Classifier Clustering and Feature Alignment for Federated Learning under Distributed Concept Drift

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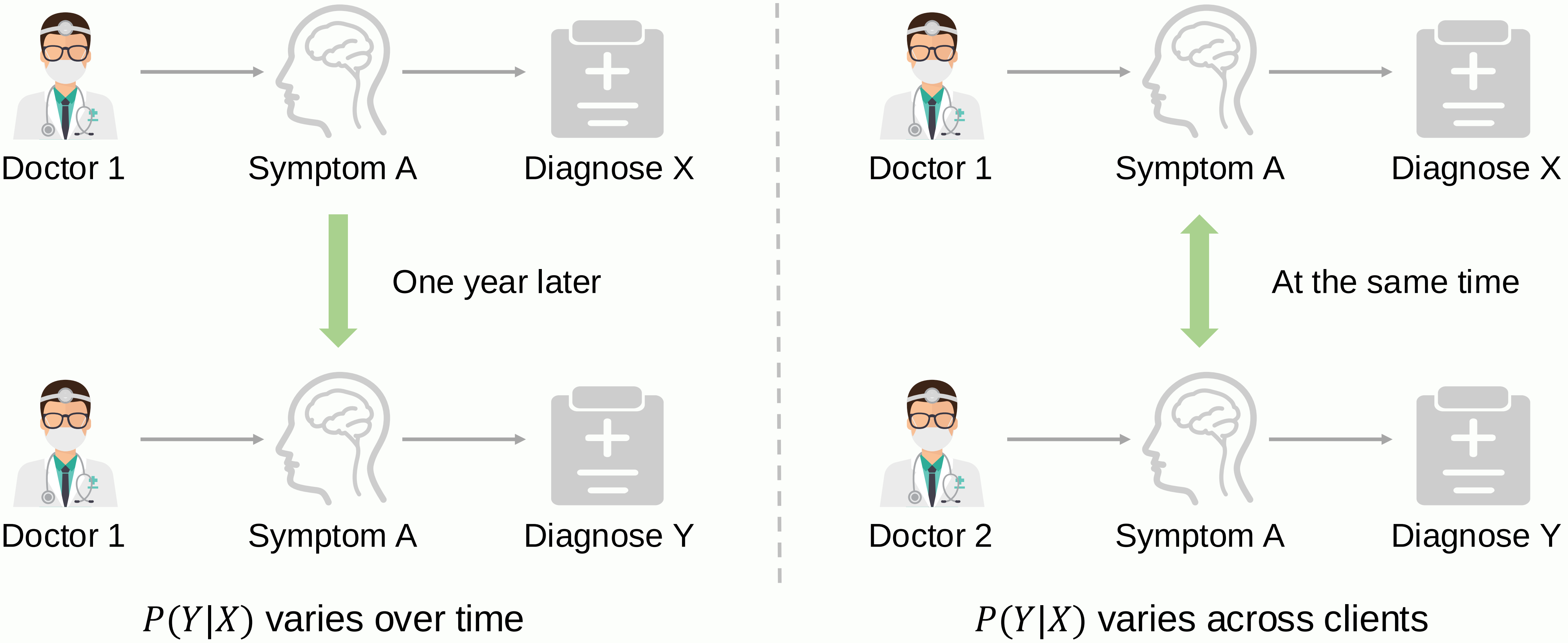
Code: https://github.com/Chen-Junbao/FedCCFA

