预训练模型

from word2vec to bert

One-Hot

为了得到索引为i的任意词的one-hot向量表示，我们创建了一个全为0的长度为N的向量，并将位置i的元素设置为1。这样，每个词都被表示为一个长度为N的向量，可以直接由神经网络使用。

由于任意两个不同词的one-hot向量之间的余弦相似度为0，所以one-hot向量不能编码词之间的相似性。

$$\frac{\mathbf{x}^\top \mathbf{y}}{\|\mathbf{x}\|\|\mathbf{y}\|} \in [-1, 1].$$

$$W = \begin{bmatrix} 1 & \cdots & \cdots & \cdots & 0 \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ 0 & \cdots & 1 & \cdots & 0 \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ 0 & \cdots & \cdots & \cdots & 1 \end{bmatrix}$$

Window-based Co-occurence Matrix

建立起窗口大小为1的共生矩阵，矩阵中数字代表两个单词出现在同一个窗口的频率，通过建立共生矩阵就可以很好的计算两个单词的相似性了。

Corpus: I like deep learning. I like NLP. I enjoy flying.

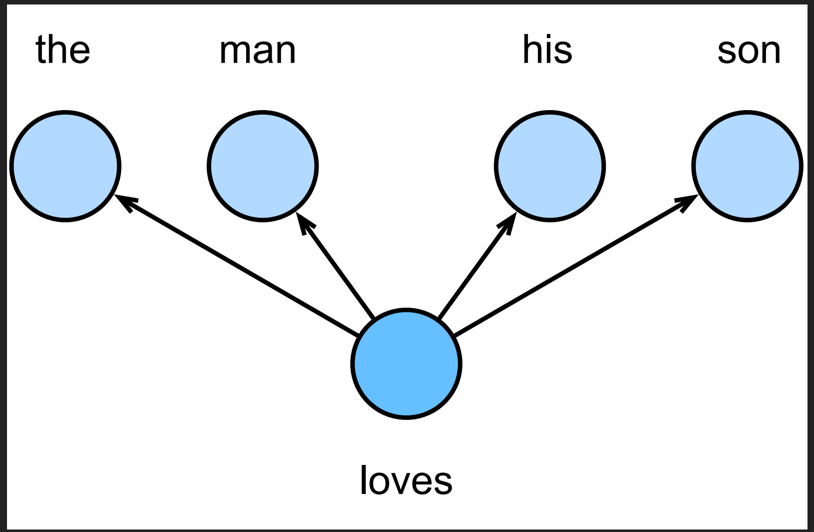
Dictionary: ['I', 'like', 'enjoy', 'deep', 'learning', 'NLP', 'flying', '.']

Self-supervised word2vec

word2vec工具是为了解决上述问题而提出的。它将每个词映射到一个固定长度的向量，这些向量能更好地表达不同词之间的相似性和类比关系。word2vec工具包含两个模型，即跳元模型（skip-gram）和连续词袋（CBOW）。其后有各种优化版本的词向量出现，比较广泛应用的有glove和fasttext。

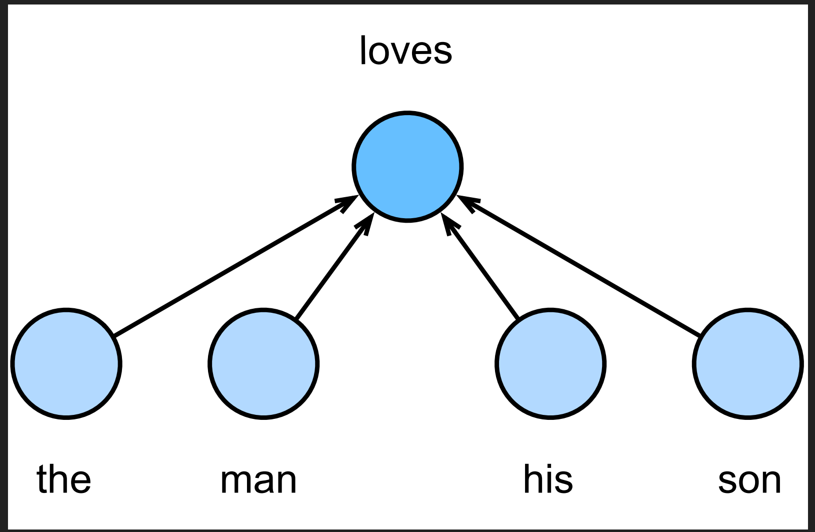
The Skip-Gram Model

$$P(\text{"the"}, \text{"man"}, \text{"his"}, \text{"son"} \mid \text{"loves"}).$$



The CBOW Model

$$P(\text{"loves"} \mid \text{"the"}, \text{"man"}, \text{"his"}, \text{"son"}).$$



$$P(w_o \mid w_c) = \frac{\exp(\mathbf{u}_o^\top \mathbf{v}_c)}{\sum_{i\in\mathcal{V}} \exp(\mathbf{u}_i^\top \mathbf{v}_c)}, v_i \in \mathbb{R}^d \& u_i \in \mathbb{R}^d$$

$$\arg\max \prod_{t=1}^{T} \prod_{-m\le j\le m,\, j\ne 0} P(w^{(t+j)} \mid w^{(t)})$$

$$P(w_c \mid w_{o_1}, \ldots, w_{o_{2m}}) = \frac{\exp\left(\frac{1}{2m}\mathbf{u}_c^\top (\mathbf{v}_{o_1} + \ldots, + \mathbf{v}_{o_{2m}})\right)}{\sum_{i\in\mathcal{V}} \exp\left(\frac{1}{2m}\mathbf{u}_i^\top (\mathbf{v}_{o_1} + \ldots, + \mathbf{v}_{o_{2m}})\right)}, v_i \in \mathbb{R}^d \& u_i \in \mathbb{R}^d$$

$$\arg\max \prod_{t=1}^{T} P(w^{(t)} \mid w^{(t-m)}, \ldots, w^{(t-1)}, w^{(t+1)}, \ldots, w^{(t+m)})$$

Self-supervised word2vec

The Skip-Gram Model

$$\text{loss} = -\sum_{t=1}^{T} \sum_{-m\leq j\leq m,\, j\neq 0} \log P(w^{(t+j)} \mid w^{(t)})$$

$$\log P(w_o \mid w_c) = \mathbf{u}_o^\top \mathbf{v}_c - \log\big(\sum_{i\in\mathcal{V}} \exp(\mathbf{u}_i^\top \mathbf{v}_c)\big)$$

$$\begin{aligned}\frac{\partial \text{log}\, P(w_o \mid w_c)}{\partial \mathbf{v}_c} &= \mathbf{u}_o - \frac{\sum_{j\in\mathcal{V}} \exp(\mathbf{u}_j^\top \mathbf{v}_c)\mathbf{u}_j}{\sum_{i\in\mathcal{V}} \exp(\mathbf{u}_i^\top \mathbf{v}_c)}\\ &= \mathbf{u}_o - \sum_{j\in\mathcal{V}} \left(\frac{\exp(\mathbf{u}_j^\top \mathbf{v}_c)}{\sum_{i\in\mathcal{V}} \exp(\mathbf{u}_i^\top \mathbf{v}_c)}\right)\mathbf{u}_j\\ &= \mathbf{u}_o - \sum_{j\in\mathcal{V}} P(w_j \mid w_c)\mathbf{u}_j\end{aligned}$$

对词典中索引为i的词进行训练后，得到v_i（作为中心词）和u_i（作为上下文词）两个词向量。在自然语言处理应用中，跳元模型的中心词向量通常用作词表示。

The CBOW Model

$$\text{loss} = -\sum_{t=1}^{T} \log P(w^{(t)} \mid w^{(t-m)}, \ldots, w^{(t-1)}, w^{(t+1)}, \ldots, w^{(t+m)})$$

$$\log\ P(w_c \mid \mathcal{W}_o) = \mathbf{u}_c^\top \bar{\mathbf{v}}_o - \log\ \big(\sum_{i\in\mathcal{V}} \exp\big(\mathbf{u}_i^\top \bar{\mathbf{v}}_o\big)\big)\text{S}$$

$$\begin{aligned}\frac{\partial \log\ P(w_c \mid \mathcal{W}_o)}{\partial \mathbf{v}_{o_i}} &= \frac{1}{2m}\left(\mathbf{u}_c - \sum_{j\in\mathcal{V}} \frac{\exp(\mathbf{u}_j^\top \bar{\mathbf{v}}_o)\mathbf{u}_j}{\sum_{i\in\mathcal{V}} \exp(\mathbf{u}_i^\top \bar{\mathbf{v}}_o)}\right)\\ &= \frac{1}{2m}\left(\mathbf{u}_c - \sum_{j\in\mathcal{V}} P(w_j \mid \mathcal{W}_o)\mathbf{u}_j\right)\end{aligned}$$

