



Perceiving and Predicting Human behaviours in the built environments

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- Assistant Professor at EPFL since 2017
- Director of the VITA lab
- 5 years at Stanford University
- Founded and advise startups (in retails)

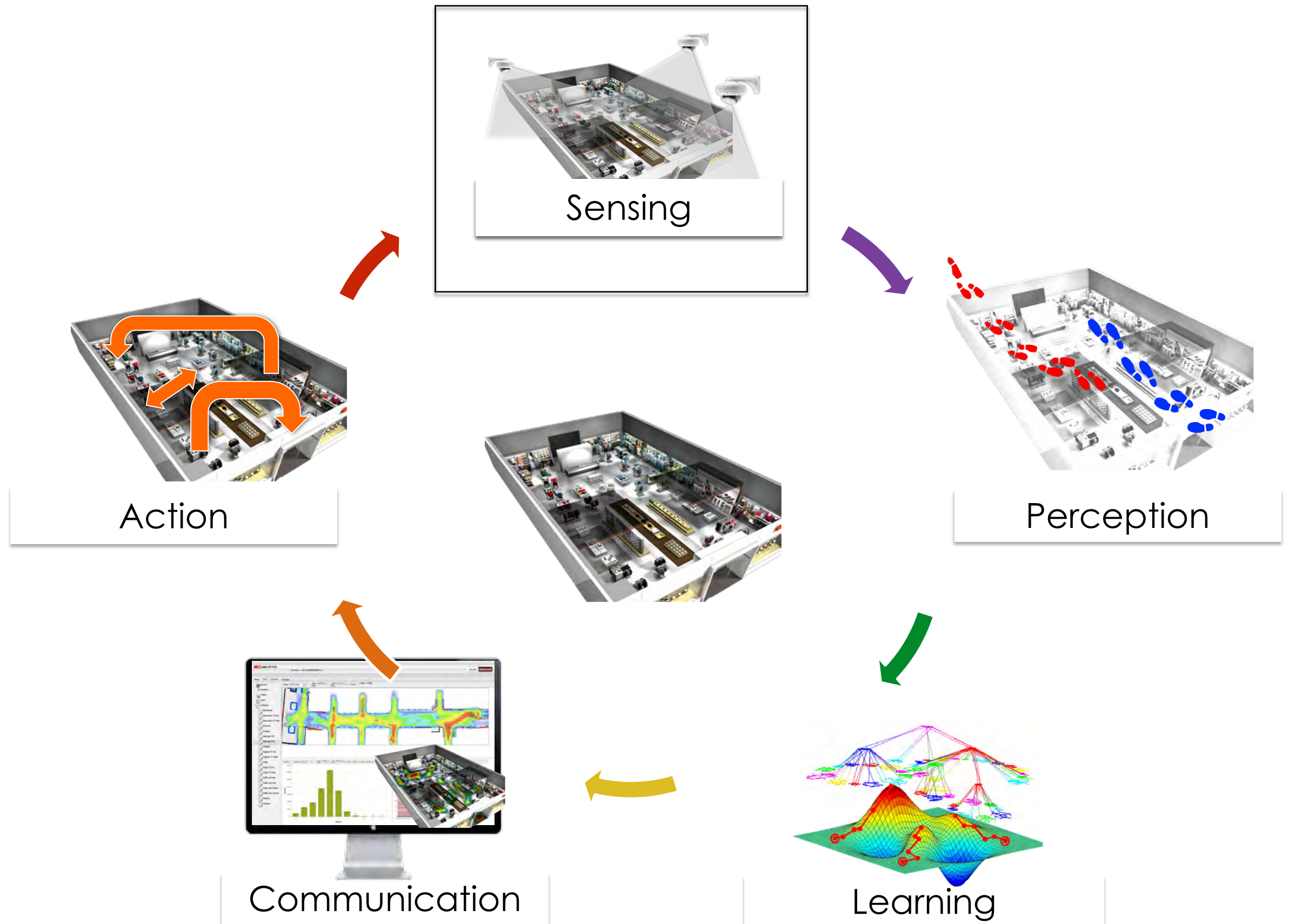
“Man is by nature a social animal” - Aristotle

How can machines learn human-human interactions?

How can machines learn human-space interactions?



AI for the built environments



2 Terminals

132 sensors

>20,000 m²

24/7 over a year

>42 million humans

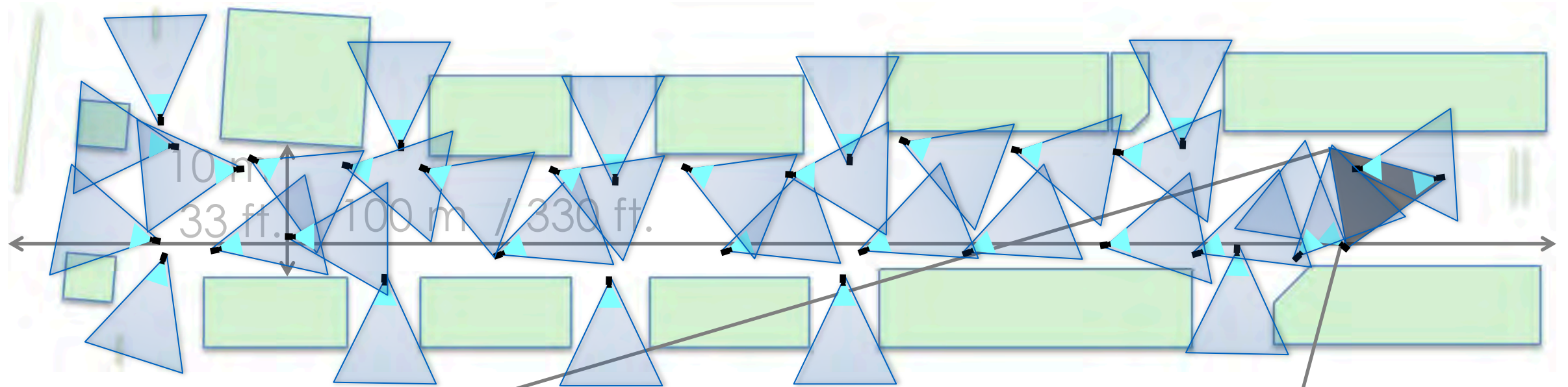
CORSICA

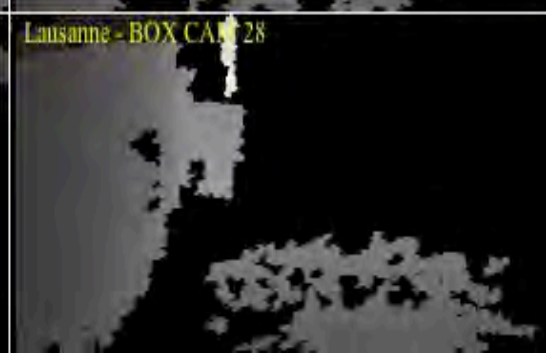


(Lausanne, Basel)

