



*How to scale up the autonomous driving models?*

# GenAD: Generalized Predictive Model for Autonomous Driving

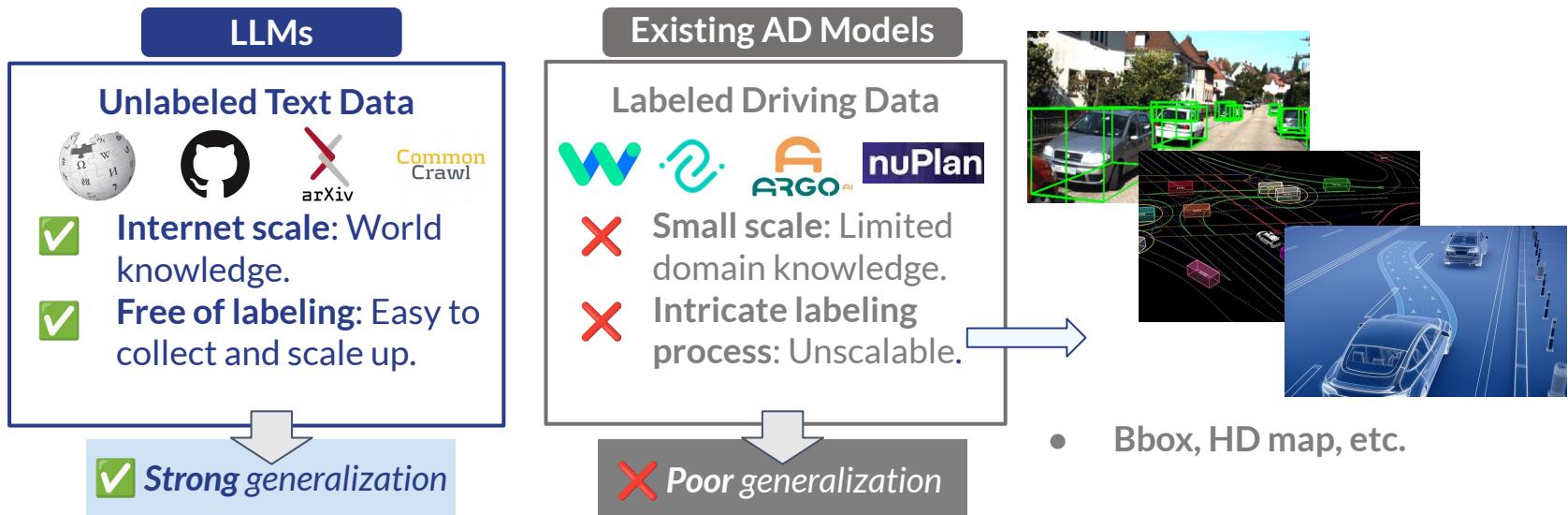
*CVPR 2024, Highlight*

arxiv.2403.09630

# Motivation (1/3) | What Makes for Generalized AD Model?

## Data Distinction:

- + LLMs pretrained on **trillions of unlabeled text tokens** exhibit strong generalization in a variety of domains and applications
- However, existing AD models are established on **limited labeled data**, which hampers their generalization

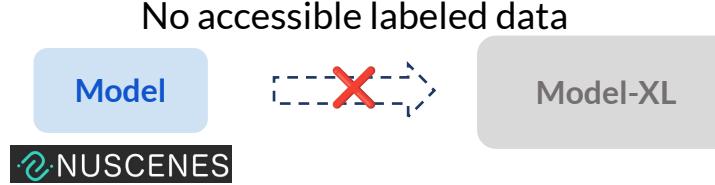


# Motivation (2/3) | What Makes for Generalized AD Model?

## Learning Objective:

- Supervised by 3D labels

 Hard to scale without sufficient labeled data



- Supervised by expert features

- Scalable with developed expert models (e.g., DINOv2)
- Focusing on specific objects (e.g., centered or large ones)
-  Ignoring critical details (e.g., small objects)



- Feature map visualization from DINOv2

 Undesirable for modeling challenging driving scenes

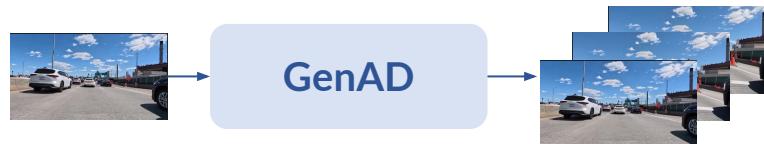
# Motivation (3/3) | What Makes for Generalized AD Model?

