User-Aware Prefix-Tuning is a Good Learner for Personalized Image Captioning

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Abstract. Image captioning bridges the gap between vision and language by automatically generating natural language descriptions for images. Traditional image captioning methods often overlook the preferences and characteristics of users. Personalized image captioning solves this problem by incorporating user prior knowledge into the model, such as writing styles and preferred vocabularies. Most existing methods emphasize the user context fusion process by memory networks or transformers. However, these methods ignore the distinct domains of each dataset. Therefore, they need to update the entire caption model parameters when meeting new samples, which is time-consuming and calculation-intensive. To address this challenge, we propose a novel personalized image captioning framework that leverages user context to consider personality factors. Additionally, our framework utilizes the prefix-tuning paradigm to extract knowledge from a frozen large language model, reducing the gap between different language domains. Specifically, we employ CLIP to extract the visual features of an image and align the semantic space using a query-guided mapping network. By incorporating the transformer layer, we merge the visual features with the user's contextual prior knowledge to generate informative prefixes. Moreover, we employ GPT-2 as the frozen large language model. With a small number of parameters to be trained, our model performs efficiently and effectively. Our model outperforms existing baseline models on Instagram and YFCC100M datasets across five evaluation metrics, demonstrating its superiority, including twofold improvements in metrics such as BLEU-4 and CIDEr.

 $\textbf{Keywords:} \ \operatorname{Personalized\ image\ captioning} \cdot \operatorname{Prefix-tuning} \cdot \operatorname{Cross-modal}.$

1 Introduction

Image captioning aims to generate descriptive sentences for image content, which has drawn a lot of attention in recent years [6, 9, 11, 34]. It has a wide range of

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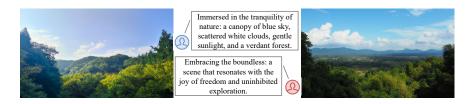


Fig. 1. Owing to the personalities of the users, similar images may exhibit varying descriptions.

applications, such as e-commerce product description, assisting individuals with visual impairments, and automating captioning for social media posts [7,28].

Previous works have explored the generation of captions using an encoderdecoder network with various attention mechanisms [35, 37]. However, the captions generated by these methods seem standardized and conservative in practical applications [14]. With the advent of social media, individuals have increasingly opted to express their personalities through posting. Fig. 1 illustrates similar images while highlighting the contrasting captions provided by the respective users. Consequently, there is a growing need for research on personalized image captioning. Some works [20, 40] have made early attempts to solve this problem by leveraging user context, such as active vocabularies and writing styles. These methods first encode the visual content with user information and then fuse them using memory networks or transformers to generate personalized captions. Although significant improvements have been achieved in personalized image captioning, one major issue remains in most existing methods. Considering the distinct domains of each social media dataset, these approaches require training the entire caption model for each dataset. Additionally, when encountering new samples, they need to update their caption model to generate sentences for the new data. This process requires both time and computing resources.

To address the above issue, we propose a novel personalized image captioning framework based on User-Aware Prefix-Tuning (UAPT). Our approach not only incorporates user-aware prior knowledge to accommodate the distinct characteristics and preferences of individuals, but also leverages the prefix-tuning paradigm [12] to exploit the linguistic capabilities of frozen large language models in order to generate precise captions, thereby bridging the gap between different domains. At first, we use the CLIP [21] image encoder to capture the visual semantics. In addition, a query-guided Mapping Network is used to align the semantic space of vision and language. To enable personalized characteristics of users, we employ transformer layers to fuse visual knowledge with user context prior knowledge and generate a fixed-size embedding sequence denoted as prefixes [12]. These prefixes, concatenated with caption embeddings, are subsequently fed into a GPT-2 model [22] to generate captions. Throughout this process, both the CLIP and GPT-2 models remain frozen. The Mapping Network and Fusion Network are end-to-end training, thus saving time and computing resources. The framework is shown in Fig. 2. This novel approach allows us to effectively capture the user's language style without requiring extensive personalized training data, making it more applicable in real-world scenarios.

The main contributions of this article can be summarized as follows:

- To the best of our knowledge, we are the first to introduce large language models to address personalized image captioning problem with the prefixtuning paradigm, solely training small network architecture.
- We propose the integration of user-aware prior knowledge with visual information to effectively capture the contextual language style of the user, enhancing personalized image captioning.
- Our model outperforms existing baseline models on both the Instagram and YFCC100M datasets across five evaluation metrics. Remarkably, metrics such as BLEU-4 and CIDEr show twofold improvements, providing substantial evidence of the superiority of our model.

