KI WISSEN
Automotive AI Powered by Knowledge

KI Wissen Final Event | 21-22 March 2024

Knowledge Integration in Tracking, Prediction and Planning

Mohamed-Khalil Bouzidi, Yue Yao, Jonas Neuhöfer, Christian Schlauch| Continental AG

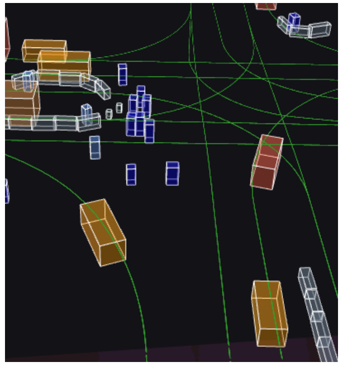
1

Motivation

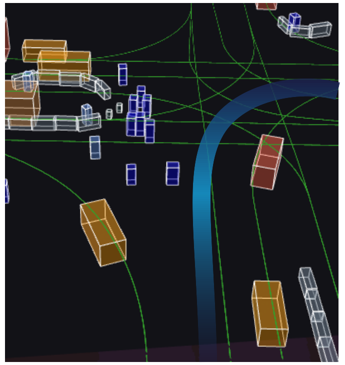
Motivation

Environment

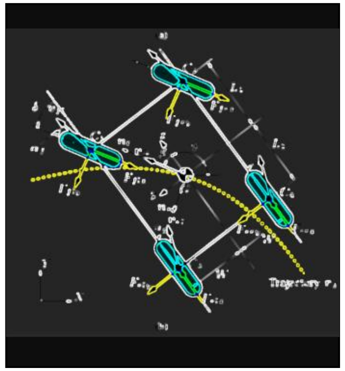
Perception & Tracking



Prediction



Planning & Control



Maturity of Machine Learning Solutions

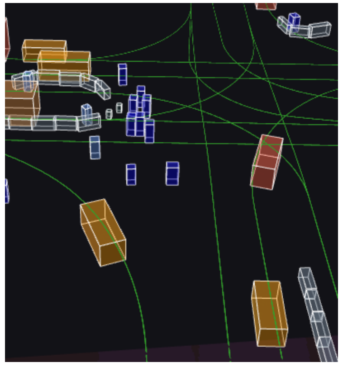
Learning-based Solutions + Knowledge-based Solutions = Hybrid AI

Combining best of both worlds!

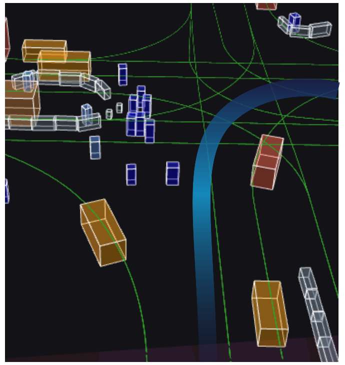
Motivation

Environment

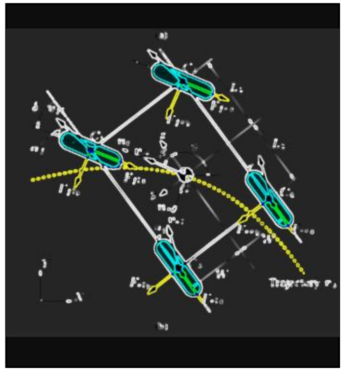
Perception & Tracking



Prediction



Planning & Control



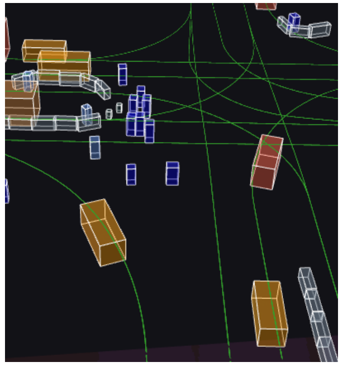
Maturity of Machine Learning Solutions

Learning-based Solutions + Knowledge-based Solutions = Hybrid AI

1. Better Performance
2. Robustness
3. Explainability
4. Data Efficiency

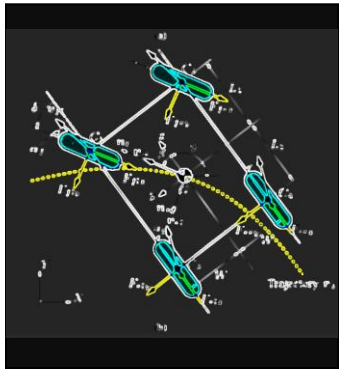
Knowledge Integration in Tracking, Prediction and Planning