A corridor with 32 sensors

Top View





Basel - IP CAM 01



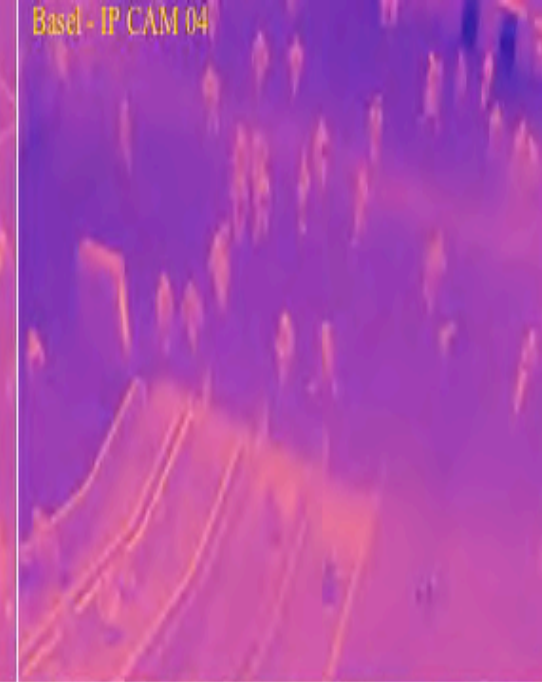
Basel - IP CAM 02



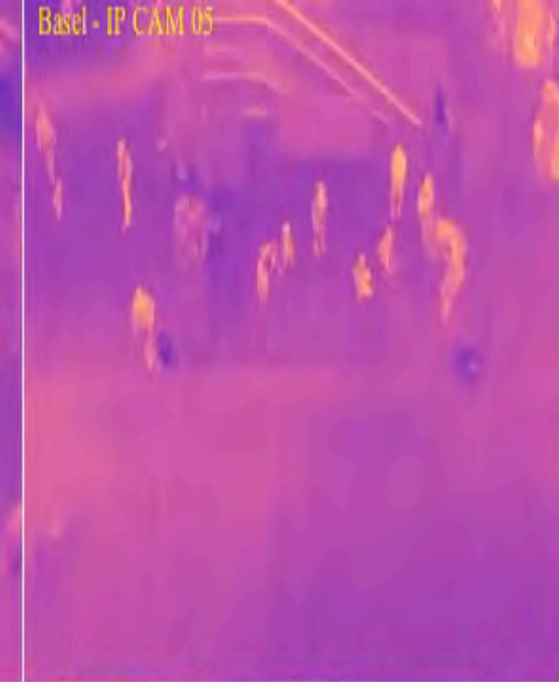
Basel - IP CAM 03



Basel - IP CAM 04



Basel - IP CAM 05



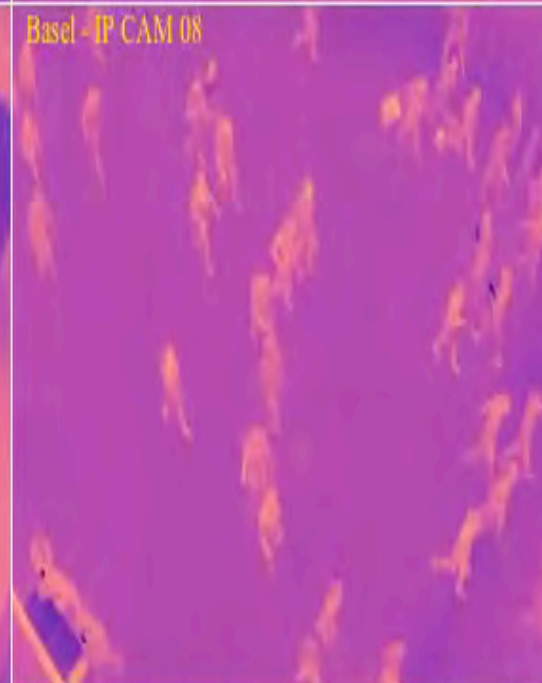
Basel - IP CAM 06



Basel - IP CAM 07



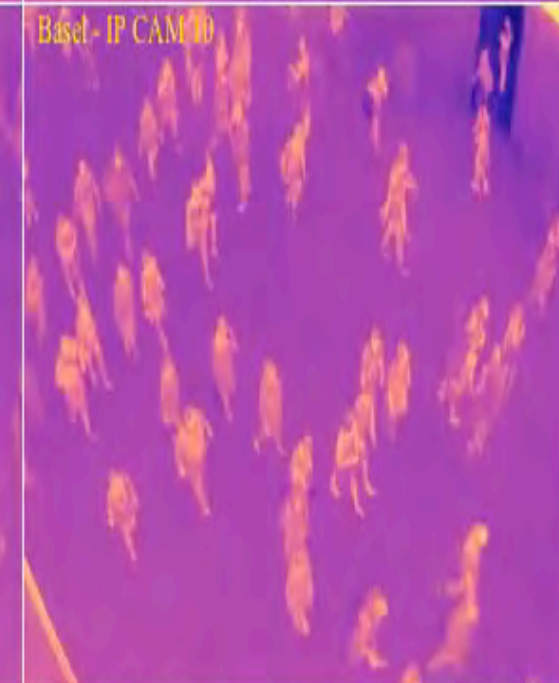
Basel - IP CAM 08



Basel - IP CAM 09



