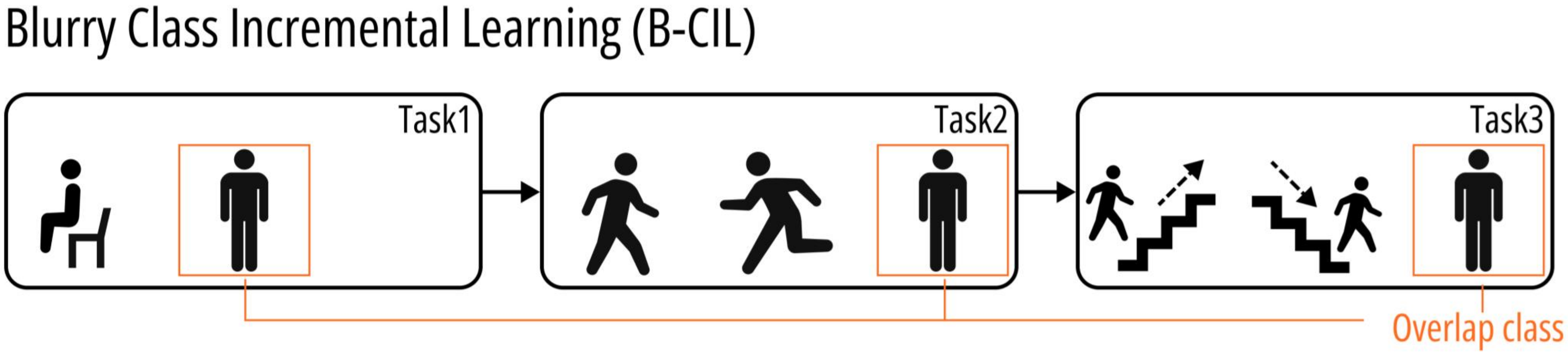
Blurry Class-Incremental Learning for IMU-Based Human Activity Recognition: An Empirical Study



2026.7.27 EMBC2026

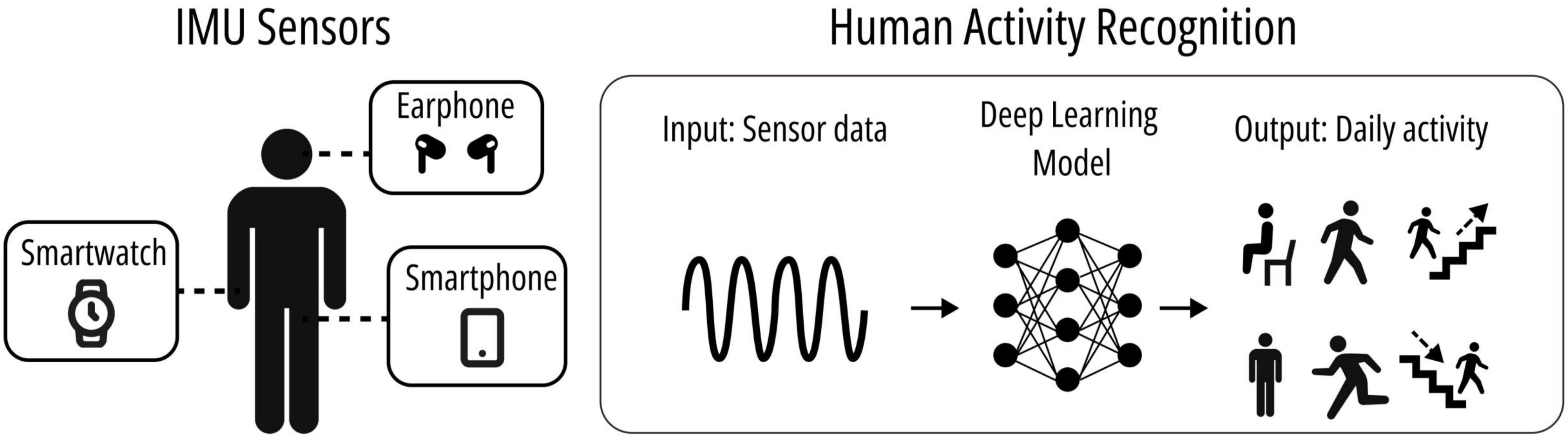
Takumi Yamamoto[1,2], Suguru Kanoga[1], Mitsunori Tada[1], Yuta Sugiura[2]
[1]National Institute of Advanced Industrial Science and Technology (AIST)
[2]Keio University

Create the Future, Collaborate Together

Digital Human

Flow of Presentation

IMU-based Human Activity Recognition (HAR)



HAR: Classify daily activities based on sensor data

IMU Sensor: Easy to deploy HAR system due to its ubiquitous nature

Problem: HAR system has to be updated

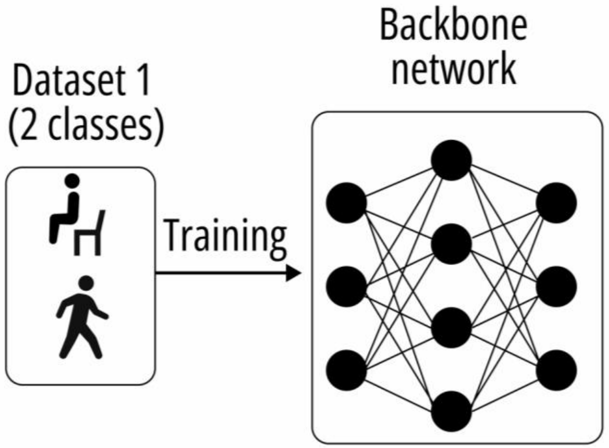
Long-term use leads user's need changes…

Problem: HAR system has to be updated

Long-term use leads user's need changes...

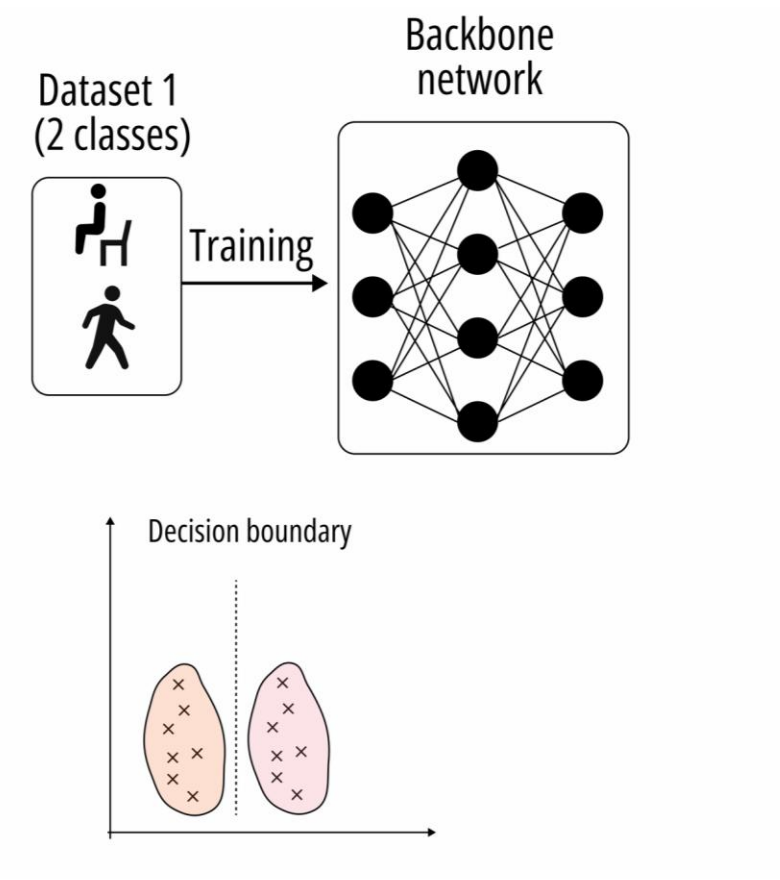
→ HAR model has to be updated to classify **both old classes and new classes** !

