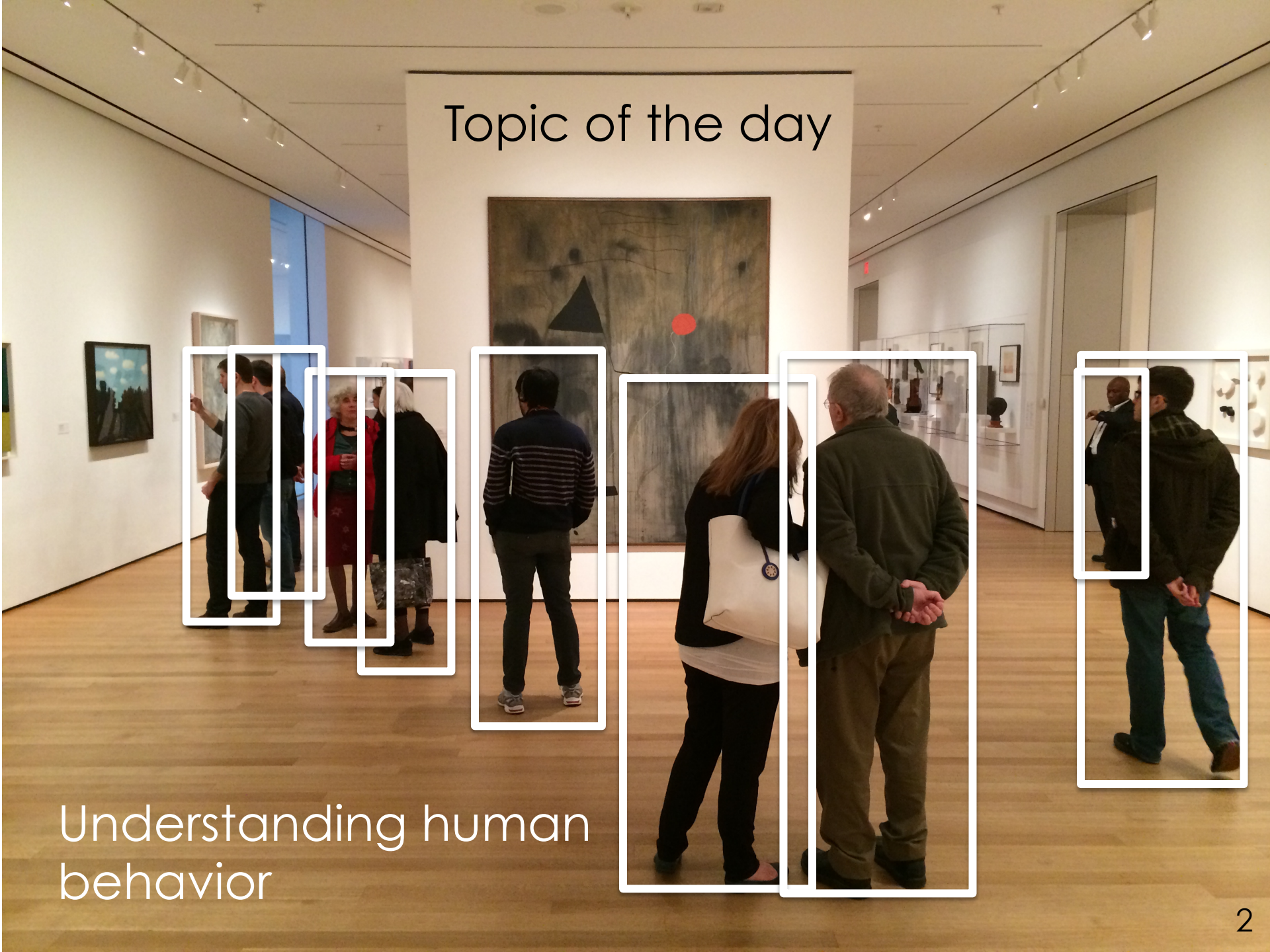
CS131
Tracking people

A. Alahi

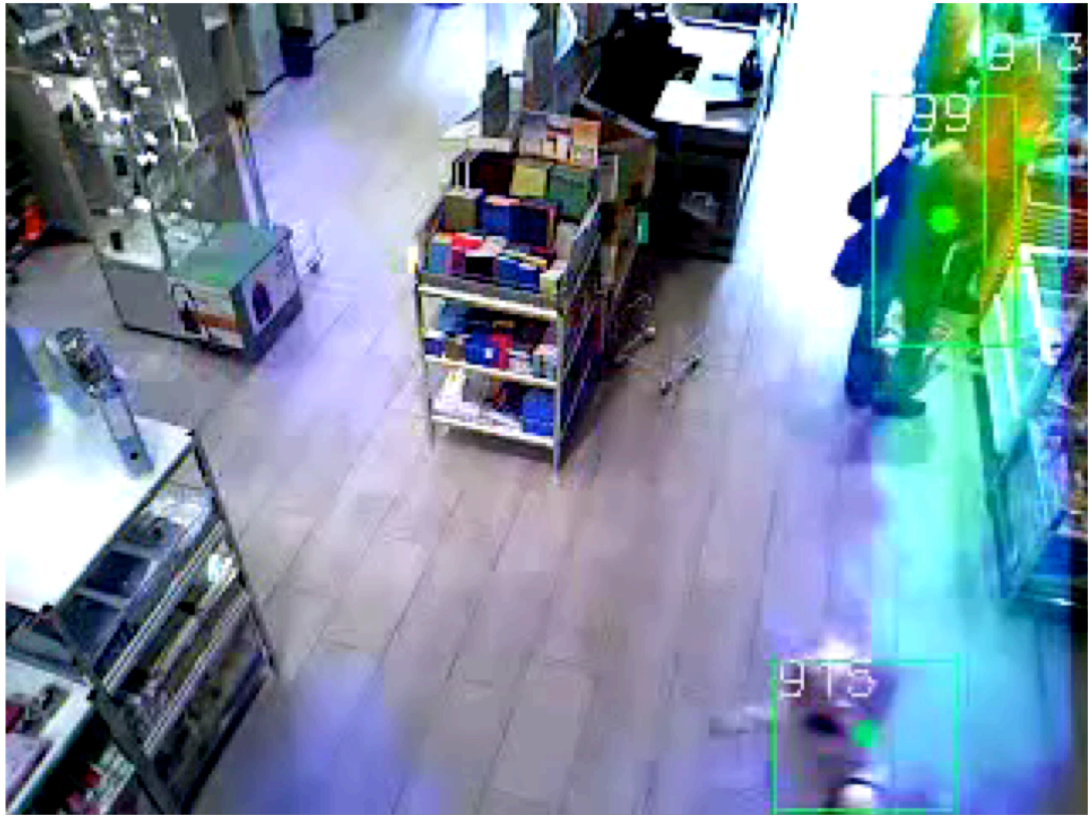
November 19th 2014


Topic of the day
Understanding human behavior

Motivation:
Elderly monitoring

Courtesy of Ph.D Guido Pusiol

Motivation:
Path-to-purchase understanding



Motivation:
Space analytics

Interaction

- Number of social interaction

Distances

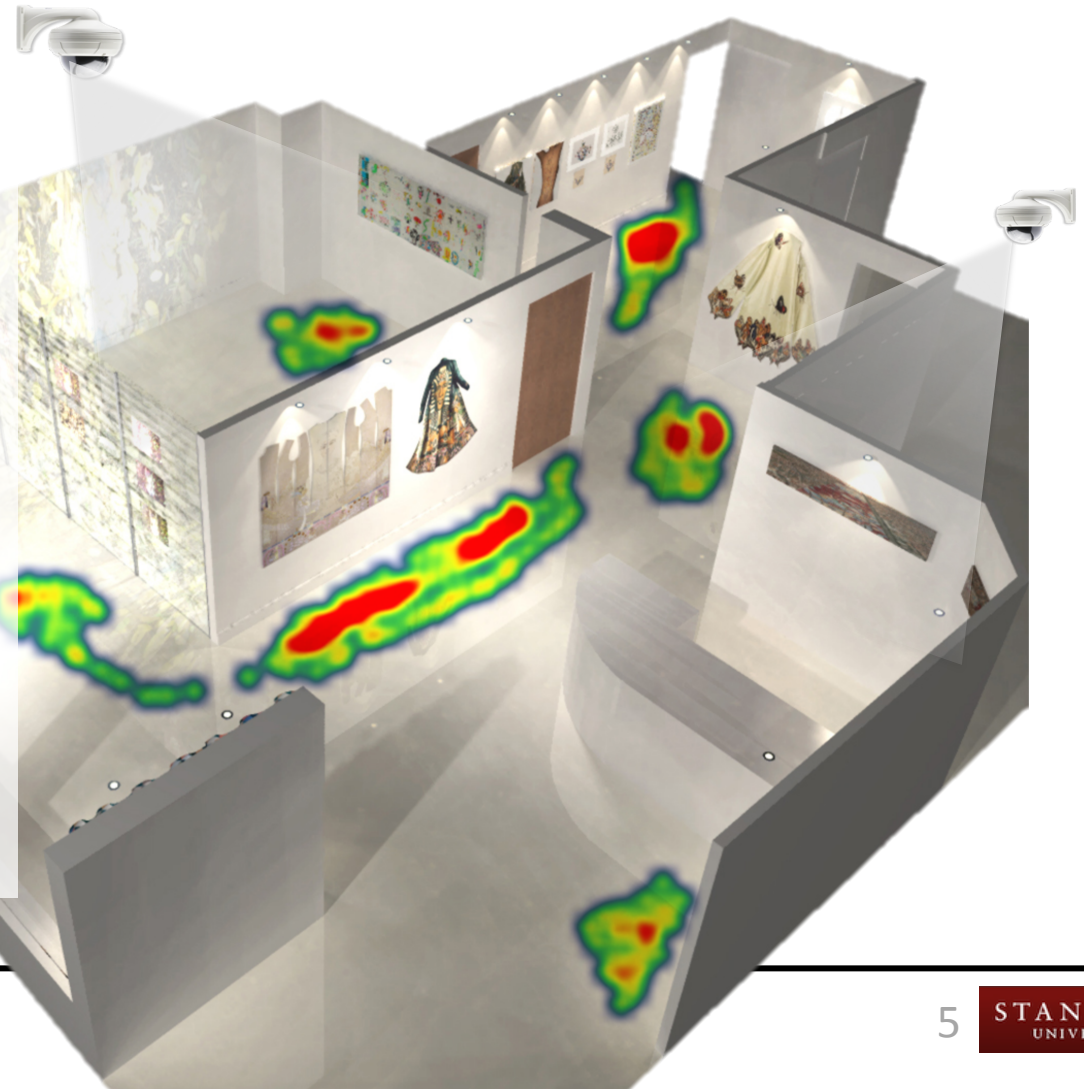
- Walked distance

Durations

- Duration in each room

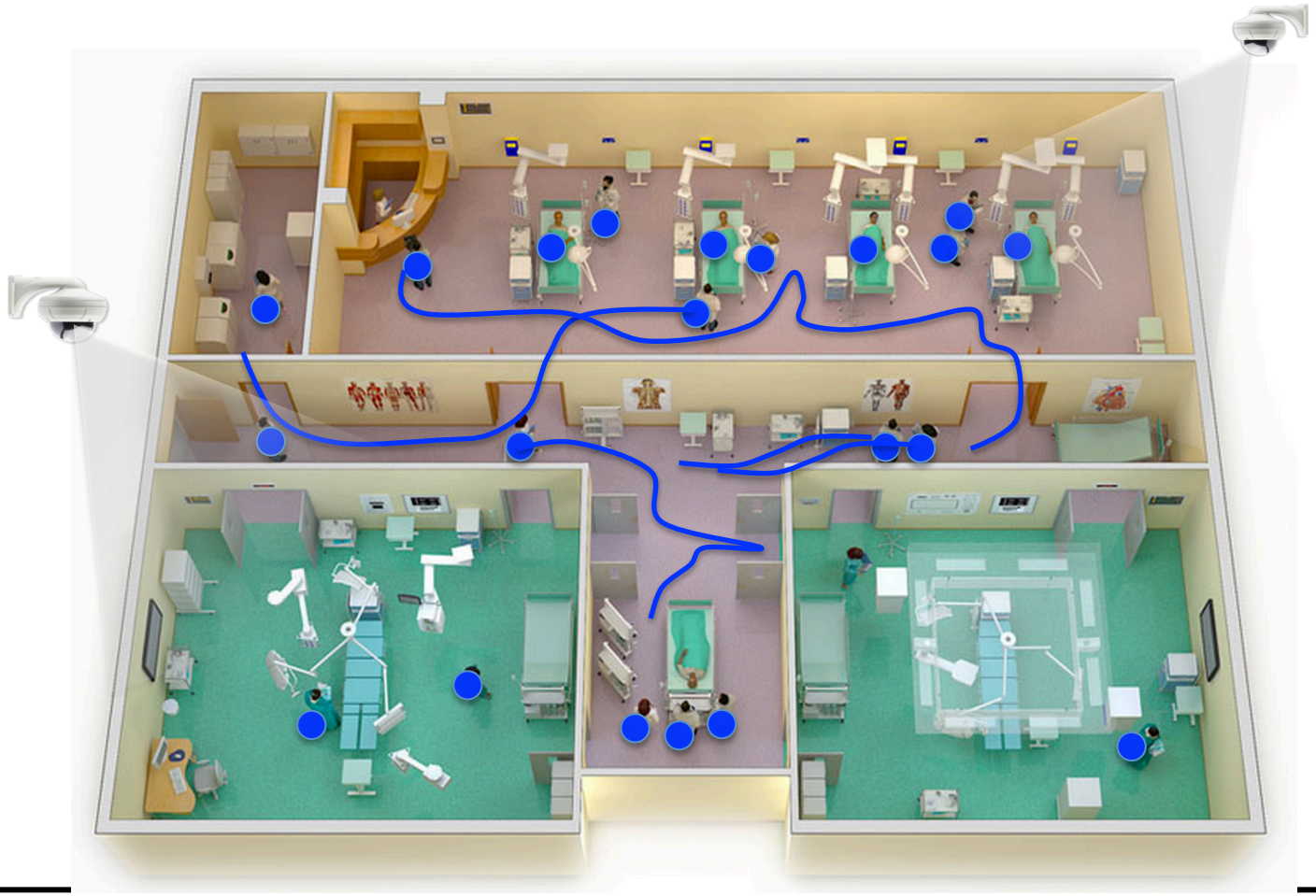
Heatmaps

- Hot spots



Motivation:
Performance analysis

Motivation:
Behavior monitoring



Motivation:
Large-space analytics

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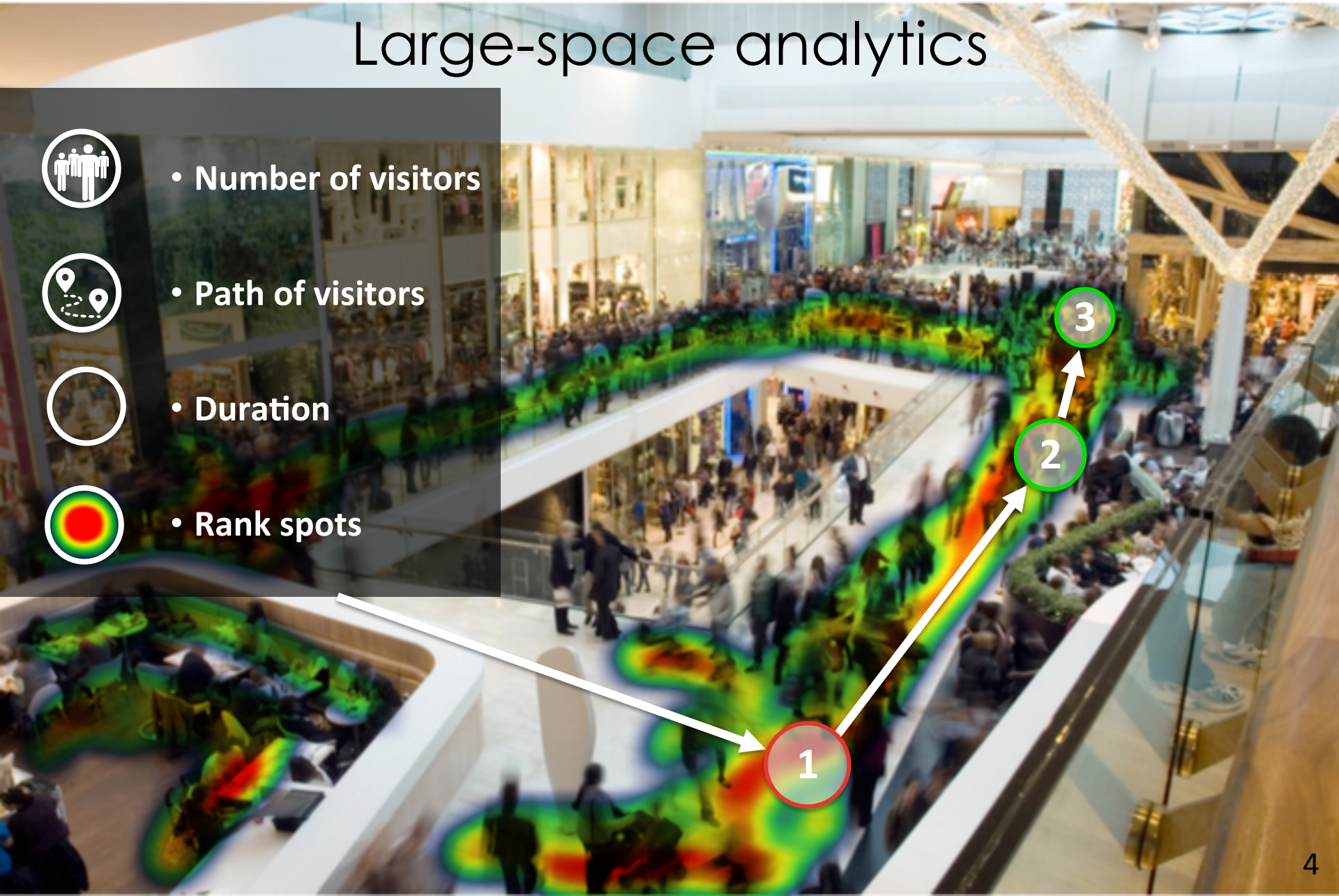
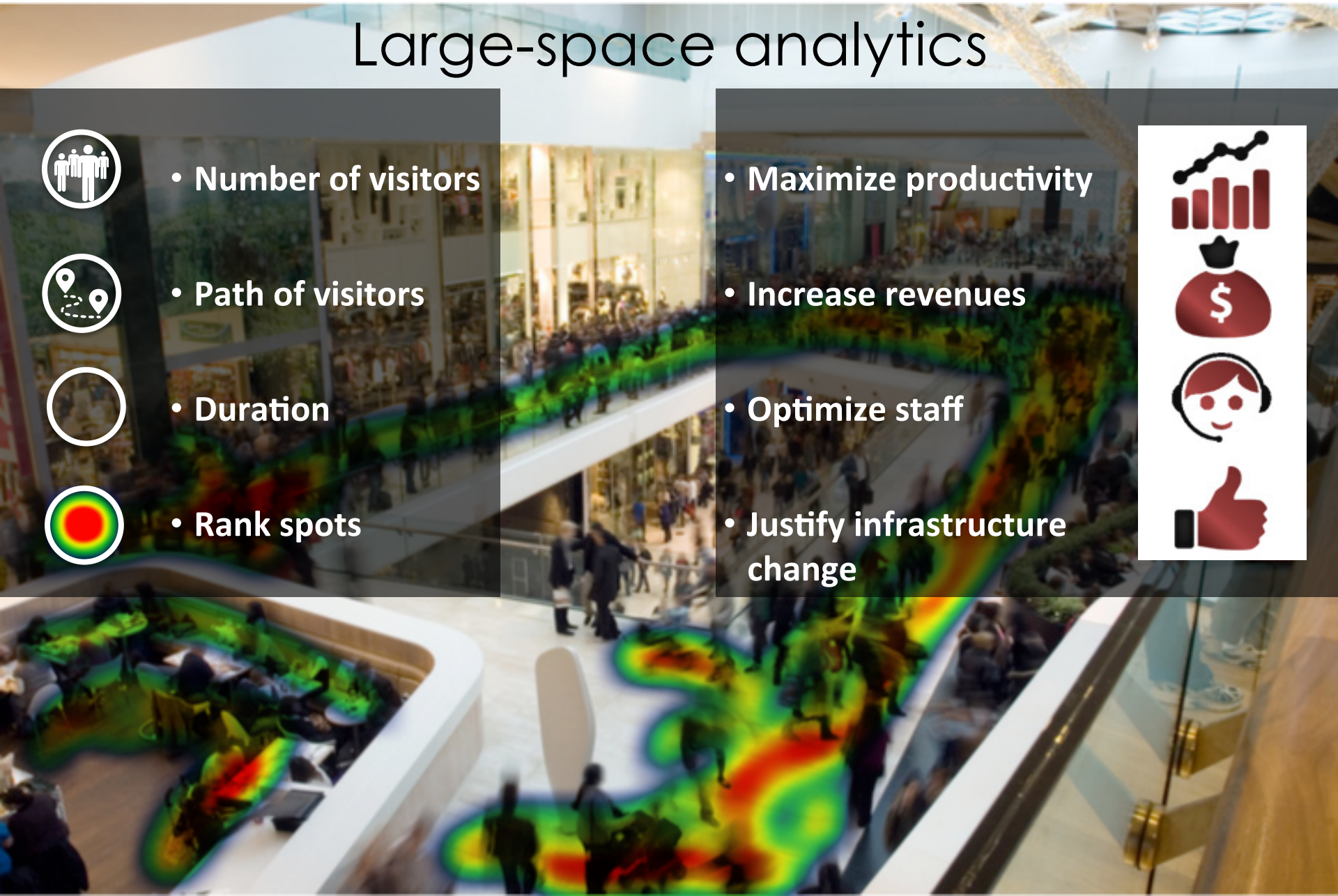
Large-space analytics



