Advancing Federated Learning: Algorithms and Use-Cases

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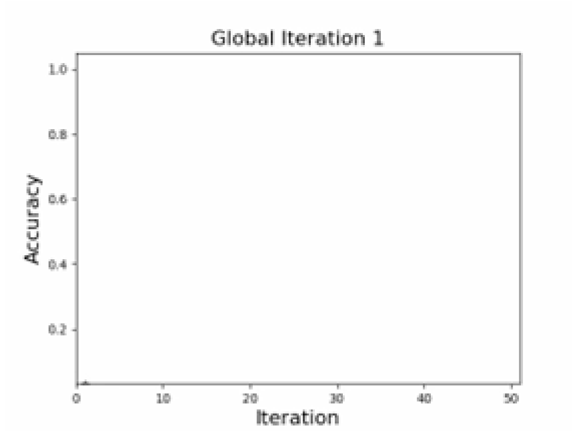
September 23, 2024

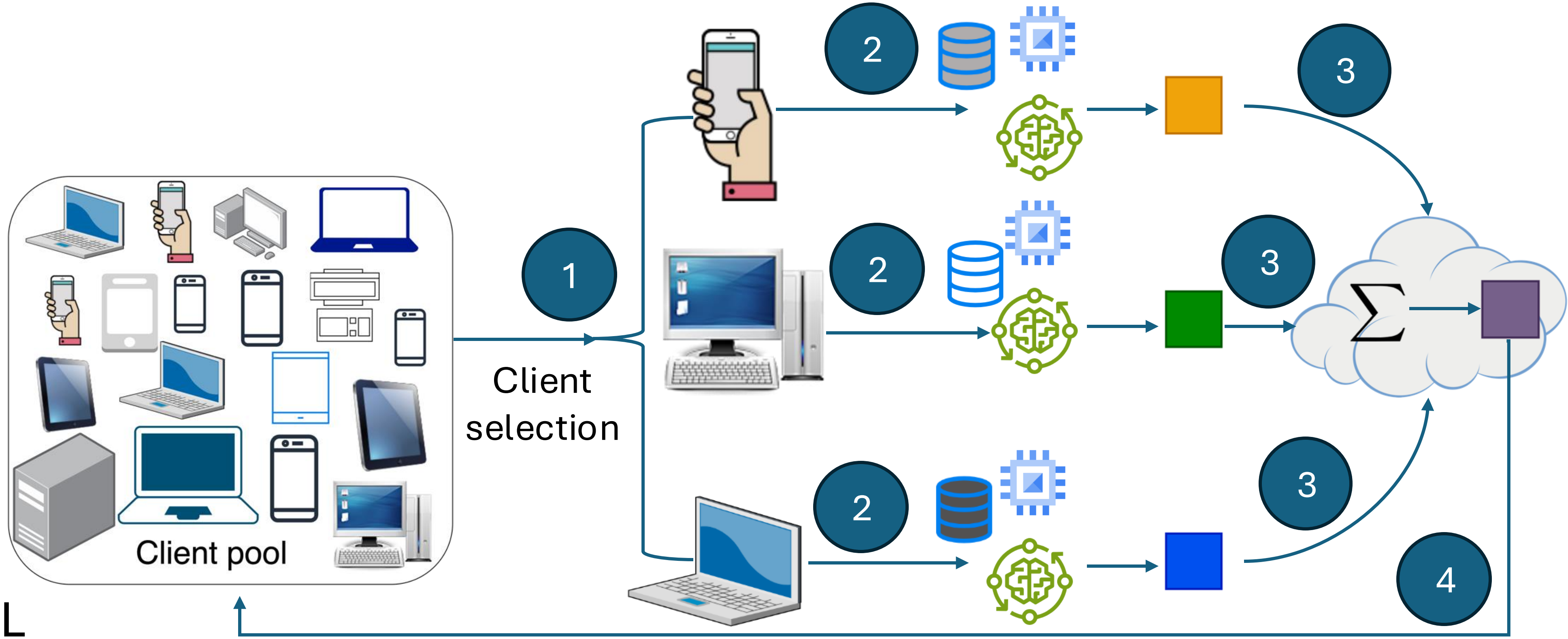
Outline

- Introduction
- Key Challenges
- Research Objectives and Contributions
- Papers I to VI
- Conclusion
- Future Scope

Federated Learning (FL)

- Collaborative learning without sharing private data



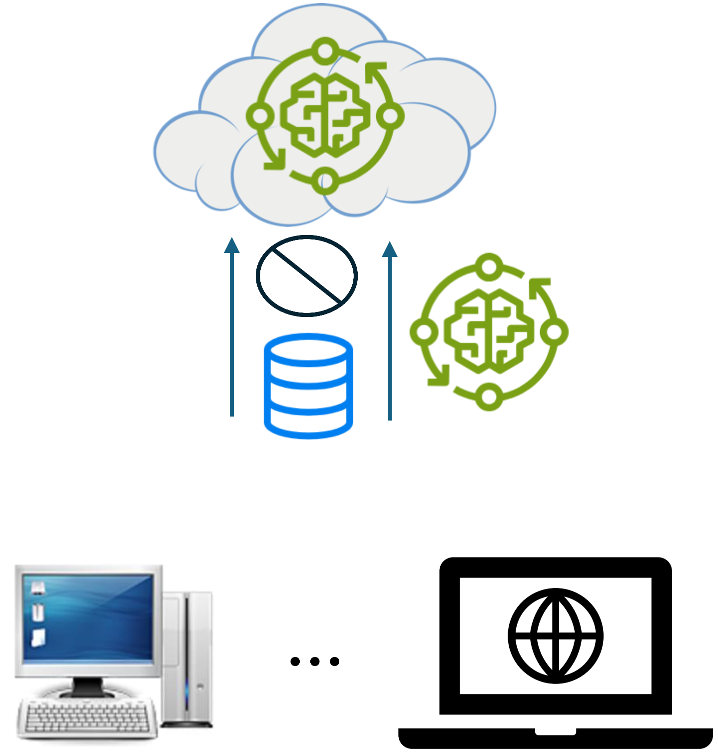


- Horizontal FL
- Train homogeneous model

Why Federated Learning?

