

# VoP: Text-Video Co-operative Prompt Tuning for Cross-Modal Retrieval

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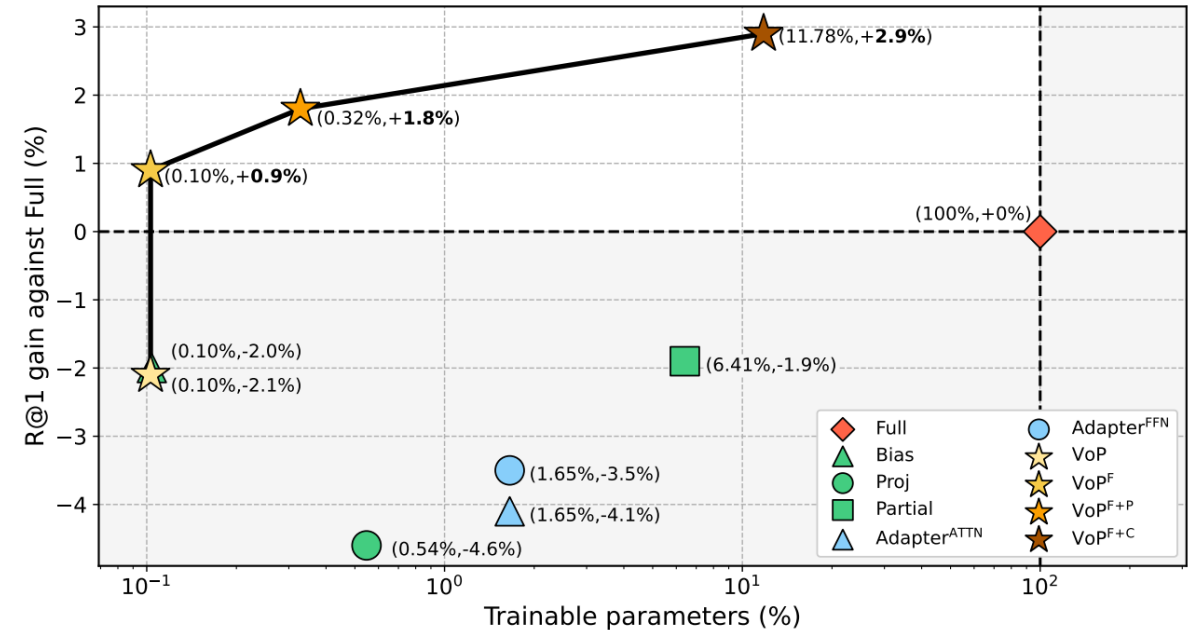
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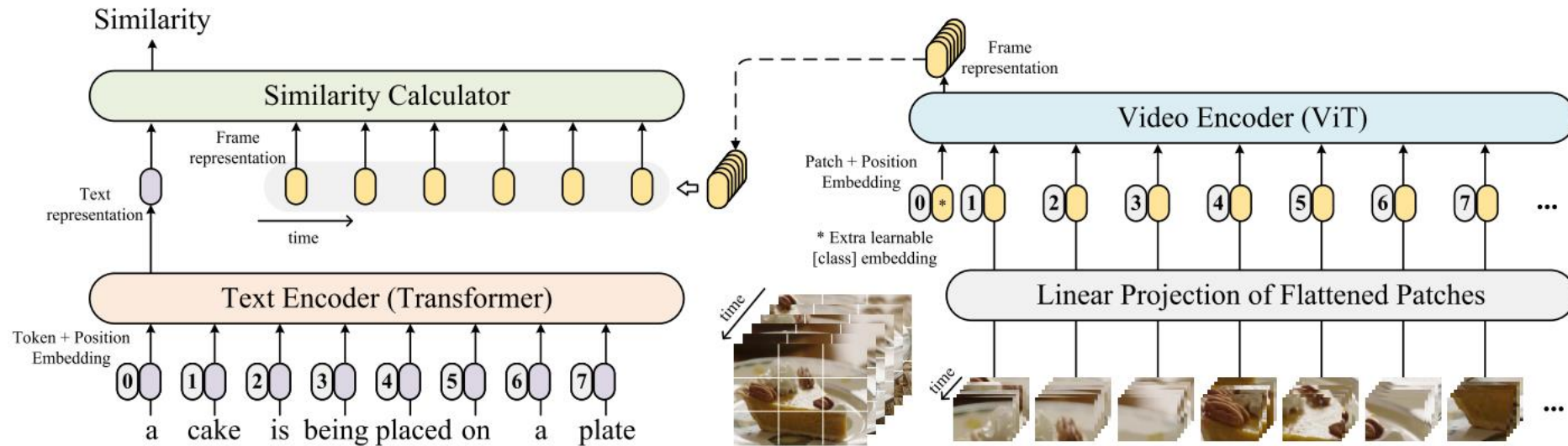
TUE-PM-233

# Summary of Highlights

- **VoP**, a powerful parameter-efficient fine-tuning baseline for text-video retrieval with only **0.1%** trainable parameters.
- **Three novel video prompts**, improving VoP by excavating temporal information in a plug-and-play manner.
- Exceeding full fine-tuning by up to 2.9% with  $6\times$  less parameter overhead (R@1 on MSR-VTT-9k).



