Weakly Supervised Video Representation Learning

with Unaligned Text for Sequential Videos

CVPR 2023

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Sequential videos



Texts

- take up the jar
- uncover the jar cap
- pour the jar
- cover the jar with the jar cap
- put down the jar



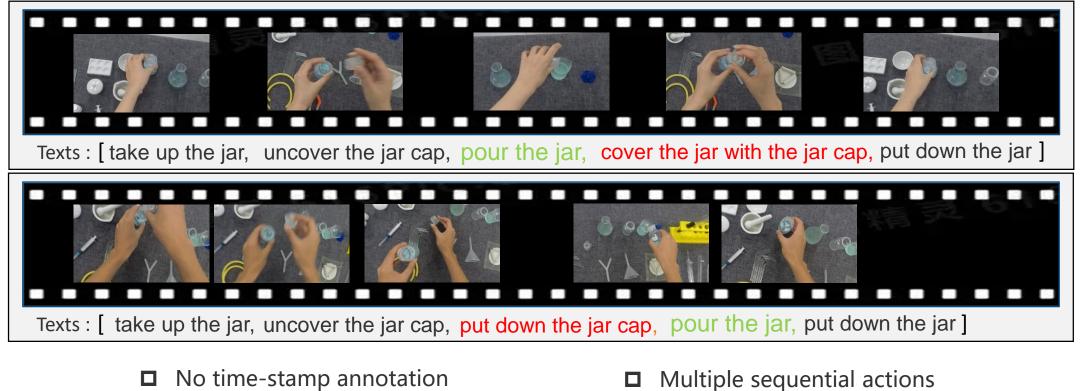
Texts

- take up the jar
- uncover the jar cap
- put down the jar cap
- pour the jar
- put down the jar

[1] The examples are from CSV dataset. "SVIP: Sequence Verification for Procedures in Videos". In CVPR 2022



Sequential Video



Step annotations

□ Similar ordering of actions

[1] The examples are from CSV dataset. "SVIP: Sequence Verification for Procedures in Videos". In CVPR 2022

(2) Previous Works

Sequence verification for procedures in videos

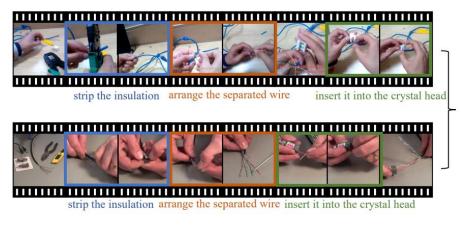


Figure 2. Positive video pair (Yicheng Qian et at.)

- Slightly different step
- Rely on additional class information
- Under supervision

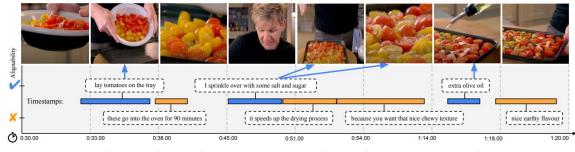


Figure 3. Negative video pair (Yicheng Qian et at.)

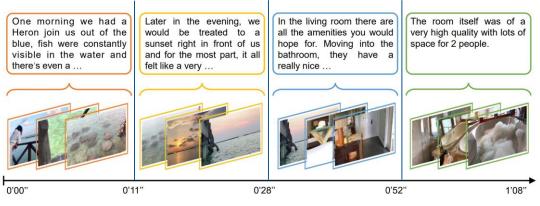
Measure video representation
Focus on every procedure

[1] Yicheng Qian et at., " SVIP: Sequence Verlfication for Procedures in Videos." In CVPR, 2022.





(1) Visual-textual mis-alignment (Han Tenda et al., CVPR 2022 Oral)[2]



(2) Video-paragraph pair (Yuchong Sun et al., NeurIPS 2022)[3]

- Visual-textual mis-alignment
 - Noisy time-step annotations
 - □ Ignore missing fine-grained alignment

- Video-paragraph pair
 - Segmented time-step annotations
 - □ Not fine-grained enough

[2] Han Tenda et al., "Temporal alignment networks for long-term video." In CVPR, 2022.