Motivation:
Large-space analytics



- Number of visitors
- Path of visitors
- Duration
- Rank spots

- Maximize productivity
- Increase revenues
- Optimize staff
- Justify infrastructure change

Understand human mobility in a large terminal over a year

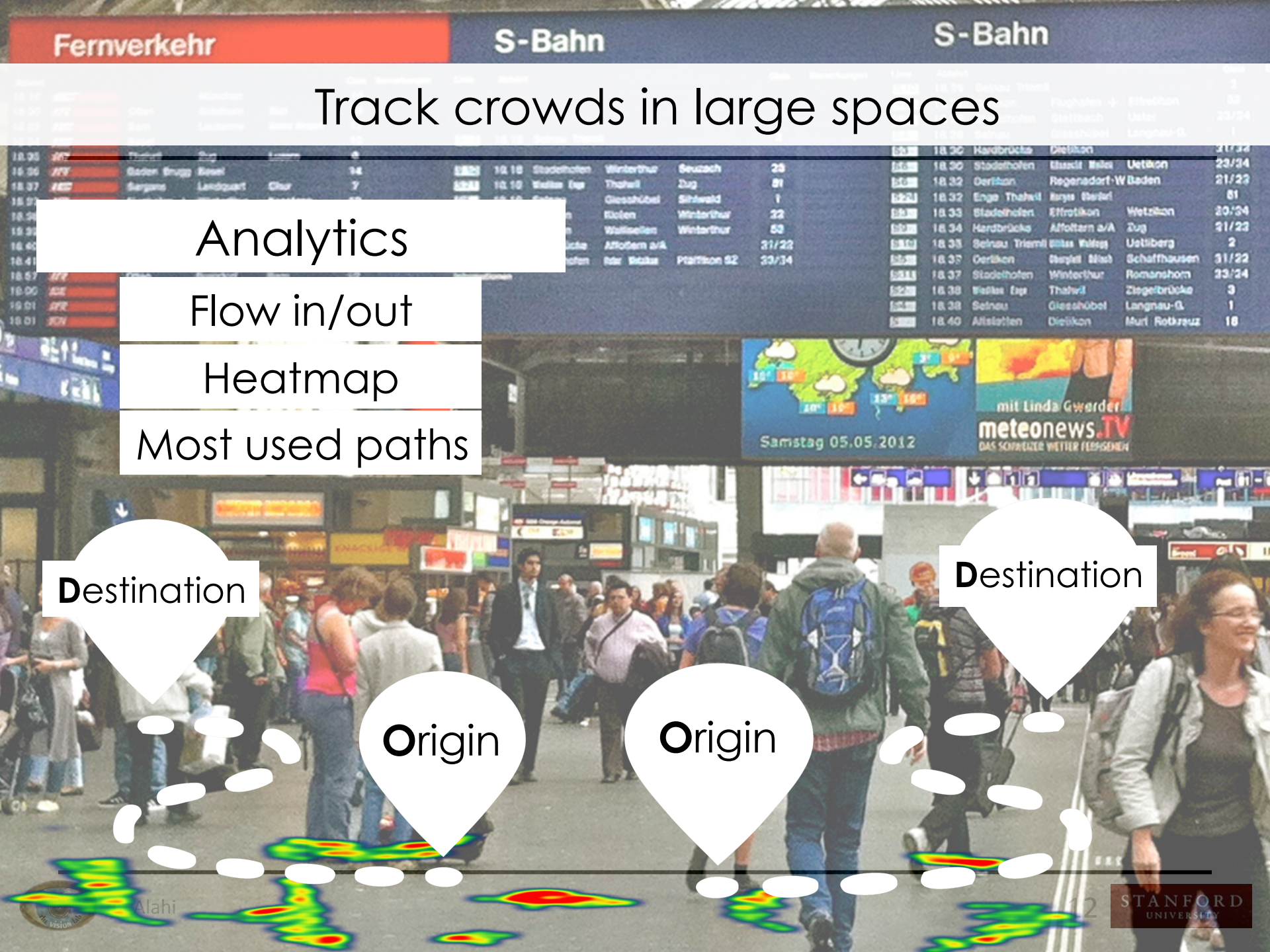
>120,000 commuters/day in 2013

>240,000 commuters/day by 2030*

Lausanne, Switzerland

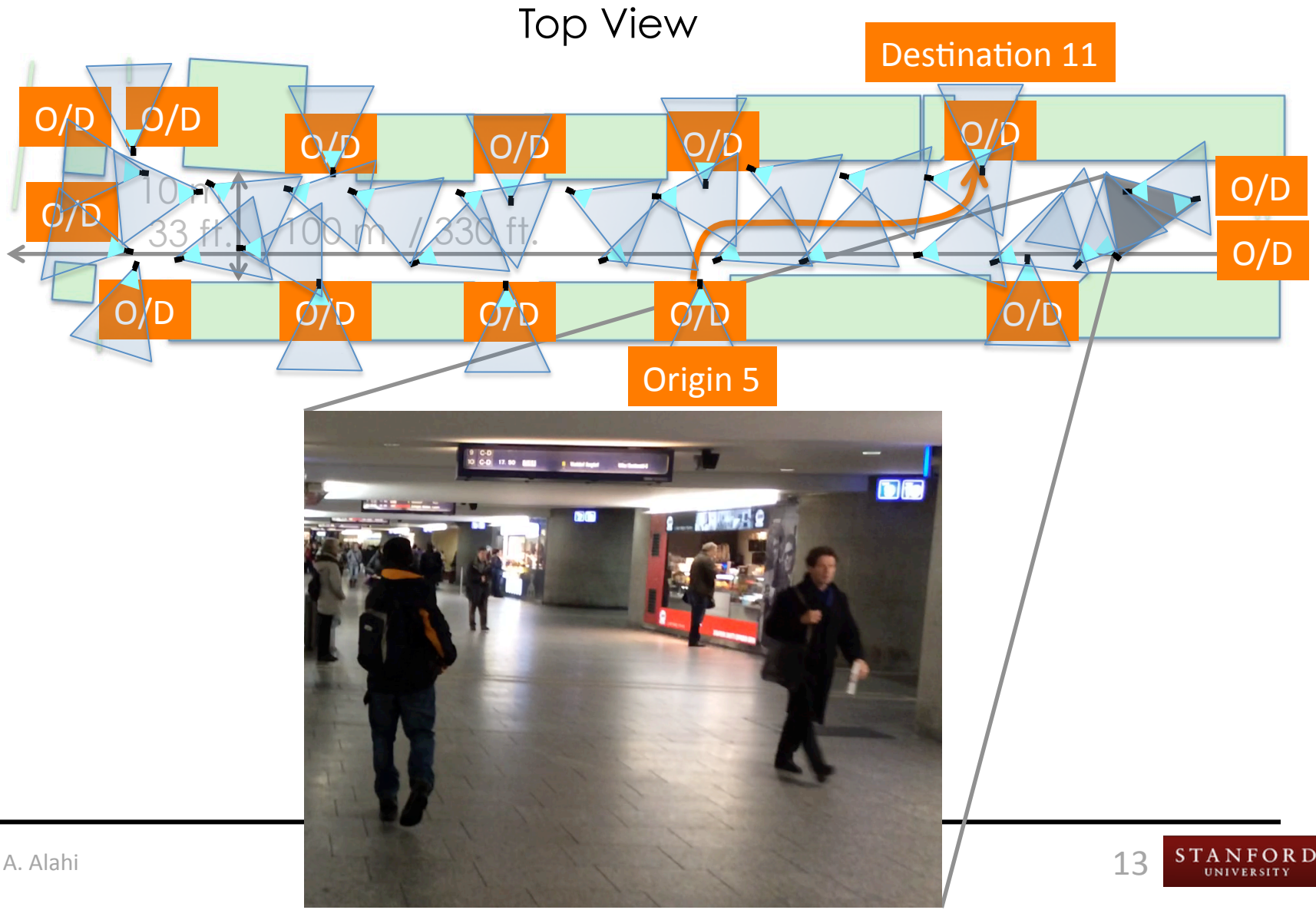
* SBB CFF FFS report leman 2030

Track crowds in large spaces

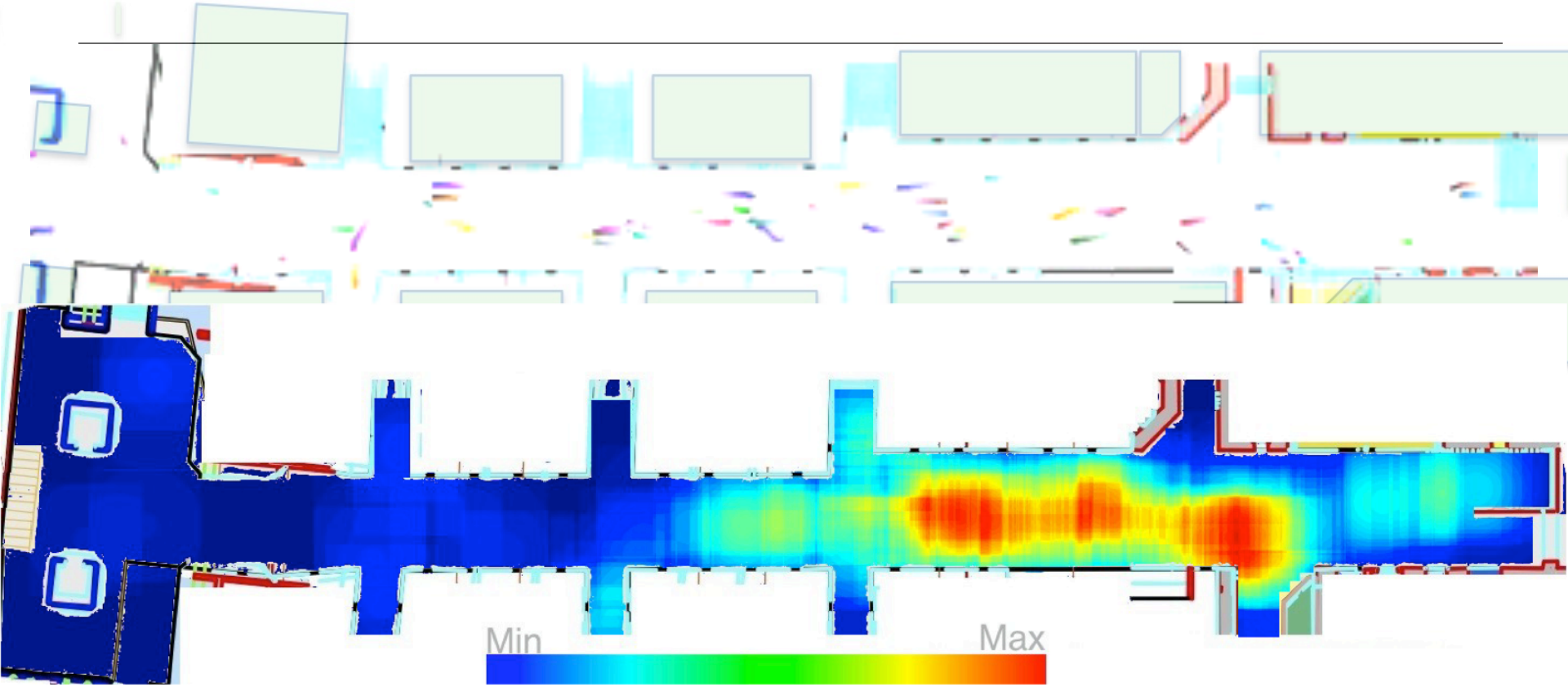


- Analytics
  - Flow in/out
  - Heatmap
  - Most used paths

A corridor with 14 Origin/Destination (O/D)



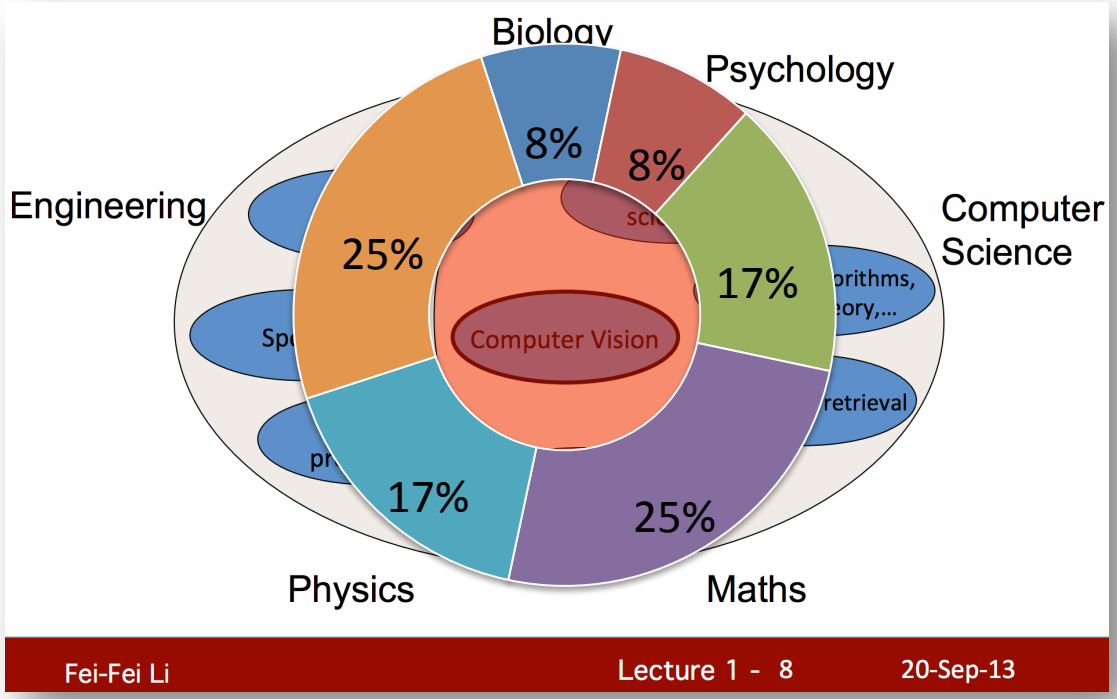
Collect long-term trajectories



# People	Av. duration	Av distance	Density (up to)	# Paths (O/D)
42 million	1 minute	100m	1 pedestrian/m^2	196

Tracking people

- Thousands scientific publications about tracking people
- What is related to tracking people?



Tracking people

- Focus of today's lecture:
  - Tracking people with
    - Video streams (vs static images)

      ⇒Prior from the scene

      ⇒Calibration data

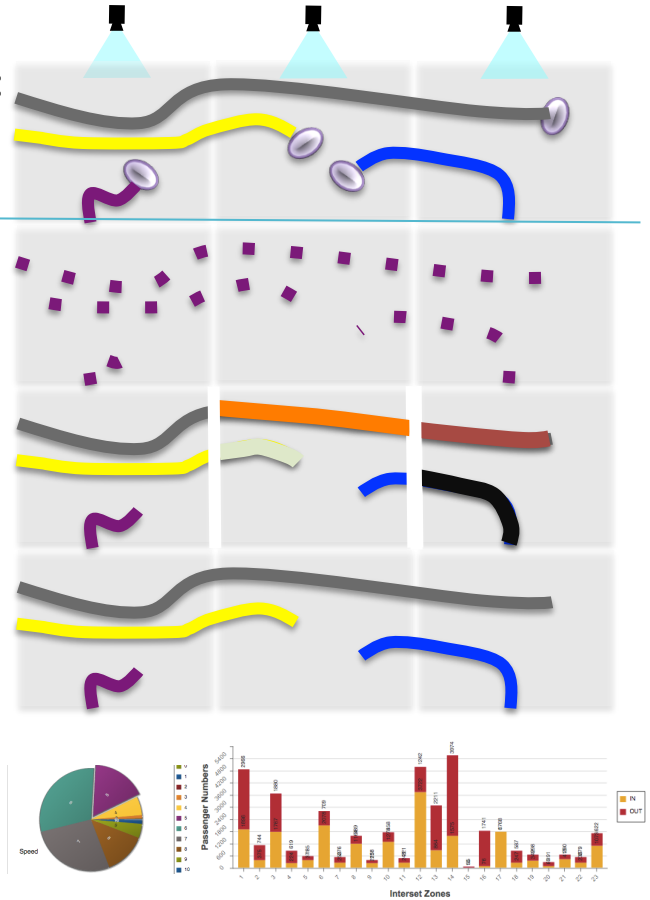
      ⇒**Mapping from image plane to real-world**

      ⇒Model temporal variation/changes

Outline:

From Foreground Extraction **To** Tracking 42 million Pedestrians

Network of 3 sensors:
4 people walking
(top view)



1 — Detection intra-sensor — >100 GB/day

2 — Tracklet Generation — 5GB/day

3 — Tracklet Association — 4 GB/day

4 — Statistic Generation — 5 GB/day

0.05 GB/day

Outline:

From Foreground Extraction **To** Tracking 42 million Pedestrians

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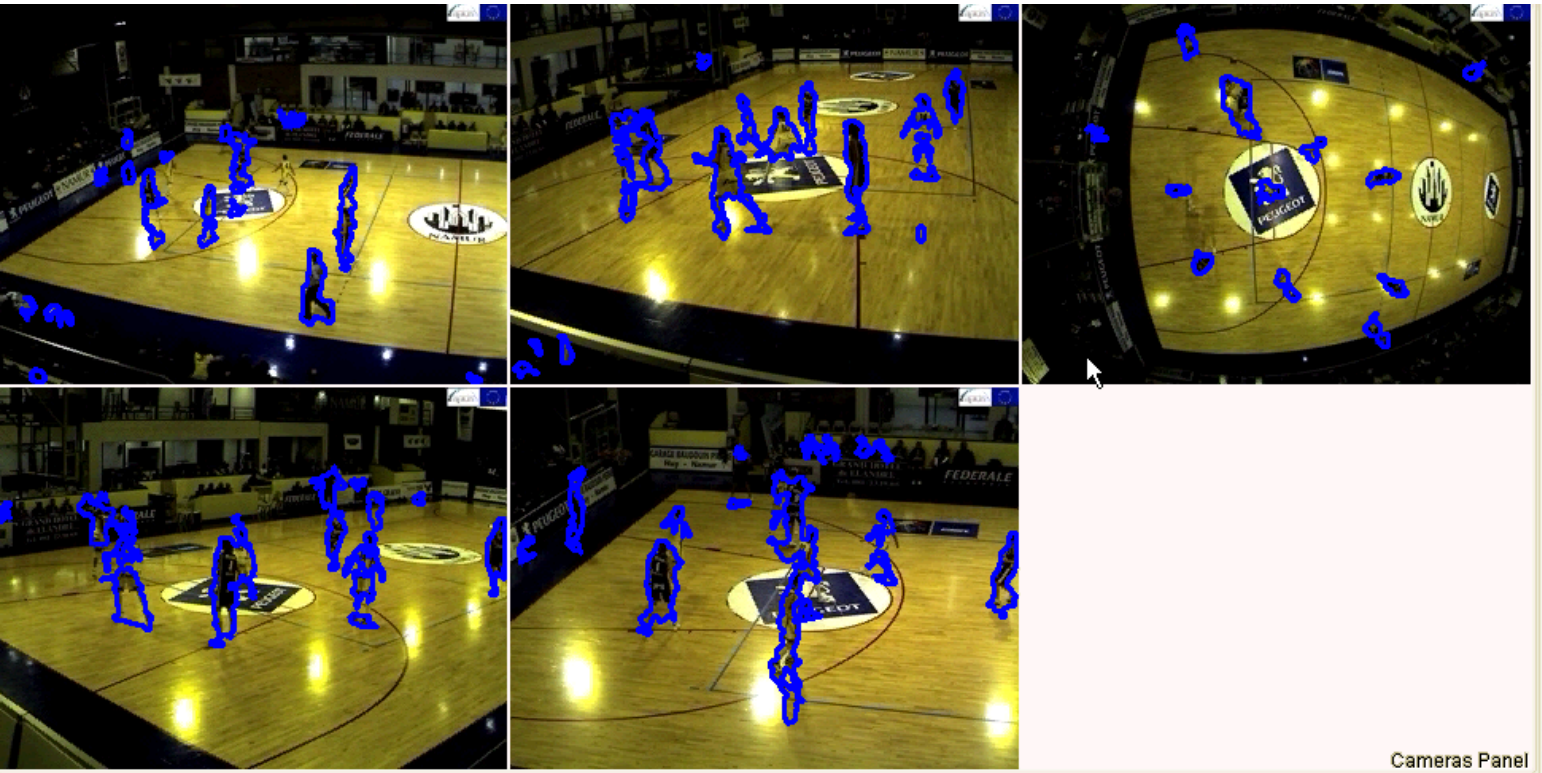
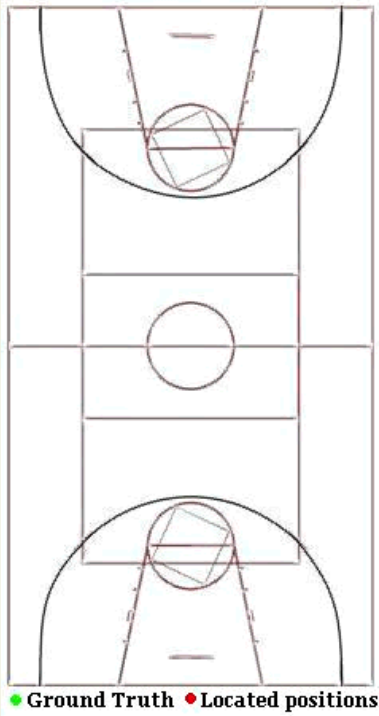
I. **Detection**
   I. Foreground extraction
   II. Pedestrian localization

