# A Cross-Season Correspondence Dataset for Robust Semantic Segmentation - Supplementary Material

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This supplementary material shows additional qualitative results for the CMU Seasons [1, 5] and RobotCar Seasons [3, 5] datasets. These results were not included in the main paper due to space constraints.

We show additional qualitative results for the CMU Seasons [1, 5] dataset in Fig. 1 and Fig. 2. Fig. 1 shows results on the test set used to measure the segmentation quality quantitatively via the mean IoU score. Consequently, we also show the reference annotations. Fig. 2 shows additional results on unannotated images from the CMU Seasons dataset. As can be expected, using correspondences, as proposed in the paper, mainly improves segmentation quality in areas most affected by seasonal changes, *e.g.*, roads, side walks, and terrain areas covered in leaves or snow.

Similarly, additional example segmentations for the RobotCar [3, 5] dataset can be seen in Fig. 3 and Fig. 4. In addition to improving the segmentation performance on the night images, adding correspondences helps with segmentation of the overexposed parts of buildings, see for example row one of Fig. 4.

For both datasets, we see a clear improvement in segmentation quality when using correspondences (E + C) compared to only using Cityscapes [2] and annotated dataset images (E) for training. This is due to the fact that the Cityscapes dataset does not exhibit strong seasonal or illumination changes. In contrast, the Mapillary Vistas dataset [4] contains images captured under a much more diverse set of conditions. Still, we observe an improvement in segmentation quality when using correspondences (V + E + C) compared to not using them (V + E).

## References

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[2] Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele. The cityscapes dataset for semantic urban scene understanding. In *Proc. CVPR*, 2016. 1

[3] Will Maddern, Geoffrey Pascoe, Chris Linegar, and Paul Newman. 1 year, 1000 km: The oxford robotcar dataset. *IJRR*, 2017. 1

[4] Gerhard Neuhold, Tobias Ollmann, Samuel Rota Bulò, and Peter Kontschieder. The mapillary vistas dataset for semantic understanding of street scenes. In *Proc. ICCV*, 2017. 1

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Figure 1. Qualitative results on the CMU Seasons test set. Four different networks are compared, the notations used are: E: trained with extra CMU annotations, C: trained with correspondence data, V: trained with Vistas training set. Row two shows a failure case where V + E + C miss-labels terrain as sidewalk.

