
Sharing Experiments Using Open Source Software



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SUMMARY

When researchers want to repeat, improve or refute prior conclusions, it is useful to have a complete and operational description of prior experiments. If those descriptions are overly long or complex, then sharing their details may not be informative.

OURMINE is a scripting environment for the development and deployment of data mining experiments. Using OURMINE, data mining novices can specify and execute intricate experiments, while researchers can publish their complete experimental rig alongside their conclusions. This is achievable because of OURMINE's succinctness. For example, this paper presents two experiments documented in the OURMINE syntax. Thus, the brevity and simplicity of OURMINE recommends it as a better tool for documenting, executing, and sharing data mining experiments.

1. Introduction

Since 2004, the authors have been involved in an open source data mining experiment. Researchers submitting to the PROMISE conference on predictive models in software engineering are encouraged to offer not just conclusions, but also the data they used to generate those conclusions. The result is nearly 100 data sets, all on-line, freely available for download [†].

The premise of this paper is that after *data sharing* comes *experiment sharing*; i.e. repositories should grow to include not just data, but the code required to run experiments over that data. This simplifies the goal of letting other researchers repeat, or even extend, data mining experiments of others. Repeating experiments is not only essential in confirming previous results, but also in providing an insightful understanding of the fundamentals

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[†]<http://promisedata.org/data>

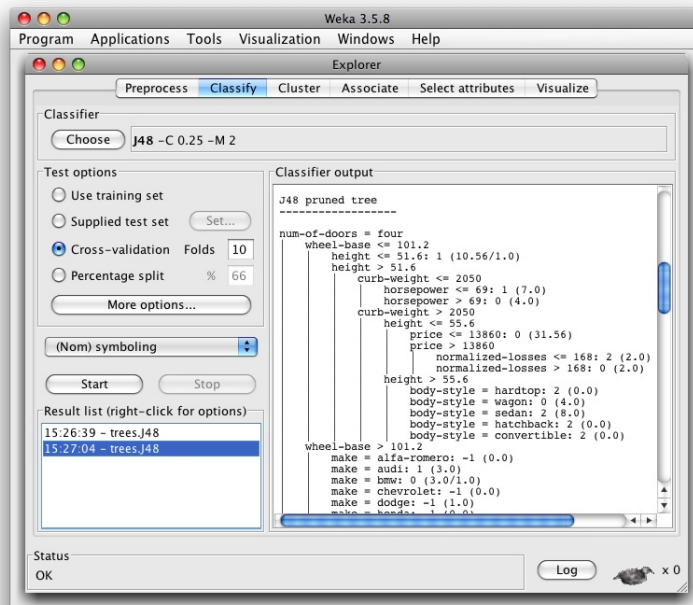


Figure 1. The WEKA toolkit running the J48 decision tree learner.

involving those experiments. Thus, it is important to have a prepared set of clearly defined and operational experiments that can be utilized in order to achieve similar prior results.

Consequently, we have been assessing data mining toolkits such as the WEKA[‡] tool of Figure 1, “R”[§], the ORANGE[¶] tool of Figure 2, RAPID-I^{||}, MLC++^{**}, and MATLAB^{††}. We find that they are not suitable for publishing experiments. Our complaint with these tools is same as that offered by Ritthoff et al. [22]:

- Proprietary tools such as MATLAB are not freely available.
- Real-world experiments are more complex than running one algorithm.

[‡]<http://www.cs.waikato.ac.nz/ml/weka/>

[§]<http://www.r-project.org/>

[¶]<http://magix.fri.uni-lj.si/orange/>

^{||}<http://rapid-i.com/>

^{**}<http://www.sgi.com/tech/mlc/>

^{††}<http://www.mathworks.com>

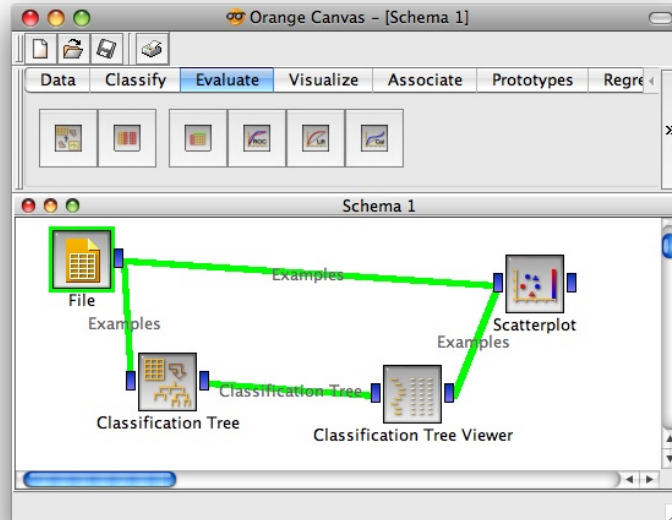


Figure 2. Orange's visual programming environment.

- Rather, such experiments or applications require *intricate combinations* of a large number of tools that include data miners, data pre-processors and report regenerators.

However, the need to “wire up” data miners within a multitude of other tools has been addressed in many ways. In WEKA's visual *knowledge flow* programming environment, for example, nodes represent different pre-processors/ data miners/ etc while arcs represent how data flows between them. A similar visual environment is offered by many other tools including ORANGE (see Figure 2). The YALE tool (now RAPID-I) built by Ritthoff et al. formalizes these visual environments by generating them from XML schemas describing *operator trees* like Figure 3.

Ritthoff et al. argues (and we agree) that the standard interface of (say) WEKA does not support the rapid generation of these intricate combinations. In our experience these visual environments are either overly elaborate, discouraging or distracting:

- These standard data mining toolkits may be overly elaborate. As shown throughout this paper, very simple UNIX scripting tools suffice for the specification, execution, and communication of experiments.
- Some data mining novices are discouraged by the tool complexity. These novices shy away from extensive modification and experimentation.

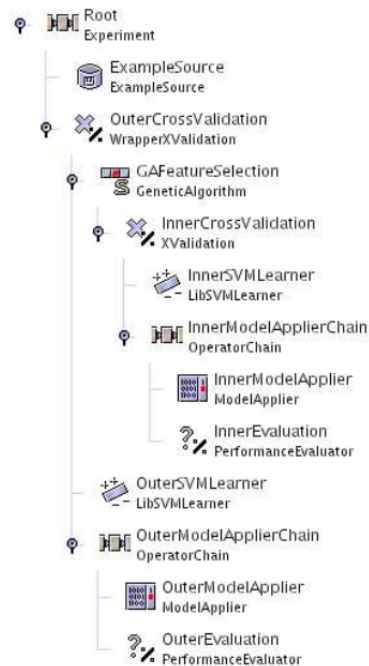


Figure 3. Rapid-I's operator trees. [18]. Internally, this tree is a nested XML expression that is traversed top-down to complete an experiment.

- Other developers may become so enamored with the impressive software engineering inside these tools that they waste much time building environments to support data mining, but never get around to the data mining itself.
- According to Menzies [13], while visual systems provide motivation for beginners, they fail in providing a good explanation device for many software engineering and knowledge engineering problems, as many of these problems are not inherently spatial. For example, suppose an entity-relationship diagram is drawn on a piece of paper. While inferences can be made from the diagram, they are not entirely dependent on the physical location of (e.g.) an entity.

A similar experience is reported by our colleagues in WVU Department of Statistics. In order to support teaching, they hide these data mining tools inside high-level scripting environments. Their scripting environments shield the user from the complexities of “R” by defining high-level LISP code that, internally, calls “R”. While a powerful language, we find that LISP can be arcane to many audiences.

OURMINE is a data mining scripting environment. The current kit has tools written in BASH/ GAWK/ JAVA/ PERL/ and there is no technical block to adding other tools written in other languages. Other toolkits impose strict limitations of the usable languages:

- MLC++ requires C++
- Extensions to WEKA must be written in JAVA.

Our preference for BASH [20]/GAWK [1] over, say, LISP is partially a matter of taste but we defend that selection as follows. Once a student learns, for example, RAPID-I's XML configuration tricks, then those learned skills are highly specific to that toolkit. On the other hand, once a student learns BASH/GAWK methods for data pre-processing and reporting, they can apply those scripting tricks to any number of future UNIX-based applications.

This paper introduces OURMINE as follows:

- First, we describe the base tool and offer some samples of coding in OURMINE;
- Next, we demonstrate OURMINE's ability to succinctly document even complex experiments.
 - OURMINE is a tool for both practitioners and researchers. Our first demonstration experiment is practitioner-focused and shows how OURMINE can be used in an industrial setting. Following experiments demonstrate OURMINE as an adequate tool for current research.

