昇思MindSpore技术公开课
大模型专题

BERT

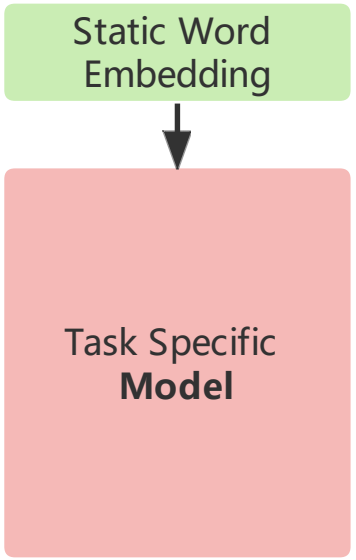
[M]S 昇思 MindSpore

目录

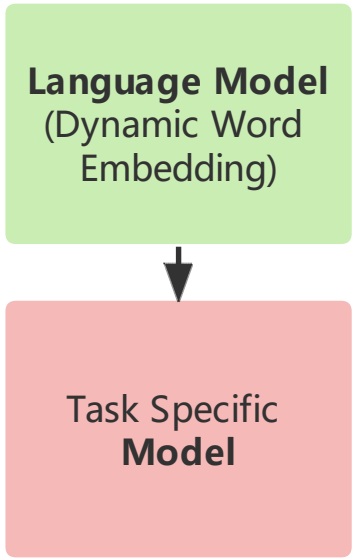
NLP中的预训练模型

语言模型的演变经历了以下几个阶段：

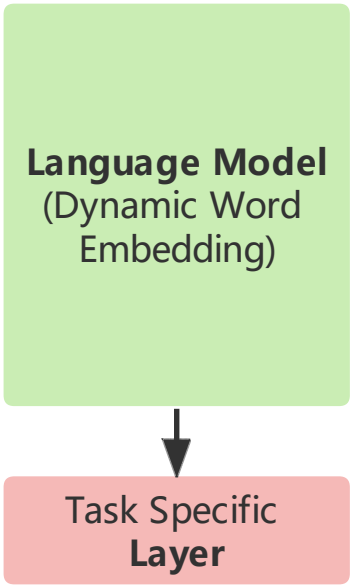
Word2Vec/Glove



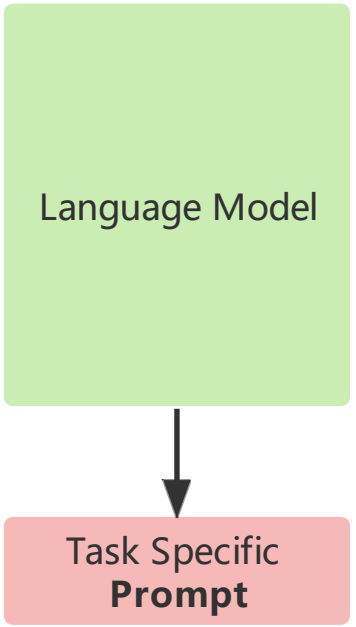
ELMo



BERT (Fine Tuning)



T5/GPT/BERT (Prompt)



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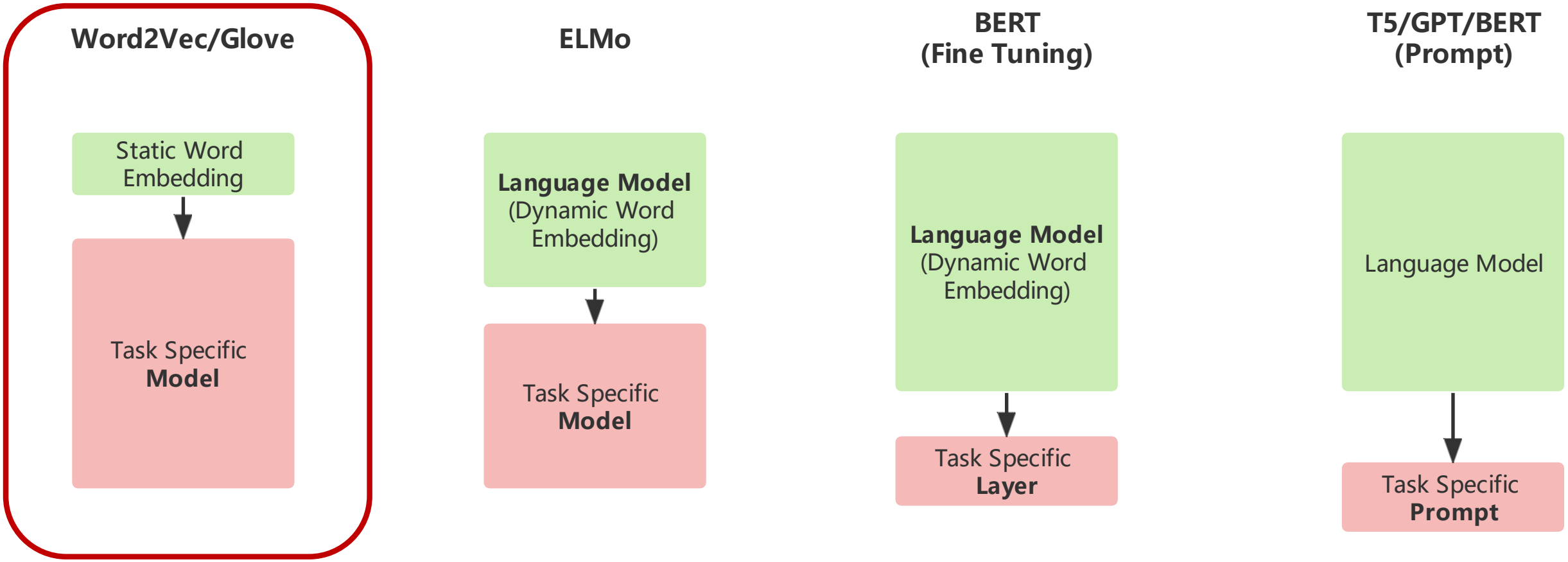
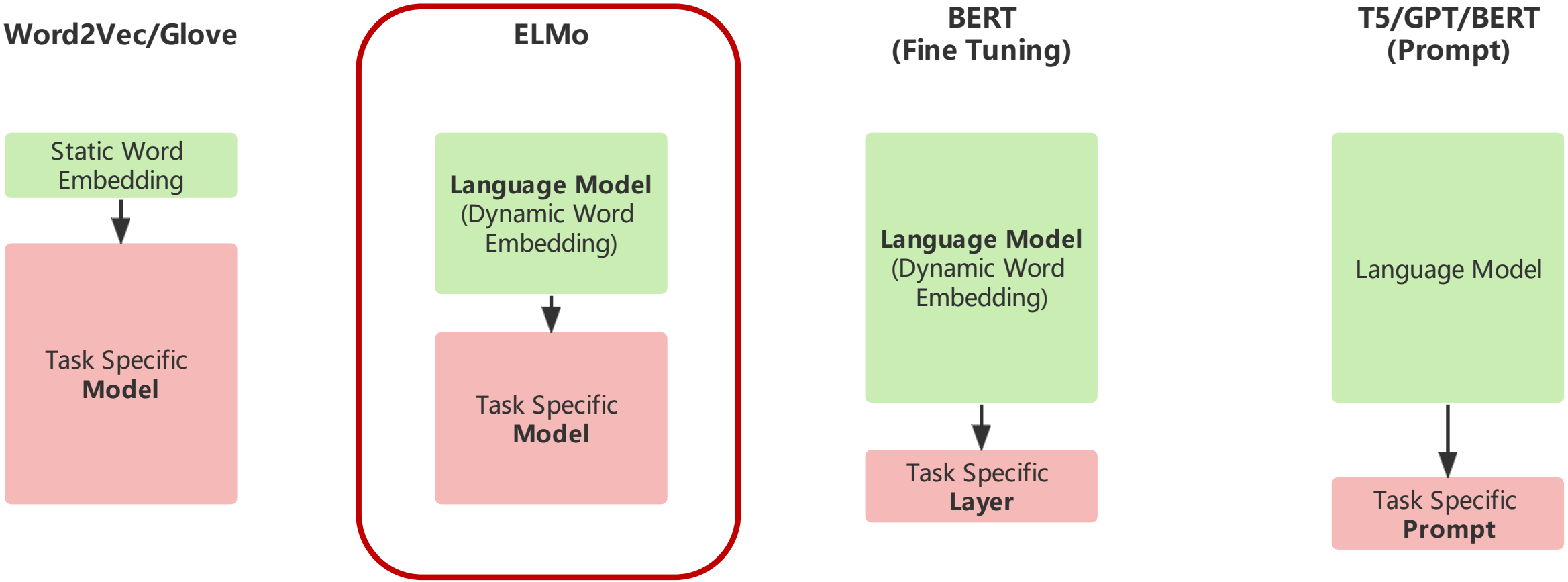