Perception & Tracking



Prediction

Planning and Control



Jonas

Yue

Christian

Mohamed

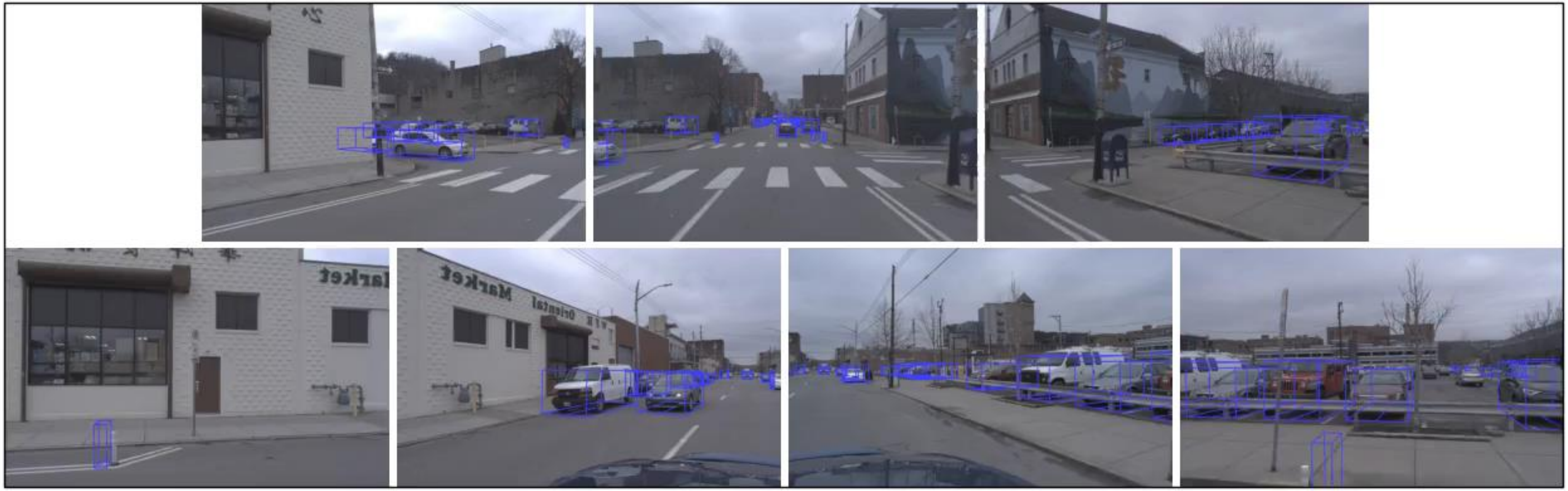
2

Perception & Tracking

Perception - Detection of Objects

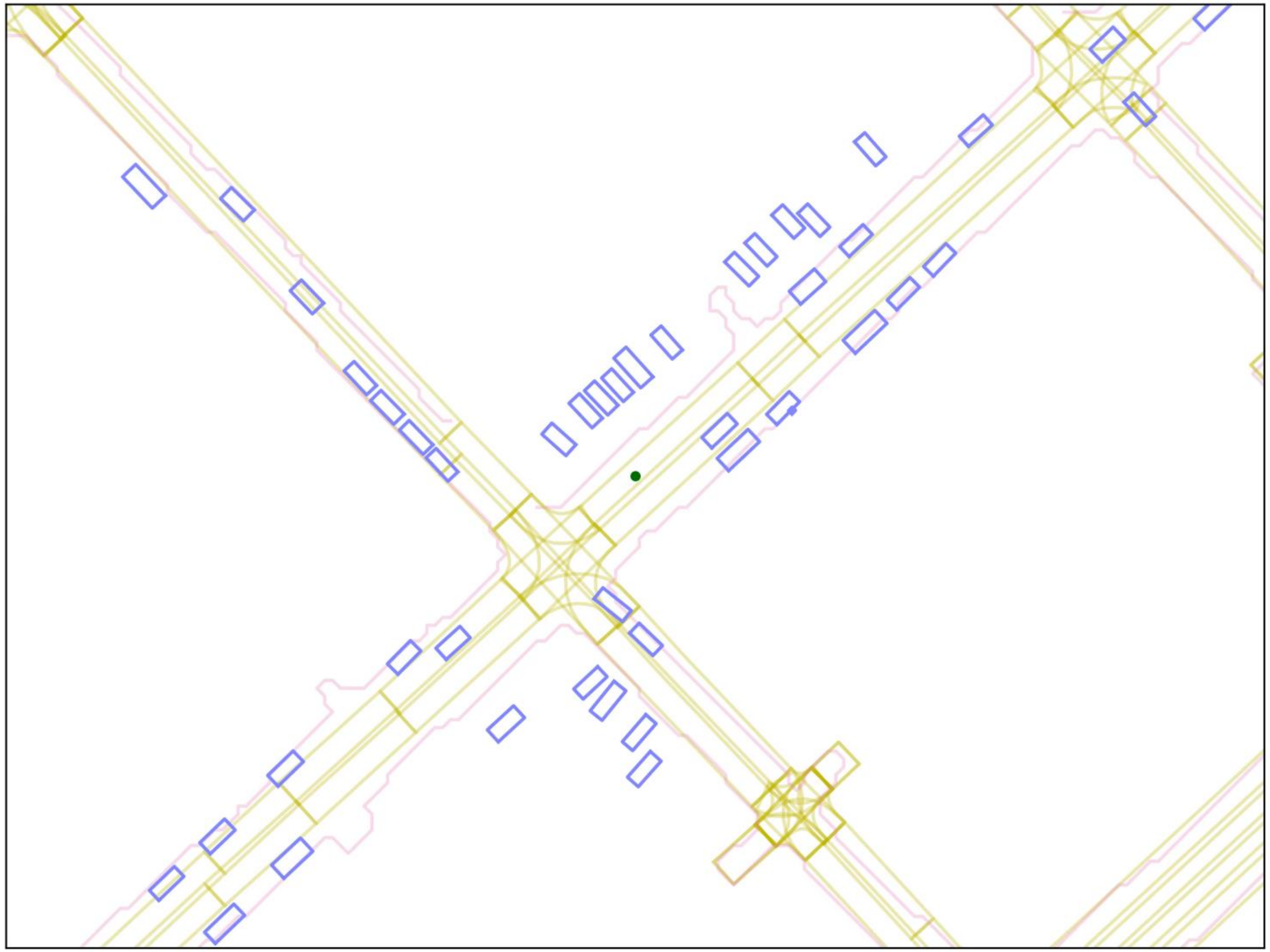
Argoverse 3D Tracking v1.1

Perception - Detection of Objects



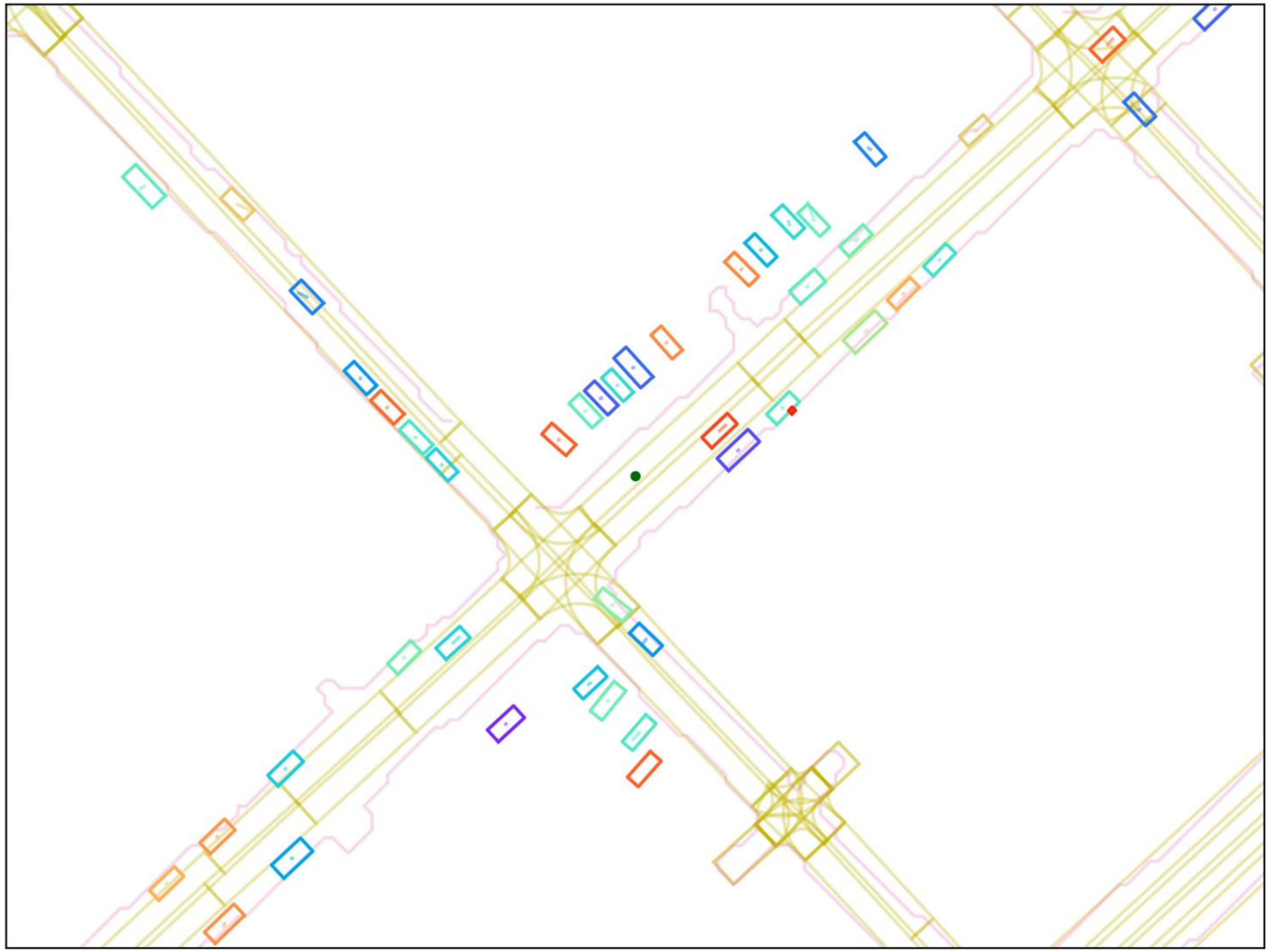
Argoverse 3D Tracking v1.1

Abstraction to Birds-Eye-View (BEV) Map



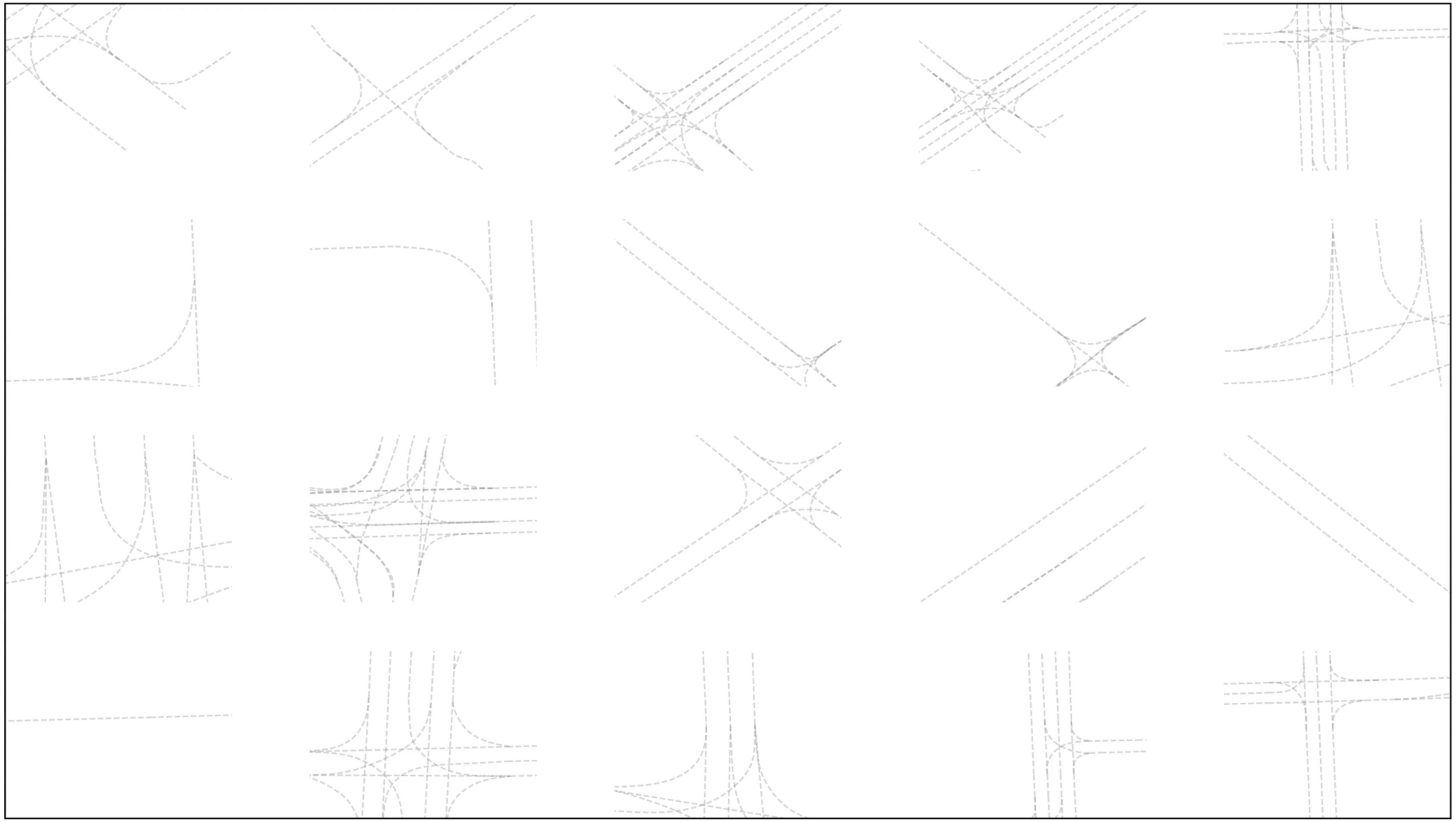
Argoverse 3D Tracking v1.1

Tracking of Objects over Time



Argoverse 3D Tracking v1.1

Tracking Challenges - Outliers



Argoverse Motion Forecasting v1.1

The Problem

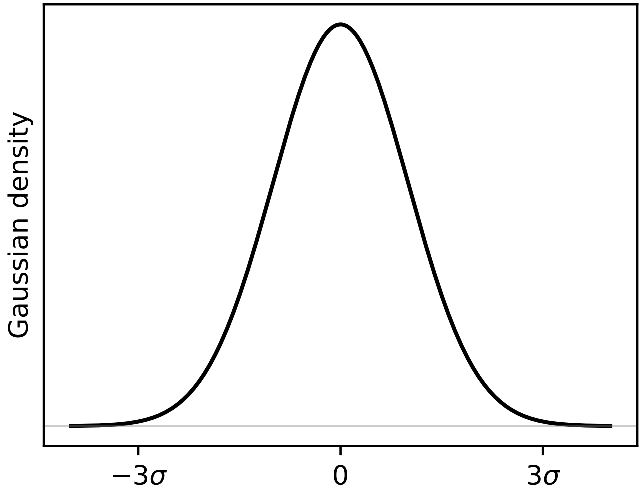
Unknown **ground truth agent states** have to be reconstructed from noisy observations only.

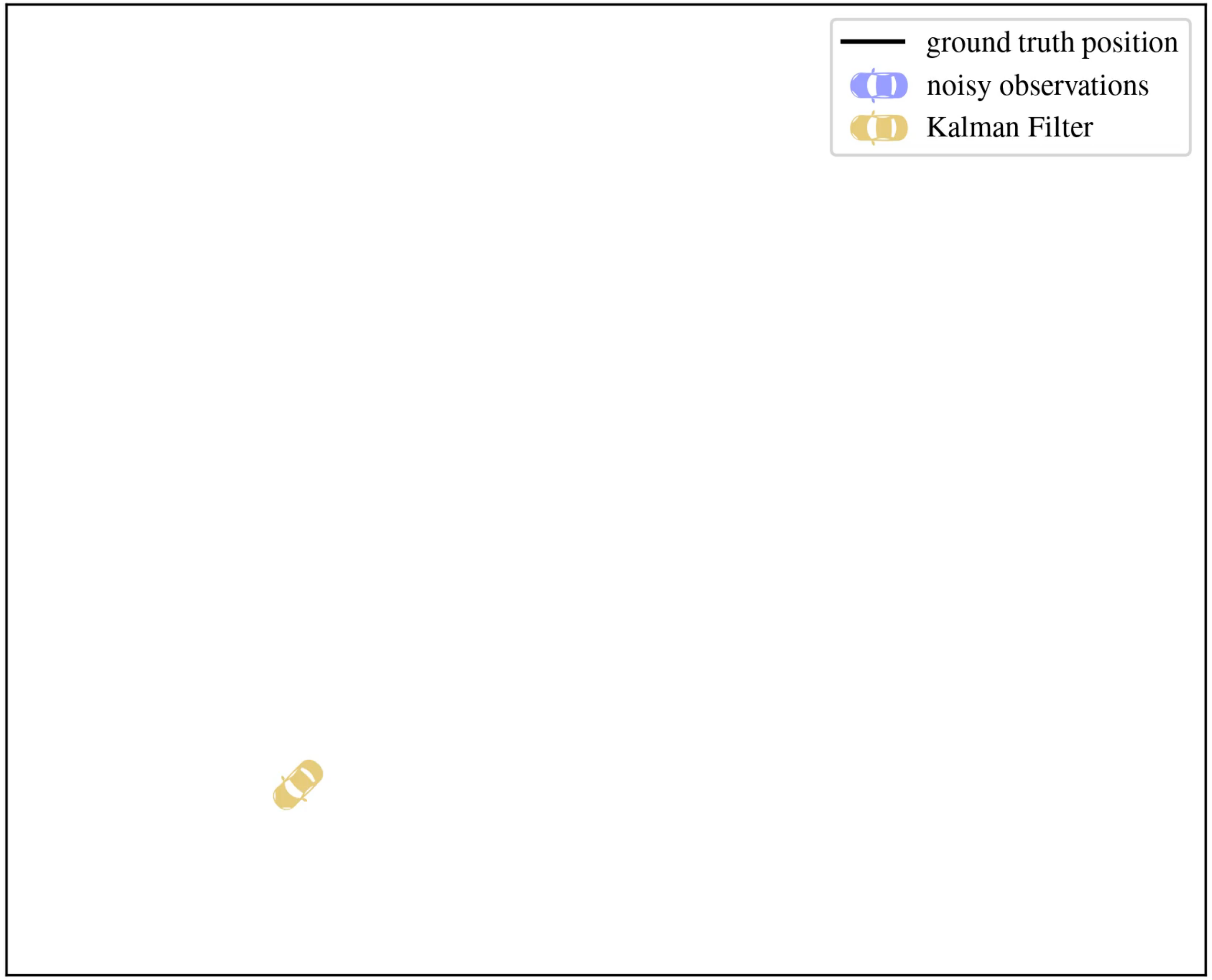
The observations might contain outliers.

Naive Approach - Gaussian Noise Assumption / Kalman Filtering

Model the noise as Gaussian. Then the best estimate can be found analytically, i.e. the Kalman Filter.

However, outliers are basically impossible under Gaussian assumptions, remember e.g. the 3-σ rule.





“Just Discard the Outliers“

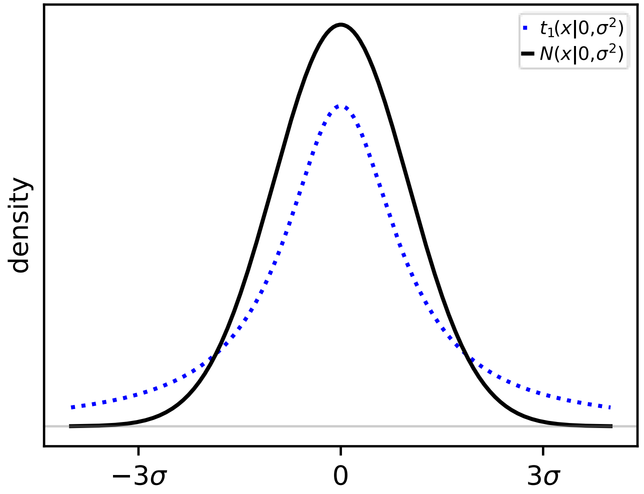
Often, outliers are detected by being too far away from the expectations and then discarded.

However, this can also discard valid observations.

Replacing Gaussian Assumptions with Student‘s t Assumptions

Our approach is - similar to existing work - to replace the Gaussian assumption with a Student‘s t-distribution assumption, which is able to explain outliers.

For the main technical contributions, you are welcome to visit us during the poster session.



