Zero-Shot and Few-Shot Video Question Answering with Multi-Modal Prompts

Deniz Engin[1] Yannis Avrithis[2]

[1]Inria, Univ Rennes, CNRS, IRISA
[2]Institute of Advanced Research in Artificial Intelligence (IARAI)

Abstract

Recent vision-language models are driven by large-scale pretrained models. However, adapting pretrained models on limited data presents challenges such as overfitting, catastrophic forgetting, and the cross-modal gap between vision and language. We introduce a parameter-efficient method to address these challenges, combining multimodal prompt learning and a transformer-based mapping network, while keeping the pretrained models frozen. Our experiments on several video question answering benchmarks demonstrate the superiority of our approach in terms of performance and parameter efficiency on both zero-shot and few-shot settings. Our code is available at `https://engindeniz.github.io/vitis`.

1. Introduction

Recent vision-language models have shown remarkable progress, driven by transformer-based *large-scale pretrained models* [10, 39, 9, 38, 17, 45, 44]. These models have been incorporated into video understanding methods, including *video question answering (VideoQA)*, through multimodal fusion on *large-scale multimodal datasets* [41, 3, 60]. However, adapting pretrained models to video-language tasks on limited data is challenging. This is because of the gap between the visual and language modalities and, more importantly, because finetuning the entire model on limited data can lead to overfitting and forgetting previously acquired knowledge.

To address the gap between modalities, transformer-based mapping networks have been employed between frozen vision and language models [42, 16, 1]. These networks map visual features to an appropriate embedding space before they are given as input to the language models. To address overfitting, parameter-efficient adaptation methods have been explored, *e.g.*, *prompt learning* [35, 37, 36] and *adapter layers* [18] on frozen pretrained models. These approaches preserve the generalization of large-scale models while reducing the number of trainable parameters.

In this work, we investigate the adaptation of large-scale visual-language models to VideoQA under scarcity of training data. Inspired by FrozenBiLM [57], we incorporate visual inputs to a frozen language model using lightweight learnable adapter layers. Beyond that, we introduce a novel *visual mapping network* that summarizes the video input while allowing for temporal interaction, inspired by [42, 20]. In addition, we introduce *multimodal prompt learning*, which diminishes the number of stored parameters when finetuning in the few-shot setting. We call our model ***Vi**deoQA with Mul**ti**-Modal Prompt**s*** (ViTiS).

We pretrain trainable parameters of ViTiS, *i.e. visual mapping network, adapter layers, visual and text prompts*, under the *masked language modeling* (MLM) objective on video-text pairs collected from the web, while the vision and language models are kept frozen. We evaluate ViTiS in the zero-shot and few-shot settings. For the latter, we finetune the model on downstream VideoQA tasks, using two approaches: (i) fine-tuning all trainable parameters, which are 8% of the total model parameters, (ii) fine-tuning only the prompts, which are 0.8% of all trainable parameters and a mere 0.06% of the total model parameters.

Our extensive experimental results on multiple open-ended VideoQA datasets demonstrate that ViTiS outperforms prior methods while requiring fine-tuning of only a few parameters for each dataset in few-shot settings. In addition, our visual mapping network contributes to better alignment and understanding of multimodal inputs, improving performance in both zero-shot and few-shot settings.

Our contributions can be summarized as follows:

1. We introduce *multimodal prompt learning* to few-shot VideoQA for the first time, fine-tuning as low as 0.06% of model parameters on downstream tasks.
2. We introduce a *visual mapping network* to VideoQA, mapping video input to the text embedding space, while supporting temporal interaction.
3. We experimentally demonstrate the strong performance of ViTiS on multiple VideoQA datasets in both zero-shot and few-shot settings.

2. Related Work

Video question answering Recent advances in vision-language models benefit from pretrained foundation models, including vision-only [10, 39] language-only [9, 38, 17, 45] and vision-language [44]. Recent video understanding methods, including VideoQA, incorporate these models by leveraging large-scale multimodal data [41, 3, 60] with different pretraining objectives, *e.g.*, *masked language modeling*, *masked image modeling*, or *predicting the next word*, to perform single or multiple vision-language tasks [48, 33, 28, 12, 55, 60, 31, 57, 1, 59, 8, 51, 34, 19, 13].