Basel - IP CAM 10



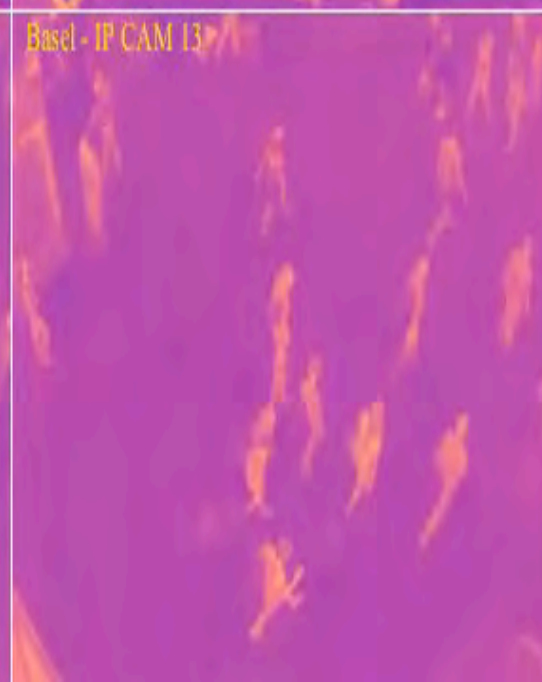
Basel - IP CAM 11



Basel - IP CAM 12



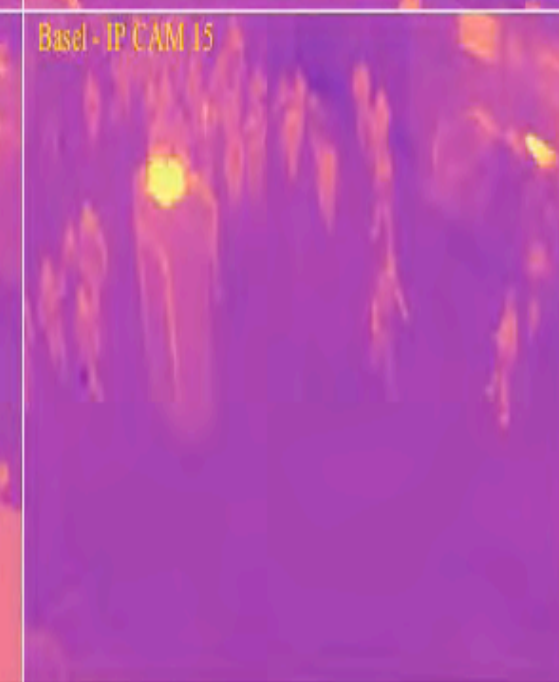
Basel - IP CAM 13



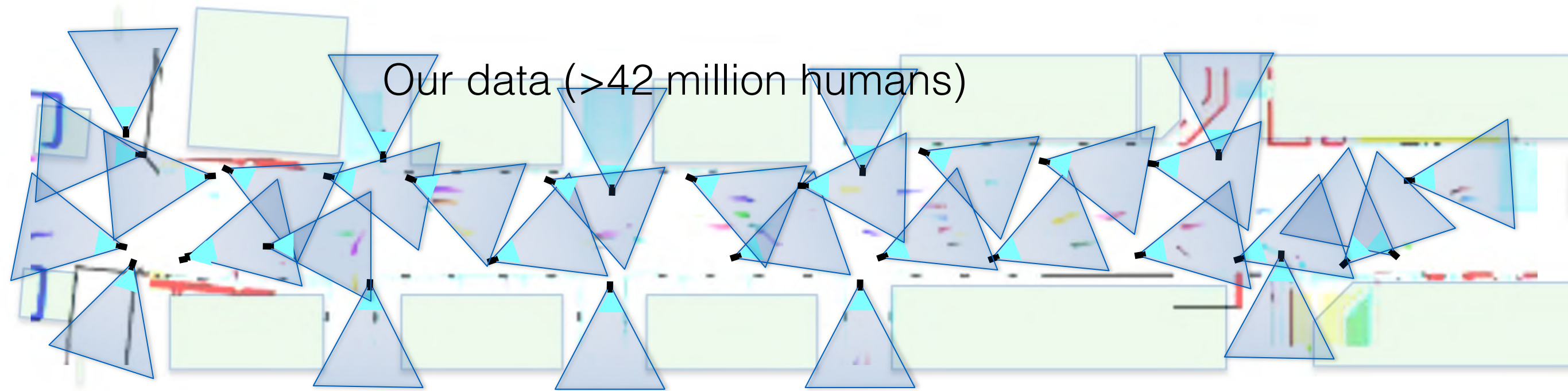
Basel - IP CAM 14



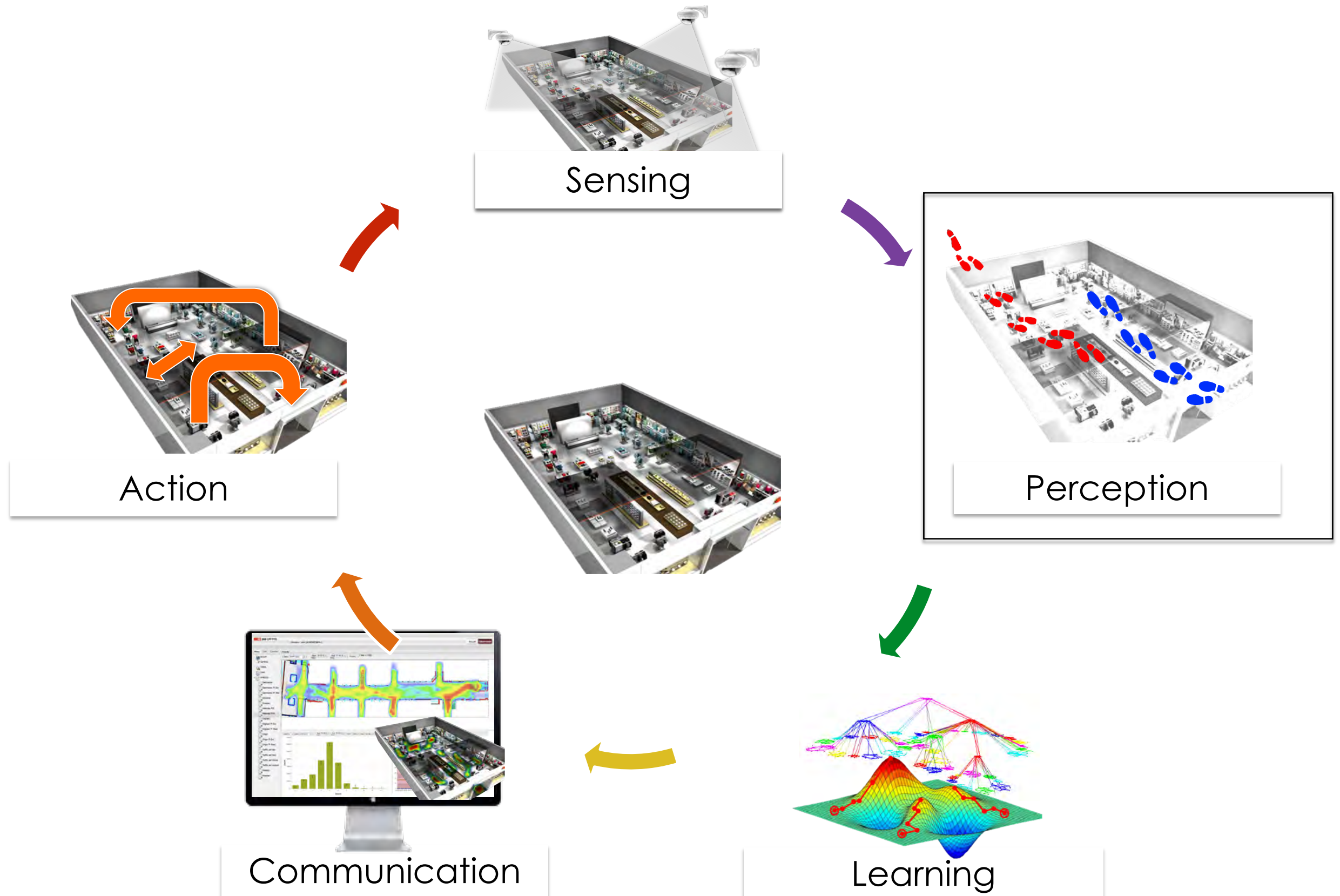
Basel - IP CAM 15



Collecting long-term trajectories

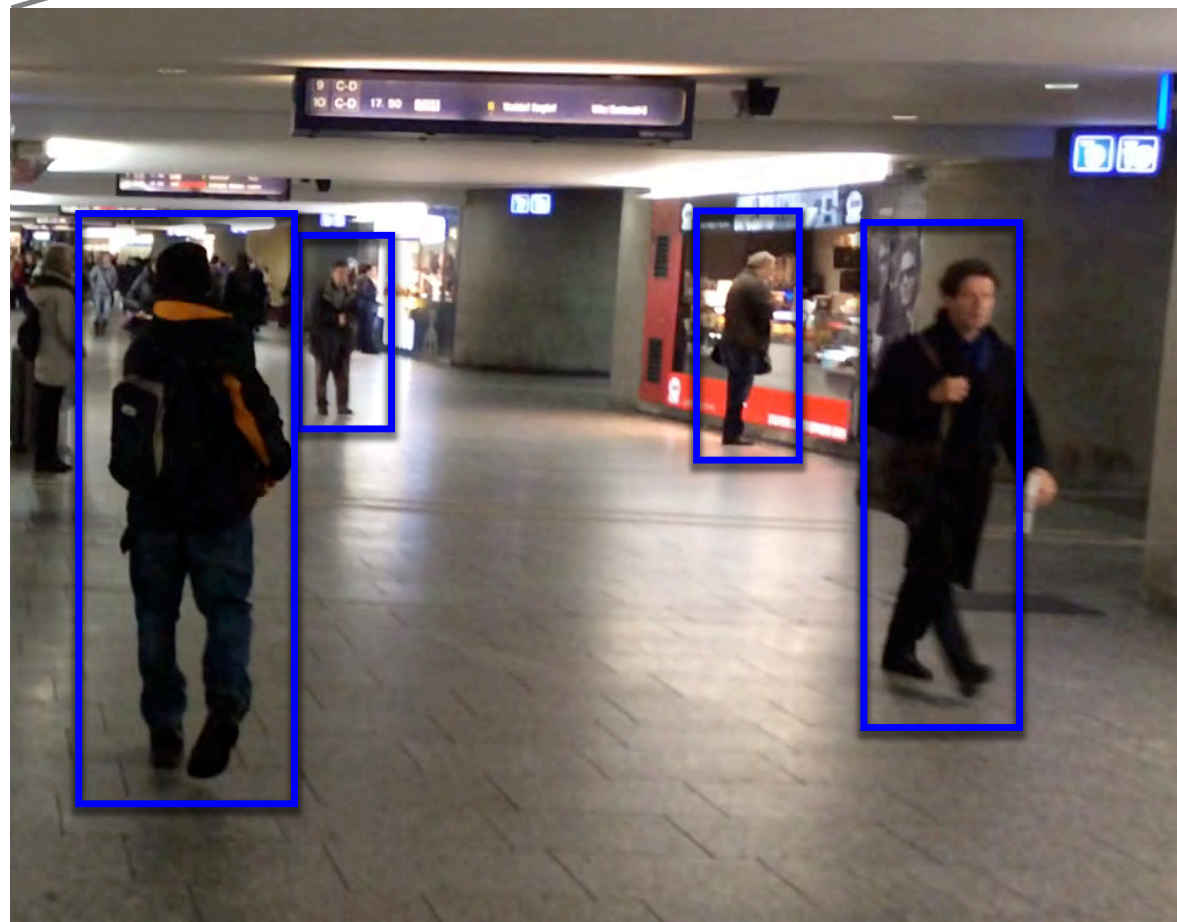
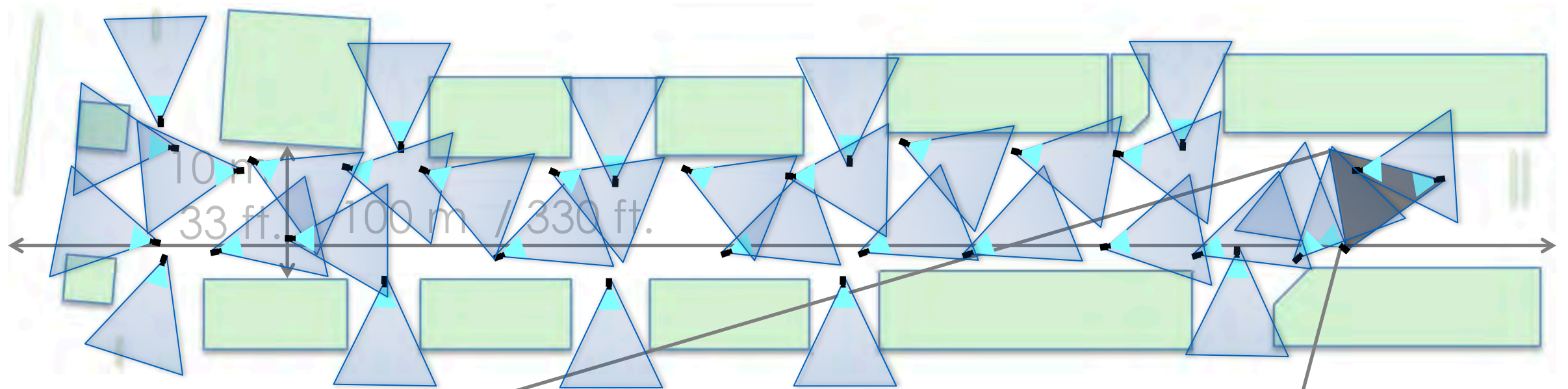


