Friedrich-Alexander-Universität
Faculty of Engineering

Context-based AI Systems for Robust Yaw Rate and Trajectory Predictions in Autonomous Driving

Lars Ullrich | 12.09.2024
Chair of Automatic Control

Agenda – Context-based AI Systems

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- Introduction
- Ego Yaw Rate Prediction
- Road User Trajectory Prediction
- Key Takeways
- Outlook

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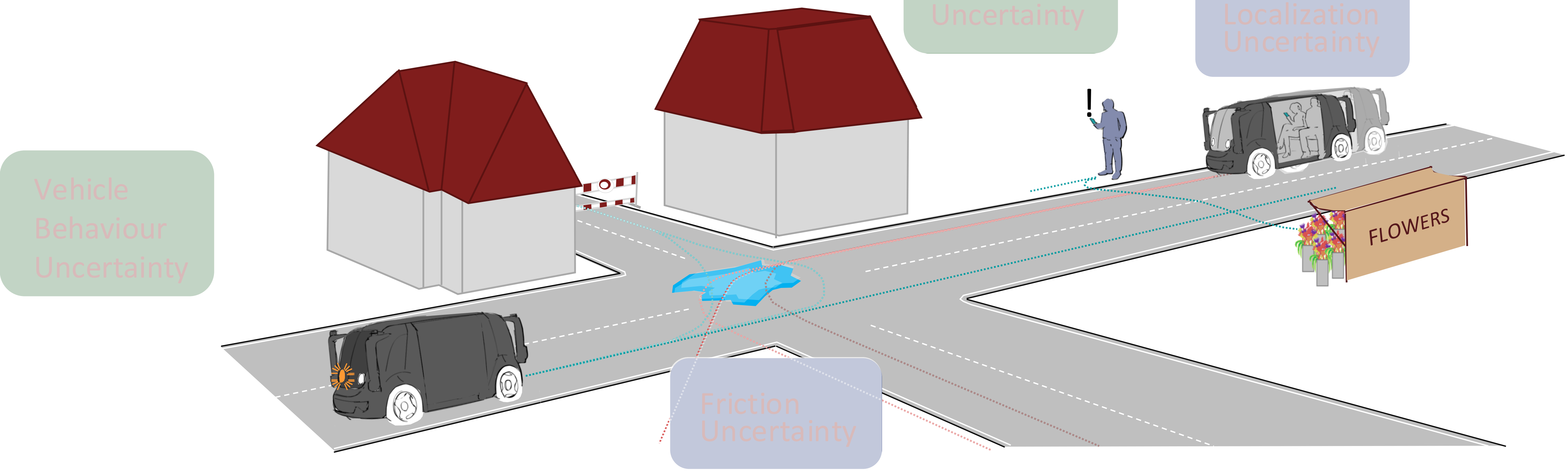
Robust Planning Through Probabilistic Methods

Trajectory predictions of nearby road users is crucial component within model predictive trajectory planning!

Ego-model is crucial component within model predictive trajectory planning!



Ego Yaw Rate Prediction

Robust Meta-Learning of Vehicle Yaw Rate Dynamics via Conditional Neural Processes

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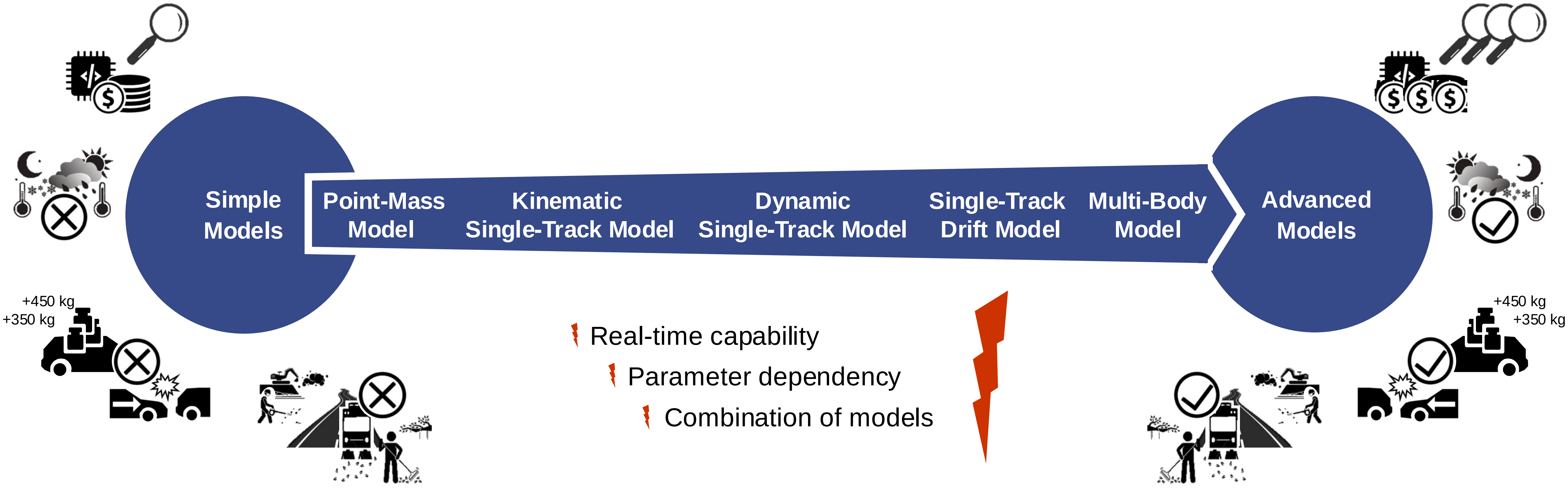
Ego Vehicle Model

- Vehicle models are key components for autonomous driving



Ego Vehicle Model

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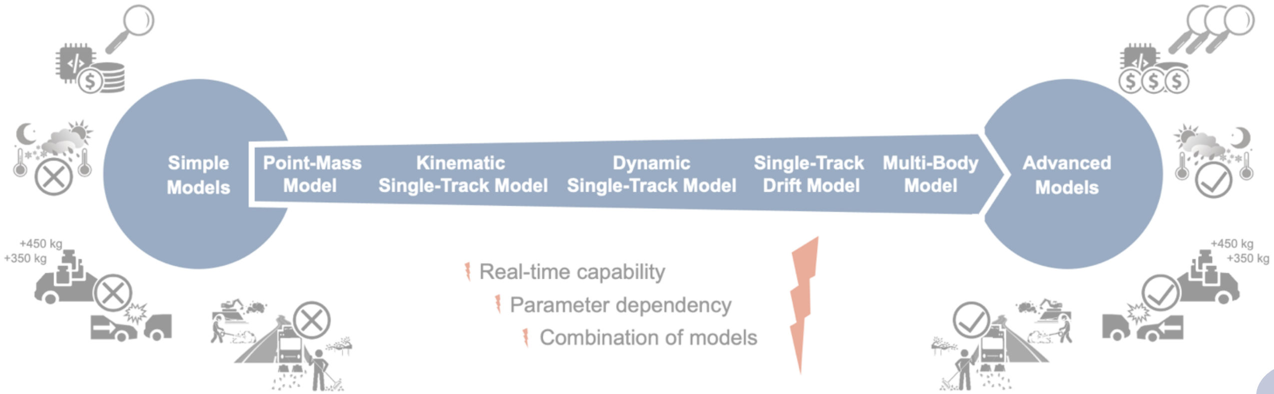
- Vehicle models are key components for autonomous driving



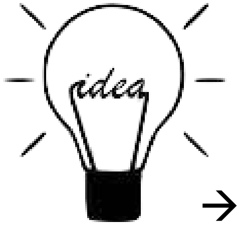
Accuracy across ODD ↑

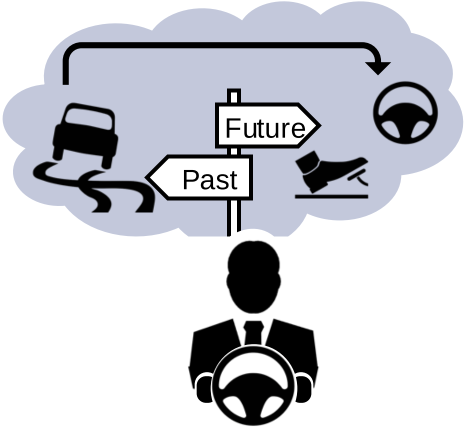
Parameter dependence ↓

Computational complexity ↓

Complex modeling
mainly affects yaw rate!

Could the yaw angle be determined differently?

