

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



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Introduction

Motivation

Inspired by large-scale vision-language model advance-ments in video tasks through multimodal datasets

Challenges in adapting pretrained models for video-language tasks on limited data:

- ► Visual-language modality gap
- Overfitting and catastrophic forgetting

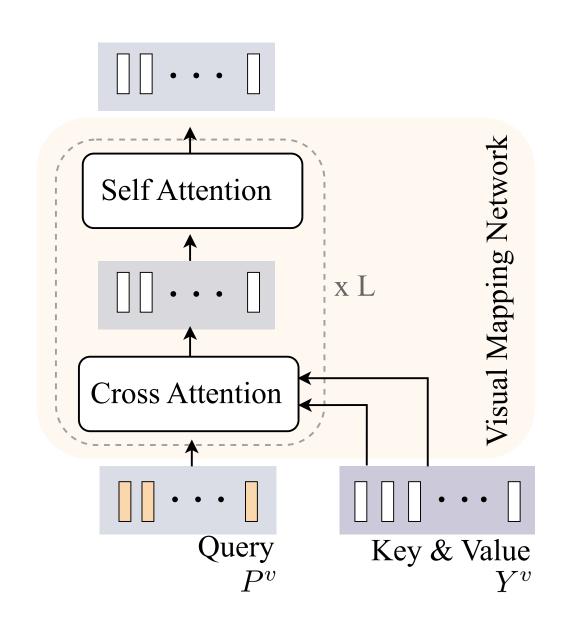
Recent Works

- ► Transformer-based mapping networks
- ► Parameter-efficient adaptation methods: prompt learning and adapters

Contributions

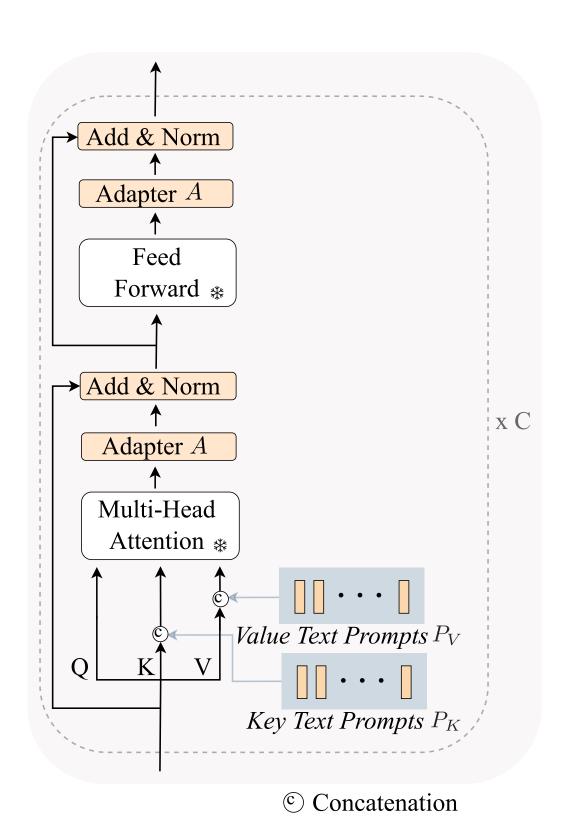
- ► Introducing multimodal prompt learning to VideoQA for the first time, reducing the number of stored and tuned parameters in few-shot setting
- ► Proposing a visual mapping network for VideoQA to summarize video input while facilitating temporal interaction
- ► Demonstrating **strong performance** across multiple VideoQA datasets in **zero-shot and few-shot** settings

