Machine Learning para los Retos de la Robótica Social

Luis Merino Cabañas
Service Robotics Laboratory
Universidad Pablo de Olavide, Sevilla

http://robotics.upo.es

Next step: robots in our daily lives

Service Robotics Lab

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People Perception

Haru (春): Tabletop Social Robot

Honda Research Institute JP

UNIVERSIDAD PABLO DE OLAVIDE SEVILLA

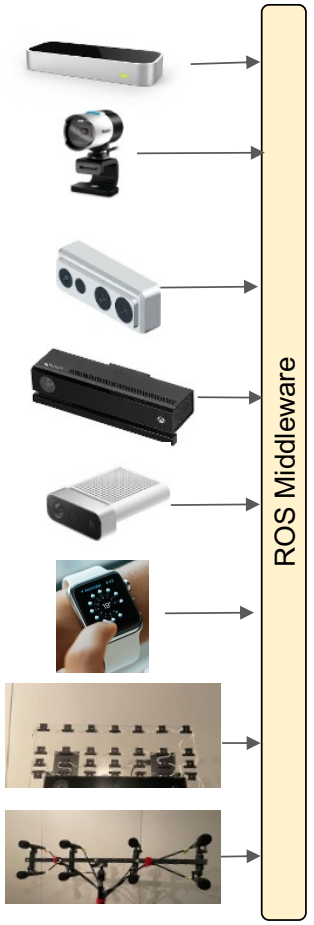
Service Robotics Lab

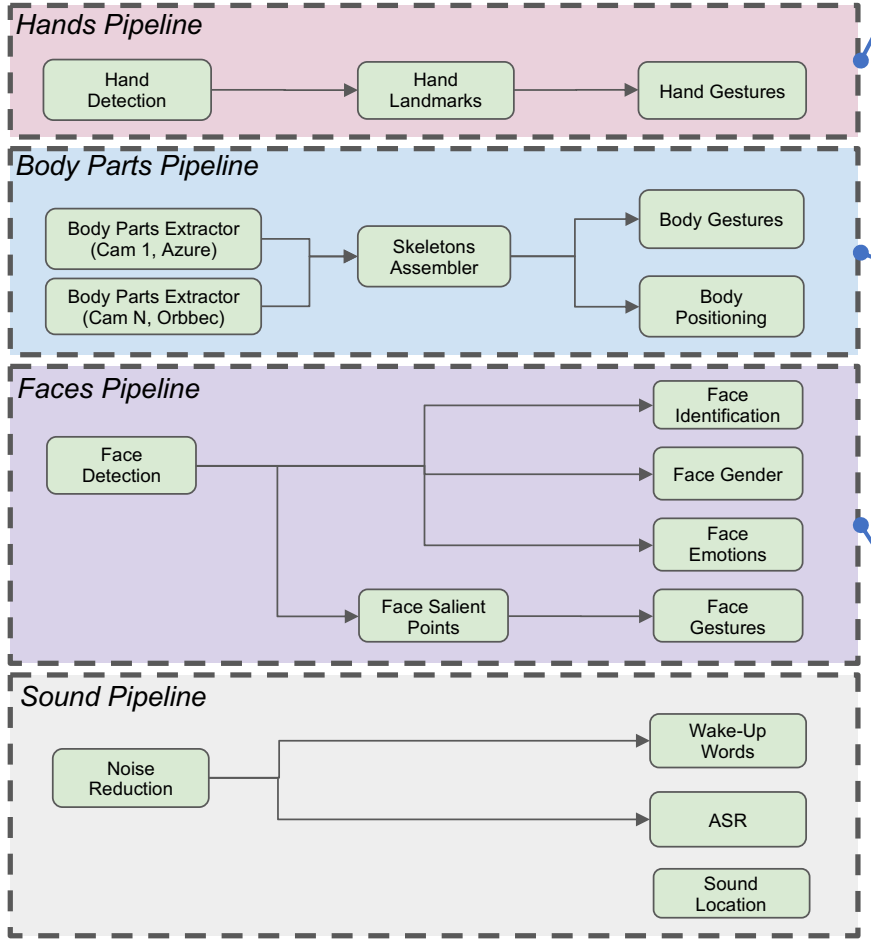
The Effects of Robot Cognitive Reliability and Social Positioning on Child-Robot Team Dynamics

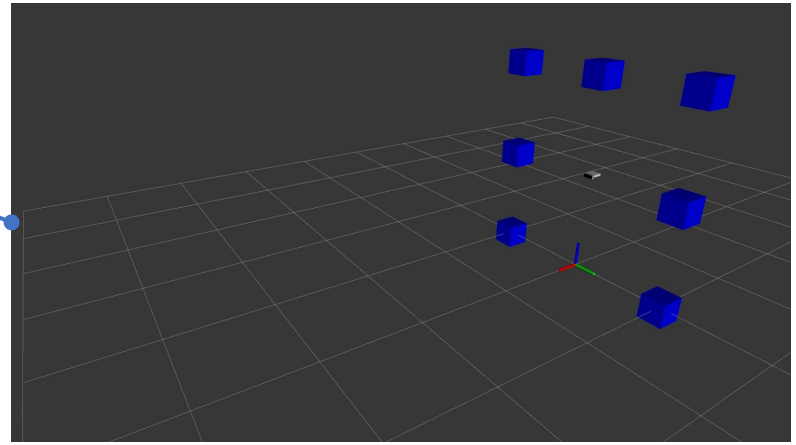
V. Charisi, L. Merino, M. Escobar, F. Caballero, R. Gomez and E. Gómez

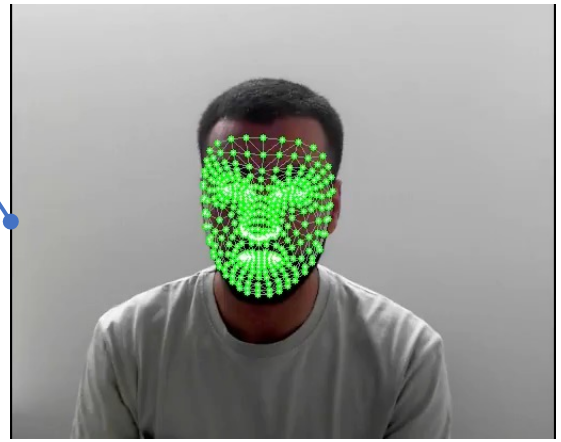
ICRA 2021

Haru's People Perception Pipeline



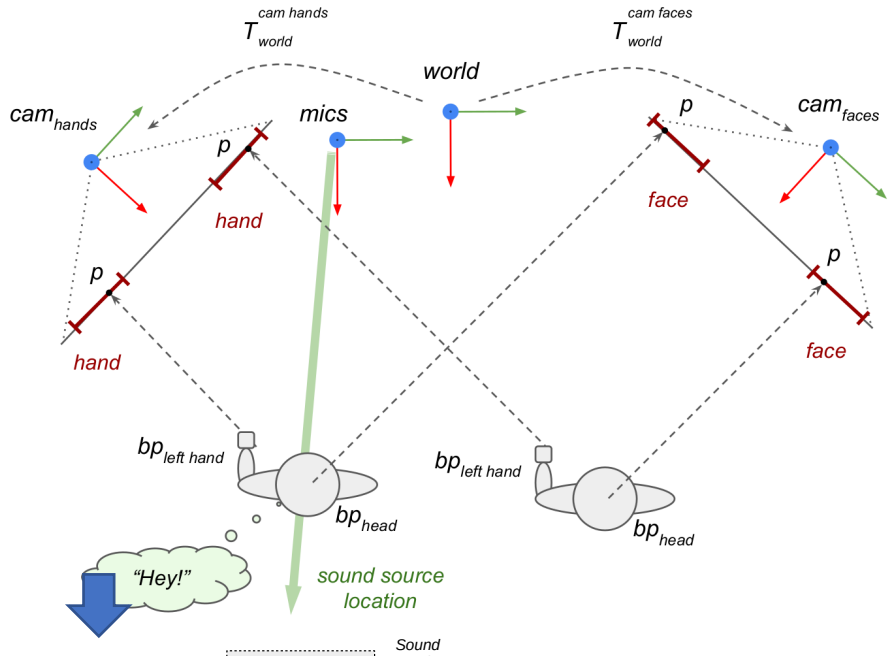


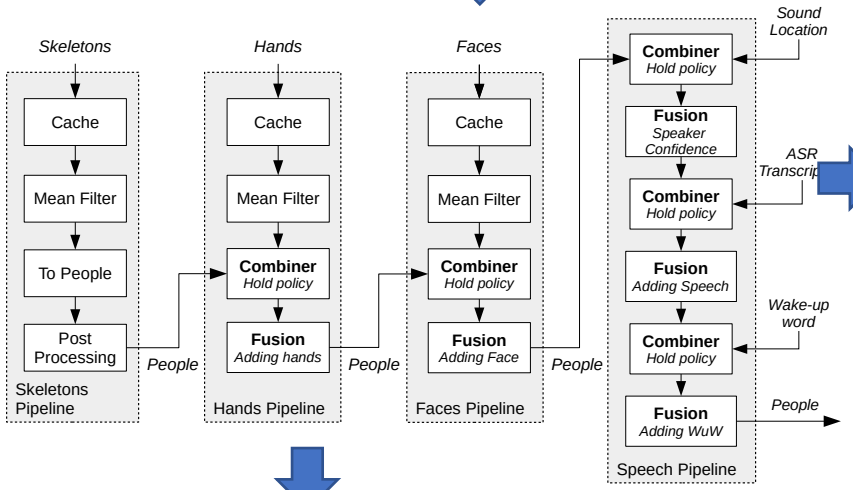


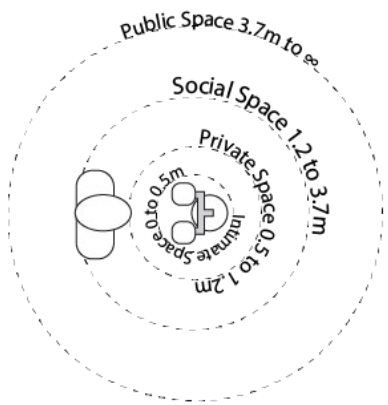


Multi-Modal People Fusion

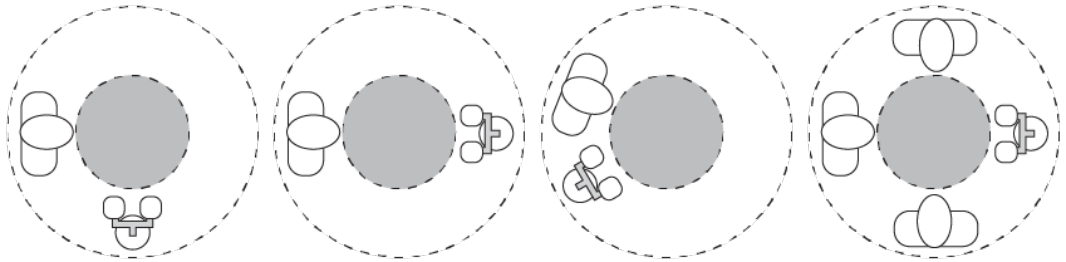
- A method to integrate global features into a unified view of the persons in the scene
- Combination of multi-modal global features employing vision and sound
- Extensible data fusion architecture based on a cascaded of filters and pipelines
- Computation of contextual features, like proxemics and F-formations







