

Efficient Multimodal Pedestrian Trajectory Prediction with Vectorized Representations





Introduction

- STELLANTIS
- 6 months internship (March to September)
- Supervised by: Julien Moreau & Lina Achaji
- Worked on Efficient Multimodal Pedestrian Trajectory Prediction

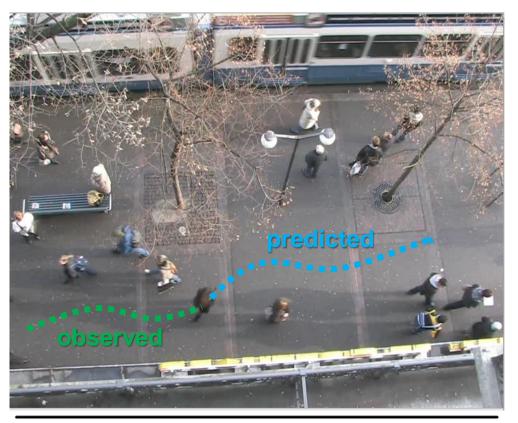


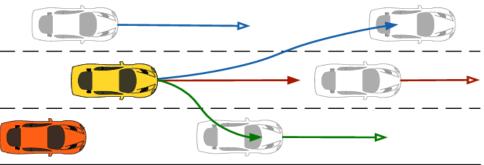
Context & Background



Pedestrians Trajectory Prediction

- Given past observations, predict future positions
- Important for Autonomous vehicles
- Predict future = anticipate and avoid Collisions
- Multimodal = multiple trajectories







Motivation

Vehicle trajectory prediction focuses on Efficiency

Pedestrian trajectory prediction, not as much...



Literature review



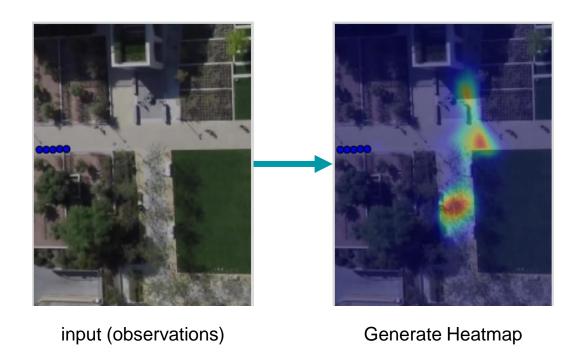






input (observations)





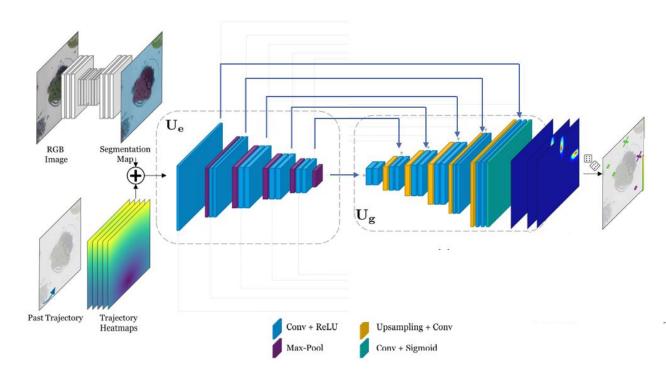








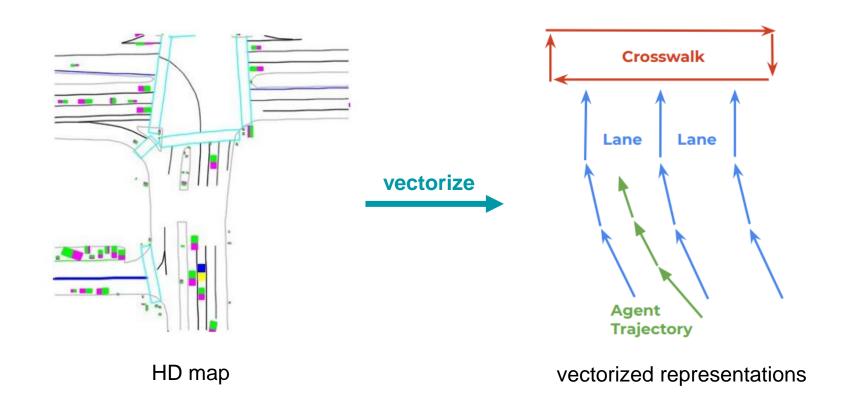
- Y-net (UC Berkeley 2020)
- **CNN** to predict the goals
- Lacks Efficiency
- All SOTA goal-based methods used it



