



# Re<sup>2</sup>TAL: Rewiring Pretrained Video Backbones for Reversible Temporal Action Localization



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KAUST



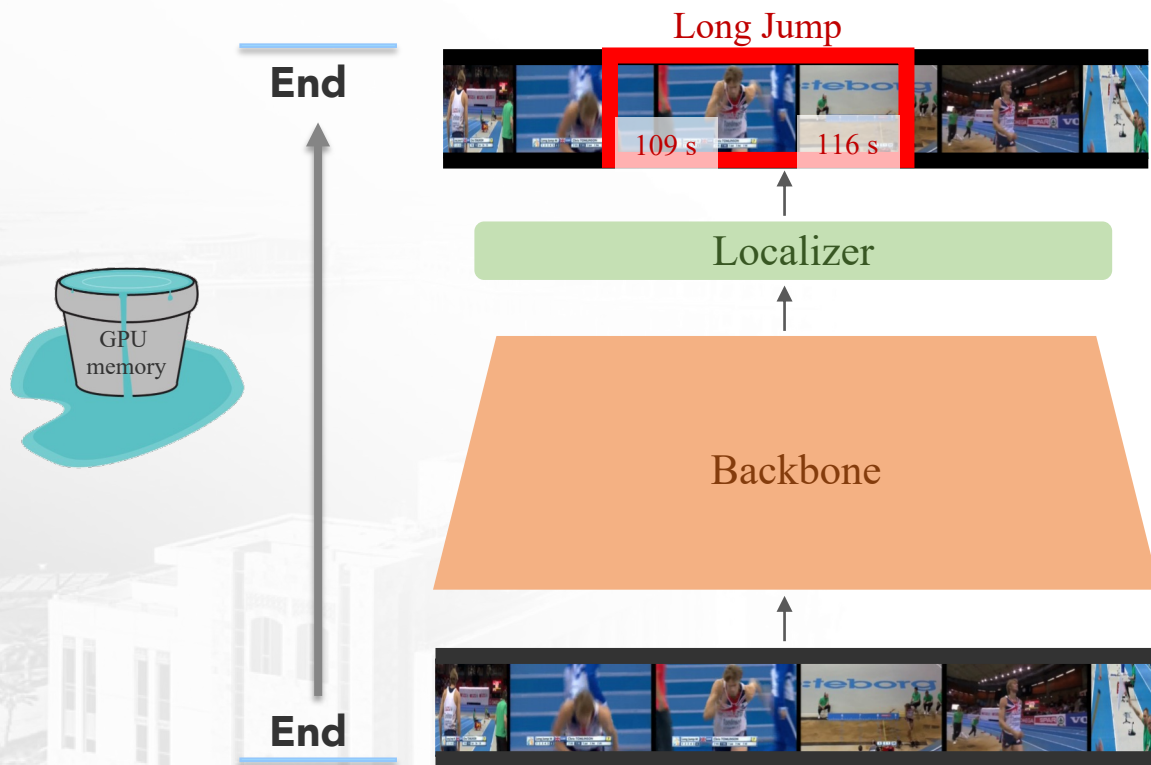
Karttikeya Mangalam  
UC Berkeley



Bernard Ghanem  
KAUST

Poster Session WED-AM-230, CVPR 2023

# Background

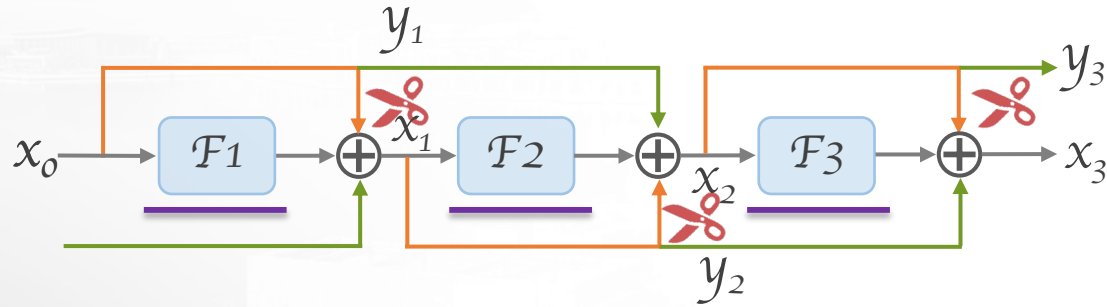


# Propose: Re<sup>2</sup>TAL



Residual modules

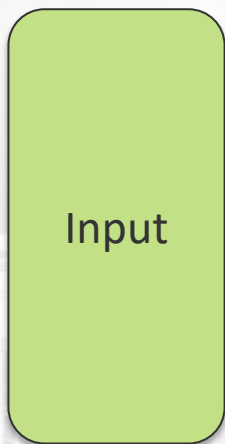
