¡¡¡¡¡¡¡ HEAD

# Actionable = Cluster + Constrast?

Rahul Krishna, Tim Menzies
Computer Science, North Carolina State University, USA
{i.m.ralk, tim.menzies}gmail.com

***Abstract*—There are many algorithms for data *classification* such as C4.5, Naive Bayes, SVM, etc. Are these enough for software data analytics? Or should we be supporting another kind of reasoning? For example, this paper does not answer "what is" (i.e. the standard classification problem), but instead offers advice on "what to change". Two approaches for learning minimal, yet effective, changes, software artifacts are explored. Lessons learned are reported.**

***Index Terms*—Prediction, case-based reasoning, data mining, software engineering.**

## I. Introduction

How should we handle "unpopulular" results for data analytics? For example, if a business manager is presented with a data mining result that troubles them (e.g. an estimate of development time that is distressingly long), what advice can we offer them on management actions to *change* hat estimate?

This is an important question, and one with much currency in industry. In the summer of 2011 and 2012, one of us (Menzies) spent two months working on-site at Microsoft Redmond, observing data mining analysts. He noted how Microsoft's data scientists discussed their data with business users. One surprising from that study was just how little time was spent inspecting of the output of data miners as compared to another process, which we call *peeking*. In *peeking*, analysts and users spend much time inspecting and discuss small samples of either raw or exemplary or synthesized project data. Further, very little of those discussions were focused on classification (the additional of a labels to some unlabelled data). Rather, much time was spent in those meetings discussion *what to do next*; i.e. trying to determine what could be altered to better improve some business outcome.

That Microsoft stufy found two common "peeking" methods. In *data engagement meetings*, users debated the implications of data displayed on a screen. In this way, users engaged with the data and with each other by monitoring each others' queries and check each others' conclusions.

Another data analysis pattern observed at Microsoft was *cluster + contrast* in which data is reduced to a few clusters. Users are then just shown the delta between those clusters. While contrasting, if feature values are the same in both clusters, then these were pruned from the reports to the user. In this way, very large data sets can be shown on one PowerPoint slide. Note that *cluster+contrast* was a tool that can be usefully employed within *data engagement meetings*.

Cluster+contrast and engagement meetings are common practices at Microsoft. Yet these methods had never been rigorously studied or certified. For both those reasons, we reflected over those tools to discover and analyze their underlying process. The result was HOW: a tool that combines two data reduction methods:

- Method1: feature selection
- Method2: centroid generation from clusters.

While Method1 is widely used [3], to the best of our knowledge, this combination has not been thoroughly explored before. Hence, this paper explores "peeking".

## II. How to Cluster

Recent results suggest we are free to select from a wide range of clustering methods. Ganesan [1] explored different clustering methods for SE data using effort and defect data from the PROMISE repository[1]; That studied explored K-Means, mini-batch-K-Means, DBscan, EM, Ward, and the WHERE algorithm discussed below. Clusters were assessed via the performance of prediction learned from the clusters by Random Forests (for defect prediction) and M5prime or linear regression (for effect estimation). Ganesan found that the details of the clustering method were less important than ensuring that a large number of clusters were generated.

Accordingly, we select a clustering method that generates $\sqrt{N}$ clusters from $N$ examples, that runs fasts, which has shown promise in prior work [2], and which ignores spurious dimensions (the last item is important since, in our experience, much SE data is "noisey"; i.e. contains signals not associated with the target variable). For the rest of this article, we use the top-down bi-clustering method described in Figure 4 which recursively divides the data in two using a dimension that captures the greatest variability in the data.

## III. How to Contrast

Once we have clusters, the next task is to offer business users lessons learned from comparing different clusters.

Once methods for doing so is a *contrast tree*. First, we cluster the data to find clusters $C_1, C_2, ...$. Next, using those clusters as class labels, we execute a decision tree algorithm to find what attributes select for different clusters. Next, to learn recommendations for a business user, we ask (1) what *current* cluster are you in?; (2) what *desired* cluster do you want to move to?; (3) what is the delta between those clusters? To answer the last question, we report the delta in the branches of the decision tree that lead to *current* and *desired*.

[1]http://openscience.us/repo

**Top down clustering using WHERE:**
The data is recursively divided in clusters using WHERE as follows:

- Find two distance cases, $X, Y$ by picking any case $W$ at random, then setting $X$ to its most distant case, then setting $Y$ to the case most distant from $X$ [**?**] (this requires only $O(2N)$ comparisons of $N$ cases).
- Project each case $Z$ onto a `Slope` that runs between $X, Y$ using the cosine rule.
- Split the data at the median $x$ value of all cases and recurses on each half (stopping when one half has less than $\sqrt{N}$ of the original population).

**Constructing Decision Trees:**
A decision tree is built using CART with entropy being used to generate splits in the data. The leaf nodes of the tree are weighted by measuring the mean of majority cluster of the leaf. To limit the size of the tree Features are pruned using information gain.