1. word2vec/Glove将离散的文本数据转换为固定长度的**静态词向量**，后根据下游任务训练不同的**语言模型**

NLP中的预训练模型

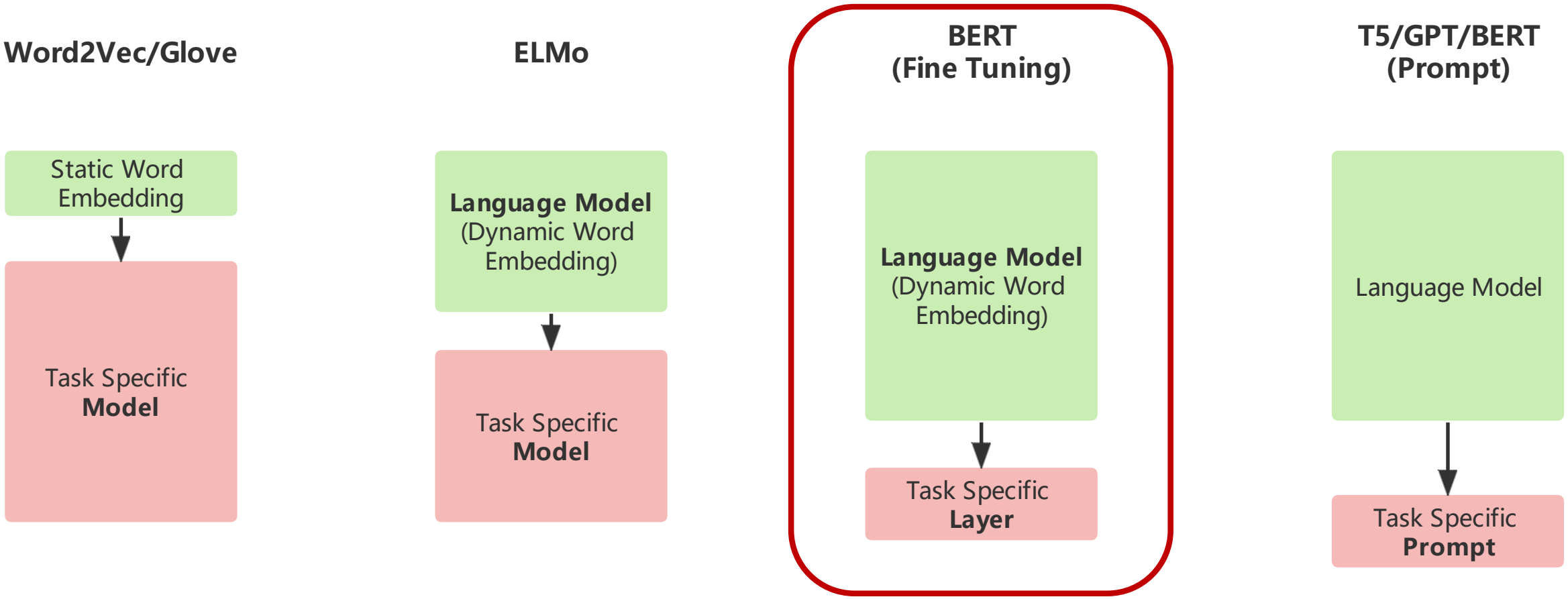
语言模型的演变经历了以下几个阶段：



2. ELMo预训练模型将文本数据**结合上下文信息**，转换为**动态词向量**，后根据下游任务训练不同的**语言模型**

NLP中的预训练模型

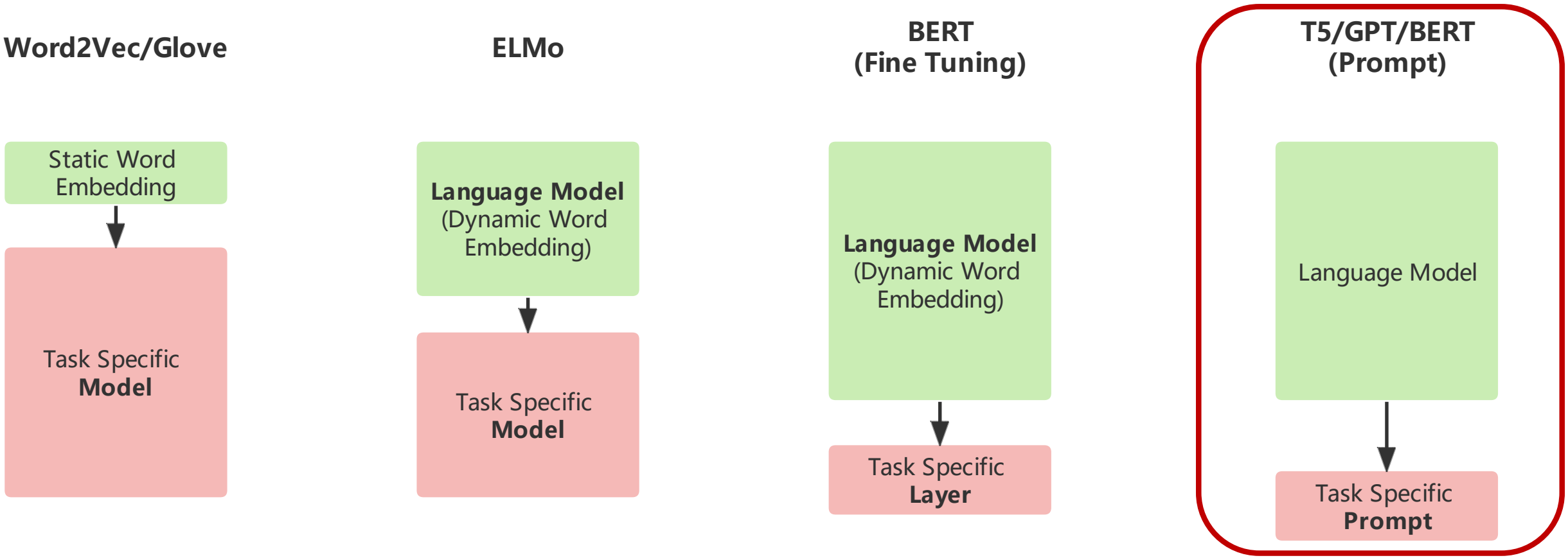
语言模型的演变经历了以下几个阶段：



3.BERT同样将文本数据转换为**动态词向量**，能够更好地捕捉**句子级别的信息与语境信息**，后续只需对BERT参数进行微调，仅重新训练最后的**输出层**即可适配下游任务

NLP中的预训练模型

语言模型的演变经历了以下几个阶段：



4.GPT等预训练语言模型主要用于**文本生成类任务**，需要通过**prompt方法**来应用于下游任务，指导模型生成特定的输出。

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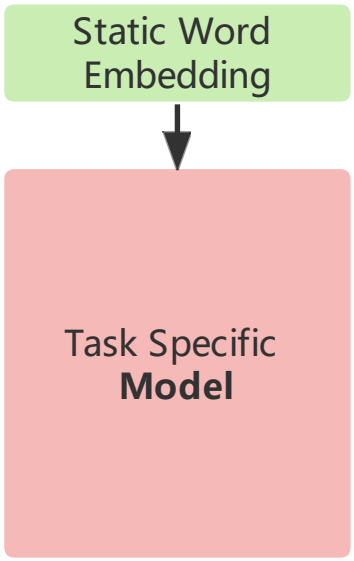
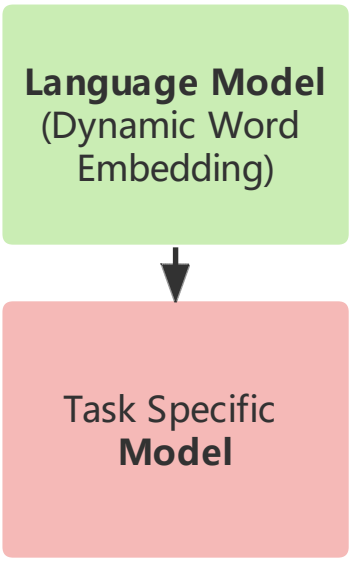


ELMo



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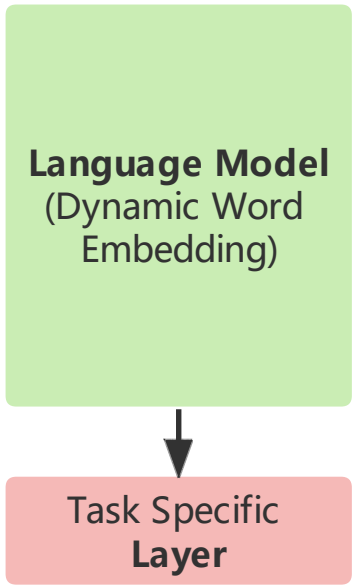
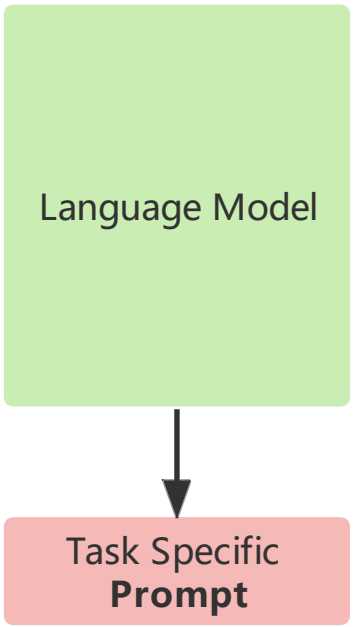


T5/GPT/BERT (Prompt)



BERT模型本质上是结合了ELMo模型与GPT模型的优势。

- 相比于ELMo，BERT仅需改动最后的输出层，而非模型架构，便可以在下游任务中达到很好的效果；
- 相比于GPT，BERT在处理词元表示时考虑到了双向上下文的信息；

目录

BERT Introduction

1 - Semi-supervised training on large amounts of text (books, wikipedia..etc).

The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.

Semi-supervised Learning Step

Model:

Dataset:

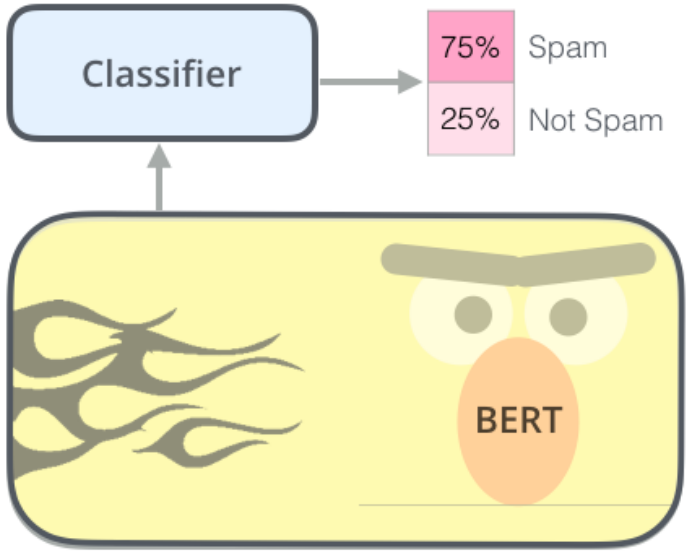
Objective:

Predict the masked word (langauge modeling)

2 - Supervised training on a specific task with a labeled dataset.

Supervised Learning Step

Model: (pre-trained in step #1)

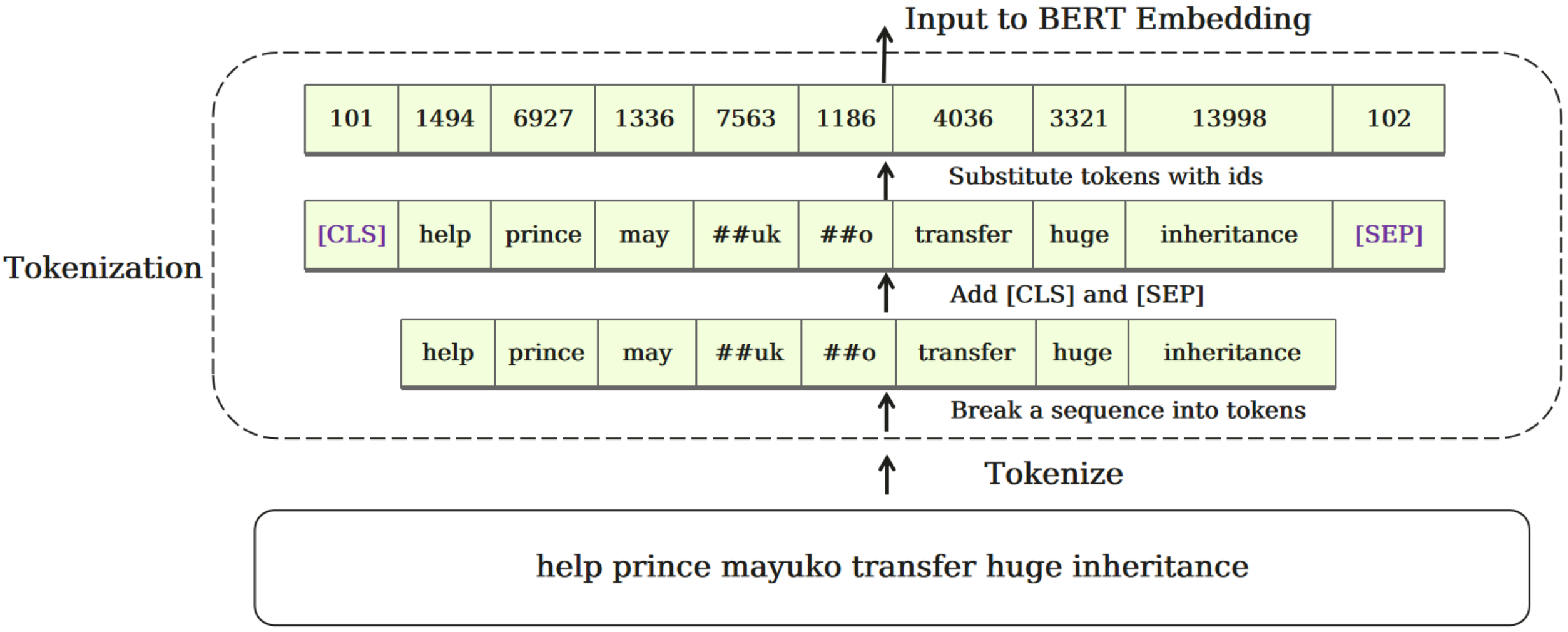


Dataset:

Email message	Class
Buy these pills	Spam
Win cash prizes	Spam
Dear Mr. Atreides, please find attached…	Not Spam

BERT Input

第一步：Tokenization， 输入的句子经过分词后，首尾添加[CLS]与[SEP]特殊字符，后转换为数字id



BERT Input

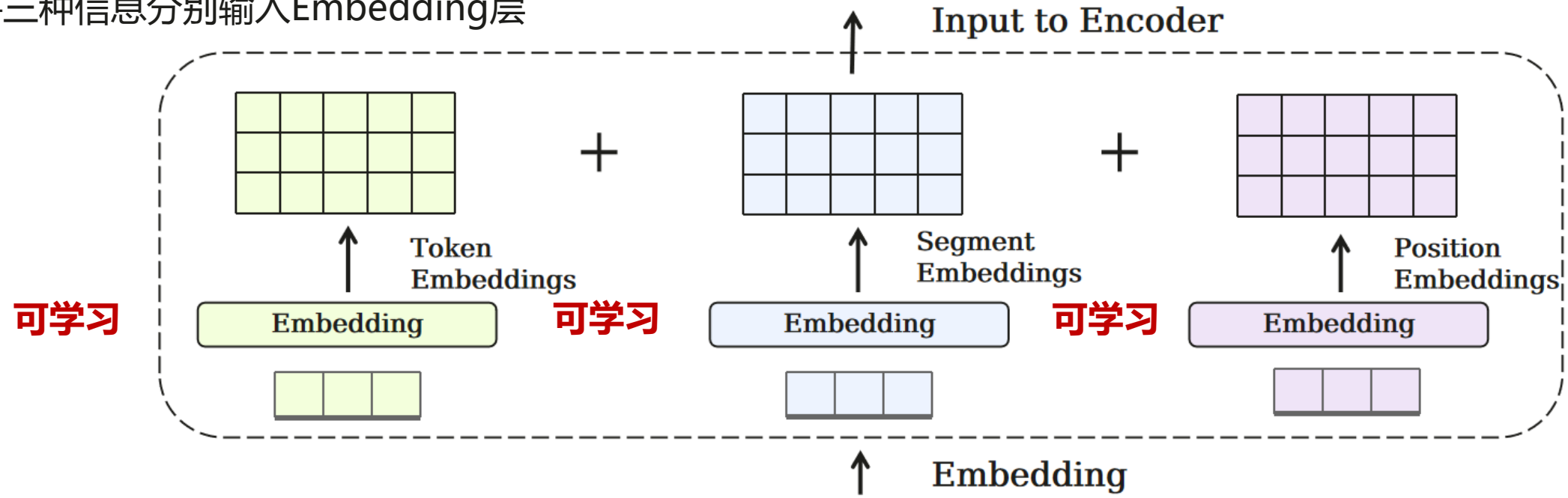
第二步：Embedding， 输入到BERT模型的信息由三部分内容组成：

- 表示内容的token ids
- 表示位置的position ids
- 用于区分不同句子的token type ids

token type ids	0	0	0	0	0	0	0	0	0	0
position ids	0	1	2	3	4	5	6	7	8	9
token ids	101	1494	6927	1336	7563	1186	4036	3321	13998	102
model input	[CLS]	help	prince	may	##uk	##o	transfer	huge	inheritance	[SEP]