[3] Yuchong Sun et al., "Long-Form Video-Language Pre-Training with Multimodal Temporal Contrastive Learning". In NeurIPS 2022

(3) Method

- ✓ Propose a contrastive learning framework
- ✓ Design multiple granularity contrastive loss

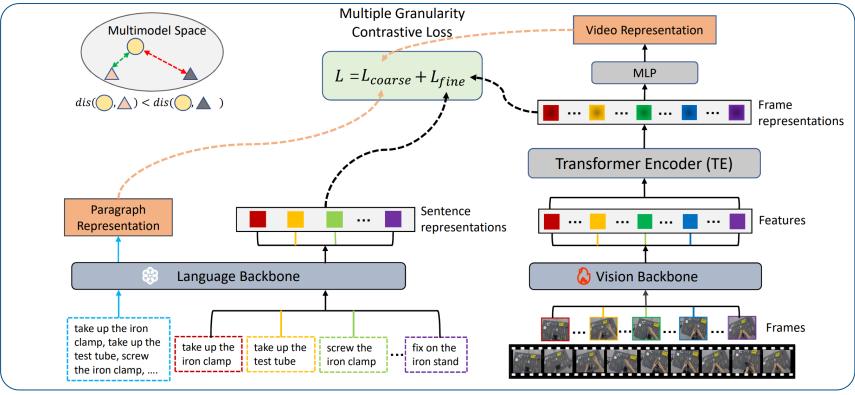


Figure 5. Overview of our framework.



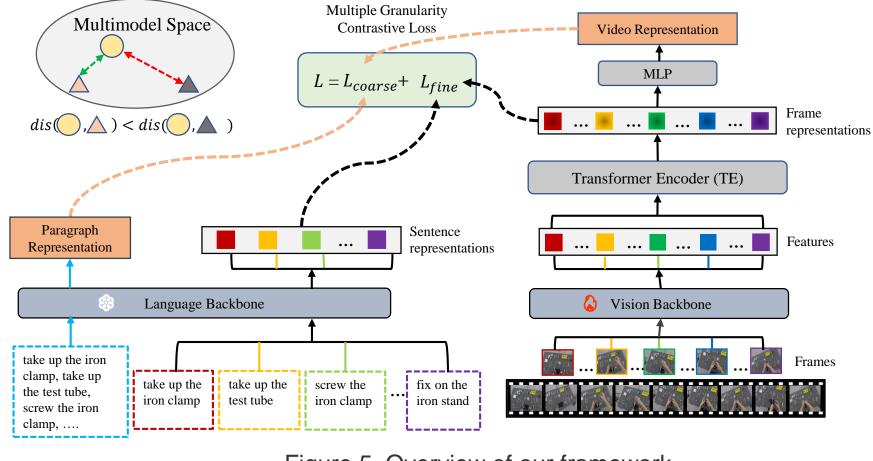
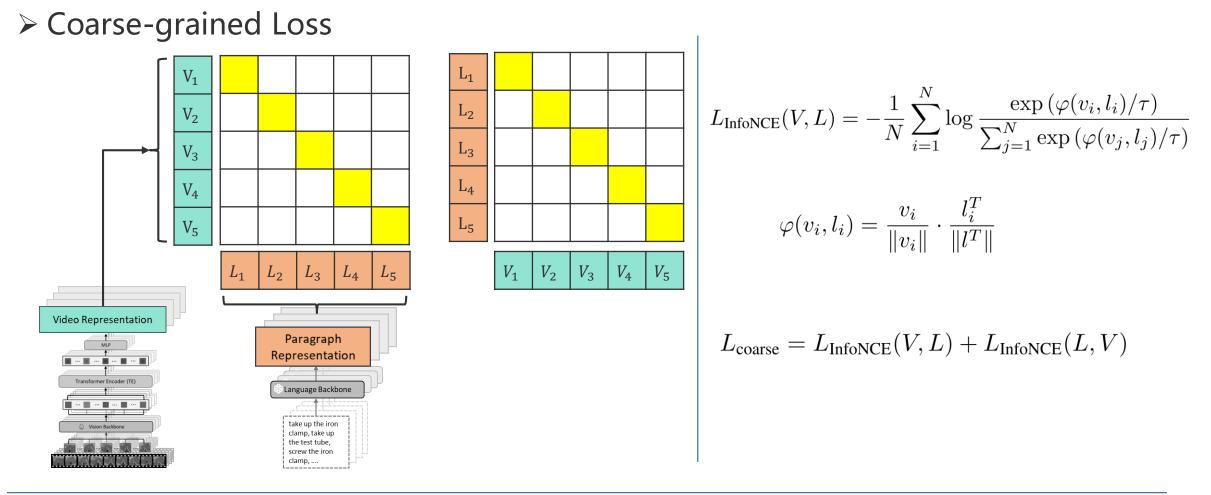


