Deep Learning

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FAST DISCOVERING THE FUTURE

Outline

Problems with RNNs

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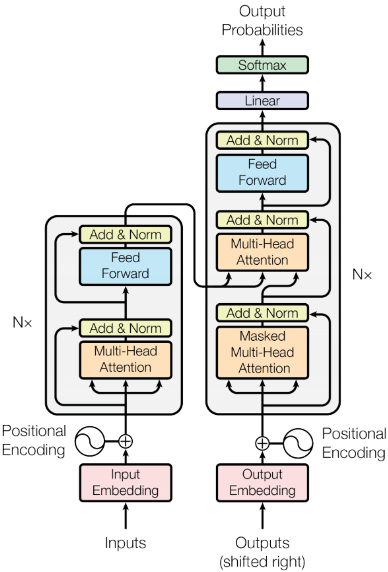
- Sequential computation prevents parallelization.
- Despite GRUs and LSTMs, RNNs still need attention mechanism to deal with long range dependencies – path length for codependent computation between states grows with sequence.
- But if attention gives us access to any state, maybe we don't need the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

Transformer



Self Attention Layer

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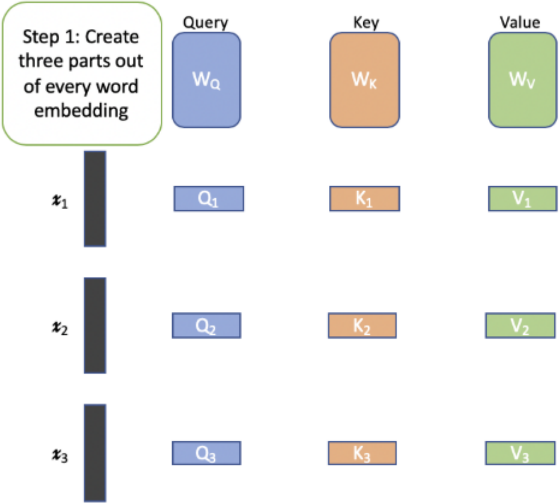
- Given an embedding x, it learns three separate smaller embeddings from it — query, key and value.
- During the training phase, the W_q, W_k, and W_v matrices are learnt to get the query, key and value embeddings.

Self Attention Layer



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- This step will be performed with every word.

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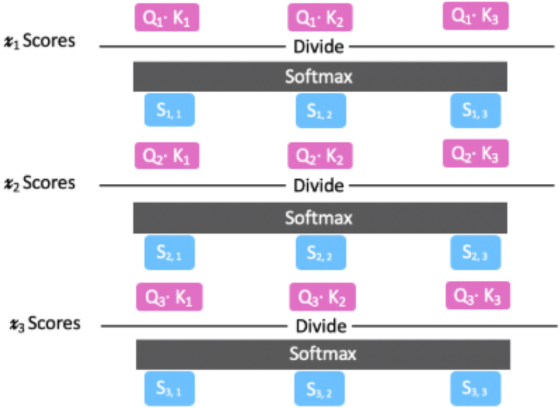

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- If the word is not relevant to x_1 then the score will be small and the corresponding value will be reduced a factor of that score and similarly the significant words will get their values bolstered by the score.