This paper is an extension of a prior publication [6]:

- This paper details functionality added since that last paper was published;
- This paper adds two new experiments to the description of OURMINE (see §3.1 and §3.3).

2. OURMINE

OURMINE was developed to help graduate students at West Virginia University document and execute their data mining experiments. The toolkit uses UNIX shell scripting. As a result, any tool that can be executed from a command prompt can be seamlessly combined with other tools.

For example, Figure 4 shows a simple bash function used in OURMINE to clean text data before conducting any experiments using it. Line 5 passes text from a file, performing tokenization, removing capitals and unimportant words found in a stop list, and then in the next line performing Porter's stemming algorithm on the result.

OURMINE allows connectivity between tools written in various languages as long as there is always a command-line API available for each tool. For example, the modules of Figure 4 are written using BASH, Awk and Perl.

The following sections describe OURMINE's functions and applications.

2.1. Built-in Data and Functions

In order to encourage more experimentation, the default OURMINE installation comes with numerous data sets:

```

1 clean(){
2   local docdir=$1
3   local out=$2

4   for file in $docdir/*; do
5     cat $file | tokens | caps | stops $Lists/stops.txt > tmp
6     stems tmp >> $out
7     rm tmp
8   done
9 }

```

Figure 4. An OURMINE function to clean text documents and collect the results. *Tokens* is a tokenizer; *caps* sends all words to lower case; *stops* removes the stop words listed in "\$Lists/stops.txt"; and *stems* performs Porter's stemming algorithm (removes confusing suffixes).

- *Text mining data sets*: including STEP data sets (numeric): ap203, ap214, bbc, bbc sport, law, 20 Newsgroup subsets [sb-3-2, sb-8-2, ss-3-2, sl-8-2]^{††}
- *Discrete UCI Machine Learning Repository datasets*: anneal, colic, hepatitis, kr-vs-kp, mushroom, sick, waveform-5000, audiology, credit-a, glass, hypothyroid, labor, pcolic, sonar, vehicle, weather, autos, credit-g, heart-c, ionosphere, letter, primary-tumor, soybean, vote, weather.nominal, breast-cancer, diabetes, heart-h, iris, lymph, segment, splice, vowel;
- *Numeric UCI Machine Learning Repository datasets*: auto93, basketball, cholesterol, detroit, fruitfly, longley, pbc, quake, sleep, autoHorse, bodyfat, cleveland, echoMonths, gascons, lowbwt, pharynx, schlvote, strike, autoMpg, bolts, cloud, elusage, housing, mbagrade, pollution, sensory, veteran, autoPrice, breastTumor, cpu, fishcatch, hungarian, meta, pwLinear, servo, vineyard.
- The defect prediction data sets from the *PROMISE repository*: CM1, KC1, KC2, KC3, MC2, MW1, PC1

OURMINE also comes with a variety of built-in functions to perform data mining and text mining tasks. For a complete list, see the appendix.

2.2. Learning and Teaching with OURMINE

Data mining concepts become complex when implemented in a complex manner. For this reason, OURMINE utilizes simple scripting tools (written mostly in BASH or GAWK) to better convey the inner-workings of these concepts. For instance, Figure 5 shows a GAWK implementation used by OURMINE to determine the TF-IDF [21] (Term Frequency * Inverse Document Frequency, described below) values of each term in a document. This script is simple and concise, while a C++ or Java implementation would be large and overly complex. An

^{††}<http://mlg.ucd.ie/datasets>

```
function train() { #update counters for all words in the record
  Docs++;
  for(I=1;I<NF;I++) {
    if( ++In[$I,Docs]==1)
      Doc[$I]++
      Word[$I]++
      Words++ }
}
function tfidf(i) { #compute tfidf for one word
  return Word[i]/Words*log(Docs/Doc[i])
}
```

Figure 5. A GAWK implementation of TF-IDF.

additional example demonstrating the brevity of OURMINE script can be seen in Figure 6, which is a complete experiment whose form can easily be taught and duplicated in future experiments.

Another reason to prefer scripting in OURMINE over the complexity of RAPID-I, WEKA, “R”, etc, is that it reveals the inherent simplicity of many of our data mining methods. For example, Figure 7 shows a GAWK implementation of a Naive Bayes classifier for discrete data where the last column stores the class symbol. This tiny script is no mere toy- it successfully executes on very large data sets such as those seen in the 2001 KDD cup and in [19]. WEKA cannot process these large data sets since it always loads its data into RAM. Figure 7, on the other hand, only requires memory enough to store one instance as well as the frequency counts in the hash table “*F*”.

More importantly, in terms of teaching, Figure 7 is easily customizable. Figure 8 shows four warm-up exercises for novice data miners that (a) introduce them to basic data mining concepts and (b) show them how easy it is to script their own data miner: Each of these tasks requires changes to less than 10 lines from Figure 7. The simplicity of these customizations fosters a spirit of “this is easy” for novice data miners. This in turn empowers them to design their own extensive and elaborate experiments.

Also from the teaching perspective, demonstrating on-the-fly a particular data mining concept helps not only to solidify this concept, but also gets the student accustomed to using OURMINE as a tool in a data mining course. As an example, if a Naive Bayes classifier is introduced as a topic in the class, an instructor can show the workings of the classifier by hand, and then immediately afterwards complement this by running Naive Bayes on a small data set in OURMINE. Also, since most of OURMINE does not use pre-compiled code, an instructor can make live changes to the scripts and quickly show the results.

We are not alone in favoring GAWK for teaching purposes. Ronald Loui uses GAWK to teaching artificial intelligence at Washington University in St. Louis. He writes:

```

1 demo004(){
2   local out=$Save/demo004-results.csv
3   [ -f $out ] && echo "Caution: File exists!" || demo004worker $out
4 }

5 # run learners and perform analysis
6 demo004worker(){

7   local learners="nb j48"
8   local data="$Data/discrete/iris.arff"
9   local bins=10
10  local runs=5
11  local out=$1

12  cd $Tmp
13  (echo "#data,run,bin,learner,goal,a,b,c,d,acc,pd,pf,prec,bal"
14  for((run=1;run<=$runs;run++)); do
15    for dat in $data; do

16      blab "data='basename $dat',run=$run"
17      for((bin=1;bin<=$bins;bin++)); do

18        rm -rf test.lisp test.arff train.lisp train.arff
19        makeTrainAndTest $dat $bin $bin
20        goals='cat $dat | getClasses --brief'

21        for learner in $learners; do

22          $learner train.arff test.arff | gotwant > produced.dat
23          for goal in $goals; do

24            cat produced.dat |
25            abcd --prefix "'basename $dat', $run, $bin, $learner, $goal" \
26                --goal "$goal" \
27                --decimals 1
28            done
29          done
30        done
31      blabln
32    done
33  done | sort -t, -r -n -k 11,11) | malign > $out

34  winLossTie --input $out --test w --fields 14 --key 4 --perform 11
35 }

```

Figure 6. A demo OURMINE experiment. This worker function begins by being called by the top level function *demo004* on lines 1-4. Noteworthy sections of the demo code are at: line 19, where training sets and test sets are built from 90% and 10% of the data respectively, lines 25-27 in which values such as *pd*, *pf* and *balance* are computed via the *abcd* function that computes values from the confusion matrix, and line 34 in which a *Wilcoxon* test is performed on each learner in the experiment using *pd* as the performance measure.


```

#naive bayes classifier in gawk
#usage: gawk -F, -f nbc.awk Pass=1 train.csv Pass=2 test.csv

Pass==1 {train()}
Pass==2 {print $NF "|" classify()}

function train( i,h) {
    Total++;
    h=$NF;    # the hypotheis is in the last column
    H[h]++;   # remember how often we have seen "h"
    for(i=1;i<=NF;i++) {
        if ($i=="?")
            continue;    # skip unknown values
        Freq[h,i,$i]++
        if (++Seen[i,$i]==1)
            Attr[i]++; # remember unique values
    }
}
function classify( i,temp,what,like,h) {
    like = -100000;    # smaller than any log
    for(h in H) {      # for every hypothesis, do...
        temp=log(H[h]/Total); # logs stop numeric errors
        for(i=1;i<=NF;i++) {
            if ( $i=="?" )
                continue;    # skip unknwon values
            temp += log((Freq[h,i,$i]+1)/(H[h]+Attr[NF])) }
        if ( temp >= like ) { # better hypothesis
            like = temp
            what=h}
        }
    }
    return what;
}

```

Figure 7. A Naive Bayes classifier for a CSV file, where the class label is found in the last column.

