

# **ReMOTS: Refining Multi-Object Tracking and Segmentation**

## **(1<sup>st</sup> Place Solution for MOTS 2020 Challenge 1)**

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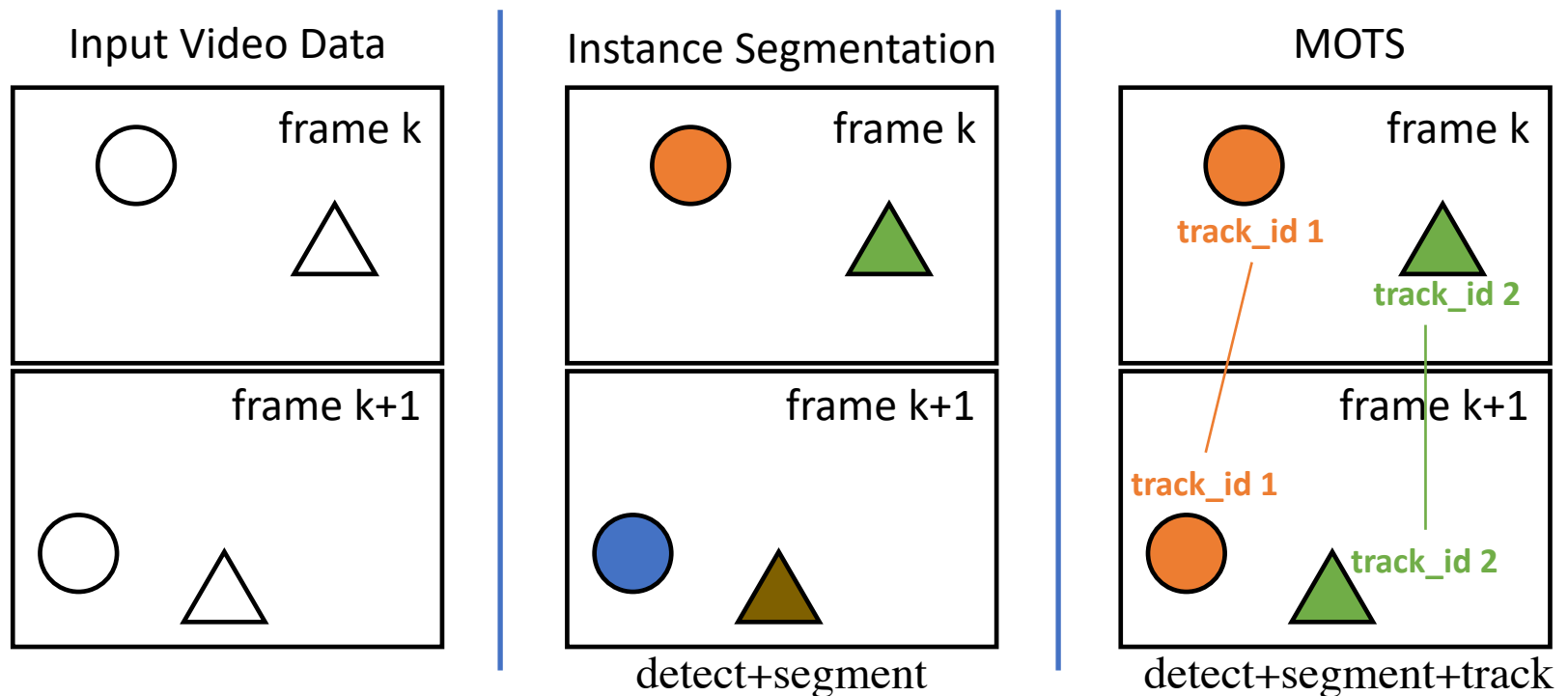
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<sup>4</sup>Kyoto University, Japan