Figure 5. Overview of our framework.



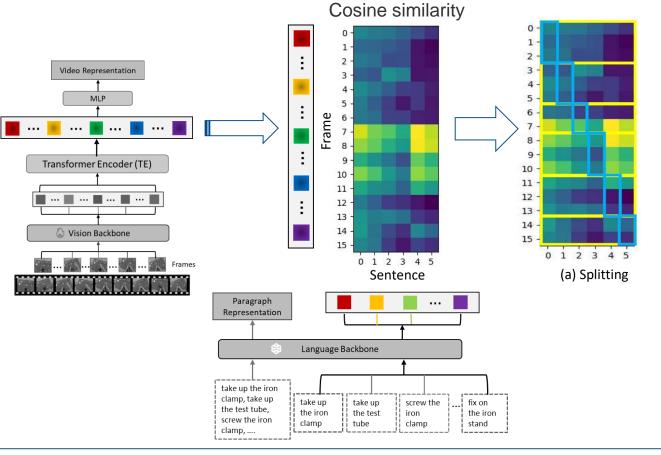




Coarse-grained loss

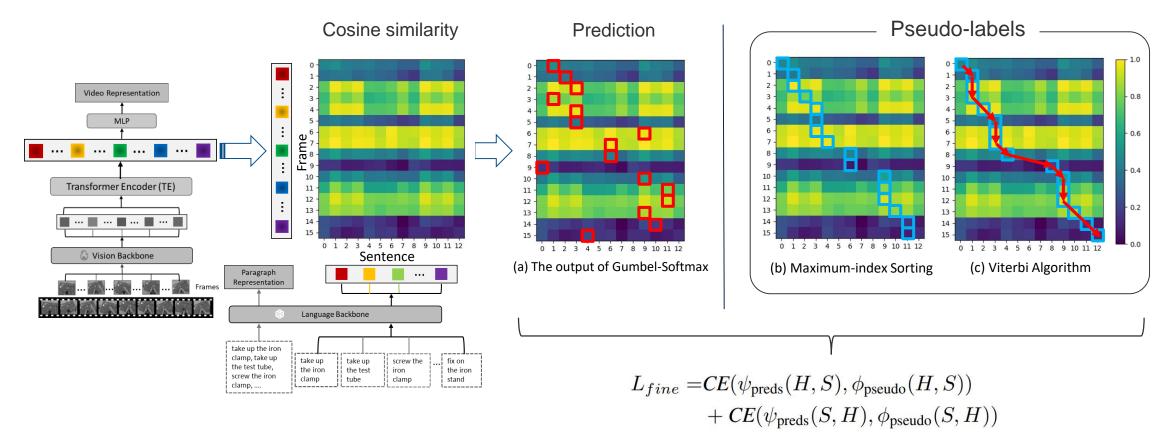
V_1 V_2 V_3 V_4 V_5 L_3 L_4 Video Representation Paragraph Representation Language Backbone take up the iron clamp, take up the test tube, screw the iron clamp, $L_{\text{InfoNCE}}(V,L) = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{\exp\left(\varphi(v_i, l_i)/\tau\right)}{\sum_{j=1}^{N} \exp\left(\varphi(v_j, l_j)/\tau\right)}$

Fine-grained loss





Fine-grained contrastive loss





Evaluation matrices

$$d = dis(v_1, v_2)$$
$$y = \begin{cases} 1, d \leq \tau \\ 0, otherwise \end{cases}$$

