

# Middle Mile & Foundation Models

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GATIK

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# Gatik

## Company Overview

# Our Mission

To deliver goods safely and efficiently using our fleet of autonomous trucks.





# Our Locations

**California, US – HQ**

Mountain View

**Texas, US**

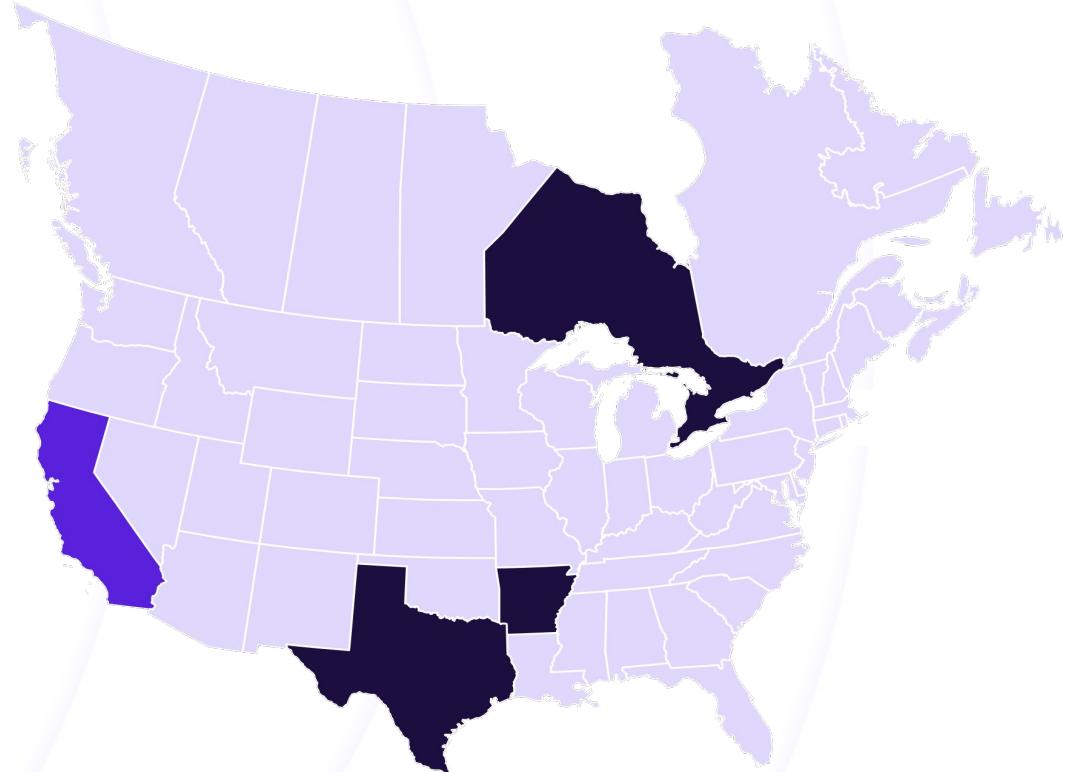
Fort Worth

**Arkansas, US**

Bentonville

**Ontario, Canada**

Toronto



# Our Strong Strategic Partnerships Enable Commercialization At Scale

## OEM and Manufacturing Partners



## Fleet Partners



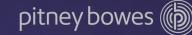
## Key Safety Partners



EDGE CASE RESEARCH



## Commercial Partners



# Middle Mile

Pros and Cons

# Middle Mile Specifics

There are a lot of differences between the common long haul trucking as well as robotaxis/last mile delivery.