# Background of Multi-Object Tracking and Segmentation (MOTS)

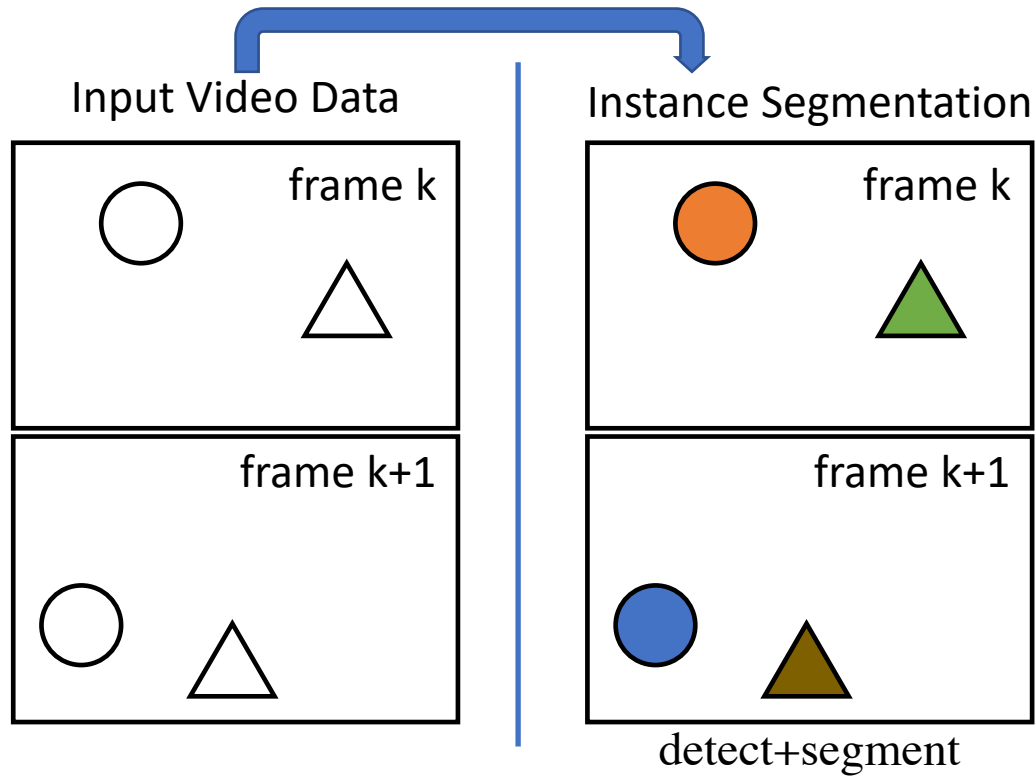
- Problem: detect, segment, and track multiple objects in videos.
- Input: a video sequence contain that multiple RGB images.
- Output: 2D mask and corresponding track ID at each frame.
- Application: action recognition, automatic driving, and others.



# Our solution for MOTS

Use off-the-shelf models

Step 1



# Instance Segmentation

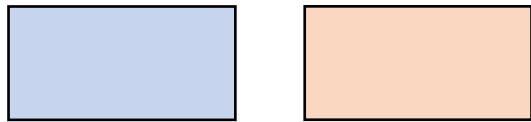
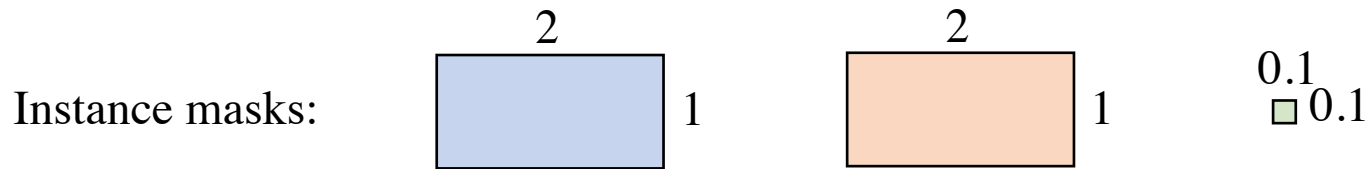
We take off-the-shelf models:

X-101-64x4d-FPN of MMDetection + Mask R-CNN X152 of Detectron 2,  
which refers to the public detection and segmentation methods.

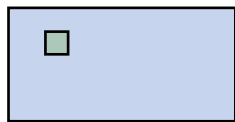
**But, how to fuse instance masks from different models?**

Fusing boxes – using NMS

Fusing masks – may also using NMS – but change IoU to IoM (Intersection over Minimum).

