

MetaSense

Few-Shot Adaptation to Untrained Conditions
in Deep Mobile Sensing

Taesik Gong Yeonsu Kim Jinwoo Shin Sung-Ju Lee

ACM SenSys₂₀₁₉

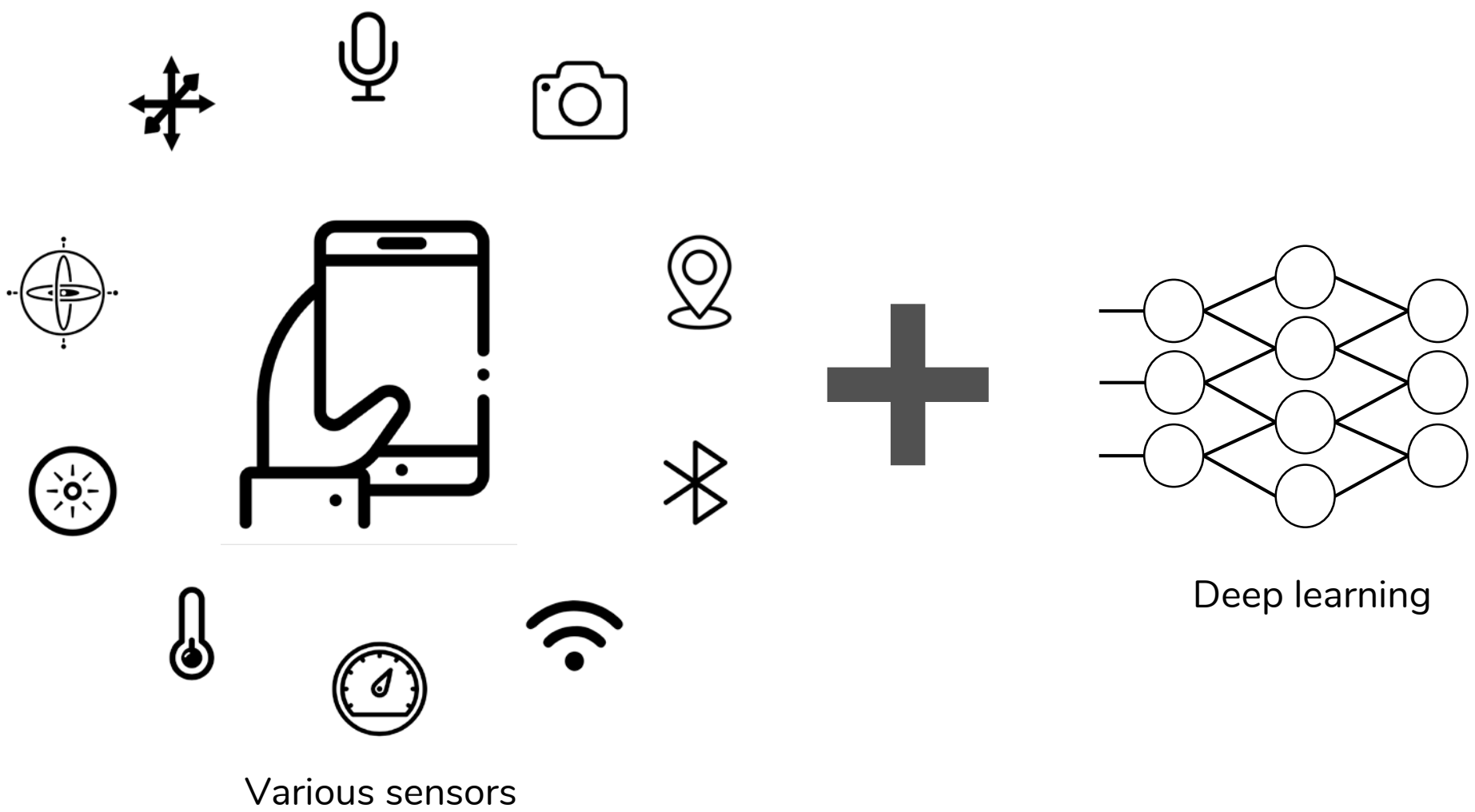


The era of mobile sensing

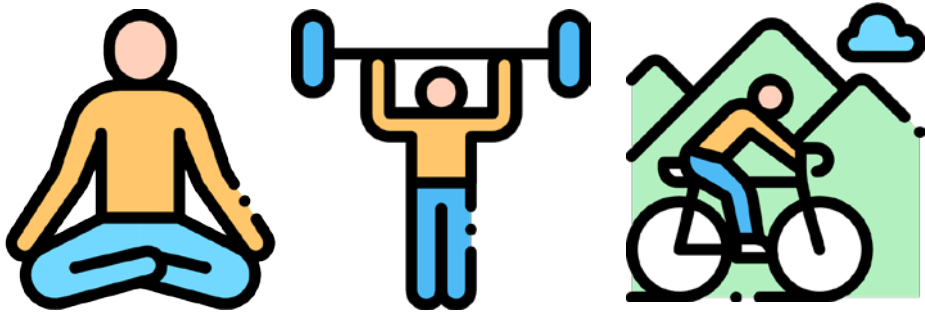


Various sensors

The era of mobile sensing



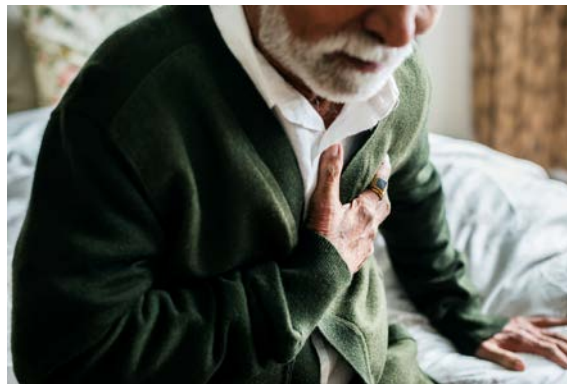
The era of mobile sensing



Activity recognition



Emotion recognition



Health care

The era of mobile sensing