2 Related Work

2.1 Image Captioning

Image captioning serves as a pivotal link between Computer Vision (CV) and Natural Language Processing (NLP), necessitating the generation of contextually and grammatically appropriate textual descriptions for images. Notable progress has been achieved in this field with the advent of deep learning techniques. Earlier approaches utilized convolutional neural network [10] to extract visual features from images and recurrent neural network [17] to generate captions [16, 32]. Subsequent studies introduced attention mechanisms, leading to improved caption quality [1, 35, 37]. In addition, there has been an emergence of large-scale vision and language pre-trained models that can be applied to image captioning [27, 34, 36, 39]. However, these models often require significant computational resources and training efforts. To address this issue, Mokady et al. [18] proposed a strategy of keeping the pre-trained weights fixed and focusing on training specific network components to bridge the gap between visual and textual representations. Despite the achievements of these efforts, they are limited to generating neutral captions, which may not fully cater to the diverse needs of users in the era characterized by the rapid emergence of social media.

2.2 Personalized Vision and Language Research

Driven by the rapid proliferation of social media and the growing demand for personalized content, numerous scholars have conducted research with a primary focus on customizing the visual and linguistic domains [3–5]. Shuster et al. [26] defined 215 potential personality traits to guide caption generation. However, in real-world scenarios, users' styles may not be adequately captured by these traits. Park et al. [20] constructed datasets specifically for personalized image captioning and employed the memory network to store the users' active vocabularies, enabling the generation of personalized captions. Long et al. [14]

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proposed a model for personalized image captioning that can be applied across different domains, thereby expanding the range of potential application scenarios. Considering users' long-term and short-term stylistic preferences, Zhang et al. [40] proposed an approach that combines these temporal dimensions. However, the implementation of this approach necessitates the collection of more detailed data. To generate captions that align with user preferences, Wang et al. [33] utilized user-provided tags as a foundational element in their methodology. Zeng et al. [38] leveraged user profiles such as age and gender to generate social media comments. Our approach eliminates the need for supplementary information, such as user profiles or posting timestamps, and only requires training a small network.

2.3 Prompt Tuning in Image Captioning

Prompt tuning enables large-scale pre-trained models to adapt to various tasks without requiring parameter adjustments. Jin et al. [8] conducted research demonstrating that even relatively simple hard prompts can enhance the performance of image captioning. Ramos et al. [25] utilized image-based retrieval techniques to extract relevant textual information from a database, thereby generating prompts that subsequently guided the process of caption generation. Taking a distinct approach, Li et al. [11] employed soft prompts by utilizing extracted visual representations as a condition for the large language model. Building upon the insights from these prior works, our research extends the application of prompt tuning to the novel and challenging domain of personalized image captioning.

3 Methods

3.1 Problem Definition

The general personalized image captioning framework can be described as follows: Given a dataset of images, captions, and user context tuples (x^i, c^i, u^i) , our objective is to learn a model to generate a caption for a target input image with a specified user language style.

During training, we optimize our model in an autoregressive manner that predicts the next token without considering future tokens by minimizing negative log-likelihood loss \mathcal{L} , *i.e.*,

$$\mathcal{L} = -\max_{\theta} \sum_{i=1}^{N} \sum_{j=1}^{L} \log p_{\theta} \left(c_{j}^{i} \mid x^{i}, u^{i}, c_{1}^{i}, \dots, c_{j-1}^{i} \right), \tag{1}$$

where θ denotes the model trainable parameters; N is the number of samples; L is the maximum length of the generated sentence.

During the process of inference, the generation of the caption is initiated by conditioning it on both the visual prefix and the user context. The subsequent

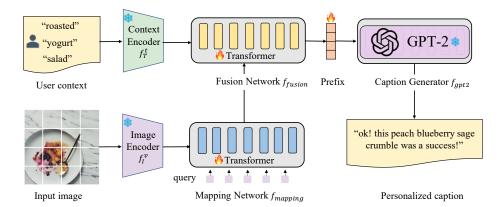


Fig. 2. Overview of our User-Aware Prefix-Tuning Network (UAPT) framework. At first, we utilize a frozen image encoder f_I^v and context encoder f_T^t to extract visual features and user-specific embeddings, respectively. Then, a query-guided mapping network $f_{mapping}$ is exploited to align vision and language semantics. Subsequently, visual knowledge and user prior knowledge are fused by a transformer based fusion network f_{fusion} to output embeddings as prefixes. Finally, the prefixes are input into a frozen large language model f_{gpt2} to generate personalized captions.

tokens are then predicted sequentially, with the assistance of the language model output. At each step, the language model assigns probabilities to all tokens in the vocabulary, and these probabilities are used to determine the next token by employing a beam search algorithm.

