Towards Generalizing to Unseen Domains with Few Labels

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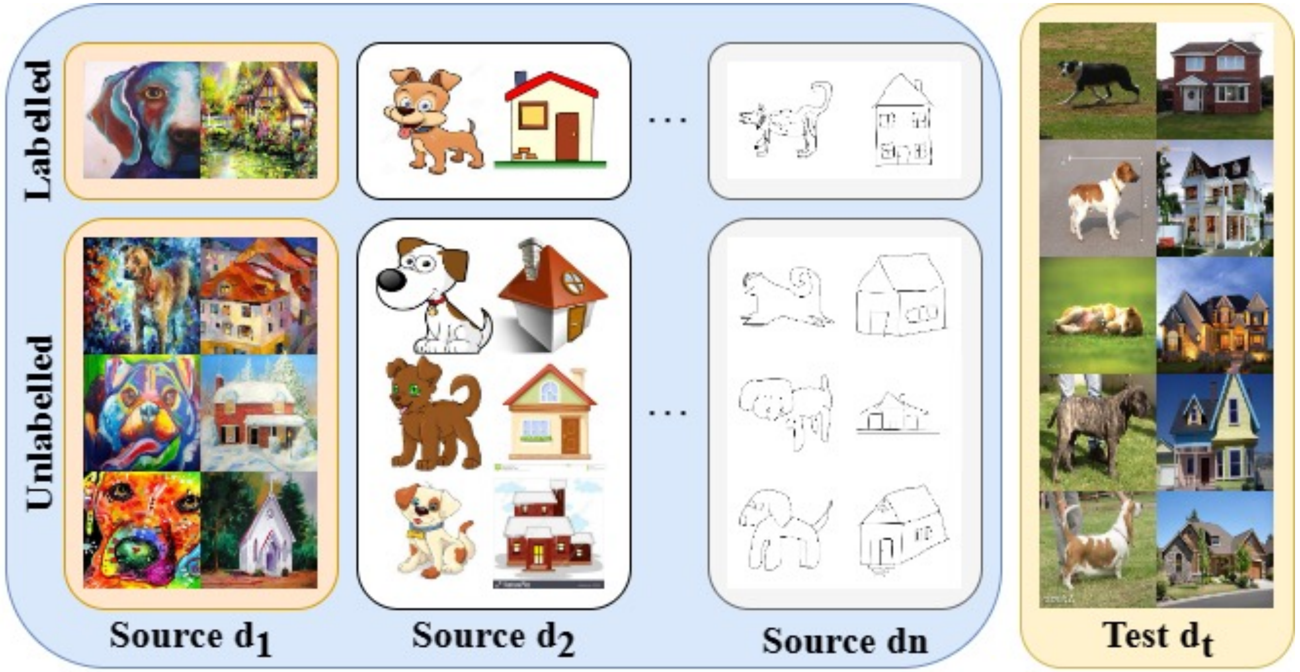
Semi Supervised Domain Generalization (SSDG)



- Limited labeled samples for each classes in training domains
  - 5- labels and 10 labels
- Test domain is unseen during training

Motivation

- **Challenge**: Limited labeled data increases overfitting risk and how to perform pseudo-labelling under different domain shifts

  Solution: Leveraging feature space to *enforce prediction consistency* by ensuring that predictions are reliable across different domains. **(Feature based conformity)**