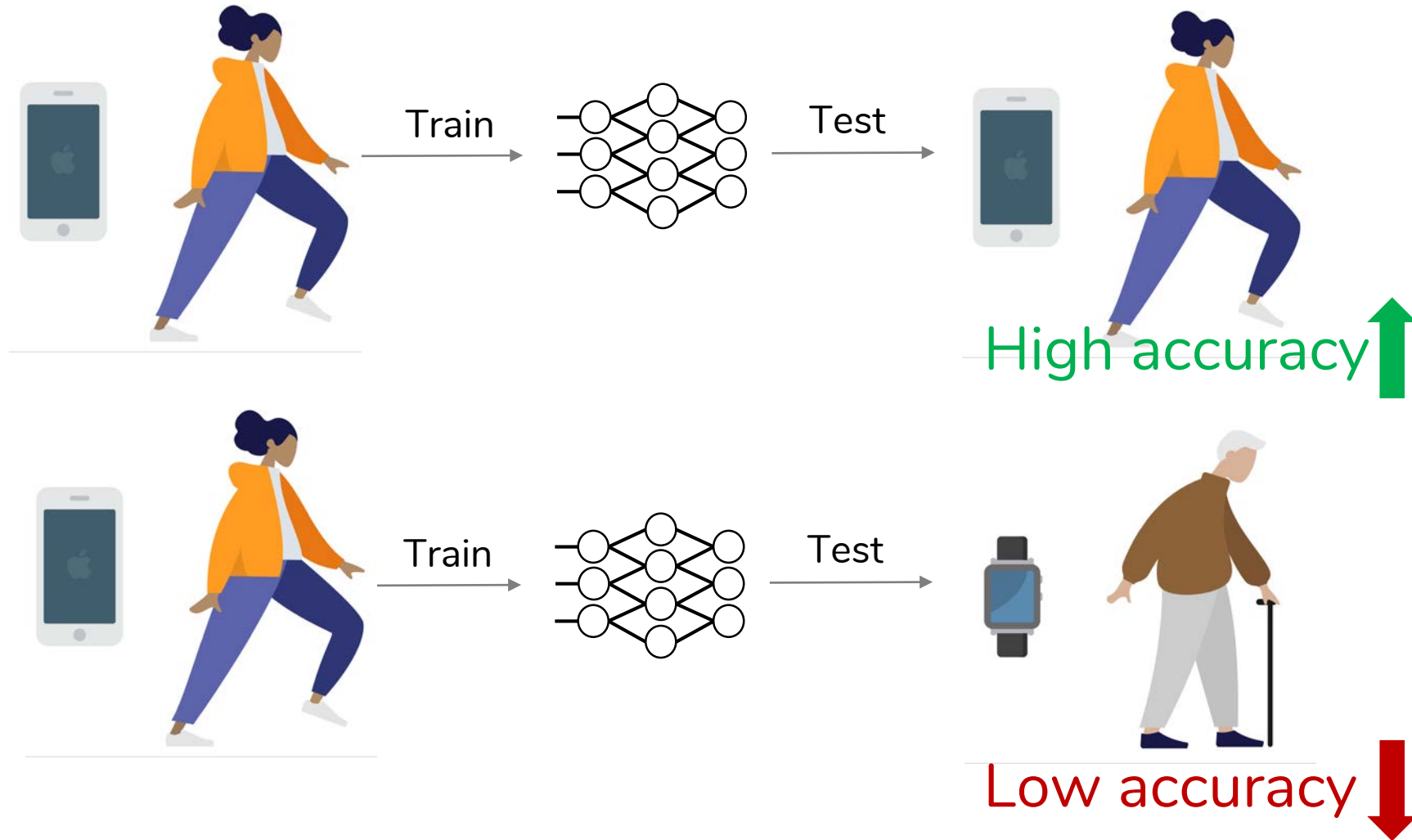
Activity recognition

Emotion recognition



Health care

Performance challenge of mobile sensing

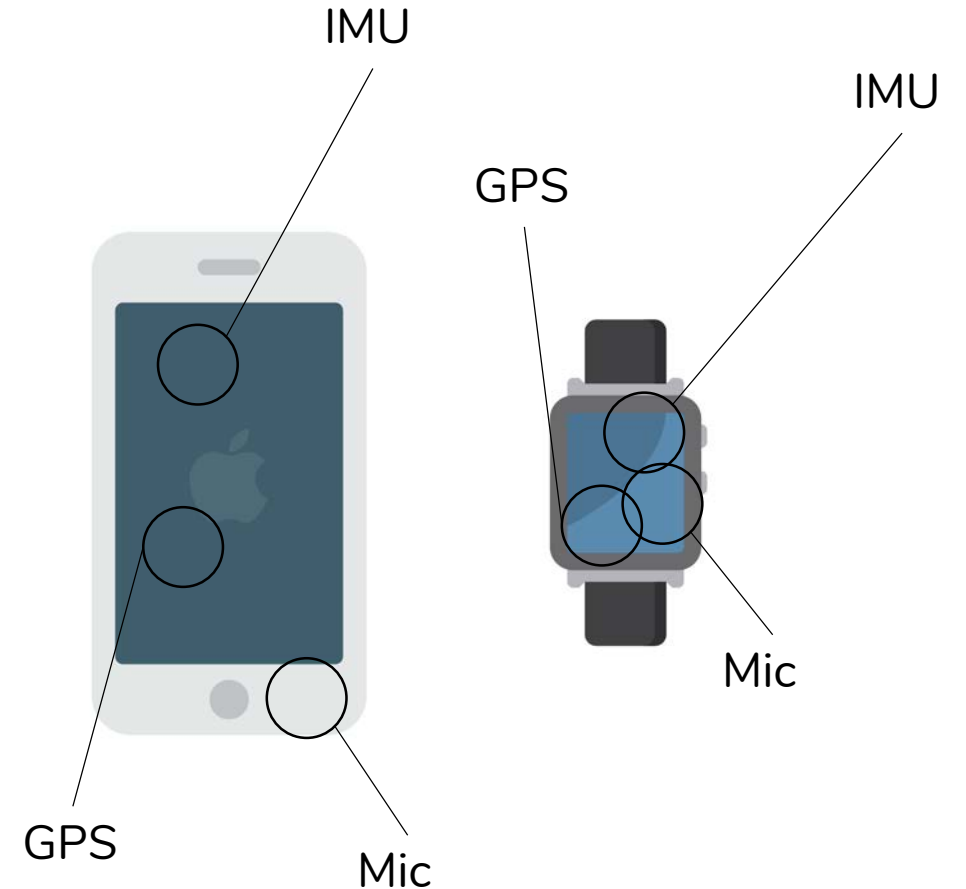


Different *individual conditions*

Users have different behaviors & physical conditions



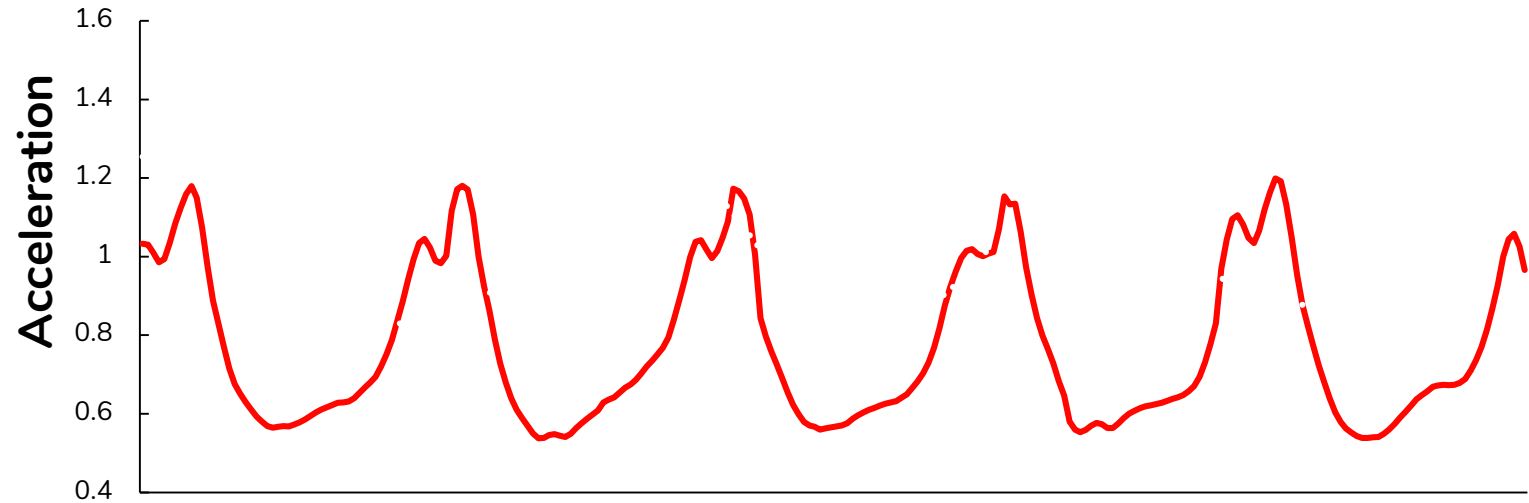
Devices have different sensor specs/location



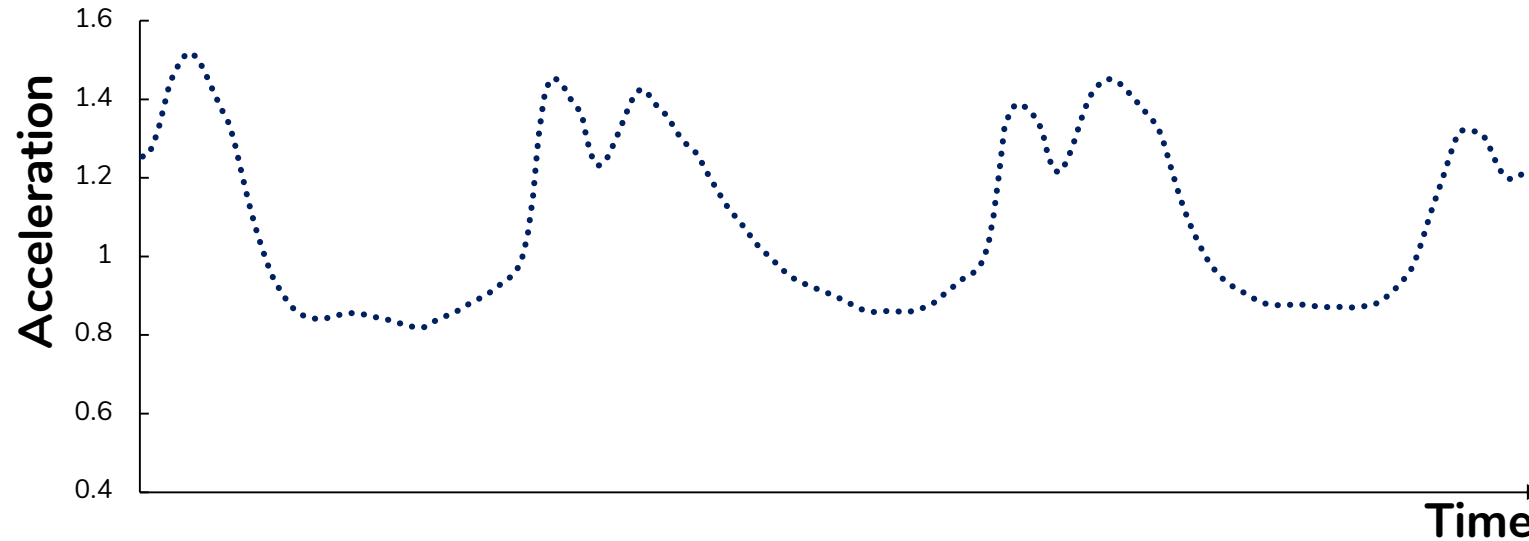
Individual conditions make inputs different



