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Uncertainty-aware complementary label queries for active learning

Key words: Active learning; Image recognition; Weak supervised learning

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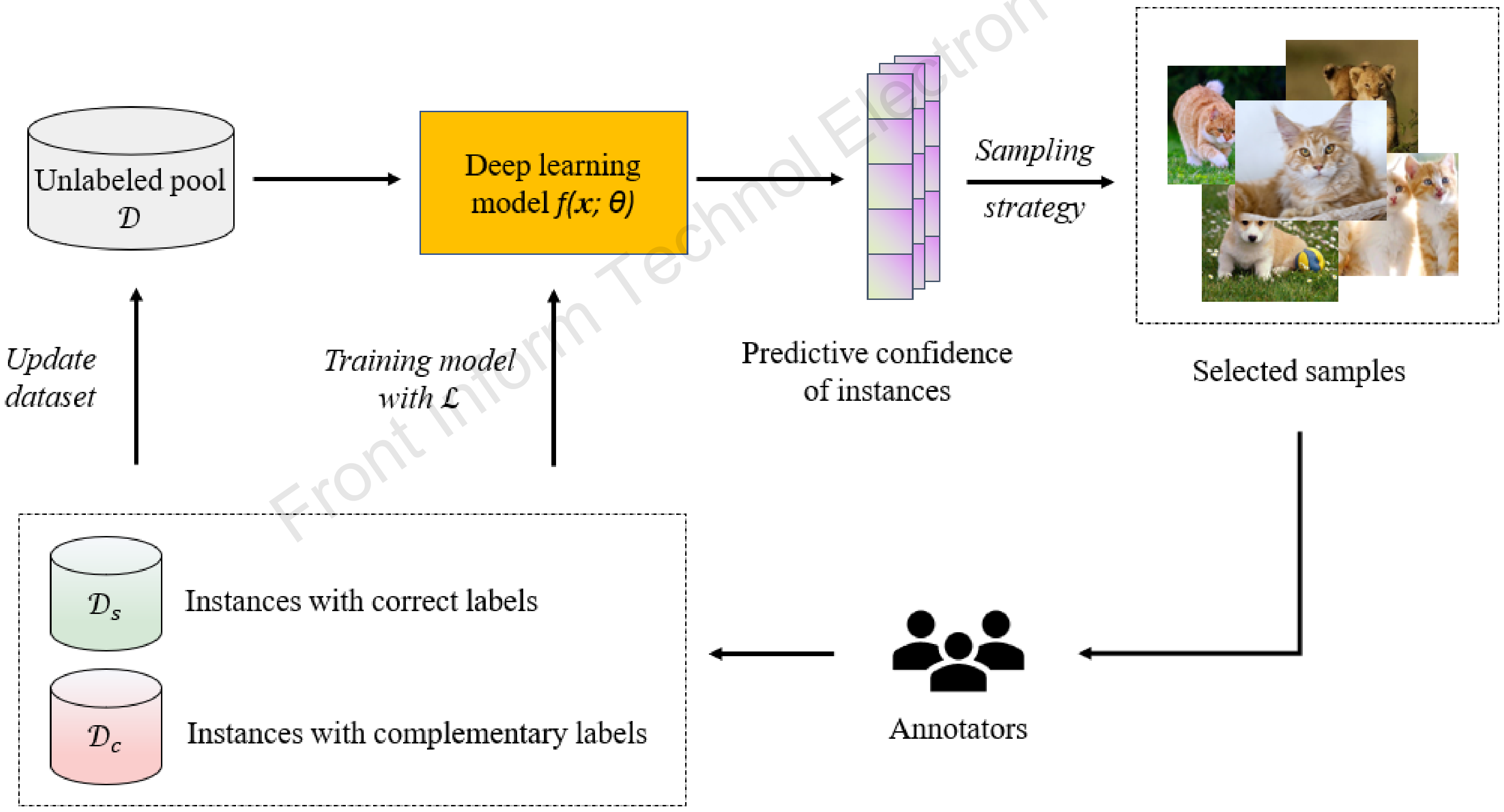
Motivation

1. Many classic active learning (AL) methods try to cut the annotation costs indirectly by minimizing the number of annotation actions. However, we try to cut the annotation costs directly by reducing the costs of a single annotation action.
2. Some other AL methods need strong labelers or extra prior knowledge. However, we plan to obtain weak annotation from only weak labelers without extra prior knowledge.
3. Existing complementary labels learning methods need strict assumption, so we combine AL and complementary labels learning to solve this issue.

