Hitting the Target: Stopping Active Learning at the Cost-Based Optimum
Supplimentary Information

May 25, 2022

1 Metric Examples

To illustrate how the metrics used in the SC discussed above behave we plot values from an exemplary run in Fig. 1. Each plot shows the *metric* as well as the true accuracy of the classifier. In a real AL scenario this would not be available, but we keep a separate hold-out set on which to evaluate accuracy so we can compare SC performance. Thresholds (if the condition uses one) are shown with dashed horizontal lines. We observe that some metrics seem to be correlated with accuracy (Stabilizing predictions) while others, such as SSNCut, are not obviously connected.

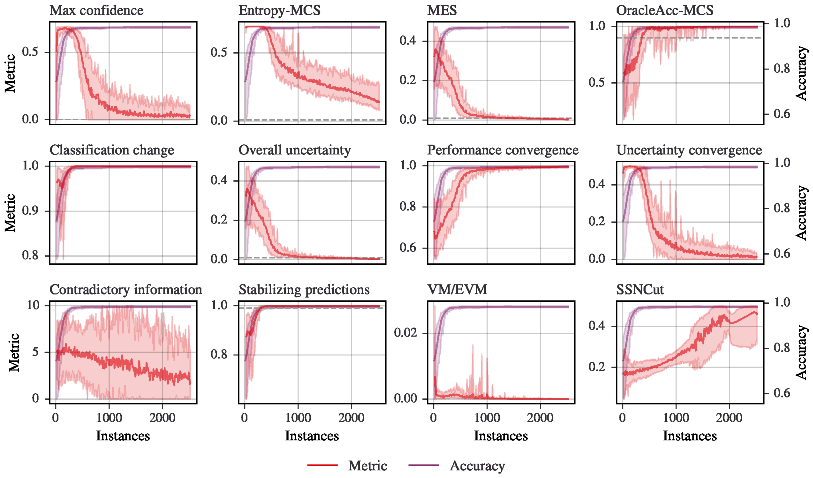


Figure 1: Exemplary metric values during an AL process. The ground-truth (but in AL unknown) accuracy is provided for comparison. These results are from the spamassassin dataset using a linear SVM. The 2.5% to 97.5% percentiles are shown in filled colour. Thresholds, if used by the condition, are displayed as a grey dashed line

2 Random Forests and Neural Networks

Although SVMs seem to be the most popular classifier choice in the AL literature, we cannot guarantee the same performance if a practitioner uses a different learning algorithm. Hence, we provide all results of this paper also for random forests and a single hidden layer NN in the appendix. For brevity, we only note the most salient differences here.

Random Forests. The most notable difference from our SVM results is the stronger performance of OracleAcc-MCS. This SC has a dominant position in the lower label cost region (using penalty) while it was absent under SVMs, this is associated with a small increase in correlation with the classifier's accuracy ($0.53{\pm}0.05 \rightarrow 0.63{\pm}0.04$). The best SC from our SVM evaluation, Stabilizing predictions and Classification change remain dominant in the balanced and high misclassification cost regions and retain top positions in our example cases. Overall the performance of SC under random forests is similar to their performance under SVMs.

Neural Networks. On NNs OracleAcc-MCS takes the place of Stabilizing predictions as the SC which dominates the balanced region in the penalty case. This is partly due to Stabilizing predictions failing to terminate at all on the avila dataset, if this is ignored it is again dominant across a wide range of cost parameters.

The correlation between SC's metrics and the classifier's accuracy also changed substantially. All bar two (Contradictory information and Max confidence) had significantly increased Pearson correlation coefficients. This is especially surprising given that the majority of prior SC were not developed on NNs. It is possible that it is intrinsically easier to estimate the performance of a NN (even uncalibrated) than the other models we evaluated, however, assessing this is beyond the scope of this paper.

Performance convergence joined the best group of SC in our mammogram example, performing substantially better than they did on SVMs. In the marketing example Stabilizing predictions's failure to stop on the avila dataset meant it lost its place among the best group leaving Classification change as the best choice.

3 Additional SVM Results

In Figures 2 and 3 we show our results when including SC with out penalty, and excluding them completely when they failed to stop respectively.