Adapting pretrained vision-language models to downstream tasks relies on fully supervised fine-tuning on VideoQA datasets in general [50, 53, 21, 29, 58, 33, 14]. Few recent works address the challenge of limited data by focusing on zero-shot [55, 56, 57, 1, 59, 32, 34] and few-shot [57, 1] open-ended VideoQA tasks. Our work is similar to [57] in leveraging a frozen video encoder and language model with adapter layers. Beyond that, we introduce a transformer-based visual mapping network between the two models, allowing for temporal interaction. In addition, we incorporate multimodal prompt learning, allowing for efficient fine-tuning in few-shot settings.

Parameter-efficient training As the size of large-scale pretrained models grows, adapting them efficiently on limited data without overfitting in an emerging research problem. A common solution is *adapters*, introduced by [18] and employed for vision-language tasks [11, 57, 49].

Another common solution is *prompting*, referring to inserting tokens to the input to guide pretrained models on downstream tasks. Prompts can be handcrafted (discrete) [4] or learned (continuous vectors) [35]. Pretrained language models demonstrate remarkable generalization to zero-shot settings with handcrafted prompts [4]. Prompt learning is introduced initially in natural language processing tasks [35, 30, 37, 36, 43, 40] and subsequently adopted in vision [22, 2] and vision-language models. In the latter case, prompts are introduced to text encoders [62, 61], or both text and vision encoders [24, 52, 27, 46], called *multimodal*. Learnable prompts can be inserted at the input level [35] and/or deep layers [36, 22]. Few recent works employ prompt learning for video understanding [23, 63, 49] and multimodal prompt learning for video classification [52, 46]. We introduce multimodal prompt learning to few-shot VideoQA for the first time.

3. Method

The proposed method, ViTiS , is illustrated in Figure 1(a), consisting of a frozen video encoder, a visual mapping network, a frozen text embedding layer and a frozen language model that includes learnable text prompts and adapter layers. Given an input video X^v, represented as a sequence of frames, and a question X^q, represented as a sequence of tokens, the problem is to predict an answer X^a that is another sequence of tokens. The model takes the concatenated sequence $X^t = (X^q, X^a)$ as input text. Parts of X^t may be masked, for example X^a is masked at inference.

Video encoder The input video is represented by a sequence of T frames, $X^v = (x_1^v, \dots, x_T^v)$. This sequence is encoded into the *frame features*

$$Y^v := f^v(X^v) = (y_1^v, \dots, y_T^v) \in \mathbb{R}^{D \times T} \tag{1}$$

by a frozen pretrained *video encoder* f^v, where D is the embedding dimension.

Visual mapping network A *visual mapping network* f^m maps the frame features Y^v to the same space as the text embeddings. The mapping is facilitated by a set of M *learnable visual prompts* $P^v \in \mathbb{R}^{D \times M}$, which are given as input along with Y^v, to obtain the *video embeddings*

$$Z^v := f^m(P^v, Y^v) \in \mathbb{R}^{D \times M}. \tag{2}$$

As shown in Figure 1(c), the architecture of f^m is based on Perceiver [20], where the latent array corresponds to our learnable visual prompts P^v. It consists of L blocks defined as

$$Z_\ell := \textsc{sa}_\ell(\textsc{ca}_\ell(Z_{\ell-1}, Y^v)) \in \mathbb{R}^{D \times M} \tag{3}$$

for $\ell = 1, \dots, L$, with input $Z_0 = P^v$. Each block ℓ maps the latent vectors $Z_{\ell-1}$ first by cross attention $\textsc{ca}_\ell$ with the frame features Y^v and then by self attention $\textsc{sa}_\ell$ to obtain Z_ℓ. In cross attention, $Z_{\ell-1}$ serves as query and Y^v as key and value. We thus iteratively extract information from the frame features Y^v into the latent vectors, which are initialized by the visual prompts. The output video embeddings are $Z^v = Z_L \in \mathbb{R}^{D \times M}$. To allow modeling of temporal relations within the video, learnable *temporal position embeddings* are added to Y^v before f^m.