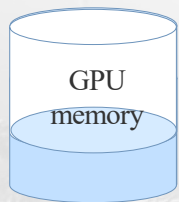
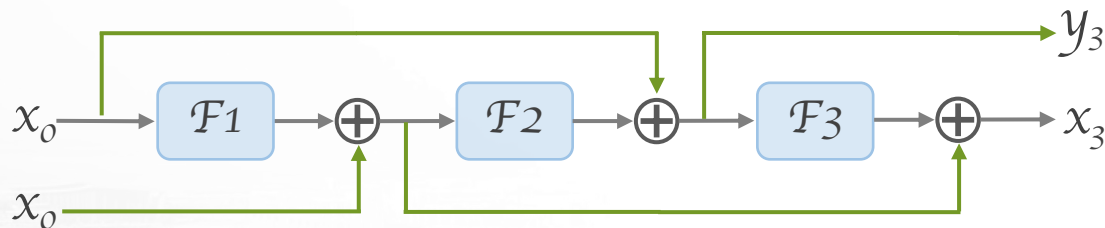
**Rewiring**



# Propose: Re<sup>2</sup>TAL



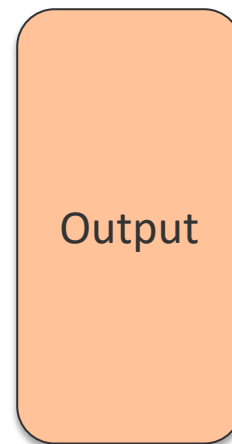
Resversible modules



Forward process



Reverse process





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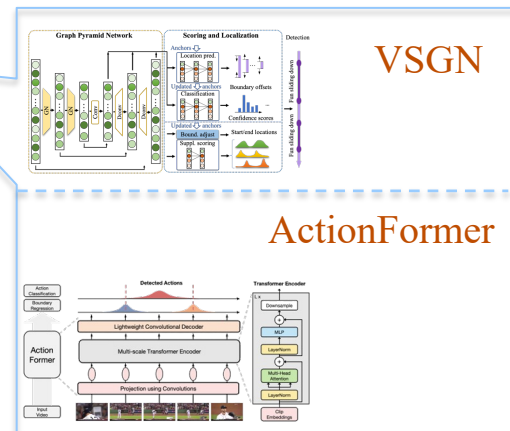
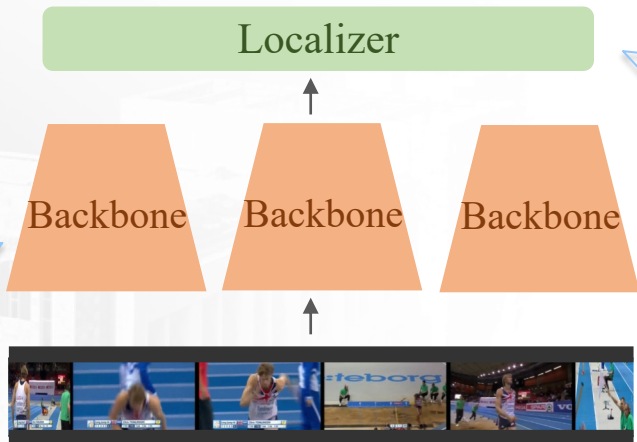
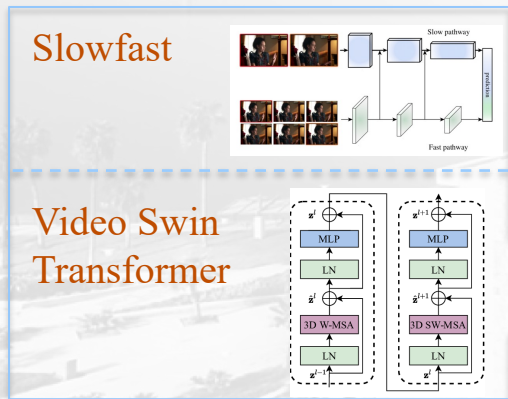
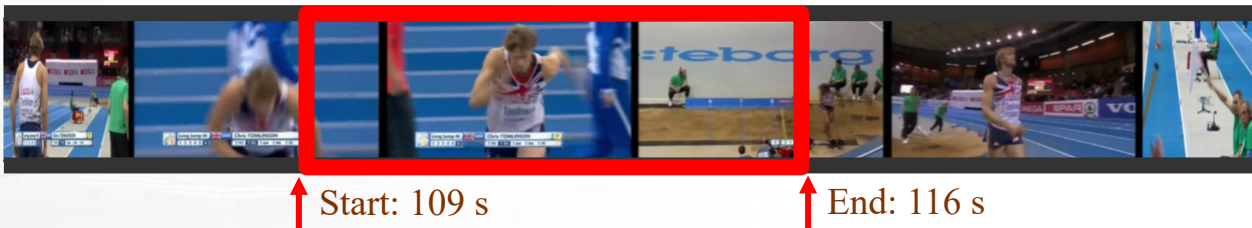
# Background and motivation

