OpenDriveLab

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

What are Good (Pre-training) Representations for Robotic Manipulation?

With a few autonomous driving work first ...

Hongyang Li

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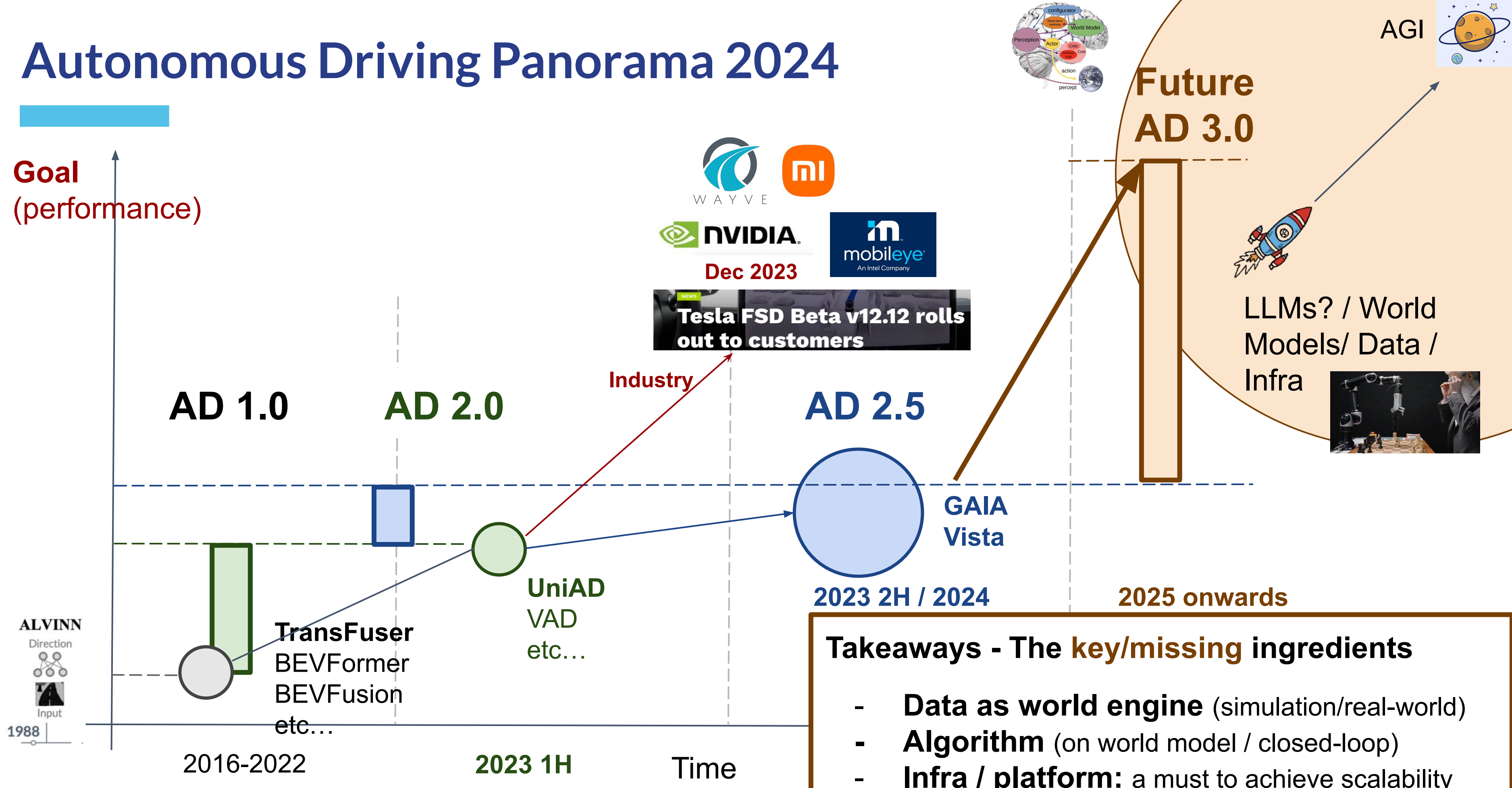
@ TU Delft, July 18 2024

Outline

- Autonomous Driving
- Introduction to Robotic Manipulation
- MPI and ClOVER
- Concluding Remarks

Autonomous Driving

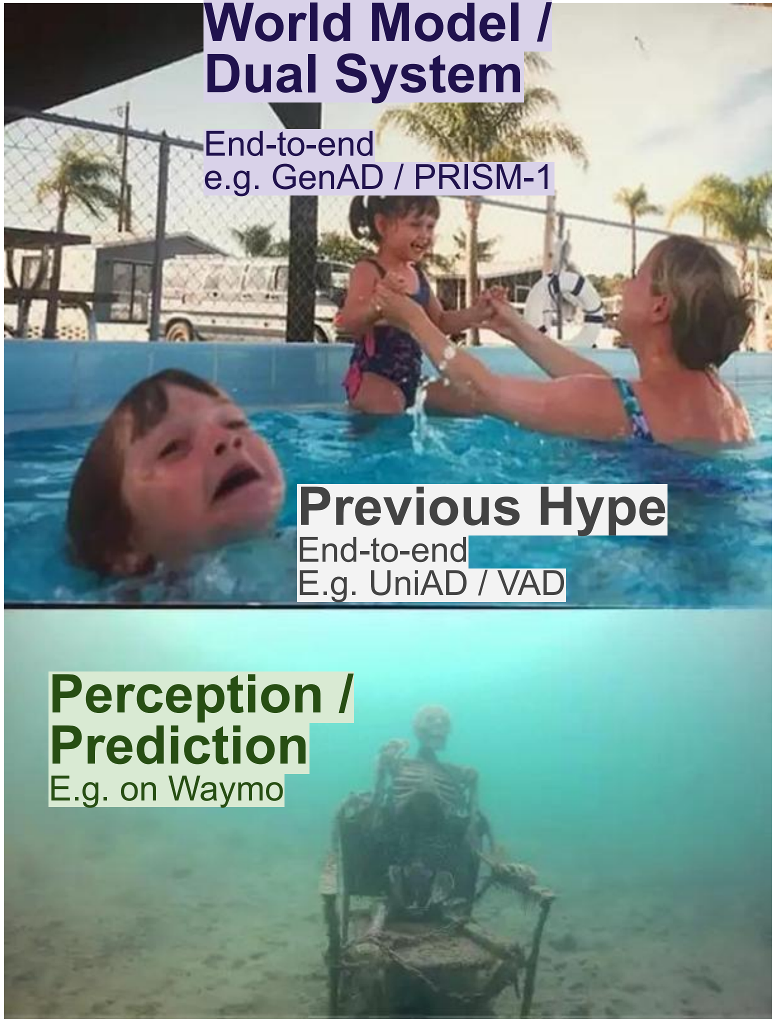
Autonomous Driving Panorama 2024



Takeaways - The key/missing ingredients

- **Data as world engine** (simulation/real-world)
- **Algorithm** (on world model / closed-loop)
- **Infra / platform:** a must to achieve scalability
- **Deployment**: dual system / onboard-chip

Any pizza left?



Autonomous Driving
Research

Academia

Q: I don't have too much resource. Is there any impact research ***left*** for autonomous driving **research** at University?

A: My guess is **Maybe.**
Open-set Perception / Motion Prediction / etc.

