

# Advancing AI in IoT Systems for Smart Health

**Xiaomin Ouyang**

Assistant Professor

Department of Computer Science and Engineering

Hong Kong University of Science and Technology



香港科技大學

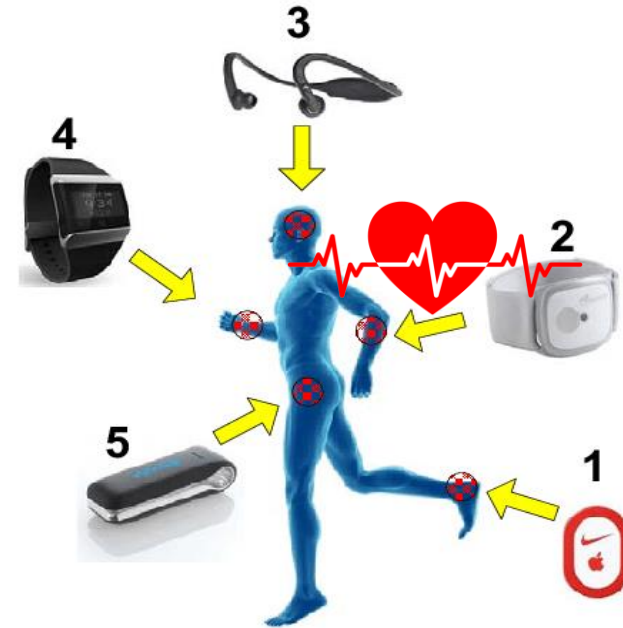
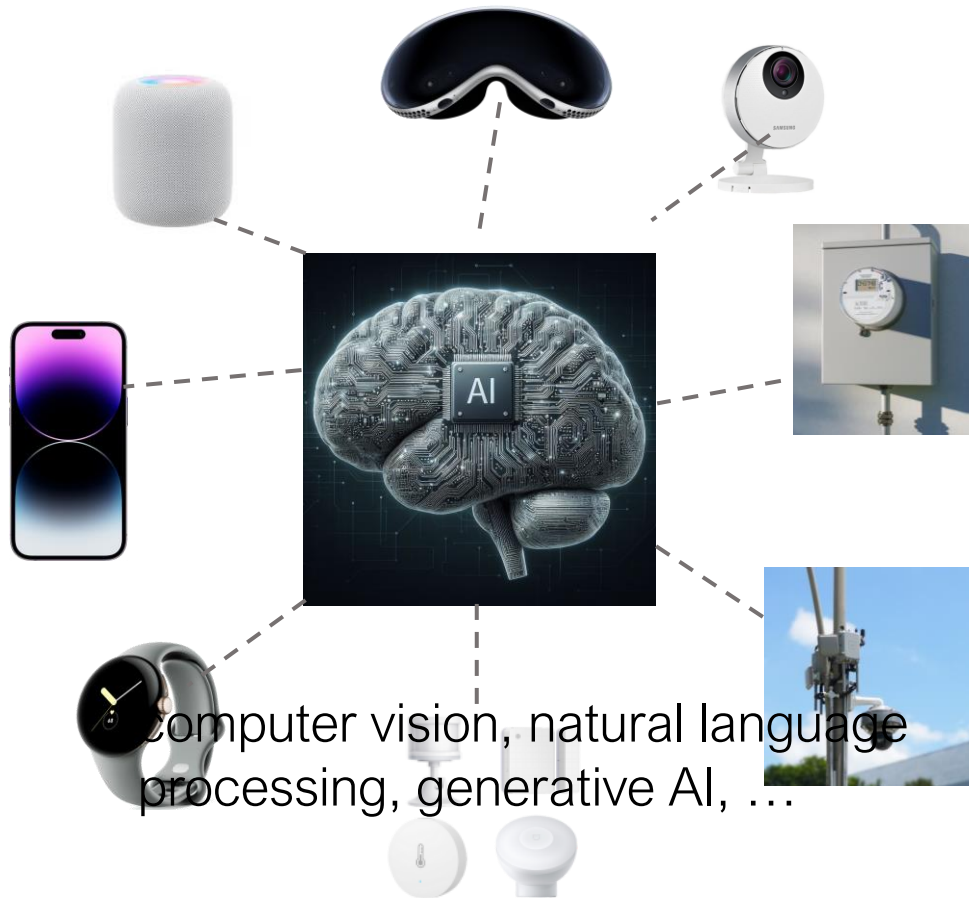
THE HONG KONG UNIVERSITY OF  
SCIENCE AND TECHNOLOGY

# LOTS of IoT and Mobile Devices in Daily Life



- In-situ sensing and networked computing

# On-Device AI for Smart Health



Smart Health

On-device AI for In-home and Community-based Health: *transfer reactive healthcare practice to **proactive, personalized, and seamless** healthcare and well-being.*

# Outline

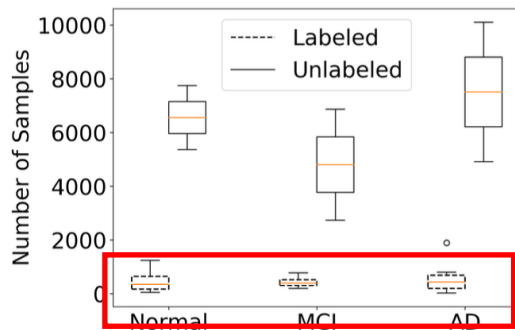
➤ **Embedded AI Systems**

➤ Smart Health

# Understanding Real-World Challenges

## ➤ Data Challenges

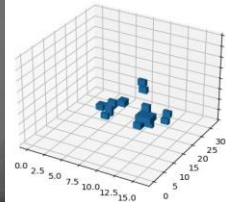
- Limited labeled data



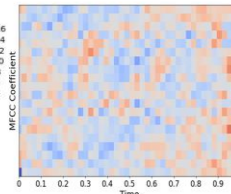
- Fusing heterogeneous modalities



Depth Image

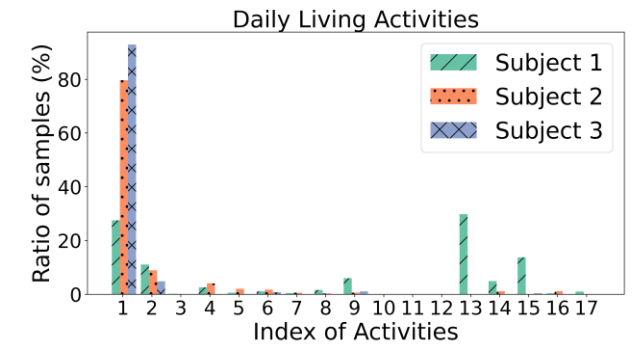


Radar Data



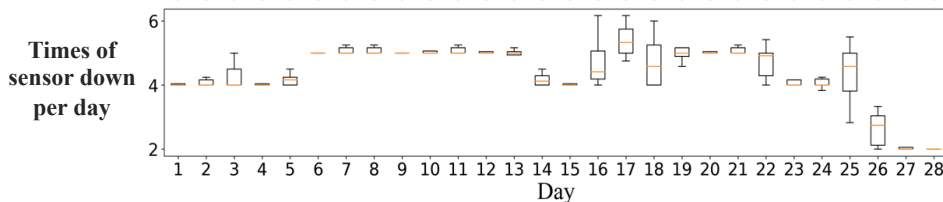
MFCC of Audio

- Non-i.i.d. distributions

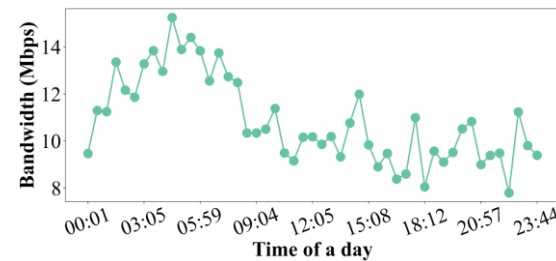


## ➤ System Challenges

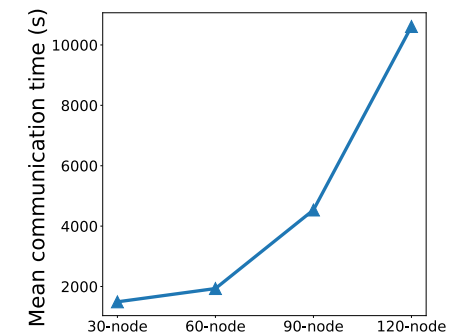
- Sensor dynamics



- Limited resources



- Scalability



- How to harness **distributed and imperfect IoT data**?
- How to make the system more **scalable, resource-efficient and robust to real-world dynamics**?