Goal prediction in Y-net



VectorNet: vectorized representations





DenseTNT

- Goal-based method, developed for vehicle trajectory predictions
- VectorNet backbone
- 1st place on the 2021 Waymo Challenge



PreTR: Prediction Transformer

- Developed in Stellantis, for pedestrian trajectory prediction
- Focuses on modeling pedestrians social interactions
- Deterministic, not multimodal

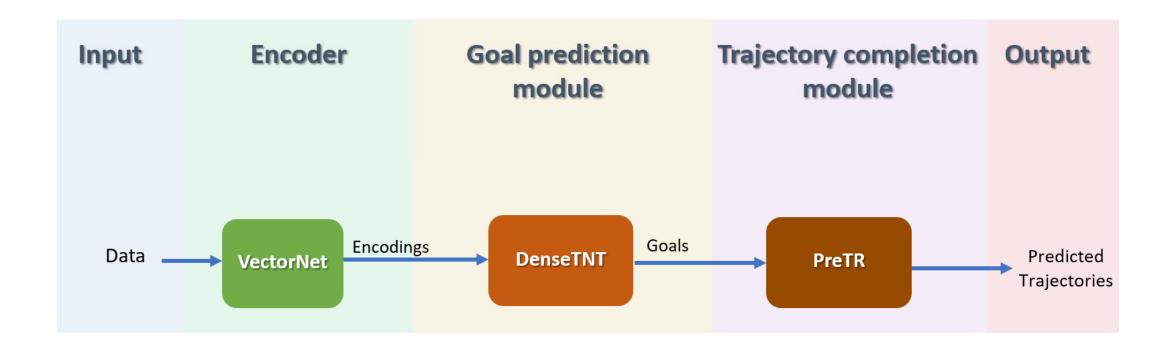


Methodology





General architecture

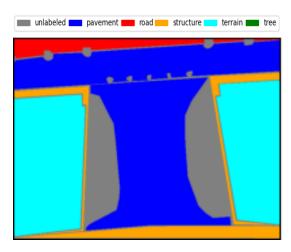






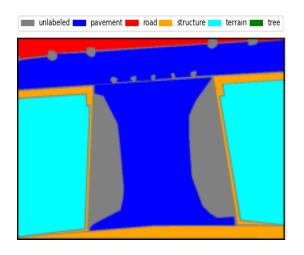


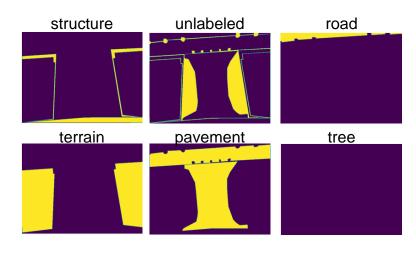






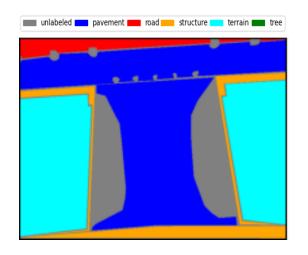


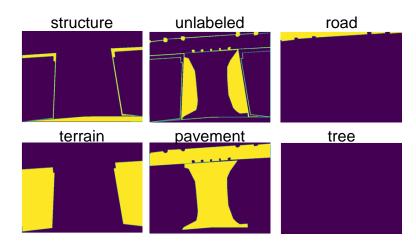


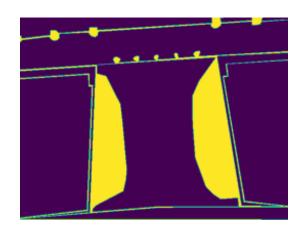




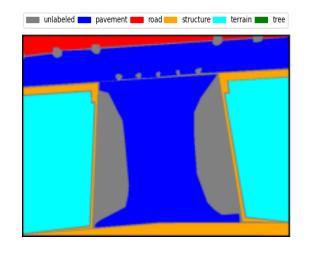


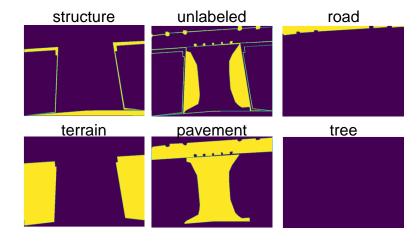