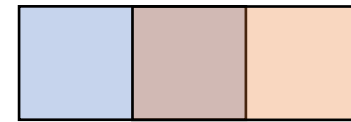


$$\text{Pixel\_IoU} = 1/3 = 0.33$$



Acceptable for bounding box,  
But not for mask.

$$\text{Pixel\_IoU} = 0.01/2 = 0.005$$



$$\text{Pixel\_IoM} = 1/2 = 0.5$$

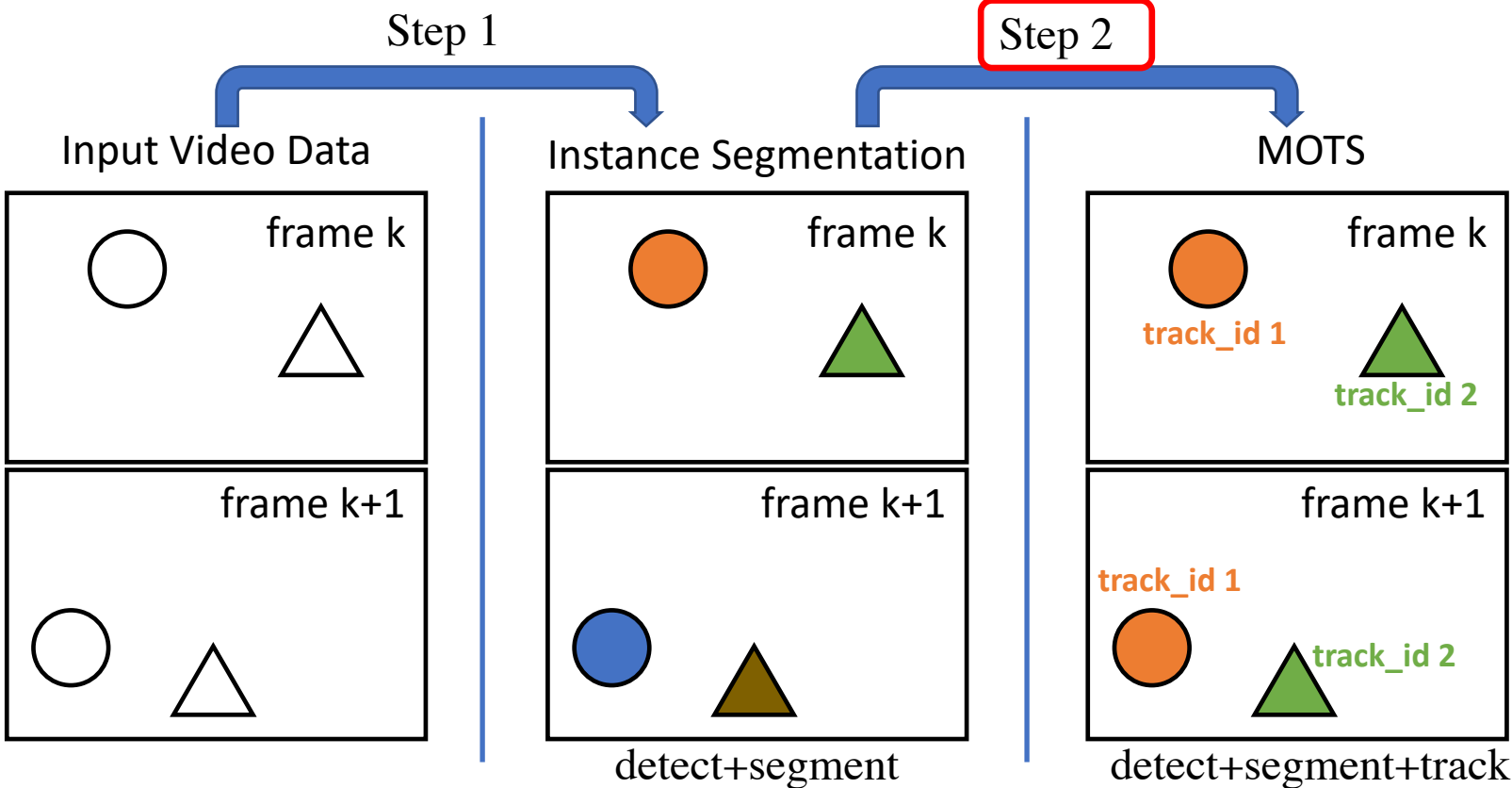


$$\text{Pixel\_IoM} = 0.01/0.01 = 1$$

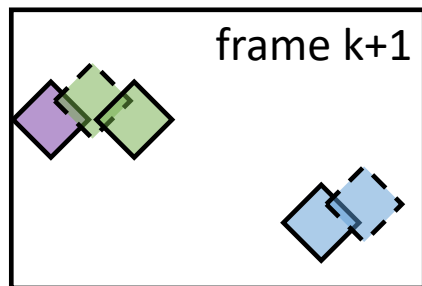
