ClusterFL: A Similarity-Aware Federated Learning System for Human Activity Recognition

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Presented by Rui Chen

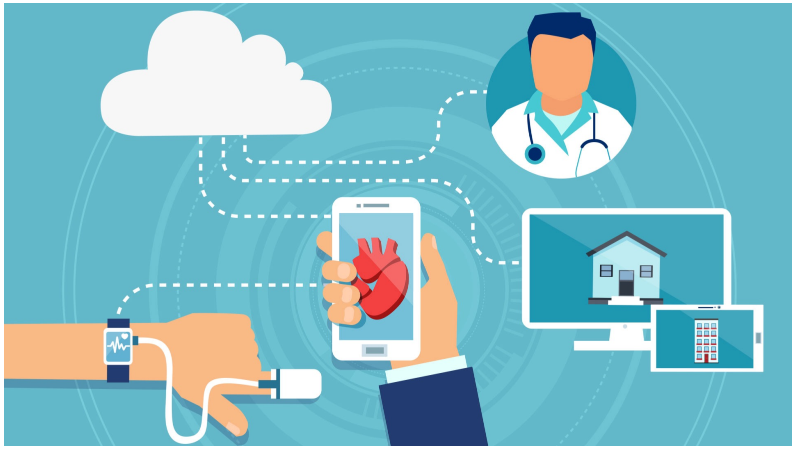
MobiSys 2021

Outline

- Motivation
- Similarity-aware federated learning framework
- Experimental Results
- Conclusion

Motivation – Human Activity Recognition

Fitness Tracking



Health monitoring

Sleep Monitoring

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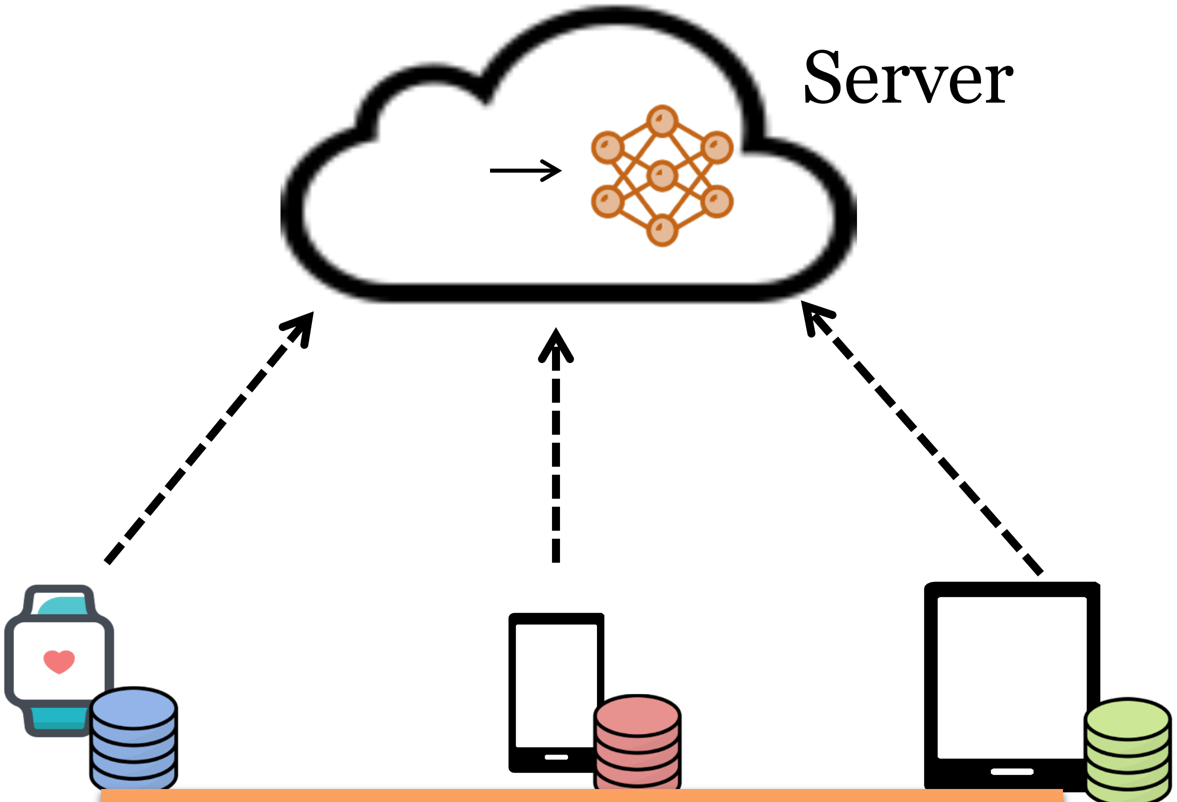
Motivation - Centralized Deep Learning

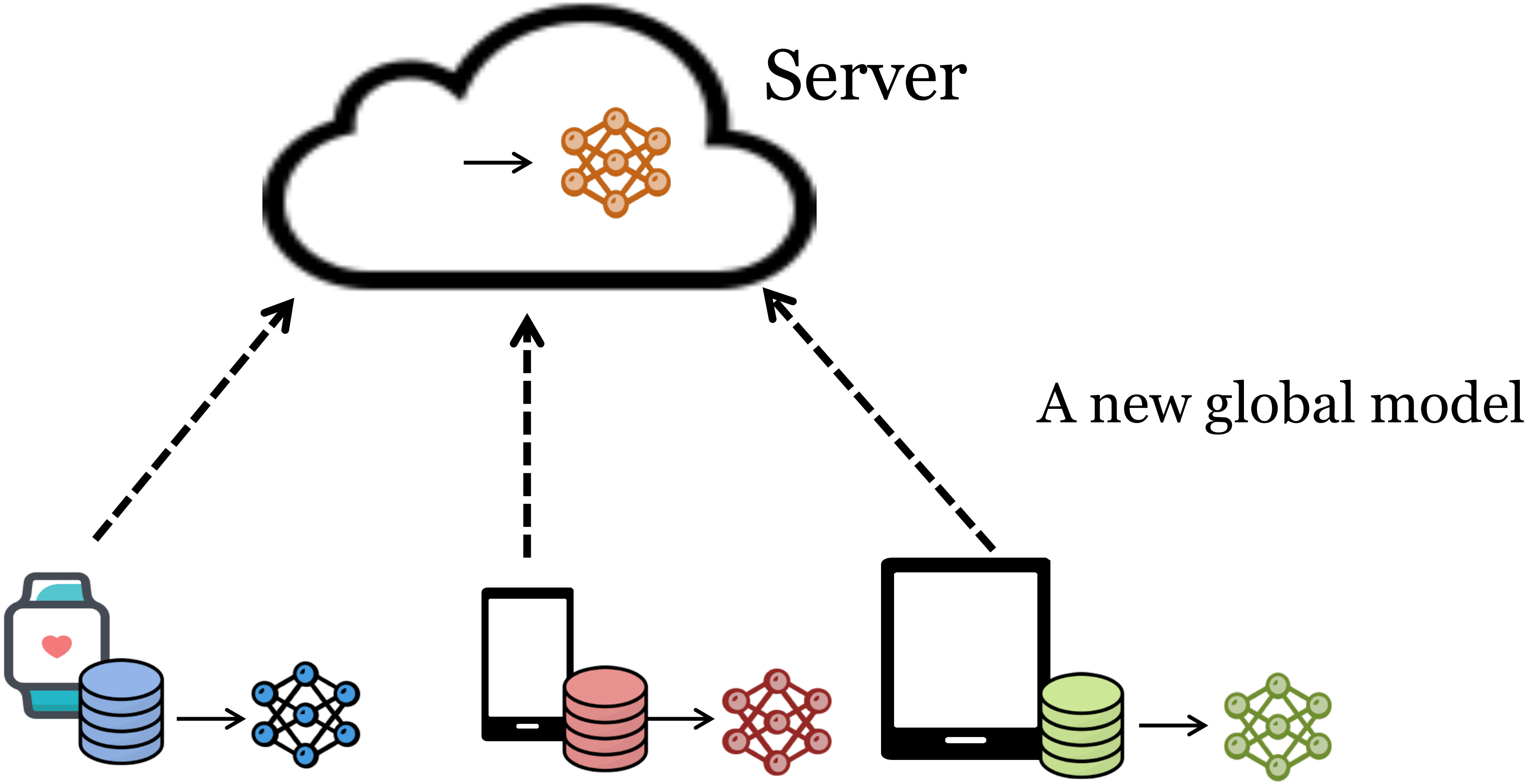
- Significant privacy concern (send raw data)