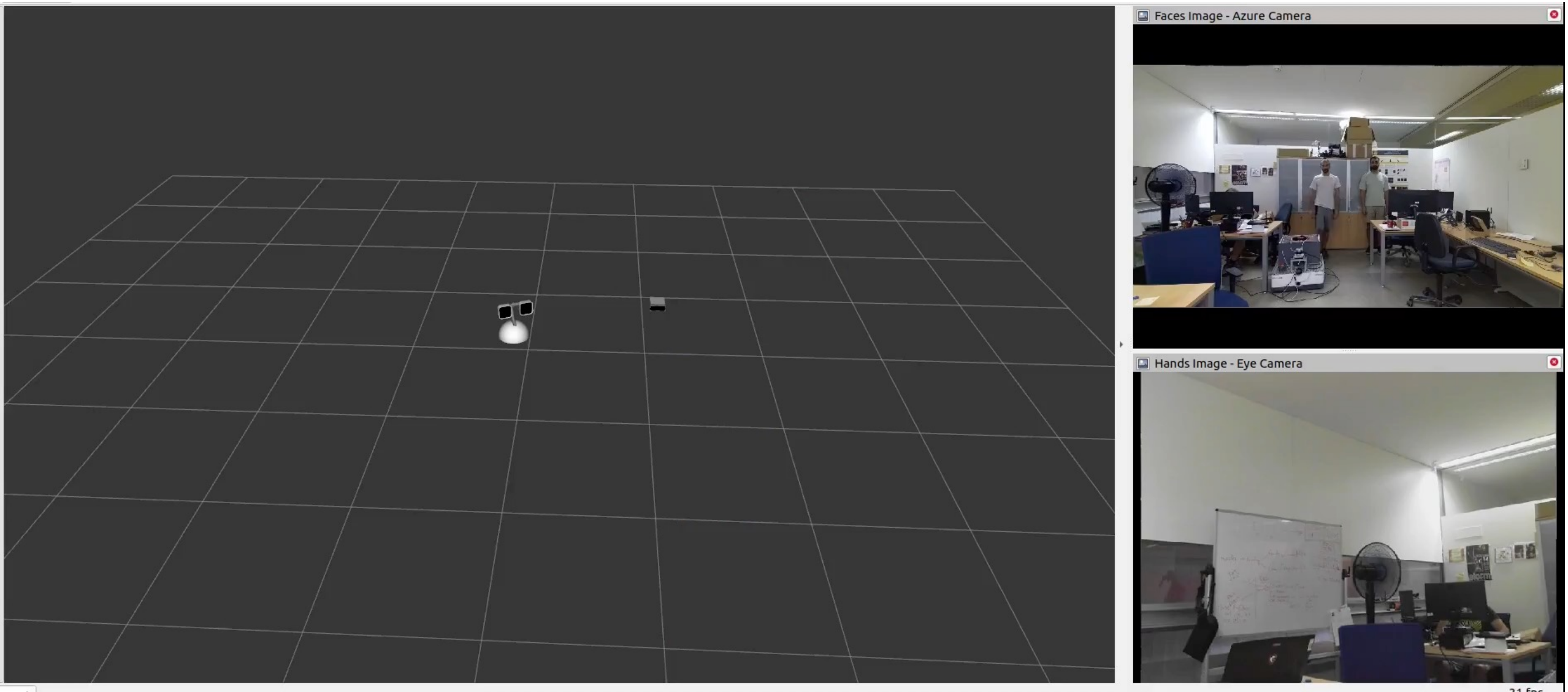
Proxemics



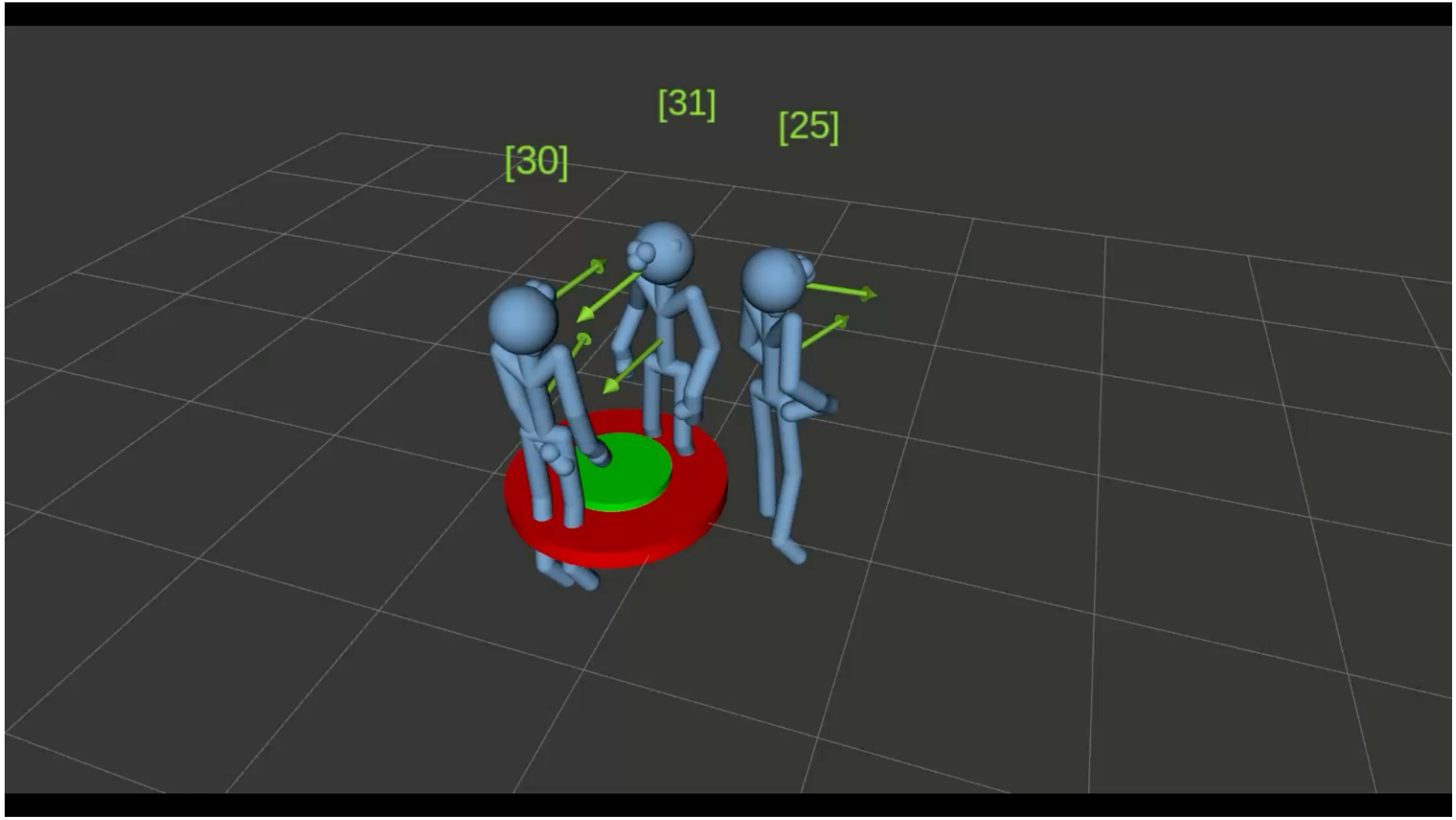
F-formations

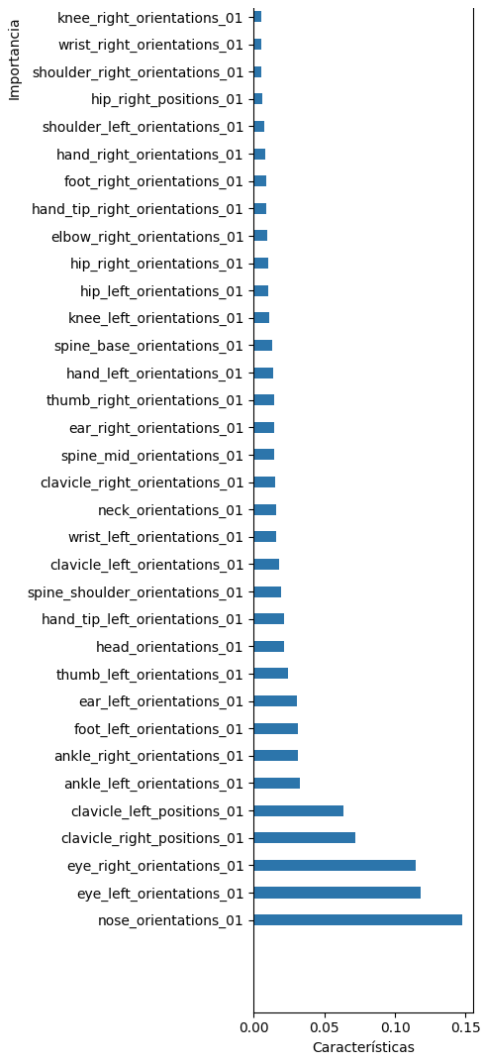
Ragel, Ricardo, et al. "Multi-modal Data Fusion for People Perception in the Social Robot Haru." *International Conference on Social Robotics*. Cham: Springer Nature Switzerland, 2022.

Multi-Modal People Fusion



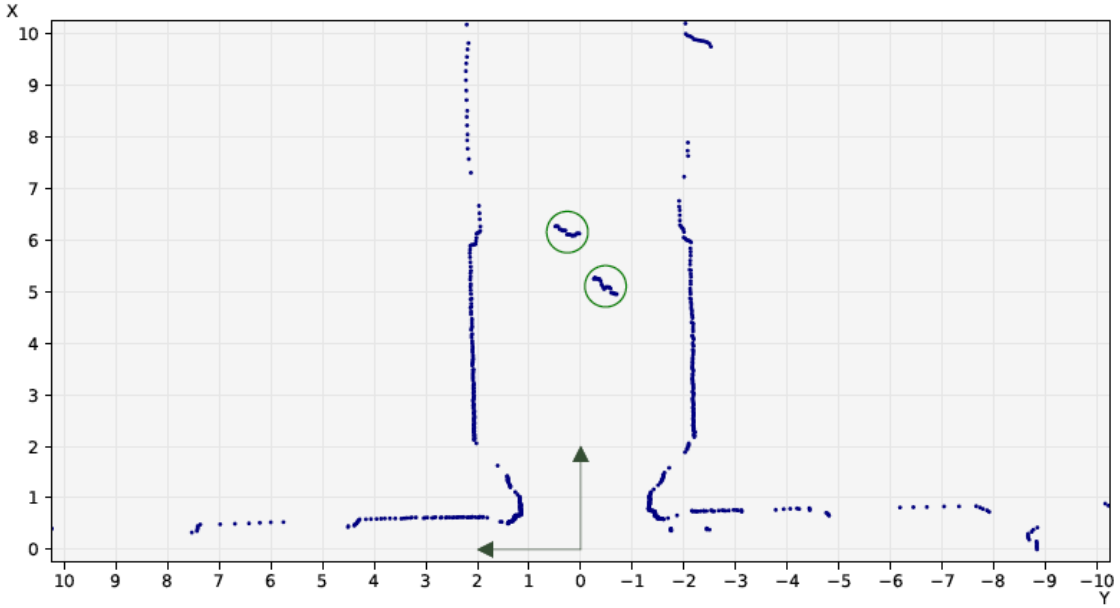
F-formations classification

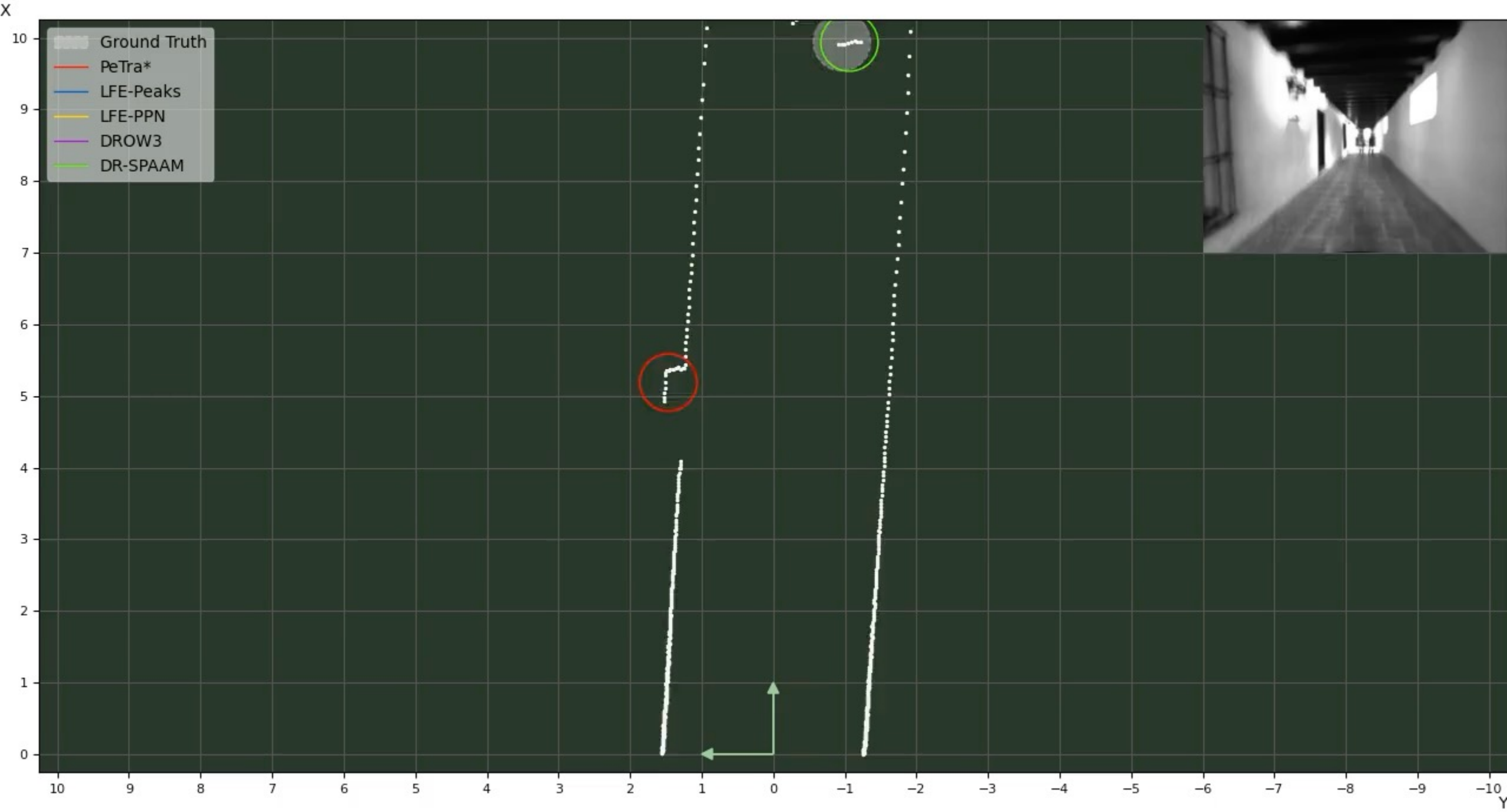




People detection with knee-high 2D LiDAR

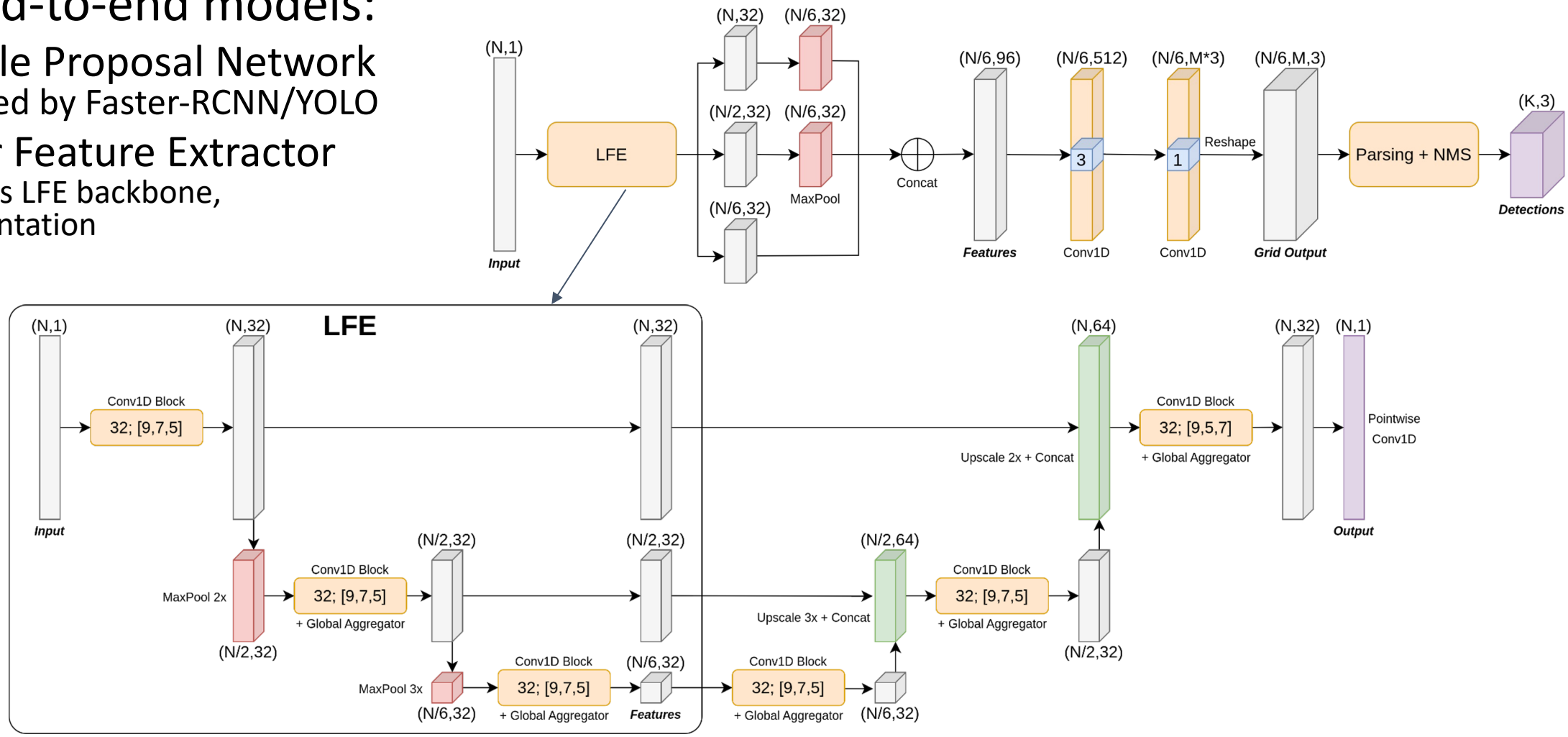
- Motivation: Low cost + Ubiquity of 2D LiDAR
- Input data: Range data vector (1D, distance in meters for each angle)
- Challenges: Few datasets, complex problem, non-deep processing
- UPO developed dataset: FROG – Real Alcázar de Sevilla



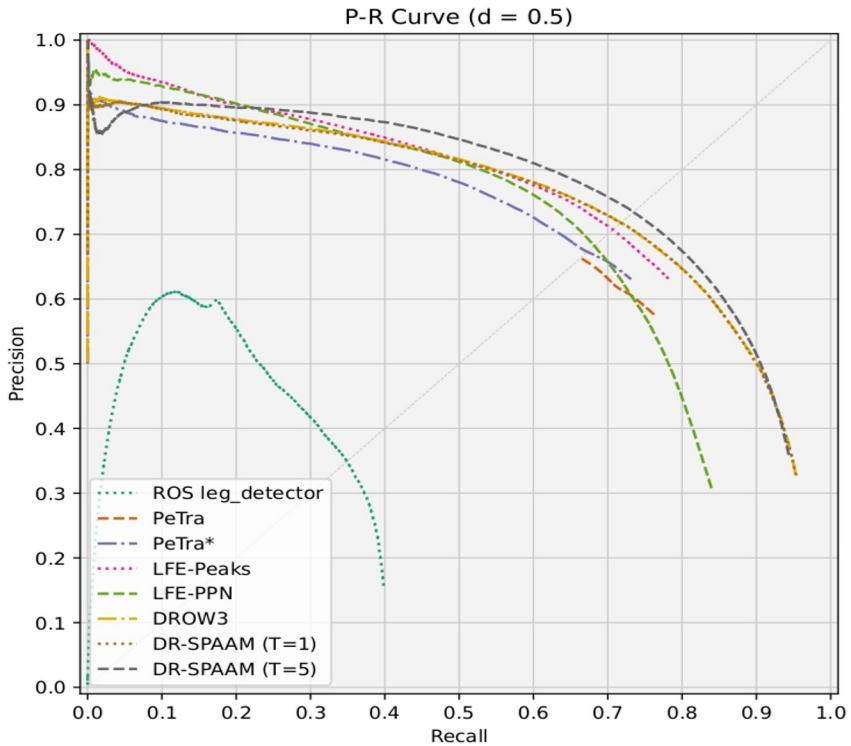

X
Y
Ground Truth
PeTra*
LFE-Peaks
LFE-PPN
DROW3
DR-SPAAM
10
9
8
7
6
5
4
3
2
1
0
−1
−2
−3
−4
−5
−6
−7
−8
−9
−10

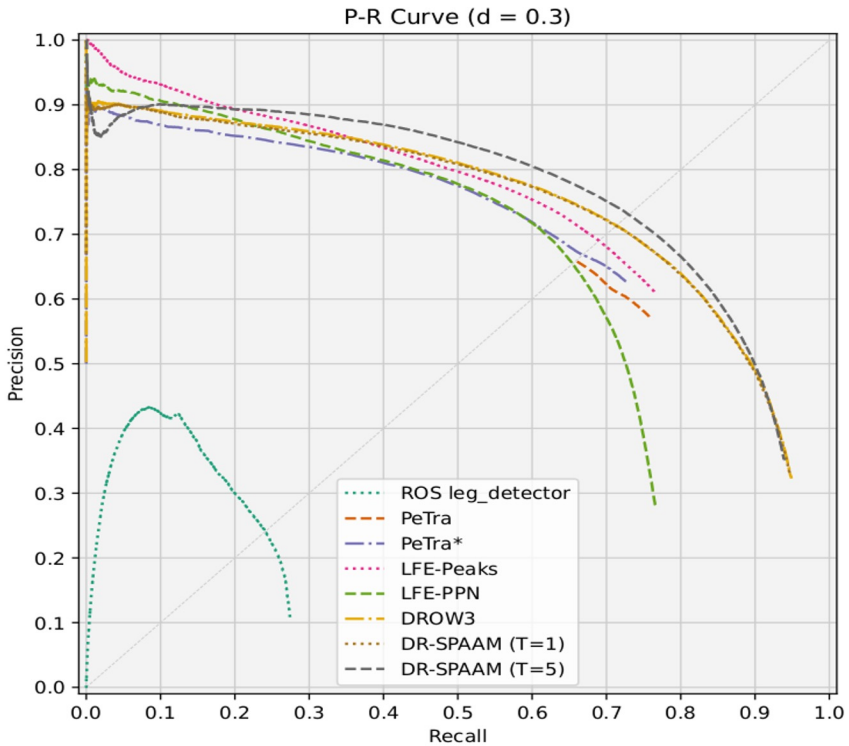
People detection with knee-high 2D LiDAR

- UPO end-to-end models:
  - People Proposal Network
    Inspired by Faster-RCNN/YOLO
  - Laser Feature Extractor
    Used as LFE backbone, segmentation



