Doctoral Candidate 1

Deep Clustering for Time Series

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- Conclusions and Future Directions

Fundamental Concepts

1 Introduction

Definition

A **time series** $\mathbf{x}_i$ is a sequence of observations with $T > 1$ time steps, $\mathbf{x}_i = \{\mathbf{x}_{i,1}, \ldots, \mathbf{x}_{i,T}\}$, where $\mathbf{x}_{i,t} \in \mathbb{R}^d$. Depending on d, each observation can be a real-valued number ($d = 1$) or a vector ($d > 1$).

Definition

Given a dataset of N time-series data $\chi = \{\mathbf{x}_1, \ldots, \mathbf{x}_N\}$, where $\mathbf{x}_i \in \mathbb{R}^{d \times T}$, the process of **time series clustering** is to partition χ in K clusters $\mathcal{C} = \{C_1, \ldots, C_K\}$, with $K < N$.

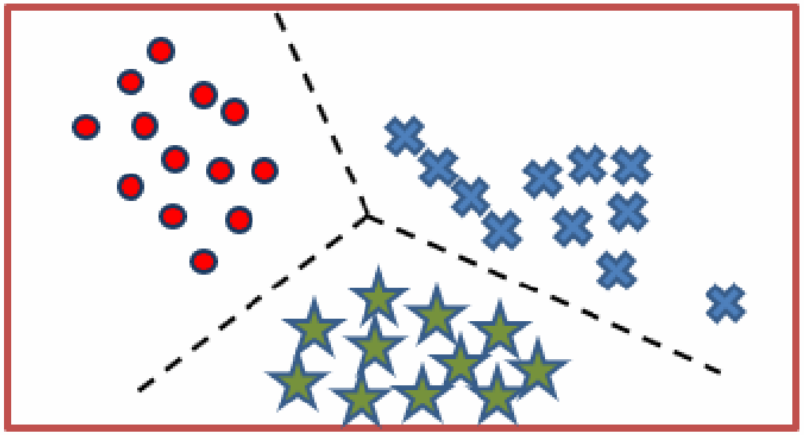
Based on the scope, time-series clustering is categorized into:

- Full time series clustering
- Subsequence clustering
- Time point clustering

Classification vs Clustering

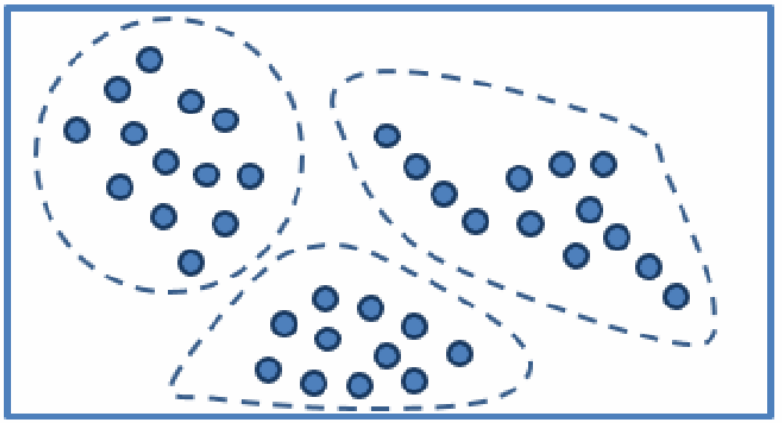
Classification

- ✗ Supervised learning
- ✗ Labels are known
- ✗ Assign data to predefined classes
- ✗ Model learns a decision boundary



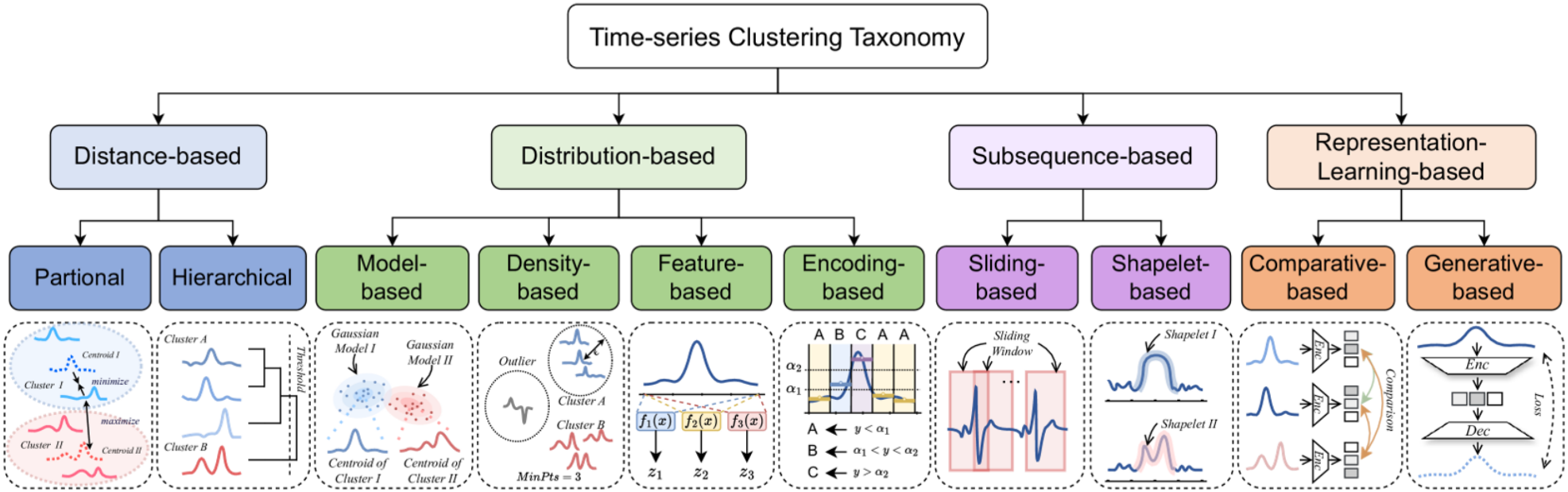
Clustering

- ✗ Unsupervised learning
- ✗ No labels available
- ✗ Discover hidden groups or behaviours
- ✗ Structure emerges from data



Taxonomy

1 Introduction



*Source: Bridging the gap: A decade review of time-series clustering methods [1]

Proposal: Mamba for Time Series

1 Introduction

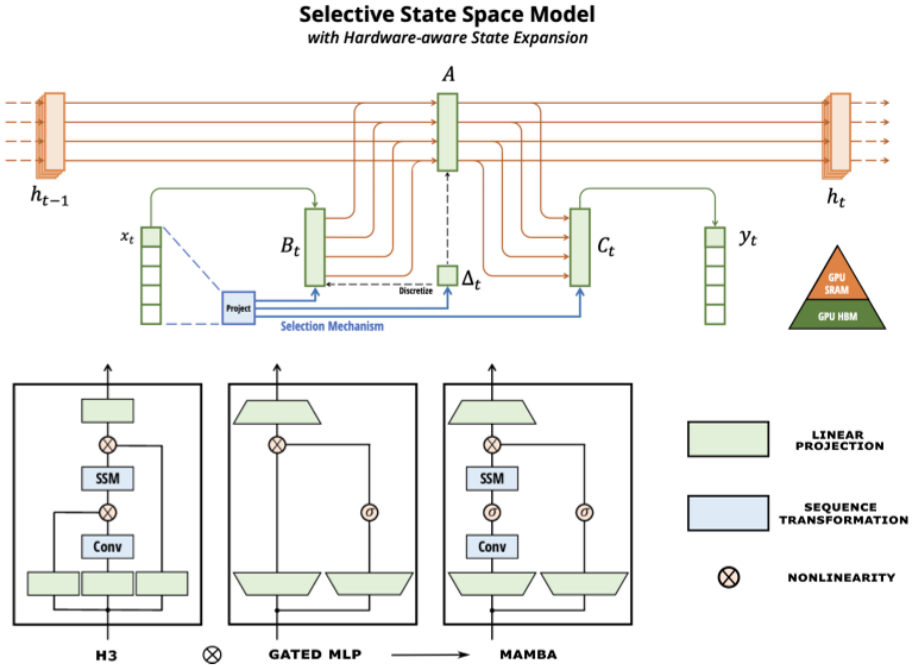
★ **High Impact:** over **5,000 citations** in a short time, showing strong adoption and relevance.

☞ **Advantages:** linear-time complexity, scalable to long sequences, and lower memory usage.

$$\mathbf{h}_t = \mathbf{A}\mathbf{h}_{t-1} + \mathbf{B}_t\mathbf{x}_t, \quad \mathbf{y}_t = \mathbf{C}_t\mathbf{h}_t$$

▲ **Causal architecture:** naturally supports online and streaming inference.

➤ **Real-World Applicability:** efficient and lightweight enough for industrial, streaming, or large-scale datasets, addressing scalability and computational constraints.



*Source: *Mamba: Linear-Time Sequence Modeling with Selective State Spaces* [2]

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Framework Overview

2 FMMVCC: Fuzzy Mamba-based Multi-View Contrastive Clustering

Our approach integrates representation learning and clustering into a unified framework for time series data.

1. Multi-View Representation

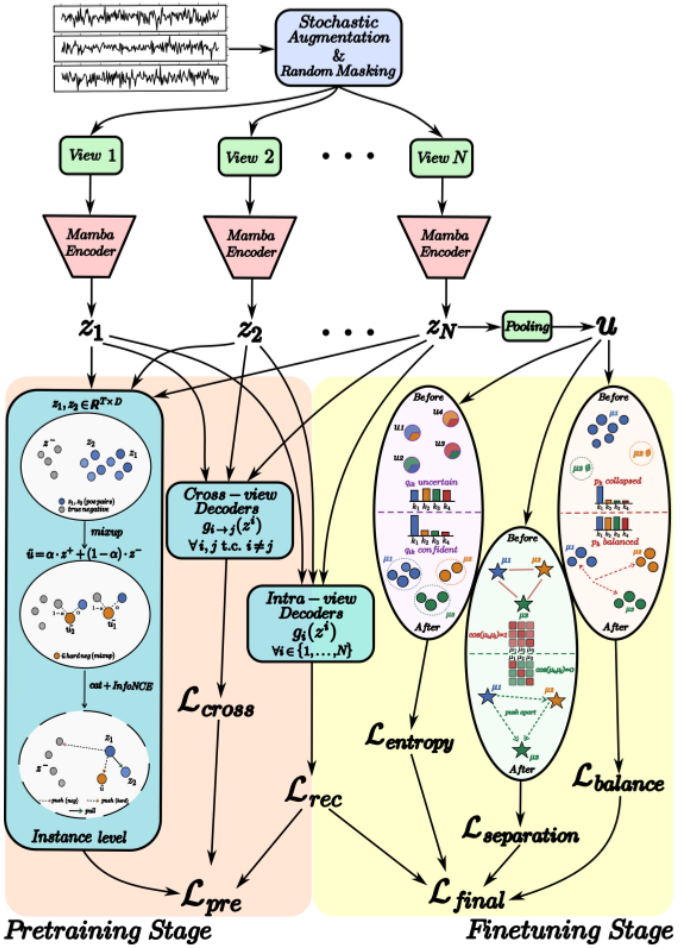
Generate multiple views via augmentations and temporal masking.

2. Mamba-based Encoding

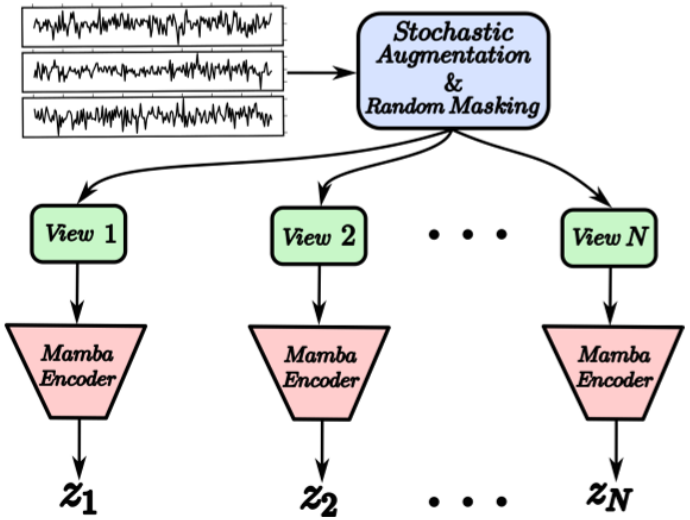
Efficient modeling of long-range dependencies via State Space Models.

