Supplementary Material of Bidirectional Uncertainty-Based Active Learning for Open Set Annotation

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1 Additional Details for Methodology

Similar to *Figure 5* in the main paper, we present the t-SNE visualization results for the other four known categories in Figure 1 to further corroborate the effectiveness of RLNL. We can notice that the unknown class examples are in a region far from each category, and empirically neural networks are prone to give overconfident outputs for data in that region.

2 Additional Details for Experiments

Figure 2 presents the variation curves for the classification accuracy of B-Margin and comparison methods on CIFAR-10 (first column), CIFAR-100 (second column), and Tiny-Imagenet (third column) under an openness ratio of 0.2 and 0.8, respectively. In Figure 3, we just change Margin and B-Margin to LC and B-LC respectively, and show complete variation curves with openness ratios of 0.2 (first row), 0.4 (second row), 0.6 (third row), and 0.8 (fourth row). Similarly, we also show the corresponding results for Entropy and B-Entropy in Figure 4. From these experimental results, we can observe that, in the open-set scenarios, measuring sample uncertainty based on margin metric tends to perform better compared to the least-confident metric and entropy metric. Compared to the comparing methods, B-LC and B-Entropy still achieve the best results in most cases. The conclusions that can be drawn are consistent with our main paper.

Figure 5 shows the average recognition rate for known class examples across queries and openness ratios on CIFAR-10 (first column), CIFAR-100 (second column), and Tiny-Imagenet (third column). Here, we first change Margin and B-Margin to LC and B-LC and show the results in the first row. Then, we change to Entropy and B-Entropy and show the corresponding results in the second row. Here, the results are similar to the B-Margin in our main paper. Therefore, the conclusions reached are also consistent.

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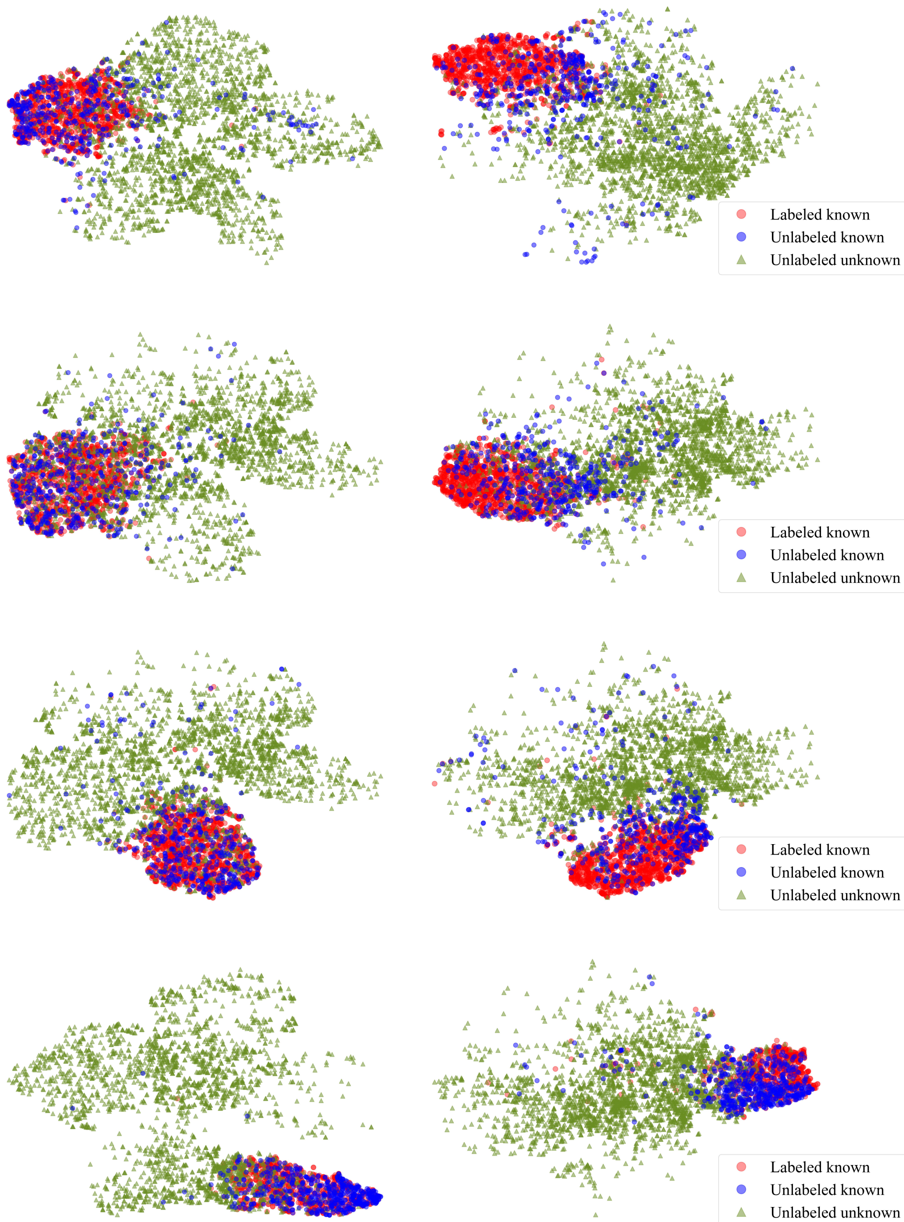

