



MBAPPE

MCTS-Built-Around Predictions for Planning Explicitly

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Introduction

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The context

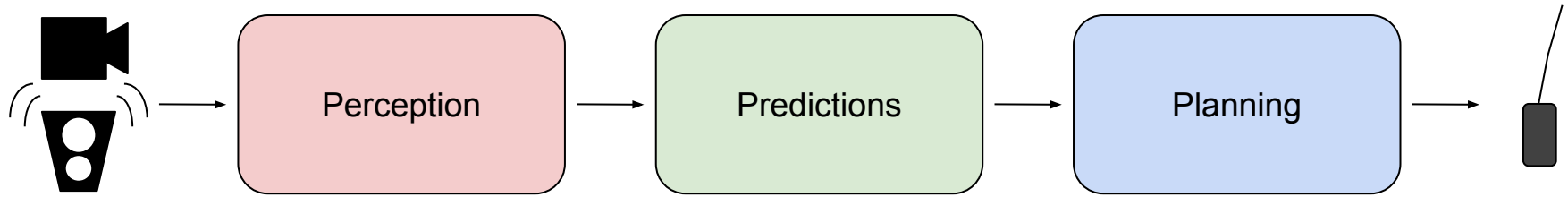


Figure 1. *General autonomous driving system pipeline.*

The context

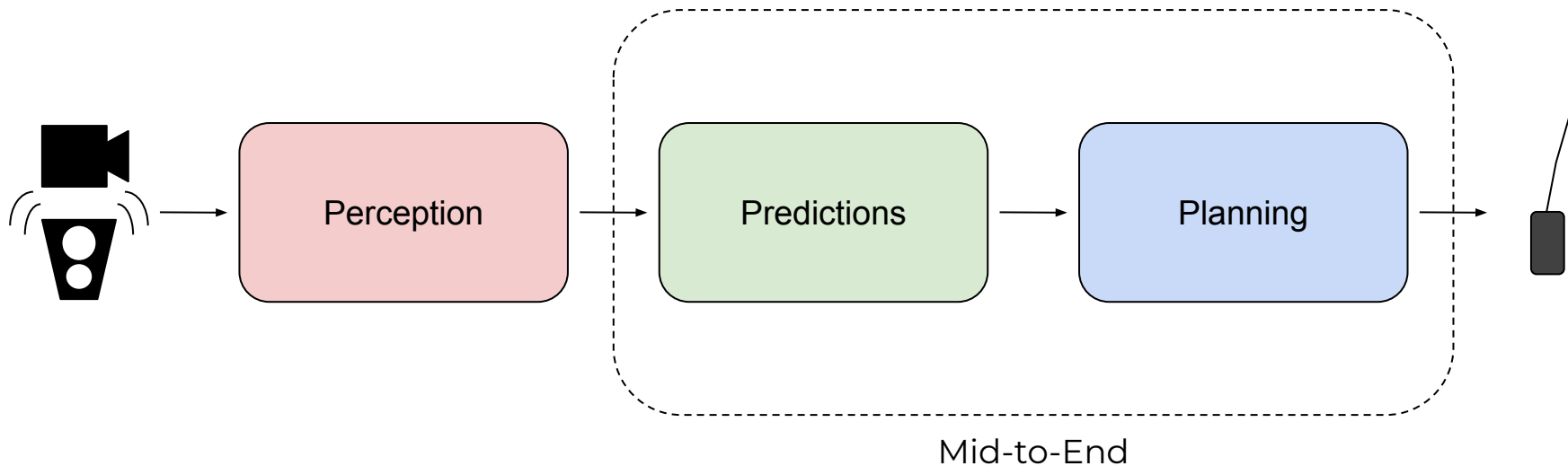


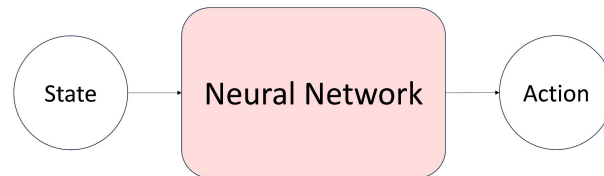
Figure 2. Deep learning and sensor technology progressed greatly. It led to significant improvement of the perception stage of autonomous driving. The focus is now shifting to the next challenges of autonomous driving: mid-to-end autonomous driving, i.e. motion planning.

