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

> Submitted on **28 Jul 2021**

综述文章太长不看版→知乎讲解，下面仅记录一些比较重要的综述内容

1. **四种范式：**

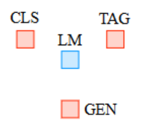
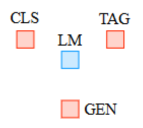
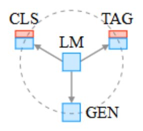
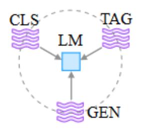
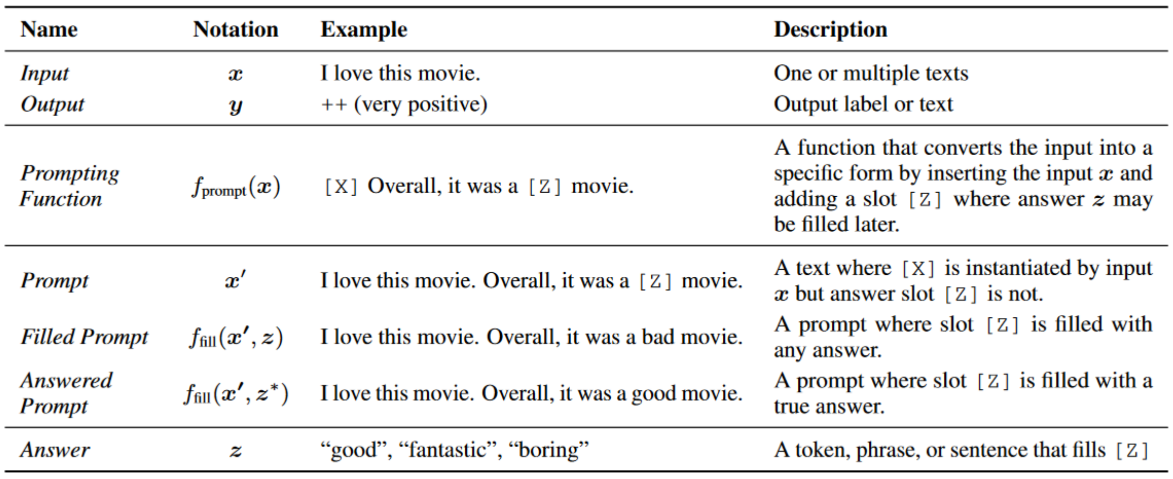
Paradigm	**Engineering**	**Task Relation**
a. Fully Supervised Learning (Non-Neural Network)	Features (e.g. word identity, part-of-speech, sentence length)	
b. Fully Supervised Learning (Neural Network)	Architecture (e.g. convolutional, recurrent, self-attentional)	
c. Pre-train, Fine-tune	Objective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

Table 1: Four paradigms in NLP. The "**engineering**" column represents the type of engineering to be done to build strong systems. The "**task relation**" column, shows the relationship between language models (LM) and other NLP tasks (CLS: classification, TAG: sequence tagging, GEN: text generation). 🟦: fully unsupervised training. 🟥: fully supervised training. ▨: Supervised training combined with unsupervised training. ≋ indicates a textual prompt. Dashed lines suggest that different tasks can be connected by sharing parameters of pre-trained models. "LM→Task" represents *adapting LMs (objectives) to downstream tasks* while "Task→LM" denotes *adapting downstream tasks (formulations) to LMs*.

   1. **Feature-Engineering(特征工程)：**纯有监督学习为主，需要一定规模的标注数据，然后学习模型参数，再基于模型对新的句子进行解码inference
   2. **Architecture-Engineering(架构工程)：**以设计新的神经网络模型为主的有监督学习
   3. **Objective-Engineering(目标工程)：**以设计新的预训练任务为代表
   4. **Prompt-Engineering(提示工程)：**比如**填空**、**前缀**等等，可以诱发/检索出大模型中所含有的实际任务所需要的

2. **Prompting Methods：**



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]`

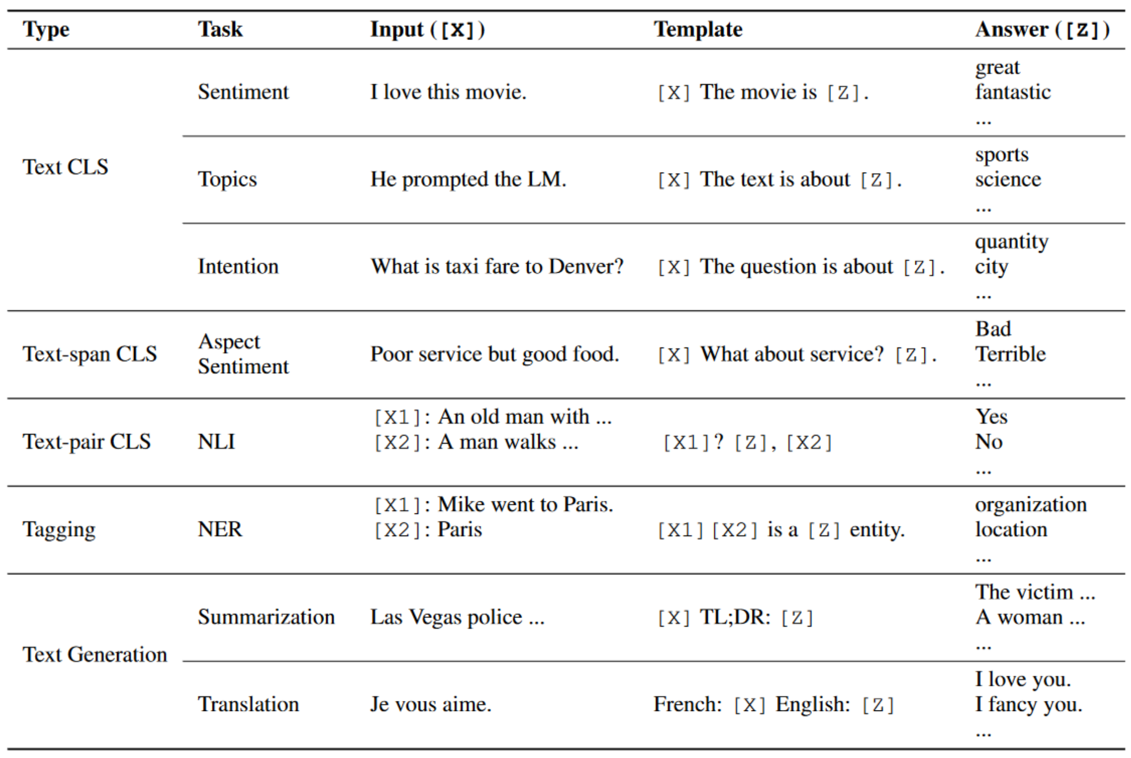
Table 2: Terminology and notation of prompting methods. $\boldsymbol{z}^*$ represents answers that correspond to true output $\boldsymbol{y}^*$.

1. **Prompting Function(提示函数)：** $f_{prompt}(\cdot)$负责把一个输入文本x变换为一个prompt x'，即为$x' = f_{prompt}(x)$
   - 首先应用一个“模板”，其中该模板应包含一个输入`slot[X]`和一个答案`slot[Z]`，`[Z]`最后会被映射给最后的输出y
   - 然后用输入文本x填充`slot[X]`

   > `[Z]`不在句子末尾的称为**cloze prompt(填空型提示)**；`[Z]`在末尾的称为**prefix prompt(前缀型提示)**

2. **填充函数：** $f_{fill}(x', z)$负责用一个候选答案z来填充prompt x'中的`[Z]`，得到的prompt称为filled prompt
3. **Answer Search(答案搜索)：** $\hat{z} = search_{z \in Z} P(f_{full(x',z);\theta})$，其中$P$即为PLM对prompt打分得到的概率。
4. **Answer Mapping：** 最后将得到的$\hat{z}$映射到任务定义的y

3. **代表性NLP任务：**



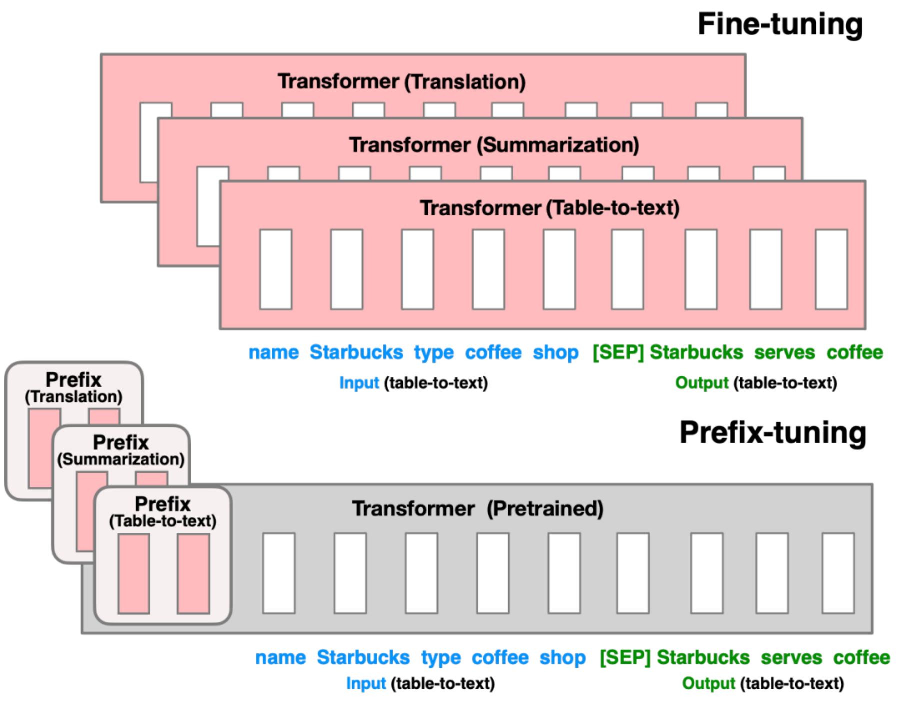
Type	Task	Input ([X])	Template	Answer ([Z])
Text CLS	Sentiment	I love this movie.	[X] The movie is [Z].	great fantastic ...
	Topics	He prompted the LM.	[X] The text is about [Z].	sports science ...
	Intention	What is taxi fare to Denver?	[X] The question is about [Z].	quantity city ...
Text-span CLS	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. ...

Table 3: Examples of *input*, *template*, and *answer* for different tasks. In the **Type** column, "CLS" is an abbreviation for "classification". In the **Task** column, "NLI" and "NER" are abbreviations for "natural language inference" (Bowman et al., 2015) and "named entity recognition" (Tjong Kim Sang and De Meulder, 2003) respectively.