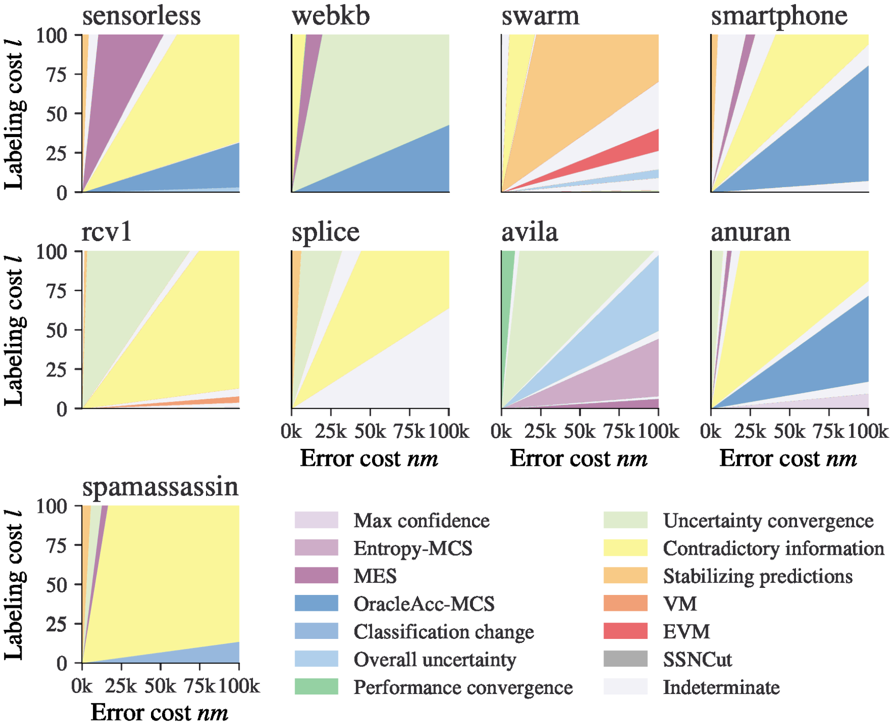


Figure 2: The regions in which each criterion is cost-optimal by dataset on SVMs. Criteria that failed to stop were included without penalty. Light grey shows regions in which no SC was statistically dominant

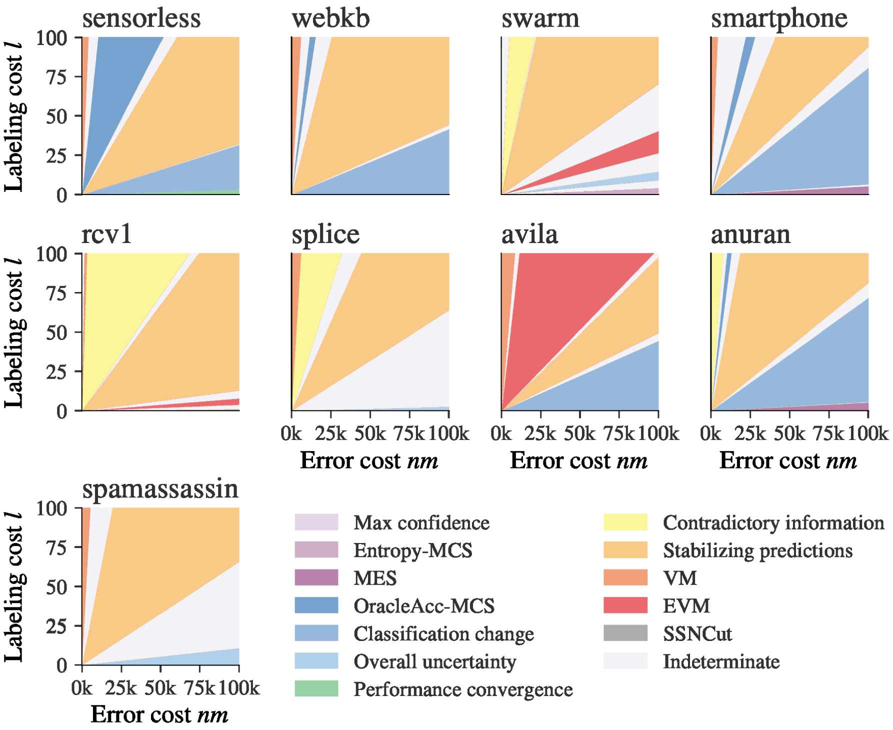


Figure 3: The regions in which each criterion is cost-optimal by dataset on SVMs. Criteria that failed to stop were excluded. Light grey shows regions in which no SC was statistically dominant

4 Random Forest Results

We present our results from evaluating stopping conditions using random forests. All figures are generated in the same manner as their SVM counterparts above. SSNCut was not evaluated under random forests as it was motivated only for SVMs. Figure 4 shows the stopping points of the conditions. Figures 5, 6, 7, and 8 show the cost-optimal SC over a range of values of the cost parameters n, m, and l. Figure 9 and 10 show the rankings of SC in our two example scenarios. Figure 11 shows the number of times each criterion stops on each dataset and the average correlations between their metrics and the classifier's accuracy. Table 2 shows the correlations between the SC's metrics and the classifier's accuracy.