BERT Input

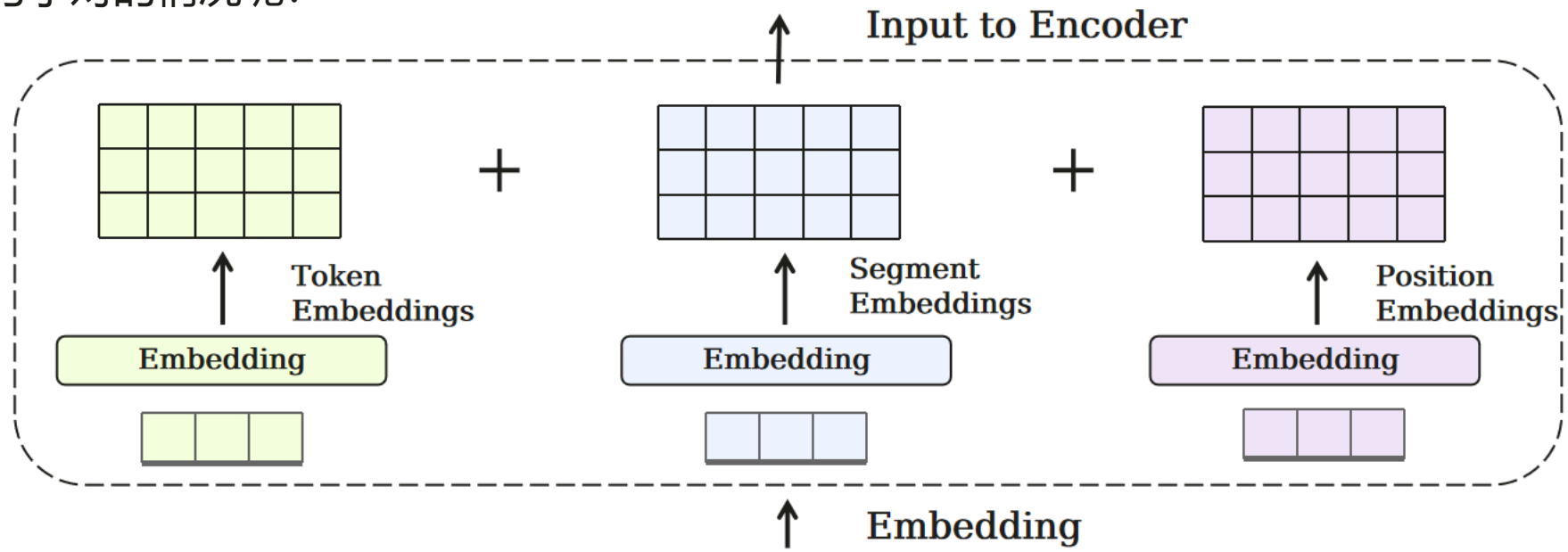
将三种信息分别输入Embedding层



token type ids	0	0	0	0	0	0	0	0	0	0
position ids	0	1	2	3	4	5	6	7	8	9
token ids	101	1494	6927	1336	7563	1186	4036	3321	13998	102
model input	[CLS]	help	prince	may	##uk	##o	transfer	huge	inheritance	[SEP]

BERT Input

如果出现输入是句子对的情况呢?

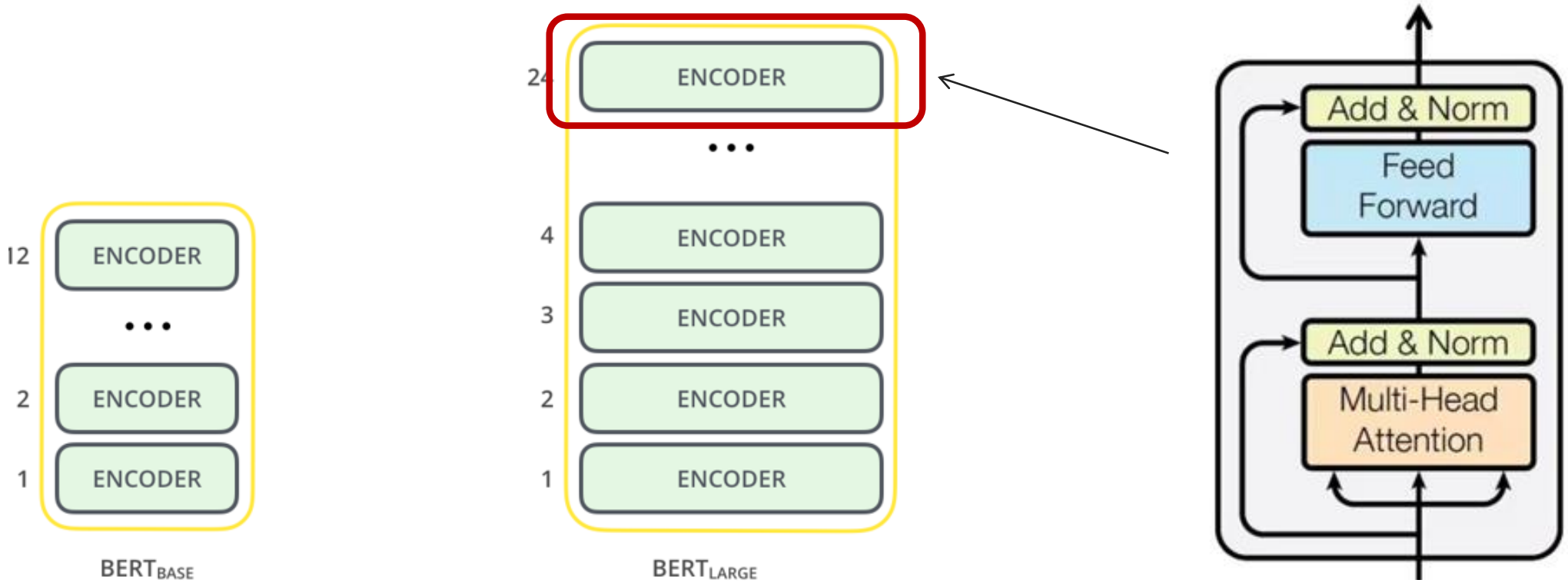


token type ids	0	0	0	0	0	0	1	1	1	1	1
position ids	0	1	2	3	4	5	6	7	8	9	10
token ids	102	1139	3676	1110	10509	102	2002	7777	2377	1158	102
model input	[CLS]	my	dog	is	cute	[SEP]	he	likes	play	##ing	[SEP]

BERT Architecture

BERT由Encoder Layer堆叠而成，Encoder Layer的组成与Transformer的Encoder Layer一致：

- 自注意力层 + 前馈神经网络，中间通过residual connection和LayerNorm连接



BERT Architecture

BERT（Bidirectional Encoder Representation from Transformers）是由Transformer的Encoder层堆叠而成，

BERT的模型大小有如下两种：

- BERT BASE：与Transformer参数量齐平，用于比较模型效果（110M parameters）
- BERT LARGE：在BERT BASE基础上扩大参数量，达到了当时各任务最好的结果（340M parameters）

model	blocks	hidden size	attention head
Transformer	6	512	8
BERT BASE	12	768	12
BERT LARGE	24	1024	16

Reference: BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

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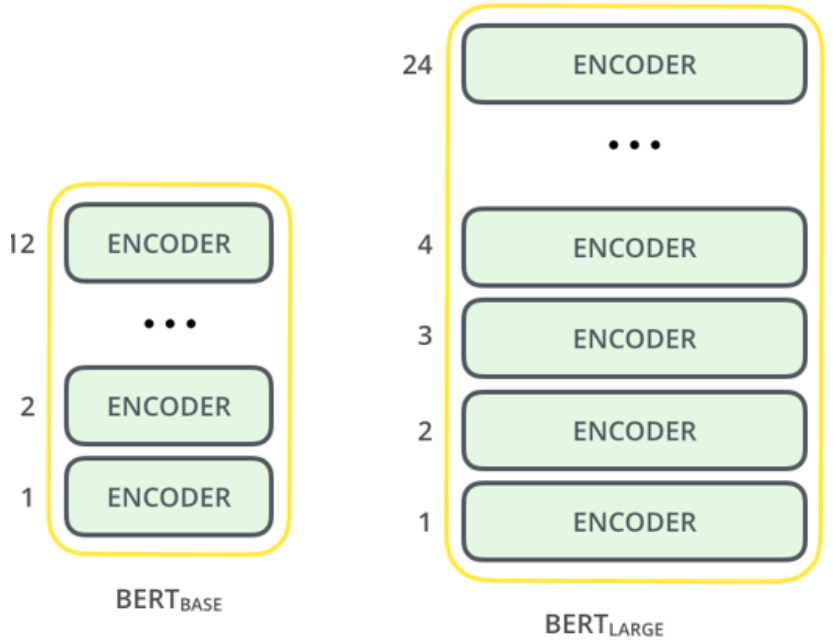
堆叠的encoder层数



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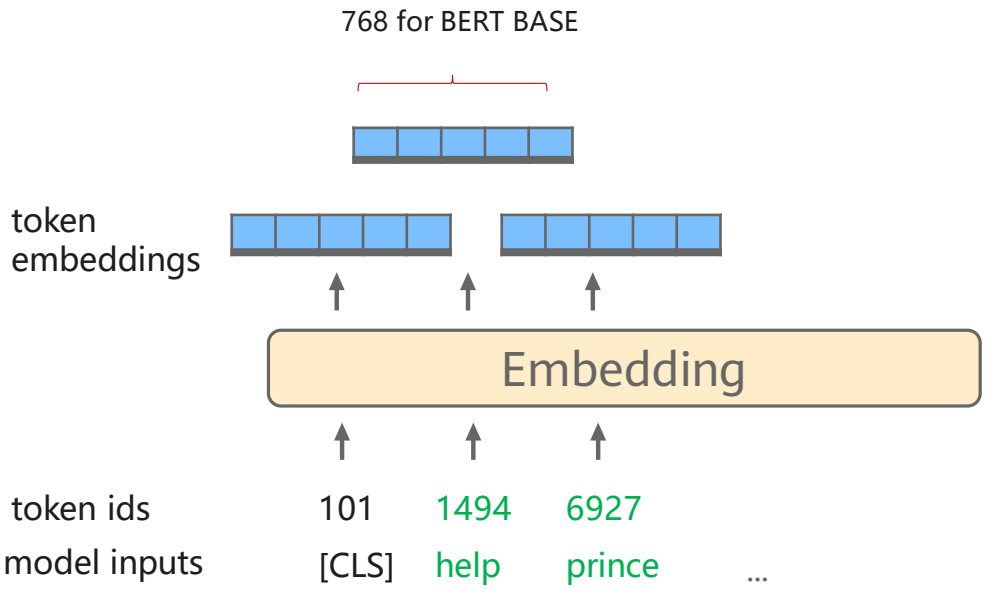
token embedding的词向量长度