ODD



Routing



Autonomy



Data



Validation

## MIDDLE MILE

# Operational Design Domain

A lot of **differences** in comparison to long haul (highway) trucking:

- Vulnerable Road Users (**VRUs**)
- Includes **semi-urban** use case
  - E.g., intersections
- **Lower speed**

## NIST ADS SAFETY MEASUREMENT AND OPERATIONAL DESIGN DOMAIN

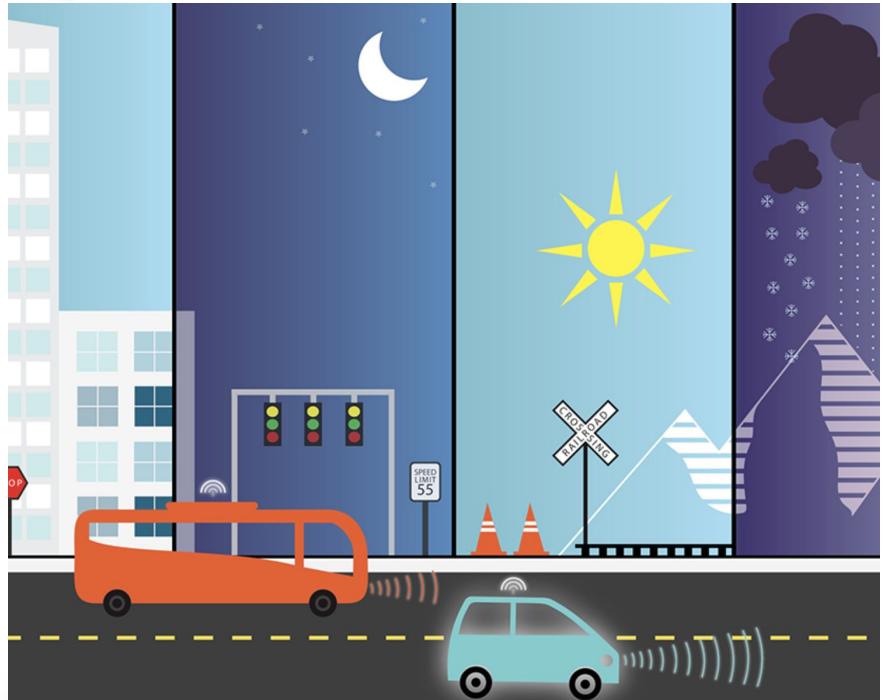


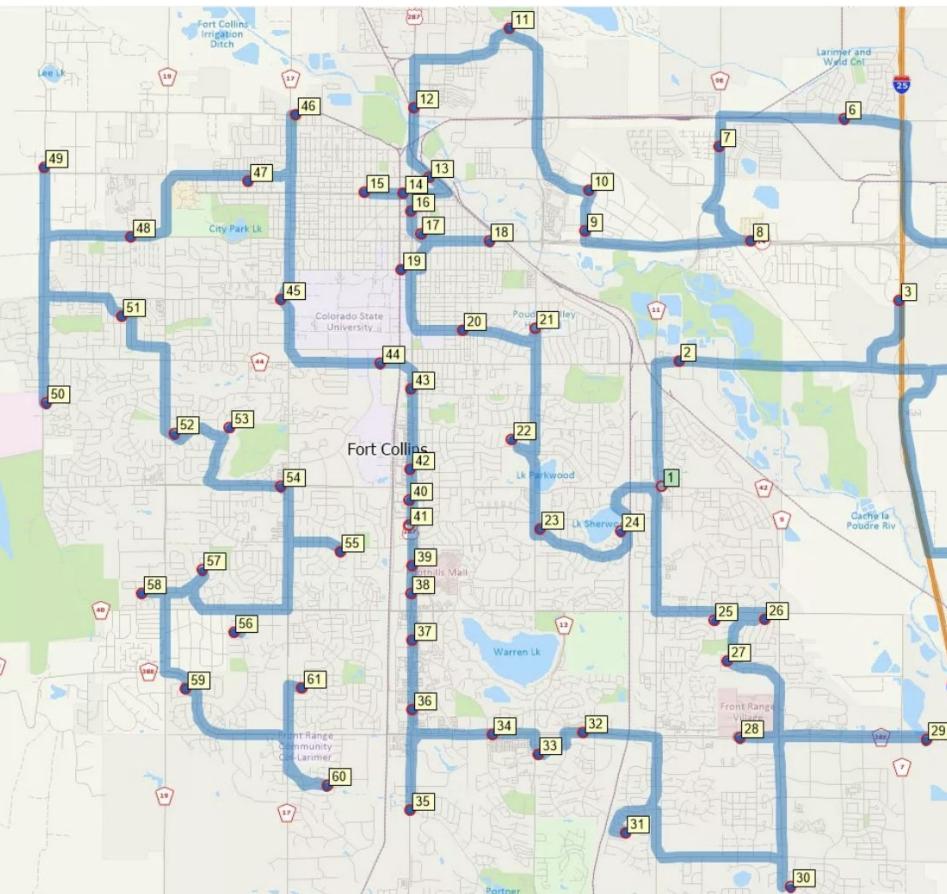
Image [source](#)

