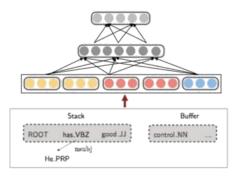
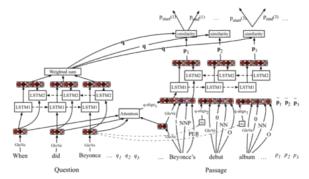
# BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding 论文导读 & Bert 详解

## Why Bert?

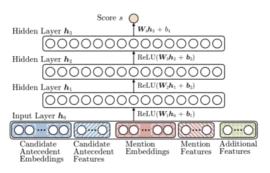
#### **Various Model Architectures for Different NLP Tasks**



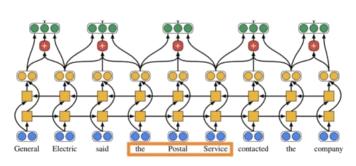
**Dependency Parsing** 



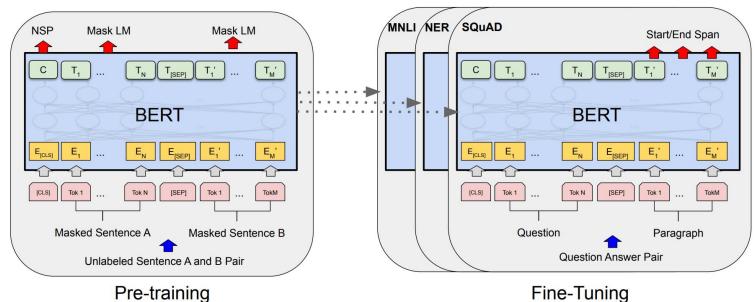
**Question Answering** 



Coreference example 1



Coreference example 2



Fine-Tuning

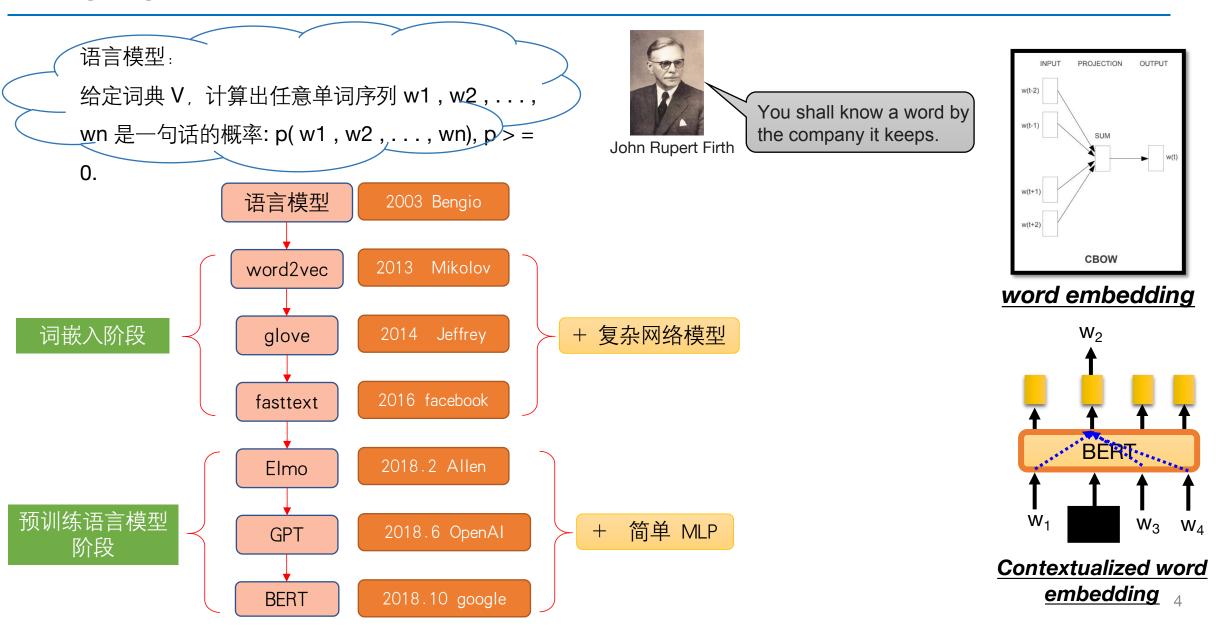
# BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin Ming-Wei Chang Kenton Lee Kristina Toutanova
Google AI Language