Distributed Concept Drift



These two types of drift may **occur simultaneously** in federated learning

Motivation

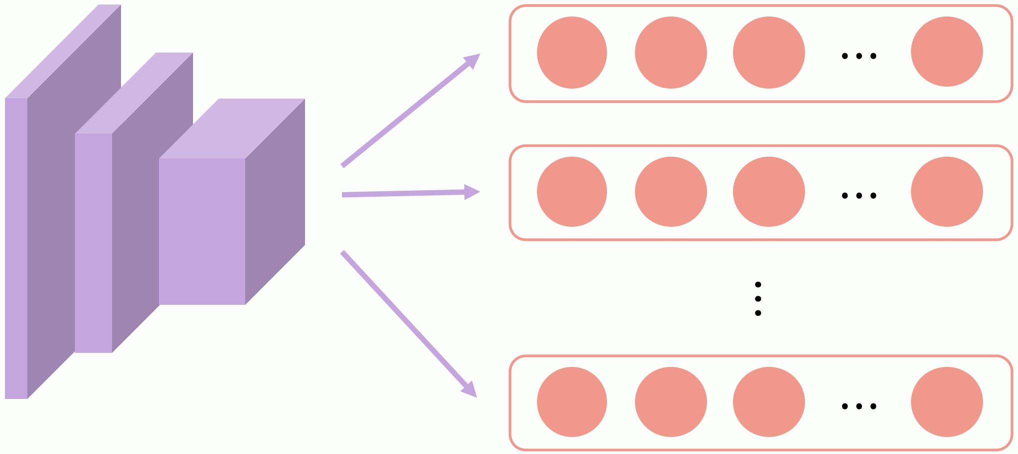
- A single model fails to adapt to distributed concept drift:

Client 1: $f(x_1;\theta) = y_1$

Client 2: $f(x_1;\theta) = y_2$

Impossible

- Marginal distribution $P(X)$ is invariant when drift occurs



Personal $P_1(Y|X)$

Personal $P_2(Y|X)$

$\vdots$

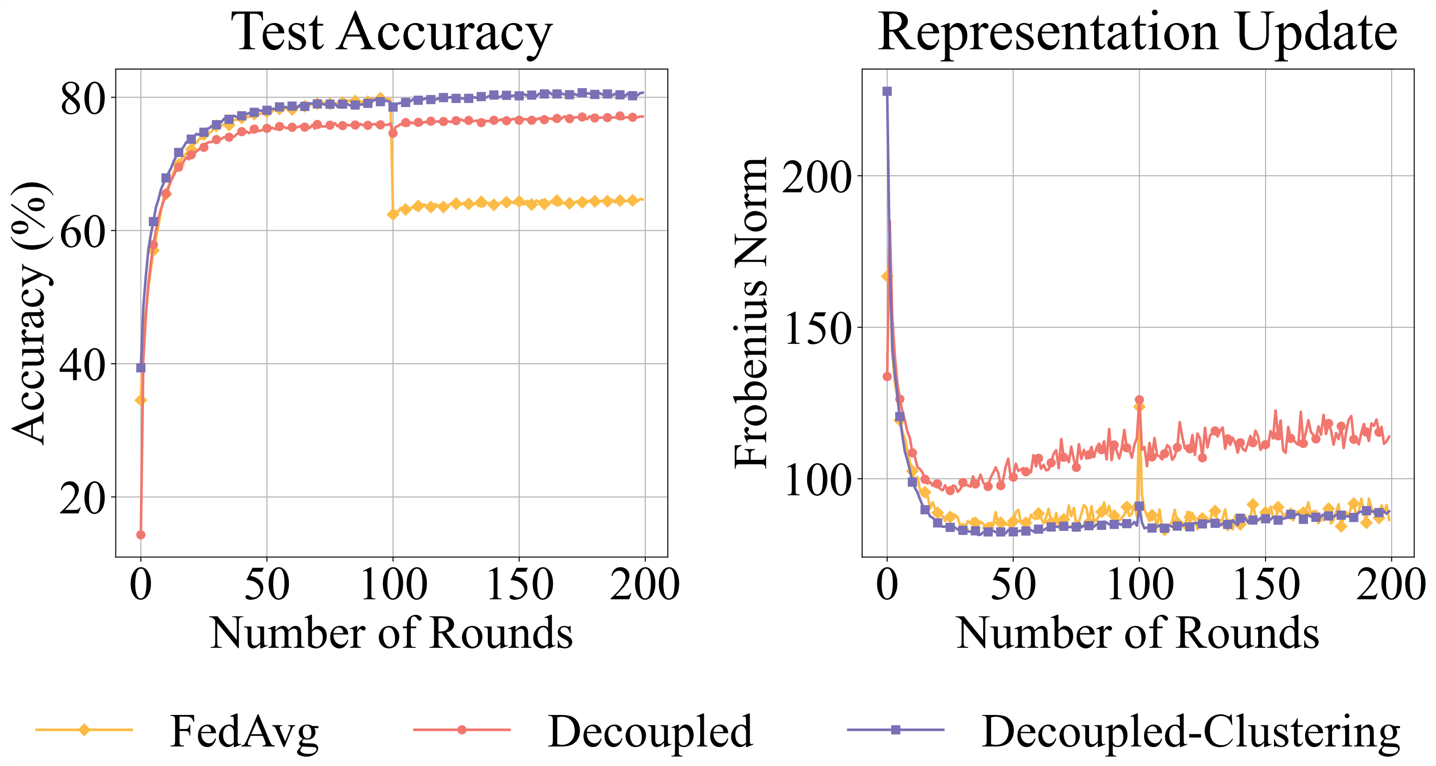
Personal $P_k(Y|X)$

Invariant $P(X)$

Feature extractor can be shared across clients, and each client owns a local classifier

Classifier Clustering

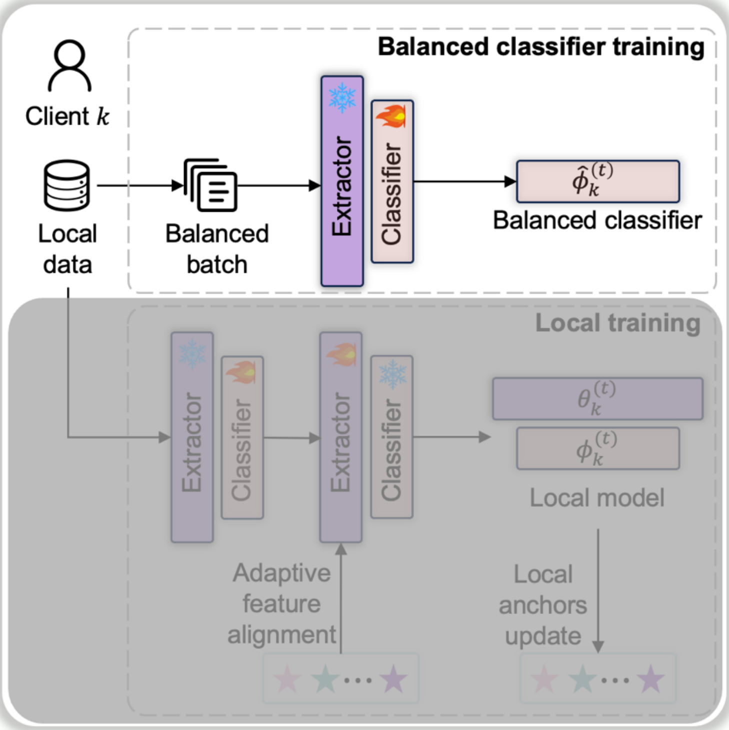
- Some clients may share the same conditional distribution $P(Y|X)$
- Merging the classifiers under the same $P(Y|X)$ can improve the generalization performance



