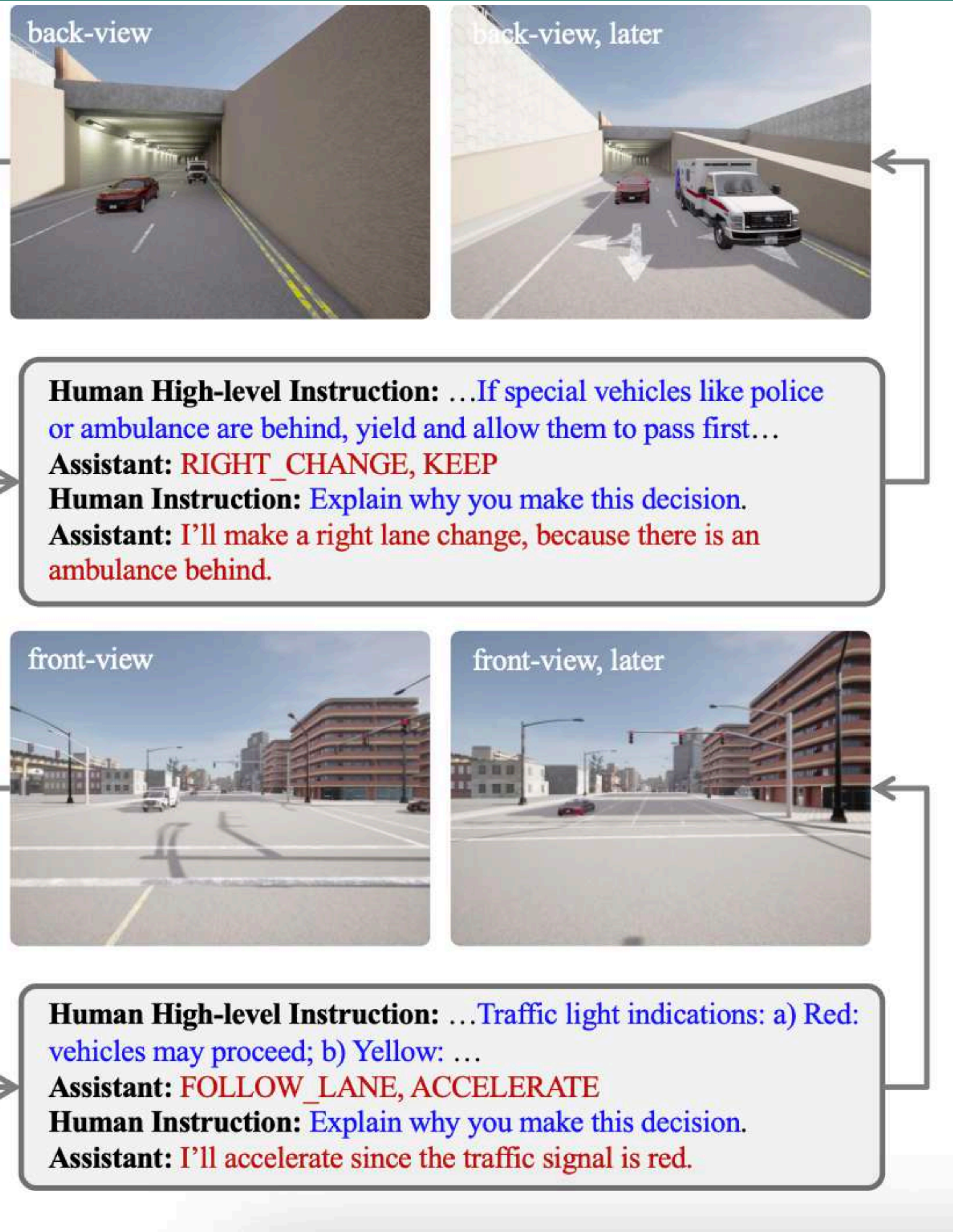
EMBODIED INTELLIGENCE FOR AUTONOMOUS SYSTEMS ON THE HORIZON

ETA: **E**fficiency through **T**hinking **A**head

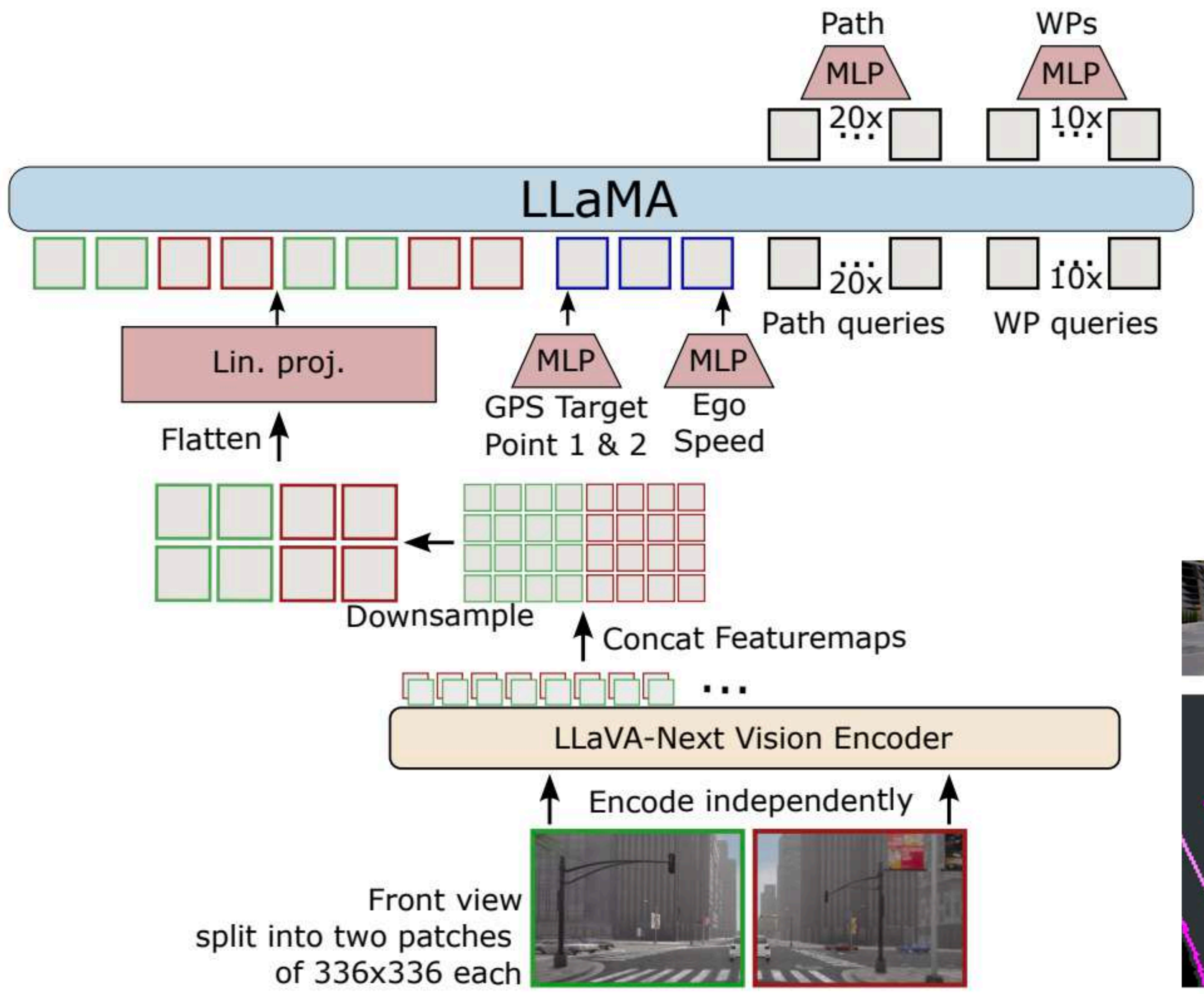
A Dual Approach to Self-Driving with Large Models

with Shadi Hamdan, Chonghao Sima, Zetong Yang, and Hongyang Li

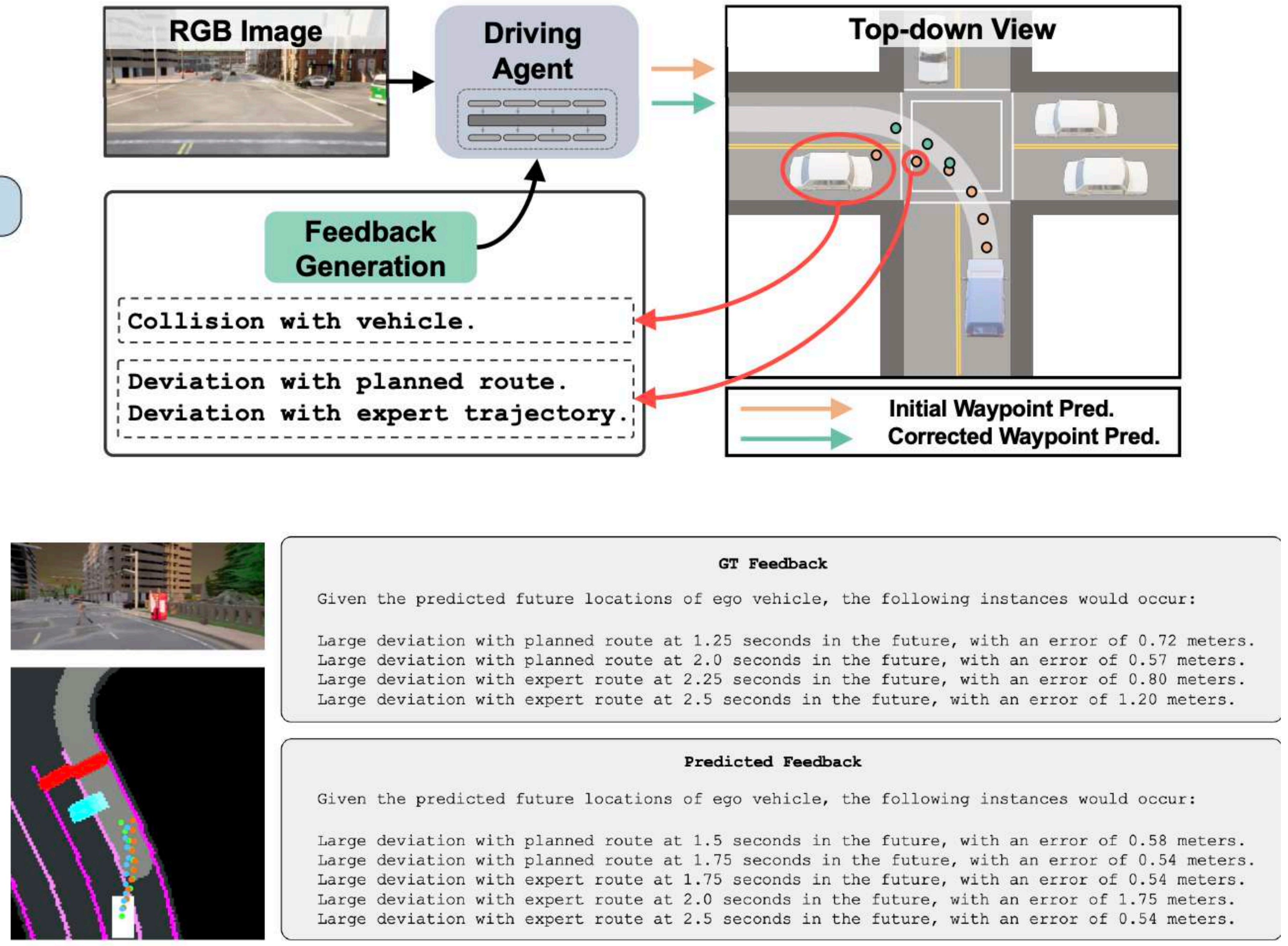
Large models are everywhere!



DriveMLM; 2023

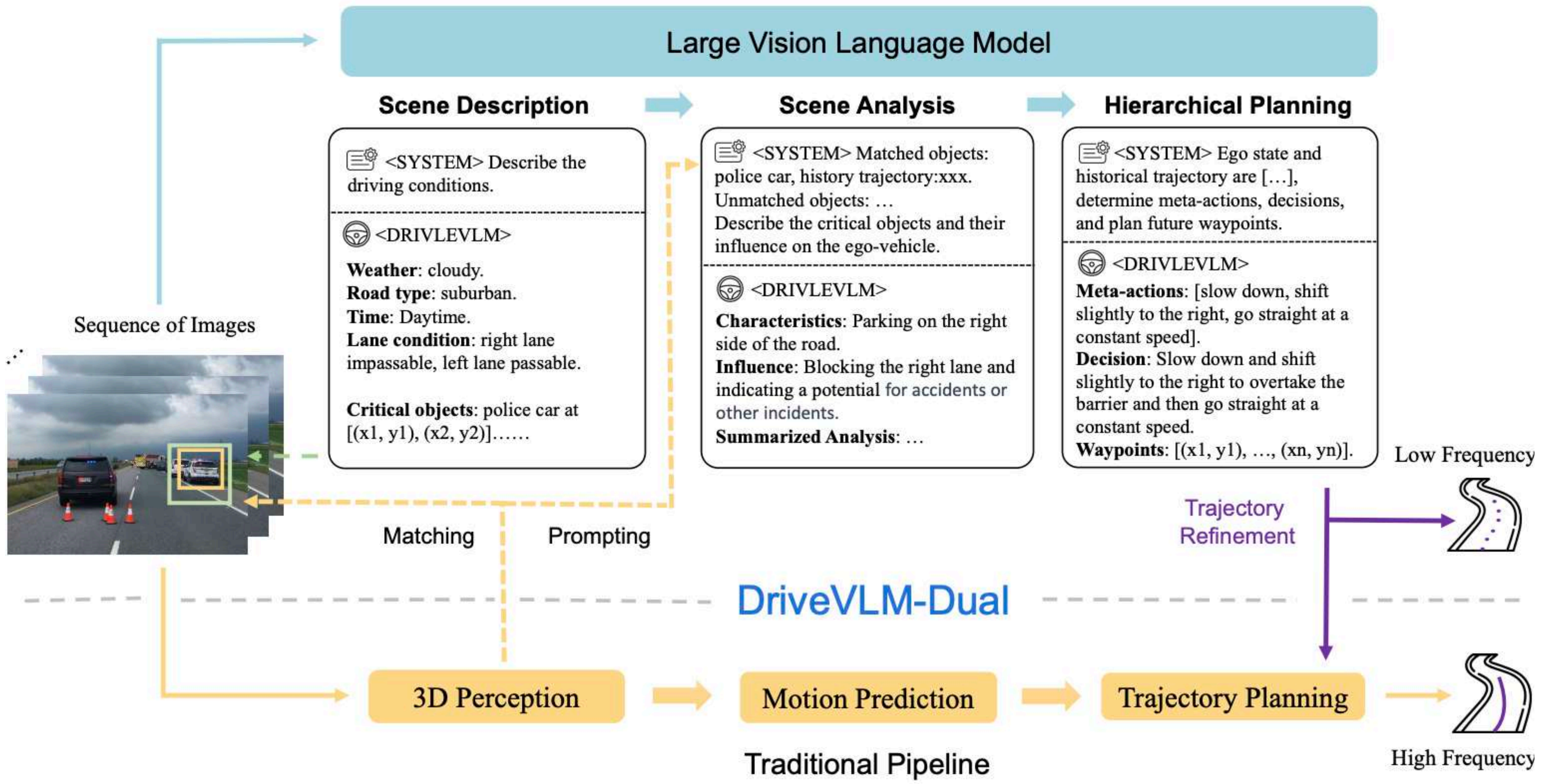


LLM4AD/CarLLaVA; 2024

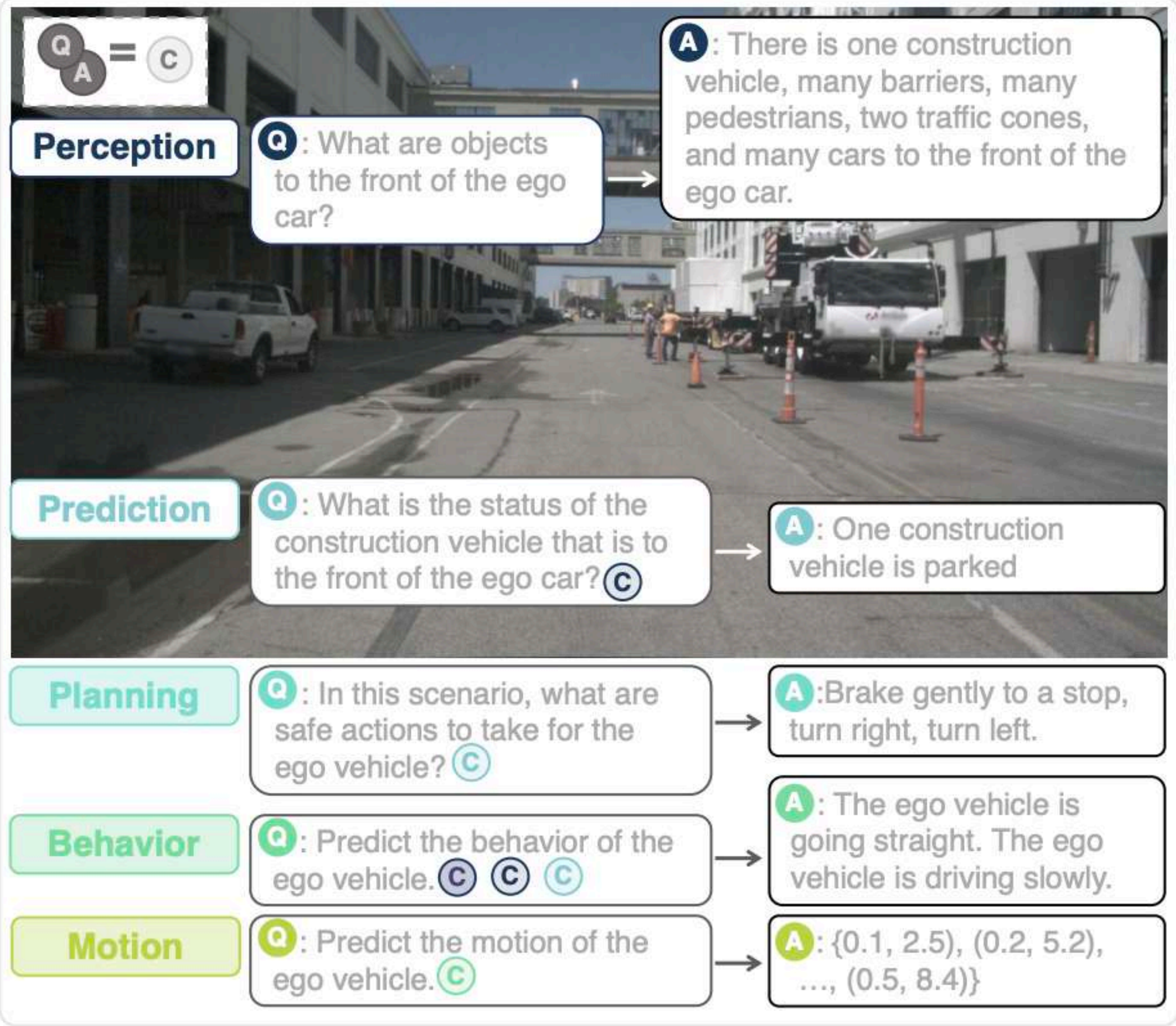


FeD; 2024

..but they are too slow.



DriveVLM; 2024

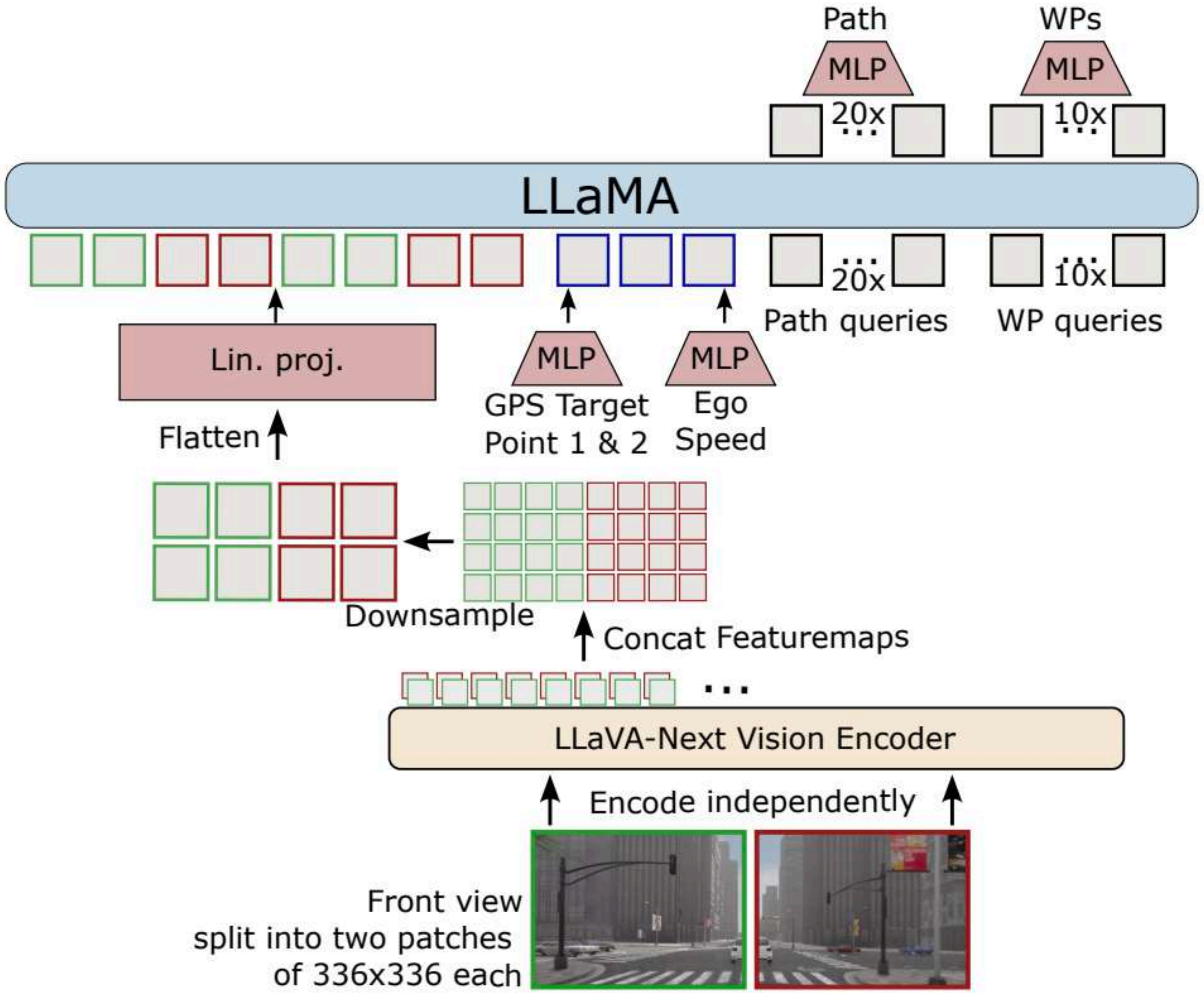


DriveLM; 2024

How to use large models efficiently for self-driving?