Underlying Principle: Finding local approximations to joint Student's t-distributions

$$\underbrace{t_\nu(x|\mu_1,\Sigma_1)}_{\text{Student's t-density evaluated at } x} \cdot t_{\nu+m}(y|\mu_2,\Sigma_2)\cdot t_{\nu+m+n}(z|\underbrace{\mu_3,\Sigma_3}_{\text{mean and (quasi) covariance}})$$

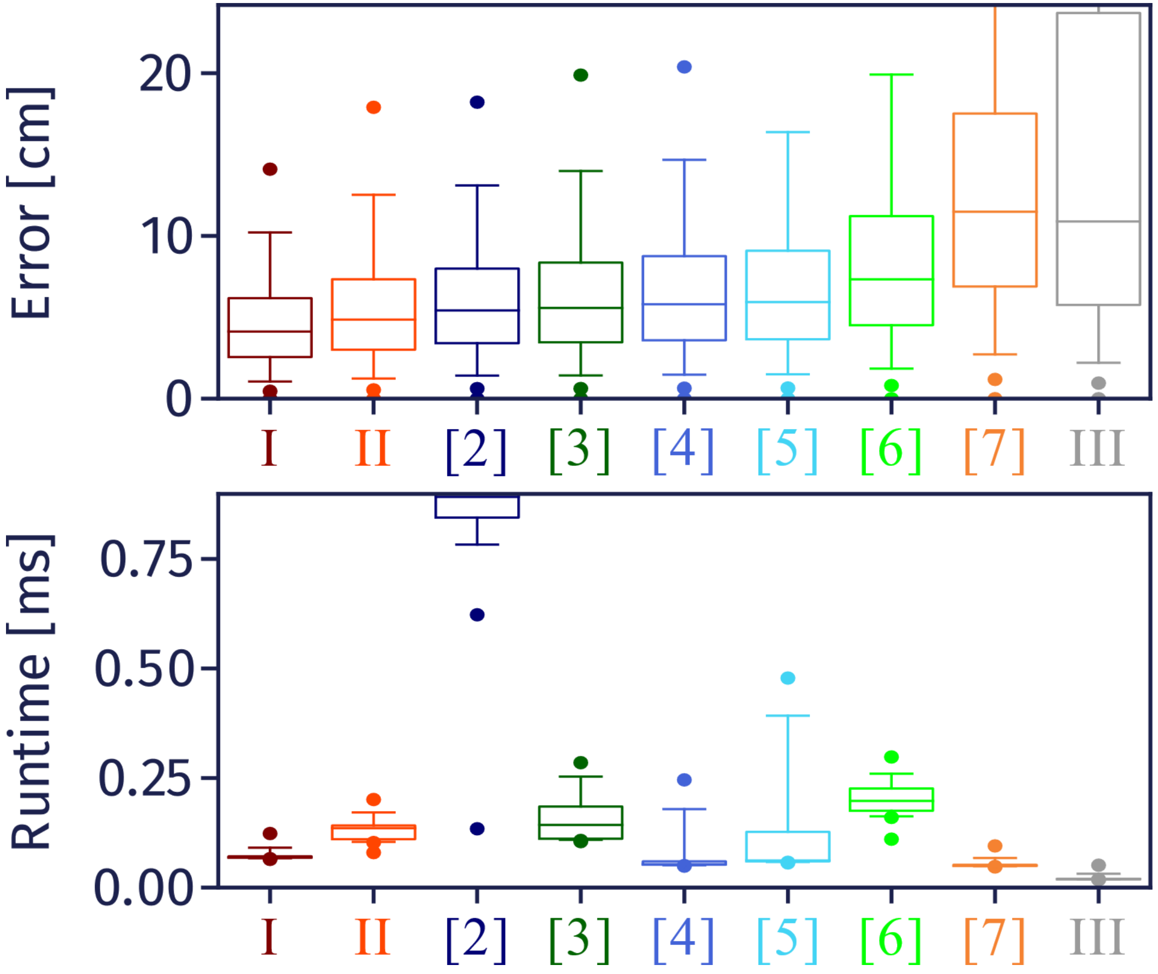
hyperparameter for frequency of outliers (ν); *dimensions of x and y* (m, n)

$$= t_\nu\left(\begin{bmatrix} x \\ y \\ z \end{bmatrix} \middle| \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix}, \begin{bmatrix} \Sigma_1 & 0 & 0 \\ 0 & a(x)\Sigma_2 & 0 \\ 0 & 0 & a(x)b(y)\Sigma_3 \end{bmatrix}\right)$$

$$a(x) = \frac{\nu+m}{\nu+(x-\mu_1)^T\Sigma_1^{-1}(x-\mu_1)},\ b(y) = \frac{\nu+m+n}{\nu+m+(y-\mu_2)^T\Sigma_2^{-1}(y-\mu_2)}$$

Qualitative Comparison to State of the Art

I: our method with known scalars a(z), b(x).
II: our method.
[2]: Y. Huang, Y. Zhang, Y. Zhao, P. Shi, and J. A. Chambers, "A novel outlier-robust Kalman filtering framework based on statistical similarity measure", 2020
[3]: G. Agamennoni, J. I. Nieto, and E. M. Nebot, "An outlier-robust Kalman filter", 2011
[4]: G. Chang, "Robust Kalman filtering based on Mahalanobis distance as outlier judging criterion", 2014
[5]: G. Chang, "Kalman filter with both adaptivity and robustness", 2014.
[6]: S. Sarkka and A. Nummenmaa, "Recursive noise adaptive Kalman filtering by variational Bayesian approximations", 2009
[7]: M. Roth, "Kalman filters for nonlinear systems and heavy-tailed noise", 2013.
III: common Kalman Filter.



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Automotive AI Powered by Knowledge

☑ Better Performance

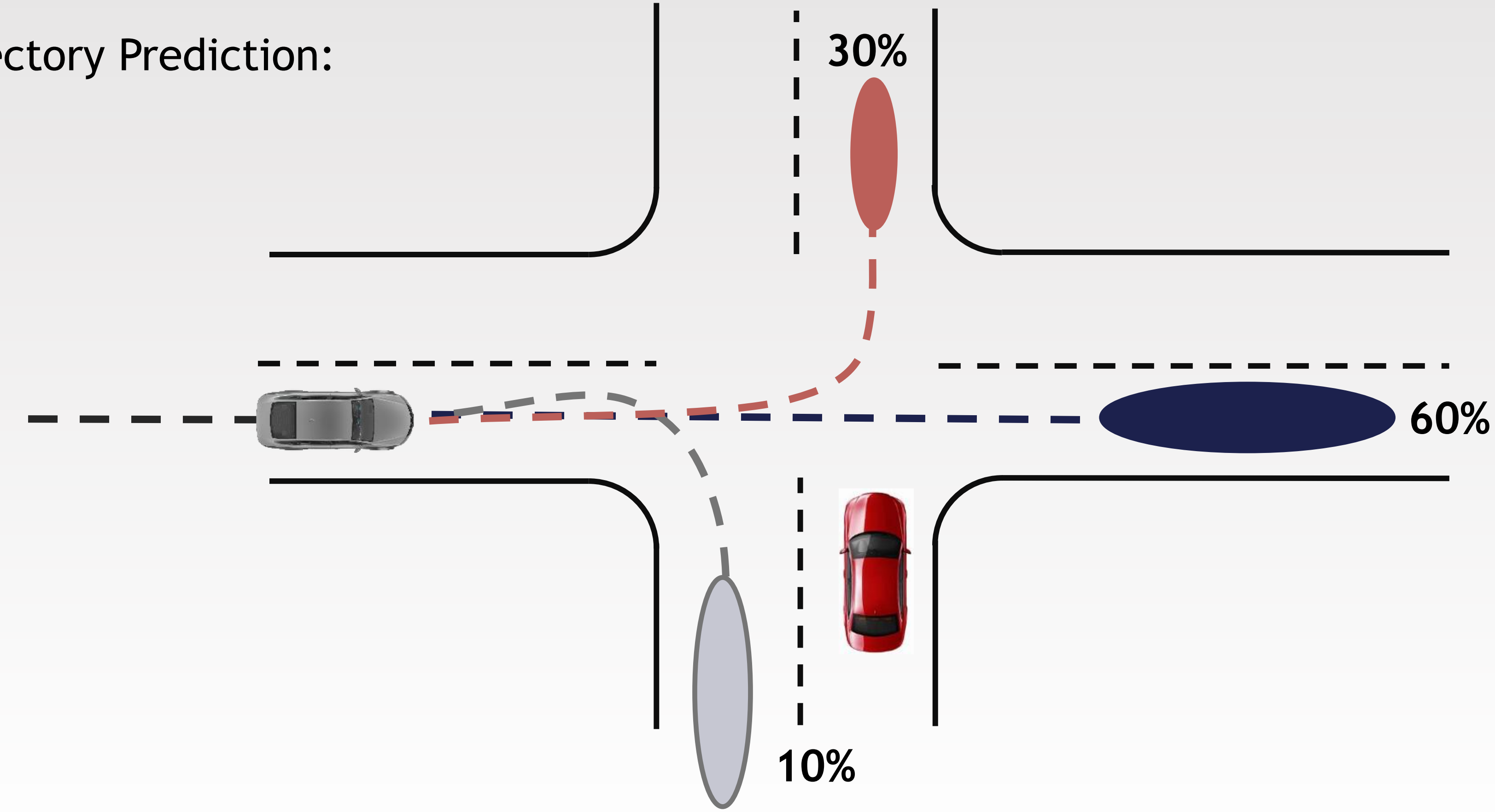
☑ More Robustness

3

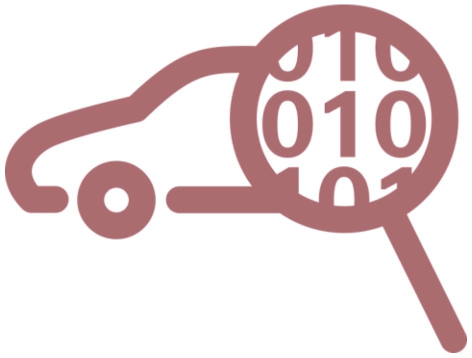
Knowledge Integration in Trajectory Prediction

Introduction

› Challenges in Long-Term Trajectory Prediction:
  › Interactions
  › Multi Modality
  › Probabilistic



Where does knowledge come from?



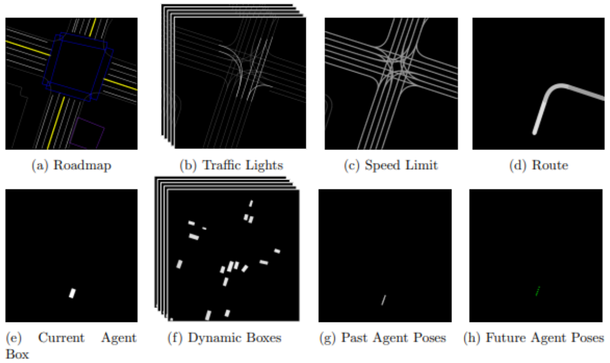
Extracted Knowledge from Data

Expert Knowledge

Extracting Knowledge from Data

Parametric Trajectory & Path Representation (Input)

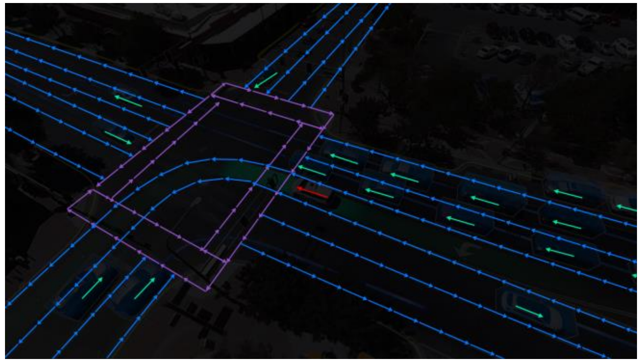
Rasterization



Bansal et al., 2018

- + Comprehensive for various information
- + Complexity doesn‘t scale with #actors
- − Non-continuous state information
- − Memory usage for storing images
- − No Labeling, overlapped trajectories

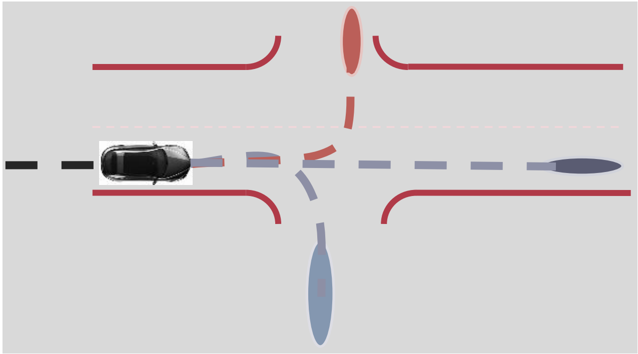
Vectorization



Gao et al., 2020

- + More compact and efficient than rasterization
- − Discreted Information
- − Accuracy of high order time derivative
- − Scales with #actors