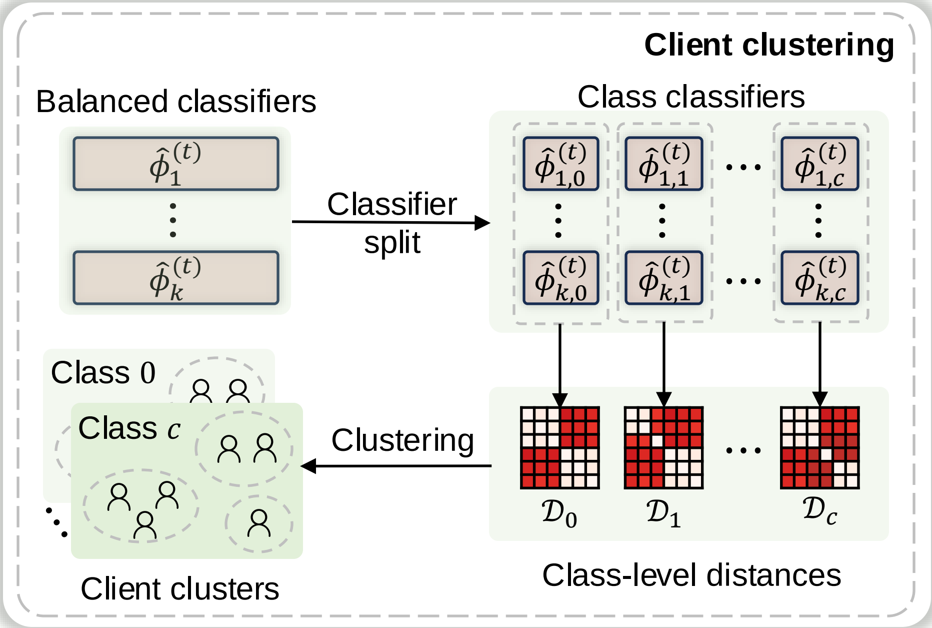
Decoupled-Clustering adapts to distributed concept drift and achieves **better performance**

Classifier Clustering

- Train classifier using a balanced batch



- Separate the classifier for each class and merge the classifiers under the same $P(Y|X)$



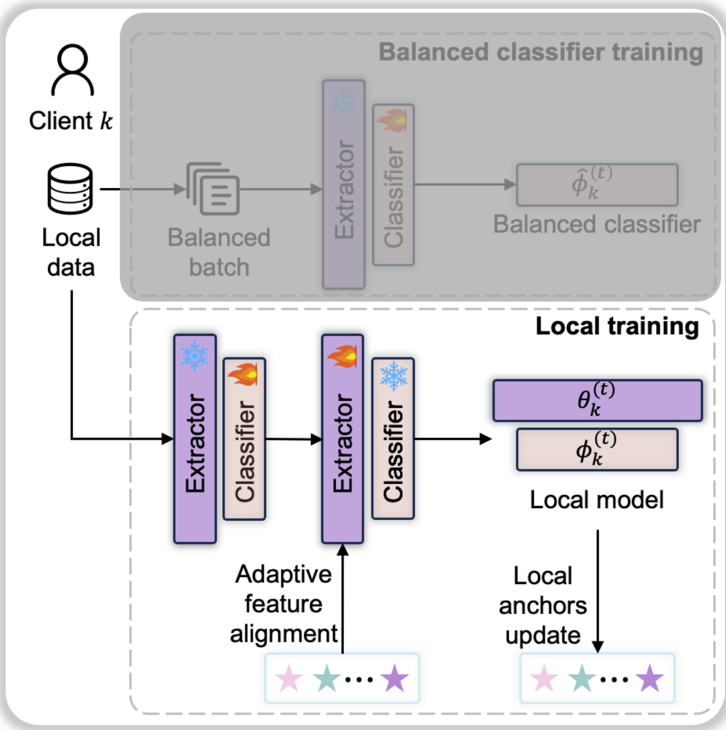
- **Why balanced batch?**
  The classifiers can be easily biased towards head classes. Train the local classifier using a balanced batch to solve this disturbance by class imbalance.

$$D_c(i,j) = \frac{1}{\left|I^{(t)}\right| - 2} \sum_{q \in I^{(t)}\{i,j\}} \left| Cos\left(\hat{\phi}_{i,c}^{(t)}, \hat{\phi}_{q,c}^{(t)}\right) - Cos\left(\hat{\phi}_{j,c}^{(t)}, \hat{\phi}_{q,c}^{(t)}\right) \right|, \forall i,j \in I^{(t)}$$

MADD: [1] Soham Sarkar and Anil K Ghosh. On perfect clustering of high dimension, low sample size data. IEEE transactions on pattern analysis and machine intelligence, 42(9):2257–2272, 2019.

