OpenDriveLab

JUNE 18-22, 2023
CVPR
VANCOUVER, CANADA

Planning-oriented Autonomous Driving

Yihan Hu* Jiazhi Yang* Li Chen*+ Keyu Li*

Chonghao Sima Xizhou Zhu Siqi Chai Senyao Du Tianwei Lin Wenhai Wang

Lewei Lu Xiaosong Jia Qiang Liu Jifeng Dai Yu Qiao Hongyang Li+

*equal contribution +project lead

Poster: THU-AM-131

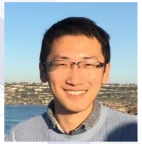
arXiv: https://arxiv.org/abs/2212.10156

Yihan

Jiazhi

Li

Keyu



Hongyang

上海人工智能实验室
Shanghai Artificial Intelligence Laboratory

Shanghai AI Laboratory | 上海人工智能实验室

JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

Planning-oriented Autonomous Driving

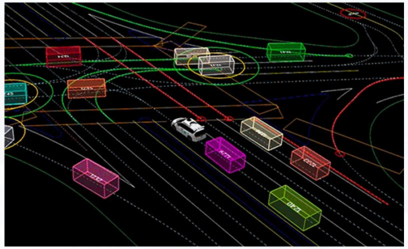
Background and Motivation

Background - Autonomous Driving (AD) Systems

Various weathers, illuminations, and scenarios

Perception → Bounding boxes → Prediction → Waypoints → Planning → Trajectory

What are around?

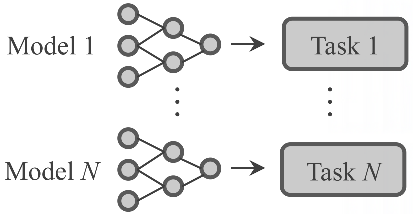


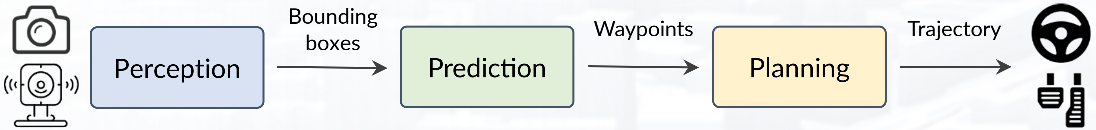
How will they go in the future?

Where should I go?

Background - Design Options for Autonomous Driving (AD) Systems

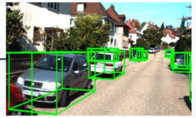
(a) Standalone Models



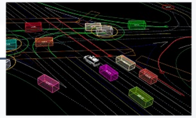


- Typical **Industry** solutions
- ✅ Independent teams for module developments
- ❌ Severe error accumulation

Isolated Optimization Objective


Object Detection

Optimization metric **mAP**


Motion Prediction

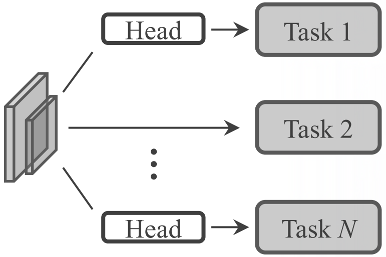
Optimization metric **minFDE**


Planning

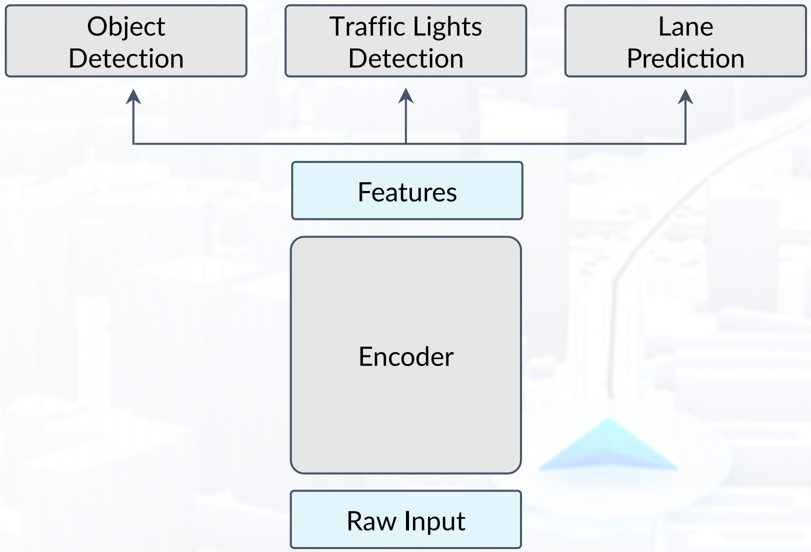
Optimization target **Safety and Comfort**