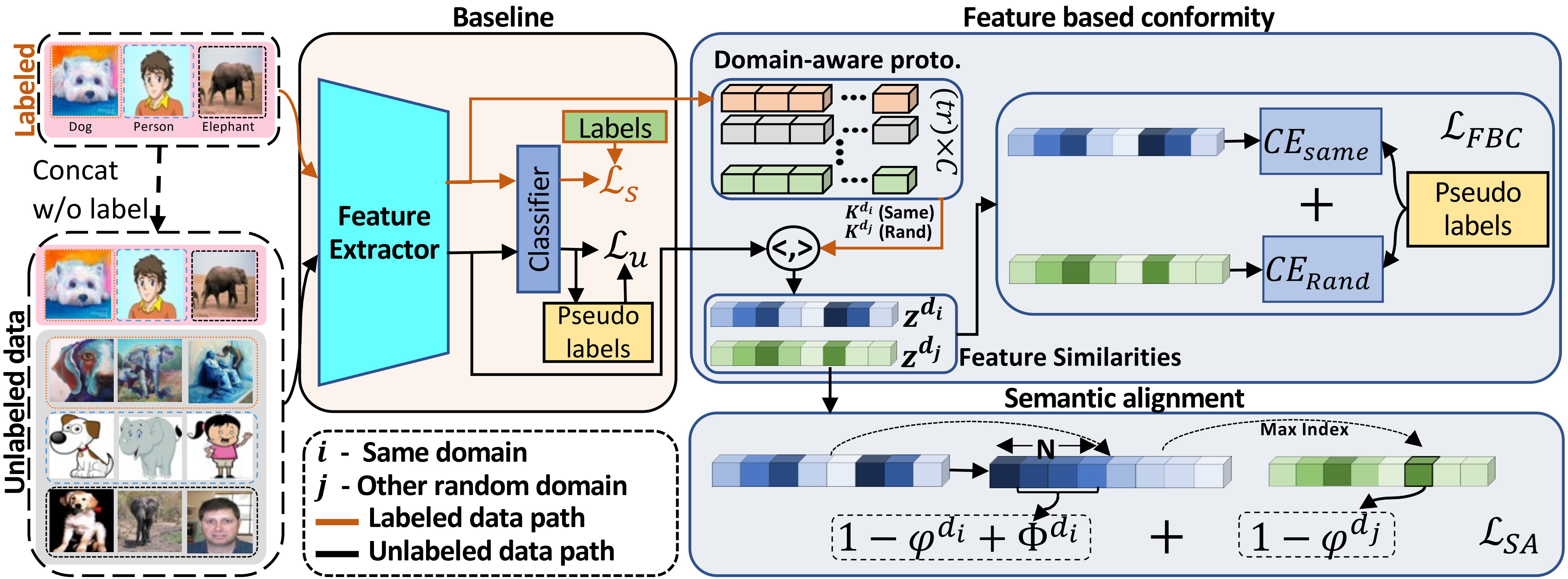
- **Challenge**: Ensuring that the model can effectively distinguish between classes under SSDG

  Solution: Regularizing semantic layout in the feature space through d*omain-aware similarity guided cohesion and repulsion*. **(Semantic alignment)**