1. **Text CLS(文本分类任务)**：该任务还可细分成**sentiment(情感分析)**、**Topics(文本"主题"分类任务)**、**Intention(意图识别)**
2. **Text-span CLS(文本片段分类任务)**
3. **Text-pair CLS(文本对自然语言推理分类任务)**
4. **Tagging(序列标注任务)**
5. **Text Generation(文本生成任务)**：该任务可细分为**Summarization(总结)**、**Translation(翻译)**

4. **Prompt Engineering(提示工程)**：分为**discrete prompts(离散提示)**、**continuous prompts(连续提示)**

   1. **discrete prompts(离散提示)**：使用具体的words/tokens
      - **prompt mining(提示挖掘)**
      - **prompt paraphrasing(提示改述)**，例如$English \rightarrow Chinese \rightarrow English$这种
      - **Gradient-based Search(基于梯度的搜索)**
      - **Prompt Generation(提示生成)**
      - **Prompr Scoring(提示打分)**
   2. **continuous prompts(连续提示)**：基于embeddings来表示prompts，prompts拥有自己的参数可以微调
      - **Prefix-Tuning(前缀微调)**


Fine-tuning
Transformer (Translation)
Transformer (Summarization)
Transformer (Table-to-text)
name Starbucks type coffee shop [SEP] Starbucks serves coffee
Input (table-to-text)
Output (table-to-text)
Prefix-tuning
Prefix (Translation)
Prefix (Summarization)
Prefix (Table-to-text)
Transformer (Pretrained)
name Starbucks type coffee shop [SEP] Starbucks serves coffee
Input (table-to-text)
Output (table-to-text)

在每个句子上加若干前缀，遇到新下游任务就修改prefix

- **Tuning Initialized with Discrete Prompts(先离散后连续)**
- **Hard-Soft Prompts Hybrid Tuning(离散+连续)**，例如将可微调的embeddings放入一个hard(离散的)prompt template

Extensible Prompts for Language Models on Zero-shot Language Style Customization

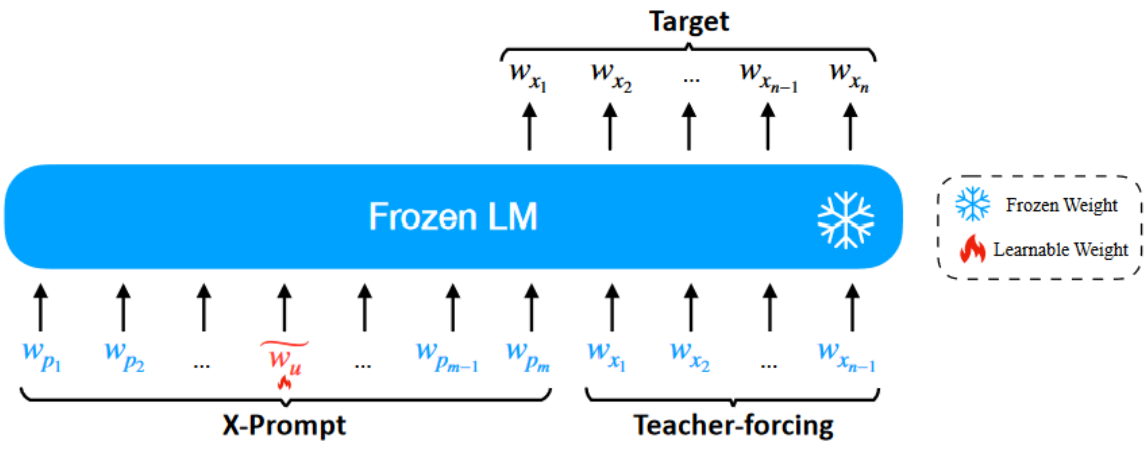
> Submitted on **1 Dec 2022**, last revised **30 Nov 2023**

1. `Introduction`

   > 提出了**eXtensible Prompt(X-Prompt)**，将**imaginary words**$\rightarrow \tilde{w}$注入**NL(natural language)**中构成**X-Prompt**，可以用于解决OOD robustness问题。同时提出**context-augmented learning(CAL)**的概念，更好地学习**imaginary words**$\rightarrow \tilde{w}$，保证其general usability
   >
   > task的类型是language style customization

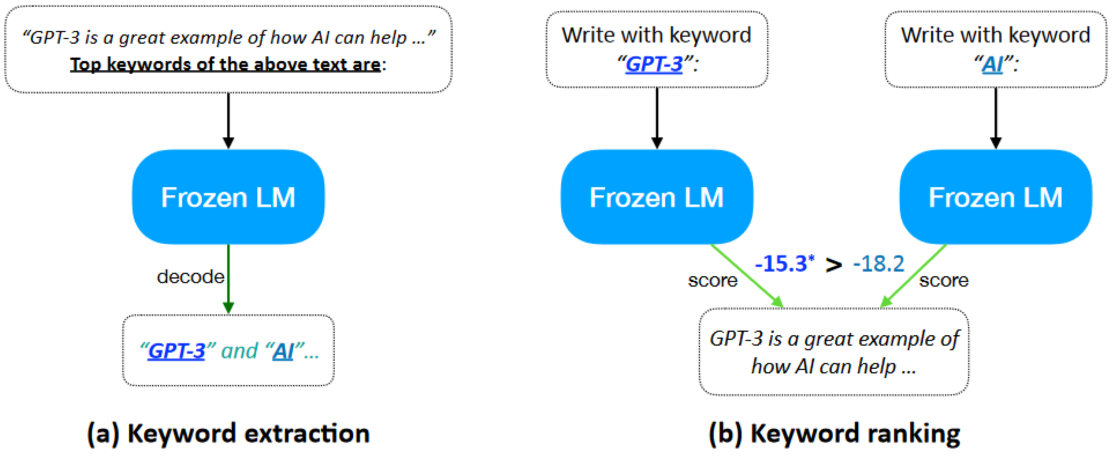
2. `eXtensible Prompt`

   - **X-Prompt**：$(w_{p_1}, \cdots, w_{p_m})$，每个$w_{p_i}$可以来自NL vocabulary V或者extensible imaginary word vocabulary $\tilde{V}$


Target
w_{x_1} w_{x_2} ... $w_{x_{n-1}}$ w_{x_n}
Frozen LM
Frozen Weight
Learnable Weight
w_{p_1} w_{p_2} ... $\widetilde{w_u}$ ... $w_{p_{m-1}}$ w_{p_m} w_{x_1} w_{x_2} ... $w_{x_{n-1}}$
X-Prompt
Teacher-forcing

- **Context-augmented learning**：假设**X-Prompt**为$(w_{p_1},\cdots,\widetilde{w_{p_u}},\cdots w_{p_m})$，那么学习**imaginary words**$\widetilde{w_{p_u}}$也即最大化$\log P(\vec{x}|w_{p_1},\cdots,w_{p_m})$，其中$\vec{x}$为training example$(w_{x_1},\cdots,w_{x_n})$
  - **Template augmentation**：给定T个**X-Prompt**，$\{(w^{(t)}_{p_1},\cdots,\widetilde{w_u},\cdots,w^{(t)}_{p_{m_t}})|1\le t\le T\}$，需要最大化$\frac{1}{T}\sum_{t=1}^{T}\log P(\vec{x}|w^{(t)}_{p_1},\cdots,\widetilde{w_u},\cdots,w^{(t)}_{p_{m_t}})$
  - **Content augmentation**：向**X-Prompt**中注入an indicative keyword，对于keyword的处理如下图。

    对每个training example$\vec{x}$提取出keyword candidates$[w^1_k,\cdots,w^C_k]$，然后每个keyword插入到一个用于rank的prompt中选出最indicative的一个keyword，也即$w^\star_k=\arg\max_{w^c_k}\log P(\vec{x}|\vec{r}(w^c_k))$，其中$\vec{r}(w^c_k)=(w^{(r)}_{p_1},\cdots,w^{(r)}_{p_{m_r}})$称为**ranking prompt template**


"GPT-3 is a great example of how AI can help ..."
Top keywords of the above text are:
Frozen LM
decode
"GPT-3" and "AI"...
(a) Keyword extraction
Write with keyword "GPT-3":
Write with keyword "AI":
Frozen LM
Frozen LM
score
-15.3* > -18.2
score
GPT-3 is a great example of how AI can help ...
(b) Keyword ranking

3. `Experiments`
   - 实验主要是测试了两个task：**open-ended text generation**、**style transfer(rewriting)**，前一个任务是测试**X-Prompt**如何instruct语言模型生成user-specific语言，后一个任务是按要求转换语言的style(比如$impolite\rightarrow polite$)
     - open-ended text generation：

1. 数据集：`Top 20 most followed users in Twitter social platform dataset`+`the Sentiment dataset5 from which we extract top 800 users’ (in total 68K) tweets (800-user dataset)`，同时剔除了test example中与training example具有相同indicative keyword的样本
2. 基本配置：base model为`OPT-6.7b`，选用`Adam`优化器......
3. 定量评估：选取的指标为`perplexity`和`accuracy`，实验结果如下图。**X-Prompt**在OOD上表现得更加好，而**Prompt tuning**、**X-Prompt(w/o CAL)**在ID上表现更好(因为它们focus on training examples)

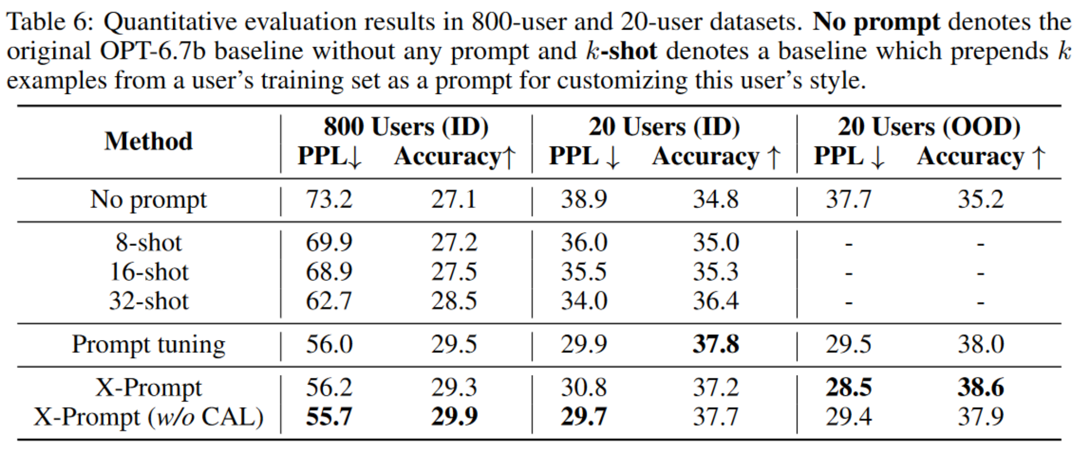


Table 6: Quantitative evaluation results in 800-user and 20-user datasets. **No prompt** denotes the original OPT-6.7b baseline without any prompt and k-**shot** denotes a baseline which prepends k examples from a user’s training set as a prompt for customizing this user’s style.