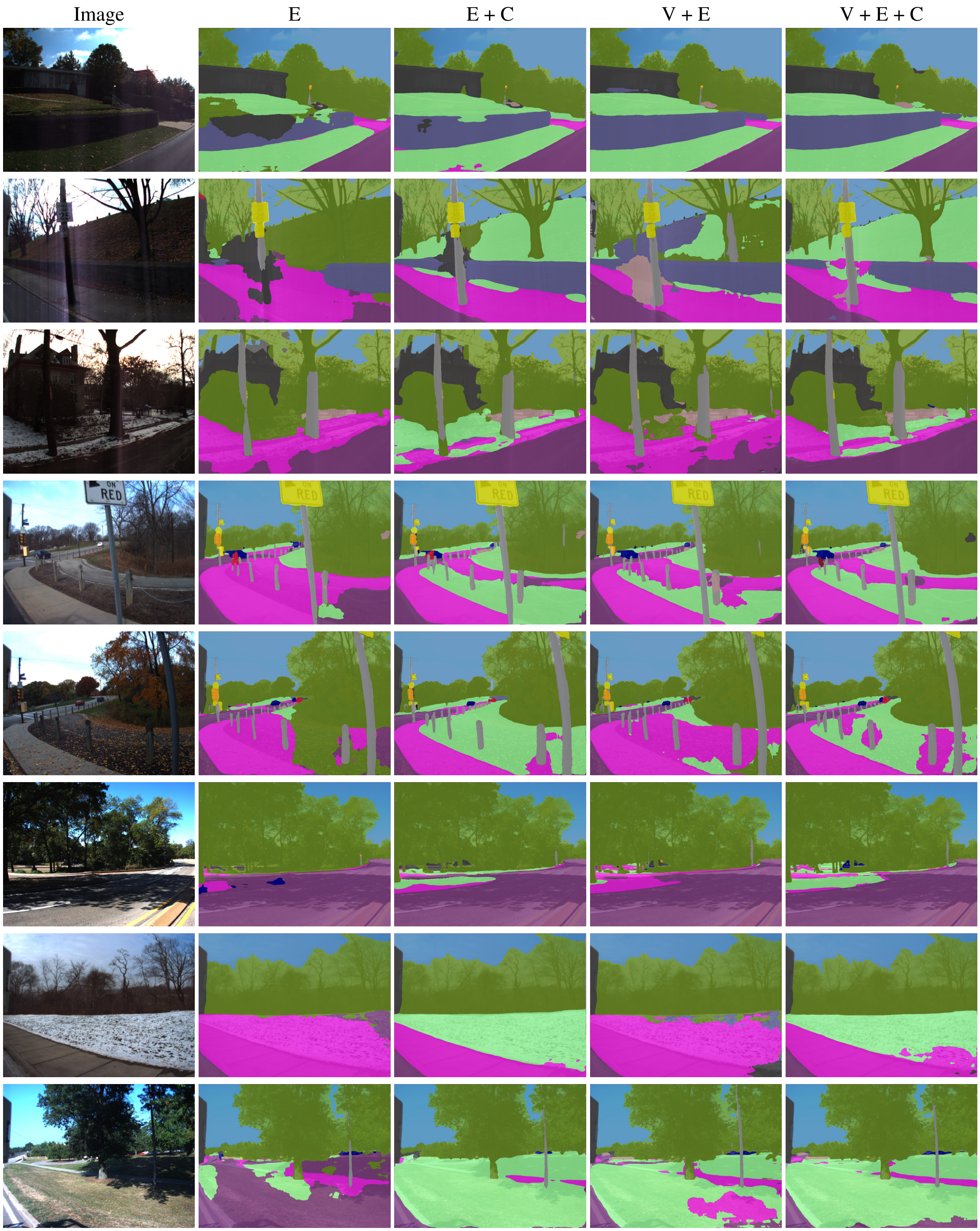

Figure 2. Additional qualitative results on unannotated images from the CMU Seasons dataset. Four different networks are compared, the notations used are: E: trained with extra CMU annotations, C: trained with correspondence data, V: trained with Vistas training set.