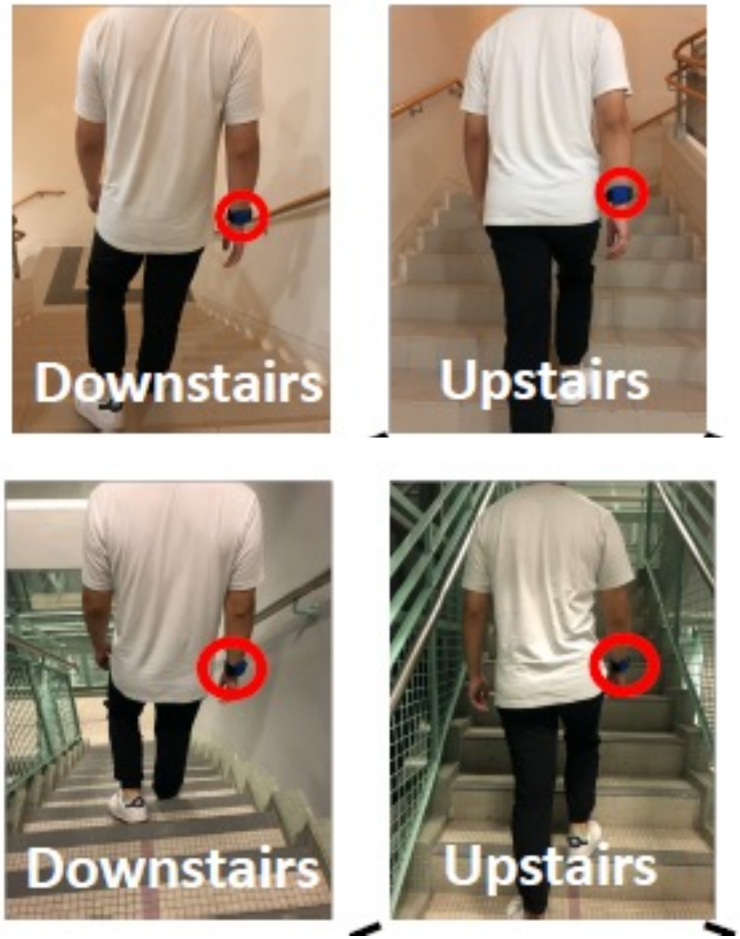
How about keep the data locally?

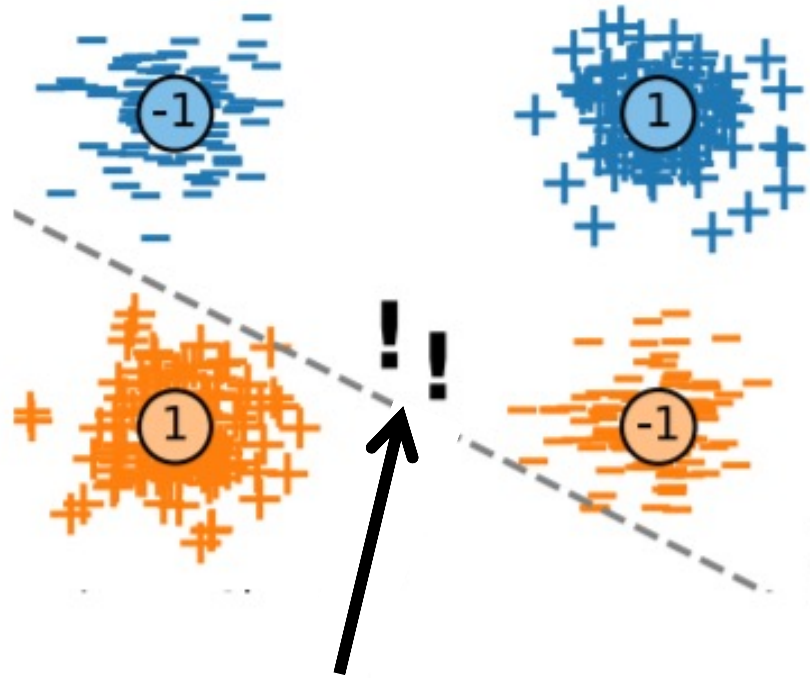
Motivation– Federated Learning

- Collaboratively training while keeping the data residing on devices.
- There is a high degree of data heterogeneity of human activity data.



Challenge – User Heterogeneity





- In this situation, a single linear classifier can not simultaneously be correct for all clients.

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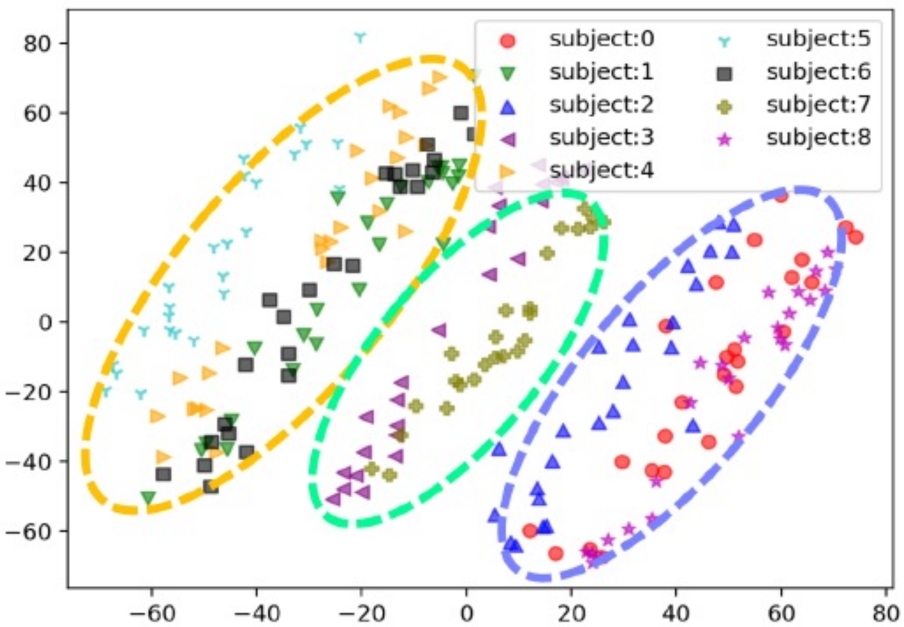
Motivation

- There exhibits intrinsic similarities among users' activities.



due to

$\Longrightarrow$

Biological features

Physical environments

Sensor bias

A clear clustering relationship among subjects in the walking dataset, where the data from the same type of smartphone is grouped to the same cluster.