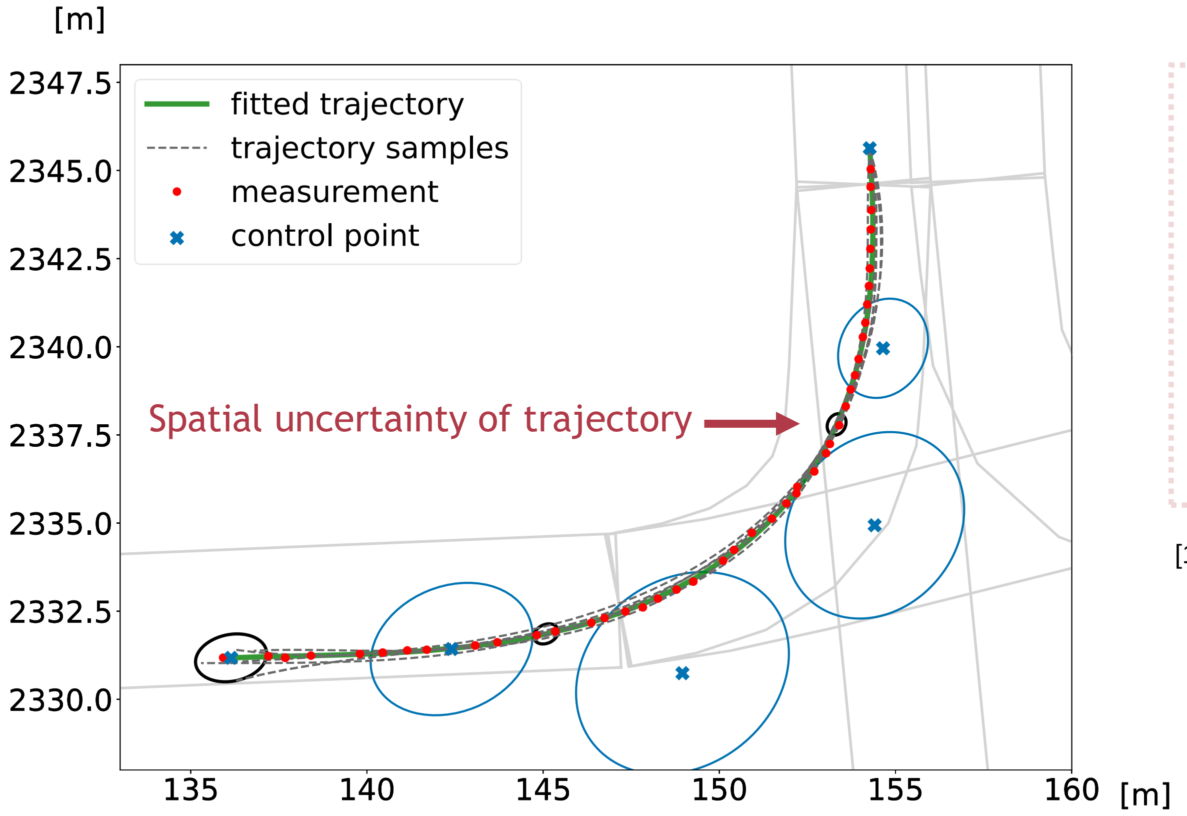
Parametric Representation



- + Physically informed
- + Continuous state information
- − Scales with #actors
- − Approximation of trajectory

Extracting Knowledge from Data
Trajectory Representation

n-degree Polynomial (e.g. n=5)

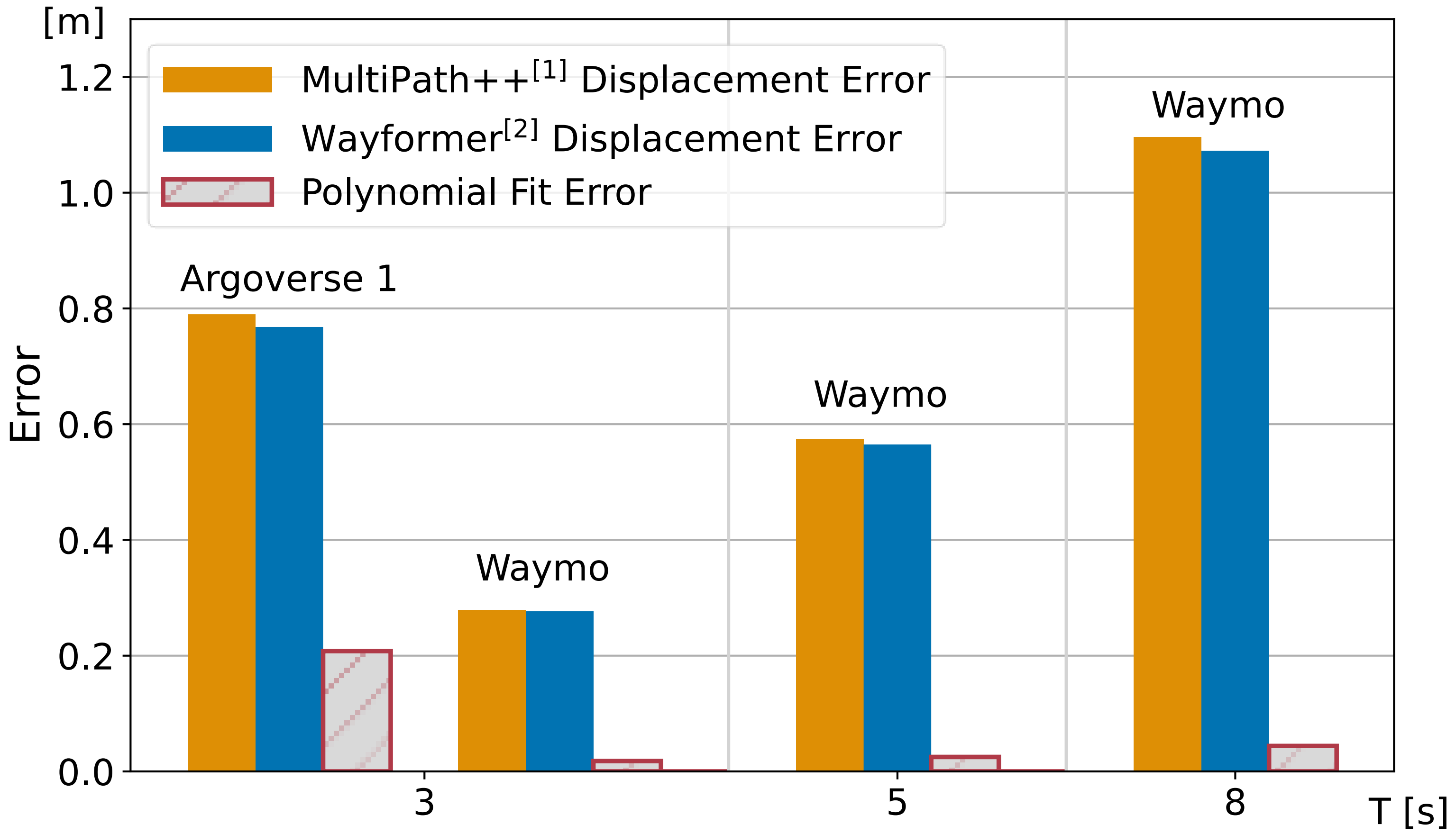


Questions studied in work [1]:

1. Fit error?
2. Parameter distributions.
3. Observation noise in dataset?
4. Model complexity, i.e. polynomial degree (n)?

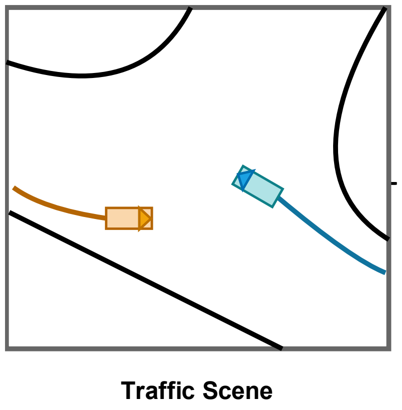
[1]: Yao et al., An Empirical Bayes Analysis of Object Trajectory Representation Models, ITSC 2023

Extracting Knowledge from Data
Results: Fit Error



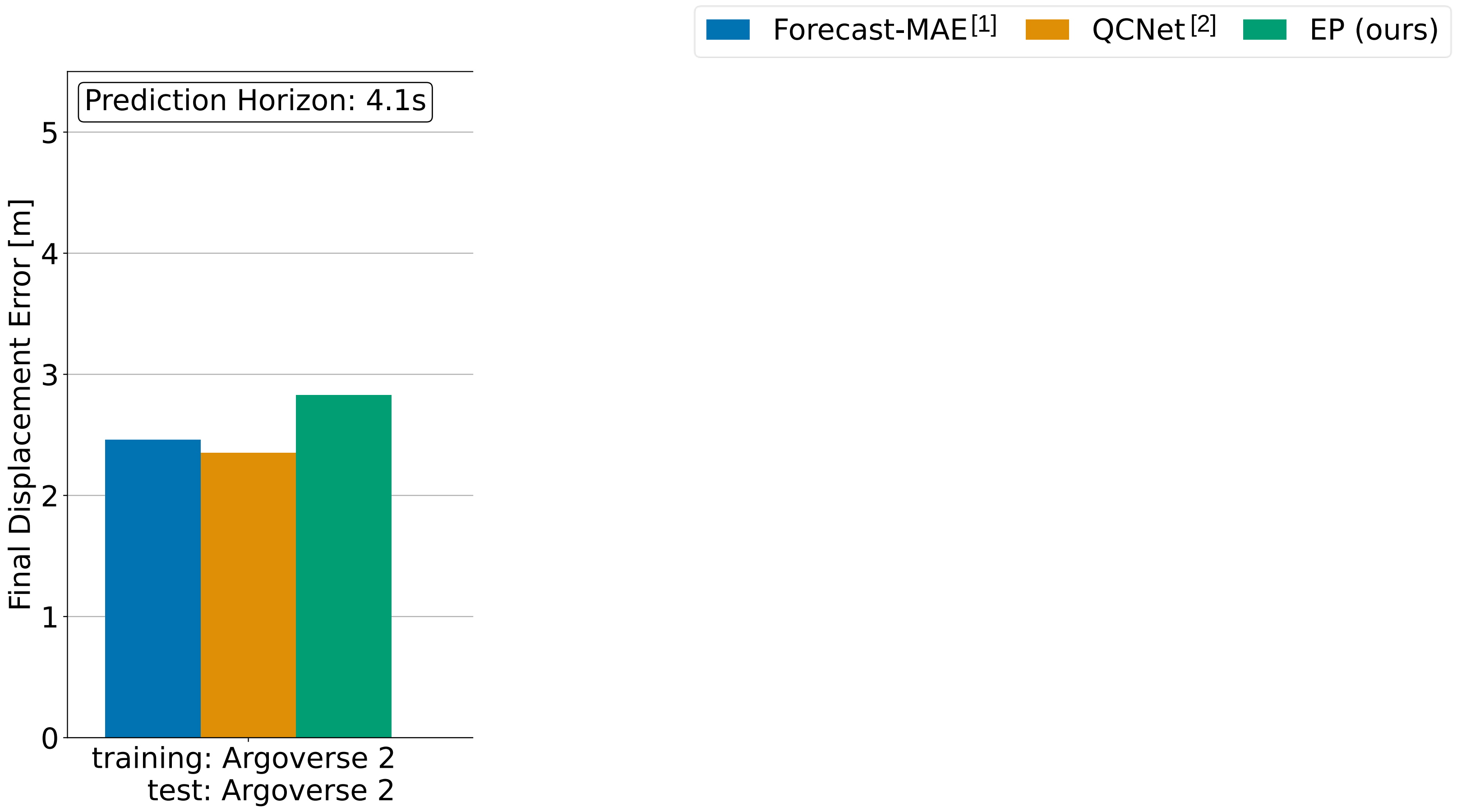
[1]: Varadarajan et al., Multipath++: Efficient information fusion and trajectory aggregation for behavior prediction, ICRA 2022
[2]: Nayakanti et al., Wayformer: Motion forecasting via simple & efficient attention networks, ICRA 2023

Integrating Knowledge
Method



Our proposed model architecture. Agent histories and road geometry are both represented via polynomials. The current object kinematics and future kinematic states predicted by the model are fused into one continuous polynomial trajectory prediction. (© Continental AG)

Integrating Knowledge
Results



[1]: Cheng et al., Forecast-MAE: Self-supervised Pre-training for Motion Forecasting with Masked Autoencoders, ICCV 2023
[2]: Zhou et al., Query-Centric Trajectory Prediction, CVPR 2023

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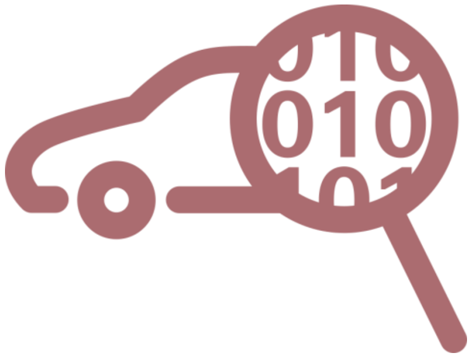
- ☑ Higher Efficiency
- ☑ More Robustness

[1]: Yao et al., An Empirical Bayes Analysis of Object Trajectory Representation Models, ITSC 2023

Where does knowledge come from?



Extracted Knowledge
from Data

Expert Knowledge

How does Expert Knowledge differ?

Physical/Scientific Knowledge

- Physics of Motion
- Formulated as generally acceptable models

➡ Reduce and verify output space to only accept feasible solutions.

Expert Knowledge

- Common Sense, Social Norms, Traffic Regulations
- Formulated as Preferences or Expectations:

➡ *„Vehicles **should** comply to speed regulations, but …“ (they don‘t comply **always**)*

➡ *„Vehicles **should** stay on lanes, **except** when …“ (an emergency vehicle appears)*

➡ Formalization difficult due to rich set of **high-risk exceptions** !

