Intelligent Embedded Systems

KNOWLEDGE MANAGEMENT AND DISCOVERY

Probabilistic Active Learning for Active Class Selection

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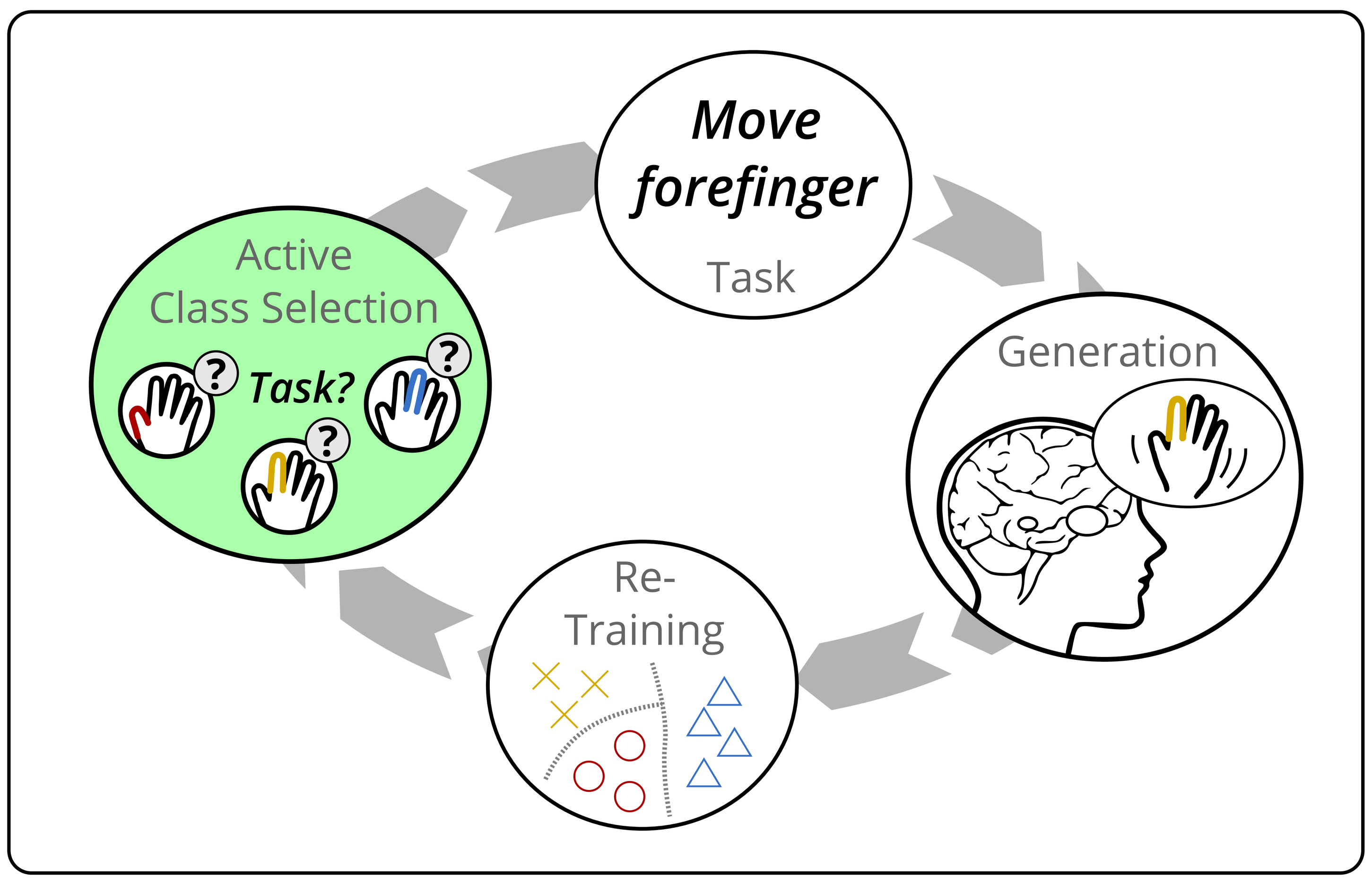
Motivation

We want to reduce training time of an active class selection task (e.g., training of a brain computer interface).