# Temporal Action Localization Faces Memory Shortage

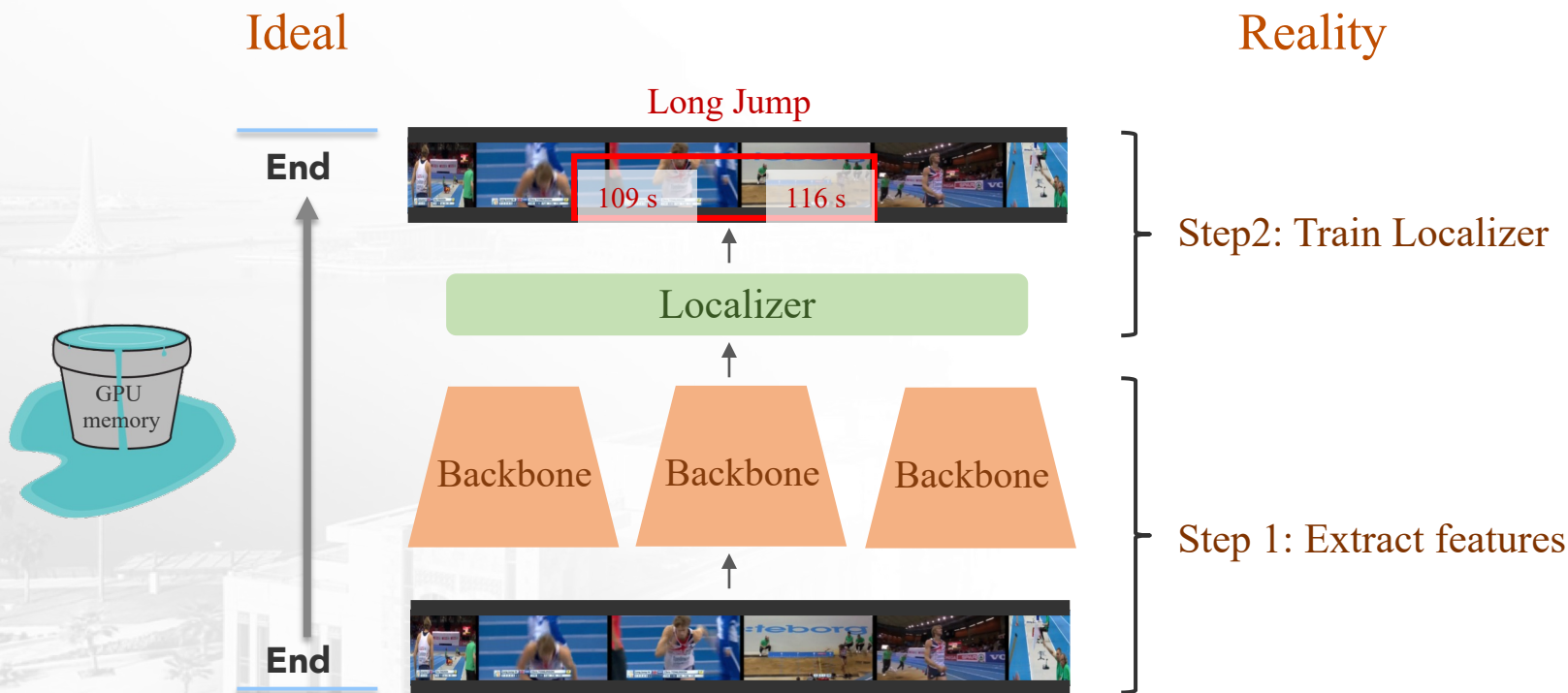


- Temporal action localization (TAL)

Action: Long Jump



# Temporal Action Localization Faces Memory Shortage

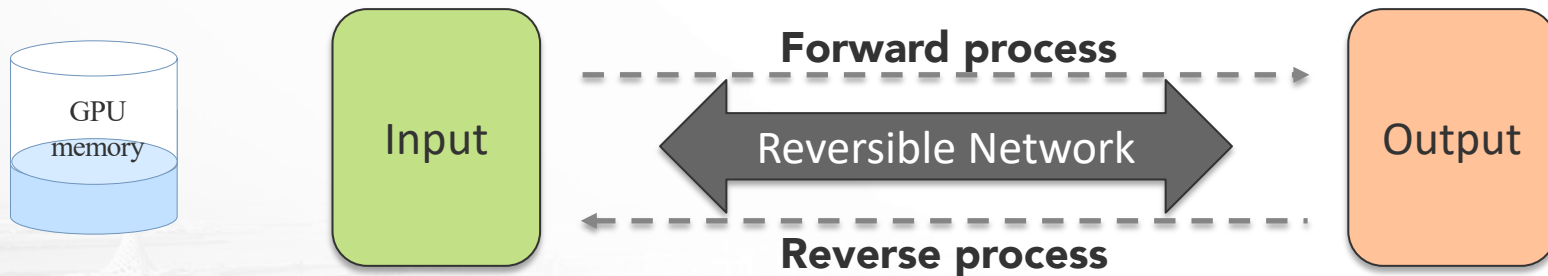




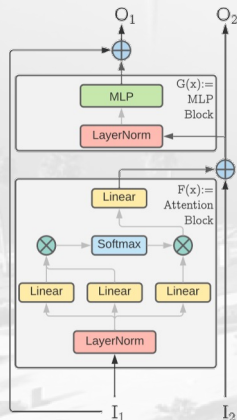
Can we use less memory for end-to-end training?



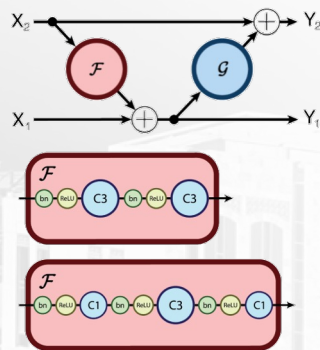
# Reversible Networks Use Less Memory



## Rev-ViT<sup>[1]</sup>



## RevNet<sup>[2]</sup>

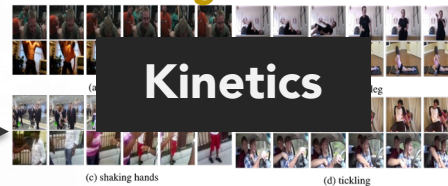


## TAL training

### Train on large image datasets



### Train on large video datasets



### Train on TAL datasets



[1] Reversible vision transformers, CVPR'22

[2] The reversible residual network: Backpropagation without storing activation, NeurIPS'17



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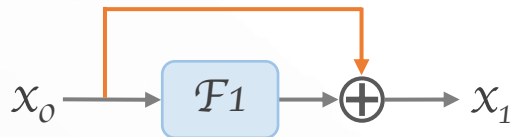


