Text-Visual Prompting for Efficient 2D Temporal Video Grounding

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→ **Output**: Starting and ending points of the target segment

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[Existing Works]

- Two-Stage “propose-and-rank” (Proposal-based)
- Regression-based (Proposal-free)
- Reinforcement learning-based

2. Temporal Video Grounding (TVG) Method Comparison

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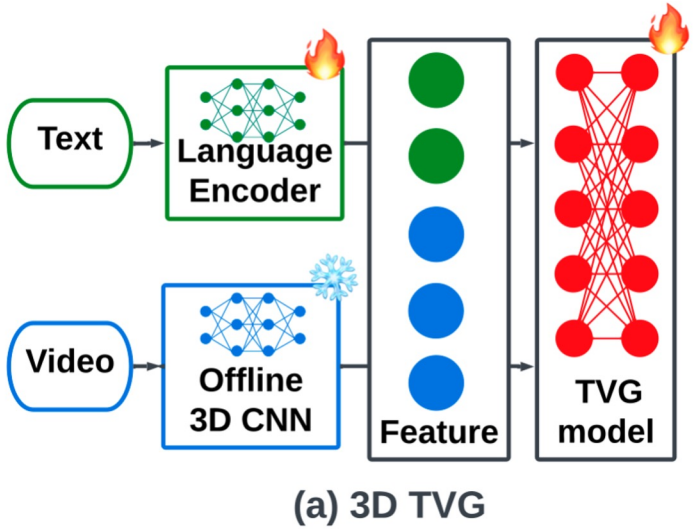
Trainable Modules | Frozen Modules | Performance Booster



(a) 3D TVG

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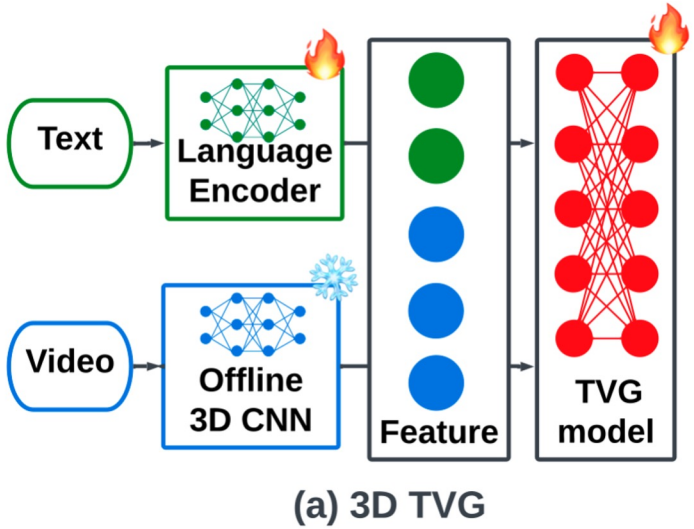

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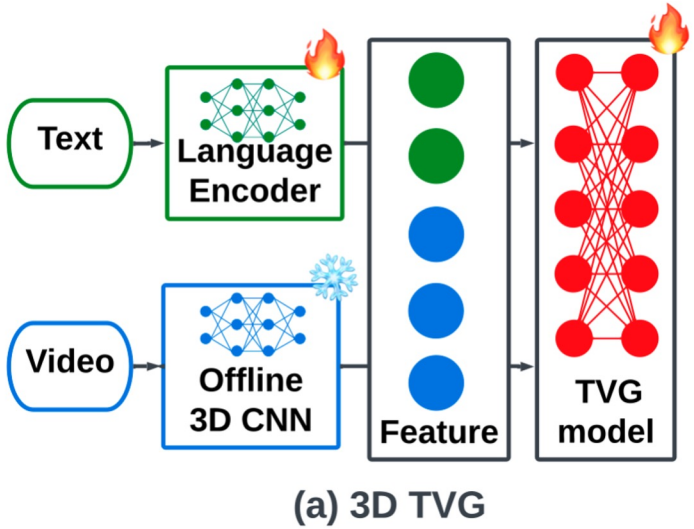

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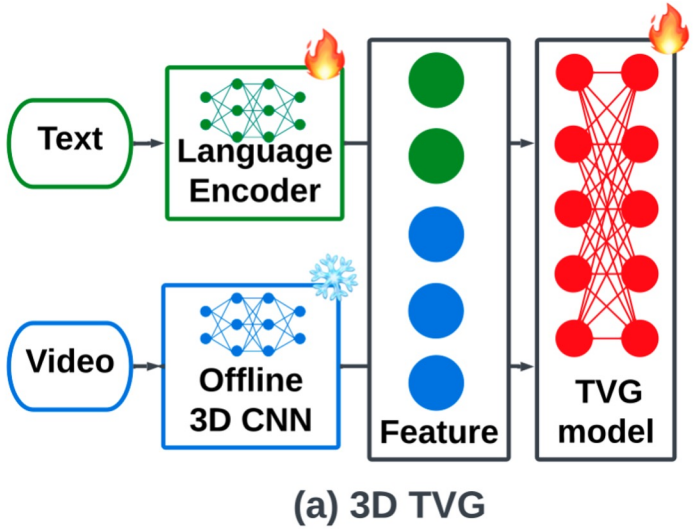

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- It is challenging to train 3D-CNNs, which is why most methods **do not involve 3D-CNNs during training** and **directly utilize the video features** extracted by offline 3D-CNNs as the video input.

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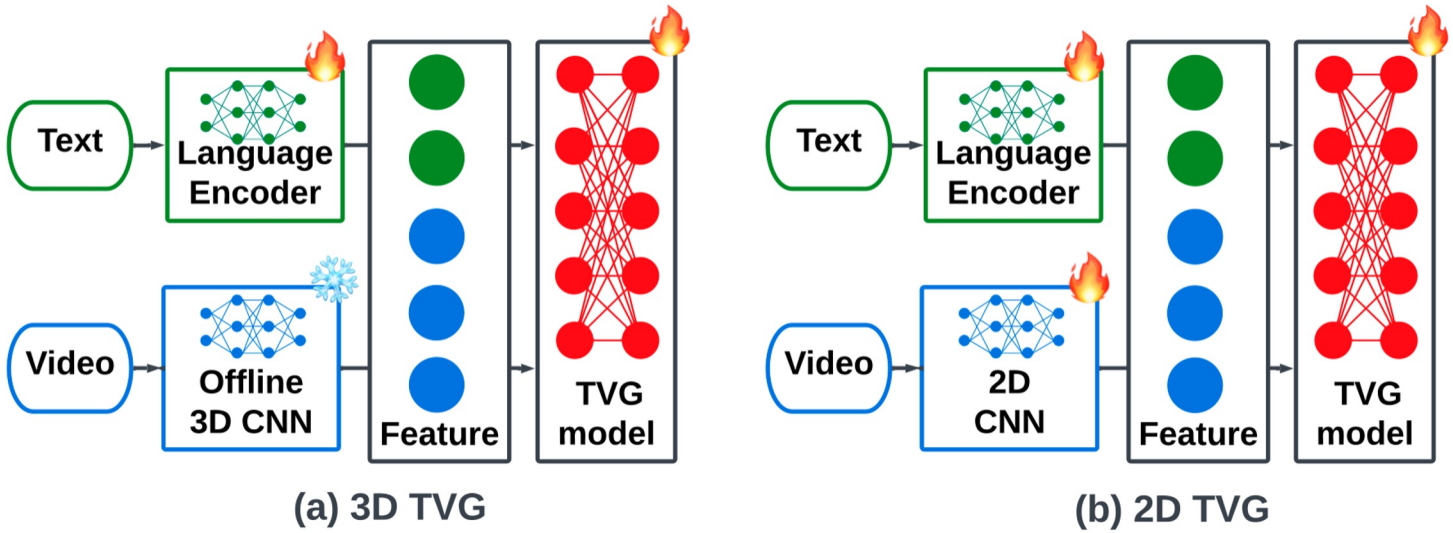

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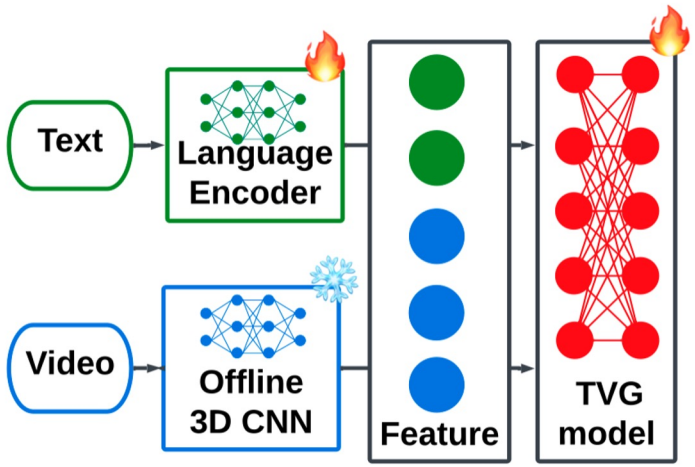

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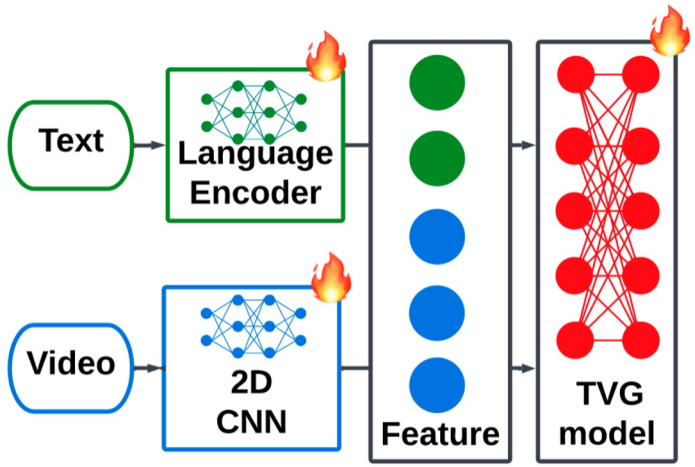

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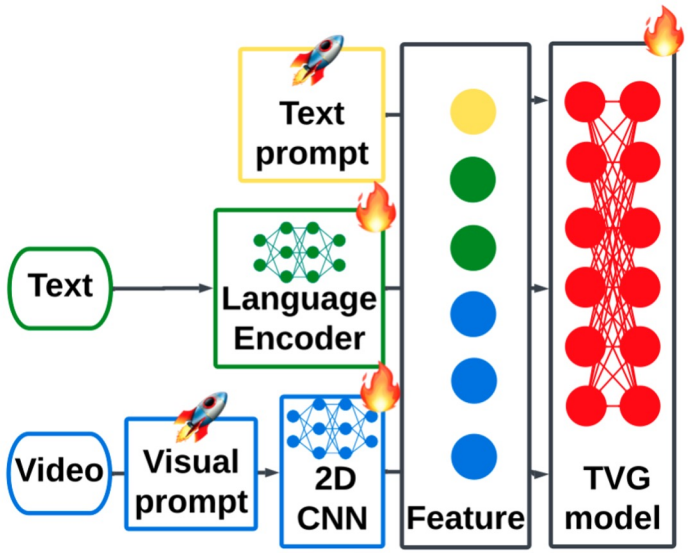

(c) TVP-based 2D TVG (Ours)

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a) 2D TVG

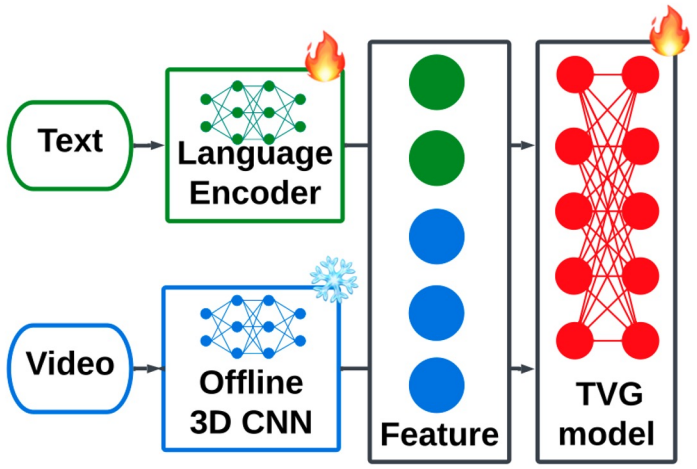
- Using 2D CNN as the video encoder.

a) TVP-Based 2D TVG

- The proposed **text-visual prompts (TVP)** compensate for the lack of spatiotemporal information in 2D CNNs for visual feature extraction.