{jacobdevlin, mingweichang, kentonl, kristout}@google.com

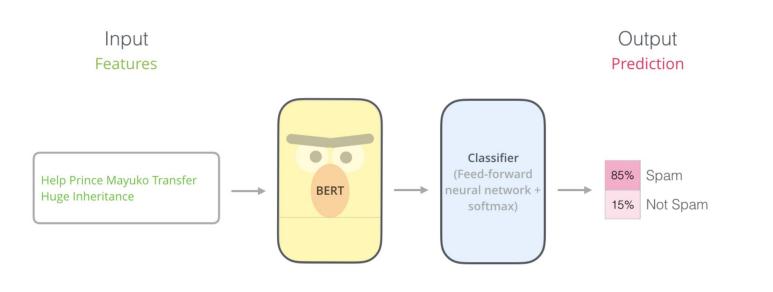
Kenton, J. D. M. W. C., & Toutanova, L. K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of NAACL-HLT (pp. 4171-4186).

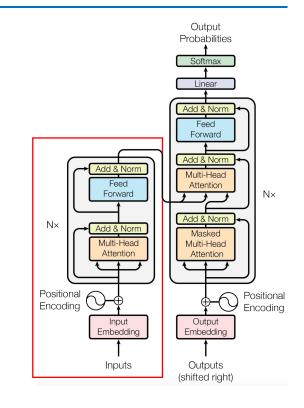
## Language Model

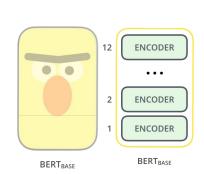


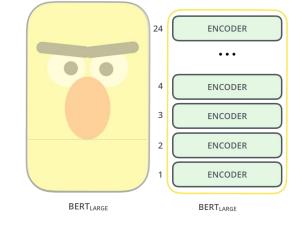
# Bert 架构

#### Bidirectional Encoder Representation from Transformer









Bert<sub>BASE</sub>: L=12, H=768, A=12, 参数总量 110M

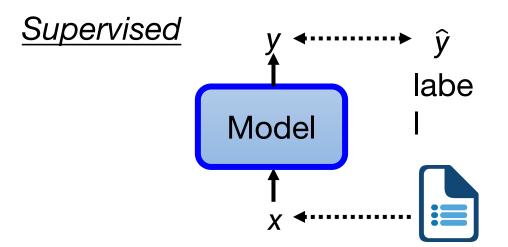
Bert<sub>LARGE</sub>: L=24, H=1024, A=16, 参数总量 340M

L: block数量

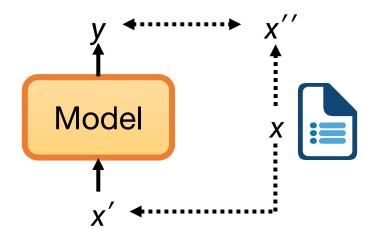
H. 隐藏层维度

A: 注意力头的数量

#### **Supervised & Self-Supervised**



## Self-supervised





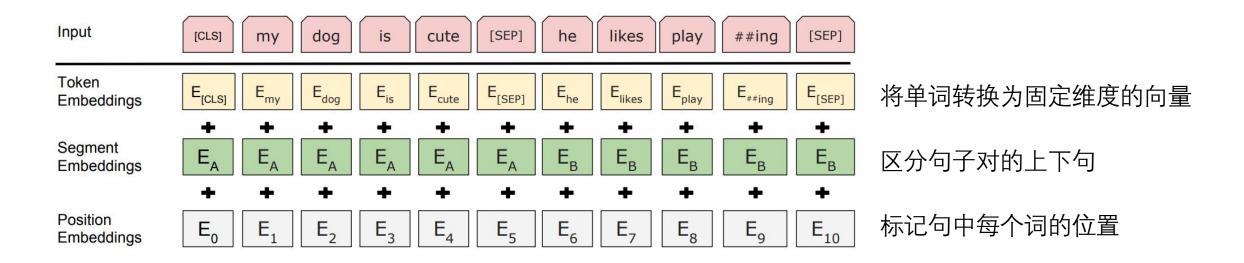
#### Yann LeCun

2019年4月30日 · 🕢

I now call it "self-supervised learning", because "unsupervised" is both a loaded and confusing term.