In the subsequent section, we introduce our proposed approach, illustrated in Fig. 2. We begin by explaining the utilization of the query-guided visual knowledge mapping module to align visual cues and language semantics. Subsequently, we demonstrate the fusion of user-aware prior knowledge with visual knowledge in order to capture the contextual style of user language for personalized image captioning. Lastly, we employ prefix tuning to prompt a frozen language model for the generation of captions.

3.2 Query-Guided Visual Knowledge Mapping

To acquire visual cues from the images, we utilize the frozen CLIP's image encoder $f_I^v(\cdot)$ to extract visual semantics.

Furthermore, we introduce a set of learnable query vectors q_i to guide the Mapping Network in extracting valuable knowledge from the existing visual feature representations. This approach provides the benefit of directing the model towards extracting feature representations that are more closely aligned with the semantics of the textual space. Simultaneously, it reduces the required training resources and accelerates the training process. Consequently, the resulting mapping representation \mathcal{V} can be reformulated as follows:

$$\mathcal{V} = f_{mapping}(f_I^v(x_i), q_i). \tag{2}$$

3.3 User-Aware Prior Knowledge Fusion

Different users often exhibit unique idioms, writing styles, and other linguistic characteristics, which can be considered as personalized traits. To achieve personalized image captioning, it is crucial to incorporate user language style contexts into the network. In this regard, we utilize TF-IDF denoted as $f_{tf-idf}(\cdot)$ to represent the users' distinctive writing habits, which can measure the importance of a word in a document [24]. Specifically, we consider each user's historical postings as a document and apply the TF-IDF to extract personalized keywords for each user. These keywords capture the unique vocabulary and writing style employed by the users in their posts. Subsequently, we input these obtained keywords into the Context Encoder, instantiated as CLIP's text encoder $f_T^t(\cdot)$, to encode them and generate a distinctive embedding vector for each user.

Furthermore, we employ a transformer $f_{fusion}(\cdot)$ to fuse the user's embedded representation with the visual projection representation, enabling a comprehensive interaction between the image information and the user's linguistic style context. This fusion facilitates a stronger correlation between the semantic information of the image and the user's style. The final fusion vector, represented as the output \mathcal{P} , can be mathematically expressed as follows:

$$\mathcal{P} = f_{fusion}(f_T^t(f_{tf-idf}(u_i)), \mathcal{V}). \tag{3}$$

3.4 Caption Generation

During the training process, we employ a pre-trained GPT-2 model to generate image captions. Specifically, we input the fusion vectors as prefixes to the GPT-2 model, allowing the model to learn the semantic information of the images and the writing habits of the users to generate the corresponding captions. In the inference process, we utilize the beam search algorithm to generate more accurate and coherent captions. The entire process can be summarized as follows:

$$C = f_{apt2}(\mathcal{P}). \tag{4}$$

4 Experiments

4.1 Dataset

We validate the performance of our model using two datasets [20]: Instagram and YFCC100M. The datasets are partitioned following the methodology outlined in [20]. Detailed statistics regarding the datasets are presented in Table 1.

To assess the feasibility and indispensability of personalization, we treat each user as a separate class and evaluate the intra-class and inter-class similarity of

Table 1. Statistics of the datasets.

Datasets	Posts	Users	Posts/User	Words/Post	Intra-class	Inter-class
Instagram	721,176	4,820	149.6	8.55	0.0330	0.0088
YFCC100M	462,036	6,197	74.6	6.30	0.1682	0.0044

Table 2. Results of evaluation metrics on the Instagram and YFCC100M datasets. The best results for each evaluation metric are marked in bold.