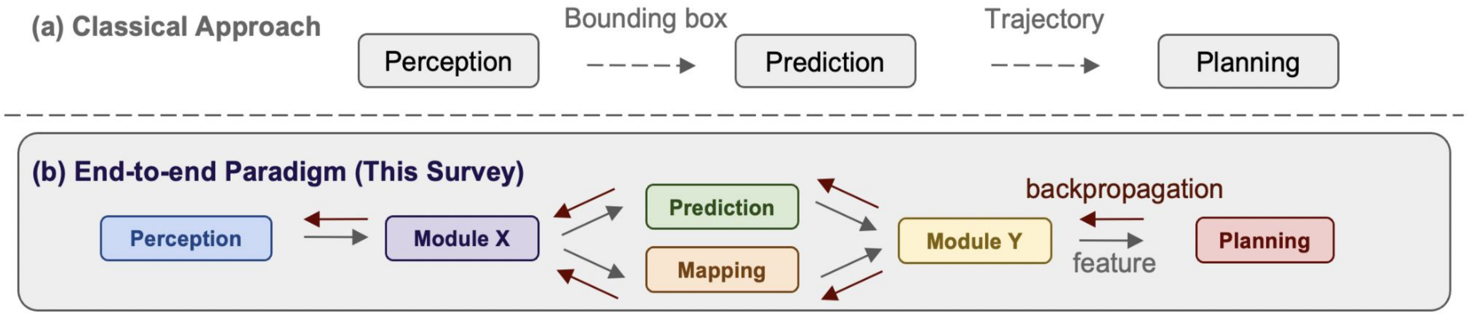
Industry

Q: We have ***lots of*** GPUs, millions of driving data. ***Could*** we leave Tesla no pizza, and achieve L4 once for all using e2e?

A: **Definitely not.**
Academia/industry should collaborate in whatsoever close manners.

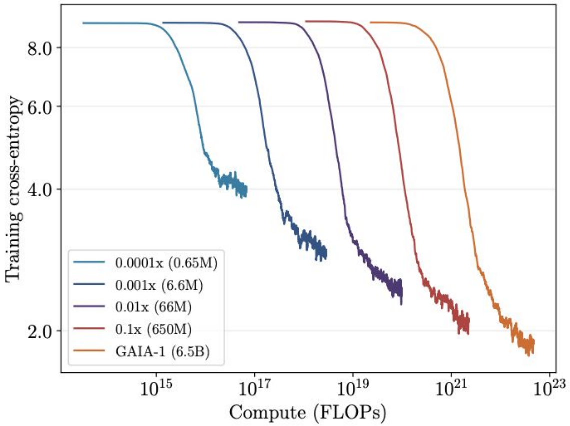
End-to-end Autonomy | True Incentive

+ **Global optimization:** when perception fails/inferior, planning still could work.



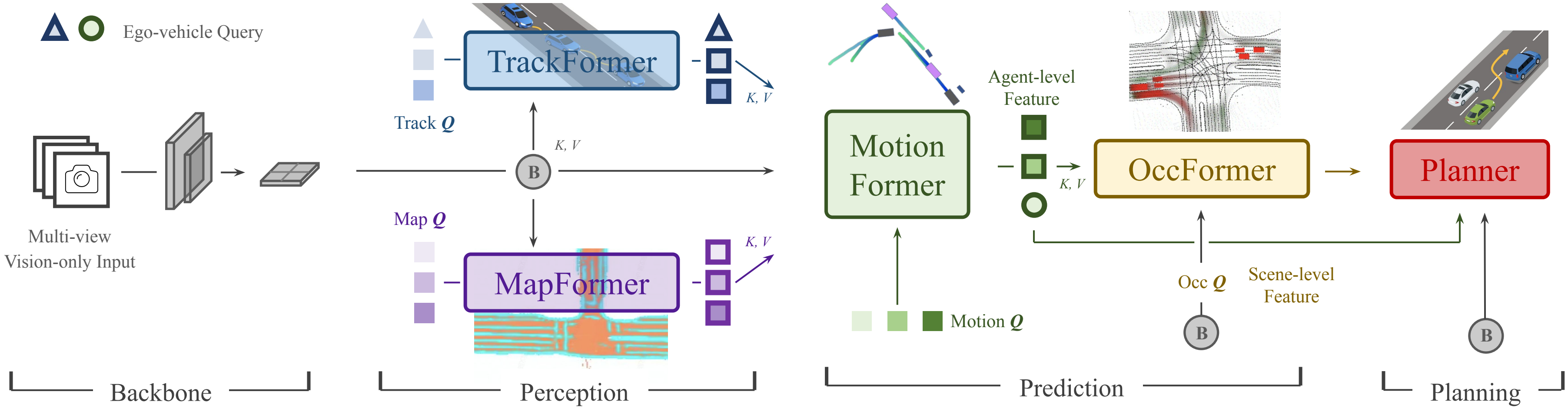
Chen et al., End-to-end Autonomous Driving:
Challenges and Frontiers, https://arxiv.org/abs/2306.16927

+ **Scaling law:** massive amount of data + infra/compute —> **strong generalization**



Hu et al. GAIA-1: A Generative World Model for Autonomous Driving https://arxiv.org/abs/2309.17080

Classic algorithm: UniAD



- Entire pipeline connected by queries
- Tasks coordinated with queries

Unified Query

- Interactions modeled by attention

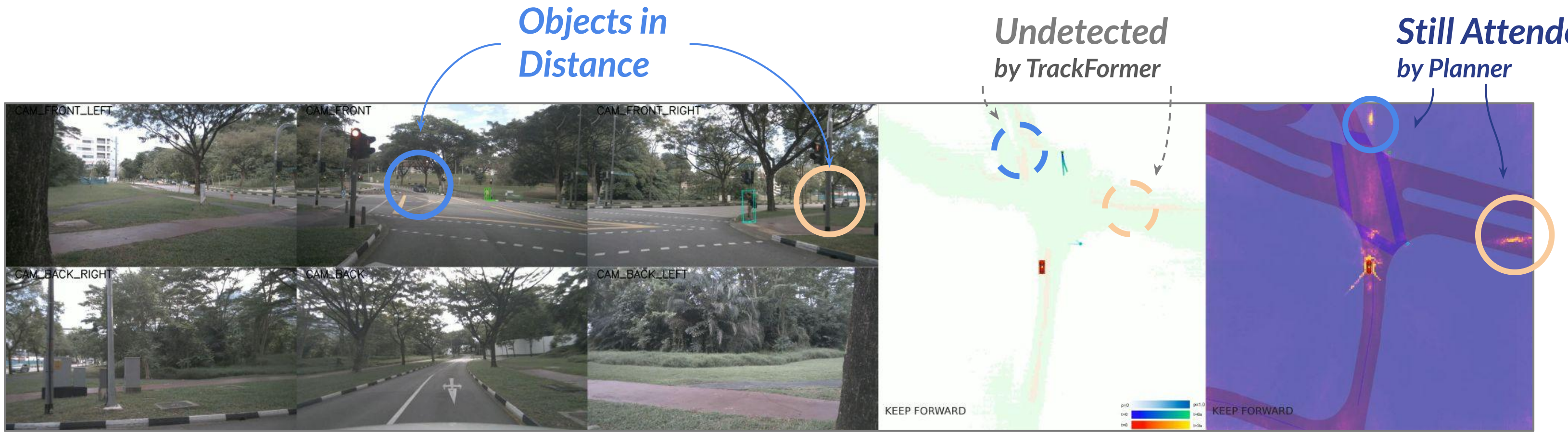
Transformer-based

First time to unify full-stack AD tasks!

Hu et al. Planning-oriented Autonomous Driving. CVPR 2023.

UniAD - Recover from Upstream Errors

Planner could still attend to ‘undetected’ regions/objects



Hu et al. Planning-oriented Autonomous Driving. CVPR 2023.

Core in UniAD: Planning-oriented, not a MTL framework.