3. Contrastive + Fuzzy Clustering

Joint representation learning and soft clustering for robust assignments.



Joint Augmentation and Masking



Multiple diverse views are generated by applying a stochastic transformation $A^{(v)}$ followed by element-wise multiplication with a temporal mask $M^{(v)}$:

$$x^{(v)} = M^{(v)} \odot A^{(v)}(x), \quad v = 1, \ldots, N$$

where $x \in \mathbb{R}^{T \times D}$, $M^{(v)} \in \{0, 1\}^{T \times D}$ is a mixed mask with a **30% missing rate**.

Stochastic Transformations $A^{(v)}$

None — **Jittering** — **Scaling** — **Permutation**

Multi-Objective Representation Learning

Consistency Decoders:

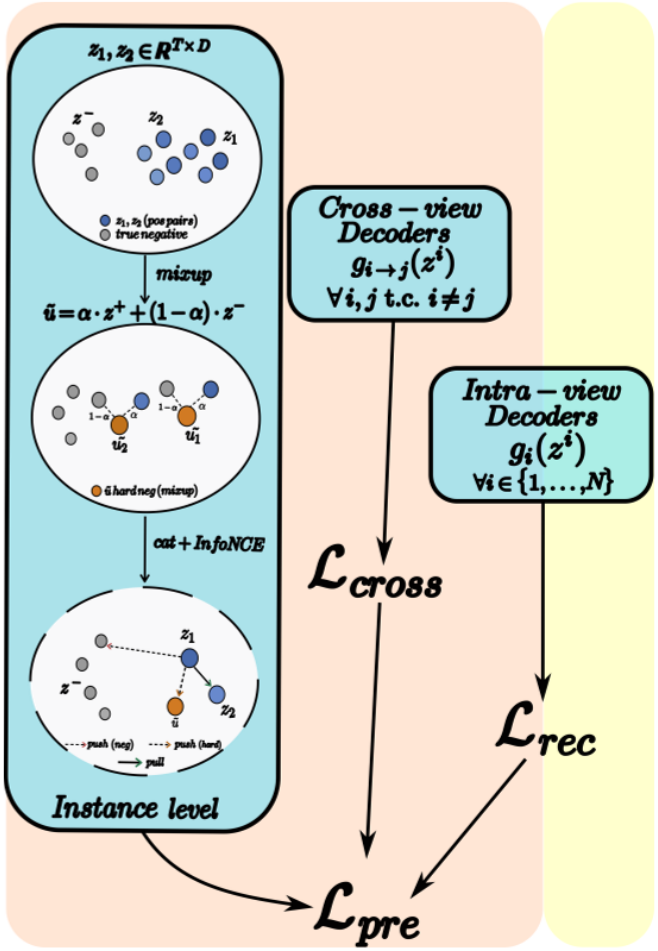
$$\mathcal{L}_{rec} = \frac{1}{N}\sum_{v=1}^{N} \|x - \hat{x}^{(v)}\|_2^2$$

$$\mathcal{L}_{cross} = \frac{1}{N(N-1)}\sum_{i\neq j} \|z^{(j)} - \tilde{z}^{(j)}\|_2^2$$

Contrastive Alignment:

$$\mathcal{L}_{contrast} = -\log \frac{\exp(\text{sim}(\tilde{z}_i, \tilde{z}_j)/\tau)}{\sum_{k=1}^{N} \exp(\text{sim}(\tilde{z}_i, \tilde{z}_k)/\tau)}$$

$$\mathcal{L}_{pre} = \lambda_1 \mathcal{L}_{contrast} + \lambda_2 \mathcal{L}_{cross} + \lambda_3 \mathcal{L}_{rec}$$



Fuzzy Clustering Optimization

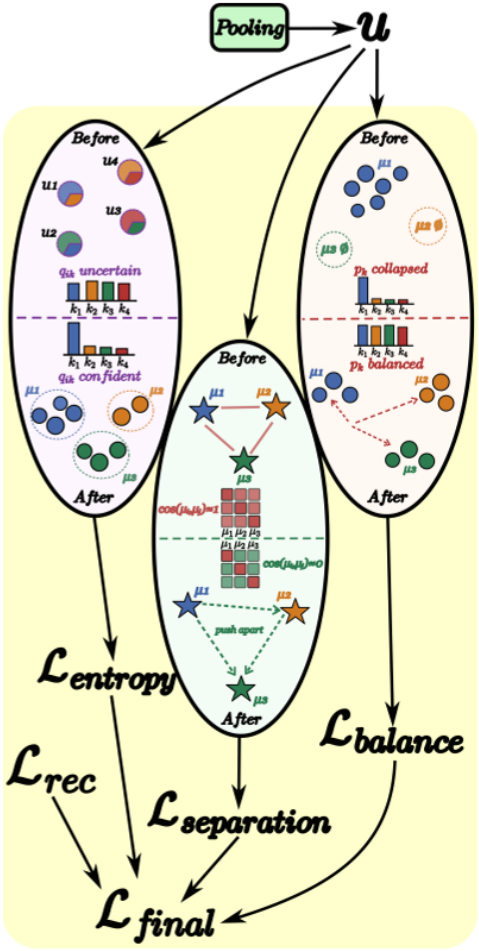
Feature Aggregation & Soft Cluster Assignments:

$$u = \frac{1}{N}\sum_{v=1}^{N} z^{(v)} \qquad q_{ik} = \frac{exp(sim(u_i, c_k)/\tau)}{\sum_{j=1}^{K} exp(sim(u_i, c_j)/\tau)}$$

Clustering Objectives:

$$\begin{cases} \mathcal{L}_{entropy} = \frac{1}{N}\sum_{i,k} q_{ik} \log q_{ik} \\ \mathcal{L}_{balance} = \sum_k p_k \log p_k, \quad p_k = \frac{1}{N}\sum_i q_{ik} \\ \mathcal{L}_{separation} = \frac{1}{K(K-1)}\sum_{i \neq j} \left(\bar{\mu}_i^\top \bar{\mu}_j\right)^2 \end{cases}$$

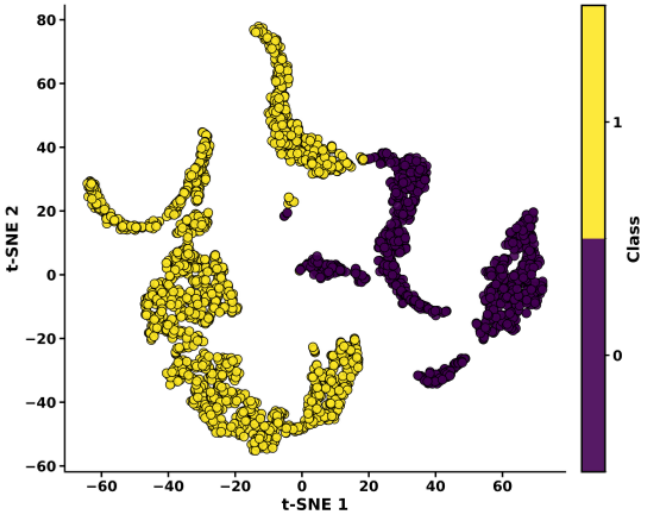
$$\mathcal{L}_{final} = \lambda_r \mathcal{L}_{rec} + \lambda_c \left(\mathcal{L}_{entropy} + \lambda_b \mathcal{L}_{balance} + \lambda_s \mathcal{L}_{separation}\right)$$



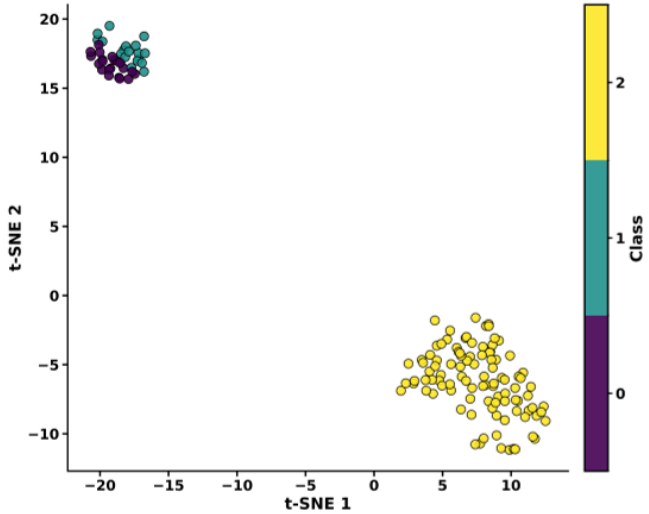
Performance Overview

2 FMMVCC: Fuzzy Mamba-based Multi-View Contrastive Clustering

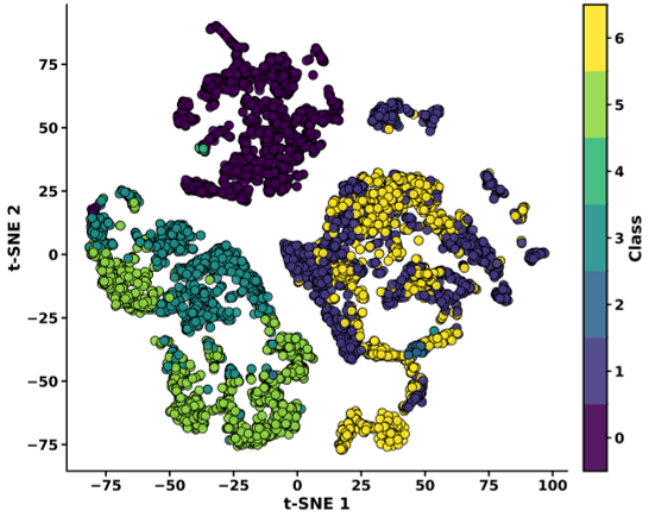
Metric	TSK-DTW[3]	HDBSCAN[4]	PG-Mamba[5]	FCACC[6]	EMTC[7]	FMMVCC
#Best Scores	12	0	3	16	0	**29**
#Second	8	5	5	**23**	2	17
Avg Rank	2.98	4.68	4.67	2.47	4.35	**1.85**