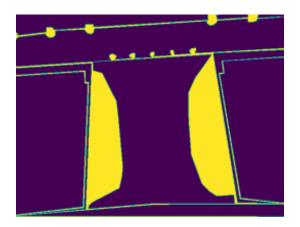






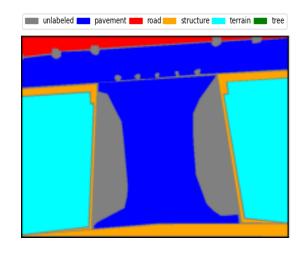


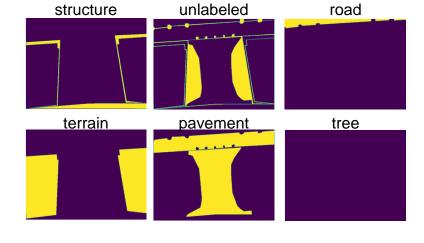


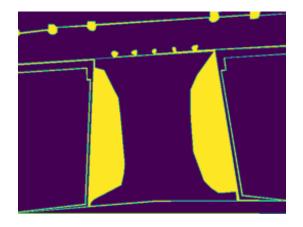




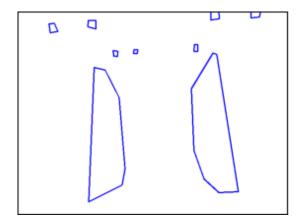




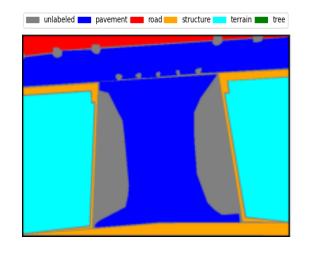


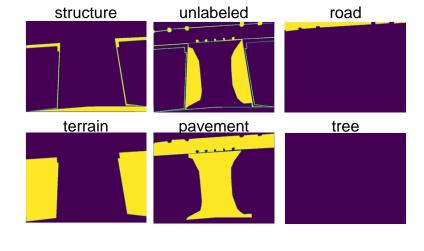


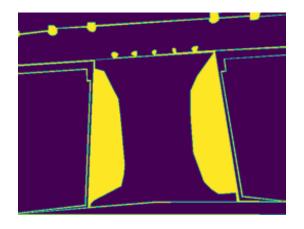


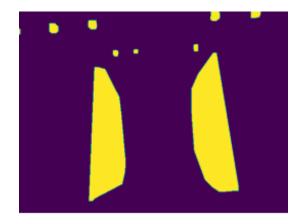


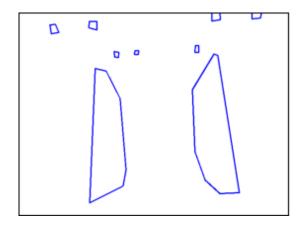


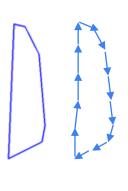












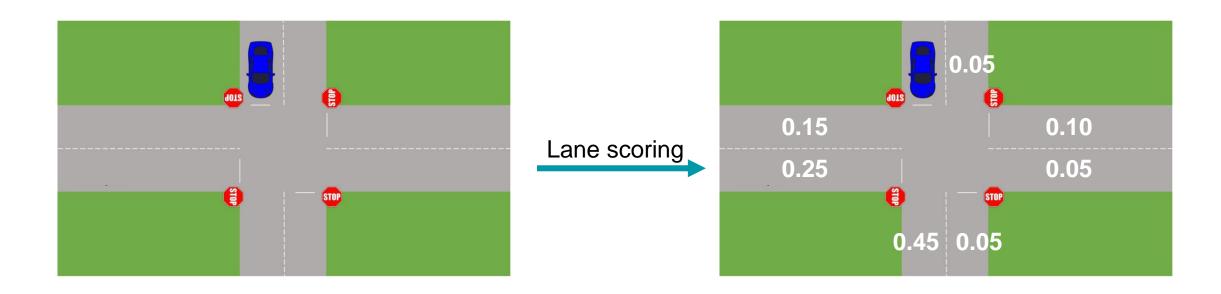


Goal prediction module

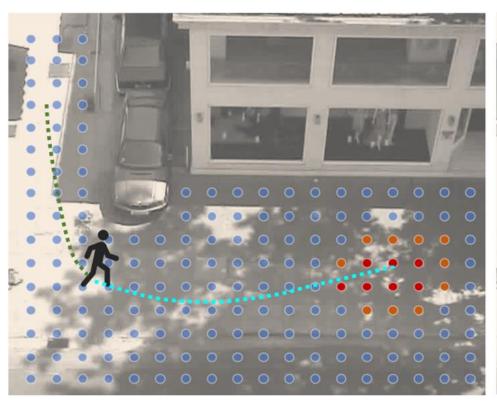
- Two stages training:
 - First stage learn to generate the Heatmap
 - Second stage learn to predict the Goals

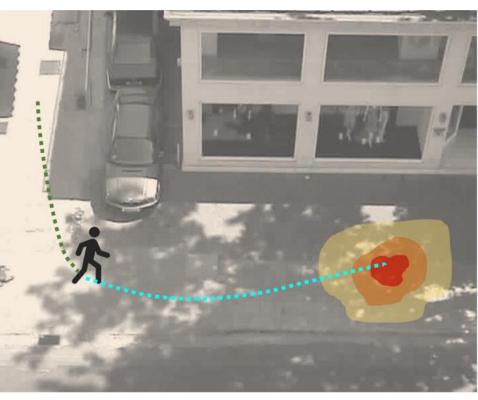


Heatmap generation



Heatmap generation





