Learning Transferable Self-attentive Representations for Action Recognition in Untrimmed Videos with Weak Supervision

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Outline

1. Introduction
2. Our Method (TSRNet)
    - Two-Stream Feature Extraction
    - Self-attentive Action Classification
    - Knowledge Transfer
    - Temporal Action Detection
3. Evaluation
4. Conclusion

Action Recognition in Videos

- Videos
  - Trimmed: fully semantic annotations (*UCF101, HMDB51, etc.*)
  - Untrimmed: typically long, may contain multiple activities, difficult for temporal annotation (*THUMOS, ActivityNet, etc.*)
- Opportunities
  - Videos provide huge and rich data for visual learning
  - Action is important in motion perception and has many applications
- Challenges
  - Temporal models and representations
  - High computational and memory cost
  - Noisy and weakly labels

Motivation

- Existing Methods on Weakly Supervised Action Detection
  - UntrimmedNets [1] utilizes a soft selection module for untrimmed video classification along with activity localization.
  - STPN [2] utilizes a sparsity constraint to detect the activities.
  - W-TALC [3] improve the localization results by optimizing two complimentary loss functions.
- Limitations
  - Limited training videos.
  - Difficult to learn the specific high-level features for untrimmed videos.
  - External background information affect the model performance greatly.

[1] Limin Wang et al. UntrimmedNets for Weakly Supervised Action Recognition and Detection, in CVPR 2017

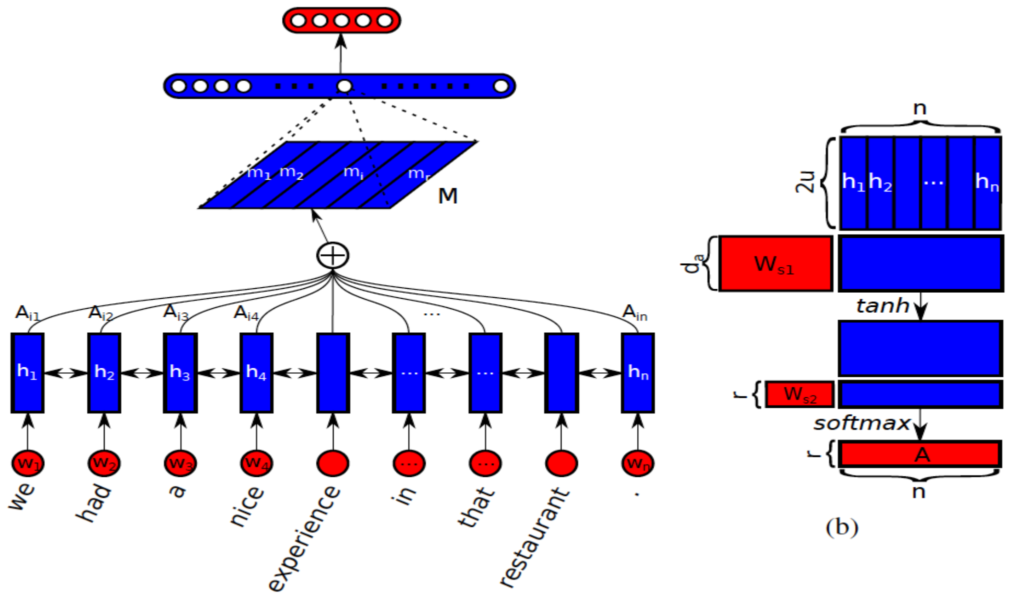
[2] Phuc Nguyen et al. Weakly Supervised Action Localization by Sparse Temporal Pooling Network, in CVPR 2018

[3] Sujoy Paul et al. W-TALC: Weakly-supervised Temporal Activity Localization and Classification, in ECCV 2018

Inspiration

Self-Attention Mechanism

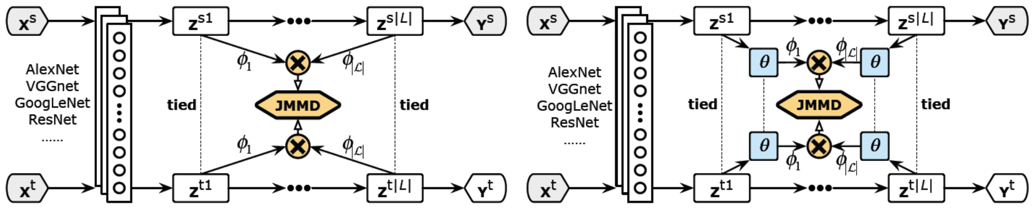
- Intra-domain exploring



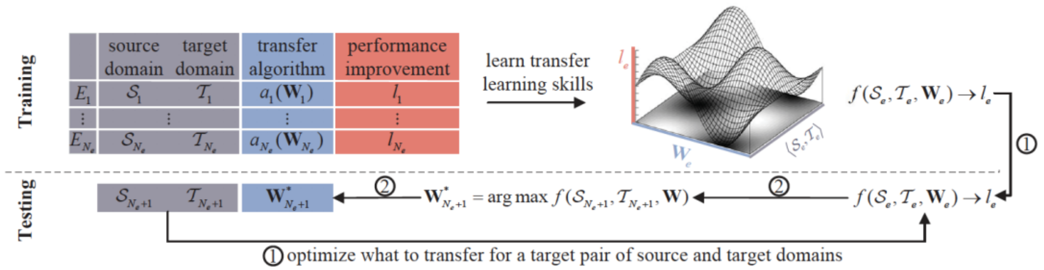
(a) (b)