AI for the built environments



A corridor with 32 sensors

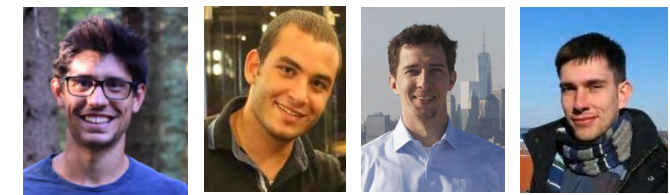
Top View



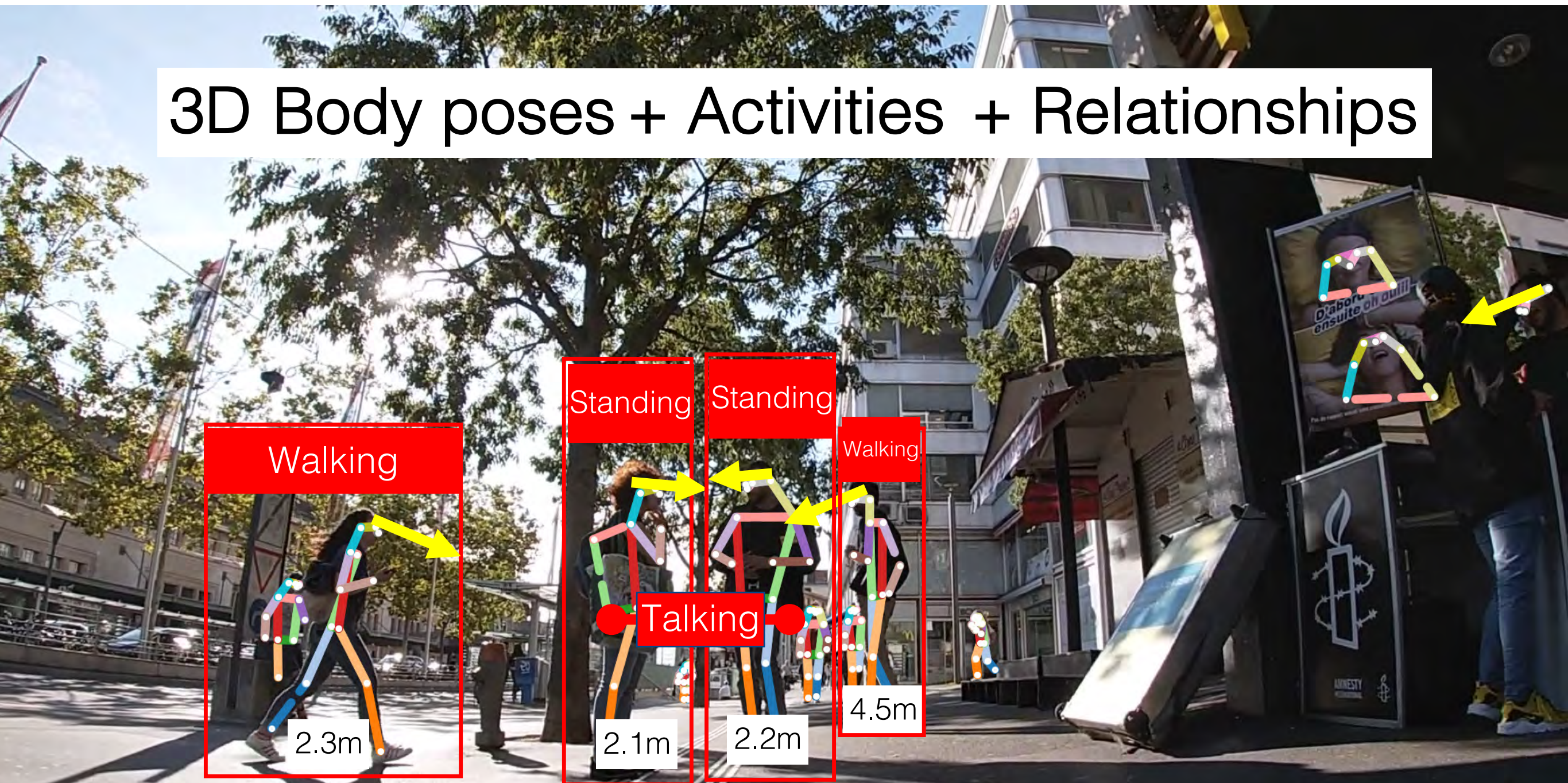
Perceiving



Perceiving Socially-aware cues



3D Body poses + Activities + Relationships



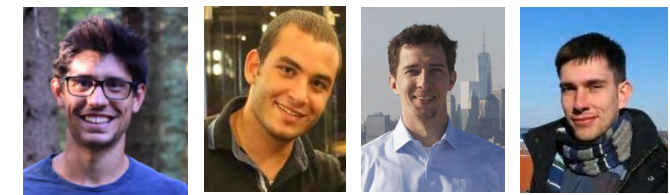
Our work

[1] PifPaf: Composite Fields for Human Pose Estimation, CVPR'19 (Live Demo: <https://vitademo.epfl.ch>)

[2] Convolutional Relational Machine for Group Activity Recognition, CVPR'19

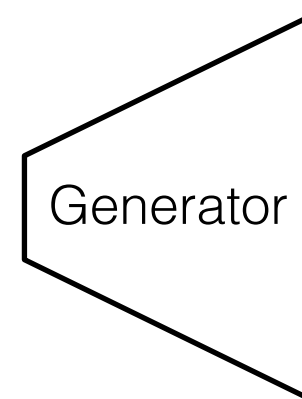
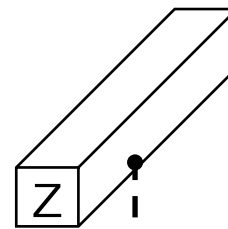
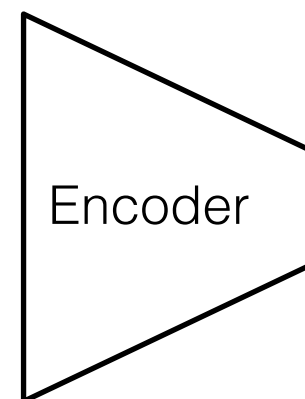
[3] Monoloco: Monocular 3D pedestrian localization and uncertainty estimation, ICCV'19

Computer vision for the built environments

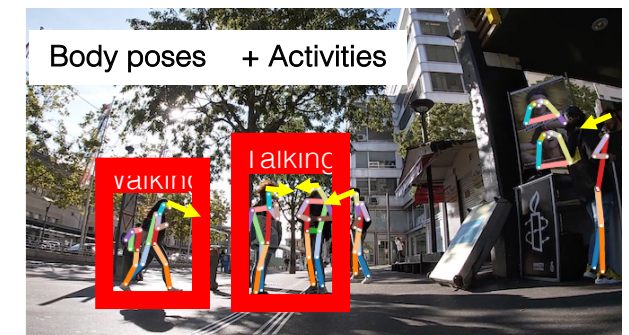


3 Challenges :

- 1- Limited resolution with partial information
- 2- Efficiency (Real-time)
- 3- Many tasks with unbalanced labels



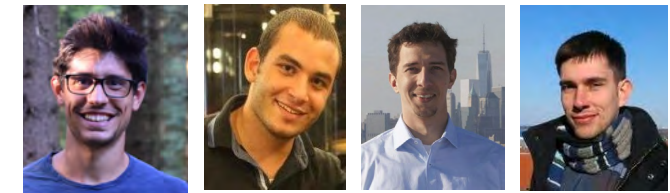
Perceive current state



Shared representation for

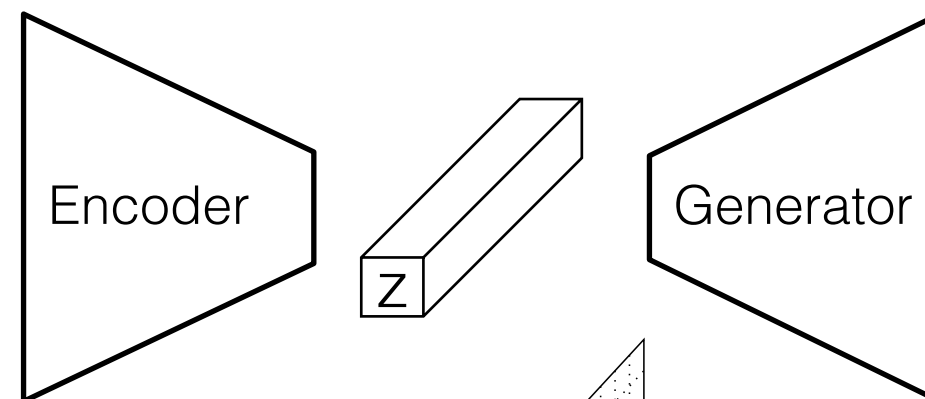
Perception

Computer vision for the built environments

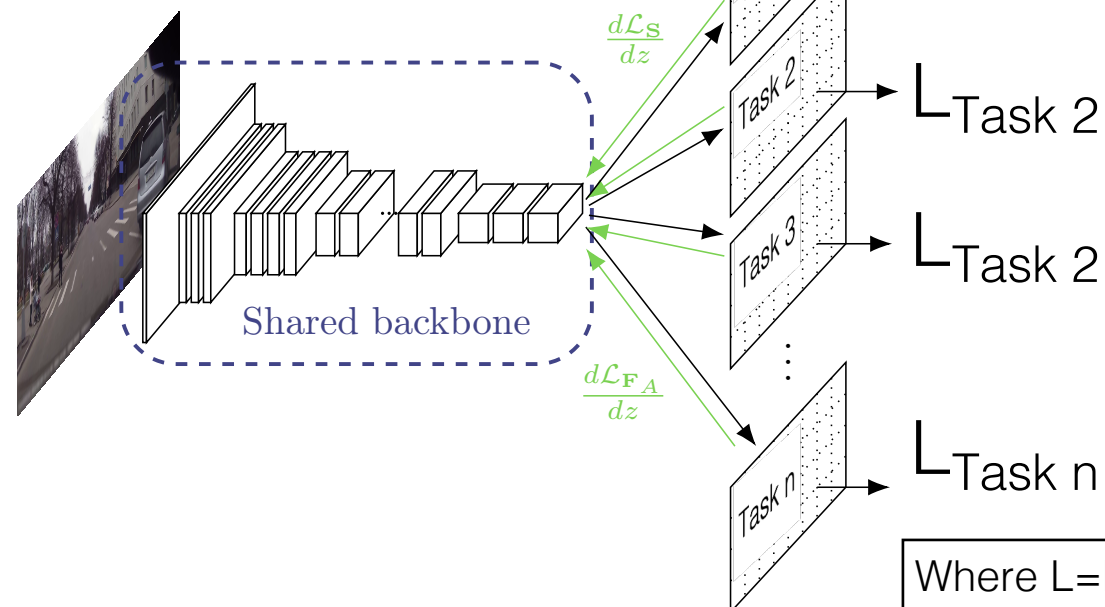
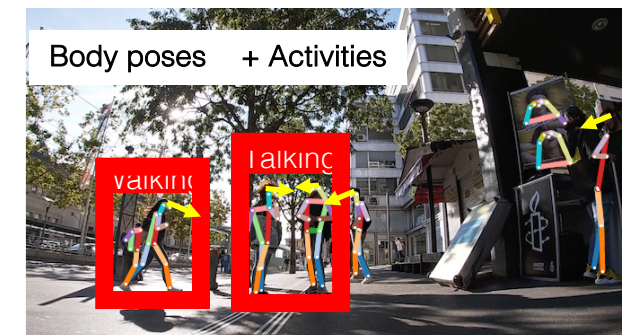


