A More Robust Baseline for Active Learning by Injecting Randomness to Uncertainty Sampling

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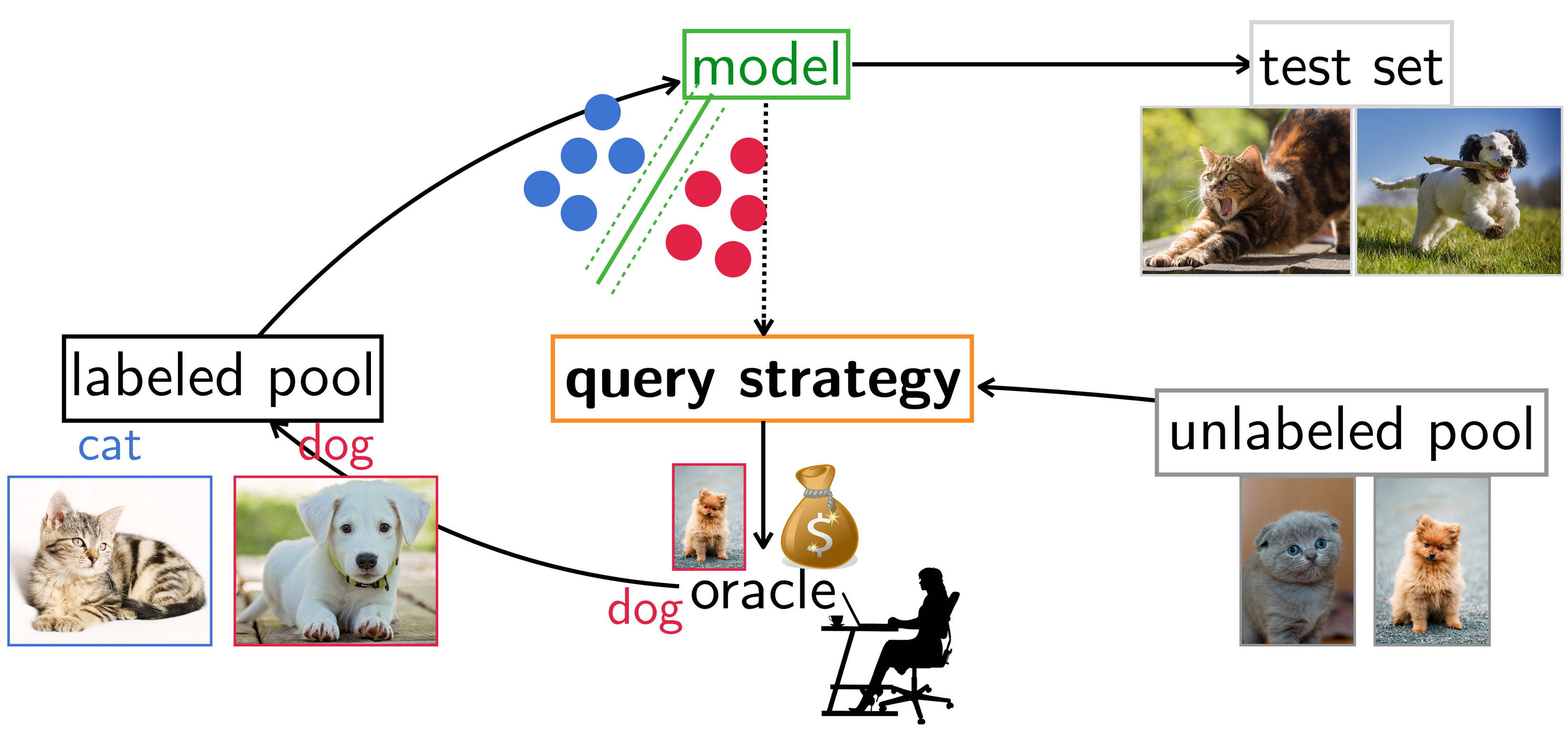
Pool-Based Active Learning

- Small labeled pool & large unlabeled pool.
- A machine learning model.
- Expensive experts for annotating.
- **Query strategy** effectively annotates unlabeled examples to improve test performance.



