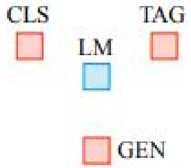
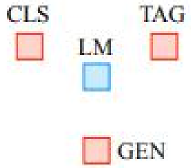
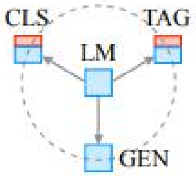
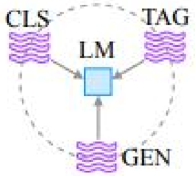
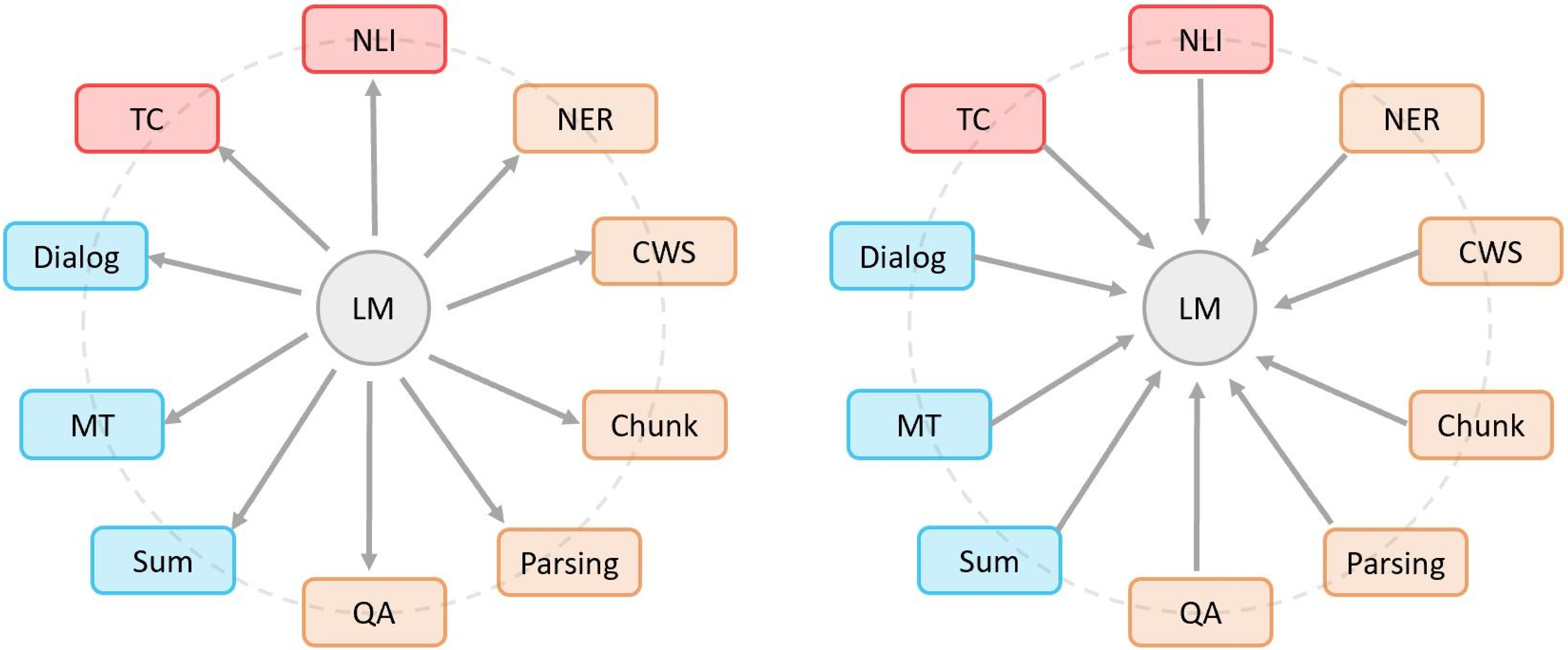
Prompt based learning

