

Assignment-Space-based Multi-Object Tracking and Segmentation

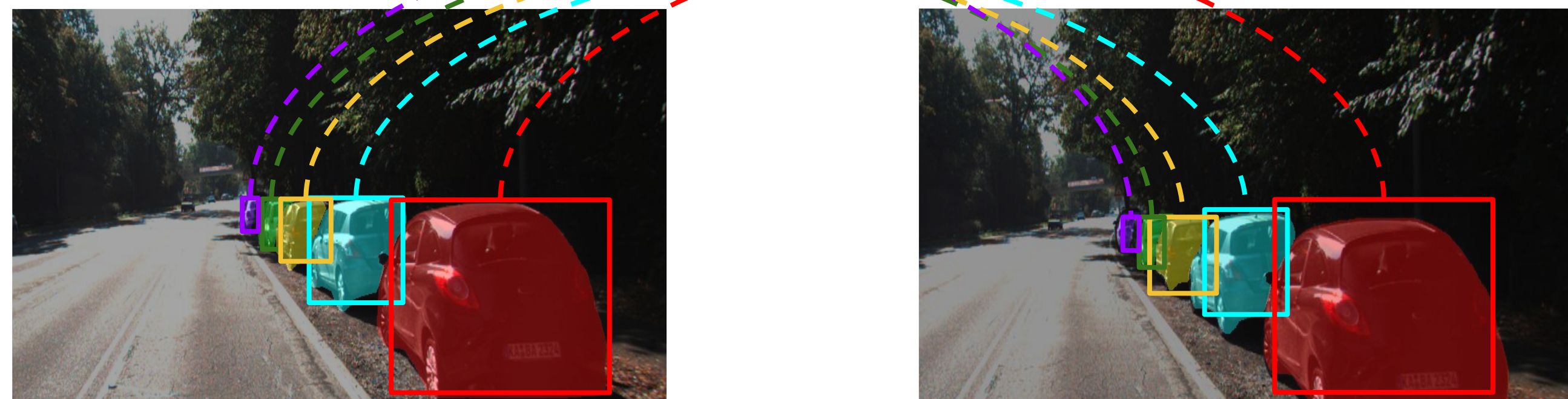
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<https://anwesachoudhuri.github.io/Assignment-Space-based-MOTS/>