Our Idea for Integrating Expert Knowledge

A ***Probabilistic Informed*** Learning Approach

Part 1

Formalize expert knowledge as probabilistic priors

Part 2

Learn priors from synthetic knowledge tasks

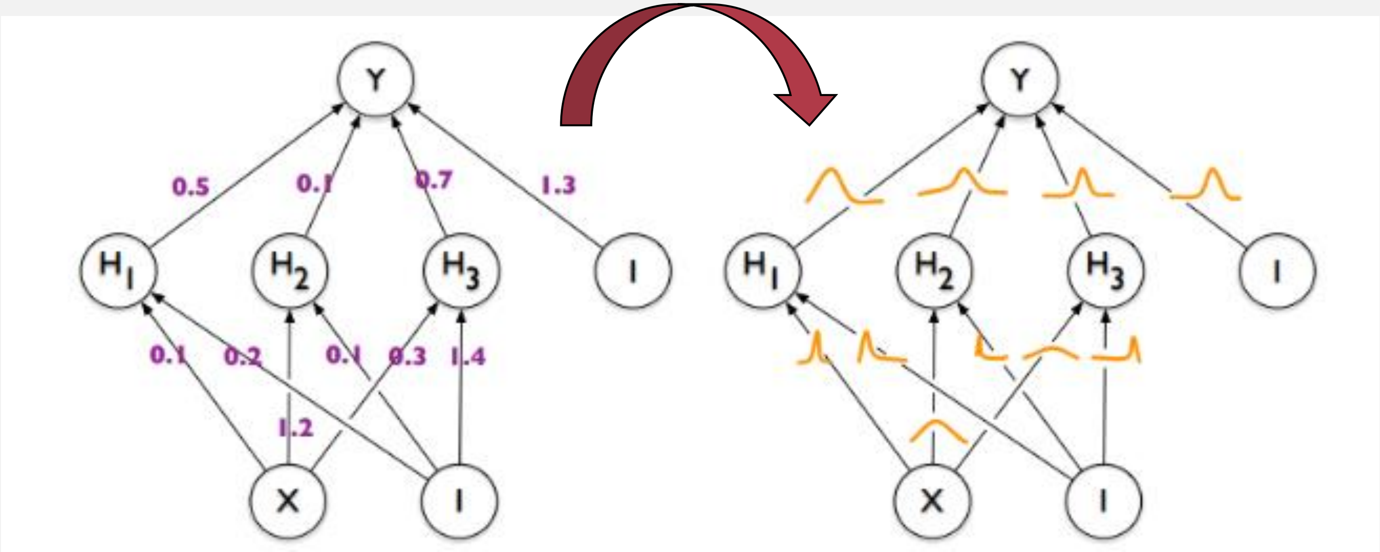
Part 3

Solve recursion using continual learning techniques

Our Idea for Integrating Expert Knowledge - Part 1

Bayesian Perspective on Prior Knowledge

Probabilistic Deep Learning Model



Bayes' Rule

$$\boxed{p(\theta|D_{\mathcal{O}})} \propto \boxed{p_\theta(y_{\mathcal{O}}|x_{\mathcal{O}})}\ \boxed{\pi_{\mathcal{B}}(\theta)}$$

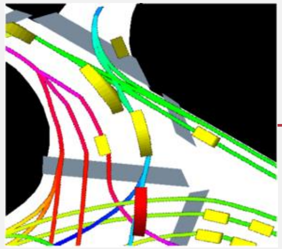
Posterior | Likelihood | Informative Prior

Our Idea for Integrating Expert Knowledge - Part 2

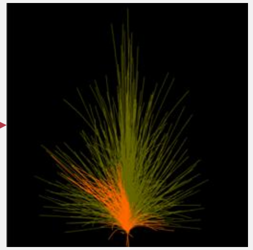
Synthetic knowledge task to learn informative prior

*„Vehicles **usually** drive on the drivable area.“*

Knowledge Task

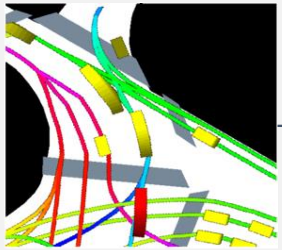


$f_1(x)$

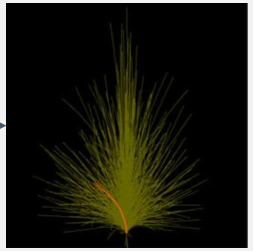


regularization

Conventional Task



$f_2(x)$

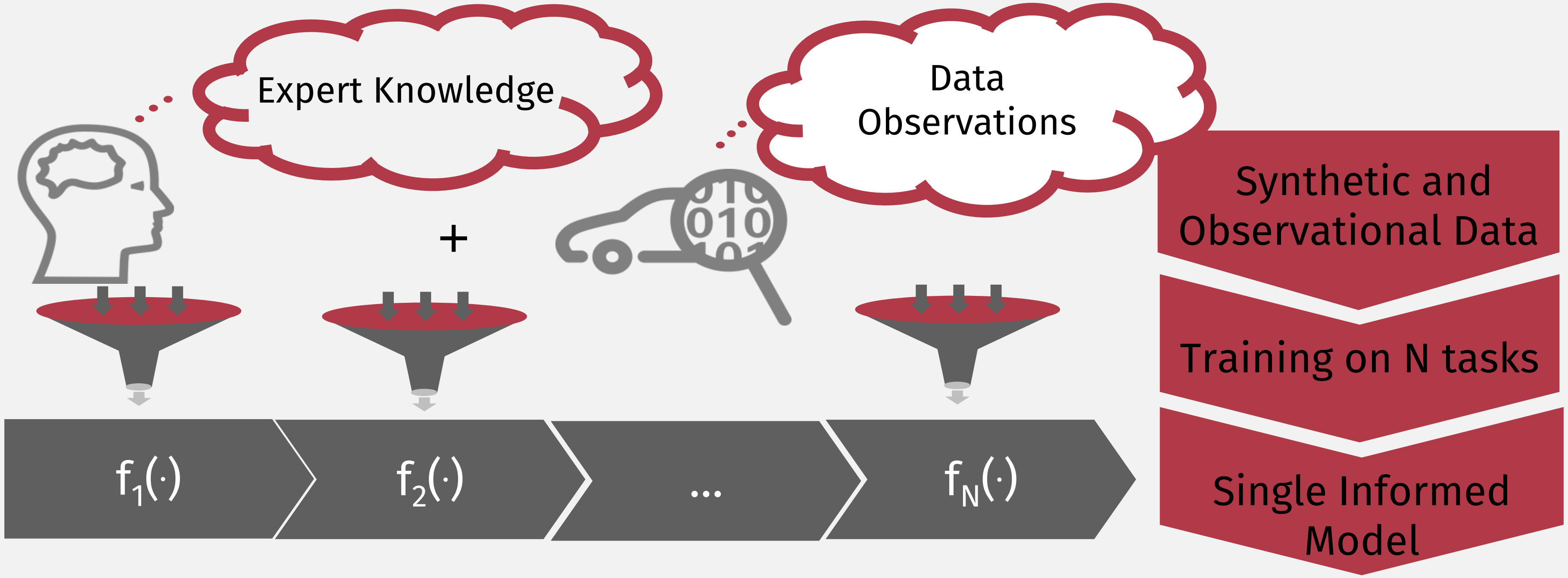


Train on multi-label set of **deduced** drivable trajectories

Train on **observed** ground-truth trajectory

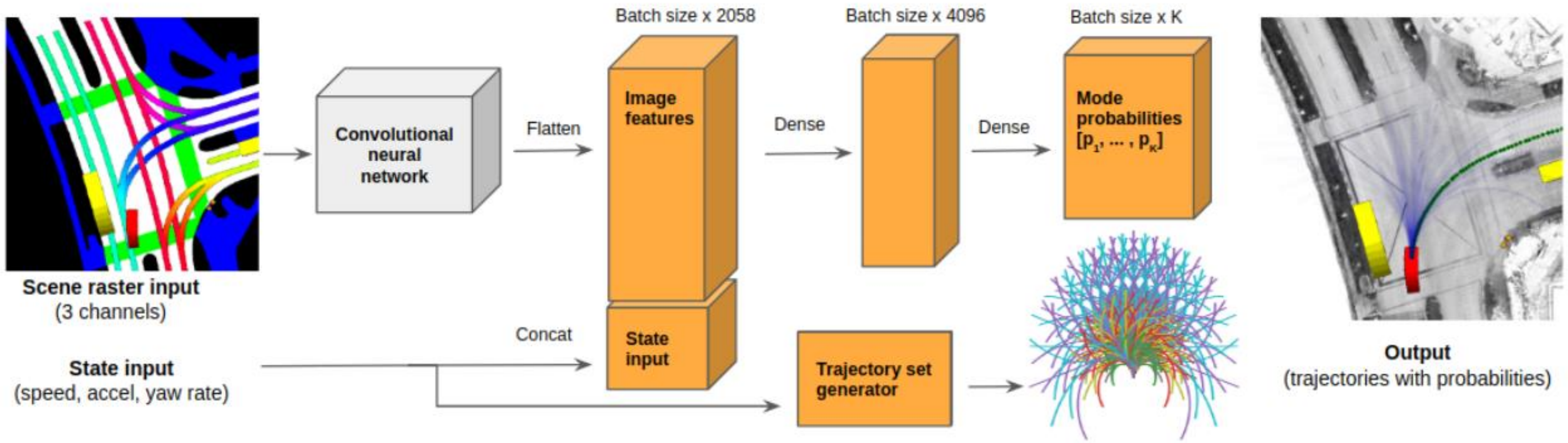
Our Idea for Integrating Expert Knowledge - Part 3

Information Pipeline = Recursion over multiple Tasks



How does it work in practice?

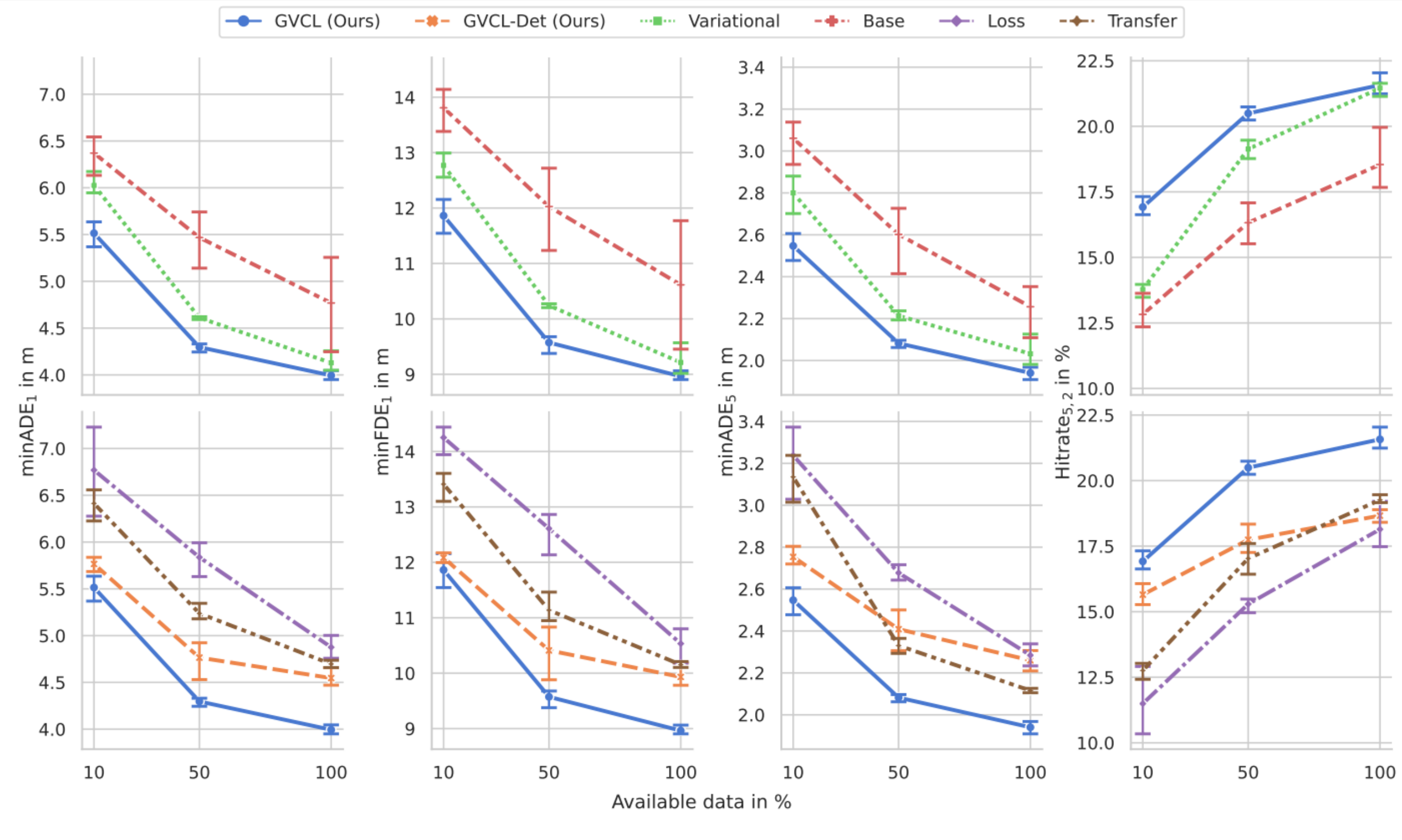
CoverNet as Baseline with our GVCL-CoverNet and CoverNet-SNGP modifications