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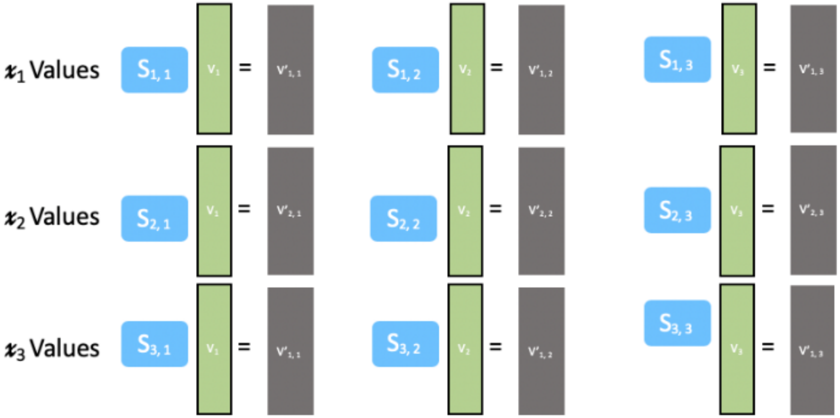
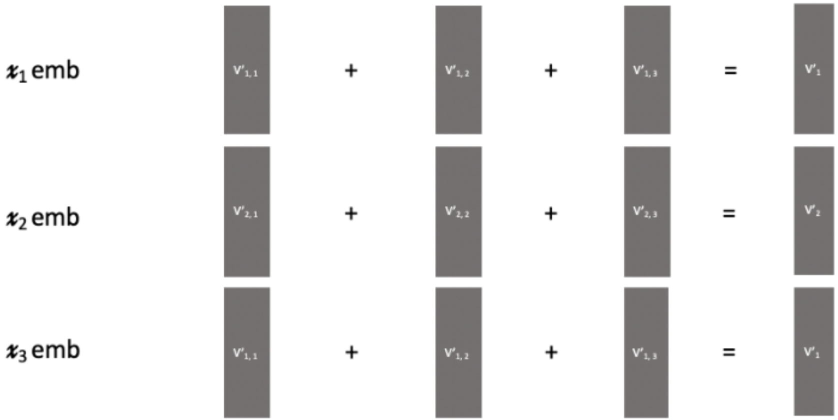


Self Attention Layer

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.



Self Attention

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

where

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- output is a convex combination of values,
- 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.

Self Attention

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- Solution:

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

Multi-Head Attention Layer

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$$\text{Multihead} = \text{Concat}\left(\text{head}_1, \ldots, \text{head}_h\right) W^o$$

where

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

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

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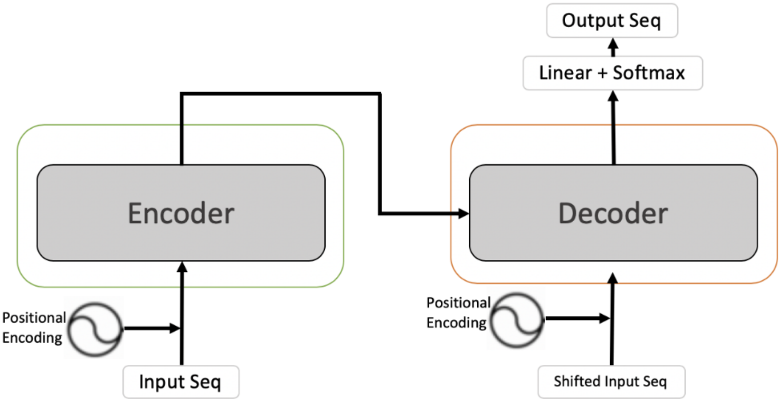
- But at the time of decoding, when trying to predict the next word in the sentence, logically, it should not know what are the words which are present after the word we are trying to predict.
- This is why the embeddings for all these are masked by multiplying with 0.

Feed-Forward Network

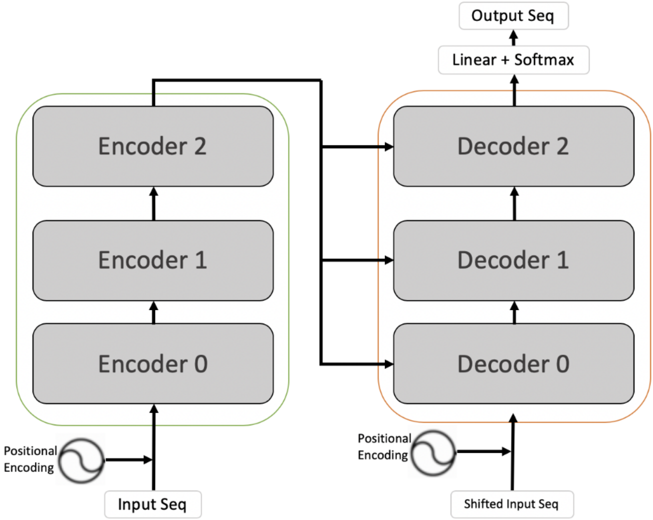
this part is a position free neural network, which consists of two fully connected layers with a ReLU activation in between:

