FAST AND ACCURATE READING COMPREHENSION BY COMBINING SELF-ATTENTION AND CONVOLUTION

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——李芸

- Background
  - Machine reading comprehension and automated question answering have become an important topic in the NLP domain.
- Task
  - Read Comprehension Task
  - Given question and document
  - Find a span in the document as a answer to the question.
- Datasets:
  - SQuAD(Rajpurkar et al.,2016)
  - each example of SQuAD is a triple of (d, q, a)

Related work

Current end-to-end machine reading comprehension and question answering models are primarily based on recurrent neural networks (RNNs) with attention.

For example: BiDAF (Seo et al., 2016)

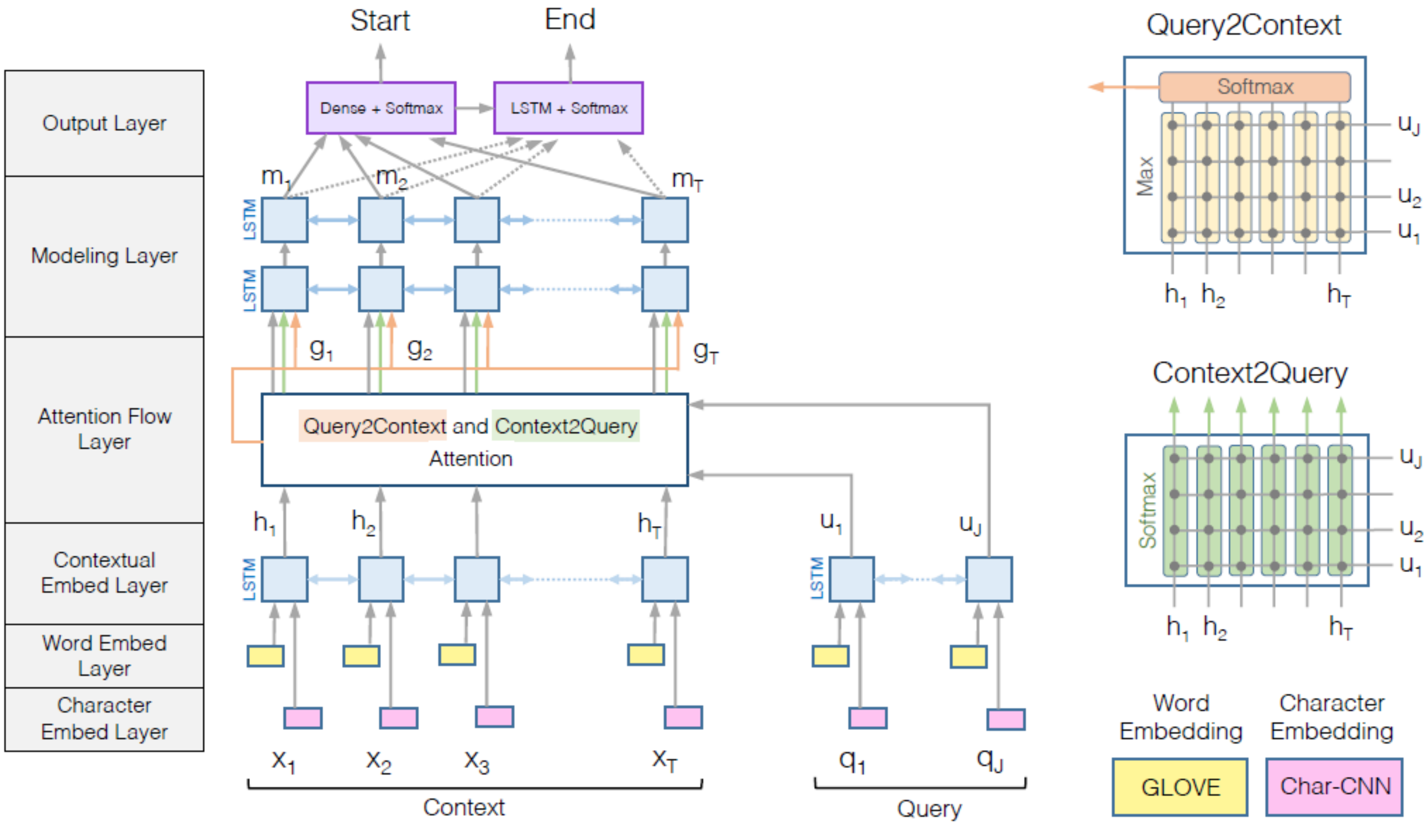


Figure 1: BiDirectional Attention Flow Model *(best viewed in color)*

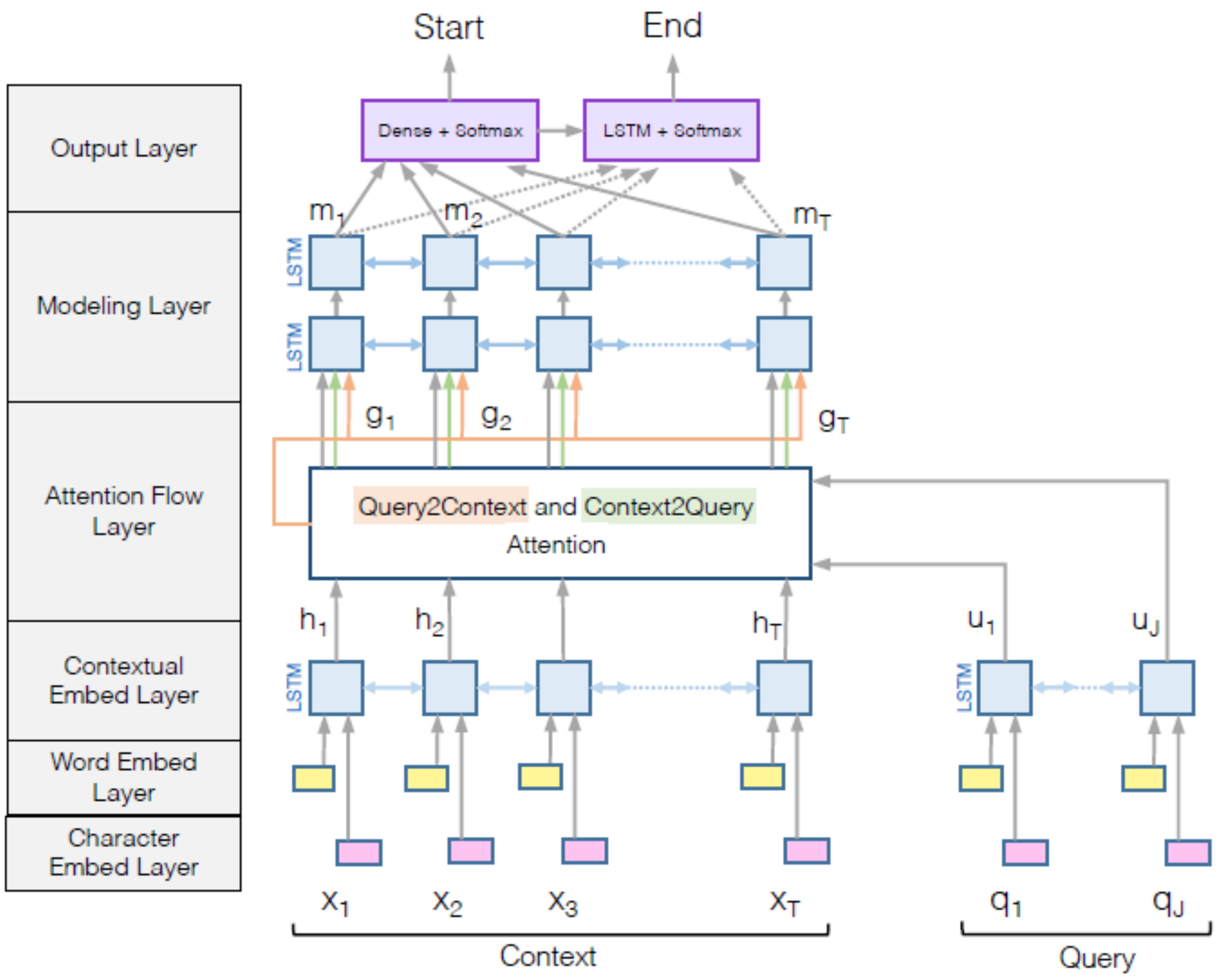
Despite their success, these models are often slow for both training and inference due to the sequential nature of RNNs.