Transfer Learning

- Inter-domain exploring



(a) Joint Adaptation Network (JAN) (b) Adversarial Joint Adaptation Network (JAN-A)



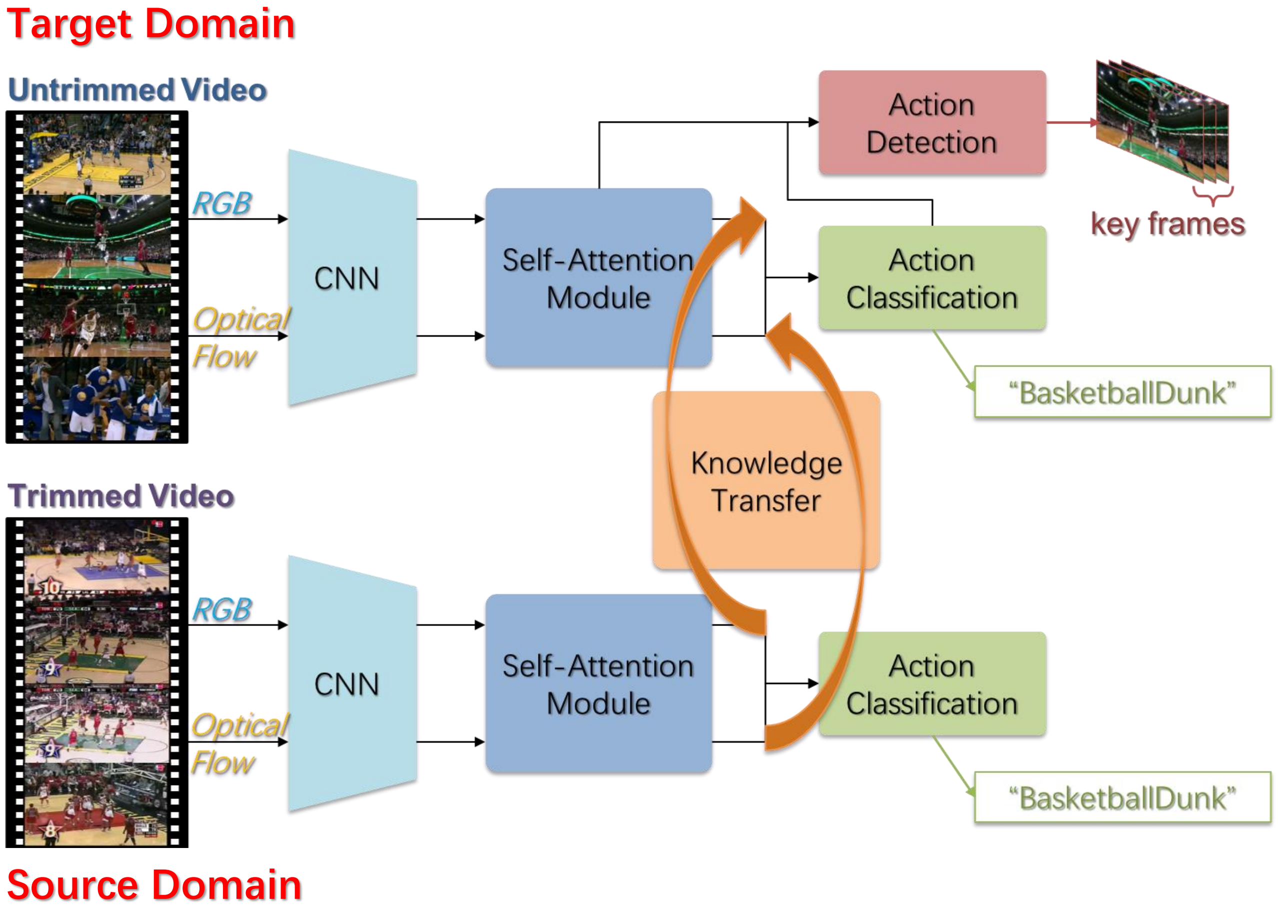
[1] Ashish Vaswani et al. Attention Is All You Need, in NIPS 2017
[2] Zhouhan Lin et al. A Structured Self-attentive Sentence Embedding, in ICLR 2017
[3] Mingsheng Long et al. Deep Transfer Learning with Joint Adaptation Networks, in ICML 2017
[4] Ying Wei et al. Transfer Learning via Learning to Transfer, in ICML 2018

Our Method (TSRNet)

- TSRNet: Transferable Self-attentive Representation learning based deep neural Network