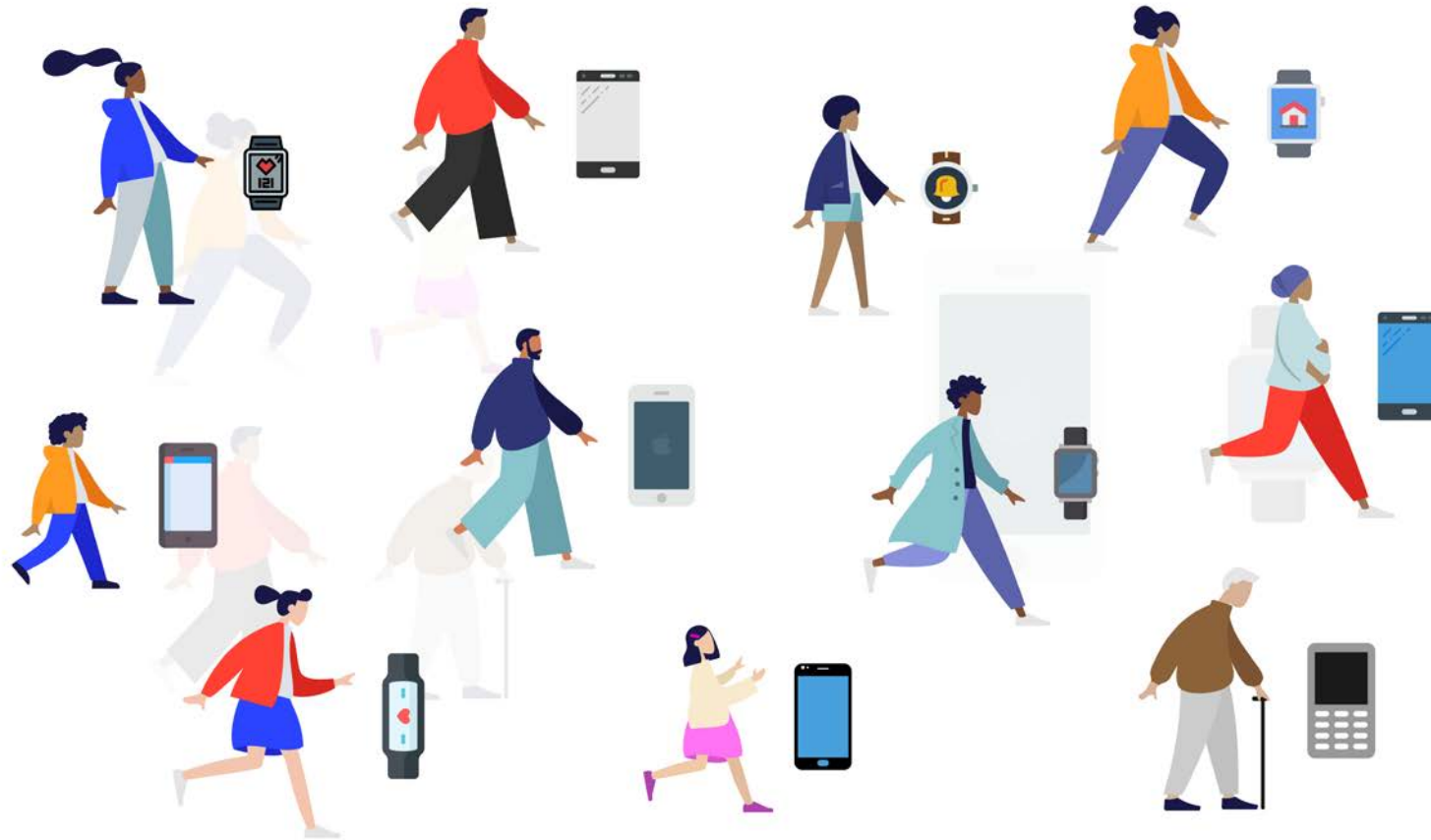
Walking



Walking



Countless individual conditions



Training on all the conditions is **infeasible**

Limitation of existing solutions

- Sensor calibration

- E.g., $\sqrt{Acc_x^2 + Acc_y^2 + Acc_z^2}$ to make orientation independent
- Targets a particular condition problem (e.g., sensor orientation only)
- Tailored to a specific sensor (e.g., IMU) or application (e.g., activity recognition)

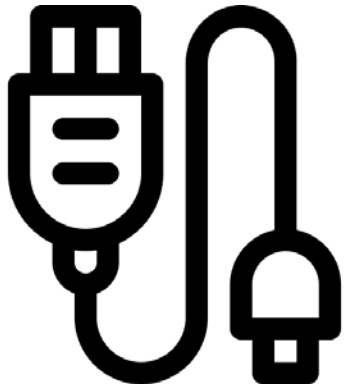
- Transfer learning with unlabeled target data

- Requires hundreds of target data
- Sometimes performs worse than without it^[*]

[*] Khan, et al. "Scaling human activity recognition via deep learning-based domain adaptation." *IEEE PerCom* '18.

Is there a general solution to overcome individual conditions with few data?

MetaSense: Few-Shot Adaptation to Untrained Conditions in Deep Mobile Sensing



Model & condition
agnostic

1 or 2

Requires few data



High accuracy



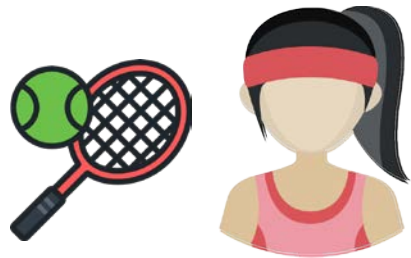
Rapid adaptation

Meta learning based few-shot adaptation to the target condition

One shot: one labeled sample per class

Meta learning? “learning to learn”

- Imitating the human’s ability of learning new concepts quickly

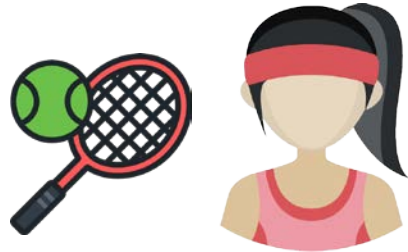


Tennis player

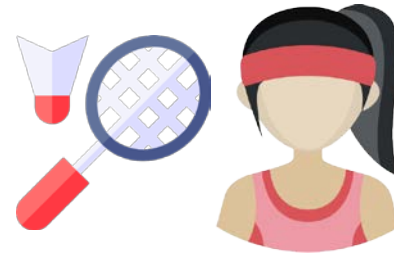


Meta learning? “learning to learn”

- Imitating the human’s ability of learning new concepts quickly



Tennis player



Badminton

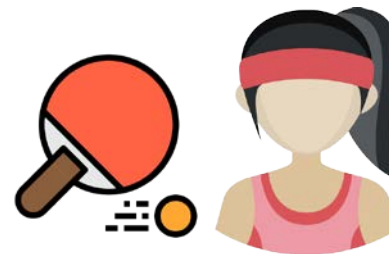
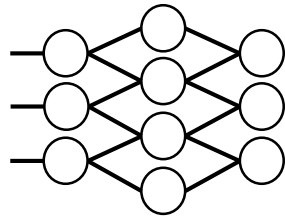


Table tennis

Meta learning? “learning to learn”

- Imitating the human’s ability of learning new concepts quickly



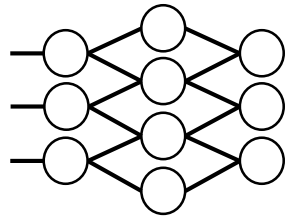
Base model

Trained on condition changes



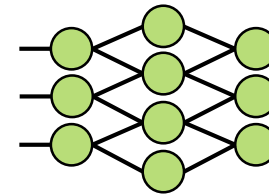
Meta learning? “learning to learn”

- Imitating the human’s ability of learning new concepts quickly

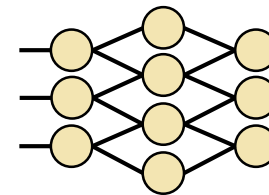


Base model

Trained on condition changes



Adapted model



Adapted model

Meta learning? “learning to learn”

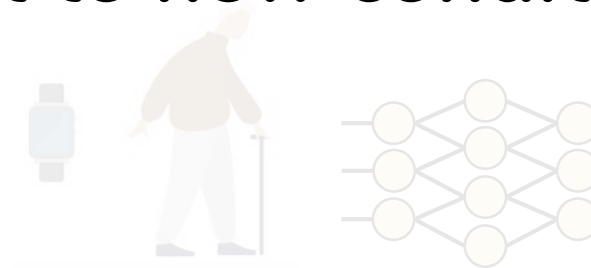
- Imitating the human’s ability of learning new concepts quickly

How to train the base model?

By **rehearsing conditions changes** while training,
the base model is trained in a way that
it **learns how to adapt to new conditions**

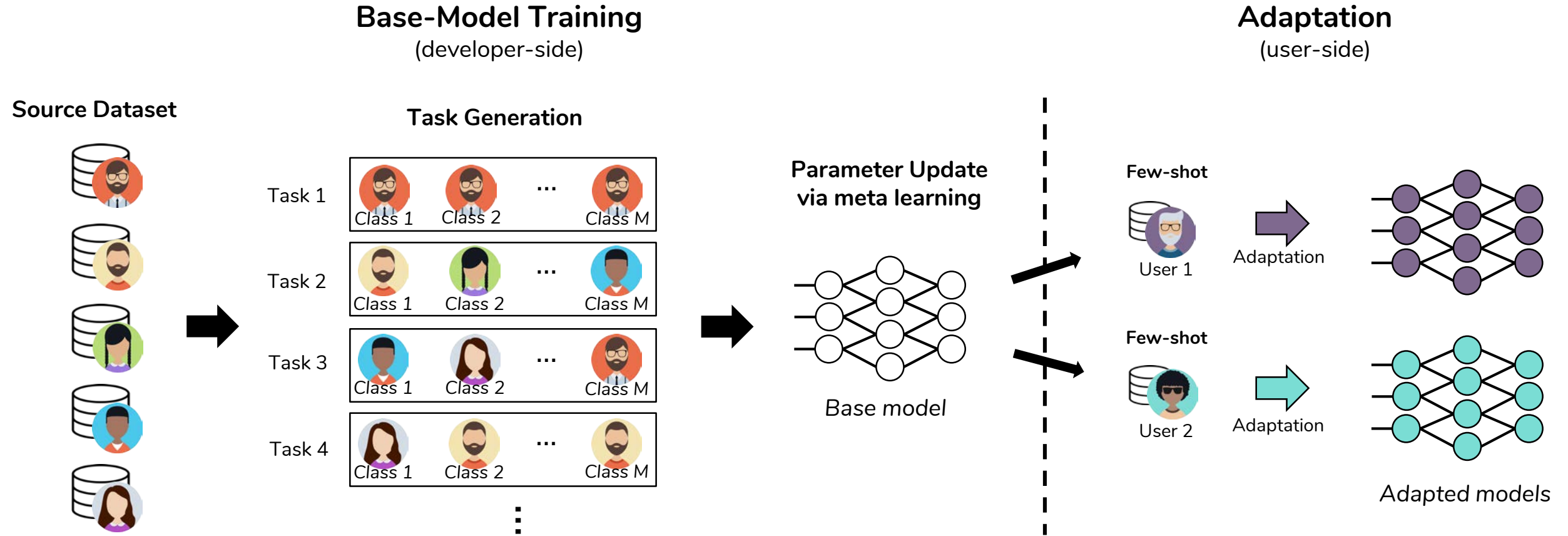
Base model

Trained on condition changes



Adapted model

MetaSense overview



Task generation in existing meta learning

Task: a single episode for training the model following the meta-objective

Task in traditional meta learning: encountering **new classes** that the model has never seen



