

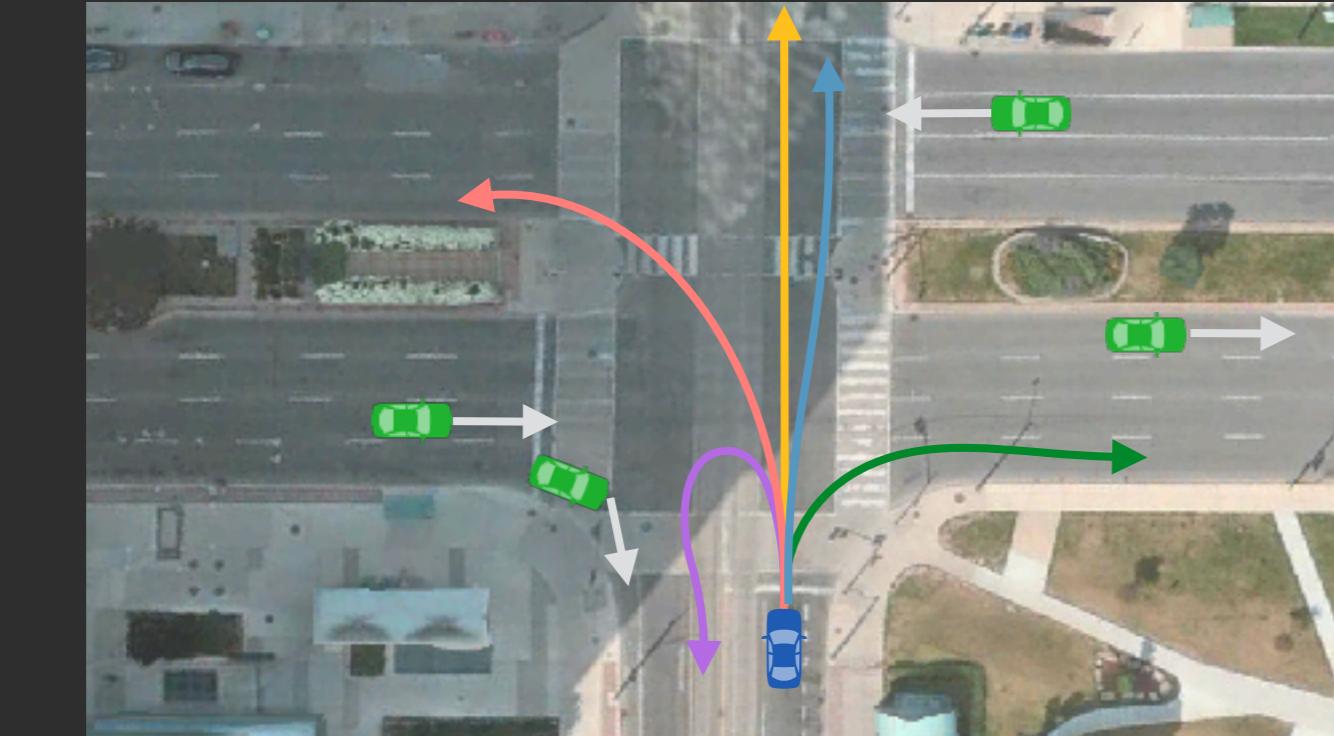


Multiple Futures Prediction

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Challenge

How to make multi-agent interactive multimodal future predictions?