  - Self-Attention Module: capture domain-specific properties

  - Transfer Module: capture general properties shared by domains



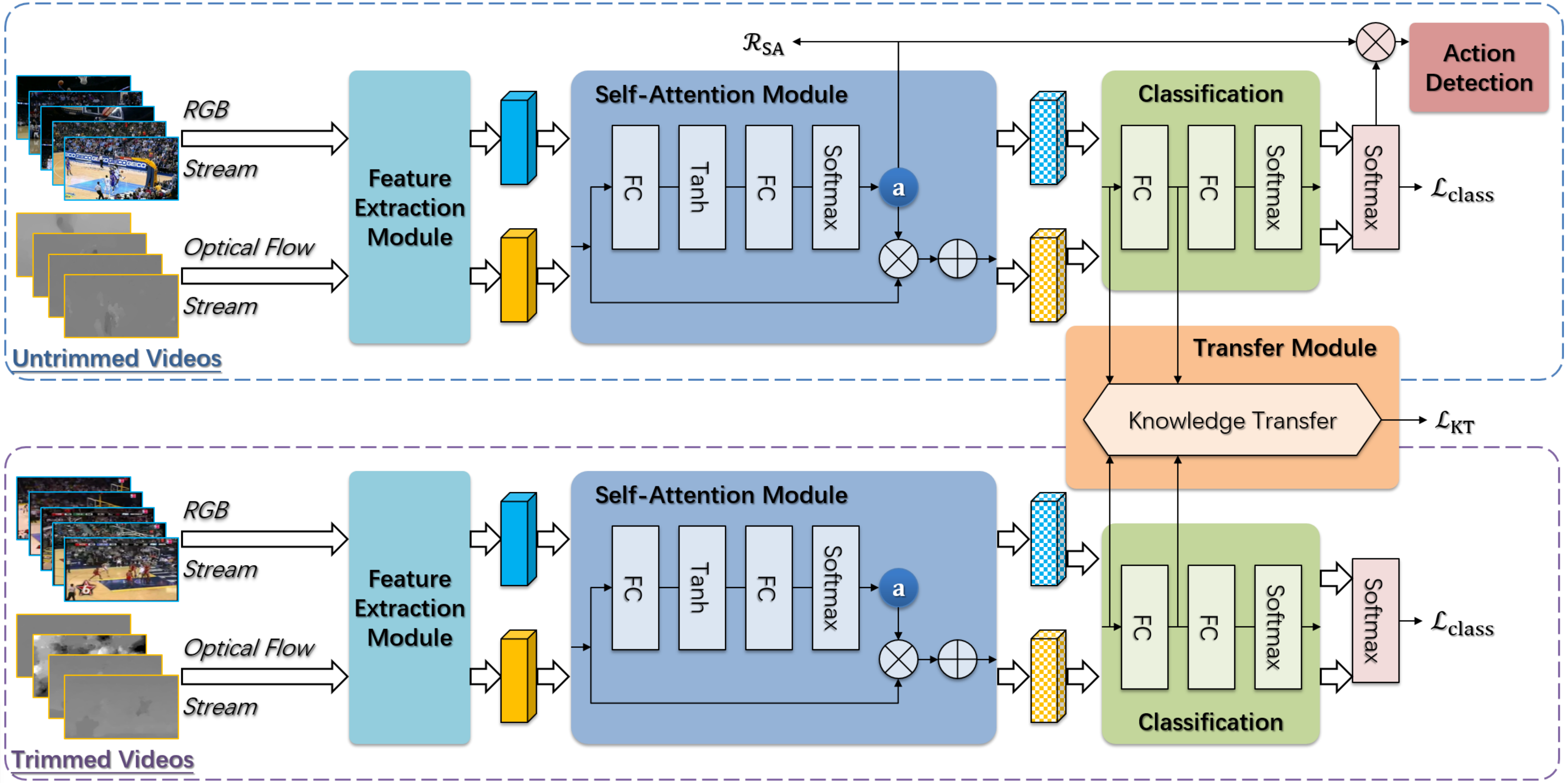
Framework

Two-stream feature extraction

Self-attentive action classification

Knowledge transfer between trimmed and untrimmed videos

Temporal action detection



Overall loss: $\mathcal{L} = \mathcal{L}_{SA} + \mathcal{L}_{KT}$

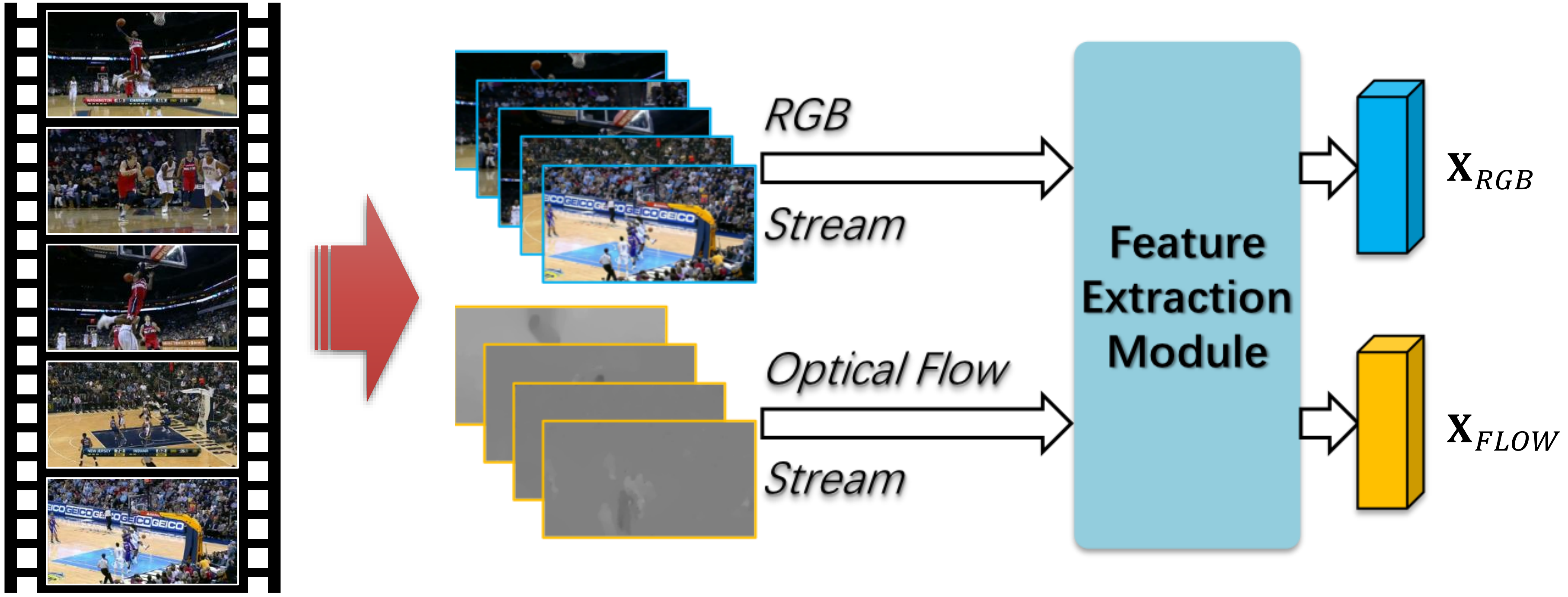
Two-Stream Feature Extraction

Two-stream feature extraction

Self-attentive action classification

Knowledge transfer between trimmed and untrimmed videos

Temporal action detection



- Base network: ResNet101
- $\mathbf{X}_{RGB}$: RGB feature matrices
- $\mathbf{X}_{FLOW}$: Optical flow feature matrices