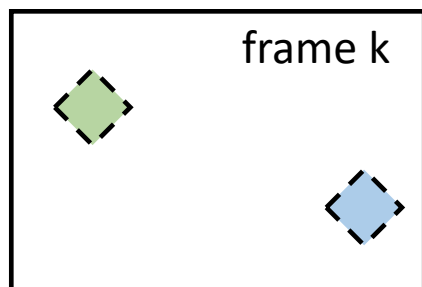
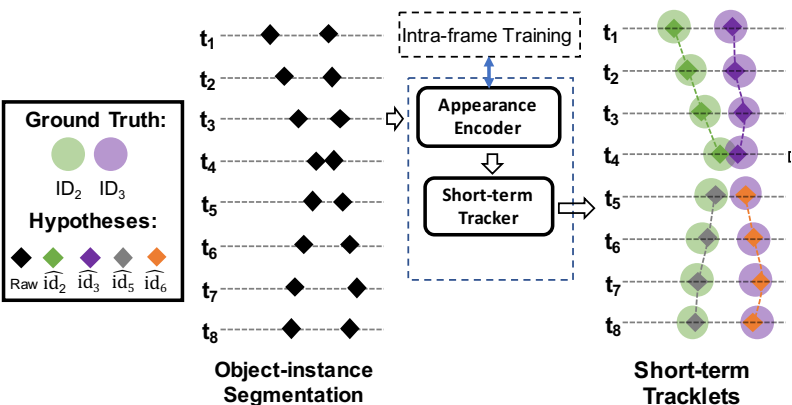
# Our solution for MOTS

We proposed an offline method, as ReMOTS (Refining Multi-Object Tracking and Segmentation ).

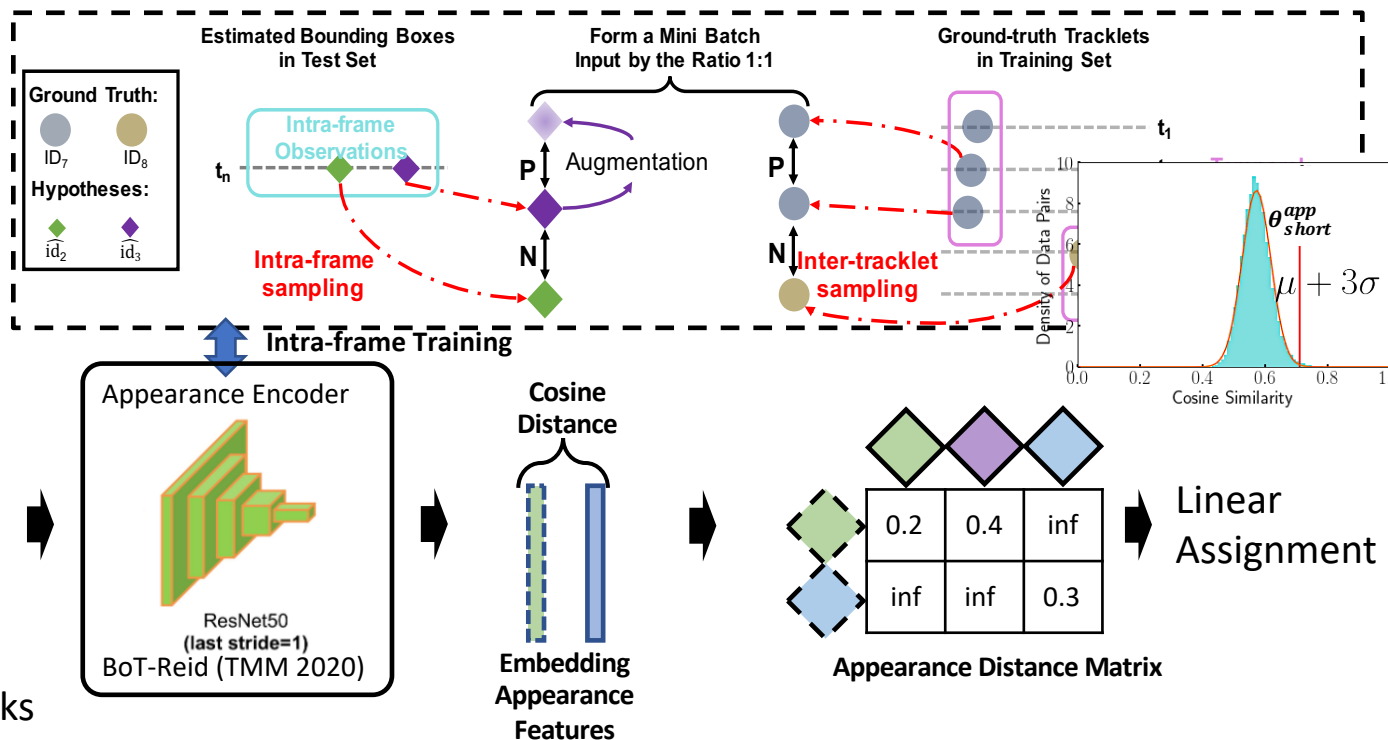
- Our main contributions:
- 1. Refine appearance features
  - 2. Automatically decide threshold



