I-Tuning: Tuning Language Models with Image for Caption Generation

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Abstract

Recently, tuning the pre-trained language model (PLM) in a parameter-efficient manner becomes a popular topic in the natural language processing area. However, most of them focus on tuning the PLM with the text-only information. In this work, we propose a new perspective to tune the frozen PLM with images for caption generation. We denote our method as I-Tuning, which can automatically filter the vision information from images to adjust the output hidden states of PLM. Evaluating on the image captioning tasks (MSCOCO and Flickr30k Captioning), our method achieves comparable or even better performance than the previous models which have 2-4 times more trainable parameters and/or consume a large amount of cross-modal pre-training data.

1 Introduction

In recent years, tuning the frozen large-scale pre-trained language model (PLM) attracts a lot of attention in the natural language processing area. We have witnessed a lot of remarkable works, including Prefix tuning (Li and Liang, 2021), Adapter tuning (Houlsby et al., 2019; Pfeiffer et al., 2020a, 2021) and Prompt tuning (Liu et al., 2021b; Lester et al., 2021). Without updating the original parameters of the large PLM, these parameter efficient tuning methods can achieve comparable or even better performance than fully fine-tuning, leading to more flexible and efficient applications of such models. However, one can notice that most of them only focus on language-only tasks.

In this work, we introduce a novel perspective to extend the parameter efficient PLM tuning to the cross-modal vision-and-language generation scenario. Our goal is to tune the frozen large PLMs with images, so that PLMs can generate captions based on the visual information with the help of their remarkable language generation ability (Radford et al., 2018, 2019; Brown et al., 2020b). The most similar work is the ClipCap model (Mokady et al., 2021), which transforms the images into the fixed-length prefix embeddings and adopts the same method as Prefix tuning to tune the frozen GPT2-large model (Radford et al., 2019). However, the image captioning performance of ClipCap is less attractive, which cannot make full use of the power of large PLM. Therefore, how to leverage the great language generation ability of a frozen PLM effectively for captions generation is still an under-explored problem.

To fill up such gap, we propose a novel method, I-Tuning (Image-Tuning, see Figure 1). For Prefix tuning and Adapter tuning, PLMs leverage the task-specific knowledge in the Prefix embeddings or the Adapter modules to adjust their output hidden states, so that the PLMs can adapt to different downstream tasks without updating their pre-trained parameters. However, there exists a misalignment problem between the language and the vision modals, hindering us directly embedding...
the extra visual knowledge in PLMs. To solve this problem, we are inspired by the idea of Memory Network (Sukhbaatar et al., 2015). The visual information of Images is extracted by the state-of-the-art pre-trained model, CLIP-ViT (Radford et al., 2021) and treated as the fixed visual memory. The I-Tuning module serves as a cross-modal filter that picks the visual information from the visual memory to adjust the output hidden states of each PLM layer. Beyond this, we also propose I-Tuning Dropping, removing the I-Tuning modules in the first few layers to further reduce the computational overhead during training and inference.

Evaluating on the image captioning tasks (MSCOCO (Lin et al., 2015) and Flickr30k (Plummer et al., 2016)), I-Tuning can outperform the baseline systems without vision-and-language pre-training (VLP). After small-scale VLP, I-Tuning achieves comparable or even better performance than the baseline VLP systems which have 2-4 times more trainable parameters and/or consume millions of distinct VLP images. In addition, we show that I-Tuning are agnostic to the PLMs (e.g., base, medium, large), which makes our method broadly applicable.

Our contributions can be summarized as follows:

• We propose a novel method, I-Tuning to tune the frozen large PLMs with images for captions generation.

• We conduct extensive experiments to corroborate the effectiveness of our I-Tuning method.

• Evaluating on the image captioning tasks, I-Tuning achieves comparable or even better performance than the baseline systems which consume much more computational resources.

2 The I-Tuning Framework

In this part, we make a detailed illustration of our I-Tuning. First, we review the parameter efficient tuning and its relation with I-Tuning in section 2.1. Beyond this, we introduce the structure of our framework in section 2.2. Finally, we present our training objective in section 2.3.