In self-supervised learning, the system learns to predict part of its input from other parts of it input. In other words a portion of the input is used as a supervisory signal to a predictor fed with the remaining portion of the input.

## 输入向量



Segment Embeddings 示例:

[CLS] 我的狗很可爱[SEP] 企鹅不擅长飞行[SEP] 000000011111111

#### 任务一: MLM (Masked Language

## Modeling)

MASK 策略示例:

对于语句"my dog is hairy",随机把句中15%的token替换为以下内容:

80%的几率被替换成[MASK]:

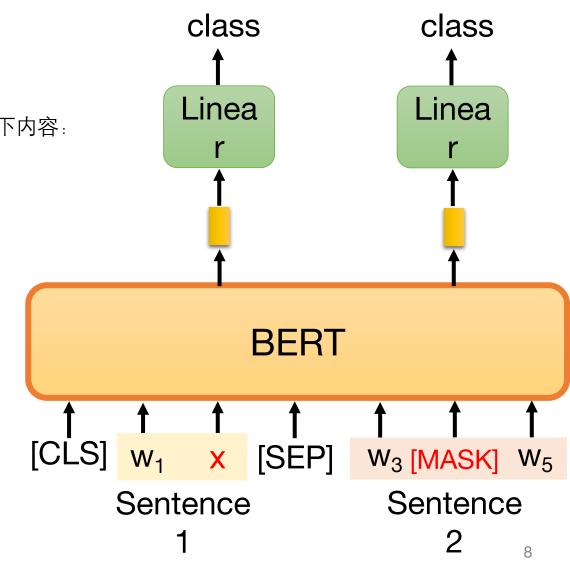
"my dog is hairy"  $\rightarrow$  "my dog is [MASK]"

10%的几率被替换成其他token:

"my dog is hairy"  $\rightarrow$  "my dog is apple"

10%的几率原封不动:

"my dog is hairy"  $\rightarrow$  "my dog is hairy"



#### 任务二: NSP (Next Sentence Prediction)

正负句子对样本:

50% 的正样本: 训练语料库中的两个连续段落

50% 的负样本:来自不同文档的两个随机段落

#### 示例:

Input: [CLS] 博学而笃志 [SEP] 切问而近思

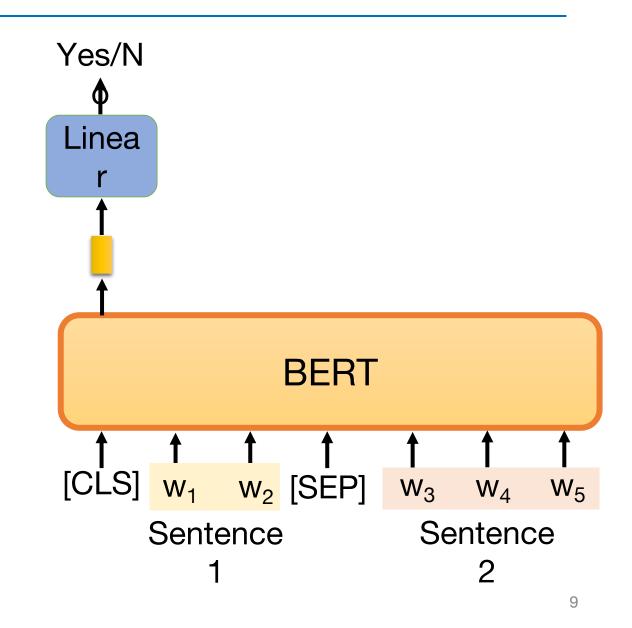
[SEP]

Target: Yes

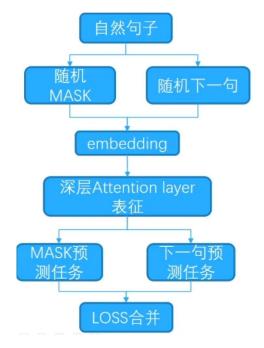
Input: [CLS] 博学而笃志 [SEP] 今天风好大

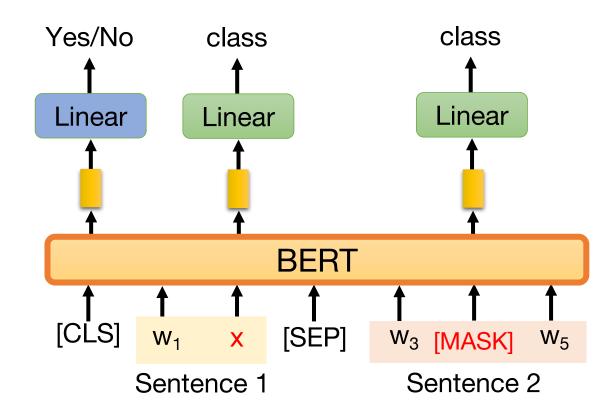
[SEP]