II. **Tracklet Generation**
   I. Data association problem
   II. Matching appearance cues

III. **Tracklet Association**
   I. Modeling Social Affinities

I. Detection: Foreground extraction





- Severely degraded foreground silhouettes
- Spatially dense distribution
- Strong occlusions

I. Detection: Foreground extraction

$$F(x,y,t+1) = \begin{cases} 1 \text{ if } \; | \, I(x,y,t) - \mathbf{B}(x,y) \, | > T \\ 0 \quad \text{otherwise} \end{cases}$$

- Frame differencing

$$\mathbf{B}(x,y) = I(x,y,t-1)$$

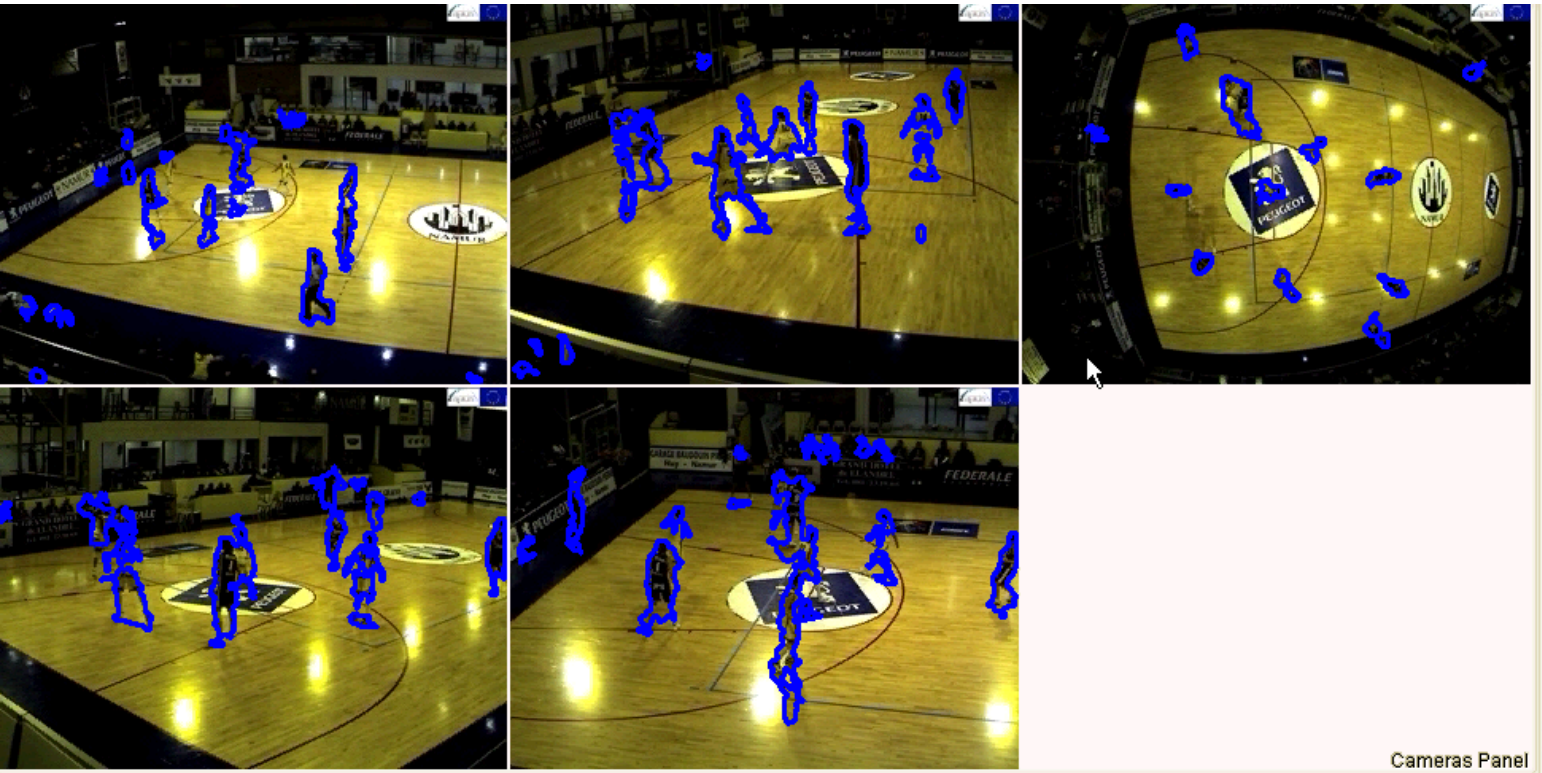
- Mean filter

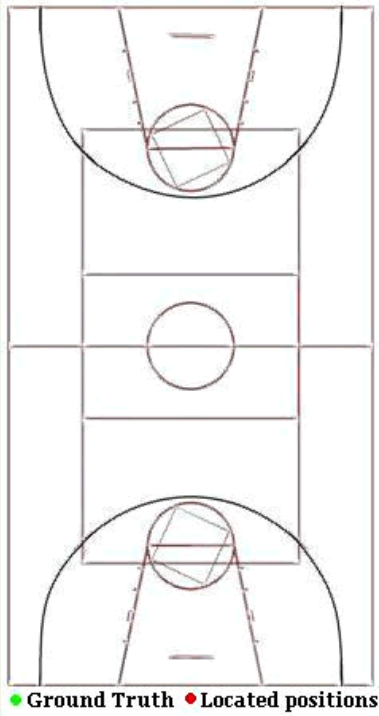
$$B(x,y) = 1/N \;\; \Sigma_{i=1\ldots N} \, I(x,y,t-i)$$

- Gaussian averaging
- GMM
- …

=> Library of 32 algorithms (*BGS library*)

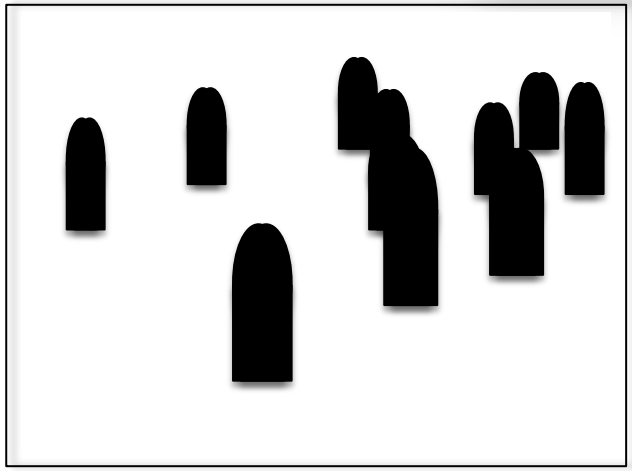
I. Detection: Foreground extraction





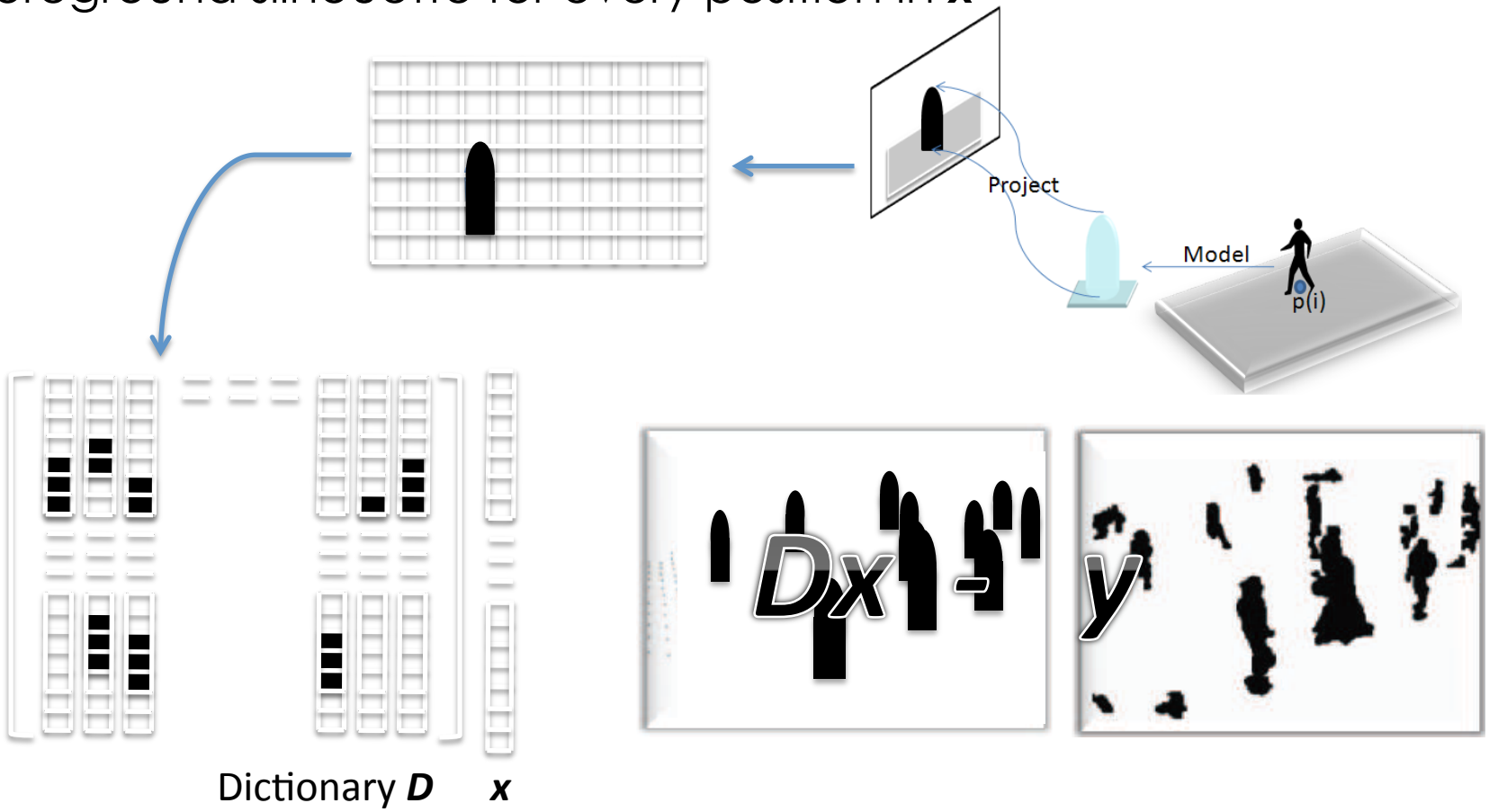
- Severely degraded foreground silhouettes
- Spatially dense distribution
- Strong occlusions

I. Detection: Pedestrian localization

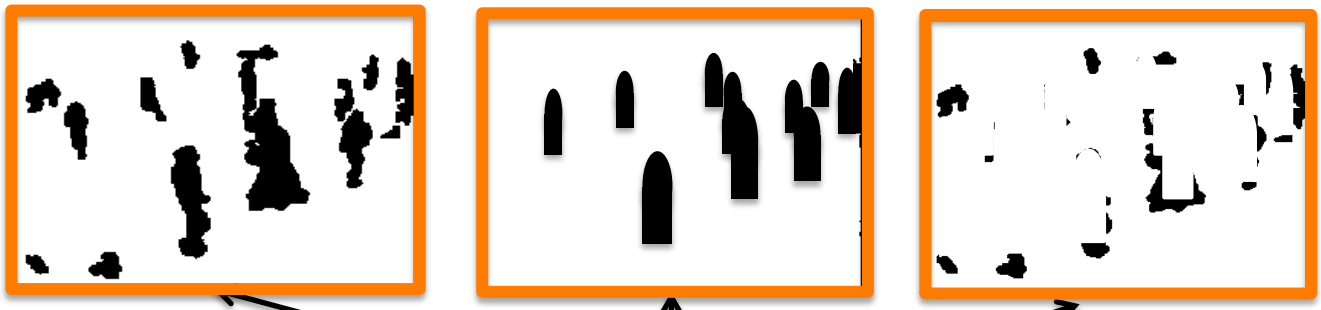


I. Detection: Calibrated Camera

- Create a dictionary ***D*** of atoms approximating the ideal foreground silhouette for every position in ***x***



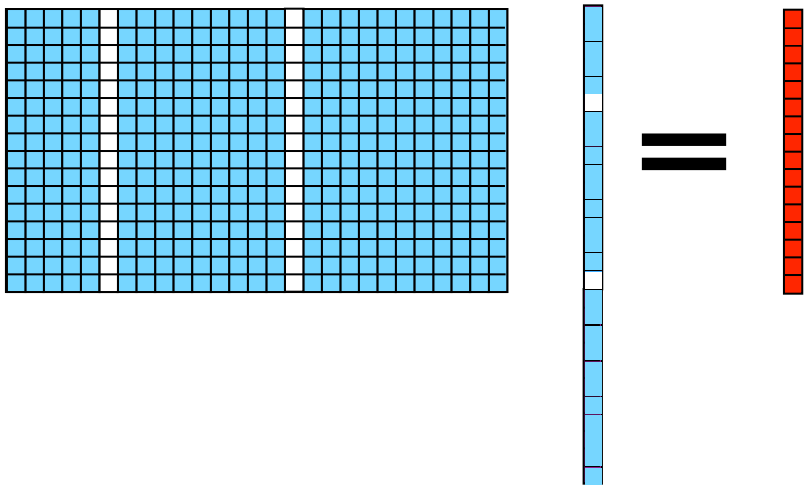
I. Detection: Sparsity driven framework



- Inverse problem: $y = Dx + n$

I. Detection: Greedy approach

D x = y



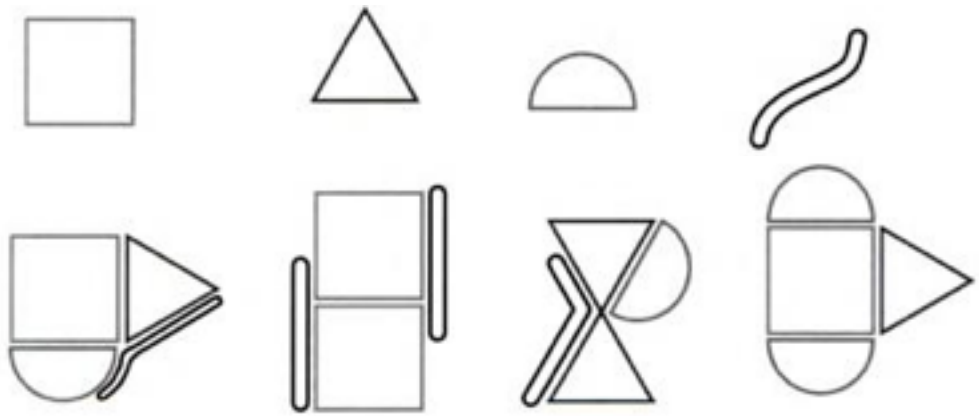
[1] S. Mallat and Z. Zhang, "Matching pursuits with time-frequency dictionaries," IEEE Transactions on signal processing,1993.

I. Detection: Sparsity driven framework

- Inverse problem: $y = Dx + n$
- Sparsity prior: $\min \|x\|_0$ s. t. $y = Dx + n$

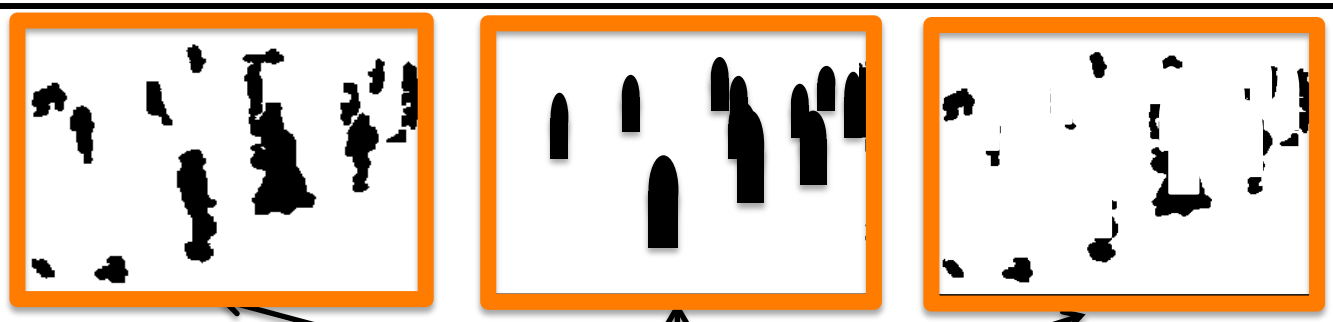
I. Detection: In praise of sparsity

"Creation is based on small number of primary, indivisible elements that combine with one another according to a few simple patterns." [1]



[1] B. Elahi, "Spirituality is a science: Foundation of Natural Spirituality"

I. Detection: Sparsity driven framework

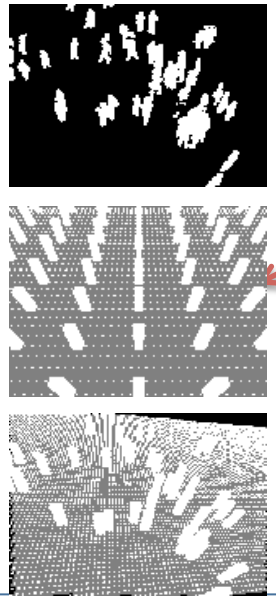


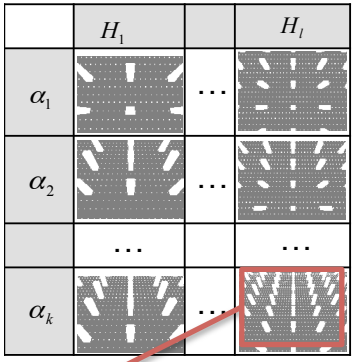
- Inverse problem: $y = Dx + n$
- Sparsity prior: $\min \|x\|_0$ s. t. $y = Dx + n$
- Basis Pursuit [1]: $\min \|x\|_1$ s. t. $y = Dx$
- BPDN: $\min \|x\|_1$ s. t $\|y - Dx\| \le n$
- Lasso: $\min \|y - Dx\|_2$ s. t $\|x\|_1 \le \varepsilon$

