Joint Optimization in Edge-Cloud Continuum for Federated Unsupervised Person Re-identification

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Person Re-identification (ReID)

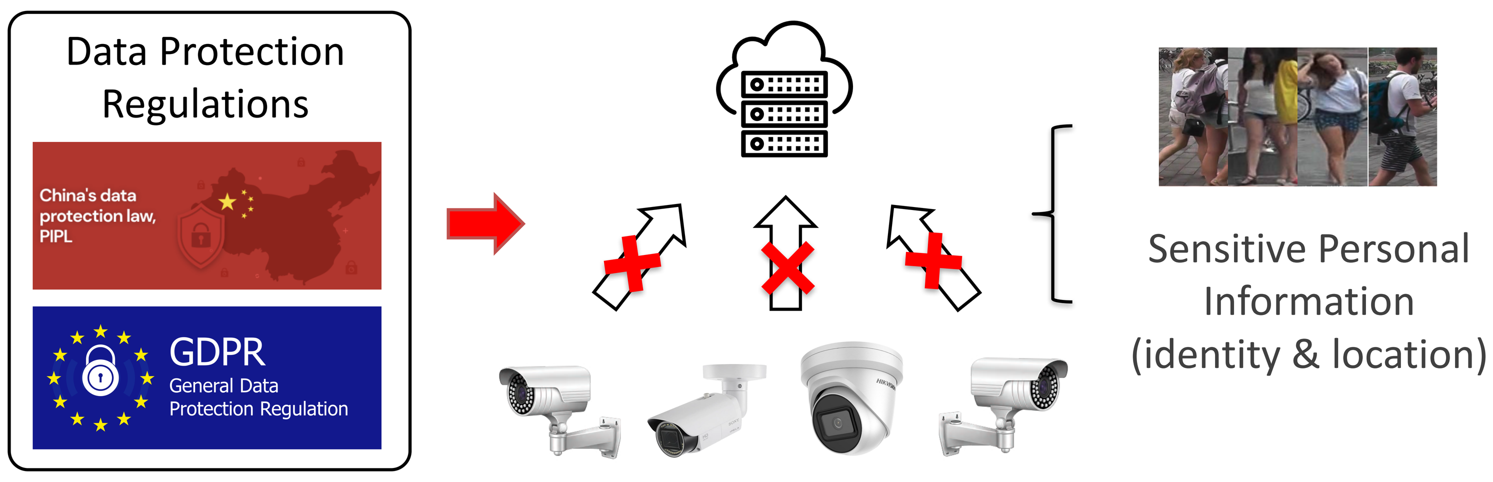
➢ Aim to re-identify a person from non-overlapping camera views.

Query Images from cameras that are **centralized** in a server

[1]

Challenges

➢ Not feasible to centralize the training images due to **data privacy protection regulations**, e.g., GDPR