Target: No



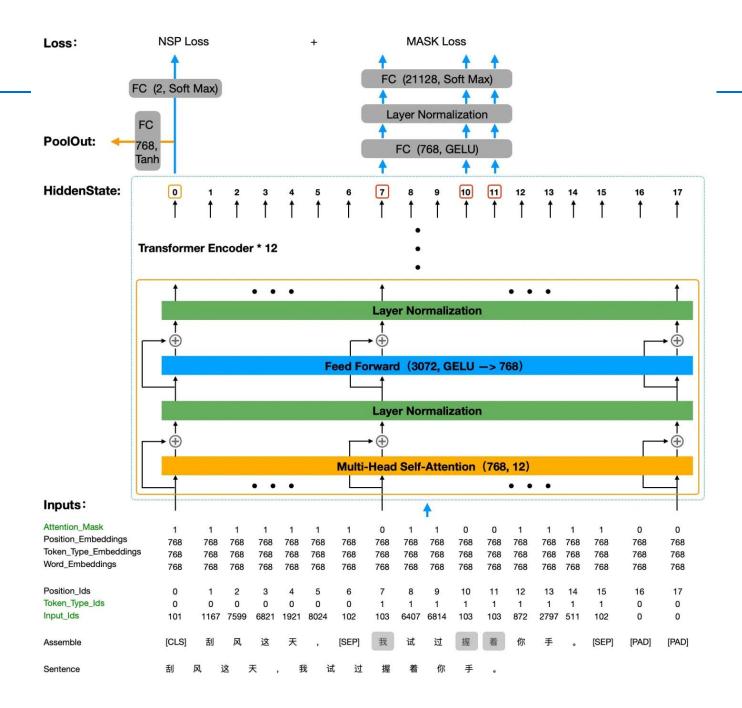
#### **Multi-Task Learning**

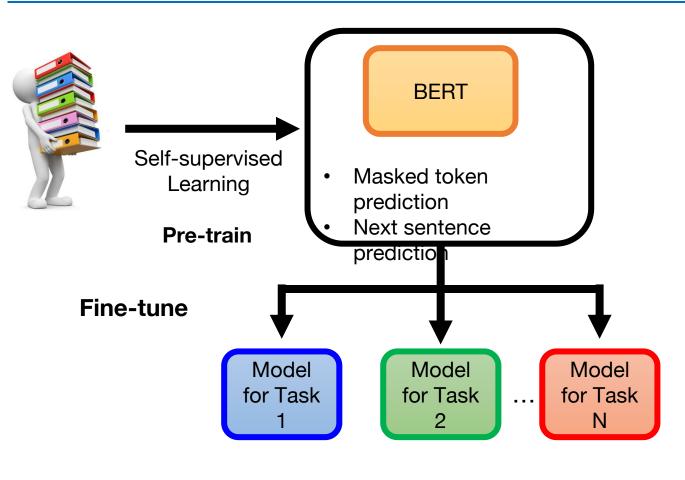




- Input: [CLS] calculus is a branch of math [SEP] panda is native to [MASK] central china [SEP]
- Targets: false, south
- -----
- Input: [CLS] calculus is a [MASK] of math [SEP] it [MASK] developed by newton and leibniz [SEP]
- Targets: true, branch, was

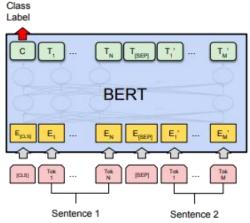
## **Multi-Task Learning**



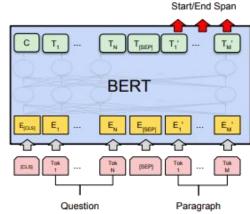




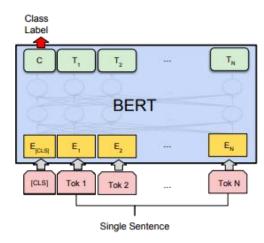
We have a little bit labeled data.



