THINK LAB

OpenDriveLab

ICCV23
PARIS

DriveAdapter: Breaking the Coupling Barrier of Perception and Planning in End-to-End Autonomous Driving

Code

Paper

Poster: THU-AM-Room “Nord”-155

arXiv: https://arxiv.org/abs/2308.00398


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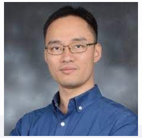
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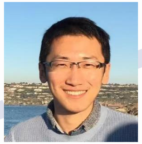
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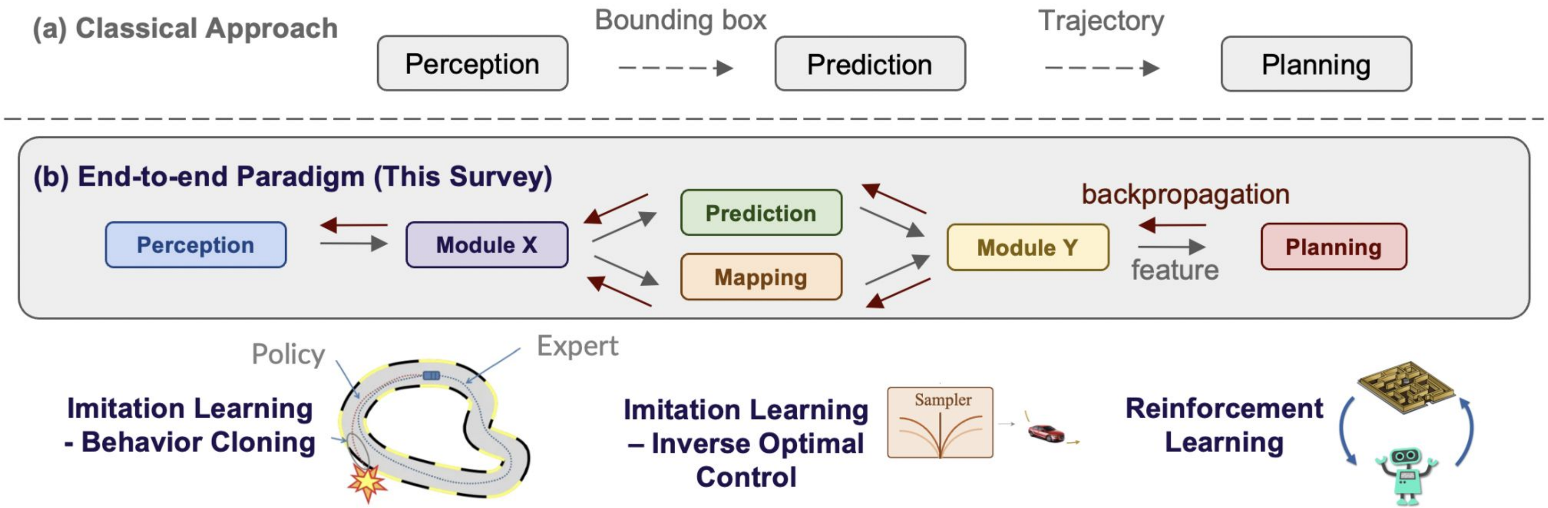
Why End-to-end Autonomous Driving?



End-to-end autonomous driving system - A suite of fully differentiable programs that:

- take raw sensor data as input
- produce a plan and/or low-level control actions as output

Why End-to-end Autonomous Driving?

...
v12 is reserved for when FSD is **end-to-end AI**, from images in to steering, brakes & acceleration out.

Advantages

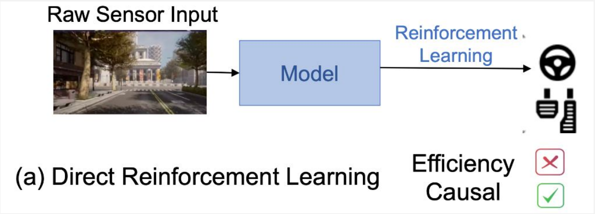
- \+ **Simplicity** in combining all modules into a single model that can be **joint trained**
- \+ Preventing cascading errors in modular design
- \+ Directly optimized **toward the ultimate task**, planning / control
- \+ Computational efficiency (all shared backbone), production-level friendly

Check out the latest **Survey Paper** here

https://github.com/OpenDriveLab/End-to-end-Autonomous-Driving

Motivation

How to balance the efficiency and causal reasoning ability?