Take CARLA Leaderboard-v2 winner:

LLM4AD/ CarLLaVA

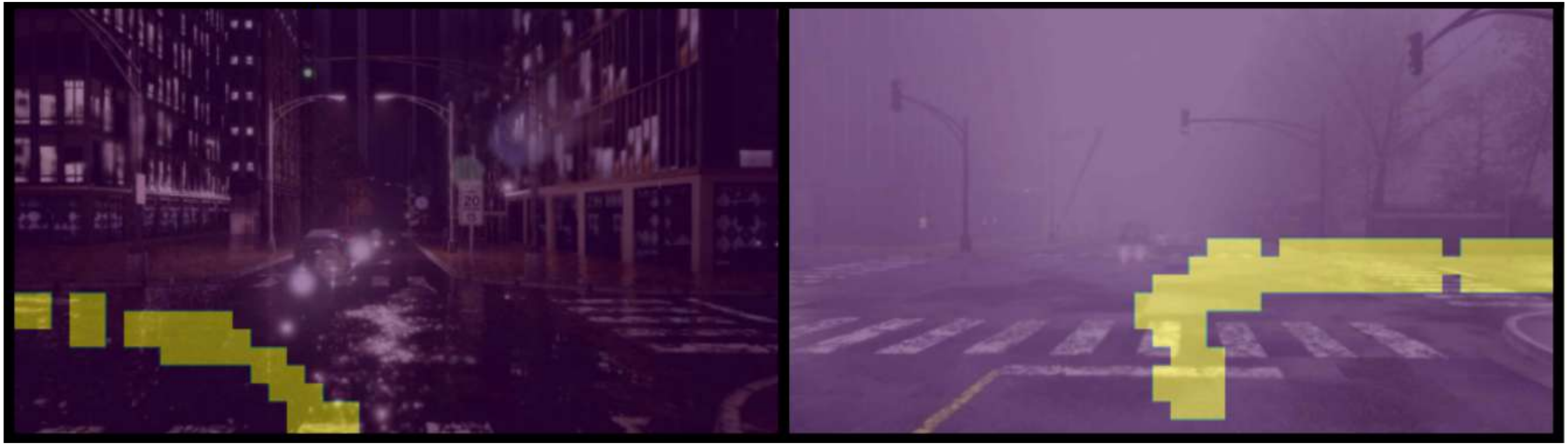


Action Mask

Better aligning actions with observations

■ Path

● Waypoints

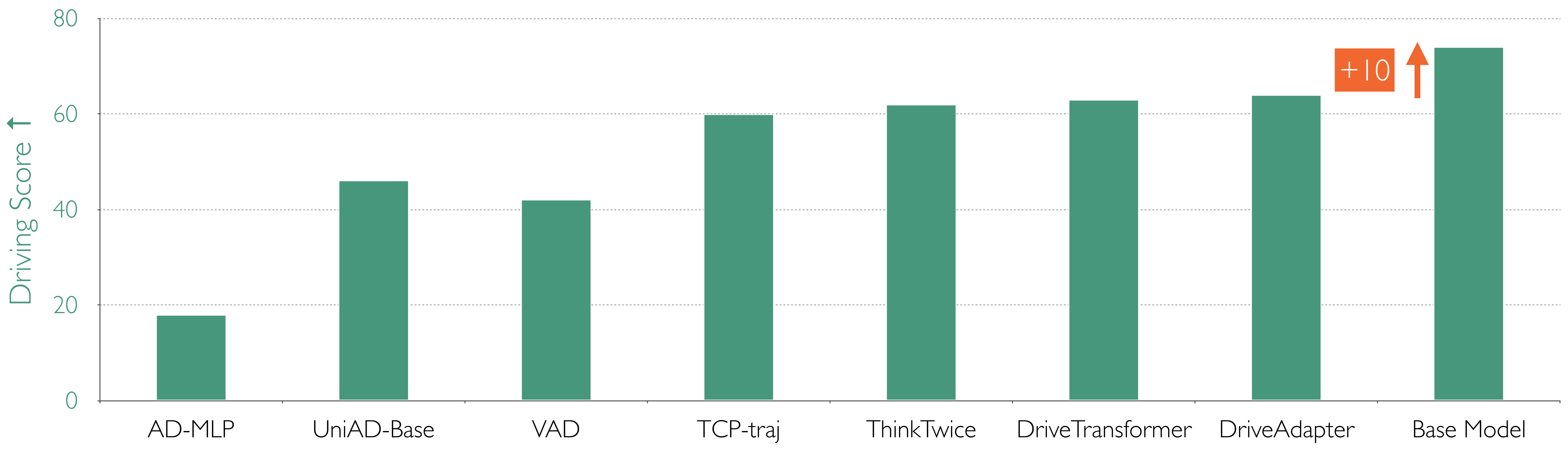


Action Mask

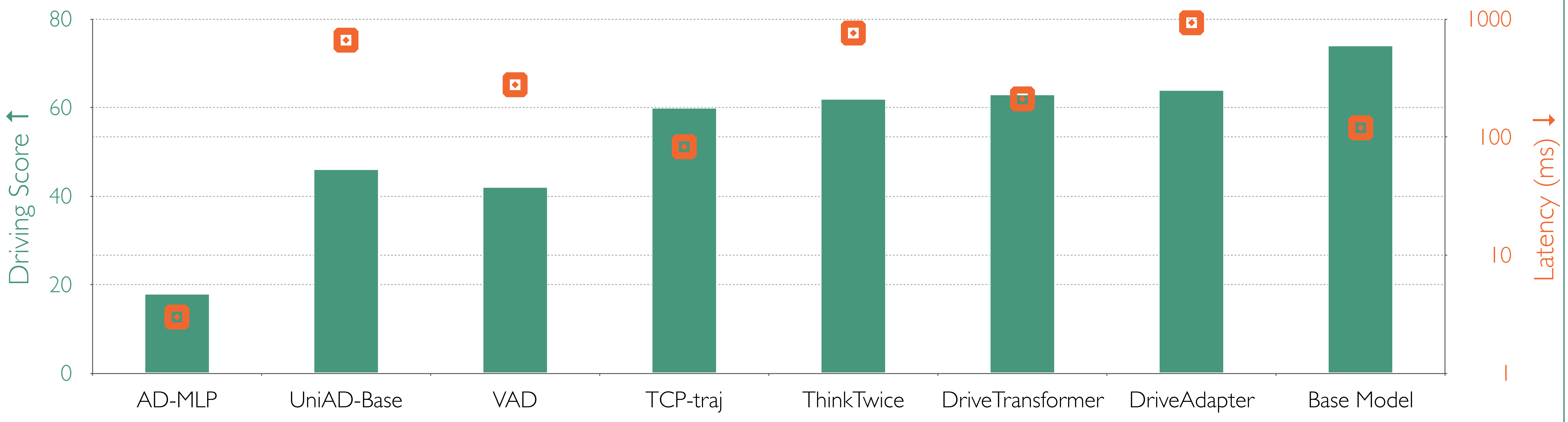
Better aligning actions with observations

Patches with path/waypoint

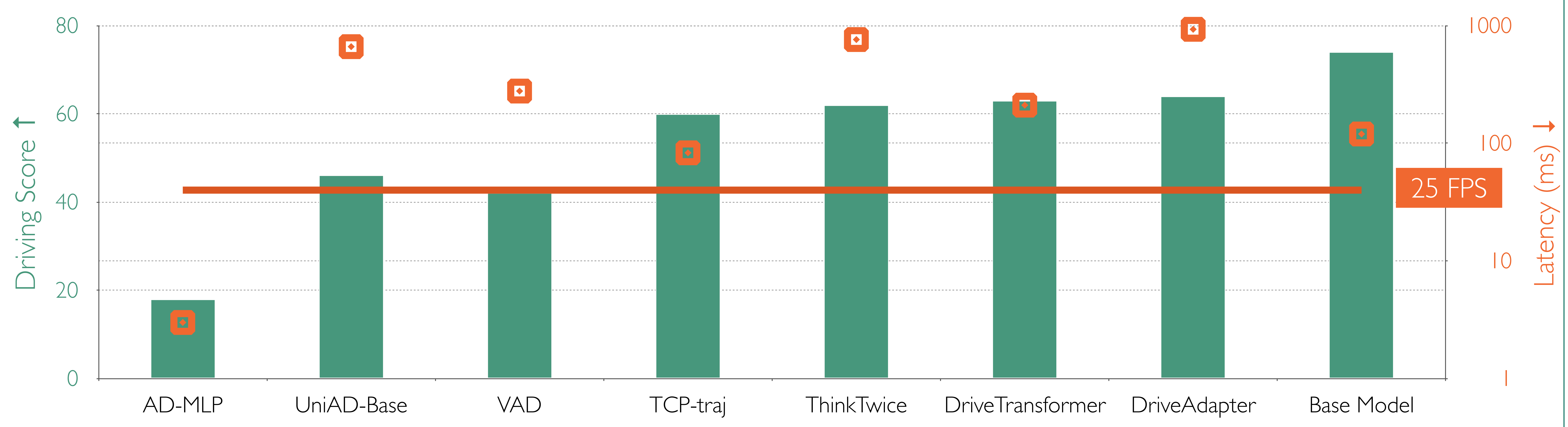
Results on Bench2Drive



Results on Bench2Drive

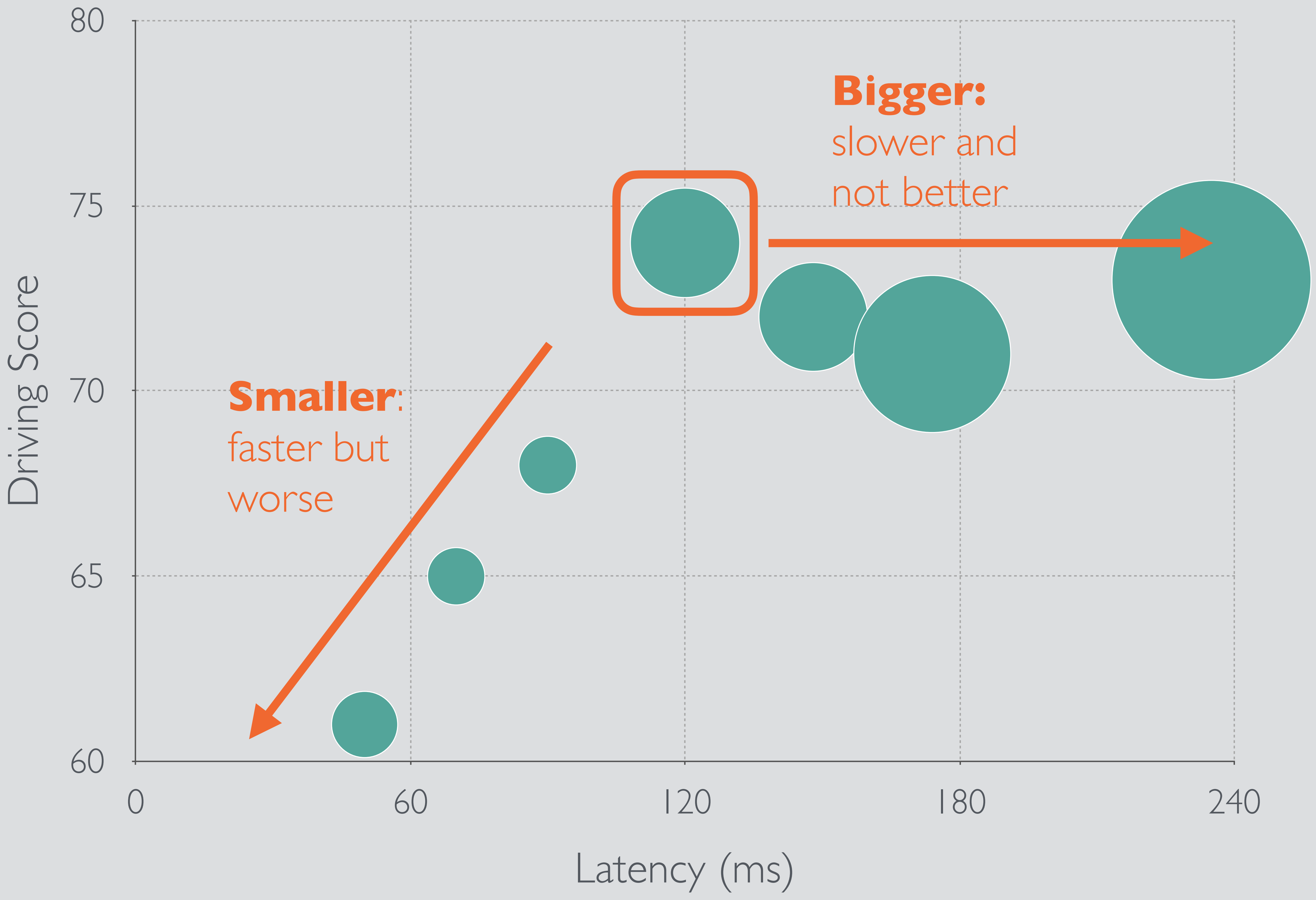


Results on Bench2Drive



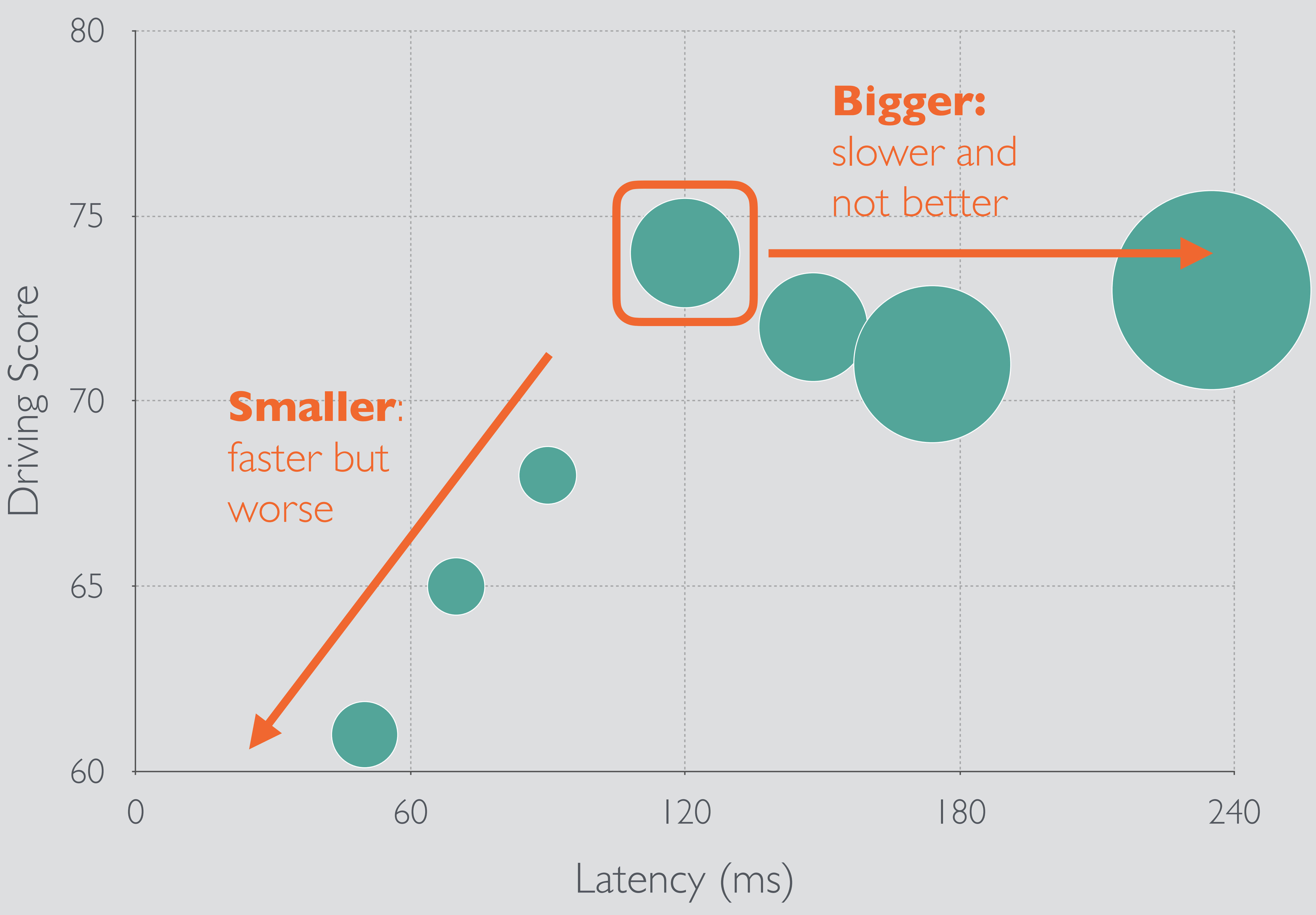
What about different large models?

- **Smaller**: faster but worse performance
- **Bigger**: slower and not better

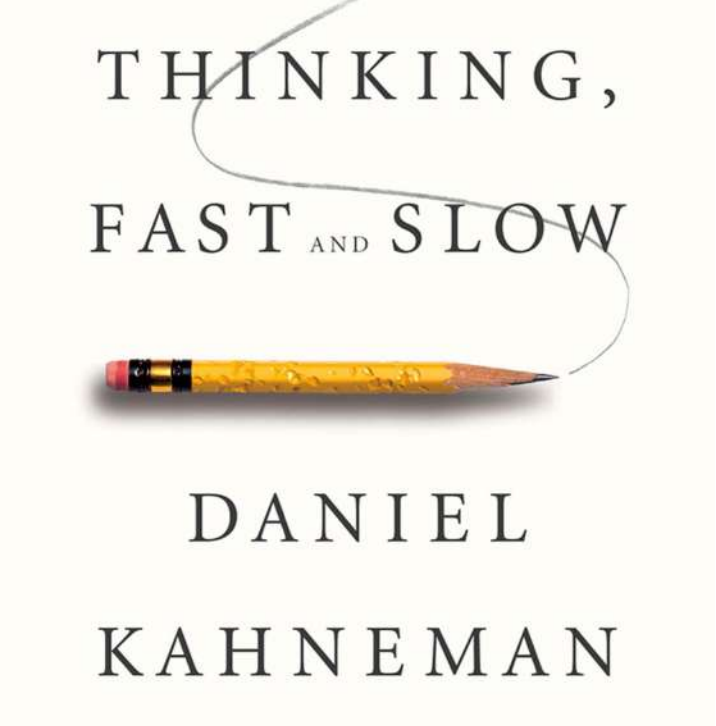


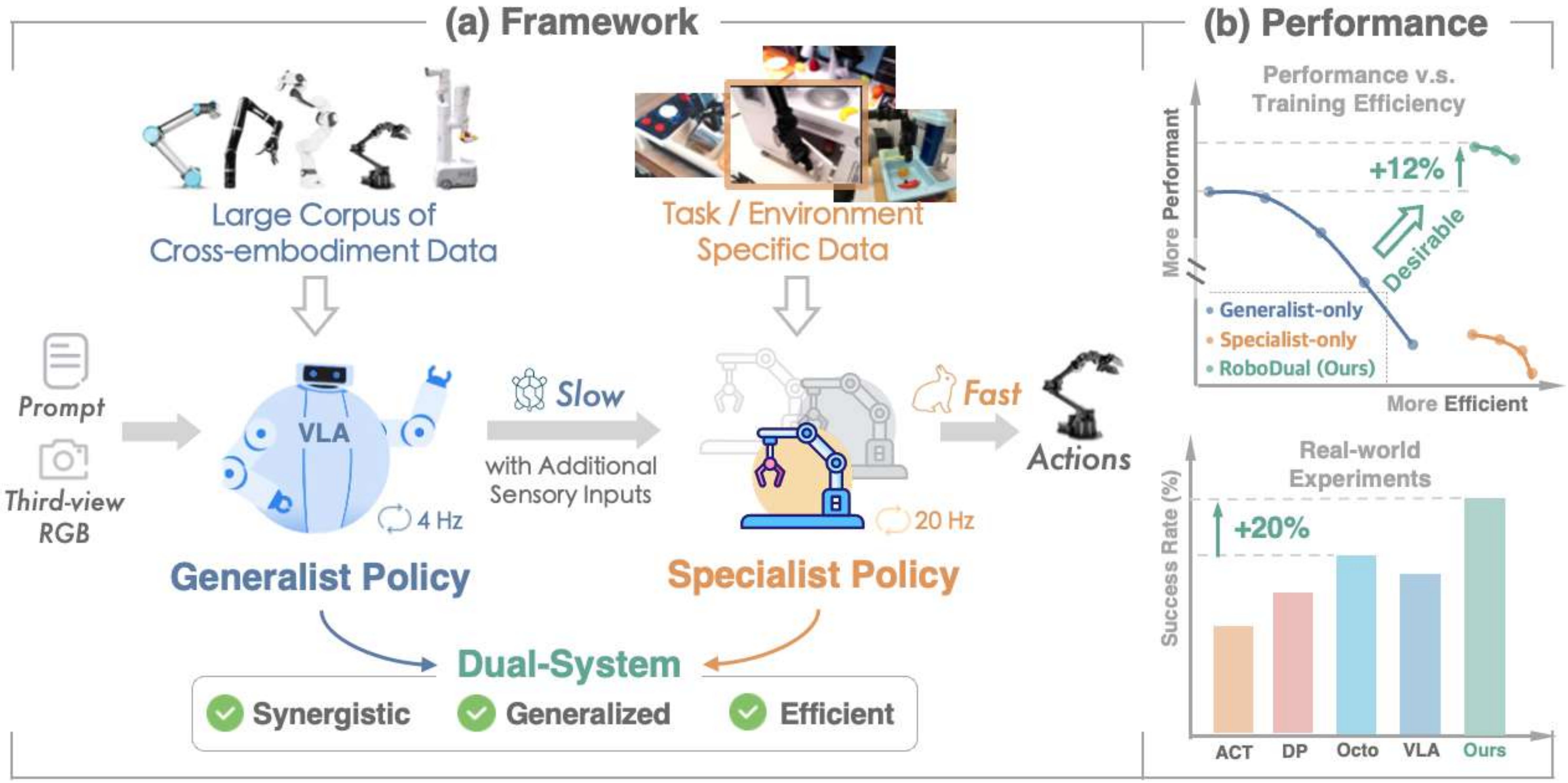
What about different large models?

- **Smaller**: faster but worse performance
- **Bigger**: slower and not better
  - Underfitting?
  - Upperbounded by expert?