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model	blocks	hidden size	attention head
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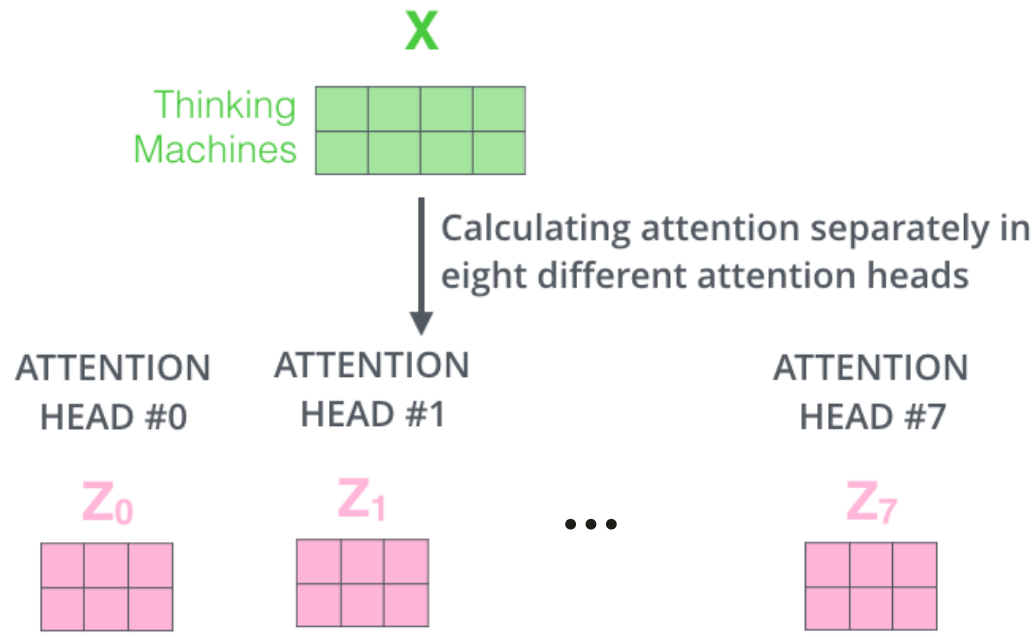
多头注意力头的数量



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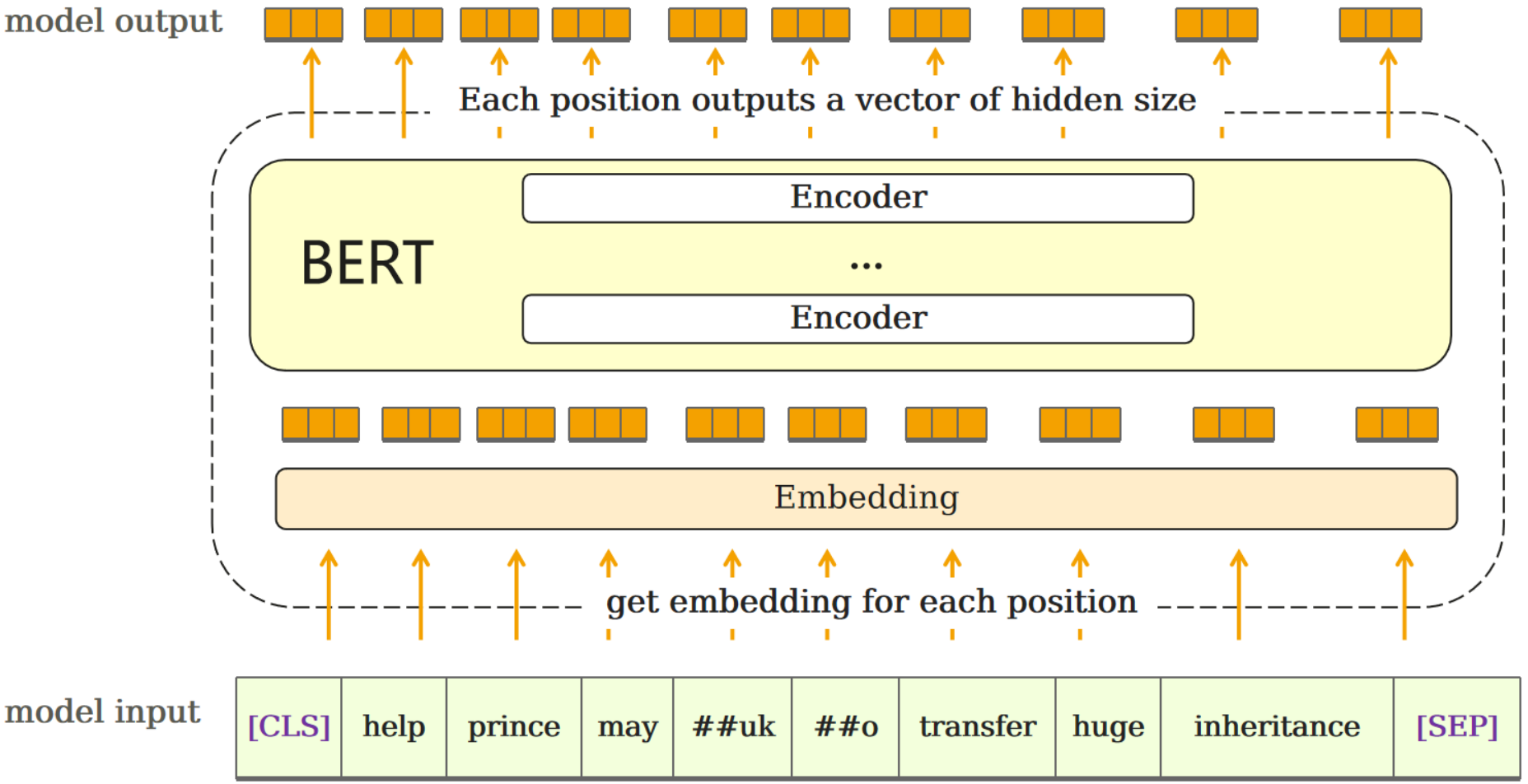
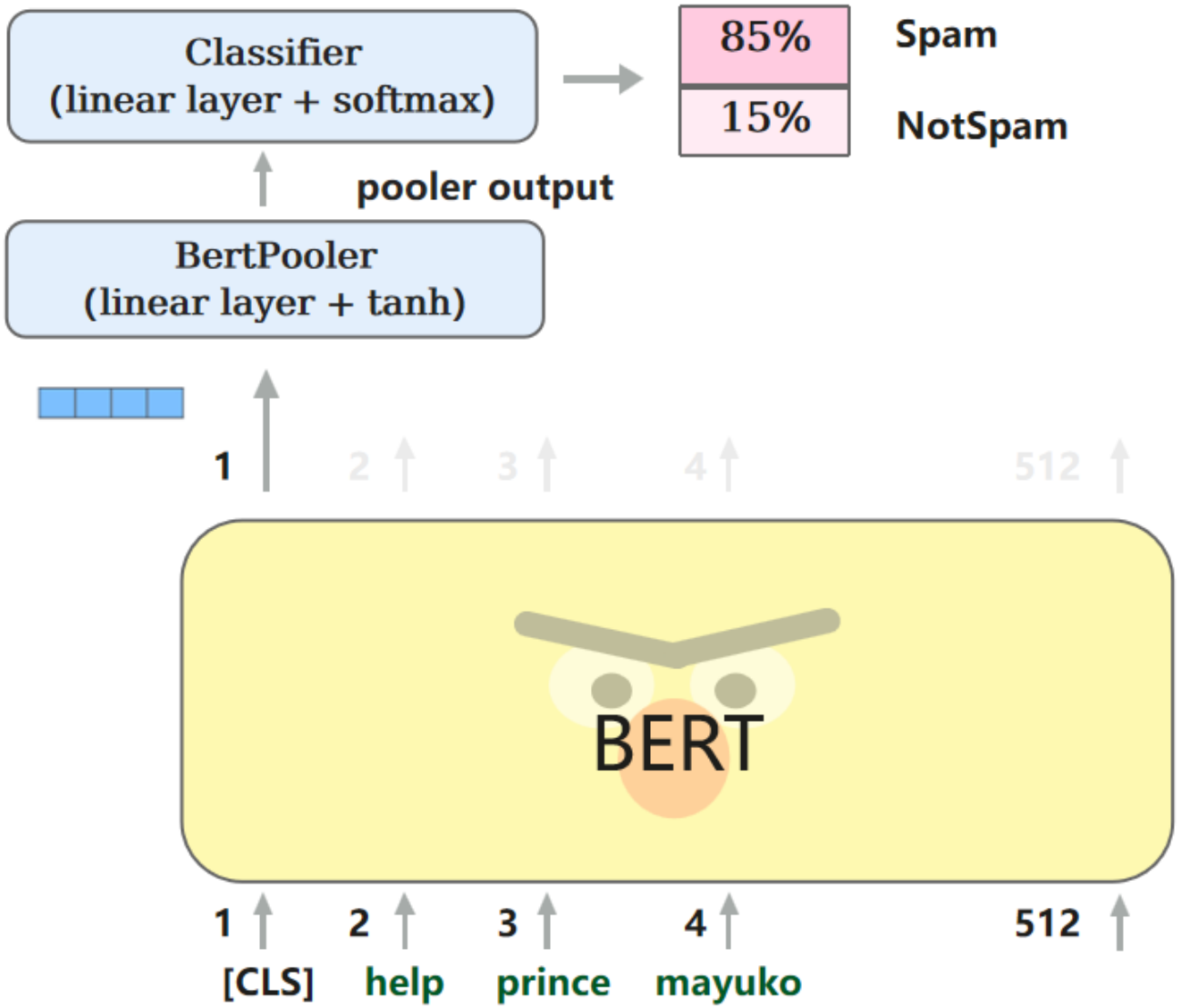
BERT Output

BERT会针对每一个位置输出大小为hidden size的向量，在下游任务中，会根据任务内容的不同，选取不同的向量放入输出层



BERT Output



例如，在诈骗邮件分类任务中，我们会将表示句子级别信息的`[CLS]` token所对应的向量，经过Bert Pooler放入classfier中，得到对spam/not spam分类的预测。

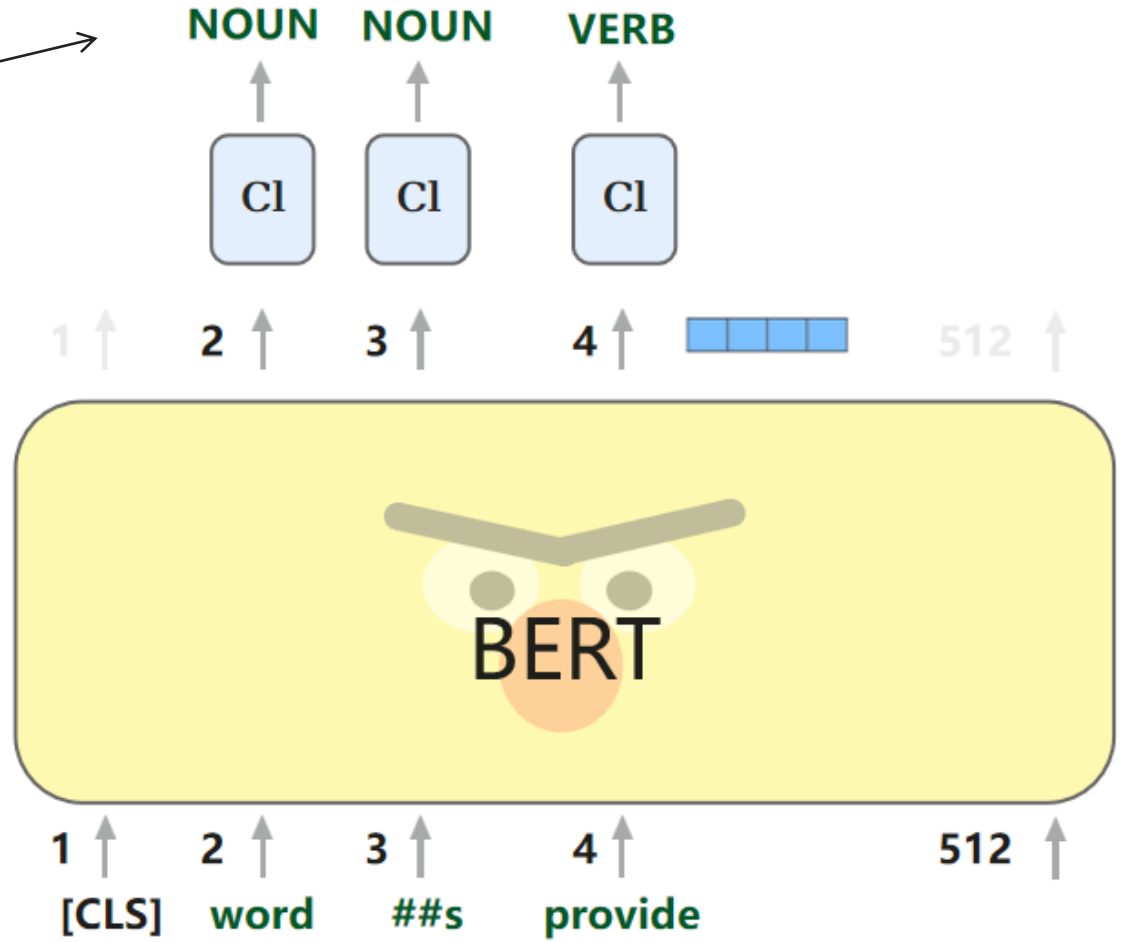
我们一般称[CLS]经过线性层+激活函数tanh的输出为**pooler output**，用于句子级别的分类/回归任务

