Disentangled Federated Learning for Tackling Attributes Skew via Invariant Aggregation and Diversity Transferring

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Outline

- Motivation
- Methods
- Results

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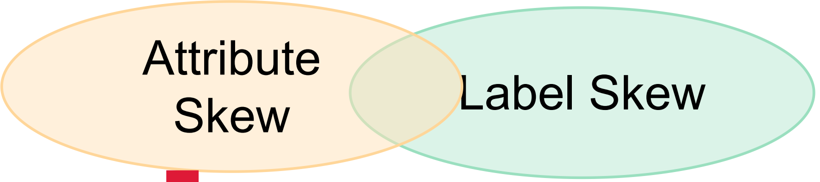
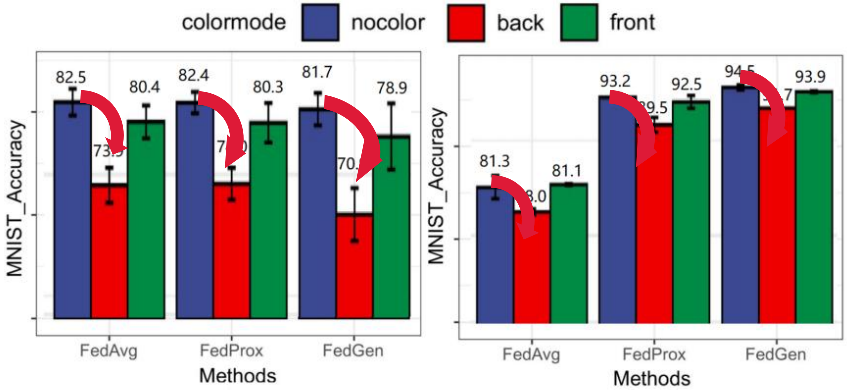
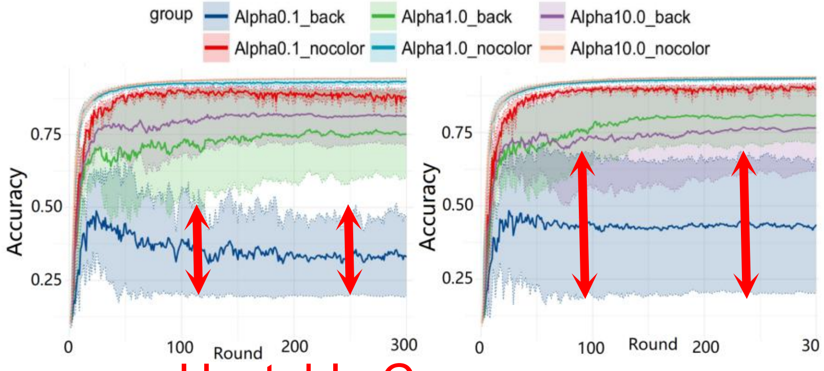
Motivation