Method	**800 Users (ID)**		**20 Users (ID)**		**20 Users (OOD)**	
	PPL↓	**Accuracy↑**	**PPL ↓**	**Accuracy ↑**	**PPL ↓**	**Accuracy ↑**
No prompt	73.2	27.1	38.9	34.8	37.7	35.2
8-shot	69.9	27.2	36.0	35.0	-	-
16-shot	68.9	27.5	35.5	35.3	-	-
32-shot	62.7	28.5	34.0	36.4	-	-
Prompt tuning	56.0	29.5	29.9	**37.8**	29.5	38.0
X-Prompt	56.2	29.3	30.8	37.2	**28.5**	**38.6**
X-Prompt (*w/o* CAL)	**55.7**	**29.9**	**29.7**	37.7	29.4	37.9

4. 定性评估：手工构建了100个在training阶段没有见过的prompt，然后让两个人对LM生成结果在三个方面做评估：Content、Style、Overall，实验结果如下图

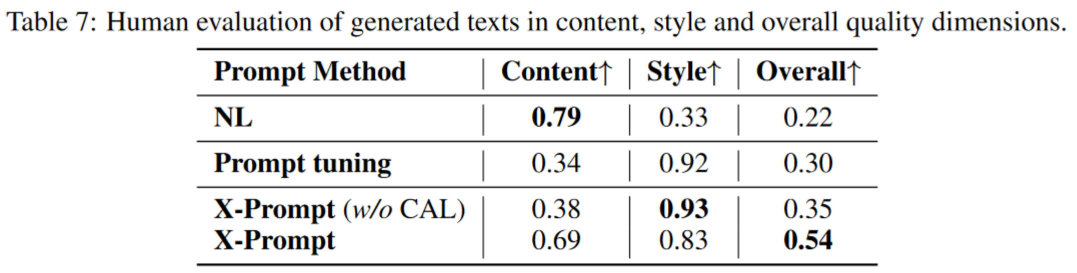


Table 7: Human evaluation of generated texts in content, style and overall quality dimensions.

Prompt Method	**Content↑**	**Style↑**	**Overall↑**
NL	**0.79**	0.33	0.22
Prompt tuning	0.34	0.92	0.30
X-Prompt (*w/o* CAL)	0.38	**0.93**	0.35
X-Prompt	0.69	0.83	**0.54**

- style transfer：

1. 数据集：`Entertainment (EM) subset of GYAFC (informal → formal)`+`POLITEREWRITE (impolite → polite)`
2. 评测指标：`BLEU(Bilingual Evaluation Understudy)，该指标常用于机器翻译`用于评测生成结果和reference的lexical similarity、`accuracy`用于评测style appropriateness、`harmonic(H-) mean`和`geometric(G-) mean`用来作为overall performance

Structured Prompting: Scaling In-Context Learning to 1,000 Examples

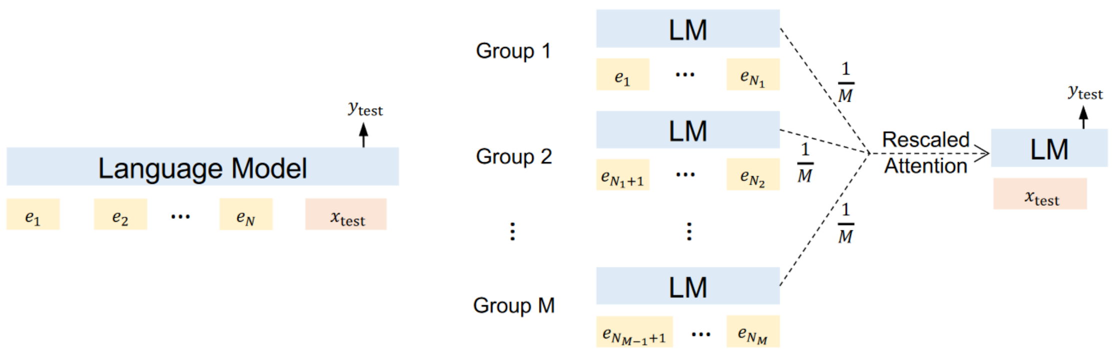
> Submitted on **13 Dec 2022**

1. `Introduction`

   > 提出了**Structured Prompting**，打破length的限制从而使得**In-Context Learning**可以用成千的examples训练。
   >
   > **In-Context Learning**：对于N-shot in-context learning，给定一个N labeled examples $D_{train} = \{(x_i, y_i)\}_{i=1}^N$，每个数据点都可用hand-crafted template T转化成一个demonstration $d_i = T(x_i, y_i)$。所有的demonstration可以被连接成$Z = d_1 \oplus \cdots \oplus d_N$，对于每个test input x_{test}，都可以构造prompt为Z和x_{test}的连接。最终的输出结果为$\arg\max_{c \in Y} P_{LM}(y^c | Z \oplus T(x_{test}))$，其中$Y$是所有可能的candidate

2. `Methods`

   -



(a) Conventional Prompting **(b) Structured Prompting**

     - **Group Context Encoding**：假设有N demonstration examples，把这些examples随机分成M组 $\{Z_i\}_{i=1}^M$，每个group为$Z_i = d_{N_{i-1}+1} \oplus \cdots \oplus d_{N_i}$，其中$N_0 = 0$、$N_M = N$

       > Position Embedding：所有group采用right align从而保证它们有相同的max position index，因此所有group到test input有相同的距离。为了让test input对所有的examplar adjacent并pay equal attention，有两种方式：1. 使用left padding，i.e. pad tokens or space tokens 2.设置最大长度，从左边truncate examplar

     - **Structured Prompting**：所有的examplar都喂进了Rescaled Attention，并连同test input一起喂进LM

       > Rescaled Attention：每一层都将所有examplar和test input的key、value连接起来，即$\hat{K} = [K_{Z_1}, \cdots, K_{Z_M}, K_x]$、$\hat{V} = [V_{Z_1}, \cdots, V_{Z_M}, V_x]$。计算attention

> 的公式为：
>
> $$\text{Attention}(Q_x, \hat{K}, \hat{V}) = A\hat{V} \tag{1}$$
>
> $$A_{ij} \propto \begin{cases} M\exp(\frac{\boldsymbol{q}_i \cdot \boldsymbol{k}_j}{\sqrt{d}}) & j \in x \\ \exp(\frac{\boldsymbol{q}_i \cdot \boldsymbol{k}_j}{\sqrt{d}}) & j \in \mathcal{Z}_1, \ldots, \mathcal{Z}_M \end{cases} \tag{2}$$
>
> where $\sum_j A_{ij} = 1$, the query vector $\boldsymbol{q}_i \in Q_x$, the key vector $\boldsymbol{k}_j \in \hat{K}^\intercal$, and d is dimension of queries and keys.

3. `Experiments`
   1. 模型：`GPT-like(decoder-only Transformer)`，对于超大模型实验，选用`BLOOM-176B`
   2. 数据集：根据三个task：text classification、multi-choice、open-ended generation从而有对应的数据集

   > 整个实验测试了Model Size为**1.3B、6.7B、13B**在三个task `text classification`、`multi-choice`、`open-ended generation`，然后又在超大模型`BLOOM-176B`上测试了上面三个task，最后进行消融实验验证Prompt Length、Scaling Factor、Alignment Strategy的重要性

How Does In-Context Learning Help Prompt Tuning

> Submitted on **22 Feb 2023**

1. `Introduction`

   > 本文主要比对了`PT(Prompt Tuning)`、`ICL(In-Context Learning)`、`IPT(Instruction Prompt Tuning)`从而来探究ICL对PT的影响
   >
   > **别的地方看到的：in-context examples主要是帮助model学习output label space和distribution of input text**

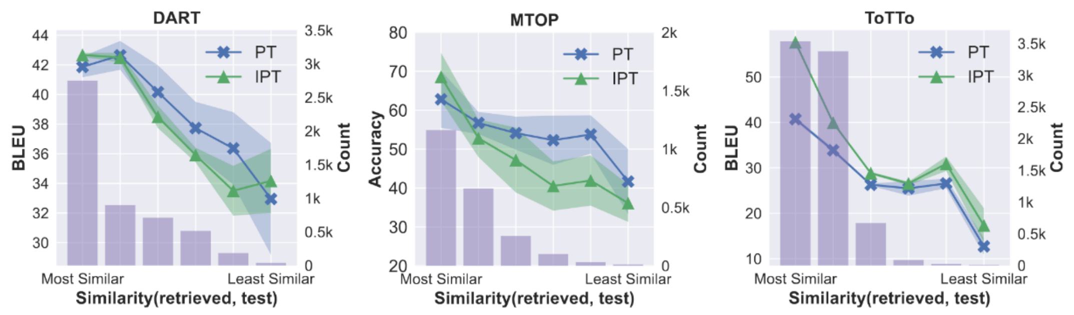
2. `Background`
   - `In-Context Learning`：在test input之前插入k个in-context input-output pairs，即为$Input_{ICL} = concat([X_{icl}; Y_{icl}]_1^k; X_{test})$
   - `Prompt Tuning`：在test input X_{test}之前加入soft tunable prompt embeddings。一系列的tunable prompt embeddings用$E = \{e_1, \cdots, e_k\}$表示，那么$Input_{PT} = concat(E; X_{test})$。注意这里的$E$需要train，所以需要$X_{train}$、$Y_{train}$
   - `Instruction Prompt Tuning`：把soft prompts和hard in-context demonstrations连接在一起，即为$Input_{IPL} = concat(E; [X_{icl}; Y_{icl}]_1^k; X_{test})$
3. `Experiments`
   1. 数据集：选用三种language generation tasks，即为`data-to-text generation`、`logic-to-text generation`、`semantic parsing`。不同任务有相应的数据集