FreezerRegularTrain



DistalPhalanx

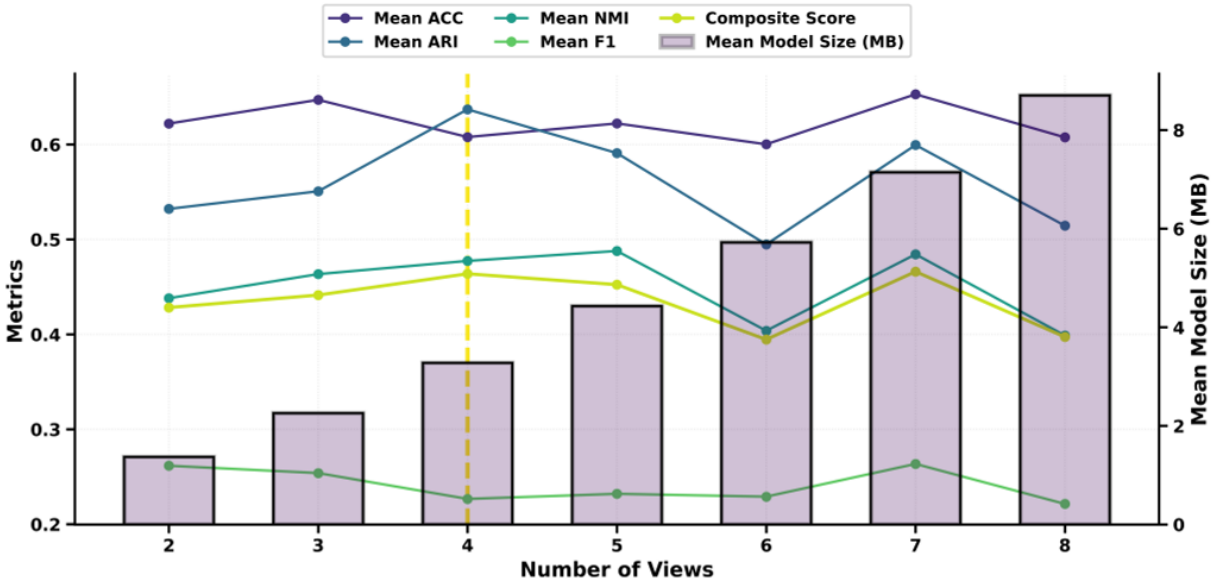


ElectricDevices

Sensitivity & Scalability Analysis

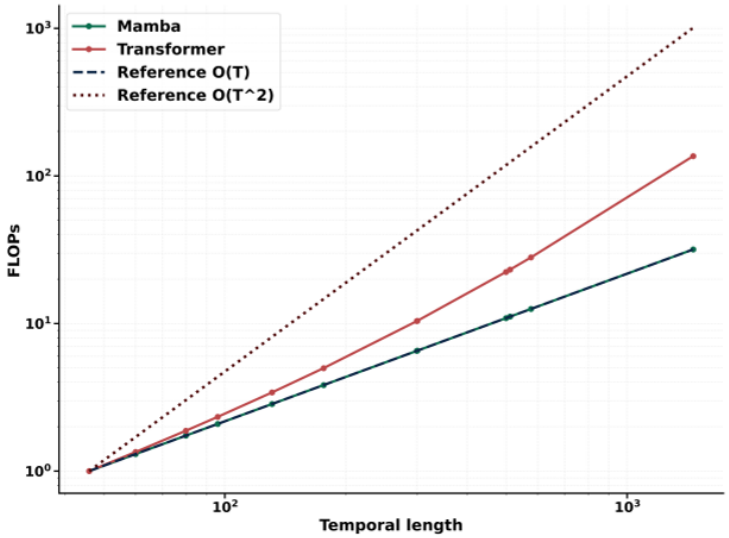
2 FMMVCC: Fuzzy Mamba-based Multi-View Contrastive Clustering

Sensitivity to the Number of Views (N)



Performance is evaluated through a **Composite Score** (ARI, ACC, F1, NMI average). Results show a non-monotonic behavior, with the best trade-off achieved at $N = 4$ **views**, balancing clustering quality and model complexity.

Scalability vs. Transformers



Compared with Transformers, FMMVCC achieves **linear complexity** ($O(T)$) thanks to Mamba selective state-space models, avoiding the quadratic cost of self-attention.

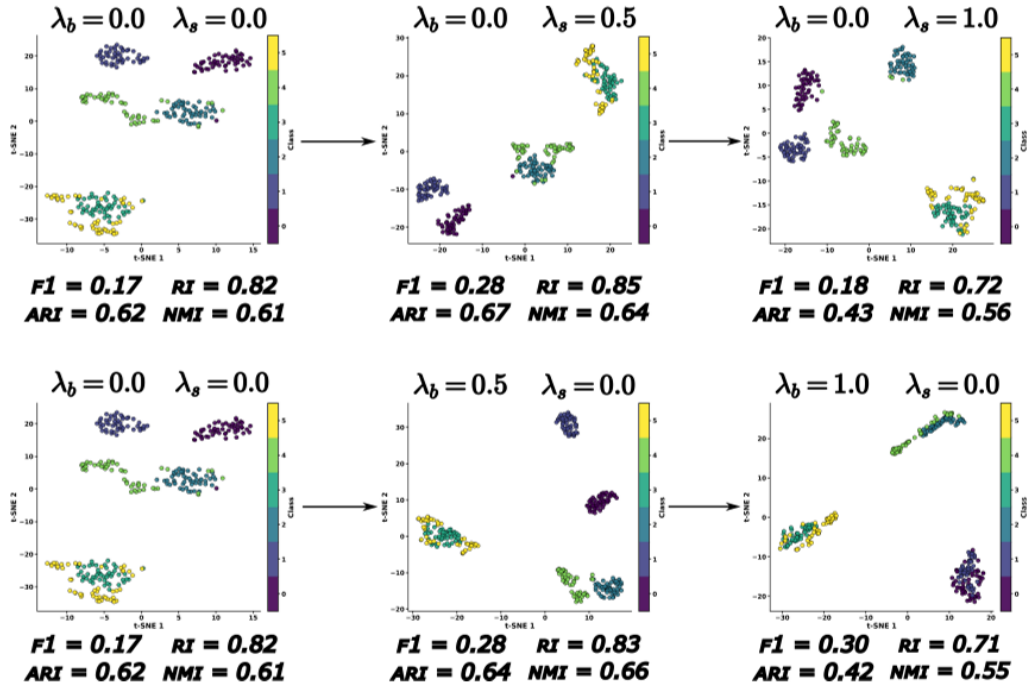
Hyperparameter Sensitivity

2 FMMVCC: Fuzzy Mamba-based Multi-View Contrastive Clustering

The clustering effectiveness relies on the trade-off between the fuzzy loss components:

Balance (λ_b): Prevents cluster collapse by ensuring a non-degenerate distribution of samples across centers.

Separation (λ_s): Maximizes inter-cluster distance, forcing the model to learn distinct decision boundaries.



Optimal Configuration

$$\lambda_b = 0.2 \quad | \quad \lambda_s = 0.5$$

Key Observation: Robust performance is maintained across a wide range of λ values, confirming the stability of the Multi-View Fuzzy objective.

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Time Series in Healthcare

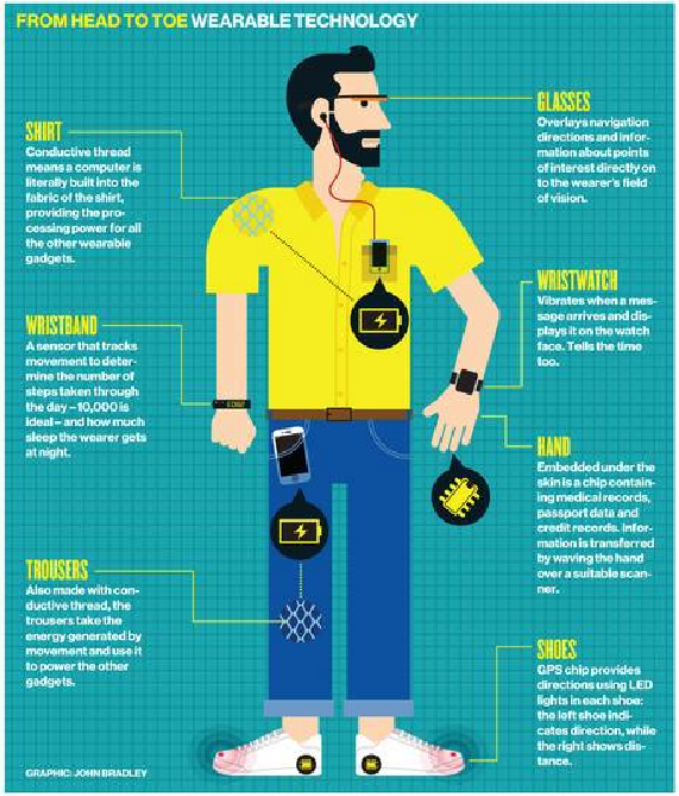
3 One-Shot Multi-View Clustering for Federated Fall Detection

Healthcare Time Series

- ✓ Continuous **sensor monitoring** in healthcare systems
- ✓ Wearables generate **multivariate time series**
- ✓ Signals include IMU, ECG, motion, physiological data
- ✓ Data is **noisy, heterogeneous, high-dimensional**

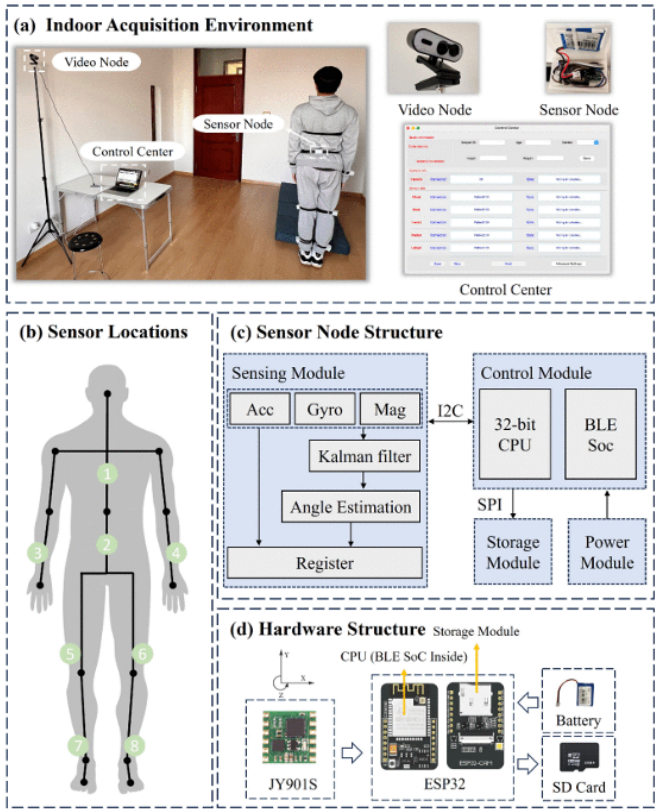
Applications

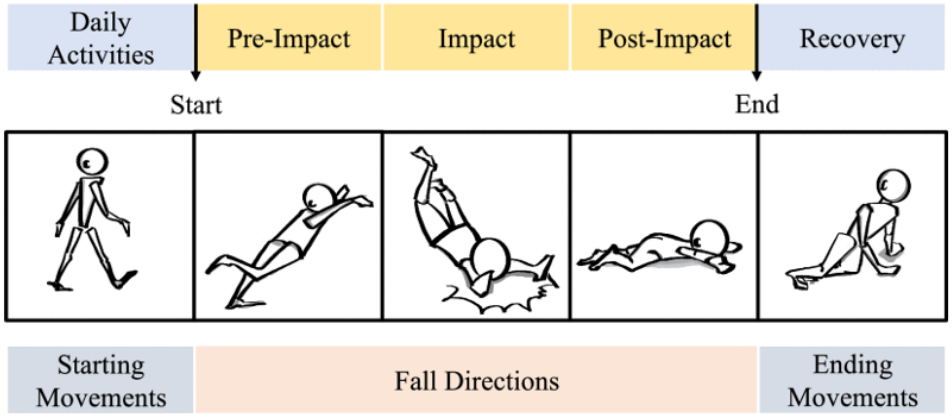
- ✓ Human Activity Recognition (HAR)
- ✓ Fall detection
- ✓ Remote patient monitoring