# Background

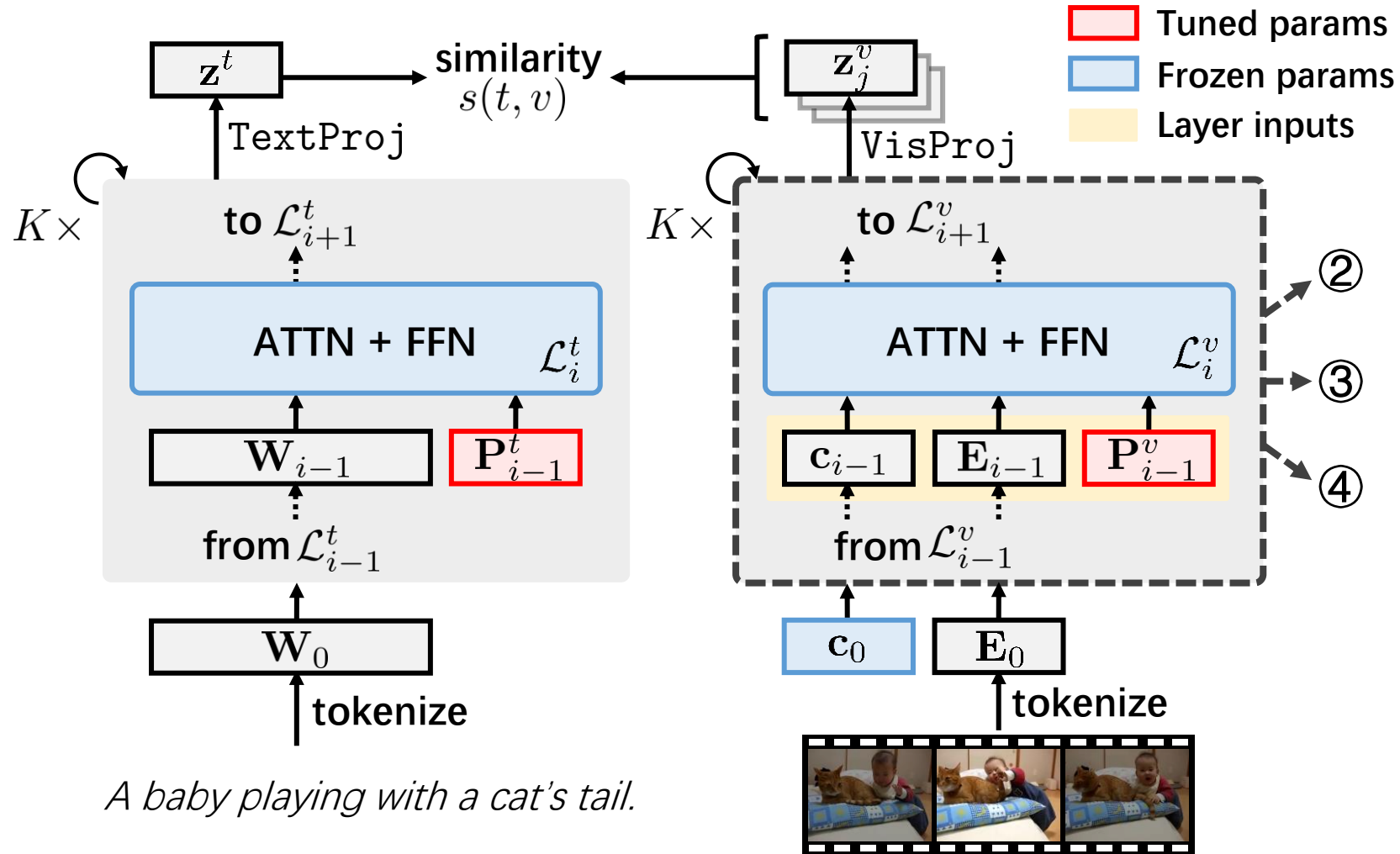


Adapting CLIP to video domains via full fine-tuning [1]

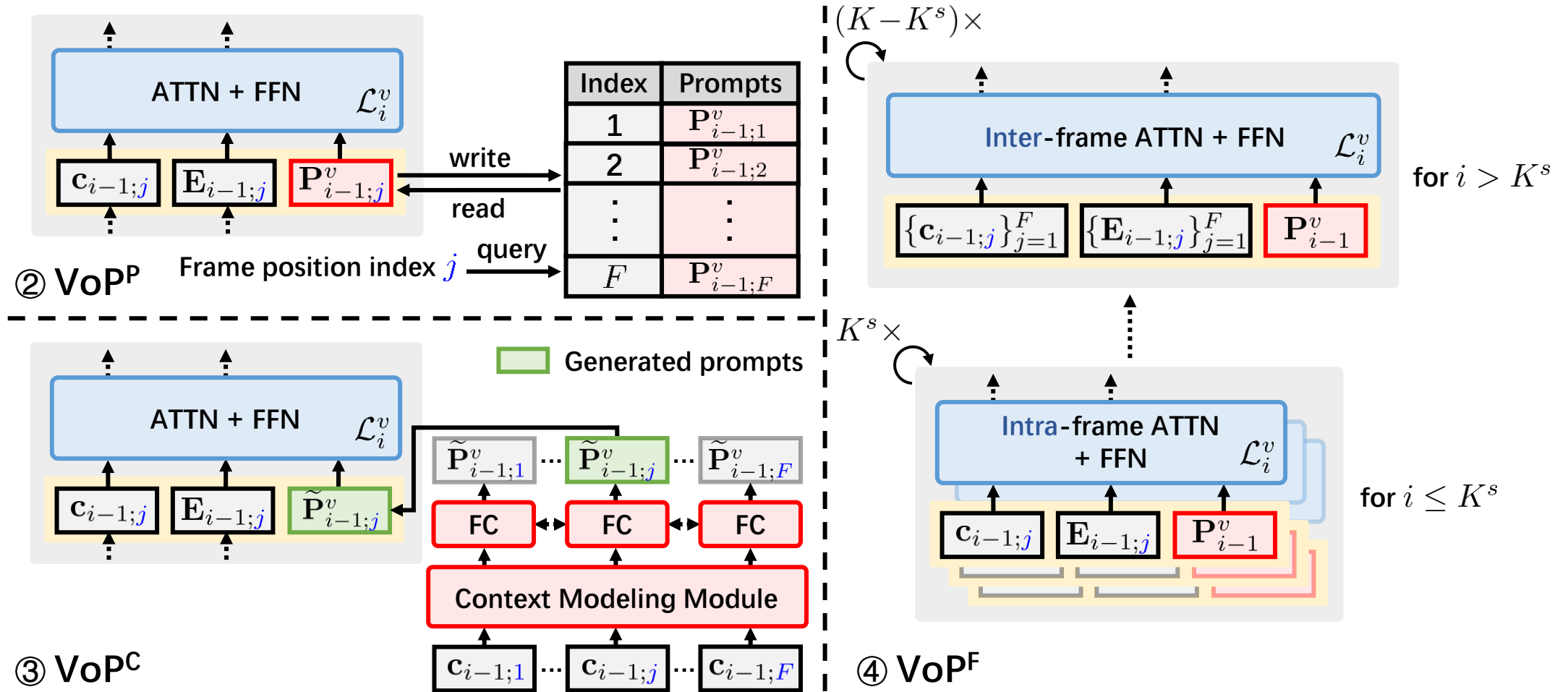
## Challenges of full fine-tuning:

- Risk of overfitting.
- Unaffordable storage overhead.

