

UNSUPERVISED DAY-NIGHT DOMAIN ADAPTATION WITH A PHYSICS PRIOR FOR IMAGE CLASSIFICATION

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1. BACKGROUND



- * **Deep neural networks** show great potential to be part of safety-critical applications, such as autonomous driving
- * A **Convolutional Neural Network (CNN)** is a common use for performing:
- * **Image classification**: the task of correctly assigning a label to a given image.
- * In this context, reliability on the performance of image classification is essential

2. INTRODUCTION

- * **Problem**: Deep image classification methods are sensitive to illumination changes - improving robustness by adding training data is often non-trivial
- * An illumination shift between train and test data can be addressed by **domain adaptation** methods

A **zero-shot setting**, where a model is trained using only samples from the source domain, explored by recent work [1] by introducing **Color Invariant Convolution (CICov)**, aiming to transform input to a domain invariant representation

Unsupervised domain adaptation (UDA) where a model is trained on source domain + unlabeled samples from target domain, promotes emergence of invariant features w.r.t. the domain shift

3. RESEARCH QUESTION

“How does the zero-shot setting with CICov compare to an unsupervised setting with/without CICov for day-night domain adaptation for image classification?”

4. METHOD

- * Color Invariant Convolution (CICov) [1]:
 - * Implements color invariant edge detectors
 - * A trainable layer that can be added as the first layer of a CNN
- * Unsupervised Domain Adaptation by Backpropagation [2]:
 - * Method for extending any feed-forward network trainable by backpropagation to perform UDA (resulting model is often referred to as DANN)
 - * Works with domain classifier connected to feature extractor via a gradient reversal layer (see Fig. 1)

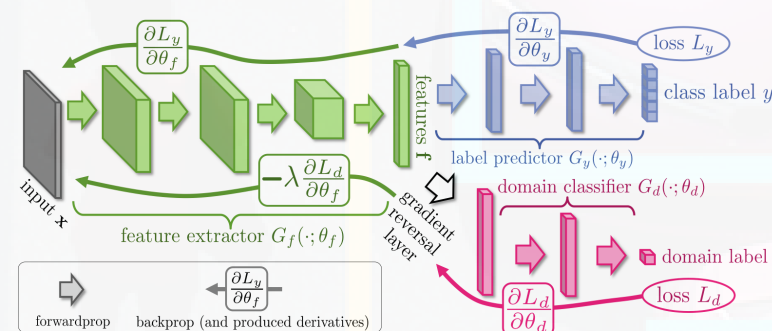


Figure 1. Unsupervised Domain Adaptation by Backpropagation [2]



Figure 2. Samples from the day (source domain) and night (target domain) test sets of the CODaN dataset [1]

5. EXPERIMENTS & RESULTS

- * **Dataset**: Common Objects Day and Night (CODaN) [1]; 10 common object classes recorded in both daytime and nighttime (see Fig. 2)
- * Zero-shot setting (Results shown in Table 1):
 - Experiment 1**: Training a baseline CNN (Resnet-18)
 - Experiment 2**: Training a CNN (Resnet-18) + CICov Unsupervised domain adaptation (Results shown in Table 2):
 - Experiment 3**: Training a DANN (= Resnet-18 + UDA)
 - Experiment 4**: Training a DANN (= Resnet-18 + UDA) + CICov

Method	Day	Night
Without CICov (resized)	68.9 ± 0.3	38.3 ± 0.4
With CICov (resized)	69.8 ± 0.7	49.4 ± 0.3

Table 1: CODaN classification accuracies of a ResNet-18 architecture averaged over three runs.

Method	Day	Night
Without CICov (resized)	68.4 ± 1.2	49.2 ± 1.5
With CICov (resized)	69.7 ± 0.5	58.2 ± 0.4

Table 2: CODaN classification accuracies of a DANN ResNet-18 architecture averaged over three runs.

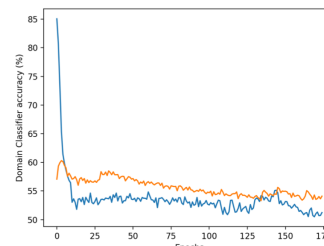


Figure 3: Accuracy of the domain classifier during the training of a ResNet-18 DANN on the CODaN dataset with CICov implemented (orange) and without CICov implemented (blue).

6. CONCLUSION/DISCUSSION

- * (i) Effectiveness CICov in ZS confirmed by our experiments, (ii) UDA performed similar to CICov in ZS, (iii) UDA + CICov performed significantly better over the other experiments.
- * Domain classifier showed that CICov does not result in full domain invariance and indicates that UDA and CICov 'reinforce' each other.

Limitation: The dataset we used (CODaN) is relatively small

=> Size of dataset + analyzing the results lead me to question the results of UDA

Limitation: The need to resize every sample due to memory constrains lead to lower results

Future work: Perform same experiments on larger datasets without resizing, further experimentation on UDA + CICov