FallTL Dataset

3 One-Shot Multi-View Clustering for Federated Fall Detection

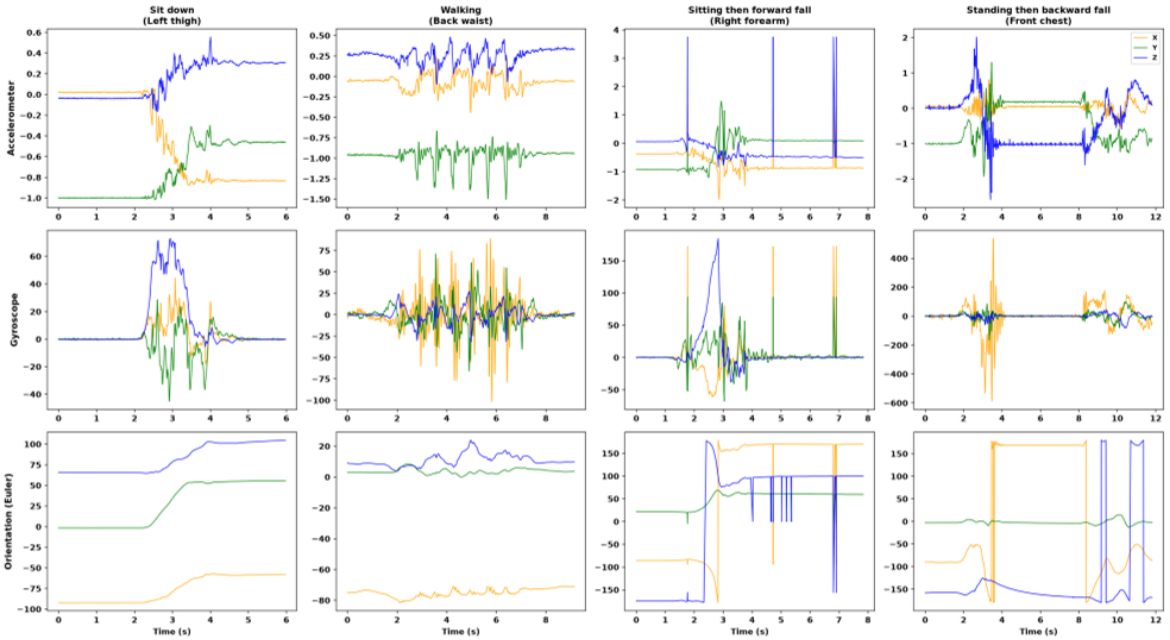


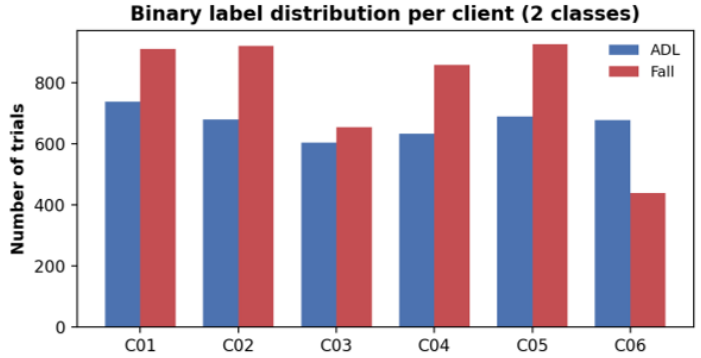


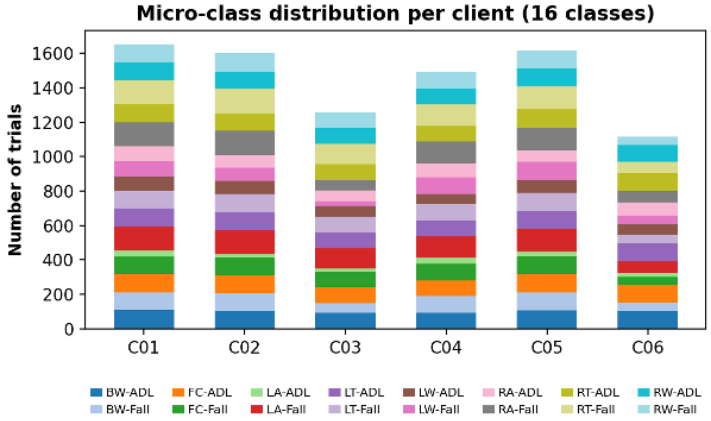
*The data are explained in: *Fall Monitoring With Single IMU: A Large-Scale Dataset and a Novel Dual-Branch Network* [8]

Understanding the Data

3 One-Shot Multi-View Clustering for Federated Fall Detection







Privacy Constraints

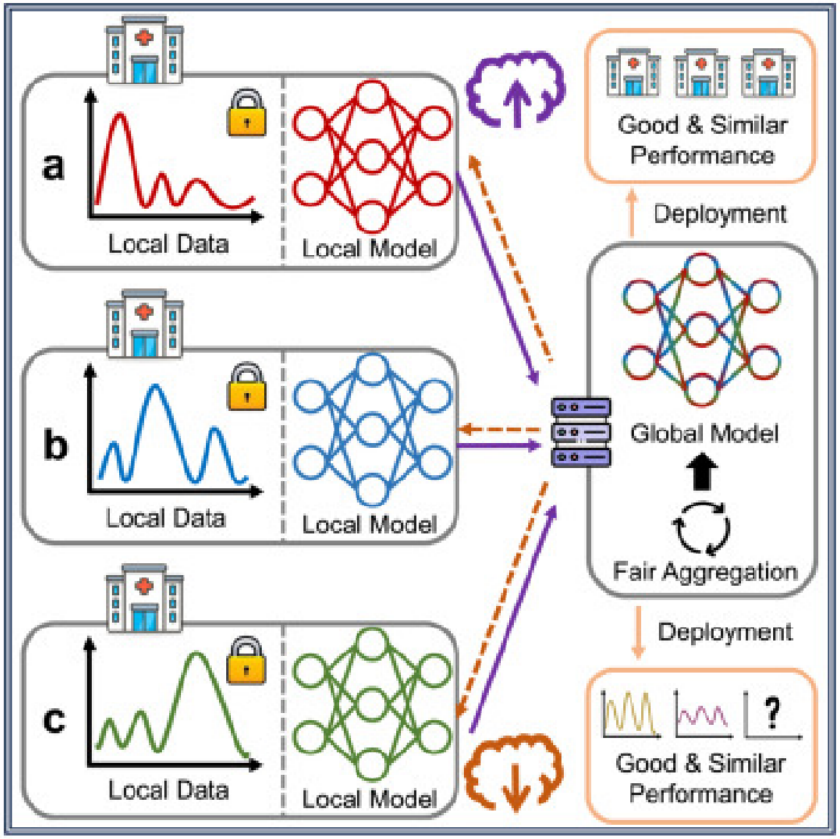
3 One-Shot Multi-View Clustering for Federated Fall Detection

Privacy in Healthcare Data

- ✓ Sensor data contains **sensitive health information**
- ✓ Centralized training is often not feasible
- ✓ Raw data cannot leave devices or hospitals

Federated Learning

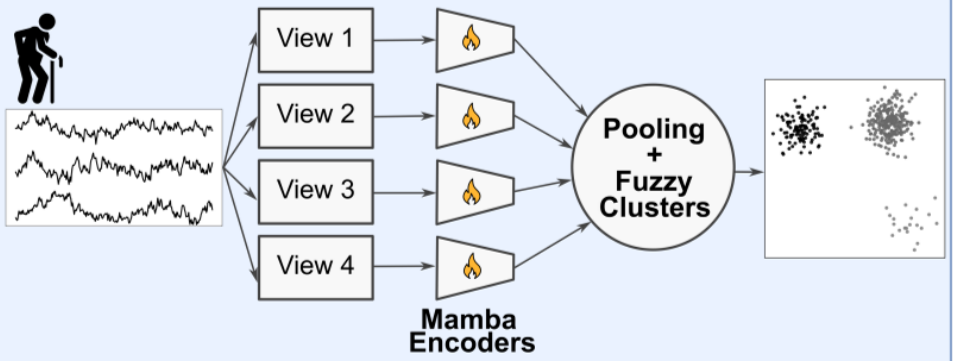
- ✓ Local training on each device/client
- ✓ No raw data sharing
- ✓ Collaborative model aggregation



Framework Overview

3 One-Shot Multi-View Clustering for Federated Fall Detection

Local Pretraining (No Communication)



Phase 1: Self-Supervised Pretraining

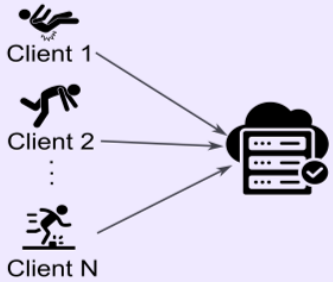
- Reconstruction Loss
- Cross-view Reconstruction Loss
- Contrastive InfoNCE Loss + Mixup

Phase 2: Clustering Finetuning

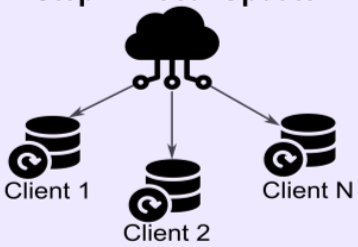
- Reconstruction Loss
- Clustering Loss = Entropy + Balance + Separation
- Learn cluster prototypes $C_1 \ldots C_k$

Transition

Step 1: One-shot FedAvg



Step 2: Local Update

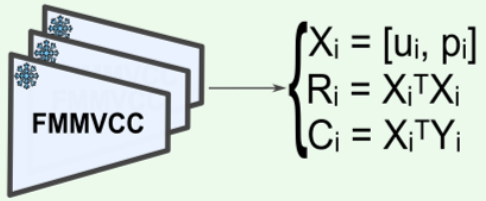


Step 3: Freezing

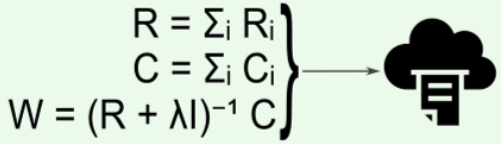


Classification

Step A: Local Statistics



Step B: One-shot Server Aggregation



Step C: Broadcast & Inference



Experimental Results

3 One-Shot Multi-View Clustering for Federated Fall Detection

Latent Representations

Encoder	K=2	K=16	Rec
Recon	0.740	0.514	0.754
EMTC	0.701	0.230	0.657
FCACC	0.783	0.607	0.800
TS2Vec	0.798	**0.658**	0.834
FMMVCC	**0.842**	0.641	**0.836**

Federated Classification

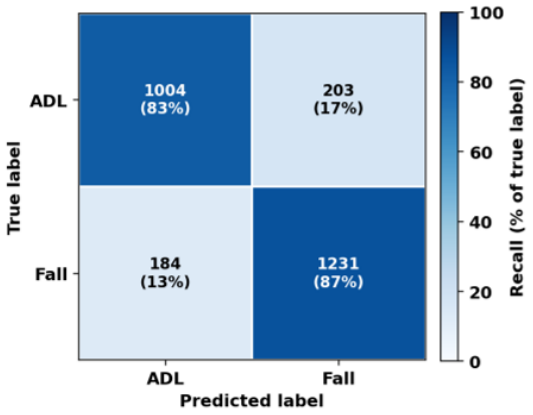
Method	K=2	K=16	Rec
FedAvg	0.736	0.343	0.707
FedProx	0.706	0.205	0.602
Shared	0.763	0.514	0.763
FedProto	**0.868**	0.539	0.821
Personalized	0.842	**0.641**	**0.836**