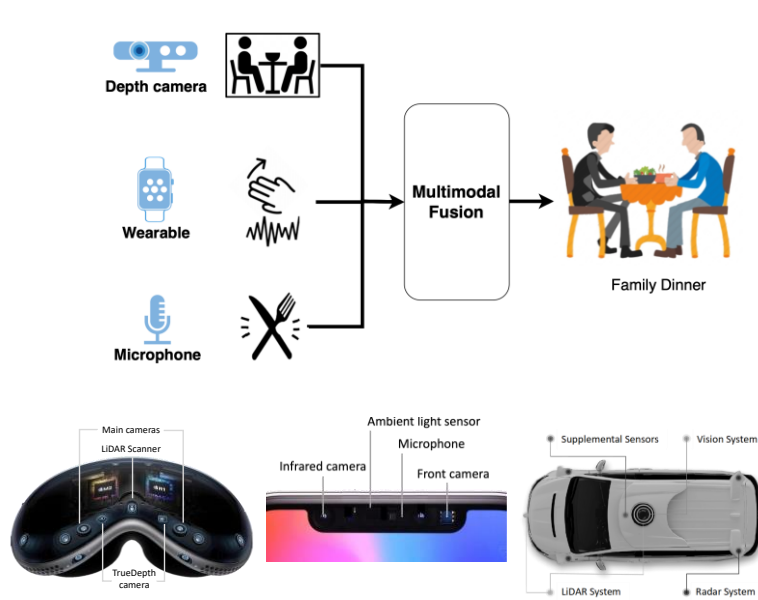
# Embedded AI Systems

## ➤ Tackling real-world **data and system challenges**

### ➤ Multimodal Learning

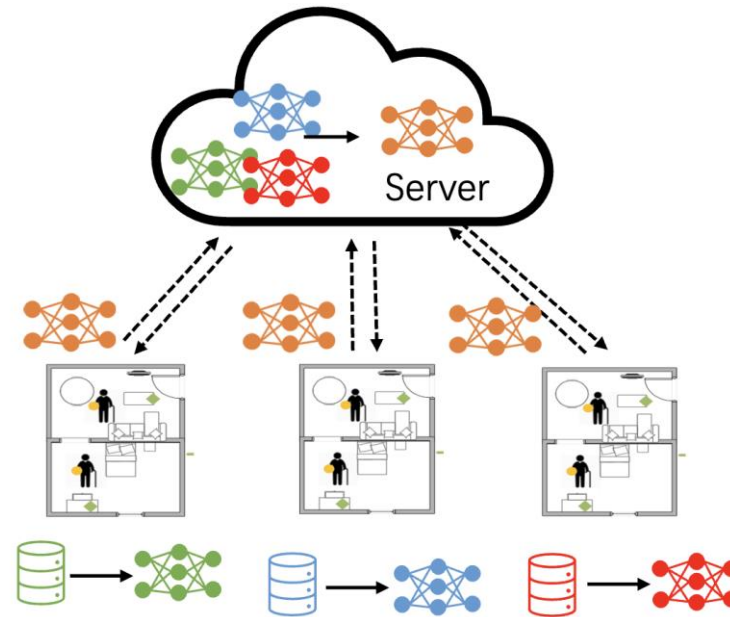
### ➤ Distributed (Federated) Learning

### ➤ Physics-Strengthened AI



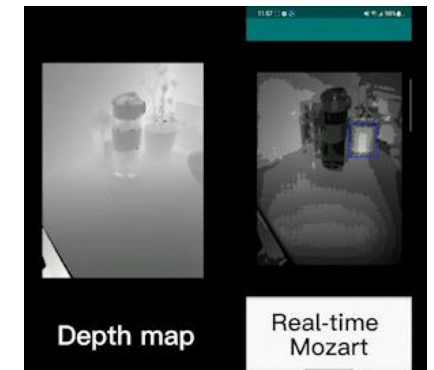
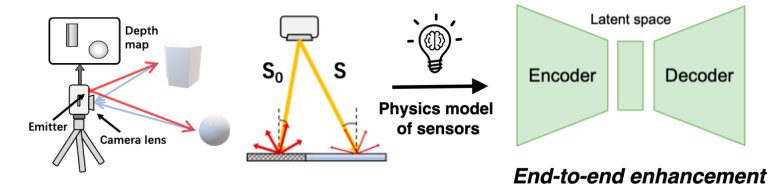
### Harness **distributed and imperfect data**

- MMBind (SenSys'25): foundational dataset
- Cosmo (MobiCom'22): small labeled data



### Address **data and resource heterogeneity**

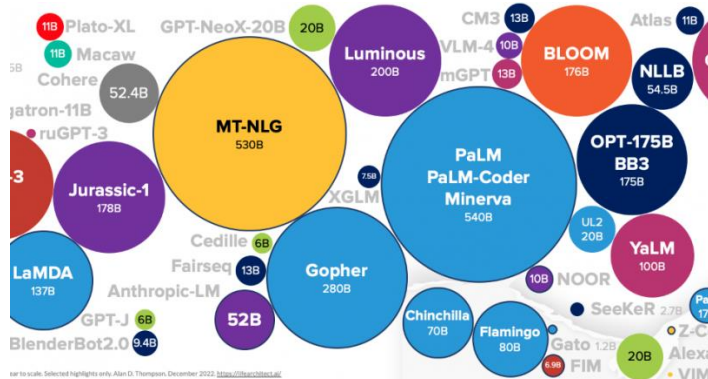
- Harmony (MobiSys'23): modality heterogeneity
- ClusterFL (MobiSys'21): scalability



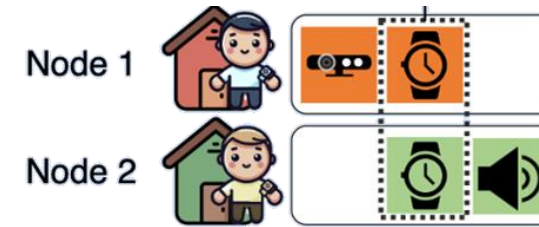
### Enhance sensing quality

- Mozart (MobiSys'23 Best Paper)
- UltraDepth (SenSys'21)

# Multimodal Learning with Distributed and Incomplete Data



Big Data in CV and NLP



Setting	Dataset	Modality	Nodes (Subjects)	Class	Sample
Cross Node (Intra Dataset)	UTD	Acc, Gyro, Skeleton	4/2/2	27	864
	MMFi	Depth, Radar, Skeleton, WiFi	20/10/20	27	1,080
	PAMAP2	Acc, Gyro, Mag	4/2/2	30	9,611
	SUN-RGBD	Image, Depth, SemSeg	N/A	5	4,620
Cross Dataset (Activity)	MotionSense	Acc, Gyro	24	6	12,636
	Shoaib-right	Acc, Mag	10	7	4,500
	Shoaib-left	Acc, Mag	10	7	4,500
	Shoaib-wrist	Acc, Mag	10	7	4,500
	RealWorld	Acc, Gyro, Mag	15	8	21,663
Cross Dataset (Gesture)	GR4DHCI	Skeleton, IR	16	7	7,339
	DHG	Skeleton, Depth	20	14	2,800
	Briareo	Skeleton, Depth, IR	40	12	1,440

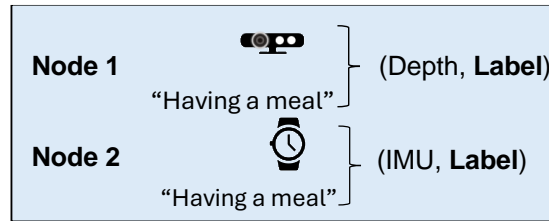
Small and Distributed Data in IoT



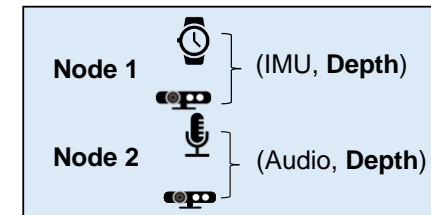
# Multimodal Learning with Distributed and Incomplete Data

## ➤ Key Question:

- Can we learn joint multimodal embeddings with **distributed and incomplete data in IoT**?