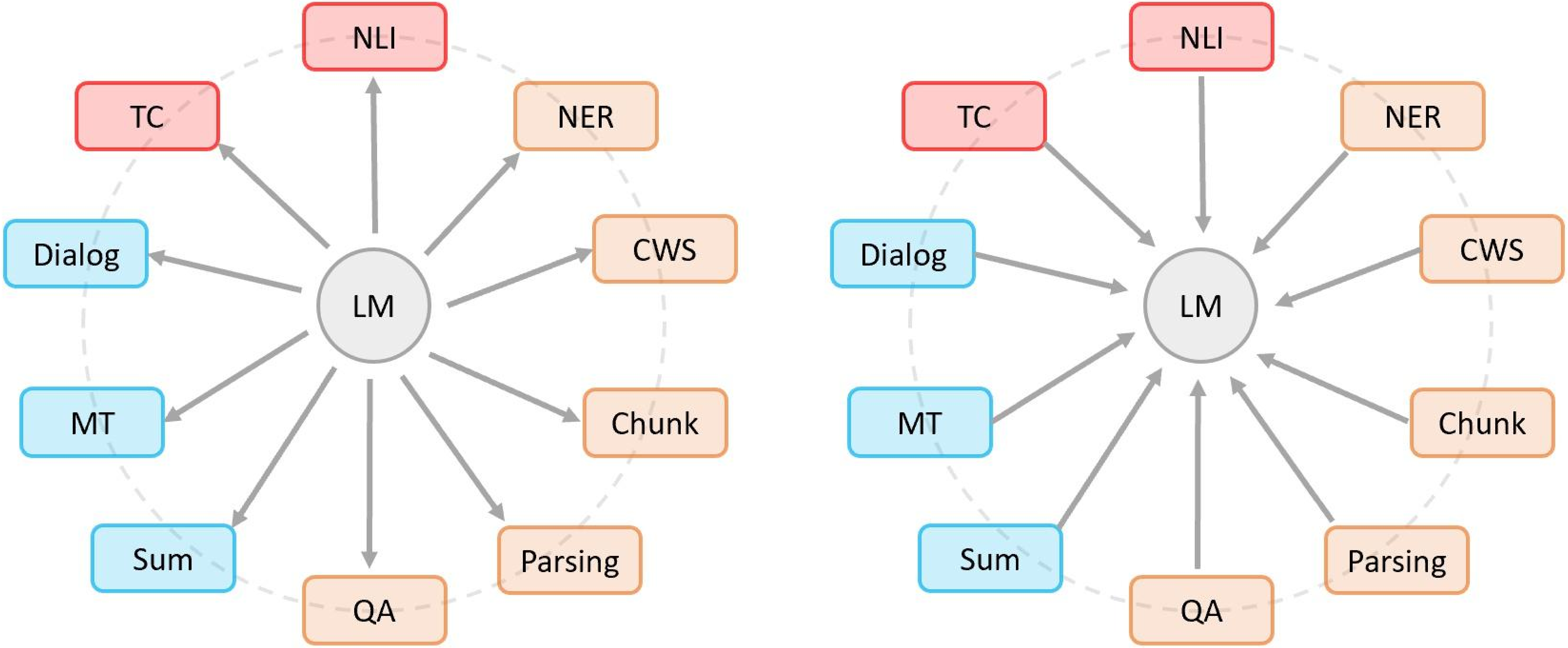
References:Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods in Natural Language Processing

Four paradigms in NLP

Paradigm	Engineering	Task Relation
a. Fully Supervised Learning (Non-Neural Network)	Features (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
c. Pre-train, Fine-tune	Objective (e.g. masked language modeling, next sentence prediction)	
d. Pre-train, Prompt, Predict	Prompt (e.g. cloze, prefix)	



Fine-tuning：用别人的参数，修改后的网络和自己的数据进行训练，使得参数适应自己的模型。预训练模型迁就下游任务，通过引入各种损失函数，添加到预训练模型中。