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Perceive current state

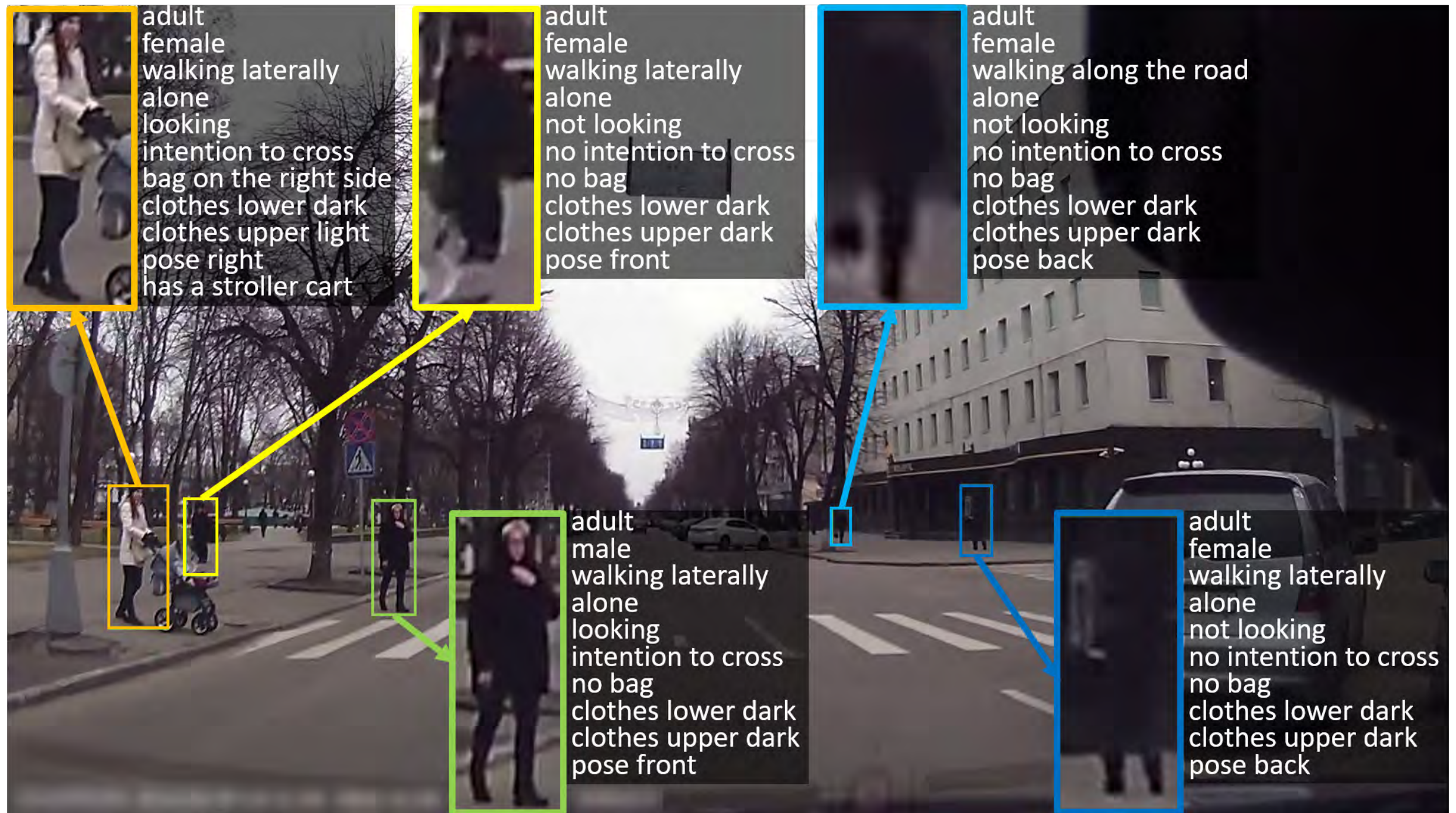


Composite fields formalism

A Feature map can jointly encode scalars and vectors

Where L=loss

Jointly Perceiving 32 Attributes on Pedestrian's Appearance, Behaviour, Intention



Perceiving Intentions

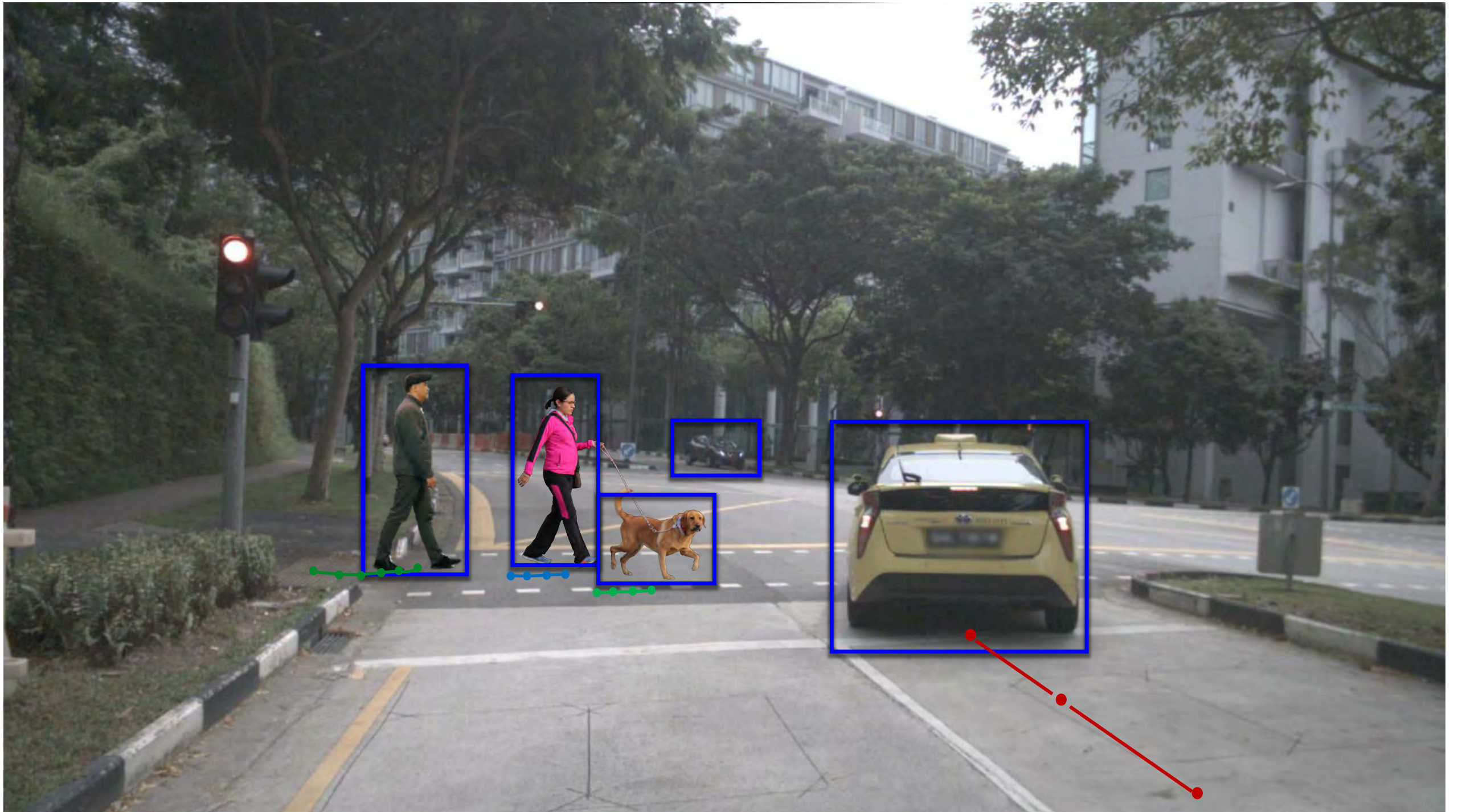


Intention to cross (in blue), or not (in green)