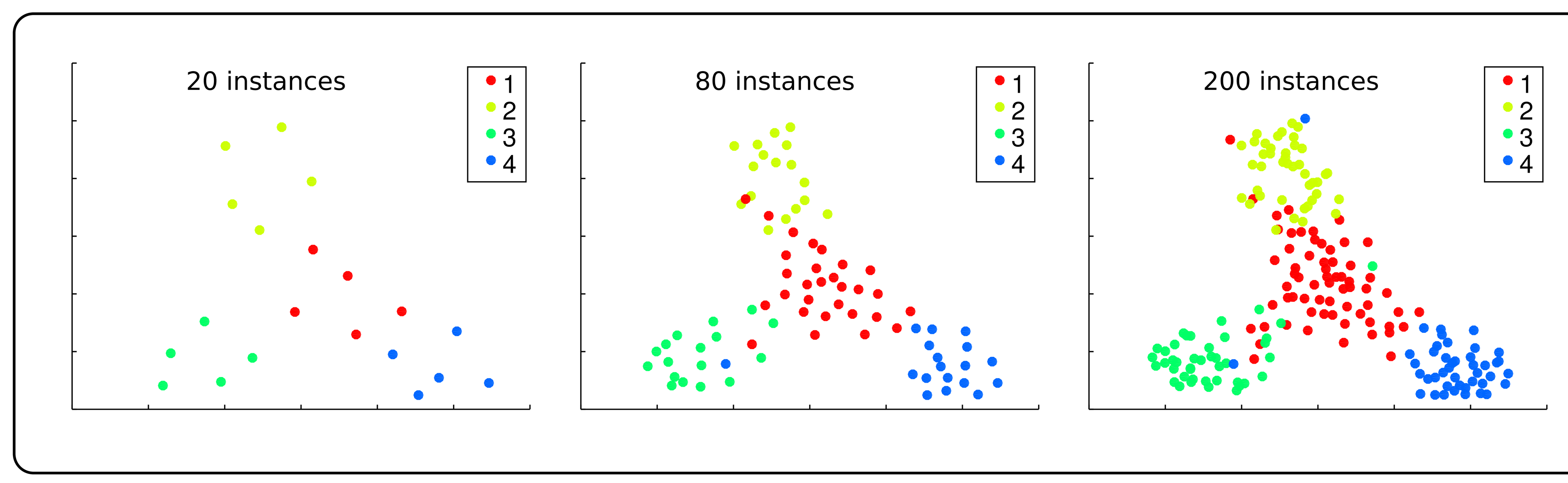
Task

To build a powerful classification system, we need training instances. In an active class selection task, we successively ask the oracle to generate an instance of a selected class.

Active Class Selection (ACS)
- selects class and asks oracle for instance
- knows classes
- low degree of freedom

vs.

Pool-based Active Learning (AL)
- selects instance and asks oracle for label
- knows distribution of instances
- high degree of freedom



Method

The main idea is to transform the ACS problem into an AL task. We use pseudo instances to simulate the generation of new instances and select the class with the highest expected performance gain.

$$y^* = \arg\max_y \left(\sum_{x_p} P(x_p \mid \mathcal{L}) \cdot P(x_p \mid \mathcal{L}_y) \cdot \text{perfGain}(KFE(x_p, (\mathcal{L})_i)) \right)$$

We use the performance gain from probabilistic active learning.

$$\text{perfGain}(\vec{k}, M) = \max_{m \le M} \left(\frac{1}{m} \left(\text{expPerf}(\vec{k}, m) - \text{expPerf}(\vec{k}, 0) \right) \right)$$

$$\text{expPerf}(\vec{k}, m) = \mathbb{E}_{\vec{p}} \left[\mathbb{E}_{\vec{l}} \left[\text{perf}(\vec{k} + \vec{l} \mid \vec{p}) \right] \right]$$

$$\text{perf}(\vec{k} + \vec{l} \mid \vec{p}) = \vec{p}_{\hat{y}} \qquad \hat{y} = \arg\max(\vec{k} + \vec{l})$$