Adaptive Feature Alignment

- Contrastive-guiding feature alignment

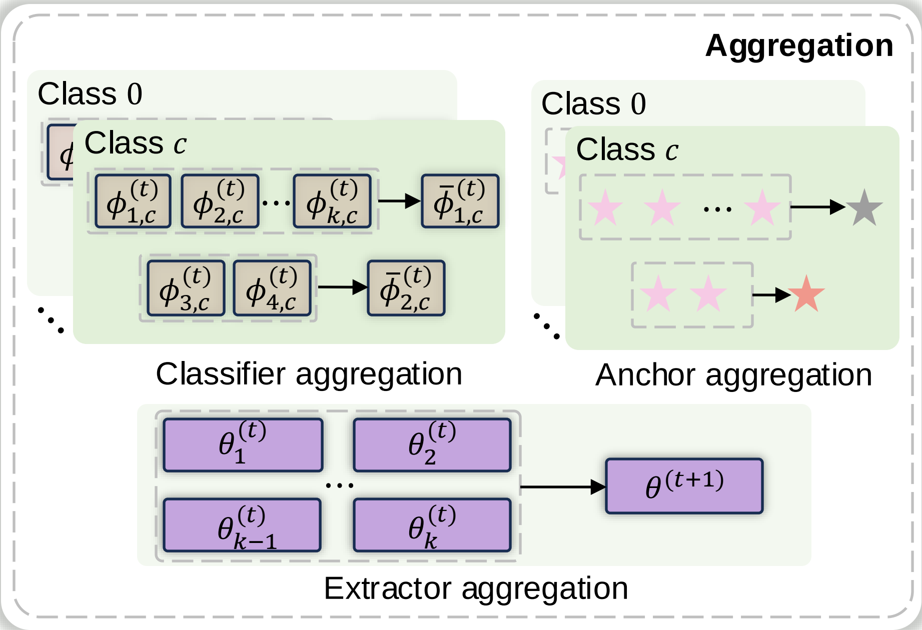


Adjust alignment weight with the **entropy of $P(Y)$**

$$G_k\left(\theta_k^{(t)}; A_k^{(t)}\right) = -\log \frac{\exp\left(sim\left(f_{\theta_k^{(t)}}(x), A_{k,c}^{(t)}/\tau\right)\right)}{\sum_{i=1}^{C} \exp\left(sim\left(f_{\theta_k^{(t)}}(x), A_{k,i}^{(t)}/\tau\right)\right)}$$

$$L_k(\theta, \phi_k) = F_k(\theta, \phi_k) + \frac{H\left(P_k^{(t)}(Y)\right)}{\gamma}$$