In this paper

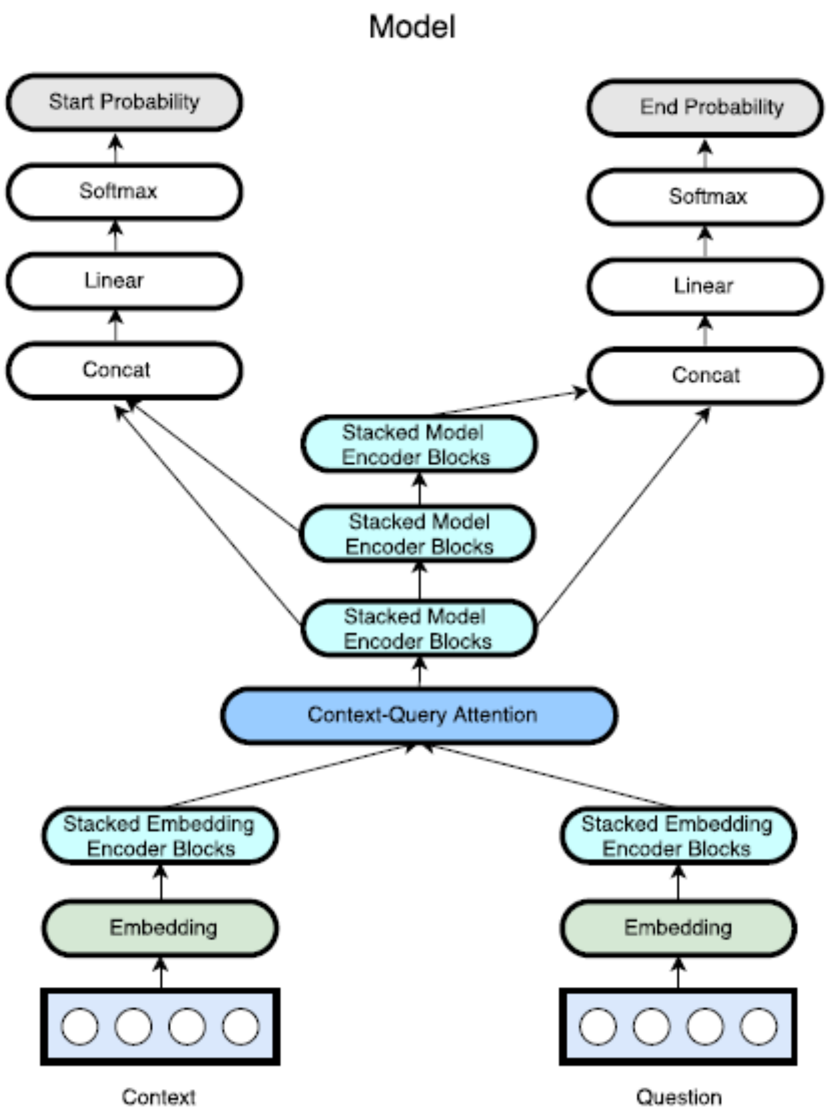
- Propose a new Q&A architecture that does not require recurrent networks.

- Combine self-attention and convolution

Model contrast

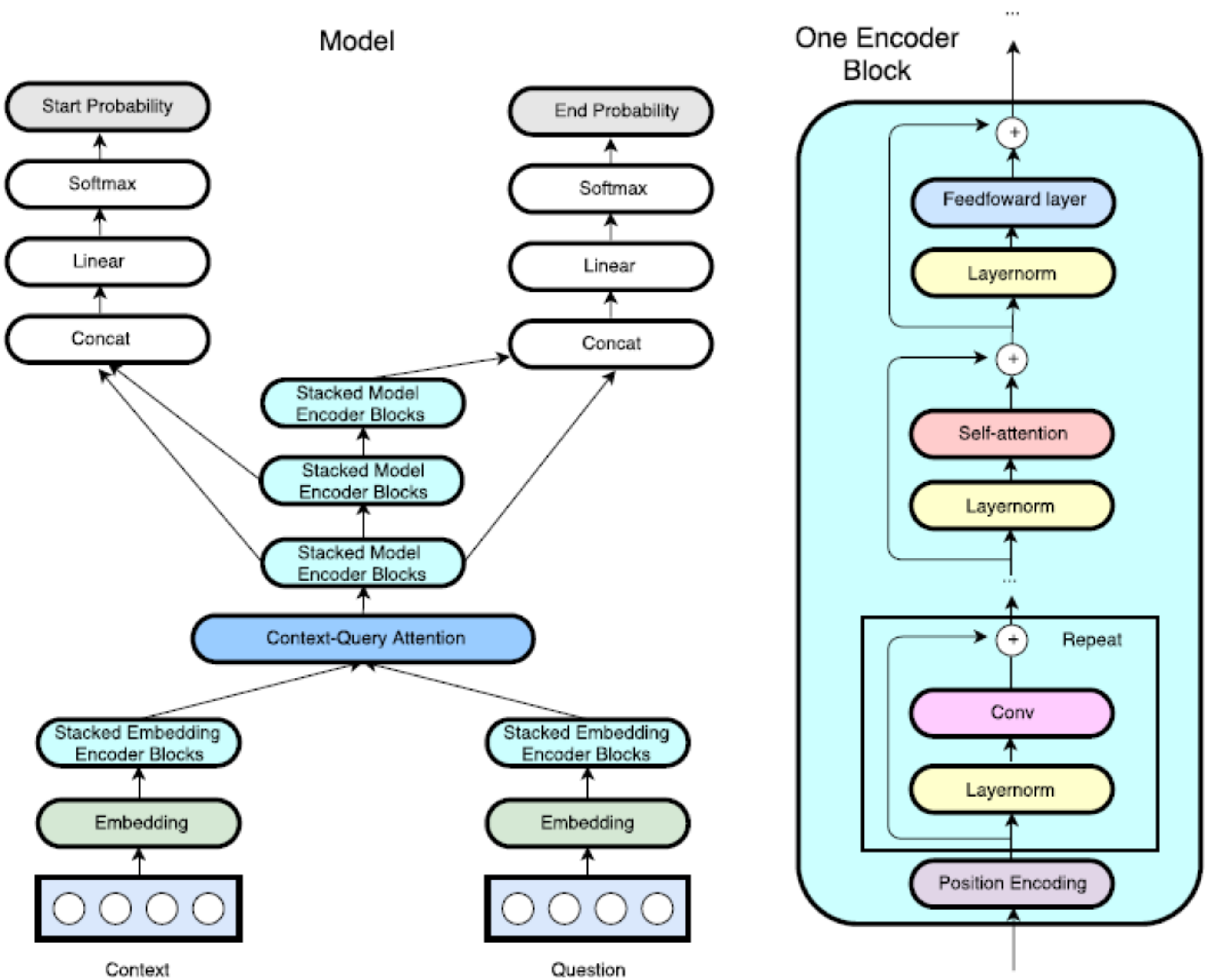


BiDAF



Our Model

Model


Model
Start Probability
Softmax
Linear
Concat
End Probability
Softmax
Linear
Concat
Stacked Model Encoder Blocks
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Stacked Model Encoder Blocks
Context-Query Attention
Stacked Embedding Encoder Blocks
Embedding
Context
Stacked Embedding Encoder Blocks
Embedding
Question
One Encoder Block
Feedfoward layer
Layernorm
Self-attention
Layernorm
Repeat
Conv
Layernorm
Position Encoding