Data ownership

Data privacy



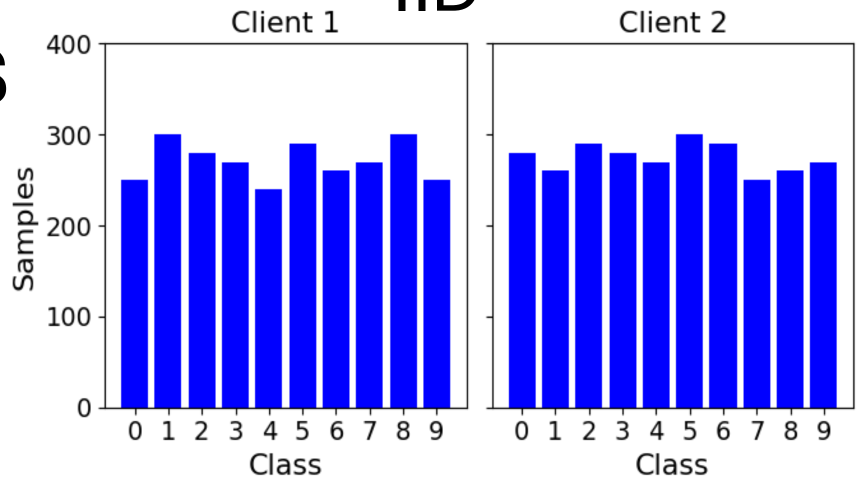
Reduced communication overhead

Powerful end devices

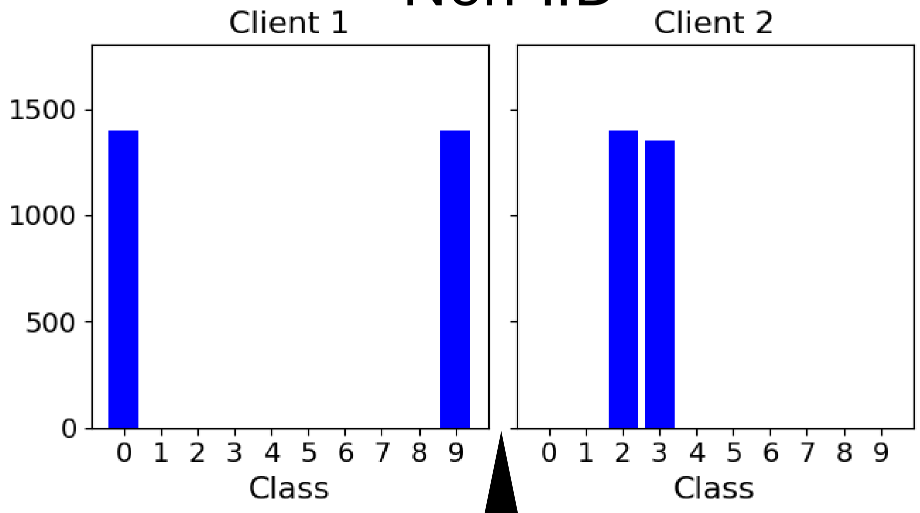
Key Challenges

- **Data heterogeneity**
- **System heterogeneity**

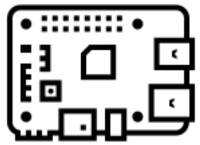
IID



Non-IID



Stragglers

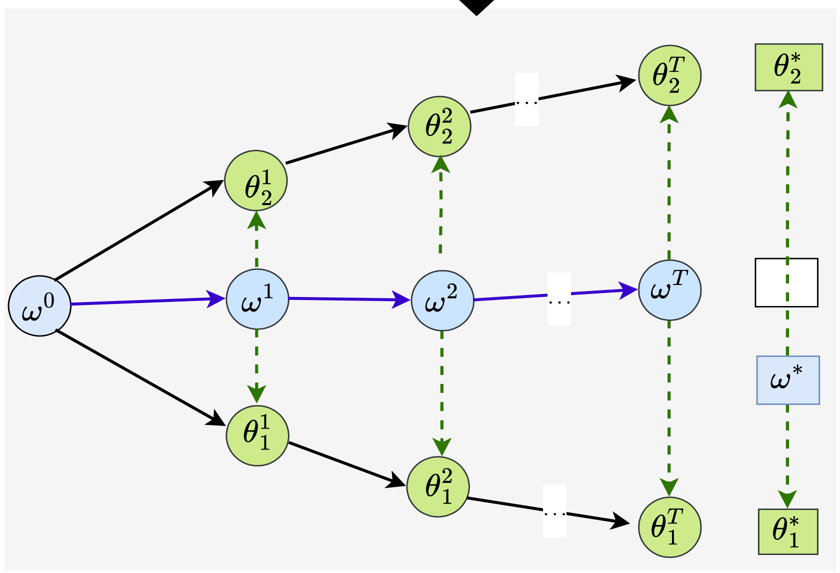


θ_1 θ_2 Local model

ω Global model

Client 1

Client 2



Client drift

- Communication
- Privacy

*Images are generated using DALL-E

Purpose

Challenges

Algorithms

Generic

Fed-FiS

Fed-MOFS

PerMFL

Fed-MOODS

FedIoT

FedHealth

FedMEM

Fed-Rec

FedScore

Clustered-FedDC

Use-case specific

Use-cases

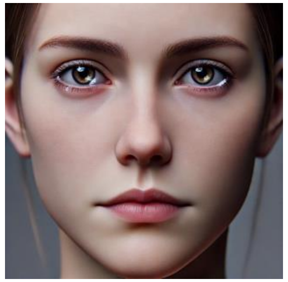
Finance

Healthcare

IoT

Recommender system

Memorable



Event memorability

Sharing other

Privacy advisor

Scopes and Assumptions

Scopes

- Horizontal federated learning
- Homogeneous model training
- Clients have full (Cross-Silo) and partial participation (Cross-Device)

Assumptions

- Data privacy
- Secured communication channel
- Model security

Research Objectives and Contributions

Data heterogeneity

RO1: Develop algorithms for feature selection in federated settings

Paper I & III

RO3: Develop personalized FL algorithm for multi-tier settings

Paper IV

Use-cases

RO4: Develop FL-enabled solutions for different use-cases

Paper V & VI

System heterogeneity

RO2: Develop algorithm for optimal client selection in federated learning

Paper II

Paper I: *Fed-FiS: A Novel Information-Theoretic Federated Feature Selection for Learning Stability*

Paper II: *Optimized and Adaptive Federated Learning for Straggler-Resilient Device Selection*

Paper III: *Cost-Efficient Feature Selection for Horizontal Federated Learning*

Paper IV: *Personalized Multi-tier Federated Learning*

Paper V: *Predicting Event Memorability using Personalized Federated Learning*

Paper VI: *The Case for Federated Learning in Developing Personalized Image Privacy Advisor*

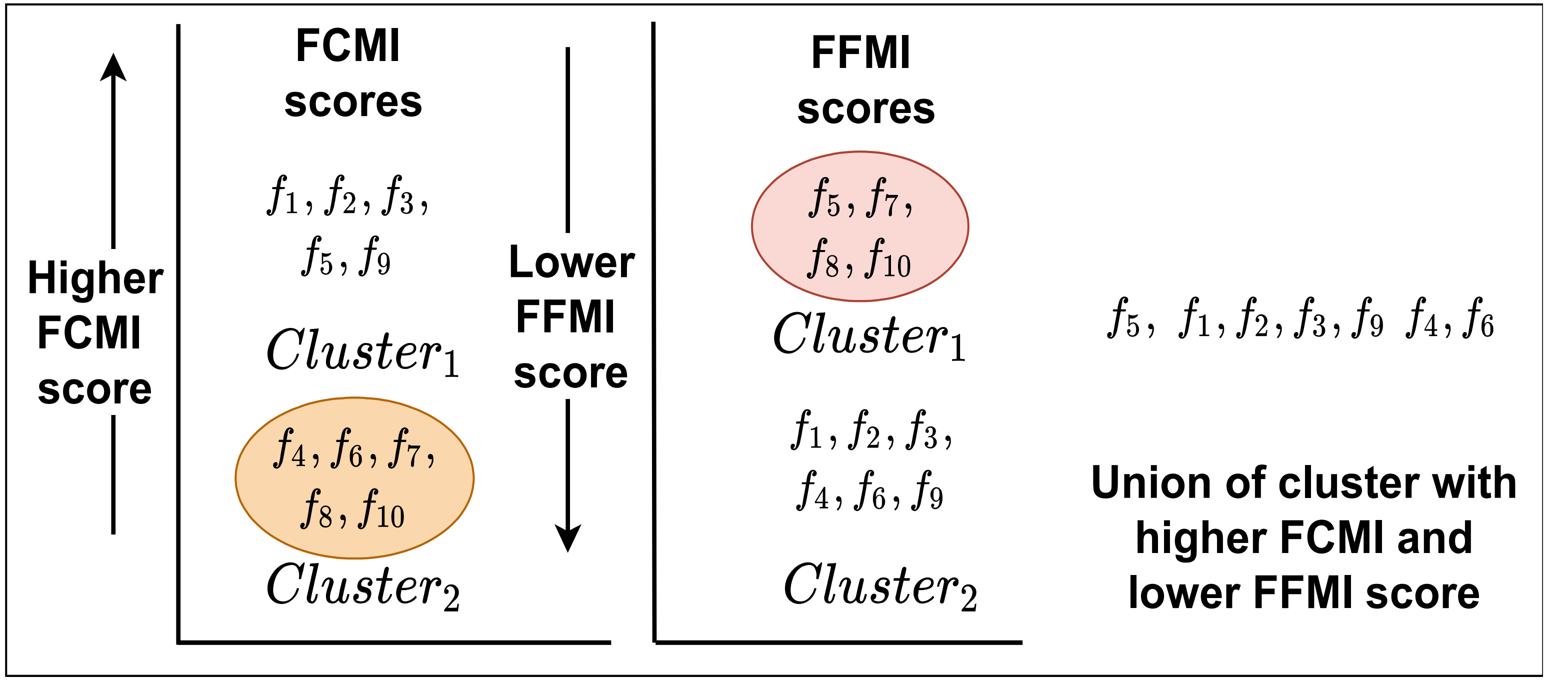
Paper I	Fed-FiS: A Novel Information-Theoretic Federated Feature Selection for Learning Stability
Paper III	Cost-Efficient Feature Selection for Horizontal Federated Learning

Problem	Effect	Solution	Impact
• Data heterogeneity • Features • Bias in features across clients	• Learning • Training time • Performance	Feature selection Fed-FiS Fed-MOFS	• Learning • Training time • Performance