Object Detection & Tracking

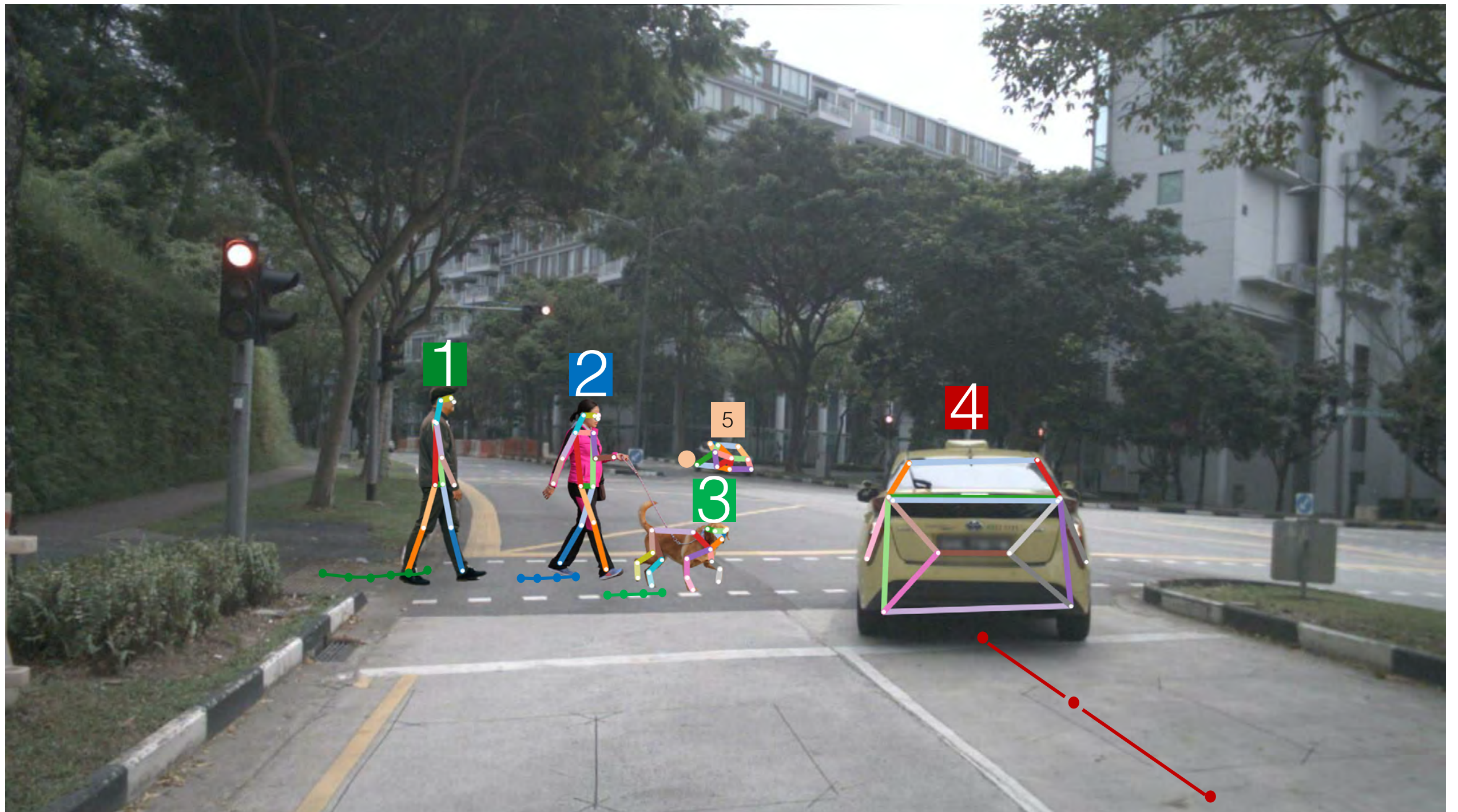
2 steps



Previous works
[1] Yolo v1...Yolo v5

Semantic keypoints

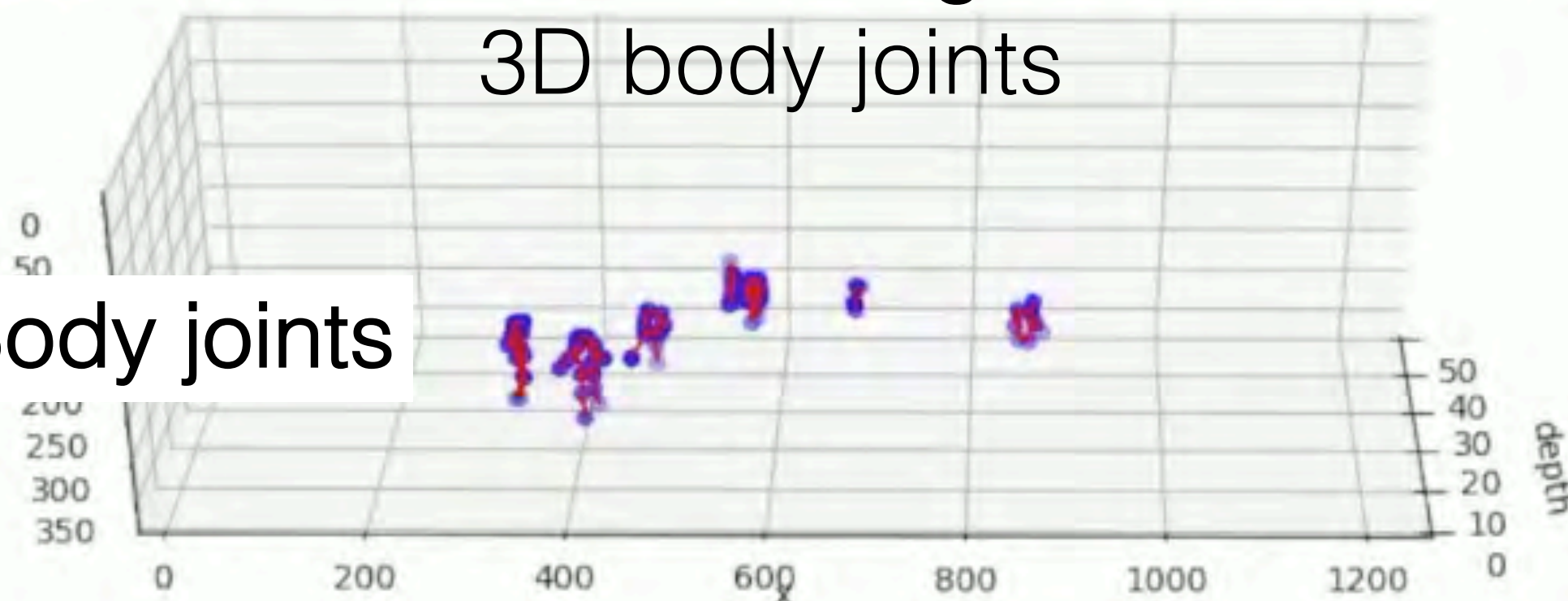
Joint Detection & Tracking



Perceiving 3D body joints



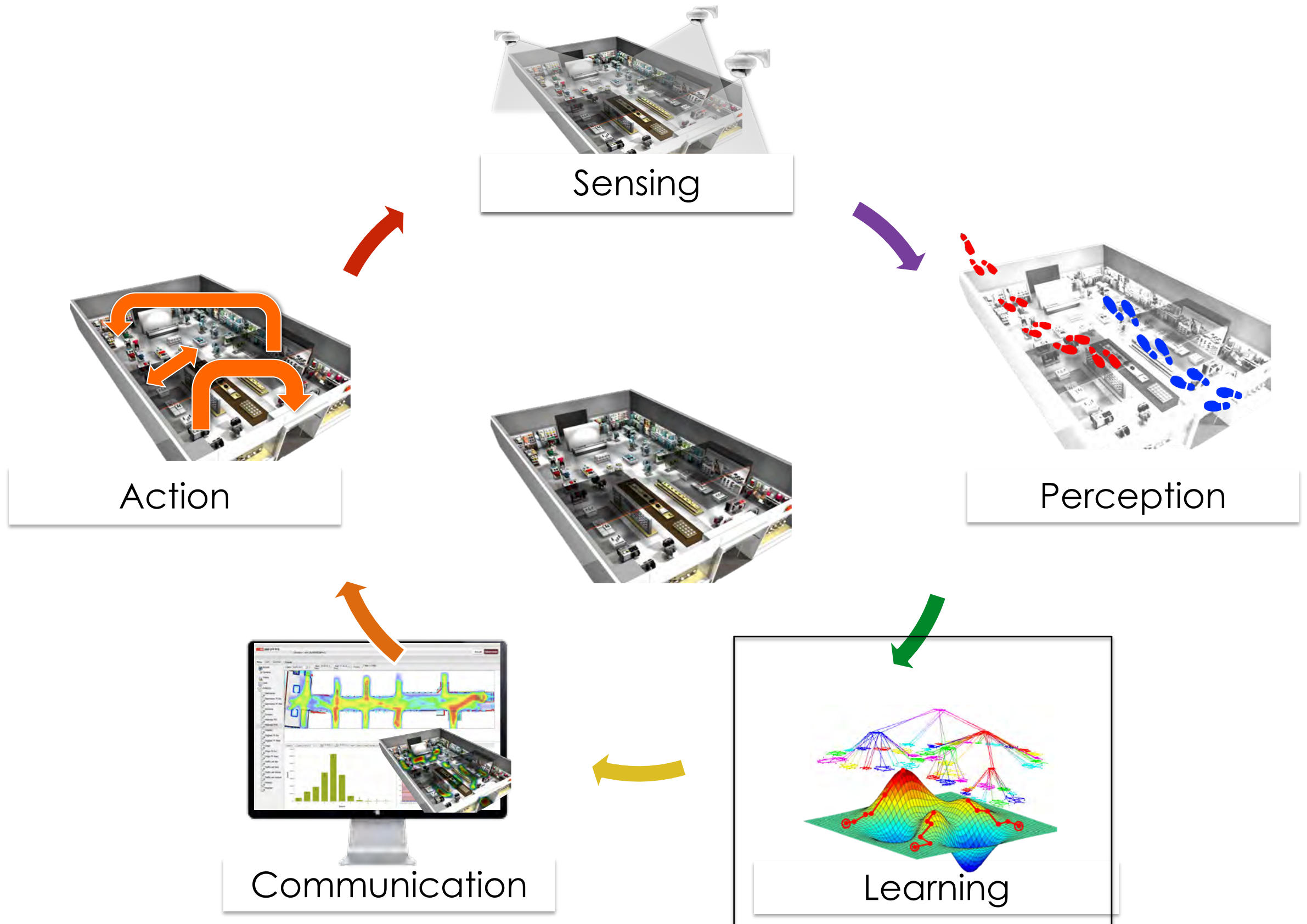
3D Body joints



[1] L. Bertoni *et al.*, MonoLoco, ICCV'19

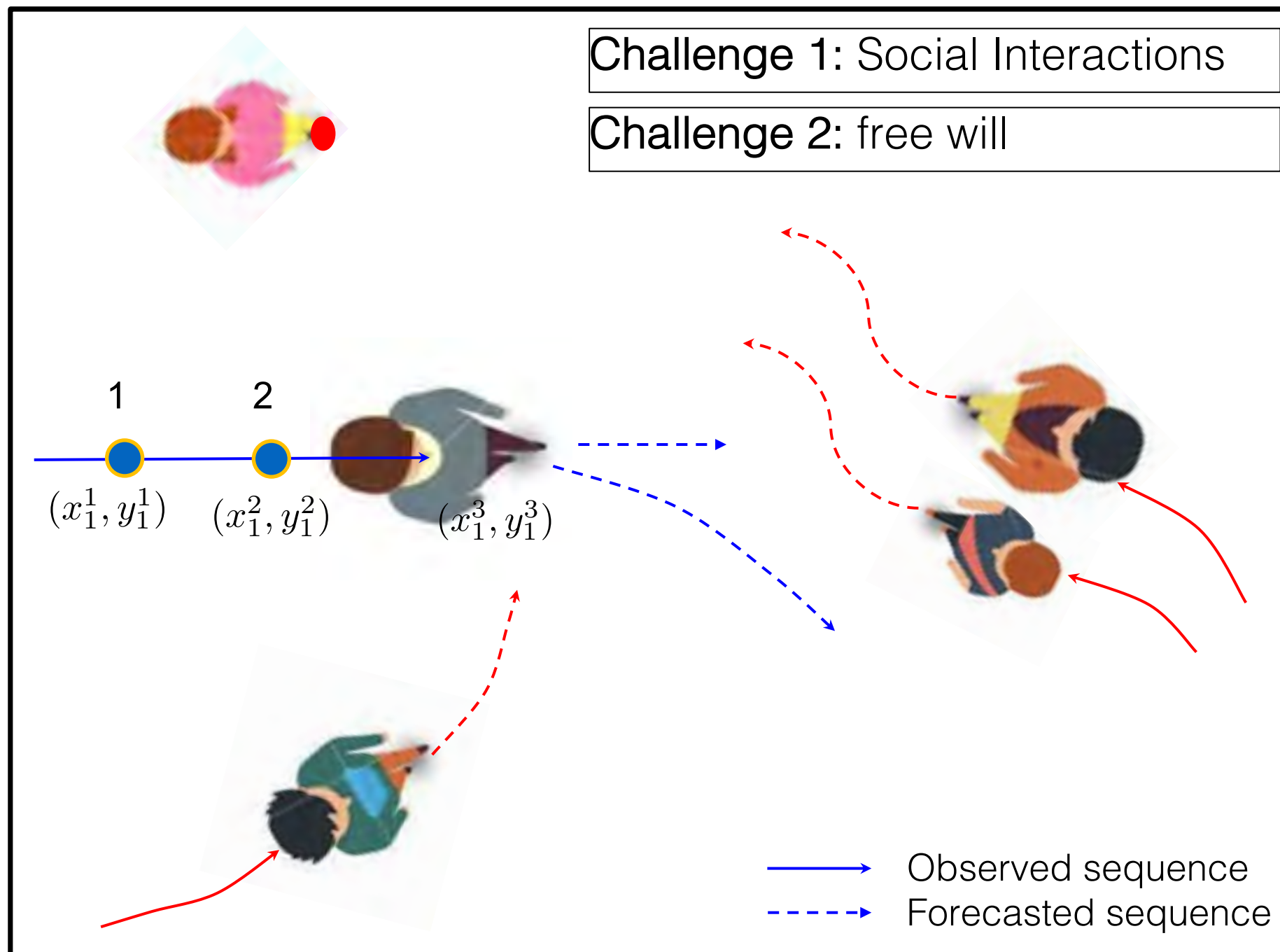
[2] W. Deng et al., Joint Human Pose Estimation and Stereo Localization, ICRA'20

AI for the built environments



Social Forecasting

Input: Given a sequence of states, *e.g.*, (x^t, y^t) coordinates in time
Output: **Predict** the future states, *e.g.*, next 5 seconds

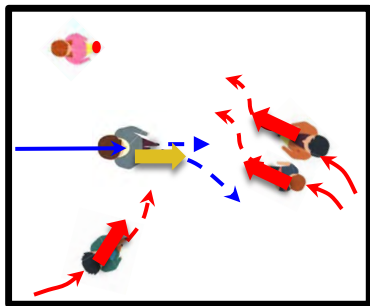


Social Forecasting

- Previous works

Knowledge-driven

- Social Forces Model [1],
 $F = F_{\text{attractive}} + F_{\text{repulsive}} \dots$



- Discrete Choice Model [2]

$$\underbrace{U}_{\text{Utility}} = \underbrace{V}_{\text{Systematic}} + \underbrace{\epsilon}_{\text{Random}}$$

✓ Interpretability
X Predictability

Previous works

[1] Helbing *et al.*, Physical review, '95

