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⁰⁵⁰ In this supplemental material, we provide the following content	S. 050
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- We show feature clustering results using extracted semantic	tea- 052
tures by employing t-SNE $[3]$ in Section 2.	053
⁰⁵⁴ – We show activation map results to indicate class-specific in	nage ⁰⁵⁴
⁰⁵⁵ regions using Class Activation Mapping (CAM) [5] in Section	on 3. 055
⁰⁵⁶ – We present comparison results against another state-of-th	e-art
domain generalization method on an additional dataset O	ffice-
Home [4] in Section 4	058
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001 2 t-SNE Embedding	001
063	063
We demonstrate t-SNE visualization results by comparing the	Dase-
line model with our proposed method in Figures 1, 2, 3, and 4 b	elow 065
on the PACS dataset [2]. From the comparison results, we can	1 see 066
that features extracted from our designed network are better	clus- 067
tered and more distinctive among the different categories	068
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¹⁸⁰ 3 Class Activation Maps

We compare our method with the baseline model in the localizations of class-specific regions on the PACS dataset [2] and results are shown in Figures 5, 6, 7, and 8 below. From the comparison results, it is shown that our method could recognize object categories with more meaningful regions of high activation values.

4 Results on the Office-Home Dataset

Table 1. Domain generalization results on the Office-Home dataset with object recognition accuracy (%) on the **ResNet15** backbone. The top results are highlighted in **bold**.

Target	ResNet-18			
Inget	DeepAll	$\mathbf{JiGen}\ [1]$	Ours	
Art	52.15	53.04	58.43	
Clipart	45.86	47.51	47.48	
Product	70.86	71.47	73.03	
Real-World	73.15	72.79	73.47	
Average	60.51	61.20	63.10	

The Office-Home dataset consists of four domains: Art, Clipart, Product, and Real-World. Each domain contains images from 65 categories, which indicates the challenges of the Office-Home dataset under the unsupervised setting. The comparison results are shown in Table 1 above. **DeepAll** is the baseline method that uniformly trains a network with images from all the domains. **JiGen** [1] adopts an additional self-supervision task by solving puzzles to constrain the network. It is observed that our proposed method outperforms JiGen by 1.9% on average.

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