Paper I and III → **Objective RO1**

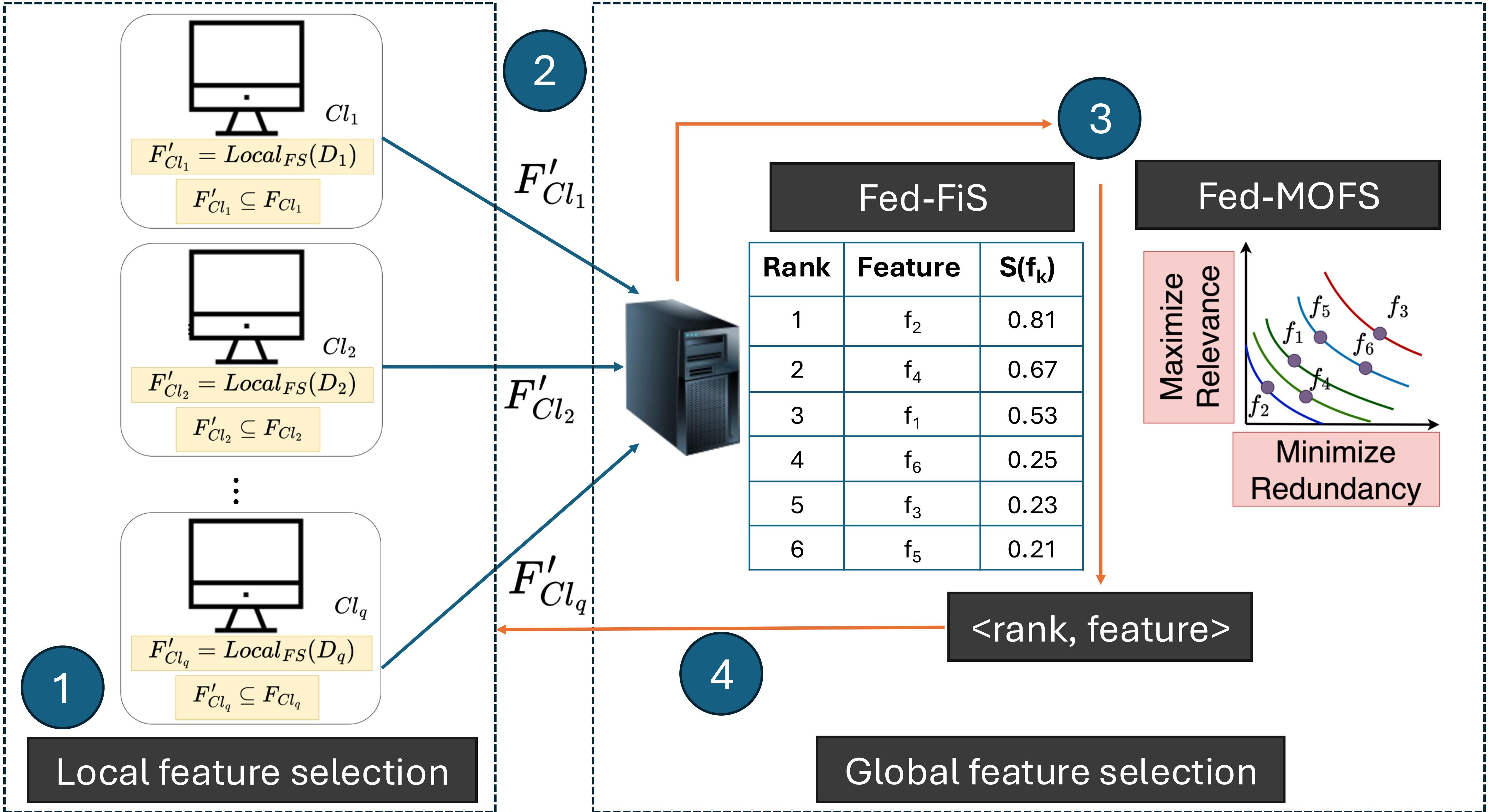
Contributions

- **Local** feature subset selection
  - FCMI (Relevance)
  - FFMI (Redundancy)
  - Clustering
- **Global** feature subset selection
  - Fed-FiS (Score-function) $S(f_k)$
  - Fed-MOFS (Multi-objective optimization)



FCMI: Feature Class Mutual Information

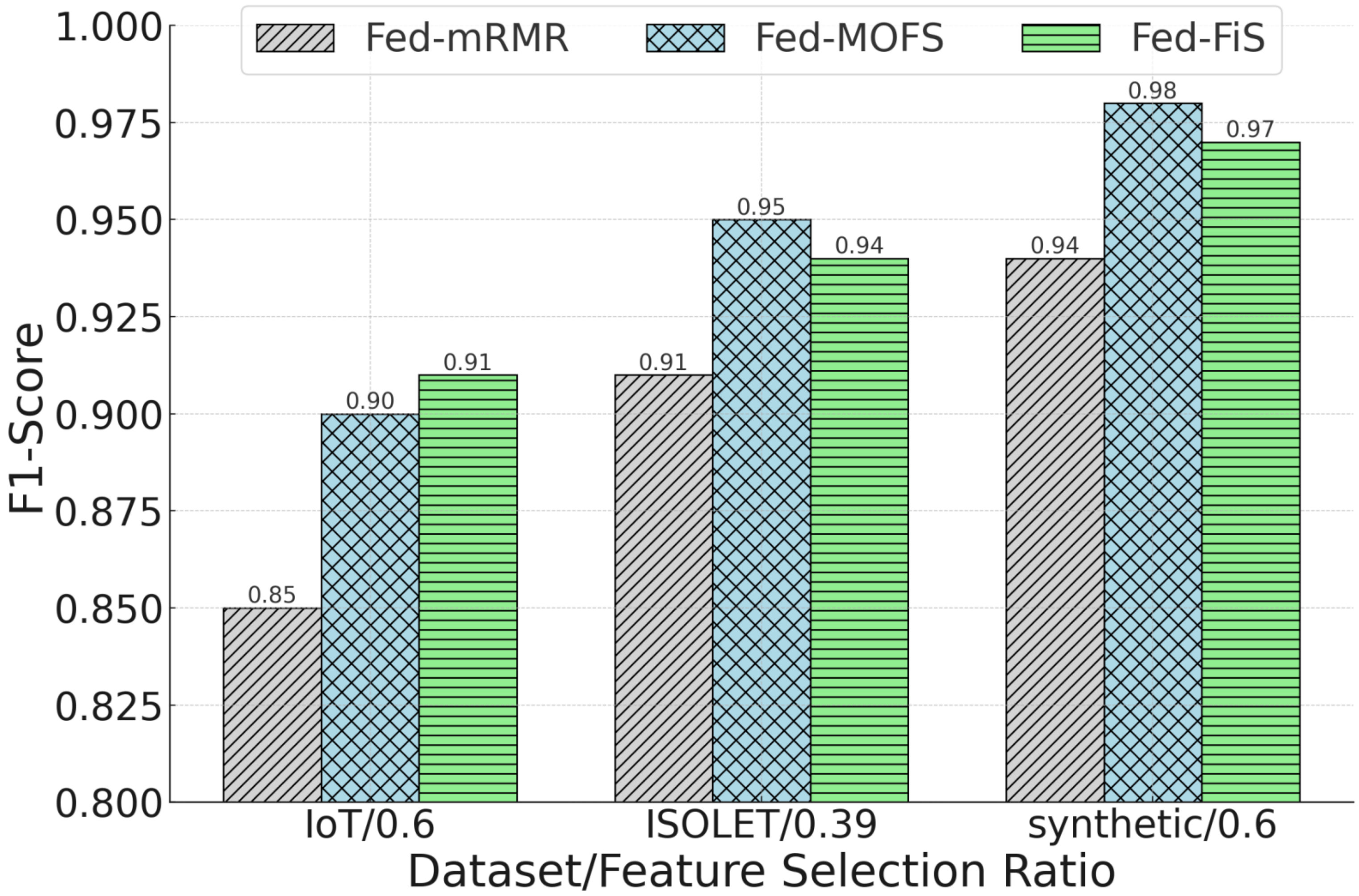
FFMI: Feature Feature Mutual Information



Rank	Feature	$S(f_k)$
1	f_2	0.81
2	f_4	0.67
3	f_1	0.53
4	f_6	0.25
5	f_3	0.23
6	f_5	0.21