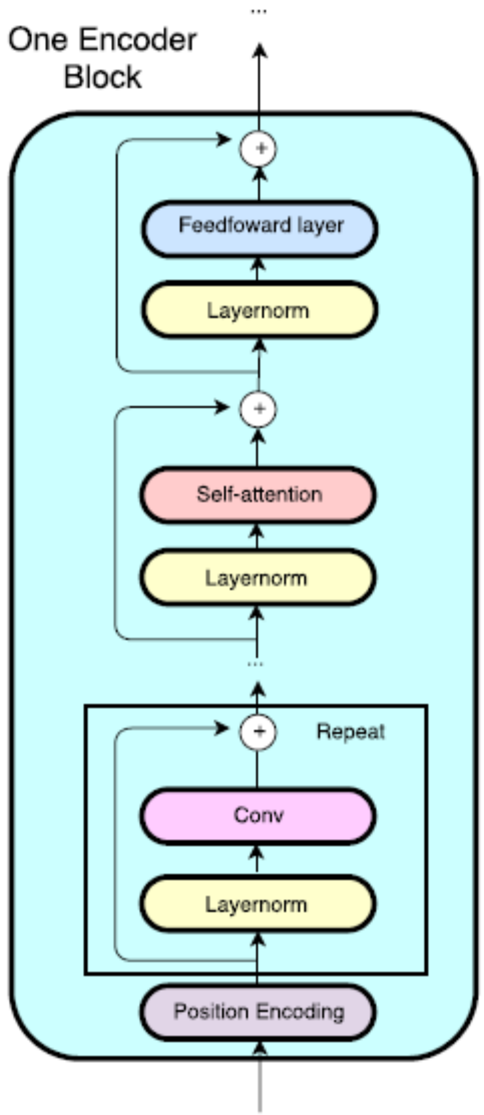
Input Embedding layer

- Word embedding
  - p1 = 300 dimensional pre-trained GloVe
- Character embedding
  - p2 = 200 dimensional trainable vector
  - concatenate all character of each word ->conv & max-pooling

- Output of this layer:

$$[x_w; x_c] \in \mathbf{R}^{p_1+p_2}$$

Embedding Encoder Layer



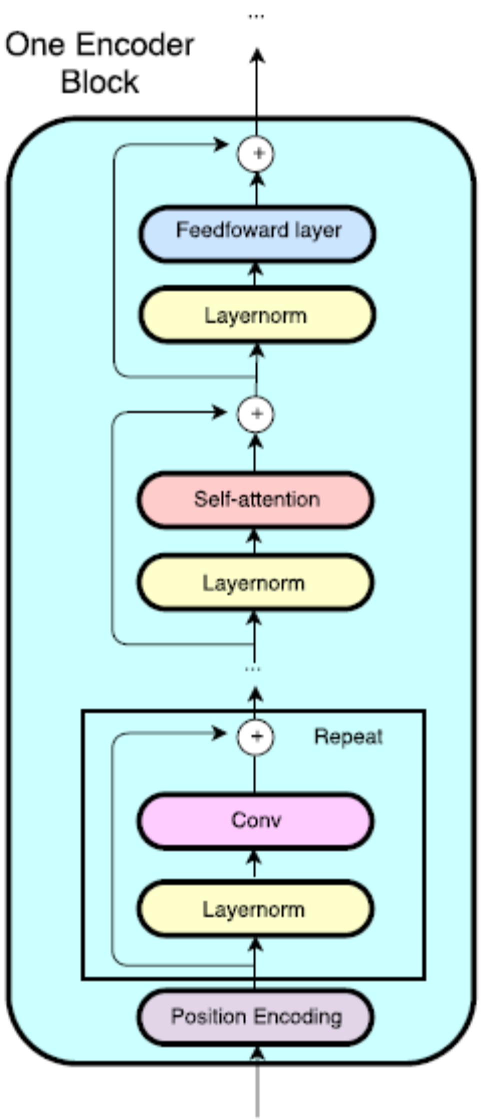
- Position Encoding:

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

Position embedding have the same dimension of d_{model};
In this paper, $d_{model} = p_1+p_2$

pos is the position
$2i$ & $2i+1$ is the dimension

Embedding Encoder Layer



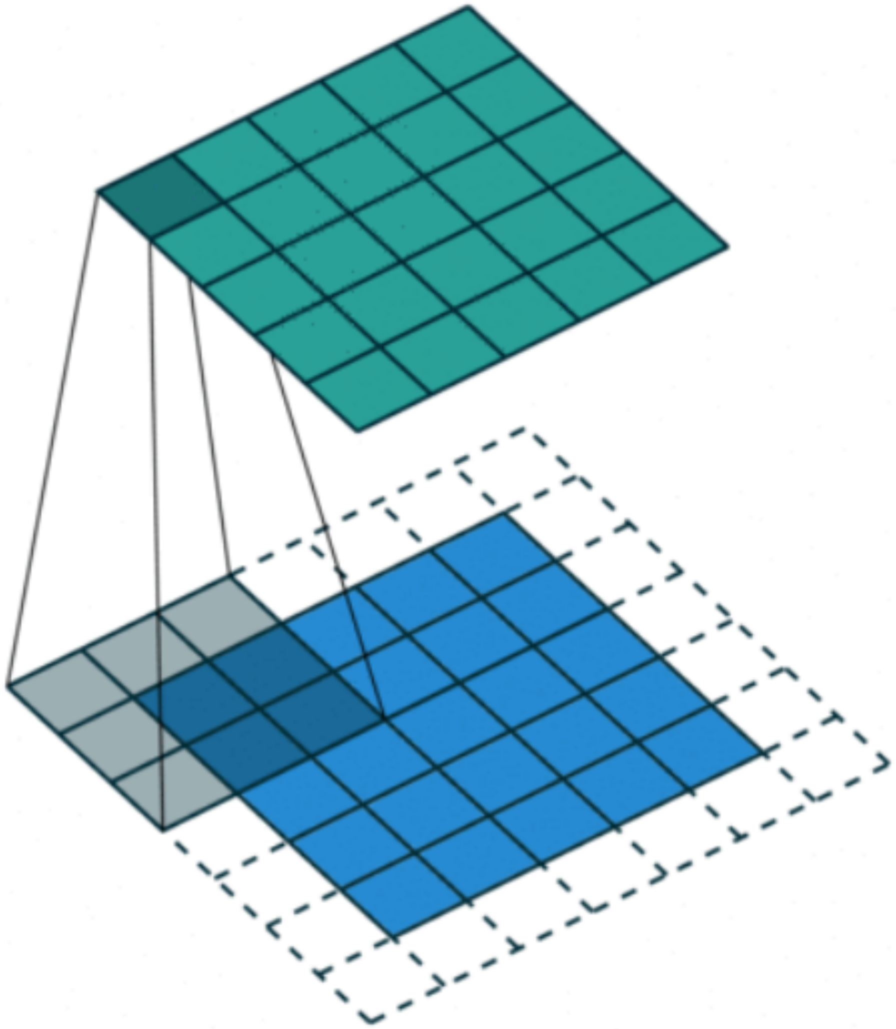
- [convolution-layer × # + self-attention-layer+ feed-forward-layer]
  - **convolution-layer**: depthwise separable convolutions
  - **self-attention-layer**: multi-head attention mechanism