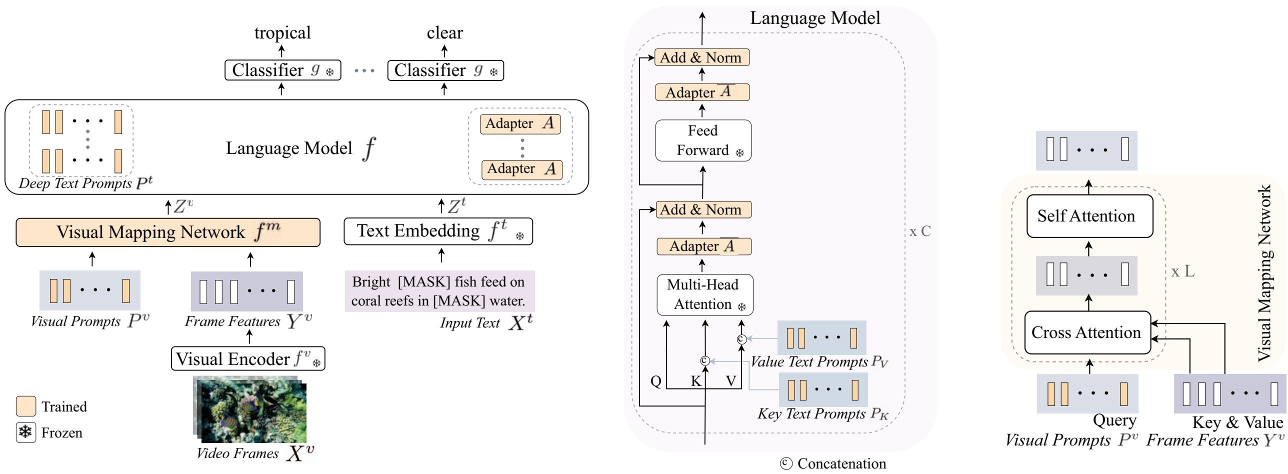
Text embedding The input text is tokenized into a sequence of S tokens, $X^t = (x_1^t, \dots, x_S^t)$. This sequence is mapped by a frozen *text embedding layer* f^t to the text embedding space,

$$Z^t := f^t(X^t) = (z_1^t, \dots, z_S^t) \in \mathbb{R}^{D \times S}. \tag{4}$$

One or more tokens are masked, in which case they are replaced by a learnable mask token.

Language model We concatenate video and text embeddings into a single input sequence $(Z^v, Z^t) \in \mathbb{R}^{D \times K}$ of length $K = M + S$. We then feed this sequence to a transformer-based bidirectional language model f to obtain an output sequence

$$f(Z^v, Z^t) \in \mathbb{R}^{D \times K} \tag{5}$$



(a) method overview (b) language model (c) visual mapping network

Figure 1: (a) ViTiS consists of a frozen video encoder f^v, a visual mapping network f^m, a frozen text embedding layer f^t, a frozen language model f and a frozen classifier head g. Given input video frames X^v and text X^t, f^v extracts frame features and f^m maps them to the same space as the text embeddings obtained by f^t. Then, f takes the video and text embeddings Z^v, Z^t as input and predicts the masked input tokens. (b) The *language model* incorporates learnable text prompts in the key and value of multi-head-attention and adapter layers after each self-attention and feed-forward layer, before LayerNorm. (c) Our *visual mapping network* consists of a number of layers, each performing cross-attention between learnable visual prompts and video frame features followed by self-attention.

of the same length. Finally, a classifier head g maps the output sequence to logit vectors over a vocabulary U. The logit vectors coresponding to masked tokens are selected to apply the loss function at training or make predictions at inference. Both f and g are pretrained and kept frozen. However, as shown in Figure 1(b), f is adapted by means of learnable deep text prompts and adapters, described next.

