

BELLWETHER 2.0

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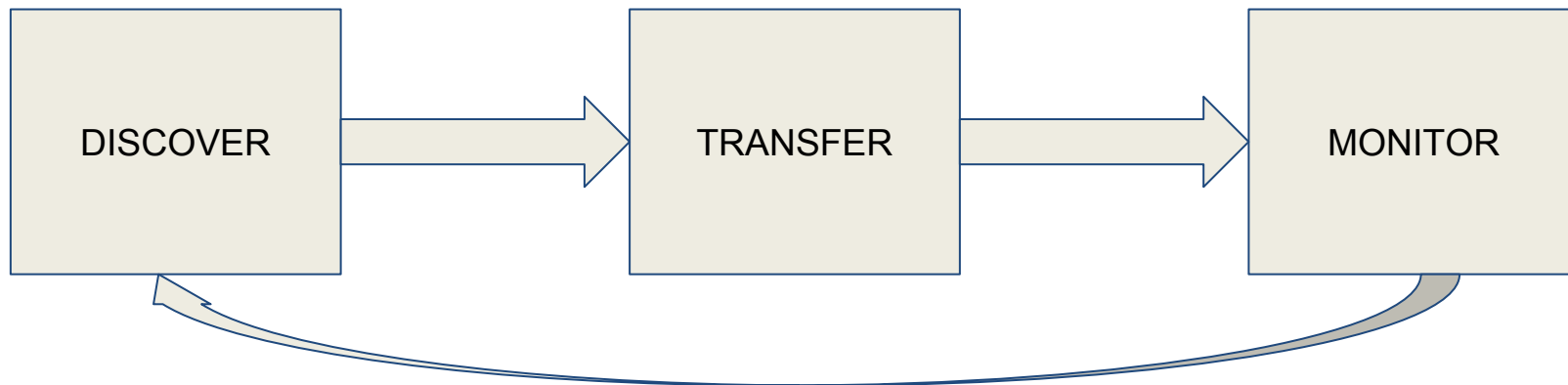
INTRODUCTION

- What is a '*bellwether*'?

A: Given N projects from a community of projects, the '*bellwether*' is that project whose data yields the best predictions on all others

ORIGINAL STUDY

- Conducted by Rahul Krishna and Prof. Menzies^[5]
- Introduced the ***bellwether method***:



MOTIVATION

- Bellwethers appear prevalent in SE data sets - *defect prediction, code smell, effort estimation*
- Useful baseline method for transfer learning
- Bellwethers mitigate conclusion instability

ISSUE ADDRESSED

- The *Discover* phase is slow

```
def discover(datasets):  
    "Identify Bellwether Datasets"  
    for data_1, data_2 in datasets:  
        def train(data_1):  
            "Construct quality predictor"  
            return predictor  
        def predict(data_1):  
            "Predict for quality"  
            return predictions  
        def score(data_1, data_2):  
            "Return accuracy of Prediction"  
            return accuracy(train(data_1), \  
                             test(data_2))  
  
    "Return data with best prediction score"
```

RESEARCH QUESTION

RQ: Can the time taken to find the bellwether dataset be reduced?

INSPIRATION - RFE^[6]

Algorithm 1: Recursive feature elimination

- 1.1 Tune/train the model on the training set using all predictors
 - 1.2 Calculate model performance
 - 1.3 Calculate variable importance or rankings
 - 1.4 **for** *Each subset size S_i , $i = 1 \dots S$* **do**
 - 1.5 Keep the S_i most important variables
 - 1.6 [Optional] Pre-process the data
 - 1.7 Tune/train the model on the training set using S_i predictors
 - 1.8 Calculate model performance
 - 1.9 [Optional] Recalculate the rankings for each predictor
 - 1.10 **end**
 - 1.11 Calculate the performance profile over the S_i
 - 1.12 Determine the appropriate number of predictors
 - 1.13 Use the model corresponding to the optimal S_i
-

INSPIRATION - BEETLE PAPER^[4]

```
1  def FindBellwether(sources, step_size, budget, thres, ↵
    lives):
2      while lives or cost > budget:
3          "Sample configurations"
4          sampled = list()
5          for source in sources:
6              "Sample step_size number of configurations"
7              sampled += source.sample(step_size)
8          "Get cost"
9          cost = get_cost(sampled)
10         "Evaluate pair-wise performances"
11         perf = get_perf(sampled)
12         "Remove non-bellwether environments"
13         sources=remove_non_bellwethers(sources, perf, ↵
            thres)
14         "Loose life if no sources are removed"
15         if prev == len(sources): lives -= 1
16         "Return a bellwether"
17     return sources[argmin(perf)]
```


