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

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# Outline

- 1. Introduction
  - Motivation
  - Overview
  - Related Work
- 2. Method (TSRNet)
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  - Localization
- 3. Evaluation
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# Motivation

- Difficulty of adaptation to **large-scale** action recognition.
- Existing **precise temporal annotations** are **limited**.
- Exact temporal extent of actions and temporal annotations may be **subjective** and **not consistent** across different persons

# Motivation

- **Expensive** and **time-consuming** to acquire a large-scale trimmed video dataset.
- Breakthroughs of **self-attention** on computer vision tasks.
- Abundant and useful information in trimmed videos contribute the use of **transfer learning**.

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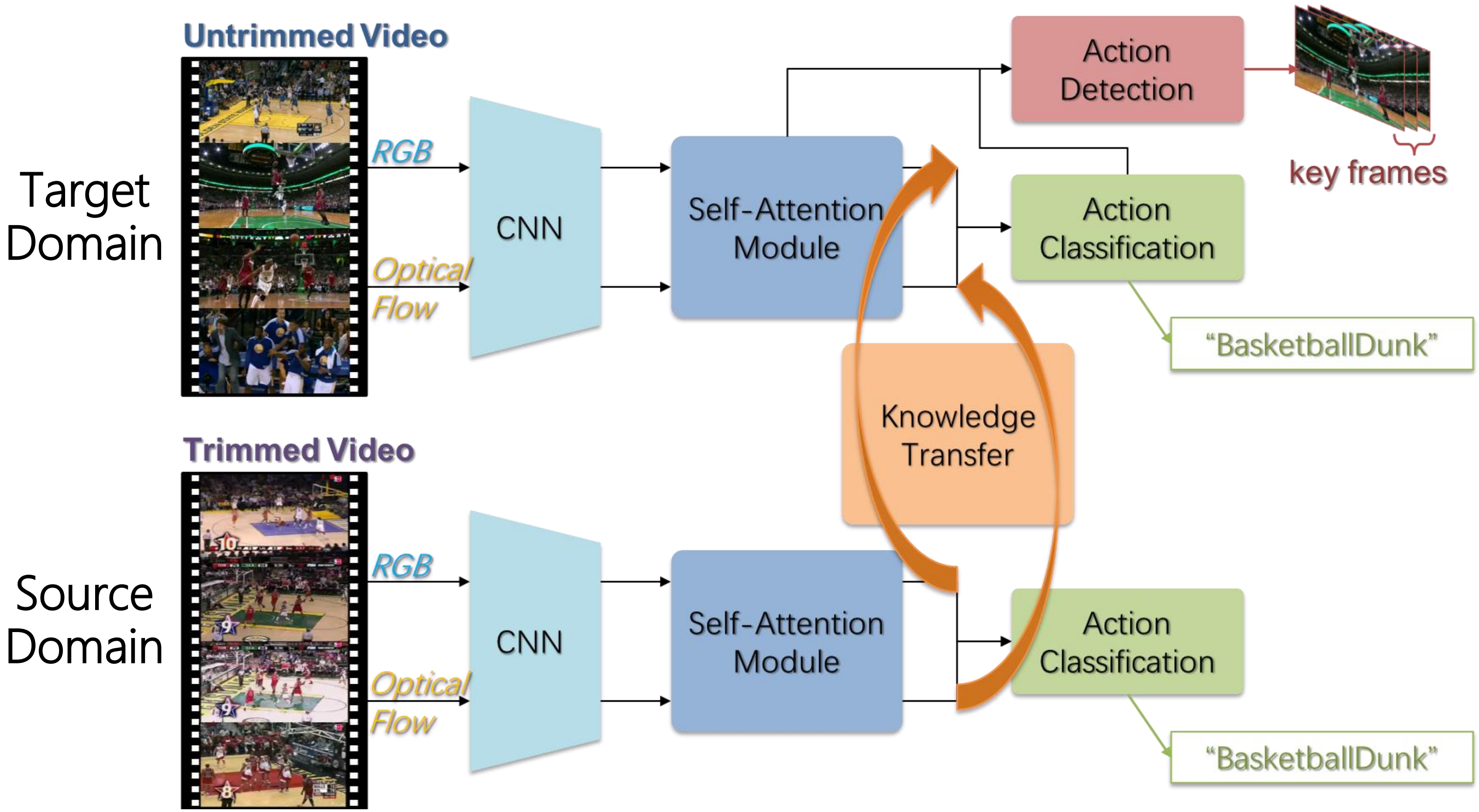
# Overview




A **self-attention module** for each domain: capture specific domain properties.
A **transfer module**: capture representations shared by domains.