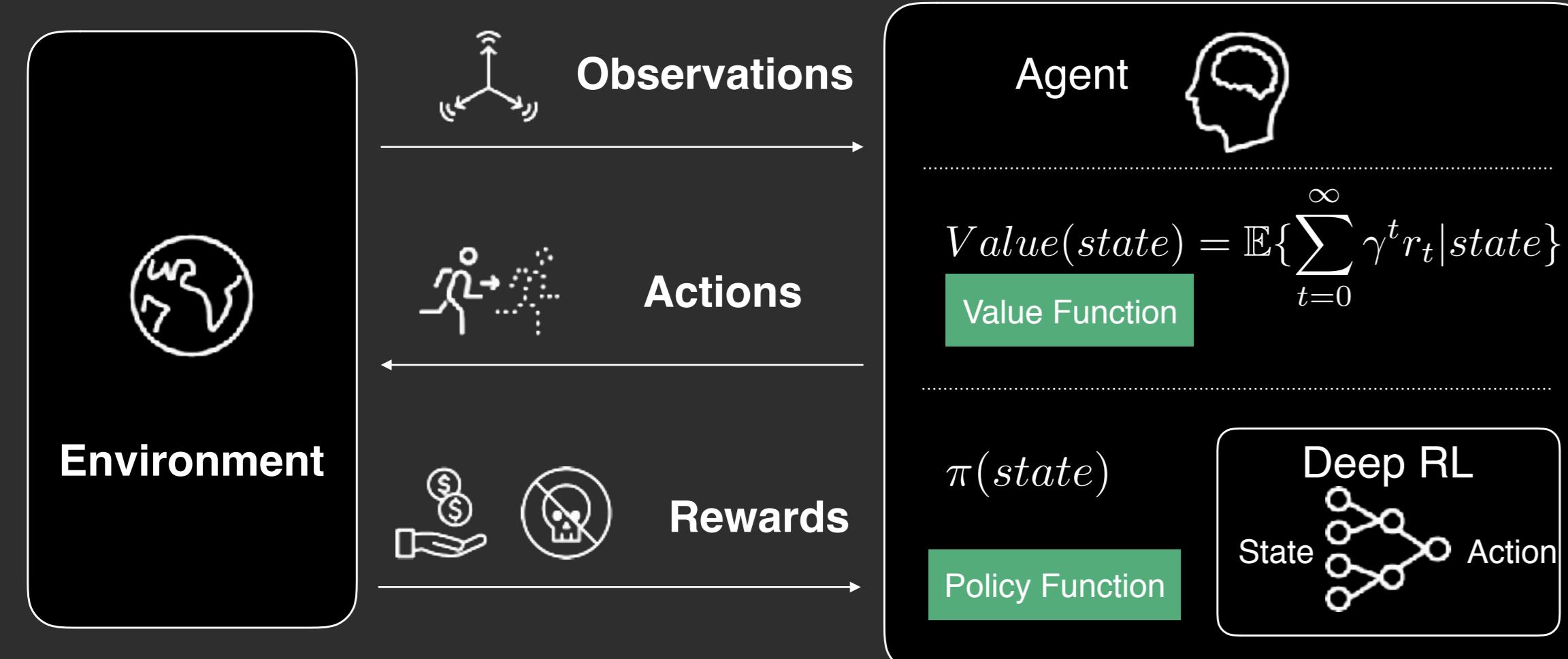
Deep RL + Self-play

- Learn policies automatically from simulation
- As training progresses, iteratively add more capable agents to the training environment
- Increases diversity and complexity of the simulation
- Leads to the learning of more robust policies