## Our Initiative:

Data: Massive online driving videos

## Learning Objective:

- Supervised by “pixels of future frames” → Video Prediction



- ✓ Scalable Data (easy to collect from the web)
- ✓ No 3D labeling needed
- ✓ Better detail preservation
- ✓ Learning world knowledge and how to drive inherently

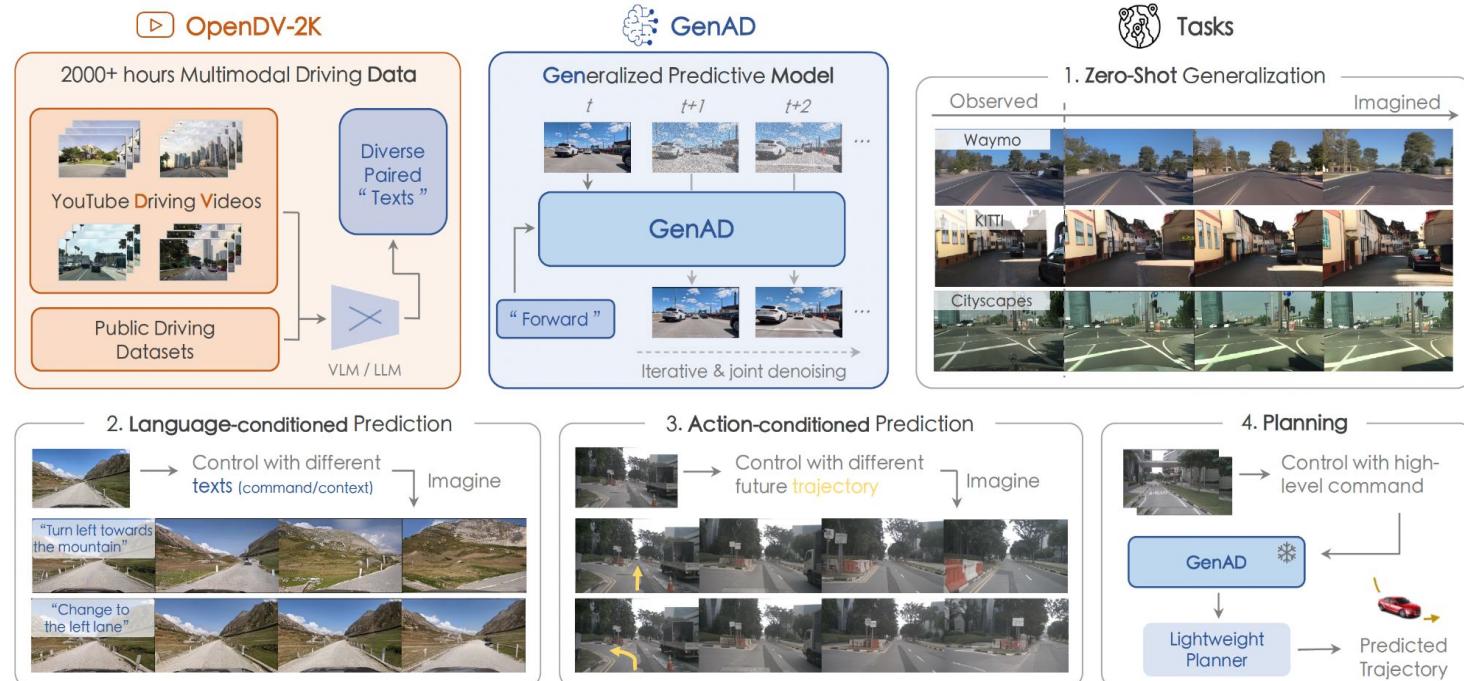
Strong generalization



▶ Massive YouTube videos, collected worldwide

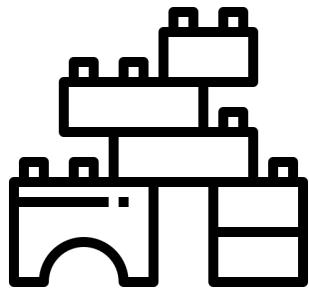
# GenAD | At a Glance

Summary: A billion-scale video prediction model trained on web-scale driving videos, demonstrating strong generalization across a wide spectrum of domains and tasks.

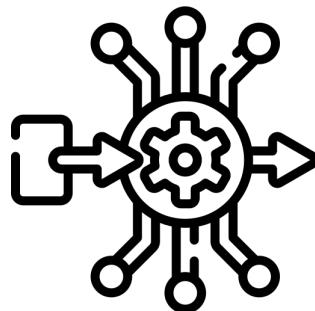


# GenAD - Overview

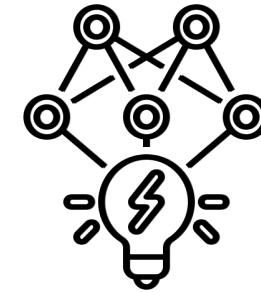
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Data