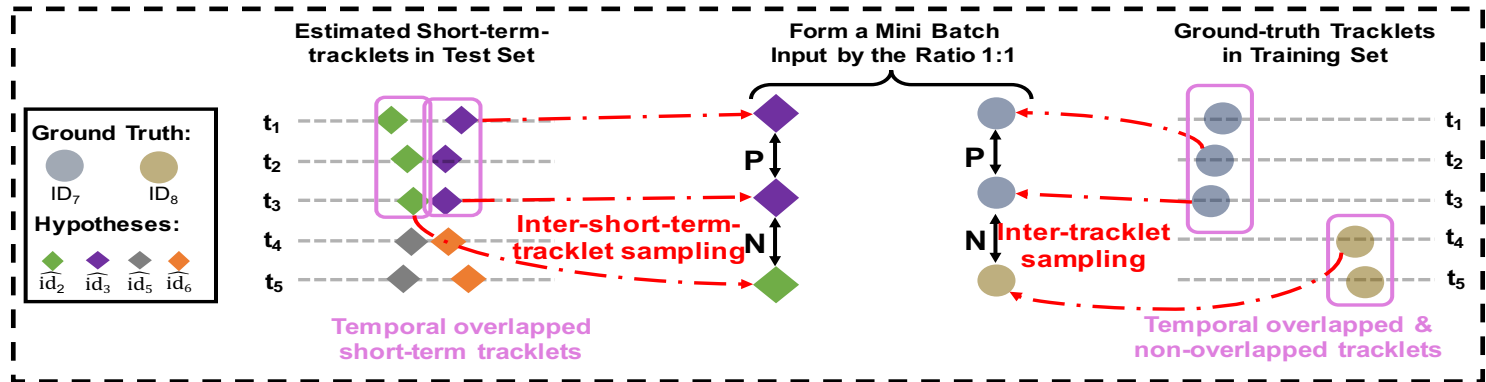
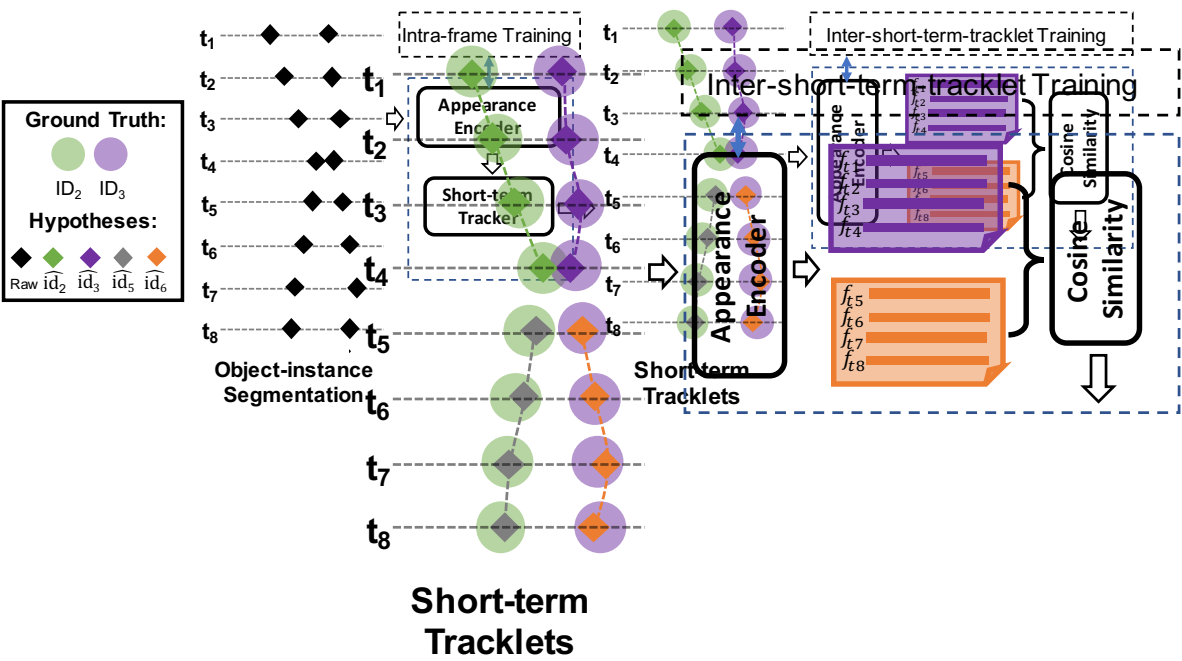
# Intra-frame Training and Short-term Tracking