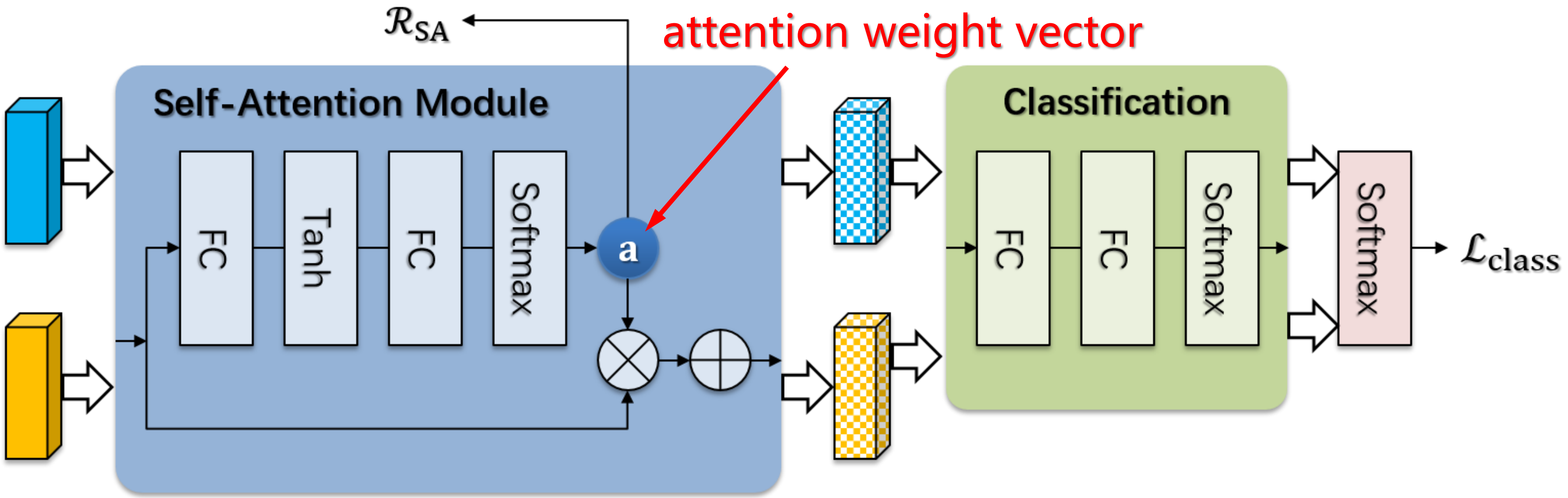
Self-Attentive Action Classification

Two-stream feature extraction

Self-attentive action classification

Knowledge transfer between trimmed and untrimmed videos

Temporal action detection



- $\mathbf{m} = \mathbf{X}\mathbf{a} = \mathbf{X}\left(\mathrm{softmax}\left(\mathbf{w_2} \cdot \tanh(\mathbf{W_1}\mathbf{X})\right)\right)^T$
- $\mathcal{L}_{SA} = \mathcal{L}_{class} + \mathcal{R}_{SA}$
  - $\mathcal{L}_{class}$: the standard multi-label cross-entropy loss
  - $\mathcal{R}_{SA} = \alpha\mathcal{R}_{smooth} + \beta\mathcal{R}_{sparsity}$
    - $\mathcal{R}_{smooth} = \sum_{i=1}^{n-1}(a_i - a_{i+1})^2$
    - $\mathcal{R}_{sparsity} = \|\mathbf{a}\|_1$