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**

Task Synergy Effect:

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

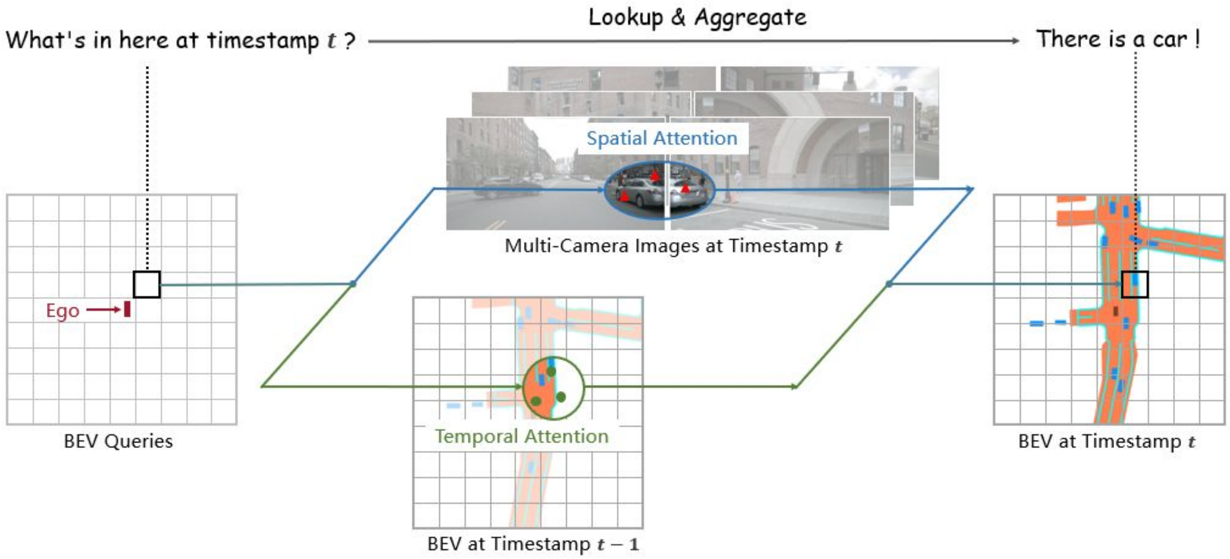
Hu et al. Planning-oriented Autonomous Driving. CVPR 2023.

BEVFormer: Motivation

Li et al. BEVFormer: Learning Bird's-Eye-View Representation from Multi-Camera Images via Spatiotemporal Transformers. ECCV 2022

In a nutshell…

A unified End-to-End framework which fuses multi-camera and temporal feature based on Deformable Attention and is suitable for various kinds of perception tasks in AD



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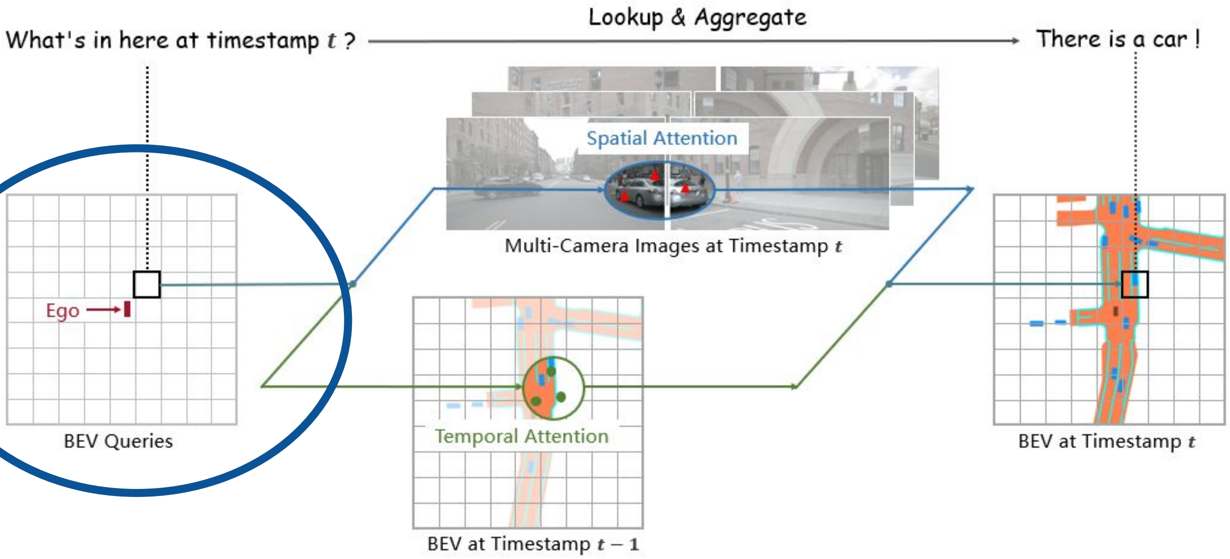
Key Recipe...

- **BEV Queries Q**: lookup to obtain BEV feature map



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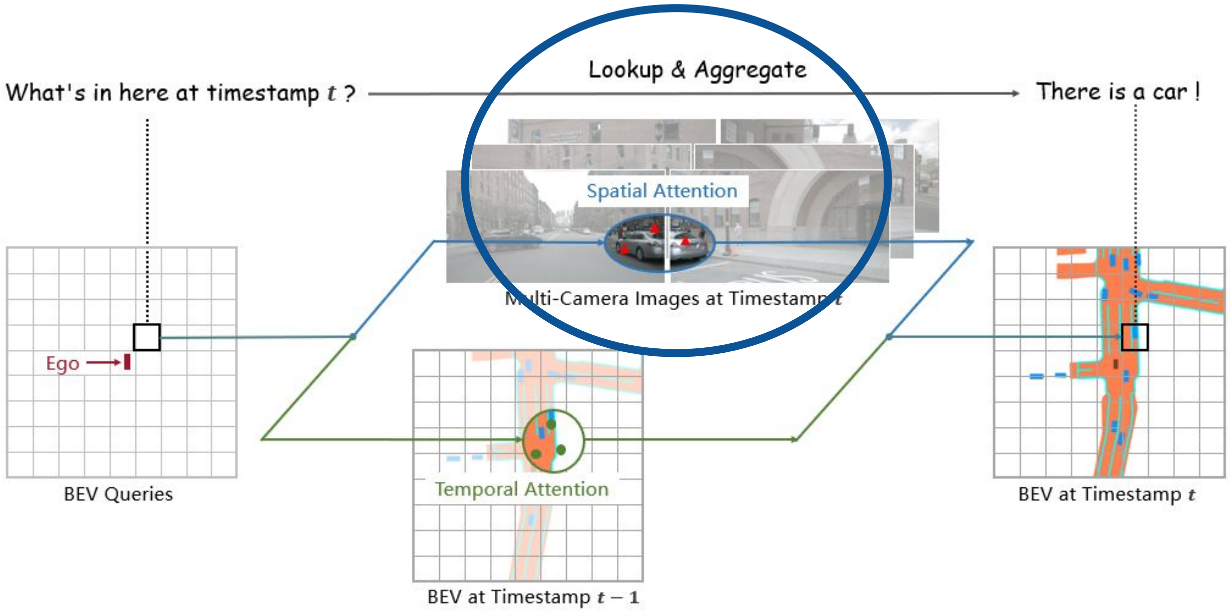