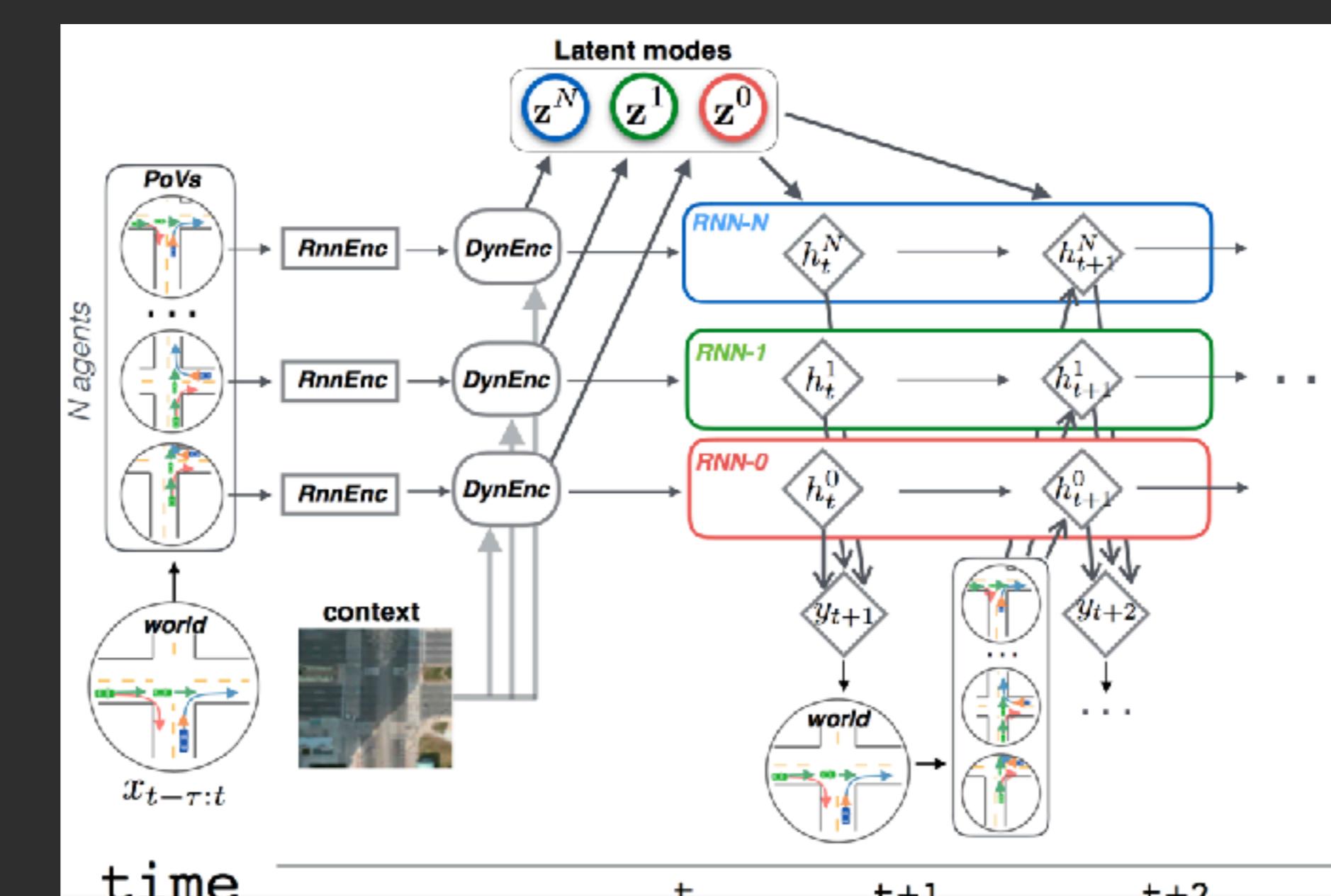
Our Contributions

- 2D sim env with topology and motion model
- Rule-based (IDM) agents with adaptive cruise control and simple lane change capabilities
- RL learning from rasterized + low dimensional inputs
- Qualitatively: learns human-like policies
- Quantitatively: improves success rate from 63% to over 98% via self-play training