## MIDDLE MILE

# Routing

We can concentrate on the **predefined routes**:

- Less and fixed routes means a **smaller ODD**
  - **Route selection** can target different **objectives**
    - E.g., safe roads, optimizing time / costs
  - **Regularity** of trips: positive **feedback** loop



## *Image source*

## MIDDLE MILE

# Autonomy I

- **Mapping:** **less** burden on *online* mapping
  - Still need to be able to **detour** and **re-route**
- **Perception:** **less** large open space *artifacts*, but more focus on VRU detection and tracking
  - Overall trucking problem:  
**sensor positions** are quite **different** from those in the open source data



Image [source](#)

## MIDDLE MILE

# Autonomy II

- **Behavior:** closer to robotaxi/urban use case
  - E.g., occlusion detection and handling
- **Controls:** need in high precision / maneuverability in case of VRU



## MIDDLE MILE

### Data

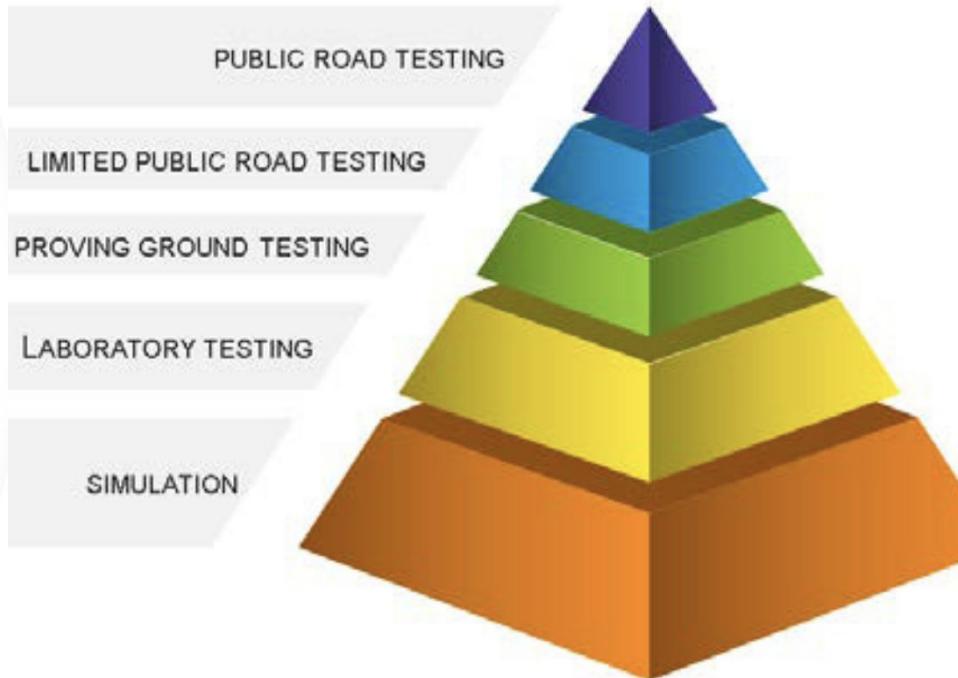
- Less coverage, but
- More route-specific behavior diversity
- Still need to *proactively* collect data of reasonable area around the fixed routes



Image [source](#)

# Validation

- **Smaller ODD means faster validation cycle**
  - Combinatorial explosion of all possible use cases is quite compact
- **Lower speed: better safety expectation**
- **VRUs: still need in generalizable solution**



*Image [source](#)*

# Foundation Models

Why?