2. Temporal Video Grounding (TVG) Method Comparison

Trainable Modules | Frozen Modules | Performance Booster



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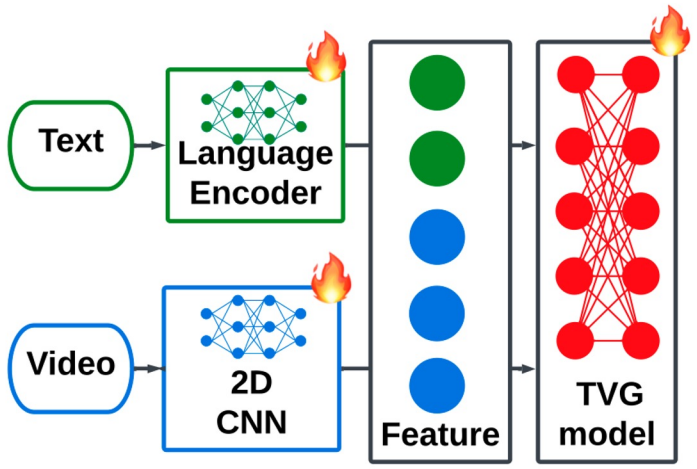

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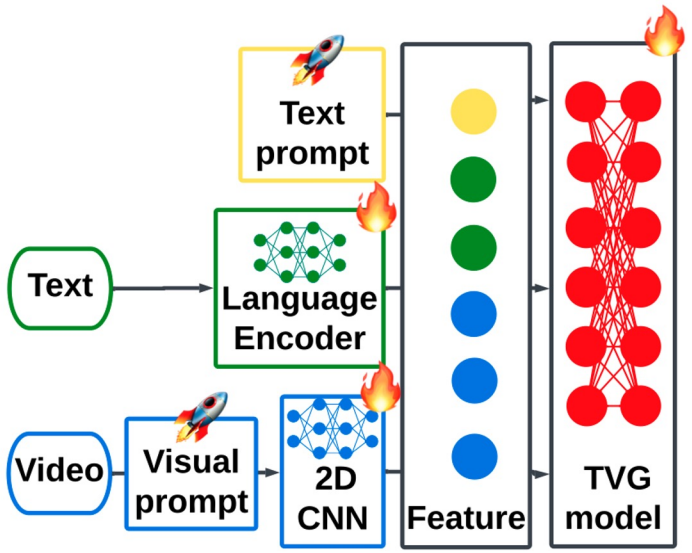

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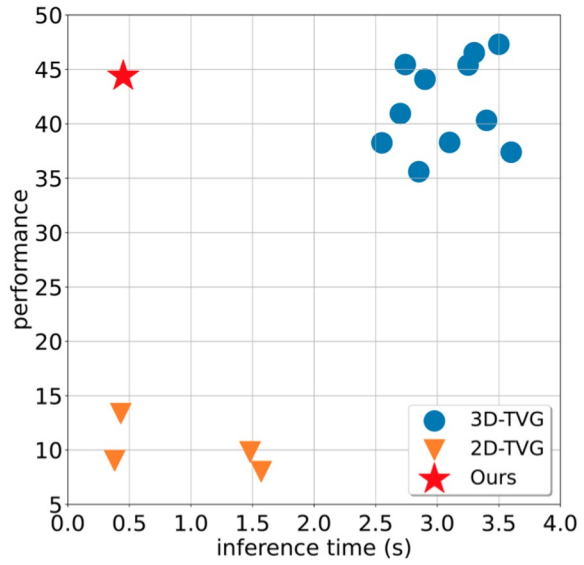

(d) Overall performance comparison

a) 3D TVG

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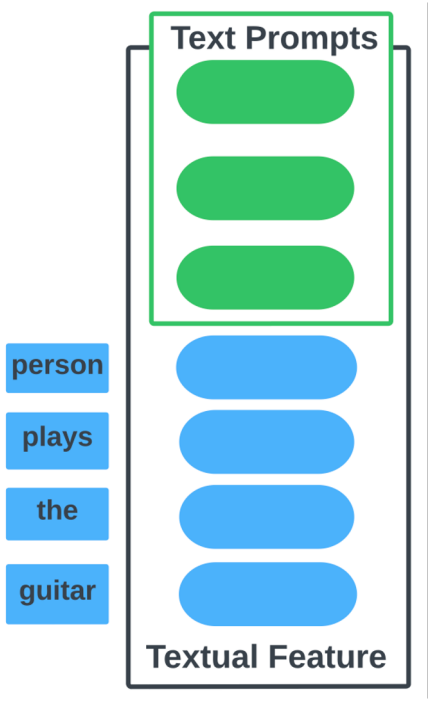

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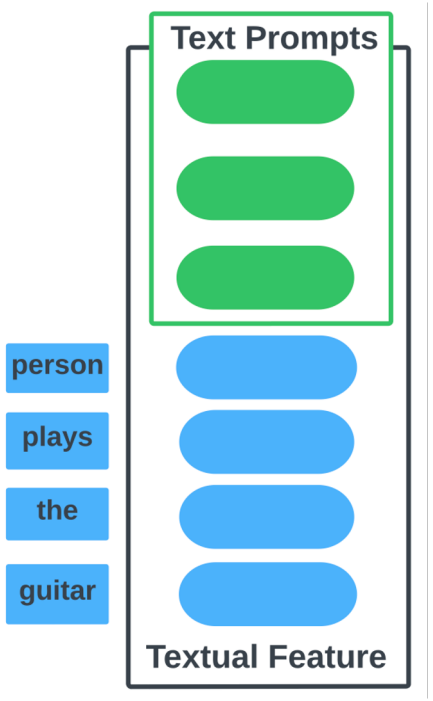

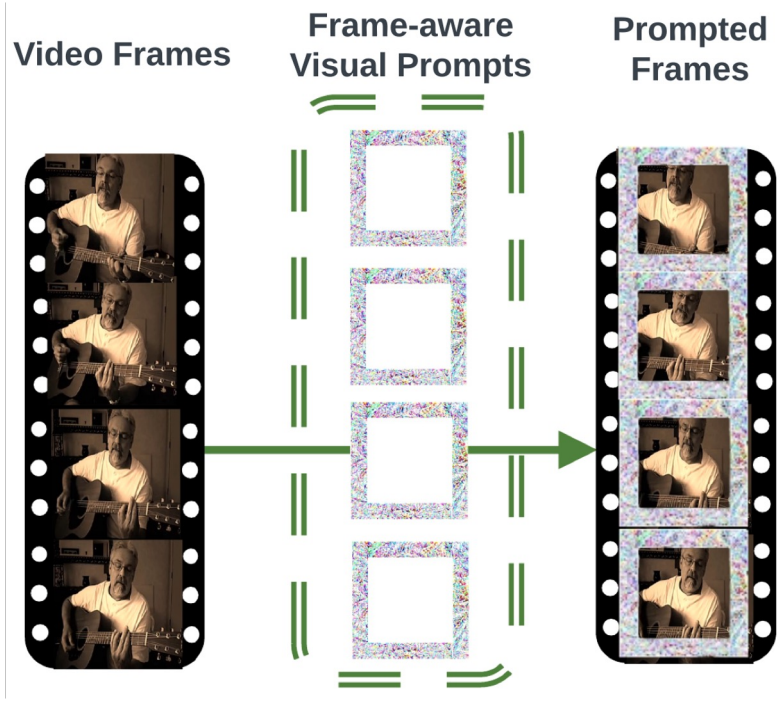

- Text prompts are directly applied in the feature space.

- A set of frame-aware visual prompts are applied to pixel space of video frames in order.

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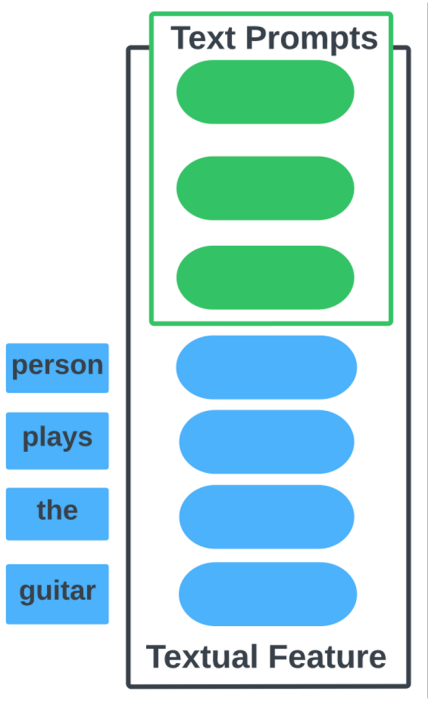