How tasks are generated: **randomly** sampled classes from a **large** dataset (e.g., ImageNet)

Task generation for mobile sensing

Challenges & considerations:

- Countless individual conditions;
How to let the base model experience **diverse individual conditions**?
- Limited amount of dataset;
How to **efficiently** leverage the limited source dataset?
- Existing meta learning algorithms assume learning new classes;
Our goal is **adapting to new conditions**

MetaSense task generation

Task in traditional meta learning: encountering **new classes** that the model has never seen

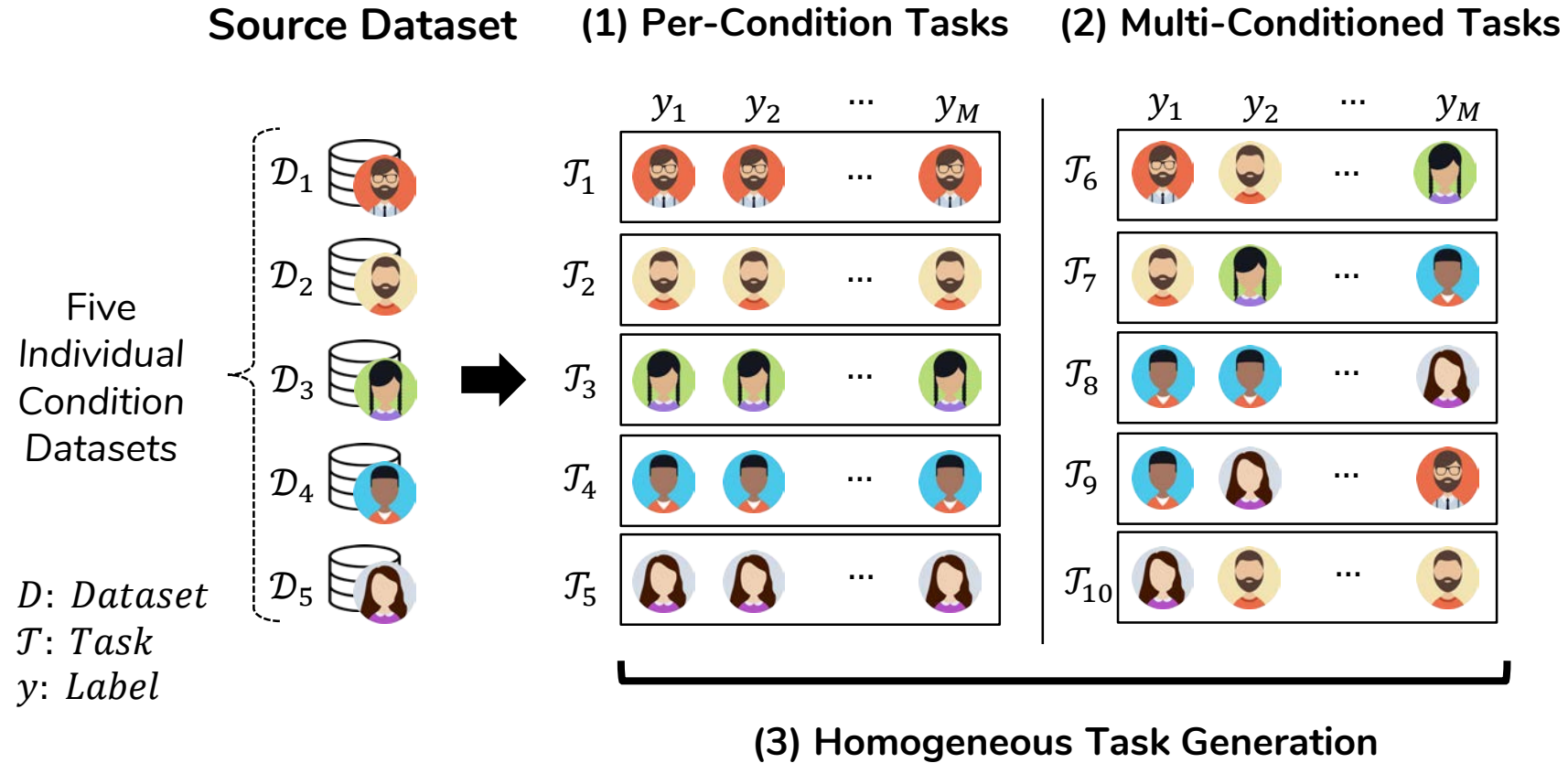
- randomly sampled classes from a large dataset

Task in MetaSense: encountering a situation where the base model performs in a **new condition**

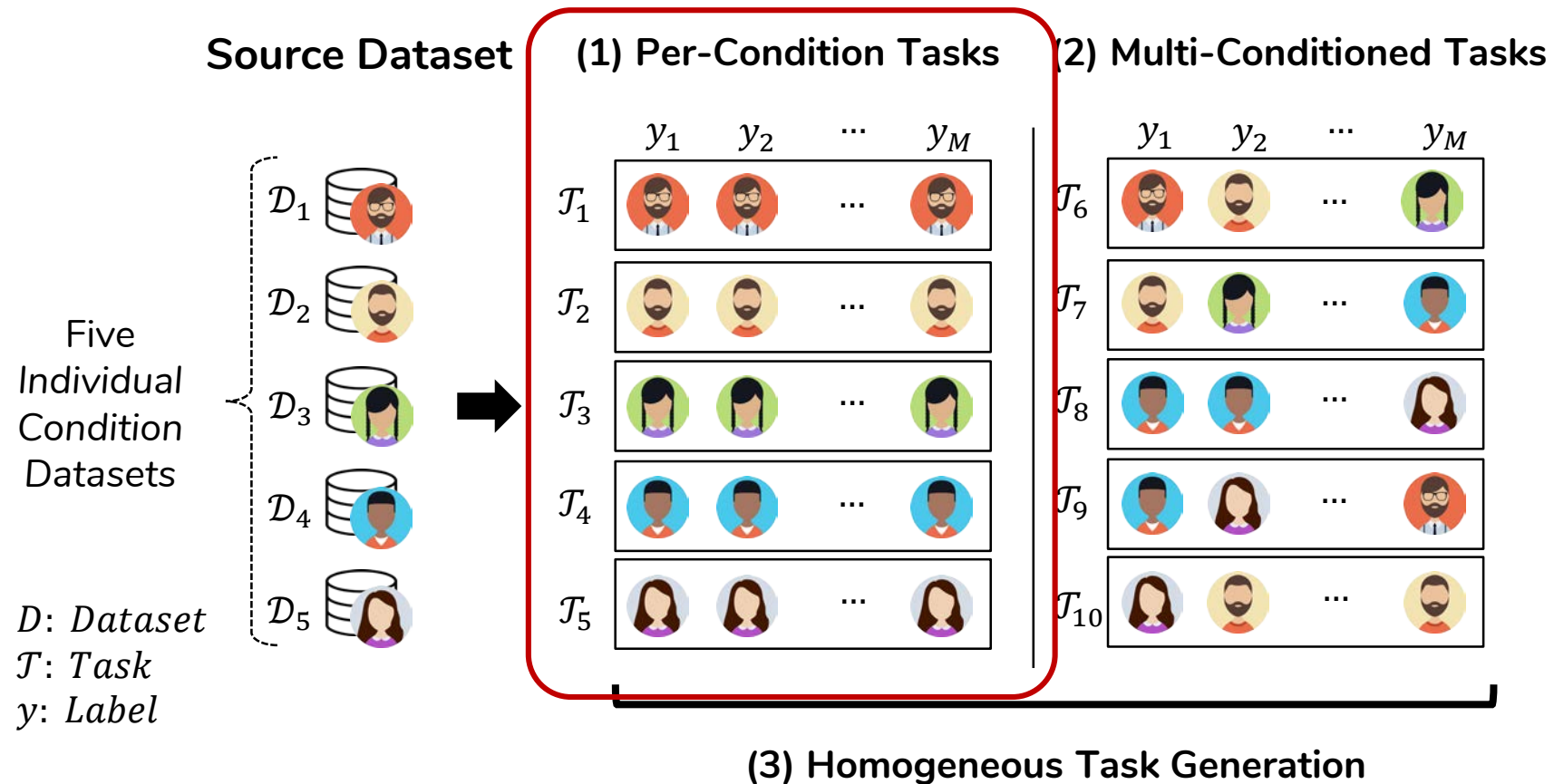
- should be diverse
- generated from limited data
- the target task has the same label set

Sol: Our three task generation strategies!