Results and Analysis

Performance across non-IID data setting



Performance

- Fed-MOFS vs Fed-mRMR
  - 4% - 5%
- Fed-FiS vs Fed-mRMR
  - 3% - 6%

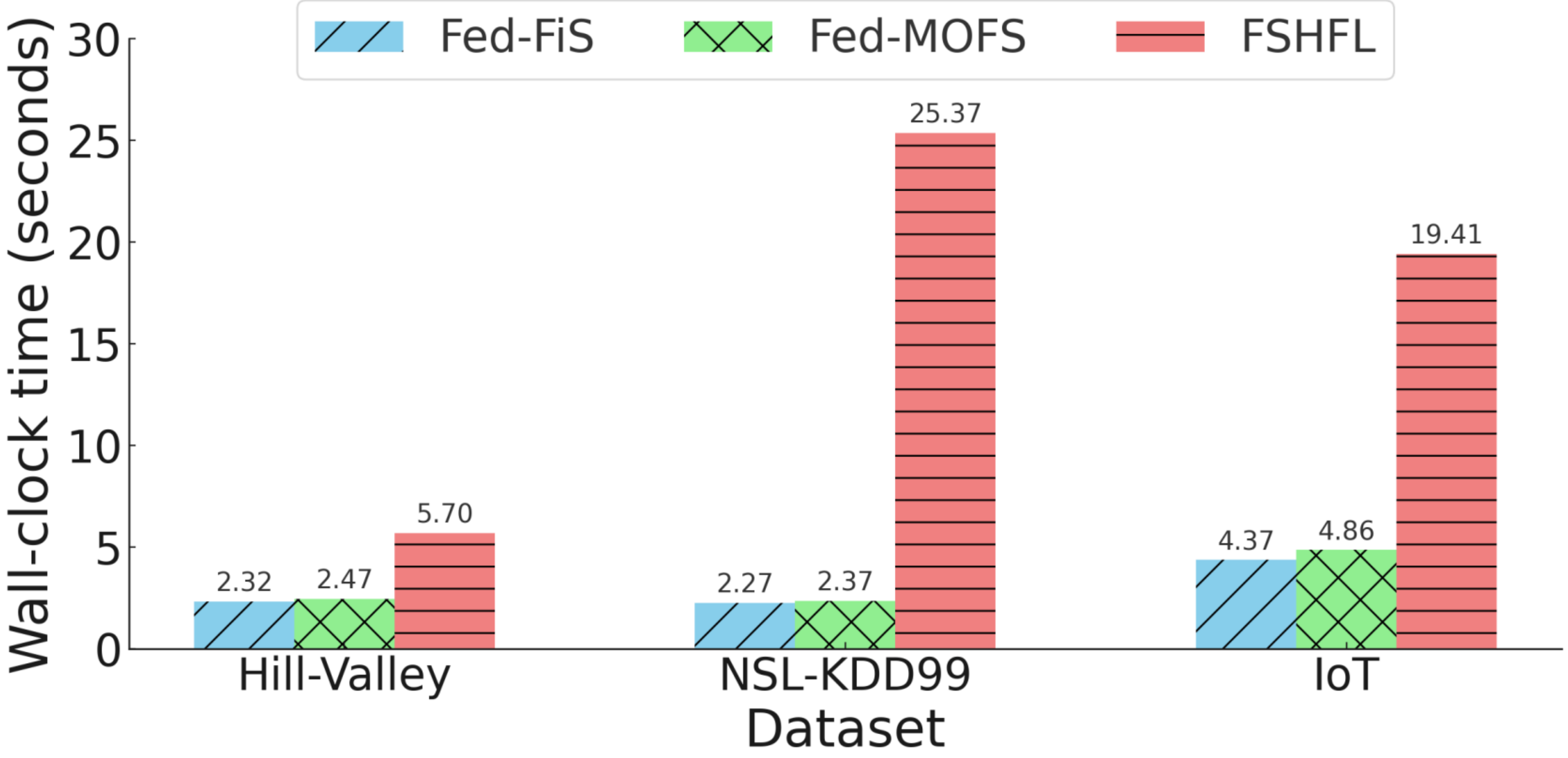
Source code

Results and Analysis

Wall-clock running time of federated feature selection algorithms

Efficiency

- Fed-FiS vs FSHFL
  - at least 2.46x
  - at most 11x
- Fed-MOFS vs FSHFL
  - at least 2.3x
  - at most 10.7x



Source code

Paper II

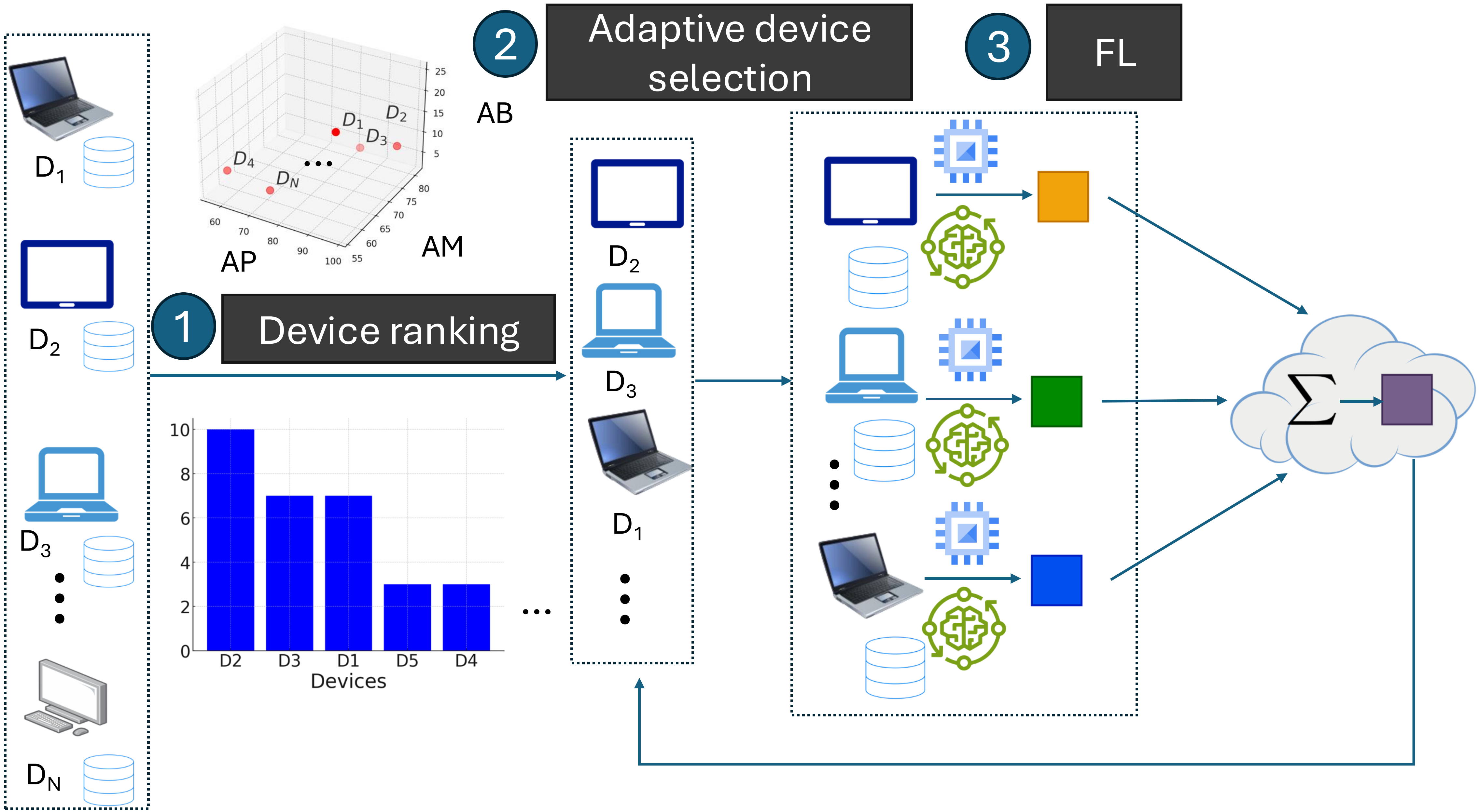
Optimized and Adaptive Federated Learning for Straggler-Resilient Device Selection

Problem	Effect	Solution	Impact
• Device heterogeneity	• Performance ↓ • Convergence ↓ • Training time ↑	Strategic Client selection ↓ Fed-MOODS	• Training time ↓ • Performance ↑ • Convergence ↑

Paper II → **Objective RO2**

Contributions

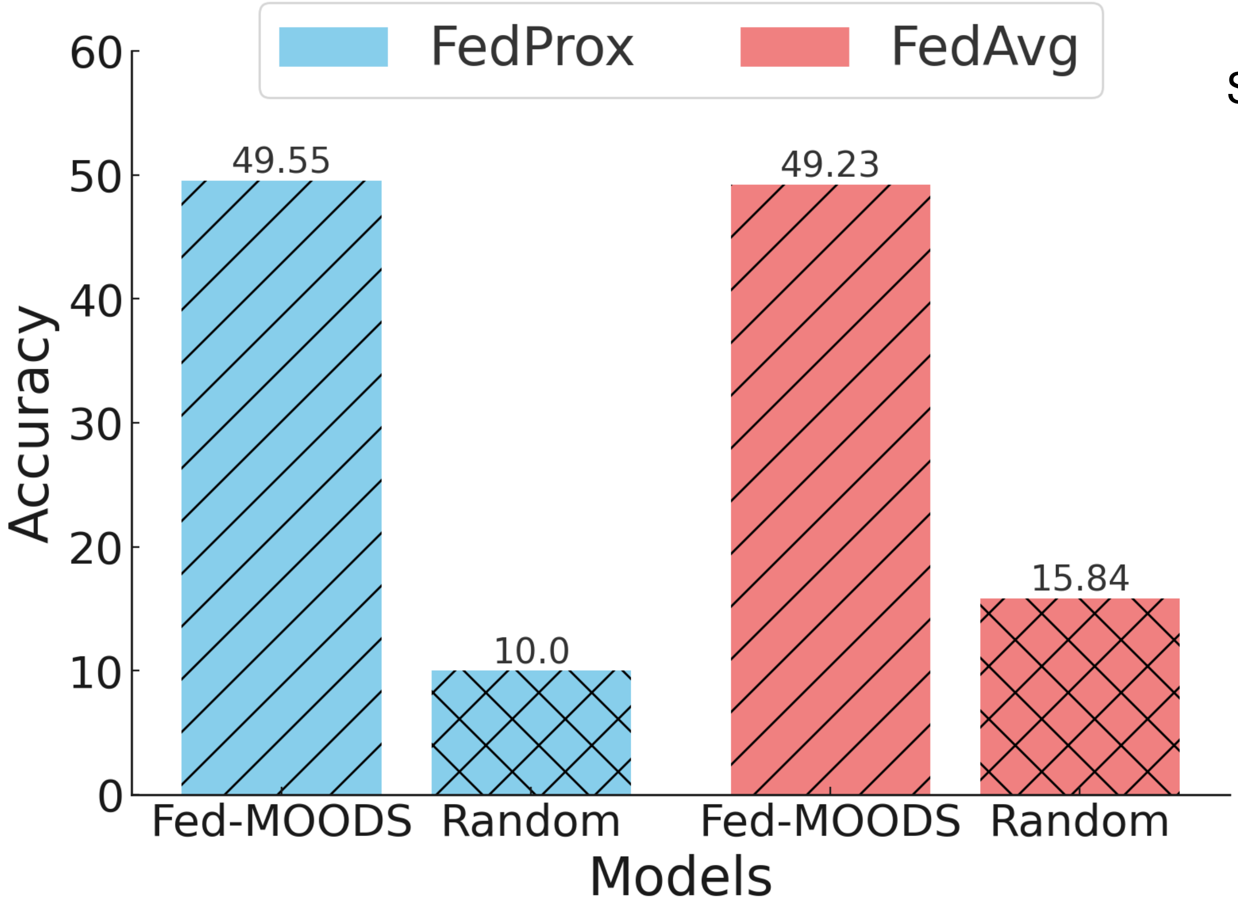
- Fed-MOODS
  - Device ranking based on the availability of
    - Processing capacity (AP)
    - Memory (AM)
    - Bandwidth (AB)
  - Adaptive device selection