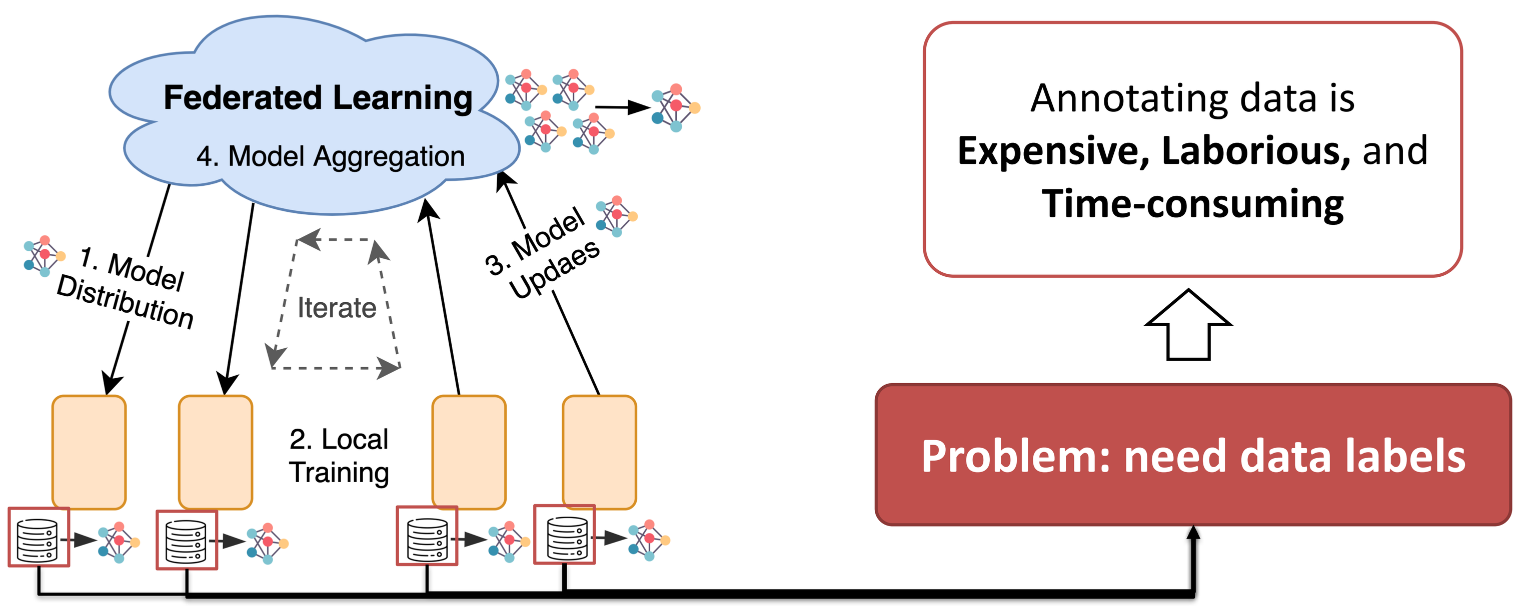


➢ Training with decentralized data suffers from statistical heterogeneity: different # images and # IDs; different illuminations, resolutions, etc.

8 Datasets used in the paper

Existing Works

➢ Federated Person ReID [2]: implement federated learning to person ReID. It trains person ReID on edges instead of centralizing images