2. 模型：`BLOOM-1.1B`、`OPT-1.3B`、`GPT-2-XL-1.5B`

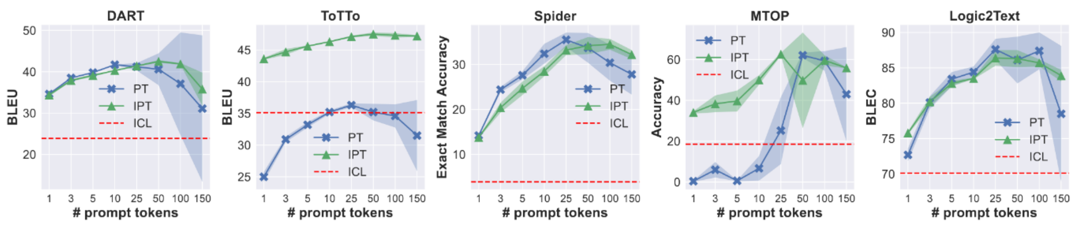
3. **实验结论(这部分可以参考)**

	ToTTo (BLEU)	Dart (BLEU)	Spider (Exact Match)	Mtop (Exact Match)	Logic2text (BLEC)
BLOOM-1.1B					
random one-shot ICL	5.8	8.3	0.4	0.0	37.6
retrieved one-shot ICL	35.1	23.9	3.9	18.5	70.1
retrieve three-shot ICL	41.3	29.7	5.0	12.7	71.0
BLOOM-1.1B					
Prompt Tuning	$36.3_{\pm 0.3}$	$41.2_{\pm 0.9}$	$35.5_{\pm 1.6}$	$25.2_{\pm 16.4}$	$87.6_{\pm 1.5}$
Instruction Prompt Tuning	$47.1_{\pm 0.2}$	$41.4_{\pm 0.1}$	$33.2_{\pm 1.1}$	$62.6_{\pm 0.7}$	$86.4_{\pm 1.1}$
OPT-1.3B					
Prompt Tuning	$38.5_{\pm 1.0}$	$44.5_{\pm 0.2}$	$14.4_{\pm 2.3}$	$6.4_{\pm 6.5}$	$80.6_{\pm 3.7}$
Instruction Prompt Tuning	$46.3_{\pm 0.9}$	$42.9_{\pm 0.4}$	$14.2_{\pm 2.1}$	$10.4_{\pm 6.5}$	$84.6_{\pm 1.0}$
GPT-2-XL-1.5B					
Prompt Tuning	$37.3_{\pm 0.2}$	$43.5_{\pm 0.2}$	$27.0_{\pm 2.1}$	$41.4_{\pm 5.6}$	$87.2_{\pm 1.6}$
Instruction Prompt Tuning	$48.0_{\pm 0.0}$	$42.1_{\pm 0.2}$	$23.0_{\pm 0.1}$	$19.8_{\pm 14.9}$	$85.8_{\pm 1.5}$

- **ICL表现得比PT差**，这说明了对于类似OOD generation task，针对target task train一小部分参数是有价值的
- **PT、IPT的表现难分伯仲**，取决于task类型和tunable parameter的数目等(work不work可能也还有数据集等因素)
- **当demonstration跟test input类似的时候，IPT可以work**。这也就说明了similar demonstration对IPT的重要性



- **IPT在有更多的soft prompt tokens的情况下比PT表现得更稳定**

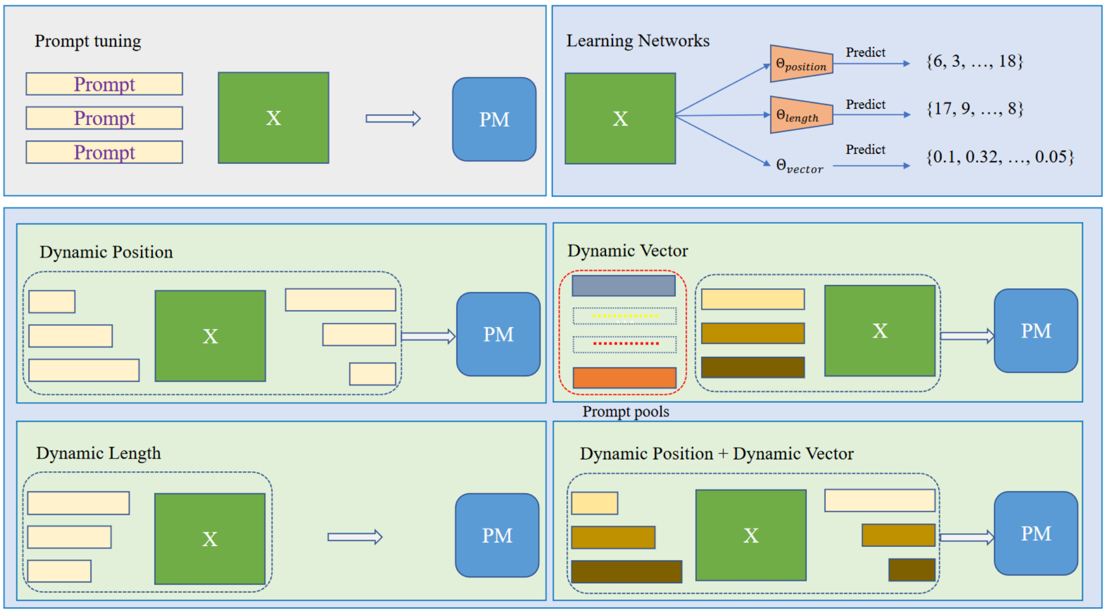


- **在有in-context demonstrations的情况下，Prompt embeddings对于新的task是transferable**

Dynamic Prompting: A Unified Framework for Prompt Tuning

> Submitted on **6 Mar 2023**, last revised **27 May 2023**

1. `Introduction`

> 提出了**DP(Dynamic Prompt)**，根据不同的instance/task来调整相对应prompt的**position、length、representation**(例如不同position相比传统的prefix/postfix可能会更好地捕捉语义信息)。**DP**的整体架构如下：
>
> 
>

2. `Methods`

   - **Unified View：**把prompt分为prefix和postfix两部分，对于输入$x \in R^{m\times d}$，query matrix是$Q = xW^W \in R^{m\times d}$ key matrix是$K = xW^K \in R^{m\times d}$ value matrix是$V = xW^V \in R^{m\times d_v}$。假设prompt的长度为$l$，那么$P = [P_1; P_2]$，其中$P_1 \in R^{l_1\times d}, P_2 \in R^{l_2\times d}$。最终的输入变成$x' = [P_1; x; P_2] \in R^{(l_1+m+l_2)\times d}$，新的key matrix变为$K' = x'W^K \in R^{(l_1+m+l_2)\times d}$ value matrix变为$V' = x'W^V \in R^{(l_1+m+l_2)\times d_v}$。通过矩阵分解：
     $Q' = \begin{bmatrix} Q_1 \\ Q \\ Q_2 \end{bmatrix}, K' = \begin{bmatrix} K_1 \\ K \\ K_2 \end{bmatrix}, V' = \begin{bmatrix} V_1 \\ V \\ V_2 \end{bmatrix}$，其中
     $Q_1, K_1 \in R^{l_1\times d}, Q_2, K_2 \in R^{l_2\times d}, V_1 \in R^{l_1\times d_v}, V_2 \in R^{l_2\times d_v}$。因此对于输入$x' = [P_1; x; P_2]$来说，attention head module变为
     $Head = Attn([P_1; x; P_2]W^Q, [P_1; x; P_2]W^K, [P_1; x; P_2]W^V) = softmax(\frac{Q'K'^T}{\sqrt{d}})V'$
     省略$\sqrt{d}$也就可以化为
     $[softmax(P_1W^QK'^T)V'; softmax(xW^QK'^T)V'; softmax(P_2W^QK'^T)V']$

        - 最终版：

          $$\begin{aligned} Head &= Attn(x', K', V') \\ &= \left[\lambda_1 * \underbrace{Attn(Q_1, K_1, V_1)}_{\text{prompt tuning}} + \lambda_2 * \underbrace{Attn(Q_1, K_2, V_2)}_{\text{postfix}} + (1-\lambda_1-\lambda_2) * \underbrace{Attn(Q_1, K, V)}_{\text{prompt tuning}}; \right. \\ & \beta_1 * \underbrace{Attn(Q, K_1, V_1)}_{\text{prompt tuning}} + \beta_2 * \underbrace{Attn(Q, K_2, V_2)}_{\text{postfix}} + (1-\beta_1-\beta_2) * \underbrace{Attn(Q, K, V)}_{\text{standard}}; \\ & \left. \gamma_1 * \underbrace{Attn(Q_2, K_1, V_1)}_{\text{postfix}} + \gamma_2 * \underbrace{Attn(Q_2, K_2, V_2)}_{\text{postfix}} + (1-\gamma_1-\gamma_2) * \underbrace{Attn(Q_2, K, V)}_{\text{postfix}} \right]. \end{aligned}$$

    - **Dynamic Prompting：**

        1. **Dynamic Position：**用一个one-layer网络POS_θ和Gumbel-Softmax优化得到针对不同task/instance的**dpos**参数，原始的prompt可以被分为$P = [P_{before}, P_{after}]$，其中$P_{before} = [P_1, \cdots, P_{dpos}], P_{after} = [P_{dpos+1}, \cdots, P_l]$，因此输入为$X' = [P_{before}; X; P_{after}]$。$POS_\theta$的输出为$\alpha \in R^{l+1}$(这是一个二进制的串，0到$l$一共有$l+1$个可能的位置，每个位置对应的值为$0/1$)，这里选用Gumbel-Softmax方式处理保证可微，$logit = Gumbel - Softmax(POS_\theta(x), \tau)$，$logit$是二进制串，只有一个位置值为1。

            - *adap_ins_pos*：关注instance层面的position变化，需要添加$d \times (l+1)$个参数
            - *adap_pos*：关注task层面的position变化，需要添加$l+1$个参数

        2. **Dynamic Length：**用一个one-layer网络LEN_θ和Gumbel-Softmax优化得到针对不同task/instance的l^*参数，即为：

            $$P \in \mathbb{R}^{l^* \times d}, l^* = \operatorname*{argmin}_i loss(LM([\hat{P}_i; X] | \hat{P}_i \in \{\hat{P}_1, \cdots, \hat{P}_l\}, \hat{P}_i \in \mathbb{R}^{i \times d})).$$

            但实际上model的输入长度要求是固定的，因此作者作了一个替代方案

        3. **Dynamic Vector：**使用prompt pools $Pool = \{P^{(1)}, \cdots, P^{(k)}\}$生成dynamic prompts，train一个小的网络P_{O_θ}来得到每个prompt $P^{(i)}$关于给定输入x的attention score，即为$P_{new} = \sum_{i=1}^{k} \beta_i \cdot P^{(i)}, \beta = softmax(P_{O_\theta}(x))$

        4. **Combination：**

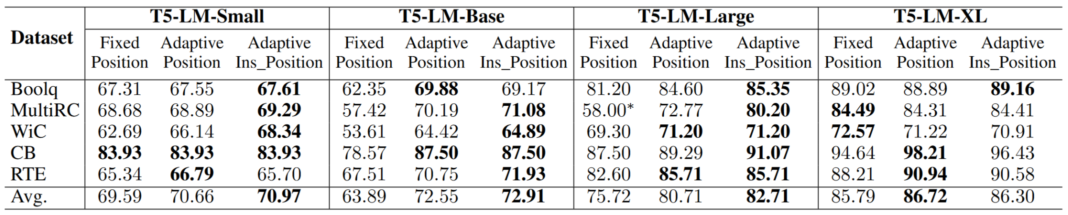
            - *adap_ins_vec_pos*：同时更新dynamic position和prompt pool
            - *adap_pos_ins_vec*：先用dynamic position学到task层面的position，然后更新instance层面的prompt pool