Text prompts To reduce the number of fine-tuned parameters at downstream tasks, we introduce attention-level text prompts in self-attention blocks at each layer of the language model, referred to as *deep text prompt learning* [36]. Given a sequence $Z \in \mathbb{R}^{D \times K}$ of token embeddings as input to a self-attention layer of the language model f, we prepend two sequences of *learnable text prompts* $P_K, P_V \in \mathbb{R}^{N \times D}$ to the key and value respectively:

$$Q := W_Q Z \quad K := [P_K \;\; W_K Z] \quad V := [P_V \;\; W_V Z], \quad (6)$$

where $W_Q, W_K, W_V \in \mathbb{R}^{D \times D}$ are the query, key and value projections respectively. The output sequence length does not change since it is determined by the query, where we do not prepend prompts. There is one pair of variables P_K, P_V for each layer of f, collectively denoted as P^t. These variables are either defined as parameters directly or parametrized by means of projections as discussed in the supplementary.

Adapters Following [57], we add adapter layers to the language model f. Given a sequence $Z \in \mathbb{R}^{D \times K}$ of token embeddings, an adapter layer A maps it through a bottleneck dimension d with a residual connection:

$$A(Z) := Z + W_2 h(W_1 Z) \in \mathbb{R}^{D \times K}, \quad (7)$$

where $W_1 \in \mathbb{R}^{d \times D}$, $W_2 \in \mathbb{R}^{D \times d}$, and h is the relu activation function. We insert an adapter module after the self-attention layer and the feed-forward layer, preceding LayerNorm in each layer of f.

Training and inference Our model is trained using the *masked language modeling* (MLM) objective, where one or more tokens of X^t are masked and the corresponding outputs are predicted over a vocabulary U. The parameters of the visual encoder f^v, text embedding layer f^t, language model f and classifier head g are pretrained and kept frozen. Only the newly introduced parameters, that is, visual prompts P^v, visual mapping network f^v, text prompts P^t and adapter layers, are optimized on video-text pairs. We then fine-tune these parameters or a smaller subset on downstream video question answering tasks, where $X^t = (X^q, X^a)$ consists of a question-answer pair and masking applies to the X^a only. At inference, X^a is masked and the corresponding output yields a prediction.

4. Experiments

4.1. Setup

Datasets We use WebVid2M [3] for pretraining. For downstream tasks, we use open-ended VideoQA datasets

#	AD	MAP	PR	TRAINED PARAM	MSRVTT -QA	MSVD -QA	ANET -QA	TGIF -QA
1		Linear		1M	18.0	30.5	27.1	44.4
2		Linear	✓	15M	36.3	46.2	32.7	54.3
3	✓	Linear		30M	35.0	45.0	32.4	53.9
4	✓	Linear	✓	44M	36.4	47.2	32.9	54.7
5		VPN		58M	24.5	37.0	26.1	50.1
6		VPN	✓	72M	36.1	47.4	34.1	55.8
7	✓	VPN		86M	34.7	46.0	32.4	54.4
8	✓	VPN	✓	101M	**36.5**	**47.8**	**37.2**	**55.9**

Table 1: Effect of our proposed components on few-shot top-1 accuracy on the validation set. Pretraining on WebVid2M [3] followed by fine-tuning all trainable parameters on downstream datasets, using 1% of training data. AD: Adapters; MAP: mapping network; PR: text prompts; VPN: our visual mapping network. ANET-QA: ActivityNet-QA.

MSRVTT-QA [53], MSVD-QA [53], ActivityNet-QA (ANET-QA) [58] and TGIF-FrameQA [21]. Following [57], we use 1% of the training data for few-shot experiments. We give more details in the supplementary.

Implementation and metrics We use CLIP ViT-L/14 [10, 44] as video encoder and DeBERTa-V2-XLarge [17] as language model. We report top-1 accuracy on public test sets for all downstream tasks, except TGIF-QA where we report on the validation set unless otherwise specified. Our model uses subtitles in the input text. We give more details in the supplementary.

4.2. Ablation

We conduct an ablation study in the few-shot setting. We provide additional analysis in the supplementary.

Model design In Table 1, we analyze the effect of different components in the model design. We observe that changing the baseline from a linear layer to *our visual mapping network* without adapters increases the performance by a large margin in most datasets (row 1→5). By adding *text prompts* to any model design (row 1→2, 3→4, 5→6, 7→8), the performance increases for all datasets. The improvement is vast in the absence of adapters.