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

Encoder-Decoder Architecture



Encoder-Decoder Architecture



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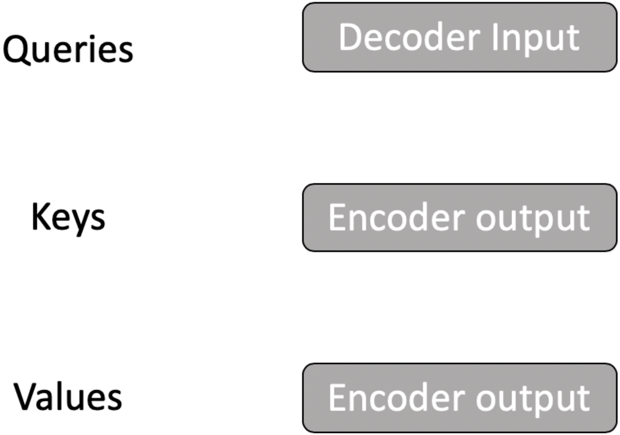
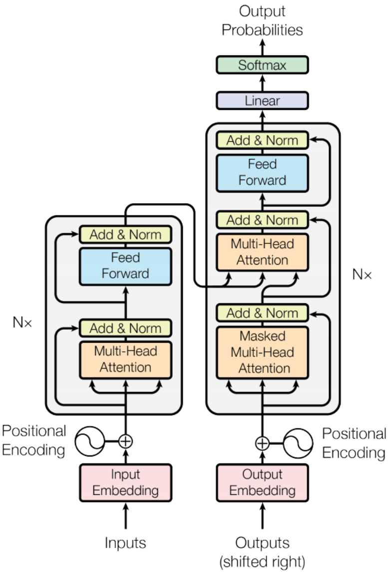


Transformer



Outline

Dilated/Atrous Convolution

Definition 1

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 convolution operator* $*$ *can be defined as*

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

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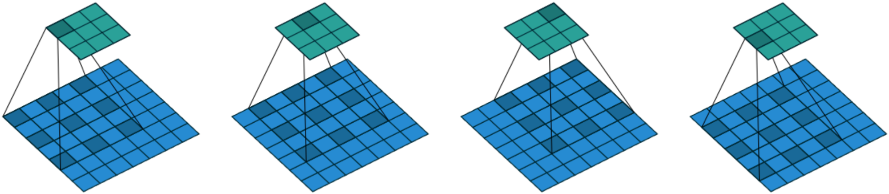
$$(F *_l k)(p) = \sum_{s+lt=p} F(s)\, k(t)$$

Dilated/Atrous Convolution



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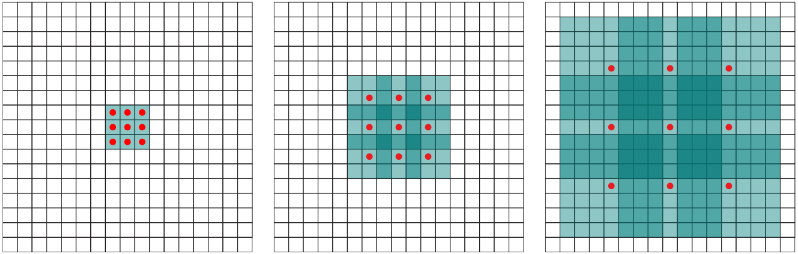


(a) (b) (c)

Figure 1: Systematic dilation supports exponential expansion of the receptive field without loss of resolution or coverage. (a) F_1 is produced from F_0 by a 1-dilated convolution; each element in F_1 has a receptive field of 3×3. (b) F_2 is produced from F_1 by a 2-dilated convolution; each element in F_2 has a receptive field of 7×7. (c) F_3 is produced from F_2 by a 4-dilated convolution; each element in F_3 has a receptive field of 15×15. The number of parameters associated with each layer is identical. The receptive field grows exponentially while the number of parameters grows linearly.

1D Dilated Convolution

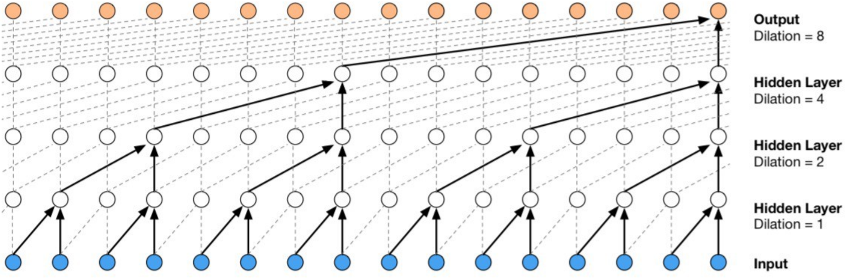
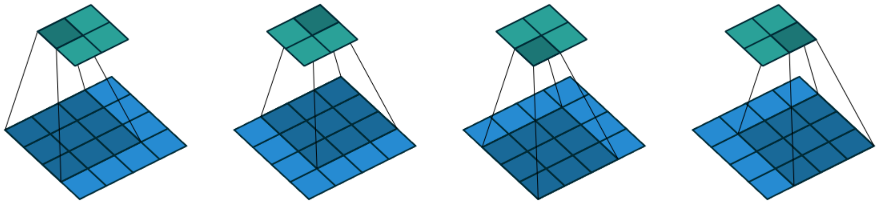


