Kuakua Chatbot based on UniLM

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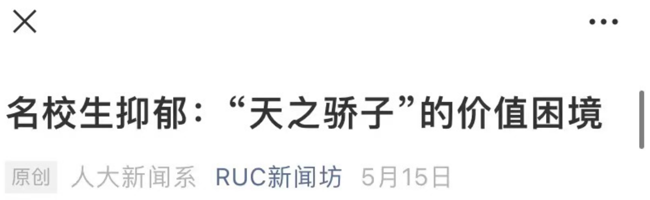
Motivation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每建立一个夸夸群，都能迅速满员的奇异现象～ 相关问题如...
2524 万热度
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夸

Motivation

为什么要做夸夸聊天机器人？

- 可以缓解压力
- 被夸是有治愈作用的，当一个人自我否定时，被夸能修复受挫的自尊心，也能让我们产生“我还不错”的喜悦感

Unified Language Model

Unified Language Model

- Language Model (LM)
  $\Rightarrow$ learn contextualized text representations
- Prediction tasks and training objectives:

	ELMo	GPT	BERT	UniLM
Left-to-Right LM	✓	✓		✓
Right-to-Left LM	✓			✓
Bidirectional LM			✓	✓
Sequence-to-Sequence LM				✓

Table 1: Comparison between language model (LM) pre-training objectives.

Unified Language Model

- **UNI**fied pre-trained **L**anguage **M**odel (UNILM)
  $\Rightarrow$ for both NLU and NLG

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Backbone Network	LM Objectives of Unified Pre-training	What Unified LM Learns	Example Downstream Tasks
Transformer with shared parameters for all LM objectives	Bidirectional LM	Bidirectional encoding	GLUE benchmark Extractive question answering
	Unidirectional LM	Unidirectional decoding	Long text generation
	Sequence-to-Sequence LM	Unidirectional decoding conditioned on bidirectional encoding	Abstractive summarization Question generation Generative question answering

Table 2: The unified LM is jointly pre-trained by multiple language modeling objectives, sharing the same parameters. We fine-tune and evaluate the pre-trained unified LM on various datasets, including both language understanding and generation tasks.

Unified Language Model

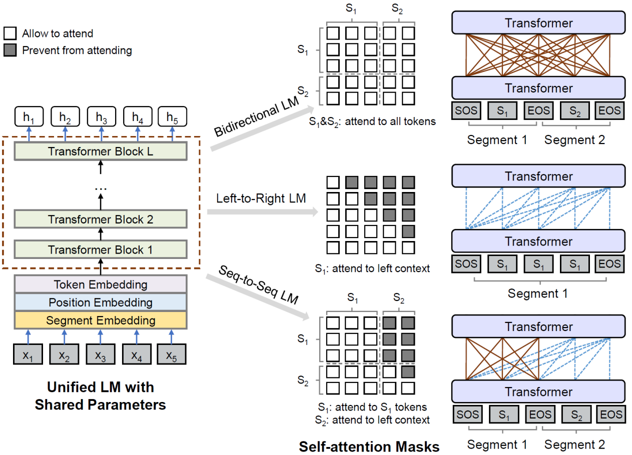


Figure 1: Overview of unified LM pre-training. The model parameters are shared across the LM objectives (i.e., bidirectional LM, unidirectional LM, and sequence-to-sequence LM). We use different self-attention masks to control the access to context for each word token. The right-to-left LM is similar to the left-to-right one, which is omitted in the figure for brevity.

Go to 2.1 Go to 2.2 Go to 2.3

1. Input Representation

- Input sequence $x = x_1 \cdots x_{|x|}$
  $\Rightarrow$ a contextualized vector representation
- $[\mathrm{SOS}]$ and $[\mathrm{EOS}]$:
  $[\mathrm{EOS}]$ not only marks the sentence boundary in NLU tasks, but also is used to learn when to terminate the decoding process in NLG tasks
- token embedding + position embedding + segment embedding

▸ Framework

2. Backbone Network: Multi-Layer Transformer

- $\{\mathbf{x}_i\}_{i=1}^{|x|} \Rightarrow \mathbf{H}^0 = \left[\mathbf{x}_1, \cdots, \mathbf{x}_{|x|}\right] \Rightarrow \mathbf{H}^l = \left[\mathbf{h}_1^l, \cdots, \mathbf{h}_{|x|}^l\right]$
  $\mathbf{H}^l = \text{Transformer}_l\left(\mathbf{H}^{l-1}\right), l \in [1, L]$
  $$\mathbf{Q} = \mathbf{H}^{l-1}\mathbf{W}_l^Q, \quad \mathbf{K} = \mathbf{H}^{l-1}\mathbf{W}_l^K, \quad \mathbf{V} = \mathbf{H}^{l-1}\mathbf{W}_l^V$$
- $\mathbf{M}_{ij} = \begin{cases} 0, & \text{allow to attend} \\ -\infty, & \text{prevent from attending} \end{cases}$
  $$\mathbf{A}_l = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d_k}} + \mathbf{M}\right)\mathbf{V}_l$$

▸ Framework

3. Pre-training Objectives

- Unidirectional LM: L2R and R2L LM objectives
- Bidirectional LM
- Sequence-to-Sequence LM
- Next Sentence Prediction (for bidirectional LM)

▸ Framework

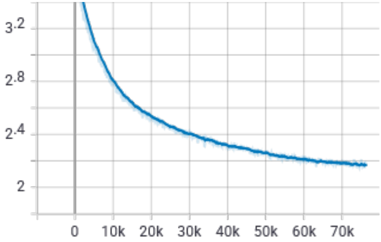
4. Setup

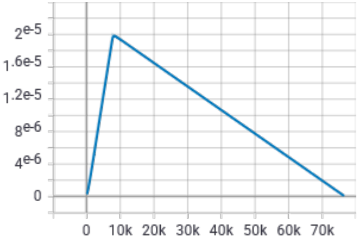
- 1/3 of the time for bidirectional LM objective
- 1/3 of the time sequence-to-sequence LM objective
- 1/6 for both left-to-right and right-to-left LM objectives
- $BERT_{LARGE}$ initialized
- 24-layer Transformer, 1024 hidden size, 16 attention heads, 340M parameters in total
- 15% token masking probability, 80% of the time randomly mask one token and 20% of the time mask a bigram or a trigram

Experiments

Experiments

- Douban Kuakua Group, 6w+ utterances, 20+MB
- hidden size: 768, attention heads: 12, hidden layers: 12
- 50 epochs: loss & learning rate





Experiments

```
user:我要死了
chatbot:你真是个勇敢的人，一定会有好事发生的
user:我要累死了
chatbot:我们都是天使
user:我只想休息
chatbot:谢谢
user:明天要去吃好吃的
chatbot:好棒
user:今天nlp展示，好紧张
chatbot:我也是，但是你不会放弃自己的想法
```

```
user:我爱你
chatbot:我也是
user:我喜欢你
chatbot:我也喜欢你
```

```
user:明天要考试
chatbot:加油！我也是考了三次
```

```
user:我很孤独，也很寂寞，没有朋友
chatbot:我们都是独一无二的人，你也很优秀哦！
```

Future Work

Future Work

- 训练是针对单轮对话进行的，未来会探索多轮夸夸对话；
- 收集更多数据，训练效果更好的基于 unilm 的夸夸对话模型；
- 探索多模态夸夸，使模型具有表情包等图像理解能力。

THANKs!