MetaSense task generation

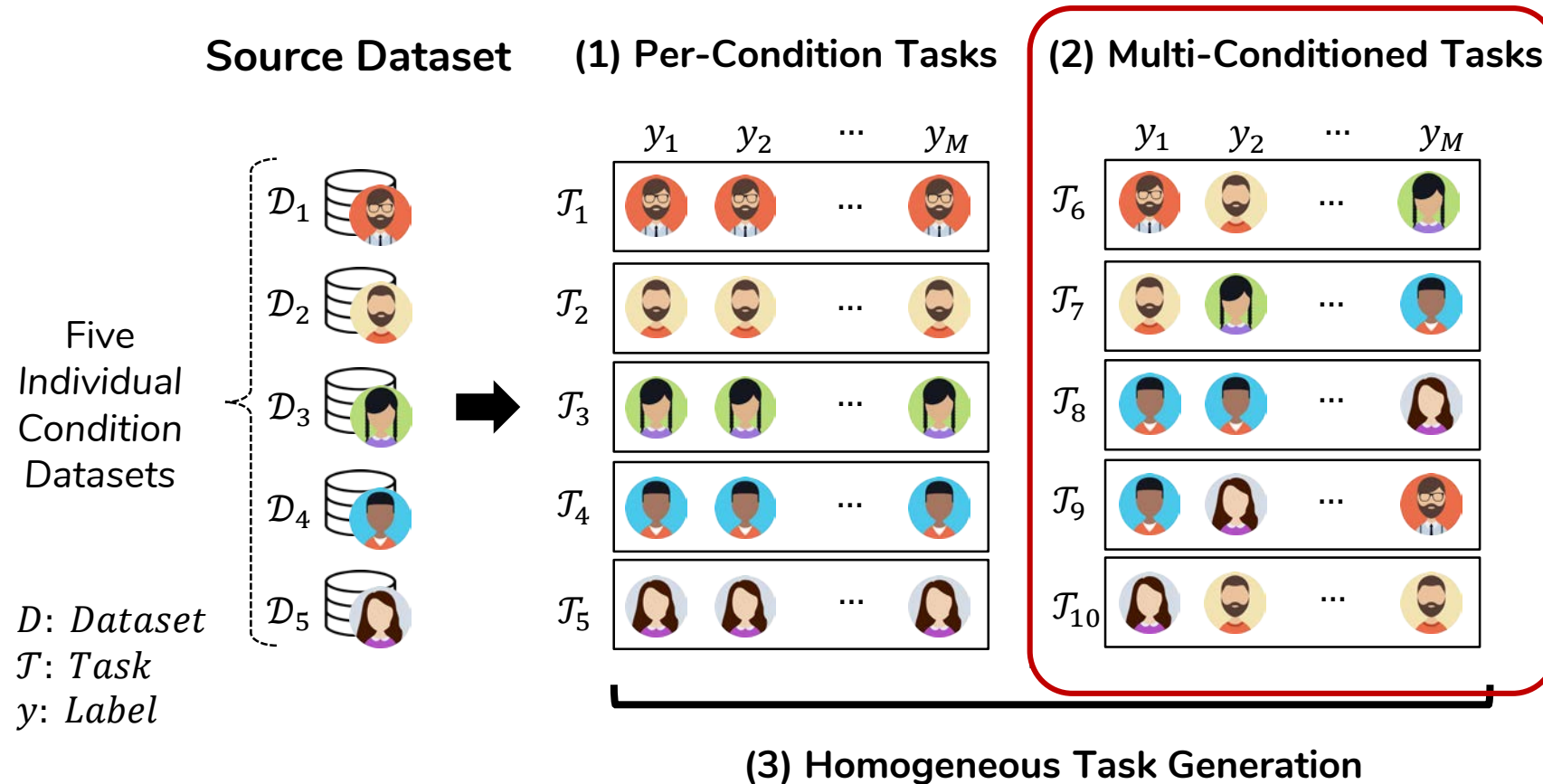


MetaSense task generation



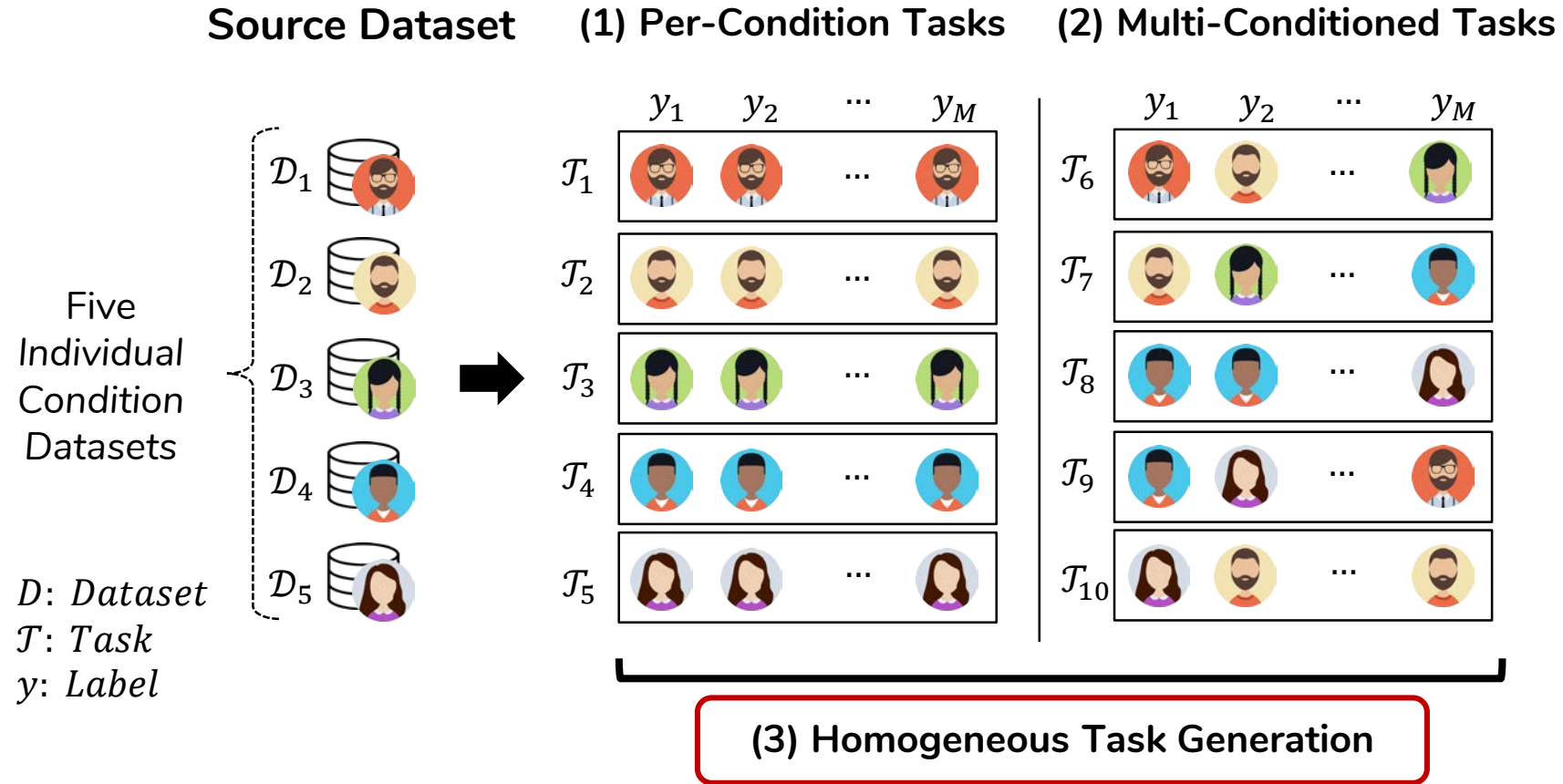
Let the base model experience **multiple real** individual conditions

MetaSense task generation



Make **diverse** tasks & **avoid overfitting** to per-condition tasks

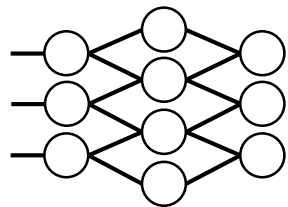
MetaSense task generation



Keep the label set to leverage the common knowledge

Training the base model

Few gradient steps (e.g., 10)
with few shots (e.g., 5)