3. `Experiments`

    1. 数据集：采用五个SuperGLUE数据集来测试模型的language understanding ability

    2. 实验结果：

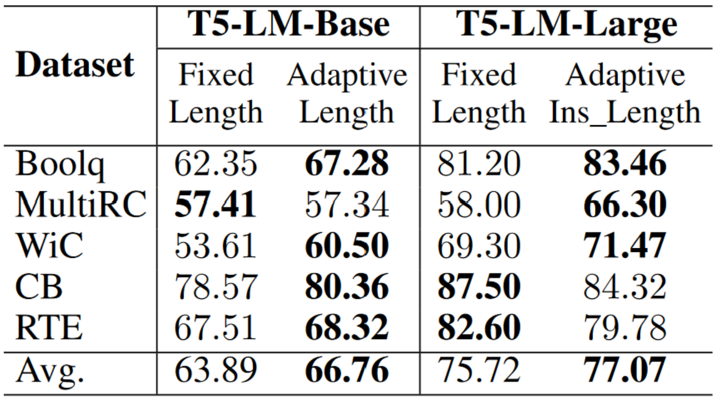
1. **Adaptive Position：**



Dataset	T5-LM-Small			T5-LM-Base			T5-LM-Large			T5-LM-XL		
	Fixed Position	Adaptive Position	Adaptive Ins_Position	Fixed Position	Adaptive Position	Adaptive Ins_Position	Fixed Position	Adaptive Position	Adaptive Ins_Position	Fixed Position	Adaptive Position	Adaptive Ins_Position
Boolq	67.31	67.55	**67.61**	62.35	**69.88**	69.17	81.20	84.60	**85.35**	89.02	88.89	**89.16**
MultiRC	68.68	68.89	**69.29**	57.42	70.19	**71.08**	58.00*	72.77	**80.20**	**84.49**	84.31	84.41
WiC	62.69	66.14	**68.34**	53.61	64.42	**64.89**	69.30	**71.20**	**71.20**	**72.57**	71.22	70.91
CB	**83.93**	**83.93**	**83.93**	78.57	**87.50**	**87.50**	87.50	89.29	**91.07**	94.64	**98.21**	96.43
RTE	65.34	**66.79**	65.70	67.51	70.75	**71.93**	82.60	**85.71**	**85.71**	88.21	**90.94**	90.58
Avg.	69.59	70.66	**70.97**	63.89	72.55	**72.91**	75.72	80.71	**82.71**	85.79	**86.72**	86.30

可以看到总体趋势是*adap_ins_pos > adap_pos > fixed_pos*，**T5-LM-Large**模型work得最好可能说明**大模型更适合prompt tuning**

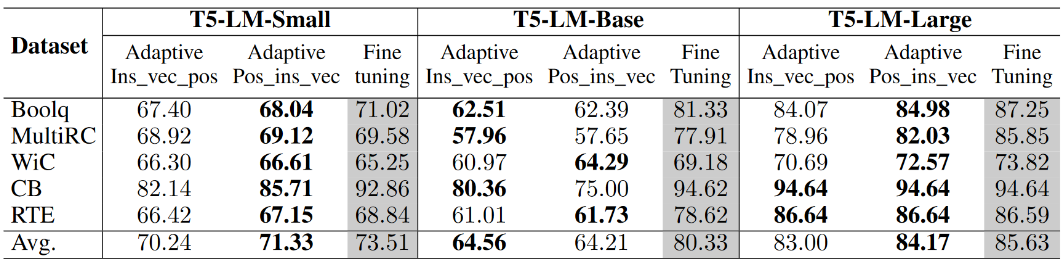
2. **Adaptive Length：**



Dataset	T5-LM-Base		T5-LM-Large	
	Fixed Length	Adaptive Length	Fixed Length	Adaptive Ins_Length
Boolq	62.35	**67.28**	81.20	**83.46**
MultiRC	**57.41**	57.34	58.00	**66.30**
WiC	53.61	**60.50**	69.30	**71.47**
CB	78.57	**80.36**	**87.50**	84.32
RTE	67.51	**68.32**	**82.60**	79.78
Avg.	63.89	**66.76**	75.72	**77.07**

虽然有提升，但是提升不如**Adaptive Position**

3. **Adaptive Prompt：**



Dataset	T5-LM-Small			T5-LM-Base			T5-LM-Large		
	Adaptive Ins_vec_pos	Adaptive Pos_ins_vec	Fine tuning	Adaptive Ins_vec_pos	Adaptive Pos_ins_vec	Fine Tuning	Adaptive Ins_vec_pos	Adaptive Pos_ins_vec	Fine Tuning
Boolq	67.40	**68.04**	71.02	**62.51**	62.39	81.33	84.07	**84.98**	87.25
MultiRC	68.92	**69.12**	69.58	**57.96**	57.65	77.91	78.96	**82.03**	85.85
WiC	66.30	**66.61**	65.25	60.97	**64.29**	69.18	70.69	**72.57**	73.82
CB	82.14	**85.71**	92.86	**80.36**	75.00	94.62	**94.64**	**94.64**	94.64
RTE	66.42	**67.15**	68.84	61.01	**61.73**	78.62	**86.64**	**86.64**	86.59
Avg.	70.24	**71.33**	73.51	**64.56**	64.21	80.33	83.00	**84.17**	85.63

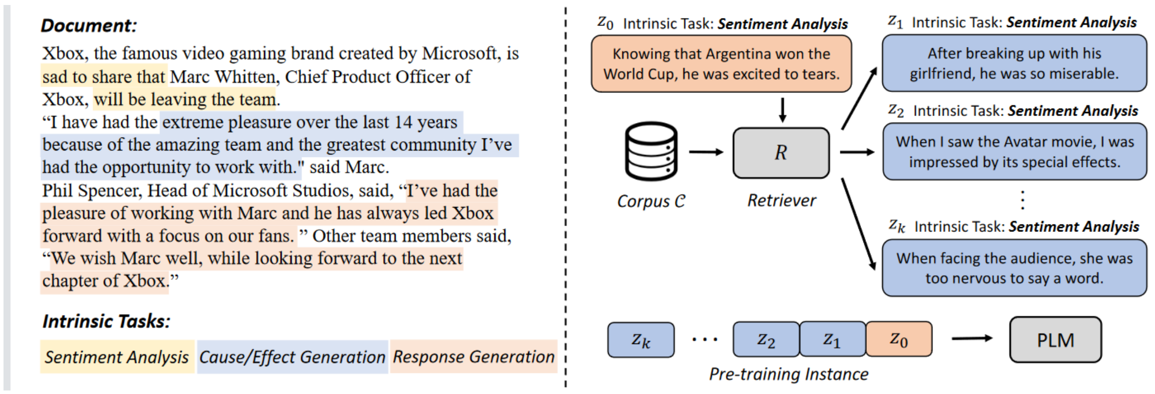
可以看到在instance层面同时更新position和propmt pool效果并不好

Pre-Training to Learn in Context

> Submitted on **16 May 2023**

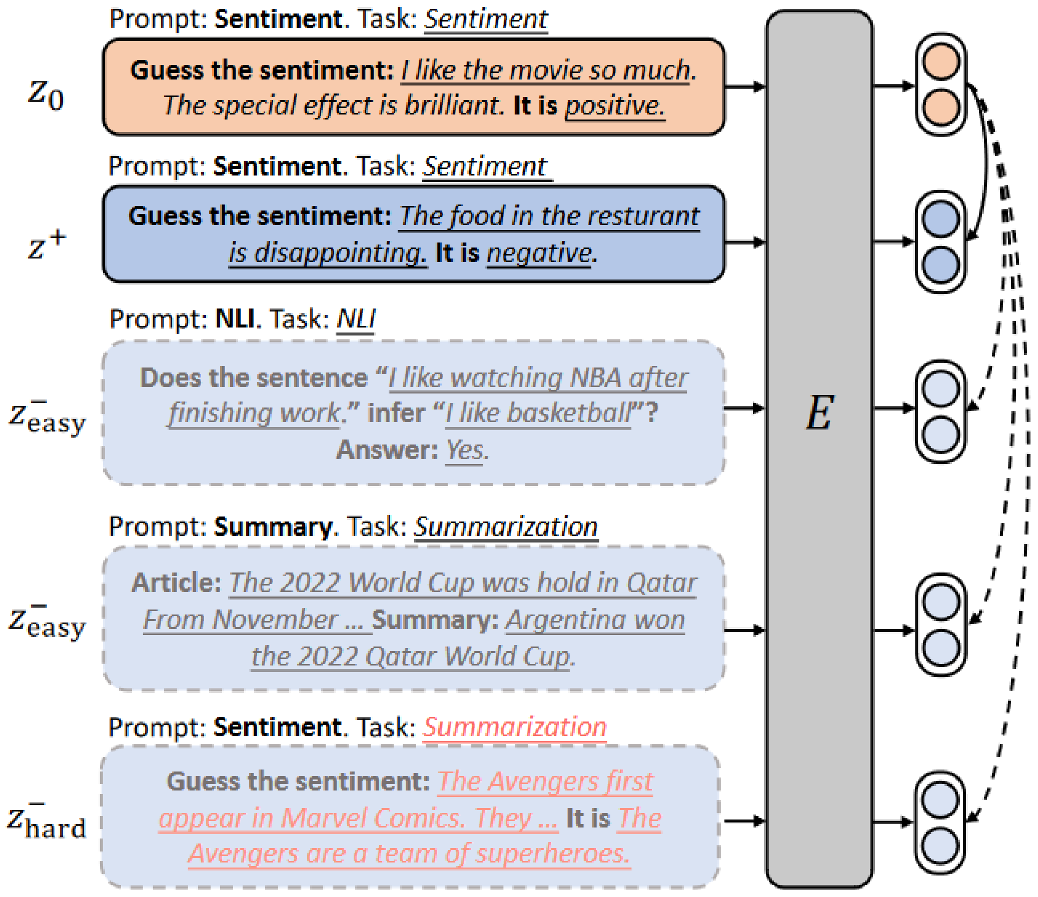
1. `Introduction`

   > 提出了**PICL(Pre-training for In-Context Learning)**，旨在提高ICL能力的同时maintain泛化能力。**PICL**主要通过在数据侧做文章来提高ICL能力：用data automatically constructed from the general plain-text corpus来预训练模型，基于**很多paragraphs都包含"intrinsic tasks"**这样的假设。
   >
   > 具体来说，把相同类型intrinsic task的paragraph连接在一起构建一个**meta-training dataset**来预训练模型。用contrastive learning的方式训一个**Encoder**使得具有相同类型intrinsic task的paragraph在向量空间中具有类似的Embedding