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# Related Work

- Action Recognition
  - Two-stream Network, C3D, Temporal Segment Network(TSN), etc.
- Temporal Action Detection
  - Fully-supervised: S-CNN, SSN, etc.;
  - Weakly-supervised: UntrimmedNet, STPN, W-TALC, etc.
- Transfer Learning
  - Maximum Mean Discrepancy(MMD), JAN, DAN, etc.
- Attention Mechanism
  - Attention mechanism used in RNN, CNN.

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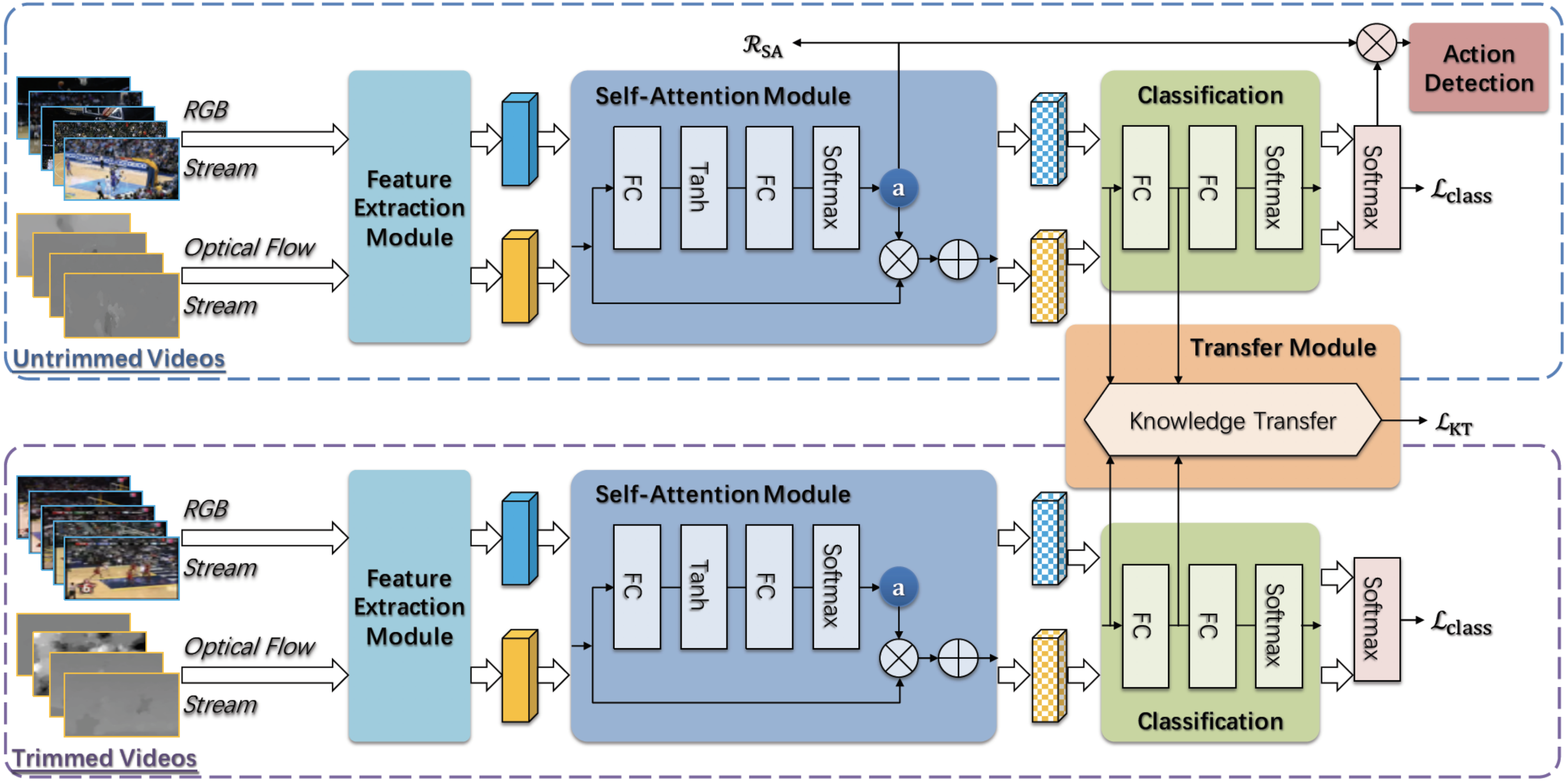
# Overview




