Appears in SIAM 2005 Data Mining Conference

HARMONY: Efficiently Mining the Best Rules for Classification [*]

Jianyong Wang and George Karypis [†]

Abstract

Many studies have shown that rule-based classifiers perform well in classifying categorical and sparse high-dimensional databases. However, a fundamental limitation with many rule-based classifiers is that they find the rules by employing various heuristic methods to prune the search space, and select the rules based on the sequential database covering paradigm. As a result, the final set of rules that they use may not be the globally best rules for some instances in the training database. To make matters worse, these algorithms fail to fully exploit some more effective search space pruning methods in order to scale to large databases.

In this paper we present a new classifier, HARMONY, which directly mines the final set of classification rules. HARMONY uses an instance-centric rule-generation approach and it can assure for each training instance, one of the highest-confidence rules covering this instance is included in the final rule set, which helps in improving the overall accuracy of the classifier. By introducing several novel search strategies and pruning methods into the rule discovery process, HARMONY also has high efficiency and good scalability. Our thorough performance study with some large text and categorical databases has shown that HARMONY outperforms many well-known classifiers in terms of both accuracy and computational efficiency, and scales well w.r.t. the database size.

1 Introduction

As one of the most fundamental data mining tasks, classification has been extensively studied and various types of classification algorithms have been proposed. Among which, one category is the rule-based classifiers [26, 27, 13, 30]. They build a model from the training database as a set of high-quality rules, which can be used to predict the class labels of unlabeled instances. Many studies have shown that rule-based classification algorithms perform very well in classifying both categorical databases [27, 25, 24, 30] and sparse high-dimensional databases such as those arising in the context of document classification [6, 5].

Some traditional rule-based algorithms like FOIL [27], RIPPER [13], and CPAR [30] discover a set of classification rules one-rule-at-a-time and employ a sequential covering methodology to eliminate from the training set the positive instances that are covered by each newly discovered rule. This *rule induction* process is done in a greedy fashion as it employs various heuristics (e.g., information gain) to determine how each rule would be extended. Due to this heuristic rule-induction process and the sequential covering framework, the final set of discovered rules are not guaranteed to be the best possible. For example, due to the removal of some training instances, the information gain is computed based on the incomplete information; thus, the variable (or literal) chosen by these algorithms to extend the current rule will be no longer the globally optimal one. Moreover, for multi-class problems, these algorithms need to be applied multiple times, each time mining the rules for one class. If the training database is large and contains many classes, the algorithms will be inefficient.

Since the introduction of association rule mining [2], many association-based (or related) classifiers have been proposed [17, 22, 7, 4, 8, 23, 15, 5, 31, 14]. Some typical examples like CBA [25] and CMAR [24] adopt efficient association rule mining algorithms (e.g., Apriori [3] and FP-growth [20]) to first mine a large number of high-confidence rules satisfying a user-specified minimum support and confidence thresholds, then use various sequential-covering schemes to select from them a set of high-quality rules to be used for classification. Since these schemes defer the selection step only after a large intermediate set of high-confidence rules have been identified, they tend to achieve somewhat better accuracy than the traditional heuristic rule induction schemes [30]. However, the drawback of these approaches is that the number of initial rules is usually extremely large, significantly increasing the rule discov-

[*]This work was supported in part by NSF CCR-9972519, EIA-9986042, ACI-9982274, ACI-0133464, and ACI-0312828; the Digital Technology Center at the University of Minnesota; and by the Army High Performance Computing Research Center (AHPCRC) under the auspices of the Department of the Army, Army Research Laboratory (ARL) under Cooperative Agreement number DAAD19-01-2-0014. The content of which does not necessarily reflect the position or the policy of the government, and no official endorsement should be inferred. Access to research and computing facilities was provided by the Digital Technology Center and the Minnesota Supercomputing Institute.

[†]Department of Computer Science and Engineering/Digital Technology Center/Army HPC Research Center, University of Minnesota. Email: {jianyong, karypis}@cs.umn.edu.

ery and selection time.

In this paper we propose a new classification algorithm, HARMONY[1], which can overcome the problems of both the rule-induction-based and the association-rule-based algorithms. HARMONY directly mines for each training instance one of the highest confidence frequent classification rules that it supports, and builds the classification model from the union of these rules over the entire set of instances. Thus HARMONY employs an *instance-centric* rule generation framework and is guaranteed to find and include the best possible rule for each training instance. Moreover, since each training instance usually supports many of the discovered rules, the overall classifier can better generalize to new instances and thus achieve better classification performance.

To achieve high computational efficiency, HARMONY mines the classification rules for all the classes simultaneously and directly mines the final set of classification rules by pushing deeply some effective pruning methods into the projection-based frequent itemset mining framework. All these pruning methods preserve the completeness of the resulting rule-set in the sense that they only remove from consideration rules that are guaranteed not to be of high quality. We have performed numerous performance studies with various databases and shown that HARMONY can achieve better accuracy while maintaining high efficiency.