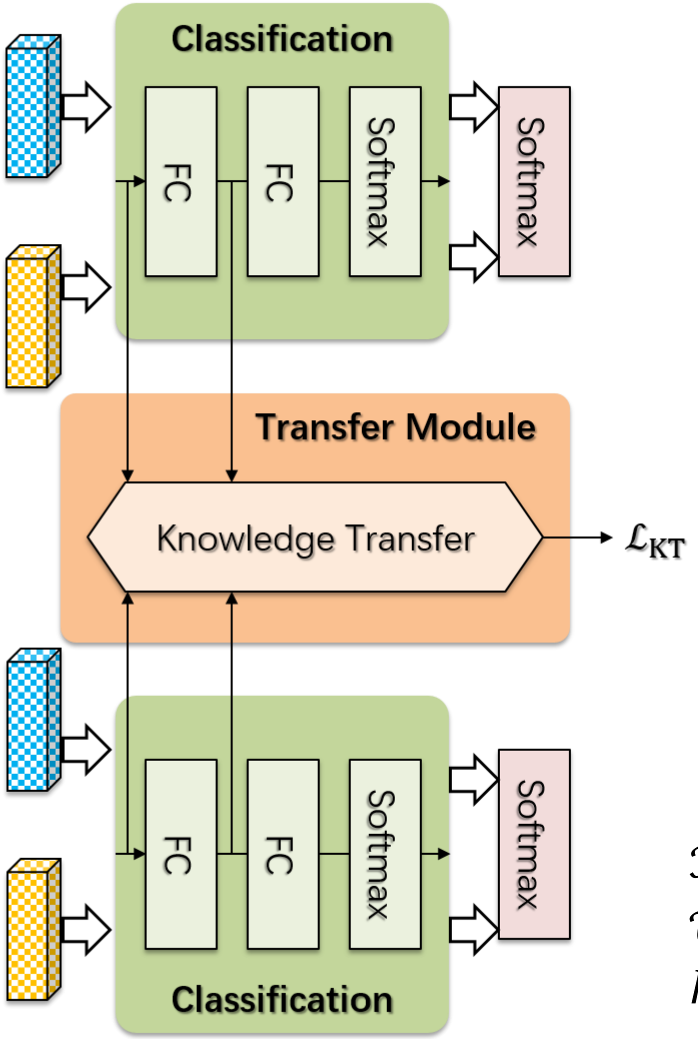
Knowledge Transfer

Two-stream feature extraction

Self-attentive action classification

Knowledge transfer between trimmed and untrimmed videos

Temporal action detection

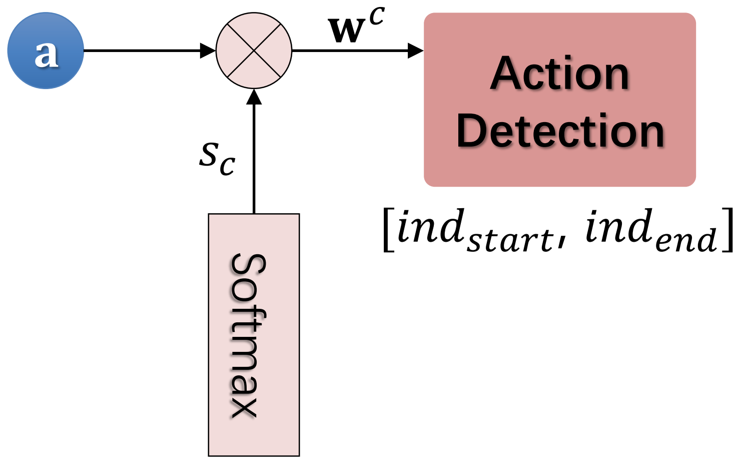


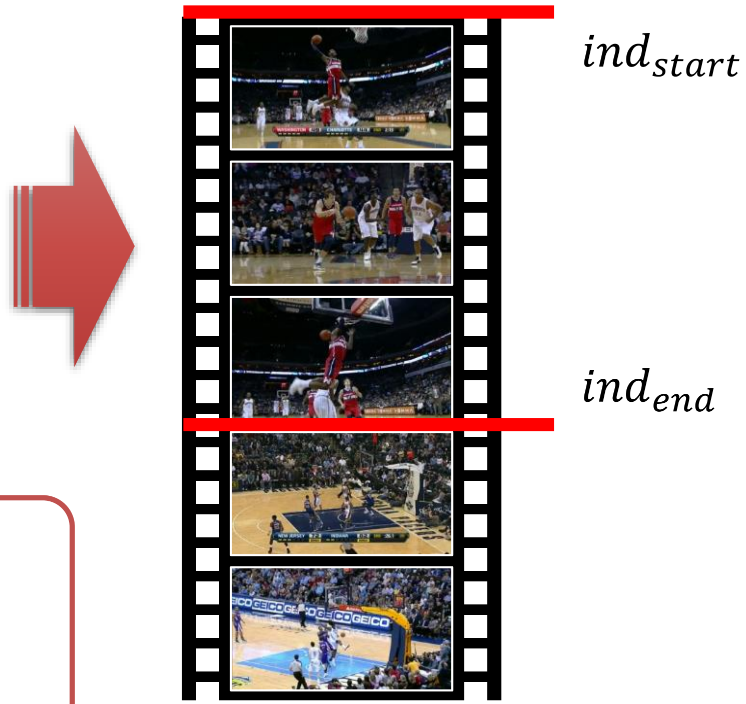
- $\mathcal{L}_{KT} = \mathcal{L}_{FC1} + \mathcal{L}_{FC2}$
  - $\mathcal{L}_{FC1} = \mathrm{MMD}^2(\mathcal{T}, \mathcal{U})$
    $$= \frac{1}{n_T^2} \sum_{i=1}^{n_T} \sum_{j=1}^{n_T} k(\mathbf{t}_i, \mathbf{t}_j) + \frac{1}{n_U^2} \sum_{i=1}^{n_U} \sum_{j=1}^{n_U} k(\mathbf{u}_i, \mathbf{u}_j) - \frac{2}{n_T \cdot n_U} \sum_{i=1}^{n_T} \sum_{j=1}^{n_U} k(\mathbf{t}_i, \mathbf{u}_j)$$
  - $\mathcal{L}_{FC2} = \mathrm{MMD}^2\left(FC1(\mathcal{T}), FC1(\mathcal{U})\right)$

$\mathcal{T} = \{\boldsymbol{t}_i|_{i=1}^{n_T}\}$: the set of features of trimmed videos
$\mathcal{U} = \{\boldsymbol{u}_i|_{i=1}^{n_U}\}$: the set of features of untrimmed videos
$k(\cdot,\cdot)$: the Gaussian kernel function

Temporal Action Detection

- Two-stream feature extraction
- Self-attentive action classification
- Knowledge transfer between trimmed and untrimmed videos
- **Temporal action detection**





- $w_i^c = a_i s_c$
- $\overline{w}_i^c = \theta \cdot w_{i,RGB}^c + (1-\theta) \cdot w_{i,Flow}^c$
- $t_{start} = \dfrac{ind_{start}}{F}, t_{end} = \dfrac{ind_{end}}{F}$

w_i^c: the weighted score of frame i for class c.