Reinforcement Learning

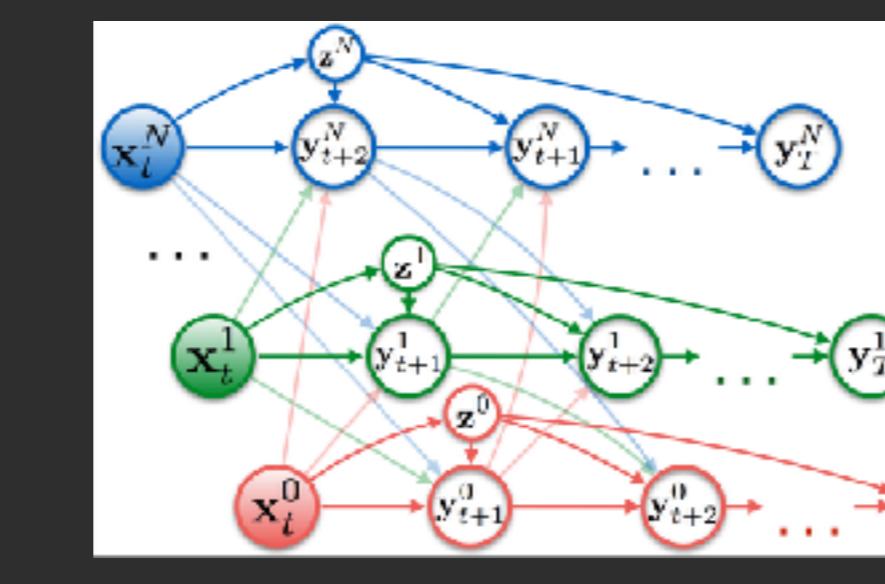


MFP Predictive Model

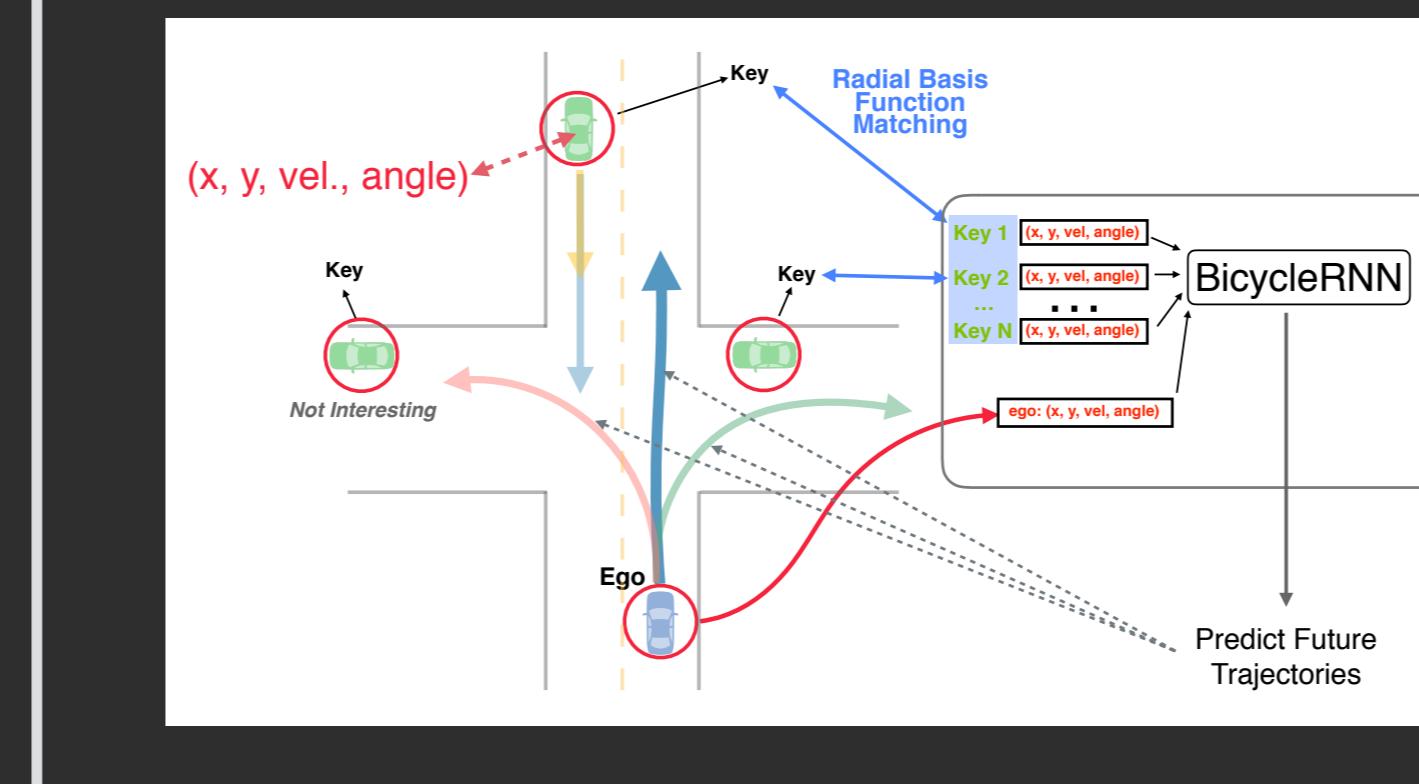


Parameters	Values
Scale	340m
Target Velocity	[10, 20] m/s
# Other Agents	[0, 10]
Spawn %	1%
Reward: Success	+100, 0