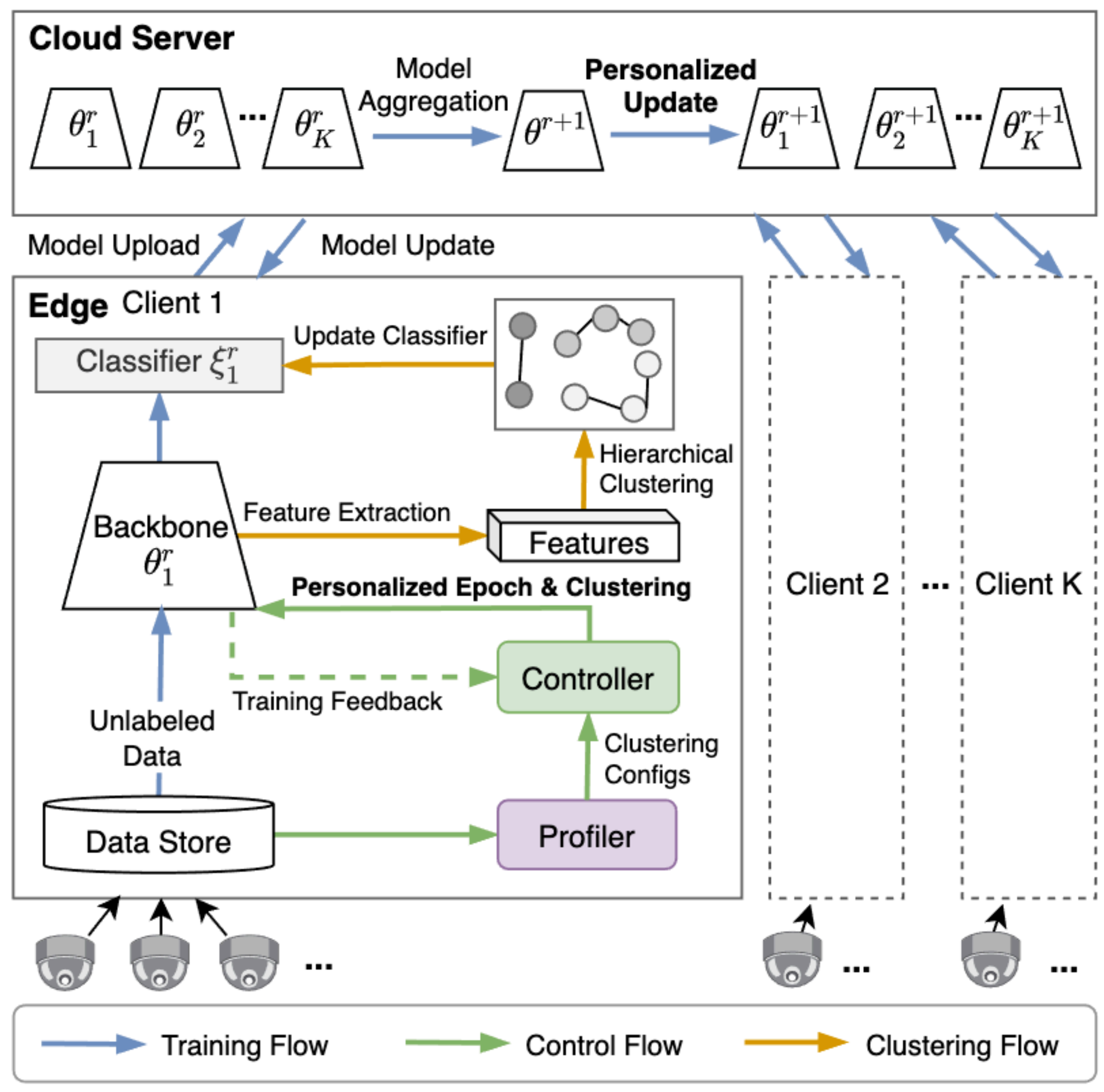
Contributions

➢ A new federated unsupervised person ReID system, FedUReID.

➢ Joint optimizations of cloud and edge to address the statistical heterogeneity among edges.

➢ Extensive experiments and ablations demonstrate the effectiveness of FedUReID with joint optimizations.

Federated Unsupervised Person ReID System



Training Flow

1. Local training: clients conduct training using local models
2. Model upload: clients upload trained backbones to the server
3. Model aggregation: server aggregates them for a new global model
4. Model update: server updates clients' local models with global model

How to address unlabeled data in clients? **(Clustering Flow)**

➢ Baseline: Hierarchical Clustering [3] to predict pseudo labels

Joint Optimizations of Cloud and Edge

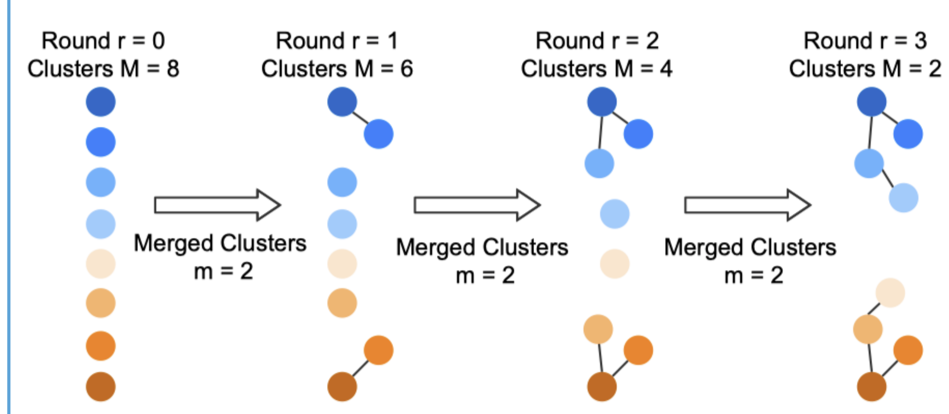
for statistical heterogeneity

Personalized Clustering (PC) @ Edge

➢ Each client uses the profiler to obtain their **personalized clusters to merge** each round, since their # IDs and # images are different.

Personalized Epoch (PE) @ Edge

➢ Clients **adjust computation** according to training feedbacks: early-stop when they have enough computation for good precision.



for *each local epoch e = 0 to E-1* **do**
  for $b \in \mathcal{B}$ **do**
    $(\theta, \xi) \leftarrow (\theta, \xi) - \eta\nabla\mathcal{L}((\theta, \xi); b)$;
    $precision_b \leftarrow$ (batch precision) ;
    $precision_{avg} \leftarrow$ (cumulative average precision)
  // Personalized epoch
  if *any* $precision_{avg} > 0.95$ *or* $precision_b == 1$ **then**
    break ;

Personalized Update (PU) @ Cloud

➢ Update clients' model with personalization by interpolating the global and local models: $\theta_k^{r+1} = \mu\theta_k^r + (1-\mu)\theta^{r+1}$