The rest of the paper is organized as follows. Section 2 introduces some basic definitions and notations. Section 3 discusses in detail the HARMONY algorithm. Section 4 describes some of the related work in this area. The thorough performance study is presented in Section 5. Finally, the paper concludes with Section 6.

2 Notations and Definitions

A *training database* $TrDB$ is a set of training instances[2], where each training instance, denoted as a triple $\langle tid, X, cid \rangle$, contains a set of items (i.e., X) and is associated with a unique training instance identifier tid, and a class identifier $cid \in \{c_1, c_2, ..., c_k\}$ (a class identifier is also called a class label, and we assume there are totally k distinct class labels in $TrDB$). Table 1 illustrates an example training database, which contains totally eight instances and two classes. Let $I=\{i_1, i_2, \ldots, i_n\}$ be the complete set of distinct items appearing in $TrDB$. An *itemset* Y is a non-empty subset of I and is called an *l-itemset* if it contains l items. An itemset $\{x_1, \ldots, x_l\}$ is also denoted by $x_1 \cdots x_l$. A training instance $\langle tid, X, cid \rangle$ is said to *contain* itemset Y if $Y \subseteq X$. The number of instances in $TrDB$ containing itemset Y is called the (absolute) *support* of itemset Y, denoted by sup_Y. The number of instances containing itemset Y and associated with a class label c_i (where $i \in \{1, 2, ..., k\}$) is called the support of $Y \cup \{c_i\}$, denoted by $sup_Y^{c_i}$. A classification rule has the form: '$Y \rightarrow c_i : sup_Y^{c_i}, conf_Y^{c_i}$', where Y is called the body, c_i the head, $sup_Y^{c_i}$ the support, and $conf_Y^{c_i} = \frac{sup_Y^{c_i}}{sup_Y}$ the confidence of the rule, respectively. In addition, we use $|TrDB|$ to denote the number of instances in database $TrDB$, and for brevity, we sometimes use the instance identifier tid to denote an instance $\langle tid, X, cid \rangle$.

Table 1: An example training database $TrDB$.

Instance identifier	Set of items	Class identifier
01	a, c, e, g	1
02	b, d, e, f	0
03	d, e, f	0
04	a, b, c, e	1
05	a, c, e	1
06	b, d, e	0
07	a, b, e	1
08	a, b, d, e	0

Given a minimum support threshold, *min_sup*, an itemset Y is *frequent* if $sup_Y \geq min\_sup$. A frequent itemset Y supported by any training instance $\langle t_j, X_j, c_i \rangle$ ($1 \leq j \leq |TrDB|$ and $1 \leq i \leq k$) is also called a frequent covering itemset of instance t_j, and '$Y \rightarrow c_i : sup_Y^{c_i}, conf_Y^{c_i}$' is called a frequent covering rule of instance t_j. Among the frequent covering rules of any instance t_j, those with the highest confidence are called the *Highest Confidence Covering Rules* w.r.t. instance t_j. We denote a Highest Confidence Covering Rule w.r.t. instance t_j by $HCCR_{t_j}$, and use $HCCR_{t_j}^{sup}$ and $HCCR_{t_j}^{conf}$ to denote its support and confidence.

3 HARMONY: An Instance-Centric Classifier

In this paper we present HARMONY, an accurate and efficient rule-based classifier with good scalability that is designed to overcome the problems of both the traditional rule-based and the recently proposed association-based classifiers. The key idea behind HARMONY is to build a classifier that instead of using various heuristic methods to discover and/or select rules, it uses the best possible rules for each training instance. As such, it takes an *instance-centric* view and directly mines the database of training instances to find at least one of the highest confidence frequent covering rules (if there is any) and include it in the final set of classification rules. Moreover, HARMONY employs some effective search strategies and pruning methods to speed up the

[1] HARMONY stands for the **H**ighest confidence cl**A**ssification **R**ule **M**ining f**O**r i**N**stance-centric classif**Y**ing.

[2]Note there may exist a test database, which is in the same form as the training database and is used to evaluate the performance of a classifier. We denote it by $TeDB$.

model learning.

The HARMONY algorithm consists of three different modules, referred to as RuleMiner, BuildModel, and NewInstanceClassification. The RuleMiner module, takes as input the training database $TrDB$ and the minimum support *min_sup*, and outputs the set of the highest confidence covering rules (abbreviated as $HCCR$). The BuildModel module, takes $HCCR$ as input and outputs a classification model (abbreviated as CM), which is used by the NewInstanceClassification module to classify a new test instance ti. The algorithmic details behind these modules are presented in the rest of this section.

3.1 Mining the Classification Rules

The rule-discovery problem that HARMONY needs to solve in order to generate the sets of rules needed by its classification methodology can be formally defined as follows. Given a training database $TrDB$ and a minimum support threshold *min_sup*, the problem is to find one of the highest confidence frequent covering rules for each of the training instances in $TrDB$ [3].