**a: the attention vector**

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# Learning

Self-attentive Action Classification

$\mathbf{m} = \mathbf{Xa} = \mathbf{X}(\mathrm{softmax}(\mathbf{w_2} \cdot \tanh(\mathbf{W_1X})))^{\mathrm{T}}$

$\mathcal{L}_{SA} = \mathcal{L}_{class} + \mathcal{R}_{SA}$

$\mathcal{R}_{SA} = \alpha\mathcal{R}_{smooth} + \beta\mathcal{R}_{sparsity}$

$\mathcal{R}_{smooth} = \sum_{i=1}^{n-1}(a_i - a_{i+1})^2, \mathcal{R}_{sparsity} = ||a||_1$

$\mathcal{L}_{class}$: the standard multi-label cross-entropy loss

$a$: attention weights vector

$\mathbf{X}$: feature matrix, $\mathbf{m}$: a weighted sum of feature vectors

# Learning

Knowledge Transfer between Trimmed and Untrimmed Videos

$\mathcal{L}_{KT} = \mathcal{L}_{FC1} + \mathcal{L}_{FC2}$

$\mathcal{L}_{FC1} = MMD^2(\mathcal{T}, \mathcal{U})$

$$= \frac{1}{n_T^2} \sum_{i=1}^{n_T} \sum_{j=1}^{n_T} k(t_i, t_j) + \frac{1}{n_U^2} \sum_{i=1}^{n_U} \sum_{j=1}^{n_U} k(u_i, u_j) - \frac{2}{n_T \cdot n_U} \sum_{i=1}^{n_T} \sum_{j=1}^{n_U} k(t_i, u_j)$$

$\mathcal{L}_{FC2} = MMD^2(FC1(\mathcal{T}), FC1(\mathcal{U}))$

$\mathcal{T} = \{\boldsymbol{t}_i|_{\mathrm{i}=1}^{n_T}\}$, $\mathcal{U} = \{\boldsymbol{u}_i|_{\mathrm{i}=1}^{n_U}\}$, represent the sets of trimmed and untrimmed videos features.

$k(\cdot,\cdot)$: the predefined Gaussian kernel function.

Total Loss: $\boldsymbol{\mathcal{L}} = \boldsymbol{\mathcal{L}_{SA}} + \boldsymbol{\mathcal{L}_{KT}}$

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# Localization

$$w_i^c = a_i s_c$$

$$\bar{w}_i^c = \theta \cdot w_{i,RGB}^c + (1-\theta) \cdot w_{i,Flow}^c$$

$$t_{start} = \frac{ind_{start}}{F}$$

$$t_{end} = \frac{ind_{end}}{F}$$

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

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

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

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

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# Settings

Evaluation is based on training on the paired datasets.

- Data for training:

  Source domain training: Trimmed videos from the source domain.

  Domain adaptation training: Untrimmed videos from the target domain.

- Test:

  Test set from the target domain

- Transfer scenarios:

  (a). UCF101 to THUMOS14

  (b). UCF101 to ActivityNet1.3

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# Accuracy

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** |

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** |

The action recognition results. TSRNet performs good performance than the other based on weakly supervised learning scheme on THUMOS14 and ActivityNet1.3 datasets.

# Accuracy

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 can not only outperform other weakly supervised learning methods, it can also outperform some fully supervised learning methods for action detection.