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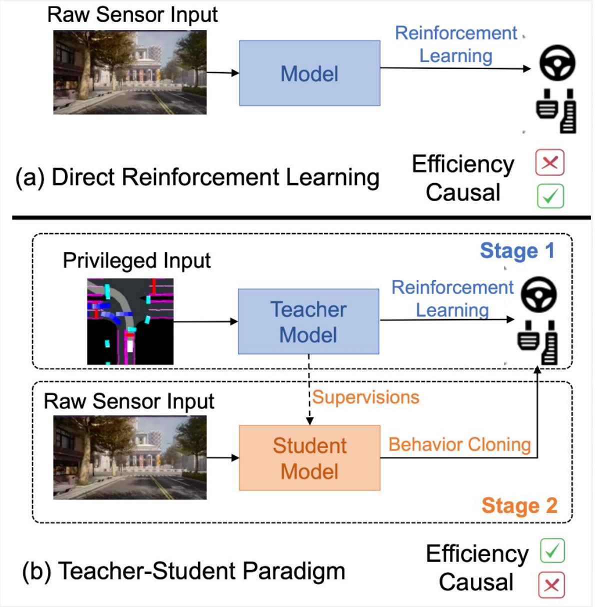

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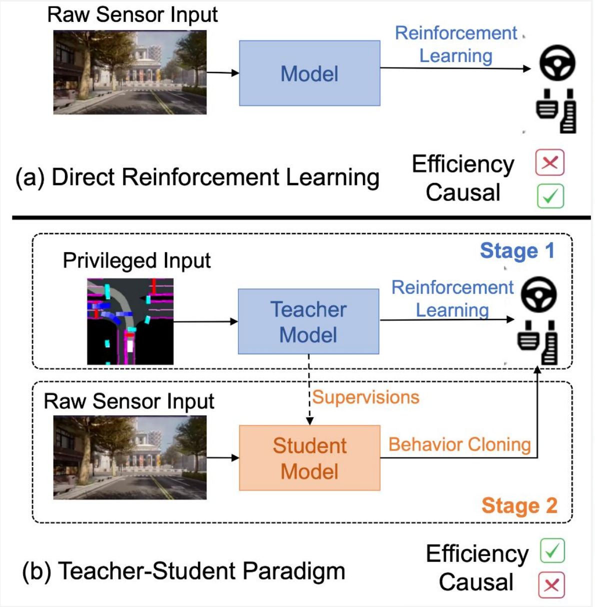
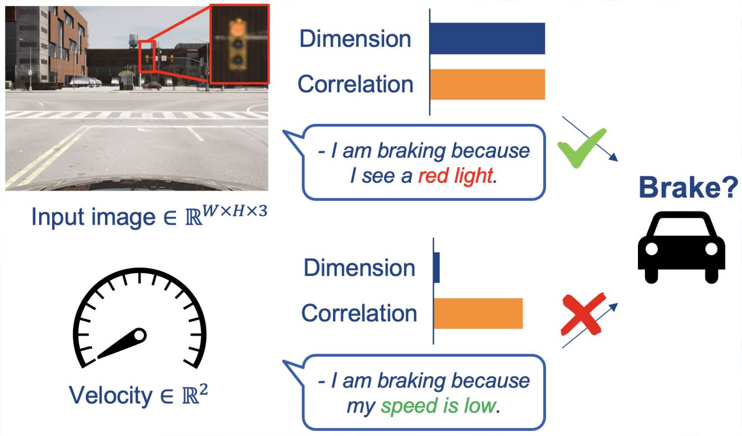
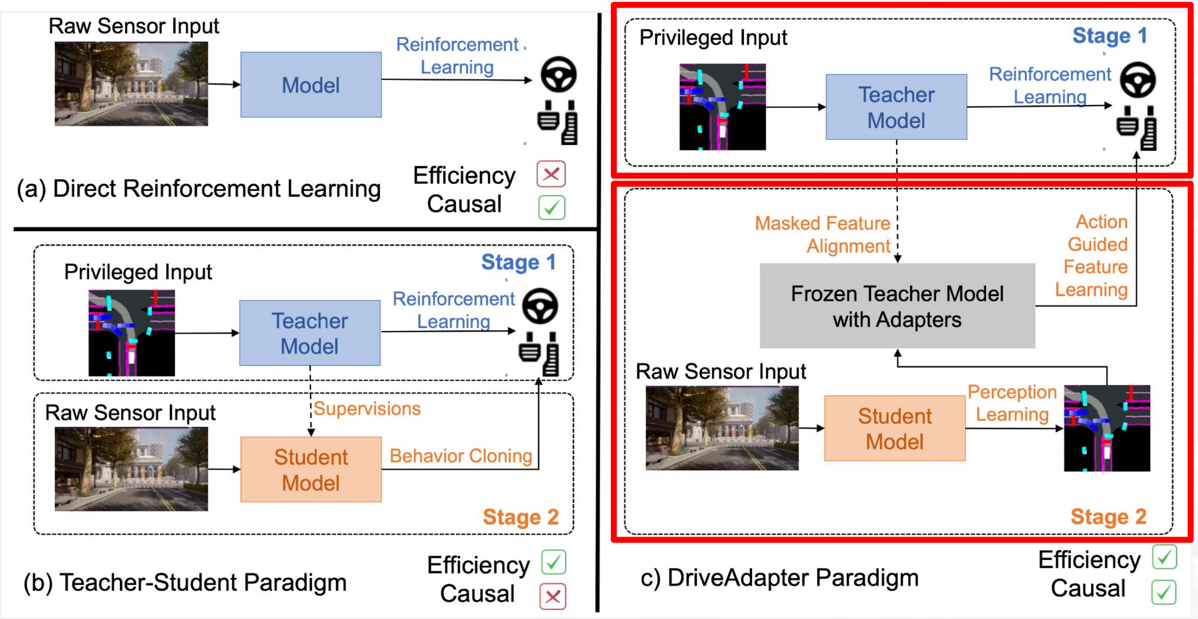