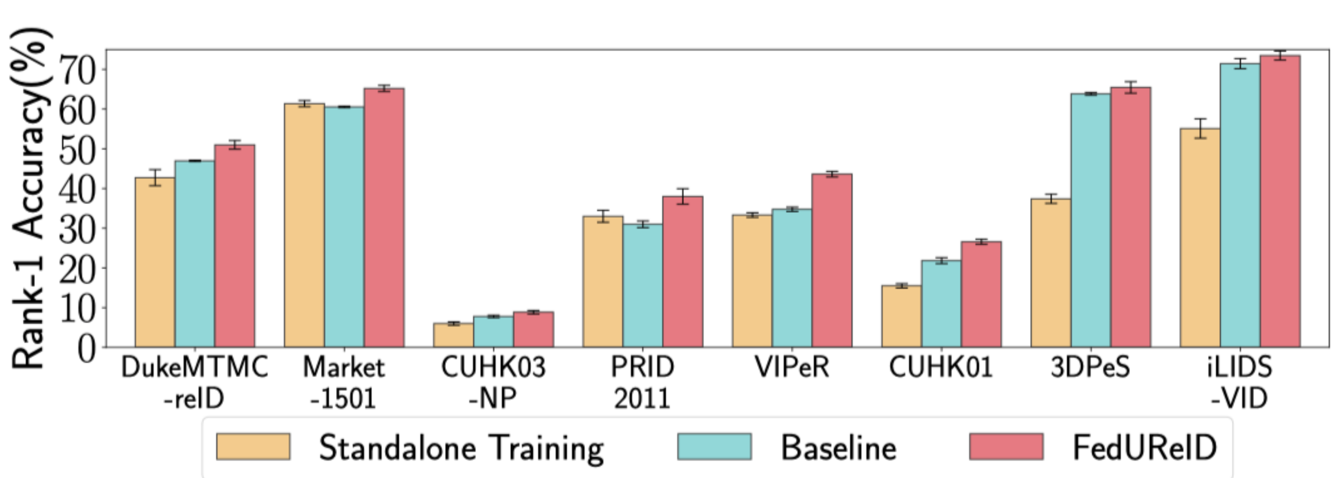
Experimental Results

Methods	Types	Market-1501 Dataset [38] (%)				DukeMTMC-reID Dataset [40] (%)			
		Rank-1	Rank-5	Rank-10	mAP	Rank-1	Rank-5	Rank-10	mAP
PUL [7]	Domain Adaptation	44.7	59.1	65.6	20.1	30.4	46.4	50.7	16.4
SPGAN [4]	Domain Adaptation	58.1	76.0	82.7	26.7	46.9	62.6	68.5	26.4
HHL [41]	Domain Adaptation	62.2	78.8	84.0	31.4	46.9	61.0	66.7	27.2
BUC [20] (Standalone)	Purely Unsupervised	61.9	73.5	78.2	29.6	40.4	52.5	58.2	22.1
Baseline	Purely Unsupervised	60.5	73.3	77.9	27.4	47.0	58.3	64.1	25.2
FedUReID (Ours)	Purely Unsupervised	**65.2**	**77.8**	**82.2**	**34.2**	**51.0**	**62.4**	**67.6**	**29.5**

(1) FedUReID with all optimizations outperforms other methods on two datasets

Datasets	Baseline	Edge			Cloud	Joint
		PC	PE	Both	PU	All
DukeMTMC-reID[40]	47.0	48.3	49.5	50.4	49.2	**51.0**
Market-1501[38]	60.5	62.5	64.0	65.1	62.2	**65.2**
CUHK03-NP[19]	7.8	8.4	7.9	8.1	8.8	**8.9**
PRID2011[11]	31.0	34.0	35.0	37.0	36.0	**38.0**
CUHK01[18]	34.8	39.3	39.2	42.6	35.4	**43.6**
VIPeR[9]	21.8	24.4	24.4	24.7	22.5	**26.6**
3DPeS[1]	63.8	65.5	64.6	**67.5**	65.0	65.5
iLIDS-VID[29]	71.4	73.5	70.4	70.4	72.5	**73.5**

(3) Ablation study: each optimization leads to better performance



(2) FedUReID with all optimizations outperforms baseline and standalone training (training with one client) on all datasets.

References

[1] Zheng, Zhedong, et al. "Unlabeled samples generated by gan improve the person re-identification baseline in vitro." ICCV. 2017.

[2] Zhuang, Weiming, et al. "Performance optimization of federated person re-identification via benchmark analysis." ACMMM. 2020.

[3] Lin, Yutian, et al. "A bottom-up clustering approach to unsupervised person re-identification." AAAI. 2019.

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