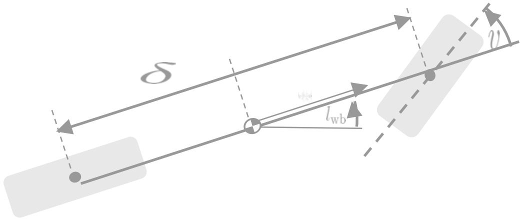
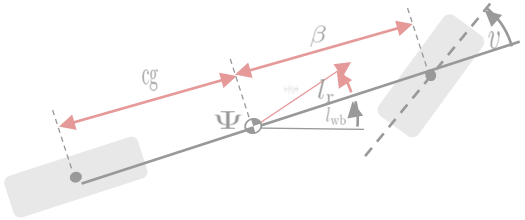
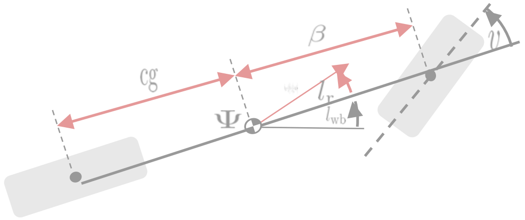




→ Human-like knowledge transfer
→ Learn to learn on current situation
→ **Meta-learning**

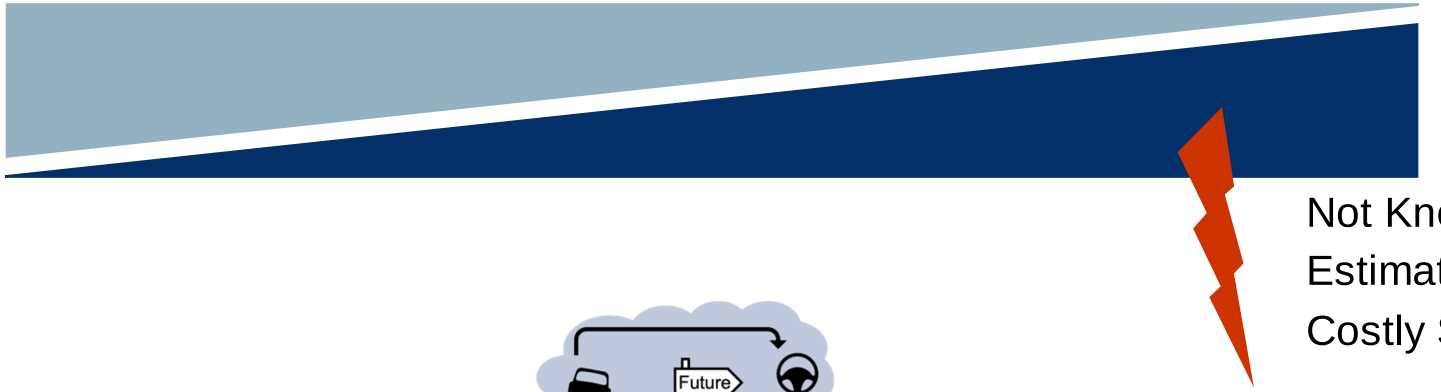
Physical Yaw Rate Predicting

- Kinematic Single-Track Model (KST)
- Dynamic Single-Track Model (DST)
- Single-Track Drift Model (STD)

Simplified

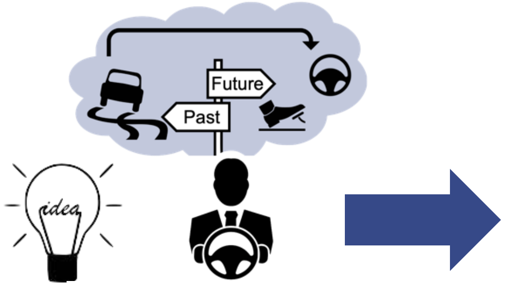
Model Error



Context Awareness

Parameter Dependence

Not Known
Estimated
Costly Sensored



Data-driven

→ Human-like
→ **Meta-learning**

Data-driven Yaw Rate Predictions

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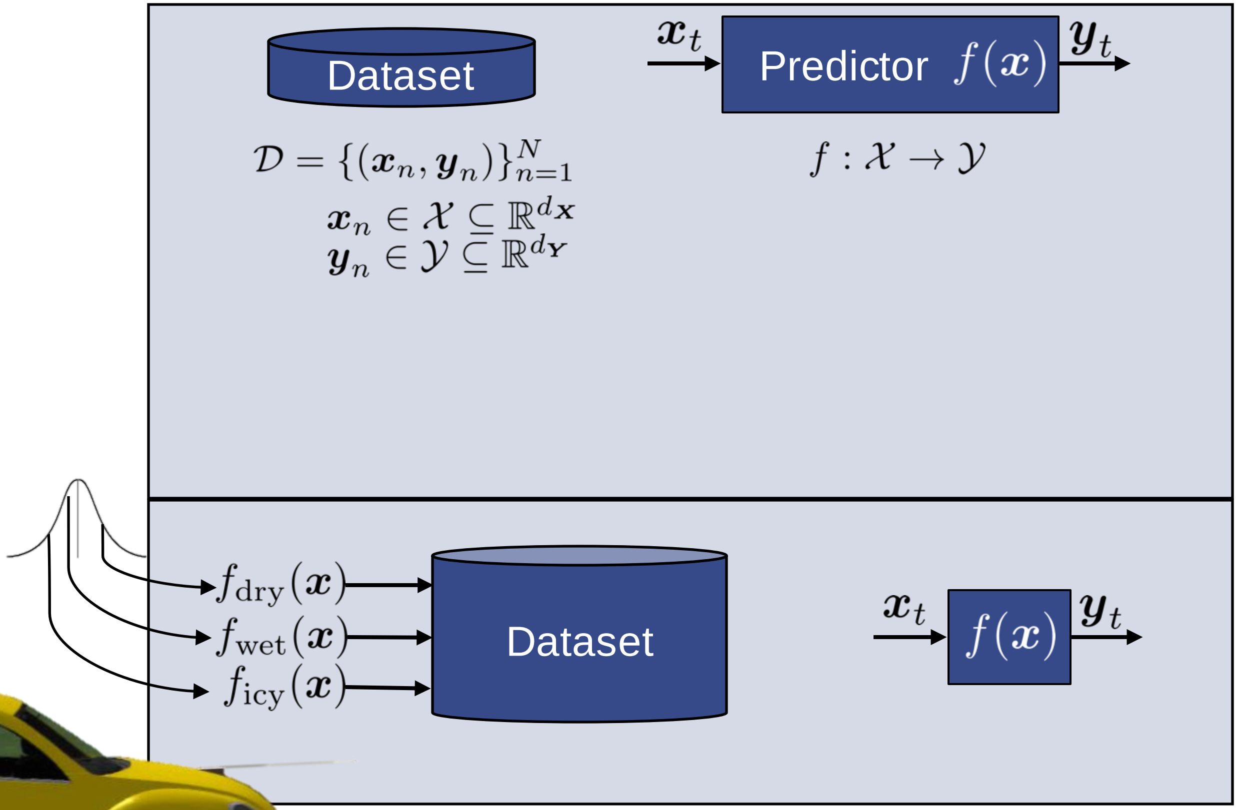
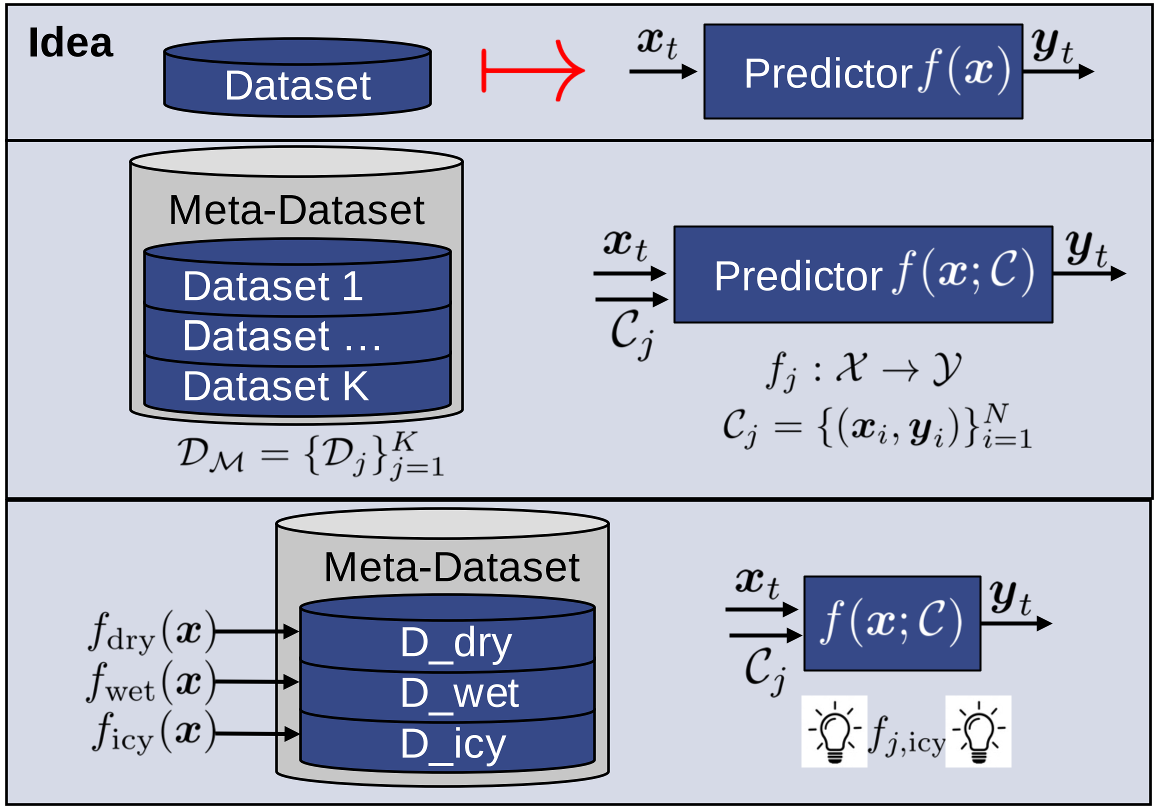
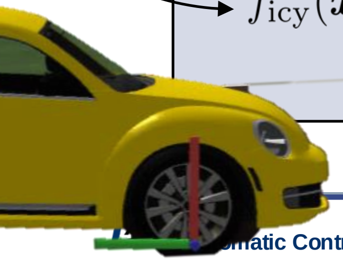
- Meta-learning: Conditional Neural Processes (CNP)