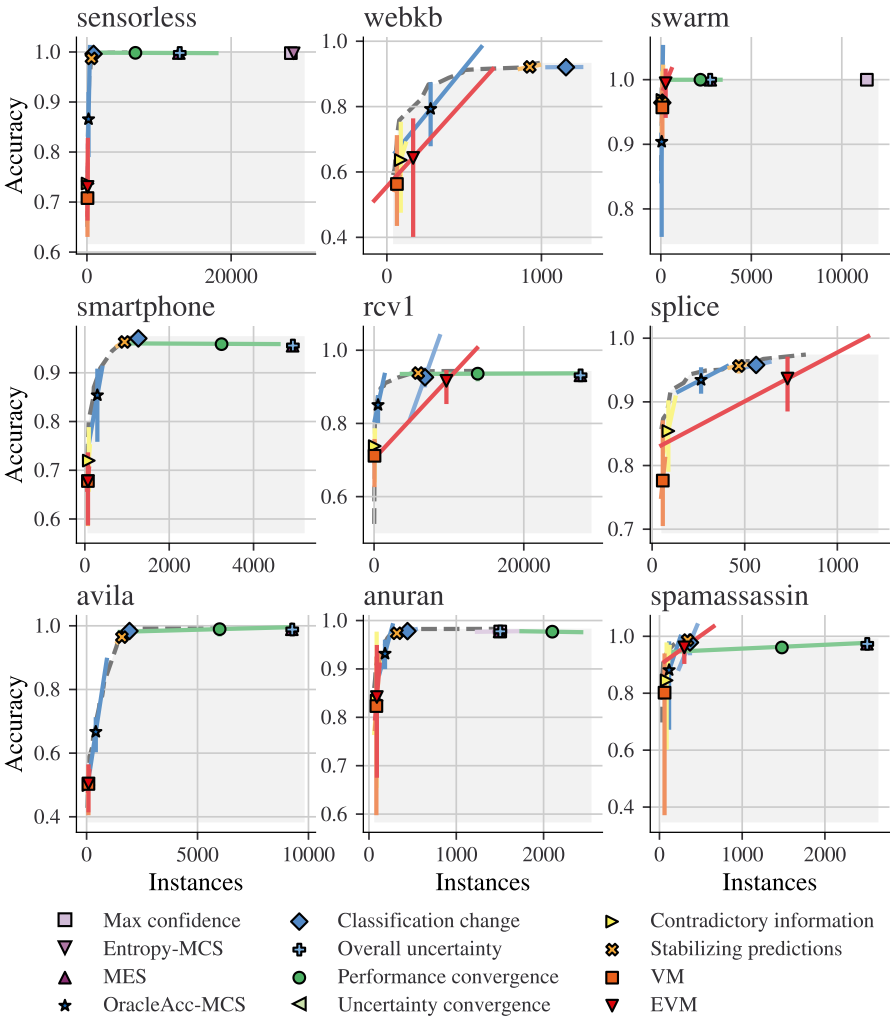


Figure 4: The accuracy and number of instances used by SC when evaluated on a random forest classifier. The dashed grey line shows the Pareto frontier. Error bars were computed from 2.5% and 97.5% percentiles and transformed by PCA

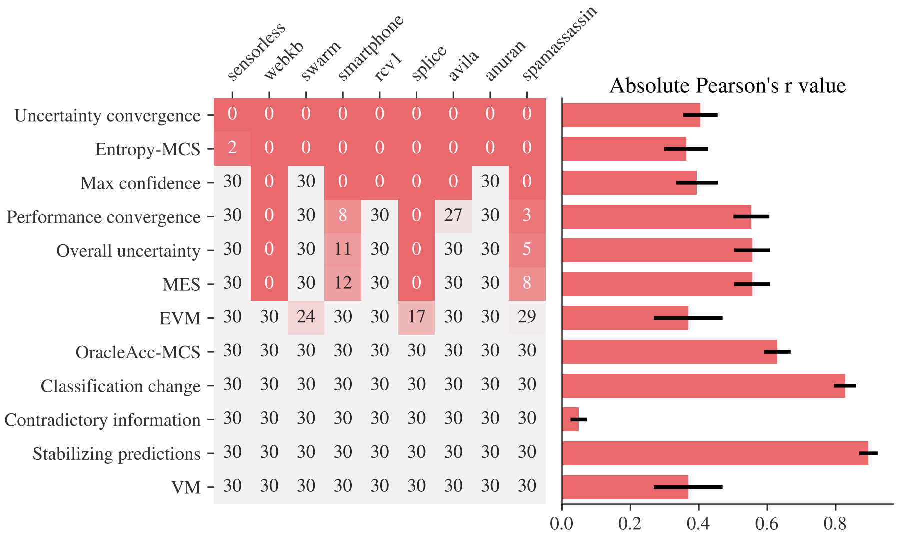


Figure 5: The regions in which each criterion was cost-optimal on random forests. Each plot shows different treatment of SC which failed to stop. In penalty they were penalized with the worst instances and accuracy, while in include/exclude they were included without penalty or excluded. Light grey shows regions in which no SC was statistically dominant

Table 1: Pearson correlation coefficients on random forests

Criterion	Correlation
Max confidence	0.39 ± 0.06
Entropy-MCS	0.36 ± 0.06
MES	0.56 ± 0.05
OracleAcc-MCS	0.63 ± 0.04
Classification change	0.83 ± 0.03
Overall uncertainty	0.56 ± 0.05
Performance convergence	0.55 ± 0.05
Uncertainty convergence	0.40 ± 0.05
Contradictory information	0.05 ± 0.02
Stabilizing predictions	0.90 ± 0.03
VM	0.37 ± 0.10
EVM	0.37 ± 0.10