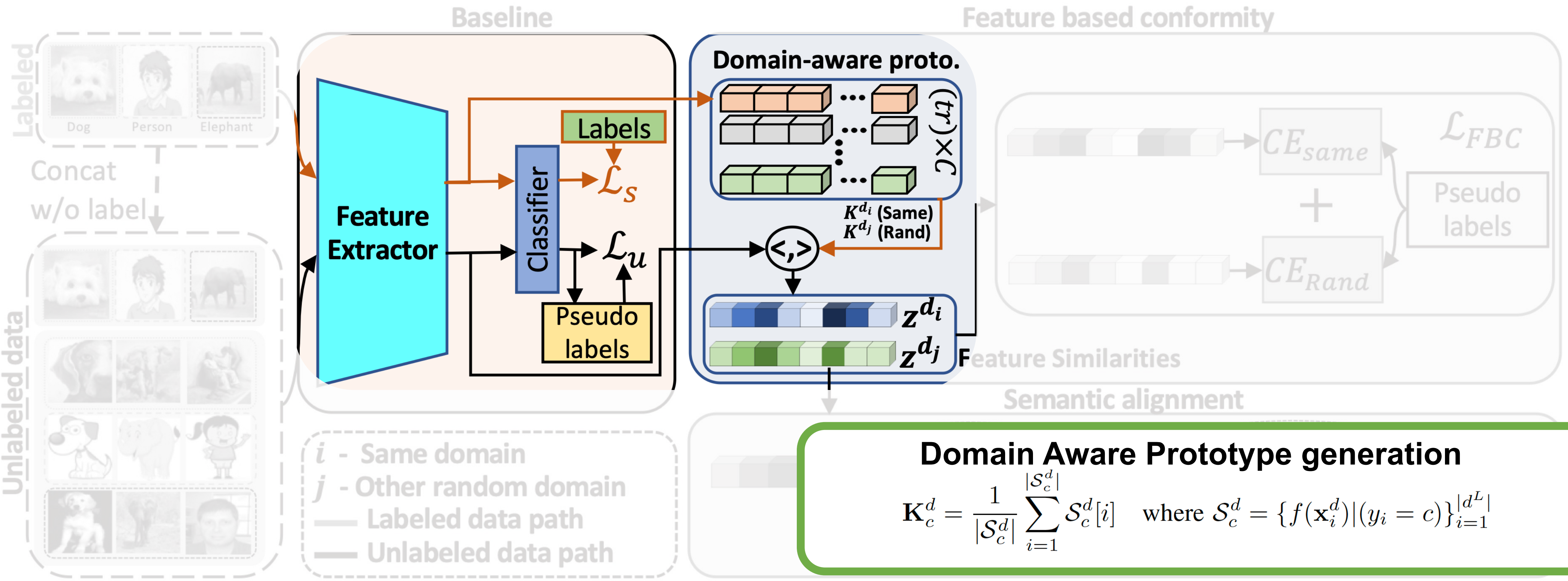
Contributions

- We Study the semi-supervised domain generalization (SSDG) problem and propose a new approach, comprised of **feature-based conformity** and **semantics alignment loss**
- **Plug-and-play** and without adding any learnable parameters
- Extensive experiments on five different DG datasets with four strong baselines: FixMatch, FlexMatch, FreeMatch, and StyleMatch

Methodology



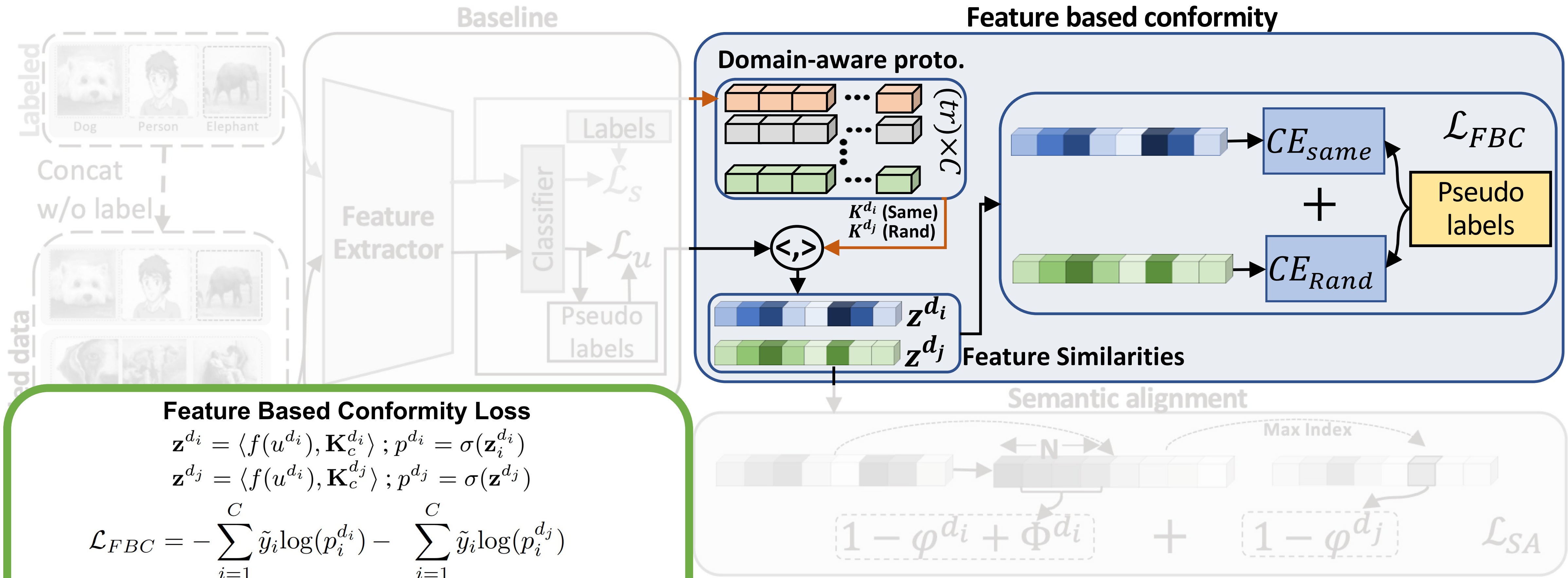
Methodology



Domain Aware Prototype generation

$$\mathbf{K}_c^d = \frac{1}{|\mathcal{S}_c^d|} \sum_{i=1}^{|\mathcal{S}_c^d|} \mathcal{S}_c^d[i] \quad \text{where } \mathcal{S}_c^d = \{f(\mathbf{x}_i^d) | (y_i = c)\}_{i=1}^{|d^L|}$$

