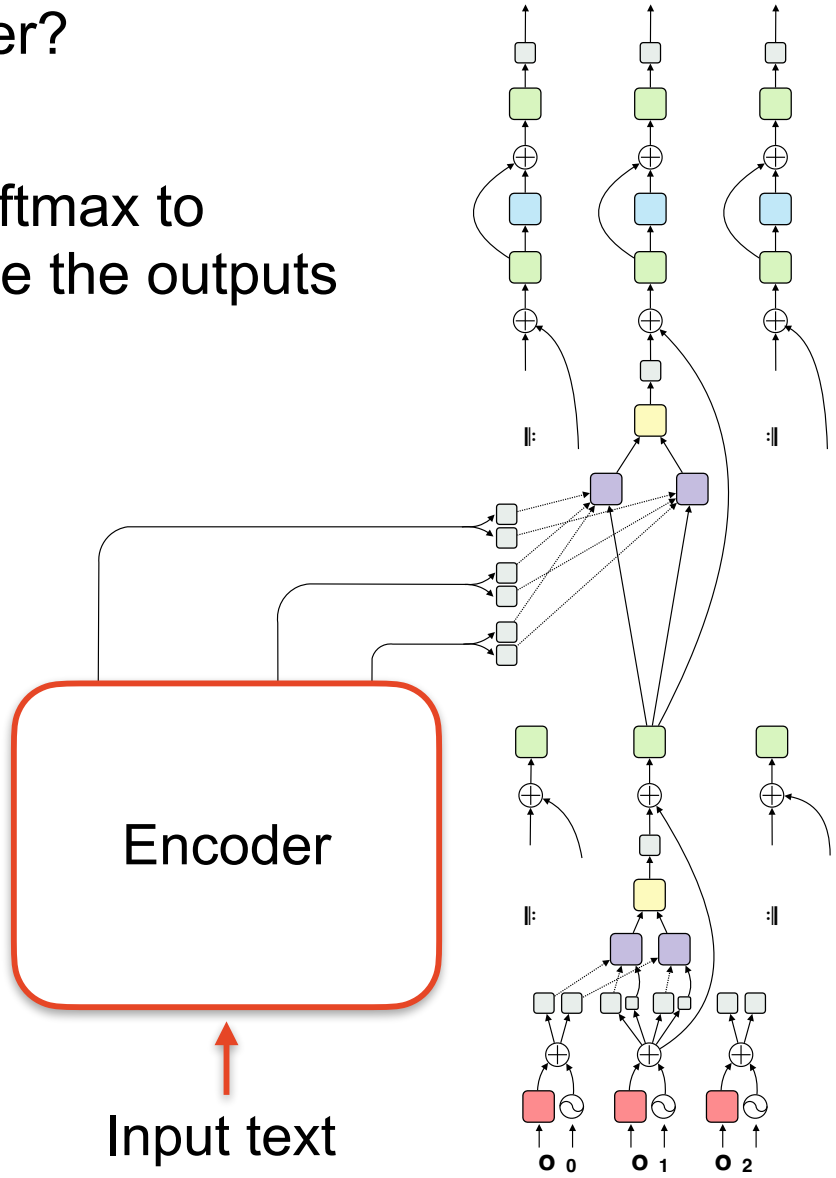
What about the decoder?