Instagram								
Methods	BLEU-1	BLEU-2	BLEU-3	BLEU-4	METEOR	ROUGE-L	CIDEr	
ShowTell	0.055	0.019	0.007	0.003	0.038	0.081	0.004	
ShowAttTell	0.106	0.015	0.000	0.000	0.026	0.026	0.049	
1NN-Im	0.071	0.020	0.007	0.004	0.032	0.069	0.059	
Seq2seq	0.050	0.012	0.003	0.000	0.024	0.065	0.034	
1NN-Usr	0.063	0.014	0.002	0.000	0.028	0.059	0.025	
1NN-UsrIm	0.106	0.032	0.011	0.005	0.045	0.104	0.084	
CSMN-P5	0.171	0.068	0.029	0.013	0.064	0.177	0.214	
${\rm CSMN\text{-}P5\text{-}Mul}$	0.145	0.049	0.022	0.009	0.049	0.145	0.143	
Ours	0.161	0.084	0.050	0.032	0.097	0.160	0.343	
YFCC100M								
Methods	BLEU-1	BLEU-2	BLEU-3	BLEU-4	METEOR	ROUGE-L	CIDEr	
ShowTell	0.027	0.003	0.000	0.000	0.024	0.043	0.003	
ShowAttTell	0.088	0.010	0.001	0.000	0.034	0.116	0.076	
1NN-Im	0.033	0.006	0.001	0.000	0.020	0.043	0.063	
Seq2seq	0.076	0.010	0.000	0.000	0.034	0.066	0.069	
1NN-Usr	0.032	0.003	0.001	0.000	0.016	0.051	0.028	
1NN-UsrIm	0.039	0.005	0.001	0.000	0.021	0.050	0.050	
CSMN-P5	0.106	0.034	0.012	0.004	0.033	0.099	0.064	
${\rm CSMN\text{-}P5\text{-}Mul}$	0.116	0.036	0.010	0.003	0.036	0.111	0.060	
Ours	0.100	0.042	0.018	0.008	0.064	0.097	0.170	

the captions. The results of this analysis, presented in the right part of Table 1, unequivocally demonstrate the existence of distinct textual preferences among individual users. This compelling evidence further supports the idea that user characteristics can be effectively captured by considering their posts.

4.2 Implementation Details

In the UAPT, both the Mapping Network and the Fusion Network consist of 5 layers of multi-head self-attention with 8 heads each. The lengths of the learnable query, visual feature representations, and user's embedding vector are 16, 16, 4 respectively. For the Image Encoder and Context Encoder, we utilize the pre-trained image encoder and text encoder from EVA-CLIP [29]. Additionally, GPT-2 (medium) [23] is employed as the Caption Generator.

Table 3. Ablation study on the YFCC100M. The best results for each evaluation metric are marked in bold.

Methods	BLEU-1	BLEU-2	BLEU-3	BLEU-4	METEOR	ROUGE-L	CIDEr
w/o Context	0.074	0.030	0.013	0.006	0.052	0.075	0.121
w/o Mapping	0.083	0.034	0.015	0.007	0.060	0.088	0.154
w/o Fusion	0.085	0.036	0.016	0.007	0.061	0.088	0.161
w/o Query	0.083	0.035	0.015	0.006	0.061	0.089	0.152
Full Model	0.100	0.042	0.018	0.008	0.064	0.097	0.170

We conduct training for 6 epochs using a batch size of 50 on a single NVIDIA GeForce RTX3090. The AdamW [15] optimizer is employed with $\beta_1 = 0.9$, $\beta_2 = 0.96$, and a weight decay rate of 0.005. To schedule the learning rate, we utilize cosine learning rate decay with a peak learning rate of 6e - 4, accompanied by linear warm-up over 6k steps. During the inference phase, the temperature of the beam search is set to 0.8, and the beam size is set to 3.

4.3 Baselines

To demonstrate the effectiveness of our model, we select several baseline models for comprehensive comparative analysis, including: 1) ShowTell [32]: ShowTell is an encoder-decoder model designed for caption generation, employing an RNN decoder. 2) ShowAttTell [35]: ShowAttTell integrates visual attention computation to capture the importance of individual image regions during word decoding. 3) 1NN-Im, 1NN-Usr, and 1NN-UsrIm [20]: These baselines employ a retrieval-based approach by utilizing the captions from the nearest training image, nearest user, or a combination of both as the basis for generating captions. 4) Seq2seq [31]: Seq2seq is a recursive neural network with three hidden LSTM layers. This baseline retrieves 60 active words from the querying user in a descending order of TF-IDF weights and predicts the corresponding caption. 5) CSMN-P5 and CSMN-P5-Mul [20]: These baselines integrated the user's active vocabulary as part of their memory network. CSMN-P5-Mul extended CSMN-P5 by incorporating multi-layer CNNs into its architecture.