Background - Design Options for Autonomous Driving (AD) Systems

(b) Multi-task Framework



- **Shared feature** for multiple tasks
- ✅ Easily extended to more tasks, Compute-efficient
- ❌ Lack of tasks' coordination

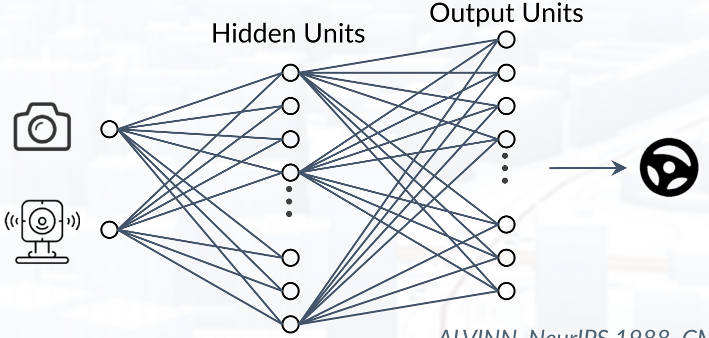


credit to *Tesla AI Day 2021*

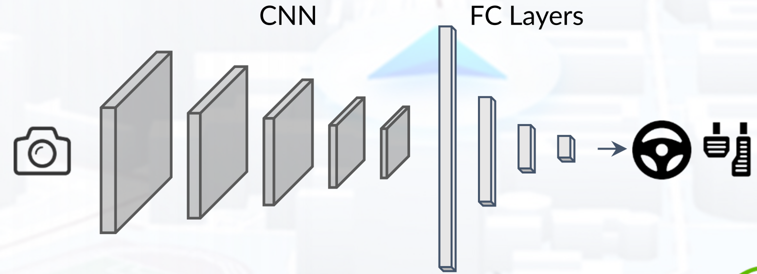
Background - Design Options for Autonomous Driving (AD) Systems

(c.1) End-to-end Framework - Vanilla Solutions

- **Direct policy learning** from sensor inputs, bypassing intermediate tasks
- ✅ Simple design with good performance in the simulator
- ❌ Deficient in interpretability



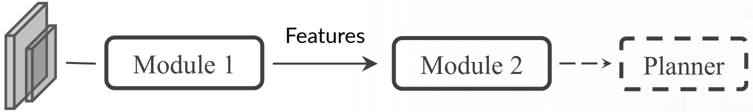
ALVINN, NeurIPS 1988. CMU



DAVE-2, arXiv 2016. Nvidia

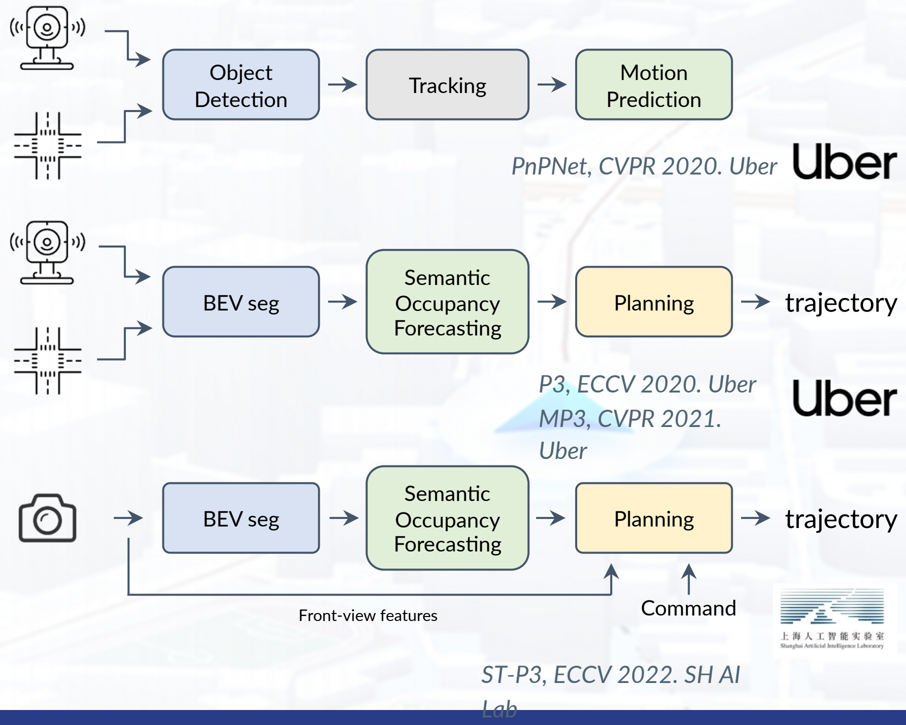
Background - Design Options for Autonomous Driving (AD) Systems