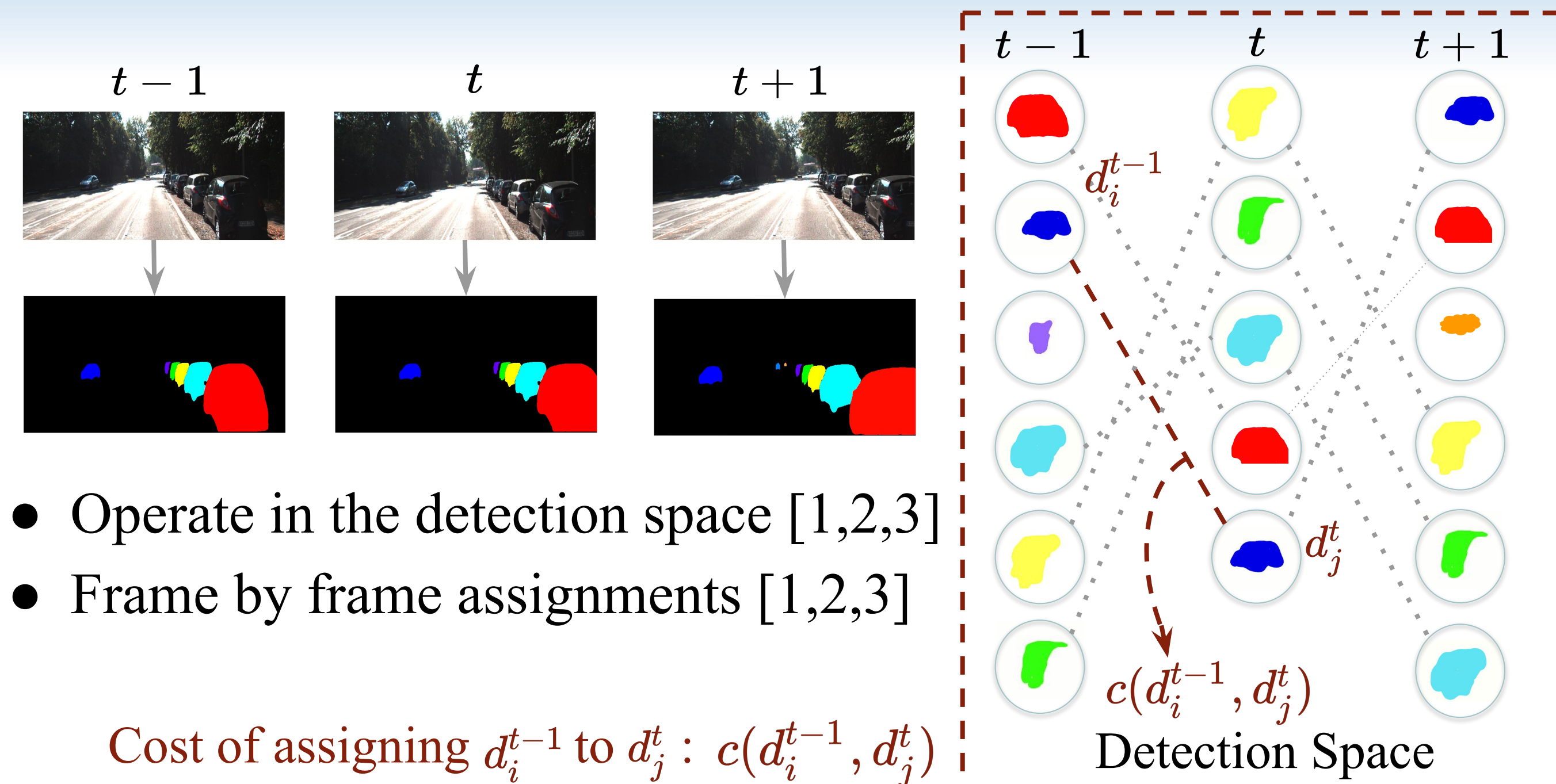


Multi-Object Tracking and Segmentation

Goal: Jointly address detection, segmentation and tracking.

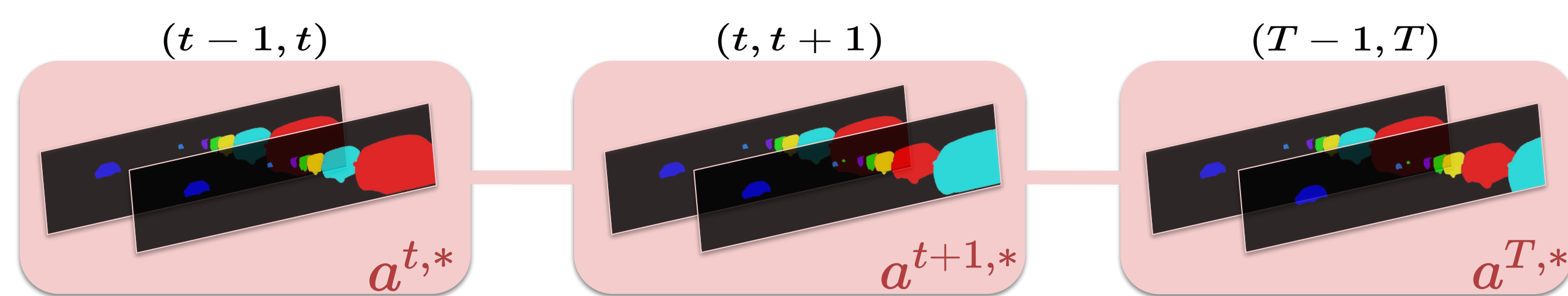


Prior Work



- Operate in the detection space [1,2,3]
- Frame by frame assignments [1,2,3]