2.1 The Recap of Parameter Efficient Tuning

Since 2019, the number of parameters in the PLMs are scaling from millions to trillions (Brown et al., 2020a; Shoeybi et al., 2020; Fedus et al., 2021; Zeng et al., 2021). Fine-tuning such gigantic PLMs on the downstream tasks consumes a huge amount of computational resources, which is not affordable for most researchers and companies. To leverage such PLMs, people come up with several parameter efficient tuning methods to adapt the PLMs on the downstream tasks without updating the pre-trained parameters (Houlsby et al., 2019; Pfeiffer et al., 2020a,b, 2021; Li and Liang, 2021; Liu et al., 2021a,b; Lester et al., 2021). Though these previous methods have different forms, He et al. (2022a) indicate that all of them can be unified as a simple composition function:

\[ h \leftarrow h + \Delta h, \] (1)

where \( h \) is the output hidden states of a PLM module. The difference between different methods is how to inject the extra information into the frozen PLMs through \( \Delta h \). Our I-Tuning framework follows the same paradigm to inject the visual information into large PLMs efficiently, so that the frozen PLMs can generate captions of given images.

2.2 Model Structure

Overview. For our framework, given an image \( v \), a visual encoder first generates the visual memory embeddings \( V_M \). Then the frozen PLM is tuned by the I-Tuning modules based on \( V_M \).

Visual Encoder and PLMs. In our framework, we adopt the state-of-the-art vision pre-trained model, CLIP-ViT (Radford et al., 2021) to generate the visual memory embeddings \( V_M \) of an image. Such model takes a sequence of image patches as input and visual representations for each patch as output. Since it has extraordinary visual recognition ability, it is widely used in the previous cross-modal vision-and-language works (Dou et al., 2021; Shen et al., 2021; Mokady et al., 2021; Luo et al., 2022). Our framework can benefit from the excellent visual representation ability of CLIP-ViT.

For the PLMs, we leverage the state-of-the-art auto-regressive PLM, GPT2 (Radford et al., 2019), which is a multi-layer Transformer Decoder model (Vaswani et al., 2017). Pre-trained with a large amount of text data, it shows remarkable language generation ability.

I-Tuning Module. In our framework, the I-Tuning module is the key component to align the cross-modal information, which is parallel to a specific PLM module (attention, feedforward or whole
language) in each layer. It is a bottleneck neural network, sharing a similar structure as the Adapter module (Pfeiffer et al., 2020a), but the non-linear activation function is replaced by a cross-attention memory network (see Figure 2). The calculation process is as follows:

\[ Q = W^Q_{\text{down}}(X) + b^Q, \]  
\[ K = W^K_{\text{down}}(V_M) + b^K, \]  
\[ V = W^V_{\text{down}}(V_M) + b^V, \]

where \( X \) is the input hidden states of a specific PLM module. Then we can get the attention scores across the visual memory embeddings:

\[ S = \text{softmax}(QK^T). \]  

Based on the scores, we can get the final I-Tuning output to adjust the output hidden states of the PLM module:

\[ \Delta h = \lambda W^O_{\text{up}} \left( \sum_i s_i V_M^i \right) + b^O, \]  

where \( \lambda \) is a scaling hyper-parameter, introduced by Hu et al. (2021).

Since the lower layers of PLMs have weaker representation ability (Jawahar et al., 2019; Rücklé et al., 2021), we also propose I-Tuning Dropping to remove the I-Tuning modules in the first-few layers (see Figure 3). As a result, backpropagating through fewer layers can further improve the training efficiency of our models.

2.3 Training Objective

The training objective is the auto-regressive language modeling conditioned on the visual information:

\[ L_{\text{ar}} = -\sum_{t=1}^{T} \log P(x_t|x_{<t}, V_M), \]  

where \( V_M \) represents the visual memory embeddings encoded by CLIP-ViT, \( T \) denotes the length of a sequence and \( x_{<t} = (x_0, ..., x_{t-1}) \). The probability of the token in the \( t \)th position is determined by all the past tokens and \( V_M \).

3 Experiments

In this section, we conduct extensive experiments to examine the effectiveness of our I-Tuning. Specifically, we first explore how to design and train our models without VLP in section 3.2. Then we compare our models with the previous works with/without VLP in section 3.3.