Supervised learning



Meta-learning





Conditional Neural Processes (CNP) – Architecture

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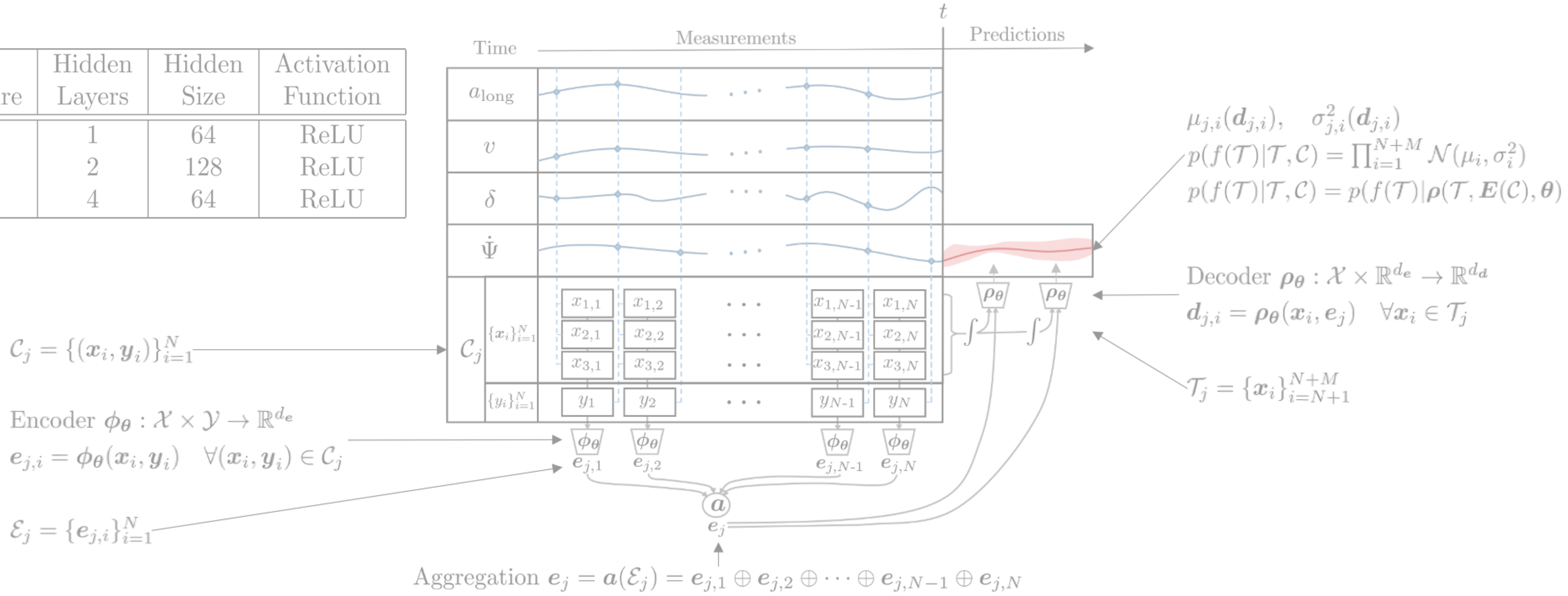
- Application specific CNP Architecture

General Modules	Network Architecture	Hidden Layers	Hidden Size	Activation Function
Feature Encoder	MLP	1	64	ReLU
Context Encoder	MLP	2	128	ReLU
Decoder	MLP	4	64	ReLU

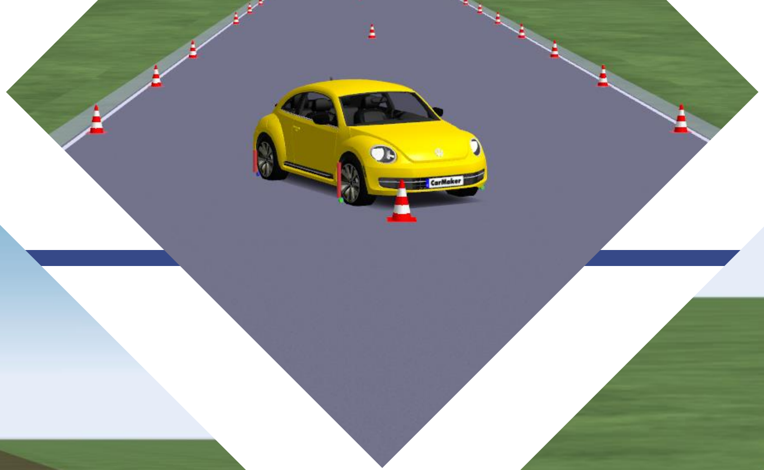
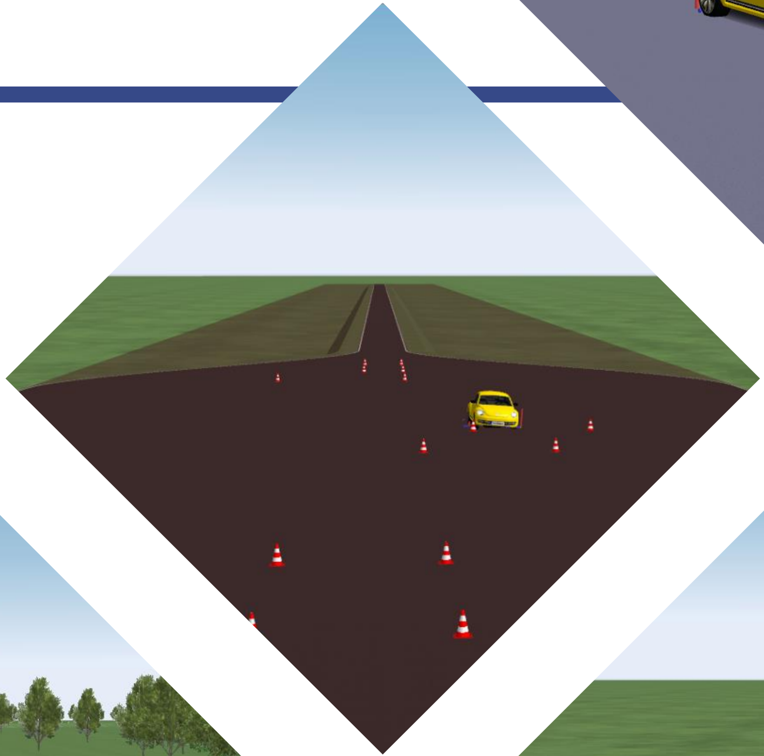


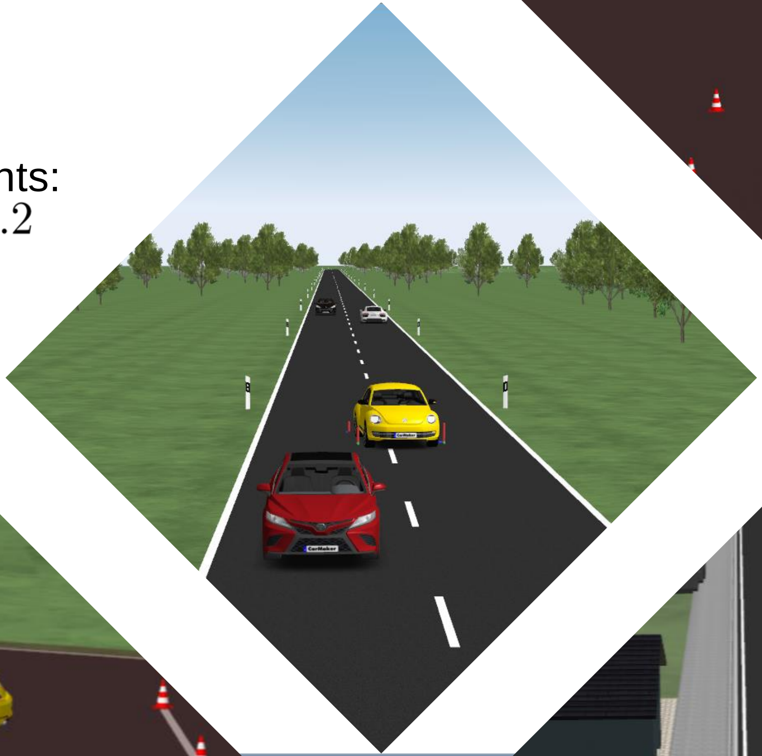
→ **Quite complex. Interested? Contact me afterwards!**

Conditional Neural Processes (CNP) – Training

- CNP training data were collected with CarMaker:
  - Two urban cases
  - Two interurban cases
  - Two longitudinal dynamic cases
  - Fourteen lateral dynamic cases

  - All with different friction coefficients: $\mu_{\text{dry}} = 1.0, \mu_{\text{wet}} = 0.5, \mu_{\text{icy}} = 0.2$
  - All in the velocity range: $0\,\text{to}\,120\,\text{km}\,\text{h}^{-1}$

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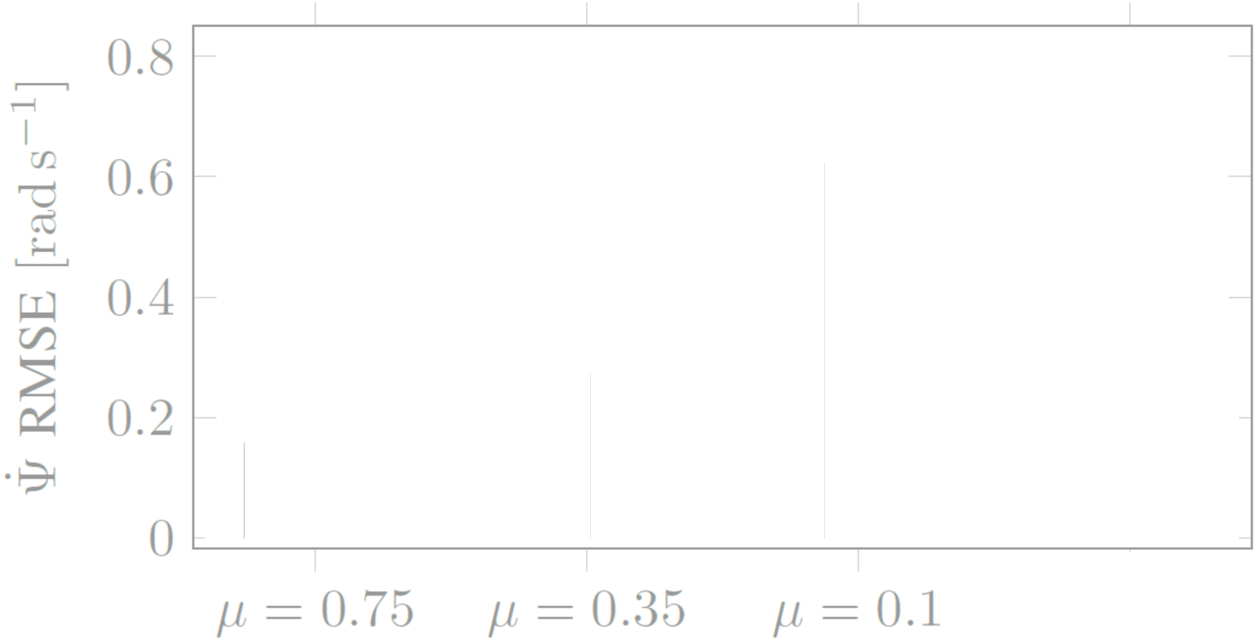
Results – Friction Variation