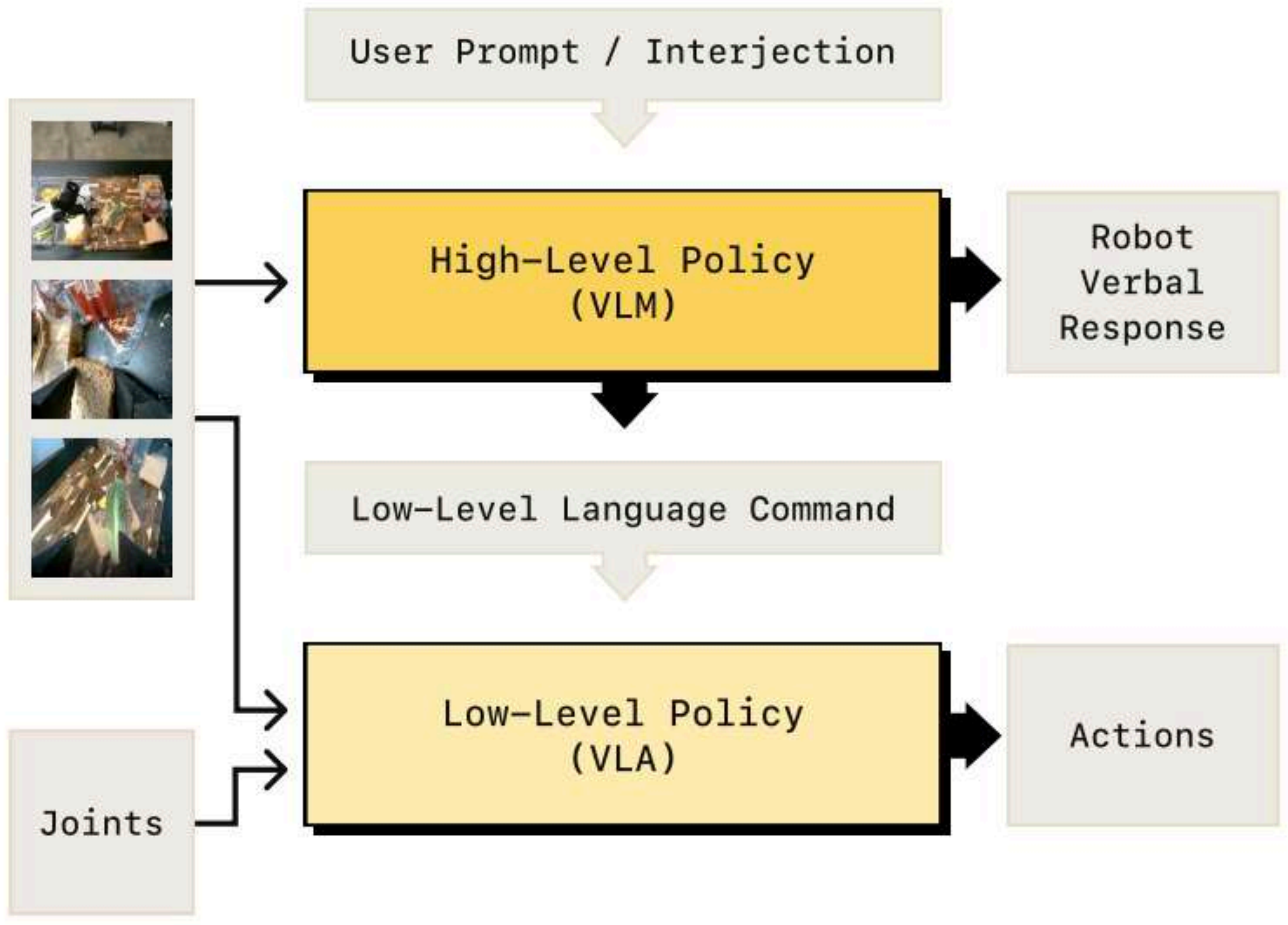


Dual approach in embodied systems



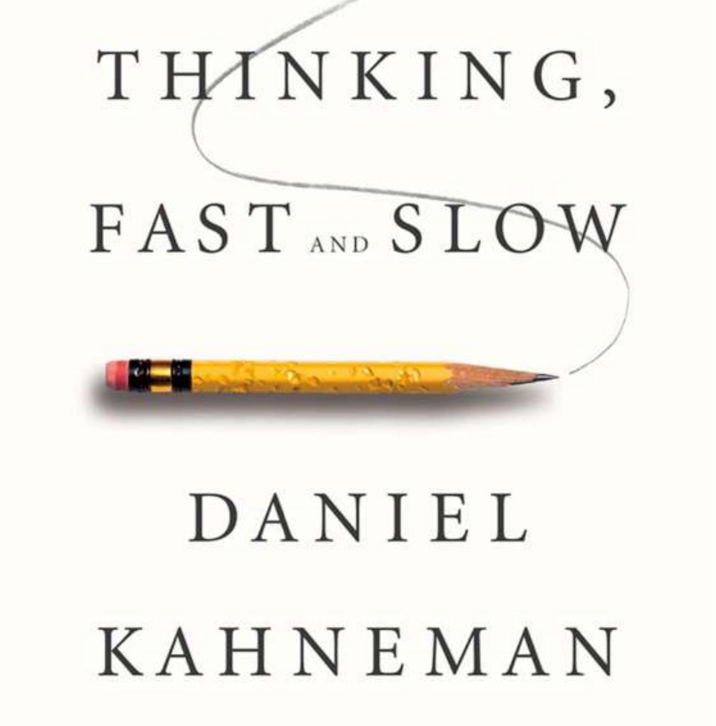


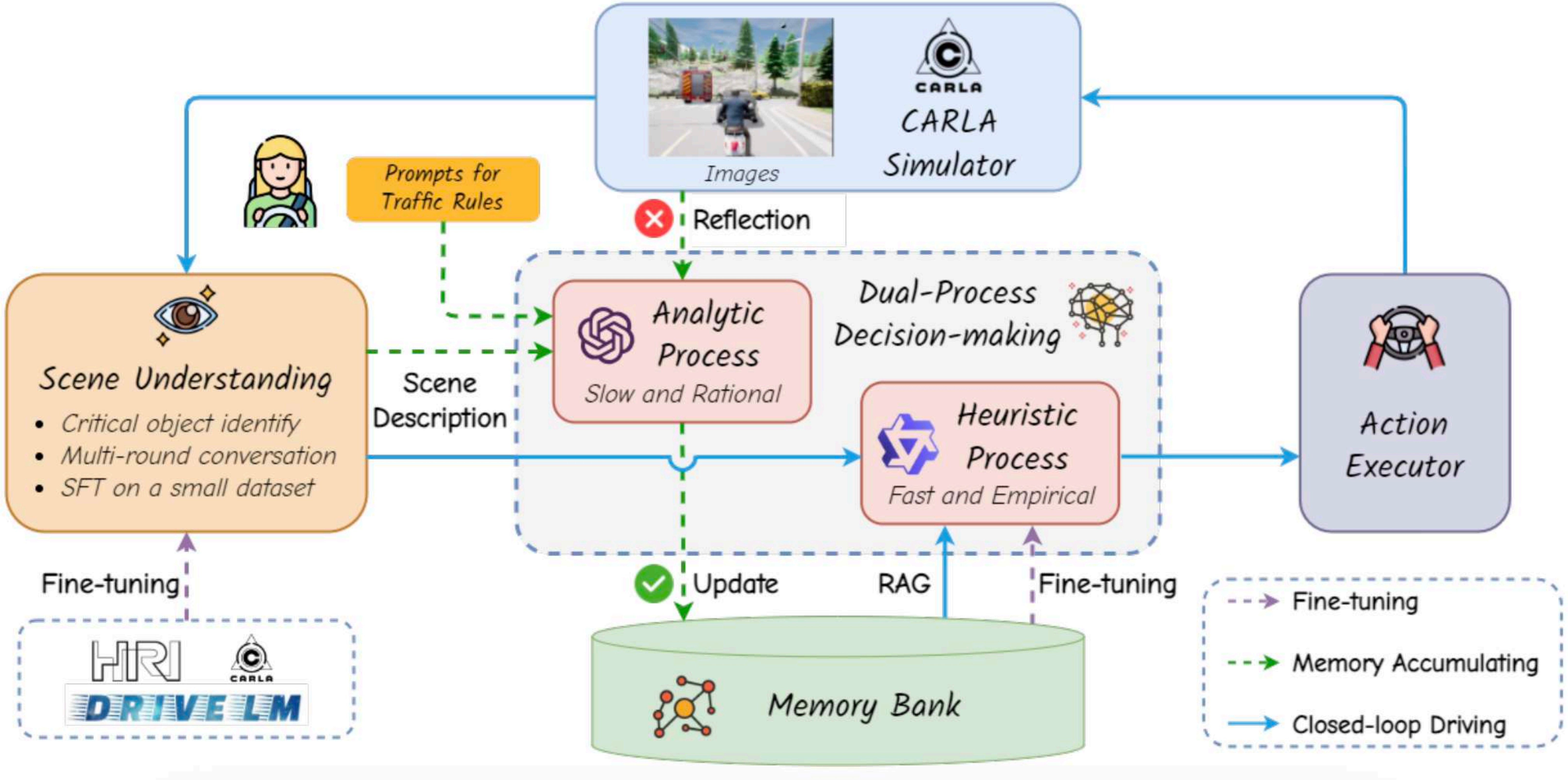
RoboDual; 2024



Hi Robot; 2025

Dual approach in driving

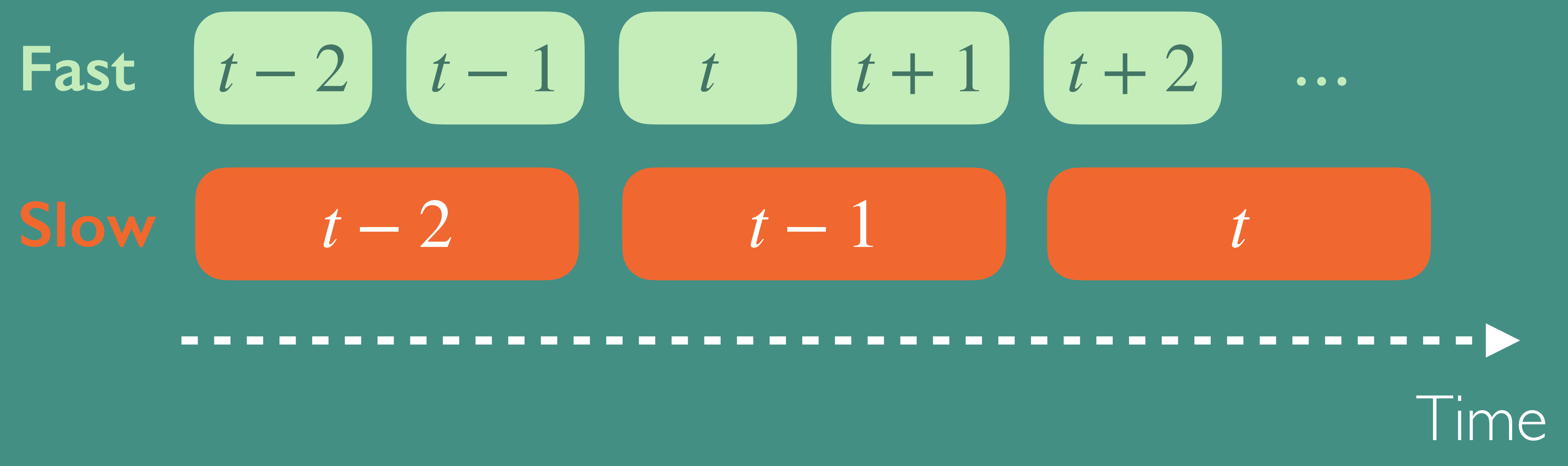




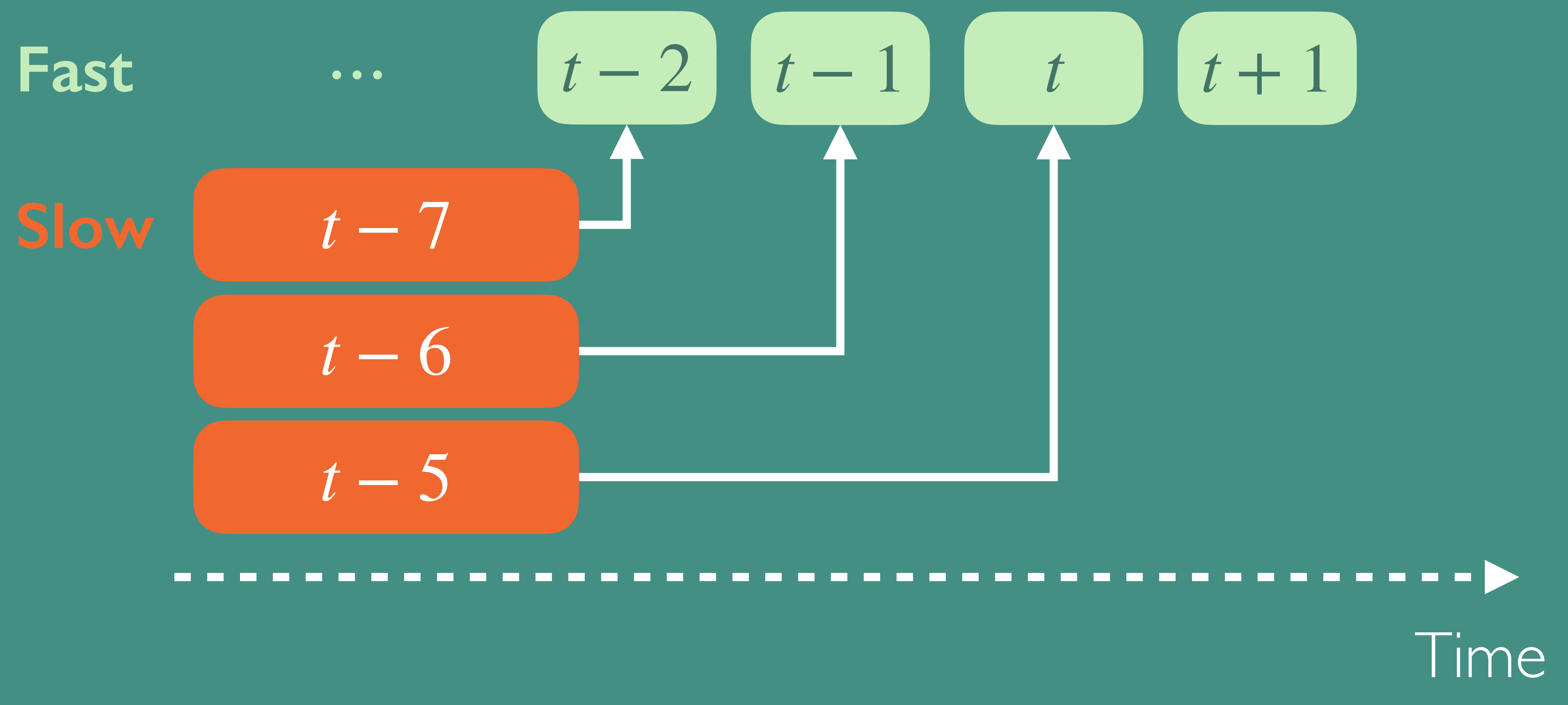
LeapAD; 2024

Dual approach

Typical Dual Paradigm

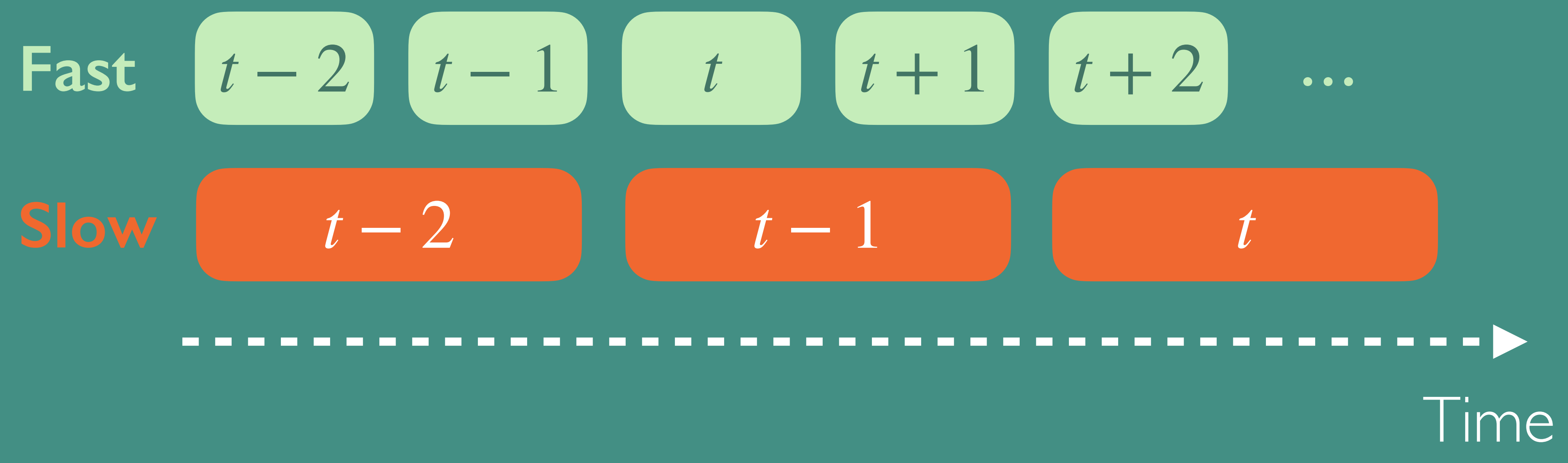


Efficiency through **T**hinking **A**head

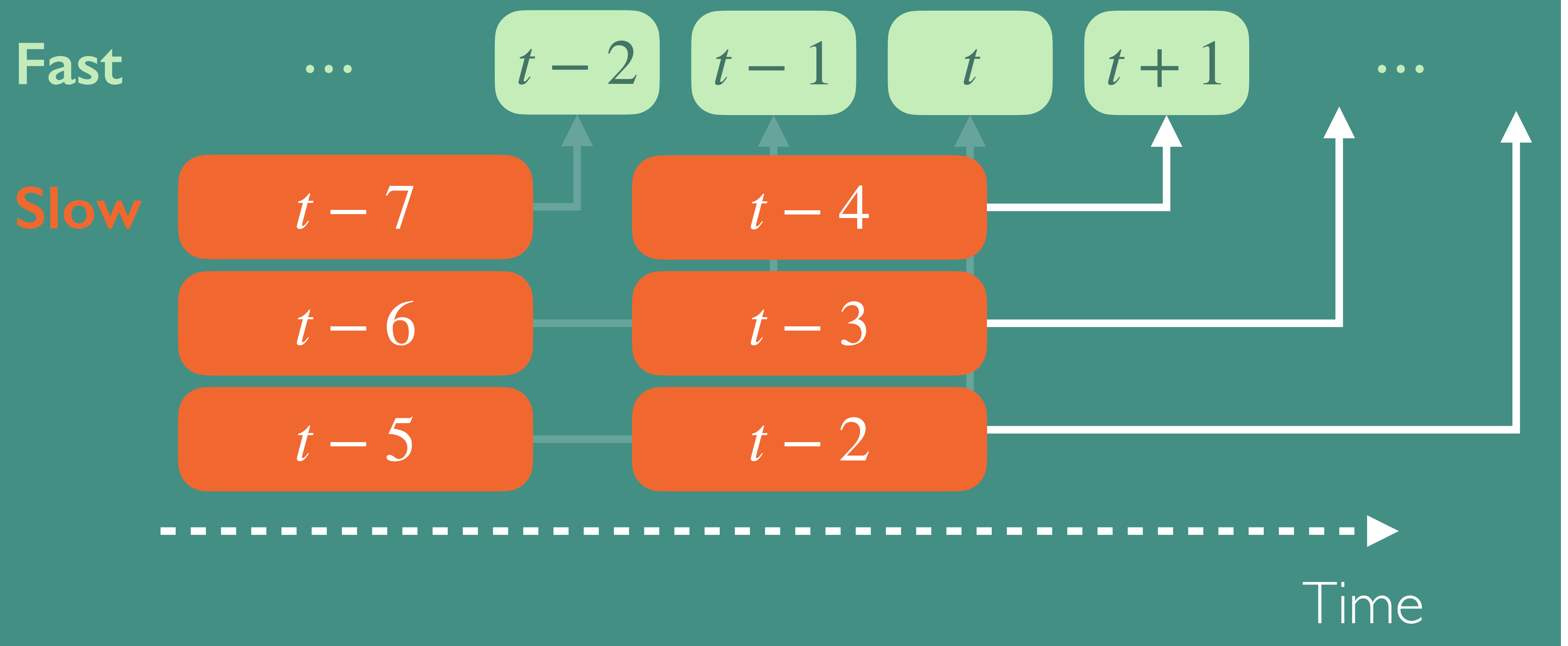


Dual approach

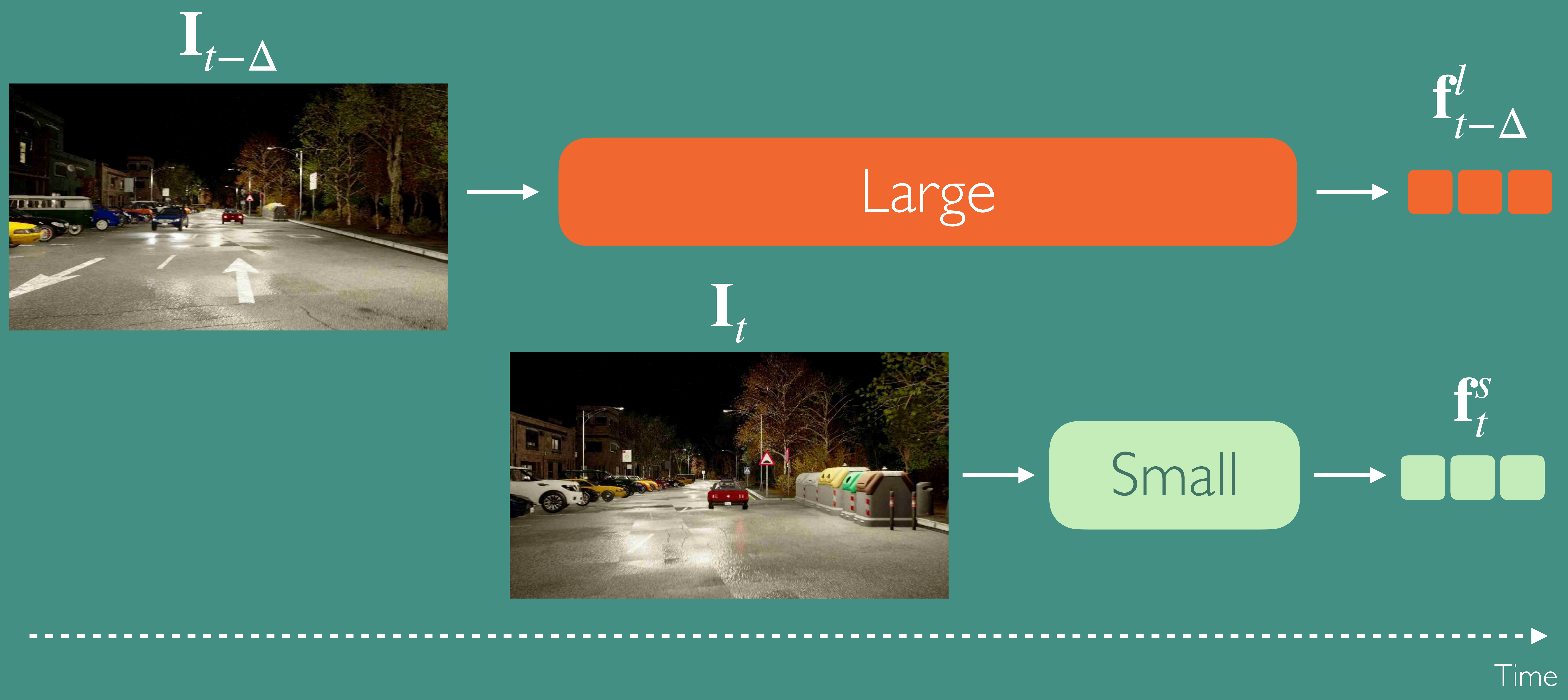
Typical Dual Paradigm



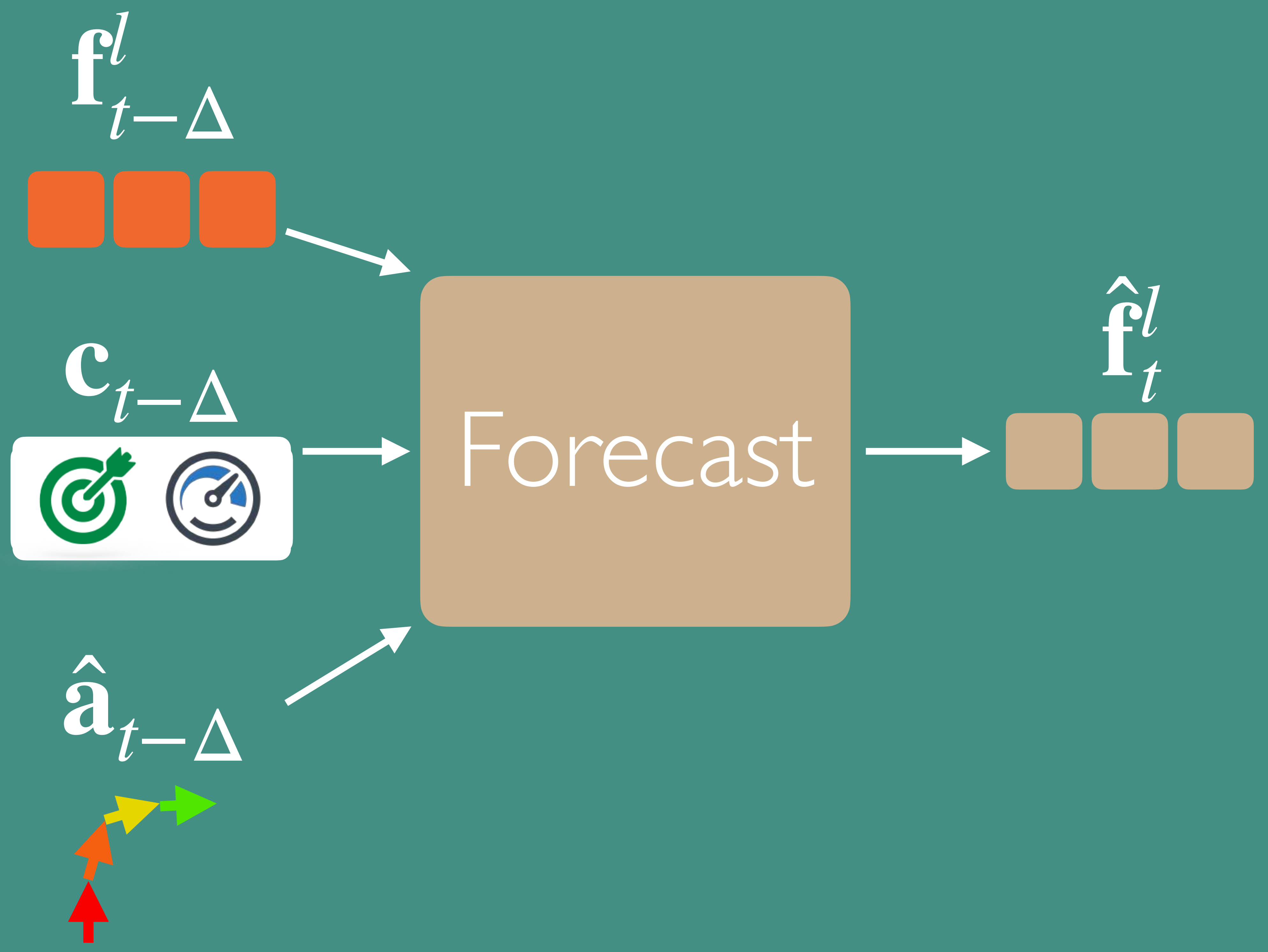
Efficiency through **T**hinking **A**head