Methodology



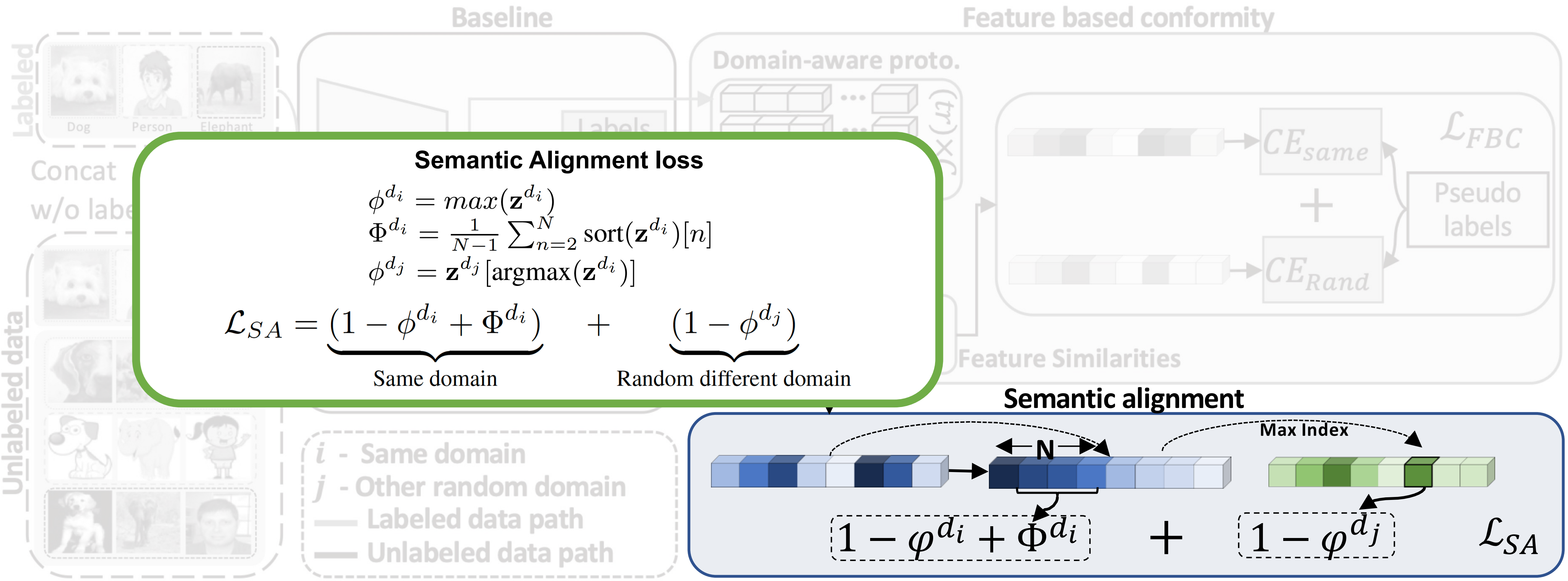
Feature Based Conformity Loss

$$\mathbf{z}^{d_i} = \langle f(u^{d_i}), \mathbf{K}_c^{d_i} \rangle \; ; \; p^{d_i} = \sigma(\mathbf{z}_i^{d_i})$$

$$\mathbf{z}^{d_j} = \langle f(u^{d_i}), \mathbf{K}_c^{d_j} \rangle \; ; \; p^{d_j} = \sigma(\mathbf{z}^{d_j})$$

$$\mathcal{L}_{FBC} = -\underbrace{\sum_{i=1}^{C} \tilde{y}_i \log(p_i^{d_i})}_{\text{Same domain}} - \underbrace{\sum_{i=1}^{C} \tilde{y}_i \log(p_i^{d_j})}_{\text{Random different domain}}$$