其他词向量的梯度可以以相同的方式获得。与跳元模型不同，连续词袋模型通常使用上下文词向量作为词表示。

Approximate Training

Negative sampling

负采样修改了原目标函数。给定中心词w_c的上下文窗口，任意上下文词w_o来自该上下文窗口的被认为是由下式建模概率的事件:

$$P(D=1\mid w_c, w_o) = \sigma(\mathbf{u}_o^\top \mathbf{v}_c)$$

用S表示上下文词w_o来自中心词w_c的上下文窗口的事件。对于这个涉及w_o的事件，从预定义分布$P(w)$中采样K个不是来自这个上下文窗口噪声词。用N_k表示噪声词w_k $(k=1,\ldots,K)$不是来自w_c的上下文窗口的事件。

$$\prod_{t=1}^{T} \prod_{-m\leq j\leq m,\ j\neq 0} P(w^{(t+j)}\mid w^{(t)})$$

$$P(w^{(t+j)}\mid w^{(t)}) = P(D=1\mid w^{(t)}, w^{(t+j)}) \prod_{k=1,\ w_k\sim P(w)}^{K} P(D=0\mid w^{(t)}, w_k)$$

Approximate Training

Negative sampling

$$
\begin{aligned}
l = -\log P(w^{(t+j)} \mid w^{(t)}) &= -\log P(D=1 \mid w^{(t)}, w^{(t+j)}) - \sum_{k=1,\ w_k \sim P(w)}^{K} \log P(D=0 \mid w^{(t)}, w_k) \\
&= -\log\ \sigma\left(\mathbf{u}_{i_{t+j}}^\top \mathbf{v}_{i_t}\right) - \sum_{k=1,\ w_k \sim P(w)}^{K} \log\left(1 - \sigma\left(\mathbf{u}_{h_k}^\top \mathbf{v}_{i_t}\right)\right) \\
&= -\log\ \sigma\left(\mathbf{u}_{i_{t+j}}^\top \mathbf{v}_{i_t}\right) - \sum_{k=1,\ w_k \sim P(w)}^{K} \log \sigma\left(-\mathbf{u}_{h_k}^\top \mathbf{v}_{i_t}\right).
\end{aligned}
$$

$$
\frac{\partial l}{v_{i_t}} = -\sigma\left(-\mathbf{u}_{i_{t+j}}^\top \mathbf{v}_{i_t}\right) \mathbf{u}_{i_{t+j}} + \sum_{k=1, w_k \sim P(w)}^{K} \sigma\left(\mathbf{u}_{h_k}^\top \mathbf{v}_{i_t}\right) \mathbf{u}_{h_k}
$$

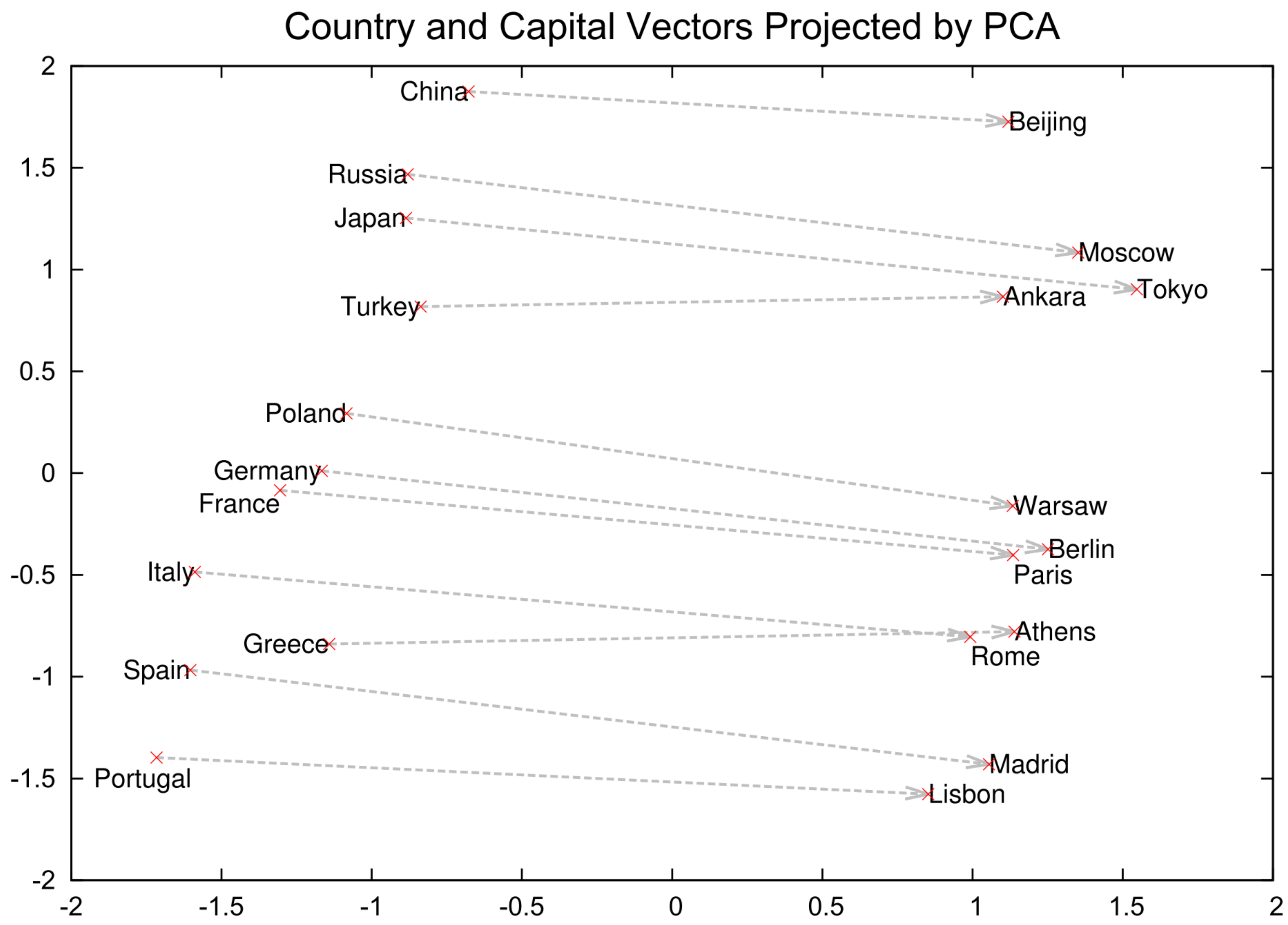
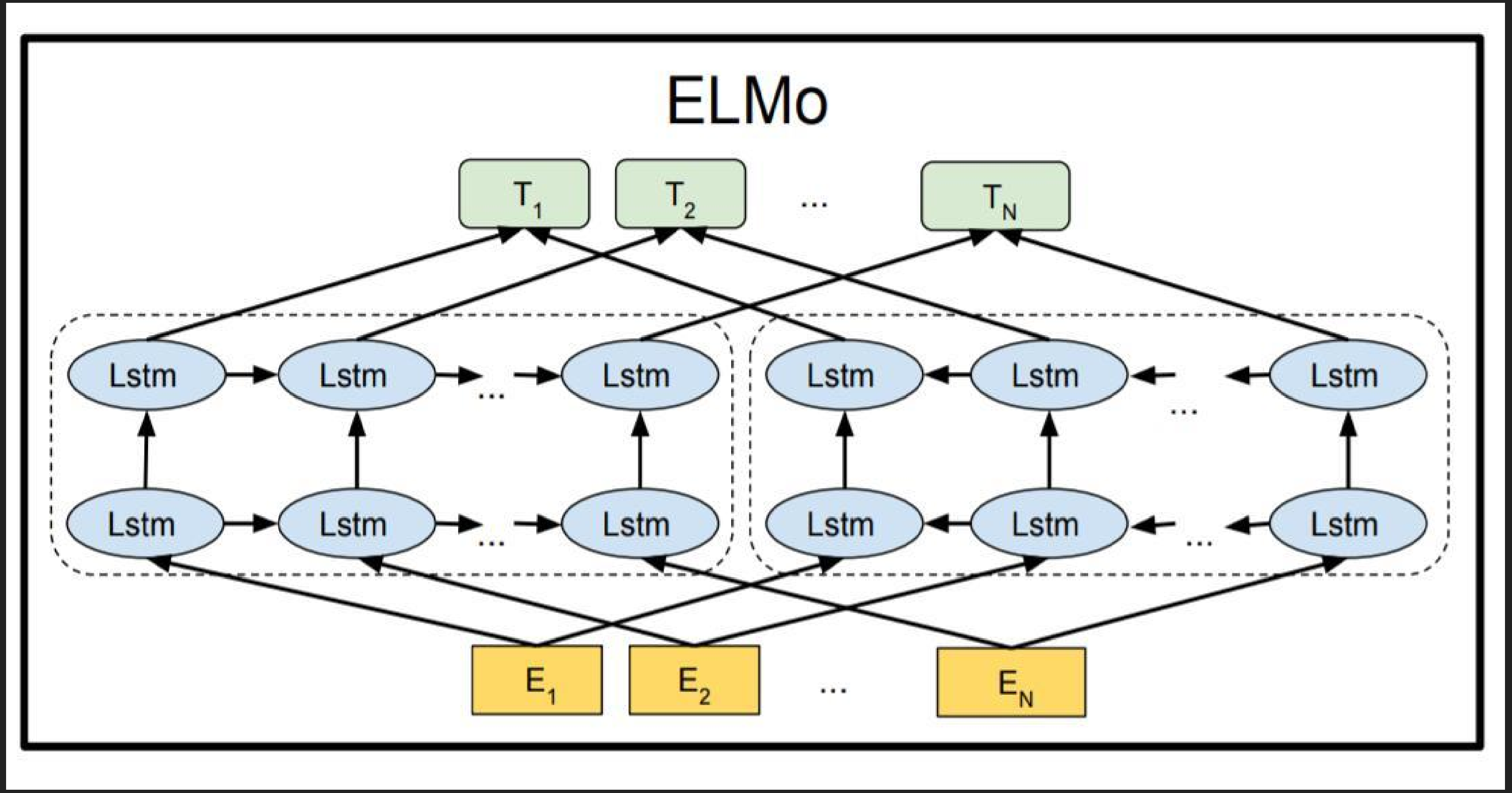


