Using Hoeffding Bounds and Project Elimination for faster Bellwether prediction

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Tasks involved in this project and their owners

Task Division	Completed by
Baseline Model	S. Kacholia, S. Sharma
Hoeffdings bound implementation	S. Kacholia, A. Nalwaya
Modified Hoeffdings bound	A. Nalwaya
Interpretation and compilation of results	S. Kacholia, S. Sharma, A. Nalwaya
Generating samples and testing algorithms	S. Sharma, A. Nalwaya
Project Elimination	A. Nalwaya
Feature Selection	A. Nalwaya

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bell·weth·er

/ˈbelˌweTHər/

noun

the leading sheep of a flock, with a bell on its neck.

- an indicator or predictor of something.
  "college campuses are often the bellwether of change"

Motivation

- *Why*: Identifying the Bellwether project among a group of projects would make the task of defect prediction easier
- *What*: Making the identification of this Bellwether project faster than the current $O(N^2)$ approach
- *How*: Using Hoeffding bounds and project elimination to reduce the dataset required for Bellwether identification

Why Bellwethers?

- Model built using Bellwether project can serve as a representative model among the projects in the same domain
- Bellwether project can serve as a baseline model for constructing different transfer learners in various domains of software engineering
- Instead of exploring all the available data, we find one dataset that offers stable results for longer period of time

Existing Approach

Train

- Use a Random Forest Classifier
- Train on data from one of the projects at a time, for all projects

Test

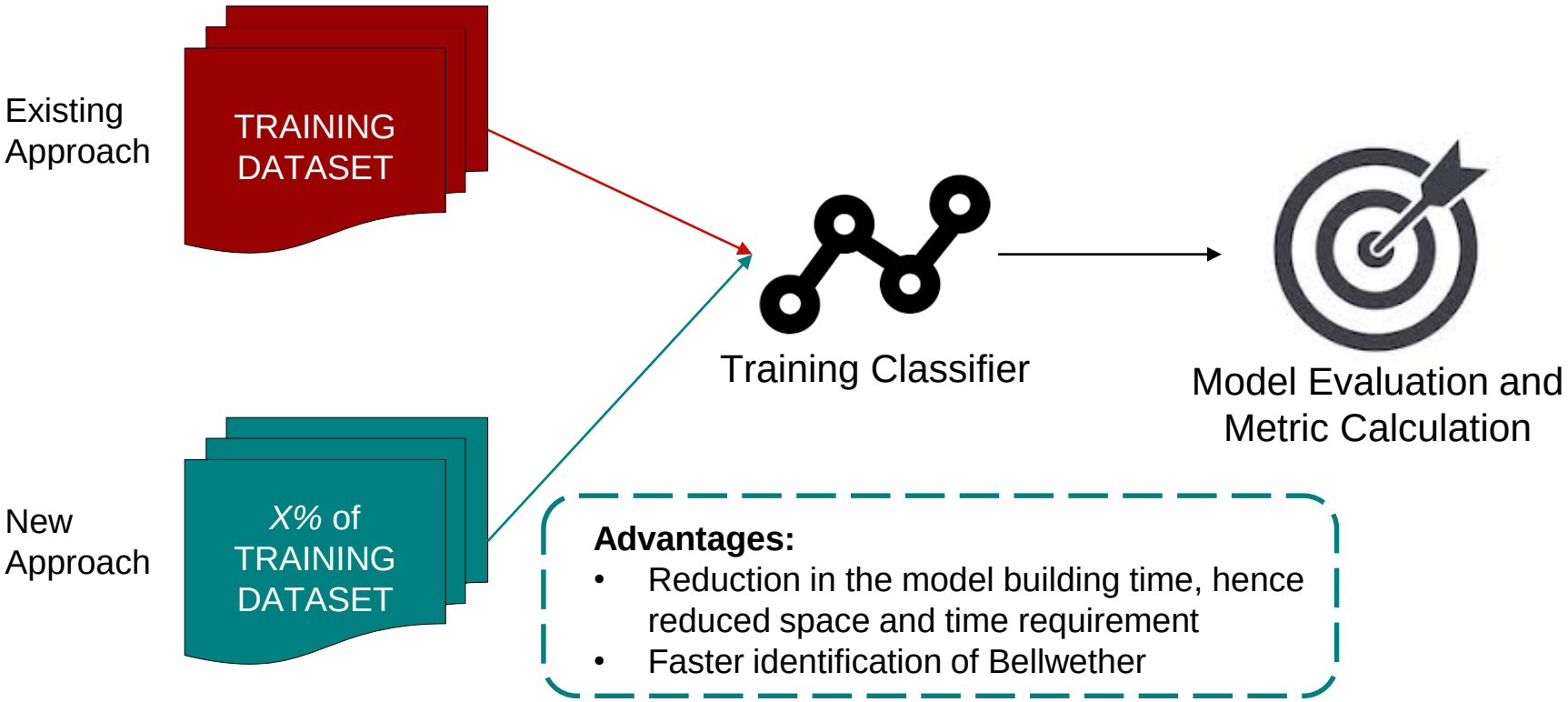
- Test on all the other projects
- Compute *g-score* for each project

