Advanced NLP

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LayerNorm

https://arxiv.org/abs/1607.06450

also see: https://arxiv.org/abs/1911.07013

$$\mathbf{x} = (x_1, x_2, \ldots, x_H)$$

$$\mu = \frac{1}{H}\sum_{i=1}^{H} x_i \qquad \sigma^2 = \frac{1}{H}\sum_{i=1}^{H} (x_i - \mu)^2$$

$$N(\mathbf{x}) = \frac{\mathbf{x} - \mu}{\sigma + \epsilon}$$

ϵ avoids div by zero

$$\mathbf{h} = \mathbf{g} \cdot N(\mathbf{x}) + \mathbf{b}$$

g and **b** are hyperparameters with dimension H

In PyTorch

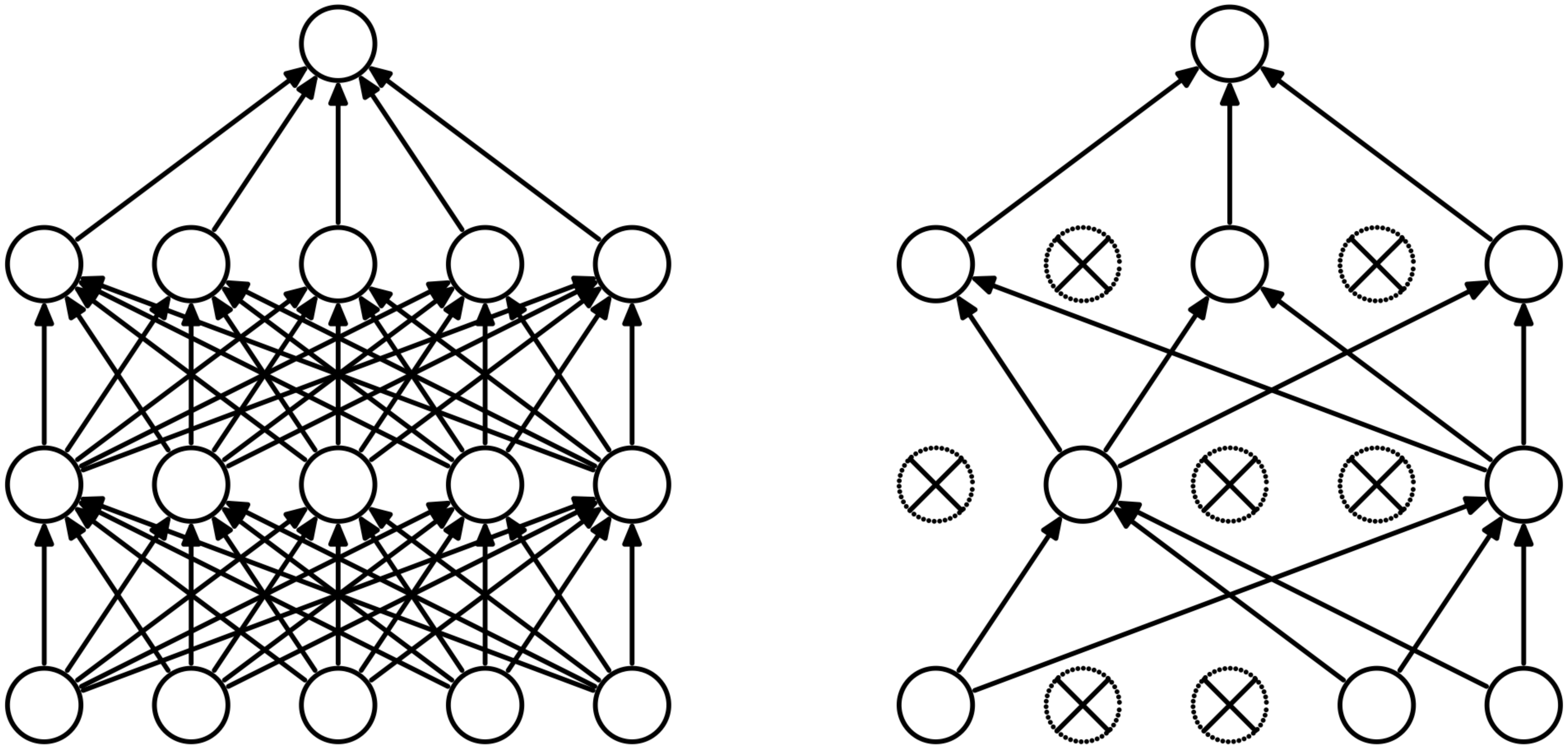
```
>>> # NLP Example
>>> batch, sentence_length, embedding_dim = 20, 5, 10
>>> embedding = torch.randn(batch, sentence_length, embedding_dim)
>>> layer_norm = nn.LayerNorm(embedding_dim)
>>> # Activate module
>>> layer_norm(embedding)
```

Dropout

https://jmlr.org/papers/v15/srivastava14a.html

https://arxiv.org/abs/1207.0580

aka how to train 2^n neural networks when it has n units



(a) Standard Neural Net (b) After applying dropout.

Before dropout

$$
\begin{aligned}
z_i^{(l+1)} &= \mathbf{w}_i^{(l+1)} \mathbf{y}^l + b_i^{(l+1)}, \\
y_i^{(l+1)} &= f(z_i^{(l+1)}),
\end{aligned}
$$

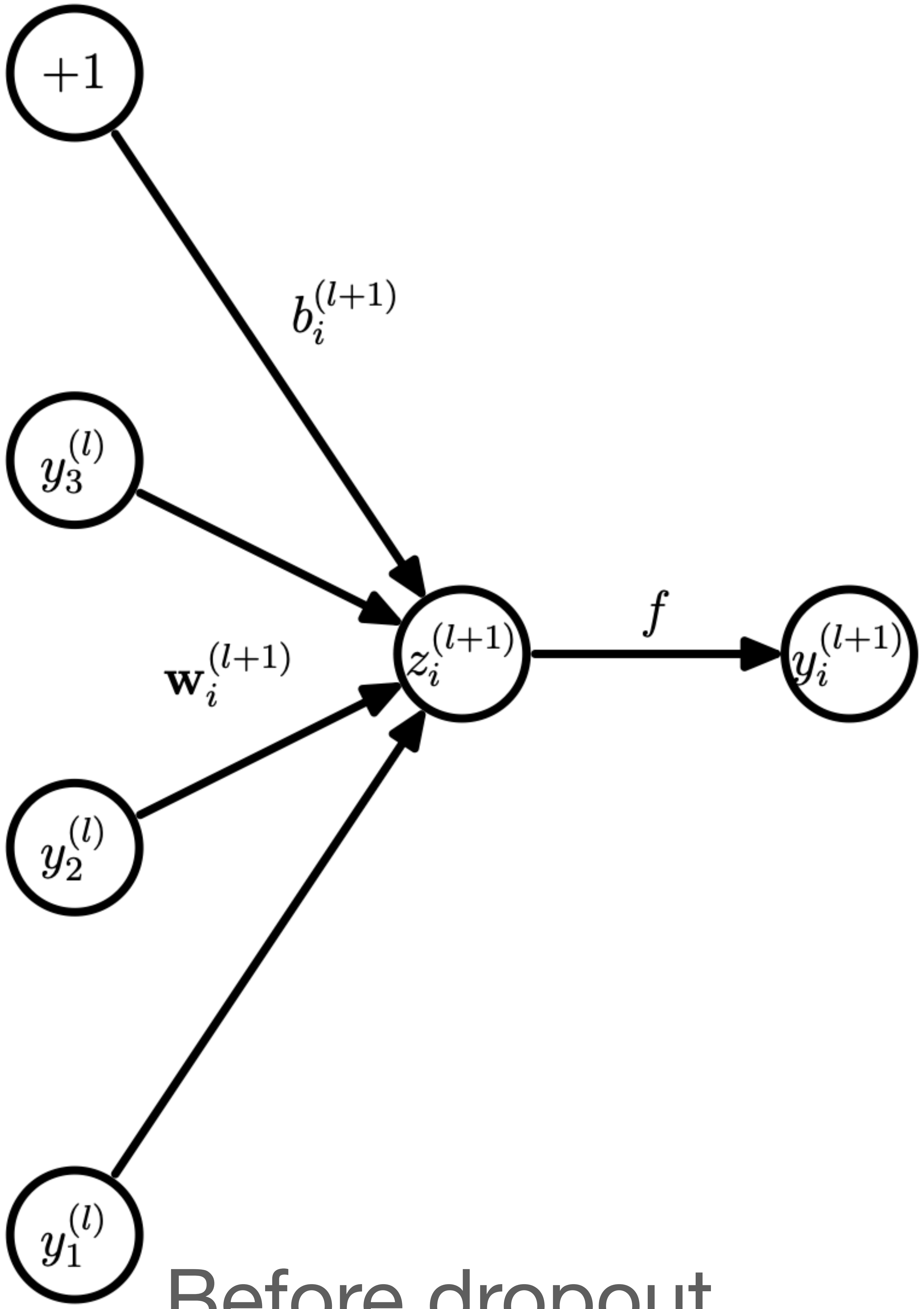
After dropout

$$
\begin{aligned}
r_j^{(l)} &\sim \mathrm{Bernoulli}(p), \\
\widetilde{\mathbf{y}}^{(l)} &= \mathbf{r}^{(l)} * \mathbf{y}^{(l)}, \\
z_i^{(l+1)} &= \mathbf{w}_i^{(l+1)} \widetilde{\mathbf{y}}^l + b_i^{(l+1)}, \\
y_i^{(l+1)} &= f(z_i^{(l+1)}).
\end{aligned}
$$

