# Socially-Aware Large Scale Forecasting

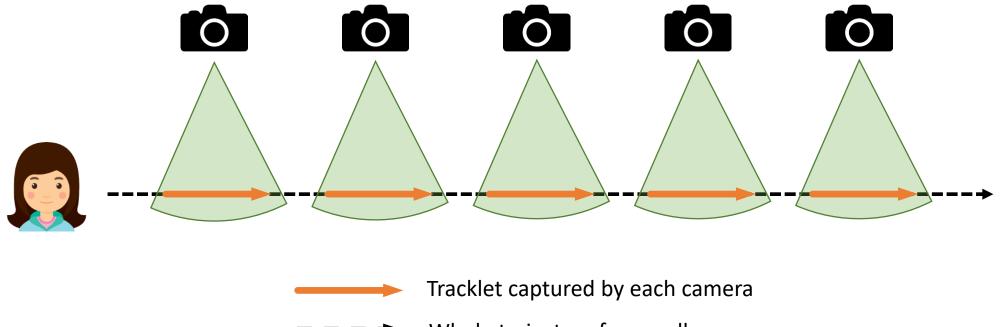
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Instructor: Kristen Grauman

Author of the paper: Alexandre Alahi, Vignesh Ramanathany, Li Fei-Fei

## Problem

• Link tracklets captured multiple cameras (example video)

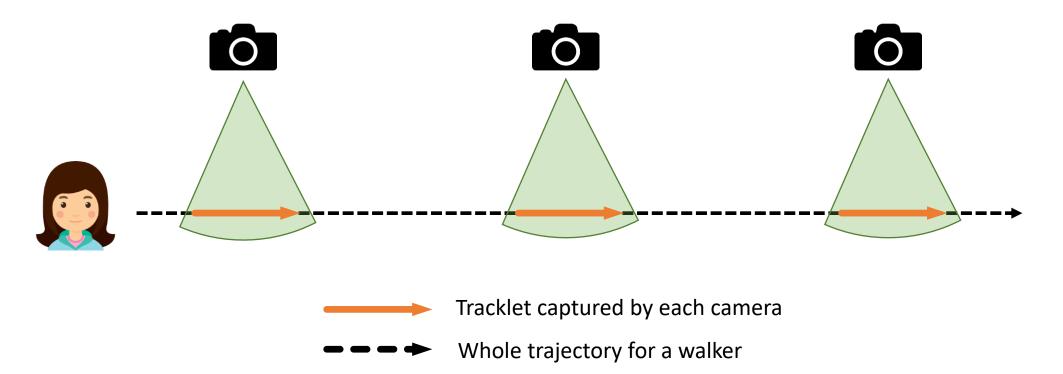


Whole trajectory for a walker

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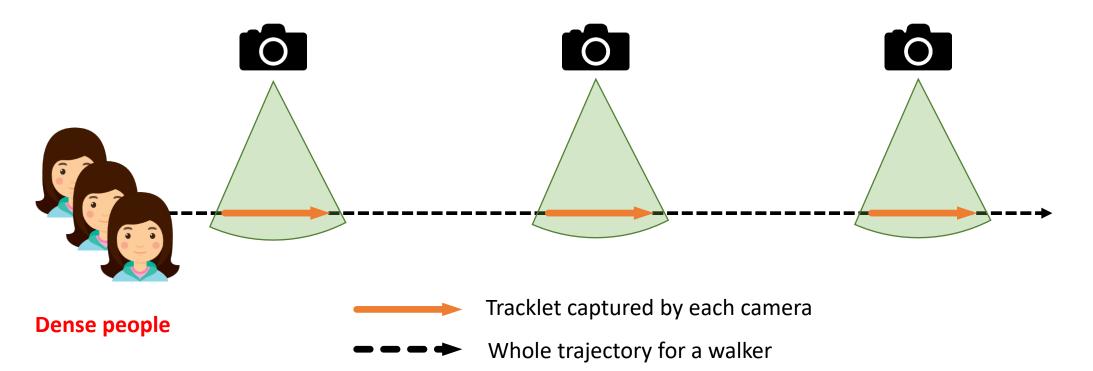
Sparse Network