Non-i.i.d

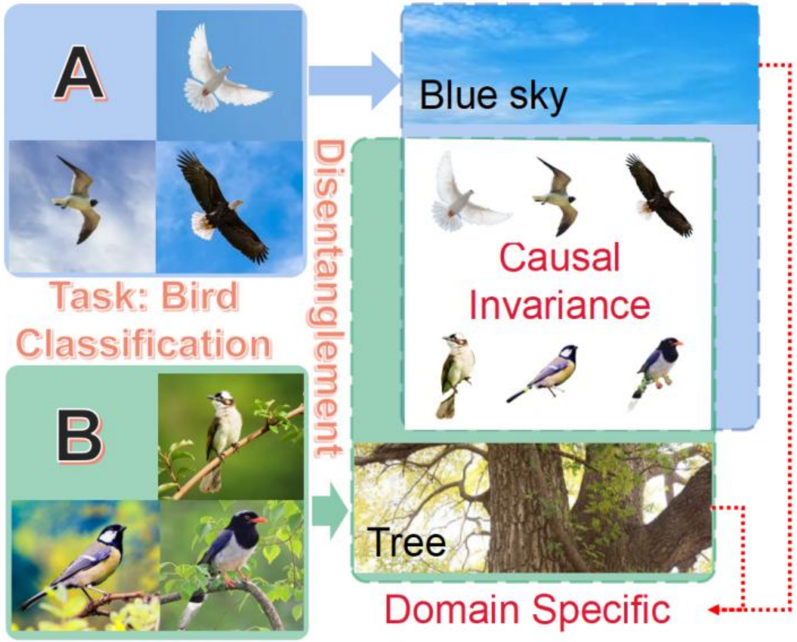




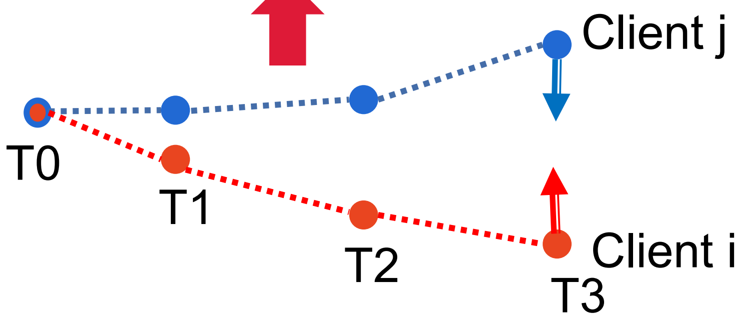
Performance Degradation



Unstable Convergence



Entangled Local-specific and Invariant Attributes



Optimization Direction Shift

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Methods

One-stage Optimization -> Alternating Local-global Optimization

$$\min_{\omega}\left\{f(\omega) := \frac{1}{N}\sum_{k=1}^{N} h_k(\omega)\right\}$$

One stage optimization

$$\min_{\omega_c}\left\{\begin{array}{c} f(\omega_c) := \frac{1}{N}\sum_{k=1}^{N} \min_{\omega_{k,s}} h_k(\omega_i) \\ \omega_i = M(\omega_c, \omega_{k,s}) = P_c\omega_c + P_s\omega_{k,s} \end{array}\right\}$$

Alternating local-global optimization

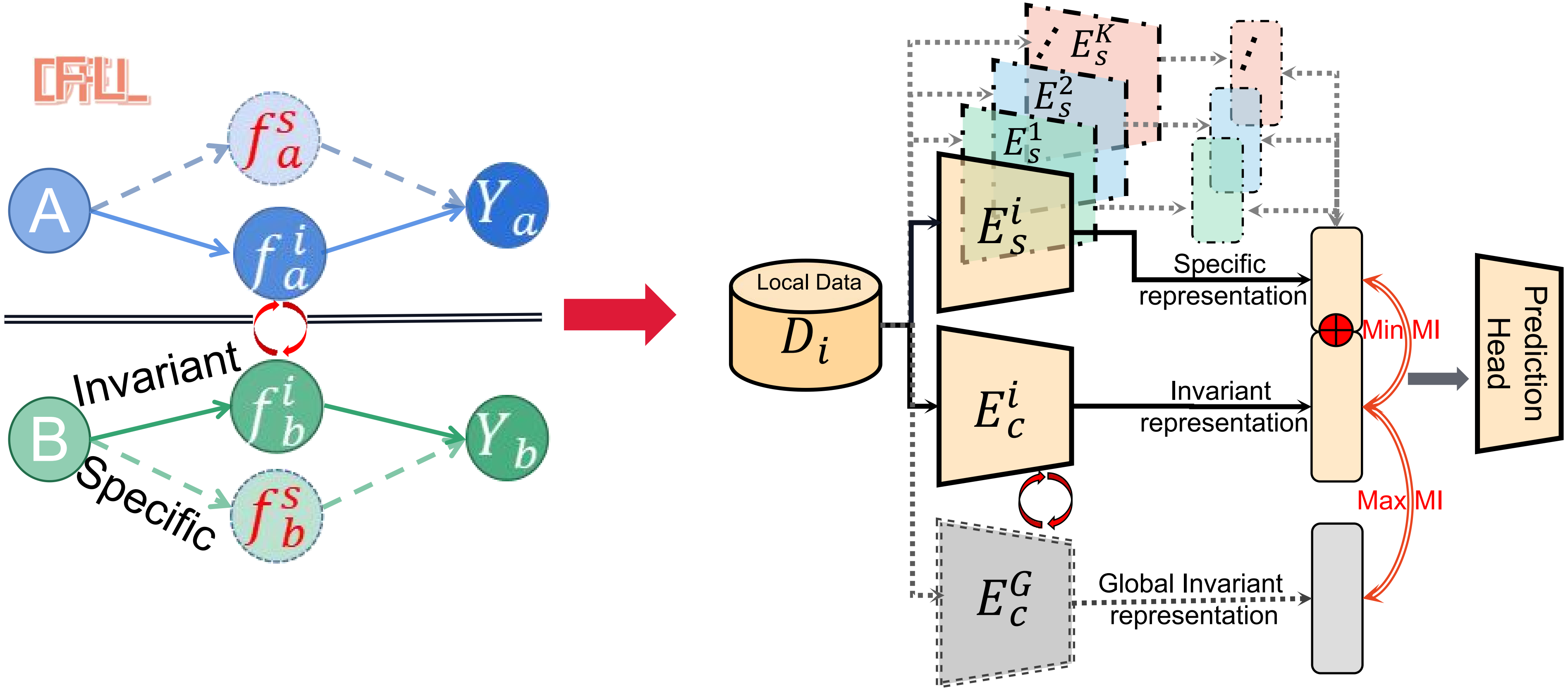
$$\omega_k^* = M(\omega_c, \omega_{k,s}^*)$$