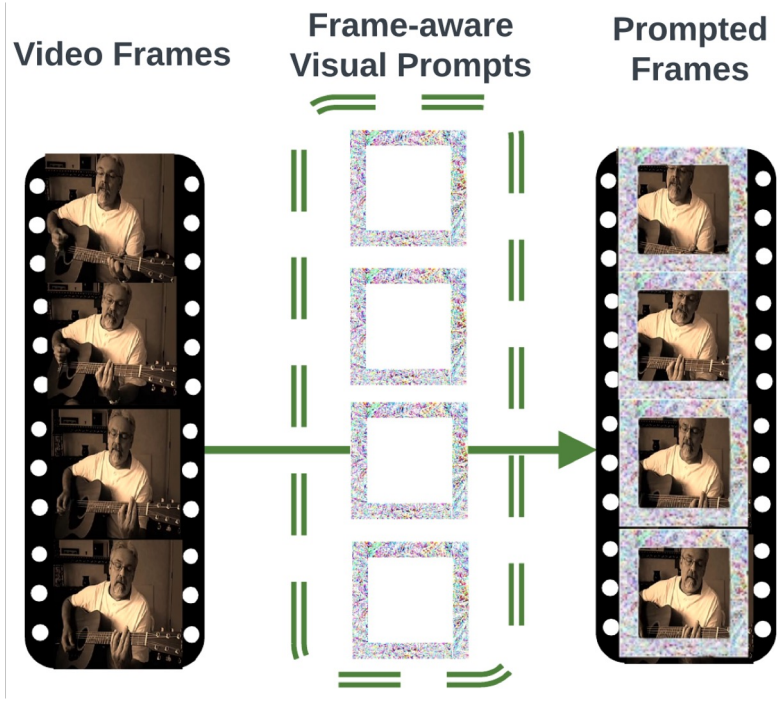

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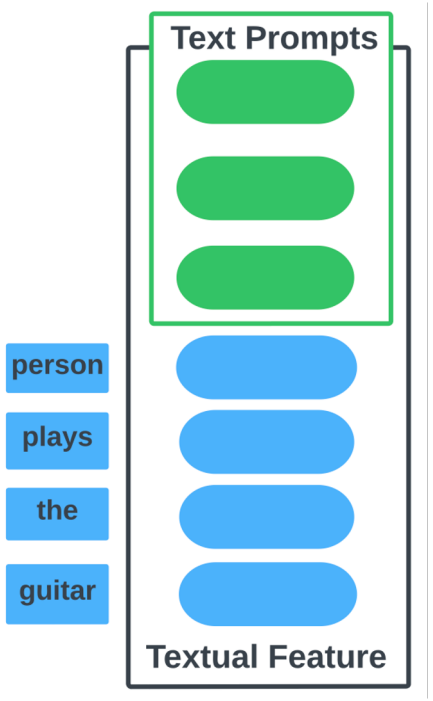

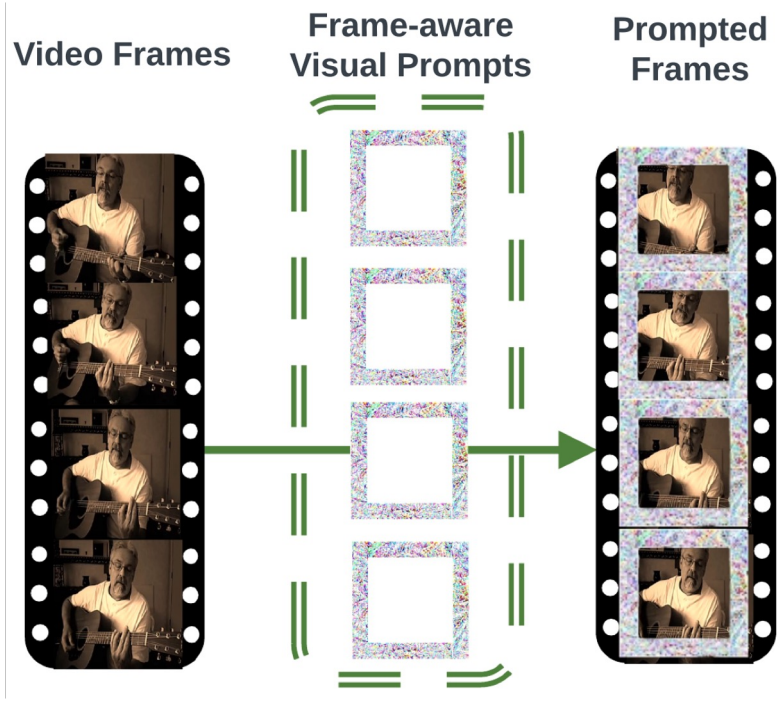

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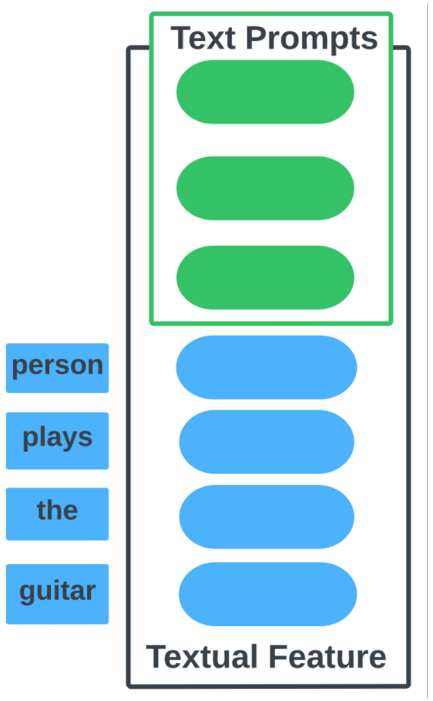

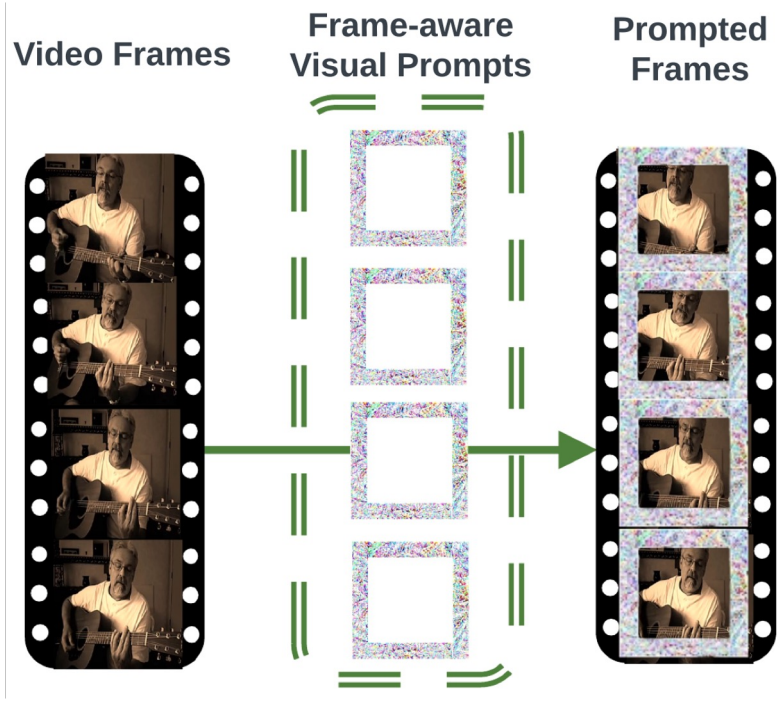

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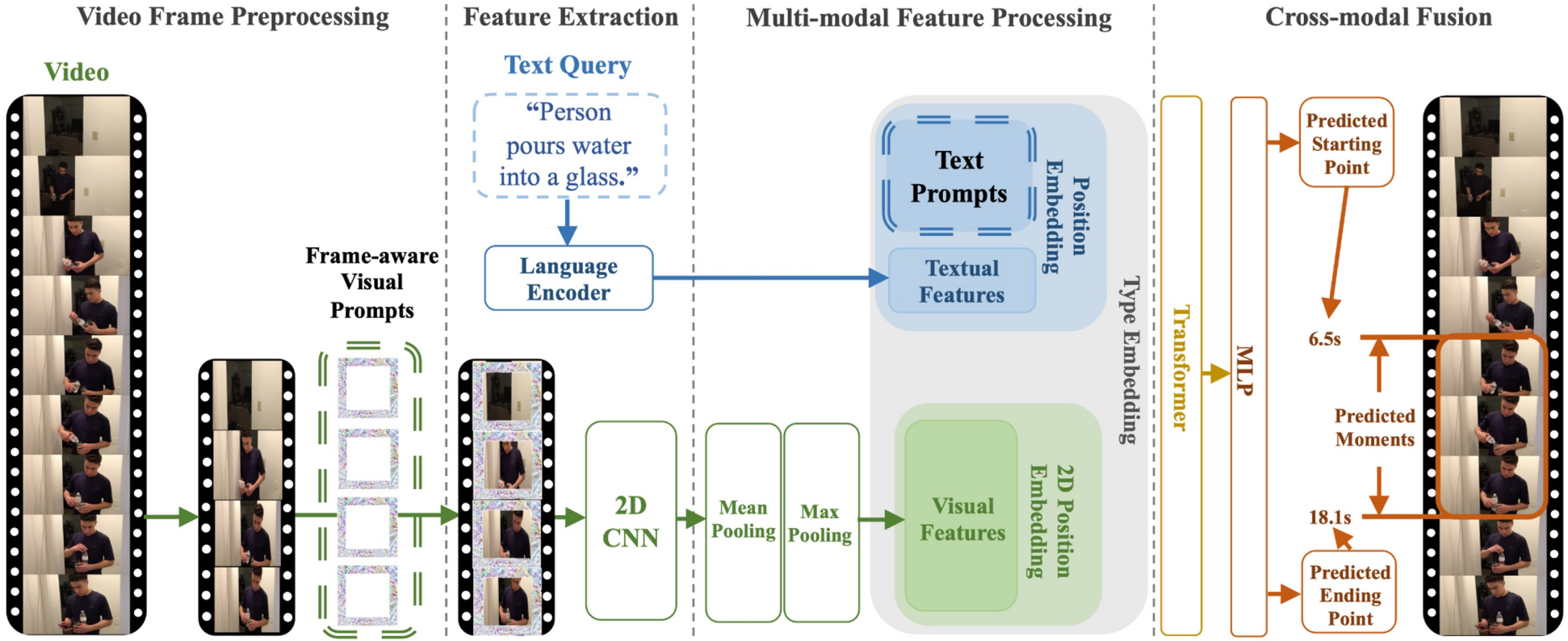
- During training, only the set of visual prompts and text prompts are updated through backpropagation.
- During finetuning, prompts are frozen, and the parameters of the TVG model and encoders are updated.
- During testing, the set of optimized visual prompts and the optimized text prompts are **applied to all test-time video-query pairs.**