Fine Tuning Approach



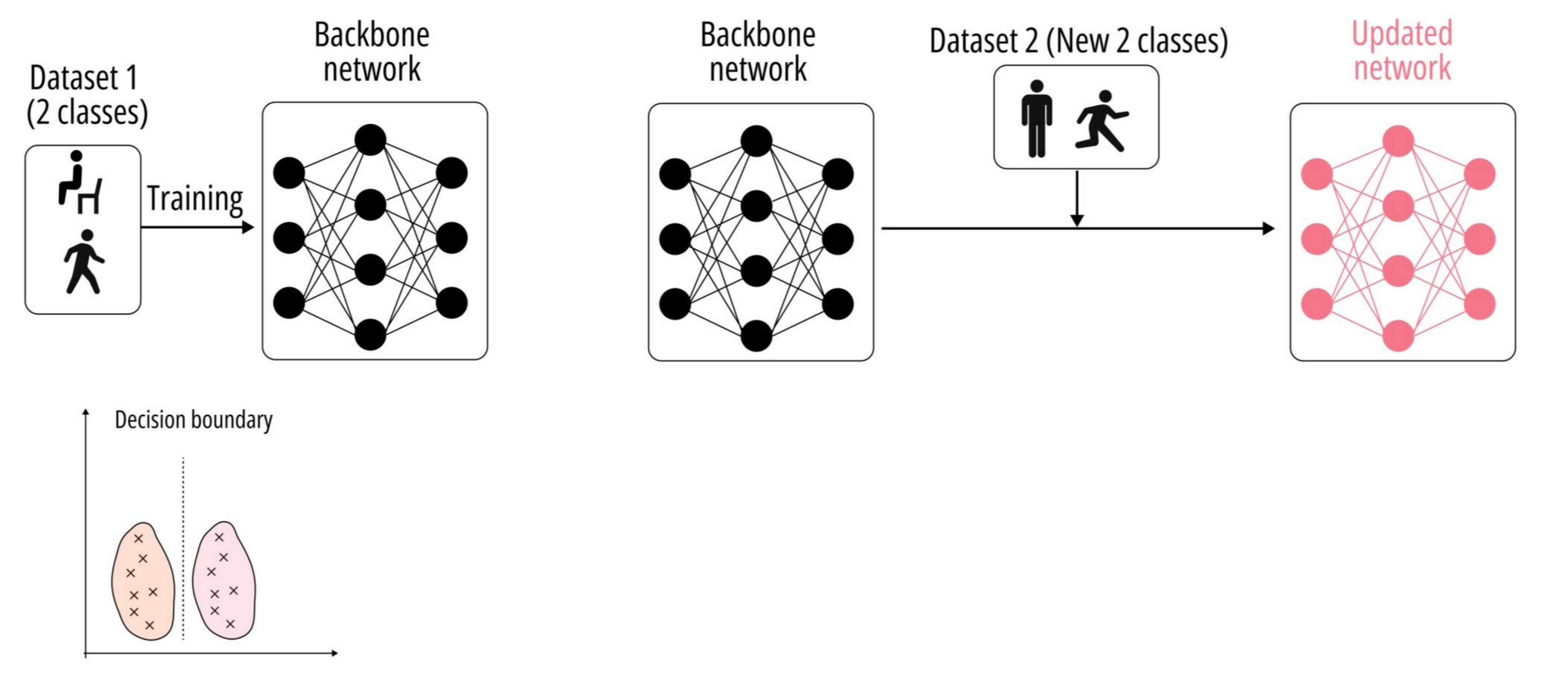
First, the network is trained in 2 classes.

Fine Tuning Approach



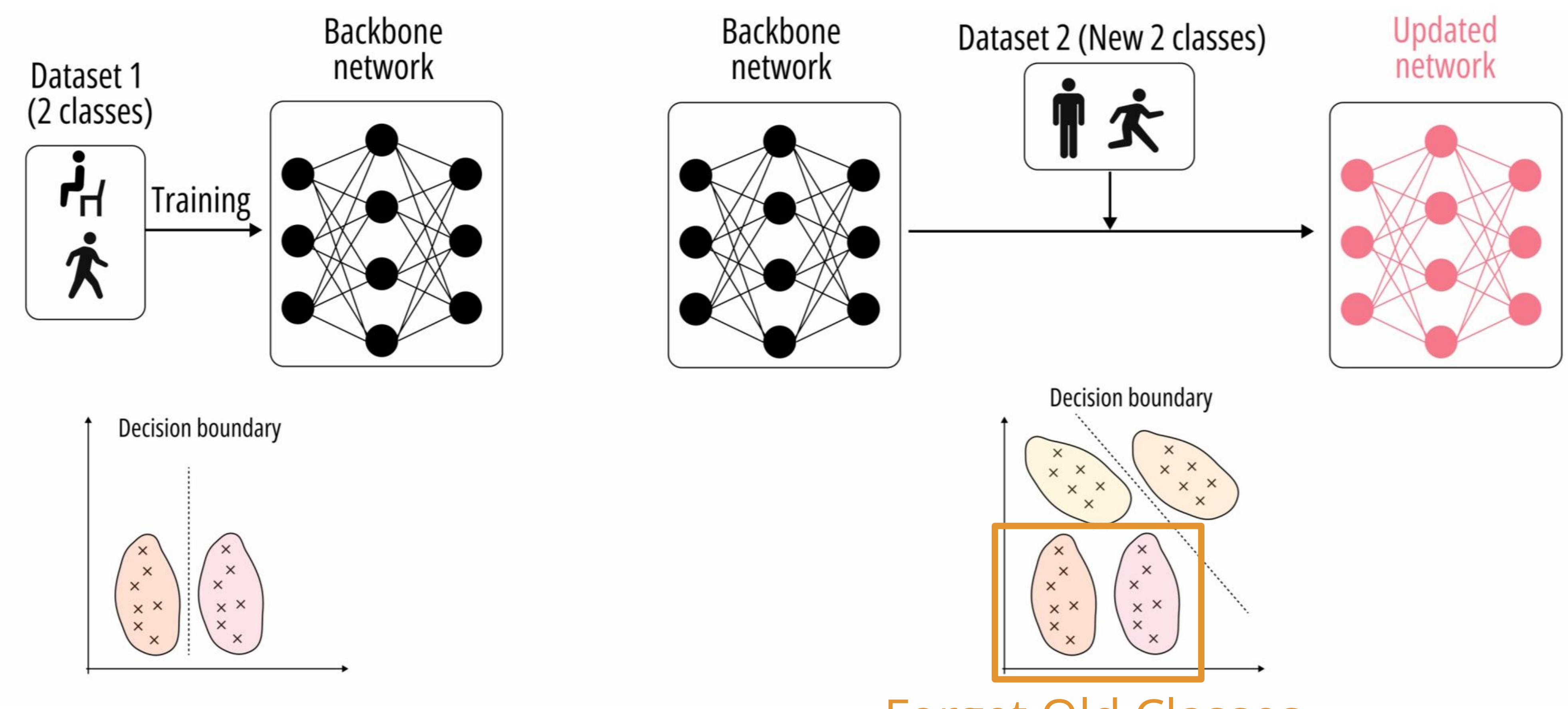
First, the network is trained in 2 classes.