Different approaches

Rule-based

$$\text{IDM [1]: } \begin{cases} \frac{dv}{dt} = a \left[1 - \left(\frac{v}{v_0}\right)^\delta - \left(\frac{s^*(v, \Delta v)}{s}\right)^2 \right] \\ s^*(v, \Delta v) = s_0 + \max \left[0, \left(vT + \frac{v\Delta v}{2\sqrt{ab}} \right) \right] \end{cases}$$

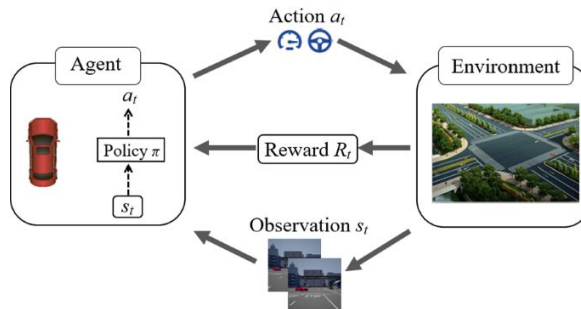
Imitation learning



- [1] Congested traffic states in empirical observations and microscopic simulations, Treiber et al.
[2] Parting with Misconceptions about Learning-based Vehicle Motion Planning, Dauner et al.

- [3] Learning by Cheating, Chen et al.
[4] TransFuser: Imitation with Transformer-Based Sensor Fusion for Autonomous Driving, Chitta et al.

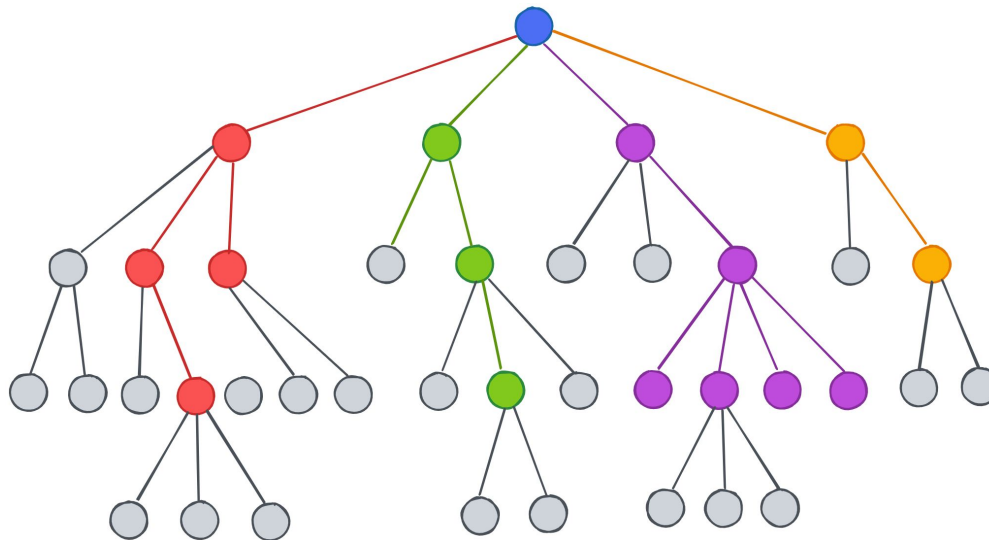
Reinforcement learning



- [5] End-to-End Model-Free Reinforcement Learning for Urban Driving using IAs, Toromanoff et al.
[6] GRI: General Reinforced Imitation and its Application to Vision-Based Autonomous Driving, Chekroun et al.

Different approaches

Monte-Carlo Tree Search (MCTS)



[8] Mastering the game of Go with deep neural networks and tree search, Silver et al.