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Motivation – Clusterability on Learning

Hopkins statistic: data X vs random data

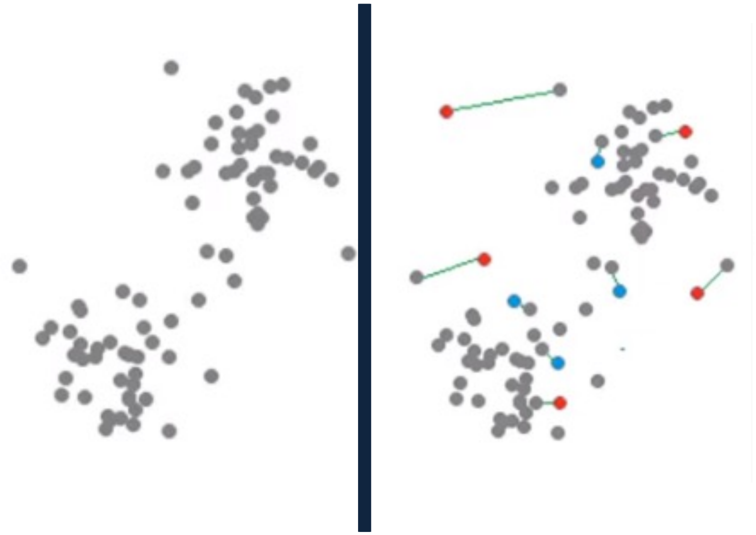
1. Blue data points ($p_1, \dots, p_m$) randomly selected from X;
2. Red data points ($q_1, \dots, q_m$) randomly generated from Uniform distribution.
3. Calculate distances:

   $\mathbf{d}_\mathrm{U}$: $q_1, \dots, q_m$ to the nearest points in X
   $\mathbf{d}_X$: $p_1, \dots, p_m$ to the nearest points in X

4. Hopkins statistic

$$\boldsymbol{H} = \frac{\sum_{i=1}^{m} \mathbf{d}_{\mathrm{U},i}}{\sum_{i=1}^{m} \mathbf{d}_{\mathrm{X},i} + \sum_{i=1}^{m} \mathbf{d}_{\mathrm{U},i}}$$

$H \approx 1$: data highly clustered
$H = 0.5$: data random
$H \approx 0$: data uniform



data X

Motivation – Clusterability on Learning

Empirical studies

- Quantifies the clustering tendency of HAR data

Dataset	SHAR	HHAR	Depth	IMU	UWB	HARBox
# of subjects/activities	30/6	9/6	9/3	7/2	8/3	121/5
Hopkins statistic	0.8813	0.7951	0.8699	0.6966	0.5742	0.8946

- The Centralized-cluster method has the bes

Grouping helps!

Method	Local	FedAvg	FTL	Centralized-single	Centralized-cluster
Mean Accuracy (%)	53.67	33.61	54.61	72.22	73.17
STD (%)	9.74	12.812	10.19	6.06	3.40

Nodes share a global model

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Contribution

- propose ClusterFL, a similarity-aware federated learning system to enable collaborative learning among similar nodes.

- introduce two communication efficient strategies: cluster-wise straggler dropout and correlation based node selection, based on the learned cluster structure.

- collect four new human activity recognition (HAR) datasets in different environments with significant dynamics

Outline

- Motivation
- Similarity-aware federated learning framework
- Experimental Results
- Conclusion

Similarity-aware FL Framework

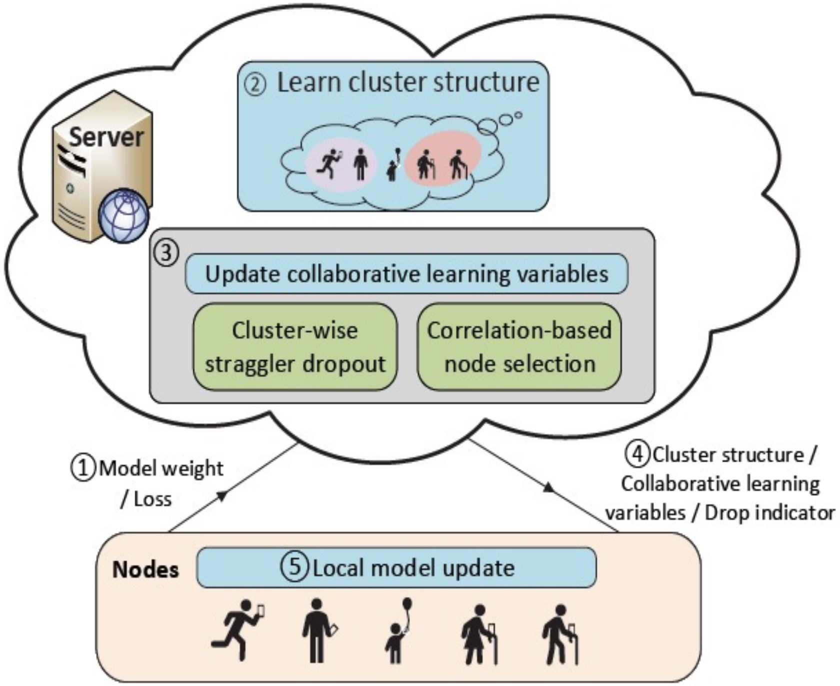

Figure 2: System Architecture of ClusterFL

Step 1: Nodes upload local model weights/loss

Step 2: The server use a **cluster indicator matrix** to quantify the clusters

Step 3: Based on the learned cluster indicator matrix, the server updates the models and **identify cluster-wise slow/less important nodes**

Step 4: The updated models and a drop indicator are send back to nodes

Step5: Nodes perform the local training

Similarity-aware FL Framework

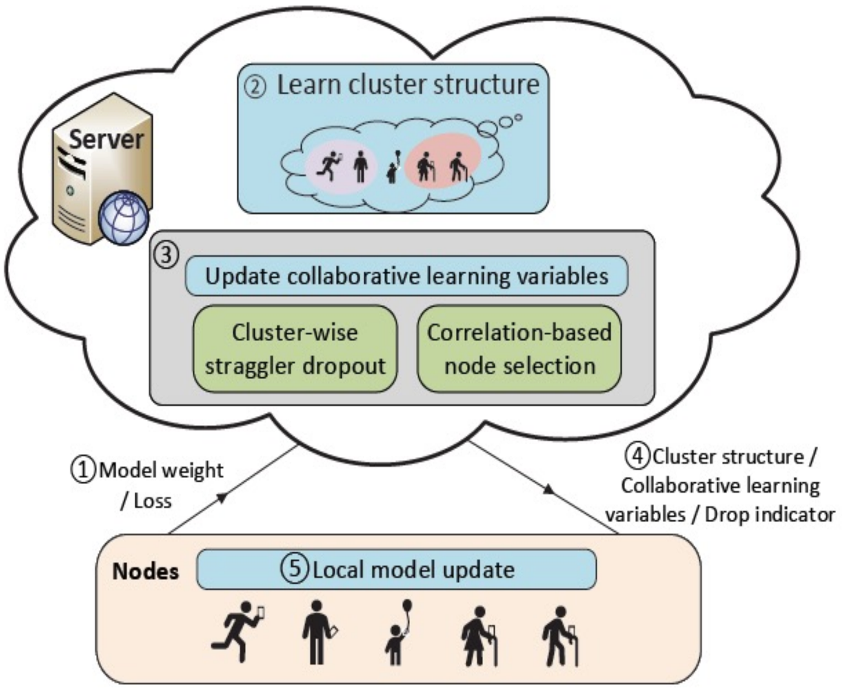

Figure 2: System Architecture of ClusterFL

- **Similarity-aware FL framework**
  - How to identify clusters
  - How to update model

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Similarity-aware FL Framework

- The *global objective* of ClusterFL

cluster indicator matrix

Local model

$\mathbf{F} \in \mathbb{R}^{M\times K}$

$$\min_{\mathbf{W},\mathbf{F}} \sum_{i=1}^{M} \frac{1}{N_i} \sum_{r=1}^{N_i} l(\mathbf{w}_i^T \mathbf{x}_i^r, y_i^r) + \underbrace{\alpha tr(\mathbf{W}\mathbf{W}^T) - \beta tr(\mathbf{F}^T \mathbf{W}\mathbf{W}^T \mathbf{F})}$$

$[\mathbf{w}_1, ..., \mathbf{w}_M]^T \in \mathbb{R}^{M\times D}$

$$\boxed{(\alpha - \beta) \sum_{i=1}^{M} ||\mathbf{w}_i||_2^2 + \beta \sum_{j=1}^{K} \sum_{v \in \mathcal{S}_j} ||\mathbf{w}_v - \overline{\mathbf{w}_j}||_2^2,}$$

Customize a model for each node

L2-Regularization

K-means clustering

Learn from the same cluster

M: the number of nodes
N_i: the number of training samples at node i's dataset
α, β: hyperparameters

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Similarity-aware FL – Alternating optimization

x_0^r : the public available data at server sides.