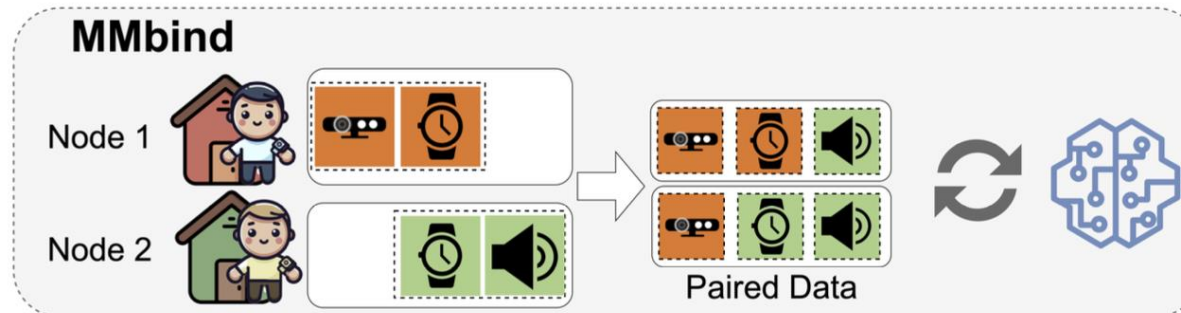
$$D1=(x_1, y),$$
$$D2=(x_2, y)$$



$$D1=(x_1, x_2),$$
$$D2=(x_2, x_3)$$

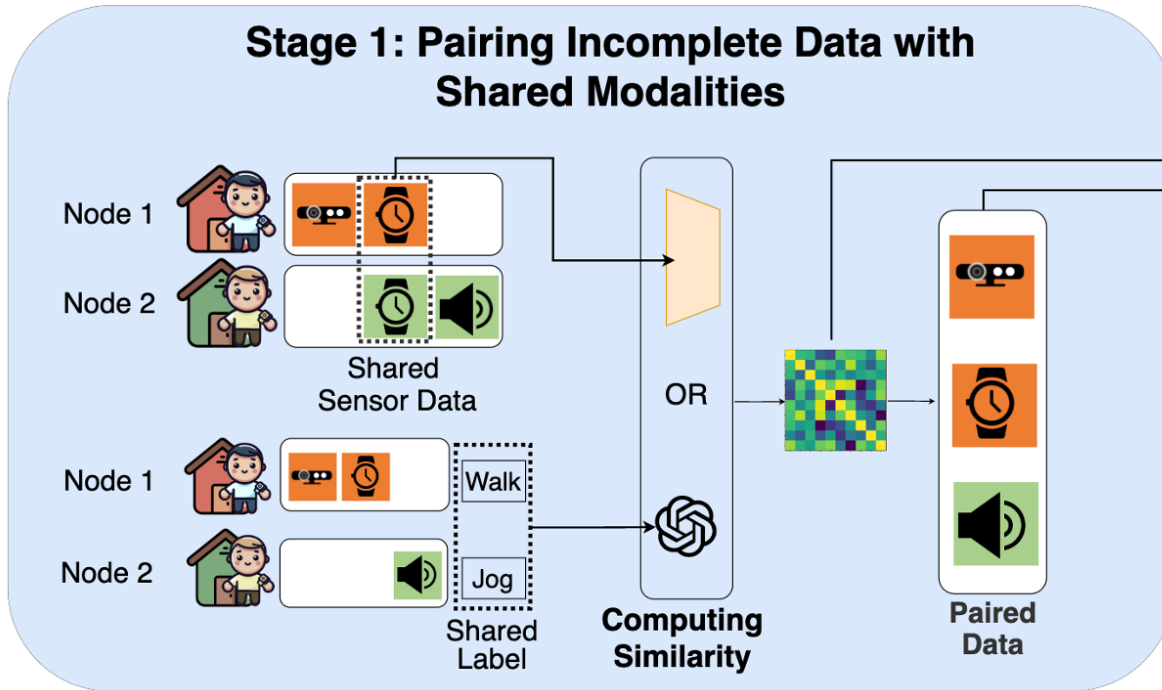
## ➤ Key Idea:

- Bind data from disparate sources and incomplete modalities with **the shared modality**
  - Shared modality: **sensor data or labels**

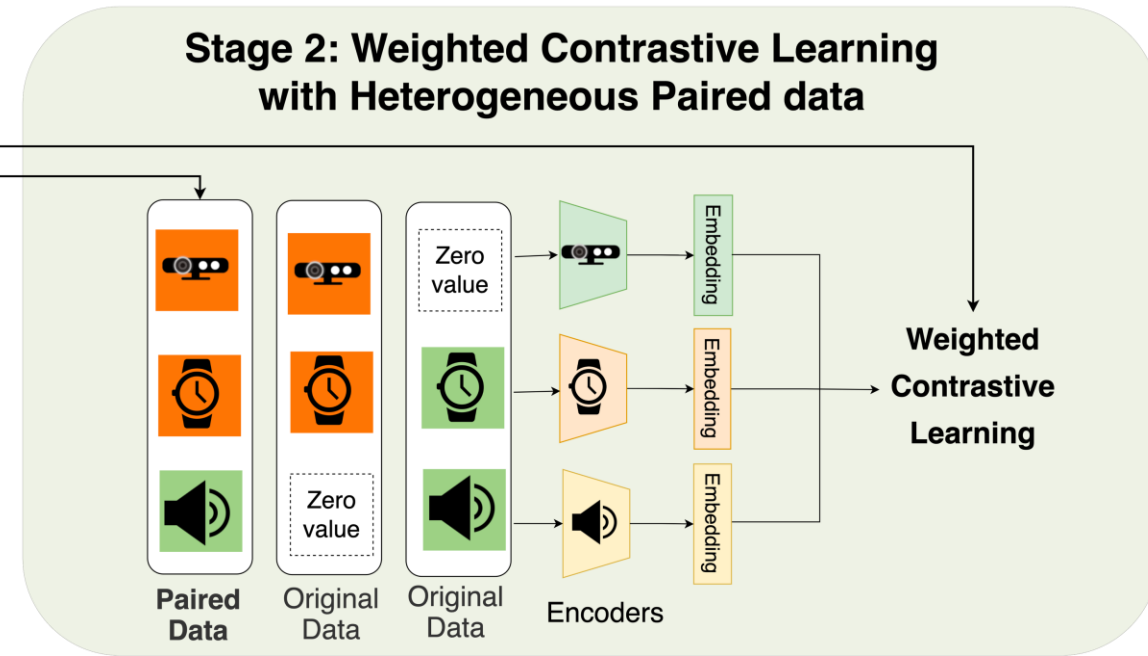


# MMBind: System Overview

## ➤ Construct Pseudo-Paired Data



## ➤ Learning with Heterogeneous Paired Data

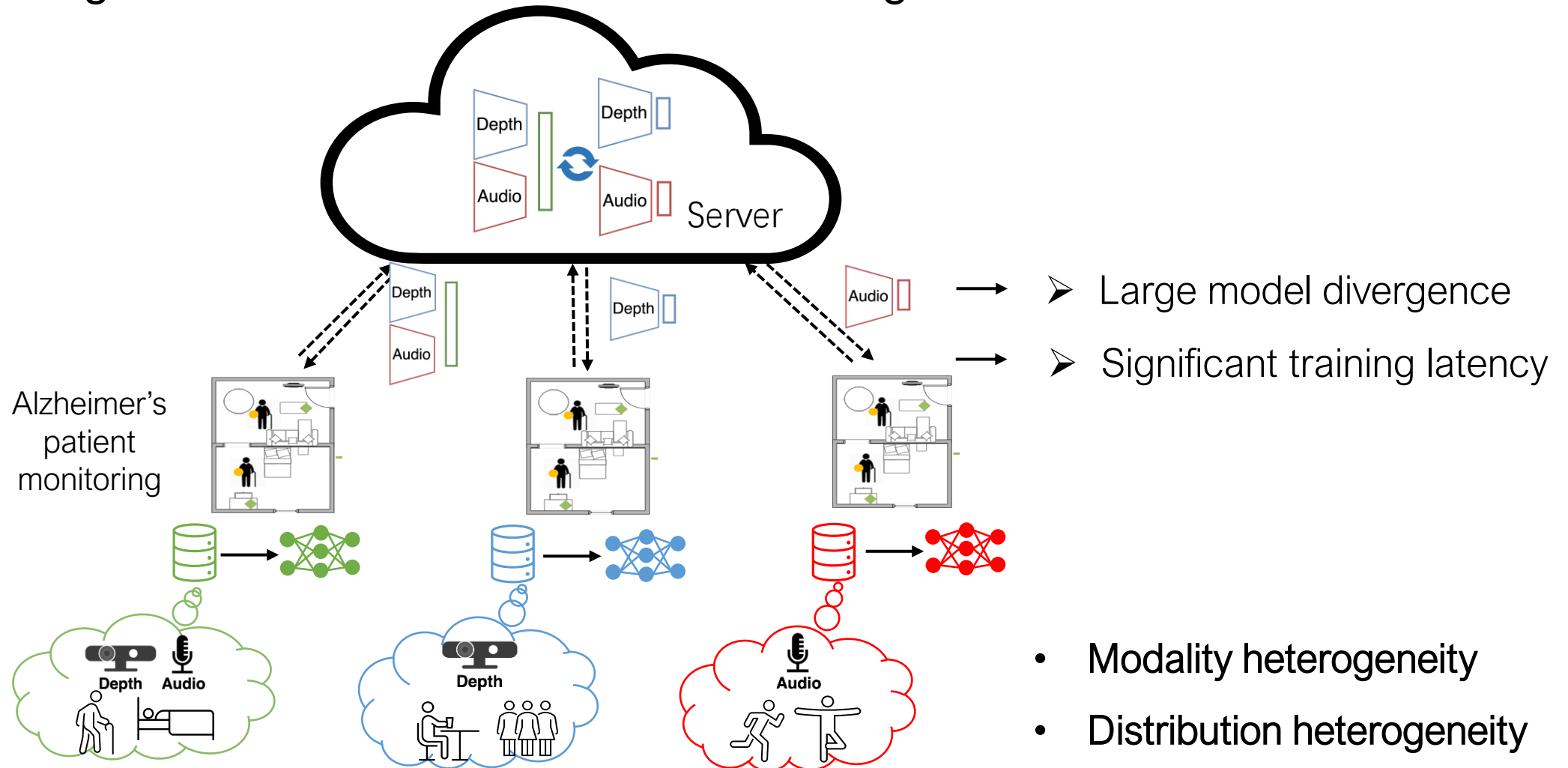


Imperfect pairing

- Data of different modalities observing similar events can be effectively used for multimodal training.
- Generate a **foundational multimodal dataset** for IoT applications