Reference: The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning)

BERT Output

例如，在词性标注任务（POS Tagging）中，我们需要获得每一个token所对应的类别，因此需要将[CLS]和[SEP]中有实际意义的token输出，分别输入对应的classifier中。

NOUN	60%
VERB	20%
ADJ	10%
…	…

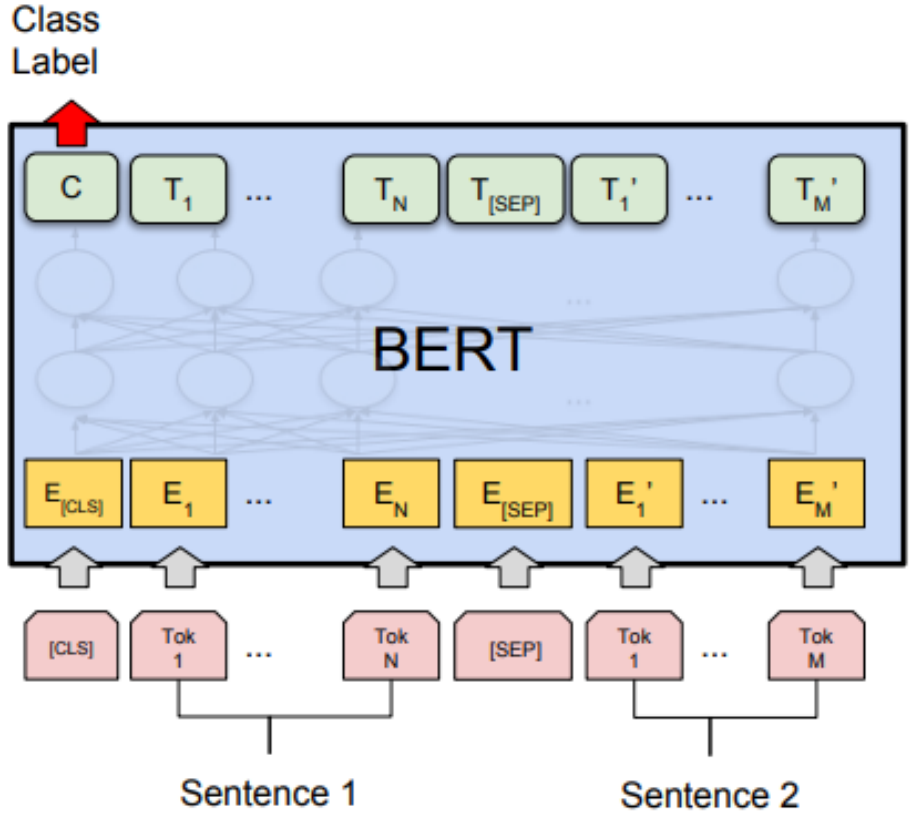


我们一般称BERT输出的每个位置对应的vector为 **sequence output**

Reference: The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning)

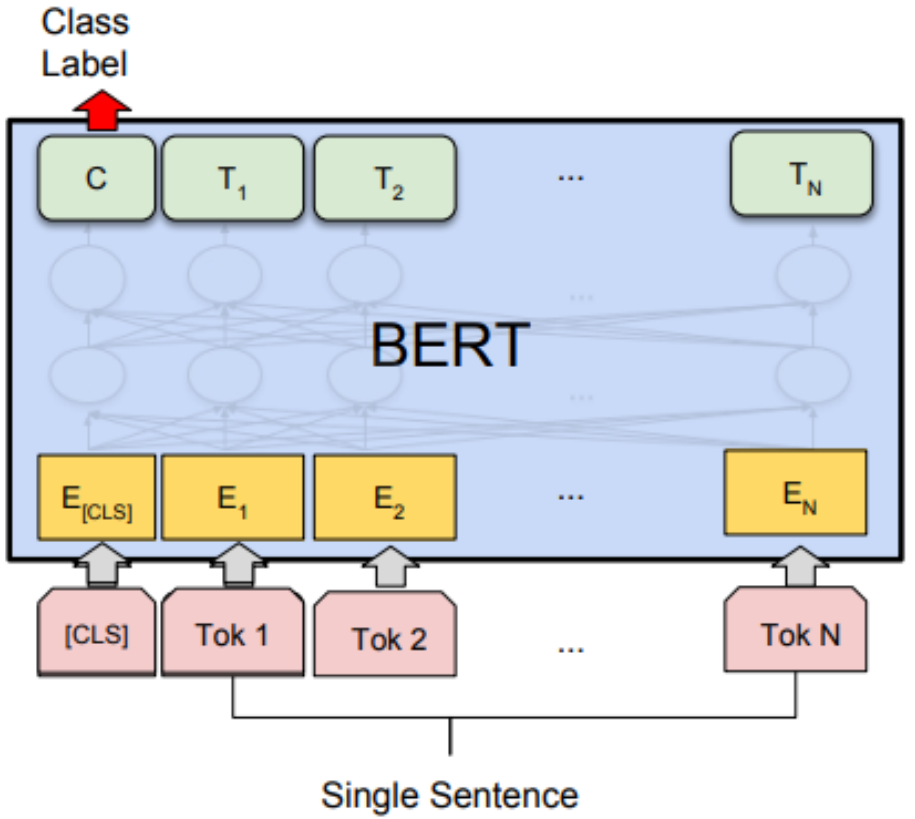
BERT的不同下游任务

句子对分类：[CLS]



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

单句子分类：[CLS]



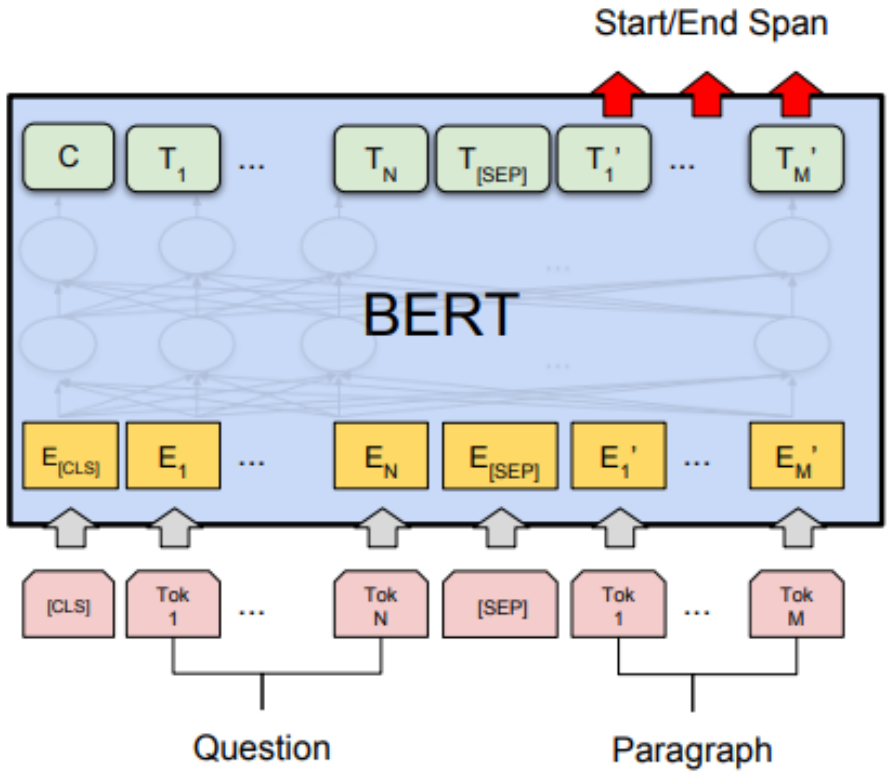
(b) Single Sentence Classification Tasks: SST-2, CoLA

Reference: BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT的不同下游任务

Q&A：第二个序列

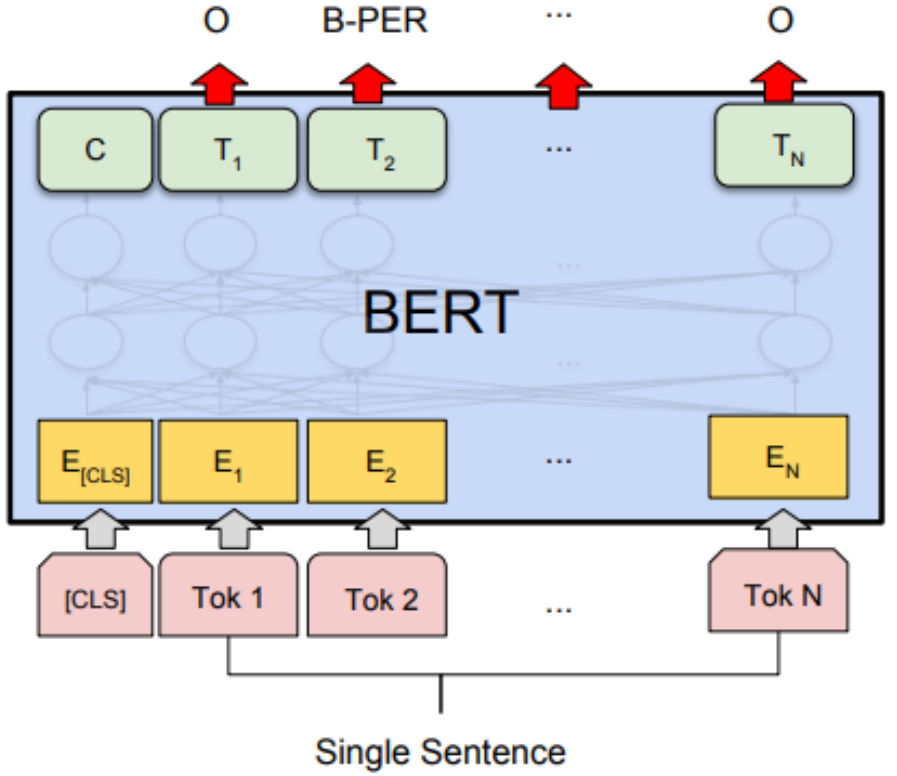
找出答案的起始与结束token



(c) Question Answering Tasks:
SQuAD v1.1

单句子Tagging：

有实际意义的token



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

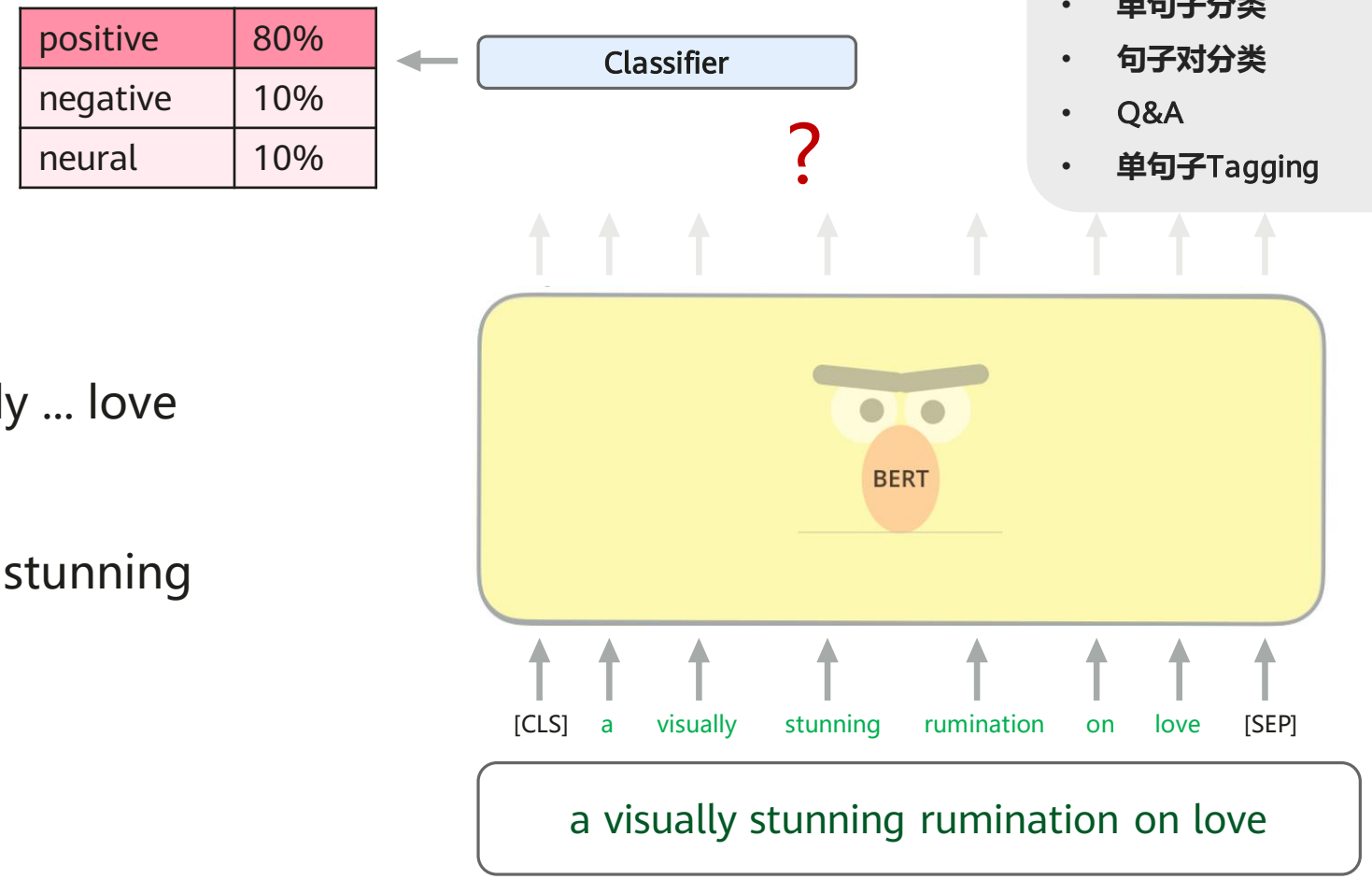
Reference: BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Quiz

3. 如果我希望基于BERT完成情感分类任务，即输入一句话，输出语句的情感色彩（positive、negative or neural），我应该选择哪一部分的输出放入classifier中?