Causal Confusion

Motivation

How to balance the efficiency and causal reasoning ability?



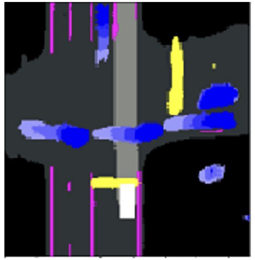
Utilize the strong RL-based privileged teacher model!

- Train a Teacher Model for Planning by RL
- End-to-End Connected by Adapter
- Train a Student Model for Perception

Challenge

Challenge 1: Student Model is not perfect

Privileged Input



Perception Result

BEVFusion + Mask2Former
2M training data

Method	Input	Driving Score ↑
Transfuser [39, 8]	Camera + LiDAR	31.0
LAV [3]	Camera + LiDAR	46.5
Student Model + Frozen Roach	Camera + LiDAR	8.9
Roach [55]	Privileged Info.	74.2
Roach + Rule [50]	Privileged Info.	**87.0**

- Directly feeding the perception results into the teacher model does **NOT** work.

Challenge

Challenge 1: Student Model is not perfect

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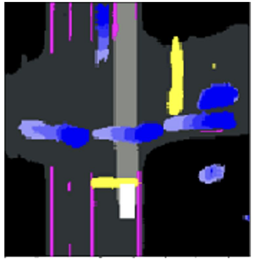

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- Directly feeding the perception results into the teacher model does **NOT** work.
- Teacher Model would be the **upper bound** of Student Model's performance