Method

Flowchart of active learning with complementary labels (ALCL)



Method

Workflow for an ALCL learner

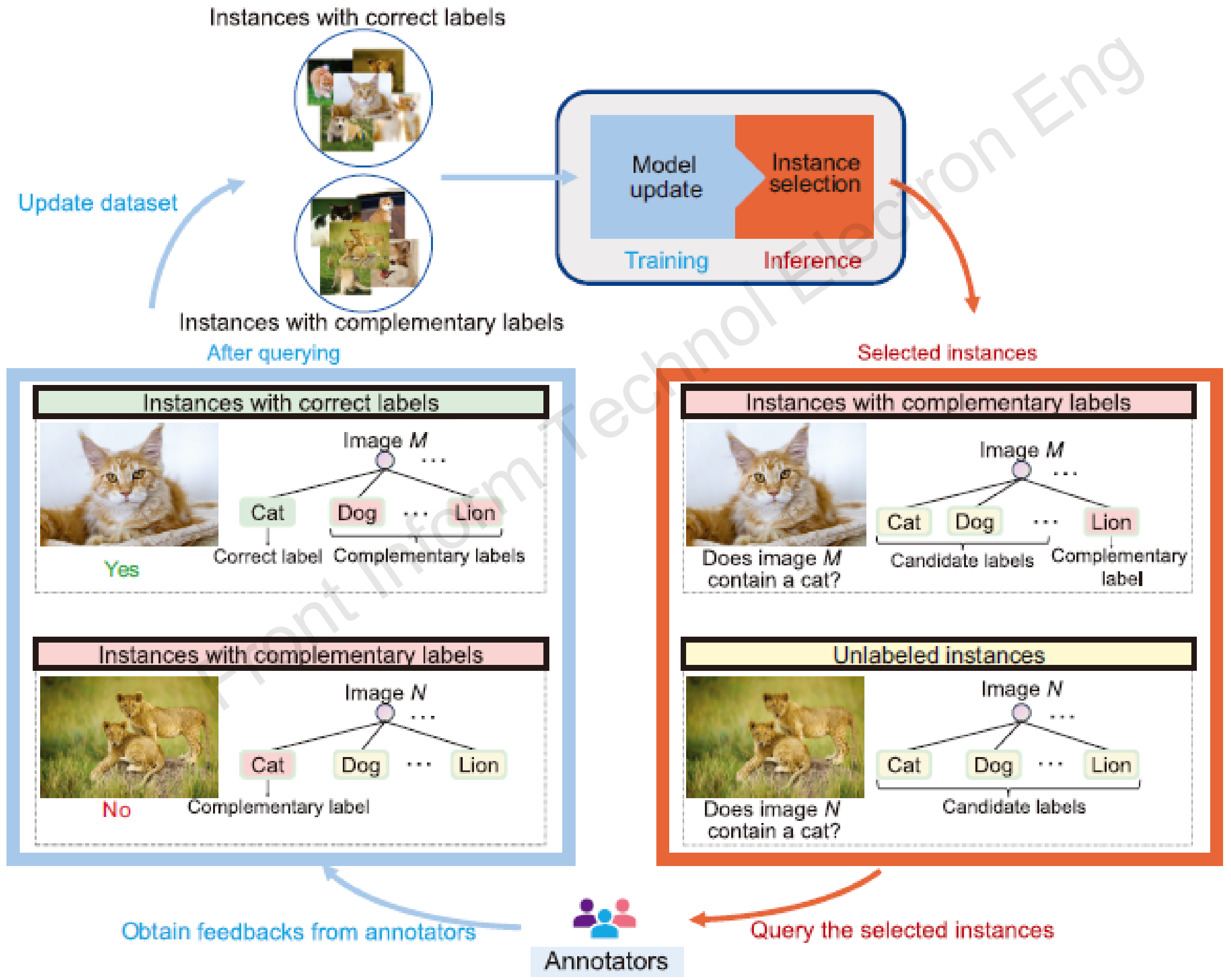


Fig. 2 Workflow for an ALCL learner (ALCL: active learning with complementary labels)

Experiments

The performance of uncertainty for sampling and deep learning (USD) with different ALCL methods