Document:
Xbox, the famous video gaming brand created by Microsoft, is sad to share that Marc Whitten, Chief Product Officer of Xbox, will be leaving the team.
"I have had the extreme pleasure over the last 14 years because of the amazing team and the greatest community I've had the opportunity to work with." said Marc.
Phil Spencer, Head of Microsoft Studios, said, "I've had the pleasure of working with Marc and he has always led Xbox forward with a focus on our fans." Other team members said, "We wish Marc well, while looking forward to the next chapter of Xbox."
Intrinsic Tasks:
Sentiment Analysis
Cause/Effect Generation
Response Generation
z0 Intrinsic Task: Sentiment Analysis
Knowing that Argentina won the World Cup, he was excited to tears.
Corpus C
R
Retriever
z1 Intrinsic Task: Sentiment Analysis
After breaking up with his girlfriend, he was so miserable.
z2 Intrinsic Task: Sentiment Analysis
When I saw the Avatar movie, I was impressed by its special effects.
zk Intrinsic Task: Sentiment Analysis
When facing the audience, she was too nervous to say a word.
zk ··· z2 z1 z0
Pre-training Instance
PLM

2. `Methods`

- 对于Corpus C中的每个paragraph z_0，首先用retriever R寻找k个与z_0具有相同类型intrinsic task的paragraphs $\{z_1, z_2, \cdots, z_k\}$，然后被检索出来的paragraphs会被视为demonstrations与z_0连接在一起：$z_k \oplus z_{k-1} \oplus \cdots \oplus z_1 \oplus z_0$，最后喂给模型
  - **Retriever：**核心是**task-semantics encoder** E**(其实就是对比学习的目标)**，作者将两个paragraph z_0和z的相似性定义为点乘$E(z_0) \cdot E(z)$
    1. `Encoder`：使用**RoBERTaBASE**作为base model，输出的vector是**输入paragraph的每个token的最后一层表示的平均**
    2. `Retrieval`：$R(z_0) = \{z_k, z_{k-1}, \cdots, z_1\} = top - k_z(E(z_0) \cdot E(z))$，具体实现调用了**FAISS**库
    3. Contrastive Learning：不同task选用下游NLP数据集，最终形成了一个dataset D。对于D中的每个z_0，正样本z^+跟z_0有相同的task类型，负样本集合为$N(z_0)$，loss可以计算为$L(z_0, z^+, N(z_0)) = -\log \frac{e^{E(z_0)\cdot E(z^+)}}{e^{E(z_0)\cdot E(z^+)} + \sum_{z^- \in N(z_0)} e^{E(z_0)\cdot E(z^-)}}$。其中$z^+$是随机sample出来的，$N(z_0)$包括两种样本：1.**Easy Negatives：** z^-_{easy} 2.**Hard Negatives：** z^+_{hard}

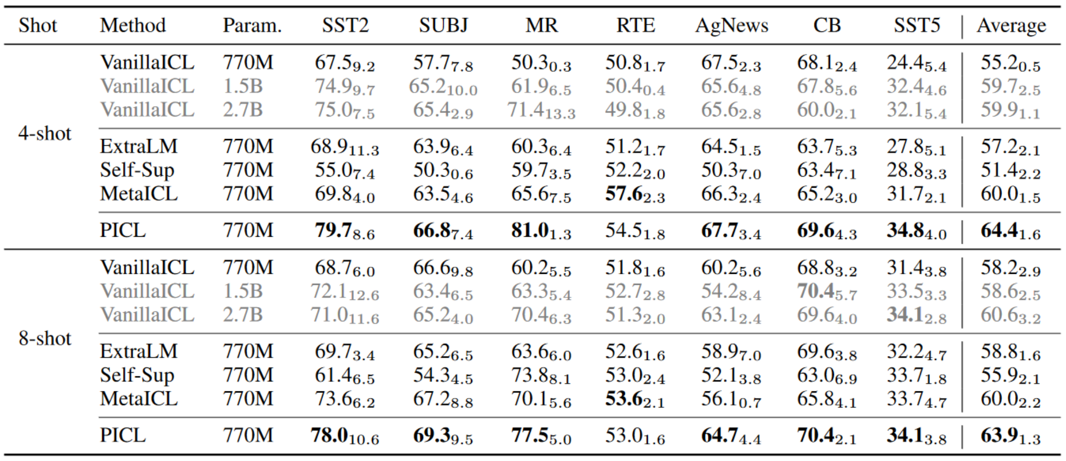

Prompt: Sentiment. Task: Sentiment
z_0
Guess the sentiment: I like the movie so much. The special effect is brilliant. It is positive.
Prompt: Sentiment. Task: Sentiment
z^+
Guess the sentiment: The food in the resturant is disappointing. It is negative.
Prompt: NLI. Task: NLI
z^-_{easy}
Does the sentence "I like watching NBA after finishing work." infer "I like basketball"? Answer: Yes.
Prompt: Summary. Task: Summarization
z^-_{easy}
Article: The 2022 World Cup was hold in Qatar From November ... Summary: Argentina won the 2022 Qatar World Cup.
Prompt: Sentiment. Task: Summarization
z^-_{hard}
Guess the sentiment: The Avengers first appear in Marvel Comics. They ... It is The Avengers are a team of superheroes.
E

- **Data Construction**：对于每个$z_0 \in C$，连接retrieved paragraphs $\{z_1, z_2, \cdots, z_k\} = R(z_0)$从而得到a pre-training instance$z_k \oplus \cdots \oplus z_0$。评价一个instance的informativeness：$s = \frac{-\sum_{i=0}^{k} \log P(z_i) + \log P(z_k \oplus z_{k-1} \oplus \cdots \oplus z_0)}{|z_k \oplus z_{k-1} \oplus \cdots \oplus z_0|}$，其中$|\cdot|$是instance的长度，$P(\cdot)$是language modeling probability
- **Pre-training**：计算了整个sequence的loss $L_{ICL}(\theta) = -\frac{1}{N}\sum_{i=1}^{N} \log P(z_k^i \oplus z_{k-1}^i \oplus \cdots \oplus z_0^i; \theta)$，再添加一个language modeling loss $L_{LM}(\theta)$。最终的优化目标为$\min_\theta \alpha L_{ICL}(\theta) + (1-\alpha) L_{LM}(\theta)$

3. `Experiments`
    1. 数据集：用`OPENWEBTEXT`、`WIKICORPUS`、`BOOKCORPUS`构建pre-training data，corpus C一共包括$80M$ paragraphs，对于每个paragraph找$k = 20$ demonstrations并连接它们到$1024 tokens$
    2. Baseline：
        - `VanillaICL`：用连接的training examples直接prompt PLM
        - `ExtraLM`：在原始的full document被分成paragraph之前进一步pre-train PLM
        - `Self-Sup`：设计了四个自监督的预训练目标 **Next Sentence Generation, Masked Word Prediction, Last Phrase Prediction, and Classification**

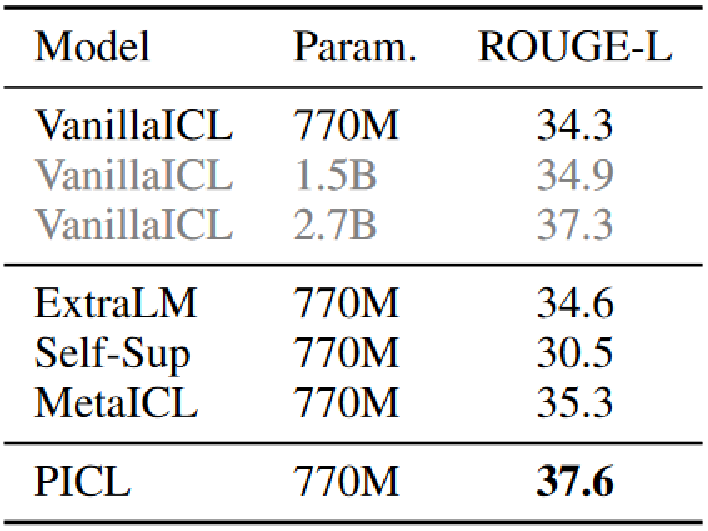
- `MetaICL`：用人工标注的下游数据集meta-train模型

3. 评估：
    - **Few-Shot Text Classification：**
        - `ExtraLM`有效，说明corpus的diversity很大；`metaICL`有效，说明meta-training对ICL的提升有作用；`Self-Sup`无效，说明训练时分类task受限的label space给模型输出带来了bias



Shot	Method	Param.	SST2	SUBJ	MR	RTE	AgNews	CB	SST5	Average
4-shot	VanillaICL	770M	$67.5_{9.2}$	$57.7_{7.8}$	$50.3_{0.3}$	$50.8_{1.7}$	$67.5_{2.3}$	$68.1_{2.4}$	$24.4_{5.4}$	$55.2_{0.5}$
	VanillaICL	1.5B	$74.9_{9.7}$	$65.2_{10.0}$	$61.9_{6.5}$	$50.4_{0.4}$	$65.6_{4.8}$	$67.8_{5.6}$	$32.4_{4.6}$	$59.7_{2.5}$
	VanillaICL	2.7B	$75.0_{7.5}$	$65.4_{2.9}$	$71.4_{13.3}$	$49.8_{1.8}$	$65.6_{2.8}$	$60.0_{2.1}$	$32.1_{5.4}$	$59.9_{1.1}$
	ExtraLM	770M	$68.9_{11.3}$	$63.9_{6.4}$	$60.3_{6.4}$	$51.2_{1.7}$	$64.5_{1.5}$	$63.7_{5.3}$	$27.8_{5.1}$	$57.2_{2.1}$
	Self-Sup	770M	$55.0_{7.4}$	$50.3_{0.6}$	$59.7_{3.5}$	$52.2_{2.0}$	$50.3_{7.0}$	$63.4_{7.1}$	$28.8_{3.3}$	$51.4_{2.2}$
	MetaICL	770M	$69.8_{4.0}$	$63.5_{4.6}$	$65.6_{7.5}$	$\mathbf{57.6}_{2.3}$	$66.3_{2.4}$	$65.2_{3.0}$	$31.7_{2.1}$	$60.0_{1.5}$
	PICL	770M	$\mathbf{79.7}_{8.6}$	$\mathbf{66.8}_{7.4}$	$\mathbf{81.0}_{1.3}$	$54.5_{1.8}$	$\mathbf{67.7}_{3.4}$	$\mathbf{69.6}_{4.3}$	$\mathbf{34.8}_{4.0}$	$\mathbf{64.4}_{1.6}$
8-shot	VanillaICL	770M	$68.7_{6.0}$	$66.6_{9.8}$	$60.2_{5.5}$	$51.8_{1.6}$	$60.2_{5.6}$	$68.8_{3.2}$	$31.4_{3.8}$	$58.2_{2.9}$
	VanillaICL	1.5B	$72.1_{12.6}$	$63.4_{6.5}$	$63.3_{5.4}$	$52.7_{2.8}$	$54.2_{8.4}$	$\mathbf{70.4}_{5.7}$	$33.5_{3.3}$	$58.6_{2.5}$
	VanillaICL	2.7B	$71.0_{11.6}$	$65.2_{4.0}$	$70.4_{6.3}$	$51.3_{2.0}$	$63.1_{2.4}$	$69.6_{4.0}$	$\mathbf{34.1}_{2.8}$	$60.6_{3.2}$
	ExtraLM	770M	$69.7_{3.4}$	$65.2_{6.5}$	$63.6_{6.0}$	$52.6_{1.6}$	$58.9_{7.0}$	$69.6_{3.8}$	$32.2_{4.7}$	$58.8_{1.6}$
	Self-Sup	770M	$61.4_{6.5}$	$54.3_{4.5}$	$73.8_{8.1}$	$53.0_{2.4}$	$52.1_{3.8}$	$63.0_{6.9}$	$33.7_{1.8}$	$55.9_{2.1}$
	MetaICL	770M	$73.6_{6.2}$	$67.2_{8.8}$	$70.1_{5.6}$	$\mathbf{53.6}_{2.1}$	$56.1_{0.7}$	$65.8_{4.1}$	$33.7_{4.7}$	$60.0_{2.2}$
	PICL	770M	$\mathbf{78.0}_{10.6}$	$\mathbf{69.3}_{9.5}$	$\mathbf{77.5}_{5.0}$	$53.0_{1.6}$	$\mathbf{64.7}_{4.4}$	$\mathbf{70.4}_{2.1}$	$\mathbf{34.1}_{3.8}$	$\mathbf{63.9}_{1.3}$

