

TITLE	
Leveraging relative geometric transformations for Domain Adaptation	
GUIDANCE	
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CONTEXT	
In ML, models trained on a source dataset often fail to generalize well on a target dataset, due to the different distributions between the two data sources. These domain shifts are common in practical applications, and the goal of Domain Adaptation (DA) is to reduce the effect of the domain shift when the target is significantly different from the source dataset. Depending on the type of data available on target and source domain, there are different type of DA problems to solve. The most interesting are Unsupervised DA (UDA, when only unlabeled samples are available for the target domain) and Source Free UDA (SFDA, when also the source data are not available, due to privacy issues).	
GOAL	
Recent works in Image Analysis and Computer Vision propose approaching DA and UDA with self-supervised tasks that are structure and semantic aware. These tasks are able to learn geometric properties and semantically meaningful representations of the images that are effective in softening the domain shift issues. One of the most common self-supervised task for this purpose is the so called Relative Rotation task, where the network is asked to solve (together with the main task) the auxiliary task of predicting the relative rotation between two copies of the same sample that differ from a rotation multiple of 90°. The objective of the thesis is to extend the current approach by first analyzing the effect on UDA and SFDA of other geometric auxiliary tasks (such as relative translation and relative scaling) and their combination. Then, since combining different auxiliary tasks require facing several issues (such as their different learning rates, or the need to estimate their weights), another objective is improving the effectiveness of such Multi-Task learning by analyzing and developing automatic (learnable) auxiliary loss adaptation techniques. These “self-paced” learning approaches aims at observing the learning progress of the auxiliary tasks and adjust accordingly (and in a dynamic way) the weights for each task. Finally, the developed approaches will be extended to the integration of different modalities, such as RGB + Depth or RGB + Event data References: - Domain Adaptation https://towardsdatascience.com/understanding-domain-adaptation-5baa723ac71f - Relative rotation for SFDA: https://arxiv.org/abs/2012.07297 - Relative rotation for multiple modalities: https://arxiv.org/abs/2004.10016 - Event data (ref: https://en.wikipedia.org/wiki/Event_camera)	
METHODOLOGY	
Pyhton-based deep learning environment based on Pytorch	
PROFILE (e.g. rather theoretical/rather practical implementation, foreknowledge (courses, methods, computer language(s) etc.))	
Literature and study – 20% Implementation – 40% Experiments – 40% Good programming skills are required.	
# of Students	1 or 2