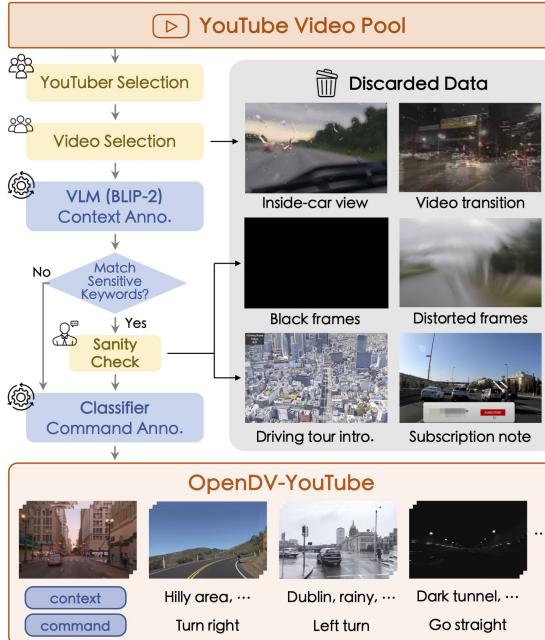


Model



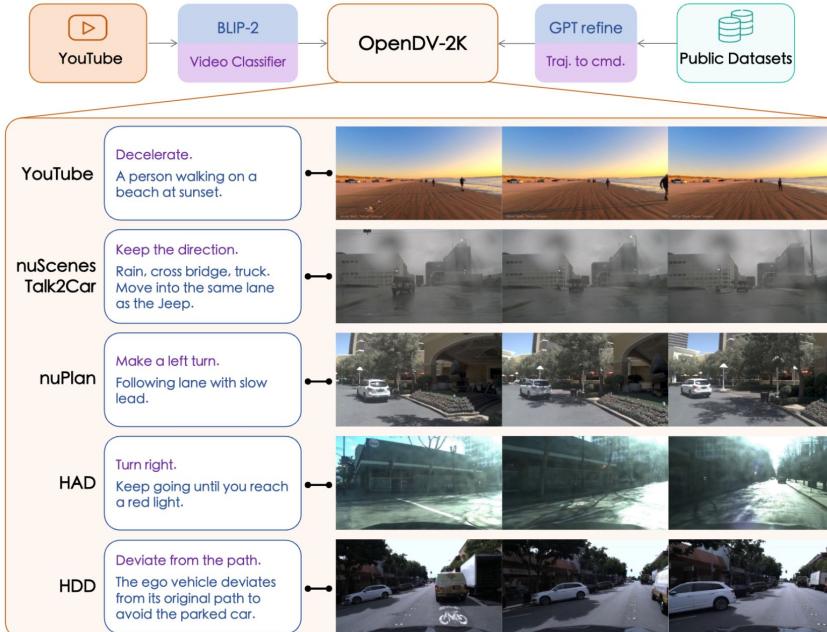
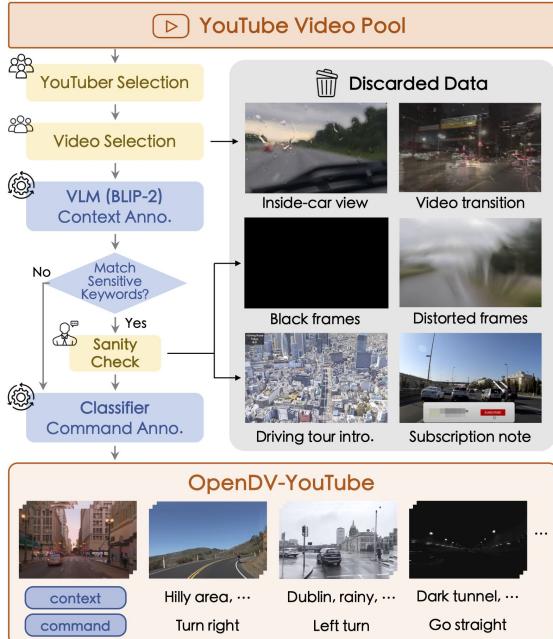
Tasks

# GenAD | Dataset



- Rigorous data collection and filtering strategy

# GenAD | Dataset



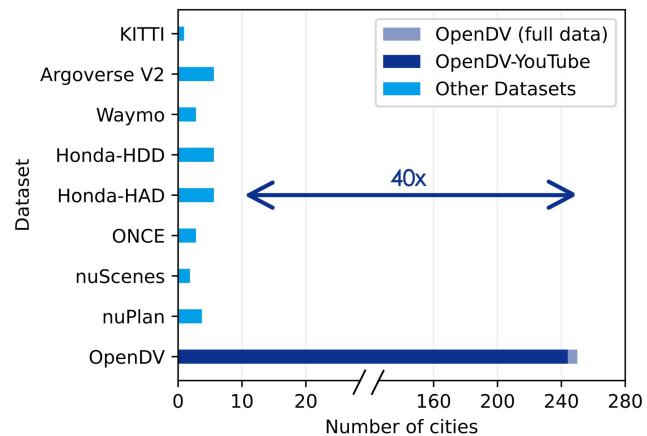
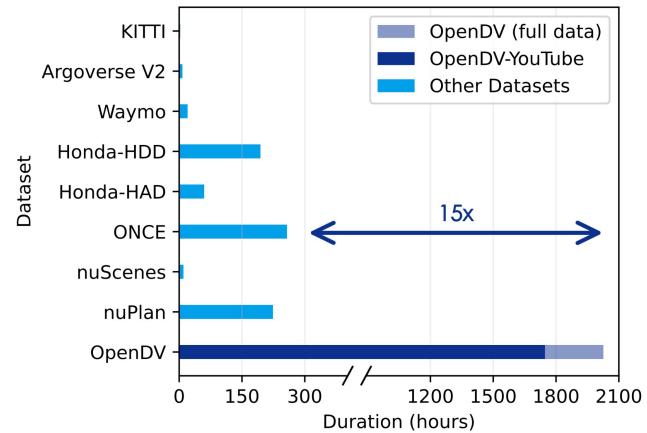
- Rigorous data collection and filtering strategy
- Multi-modal and Multi-source Nature
  - Sourced from both online videos and public datasets for diversity
  - Paired with textual **context** and **command**