τ : parameter to adjust the sensitivity of the model outputs

- Fixed **W**, optimize **F**

  $\longrightarrow$ via the similarity of the node models

$$D_{KL}(\mathbf{w}_i, \mathbf{w}_j) = \frac{1}{N_O} \sum_{r=1}^{N_O} \delta(\mathbf{w}_i, \mathbf{x}_o^r) log \frac{\delta(\mathbf{w}_i, \mathbf{x}_o^r)}{\delta(\mathbf{w}_j, \mathbf{x}_o^r)}$$

$$\delta(\mathbf{w}_i, \mathbf{x}_o^r) = softmax(\frac{\Phi(\mathbf{w}_i, \mathbf{x}_o^r)}{\tau})$$

pre-softmax output of model

- K-means clustering $\mathbf{F} \in \mathbb{R}^{M \times K}$

Unknown

$F_{i,j} = \frac{1}{\sqrt{N_j}}$ if node i belongs to j-th cluster and $Fi, j = 0$ otherwise

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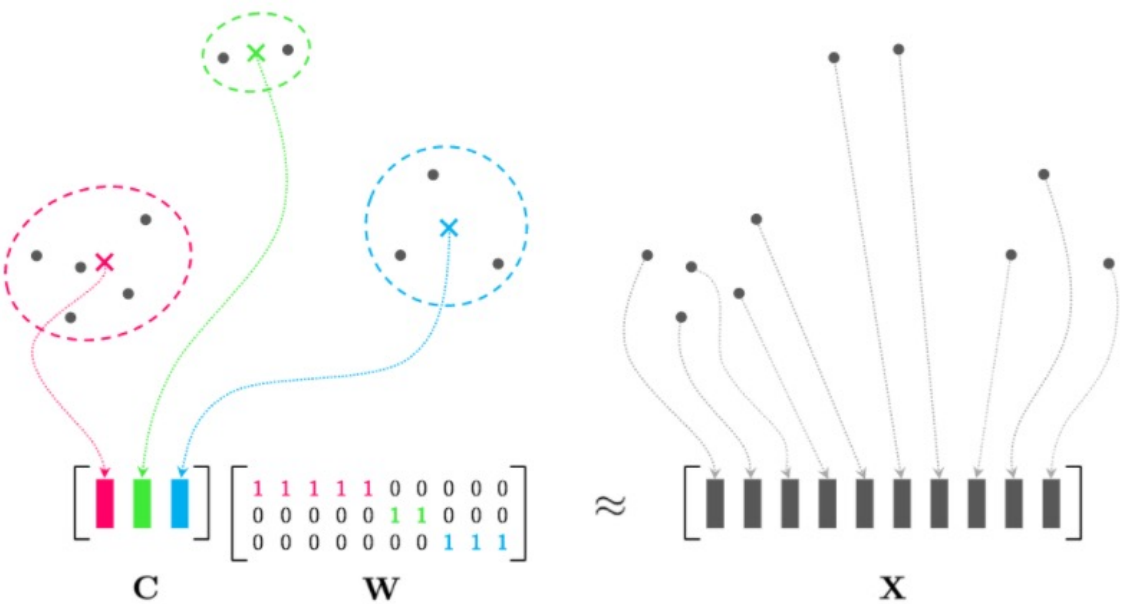
Similarity-aware FL -- Cluster indicator

- *K*-means clustering

Unknown number of clusters K

Solution[1]: principal components analysis (PCA)



[1] Ding et al. K-means clustering via principal component analysis. 2004

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Similarity-aware FL -- Cluster indicator

- Fixed **W**, optimize **F**

Solution[1]: Based on the KL divergence matrix $\mathbf{D} \in \mathbb{R}^{M \times M}$

M-1 principal components

Normalized indicators F

$$\mathbf{P} = Q_{M-1} Q_{M-1}^{T} \in \mathbb{R}^{M \times M} \implies F_{ij} = \frac{P_{ij}}{\sqrt{\sum_{i=1}^{M} P_{ij}}}$$

$(\text{set } P_{ij} = 0 \text{ if } P_{ij} < 0)$

P is the continuous solution of K-means clustering to approximate **F.**[1]

[1] Ding et al. K-means clustering via principal component analysis. 2004

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Similarity-aware FL – Alternating optimization

- Fixed **F**, optimize **W**, **Ω**

$$\min_{\mathbf{W},\Omega} f(\mathbf{W}) + g(\Omega)$$
$$s.t.\ \mathbf{F}^T\mathbf{W} - \Omega = 0$$
$$\text{where: } f(\mathbf{W}) = \sum_{i=1}^{M} \frac{1}{N_i} \sum_{r=1}^{N_i} l_t(\mathbf{w}_i^T \mathbf{x}_i^r, y_i^r) + \alpha tr(\mathbf{W}\mathbf{W}^T)$$
$$g(\Omega) = -\beta tr(\Omega\Omega^T)$$

- node update **W**:

$$\mathbf{w}_i^{t+1} = \arg\min_{\mathbf{w}_i} \frac{1}{N_i} \sum_{r=1}^{N_i} l_t(\mathbf{w}_i^T \mathbf{x}_i^r, y_i^r) + (\alpha + \frac{\rho}{2} \sum_{j=1}^{K} F_{ij}^2)||\mathbf{w}_i||_2^2 + \sum_{j=1}^{K} F_{ij}(\mathbf{U}_j^t - \rho\Omega_j^t)^T \cdot \mathbf{w}_i$$

- server update **U**, **Ω**:

$$\Omega_j^{t+1} = \arg\min_{\Omega_j} -\beta||\Omega_j||_2^2 - \Omega_j \cdot (\mathbf{U}_j^t)^T + \frac{\rho}{2}||\Omega_j - \mathbf{F}_j^T\mathbf{W}^{t+1}||_2^2$$
$$\mathbf{U}_j^{t+1} = \mathbf{U}_j^t + \rho(\mathbf{F}_j^T\mathbf{W}^{t+1} - \Omega_j^{t+1})$$

Similarity-aware FL

Algorithm 1: Alternating Optimization of ClusterFL

Initialization : set $\mathbf{W} = 0^{M \times D}$, $\mathbf{F} = \mathbf{0}^{M \times M}$

for $h = 0$ *to* H **do**

  1. Optimization of **W** with **F** fixed.

  for $t = 0$ *to* T **do**

    node update: parallelly update $\mathbf{w}_i$(i = 1,...,M)

      $\mathbf{w}_i^{t+1} \leftarrow \textbf{Local SGD}(\mathbf{w}_i^t, (\mathbf{x}_i^r, y_i^r), \mathrm{F}, \Omega, \mathrm{U})$

    server update: update Ω and U

    for $j = 1$ *to* K **do**

      $\Omega_j^{t+1} \leftarrow \arg\min_{\Omega_j} \mathrm{L}_\rho(\Omega_\mathrm{j}, \mathrm{U}_j^t, \mathrm{F}_j^t, \mathrm{W}^{t+1})$

      $\mathrm{U}_j^{t+1} \leftarrow \mathrm{U}_j^t + \rho(\mathrm{F}_j \mathrm{W}^{t+1} - \Omega_j^{t+1})$

    end

  end

  2. Optimization of **F** with **W** fixed.

  server update: Update **F** based on Section 5.3

end

Similarity-aware FL Framework

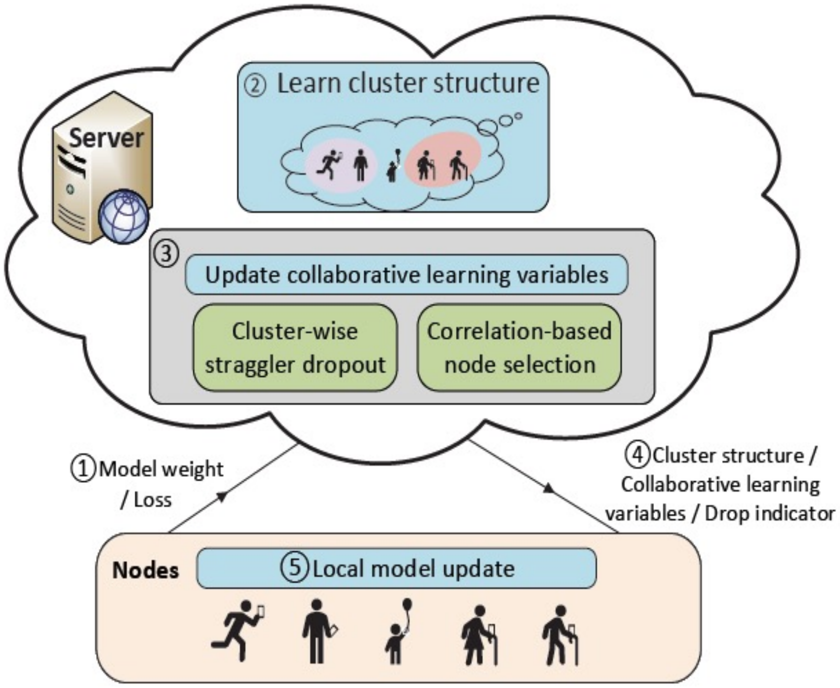

Figure 2: System Architecture of ClusterFL

- **Similarity-aware FL framework**
  - How to identify clusters
  - How to update model
- **Communication Efficiency**
  - How to handle straggler
  - How to identify "important" nodes

