

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 the distribution of standalone clusters but they do not make any determination on input-output dependency. 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 an 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.

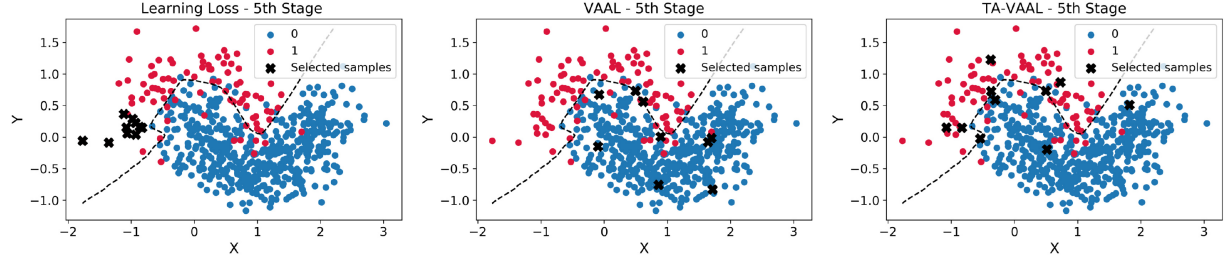


Figure 1: Visual results of active learning methods (Learning loss [40], VAAL [31], our TA-VAAL) on imbalanced toy example at the 5th stage. *Red* and *blue* dots indicate samples assigned to class 0 and 1, respectively. Ten samples at that stage (denoted by *black* cross) were selected using each method. 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

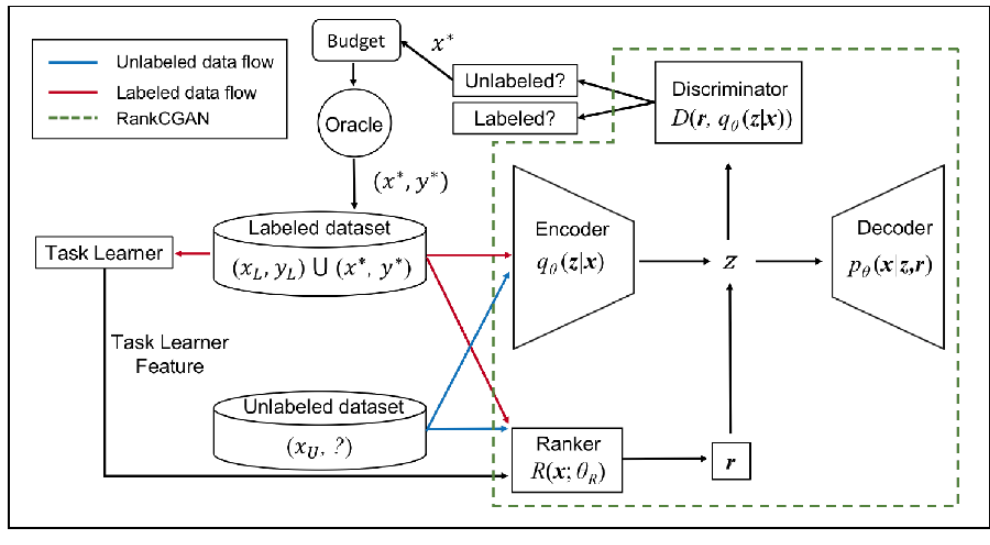


Figure 2: TA-VAAL

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