Learning to Schedule Re-identification Queries in Multi-Camera Networks

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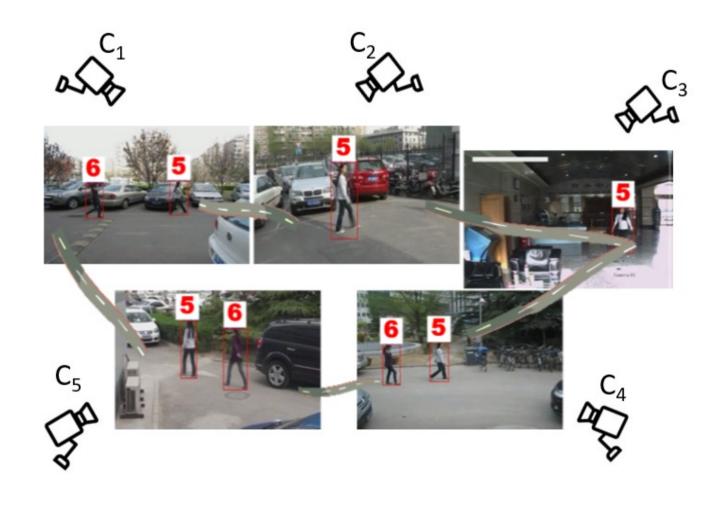
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Motivation

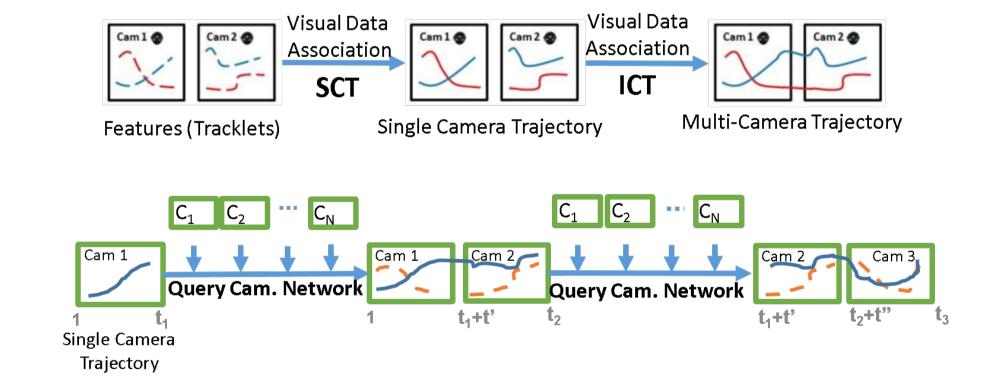
Camera Networks are used for several video analytics applications. For example, person tracking in camera networks for surveillance.



Typical Multi-Camera Tracking Pipeline

- 1. At a given time step, select a candidate camera to query
- 2. In selected camera, detect candidate targets followed by reidentification query to find the target's within-frame spatial location

Existing Approaches



- Largely focus on visual data association
- Querying even during blind spots, results in redundant querying and impacts tracking performance

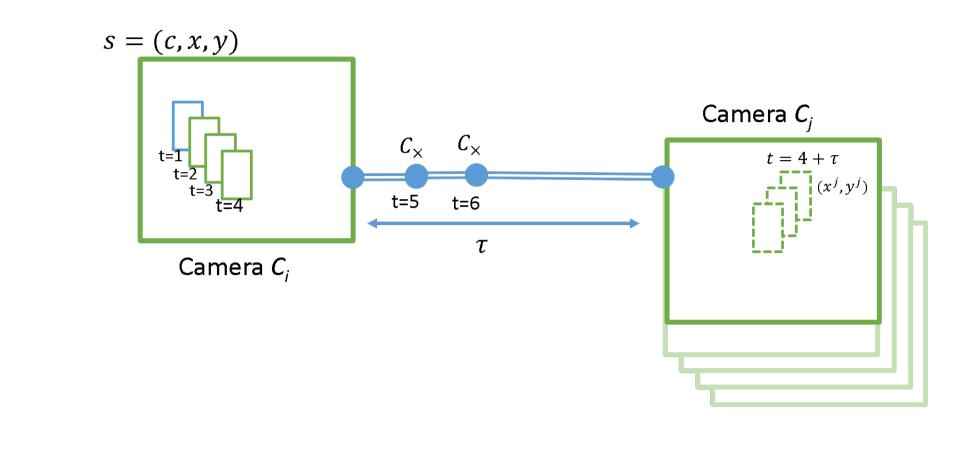
Key Challenges

- 1. Unconstrained paths/ camera network topology is not always known
- 2. Blind spots between cameras
- 3. Very large amount of data to process