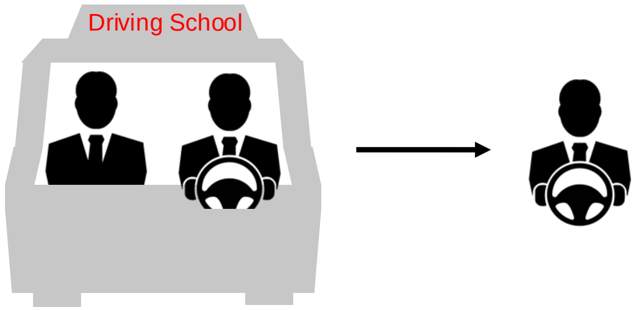
- Change of friction coefficients to: $\mu_{\text{test}} \in \{0.75, 0.35, 0.1\} \quad (\mu_{\text{training}} \in \{1.0, 0.5, 0.2\})$
- Evaluation in all 20 cases with velocity variations



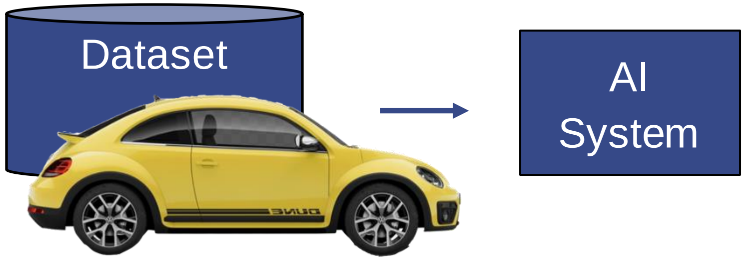
→ **Similar results for other variations (e.g. mass, scenario)!**

Generalization?

- Does the context-based AI system (CNP) generalize like a human?
  - Human



  - AI system



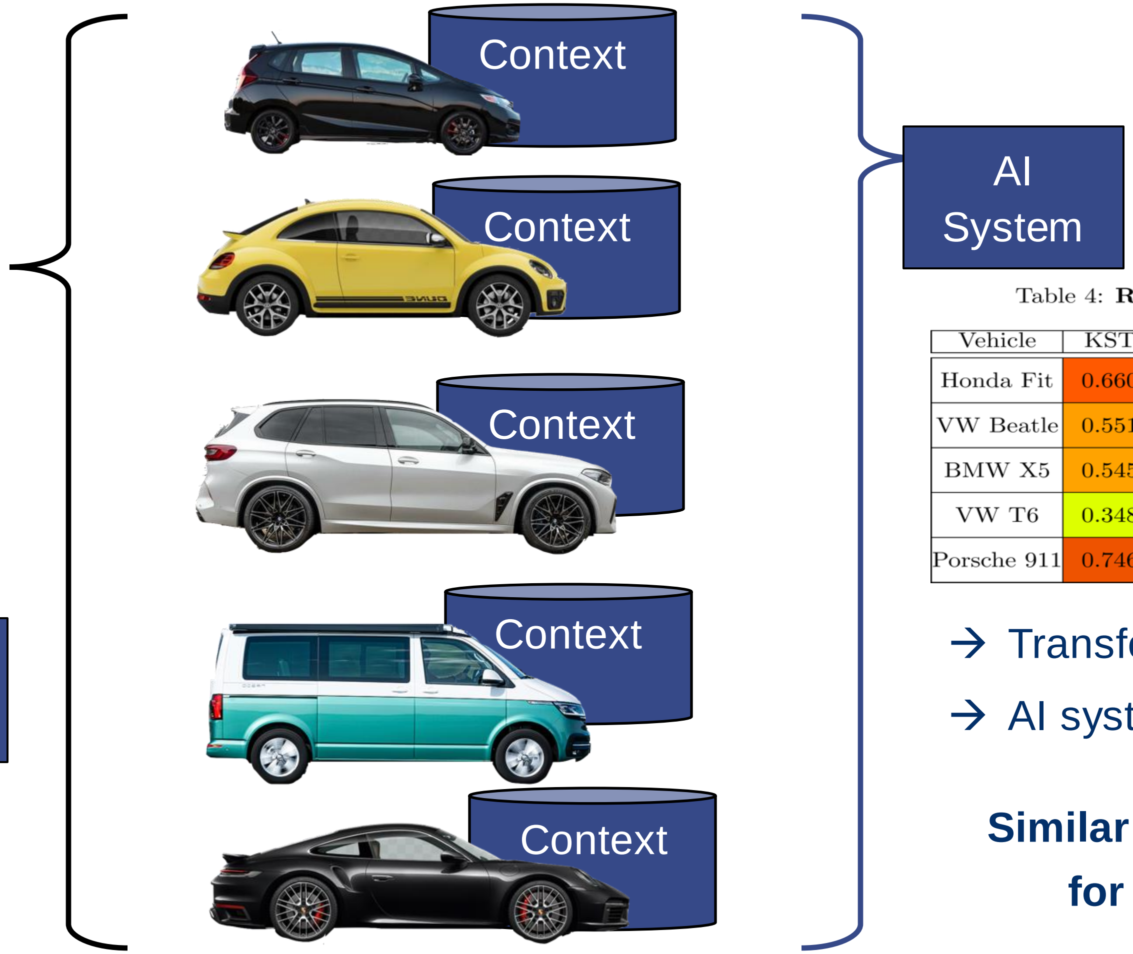


Table 4: **RMSE Vehicle variation icy roads.**

Vehicle	KST	DST	DST(μ)	STD	STD(μ)	CNP
Honda Fit	0.660	0.620	0.657	0.387	0.251	0.260
VW Beatle	0.551	0.539	0.606	0.347	0.137	0.217
BMW X5	0.545	0.536	0.477	0.422	0.401	0.284
VW T6	0.348	0.339	0.280	0.325	0.244	0.179
Porsche 911	0.746	0.781	0.785	0.472	0.254	0.356

→ Transferable without retraining

→ AI system is able to generalize

Similar results are achieved for other variations!

Ego Yaw Rate Prediction

- Accuracy across ODD ↑ ✓
- Parameter dependence ↓ ✓
- Computational complexity ↓ ✓

Ego-model is crucial component within model predictive trajectory planning!

Takeaway I:

- Empirical magic formula (Pacejka tire model) can be reconsidered via data-driven methodologies
- Estimated/sensorized parameter determination up to model updating/blending can be reconsidered via context-based AI systems
- Data-driven context-based AI systems enable to reduce physical model induced assumptions

Thus, context-based AI system for yaw rate predictions could enhance, e.g., a kinematic single-track model