Figure 2: Two-dimensional PCA projection of the 1000-dimensional Skip-gram vectors of countries and their capital cities. The figure illustrates ability of the model to automatically organize concepts and learn implicitly the relationships between them, as during the training we did not provide any supervised information about what a capital city means.

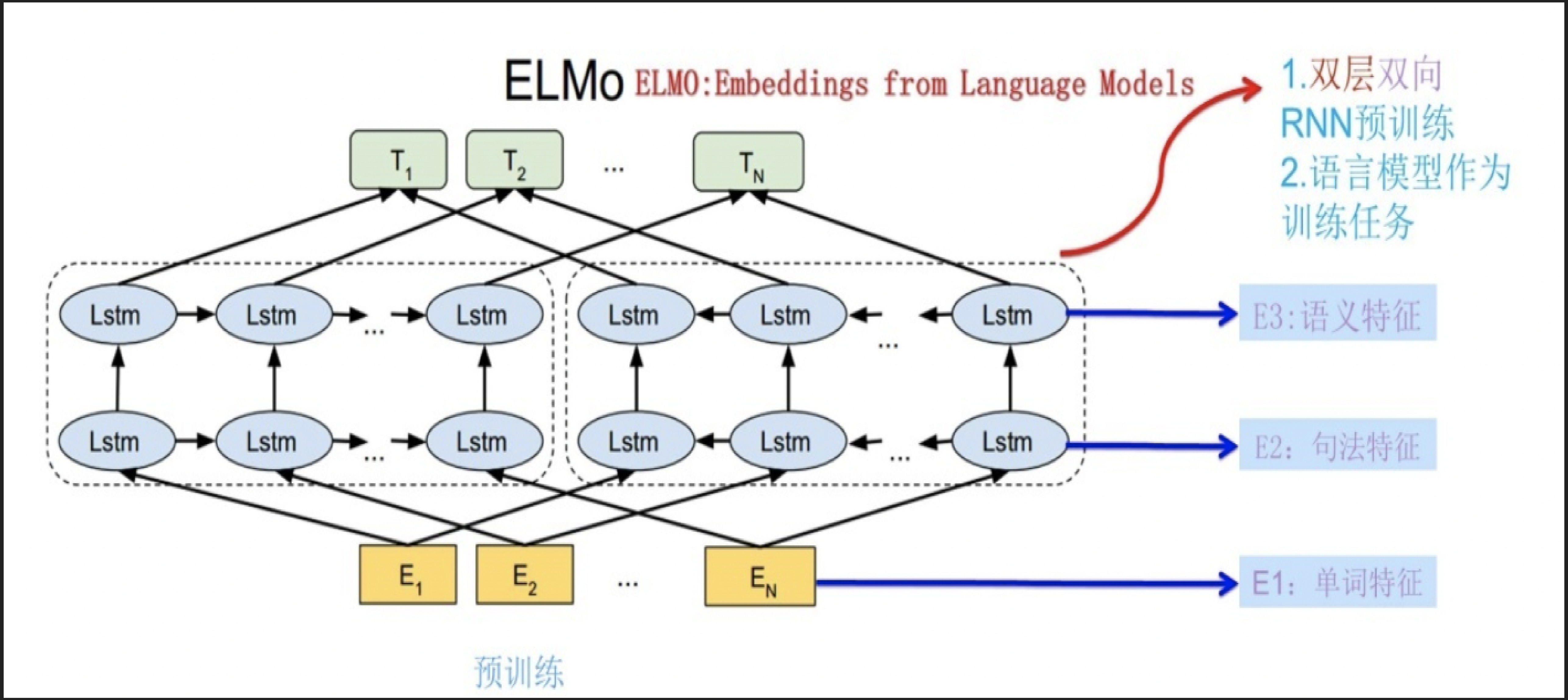
ELMo

word2vec和GloVe都将相同的预训练向量分配给同一个词，而不考虑词的上下文（如果有的话）。单身人的来由：原来是喜欢一个人；现在是喜欢一个人。“一个人”一词有完全不同的含义；因此，同一个词可以根据上下文被赋予不同的表示。



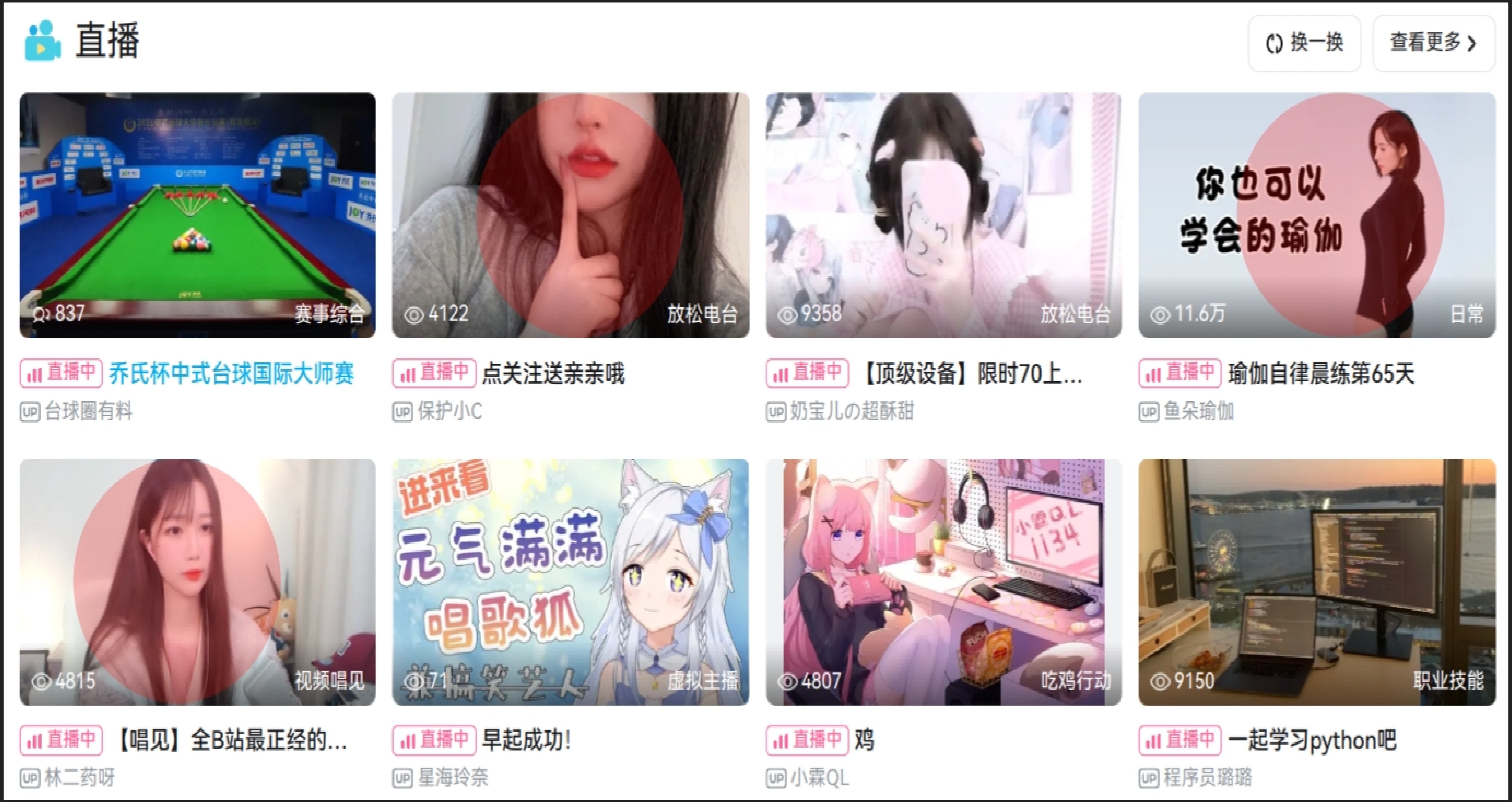
$$\sum_{k=1}^{N}(\log p(t_k|t_1,\ldots,t_{k-1};\Theta_x,\overrightarrow{\Theta}_{LSTM},\Theta_s)+\log p(t_k|t_{k+1},\ldots,t_N;\Theta_x,\overleftarrow{\Theta}_{LSTM},\Theta_s))$$