A naïve way of solving this problem is to use an existing frequent closed itemset discovery algorithm to first generate all frequent closed itemsets, and then extract from them the highest confidence rule for each training database instance. However, this approach is not very computationally efficient because the number of frequent closed itemsets is usually huge, and both the itemset generation and rule selection are very expensive. For this reason, HARMONY adopts another more efficient way. It directly mines the final set of highest confidence classification rules. By maintaining the highest confidence among the covering rules mined so far for each instance, HARMONY can employ some efficient pruning methods to accelerate the rule discovery.

Note that although we mainly focus on mining any one of the highest confidence frequent covering rules for each training instance, it is straightforward to revise HARMONY to mine the complete set of the highest confidence frequent covering rules or the one with the highest support for each training instance.

3.1.1 Rule Enumeration

The projection-based itemset enumeration framework has been widely used in many frequent itemset mining algorithms [20, 1, 18], and will be used by HARMONY as the basis in enumerating the classification rules. Given a training database $TrDB$ and a minimum support *min_sup*, HARMONY first computes the frequent items by scanning $TrDB$ once, and sorts them to get a list of frequent items (denoted by *f_list*) according to a certain ordering scheme. Assume the *min_sup* is 3 and the lexicographical ordering is the default ordering scheme, the *f_list* computed from Table 1 is $\{a, b, c, d, e\}$. HARMONY applies the *divide-and-conquer* method plus the *depth-first search strategy*. In our example, HARMONY first mines the rules whose body contains item 'a', then mines the rules whose body contains 'b' but no 'a', ..., and finally mines the rules whose body contains only 'e'. In mining the rules with item 'a', item 'a' is treated as the current prefix, and its conditional database (denoted by $TrDB|_a$) is built and the *divide-and-conquer* method is applied recursively with the depth-first search strategy. To build conditional database $TrDB|_a$, HARMONY first identifies the instances in $TrDB$ containing 'a' and removes the infrequent items, then sorts the left items in each instance according to the *f_list* order, finally $TrDB|_a$ is built as $\{\langle 01, ce, 1\rangle, \langle 04, bce, 1\rangle, \langle 05, ce, 1\rangle, \langle 07, be, 1\rangle, \langle 08, be, 0\rangle\}$ (infrequent items 'd' and 'g' are removed). Following the *divide-and-conquer* method, HARMONY first mines the rules with prefix 'ab', then mines rules with prefix 'ac' but no 'b', and finally mines rules with prefix 'ae' but no 'b' nor 'c'.

During the mining process, when HARMONY gets a new prefix, it will generate a set of classification rules w.r.t. the training instances covered by the prefix. For each training instance, it always maintains one of its currently highest confidence rules mined so far. Assume the current prefix P is 'a' (i.e., P='a'). As shown in the above example, P covers five instances with *tids* 01, 04, 05, 07, and 08. HARMONY computes the covering rules according to the class distribution w.r.t. the prefix P. In this example, sup_P=5, sup_P^0=1, sup_P^1=4, and HARMONY generates two classification rules:

Rule 1: $a \rightarrow 0 : 1, \frac{1}{5}$

Rule 2: $a \rightarrow 1 : 4, \frac{4}{5}$

Rule 1 covers the instance with *tid* 08, while Rule 2 covers the instances with *tids* 01, 04, 05 and 07. Up to this point, we have $HCCR_{01} = HCCR_{04} = HCCR_{05} = HCCR_{07}$ = Rule 2, and $HCCR_{08}$ = Rule 1.

3.1.2 Ordering of the Local Items

In the above rule enumeration process, we used the lexicographical ordering as an illustration to sort the set of local frequent items in order to get the *f_list*. Many projection-based frequent itemset mining algorithms use

[3]Note the input training database must be in the form that is consistent with the corresponding definition in Section 2, otherwise, the training database should be first converted to that form. For example, a numerical database should be first discretized into a categorical one in order to use HARMONY to build the model.

the item support to order the local frequent items (e.g., the support descending order was adopted in [20] as the ordering scheme). However, because we are interested in the highest confidence rules w.r.t. the training instances, the support-based ordering schemes may not be the most efficient and effective ways. As a result, we propose the following three new ordering schemes as the alternatives.

Let the current prefix be P, its support be sup_P, the support and confidence of the classification rule w.r.t. prefix P and class label c_i, '$P \rightarrow c_i$', be $sup_P^{c_i}$ and $conf_P^{c_i}$, respectively, the set of local frequent items be $\{x_1, x_2, ..., x_m\}$, the number of prefix P's conditional instances containing item x_j $(1 \leq j \leq m)$ and associated with class label c_i $(1 \leq i \leq k)$ be $sup_{P\cup\{x_j\}}^{c_i}$, and the support of $P \cup \{x_j\}$ be $sup_{P\cup\{x_j\}} = \sum_{i=1}^{k} sup_{P\cup\{x_j\}}^{c_i}$.