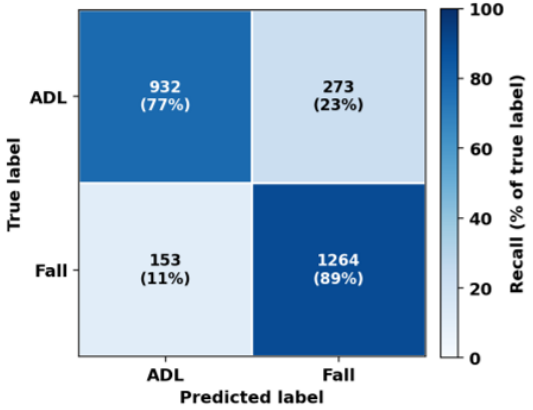
Alignment vs Discriminability

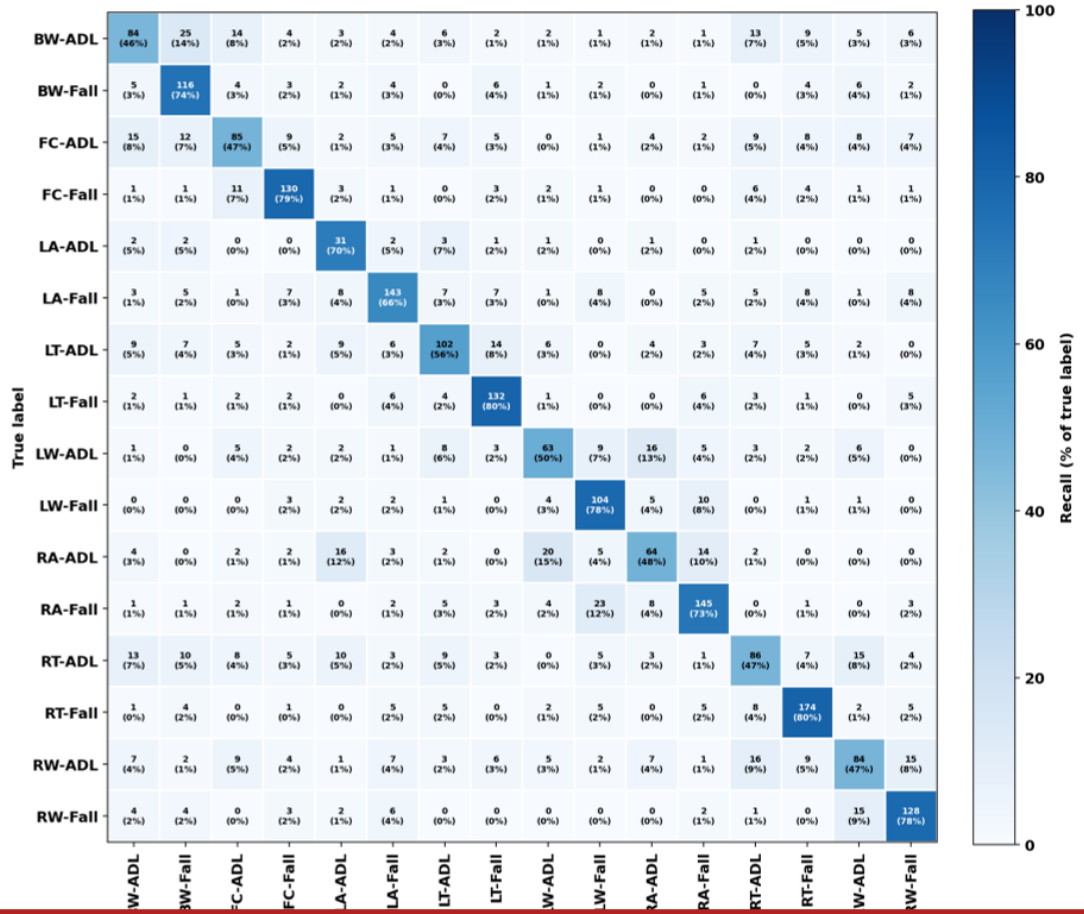
Encoder	ADL		Fall		F-J	ACC
	PD	CORAL	PD	CORAL		
Reconstruction	0.0204	0.0033	0.0313	0.0031	4.09	0.740
TS2Vec	0.0573	0.0120	0.0783	0.0135	5.68	**0.804**
FCACC	0.0381	0.0051	0.0539	0.0065	6.15	0.783
EMTC	**0.1869**	**0.1228**	0.1991	**0.1324**	6.57	0.700
FMMVCC	0.1803	0.0977	**0.2897**	0.1247	**8.96**	**0.842**
Supervised	0.2408	0.1240	0.3765	0.1332	191.6	0.856

Classification Performances

3 One-Shot Multi-View Clustering for Federated Fall Detection

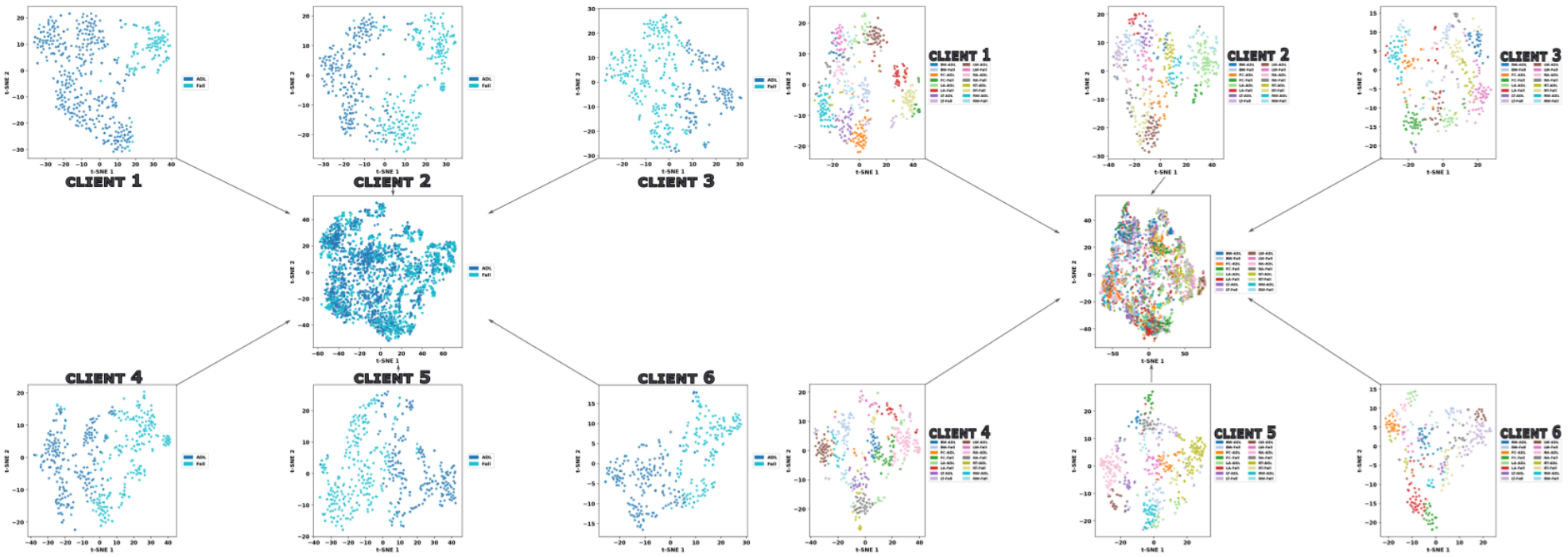






Representation Separability

3 One-Shot Multi-View Clustering for Federated Fall Detection



Fuzzy Membership Contribution

FL Strategy	Input	K = 2	K = 16	Rec
FedAvg	$z + p$	0.740	0.360	0.714
	z	0.736	0.343	0.707
	p	0.557	0.124	0.532
FedProx	$z + p$	0.703	0.234	0.636
	z	0.706	0.205	0.602
	p	0.554	0.122	0.519
Shared	$z + p$	0.764	0.524	0.769
	z	0.763	0.514	0.763
	p	0.517	0.121	0.531
FedProto	$z + p$	**0.864**	0.557	0.824
	z	**0.868**	0.539	0.821
	p	**0.609**	0.219	0.600
Personal.	$z + p$	0.845	**0.632**	**0.832**
	z	0.842	**0.641**	**0.836**
	p	0.567	**0.255**	**0.634**

Ablation Insights

✗ Latent embedding is the dominant source of discriminative information across all FL strategies.

✗ Fuzzy membership alone is insufficient and leads to a strong performance degradation.

✗ Concatenation provides only marginal gains, confirming that p is auxiliary.

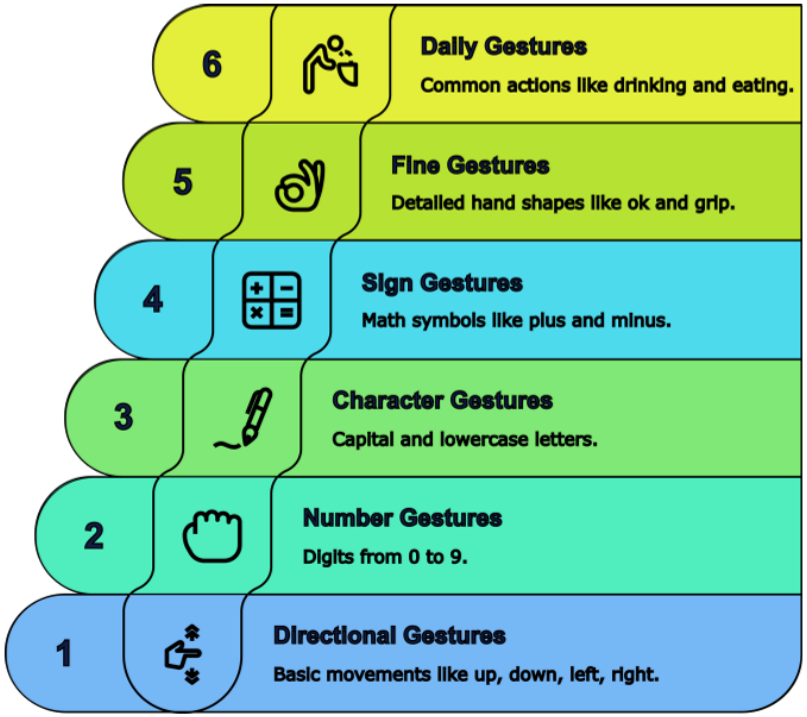
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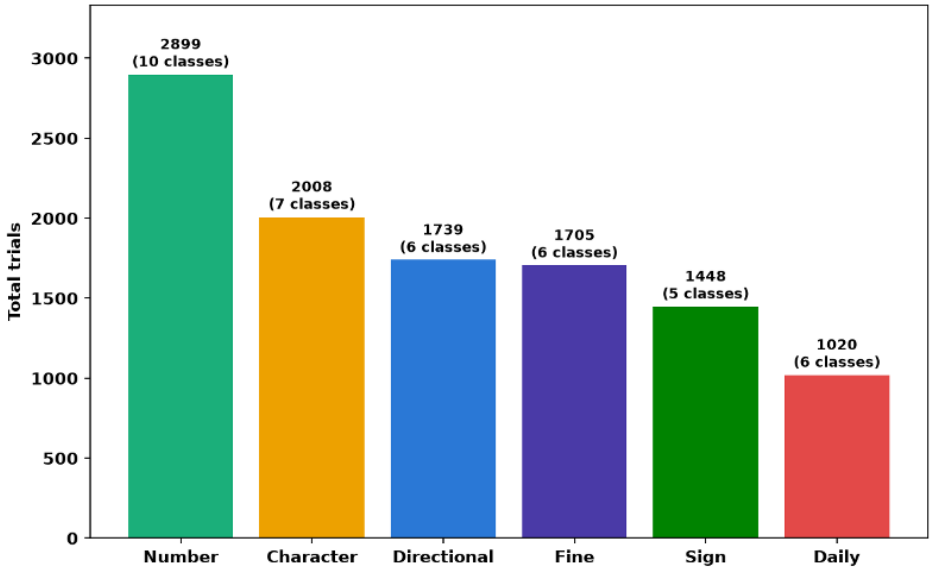
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Understanding the Data

4 XAI - FMMVCC





*The data are available in: WriGest-Zenodo [9]

Understanding the Data

4 XAI - FMMVCC

Class Imbalance Challenge

✗ Contains highly imbalanced gesture classes.