Fig. 1: The t-SNE feature visualization of labeled data, unlabeled known class data, and unlabeled unknown class data on CIFAR-10 with an openness ratio of 0.5 before and after performing RLNL. Each line corresponds to a known category, with the results before performing RLNL on the left side and after on the right side.

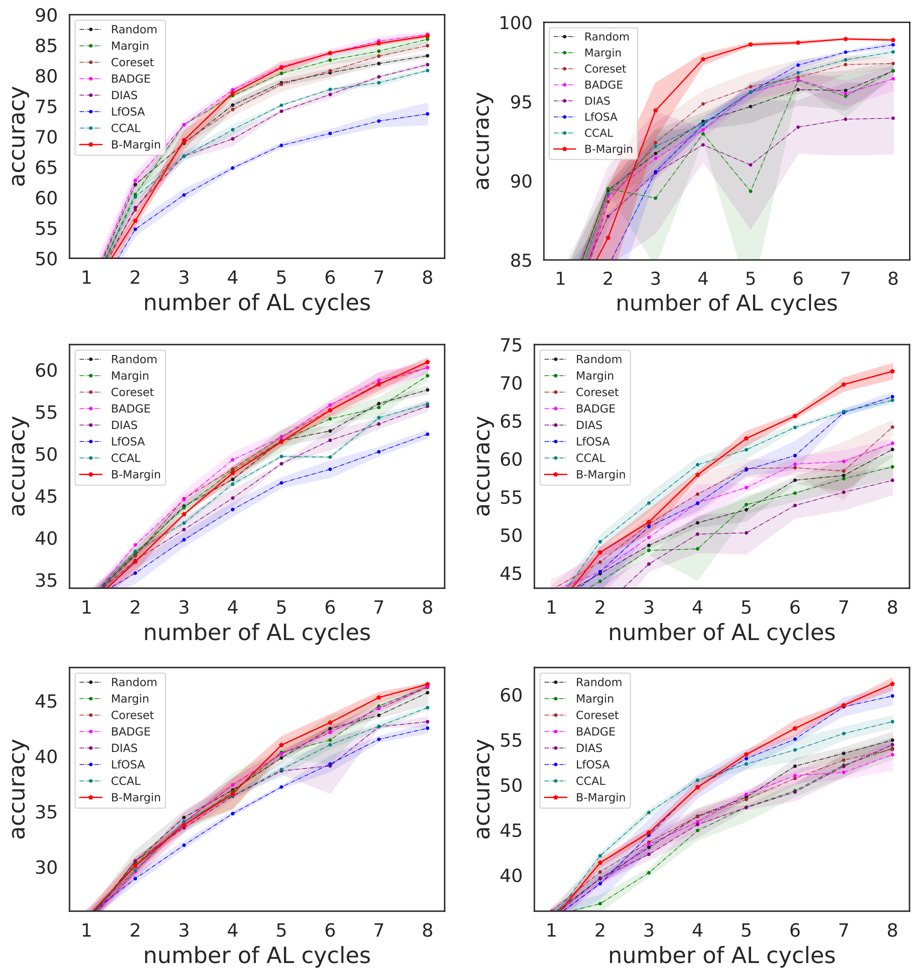

Fig. 2: Accuracy comparison on CIFAR-10 (first row), CIFAR-100 (second row), and Tiny-Imagenet (third row). The ratio of unknown class examples to the total number of examples is fixed at 0.2 (first column) and 0.8 (second column) for each dataset.