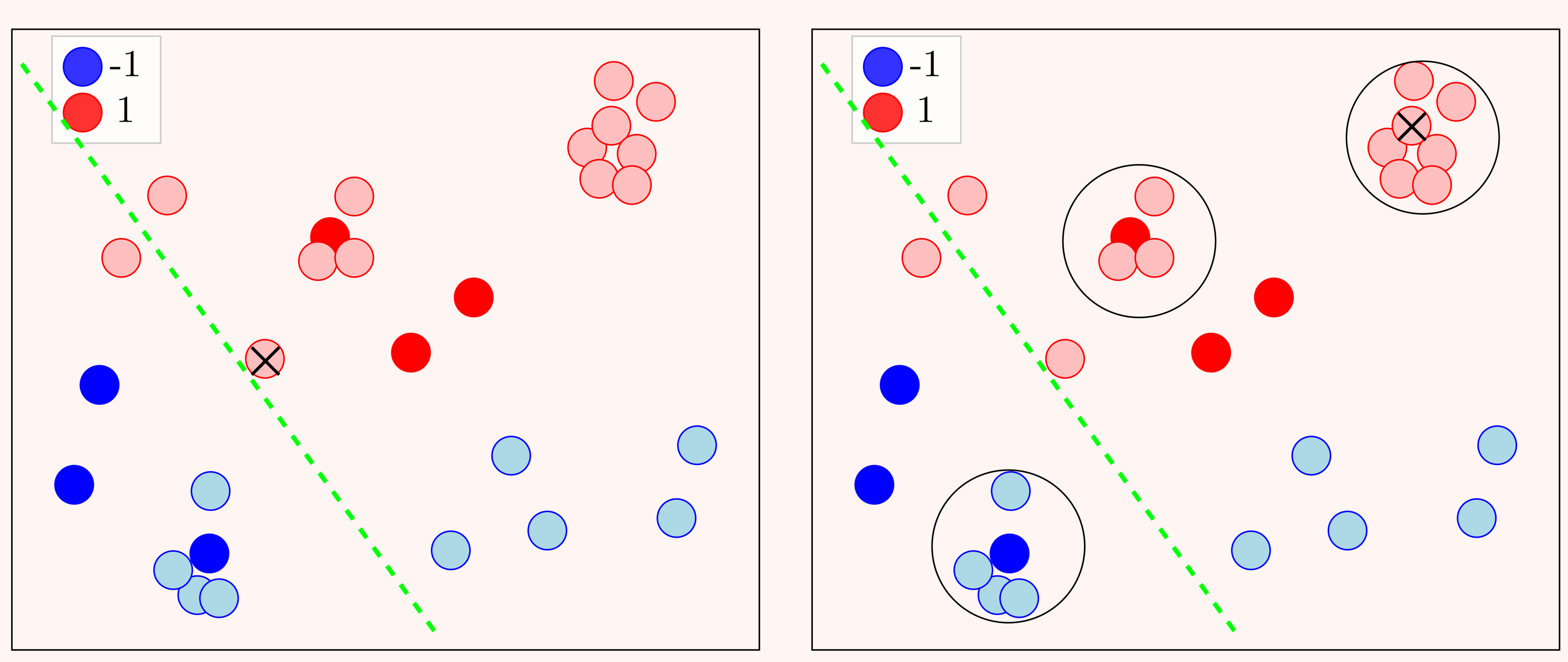
Motivation

Goal in the research community. 'Good query strategy' outperforms random sampling (RS).

➽ Previous experience. Uncertainty sampling (US) is a strong baseline.

Challenge in practical usage. US fails in sampling bias.

➽ Current solutions. Design sophisticated query strategies, e.g., Core-Set, DWUS, QUIRE, HintSVM.
➽ However, sophisticated query strategies still fail to overcome this problem comprehensively.

