Continual Learning for Out-of-Distribution Pedestrian Detection

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Introduction

Overview: Pedestrian detection is a cornerstone in machine vision applications like autonomous vehicles and surveillance. Despite advancements, existing models struggle with performance degradation in cross-dataset scenarios, known as the out-of-distribution generalization problem. This issue is particularly evident when datasets differ in weather conditions or geographical locations.

Problem Statement: Current solutions often resort to fine-tuning on new datasets, which leads to catastrophic forgetting and a significant drop in performance on the original dataset.

Our Approach: We introduce a Continual Learning (CL) approach to tackle this problem, specifically modifying Elastic Weight Consolidation (EWC) and integrating it with Faster R-CNN. This allows the model to adapt to new data distributions without forgetting the old ones.

Key Contributions:

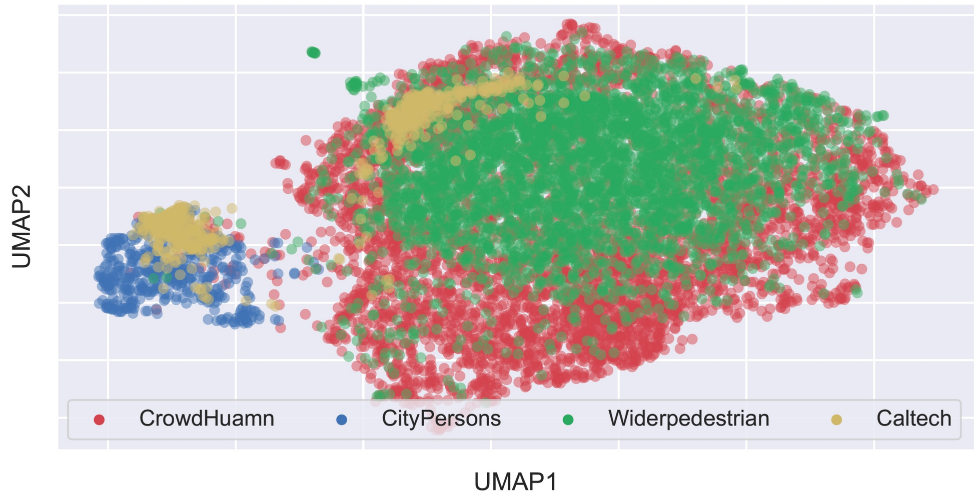
1.Novel CL-based Solution: We propose a continual learning-based solution to address out-of-distribution generalization in pedestrian detection.

2.EWC Adaptation: We adapt EWC for pedestrian detection task.

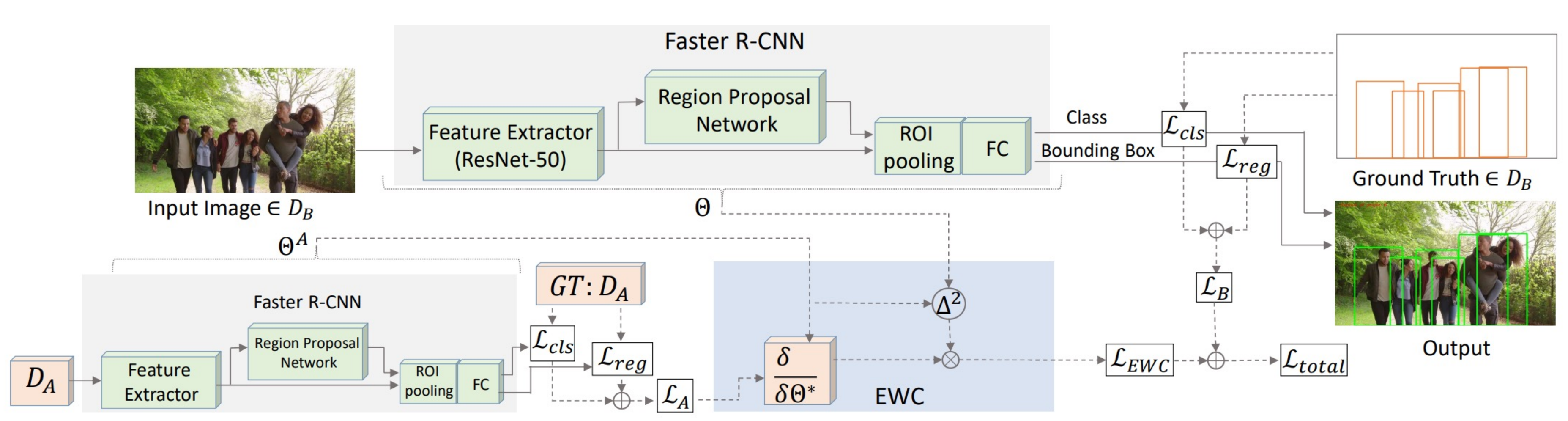
3.Open Source: Upon acceptance, our code will be made publicly available.