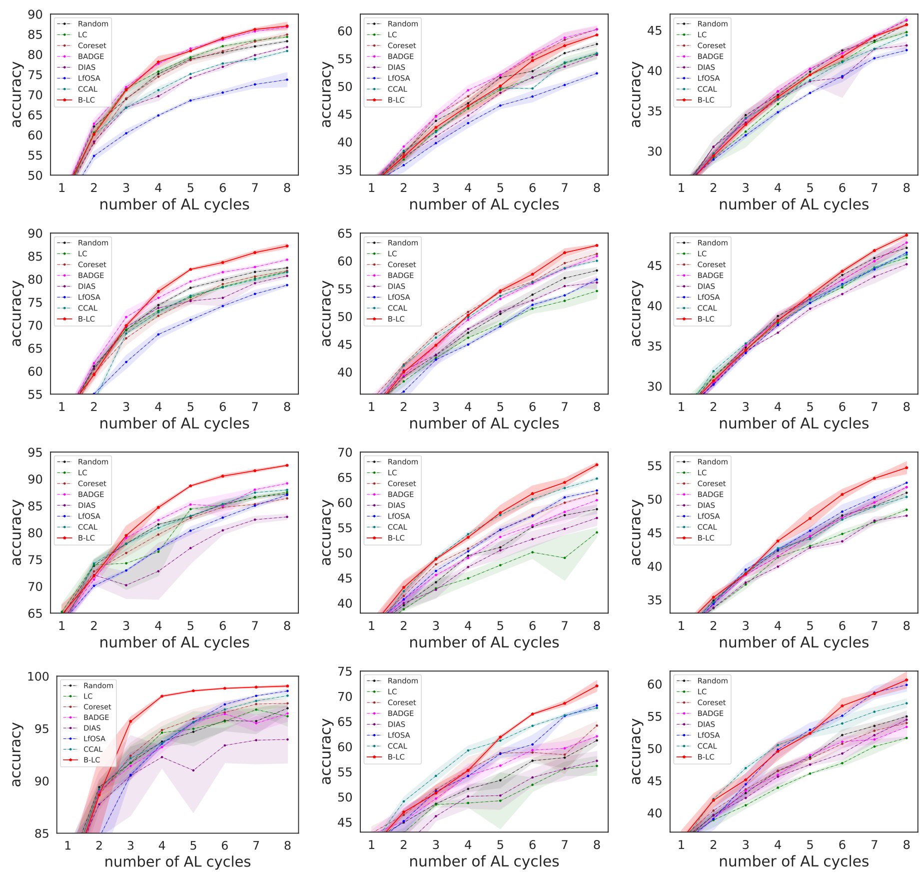

Fig. 3: Accuracy comparison on CIFAR-10 (first column), CIFAR-100 (second column), and Tiny-Imagenet (third column). We change Margin and B-Margin to LC and B-LC, respectively. The ratio of unknown class examples to the total number of examples is fixed at 0.2 (first row), 0.4 (second row), 0.6 (third row), and 0.8 (fourth row) for each dataset.