Road User Trajectory Prediction

Transfer Learning Study of Motion Transformer-based Trajectory Predictions

Trajectory Prediction

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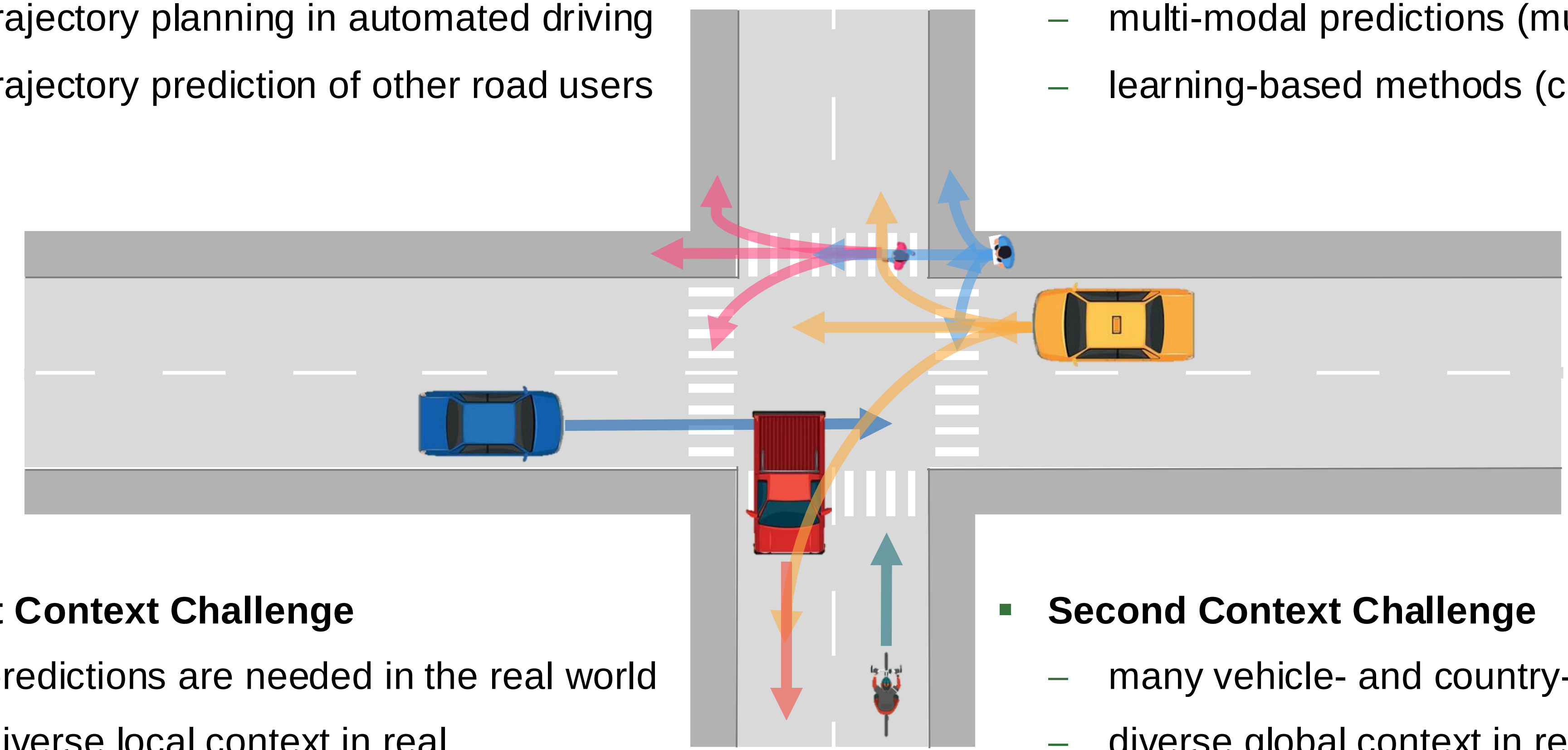
- **Background**
  - trajectory planning in automated driving
  - trajectory prediction of other road users
- **State of the Art**
  - multi-modal predictions (multiple behavioral decisions)
  - learning-based methods (context/open world)



- **First Context Challenge**
  - predictions are needed in the real world
  - diverse local context in real
- **Second Context Challenge**
  - many vehicle- and country-specific shifts
  - diverse global context in real world

First Challenge: Local Context

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- One approach: Motion Transformers
- Generative Pre-trained Transformers (e.g. ChatGPT)

What is IPG CarMaker? Give a single sentence statement.

Local Context

IPG CarMaker is a simulation software used for testing and validating vehicle dynamics, driver assistance systems, and automated driving functions in virtual environments.

Another Solution

How is the vehicle model designed? Give a single sentence statement.

The vehicle model in IPG CarMaker is designed using a modular approach that allows for detailed customization and simulation of various vehicle components, including the chassis, drivetrain, suspension, and tires, to accurately replicate real-world vehicle behavior.

Local Context Evolution

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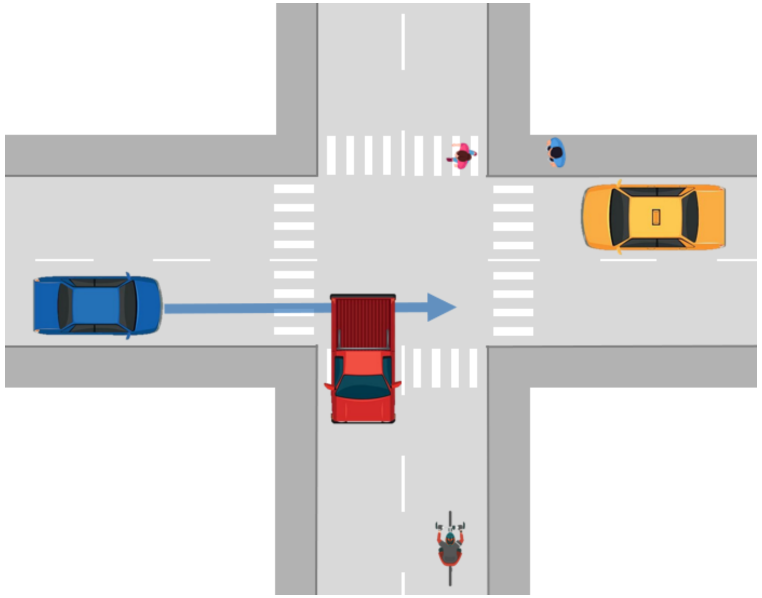
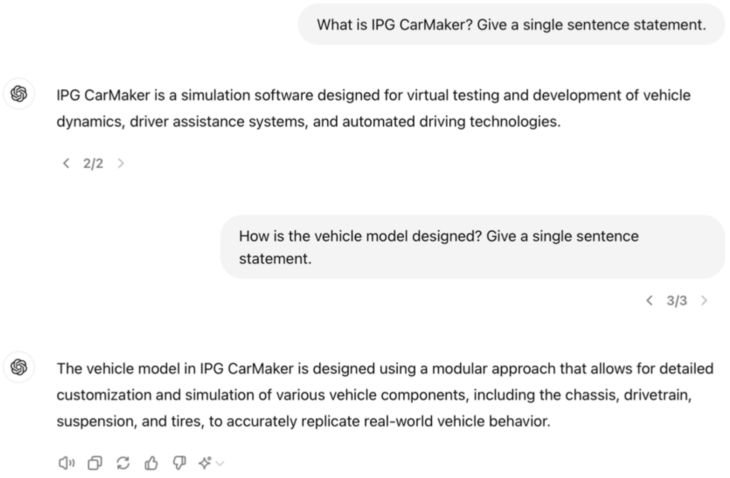
First Challenge: Local Context

- One approach: Motion Transformers

- Generative Pre-trained Transformers (e.g. ChatGPT)





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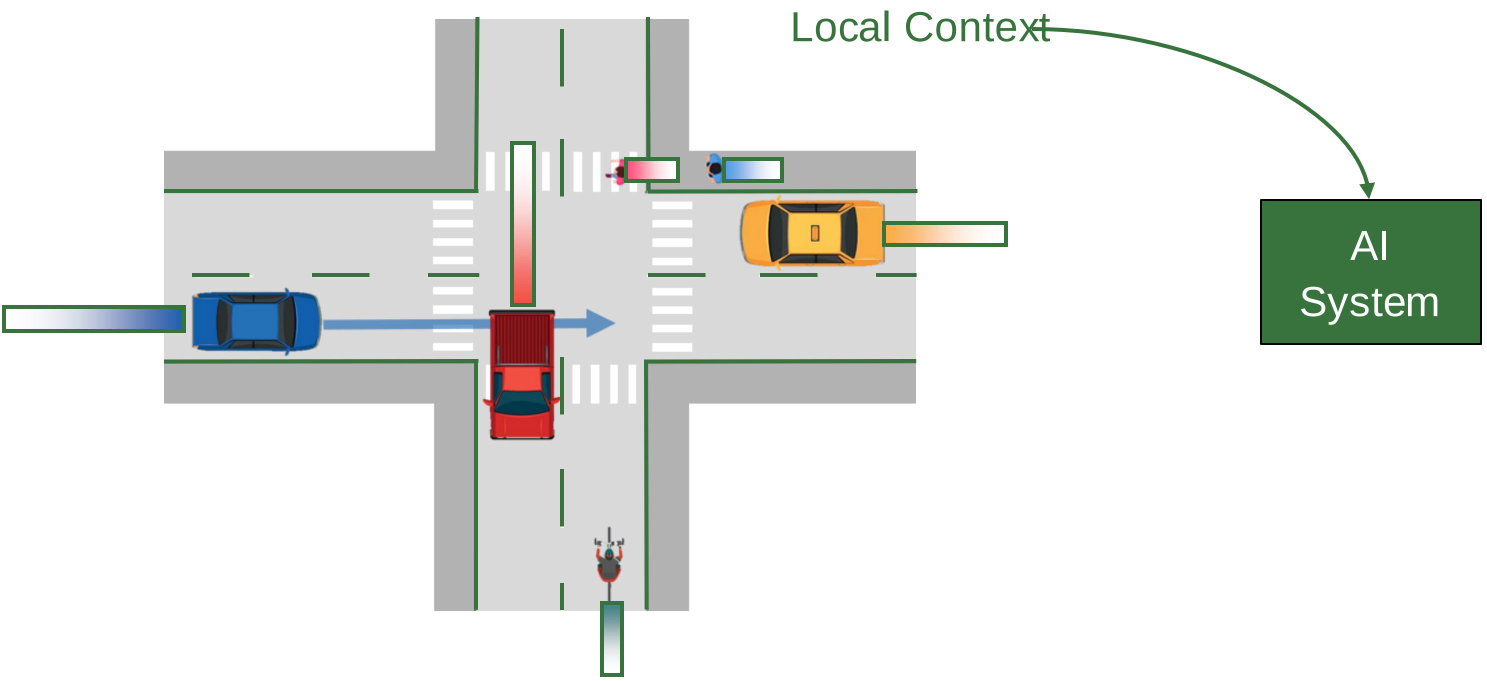
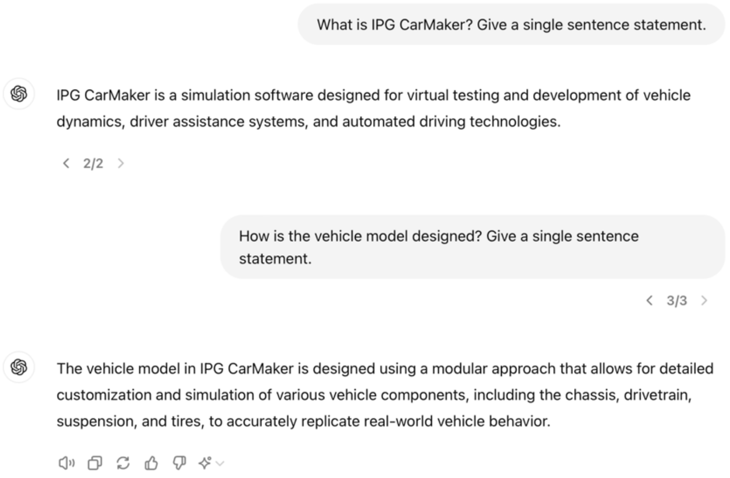
First Challenge: Local Context

- One approach: Motion Transformers
- Generative Pre-trained Transformers (e.g. ChatGPT)




What is IPG CarMaker? Give a single sentence statement.