$$G = \frac{2 * pd * (1 - pf)}{(1 + pd - pf)}$$

Bellwether Prediction

- Calculate median *g-score*
- Project with best median *g-score* is declared as *"Bellwether"*

New approach reduces the amount of data used for training classifier



Research Questions

RQ1 : Can we predict which dataset will be the bellwether?

RQ2 : Can we reduce the time to find bellwether by reducing the size of data?

RQ3 : Does Hoeffding sampling give better performance that project elimination?

RQ4 : Does feature selection improve the time for bellwether identification?

Sampling using Hoeffding Bounds

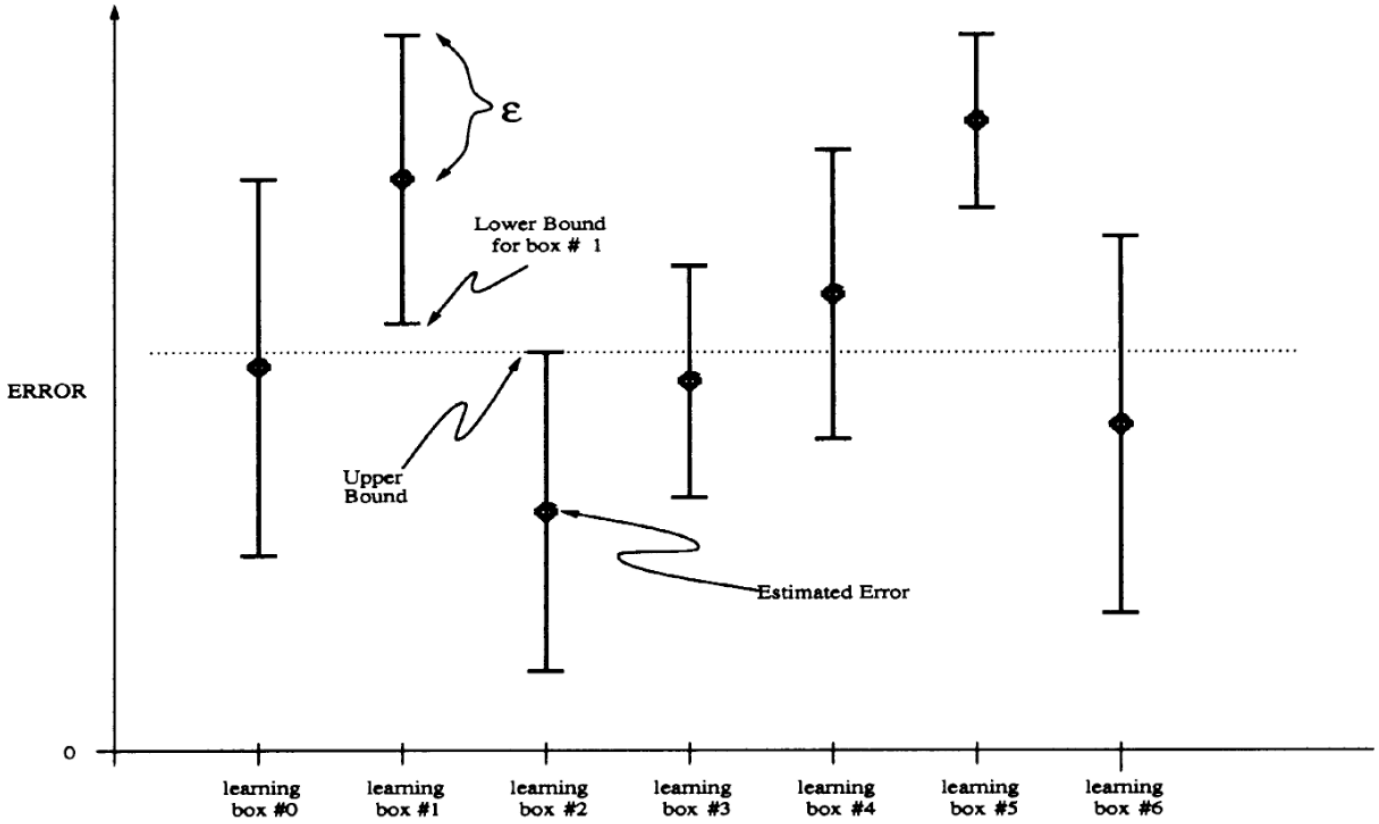
- Iteratively keep on adding data points from the data till a sufficient number of points have been picked
- Finding how close is estimated error from true error