ETA: Async model



ETA: Async model



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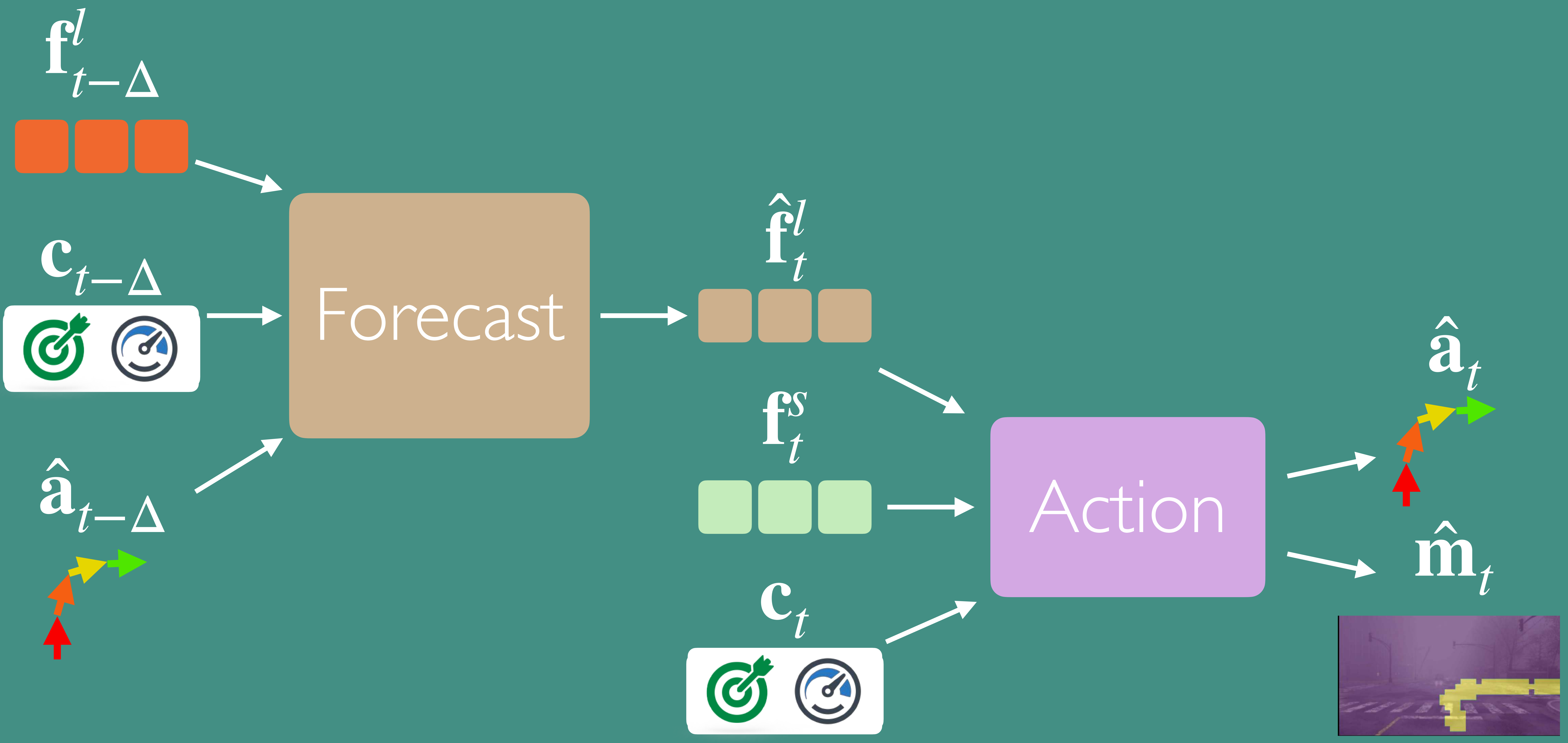

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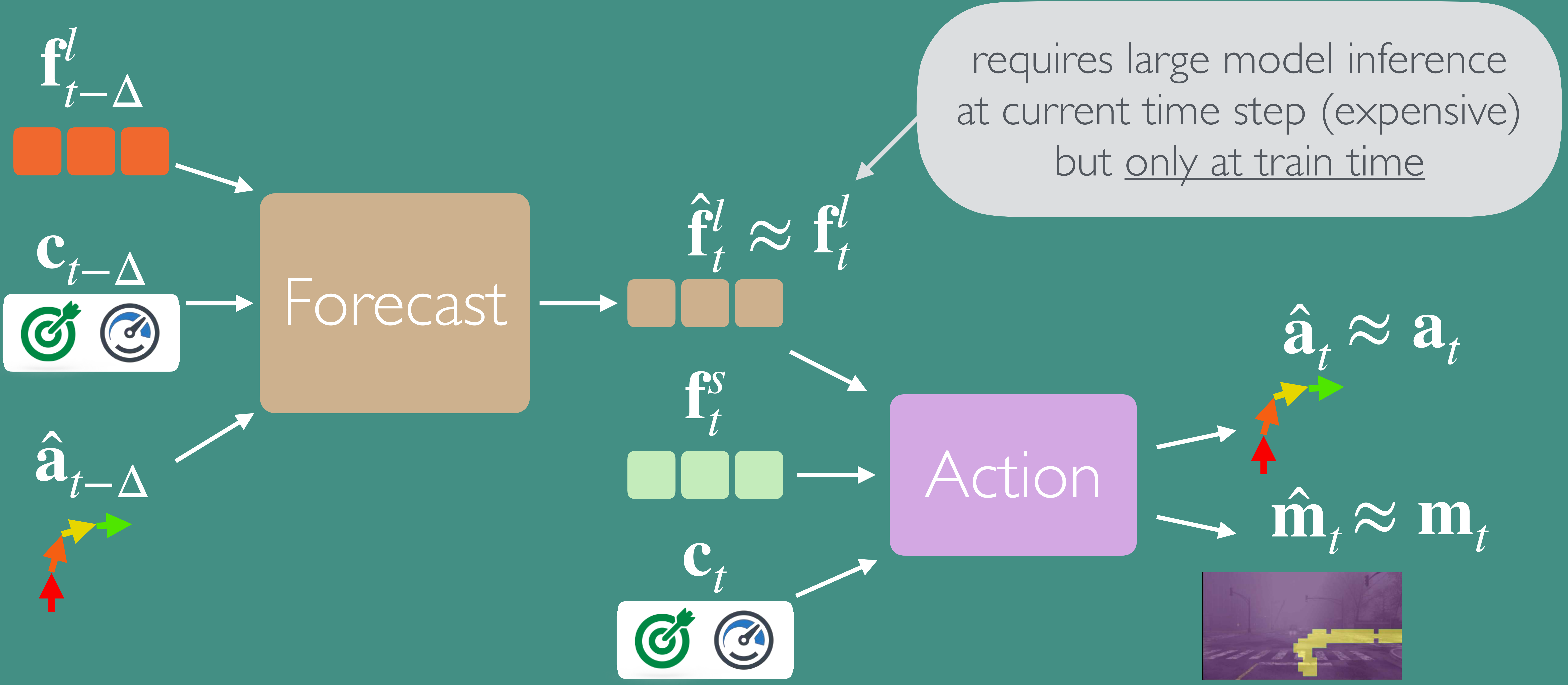
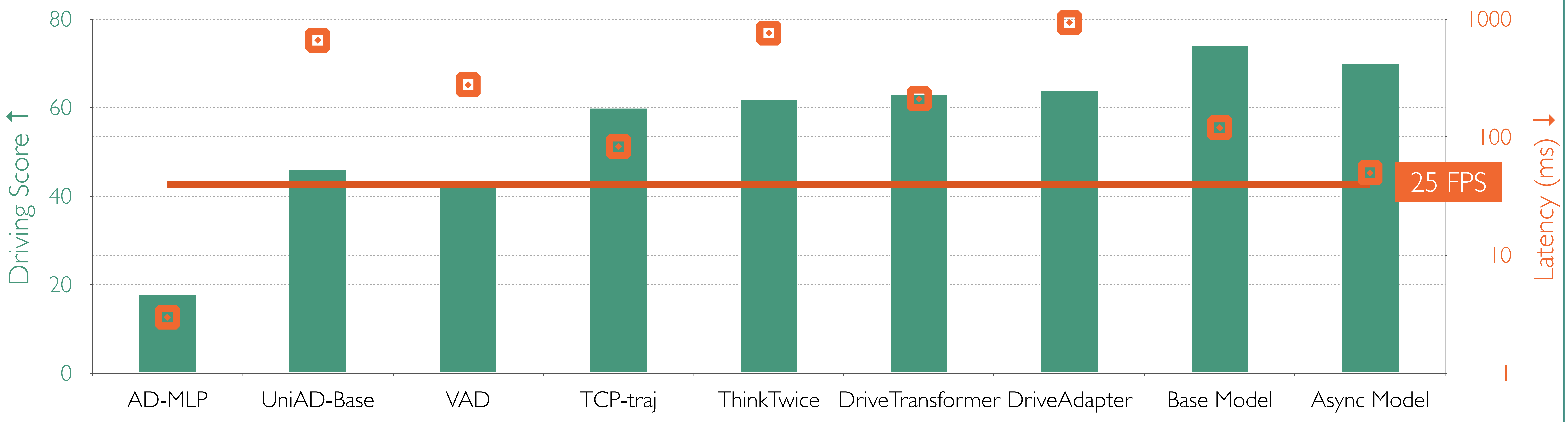
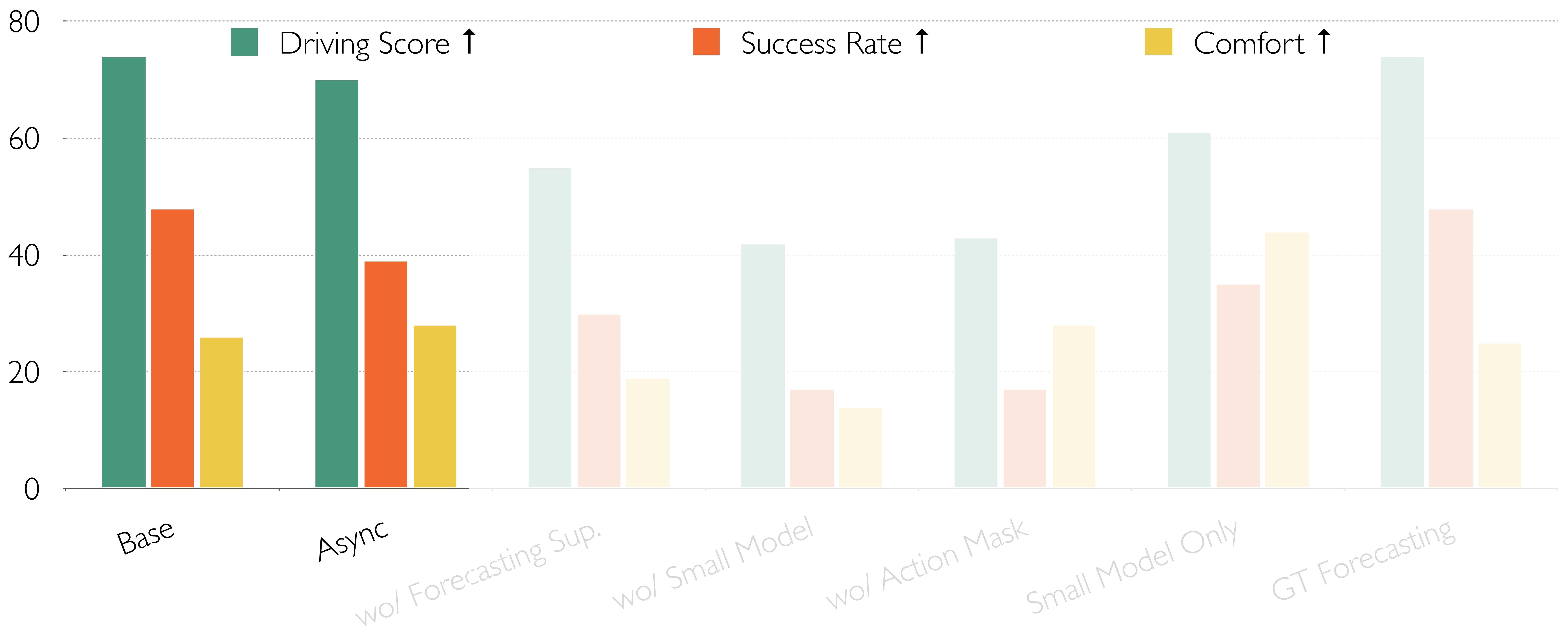


Results on Bench2Drive



How does it work?



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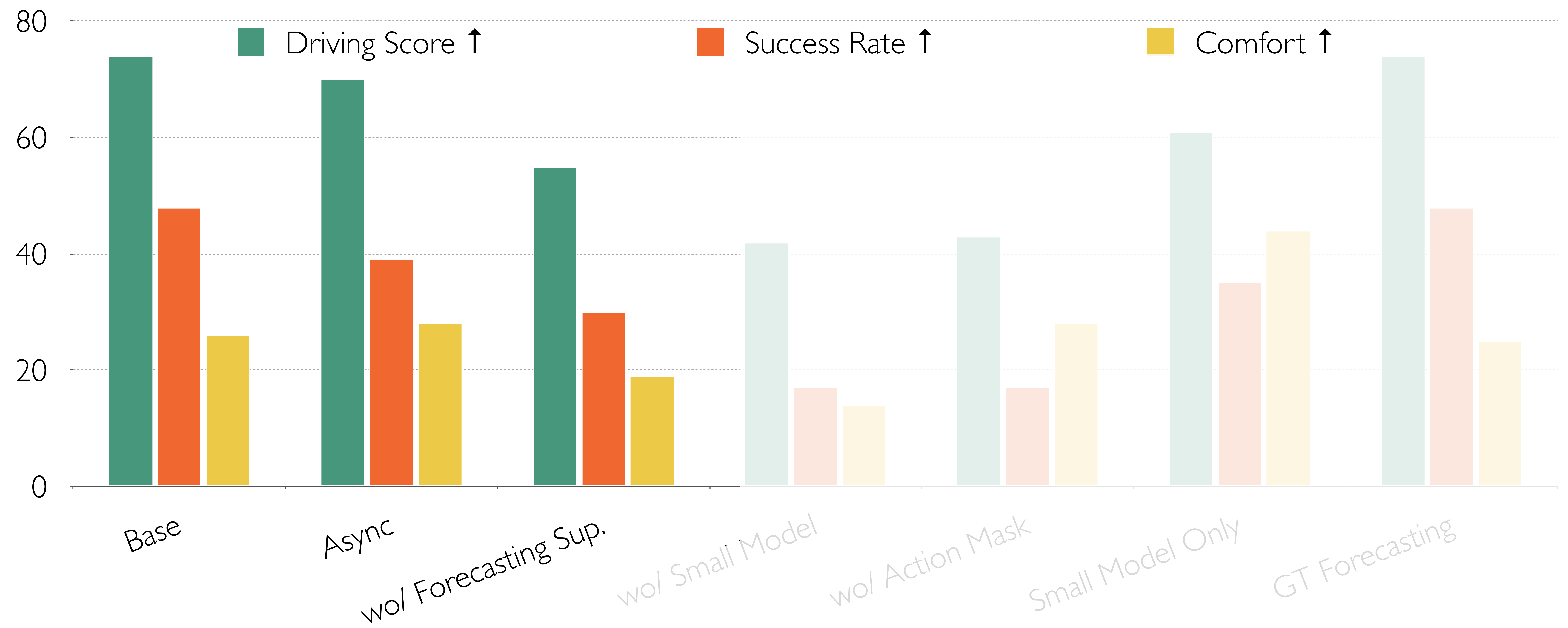

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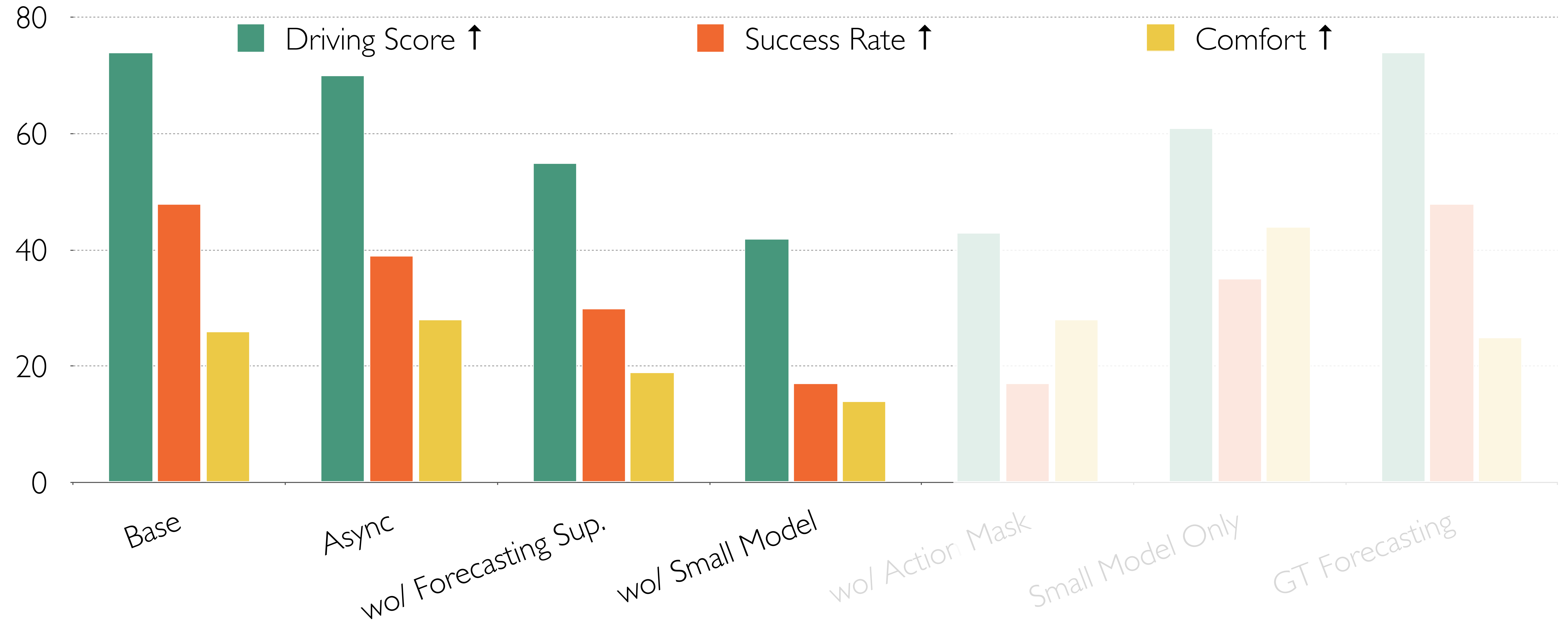

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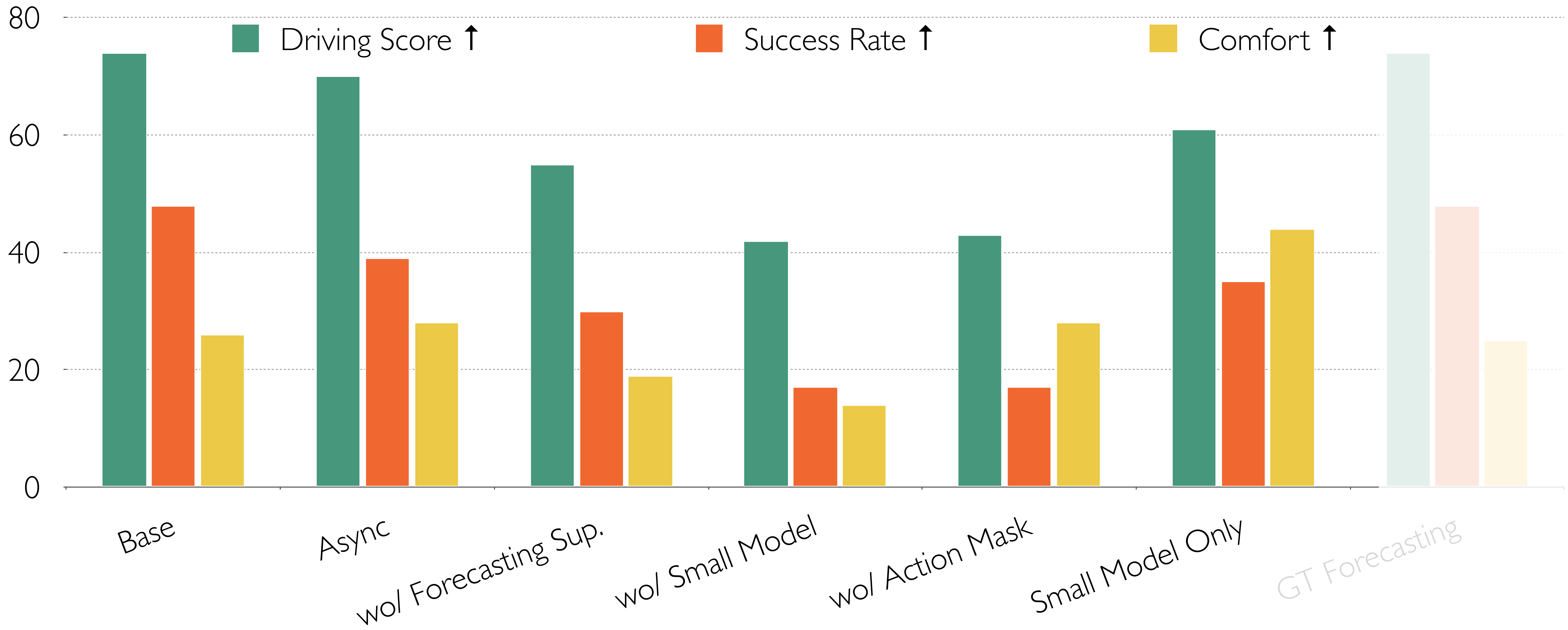

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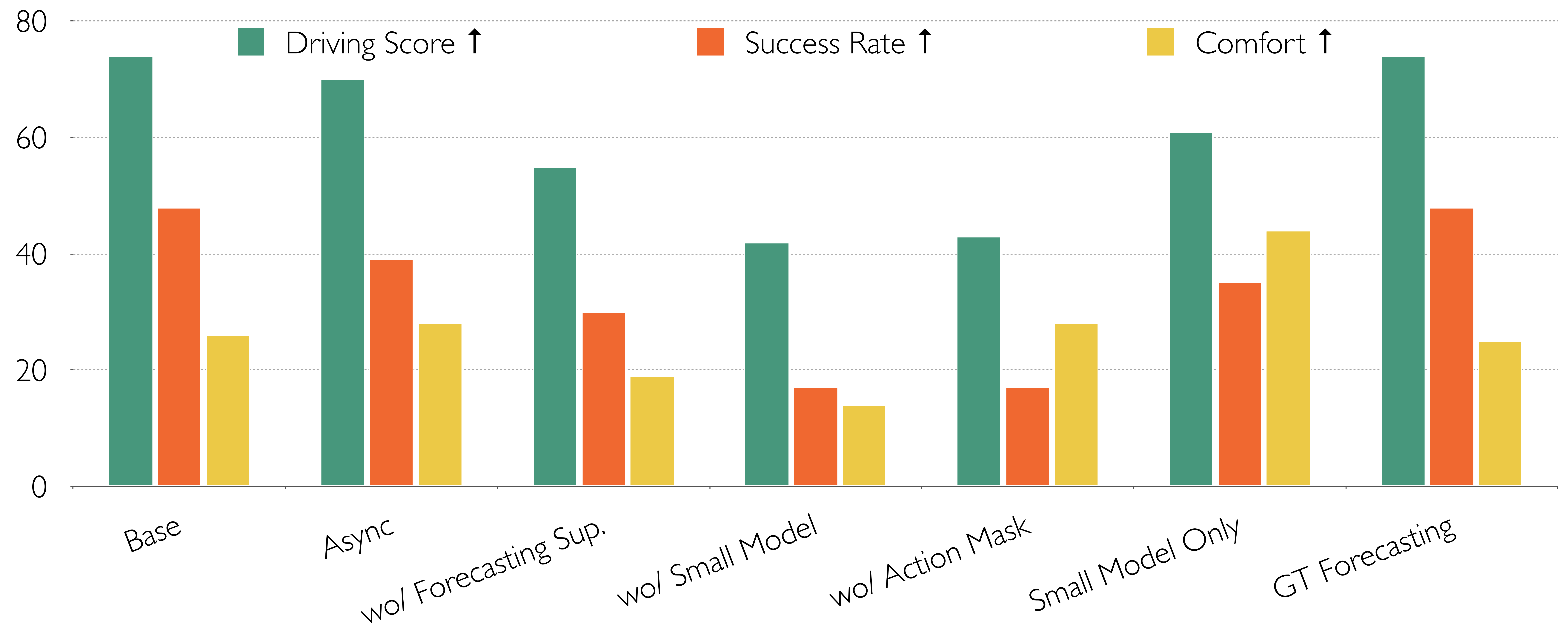


