

Soft Separation and Distillation: Toward Global Uniformity in Federated Unsupervised Learning

Hung-Chieh Fang, Hsuan-Tien Lin, Irwin King, Yifei Zhang



Background

Unsupervised Representation Learning

Alignment: make similar samples closer

Uniformity: keep maximal information

Federated Learning

- non-iid data dist. across clients
- clients cannot share features or raw data

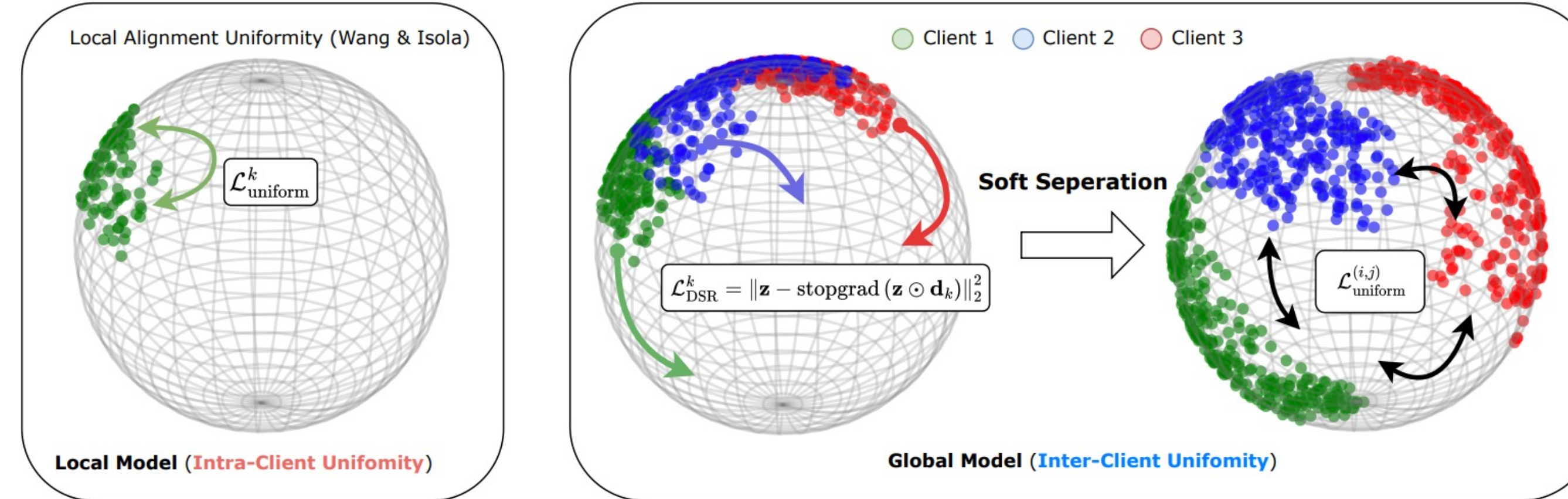
Global Uniformity?

Limited Inter-client Uniformity

$$\mathcal{L}_{\text{uniform}} = -\log \left(\underbrace{\sum_{k=1}^K \mathbb{E}_{\mathbf{z}, \mathbf{z}' \sim p_k(\mathbf{z})} [e^{-t \|\mathbf{z} - \mathbf{z}'\|_2^2}]}_{\text{intra-client } \mathcal{L}_{\text{uniform}}^k} + \underbrace{\sum_{i \neq j} \mathbb{E}_{\mathbf{z} \sim p_i(\mathbf{z}), \mathbf{z}' \sim p_j(\mathbf{z})} [e^{-t \|\mathbf{z} - \mathbf{z}'\|_2^2}]}_{\text{inter-client } \mathcal{L}_{\text{uniform}}^{(i,j)}} \right),$$

Problem: Under *non-iid* setting, local optimization fail to achieve global (inter-client) uniformity.