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Similarity-aware FL Framework

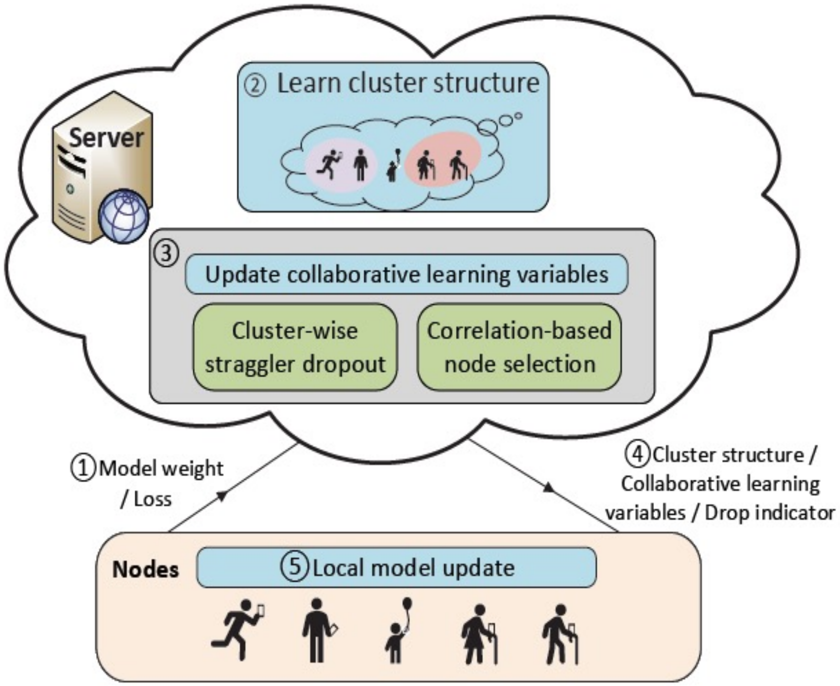


Figure 2: System Architecture of ClusterFL

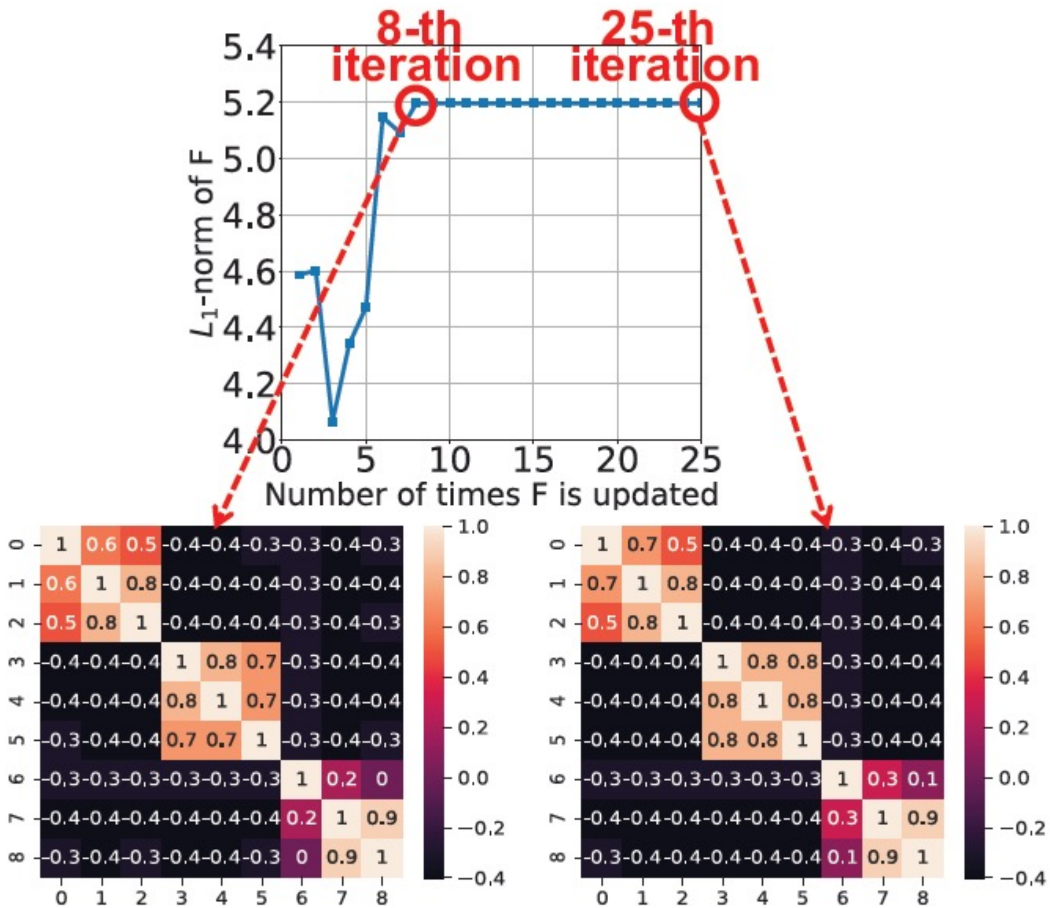
- **Communication Efficiency**
  - How to handle straggler
  - How to identify "important" nodes

Idea: leverage cluster structure to drop the nodes while keep the similar accuracy

Optimizing Communication Performance

The cluster relationship can be learned in the early stage.

F



Optimizing Communication Performance

✓ Drop the cluster-wise stragglers (the nodes who converge slower)

According to cluster structure **F**, we can measure the cluster-wise convergence performance:

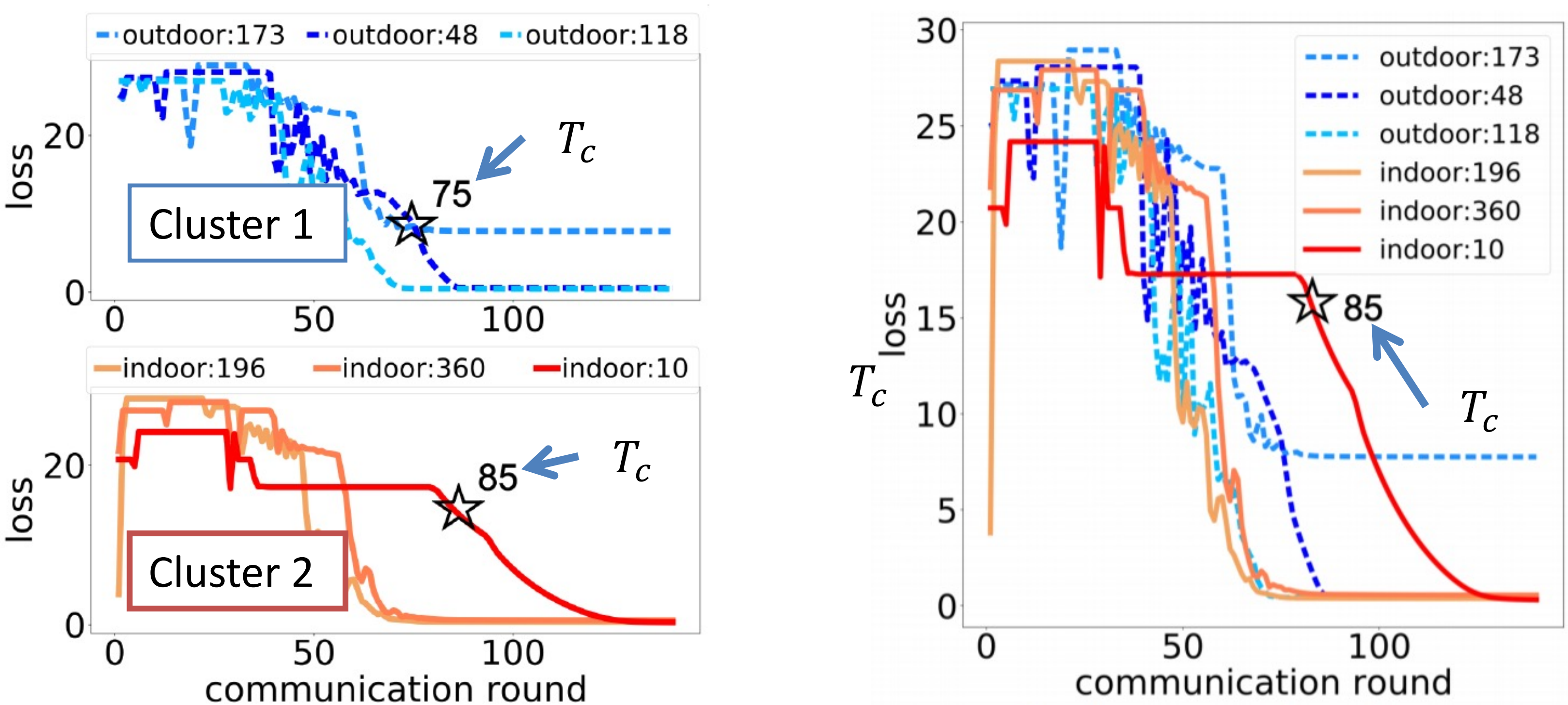
$$\varepsilon_q^t = \frac{|loss_q(t) - loss_q(t-1)|}{\sum_{q=1}^{N_j} |loss_q(t) - loss_q(t-1)|}$$

$$\gamma_q = \frac{1}{T_c} \sum_{t=1}^{T_c} \varepsilon_q^t \quad for\ q = 1, 2, \dots, N_j$$

T_c: the threshold of iteration for determining stragglers at each cluster

Optimizing Communication Performance

✓ Drop the cluster-wise stragglers (the nodes who converge slower)



(a) Within clusters

(b) Among all nodes

More dynamic and flexible

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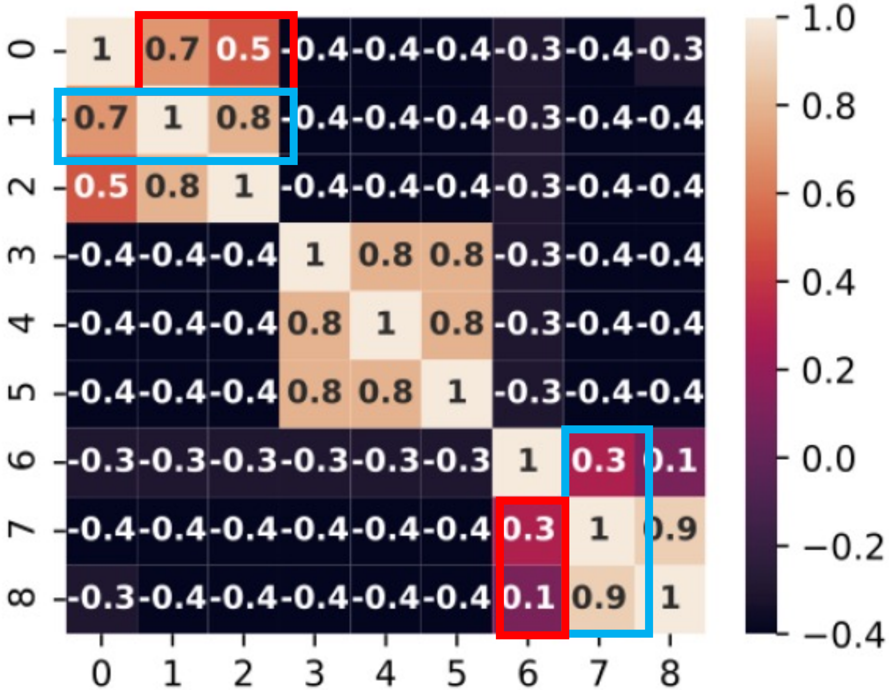
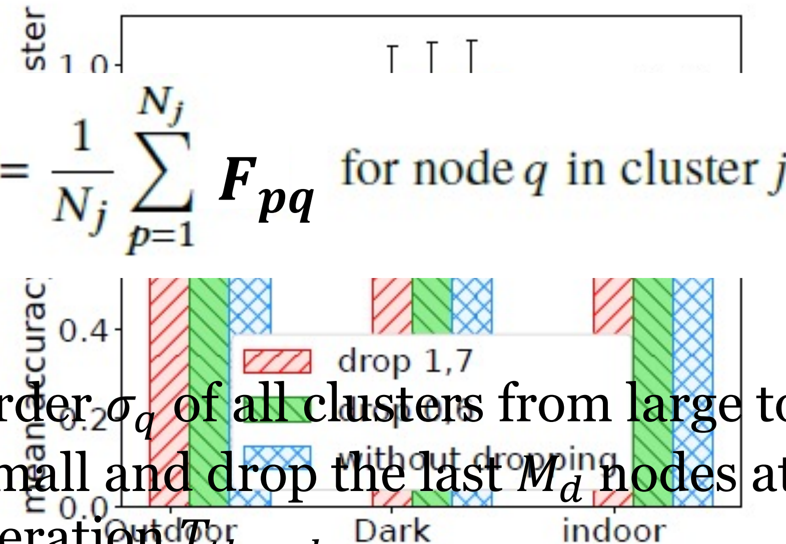
Optimizing Communication Performance

✓ Drop nodes whose data is less related to other nodes in the same cluster.

- Node 0 has weaker correlations in the first cluster. (Outdoor)
- Node 1 has stronger correlations in the first cluster.



$$\sigma_q = \frac{1}{N_j} \sum_{p=1}^{N_j} \boldsymbol{F}_{pq} \quad \text{for node } q \text{ in cluster } j$$



order σ_q of all clusters from large to small and drop the last M_d nodes at iteration T_{thresh}.

(b) Mean accuracy of each cluster

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Experiment Setup

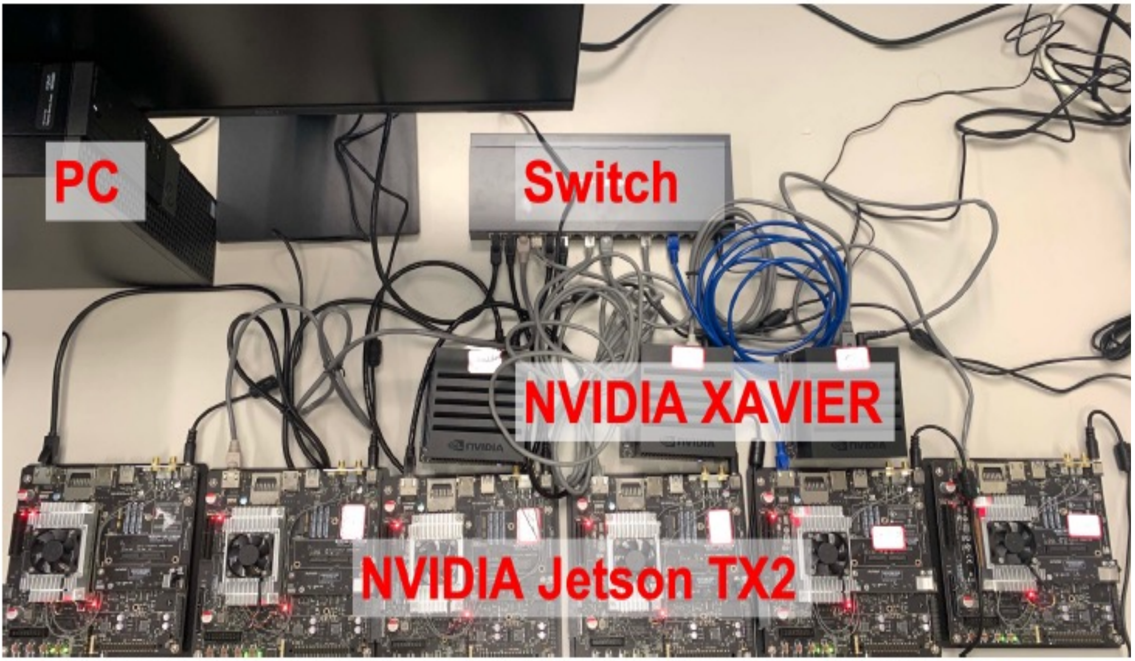

Figure 10: Hardware Setup

- The server and nodes are connected via a TP-link TL-SG2016K switch.
- The power are measured via the on-board power monitoring sensor TIINA3221x.