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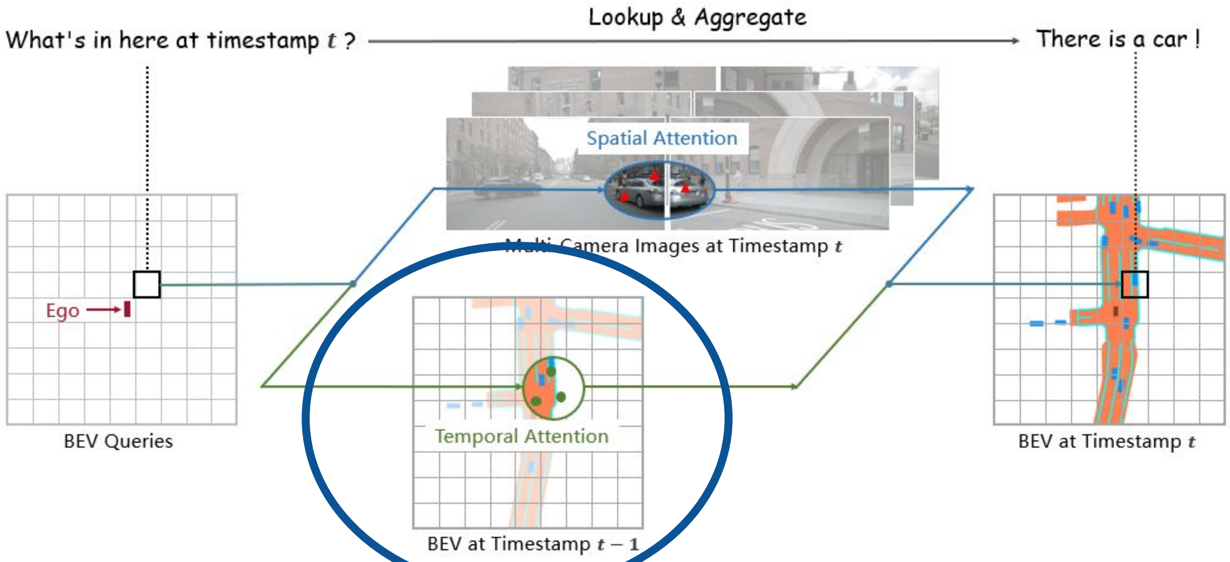
- **BEV Queries Q** : lookup to obtain BEV feature map
- **Spatial Cross-Attention** : fuse multi-camera feature
- **Temporal Self-Attention** : **aggregate temporal BEV feature**



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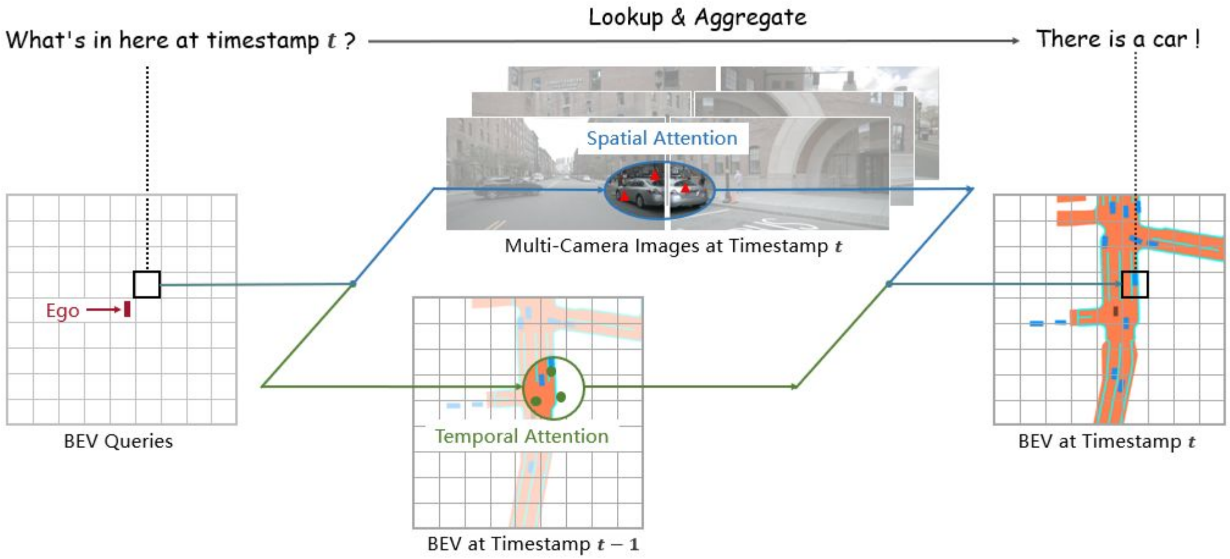
Comment

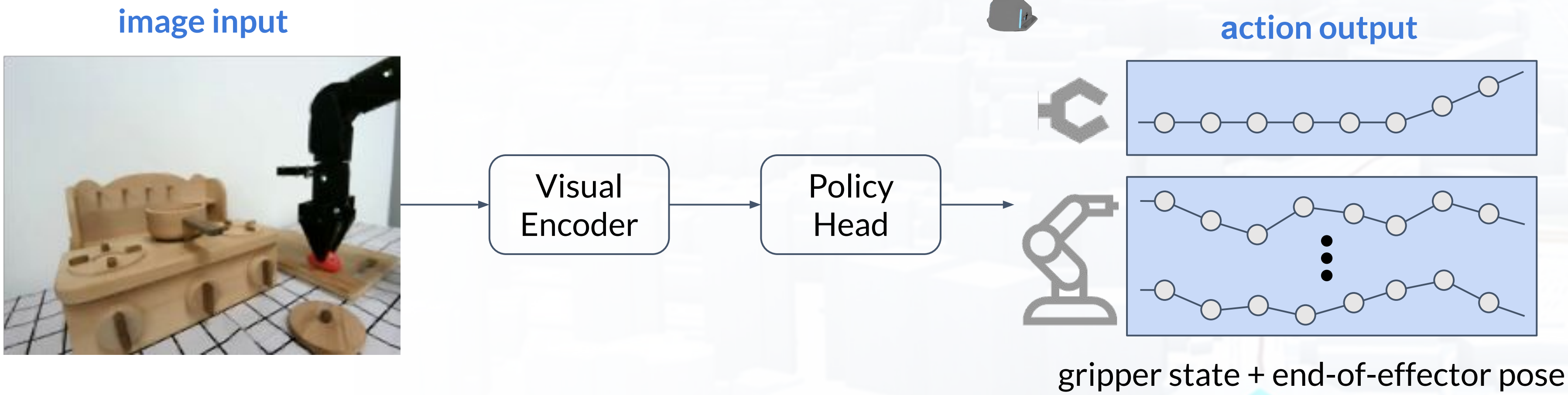
- Using **learnable** queries to represent real world from BEV view
- Look up spatial features in images and temporal features in previous BEV map, aka **Spatial-temporal**



BEVFormer: Demo

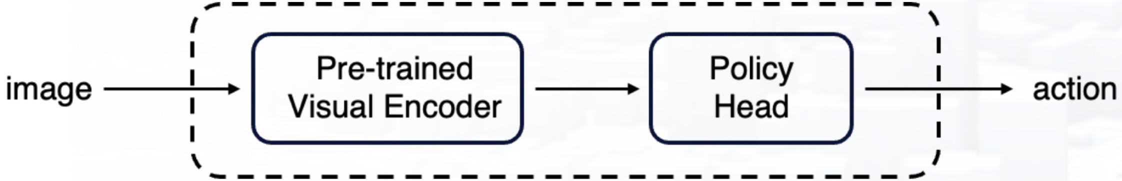
Introduction to Robotic Manipulation

Introduction | Visuomotor control



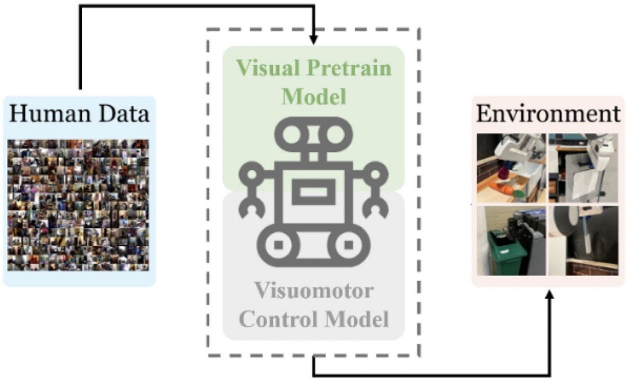
Introduction | Representation Learning for Robotic Manipulation

Pre-trained representations (e.g. CLIP feature) ***enable*** efficient robot learning.