Depthwise separable convolutions

- Memory efficient
- Have better generation

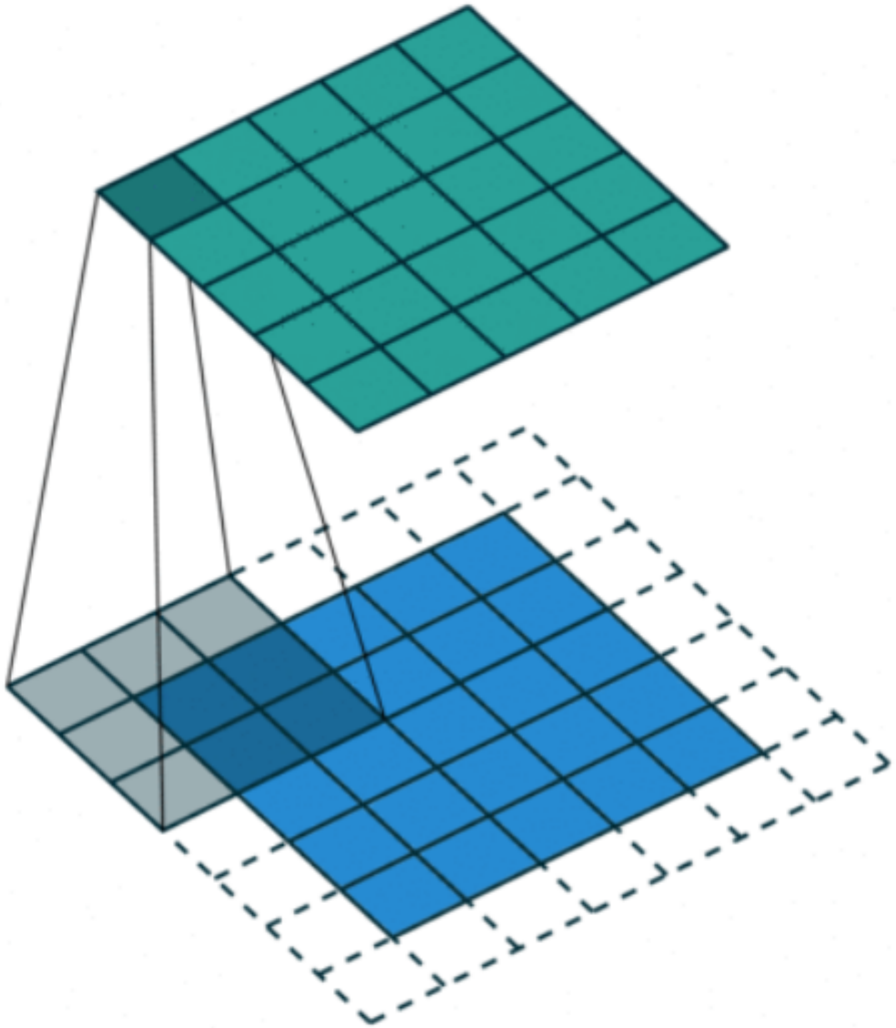
- kernel size = 7
- Filters = 128

Convolutions 参数



- 卷积核大小，Kernel size
- 步长，Stride
- 边界扩充，Padding
- 输入&输出通道数量，Input & Output Channels

Convolutions 处理过程



5×5 的图像

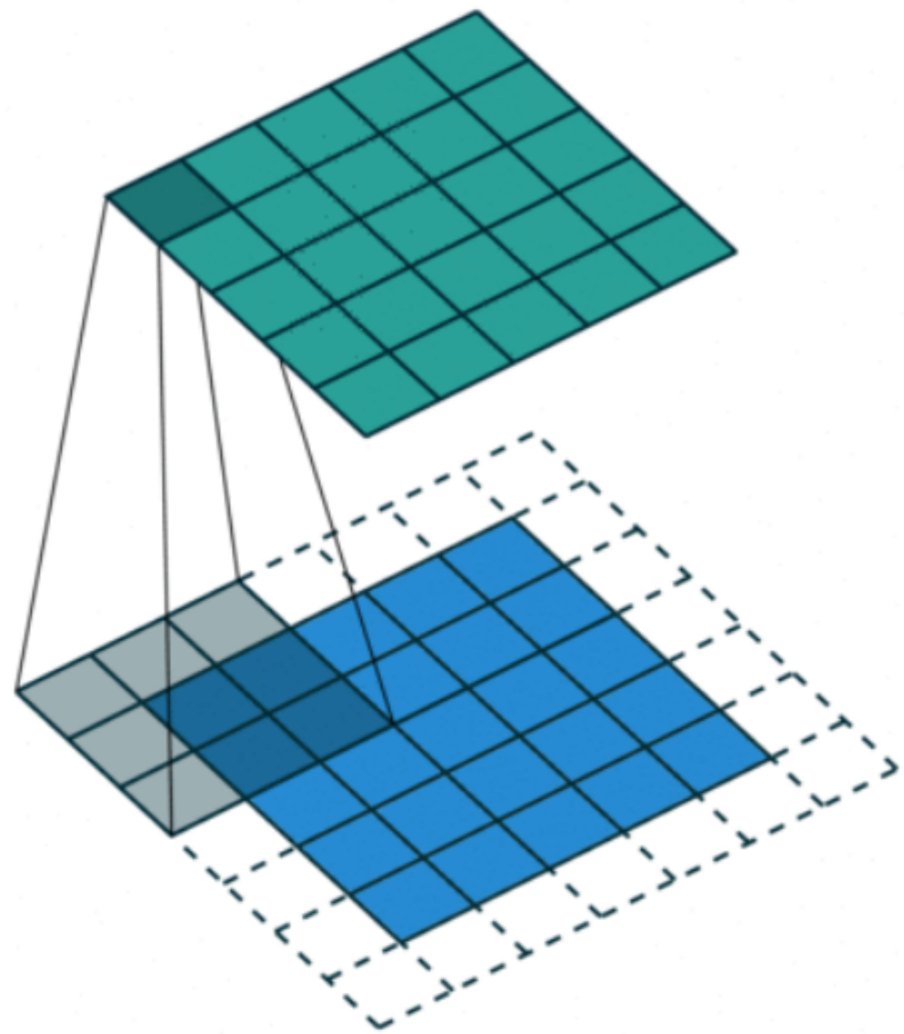
Input channels：16

设置：kernel Size = 3×3

output channels:32

1. 使用大小为3×3的filter对图像的每一个channel进行处理，得到16个feature map；
2. 对每个channel对应的feature map进行融合得到5×5×1；
3. 使用32个filter重复1，2步，最终得到输出5×5×32。

