We thank the reviewers for their thoughtful feedback! We are encouraged they found our idea to be novel (R1,R2,R4,R5), our performance remarkable (R1,R2,R3,R4,R5) and identified our contribution to this challenging OSUDA problem (R2,R3,R4,R5). We are pleased to get a positive average score where R2,R4 and R5 gave positive feedback. We begin by answering two **common concerns (CC)**. We will incorporate all feedback in the revision.

R3,R4/CC1. About the motivation. **A.** Here we'd like to emphasize our motivation for ASM again. Our core viewpoint is that not only data labeling but also data collection itself might be challenging. Such challenge could come from data privacy or acquisition condition. For example, it could be hard to acquire rare disease information with privacy or to shoot videos under extreme weather conditions. In fact, we have given some examples in **Broader Impact** for it. We believe our spirit is in line with the prevailing trends of few-shot learning.

R1,R2,R4/CC2. When facing more obscure domain shift beyond "style difference". **A.** We thank reviewers for the insightful concern. Style difference is one of the vital causes for domain shift, while ASM is tailored for addressing such style gap. Howbeit, we acknowledge that ASM is an early attempt towards the challenging OSUDA problem and has it own range of application. As we pointed out in **Conclusion**, we left it as the future work to cope with more general domain shift such as Office-31.

R1/Q1. RAIN seems only a complex version of AdaIN, which is not very attractive. **A.** We thank R1 for identifying the novelty and superiority of our work. However, maybe we did not illustrate it clear enough and make R1 miss the focus of our contribution. The uppermost contribution of our work is the design of an adversarial paradigm (ASM) tailored for OSUDA, as acknowledged by other reviewers, while RAIN should only be regarded as an indispensable module to achieve the paradigm. Besides, we argue that RAIN is not a "mere complex", but a *premium* version of AdaIN because:1) RAIN has benefits of end-to-end training and differentiable searching with negligible computation cost; 2) We can regard "anchored sampling" (see **Appendix C**) as AdaIN in OSUDA scenario. As demonstrated in this ablation study, the new style generated by AdaIN is much limited comparing to RAIN, especially in a one-shot setting.

R1/Q2. No comparison with CycleGAN-based methods. **A.** In fact we have compared ASM with CycleGAN directly in both classification and segmentation task (see **Table 1 and 2**). Besides, we have compared ASM with OST and MUNIT, which are both CycleGAN-based methods.

R3/Q1. How to use the single target sample? **A.** We have given a detailed description on how the single target sample is used in **Figure 3** and **Algorithm 1**. Please allow us to use simple sentences here to explain it again. The initial style vector ε_1 is indeed from a Gaussian distribution, but such Gaussian distribution is defined by ψ (mean) and ξ (variance). **ψ and ξ are both extracted from the single target sample x_t by RAIN.**

R4/Q1. Lack of discussion on domain generalization. **A.** Different from OSUDA setting, most DG methods leverage multiple labeled source domains but no target data. We will add discussions on these methods in revision.

R4/Q2. Sensibility to the search depth. **A.** The performance is not very sensitive to search depth if the depth is in an appropriate range. For classification, the accuracy drops around 2% when depth $5 \rightarrow 10$. For segmentation, the mIoU drops around 1% when depth $2 \rightarrow 4$ (see **Appendix C, Fig.1**). An overlarge search depth would lead to unreasonable styles, so it is easy to determine an appropriate depth by observing the generated samples.

R4/Q3. Sensibility to the target sample choice. **A.** We think it is a common issue for the one-shot learning, and our answer is twofold. 1) ASM has a wide search scope, as shown in **Fig.4 (Right)**. Taking the day and night scene as an example, when ASM learns the dark style well, the search direction may change to the bright style. The wider search space relieves the performance sensitivity to the target sample. Besides Fig.4, We will give more visualisation analysis in revision. 2) We run each OSUDA experiment for 5 times with different target samples (see **Sec. 4.1**). We find the performances are stable in most cases. In summary, we do not need a specific target sample for good performance.

R4/Q4. Latent space smoothness. **A.** We use a **large** dataset of style images to train RAIN. According to the VAE, all these reasonable styles are embedded in a Gaussian distribution and the latent space is supposed to be dense and smooth. As we observed in experiments, the styles searched around the anchor are reasonable.

R5/Q1. It is hard to be sure what drives the performance. **A.** We experimentally proved that ASM drives the performance. RAIN alone (anchored or random sampling) performs equally with OST (see Tab.2 in main text and Tab.2 in appendix) but ASM consistently outperforms OST. It indicates that ASM mechanism is the promoting factor while RAIN is only a module to achieve the mechanism. Besides, we believe the comparisons are fair. We uniformly use ResNet-101 for seg. and ResNet-18 for clas., using same data augmentation and same number of training epochs.

R5/Q2. Writing could be improved and simplified. **A.** We will polish our writing to make it easier to follow.

R5/Q3. About theoretical grounding principle. **A.** ASM employs the searched target styles to stylize the source images in order to decrease the domain distribution discrepancy in input space, which is consistent with the theory of Ben-David et al [1]. Besides, the establishment of the adversarial mechanism is inspired by the the Gradient Reverse Layer (GRL) [2]. We will add these theoretical insights in revision. **R5/Q4.** Missing discussion. **A.** We will add detailed discussions and cite related papers about domain randomization and data augmentation. **R5/Q5.** Unreasonable styles. **A.** Please kindly refer to R4/Q2 & R4/Q4. //**[1]** A theory of learning from different domains. Machine Learning 2010. **[2]** Unsupervised Domain Adaptation by Backpropagation. ICML 2015.