OUR APPROACH

```
1 discoverBellwether(datasets, n_rep):
2     repeat n_rep times:
3         Initialize lives, x, step_size
4         while lives > 0:
5             for dataset_1, dataset_2 in datasets:
6                 data1 = sample x% of dataset_1
7                 data2 = sample x% of dataset_2
8                 predictor = train(data1)
9                 G_score[dataset_1, dataset_2] = score(test(predictor, data2))
10            rank and eliminate datasets based on median g-score
11            if no dataset to eliminate:
12                lives = lives - 1
13                x = x + step_size
14            for each dataset not eliminated:
15                increment its wins
16    return dataset with most wins
```

TWO VERSIONS FOR ELIMINATION

- Throw away bottom $\frac{1}{3}$ of datasets sorted with median G-Score in each iteration
- Throw away datasets with median G-Score lower than threshold in each iteration

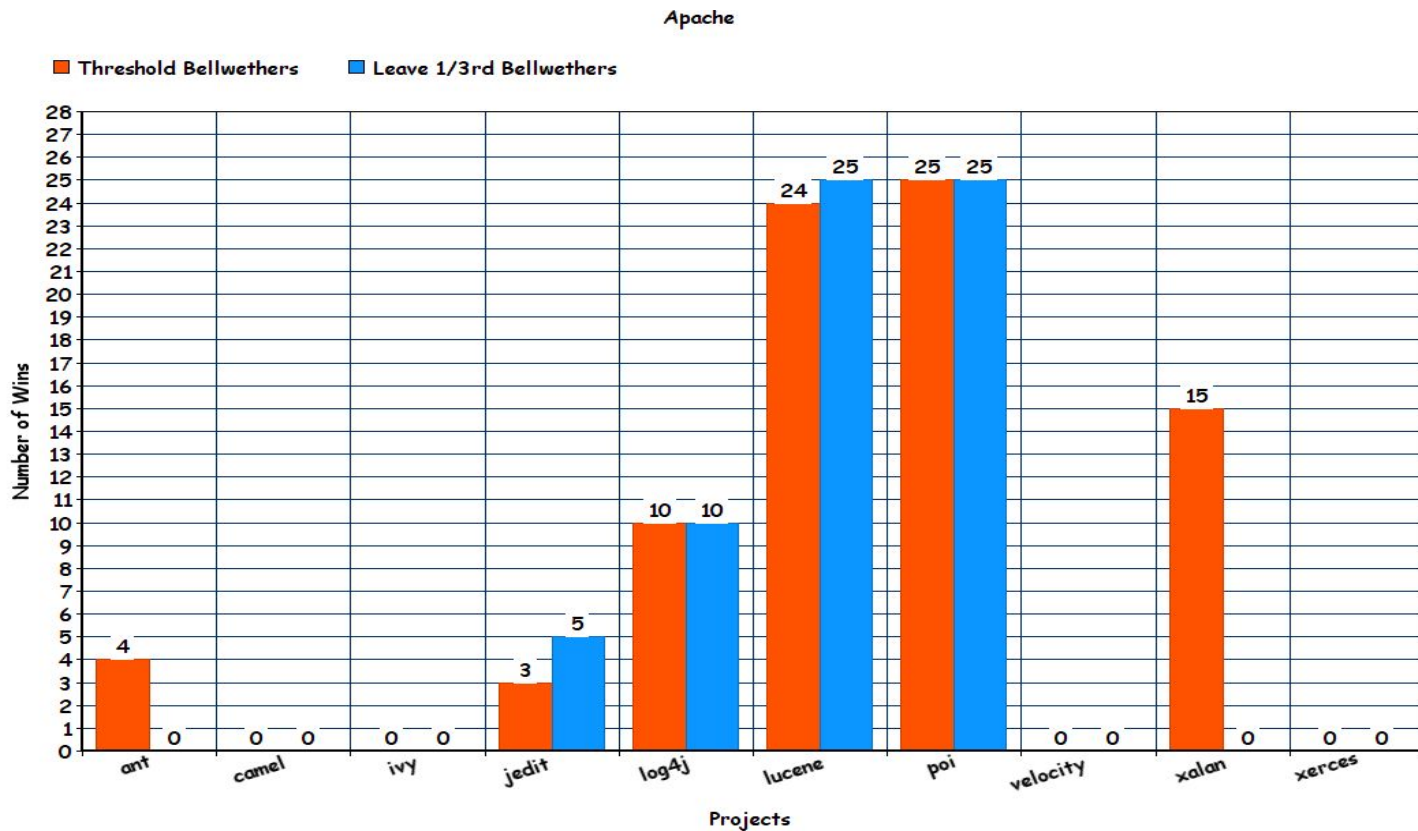
DATA SET DESCRIPTION

- The AEEEM dataset was gathered by D'Amborse et al. [1], it contains 61 metrics, 5371 instances, 893 defective instances.
- The RELINK community data was obtained from work by Wu et al. [2] , it contains 26 metrics, 649 total instances, 238 defective instances
- The Apache community data was gathered by Jureczko et al. [3]. This dataset contains records of the number of known defects for each class using a post-release bug tracking system. The classes are described in terms of 20 OO metrics, including CK metrics and McCabes complexity metrics.