Depthwise separable convolutions处理过程



通道分离+深度卷积

depthwise separable convolution

= depthwise convolution + pointwise convolution

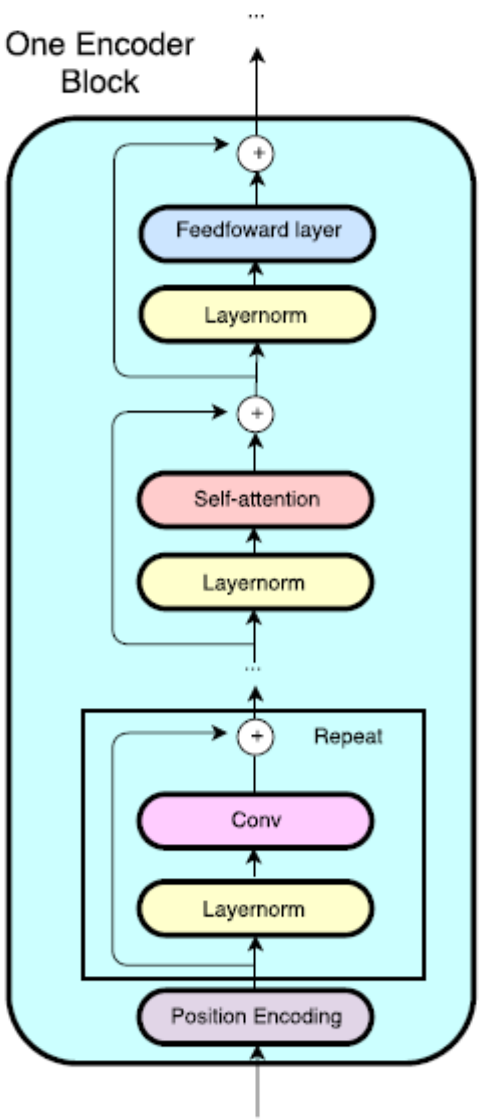
常用深度乘数（depth multiplier）设为1

1. 使用卷积核大小为3×3的filter对图像的每一个channel进行处理，得到16个feature map；
2. 使用32个卷积核大小为1×1的filter对遍历这16个feature map，进行相加融合。
3. 得到输出5×5×32。

Convolutions 与 Depthwise Separable Convolutions 中的参数数量计算

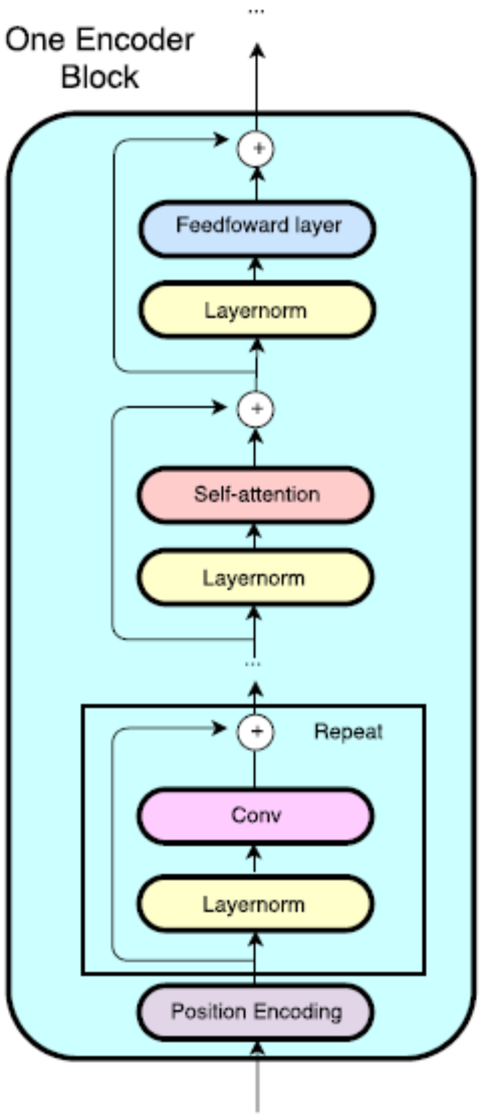
- 使用传统convolutions，需要的参数数量为：
  - $3 \times 3 \times 16 \times 32 = 4680$
- 使用Depthwise Separable Convolutions，需要的参数数量为：
  - $3 \times 3 \times 16 + 32 \times 1 \times 1 \times 16 = 656$
- Memory efficient！

Embedding Encoder Layer



- **convolution-layer**: depthwise separable convolutions
- Input channels: $p_1 + p_2$ =500
- kernel size = 7
- Filters = 128
- Repeat: 4

Embedding Encoder Layer

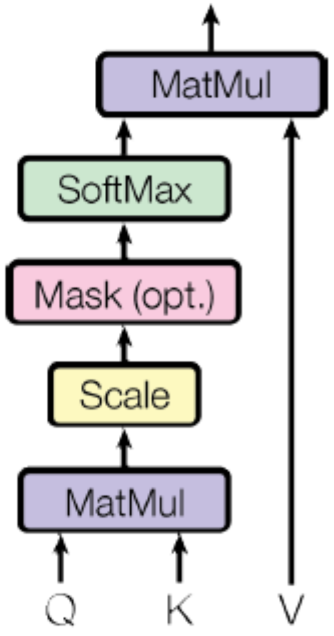


- **self-attention-layer**:

  multi-head attention mechanism

Attention

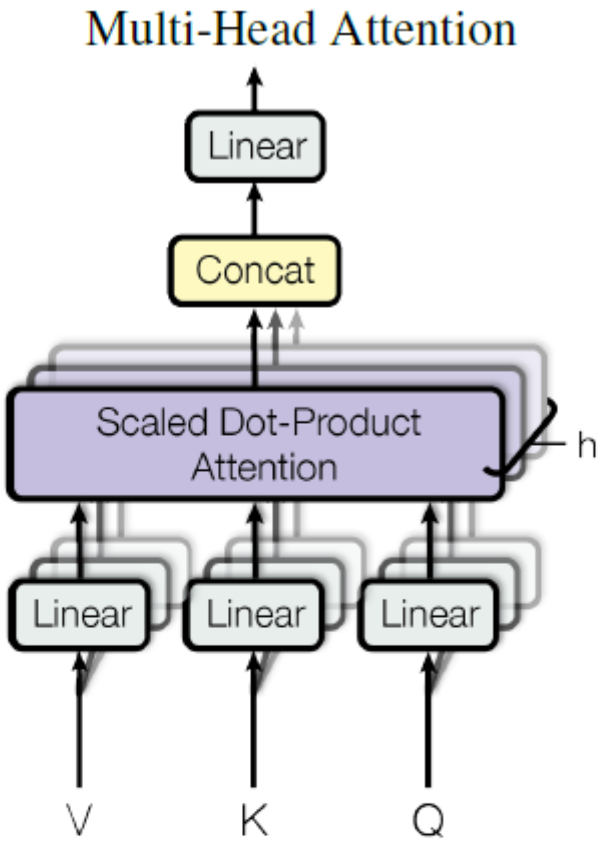
Scaled Dot-Product Attention



An attention function can be described as mapping a query and a set of key-value pairs to an output ;