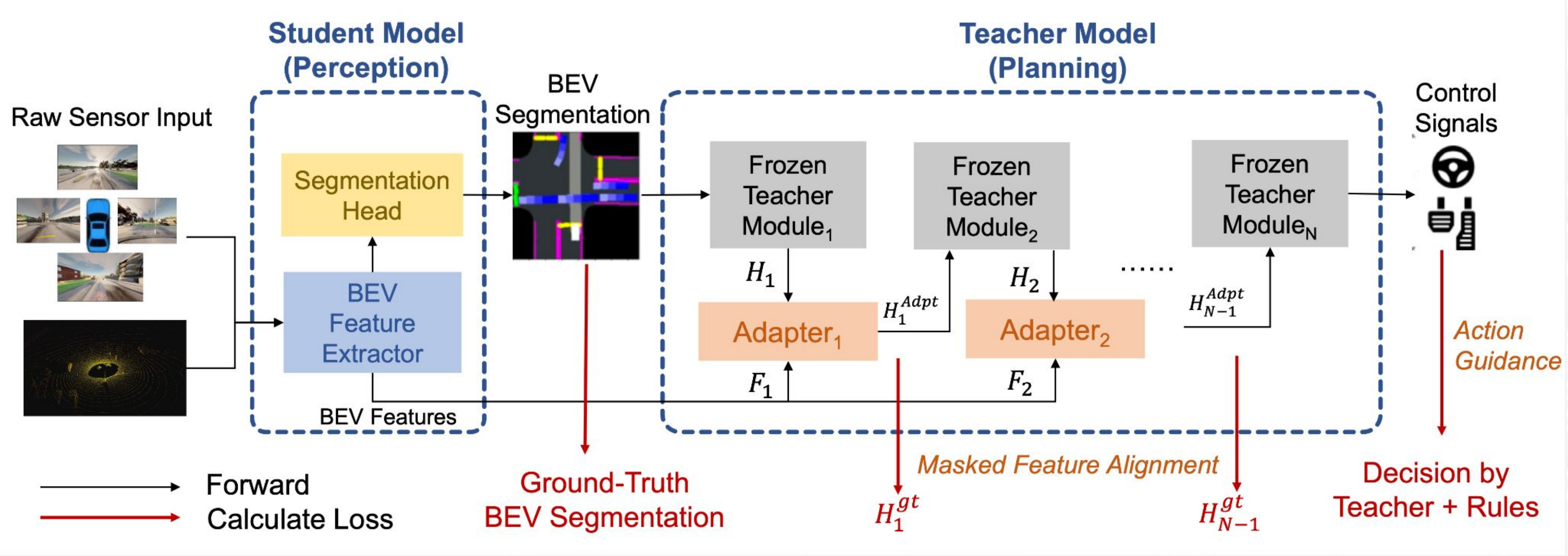
Challenge 2: Teacher Model is not perfect

Example: Emergency brake if there is any obstacle in the front - **require privileged information**

```
## Rules for emergency brake
should_brake = self.collision_detect()
only_ap_brake = True if (control.brake <= 0 and should_brake) else False
if should_brake:
    control.steer = control.steer * 0.5
    control.throttle = 0.0
    control.brake = 1.0
```

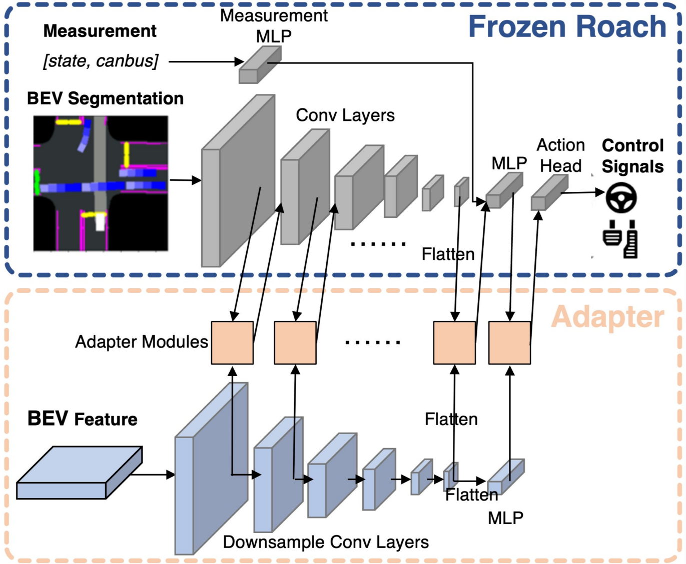
Learn from human guidance and correction instead solely depending on the RL teacher

Method - DriveAdapter



Method

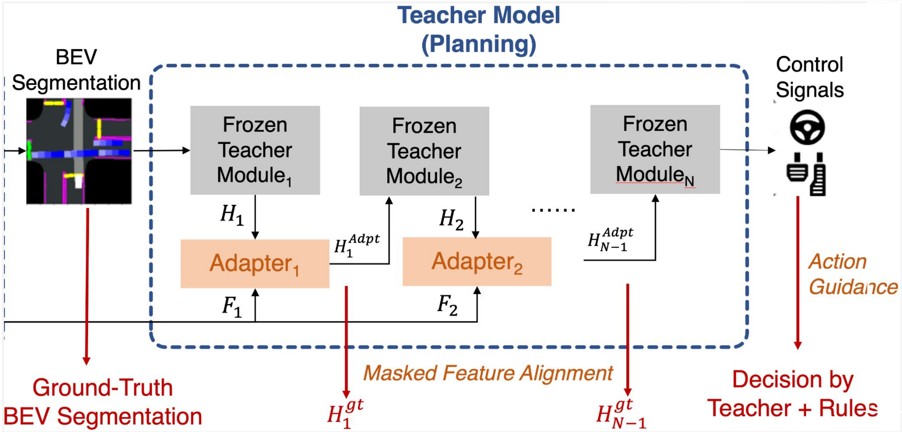
Idea 1: Deal with the distribution shift between perception GT and prediction