## Problem

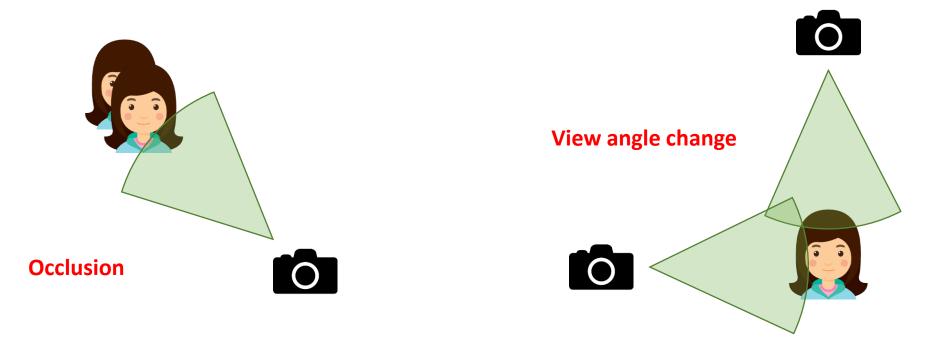
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Sparse Network



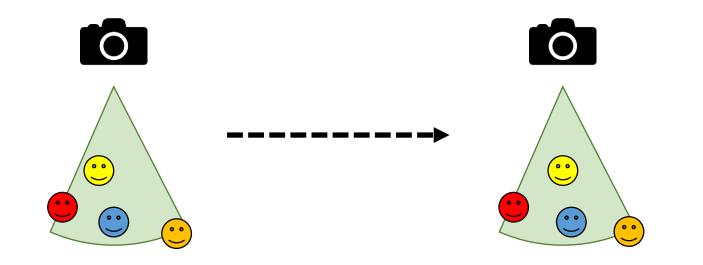
# **Possible Solutions**

- Appearance based recognition
  - Highly occluded by others
  - View angles change at different cameras



# Socially-Aware Approach

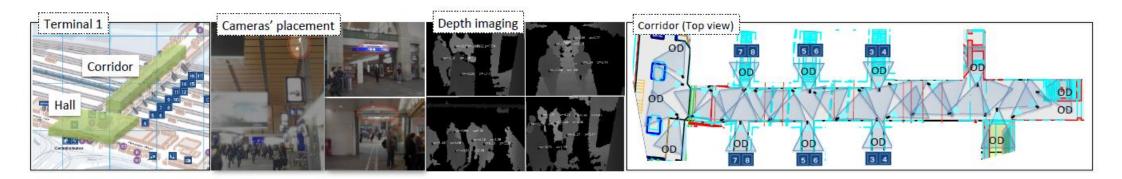
- Social affinity: motion affinity of neighboring individuals (example video)
  - Friends, relatives, and co-workers
  - Leader-follower model



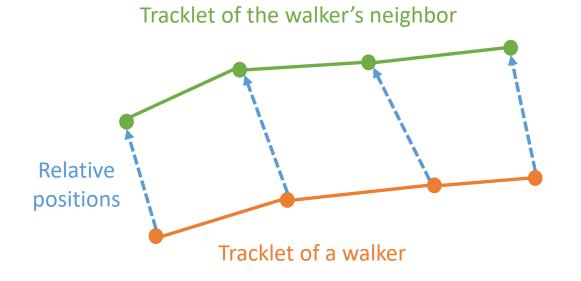
# Data Collection

- Deploy a dense camera network in train stations
- Video data processing
  - Walker detection
  - Tracklet generation