Video sequence verification

	Text Encoder	Weakly Supervised (w/o CLS)			
Method		CSV	Diving-SV	COIN-SV	
MIL-NCE [30]	MLP [30]	53.02	58.49	47.95	
CAT [35]		70.63	77.87	47.70	
VideoSwin [28]+MLP		62.48	60.88	54.73	
CLIP [37]+TE [10]+Pool	CLIP [37]	58.67	72.13	49.79	
CLIP [37]+TE [10]+MLP		74.82	81.47	50.13	
Ours	CLIP [37]	79.80	85.19	52.56	

Table 1. Results of representation learning for weakly supervised video sequence verification task.



Video sequence verification

		Supervised (w CLS)			
Method	Pre-train	CSV	Diving-SV	COIN-SV	
MIL-NCE [29]	HowTo100M [30]	56.16	63.43	47.80	
Swin [26]	K-400 [5]	54.06	73.10	43.70	
TRN [57]	K-400 [5]	80.32	80.69	57.19	
CAT [34]	K-400 [5]	83.02	83.11	51.13	
CLIP [36]+TE [10]+MLP	CLIP [36]	79.38	83.48	48.50	
Ours (weakly supervised)	CLIP [36]	79.80	85.19	52.56	
Ours	CLIP [36]	86.92	86.09	59.57	

		Weakly supervised (w/o CLS)			Supervised (w CLS)		
Method	Backbone	Def.	No Rep.	Rep.	Def.	No Rep.	Rep.
CAT [1]	ResNet50	47.70	57.82	49.99	51.13	63.25	45.96
CLIP+TE+MLP	CLIP-ViT	50.83	65.28	53.73	48.50	65.21	51.25
Ours	CLIP-ViT	52.55	68.98	56.16	59.57	77.78	54.95

Table 2. Results of downstream video sequence verification task under supervised.



Text-to-video matching

Video classification

	Text-to-Video Matching
Method	CSV-Matching
MIL-NCE [29]	60.02
CAT [34]	53.54
CLIP [36] +TE [10] +MLP	62.67
Ours	65.23

Table 3. Results of text-to-video matching task on our proposed benchmark *CSV-Matching*. We evaluate the results using AUC.

Method	Backbone	Loss	Classification(Acc)
CAT [40]	ResNet-50	CLS, SEQ	61.08
CLIP [42]+TE+MLP	CLIP-ViT	CLS, SEQ	63.24
Ours (w/o multi-grained loss)	CLIP-ViT	CLS, SEQ	-
Ours(CLS)	CLIP-ViT	CLS, SEQ, Multi-grained loss	69.57

Table 4. Results of video classification on CSV.

(5) Ablation Studies

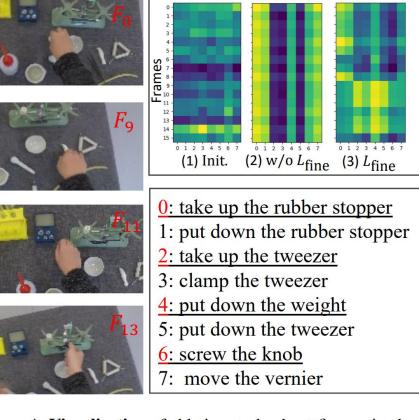


Figure 4. **Visualization** of ablation study about fine-grained contrastive loss.

Method	L_{fine}	L_{coarse}	CSV
	X	X	83.58
	1	X	84.85
Ours (w CLS)	X	\checkmark	84.32
	1	1	86.92

Table 6. Ablation studies of our proposed multiple granularity contrastive loss on CSV. To verify the effectiveness of L_{fine} and L_{coarse} separately, we conduct experiments on video verification task.

Method	L_{fine}	Pseudo-label generation	CSV
	X	X	74.82
		split	72.75
Ours	1	viterbi	78.46
		sort	79.80

Table 7. Ablation studies of the type of pseudo-label generation on our proposed method.

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Paper: https://arxiv.org/abs/2303.12370

Code: https://github.com/svip-lab/WeakSVR