- Aggregation of classifiers, extractors and anchors



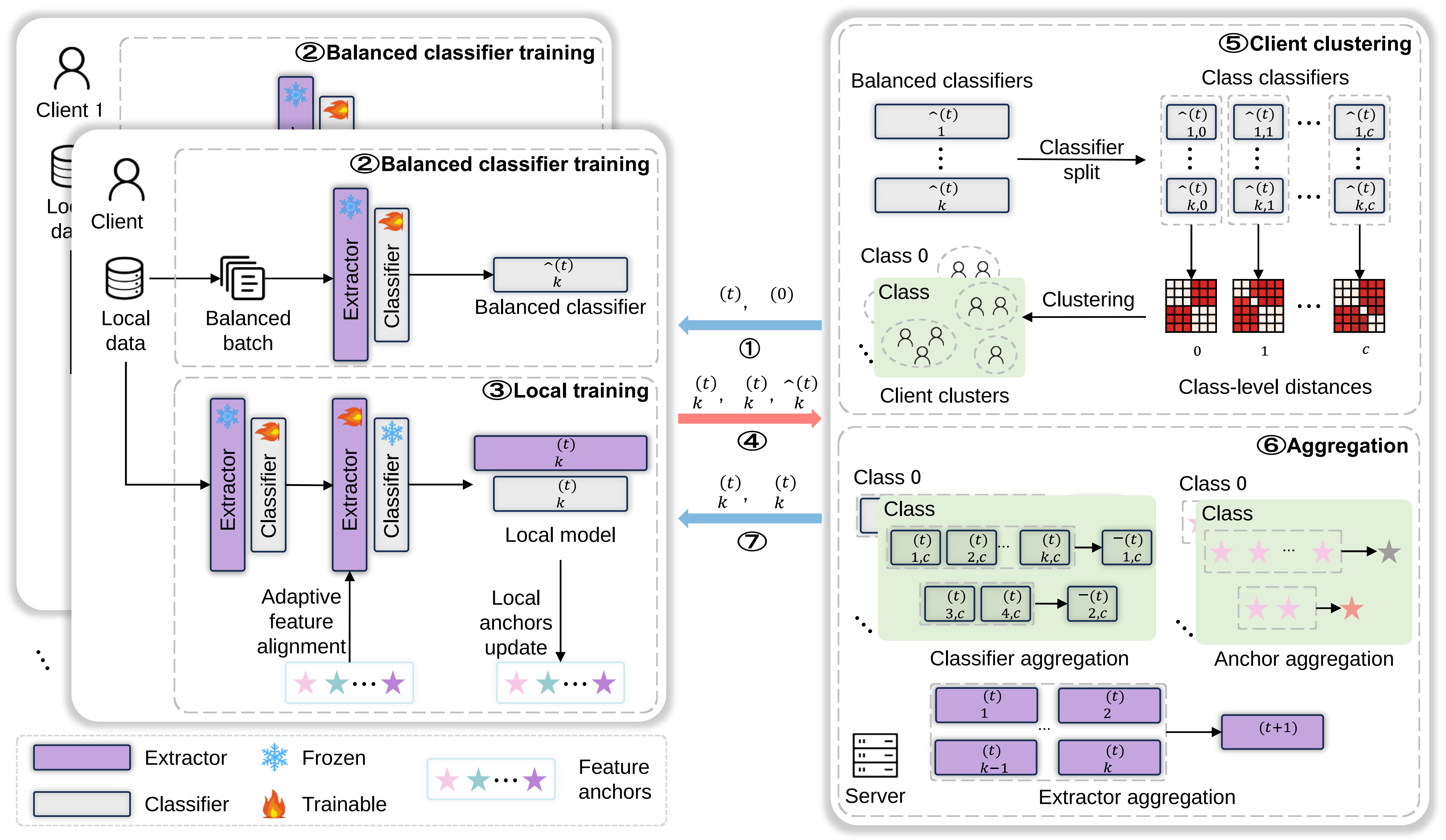
$$\phi_{m,c} = \frac{1}{\left|S_{m,c}^{(t)}\right|} \sum_{k \in S_{m,c}^{(t)}} \phi_{k,c}^{(t)}, \forall S_{m,c}^{(t)} \in S_c^{(t)}$$

$$A_{m,c}^{(t)} = \frac{1}{\left|S_{m,c}^{(t)}\right|} \sum_{k \in S_{m,c}^{(t)}} a_{k,c}^{(t)}, \forall S_{m,c}^{(t)} \in S_c^{(t)}$$

$$\theta^{(t+1)} = \frac{1}{\sum_{k \in I^{(t)}} \left|D_k^{(t)}\right|} \sum_{k \in I^{(t)}} \left|D_k^{(t)}\right| \theta_k^{(t)}$$

