Source-Guided Similarity Preservation for Online Person Re-Identification
Supplementary Materials

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September 3, 2023

This supplementary material contains additional results, analysis, and details about the S2P framework. The following items are included:

- We provide more details about the implementation of MMT, SpCL and IDM in the OUDA setting (Sec. A).
- We present the results of two dataset configurations that are not discussed in the main paper, namely, Market→CUHK and RandPerson→CUHK (Sec. B).
- We conduct additional ablation studies. First, we show the impact of increasing the number of tasks in the OUDA setting on the performance of S2P. Second, we validate the choice of hyperparameters and the model used for inference. And finally, we compare the performance of S2P and other UDA methods in the source domain while adapting to the target domain (Sec. C). Note that, considering the consistent performances of MMT and SpCL across datasets (refer to Table 1 of the main paper), we conduct our additional ablation studies with those two methods to derive conclusions that more likely hold true across multiple use cases.

A Additional Implementation Details

In this section, we provide additional details about the implementation of the different frameworks. In the main paper Table 1, we compare the performance of S2P with three state-of-the-art UDA methods, namely MMT, SpCL and IDM. We follow [5] to implement and adapt those methods to the OUDA setting. In [5], the authors run experiments of the *strong baseline* in the OUDA setting while varying the number of epochs. They observed that the best performance is achieved using 20 epochs. We keep the same hyper-parameters for MMT, S2P-MMT, SpCL, S2P-SpCL, IDM and S2P-IDM in Table 1.

In contrast to [5, 3], we do not consider the DukeMTMC-ReID dataset, because it has been retracted by its original authors in response to a report[1] that shows that the Duke dataset was used by a few companies for some research projects that violate Human Rights.

B Additional Comparison with the State-of-the-art

In this section, we provide results of complementary configurations that are not reported in the main paper: RP

[1]https://exposing.ai/duke_mtmc

Method	RP → C		M → C	
	mAP	Rank-1	mAP	Rank-1
Strong Baseline [2]	$2.5_{\pm0.1}$	$1.6_{\pm0.1}$	$6.9_{\pm1.4}$	$6.1_{\pm1.2}$
MMT [3]	$21.0_{\pm0.4}$	$21.5_{\pm0.4}$	$\underline{32.9}_{\pm0.3}$	$\underline{32.9}_{\pm0.4}$
SpCL [4]	$13.2_{\pm2.2}$	$12.3_{\pm2.4}$	$12.4_{\pm0.5}$	$11.9_{\pm1.1}$
S2P-MMT (ours)	$\underline{23.8}_{\pm1.9}$	$\underline{23.8}_{\pm2.1}$	$\mathbf{34.8}_{\pm2.1}$	$\mathbf{35.9}_{\pm0.3}$
S2P-SpCL (ours)	$\mathbf{27.8}_{\pm0.3}$	$\mathbf{28.1}_{\pm0.4}$	$31.2_{\pm0.2}$	$31.5_{\pm0.1}$

Table 1: Performance of S2P and three state-of-the-art methods in two additional OUDA-Rid tasks.

→ C, and M→C. In Table 1, we report the mAP and the Rank-1 of the *strong baseline*, SpCL, MMT, and our framework S2P-MMT and S2P-SpCL. We can see that S2P has the best performances on both configurations. For example, the mAP of SpCL goes from 13.2 to 27.8, and from 12.4 to 31.2, in both configurations, respectively, when integrated into our S2P framework.

C Additional Ablation Studies

Increasing the number of tasks. We conduct an additional experiment using MSMT as the target dataset to evaluate the impact of increasing the number of tasks. Since MSMT is a much larger dataset than Market and CUHK, increasing the number of tasks to ten results in smaller data partitions, but the task partitions remain comparable to those of Market or CUHK in a five-task OUDA setting in terms of the number of images. This experiment extends the results of the main paper by augmenting the number of tasks while keeping the same number of images per task. S2P outperforms the UDA state-of-the-art in terms of mAP for MMT and SpCL as shown in Fig. 1. These results demonstrate the effectiveness of S2P even when additional tasks are introduced, highlighting the efficacy of our technique in increasingly complex scenarios.

Weights of the losses. Here, we validate the weights of the different losses in S2P. When implementing $\mathcal{L}_{ReID}$, we employ the weighting parameters provided in the respective original papers [4, 3, 1] in S2P-SpCL, S2P-MMT and S2P-IDM. For the sake of simplicity, the weight of $\mathcal{L}_{ReID}$ is then set to 1 in all our experiments regardless of the chosen pseudo-labeling method. For $\mathcal{L}_{KD}$ and $\mathcal{L}_{MMD}$, we show in Table 2 a comparison in mAP of S2P-SpCL when varying the corresponding weights λ_{KD} and λ_{MMD}. We observe that the best performances are obtained with $\lambda_{KD} = 1$ and $\lambda_{MMD} = 0.03$. We also notice that S2P is not very sensitive to the weights of the losses and remains, in all cases, above the performance of the original SpCL (15.6 in Table 1 of the main paper).

λ_{MMD} \ λ_{KD}	0.1	1	10
0.003	31.7	33.3	31
0.03	31.1	**34.3**	31.4
0.3	28.4	32.2	29.7

Table 2: Ablation study on the weights of the two main losses of S2P λ_{KD} and λ_{MMD}. The table shows the mAP of S2P-SpCL in the MSMT→CUHK configuration. The best performing configuration is shown in **bold**.