Cost of assigning d_i^{t-1} to d_j^t : $c(d_i^{t-1}, d_j^t)$



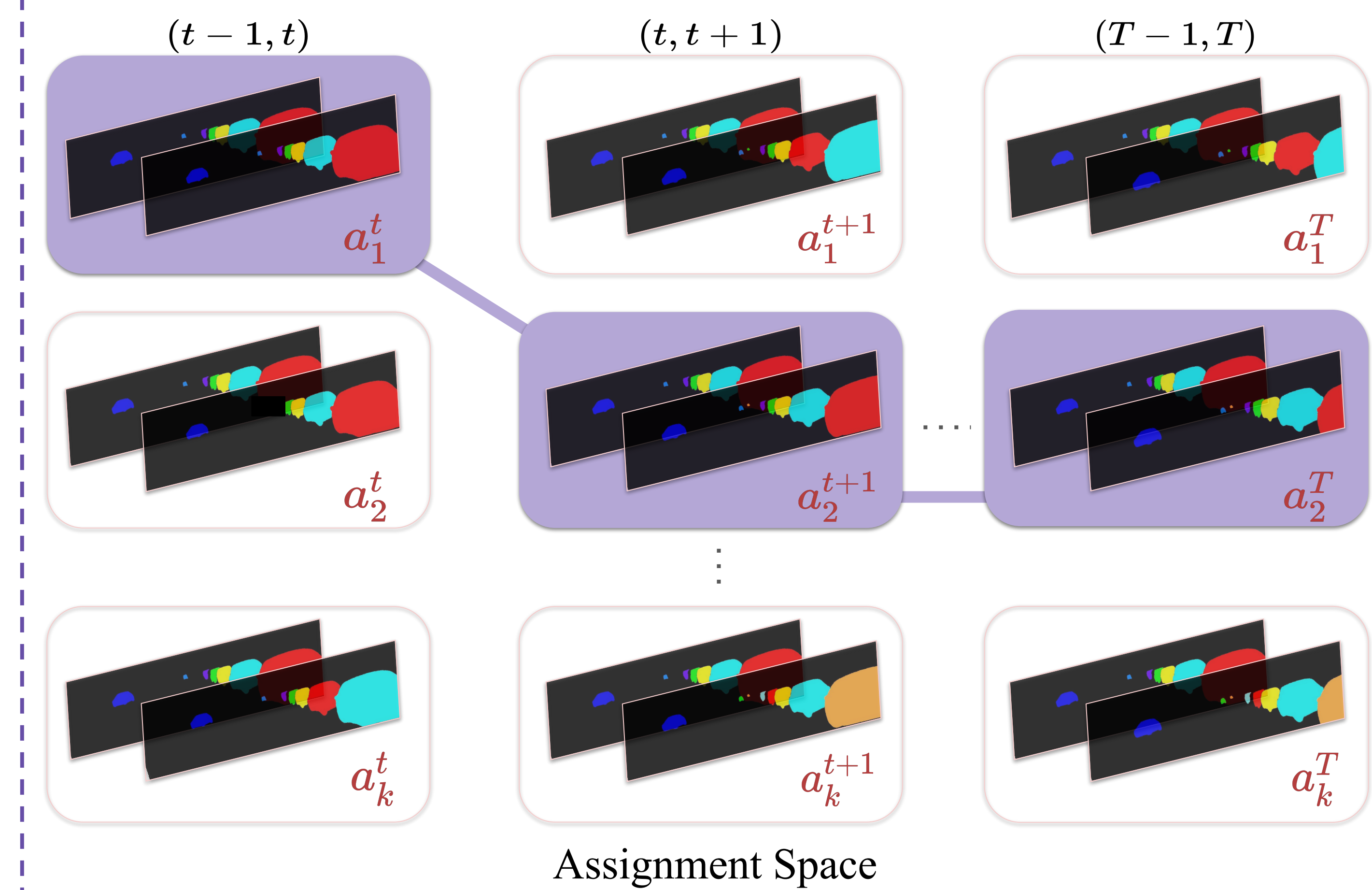
Best local assignment matrix between frame-pair $(t-1, t)$:

$$a^{t,*} = \arg \min_{a^t \in \mathcal{A}} \sum_{i,j} a^t(d_i^{t-1}, d_j^t) c(d_i^{t-1}, d_j^t)$$

[1] Voigtlaender et al., CVPR 2019
 [2] Luiten et al., RAL 2020
 [3] Xu et al., ECCV 2020

Assignment-Space-based MOTS

Step 1:



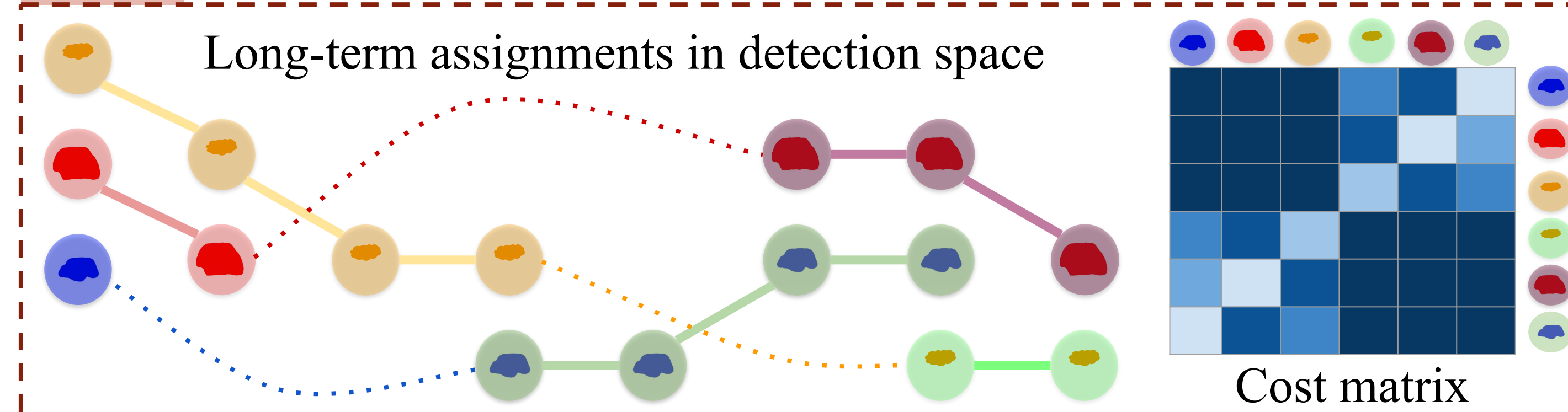
- k-best assignments for frame-pair $(t-1, t) : a_1^t, \dots, a_k^t$
- Corresponding indices: $y^t = 1, \dots, k$
- Valid path: $y = (y^1, \dots, y^t, \dots, y^T)$
- Cost of path $y : \mathcal{L}(y) = \sum_{t=1}^T \phi_1^t(y^t) + \sum_{t=1}^{T-1} \phi_2^t(y^t, y^{t+1})$