**Generating contrast sets:**

- Identify current position on the tree.
- Identify the nearest "Better" branch.
- Identify the "Delta" between the cluster.

Fig. 1: A summary of Contrast Trees

## A. *How does a contrast tree work?*

Contrast trees works by building a simple decision tree based on entropy, as in the classification and regression trees. Contrast tree uses the WHERE clustering algorithm, which in-turn uses FASTMAP [] to compute clusters that contain instances that are spatially close. Each cluster is assigned a unique cluster id. Then, a simple decision tree is built using a standard classification and regression tree (CART). The tree is built with the following tunable features:

- *Entropy* is used as criteria for generating optimum cuts while building the decision trees. These were shown to be consistent in giving high performance across most data.
- *Minimum samples per leaf* defines the minimum number of instances in a leaf of the decision tree.
- *Max depth* defines the number of levels of recursive splits that are allowed in the tree.

Decision trees can be used to generate a decision rule, which when applied to solution sets must theoretically improve performance. To generate rules – a tree is constructed with some training data, and for every instance in a the test data, we find a branch in the tree that best matches the test data. All instances that needs improvement in the test data constitute the "worst" set W. We find the nearest branch, "B", in the tree with better performance. The difference between W and B constitutes the decision rules.

A contrast set, "C" is simply a collection of all the decision rules. It can be obtained traversing through the tree from "W" to "B" and tracking all the branch variables along this path. Note that the branch variables use decision ranges instead of single point solutions, making implementation of the rules in real life feasible.

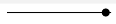
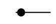
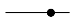
| Rank | Treatment | Median | IQR | |
|---|---|---|---|---|
| 1 | Ant (Tree) | 0.67 | 0.41 |  |
| 1 | Jedit (Tree) | 0.68 | 0.13 |  |
| 1 | Ant (WHAT) | 0.7 | 0.13 | |
| 1 | Jedit(WHAT) | 0.72 | 0.25 |  |

Fig. 2: Results comparing the performance scores on sample projects from the Jurezcko data sets.

## B. *Why would it work?*

Contrast set seemed like it would be a fine tool for generating decision rules. They present some key advantages which are listed below:l

- They allow the user to exert a fine grain control over the parameters that needs to be changed, while providing a way to visualize the recommended changes.
- The changes suggested by the contrast sets are inherently local in nature, making the changes practical and potentially easy to implement.
- The contrast tress require a worst case time complexity of $O(n)$, which is a function in linear time.

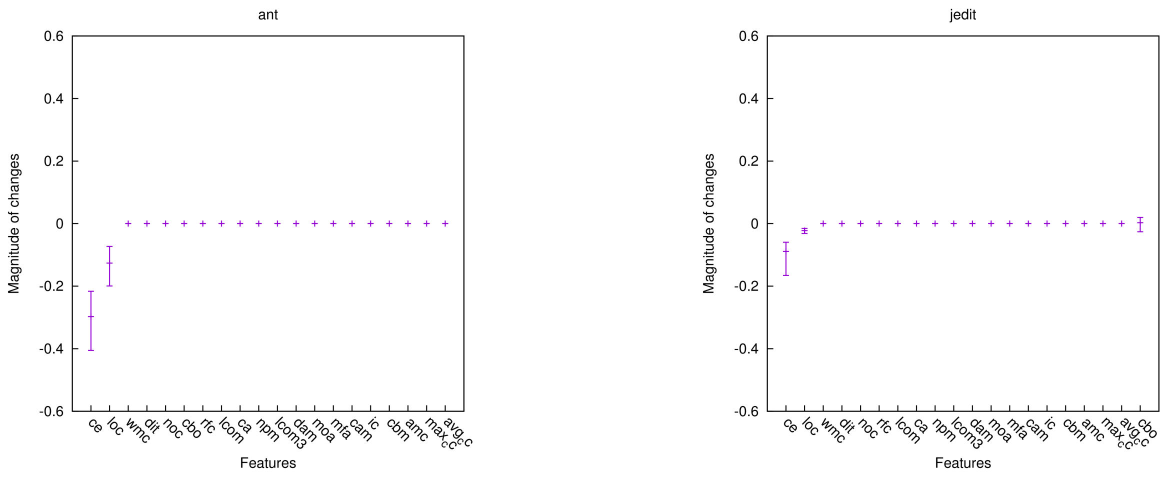
## C. *Reasons for failure*

Although the idea seemed ideal, initial implementation of the contrast tree provided results that were discouraging. One of the major problems with using contrast trees was that the trees were rather large. The initial motivation was that the trees could serve as a medium for experts to identify and explore solution spaced that were local to the problem. The size of the decision tree jeopardized the readability of the solutions by increasing the complexity. In our efforts to reduce the size of the tree, we devised a pruning method, that prunes away irrelevant branches that do not contribute better solutions. The smaller trees, while being easier to understand, posed another problem: the test instances were too dissimilar to the leaves in the tree. This meant that the relevance of the contrast set could not be justified.