There is no issue of user-interface. This forces the programmer to return to the question of what the program does, not how it looks. There is no time spent programming a binsort when the data can be shipped to /bin/sort in no time. [10]

Function documentation provides a way for newcomers to OURMINE to not only get to know the workings of each function, but also add to and modify the current documentation. Instead of asking the user to implement a more complicated “man page”, OURMINE uses a very simple system consisting of keywords such as *name*, *args* and *eg* to represent a function name, its arguments and an example of how to use it. Using this documentation is simple. Entering *funcs* at the OURMINE prompt provides a sorted list of all available functions in ourmine. Then, by typing *help X*, where *X* is the name of the function, information about that function is printed to the screen. See Figure 9 for an example of viewing the help document for the function *j4810*. Documentation for a function is added by supplying a text file to the helpdocs directory in OURMINE named after the function.

1. Modify Figure 7 so that there is no train/test data. Instead, make it an incremental learning. Hint: 1) call the functions *train*, then *classify* on every line of input. 2) The order is important: always *train* before *classifying* so the the results are always on unseen data.
2. Convert Figure 7 into HYPERPIPES [3]. Hint: 1) add globals $Max[h, i]$ and $Min[h, i]$ to keep the max/min values seen in every column “*i*” and every hypothesis class “*h*”. 2) Test instance belongs to the class that most overlaps the attributes in the test instance. So, for all attributes in the test set, sum the returned values from *contains1*:


```
function contains1(h,i,val,numerip) {
  if(numericp)
    return Max[h,i] >= val && Min[h,i] <= val
  else return (h,i,value) in Seen
}
```
3. Use Figure 7 to implement an anomaly detector. Hint: 1) make all training examples get the same class; 2) an anomalous test instance has a likelihood $\frac{1}{\alpha}$ of the mean likelihood seen during training (*alpha* needs tuning but *alpha* = 50 is often useful).
4. Using your solution to #1, create an incremental version of HYPERPIPES and an anomaly detector.

Figure 8. Four Introductory OURMINE programming exercises.

```
Function: j4810
Arguments: <data (arff)>
Example(s): j4810 weather.arff
Description: Uses a j48 decision tree learner on the input data

Function Code:
=====
j4810 () {
  local learner=weka.classifiers.trees.J48
  $Weka $learner -C 0.25 -M 2 -i -t $1
}
```

Figure 9. Function help in OURMINE.

3. Using Ourmine for Industrial and Research Purposes

OURMINE is not just a simple demonstration system for novice data miners. It is also a tool for commercial practitioners and researchers alike. In order to demonstrate OURMINE’s utility for practitioners, our first demonstration experiment is an example of selecting the right learner and sample size for a particular domain.

- In part A of this first experiment, we show a very simple example of how practitioners can “tune” learners to data sets in order to achieve better results. This is shown through the comparison of learners (Naive Bayes, J48, One-r, etc.) training on raw data, and on discretized data.

- In part B of this experiment, we demonstrate how *early* our predictors can be applied. This is accomplished through incremental, random sampling of the data, to which the winning method from Part A is applied. The objective here is to report the smallest number of cases required in order to learn an adequate theory.

As software engineering researchers, we use OURMINE to generate publications in leading software engineering journals and conferences. For example, in the last three years, we have used OURMINE in this way to generate [2,6,14,16,17,23]. In order to demonstrate OURMINE's application to research, we present here two further experiments. Experiment #2 reproduces an important recent result by Turhan et al. [23]. Kitchenham et al. report that there is no clear consensus on the relative value of effort estimation models learned from either local or imported data [8]. Since this matter has not been previously studied in the defect prediction literature, Turhan et al. conducted a series of experiments with ten data sets from different companies. In their *within-company* (WC) experiments, defect predictors were learned from 90% of the local data, then tested on the remaining 10%. In the *cross-company* (CC) experiments, defect predictors were learned from nine companies then tested on the tenth. Turhan et al. found that the CC predictions were useless since they suffered from very high false alarm rates. However, after applying a simple *relevancy filter*, they found that imported CC learning yielded predictors that were nearly as good as the local WC learning. That is, using these results, we can say that organizations can make quality predictions about their source code, even when they lack local historical logs.

Experiment #3 checks a recent text mining result from an as-yet-unpublished WVU masters thesis. Matheny [11] benchmarked various lightweight learning methods (TF*IDF, the GENIC stochastic clusterer) against other, slower, more rigorous learning methods (PCA, K-means). As expected, the rigorous learning methods ran much slower than the stochastic methods. But, unexpectedly, Matheny found that the lightweight methods perform nearly as well as the rigorous methods. That is, using these results, we can say that text mining methods can scale to much larger data sets.

The rest of this section describes the use of OURMINE to reproduce Experiment #1, #2 and #3.

3.1. Experiment I: Commissioning a Learner

OURMINE's use is not only important to researchers, but also to practitioners. To demonstrate this, two very simple experiments were conducted using seven PROMISE data sets (CM1, KC1, KC2, KC3, MC2, MW1, PC1). The aim of this experiment is to commission a data mining system for a local site. When selecting the right data miners for a particular source of data, three issues are:

1. What learners to use?
2. What discretizers to use?
3. How much data is required for adequate learning?

Given software being released in several stages, OURMINE can be used on stage 1 data to find the right answers to the above questions. These answers can be applied on stages 2,3,4, etc.

In Part A of this experiment, four learners (Naive Bayes, J48, ADTree, One-R) are trained using undiscretized data, and then the same learners are trained on discretized data for a total of eight combinations. While this represents a highly simplified proof-of-concept, from it we can illustrate how our learners can be integrated with other techniques to find the best treatment for the data set(s) of concern. Practitioners can then short-circuit their experiments by only performing further analyses on methods deemed worthwhile for the current corpus. In turn, this decreases the amount of time in which results can be obtained.

In Part B of the experiment, the winning treatment from Part A is used with randomly selected, incremental sizes of training data. In this experiment, it can be shown how early our quality predictors can be applied based on the smallest number of training examples required to learn an adequate theory. Predictors were trained using $N = 100$, $N = 200$, $N = 300$... randomly selected instances up to $N = 1000$. For each training set size N , 10 experiments were conducted using $|Train| = 90\% * N$, and $|Test| = 100$. Both $Train$ and $Test$ were selected at random for each experiment. Our random selection process is modeled after an experiment conducted by Menzies et. al. [15]. In that paper, it was found that performance changed little regardless of whether fewer instances were selected (e.g. 100), or much larger sizes on the order of several thousand. Additionally, it was determined that larger training sizes were actually a disadvantage, as variance increased with increasing training set sizes.

3.1.1. Results

Our results for Part A and B of this experiment use pd (probability of detection) values sorted in decreasing order, and pf (probability of false alarm) values sorted in increasing order. These values assess the classification performance of a binary detector, and are calculated as follows. If $\{a, b, c, d\}$ are the true negatives, false negatives, false positives, and true positives (respectively) found by the detector then $pd = recall = \frac{d}{b+d}$ and $pf = \frac{c}{a+c}$. Note that a higher pd is better, while a lower pf is better.

The last column of each figure shows quartile charts of the methods' pd and pf values. The black dot in the center of each plot represents the median value, and the line going from left to right from this dot show the second and third quartile respectively.

Column one of each figure gives a method its rank based on a Mann-Whitney test at 95% confidence. A rank is determined by how many times a learner or learner/filter wins compared to another. The method that wins the most number of times is given the highest rank.

Figure 14 and Figure 15 show the results from Part A of the experiment. As can be seen, ADTrees (Alternating Decision Trees) [5] trained on discretized data yields the best results:

- Mann-Whitney test ranking (95% confidence): ADTrees + discretization provides the highest rank for both PD and PF results
- Medians & Variance: ADTrees + discretization results in the highest median/lowest variance for PD, and the lowest variance for PF, with only a 1% increase over the lowest median

Results from Part B of the experiment are shown in Figure 16 and Figure 17. Using the winning method from Part A, or learning using ADTrees on discretized data, results show that unquestionably a training size of $N = 600$ instances is the best number to train our defect

predictors using the aforementioned experiment setup. This is clear when considering $N = 600$ maintains the highest Mann-Whitney ranking (again using 95% percent confidence), as well as the highest PD and lowest PF medians.