Maximum confidence descending order. Given a local item x_j $(1 \leq j \leq m)$ w.r.t. P, we can compute k rules with body $P \cup \{x_j\}$, among which, the i-th rule with rule head c_i is:

$$P \cup \{x_j\} \rightarrow c_i \ : \ sup_{P\cup\{x_j\}}^{c_i}, \ \frac{sup_{P\cup\{x_j\}}^{c_i}}{sup_{P\cup\{x_j\}}}$$

The highest confidence among the k rules with body $P \cup \{x_j\}$ is called the maximum confidence of local item x_j, and is defined as the following:

$$\frac{\max_{\forall i, 1 \leq i \leq k} \ sup_{P\cup\{x_j\}}^{c_i}}{sup_{P\cup\{x_j\}}} \tag{3.1}$$

To mine the highest confidence covering rules as quickly as possible, a good heuristic is to sort the local frequent items in their maximum confidence descending order.

Entropy ascending order. The widely used entropy to some extent measures the purity of a cluster of instances. If the entropy of the set of instances containing $P \cup \{x_j\}$ $(1 \leq j \leq m)$ is small, it is highly possible to generate some high confidence rules with body $P \cup \{x_j\}$. Thus another good ordering heuristic is to rank the set of local frequent items in their entropy ascending order, and the entropy w.r.t. item x_j is defined as follows:

$$-\frac{1}{\log k} \sum_{i=1}^{k} \left(\frac{sup_{P\cup\{x_j\}}^{c_i}}{sup_{P\cup\{x_j\}}}\right) \log\left(\frac{sup_{P\cup\{x_j\}}^{c_i}}{sup_{P\cup\{x_j\}}}\right) \tag{3.2}$$

Correlation coefficient ascending order. Both the maximum confidence descending order and entropy ascending order do not consider the class distribution of the conditional database w.r.t. prefix P, which may cause some problems in some cases. Let us see an example. Assume the number of class labels k=2, $sup_P^{c_1} = 12$, and $sup_P^{c_2} = 6$, then we can get two rules with body P as follows:

Rule 3: $P \rightarrow c_1 : 12, \frac{12}{18}$
Rule 4: $P \rightarrow c_2 : 6, \frac{6}{18}$

Suppose there are two local items, x_1 and x_2, and $sup_{P\cup\{x_1\}}^{c_1}=2$, $sup_{P\cup\{x_1\}}^{c_2}=1$, $sup_{P\cup\{x_2\}}^{c_1}=1$, and $sup_{P\cup\{x_2\}}^{c_2}=2$. According to Equation 3.1 and Equation 3.2, the maximum confidence and entropy w.r.t. item x_1 are equal to the corresponding maximum confidence and entropy w.r.t. x_2. Thus we cannot determine which one of x_1 and x_2 should be ranked higher. However, because the conditional database $TrDB|_{P\cup\{x_1\}}$ has the same class distribution as conditional database $TrDB|_P$, we cannot generate rules with body $P \cup \{x_1\}$ and a confidence higher than those with body P (i.e., Rule 3 and Rule 4). The two rules with body $P \cup \{x_1\}$ are shown as the following.

Rule 5: $P \cup \{x_1\} \rightarrow c_1 : 2, \frac{2}{3}$
Rule 6: $P \cup \{x_1\} \rightarrow c_2 : 1, \frac{1}{3}$

If we examine the rules generated from prefix itemset $P \cup \{x_2\}$ as shown in Rule 7 and Rule 8, we can see Rule 8 has higher confidence than Rule 4, and can be used to replace Rule 4 for the instances covered by Rule 8. In this case, item x_2 should be ranked before item x_1.

Rule 7: $P \cup \{x_2\} \rightarrow c_1 : 1, \frac{1}{3}$
Rule 8: $P \cup \{x_2\} \rightarrow c_2 : 2, \frac{2}{3}$

This example suggests that the more similar the class distribution between conditional databases $TrDB|_P$ and $TrDB|_{P\cup\{x_j\}}$ $(1 \leq j \leq m)$, the lower is the possibility to generate higher confidence rules from $TrDB|_{P\cup\{x_j\}}$. Because the correlation coefficient is a good metric in measuring the similarity between two vectors (the larger the coefficient, the more similar the two vectors), it can be used to rank the local items. In HARMONY, the correlation coefficient ascending order is by default adopted to sort the local items.

Let $\overline{sup_P}$ be $\frac{1}{k}\sum_{i=1}^{k} sup_P^{c_i}$, $\overline{sup_{P\cup\{x_j\}}}$ be $\frac{1}{k}\sum_{i=1}^{k} sup_{P\cup\{x_j\}}^{c_i}$, σ_P be $\sqrt{\frac{1}{k}\sum_{i=1}^{k}(sup_P^{c_i})^2 - \overline{sup_P}^2}$, $\sigma_{P\cup\{x_j\}}$ be $\sqrt{\frac{1}{k}\sum_{i=1}^{k}(sup_{P\cup\{x_j\}}^{c_i})^2 - \overline{sup_{P\cup\{x_j\}}}^2}$, the correlation coefficient between prefix P and $P \cup \{x_j\}$ $(1 \leq j \leq m)$ is defined as follows.

$$\frac{\frac{1}{k}\sum_{i=1}^{k}(sup_P^{c_i} \times sup_{P\cup\{x_j\}}^{c_i} - \overline{sup_P} \times \overline{sup_{P\cup\{x_j\}}})}{\sigma_P \times \sigma_{P\cup\{x_j\}}} \tag{3.3}$$

3.1.3 Search Space Pruning

Unlike the association-based algorithms, HARMONY directly mines the final set of classification rules. By maintaining the current highest confidence among the covering rules for each training instance during the mining process, some effective pruning methods can be proposed to improve the algorithm efficiency.