Hint: 该任务属于什么类型的任务?

- 单句子分类
- 句子对分类
- Q&A
- 单句子Tagging



A. [CLS]

B. a visually ... love

C. [SEP]

D. visually stunning

Quiz

3. 如果我希望基于BERT完成情感分类任务，即输入一句话，输出语句的情感色彩（positive、negative or neural），我应该选择哪一部分的输出放入classifier中?

Hint: 该任务属于什么类型的任务?

- **单句子分类**
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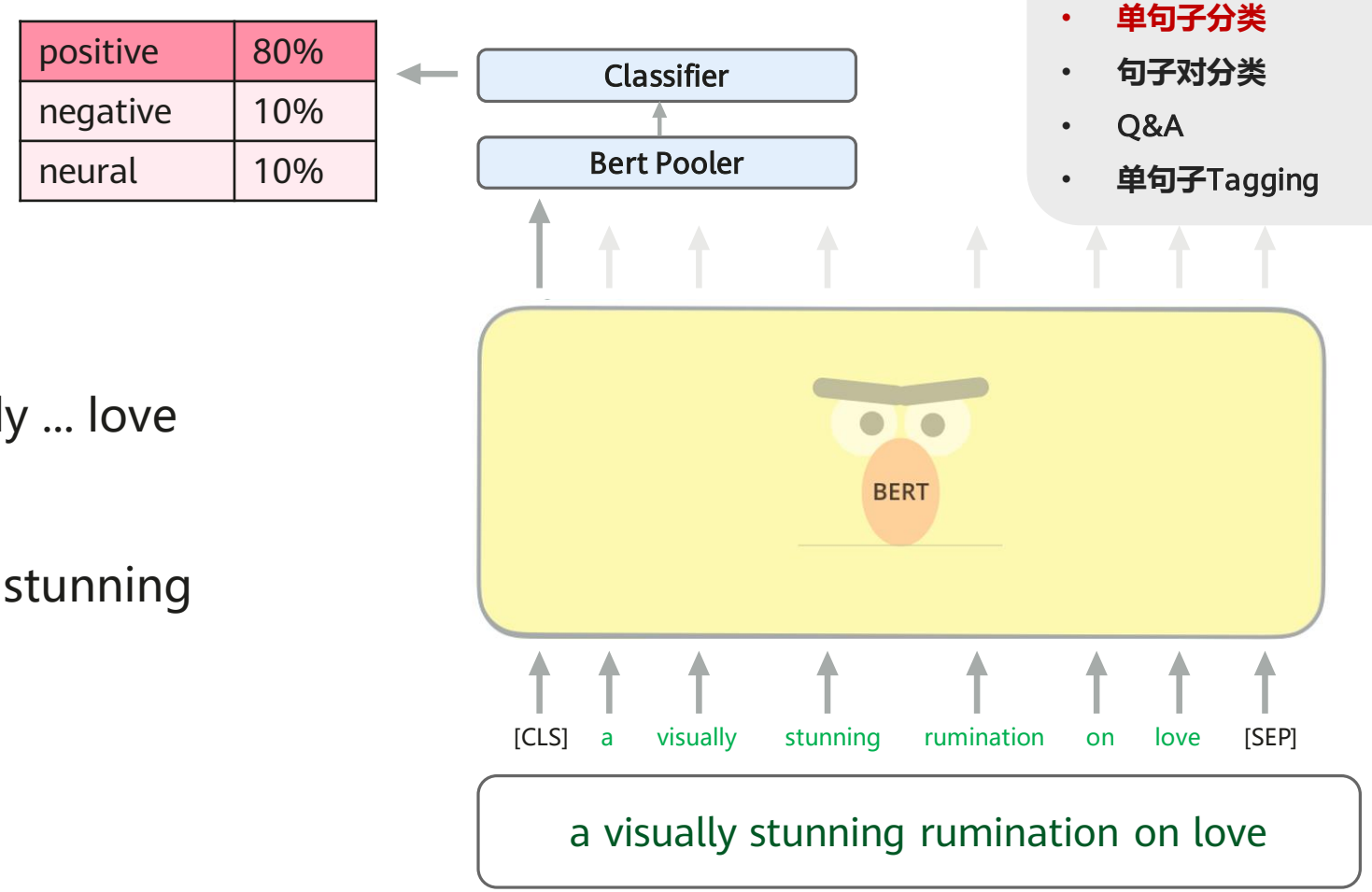
- Q&A
- **单句子Tagging**