People detection with knee-high 2D LiDAR





	0.5 m			0.3 m			
	AP	Peak F_1	EER	AP	Peak F_1	EER	Time
ROS `leg_detector`	20.0	35.2	34.9	10.5	24.3	24.1	1.77ms
PeTra	47.9	66.6	66.4	47.5	66.1	65.9	28.17ms
PeTra*	59.1	67.9	67.3	58.7	67.4	66.8	—
LFE-Peaks *(ours)*	62.4	70.7	70.7	61.4	69.0	69.0	1.76ms
LFE-PPN *(ours)*	65.6	68.4	68.2	59.2	65.8	65.4	1.49ms
DROW3 $(T = 1)$	72.3	72.0	71.8	71.8	71.6	71.4	13.08ms
DR-SPAAM $(T = 1)$	72.2	72.1	71.8	71.6	71.6	71.3	13.95ms
DR-SPAAM $(T = 5)$	74.2	73.6	73.4	73.7	73.2	73.0	13.99ms

Fernando Amodeo, Noé Perez-Higueras, Luis Merino, Fernando Caballero, FROG: A new people detection dataset for knee-high 2D range finders, 2023
https://github.com/robotics-upo/2DLaserPeopleBenchmark
https://arxiv.org/abs/2306.08531

Context Estimation

NHA

Never Home Alone

eurecat
Centre Tecnològic de Catalunya

UOC
Universitat Oberta de Catalunya

UNIVERSIDAD PABLO DE OLAVIDE SEVILLA

FS
FundeSalud Extremadura

SJD
Sant Joan de Déu
Fundació de Recerca

PAL ROBOTICS

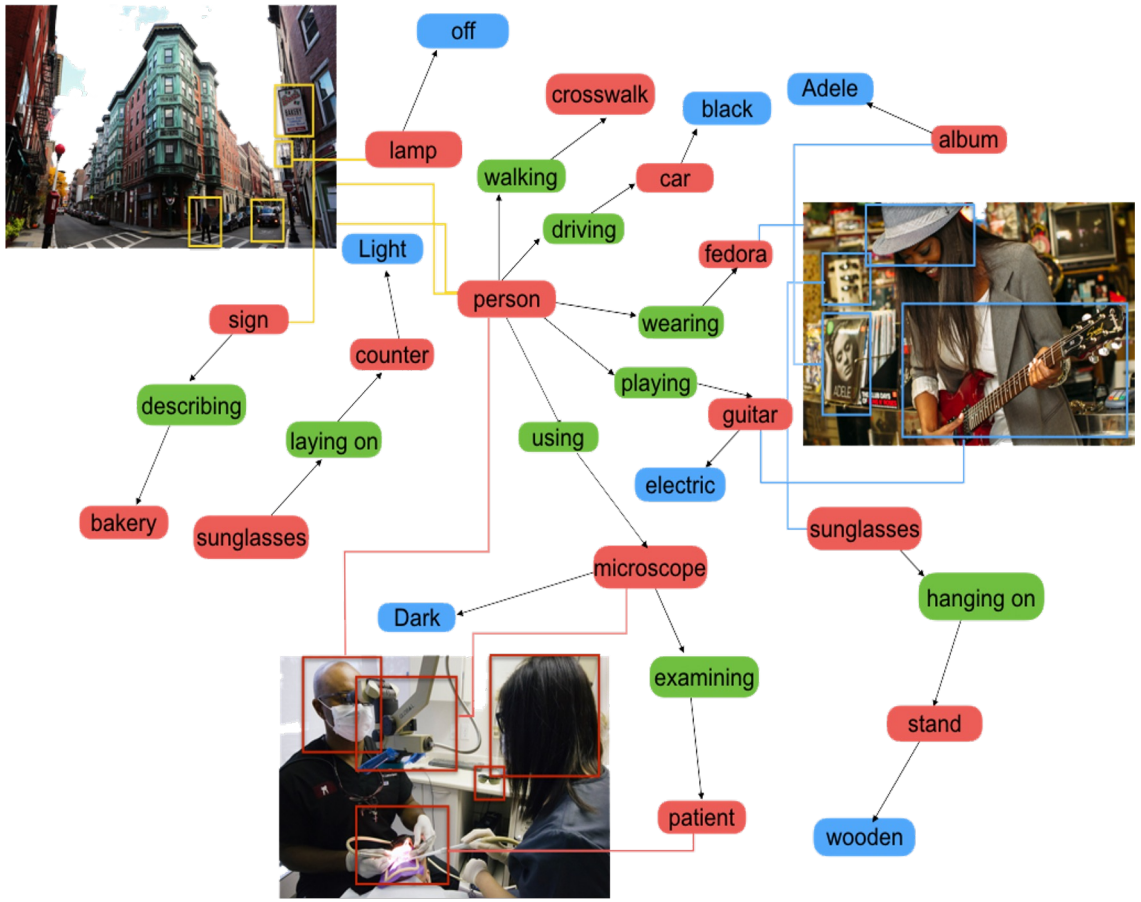
LIGHTHOUSE
DISRUPTIVE INNOVATION GROUP

NHoA

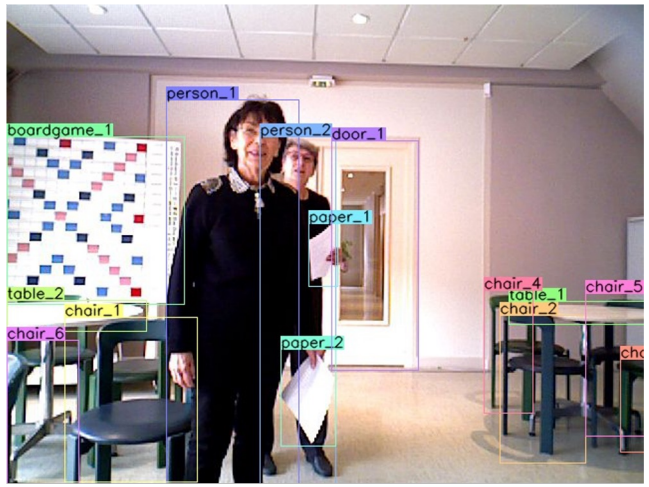
- Goal: Automatic scene description by social robots
- Motivation:
  - Description of scenes for visually impaired
  - Feeding robot knowledge bases for semantic perception

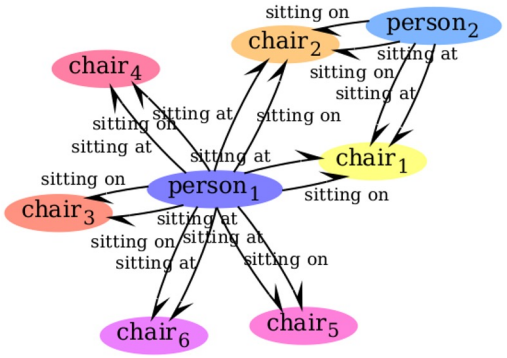
Existing work

- Datasets:
  - Visual Relationship Dataset (VRD)
  - Visual Genome (VG) and its many derivatives
  - Models: VRD-RANS, VR-LP, VTE, IMP, Motifs, …
- Problems:
  - Biased, noisy, overly general datasets
  - Unrealistic images

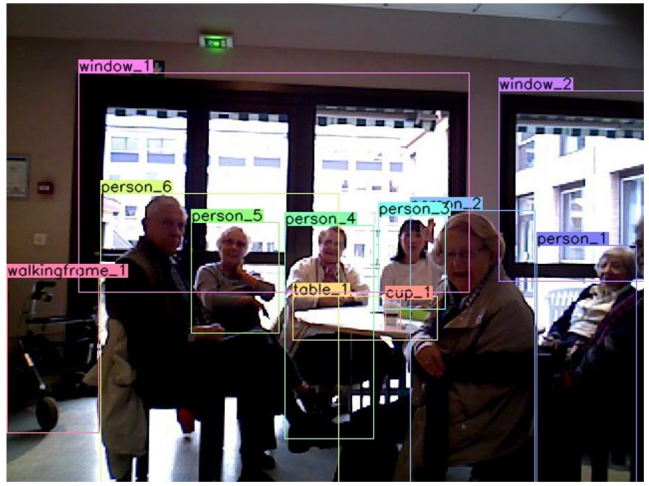


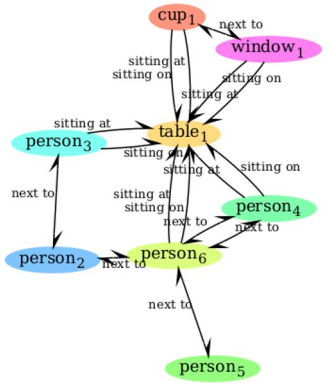
Qualitative tests





Person 1 is sitting on chairs 1, 2, 3, 4, 5 and 6.
Person 2 is sitting on chairs 1 and 2.





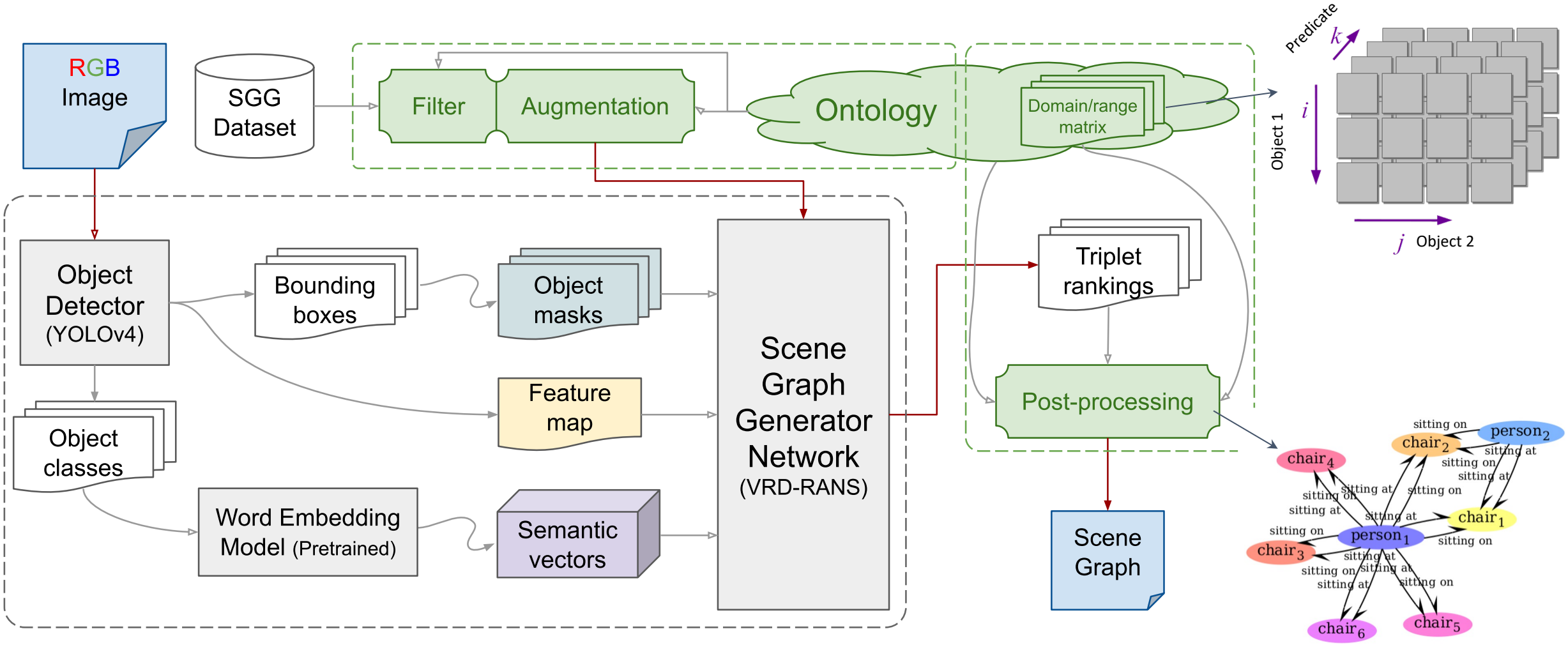
Persons 3, 4, 5 are sitting at table 1.
Person 2 is next to Person 3 and 4.
Person 3 is next to Person 2.
Person 4 is next to Person 6.
Person 5 is next to Person 6.
Person 6 is next to Person 2 and 4.

Main proposals

- Specific Idea: Design and train a scene graph generation ML model taking into account domain specific information
- Prior domain knowledge: Ontology
- Datasets:
  - Filter and preprocess an existing dataset using ontology ✓
- Process:
  - Adapt and reimplement an existing model architecture ✓
  - Filter impossible outputs according to ontology ✓

Fernando Amodeo, Fernando Caballero, Natalia Díaz-Rodríguez, Luis Merino (2022) OG-SGG: Ontology-Guided Scene Graph Generation. A Case Study in Transfer Learning for Telepresence Robotics. ArXiv
https://github.com/robotics-upo/og-sgg

Main proposals



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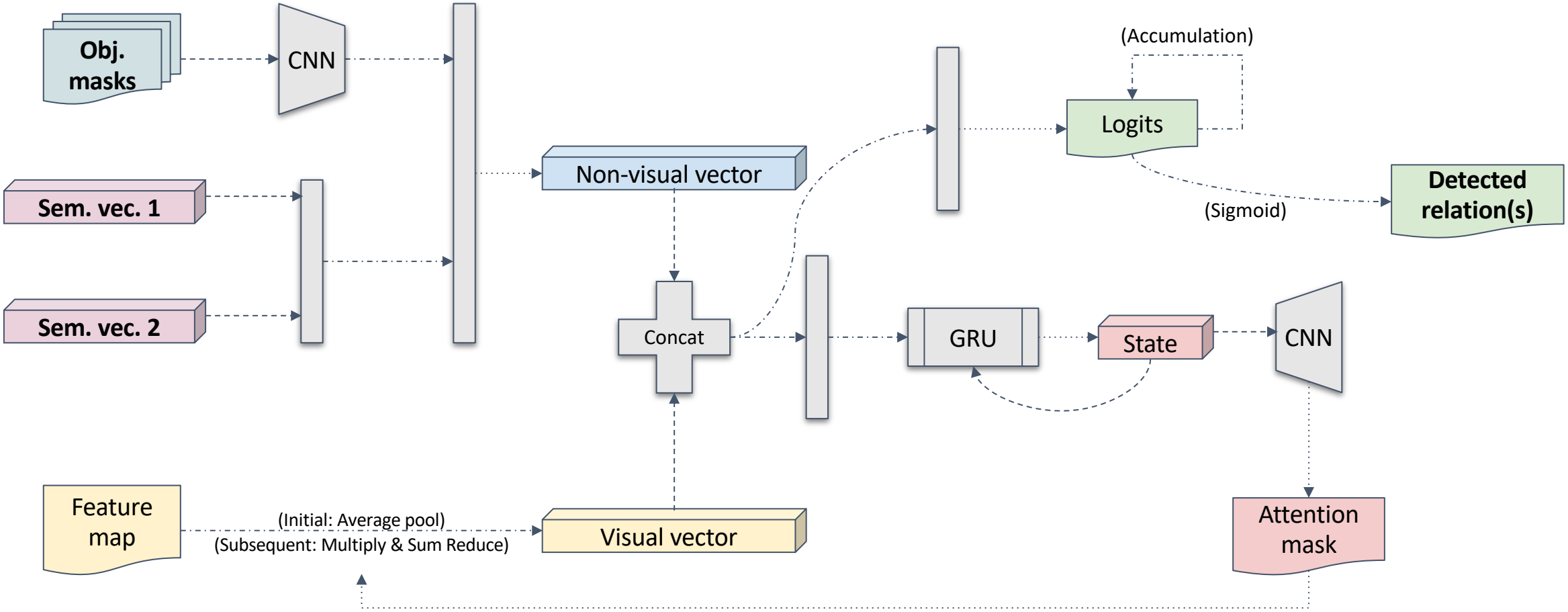
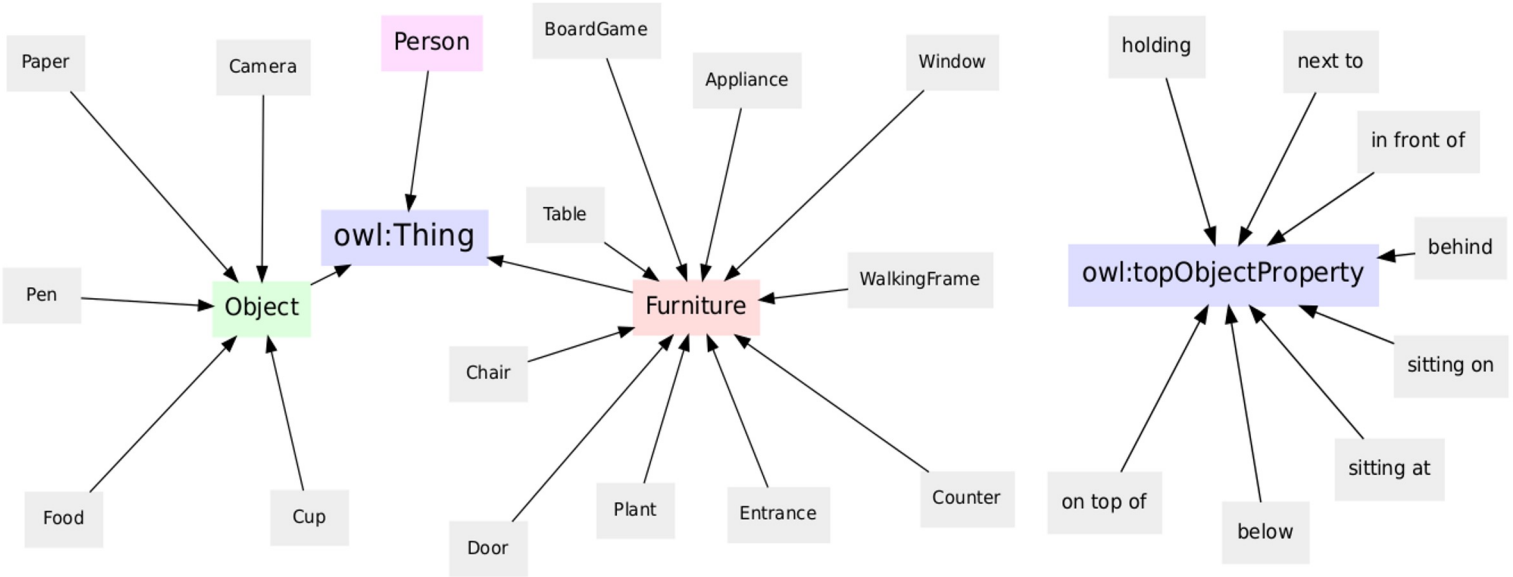
Scene Graph Generator