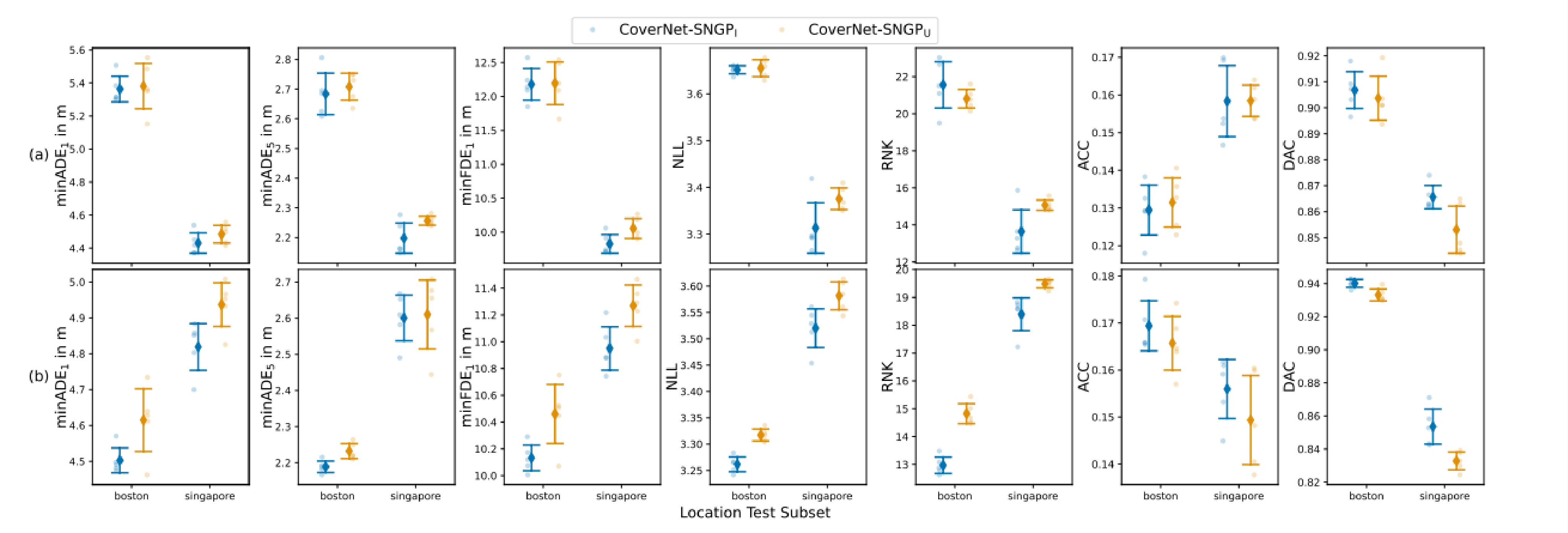
How does it work in Practice?
- Qualitative Results on NuScenes

Red – w/o expert knowledge
Yellow – w/ expert knowledge
Green – ground truth

How does it work in Practice?
- Quantitative Results on NuScenes



How does it work in Practice?
- Quantitative Results on NuScenes



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- ☑ Better Performance
- ☑ Higher Data Efficiency
- ☑ More Robustness (to location-transfers)

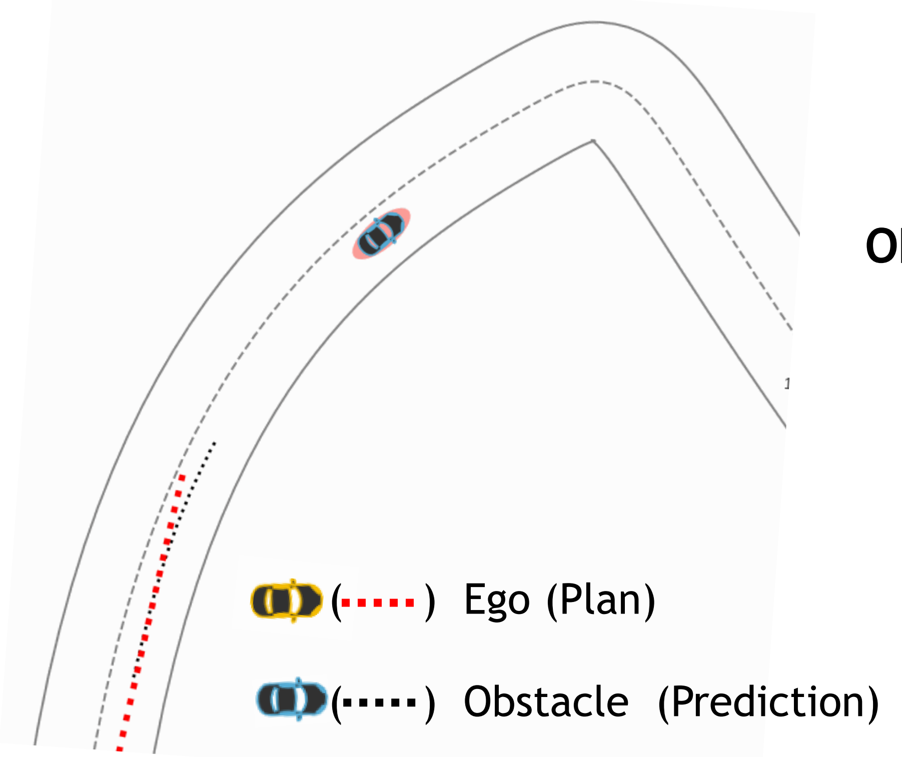
[1] Schlauch et al.: Informed Priors for Knowledge Integration in Trajectory Prediction, European Conference on Machine Learning (ECML), 2023
[2] Schlauch et al.: Informed Spectral Normalized Gaussian Processes for Trajectory Prediction, preprint, 2024

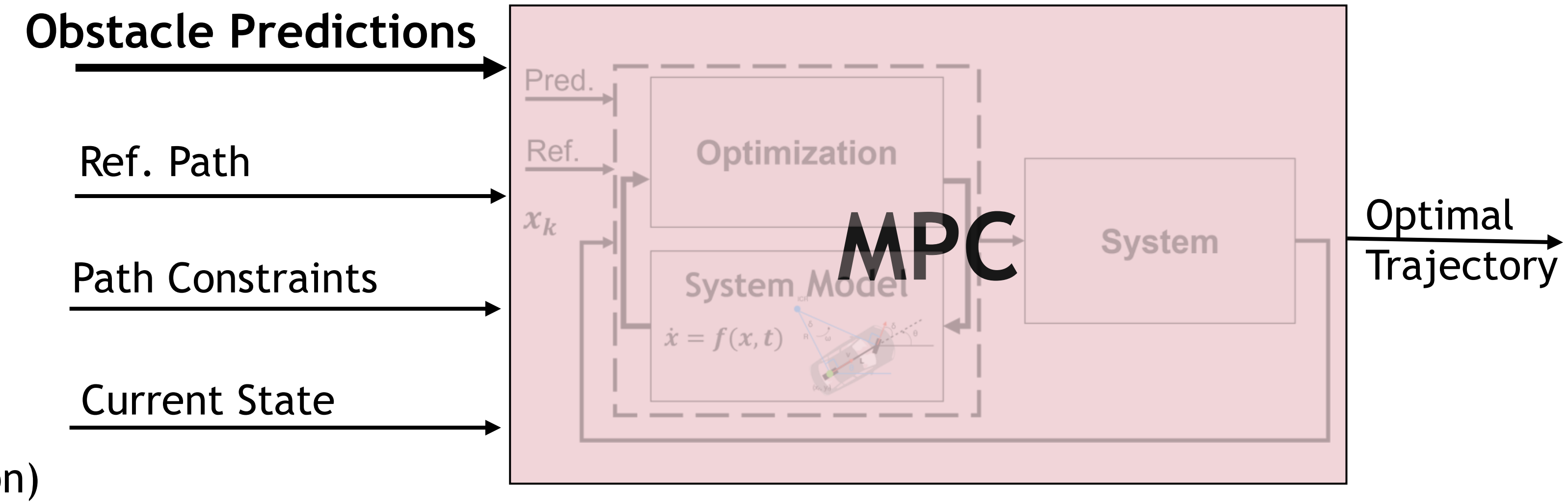
4

Hybrid Architecture in Motion Planning

Obstacle Predictions

Model Predictive Control (Baseline Planner)



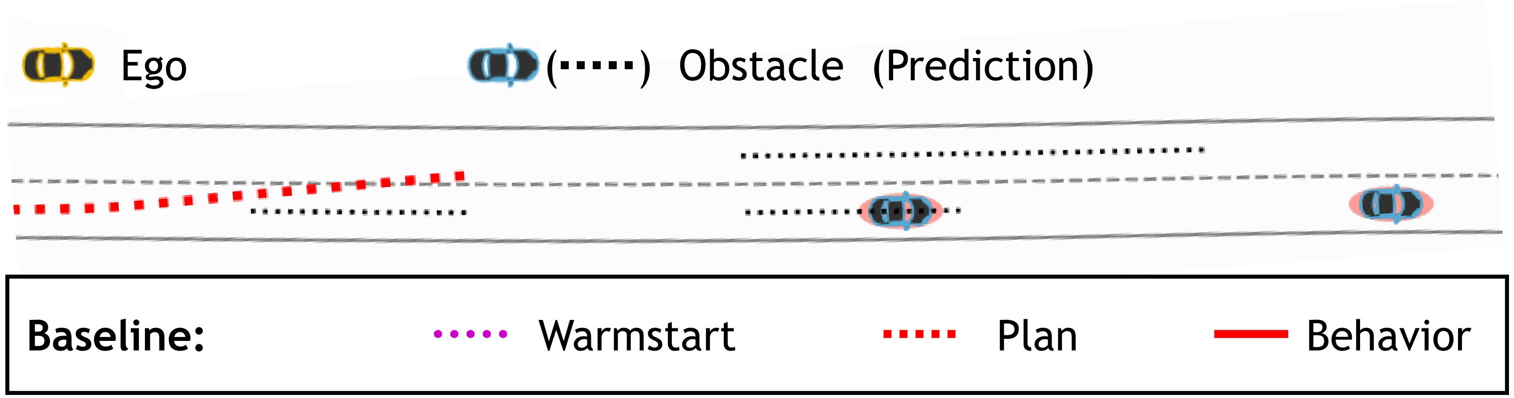


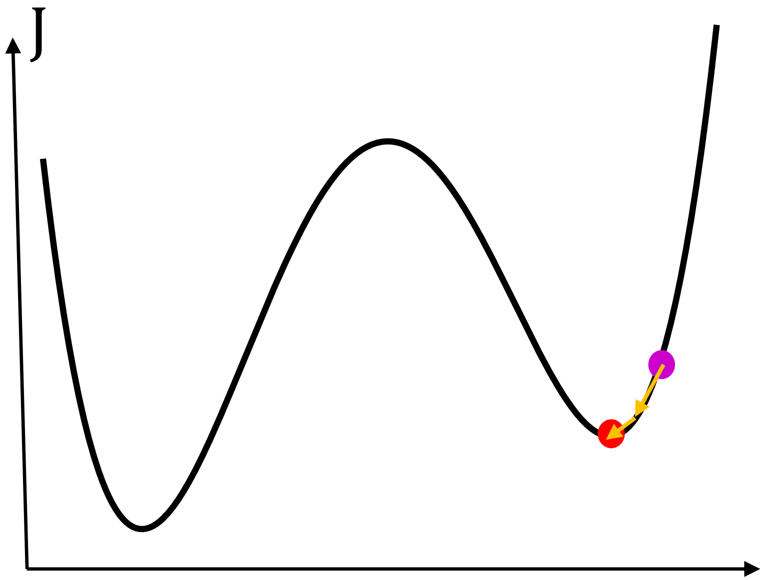
MPC in a Nutshell:

- Finds local optimal trajectory
- Under consideration constraints (kinematic, path, collision etc.)