A. [CLS]

B. a visually ... love

C. [SEP]

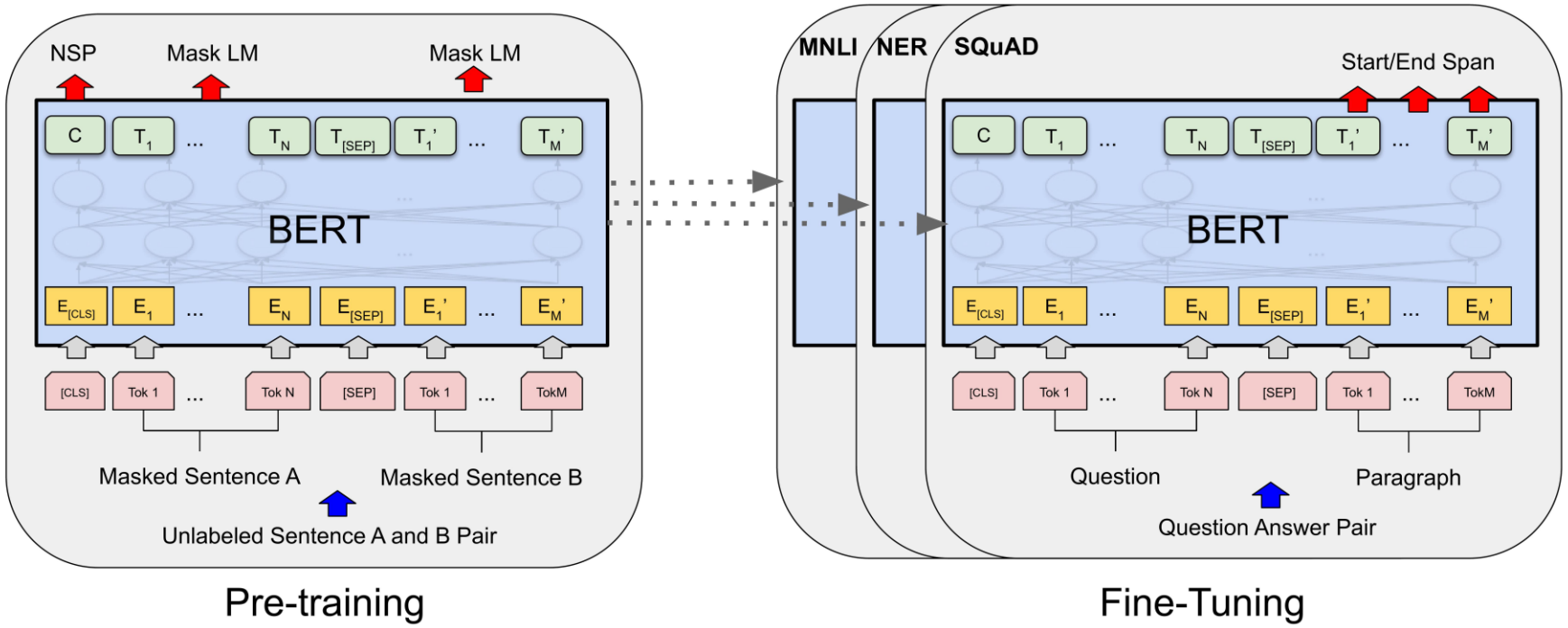
D. visually stunning

目录

BERT预训练

BERT预训练任务有两种：Masked Language Modelling（MLM） 和 Next Sentence Prediction（NSP）。

- MLM：随机遮盖输入句子中的一些词语，并预测被遮盖的词语是什么（完形填空）
- NSP：预测两个句子是不是上下文的关系



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Masked Language Model（MLM）

Masked Language Modelling（MLM） 捕捉词语级别的信息

1. 在输入中随机遮盖15%的token

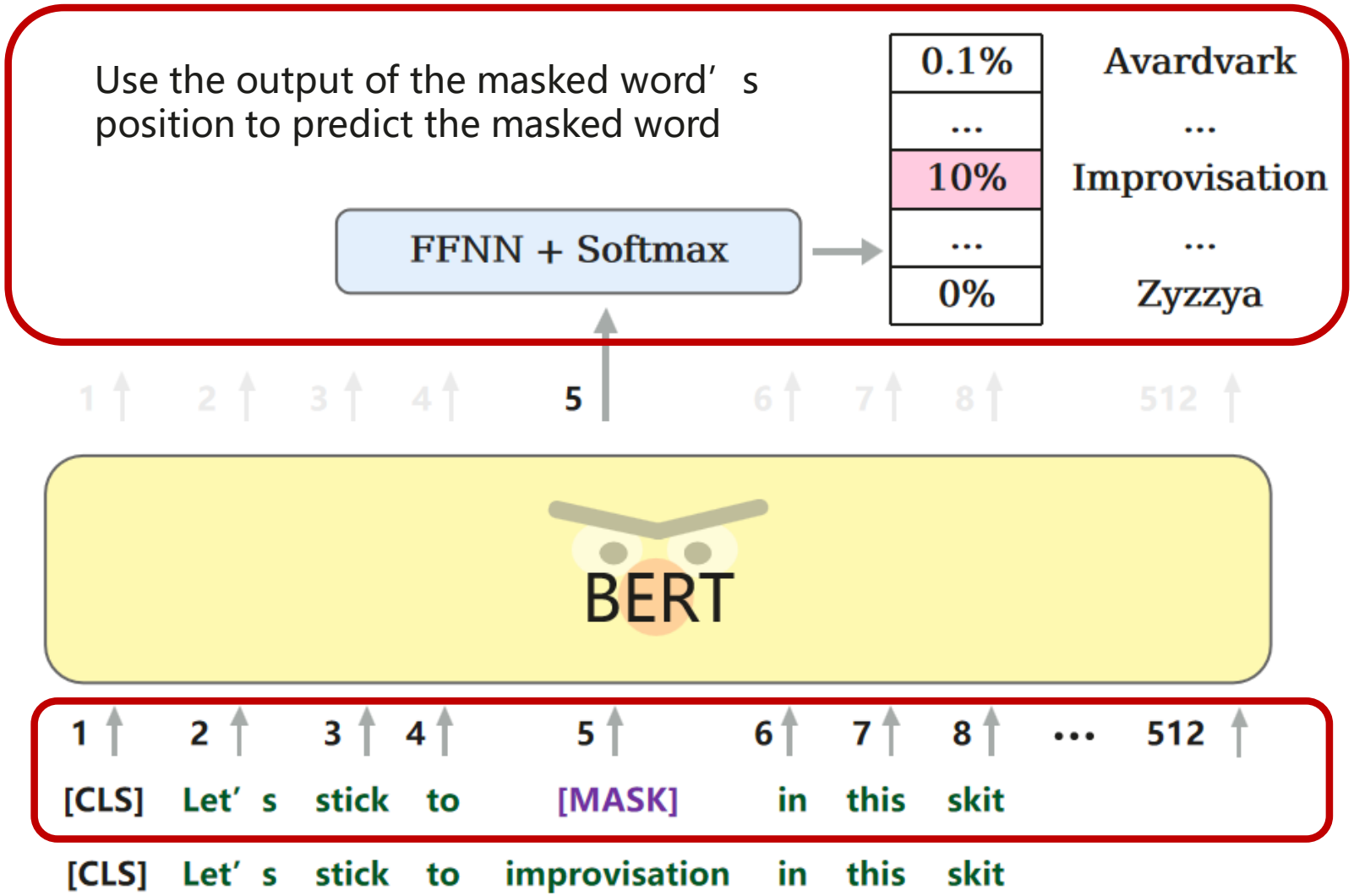
   （即将token替换为[MASK]）

2. 将[MASK]位置对应的BERT输出

   放入输出层中，预测被遮盖的

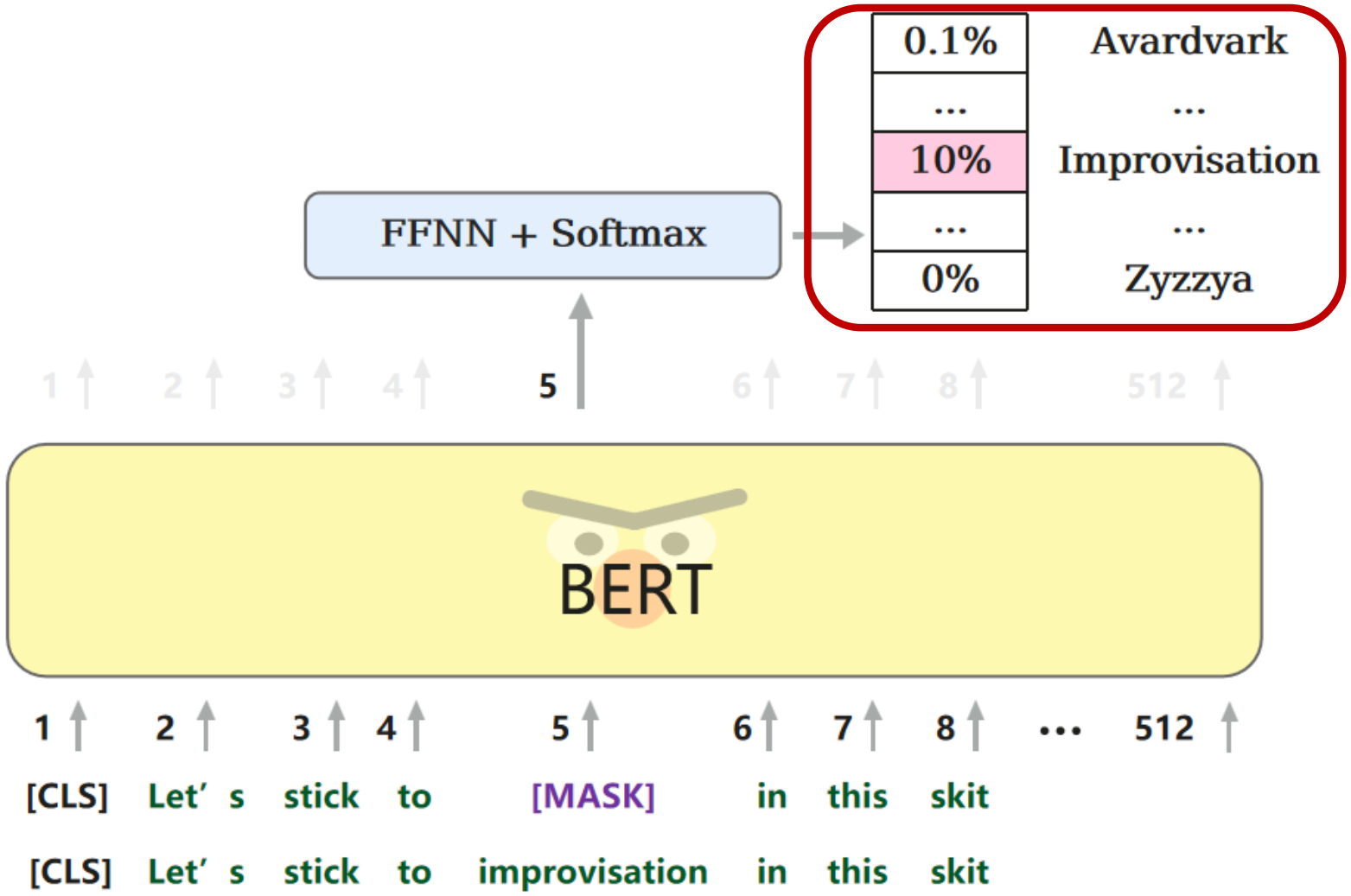
   token

问题一：如何进行预测?



Masked Language Model（MLM）

在将[MASK]位置所对应的BERT输出放入输出层后，本质上是在进行一个多分类任务



1. 我们事先会建立一个词表，覆盖所有英语单词

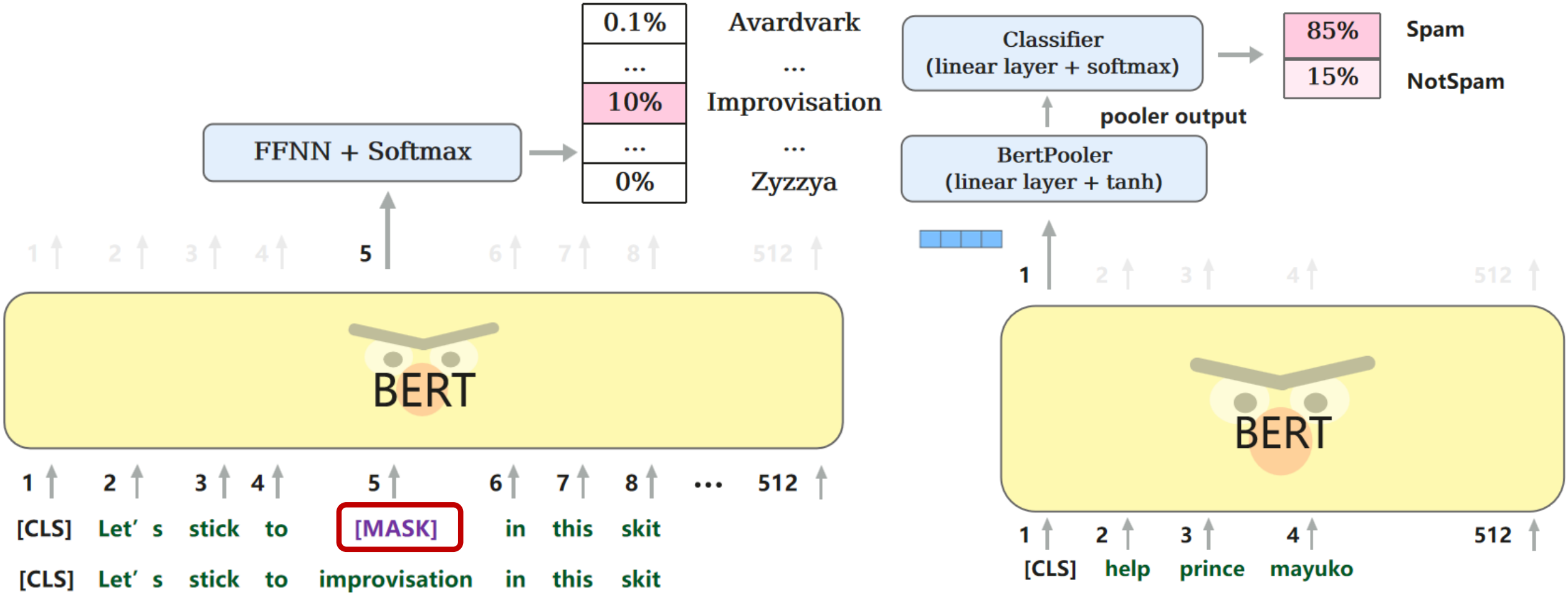
aardvark
aarhus
...
improvisation
...
zyzzyva

2. classifier计算每个词对应被遮盖的token的概率，并选取概率最高的词语作为预测结果

aardvark	0.1%
aarhus	0.1%
...	...
improvisation	10%
...	...
zyzzyva	0%

Masked Language Model（MLM）

在将[MASK]位置所对应的BERT输出放入输出层后，本质上是在进行一个多分类任务

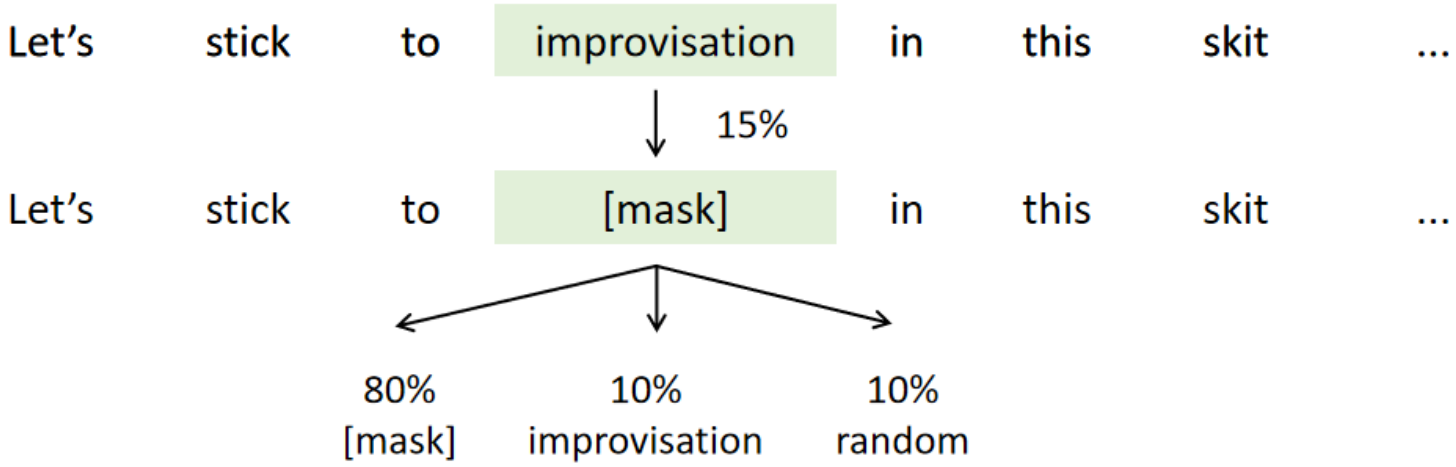


问题二：BERT进行推理时，输入并没有[MASK]

Masked Language Model（MLM）

为了使得预训练任务和推理任务尽可能接近，BERT在随机遮盖的15%的tokens中又进行了进一步的处理：

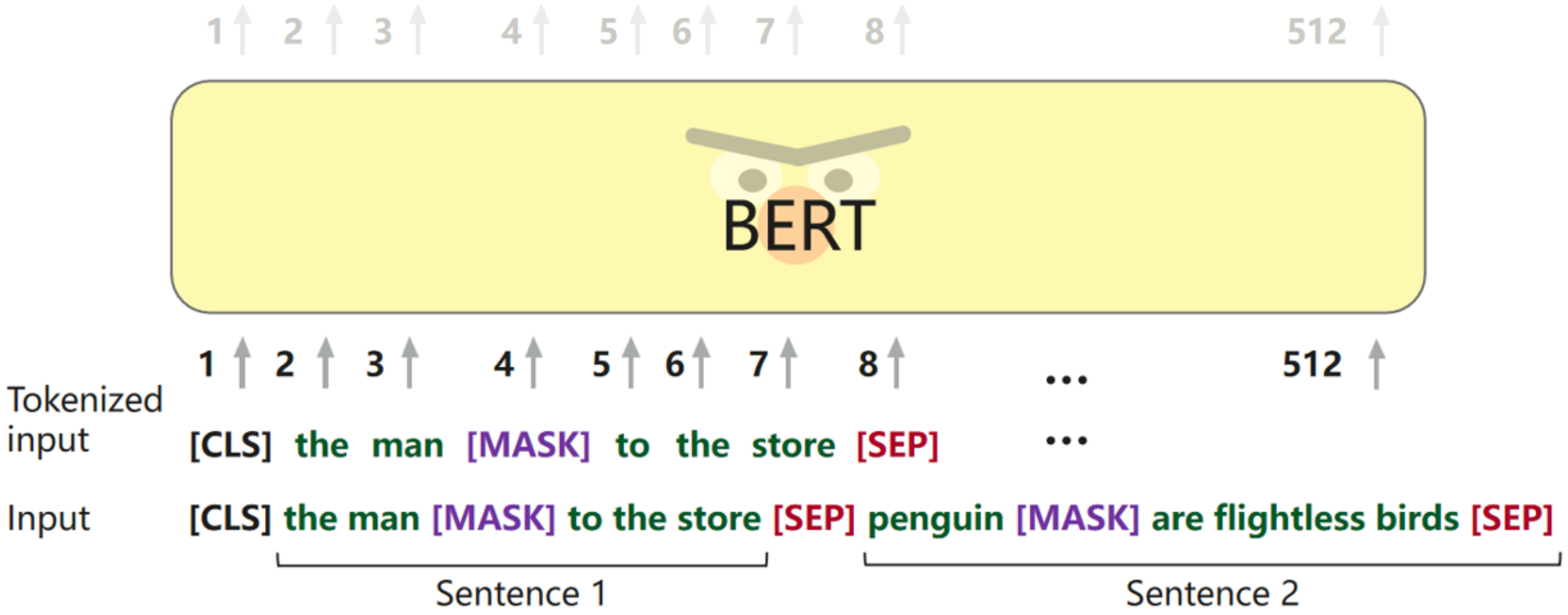
- 80%的概率替换为[MASK]
- 10%的概率替换为文本中的随机词
- 10%的概率不进行替换，保持原有的词元