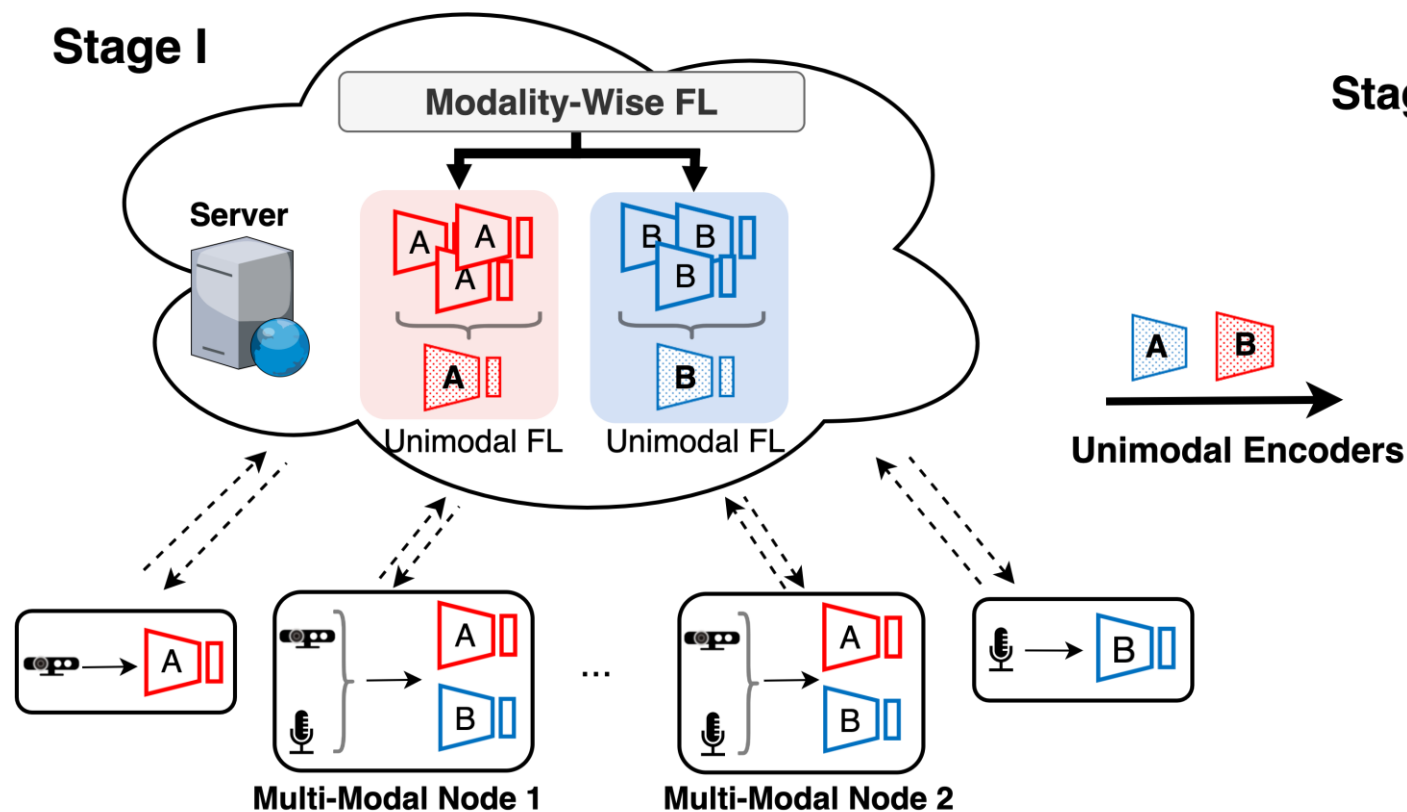
# Distributed Model Training after Deployment

## ➤ Challenges of Multi-Modal Federated Learning



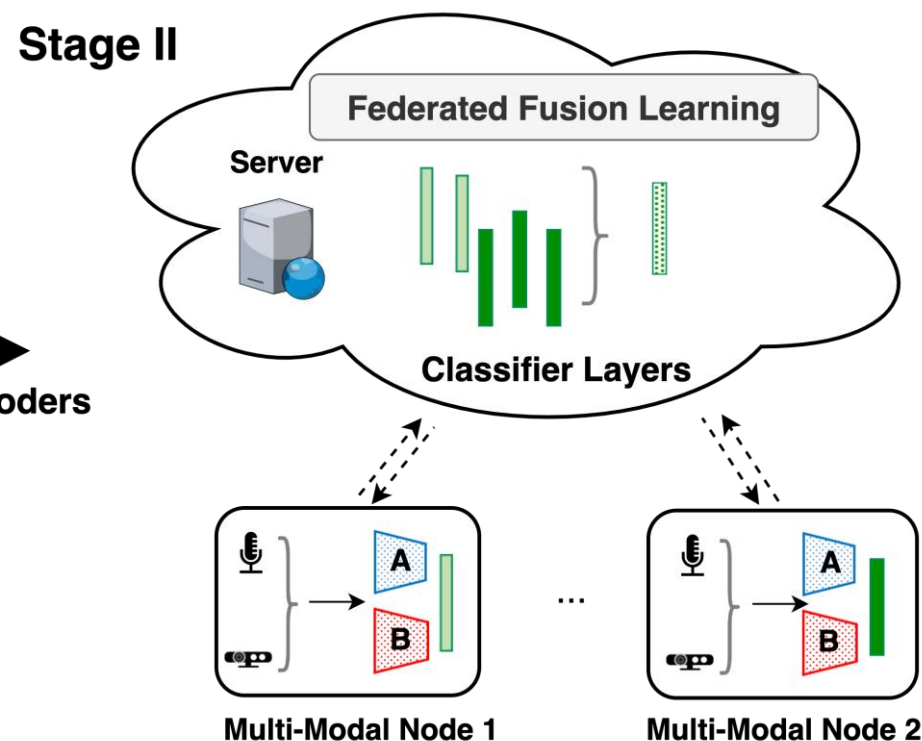
# A Two-Stage Framework for Multi-Modal FL

