Unified Alignment Protocol: Making Sense of the Unlabeled Data in New Domains (WACV 2026 oral)

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Problem Statement

- Semi-Supervised Federated Learning (SSFL) is gaining popularity over conventional Federated Learning in many real-world applications. Due to the practical limitation of limited labeled data on the client side
- SSFL considers that participating clients train with unlabeled data, and only the central server has the necessary resources to access limited labeled data
- However, traditional SSFL assumes that the data distributions in the training phase and testing phase are the same
- The core challenge is improving model generalization to new, unseen domains while the client participate in SSFL
- However, the decentralized setup of SSFL and unsupervised client training necessitates innovation to achieve improved generalization across domains

Possible Solution

- SSFL approaches
- Extending Federated Domain Generalization approaches

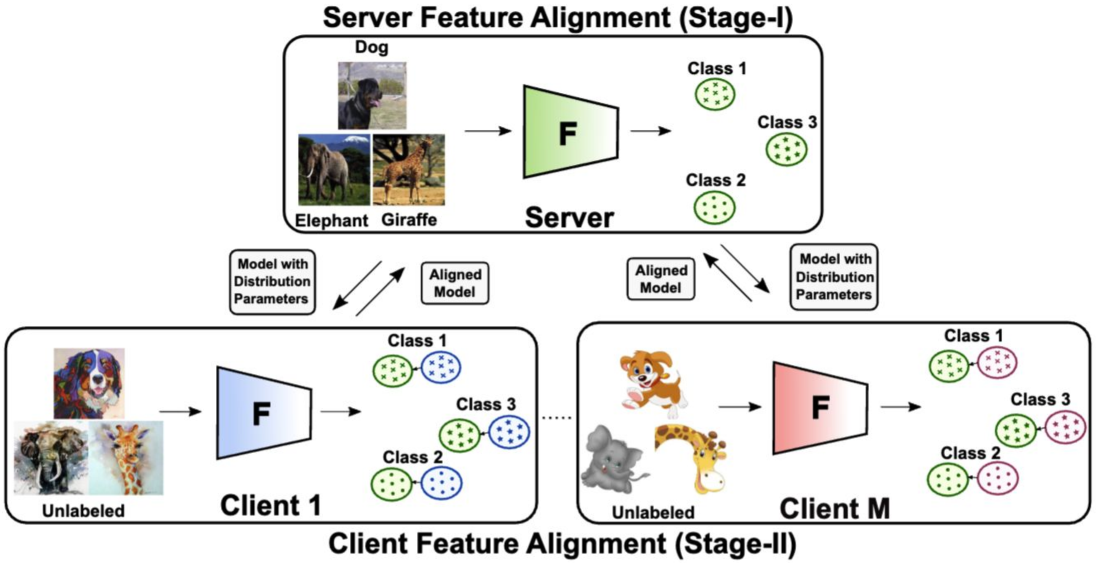
Bottleneck in possible solutions

Methods	Single Domain	Centralized Setup	Client Labels	Cartoon	Photo	Sketch
SOTA SSFL [6]	✓	✗	✗	52.20	52.39	24.95
SOTA FDG [42]	✗	✗	✓	24.46	18.50	17.72
UAP (Ours)	✗	✗	✗	**75.73**	**64.84**	**61.67**

- Existing SSFL approach do not generalize well to unseen test domains.
- Existing FDG techniques underperforms to achieve S-FDG

Our Proposed UAP Method

Two stages: Server Feature Alignment (Stage I) and Client Feature Alignment (Stage II)



Our Proposed UAP Method

Server Feature Alignment (Stage I)

Server trains with labeled data to learn a parametric feature distribution

$$\mathbf{p}_s(\mathbf{z}|\mathbf{y}=k) \approx \mathcal{N}_k(\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k), \quad \forall k \in \mathcal{C}$$

$$\mathcal{L}_{\mathbf{server}} = \mathcal{L}_{\mathbf{CE}}(\hat{\mathbf{y}}, \mathbf{y}) + \alpha \cdot \mathcal{L}_{\mathbf{CDD}} + \beta \cdot \mathcal{L}_{\mathbf{COV}}$$