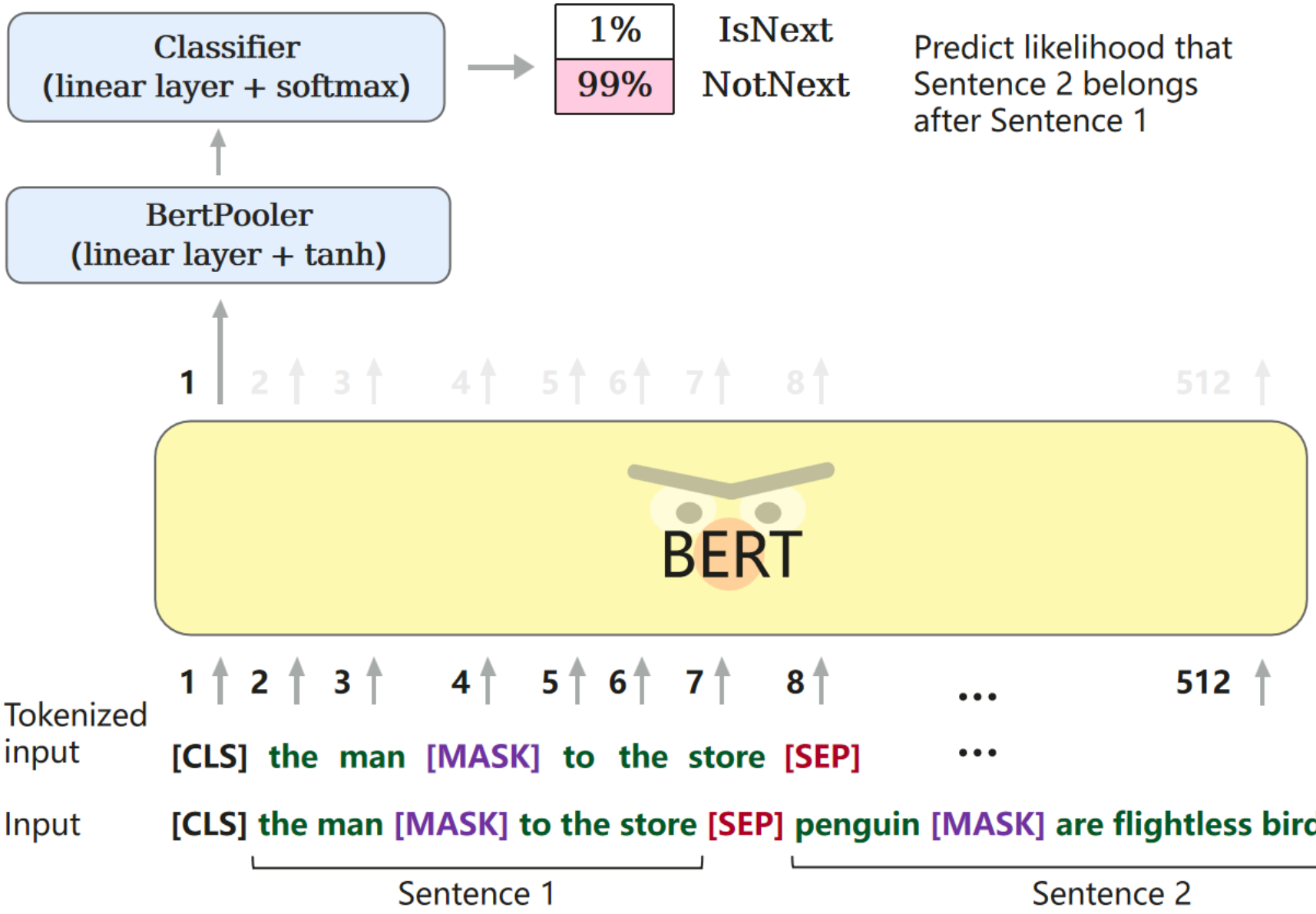
Next Sentence Prediction（NSP）

Next Sentence Prediction (NSP) 捕捉句子级别信息，简单来说是一个针对句子对的分类问题，判断一组句子中，句子B是否为句子A的下一句（IsNext or NotNext）

句子级别的分类任务，应该选取哪个位置的输出放入classifier?



Next Sentence Prediction（NSP）



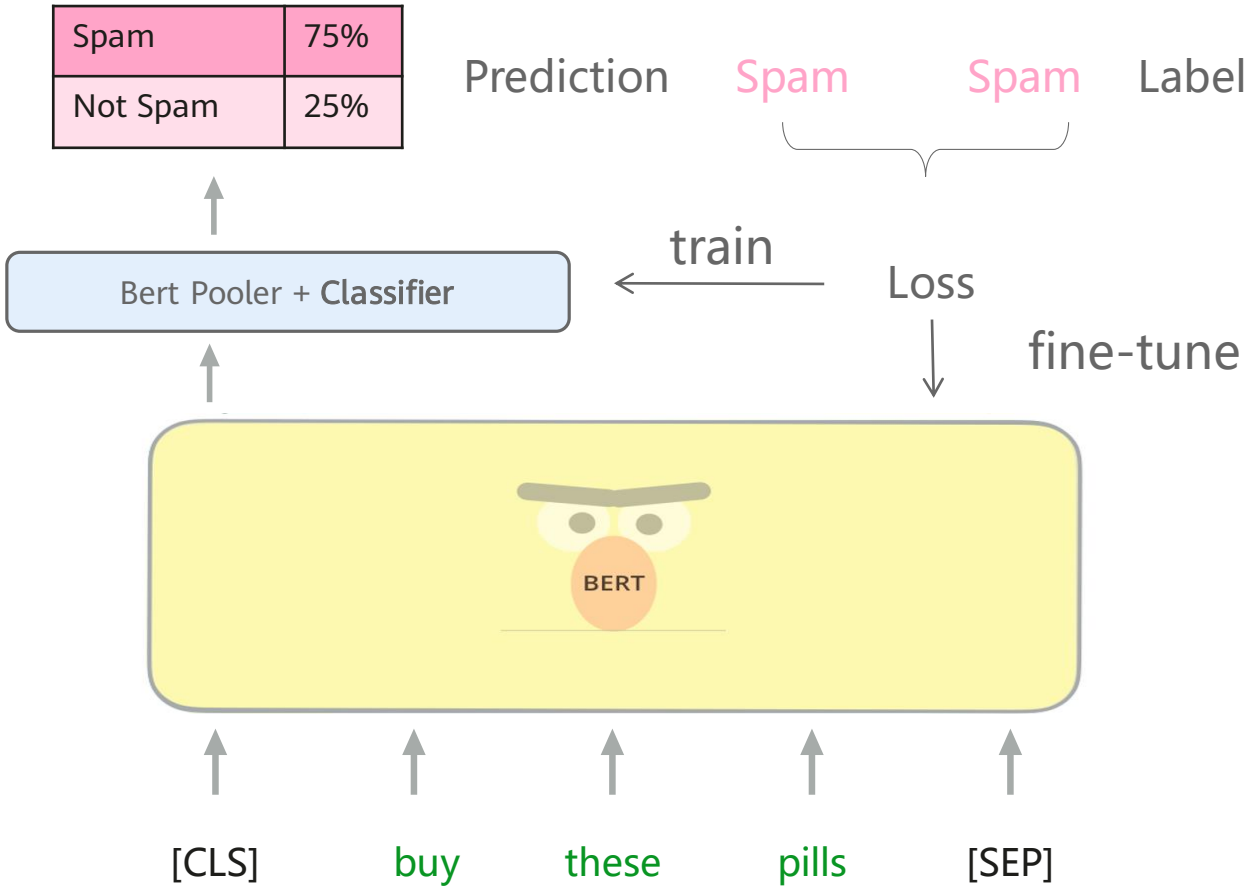
Next Sentence Prediction (NSP) 捕捉句子级别信息

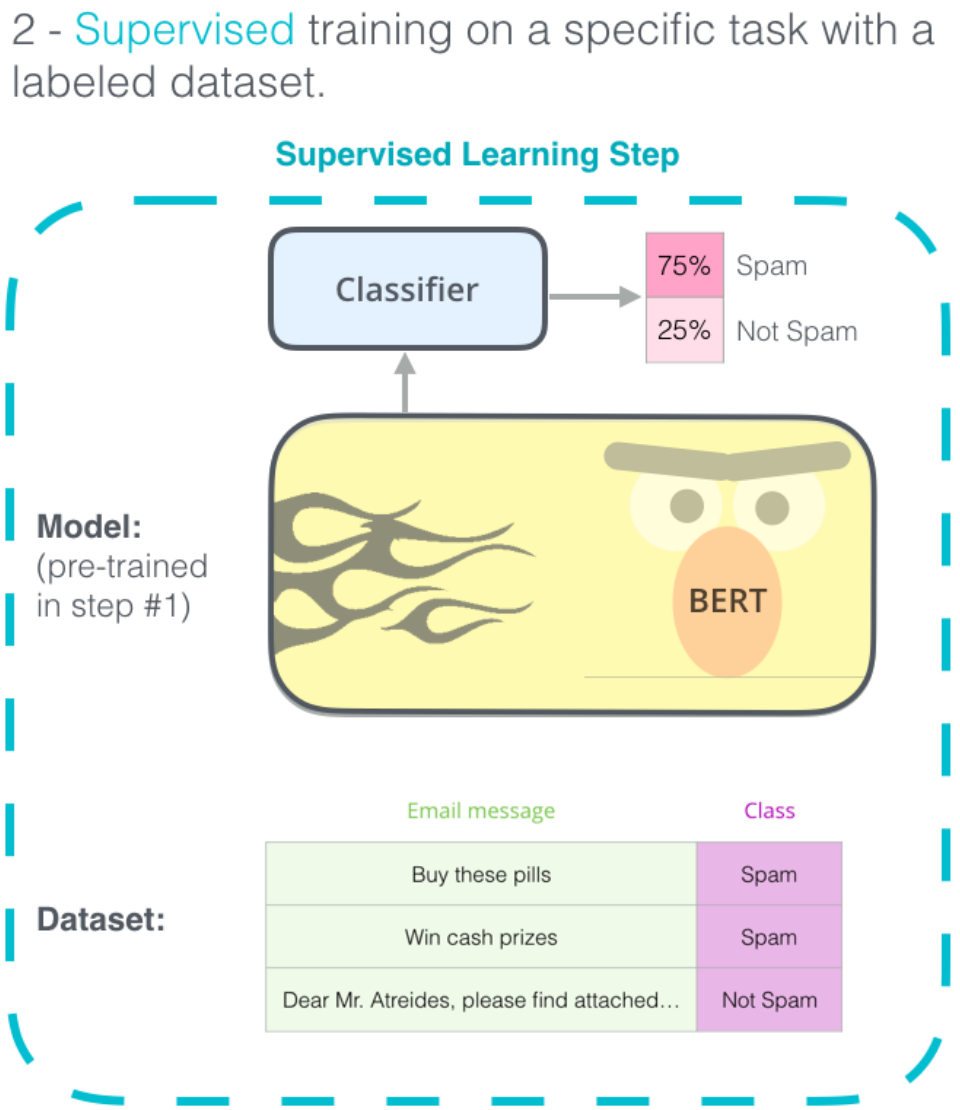
- 针对句子对的二分类问题
- 判断一组句子中，句子B是否为句子A的下一句（IsNext or NotNext）

目录

BERT Fine-tuning

在下游任务中，我们使用少量的标注数据（labelled data）对预训练Transformer编码器的所有参数进行微调，额外的输出层将从头开始训练。





Reference: The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning)

Thank you.

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