Soft Separation and Distillation

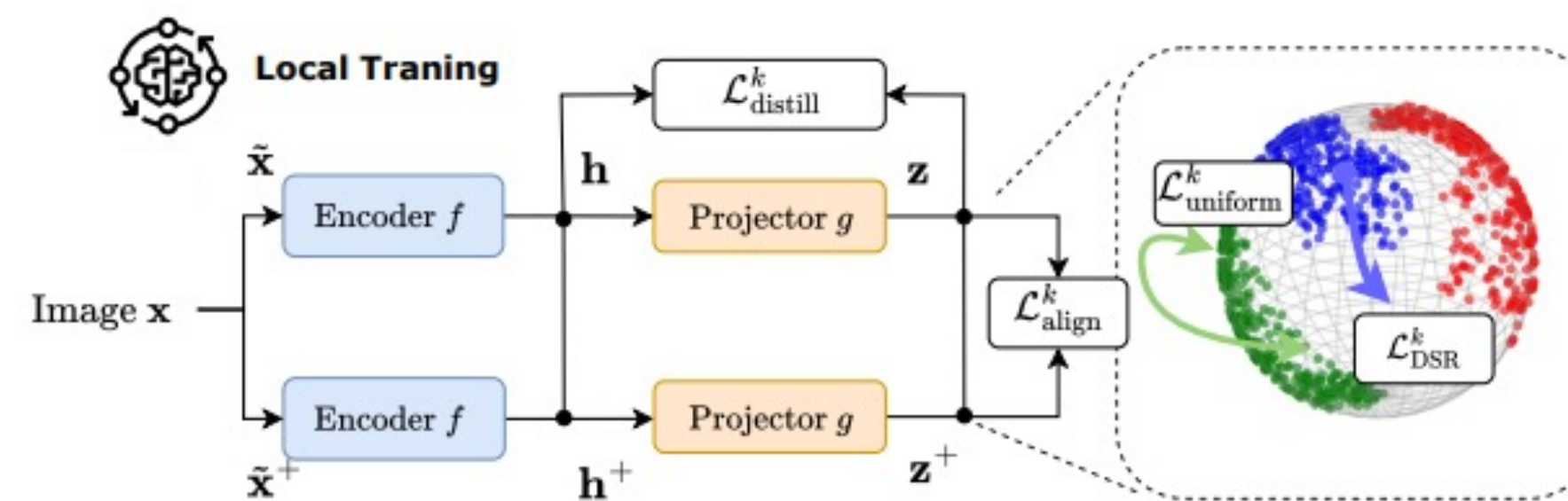


Dimensional-Scaled Regularization

$$\mathcal{L}_{\text{DSR}}^k = \mathbb{E}_{\mathbf{z} \sim p_k(\mathbf{z})} [\|\mathbf{z} - \text{stopgrad}(\mathbf{z} \odot \mathbf{d}_k)\|_2^2],$$

Key idea: assign client-specific subspaces, encouraging representations to spread toward diverse directions