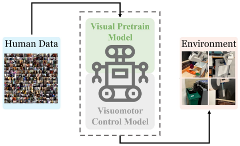
Rutav Shah, Vikash Kumar. RRL: Resnet as representation for Reinforcement Learning. In *ICML*, 2021.
Apoorv Khandelwal, et al. Simple but Effective: CLIP Embeddings for Embodied AI. In *CVPR*, 2022.

However, in-domain robot data is ***scarce***.



To address this limitation:
leverage large-scale human video datasets (e.g. Ego4D)
to extract generalizable features.

Research Roadmap



CoRL 2022
R3M[2]

RSS 2023 Best Paper Finalist
Voltron[4]

RSS 2024
MPI (Ours)

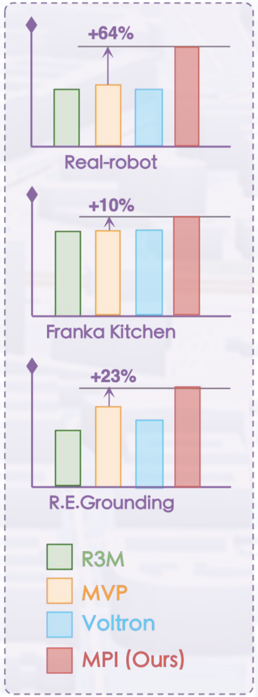
2022/03 — CoRL — 2022/09 — 2023/02 ROBOTICS SCIENCE AND SYSTEMS — 2023/12 — 2024/02 ROBOTICS SCIENCE AND SYSTEMS — Time

2022/03 CoRL — ICLR — ICLR

MVP [1]
CoRL 2022 Oral

VIP[3]
ICLR 2023 Spotlight

GR-1[5]
ICLR 2024



MPI exhibits stronger generalization capability c.f. R3M, MVP and Voltron.

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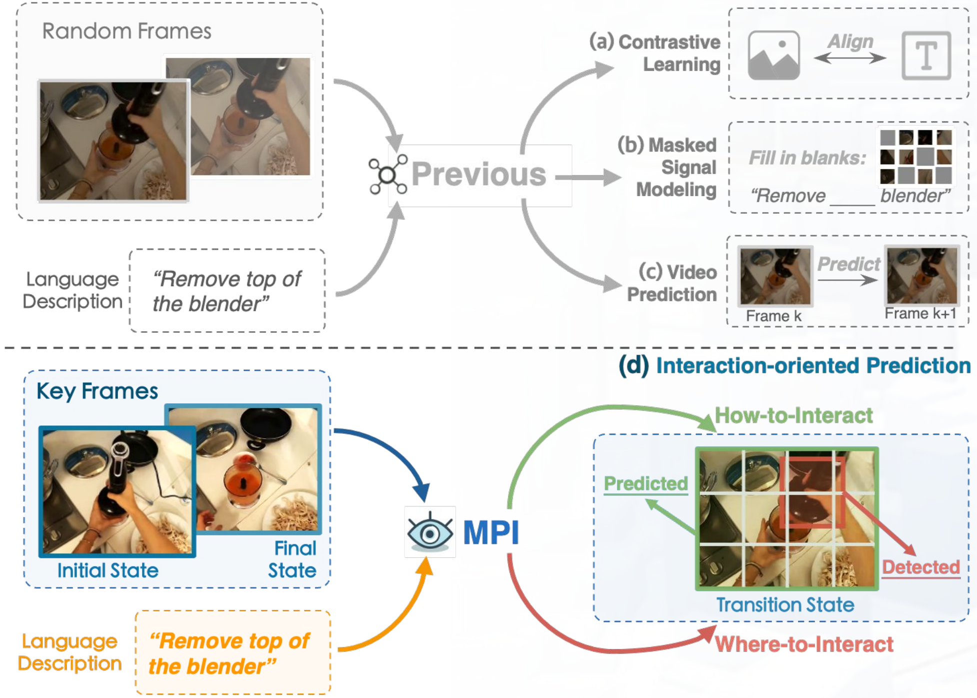
How to learn a good visual representation in pre-training?

MPI: Manipulation by Prediction Interaction

Motivation



Lack of Explicit Interaction Modeling

Prior Work

- (a) R3M: utilize contrastive learning, focus on high-level semantics.
- (b) MVP: apply MAE, focus on low-level pixel-wise information.
- (c) GR-1: sequential video prediction, but introduce noise or redundant information
  ❌ *effectively capture the dynamic interactions*

Ours

- Reflect upon the pre-training objectives
- Instill interactive dynamics by proposing an interaction-oriented prediction paradigm

Interactive dynamics: *the patterns of behavior and physical interactions that occur between a robot and the environment*

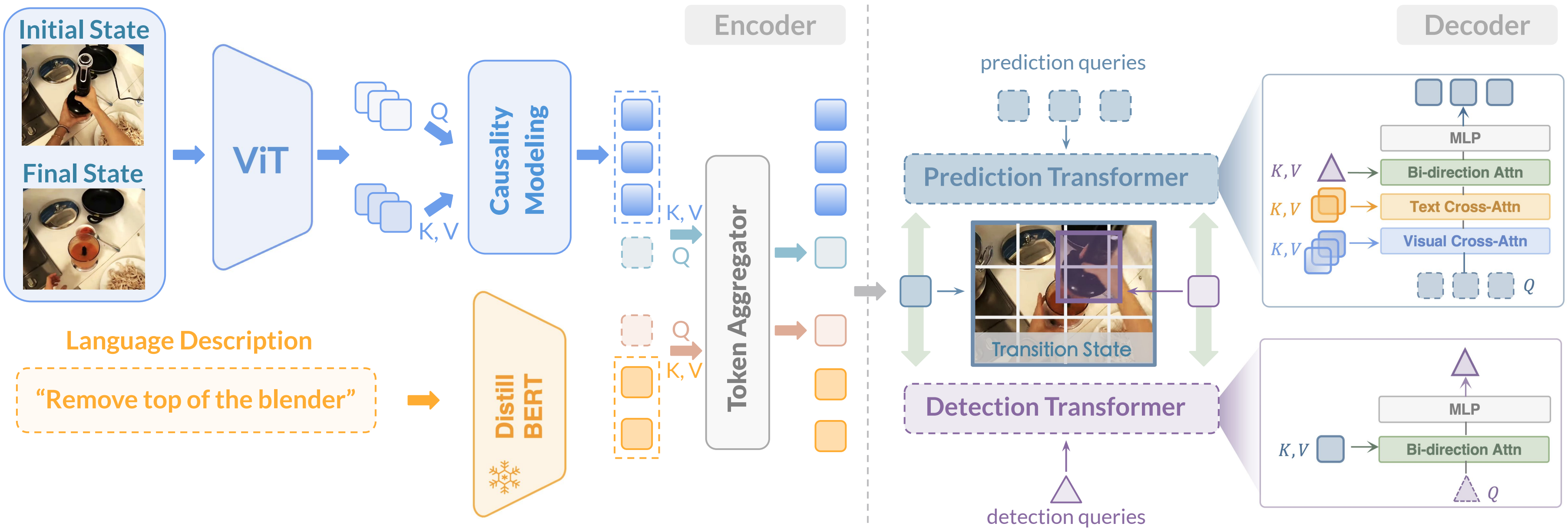
MPI | Pipeline and Framework

Pre-training dataset

Ego4d hand-and-object subset | Keyframes

Two Training Objectives

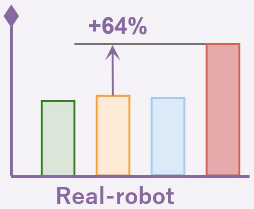
“how to interact” | “where to interact”