[7] Combining planning and deep reinforcement learning in tactical decision making for autonomous driving, Hoel et al.

Our contribution

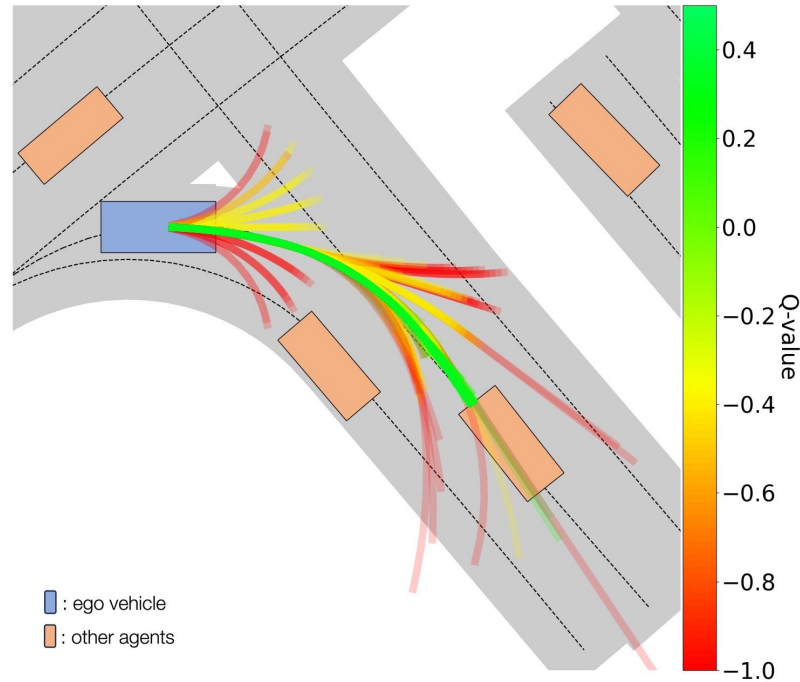
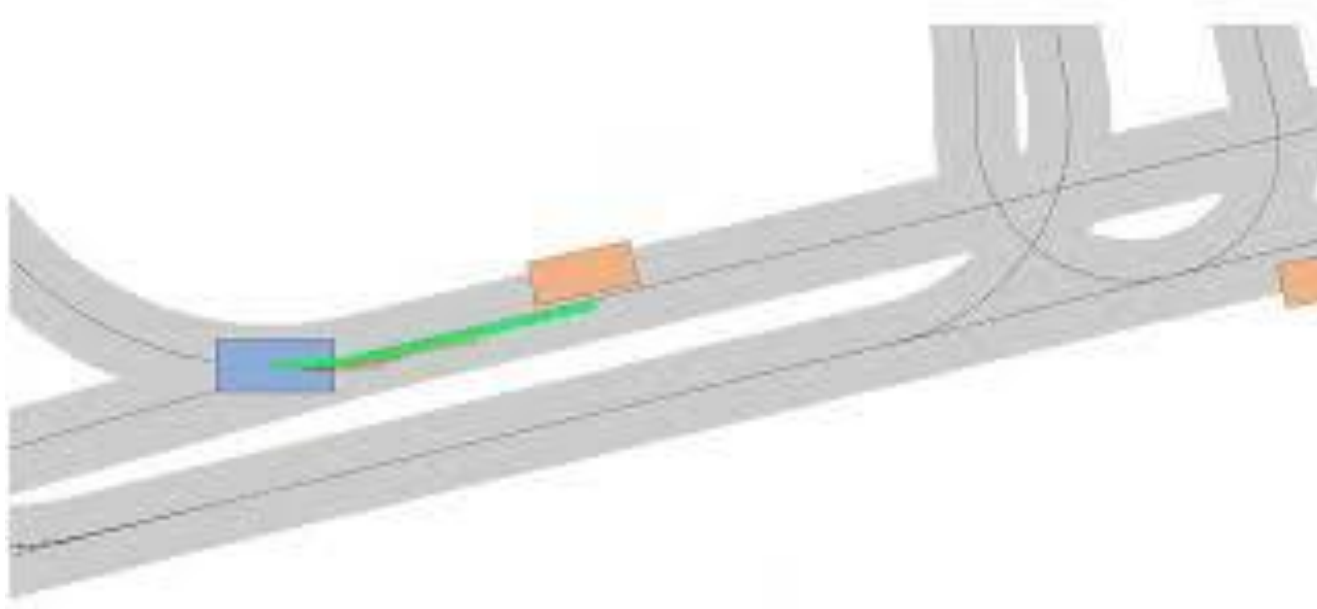


