

# 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

## 3. RESEARCH QUESTION

*"How does the zero-shot setting with CICConv compare to an unsupervised setting with/without CICConv for day-night domain adaptation for image classification?"*

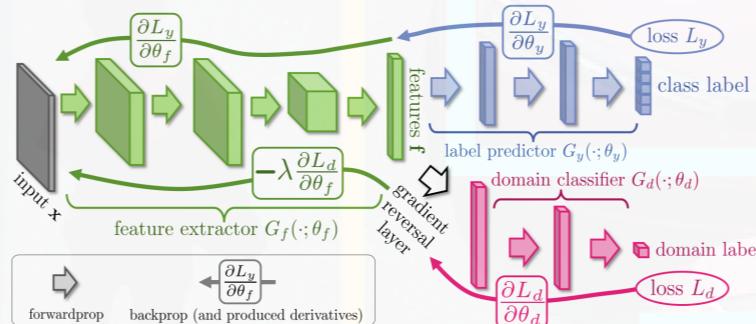


Figure 1. Unsupervised Domain Adaptation by Backpropagation [2]



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) + CICConv  
Unsupervised domain adaptation (Results shown in Table 2):  
**Experiment 3:** Training a DANN (= Resnet-18 + UDA)  
**Experiment 4:** Training a DANN (= Resnet-18 + UDA) + CICConv

| Method                    | Day            | Night          |
|---------------------------|----------------|----------------|
| Without CICConv (resized) | $68.9 \pm 0.3$ | $38.3 \pm 0.4$ |
| With CICConv (resized)    | $69.8 \pm 0.7$ | $49.4 \pm 0.3$ |

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

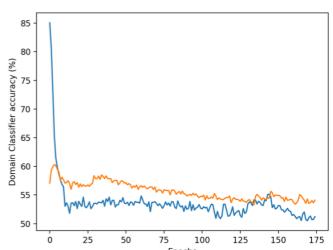


Figure 3: Accuracy of the domain classifier during the training of a ResNet-18 DANN on the CODaN dataset with CICConv implemented (orange) and without CICConv implemented (blue).

| Method                    | Day            | Night          |
|---------------------------|----------------|----------------|
| Without CICConv (resized) | $68.4 \pm 1.2$ | $49.2 \pm 1.5$ |
| With CICConv (resized)    | $69.7 \pm 0.5$ | $58.2 \pm 0.4$ |

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

## 6. CONCLUSION/DISCUSSION

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

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 (CICConv), 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

## 4. METHOD

- \* Color Invariant Convolution (CICConv) [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)