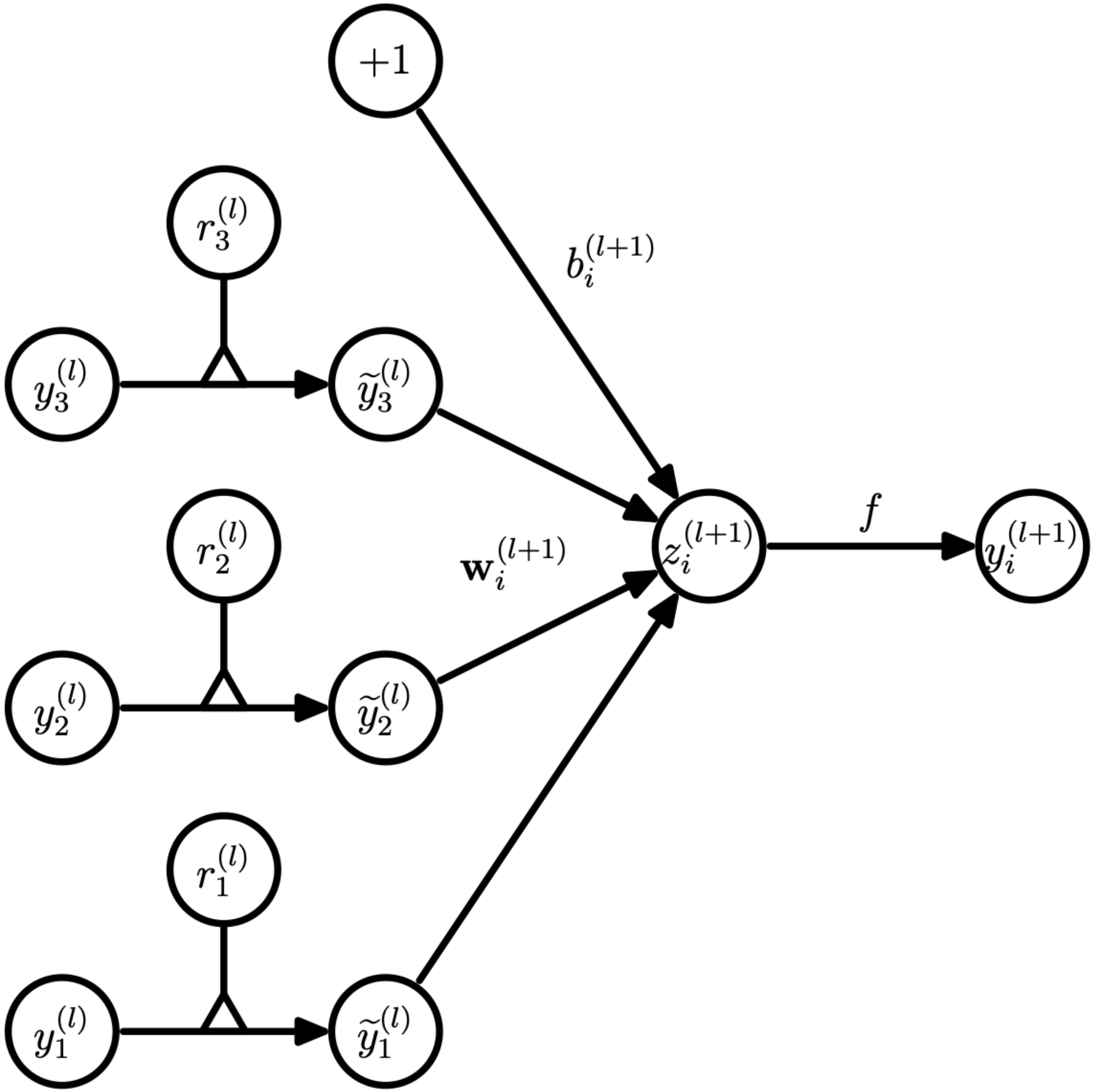
In PyTorch

```
>>> m = nn.Dropout(p=0.2)
>>> input = torch.randn(20, 16)
>>> output = m(input)
```

default: 0.5



Before dropout



After dropout

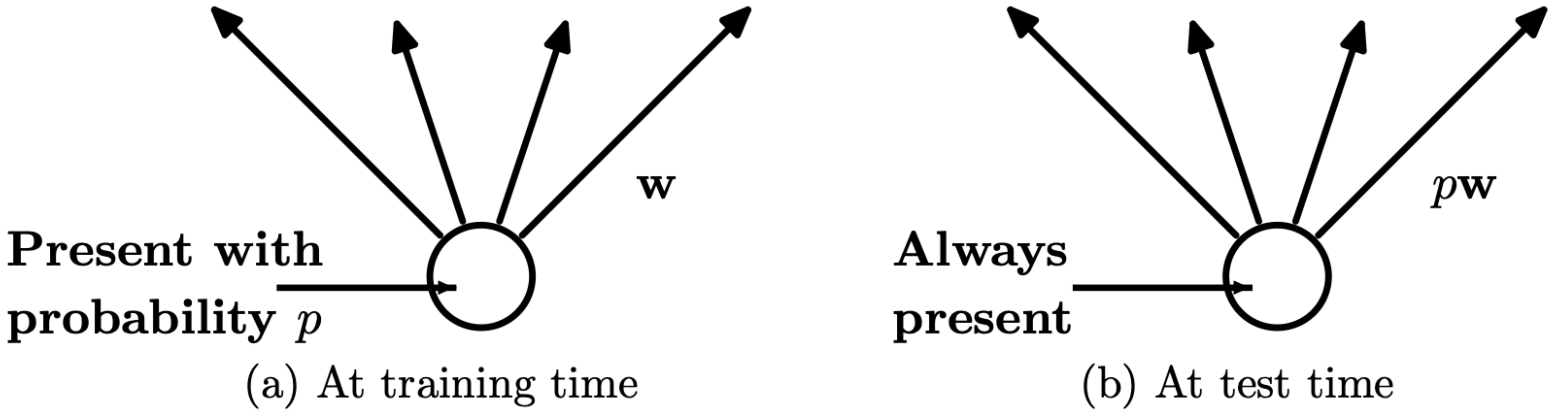


Figure 2: **Left**: A unit at training time that is present with probability p and is connected to units in the next layer with weights **w**. **Right**: At test time, the unit is always present and the weights are multiplied by p. The output at test time is same as the expected output at training time.

In Pytorch the outputs are scaled by a factor of $\frac{1}{1-p}$ during training so at inference/test/evaluation time the dropout function simply computes the identity function