# GenAD | Dataset

- Largest public dataset for autonomous driving
- $\geq 2059$  hours,  $\geq 244$  cities

	Dataset	Duration (hours)	Front-view Frames	Geographic Diversity Countries	Diversity Cities	Sensor Setup
X	KITTI [30]	1.4	15k	1	1	fixed
X	Cityscapes [21]	0.5	25k	3	50	fixed
X	Waymo Open* [97]	11	390k	1	3	fixed
X	Argoverse 2* [109]	4.2	300k	1	6	fixed
✓	nuScenes [12]	5.5	241k	2	2	fixed
✓	nuPlan* [13]	120	4.0M	2	4	fixed
✓	Talk2Car [24]	4.7	-	2	2	fixed
✓	ONCE [72]	144	7M	1	-	fixed
✓	Honda-HAD [51]	32	1.2M	1	-	fixed
✓	Honda-HDD-Action [84]	104	1.1M	1	-	fixed
✓	Honda-HDD-Cause [84]	32	-	1	-	fixed
✓	OpenDV-YouTube (Ours)	1747	60.2M	$\geq 40^\dagger$	$\geq 244^\dagger$	uncalibrated
-	OpenDV-2K (Ours)	<b>2059</b>	<b>65.1M</b>	$\geq 40^\dagger$	$\geq 244^\dagger$	uncalibrated

OpenDV-2K (Ours) 

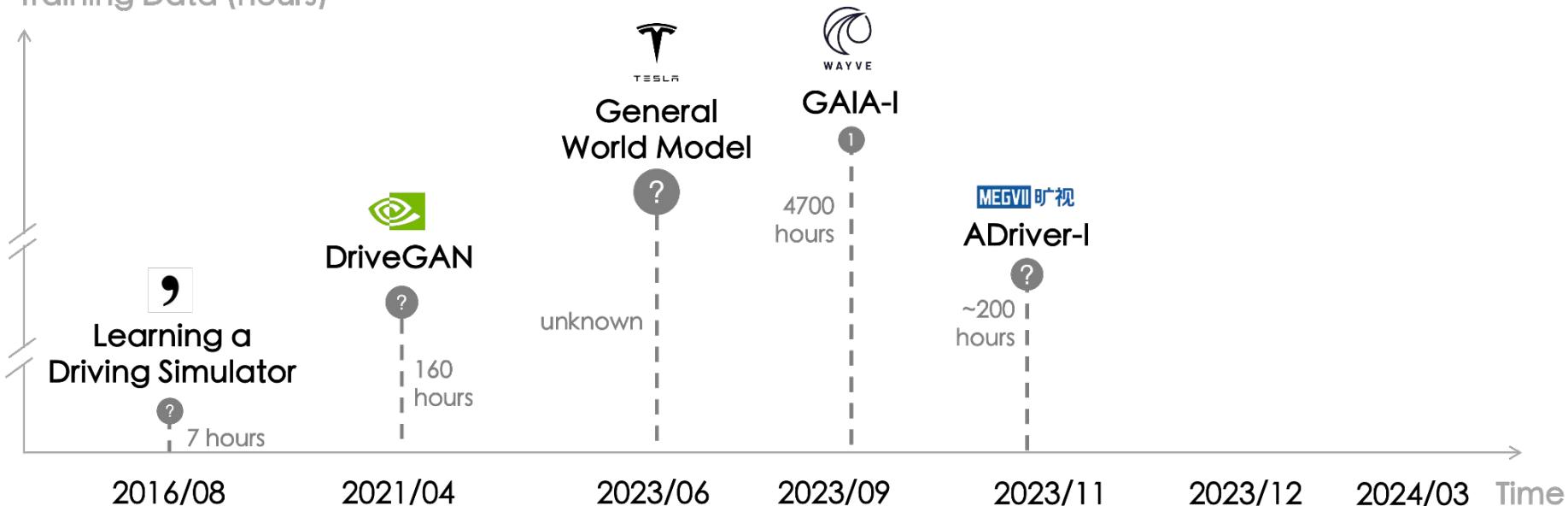


# GenAD | Dataset

- Comparison of the data consumption for predictive driving models

● Private Data  
● Public Data

Training Data (hours)