Datasets

Selecting CityPersons and CrowdHuman based on the distributions of the datasets. These two datasets are further apart compared to others commonly used in the field.



Proposed Method



we employ Faster R-CNN as the backbone pedestrian detector. The network is fine-tuned on the new distribution using EWC to ensure the previously learned distribution is not forgotten.

Loss

The loss function consists of two terms where $\mathcal{L}_B$ is the Faster R-CNN loss for learning pedestrian detection on the second dataset This loss is is the sum of classification loss and bounding box regression loss.

The second term is $\mathcal{L}_{EWC}$ which is a regularization term added to prevent catastrophic forgetting.

$$\mathcal{L}_{total} = \mathcal{L}_B(\mathcal{P}(\theta, \mathrm{A}, X), Y) + \mathcal{L}_{EWC}(\theta)$$

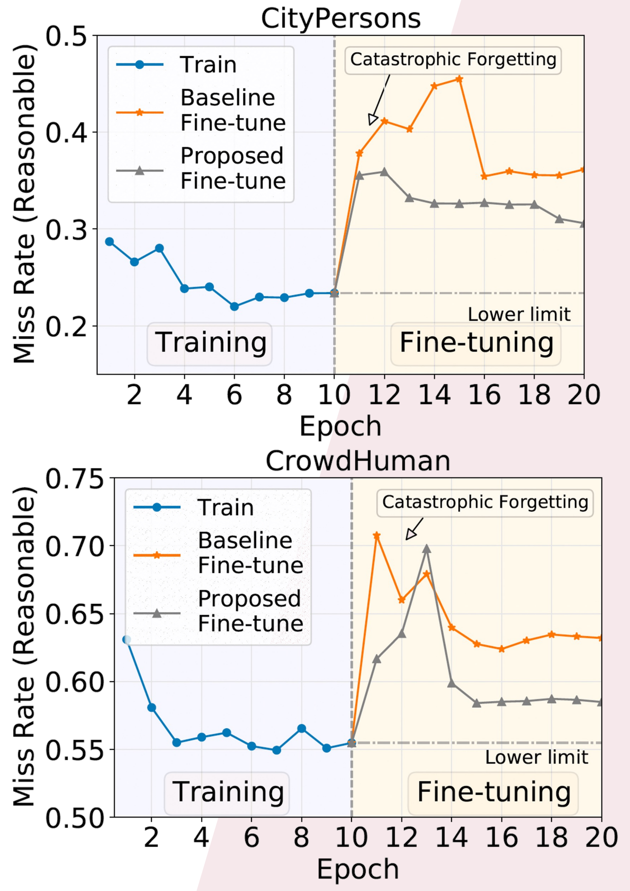
$$\mathcal{L}_{EWC}(\theta) = \sum_{i=1}^{k} \frac{\lambda}{2} \mathcal{F}_i (\theta_i - \theta_i^A)^2$$

This loss penalized the change of the weights based on the importance of those weights. In this work, rather than calculating F using the gradient of the output, we are using the gradient of the loss:

$$\mathcal{F}_i = \frac{1}{n} \sum_{X,Y \in \mathcal{D}_{Train}^A} \left(\frac{\delta \log(\mathcal{P}(\theta, \mathrm{A}, X), Y)}{\delta \theta_i} \,|\, \theta = \theta^A \right)$$

Results and Discussions

The model is first trained on the first dataset, and then fine-tuned in two different ways on the second dataset, once without any regularization loss and once using the proposed loss. The reasonable miss rate is calculated as the evaluation metric on the first dataset. The results shows that using the proposed loss the catamorphic forgetting is minimized.



Furthermore, we compare the miss rate percentage increase on different models after fine tuning as the indicator of catastrophic forgetting. The results demonstrates that the proposed model minimize the drop when being adapted to the new distribution.

Table 2: Miss rate ($MR^{-2}(\downarrow)$) percentage increase.

Model	Scenario 1 CrowdHuman	Scenario 2 CityPersons
Faster R-CNN (ResNet-no TL) [22]	30%	41%
Faster R-CNN (MobileNet) [22]	13%	62%
Faster R-CNN (ResNet) [22]	14%	54%
FPN [25]	16%	43%
Cascade R-CNN [12]	17%	41%
HRNet [26]	-	40%
Swin-Trans [27]	-	81%
Proposed	**5%**	**34%**

Summary

We've developed a Continual Learning approach that modifies Elastic Weight Consolidation to tackle catastrophic forgetting in pedestrian detection. Our method effectively learns new data distributions while retaining knowledge of previous ones. Future work will explore replay memory and vision transformers to further enhance performance.

Acknowledgement

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