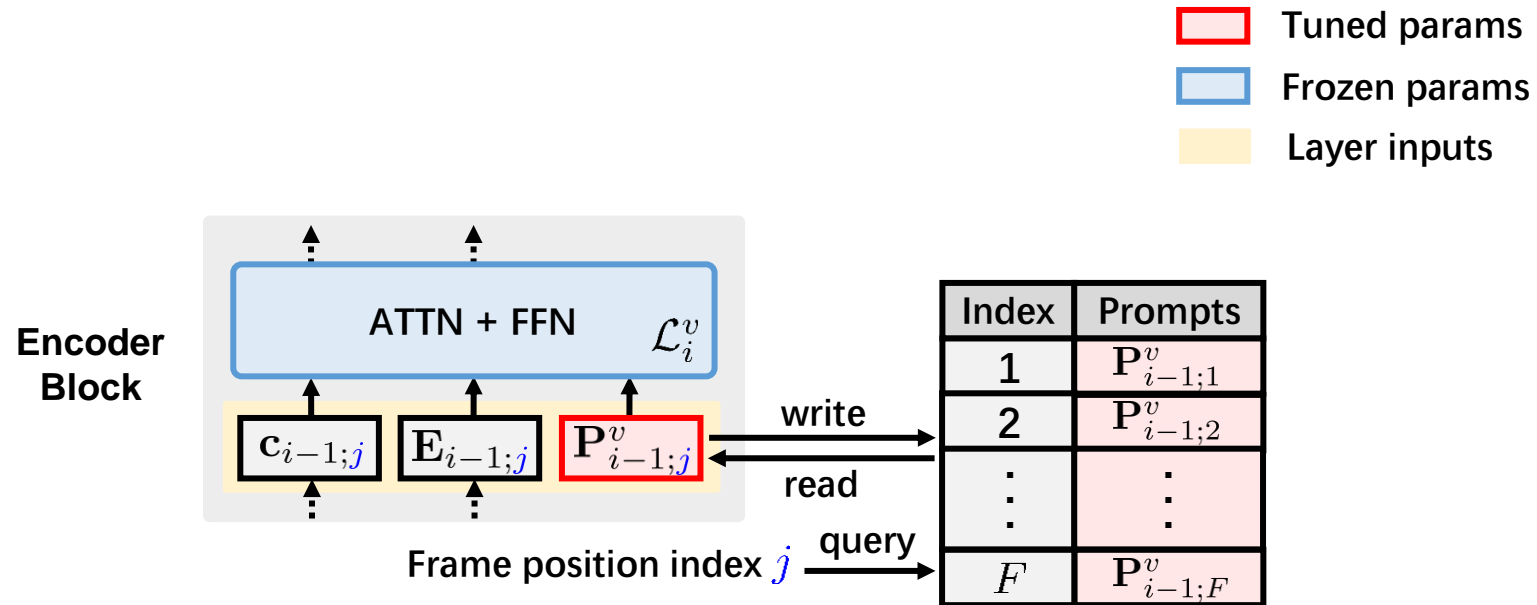
# Text-Video Co-operative Prompt Tuning (VoP)