Figure 3. Visualization of the exploration done by MBAPPE in different scenarios. We display the bird-eye-view trajectory pieces in xy coordinates. MBAPPE selects the which maximized the Q-value (in green).

Our contribution



Animated Figure 3. Visualization of the exploration done by MBAPPE in different scenarios. We display the bird-eye-view trajectory pieces in xy coordinates. MBAPPE selects the which maximized the Q-value (in green).



Methodology

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MBAPPE Pipeline

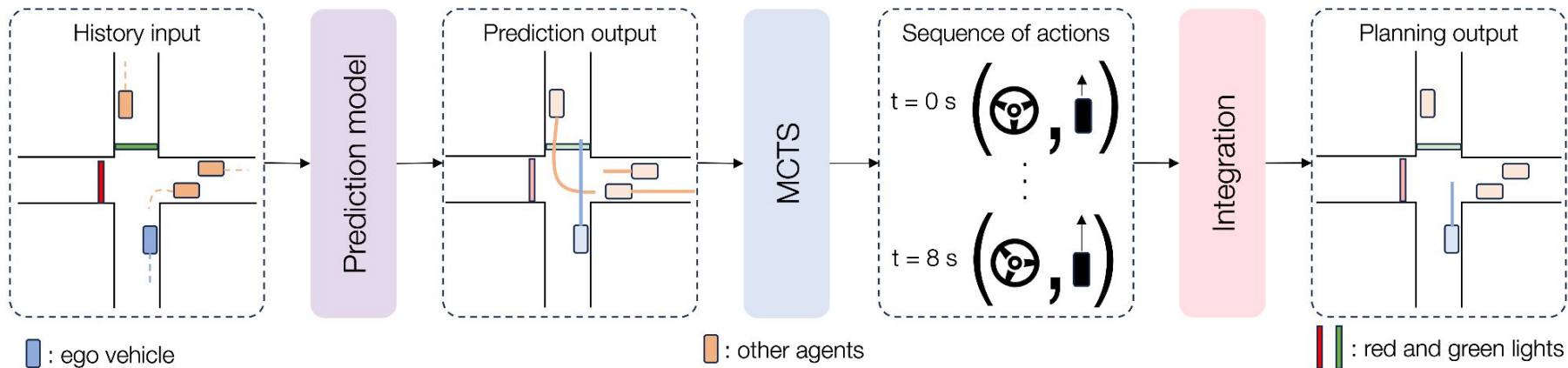


Figure 4. A prediction model infers future trajectories of other agents in the scene. This information is fed to the MCTS which outputs a sequence of consecutive actions. Those are integrated to form an improved trajectory planning for the ego.