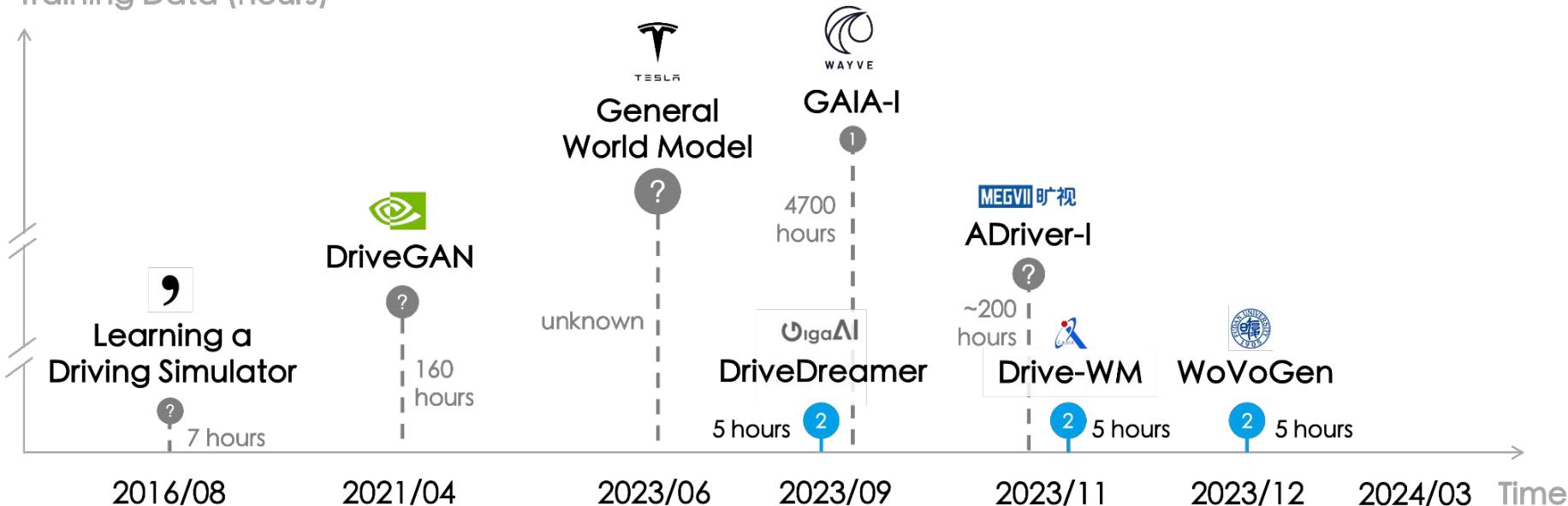


# GenAD | Dataset

- Comparison of the data consumption for predictive driving models

● Private Data  
● Public Data

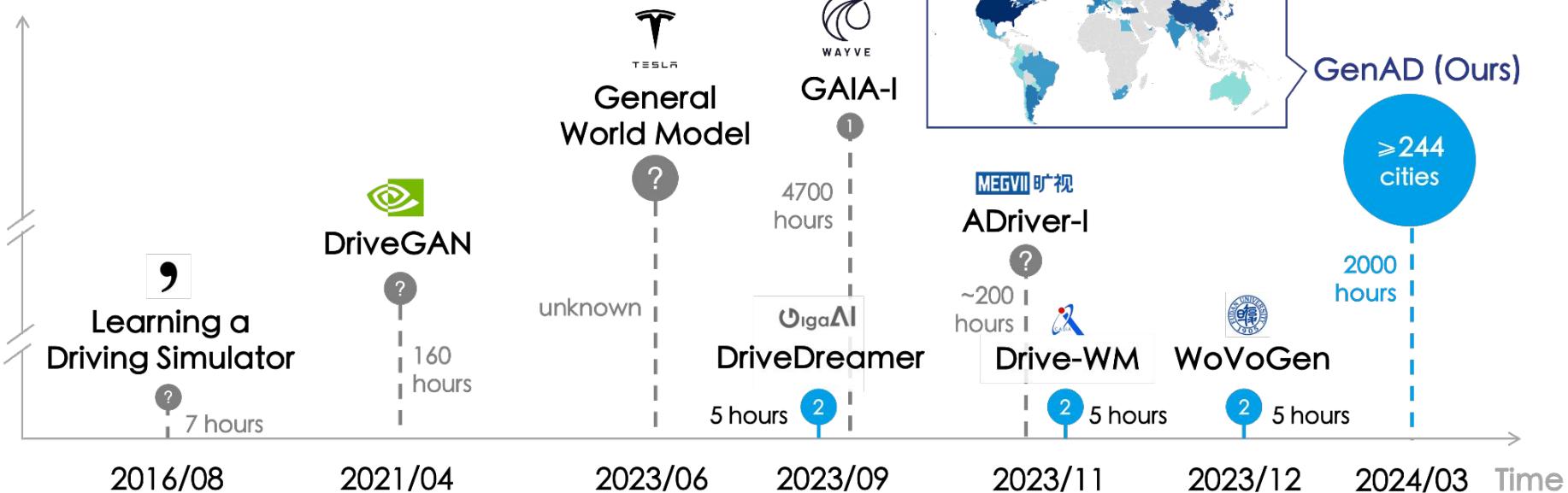
Training Data (hours)