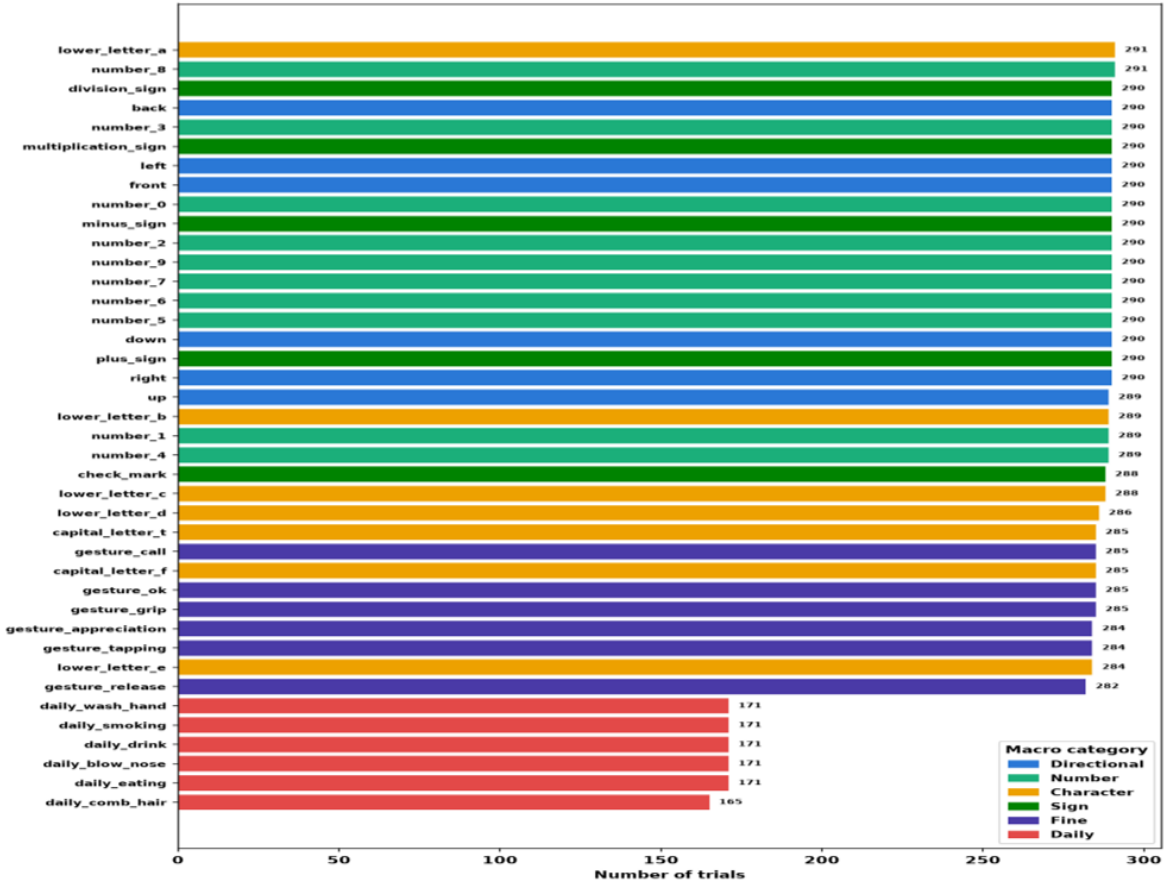
✗ Dominant classes may bias representation learning and clustering.

✗ XAI helps identify whether clusters are driven by meaningful temporal and sensor patterns.

Research Goal

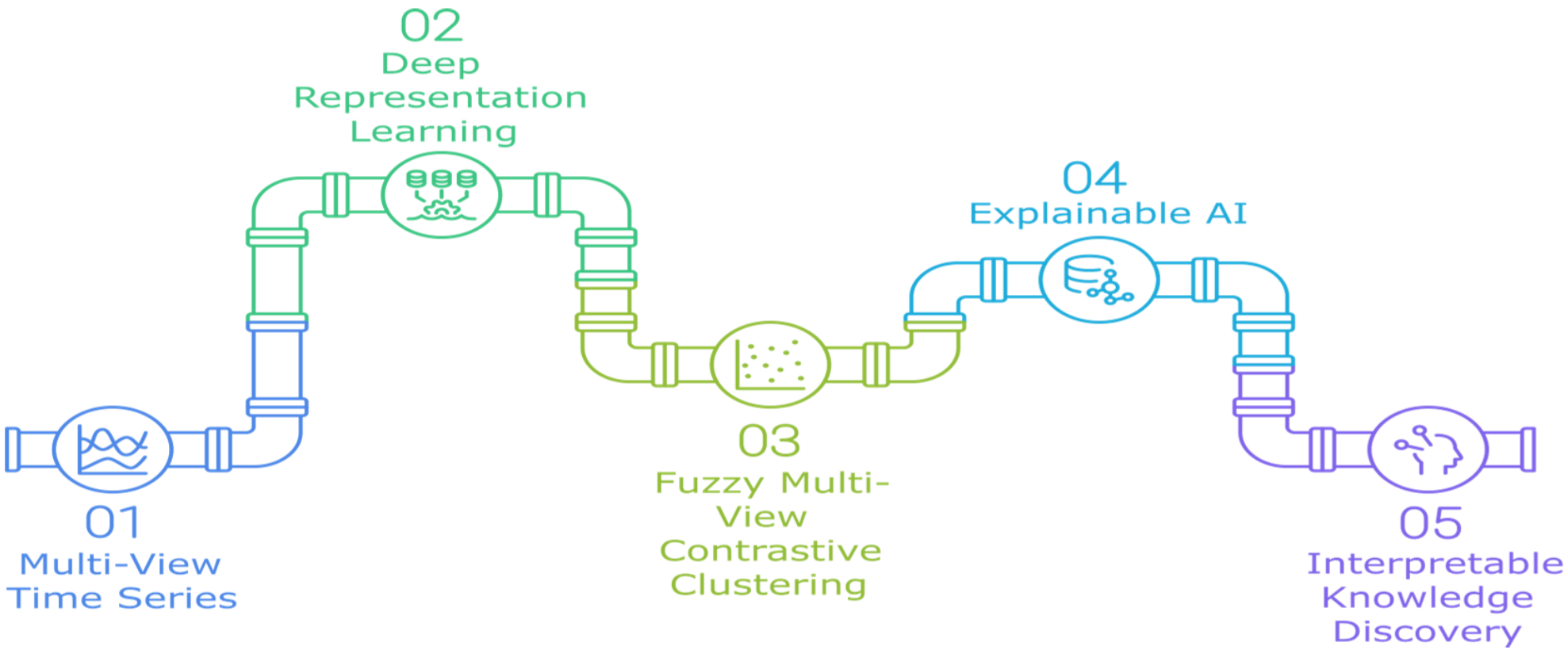
➠ Understand cluster formation.

➠ Reveal important sensors and temporal regions.