Fine Tuning Approach



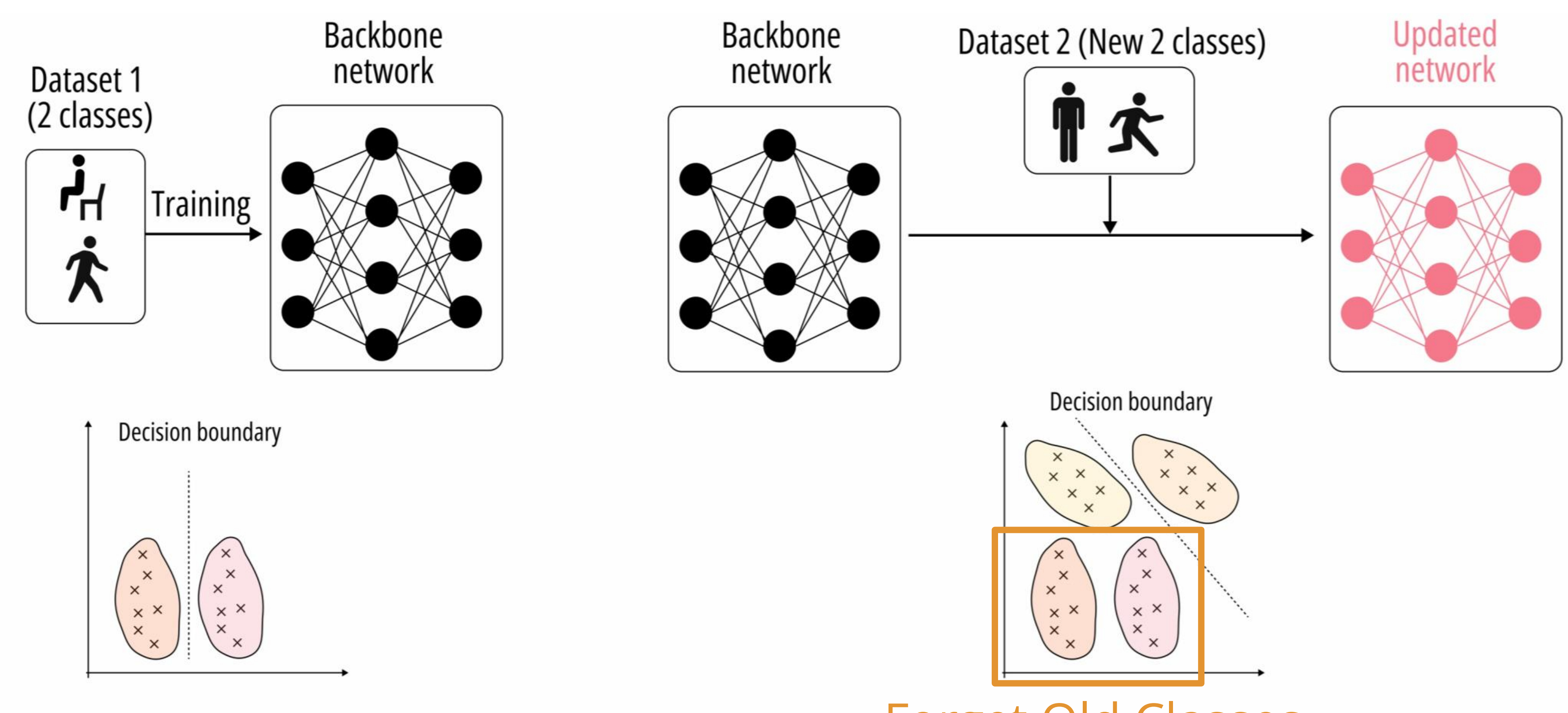
Second, users want to add new two classes.

Fine Tuning Approach



Forget Old Classes

Fine Tuning Approach



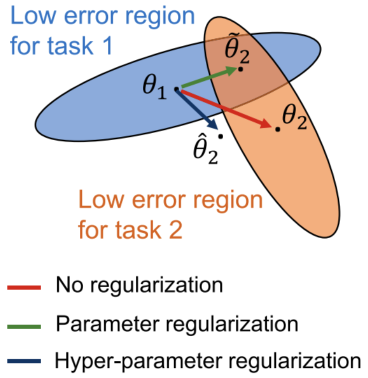
Forget Old Classes

Fine tuning approaches cause "Catastrophic forgetting".

Continual Learning Method

Continual Learning (CL) is the method to update the ML model without catastrophic forgetting.

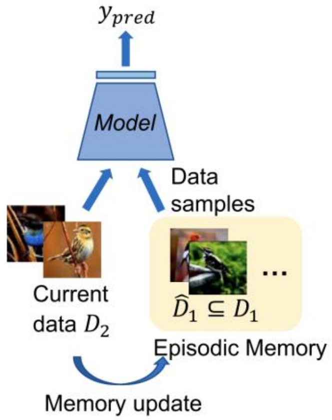
Regularization Method



[Wickramasinghe, 2023]

Giving the restriction for updating the parameters

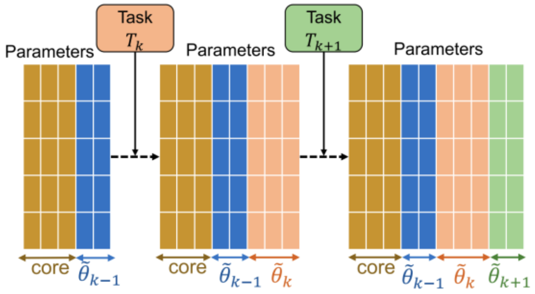
Replay Method



[Wickramasinghe, 2023]

Utilize the data in memory

Parameter Isolation Method



[Wickramasinghe, 2023]

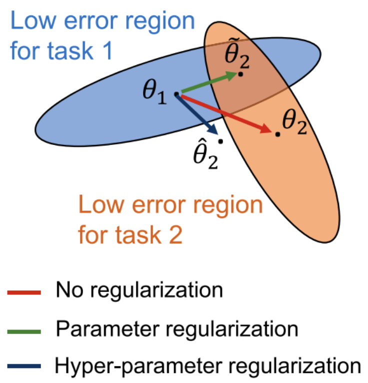
Update the architecture

[Wickramasinghe, 2023] Wickramasinghe, Buddhi, Gobinda Saha, and Kaushik Roy. "Continual learning: A review of techniques, challenges, and future directions." IEEE Transactions on Artificial Intelligence 5.6 (2023): 2526-2546.

Continual Learning Method

Continual Learning (CL) is the method to update the ML model without catastrophic forgetting.

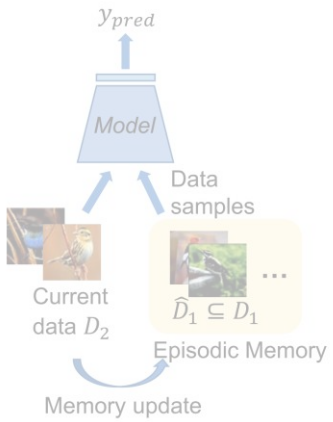
Regularization Method



[Wickramasinghe, 2023]

Giving the restriction for updating the parameters

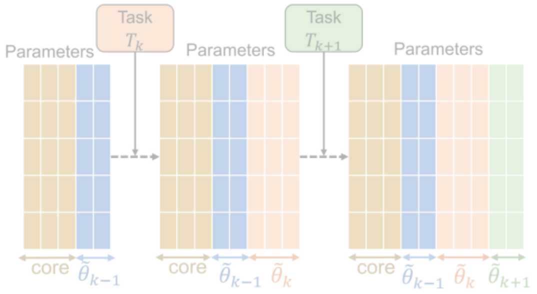
Replay Method



[Wickramasinghe, 2023]

Utilize the data in memory

Parameter Isolation Method



[Wickramasinghe, 2023]

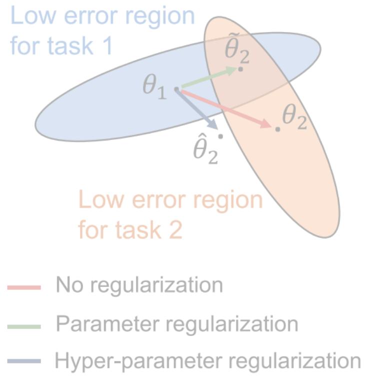
Update the architecture

[Wickramasinghe, 2023] Wickramasinghe, Buddhi, Gobinda Saha, and Kaushik Roy. "Continual learning: A review of techniques, challenges, and future directions." IEEE Transactions on Artificial Intelligence 5.6 (2023): 2526-2546.

Continual Learning Method

Continual Learning (CL) is the method to update the ML model without catastrophic forgetting.

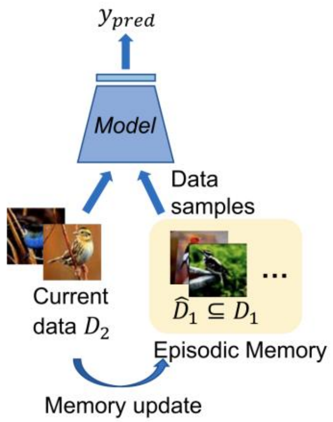
Regularization Method



[Wickramasinghe, 2023]

Giving the restriction for updating the parameters

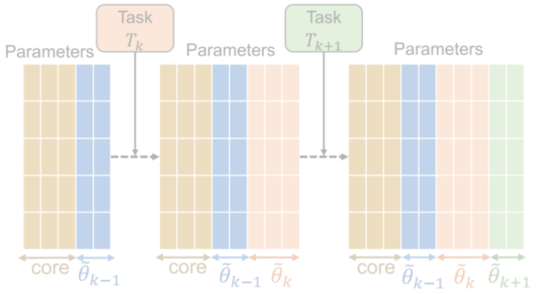
Replay Method



[Wickramasinghe, 2023]

Utilize the data in memory

Parameter Isolation Method



[Wickramasinghe, 2023]

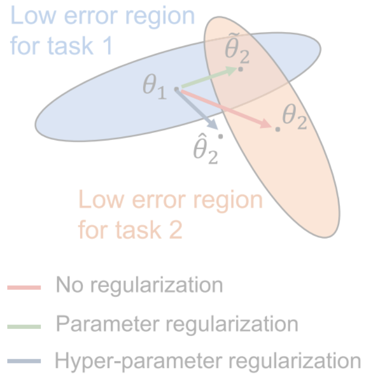
Update the architecture

[Wickramasinghe, 2023] Wickramasinghe, Buddhi, Gobinda Saha, and Kaushik Roy. "Continual learning: A review of techniques, challenges, and future directions." IEEE Transactions on Artificial Intelligence 5.6 (2023): 2526-2546.