Support equivalence item elimination. Given the current prefix P, among its set of local frequent items $\{x_1, x_2, ..., x_m\}$, some may have the same support as P. We call them support equivalence items and can be safely pruned according to the following Lemma 3.1.

LEMMA 3.1. ***(Support equivalence item pruning)*** *Any local item x_j w.r.t. prefix P can be safely pruned if it satisfies $sup_{P\cup\{x_j\}} = sup_P$.*

Proof. Because $sup_{P\cup\{x_j\}} = sup_P$ holds, $TrDB|_P$ and $TrDB|_{P\cup\{x_j\}}$ contain the same set of conditional instances; thus, their class distributions are also the same and the following equation must hold:

$\forall i, 1 \le i \le k, sup^{c_i}_{P\cup\{x_j\}} = sup^{c_i}_P$

Given any itemset, Y, which can be used to extend P (Y can be empty), can also be used to extend $P\cup\{x_j\}$, and the following must hold:

$\forall i, 1 \le i \le k, sup^{c_i}_{P\cup\{x_j\}\cup Y} = sup^{c_i}_{P\cup Y}$

We can further have the following equation:

$\forall i, 1 \le i \le k, \frac{sup^{c_i}_{P\cup\{x_j\}\cup Y}}{sup_{P\cup\{x_j\}\cup Y}} = \frac{sup^{c_i}_{P\cup Y}}{sup_{P\cup Y}}$

This means the confidence of the rule '$P \cup \{x_j\} \cup Y \rightarrow c_i$' is equal to the confidence of the rule '$P \cup Y \rightarrow c_i$', and we cannot generate higher confidence rules from prefix $P \cup \{x_j\} \cup Y$ in comparison with the rules with body $P \cup Y$. Thus item x_j can be safely pruned. □

Note $P \cup Y$ is a subset of $P \cup \{x_j\} \cup Y$, by pruning item x_j, we prefer the more generic classification rules. A similar strategy was adopted in [7, 14].

Unpromising item elimination. Given the current prefix P, any one of its local frequent items, x_j ($1 \le j \le m$), any itemset Y that can be used to extend $P \cup \{x_j\}$ (where Y can be empty and $P \cup \{x_j\} \cup Y$ is frequent), and any class label c_i ($1 \le i \le k$), the following equation must hold:

$$conf^{c_i}_{P\cup\{x_j\}\cup Y} = \frac{sup^{c_i}_{P\cup\{x_j\}\cup Y}}{sup_{P\cup\{x_j\}\cup Y}} \le \frac{sup^{c_i}_{P\cup\{x_j\}\cup Y}}{min\_sup} \le \frac{sup^{c_i}_{P\cup\{x_j\}}}{min\_sup}$$

Because $conf^{c_i}_{P\cup\{x_j\}\cup Y} \le 1$ also holds, we have the following equation:

$$conf^{c_i}_{P\cup\{x_j\}\cup Y} \le \min\{1, \frac{sup^{c_i}_{P\cup\{x_j\}}}{min\_sup}\} \tag{3.4}$$

LEMMA 3.2. ***(Unpromising item pruning)*** *For any conditional instance $\langle t_l, X_l, c_i\rangle \in TrDB|_{P\cup\{x_j\}}$ ($\forall l$, $1 \le l \le |TrDB|_{P\cup\{x_j\}}|$, and $1 \le i \le k$), if the following always holds, item x_j is called an unpromising item and can be safely pruned.*

$$HCCR^{conf}_{t_l} \ge \min\{1, \frac{sup^{c_i}_{P\cup\{x_j\}}}{min\_sup}\} \tag{3.5}$$

Proof. By combining Equation 3.4 and Equation 3.5 we get that for any itemset Y (Y can be empty) the following must hold:

$$conf^{c_i}_{P\cup\{x_j\}\cup Y} \le HCCR^{conf}_{t_l}$$

This means that any rule mined by growing prefix $P \cup \{x_j\}$ will have a confidence that is no greater than the current highest confidence covering rules (with the same rule head) of any conditional instance in $TrDB|_{P\cup\{x_j\}}$; thus, item x_j can be safely pruned. □

Unpromising conditional database elimination. Given the current prefix P, any itemset Y (where Y can be empty and $P \cup Y$ is frequent), any class label c_i ($1 \le i \le k$), the confidence of rule '$P \cup Y \rightarrow c_i$', $conf^{c_i}_{P\cup Y}$, must satisfy the following equation:

$$conf^{c_i}_{P\cup Y} = \frac{sup^{c_i}_{P\cup Y}}{sup_{P\cup Y}} \le \frac{sup^{c_i}_{P\cup Y}}{min\_sup} \le \frac{sup^{c_i}_P}{min\_sup}$$