→ Safe & comfortable behavior

MPC in Non-Convex Problems

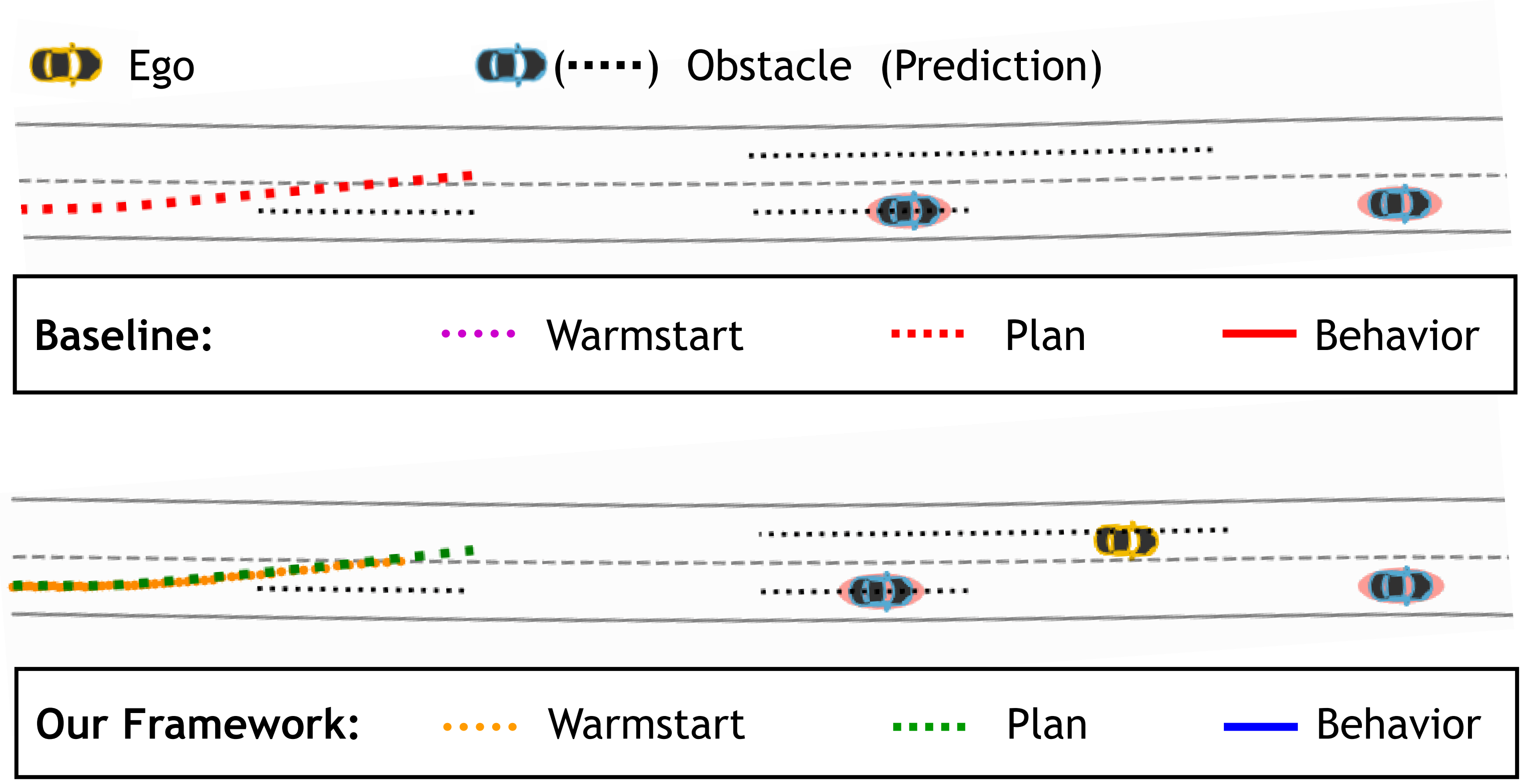


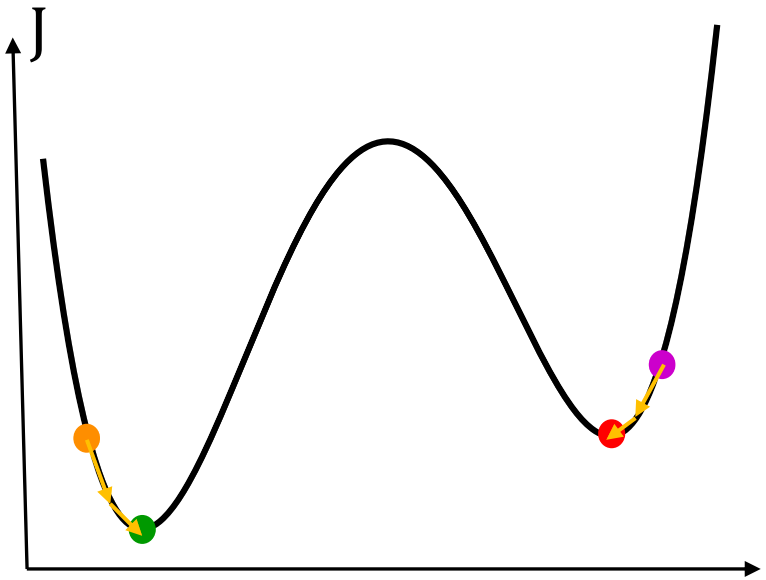


Limitations of MPC adressed by our approach:

1. Convergence to local optimum if initial guess too close
   - Problematic especially in crowded environments since obstacles cause multiple local minima

MPC in Non-Convex Problems





Limitations of MPC adressed by our approach:

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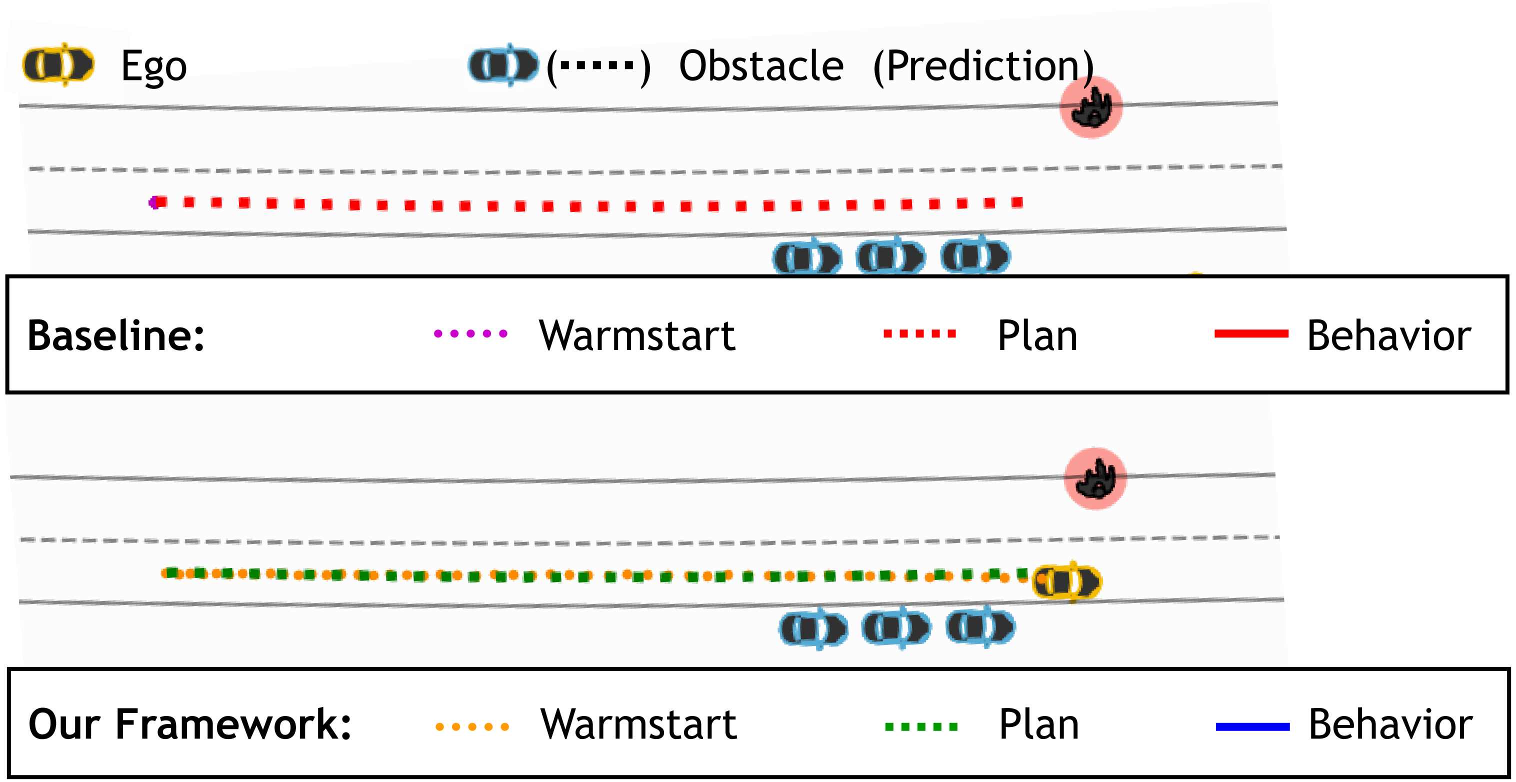
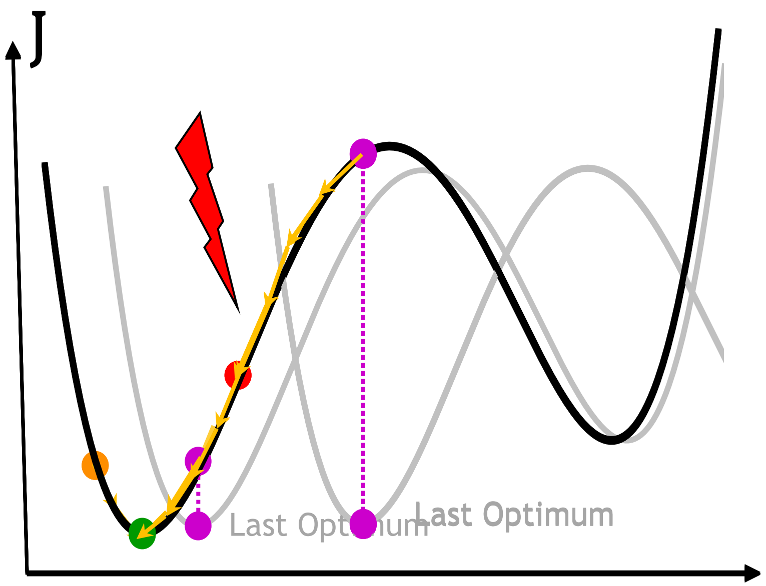
MPC in Uncertain Fast-Changing Traffic



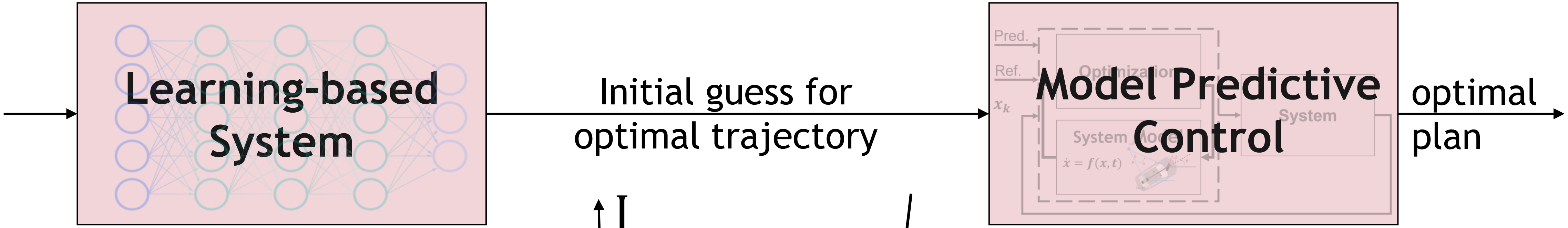


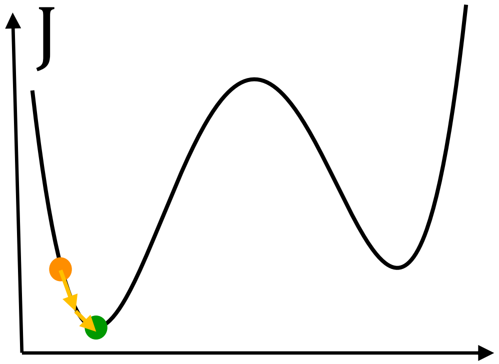
Limitations of MPC adressed by our approach:

2. Slow convergence if Optimum is too far from initial guess (many optimization steps)
   - Problematic especially in unknown fast-changing environments where last optimum is far from new one

Basic Idea of our Method: Learning-aided Warmstart

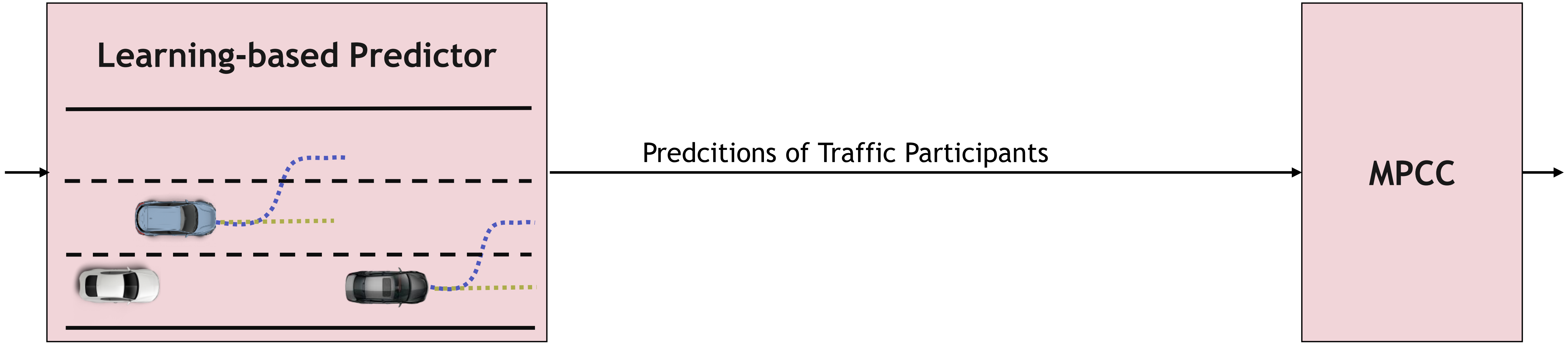
Warmstart: Initializing the optimizer with a near-optimal solution to improve convergence quality