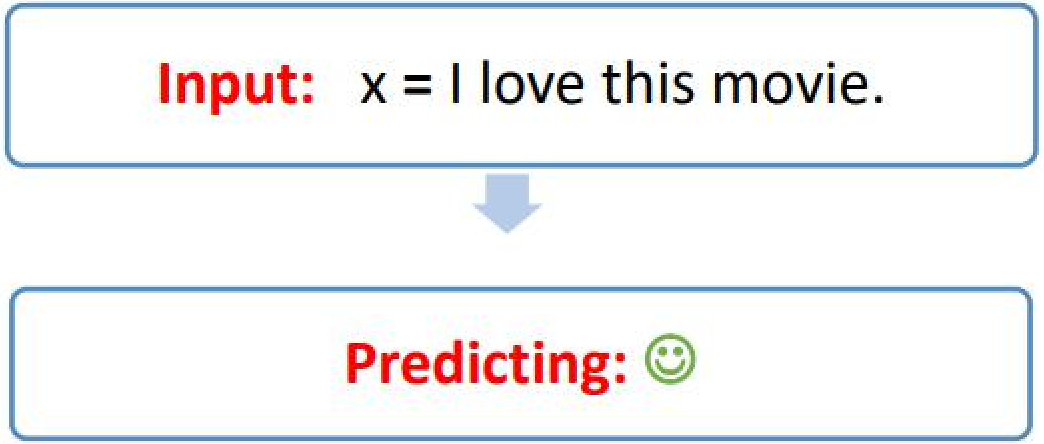


Prompt:下游任务迁就预训练语言模型，对不同任务进行同构，使得下游任务适配预训练语言模型

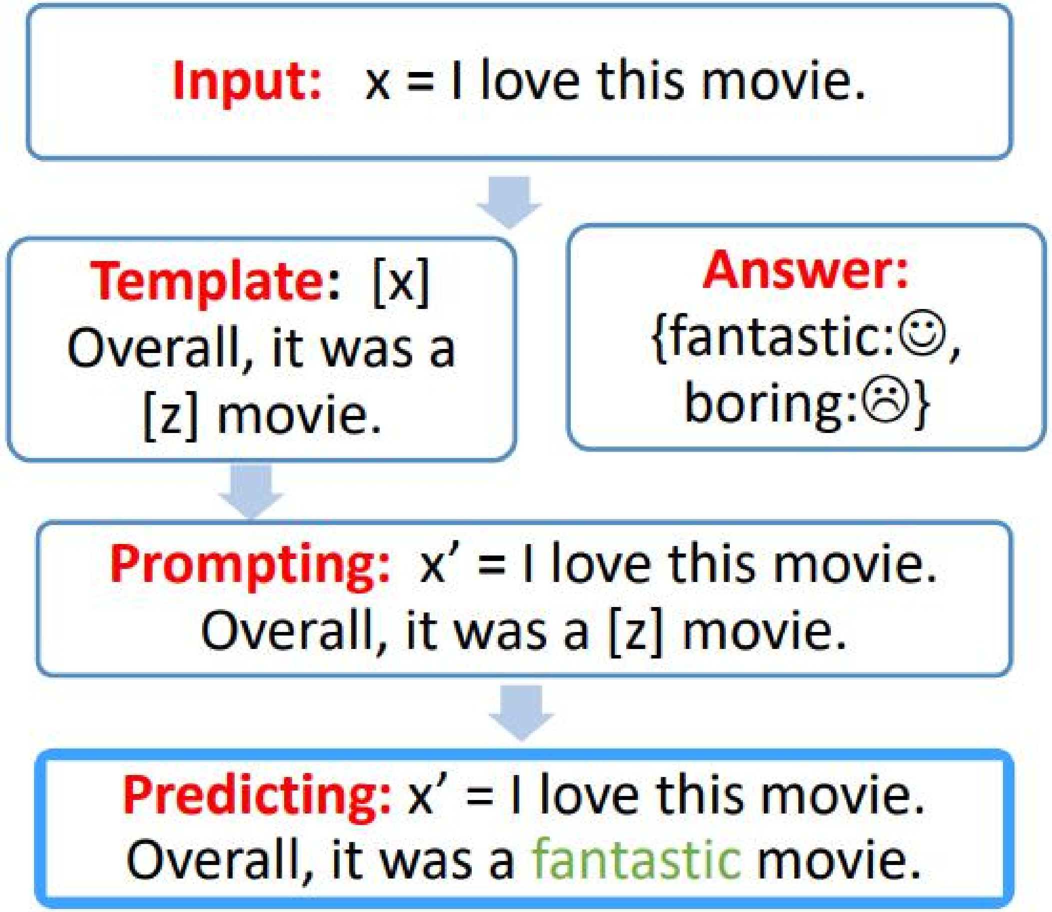
术语和符号

Name	Notation	Example	Description
Input	$\boldsymbol{x}$	I love this movie.	One or multiple texts
Output	$\boldsymbol{y}$	++ (very positive)	Output label or text
Prompting Function	$f_{\text{prompt}}(\boldsymbol{x})$	`[X]` Overall, it was a `[Z]` movie.	A function that converts the input into a specific form by inserting the input $\boldsymbol{x}$ and adding a slot `[Z]` where answer $\boldsymbol{z}$ may be filled later.
Prompt	$\boldsymbol{x}'$	I love this movie. Overall, it was a `[Z]` movie.	A text where `[X]` is instantiated by input $\boldsymbol{x}$ but answer slot `[Z]` is not.
Filled Prompt	$f_{\text{fill}}(\boldsymbol{x}', \boldsymbol{z})$	I love this movie. Overall, it was a bad movie.	A prompt where slot `[Z]` is filled with any answer.
Answered Prompt	$f_{\text{fill}}(\boldsymbol{x}', \boldsymbol{z}^*)$	I love this movie. Overall, it was a good movie.	A prompt where slot `[Z]` is filled with a true answer.
Answer	$\boldsymbol{z}$	"good", "fantastic", "boring"	A token, phrase, or sentence that fills `[Z]`