    - **Instruction Following：**测试模型的泛化性



Model	Param.	ROUGE-L
VanillaICL	770M	34.3
VanillaICL	1.5B	34.9
VanillaICL	2.7B	37.3
ExtraLM	770M	34.6
Self-Sup	770M	30.5
MetaICL	770M	35.3
PICL	770M	**37.6**

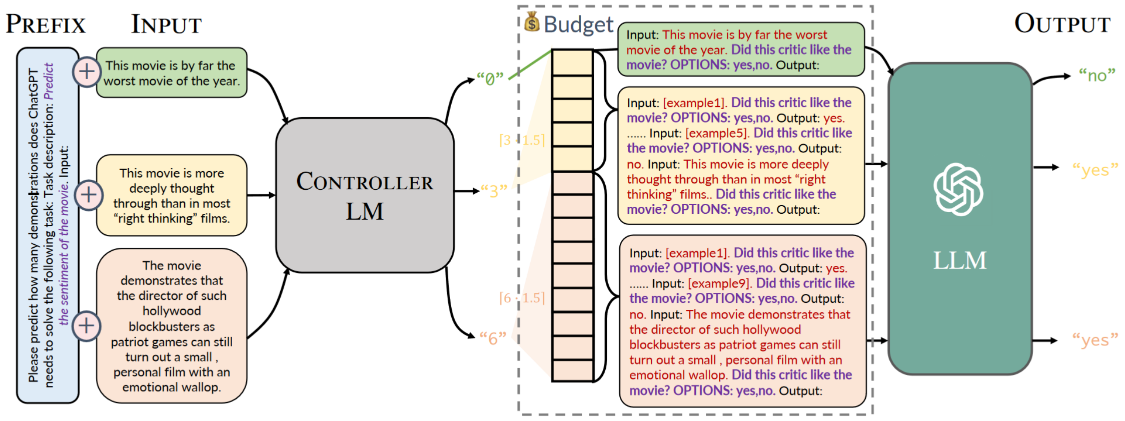
        - `PICL`比`MetaICL`在更多的task上表现得更好说明了**与直接在下游任务上微调相比，在intrinsic task上预训练更能提升ICL能力、泛化能力更强。**`PICL`在text generation等任务上表现更好而`MeatICL`在**“Yes/No”**问题上表现更好，说明在下游数据集训练会导致对某些label过拟合

> 文章后面探究了**Retriever**、**Demonstration Number**、**Filtering**、**Full Documents**、**Data Amount**、**Data Comparison**的影响

Efficient Prompting via Dynamic In-Context Learning

> Submitted on **18 May 2023**

1. `Introduction`

   > 提出了**DYNAICL(Dynamic In-Context Learning)**，为有效解决performance-efficiency trade-off问题提供了一种方案。model size和sample size是影响计算低效的两个原因，后者可以通过减少prompt长度实现，而prompt长度受到in-context learning使用demonstration数目的影响。因此该论文的核心是train一个meta controller来分配in-context demonstration的数目
   >
   > 
   >

PREFIX
   > INPUT
   > Please predict how many demonstrations does ChatGPT needs to solve the following task: Task description: Predict the sentiment of the movie. Input:
   > This movie is by far the worst movie of the year.
   > This movie is more deeply thought through than in most "right thinking" films.
   > The movie demonstrates that the director of such hollywood blockbusters as patriot games can still turn out a small , personal film with an emotional wallop.
   > CONTROLLER LM
   > "0"
   > "3"
   > "6"
   > [3 · 1.5]
   > [6 · 1.5]
   > Budget
   > Input: This movie is by far the worst movie of the year. Did this critic like the movie? OPTIONS: yes,no. Output:
   > Input: [example1]. Did this critic like the movie? OPTIONS: yes,no. Output: yes. ...... Input: [example5]. Did this critic like the movie? OPTIONS: yes,no. Output: no. Input: This movie is more deeply thought through than in most "right thinking" films.. Did this critic like the movie? OPTIONS: yes,no. Output:
   > Input: [example1]. Did this critic like the movie? OPTIONS: yes,no. Output: yes. ...... Input: [example9]. Did this critic like the movie? OPTIONS: yes,no. Output: no. Input: The movie demonstrates that the director of such hollywood blockbusters as patriot games can still turn out a small , personal film with an emotional wallop. Did this critic like the movie? OPTIONS: yes,no. Output:
   > LLM
   > OUTPUT
   > "no"
   > "yes"
   > "yes"

2. `Methodology`

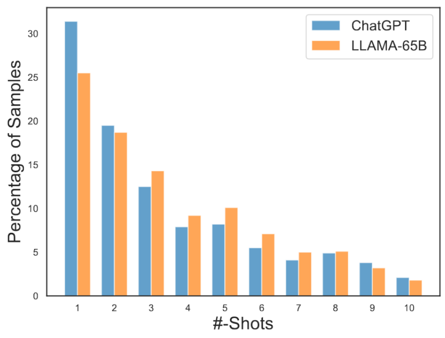
   - **Meta Controller**：采用instruction-tuned model **FLAN-T5**作为base model，主要关注分类任务。训练分为**两阶段**
     - 第一阶段目标是train一个meta controller，可以使得**generalist model, like Chatgpt**生成**"good output"**的同时利用最少的in-context examples，输出所需的example数目k，即为下图(其中t是一个threshold)。

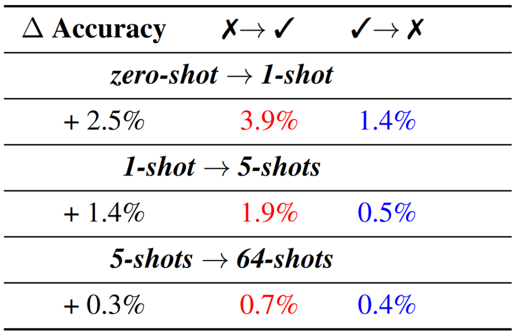
       $$k^* = \min_{k \in \mathbb{N}} \left\{ k \,\middle|\, \mathbb{E}_{(x_{i_1}, y_{i_1}) \ldots (x_{i_k}, y_{i_k})) \sim \mathcal{D}^k} \left[\mathrm{Acc}(\mathcal{G}(P, \mathcal{T}(x_1, y_1) \oplus \cdots \oplus \mathcal{T}(x_k, y_k))) \right] > t \right\}$$

       where D^k denotes all subsets of the training data of size k.
     - 第二阶段是利用**强化学习**来微调meta controller
   - **Dynamic In-Context Example Allocation**：考虑到实际的computation budget，假设总共有K samples N tokens 每个example的平均长度为L，平均分配的baseline为$\frac{N}{K \times L}$。**DYNAICL的分配策略是** $E(P) = [\beta \cdot (C(P)/\widetilde{C}) \cdot N/(K \cdot L)]$，其中$C(P)$是meta controller的预测结果，$[\cdot]$代表取整操作，$\widetilde{C}$是所有examples的平均预测结果，$\beta$是token saving ration

3. `Experiments`

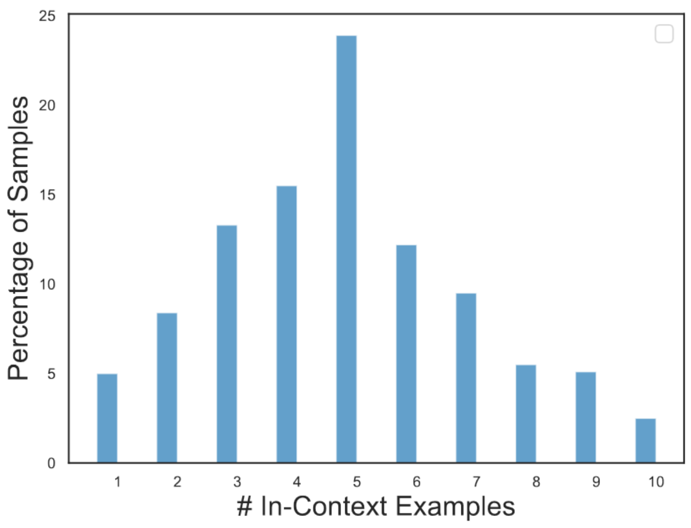
1. 数据集：选用`a subset in the FLAN collection containing 30+ classification tasks`来训练meta controller，大部分数据集都是分类任务，用作训练；少部分数据集不是分类任务，用作评估。同时一些分类任务对应的数据集会作为unseen task来评估
2. 模型：选用`ChatGPT`作为generalist model，`LLAMA-65B`作为unseen generalist model评估meta controller的泛化性
3. Baseline：
   - **uniform baseline**：每个sample分配相同数目的in-context examples
   - **random baseline**：遵循高斯分布随机选取一定数量的in-context examples
4. Preliminary：





△ Accuracy	✗→✓	✓→✗
zero-shot → 1-shot		
+ 2.5%	3.9%	1.4%
1-shot → 5-shots		
+ 1.4%	1.9%	0.5%
5-shots → 64-shots		
+ 0.3%	0.7%	0.4%

   根据上图可以看出大部分可能只需要很少的shots就可以work，且越多的shots效果提升并不明显
5. 结果：
   1. 相同performance节省token，相同token在performance上表现更好
   2. 对于Unseen Generalist Model、Unseen Task都有很好的泛化性
   3. in-context examples的分布(target budget设为5)：



(b) Distribution of samples (on seen tasks) according to the number of in-context examples allocated for them. The computational budget is fixed to 5 in-context examples per sample.