VPN: Visual Mapping Network



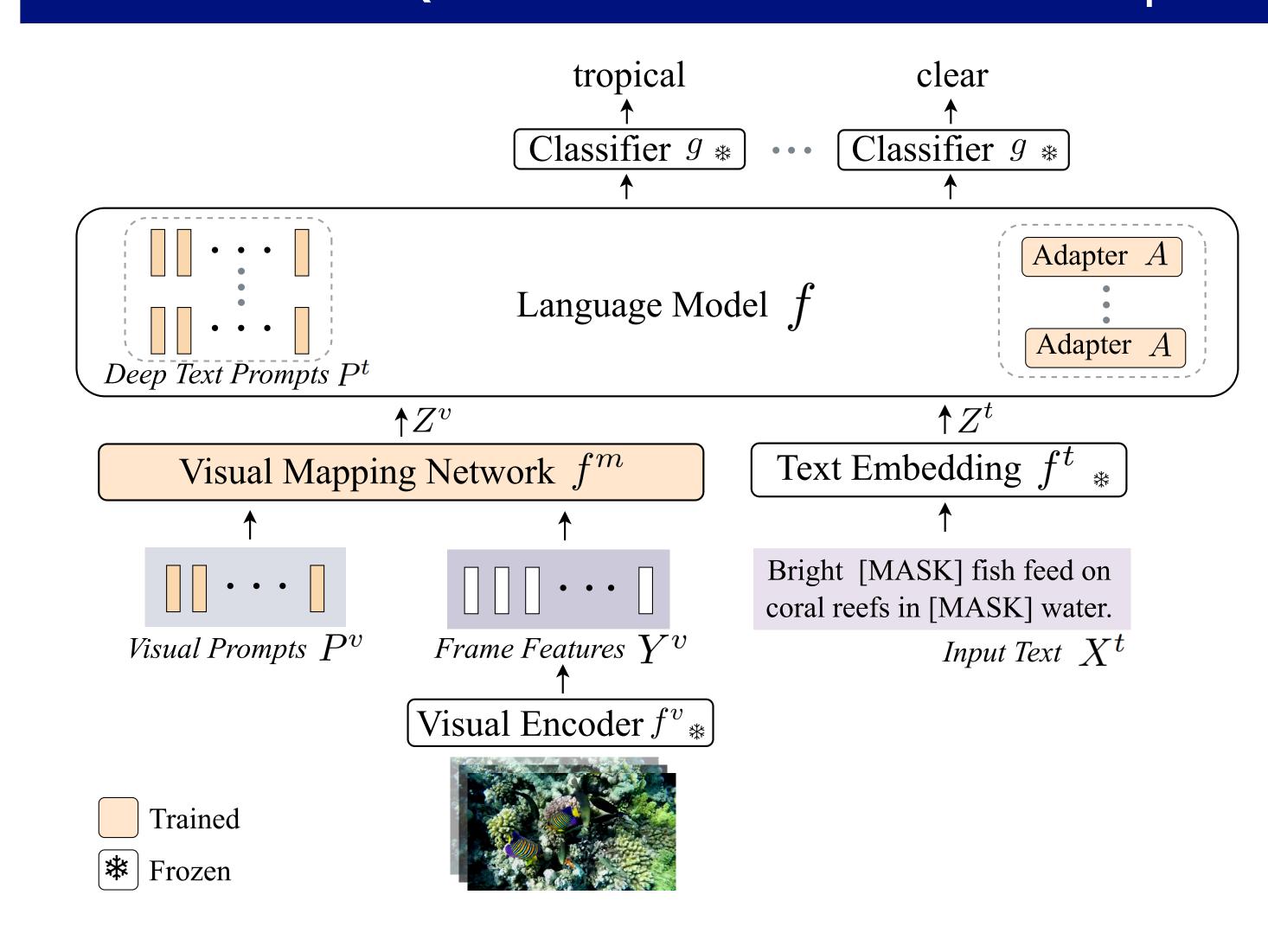
- ► VPN aligns frame features with text embeddings
- ► Learnable visual prompts represent video after iteratively interact with frame features

Language Model: Prompts and Adapters



- ► Learnable text prompts in the key and value of multi-head attention
- ► Adapter layer maps tokens to bottleneck dimension with residual connection

ViTiS: VideoQA with Multi-Modal Prompts



Zero-Shot VideoQA Results

► Pre-Training: All trainable parameters trained under MLM by keeping vision and language models frozen on WebVid2M

Method	Sub	#Tra Img	INING Vid	MSRVTT -QA	Msvd -QA	ANET -QA	TGIF -QA
CLIP [1]		400M	_	2.1	7.2	1.2	3.6
RESERVE [2]	\checkmark	_	20M	5.8	_	_	_
LAVENDER [3]		3M	2.5M	4.5	11.6	_	16.7
Flamingo [4]		2.3B	27M	17.4	35.6	_	_
FrozenBiLM [1]	\checkmark	_	10M	16.7	33.8	25.9	41.9
ViTiS (Ours)	\checkmark	_	2.5M	18.1	36.1	25.5	45.5

Few-Shot VideoQA Results

- ► Few-Shot Fine-tuning: 1% of training data [1]
 - ATP: Fine-tune all trainable parameters (8% of total)
 - Prompts: Fine-tune only prompts (0.06% of total)

Method	Trained : Modules	#Trained Params				
FrozenBiLM [1]	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

References

- 1. A. Yang, et al., Zero-shot video question answering via frozen bidirectional language models. In *NeurIPS*, 2022.
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- 3. L. Li, et al., Lavender: Unifying video-language understanding as masked language modeling. In CVPR, 2023.
- 4. J. Alayrac, et al., Flamingo: a visual language model for few-shot learning. In NeurIPS, 2022.