Training strategies for domain generalisation in object detection for autonomous driving

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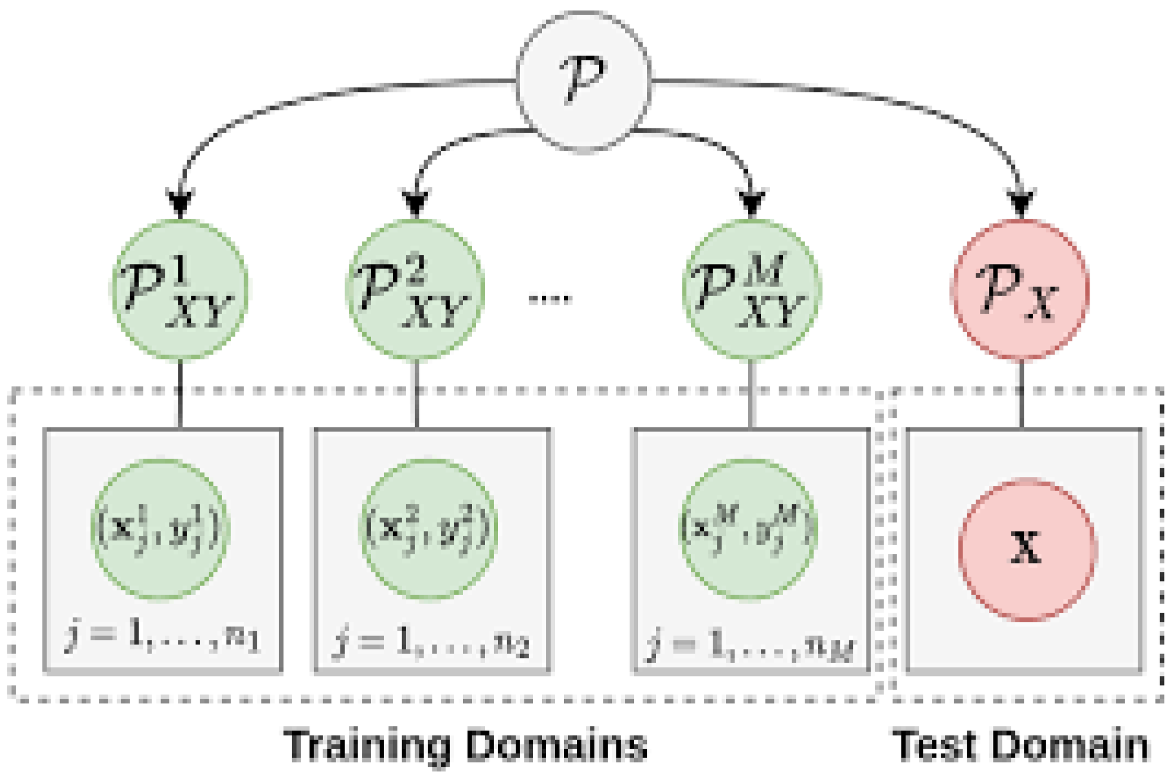
Introduction

Robust, reliable, fast and adaptable object detection systems are crucial in evolving autonomous driving areas. Training a detection model that works well in diverse weather conditions is challenging. Domain generalisation addresses these domain shifts caused by various sensor types, lighting, and imaging conditions. Different training strategies were implemented to help the model find the domain's common features and increase the model's capability to work well on unseen target domains. Faster RCNN with ResNet50 backbone was implemented as the detection algorithm, ACDC data set [1] (adverse conditions dataset city) as training data, and the Cityscape data set as the test data.



Domain Generalisation

Aim and Objectives

The primary goal of this project is to achieve domain generalisation in object detection for autonomous driving. To attain this, diverse training strategies are employed within the model's training process.

Methodology

The experiments to study different training strategies were designed in three stages to implement and evaluate the performance of each method.

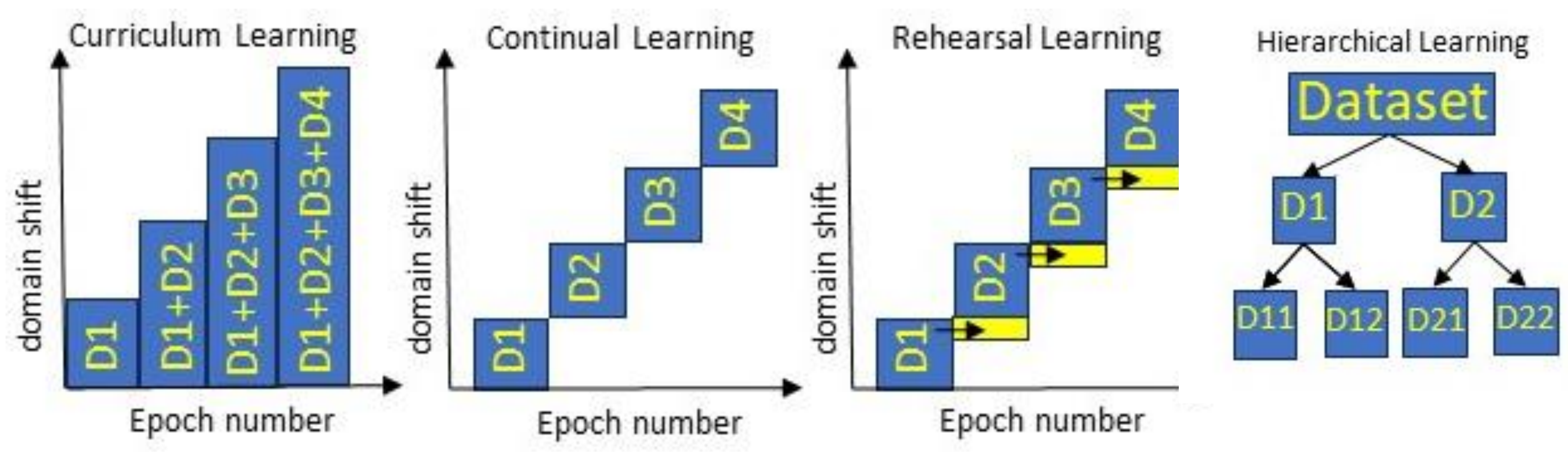
1- Baseline evaluation: Faster R-CNN [2] and DG Faster R-CNN [3] with different learning parameters