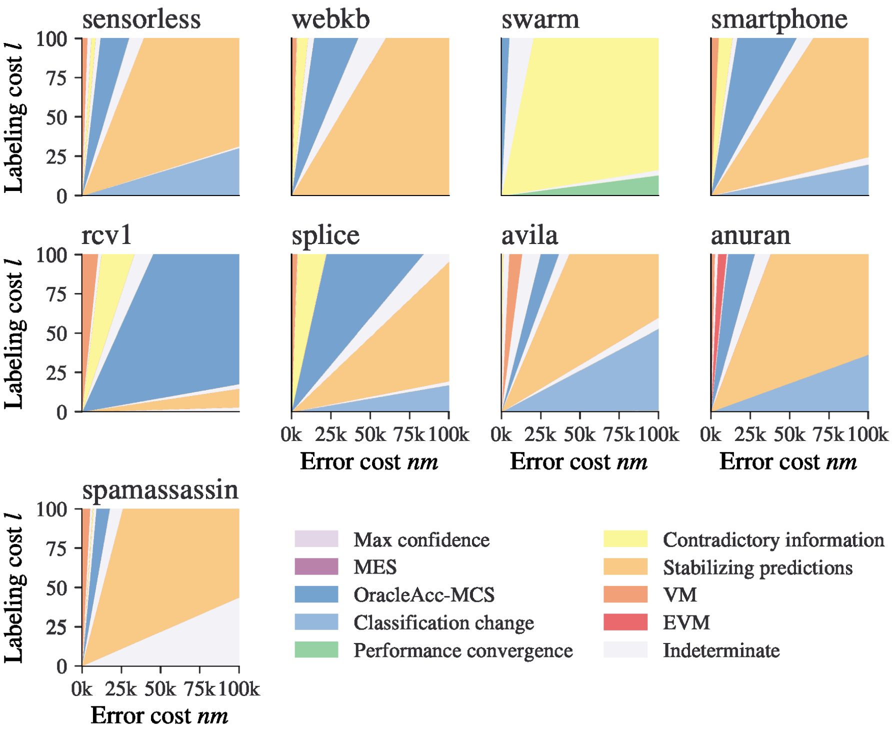


Figure 6: The regions in which each criterion is cost-optimal by dataset on random forests. Criteria were penalised for each split of each dataset on which they failed to stop. Light grey shows regions in which no SC was statistically dominant

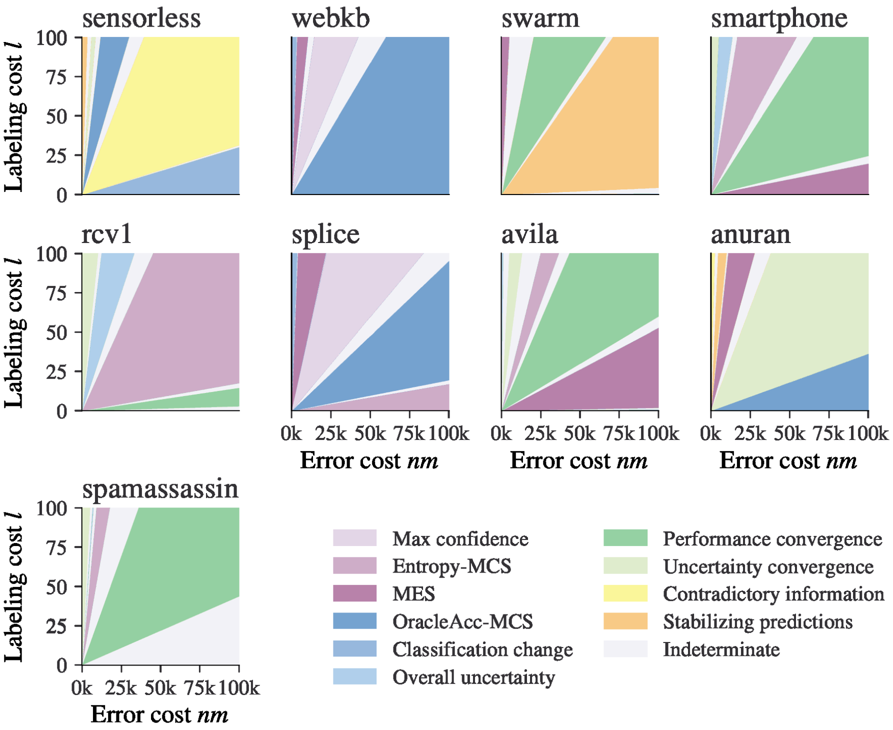


Figure 7: The regions in which each criterion is cost-optimal by dataset on random forests. Criteria that failed to stop were included without penalty. Light grey shows regions in which no SC was statistically dominant