4. Text-Visual Prompt for 2D TVG



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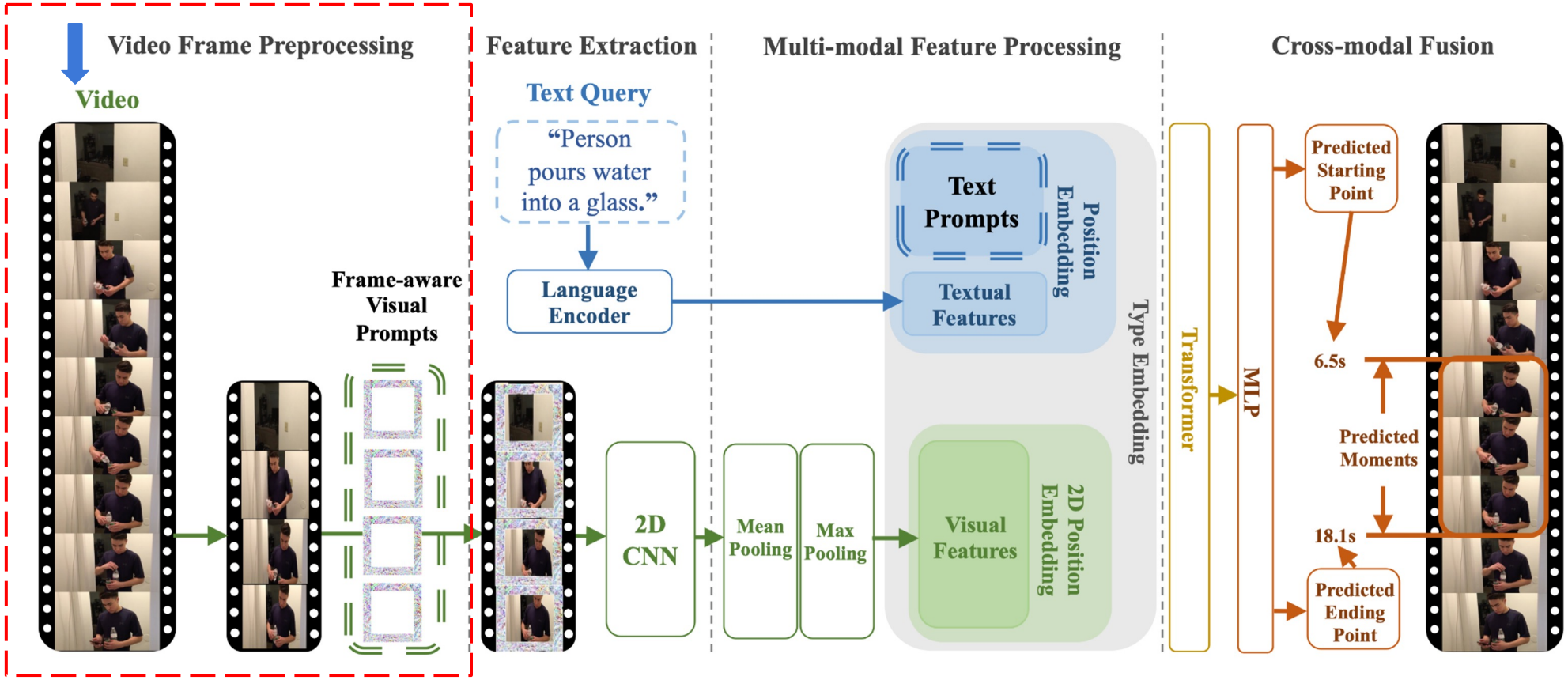

Video frame preprocessing

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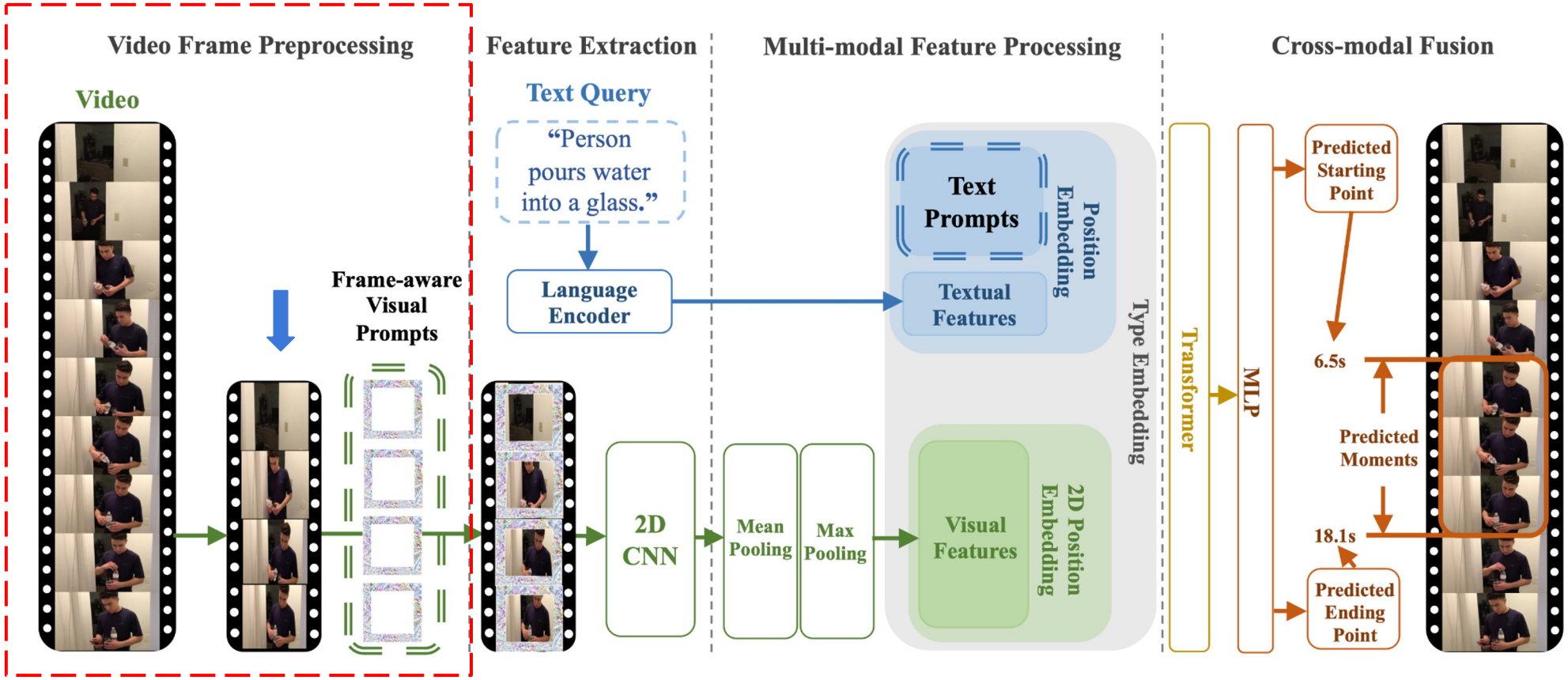

Video frame preprocessing

1) Uniformly sample frames from input video.

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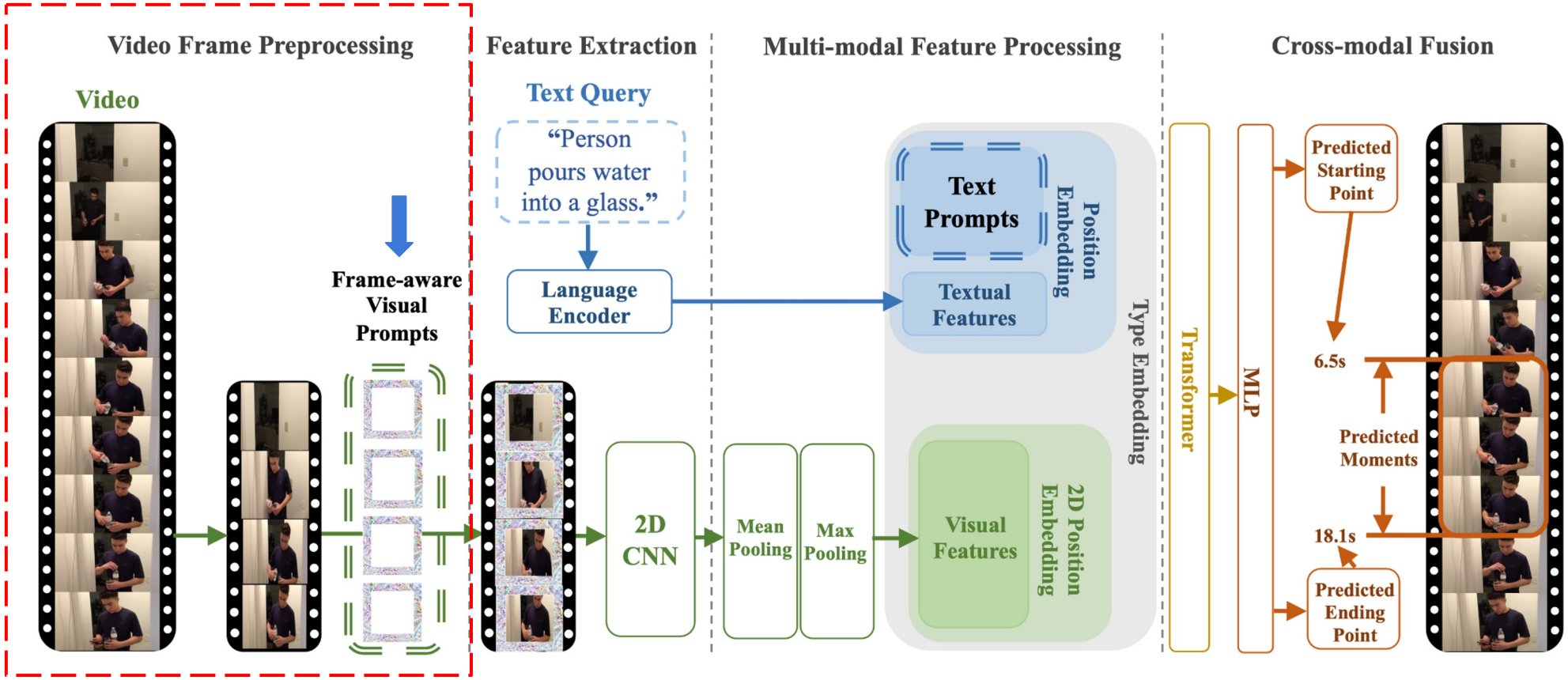

Video frame preprocessing

1) Uniformly sample frames from input video.