2- Training strategies: curriculum learning, continual learning, rehearsal learning, hierarchical learning

3- Combine approaches: Different combinations of curriculum and hierarchical training with feature alignment

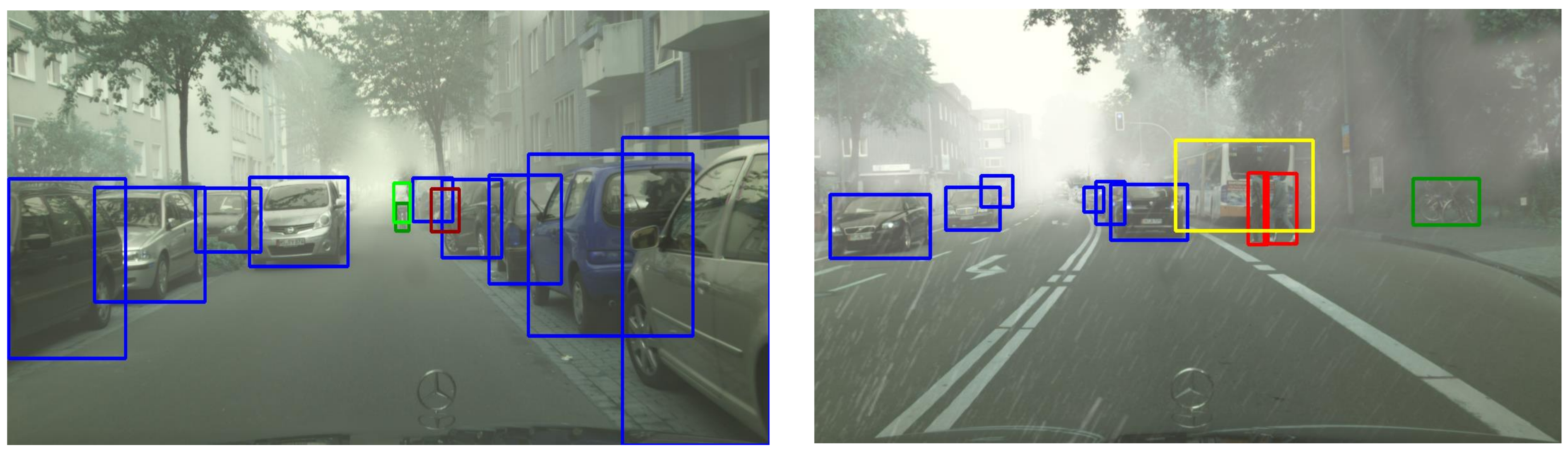
Source domains: ACDC dataset with four domains: nighttime, fog, snow, and rain

Target domains: Cityscapes' foggy and rainy



Training Strategies

Object detection on Cityscapes' foggy and rainy data set
no training strategy



Object detection on Cityscapes' foggy and rainy data set
curriculum learning

Results

metric: mAP/WmAP	Cityscapes rainy	Cityscapes foggy	average
Faster R-CNN			
Base line	63.41/69.93	65.54/73.07	64.48/71.5
continual	60.01/68.42	65.19/74.27	62.6/71.35
rehearsal	64.43/75.04	67.93/76.67	66.18/75.86
curriculum	72.54/78.35	68.68/77.43	**70.61/77.89**
DGFaster R-CNN			
Base line	72.95/76.69	67.29/75.56	70.12/76.12
Hierarchical	61.75/71.36	68.69/77.51	65.22/74.44
combine	73.29/78.52	69.11/78.49	**71.2/78.51**

Conclusion:

- Using curriculum learning with Faster R-CNN baseline architecture has the most contribution to domain generalisation between all training strategies, especially when followed by feature alignment (combine)
- Curriculum learning matches the performance of the feature alignment method for the domain generalisation approach
- The arrangement of domains influences the training procedure in some learning strategies, such as curriculum learning, and plays an essential role in the domain generalisation approach

References

[1] ACDC Dataset (ethz.ch)
{2] Ren, S., He, K., Girshick, R., and Sun, J.: 'Faster r-cnn: Towards real-time object detection with region proposal networks', Advances in neural information processing systems, 2015, 28
[3] Seemakurthy, K., Fox, C., Aptoula, E., and Bosilj, P.: 'Domain generalisation for object detection, arXiv preprint arXiv:2203.05294, 2022

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