- **Reduce the error in an end-to-end layer-by-layer manner:**
  - Roach (teacher model) = 6 Convs -> flatten -> 4 linears
  - **Adapter module after each layer**
  - Adapter Input: $\boldsymbol{H}_{i-1}^{\text{Adpt}} = \text{Adapter}_{i-1}([\boldsymbol{H}_{i-1}; \boldsymbol{F}_{i-1}])$
  - Adapter Output: $\boldsymbol{H}_i = \text{Teacher}_i(\boldsymbol{H}_{i-1}^{\text{Adpt}})$
  - Adapter Target/Label: GT feature map of teacher

Method

Idea 2: Inject the driving knowledge within rules into the model



- **Store the knowledge in the Adapter module:**
  - Target: let the frozen teacher action head output corrected action
  - Mask feature alignment loss for failure cases - not to learn the undesired feature map
  - Directly apply action loss for failure cases - guide the middle feature maps by backpropagation

Experiments

🚀 SOTA driving performance on CARLA closed-loop benchmark

Method	Teacher	Student	Reference	DS↑	RC↑	IS↑
CILRS [11]	Rule-Based	Behavior Cloning	CVPR 19	7.8	10.3	0.75
LBC [4]	Imitation Learning	Behavior Cloning + DAgger	CoRL 20	12.3	31.9	0.66
Transfuser [39, 8]	Rule-based	Behavior Cloning	TPAMI 22	31.0	47.5	**0.77**
Roach [55]	Reinforcement Learning	Behavior Cloning + DAgger	ICCV 21	41.6	96.4	0.43
LAV [3]	Imitation Learning	Behavior Cloning	CVPR 22	46.5	69.8	0.73
TCP [50]	Reinforcement Learning	Behavior Cloning	NeurIPS 22	57.2	80.4	0.73
ThinkTwice [26]	Reinforcement Learning	Behavior Cloning	CVPR 23	65.0	95.5	0.69
DriveAdapter	Reinforcement Learning	Frozen Teacher + Adapter	Ours	61.7	92.3	0.69
DriveAdapter + TCP	Reinforcement Learning	Frozen Teacher + Adapter	Ours	**65.9**	94.4	0.72
MILE*† [18]	Reinforcement Learning	Model-Based Imitation Learning	NeurIPS 22	61.1	**97.4**	0.63
Interfuser* [43]	Rule-Based	Behavior Cloning + Rule	CoRL 22	68.3	95.0	-
ThinkTwice* [26]	Reinforcement Learning	Behavior Cloning	CVPR 23	70.9	95.5	0.75
DriveAdapter + TCP*	Reinforcement Learning	Frozen Teacher + Adapter	Ours	**71.9**	97.3	0.74

Ablation

Method	DS↑	RC↑	IS↑
DriveAdapter	61.7	92.3	0.69
w/o Feature Alignment Loss	45.4	69.1	0.66
w/o Mask for Feature Alignment	56.9	85.4	0.65
w/o Action Loss	47.1	90.5	0.52

Ablation on loss terms of the adapter

- All loss designs are important
- Feature alignment loss with mask for longer route completion
- Action loss for less infraction

Method	DS↑	RC↑	IS↑
DriveAdapter	61.7	92.3	0.69
Adapter at Early Stage	47.2	93.9	0.47
Adapter at Late Stage	54.3	79.9	0.69
w/o BEV Raw Feature	34.8	82.3	0.43
Unfrozen Teacher Model	49.0	73.2	0.72

Ablation on the design of the adapter

- Unfrozen teacher model ~= train from scratch
- Use raw feature to avoid information loss
- All adapters are useful

One-page Summary

- **Breaking the coupling barrier of Perception and Planning:**
  - Driving knowledge from millions of steps of exploration by RL -> ***causal reasoning*** (MDP; reward), ***robustness*** (all kinds of strange cases/scenarios during exploration)
  - ***Efficient*** training for the student model

- **Masked feature distillation:** Combine the knowledge of learning-based teacher and human designed rules

- **Real-world application (potential):** A teacher on large-scale real-world motion dataset , and use DriveAdapter to solve domain adaptation for deployment

- **A Further Step towards Real-world End-to-end Autonomous Driving!**

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THANKS

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