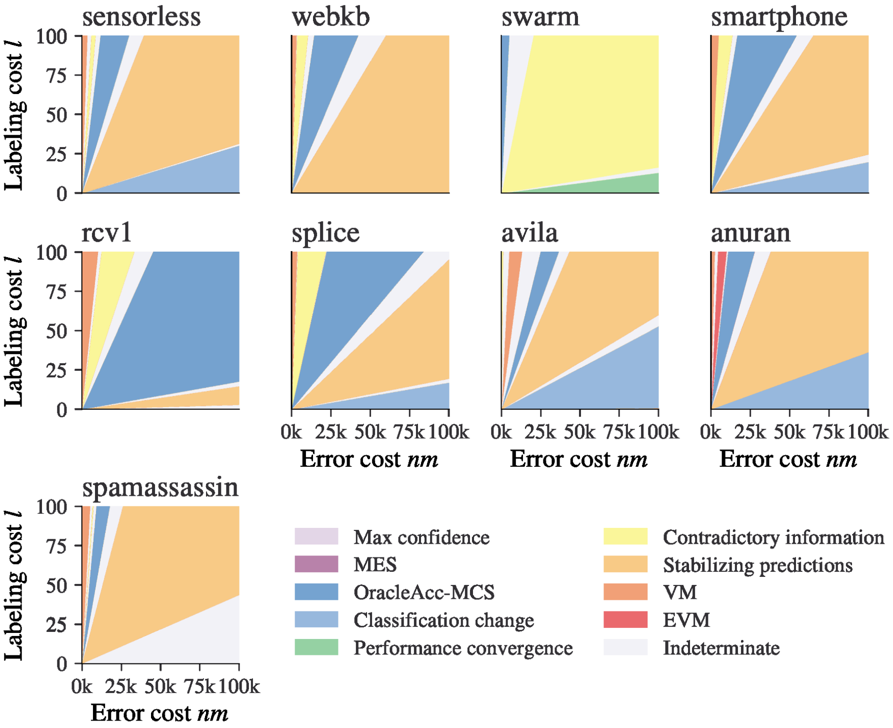


Figure 8: The regions in which each criterion is cost-optimal by dataset on random forests. Criteria that failed to stop were excluded. Light grey shows regions in which no SC was statistically dominant

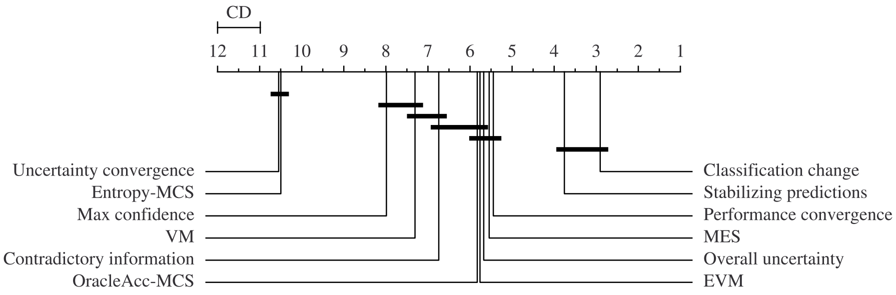


Figure 9: The relative cost of SC for an example scenario classifying mammograms using a random forest model

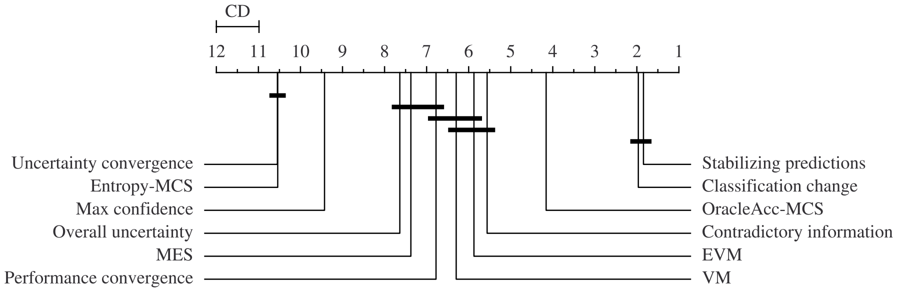


Figure 10: The relative cost of SC for an example scenario selecting potential customers using a random forest model

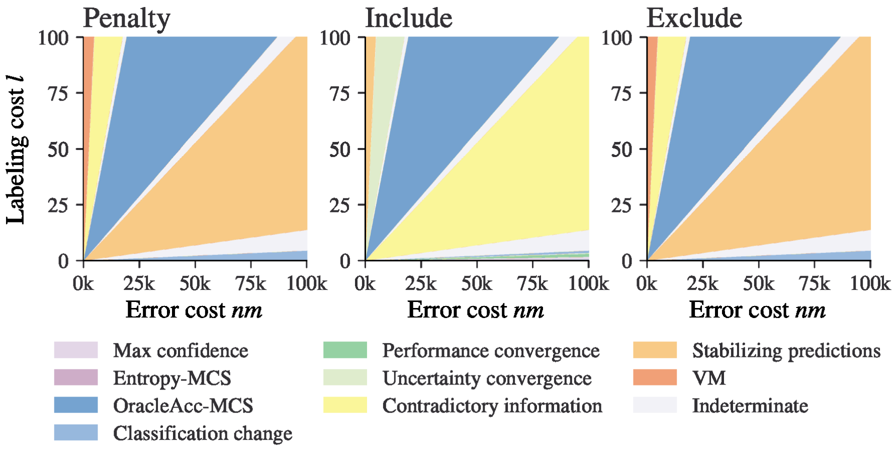


Figure 11: Left: the number of times each criterion stopped on each dataset using random forests out of 30 splits. Right: the Pearson correlation coefficient between each SC's metric and the classifier's accuracy. The black shows the standard error of the mean across datasets

5 Neural Network Results

We present our results from evaluating stopping conditions using a single hiden layer NN. All figures are generated in the same manner as their SVM counterparts above. SSNCut was not evaluated under NNs as it was motivated only for SVMs. rcv1 was not used in our NN evaluations as the large size and high dimensionality made it computationally expensive. Figure 12 shows the stopping points of the conditions. Figures 13, 14, 15, and 16 show the cost-optimal SC over a range of values of the cost parameters n, m, and l. Figure 17, and 18 show the rankings of SC in our two example scenarios. Figure 19 shows the number of times each criterion stops on each dataset and the average correlations between their metrics and the classifier's accuracy. Table 2 shows the correlations between the SC's metrics and the classifier's accuracy.