Method



Input: x = I love this movie.
Predicting: ☺



Input: x = I love this movie.
Template: [x] Overall, it was a [z] movie.
Answer: {fantastic:☺, boring:☹}
Prompting: x’ = I love this movie. Overall, it was a [z] movie.
Predicting: x’ = I love this movie. Overall, it was a fantastic movie.

常见任务的prompt、predict示例

Type	Task	Input ([X])	Template	Answer ([Z])
Text CLS	Sentiment	I love this movie.	[X] The movie is [Z].	great fantastic ...
	Topics	He prompted the LM.	[X] The text is about [Z].	sports science ...
	Intention	What is taxi fare to Denver?	[X] The question is about [Z].	quantity city ...
Text-span CLS	Aspect Sentiment	Poor service but good food.	[X] What about service? [Z].	Bad Terrible ...
Text-pair CLS	NLI	[X1]: An old man with ... [X2]: A man walks ...	[X1]? [Z], [X2]	Yes No ...
Tagging	NER	[X1]: Mike went to Paris. [X2]: Paris	[X1] [X2] is a [Z] entity.	organization location ...
Text Generation	Summarization	Las Vegas police ...	[X] TL;DR: [Z]	The victim ... A woman ... ...
	Translation	Je vous aime.	French: [X] English: [Z]	I love you. I fancy you. ...