Sparse heatmap

Dense heatmap



Goal prediction

Offline optimization-based algorithm for pseudo-labels loss



Winner-Takes-All loss

$$\mathcal{L}_{ ext{wta}} = \min_{c_i \in \hat{C}} \left\| c_i - y_{T_{pred}} \right\|$$

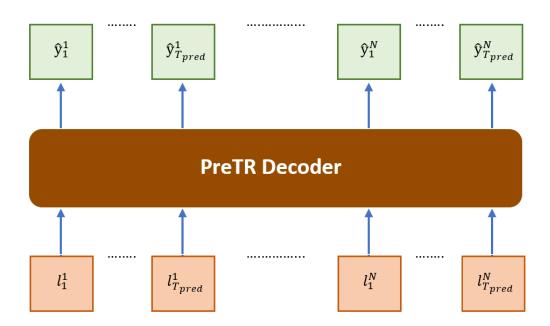


Trajectory completion module

- Feed the goals to PreTR
- Given a goal, predict a trajectory
- K predicted goals = K different trajectories

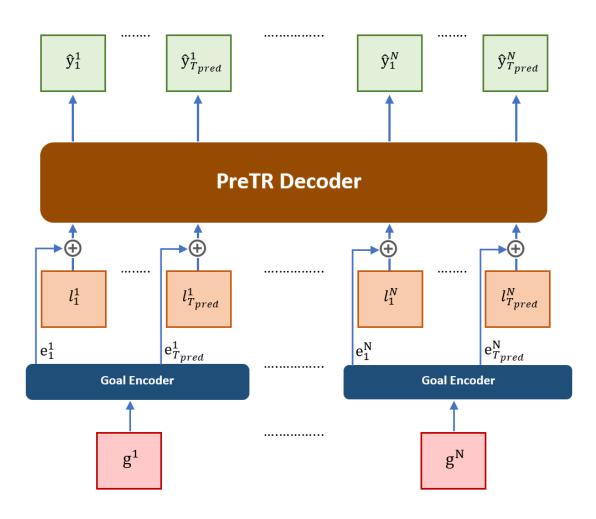


Trajectory completion module





Trajectory completion module





Results





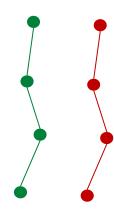
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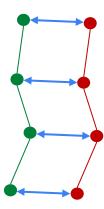


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 - minFDE (minimum final displacement error)
 - minADE (minimum average displacement error)