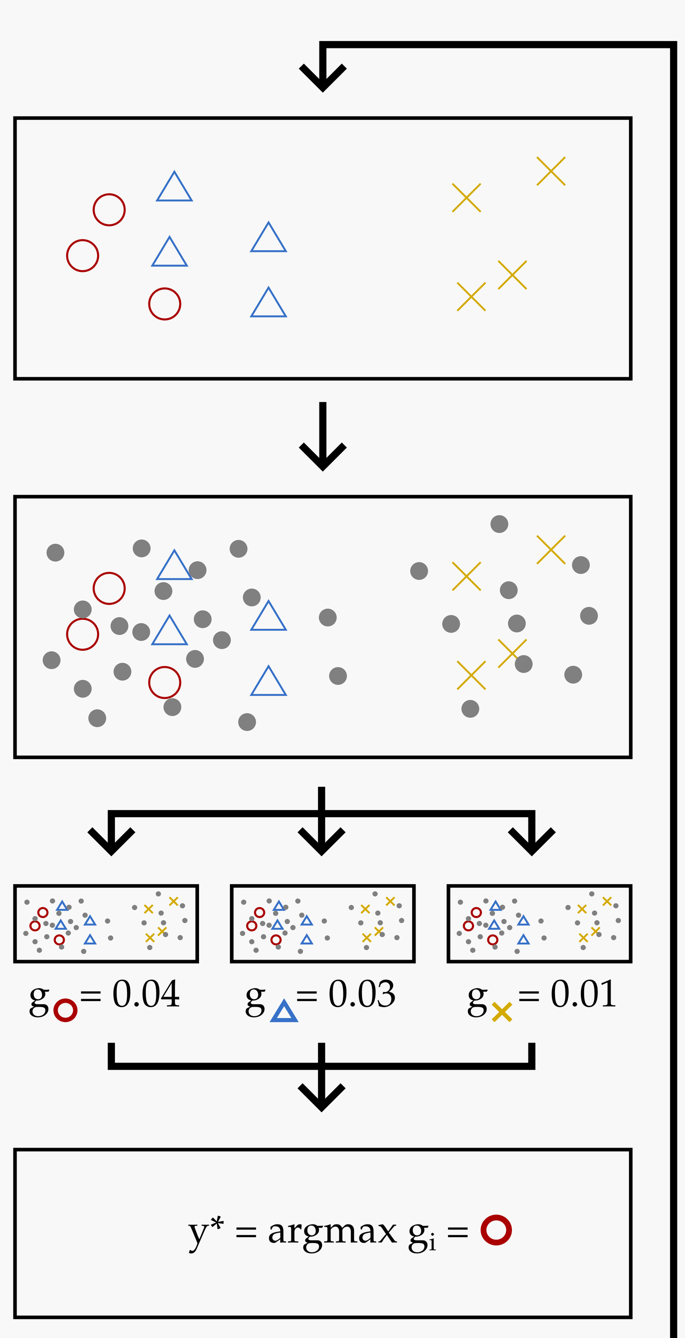
Our ACS loop

Collect the currently available instances to train a classification model

Generate a specified number of **pseudo instances** from every class distribution to **transform the ACS task into an AL task**