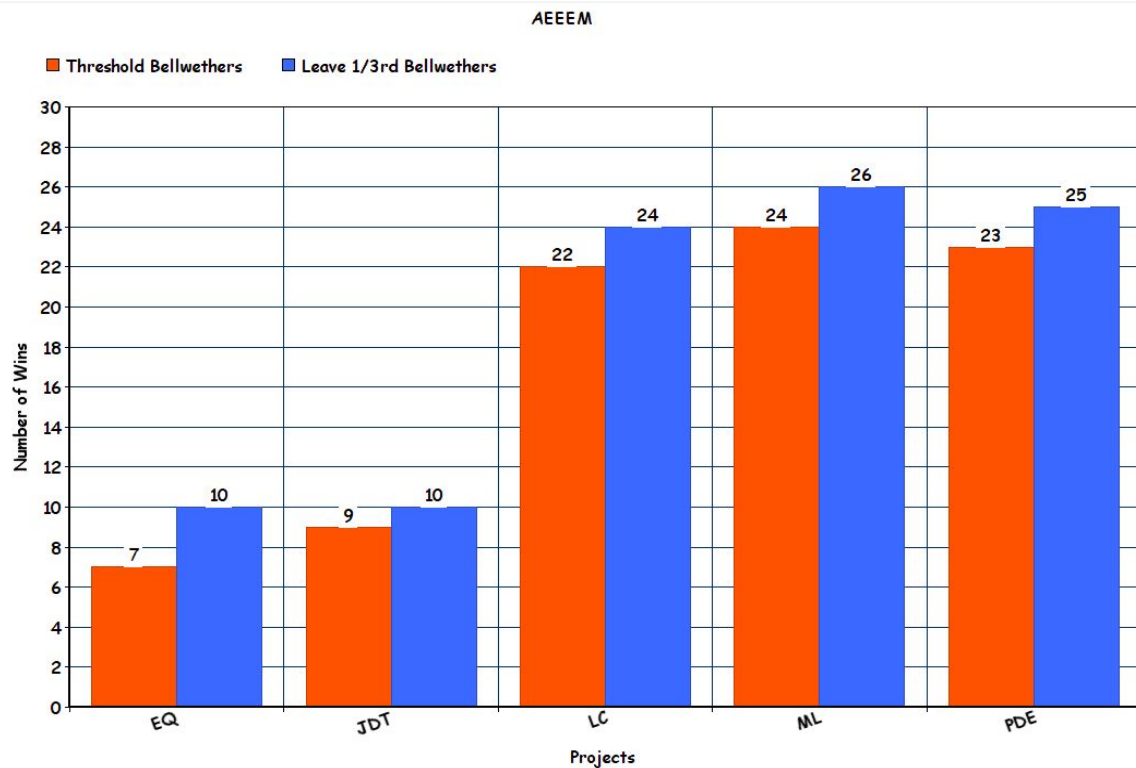
EXPERIMENTAL SETUP

- Threshold value = 52
- sample size = 0.25, incremented by 0.05
- Lives = 10

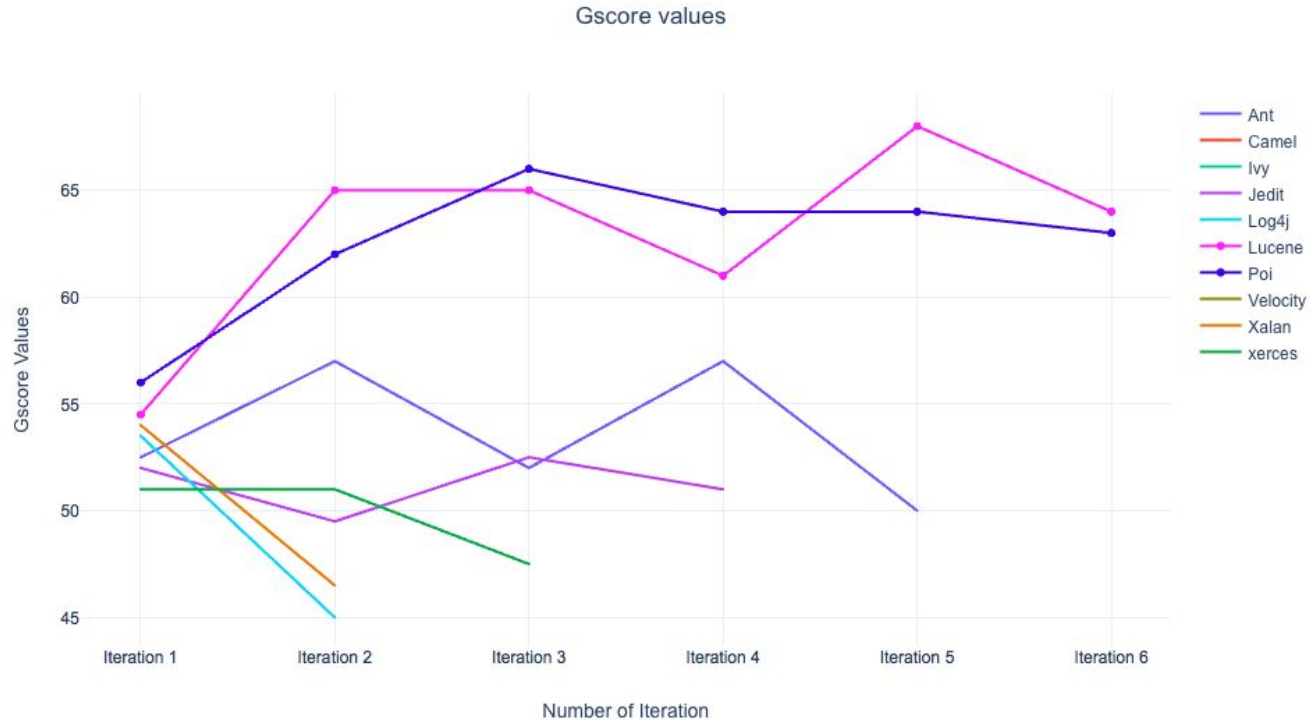
RESULTS



RESULTS



G-SCORES



FUTURE WORK

- Predicting the threshold values for optimal bellwethers
- Analysis of trade-off between different parameters
- Combining our method with Hoeffding Racing

References

- [1] D'Ambros, Marco, Michele Lanza, and Romain Robbes. "Evaluating defect prediction approaches: a benchmark and an extensive comparison." *Empirical Software Engineering* 17. 4-5 (2012): 531-577.
- [2] Bavota, Gabriele. "Mining unstructured data in software repositories: current and future trends." *Software Analysis, Evolution, and Reengineering (SANER), 2016 IEEE 23rd International Conference on*. Vol. 5. IEEE, 2016.
- [3] Jureczko, Marian, and Lech Madeyski. "Towards identifying software project clusters with regard to defect prediction." *Proceedings of the 6th International Conference on Predictive Models in Software Engineering*. ACM, 2010.
- [4] Nair, Vivek, et al. "Transfer Learning with Bellwethers to find Good Configurations." *arXiv preprint arXiv:1803.03900* (2018).
- [5] Krishna, Rahul, and Tim Menzies. "Bellwethers: A Baseline Method For Transfer Learning." *IEEE Transactions on Software Engineering* (2018).
- [6] Max, "Recursive Feature Elimination" <https://topepo.github.io/caret/recursive-feature-elimination.html#search>

THANK YOU!