# Proposed Re<sup>2</sup>TAL

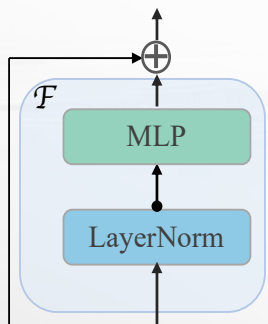
# Proposed Re<sup>2</sup>TAL



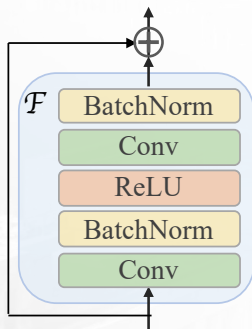
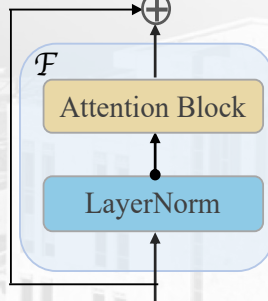
Residual module



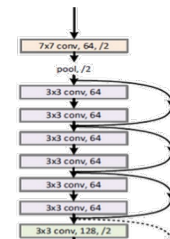
Transformer MLP block



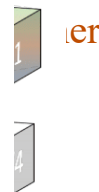
Transformer attention block



Resnet block



Future neural networks

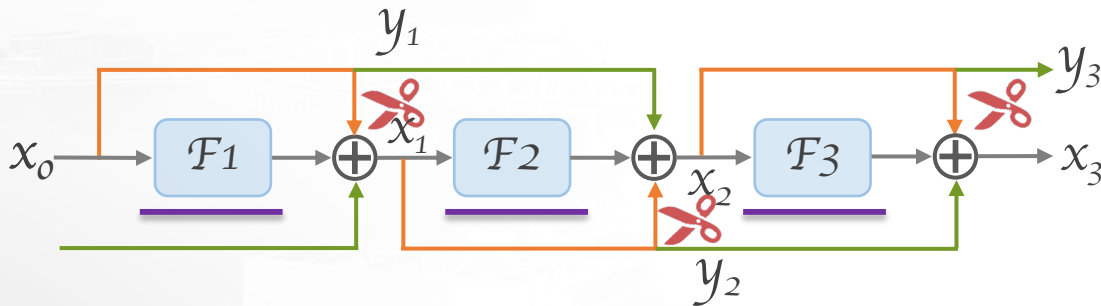


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Network of residual modules

**Rewiring**

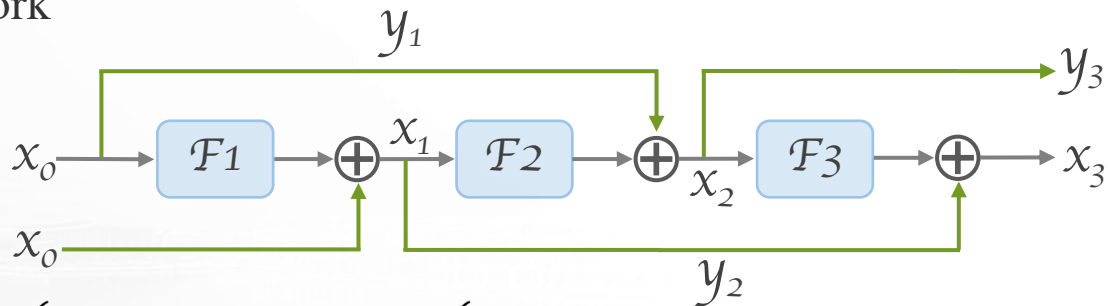


# Proposed Re<sup>2</sup>TAL

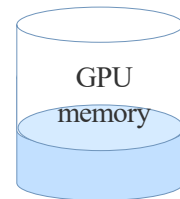


## Resversible network

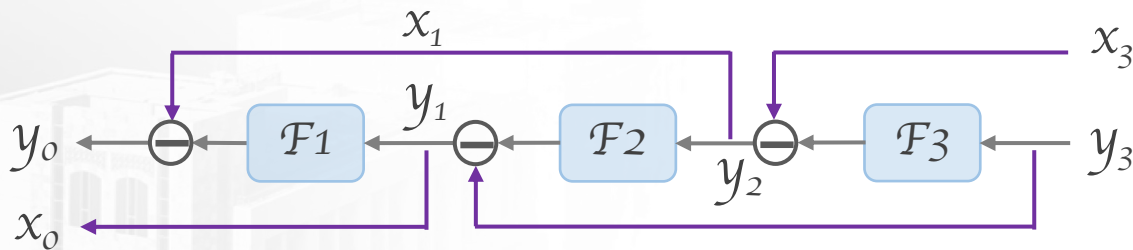
Forward



$$\begin{cases} y_1 = x_0 \\ x_1 = \mathcal{F}_1(x_0) + y_0, \end{cases} \Rightarrow \begin{cases} y_2 = x_1 \\ x_2 = \mathcal{F}_2(x_1) + y_1. \end{cases}$$