Test dataset: TERESA

- Scenario: Telepresence robot for elderly care
- Simple ontology
- Domain/Range restrictions, Inverse/Functionality/Transitivity/etc
- 25 images
- Object/predicate annotations (with help from ontology)

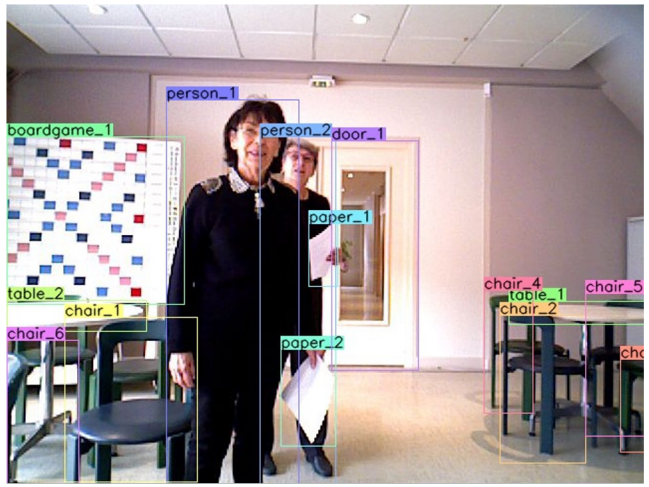


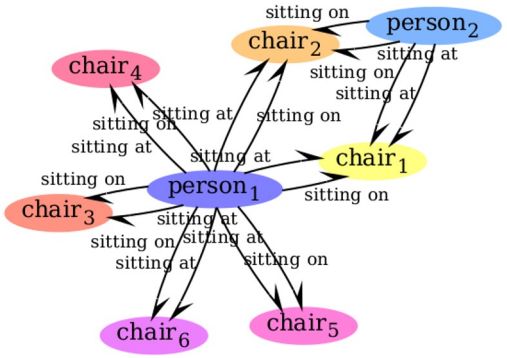
Quantitative tests

Dataset	Post	Metrics for Predicate Detection (PredDet)											
		R@K (**k** = 1)			**R@K** (**k** = 8)			**mR@K** (**k** = 1)			**mR@K** (**k** = 8)		
		20	50	100	20	50	100	20	50	100	20	50	100
VG-SGG unmodified dataset	✗	27.0	34.7	41.9	23.8	34.8	51.1	19.1	30.6	36.4	29.3	42.7	57.0
	✓	28.4	36.0	43.2	29.5	42.2	57.9	32.4	44.6	51.1	33.5	49.7	**63.0**
VG-SGG with filtering	✗	40.0	43.4	47.7	42.0	49.0	60.0	42.2	48.8	50.9	43.5	51.5	57.4
	✓	44.7	47.9	53.2	**46.5**	53.4	66.3	44.0	51.2	**53.6**	44.7	**53.9**	60.5
VG-SGG with filtering/augmentation	✗	39.8	43.9	48.6	40.7	49.8	61.5	42.5	47.1	50.6	43.4	51.2	57.9
	✓	**44.9**	**49.3**	**54.0**	**46.5**	**54.0**	**68.3**	**44.6**	**49.9**	53.3	**45.2**	53.0	61.7
VG-indoor unmodified dataset	✗	26.1	33.7	40.2	26.0	41.4	56.1	10.5	20.6	25.2	19.8	35.5	53.6
	✓	30.7	38.4	45.2	32.7	45.6	59.6	22.0	39.5	44.7	23.3	39.5	58.1
VG-indoor with filtering	✗	41.2	41.3	46.7	42.2	48.1	59.2	43.7	50.6	45.5	44.7	56.0	65.8
	✓	43.6	45.3	51.8	**44.2**	**51.5**	**62.8**	45.0	52.9	59.6	**47.1**	57.7	**69.3**
VG-indoor with filtering/augmentation	✗	42.1	42.6	46.9	42.2	48.5	58.1	45.5	53.0	56.1	46.2	56.8	63.8
	✓	**44.4**	**46.1**	**51.9**	43.3	**51.5**	62.0	**46.8**	**54.8**	**61.0**	46.6	**58.3**	66.6

Notice that the test set is completely different from the training set!

Qualitative tests





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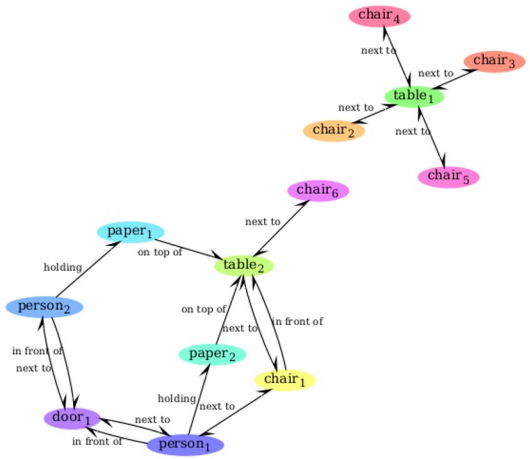
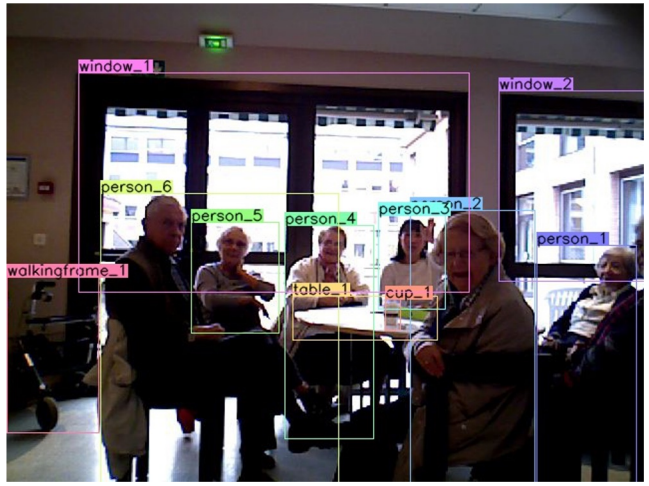
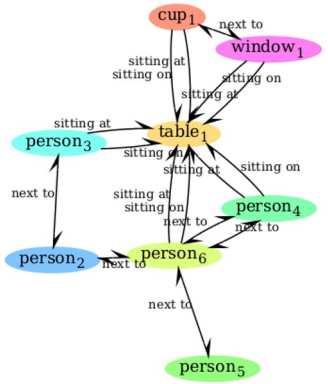


Person 1 and 2 are in front of a door.
Person 1 is holding a piece of paper.
Person 1 is next to chair 1.
Person 2 is holding a piece of paper.





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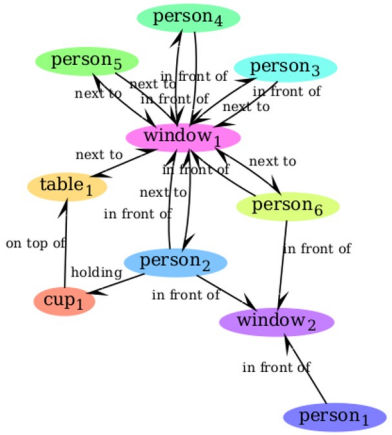
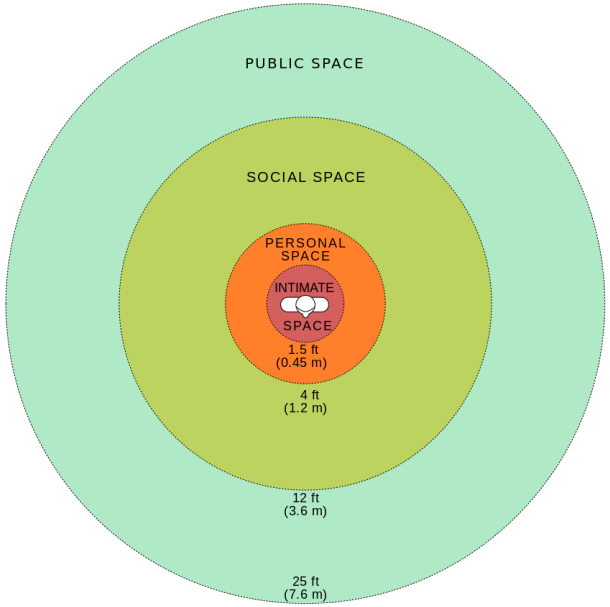


Persons 1 and 2 are in front of a window.
Persons 2, 3, 4, 5 and 6 are in front of a window.
Person 2 is holding a cup.

Human-aware navigation

Human-aware path planning

- Encoding social norms into path/motion planners
- Social navigation tasks are easier to **demonstrate** than formalise
- Given demonstrations by humans: **Learning by Demonstration**

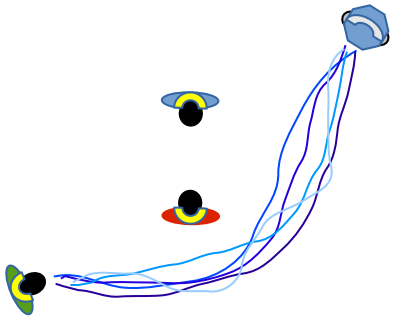


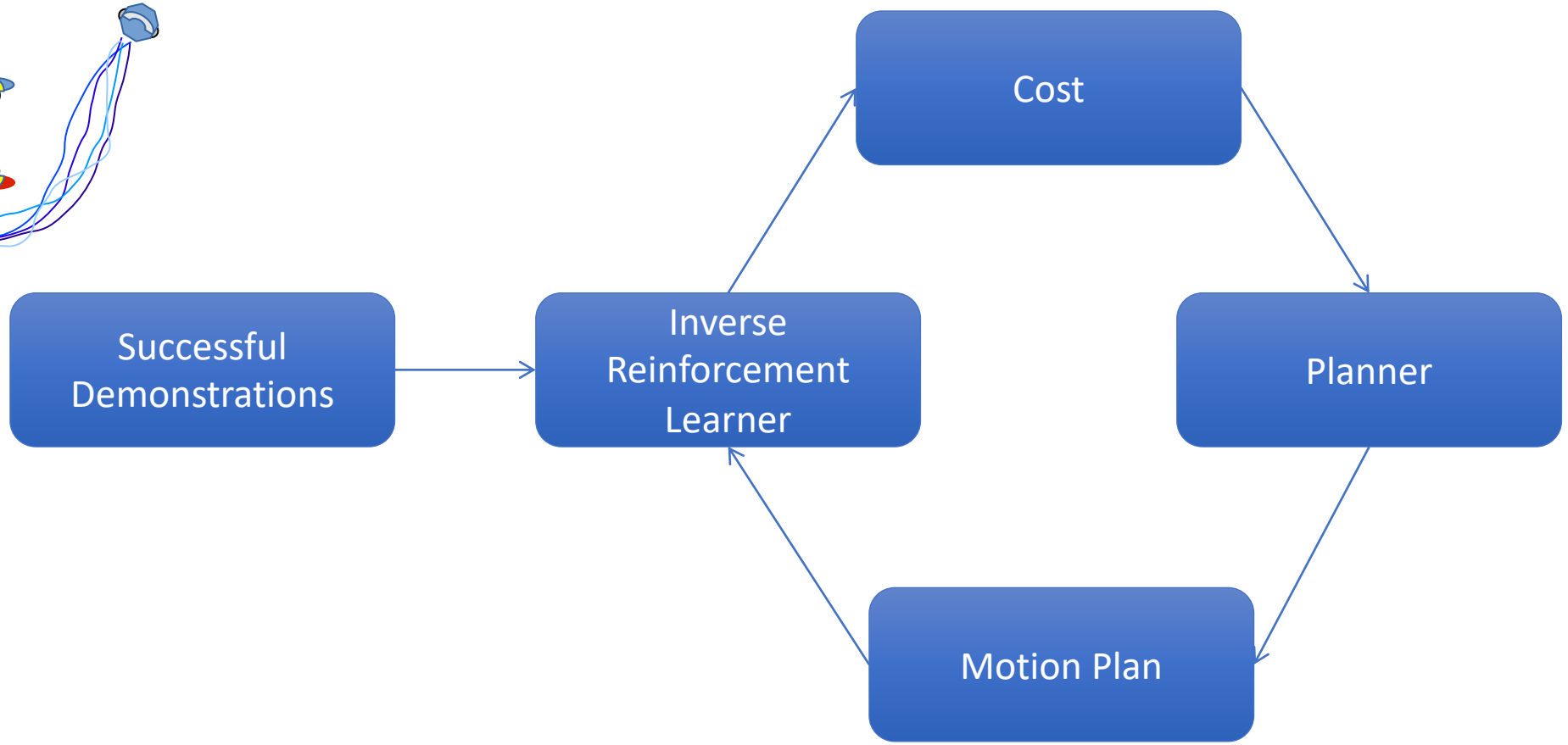
Learning navigation cost functions from demonstrations

- Inverse Reinforcement Learning (IRL) approach

- Given **successful demonstrations**, estimate **cost function** thee demonstrator is minimising

Inverse Reinforcement Learning





Inverse Reinforcement Learning

- Initial formulations using discrete Markov Decision Processes (MDPs) as planners
- MDPs defined by the tuple <S,A,T,R>:
  - S: state space
  - A: action space
  - T: transition function, $T(x',a,x)=p(x'|x,a)$
  - R: reward (cost) function, $R(x,a)$
- Solving a MDP is finding a policy $\pi^*(x)$ that maximizes (minimizes) cumulative reward (cost)

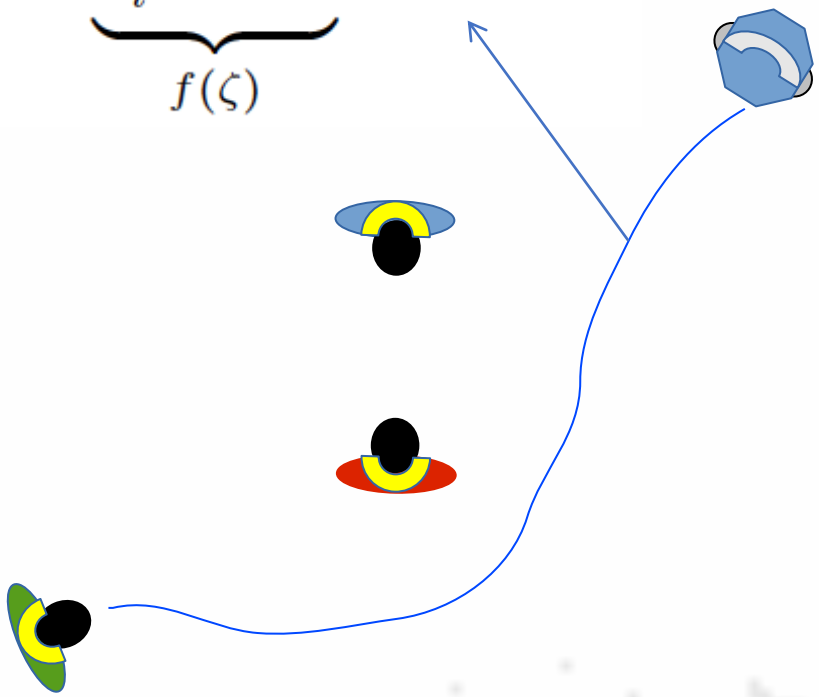
Inverse Reinforcement Learning

- IRL as an “incomplete” MDP, <S,A,T>
- Given a set of demonstrations by an expert, determine the cost (reward) function used by the demonstrator
  - Cost function as a linear combination of features:

$$c(x) = \sum_j \omega_j f_j(x) = \omega^T f(x)$$

Inverse Reinforcement Learning

$$c(\zeta) = \sum_i c(x_i) = \omega^T \underbrace{\sum_i f(x_i)}_{f(\zeta)} = \omega^T f(\zeta)$$



Inverse Reinforcement Learning

- IRL as an “incomplete” MDP, <S,A,T>
- Given a set of demonstrations by an expert, determine the cost (reward) function used by the demonstrator
  - Cost function as a linear combination of **features**:

$$c(x) = \sum_j \omega_j f_j(x) = \omega^T f(x)$$

- Determine weights so that the planner returns the same features as the demonstrations in expectation (Abbeel and Ng, 2004)

$$\mathbb{E}(f(\zeta)) = \frac{1}{D} \sum_{i=1}^{D} f(\zeta_i)$$

Inverse Reinforcement Learning

$$\frac{1}{D}\sum_{i=1}^{D} f(\zeta_i)$$

Maximum Entropy Inverse Reinforcement Learning

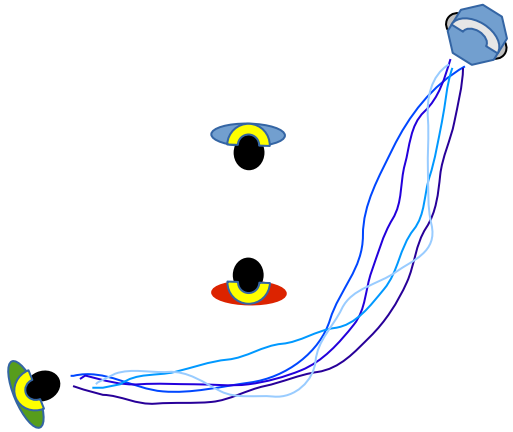
- Challenges:
  - Expert suboptimal
- Maximum Entropy Assumption (Ziebart et al., 2008)
  - Probability distribution on paths that does not exhibit any additional preference except feature expectation

$$p(\zeta|\omega) = \frac{1}{Z(\omega)} e^{-\omega^T f(\zeta)}$$

Issues with discrete MDP-based IRL

- Discretization
- Scalability with the state space
  - It renders difficult to include new information about the problem
  - For instance, reasoning about static obstacles, goals, etc
- However, good motion planners available (RRT* for instance)
  - They reason about obstacles, they can reason about dynamics and kinematics of the robot, etc