$$\min_{\omega_c}\left\{f(\omega_c) := \frac{1}{N}\sum_{k=1}^{N} h_k(\omega_k^*)\right\}$$

$$\omega_{k,s}^* = \arg\min_{\omega_{k,s}} h_k(M(\omega_c, \omega_{k,s}))$$

Methods

Single branch-> Two Branch



Methods

Convergence

1. Non-convex and L-Lipschitz smoothness of f:

$$\|\triangledown f(\omega) - \triangledown f(\omega')\| \leqslant L \|\omega - \omega'\|, \forall \omega, \omega'$$

2. Polyak-Łojasiewicz of I_c, I_s:

$$\left\|\triangledown I_c\left(\omega, \omega_c^t\right) - \triangledown I_c\left(\omega', \omega_c^t\right)\right\| \geqslant \mu_{I_c} \|\omega - \omega'\|, \forall \omega, \omega'$$
$$\left\|\triangledown I_s\left(\omega, \omega_c^t\right) - \triangledown I_s\left(\omega', \omega_c^t\right)\right\| \geqslant \mu_{I_s} \|\omega - \omega'\|, \forall \omega, \omega'$$

3. $\overline{\mu}-$strongly convex of h_k and Polyak-Łojasiewicz:

$$\left\|\triangledown h_k(M(\omega_c, \omega_{k,s}^{t+1,*}), \omega_c^t) - \triangledown h_k(M(\omega_c', \omega_{k,s}^{t+1,*}), \omega_c^t)\right\| \geq \overline{\mu} \|\omega_c - \omega_c'\|$$

4. Bounded second moments of I_c, I_s gradient:

$$\mathbb{E}_k\left[\left\|\triangledown I_c\left(\omega, \omega_c^t\right)\right\|^2\right] \leqslant \epsilon_c^2, \exists \epsilon_c$$
$$\mathbb{E}_k\left[\left\|\triangledown I_s\left(\omega, \omega_c^t\right)\right\|^2\right] \leqslant \epsilon_s^2, \exists \epsilon_s$$

$$\mathbb{E}_{s_t}[f(\omega_c^{t+1})] \leqslant f(\omega_c^t) - \alpha\left\|\triangledown f(\omega_c^t)\right\| + \beta\epsilon_s^2 - \eta_c\epsilon_c^2$$

$$\frac{1}{T}\sum_{t=0}^{T-1}\|\triangledown f(\omega_c^t)\| \leqslant \frac{1}{\alpha T}\left(f(\omega_c^0) - f^*\right) + \beta\epsilon_s^2 - \eta_c\epsilon_c^2$$

DFL is convergent even if only part of the extractor participates in the aggregation, based on the bounded gradient of the local specific branch.