3.1 Setup

Default Model Configuration. In our experiments, we adopts CLIP-ViT B/16\(^1\) pre-trained model as our visual encoder and GPT2 pre-trained model as our language decoder. CLIP-ViT contains 12 transformer layers with 768 model size and 12 attention heads. For GPT2, we include 4 different model sizes, including GPT2-distill\(^2\) (6 layers), GPT2-base\(^3\) (12 layers), GPT2-medium\(^4\) (24 layers)

\(^1\)https://huggingface.co/openai/clip-vit-base-patch16
\(^2\)https://huggingface.co/distilgpt2
\(^3\)https://huggingface.co/gpt2
\(^4\)https://huggingface.co/gpt2-medium
and GPT2-large\(^5\)(36 layers). The number of parameters are ranging from 82M to 774M. For the I-Tuning modules, we initialize their parameters randomly. The other model parameters details can be seen in the Appendix.

Datasets. For VLP, we use a small-scale cross-modal datasets, Visual Genome\(^6\) which contains 110k distinct images and 5.4M captions. For evaluation, we choose to use two different datasets, including MSCOCO Captions\(^7\) and Flickr30k.\(^8\) In these two datasets, each image corresponds to 5 different captions. We follow the standard Karpathy’s split (Karpathy and Fei-Fei, 2015) to split 113.2k/5k/5k and 29.8k/1k/1k images for train/val/test, respectively. We adopt 4 standard evaluation metrics to evaluate the generated captions, including CIDEr (Vedantam et al., 2015), BLEU@4 (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005) and SPICE (Anderson et al., 2016). For simplicity, we also denote CIDEr as C, BLEU@4 as B@4, METEOR as M and SPICE as S.

Implementation Details. For all the experiments, the parameters of CLIP-ViT and GPT-like models are frozen. We train our models with the AdamW optimization algorithm (Loshchilov and Hutter, 2019), 4k batch size, mixed-precision training and FP16. For VLP, our models are pre-trained with 10 epochs. For training on downstream tasks, our models are trained with 30 epochs. We also adopt the linear learning rate decay strategy. The warm-up step is set to 10% of the total training steps. For inference, we use the beam search (beam size = 5) to generate captions. Each image is resized into the size of 288x288 with center-crop. The other hyper-parameters can be found in the Appendix. All experiments are conducted on 8 NVIDIA A100 GPUs.

Baseline System. To evaluate our method comprehensively, we include several previous works in the comparison. The first type is the works that do not use any VLP, including NBT (Lu et al., 2018), SGAE (Yang et al., 2018), AoANet (Huang et al., 2019), BUTD (Anderson et al., 2018), GVD (Zhou et al., 2019a) and ClipCap (Mokady et al., 2021). The last one, ClipCap shares a similar idea as ours, which parameter efficiently tunes GPT2-large with Prefix-tuning. The second type is the works with VLP, including OSCAR (Li et al., 2020), Unified VLP (Zhou et al., 2019b), XGPT (Xia et al., 2020), UNICORN (Yang et al., 2021), VL-BART/T5 (Cho et al., 2021) and VC-GPT (Luo et al., 2022). All of these VLP models contain 2-4 times more trainable parameters than ours and/or consume a large amount of cross-modal pre-training data. Beyond this, we also include the performance of the state-of-the-art VLP model, SimVLM (Wang et al., 2021b), as our upper bound, which is pre-trained with 1.8B un-publicly cross-modal datasets.

### Table 1: If the I-Tuning module is parallel to the Feedforward PLM module, it achieves the best performance.

| PLM Module      | MSCOCO (val) |
|-----------------|--------------|
|                 | C  | B@4 | M  | S  |
| Attention       | 109.1 | 32.9 | 27.6 | 20.6 |
| Feedforward     | 110.3 | 33.6 | 27.6 | 20.7 |
| Whole Layer     | 109.4 | 33.4 | 27.6 | 20.4 |

3.2 Exploration without VLP

Since pre-training is time-consuming, we perform exploration on how to design and train our models without cross-modal pre-training. We use the GPT2-base as our basic language decoder. All models are trained with the MSCOCO training set and evaluated on the MSCOCO validation set.

