Supplementary Material for
Semi-Supervised Learning by Augmented Distribution Alignment

Qin Wang[1], Wen Li[1*], Luc Van Gool[1,2]
[1]ETH Zurich [2]KU Leuven
qwang@student.ethz.ch {liwen,vangool}@vision.ee.ethz.ch

In this supplementary, we provide additional visualization results to demonstrate that our proposed Augmented Distribution Alignment is able to effectively address the impact by empirical distribution mismatch of labeled and unlabeled data in semi-supervised learning.

In particular, in Section 5.3 of the main paper, we have provided the visualization results for the baseline CNN model and our ADA-Net, in which we have demonstrated the existence of empirical distribution mismatch with the baseline CNN model, and how our ADA-Net successfully healed it. In this supplementary, we will show that the empirical distribution mismatch still exists for state-of-the-art SSL models like the VAT model [2], and our proposed Augmented Distribution Alignment is able to boost the VAT model by addressing the empirical distribution mismatch of labeled and unlabeled samples.

1. Visualization on VAT+Ent and ADA-Net+

In Section 5.4 of the main paper, we have shown that our Augmented Distribution Alignment can be used to further boost the performance of state-of-the-art model VAT+Ent. The new model was referred to as ADA-Net+ in Section 5.4 of the main paper.

To investigate how ADA-Net+ works, we follow the methods in Section 5.3 of the main paper to visualize the features using t-SNE and the feature distributions using kernel density estimation on the SVHN dataset. As the same as in Section 5.4 of the main paper, Conv-Large[2, 3] is used the backbone network.

1.1. Feature Visualization

We first compare the SVHN features of labeled and unlabeled data obtained by t-SNE. Similarly as in Section 5.3 of the main paper, a considerable distribution mismatch can be observed for the baseline CNN model (see the first row of Figure A1). By applying virtual adversarial training and entropy loss, VAT-Ent [2] partially alleviates the distribution mismatch, as shown in the second row of Figure A1. However, the empirical distribution mismatch can still be observed around each cluster as highlighted by circles. In comparison, with our proposed Augmented Distribution Alignment method, the final ADA-Net+ model exhibits a better and clean alignment between labeled and unlabeled samples, which also validates the effectiveness of proposed approach.

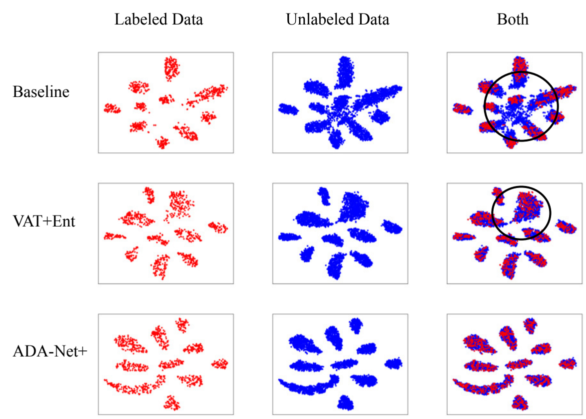

Figure A1. Visualization of SVHN features obtained by baseline CNN, VAT+Ent, and our ADA-Net+ using t-SNE. For baseline CNN model and the VAT+Ent model, empirical distribution mismatch between labeled and unlabeled samples can be observed to some extent, while our ADA-Net+ well reduces such alignment by using the proposed augmented distribution alignment method.

1.2. Feature Distribution

The empirical distribution mismatch can be further validated by the kernel density estimation in Figure A2. Similar to the observation in t-SNE visualization, VAT-Ent method is able to partly alleviate the distribution mismatch, and increase the overlap between the density functions of labeled and unlabeled distributions. By explicitly aligning the distributions, ADA-Net+ better aligns the distributions, thus leading to improved classification performance as shown in

*The corresponding author

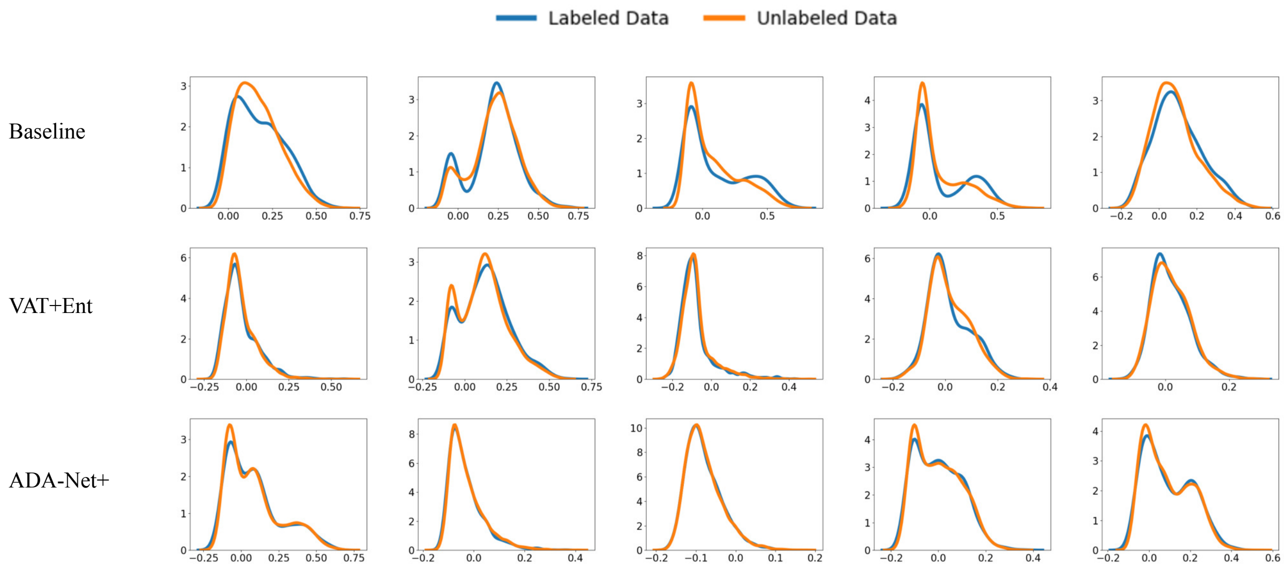

Figure A2. Kernel density estimation of labeled and unlabeled samples of the SVHN Dataset based on the first five feature activations of baseline Conv-Large [2, 3], VAT-Ent, and our ADA-Net+. Considerable distribution mismatch between labeled and unlabeled data can be observed for Conv-Large (top row). Compared with baseline Conv-Large, VAT-Ent is able to increase the overlap area to some extent, but distribution mismatch can still be observed (middle row). The two distributions are aligned better with our ADA-Net+ (bottom row).

Table 2 of the main paper.

Table A1. Average overlapping coefficient (AOC) [1] between labeled and unlabeled data over all feature activations obtained by different methods.

	AOC
Baseline CNN	84.18%
VAT+Ent [2]	90.39%
ADA-Net+	93.49%

In addition to the visualization of kernel density estimation, we also provide a quantitative comparison by calculating the overlapping coefficient [1] of density estimations, *i.e.*, the overlapped area by the density functions of labeled and unlabeled samples. We report the average overlapping coefficient (AOC) on all feature activations for different methods in Table A1. It clearly shows that the proposed method ADA-Net+ is able to further improve the distribution alignment. This further explains why integrating our method with VAT-Ent is able to achieve better performance, and also suggests that our augmented distribution alignment is is generally complementary to other SSL models, as we deal the SSL problem from a new perspective on empirical distribution mismatch which was not considered by other works.

References

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