1
Device ranking
2
Adaptive device selection
3
FL
D1
D2
D3
DN
D4
AB
AM
AP
25
20
15
10
5
80
75
70
65
60
55
60
70
80
90
100
10
8
6
4
2
0
D2
D3
D1
D5
D4
Devices
Σ

Results and Analysis

Fed-MOODS vs Random selection



Dataset: CIFAR10

Source code

Performance when 90% are stragglers

With Fed-MOODS

- FedProx 39.55 %
- FedAvg 33.39%

Paper IV

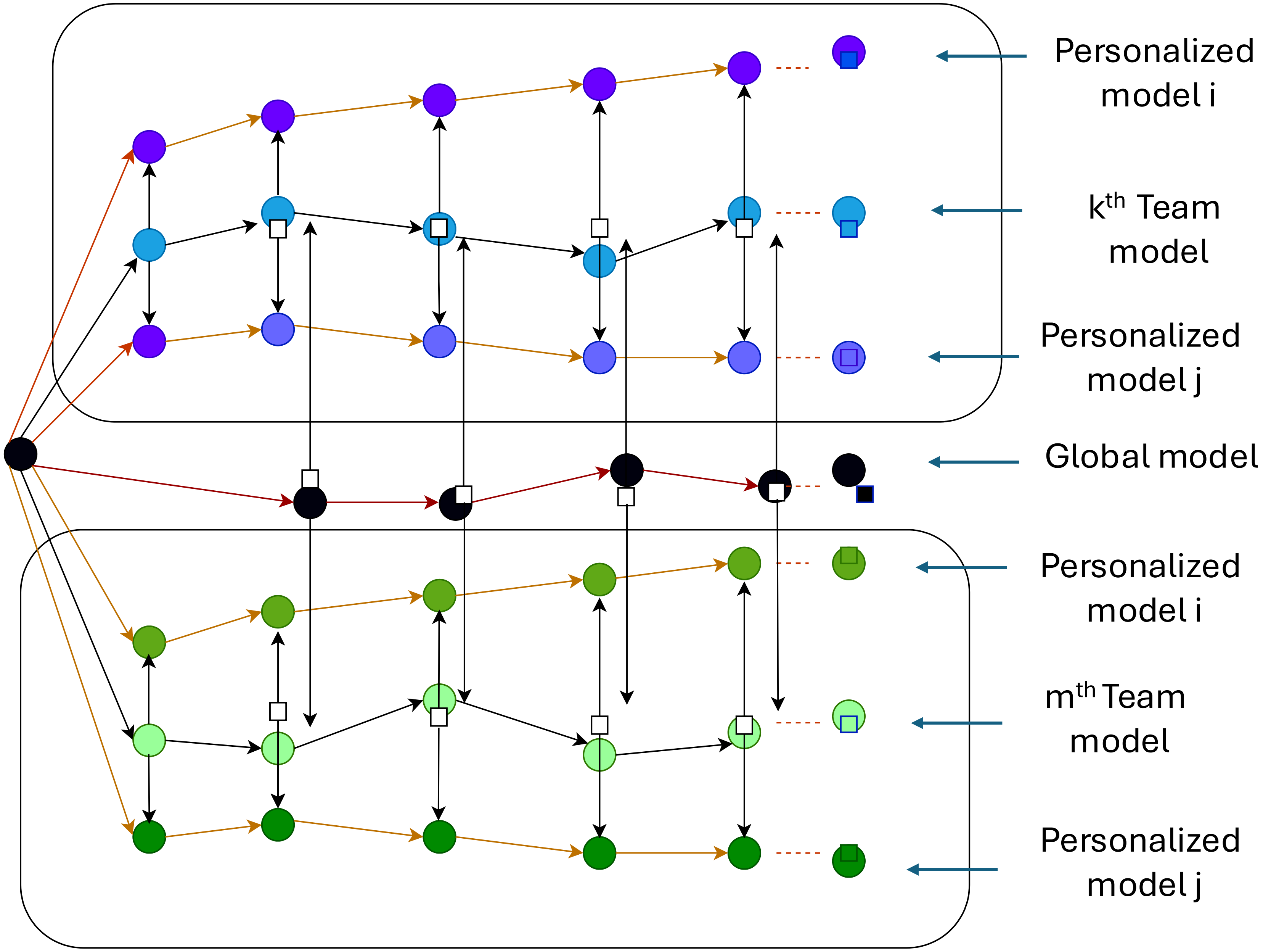
Personalized Multi-tier Federated Learning

Problem	Effect	Solution	Impact
• Data heterogeneity • Client drift	• Generalization performance Client i Client j • Convergence • Global iteration	Personalized model PerMFL	• Performance Client i Client j • Convergence • Global iteration

Paper III → **Objective (RO3)**

Contributions

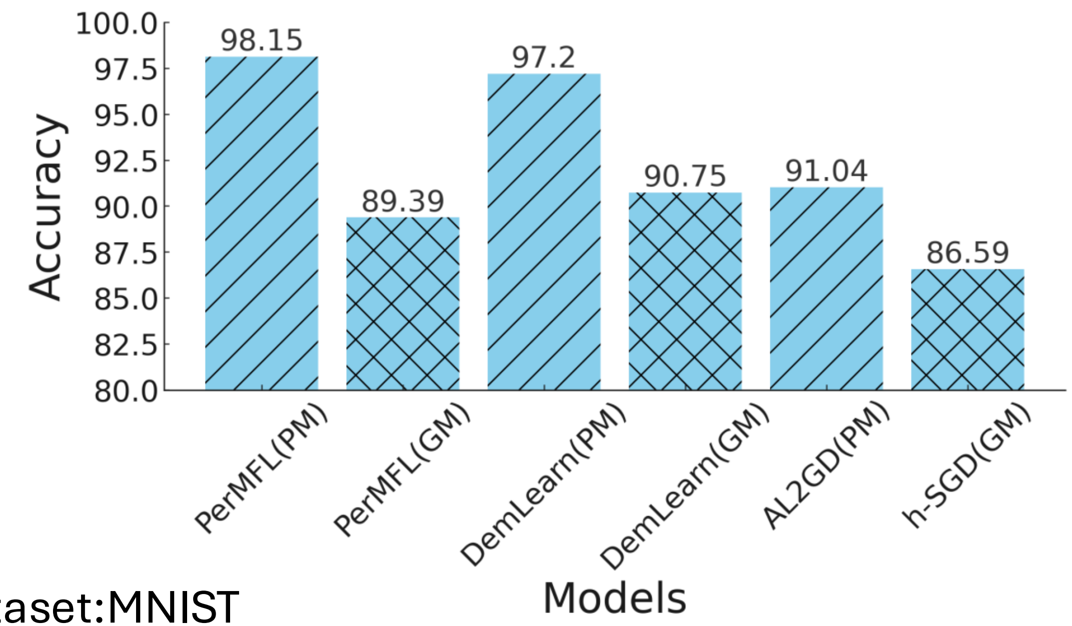
- PerMFL
  - A global model
  - Personalized team models
  - Personalized device models