Continual Learning Method

Continual Learning (CL) is the method to update the ML model without catastrophic forgetting.

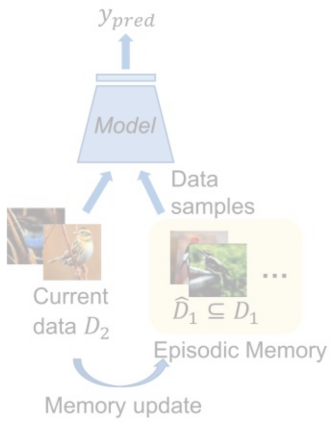
Regularization Method



[Wickramasinghe, 2023]

Giving the restriction for updating the parameters

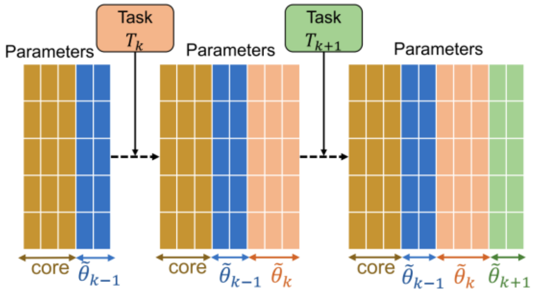
Replay Method



[Wickramasinghe, 2023]

Utilize the data in memory

Parameter Isolation Method



[Wickramasinghe, 2023]

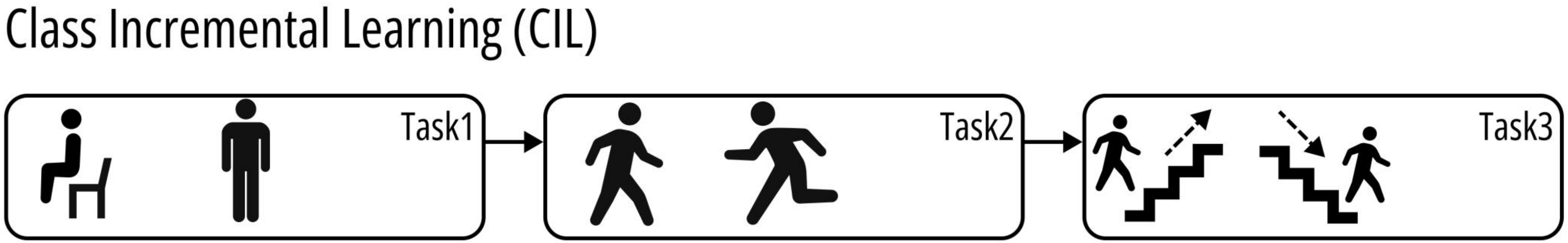
Update the architecture

[Wickramasinghe, 2023] Wickramasinghe, Buddhi, Gobinda Saha, and Kaushik Roy. "Continual learning: A review of techniques, challenges, and future directions." IEEE Transactions on Artificial Intelligence 5.6 (2023): 2526-2546.

Continual Learning Scenario

Class Incremental Learning (CIL)

Continual Learning Scenario



Real-world systems rarely operate under conditions where classes are disjoint across tasks.

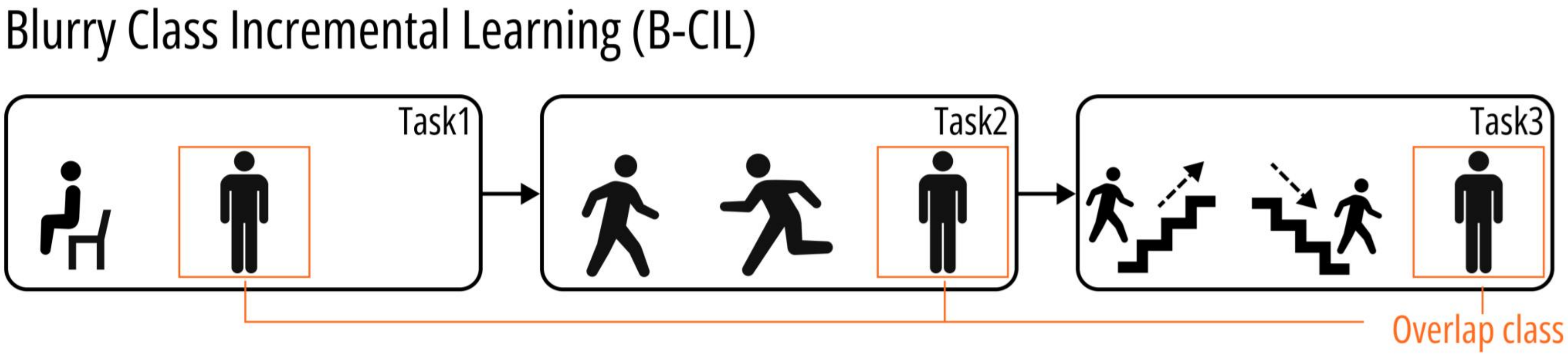
Continual Learning Scenario

Class Incremental Learning (CIL)

Real-world systems rarely operate under conditions where classes are disjoint across tasks.

Blurry Class Incremental Learning (B-CIL)

Research Questions



RQ1: Which CL methods are most effective in B-CIL scenarios for IMU-based HAR?

→ Evaluate nine CL methods on two IMU-based HAR dataset.

RQ2: How does the degree of class overlap influence the performance of CL methods in B-CIL scenarios?

→Evaluate the CL methods under B-CIL scenarios with different levels of class overlap.

Flow of Presentation

Digital Human

AIST
Create the Future, Collaborate Together

Background & Motivation

Experiment

Results

Future Work

Dataset

	UCI-HAR [Anguita, 2013]	USC-HAD [Zhang, 2012]
Number of Subjects	30	14
Activities	#6  standing, sitting, lying, walking, walking upstairs, walking downstairs	#12  walking forwards, walking left, walking right, walking upstairs, walking downstairs, running  jumping, sitting, standing, sleeping, elevator up, elevator down
Sampling rate	50Hz	100Hz
Windows Shape	128 x 9	128 x 6

We used two public datasets; UCI-HAR and USC-HAD.

[Anguita, 2013] Anguita et al., " A public domain dataset for human activity recognition using smartphones.", Esann. Vol. 3. No. 1. 2013.
[Zhang, 2012] Zhang et al., "USC-HAD: A daily activity dataset for ubiquitous activity recognition using wearable sensors.", Proceedings of the 2012 ACM conference on ubiquitous computing.

Dataset

Digital Human

AIST Create the Future, Collaborate Together

	UCI-HAR[Anguita, 2013]	USC-HAD[Zhang, 2012]
Number of Subjects	30	14
Activities	#6 standing, sitting, lying, walking, walking upstairs, walking downstairs	#12 walking forwards, walking left, walking right, walking upstairs, walking downstairs, running, jumping, sitting, standing, sleeping, elevator up, elevator down
Sampling rate	50Hz	100Hz
Windows Shape	128 x 9	128 x 6

We used two public datasets; UCI-HAR and USC-HAD.

[Anguita, 2013] Anguita et al., " A public domain dataset for human activity recognition using smartphones.", Esann. Vol. 3. No. 1. 2013.
[Zhang, 2012] Zhang et al., "USC-HAD: A daily activity dataset for ubiquitous activity recognition using wearable sensors.", Proceedings of the 2012 ACM conference on ubiquitous computing.