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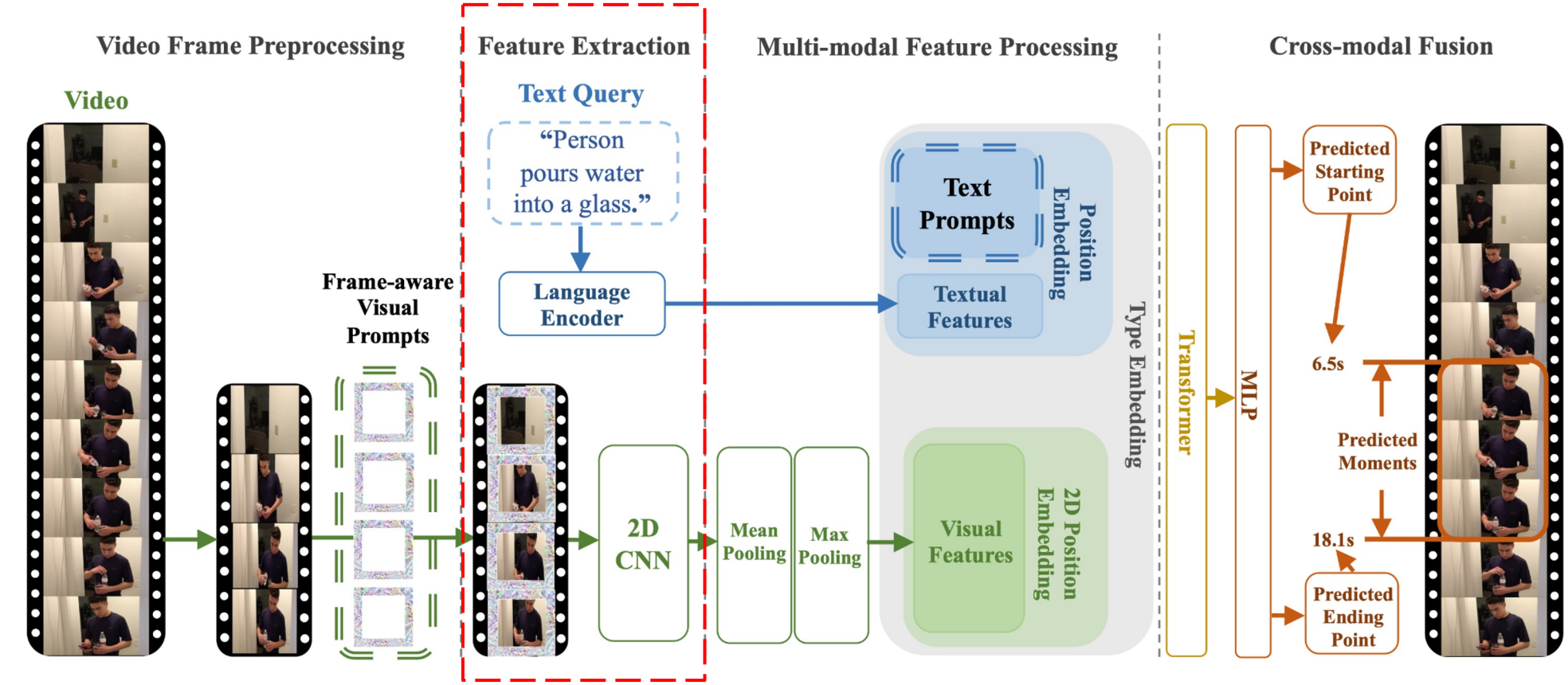

Feature extraction

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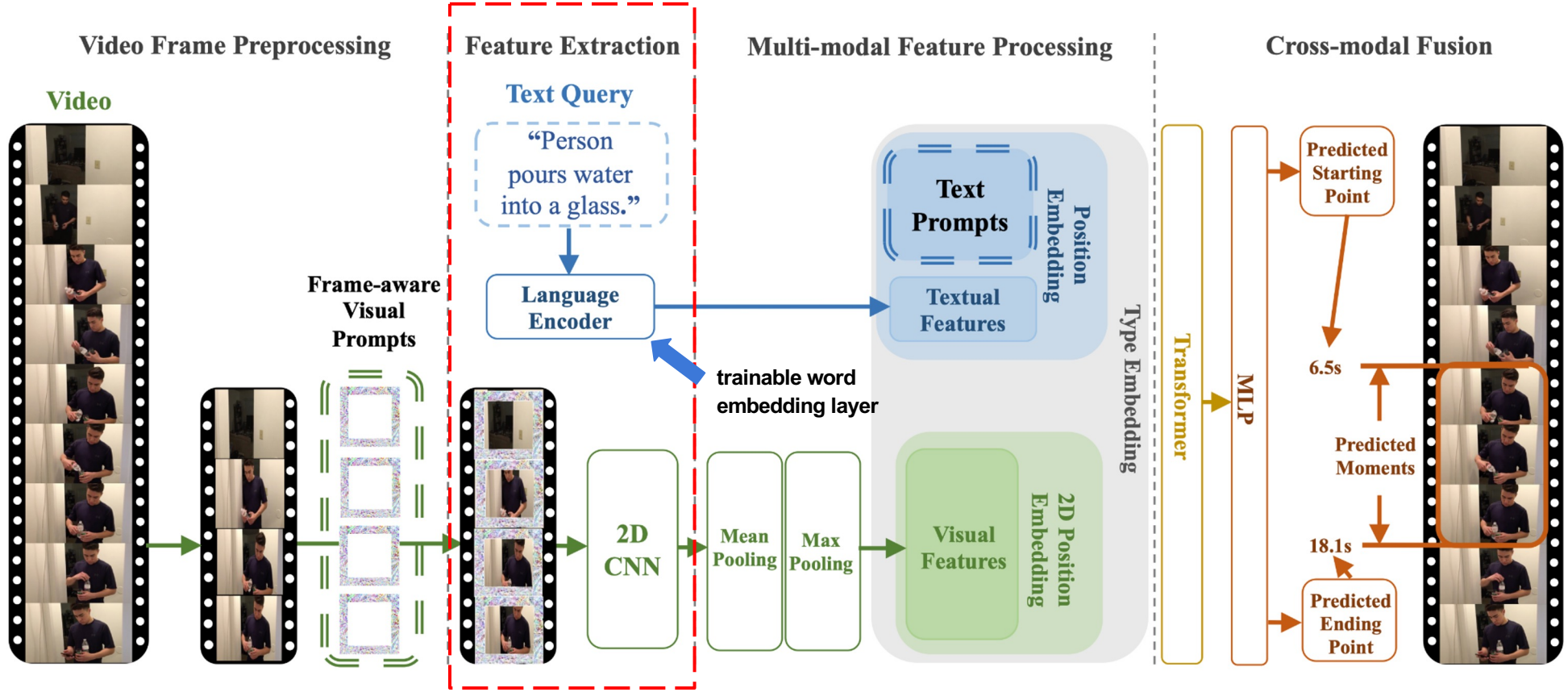

Feature extraction

1) The language encoder extracts textual features.

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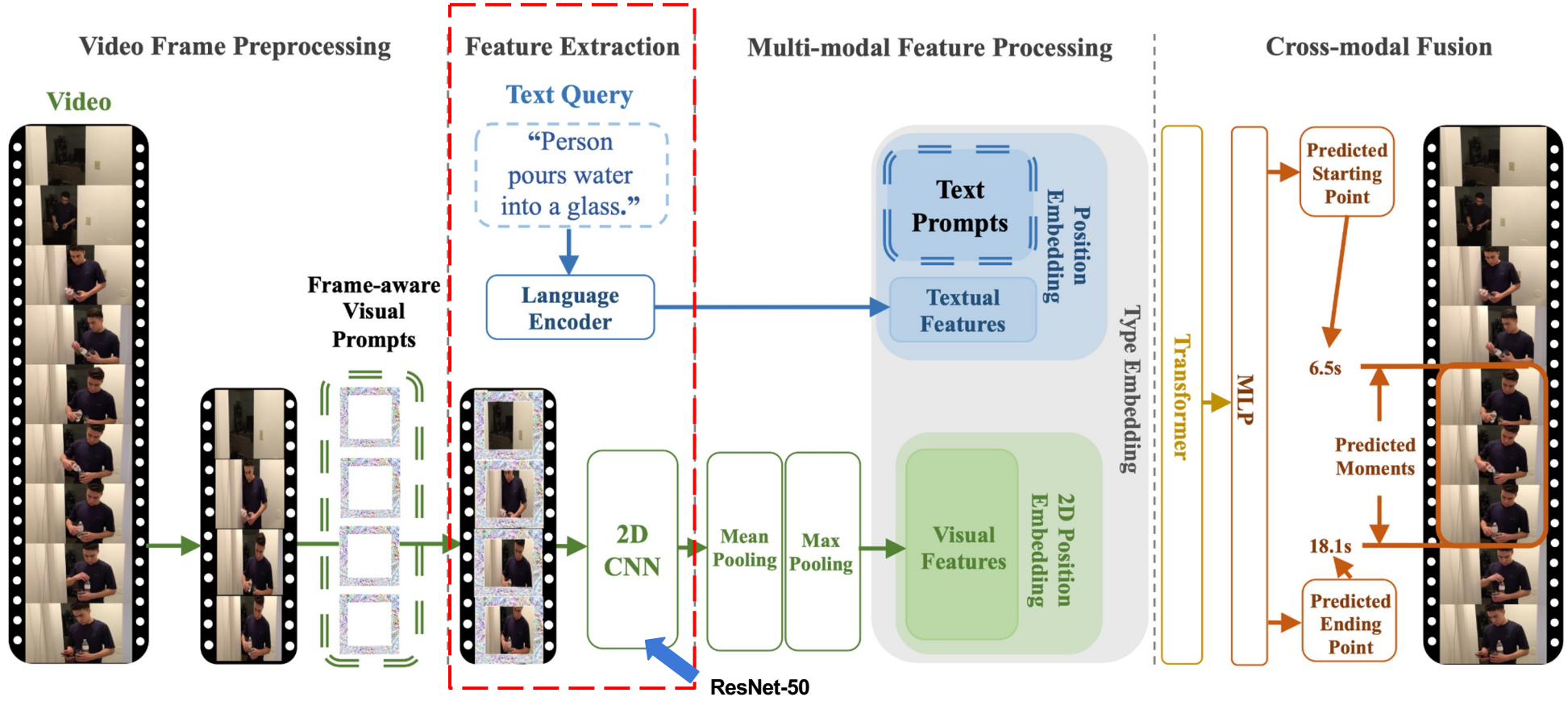

Feature extraction

1) The language encoder extracts textual features.

2) 2D CNN extracts features from sampled video frames with visual prompts.

