Deep Learning

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Outline

1. Transformers
2. Dilated and Transposed Convolutions

Problems with RNNs

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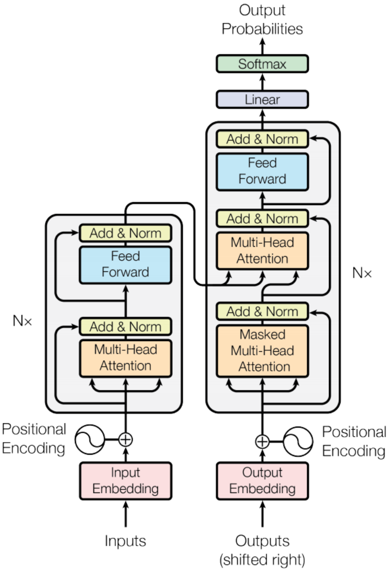
- Sequential computation prevents parallelization.
- Despite GRUs and LSTMs, RNNs still need attention mechanism to deal with long range dependencies – path length for codependent computation between states grows with sequence.
- But if attention gives us access to any state, maybe we don't need the RNN?

Transformer



Self Attention Layer

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- Given an embedding x, it learns three separate smaller embeddings from it — query, key and value.
- During the training phase, the W_q, W_k, and W_v matrices are learnt to get the query, key and value embeddings.

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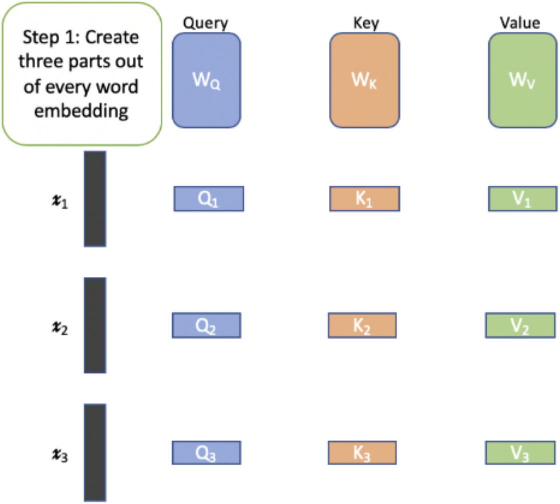

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- This step will be performed with every word.

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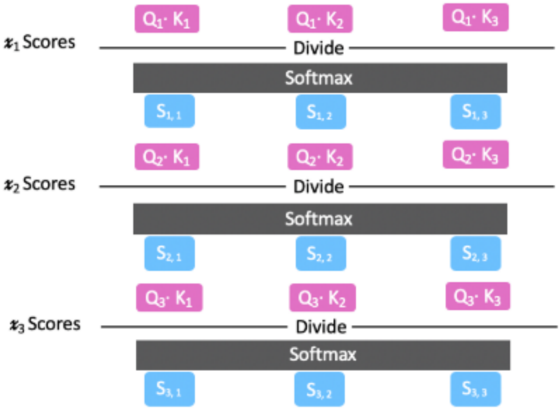

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- If the word is not relevant to x_1 then the score will be small and the corresponding value will be reduced a factor of that score and similarly the significant words will get their values bolstered by the score.