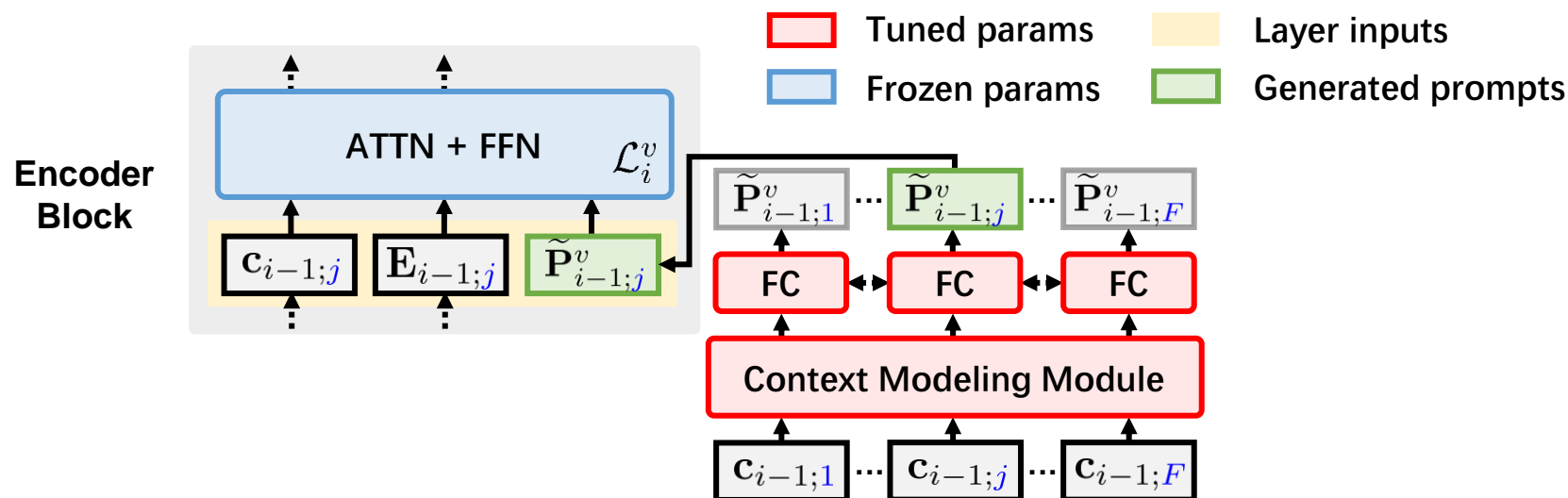
# VoP with Video-specific Prompts



# Position-specific Video Prompts

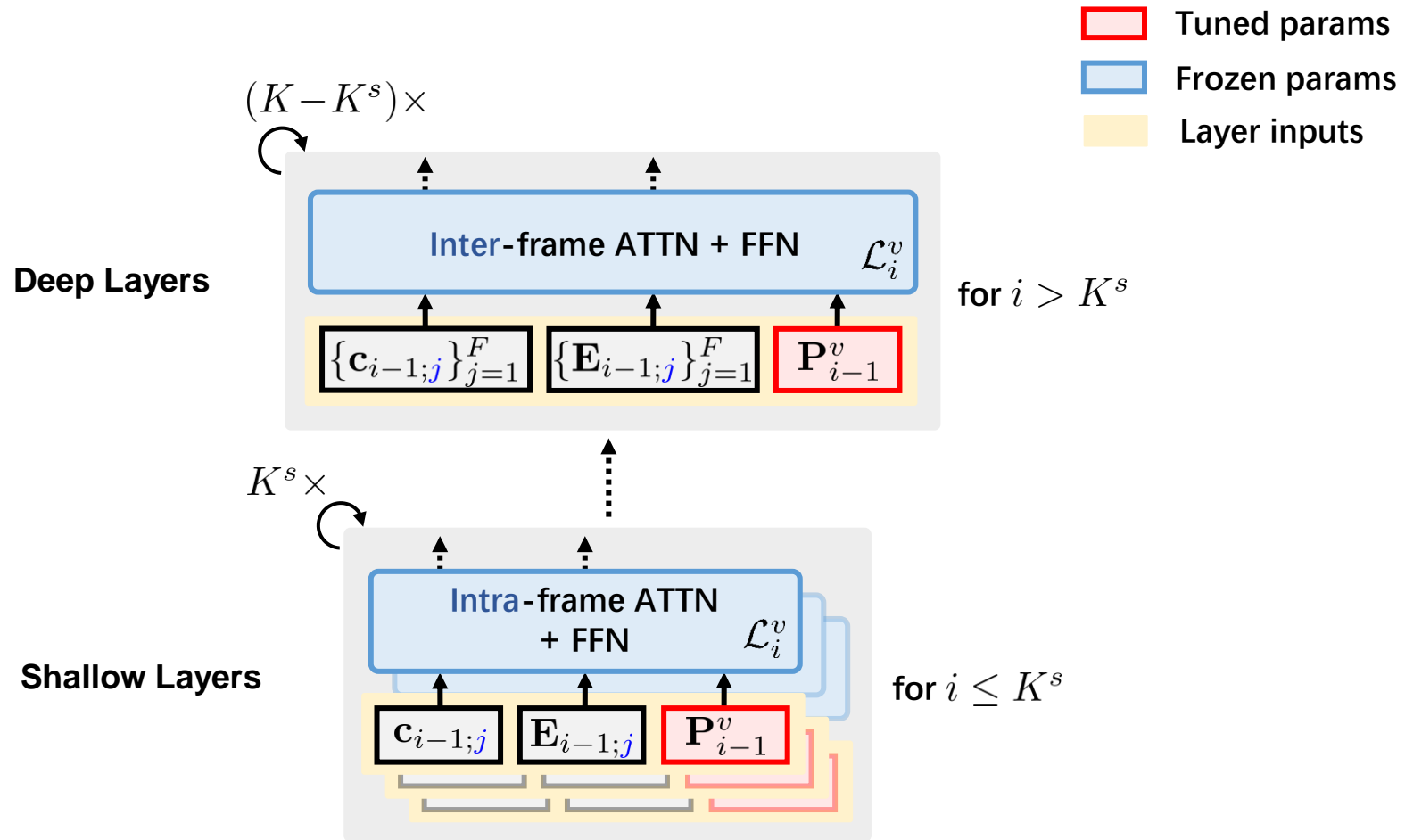


# Context-specific Video Prompts



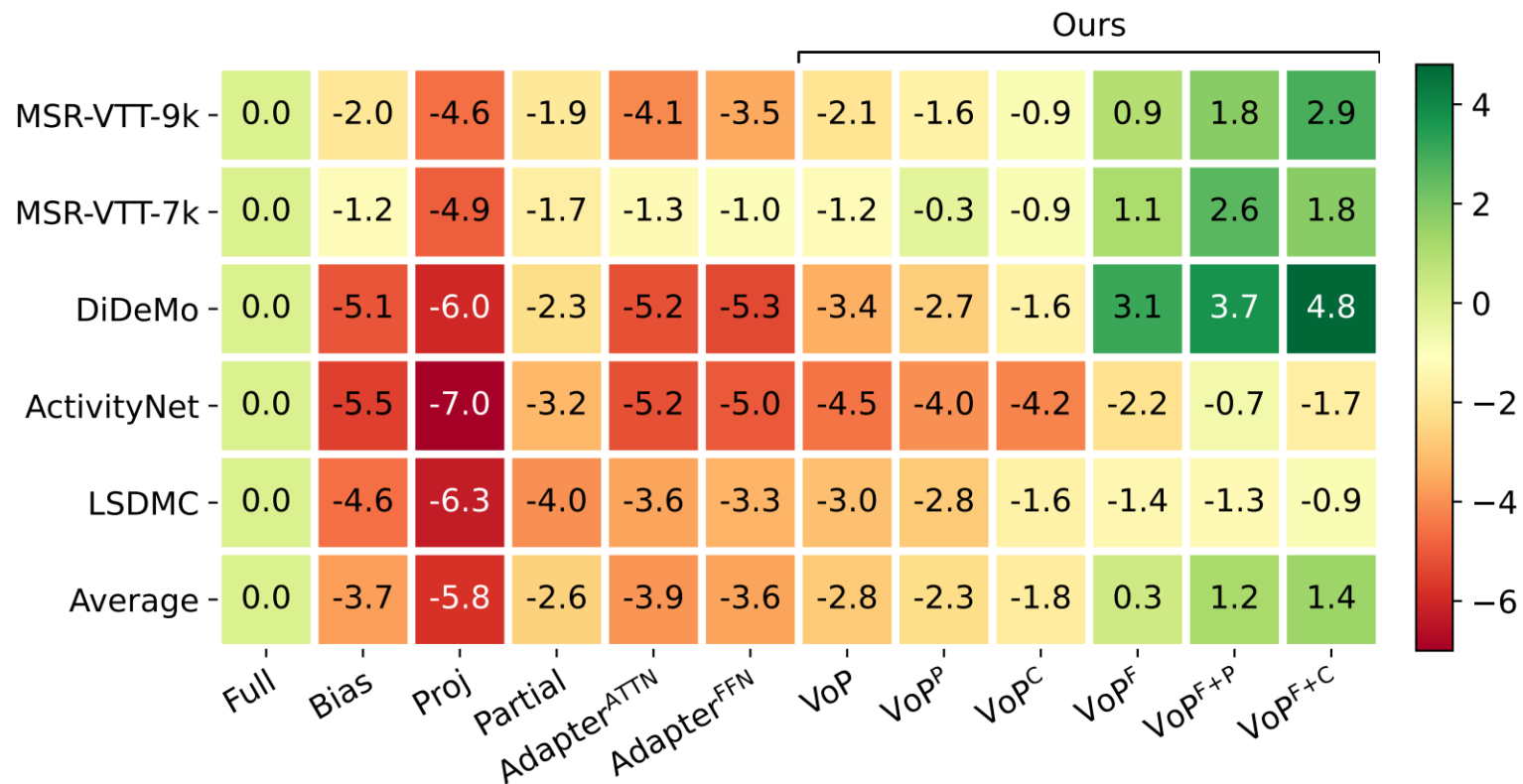
Choice of CMM	MSR-VTT-9k			MSR-VTT-7k			DiDeMo			ActivityNet			LSMDC		
	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10
Transformer	40.1	68.2	78.8	39.5	68.2	78.1	<b>40.4</b>	67.3	77.3	32.0	61.5	74.9	20.3	39.5	47.8
LSTM	40.6	<b>69.5</b>	<b>79.7</b>	39.5	<b>69.3</b>	78.0	38.6	66.7	77.0	32.4	62.0	75.4	19.6	38.2	47.7
BiLSTM	<b>40.8</b>	68.1	79.0	<b>40.0</b>	67.3	<b>78.2</b>	40.0	<b>68.0</b>	<b>78.5</b>	<b>32.6</b>	<b>62.5</b>	<b>76.5</b>	<b>20.4</b>	<b>40.0</b>	<b>48.1</b>

