Paper: Multi-Anchor Active Domain Adaptation for Semantic Segmentation

1. What problem does this paper try to solve, i.e., its motivation

The Motivation for this paper comes from challenges which are associated with unsupervised domain adaptation (UDA) in semantic segmentation. Semantic Segmentation require a large amount, this paper aims to reduce this problem by using UDA where model trained on synthetic data will be used on real time data without any extensive manual annotation. Regular UDA methods force target domain data to fit source domain data which can distort the information of target domain.

2. How does it solve the problem?

Proposed method is divided into 2 steps. First active target sample selection based on multiple anchors of the source domain and then semi-supervised domain adaptation by a novel multi-anchor soft alignment loss.

To create anchors vectors from different categories are concatenated into a single vector for each image and then clustering is performed. The centres of these clusters are called as anchors and are used as the source domain clusters against which the target will be compared for active sample selection.

Measure the distance between the target-domain samples and the source-domain anchors. If the distance is high then it will contain target domain specific information. These are selected as active target samples and then we manually annotate them to learn about the target domain.

These annotated samples are then added to training which will help to learn exclusive information on target domain. After training the model on both active target sample and labelled source samples, it gets an improvement in performance.

The model is then used to computer pseudo labels on unlabelled target domain samples and target domain anchors. As anchors are just a estimation they are corrected dynamically but clusters might change drastically so they use exponential moving average which prevents sudden changes that could destroy training process.

Combine the source data, labelled target samples, unlabelled target samples for semi supervised training. The paper has proposed a soft alignment loss, minimizing of it will allow the features of target samples to align more closely with anchors. Pseudo labels previously made are also added to the supervision.

MADA shows improvement over traditional unsupervised domain adaptation methods and achieve a high performance with less manual annotation. This method surpasses Active Domain Adaptation Approach by 5.6% confirming that multi anchor strategy is better.

3. A list of novelties/contributions

This paper is the first to integrate active learning into domain adaptation for semantic segmentation. With little

This paper also proposes the use of multi anchors to represent source's multimodal distribution with help of clustering-based method which allowed to find the target domain samples which are totally opposite of the source domain samples.

Soft Alignment loss is introduced to align target sample to target anchors which notably improved the segmentation process.

4. What do you think are the downsides of the work?

This methodology depends too much on the accuracy of clustering algorithms. If clustering algorithms were not able to capture clusters, then it will after the selection of target anchors and overall model performance. Different clustering algorithm may give different results. Introduction of novel soft alignment loss and multiple anchors add a layer of complexity to the method. The implementation may get more challenging.

Paper: Compute-Efficient Active Learning

1. What problem does this paper try to solve, i.e., its motivation

This paper aims to solve the computational problems which come with dealing with large dataset. Active Learning paves a way to reduce the labeling cost but it comes with requirements of computational resources which affects the scalability and efficiency negatively.

2. How does it solve the problem?

This function mainly focusses on using historic evaluation values from previous acquisition function to help for creating the subsamples. Each epoch involves selection of data points which is done on basis of score by acquisition function in the past. If the score previously was high then they might contain important information which might increase model's learning and accuracy.
The research also shows that samples can be removed from the unlabeled dataset which have very low acquisition value. This reduces the computational requirement and also reduces the need of storage for the dataset.
Instead of focusing on the whole dataset, it will now focus on "candidate" pool which is created based on past acquisition. The reduced set of data points optimizes the model by prioritizing on the samples that are expected to enhance the performance.
Proposed method for candidate pool acquisition is made general and is suitable for regression problem besides classification. Paper mentions flexibility with different algorithms for subsampling strategy such as Shannon entropy with MC Dropout and Variation Ratios, ensemble score, BALD.
In this way proposed method reduces the computational load required for active learning by focusing on reduced candidate pool.

3. A list of novelties/contributions

The paper presents a novel subsampling technique which uses historical acquisition function evaluation to create subsamples from the original dataset which helps in reducing storage demands and computational burden.
The proposed method is versatile and can be incorporated with various different known acquisition functions like BALD, ensemble scores.

4. What do you think are the downsides of the work?

The approach is too much reliable on historical data. This would work only if historical data do not change drastically such that it will help the prediction of future values. In rapidly changing applications and its dataset this method might not be able to work accurately.
If the dataset is not diverse and very small then creating the candidate pool from original dataset based on acquisition function could potentially miss out informative samples.

Paper: Learning Loss for Active Learning

1. What problem does this paper try to solve, i.e., its motivation
The paper states that recent methods which have proposed active learning for their deep learning application is specific to their target tasks or computationally expensive for large networks. This motivated them to propose active learning method which works with deep learning and can be applied across various task without requiring task specific design.

2. How does it solve the problem?
The process begins with unlabeled data from which human annotate a smaller dataset and creating initial labeled dataset. A loss prediction module is attached to target model. After the initial training, model is evaluated on unlabeled dataset and with loss prediction module. Then a human annotates the points with highest losses. This cycles repeats until satisfactory results are obtained.
Loss Prediction Module:
It is attached with the target model and learns with it so as to remove the need for another learning stage for it. It is smaller than the target module to reduce the computational cost. Features maps are extracted from various hidden layers of the target model and allowing the module to consider only the necessary information to calculate the accurate loss prediction.
Learning Loss:
The target model generate prediction and loss prediction module predicts the loss for each data point. During the learning two losses are calculated. The target loss is calculated using target model prediction and label of the point. The loss prediction loss is calculated using predicted loss from loss prediction module and target model loss. This helps in training of the loss of the data points. The final loss is calculated by combining target loss and scaled loss prediction loss. Initially authors considered using mean squared error but found it unsuitable because of changing scale of real loss during the training. When tried to minimize MSE they failed to create a good loss prediction module. They used method that compares the pair of samples allowing the loss prediction module to focus on relative differences between prediction rather than absolute values. This approach adapt to change in scale of target model loss during learning. This help to identify the most informative data points for annotation and which in turn helps the accuracy of active learning process.
This approach is then tested with various tasks and compared with entropy based sampling, random sampling and core set sampling:
Image Classification(Dataset CIFAR-10, Model ResNet-18): The proposed method does better than other methods.. It achieves an accuracy of 91.01%
Image Classification(Dataset PASCAL VOC 2007 and 2012, Model Single Shot Multibox Detector (SSD) with a VGG-16 backbone): It achieves a mean average precision of 73.38% compared to 72.22% and 71.71% of entropy and core set methods.
Human Pose Estimation(Dataset MPII Human Pose, Model Stacked Hourglass Networks): At the end of cycle the proposed method attains 80.46 Percentage of Correct Key-points as opposed to 78.99 and 79.85 compared to entropy and core set method.

3. A list of novelties/contributions

This paper presents loss prediction module which allows the predict loss of unlabeled data points and allowing us to identify the important data points.

They proposed a method which is task agnostic as previously only target specific.

4. What do you think are the downsides of the work?

The paper proposes the usage of data points solely based on predicted losses and does not take into consideration the characterstic of data like diversity or density. This could potentially drop the effectiveness of the method.