IPG CarMaker is a simulation software designed for virtual testing and development of vehicle dynamics, driver assistance systems, and automated driving technologies.

2/2

How is the vehicle model designed? Give a single sentence statement.

3/3

The vehicle model in IPG CarMaker is designed using a modular approach that allows for detailed customization and simulation of various vehicle components, including the chassis, drivetrain, suspension, and tires, to accurately replicate real-world vehicle behavior.

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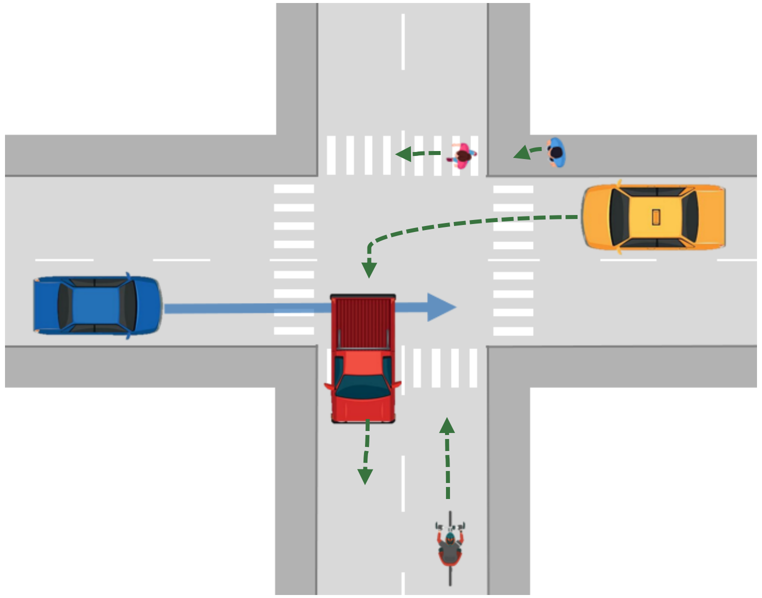
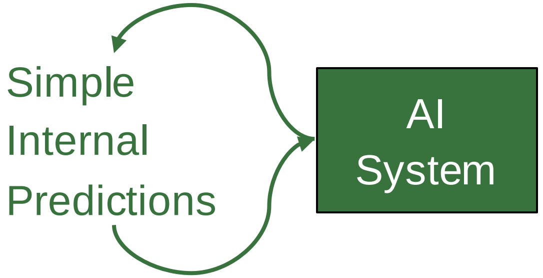
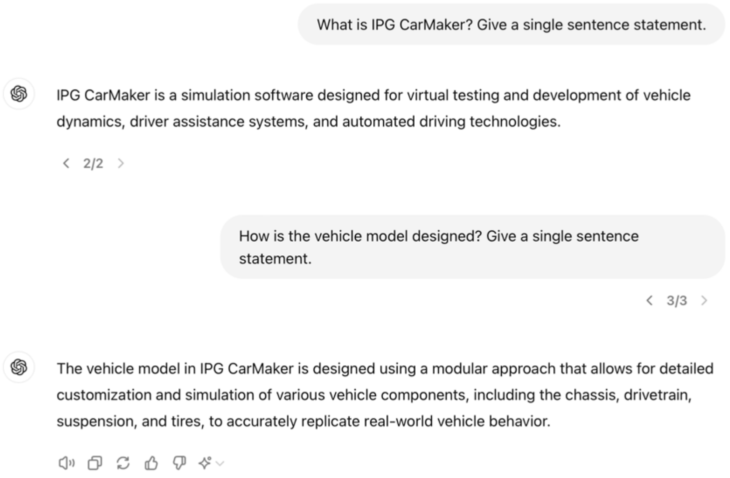
First Challenge: Local Context

- One approach: Motion Transformers





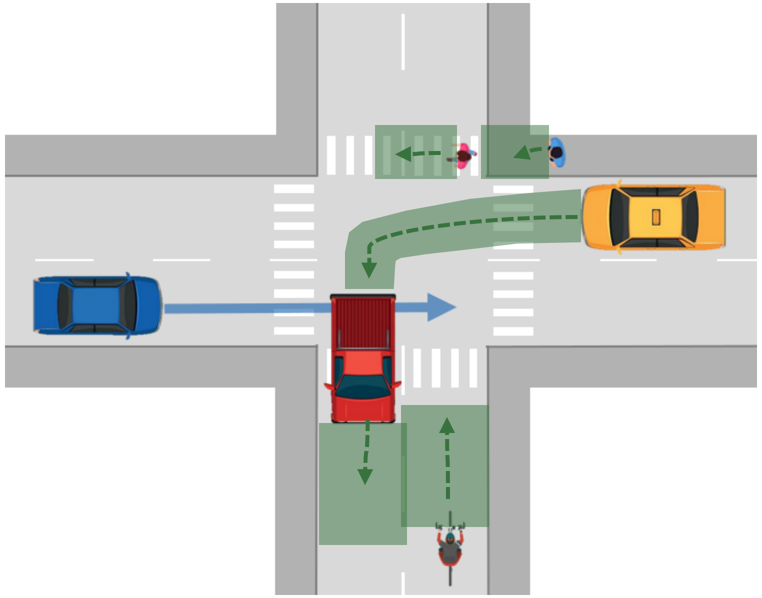
- Generative Pre-trained Transformers (e.g. ChatGPT)

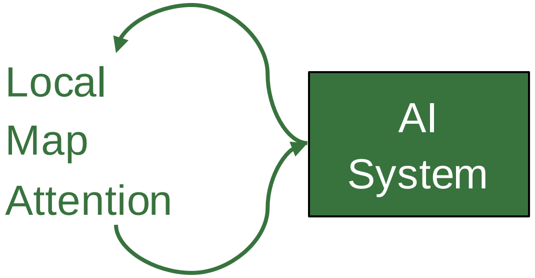


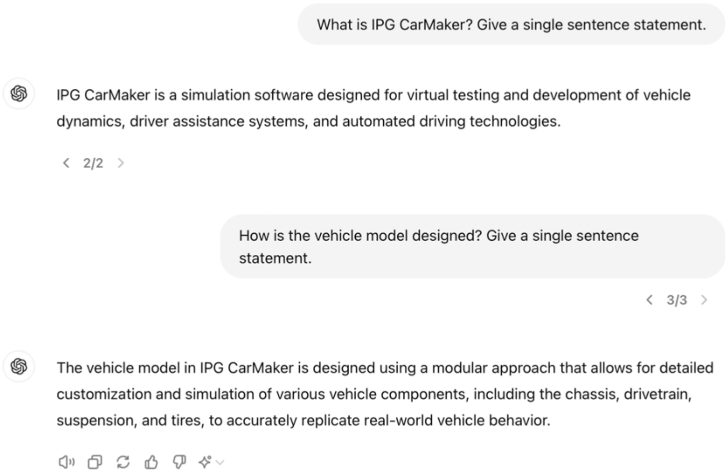
First Challenge: Local Context

- One approach: Motion Transformers

- Generative Pre-trained Transformers (e.g. ChatGPT)







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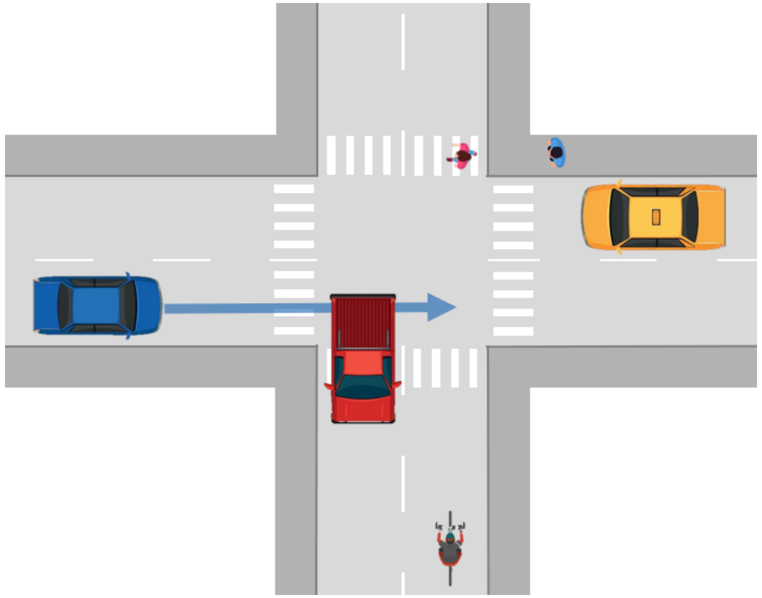
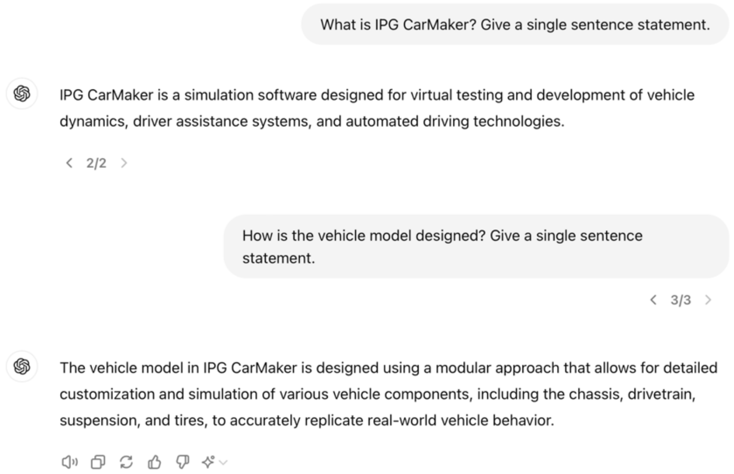
First Challenge: Local Context