Performance of the teacher. In what follows, we justify the choice of the teacher model for inference. Table 3 shows the performance of S2P-MMT and S2P-SpCL using the student and teacher networks in inference. In the OUDA setting, we show that the teacher model in S2P guides the training of the student model. Furthermore, the teacher in turn benefits from the accuracy of the student models by leveraging the previously acquired knowledge, hence giving more accurate predictions. Table 3 shows that in all the aforementioned configurations, we get better results when deploying the teacher model for inference, rather than the student model.

Performance on the source domain. In Fig. 2, we show the evolution of the mAP of both MMT and S2P-MMT on the source domain when considering two different configurations: a) Market→MSMT and b) Market→CUHK. We observe that the performance on the source domain is improved during the first task of OUDA. After the first task, the performance of MMT on the source domain drops in both configurations, showing that the model focuses more on capturing the distribution of the target domain, hence overfitting the upcoming tasks and forgetting the previously acquired knowledge on the source domain. On the contrary, the performance of S2P-MMT on the source domain remains relatively high and

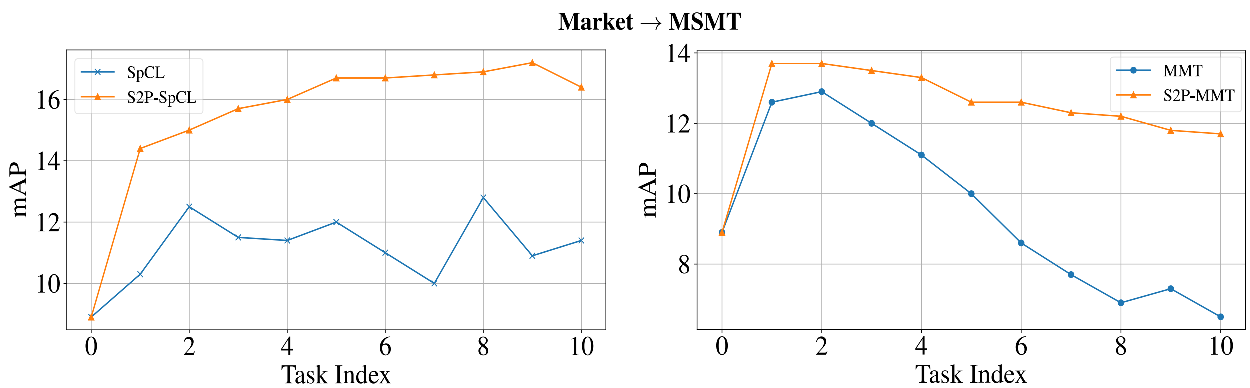

Figure 1: Comparison of S2P with other state-of-the-art methods in terms of mAP vs. task index in a 10-tasks OUDA Market→MSMT configuration

Method	**MS → M**		**MS → C**		**M → MS**		**M → C**	
	mAP	**Rank-1**	**mAP**	**Rank-1**	**mAP**	**Rank-1**	**mAP**	**Rank-1**
S2P-MMT (student)	63.1	82	28.3	28.5	14.1	35.2	26.2	26.3
S2P-MMT (teacher)	**70**	**87.1**	**40.4**	**42.4**	**19.5**	**43.3**	**34.8**	**35.9**
S2P-SpCL (student)	61.9	81.9	30.7	31.9	17.5	41.5	21.4	21.6
S2P-SpCL (teacher)	**69.1**	**87.1**	**34.3**	**35.1**	**20.2**	**46.1**	**31.2**	**31.5**

Table 3: Ablation study on the choice of the inference model in the S2P framework. We compare the performance of S2P in the last task in four real-to-real OUDA-Rid tasks when using the student and the teacher models at inference time. The best performing method on each dataset is shown in **bold**.

stable after the first task, showing that our S2P framework effectively maintains a common feature space for the source and target domains.

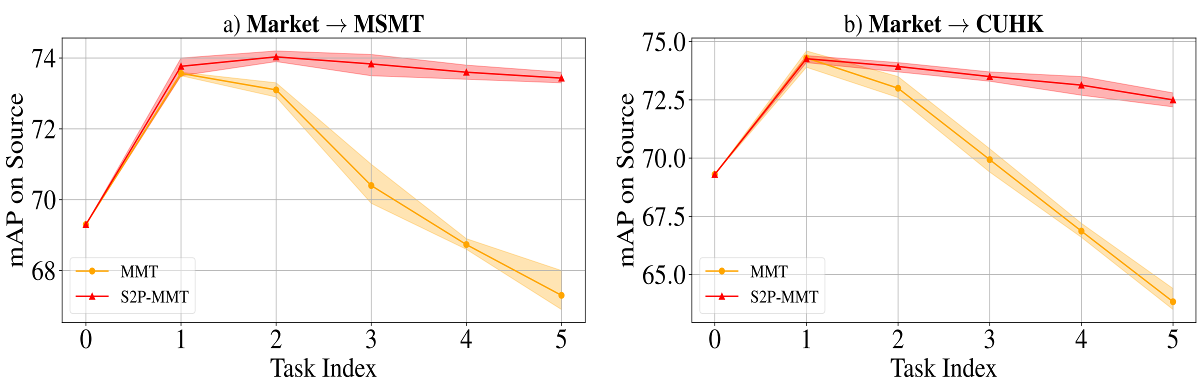

Figure 2: Performance of MMT and S2P-MMT on the source domain in two OUDA tasks: a) Market→MSMT and b) Market→CUHK.

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