Our Proposed UAP Method

Client Feature Alignment (Stage II)

Client trains with unlabeled data and uses server feature distribution to align client features

$$\mathbf{p}_s(\mathbf{z}|\mathbf{y}=k) \approx \mathcal{N}_k(\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k), \quad \forall k \in \mathcal{C}$$

$$\mathcal{L}_{\mathbf{client}} = \mathcal{L}_{\mathbf{CE}}(\hat{\mathbf{y}}, \tilde{\mathbf{y}}) + \alpha \cdot \mathcal{L}_{\mathbf{CDD}} + \beta \cdot \mathcal{L}_{\mathbf{COV}}$$

Results

Method	Unseen Test Domain	**A**			**C**		
	Server Trained on	C	P	R	A	P	R
SSFL		44.38	40.75	53.23	39.06	39.04	46.92
UAP (Ours)		**48.95**	**47.51**	**55.95**	**44.28**	**44.51**	**48.48**

Table 4. *Performance comparison of baseline SSFL and UAP across two test domains A and C in the OfficeHome dataset (rest are in supplementary).*

Method	Unseen Test Domain	**A**			**C**		
	Server Trained on	C	P	S	A	P	S
SSFL		64.65	40.19	36.28	69.97	21.20	37.12
UAP (Ours)		**75.73**	**64.40**	**67.92**	**70.65**	**51.96**	**67.49**

Table 2. *Performance comparison of baseline SSFL and UAP across two test domains A and C from PACS dataset (rest are in supplementary).*

Results

Method	Cartoon	GAIN	Photo	GAIN	Sketch	GAIN
CBAFed [16]	45.41		48.49		15.33	
FedDG [22]	41.70		34.52		52.15	
FedDG-GA [42]	24.46		18.50		17.72	
FedGMA [34]	41.11		16.94		27.93	
FedSR [34]	29.34		19.94		27.49	
RScFed [20]	65.91		14.40		31.20	
SemiFL [6]	52.20		52.39		24.95	
UAP (Ours)	**75.73**	+9.82	**64.40**	+12.01	**67.92**	+15.77

Table 5. *Comparative DG performance of SSFL and FDG methods trained with Pseudo labels and our proposed UAP on PACS dataset. The GAIN column shows performance improvement of our method compared to the second best method (highlighted by underline).*

Loss	Cartoon	Photo
$\mathcal{L}_{CE}$	64.65	40.19
$\mathcal{L}_{CE} + \alpha \cdot \mathcal{L}_{CDD}$	72.61	58.25
$\mathcal{L}_{CE} + \alpha \cdot \mathcal{L}_{CDD} + \beta \cdot \mathcal{L}_{COV}$ (UAP)	**75.73**	**64.40**

Table 6. *Effect of different loss on UAP (PACS dataset).*

Method	VGG11		ResNet18		DenseNet121		DeiT-B		ViT-B	
	C	P	C	P	C	P	C	P	C	P
SSFL	59.33	23.44	64.65	40.19	74.51	61.72	89.45	75.44	77.88	63.33
UAP	**63.33**	**56.59**	**75.73**	**64.40**	**80.86**	**66.89**	**90.04**	**83.84**	**80.03**	**67.87**

Table 7. *Performance with different model architectures on PACS dataset across two server training domains.*

Method	M=2		M=6		M=8	
	Cartoon	Photo	Cartoon	Photo	Cartoon	Photo
SSFL	64.65	40.19	61.08	32.47	70.31	31.20
UAP	**75.73**	**64.40**	**73.34**	**63.14**	**75.05**	**64.21**

Table 8. *Performance with different number of clients (M) on PACS dataset across two server training domains.*

Summary

- Achieving model generalization in SSFL setting is challenging due to decentralized client training and lack of labeled data on client side
- Existing SSFL approaches and extending FDG approaches underperforms
- To address this issue, in this work, we propose a novel framework for model generalization in SSFL setting
- We propose a two stage approach where server first train with labeled data to learn a standard parametric distribution and then communicates this to the server without any communication overhead
- And client then aligns client features with the communicated feature distribution

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Thank You!