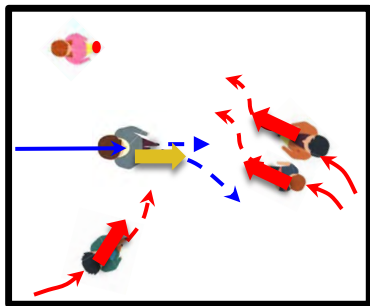
[2] Antonini *et al.*, Transportation Research, '06

Social Forecasting

■ Previous works

Knowledge-driven

- Social Forces Model [1],
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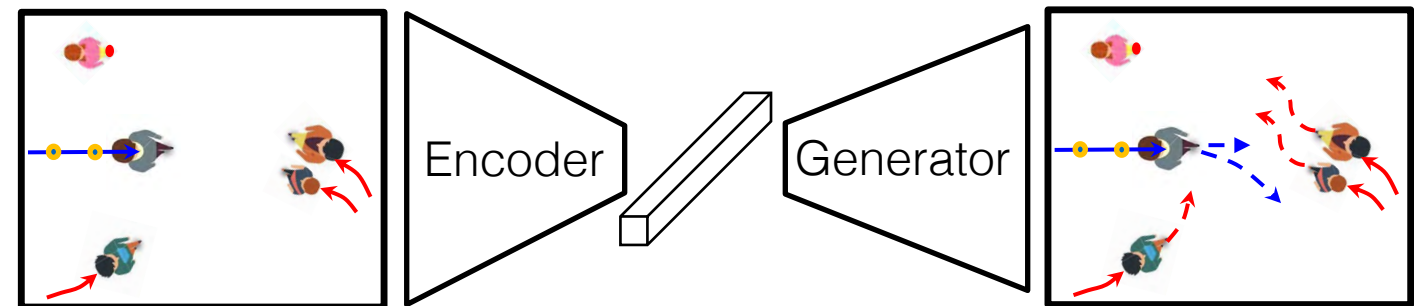
- Discrete Choice Model [2]

$$\underbrace{U}_{\text{Utility}} = \underbrace{V}_{\text{Systematic}} + \underbrace{\epsilon}_{\text{Random}}$$

✓ Interpretability
X Predictability

■ Our works

Data-driven methods



X Interpretability
✓ Predictability

Previous works

[1] Helbing *et al.*, Physical review, '95

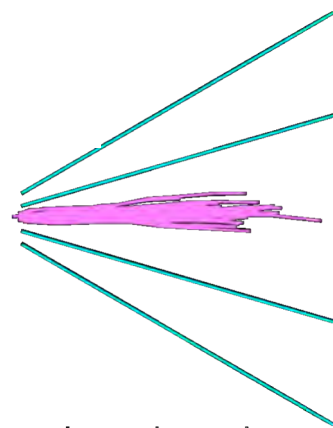
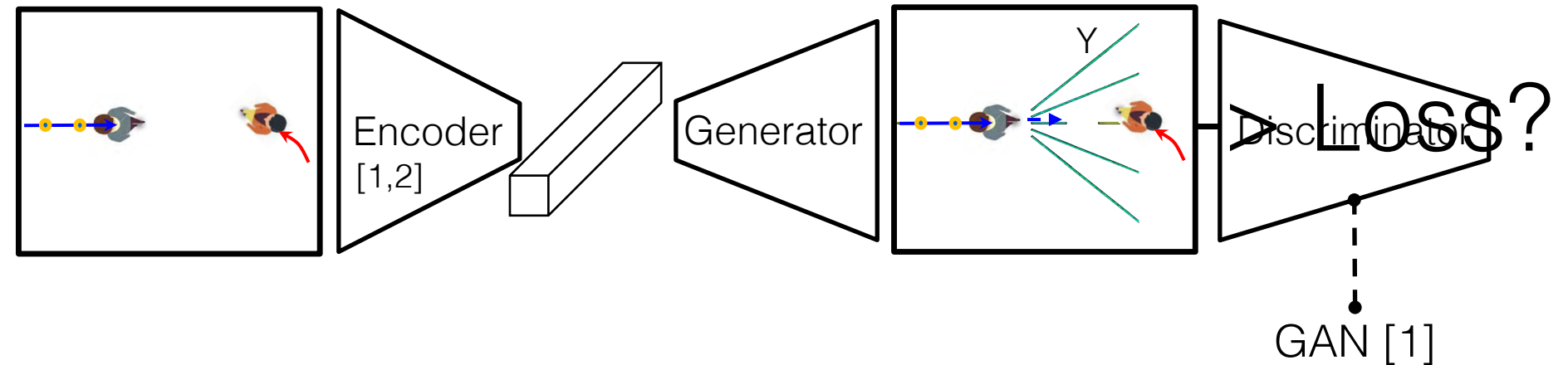
[2] Antonini *et al.*, Transportation Research, '06

Social Forecasting

Learning Representation of Crowds

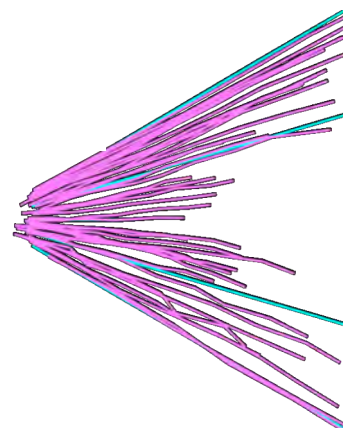


Challenge 2: Free will



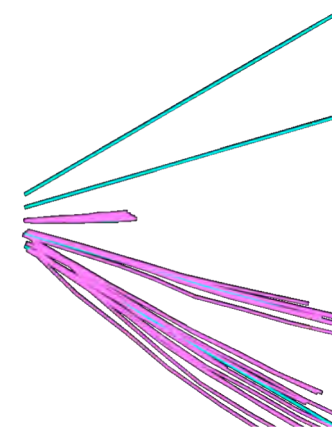
Average L2
Loss

$$\ell_{Recon} = \frac{1}{K} \sum_k \|Y_i - \hat{Y}_i^{(k)}\|$$

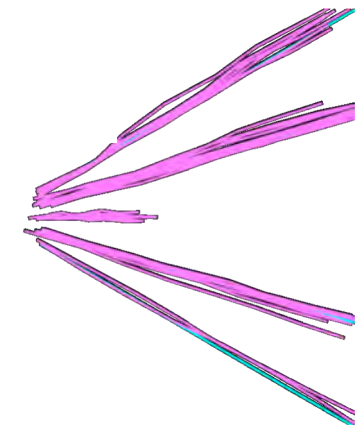


Winner-takes-all
Loss

$$\mathcal{L}_{variety} = \min_k \|Y_i - \hat{Y}_i^{(k)}\|$$



Adversarial
Loss [1]