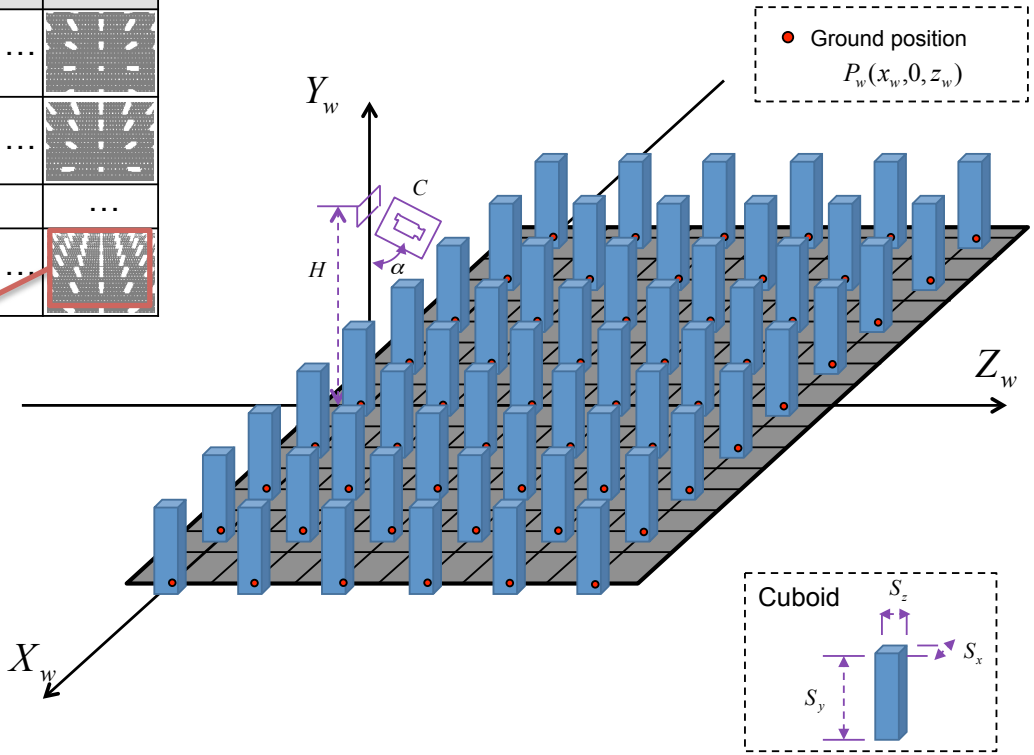
[1] S. S. Chen, D. Donoho, and M. Saunders, "Atomic decomposition by basis pursuit," SIAM Journal on Scientific Computing

I. Detection: Pedestrian localization

- Foreground extraction
- Used Dictionary
- Localization

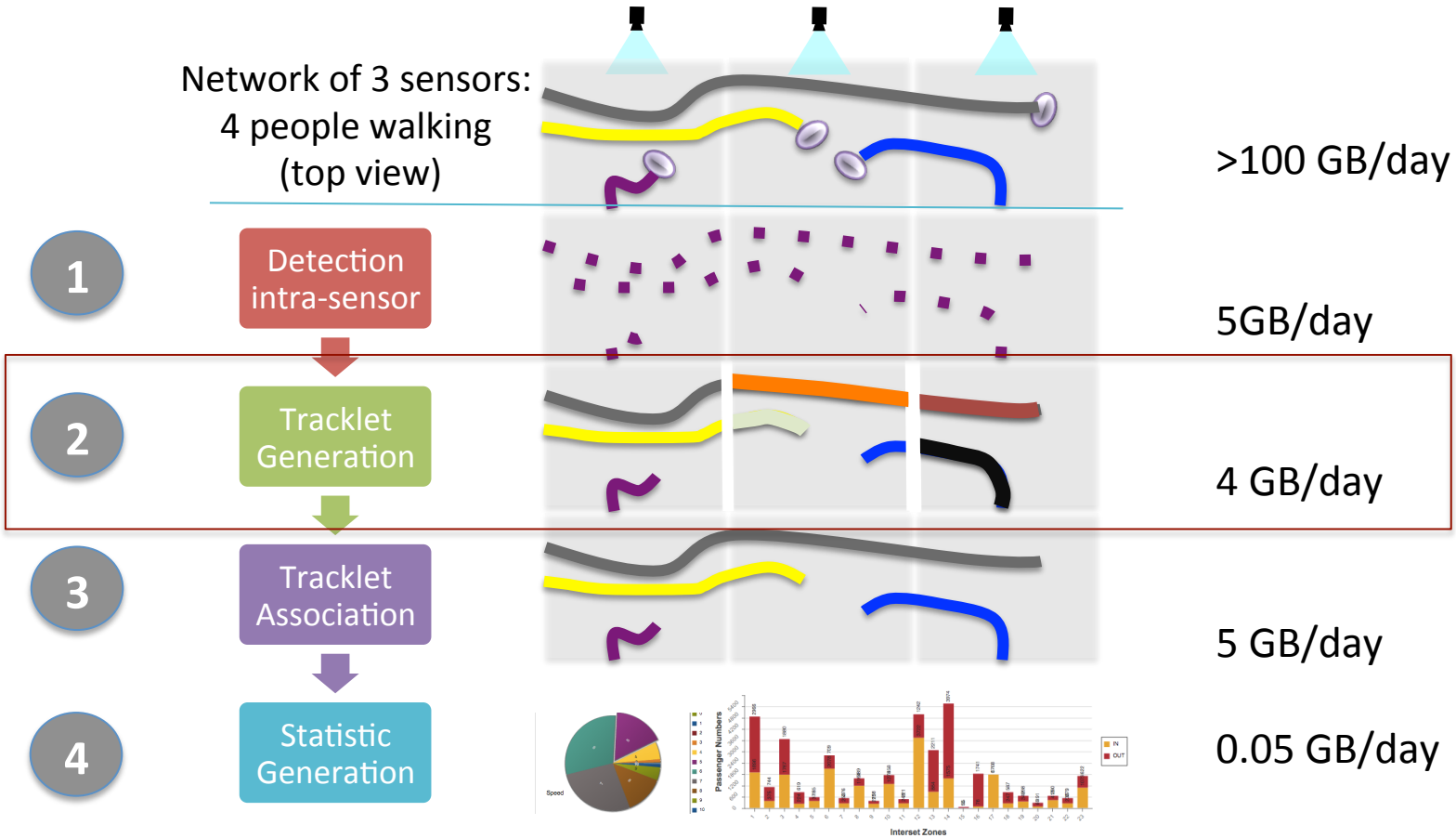






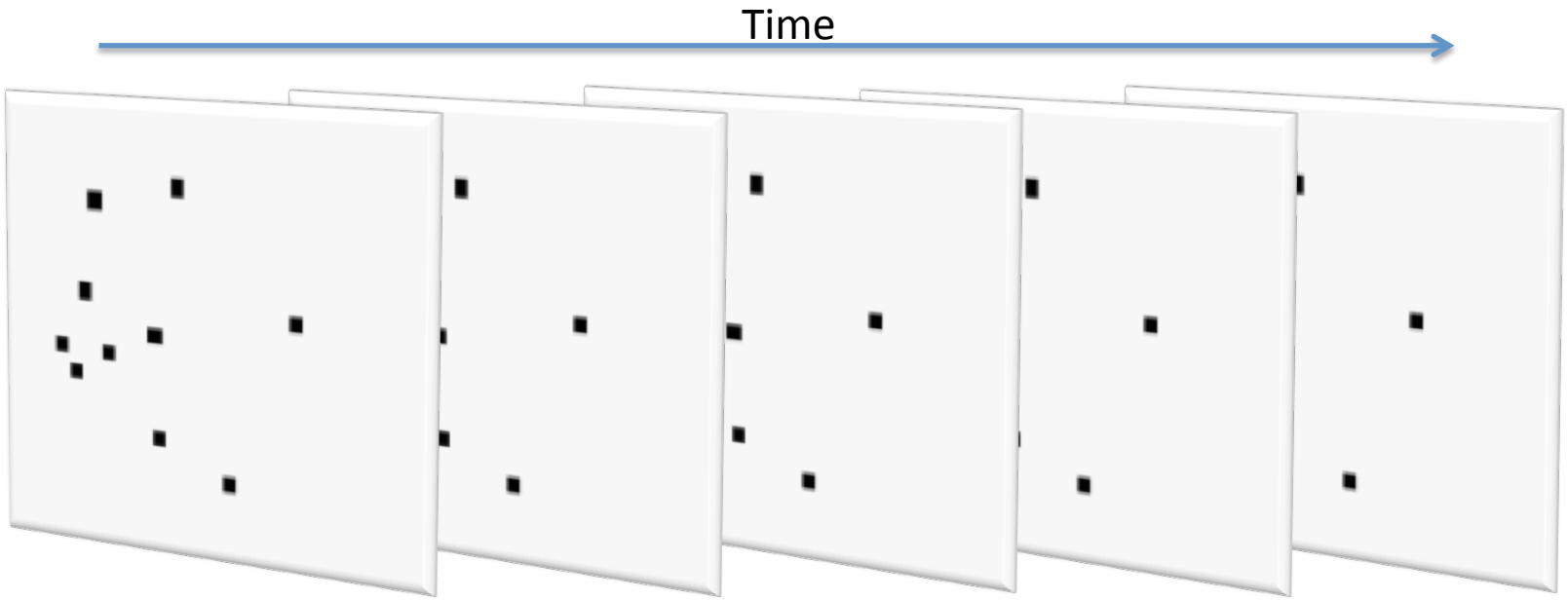
Outline:

From Foreground Extraction **To** Tracking 42 million Pedestrians

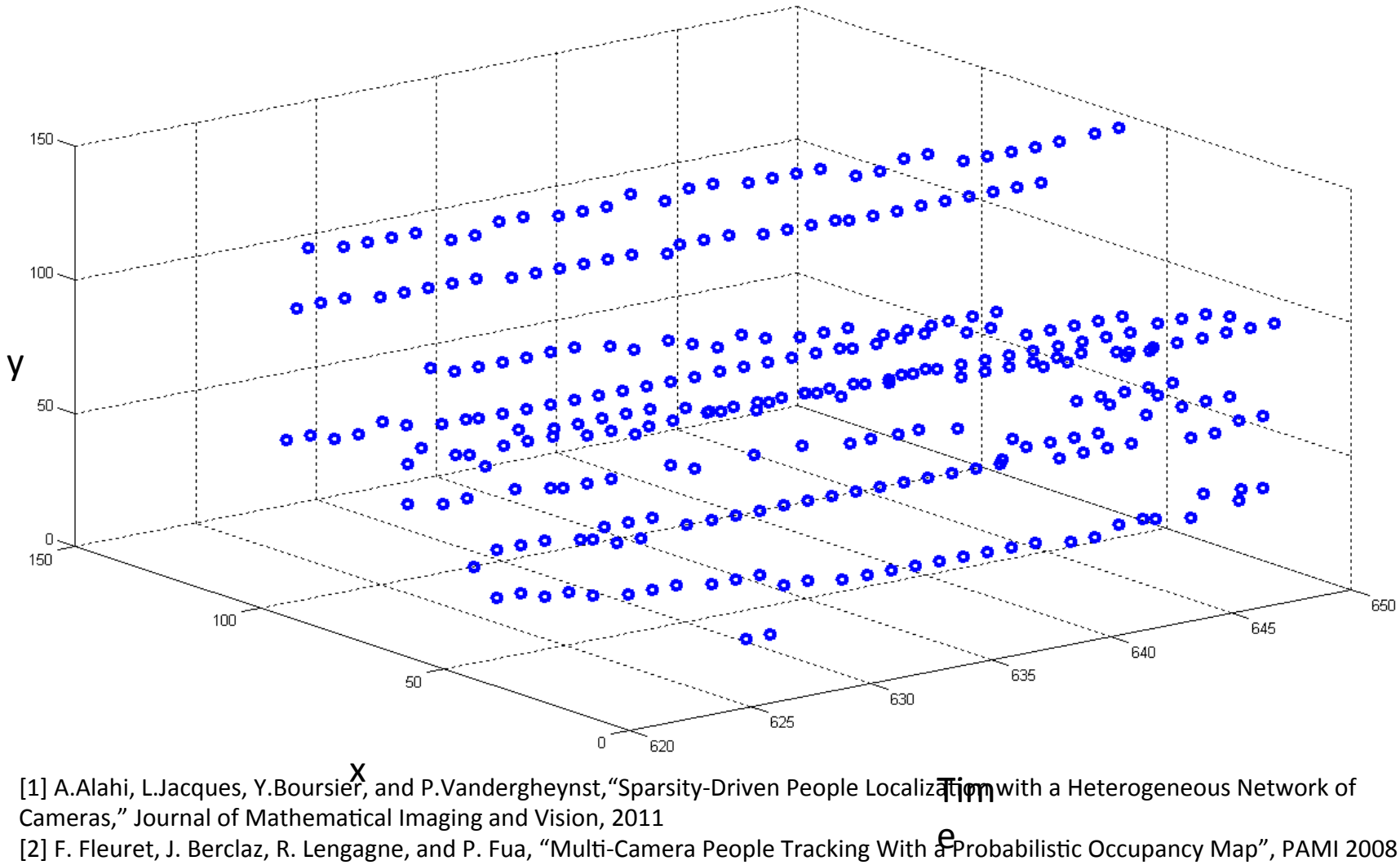


II. Tracklet generation: Data Association Problem

- Create a Directed Acyclic Graph G= (N,E) where
  - N= The detected ground plane points across time
  - E= The connectivity cost between the detections (based on motion/appearance model)

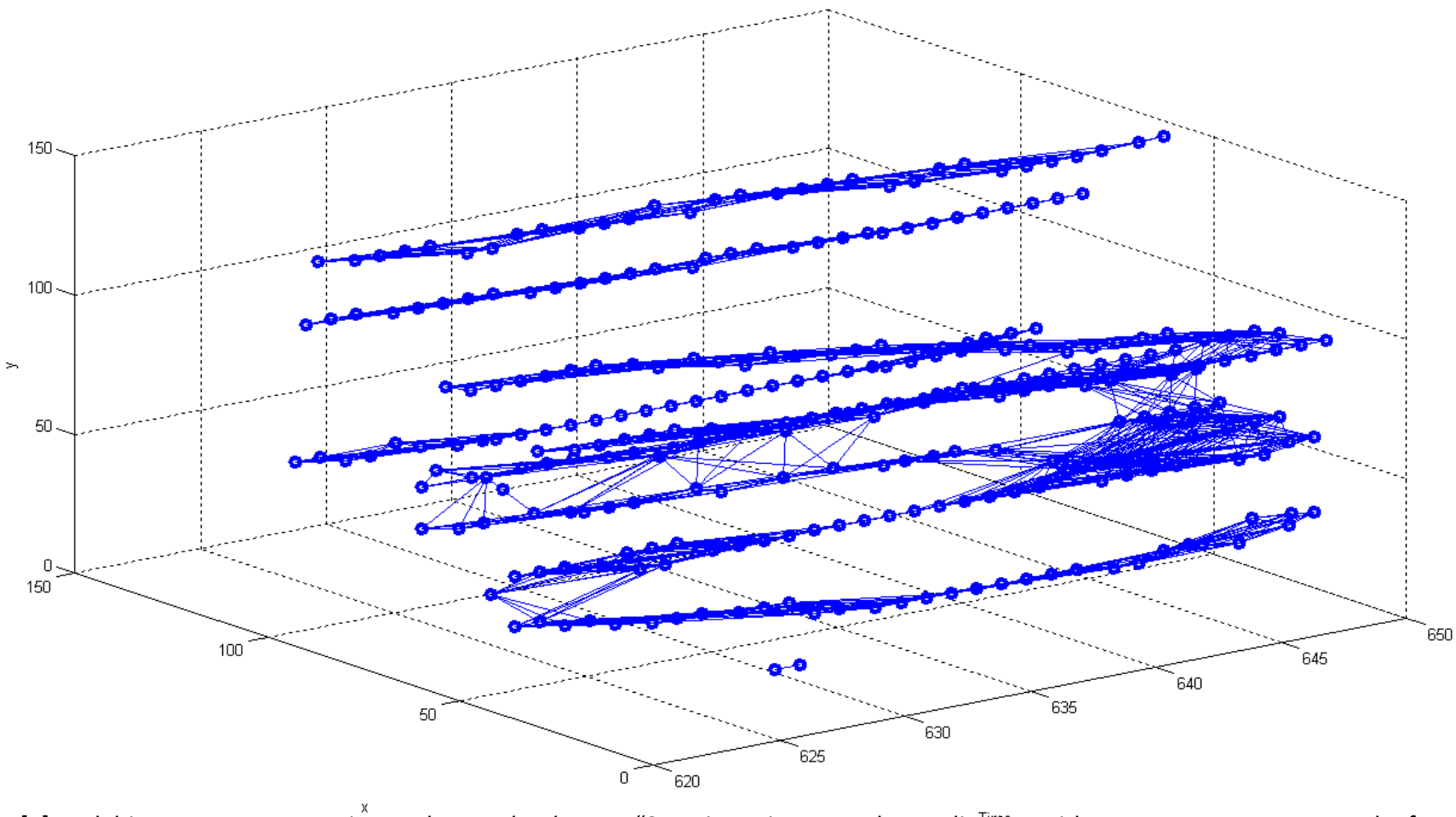


II. Tracklet generation: Data Association Problem



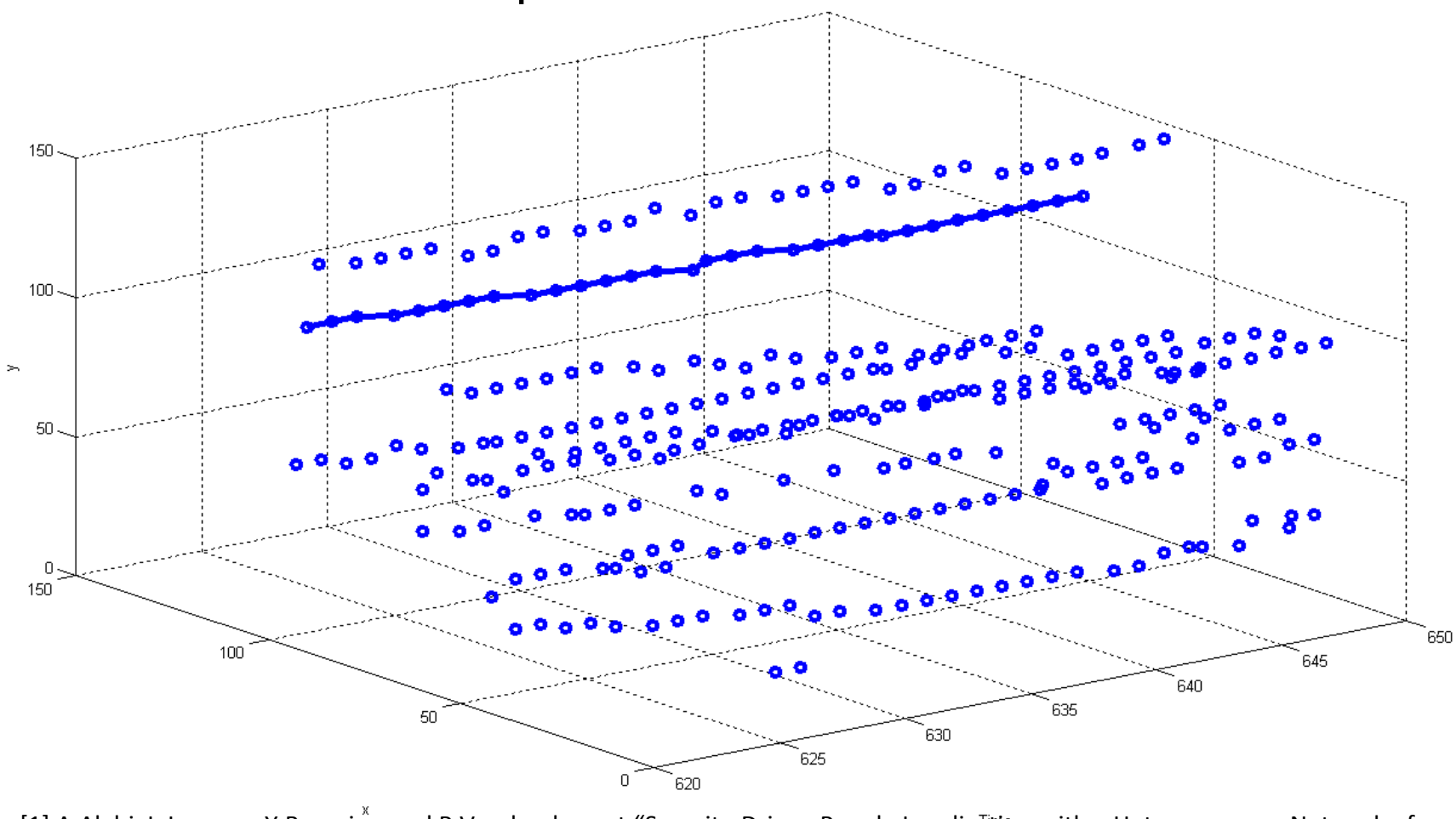
[1] A.Alahi, L.Jacques, Y.Boursier, and P.Vandergheynst,"Sparsity-Driven People Localization with a Heterogeneous Network of Cameras," Journal of Mathematical Imaging and Vision, 2011
[2] F. Fleuret, J. Berclaz, R. Lengagne, and P. Fua, "Multi-Camera People Tracking With a Probabilistic Occupancy Map", PAMI 2008

II. Tracklet generation: Create a DAG



[1] A.Alahi, L.Jacques, Y.Boursier, and P.Vandergheynst,"Sparsity-Driven People Localization with a Heterogeneous Network of Cameras," Journal of Mathematical Imaging and Vision, 2011
[2] F. Fleuret, J. Berclaz, R. Lengagne, and P. Fua, "Multi-Camera People Tracking With a Probabilistic Occupancy Map", PAMI 2008