ELMo


ELMo ELMO:Embeddings from Language Models
1.双层双向
RNN预训练
2.语言模型作为
训练任务
T1
T2
...
TN
Lstm
E3:语义特征
E2：句法特征
E1：单词特征
E1
E2
EN
预训练

Attention Mechanisms

Using the nonvolitional cue



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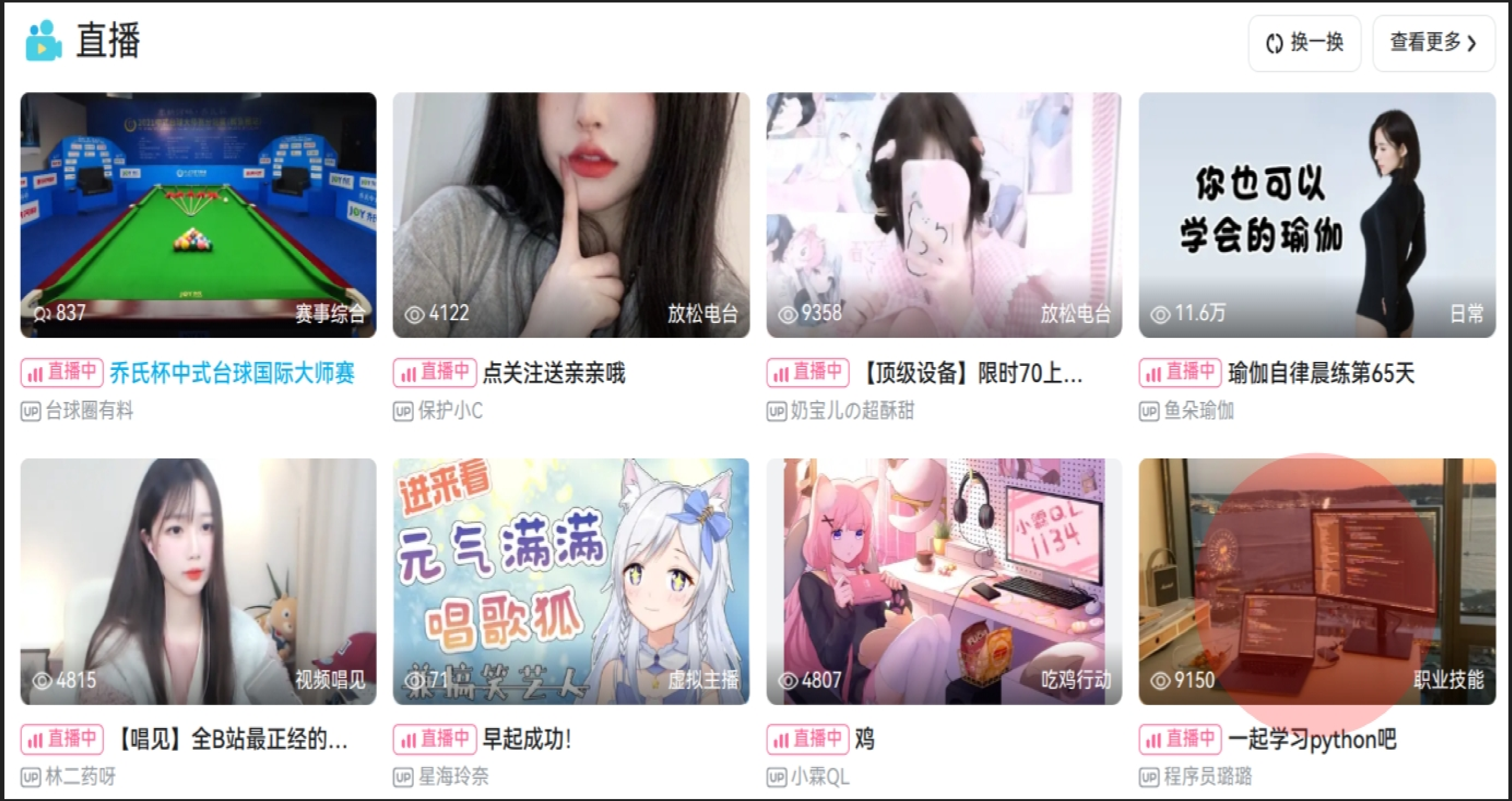
Attention Mechanisms

Using the volitional cue



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直播中 瑜伽自律晨练第65天
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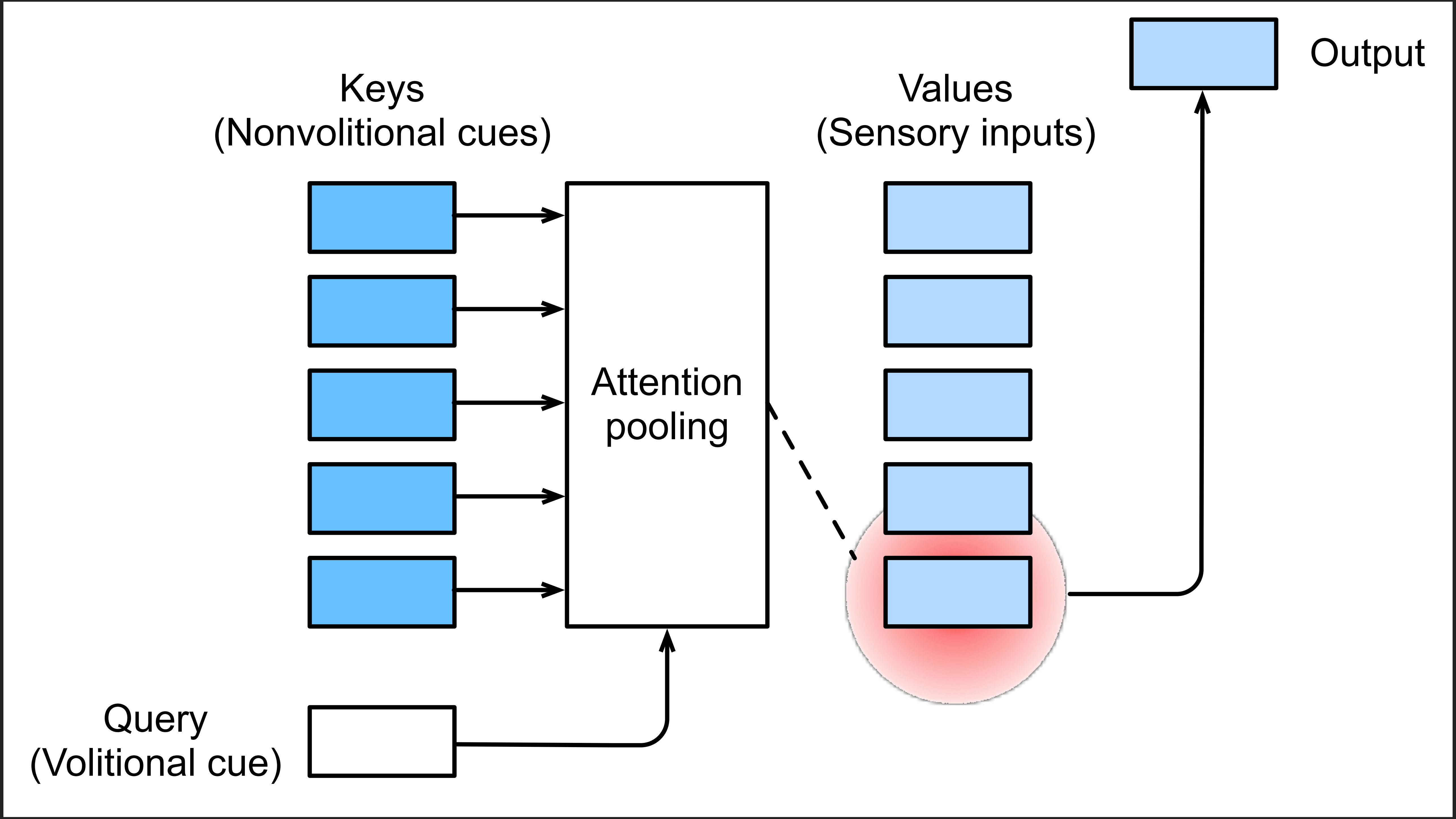
Attention Mechanisms