Results

Evaluation Metrics: $minADE_{20} \downarrow / minFDE_{20} \downarrow [meters]$									
Method	ETH	HOTEL	UNIV	ZARA1	ZARA2	AVG			
Social-LSTM (Alahi et al., 2016)	1.09/2.35	0.79/1.76	0.67/1.40	0.47/1.00	0.56/1.17	0.72/1.54			
Social-GAN (Gupta et al., 2018)	0.81/1.52	0.72/1.61	0.60/1.26	0.34/0.69	0.42/0.84	0.58/1.18			
Goal-GAN (Dendorfer et al., 2020)	0.59/1.18	0.19/0.35	0.60/1.19	0.43/0.87	0.32/0.65	0.43/0.85			
ST-GAT (Huang et al., 2019)	0.65/1.12	0.35/0.66	0.52/1.10	0.34/0.69	0.29/0.60	0.43/0.83			
MG-GAN (Dendorfer et al., 2021)	0.47/0.91	0.14/0.24	0.54/1.07	0.36/0.73	0.29/0.60	0.36/0.71			
Transformer-TF (Giuliari et al., 2020)	0.61/1.12	0.18/0.30	0.35/0.65	0.22/0.38	0.17/0.32	0.31/0.55			
STAR (Yu et al., 2020)	0.36/0.65	0.17/0.36	0.31/0.62	0.26/0.55	0.22/0.46	0.26/0.53			
PECNet (Mangalam et al., 2020b)	0.54/0.87	0.18/0.24	0.35/0.60	0.22/0.39	0.17/0.30	0.29/0.48			
Trajectron++ (Salzmann et al., 2021)	0.39/0.83	0.12/0.21	0.20/0.44	0.15/0.33	0.11/0.25	0.19/0.41			
AgentFormer (Yuan et al., 2021)	0.45/0.75	0.14/0.22	0.25/0.45	0.18/0.30	0.14/0.24	0.23/0.39			
Goal-SAR (Chiara et al., 2022)	0.28/0.39	0.12/0.17	0.25/0.43	0.17/0.26	0.15/0.22	0.19/0.29			
Y-net (Mangalam et al., 2020a)	0.28/0.33	0.10/0.14	0.24/0.41	0.17/0.27	0.13/0.22	0.18/0.27			
NSP-SFM (Yue et al., 2023)	0.25/0.24	0.09/0.13	0.21/0.38	0.16/0.27	0.12/0.20	0.17/0.24			
Ours	0.52/0.65	0.17/0.24	0.32/0.50	0.24/0.37	0.21/0.31	0.30/0.42			
\pm std	\pm 0.01/0.03	$\pm 0.00/0.01$	$\pm 0.01/0.01$	$\pm 0.00/0.01$	$\pm 0.00/0.01$	\pm 0.00/0.01			
Ours (offline)	0.54/0.69	0.17/0.27	0.32/0.49	0.26/0.39	0.22/0.34	0.30/0.44			
\pm std	$\pm 0.01/0.04$	$\pm 0.00/0.00$	\pm 0.00/0.00	$\pm 0.01/0.01$	$\pm 0.02/0.01$	\pm 0.00/0.01			

CNN



Efficiency

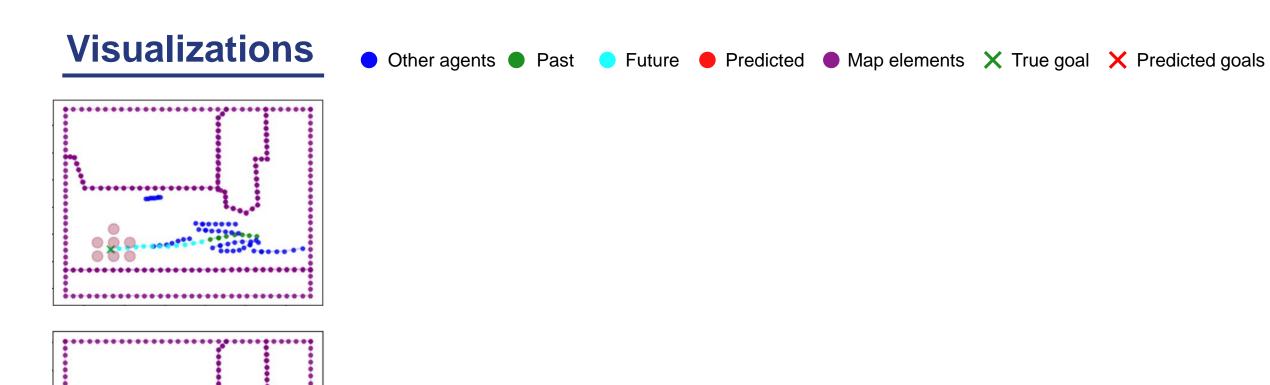
Model	Trai	ning	Inference		
	UNIV	ZARA1	UNIV	ZARA1	
Goal-SAR	16:54:45	15:33:48	02:12:16	00:06:10	
Ours (offline)	04:36:58	08:38:04	00:04:55	00:00:28	
Ours	02:31:15	04:49:40	00:04:52	00:00:26	