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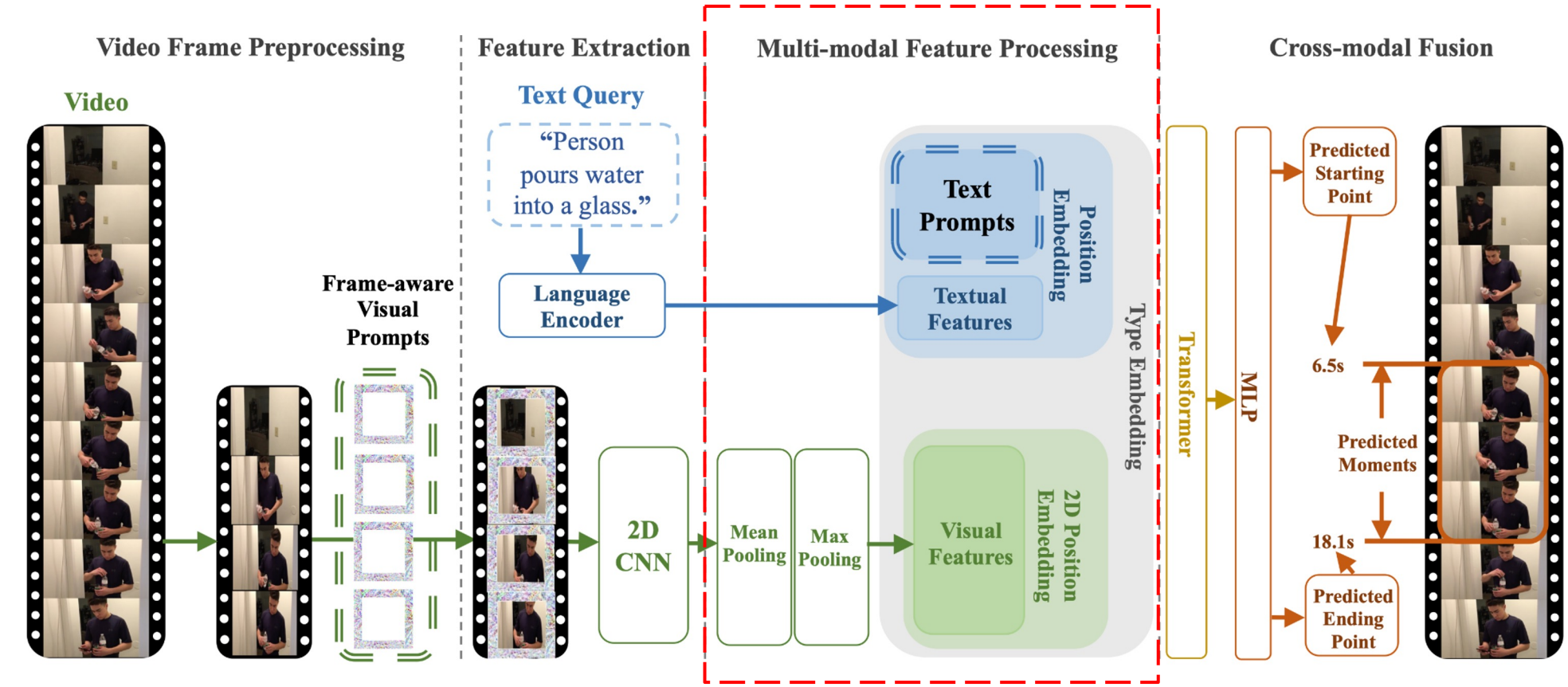

Multimodal feature processing

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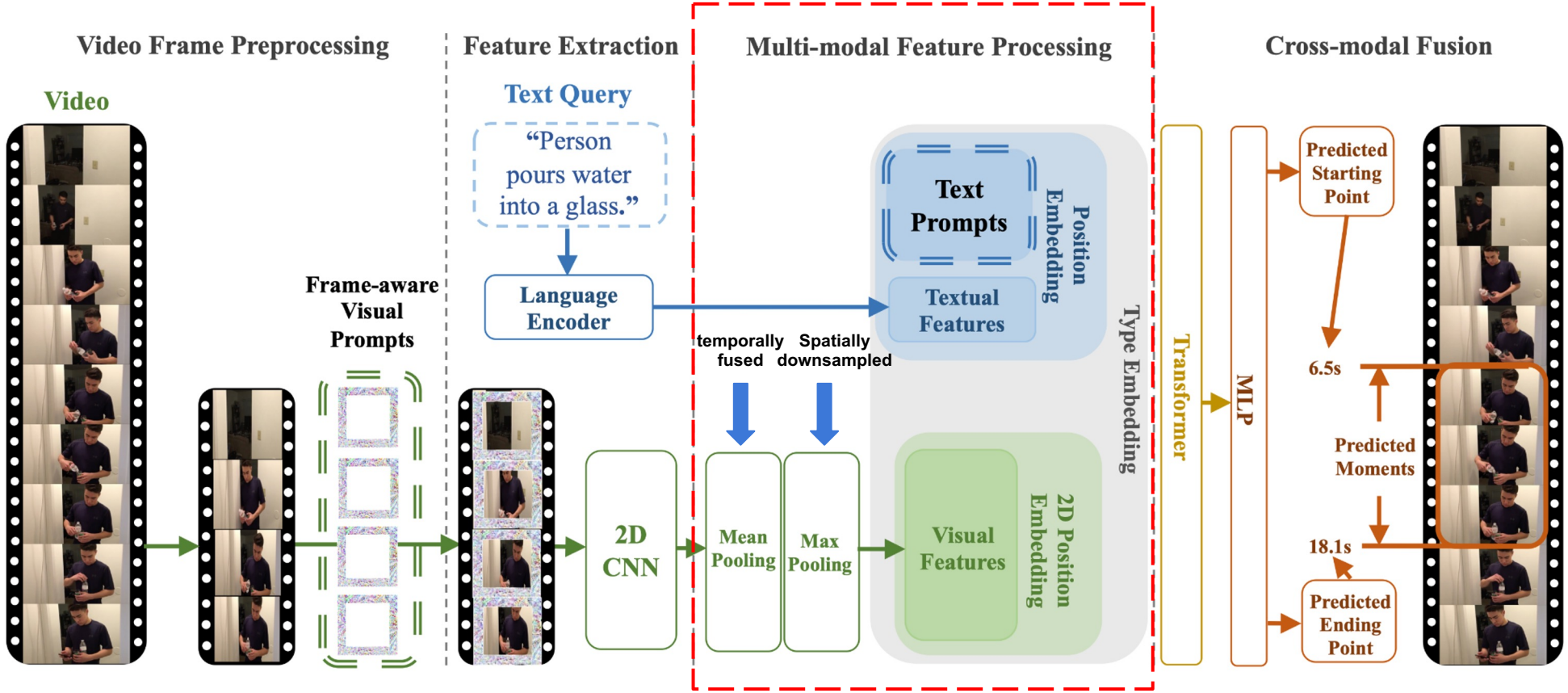

Multimodal feature processing

1) Visual features would be temporally fused and spatially downsampled by mean pooling and max pooling, respectively.

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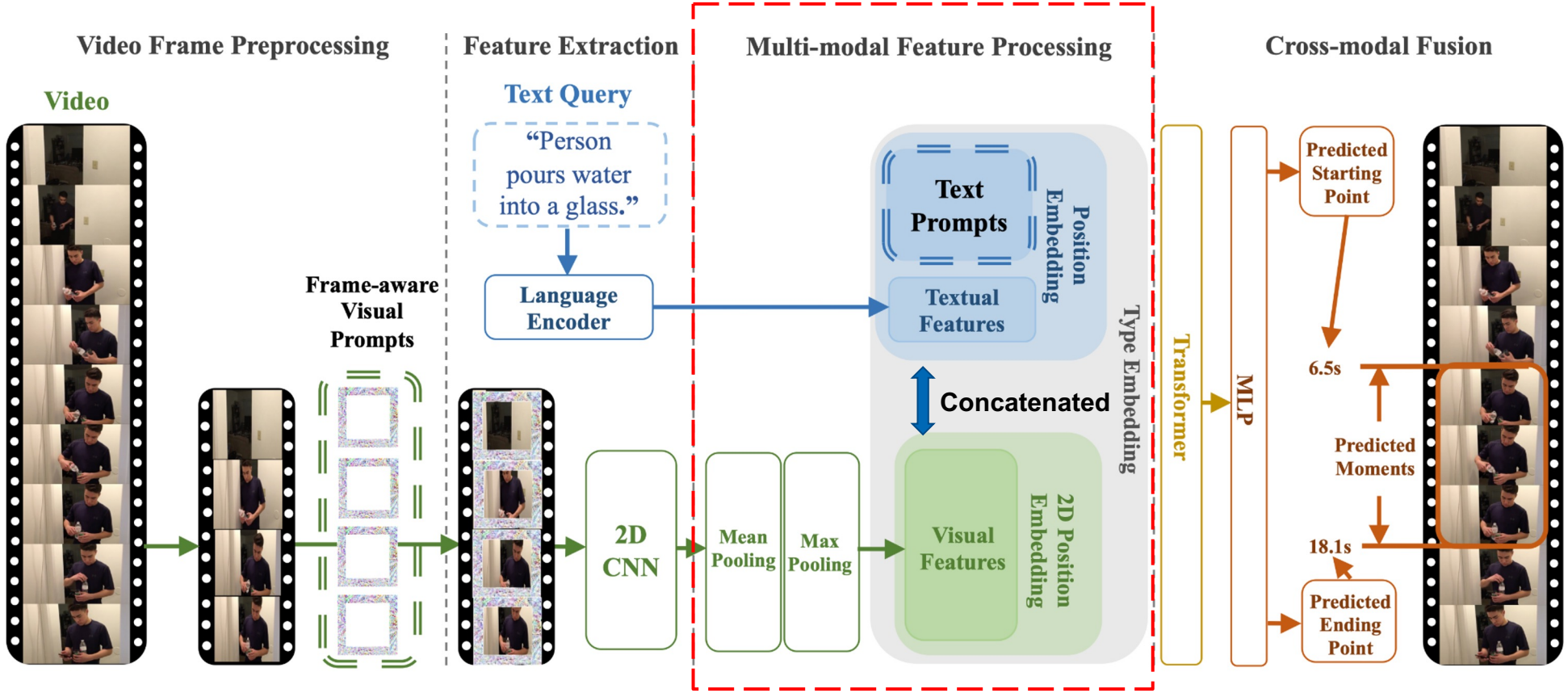

Multimodal feature processing

1) Visual features would be temporally fused and spatially downsampled by mean pooling and max pooling, respectively.

2) The 2D visual features would be concatenated with textual features and text prompts.

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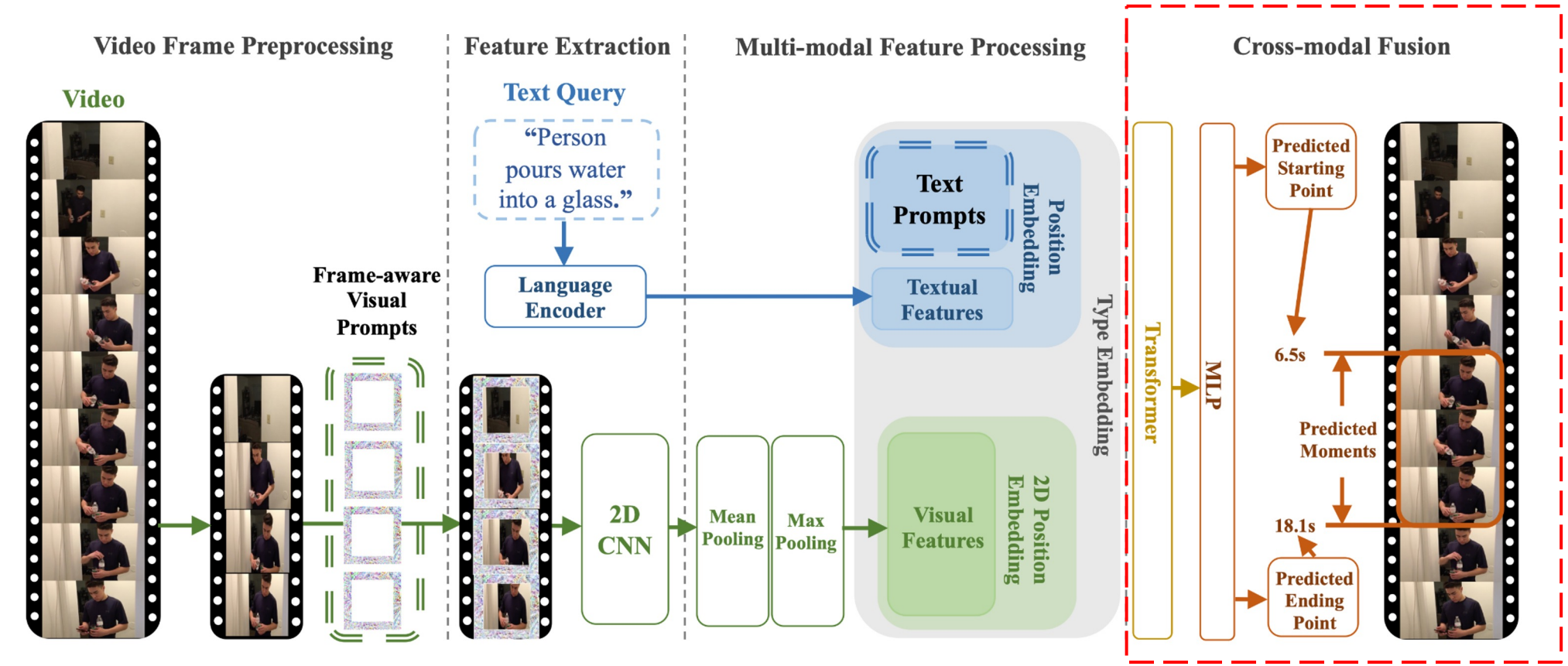