For masks of frame k, consider all of IoU > 0 masks of frame k+1 for matching



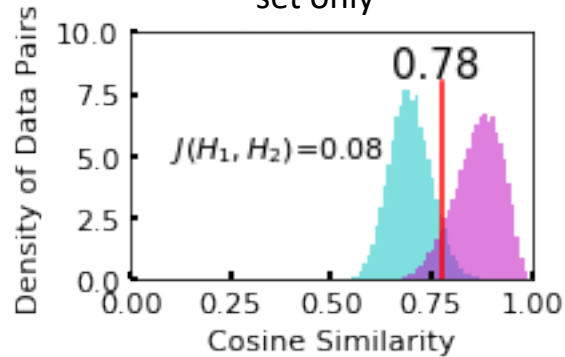
# Inter-short-term-tracklet Training



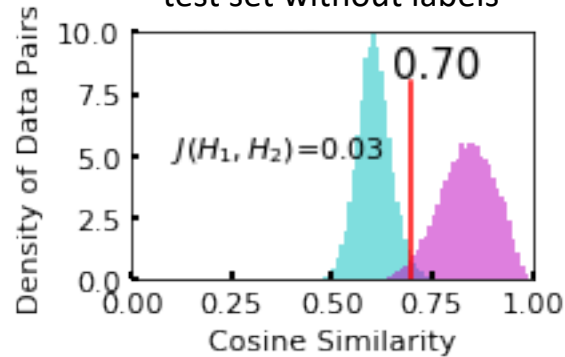
# What Happened in Each Step of Appearance Training

$J(H_1, H_2)$  represents Jaccard Index of two normalized histograms  $H_1$  and  $H_2$ .