(c.2) End-to-end Framework - Explicit / Interpretable Design



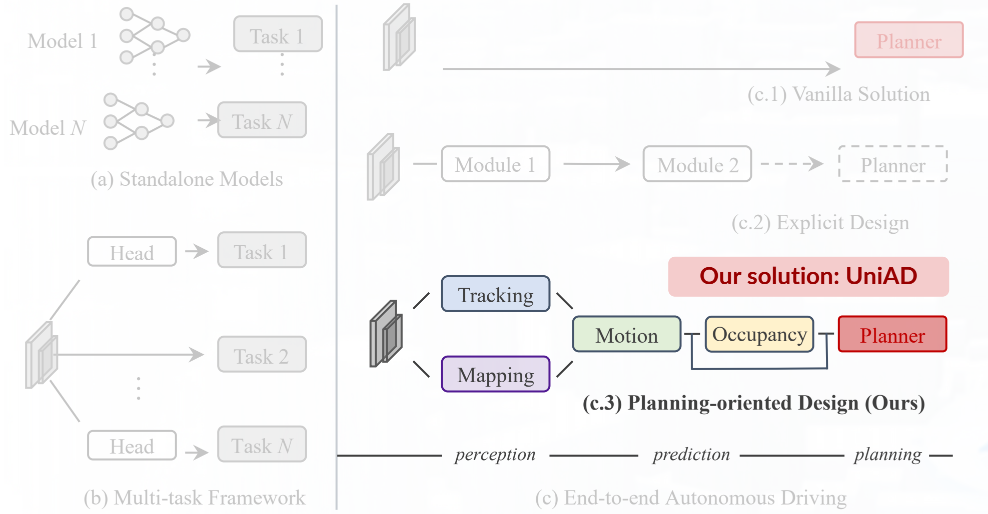
- Introducing **intermediate tasks** to assist planning
- ✅ Better interpretability (e.g. Bird's-eye-view, BEV)
- ❌ Lack some crucial components[1]

1. *The necessities of each component is mentioned in Appendix.*



Motivation- Towards Reliable Planning

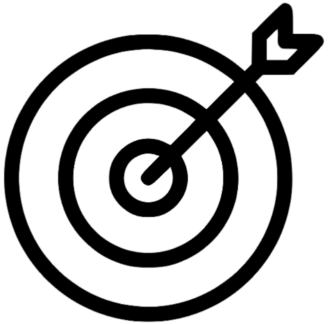
Ours: Planning-oriented Autonomous Driving



What do we want:

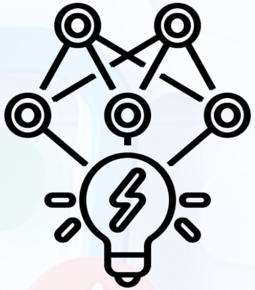
- ✅ Unify full-stack AD tasks
- ✅ Coordinate all task towards safe planning

UniAD - Overview



Which tasks?

How to construct?



How to train?

Planning-oriented Autonomous Driving

Delving into Details

UniAD - Which Tasks?

Perception System

- Object **Detection**
- Object **Tracking**
- **Online Mapping**
- …

Track agents behavior

Guide with map (lane)