$$\Pr(|E_{true} - E_{est}| > \epsilon) < 2e^{-2n\epsilon^2/B^2}$$

- We estimate the number of samples required using

$$n > \frac{B^2 \log(2/\delta)}{2\epsilon^2}$$

Sampling using Hoeffding Bounds



The upper bound of learning box #2 eliminates the learning boxes #1 and #5

Project Elimination to reduce the candidate projects

- Core idea behind this approach is to eliminate projects having significantly poor performance from the pool of candidate projects
- This will reduce the number of projects required to be analyzed for making bellwether identification
- Conditions for elimination:
  - Project is testing on atleast 1/3rd of the projects
  - G-score value is less than the threshold value

Project Elimination to reduce the candidate projects

Algorithm

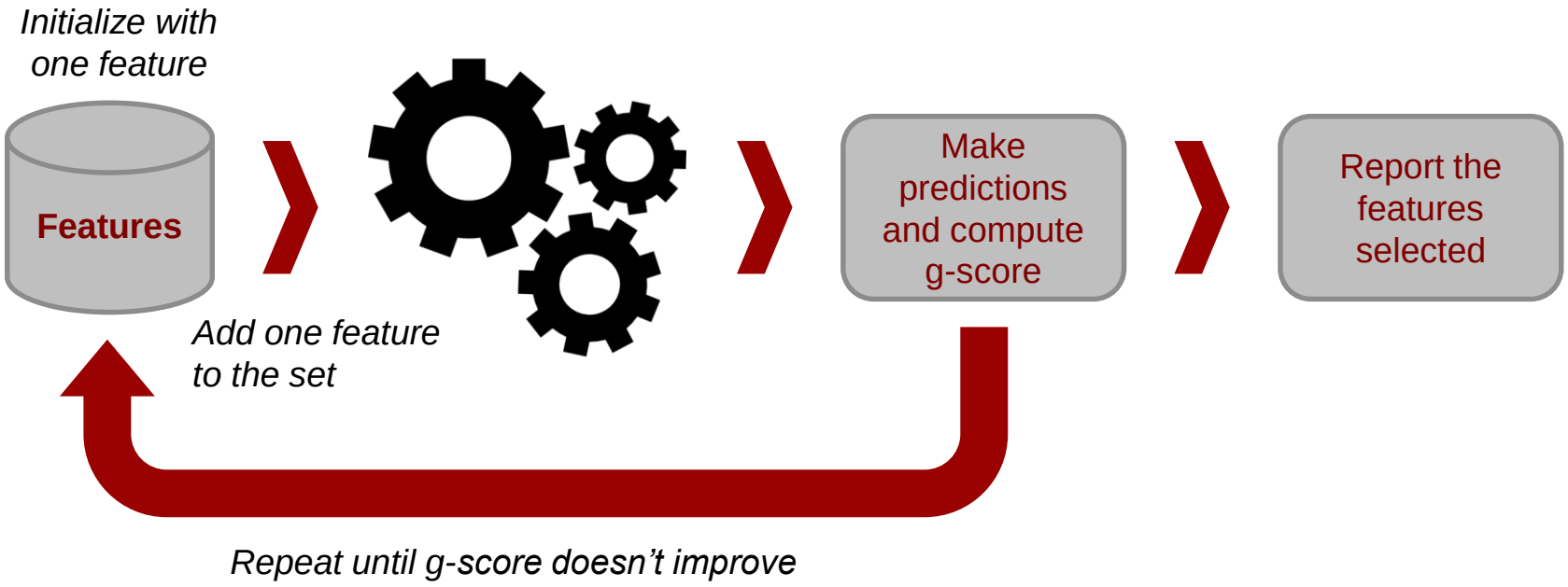
```
for each project do
      load X_train, y_train
      train random forest classifier
      set threshold g-score
      for all other projects
            load X_test, y_test
            make predictions
            compute g-score
            if g-score < threshold and #projects tested >= 3:
                  g-score = 0
            append results, g-score
return results
```