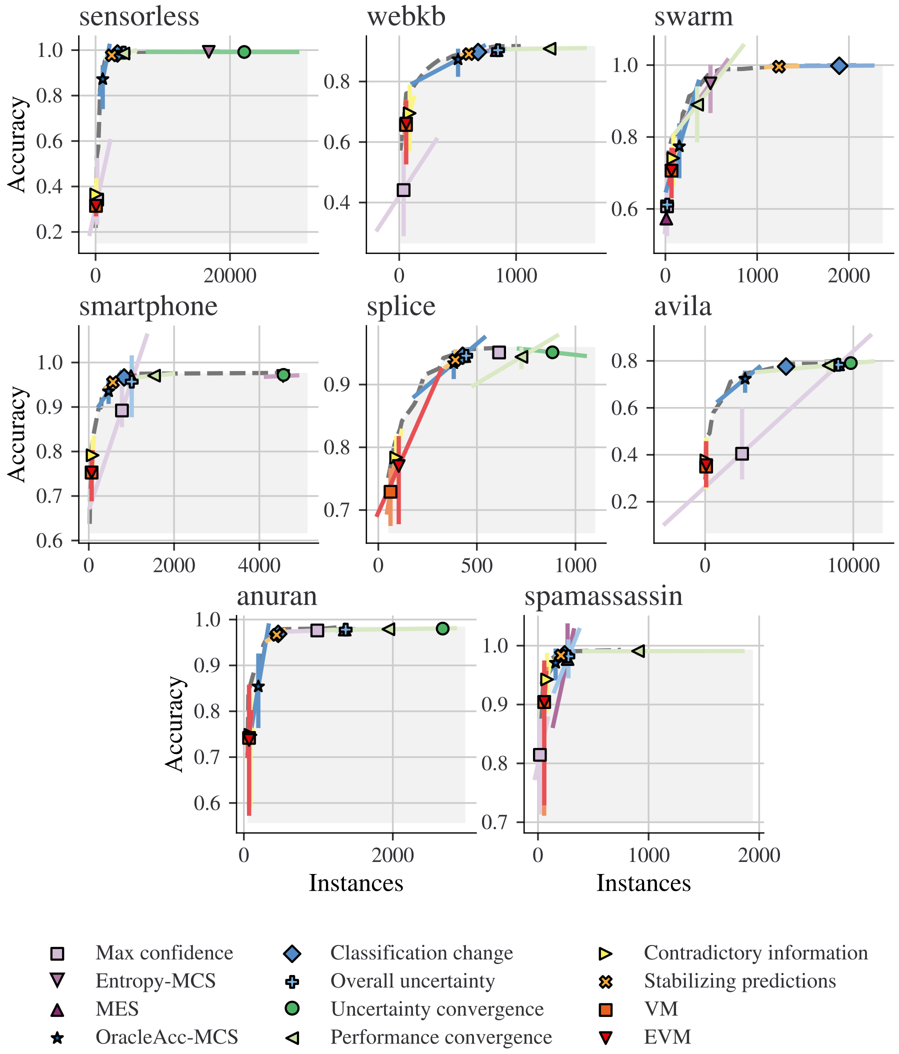


Figure 12: The accuracy and number of instances used by SC when evaluated on an NN. The dashed grey line shows the Pareto frontier. Error bars were computed from 2.5% and 97.5% percentiles and transformed by PCA

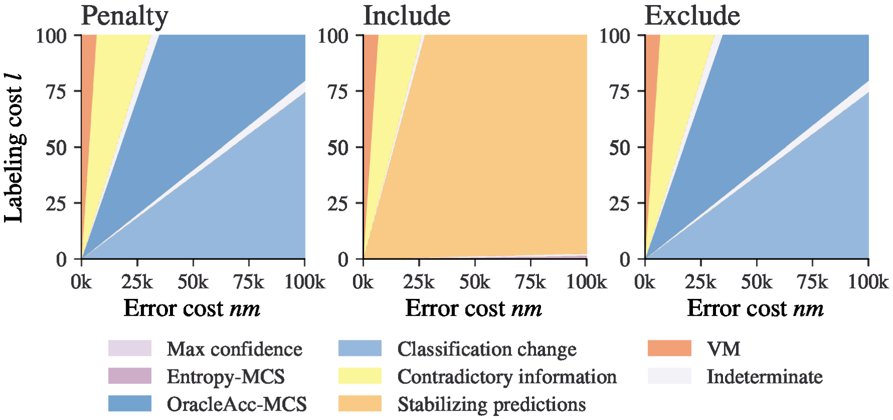


Figure 13: The regions in which each criterion was cost-optimal on an NN. Each plot shows different treatment of SC which failed to stop. In penalty they were penalized with the worst instances and accuracy, while in include/exclude they were included without penalty or excluded. Light grey shows regions in which no SC was statistically dominant

