Summary

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Task-Aware Variational Adversarial Active Learning

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Deep learning requires large amounts of data to train properly and the high cost of labeling entire datasets have created an urgent need for more efficient learning algorithms. *Active learning (AL) aims to improve learning by querying the most informative samples to be annotated unlabeled pool*. Existing AL methods can be categorized into two main groups, *task-agnostic* and *task-aware*. In this paper, the authors propose a novel method that combines the two approaches and is able to achieve state-of-the-art performance on multiple classification benchmarks.

Task-agnostic (or distribution-based) methods rely on distribution of labeled or input data, $P(x)$ to identify *influential data points*. Such techniques query samples in high-density regions and are good for learning distribution of standalone clusters but they do not make any determination on input-output depency. This becomes particularly important in classification tasks where there is always the possibility of partial distribution overlap among latent space variables from different classes.

Task-aware (or model uncertainty-based) methods address this limitation by modeling such dependence, e.g. via estimating the conditional distribution $P(y|x)$. Such methods identify *difficult data points* by querying samples from high uncertainty regions, e.g. overlapping or boundary regions. Task-agnostic methods do not exploit structures from tasks and task-aware methods do not seem to well-utilize overall data distribution. Recently, SRAAL introduced a method that combines task-aware and task-agnostic approached with a uncertainty indicator and with a unified representation for both labeled and unlabeled data [1]. Even though SRAAL achieved state-of-the-art performance, it did not use information directly about the task [2] and its learner seems to be limited to only VAE-type networks with a latent space for its unified representation.

In this paper, the authors propose a novel method which builds upon variational adversarial active learning [3] and utilizes [2] to exploit the structure $P(y|x)$ of the problem at hand. Moreover, the authors, 1) propose to relax the goal of loss prediction module from accurate loss prediction to loss ranking prediction [4]. 2) Introduce *Task-Aware Variational Adversarial Active Learning* (TA-VAAL) to embed the normalized ranking loss information from any given task learner (with or without latent state representation). 3) Demonstrate state-of-the-art performance over Learning Loss [2], VAAL [3], Coreset [5], Monte-Carlo dropout [6] on CIFAR10, CIFAR100, Caltech101, imbalanced CIFAR10, and on Cityscapes semantic segmentation benchmark dataset.

Learning Loss Ranker Based on [2], it trains to predict relative rankings of losses instead of predicting the actual losses. The loss rankings are then embedded into the latent space of VAAL with the conditional latent variable r. Moreover, the ranker estimator is a smooth differentiable function with nice convergence properties for optimization.

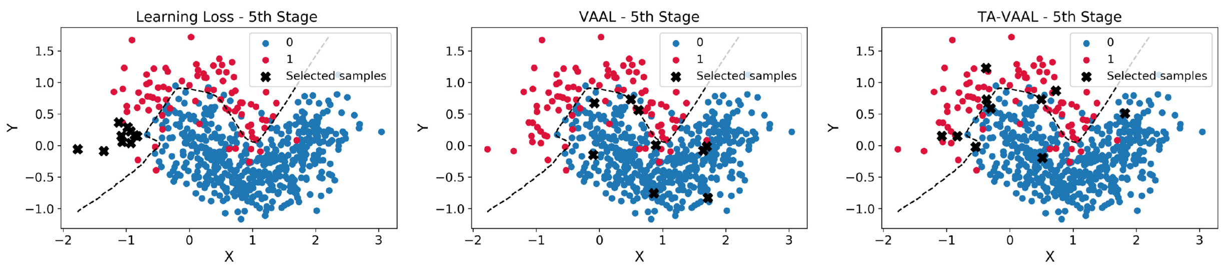

Figure 1: Visual results of active learning methods (Learning loss [40], VAAL [31], our TA-VAAL) on imbalanced toy example at the 5th stage. *Red* and *blue* dots indicate samples assigned to class 0 and 1, respectively. Ten samples at that stage (denoted by *black* cross) were selected using each method. The oracle decision boundary of the model is shown as a black dash line. Learning loss identified difficult samples near the decision boundary and VAAL found influential samples over the entire set. Our TA-VAAL selected samples that are both difficult (near decision boundary) and influential (over the entire set).

Figure 1

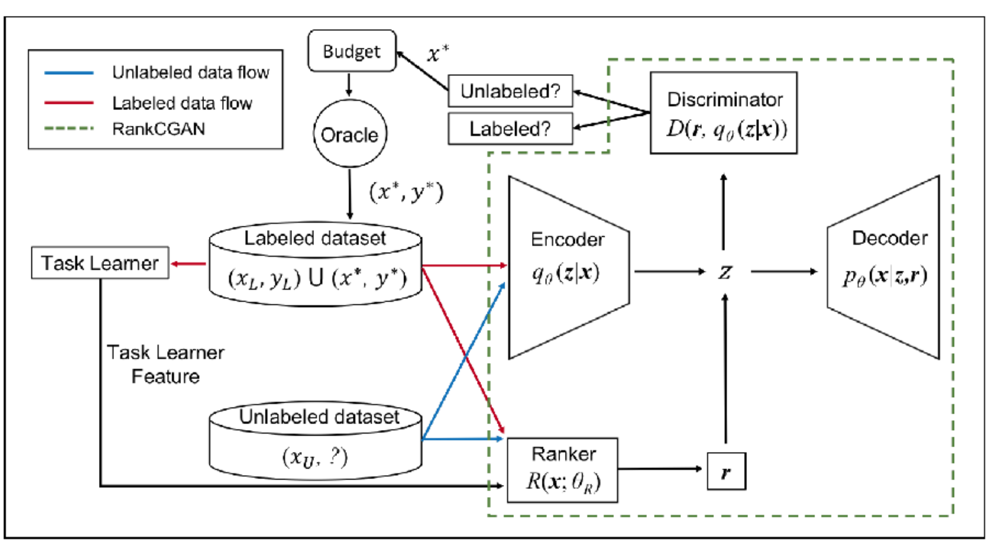

Figure 2: TA-VAAL

References

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