Crossmodal fusion

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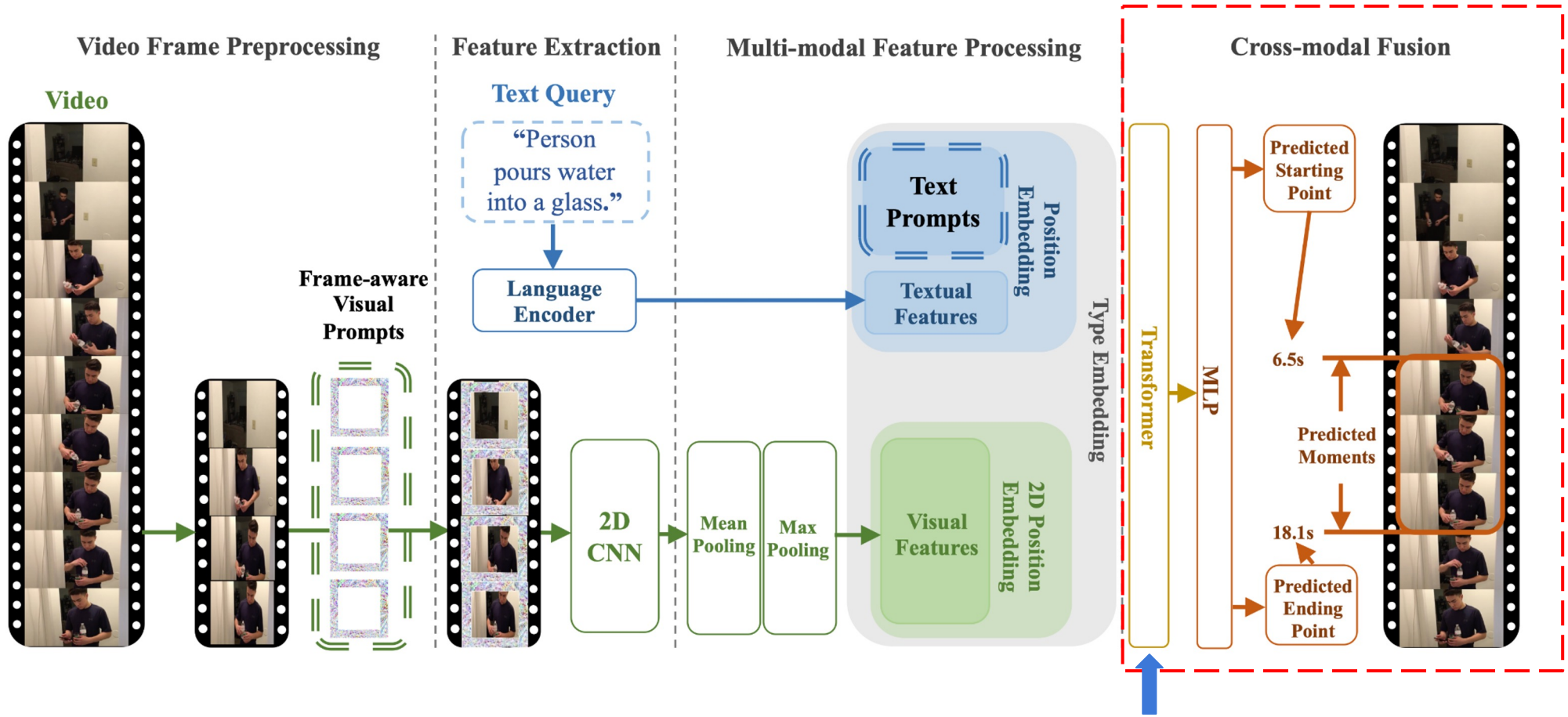

Crossmodal fusion

1) The multimodal features would be processed by a 12-layer transformer encoder,

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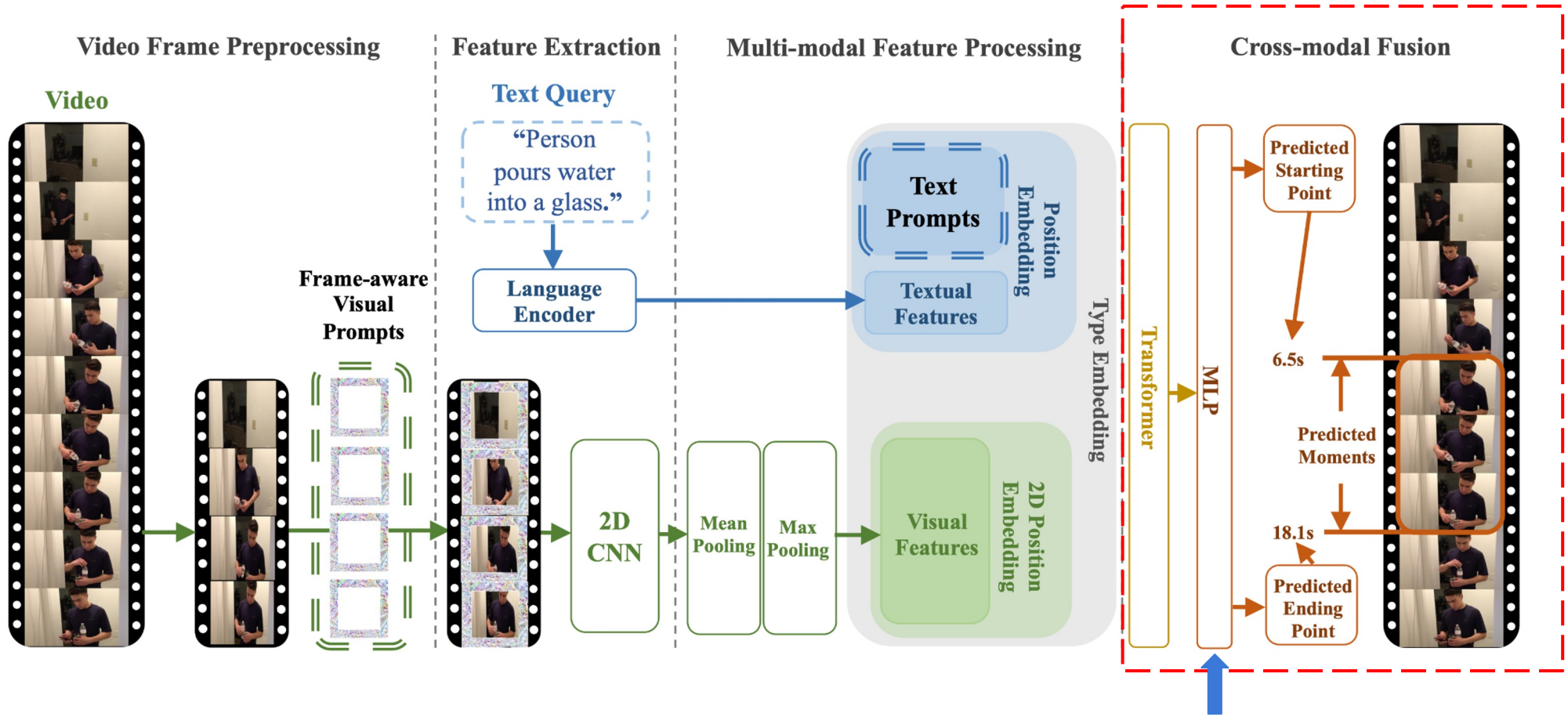

Crossmodal fusion

1) The multimodal features would be processed by a 12-layer transformer encoder,

2) MLP would predict the starting/ending time points of the target moment.

6. Training Pipeline

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a) **Cross-modal pretraining** on large-scale image-text datasets.
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c) **Prompt training.** ← Base model parameter are frozen !

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d) **Base model finetuning.** ← Text-Visual Prompts are frozen !

7. Dataset

Dataset	Charades-STA	ActivityNet Captions
Domain	Indoor Activity	Indoor/Outdoor Activity
# Videos	6,672	14,926
Avg. Video Length (*second*)	30.6	117.6
# Moments	11,767	71,953
Avg. Moment Length (*second*)	8.1	37.1
Vocabulary Size	1,303	15,505
# Queries	16,124	71,953
Avg. Query Length (*word*)	7.2	14.4

Table 1. Statics of temporal video grounding benchmark datasets (Charades-STA and ActivityNet Captions datasets).

8. Evaluation Metric

Acc(R@1, IoU=m)

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Acc(R@1, IoU=m)

The percentage of predicted moments
achieving IoU higher than *m* with the groundtruth moment.

8. Experimental Results

Table 2. Performance comparison of different thresholds m on the Charades-STA dataset.

Type	Method	Visual Feature	Acc(R@1, IoU=m) m=0.3	m=0.5	m=0.7
3D TVG	BPNet [53]	C3D	55.46	38.25	20.51
	LPNet [52]	C3D	59.14	40.94	21.13
	QSPN [55]	C3D	54.70	35.60	15.80
	TSP-PRL [51]	C3D	-	45.45	24.75
	TripNet [15]	C3D	54.64	38.29	16.07
	DRN [59]	C3D	-	45.40	26.40
	CPNet [28]	C3D	-	40.32	22.47
	DEBUG [34]	C3D	54.95	37.39	17.92
	ExCL [14]	I3D	61.50	44.1	22.40
	VSLNet [63]	I3D	64.30	**47.31**	**30.19**
	MAN [61]	I3D	-	46.53	22.72
2D TVG	CTRL [12]	VGG	13.5	9.82	-
	MCN [1]	VGG	17.46	8.01	-
	ABLR [58]	VGG	24.36	9.01	-
	SAP [5]	VGG	27.42	13.36	-
Ours					
TVP-Based 2D TVG	Base w/o prompts	ResNet	61.29	40.43	19.89
	Base + Visual Prompts		65.38	44.31	20.22
	Base + Text Prompts		65.81	43.44	20.65
	Base + Both Prompts		**65.92**	44.39	21.51

Table 3. Performance comparison of different thresholds m on the ActivityNet Captions dataset.