Exploring Feature Selection algorithms to filter unimportant attributes

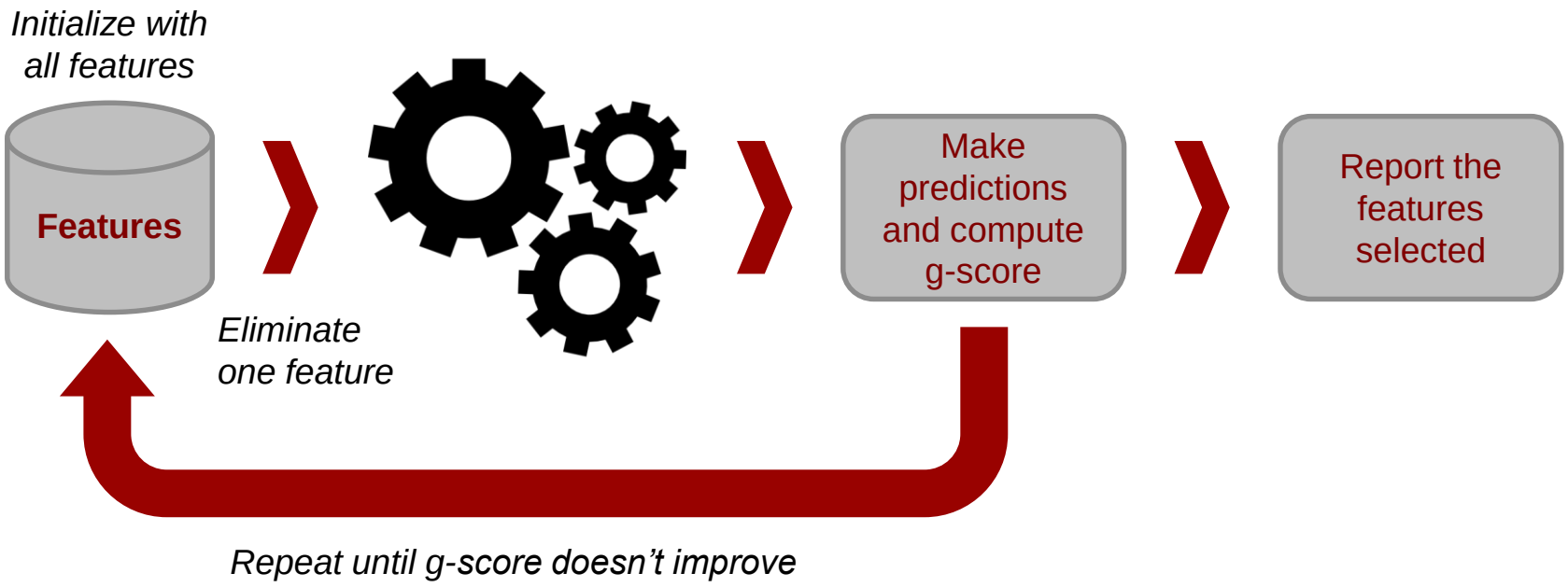
In this work, we have explored the following feature selection algorithms:

- Forward feature selection
- Backward feature elimination
- Information Gain as a feature selector
- Correlation as a feature selector