Are Large Language Models Good Prompt Optimizers?

> Submitted on **3 Feb 2024**

1. `Introduction`

   > 这篇paper探究了LLM optimizer在reflection时很难找到error真正的原因，往往会被LLM之前的knowledge影响而不是真正地reflect error。因此提出了**ABO(Automatic Behavior Optimization)**这个框架
   >
   > LLM-based Automatic Prompt Optimization有两种方法：**Resampling-based methods**、**Reflection-based methods**

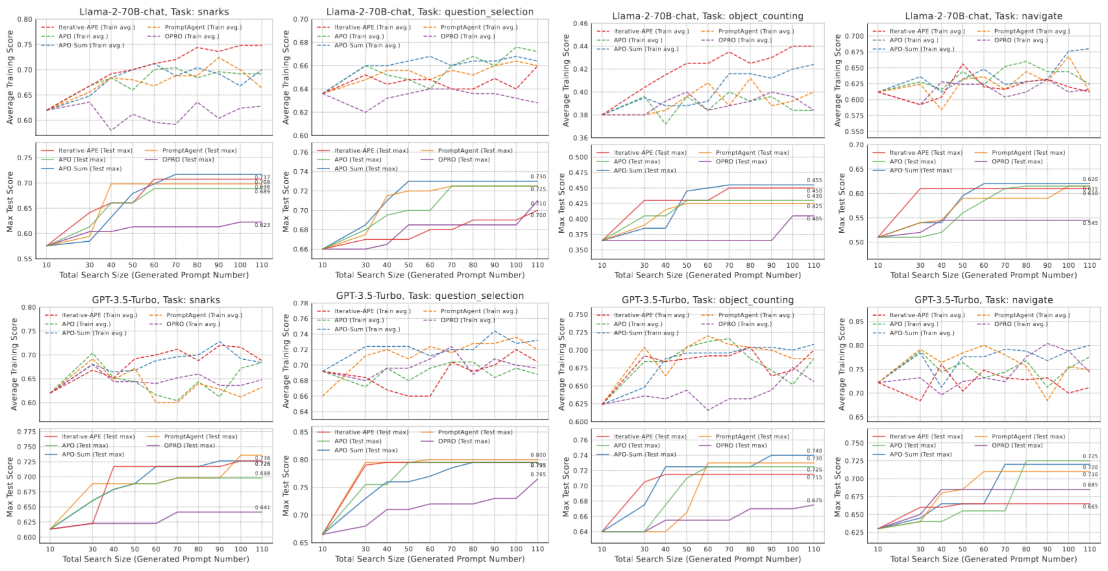
2. `Background`

   - LLM-based Automatic Optimization的框架通常有三个部分：
     - **Prompt Initialization：**可以是Manual Prompt Initialization，也可以是LLM-based Prompt Initialization
     - **Search Strategy**
     - **Prompt Updating：**分为`Resampling-based Prompt Regeneration`(保持语义的同时在最优的prompt附近选取)、`Explicit Reflection-based Prompt Optimization`(LLM-based prompt optimizer分析error然后产生feedback，之后refine current prompt)、`Implicit Reflection-based Prompt Optimization`(根据历史prompt和对应的score，产生一系列refined prompt)

3. `Basic Experiments`

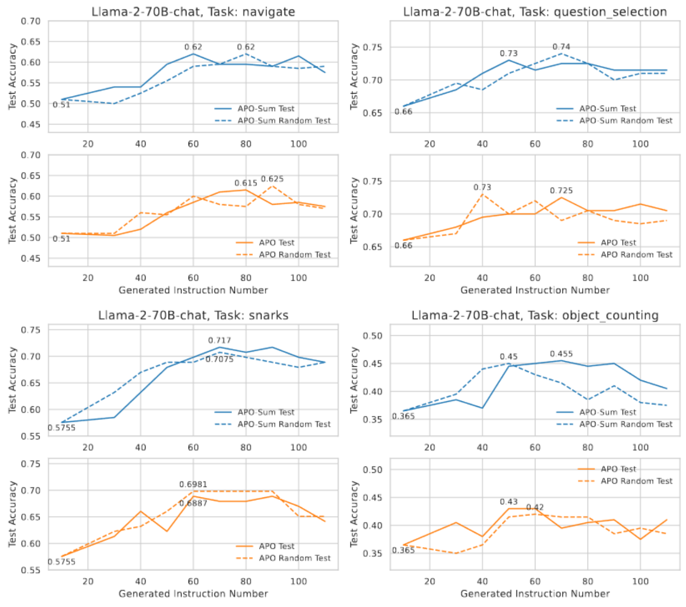
   1. baseline：
      - `Iterative-APE`(resampling-based prompt regeneration method)
      - `APO`(explicit reflection-based method，每一步APO instruct LLM optimizer为现在的error生成三个reason，然后据此生成新的prompt)
      - `PromptAgent`(APO的一个扩展)
      - `APO-Sum`(APO的一个扩展，在reflection阶段总结reason)
      - `OPRO`(implicit reflection-based method)

2. Result：



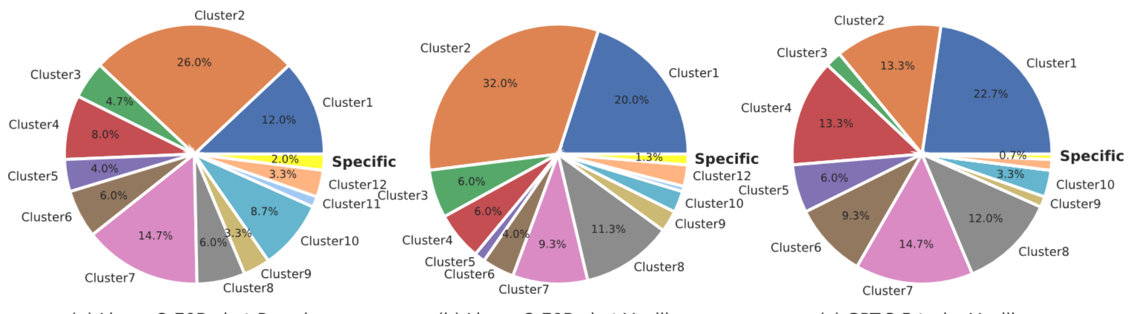
- LLM optimizer可能不是一个好的implicit reflection-based prompt optimizer

4. `Did the LLM-based Prompt Optimizers Perform Valid Reflection?`
   - **Experiment1：**两个setting，一个为`Vanilla`(standard reflection setting)，另一个为`Pseudo`(将real error examples换为pseudo error examples，生成方法为uniformly flip the LLM's predictions for all training examples)。结果为：



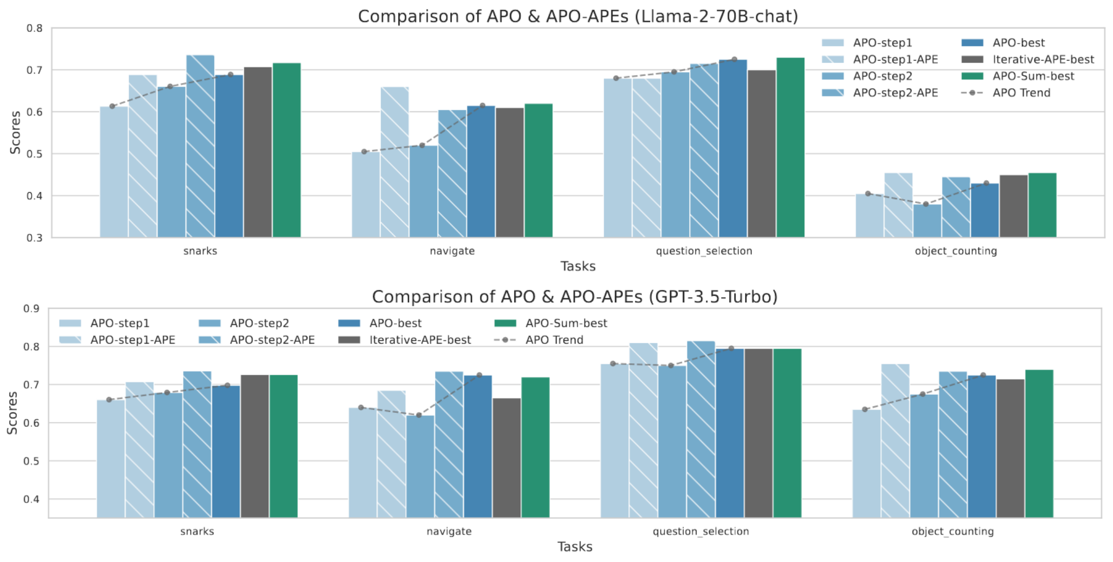
，可以看到最终的accuracy并无太大差距，说明无论是true error distribution还是pseudo error distribution，LLM optimizer都可以产生类似的feedback从而使得结果相差不大

   - **Experiment2：**探究了几种setting下feedback的分布问题，同时也探究了在Instance层面上的feedback重复问题


(a) Llama-2-70B-chat-Pseudo (b) Llama-2-70B-chat-Vanilla (c) GPT-3.5-turbo-Vanilla

LLM-based reflection过程更可能是LLM根据它prior knowledge进行分析，而不是根据真正的reason

5. `How is the Quality of the Refined Prompts and How They Affect the Target Models’ Behavior?`
    - **Experiment1**：从语义上来测试prompt，也就是将`iterative-APE`用到`APO`的第一步/第二步上



APO能够在某个reflection的过程中做出valid的semantic alternation，但并不总是valid

    - **Experiment2**：探究了target model的instruction following的能力

6. `Automatic Behavior Optimization`

- 该框架的具体步骤：

1. At each step, the LLM optimizer is instructed to generate step-by-step prompts.

2. Next, we utilize the LLM optimizer to write an “Instruction-following Demonstration” for each prompt, i.e., an example illustrating how to strictly follow every detail of the given prompt. This practice aims to enhance the controllability of the prompt optimization process by ensuring any improvement made will be strictly followed by the target models.

3. During the reflection and prompt refinement process, given error examples, the LLM optimizer is required to identify the failure step of the target model and refine the prompt by further breaking down the solution at the problematic step. This aims to avoid invalid feedback by utilizing the LLM optimizer to perform more objective tasks during reflection.

4. For each refined prompt, the instruction-following demonstration is also updated to illustrate how to strictly follow the refined steps.