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1 Title:
Unsupervised Domain Adaptation for Semantic Segmentation via Class-Balanced Self-Training

2 Summary:
This paper proposes to use curriculum based self-training to achieve unsupervised domain adaptation. In alternation, pseudo labels are predicted on target samples, and network is trained using these predicted pseudo-labels. Curriculum is embedded into the loss function through a sparsity term, in that the loss function encourages pseudo-labels with high confidence, and the pseudo-labels are obtained by solving an IPP on this loss. Further, a class balancing term is proposed to tackle class imbalance, and a spatial prior is proposed to incorporate spatial domain knowledge. Promising quantitative and qualitative results are presented on semantic segmentation tasks.

3 Strengths:
i) An implicit domain adaptation is achieved without requiring adversarial losses or distribution matching. The loss function is simple and straight-forward and in line with the intuition in deep learning that simplest things often work the best. ii) Spatial prior formulation as frequencies at spatial location and its injection into the loss function as a negative logarithm is very intuitive and applicable across many semantic segmentation methods. iii) Adding a simple negative L1 term on pseudo-labels in the loss function allows to implicitly select high-confidence samples is applicable across tasks such as active learning, domain generalization. iv) The ablation studies are very clear

4 Weaknesses:
i) A single parameter k controls the sparsity of selected samples. While this is desirable, the the selection algorithm proposed is merely heuristic and further analysis is required for wide-spread applicability of this method. ii) A major assumption about positive correlation between confidence and accuracy is made. This is not always valid, especially when the domain shift is large. An analysis on the relation between confidence of predictions and accuracy should have been provided or cited. iii) During training, solving an IPP after each mini-batch is computationally expensive. Convergence is also not discussed.

5 Analysis of Experiments:
i) Most improvement is obtained after incorporating class balancing term, as opposed to the self-training term in Table 1. and Table 2., m. This indicates class imbalance in more prominent than domain shift in these tasks (CityScapes->NTHU, SYNTHIA->CityScapes) ii) Table 3. shows huge improvement with self-training and further improvement upon introducing class balance and spatial prior terms on GTAV->CityScapes validating paper's hypothesis. iii) Table 4. and Table 5. show marked qualitative improvement in results.

6 Possible Extensions:
i) A more systematic approach to estimate confidence of predictions using Bayesian Neural Networks can be used to impose a curriculum instead of assuming the soft-max to represent true probabilities. ii) Explicit domain adaptation in conjunction with proposed self-training mechanism is an interesting direction to explore. Self-training acts as a regularizer to the distribution matching terms. .