Prediction System

- **Motion** Forecasting
- **Occupancy** Prediction
- …

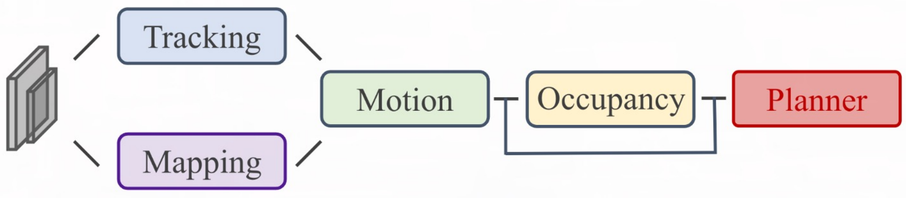
Interact with environment

Find free space

Planning

- …

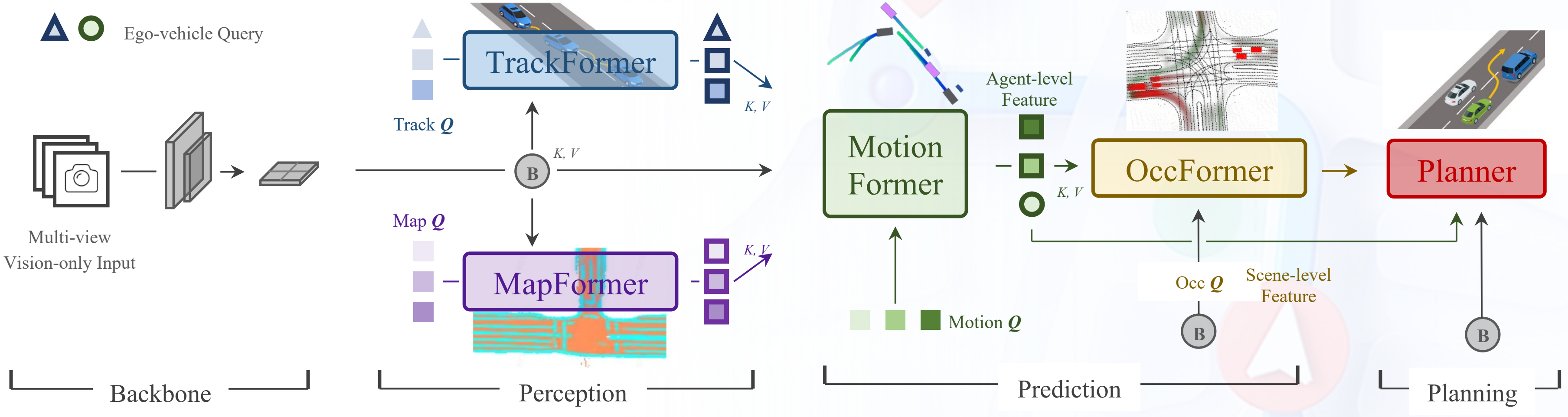
Incorporate all tasks in a ***hierarchical*** manner



- Five **safety-critical tasks**: Model the static and dynamic information
- Task hierarchy: Tasks are ***well-organized*** to optimize information flow to the planner

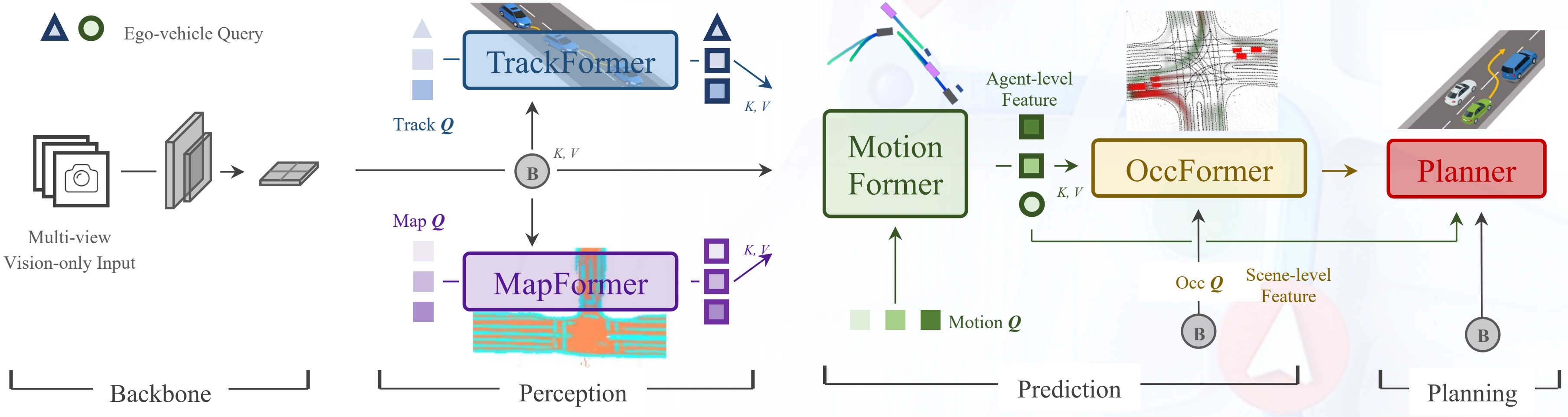
UniAD - How to Construct? Pipeline

- Track agents across time
- Predict long-term trajectory
- Plan final trajectory
- Avoid collision



- Segment map elements
- Scene-level representation

UniAD - How to Construct? Pipeline



- **Entire pipeline connected by queries**
- **Tasks coordinated with queries**
- **Interactions modeled by attention**

Unified Query

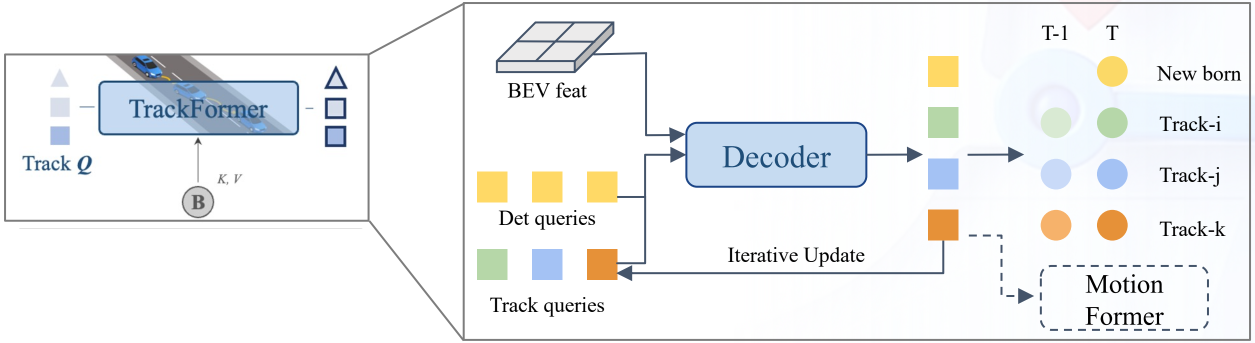
Transformer-based

First time to unify full-stack AD tasks!