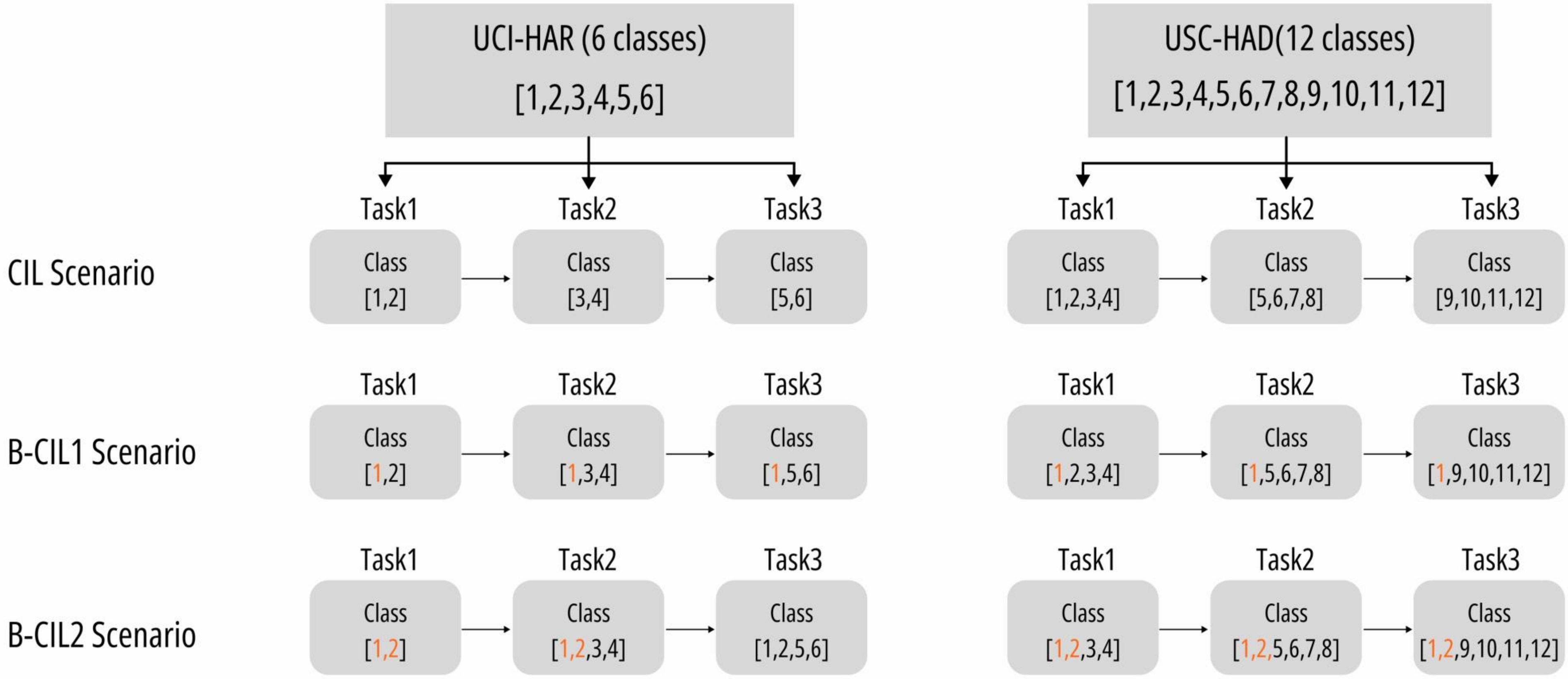
Dataset

	UCI-HAR[Anguita, 2013]	USC-HAD[Zhang, 2012]
Number of Subjects	30	14
Activities	#6 standing, sitting, lying, walking, walking upstairs, walking downstairs	#12 walking forwards, walking left, walking right, walking upstairs, walking downstairs, running, jumping, sitting, standing, sleeping, elevator up, elevator down
Sampling rate	50Hz	100Hz
Windows Shape	128 x 9	128 x 6

We used two public datasets; UCI-HAR and USC-HAD.

[Anguita, 2013] Anguita et al., " A public domain dataset for human activity recognition using smartphones.", Esann. Vol. 3. No. 1. 2013.
[Zhang, 2012] Zhang et al., "USC-HAD: A daily activity dataset for ubiquitous activity recognition using wearable sensors.", Proceedings of the 2012 ACM conference on ubiquitous computing.