Methods

Techniques

- **Representation Disentanglement**

$$L_{MI}^{k} := \underbrace{I_s(E_s^k(x^k), E_c^k(x^k))}_{\text{Local MI minimization}} - \underbrace{I_c(E_c^k(x^k), E_c^G(x^k))}_{\text{Global MI maximization}}$$

- **Invariant Aggregation**

$$\mathbb{E}_c^G = \omega_k \mathbb{E}_c^k = \sum_{k=1}^{K} \frac{n_k}{N} \mathbb{E}_c^k$$

- **Diversity Transferring**

$$\left\{R_A^{k,j}\right\} := \left\{\underbrace{E_s^j(x^k)}_{\text{cross-domain specific extractors}} \bigoplus \underbrace{E_c^k(x^k)}_{\text{local invariant extractor}} | j \in |K|\right\}$$

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Results

Verification

Top-1 test accuracy of verifications on Colored-MNIST, 3Dshapes, dSprites.

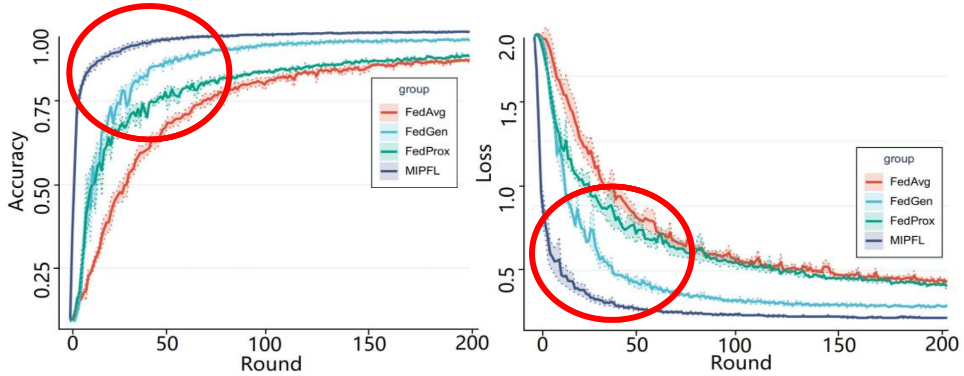
Dataset	Attributes	clients	FedAvg	FedProx	FedGen	DFL
Colored-MNIST	BG color	10/20	88.88±0.28	89.93±0.87	93.47±0.26	**95.91±0.13**
3Dshapes	BG color	20/50	98.57±0.46	98.16±0.79	98.38±0.47	**99.37±0.09**
3Dshapes	Scale	10/10	89.34±1.25	89.93±1.43	76.57±9.18	**90.38±0.56**
dSprites	Orientation	20/40	73.55±4.78	71.64±5.23	82.69±1.82	**86.74±2.09**

Ablation study of DFL in Colored-MNIST

	Invariant Aggregation	Diversity Transferring	DFL
10/20	√		95.11±0.13
Ratio=0.5		√	95.29±0.33
BG-color	√	√	**96.02±0.30**

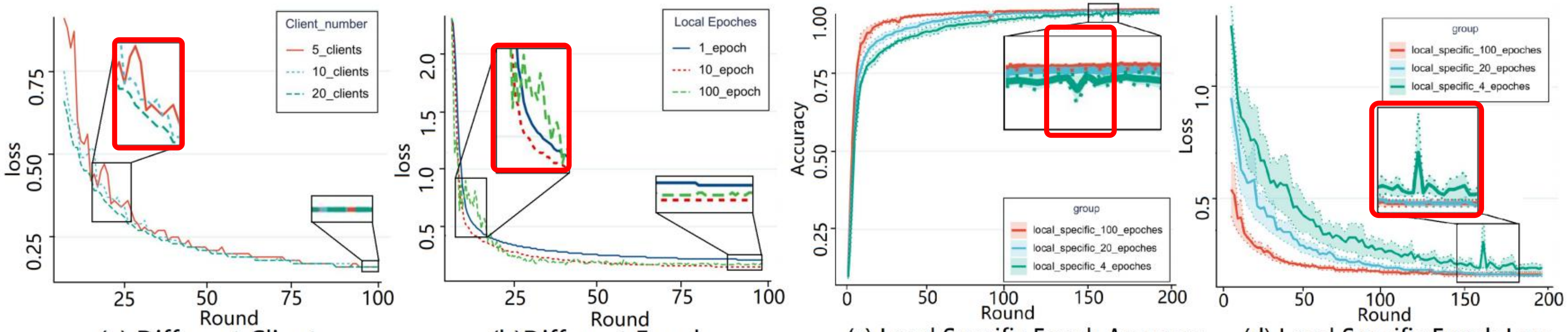
Results

Verification



(a) Accuracy of ColorMinst (b) CE Loss of ColorMinst

Accuracy and cross-entropy curves as communication increase, and the Accuracy curve as client number increases.