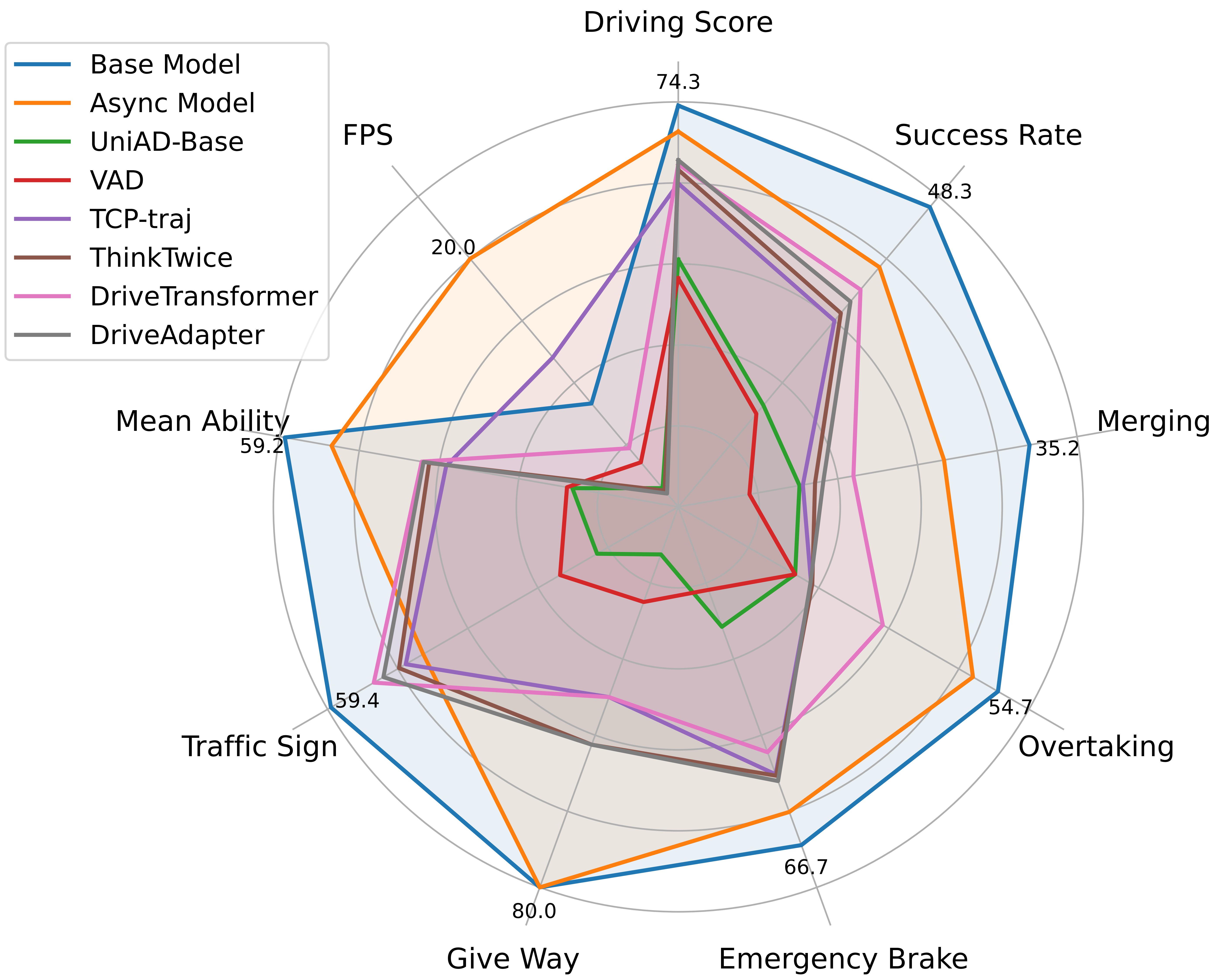
Specific skills

Async ≈ Base in:

- Overtaking
- Emergency braking
- Give way

Large gaps in:

- Traffic sign handling
- Merging



What is missing?

- Improving forecasting
- Figuring out how to use larger vision encoders
- Trying different experts, i.e. PDMLite
- Improving run-time further

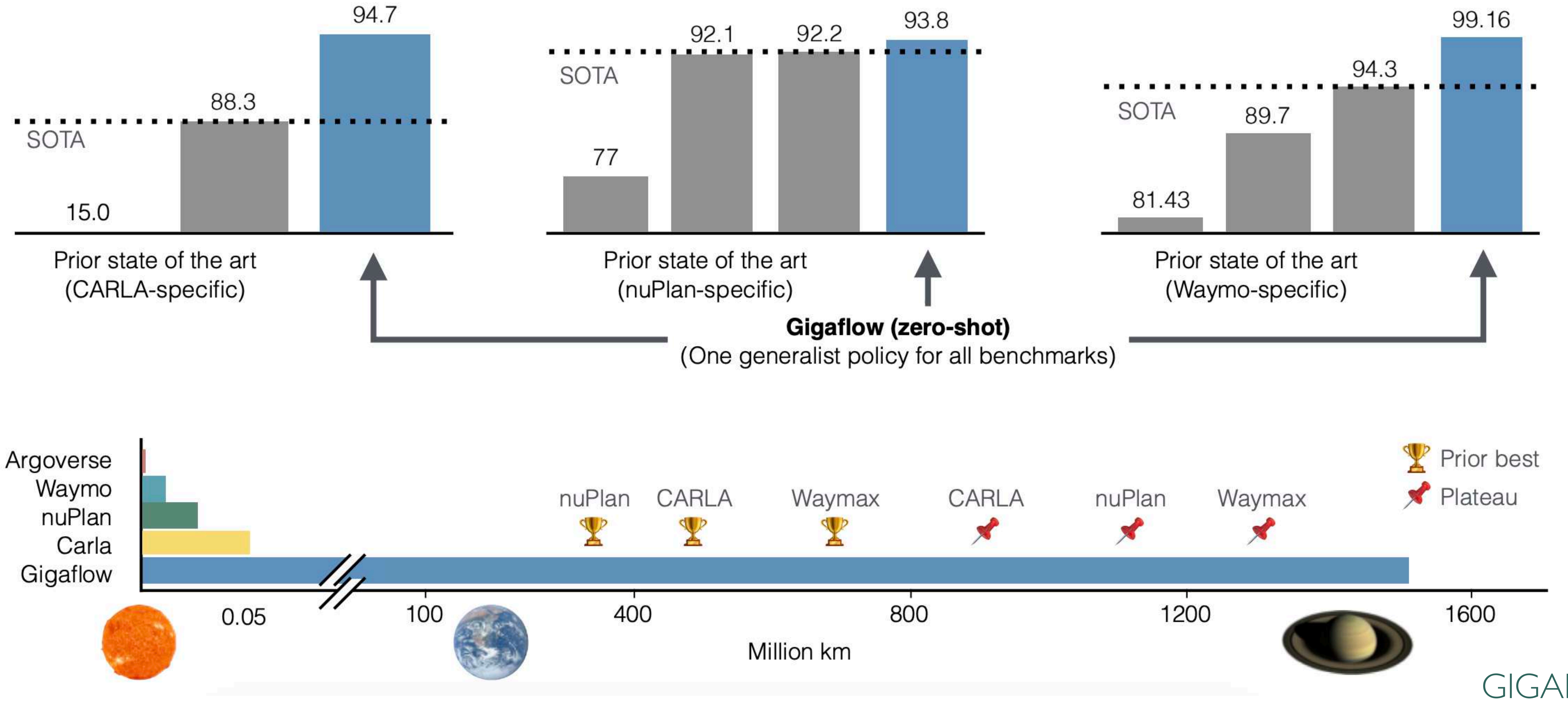
EMBODIED INTELLIGENCE FOR AUTONOMOUS SYSTEMS ON THE HORIZON

RELACS:

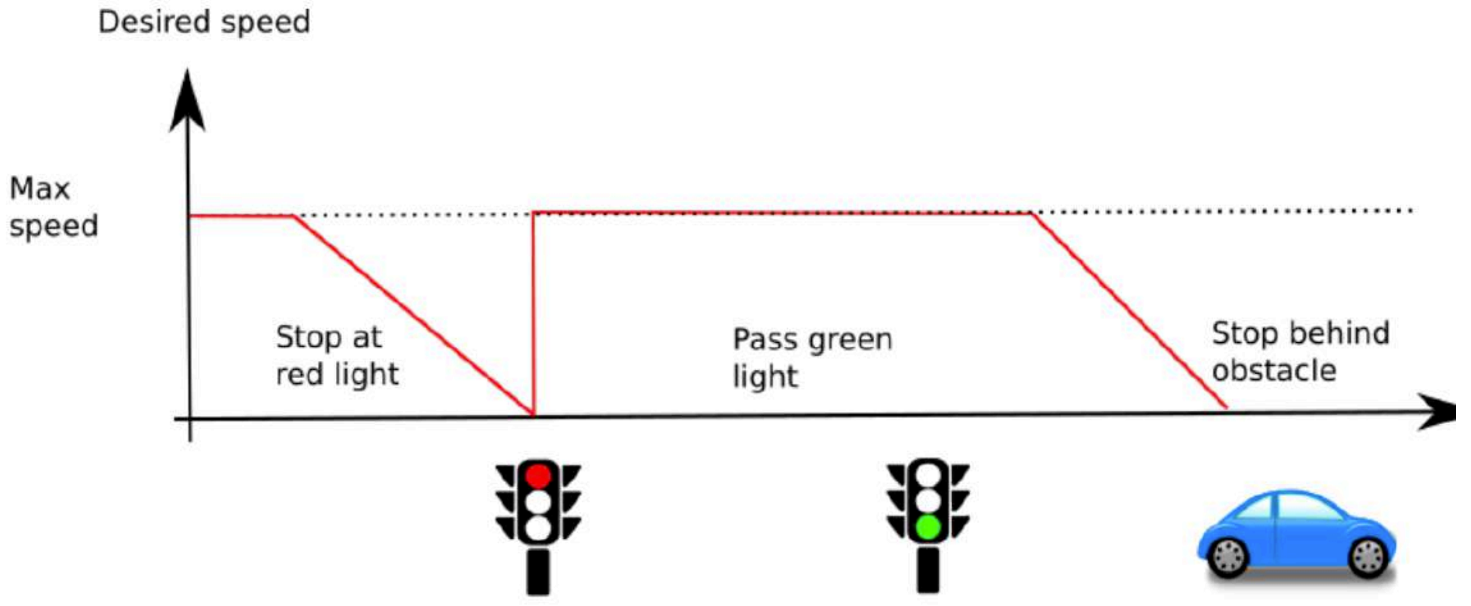
Reward Learning for Autonomous Driving using Counterfactuals

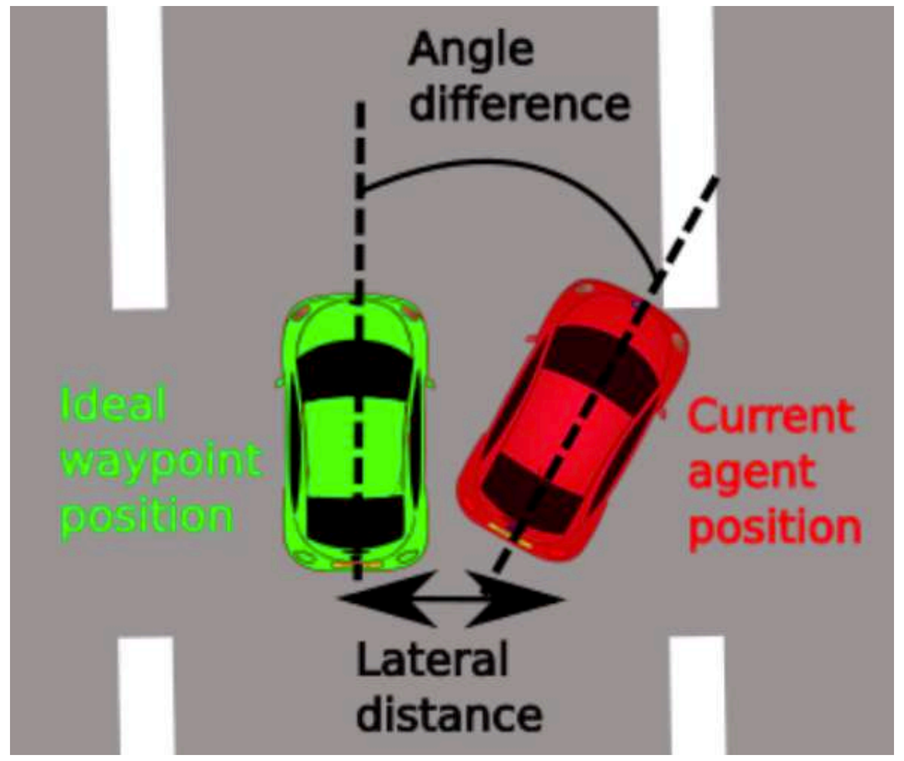
with Eray Çakar, Shadi Hamdan, Jiazhi Yang, Tianyu Li, Caojun Wang, and Hongyang Li

Increasing importance of planning



GIGAFLOW; 2025



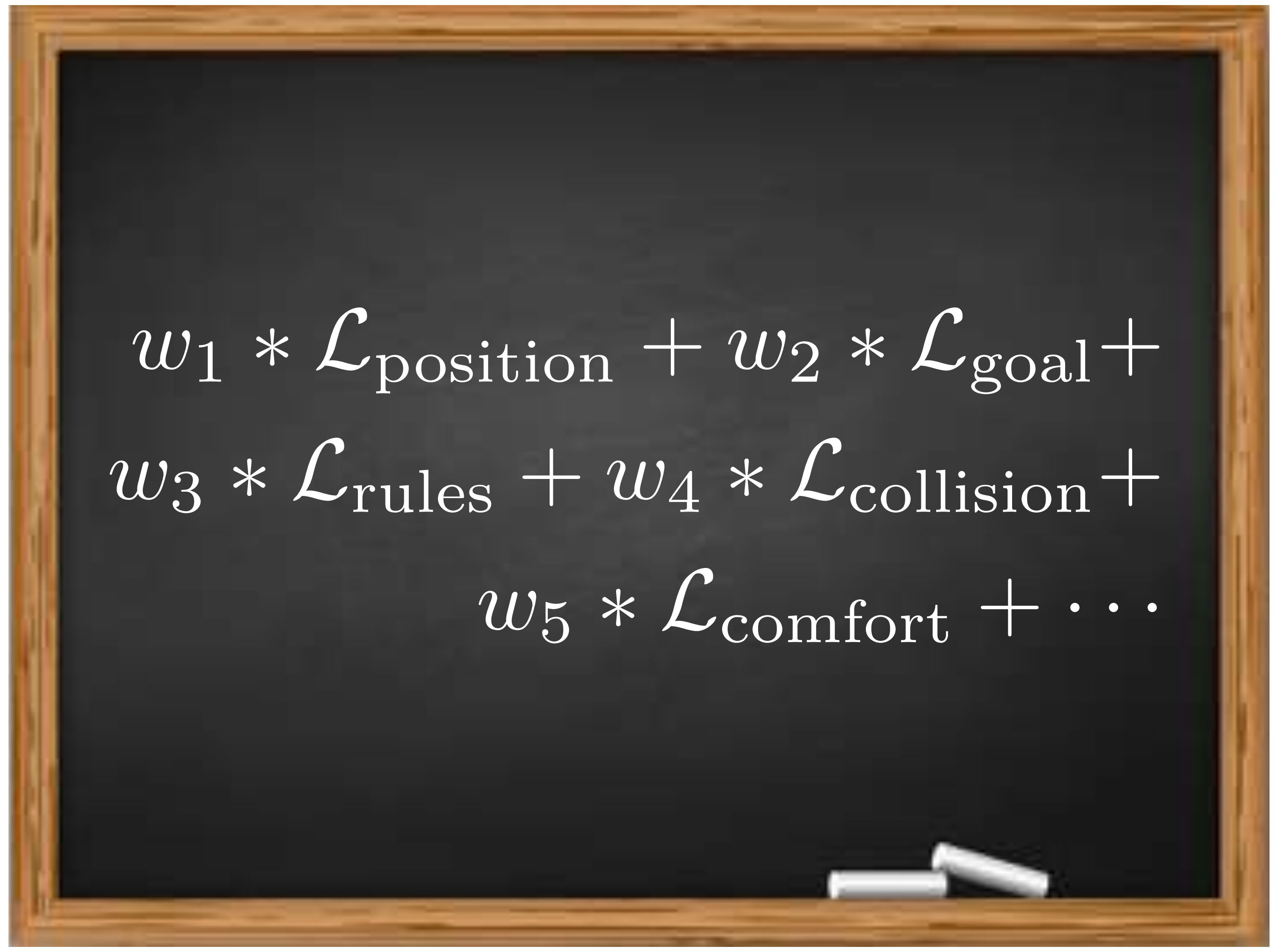


Hand-designed rewards

Implicit Affordances, ROACH

Ground truth measurements

...



Hand-designed rewards

Implicit Affordances, ROACH

Ground truth measurements

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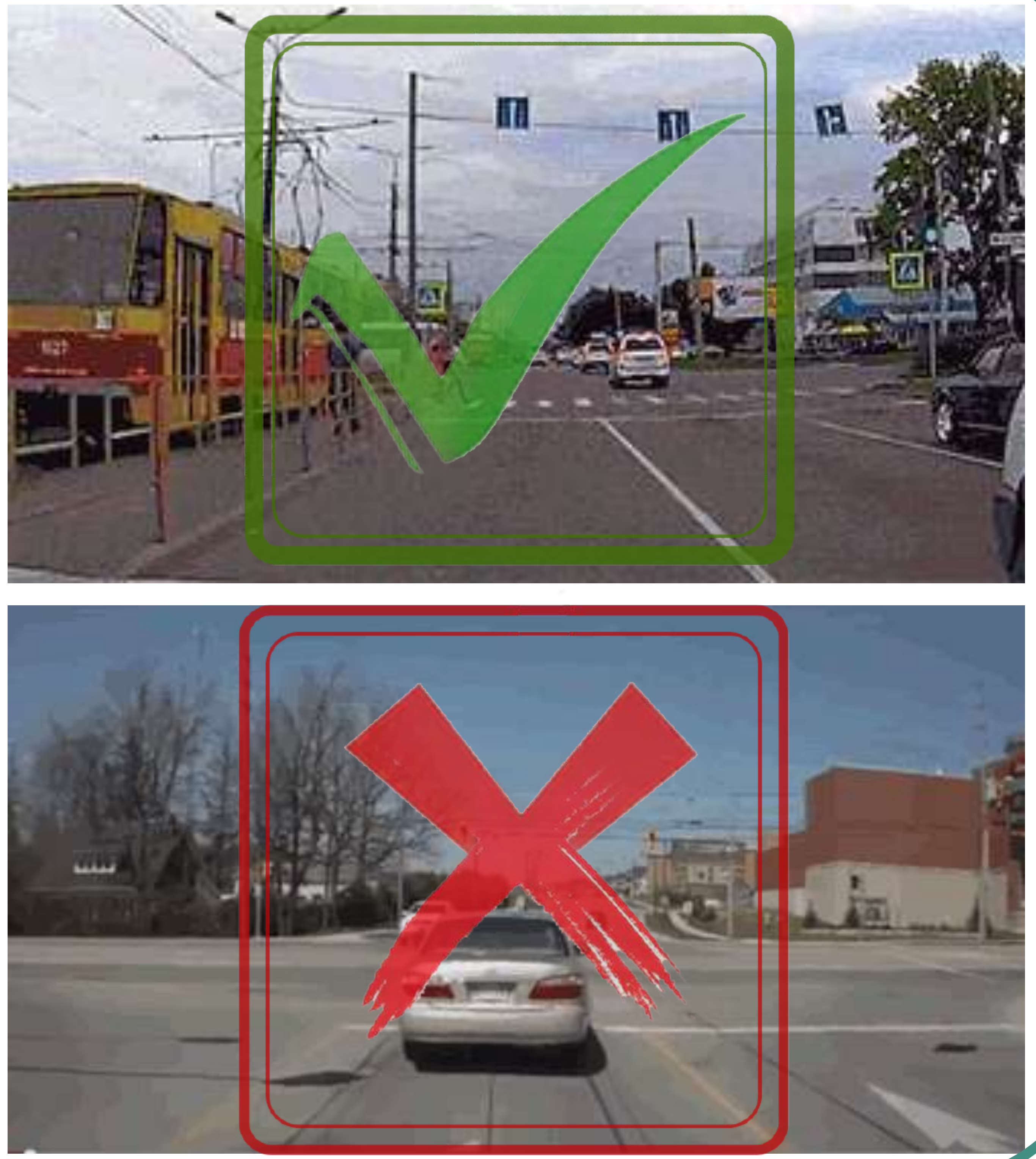
Reward engineering

What to consider?

How to weight?

…



Hand-designed rewards

Implicit Affordances, ROACH

Ground truth measurements

…

Reward engineering

What to consider?

How to weight?