MCTS-steps

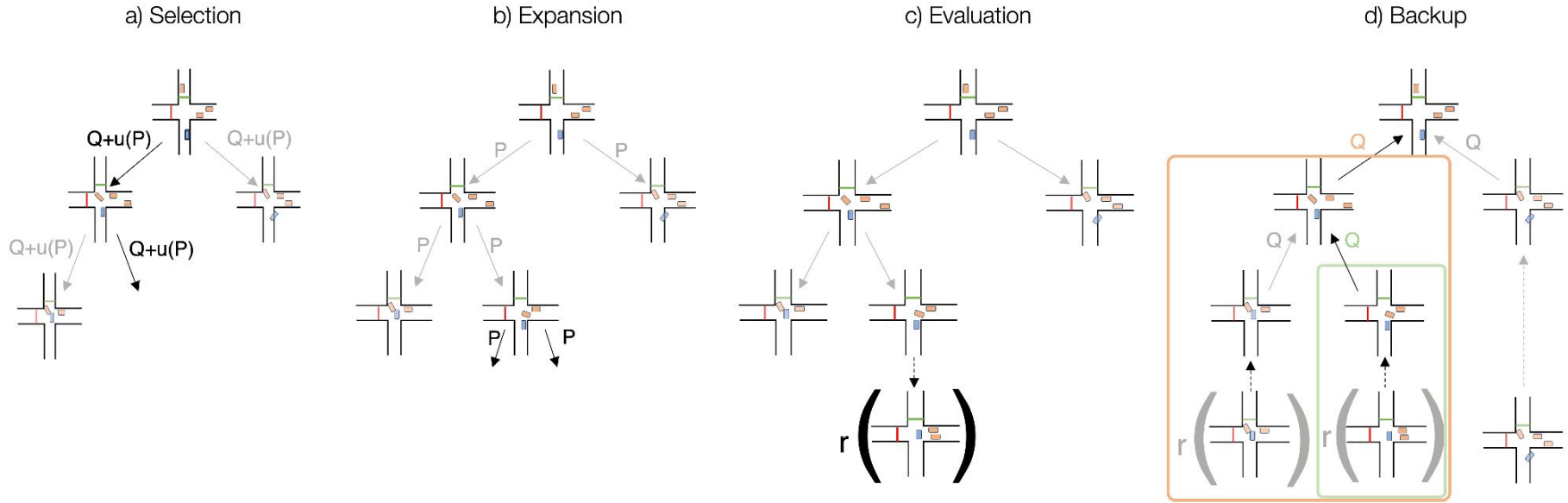


Figure 5. a) Each simulation traverses the tree by selecting the edge with maximum action-value Q , plus a bonus $u(P)$ that depends on stored prior probability for that edge. b) The leaf node is possibly expanded following some probabilities depending on the prior P and the continuity constraints. c) After the simulation, the leaf node is evaluated by explicitly computing the reward r . d) Q -values are updated so means of the rewards r in the sub-tree below each actions are tracked.