Clients in the same cluster $k \in S_{m,c}^{(t)}$ share
the clustered classifiers and anchors

FedCCFA

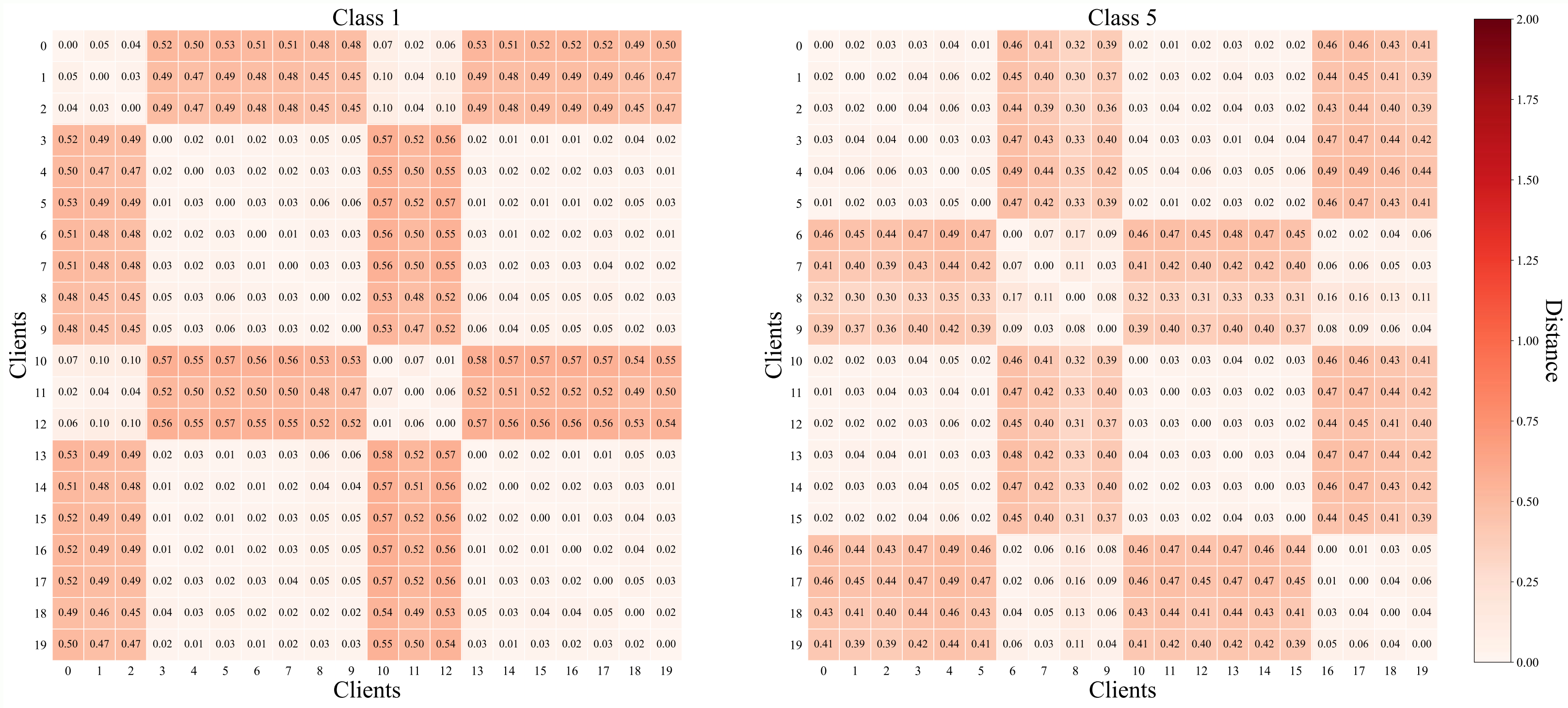

Client 1
②Balanced classifier training
Client
Local data
Balanced batch
Extractor
Classifier
Balanced classifier
③Local training
Local model
Adaptive feature alignment
Local anchors update
Extractor
Frozen
Feature anchors
Classifier
Trainable
①
④
⑦
⑤Client clustering
Balanced classifiers
Class classifiers
Classifier split
Class 0
Class
Clustering
Client clusters
Class-level distances
⑥Aggregation
Class 0
Class
Classifier aggregation
Anchor aggregation
Server
Extractor aggregation