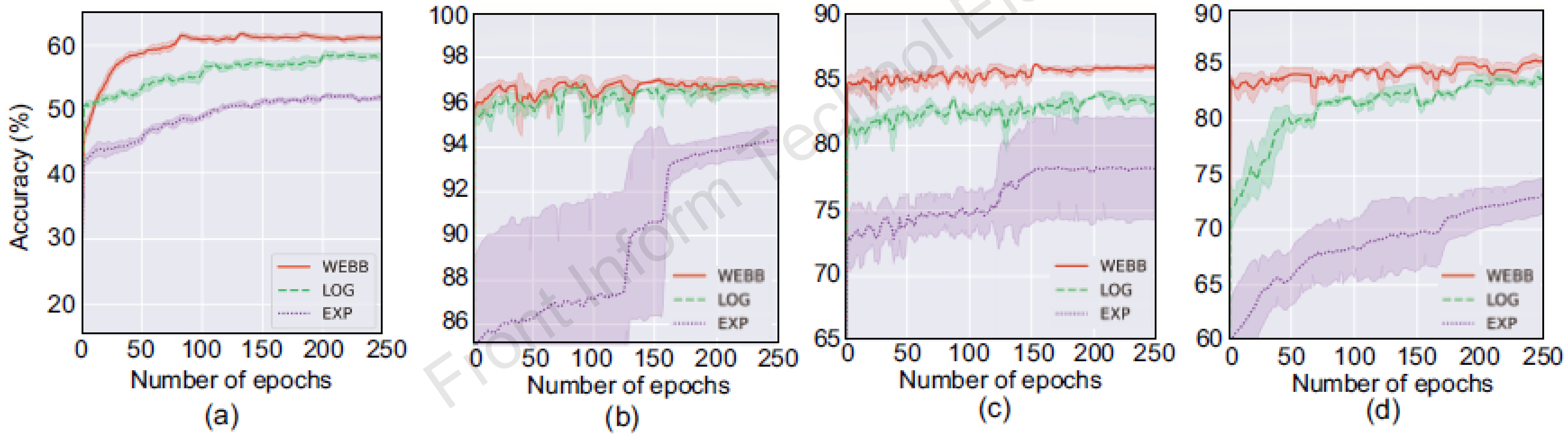


Fig. 3 Experimental results across diverse datasets and models with varied sampling strategies: (a) CIFAR-10; (b) MNIST; (c) Fashion-MNIST; (d) Kuzushiji-MNIST. Dark colors represent the average accuracy derived from the five trials, while light colors denote the corresponding standard deviation

Method

Sampling strategy USD and the comparison with other methods

$$\mathcal{L}_u(x,y) = \frac{1}{\sigma^2(x)}\mathcal{L}(x,y) + \log\sigma^2(x)$$

$$\mathcal{L}_{1u} = \frac{1}{K}\sum_{i=1}^{n}\sum_{k=1}^{K}\frac{w_{ik}}{\sigma^2(x_i)\sum\limits_{j=1}^{n} w_{jk}}\left(-\log\sum_{m\notin Y_i} p(m|x_i)\right) + \sum_{i=1}^{n}\log\sigma^2(x_i), \qquad (3)$$

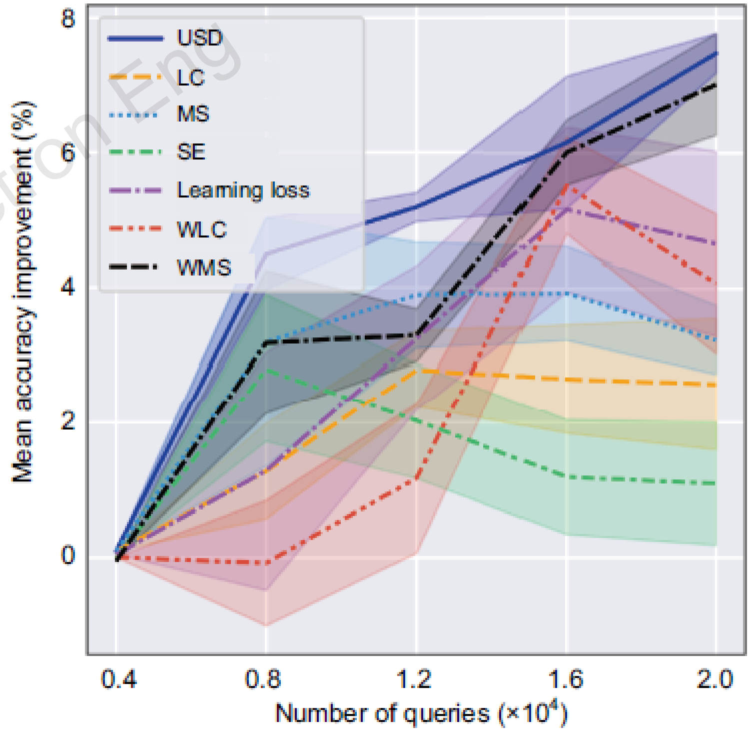


Fig. 4 Mean accuracy enhancements with standard deviation (denoted by shading) of active learning methods compared to the random sampling baseline, across the number of queries on CIFAR-10. Dark colors represent the mean accuracy of the five trials, while light colors indicate the standard deviation. The loss function used in these trials is from WEBB

Conclusions

1. We expound the motivation of ALCL and design the framework of ALCL learner.
2. We design a sampling strategy USD, which uses the uncertainty to guide the queries of active learning, and we upgrade some existing methods.
3. Comprehensive experimental results validate the performance of our method.

Shengyuan LIU received his BS degree in computer science and technology from Zhejiang University, Hangzhou, China, in 2021. He is currently pursuing his MS degree in computer science and technology at Zhejiang University. His research interests focus on diffusion model and artificial intelligence generated content.

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