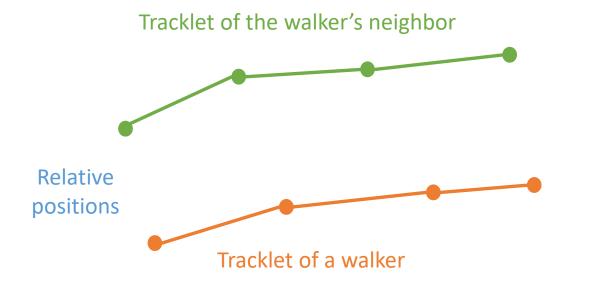
Monitoring area	Density	Travel time	Distance	Speed	Traffic / day	Total
$20.000m^2$	up to 1 ped/ $m^2$	1 min	100 m	$1.37 \ m/s$	100.000-250.000/terminal	42 million trajectories



- SAM features: the way to quantify the social affinity
- To extract SAM features, first derive the relative positions between the surrounding tracklets in each video



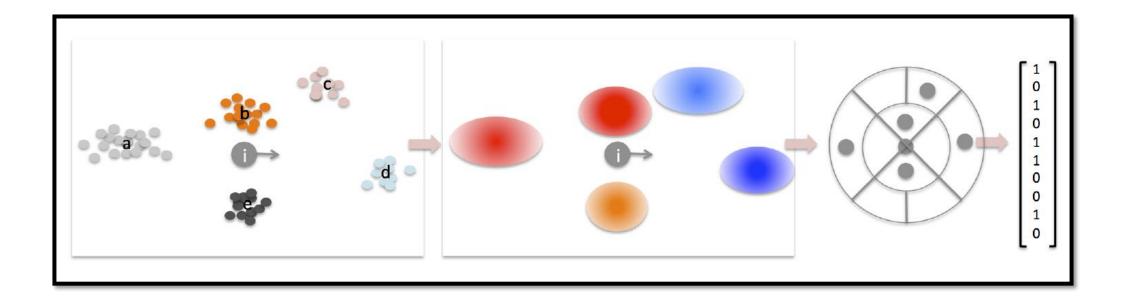
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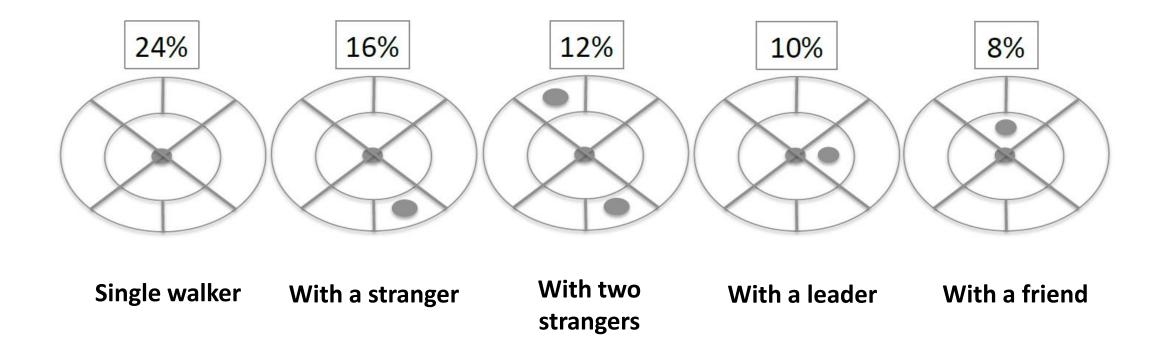
Use the position of the walker as the reference