More importantly, perhaps, it should be noted that while the most beneficial number of training instances remains 600, we can still consider a significantly smaller value of, say, $N = 300$ without much loss in performance; a training size of just 300 yields a loss in PD ranking of only one, with a 3% decrease in median, while PF ranking is identical to our winning size and sporting medians of a mere 3% increase.

3.2. Experiment II: Within vs Cross-Company Data

OURMINE was used to reproduce Turhan et al.'s experiment - with a Naive Bayes classifier in conjunction with a k-Nearest Neighbor (k-NN) relevancy filter. Relevancy filtering is used to group similar instances together in order to obtain a learning set that is homogeneous with the testing set. Thus, by using a training set that shares similar characteristics with the testing set, it is assumed that a bias in the model will be introduced. The k-NN filter works as follows. For each instance in the test set:

- the k nearest neighbors in the training set are chosen.
- duplicates are removed
- the remaining instances are used as the new training set.

3.2.1. Building the Experiment

The entire script used to conduct this experiment is shown in Figure 10.

To begin, the data in this study were the same as used by Gay et al. [6]; seven PROMISE defect data sets (CM1, KC1, KC2, KC3, MC2, MW1, PC1) were used to build seven combined data sets each containing $\frac{6}{7}$ -th of the data. For instance, the file *combined_PC1.arff* contains all seven data sets *except* PC1. This is used as the training set for the cross-company (CC) data. For example, if we wished to learn on all training data except for PC1, this would be a valid data set representation for a cross-company experiment.

Next, as can be seen in line 15 of Figure 10, a 10-way cross validation was conducted by calling *makeTrainAndTest*, which is a built-in OURMINE function that randomly shuffles the data and constructs both a test set, containing 10% of the data, and a training set containing 90% of the data. This was repeated ten times, and the resulting data was used in proceeding studies. For instance, in lines 18-24, the original test and training sets are used for the first WC study. However, in the WC experiment using relevancy filtering (lines 25-31), the same test set is used, but with the newly created training set. Lines 32-38 show the first CC study. This study is identical to the WC study except that as we saw before, we use *combined_X.arff* files, instead of *shared_X.arff*.

We chose to use a Naive Bayes classifier for this study because this is what was chosen in the original experiment conducted by Turhan et al. in [23], as well as because Naive Bayes has been shown to be competitive on PROMISE defect data against other learners [9].

```

1 promiseDefectFilterExp(){
2   local learners="nb"
3   local datanames="CM1 KC1 KC2 KC3 MC2 MW1 PC1"
4   local bins=10
5   local runs=10
6   local out=$Save/defects.csv
7   for((run=1;run<=$runs;run++)); do
8     for dat in $datanames; do
9       combined=$Data/promise/combined_$dat.arff
10      shared=$Data/promise/shared_$dat.arff
11      blabln "data=$dat run=$run"
12      for((bin=1;bin<=$bins;bin++)); do
13        rm -rf test.lisp test.arff train.lisp train.arff
14        cat $shared |
15        logArff 0.0001 "1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19" > logged.arff
16        makeTrainAndTest logged.arff $bins $bin
17        goals='cat $shared | getClasses --brief'
18
19        for learner in $learners; do
20          blabln "WC"
21          $learner train_shared.arff test_shared.arff | gotwant > produced.dat
22          for goal in $goals; do
23            extractGoals goal "$dat,$run,$bin,WC,$learner,$goal" 'pwd'/produced.dat
24          done
25          blabln "WCkNN"
26          rm -rf knn.arff
27          $Clusterers -knn 10 test_shared.arff train_shared.arff knn.arff
28          $learner knn.arff test_shared.arff | gotwant > produced.dat
29          for goal in $goals; do
30            extractGoals goal "$dat,$run,$bin,WCkNN,$learner,$goal" 'pwd'/produced.dat
31          done
32          blabln "CC"
33          makeTrainCombined $combined > com.arff
34          cat com.arff | logArff 0.0001 "1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19" > logged.arff
35          $learner logged.arff test_shared.arff | gotwant > produced.dat
36          for goal in $goals; do
37            extractGoals goal "$dat,$run,$bin,CC,$learner,$goal" 'pwd'/produced.dat
38          done
39          blabln "CkNN"
40          makeTrainCombined $combined > com.arff
41          cat com.arff |
42          logArff 0.0001 "1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19" > logged.arff
43          $Clusterers -knn 10 test_shared.arff logged.arff knn.arff
44          $learner knn.arff test_shared.arff | gotwant > produced.dat
45          for goal in $goals; do
46            extractGoals goal "$dat,$run,$bin,CkNN,$learner,$goal" 'pwd'/produced.dat
47          done
48        done
49      done
50    done ) | malign | sort -t, -r -n -k 12,12 > $out

```

Figure 10. The OURMINE script used in conducting the WC vs. CC experiment.

3.2.2. Results

Our results for this experiment can be found in Figure 18 and Figure 19. The following are important conclusions derived from these results:

- When CC data is used, relevancy filtering is crucial. According to our results, cross-company data with no filtering yields the worst pd and pf values.
- When relevancy filtering is performed on this CC data, we obtain better pd and pf results than using just CC and Naive Bayes.
- When considering only filtered data or only unfiltered data, the highest pd and lowest pf values are obtained by using WC data as opposed to CC data. This suggests that WC data gives the best results.

These finds were consistent with Turhan et al.'s results:

- Significantly better defect predictors are produced from using WC data.
- However, CC data leads to defect predictors nearly as effective as WC data when using relevancy filtering.

Thus, this study also makes the same conclusions as Turhan et al. A company should use local data to develop defect predictors if that local development data is available. However, if local data is not available, relevancy-filtered cross-company data provides a feasible means to build defect predictors.

3.3. Experiment III: Scaling Up Text Miners

As stated above, the purpose of this experiment conducted for this paper is to verify if lightweight data mining methods perform worse than more thorough and rigorous ones.

The data sets used in this experiment are:

- EXPRESS schemas: AP-203, AP-214
- Text mining datasets: BBC, Reuters, The Guardian (multi-view text datasets), 20 Newsgroup subsets: sb-3-2, sb-8-2, ss-3-2, sl-8-2

3.3.1. Classes of Methods

This experiment compares different *row* and *column* reduction methods. Given a table of data where each row is one example and each column counts different features, then:

- Row reduction methods *cluster* related rows into the same group;
- Column reduction methods remove columns with little information.

Reduction methods are essential in text mining. For example:

- A standard text mining corpus may store information in tens of thousands of columns. For such data sets, column reduction is an essential first step before any other algorithm can execute

- The process of clustering data into similar groups can be used in a wide variety of applications, such as:
 - Marketing: finding groups of customers with similar behaviors given a large database of customer data
 - Biology: classification of plants and animals given their features
 - WWW: document classification and clustering weblog data to discover groups of similar access patterns.

3.3.2. The Algorithms

While there are many clustering algorithms used today, this experiment focused on three: a naive K-Means implementation, GenIc [7], and clustering using canopies [12]:

1. K-means, a special case of a class of EM algorithms, works as follows:
 - (a) Select initial K centroids at random;
 - (b) Assign each incoming point to its nearest centroid;
 - (c) Adjusts each cluster's centroid to the mean of each cluster;
 - (d) Repeat steps 2 and 3 until the centroids in all clusters stop moving by a noteworthy amount

Here we use a naive implementation of K-means, requiring $K * N * I$ comparisons, where N and I represent the total number of points and maximum iterations respectively.

2. GenIc is a single-pass, stochastic clustering algorithm. It begins by initially selecting K centroids at random from all instances in the data. At the beginning of each generation, set the centroid weight to one. When new instances arrive, nudge the nearest centroid to that instance and increase the score for that centroid. In this process, centroids become “fatter” and slow down the rate at which they move toward newer examples. When a generation ends, replace the centroids with less than X percent of the max weight with N more random centroids. Genic repeats for many generations, then returns the highest scoring centroids.
3. Canopy clustering, developed by Google, reduces the need for comparing all items in the data using an expensive distance measure, by first partitioning the data into overlapping subsets called *canopies*. Canopies are first built using a cheap, approximate distance measure. Then, more expensive distance measures are used inside of each canopy to cluster the data.