In addition, because $conf^{c_i}_{P\cup Y} \le 1$ also holds, we have the following equation:

$$conf^{c_i}_{P\cup Y} \le \min\{1, \frac{sup^{c_i}_P}{min\_sup}\} \tag{3.6}$$

LEMMA 3.3. ***(Unpromising conditional database pruning)*** *For any conditional instance $\langle t_l, X_l, c_i\rangle \in TrDB|_P$ ($\forall l, 1 \le l \le |TrDB|_P|$, and $1 \le i \le k$), if the following always holds, the conditional database $TrDB|_P$ can be safely pruned.*

$$HCCR^{conf}_{t_l} \ge \min\{1, \frac{sup^{c_i}_P}{min\_sup}\} \tag{3.7}$$

Proof. By combining Equation 3.6 and Equation 3.7 we can get that for any itemset Y (Y can be empty) and $\forall l, 1 \le l \le |TrDB|_P|$, $\langle t_l, X_l, c_i\rangle \in TrDB|_P$ ($1 \le i \le k$), the following must hold:

$$conf^{c_i}_{P\cup Y} \leq HCCR^{conf}_{t_l}$$

This means that any rule mined by growing prefix P will have a confidence that is no greater than the current highest confidence rules (with the same rule head) of any conditional instance in $TrDB|_P$; thus, the whole conditional database $TrDB|_P$ can be safely pruned. □

```
ALGORITHM 1.1: RuleMiner(TrDB, min_sup)
INPUT: (1) TrDB: a training database, and (2) min_sup: a minimum support threshold.
OUTPUT: (1) HCCR: the set of the highest confidence frequent covering rules w.r.t. each instance in TrDB.
01. for all $t_i \in$ TrDB
02.     $HCCR_{t_i} \leftarrow \emptyset$;
03. call ruleminer($\emptyset$, TrDB).
```

```
SUBROUTINE 1.1 : ruleminer(pi, cdb)
INPUT: (1) pi: a prefix itemset, and (2) cdb: the conditional database w.r.t. prefix pi.
04. if(pi $\neq \emptyset$)
05.     for all $\langle t_l, X_l, c_j\rangle \in$ cdb
06.         if($HCCR^{conf}_{t_l} < \frac{sup^{c_j}_{pi}}{sup_{pi}}$)
07.             $HCCR_{t_l} \leftarrow$ rule 'pi $\rightarrow c_j$';
08. I $\leftarrow$ find_frequent_items(cdb,min_sup);
09. S $\leftarrow$ support_equivalence_item_pruning(I);  I $\leftarrow$ I - S;
10. S $\leftarrow$ unpromising_item_pruning(I, cdb); I $\leftarrow$ I - S;
11. if(I $\neq \emptyset$)
12.     if(unpromising_conditional_database_pruning(I,pi,cdb))
13.         return;
14.     correlation_coefficient_ascending_ordering(I);
15.     for all x $\in$I do
16.         $pi' \leftarrow pi \cup \{x\}$;
17.         $cdb' \leftarrow$ build_cond_database($pi'$, cdb);
18.         call ruleminer($pi'$, $cdb'$);
```

3.1.4 The Integrated Rule Mining Algorithm

The overall structure of the RuleMiner algorithm is shown in ALGORITHM 1.1. First, it initializes the highest confidence classification rules w.r.t. each training instance to empty (lines 01-02), then enumerates the classification rules by calling subroutine *ruleminer*($\emptyset$, *TrDB*) (line 03). Subroutine *ruleminer*() takes as input a prefix itemset *pi* and its corresponding conditional database *cdb*. For each conditional instance, it checks if a classification rule with higher confidence can be computed from the current prefix *pi*, if so, it replaces the corresponding instance's current highest confidence rule with the new rule (lines 04-07). It then finds the frequent local items by scanning *cdb* (line 08), prunes invalid items based on the *support equivalence item pruning* method and the *unpromising item pruning* method (lines 09-10). If the set of valid local items is empty or the whole conditional database *cdb* can be pruned based on the *unpromising conditional database* pruning method, it returns directly (lines 11-13). Otherwise, it sorts the left frequent local items according to the correlation coefficient ascending order (line 14), and grows the current prefix (line 16), builds the conditional database for the new prefix (line 17), and recursively calls itself to mine the highest confidence rules from the new prefix (line 18).