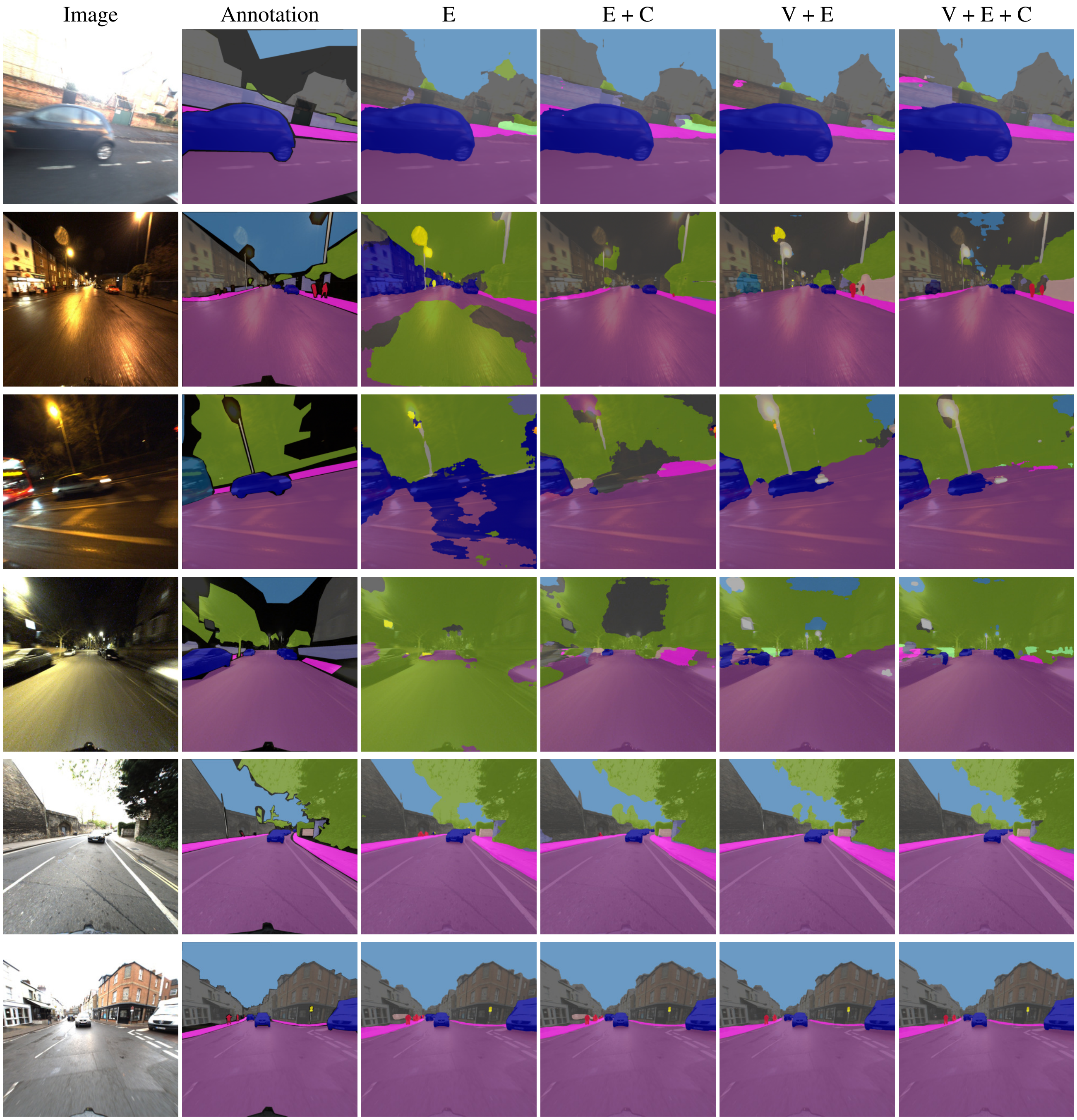

Figure 3. Qualitative results on the RobotCar Seasons test set. Four different networks are compared, the notations used are: E: trained with extra RobotCar annotations, C: trained with correspondence data, V: trained with Vistas training set.

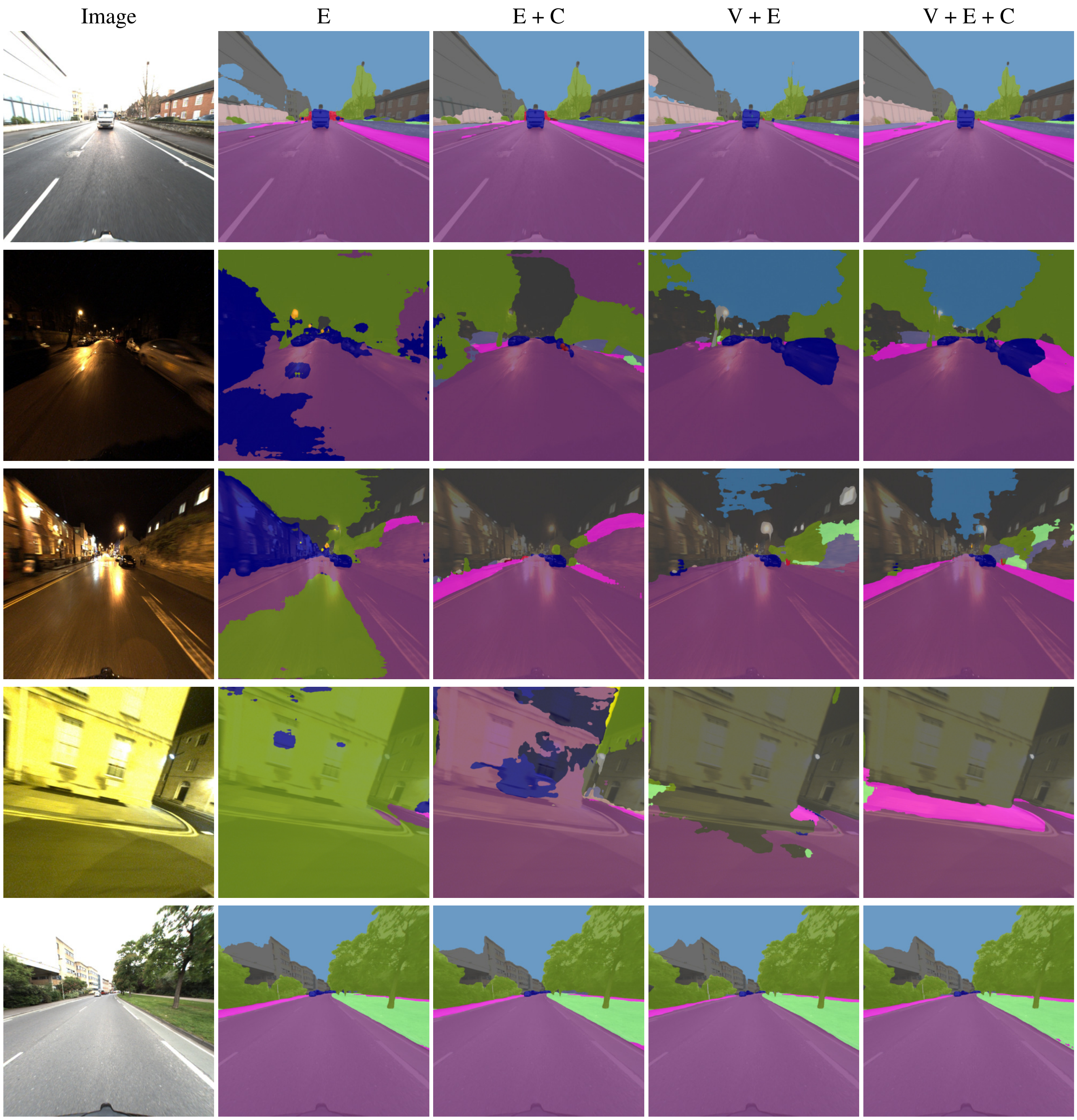


Figure 4. Additional qualitative results on unannotated images from the RobotCar Seasons dataset. Four different networks are compared, the notations used are: E: trained with extra RobotCar annotations, C: trained with correspondence data, V: trained with Vistas training set.