4.4 Quantitative Analysis

We utilize BLEU [19], METEOR [2], ROUGE-L [13], and CIDEr [30] as evaluation metrics. Table 2 presents the performance of UAPT and the compared baselines on the two datasets. The first part of the table corresponds to architectures without personalization, while the remaining results incorporate personalization. Across both datasets, our model outperforms the existing baseline models across five evaluation metrics. In the Instagram dataset, our model achieves significant improvements, surpassing other baseline models by more than double in metrics such as BLEU-3, BLEU-4, and CIDEr. Similarly, in the YFCC100M dataset,

our model demonstrates substantial enhancements, more than doubling the performance of the baseline models in terms of BLEU-4 and CIDEr scores. These findings conclusively demonstrate the superior performance of our model.

4.5 Ablation Study

We perform ablation experiments to evaluate the effectiveness of each component in the model, as shown in Table 3. These experiments included the following variations: 1) "w/o Context" which removes the Context Encoder; 2) "w/o Mapping" which eliminates the Mapping Network; 3) "w/o Fusion" which excludes the Fusion Network; 4) "w/o Query" where the value of learnable query is set to 0 and the weights are frozen.

The exclusion of any component from the model results in a decline in the evaluation metrics, highlighting the indispensability of each constituent. Among the variations, the impact of "w/o Context" is the most pronounced, emphasizing the importance of user-aware prior knowledge in generating higher-quality captions. This finding further supports the notion that our model successfully constructs unique embedding sequences for each user, enabling accurate guidance in generating personalized captions.

4.6 Qualitative Analysis

Fig. 3 presents authentic examples of generated captions from the Instagram and YFCC100M datasets. Each instance includes the ground truth (GT) caption, captions generated by the original posting user (Poster) and other users (User1, User2, and User3).

By employing our model, we can generate captions for Posters that are either identical or remarkably similar to the GT. It is noteworthy that even in situations where the correlation between images and text is relatively weak, as demonstrated in the second and third examples, our model can still generate captions that align with the users' preferences by acquiring knowledge of their writing patterns. Moreover, these examples reveal user-specific vocabulary tendencies. For example, User2 often uses "enjoy" in captions, and User3 frequently expresses emotions through "i love". This demonstrates our model's proficiency in capturing users' characteristics and generating captions that align with their preferences and styles. Moreover, different users produce captions in their distinctive styles for the same image, further substantiating our model's personalized generation capability.

In the YFCC100M dataset, it is noteworthy that our model demonstrates the capability to generate captions that exhibit a higher level of precision and specificity compared to the GT, as exemplified in the third example. This observation underscores the remarkable performance and potential of our model.





ride on the river. (User3) i love the view from

(GT) day 222 365 custom designed numbers everyday. (Poster) day 355 365 custom designed numbers everyday. (User1) just a few more days to see more of this beautiful design.

(User2) enjoyed the simplicity (User3) i love this design.



(GT) picture 3 give the best caption photo by @username. (Poster) picture 24 give the best caption photo credits to @username (User1) i'm a little bit of a

sauirrel (User2) this is my favorite picture of a squirrel (User3) when you see a

squirrel in the park



(GT) happy father's day. (Poster) happy father's day. (User1) happy father's day to

(User2) happy father's day to the best dad in the world. (User3) happy father's day to my dad



(GT) i love this fish. (Poster) i love this fish. (User1) a pair of fish in the aguarium at the miamisburg (User2) some of the fish that

were in the aquarium at the time of this photo (User3) some fish in the



(GT) starry night on top of the (Poster) starry night at the rim of the world. (User1) the night sky at the

dawn of the day (User2) moonlight over the mountains (User3) the moon at the top of the mountain



(GT) tern in flight. (Poster) snowy tern in flight. (User1) a tern in flight. (User2) caspian tern at dusk. (User3) the king of all terns.



(GT) golden temple at the center of angkor wat. (Poster) a view of the main temple at angkor wat. (User1) another view of the upper tiers of the palace. (User2) sunset at the top of a temple at angkor wat (User3) sunrise at angkor wat.

Fig. 3. Examples from Instagram (top) and YFCC100M (bottom).