Apply softmax to determine the outputs



Softmax

Feed Forward

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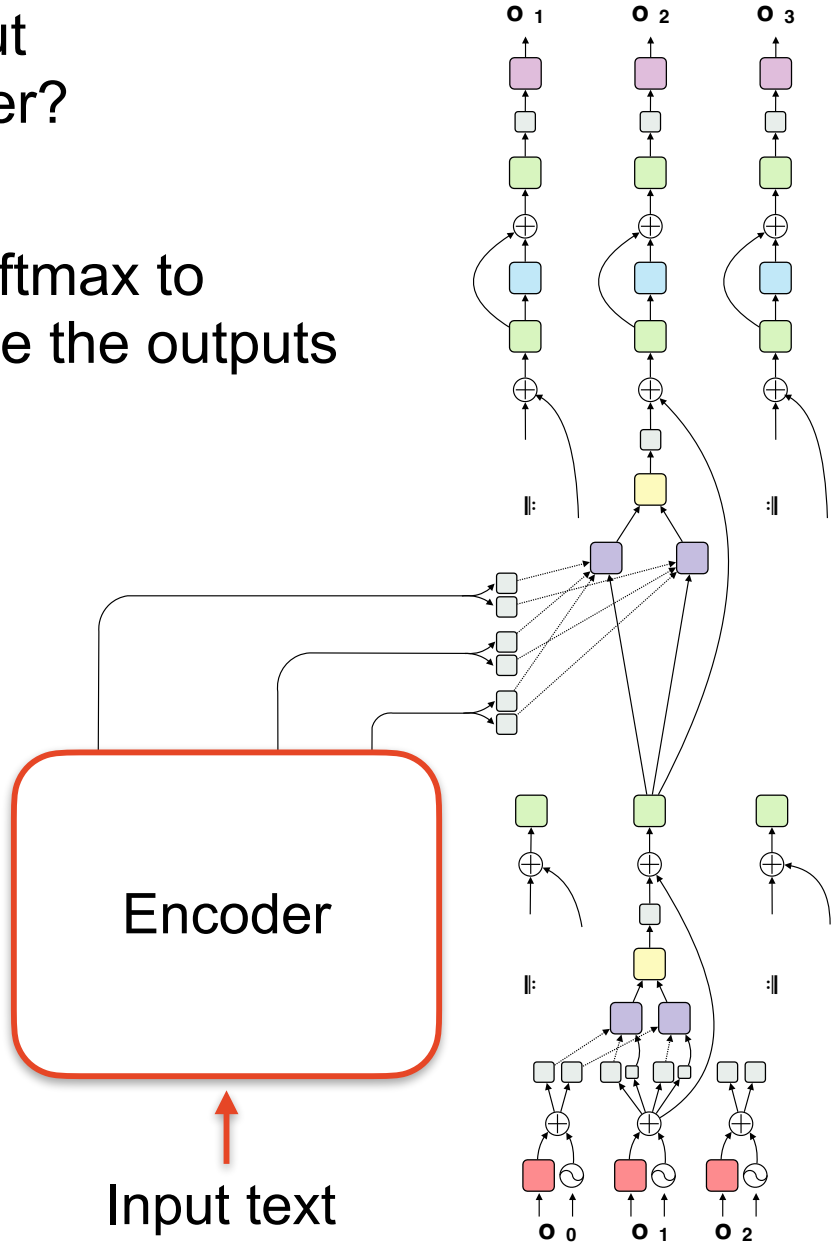