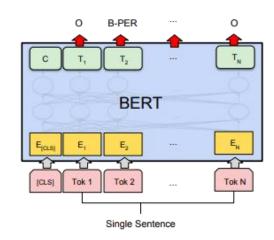
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



(c) Question Answering Tasks: SQuAD v1.1



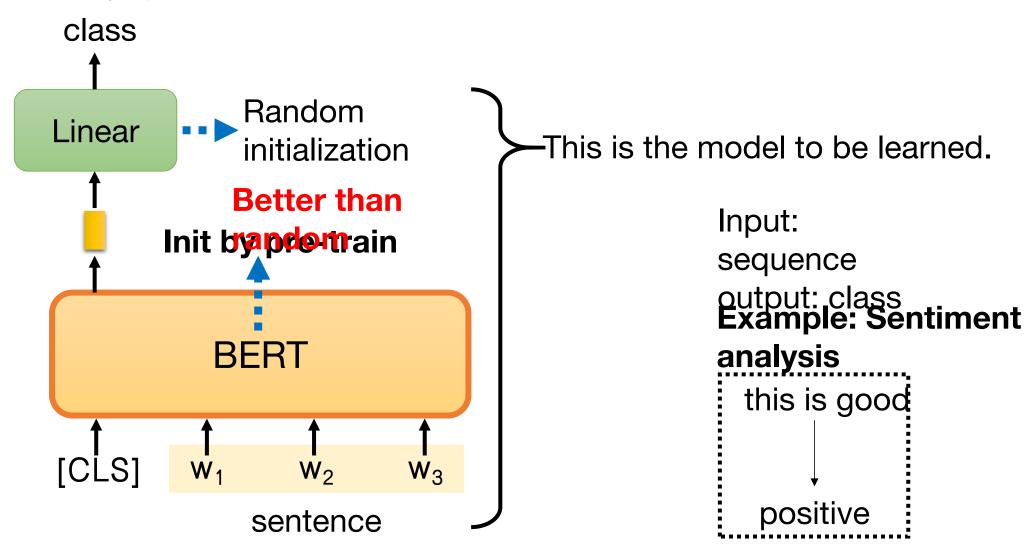
(b) Single Sentence Classification Tasks: SST-2, CoLA



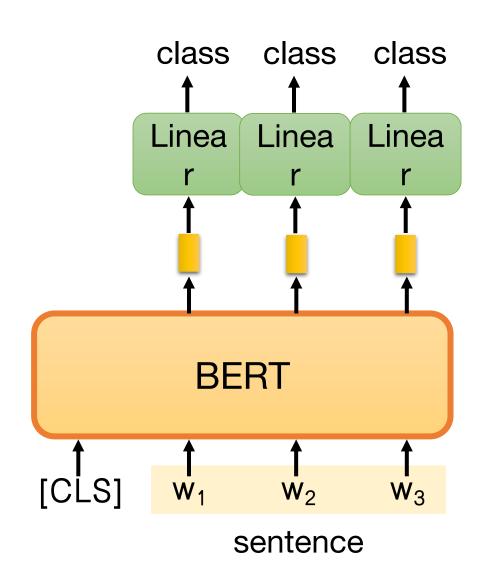
(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