- One approach: Motion Transformers
- Generative Pre-trained Transformers (e.g. ChatGPT)



Refinement

AI System



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First Challenge: Local Context

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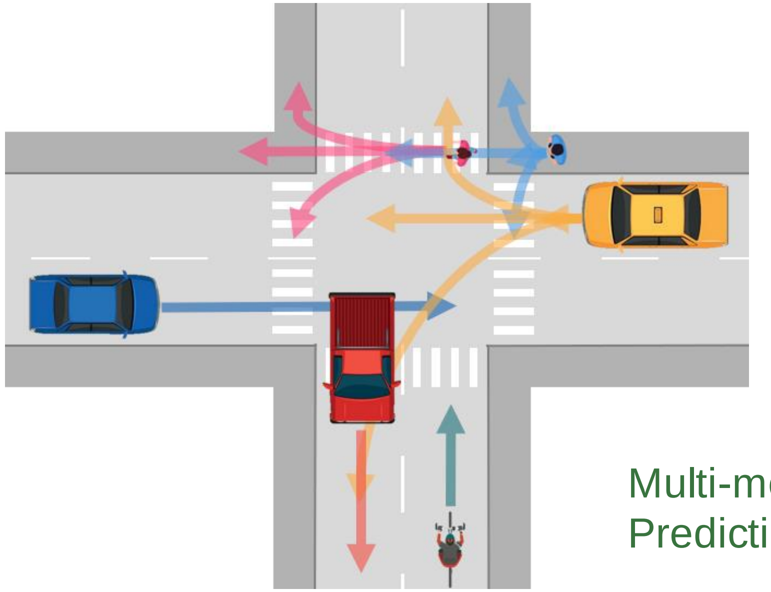

AI System

Multi-modal Predictions

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2/2

How is the vehicle model designed? Give a single sentence statement.

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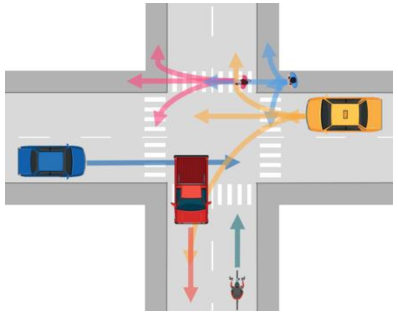
First Challenge: Local Context

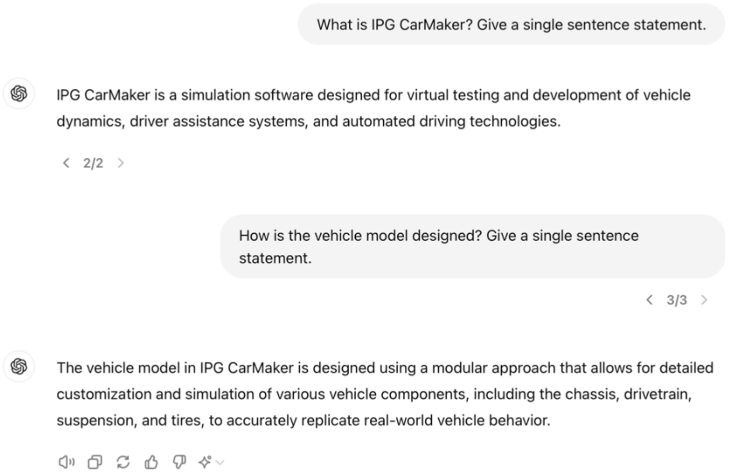
- One approach: Motion Transformers



  - attention-based approach
  - considers multi-modality
  - addresses spatial-temporal aspects

→ enables local context and interaction awareness

- Generative Pre-trained Transformers (e.g. ChatGPT)



Second Challenge: Global Context

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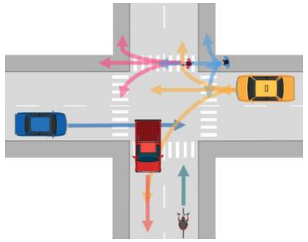
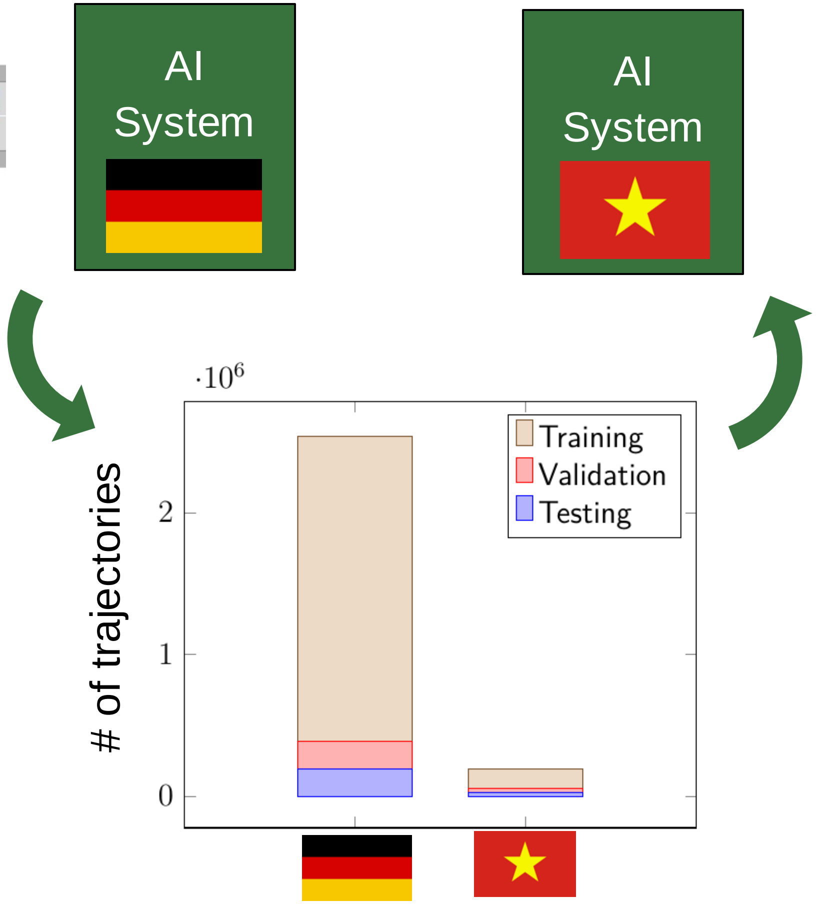
- Differences around the globe



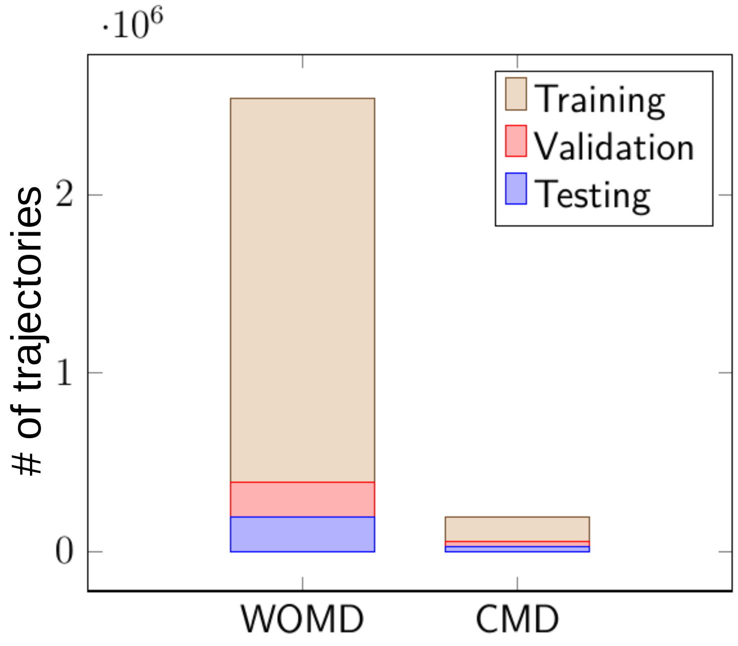
- One Solution: Transfer Learning



CarMaker – Transfer Learning Study

Dataset Setup

Dataset	WOMD	CMD
Source / Target Environment Setting	Source US Roads	Target German Roads
Number of Scenarios Duration of Each Scenario Trajectory Sampling Rate	575,205 9 seconds 10Hz	190,933 9 seconds 10Hz
Training Split Validation Split Test Split	$84.\overline{6}\%$ (487,005) $7.\overline{6}\%$ (44,100) $7.\overline{6}\%$ (44,100)	70% (133,653) 15% (28,640) 15% (28,640)
Total Trajectories Agent Split (Veh./Cyc./Ped.)	2,566,096 70/7/23%	190,933 100/0/0%