Best path: $y^* = \arg \min_{y \in \mathcal{Y}} \mathcal{L}(y)$

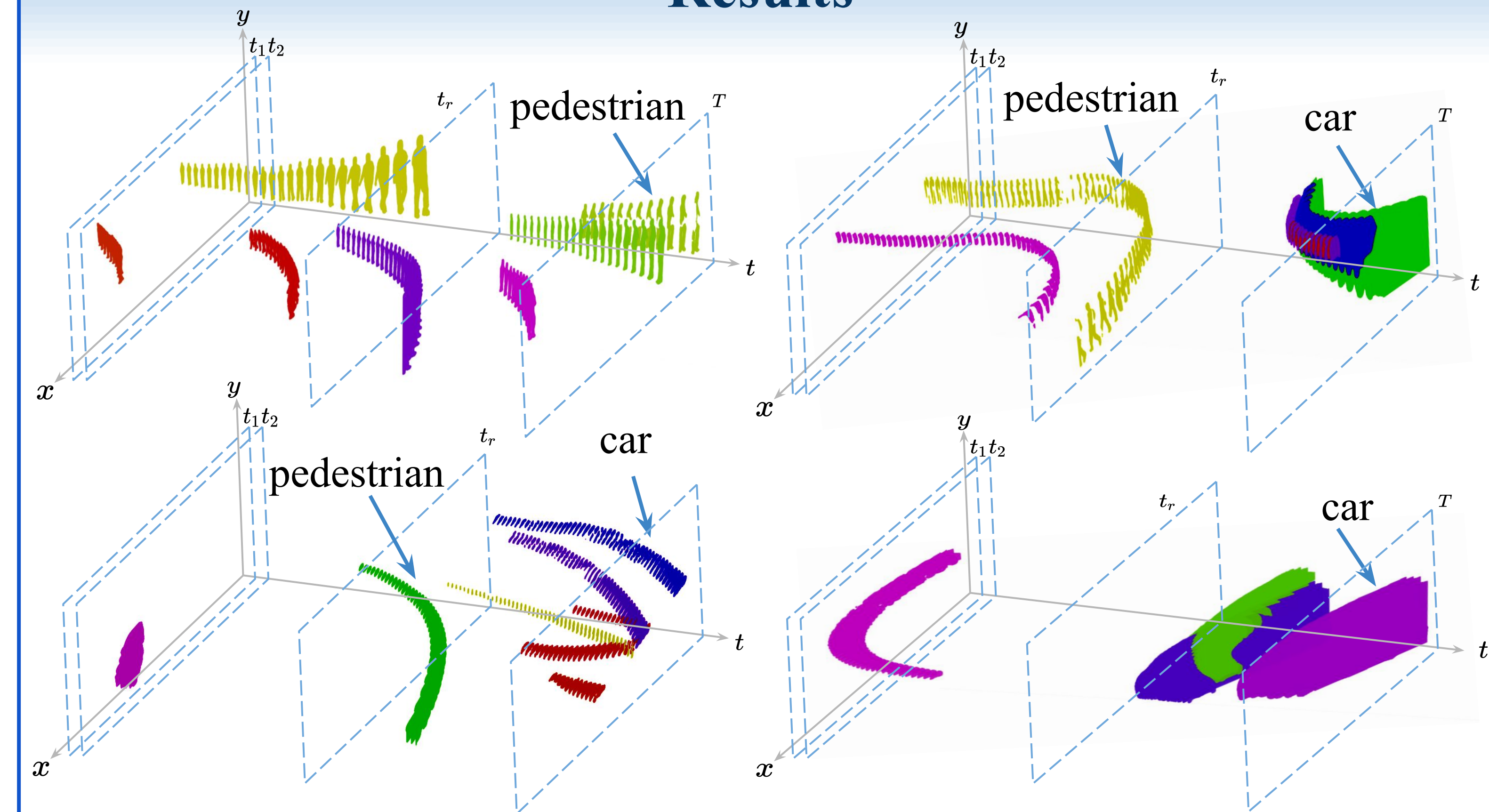
Node Cost: $\phi_1(y^t) = \sum_{i,j} a_{y^t}^t(d_i^{t-1}, d_j^t) c(d_i^{t-1}, d_j^t)$

Edge Cost: $\phi_2(y^t, y^{t+1}) = \sum_{i,j,s} (a_{y^t}^t(d_i^{t-1}, d_j^t) \times a_{y^{t+1}}^{t+1}(d_j^t, d_s^{t+1})) c(d_i^{t-1}, d_s^{t+1})$