Zeng et al, Learning Manipulation by Predicting Interaction, RSS 2024

MPI | Experiments

Performance Comparison



R3M — Stanford University, Meta — CoRL 2022

MVP — Berkeley University of California — CoRL 2022 oral

Voltron — Stanford University, Toyota — RSS 2023 best paper finalist

MPI (Ours)

Generalization Validation

Robustness to Visual Distractions

(a) Original Setting

(b) BG. Distraction

(c) Obj. Variation

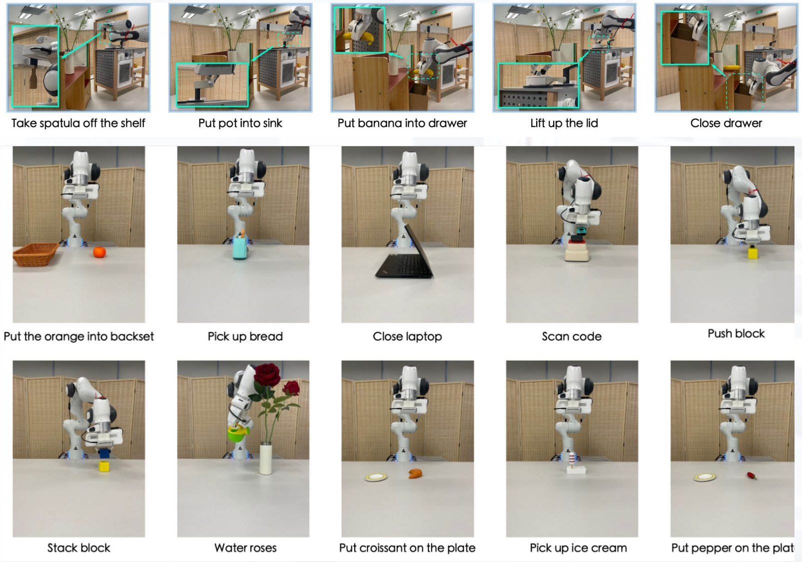
Evaluation Suite

- Evaluations on visuomotor control: both in real world and in simulation(Franka Kitchen, MetaWorld) 🦾
- Referring Expression Grounding 👀👉

Real-robot Experiment Setting

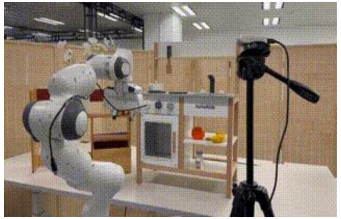
5 complex kitchen environment

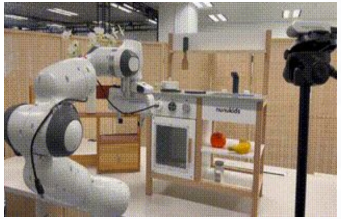
10 clean background

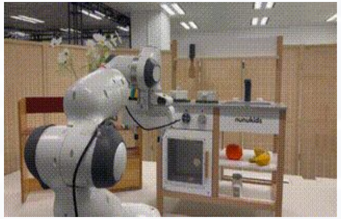


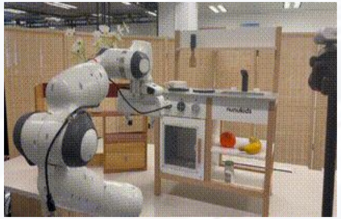
MPI - Testament on Real Robots

Demo in kitchen environment





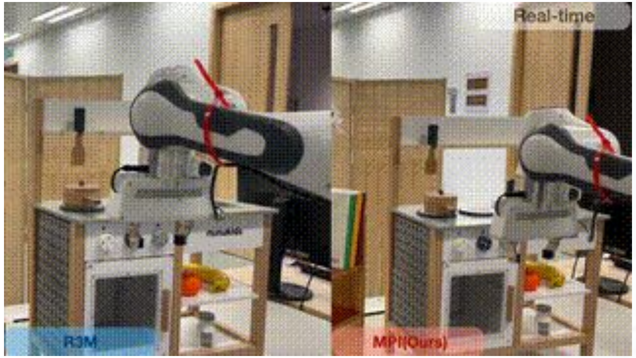




Validation on generalization

Object Variation

White plastic pot → Wooden pot

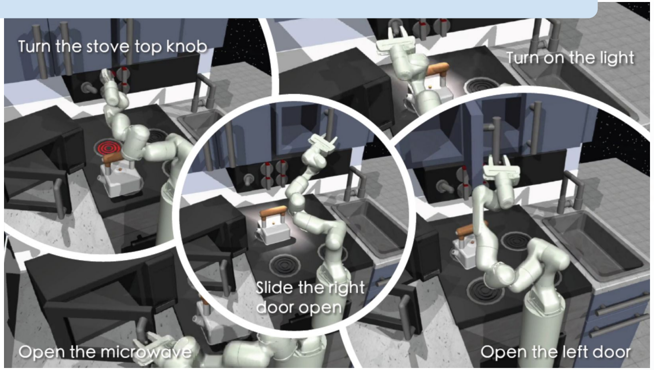


Background Distraction

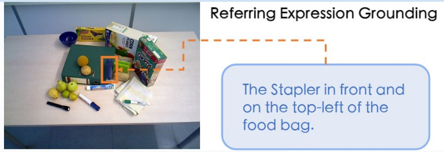
Daisies → Roses

MPI - Experiments

Visuomotor Control in Simulation



Referring Expression Grounding



Method	Embedding	Average Precision (AP) @0.25	@0.5	@0.75
R3M [36]	$\mathbb{R}^{2048}$	85.27	71.79	42.66
MVP [40]	$\mathbb{R}^{384}$	93.07	85.32	60.37
Voltron [24]	$\mathbb{R}^{196\times384}$	92.93	84.70	57.61
MPI (Ours)*	$\mathbb{R}^{384}$	**96.29**	**92.10**	71.87
MPI (Ours)	$\mathbb{R}^{196\times384}$	96.04	92.05	**74.40**

The experimental results reveal that MPI yields **state-of-the-art** performance on a broad spectrum of downstream tasks.

TABLE II: **Results of single-task visuomotor control on Franka Kitchen.** We report the success rate (%) over 50 randomly sampled trajectories. We **bold** the best result for models with similar parameters and underline the second. "INSUP." represents classification-based supervised learning on ImageNet. MPI consistently exhibits superior performance across multiple tasks.

Method	Backbone	Param.	Turn knob	Open door	Flip switch	Open microwave	Slide door	Average
INSUP. [21]	ResNet50	25.6M	28.0	18.0	50.0	26.7	75.7	39.7
CLIP [39]	ResNet50	25.6M	26.3	13.0	41.7	24.7	86.3	38.4
R3M [36]	ResNet50	25.6M	53.3	**50.7**	86.3	59.3	97.7	69.5
Voltron [24]	ViT-Small	22M	71.7	45.3	**95.3**	40.3	99.7	70.5
MPI (Ours)	ViT-Small	22M	**83.3**	50.3	89.0	**59.7**	**100.0**	**76.5**
MVP [40]	ViT-Base	86M	79.0	48.0	90.7	41.0	**100.0**	71.7
Voltron [24]	ViT-Base	86M	76.0	45.3	91.0	41.0	99.3	70.5
MPI (Ours)	ViT-Base	86M	**89.0**	**57.7**	**93.7**	**54.0**	**100.0**	**78.9**

TABLE III: **Results of single-task visuomotor control on Meta-World simulation environment.** We report the success rate (%) over 50 randomly sampled trajectories. The best results are **bolded** and the second highest are underlined. MPI showcases exemplary performance across three tasks, exhibiting a superior average success rate in comparison to prior methods.