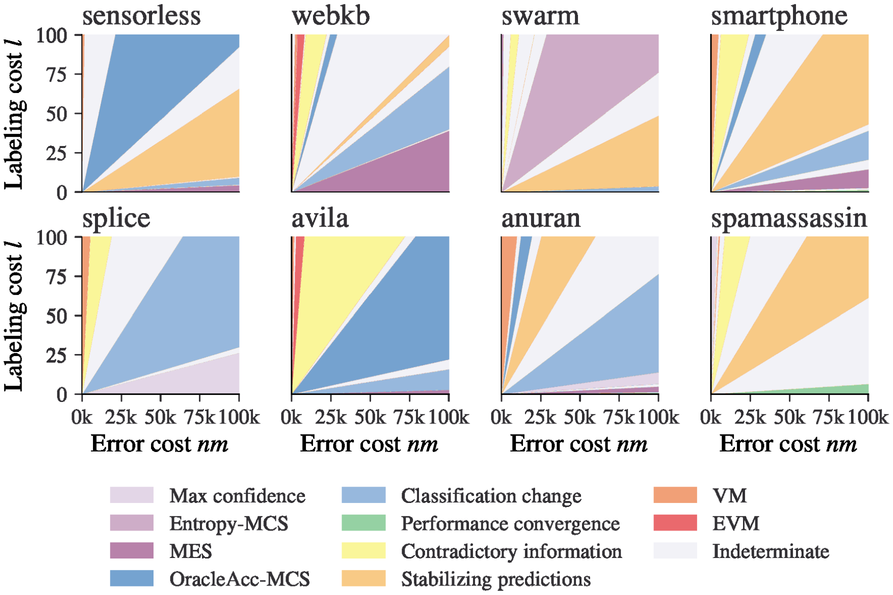


Figure 14: The regions in which each criterion is cost-optimal by dataset on an NN. Criteria were penalised for each split of each dataset on which they failed to stop

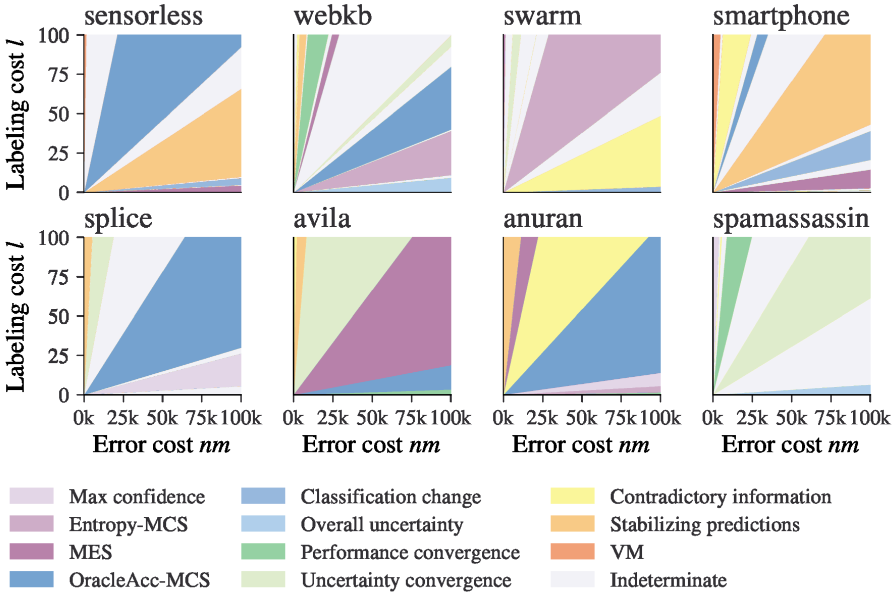


Figure 15: The regions in which each criterion is cost-optimal by dataset on an NN. Criteria that failed to stop were included without penalty. Light grey shows regions in which no SC was statistically dominant

Table 2: Pearson correlation coefficients on NNs

Criterion	Correlation
Max confidence	0.51 ± 0.04
Entropy-MCS	0.61 ± 0.03
MES	0.85 ± 0.03
OracleAcc-MCS	0.65 ± 0.02
Classification change	0.89 ± 0.02
Overall uncertainty	0.81 ± 0.03
Performance convergence	0.84 ± 0.03
Uncertainty convergence	0.58 ± 0.02
Contradictory information	0.05 ± 0.03
Stabilizing predictions	0.92 ± 0.02
VM	0.54 ± 0.06
EVM	0.54 ± 0.06

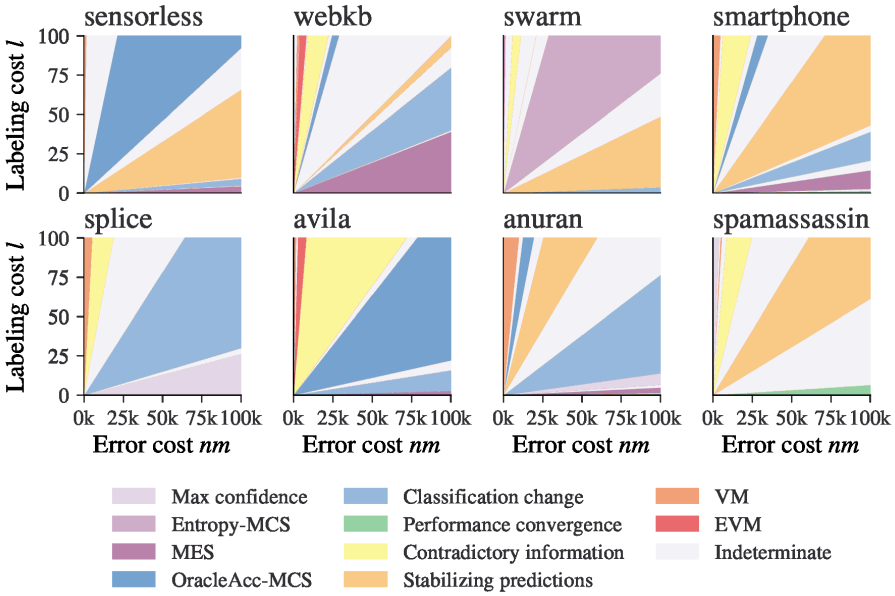


Figure 16: The regions in which each criterion is cost-optimal by dataset on an NN. Criteria that failed to stop were excluded. Light grey shows regions in which no SC was statistically dominant