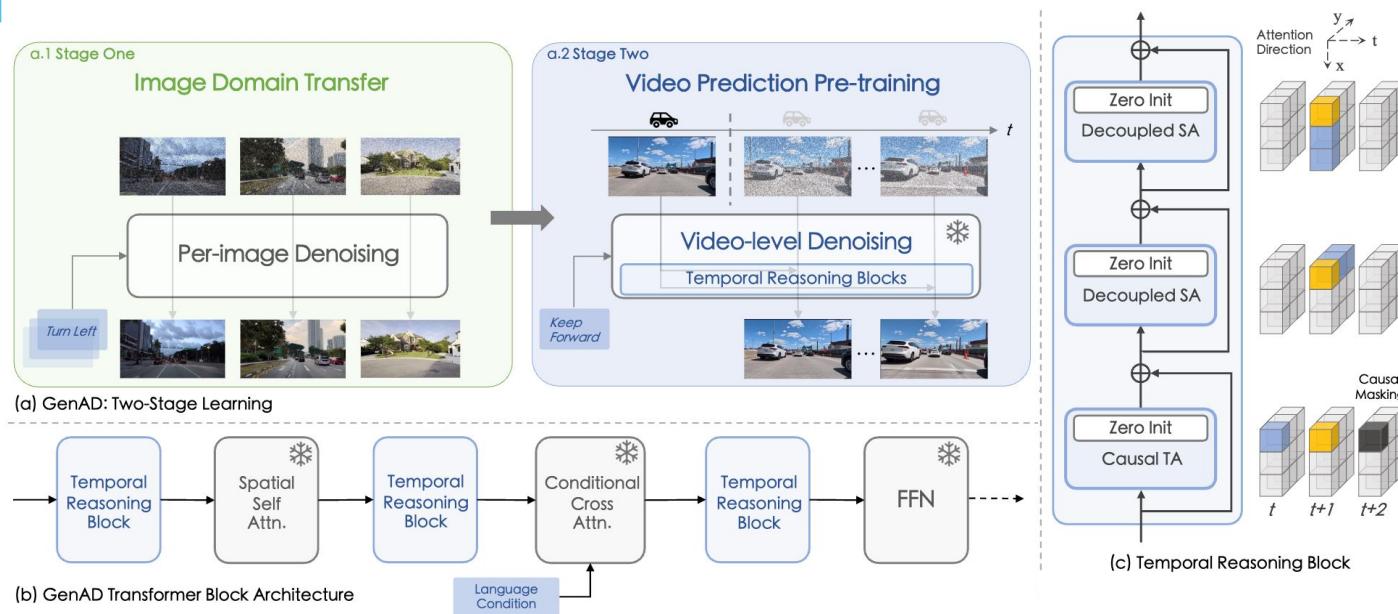
# GenAD | Dataset

- Comparison of the data consumption for predictive driving models

Training Data (hours)