# Function-specific Video Prompts



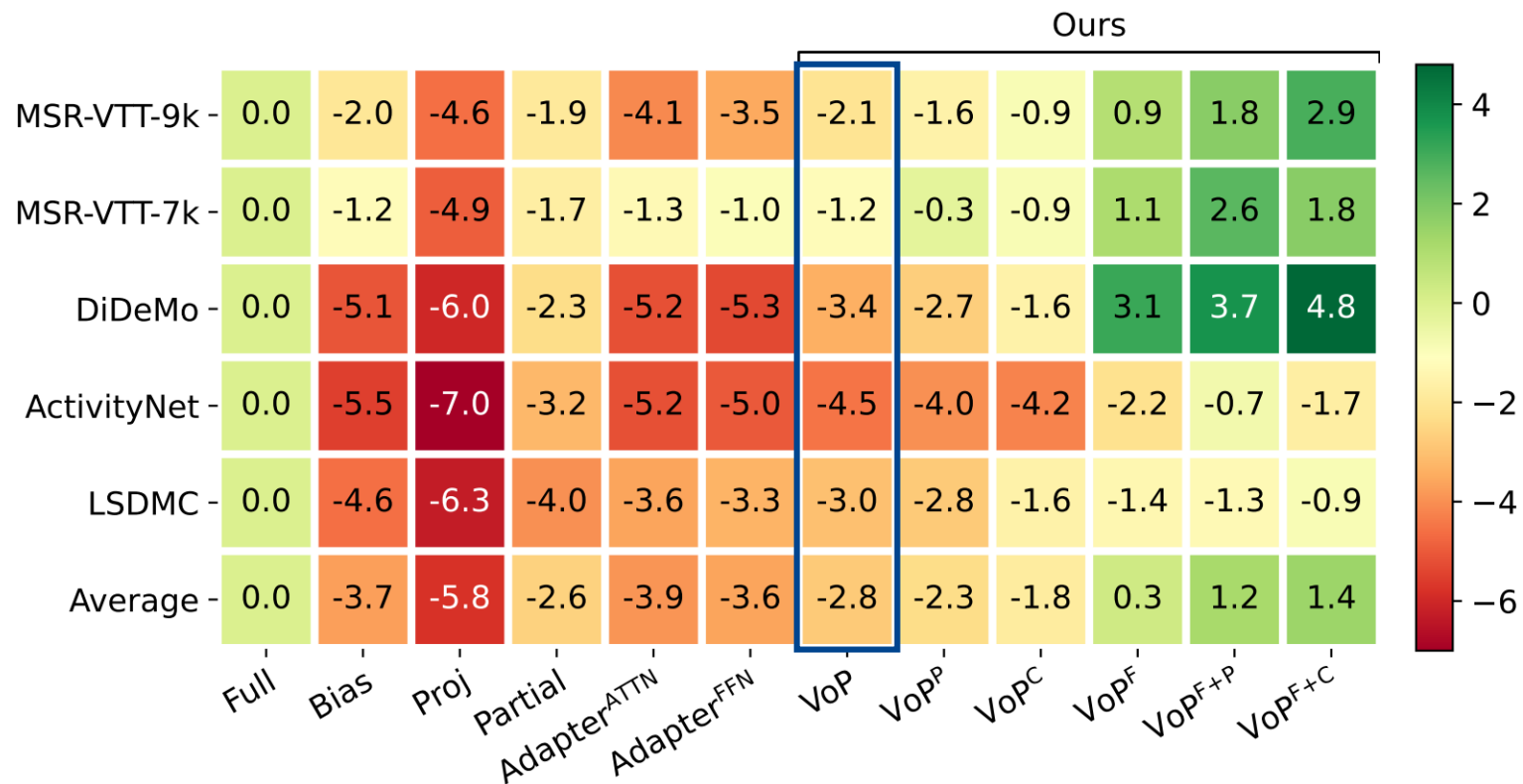


# Main Results



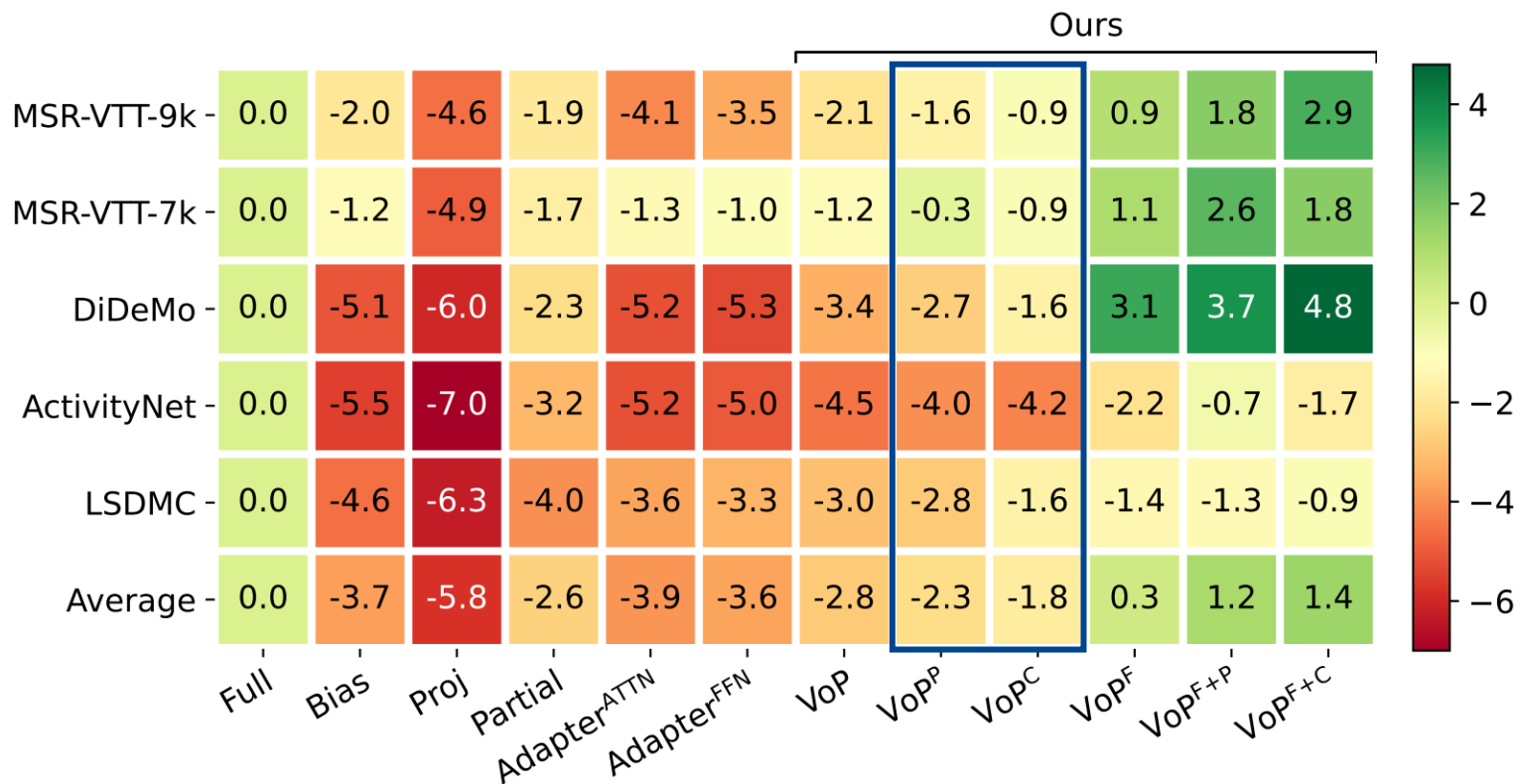
Text-to-video R@1 gains of all methods in comparison against full fine-tuning