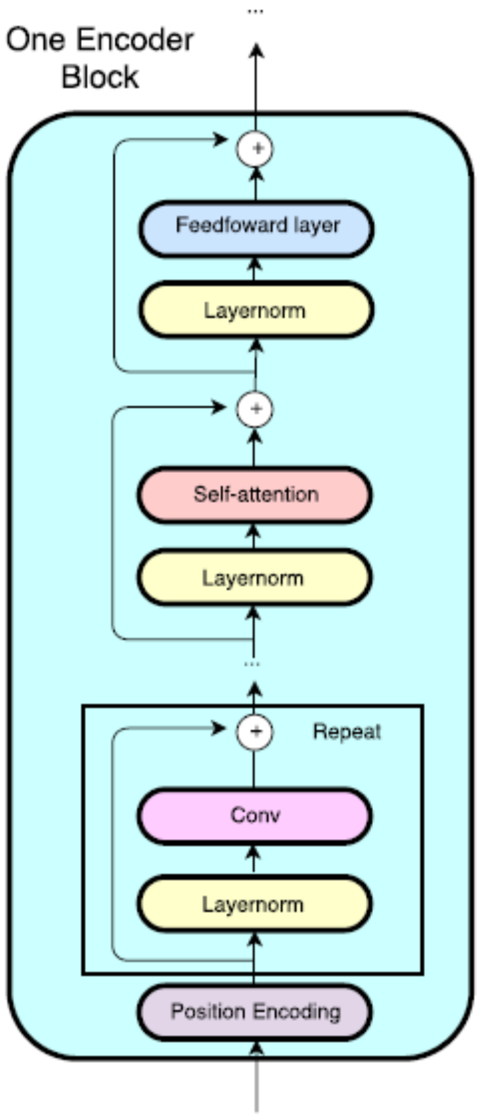
$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

Multi-head Attention



$$\mathrm{MultiHead}(Q,K,V) = \mathrm{Concat}(\mathrm{head_1}, ..., \mathrm{head_h})W^O$$
$$\text{where head}_{\mathrm{i}} = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

Embedding Encoder Layer



Input :

$x \in R^{p_1+p_2}$, ($p_1 + p_2$ = 500)

Conv:

kernel size = 7

number of filters: 128

number of conv layers: 4

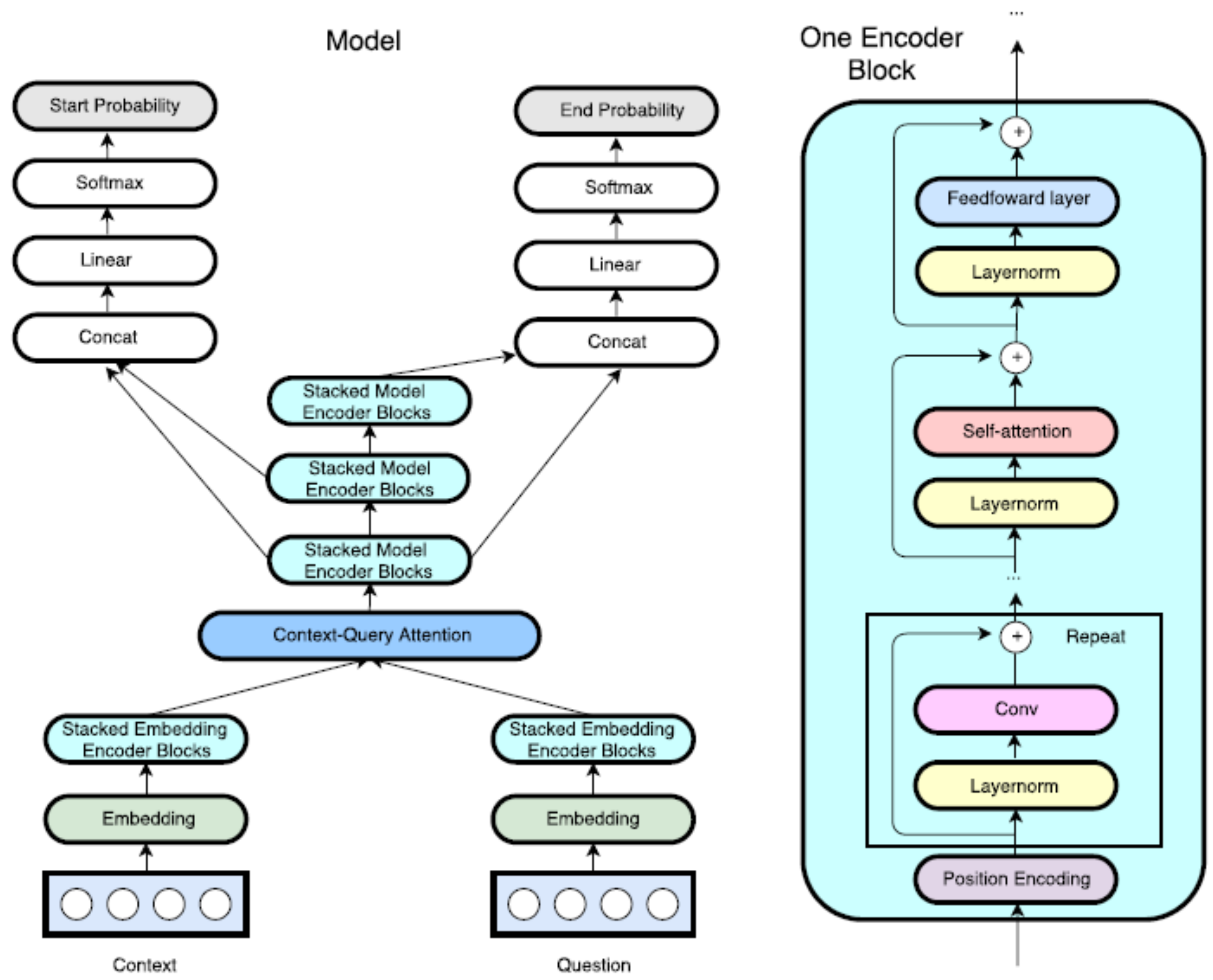
Self-attention:

number of heads : 8

Output:

$x \in R^{128}$

Model



Model
Start Probability
Softmax
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Concat
End Probability
Softmax
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Concat
Stacked Model
Encoder Blocks
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Stacked Model
Encoder Blocks
Context-Query Attention
Stacked Embedding
Encoder Blocks
Stacked Embedding
Encoder Blocks
Embedding
Embedding
Context
Question
One Encoder
Block
Feedfoward layer
Layernorm
Self-attention
Layernorm
Repeat
Conv
Layernorm
Position Encoding

Context-Query Attention Layer

- $\mathbf{C}$: encoded context,

  length = n

- $\mathbf{Q}$: encoded query,

  length = m

- S : similarity matrix $S \in R^{n \times m}$

  similarity function :