II. Tracklet generation: Select longuest shortest path with smallest cost



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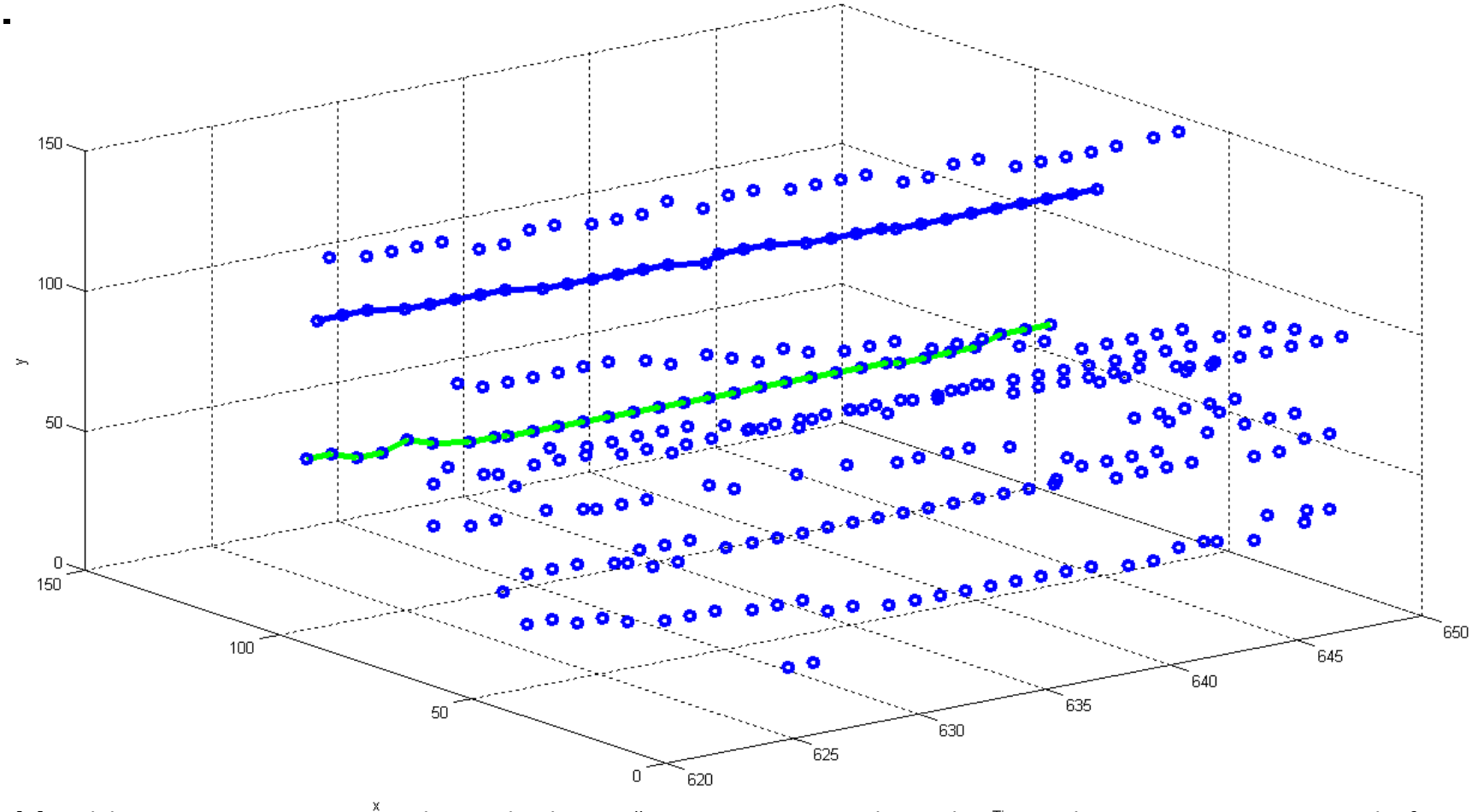
II. Tracklet generation: Iterate



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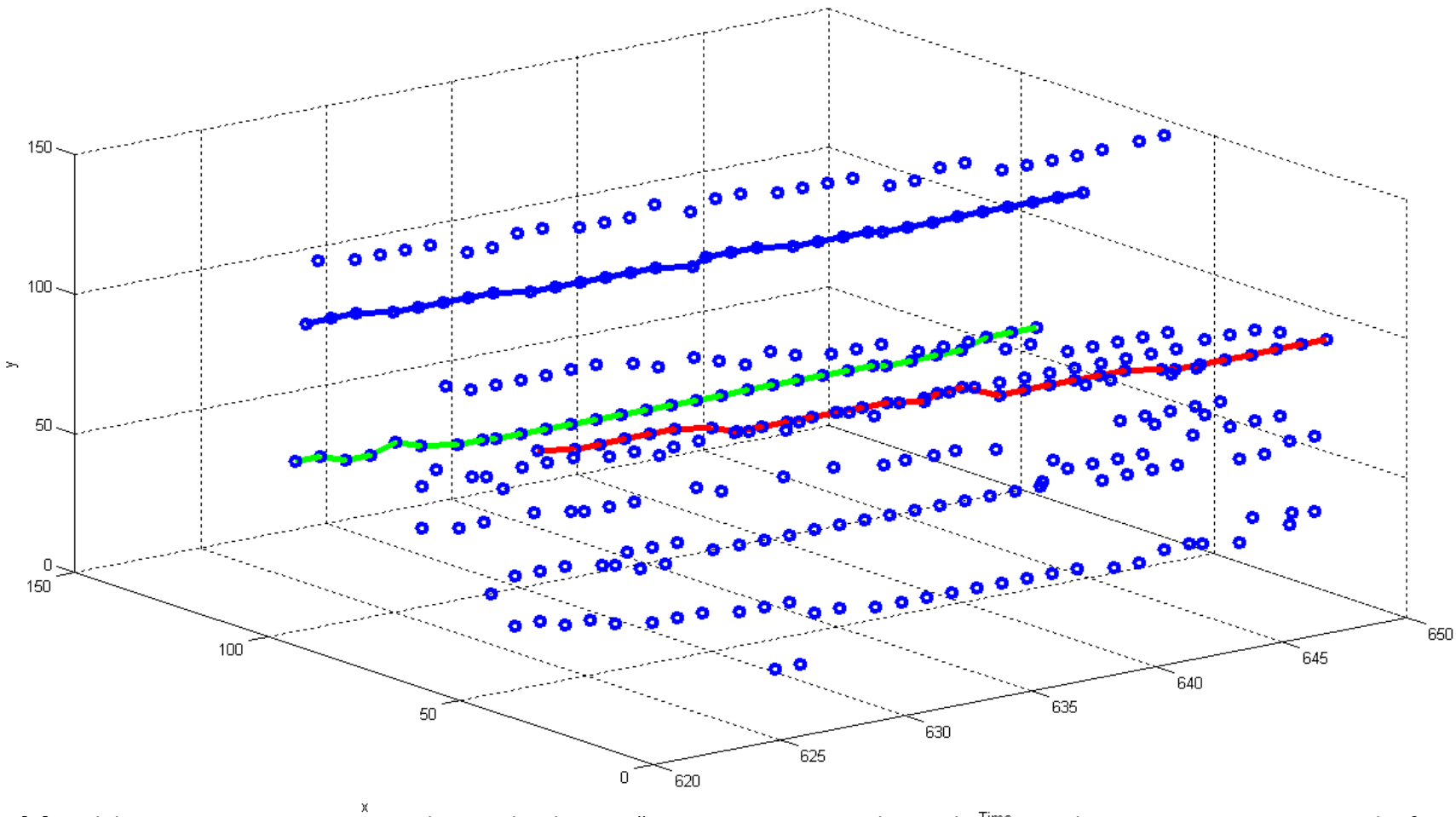

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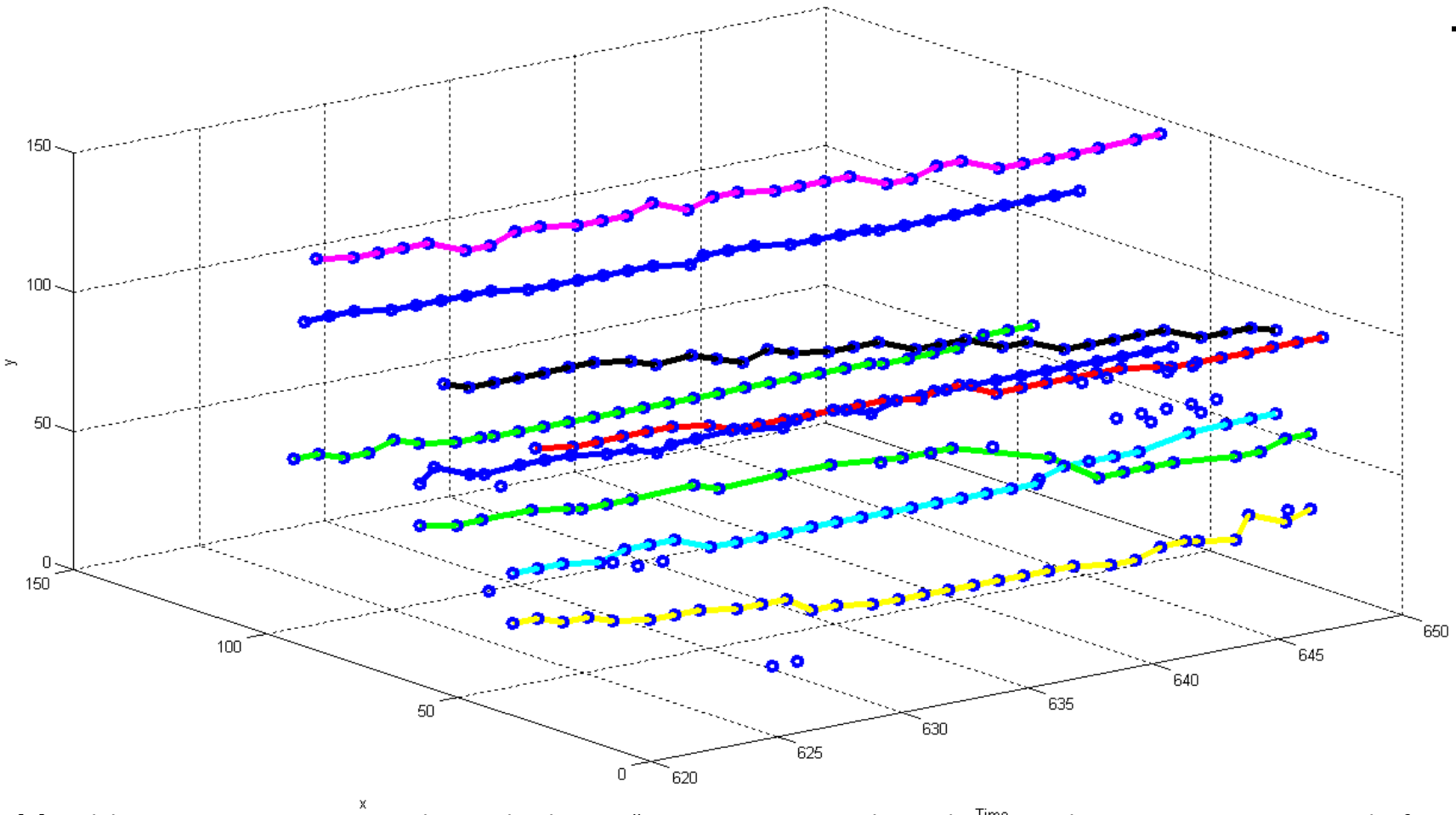
[2] F. Fleuret, J. Berclaz, R. Lengagne, and P. Fua, "Multi-Camera People Tracking With a Probabilistic Occupancy Map", PAMI 2008

II. Tracklet generation: Till no more paths

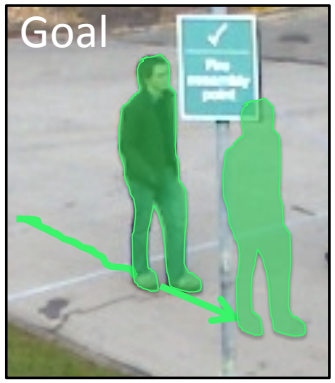


[1] A.Alahi, L.Jacques, Y.Boursier, and P.Vandergheynst,"Sparsity-Driven People Localization with a Heterogeneous Network of Cameras," Journal of Mathematical Imaging and Vision, 2011
[2] F. Fleuret, J. Berclaz, R. Lengagne, and P. Fua, "Multi-Camera People Tracking With a Probabilistic Occupancy Map", PAMI 2008

II. Tracklet Generation: Edge cost

- Motion model with social interactions
- Appearance model

II. Tracklet generation: Modeling social interactions



Images courtesy of [1]

$$\mathbf{F}_i = \mathbf{F}_i^{Goal} + \boxed{\mathbf{F}_i^{Avoidance}} + \mathbf{F}_i^{Attraction} + \mathbf{F}_i^{Scene}$$

$$\mathbf{F}_i^{Avoidance} = \sum_{j \in P \setminus i} \mathbf{f}_{j \to i}^{Avoidance},$$

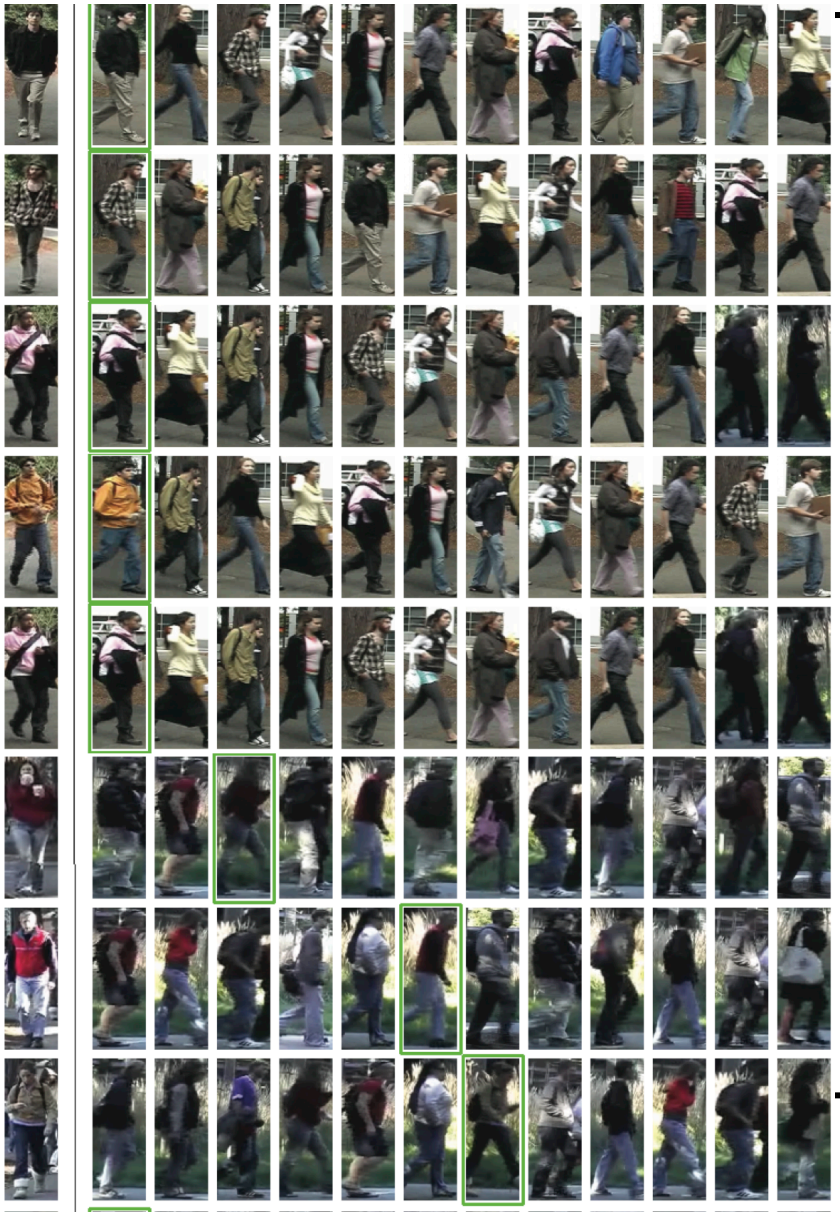
where

$$\mathbf{f}_{j \to i}^{Avoidance} = \alpha e^{\frac{d_p - d_{ij}}{\beta}} \mathbf{n}_{j \to i}$$

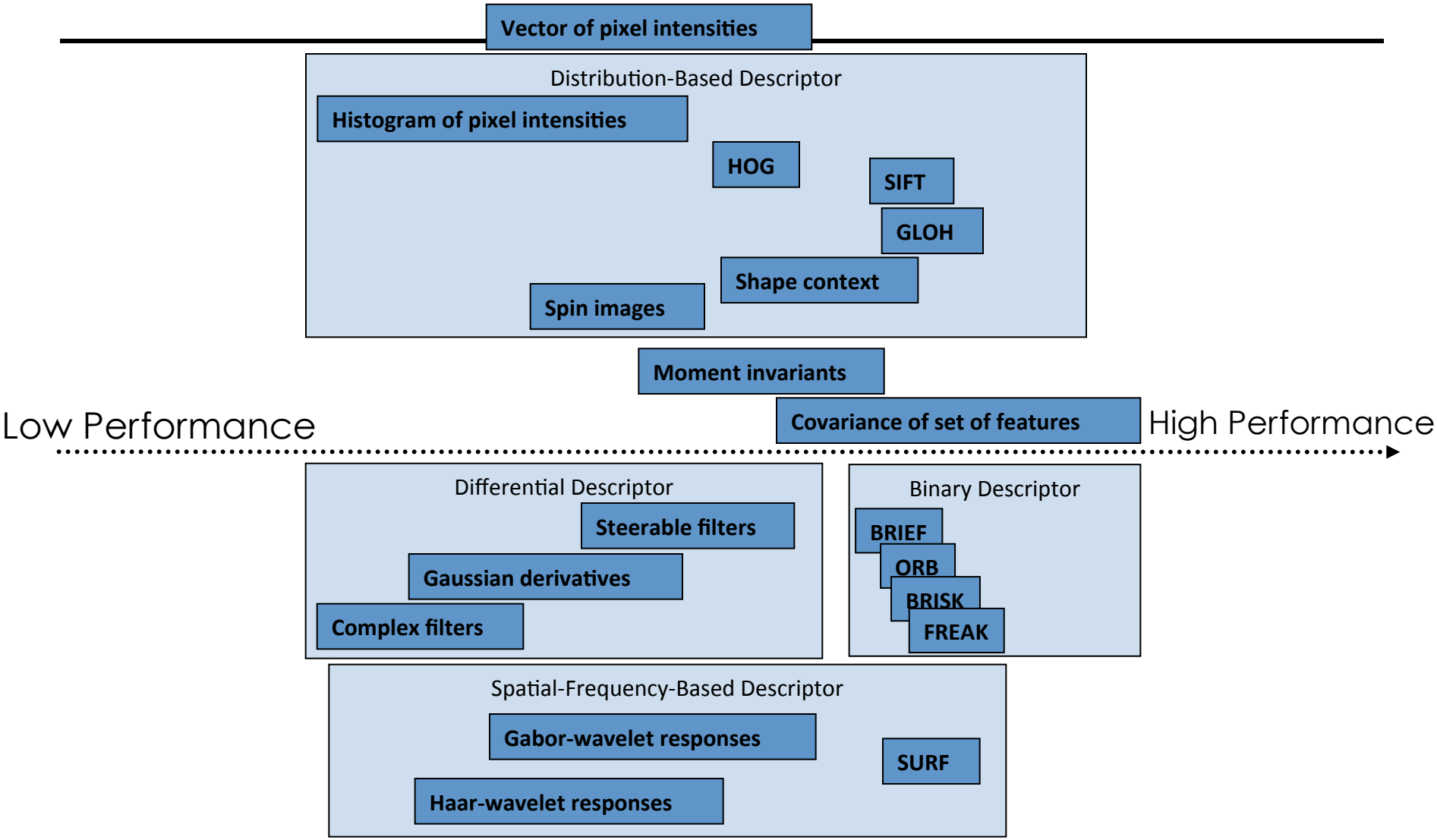
$$\frac{d}{dt}\mathbf{v} = \frac{\mathbf{F}_i}{m},$$

[1] Laura Leal-Taixé, Bodo Rosenhahn, “Pedestrian interaction in tracking: the social force model and global optimization methods”, Springer 2012

II. Tracklet Generation: Modeling appearance cues



II. Tracklet Generation: An arm-race of image descriptors



[1] Gabriel, P., Hayet, J., Piater, J., Verly, J.: Object tracking using color interest points
[2] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection,",
[3] O. Tuzel, F. Porikli, and P. Meer, "Region covariance: A fast descriptor for detection and classification,".