Visualizations

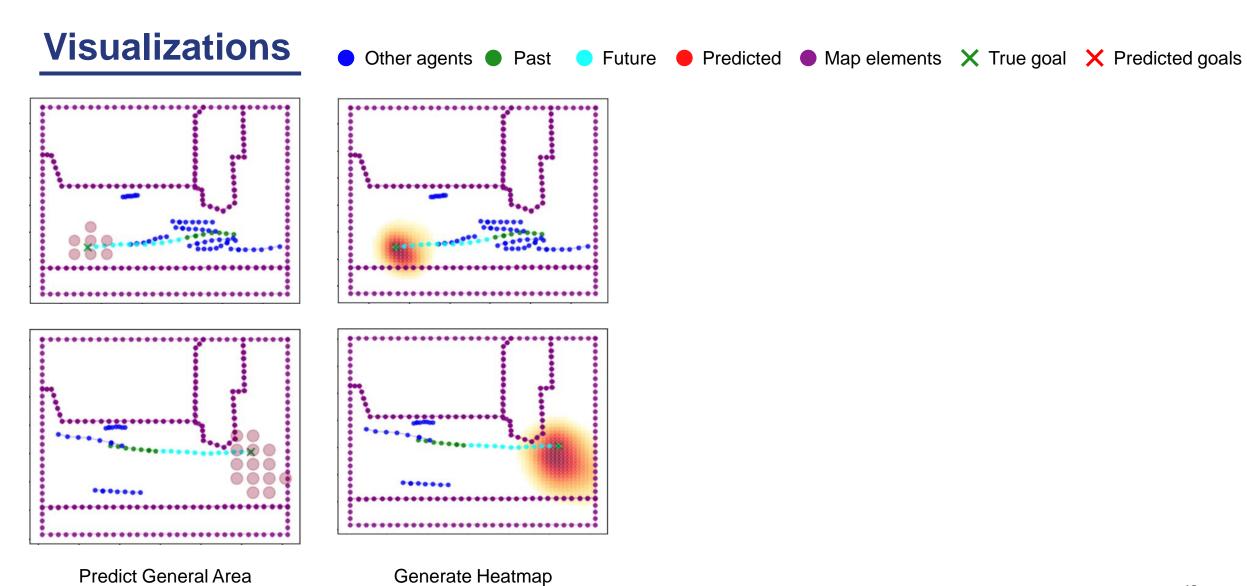
Other agents ● Past ● Future ● Predicted ● Map elements 🗙 True goal 🗙 Predicted goals