Scenario Settings

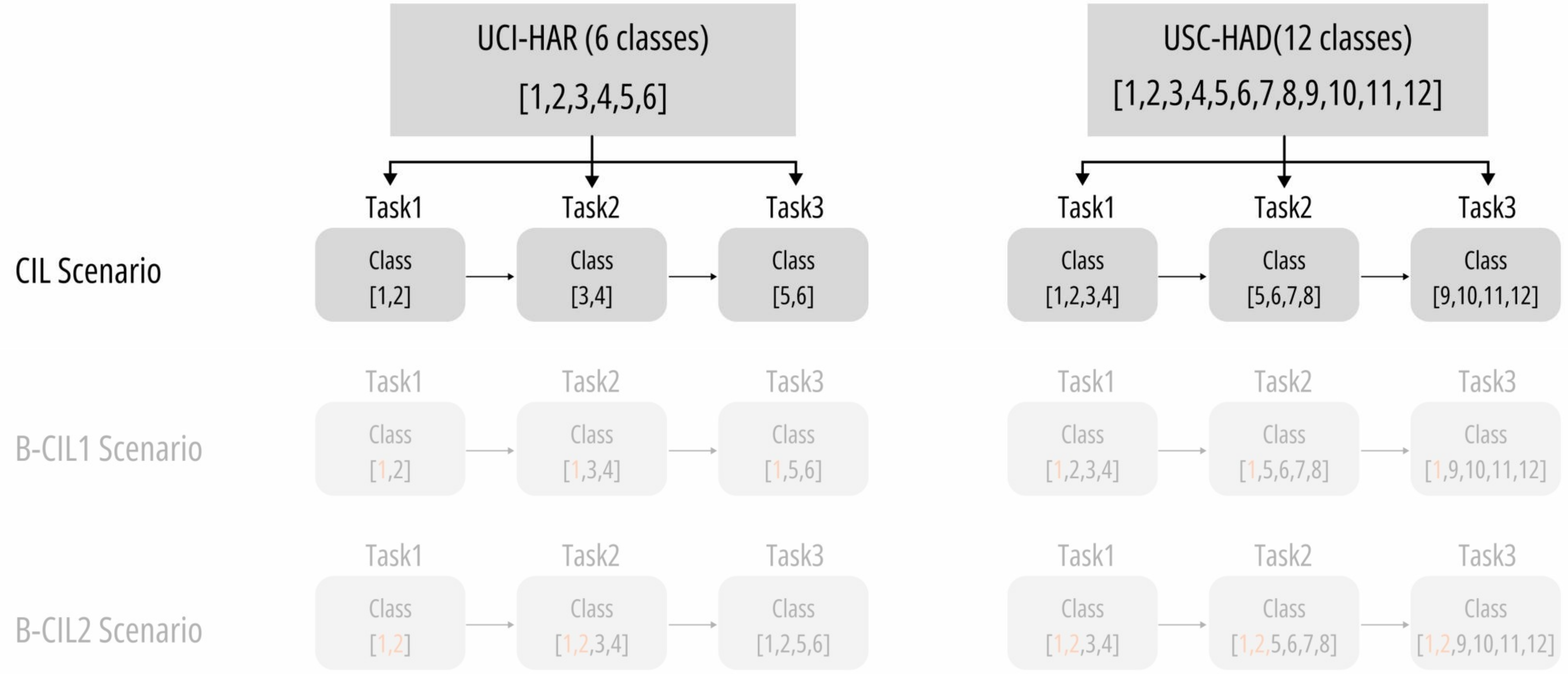


CIL: Activities are divided into 3 tasks

B-CIL1: One overlap class

B-CIL2: Two overlap class

Scenario Settings

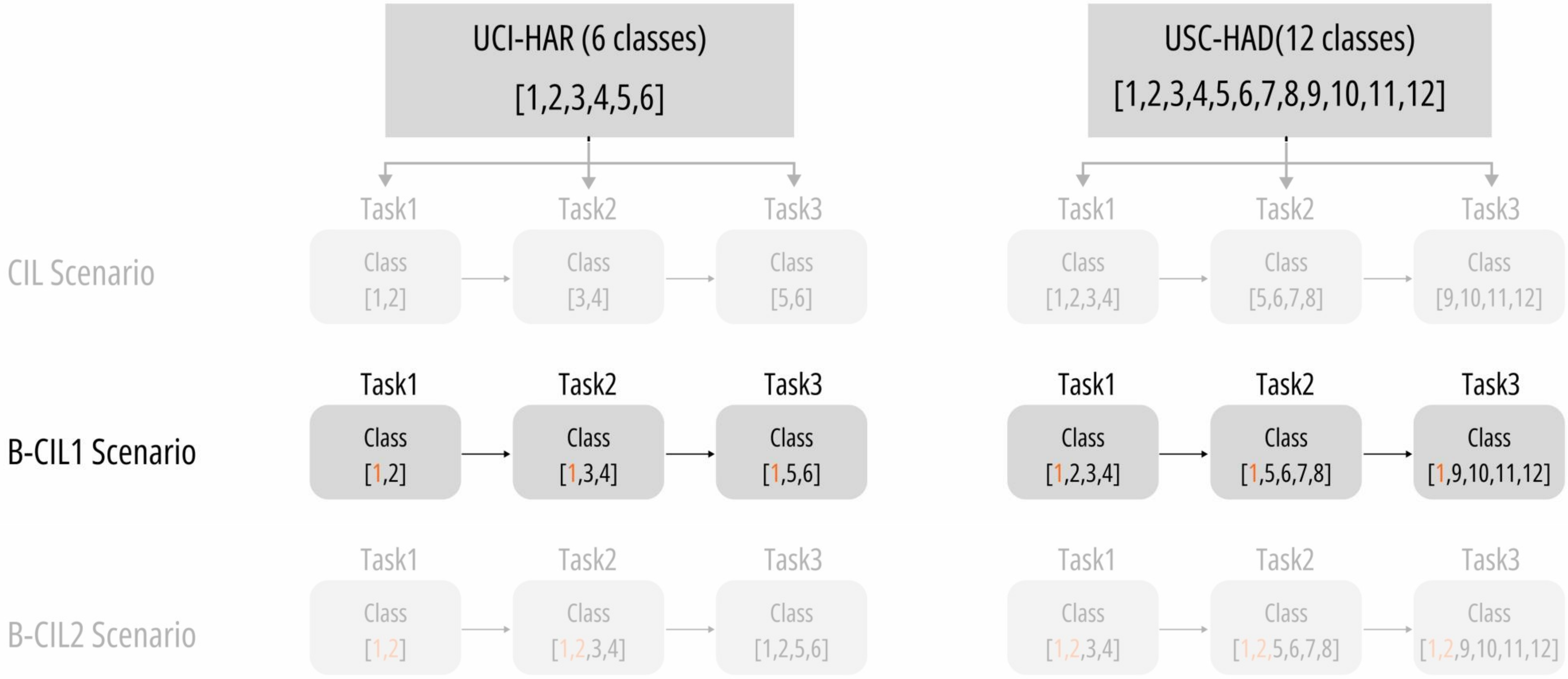


CIL: Activities are divided into 3 tasks

B-CIL1: One overlap class

B-CIL2: Two overlap class

Scenario Settings

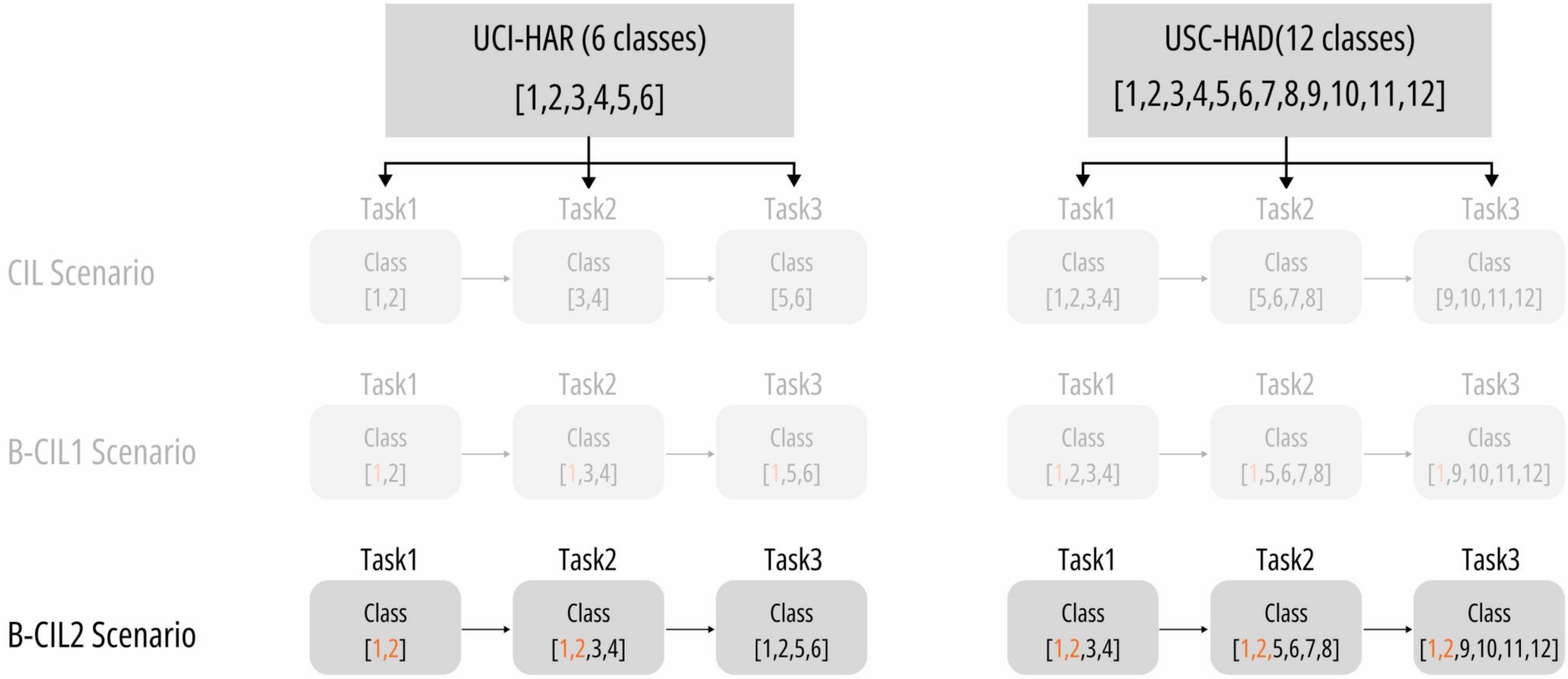


CIL: Activities are divided into 3 tasks

B-CIL1: One overlap class

B-CIL2: Two overlap class

Scenario Settings



CIL: Activities are divided into 3 tasks

B-CIL1: One overlap class

B-CIL2: Two overlap class

Deep Learning Method

<table>
<tr><td>Backbone model</td><td colspan="2">1D-CNN</td></tr>
<tr><td rowspan="2">CL methods</td><td>Regularization-based method</td><td>LwF, EWC, MAS, SI</td></tr>
<tr><td>Replay-based method</td><td>ER, DER, FastICARL, ASER, GR</td></tr>
<tr><td>Baseline</td><td colspan="2">Naïve (fine-tuning) & Offline</td></tr>
</table>

Deep Learning Method

Backbone model	1D-CNN	
CL methods	Regularization-based method	LwF, EWC, MAS, SI
	Replay-based method	ER, DER, FastICARL, ASER, GR
Baseline	Naïve (fine-tuning) & Offline	

Deep Learning Method

Backbone model	1D-CNN	
CL methods	Regularization-based method	LwF, EWC, MAS, SI
	Replay-based method	ER, DER, FastICARL, ASER, GR
Baseline	Naïve (fine-tuning) & Offline	

Deep Learning Method

Backbone model	1D-CNN	
CL methods	Regularization-based method	LwF, EWC, MAS, SI
	Replay-based method	ER, DER, FastICARL, ASER, GR
Baseline	Naïve (fine-tuning) & Offline	