Type	Method	Visual Feature	Acc(R@1, IoU=m) m=0.3	m=0.5	m=0.7
3D TVG	CTRL [12]	C3D	28.70	14.00	-
	BPNet [53]	C3D	59.98	42.07	24.69
	LPNet [52]	C3D	**64.29**	**45.92**	25.39
	QSPN [55]	C3D	45.30	27.70	13.60
	TSP-PRL [51]	C3D	56.02	38.83	-
	TripNet [15]	C3D	48.42	32.19	13.93
	DRN [59]	C3D	-	45.45	24.36
	CPNet [28]	C3D	-	40.56	21.63
	ABLR [58]	C3D	55.67	36.79	-
	DEBUG [34]	C3D	55.91	39.72	-
	ExCL [14]	C3D	63.00	43.60	24.10
	VSLNet [63]	C3D	63.16	43.22	**26.16**
Ours					
TVP-Based 2D TVG	Base w/o prompts	ResNet	57.20	40.16	19.14
	Base + Visual Prompts		60.12	43.39	23.71
	Base + Text Prompts		60.48	42.58	24.39
	Base + Both Prompts		60.71	43.44	25.03

8. Experimental Results

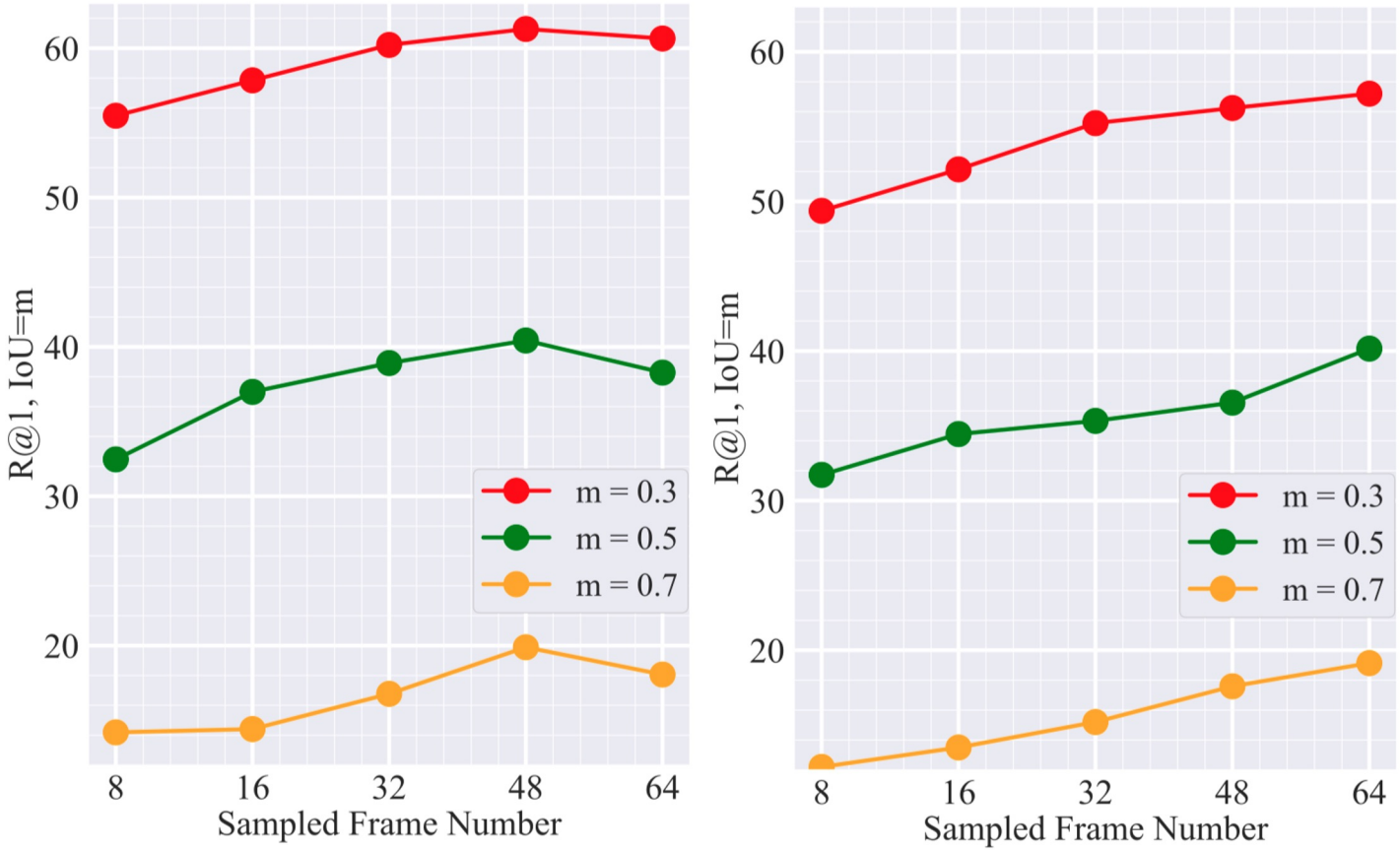

Figure 4. Impact of sampled frame number.

8. Experimental Results

Table 4. The performance comparison of different visual prompt sizes on Charades-STA dataset.

Visual Prompt Size	Acc(R@1, IoU=m) m=0.3	m=0.5	m=0.7	Prompt + Frame
0	61.29	40.43	19.89	
16	61.29	40.43	20.00	
32	61.94	39.78	19.35	
48	63.66	42.37	20.00	
72	63.87	43.66	19.78	
96	**65.38**	**44.31**	**20.22**	
128	64.73	43.66	19.78	

Table 5. The performance comparison of different text prompt sizes on Charades-STA dataset.

Text Prompt Size	Acc(R@1, IoU=m) m=0.3	m=0.5	m=0.7
0	57.20	40.16	19.14
5	65.38	41.94	20.43
10	**65.81**	43.44	20.65
15	65.59	43.23	21.29
20	64.95	**43.87**	**21.51**
25	63.66	42.80	20.65
30	64.46	42.63	20.51

8. Experimental Results

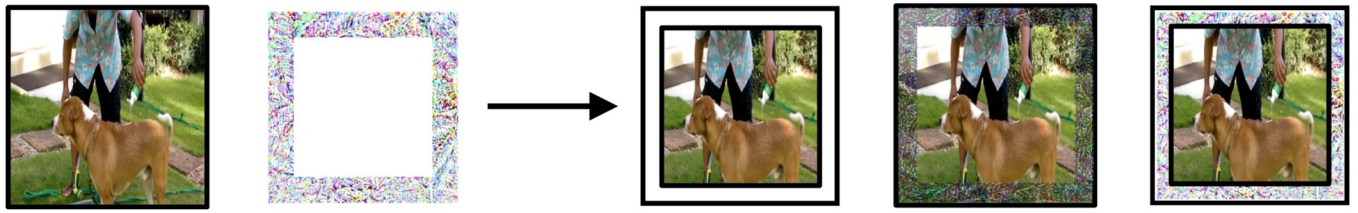

Table 6. The performance comparison of different visual prompt operations (‘*remove*’, ‘*add*’, ‘*replace*’) with fixed visual prompt size $p = 96$ on Charades-STA and ActivityNet Captions datasets.

Operation	Charades-STA			ActivityNet Captions		
	R@1, IoU=m			R@1, IoU=m		
	m=0.3	m=0.5	m=0.7	m=0.3	m=0.5	m=0.7
Original	61.29	40.43	19.89	57.20	40.16	19.14
Remove	61.29	40.43	20.0	57.20	40.16	19.14
Add	61.08	39.57	20.22	57.15	40.16	19.27
Replace	**65.38**	**44.31**	**20.22**	**60.12**	**43.39**	**23.71**

8. Experimental Results

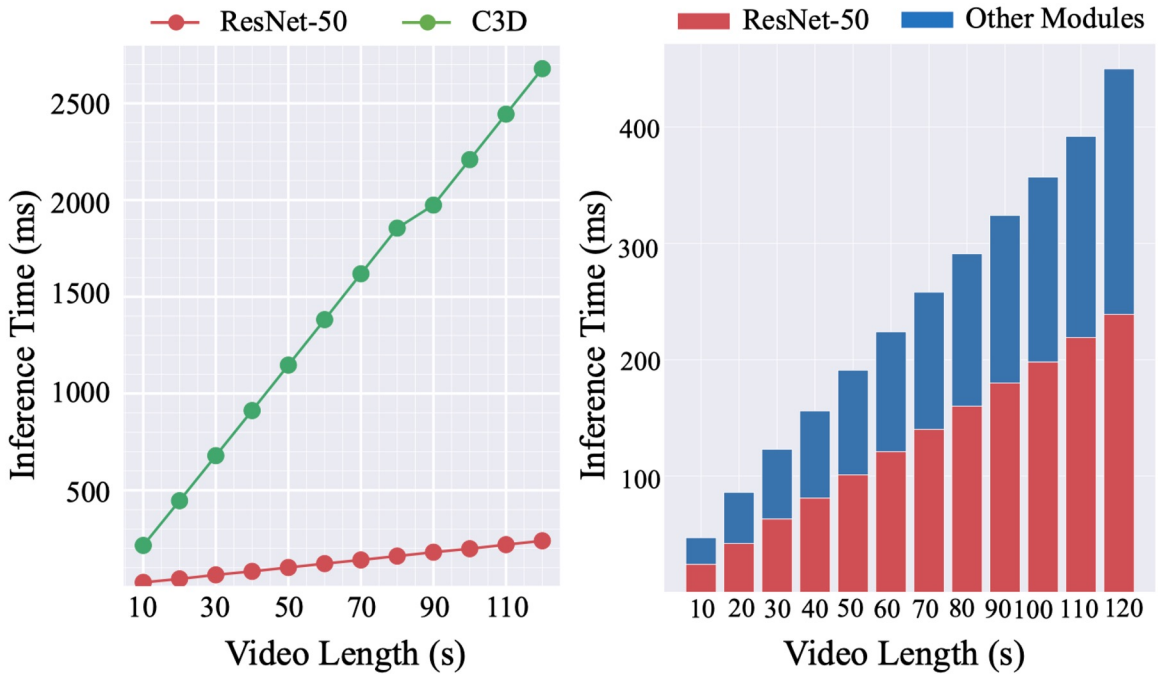

Figure 5. Inference time comparison. (a) inference time comparison between 2D vision encoder (ResNet-50) and 3D vision encoder (C3D). (b)inference time comparison between the vision encoder and the other modules of the 2D TVG model, where the sampled frame number for our TVP framework is 1.2× the length of the video in seconds.

THANKS for watching! !

Any Questions?

More Details on Project Website