$s_c = [s_1, s_2, \dots, s_m]^T \in \mathbb{R}^{m\times 1}$: the output of softmax layer.

$[ind_{start}, ind_{end}]$: the frame indices of starting and ending positions.

F: the fps (frames per second) of videos.

Experiments – Settings

- Evaluation Datasets

	# Training Data	# Testing Data
THUMOS14	1,010	10,024
ActivityNet1.3	1,574	4,926

- Transfer Dataset

# Overlapping Classes	THUMOS14	ActivityNet1.3
UCF101	20	200

Experiments – Settings

- Implementations Details

Hyper-parameters	Settings
Batch Size	16
Momentum	0.9
Dropout	0.8
Learning Rate	0.0001(RGB) / 0.0005(Optical Flow)
Sampling Rate	30 fps (frames per second)
Decay Rate	Decrease every 5,000 iterations by 10

Results – Action Classification

- Action recognition on **THUMOS14**

Table 1: Classification accuracy (%) of all the methods on the THUMOS14 dataset for action recognition. Note that SRNet is a simpler version of TSRNet, which excludes the knowledge transfer module.

	RGB	Optical Flow	Fusion
(Wang and Schmid 2013)	-	-	63.1
(Wang et al. 2016)(3 seg)	-	-	78.5
(Wang et al. 2017)	-	-	82.2
Two-Stream	68.2	71.6	73
SRNet	72.3	76.2	79.4
TSRNet	**74.4**	**79.6**	**87.1**

Two-Stream: TSRNet w/o (Self-Attention & Knowledge Transfer module)

SRNet: TSRNet w/o Knowledge Transfer module

Results – Action Classification

- Action recognition on **ActivityNet1.3**

Table 2: Classification accuracy (%) of all the methods on the ActivityNet1.3 dataset for action recognition. Note that SRNet is a simpler version of TSRNet, which excludes the knowledge transfer module.

	RGB	Optical Flow	Fusion
Two-Stream	71.4	73.5	79.2
SRNet	74.3	80.1	86.9
TSRNet	**79.7**	**84.3**	**91.2**

Two-Stream: TSRNet w/o (Self-Attention & Knowledge Transfer module)

SRNet: TSRNet w/o Knowledge Transfer module

Results – Action Detection

- Action detection on **THUMOS14**

Table 3: Comparisons on the THUMOS14 dataset for action detection.

	Method	mAP@IoU (%)								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Full supervision	(Richard and Gall 2016)	39.7	35.7	30.0	23.2	15.2	-	-	-	-
	(Shou, Wang, and Chang 2016)	47.7	43.5	36.3	28.7	19.0	10.3	5.3	-	-
	(Yeung et al. 2016)	48.9	44.0	36.0	26.4	17.1	-	-	-	-
	(Alwassel, Heilbron, and Ghanem 2017)	49.6	44.3	38.1	28.4	19.8	-	-	-	-
	(Lin, Zhao, and Shou 2017)	50.1	47.8	43.0	35.0	24.6	-	-	-	-
	(Yuan et al. 2016)	51.4	42.6	33.6	26.1	18.8	-	-	-	-
	(Shou et al. 2017)	-	-	40.1	29.4	23.3	13.1	7.9	-	-
	(Xu, Das, and Saenko 2017)	54.5	51.5	44.8	35.6	28.9	-	-	-	-
	(Zhao et al. 2017)	**66.0**	**59.4**	**51.9**	**41.0**	**29.8**	-	-	-	-
Weak supervision	(Wang et al. 2017)	44.4	37.7	28.2	21.1	13.7	-	-	-	-
	(Singh and Lee 2017)	36.4	27.8	19.5	12.7	6.8	-	-	-	-
	(Nguyen et al. 2017)	52.0	44.7	35.5	25.8	16.9	9.9	4.3	1.2	0.1
	(Nguyen et al. 2017)	45.3	38.8	31.1	23.5	16.2	9.8	5.1	2.0	0.3
	TSRNet (w/o $\mathcal{L}_{FC2}$)	53.5	45.3	35.9	26.5	17.2	10.4	5.31	1.93	0.21
	TSRNet	**55.9**	**46.9**	**38.3**	**28.1**	**18.6**	**11.0**	**5.59**	**2.19**	**0.29**

TSRNet (w/o $\mathcal{L}_{FC2}$): TSRNet w/o the 2nd Knowledge Transfer

Results – Action Detection

- Action detection on **ActivityNet1.3**

Table 4: Comparisons on the ActivityNet1.3 dataset for action detection.