Methodology



Semantic Alignment loss

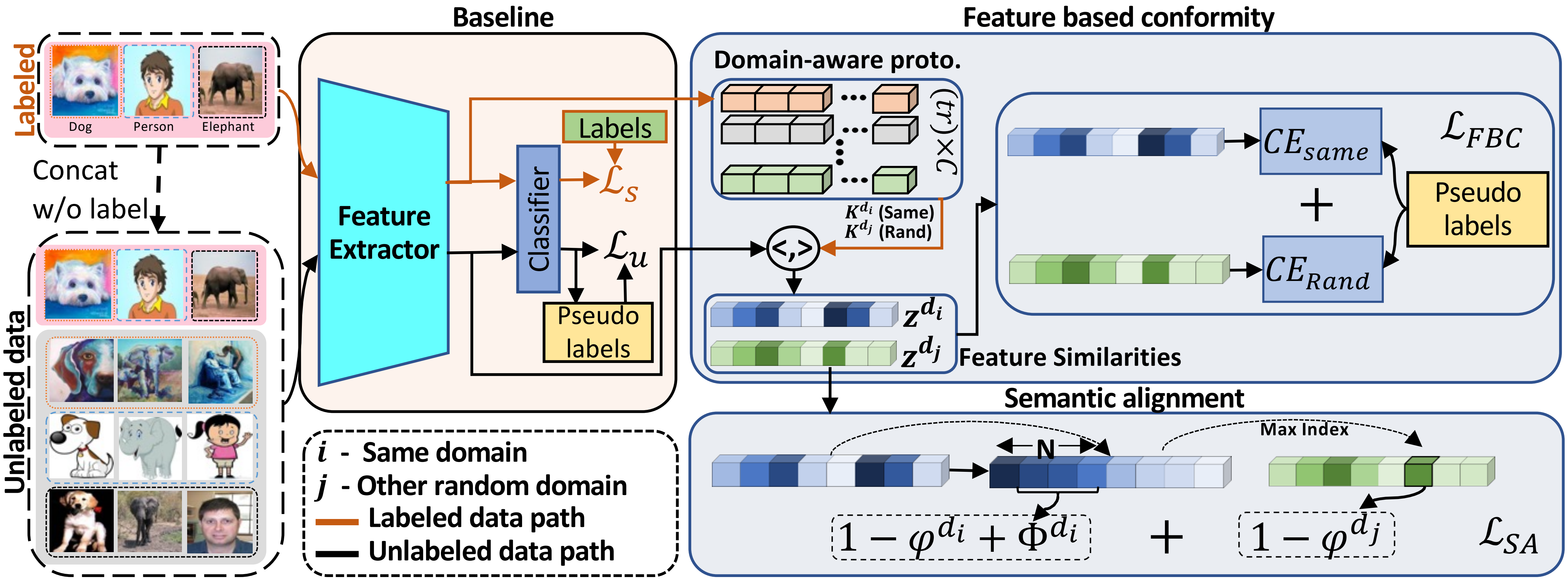
$$\phi^{d_i} = max(\mathbf{z}^{d_i})$$

$$\Phi^{d_i} = \frac{1}{N-1}\sum_{n=2}^{N} \mathrm{sort}(\mathbf{z}^{d_i})[n]$$

$$\phi^{d_j} = \mathbf{z}^{d_j}[\mathrm{argmax}(\mathbf{z}^{d_i})]$$

$$\mathcal{L}_{SA} = \underbrace{(1 - \phi^{d_i} + \Phi^{d_i})}_{\text{Same domain}} \quad + \quad \underbrace{(1 - \phi^{d_j})}_{\text{Random different domain}}$$

Methodology



$$\mathcal{L} = \mathcal{L}_s + \mathcal{L}_u + \mathcal{L}_{FBC} + \mathcal{L}_{SA}$$

Results

Model	PACS	OH	VLCS	DigitsDG	TerraInc.
ERM	59.8 ± 2.5	56.7 ± 0.8	68.0 ± 0.5	29.1 ± 2.9	23.5 ± 1.4
EntMin	64.2 ± 2.2	57.0 ± 0.8	66.2 ± 0.3	39.3 ± 2.8	26.6 ± 2.6
MeanTeacher	61.5 ± 1.4	55.9 ± 0.5	66.2 ± 0.4	38.8 ± 2.9	25.0 ± 2.8
FlexMatch	72.7 ± 1.2	53.7 ± 0.7	56.2 ± 2.1	68.9 ± 1.2	26.4 ± 1.8
FreeMatch	74.0 ± 2.7	56.2 ± 0.2	61.6 ± 1.3	67.5 ± 2.4	30.1 ± 1.2
FixMatch	76.6 ± 1.2	57.8 ± 0.3	70.0 ± 2.1	66.4 ± 1.4	30.5 ± 2.2
StyleMatch	79.4 ± 0.9	59.7 ± 0.2	73.5 ± 0.6	65.9 ± 1.9	29.9 ± 2.8
FlexMatch + Ours	75.3 ± 1.2	55.8 ± 0.4	58.7 ± 1.0	$\mathbf{73.1 \pm 1.1}$	30.9 ± 1.0
FreeMatch + Ours	77.3 ± 1.7	58.0 ± 0.4	62.6 ± 1.3	72.2 ± 0.4	32.4 ± 2.9
FixMatch + Ours	78.2 ± 1.2	59.0 ± 0.4	72.2 ± 1.0	70.4 ± 1.4	$\mathbf{34.7 \pm 1.9}$
StyleMatch + Ours	$\mathbf{80.5 \pm 1.1}$	$\mathbf{60.3 \pm 0.6}$	$\mathbf{74.2 \pm 0.5}$	67.7 ± 1.7	32.5 ± 1.8