Flow of Presentation

Background & Motivation

Experiment

Results

Future Work

Results

Metrics	Dataset	Scenario	Naïve	Offline	LwF	EWC	MAS	SI	ER	DER	ASER	FastICARL	GR
$\mathcal{A}_T$	UCI-HAR	CIL	33.04	98.00	34.35	35.36	40.47	34.35	70.97	66.62	**96.76**	66.44	36.34
		B-CIL1	61.16	98.00	65.49	63.52	70.58	63.91	89.17	88.74	**98.86**	89.69	62.70
		B-CIL2	82.52	98.00	83.15	83.44	84.60	80.56	96.00	92.83	**99.40**	95.64	83.49
	USC-HAD	CIL	32.82	91.43	38.72	37.15	38.69	33.64	76.94	64.42	**94.11**	73.13	29.23
		B-CIL1	49.07	91.43	57.11	54.75	54.59	51.55	82.58	72.32	**95.67**	80.93	54.49
		B-CIL2	58.04	91.43	62.34	65.18	60.79	57.17	86.78	77.30	**96.28**	78.67	50.85

Results: Compared with Baseline

Metrics	Dataset	Scenario	Naïve	Offline	LwF	EWC	MAS	SI	ER	DER	ASER	FastICARL	GR
$\mathcal{A}_T$	UCI-HAR	CIL	33.04	98.00	34.35	35.36	40.47	34.35	70.97	66.62	**96.76**	66.44	36.34
		B-CIL1	61.16	98.00	65.49	63.52	70.58	63.91	89.17	88.74	**98.86**	89.69	62.70
		B-CIL2	82.52	98.00	83.15	83.44	84.60	80.56	96.00	92.83	**99.40**	95.64	83.49
	USC-HAD	CIL	32.82	91.43	38.72	37.15	38.69	33.64	76.94	64.42	**94.11**	73.13	29.23
		B-CIL1	49.07	91.43	57.11	54.75	54.59	51.55	82.58	72.32	**95.67**	80.93	54.49
		B-CIL2	58.04	91.43	62.34	65.18	60.79	57.17	86.78	77.30	**96.28**	78.67	50.85

Better than Naïve

vs Naïve

- Most methods are better than Naive

vs Offline

Results: Compared with Baseline

Metrics	Dataset	Scenario	Naïve	Offline	LwF	EWC	MAS	SI	ER	DER	ASER	FastICARL	GR
$\mathcal{A}_T$	UCI-HAR	CIL	33.04	98.00	34.35	35.36	40.47	34.35	70.97	66.62	**96.76**	66.44	36.34
		B-CIL1	61.16	98.00	65.49	63.52	70.58	63.91	89.17	88.74	**98.86**	89.69	62.70
		B-CIL2	82.52	98.00	83.15	83.44	84.60	80.56	96.00	92.83	**99.40**	95.64	83.49
	USC-HAD	CIL	32.82	91.43	38.72	37.15	38.69	33.64	76.94	64.42	**94.11**	73.13	29.23
		B-CIL1	49.07	91.43	57.11	54.75	54.59	51.55	82.58	72.32	**95.67**	80.93	54.49
		B-CIL2	58.04	91.43	62.34	65.18	60.79	57.17	86.78	77.30	**96.28**	78.67	50.85

Better than Offline!

vs Naïve

- Most methods are better than Naïve

vs Offline

- Most methods are lower than Offline
- Surprisingly, some case in ASER is better than Offline:
  - ASER retains only informative samples, whereas Offline incorporates all data including noise/outliers.

Results

Metrics	Dataset	Scenario	Naïve	Offline	LwF	EWC	MAS	SI	ER	DER	ASER	FastICARL	GR
$\mathcal{A}_T$	UCI-HAR	CIL	33.04	98.00	34.35	35.36	40.47	34.35	70.97	66.62	**96.76**	66.44	36.34
		B-CIL1	61.16	98.00	65.49	63.52	70.58	63.91	89.17	88.74	**98.86**	89.69	62.70
		B-CIL2	82.52	98.00	83.15	83.44	84.60	80.56	96.00	92.83	**99.40**	95.64	83.49
	USC-HAD	CIL	32.82	91.43	38.72	37.15	38.69	33.64	76.94	64.42	**94.11**	73.13	29.23
		B-CIL1	49.07	91.43	57.11	54.75	54.59	51.55	82.58	72.32	**95.67**	80.93	54.49
		B-CIL2	58.04	91.43	62.34	65.18	60.79	57.17	86.78	77.30	**96.28**	78.67	50.85

regularization Replay

RQ1: Which CL methods are most effective in B-CIL scenarios for IMU-based HAR?

- Replay-based methods outperformed regularization methods.
- Especially, ASER achieved the highest Final Average Accuracy.

Results

Metrics	Dataset	Scenario	Naïve	Offline	LwF	EWC	MAS	SI	ER	DER	ASER	FastICARL	GR
$\mathcal{A}_T$	UCI-HAR	CIL	33.04	98.00	34.35	35.36	40.47	34.35	70.97	66.62	**96.76**	66.44	36.34
		B-CIL1	61.16	98.00	65.49	63.52	70.58	63.91	89.17	88.74	**98.86**	89.69	62.70
		B-CIL2	82.52	98.00	83.15	83.44	84.60	80.56	96.00	92.83	**99.40**	95.64	83.49
	USC-HAD	CIL	32.82	91.43	38.72	37.15	38.69	33.64	76.94	64.42	**94.11**	73.13	29.23
		B-CIL1	49.07	91.43	57.11	54.75	54.59	51.55	82.58	72.32	**95.67**	80.93	54.49
		B-CIL2	58.04	91.43	62.34	65.18	60.79	57.17	86.78	77.30	**96.28**	78.67	50.85

B-CIL2 > B-CIL1 > CL

RQ1: Which CL methods are most effective in B-CIL scenarios for IMU-based HAR?

- Replay-based methods outperformed regularization method.
- Especially, ASER achieved the highest Final Average Accuracy.

RQ2: How does the degree of class overlap influence the performance of CL methods in B-CIL scenarios?

- In most cases, B-CIL2 > B-CIL1 > CL

Flow of Presentation

Digital Human

AIST
Create the Future, Collaborate Together

Background & Motivation

Experiment

Results

Future Work

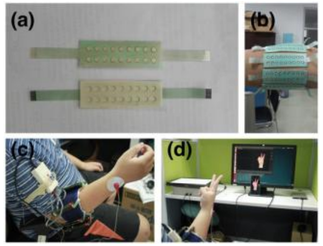
Future Work

Other datasets

Other IMU-based HAR

[Chan, 2024]

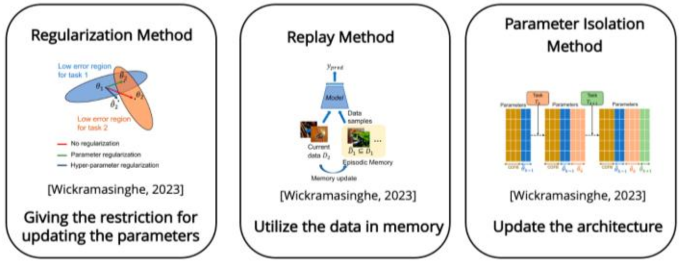
Other modality (e.g. s-EMG)



[Du, 2017]

Other CL method

Parameter isolation method

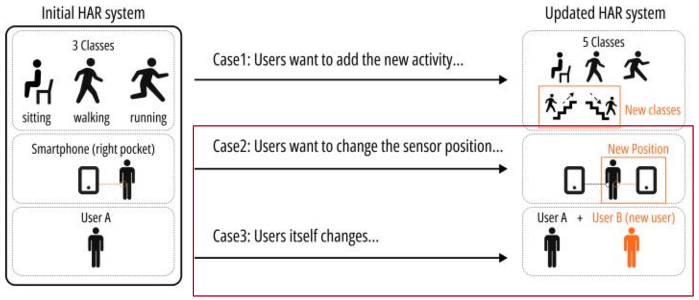


Already Explored

Not Explored

Other CL Scenarios

Domain Incremental Learning



[Chan, 2024] Chan et al. , "CAPTURE-24: A large dataset of wrist-worn activity tracker data collected in the wild for human activity recognition." Scientific Data 11.1 (2024): 1135.
[Du, 2017] Du et al., "Surface EMG-based inter-session gesture recognition enhanced by deep domain adaptation." Sensors 17.3 (2017): 458.