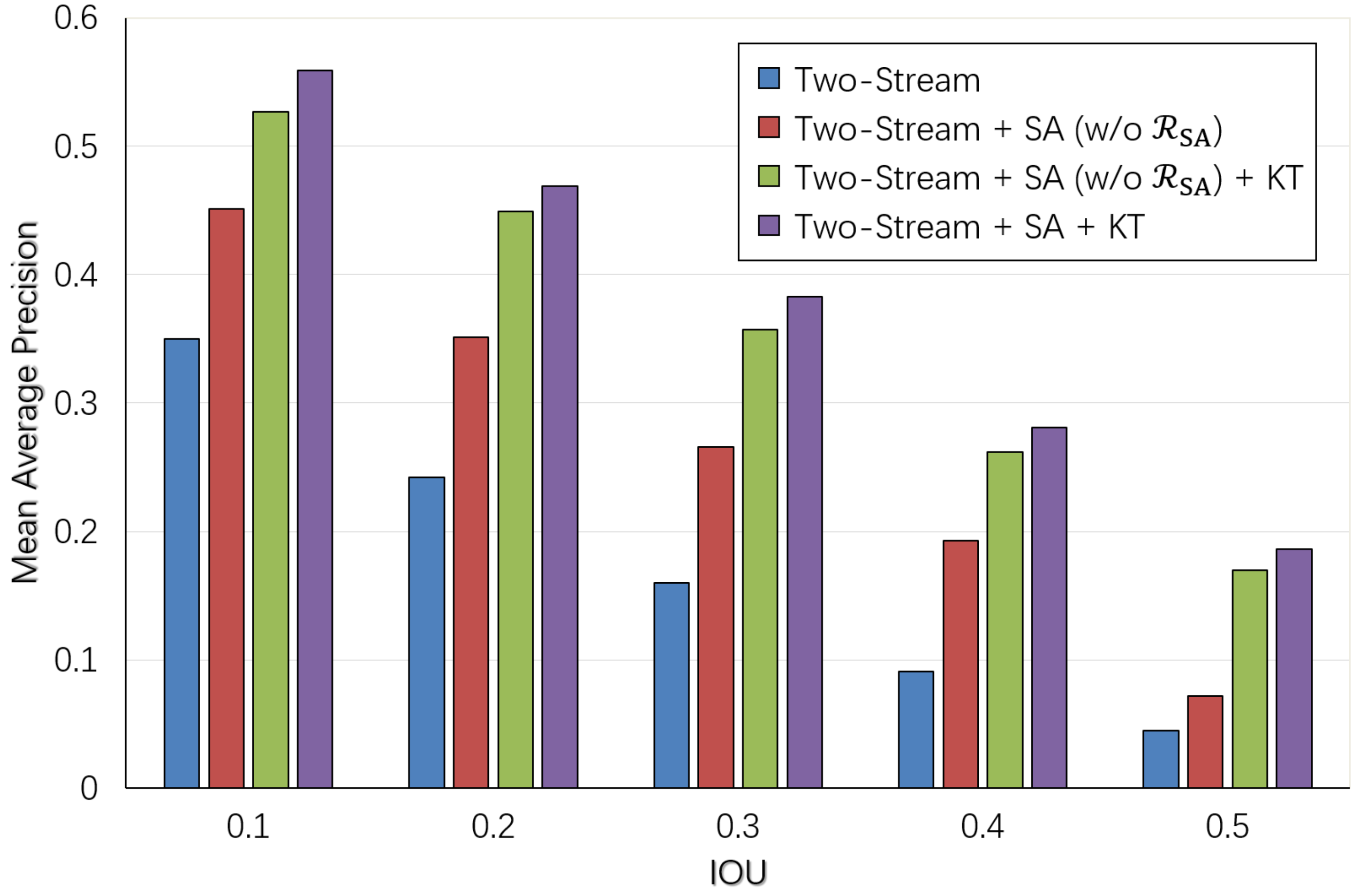
	Methods	mAP@IoU (%)			
		0.5	0.75	0.95	Average
Full supervision	(Singh and Cuzzolin 2016)	34.5	-	-	11.3
	(Xu, Das, and Saenko 2017)	26.8	-	-	-
	(Xiong et al. 2017)	29.1	23.5	5.5	-
	(Heilbron et al. 2017)	40.0	17.9	4.7	21.7
	(Shou et al. 2017)	45.3	26.0	0.2	23.8
	(Zhao et al. 2017)	39.12	23.48	5.49	23.98
	(Lin et al. 2018)	**52.50**	**33.53**	**8.85**	**33.72**
Weak supervision	(Nguyen et al. 2017)	29.3	16.9	2.6	-
	TSRNet (pretrained:[ResNet101@ImageNet])	29.9	17.2	2.71	19.56
	TSRNet (pretrained:[TSRNet@overlap30])	**33.1**	**18.7**	**3.32**	**21.78**

TSRNet (pretrained: [ResNet101@ImageNet]): using ResNet101 pretrained on ImageNet to initialize the feature extraction module of TSRNet

TSRNet (pretrain: [TSRNet@overlap30]): using the overlapping 30 classes between UCF101 and ActivityNet1.3 to initialize the entire TSRNet