…

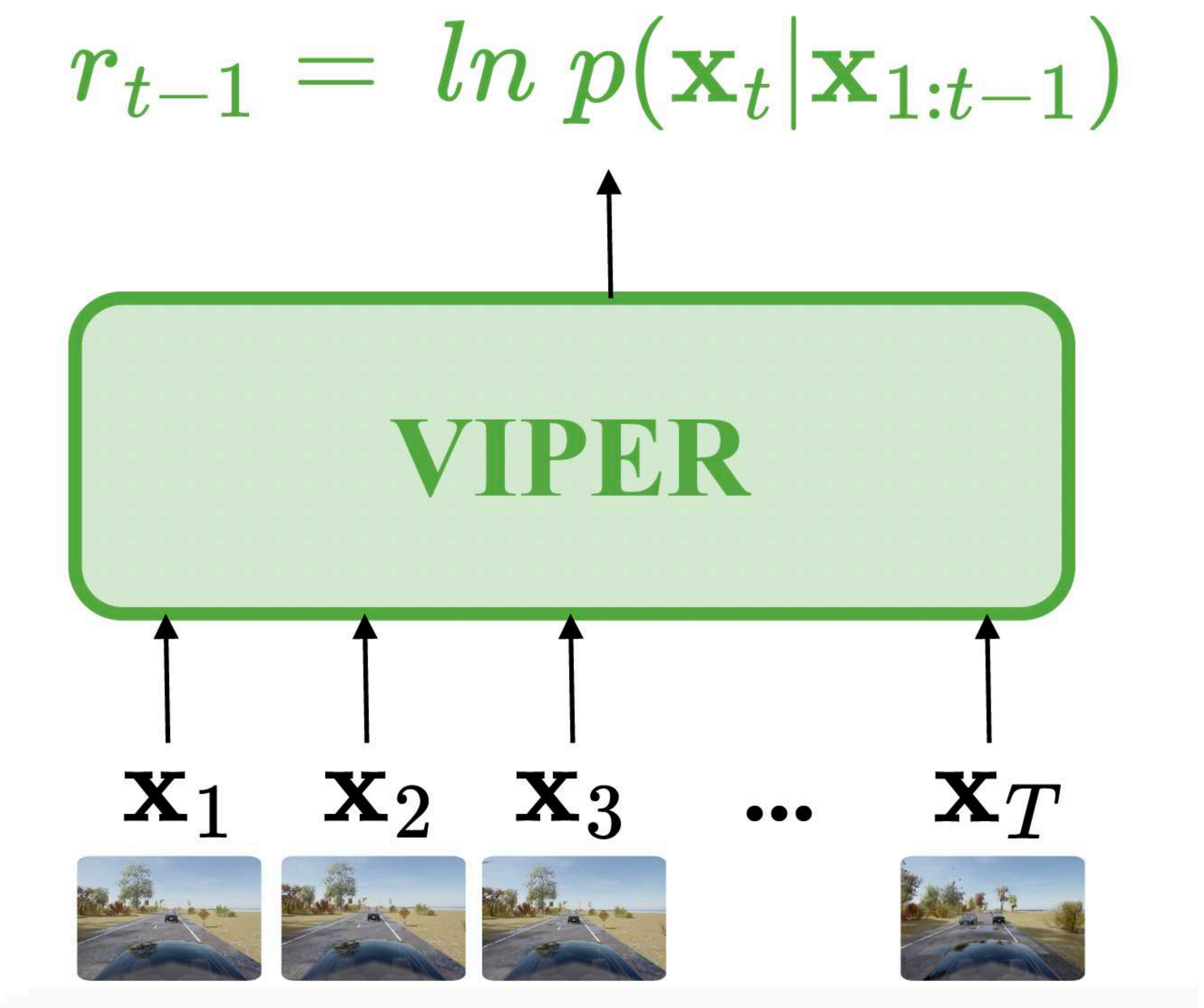
Reward learning

Potential to scale to real-world

Without reward engineering

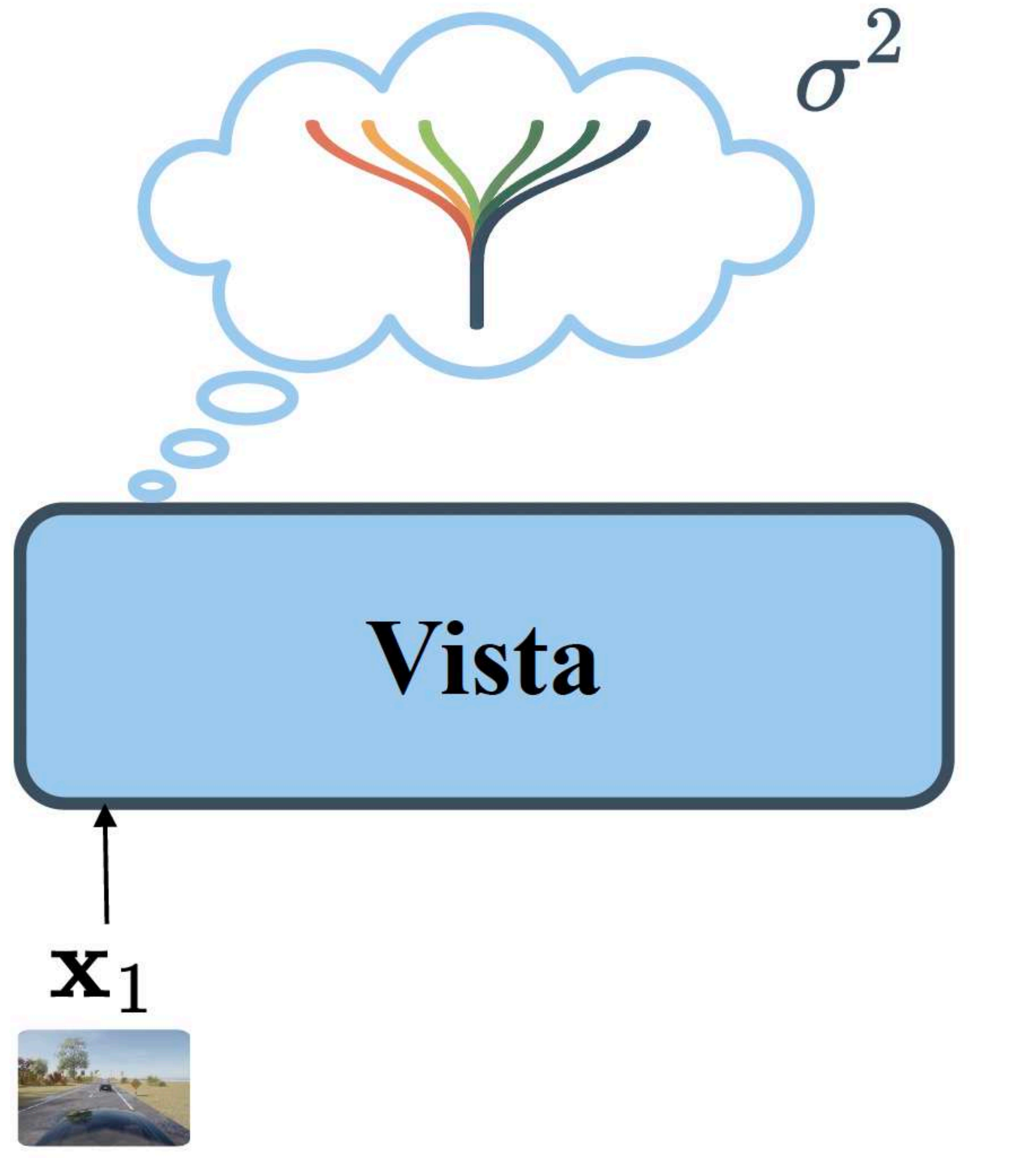
Likelihood-based rewards

VIPER; 2023



Likelihood-based rewards

Vista; 2024



Expert

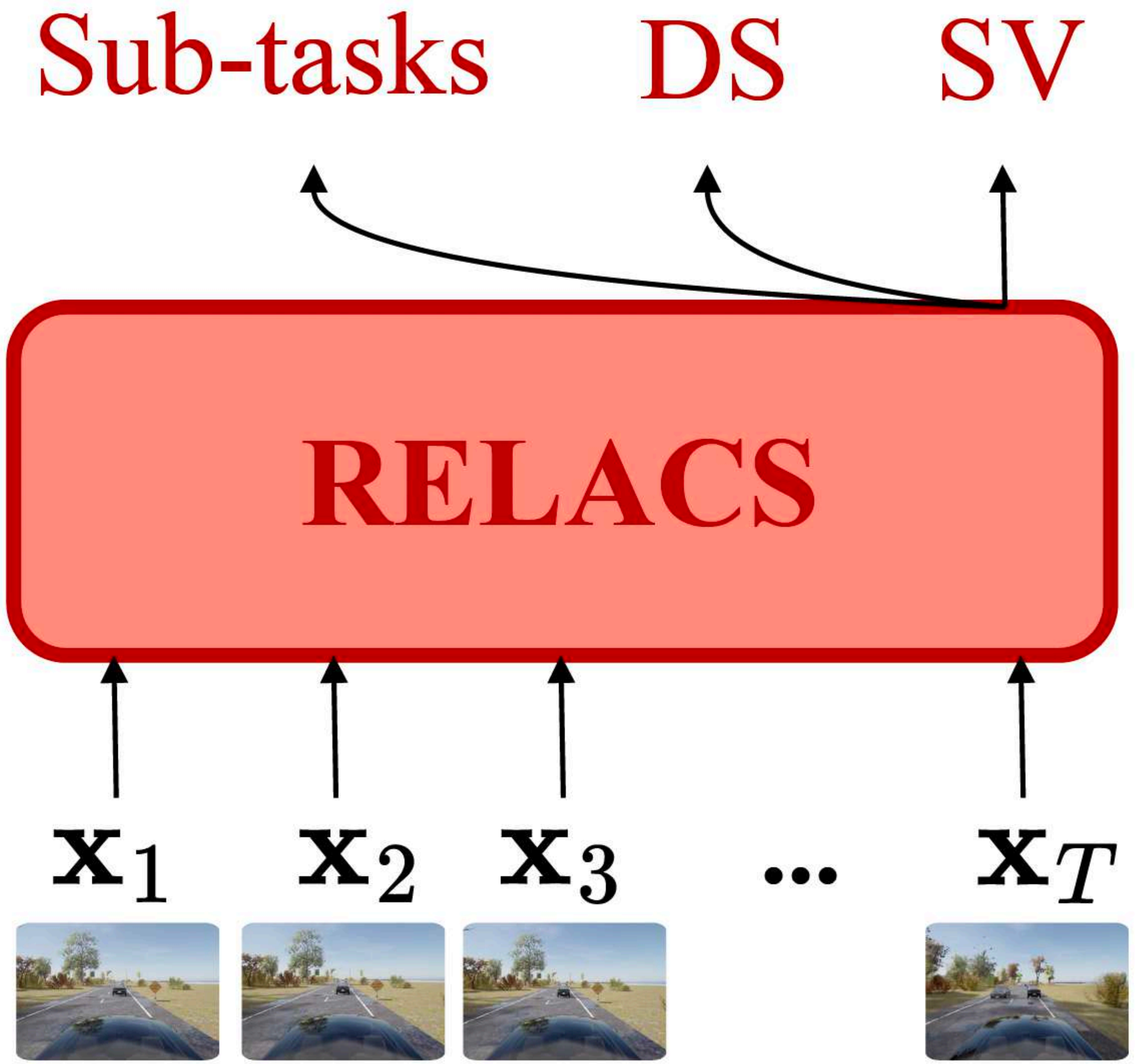
Crash

Likelihood-based: ✓

Likelihood-based: ✓

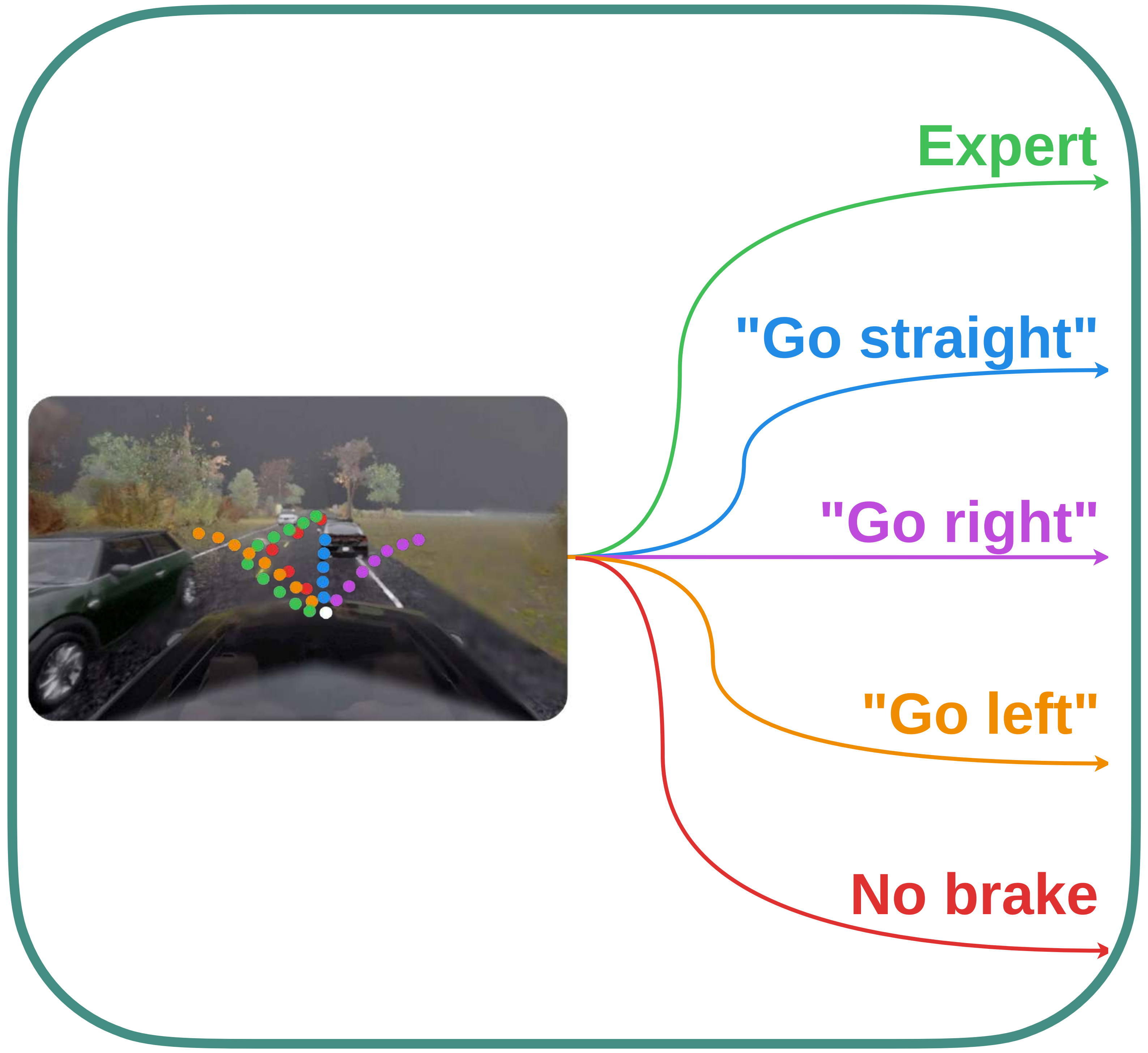

Expert
Vista: 0.87
VIPER: 0.47
Likelihood-based:
Crash
Vista: 0.84
VIPER: 0.36
Likelihood-based:
High Uncertainty
Vista: 0.77
VIPER: 0.22
Likelihood-based:

A dedicated reward model, independent of future prediction.




Expert
Vista: 0.87
VIPER: 0.47
RELACS: 1.00
Likelihood-based: ✓
Our method: ✓
Crash
Vista: 0.84
VIPER: 0.36
RELACS: 0.46
Likelihood-based: ✓
Our method: ✓
High Uncertainty
Vista: 0.77
VIPER: 0.22
RELACS: 1.00
Likelihood-based: ✗
Our method: ✓

How to learn what should be low-reward?



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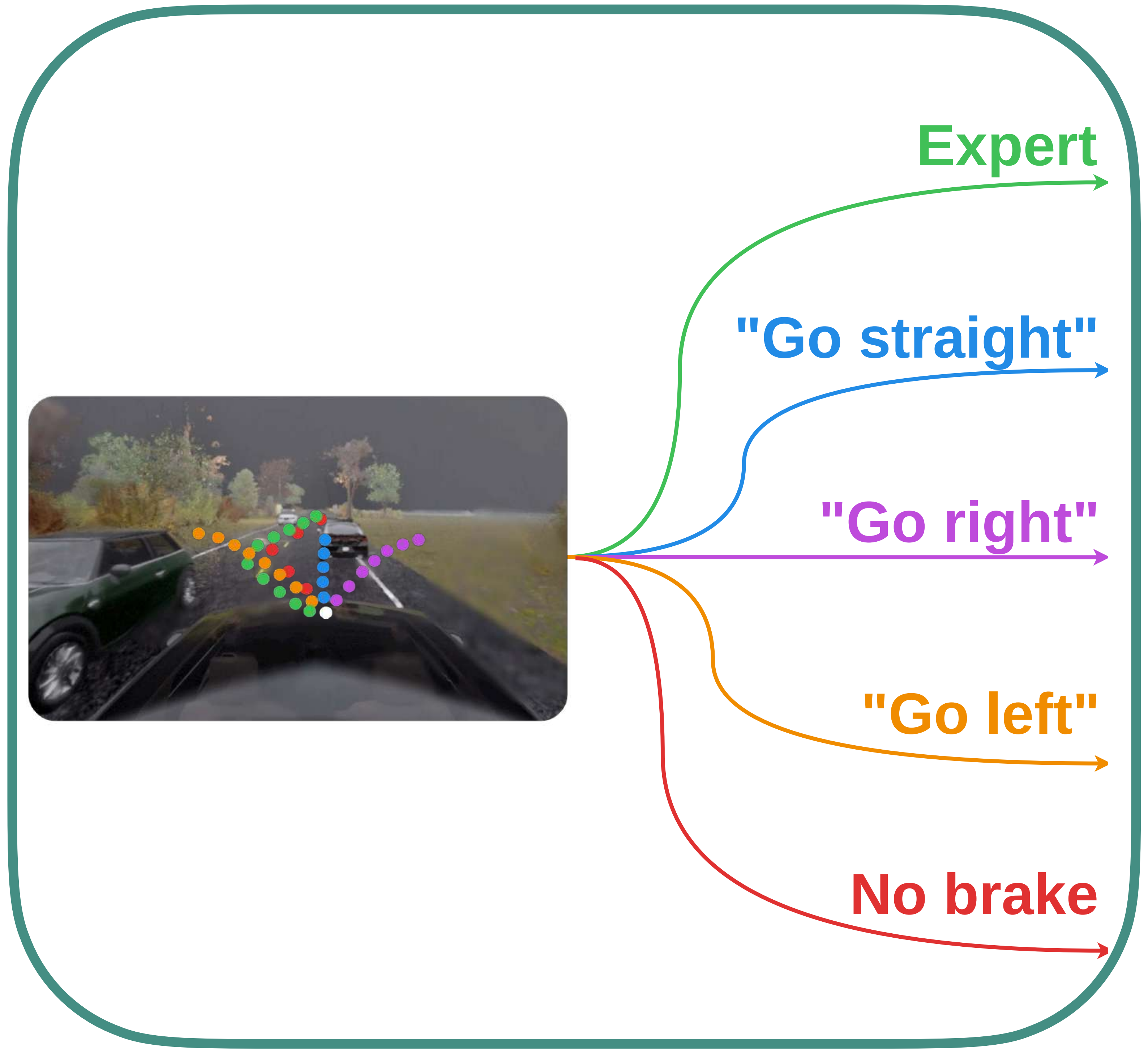