# Middle Mile: Challenges



### Restriction != Simplicity

Actually, Middle Mile is a combination of everything (although on a smaller scale): domains, use cases, behaviors, etc.



### Safety and OOD

No any collected data of a reasonable size would contain super rare safety-critical examples. AD deployment is dependent on its safety.



### Adjustability

Trucking use case is far from usual robotaxi domain: different sensors, different planning-control feedback loop, stricter requirements on perception.

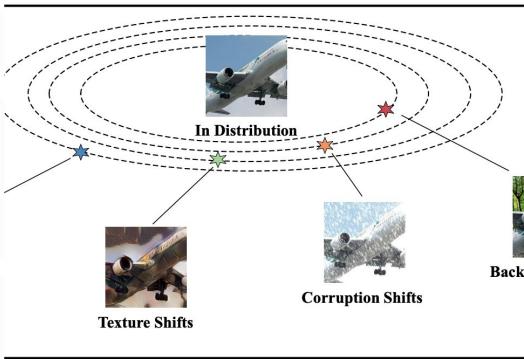


### Adaptation

Need to quickly adapt to road works, closed roads, incorrect prior information. Moreover, even for one truck, its dynamics is different w.r.t. its load.

## FOUNDATION MODELS

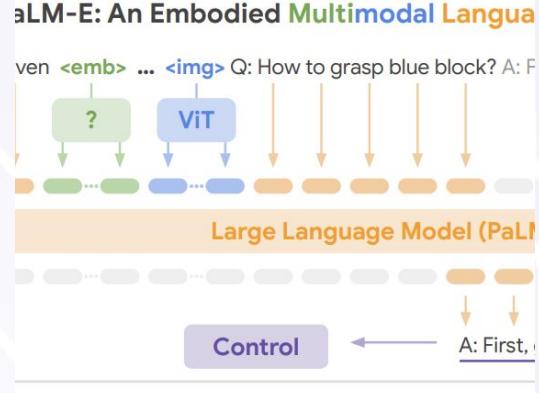
# Why FMs for Middle Mile?



[Image source](#)

## Generalization

Generalization to raw inputs, different locations, and multi-modal behaviors including out-of-distribution analysis.



[Image source](#)

## Flexibility

Through the Visual-Language Model unified interface, any data modality encoders can be used (and even in any combination and order!).



## Data

No need in huge pre-training (it's already done!). Auto-labeling / open-vocabulary capabilities save a lot of resources.

## FOUNDATION MODELS

# Examples of Foundation Models in AD

### DriveLM:

#### Driving with Graph Visual Question Answering

Chonghao Sima<sup>4,1\*</sup> Katrin Renz<sup>2,3\*</sup> Kashyap Chitta<sup>2,3</sup> Li Chen<sup>4,1</sup>  
Hanxue Zhang<sup>1</sup> Chengen Xie<sup>1</sup> Jens Beißwenger<sup>2,3</sup> Ping Luo<sup>4</sup>  
Andreas Geiger<sup>2,3†</sup> Hongyang Li<sup>1†</sup>

### LMDrive: Closed-Loop End-to-End Driving with Large Language Models

Hao Shao<sup>1,2</sup> Yuxuan Hu<sup>3</sup> Letian Wang<sup>4</sup>  
Steven L. Waslander<sup>4</sup> Yu Liu<sup>2,5</sup> Hongsheng Li<sup>1,3,5</sup>