Results and Analysis

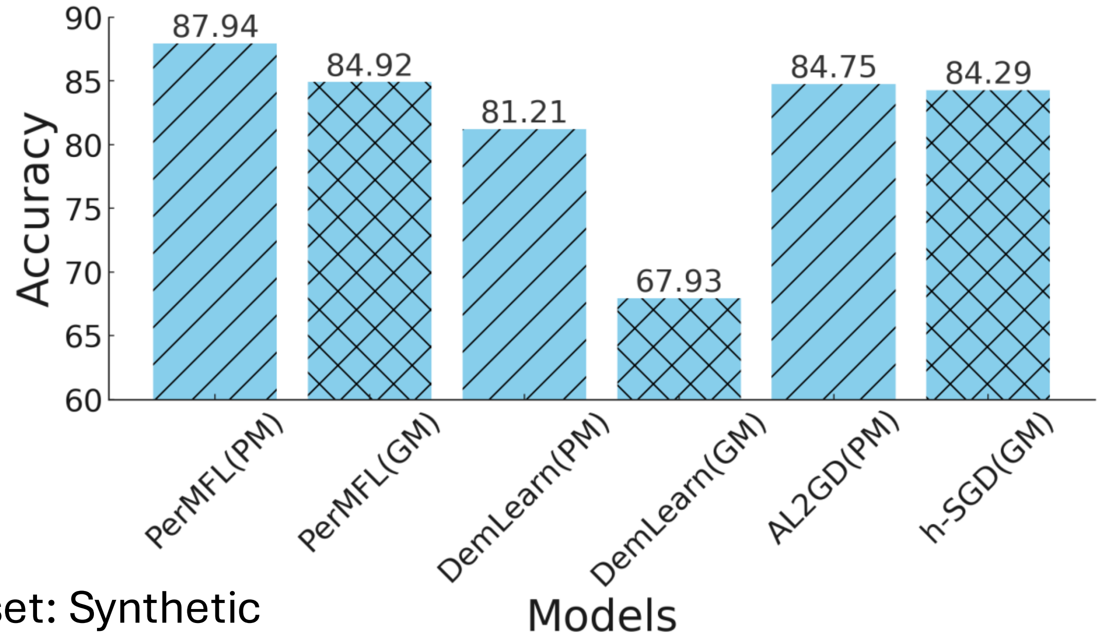
Source code

Non-convex



Dataset:MNIST

Convex



Dataset: Synthetic

- Performance of PerMFL (PM)

Non-convex | Convex

- Performance of PerMFL (GM)

Non-convex $\cong$ | Convex

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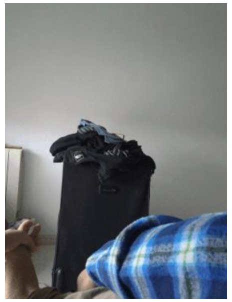
Paper V

Predicting Event Memorability using Personalized Federated Learning

Visual Lifelog

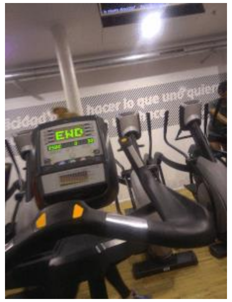
- Visual life-log images acquired via wearable cameras
  - Automatically record life moments
  - 2 images per min to 30 FPS
  - ~1500 images per day

Memory augmentation - Periodic review of memorable events, interactions, etc.



Home

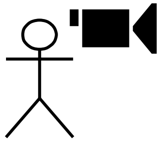
Outdoor



Gym

Public transport

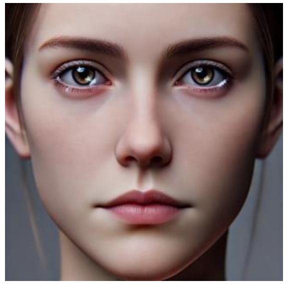
Event Memorability



Lifelog data

Not memorable

Memorable



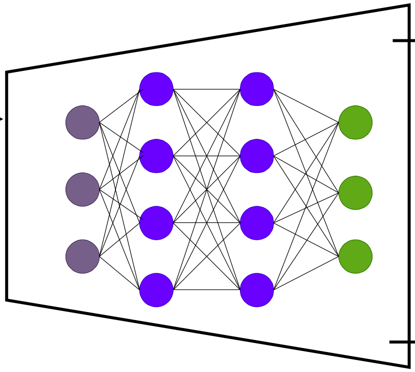
Lifelog Image

Contextual Data

<u>Temporal context:</u>
Duration of event, Time difference from start/end of event, etc.

<u>Visuo-semantic context:</u>
Distinctness of image, place, activity, presence of human etc.