UniAD - How to Construct?

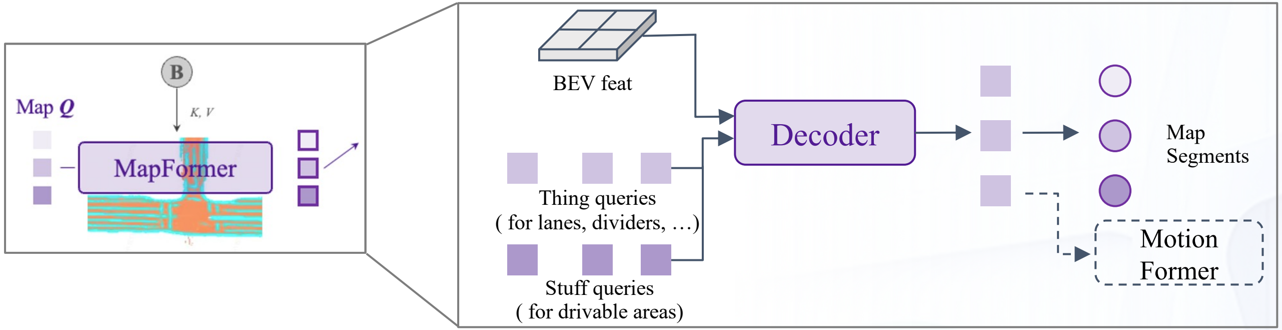
Perception — Prediction — Planning

TrackFormer - MOTR (ECCV 2022)



- **End-to-end trainable** tracking without post-association

MapFormer - Panoptic SegFormer (CVPR 2022)

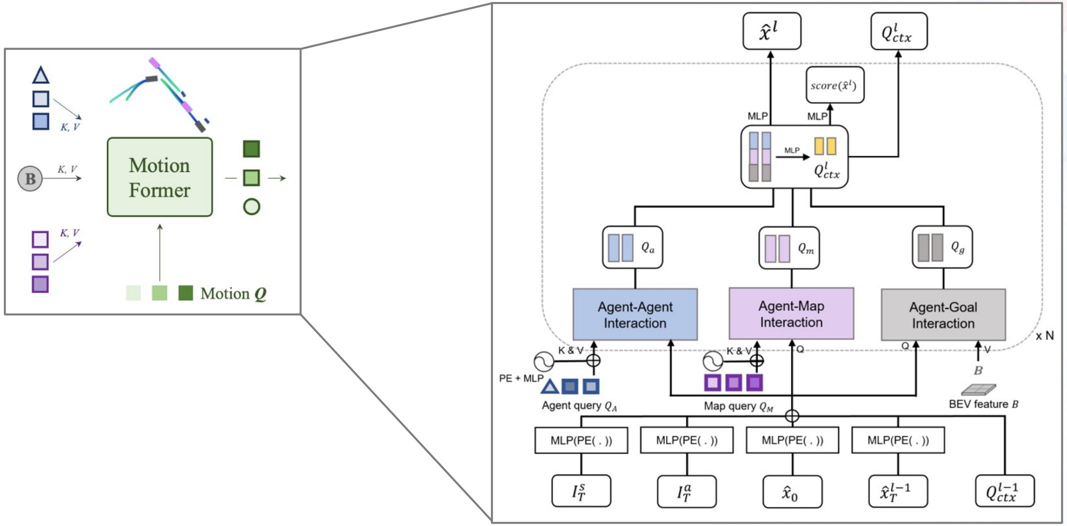


- Each query represents a map element

UniAD - How to Construct?