Step 2:

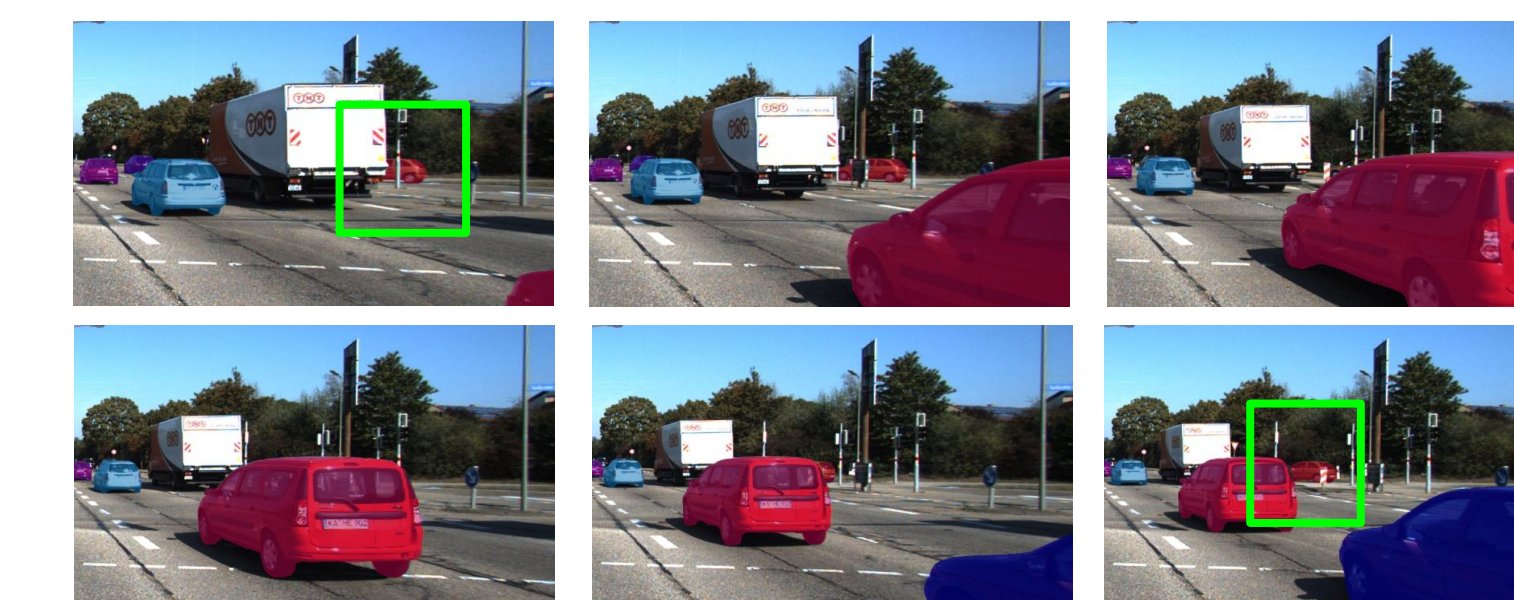


Results



KITTI-MOTS Test (Pedestrian)

Method	HOTA	AssA
TrackR-CNN	41.93	33.84
PointTrack	54.44	48.08
MOTSFusion	54.04	49.45
Ours	58.81	57.67



KITTI-MOTS Test (Car)

Method	HOTA	AssA
TrackR-CNN	56.63	46.43
PointTrack	61.95	48.83
Ours	68.73	62.24

KITTI-MOTS Val (Car)

Method	k	AssA
Ours	1	76.4
Ours	2	79.9
Ours	5	80.0
Ours	15	81.8

MOTSChallenge Test

Method	sMOTSA	MOTSA	IDF1	IDS
TrackR-CNN	40.60	55.2	42.44	567
Ours	55.01	64.2	64.00	330