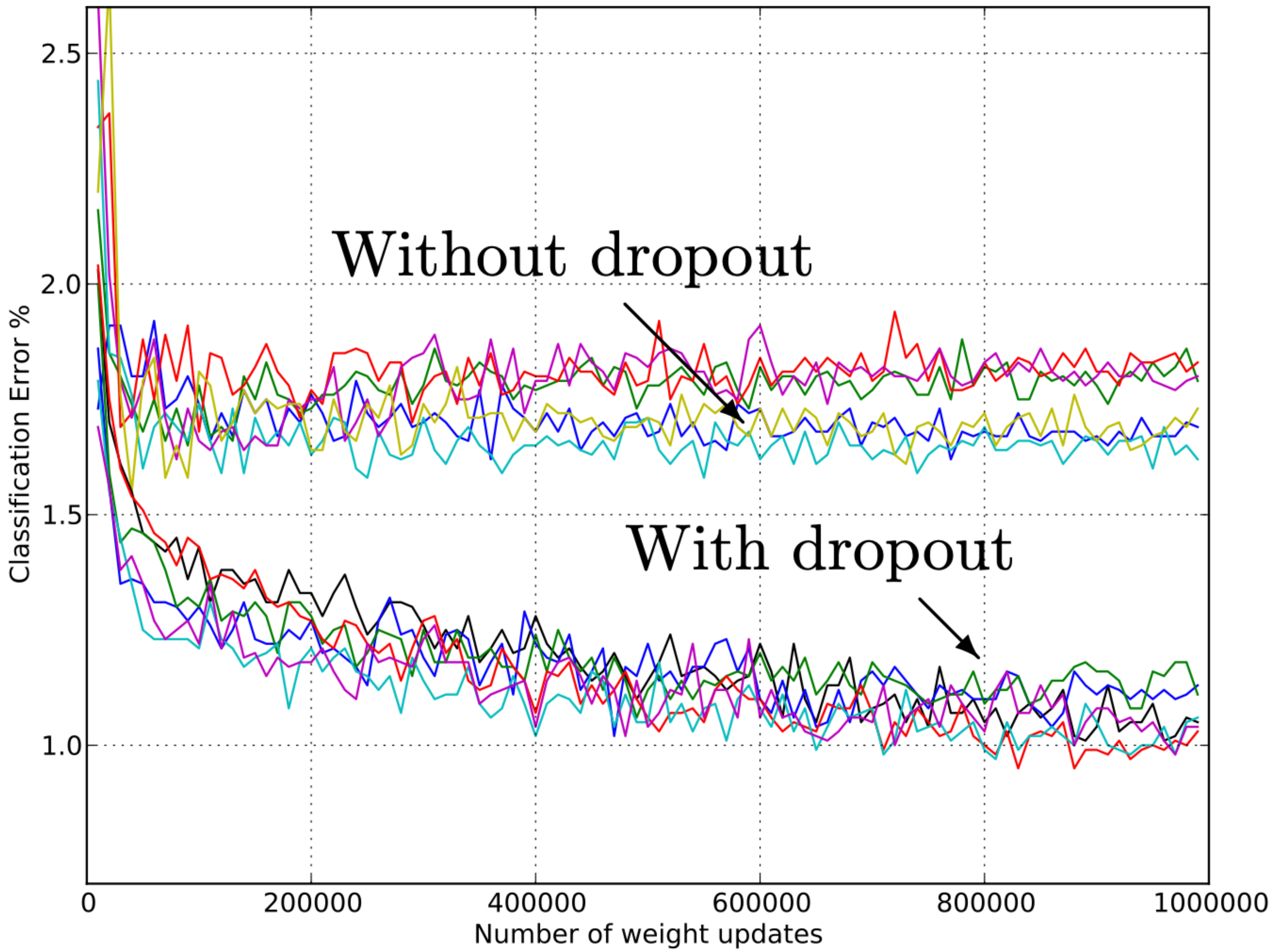
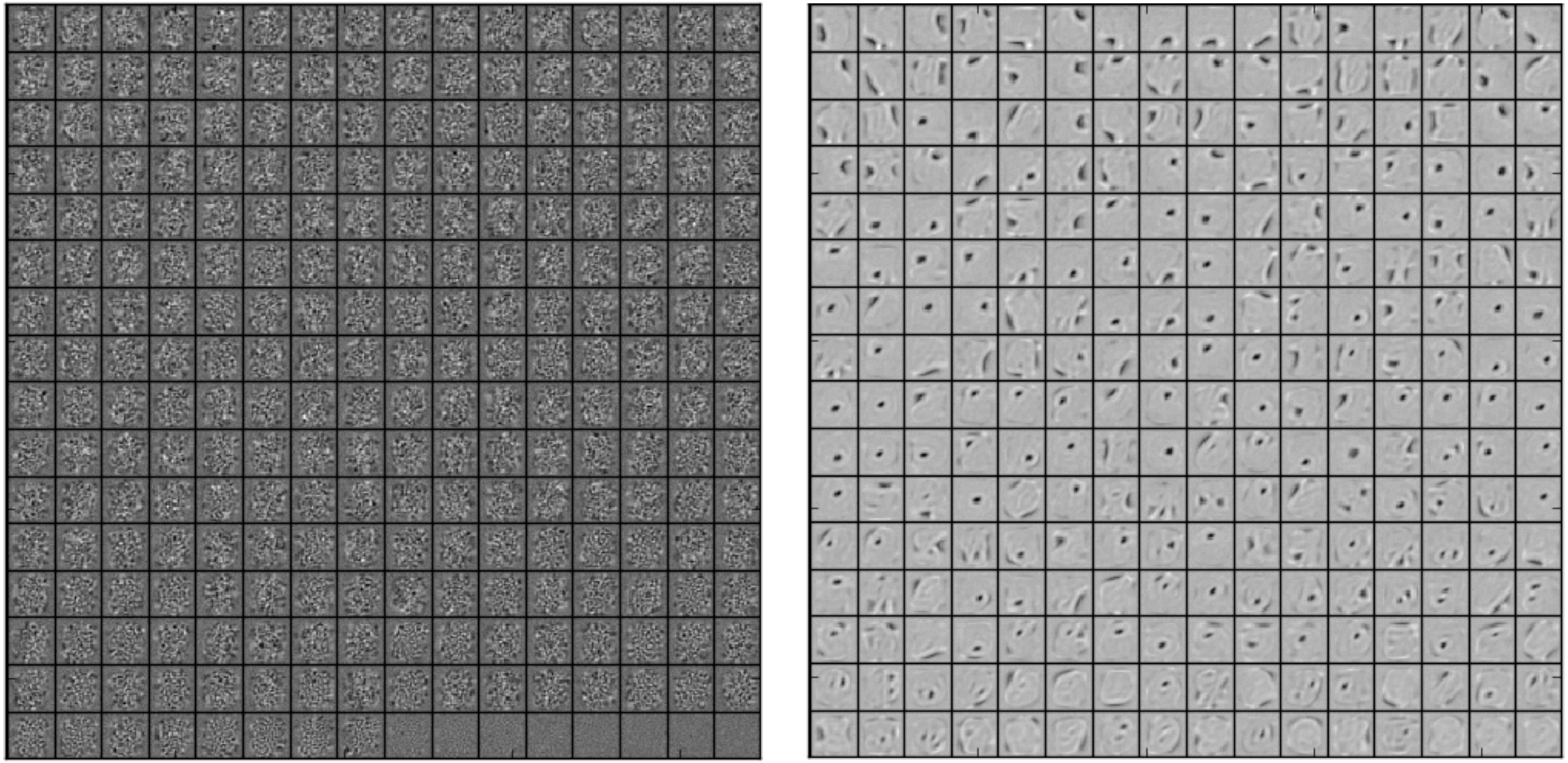


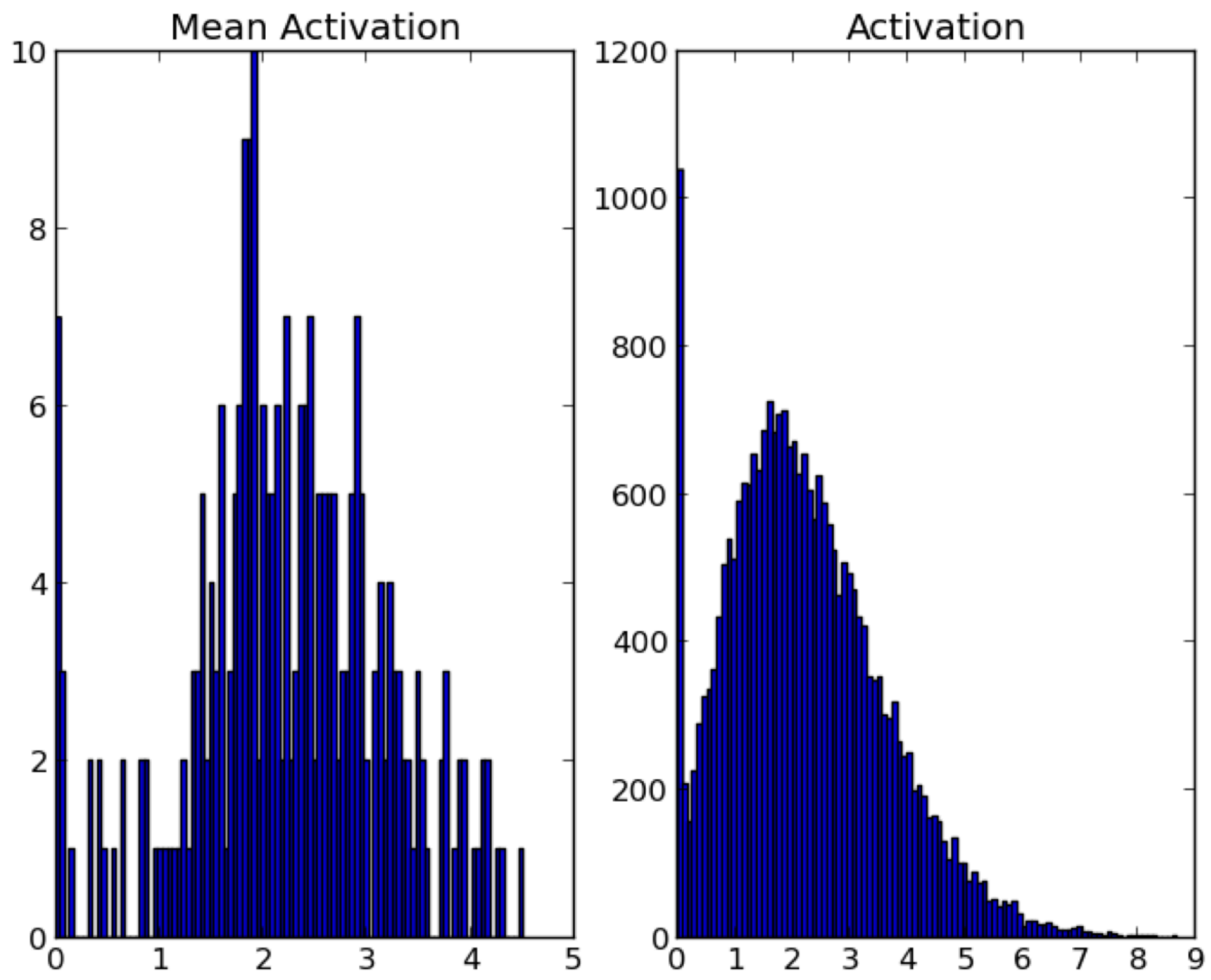
Figure 4: Test error for different architectures with and without dropout. The networks have 2 to 4 hidden layers each with 1024 to 2048 units.