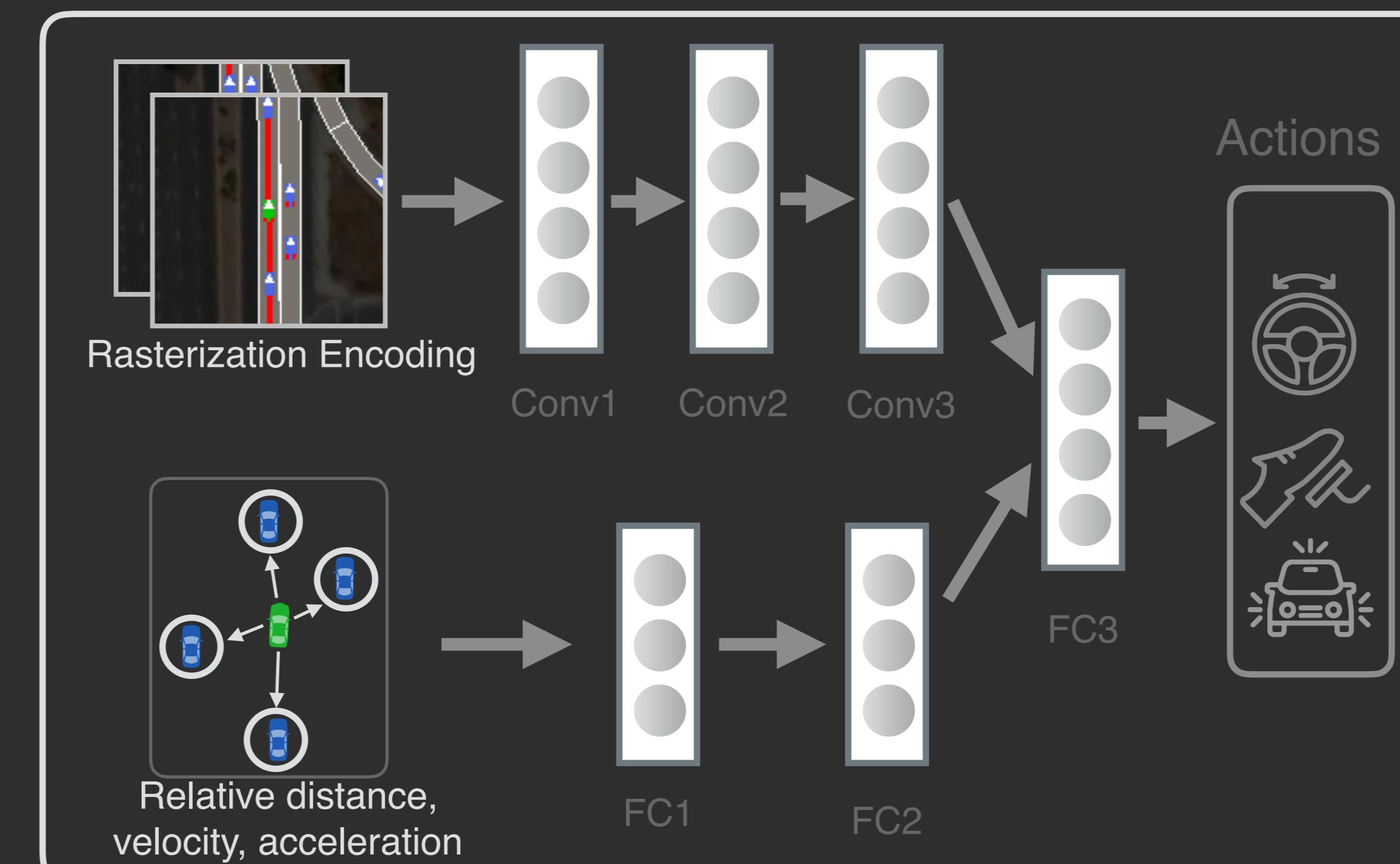
Graphical Model



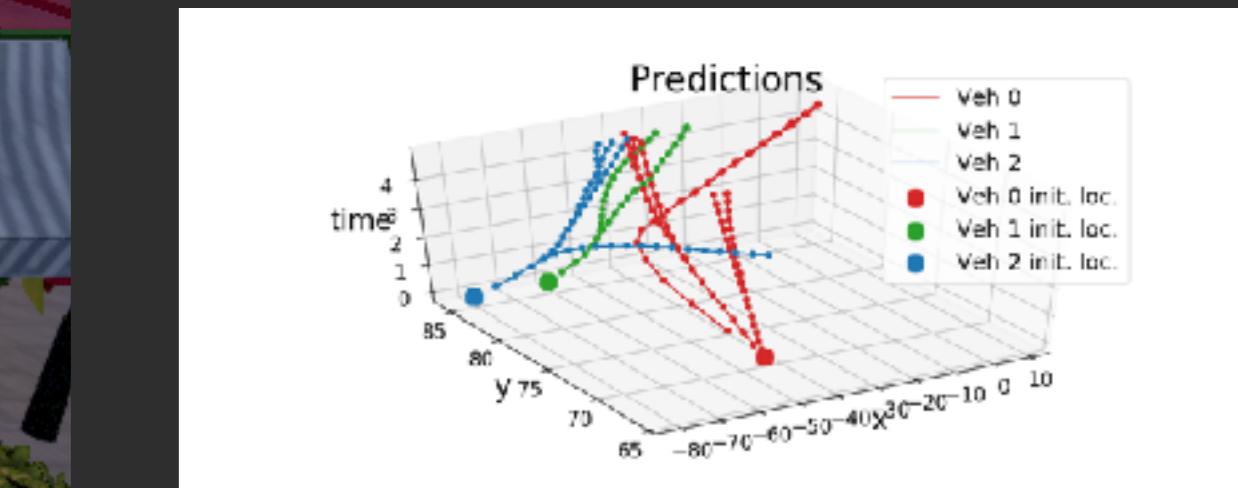
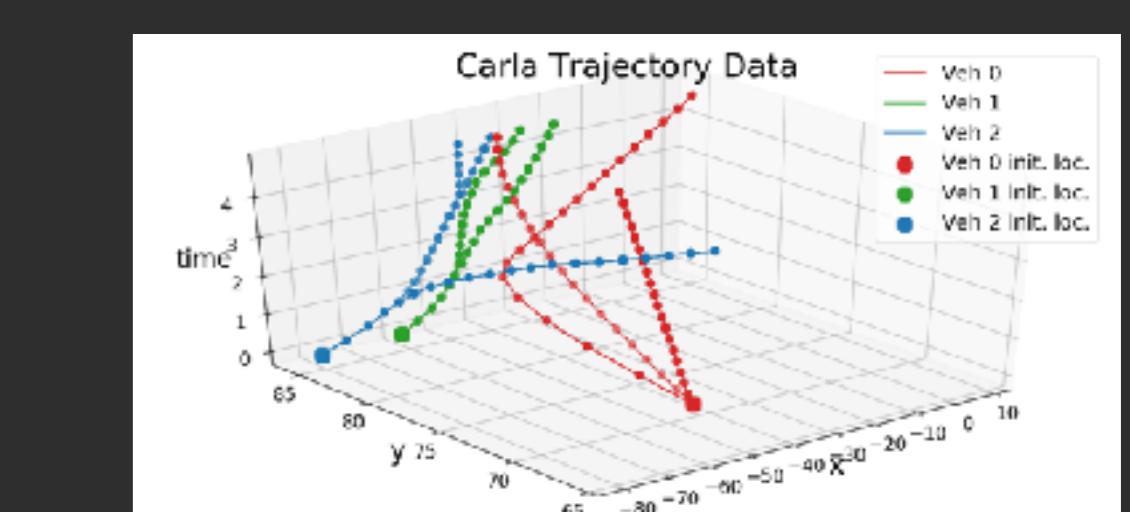
Dynamic Attention Encoding