The model design that includes a linear mapping network and adapter layers (row 3) corresponds to FrozenBiLM [57] trained on WebVid2M. While using only our visual mapping network and text prompts (row 6) already works better than FrozenBiLM trained on WebVid2M, we further improve performance by incorporating adapter layers: our full model (row 8) achieves the best performance overall.

4.3. Results

Zero-shot A comparison with state-of-the-art methods on open-ended zero-shot VideoQA is given in Table 2. We observe an outstanding performance of our method across different VideoQA benchmarks, despite using significantly less pretraining data compared to other methods. Our performance on ActivityNetQA [58] is on par with FrozenBiLM [57]. Lavender [34] employs a multi-task training approach, transforming different vision-language tasks into MLM. Reserve [59] uses GPT-3 [5] to convert questions into masked sentences. Flamingo [1] uses a frozen auto-regressive language model trained on an extreme-scale dataset. By contrast, our method leverages a lighter frozen language model trained on 2.5M video-text pairs.

METHOD	SUB	#TRAINING IMG	#TRAINING VID	MSRVTT -QA	MSVD -QA	ANET -QA	TGIF -QA
CLIP [44]		400M	–	2.1	7.2	1.2	3.6
RESERVE [59]	✓	–	20M	5.8	–	–	–
LAVENDER [34]		3M	2.5M	4.5	11.6	–	16.7
Flamingo [1]		2.3B	27M	17.4	35.6	–	–
FrozenBiLM [57]	✓	–	10M	16.7	33.8	**25.9**	41.9
ViTiS (Ours)	✓	–	2.5M	**18.1**	**36.1**	25.5	**45.5**

Table 2: *Zero-shot VideoQA* top-1 accuracy on test sets, except TGIF-QA on the validation set. Number of pretraining data: image-text/video-text pairs. SUB: subtitle input. CLIP: CLIP ViT-L/14. Flamingo: Flamingo-80B. An extended version is given in the supplementary.

METHOD	TRAINED MODULES	#TRAINED PARAMS	MSRVTT -QA	MSVD -QA	ANET -QA	TGIF -QA
FrozenBiLM [57]	ATP	30M	36.0	46.5	33.2	55.1
ViTiS (Ours)	ATP	101M	36.5	47.6	33.1	55.7
ViTiS (Ours)	Prompts	0.75M	**36.9**	**47.8**	**34.2**	**56.2**

Table 3: *Few-shot VideoQA* top-1 accuracy on test sets, except TGIF-QA on the validation set. Number of trained parameters: fine-tuned on the downstream dataset, using 1% of training data. ATP: All trainable parameters.

Few-shot We fine-tune our method on 1% of the training data by following [57], which introduced the few-shot VideoQA task in this form. Table 3 compares our method with [57]. We use two strategies, fine-tuning (i) all trainable parameters and (ii) only prompts. The latter works best, consistently outperforming [57] while diminishing the number of fine-tuned parameters. We also compare with works using in-context learning in the supplementary.

5. Conclusion

In this work, we explored the adaptation of large-scale pretrained vision and language models for VideoQA under scarcity of data. We introduced multi-modal prompt learning and a visual mapping network to address challenges in such adaptation. Our method consistently outperforms prior works, while requiring minimal parameter fine-tuning in few-shot VideoQA.

Acknowledgements This work was granted access to the HPC resources of IDRIS under the allocation 2022-AD011012263R2 made by GENCI.

References

[1] Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katherine Millican, Malcolm Reynolds, et al. Flamingo: a visual language model for few-shot learning. In *Proc. NeurIPS*, 2022. 1, 2, 4, 3

[2] Hyojin Bahng, Ali Jahanian, Swami Sankaranarayanan, and Phillip Isola. Exploring visual prompts for adapting large-scale models. *arXiv preprint arXiv:2203.17274*, 2022. 2

[3] Max Bain, Arsha Nagrani, Gül Varol, and Andrew Zisserman. Frozen in time: A joint video and image encoder for end-to-end retrieval. In *Proc. ICCV*, 2021. 1, 2, 3, 4

[4] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. In *Proc. NeurIPS*, 2020. 2

[5] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. In *Proc. NeurIPS*, 2020. 4