• Extract SAM features

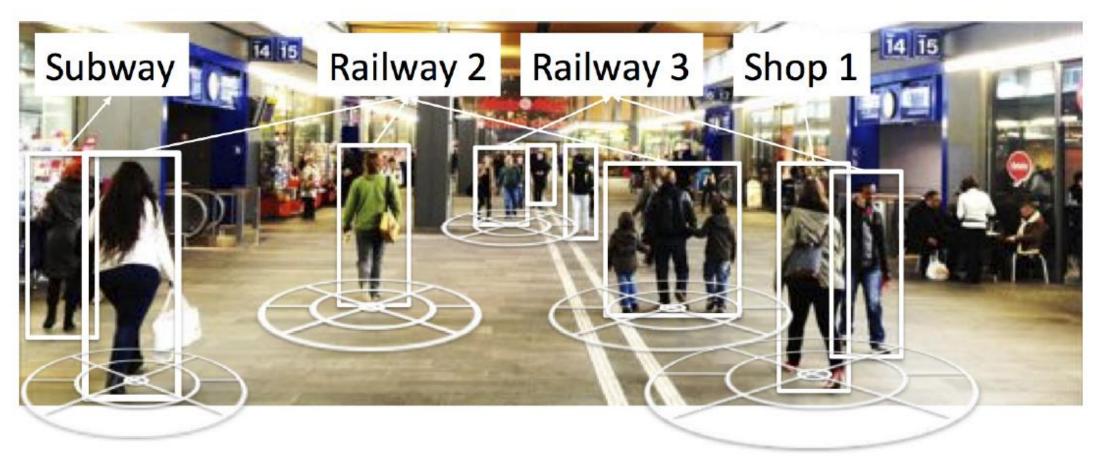




• Most common SAM features in the dataset



• Most common SAM features in the dataset



# **Problem Formulation**

- A sparse network of cameras for a public place (a railway terminal)
- Entry points of the place: origin
- Exit points of the place: destination
- Tracklet sets: *O*, *D*, *X*
- The **trajectory** for a walker:  $t = (o_t, x_t^1, x_t^2, ..., x_t^n, d_t)$

GOAL: find all trajectories connecting origins and destinations

## **Problem Formulation**

- The set of all trajectories, T
- Find T that maximize its likelihood based on tracklet observations X

$$\max_{T} P(T|X) = \max_{T} \frac{P(T,X)}{P(X)} = \max_{T} P(T,X) = \max_{T} P(X|T)P(T)$$

## Problem formulation

• Conditional probability P(X|T)

$$P(X|T) = \prod_{t \in T} \prod_{x \in X_t} P_{tp}(x)$$

• The trajectory probability P(T)

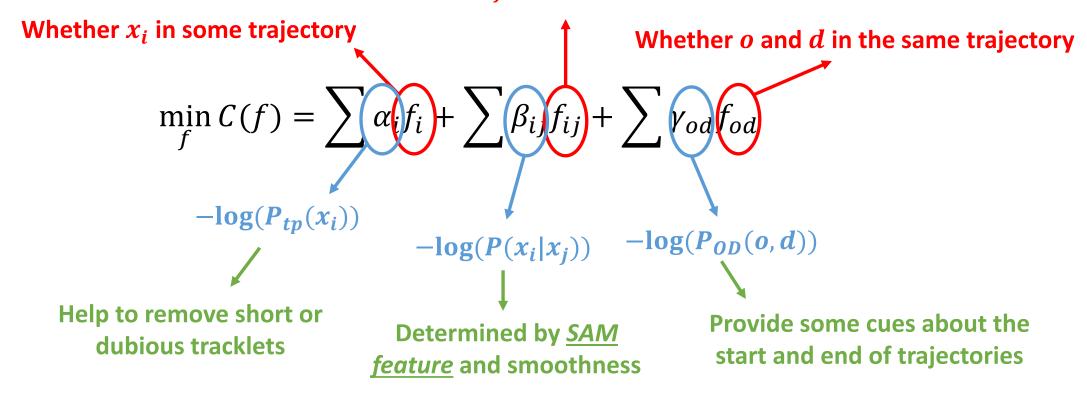
$$P(T) = \prod_{t \in T} P(t)$$

 $P(t) = P_{OD}(o_t, d_t) P(x_t^1 | o_t) P(x_t^2 | x_t^1) \dots P(d_t | x_t^n)$ 

# **Problem Formulation**

• Log likelihood conversion

Whether  $x_i$  and  $x_j$  linked together



# Optimization

- The formulized problem is similar with a network-flow problem
- Except the prior term
- Using heuristic to amortize the prior terms into transition terms

$$\min_{f} C(f) = \sum \alpha_{i} f_{i} + \sum \beta_{ij} f_{ij} + \sum \gamma_{od} f_{od}$$