Discussion. The above RuleMiner() algorithm takes as input a uniform support threshold for all classes; however, it can be easily revised to take class-specific support thresholds as input. That is, the user can specify a support threshold for each class. This is sometimes beneficial for some imbalanced databases. However, due to limited space, we will do not elaborate the details and leave it to the interested readers.

```
ALGORITHM 1.2: BuildModel(HCCR)
INPUT: (1) HCCR: the set of the highest confidence covering rules.
OUTPUT: (1) CM: the classification model (i.e., k groups of ranked rules).
01. Cluster_rules_into_k_groups(HCCR);//according to class label
02. for each group of rules
03.     Sort_rules();//in confidence and support descending order
```

```
ALGORITHM 1.3: NewInstanceClassification(CM, ti)
INPUT: (1) CM: the classification model, (2) ti: a test instance.
OUTPUT: (1) PCL: a predicted class label (or a set of class labels).
01. for j=1 to k //$CM_j$: the j-th group of rules in CM
        //$SCR_j$: the score for ti computed from $CM_j$
02.     $SCR_j \leftarrow$ComputeScore($CM_j$, ti);
03. PCL $\leftarrow$ PredictClassLabel(SCR).
```

3.2 Building the Classification Model

After the set of the highest confidence covering rules have been mined, it will be straightforward to build the classification model. HARMONY first groups the set of the highest confidence covering rules into k groups according to their rule heads (i.e., class labels), where k is the total number of distinct class labels in the training database. Within the same group of rules, HARMONY sorts the rules in their confidence descending order, and for the rules with the same confidence, sorts them in support descending order. In this way, HARMONY prefers the rules with higher confidence, and the rules with higher support if the confidence is the same. The BuildModel algorithm is shown in ALGORITHM 1.2.

3.3 Classifying a New Instance

After the classification model, *CM*, has been built, it can be used to classify a new test instance, *ti*, using the NewInstanceClassification algorithm shown in ALGORITHM 1.3. HARMONY first computes a score w.r.t. *ti* for each group of rules in *CM* (lines 01-02), and predicts for *ti* a class label or a set of class labels if the underlying classification is a multi-class multi-label problem (i.e., each instance can be associated with several class labels).

Scoring function. In HARMONY, the score for a certain group of rules is defined in three different ways. The first scoring function is called *HIGHEST*, which computes the score as the highest confidence among the covering rules w.r.t. test instance ti (by a 'covering rule', we mean its rule body is a subset of ti). The second method is based on the *ALL* function. It is the default scoring function in HARMONY and computes the score as the sum of the confidences of all the covering rules w.r.t. ti. The third function is called *TOP-K*, where K is a user-specified parameter. It computes the score for a group of rules as the sum of the top K highest confidences of the covering rules w.r.t. ti. The *HIGHEST* and *ALL* functions can be thought of as two special cases of the *TOP-K* function when K is set at 1 and $+\infty$. For a multi-class single-label classification problem, HARMONY simply chooses the class label with the highest score as the predicted class label. While for a multi-class multi-label classification problem, the prediction is a little complicated.

Multi-class multi-label classification. In [5], the *dominant factor*-based method was proposed to predict the class labels for a multi-class multi-label classification problem and works as follows. Given a user-specified *dominant factor* γ, let the class label with the highest score be c_{max} and the corresponding highest score w.r.t. test instance ti be $SCORE_{ti}^{c_{max}}$, then any class label whose corresponding score is no smaller than $SCORE_{ti}^{c_{max}} \times \gamma$ is a predicted class label for ti. This method has been verified to be effective in practice [5]. However, in many imbalanced classification problems, the average confidence of each group of classification rules may be quite different from each other, this uniform *dominant factor*-based method will not work well. A large *dominant factor* may lead to low recalls (i.e., the percentage of the total test instances for the given class label that are correctly classified) for the classes with low average rule confidences, while a small *dominant factor* can lead to low precisions (i.e., the percentage of predicted instances for the given class label that are correctly classified) for the classes with high average rule confidences. To overcome this problem, HARMONY adopts a *weighted dominant factor*-based method. Let the average confidence of the group of classification rules w.r.t. class label c_k be $conf_{c_k}^{avg}$, the score w.r.t. instance ti and class label c_k be $SCORE_{ti}^{c_k}$. Instance ti is predicted to belong to class c_k if it satisfies the equation:

$$SCORE_{ti}^{c_k} \geq SCORE_{ti}^{c_{max}} \times \gamma \times \left(\frac{conf_{c_k}^{avg}}{conf_{c_{max}}^{avg}}\right)^{\delta}$$

Here, δ ($\delta \geq 0$) is called the *score differentia factor* and the larger the δ, the more the difference of the *weighted dominant factors* (i.e., $\gamma \times (\frac{conf_{c_k}^{avg}}{conf_{c_{max}}^{avg}})^{\delta}$) among different class labels. It is set to 1 by default in HARMONY.

4 Related Work

There are two classes of algorithms that are directly related to this work. One is the traditional rule-induction-based methods and the other is the recently proposed association-rule-based methods. Both of these classes share the same idea of trying to find a set of classification rules to build the model. The rule-induction-based classifiers like C4.5 [26], FOIL [27], RIPPER [13], and CPAR [30] use various heuristics such as information gain (including Foil gain) and gini index to identify the best variable (or literal) by which to grow the current rule, and many of them follow a sequential database covering paradigm to speed up rule induction. The association-based classifiers adopt another approach to find the set of classification rules. They first use some efficient association rule mining algorithms to discover the complete (or a large intermediate) set of association rules, from which the final set of classification rules can be chosen based on various types of sequential database covering techniques. Some typical examples of association-based methods include CBA [25], CMAR [24], and ARC-BC [5].