Pre-trained Language Models

LMs	x			y			Application
	Mask	Noise	Main Obj.	Mask	Noise	Main Obj.	
L2R	Diagonal	None	SLM	-	-	-	NLU & NLG
Mask	Full	Mask	CTR	-	-	-	NLU
Prefix	Full	Any	CTR	Diagonal	None	SLM	NLU & NLG
En-De	Full	Any	None†	Diagonal	None	FTR/CRT	NLU & NLG

Prompt Engineering

- *Prompt shape*
- *Manual Template*
- *Automated Template*

离散Prompts

连续prompts

- *Prompt-based Training Strategies*

Prompt shape

Cloze prompt
（填充文本字符串空白的完形填空）

(Prefix) prompt
（延续字符串前缀的前缀）

对于有关生成的任务或使用标准自回归 LM 解决的任务，前缀 prompt 往往更有帮助，因为它们与模型从左到右的性质刚好吻合。

对于使用掩码 (Mask) LM 解决的任务（比如，BERT），完形填空 prompt 则非常合适，因为它们与预训练任务的形式非常匹配。

Manual Template

优：直观

缺：耗费时间和人力，可能无法发现最优模板

Automated Template

离散Prompts

模板搜索空间是离散的，自动生成由自然语言的词组成的prompt，每个token都是自然语言中真实的word。

连续prompts

模板搜索空间是连续的，直接作用于embedding层，每个token是虚拟的word，由连续的向量表示。

离散Prompts

- prompt mining

给定输入【x】和输出【y】，找到x和y的中间词或依赖路径，选取最频繁出现的中间词或依赖路径作为模板。

Eg：[X] middle words [Z]"

- prompt paraphrasing

根据现有的prompt，将其转述成另一组其他候选的prompt，然后选择效果最好的（同义词替换等）

- Gradient-based search

梯度下降搜索方法：在单词候选集选择此并组成prompt，利用梯度下降的方式不断组合，找出最合适的词和模板

离散Prompts

Prompt Generation

将T5引入模板搜索的过程，让T5生成模板词（域自适应算法：为每个输入生成一种唯一的域相关特征，然后把输入和特征连接应用到下游任务）

Prompt scoring

人工制造模板候选，把相应的【x】和【z】都填上成为prompt，并使用双向LM为prompt打分，选取高分prompt。

连续prompts

- Prefix tuning

  在输入钱添加一串连续的向量，可以保持PLM的参数不懂，仅训练合适的前缀。在给定一个可训练的前缀矩阵和一个固定的参数化为θ的PLM的对数目标上的优化

- Tuing Initialized with Discrete Prompts

  先用一个离散prompt搜索方法定义了一个模板，然后基于该模板初始化虚拟的token，最后微调这些token的embedding以提高准确率。

- Hard-Soft Prompt Hybrid Tuning

  手工设计和自动学习的结合

  在手工设计的模板中插入一些可学习的embedding。“P-Tuning”方法，通过在input embedding中插入可训练的变量来学习连续的prompts。该方法使用BiLSTM的输出来表示prompt embeddings，以便让prompt tokens之间有一定的交互。

Answer Engineering

Shape

Design

Manual Design:同prompt一样，直观但不理想

Answer Search：

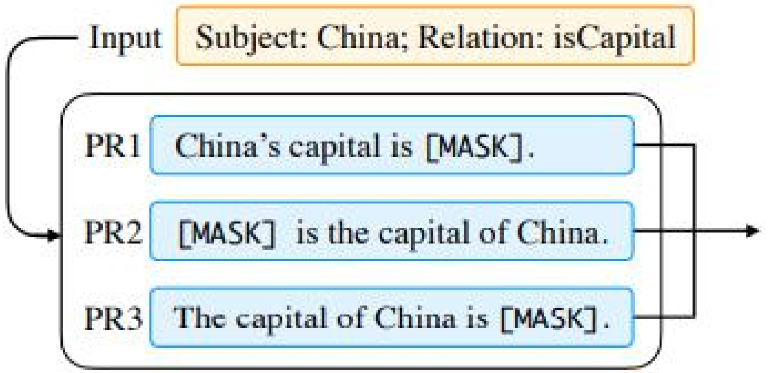
Discrete—利用分类器，根据样本选择词的生成概率，构建answer，迭代地计算单词s的适用性作为标签y的代表性答案z。
利用训练数据将固定模板的LM与每个答案映射进行微调，并根据开发集上的准确率选择最佳标签词作为答案。
（挖词，填空，构建集合，训练，缩小集合）

