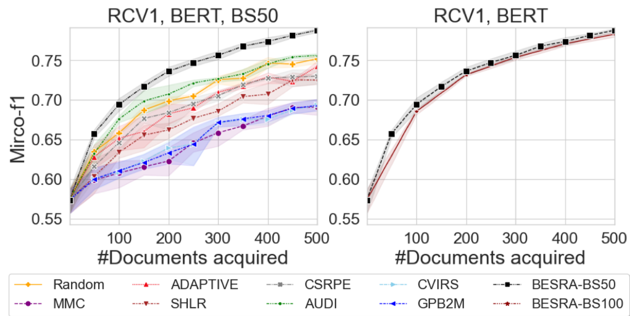

Figure 6: Left: Learning curves of ALs with batch size 50 on RCV1. Right: Learning curves for BESRA with batch sizes $B \in \{50, 100\}$ on RCV1. All results were run with 5 different random seeds

Batch Size

Figure 6 indicate that BESRA consistently outperforms other ALs when using a batch size of 50. Additionally, during the early stages of acquisition, BESRA performs more effectively with smaller batch sizes (50) than with larger batch sizes (100), aligning with the results reported in (**??**). We hypothesise that at the early acquisition stages, due to the lack of knowledge, the model trained with a limited number of samples has high uncertainty and lacks calibration, thus acquiring a large batch of samples can result in noise. Additional experiments conducted on other MLTDs can be found in the Appendix.

Beta Parameters

In this subsection, we delve into the implications of varying Beta scores on the performance of AL, with a particular emphasis on how these scores influence the penalization behaviour of the active learner. We evaluated a range of α and β values, associated with distinct Beta scores as shown in Eq (5). Our evaluations spanned three representative datasets, ranging from relatively balanced (i.e., BIBTEX) to highly imbalanced (i.e., Yahoo). To gain a comprehensive understanding of how different α and β values impact the outcomes, we considered several scoring methods including the Brier score and Logarithmic score (which provide equal penalization), alongside four distinct scenarios of Beta score. These scenarios include (1) mild penalization on False Positives (FPs) where $\alpha = 1$ and $\beta = 0.1$, (2) light penalization on False Negatives (FNs) with $\alpha = 0.1$ and $\beta = 1$, (3) moderate penalization on FNs defined by $\alpha = 0.1$ and $\beta = 3$, and finally (4) stringent penalization on FNs denoted by $\alpha = 0.1$ and $\beta = 10$.

Insights from Figure 5 reveal that the Brier and Logarithmic scores, as well as the scenario with $\alpha = 1$ and $\beta = 0.1$, consistently underperform across various imbalance levels within MLTDs. Such results are consistent with our prior expectations, considering the inherent label imbalance challenges. A significant reason for this underperformance is the equal penalization rendered to both FN and FP outcomes by the Brier and Logarithmic scores. Additionally, the specific scenario of $\alpha = 1$ and $\beta = 0.1$ tends to disproportionately penalize FPs, thereby dampening performance. When evaluating the effect of α and β values focused on penalizing FNs, we note that while light penalization settings (i.e., $\alpha = 0.1$, $\beta = 1$) have a negligible impact on enhancing the active learner's effectiveness, the more stringent configuration of $\alpha = 0.1$ and $\beta = 10$ offers notable improvements, especially in highly imbalanced datasets. However it does not necessarily culminate in the optimal active learner. Instead, a moderate penalization strategy with $\alpha = 0.1$ and $\beta = 3$ consistently stands out as the most effective across MLTDs.

Conclusion

We have introduced BESRA, a novel acquisition strategy for MLAL. This generalizes the recently published BEMPS using the Beta family of proper scoring rules, which allow customizable asymmetric scoring rules that effectively address the challenges such as imbalanced data associated with multi-label learning. Moreover, by our methodical construction, the use of BESRA provably converges to optimal solutions. Through empirical studies conducted on synthetic and real-world datasets, we have demonstrated the effectiveness of BESRA in acquiring highly informative samples for multi-label active learning, consistently surpassing seven existing acquisition strategies. This finding highlights the crucial role of Beta Scoring Rules and their great potential for AL with tailored acquisition strategies. Future research can further explore combinations of Alpha and Beta values for specific datasets, addressing a current limitation of BESRA.

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