Scaling Impression

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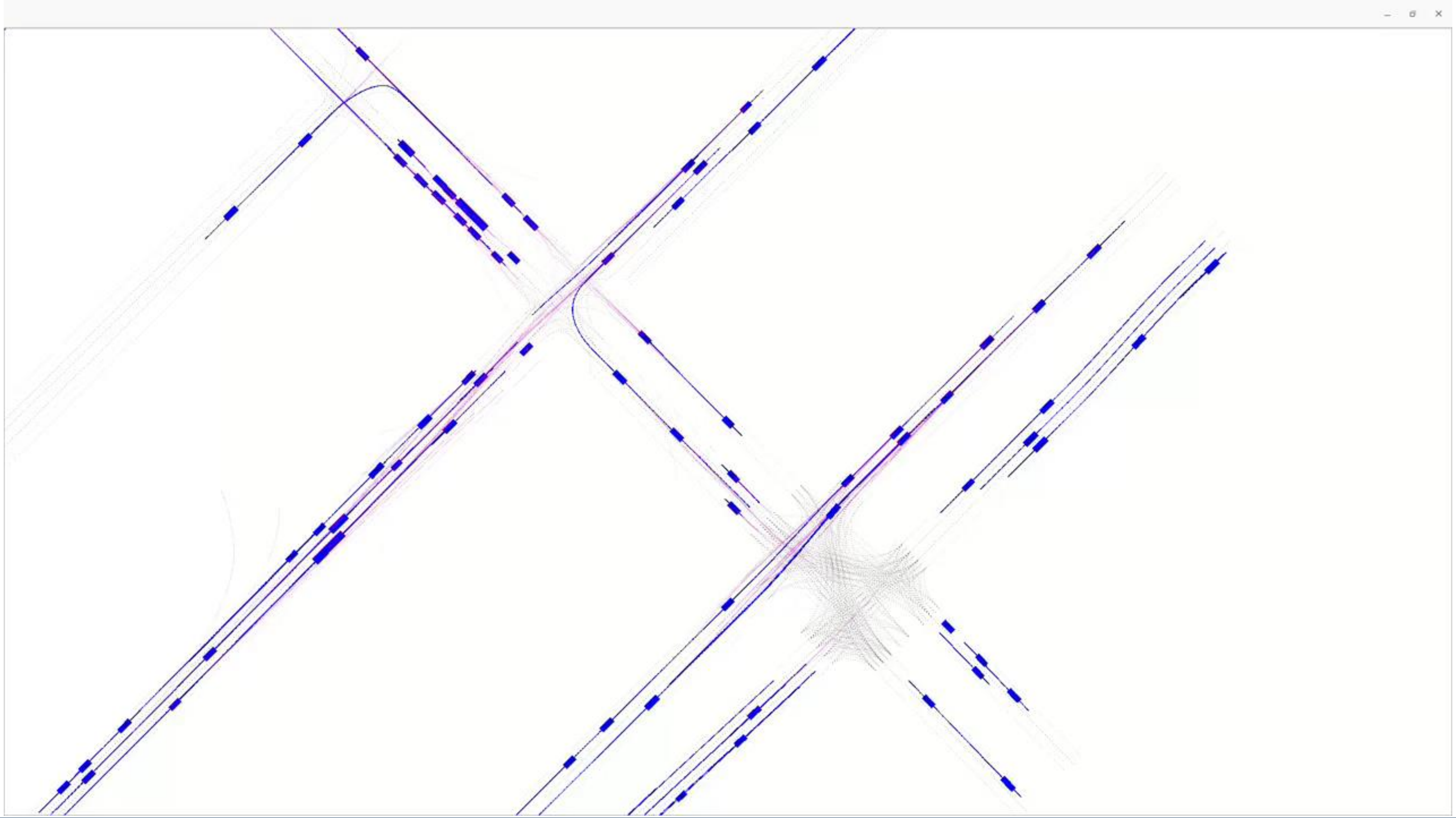

Numerical Results

- **Performance results**

	Source Dataset				Target Dataset			
	mAP ↑	minADE ↓	minFDE ↓	MissRate ↓	mAP ↑	minADE ↓	minFDE ↓	missRate ↓
Target Baseline (TB)	0.0917	4.6698	10.2989	0.6901	0.2078	2.4123	5.2653	0.4720
Source Baseline (SB)	**0.3968**	0.8880	**1.6266**	0.1723	0.2947	1.5261	3.4756	0.3152
Multi-task learning (MTL)	0.3290	**0.8864**	1.6550	**0.1647**	0.2391	1.9461	4.2792	0.3923
Fine-tuned (FT)	0.1774	1.9257	3.4042	0.3973	**0.6611**	**0.6508**	**1.2165**	**0.0782**
Fine-tuned decoder (FTD)	0.1887	1.6017	3.0359	0.3794	0.4413	0.9639	1.7298	0.1802
Fine-tuned encoder (FTE)	0.1925	1.8823	3.4256	0.3914	0.4968	0.8308	1.6501	0.1669
Feature reuse (FR)	0.1928	1.4524	2.7074	0.3588	0.3785	1.2275	2.4087	0.2684

- **Computational demand**

Total training duration for each model

Training duration on target data only

→ **Fine-tuning yields the best results**

→ **Further details can be found in the paper**

Qualitative Results

- Visual comparison between the source baseline model and the fine-tuned model on a CMD target dataset scenario

(a) Source baseline model used on CMD.

(b) Fine-tuned model used on CMD.

- Visual demonstration of catastrophic forgetting

(a) Source baseline model used on WOMD.

(b) Fine-tuned model used on WOMD.

→ Further details can be found in the paper

Road User Trajectory Prediction

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Trajectory predictions of nearby road users is crucial component within model predictive trajectory planning!

- Consider local context ✓
- Address global context ✓
- Insights for future innovations ✓

Takeaway II:

- ➢ Context-based AI system increases situation and interaction awareness
- ➢ Context-based AI system could be transferred to adapt to global differences
- ➢ Context-based AI system improves trajectory planning

Thus, context-based AI system for trajectory predictions could enhance ego trajectory planning

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Robust Planning Through Probabilistic Methods

Overall Takeaway:

- ➢ Context-based AI systems enable improved autonomy
- ➢ Data-driven is a great complement to knowledge-based approaches
- ➢ Alongside software-defined vehicles, data is becoming increasingly important

Thus, achieving higher autonomy is based on complex systems that include AI.

❖ Therefore, the product development processes need to be updated

Expanding the Classical V-Model

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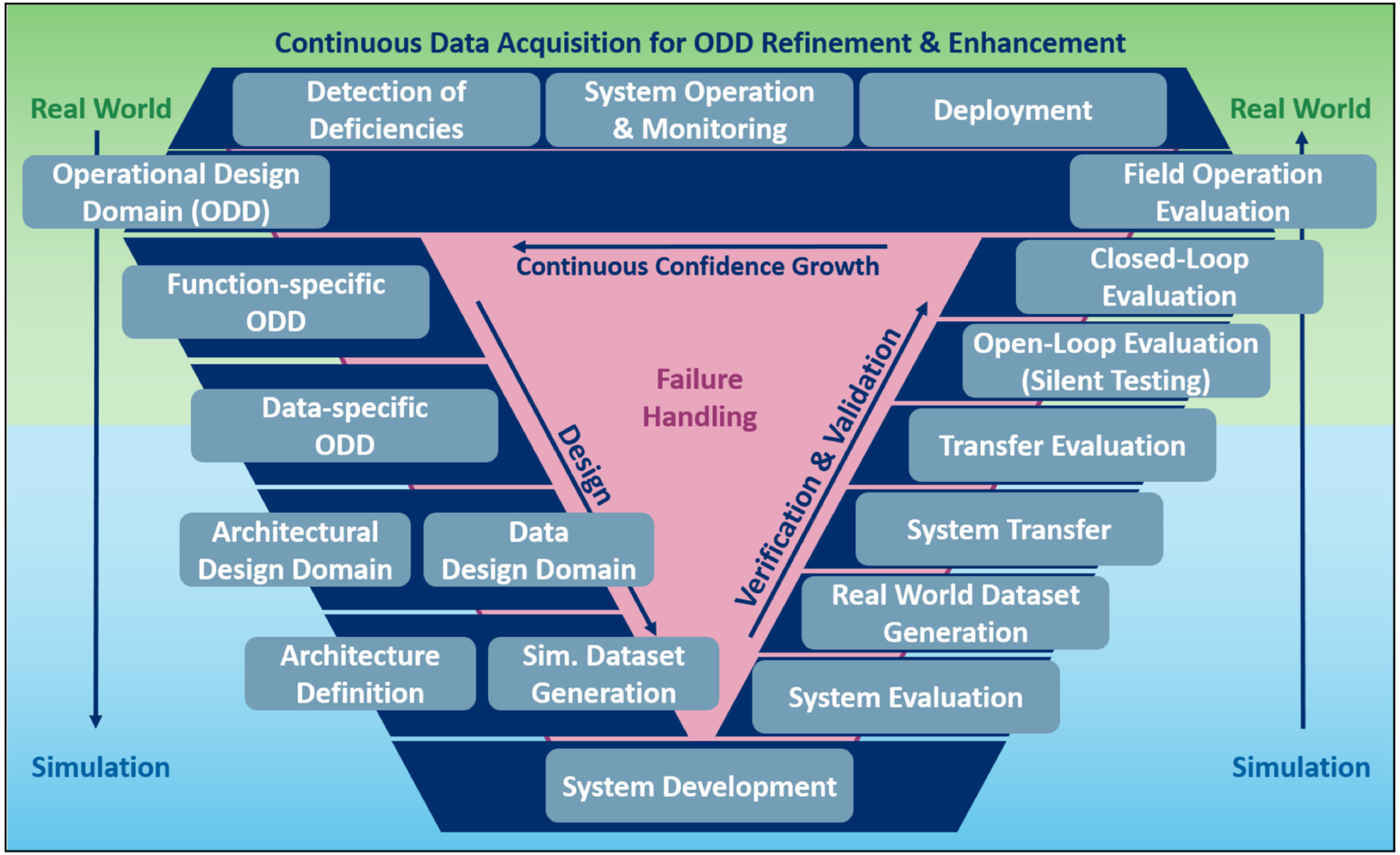

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Thanks for your attention!

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