3.2.1 Where to Place the I-Tuning Module?

In a Transformer layer of the PLMs, there are two different sub-networks, Attention and Feedforward. Then, there are three ways for us to place our I-Tuning module in each layer: (1) parallel to Attention; (2) parallel to Feedforward; (3) parallel to the whole layer.

Table 1 compares these three different designs empirically. Placing the I-Tuning module parallel to Feedforward in each layer achieves the best performance, which is also inline with He et al. (2022a). Such design can be considered as a special MoE network (Fedus et al., 2021) without gating. The original Feedforward is a single-modal expert and the I-Tuning module is a cross-modal expert. In the following experiments, we choose this design as our default setting.

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\(^5\)https://huggingface.co/gpt2-large
\(^6\)http://visualgenome.org/
\(^7\)https://cocodataset.org/#home
\(^8\)http://hockenmaier.cs.illinois.edu/DenotationGraph/
Figure 4: Comparison different scalar factors for I-Tuning on MSCOCO. When the scalar is set to 4, our model achieves the best overall performance.

Figure 5: Increasing the image resolution degenerates model performance.

### 3.2.2 Scaling Factor and Image Resolution

In this part, we intend to examine two tricks in our I-Tuning module. First, Hu et al. (2021) and He et al. (2022a) indicate that multiplying the output hidden states of the tuning module by a scaling factor $(\lambda \geq 1)$ leads to better performance. We compare different scaling factors for our models. Figure 4 reveals that setting the scaling factor to 4 achieves the best overall performance.

The second trick is for image resolution. Dou et al. (2021) find that increasing the image resolution can boost their model performance on downstream tasks. Similar results are also discussed by Yuan et al. (2021); Kim et al. (2021); Luo et al. (2022). To examine this trick, we compare different image resolutions for our models. Figure 5 indicates that increasing the image resolution degenerates our model performance. The possible reason is that the pre-training resolution of CLIP-ViT is different from ours. We need to first interpolate the position embeddings of CLIP-ViT. However, the parameters of the frozen vision encoder cannot be updated to adapt to the interpolation. As a result, increasing the image resolution leads to larger gaps. Therefore, we chose to use the smallest image size (288x288) as our default setting.

### 3.2.3 Scaling Law

According to the scaling law of neural language model (Kaplan et al., 2020), larger PLMs have better performance and are much more sample efficient. We examine such law in our cross-modal setting. We adopt four different sizes of the GPT2 model, including GPT2-Distill,\(^9\) GPT2-Base, GPT2-Medium and GPT2-Large. Table 2 indicates that scaling up frozen GPT2 can lead to better overall performance. Especially, the performances of Medium and Large are already comparable to some VLP models after pre-training.

### 3.2.4 I-Tuning Dropping

Since the lower layers of PLMs have weaker representation ability, we investigate whether we can drop the I-Tuning modules in the first few layers. In this part, we focus on the GPT2-Large, which is a 36-layer model. If we place the I-Tuning module in each layer, the number of trainable parameters is up to 94.5M. Though this number is far less than [9]GPT2-Distill is pretrained with the supervision of GPT2-Base with the OpenWebTextCorpus of Huggingface.
Table 3: Comparisons with previous models on MSCOCO and Flickr Image Captioning. **Bold** indicates the best score of our I-Tuning models. #Images represents the number of distinct images during VLP. #Params represents the number of trainable parameters. For our I-Tuning models, the number in “(xxx%)” represents the percentage of trainable parameters to the total number of parameters. All models are fine-tuned with cross-entropy loss.

3.3 Comparing with Previous Works

In section 3.2, we conduct an extensive exploration of our I-Tuning method without VLP. In this part, we compare with the previous works to verify the effectiveness of our method. All results are reported on the test sets.

3.3.1 Quantitative Evaluation

Table 3.3 reveals that our method achieves comparable or even better performance than the baseline systems which contains 2-4 times more trainable parameters and/or consume much more VLP data. Compared with ClipCap, it shares a similar idea as ours to tune the PLM in a parameter efficient manner, but one can notice that our method with GPT2-Base already outperforms ClipCap with GPT2-Large. For our model with I-Tuning Dropping, it only contains 47.2M trainable parameters, but it can retain the same level of performance as its counterpart without dropping.

All quantitative results corroborate the effectiveness of our method to leverage the great language generation power of the frozen GPT-like models.