Problem Statement

To intelligently query a camera for efficient target tracking:

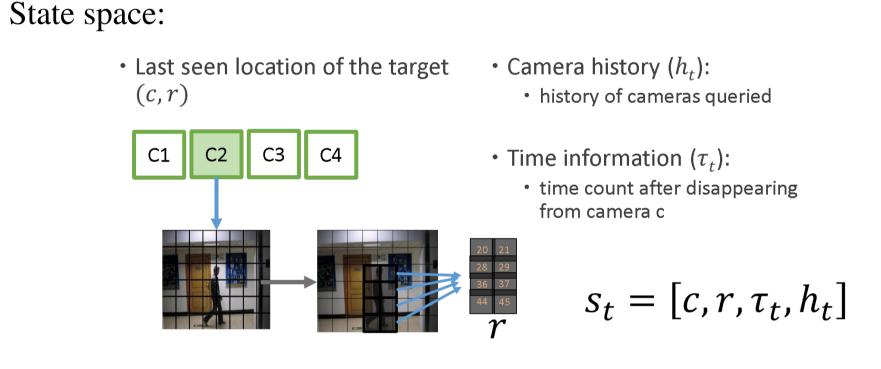
- 1. Decide to query or to wait?
- 2. Select which camera, if decided to query?



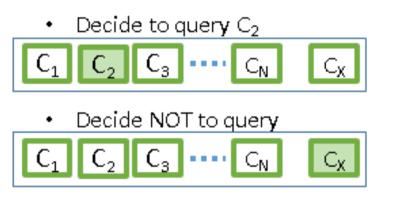
Contributions

- 1. Formulation using Markov Decision Process (MDP)
- 2. Learning a policy to intelligently select cameras to reduce redundant re-identification queries
- 3. Learning directly from data

Markov Decision Process (MDP)



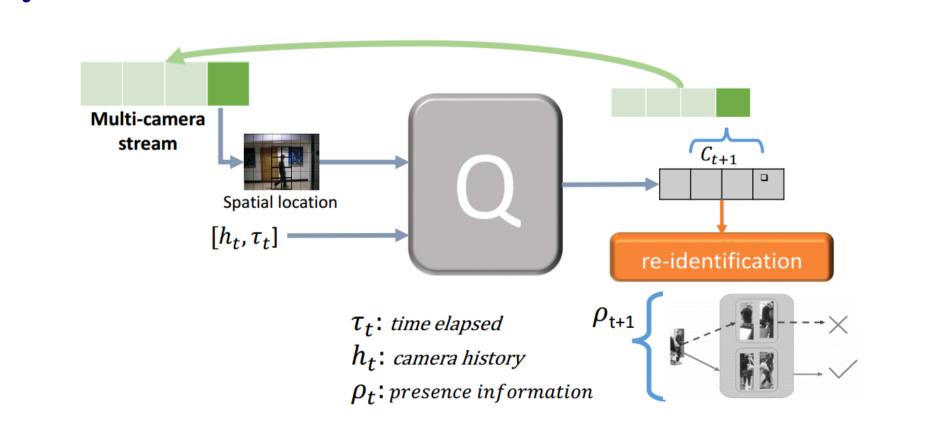
Action space:



Reward function:

$$R(s_t) = \begin{cases} +1 & \text{if target is present in } s_t \\ -1 & \text{otherwise} \end{cases}$$
 (1)

System Architecture



The state-action value function is learned iteratively using Q-learning:

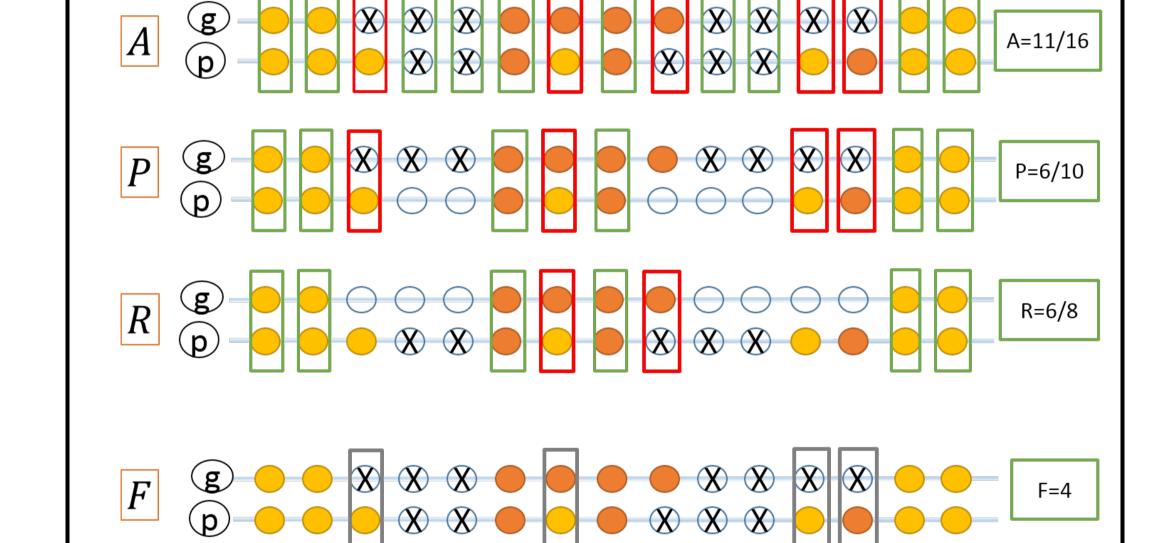
$$Q(s_t, a_t) \Leftarrow Q(s_t, a_t) + \alpha \left(R(s_{t+1}) + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t) \right)$$

Evaluation

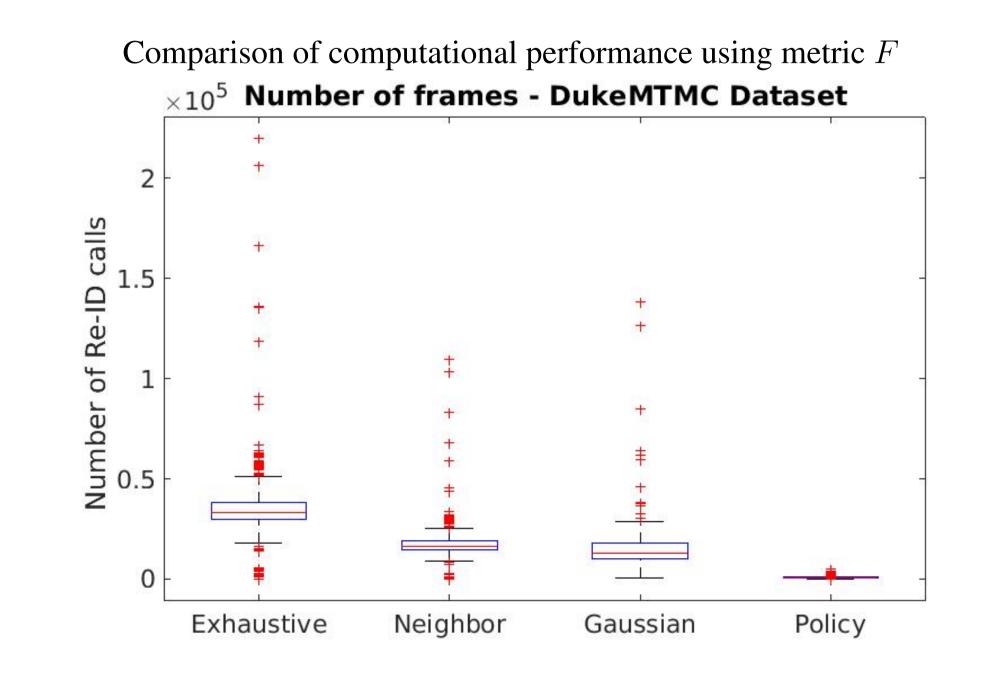
We have used NLPR MCT [1] and DukeMTMC [2] dataset for performance evaluation. The datasets caters to real environments.