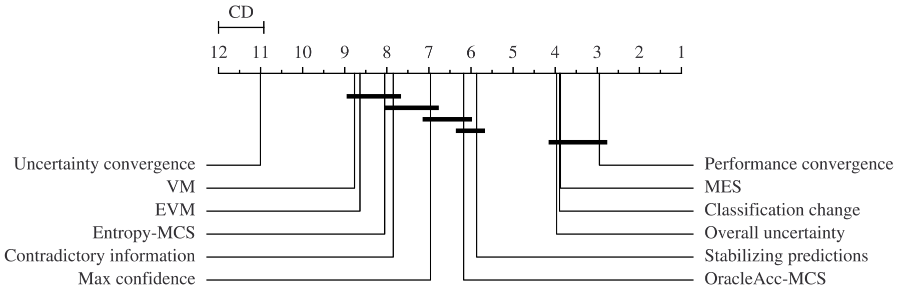


Figure 17: The relative cost of SC for an example scenario classifying mammograms using an NN

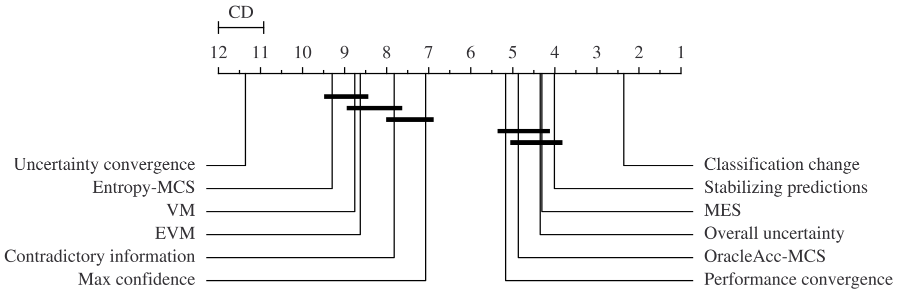
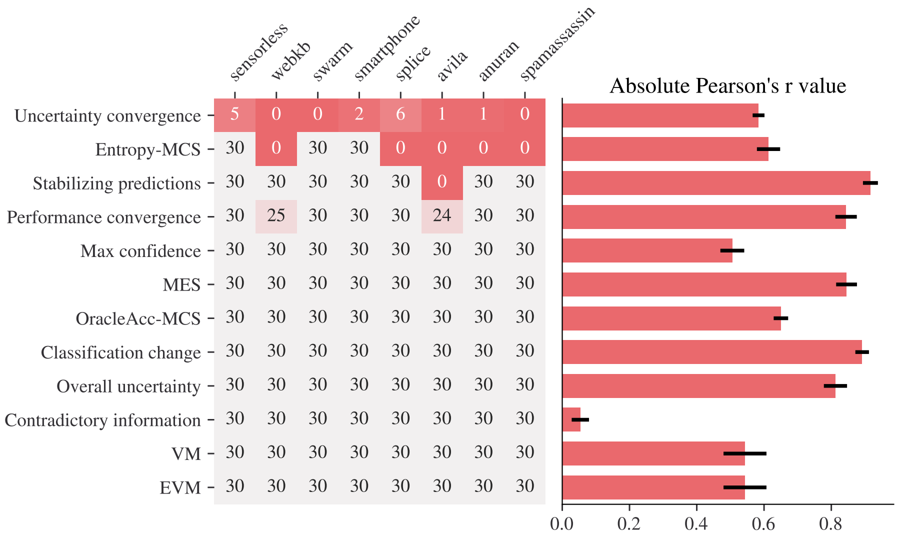


Figure 18: The relative cost of SC for an example scenario selecting potential customers using an NN



	sensorless	webkb	swarm	smartphone	splice	avila	anuran	spamassassin
Uncertainty convergence	5	0	0	2	6	1	1	0
Entropy-MCS	30	0	30	30	0	0	0	0
Stabilizing predictions	30	30	30	30	30	0	30	30
Performance convergence	30	25	30	30	30	24	30	30
Max confidence	30	30	30	30	30	30	30	30
MES	30	30	30	30	30	30	30	30
OracleAcc-MCS	30	30	30	30	30	30	30	30
Classification change	30	30	30	30	30	30	30	30
Overall uncertainty	30	30	30	30	30	30	30	30
Contradictory information	30	30	30	30	30	30	30	30
VM	30	30	30	30	30	30	30	30
EVM	30	30	30	30	30	30	30	30

Figure 19: Left: the number of times each criterion stopped on each dataset using an NN out of 30 splits. Right: the Pearson correlation coefficient between each SC's metric and the classifier's accuracy. The black shows the standard error of the mean across datasets