Using the volitional cue



Attention Mechanisms

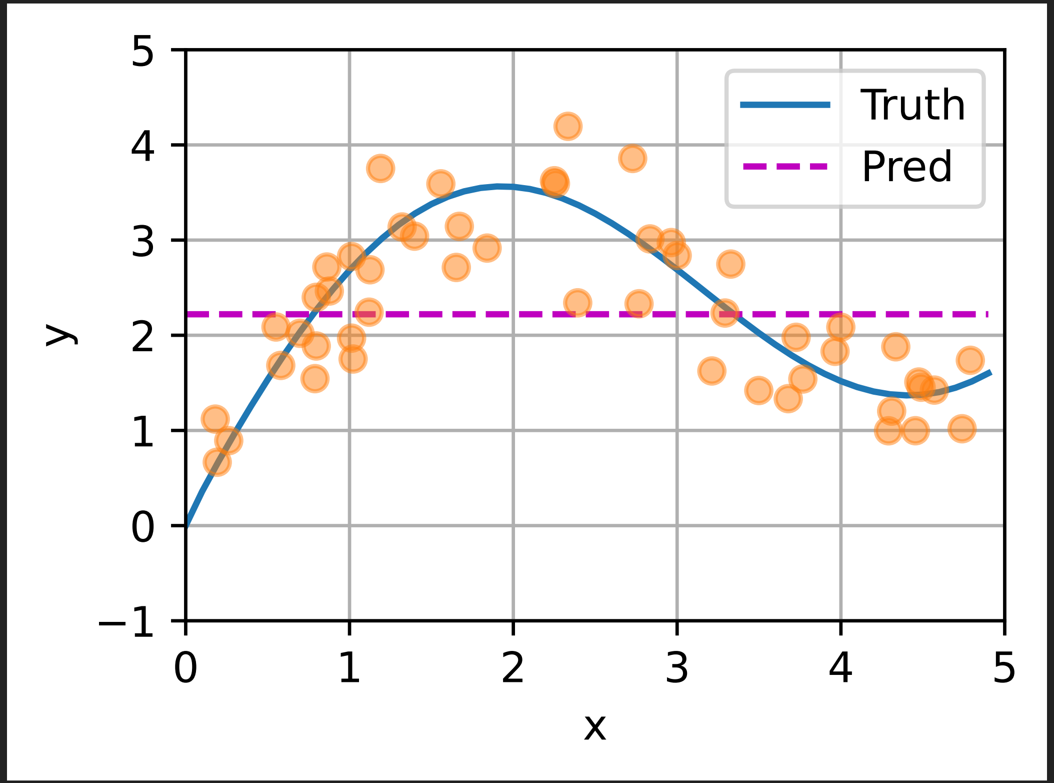
Attention Pooling Nadaraya-Watson Kernel Regression $y_i = 2\sin(x_i) + x_i^{0.8} + \epsilon,$