[6] Fabian Caba Heilbron, Victor Escorcia, Bernard Ghanem, and Juan Carlos Niebles. ActivityNet: A large-scale video benchmark for human activity understanding. In *Proc. CVPR*, 2015. 1

[7] David Chen and William Dolan. Collecting highly parallel data for paraphrase evaluation. In *Proc. ACL*, 2011. 1

[8] Feng Cheng, Xizi Wang, Jie Lei, David Crandall, Mohit Bansal, and Gedas Bertasius. VindLU: A recipe for effective video-and-language pretraining. In *Proc. CVPR*, 2023. 2

[9] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proc. NAACL*, 2019. 1, 2

[10] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. In *Proc. ICLR*, 2021. 1, 2, 4

[11] Constantin Eichenberg, Sidney Black, Samuel Weinbach, Letitia Parcalabescu, and Anette Frank. MAGMA–multimodal augmentation of generative models through adapter-based finetuning. In *Proc. Findings of EMNLP*, 2022. 2

[12] Tsu-Jui Fu, Linjie Li, Zhe Gan, Kevin Lin, William Yang Wang, Lijuan Wang, and Zicheng Liu. Violet: End-to-end video-language transformers with masked visual-token modeling. *arXiv preprint arXiv:2111.12681*, 2021. 2

[13] Tsu-Jui Fu, Linjie Li, Zhe Gan, Kevin Lin, William Yang Wang, Lijuan Wang, and Zicheng Liu. An empirical study of end-to-end video-language transformers with masked visual modeling. In *Proc. CVPR*, 2023. 2

[14] Noa Garcia, Mayu Otani, Chenhui Chu, and Yuta Nakashima. KnowIT VQA: Answering knowledge-based questions about videos. In *Proc. AAAI*, 2020. 2

[15] Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. Making the V in VQA matter: Elevating the role of image understanding in Visual Question Answering. In *Proc. CVPR*, 2017. 4

[16] Tengda Han, Max Bain, Arsha Nagrani, Gül Varol, Weidi Xie, and Andrew Zisserman. AutoAD: Movie description in context. In *Proc. CVPR*, 2023. 1

[17] Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen. DeBERTa: Decoding-enhanced bert with disentangled attention. In *Proc. ICLR*, 2021. 1, 2, 4

[18] Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. Parameter-efficient transfer learning for NLP. In *Proc. ICML*, 2019. 1, 2

[19] Jingjia Huang, Yinan Li, Jiashi Feng, Xinglong Wu, Xiaoshuai Sun, and Rongrong Ji. Clover: Towards a unified video-language alignment and fusion model. In *Proc. CVPR*, 2023. 2

[20] Andrew Jaegle, Felix Gimeno, Andy Brock, Oriol Vinyals, Andrew Zisserman, and Joao Carreira. Perceiver: General perception with iterative attention. In *Proc. ICML*, 2021. 1, 2

[21] Yunseok Jang, Yale Song, Youngjae Yu, Youngjin Kim, and Gunhee Kim. Tgif-QA: Toward spatio-temporal reasoning in visual question answering. In *Proc. CVPR*, 2017. 2, 4, 1

[22] Menglin Jia, Luming Tang, Bor-Chun Chen, Claire Cardie, Serge Belongie, Bharath Hariharan, and Ser-Nam Lim. Visual prompt tuning. In *Proc. ECCV*, 2022. 2

[23] Chen Ju, Tengda Han, Kunhao Zheng, Ya Zhang, and Weidi Xie. Prompting visual-language models for efficient video understanding. In *Proc. ECCV*, 2022. 2

[24] Muhammad Uzair Khattak, Hanoona Rasheed, Muhammad Maaz, Salman Khan, and Fahad Shahbaz Khan. MaPLe: Multi-modal prompt learning. In *Proc. CVPR*, 2023. 2

[25] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In *Proc. ICLR*, 2015. 2

[26] Taku Kudo and John Richardson. SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. In *Proc. EMNLP: System Demonstrations*, 2018. 1

[27] Yi-Lun Lee, Yi-Hsuan Tsai, Wei-Chen Chiu, and Chen-Yu Lee. Multimodal prompting with missing modalities for visual recognition. In *Proc. CVPR*, 2023. 2