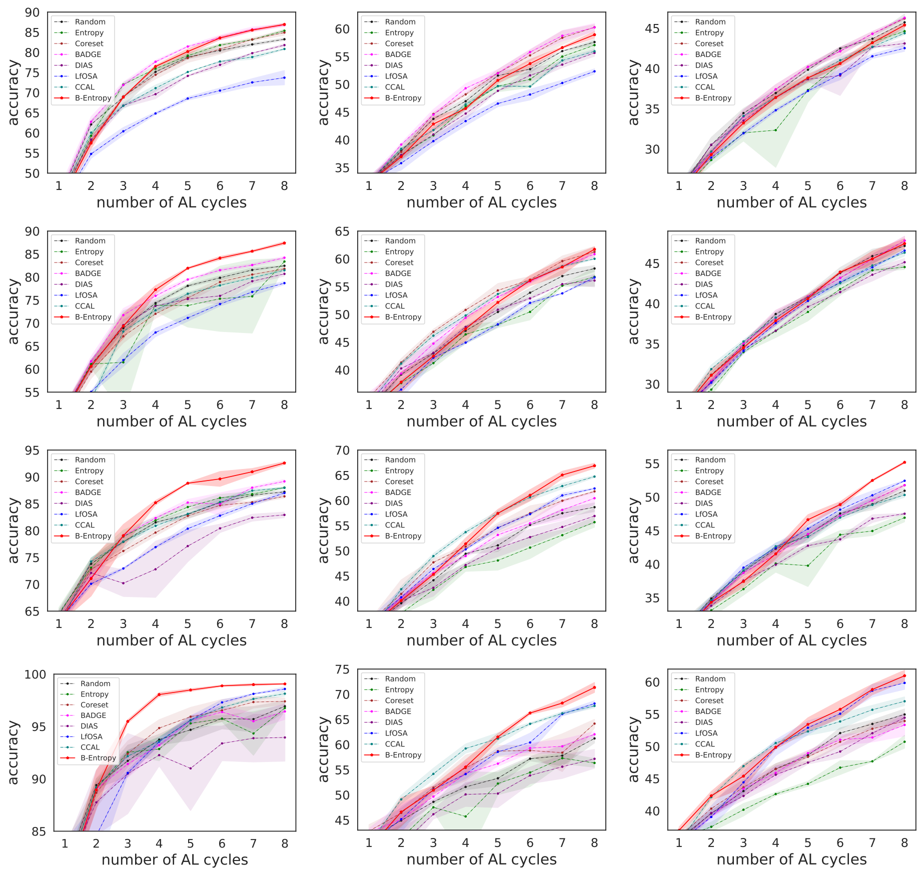

Fig. 4: Accuracy comparison on CIFAR-10 (first column), CIFAR-100 (second column), and Tiny-Imagenet (third column). We change Margin and B-Margin to Entropy and B-Entropy, respectively. The ratio of unknown class examples to the total number of examples is fixed at 0.2 (first row), 0.4 (second row), 0.6 (third row), and 0.8 (fourth row) for each dataset.

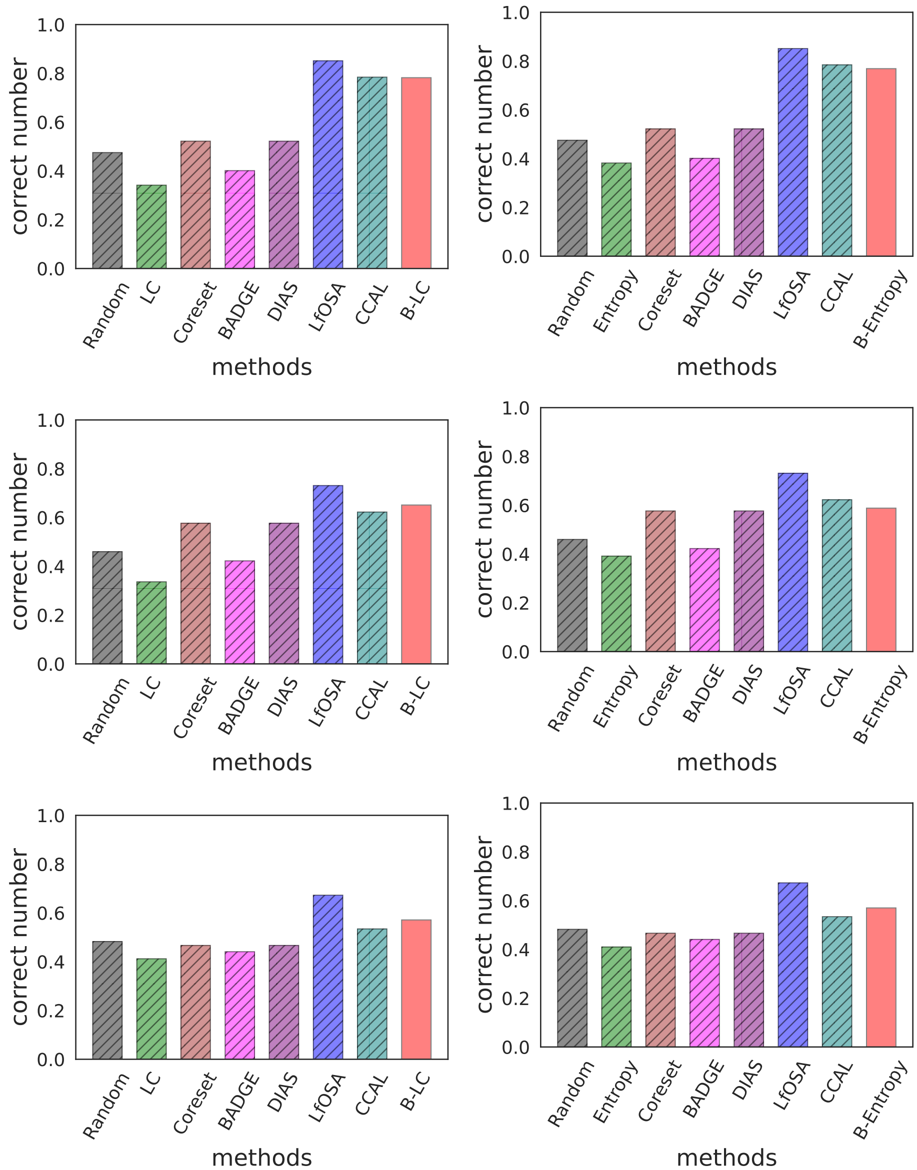

Fig. 5: The average recognition rate on CIFAR-10 (first row), CIFAR-100 (second row), and Tiny-Imagenet (third row). We change Margin and B-Margin to LC and B-LC in the first column, and to Entropy and B-Entropy in the second column.