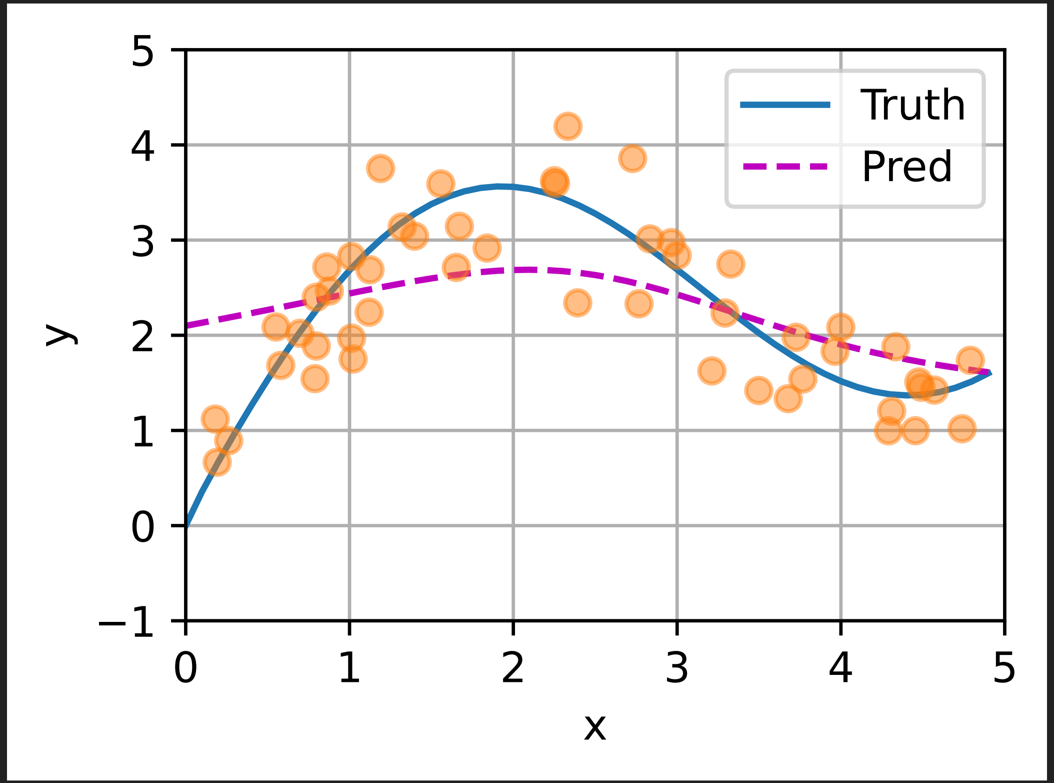
average pooling

$$f(x) = \frac{1}{n}\sum_{i=1}^{n} y_i$$

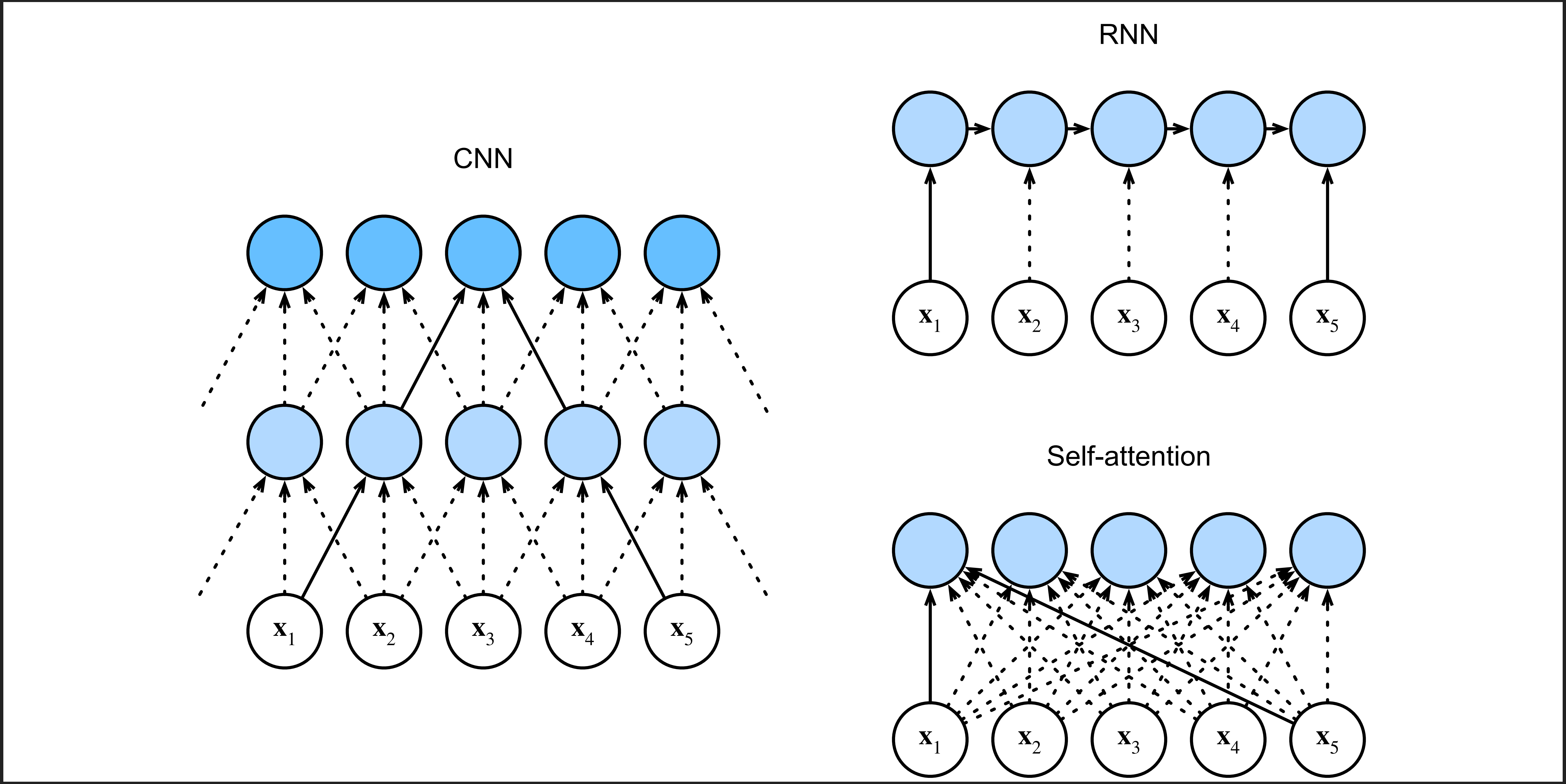
attention pooling

$$f(x) = \sum_{i=1}^{n} \frac{K(x - x_i)}{\sum_{j=1}^{n} K(x - x_j)} y_i,$$

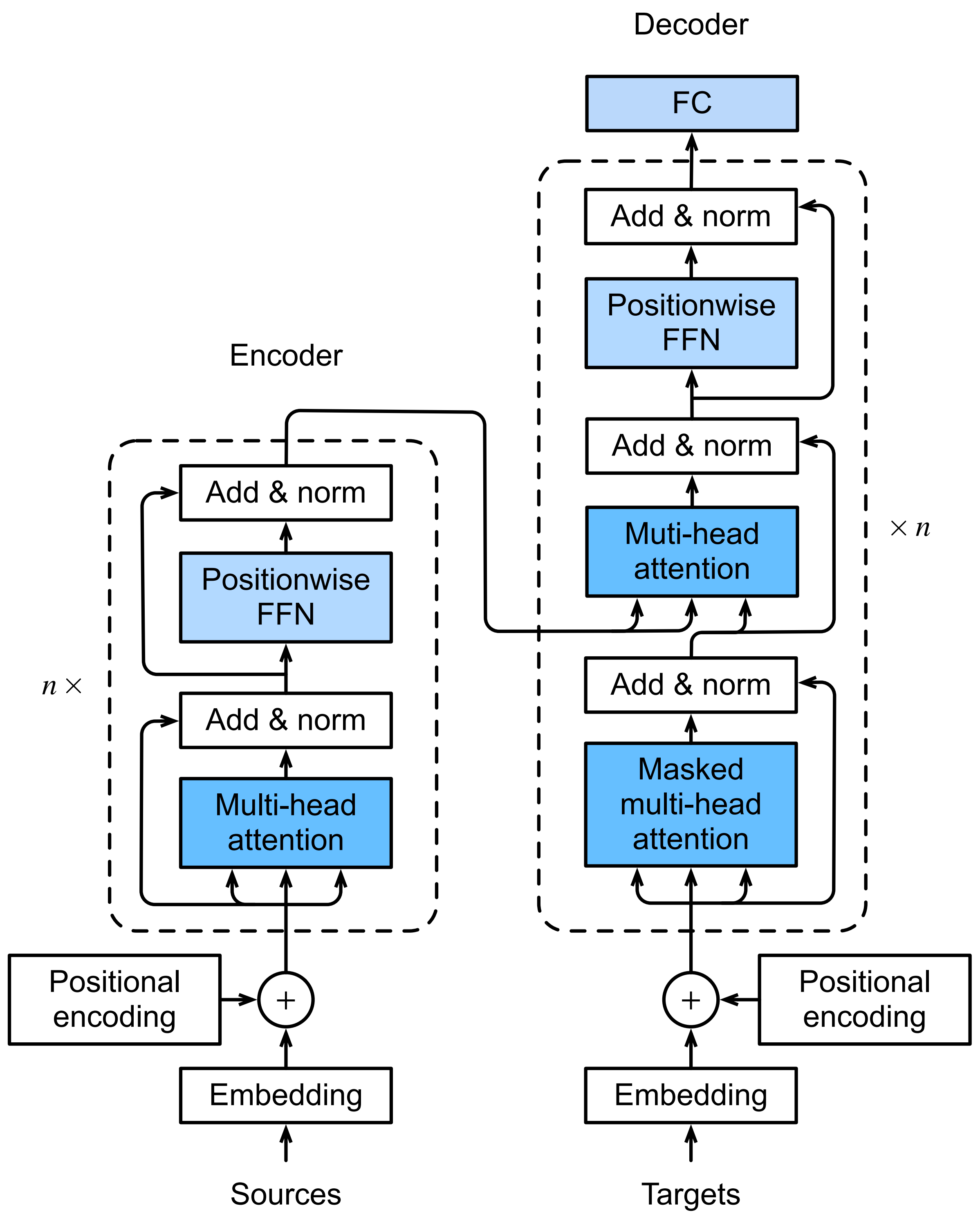




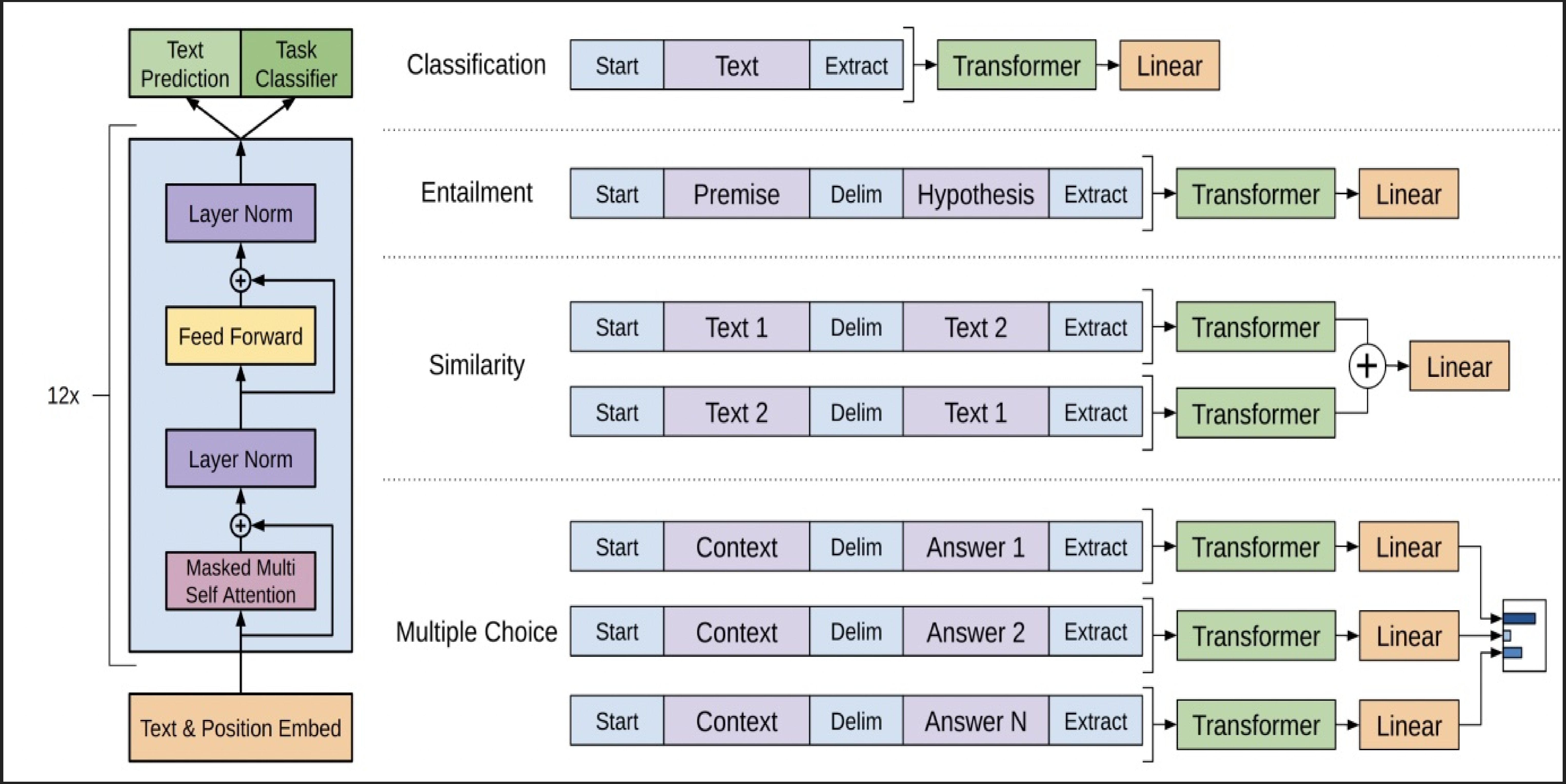
Attention Mechanisms



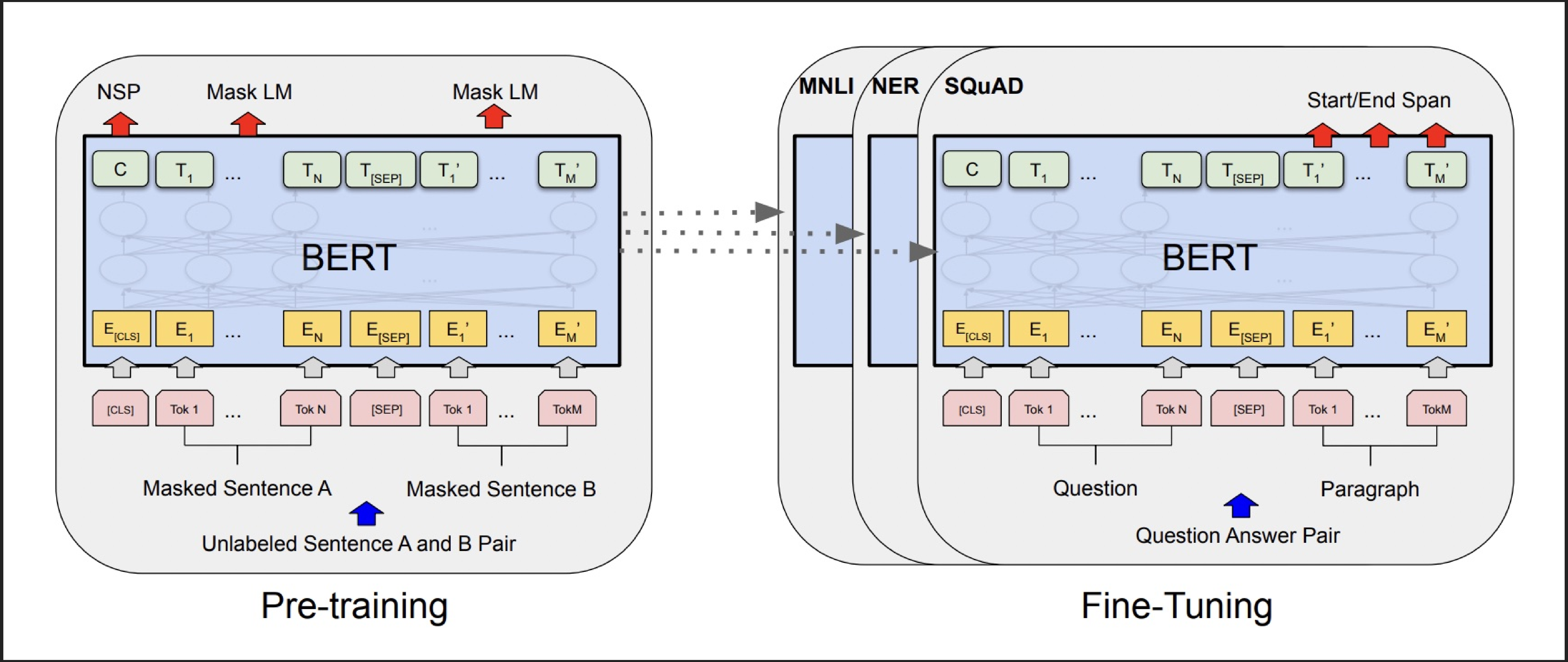
Transformer



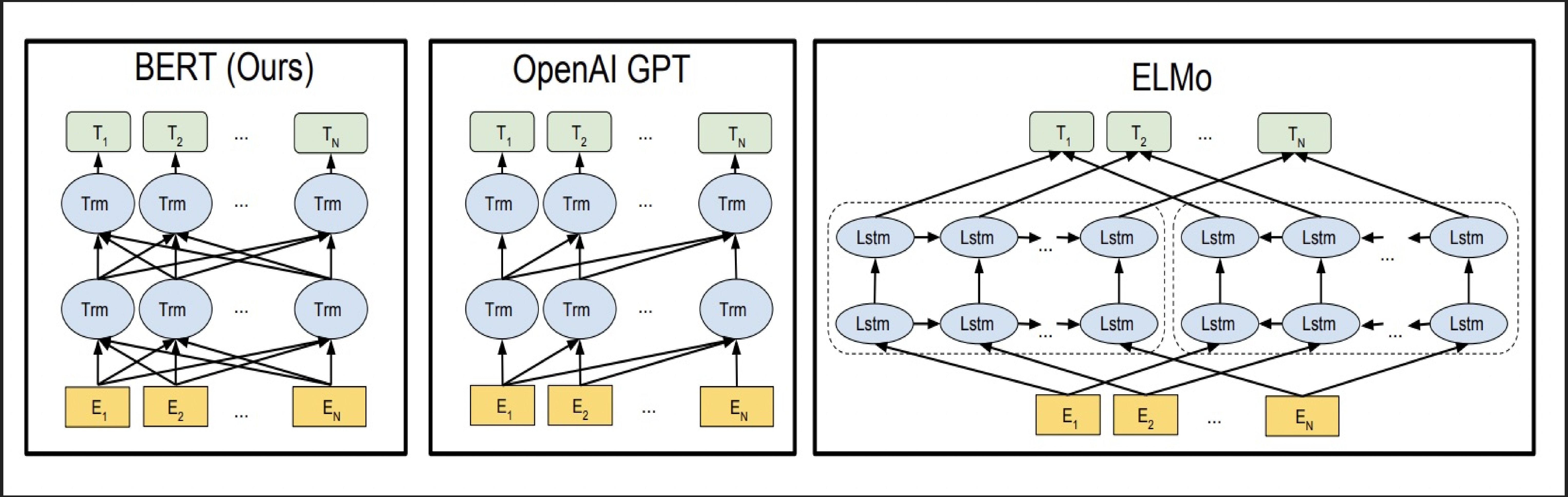
GPT


Text Prediction
Task Classifier
12x
Layer Norm
Feed Forward
Layer Norm
Masked Multi Self Attention
Text & Position Embed
Classification
Start
Text
Extract
Transformer
Linear
Entailment
Start
Premise
Delim
Hypothesis
Extract
Transformer
Linear
Similarity
Start
Text 1
Delim
Text 2
Extract
Transformer
Start
Text 2
Delim
Text 1
Extract
Transformer
Linear
Multiple Choice
Start
Context
Delim
Answer 1
Extract
Transformer
Linear
Start
Context
Delim
Answer 2
Extract
Transformer
Linear
Start
Context
Delim
Answer N
Extract
Transformer
Linear