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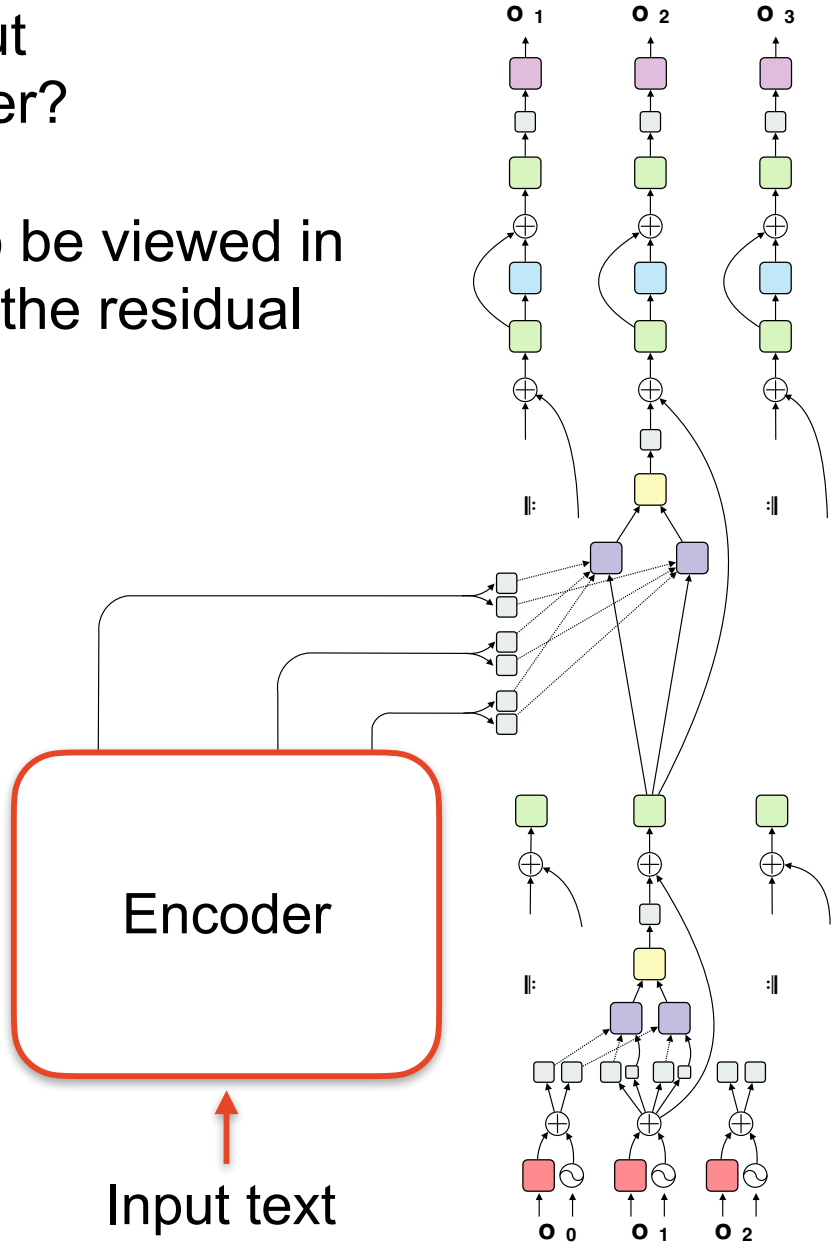
What about the decoder?

Can also be viewed in terms of the residual stream



Softmax

Feed Forward

$\max(\mathbf{0}, \mathbf{x}\mathbf{W_1} + \mathbf{b_1})\mathbf{W_2} + \mathbf{b_2}$

Layer Norm

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Concatenate

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Linear transform

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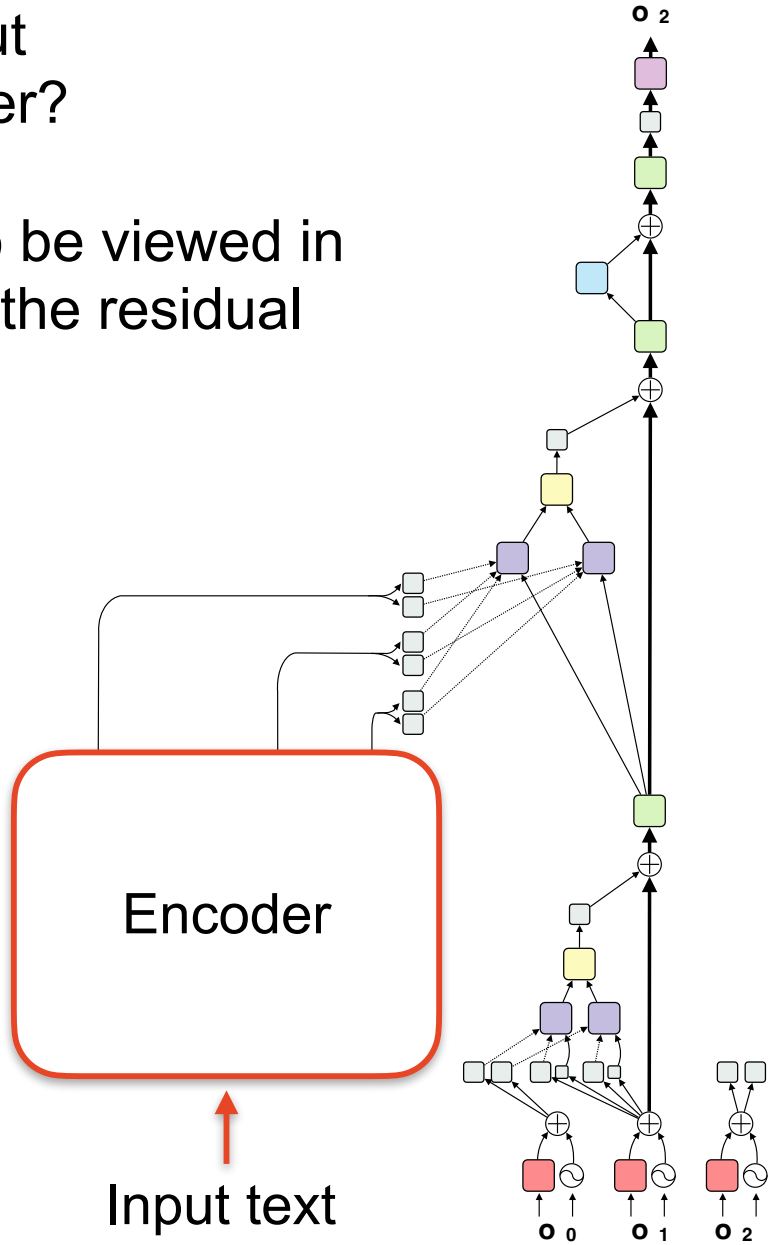