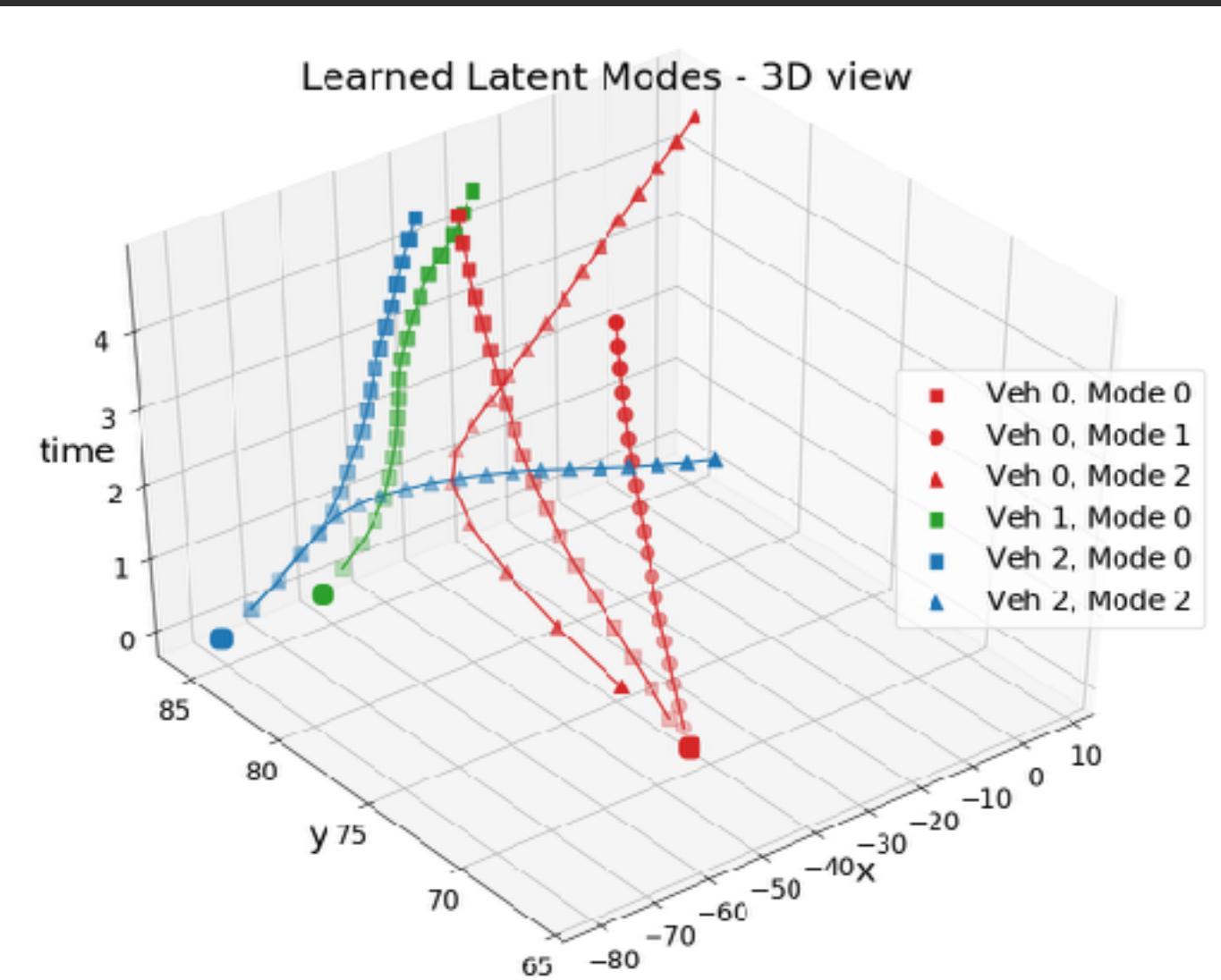
Network Architecture



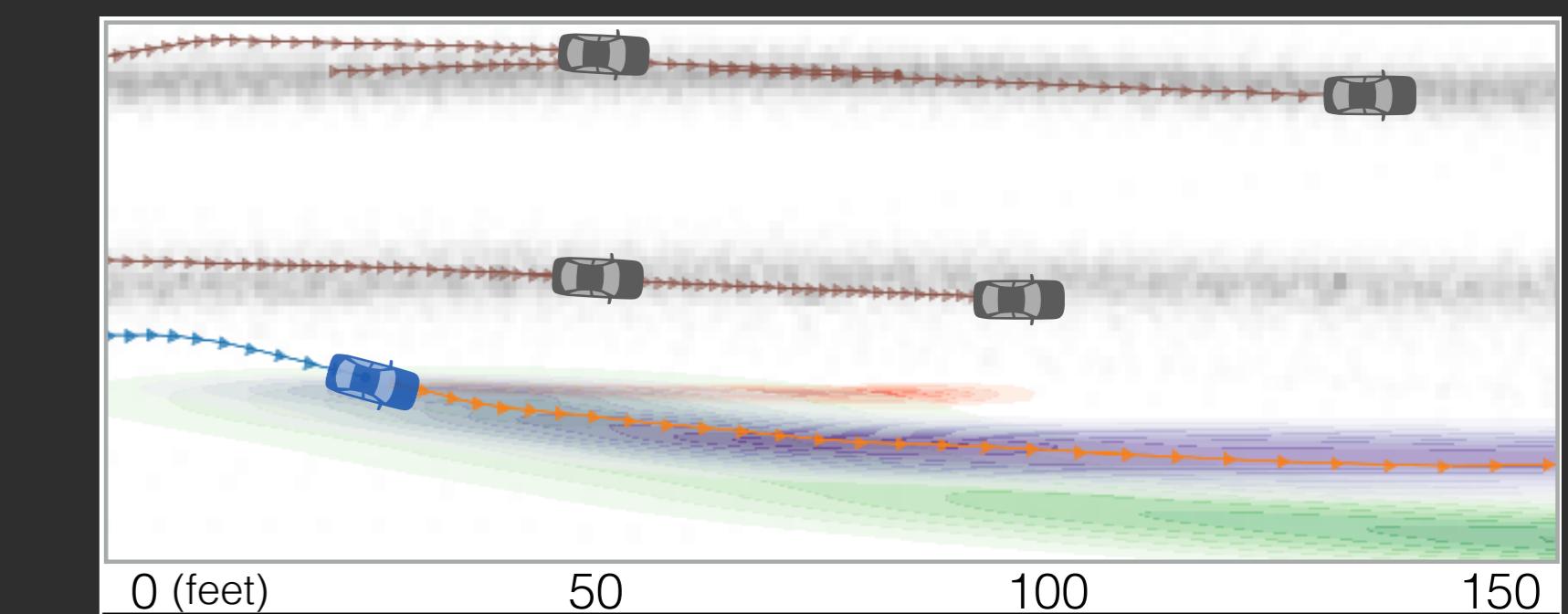