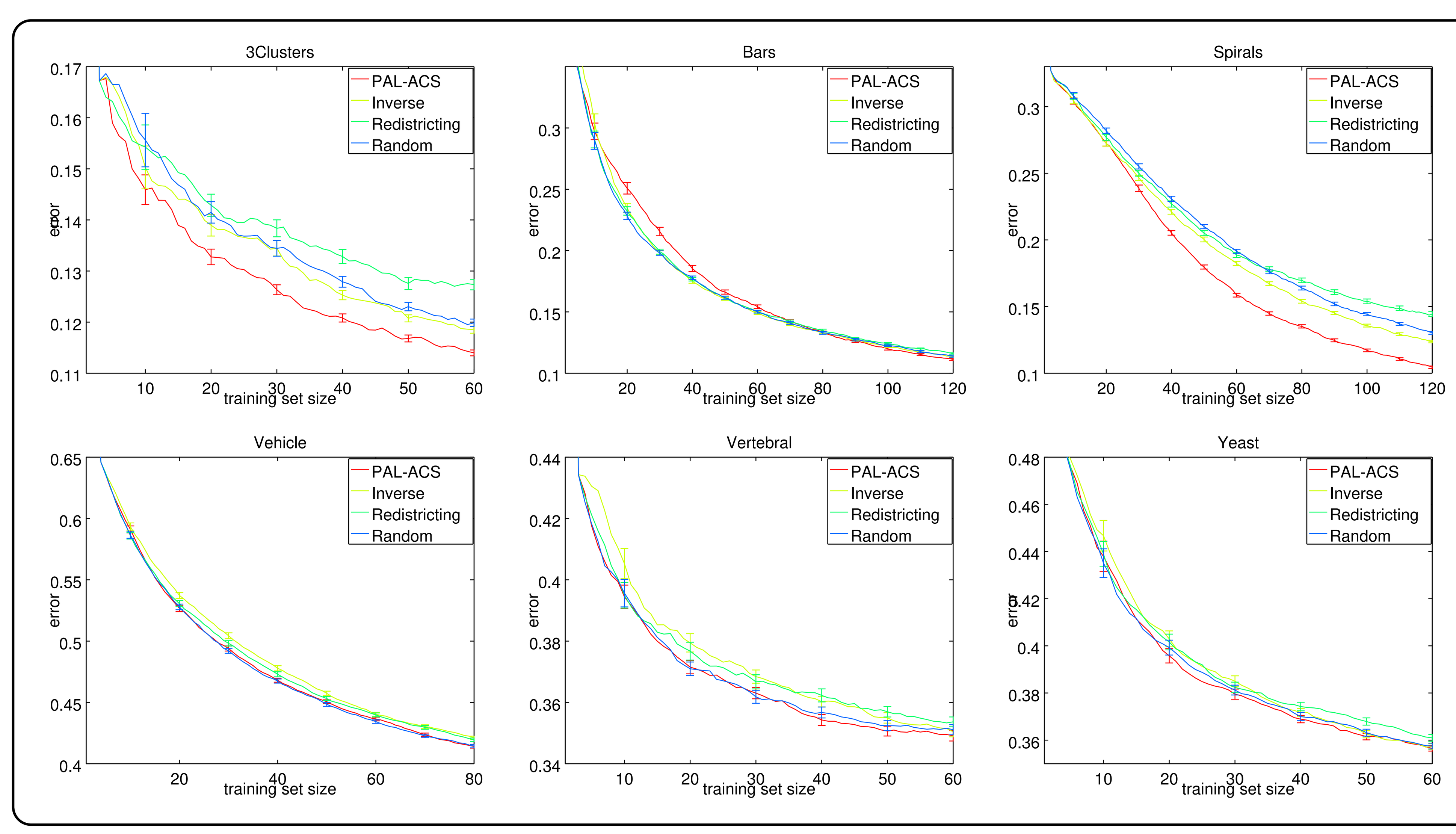
Calculate performance gain for each class separately using **Probabilisitic Active Learning**

Select most beneficial class and generate a new instance



Results

The learning curves show the methods' hold-out error w. r. t. the number of generated instances. Our method **PAL-ACS is advantageous** in situations of differently complex decision boundaries and **comparable to Random** when the best strategy is to sample uniformly.



Conclusion

We proposed a new method PAL-ACS which is based on the probabilistic active learning framework and therefore transforms the ACS problem into an AL task using pseudo instances. The experimental evaluation shows our method's superiority on datasets where a non-uniform sampling improves the classifier's performance. On datasets with equally complex classes, our method identifies uniform sampling to be the best. Thus, in contrast to other active class selection methods, it performs comparably well with random sampling which is a uniform sampler per default.

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References: Daniel Kottke, Georg Krempl, Dominik Lang, Johannes Teschner, and Myra Spiliopoulou. Multi-class probabilistic active learning. In Proc. of the European Conf. on Artificial Intelligence 2016 (ECAI). IOS Press, 2016.

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