An interpretable method

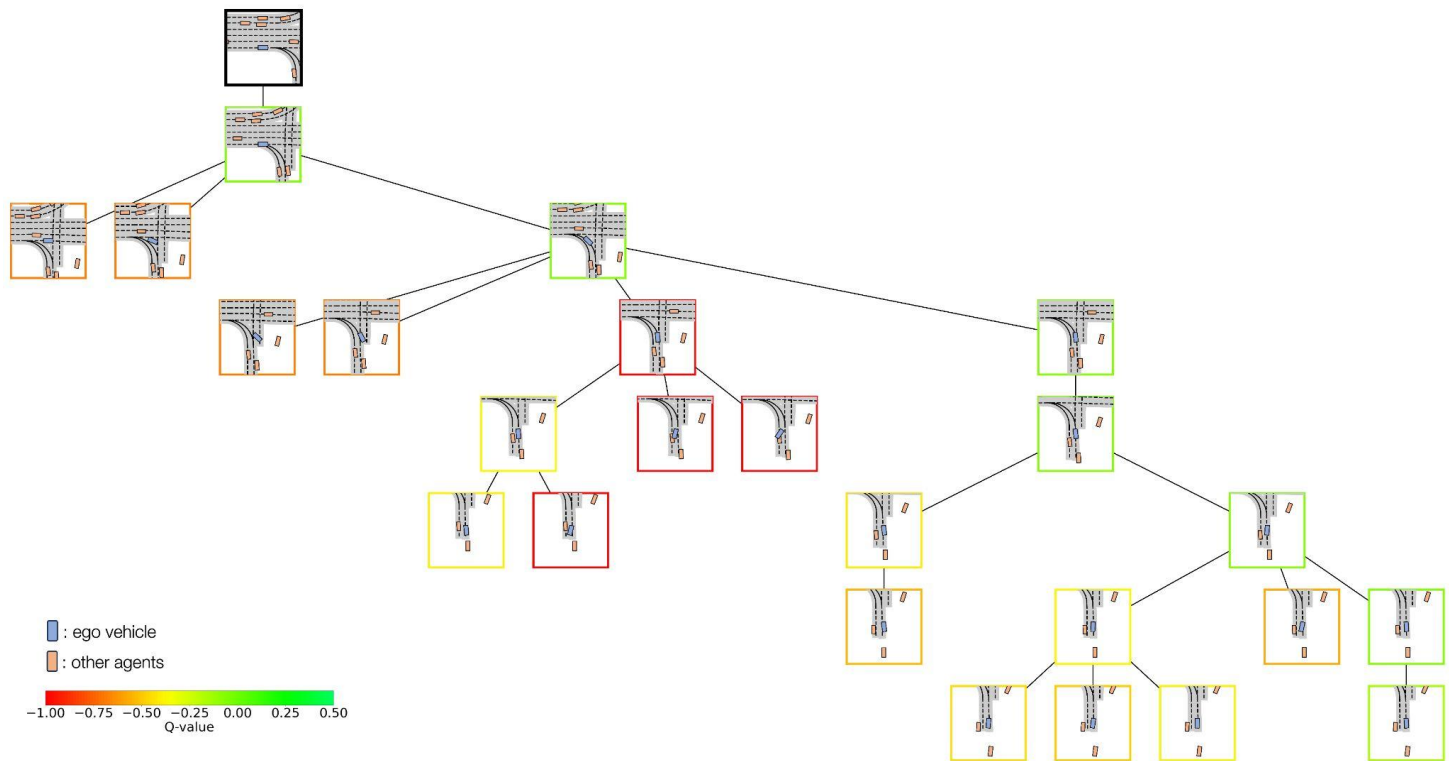


Figure 6. A subset of a decision tree obtained with MCTS exploration. Nodes are colored according to their Q-value. The root node correspond to the present state of the vehicle in the nuPlan simulator.



Experimental results

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Quantitative results

Method	CR ↓	DA ↓	EP ↑	Score ↑
Urban Driver MA	34%	26%	96%	47%
GameFormer Planner	6%	4%	98%	84%
PDM-Hybrid	2%	0%	99%	93%
IDM	12%	6%	95%	76%
GC-PGP	-	-	-	57%
PlanCNN	-	-	-	73%
MBAPPE (GameFormer)	3%	2%	98%	90%
MBAPPE (Urban Driver)	5%	2%	96%	86%

Table 1. *Val14 benchmark on the nuPlan simulator. Score is nuPlan closed-loop non reactive agents metric. CR: collision rate, DA: driving area not compliance, EP: ego progress. Notably, MBAPPE delivers state-of-the-art performance, and is an improvement operator over predictive models.*

[9] Urban Driver: Learning to Drive from Real-world Demonstrations Using Policy Gradients, Scheel et al.

[10] GameFormer: Game-theoretic Modeling and Learning of Transformer-based Interactive Prediction and Planning for Autonomous Driving, Huang et al.

[11] From Prediction to Planning With Goal Conditioned Lane Graph Traversals, Hallgarten et al.

[12] PlanT: Explainable Planning Transformers via Object-Level Representations, Renz et al.

[13] MBAPPE: MCTS-Built-Around Prediction for Planning Explicitly, Chekroun et al.



Conclusion

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Conclusion

- MBAPPE extends MCTS to partially learned environments,
- It gives SOTA results on nuPlan simulator,
- It is a refinement operator for planning models,
- It is **interpretable**: a critical attribute for safe and reliable autonomous driving systems,
- Preliminary draft version: Honorable mention for Innovation Award in nuPlan challenge 2023.



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