# Main Results



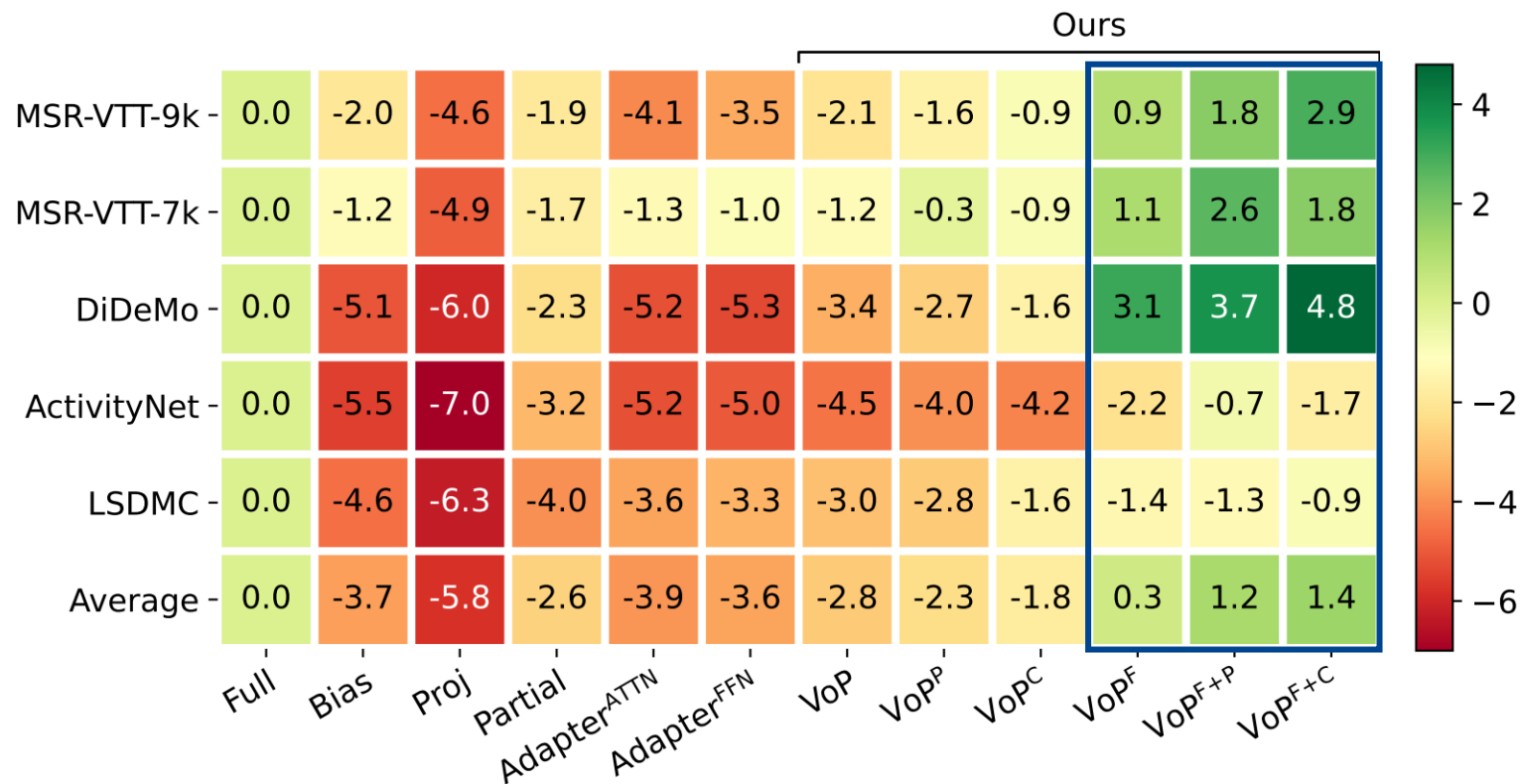
Text-to-video R@1 gains of all methods in comparison against full fine-tuning

# Main Results



Text-to-video R@1 gains of all methods in comparison against full fine-tuning

# Main Results



Text-to-video R@1 gains of all methods in comparison against full fine-tuning

# Main Results: MSR-VTT-9k

Methods	Params (M)	<i>t2v</i>					<i>v2t</i>				
		R@1	R@5	R@10	MnR↓	MdR↓	R@1	R@5	R@10	MnR↓	MdR↓
Full	119.8 (100%)	41.7	69.2	79.0	16.5	2.0	42.5	<u>70.9</u>	<b>81.4</b>	<b>11.0</b>	2.0
Bias [6]	0.1 (0.104%)	39.7	66.5	77.3	17.3	2.0	41.1	<u>68.4</u>	79.2	13.6	2.0
Proj [17]	0.7 (0.547%)	37.1	63.0	76.1	20.5	3.0	37.2	64.6	75.9	16.7	3.0
Partial [17]	7.7 (6.410%)	39.8	65.3	75.9	19.3	2.0	37.9	66.1	77.4	15.5	3.0
Adapter <sup>ATTN</sup> [12]	2.0 (1.655%)	37.6	63.2	75.8	18.7	3.0	39.6	66.5	76.8	14.7	2.0
Adapter <sup>FFN</sup> [7]	2.0 (1.655%)	38.2	63.5	76.4	17.9	3.0	39.9	66.8	77.7	14.2	2.0
<b>VoP</b>	0.1 (0.103%)	39.6	66.7	77.8	17.2	2.0	42.1	68.8	80.7	12.4	2.0
<b>VoP<sup>P</sup></b>	0.5 (0.441%)	40.1	65.7	77.7	16.9	2.0	42.5	70.0	79.9	12.4	2.0
<b>VoP<sup>C</sup></b>	14.3 (11.898%)	40.8	68.1	79.0	<u>15.8</u>	2.0	42.3	70.1	81.1	<u>11.4</u>	2.0
<b>VoP<sup>F</sup></b>	0.1 (0.103%)	42.6	68.4	78.7	<u>15.8</u>	2.0	42.4	70.5	81.0	<b>11.0</b>	2.0
<b>VoP<sup>F+P</sup></b>	0.4 (0.328%)	<u>43.5</u>	<u>69.3</u>	<u>79.3</u>	<b>14.8</b>	2.0	<u>43.6</u>	<b>71.2</b>	<u>81.2</u>	<b>11.0</b>	2.0
<b>VoP<sup>F+C</sup></b>	14.1 (11.785%)	<b>44.6</b>	<b>69.9</b>	<b>80.3</b>	16.3	2.0	<b>44.5</b>	70.7	80.6	11.5	2.0