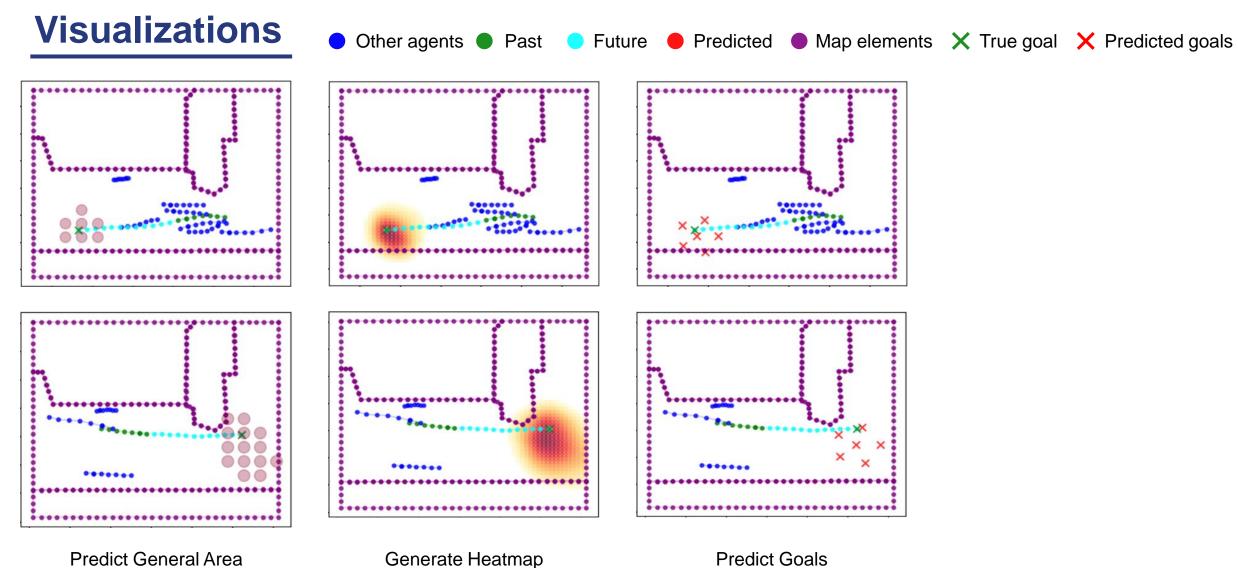
Introdcution > Context > Literature review > Methodology > Results > Conclusion

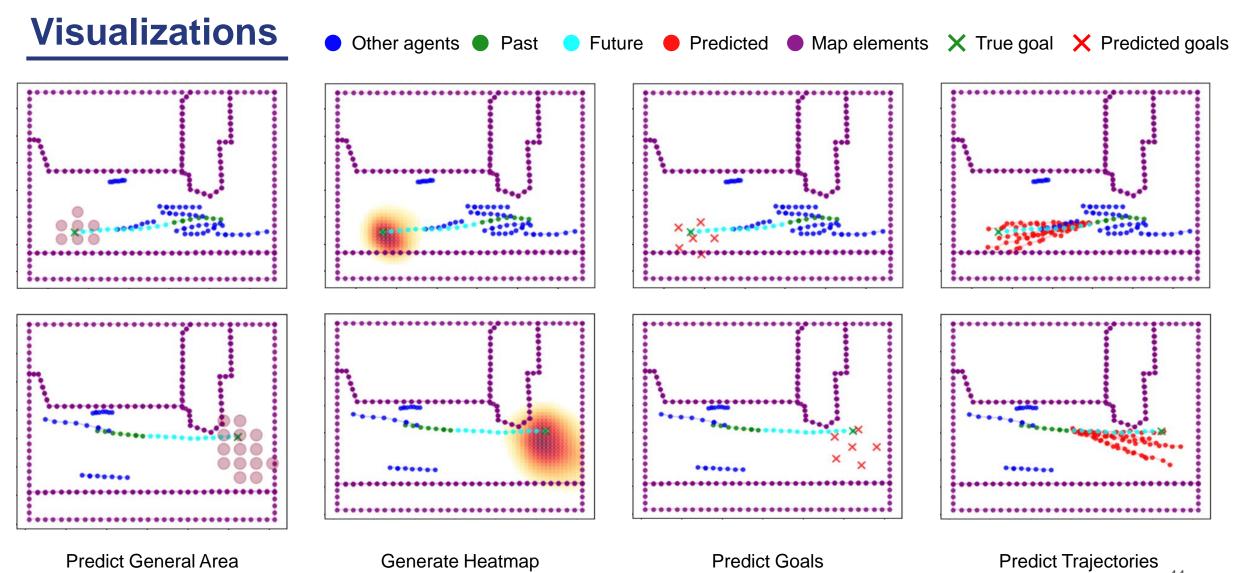




Introdcution > Context > Literature review > Methodology > Results > Conclusion









Conclusion





Conclusion & Perspective

- Important gap with CNN-based methods, but more efficient
- Adapt vectorized representations to the pedestrian's case