Perception — **Prediction** — Planning

MotionFormer (Proposed in UniAD)



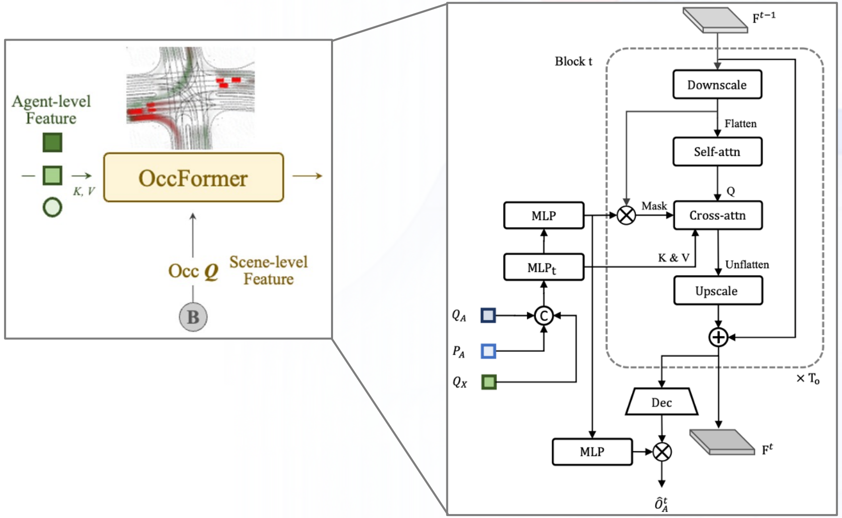
- Diverse **relation modelings** via attentions: Agent-agent, agent-map, agent-goal

- **Non-linear optimization**: Adjust ground-truth trajectory based on upstream predictions

UniAD - How to Construct?

Perception — **Prediction** — Planning

OccFormer (Proposed in UniAD)

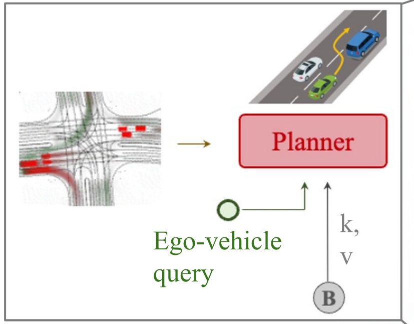


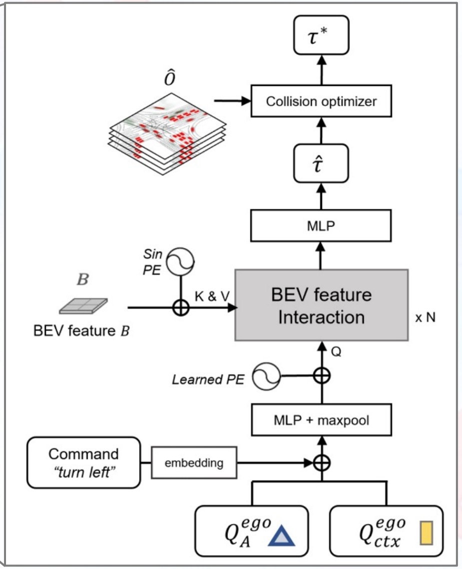
- **Encode agent-wise knowledge** into the scene representation
- Predict **occupancy as attention mask** to restrict the interactions between the agents and their corresponding BEV features.

UniAD - How to Construct?

Perception — Prediction — **Planning**

Planner (Proposed in UniAD)



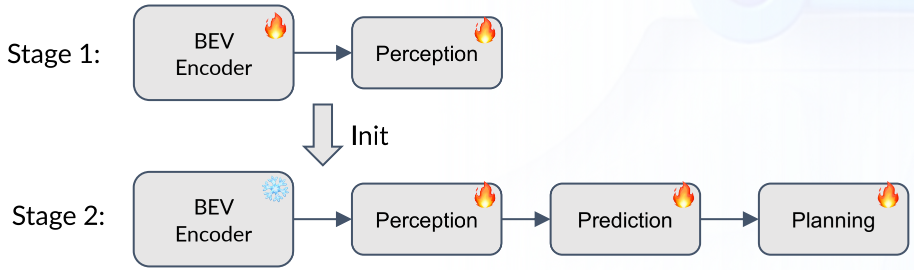


- **Ego-vehicle query:** consistently models the ego-vehicle
- **Collision optimization:** Steer the predicted trajectories clear of predicted occupancy.

The Recipe - How to Train?

Two-phase training. Perception stage + End-to-end stage

- The stabilized perception capability helps the end-to-end stage **converge faster**