Experiment Setup

- **Dataset**: four new human activity recognition (HAR) datasets

Application	Task	Data Dimension	Number of Subjects	Number of Data Records	Sensor	Environment
Human Movement Detection using UWB	with/without Human Movement	55	8	663	Decawave DWM1000 UWB	node 0,1 from parking lot node 2,3,4 from corridor node 5,6,7 from room
Walking Activity Recognition using IMU	walking on corridors/ upstairs/downstairs	900	7	1369	LPMS-B2 IMU	node 0,1,2,3 from building 1 node 4,5,6 from building 2
Gesture Recognition using Depth Camera	good/ok/ victory/stop/fist	1296	9	7422	PicoZense DCAM710	node 0,1,2 from "outdoor" node 3,4,5 from "dark" node 6,7,8 from "indoor"
HARBox: ADL Recognition using Smartphones	walking/hopping/ phone calls/waving/typing	900	121	32935	77 different smartphone models	121 subjects (17-55 years old) Sampling rate: 43.5-57.5Hz

- **Models**: SVM for human movement detection;
  Five-layer NN for walking activity recognition;
  Five-layer CNN for depth camera gesture recognition.

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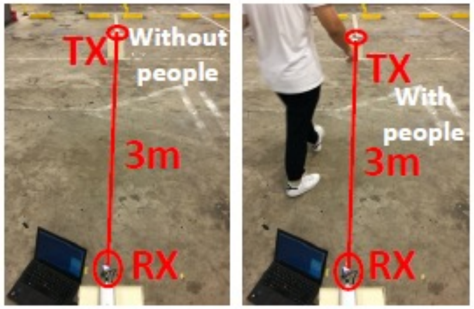
Experiment Setup

- **Baseline**:
  1) Local training
  2) Federated average[1] (FedAvg)
  3) Federated transfer learning[2] (FTL)
  4) Centralize (single) model training

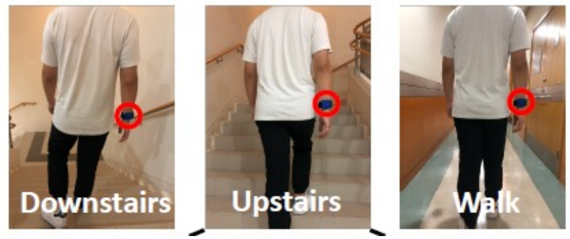
[1] McMahan Communication-Efficient Learning of Deep Networks from Decentralized Data, 2017

[2] Feng et alPmf: A privacy-preserving human mobility prediction framework via federated learning. 2019

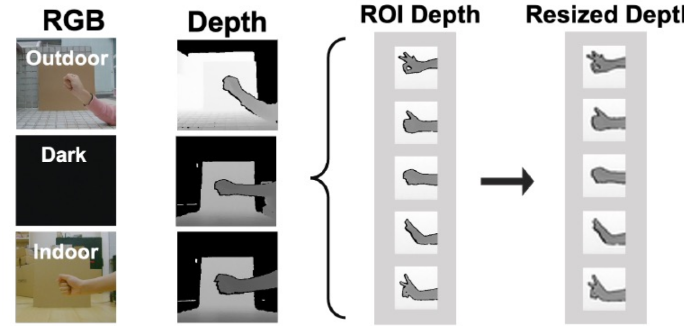
Visualization of Different Datasets



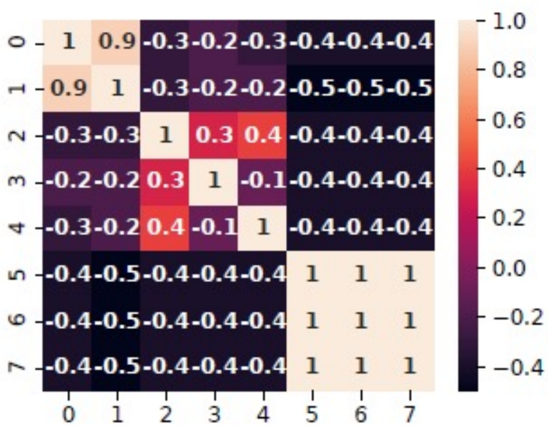
multi-path effect of
Ultra Wide Band signals



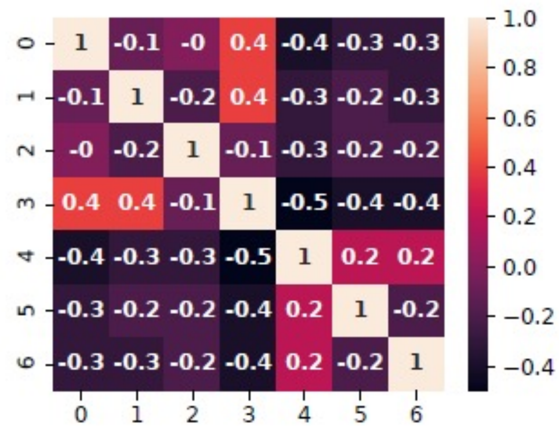
Sensor data from
smart watch



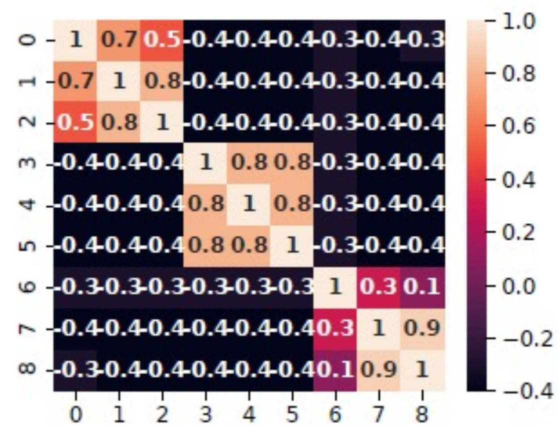
Camera image data



(a) UWB structure



(b) IMU structure



(c) Depth structure

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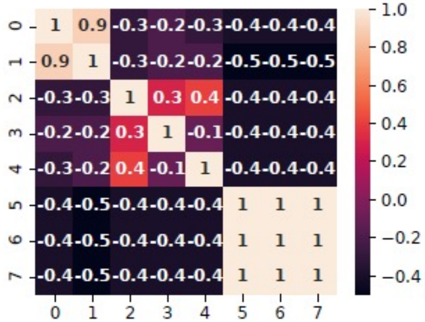
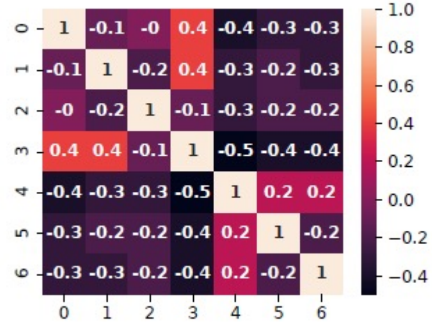
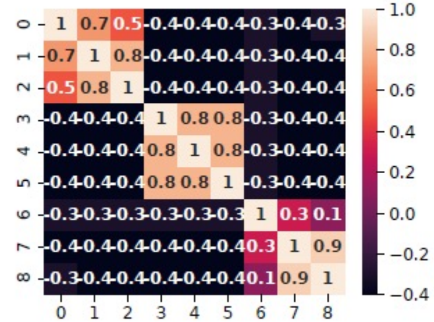
Performance on Different Datasets



(a) UWB structure



(b) IMU structure



(c) Depth structure

	Local	FedAvg	FTL	Centralized	ClusterFL
UWB	71.67%	86.25%	87.30%	**92.71%**	**92.71%**
IMU	88.29%	82.00%	86.20%	84.19%	**89.05%**
Depth	67.91 %	63.75%	63.86%	**96.82%**	70.68%

Table 5: Mean accuracy in unbalanced data settings

- ClusterFL outperforms Local/FedAvg/FTL in model accuracy.
- For the IMU dataset, ClusterFL has the best performance in model accuracy.