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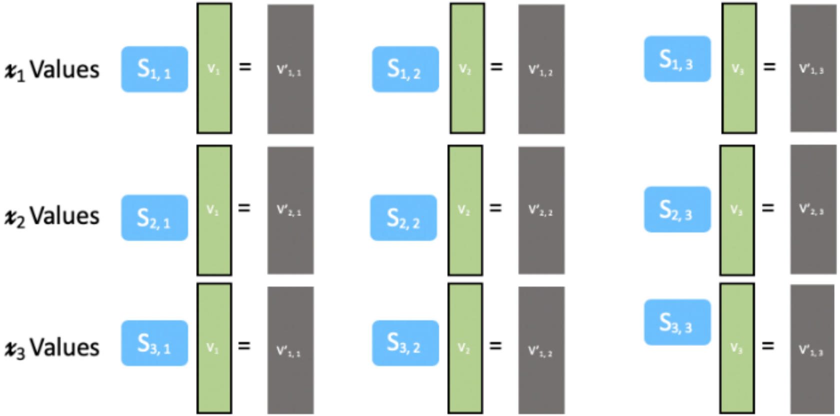
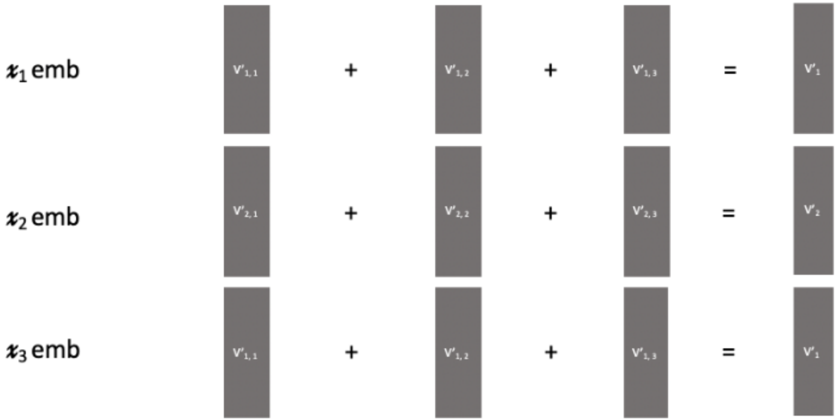


Self Attention Layer

Finally, the word x1 will create a new ‘value’ for itself by summing up the values received. This will be the new embedding of the word.



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$$\text{Attention}(q, K, V) = \sum_i \frac{e^{q \cdot k_i}}{\sum_j e^{q \cdot k_j}} v_i$$

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- inputs: a query q and a set of key-value (K-V) pairs to an output,

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- weight of each value is computed by an inner product of query and corresponding key,
- queries and keys have the same dimensionality d_k, values have d_v.

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- Solution:

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Multi-Head Attention Layer

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$$\text{Multihead}\left(Q, K, V, h\right) = \text{Concat}\left(\text{head}_1, \dots, \text{head}_h\right) W^o$$

where

$$\text{head}_i = \text{Attention}\left(QW_i^Q, KW_i^K, VW_i^V\right)$$

$$W_i^Q \in \mathbb{R}^{d_{model} \times d_k}, W_i^K \in \mathbb{R}^{d_{model} \times d_k}, W_i^V \in \mathbb{R}^{d_{model} \times d_v}, W^O \in \mathbb{R}^{hd_v \times d_{model}}$$

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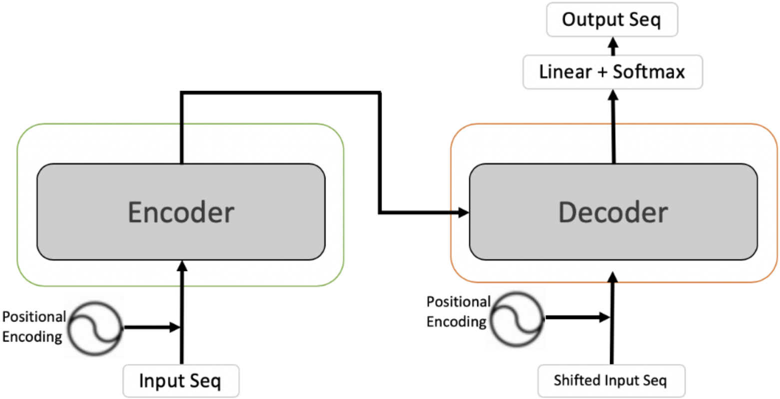
- This is why the embeddings for all these are masked by multiplying with 0.