[28] Jie Lei, Linjie Li, Luowei Zhou, Zhe Gan, Tamara L Berg, Mohit Bansal, and Jingjing Liu. Less is more: Clipbert for video-and-language learning via sparse sampling. In *Proc. CVPR*, 2021. 2

[29] Jie Lei, Licheng Yu, Mohit Bansal, and Tamara Berg. TVQA: Localized, compositional video question answering. In *Proc. EMNLP*, 2018. 2

[30] Brian Lester, Rami Al-Rfou, and Noah Constant. The power of scale for parameter-efficient prompt tuning. In *Proc. EMNLP*, 2021. 2

[31] Dongxu Li, Junnan Li, Hongdong Li, Juan Carlos Niebles, and Steven CH Hoi. Align and prompt: Video-and-language pre-training with entity prompts. In *Proc. CVPR*, 2022. 2

[32] Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. BLIP: Bootstrapping language-image pre-training for unified vision-language understanding and generation. In *Proc. ICML*, 2022. 2, 3, 4

[33] Linjie Li, Yen-Chun Chen, Yu Cheng, Zhe Gan, Licheng Yu, and Jingjing Liu. HERO: Hierarchical encoder for video+ language omni-representation pre-training. In *Proc. EMNLP*, 2020. 2

[34] Linjie Li, Zhe Gan, Kevin Lin, Chung-Ching Lin, Zicheng Liu, Ce Liu, and Lijuan Wang. Lavender: Unifying video-language understanding as masked language modeling. In *Proc. CVPR*, 2023. 2, 4, 3

[35] Xiang Lisa Li and Percy Liang. Prefix-Tuning: Optimizing continuous prompts for generation. In *Proc. ACL*, 2021. 1, 2

[36] Xiao Liu, Kaixuan Ji, Yicheng Fu, Weng Tam, Zhengxiao Du, Zhilin Yang, and Jie Tang. P-tuning: Prompt tuning can be comparable to fine-tuning across scales and tasks". In *Proc. ACL*, 2022. 1, 2, 3

[37] Xiao Liu, Yanan Zheng, Zhengxiao Du, Ming Ding, Yujie Qian, Zhilin Yang, and Jie Tang. GPT understands, too. *arXiv preprint arXiv:2103.10385*, 2021. 1, 2

[38] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. RoBERTa: A robustly optimized BERT pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019. 1, 2

[39] Ze Liu, Jia Ning, Yue Cao, Yixuan Wei, Zheng Zhang, Stephen Lin, and Han Hu. Video swin transformer. In *Proc. CVPR*, 2022. 1, 2

[40] Rabeeh Karimi Mahabadi, Luke Zettlemoyer, James Henderson, Lambert Mathias, Marzieh Saeidi, Veselin Stoyanov, and Majid Yazdani. PERFECT: prompt-free and efficient few-shot learning with language models. In *Proc. ACL*, 2022. 2

[41] Antoine Miech, Dimitri Zhukov, Jean-Baptiste Alayrac, Makarand Tapaswi, Ivan Laptev, and Josef Sivic. HowTo100M: Learning a text-video embedding by watching hundred million narrated video clips. In *Proc. ICCV*, 2019. 1, 2

[42] Ron Mokady, Amir Hertz, and Amit H Bermano. ClipCap: CLIP prefix for image captioning. *arXiv preprint arXiv:2111.09734*, 2021. 1

[43] Guanghui Qin and Jason Eisner. Learning how to ask: Querying LMs with mixtures of soft prompts. In *Proc. NAACL*, 2021. 2

[44] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *Proc. ICML*, 2021. 1, 2, 4, 3

[45] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *Technical Report*, 2019. 1, 2

[46] Hanoona Rasheed, Muhammad Uzair Khattak, Muhammad Maaz, Salman Khan, and Fahad Shahbaz Khan. Fine-tuned clip models are efficient video learners. In *Proc. CVPR*, 2023. 2

[47] Manli Shu, Weili Nie, De-An Huang, Zhiding Yu, Tom Goldstein, Anima Anandkumar, and Chaowei Xiao. Test-time prompt tuning for zero-shot generalization in vision-language models. In *Proc. NeurIPS*, 2022. 4