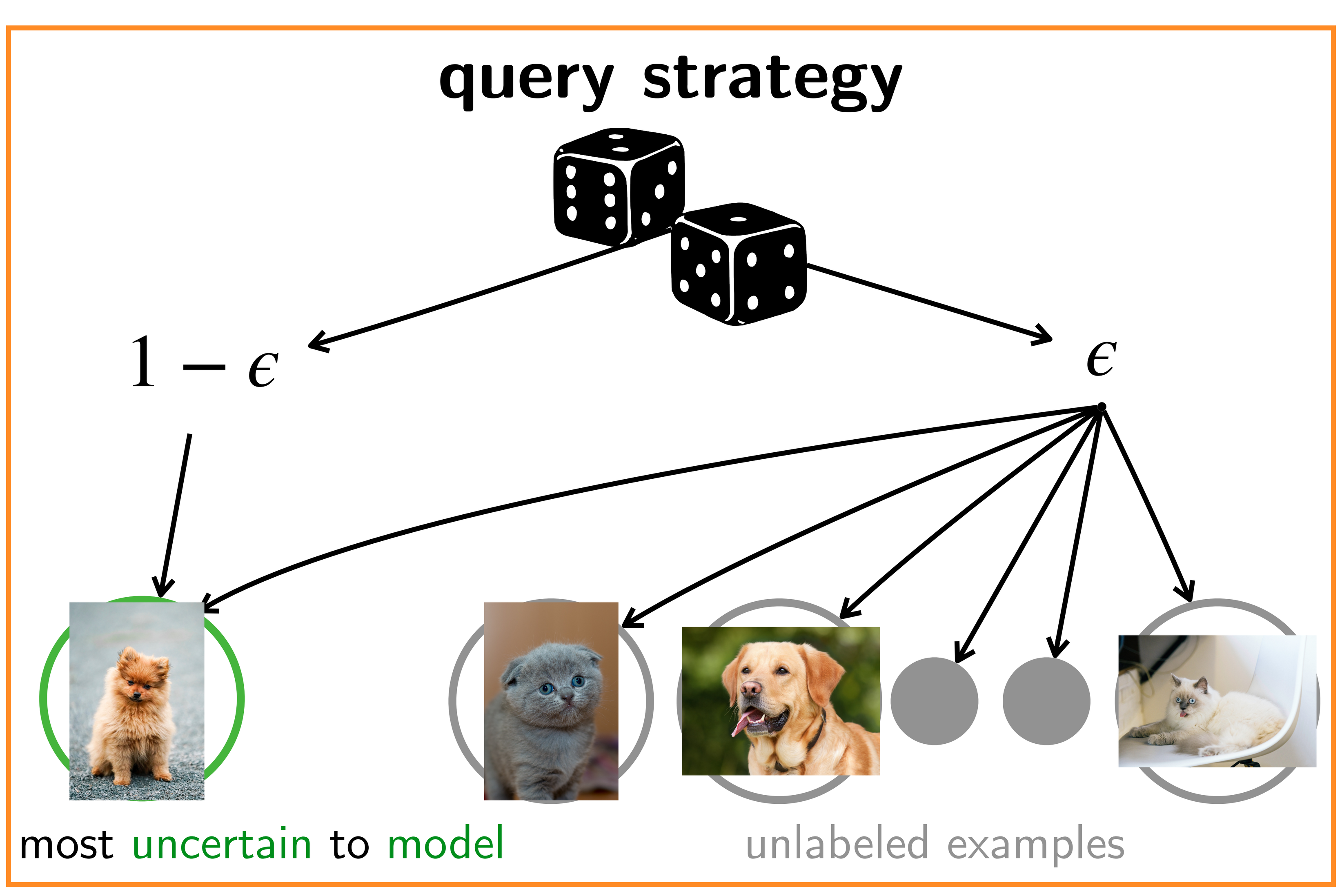


(a) Uncertainty Sampling (b) Diversity Sampling

ϵ-Uncertainty Sampling

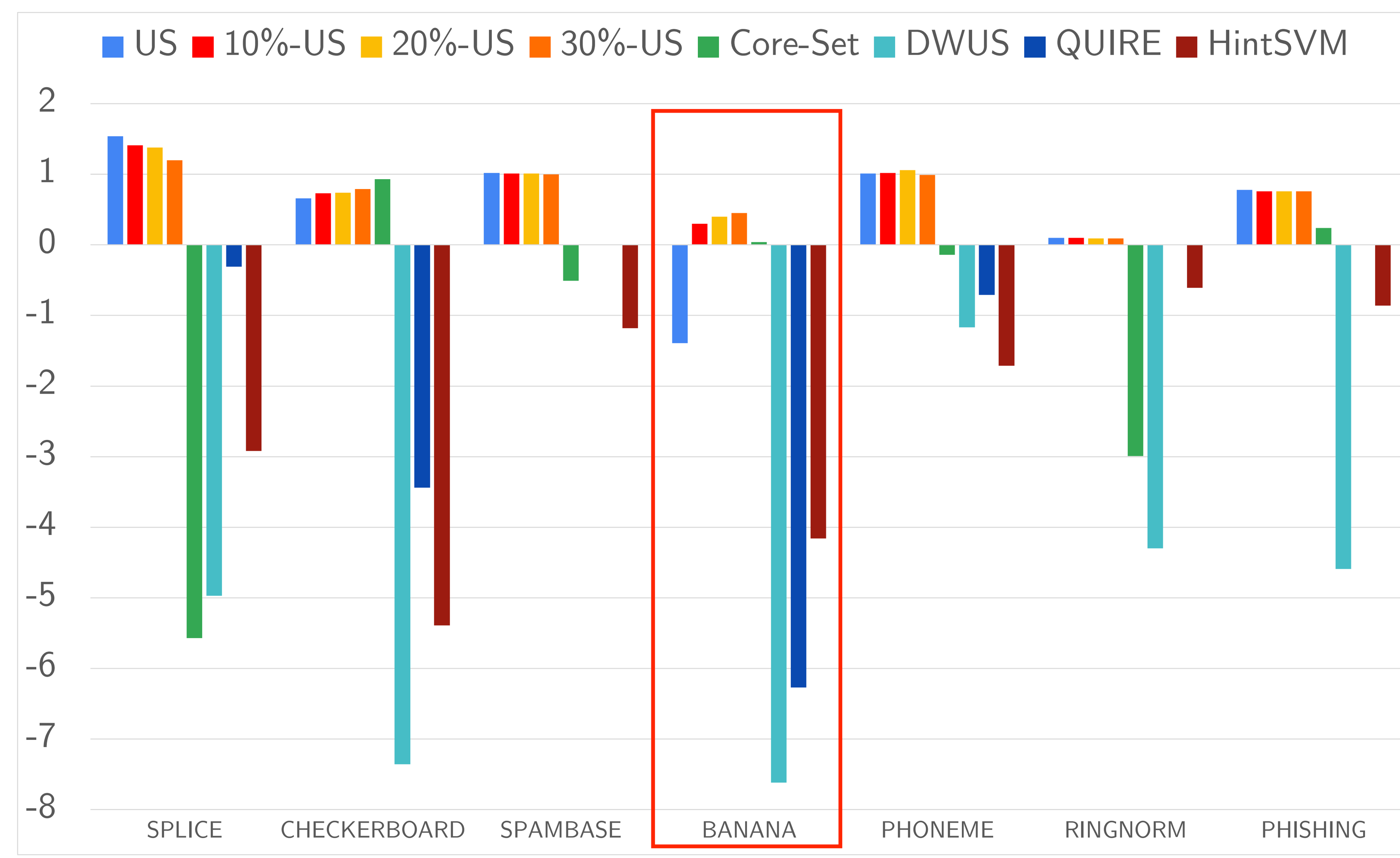
Straightforward alternative solution.

- RS is regarded as one of diversity sampling.
- Combining diversity and uncertainty sampling with a random number.
- Injecting small randomness ϵ % to explore non-boundary regions.



Benchmarking Results

Compare ϵ-uncertainty sampling with $\{10\%, 20\%, 30\%\}$ randomness and classic query strategies on 26 binary datasets.