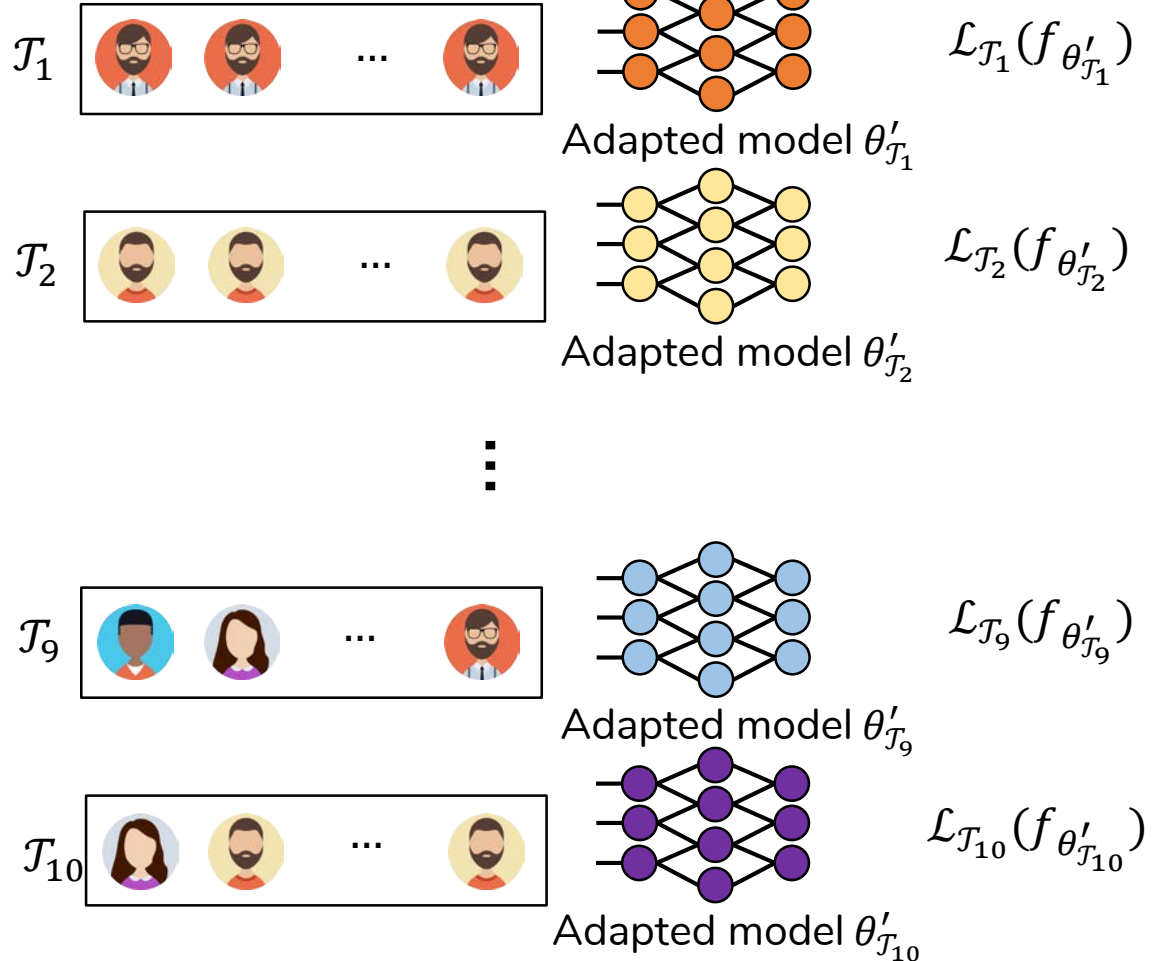
Base model θ

Meta objective:

Minimize the **sum of task losses**

$$\theta \leftarrow \theta - \beta \nabla_{\theta} \sum_{\mathcal{T}_i} \mathcal{L}_{\mathcal{T}_i}(f_{\theta'_{\mathcal{T}_i}})$$

Adapting to each condition



Training the base model

Few gradient steps (e.g., 10)
with few shots (e.g., 5)

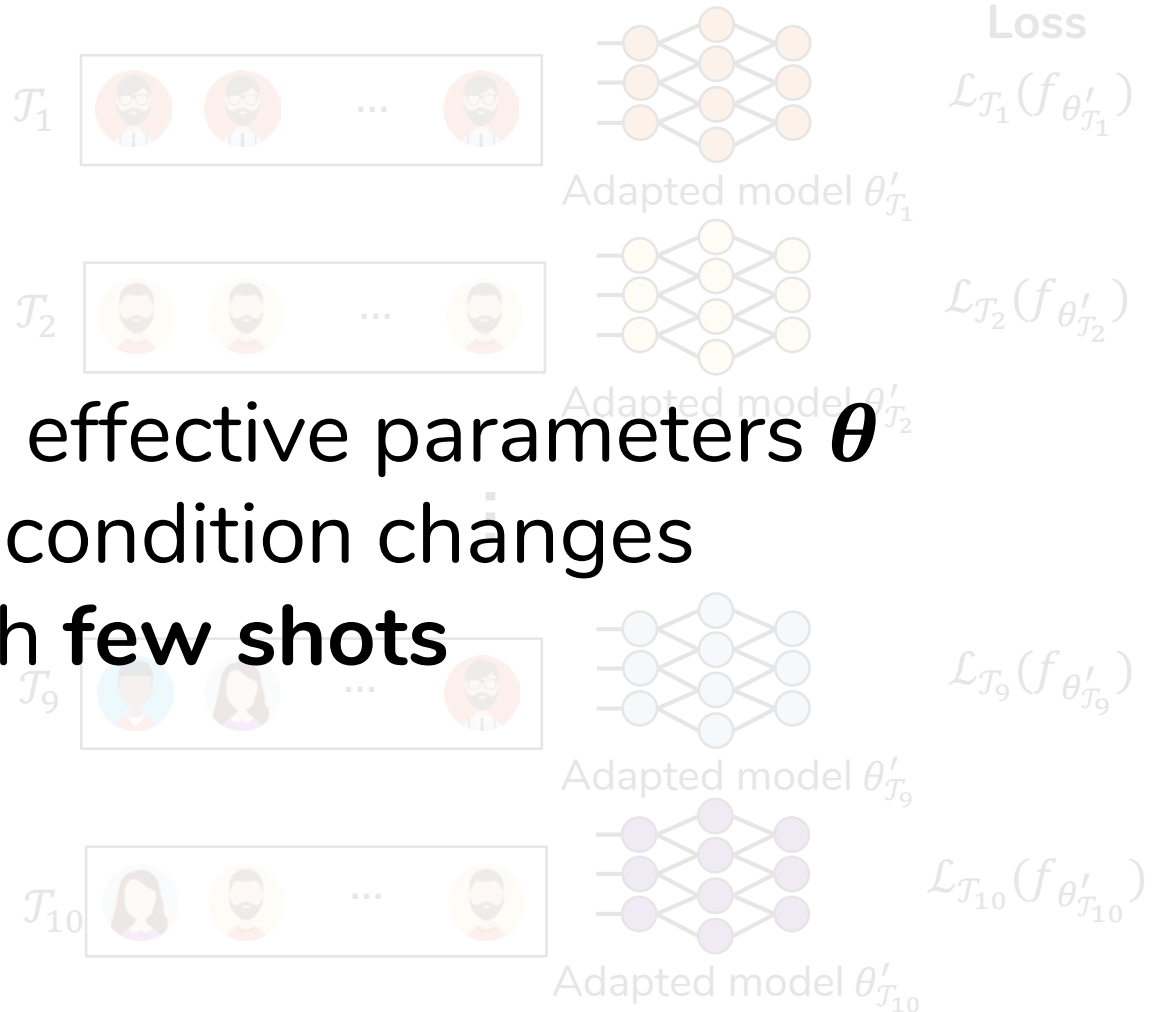


The base model learns effective parameters θ
that can adapt to condition changes
rapidly with few shots

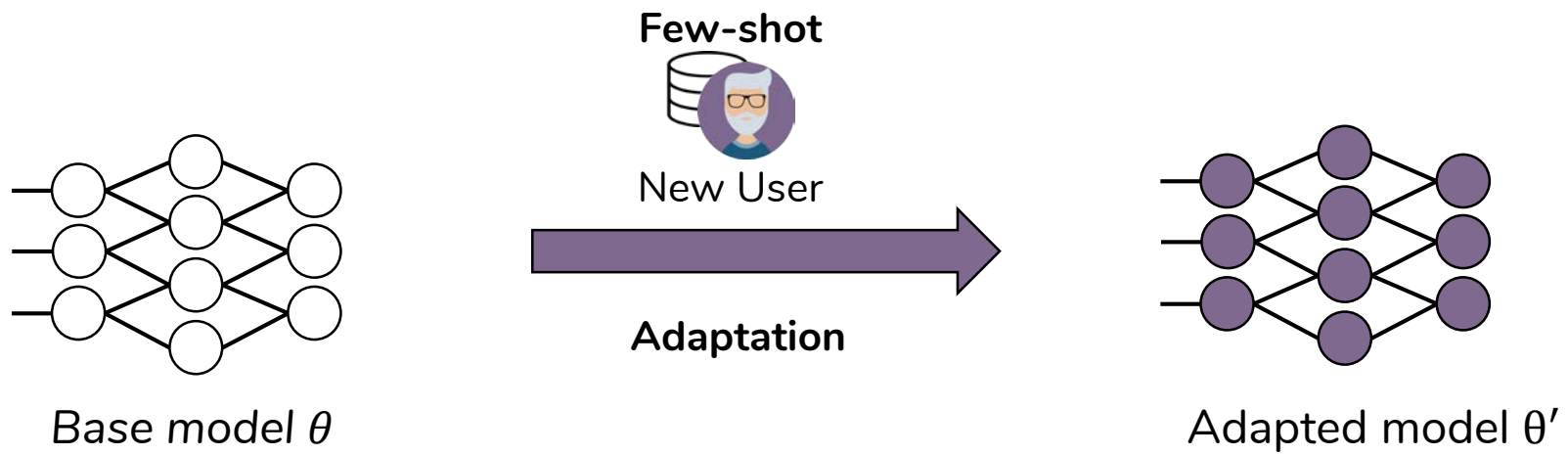
Base model θ

Meta objective:
Minimize the sum of task losses

$$\theta \leftarrow \theta - \beta \nabla_{\theta} \sum_{\mathcal{T}_i} \mathcal{L}_{\mathcal{T}_i}(f_{\theta'_{\mathcal{T}_i}})$$



Adaptation



Evaluation

1. How **well** does MetaSense perform against existing approaches?
2. How **effective** are MetaSense's three **task generation strategies**?
3. How **rapidly** can MetaSense adapt to the target condition?