# Accuracy

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** |

Note that the 'pretrained:[TSRNet@overlap30]' represents that we use the classes with overlapping labels found between the UCF101 and ActivityNet1.3 datasets to initialize the TSRNet and train it using the whole classes. The 'pretrained:[ResNet101@ImageNet]' represents that we use the ResNet101 pretrained on ImageNet dataset to initialize the TSRNet and then train it.

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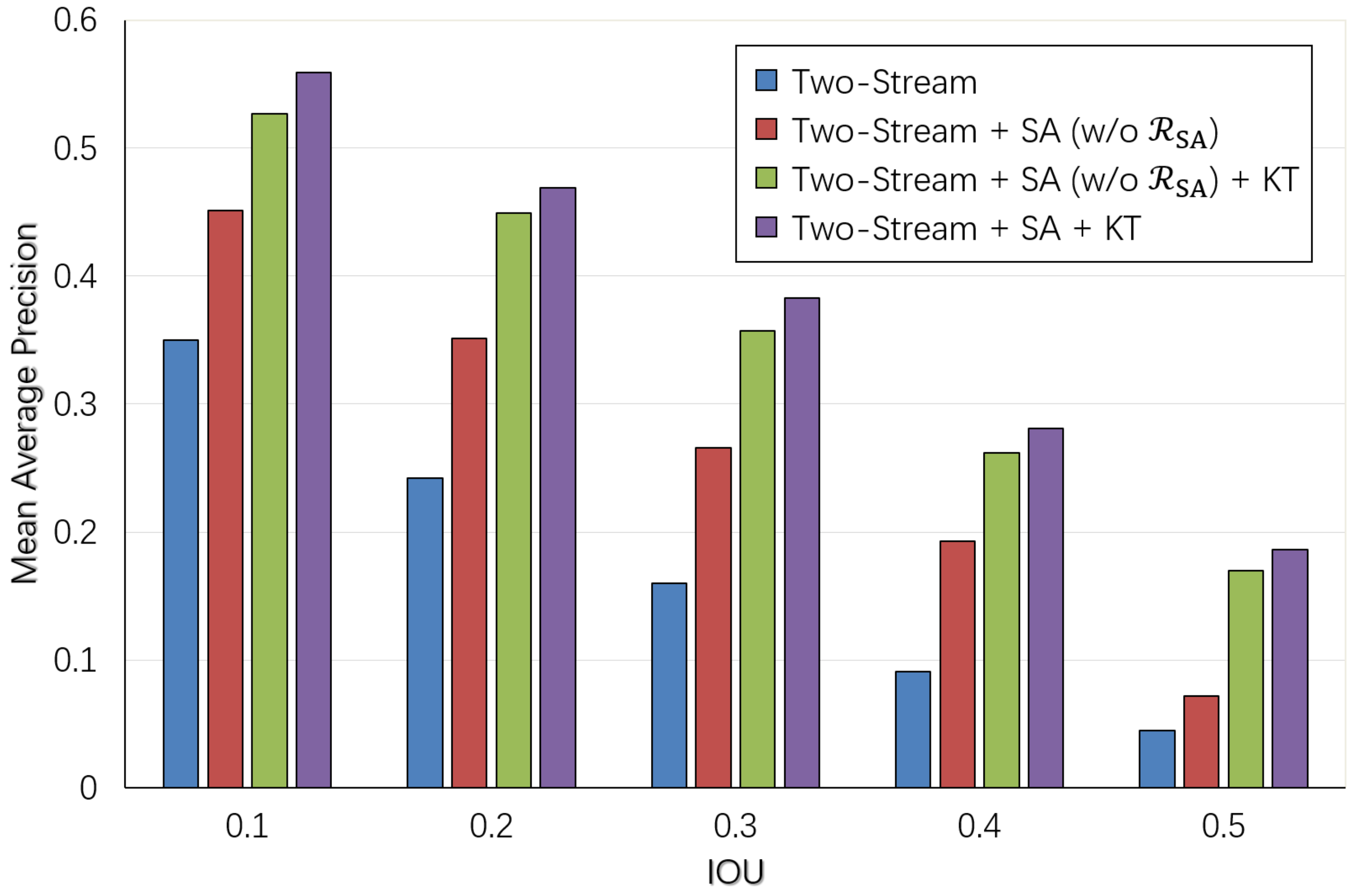
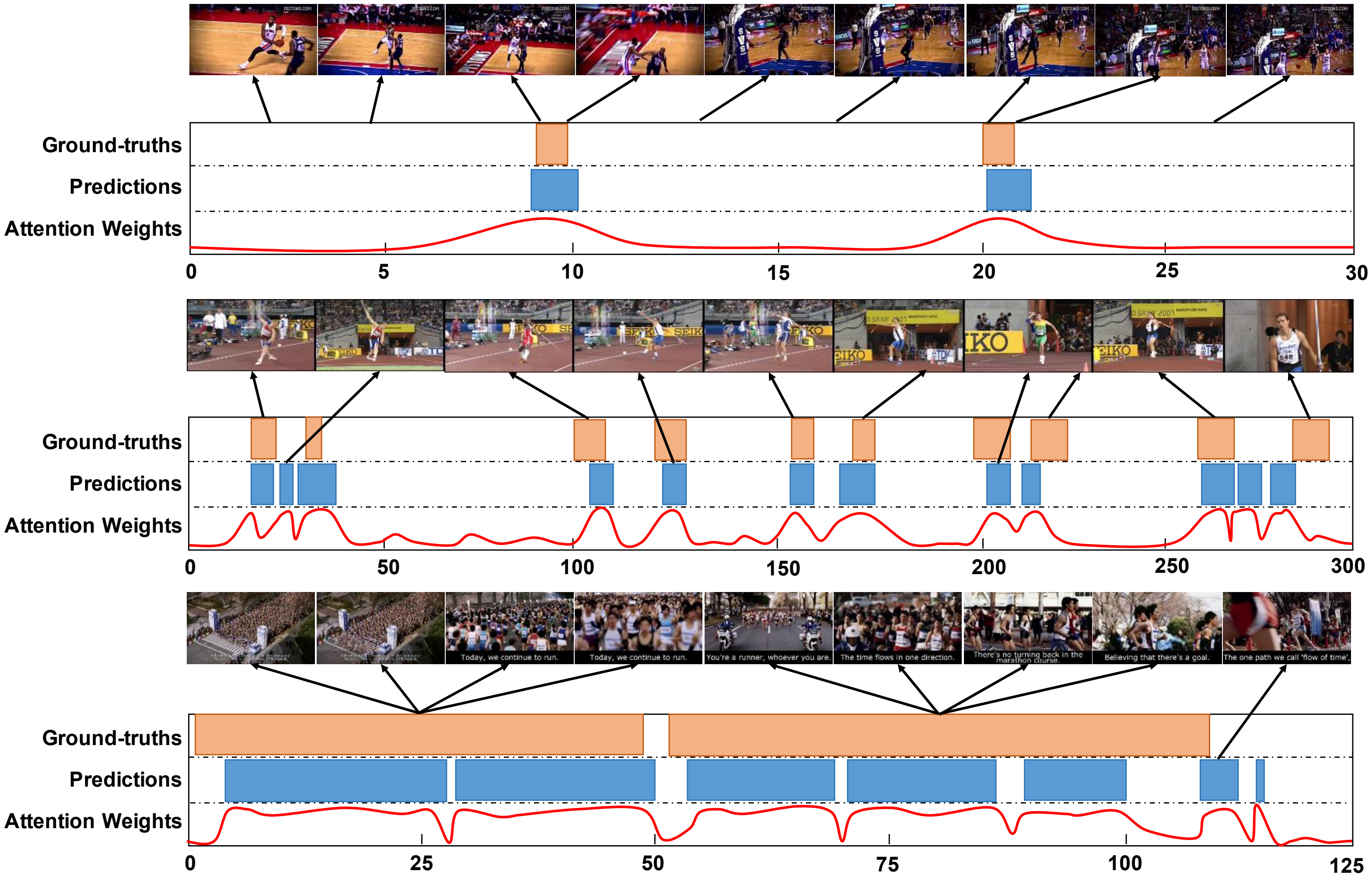



The results of baselines and the full model among different IoUs.
The self-attention with regularization loss and knowledge transfer contribute substantially to the model performance improvement.

# Analysis




Qualitative results on THUMOS14 (top and middle) and ActivityNet1.3 (bottom).

# Thank you!
# Questions & Answers!