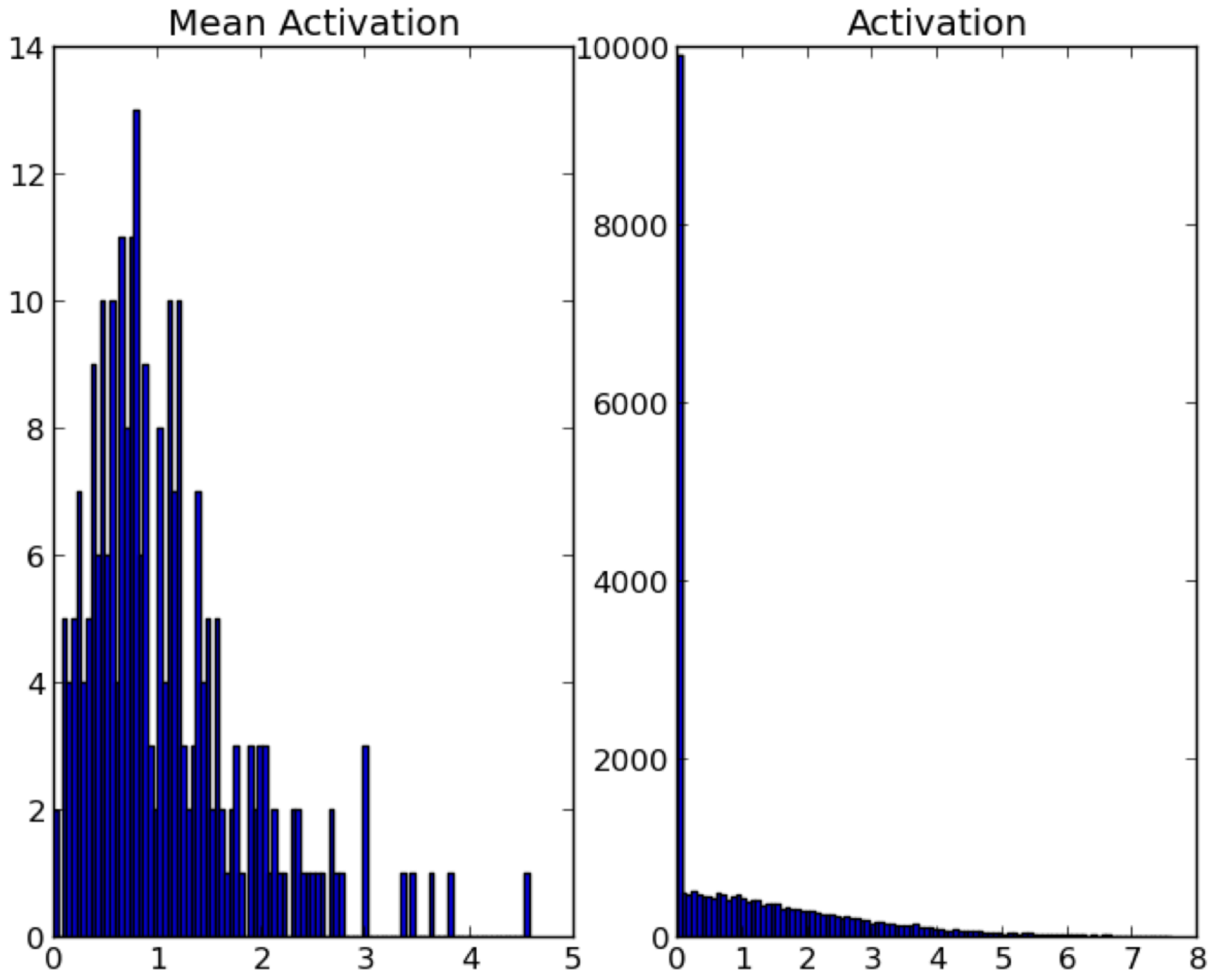
(a) Without dropout

(b) Dropout with $p = 0.5$.

Figure 7: Features learned on MNIST with one hidden layer autoencoders having 256 rectified linear units.



(a) Without dropout



(b) Dropout with $p = 0.5$.

Figure 8: Effect of dropout on sparsity. ReLUs were used for both models. **Left**: The histogram of mean activations shows that most units have a mean activation of about 2.0. The histogram of activations shows a huge mode away from zero. Clearly, a large fraction of units have high activation. **Right**: The histogram of mean activations shows that most units have a smaller mean mean activation of about 0.7. The histogram of activations shows a sharp peak at zero. Very few units have high activation.

Attention Is All You Need

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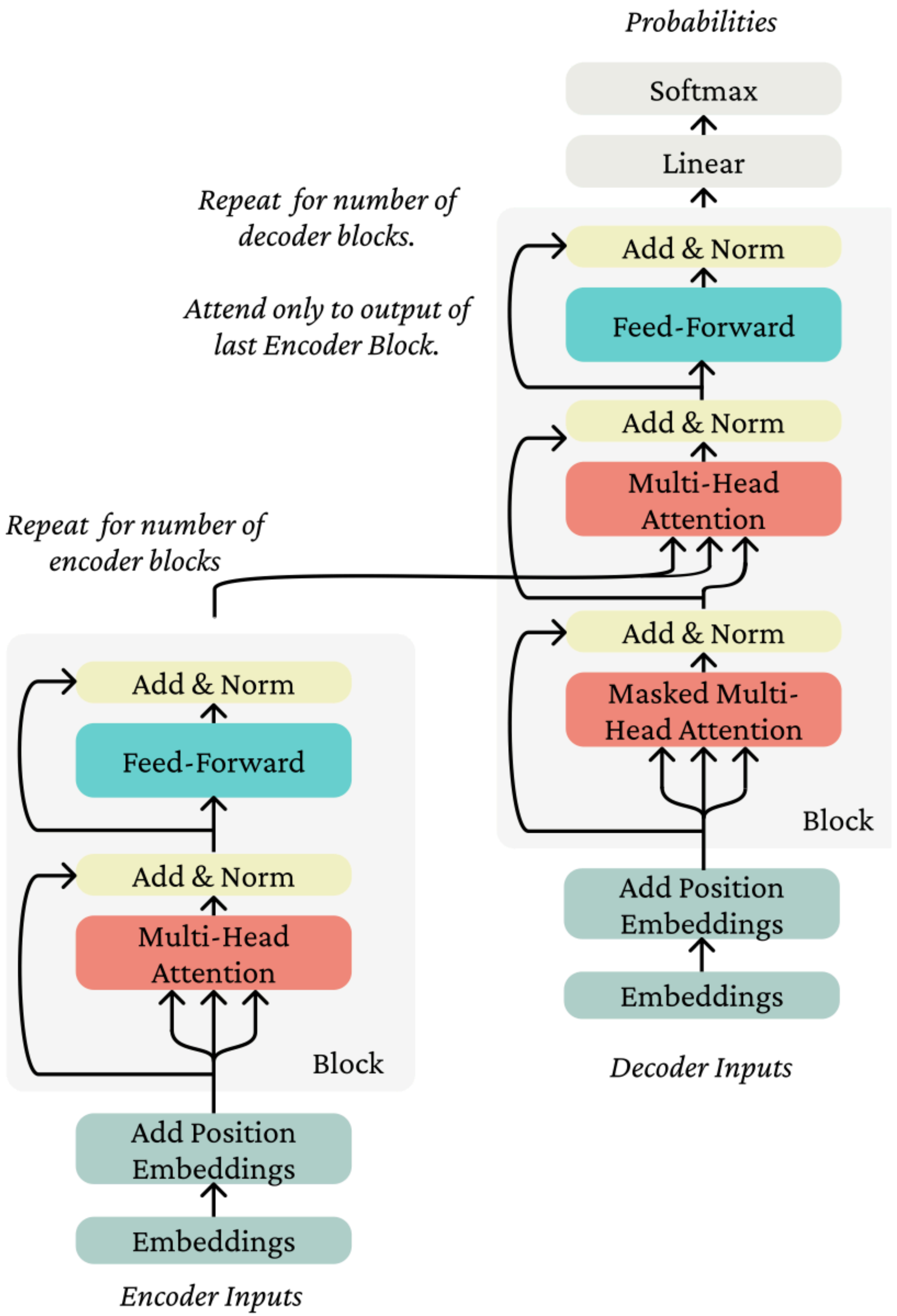
https://arxiv.org/abs/1409.0473

NIPS (2017)