Reverse



$$\begin{cases} x_0 = y_1 \\ y_0 = x_1 - \mathcal{F}_1(x_0), \end{cases} \Leftarrow \begin{cases} x_1 = y_2 \\ y_1 = x_2 - \mathcal{F}_2(x_1). \end{cases}$$

# Re<sup>2</sup>TAL End-to-end Training



Prepare a video model with pretrained parameters



Rewire the residual connection in the video model as proposed



Load the pretrained parameters into the rewired model



Finetune for several epochs on the pretraining task



Ready for use for TAL (and other tasks)



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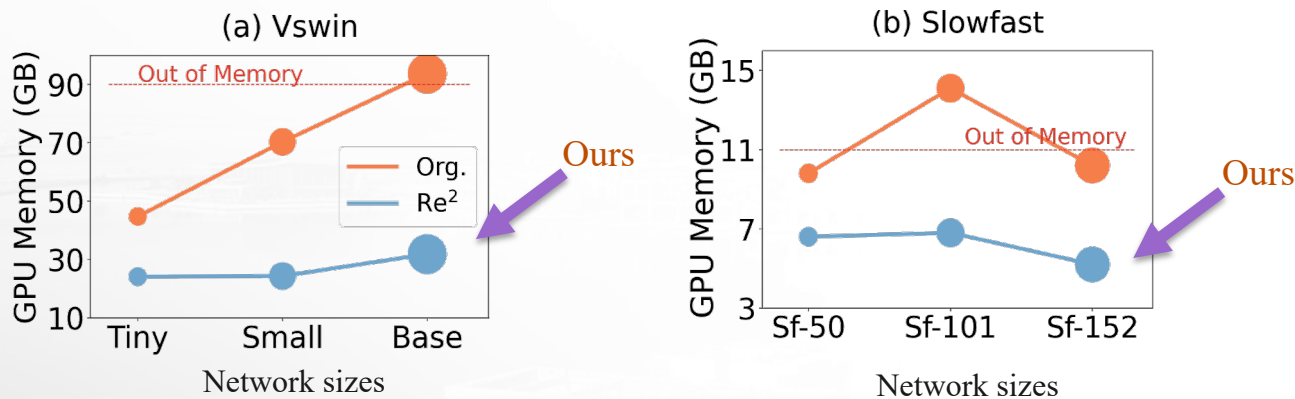


# Experimental Results

# Experiments: Compared to Non-reversible TAL



- Memory consumption is reduced



- Accuracy is preserved

Average mAP (%)

Model	Tiny	Small	Base	Model	50	101	152
Vswin	34.36	33.86	<b>34.47</b>	Slowfast	34.60	35.04	<b>34.61</b>
Re <sup>2</sup> Vw	<b>34.47</b>	<b>34.04</b>	34.09	Re <sup>2</sup> Slowf	<b>34.93</b>	<b>35.24</b>	34.54