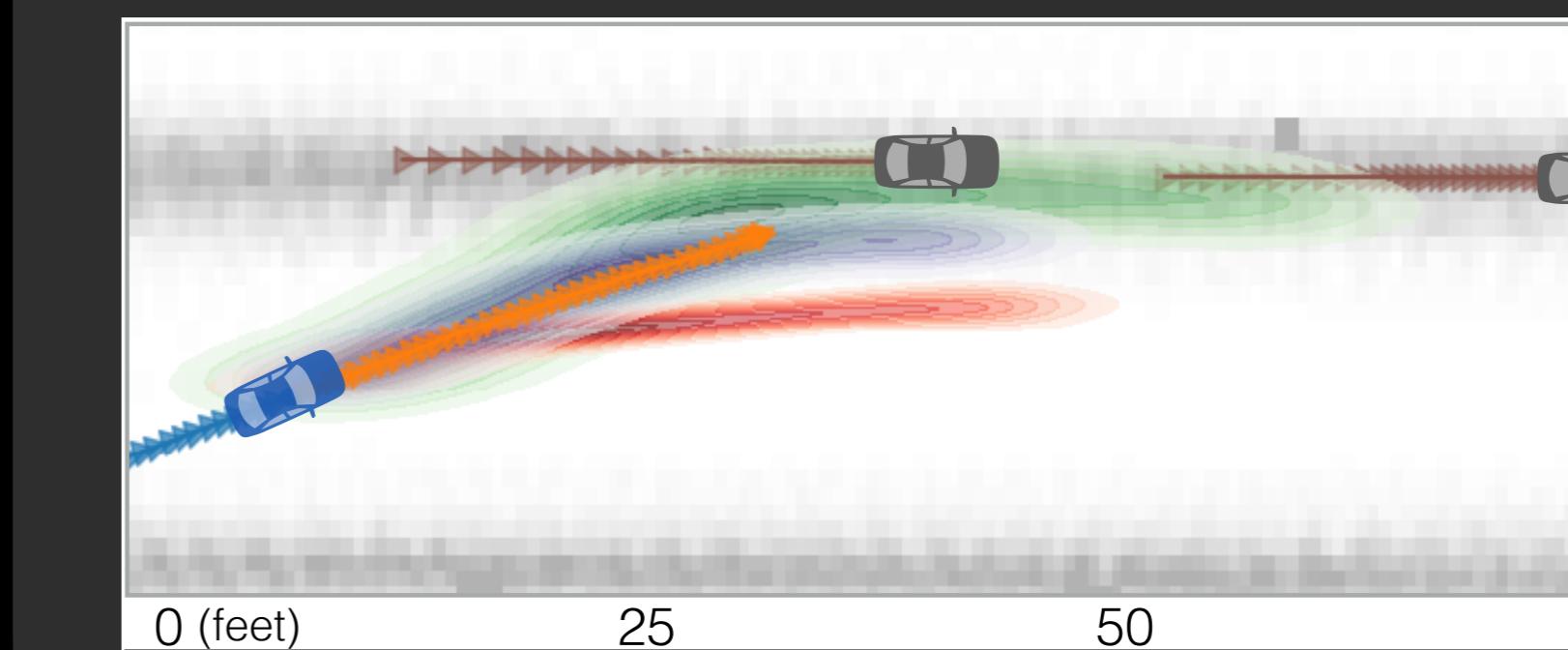
Experimental Results - Qualitative