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Transformer Encoder-Decoder

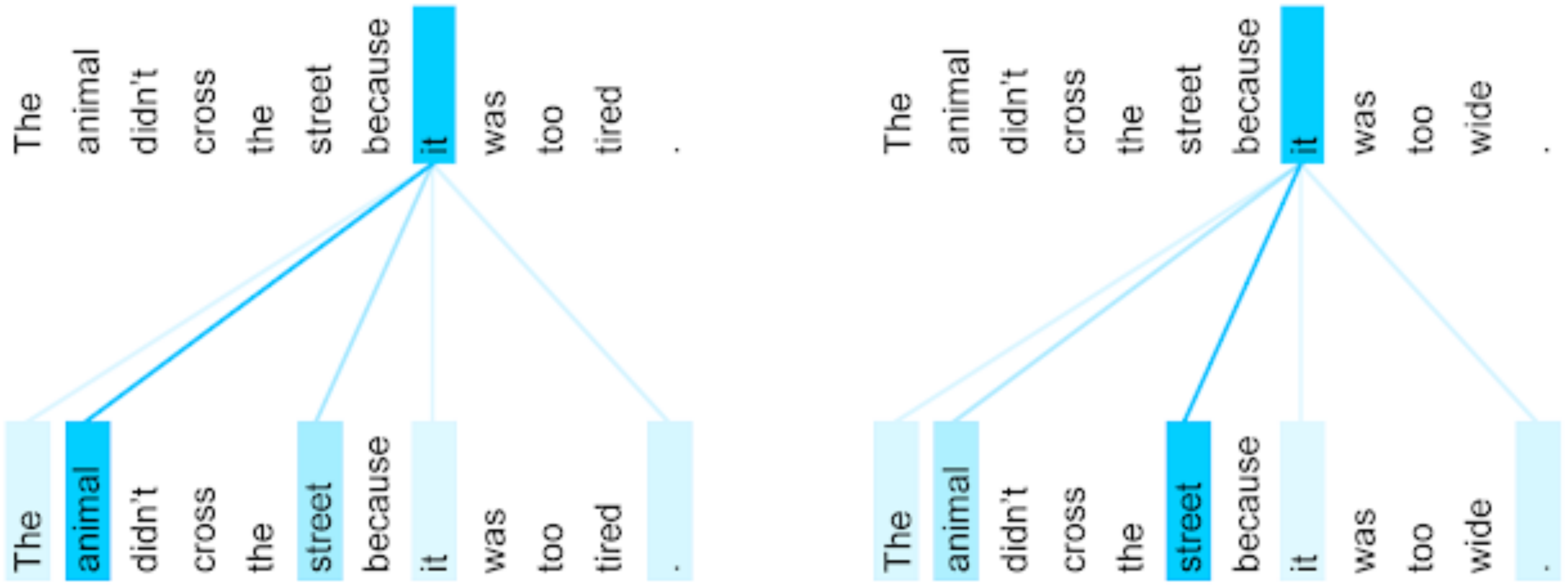
https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

The animal didn't cross the street because it was too tired.
L'animal n'a pas traversé la rue parce qu'il était trop fatigué.

The animal didn't cross the street because it was too wide.
L'animal n'a pas traversé la rue parce qu'elle était trop large.

the translation for “it” depends on the gender of the noun it refers to - and in French “animal” and “street” have different genders

https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html



The encoder self-attention distribution for the word "it" from the 5th to the 6th layer of a Transformer trained on English to French translation (one of eight attention heads).

https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

Self Attention

- Take a query vector (based on one token)
- Do a "**soft lookup**" in a key-value store; **pick up** the key **most like** the query and return the value vector
- "**pick up**" = return the average value based on a probability distribution
- "**most like**" = higher probability for a key means it is **more like** the query
- "**more like**" = dot product e.g.
- In *self attention* we use the same tokens for queries, keys and values

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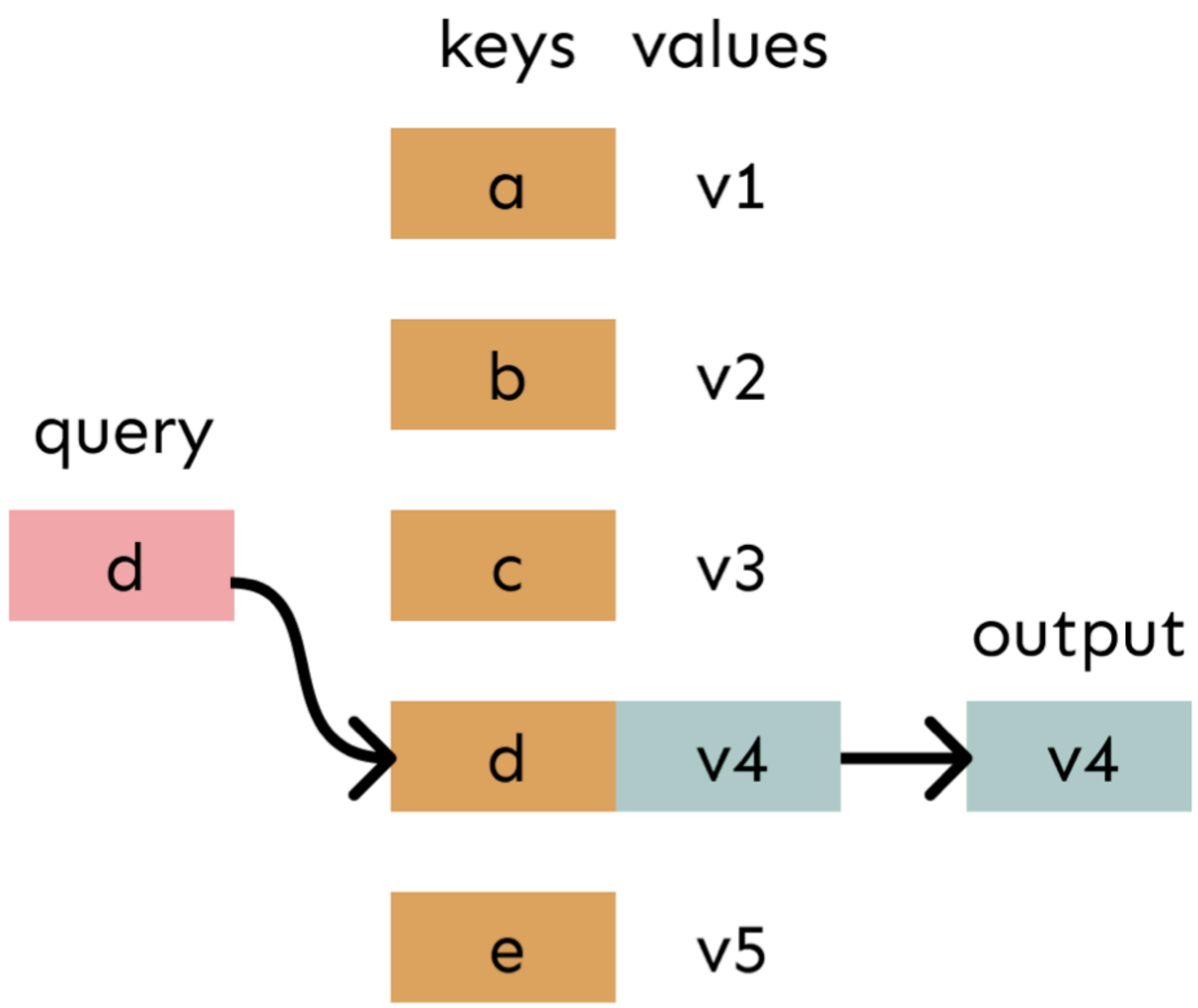
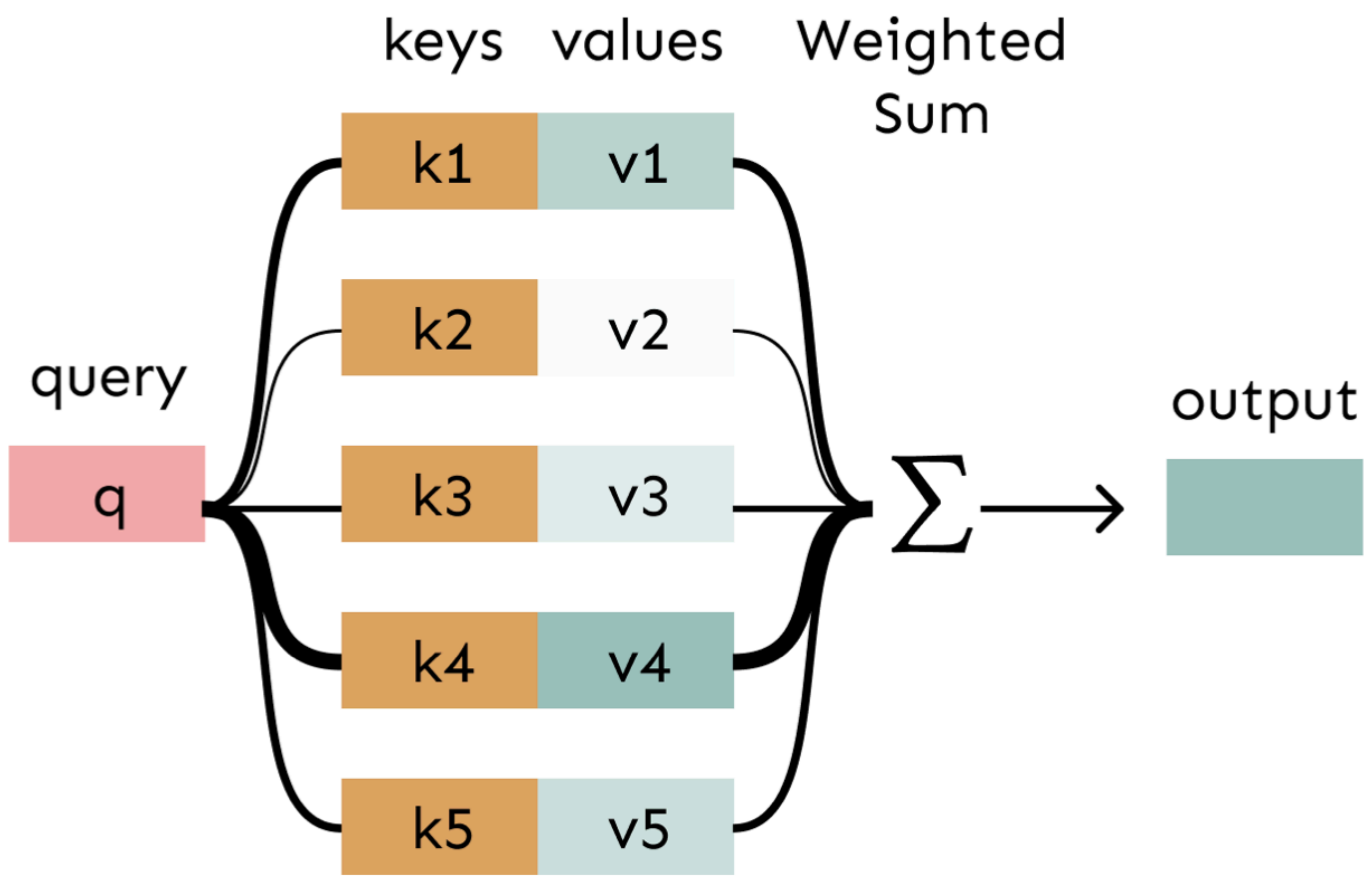