Results – Ablation Study

- Ablation study on **THUMOS14**



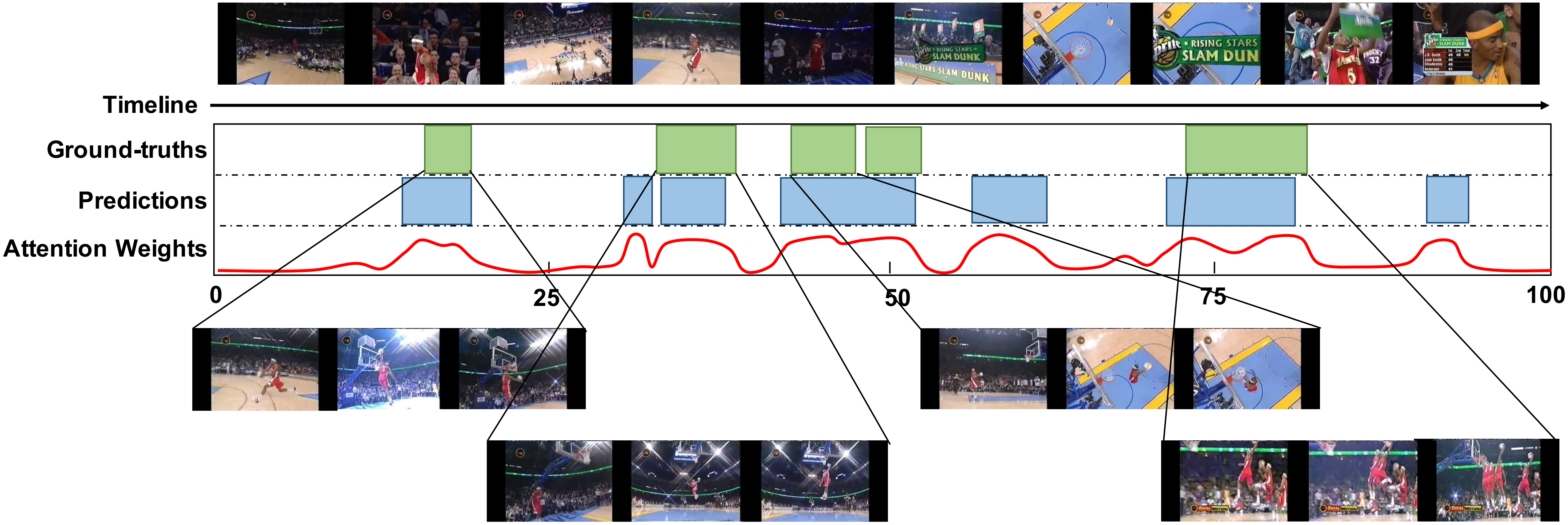
SA: the self-attention module

KT: the knowledge transfer module

Two-Stream + SA + KT: the full implementation of TSRNet

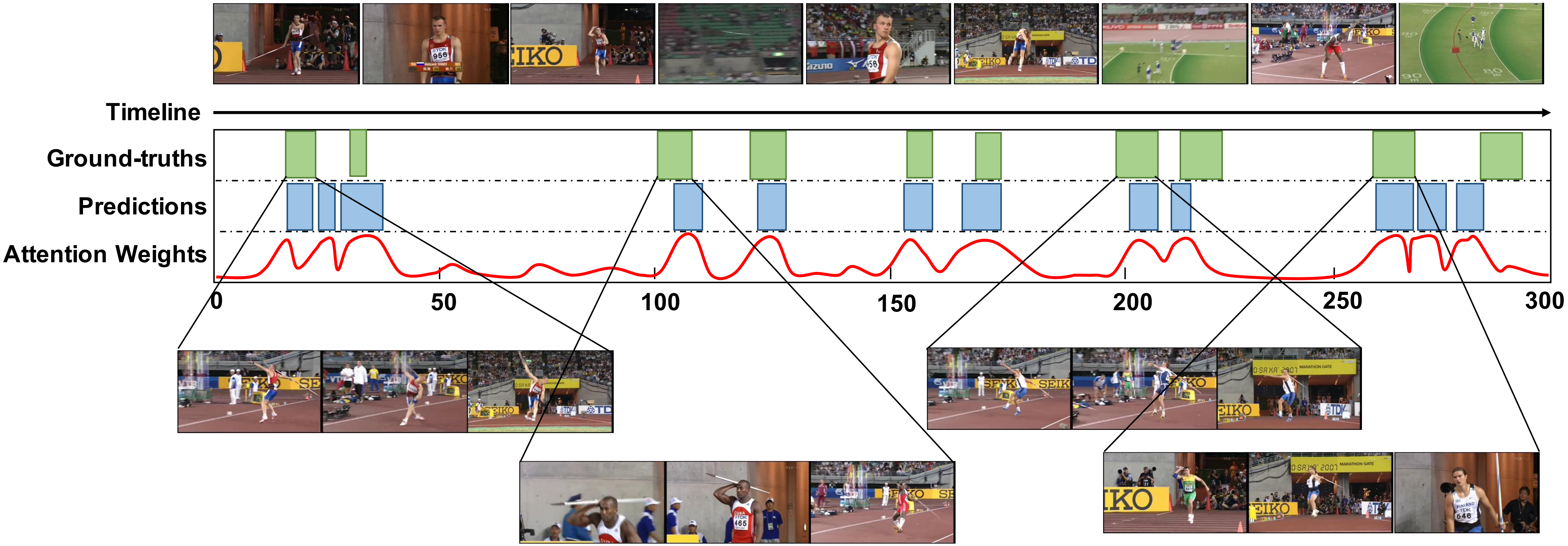
Results – Qualitative Evaluation

- Qualitative evaluation on **THUMOS14**



Results – Qualitative Evaluation

- Qualitative evaluation on **ActivityNet1.3**



Conclusion

- TSRNet is the first to introduce Knowledge Transfer for action recognition in untrimmed videos with weak supervision
  - Knowledge of additional trimmed videos is effectively leveraged and transferred to improve the classification performance for untrimmed ones.
- TSRNet adopts Self-Attention mechanism to obtain frame-levels analysis
  - Frames with higher self-attentionweights can be selected out for the purpose of temporal action localization/detection in videos.
- TSRNet outperforms the existing state-of-the-art competitors
  - Extensive experiments on two challenging untrimmed video datasets (i.e., THUMOS14 and ActivityNet1.3) show promising results

Thank you!
Questions & Answers