Method	Backbone	Param.	Assemble	Pick & Place	Press Button	Open Drawer	Hammer	Average
R3M [36]	ResNet50	25.6M	**94.0**	60.3	66.3	100	93.7	82.9
MVP [40]	ViT-Base	86M	82.7	**82.0**	62.7	100	95.7	84.6
Voltron [24]	ViT-Small	22M	72.3	57.3	30.7	100	83.0	68.7
MPI (Ours)	ViT-Small	22M	69.0	64.0	**98.7**	**100**	**96.0**	**85.7**

MPI | Takeaways

- By instructing the model towards ***predicting*** transition frames and ***detecting*** manipulated objects, the model can foster better comprehension of "how-to-interact" and "where-to-interact".
- Interaction-level feature yields enhanced generalizability.
- The tasks of predicting transition frame and detecting manipulated objects can promote each other.

Project page

Code on Github

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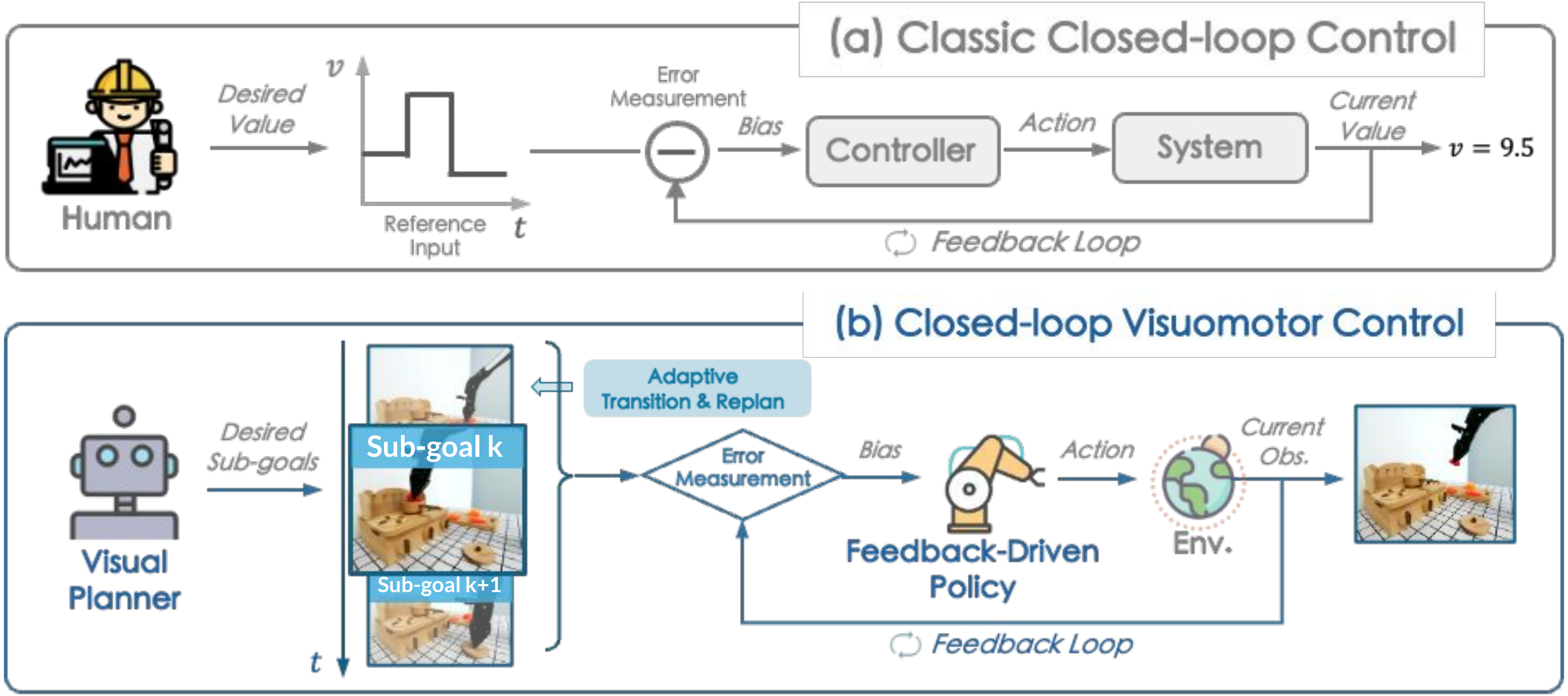
How to "calibrate" intermediate state towards better policy actions?

CLOVER: Closed-Loop Visuomotor Control with Generative Expectation for Robotic Manipulation

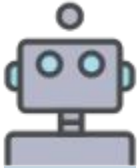
Motivation

From classic control to visuomotor policy



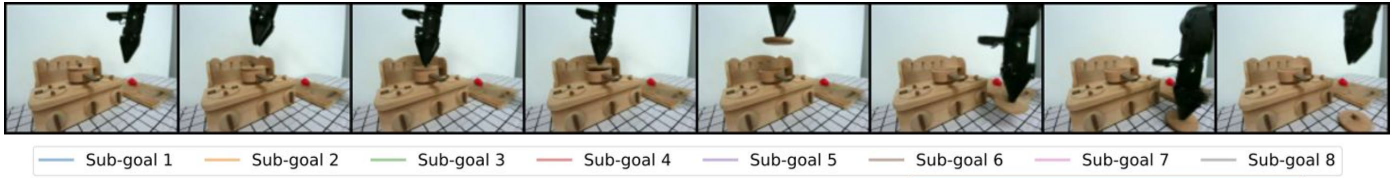
CLOVER: Adaptive Subgoal Transition + Re-planning + Completion Assessment

Key observation



Diffusion Model

Generated Sub-goals

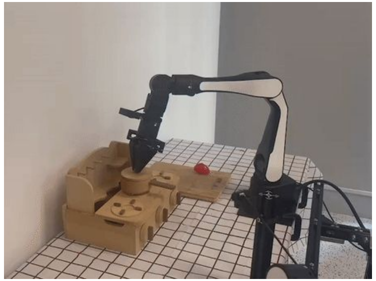


Guide

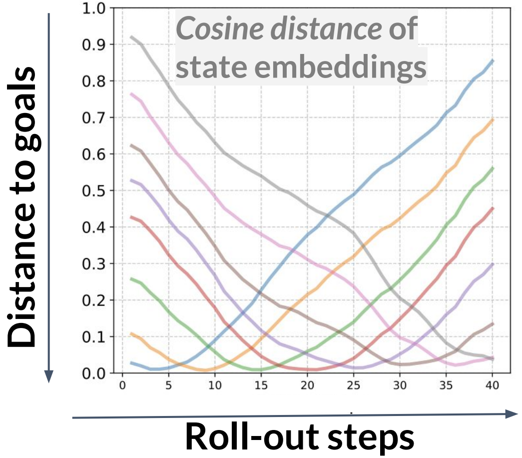
Align

Actual Roll-out

Policy



State Embeddings:
Effectively measures current-to-goal errors.