Standard key-value lookup



Self attention key-value lookup

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Self Attention

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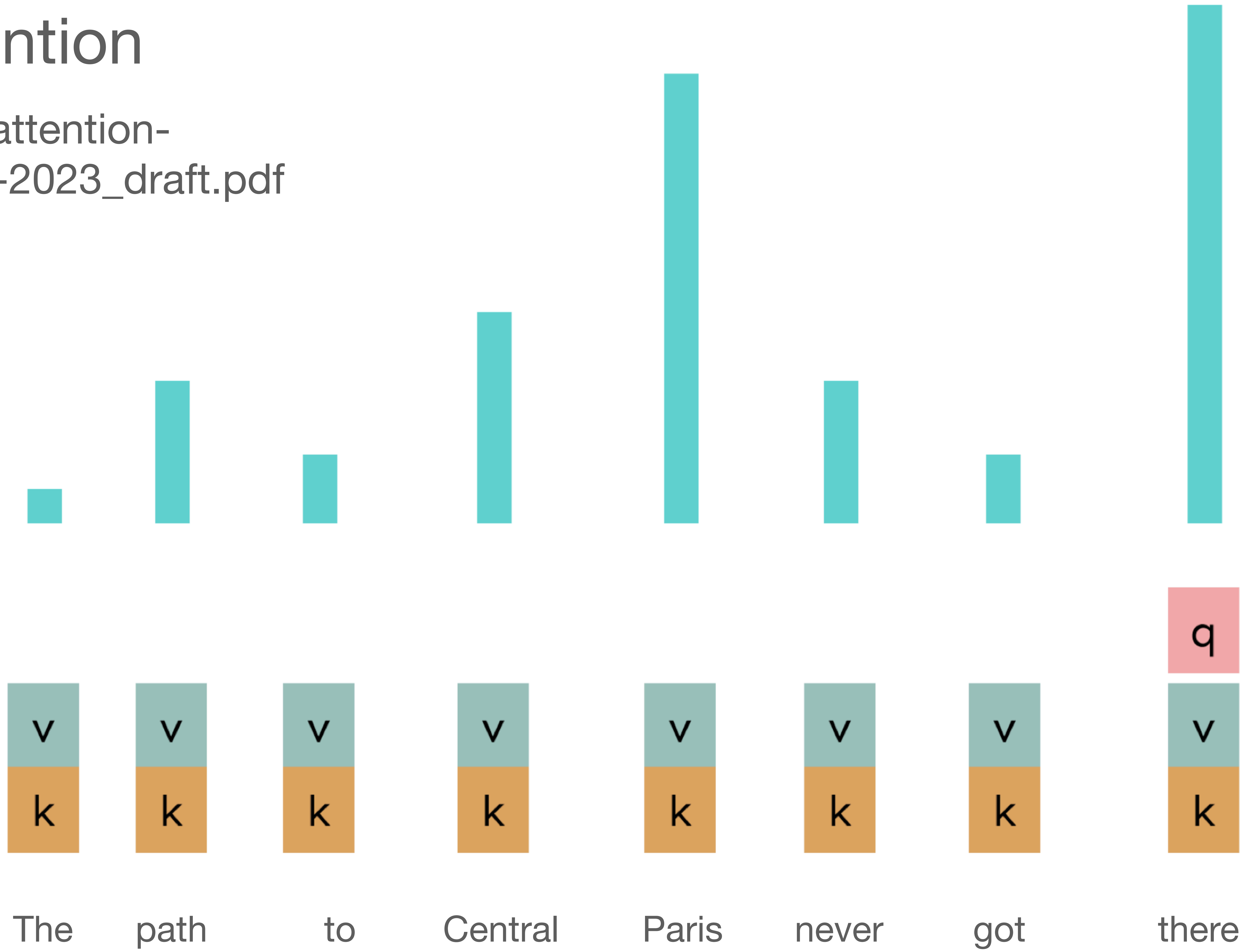

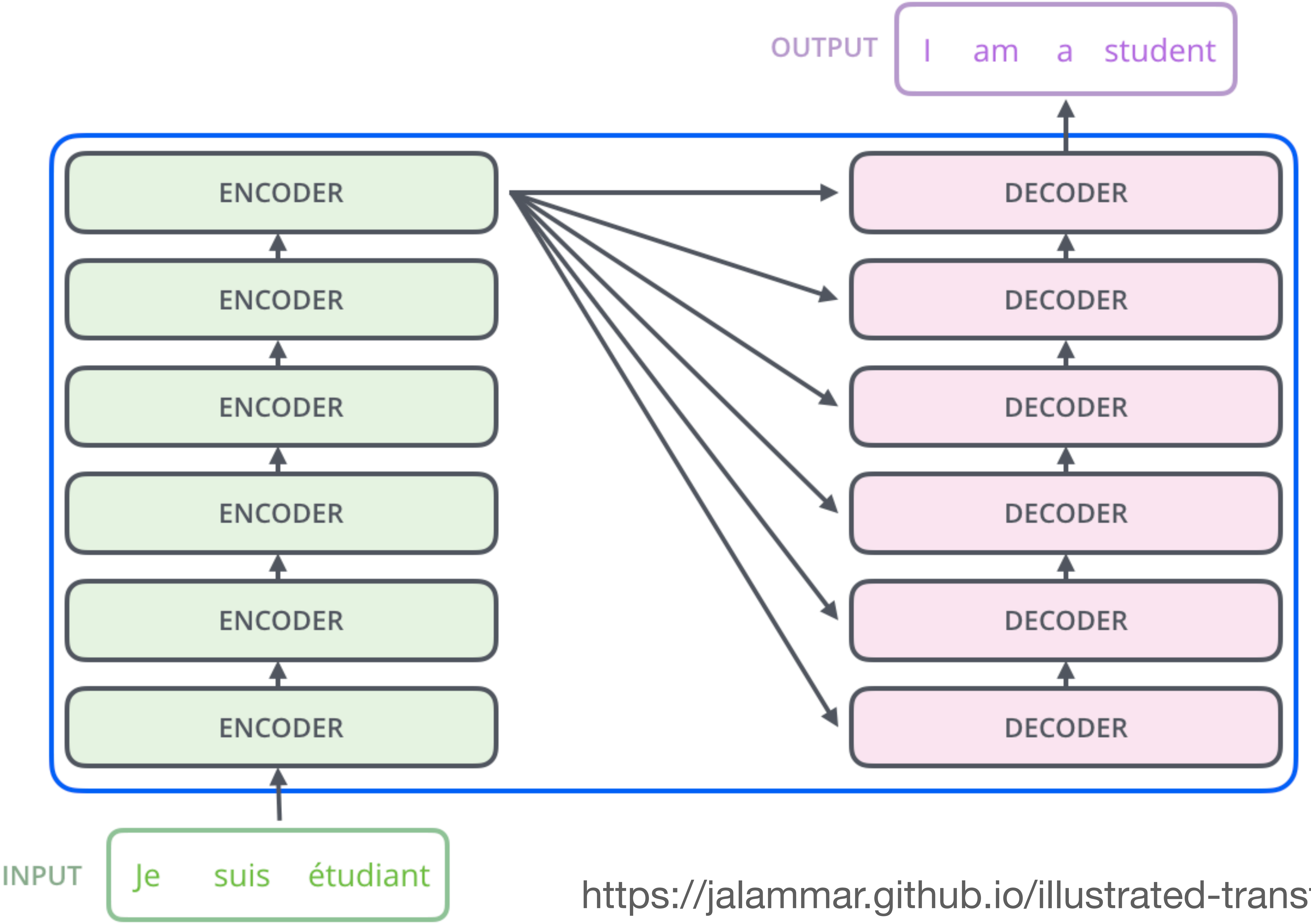

https://jalammar.github.io/illustrated-transformer/

Self-attention

keys, queries and values from the same sequence

- Let $\mathbf{w} = (w_1, \ldots, w_n)$ be a sequence of tokens, like "Cuba is the capital of"
- For each w_i let $\mathbf{x}_i = E\mathbf{w}_i$ where $E \in \mathbb{R}^{d \times |V|}$ is an embedding matrix. V is the vocabulary.
- Let Q, K, V be matrices in $\mathbb{R}^{d \times d}$
  - $\mathbf{q}_i = Q\mathbf{x}_i$
  - $\mathbf{k}_i = K\mathbf{x}_i$
  - $\mathbf{v}_i = V\mathbf{x}_i$

