Open-Set Domain Adaptation through Self-Supervision

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Abstract

- sentence describing the problem - sentence describing our proposed method - sentence summarising the results - sentence about the variations - sentence about the variation results

1. Introduction

In the computer vision research area large amounts of unlabeled data are available, however the cost of labeling this data is high [3]. Domain adaptation is one technique that can be used to exploit the unlabeled data by first training a model on labeled data from a different but similar domain (the *source* domain), and then applying this model to the unlabeled data (the *target* domain). This technique assumes the distribution of both source and target domains are similar and describe the same class labels, also known as the *closed-set* scenario [1]. When applied to real-word scenarios however it is possible that the target domain includes previously unseen classes, known as the *open-set* scenario. These extra class labels in the target domain will cause performance degradation of the classification model and should be identified and isolated. The problem thus consists of two steps: first separating the target domain into known and unknown samples; then conducting domain alignment between the source domain and the known samples of the target domain.

Self-supervised learning can be used to separate the known class samples in the target domain from the unknown samples. Self-supervised learning involves the transformation of data using a known transform (for example by using image rotation), then training a model to predict the transformation [7]. When used in an object classification task and considering the image rotation transformation, the correct orientation of an object is domain-invariant. In this way the model can be trained to predict the correct orientation of

the image using data from the source domain, then applied to the images of the target domain. If the orientation of a sample in the target domain is predicted correctly then it is considered to be of a *known* class. Contrarily if the orientation is not prediction correctly it is labelled as *unknown*.

Domain adaptation can then be performed between the samples in the source domain and the samples recognized as known in the target domain. When applying domain adaptation to an open-set scenario (Open-Set Domain Adapatation or OSDA) the samples classified as unknown can be treated as a separate class and incorporated into the Closed-Set Domain Adaptation (CSDA) task [2]. The self-supervised rotation task can also be used to reduce the domain shift during this step, using the Rotation-based Open Set (ROS) method developed by Bucci *et al.* [1].

This study investigates the use of a simplified ROS method for object classification on the *Office-Home* dataset [6]. Alternative self-supervised tasks as well as the inclusion of center-loss are also considered and their performance on the object classification task is evaluated.

2. Related Work

Anomaly detection, or outlier/novelty detection, in an open-set scenario can be used to detect samples belonging to the unknown or unseen class. Various different approaches for anomaly detection have been used in the literature as applied to the open-set scenario. Golan and El-Yanic [4] present a method for using geometric transformations to create a self-labeled dataset. In this way the neural classifier learns features that are effective for the detection of anomalies. Sakurada and Yairi [5] on the other hand make use of autoencoders with dimensionality reduction. This method assumes the data have correlations that can clearly separate normal and anomalous samples when reduced to a lower dimensional subspace. After the test data is projected into the subspace it is then reconstructed and the corresponding reconstruction error is used to identify

the anomalous samples.

Not sure if the Sakurada study is relevant to our work

Self-supervised learning... [7], Komodakis,

Domain adaptation ... Calucci, Csurka, Pau

Rotation-based Open Set... [1]

- what's been done in the past on this topic - Summarise each of the cited references - Cite some papers about the variations we did - other variations which might be interesting (but that we didnt do) - if space -

3. Method

- describe in detail the method used - the network used - include the diagrams here and explain them - explain the evaluation parameters that will be used

4. Experiments

- start with parameter tuning of learning rate and epochs, include graph to justify decision - ablation study: hyperparameter tuning of weights and threshold value, include graphs or tables of values

5. Variations

- describe each of the variations - present results of the performance of the model and compare with the baseline for each of the variations

6. Conclusions

- summarise the results - add future recommendations

6.1. Acknowledgements

References

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