$$f(q, c) = W_0[q, c, q \odot c]$$

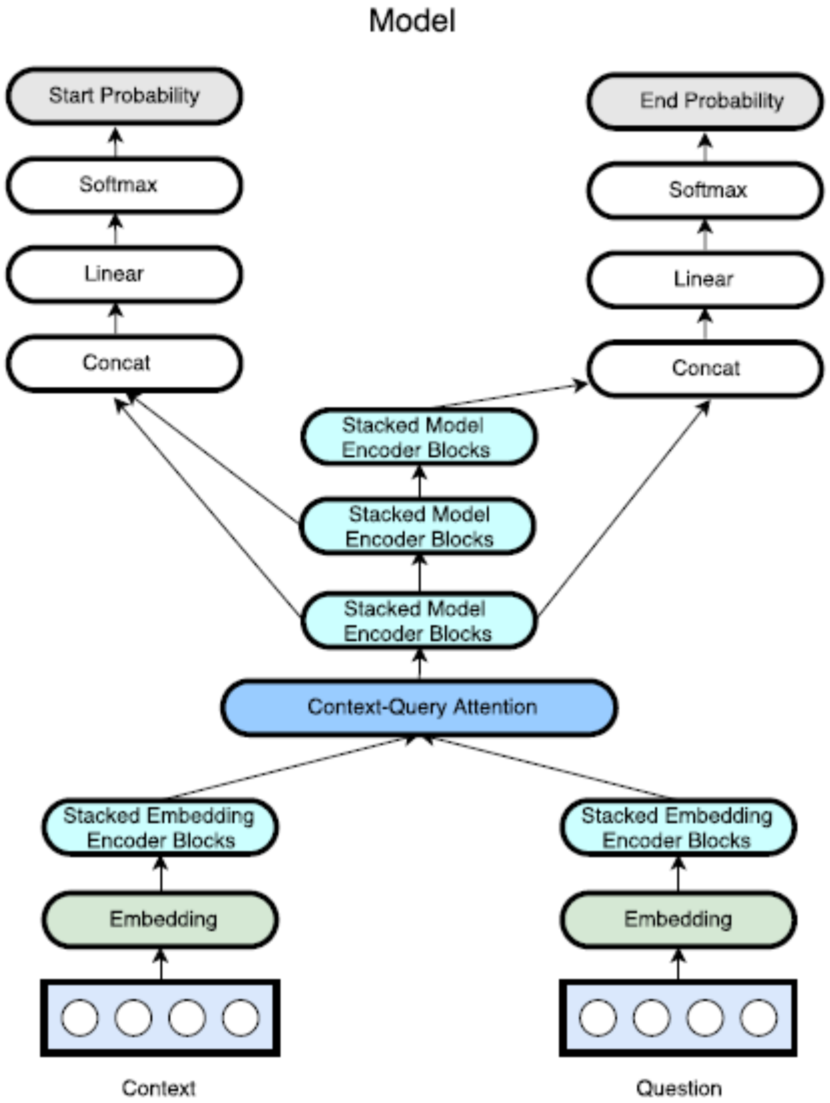
- Compute the row normalized matrix $\bar{S}$ of S
- query-to-context attention:

  A = $\bar{S} \cdot Q^T \in R^{n \times d}$

- Compute the column normalized matrix $\bar{\bar{S}}$ of S
- context-to-query attention:

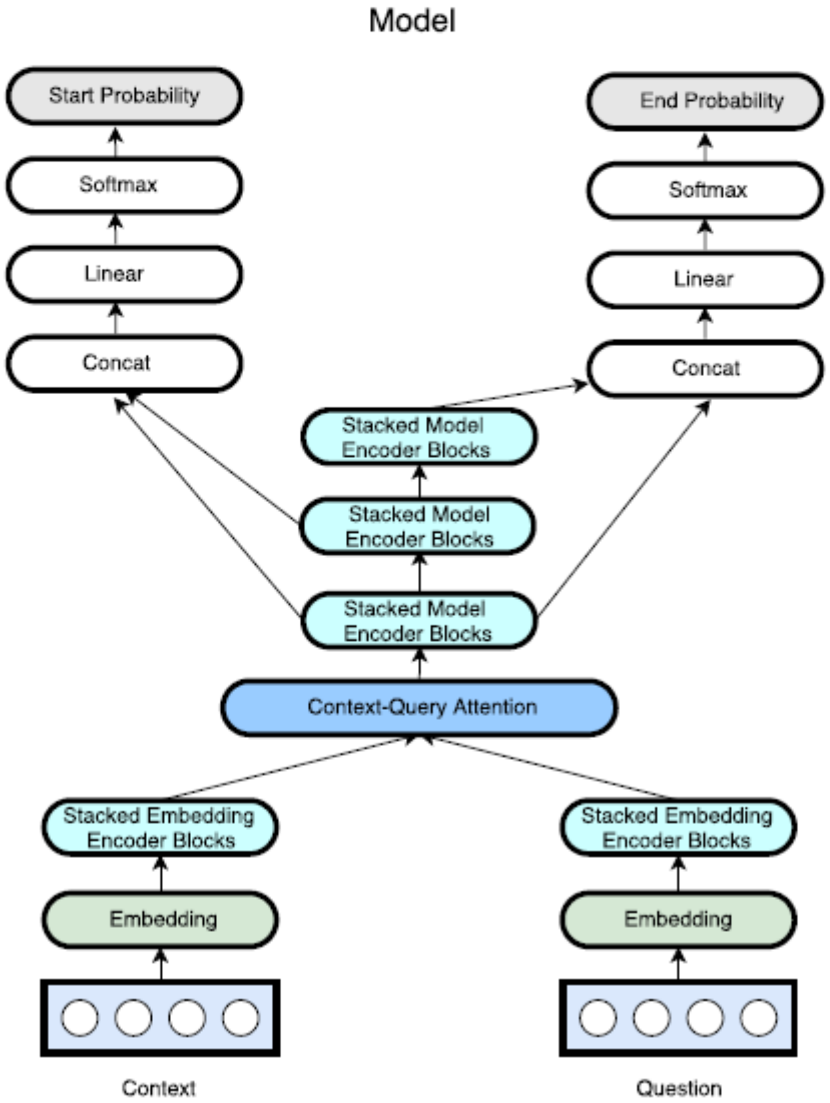
  B = $\bar{S} \cdot \bar{\bar{S}} \cdot C^T \in R^{n \times d}$

Model Encoder Layer



- Q2C attention: A ∈ $R^{n \times d}$
- C2Q attention: B ∈ $R^{n \times d}$
- Input of this layer at each position:
  - [c, a, c ⊙ a, c ⊙ b]