**Downstream Tasks** 

## 应用场景 1 文本分类



## 应用场景 2 序列标注

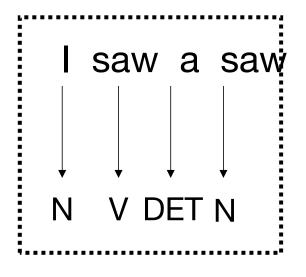


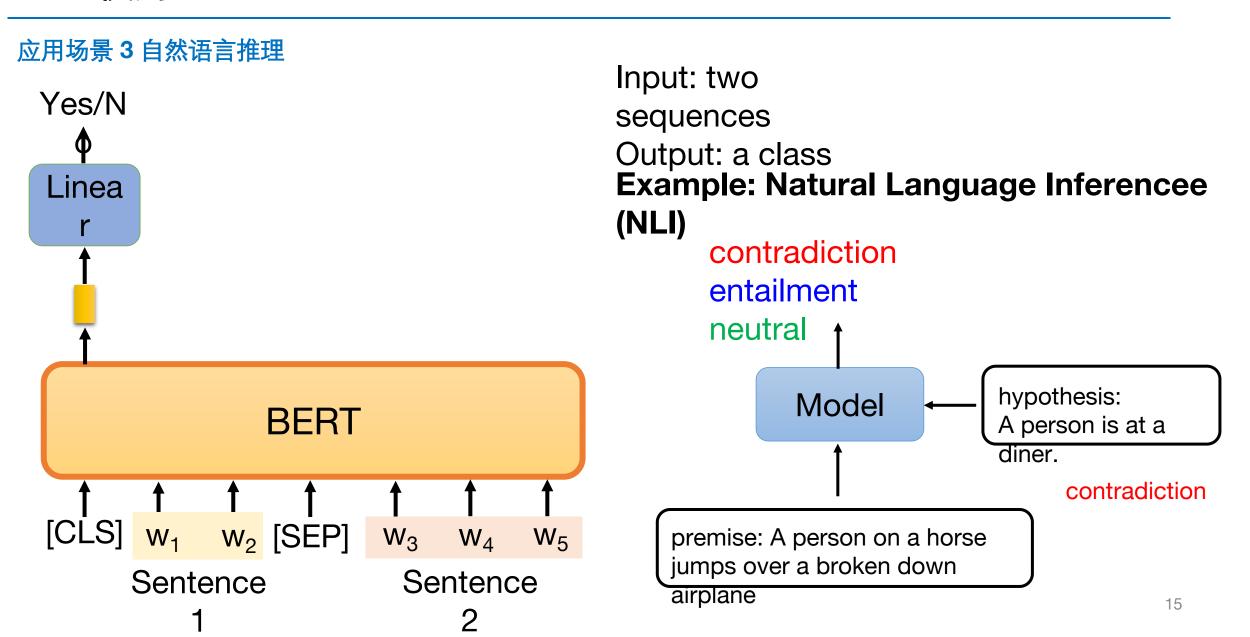
Input: sequence

output: same as input

**Example: POS** 

tagging

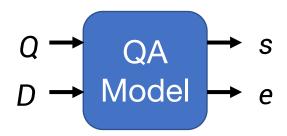




#### 应用场景 4 抽取式问答

**Query**: 
$$Q = \{q_1, q_2, \dots, q_M\}$$

**Document** 
$$\mathcal{D} = \{d_1, d_2, \dots, d_N\}$$



output: two integers (s, e)

**Answer**: 
$$A = \{d_s, \dots, d_e\}$$

In meteorology, precipitation is any product of the condensation of 17 spheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain 77 atte 79 cations are called "showers".

What causes precipitation to fall?