# Main Results: MSR-VTT-7k

Methods	Params (M)	<i>t2v</i>					<i>v2t</i>				
		R@1	R@5	R@10	MnR↓	MdR↓	R@1	R@5	R@10	MnR↓	MdR↓
Full	119.8 (100%)	40.9	67.9	78.4	18.3	2.0	41.7	<u>69.6</u>	79.7	12.7	2.0
Bias [6]	0.1 (0.104%)	39.7	65.9	76.7	17.9	2.0	41.2	<u>66.6</u>	78.9	14.0	2.0
Proj [17]	0.7 (0.547%)	36.0	63.6	74.6	21.4	3.0	36.9	63.6	74.6	17.8	3.0
Partial [17]	7.7 (6.410%)	39.2	64.0	74.7	20.9	3.0	37.7	63.6	74.9	16.9	3.0
Adapter <sup>ATTN</sup> [12]	2.0 (1.655%)	39.6	65.4	76.8	16.8	2.0	41.6	67.6	79.8	12.4	2.0
Adapter <sup>FFN</sup> [7]	2.0 (1.655%)	39.9	65.3	76.9	16.8	2.0	41.6	67.6	79.2	12.7	2.0
<b>VoP</b>	0.1 (0.103%)	39.7	66.7	77.9	16.7	2.0	41.4	68.8	<b>80.8</b>	12.5	2.0
<b>VoP<sup>P</sup></b>	0.5 (0.441%)	40.6	66.0	76.7	16.6	2.0	41.6	69.0	79.5	12.3	2.0
<b>VoP<sup>C</sup></b>	14.3 (11.898%)	40.0	67.3	78.2	17.0	2.0	41.7	69.4	79.1	12.3	2.0
<b>VoP<sup>F</sup></b>	0.1 (0.103%)	42.0	67.4	78.2	16.2	2.0	42.8	68.4	79.8	12.3	2.0
<b>VoP<sup>F+P</sup></b>	0.4 (0.328%)	<b>43.5</b>	<u>68.1</u>	<u>79.2</u>	<u>16.0</u>	2.0	<u>43.4</u>	<b>71.0</b>	<u>80.4</u>	<b>11.3</b>	2.0
<b>VoP<sup>F+C</sup></b>	14.1 (11.785%)	<u>42.7</u>	<b>68.2</b>	<b>79.3</b>	<b>15.9</b>	2.0	<b>44.2</b>	<u>69.6</u>	<b>80.8</b>	<u>11.4</u>	2.0

# Main Results: DiDeMo

Methods	Params (M)	<i>t2v</i>					<i>v2t</i>				
		R@1	R@5	R@10	MnR↓	MdR↓	R@1	R@5	R@10	MnR↓	MdR↓
Full	119.8 (100%)	41.6	68.4	78.2	17.7	2.0	40.2	68.4	78.7	11.9	2.0
Bias [6]	0.1 (0.104%)	36.5	63.4	75.2	24.8	3.0	36.8	65.7	75.8	15.1	2.0
Proj [17]	0.7 (0.547%)	35.6	61.3	72.6	24.4	3.0	34.5	60.9	72.6	18.8	3.0
Partial [17]	7.7 (6.410%)	39.3	65.5	75.7	22.3	2.0	36.9	64.2	74.5	17.0	2.0
Adapter <sup>ATTN</sup> [12]	2.0 (1.655%)	36.4	62.8	73.9	23.5	3.0	36.3	64.4	74.8	15.4	2.0
Adapter <sup>FFN</sup> [7]	2.0 (1.655%)	36.3	63.4	75.4	22.9	3.0	35.6	64.3	75.6	14.8	3.0
<b>VoP</b>	0.1 (0.103%)	38.2	66.9	76.1	19.8	2.0	38.1	65.7	76.5	13.5	2.0
<b>VoP<sup>P</sup></b>	0.5 (0.441%)	38.9	67.7	78.1	17.2	2.0	40.6	68.3	78.6	11.6	2.0
<b>VoP<sup>C</sup></b>	14.3 (11.898%)	40.0	68.0	78.5	18.3	2.0	39.1	65.3	76.7	13.8	3.0
<b>VoP<sup>F</sup></b>	0.1 (0.103%)	44.7	70.8	79.7	15.7	2.0	43.5	70.9	<u>81.4</u>	<u>9.8</u>	2.0
<b>VoP<sup>F+P</sup></b>	0.4 (0.328%)	<u>45.3</u>	<b>72.3</b>	<u>80.4</u>	<u>13.8</u>	2.0	<b>44.7</b>	<u>71.2</u>	81.1	9.9	2.0
<b>VoP<sup>F+C</sup></b>	14.1 (11.785%)	<b>46.4</b>	<u>71.9</u>	<b>81.5</b>	<b>13.6</b>	2.0	<u>44.4</u>	<b>71.8</b>	<b>81.8</b>	<b>9.5</b>	2.0

# Main Results: ActivityNet

Methods	Params (M)	<i>t2v</i>					<i>v2t</i>				
		R@1	R@5	R@10	MnR↓	MdR↓	R@1	R@5	R@10	MnR↓	MdR↓
Full	119.8 (100%)	<b>36.8</b>	<b>66.9</b>	<b>80.1</b>	<b>9.3</b>	3.0	<b>38.9</b>	<b>70.1</b>	<b>81.9</b>	<b>8.4</b>	2.0
Bias [6]	0.1 (0.104%)	31.3	60.3	74.2	13.4	3.0	33.7	63.8	77.6	11.4	3.0
Proj [17]	0.7 (0.547%)	29.8	59.1	73.3	14.2	4.0	31.1	60.6	74.6	13.1	3.0
Partial [17]	7.7 (6.410%)	33.6	64.0	77.8	<u>10.6</u>	3.0	33.4	64.6	77.8	10.2	3.0
Adapter <sup>ATTN</sup> [12]	2.0 (1.655%)	31.6	60.5	74.4	13.1	3.0	33.3	63.6	77.1	11.3	3.0
Adapter <sup>FFN</sup> [7]	2.0 (1.655%)	31.8	61.0	75.0	12.8	3.0	33.6	63.9	77.3	11.1	3.0
<b>VoP</b>	0.1 (0.103%)	32.3	61.9	75.5	12.4	3.0	33.7	64.7	77.2	11.1	3.0
<b>VoP<sup>P</sup></b>	0.5 (0.441%)	32.8	62.3	75.4	12.3	3.0	34.8	65.0	78.2	10.7	3.0
<b>VoP<sup>C</sup></b>	14.3 (11.898%)	32.6	62.5	76.5	12.0	3.0	34.2	64.8	78.4	10.7	3.0
<b>VoP<sup>F</sup></b>	0.1 (0.103%)	34.6	62.6	76.4	11.6	3.0	35.5	65.1	77.4	10.2	3.0
<b>VoP<sup>F+P</sup></b>	0.4 (0.328%)	<u>36.1</u>	<u>65.5</u>	<u>78.5</u>	10.9	3.0	<u>36.3</u>	<u>65.9</u>	<u>79.2</u>	<u>10.1</u>	3.0
<b>VoP<sup>F+C</sup></b>	14.1 (11.785%)	35.1	63.7	77.6	11.4	3.0	35.6	<u>65.9</u>	77.8	10.4	3.0



