CS482/682 Final Project Proposal

Domain-Unsupervised Learning for Image Classification

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1 Proposal

Background Generalizability is mission critical of any machine learning algorithm as the ability to generalize in the presence of varying data distribution aligns with real-world scenarios. Specifically in image classification, domain shift can be challenging for models to overcome. Various techniques have been developed to combat this challenge including domain-adversarial training that enables the model to become adept at extracting domain-invariant features that generalize across different data distributions1, 2. Specifically in this proposal we focus on a domain-unsupervised algorithm that handles domain shift implies greater robustness and usefulness in adopting and implementing the model in practice.

Objective Our goal is to build, validate, and test a domain-unsupervised image classification algorithm that generalize well when faced with domain shift without knowing the other domains exist.

Dataset We will use the Office-Home3, 4 dataset curated by Jose Eusebio et al. This dataset contains roughly 15,500 images of 65 different classes of objects common to most homes and offices. There are 4 domains of images: 1) artistic images, clip art, product images (without background), and real-world images (captured with a camera). We will train the model on a dataset with images obtained from certain modalities, and then test the algorithm with datasets obtained via a modality that was not present in the training dataset. Specific steps are as follows:

1. Use 3 domains (artistic images, clip art, and product images) for training and validation.
2. Split the training dataset into training and validation.
3. Build a preliminary image classification model using supervised learning method.
4. Measure the training performance using loss and accuracy.
5. Measure test performance (loss and accuracy) using the test dataset (real-world images captured by a camera with more noise than images from the other domains)
6. Compare the performance against published models.
7. Fine-tune the architecture and hyperparameters to improve the model performance.
8. Report the final performance measures over training epochs and visualize test predictions. We may also include other comprehensive analysis like PCA of the feature space to illustrate how well the model is able to generalize to new domain.

References

1. Ganin, Yaroslav, et al. "Domain-adversarial training of neural networks." The journal of machine learning research 17.1 (2016): 2096-2030.

2. French, Geoffrey, Michal Mackiewicz, and Mark Fisher. "Self-ensembling for visual domain adaptation." arXiv preprint arXiv:1706.05208 (2017).

3. Venkateswara H, Eusebio J, Chakraborty S, Panchanathan S. Deep hashing network for unsupervised domain adaptation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition; 2017. p. 5018-27

4. Zhang, Youshan, and Brian D. Davison. "Impact of imagenet model selection on domain adaptation." Proceedings of the IEEE/CVF winter conference on applications of computer vision workshops. 2020.