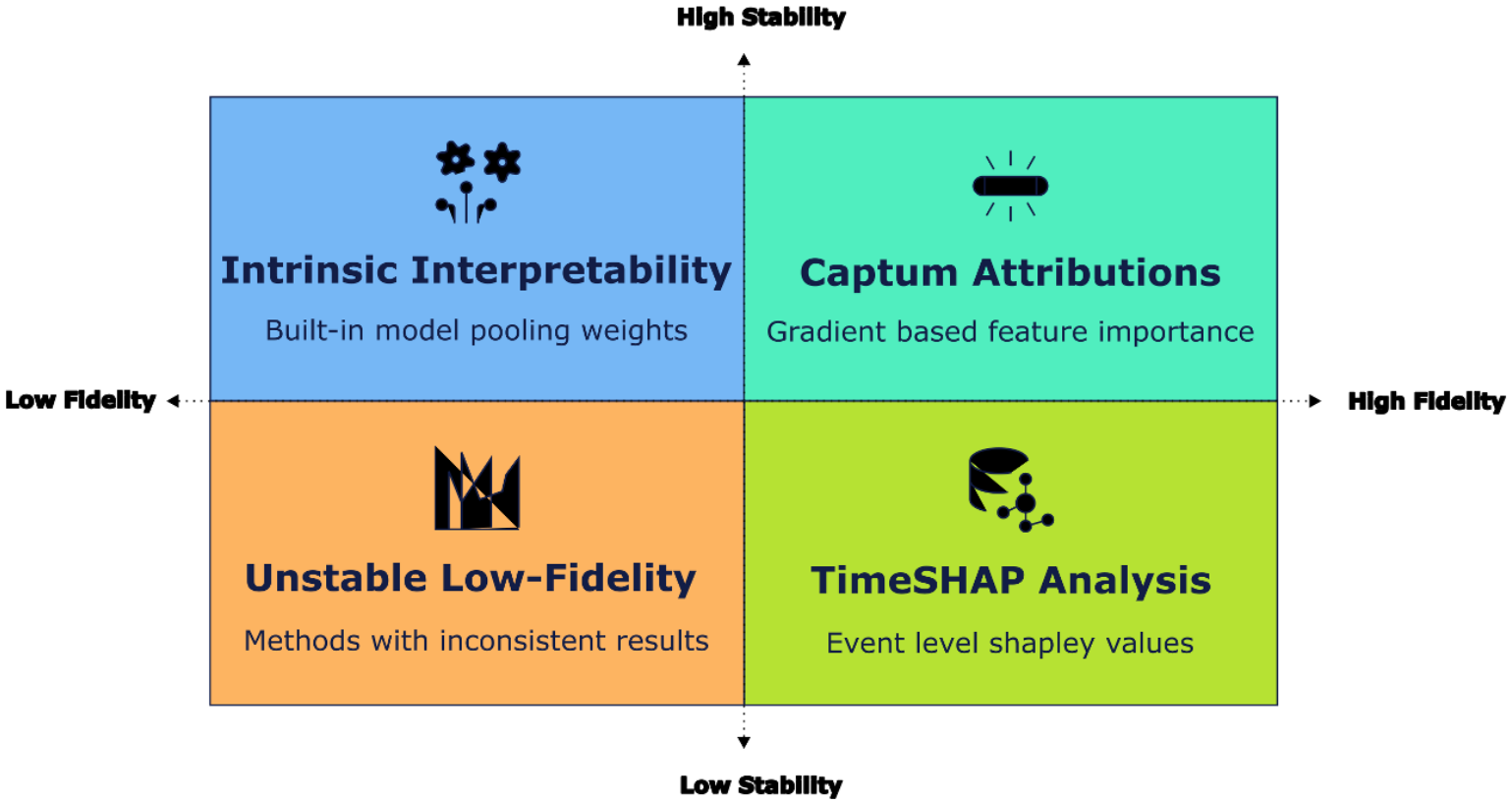
Framework Overview

4 XAI - FMMVCC



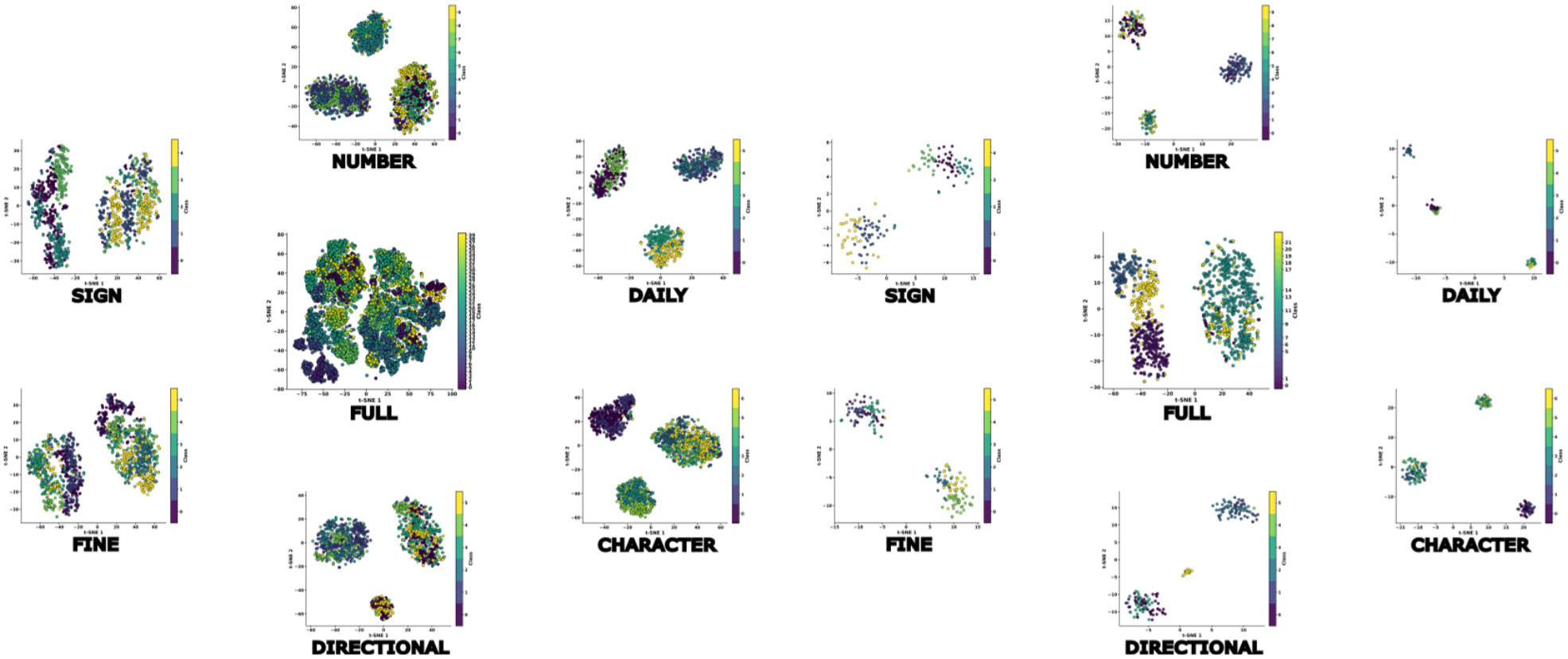
Explainable Models

4 XAI - FMMVCC



Latent Space Visualization

4 XAI - FMMVCC



Train latent space

Test latent space

Performance and Interpretability

4 XAI - FMMVCC

View-Ablation Importance

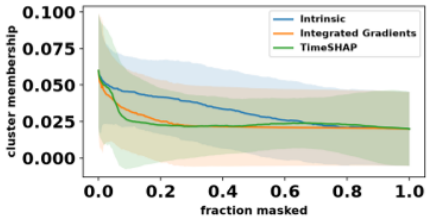
Configuration	V0 *(none)*	V1 *(jit.)*	V2 *(scal.)*	V3 *(perm.)*
Full	0.024	**0.148**	0.026	0.027
Character	0.070	**0.081**	0.055	0.041
Daily	0.121	**0.125**	0.117	0.116
Directional	0.016	**0.023**	0.008	0.005
Fine	0.166	0.183	0.178	**0.223**
Number	0.004	0.004	**0.153**	0.004
Sign	0.137	0.141	0.132	**0.192**

Clustering Performance

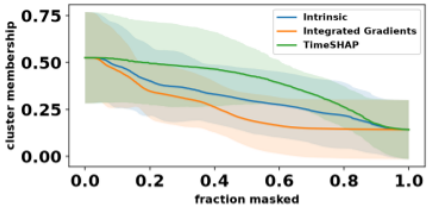
Configuration	AC	ACC	ARI	NMI	RI	F1
Full	23/40	0.913	0.941	0.668	0.983	**0.094**
Character	7/7	0.942	0.900	0.715	0.971	0.512
Daily	6/6	0.934	0.742	0.595	0.933	0.513
Directional	6/6	0.938	0.883	0.652	0.966	0.520
Fine	6/6	0.928	0.766	0.466	0.938	0.421
Number	10/10	0.931	0.893	0.663	0.969	0.392
Sign	5/5	0.925	0.625	0.401	0.908	0.455

Fidelity and Stability

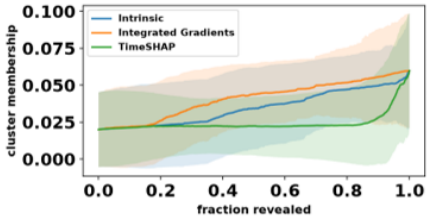
4 XAI - FMMVCC



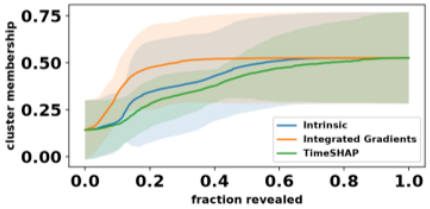
Deletion – Full



Deletion – Directional



Insertion – Full



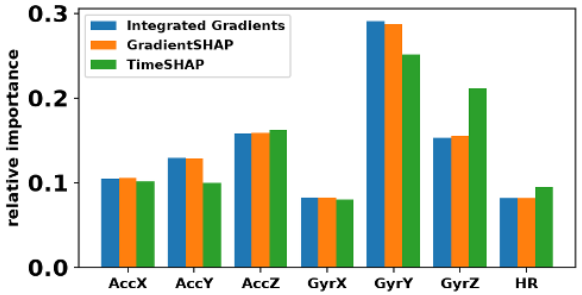
Insertion – Directional

Configuration	Intrinsic		IG		TimeSHAP		Stability
	DEL	INS	DEL	INS	DEL	INS	
Full	0.031	0.034	**0.022**	**0.040**	0.023	0.023	−0.005
Character	0.277	0.258	**0.199**	**0.349**	0.267	0.266	−0.016
Daily	0.368	0.368	**0.274**	**0.455**	0.346	0.348	0.014
Directional	0.311	0.426	**0.251**	**0.479**	0.405	0.382	−0.018
Fine	0.292	0.261	**0.205**	**0.380**	0.274	0.288	0.040
Number	0.240	0.227	**0.155**	**0.280**	0.208	0.213	0.010
Sign	0.439	0.440	**0.340**	**0.553**	0.461	0.473	−0.004

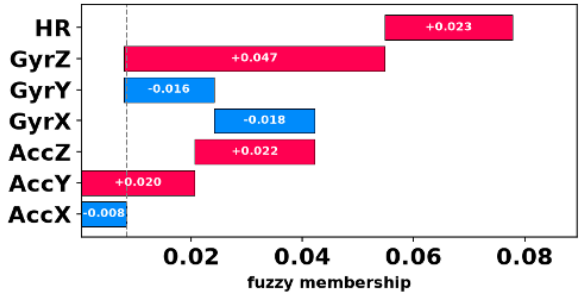
DEL: Deletion AUC (↓), **INS**: Insertion AUC (↑).

Qualitative XAI Results

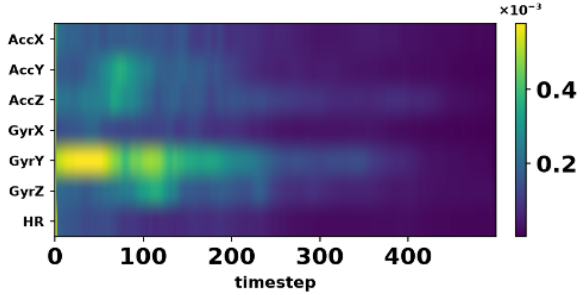
4 XAI - FMMVCC



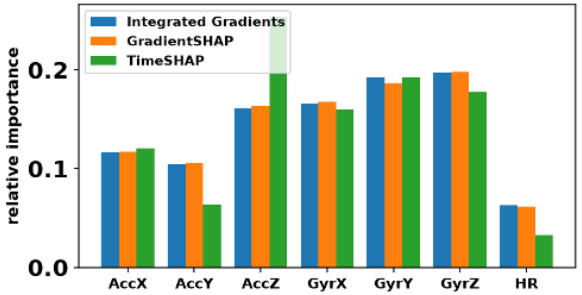
Channel Importance



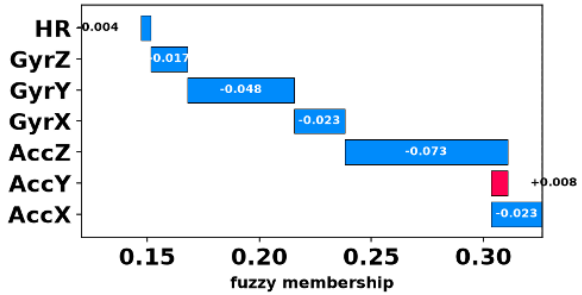
TimeSHAP



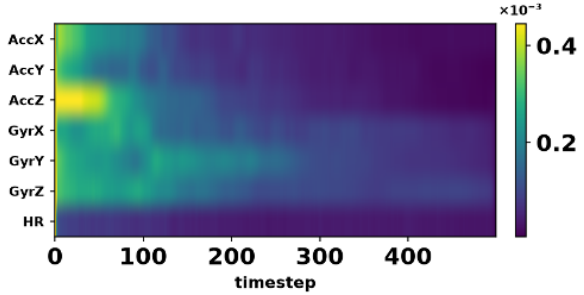
IG Heatmap



Channel Importance



TimeSHAP



IG Heatmap

Top row: **Number**. Bottom row: **Directional**.

Nearest-Medoid Cluster Prototype

4 XAI - FMMVCC

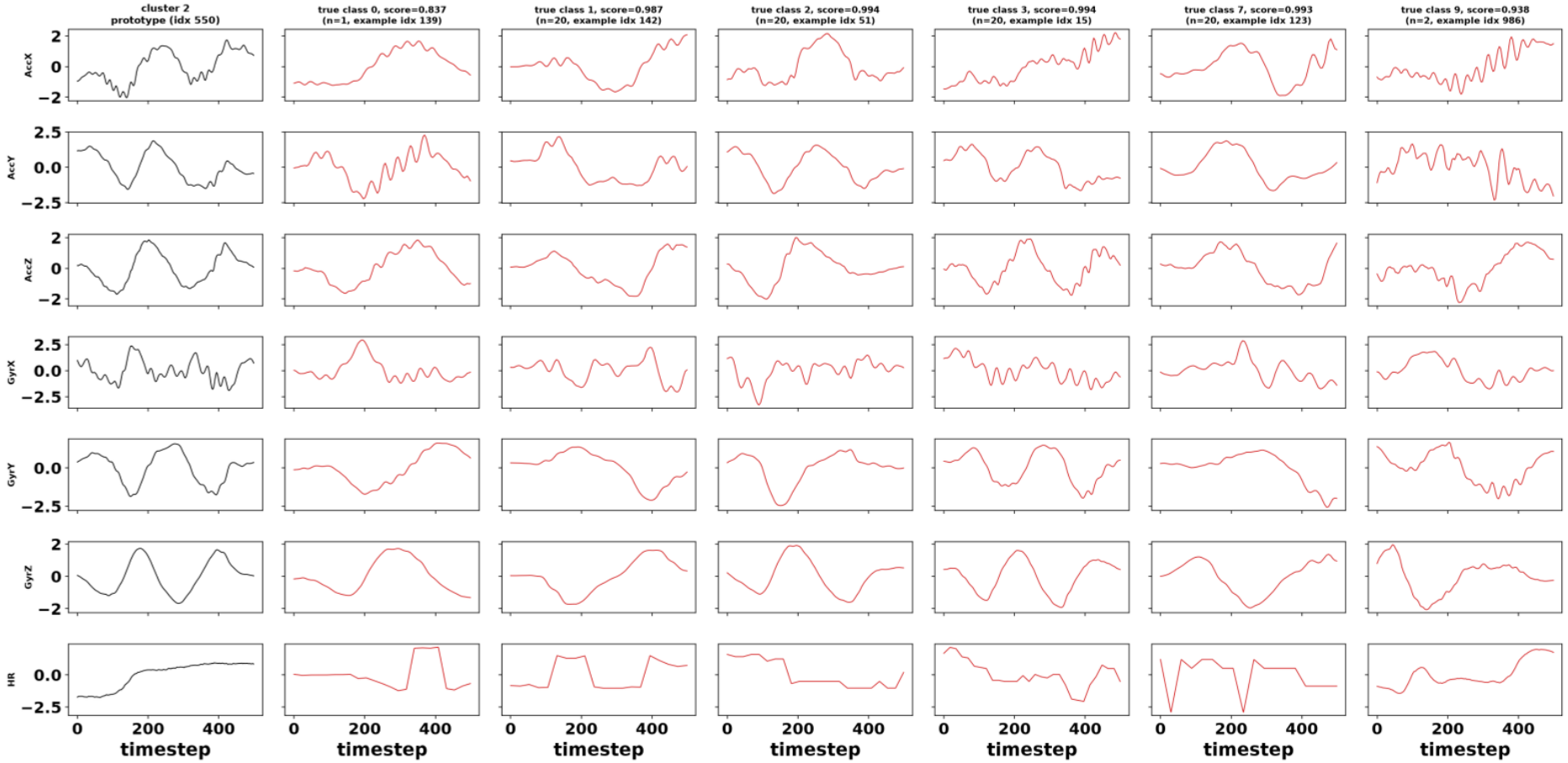


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5 Multivariate FMMVCC

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- Conclusions and Future Directions

Experimental Setting

- ✓ Same pipeline as the univariate case: Multi-View Generation → Mamba Encoding → Contrastive + Fuzzy Clustering.
- ✓ Evaluation on the **16 UEA Multivariate** datasets (2–1345 channels, different lengths and class counts).
- ✓ Same hyperparameter search: $\lambda_s \in \{0, 0.5, 1\}$, $\lambda_b \in \{0, 0.2, 0.5, 1\}$.
- ✓ Three multivariate implementations were explored; only the best-performing variant is presented here.