As to column reduction, we will focus on two methods:

1. PCA, or Principal Components Analysis, is a reduction method that treats every instance in a dataset as a point in N -dimensional space. PCA looks for new dimensions that better fit these points— by mapping data points to these new dimensions where the variance is found to be maximized. Mathematically, this is conducted by utilizing eigenvalue decompositions of a data covariance matrix or singular value decomposition of a data

[†]http://home.dei.polimi.it/matteucc/Clustering/tutorial_html/

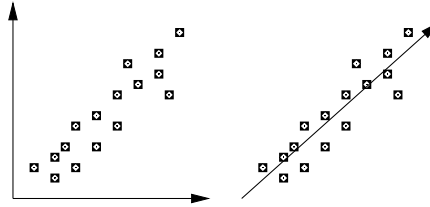


Figure 11. A PCA dimension feature.

matrix. Figure 11 shows an example of PCA. Before, on the left-hand-side, the data exists in a two-dimensional space, neither of which captures the distribution of the data. Afterwards, on the right-hand-side, a new dimension has been synthesized that is more relevant to the data distribution.

2. TF-IDF, or term frequency times inverse document frequency, reduces the number of terms (dimensions) by describing how important a term is in a document (or collection of documents) by incrementing its importance according to how many times the term appears in a document. However, this importance is also offset by the frequency of the term in the entire corpus. Thus, we are concerned with only terms that occur frequently in a small set of documents, and very infrequently everywhere else. To calculate the TF*IDF value for each term in a document, we use the following equation:

$$Tf * Idf(t, D_j) = \frac{tf(t_i, D_j)}{|D_j|} \log\left(\frac{|D|}{df(t_i)}\right) \quad (1)$$

where $tf(t_i, D_j)$ denotes the frequency of term i in document j , and $df(t_i)$ represents the number of documents containing term i . Here, $|D|$ denotes the number of documents in the corpus, and $|D_j|$ is the total number of terms in document j . To reduce all terms (and thus, dimensions), we must find the sum of the above in order to assign values to terms across *all* documents

$$Tf * Idf_{sum}(t) = \sum_{D_j \in D} Tf * Idf(t, D_j) \quad (2)$$

In theory, TF*IDF and GenIc should perform worse than K-Means, canopy clustering and PCA:

- Any single-pass algorithm like GenIc can be confused by “order effects”; i.e. if the data arrives in some confusing order then the single-pass algorithm can perform worse than other algorithms that are allowed to examine all the data.
- TF*IDF is a heuristic method while PCA is a well-founded mathematical technique

On the other hand, the more rigorous methods are slower to compute:

- Computing the correlation matrix used by PCA requires at least a $O(N^2)$ calculation.
- As shown below, K-means is much slower than the other methods studied here.

3.3.3. Building the Experiment

This experiment was conducted entirely with OURMINE using a collection of BASH scripts, as well as custom Java code. The framework was built as follows:

1. A command-line API was developed in Java for parsing the data, reducing/clustering the data, and outputting the data. Java was chosen due to its preferred speed for the execution of computationally expensive instructions.
2. The data was then iteratively loaded into this Java code via shell scripting. This provides many freedoms, such as allowing parameters to be altered as desired, as well as outputting any experimental results in any manner seen fit.

Figure 12 shows the OURMINE code for clustering data using the K-means algorithm. Shell scripting provides us with much leverage in this example. For instance, by looking at Lines 2-5, we can see that by passing the function four parameters, we can cluster data in the range from $minK$ to $maxK$ on all data in $dataDir$. This was a powerful feature used in this experiment, because it provides the opportunity to run the clusterer across multiple machines simultaneously. As a small example, suppose we wish to run K-means across three different machines with a minimum K of 2 and a maximum K of 256. Since larger values of K generally yield longer runtimes, we may wish to distribute the execution as follows:

```
Machine 1: clusterKmeansWorker 256 256 0 dataDir
Machine 2: clusterKmeansWorker 64 128 2 dataDir
Machine 3: clusterKmeansWorker 2 32 2 dataDir
```

Lines 9-13 of Figure 12 load the data from $dataDir$ for every k , and formats the name of the output file. Then, lines 15-19 begin the timer, cluster the data, and output statistical information such as k , the dataset, and runtime of the clusterer on that data set. This file will then be used later in the analysis of these clusters.

Similarly, the flags in line 16 can be changed to perform a different action, such as clustering using GenIc or Canopy, by changing $-k$ to $-g$ or $-c$ respectively, as well as finding cluster similarities (as described below) and purities, by using $-sim$ and $-purity$ as inputs.

Since any number of variables can be set to represent different libraries elsewhere in OURMINE, the variable

`$Reducers`

is used for the dimensionality reduction of the raw dataset, as seen in Figure 13, whose overall structure is very similar to Figure 12.

3.4. Results

To determine the overall benefits of each clustering method, this experiment used both cluster similarities, as well as the runtimes of each method.

```

1 clusterKmeansWorker(){
2   local minK=$1
3   local maxK=$2
4   local incVal=$3
5   local dataDir=$4
6   local stats="clusterer,k,dataset,time(seconds)"
7   local statsfile=$Save/kmeans_runtimes
8   echo $stats >> $statsfile
9   for((k=$minK;k<=$maxK;k*=$incVal)); do
10    for file in $dataDir/*.arff; do
11      filename='basename $file'
12      filename=${filename%. *}
13      out=kmeans_k="$k"_$filename.arff
14      echo $out
15      start=$(date +%s.%N)
16      $Clusterers -k $k $file $Save/$out
17      end=$(date +%s.%N)
18      time=$(echo "$end - $start" | bc)
19      echo "kmeans,$k,$filename,$time" >> $statsfile
20    done
21  done
22 }

```

Figure 12. An OURMINE worker function to cluster data using the K-means algorithm. Note that experiments using other clustering methods (such as GenIc and Canopy), could be conducted by calling line 16 above in much the same way, but with varying flags to represent the clusterer.

3.4.1. Similarities

Cluster similarities tell us how similar points are, either within a cluster (*Intra*-similarity), or with members of other clusters (*Inter*-similarity). The idea here is simple: gauge how well a clustering algorithm groups similar documents, and how well it separates different documents. Therefore, intra-cluster similarity values should be maximized, while minimizing inter-cluster similarities.

Similarities are obtained by using the cosine similarity between two documents. The cosine similarity measure defines the cosine of the angle between two documents, each containing vectors of terms. The similarity measure is represented as

$$\text{sim}(D_i, D_j) = \frac{D_i \cdot D_j}{\|D_i\| \|D_j\|} = \cos(\theta) \quad (3)$$

where D_i and D_j denote two term frequency vectors for documents i and j , and where the denominator contains magnitudes of these vectors.

Cluster similarities are determined as follows:

- Cluster intra-similarity: For each document d in cluster C_i , find the cosine similarity between d and all documents belonging to C_i

```

1 reduceWorkerTfidf(){
2   local datadir=$1
3   local minN=$2
4   local maxN=$3
5   local incVal=$4
6   local outdir=$5
7   local runtimes=$outdir/tfidf_runtimes

8   for((n=$minN;n<=$maxN;n+=$incVal)); do
9     for file in $datadir/*.arff; do
10      out='basename $file'
11      out=${out%.*}
12      dataset=$out
13      out=tfidf_n="$n"_$out.arff
14      echo $out
15      start=$(date +%s)
16      $Reducers -tfidf $file $n $outdir/$out
17      end=$(date +%s)
18      time=$((end - start))
19      echo "tfidf,$n,$dataset,$time" >> $runtimes
20    done
21  done
22 }

```

Figure 13. An OURMINE worker function to reduce the data using TF-IDF.

- Cluster inter-similarity: For each document d in cluster C_i , find the cosine similarity between d and all documents belonging to all other clusters

Thus the resulting sum of these values represents the overall similarities of a clustering solution. Figure 20 shows the results from the similarity tests conducted in this experiment. The slowest clustering and reduction methods were set as a baseline, because it was assumed that these methods would perform the best. With intra-similarity and inter-similarity values normalized to 100 and 0 respectively, we can see that surprisingly, faster heuristic clustering and reduction methods perform just as well or better than more rigorous methods. *Gain* represents the overall score used in the assessment of each method, and is computed as a method's cluster *intra*-similarity value minus its *inter*-similarity value. Thus, the conclusions from this experiment shows that fast heuristic methods are sufficient for large data sets due to their scalability and performance.

