Domain Generalisation with Domain Augmented Supervised Contrastive Learning (Student Abstract)

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Abstract

Domain generalisation (DG) methods address the problem of domain shift, when there is a mismatch between the distributions of training and target domains. Data augmentation approaches have emerged as a promising alternative for DG. However, data augmentation alone is not sufficient to achieve lower generalisation errors. This project proposes a new method that combines data augmentation and domain distance minimisation to address the problems associated with data augmentation and provide a guarantee on the learning performance, under an existing framework. Empirically, our method outperforms baseline results on DG benchmarks.

Introduction

Domain shift is a classical machine learning problem, when the distribution of the training data that the model is calibrated on is different from the distribution of the target data that the model encounters when deployed (Quionero-Candela et al. 2009) (a non-i.i.d problem). Domain generalisation (DG) is a domain shift problem that presumes access to training data from different but related domains, and that aims to construct a robust model that can make accurate predictions on latent target domains (Li et al. 2017).

Data augmentation emerged as a promising alternative for DG, given that adversarial examples can be generated for training at negligible costs (Zhang et al. 2019). However, data augmentation approaches provide no universal guarantee on prediction performance. More precisely, even in i.i.d settings, unsuitable data augmentation can severely impact the test performance. For instance, for the MNIST dataset, (i) augmentations such as vertical/horizontal flipping and excessive rotation may generate unrealistic or even incorrect annotated adversarial examples, and (ii) using such augmented images for training may introduce the label noise issue and further complicate the problem.

Methods to identify augmentation functions that improve test performances have been developed (Cubuk et al. 2019), which involve learning the magnitudes and application probabilities of a set of stochastic augmentation functions that give the best accuracy on the validation dataset. However, such methods are not applicable in a non-i.i.d setting, when the distribution of the validation dataset is not reflective of unseen target distributions. Moreover, for DG problems, data augmentation can violate the necessary conditions (David et al. 2010), by (1) increasing the source-target distance, and (2) violating the invariant labelling assumption.

Methodology

Albuquerque et al. (2019) considered a special case of DG in which the target domain is a convex combination of the target domains. However, the number of target domains that this technique can cover is limited if the convex region of the training domains is small to begin with. Extending on this idea, we include target distributions that can be represented as a convex combination of the training and the augmented training domains (Figure 1).

Figure 1: DASCL framework that combines realistic domain augmentation and domain distance minimisation.
Table 1: Mean and std dev accuracy results (in %) on PACS using Alexnet. Targets are domains withheld from training, sources are the non-withheld domains used for training. The best results are highlighted in bold (up to the decimal value).

| Target | P   | A   | C   | S   | Average |
|--------|-----|-----|-----|-----|---------|
| MMLD   | 88.98 | 69.27 | 72.83 | 66.44 | 74.38   |
| MASF   | **90.68** | 70.35 | 72.46 | 67.33 | 75.21   |
| G2DM   | 88.12 | 66.60 | **73.36** | 66.19 | 73.55   |
| Deepall| 88.89 | 68.14 | 70.19 | 61.07 | 72.06   |
| DASCL  | **89.80** | **71.71** | 71.55 | **72.77** | **76.41** |
| Std.dev | 0.81 | 1.17 | 1.14 | 0.98 | 0.39    |

Table 2: Mean and standard deviation of the classification AUC results (in %) on the Medical dataset using Alexnet.

| Target | Chexpert | Chest14 | Padchest | Average |
|--------|----------|---------|----------|---------|
| Deepall| 76.53    | 85.88   | 83.13    | 81.85   |
| Std.dev| 1.22     | 2.28    | 1.35     | 0.93    |
| MMLD   | 75.40    | 87.70   | 84.99    | 82.70   |
| Std.dev| 2.30     | 1.53    | 0.29     | 1.14    |
| DASCL  | **77.54** | **88.83** | **87.31** | **84.55** |
| Std.dev| 1.15     | 0.92    | 1.21     | 0.62    |

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