Output for each word is a weighted sum of values:

$$\mathbf{o}_i = \sum_j \text{softmax}_j(\mathbf{q}_i^T \mathbf{k}_j) \cdot \mathbf{v}_i$$

Self Attention: Three Problems

Problem	Solution
Encoder and decoder has no inherent notion of ordering. It's just a bag of words.	Add position representations to each token
Just a weighted average of a vector. No non-linearities.	Apply feedforward network to each self attention output
Decoder should not look into the future while training the predictor.	Mask out the future by setting attention weights to zero.

Self-attention

Fixing the sequence order problem

- We need to encode the order of the tokens in a sentence in the keys, values and queries
- We want a position embedding (similar to a word embedding)
- Let $\mathbf{p}_i \in \mathbb{R}^d$ for $i \in 1,\ldots,n$ be the position embeddings
- If $\mathbf{x}_i$ is the embedding for the word w_i then the combined word plus position embedding is $\tilde{\mathbf{x}}_i = \mathbf{x}_i + \mathbf{p}_i$
- Either concatenate $\mathbf{x}_i$ and $\mathbf{p}_i$ or just add them. Adding is more common.

Position embeddings without learning

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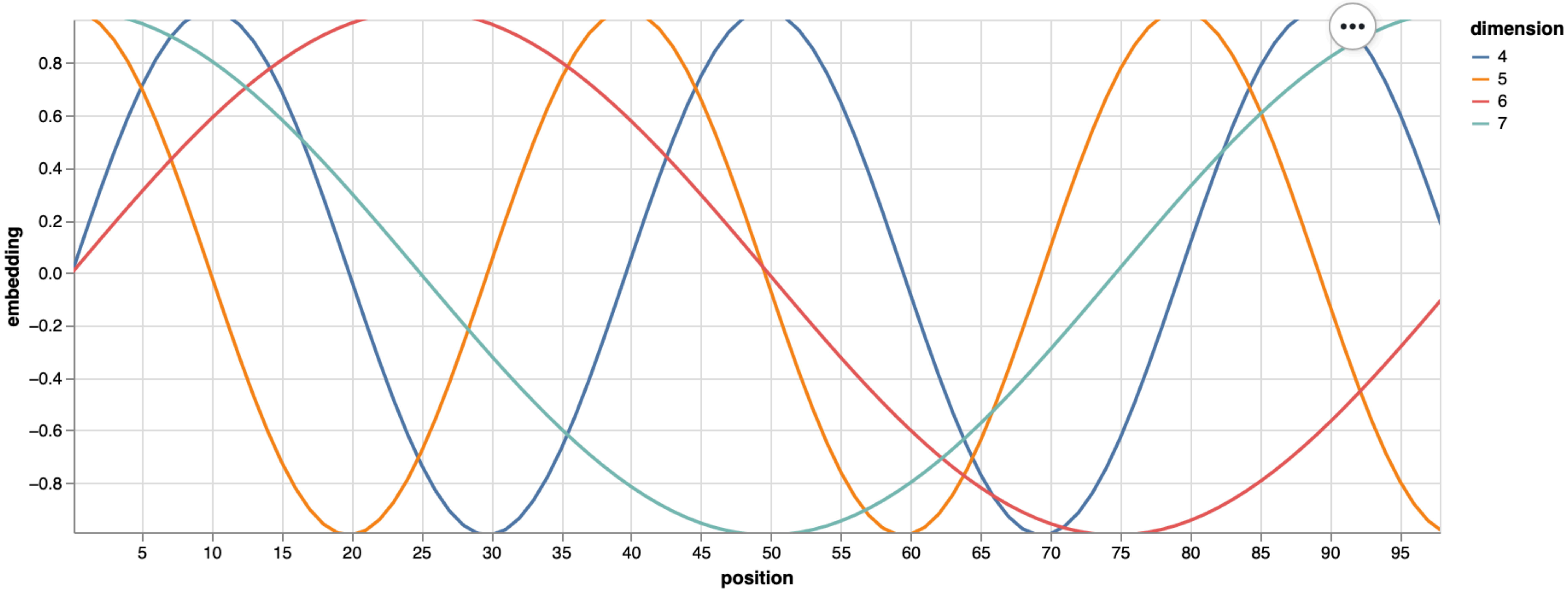
Use a periodic function like sine and cosine with different periods to get an embedding vector without any parameter updates.

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



http://nlp.seas.harvard.edu/annotated-transformer/#positional-encoding

Pros:

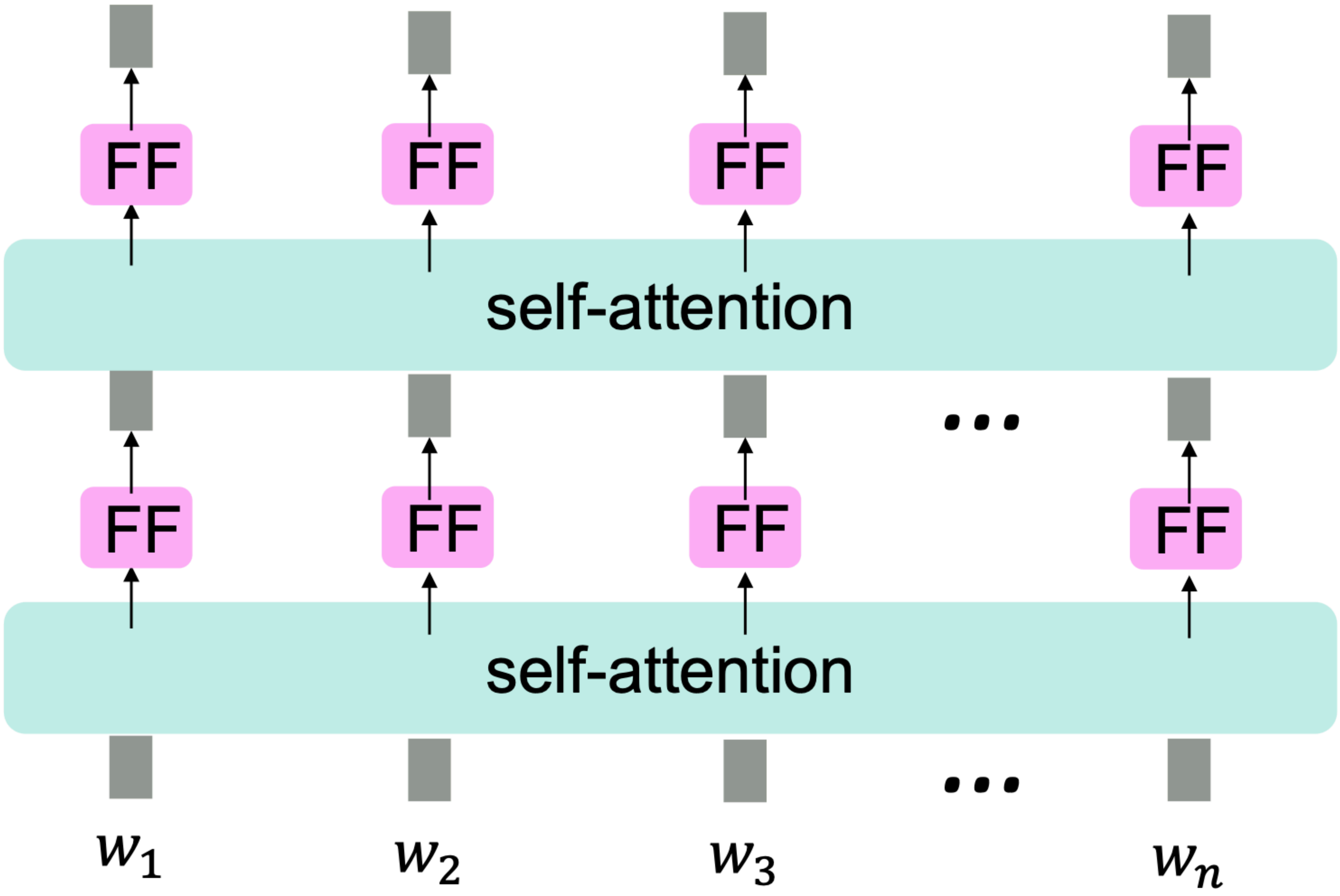
* Periodicity means absolute position is not important
* Can extrapolate to longer sequences as periods restart