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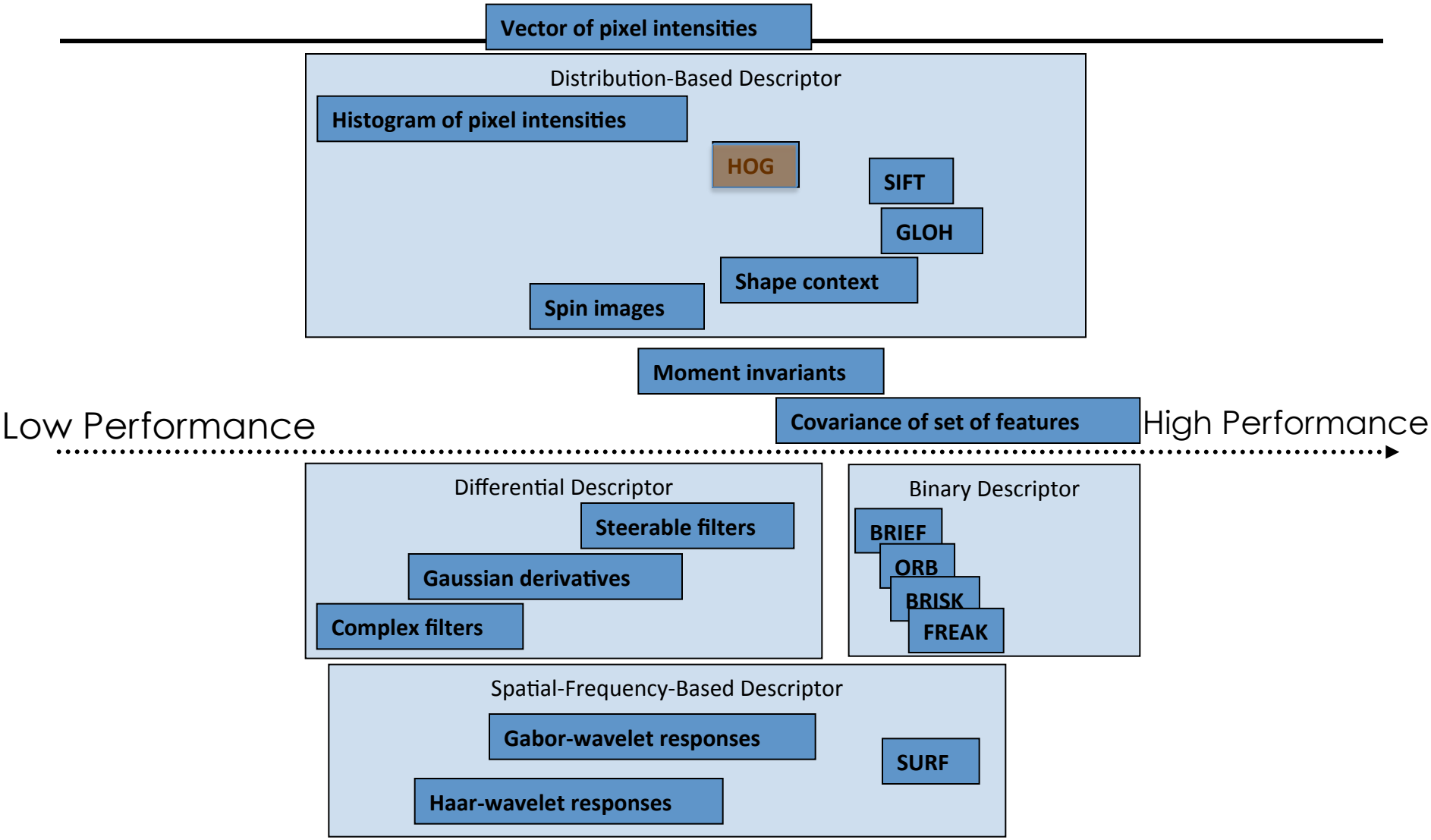

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II. Tracklet Generation: HOG

Image gradient

- The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$

$\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$

$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$

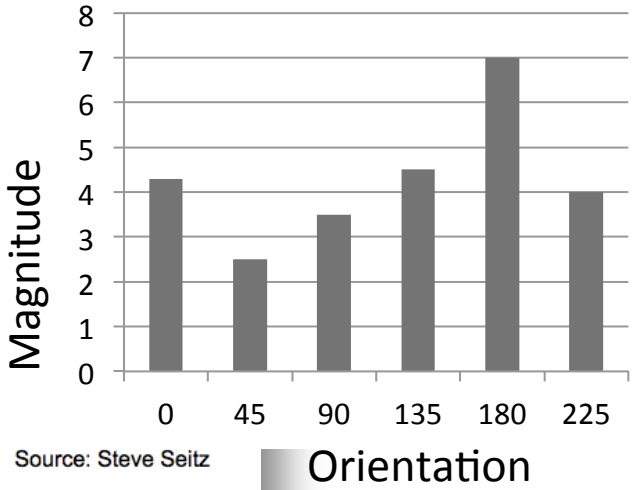
The gradient points in the direction of most rapid increase in intensity

The gradient direction is given by $\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$

- how does this relate to the direction of the edge?

The *edge strength* is given by the gradient magnitude

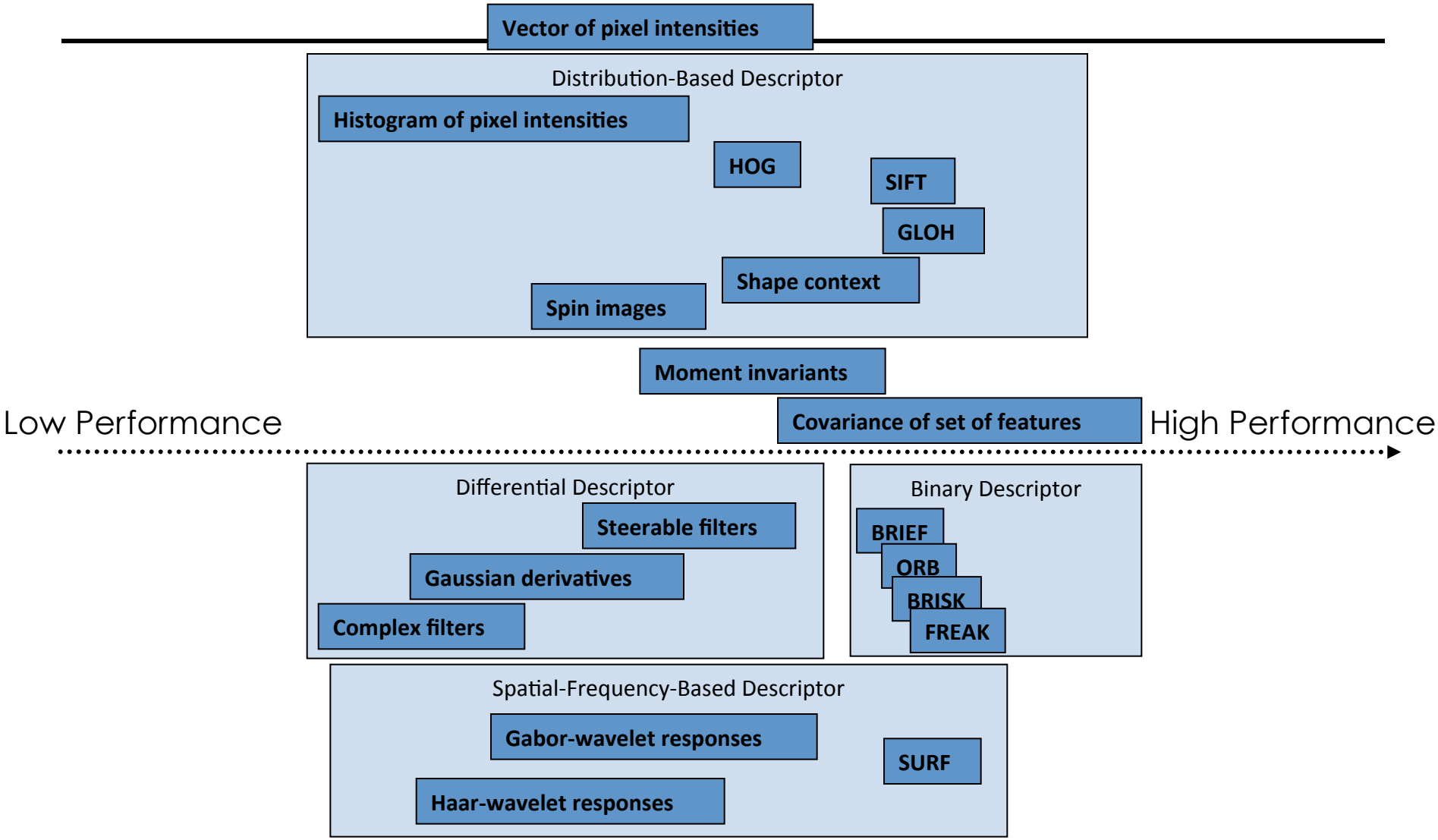
$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$



Source: Steve Seitz

Fei-Fei Li Lecture 5 - 18 25-Sep-13

II. Tracklet Generation: An arm-race of image descriptors



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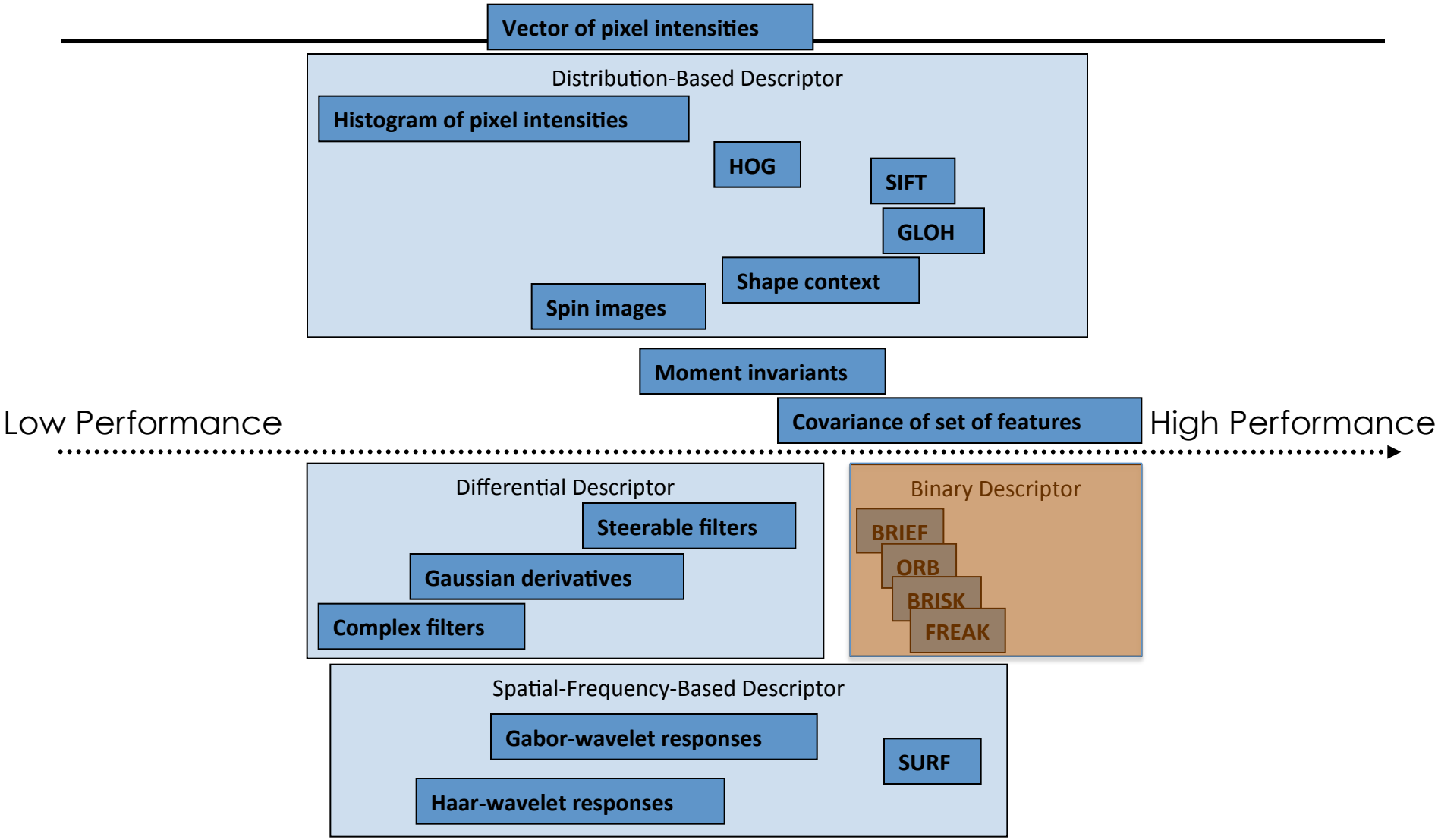

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[3] O. Tuzel, F. Porikli, and P. Meer, "Region covariance: A fast descriptor for detection and classification,".

II. Tracklet Generation: Binary descriptors

II. Tracklet Generation: BRIEF[1] / ORB[2] / BRISK[3]

[1] Calonder, Michael, et al. "Brief: Binary robust independent elementary features." *ECCV 2010*.
[2] Rublee, Ethan, et al. "ORB: an efficient alternative to SIFT or SURF. " ICCV 2011
[3] Leutenegger,. , et al. "BRISK: Binary robust invariant scalable keypoints." ICCV 2011

II. Tracklet Generation: BRIEF[1] / ORB[2] / BRISK[3]

[1] Calonder, Michael, et al. "Brief: Binary robust independent elementary features." *ECCV 2010*.
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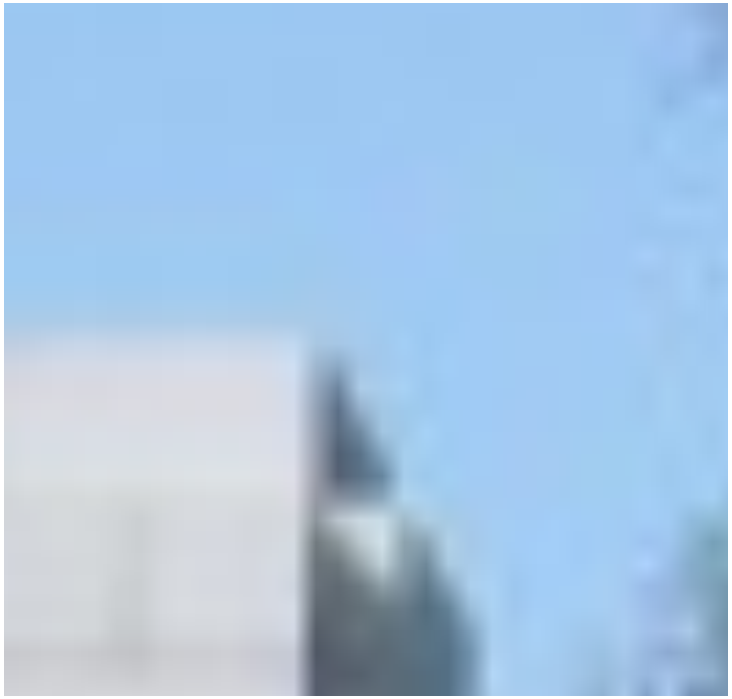
II. Tracklet Generation: BRIEF[1] / ORB[2] / BRISK[3]



[1] Calonder, Michael, et al. "Brief: Binary robust independent elementary features." *ECCV 2010*.
[2] Rublee, Ethan, et al. "ORB: an efficient alternative to SIFT or SURF. " ICCV 2011
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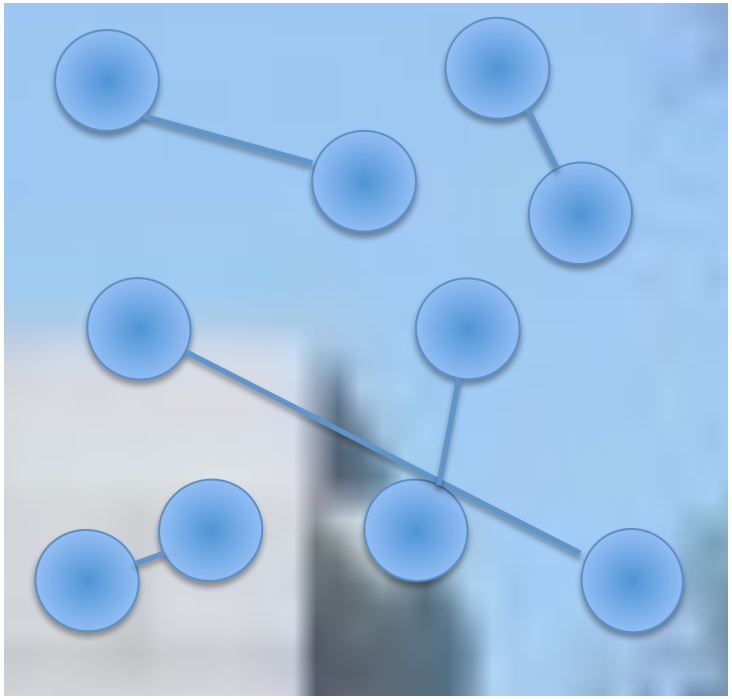
II. Tracklet Generation: **BRIEF[1]** / ORB[2] / BRISK[3]



A sequence of 1-bit DoG

[1] Calonder, Michael, et al. "Brief: Binary robust independent elementary features." *ECCV 2010*.
[2] Rublee, Ethan, et al. "ORB: an efficient alternative to SIFT or SURF. " ICCV 2011
[3] Leutenegger,. , et al. "BRISK: Binary robust invariant scalable keypoints." ICCV 2011

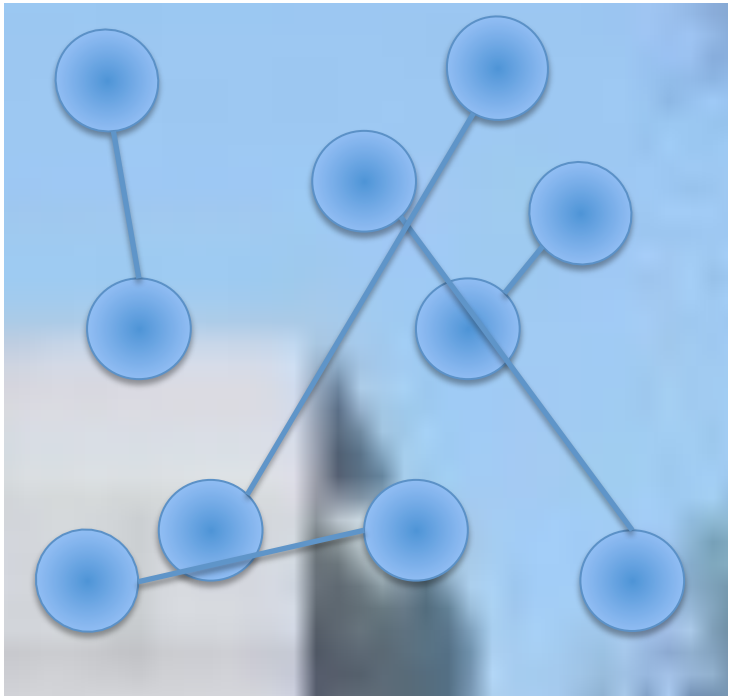
II. Tracklet Generation: BRIEF[1] / **ORB[2]** / BRISK[3]

- Select

1) Most discriminant

AND

2) Less correlated



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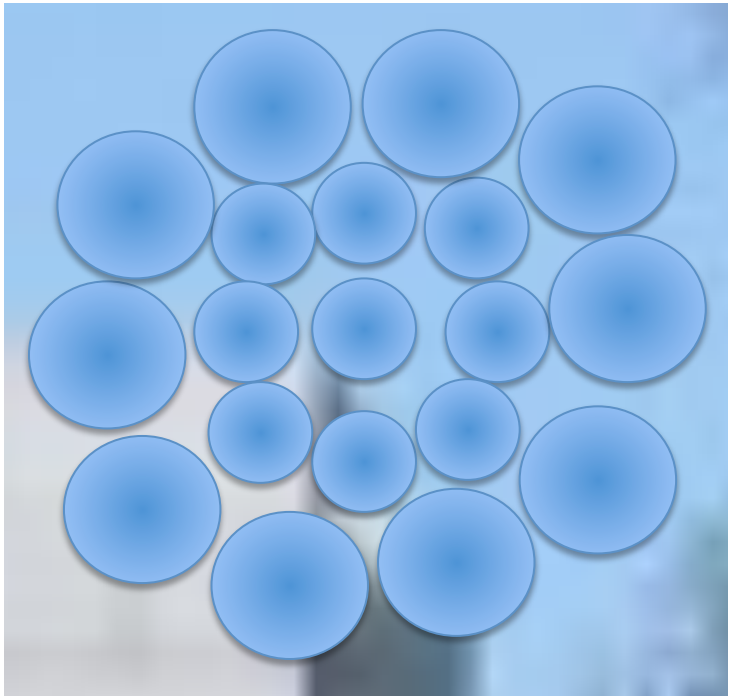
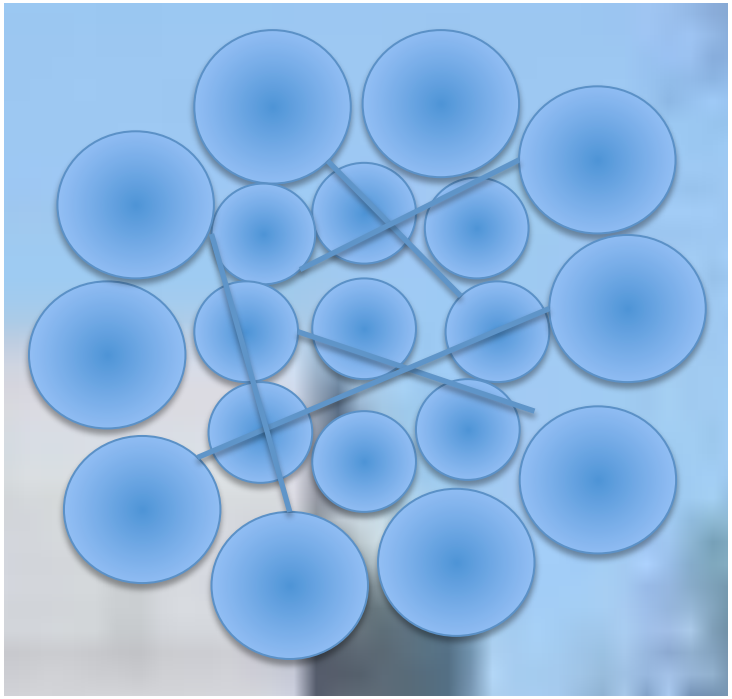
II. Tracklet Generation: BRIEF[1] / ORB[2] / **BRISK[3]**