### DriveMLM: Aligning Multi-Modal Large Language Models with Behavioral Planning States for Autonomous Driving

Wenhai Wang<sup>2,1\*</sup>, Jiangwei Xie<sup>3\*</sup>, ChuanYang Hu<sup>3\*</sup>, Haoming Zou<sup>4\*</sup>, Jianan Fan<sup>3\*</sup>, Wenwen Tong<sup>3\*</sup>, Yang Wen<sup>3\*</sup>, Silei Wu<sup>3\*</sup>, Hanming Deng<sup>3\*</sup>, Zhiqi Li<sup>5,1\*</sup>, Hao Tian<sup>3</sup>, Lewei Lu<sup>3</sup>, Xizhou Zhu<sup>6,3</sup>, Xiaogang Wang<sup>2,3</sup>, Yu Qiao<sup>1</sup>, Jifeng Dai<sup>6,1✉</sup>

### DOLPHINS: MULTIMODAL LANGUAGE MODEL FOR DRIVING

Yingzi Ma<sup>1</sup> Yulong Cao<sup>2</sup> Jiachen Sun<sup>3</sup> Marco Pavone<sup>2,4</sup> Chaowei Xiao<sup>1,2</sup>



### DriveGPT4: Interpretable End-to-end Autonomous Driving via Large Language Model

Zhenhua Xu<sup>1</sup> Yujia Zhang<sup>2</sup> Enze Xie<sup>3\*</sup> Zhen Zhao<sup>4</sup> Yong Guo<sup>3</sup>  
Kwan-Yee. K. Wong<sup>1</sup> Zhenguo Li<sup>3</sup> Hengshuang Zhao<sup>1\*</sup>

### DRIVEVLM: The Convergence of Autonomous Driving and Large Vision-Language Models

Xiaoyu Tian<sup>1\*</sup> Junru Gu<sup>1\*</sup> Bailin Li<sup>2\*</sup> Yicheng Liu<sup>1\*</sup> Yang Wang<sup>2</sup> Zhiyong Zhao<sup>2</sup>  
Kun Zhan<sup>2</sup> Peng Jia<sup>2</sup> Xianpeng Lang<sup>2</sup> Hang Zhao<sup>1†</sup>

### GPT-DRIVER: LEARNING TO DRIVE WITH GPT

Jiageng Mao<sup>1</sup> Yuxi Qian<sup>1</sup> Junjie Ye<sup>1</sup> Hang Zhao<sup>2</sup> Yue Wang<sup>1</sup>

### VLP: Vision Language Planning for Autonomous Driving

Chenbin Pan<sup>1\*</sup> Burhaneddin Yaman<sup>2</sup> Tommaso Nesti<sup>2</sup> Abhirup Mallik<sup>2</sup>  
Alessandro G Allievi<sup>2</sup> Senem Velipasalar<sup>1</sup> Liu Ren<sup>2</sup>

## FOUNDATION MODELS

# The Problems with Foundation Models in AD

### Efficiency



No one HW architecture allows at least 10 Hz inference now. With CoT, RAG, and other techniques the latency only increases.

### Pre-trained AD model



There is no pre-trained model that can be used as a plug-and-play solution. Open-source LLMs need careful fine-tuning.

### Implicit bias



While there is a big hope of a FM to capture all aspects of driving, it would be quite hard to get the real understanding of its knowledge frontiers: hallucinations, uncertainty estimation, etc.

### AD Specifics



3D (and unstructured point clouds in particular) generalization performance is far from being at acceptable level. Much stricter requirements on hallucination avoidance (safety). Custom Chain-of-Thoughts (Localization+Mapping – Perception – Prediction – Planning – Control).

# Conclusion

# Conclusion

1. **Middle Mile** is a **unique intersection** of tasks, requirements, and challenges
2. **Foundation Models** are **eventually inevitable** for the Middle Mile – mostly because of their generalization capabilities
3. We still need to **pave the road** for the **safe** and **practical** applications of FM in AD



# Thank you!