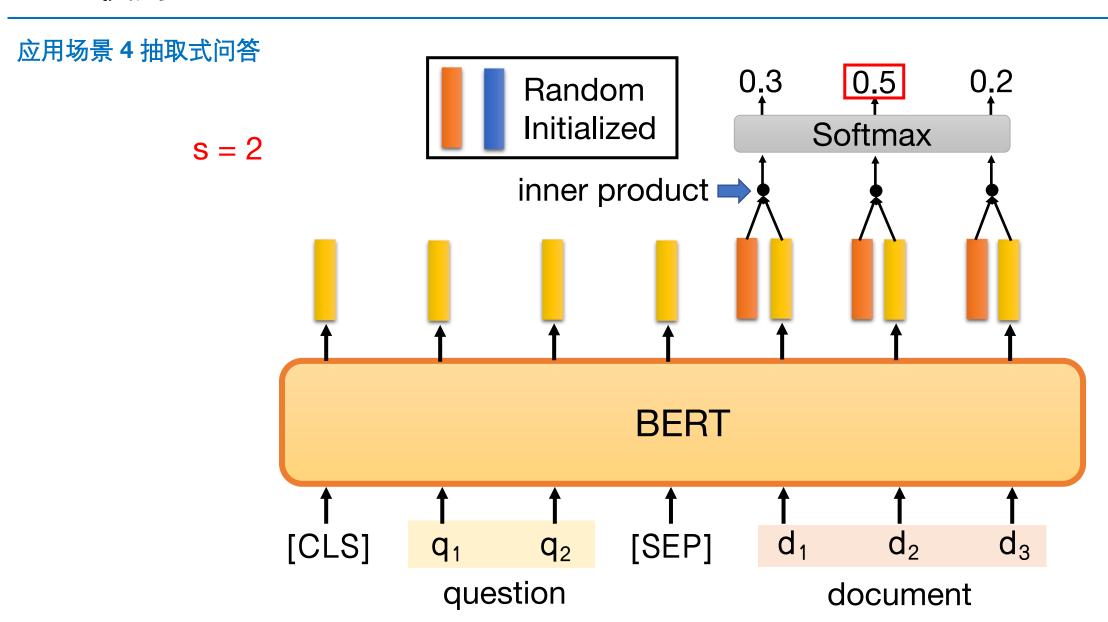
gravity 
$$s = 17, e = 17$$

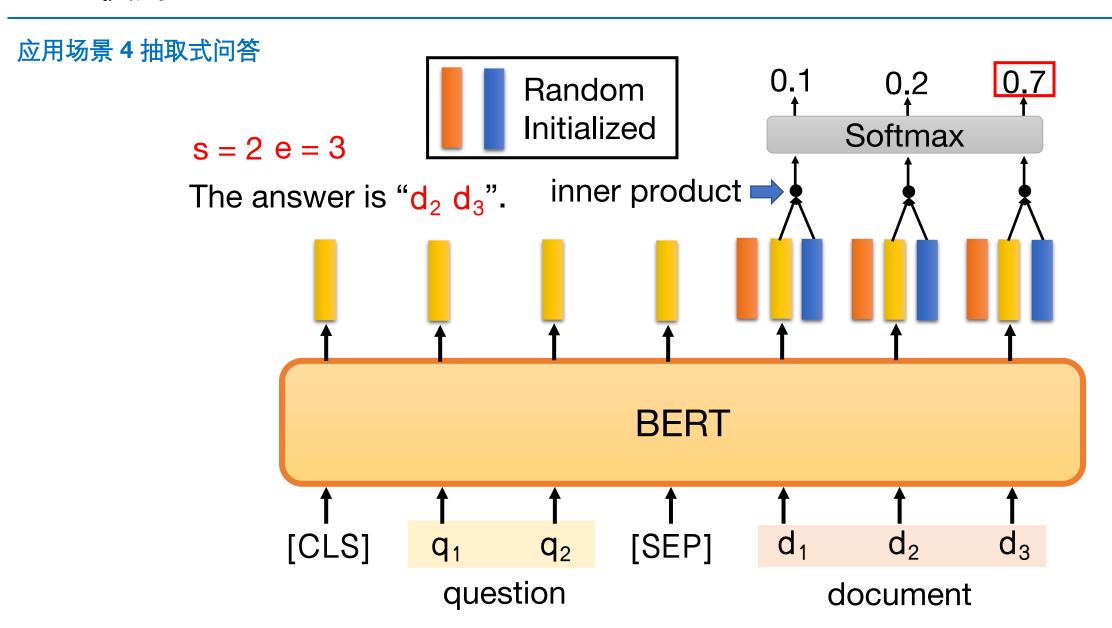
What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?

graupel

Where do water droplets collide with ice crystals to form precipitation?

within a cloud 
$$s = 77, e = 79$$





## 应用场景 4 抽取式问答

#### 北京奥运会是哪年举办?

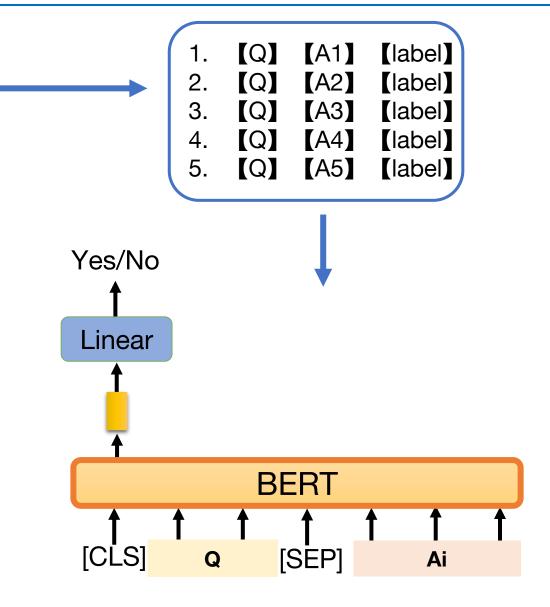
第29届夏季奥林匹克运动会(Games of the xxix olympiad), 又称2008年北京奥运会,2008年8月8日晚上8时整在中华人民 共和国首都北京举办。【1】