Populations	Population Agent Types			
	IDM	RL	SP1	SP2
Popul. 1	100%	0%	0%	0%
Popul. 2	50%	50%	0%	0%
Popul. 3	30%	30%	40%	0%
Popul. 4	10%	20%	30%	40%



NGSIM Results



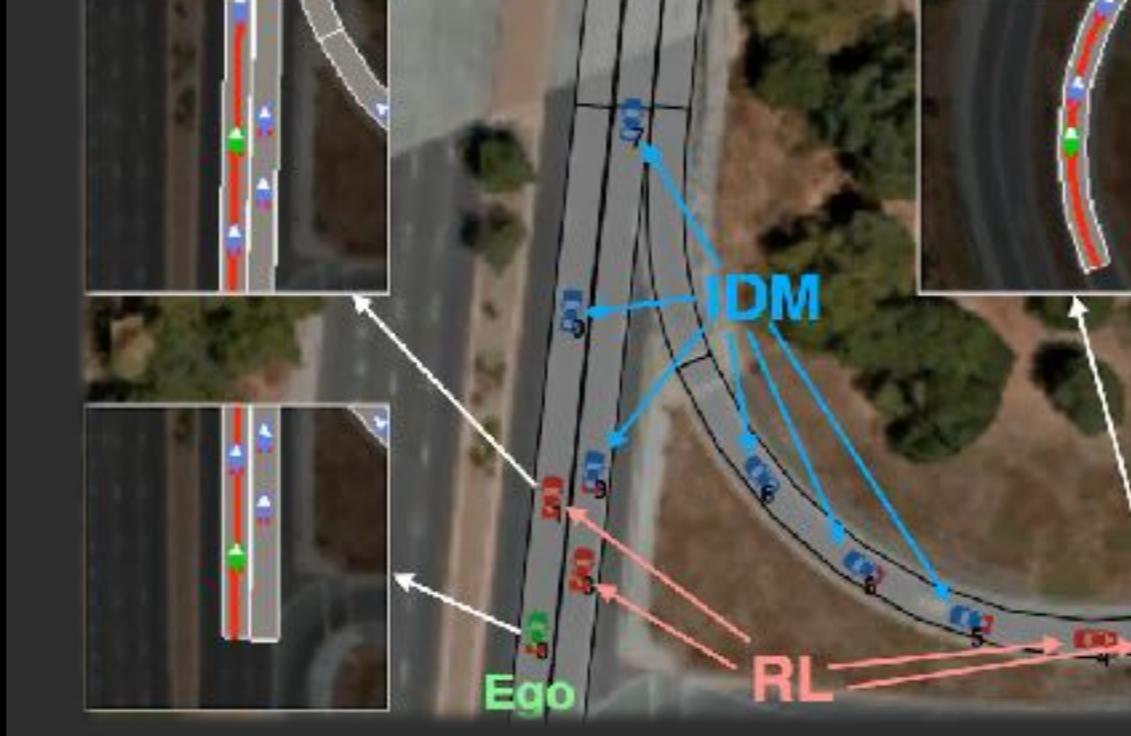
Experimental Results - Quantitative

Stage	Agents	Training		Testing - Success rate % (Collision rate %)			
		Training with Populations	Test against Population 1	Population 2	Population 3	Population 4	
0	IDM	N/A	62.8% (0.8%)				
1	RL	IDM (Population 1)	94.8% (4.0%)	77.2% (12.4%)			
2	Self-play 1	IDM+RL+SP1 (Population 3)	96.0% (3.6%)	91.2% (4.4%)	95.2% (3.2%)		
3	Self-play 2	IDM+RL+SP1+SP2 (Population 4)	93.2% (6.0%)	94.8% (4.8%)	95.2% (4.4%)	98.2% (1.4%)	

RL training

- Goal: **(A,B, or C) -> (D,E, or F)**
- Model-free training with policy gradient methods
- Input: rasterization + relative features
- Rewards: Success: +100. Collision: -500
- Initially trained with rule-based agents
- Reward shaping is critical

Self-play Training



- RL overfits to environments
- While training, add RL-trained agents back to simulation: **sparring partners**
- Self-play increases complexity
- Learns interesting merge behaviors

Training Populations

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