II. Tracklet Generation: BRIEF[1] / ORB[2] / **BRISK[3]**



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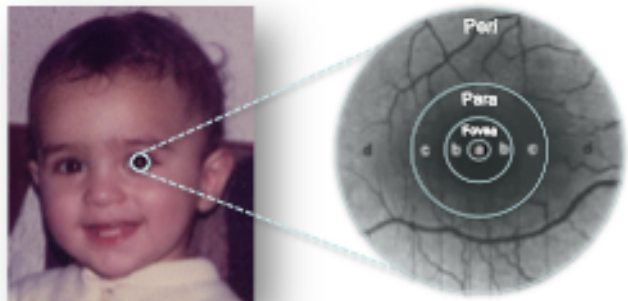
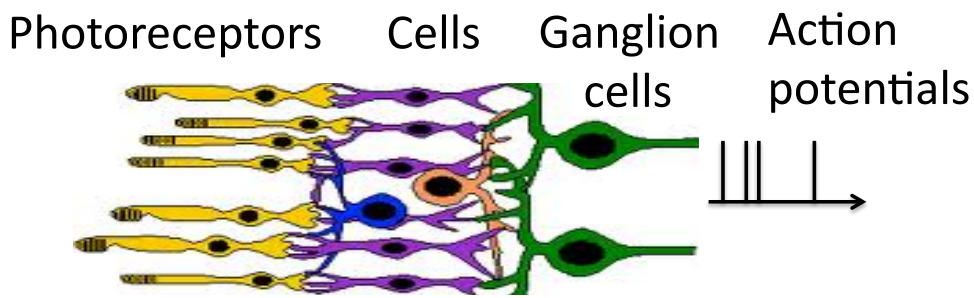
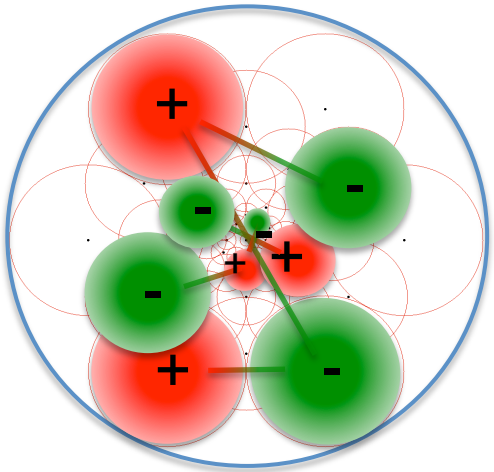
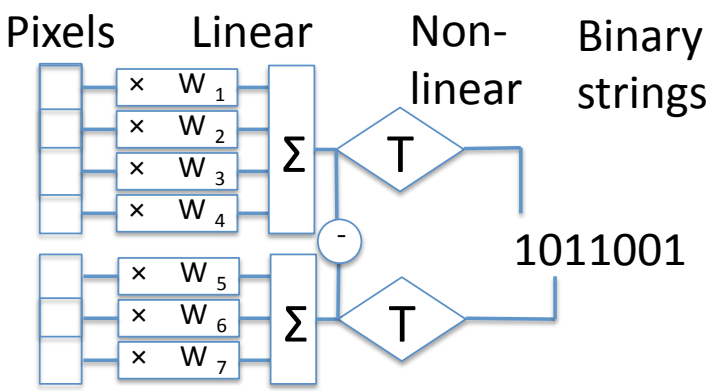
[2] Rublee, Ethan, et al. "ORB: an efficient alternative to SIFT or SURF. " ICCV 2011
[3] Leutenegger,. , et al. "BRISK: Binary robust invariant scalable keypoints." ICCV 2011

II. Tracklet Generation: Retina-inspired [1]





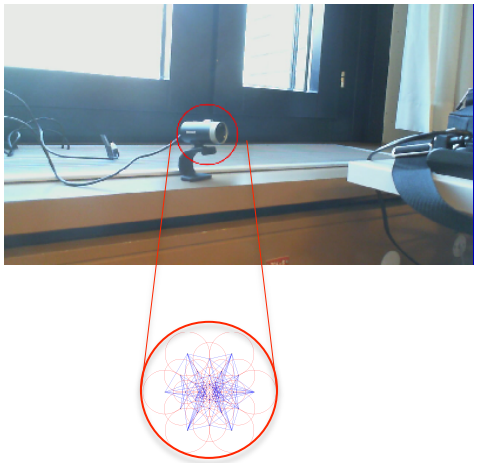




[1] Alahi, et al. "Freak: Fast retina keypoint." *CVPR 2012*

II. Tracklet Generation: Saccadic search

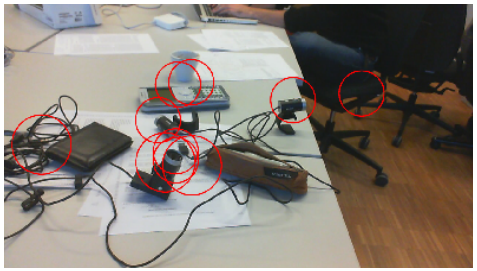
Object of interest

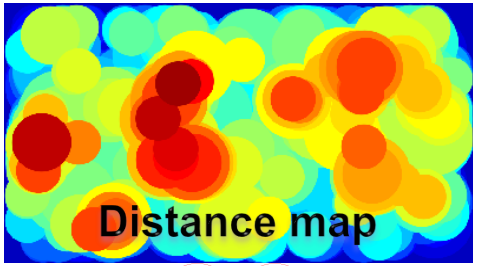


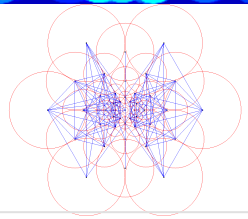
10101010...1010101

512 bits descriptor

Target image to search



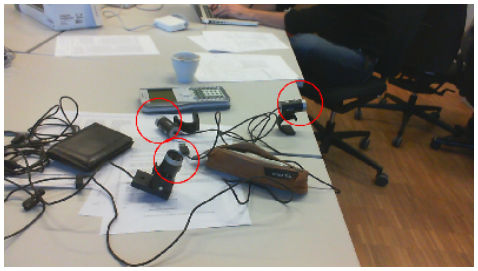


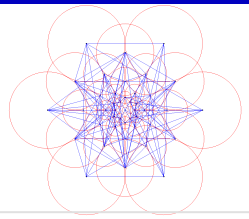


10101010

Filtering with first 128 bits

Matched objects





010101

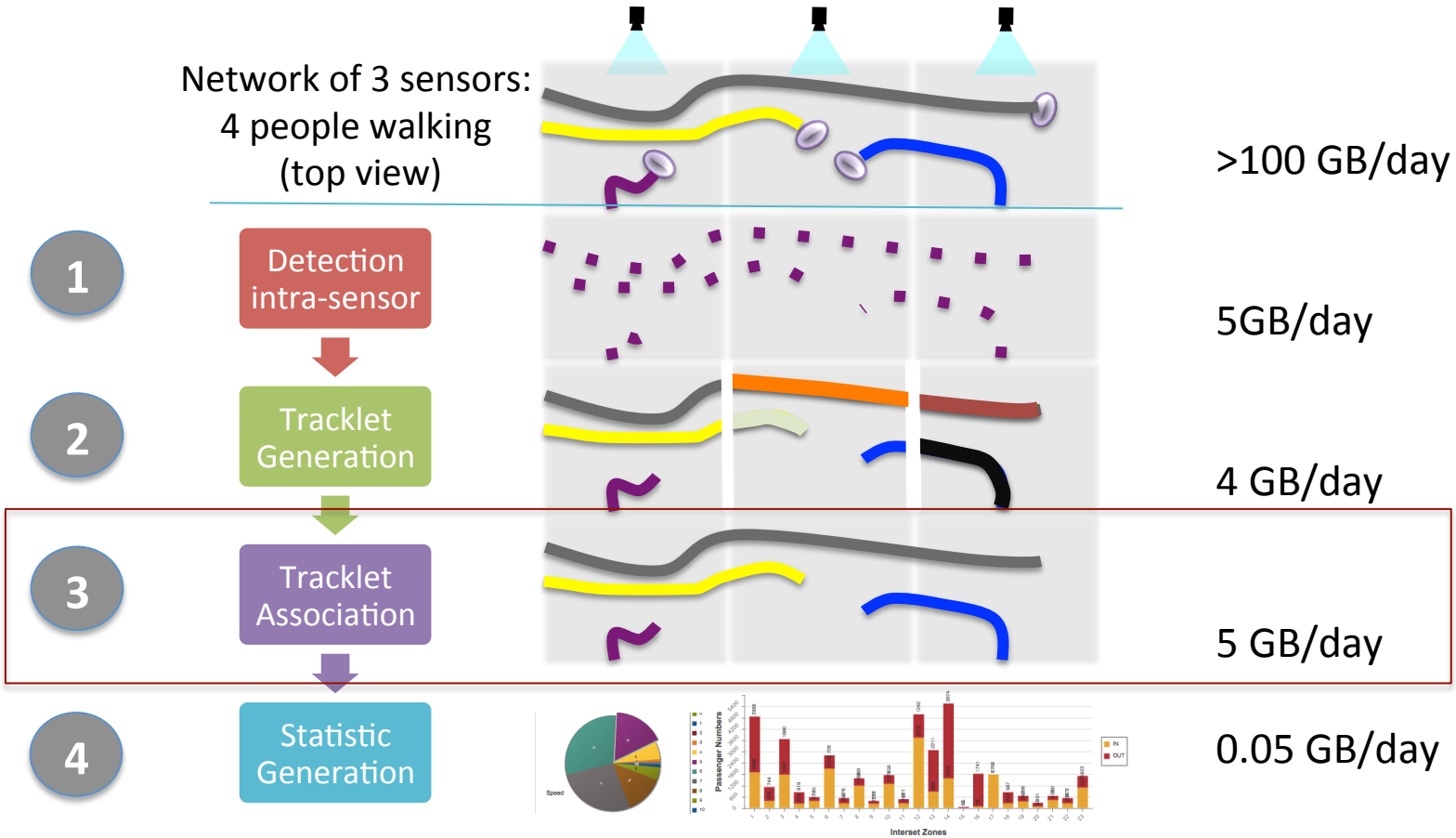
Matching with last 128 bits

[1] Alahi, et al. "Freak: Fast retina keypoint." *CVPR 2012*

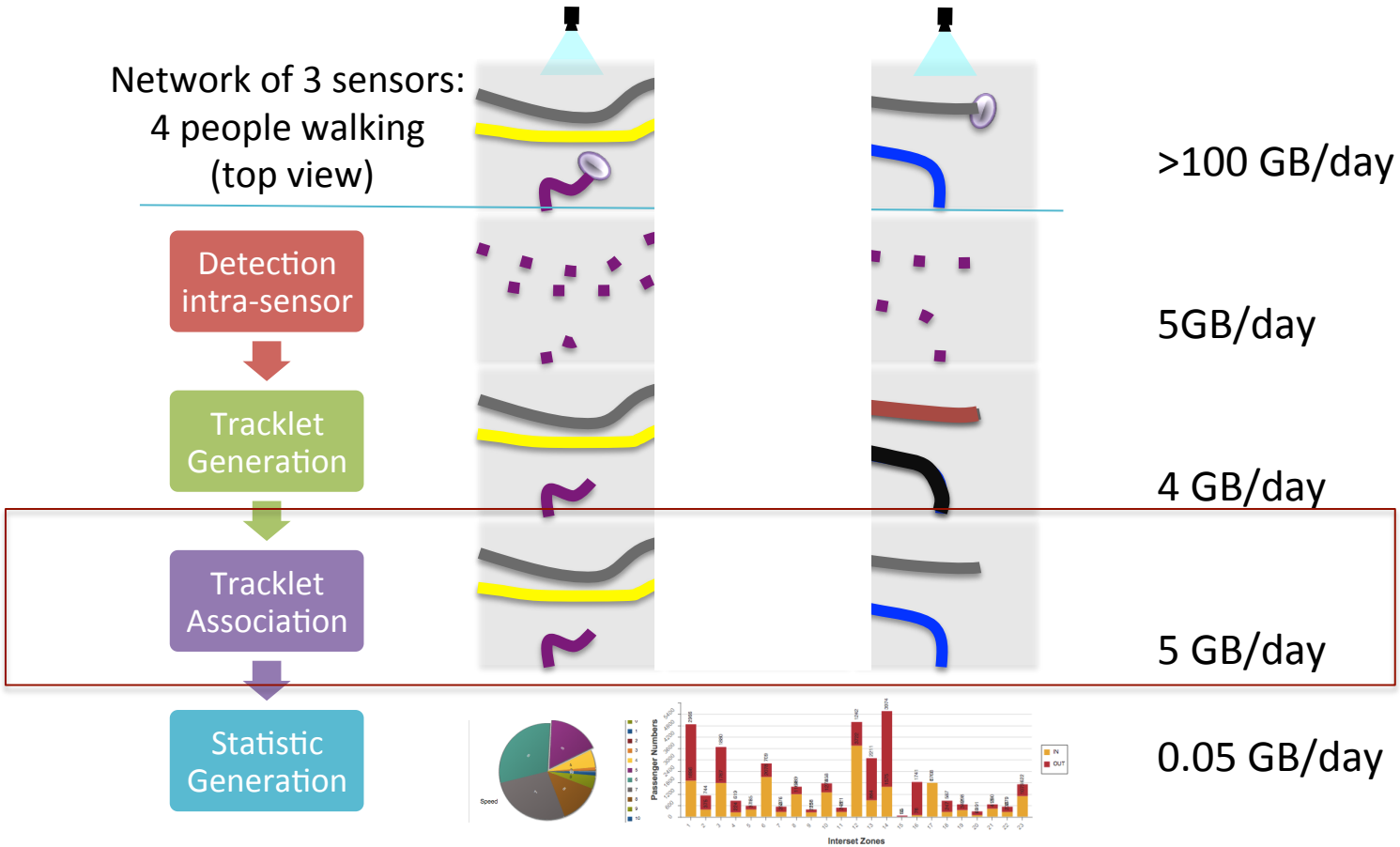
Tracking Example

Outline:

From Foreground Extraction **To** Tracking 42 million Pedestrians



Tracklet association in scattered network



III- Tracklet association: Problem formulation

Let:

- **T**: all long term trajectories
- **t**: tracklets (tracklets capture within each camera)
- Problem: Maximizing the a posterior probability (MAP) of **T** :

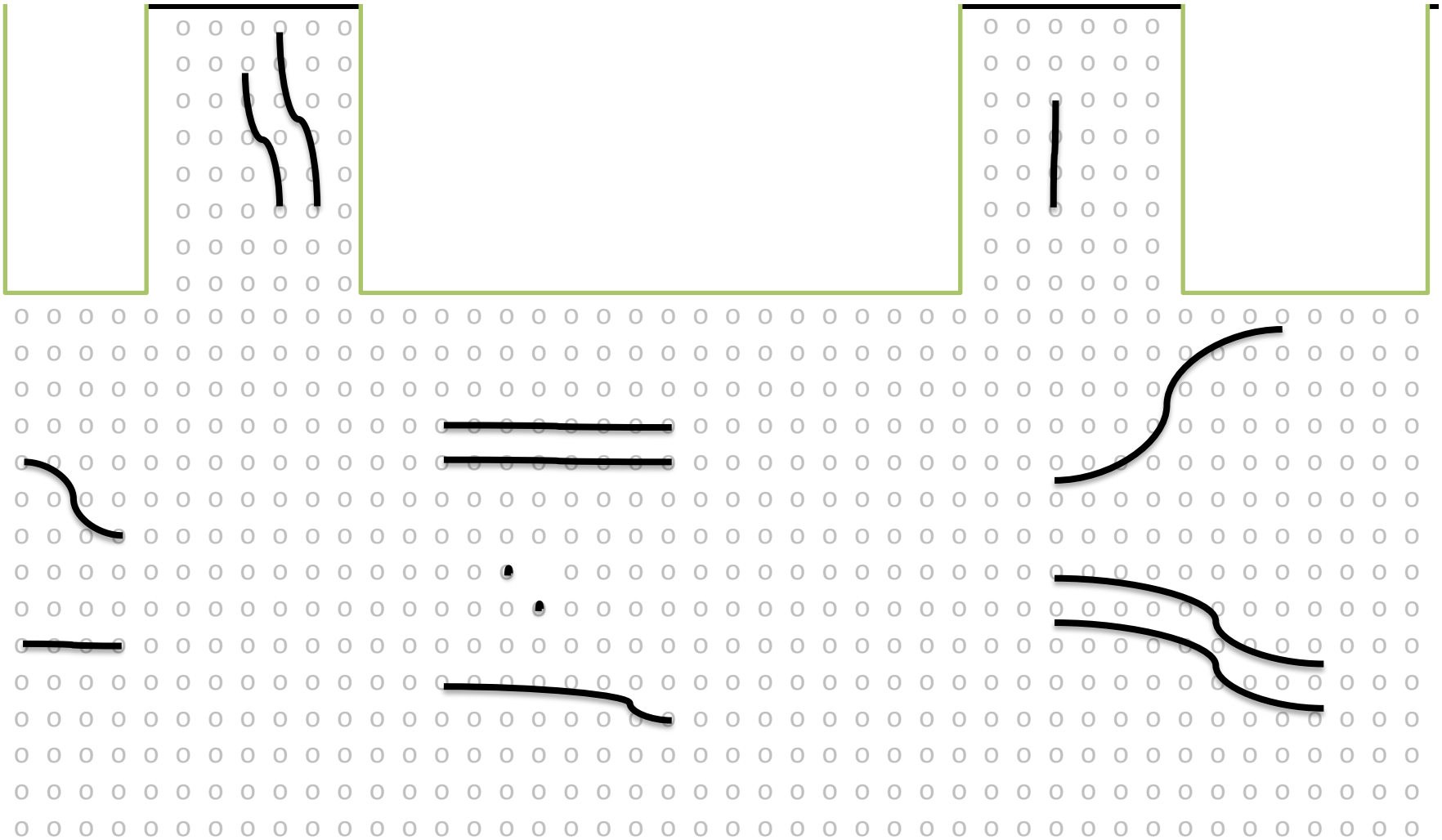
$$\mathbf{T}^* = \arg\max_{\mathbf{T}} P(\mathbf{T} \mid \mathbf{t}) \quad (1)$$

$$= \arg\max \Pi_i P(\mathbf{t}_i \mid \mathbf{T}) P(\mathbf{T}) \quad (2),$$

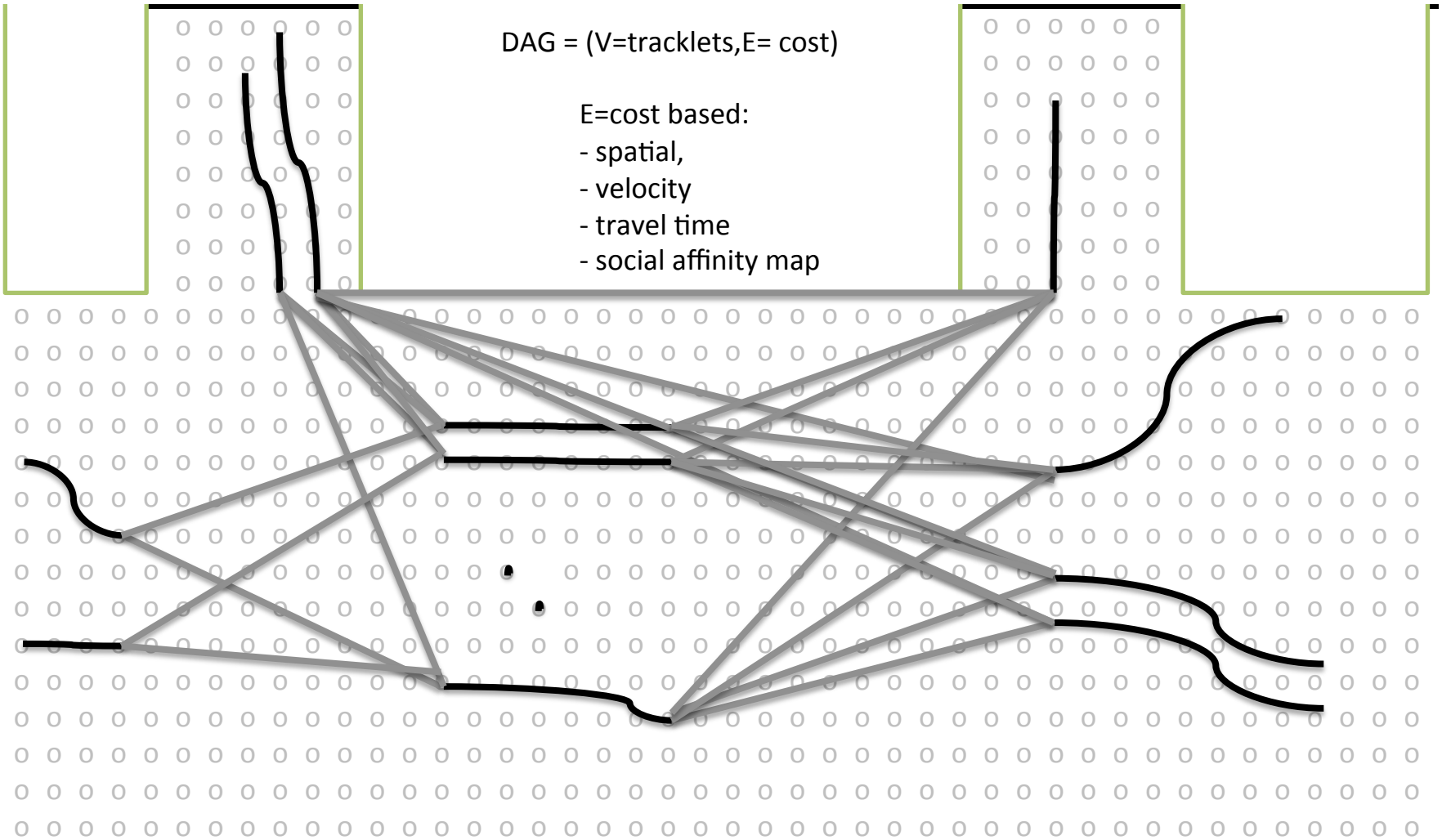
where $P(\mathbf{T}) = \Pi_k P(\mathbf{T}_k)$ (since trajectories do not overlap)