Shared matching. Matching results of tracking reused in motion and occupancy

- Consistent learning of agent identities
- Converging faster

Planning-oriented Autonomous Driving

Experiments

UniAD - Ablation Results

Tasks benefit🚀each other and contribute to safe planning

ID	Modules					Tracking			Mapping		Motion Forecasting			Occupancy Prediction				Planning	
	Track	Map	Motion	Occ.	Plan	AMOTA↑	AMOTP↓	IDS↓	IoU-lane↑	IoU-road↑	minADE↓	minFDE↓	MR↓	IoU-n.↑	IoU-f.↑	VPQ-n.↑	VPQ-f.↑	avg.L2↓	avg.Col.↓
0*	✓	✓	✓	✓	✓	0.356	1.328	893	0.302	0.675	0.858	1.270	0.186	55.9	34.6	47.8	26.4	1.154	0.941
1	✓					0.348	1.333	791	-	-	-	-	-	-	-	-	-	-	-
2		✓				-	-	-	**0.305**	0.674	-	-	-	-	-	-	-	-	-
3	✓	✓				0.355	1.336	785	0.301	0.671	-	-	-	-	-	-	-	-	-
4			✓			-	-	-	-	-	0.815	1.224	0.182	-	-	-	-	-	-
5	✓		✓			0.360	1.350	919	-	-	0.751	1.109	0.162	-	-	-	-	-	-
6	✓	✓	✓			0.354	1.339	820	0.303	0.672	0.736(-9.7%)	1.066(-12.9%)	0.158	-	-	-	-	-	-
7				✓		-	-	-	-	-	-	-	-	60.5	37.0	52.4	29.8	-	-
8	✓			✓		0.360	**1.322**	809	-	-	-	-	-	62.1	38.4	52.2	32.1	-	-
9	✓	✓	✓	✓		0.359	1.359	1057	0.304	**0.675**	**0.710**(-3.5%)	**1.005**(-5.8%)	**0.146**	**62.3**	39.4	**53.1**	32.2	-	-
10					✓	-	-	-	-	-	-	-	-	-	-	-	-	1.131	0.773
11	✓	✓	✓		✓	**0.366**	1.337	889	0.303	0.672	0.741	1.077	0.157	-	-	-	-	1.014	0.717
12	✓	✓	✓	✓	✓	0.358	1.334	**641**	0.302	0.672	0.728	1.054	0.154	**62.3**	**39.5**	52.8	**32.3**	**1.004**	**0.430**

Conclusion:

- **ID. 4-6:** Track & Map → Motion🚀
- **ID. 7-9:** Motion🚀 ↔ Occupancy🚀
- **ID. 10-12:** Motion & Occupancy → Planning🚀

UniAD - Results

Even outperforms LiDAR-based counterparts on planning

Planning

†: LiDAR-based

Camera-based

Method	L2(m)↓ 1s	2s	3s	Avg.	Col. Rate(%)↓ 1s	2s	3s	Avg.
NMP† [88]	-	-	2.31	-	-	-	1.92	-
SA-NMP† [88]	-	-	2.05	-	-	-	1.59	-
FF† [36]	0.55	1.20	2.54	1.43	0.06	0.17	1.07	0.43
EO† [42]	0.67	1.36	2.78	1.60	0.04	0.09	0.88	0.33
ST-P3 [37]	1.33	2.11	2.90	2.11	0.23	0.62	1.27	0.71
UniAD	**0.48**	**0.96**	**1.65**	**1.03**	**0.05**	**0.17**	**0.71**	**0.31**

UniAD - Results

SOTA performance on all investigated tasks

Multi-object Tracking

Method	AMOTA↑	AMOTP↓	Recall↑	IDS↓
Immortal Tracker† [82]	0.378	1.119	0.478	936
ViP3D [30]	0.217	1.625	0.363	-
QD3DT [35]	0.242	1.518	0.399	-
MUTR3D [91]	0.294	1.498	0.427	3822
UniAD	**0.359**	**1.320**	**0.467**	**906**

Motion Forecasting

Method	minADE(m)↓	minFDE(m)↓	MR↓	EPA↑
PnPNet† [50]	1.15	1.95	0.226	0.222
ViP3D [30]	2.05	2.84	0.246	0.226
Constant Pos.	5.80	10.27	0.347	-
Constant Vel.	2.13	4.01	0.318	-
UniAD	**0.71**	**1.02**	**0.151**	**0.456**

Mapping

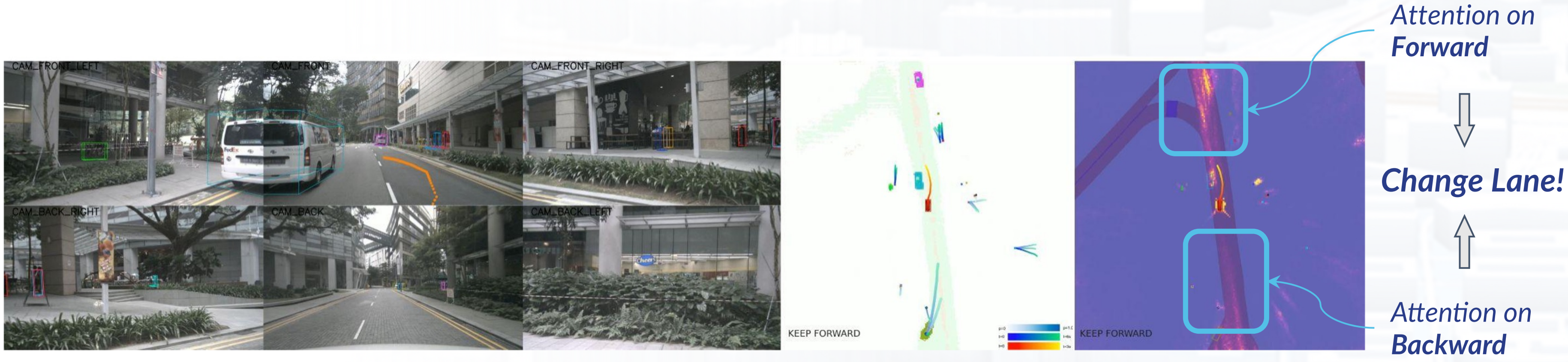
Method	Lanes↑	Drivable↑	Divider↑	Crossing↑
VPN [63]	18.0	76.0	-	-
LSS [66]	18.3	73.9	-	-
BEVFormer [48]	23.9	**77.5**	-	-
BEVerse† [92]	-	-	**30.6**	**17.2**
UniAD	**31.3**	69.1	25.7	13.8