Figure 3: Visualization of a stack of *dilated* causal convolutional layers.

Convolution as a Matrix Operation



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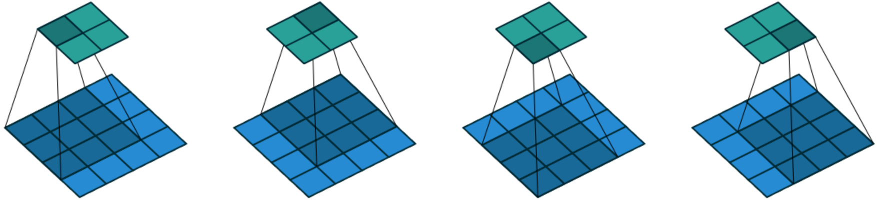
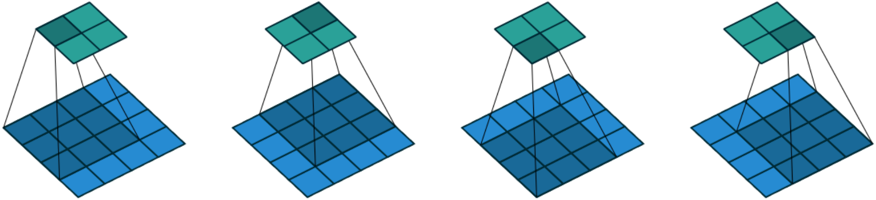


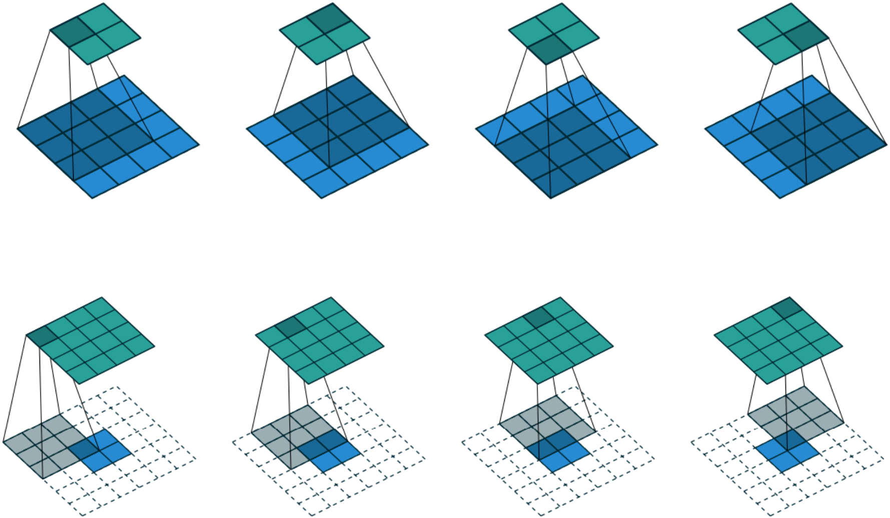
$$\begin{pmatrix} w_{0,0} & w_{0,1} & w_{0,2} & 0 & w_{1,0} & w_{1,1} & w_{1,2} & 0 & w_{2,0} & w_{2,1} & w_{2,2} & 0 & 0 & 0 & 0 & 0 \\ 0 & w_{0,0} & w_{0,1} & w_{0,2} & 0 & w_{1,0} & w_{1,1} & w_{1,2} & 0 & w_{2,0} & w_{2,1} & w_{2,2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & w_{0,0} & w_{0,1} & w_{0,2} & 0 & w_{1,0} & w_{1,1} & w_{1,2} & 0 & w_{2,0} & w_{2,1} & w_{2,2} & 0 \\ 0 & 0 & 0 & 0 & 0 & w_{0,0} & w_{0,1} & w_{0,2} & 0 & w_{1,0} & w_{1,1} & w_{1,2} & 0 & w_{2,0} & w_{2,1} & w_{2,2} \end{pmatrix}$$

This linear operation takes the input matrix flattened as a 16-dimensional vector and produces a 4-dimensional vector that is later reshaped as the 2×2 output matrix.