(a) Different Clients (b)Different Epoches (c) Local Specific Epoch Accuracy (d) Local Specific Epoch Loss

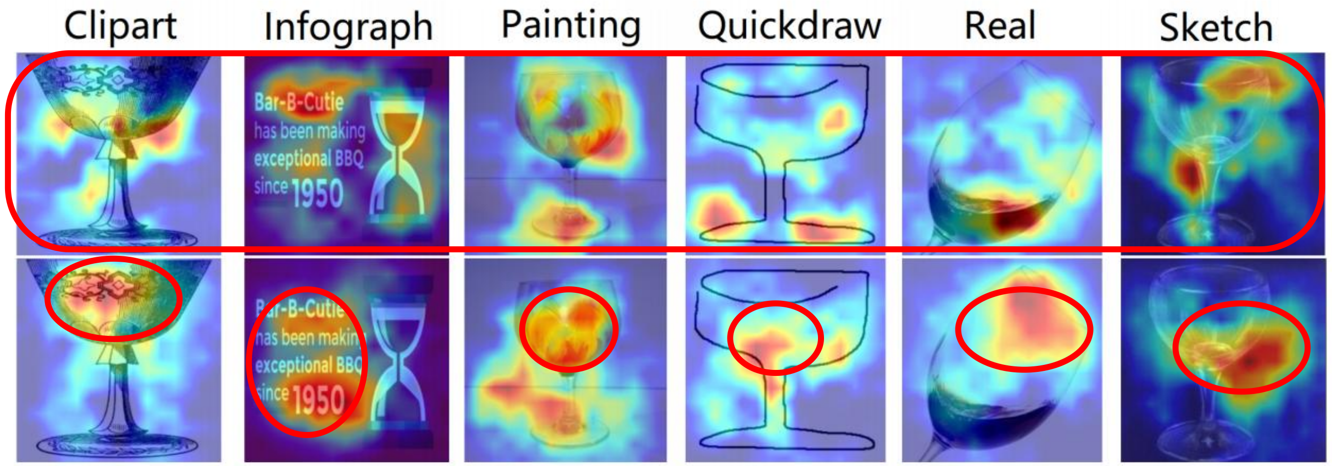
Loss curves with different client participation and different local epochs, and the accuracy and cross-entropy loss curves.

Results

Application

Top-1 test accuracy of application on DomainNet.

		Clipart	Infograph	Painting	Quickdraw	Real	Sketch	Avg
FedAvg	DomainNet	77.70	37.29	62.84	73.00	70.67	72.56	65.68
FedProx	Backbone	77.71	38.96	62.20	72.50	71.08	71.12	65.60
FedBN	=AlexNet	76.43	35.31	65.11	83.60	74.45	74.55	68.24
DFL	Top-10 Classes	**77.76**	**41.55**	**66.88**	**84.10**	**76.42**	**74.65**	**70.23**
FedAvg	DomainNet	96.32	60.12	94.83	82.10	95.81	93.68	87.14
FedProx	Backbone	96.58	60.27	94.67	82.90	95.15	94.04	87.27
FedBN	=ResNet101	**97.15**	61.34	94.80	87.00	96.63	94.95	88.65
DFL	Top-10 Classes	96.20	**61.64**	**95.01**	**89.60**	**96.73**	**95.67**	**89.14**
SingleSet	ResNet101	69.3	34.5	66.3	66.8	80.1	60.7	62.95
DFL	All 345 Classes	**78.4**	**38.2**	**71.2**	**70.4**	**82.7**	**68.6**	**68.25**



Visualization of DomainNet.

University of Science and Technology of China

CRIPAC

智能感知与计算研究中心

Center for Research on Intelligent Perception and Computing

ICML

International Conference On Machine Learning

THANK YOU