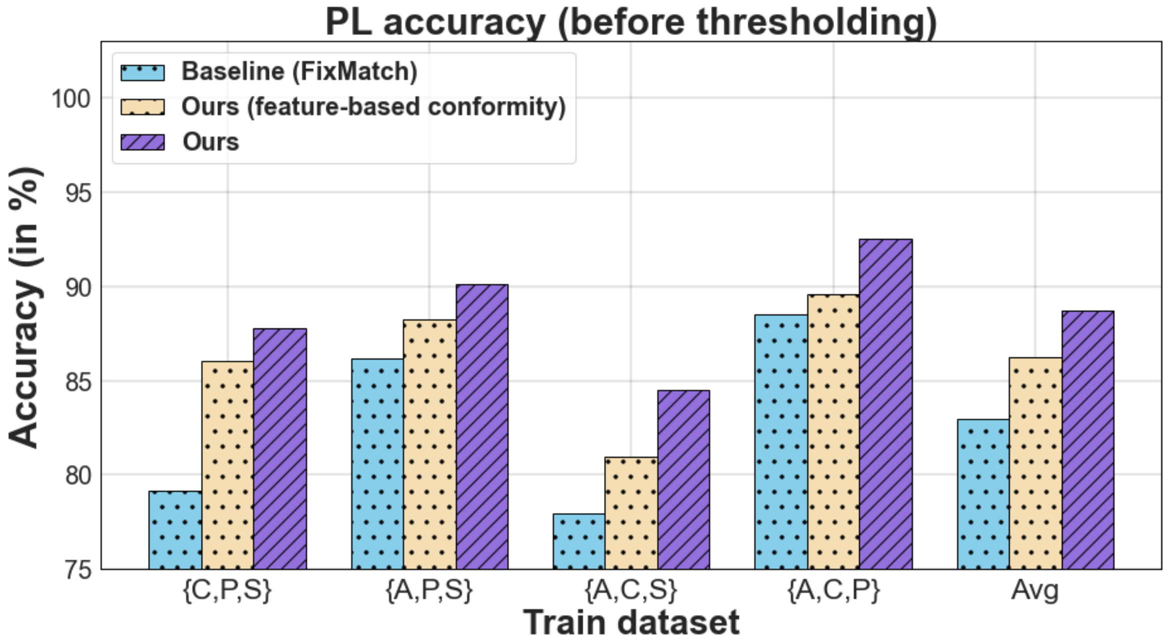
SSDG accuracy (%) with 10 labels per class. (Average over 5 independent seeds is reported.)