BERT

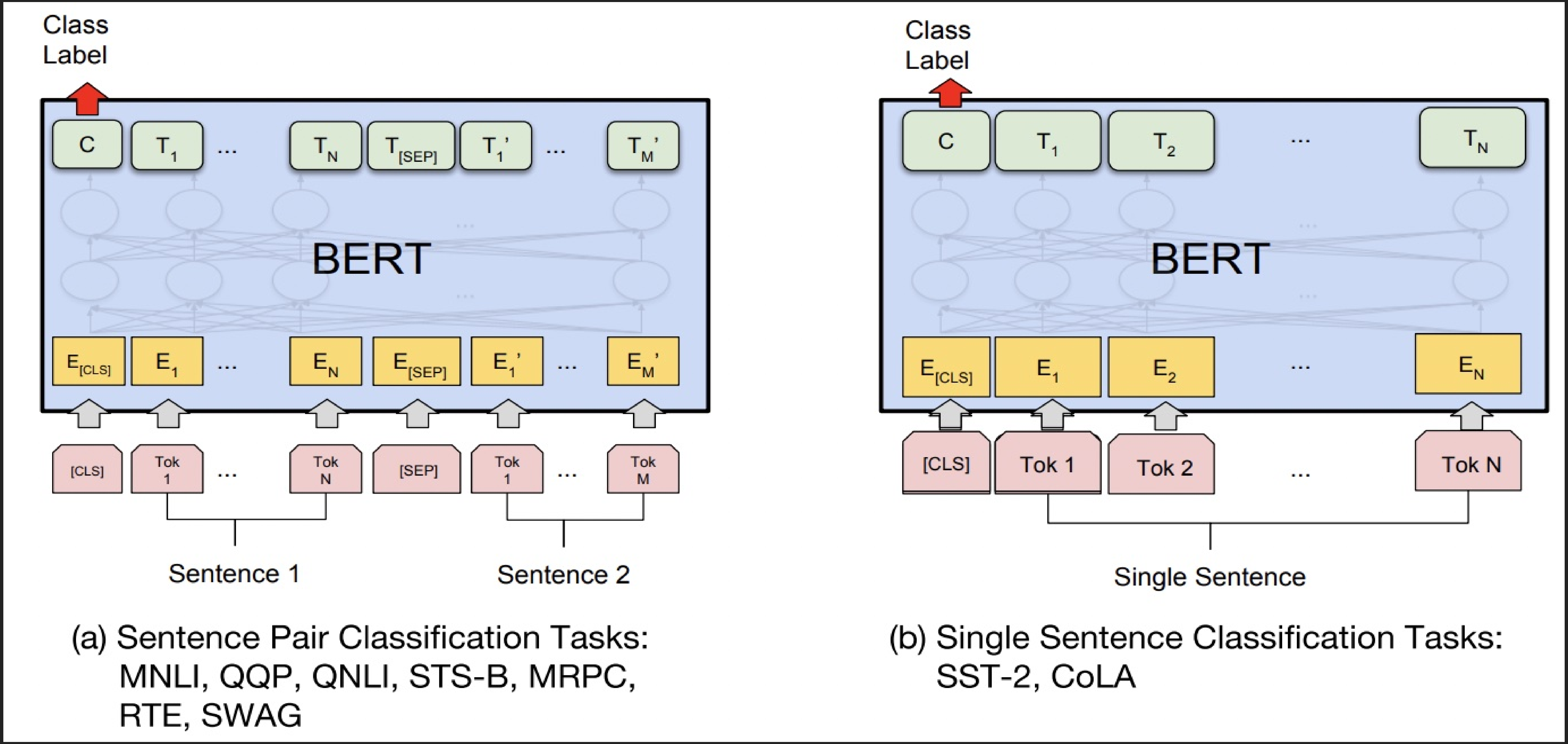

NSP
Mask LM
Mask LM
C
T_1
T_N
$T_{[SEP]}$
T_1'
T_M'
BERT
$E_{[CLS]}$
E_1
E_N
$E_{[SEP]}$
E_1'
E_M'
[CLS]
Tok 1
Tok N
[SEP]
Tok 1
TokM
Masked Sentence A
Masked Sentence B
Unlabeled Sentence A and B Pair
Pre-training
MNLI
NER
SQuAD
Start/End Span
Question
Paragraph
Question Answer Pair
Fine-Tuning

BERT

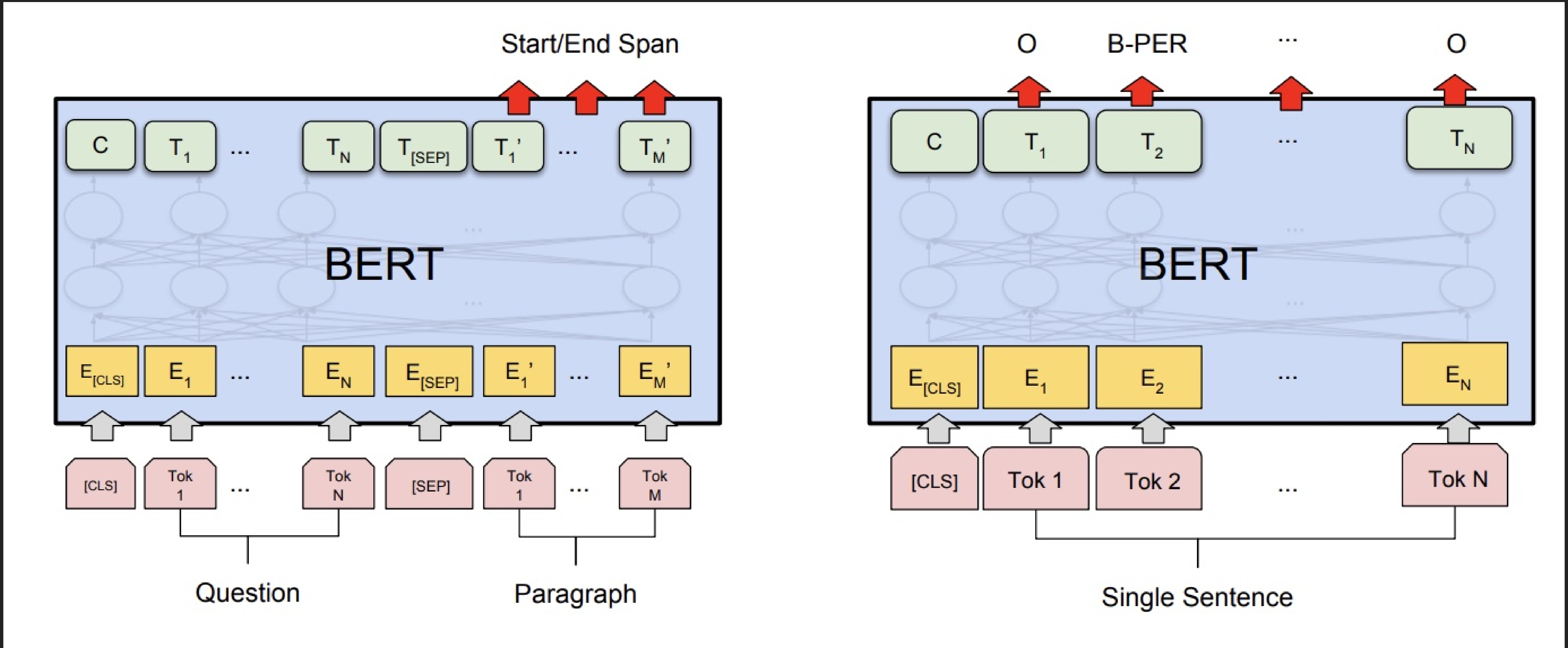


BERT是transformer的encoder部分，GPT是decoder拿掉multi-head以后的部分，把ELMo的LSTM换成transformer就是BERT。回过头，BERT可以看做是deep CBOW。

BERT


Class Label
C
T_1
...
T_N
$T_{[SEP]}$
T_1'
...
T_M'
BERT
$E_{[CLS]}$
E_1
...
E_N
$E_{[SEP]}$
E_1'
...
E_M'
[CLS]
Tok 1
...
Tok N
[SEP]
Tok 1
...
Tok M
Sentence 1
Sentence 2
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG
Class Label
C
T_1
T_2
...
T_N
BERT
$E_{[CLS]}$
E_1
E_2
...
E_N
[CLS]
Tok 1
Tok 2
...
Tok N
Single Sentence
(b) Single Sentence Classification Tasks: SST-2, CoLA

BERT



(c) Question Answering Tasks:
SQuAD v1.1

(d) Single Sentence Tagging Tasks:
CoNLL-2003 NER