Forward Feature Selection



Backward Feature Elimination



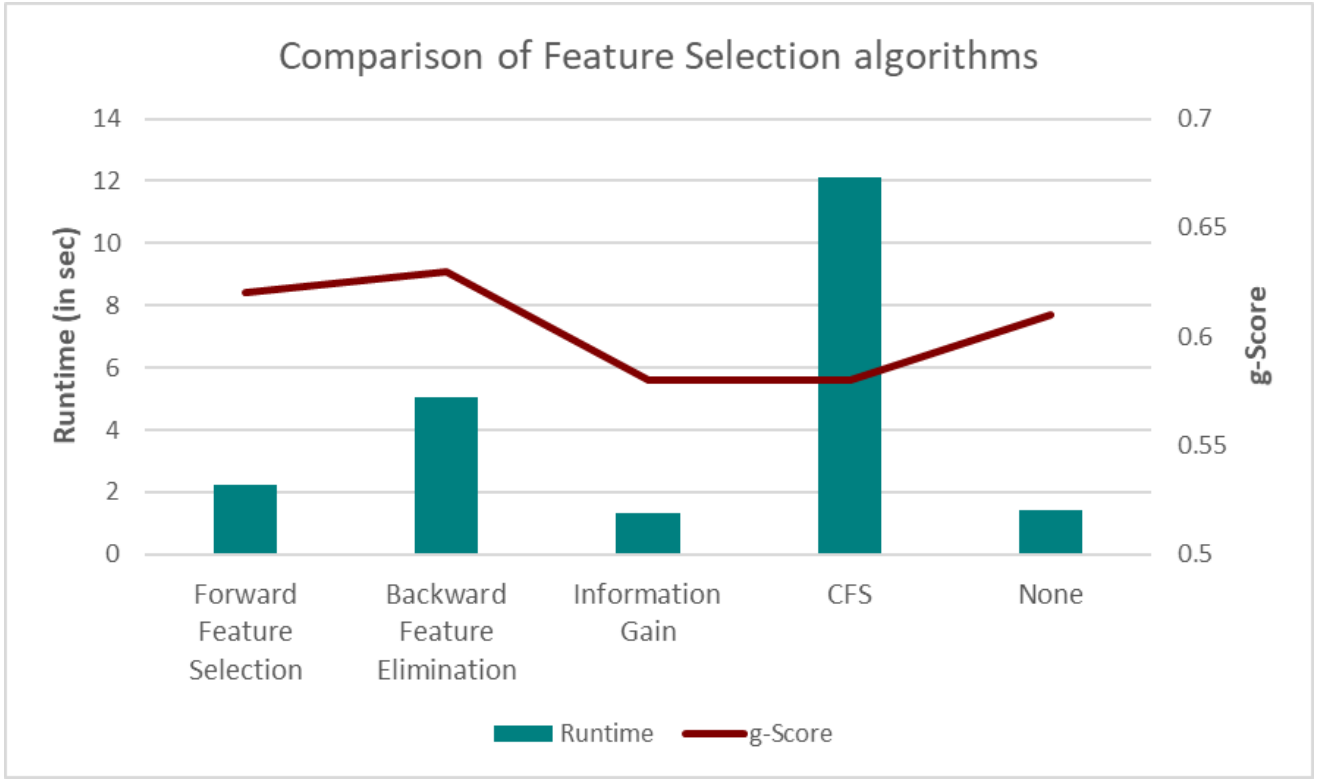
Information Gain as a feature selector

- Entropy-based feature evaluation method
- *Information Gain:* Amount of information provided by a feature for the items to be predicted
- Information gain for each attribute is calculated and attributes with higher values of information gain are chosen
- Attributes with lower information gain are eliminated since they do not provide significant information about the class label

Correlation-based Feature Selection (CFS)

- Evaluates subsets of attributes rather than individual attributes
- Considers the usefulness of individual attributes for predicting class label and also the inter-correlation between attributes
- *Ideal subset:* High correlation with class while low inter-correlation with each other
- Computes correlation between attributes and applies heuristic search strategy for finding ideal subset

Comparison of these feature selection algorithms



NOTE: These results are for the Bellwether project (poi)

Key takeaways from the feature selection approaches

- None of the approaches provide a significant improvement of g-score than conventional Random Forest Classifier
- Forward selection and Backward elimination methods operate in a sequential manner and hence do not cover all subsets
- Information gain takes each attribute but does not account of relationship between attributes
- CFS answers the shortcomings of other approaches but takes a lot of time to run without any proportional improvement