# Main Results: LSMDC

Methods	Params (M)	$t2v$					$v2t$				
		R@1	R@5	R@10	MnR↓	MdR↓	R@1	R@5	R@10	MnR↓	MdR↓
Full	119.8 (100%)	<b>22.0</b>	39.9	<b>49.9</b>	<b>56.8</b>	11.0	<u>21.9</u>	40.0	48.2	<b>50.7</b>	12.0
Bias [6]	0.1 (0.104%)	17.4	36.2	44.9	73.2	14.0	<u>18.0</u>	36.0	44.9	62.2	15.0
Proj [17]	0.7 (0.547%)	15.7	32.7	40.8	83.7	20.0	17.1	32.6	39.9	76.4	21.0
Partial [17]	7.7 (6.410%)	18.0	33.8	41.8	79.9	18.0	15.9	33.2	41.5	72.3	18.0
Adapter <sup>ATTN</sup> [12]	2.0 (1.655%)	18.4	38.0	46.4	68.9	13.0	19.7	37.6	46.3	55.4	13.0
Adapter <sup>FFN</sup> [7]	2.0 (1.655%)	18.7	38.9	47.3	63.6	13.0	19.8	38.4	47.0	57.8	12.0
Ju <i>et al.</i> [18] †	4.8 (3.990%)	18.8	38.5	47.9	-	12.3	-	-	-	-	-
<b>VoP</b>	0.1 (0.103%)	19.0	37.9	46.5	66.9	14.0	18.5	36.1	45.3	59.5	14.0
<b>VoP<sup>P</sup></b>	0.5 (0.441%)	19.2	38.3	47.3	64.4	12.0	19.7	38.9	48.1	55.4	12.0
<b>VoP<sup>C</sup></b>	14.3 (11.898%)	20.4	40.0	48.1	65.9	12.0	20.3	38.7	48.5	56.9	11.0
<b>VoP<sup>F</sup></b>	0.1 (0.103%)	20.6	39.5	49.1	60.3	11.0	21.2	39.4	<u>49.2</u>	52.3	11.0
<b>VoP<sup>F+P</sup></b>	0.4 (0.328%)	20.7	<u>40.7</u>	<u>49.7</u>	<u>59.1</u>	11.0	21.5	<b>40.6</b>	<b>50.7</b>	<u>50.8</u>	10.0
<b>VoP<sup>F+C</sup></b>	14.1 (11.785%)	<u>21.1</u>	<b>40.9</b>	49.6	60.1	11.0	<b>22.3</b>	<u>40.3</u>	<b>50.7</b>	51.1	10.0

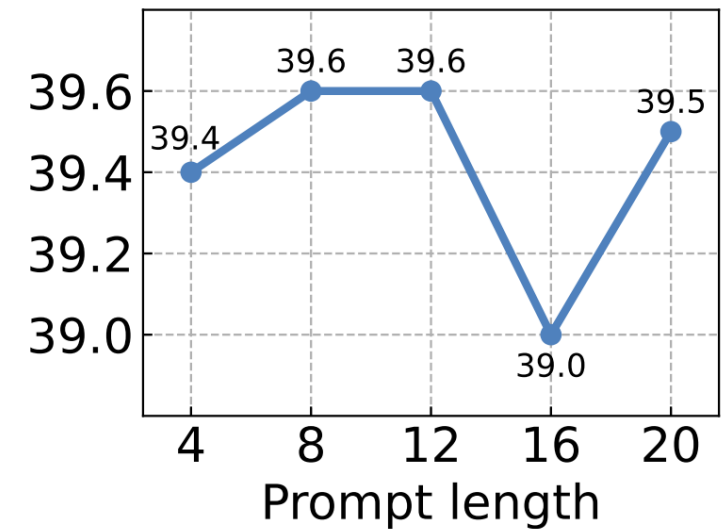
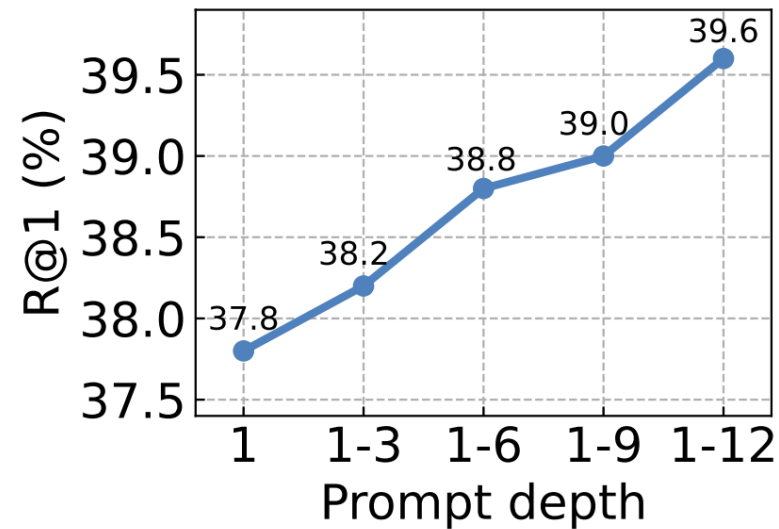
# Ablation Study

Textual	Visual	R@1	R@5	R@10	MnR↓	MdR↓
		31.5	52.8	63.6	42.9	5.0
	✓	36.5	62.7	75.1	18.3	3.0
✓		36.3	63.4	75.0	20.3	3.0
✓	✓	<b>39.6</b>	<b>66.7</b>	<b>77.8</b>	<b>17.2</b>	<b>2.0</b>

**Prompting both encoders (i.e. VoP) > Uni-modal prompts > applying CLIP without tuning**

# Ablation Study

1. Inserting prompts into **every layer** of both encoders contributes to the best results.
2. Using **only 8 prompt tokens** remains a competitive performance with parameter efficiency.



# Qualitative Results

The water safety teams arrives with the safety devices and water bike to save a person who had been drifted away.

Partial



Full  
 VoP  
 VoP<sup>F+C</sup>



Someone looking at a Japanese book.

Full



Partial  
 VoP  
 VoP<sup>F+C</sup>



A man looks up towards a cathedral's organ pipes and talks to a priest in a confessional.

Partial  
 VoP



Full  
 VoP<sup>F+C</sup>



A baby playing with a cat's tail.

Full  
 Partial  
 VoP



VoP<sup>F+C</sup>



Figure 7. **Qualitative results of four tuning methods: Full, Partial, VoP and VoP<sup>F+C</sup>.** Given the query text, we represent the rank-1 retrieval result of each method, which can be **incorrect** (each first row) or **ground truth** (each second row).

# Thank you for listening!

## VoP: Text-Video Co-operative Prompt Tuning for Cross-Modal Retrieval

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arXiv



Project page



Github