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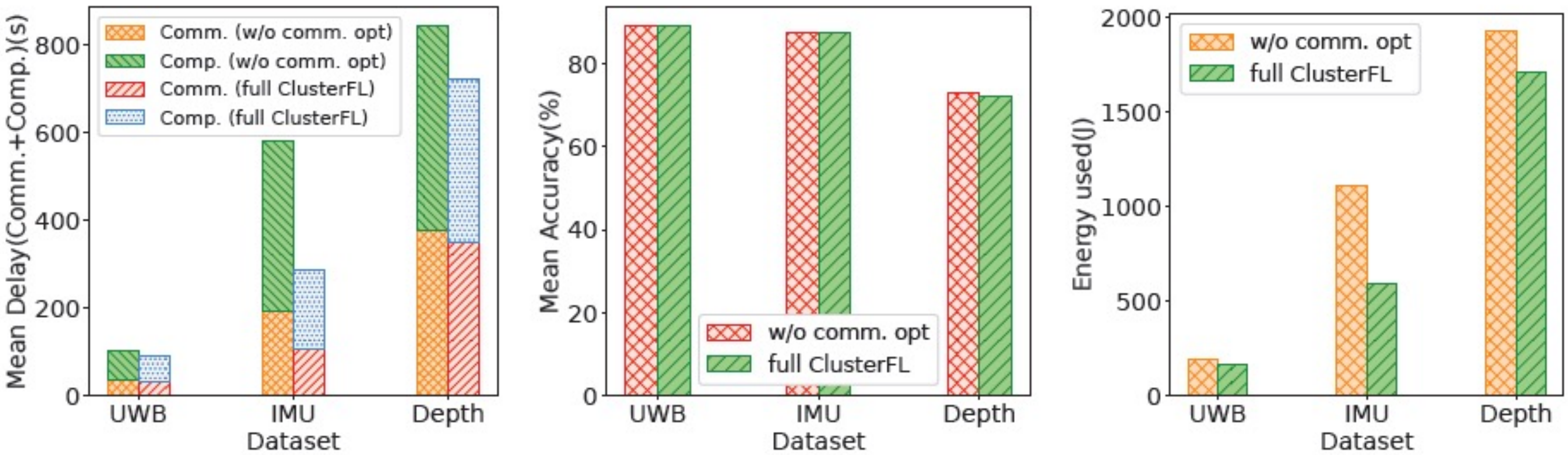
Performance on Different Datasets

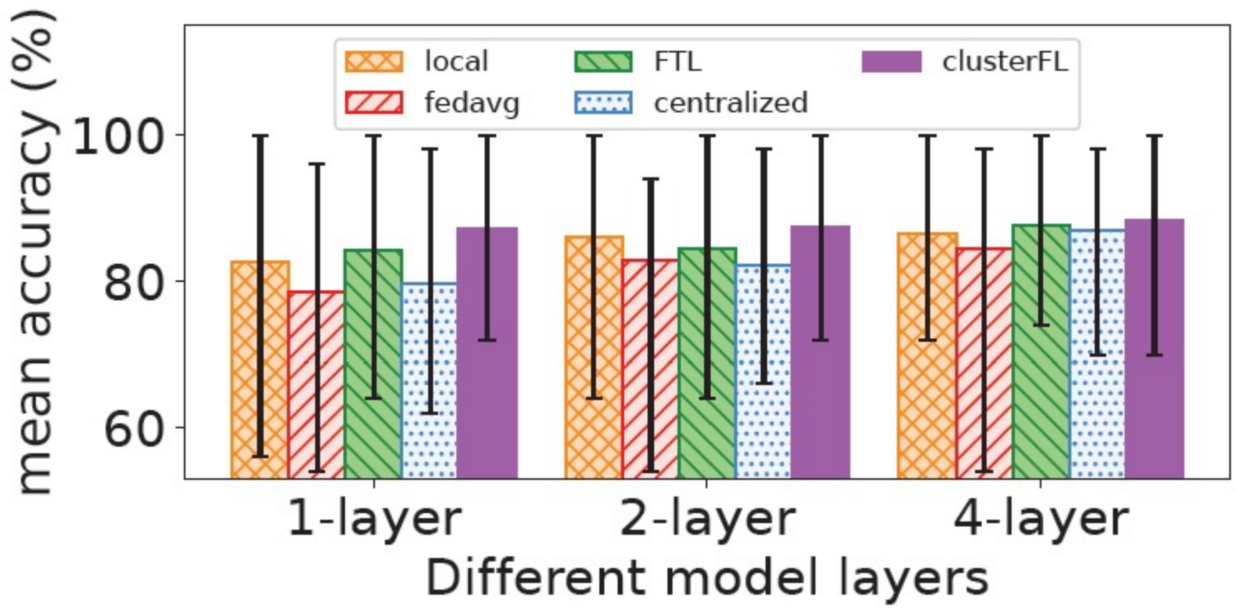


(a) Time delay **(b) Accuracy** **(c) Energy**

- ClusterFL can reduce more than 20% communication latency while maintaining almost the same accuracy performance.

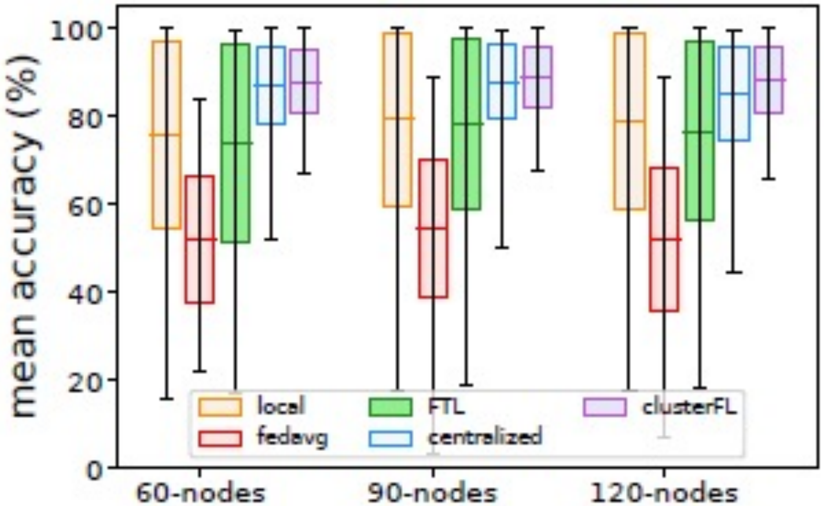
Performance on Model Depths

IMU dataset



- When the model becomes deeper, the accuracy of all methods tends to increase.
- ClusterFL has a more “stable" accuracy performance under different learning models

Performance on the scalability of ClusterFL



(a) Mean accuracy

(b) Mean commu. cost per node

- When the number of nodes increases, the mean accuracy of centralized learning slightly decreases, suggesting the heterogeneity of user' data.
- ClusterFL has a significantly smaller variation of accuracy among nodes and save more than 50% communication time.

Conclusion

- ClusterFL features a novel federated learning framework enabling collaborative learning among similar nodes

- ClusterFL integrates two effective communication optimization mechanisms based on the learned cluster structure.

- ClusterFL outperforms several learning paradigms and reduce more than 50% communication latency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