## ➤ Modality-Wise Federated Learning



- Collaboratively train **unimodal encoders**

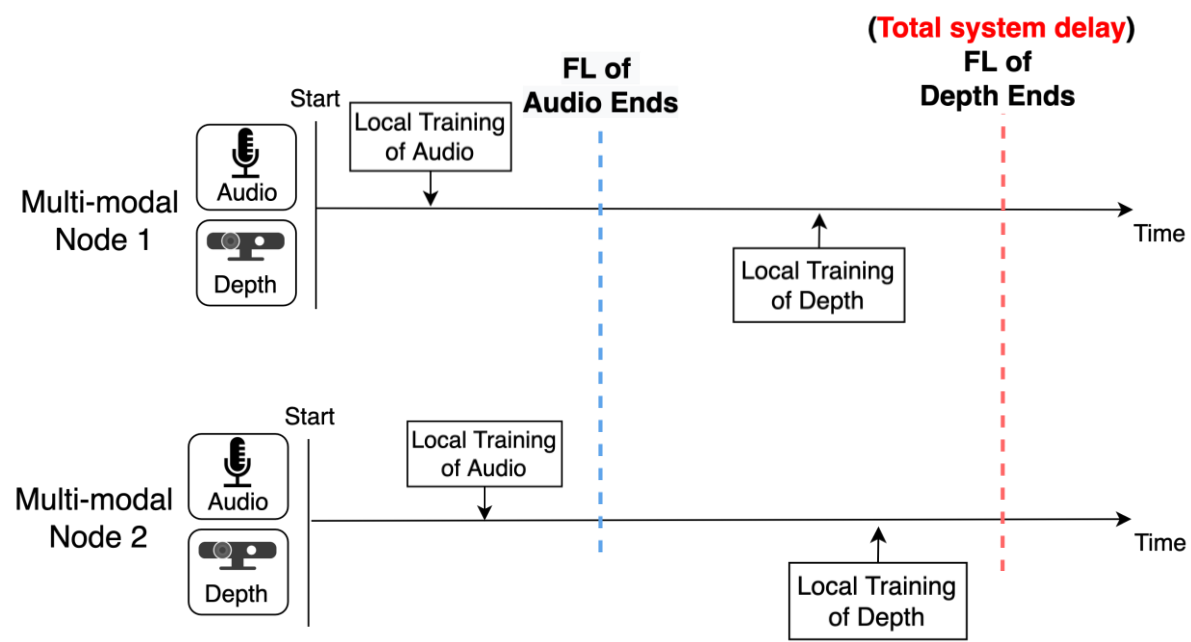
## ➤ Federated Fusion Learning




- Collaboratively train the **multi-modal classifier**

# Reducing Training Latency

## ➤ Imbalanced Training Delays




## ➤ Balance-Aware Resource Allocation



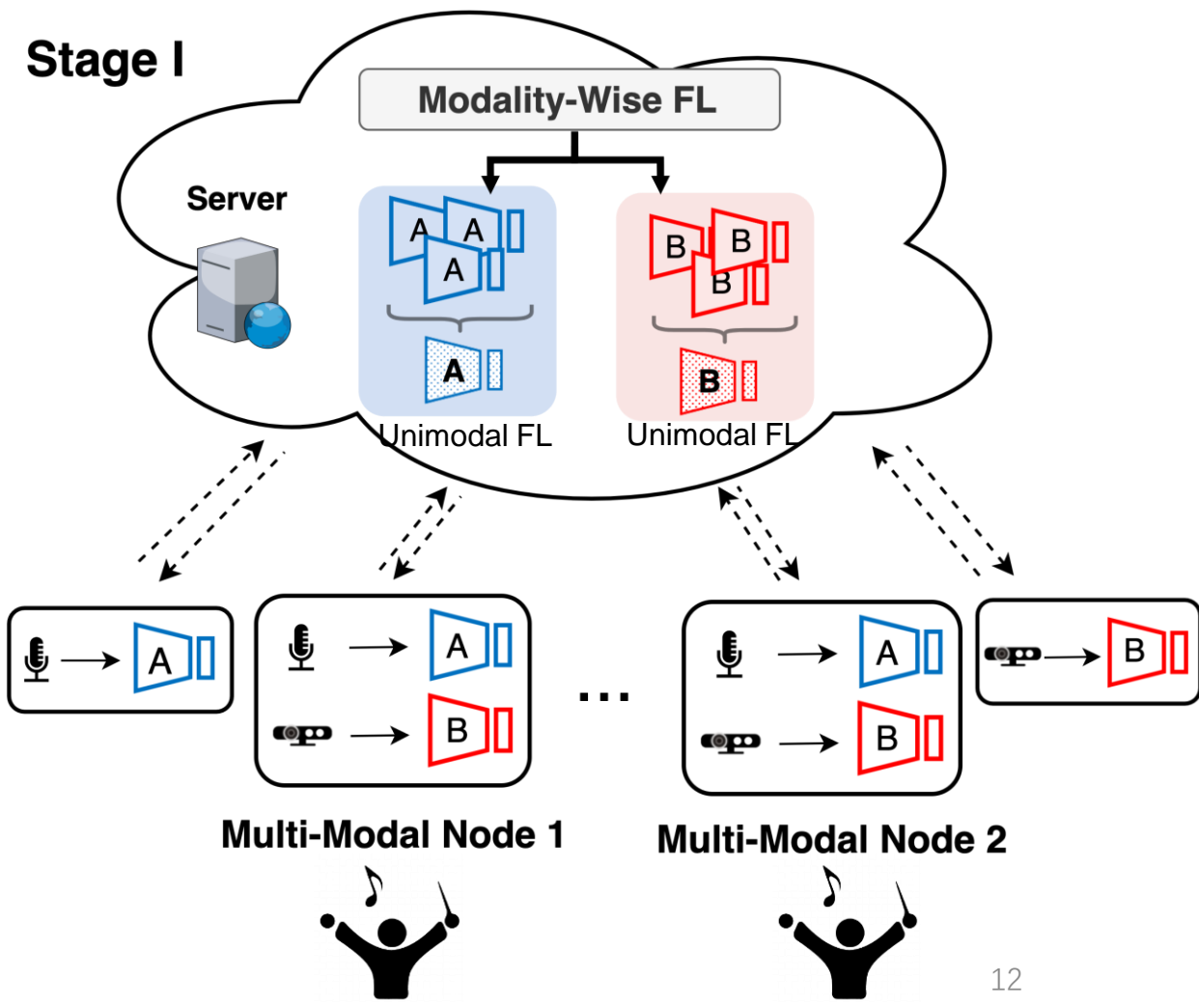
Audio

Less resources



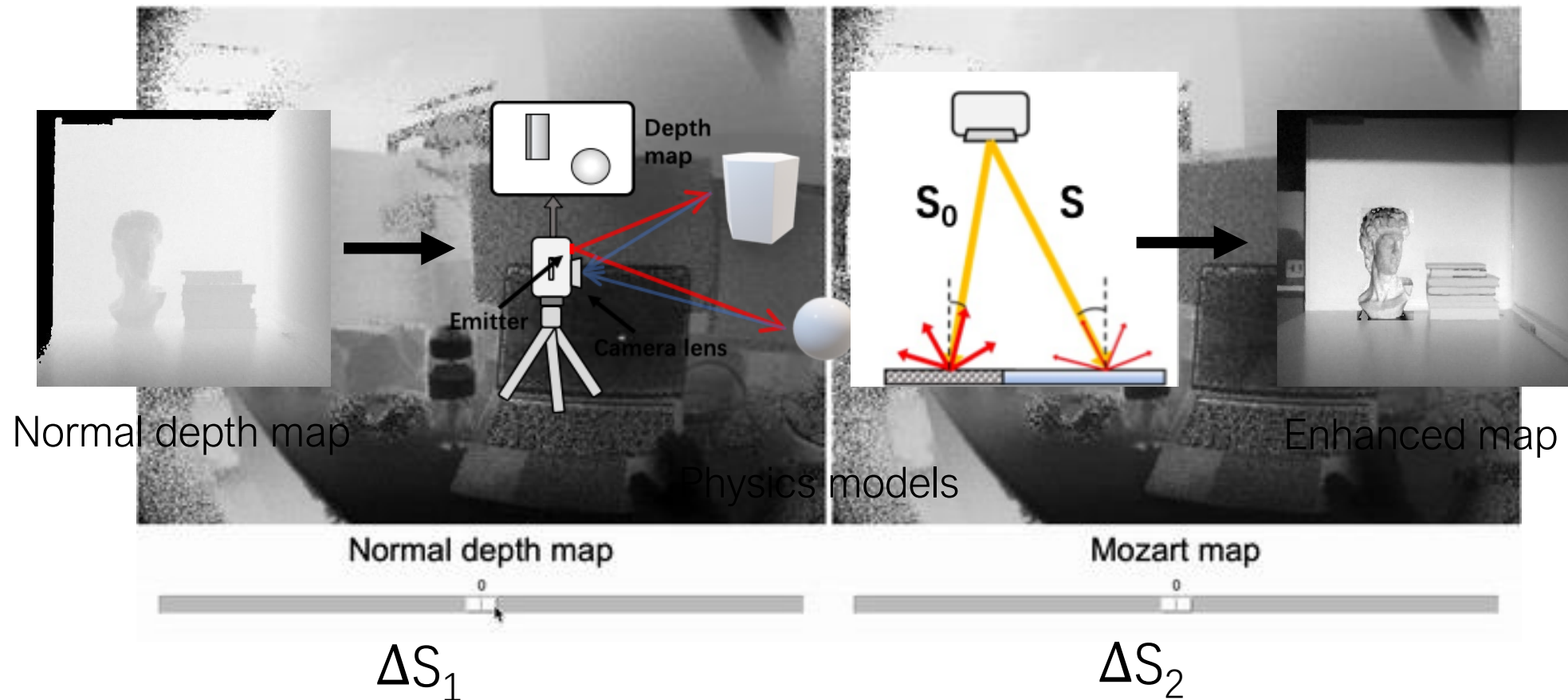
Depth

More resources



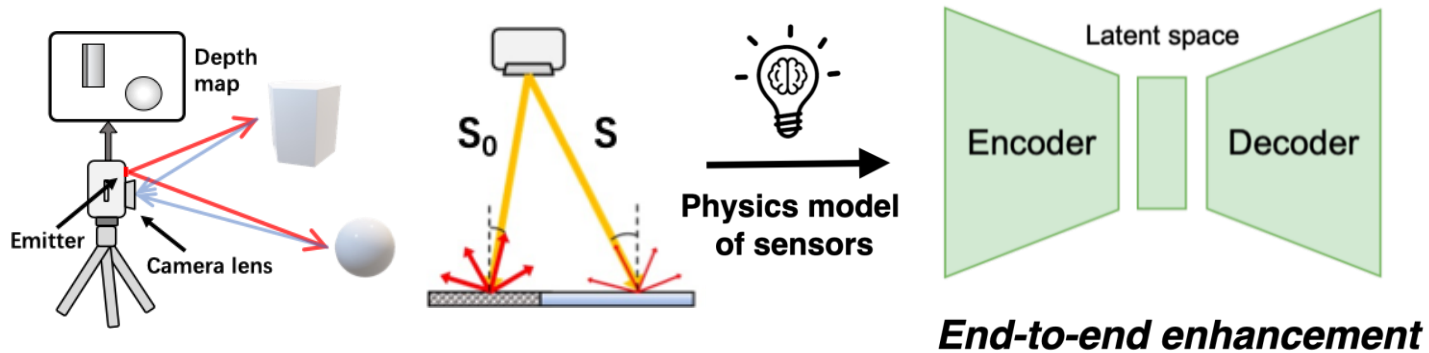
# Physics-Strengthened AI for Robust Sensing