Softmax

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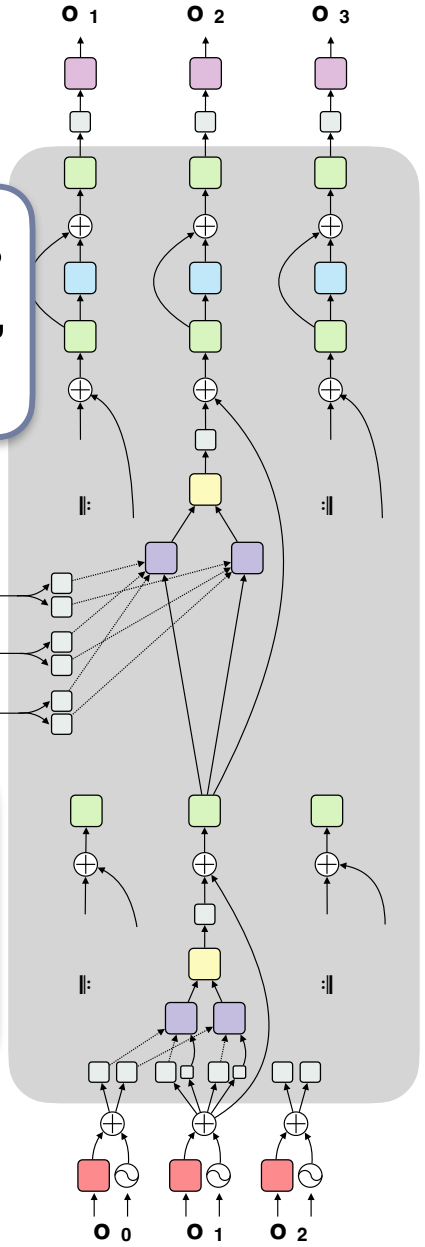
This is the Transformer decoder! (Almost)

The shaded area is repeated in a stack, 6 times

Usually more than 2 heads (original paper had 8)