Projector Distillation

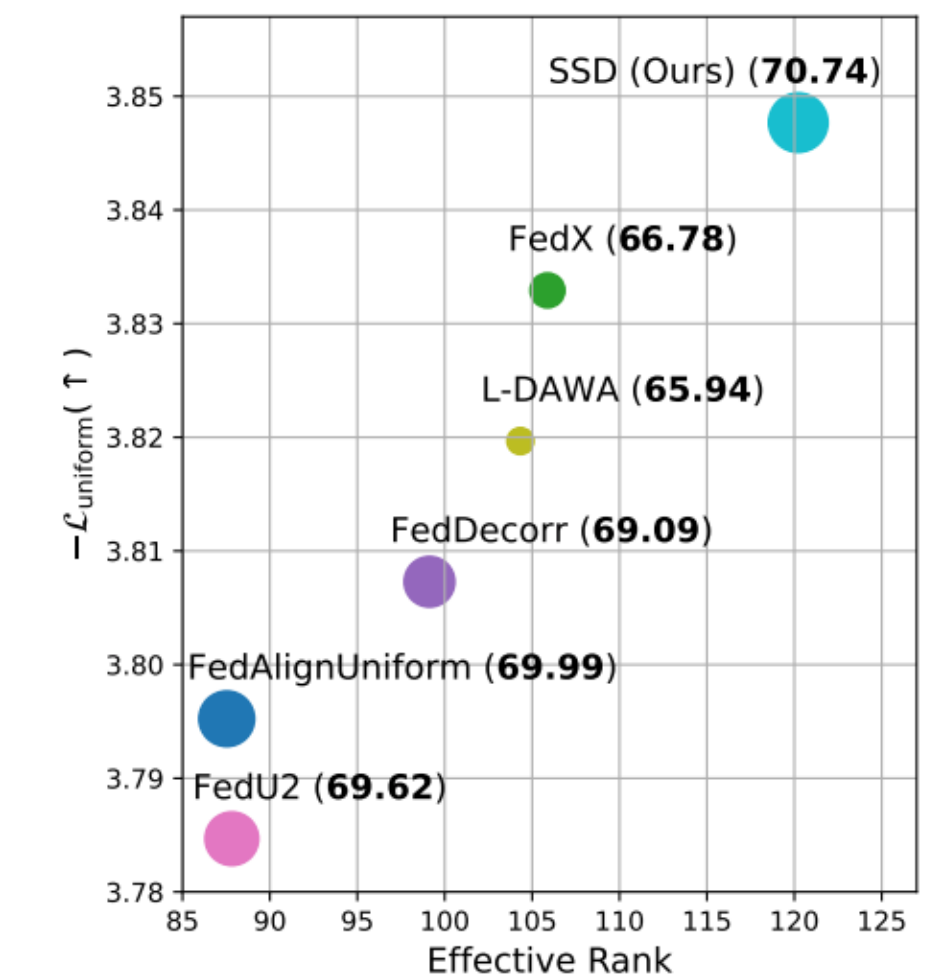


$$\mathcal{L}_{\text{distill}}^k = \mathbb{E}_{x \sim p_k(x)} [D_{\text{KL}}(\sigma(\mathbf{h}) \parallel \sigma(\mathbf{z}))],$$

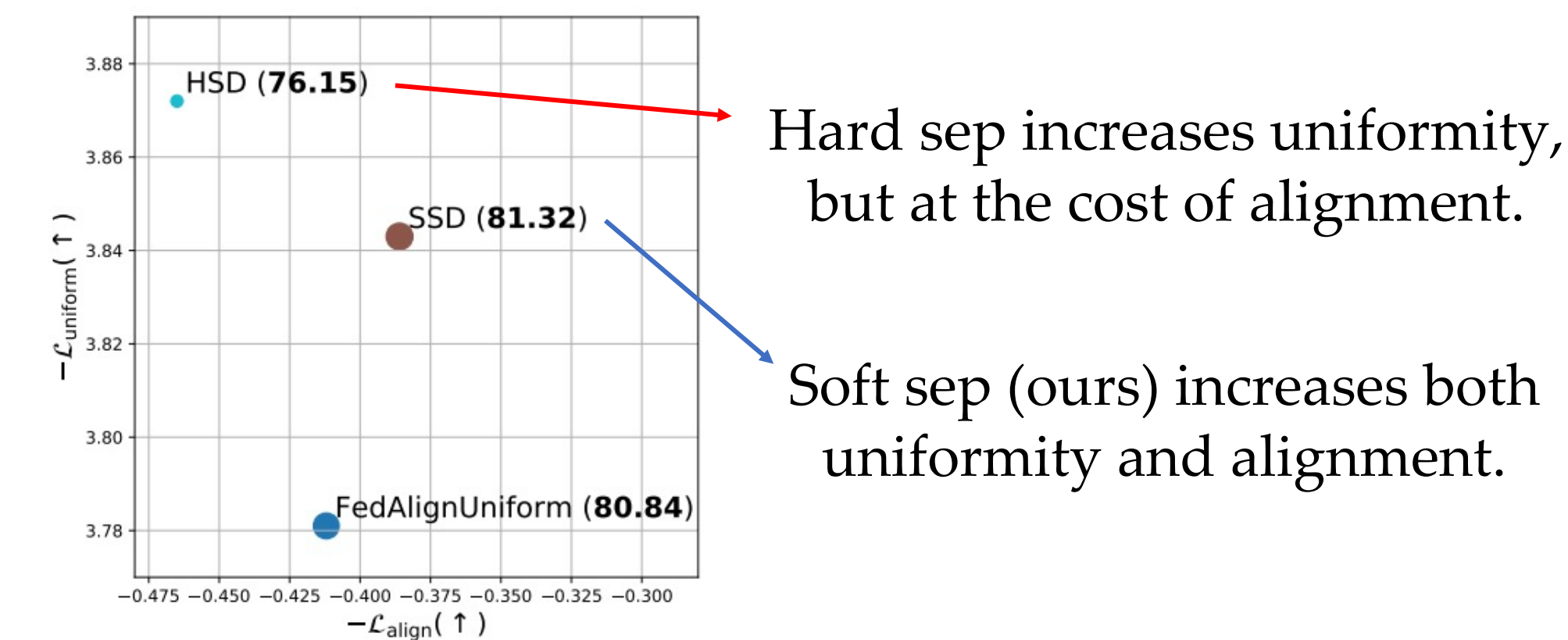
Why? Empirically, DSR enhances uniformity at the *embedding* level, but does not transfer to *representation* level.

Experiments

Transfer Learning



Soft vs. Hard Separation



Why not remove the projector?

	Projector	LP	$-\mathcal{L}_{\text{uniform}} (\uparrow)$
FedAlignUniform	✗	73.16	3.72
+ DSR	✗	76.14 (+2.98)	3.77 (+0.05)
FedAlignUniform	✓	80.84	3.79
+ DSR	✓	81.05 (+0.21)	3.81 (+0.02)