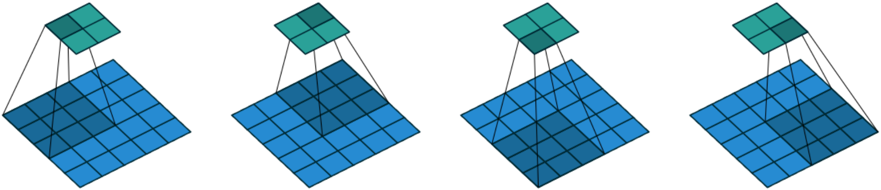
Transposed Convolution (stride=0)



Transposed Convolution (stride=0)



Transposed Convolution (stride=1)



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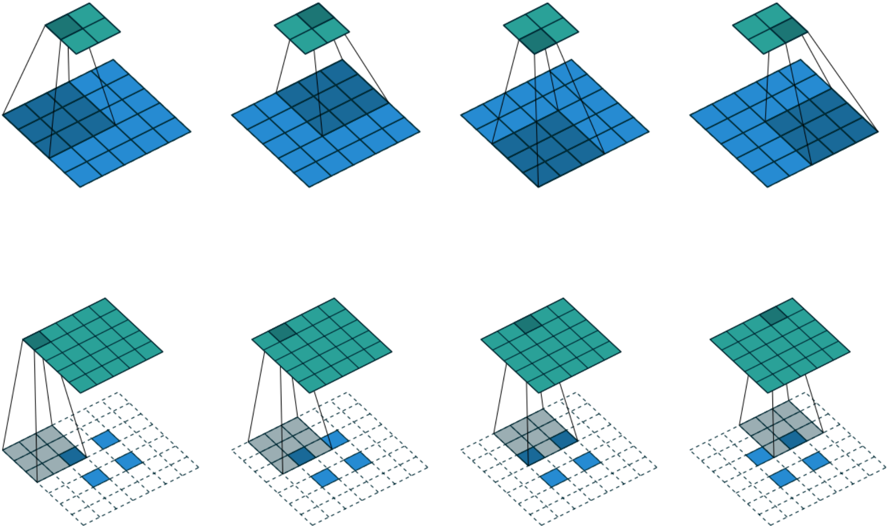
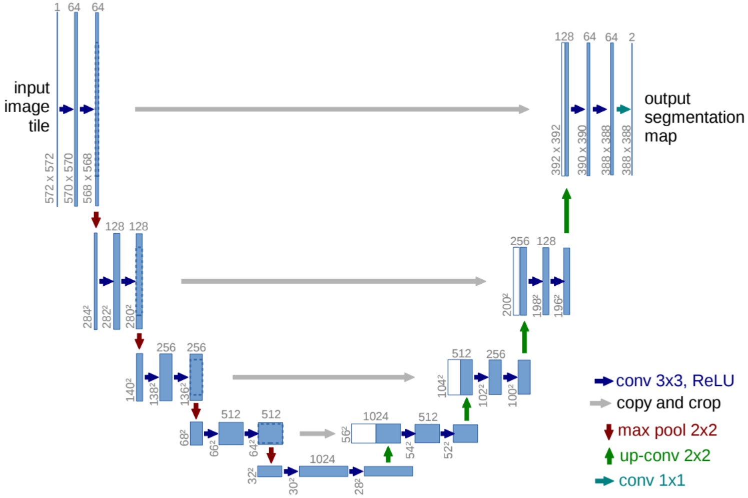


UNet


1 64 64
input
image
tile
572 x 572
570 x 570
568 x 568
128 128
284²
282²
280²
256 256
140²
138²
136²
512 512
68²
66²
64²
1024
32²
30²
28²
56²
1024
512
54²
52²
104²
512 256
102²
100²
200²
256 128
198²
196²
128 64 64 2
392 x 392
390 x 390
388 x 388
388 x 388
output
segmentation
map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1