4. Discussion

Productivity of a development environment depends on many factors. In our opinion, among the most important of these are simplicity, power and motivation provided by the environment. There exists an intricate balance between simplicity and power. If a tool is too simple, a user's

actions are confined to a smaller space, thus decreasing the overall power and intricacy of the system. Also, exceedingly simple environments can restrict our learning process because we are not forced to learn or implement new ideas. However, even though a tool yields a great number of features, the options presented to a user can be overly complex and thus discourage further experimentation. We find that quick, yet careful experiment building promotes more motivation and interest to work on and finish the task.

Practitioners and researchers can both benefit from using OURMINE's syntax based on widely recognized languages. While practitioners are offered extensive freedom in modifying and extending the environment to be used as necessary, researchers can duplicate previously published experiments whose results could change the way we view data mining and software engineering.

5. Conclusions

The next challenge in the empirical SE community will be to not only share data, but to share experiments. We look forward to the day when it is routine for conference and journal submissions to come not just with supporting data but also with a fully executable version of the experimental rig used in the paper. Ideally, when reviewing papers, program committee members could run the rig and check if the results recorded by the authors are reproducible.

This paper has reviewed a UNIX scripting tool called OURMINE as a method of documenting, executing, and sharing data mining experiments. We have used OURMINE to reproduce and check several important result. In our first experiment, we learned that:

- First, “tune” our predictors to best fit a data set or corpus, and to select the winning method based on results.
- Secondly, understand how *early* we can apply these winning methods to our data by determining the fewest number of examples required in order to learn an adequate theory.

In our second experiment, we concluded that:

- When local data is available, that data should be used to build defect predictors
- If local data is not available, however, imported data can be used to build defect predictors when using *relevancy filtering*
- Imported data that uses *relevancy filtering* performs nearly as well as using local data to build defect predictors

In our third experiment, we learned:

- When examining cluster inter/intra similarities resulting from each clustering/reduction solution, we found that faster heuristic methods can outperform more rigorous ones when observing decreases in runtimes.
- This means that faster solutions are suitable on large datasets due to *scalability*, as well as performance.

We prefer OURMINE to other tools. Four features are worthy of mention:

-
1. OURMINE is very succinct. As seen above, a few lines can describe even complex experiments.
 2. OURMINE's experimental descriptions are complete. There is nothing hidden in Figure 10; it is not the pseudocode of an experiment, it is the experiment.
 3. OURMINE code like in Figure 10, Figure 12 and Figure 13 is executable and can be executed by other researchers directly.
 4. Lastly, the execution environment of OURMINE is readily available. Unlike RAPID-I, WEKA, "R", etc, there is nothing to debug or install. Many machines already have the support tools required for OURMINE. For example, we have run OURMINE on Linux, Mac, and Windows machines (with Cygwin installed).

Like Ritthol et al., we doubt that the standard interfaces of tools like WEKA, etc, are adequate for representing the space of possible experiments. Impressive visual programming environments are not the answer: their sophistication can either distract or discourage novice data miners from extensive modification and experimentation. Also, we find that the functionality of the visual environments can be achieved with a few BASH and GAWK scripts, with a fraction of the development effort and a greatly increased chance that novices will modify the environment.

OURMINE is hence a candidate format for sharing descriptions of experiments. The data mining community might find this format unacceptable but discussions about the drawbacks (or strengths) of OURMINE would help evolve not just OURMINE, but also the discussion on how to represent data mining experiments for software engineering.

Reply to Reviewers

Thank you for your careful reviews of this paper. Our replies to your helpful suggestions are shown below in plain font, and reviewer comments are shown in *italic* font.

Reviewer #1

Authors present an open source toolkit for sharing data mining experiments in the context of software research. They describe two recent cases from software research by replicating their results with ourmine. The main contribution of the manuscript is the presentation and discussion of the tool rather than providing new results, which is totally ok for me, considering the importance of replications in empirical software engineering.

Thank you for this comment.

While I find the manuscript interesting, easy to read and clearly described for research community, I have concerns regarding the way it addresses practitioners. My perception of the scope of SPE is that it is more focused on practitioners. There are no major problems whatsoever with the manuscript in a technical sense, however I have concerns whether it contributes to people dealing with software design and implementation. Therefore I am not sure if SPE is the right place to publish this work.

We agreed. The previous draft only showed examples of using OURMINE for research purposes. Clearly, for this venue, such usage is interesting but not the main focus of this journal. We handle this issue as mentioned after the next comment.

While the new text-mining experiment may be relevant for data mining research, I cannot see its additional (practical) impacts for software people, different than the prior publication. Therefore, I would recommend the authors to craft a third case design that specifically addresses practitioners and shows the usability of their tool in the development environment. I think that would be a relevant contribution for publication in SPE.

This is a very helpful suggestion; the importance of an environment should extend to not only researchers, but also the software people. We need to show that this toolkit is useful not only for leading edge research, but also for practical users.

Prompted by this comment, we have moved the old experiments behind a new experiment. This new experiment (called Experiment I in this draft) shows how a practitioner can use OURMINE to commission the right combination of learning tools and data sets for a particular data source.

It would also be better to see a discussion section, where the relevancy for practitioners is discussed. I would suggest right before conclusions. In the current flow, there is a sudden jump from text-mining experiment to conclusions and makes the reader feel that something is

missing.

We have addresses this comment in two ways:

- As mentioned above, we have added a new experiment describing how to use OURMINE for a practical real-world data mining task (commissioning the data mining system for a particular environment);
- A discussion section has been added (see section 4);

Conclusion, last paragraph: You should address a more general audience than the Promise community.

The text has been altered to address a more general audience, and not just the Promise community. Please see this on page 22.

Figure2 caption: "green lines", edit unless you will publish a color copy.

Reference to color in Figure 2 has been removed.

Section 2.2 what does TF-IDF stand for?

Its meaning (Term Frequency * Inverse Document Frequency) has been added to the text. See page 6, section 2.2.

Figure 10 is cited in the text between figures 6 and 7.

The figures and their order are better presented now.

Figure 5: I do not think this is necessary, since you already provide a complete list in the appendix. Also it is more like a table than a figure.

The table is now removed from the text completely. A reference to the appendix is only mentioned. See page 6, section 2.1.

Section 3: End of first paragraph: ordering of references.

Reference order is now correct. See page 11, section 3.

Page 11: first bullet at the bottom of the page, "organizations 'can/may(?)' make"

Wording in this statement is now added to fit the desired meaning. See page 11, section 3.

Section 3.1.1: Gay et al.: A reference is missing

Reference is added. See page 13, section 3.2.1.

After section 3.1.2 there is a problem with the numbering of figures. Figures cited as 12 and 13 are indeed 15 and 16. Other figure numbers are also wrong after this point.

Figure references are now correct.

Page 14: footnote: already given as a footnote in page 5.

Extra footnote is removed. See page 15.

Description of PCA: "PCA looks for new dimensions that better fit these points" What is meant by a dimension fitting points? I would suggest smt like: "PCA maps the data points to a new dimension where the variance is maximized."

Text is changed regarding PCA as per the reviewer's suggestion. Please see page 17, column reduction method 1.

Reviewer #2

In this paper, the authors (whose contribution to the empirical software engineering community I rate very highly) make a case for their data mining scripting environment OURMINE and discuss its use for teaching and research purposes. In my opinion, the paper is well written and fits very well into the scope of this journal. Therefore my recommendation is to accept it after minor revision (as outlined below).

Thank you for this comment.

Page 3, line 51: the term spatial is somewhat vague, perhaps the authors could give an example of a concept that is hard to express graphically.

A brief example is given to support our usage of the term. See page 4.

Datasets included with OURMINE (bottom of page 5, top of page 6): include reference for their origin (e.g. UCI machine learning repository).

UCI reference given to each data set. See page 6.

Page 36, lines 35-38, high false alarm rates: true, but they also had somewhat higher detection rates and pd and pf are dependent on a cut-off. When redoing these experiments later on, it could have been interesting to look at other ranking-based performance measures, or alternatively the authors could briefly refer to the existence of other measures and the debate about which is most appropriate?

It is true that an interesting comparison between a multitude of performance measures could be empirically analyzed here, and has been done elsewhere [4]. However, in our experience,

analyzing statistical ranking (e.g. Mann-Whitney U Test), variance, recall (PD) and PF remains a succinct way of representing experimental results of classifiers.

Page 12, line 29-37: this part of the setup I felt could be explained more clearly.

Supporting text has been included to help clarify this part of the setup. See page 13.

Page 12, line 40: I believe Nave Bayes was not (significantly) better but competitive with several other learners.

This has been rephrased for clarity. See page 13, section 3.2.1.