5 Conclusions

In this paper, we have proposed a novel personalized image captioning framework based on user-aware prefix-tuning. Our method utilizes query-guided visual knowledge mapping for aligning vision and language semantics, while also fusing user-aware prior knowledge to consider the characteristics and preferences of users. Finally, we leverage prefix-tuning to extract knowledge from frozen large language model, narrowing the gap between different semantic domains. With a small number of parameters to be trained, our model boosts the performance efficiently and effectively. The experiments conducted on two publicly available datasets demonstrate the superiority of our model and validate the contributions of our method.

In the future, we will explore how to integrate more fine-grained user context to generate more captivating and tailored descriptions for personalized image captioning.

Acknowledgments

This work is supported by the Fundamental Research Funds for the Central Universities (No.226-2023-00045) and National Natural Science Foundation of China (No.62106219).

References

- Anderson, P., He, X., Buehler, C., Teney, D., Johnson, M., Gould, S., Zhang, L.: Bottom-up and top-down attention for image captioning and visual question answering. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 6077–6086 (2018)
- 2. Banerjee, S., Lavie, A.: 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. pp. 65–72 (2005)
- 3. Cao, S., Chai, W., Hao, S., Wang, G.: Image reference-guided fashion design with structure-aware transfer by diffusion models. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 3524–3528 (2023)
- Cao, S., Chai, W., Hao, S., Zhang, Y., Chen, H., Wang, G.: Difffashion: Referencebased fashion design with structure-aware transfer by diffusion models. arXiv preprint arXiv:2302.06826 (2023)
- Chai, W., Guo, X., Wang, G., Lu, Y.: Stablevideo: Text-driven consistency-aware diffusion video editing. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 23040–23050 (2023)
- Chai, W., Wang, G.: Deep vision multimodal learning: Methodology, benchmark, and trend. Applied Sciences 12(13), 6588 (2022)
- Hossain, M.Z., Sohel, F., Shiratuddin, M.F., Laga, H.: A comprehensive survey of deep learning for image captioning. ACM Computing Surveys (CsUR) 51(6), 1–36 (2019)
- 8. Jin, W., Cheng, Y., Shen, Y., Chen, W., Ren, X.: A good prompt is worth millions of parameters? low-resource prompt-based learning for vision-language models. arXiv preprint arXiv:2110.08484 (2021)
- 9. Karpathy, A., Fei-Fei, L.: Deep visual-semantic alignments for generating image descriptions. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 3128–3137 (2015)
- Krizhevsky, A., Sutskever, I., Hinton, G.E.: Imagenet classification with deep convolutional neural networks. Communications of the ACM 60(6), 84–90 (2017)
- 11. Li, J., Li, D., Savarese, S., Hoi, S.: Blip-2: Bootstrapping language-image pretraining with frozen image encoders and large language models. arXiv preprint arXiv:2301.12597 (2023)
- 12. Li, X.L., Liang, P.: Prefix-tuning: Optimizing continuous prompts for generation. arXiv preprint arXiv:2101.00190 (2021)
- 13. Lin, C.Y.: Rouge: A package for automatic evaluation of summaries. In: Text summarization branches out. pp. 74–81 (2004)
- 14. Long, C., Yang, X., Xu, C.: Cross-domain personalized image captioning. Multimedia Tools and Applications **79**, 33333–33348 (2020)
- 15. Loshchilov, I., Hutter, F.: Decoupled weight decay regularization. arXiv preprint arXiv:1711.05101 (2017)