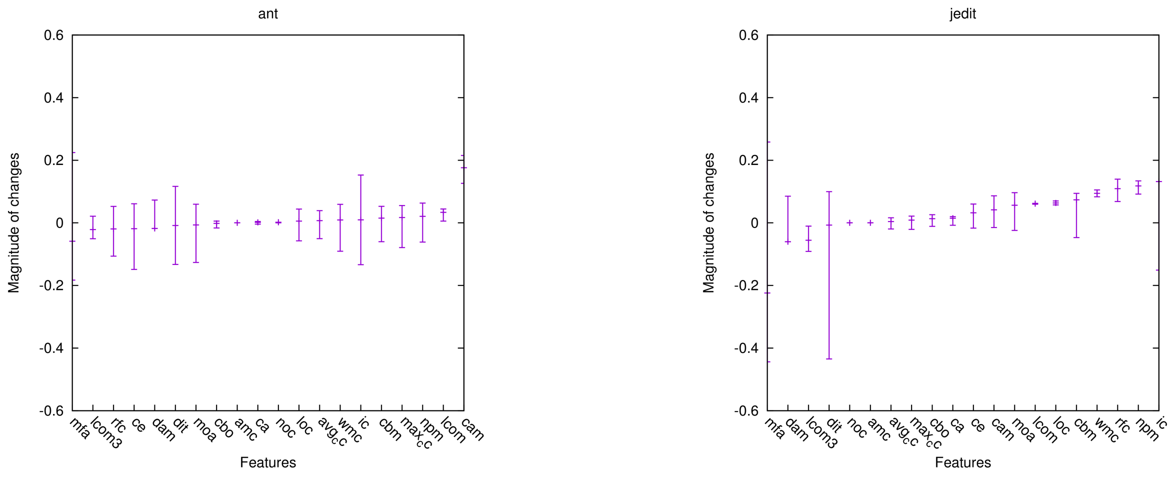
The depth of the tree also influences the performance of contrast sets. The depth is represented by levels of splits in the tree, and this parameter determines the number of features that require changes. If the tree is too shallow, the changes suggested by the planner are too little to make any difference. On the other hand, deeper trees leads to over-fitting and therefore suggests too many changes when not required.

A study was conducted on numerous examples of the Jureczko object-oriented static code data sets []: Ant, Camel, Ivy, Jedit, Log4j, Lucene, Poi, Synapse, Velocity, Xalan, Xerces [2]. On these data sets, the plans generated by contrast tree advise how to change static code attributes in order to reduce defects in Java classes. The challenges with contrast trees had a profound impact on the performance, as shown in figure **??**.

[2]Available from the object-oriented defects section of the PROMISE respository openscience.us/repo/defect/ck.



(a) Tree Learner



(b) WHAT

Fig. 3: Performance Comparision

## D. *What worked?*

Contrast tree is the second generation of our efforts to use contrast set learners for planning case based reasoning. W2 represents the first generation of our work. W2 is a CBR planner that reflected over the delta of raw attributes []. However, it frequently suffered from an optimization failure. When its plans were applied, performance improved in only $\frac{1}{3}$rd of test cases.

Generation two of our work resulted in the development of contrast trees. It uses a recursive clustering method discussed above followed by summarizing these recursive divisions into a tree structure. Although the initial results with contrast tree were weak, they were somewhat positive. We tried to extend and improve the contrast tree prototype, however the results were not encouraging. The tree-based approach suffered from one key issue: the local changes were highly ineffective in reducing the defects, see figure **??**. In addition, it also faced the optimization failure problem, which was also seen with W2.

As a continuation of the contrast tree work, we built HOW as a simpler approach that was to provide a baseline result, above which contrast tree was meant to do better. However, HOWs results were so good that we threw away months of work on tree-based planning with contrast tree.

## IV. Future Work

Now, we strongly recommend HOW over contrast tree (and W2) since, as shown by the following results, HOWs plans never lead to performance getting worse. Also, when HOW did improve the expected values of the performance, those performance improvements were an order of magnitude larger than those seen with contrast tree.

## References

[1] Divya Ganesan. Exploring essential content of defect prediction and effort estimation through data reduction. Master's thesis, Computer Science, West Virginia University, 2014.

[2] Tim Menzies, Andrew Butcher, David Cok, Andrian Marcus, Lucas Layman, Forrest Shull, Burak Turhan, and Thomas Zimmermann. Local versus global lessons for defect prediction and effort estimation. *IEEE Transactions on Software Engineering*, 39(6):822–834, 2013.

[3] Tim Menzies, Zach Milton, Burak Turhan, Bojan Cukic, Yue Jiang, and Aye Bener. Defect prediction from static code features: Current results, limitations, new approaches. *Automated Software Engineering*, 17(4):375–407, 2010.