- Enhancing ToF Depth Sensing with Lambertian Reflection Model



# Physics-Strengthened AI for Robust Sensing

- Integrate First-principle Model with ML



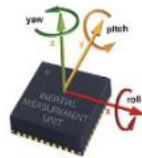
- Enhancing Mobile Sensing



Microphone



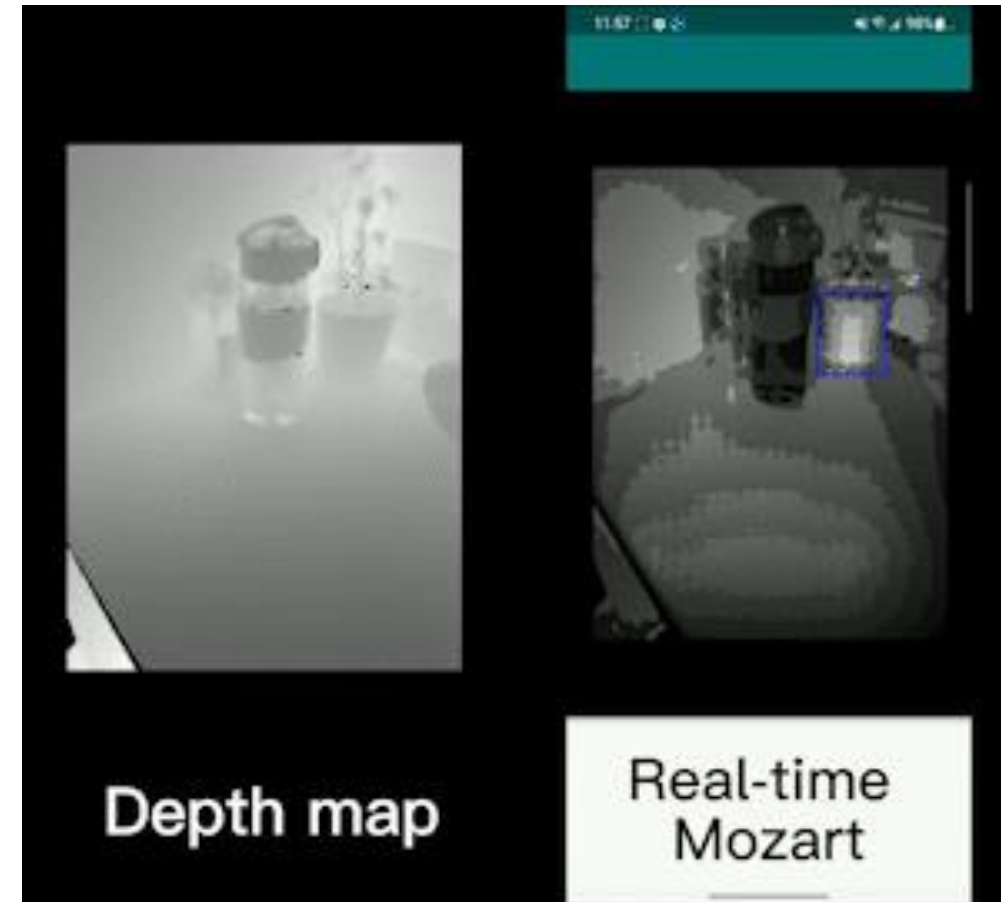
mmWave Radar



IMU



PPG

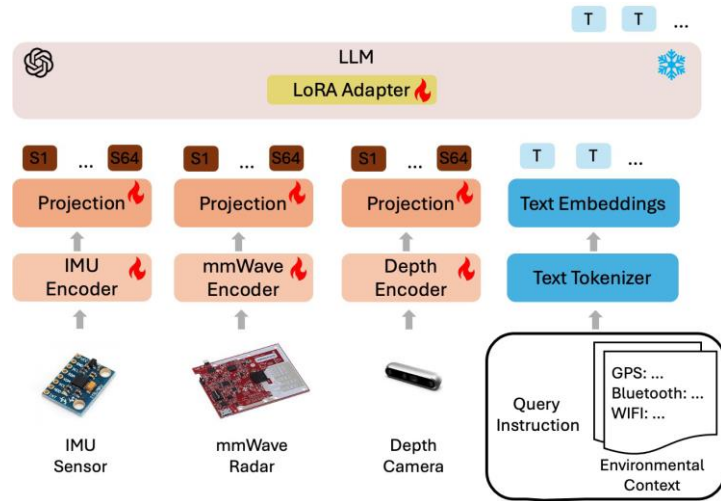




# Embedded AI Systems

## ➤ Tackling real-world data and system challenges

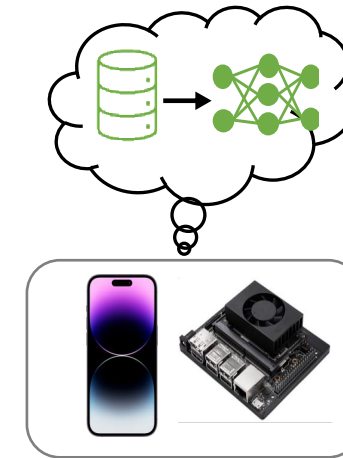
### ➤ Ongoing Works



LLMs for sensing

Activity \ Hour	Sleeping	Watching TV	...	Having a meal
00:00 - 01:00 am	✓			
...				
10:00 - 11:00 am		✓		
11:00 - 12:00 am				✓
...				

Weak labels



Efficient on-device inference

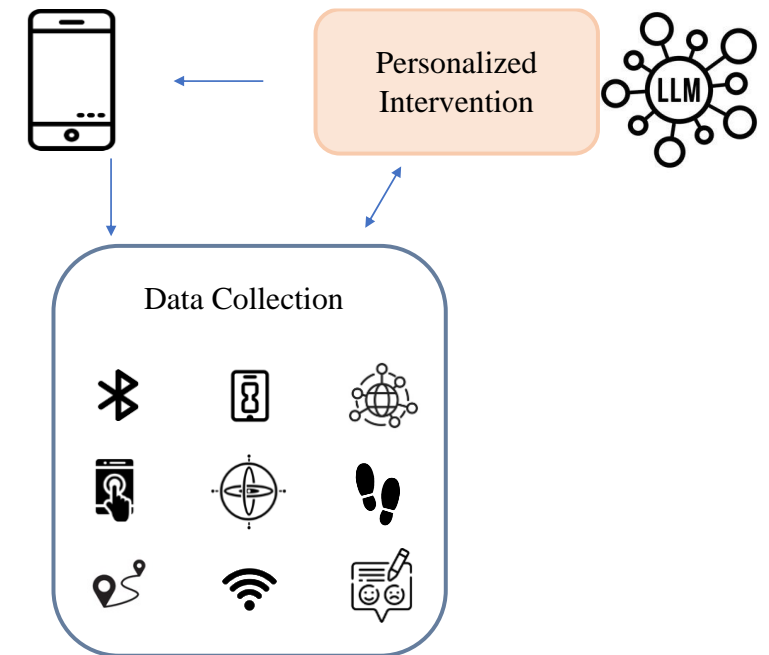
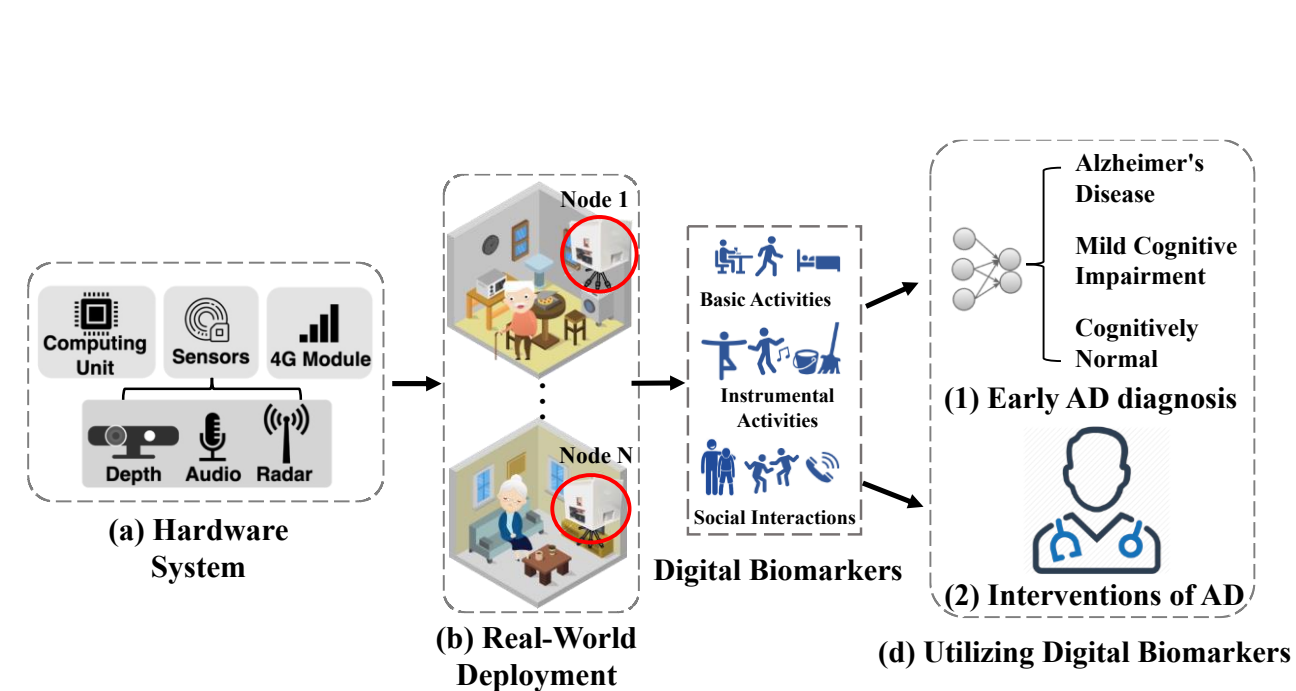


# Outline

➤ Embedded AI Systems

➤ **Smart Health**

# Smart Devices for In-home and Community-based Healthcare



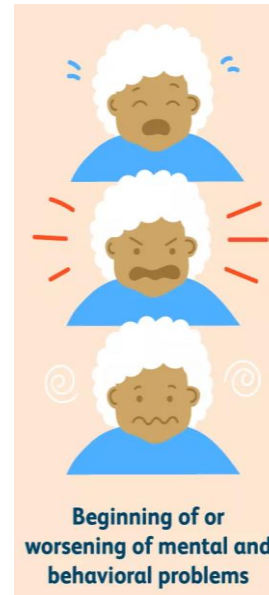
➤ **Multimodal Sensor Systems for Alzheimer's Monitoring**

➤ **LLM-Powered Mobile Intervention Systems**

# Alzheimer's Disease (AD)

## ➤ A Global Health Challenge

Progressive  
Degenerative  
Irreversible



## ➤ Current Diagnosis Approaches



Screening test

Interview



MRI test

In 2024, over **55 million people** worldwide had Alzheimer's disease, which costs over **\$13,00 billion** for the managed healthcare system.