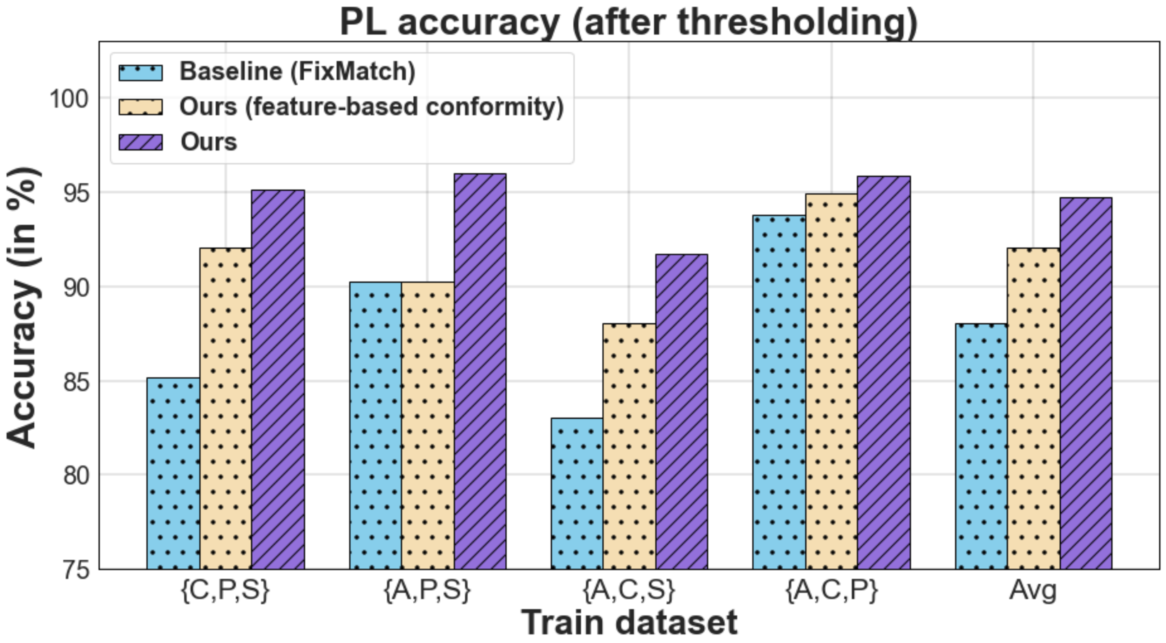
Results

Model	PACS	OH	VLCS	DigitsDG	TerraInc.
ERM	51.2 ± 3.0	51.7 ± 0.6	67.2 ± 1.8	22.7 ± 1.0	22.9 ± 3.0
EntMin	55.9 ± 4.1	52.7 ± 0.5	66.5 ± 1.0	28.7 ± 1.3	21.4 ± 3.5
MeanTeacher	53.3 ± 4.0	50.9 ± 0.7	66.4 ± 1.0	28.5 ± 1.4	20.9 ± 2.9
FlexMatch	65.1 ± 2.5	48.8 ± 0.3	56.0 ± 2.8	59.0 ± 2.0	24.9 ± 4.3
FreeMatch	72.8 ± 1.2	53.8 ± 0.7	60.3 ± 1.7	58.9 ± 1.4	23.5 ± 2.7
FixMatch	73.4 ± 1.3	55.1 ± 0.5	69.9 ± 0.6	56.0 ± 2.2	28.9 ± 2.3
StyleMatch	78.4 ± 1.1	56.3 ± 0.3	72.5 ± 1.5	55.7 ± 1.6	28.7 ± 2.7
FlexMatch + Ours	71.0 ± 1.4	51.3 ± 0.1	58.0 ± 2.1	$\mathbf{66.2 \pm 0.6}$	28.8 ± 2.6
FreeMatch + Ours	73.7 ± 3.6	55.0 ± 0.2	62.1 ± 1.4	65.0 ± 1.5	26.5 ± 3.2
FixMatch + Ours	77.3 ± 1.1	55.8 ± 0.2	71.3 ± 0.7	62.0 ± 1.5	$\mathbf{33.2 \pm 2.0}$
StyleMatch + Ours	$\mathbf{79.3 \pm 0.9}$	$\mathbf{56.5 \pm 0.2}$	$\mathbf{72.9 \pm 0.7}$	58.7 ± 1.7	30.4 ± 3.7