Answer Shape

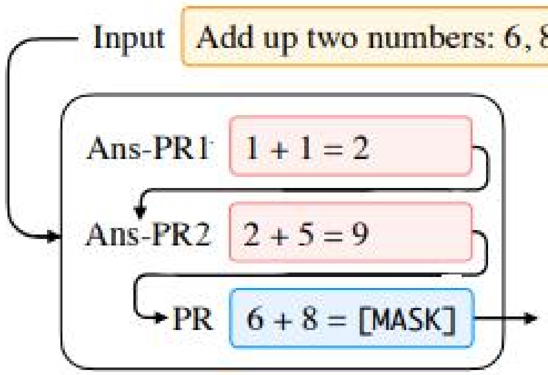
- Token：预训练 LM 词汇表中的一个 token，或者词汇子集；
- Span：短的 multi-token span，这些通常与 cloze prompt 一起使用；
- 句子或文档：这些通常与前缀 prompt 一起使用。

multi-prompt（多重 prompt ）

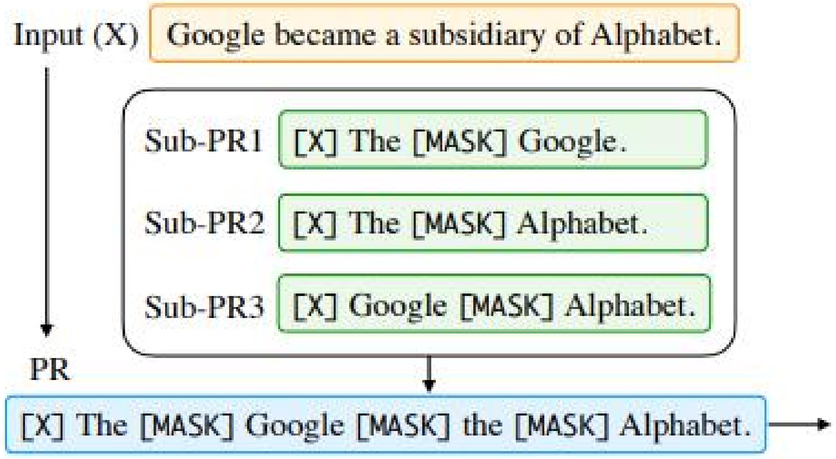
- prompt 集成
- prompt 增强
- prompt 合成
- prompt 分解



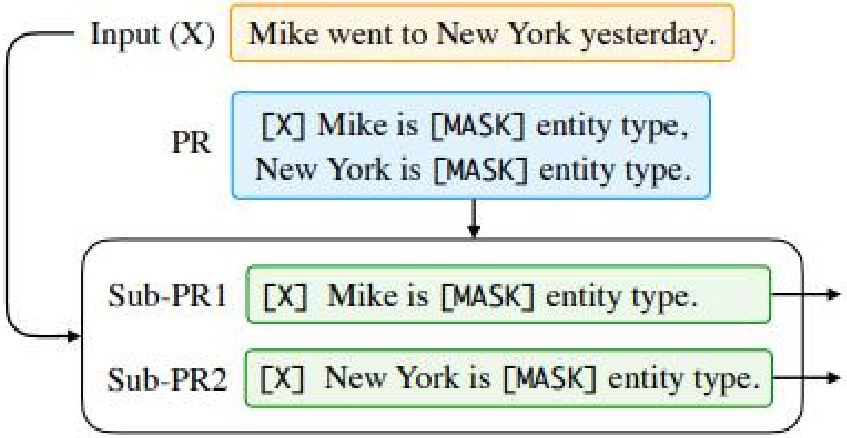
(a) Prompt Ensembling.



(b) Prompt Augmentation.



(c) Prompt Composition.



(d) Prompt Decomposition.

问题

- prompt和Masked Language Model有什么不一样?