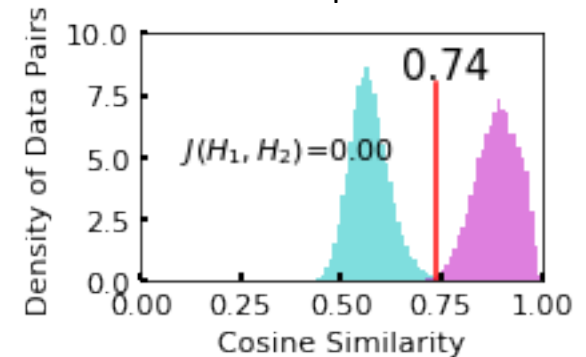
(1) After Trained on the train set only



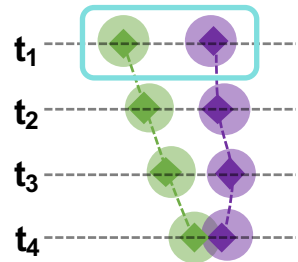
(2) After Intra-frame training on test set without labels



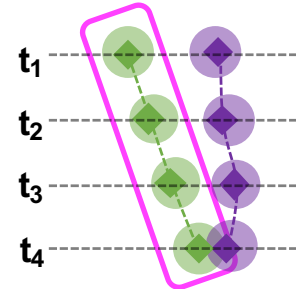
(3) After Inter-short-tracklet training on test set with pseudo labels



Intra-frame instance masks



Intra-short-tracklet instance mask







# Comparison with others on MOTSChallenge 1

## Benchmark Statistics

Tracker	↑sMOTSA	IDF1	MOTSA	MOTSP	MODSA	MT	ML	TP	FP	FN	Recall	Precision	ID Sw.	Frag	Hz	
<a href="#">ReMOTS</a> 1.	69.9 ±3.6	75.0 ±5.6	83.9	84.0	85.1	248 (75.6)	12 (3.7)	28,270	819	3,999	87.6	97.2	388 (442.9)	621 (708.8)	0.3	
	May benefit from refinement						May benefit from mask fusion						Anonymous submission			
<a href="#">PTPM</a> 2.	68.8 ±3.5	68.5 ±6.2	82.6	84.1	83.7	244 (74.4)	19 (5.8)	28,108	1,084	4,161	87.1	96.3	368 (422.5)	560 (642.9)	10.1	
	Anonymous submission															
<a href="#">GMPHD_SAF</a> 3.	68.4 ±3.0	64.9 ±5.5	82.6	83.9	84.4	248 (75.6)	10 (3.0)	28,382	1,161	3,887	88.0	96.1	569 (646.9)	770 (875.5)	3.8	
	Anonymous submission															
<a href="#">PT</a> 4.	66.8 ±4.9	67.3 ±6.8	79.9	84.5	81.1	234 (71.3)	20 (6.1)	27,215	1,059	5,054	84.3	96.3	370 (438.7)	629 (745.8)	0.4	
	Anonymous submission															
<a href="#">DD_Vision</a> 5.	66.6 ±6.2	71.8 ±7.3	79.7	84.4	80.7	243 (74.1)	15 (4.6)	27,114	1,067	5,155	84.0	96.2	341 (405.8)	559 (665.3)	1.6	
	Anonymous submission															
<a href="#">Lif_TS</a> 6.	66.3 ±3.4	75.0 ±5.0	79.6	84.2	80.1	224 (68.3)	32 (9.8)	27,112	1,254	5,157	84.0	95.6	182 (216.6)	525 (624.9)	2.3	
	Anonymous submission															
<a href="#">PA</a> 7.	66.2 ±7.1	76.4 ±5.3	78.9	84.6	79.5	235 (71.6)	21 (6.4)	26,516	849	5,753	82.2	96.9	216 (262.9)	449 (546.4)	2.5	
	Anonymous submission															

Since our strategy can be easily adapted to others, will other methods get better performance by applying our appearance encoder and merging?

# Limitations of ReMOTS

1. An offline approach.
  - It worth to explore how to bring it to online approach.
2. It is challenging for ReMOTS to handle objects with similar appearance. e.g., good for persons (wear different clothes) but not very useful for vehicles (similar textures)
3. Trajectory is not considered in our short-term tracker. Failed to associate fast moving objects.



*Slowly moving person with diverse clothes*



*Fast moving car with similar appearance*

# Conclusion

- Unlabeled target videos can be used for learning better appearance features, but should take care of the potential of introducing noises.
- The suitable hyper parameters for data association may varies from case to case, and the statistical information of tracklets can be used to adjust them.
- It is preferred to accommodate some insights of ReMOTS to online MOTs.

**Thanks for your listening**