Feed-Forward Network

this part is a position free neural network, which consists of two fully connected layers with a ReLU activation in between:

$$\mathrm{FFN}(x) = W_2 \cdot \mathrm{ReLU}(W_1 x + b_1) + b_2$$

Encoder-Decoder Architecture



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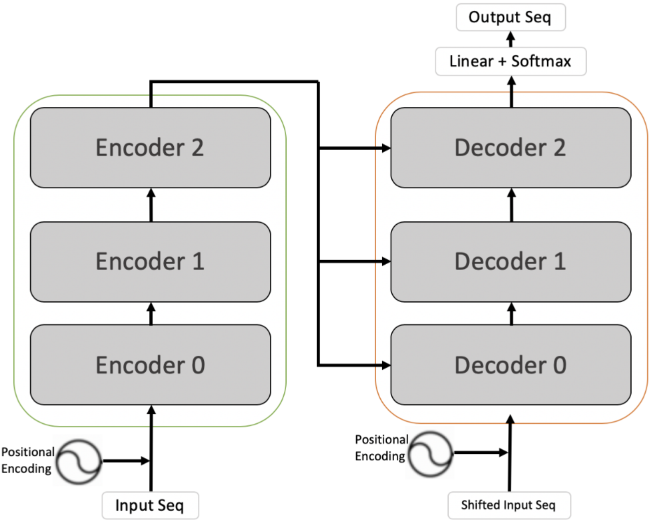
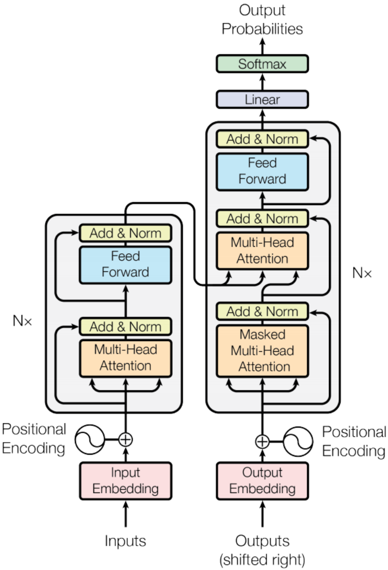


Encoder-Decoder Architecture

Queries	Decoder Input
Keys	Encoder output
Values	Encoder output

Transformer



Outline

Dilated/Atrous Convolution

Definition 1

Let $F : \mathbb{Z}^2 \rightarrow \mathbb{R}$ *be a discrete function. Let* $\Omega_r : [-r, r] \cap \mathbb{Z}^2$ *and let* $k : \Omega_r \rightarrow \mathbb{R}$ *be a discrete filter of size* $(2r+1)^2$*. The discrete convolution operator* $*$ *can be defined as*

$$(F * k)(p) = \sum_{s+t=p} F(s)\, k(t)$$

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Let $F : \mathbb{Z}^2 \to \mathbb{R}$ be a discrete function. Let $\Omega_r : [-r, r] \cap \mathbb{Z}^2$ and let $k : \Omega_r \to \mathbb{R}$ be a discrete filter of size $(2r+1)^2$. The discrete l-dilated convolution operator $*_l$ can be defined as

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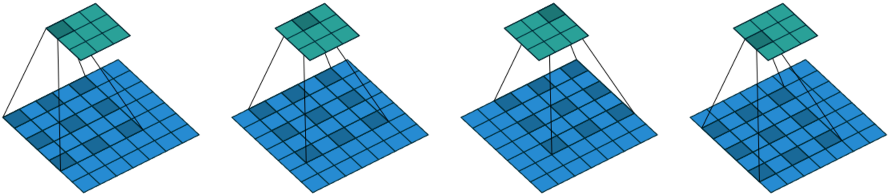
Dilated/Atrous Convolution



1D Dilated Convolution

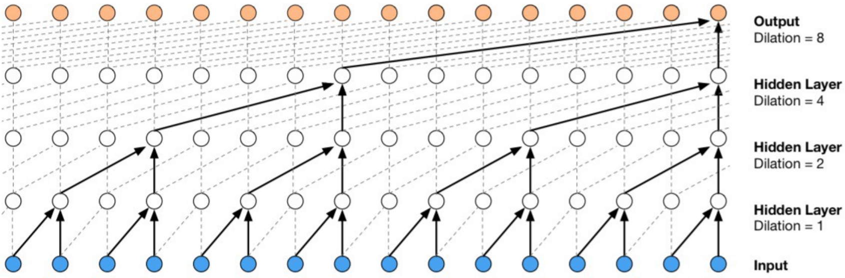


Figure 3: Visualization of a stack of *dilated* causal convolutional layers.