Generalized Accuracy under Sudden Drift

Method	Fashion-MNIST		CIFAR-10		CINIC-10	
	20 clients	100 clients	20 clients	100 clients	20 clients	100 clients
FedAvg	67.81±1.12	68.15±1.98	60.96±0.37	58.15±0.23	49.69±0.16	46.18±0.39
FedProx	69.25±0.60	68.47±0.19	61.25±0.20	57.68±0.11	49.45±0.40	46.11±0.59
SCAFFOLD	69.92±1.24	69.66±0.24	58.67±0.39	45.87±1.29	46.34±0.70	37.94±1.43
FedFM	68.48±0.79	69.12±0.34	60.61±0.27	57.51±0.35	50.25±0.11	46.23±0.81
AdapFedAvg	69.30±1.06	68.86±0.53	60.92±0.20	58.23±0.30	49.86±0.36	46.34±0.19
Flash	10.00±0.00	71.16±0.28	59.84±0.75	60.49±0.27	49.44±0.41	49.28±0.40
pFedMe	82.37±0.09	77.66±0.17	58.92±1.64	44.15±1.08	41.34±0.22	37.76±0.78
Ditto	78.51±0.82	79.62±0.31	67.45±0.01	63.35±0.67	51.06±0.26	48.40±0.34
FedRep	81.99±0.37	81.07±0.29	64.51±0.86	53.30±1.51	44.00±0.26	38.15±0.14
FedBABU	79.83±0.18	81.68±0.10	58.87±0.50	55.29±0.61	41.24±0.90	40.49±0.30
FedPAC	84.00±0.47	87.24±0.16	66.47±0.30	64.73±1.22	44.38±0.18	46.22±0.47
IFCA	87.02±0.06	88.25±0.21	61.24±0.32	57.31±0.44	44.04±2.00	45.43±0.22
FedDrift	78.95±1.30	87.75±0.04	48.17±2.43	57.26±0.36	34.23±0.04	45.60±1.07
FedCCFA	**89.50±0.10**	**89.39±0.14**	**76.95±0.63**	**73.21±0.82**	**51.12±1.70**	**52.62±0.51**

FedCCFA achieves **SOTA performance**

Classifier Clustering Results



Clustering input	CIFAR-10
local classifiers	68.39±0.71
balanced classifiers	73.21±0.82
oracle	73.55±0.27

- Our clustering method **effectively measures the distance** between each client
- Classifier clustering significantly **improves generalization performance**

Adaptive Feature Alignment Results

Alignment methods	CIFAR-10
w/o alignment	71.40±0.43
w/o clustered	72.77±0.71
w/ clustered	73.21±0.82

Weight	$Dir(0.01)$	$Dir(0.1)$	$Dir(0.5)$
fixed (0)	62.46±0.92	69.33±1.47	72.78±0.53
fixed (0.1)	57.86±1.91	70.72±0.83	73.83±0.53
fixed (1.0)	40.89±3.97	67.43±1.08	74.80±0.41
$\gamma = 10$	60.30±0.79	69.75±0.19	74.97±0.48
$\gamma = 20$	61.29±0.59	70.21±0.48	74.44±0.26
$\gamma = 50$	62.15±0.49	70.11±1.05	73.32±0.06

Clustered feature anchors facilitate **more precise feature alignment** under drift
Adaptive alignment weight is **robust to the degree of heterogeneity**

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NEURAL INFORMATION PROCESSING SYSTEMS

Thank You!

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https://arxiv.org/abs/2410.18478

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