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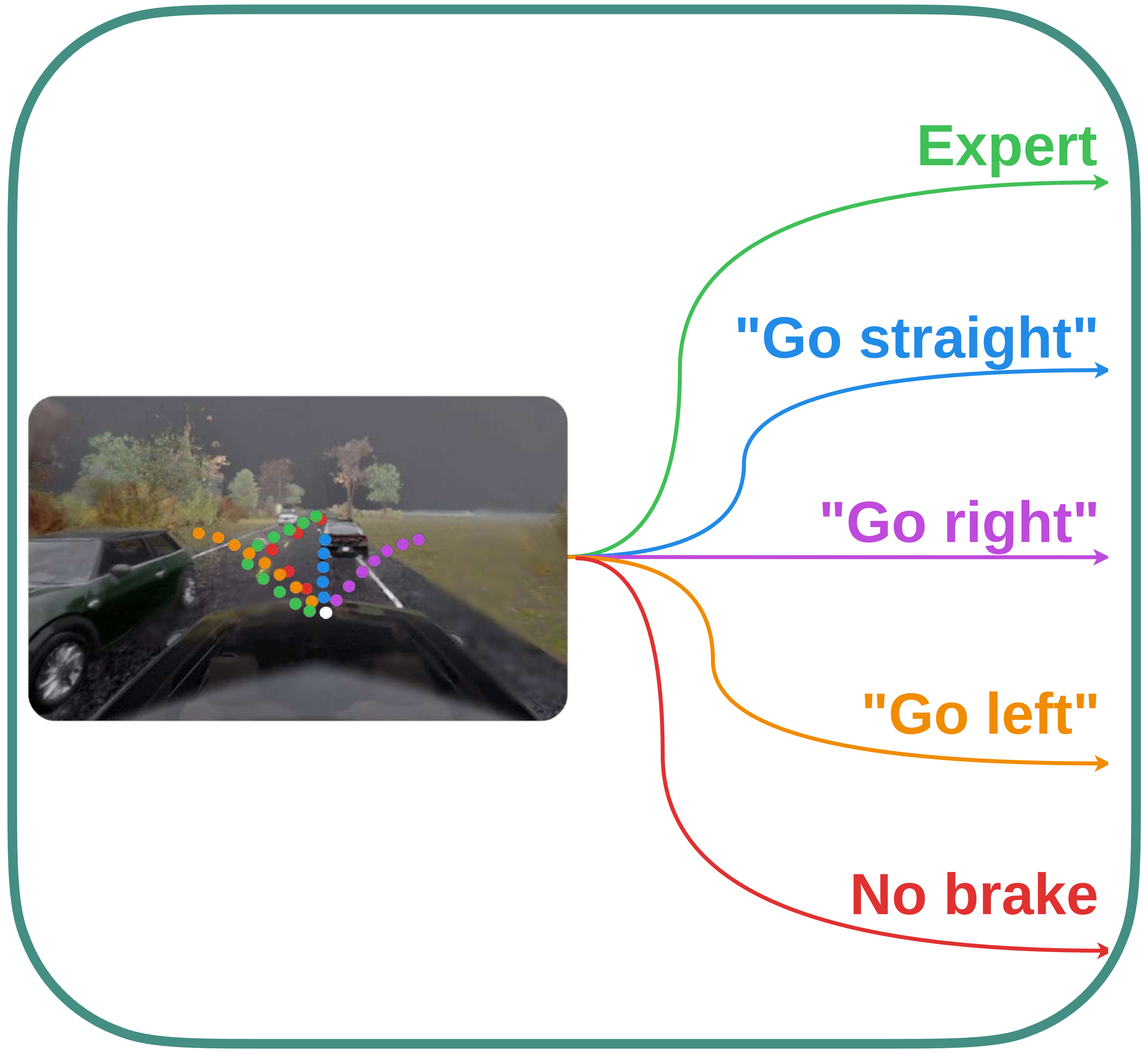
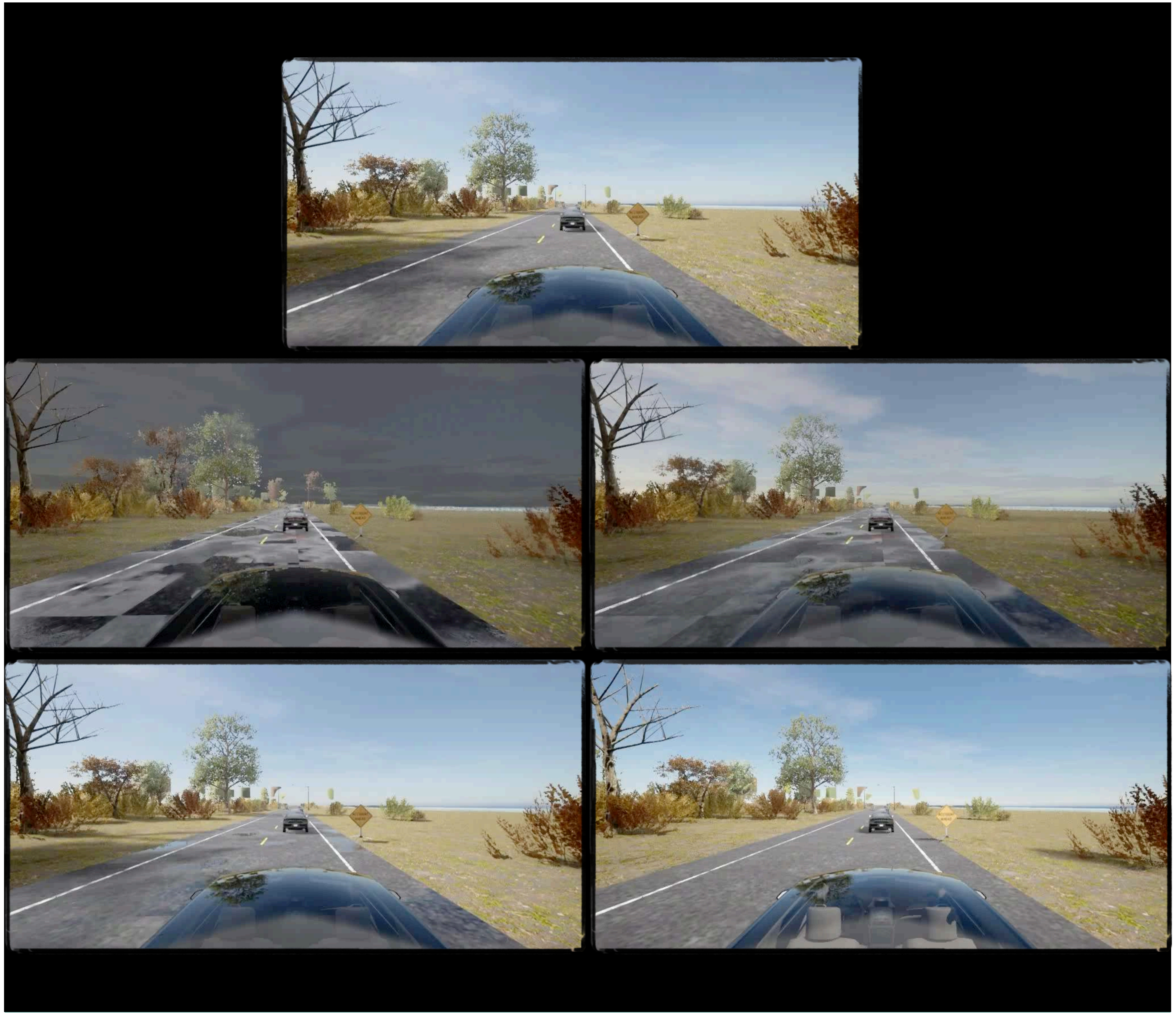
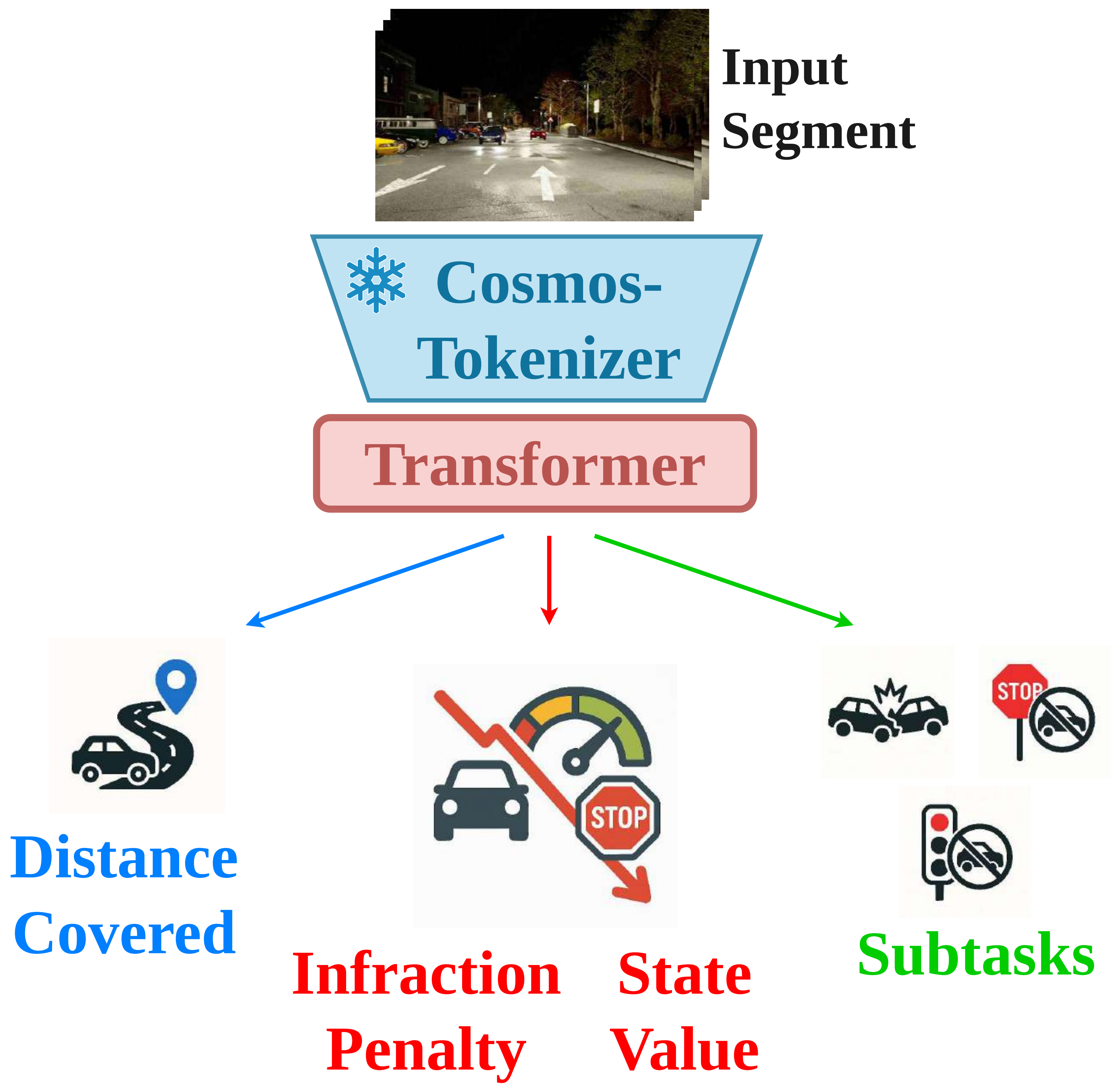
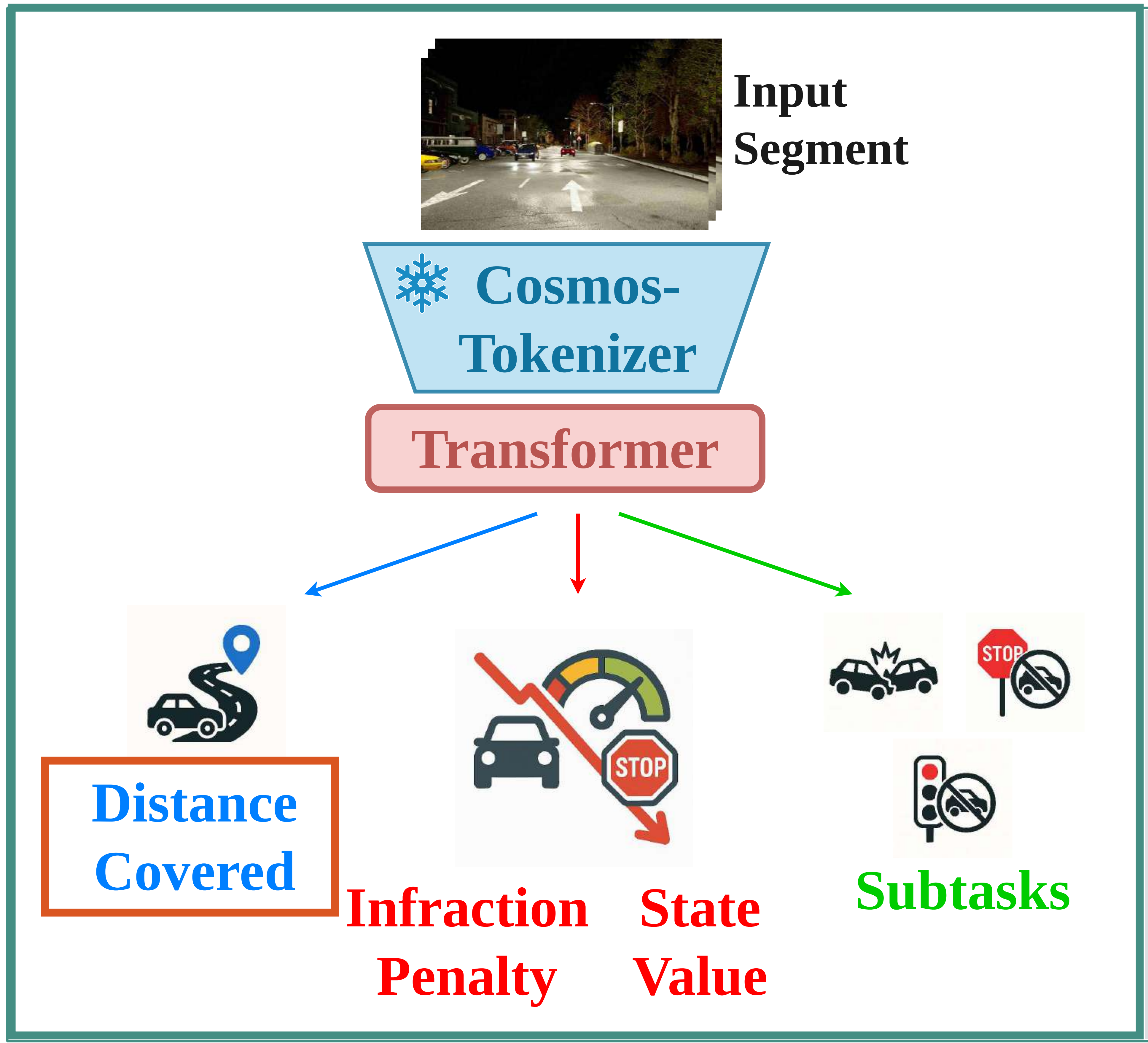




Reward learning from counterfactuals



Reward specification



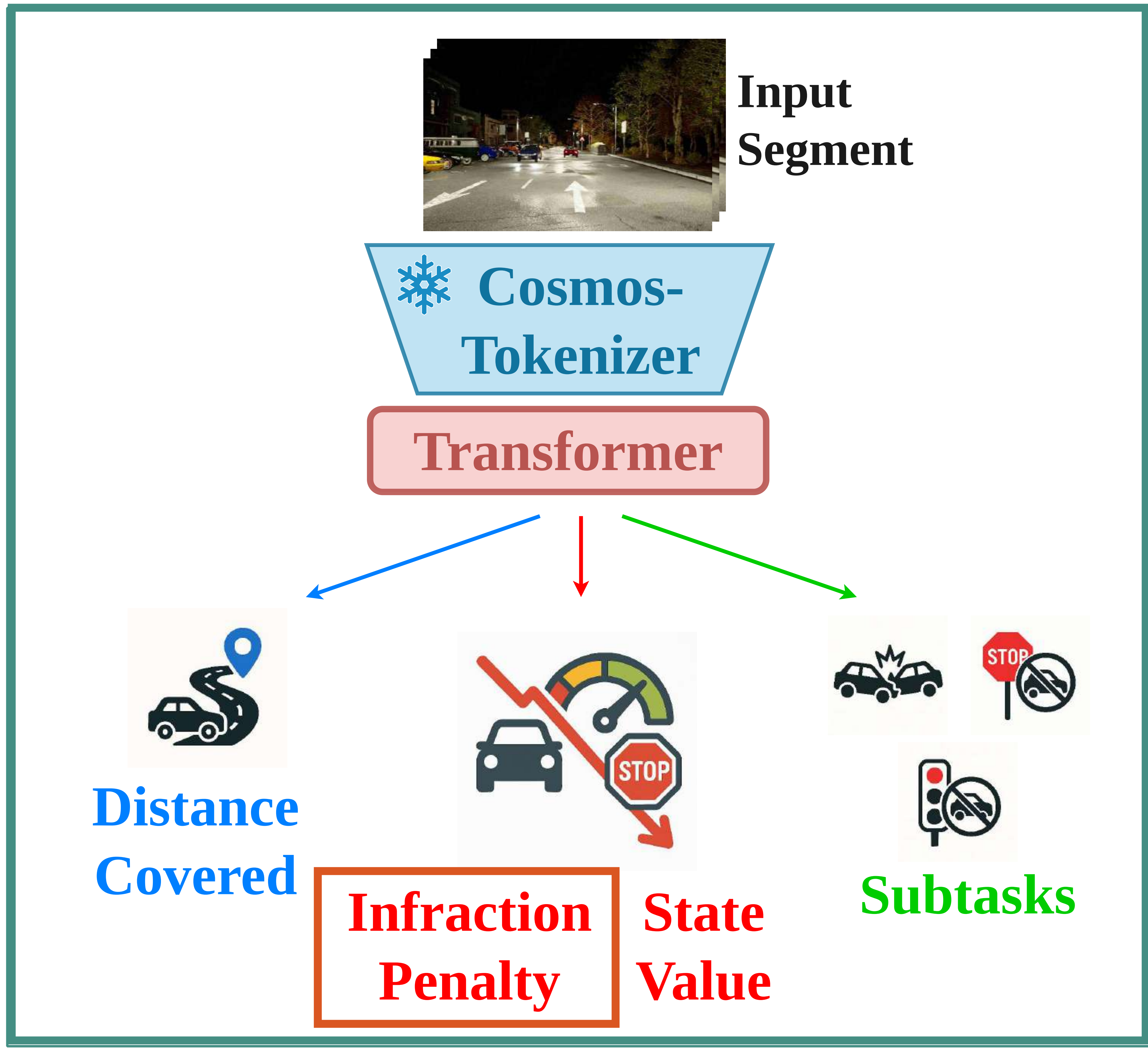
$$\text{DrivingScore} = \boxed{\text{RouteCompletion}} \times \text{InfractionPenalty}$$

RC : % of the route completed

map or goal dependency

$$\text{DistanceCovered} = \text{RC} \times \text{RouteLen}$$

Reward specification

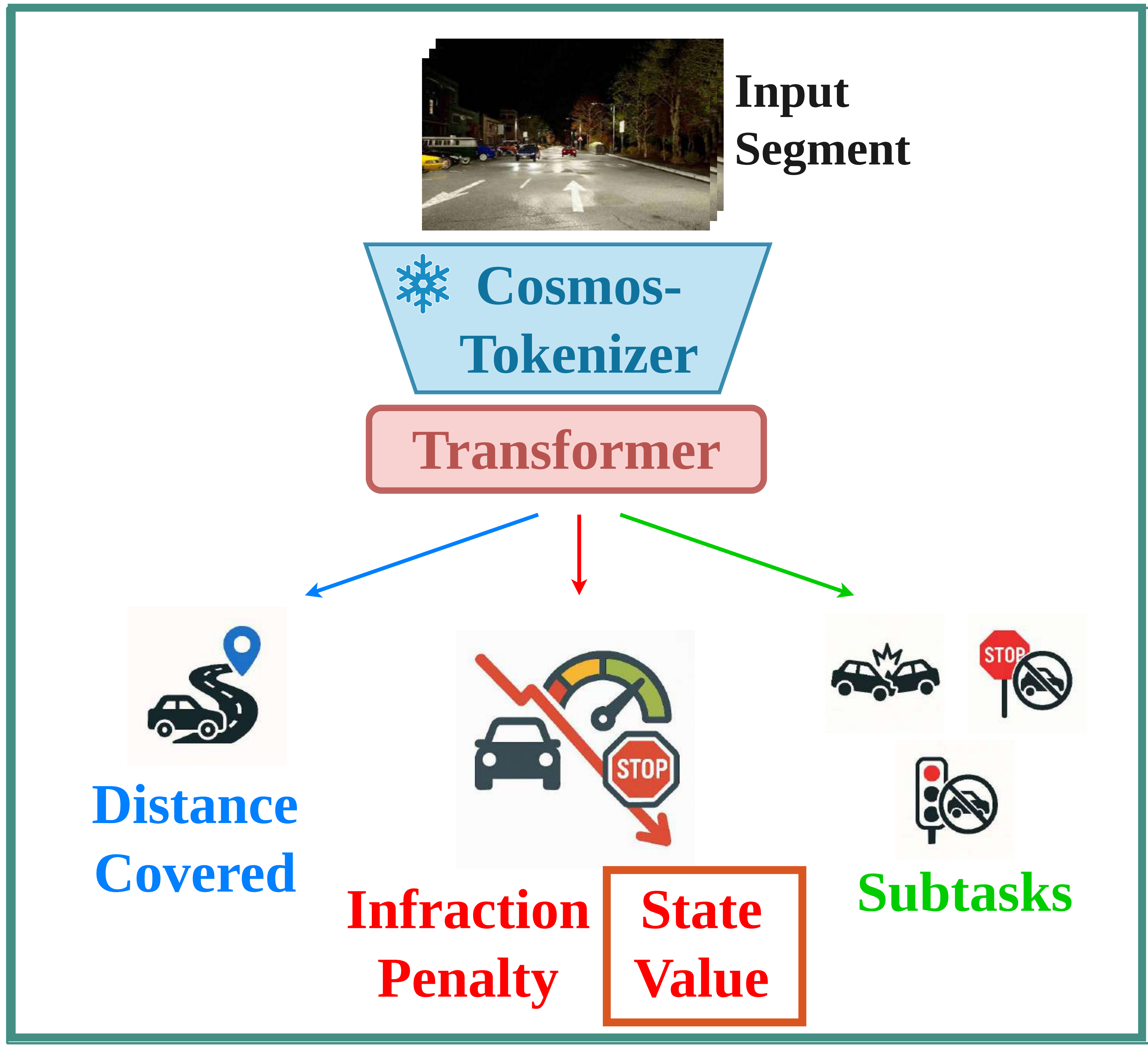


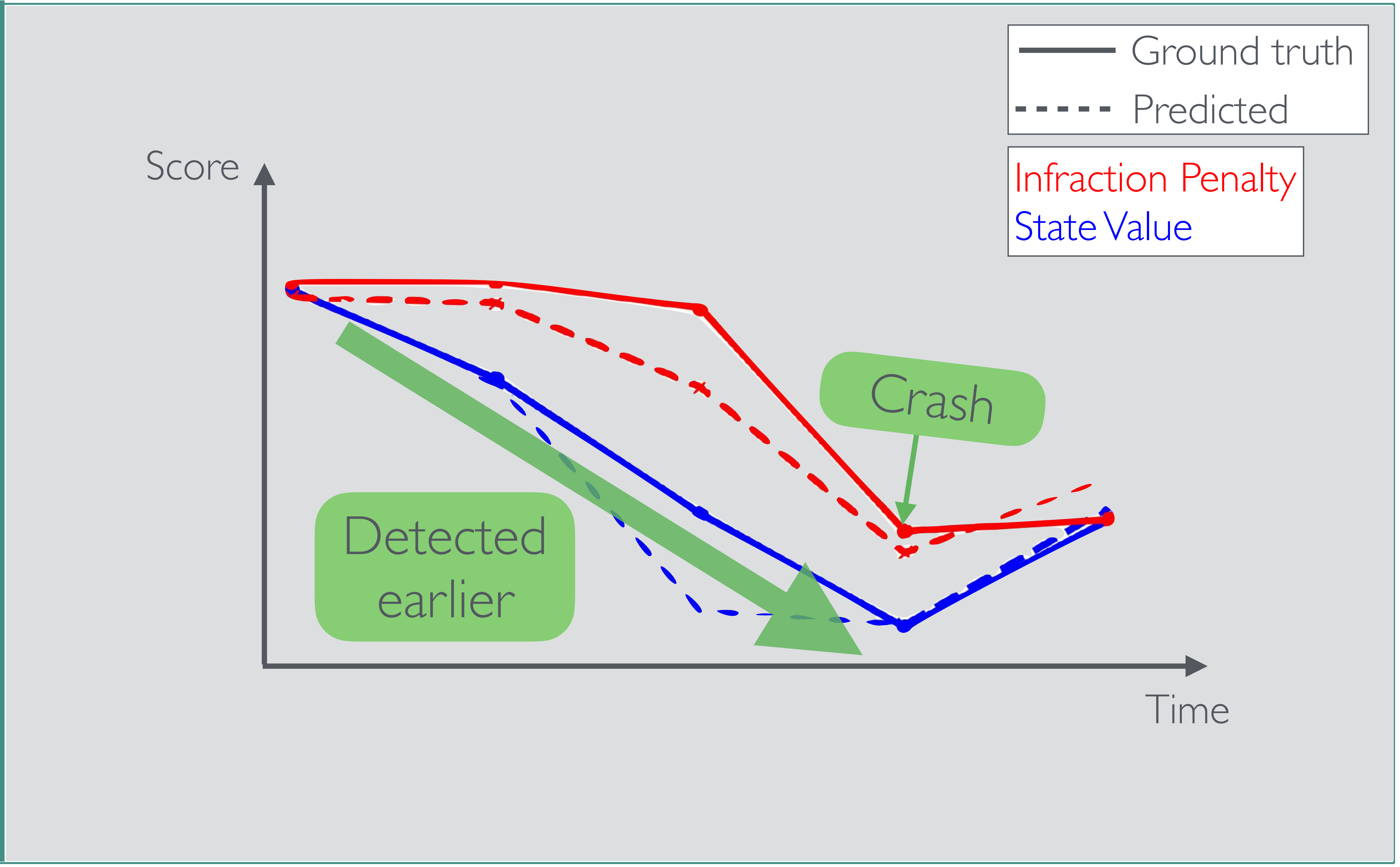
$$\text{DrivingScore} = \text{RouteCompletion} \times \boxed{\text{InfractionPenalty}}$$

$$\text{IP} = \prod_j c_j^{\#I_j}$$

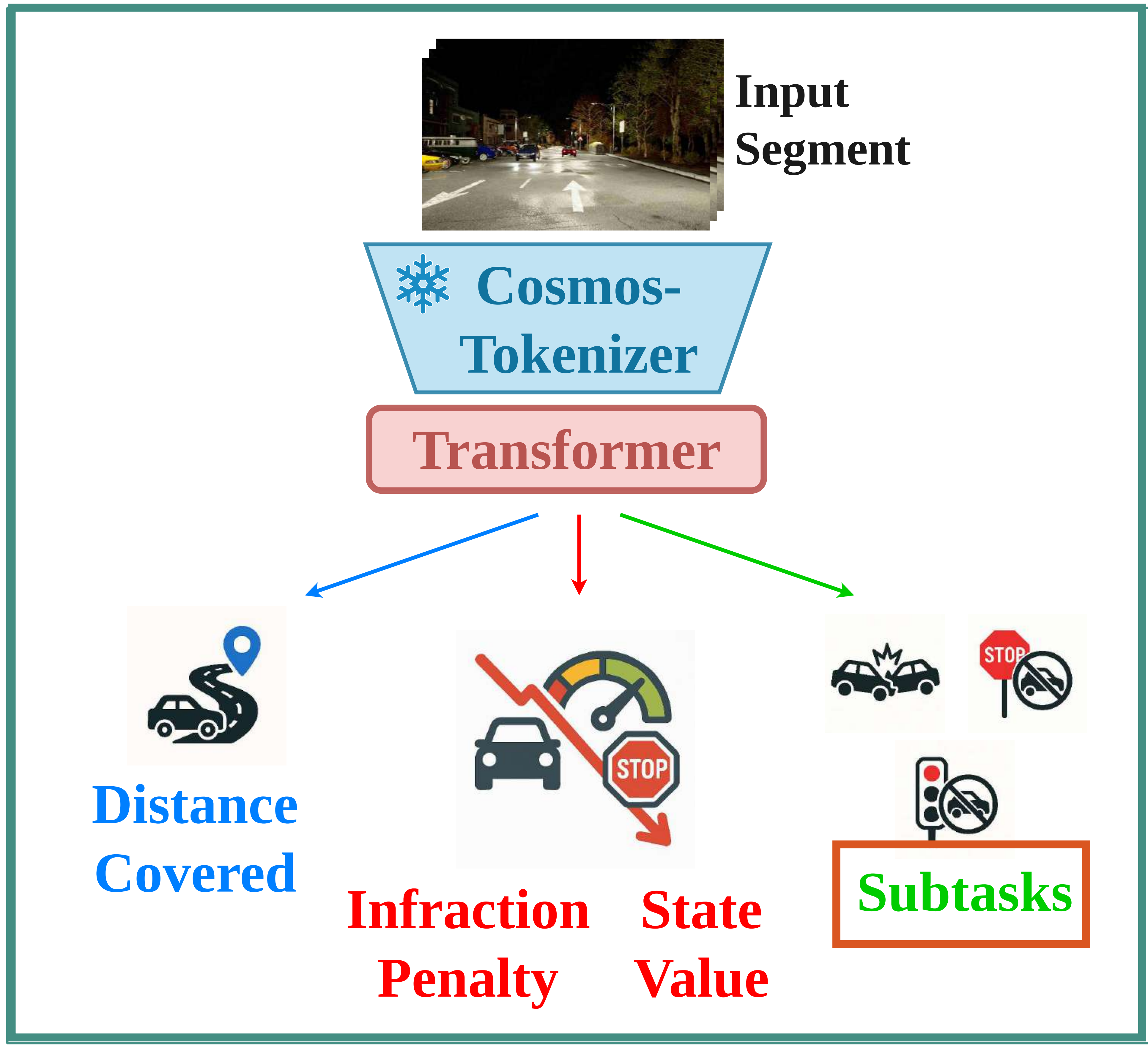
Infraction (I)	Coeff. (c)
Collision w/ pedestrians	0.50
Collision w/ vehicles	0.60
Collision w/ static	0.65
Running a red light	0.70
Running a stop sign	0.80