Learning from demonstrations with RRT*

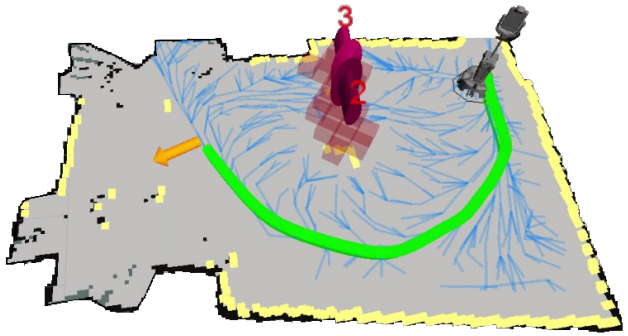


Successful Demonstrations

IRL-RRT*

Cost function

$$c(\zeta) = \sum_i c(x_i) = \omega^T \underbrace{\sum_i f(x_i)}_{f(\zeta)} = \omega^T f(\zeta)$$



RRT* motion planner

Trajectories

Learning from demonstrations with RRT*

- Maximum Entropy IRL for continuous spaces (Kretzschmar et al., 2014)

$$p(\zeta|\omega) = \frac{1}{Z(\omega)} e^{-\omega^T f(\zeta)}$$

- Determine the weights that maximize the (log-)likelihood of the demonstrations

$$\mathcal{L}(\mathcal{D}|\omega) = -D \log(Z(\omega)) + \sum_{i=1}^{D} (-\omega^T f(\zeta_i))$$

- The gradient is given by: $$\frac{\partial \mathcal{L}(\mathcal{D}|\omega)}{\partial \omega} = D(\mathbb{E}(f(\zeta)) - \frac{1}{D} \sum_{i=1}^{D} f(\zeta_i))$$

Learning from demonstrations with RRT*

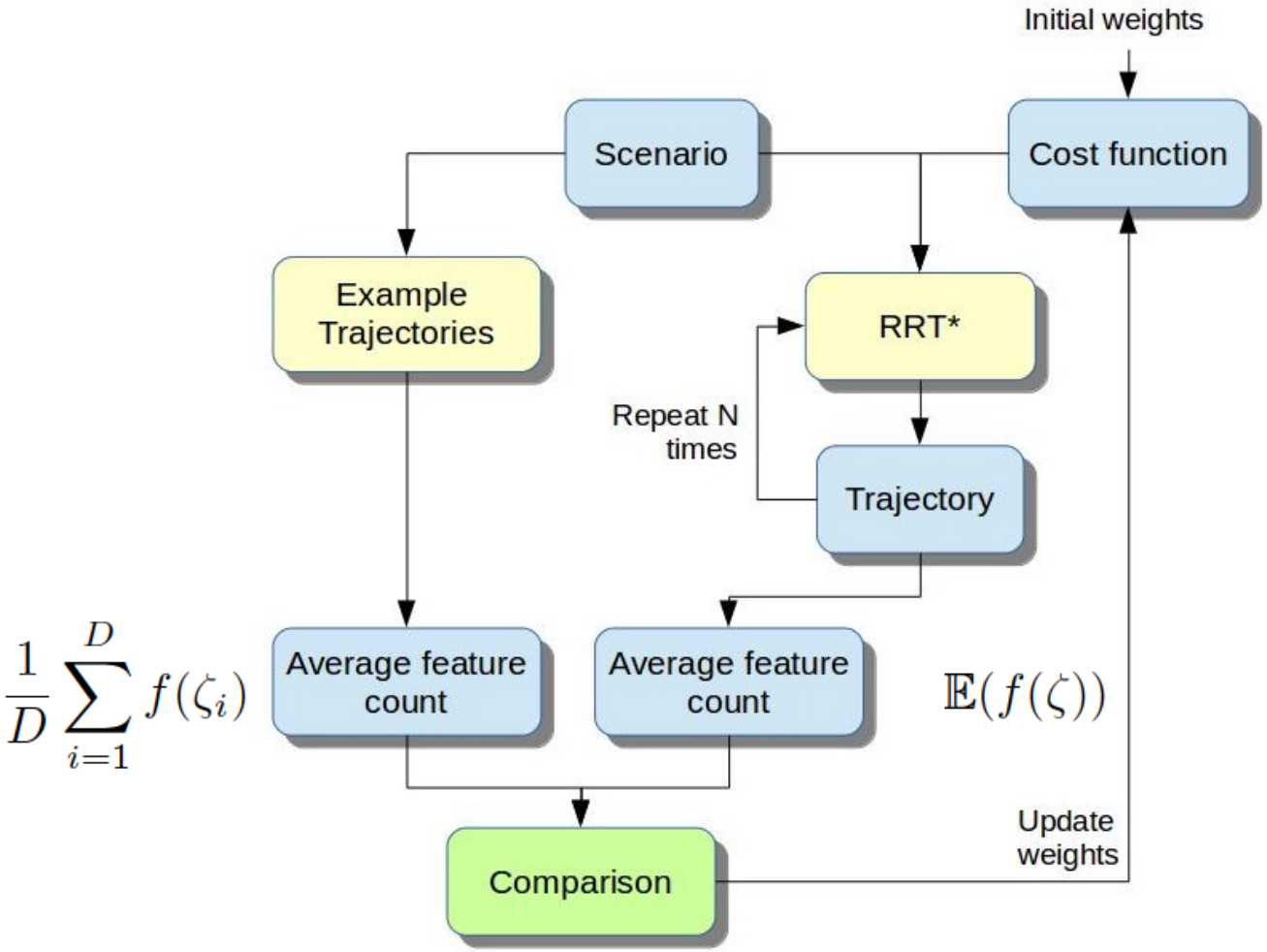
- Problem: evaluate the expected feature counts

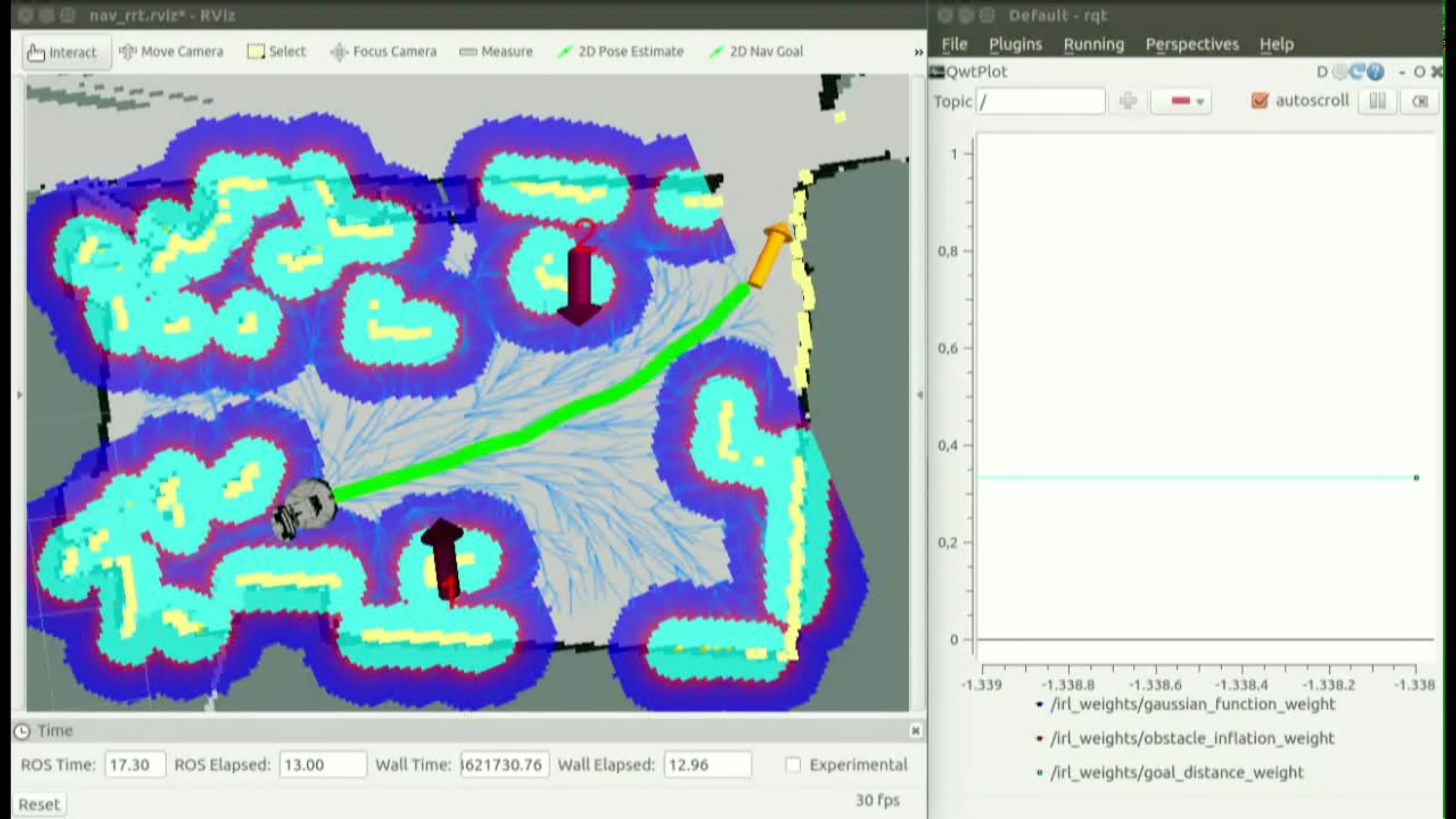
$$\mathbb{E}(f(\zeta)) = \frac{1}{Z(\omega)} \int f(\zeta) e^{-\omega^T f(\zeta)} d\zeta$$

- Approximate it by the features of the best RRT* trajectory (minimum cost)

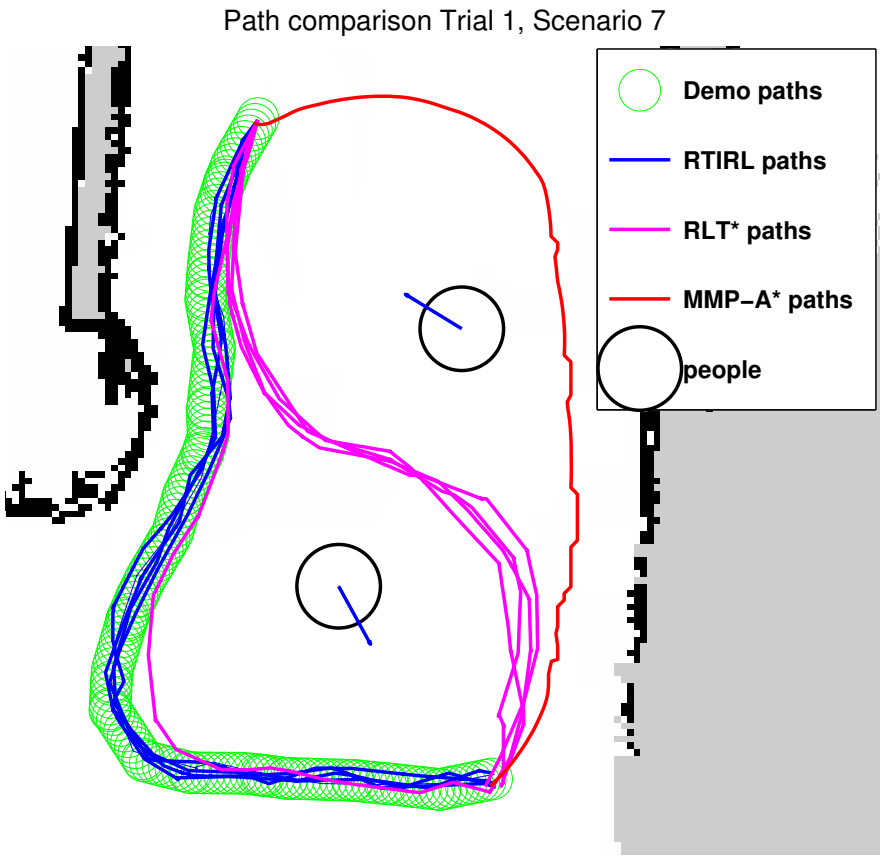
- RRT* is asymptotically optimal:
  - Run several iterations to account for variations

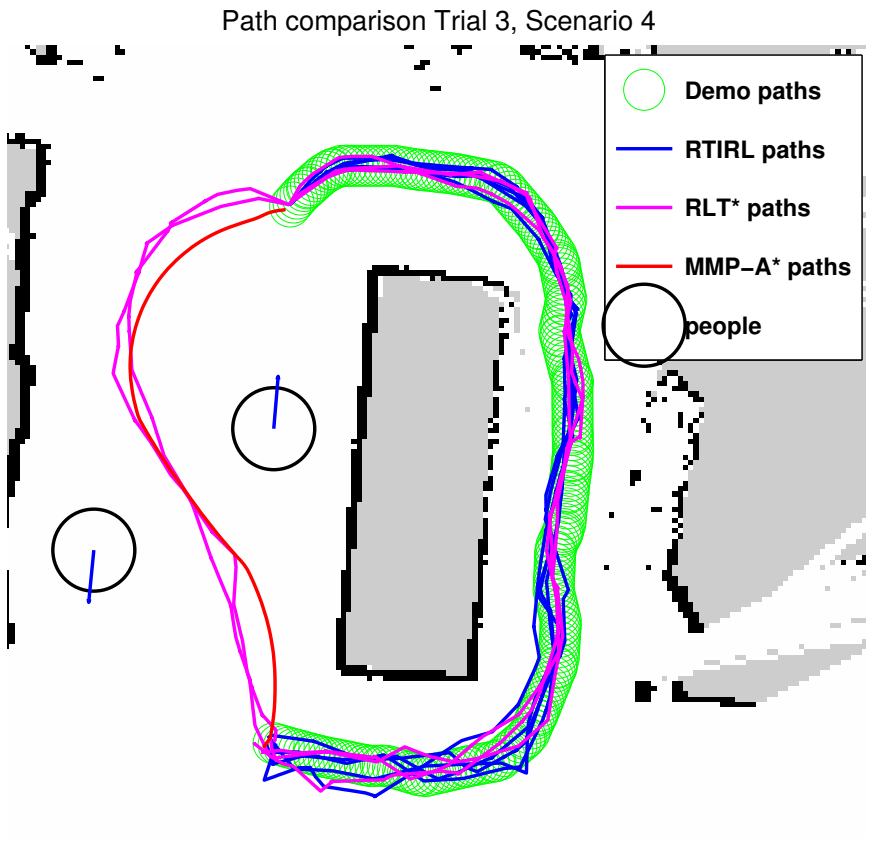
Learning from demonstrations with RRT*




nav_rrt.rviz* - RViz
Interact
Move Camera
Select
Focus Camera
Measure
2D Pose Estimate
2D Nav Goal
Time
ROS Time: 17.30
ROS Elapsed: 13.00
Wall Time: 621730.76
Wall Elapsed: 12.96
Experimental
Reset
30 fps
Default - rqt
File
Plugins
Running
Perspectives
Help
QwtPlot
Topic /
autoscroll
1
0,8
0,6
0,4
0,2
0
-1.339
-1.338.8
-1.338.6
-1.338.4
-1.338.2
-1.338
/irl_weights/gaussian_function_weight
/irl_weights/obstacle_inflation_weight
/irl_weights/goal_distance_weight

Learning from demonstrations with RRT*

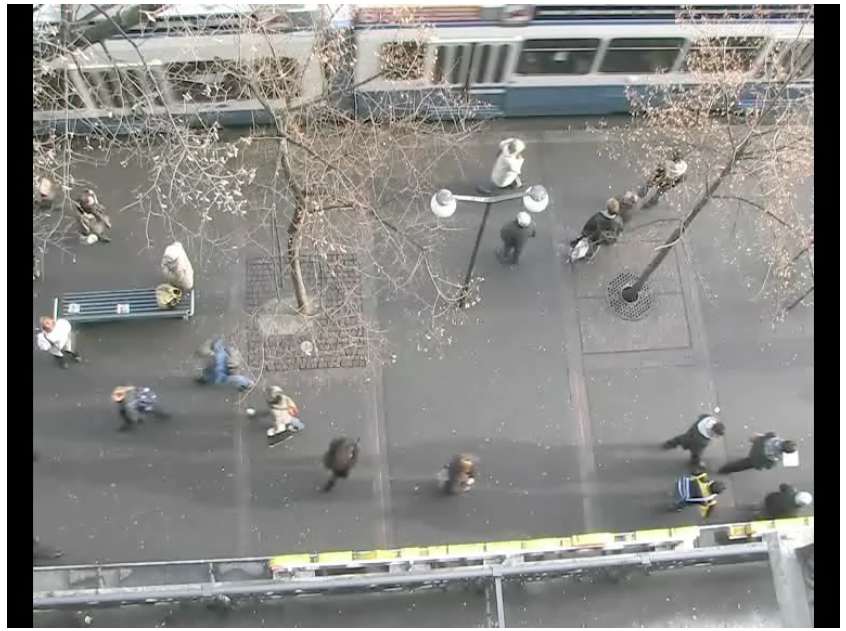




Noé Pérez-Higueras, Fernando Caballero, and Luis Merino. Teaching robot navigation behaviours to optimal RRT planners. In *International Journal of Social Robotics*, 2018.
https://github.com/robotics-upo/upo_nav_irl