- Mao, J., Xu, W., Yang, Y., Wang, J., Yuille, A.L.: Explain images with multimodal recurrent neural networks. arXiv preprint arXiv:1410.1090 (2014)
- 17. Mikolov, T., Karafiát, M., Burget, L., Cernockỳ, J., Khudanpur, S.: Recurrent neural network based language model. In: Interspeech. vol. 2, pp. 1045–1048. Makuhari (2010)
- 18. Mokady, R., Hertz, A., Bermano, A.H.: Clipcap: Clip prefix for image captioning. arXiv preprint arXiv:2111.09734 (2021)
- 19. Papineni, K., Roukos, S., Ward, T., Zhu, W.J.: Bleu: a method for automatic evaluation of machine translation. In: Proceedings of the 40th annual meeting of the Association for Computational Linguistics. pp. 311–318 (2002)
- Park, C.C., Kim, B., Kim, G.: Towards personalized image captioning via multimodal memory networks. IEEE transactions on pattern analysis and machine intelligence 41(4), 999–1012 (2018)
- Radford, A., Kim, J.W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., Sastry, G., Askell, A., Mishkin, P., Clark, J., et al.: Learning transferable visual models from natural language supervision. In: International conference on machine learning. pp. 8748–8763. PMLR (2021)
- 22. Radford, A., Narasimhan, K., Salimans, T., Sutskever, I., et al.: Improving language understanding by generative pre-training (2018)
- Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., Sutskever, I., et al.: Language models are unsupervised multitask learners. OpenAI blog 1(8), 9 (2019)
- 24. Ramos, J., et al.: Using tf-idf to determine word relevance in document queries. In: Proceedings of the first instructional conference on machine learning. vol. 242, pp. 29–48. Citeseer (2003)
- Ramos, R., Martins, B., Elliott, D., Kementchedjhieva, Y.: Smallcap: Lightweight image captioning prompted with retrieval augmentation. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 2840– 2849 (2023)
- 26. Shuster, K., Humeau, S., Hu, H., Bordes, A., Weston, J.: Engaging image captioning via personality. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 12516–12526 (2019)
- 27. Song, E., Chai, W., Wang, G., Zhang, Y., Zhou, H., Wu, F., Guo, X., Ye, T., Lu, Y., Hwang, J.N., et al.: Moviechat: From dense token to sparse memory for long video understanding. arXiv preprint arXiv:2307.16449 (2023)
- 28. Stefanini, M., Cornia, M., Baraldi, L., Cascianelli, S., Fiameni, G., Cucchiara, R.: From show to tell: A survey on deep learning-based image captioning. IEEE transactions on pattern analysis and machine intelligence **45**(1), 539–559 (2022)
- 29. Sun, Q., Fang, Y., Wu, L., Wang, X., Cao, Y.: Eva-clip: Improved training techniques for clip at scale. arXiv preprint arXiv:2303.15389 (2023)
- 30. Vedantam, R., Lawrence Zitnick, C., Parikh, D.: Cider: Consensus-based image description evaluation. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 4566–4575 (2015)
- 31. Vinyals, O., Kaiser, Ł., Koo, T., Petrov, S., Sutskever, I., Hinton, G.: Grammar as a foreign language. Advances in neural information processing systems 28 (2015)
- 32. Vinyals, O., Toshev, A., Bengio, S., Erhan, D.: Show and tell: A neural image caption generator. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 3156–3164 (2015)
- 33. Wang, L., Chu, X., Zhang, W., Wei, Y., Sun, W., Wu, C.: Social image captioning: Exploring visual attention and user attention. Sensors **18**(2), 646 (2018)

- 34. Wang, W., Bao, H., Dong, L., Bjorck, J., Peng, Z., Liu, Q., Aggarwal, K., Mohammed, O.K., Singhal, S., Som, S., et al.: Image as a foreign language: Beit pretraining for all vision and vision-language tasks. arXiv preprint arXiv:2208.10442 (2022)
- 35. Xu, K., Ba, J., Kiros, R., Cho, K., Courville, A., Salakhudinov, R., Zemel, R., Bengio, Y.: Show, attend and tell: Neural image caption generation with visual attention. In: International conference on machine learning. pp. 2048–2057. PMLR (2015)
- 36. Xu, Y., Xu, Z., Chai, W., Zhao, Z., Song, E., Wang, G.: Devil in the number: Towards robust multi-modality data filter. arXiv preprint arXiv:2309.13770 (2023)
- 37. You, Q., Jin, H., Wang, Z., Fang, C., Luo, J.: Image captioning with semantic attention. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 4651–4659 (2016)
- 38. Zeng, W., Abuduweili, A., Li, L., Yang, P.: Automatic generation of personalized comment based on user profile. arXiv preprint arXiv:1907.10371 (2019)
- 39. Zhang, P., Li, X., Hu, X., Yang, J., Zhang, L., Wang, L., Choi, Y., Gao, J.: Vinvl: Revisiting visual representations in vision-language models. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 5579–5588 (2021)
- 40. Zhang, W., Ying, Y., Lu, P., Zha, H.: Learning long-and short-term user literal-preference with multimodal hierarchical transformer network for personalized image caption. In: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 34, pp. 9571–9578 (2020)