About **1/9** people aged 65 and older have Alzheimer's.

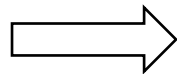
- Intrusive and labor-intensive
- About **75%** undiagnosed worldwide

# Digital Biomarkers for Early AD Diagnosis

- Leverage **AI and sensor devices** to capture physiological, behavioral and lifestyle symptoms of AD in natural living environments.



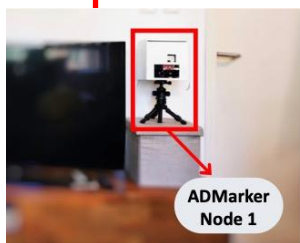
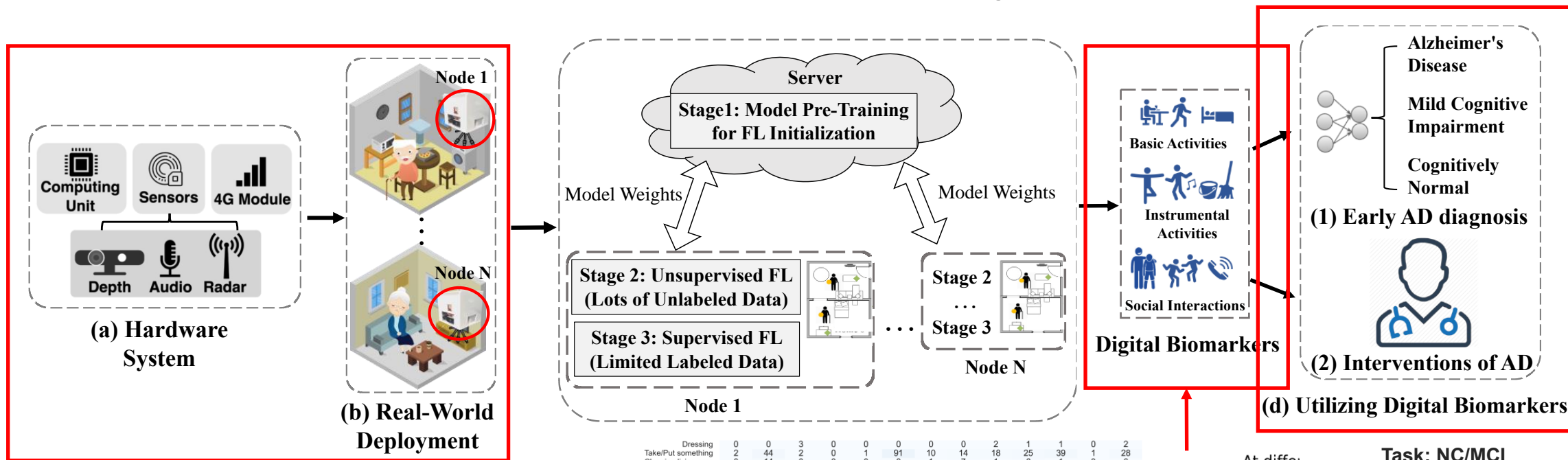
- Multi-dimensional
- Complex and dynamic



Need **multiple sensor modalities**

# ADMarker: System Overview

- An end-to-end system for detecting multi-dimensional AD digital biomarkers in home environments.



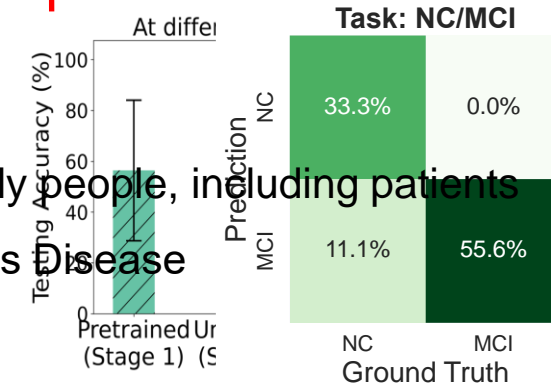
Daily Living Activities	Dressing	0	0	3	0	0	0	0	0	2	1	1	0	2
	Take/Put something	2	44	2	0	1	91	10	14	18	25	39	1	28
	Cleaning living area	0	14	0	0	0	0	1	7	1	8	1	3	6
	Grooming	2	16	0	2	4	10	0	6	2	10	16	14	12
	Wiping hands	0	18	11	0	1	1	0	2	4	2	1	0	5
	Drinking	9	6	3	0	8	9	7	1	6	12	9	4	17
	Eating	61	164	219	3	277	103	21	2	54	47	160	11	65
	Smoking	0	0	0	0	0	0	0	0	0	0	0	0	0
	Sneezing/Coughing	0	2	0	0	0	0	1	0	0	1	19	0	1
	Writing	0	0	0	0	0	1	0	0	33	0	0	0	0
	Watching TV	209	103	0	0	0	22	0	0	100	0	135	29	324
	Using phone/Phone call	0	34	0	0	0	40	0	4	300	7	245	3	53
	Exercising	0	14	0	1	0	38	2	0	1	46	1	0	149
	Talking with others	38	9	96	0	4	37	1	0	117	20	6	22	4
	Stretching	0	6	17	0	0	0	0	0	0	8	108	0	0
Other static activities	Other static activities	85	87	421	249	1573	55	111	0	0	0	0	0	0
	Other non-static activities	31	55	29	13	30	33	44	31	56	41	87	9	120

Basic Body Movements	Walking	5	16	1	0	28	55	13	56	5	54	47	10	27
	Sitting	384	516	794	262	435	303	142	242	740	183	651	177	610
	Standing	4	35	2	4	24	77	34	45	10	116	61	12	195
	Lying	43	0	0	0	1400	4	0	0	0	0	0	0	239
	Moving in/out of chair	1	5	3	2	10	1	5	4	5	0	12	0	15
		AD	AD	AD	AD	AD	MCI	MCI	MCI	MCI	Normal	Normal	Normal	Normal

Subjects

Over 100 elderly people, including patients with Alzheimer's Disease



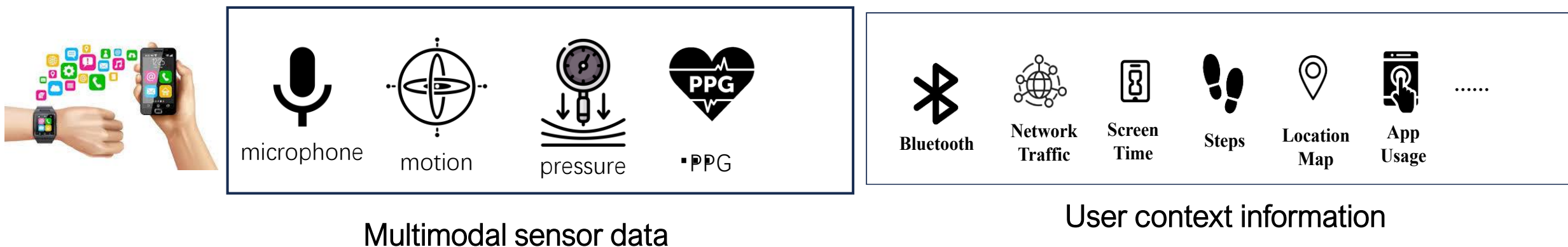
# A Real-World Demo



**In collaborations with  
CUHK Prince of Wales  
Hospital and HKU for  
AD behavior monitoring.**

# LLM-Powered Mobile Sensing for Personalized Intervention

## ➤ Mobile devices



## ➤ Large language models (LLMs)

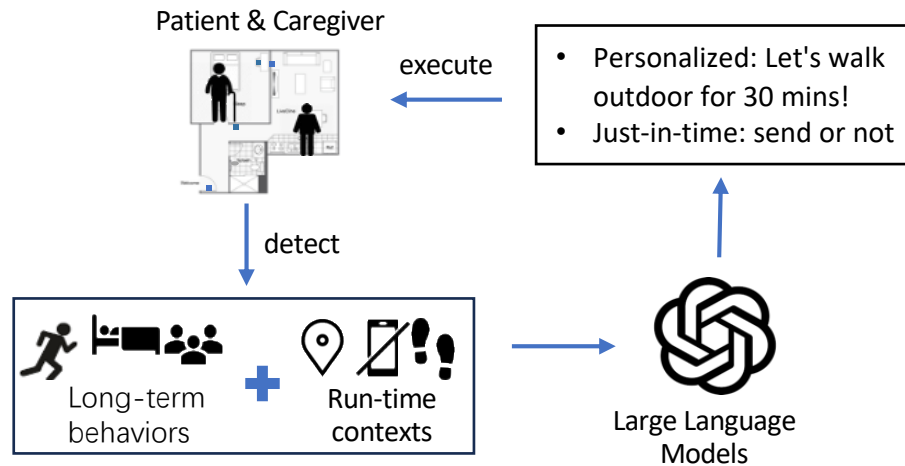


- **Reasoning** ability: interpret heterogeneous information to enable complex sensing tasks
- **Generative** ability: personalized user suggestion/recommender