Evaluation: data collection

- 10 different users and devices
 - = 10 individual conditions
- Activity recognition (IMU)
 - 9 activities
- Speech recognition (MIC)
 - 14 keywords

User	Device	Type	IMU rate
P1	Samsung Galaxy J7	Phone	100Hz
P2	Google Nexus5	Phone	200Hz
P3	Essential Phone	Phone	400Hz
P4	Google Pixel2	Phone	400Hz
P5	HUAWEI P20	Phone	500Hz
P6	Samsung Galaxy S9	Phone	500Hz
P7	LG G5	Phone	200Hz
P8	LG Urbane	Watch	200Hz
P9	LG G Style	Watch	100Hz
P10	ASUS Zenwatch3	Watch	100Hz

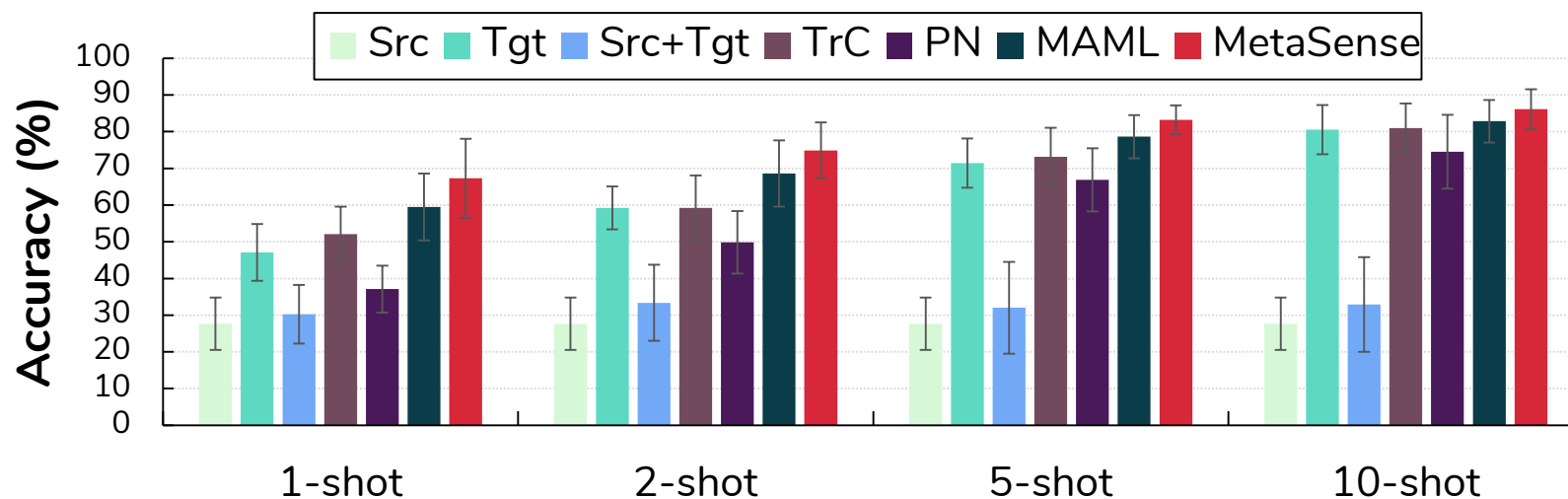
Evaluation: baselines

- **Src**: training with the **source** data only
 - **Tgt**: training with the **target** data only
 - **Src+Tgt**: training with both the **source** and **target** data
 - **TrC** (Transfer Convolutional), AAAI '18
 - The state-of-the-art **transfer learning** with few shots for human activity recognition
 - **PN** (Prototypical Network), NIPS '17
 - **Meta learning**; Generates prototypes for each class with few shots
 - **MAML** (Model-agnostic meta learning), ICML '17
 - **Meta learning**; Trains sensitive model parameters for task changes
- *Source data: 9 conditions
*Target data: 1 condition