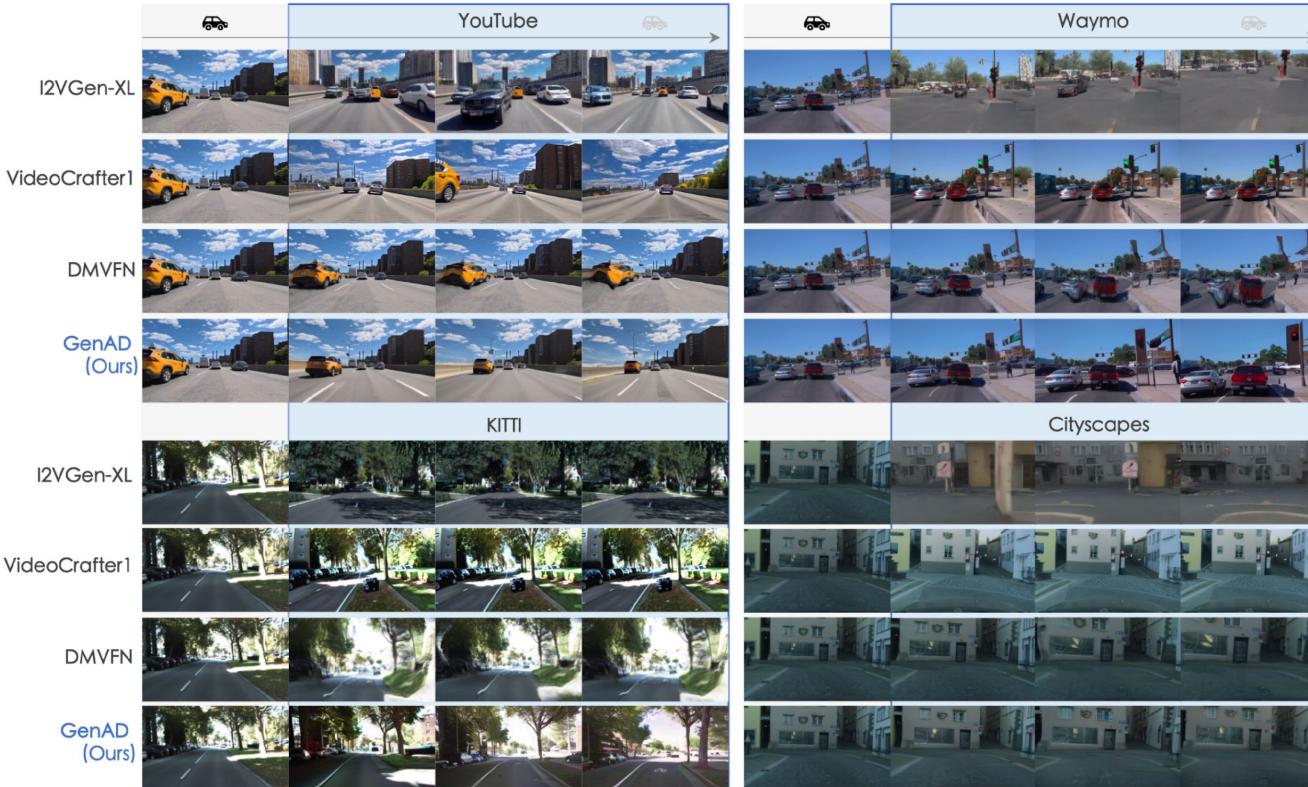


# Algorithm | Video Prediction Model for Driving



- **Two-stage Training:**
  - Tuning the **image generation model (SDXL)** into a highly-capable **video prediction model**
- **Model Specializations for Driving:**
  - Causal Temporal Attention: coherent and consistent future prediction
  - Decoupled Spatial Attention: efficient long-range modeling
  - Interleaved temporal blocks: sufficient spatiotemporal interaction

# Result on Tasks (1/4) | Zero-shot Generalization (Video Prediction)



- Zero-shot video prediction on unseen datasets including Waymo, KITTI and Cityscapes
- Outperforming competitive general video generation models

## Result on Tasks (2/4) | Language-conditioned Prediction

### 2. Language-conditioned Prediction



Controlling the future evolvement  
with language

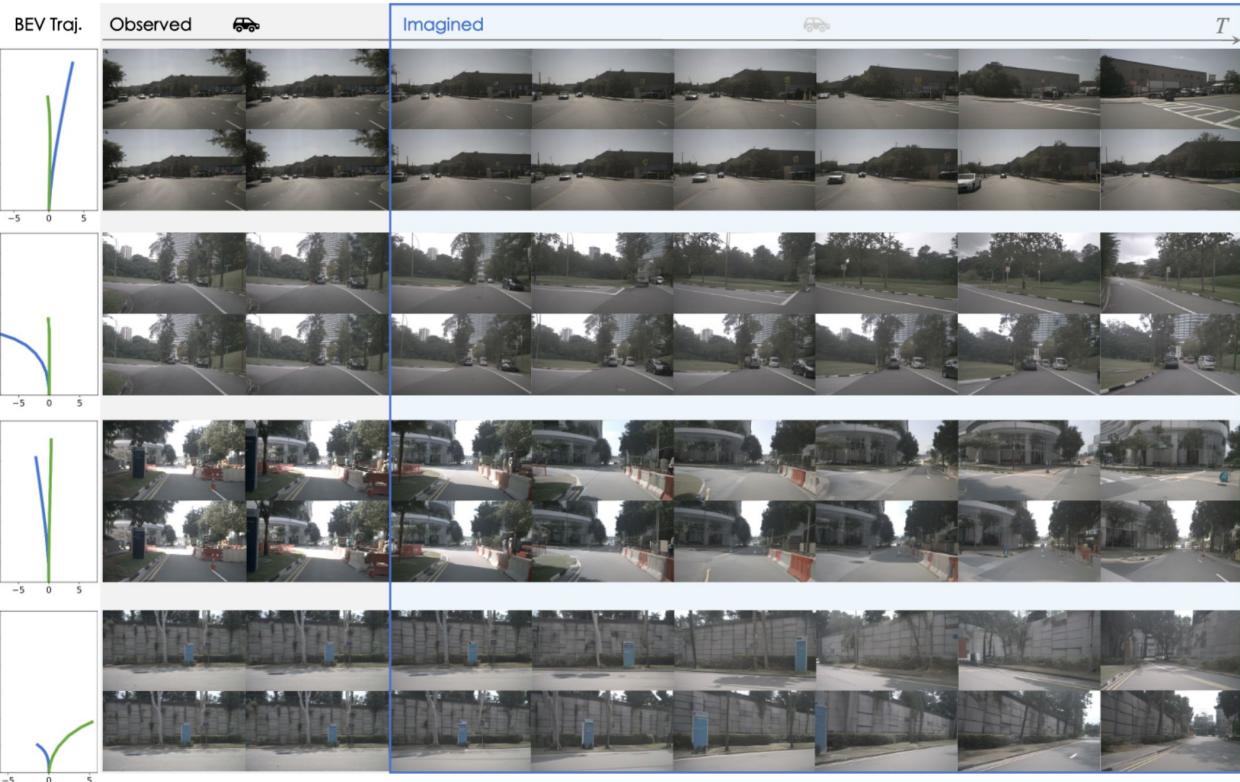


# Result on Tasks (3/4) | Action-conditioned Prediction (Simulation)

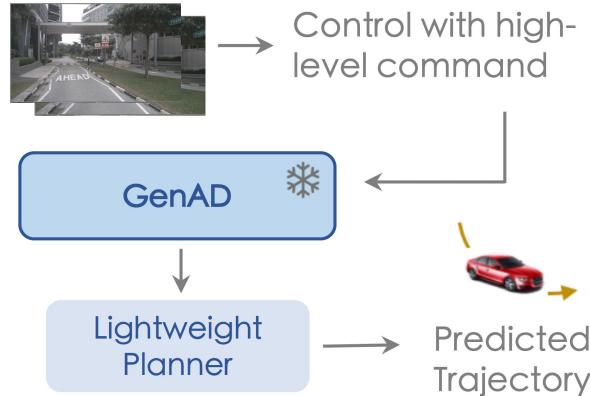
Method	Condition	nuScenes
		Action Prediction Error ( $\downarrow$ )
Ground truth	-	0.9
GenAD	text	2.54
GenAD-act	text + traj.	<b>2.02</b>

Table 4. **Task on Action-conditioned prediction.** Compared to GenAD with text conditions only, GenAD-act enables more precise future predictions that follow the action condition.