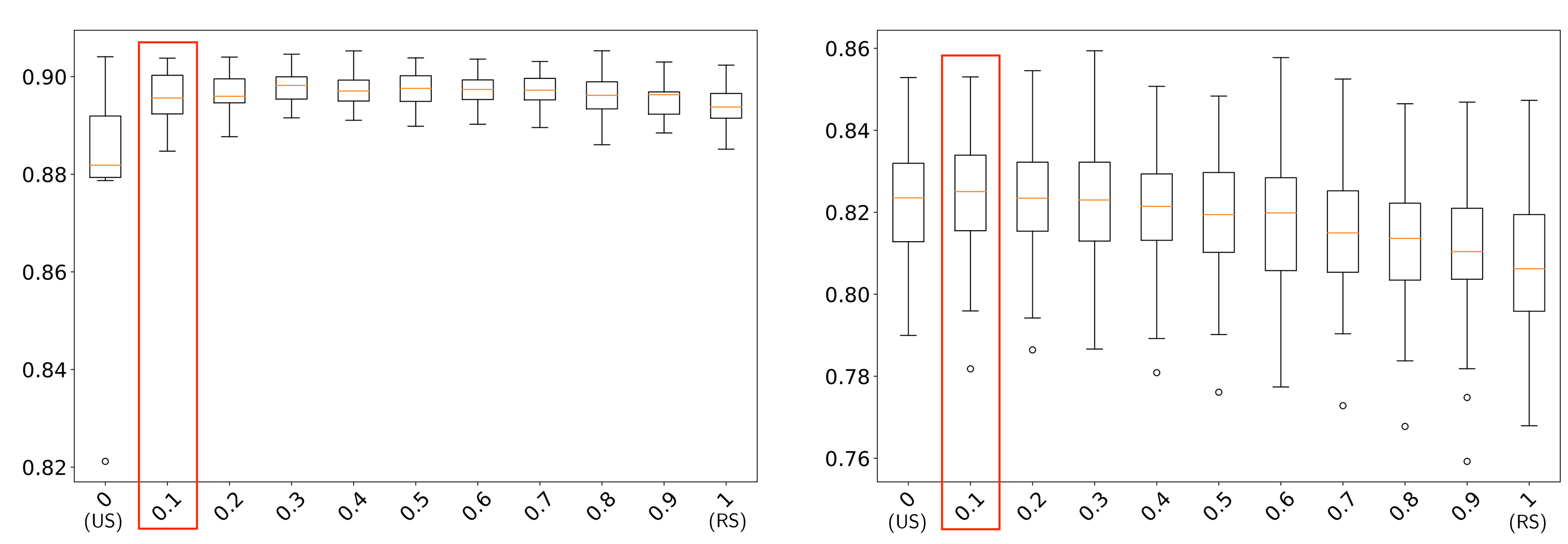
Difference mean AULC of a query strategy from RS on large datasets

- US might fail on some datasets, training-test split, constitute of the initial labeled pool.
- ϵ-Uncertainty sampling robustly achieves competitive results on most datasets.

Sutdy on Hyper-Parameter ϵ

Sensitivity Analysis of ϵ-Uncertainty Sampling.

- US fails (Left): Improvement by small randomness is significant.
- US works (Right): Hurt by small randomness is negligible.



(a) AULC for various ϵ on BANANA (b) AULC for various ϵ on SPLICE

Bias-Variance Analysis of Randomness. Small randomness significantly reduces the bias of pure US and enlarges a little variance for test error. (Please see the detail in the paper.)

- Using $\epsilon = 10\%$ is the robust baseline in realistic.
- Injecting the randomness can reduce the bias for pure US.

Conclusions

- Robust baseline for active learning is necessary for practical usage.
- ϵ-Uncertainty sampling is effective but disregard.
- Sensitivity analysis and bias-variance analysis to realize the benefits of injecting randomness.
- Active learning benchmarks can facilitate the research community.

https://github.com/ariapoy/active-learning-benchmark

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