Alternative Implementations

- ✗ **Single-view ablation:** one shared encoder/decoder for all views, replacing contrastive learning with a KL objective. Competitive on some datasets but no consistent improvement.
- ✗ **Refined clustering objective:** DEC-style target sharpening with entropy/separation decomposition and uncertainty-weighted losses. More sophisticated, yet lower overall performance.
- ➤ Both variants remain useful as ablations and future research directions, while the original multi-view formulation is still the strongest approach.

What Changed Across Variants

5 Multivariate FMMVCC

Aspect	Old	Refined	Single	DEC
Pretraining	Contrastive on $\tilde{z}$	Contrastive on $\tilde{z}$	KL + reconstruction	Contrastive on z
Reconstruction	Normalized by N_{samples}	None	None	None
Clustering	Entropy + balance + separation	Sharpening ($q \leftarrow q^2$)	Same as Refined	DEC target + entropy + separation
Center update	Fuzzy (m-weighted)	Fuzzy (m-weighted)	Fuzzy (m-weighted)	Weighted mean
Loss weighting	Softplus	$\exp(-\log w) + \log w$ (clamped)	$\exp(-\log w) + \log w$ (clamped)	$\exp(-\log w) + \log w$ (clamped)
Balance	Explicit	Explicit	Explicit	Sinkhorn balancing

Overall Comparison

Comparison over the **16 UEA datasets** shared by all variants.
Weighted score:

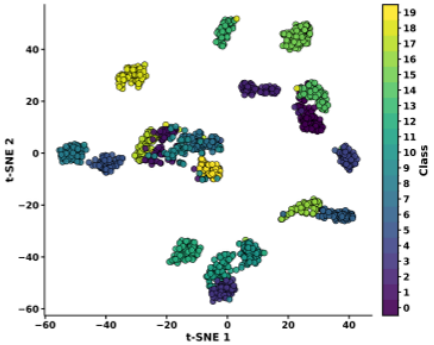
$$0.40\,ARI + 0.35\,NMI + 0.20\,ACC + 0.05\,F1$$

Variant	ACC	NMI	ARI	F1	RI	Score
Refined	0.686	**0.456**	**0.539**	**0.485**	**0.804**	**0.536**
Single	0.654	0.363	0.477	0.410	0.776	0.469
Old	0.667	0.358	0.462	0.415	0.762	0.464
DEC	0.639	0.305	0.409	0.368	0.719	0.416

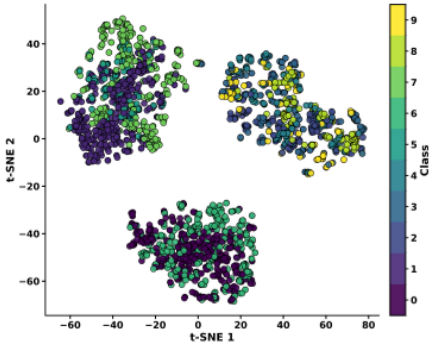
Latent space comparison

5 Multivariate FMMVCC

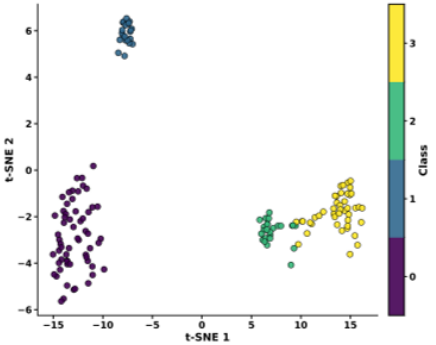
Old



Character Trajectories

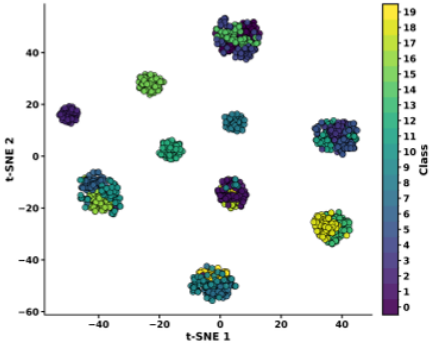


Spoken Arabic Digits

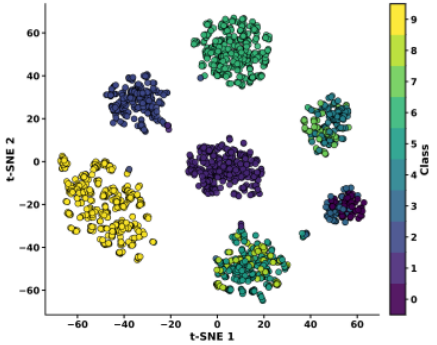


Racket Sports

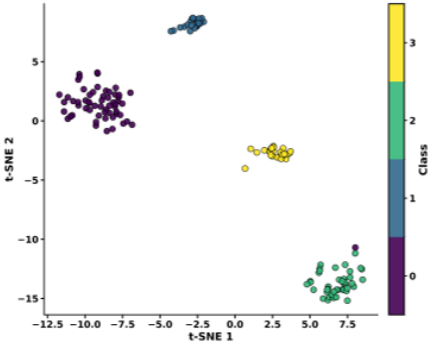
Refined



Character Trajectories



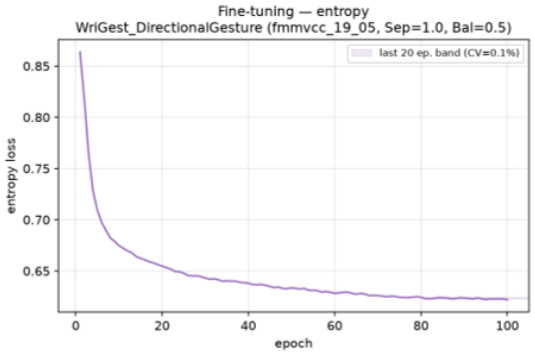
Spoken Arabic Digits

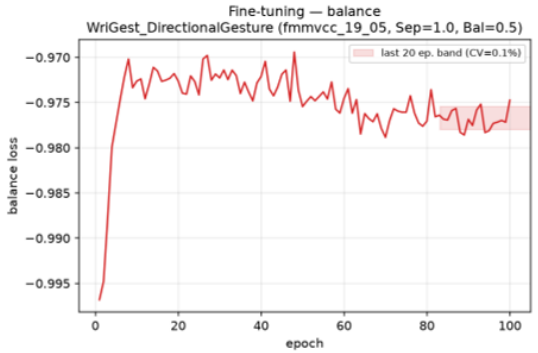


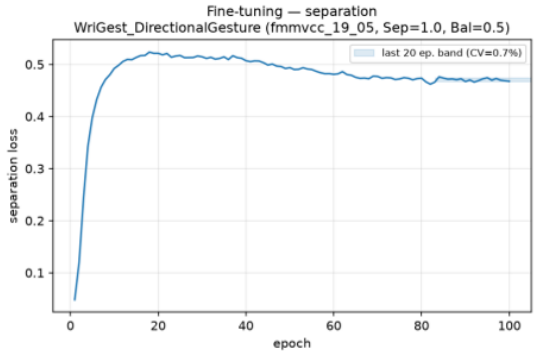
Racket Sports

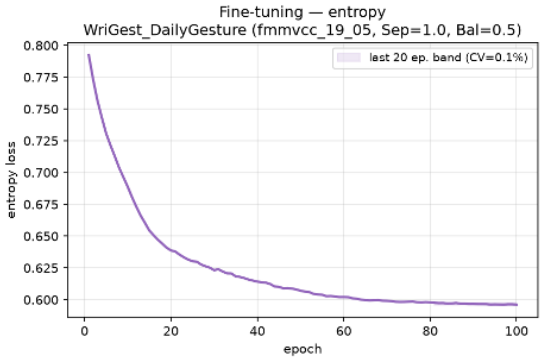
Open Issue: Balance Loss

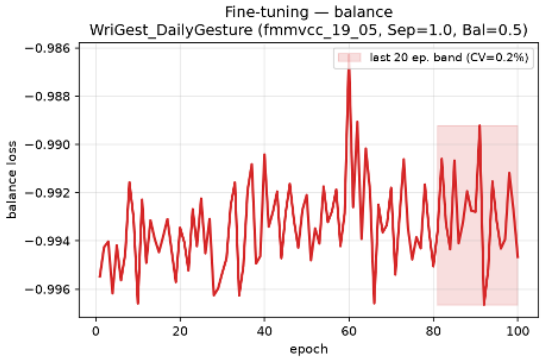
5 Multivariate FMMVCC











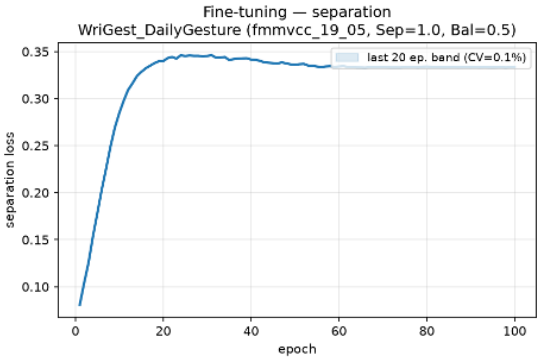


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Conclusions

- ✓ Proposed a unified **Mamba-based multi-view fuzzy clustering** framework for time-series representation learning.
- ✓ Demonstrated strong clustering performance on both **univariate** and **multivariate** benchmarks.
- ✓ Extended the learned representations to **Federated Learning**, obtaining competitive results for privacy-preserving healthcare applications.
- ✓ Improved the interpretability of deep clustering through **intrinsic and post-hoc XAI analyses**, providing insights into cluster formation and temporal relevance.
- ✓ Overall, the proposed framework combines **accuracy, scalability and interpretability** for modern time-series clustering.

Future Directions – Model

- ? Further investigate the **clustering objective**, refining the balance, separation and uncertainty-aware losses.
- ? Explore adaptive weighting strategies and dynamic optimization of the different loss components.
- ? Compare the proposed framework with additional recent sequence models (e.g., Transformer-based, SSM-based and hybrid architectures).
- ? Extend the experimental evaluation on larger and more heterogeneous **multivariate** time-series benchmarks.

Future Directions – Federated Learning & XAI

- ? Investigate more realistic FL scenarios with non-IID clients, client drift and asynchronous communication.
- ? Study personalized and communication-efficient federated clustering strategies.
- ? Develop intrinsically explainable clustering models, integrating interpretability directly into the optimization process.
- ? Validate explanation quality through user studies and domain-specific evaluation protocols.
- ? Develop an interactive latent space that allows users to project new samples, identify their closest prototype, and detect whether they belong to an existing cluster or represent anomalies.

FMMVCC: Fuzzy Mamba-based Multi-View Contrastive Clustering for Univariate Time Series

Best Student Paper Award
6th International Conference on Machine Learning and Intelligent Systems Engineering (MLISE 2026). Preprint available on arXiv: https://arxiv.org/html/2607.07258v1

Less Federation, More Personalization:
One-Shot Multi-View Clustering for Federated Fall Detection

Submitted to ACM MobiHoc 2026

Explaining Fuzzy Mamba-Based Multi-View Clustering:
An XAI Analysis of State-Space Models for Multivariate Time Series

Submitted to IEEE ICDM 2026

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6 Conclusions and Future Directions

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AI+DA

POLITÉCNICA

Deep Clustering for Time Series

Thank you for listening!

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