Encoder

Input text



Softmax

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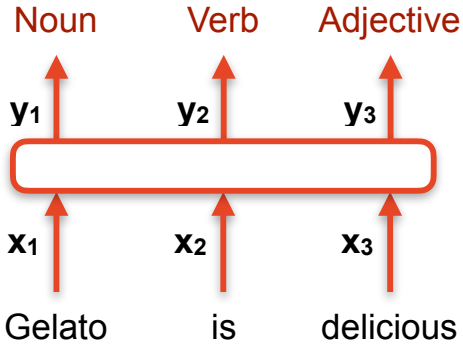
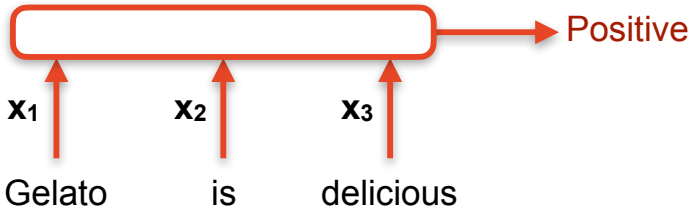
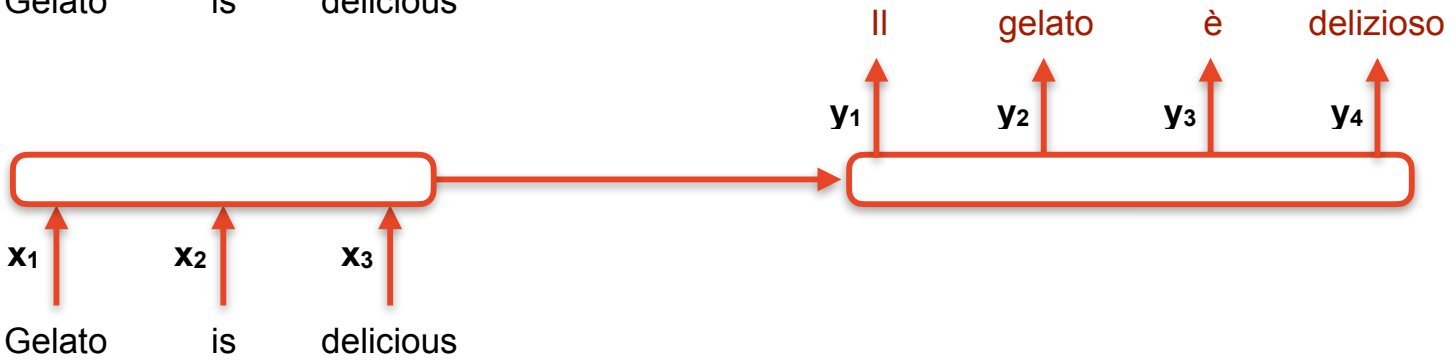
How do we use this? - Just like the RNN encoder-decoders



Or use it to create contextual word representations that go into another model





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Initial results showed slight accuracy gains, big efficiency gains

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	**$3.3 \cdot 10^{18}$**	
Transformer (big)	**28.4**	**41.8**	$2.3 \cdot 10^{19}$	

Vaswani, et al., (NeurIPS 2017)

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Over time, transformer models came to be dominant

Summarisation (Lin, et. al., ICLR 2018)

Model	Test perplexity	ROUGE-L
seq2seq-attention, $L = 500$	5.04952	12.7
Transformer-ED, $L = 500$	2.46645	34.2
Transformer-D, $L = 4000$	2.22216	33.6
Transformer-DMCA, no MoE-layer, $L = 11000$	2.05159	36.2
Transformer-DMCA, MoE-128, $L = 11000$	1.92871	37.9
Transformer-DMCA, MoE-256, $L = 7500$	1.90325	38.8

GLUE Benchmark - a range of tasks (Devlin, et. al., NAACL 2019)

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7
BiLSTM+ELMo	.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8
OpenAI GPT	.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4
$\text{BERT}_{\text{LARGE}}$	**.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**

GPT 1

BERT

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BERT

include

WordPiece tokenisation (last lecture)
+
Transformer architecture (this lecture)
+
Data
=
High performance!

This was the moment when training large models became out of reach for most university research labs

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Faster training means they can scale

Original paper (2017)

	N	d_{model}	d_{ff}	h	d_k	d_v
base	6	512	2048	8	64	64

GPT-3 (2020)

Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}
GPT-3 Small	125M	12	768	12	64
GPT-3 Medium	350M	24	1024	16	64
GPT-3 Large	760M	24	1536	16	96
GPT-3 XL	1.3B	24	2048	24	128
GPT-3 2.7B	2.7B	32	2560	32	80
GPT-3 6.7B	6.7B	32	4096	32	128
GPT-3 13B	13.0B	40	5140	40	128
GPT-3 175B or “GPT-3”	175.0B	96	12288	96	128