Adversarial
Loss w/
Collab. Sampling [2]

Our work

[1] Social GAN (Generative Adversarial Network), CVPR'18

[2] Collaborative Sampling in Generative Adversarial Networks, AAAI'20

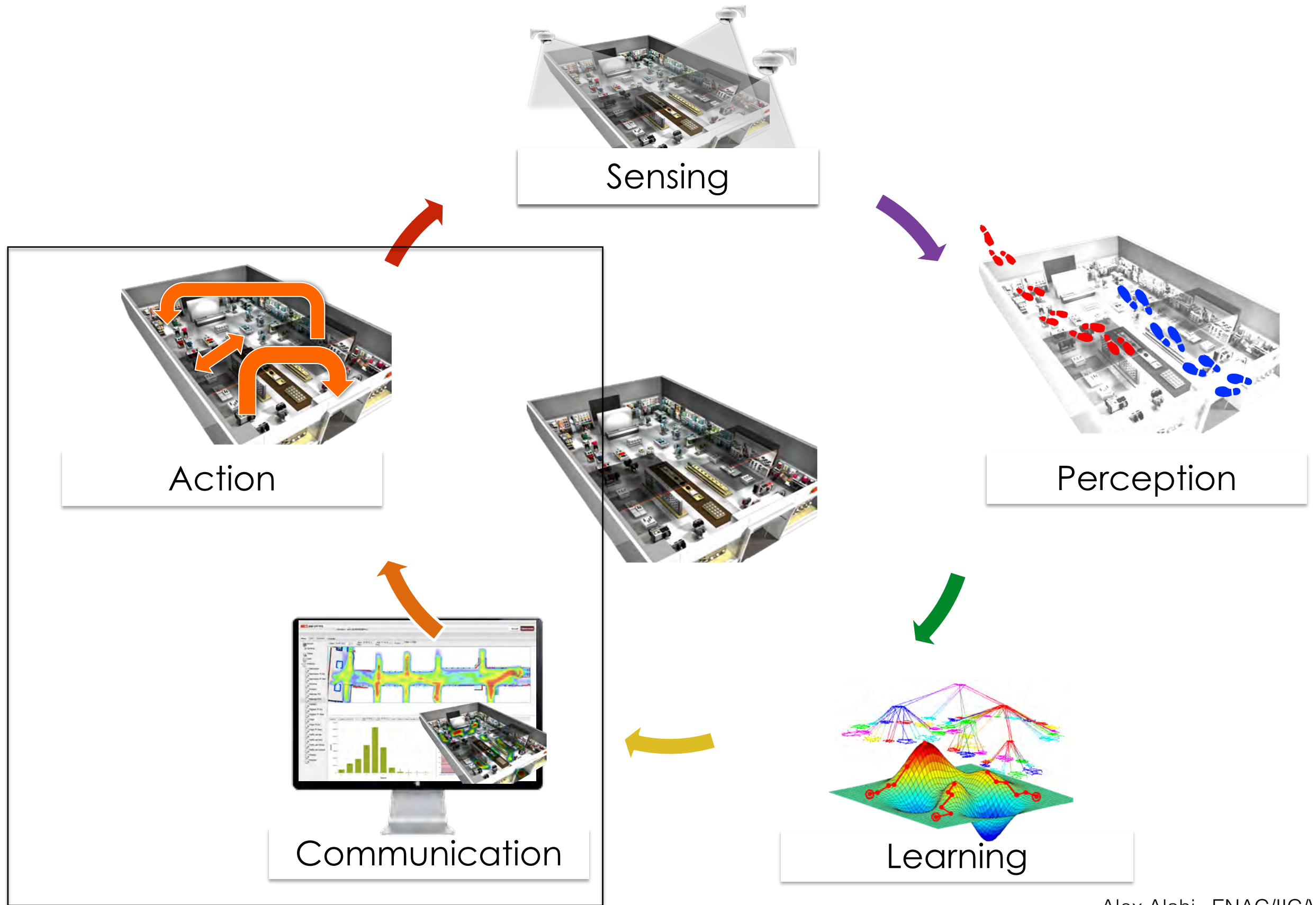


Performance evaluation

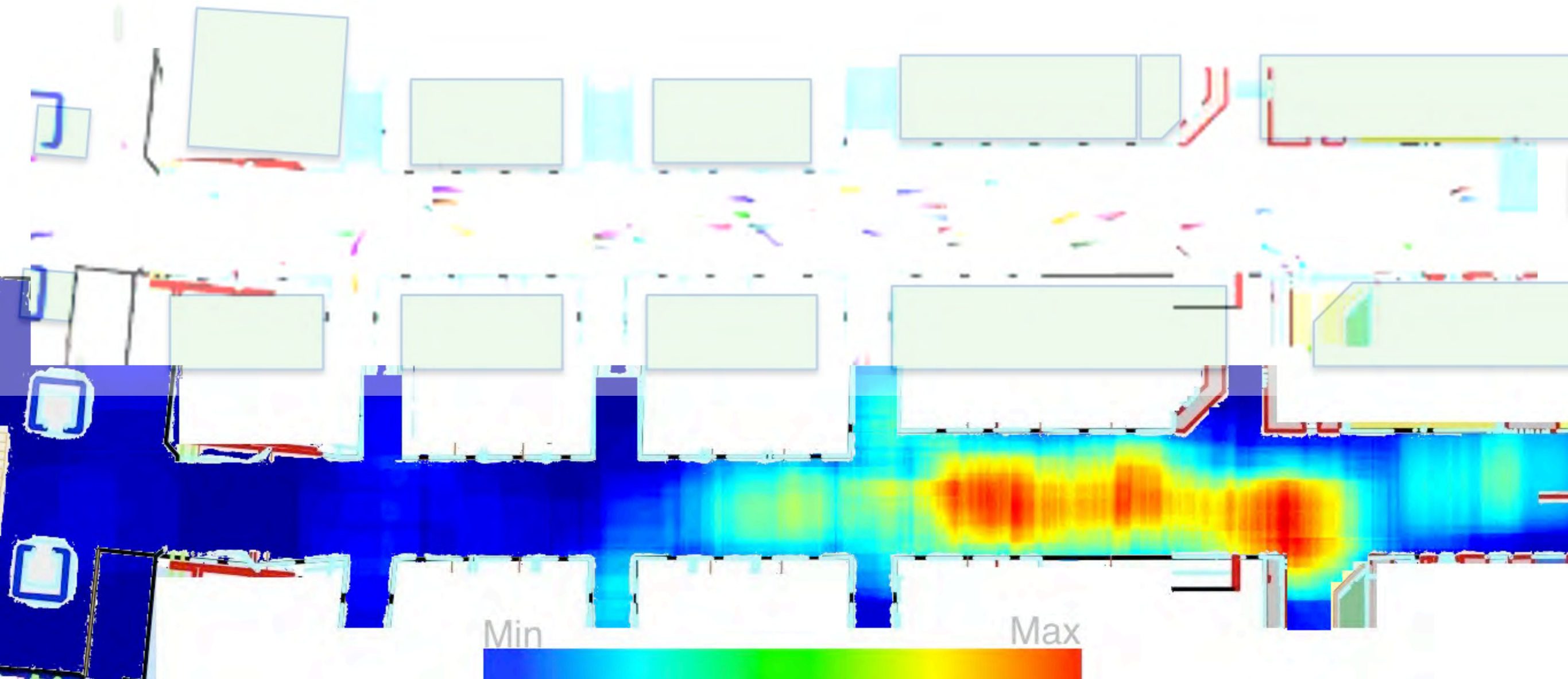
	Methods*	ADE/FDE	
Knowledge-driven	Kalman Filter	0.87/1.69	0
	DCM '06	0.67/1.42	
	Social Force '98	0.89/1.53	
	ORCA '08	0.68/1.40	
Our data-driven	LSTM '14	0.61/1.31	7
	S-GAN '18	0.57/1.24	
	S-LSTM '16	0.54/1.17	
	D-LSTM '20	0.57/1.24	
		0.55/1.18	7.6

ADE: Average displacement error in m
 FDE: Final displacement error in m
 All references available in [1]

AI for the built environments



What can we learn from all these trajectories?



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



Bertoni, L., Kreiss, S., Alahi, A,
Perceiving humans: from monocular 3D localization to social
distancing,
arxiv



Thank you

VITA

#Open Science



#Open Science



Code on-line: vita.epfl.ch/code

Perception:

- [1] S. Kreiss et al., OpenPifPaf **library** for pose estimation, **CVPR'19 (licensed)**
- [2] L. Bertoni et al., Monocular 3D Pedestrian Localization and Uncertainty Estimation, **ICCV'19**
- [3] L. Bertoni et al., MonStereo, Stereo 3D detection
- [4] L. Bertoni et al., Perceiving Social Distancing, **ITS'20**
- [5] G. Adaimi et al., Perceiving Traffic from Aerial Images
- [6] G. Adaimi et al., Deep Visual Re-identification with Confidence

Prediction:

- [7] Kothari et al., Trajnet++ **library** for spatio-temporal forecasting tasks (>15 implemented models)

Planning:

- [8] C. Chen et al., Crowd-Robot Interaction: Crowd-aware Robot Navigation with Attention-based Deep Reinforcement Learning, **ICRA'19**

Generative models:

- [9] Y. Liu* et al., Collaborative Sampling in GAN, **AAAI'20**
- [10] A. Carlier et al., Deep SVG, **NeurIPS'20**

DCM + NN

- [11] B. Sifringer et al., L-MNL, **TRB'20**

Tools

- [12] Video Ultimate labeling