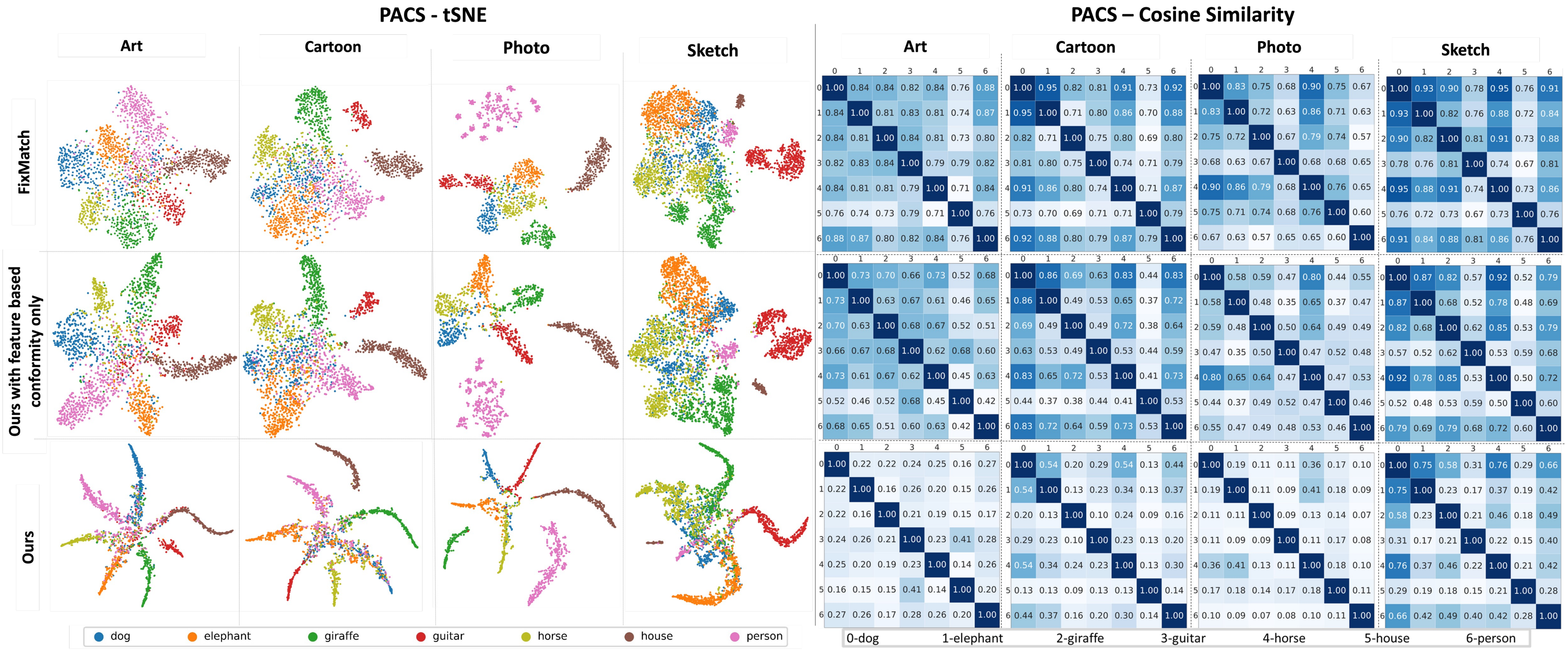
SSDG accuracy (%) with 5 labels per class. (Average over 5 independent seeds is reported.)

Pseudo labelling accuracy





Feature representation analysis



Ablation

Method	Avg Acc.
Fixmatch Baseline	73.4
$+ \mathcal{L}_{\mathrm{FBC(same-domain)}}$	76.0
$+ \mathcal{L}_{\mathrm{FBC(different-domain)}}$	74.9
$+ \mathcal{L}_{\mathrm{FBC}}$	76.7
$+ \mathcal{L}_{\mathrm{SA}}$	74.8
$+ \mathcal{L}_{\mathrm{FBC}} + \mathcal{L}_{\mathrm{SA(same-domain)}}$	77.0
$+ \mathcal{L}_{\mathrm{FBC}} + \mathcal{L}_{\mathrm{SA}}$ (Ours)	**77.3**

Ablation

Algorithm	RN 50	RN 101	Vit-S/32	Vit-B/32	CLIP-B/32
FixMatch[32]	$61.3_{\pm 0.4}$	$62.8_{\pm 0.2}$	$63.7_{\pm 0.5}$	$72.0_{\pm 0.4}$	$75.3_{\pm 0.6}$
FixM. +Ours	$\mathbf{62.1}_{\pm 0.4}$	$\mathbf{64.2}_{\pm 0.1}$	$\mathbf{64.4}_{\pm 0.3}$	$\mathbf{72.9}_{\pm 0.3}$	$\mathbf{78.9}_{\pm 0.4}$

Algorithm	5	10	25	50	100
ERM[35]	$51.2_{\pm 1.0}$	$59.8_{\pm 2.5}$	$66.7_{\pm 2.2}$	$71.2_{\pm 1.9}$	$75.7_{\pm 1.6}$
FixMatch[32]	$72.8_{\pm 1.2}$	$76.6_{\pm 1.2}$	$77.6_{\pm 1.4}$	$78.7_{\pm 0.4}$	$79.4_{\pm 1.4}$
FixM.+Ours	$\mathbf{77.3}_{\pm 1.1}$	$\mathbf{78.2}_{\pm 1.2}$	$\mathbf{79.3}_{\pm 1.8}$	$\mathbf{79.6}_{\pm 1.0}$	$\mathbf{80.4}_{\pm 0.6}$

Conclusion

- Goal: Semi Supervised Domain Generalization
- Approach: Proposed feature-based conformity loss and Semantic Alignment loss.
- Our approach,
    - Aligns posterior distributions from different views.
    - Regularizes the semantic layout of feature space.
    - Is plug-and-play, parameter-free, and model-agnostic, allowing seamless integration into various baselines.
- Show consistent and notable gains over four recent baselines

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