Reward specification





Reward specification

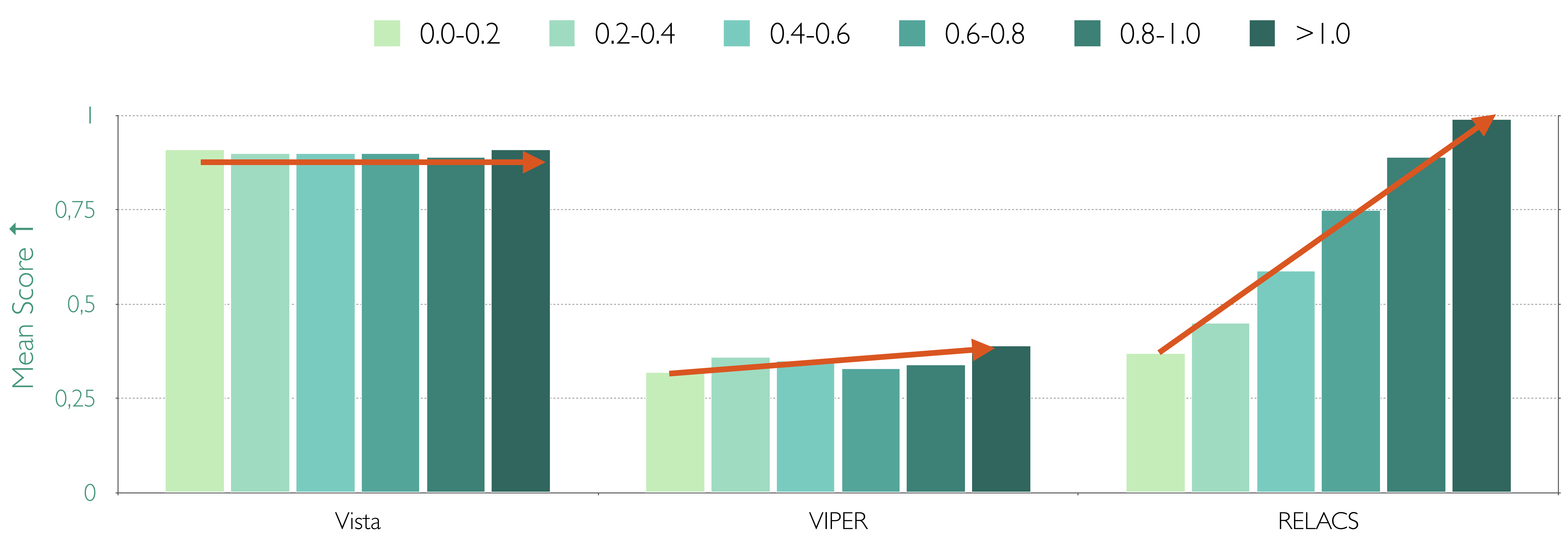


Infraction Type
Collision w/ pedestrians
Collision w/ vehicles
Collision w/ static
Running a red light
Running a stop sign

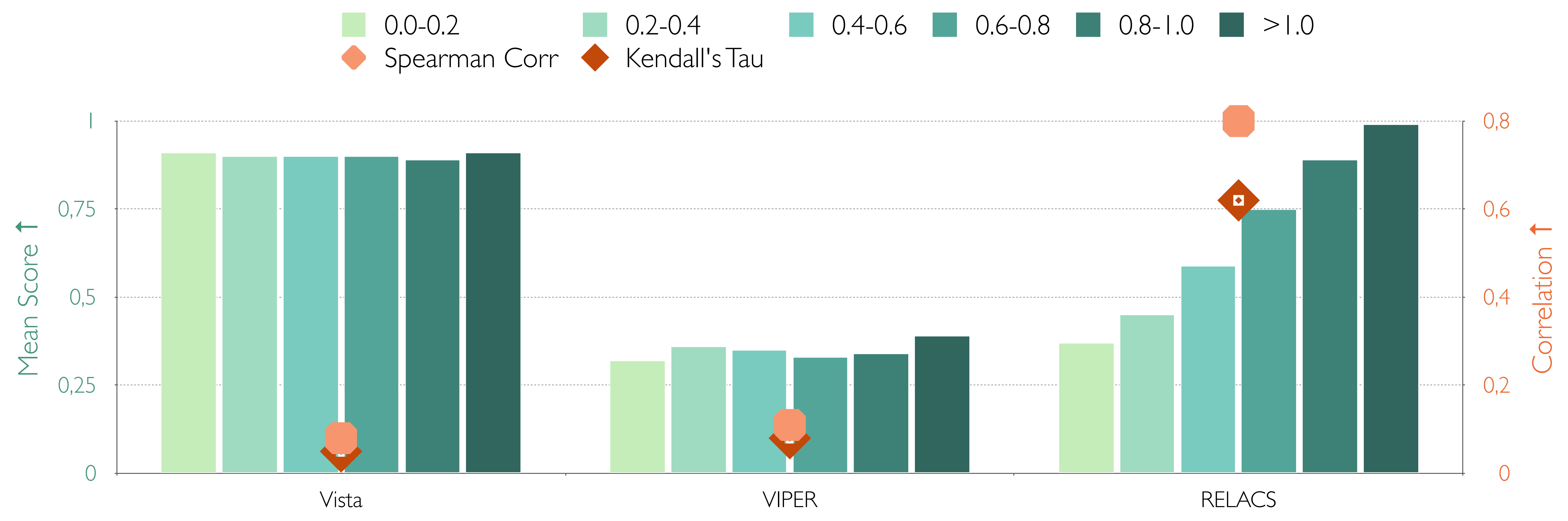
Validating on CARLA

0.0-0.2 | 0.2-0.4 | 0.4-0.6 | 0.6-0.8 | 0.8-1.0 | >1.0

Validating on CARLA



Validating on CARLA

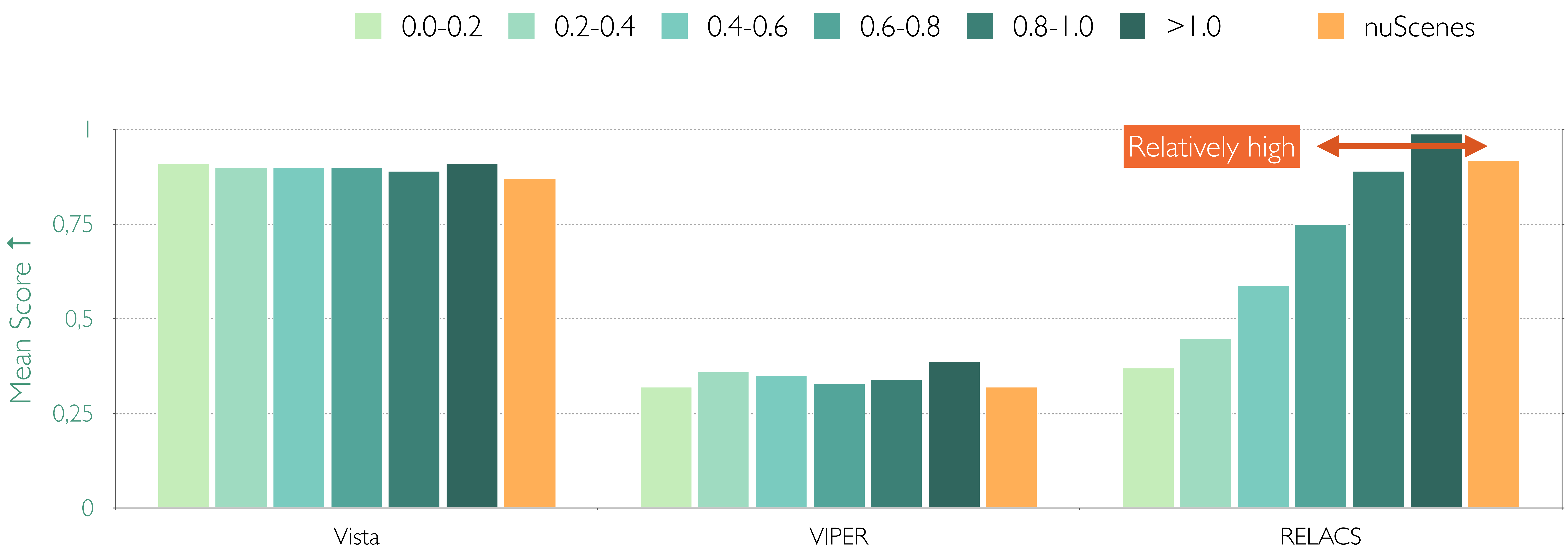


Validating on CARLA

0.0-0.2 | 0.2-0.4 | 0.4-0.6 | 0.6-0.8 | 0.8-1.0 | >1.0

Does it generalize to nuScenes?

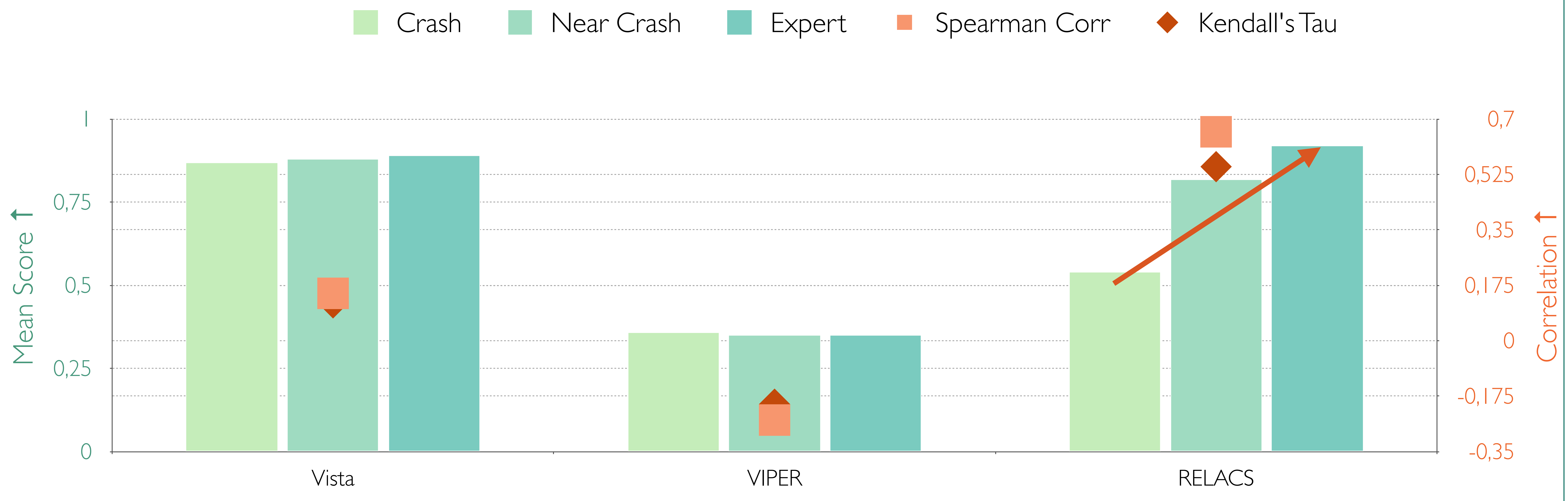
NUSCENES



YouTube CarCrash

Crash Near Crash Expert

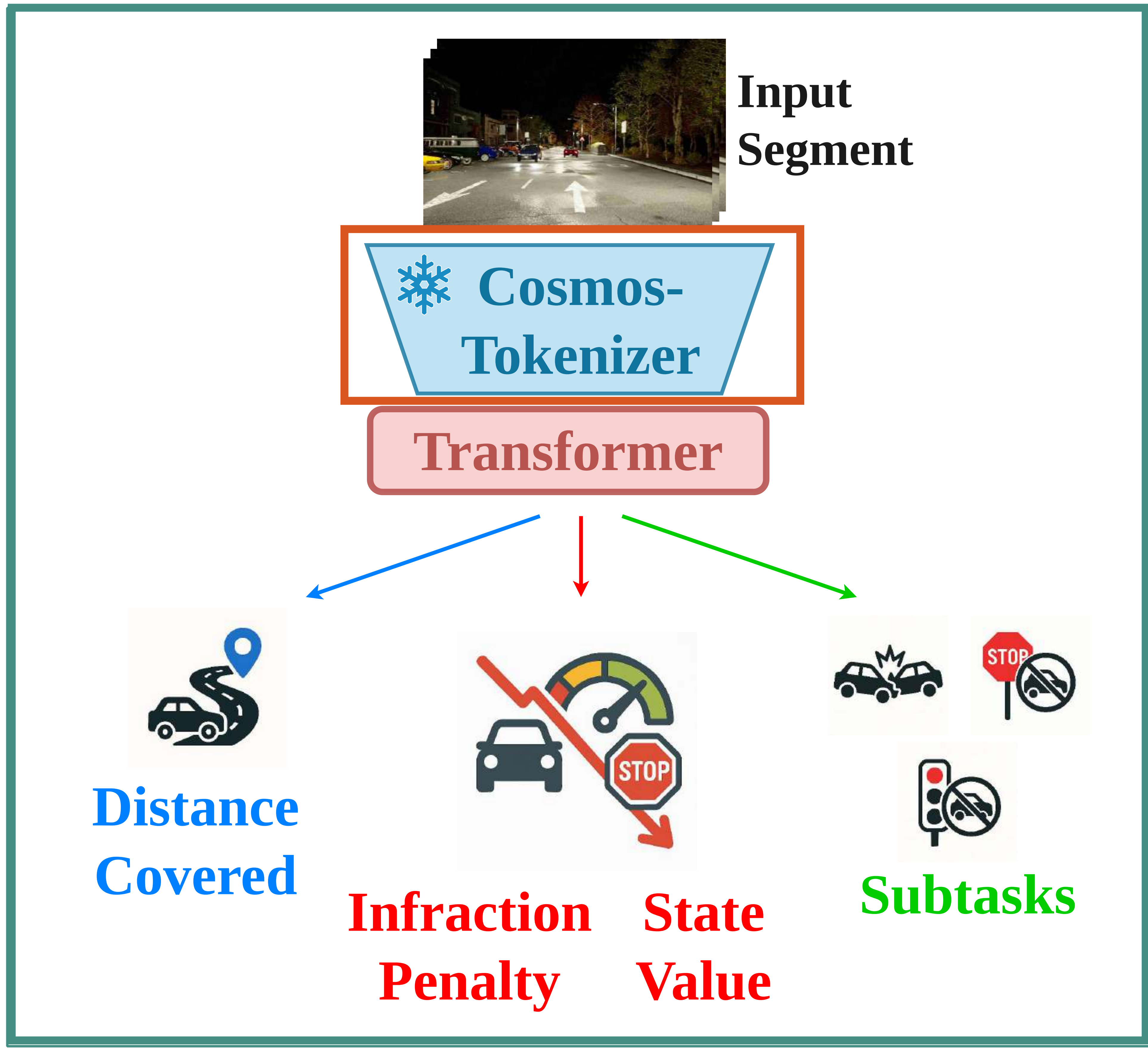
YouTube CarCrash

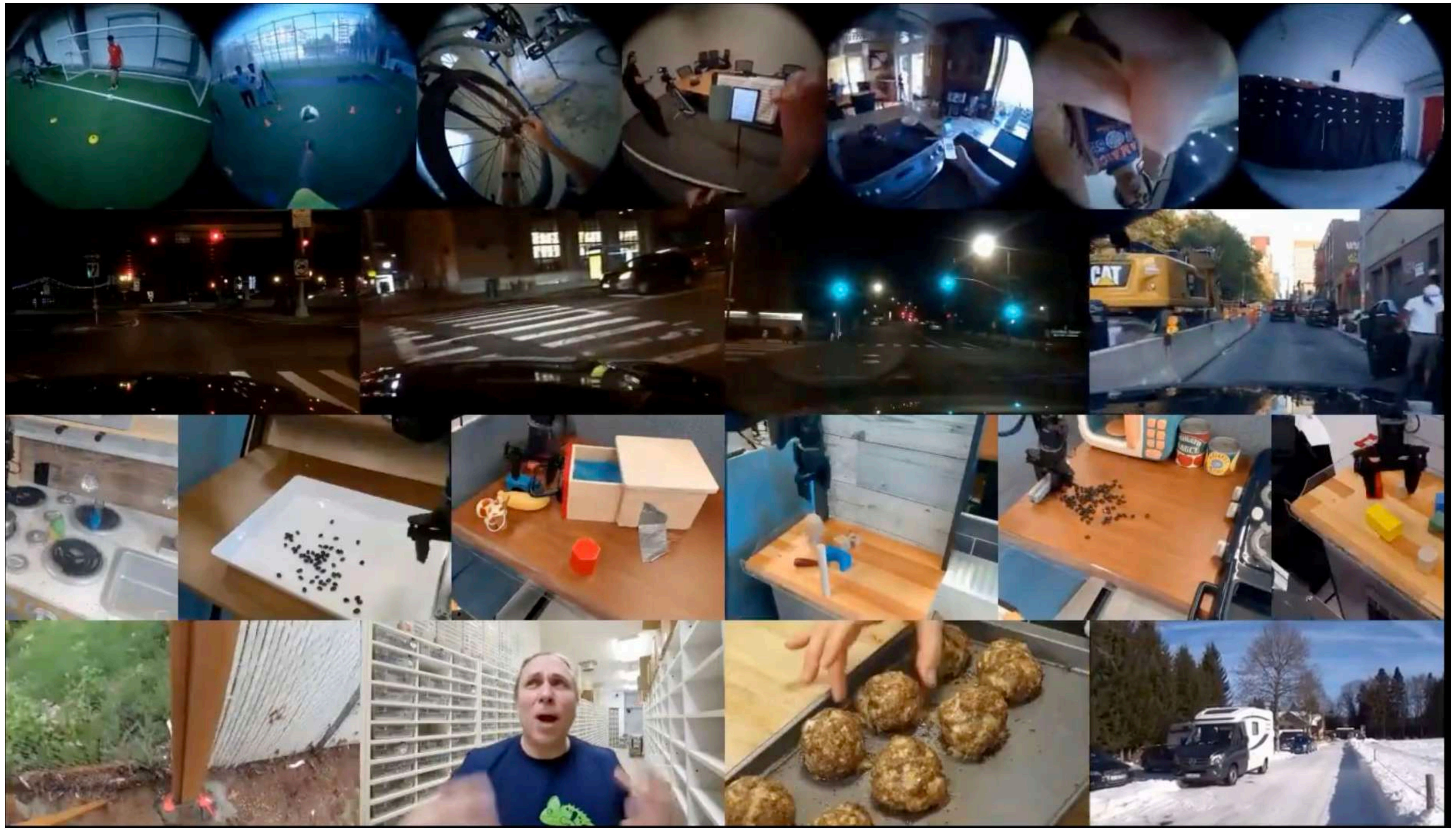


YouTube CarCrash

Crash Near Crash Expert

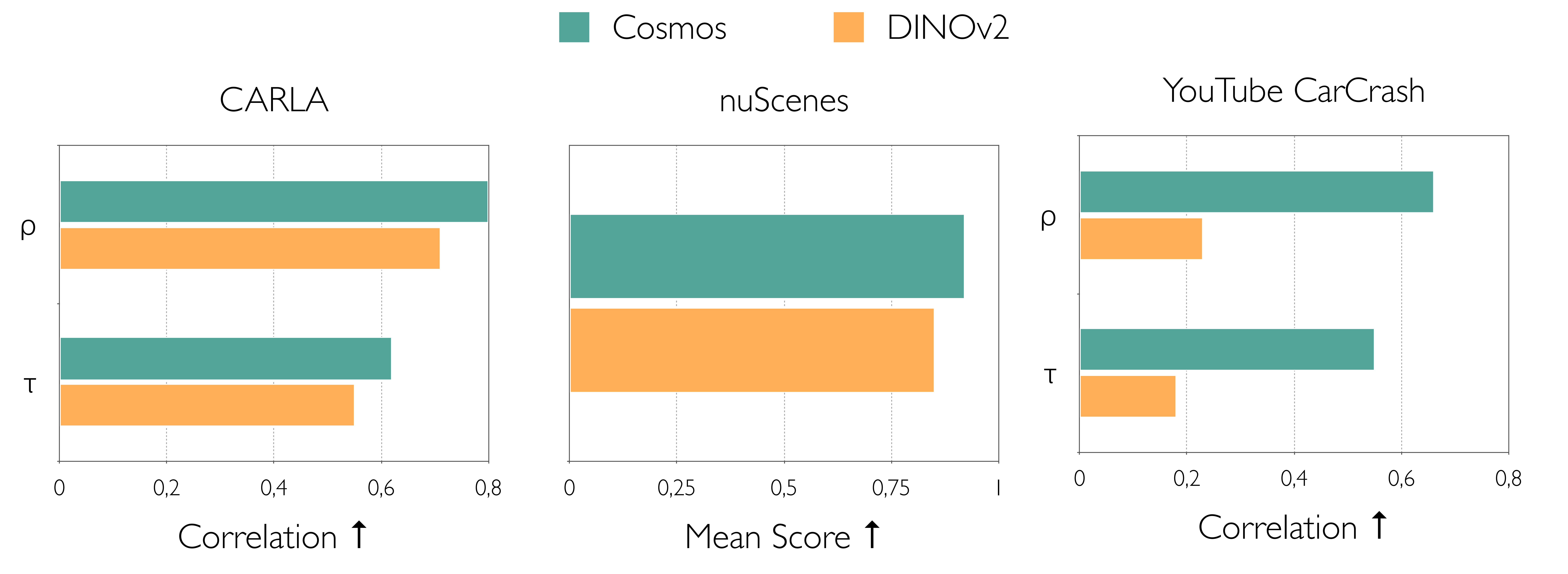
Why does it generalize?





NVIDIA Cosmos; 2025

Why does it generalize?



NAVSIM: Ego progress

Real

NAVSIM: Ego progress

Rendered slower

Real

Rendered faster

NAVSIM: Ego progress

Distance Covered

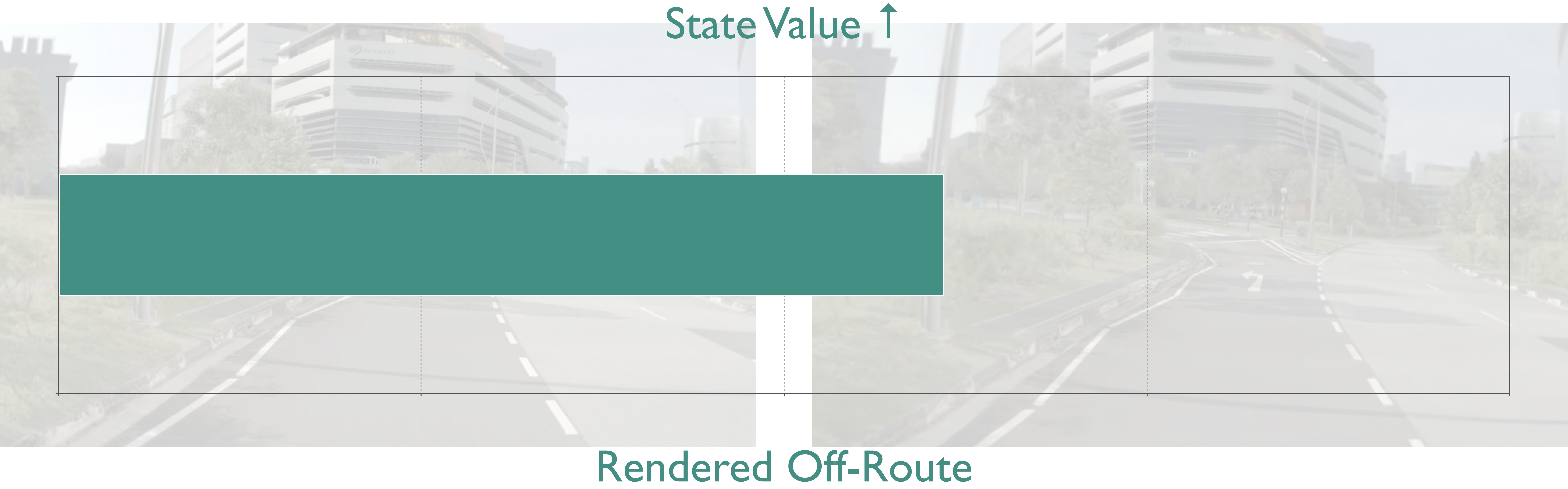
Faster

NAVSIM: Route deviation

Real

Rendered Off-Route

NAVSIM: Route deviation



Remaining problems and future work

- Imbalance in crash types
  - Data augmentation for synthetic infraction generation
  - Active data collection methods
- Infractions are temporally sparse.
  - Infraction localization
- Real-time closed-loop planners

Counterfactual

Thanks!