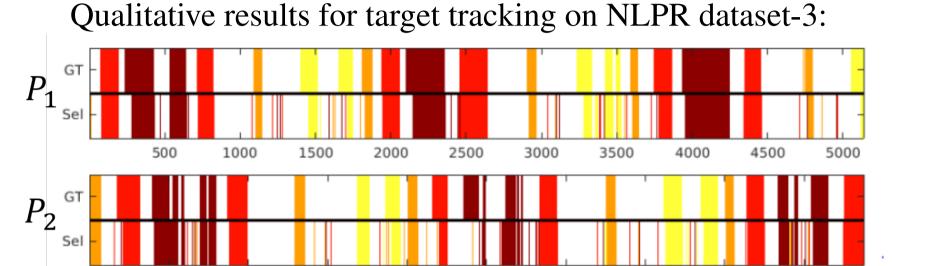
	NLPR1	NLPR2	NLPR3	NLPR4	DukeMTMC
#Cameras	3	3	4	5	8
Duration	20 min	20 min	3.5 min	24 min	1hr 25min
FPS	20	20	25	25	60
#People	235	255	14	49	2834

We use Accuracy (A), Precision (P), Recall (R), and number of frames queried (F) metric to evaluate camera selection performance:



Results

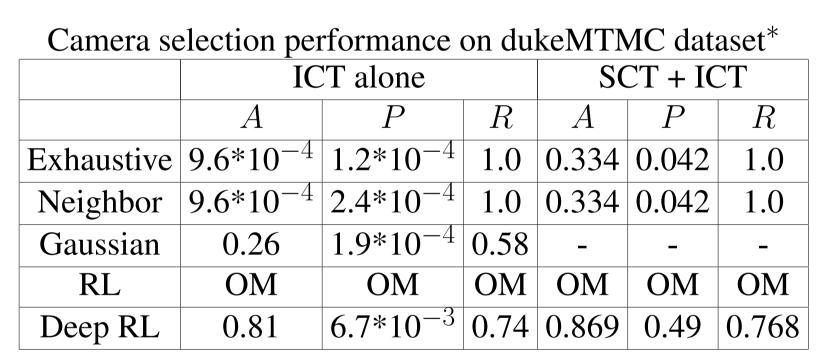




Camera selection performance on NLPR dataset:

Camera1 Camera2 Camera3 Camera4

	Set-3			Set-4					
	A	P	R	A	P	R			
	Inter-camera Tracking (ICT)								
Exhaustive	0.008	0.002	1.0	0.017	0.003	1.0			
Neighbor	0.008	0.003	1.0	0.017	0.006	1.0			
Gaussian	0.36	0.007	0.571	0.33	0.0078	0.168			
RL	0.685	0.026	0.929	0.519	0.027	0.808			
Deep RL*	0.58	0.02	0.88	0.76	0.03	0.83			
	Single-camera tracking (SCT) + ICT								
Exhaustive	0.42	0.10	1.0	0.56	0.11	1.0			
Neighbor	0.42	0.14	1.0	0.56	0.18	1.0			
RL	0.76	0.64	0.86	0.77	0.61	0.91			
Deep RL*	0.73	0.60	0.88	0.93	0.73	0.84			



OM = Out of Memory error

*(extension of our ICAPS-2019 paper [3])

Acknowledgement

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References

- [1] Y. Lee, Z. Tang, J. Hwang, and Y. Online-learning-based human tracking across non-overlapping cameras. *IEEE Trans. on Circuits and Systems for Video Technology*, 28(10):2870–2883, Oct 2018.
- [2] Ergys Ristani and Carlo Tomasi. Features for multi-target multi-camera tracking and re-identification. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2018.
- [3] Anil Sharma, Saket Anand, and Sanjit K. Kaul. Reinforcement learning based querying in camera networks for efficient target tracking. In *Proceedings of International Conference on Automated Planning and Scheduling (ICAPS)*, 2019.