Output Layer

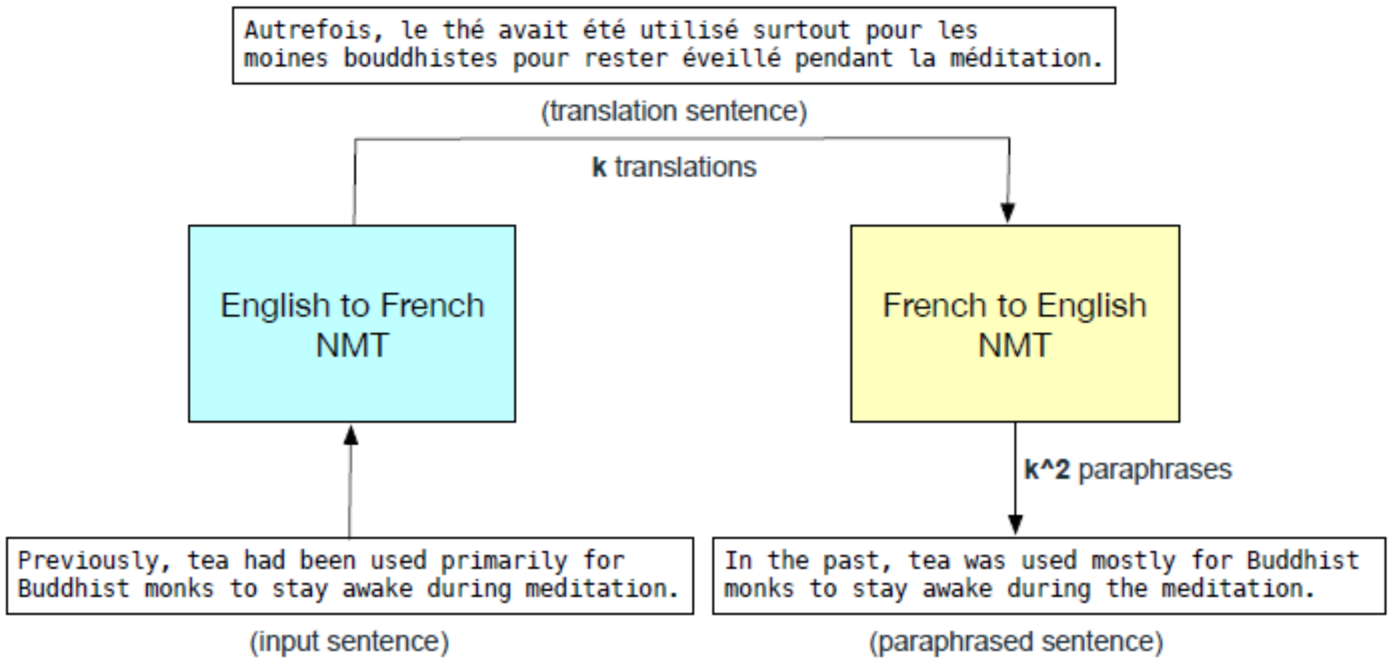


- Predict the probability of each position in the context being the start or end of an answer span.
- Start: $p^1 = \text{softmax}(W_1[M_0; M_1])$
- End: $p^2 = \text{softmax}(W_2[M_0; M_2])$
- Score of a span：
  - Product of its start position and end position probabilities.
- Object function:

$$L(\theta) = -\frac{1}{N}\sum_i^N \left[\log(p^1_{y^1_i}) + \log(p^2_{y^2_i})\right]$$

Data Augmentation By Backtranslation

- Train with more data.
- Idea：
  - Use two translation models: English to French; French to English



Handling SQuAD Documents and Answers

- each example of SQuAD is a triple of (d, q, a)
- Keep q unchanged, generate new triples (d', q, a')
- d' : simply replace each sentence in d with a randomly-selected paraphrase.
- a' ： compute score between each word in s' and the start/end words of a.

	Sentence that contains an answer	Answer
Original	All of the departments in the College of Science offer PhD programs, except for the Department of Pre-Professional Studies.	Department of Pre-Professional Studies
Paraphrase	All departments in the College of Science offer PHD programs with the exception of the Department of Preparatory Studies.	Department of Preparatory Studies

Experiment

- Accuracy:
  - F1: measure the portion of overlap tokens between the answer and groundtruth;
  - EM: exact match, 0/1

	Published[11]	LeaderBoard[12]
Single Model	EM / F1	EM / F1
LR Baseline (Rajpurkar et al., 2016)	40.4 / 51.0	40.4 / 51.0
Dynamic Chunk Reader (Yu et al., 2016)	62.5 / 71.0	62.5 / 71.0
Match-LSTM with Ans-Ptr (Wang & Jiang, 2016)	64.7 / 73.7	64.7 / 73.7
Multi-Perspective Matching (Wang et al., 2016)	65.5 / 75.1	70.4 / 78.8
Dynamic Coattention Networks (Xiong et al., 2016)	66.2 / 75.9	66.2 / 75.9
FastQA (Weissenborn et al., 2017)	68.4 / 77.1	68.4 / 77.1
BiDAF (Seo et al., 2016)	68.0 / 77.3	68.0 / 77.3
SEDT (Liu et al., 2017a)	68.1 / 77.5	68.5 / 78.0
RaSoR (Lee et al., 2016)	70.8 / 78.7	69.6 / 77.7
FastQAExt (Weissenborn et al., 2017)	70.8 / 78.9	70.8 / 78.9
ReasoNet (Shen et al., 2017b)	69.1 / 78.9	70.6 / 79.4
Document Reader (Chen et al., 2017)	70.0 / 79.0	70.7 / 79.4
Ruminating Reader (Gong & Bowman, 2017)	70.6 / 79.5	70.6 / 79.5
jNet (Zhang et al., 2017)	70.6 / 79.8	70.6 / 79.8
Conductor-net	N/A	72.6 / 81.4
Interactive AoA Reader (Cui et al., 2017)	N/A	73.6 / 81.9
Reg-RaSoR	N/A	75.8 / 83.3
DCN+	N/A	74.9 / 82.8
AIR-FusionNet	N/A	76.0 / 83.9
R-Net (Wang et al., 2017)	72.3 / 80.7	76.5 /84.3
BiDAF + Self Attention + ELMo	N/A	**77.9/ 85.3**
Reinforced Mnemonic Reader (Hu et al., 2017)	73.2 / 81.8	73.2 / 81.8
Dev set: Our Model	**73.6 / 82.7**	N/A
Dev set: Our Model + data augmentation $\times 2$	**74.5 / 83.2**	N/A
Dev set: Our Model + data augmentation $\times 3$	**75.1 / 83.8**	N/A
Test set: Our Model + data augmentation $\times 3$	**76.2 / 84.6**	76.2 / 84.6

Experiment

- Speed over RNNs
  - Replace each encoder block with a stack of bi-LSTM.
  - Speed = batches/second

	Ours	RNN-1-128	Speedup	RNN-2-128	Speedup	RNN-3-128	Speedup
Training	**3.2**	1.1	**2.9x**	0.34	**9.4x**	0.24	**13.3x**
Inference	**8.1**	2.2	**3.7x**	1.3	**6.2x**	0.92	**8.8x**

Experiment

- Speed over BiDAF model

	Train time to get 77.0 F1 on Dev set	Train speed	Inference speed
Our model	3 hours	102 samples/s	259 samples/s
BiDAF	15 hours	24 samples/s	37samples/s
Speedup	**5.0x**	**4.3x**	**7.0x**

BiDAF (Seo et al., 2016)	68.0 / 77.3	68.0 / 77.3
Dev set: Our Model	**73.6 / 82.7**	N/A
Dev set: Our Model + data augmentation ×2	**74.5 / 83.2**	N/A
Dev set: Our Model + data augmentation ×3	**75.1 / 83.8**	N/A
Test set: Our Model + data augmentation ×3	**76.2 / 84.6**	76.2 / 84.6

Abalation study and analysis

	EM / F1	Difference to Base Model EM / F1
Base Model	73.6 / 82.7	
- convolution in encoders	70.8 / 80.0	-2.8 / -2.7
- self-attention in encoders	72.2 / 81.4	-1.4 / -1.3
replace sep convolution with normal convolution	72.9 / 82.0	- 0.7 / -0.7
+ data augmentation ×2 (1:1:0)	74.5 / 83.2	+0.9 / +0.5
+ data augmentation ×3 (1:1:1)	74.8 / 83.4	+1.2 / +0.7
+ data augmentation ×3 (1:2:1)	74.3 / 83.1	+0.7 / +0.4
+ data augmentation ×3 (2:2:1)	74.9 / 83.6	+1.3 / +0.9
+ data augmentation ×3 (2:1:1)	75.0 / 83.6	+1.4 / +0.9
+ data augmentation ×3 (3:1:1)	**75.1 / 83.8**	**+1.5 / +1.1**
+ data augmentation ×3 (4:1:1)	75.0 / 83.6	+1.4 / +0.9
+ data augmentation ×3 (5:1:1)	74.9 / 83.5	+1.3 / +0.8

Table 5: An ablation study of data augmentation and other aspects of our model. The reported results are obtained on the *development set*. For rows containing entry "data augmentation", "$\times N$" means the data is enhanced to N times as large as the original size, while the ratio in the bracket indicates the sampling ratio among the original, English-French-English and English-German-English data during training.

Conclusion

- Core innovation:
  - Remove the recurrent neural networks
  - Parallel computation

- Depthwise separable convolution
- Multi-head Self-attention
- Data Augment technique