Cons:

* Not learnable
* Extrapolation does not work that well for some applications

Self Attention Encoder using a Feed-forward Network

$$m_i = MLP(\mathrm{output}_i)$$
$$= W_2 * \mathrm{ReLU}(W_1\ \mathrm{output}_i + b_1) + b_2$$



Intuition: the feed-forward (FF) network processes the attention vector and makes it usable by the next layer

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Decoders should **not** see into the future

* During training we mask the attention vector by setting attention scores to $-\infty$
* During inference, we decode from left to right and use the output from previous time-step as input to the next

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

We can only look at the non-greyed out words in the attention vector

For encoding these words

	[START]	The	chef	who
[START]		$-\infty$	$-\infty$	$-\infty$
The			$-\infty$	$-\infty$
chef				$-\infty$
who				

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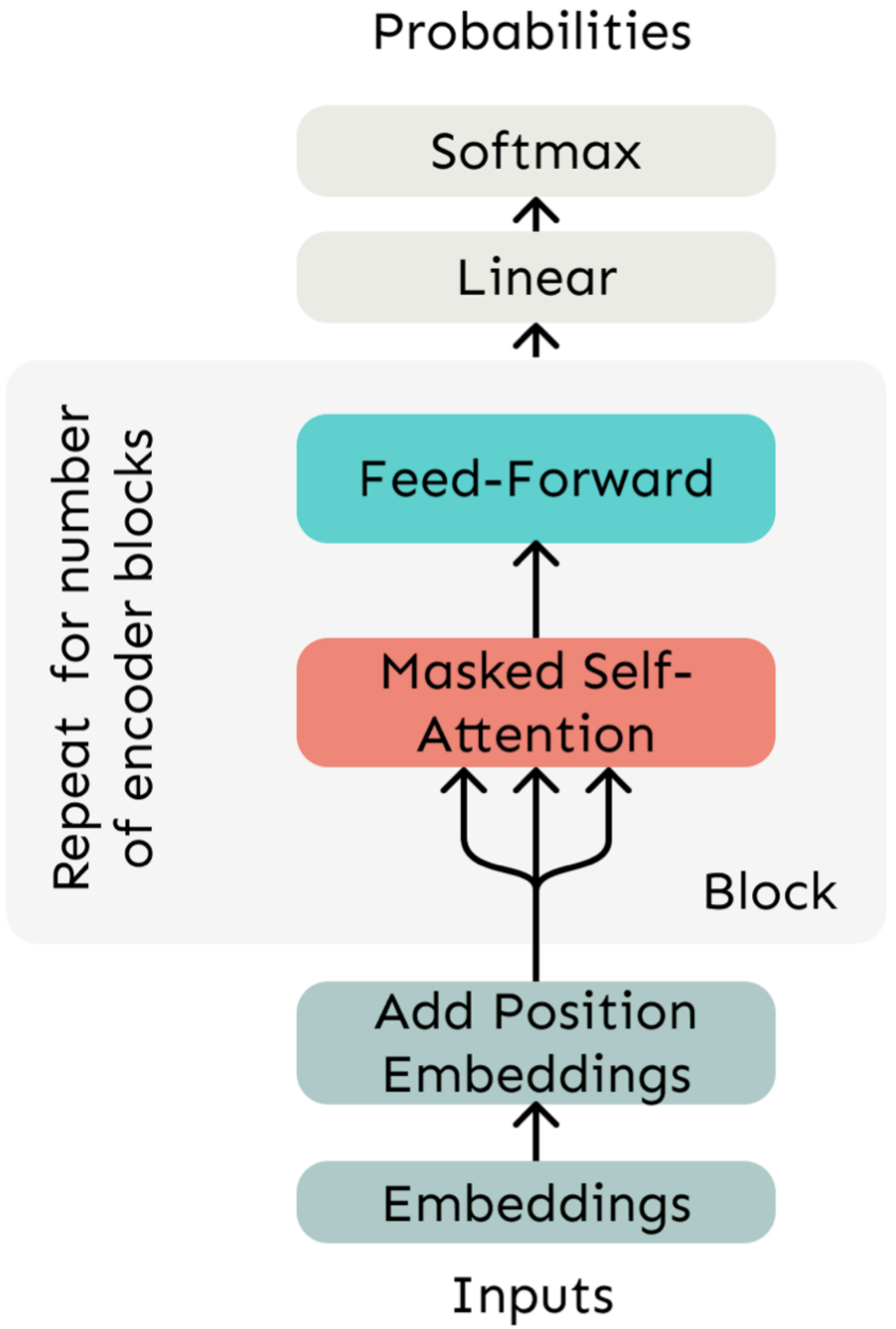
Self-attention building block

* **Self attention**
  * need this!

* **Position embeddings**
  * since self-attention is unordered

* **Nonlinearities**
  * For the output of attention block
  * Simple feed-forward network that is easy to train

* **Masking**
  * To parallelize operations while not looking at the future (during training)
  * Enforces training to behave like inference



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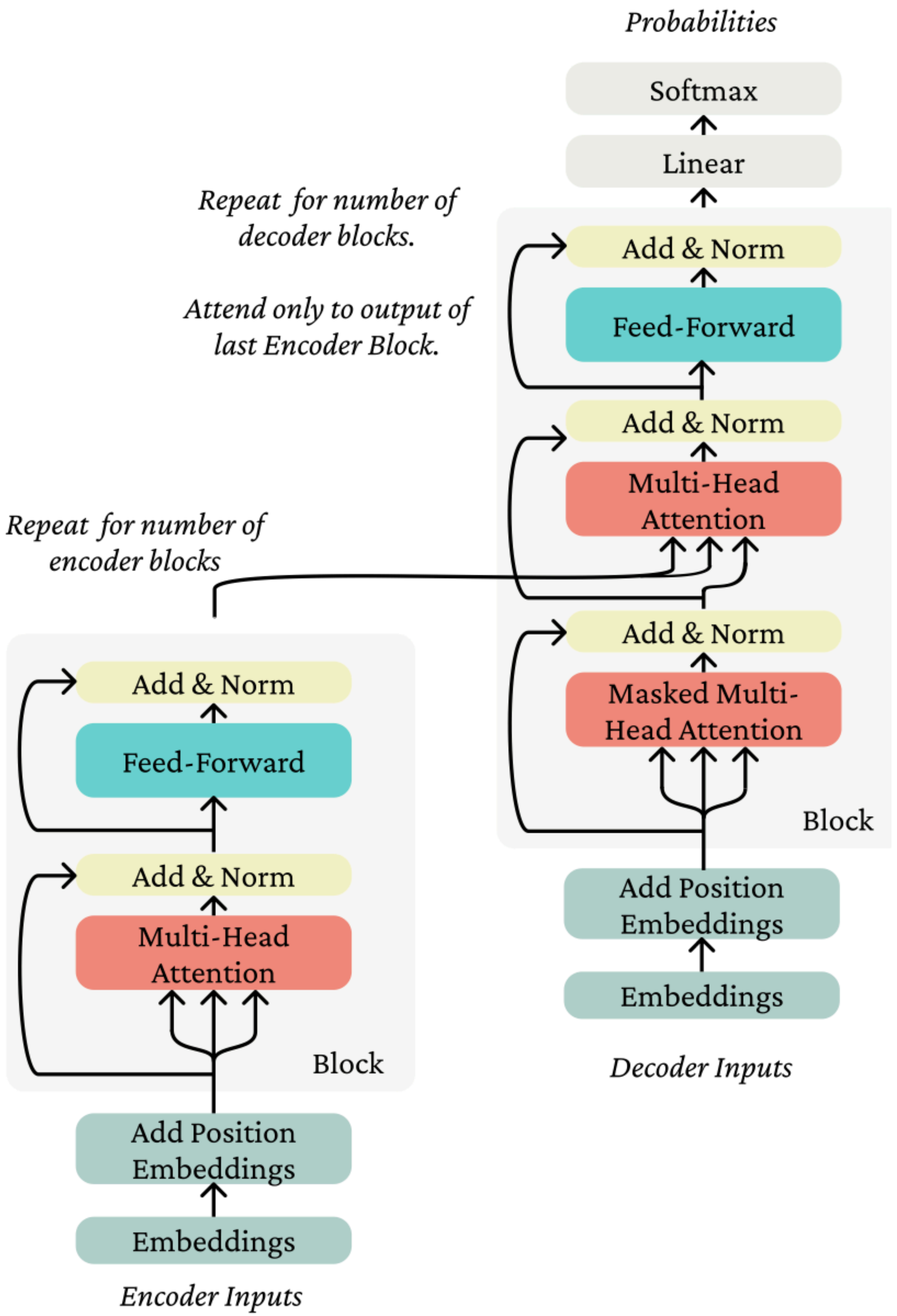

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Transformer Encoder-Decoder