Applying IRL to human-aware motion planning

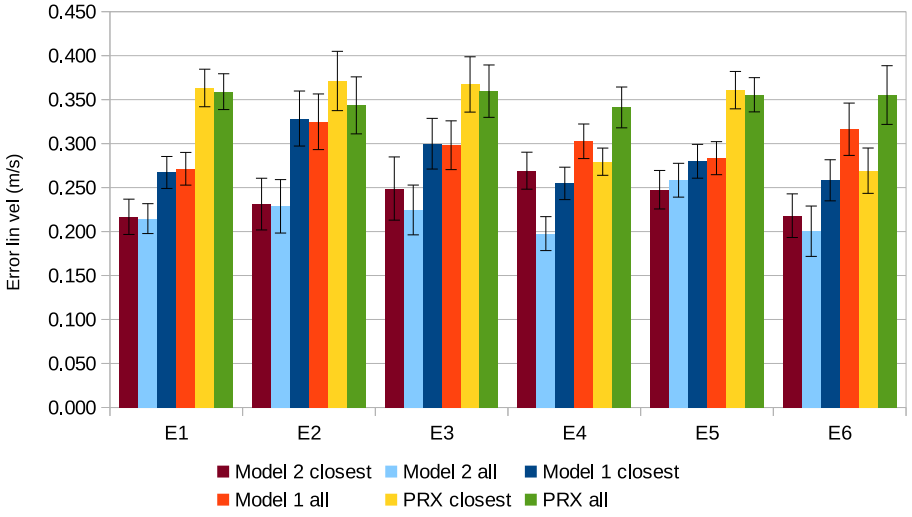
- Demonstrations: human navigation datasets
  - ETHZ BIWI Walking Pedestrians dataset

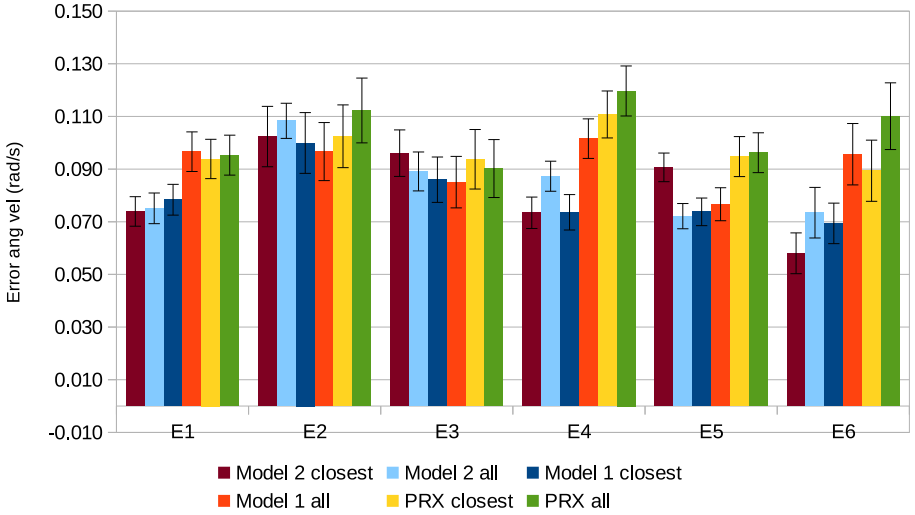


Scenario DS1

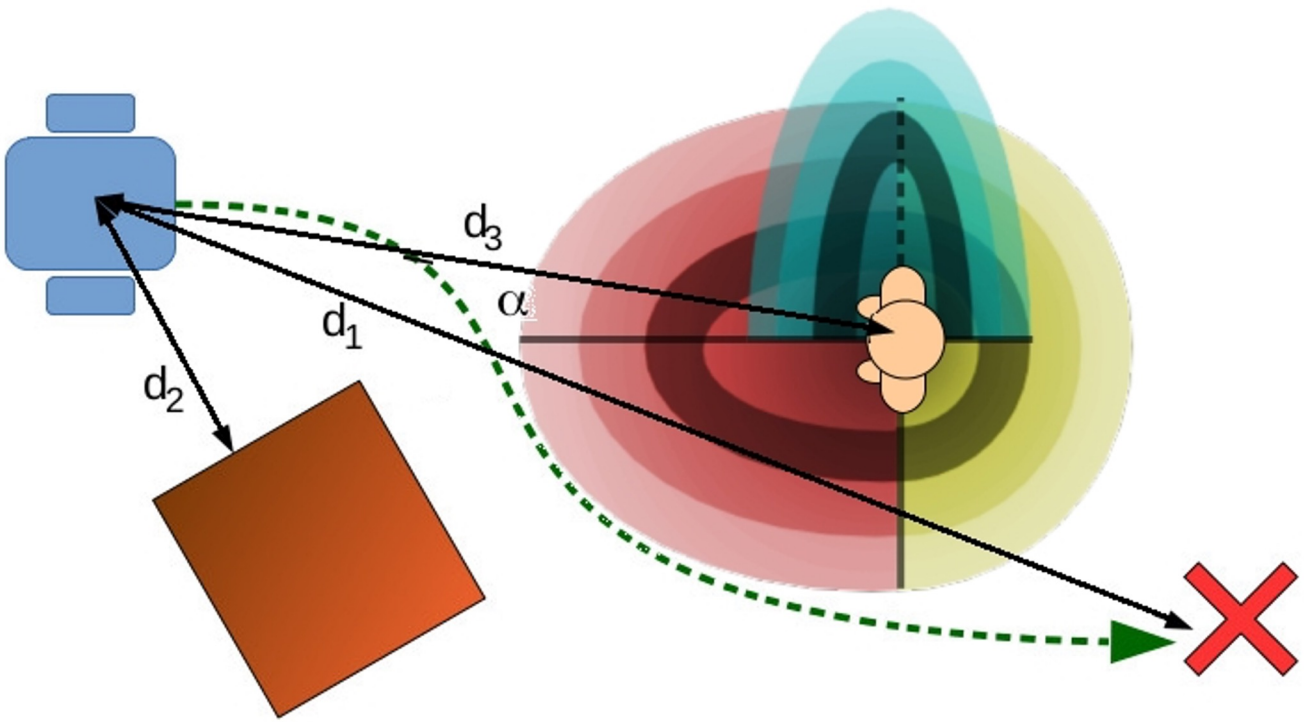
Scenario DS2

Applying IRL to human-aware motion planning





Features for social navigation



Distance to goal

Distance to closest obstacle

Distance and relative angle to person (front Gaussian)

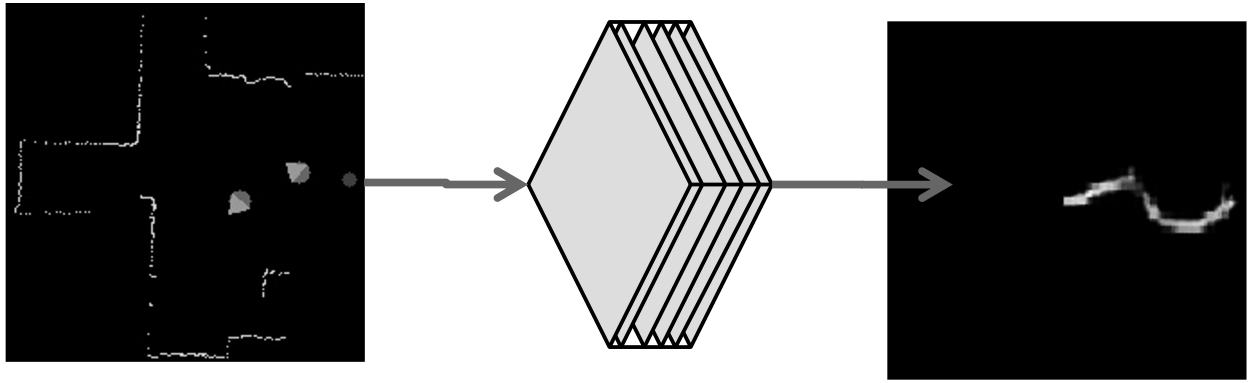
Distance and relative angle to person (rear Gaussian)

Distance and relative Angle to person (right side Gaussian)

$$c(x_k) = \omega_1 \cdot f_1(x_k) + \omega_2 \cdot f_2(x_k) + \omega_3 \cdot f_3(x_k) + \omega_4 \cdot f_4(x_k) + \omega_5 \cdot f_5(x_k)$$

Using Deep Networks to Learn Human-Aware Path Planning

- Using Deep Networks for path planning directly from sensor input
- Path planning as a classification problem
  - Use a Fully Convolutional Network (FCN) to directly predict the path given an scenario

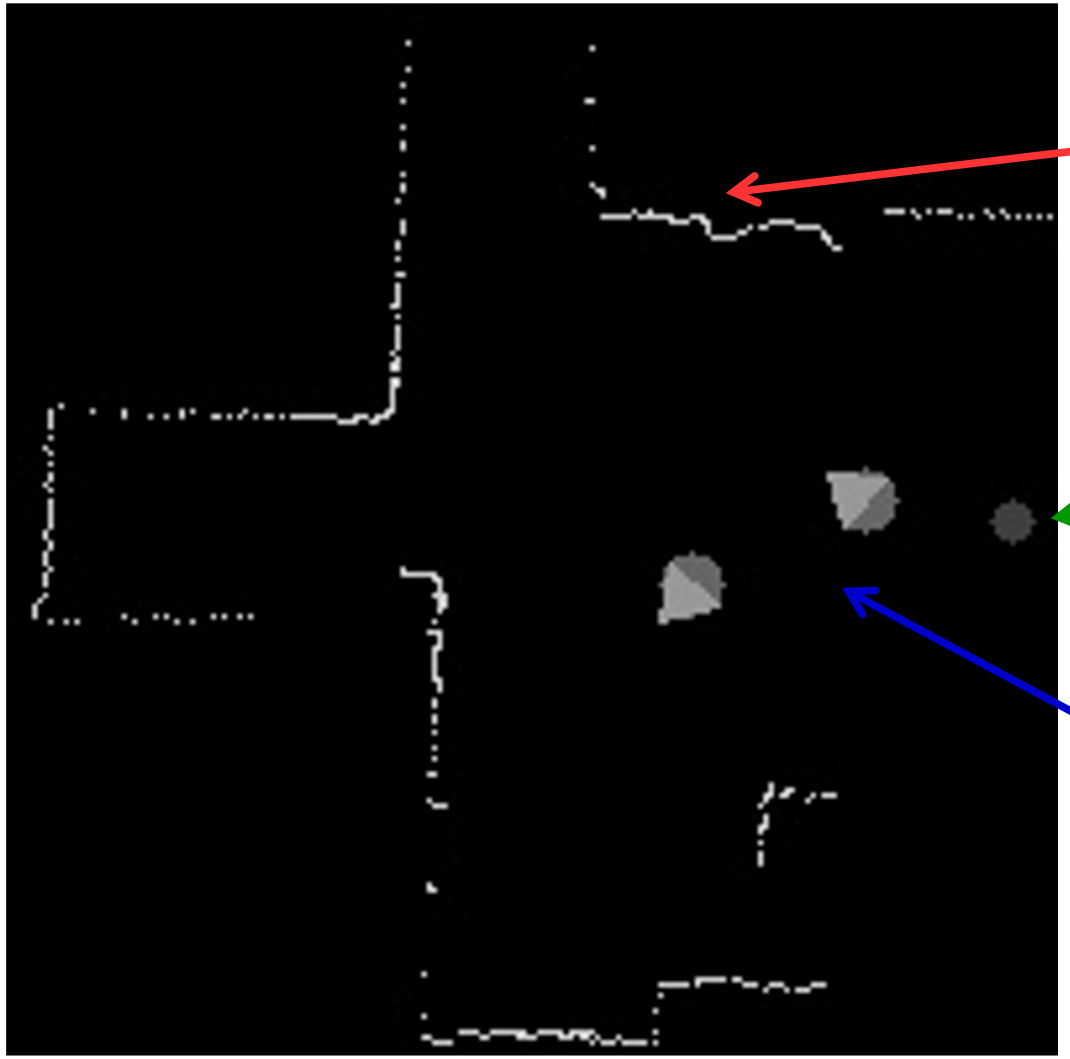



Camera
Reset
30 fps

Using Deep Networks to Learn Human-Aware Path Planning

FCN input:

- **200x200 px**
- **res: 0.05 m/px**
- **Robot-centered**



OBSTACLES
(Laser readings)

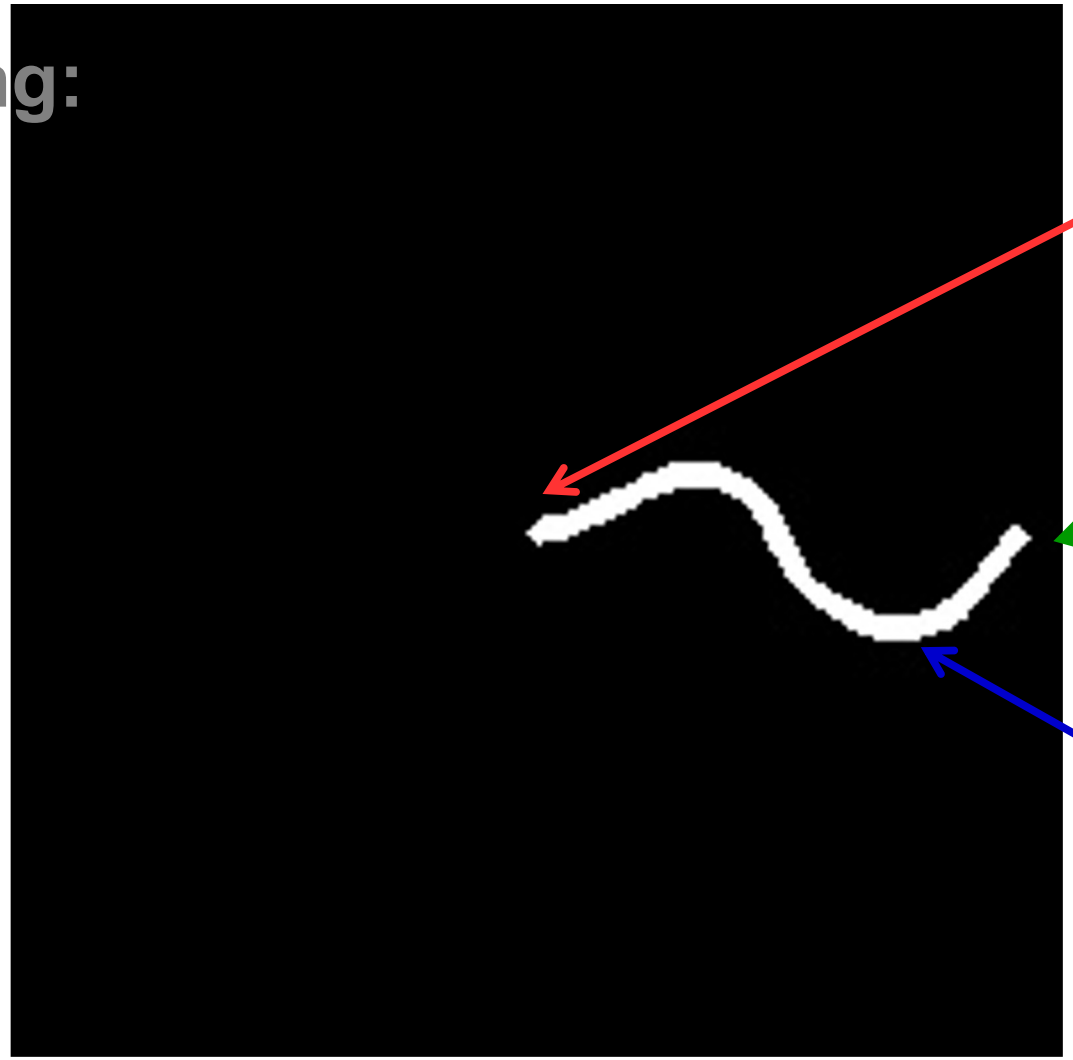
GOAL

PEOPLE
(position and orientation)

Using Deep Networks to Learn Human-Aware Path Planning

Labels for training:

- **200x200 px**
- **res: 0.05 m/px**
- **robot-centered**

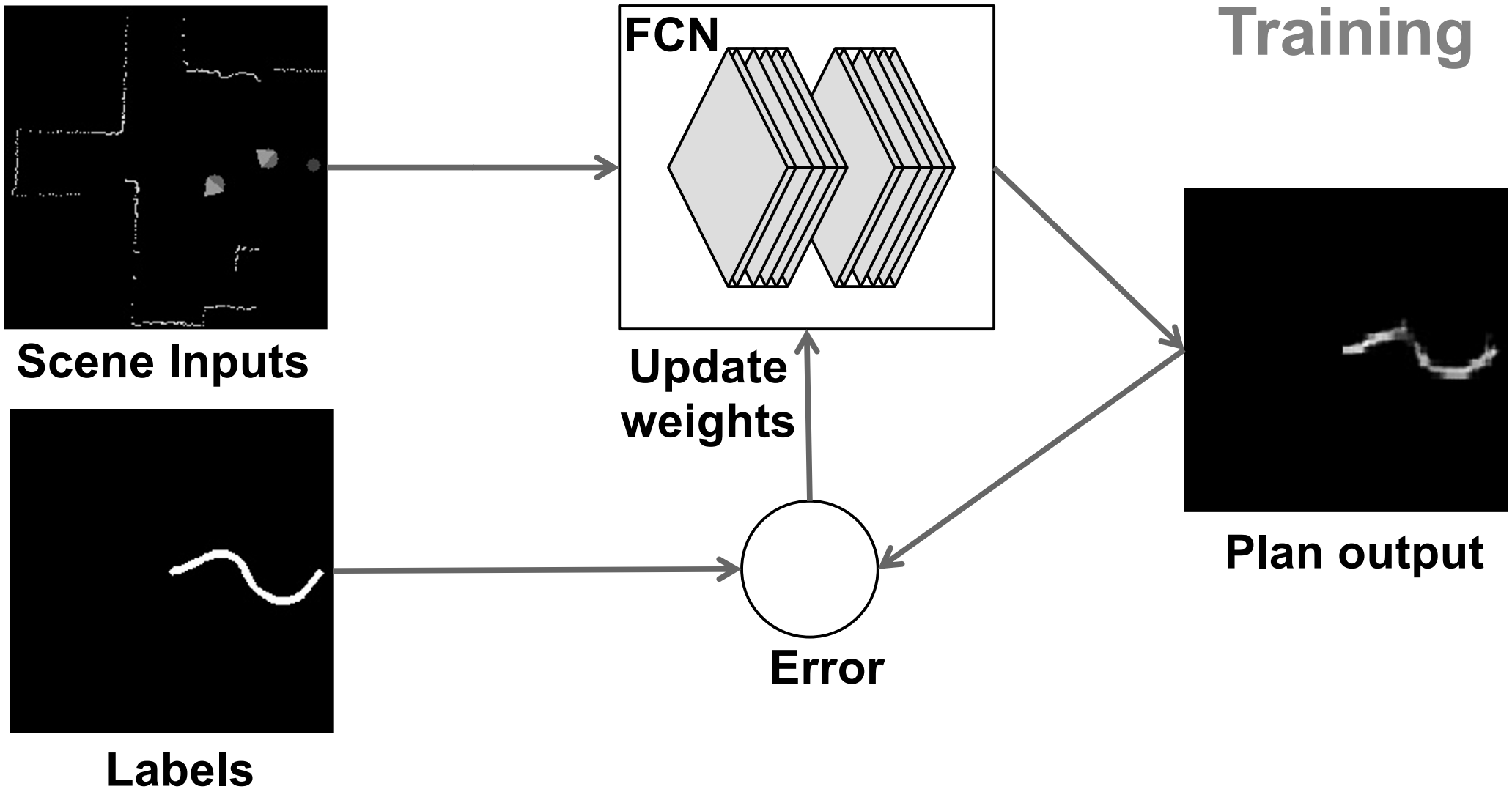


ROBOT POSITION (centered looking to the right)

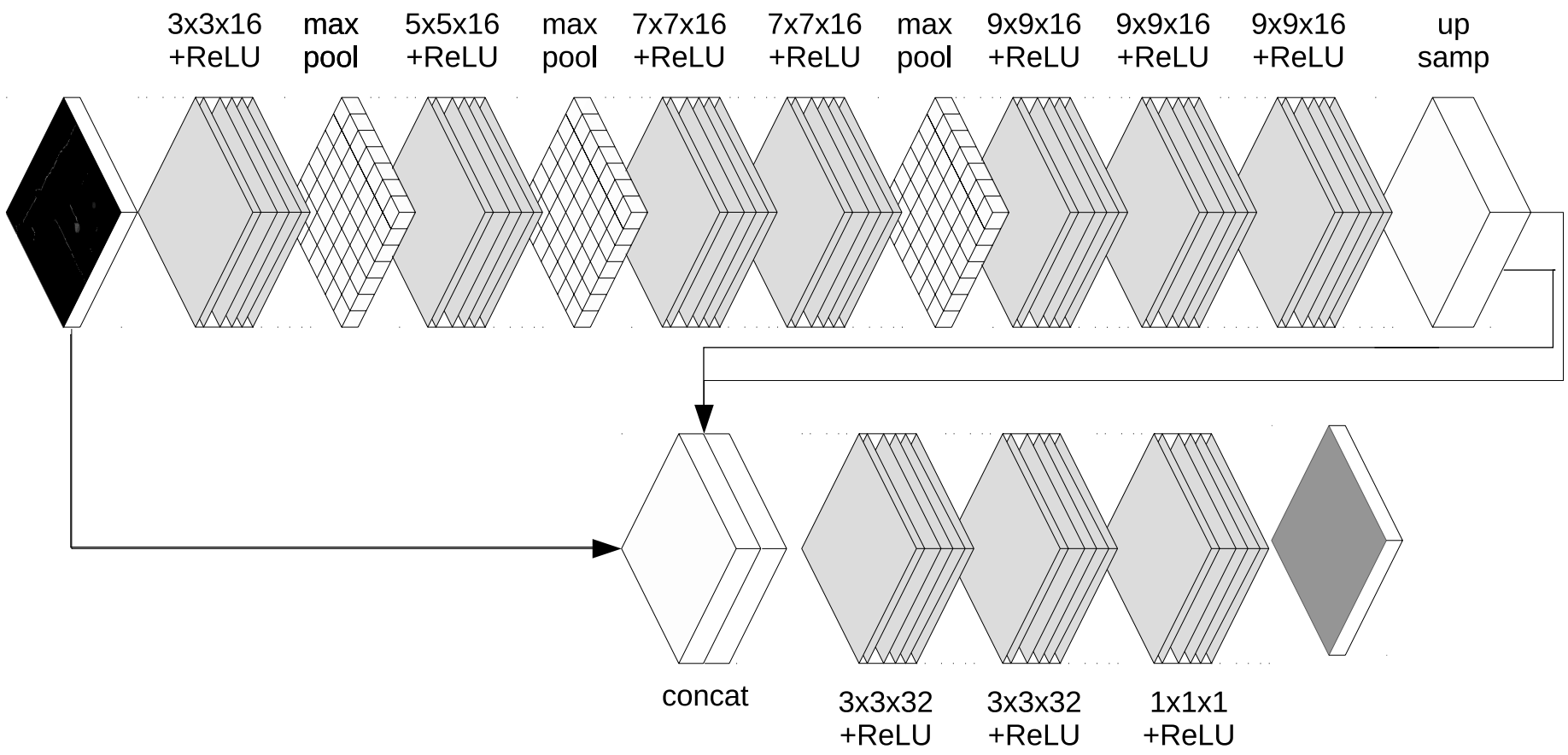
GOAL POSITION

PATH TO GOAL

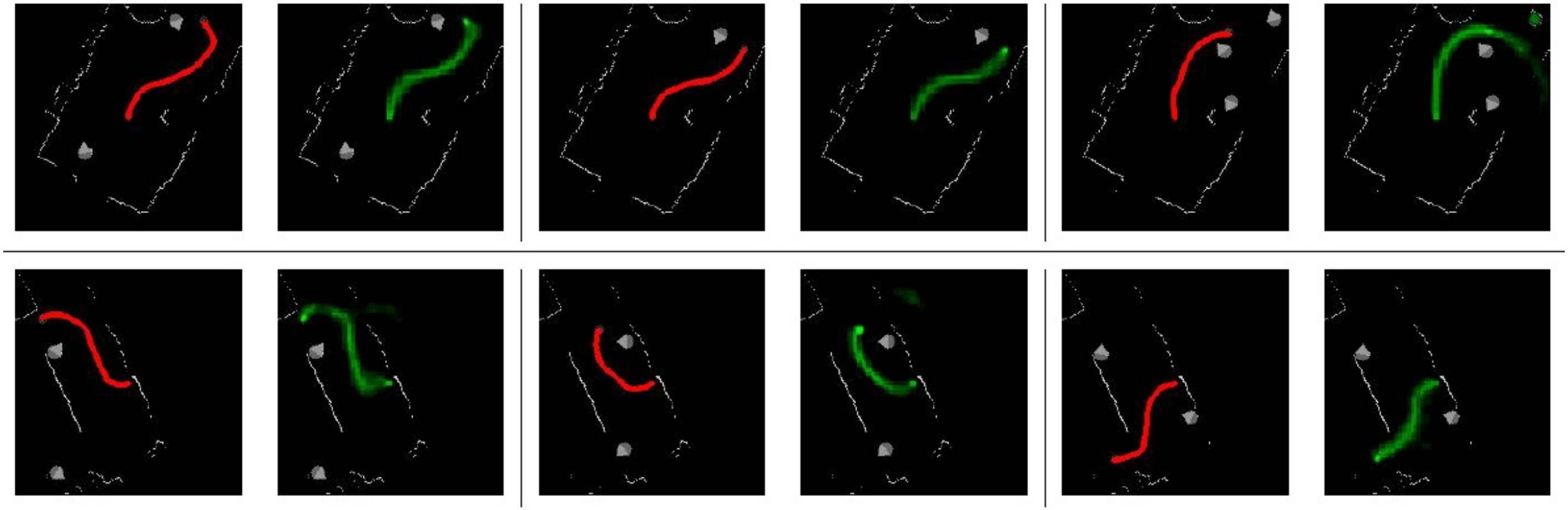
Using Deep Networks to Learn Human-Aware Path Planning



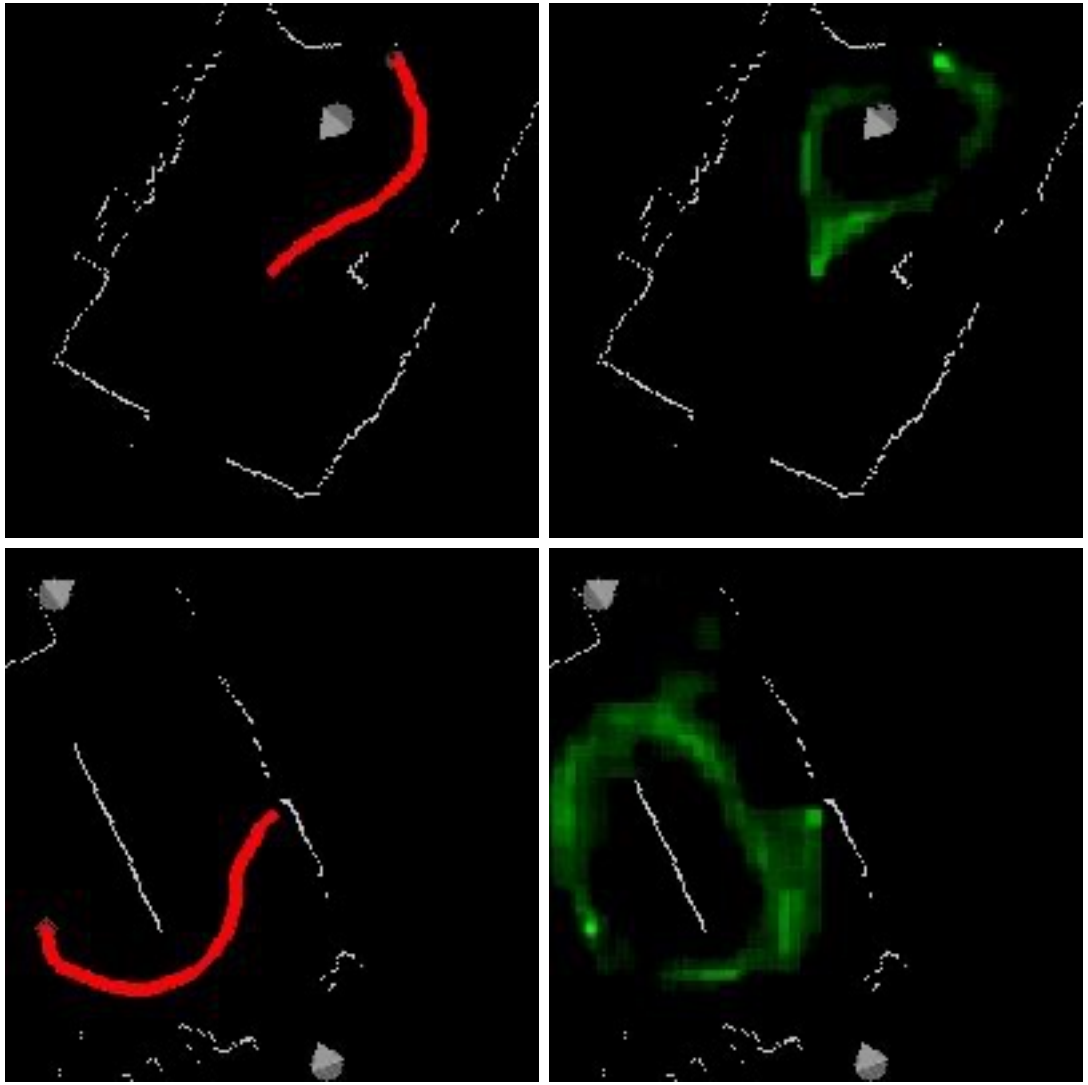
FCN architecture

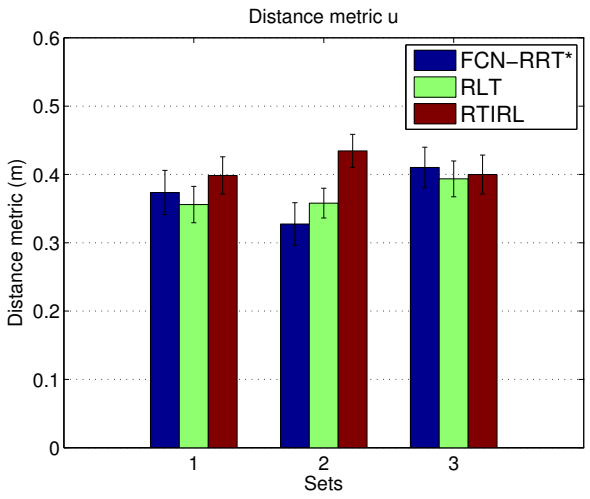


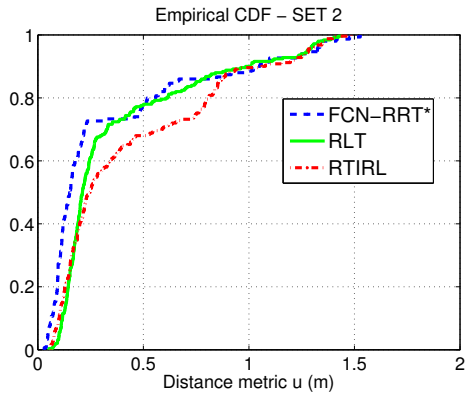
Validation of the FCN

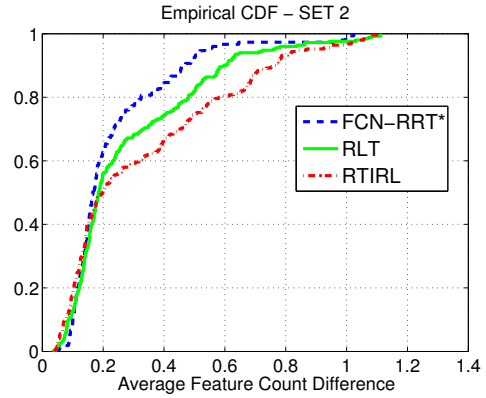


Validation of the FCN









N. Pérez-Higueras, F. Caballero and L. Merino, Learning Human-Aware Path Planning with Fully Convolutional Networks. In *Proceedings of the IEEE International Conference on Robotics and Automation*, ICRA, 2018

https://github.com/robotics-upo/upo_fcn_learning

Robot Expressivity

Haru’s Expressivity

- amused_3
- cheerful_3
- curious_3
- grumpy_3
- guilty_3
- sympathetic_3
- worried_3
- amused_7
- cheerful_7
- guilty_7
- sympathetic_7

- worried_7
- amused_10
- cheerful_10
- curious_10
- ecstatic_10
- guilty_10
- listening_10
- sympathetic_10
- listening_0
- listening_1
- listening_2

- thinking_0
- thinking_1
- thinking_2
- waking_up_1
- waking_up_2
- grumpy_7

Expressivity through motion

- Given animations designed to convey expressions like agreement or disagreement, happiness, sadness or shyness.
- We consider the question if such animations can be combined so to generate automatically expressions like, for instance, a shy disagreement.
- How the motion trajectories should be interpolated:
  - The manifold of motions representing a particular expression is complex.
  - Learning approaches can be applied to extract the relevant information, but only a handful of animations are available.