2008年北京奥运会主办城市是北京,上海、天津、沈阳、秦皇岛、青岛为协办城市。【2】

香港承办马术项目。【3】

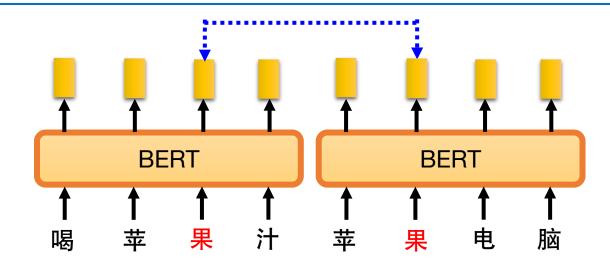
2008年北京奥运会共有参赛国家及地区204个,参赛运动员 11438人,设302项(28种)运动,共有60000多名运动员、 教练员和官员参。加【4】

2008年北京奥运会共创造43项新世界纪录及132项新奥运纪录, 共有87个国家和地区在赛事中取得奖牌,中国以51枚金牌居金牌榜首名,是奥运历史上首个登上金牌榜首的亚洲国家。【5】



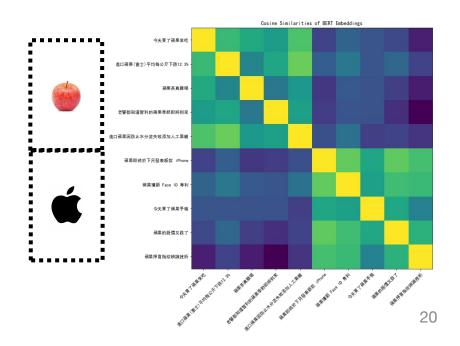
# BERT 表征可视化

compute cosine similarity



The tokens with similar meaning have similar embedding.

吃苹果 吃苹果 。 。 意 電 ・ 本果手机



# 总结

- 1. 预训练的有效性: BERT 改变了游戏规则,是因为相比设计复杂巧妙的网络结构,在海量无监督数据上预训练得到的BERT语言表示+少量训练数据微调的简单网络模型的实验结果取得了很大的优势。
- 2. 网络深度:基于传统语言模型 (NNLM, CBOW等) 获取词向量的表示已经在 NLP领域获得很大成功, 而 BERT 预训练网络基于 Transformer 的 Encoder, 可以做得很深。
- 3. 双向语言模型:在 BERT 之前,ELMo 和 GPT 的主要局限在于标准语言模型是单向的,GPT 使用 Transformer 的 Decoder 结构,只考虑了上文的信息。ELMo 从左往右的语言模型和从右往左的语言模型其实是分开训练的,共享 embedding,将两个方向的 LSTM 拼接并不能真正表示上下文,其本质仍是单向的,且多层 LSTM难训练。
- **4. 目标函数**:对比以往语言模型任务只做预测下一个位置的单词,想要训练包含更多信息的语言模型,就需要让语言模型完成更复杂的任务,BERT 主要完成完形填空和句对预测的任务,即两个 loss:一个是 Masked Language Model,另一个是 Next Sentence Prediction。

# 参考资料

- BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding (ailab-ua.github.io)
- The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning) Jay Alammar Visualizing machine learning one concept at a time. (jalammar.github.io)
- Hung-yi Lee (ntu.edu.tw)
- WordEmbedding发展史(语言模型演变史) 知乎 (zhihu.com)
- BERT详解(附带ELMo、GPT介绍) bert算法 数学家是我的理想 数学家是我理想的博客-CSDN博客
- BERT模型详解 李理的博客 (fancyerii.github.io)
- BERT论文的解读 PPT\_bert介绍ppt\_SimonChenHere的博客-CSDN博客
- 一张图看懂BERT 知乎 (zhihu.com)
- NLP——Bert核心内容 知乎 (zhihu.com)
- 关于Cbow, Transformer, Elmo, GPT, Bert 知乎 (zhihu.com)
- BERT详解:概念、原理与应用\_\_StarryNight\_的博客-CSDN博客
- LeeMeng 進擊的 BERT: NLP 界的巨人之力與遷移學習