# LLM-Assisted Mobile Sensing for Personalized Intervention

## ➤ Deliver Personalized and Just-in-Time Intervention

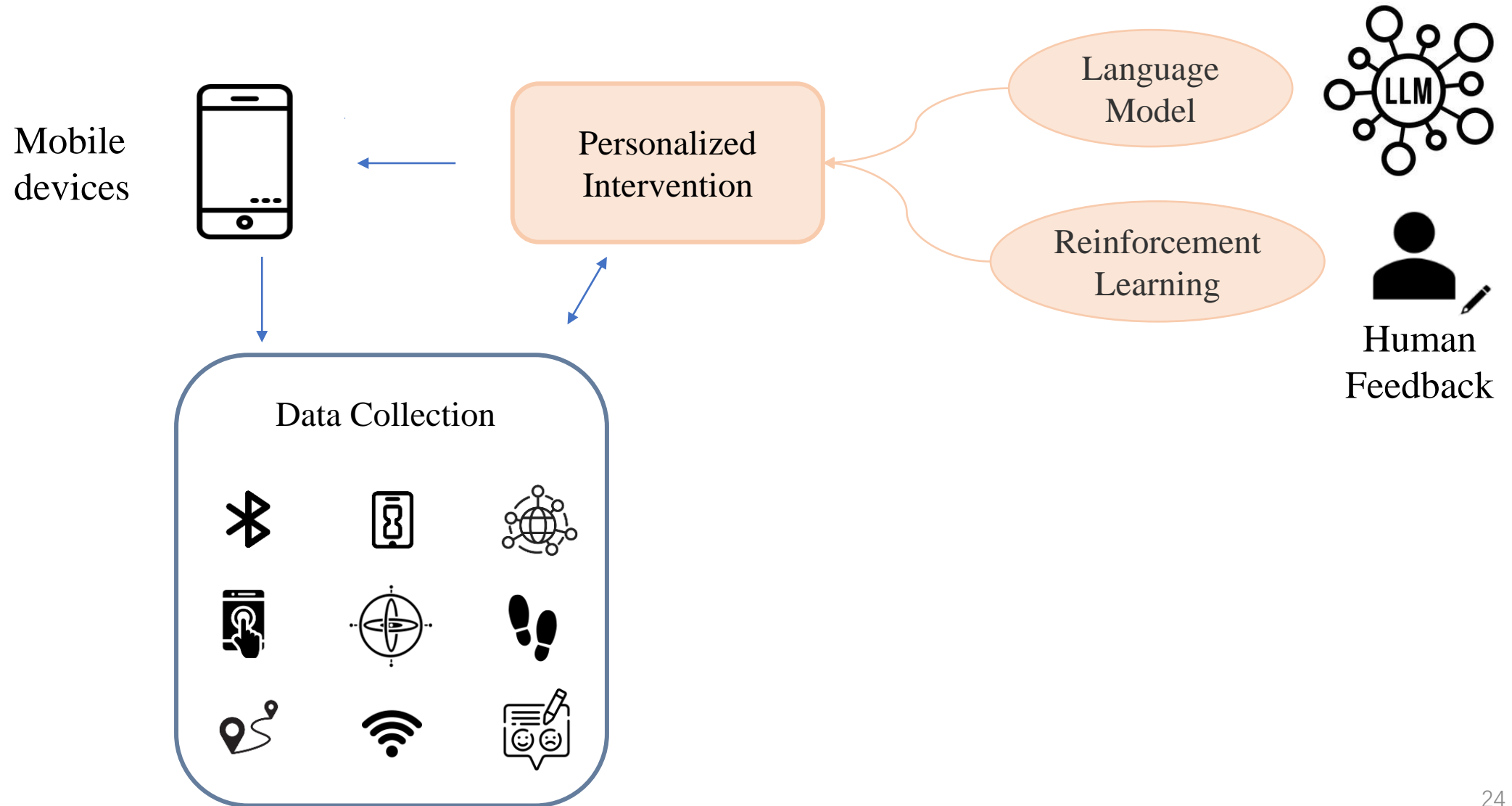


- **Personalized:**
  - E.g., frequent reminder for physically inactive users
- **Just-in-time:**
  - no reminders when “working” or “sleeping”





# System Overview



# Demo



香港科技大學  
THE HONG KONG UNIVERSITY OF  
SCIENCE AND TECHNOLOGY

## ➤ MobiBox APP

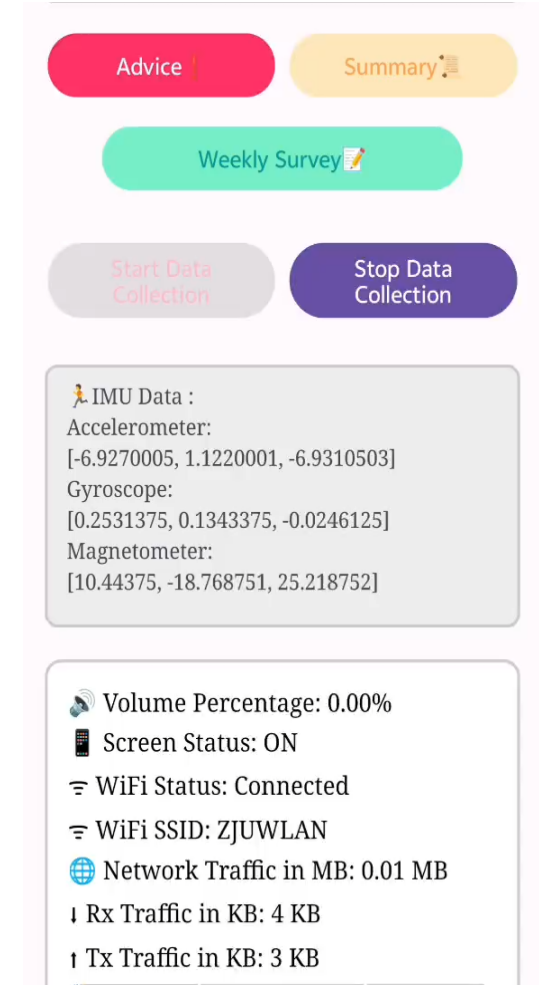
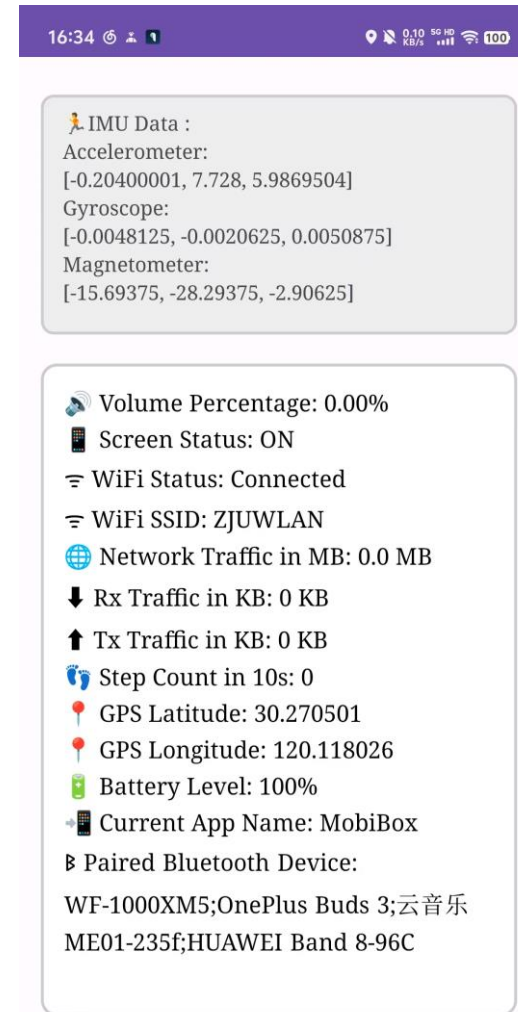
### ➤ Data Collection

IMU (Accelerometer / Gyroscope / Magnetic),  
GPS, Screen & App Usage, Battery Status,  
Bluetooth connection, Network Traffic, Step  
Count, Wi-Fi Connections.

### ➤ Daily & Weekly Activity Summary

### ➤ Bump-up **Intervention Suggestion**

**In collaborations with CUHK and HKU for  
AI-powered dementia intervention.**



# Summary

## ➤ Embedded AI systems

- Tackling real-world data and system challenges

## ➤ Building and deploying end-to-end AIoT systems for smart health

- Working with interdisciplinary teams and medical researchers

# Thanks!

- Xiaomin Ouyang
- Assistant Professor @ HKUST CSE
- [xmouyang@cse.ust.hk](mailto:xmouyang@cse.ust.hk)
- <https://xmouyang.github.io/>



Visit My Page



My WeChat Account



香港科技大學

THE HONG KONG UNIVERSITY OF  
SCIENCE AND TECHNOLOGY