3.3.2 Qualitative Evaluation

Table 4 presents the image captioning examples of our I-Tuning, OSCAR and ClipCap for the first 4 images in the MSCOCO test set. As can be seen, the generated captions of I-Tuning depict the image successfully. Compared with the baseline systems, our work can identify the movement of the people in the image. For example, our model can recognize that the little girl is blowing the candles, while ClipCap and OSCAR cannot. However, one can notice that our method cannot recognize the bike in the third image. The same error also exists in ClipCap. The possible reason is that the bike is
mixed with the man in the image, which is hard for models to recognize.

4 Visualization

In this section, we visualize the cross-attention maps in our I-Tuning to examine whether it learns the cross-modal alignment implicitly. We randomly choose an image in the MSCOCO dataset and present the cross-attention heatmaps in the final I-Tuning model of GPT2-Large. In Figure 7, our I-Tuning module can correctly attend to the corresponding regions given different tokens. These examples reveal that our method can learn visual grounding implicitly.

5 Related Work

Recently, we have witnessed that the model size of a PLM becomes larger and larger, which makes us hard to fully fine-tune such models. To make use of them without updating the pre-trained parameters, researchers have come up with several great works, including Prefix tuning (Li and Liang, 2021), Adapter tuning (Houlsby et al., 2019; Pfeiffer et al., 2020a,b, 2021; Wang et al., 2021a; Zhang et al., 2021) and Prompt tuning (Liu et al., 2021b,a; Lester et al., 2021; He et al., 2022b; Zhang et al., 2022). All of them provide effective methods to adapt the frozen PLMs on the downstream tasks. However, most of them only focus on the natural language processing area. Our I-Tuning extends the parameter efficient PLM tuning idea to the cross-modal setting.

In addition, the most similar works are proposed by Mokady et al. (2021) and Tsimpoukelli et al. (2021). Both of them extend the Prefix tuning into the cross-modal setting. However, their models are less competitive on the image captioning tasks. Li and Liang (2021) also points out that directly optimizing the prefix is very sensitive to the learning rate and the parameter initialization. Therefore, we choose not to design I-Tuning based on the Prefix tuning.

Beyond this, there is an explosion of works about cross-modal vision-and-language pre-training (Zhou et al., 2019b; Li et al., 2020; Xia et al., 2021).
et al., 2020; Cho et al., 2021; Wang et al., 2021b; Dou et al., 2021; Luo et al., 2022). Most of them focus on how to train a cross-modal from scratch, but the goal of our work is to parameter efficiently tune the PLMs with images for captions generation.

6 Conclusion

In this paper, we present I-Tuning for parameter efficient tuning PLMs with images for captions generation. Extensive experiments are conducted on how to design and train our framework. Evaluating on the image captioning tasks, I-Tuning achieves comparable or even better performance than the previous works which contain 2-4 times more trainable parameters and/or consume much more cross-modal pre-training data.

References

Peter Anderson, Basura Fernando, Mark Johnson, and Stephen Gould. 2016. Spice: Semantic propositional image caption evaluation.

Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. 2018. Bottom-up and top-down attention for image captioning and visual question answering.

Satanjeev Banerjee and Alon Lavie. 2005. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization, pages 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020a. Language models are few-shot learners.

Jaemin Cho, Jie Lei, Hao Tan, and Mohit Bansal. 2021. Unifying vision-and-language tasks via text generation. In Proceedings of the 38th International Conference on Machine Learning, volume 139 of Proceedings of Machine Learning Research, pages 1931–1942. PMLR.

Zi-Yi Dou, Yichong Xu, Zhe Gan, Jianfeng Wang, Shuohang Wang, Lijuan Wang, Chenguang Zhu, Pengchuan Zhang, Lu Yuan, Nanyun Peng, Zicheng Liu, and Michael Zeng. 2021. An empirical study of training end-to-end vision-and-language transformers.

William Fedus, Barret Zoph, and Noam Shazeer. 2021. Switch transformers: Scaling to trillion parameter models with simple and efficient sparsity.

Junxian He, Chunting Zhou, Xuezhe Ma, Taylor Berg-Kirkpatrick, and Graham Neubig. 2022a. Towards a unified view of parameter-efficient transfer learning.