[48] Chen Sun, Austin Myers, Carl Vondrick, Kevin Murphy, and Cordelia Schmid. VideoBERT: A joint model for video and language representation learning. In *Proc. CVPR*, 2019. 2

[49] Yi-Lin Sung, Jaemin Cho, and Mohit Bansal. Vl-adapter: Parameter-efficient transfer learning for vision-and-language tasks. In *Proc. CVPR*, 2022. 2

[50] Makarand Tapaswi, Yukun Zhu, Rainer Stiefelhagen, Antonio Torralba, Raquel Urtasun, and Sanja Fidler. MovieQA: Understanding stories in movies through question-answering. In *Proc. CVPR*, 2016. 2

[51] Alex Jinpeng Wang, Yixiao Ge, Rui Yan, Ge Yuying, Xudong Lin, Guanyu Cai, Jianping Wu, Ying Shan, Xiaohu Qie, and Mike Zheng Shou. All in one: Exploring unified video-language pre-training. In *Proc. CVPR*, 2023. 2

[52] Syed Talal Wasim, Muzammal Naseer, Salman Khan, Fahad Shahbaz Khan, and Mubarak Shah. Vita-CLIP: Video and text adaptive clip via multimodal prompting. In *Proc. CVPR*, 2023. 2

[53] Dejing Xu, Zhou Zhao, Jun Xiao, Fei Wu, Hanwang Zhang, Xiangnan He, and Yueting Zhuang. Video question answering via gradually refined attention over appearance and motion. In *Proc. ACM Multimedia*, 2017. 2, 4, 1

[54] Jun Xu, Tao Mei, Ting Yao, and Yong Rui. MSR-VTT: A large video description dataset for bridging video and language. In *Proc. CVPR*, 2016. 1

[55] Antoine Yang, Antoine Miech, Josef Sivic, Ivan Laptev, and Cordelia Schmid. Just ask: Learning to answer questions from millions of narrated videos. In *Proc. ICCV*, 2021. 2, 3, 4

[56] Antoine Yang, Antoine Miech, Josef Sivic, Ivan Laptev, and Cordelia Schmid. Learning to answer visual questions from web videos. *IEEE TPAMI*, 2022. 2, 3, 4

[57] Antoine Yang, Antoine Miech, Josef Sivic, Ivan Laptev, and Cordelia Schmid. Zero-shot video question answering via frozen bidirectional language models. In *Proc. NeurIPS*, 2022. 1, 2, 3, 4

[58] Zhou Yu, Dejing Xu, Jun Yu, Ting Yu, Zhou Zhao, Yueting Zhuang, and Dacheng Tao. Activitynet-QA: A dataset for understanding complex web videos via question answering. In *Proc. AAAI*, 2019. 2, 4, 1

[59] Rowan Zellers, Jiasen Lu, Ximing Lu, Youngjae Yu, Yanpeng Zhao, Mohammadreza Salehi, Aditya Kusupati, Jack Hessel, Ali Farhadi, and Yejin Choi. MERLOT Reserve: Neural script knowledge through vision and language and sound. In *Proc. CVPR*, 2022. 2, 4, 3

[60] Rowan Zellers, Ximing Lu, Jack Hessel, Youngjae Yu, Jae Sung Park, Jize Cao, Ali Farhadi, and Yejin Choi. MERLOT: Multimodal neural script knowledge models. In *Proc. NeurIPS*, 2021. 1, 2

[61] Kaiyang Zhou, Jingkang Yang, Chen Change Loy, and Ziwei Liu. Conditional prompt learning for vision-language models. In *Proc. CVPR*, 2022. 2

[62] Kaiyang Zhou, Jingkang Yang, Chen Change Loy, and Ziwei Liu. Learning to prompt for vision-language models. *IJCV*, 2022. 2

[63] Xizhou Zhu, Jinguo Zhu, Hao Li, Xiaoshi Wu, Hongsheng Li, Xiaohua Wang, and Jifeng Dai. Uni-perceiver: Pre-training unified architecture for generic perception for zero-shot and few-shot tasks. In *Proc. CVPR*, 2022. 2