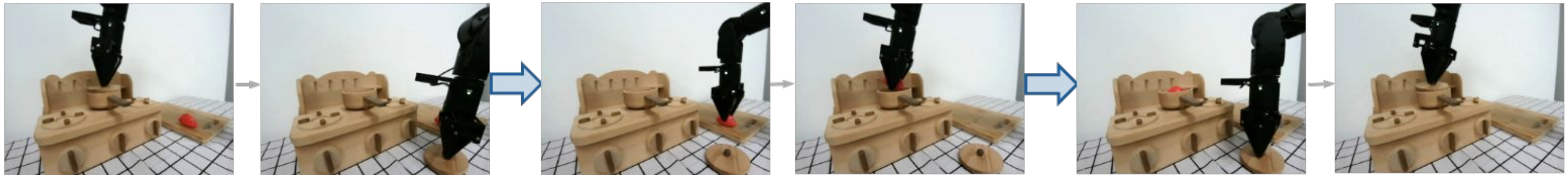


Bu, et al, Closed-Loop Visuomotor Control with Generative Expectation for Robotic Manipulation, in submission

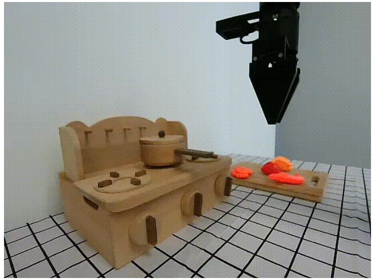
Experiments

Real-world Robots: Consecutive Tasks

Sub-task 1: lift up the pot lid　　Sub-task 2: put the fish into the pot　　Sub-task 3: put the lid on the pot



➔ Substantial improvement over language-conditioned behaviour cloning baselines



+30%

Method	Task completed in a row (%) ↑ 1	2	3	Avg. Len. ↑
ACT [53]	46.7	13.3	0.0	0.6
R3M [54]	53.3	20.0	0.0	0.7
RT-1 [49]	66.7	40.0	0.0	1.1
CLOVER (Ours)	**93.3**	**86.7**	**26.7**	**2.1**

Experiments

Simulation: CALVIN Benchmark

- **+8%** v.s. 3D Diffuser Actor (previous SOTA) with more inputs
- **+30%** v.s. Previous "Planner + Executor" Method

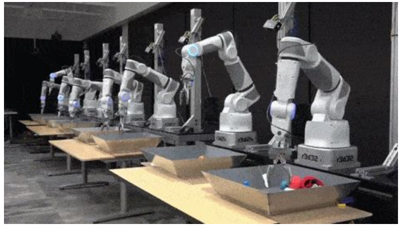
Method	Type	Train episodes	Task completed in a row (%) ↑ 1	2	3	4	5	Avg. Len. ↑
MCIL [47]	Language-conditioned Behaviour Cloning	All	30.4	1.3	0.2	0.0	0.0	0.31
HULC [48]		All	41.8	16.5	5.7	1.9	1.1	0.67
RT-1 [49]		Lang	53.3	22.2	9.4	3.8	1.3	0.90
RoboFlamingo [50]		Lang	82.4	61.9	46.6	33.1	23.5	2.48
GR-1 [51]		Lang	85.4	71.2	59.6	49.7	40.1	3.06
3D Diffuser Actor [52]	Diffusion Policy	Lang	92.2	78.7	63.9	51.2	41.2	3.27
UniPi* [14]	Planner + Executor	All	56.0	16.0	8.0	8.0	4.0	0.92
SuSIE [15]		All	87.0	69.0	49.0	38.0	26.0	2.69
CLOVER (Ours)		Lang	**96.0**	**83.5**	**70.8**	**57.5**	**45.4**	**3.53**

Concluding Remarks

What's Next for Robotic Manipulation

Data Collection

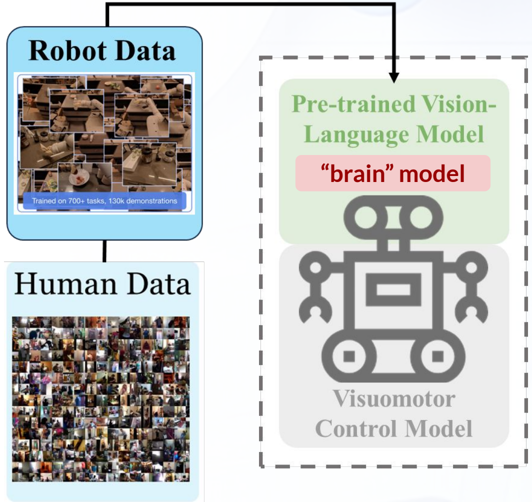
Programming



Tele-operation

Engine / Pre-training

Pre-train a "brain" model for robotic "upper body" tasks.



generali
-zation

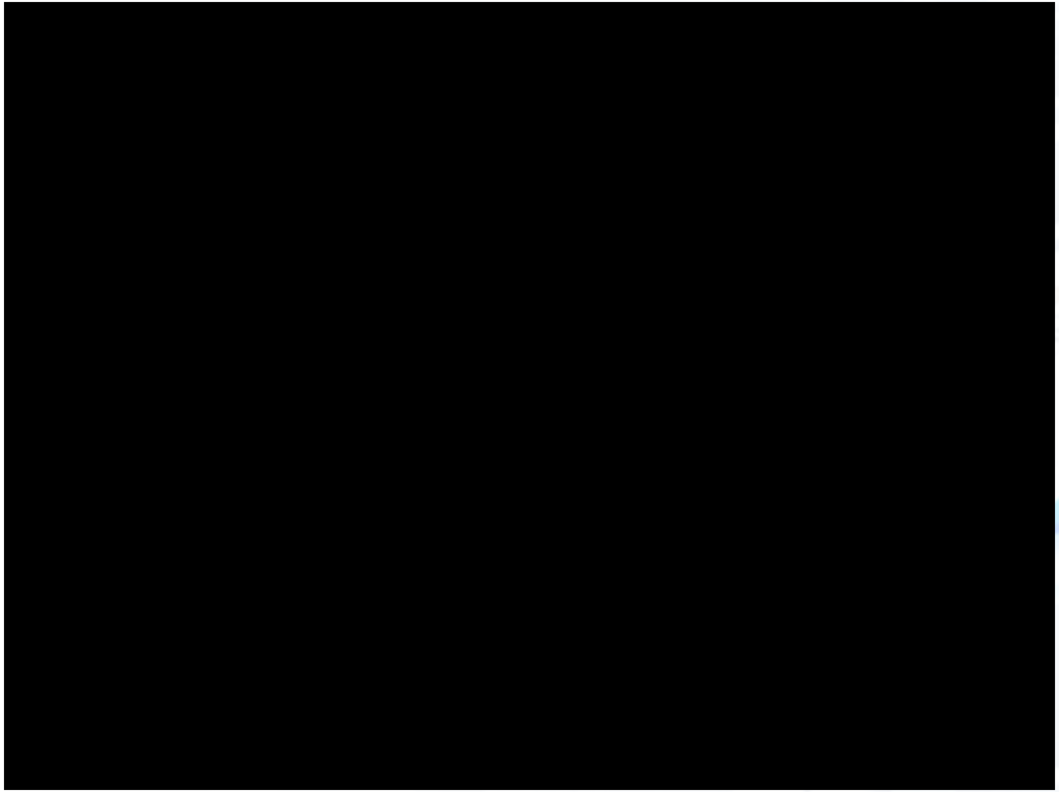
General-purpose, interpretable embodied foundation model with causal reasoning capabilities

Application / Task

Fixed Manipulation

Mobile Manipulation

Humanoid Robots for Manufacturing



Kudos to Our Fantastic Members / Collaborators

Also the slide credit

Meet our team in
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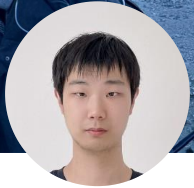

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And many others …

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