Page 14, line 35: data mining -> text mining. Also, lightweight data mining methods are almost by definition quicker (not slower): it is probably only the second question (whether they perform worse) that needs to be included here.

Only the performance has been included. See page 15, section 3.3.

Page 16, formulas (1) and (2): notation and symbols used are not fully defined; the notation here needs to be made self-contained.

More clear definitions of notation and symbols found in the formulas have been added. See their definitions on page 17.

Similarly for page 18, formula (3): make sure you indicate clearly here that the denominator contains the norms of the term frequency vectors of the documents.

This has been included in the text. See the description on page 19.

Page 19, line 44: it is not because of their scalability that fast heuristic methods are sufficient but because they are shown to perform well.

Performance is added to valid portions of the text when describing the benefits of the algorithms used in this experiment. See page 17, section 3.3.2 and page 20 section 3.4.1.

Figure 17: add explanation in the text that gain is percentage improvement in IntraSim minus InterSim.

This explanation has been added to the text. See page 20, section 3.4.1.

Finally, a general remark that I feel does not have to be addressed in this paper but that could be perhaps looked at in future work relates to the question of whether scripting or visual approaches are better in this context. I am not entirely convinced by some of the authors' arguments of why a scripting environment is to be preferred to a visual environment,

particularly for teaching purposes. Data mining is not only taught to computer science students but possibly also to students with much more limited programming experience (who might find it more difficult familiarizing themselves with an environment such as OURMINE). Also, an extensive body of research literature is available that studies visual programming languages: here perhaps ideas could be found for a more elaborate discussion of advantages and disadvantages or even for designing an experiment in which one would empirically compare the effectiveness of scripting vs. visual approaches?

Thank you for this comment concerning possible future work in this area. We also feel that there are certain advantages of visual programming languages, as stated in the paper. For instance, we too can consider the benefit of VPLs over a scripting environment for those who have little to no exposure to programming and who want to have a basic foundation of data mining experimentation. In this respect, our discussion on this matter was motivated most toward senior or graduate level computer science courses teaching data mining at a university. These courses are assumed to have programming.

However, visual representations found in other tools can also be complex, as implied in the paper. Our argument remains that more advanced experiments require that the user learn more intricate aspects of a tool (logically) and thus must learn additional material that will most likely be useless outside of that tool. This is in contrast to general, widely used scripting languages as those discussed in the text. Knowledge of these languages can be utilized in a multitude of fields outside of data mining.

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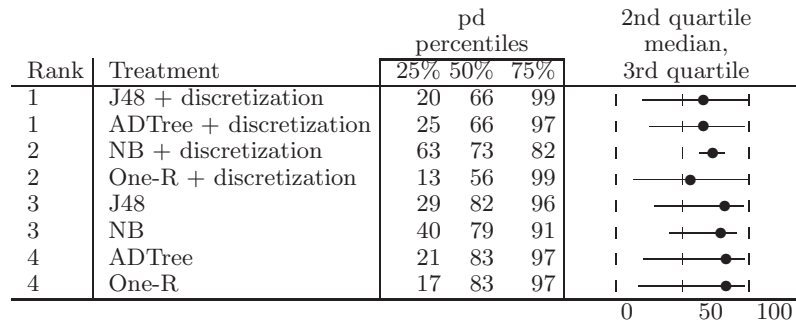


Figure 14. Experiment #1 - Part A - (Learner tuning). Probability of Detection (PD) results, sorted by rank then median values.

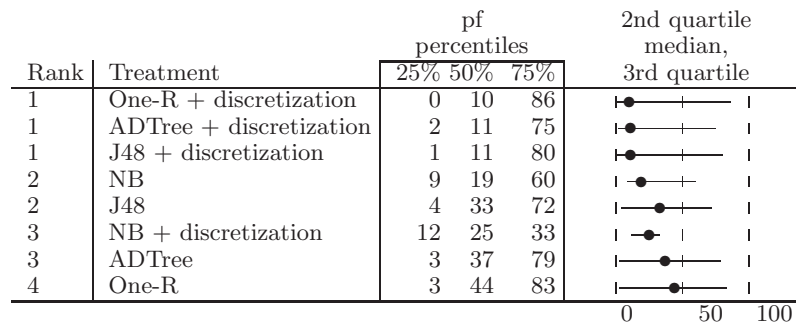


Figure 15. Experiment #1 - Part A - (Learner tuning). Probability of False Alarm (PF) results, sorted by rank then median values.

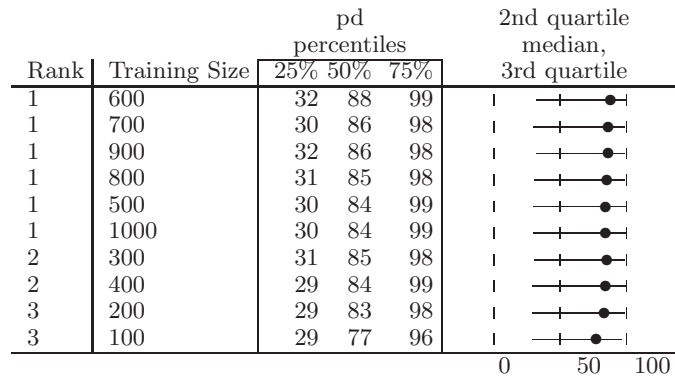


Figure 16. Experiment #1 - Part B - (Random Sampling). Probability of Detection (PD) results, sorted by rank then median values.

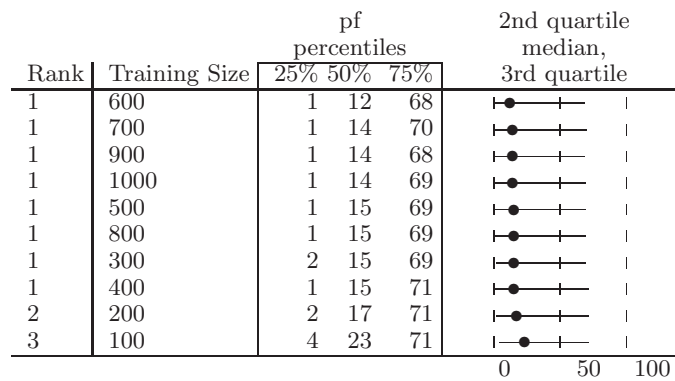


Figure 17. Experiment #1 - Part B - (Random Sampling). Probability of False Alarm (PF) results, sorted by rank then median values.

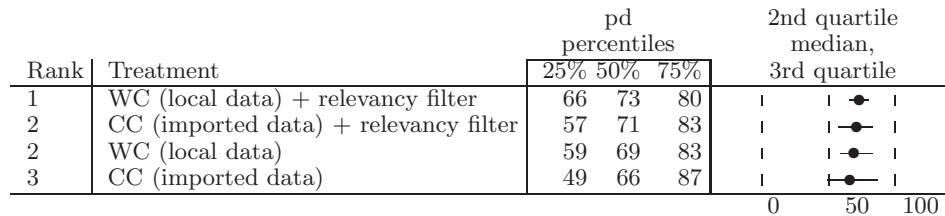


Figure 18. Experiment #2 (WC vs. CC). Probability of Detection (PD) results, sorted by rank then median values.

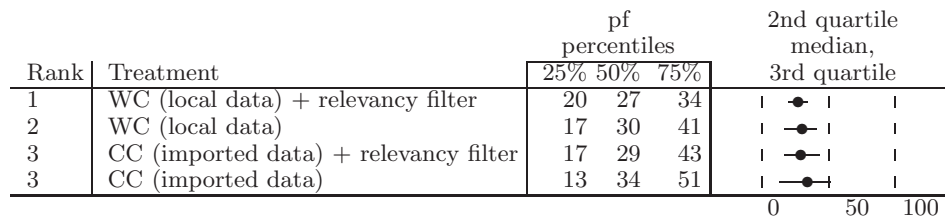


Figure 19. Experiment #2 (WC vs. CC). Probability of False Alarm (PF) results, sorted by rank then median values.

Reducer and Clusterer	Time	InterSim	IntraSim	Gain
TF-IDF*K-means	17.52	-0.085	141.73	141.82
TF-IDF*GenIc	3.75	-0.14	141.22	141.36
PCA*K-means	100.0	0.0	100.0	100.0
PCA*Canopy	117.49	0.00	99.87	99.87
PCA*GenIc	11.71	-0.07	99.74	99.81
TF-IDF*Canopy	6.58	5.02	93.42	88.4

Figure 20. Experiment #3 (Text mining). Similarity values normalized according to the combination of most rigorous reducer and clusterer. Note that *Gain* is a value representing the difference in cluster intrasimilarity and intersimilarity.