Simulating the future with user-specified trajectory



## Result on Tasks (4/4) | Planning



Method	# Trainable Params.	nuScenes	
		ADE ( $\downarrow$ )	FDE ( $\downarrow$ )
ST-P3* [20]	10.9M	2.11	2.90
UniAD* [22]	58.8M	1.03	1.65
GenAD (Ours)	0.8M	1.23	2.31

Table 5. **Task on Planning.** A lightweight MLP with *frozen* GenAD gets competitive planning results with  $73\times$  fewer trainable parameters and front-view image alone. \*: multi-view inputs.

- Speeding up training by **3400 times (vs. UniAD)**
- Demonstrating the **effectiveness of the learned spatiotemporal representations**

# Summary

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- **Largest Public Driving Dataset:**
  - OpenDV-2K provides **2059 hours** of **worldwide** driving videos.
- **Generalized Predictive Model for Autonomous Driving:**
  - GenAD can predict plausible futures with **language** conditions and generalize to **unseen** datasets in a **zero-shot** manner.
- **Broad Applications:**
  - GenAD can readily adapt to **planning** and **simulation**.



(Follow-up work)

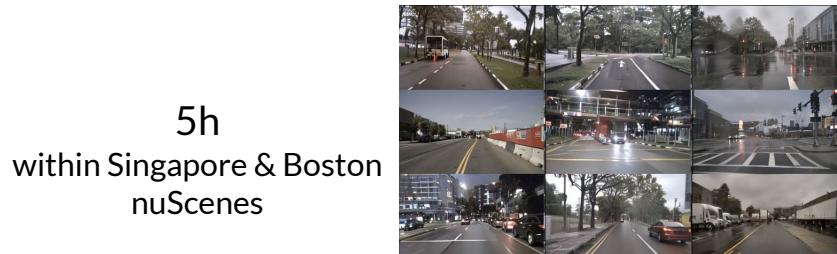
*How to build a generally applicable driving world model?*

# Vista: A Generalizable Driving World Model with High Fidelity and Versatile Controllability

arxiv.2405.17398

# Limitations of Existing Driving World Models

- **Generalization:** limited data scale and geographical coverage



- **Representation capacity:** low resolution and low frame rate



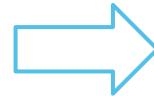
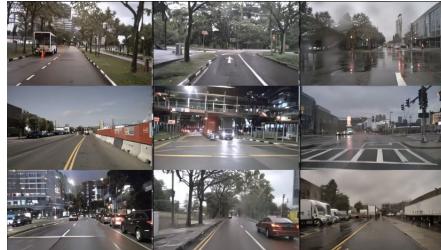
- **Control flexibility:** single modality, incompatible with planning algorithms



# Our Investigation: A Generalizable Driving World Model

- **Generalization:** largest driving video dataset

5h  
within Singapore & Boston  
nuScenes



1740h  
worldwide

- **Representation capacity:** high spatiotemporal resolution

80×160  
DriveSim  
(2016/08)

128×192  
DriveDreamer  
(2023/09)

192×384  
Drive-WM  
(2023/11)

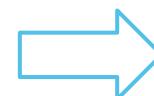
256×256  
DriveGAN  
(2021/04)

256×448  
WoVoGen  
(2021/12)

256×448  
GenAD  
(2023/03)

288×512  
GAIA-1  
(2023/09)

576×1024



- **Control flexibility:** multi-modal action inputs

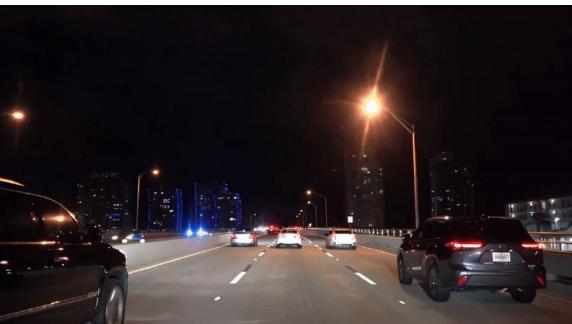


# Capability of Vista

- High-fidelity future prediction



- Continuous long-horizon rollout (15 seconds)



# Capability of Vista

- Zero-shot action controllability

turn left



go straight



turn right



stop



- Provide reward without ground truth actions



## Summary

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- **Vista is a generalizable driving world model that can:**
  - *Predict high-fidelity futures in open-world scenarios.*
  - *Extend its predictions to continuous and long horizons.*
  - *Execute multi-modal actions (steering angles, speeds, commands, trajectories, goal points).*
  - *Provide rewards for different actions without accessing ground truth actions.*



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# Thanks

<https://opendrivelab.com/>