Occupancy Prediction

Method	IoU-n.↑	IoU-f.↑	VPQ-n.↑	VPQ-f.↑
FIERY [34]	59.4	36.7	50.2	29.9
StretchBEV [1]	55.5	37.1	46.0	29.0
ST-P3 [37]	-	38.9	-	32.1
BEVerse† [92]	61.4	**40.9**	54.3	**36.1**
UniAD	**63.4**	40.2	**54.7**	33.5

UniAD - Visualizations

Planner attends to crucial areas in complex scenes

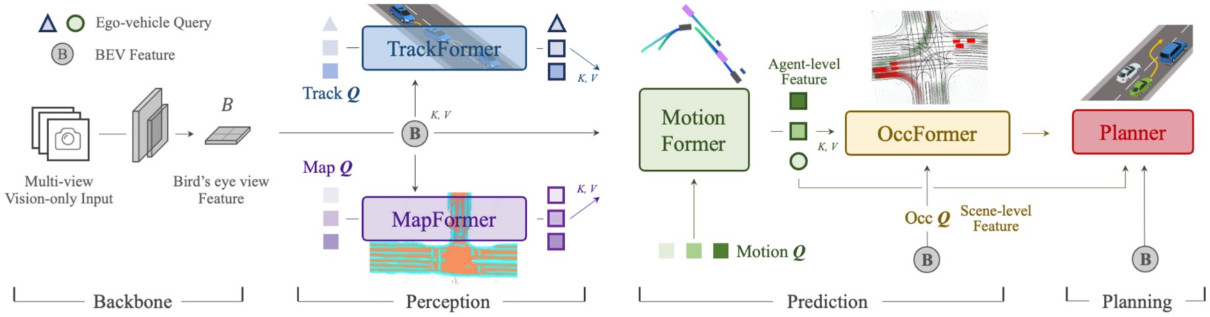


UniAD - Recover from Upstream Errors

Planner could still attend to ‘undetected’ regions/objects

One-page Summary

- **Planning-oriented Philosophy**: An end-to-end autonomous driving (AD) framework in pursuit of safe planning, equipped with a wide span of AD tasks.
- **Unified Query** design: *Queries* as interfaces to connect and coordinate all tasks.
- **State-of-the-art (SOTA) Performance** with vision-only input.
- **First Step towards Autonomous Driving Foundation Models**



JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

What's next? beyond UniAD

Embracing Foundation Models for Autonomous Driving

UniAD v2

Data & Training Strategy

- Multiple datasets with labels for various tasks?

Shippable Algorithm

- More modules integration, extensible to applications (e.g. V2X)

Closed-loop System

- Closed-loop training and testing in simulator & real world

CARLA

Check out the latest **Survey Paper**!

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

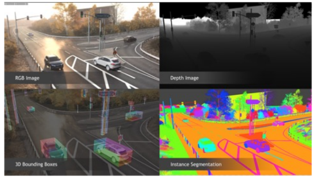
Beyond UniAD: DriveAGI

Data-centric Pipeline

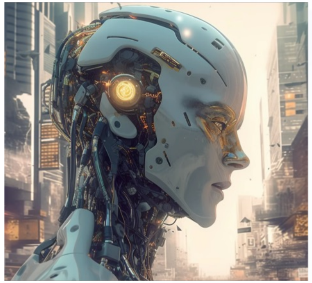
Data Collection

Motional
ARGO AI
lyft
YouTube

Data Generation



Pre-training DriveCore



Universal Foundation Model
for autonomous driving

How to formulate?
What's the objective goal?

Applications

Autonomous Driving

Broader Impact

Partial photo by courtesy of online resources.

OpenDriveLab

Poster: THU-AM-131

THANKS

https://opendrivelab.com

上海人工智能实验室
Shanghai Artificial Intelligence Laboratory

WUHAN UNIVERSITY 1893 武汉大学

sensetime