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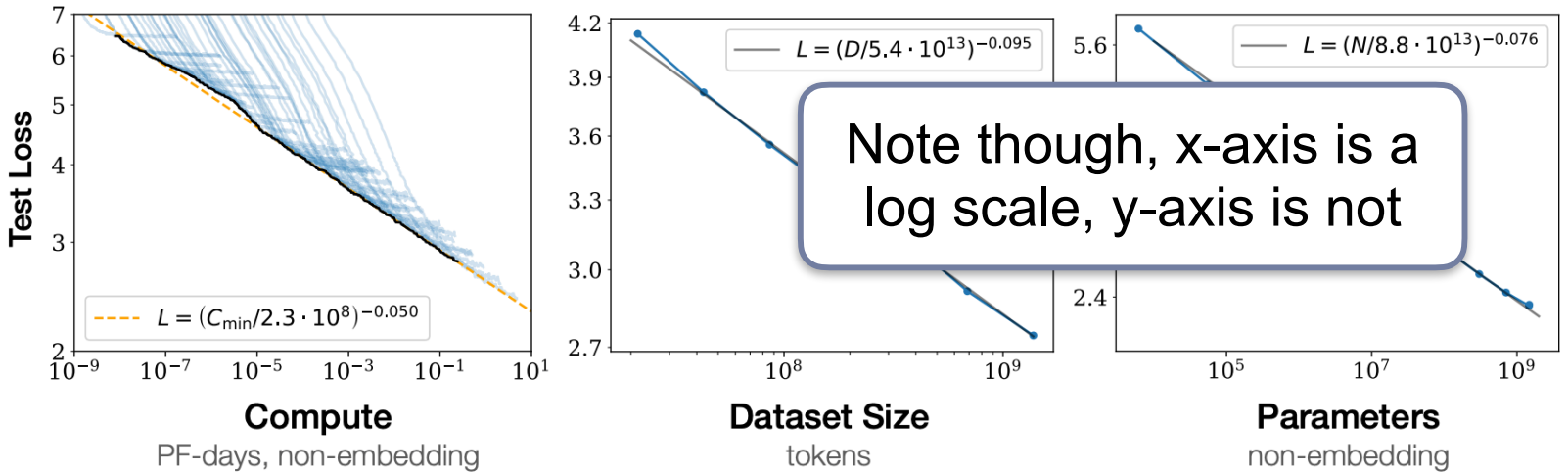
They scale very well to more compute, data, and parameters



Note though, x-axis is a log scale, y-axis is not

This is where 'scaling laws' come from - methods to estimate the best model size given a certain amount of data and a budget for training

Kaplan, et al., (arXiv 2020)

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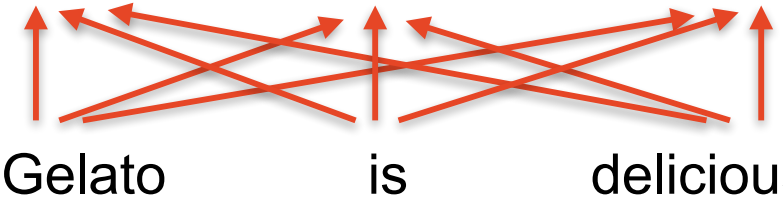
But, attention is quadratic, will that be an issue?