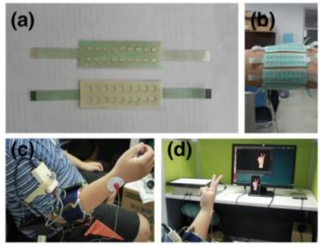
Future Work

Other datasets

Other IMU-based HAR

[Chan, 2024]

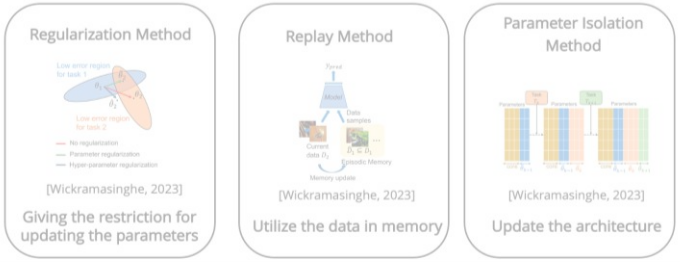
Other modality (e.g. s-EMG)



[Du, 2017]

Other CL method

Parameter isolation method

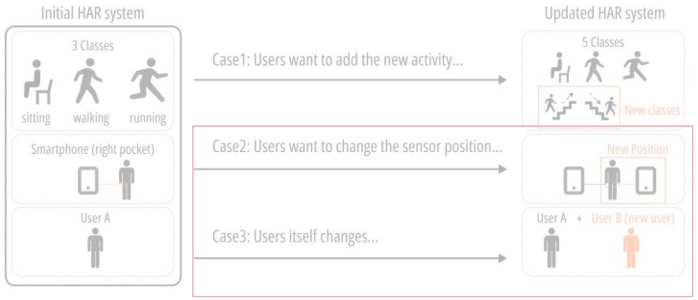


Already Explored

Not Explored

Other CL Scenarios

Domain Incremental Learning

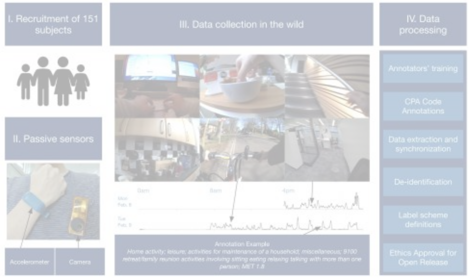


[Chan, 2024] Chan et al. , "CAPTURE-24: A large dataset of wrist-worn activity tracker data collected in the wild for human activity recognition." Scientific Data 11.1 (2024): 1135.
[Du, 2017] Du et al., "Surface EMG-based inter-session gesture recognition enhanced by deep domain adaptation." Sensors 17.3 (2017): 458.

Future Work

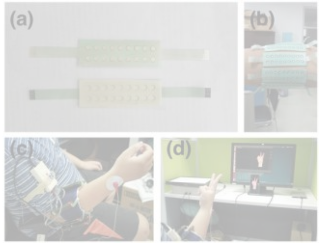
Other datasets

Other IMU-based HAR



[Chan, 2024]

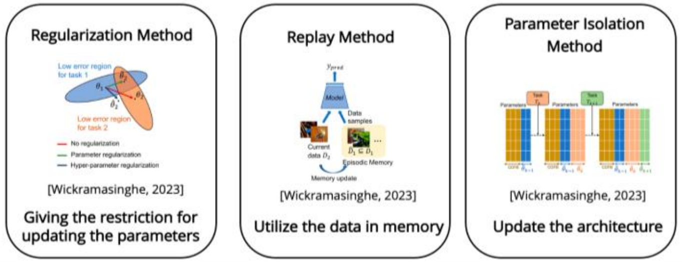
Other modality (e.g. s-EMG)



[Du, 2017]

Other CL method

Parameter isolation method

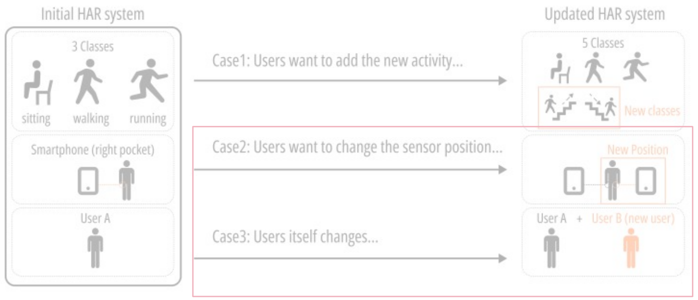


Already Explored

Not Explored

Other CL Scenarios

Domain Incremental Learning

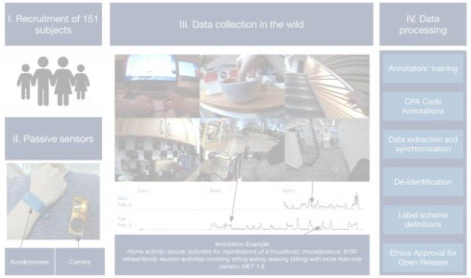


[Chan, 2024] Chan et al. , "CAPTURE-24: A large dataset of wrist-worn activity tracker data collected in the wild for human activity recognition." Scientific Data 11.1 (2024): 1135.
[Du, 2017] Du et al., "Surface EMG-based inter-session gesture recognition enhanced by deep domain adaptation." Sensors 17.3 (2017): 458.

Future Work

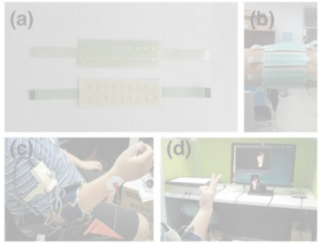
Other datasets

Other IMU-based HAR



[Chan, 2024]

Other modality (e.g. s-EMG)

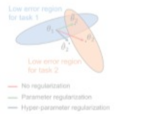


[Du, 2017]

Other CL method

Parameter isolation method

Regularization Method



[Wickramasinghe, 2023]

Giving the restriction for updating the parameters

Replay Method

[Wickramasinghe, 2023]

Utilize the data in memory

Parameter Isolation Method

[Wickramasinghe, 2023]

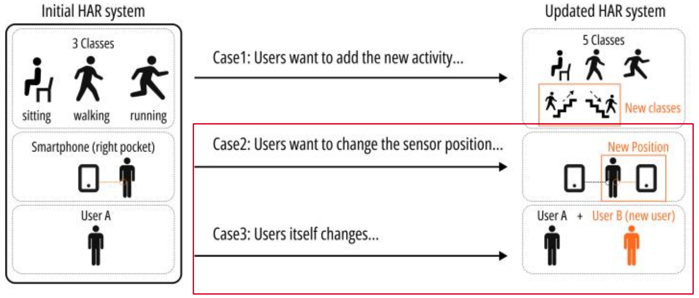
Update the architecture

Already Explored

Not Explored

Other CL Scenarios

Domain Incremental Learning



[Chan, 2024] Chan et al. , "CAPTURE-24: A large dataset of wrist-worn activity tracker data collected in the wild for human activity recognition." Scientific Data 11.1 (2024): 1135.
[Du, 2017] Du et al., "Surface EMG-based inter-session gesture recognition enhanced by deep domain adaptation." Sensors 17.3 (2017): 458.

Summary

Blurry Class-Incremental Learning for IMU-Based Human Activity Recognition: An Empirical Study

Takumi Yamamoto[1,2], Suguru Kanoga[1], Mitsunori Tada[1], Yuta Sugiura[2]
[1]National Institute of Advanced Industrial Science and Technology (AIST)
[2]Keio University

Background	Continual learning methods are effective for building ML model that support long-term deployment.
Motivation	B-CIL have not gained the attention for IMU-base HAR.
Experiment	• Evaluate nine CL method under B–CIL Scenarios with different levels of class overlap (B-CIL1 & B-CIL2) • Use two public dataset
Results	• Replay-based methods outperformed regularization method. • Especially, ASER achieved the highest Final Average Accuracy. • In most case, B-CIL2 > B-CIL1 > CL
Future Work	• Other datasets, other CL methods, and other scenarios

This work was partially supported by JSPS KAKENHI Grant-in-Aid for Scientific Research (B) Grant Number JP23K28135 and Programs for Bridging the gap between R&D and the Ideal society (society 5.0) and Generating Economic and social value (BRIDGE) /Practical Global Research in the AI ×Robotics Services, implemented by the Cabinet Office, Government of Japan.