Pan He, Yuxi Chen, Yan Wang, and Yanru Zhang. 2022b. Protum: A new method for prompt tuning based on "[mask]".

Neil Houlsby, Andrei Girgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentín De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for NLP. In Proceedings of the 36th International Conference on Machine Learning, volume 97 of Proceedings of Machine Learning Research, pages 2790–2799. PMLR.

Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2021. Lora: Low-rank adaptation of large language models.

Lun Huang, Wenmin Wang, Jie Chen, and Xiao-Yong Wei. 2019. Attention on attention for image captioning.

Ganesh Jawahar, Benoît Sagot, and Djamé Seddah. 2019. What does BERT learn about the structure of language? In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 3651–3657, Florence, Italy. Association for Computational Linguistics.

Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. 2020. Scaling laws for neural language models.

Andrei Karpathy and Li Fei-Fei. 2015. Deep visual-semantic alignments for generating image descriptions.
you need. In *Advances in Neural Information Processing Systems*, volume 30, pages 5998–6008. Curran Associates, Inc.

Ramakrishna Vedantam, C. Lawrence Zitnick, and Devi Parikh. 2015. Cider: Consensus-based image description evaluation.

Ruize Wang, Duyu Tang, Nan Duan, Zhongyu Wei, Xuanjing Huang, Jianshu Ji, Guihong Cao, Daxin Jiang, and Ming Zhou. 2021a. K-Adapter: Infusing Knowledge into Pre-Trained Models with Adapters. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 1405–1418, Online. Association for Computational Linguistics.

Zirui Wang, Jiahui Yu, Adams Wei Yu, Zihang Dai, Yulia Tsvetkov, and Yuan Cao. 2021b. Simvlm: Simple visual language model pretraining with weak supervision.

Qiaolin Xia, Haoyang Huang, Nan Duan, Dongdong Zhang, Lei Ji, Zhifang Sui, Edward Cui, Taroon Bharti, Xin Liu, and Ming Zhou. 2020. Xgpt: Cross-modal generative pre-training for image captioning.

Xu Yang, Kaihua Tang, Hanwang Zhang, and Jianfei Cai. 2018. Auto-encoding scene graphs for image captioning.

Zhengyuan Yang, Zhe Gan, Jianfeng Wang, Xiaowei Hu, Faisal Ahmed, Zicheng Liu, Yumao Lu, and Lijuan Wang. 2021. Crossing the format boundary of text and boxes: Towards unified vision-language modeling.

Li Yuan, Qibin Hou, Zihang Jiang, Jiashi Feng, and Shuicheng Yan. 2021. Volo: Vision outlooker for visual recognition.

Wei Zeng, Xiaozhe Ren, Teng Su, Hui Wang, Yi Liao, Zhiwei Wang, Xin Jiang, ZhenZhang Yang, Kaisheng Wang, Xiaoda Zhang, Chen Li, Ziyang Gong, Yifan Yao, Xinjing Huang, Jun Wang, Jianfeng Yu, Qi Guo, Yue Yu, Yan Zhang, Jin Wang, Hengtao Tao, Dasean Yan, Zexuan Yi, Fang Peng, Fangqing Jiang, Han Zhang, Lingfeng Deng, Yehong Zhang, Zhe Lin, Chao Zhang, Shaojie Zhang, Mingyue Guo, Shanzhi Gu, Gaojun Fan, Yaowei Wang, Xuefeng Jin, Qin Liu, and Yonghong Tian. 2021. Pangu-α: Large-scale autoregressive pretrained chinese language models with auto-parallel computation.

Ningyu Zhang, Luoqiu Li, Xiang Chen, Shumin Deng, Zhen Bi, Chuanqi Tan, Fei Huang, and Huajun Chen. 2022. Differentiable prompt makes pre-trained language models better few-shot learners.

Rongsheng Zhang, Yinhe Zheng, Xiaoxi Mao, and Minlie Huang. 2021. Unsupervised domain adaptation with adapter.

Luowei Zhou, Yannis Kalantidis, Xinlei Chen, Jason J. Corso, and Marcus Rohrbach. 2019a. Grounded video description.

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### A Hyperparameters

This section is not ready for the preprint version.