• Solve by k-shortest path approach

# Optimization

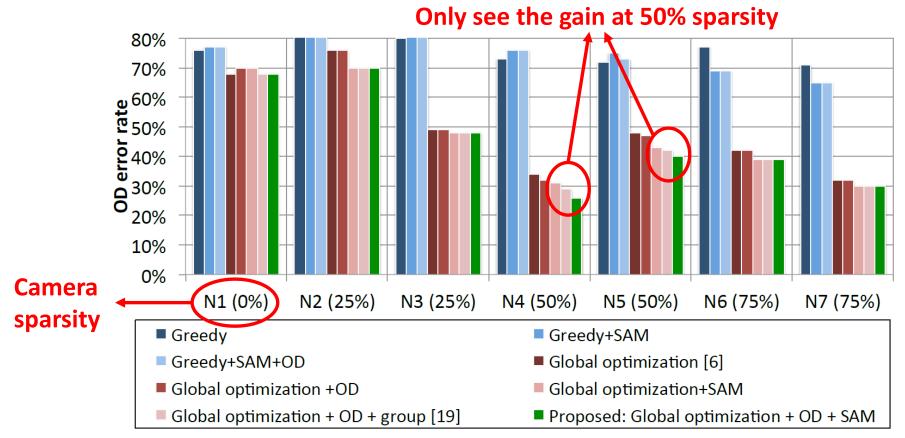
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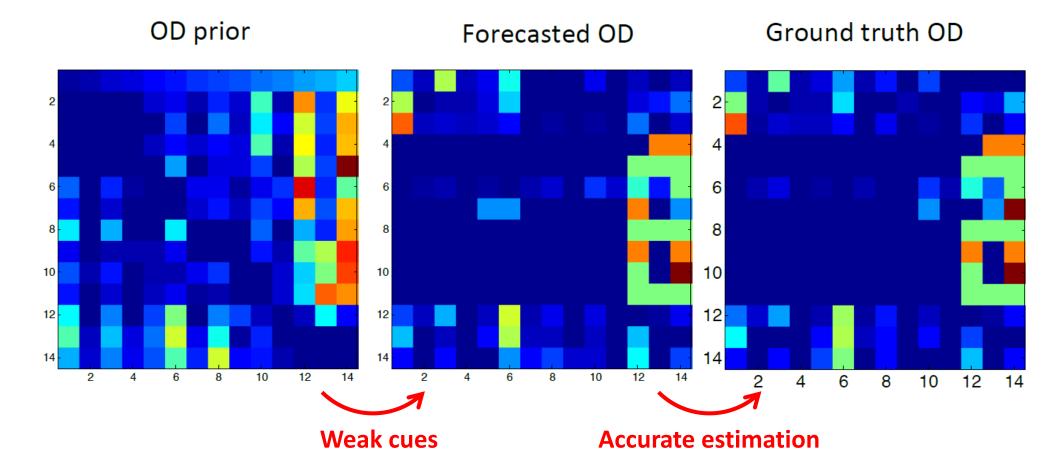
#### Results

Origin and destination tracklet matching error



## Results

• Qualitative results: origin-destination distribution



#### Conclusion

- Collect a **dataset** with 42 million of tracklets
- There are **social affinities** among crowded walkers
- Such features can be used to **improve the trajectory linking quality**
- Future work: learn how to deploy limited number of cameras to maximize the performance