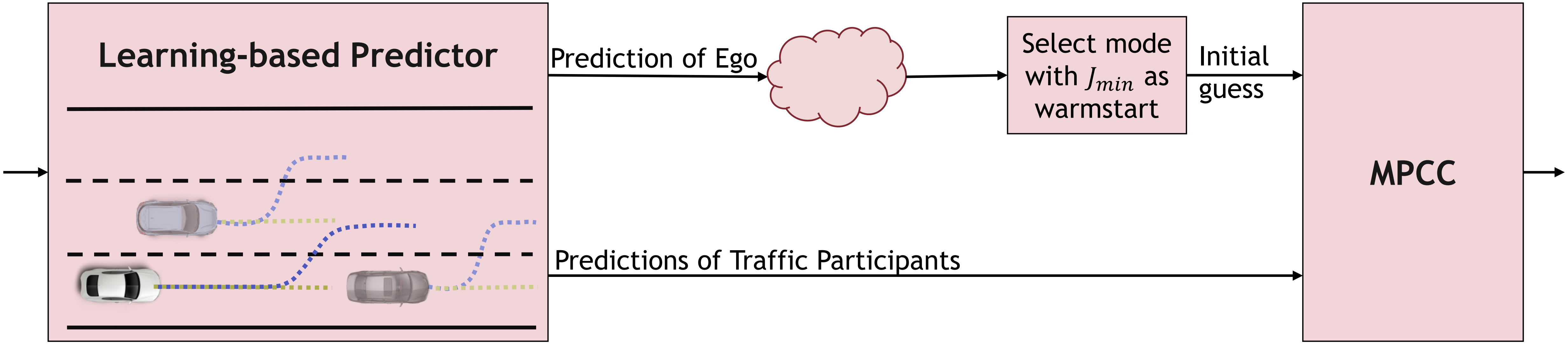
- ⊕ Faster convergence of MPC
- ⊕ Find good enough local Optimum
- ⊕ Constraints are explicitly considered (→ Safety, Feasibility)

Multimodal Interaction-aware Trajectory Predictor



- Prediction of Traffic Participants is required for Motion Planning
- SotA Predictors are multimodal **(Multimodal Predictions often correspond to homotopy classes)**

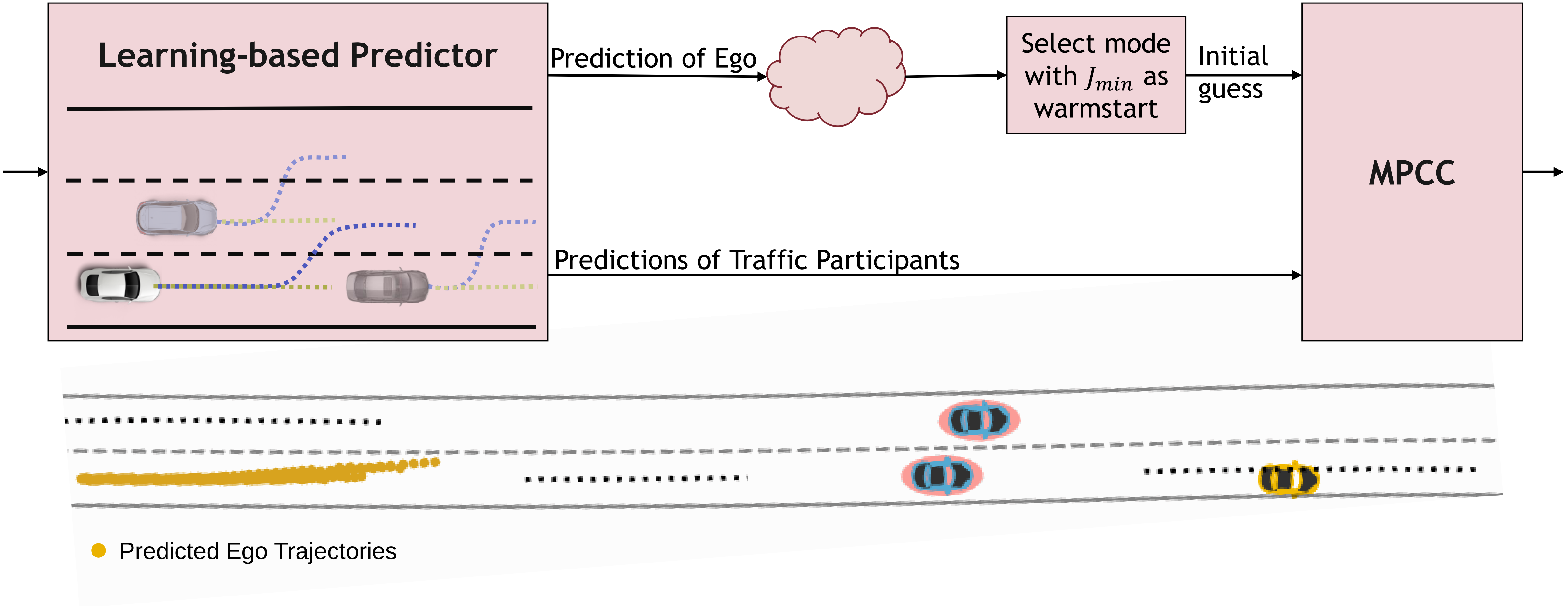
Multimodal Interaction-aware Trajectory Predictor



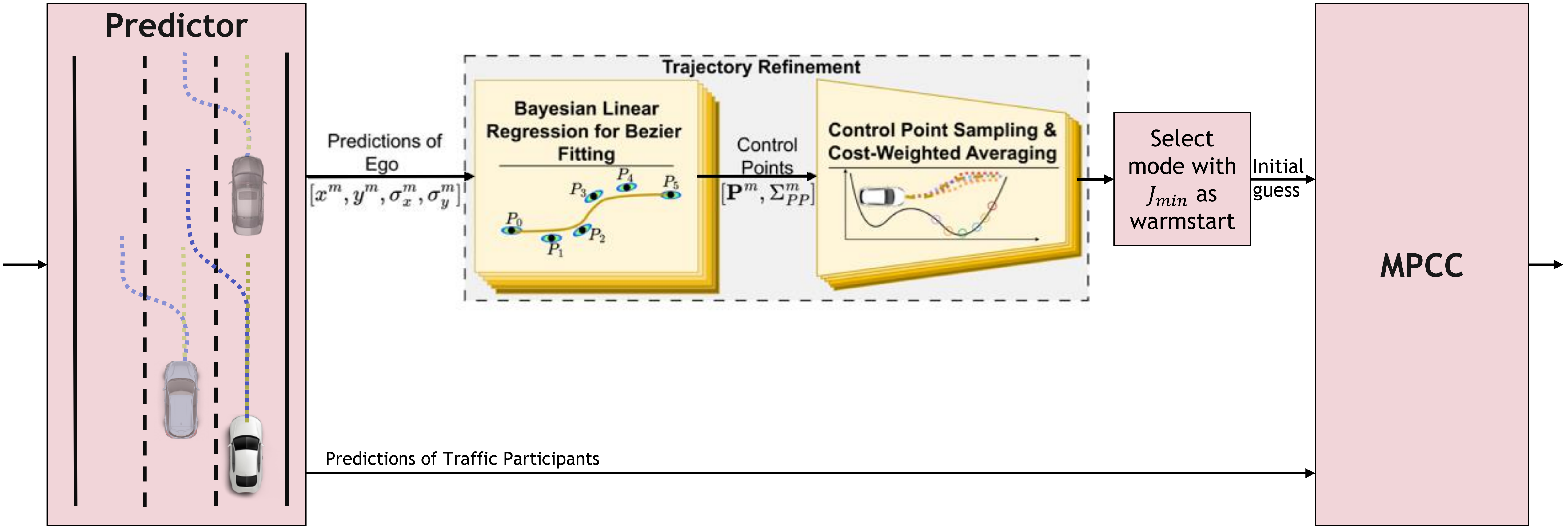
- Prediction of Traffic Participants is required for Motion Planning
- SotA Predictors are multimodal **(Multimodal Predictions often correspond to homotopy classes)**

→ **Why not predict Ego Vehicle in parallel?**

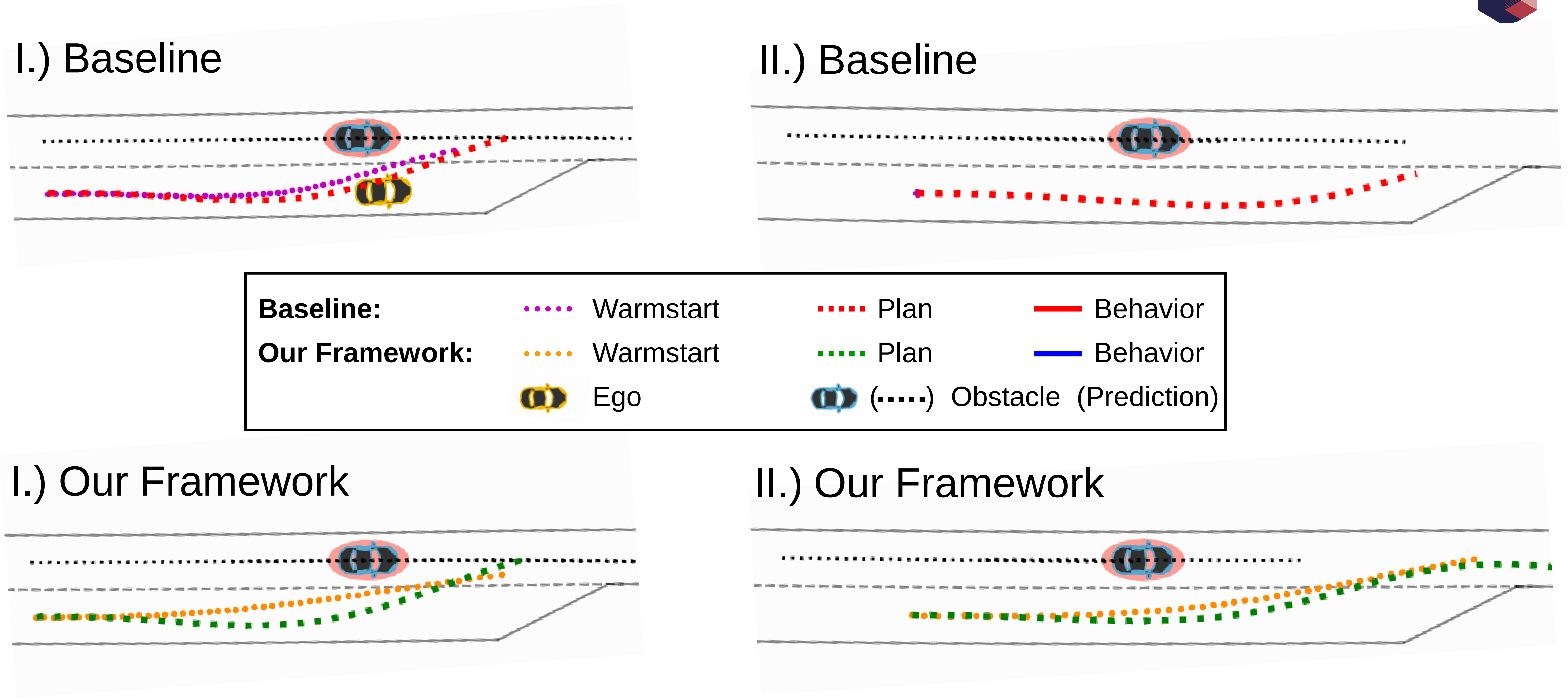
Multimodal Interaction-aware Trajectory Predictor



Multimodal Interaction-aware Trajectory Predictor



Examples from the Evaluation



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- More Robustness

[1] Bouzidi et al.: Learning-Aided Warmstart of Model Predictive Control in Uncertain Fast-Changing Traffic, IEEE International Conference on Robotics and Automation (ICRA), 2024

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Summary

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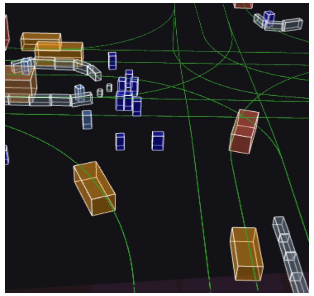
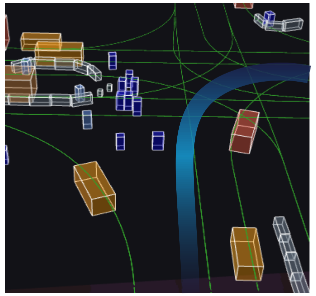
Contributions:

- Developed an efficient outlier-robust filter outperforming state of the art. Showcased that outliers cannot be simply ignored, since the judgment what might be outliers can be flawed.
- The parametric representation models object trajectories with high fidelity and significantly improve model efficiency and robustness in out-of-distribution testing.
- Developed a probabilistic informed learning approach to integrate prior expert knowledge to improve data efficiency and robustness
- Designed a learning-aided Motion Planner which improves convergence quality in fast-changing unknown scenarios and helps to prevent undesired local minima

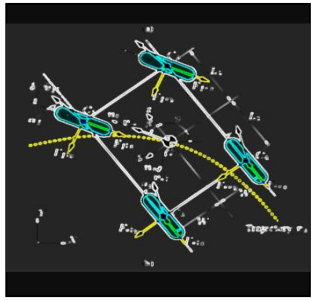
Perception & Tracking



Prediction



Planning and Control



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KI FAMILIE

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