Event Memorability model



Level of memory recall induced

0 - Absolutely no memory recall of the event

⋮

9 - Recall several vivid details of the event

Use image in memory/cognitive training app

*Image of inter-subject variation is generated using DALL-E

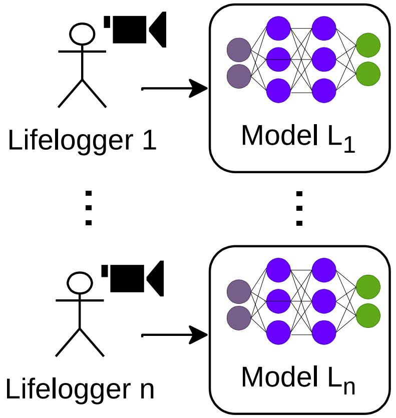
Problem

- Event memorability prediction
- Data heterogeneity
- Inter-subject variation

My score 9

Random audience 5

Effect

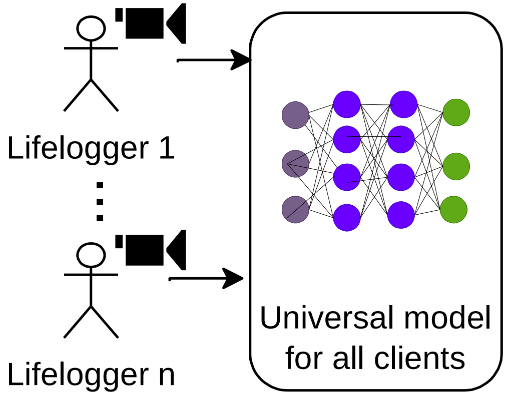


Privacy

Accuracy

Self-rating load

Siloed model

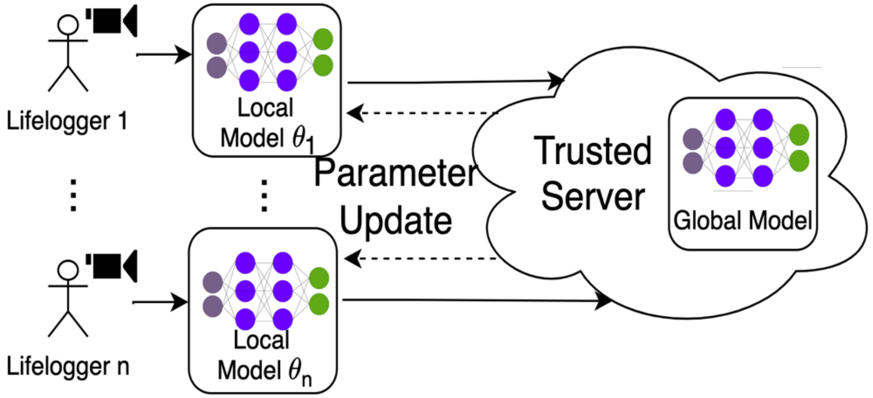


Privacy

Accuracy

Self-rating load

Centralized



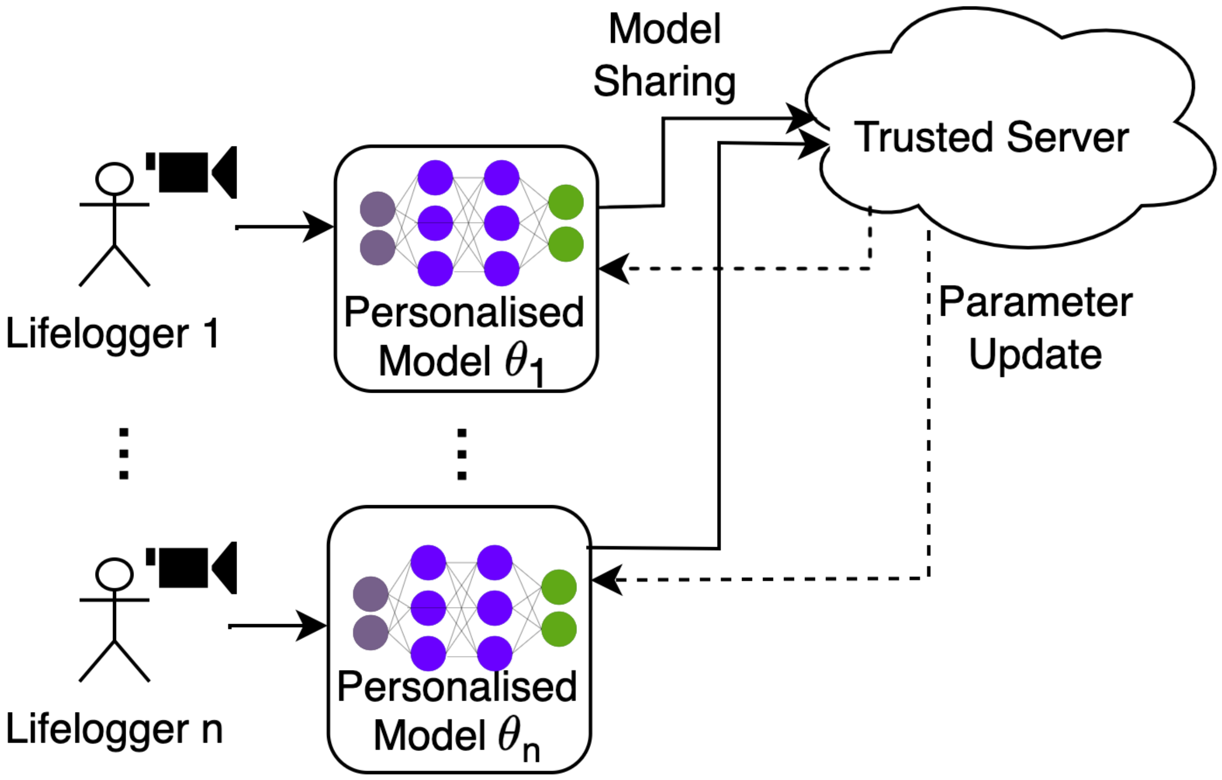
Privacy

Accuracy

Self-rating load

Global model

Solution



Effect

Privacy

Accuracy

Self-rating load

Paper V → **Objective RO3 and RO4**

Contributions

FedMEM

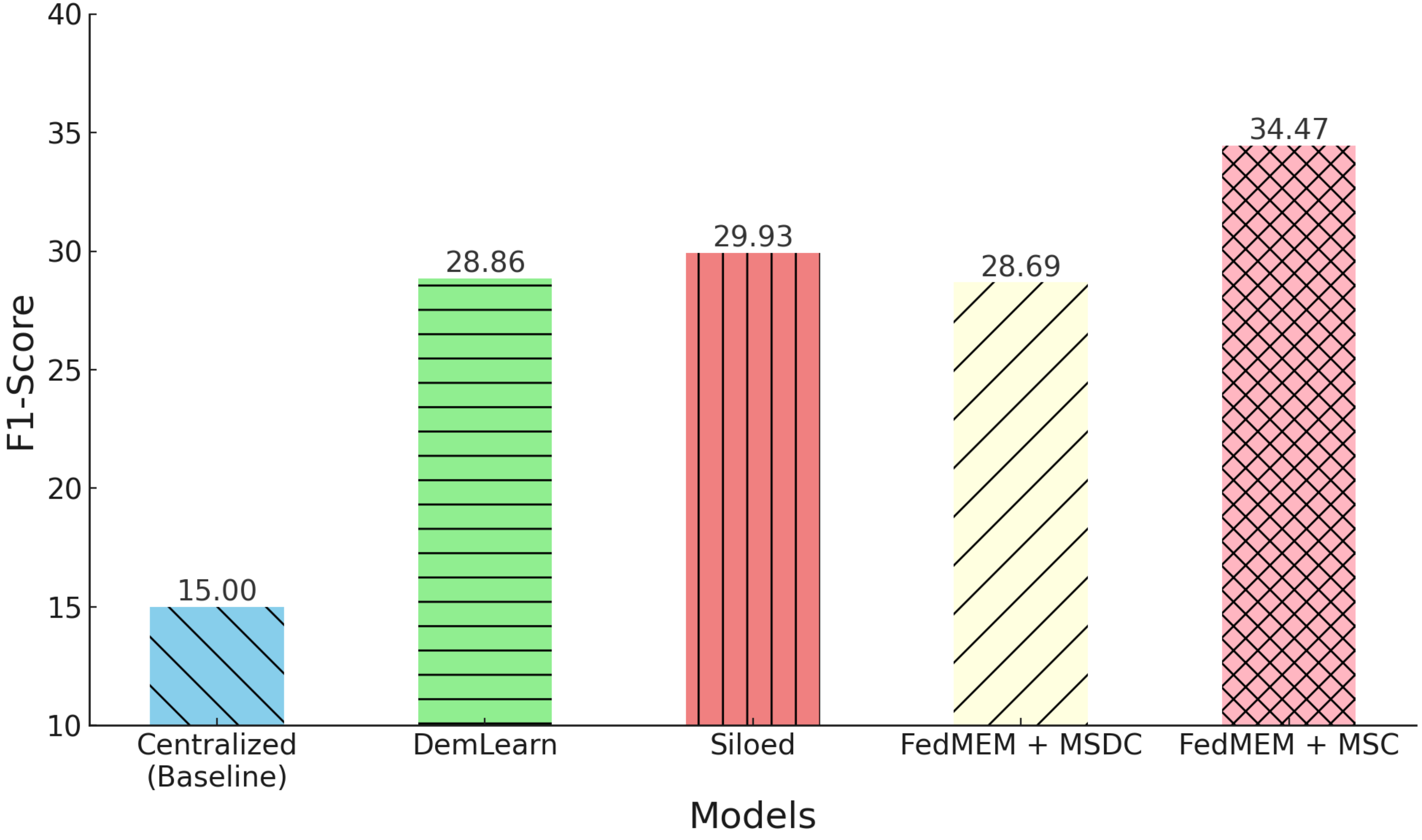
- Clustered personalized FL

- **Memorability Score Distribution -** based **Clustering (MSDC)** of the lifeloggers

- **Model Similarity Score (MSC)** between lifeloggers, cluster model, and global model

- MSC based clustering

Results and Analysis



Source code

Performance

FedMEM+MSC

- Siloed 4.54%
- FedMEM+MSDC 5.78%
- DemLearn 5.61%
- Baseline 19.47%

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Paper VI

The Case for Federated Learning in Developing Personalized Image Privacy Advisor

Privacy Advisor

- Key functions
  - Detect sensitive information
  - Personalized risk assessment
- Recommendations for users
  - Advice on photo sharing
  - Suggestions for obfuscation

Image privacy advisor application

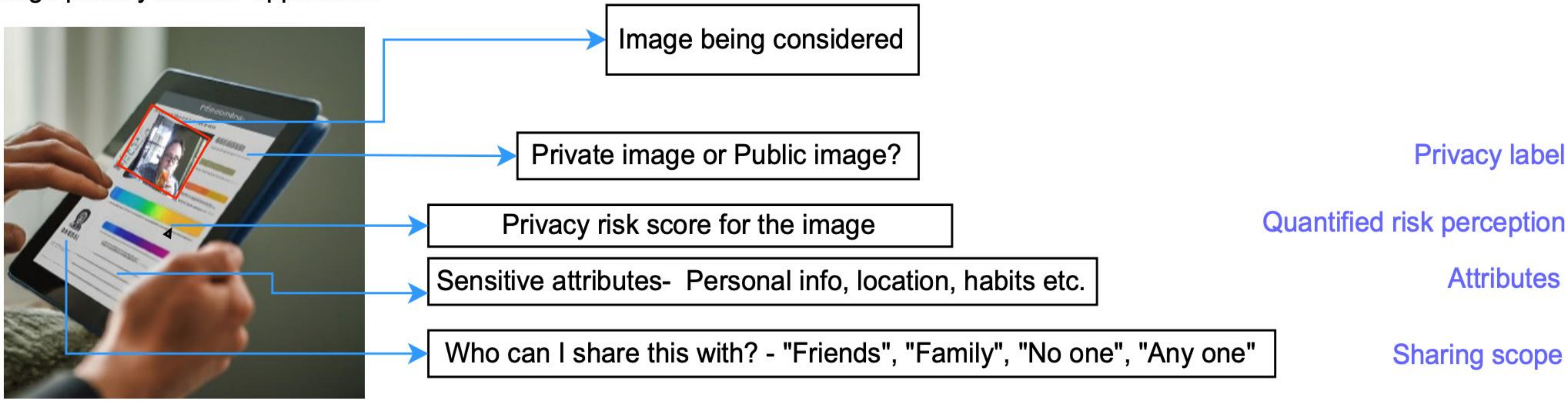


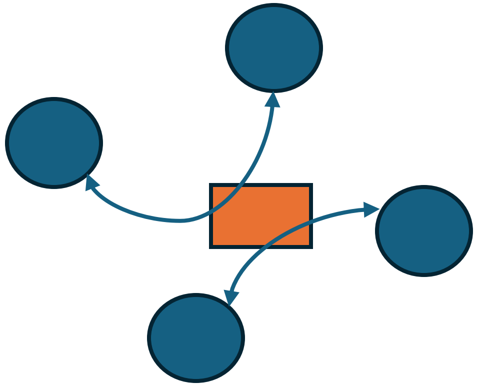
*Image of cat is generated using DALL-E

Problem	Effect	Solution	Impact
• Data heterogeneity • Data scarcity • Inter-subject variation	Non-federated Privacy Accuracy	Clustered-personalized FL Data heterogeneity	Privacy Accuracy
	Federated-global Privacy Accuracy	Daisy chaining → Data scarcity	

