**TL;DR**

- We propose a loss measurement **Temporal Output Discrepancy (TOD)** to estimate the loss of unlabeled samples.
- We demonstrate TOD is a lower-bound of accumulated sample loss.
- Based on TOD, we develop an unlabeled data sampling strategy and a semi-supervised learning scheme for active learning.

**Background**

- **Active learning (AL)** aims to interactively query a human annotator oracle to annotate a small proportion of informative samples in an unlabeled dataset.
- We focus on uncertainty-aware AL, which selects the most uncertain samples in context of a learned model.

**TOD: An Effective Loss Estimation Method**

- **Temporal Output Discrepancy (TOD):** The discrepancy of outputs of a neural network at different GD iterations.

\[
D^{(T)}_t(x) \triangleq \| f(x; w_{t+T}) - f(x; w_t) \|
\]

- **Why TOD measures the sample loss?**
  i) Firstly, connecting one-step TOD to sample loss \( L(x) \):
  \[
  D^{(1)}_t(x) \leq \eta \sqrt{2L(x)} \| \nabla_w f(x; w_t) \|^2
  \]
  ii) Then for \( T \)-step TOD, we have
  \[
  D^{(T)}_t(x) \leq \sqrt{2} \eta \sum_{t=1}^{T} \left( \sqrt{r_t} \| \nabla_w f(x; w_t) \|^2 \right)
  \]
  iii) Let gradient norm of \( f \) be upper-bounded by a constant \( C \),
  \[
  D^{(T)}_t(x) \leq \sqrt{2T} \eta C \sum_{t=1}^{T} \sum_{t=1}^{T} r_t(x)
  \]

Thus, TOD is a lower bound of square root of accumulated loss \( L(x) \) during \( T \) GD iterations.

**TOD-based Active Sampling Strategy**

- We further propose an unlabeled data sampling strategy, named **Cyclic Output Discrepancy (COD)**, for active learning. COD estimates the sample loss by measuring the distance of model outputs between two consecutive active learning cycles.

**TOD-based Semi-Supervised Active Learning**

- We propose a TOD-based unsupervised loss to minimize the distance between the current task model and a baseline model. The parameters of baseline model is an exponential moving average of historical model parameters.

\[
L(x) = \text{task loss} + \text{unsupervised loss}
\]

- The optimization objective of semi-supervised AL consists of task loss and unsupervised loss .

**Experiments**

- **Performance:** TOD-based AL methods perform well on various image classification and segmentation datasets.

**Study on Active Sampling:**

- COD-based active sampling strategy outperforms existing AL methods.

**Study on Semi-Supervised Learning:**

- (i) SSL can improve AL performance; (ii) TOD is effective for SSL.

**Efficiency:**

- COD is more efficient than previous AL methods, as it only relies on task model and does not introduce extra models.

**Table 1:** Active sampling efficiency.

<table>
<thead>
<tr>
<th>Method</th>
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<th>SVHN</th>
<th>Caltech-101</th>
<th>Extra</th>
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<th>VAAL (ICCV’19)</th>
<th>LL4AL (CVPR’19)</th>
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</tr>
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<td>91.4s</td>
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<td>13.0s</td>
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<td>7.2s</td>
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**Study on SSL methods.**

**Table 2:** Study on SSL methods.

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**Fig.2:** COD values are consistent with the real loss values.

**Fig.3:** Semi-supervised AL.

**Fig.4:** AL performance of image classification datasets. Blue solid/dashed lines denote our method with/without semi-supervised training.

**Fig.5:** Study on active sampling.

**Fig.6:** Study on SSL methods.

**Code**

https://github.com/siyuhuang/TOD

**Contact**

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