$P(\mathbf{T}_k) = P(\mathbf{t}^s_k) \ldots P(\mathbf{t}^t_k \mid \mathbf{t}^{t-1}_k)\, P(\mathbf{t}^e_k)$ (markov chain)

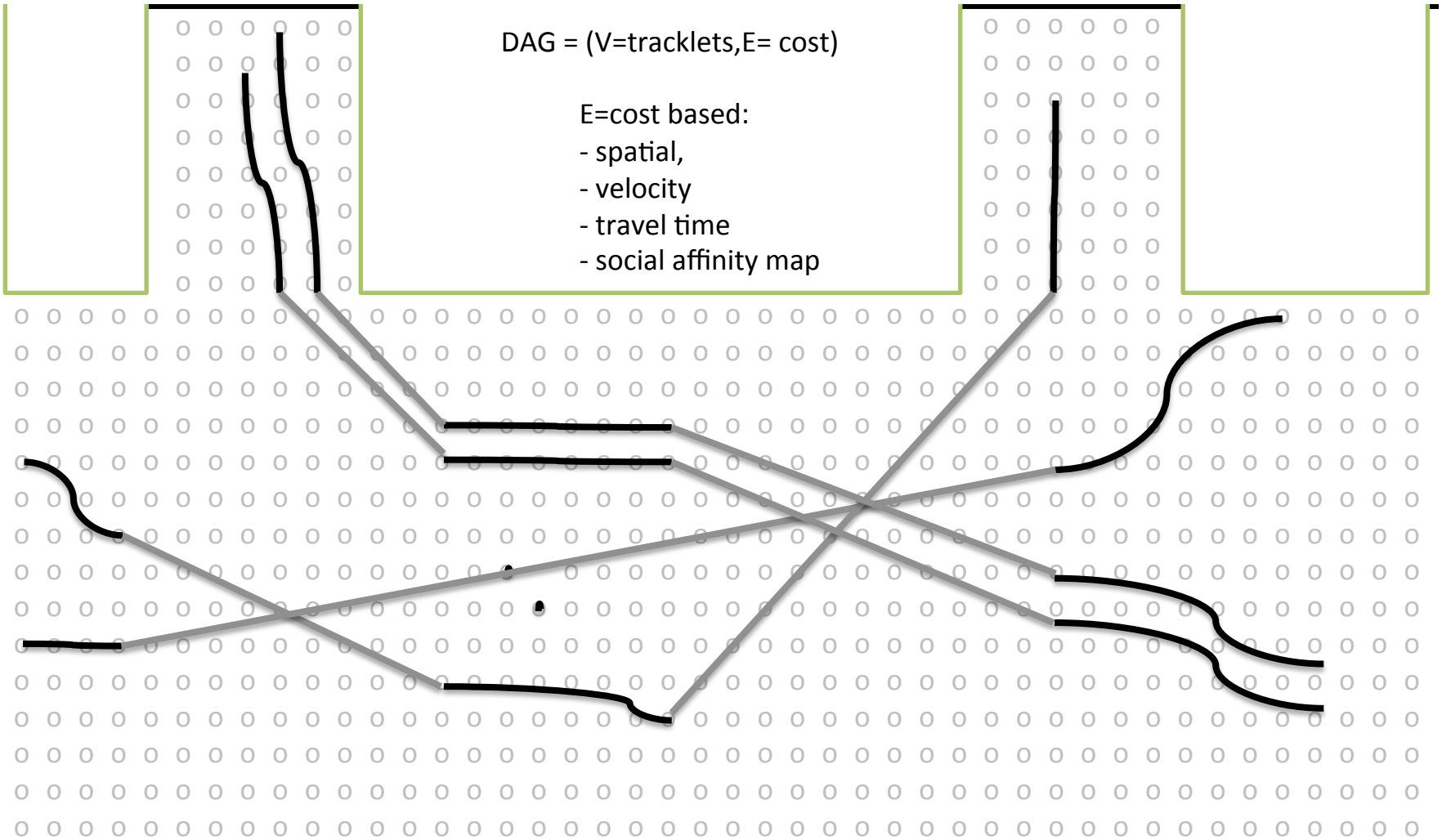
III. Tracklet association (Top view)



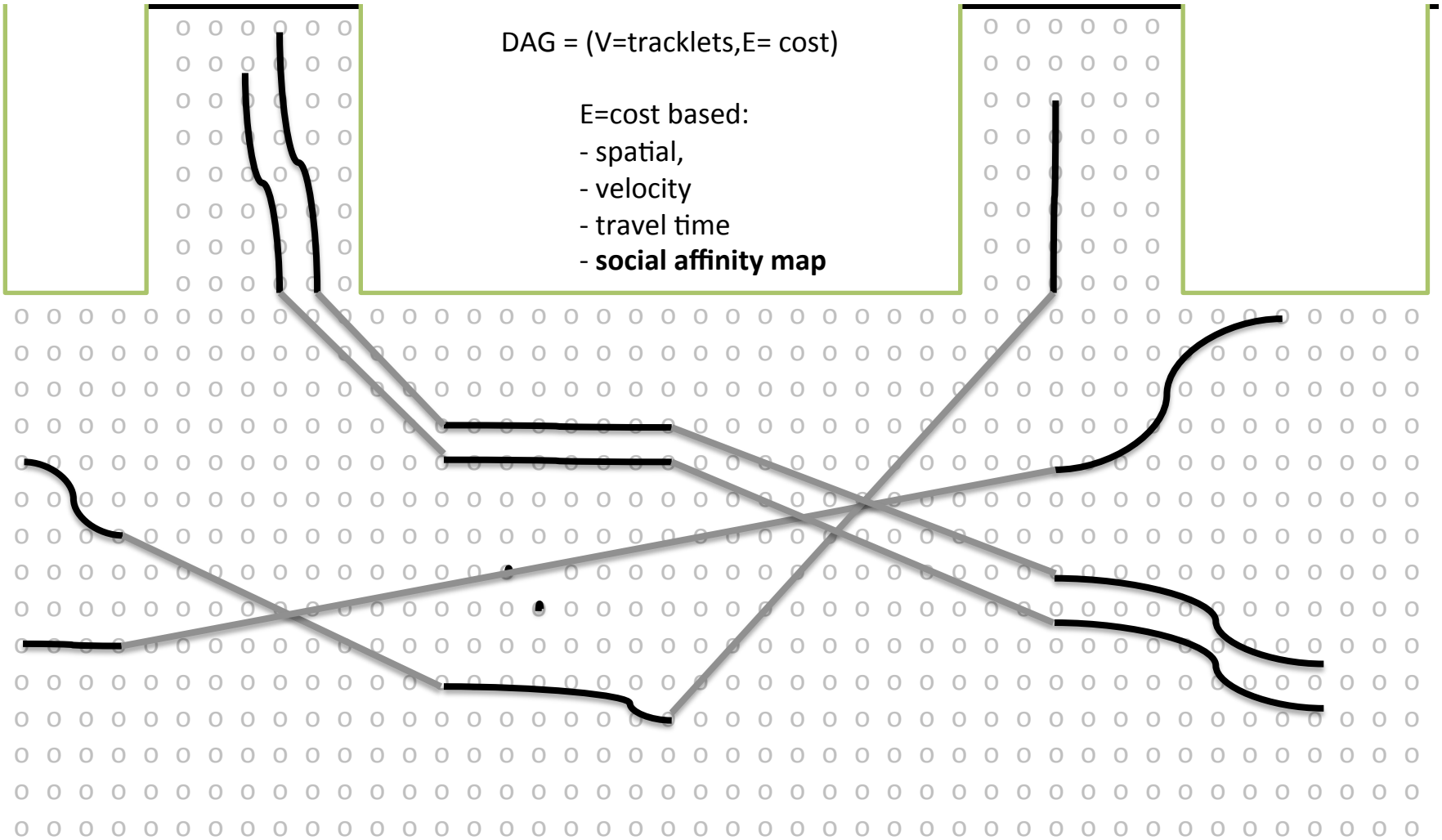
III. Tracklet association (Top view)



III. Tracklet association (Top view)



III. Tracklet association (Top view)

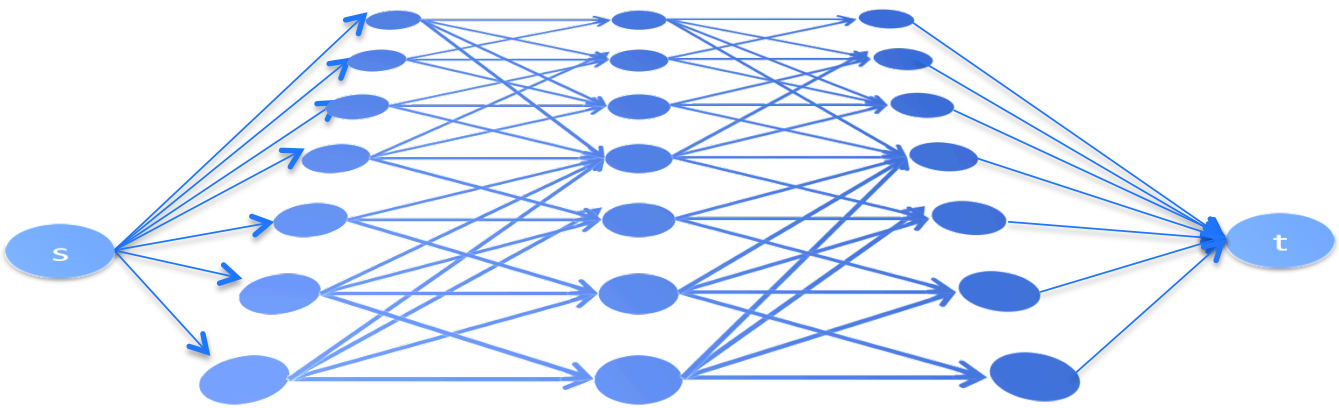


Network flow optimization

Objective: minimum cost maximum flow

$$\arg\min_{f} c(f)$$

$$c(f) = \sum \alpha_i f_i + \sum \beta_{ij} f_{ij}$$



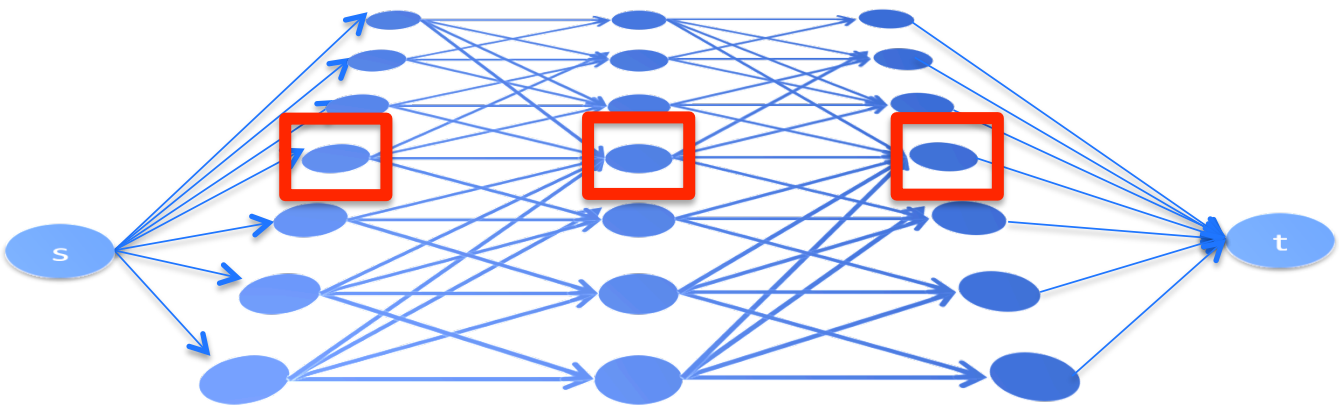
Where α_i, β_{ij}, γ_{OD} are the costs, and f_i the flows

Network flow optimization

Objective: minimum cost maximum flow

$$\arg\min_{f} c(f)$$

$$c(f) = \boxed{\sum \alpha_i f_i} - \sum \beta_{ij} f_{ij}$$



Cost α_i based:

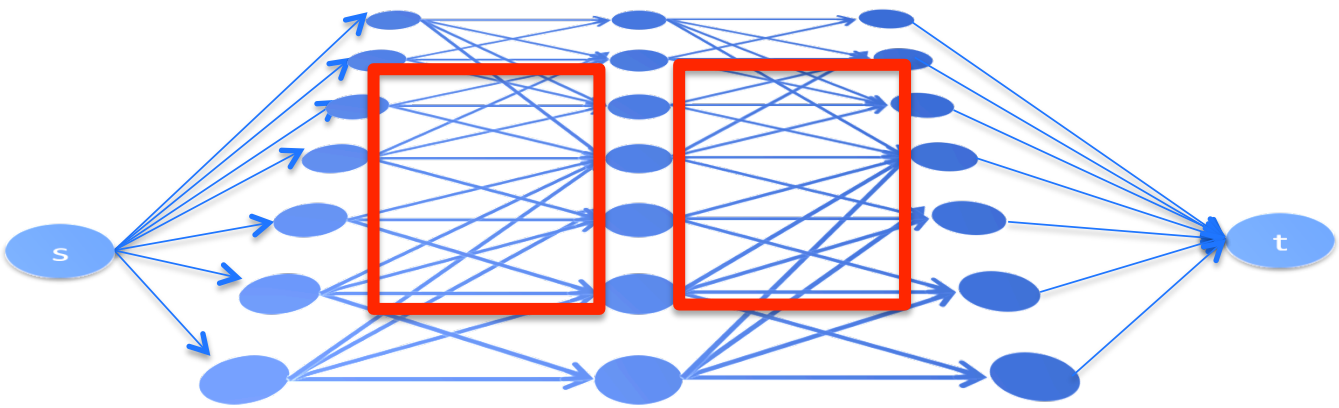
- Detection likelihood

Network flow optimization

Objective: minimum cost maximum flow

$$\arg\min_{f} c(f)$$

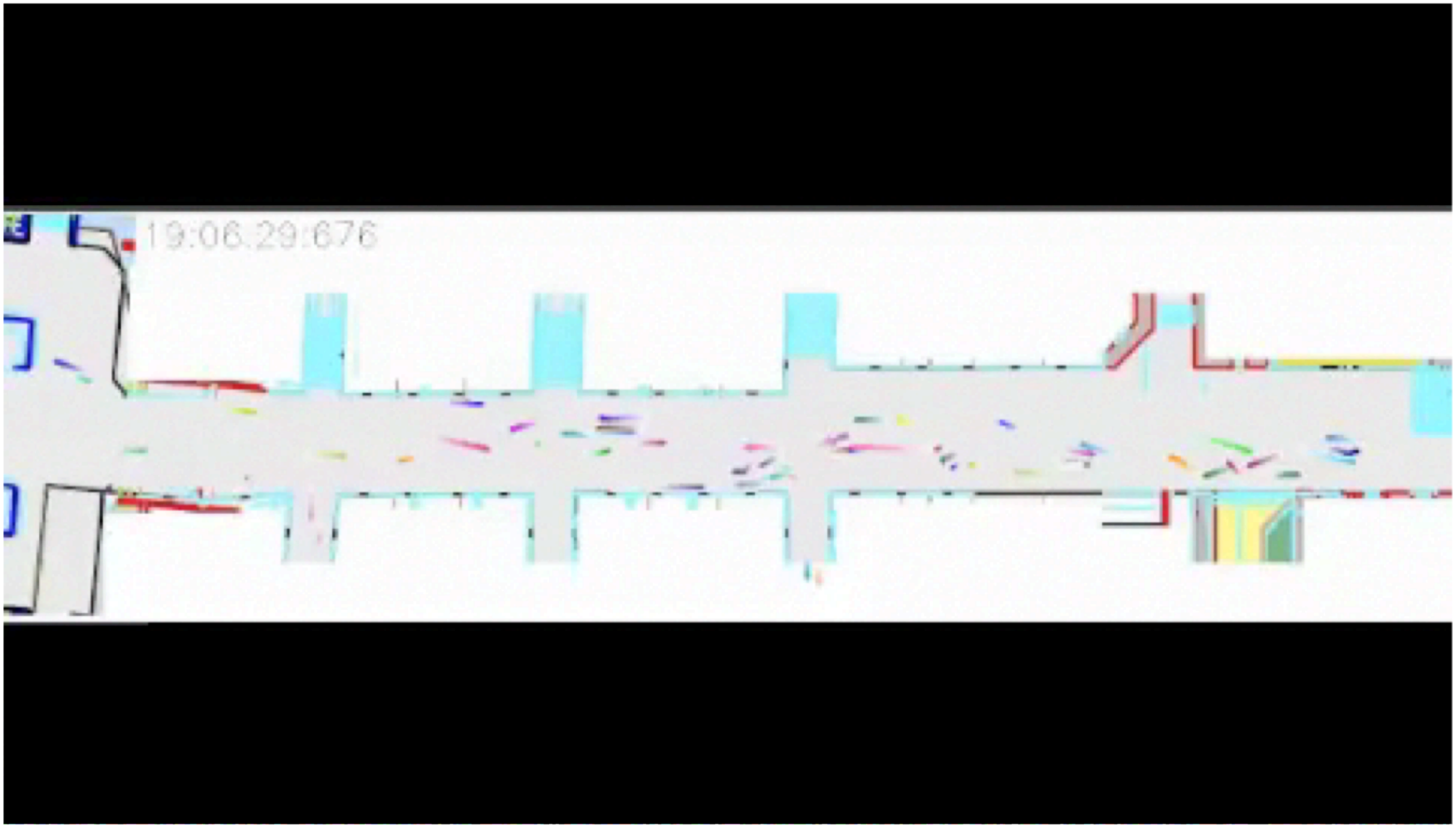
$$c(f) = \sum \alpha_i f_i - \boxed{\sum \beta_{ij} f_{ij}}$$



Cost β_{ij} based:

- spatial
- velocity
- **S**ocial **A**ffinity **M**ap

Tracklet association
With Social Affinity Map



Conclusion

A new dimension to "Google Analytics":
Analyzing people outside of website