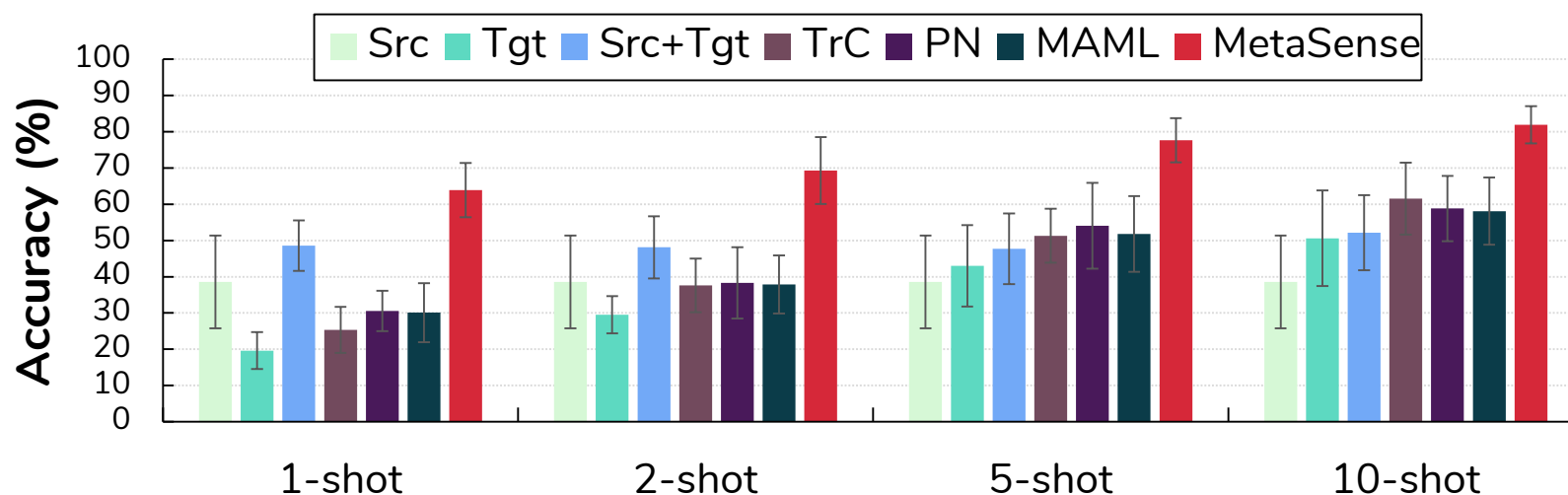
Comparison with the baselines



Activity Recognition



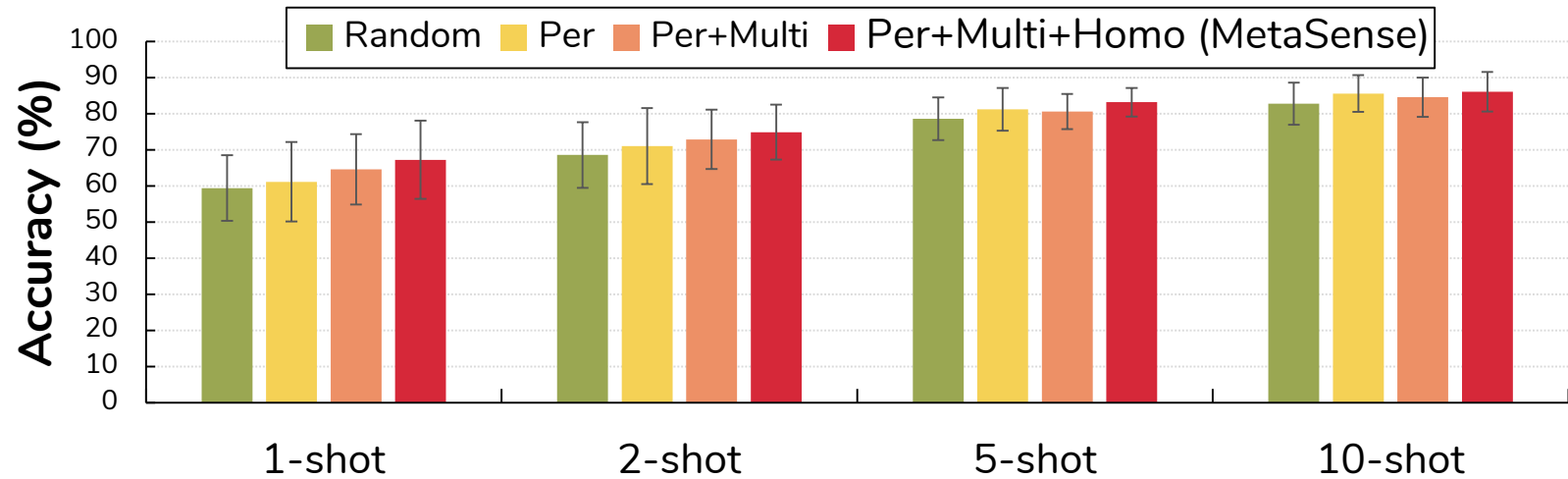
Speech Recognition



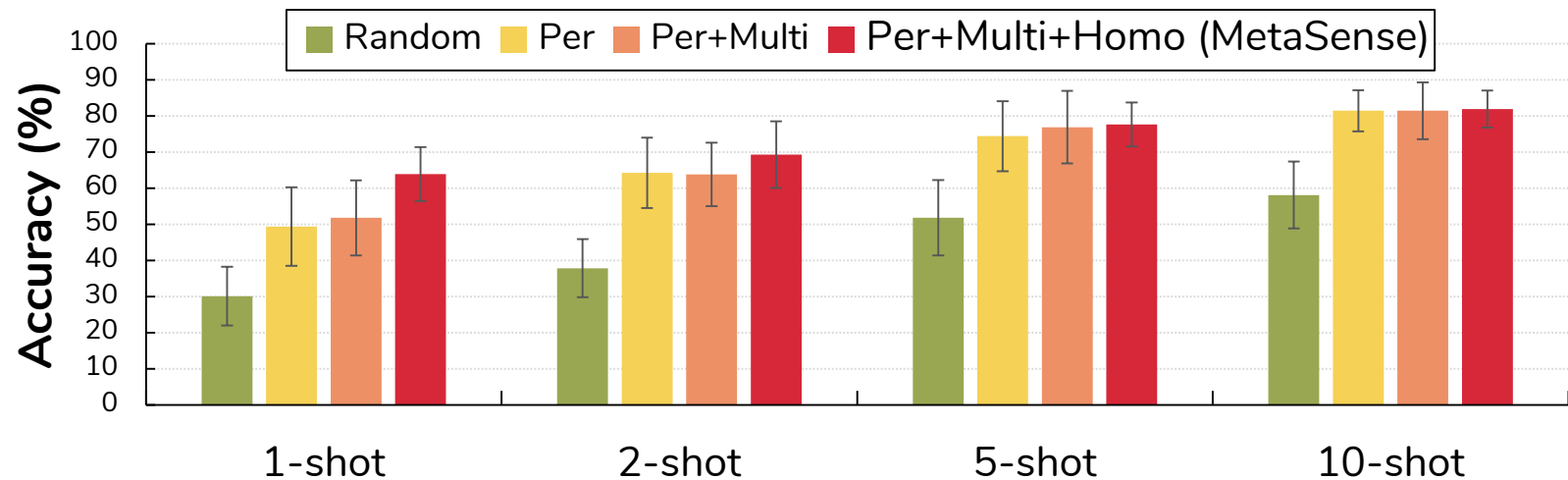
Effectiveness of task generation



Activity Recognition



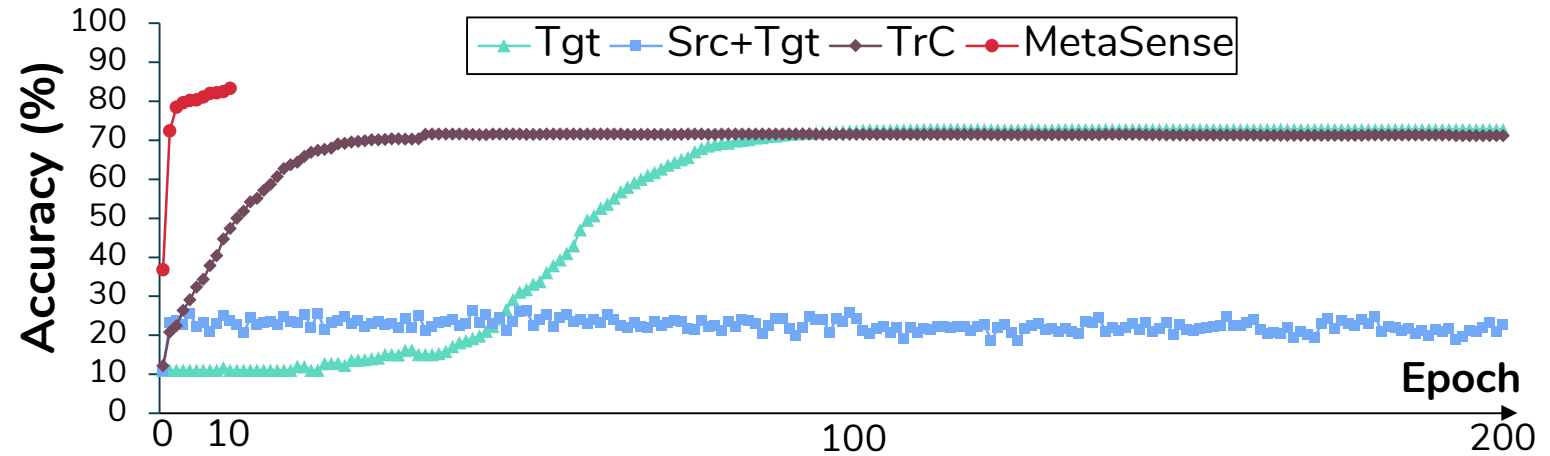
Speech Recognition



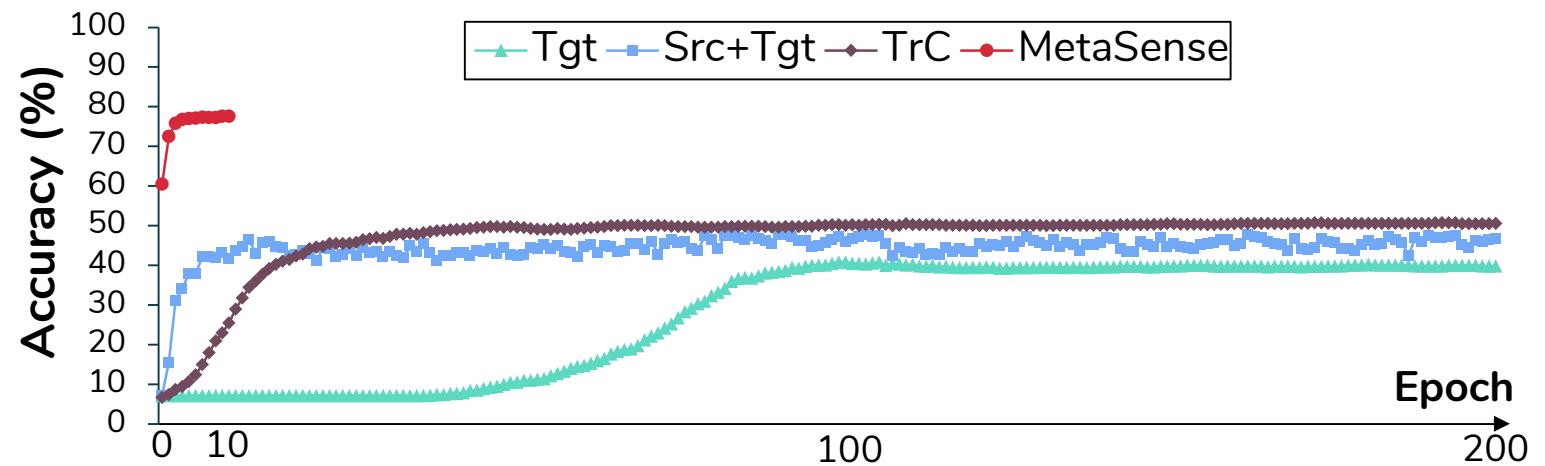
MetaSense quickly adapts to the target



Activity Recognition



Speech Recognition

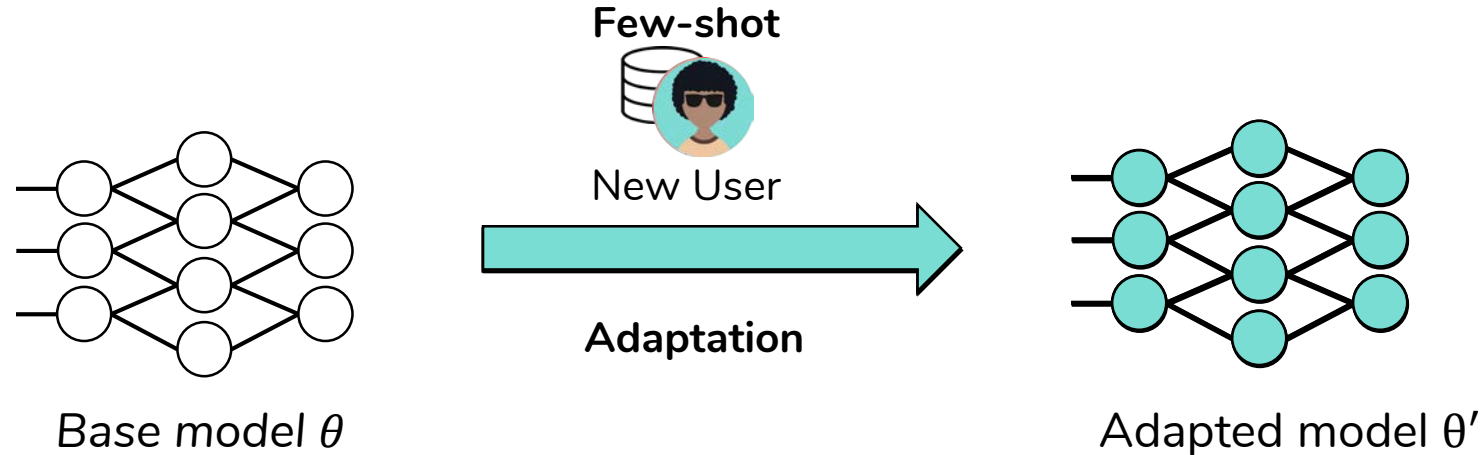


Conclusion

- MetaSense: the **first meta learning solution** for adapting to untrained conditions in mobile sensing
- We propose **three task generation strategies** to resolve challenges in adopting meta learning to mobile sensing
- MetaSense **outperforms** transfer learning by 18% and other meta learning schemes by 15% in terms of accuracy

MetaSense

A step towards the mainstream adoption of mobile sensing for practical impact.



<https://nmsl.kaist.ac.kr/projects/metasense>

Contact: taesik.gong@kaist.ac.kr