Encoding the demonstrated trajectories

- Each animation includes a demonstrated trajectory:
  - Temporal evolution of the 5 degrees of freedom
  - Expression
  - Intensity
- TP-GMM method (Calinon, 2015) to encode these examples

Encoding the demonstrated trajectories

Demonstrated Trajectories

Joint Distribution on Features

$$p(\mathbf{f}) = \sum_{i=1}^{k} \omega_i \mathcal{N}(\mathbf{f}; \mu^i, \Sigma^i) \qquad \mathbf{f} = [\mathbf{f}_{\mathcal{I}}^T, \mathbf{f}_{\mathcal{O}}^T]^T$$

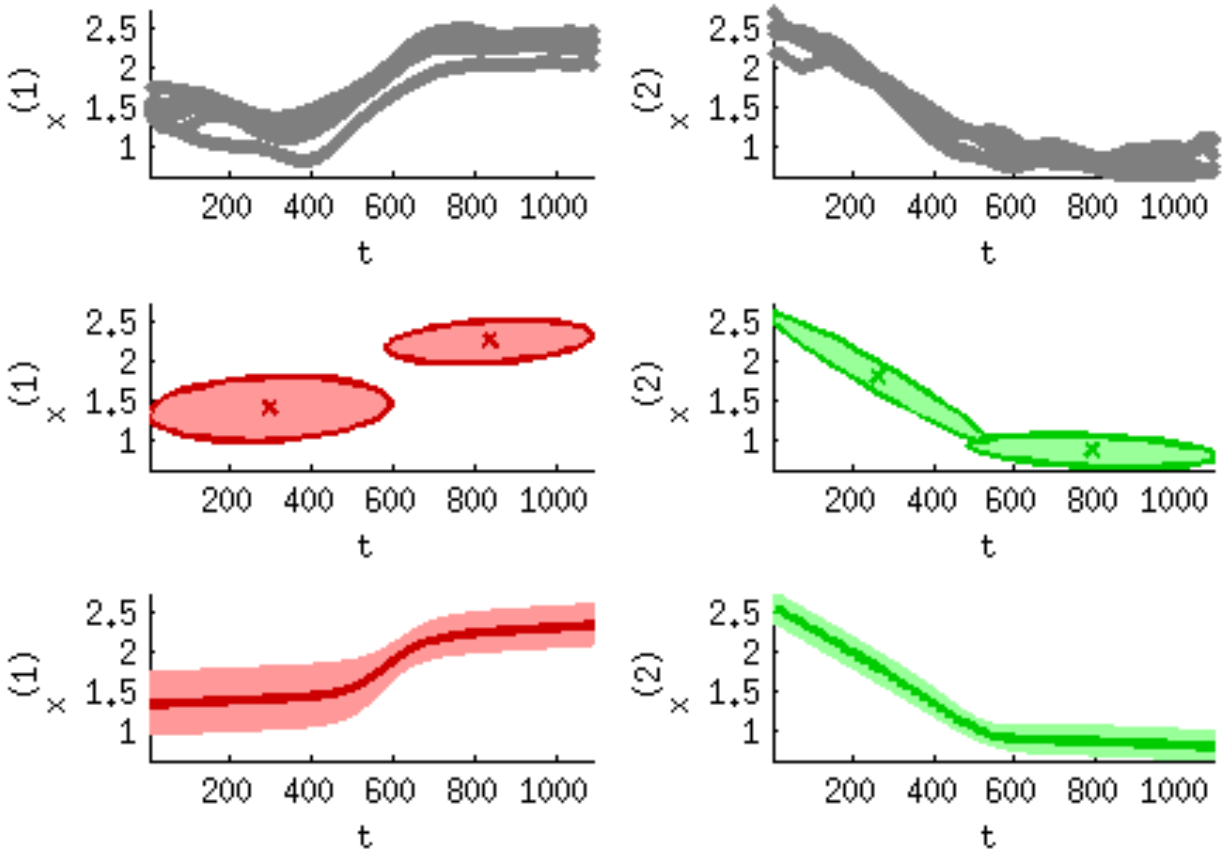
Time instants, Expression, Intensity

Position of joints

Generation of new trajectories

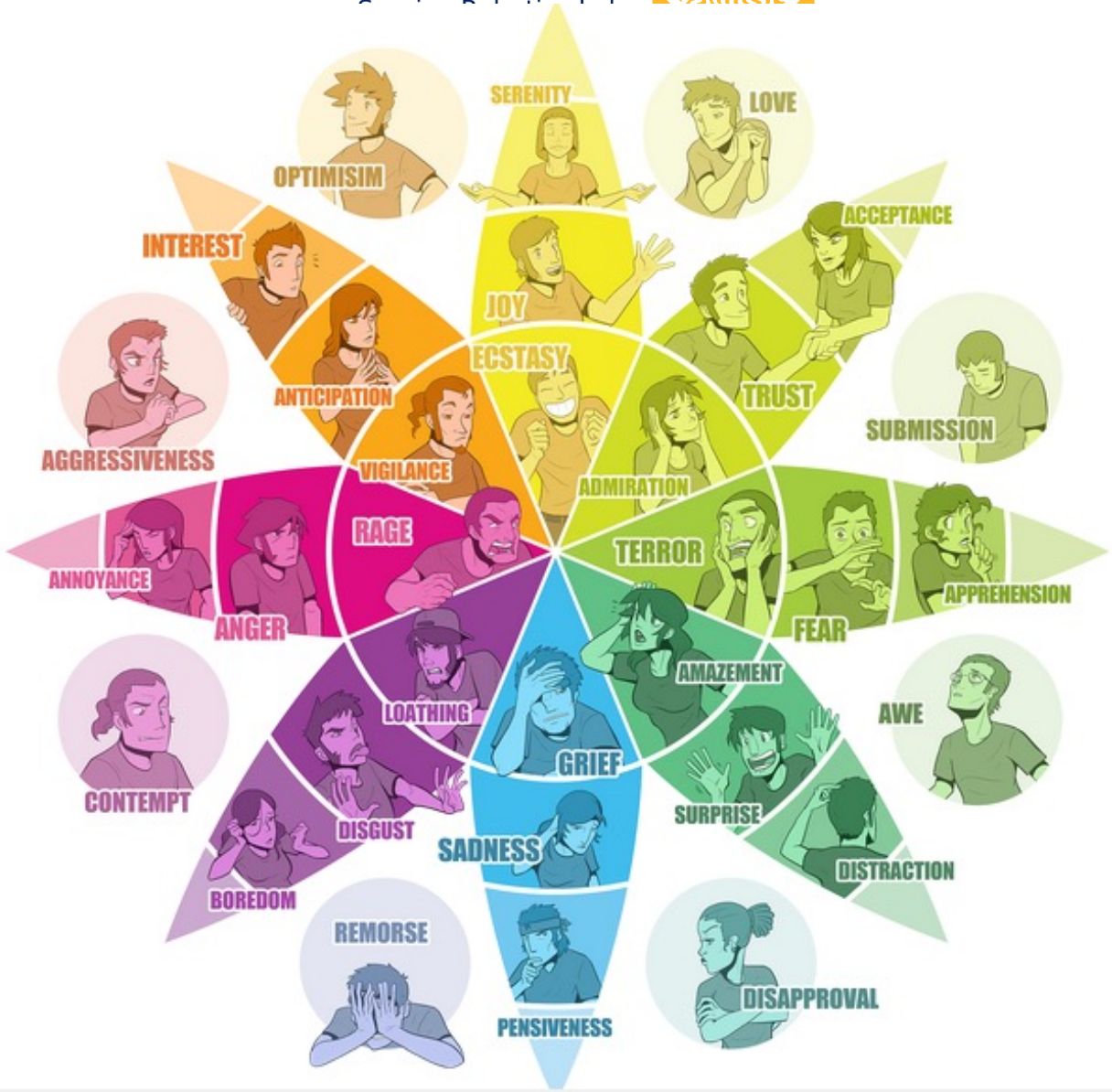
$$p(\mathbf{f}_{\mathcal{O}}|\mathbf{f}_{\mathcal{I}}) = \sum \pi_i p(\mathbf{f}_{\mathcal{O}}|\mathbf{f}_{\mathcal{I}}, i)$$

$$p(\mathbf{f}_{\mathcal{O}}|\mathbf{f}_{\mathcal{I}}, i) = \mathcal{N}(\mathbf{f}_{\mathcal{O}}; \mu^i_{\mathcal{O}|\mathcal{I}}(\mathbf{f}_{\mathcal{I}}), \Sigma^i_{\mathcal{O}|\mathcal{I}})$$

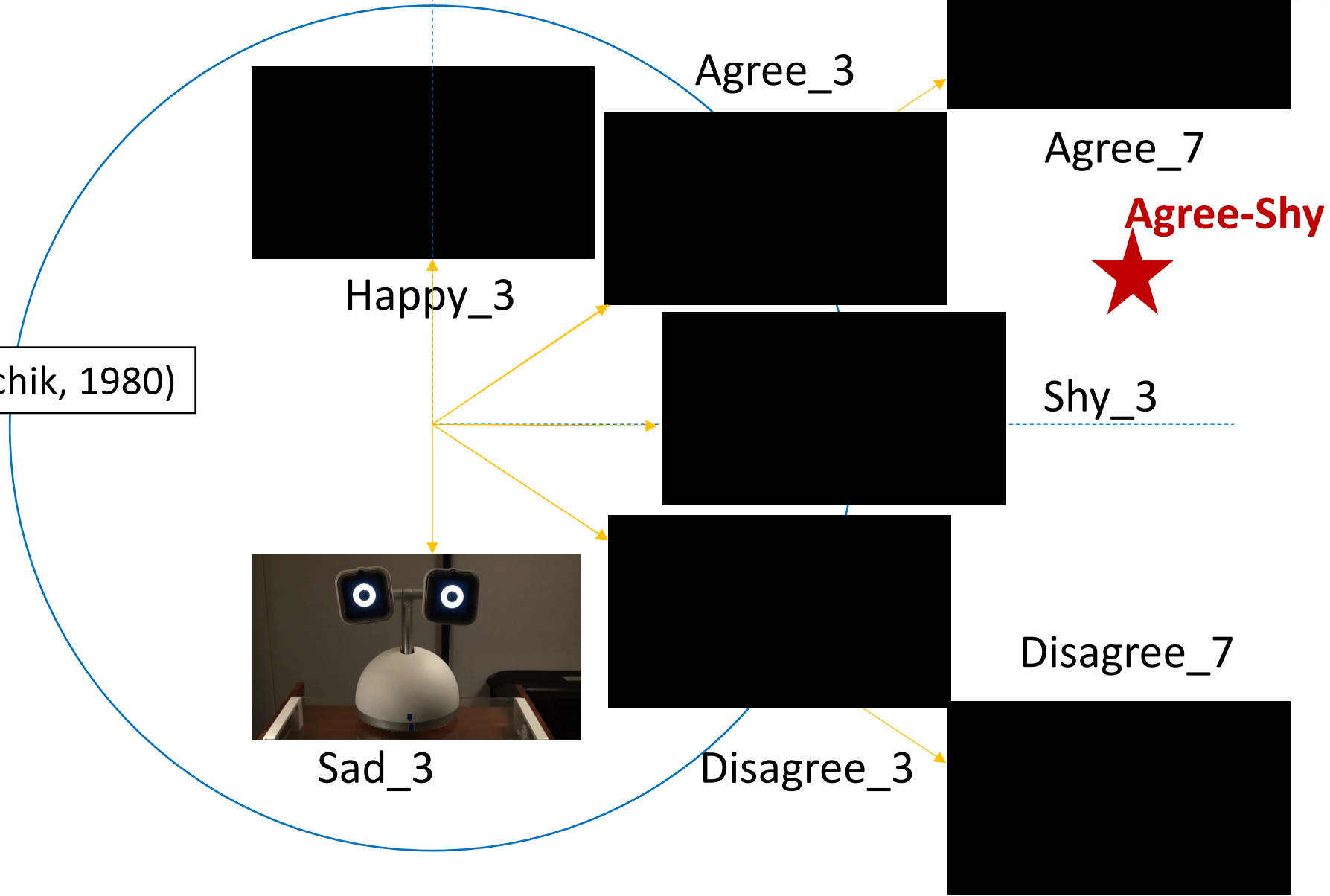


Encoding the demonstrated trajectories

Wheel of Emotion (Plutchik, 1980)



Encoding the demonstrated trajectories



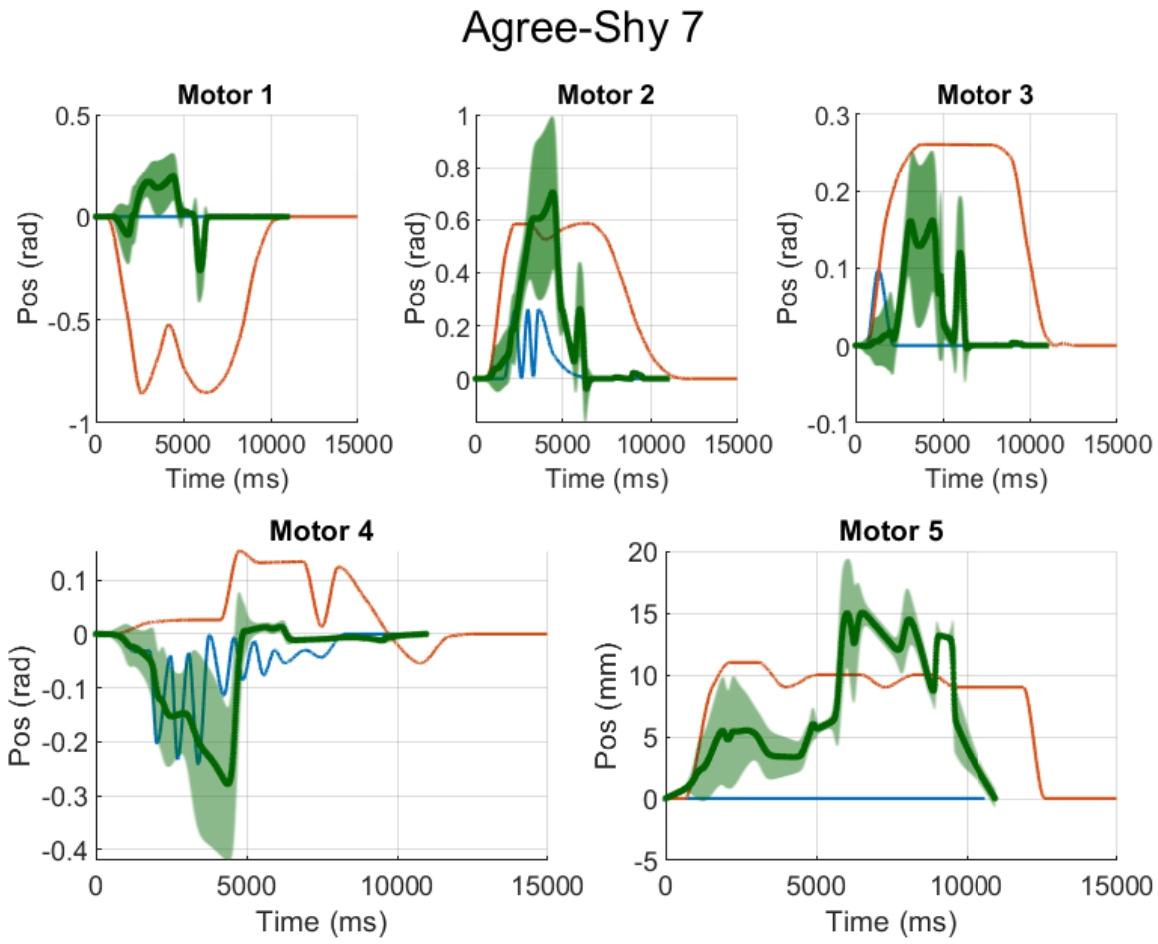
Wheel of Emotion (Plutchik, 1980)

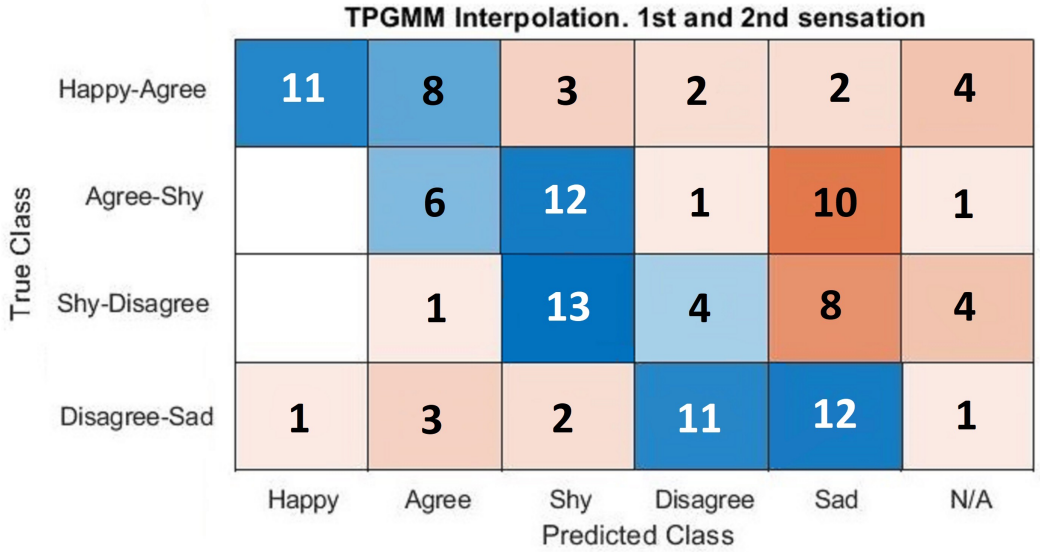
Agree 7

Shy 7

Agree – Shy
TPGMM

Generating Interpolated Motion





Gonzalo Mier, Fernando Caballero, Keisuke Nakamura, Luis Merino, and Randy Gomez.
Generation of expressive motions for a tabletop robot interpolating from hand-made animations.
In *Proceedings of the IEEE International Conference on Robot and Human Interactive Communication*, RO-MAN, 2019.

Conclusions and Outlook

- Social robotics require to consider the presence of people as a central part of a robot architecture
- Multi-modal perception of people is key
- Pertinent, expressive and legible robot behavior are required
- Data-driven approaches: social behaviors easy to demonstrate than to formalise

Machine Learning para los Retos de la Robótica Social

Luis Merino Cabañas

Service Robotics Laboratory

http://robotics.upo.es