Comparing results from Hoeffding bounds and Project Elimination

Project	Baseline Approach	Hoeffding Bounds	Modified Hoeffding Bounds
ant	0.18	0.18	0.19
camel	0.24	0.25	0.24
ivy	0.09	0.12	0.12
jedit	0.04	0.03	0.04
log4j	0.34	0.34	0.32
lucene	0.52	0.52	0.51
poi	**0.61**	**0.62**	**0.61**
velocity	0.49	0.49	0.49
xalan	0.56	0.58	0.57
xerces	0.42	0.43	0.43

- ***'poi'*** is the bellwether dataset for the baseline method as well as after the implementation of Hoeffding bounds.
- Training data of around ~8.5% for each dataset gives similar results, **reducing the time and data required for training effectively**.

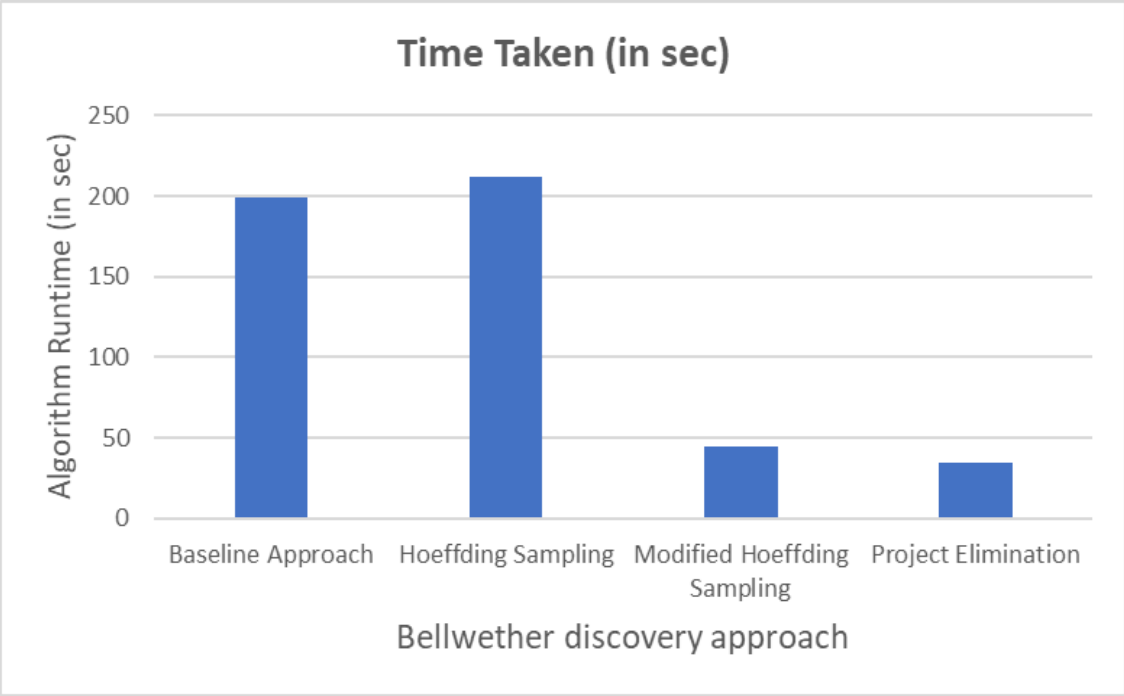
Project elimination performance

Project	Baseline Approach	Project Elimination
ant	0.18	0.0
camel	0.24	0.0
ivy	0.09	0.0
jedit	0.04	0.0
log4j	0.34	0.0
lucene	0.52	0.54
poi	**0.61**	**0.61**
velocity	0.49	0.49
xalan	0.56	0.57
xerces	0.42	0.41

Key takeaways:

- ***'poi'*** remains the bellwether project for this approach also
- Projects which are pruned are assigned value 0
- G-score values are very close to those obtained by the baseline approach

Average runtime for all the approaches for Bellwether identification



Experiment	Runtime (in sec)
Baseline Approach	199.32
Hoeffding Sampling	211.57
Modified Hoeffding Sampling	44.16
Project Elimination	34.63

Future Work / Open issues

- Exploring alternative sampling techniques
- Extending this work to different target domains like code smells, issue lifetime estimation and effort estimation
- Racing between project elimination and sampling