Client 1 Client 2

Private

Sharing other



Paper VI → **Objective RO3 and RO4**

Contributions

Available clients

ResourceFul (RF) ☒

Resource-Limited (RL) ✓

Data scarcity

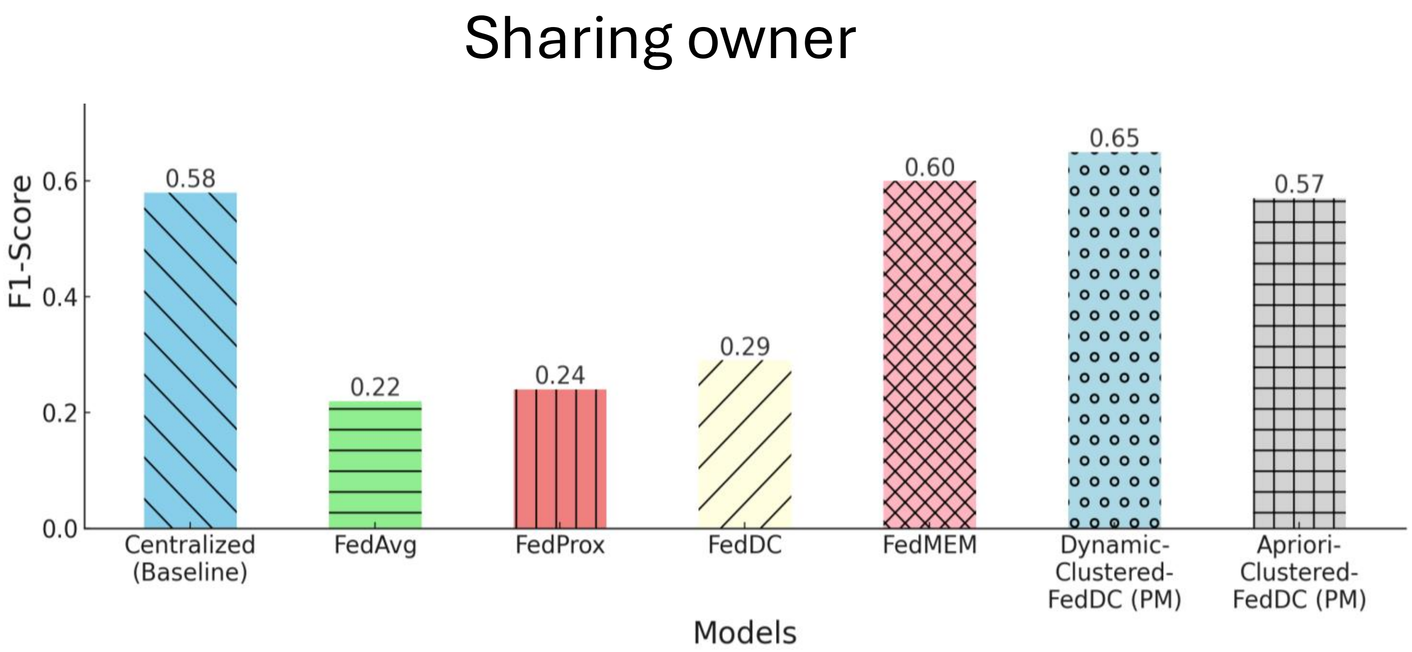
Dynamic-Clustered-FedDC

- RF and RL both performs daisy-chaining

Apriori-Clustered-FedDC

- Clusters based on the personality of the users
- RL performs daisy-chaining

Results and analysis



Performance (Sharing owner)

- Dynamic-Clustered-FedDC (PM)
  - 5% better than FedMEM
  - 7% better than Baseline
  - 36% better than FedDC
  - 41% better than FedProx
  - 43% better than FedAvg

Source code

Conclusion

Focused challenges →	• Data heterogeneity • System heterogeneity
Paper I and III →	Feature selection in horizontal FL
Paper II →	Mitigation of stragglers' effect in FL
Paper IV →	Personalized FL in multi-tier settings
Paper V →	Event memorability prediction using personalized FL
Paper VI →	Personalized image privacy advisor

Future Scope

Model heterogeneity → Inconsistency in sharing → Knowledge-Distillation in FL

Continual data → Catastrophic forgetting + Data heterogeneity →

- Rehearsal/Experience replay
- Task-aware FL

Acknowledgement

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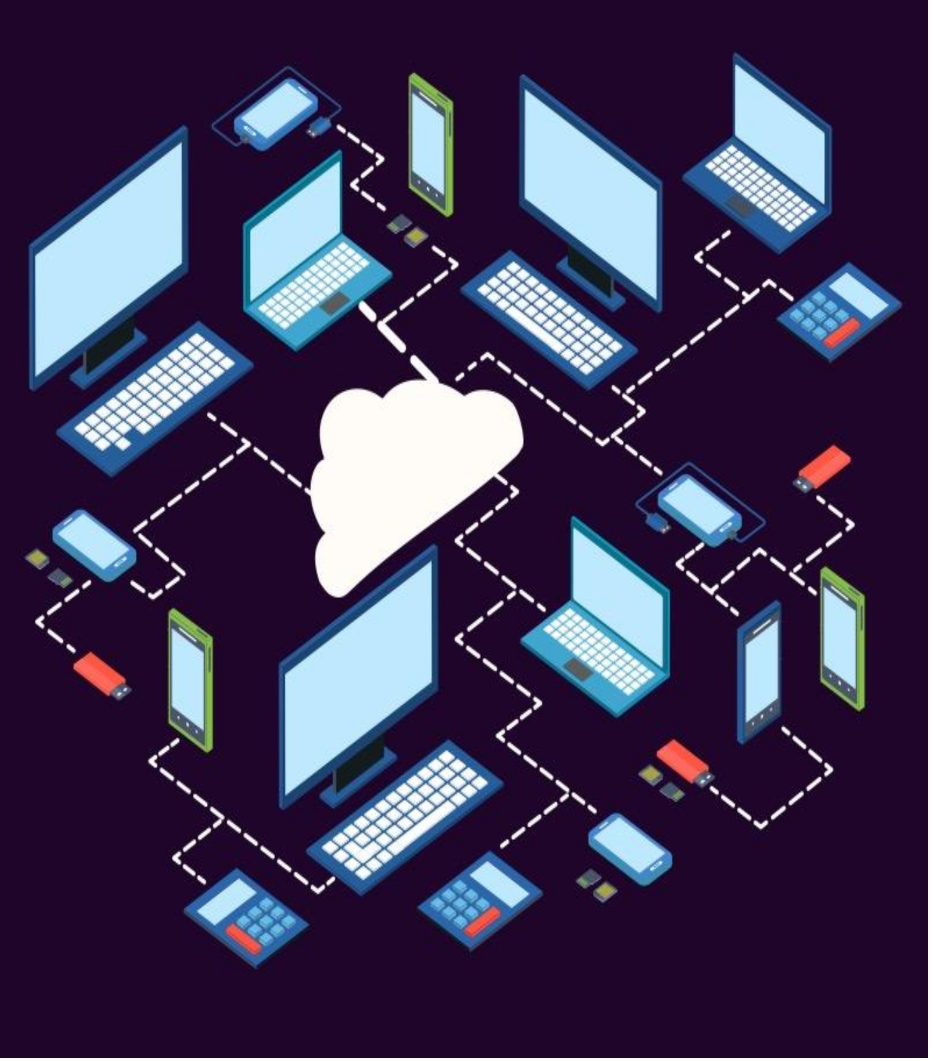

Publication list

Paper I : Sourasekhar Banerjee, Erik Elmroth, and Monowar Bhuyan. *Fed-FiS: A Novel Information-Theoretic Federated Feature Selection for Learning Stability*. Proceedings of the 28th International Conference on Neural Information Processing (ICONIP), Springer, Vol. 1516, pp. 480-487, 2021.

Paper II: Sourasekhar Banerjee, Xuan-Son Vu, and Monowar Bhuyan. *Optimized and Adaptive Federated Learning for Straggler-Resilient Device Selection*. Proceedings of the International Joint Conference on Neural Networks (IJCNN), IEEE, pp. 1-9, 2022.

Paper III: Sourasekhar Banerjee, Devvjiit Bhuyan, Erik Elmroth, and Monowar Bhuyan. *Cost-Efficient Feature Selection for Horizontal Federated Learning*. IEEE Transactions on Artificial Intelligence (TAI), IEEE, doi: 10.1109/TAI.2024.3436664, pp. 1-15, 2024.

Paper IV: Sourasekhar Banerjee, Ali Dadras, Alp Yurtsever and Monowar Bhuyan. *Personalized Multi-tier Federated Learning*. Accepted for publication in the 31st International Conference on Neural Information Processing (ICONIP), pp. 1-16, 2024. **(Accepted)**

Paper V: Sourasekhar Banerjee, Debaditya Roy, Vigneshwaran Subbaraju, and Monowar Bhuyan. *Predicting Event Memorability using Personalized Federated Learning*. pp. 1-8, 2024. **(Submitted)**

Paper VI: Sourasekhar Banerjee, Vengateswaran Subramaniam, Debaditya Roy, Vigneshwaran Subbaraju, and Monowar Bhuyan. *The Case for Federated Learning in Developing Personalized Image Privacy Advisor*. pp. 1-12, 2024. **(Submitted)**

Thank You!

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