# Experiments: Compared to Other Methods on TAL



mAPs (%) at tIoU thresholds

Method	Backbone	E2E	Flow	Mem	ActivityNet-v1.3				THUMOS-14				
					0.5	0.75	0.95	Avg.	0.3	0.4	0.5	0.6	0.7
TAL-Net [8]	I3D	✗	✓	-	38.23	18.30	1.30	20.22	53.2	48.5	42.8	33.8	20.8
BMN [36]	TSN	✗	✓	-	50.07	34.78	8.29	33.85	56.0	47.4	38.8	29.7	20.5
G-TAD [69]	TSN	✗	✓	-	50.36	34.60	9.02	34.09	54.5	47.6	40.2	30.8	23.4
TSI [41]	TSN	✗	✓	-	51.18	35.02	6.59	34.15	61.0	52.1	42.6	33.2	22.4
BC-GNN [4]	TSN	✗	✓	-	50.56	34.75	9.37	34.26	57.1	49.1	40.4	31.2	23.1
VSGN [73]	TSN	✗	✓	-	52.38	36.01	8.37	35.07	66.7	60.4	52.4	41.0	30.4
ActionFormer [71]	I3D	✗	✓	-	53.50	36.20	8.20	35.60	82.1	77.8	71.0	59.4	43.9
PBRNet [39]	I3D	✓	✓	-	53.96	34.97	8.98	35.01	58.5	54.6	51.3	41.8	29.5
AFSD [35]	I3D	✓	✓	12	52.40	35.30	6.50	34.40	67.3	62.4	55.5	43.7	31.1
R-C3D [66]	C3D	✓	✗	-	26.80	-	-	-	44.8	35.6	28.9	-	-
DaoTAD [63]	I3D	✓	✗	11	-	-	-	-	62.8	-	53.8	-	30.1
TALLFormer [10]	VSwin-Base	✓	✗	29	54.10	36.20	7.90	35.60	76.0	-	63.2	-	34.5
ActionFormer [71]	VSwin-Tiny	✗	✗	-	53.83	35.82	7.27	35.17	70.8	64.7	55.7	42.2	27.0
<b>ActionFormer + Re<sup>2</sup>TAL</b>	Re <sup>2</sup> VSwin-Tiny	✓	✗	24	54.75	37.81	9.03	36.80	77.0	71.5	62.4	49.7	36.3
ActionFormer [71]	Slowfast-101	✗	✗	-	53.98	37.00	8.87	36.09	72.7	66.9	58.6	46.4	33.1
<b>ActionFormer + Re<sup>2</sup>TAL</b>	Re <sup>2</sup> Slowfast-101	✓	✗	6.8	<b>55.25</b>	<b>37.86</b>	<b>9.05</b>	<b>37.01</b>	<b>77.4</b>	<b>72.6</b>	<b>64.9</b>	<b>53.7</b>	<b>39.0</b>

● New SOTA

● Improves over feature-based training



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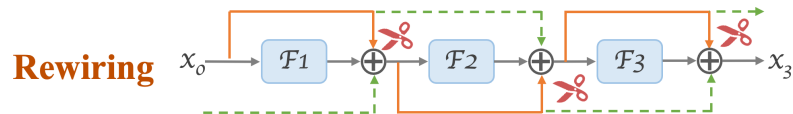
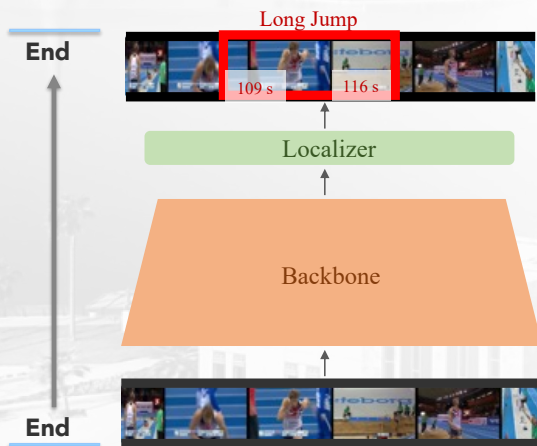


# Conclusions

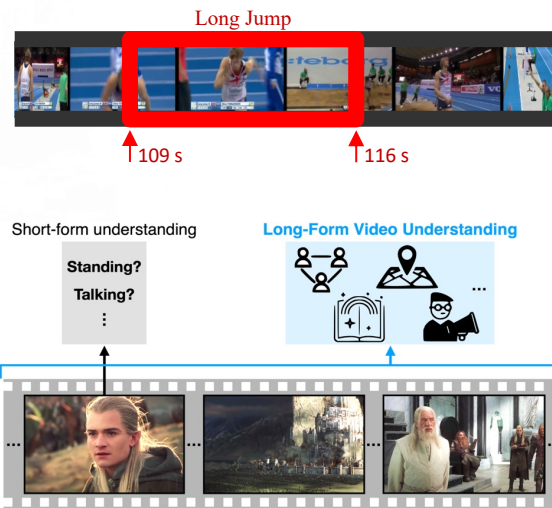
# Conclusions



- Rewiring to be reversible (Re<sup>2</sup>)
- End-to-end training



- Apply to memory-intensive tasks





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Website



Paper



Code