Installing OURMINE

OURMINE is an open source toolkit licensed under GPL 3.0. It can be downloaded and installed from <http://code.google.com/p/ourmine>.

OURMINE is a command-line environment, and as such, system requirements are minimal. However, in order to use OURMINE three things must be in place:

- A Unix-based environment. This does not include Windows. Any machine with OSX or Linux installed will do.
- The Java Runtime Environment. This is required in order to use the WEKA, as well as any other Java code written for OURMINE.
- The GAWK Programming Language. GAWK will already be installed with up-to-date Linux versions. However, OSX users will need to install this.

To install and run OURMINE, navigate to <http://code.google.com/p/ourmine> and follow the instructions.

Built-in OURMINE Functions
Utility Functions I

Function Name	Description	Usage
abcd	Performs confusion matrix computations on any classifier output. This includes statistics such as \$pd, \$pf, \$accuracy, \$balance and \$f-measure	<code>— abcd -prefix -goal</code> , where <i>prefix</i> refers to a string to be inserted before the result of the <i>abcd</i> function, and <i>goal</i> is the desired class of a specific instance.
arffToLisp	Converts a single .arff file into an equivalent .lisp file	<code>arffToLisp \$dataset.arff</code>
blab	Prints to the screen using a separate environment. This provides the ability to print to the screen without the output interfering with the results of an experiment	<code>blab \$message</code>
blabln	The same as blab, except this will print a new line after the given output	<code>blabln \$message</code>
docsToSparff	Converts a directory of document files into a sparse .arff file. Prior to building the file, however, the text is cleaned	<code>docsToSparff \$docDirectory \$output.sparff</code>
docsToTfidfSparff	Builds a sparse .arff file from a directory of documents, as above, but instead constructs the file based on TF-IDF values for each term in the entire corpus.	<code>docsToTfidfSparff \$docDirectory \$numberOfAttributes \$output.sparff</code>
formatGotWant	Formats an association list returned from any custom LISP classifier containing actual and predicted class values in order to work properly with existing OURMINE functions	<code>formatGotWant</code>
funs	Prints a sorted list of all available OURMINE functions	<code>funs</code>
getClasses	Obtains a list of all class values from a specific data set	<code>getClasses</code>
getDataDefun	Returns the name of a .arff relation to be used to construct a LISP function that acts as a data set	<code>getDataDefun</code>
gotwant	Returns a comma separated list of actual and predicted class values from the output of a WEKA classifier	<code>gotwant</code>
help	When given with an OURMINE function, prints helpful information about the function, such as a description of the function, how to use it, etc.	<code>help \$function</code> , where <i>\$function</i> is the name of the function

Utility Functions II

Function Name	Description	Usage
makeQuartiles	Builds quartile charts using any key and performance value from the abcd results (see above)	<i>makeQuartiles \$csv \$keyField \$performanceField</i> , where <i>\$keyField</i> can be a learner/treatment, etc., and <i>\$performanceField</i> can be any value desired, such as <i>pd</i> , <i>accuract</i> , etc.
makeTrainAndTest	Constructs a training set and a test set given an input data set. The outputs of the function are train.arff, test.arff and also train.lisp and test.lisp	<i>makeTrainAndTest \$dataset \$bins \$bin</i> , where <i>\$dataset</i> refers to any data set in correct .arff format, <i>\$bins</i> refers to the number of bins desired in the construction of the sets, and <i>\$bin</i> is the bin to select as the test set. For instance, if 10 is chosen as the number of bins, and 1 is chosen as the test set bin, then the resulting training set would consist of 90% of the data, and the test set would consist of 10%.
malign	Neatly aligns any comma-separated format into an easily readable format	<i>malign</i>
medians	Computes median values given a list of numbers	<i>medians</i>
quartile	Generates a quartile chart along with min/max/median values, as well as second and third quartile values given a specific column	<i>quartile</i>
show	Prints an entire OURMINE function so that the script can be seen in its entirety	<i>show \$functionName</i>
winLossTie	Generates win-loss-tie tables given a data set. Win-loss-tie tables, in this case, depict results after a statistical analysis test on treatments. These tests include the Mann-Whitney-U test, as well as the Ranked Wilcoxon test	<i>winLossTie -input \$input.csv -fields \$numOfFields -perform \$performanceField -key \$keyField -confidence</i> , where <i>\$input.csv</i> refers to the saved output from the <i>abcd</i> function described above, <i>\$numOfFields</i> represents the number of fields in the input file, <i>\$performanceField</i> is the field on which to determine performance, such as <i>pd</i> , <i>pf</i> , <i>acc</i> , <i>\$keyField</i> is the field of the key, which could be a learner/treatment, etc., and <i>\$confidence</i> is the percentage of confidence when running the test. The default confidence value is 95%

Learners

Function Name	Description	Usage
adtree	Calls WEKA's Alternating Decision Tree	<i>adtree \$train \$test</i>
bnet	Calls WEKA's Bayes Net	<i>bnet \$train \$test</i>
j48	Calls WEKA's J48	<i>j48 \$train \$test</i>
nb	Calls WEKA's Naive Bayes	<i>nb \$train \$test</i>
oner	Calls WEKA's One-R	<i>oner \$train \$test</i>
rbfnet	Calls WEKA's RBFNet	<i>rbfnet \$train \$test</i>
ridor	Calls WEKA's RIDOR	<i>ridor \$train \$test</i>
zeror	Calls WEKA's Zero-R	<i>zeror \$train \$test</i>

Preprocessors

Function Name	Description	Usage
caps	Reduces capitalization to lowercase from an input text	<i>caps</i>
clean	Cleans text data by removing capitals, words in a stop list, special tokens, and performing Porter's stemming algorithm	<i>clean</i>
discretize	Discretizes the incoming data via WEKA's discretizer	<i>discretize \$input.arff \$output.arff</i>
logArff	Logs numeric data in incoming data	<i>logArff \$minVal \$fields</i> , where <i>\$minVal</i> denotes the minimum value to be passed to the log function, and <i>\$fields</i> is the specific fields on which to perform log calculations
stems	Performs Porter's stemming algorithm on incoming text data	<i>stems \$inputFile</i>
stops	Removes any terms from incoming text data that are in a stored stop list	<i>stops</i>
tfidf	Computes TF*IDF values for terms in a document	<i>tfidf \$file</i>
tokens	Removes unimportant tokens or whitespace from incoming textual data	<i>tokens</i>

Feature Subset Selectors

Function Name	Description	Usage
cfs	Calls WEKA's Correlation-based Feature Selector	<i>cfs \$input.arff \$numAttributes \$out.arff</i>
chisquared	Calls WEKA's Chi-Squared Feature Selector	<i>chisquared \$input.arff \$numAttributes \$out.arff</i>
infogain	Calls WEKA's Infogain Feature Selector	<i>infogain \$input.arff \$numAttributes \$out.arff</i>
oneR	Calls WEKA's One-R Feature Selector	<i>oneR \$input.arff \$numAttributes \$out.arff</i>
pca	Calls WEKA's Principal Components Analysis Feature Selector	<i>pca \$input.arff \$numAttributes \$out.arff</i>
relief	Calls WEKA's RELIEF Feature Selector	<i>relief \$input.arff \$numAttributes \$out.arff</i>

Clusterers

Function Name	Description	Usage
K-means	Calls custom Java K-means	<i>\$Clusterers -k \$k \$input.arff \$out.arff</i> , where <i>\$k</i> is the initial number of centroids
Genic	Calls custom Java GeNic	<i>\$Clusterers -g \$k \$n \$input.arff \$out.arff</i> , where <i>\$k</i> is the initial number of centroids, and <i>\$n</i> is the size of a generation
Canopy	Calls custom Java Canopy Clustering	<i>\$Clusterers -c \$k \$p1 \$p2 \$input.arff \$out.arff</i> , where <i>k</i> is the initial number of centroids, <i>\$p1</i> is a similarity percentage value for the outer threshold, and <i>\$p2</i> is a similarity percentage value for the inner threshold. If these percentages are not desired, a value of 1 should be provided for both
EM	Calls WEKA's Expectation-Maximization Clusterer	<i>em \$input.arff \$k</i> , where <i>\$k</i> is the initial number of centroids