Lots of clever variants to avoid it!
- PerFormer
- LongFormer
- LinFormer

But… it turns out that the bigger issue is memory bandwidth

Most notable improvement - FlashAttention

Feedforward computation dominates as model size increases

3 minute Break - stretch and visit Menti

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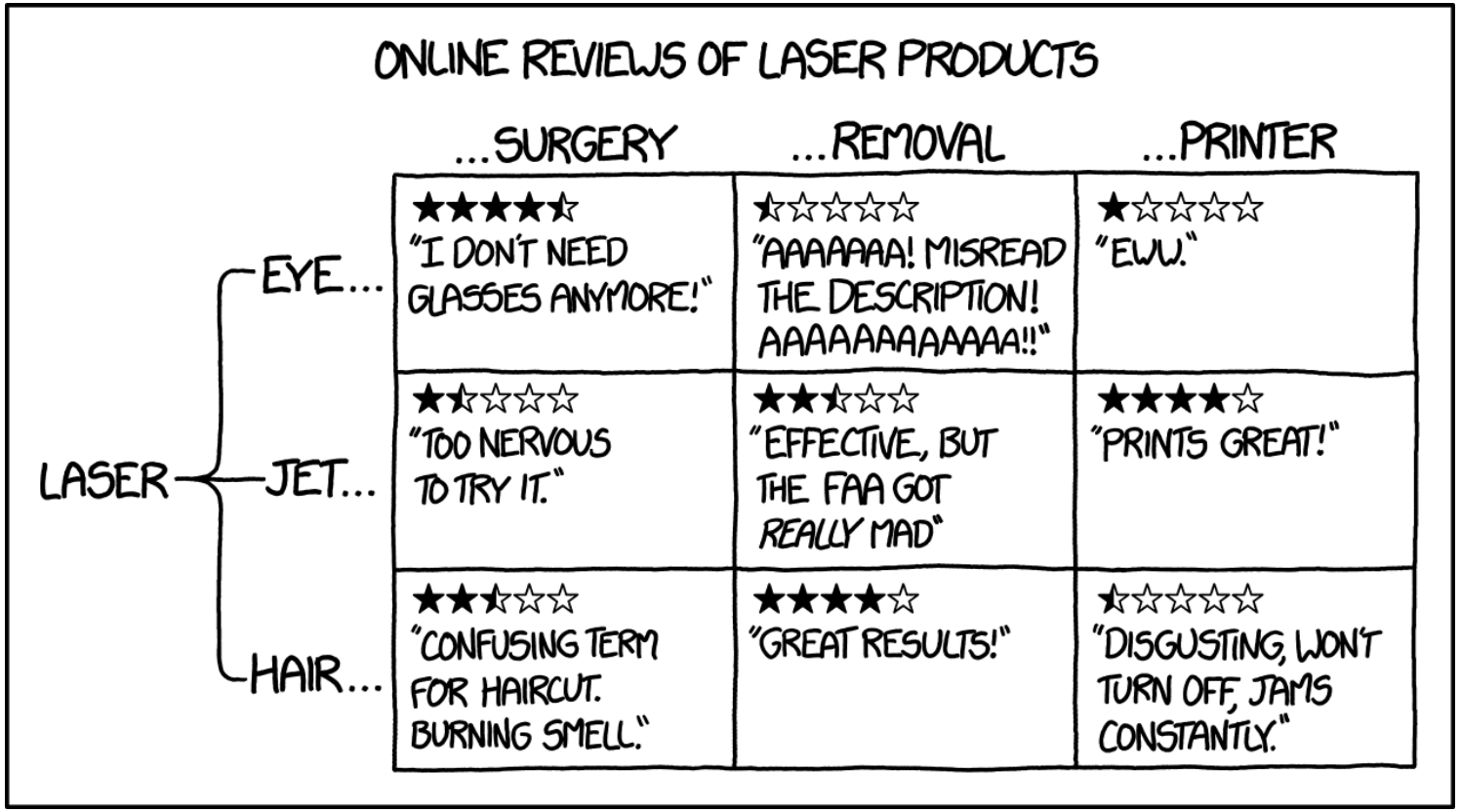
Laser Products



[ERRORS: HAIR JAM. COLOR-SAFE CONDITIONER CARTRIDGE RUNNING LOW. LEGAL-SIZE HAIR TRAY EMPTY, USING LETTER-SIZE HAIR ONLY.]

Source: https://xkcd.com/1681/

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Lab Preview

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1. multiple stack : better performance, more scenario?

2. mask purpose

HuggingFace!

3. rotary positional embedding

Mid-semester survey

https://forms.office.com/r/4aHbx4U4mY

All questions optional

I will read (manually - no AI!) and report back results + my plans in response

Muddy Card

https://saipll.shinyapps.io/student-interface/

If you do not wish to participate in the study, use the Ed form instead

Go to Ed → Lessons → Muddy Cards Lecture 7