In contrast to the rule-induction-based algorithms, HARMONY does not apply any heuristic pruning methods and the sequential database covering approach. Instead, it follows an instance-centric framework and mines the covering rules with the highest confidence for each instance, which can achieve better accuracy. At the same time, by maintaining one of the currently best rules for each training instance and pushing deeply several effective pruning methods into the projection-based frequent itemset mining framework [20, 1, 18], HARMONY directly mines the final set of classification rules, which avoids the time consuming rule generation and selection process used in several association-based classifiers [25, 24, 5].

The idea of directly mining a set of high confidence classification rules is similar to those in [7, 14]. Unlike these methods, HARMONY does not need the user to specify the minimum confidence and/or chi-square. Instead, it mines for each training instance one of the highest confidence frequent rules that it covers. In addition, by maintaining one of the currently best classification rules for each instance, HARMONY is able to incorporate some new pruning methods under the unpromising item (or conditional database) pruning framework, which has been proven very effective in pushing deeply the length-decreasing support constraint or tough block constraints into closed itemset mining [28, 18].

Table 2: UCI database characteristics.

Database	# instances	# items	# classes
adult	48842	131	2
chess	28056	66	18
connect	67557	66	3
led7	3200	24	10
letRegcog	20000	106	26
mushroom	8124	127	2
nursery	12960	32	5
pageBlocks	5473	55	5
penDigits	10992	90	10
waveform	5000	108	3

5 Empirical Results

5.1 Test Environment and Databases

We implemented HARMONY in C and performed the experiments on a 1.8GHz Linux machine with 1GB memory. We first evaluated HARMONY as a frequent itemset mining algorithm to show the effectiveness of the pruning methods, the algorithm efficiency and scalability. Then we compared HARMONY with some well-known classifiers on both categorical and text databases.

The UCI Databases. Many previous studies used some small databases to evaluate both the accuracy and efficiency of a classifier. For example, most of the 26 databases used in [25, 24, 30] only contain several hundred instances, which means the test databases contain too few test instances (i.e., only a few tens) if the 10-fold cross validation is adopted to evaluate the classification accuracy. In this paper, we mainly focus on relatively large databases. By large, we mean the database should contain no fewer than 1000 instances.

In [12], the author used 23 UCI databases to compare FOIL and CPAR algorithms. Among these 23 databases, 10 of them are large databases and will be used to compare HARMONY with FOIL, CPAR, and SVM [4]. The characteristics of these databases are summarized in Table 2. All the 10 databases were obtained from the author of [12] and the 10-fold cross validation is used for comparison with FOIL, CPAR, and SVM. Among these databases, *connect* is a too dense database, during the 10-fold cross validation in our experiments HARMONY only used the items whose supports are no greater than 20,000 to generate rules for this database.

[4]The numerical attributes in these databases have been discretized by the author of [12], and the discretization technique is different from those used in [25, 24, 30]; thus, the performance reported here may be different from the previous studies even for the same algorithm and the same database.

Table 3: Top 10 topics in reuters-21578.

Category Name	# train labels	# test labels
acq	1650	719
corn	181	56
crude	389	189
earn	2877	1087
grain	433	149
interest	347	131
money-fx	538	179
ship	197	89
trade	369	118
wheat	212	71
total	7193	2787

Table 4: Class distribution in *sports* database.

Class Name	Number of labels
baseball	3412
basketball	1410
football	2346
hockey	809
boxing	122
bicycle	145
golf	336
total	8580

Text Databases. We also used two text databases in our empirical evaluation. The first database is the popularly used 'ModeApte' split version of the reuters-21578 collection, which was preprocessed and provided by the authors of [11], and both the database and its description are available at [10]. After preprocessing, it contains totally 8575 distinct terms, 9603 training documents, and 3299 test documents. Like many other studies [21, 16, 5, 11], we are more interested in the top 10 most common categories (i.e., topics). These ten largest categories form 6488 training documents and 2545 test documents. A small portion of the training and test documents are associated with multiple category labels (that is, *reuter-21578* is a multi-class multi-label database). In our experiments, we treated each one of the training documents with multiple labels as multiple documents, each one with a distinct label. The top 10 categories and their corresponding number of labels in the training and test databases are described in Table 3. The second text database is *sports*, which was obtained from San Jose Mercury (TREC). In our experiments, we removed some highly frequent terms, and finally it contains totally 8580 documents, 7 classes, and about 1748 distinct terms. The seven classes and their corresponding number of documents are shown in Table 4.

5.2 Experimental Results

5.2.1 Evaluate HARMONY as a Frequent Itemset Mining Algorithm

To mine the highest confidence covering rule(s) for each instance, a naïve method is like the association-based classifiers: first use an efficient association rule mining algorithm to compute the complete set of classification rules, from which the set of the highest confidence covering rules w.r.t. each instance can be selected. Our empirical results show that this method is usually inefficient if the database is large and a more efficient way is to push some effective pruning methods into the frequent itemset mining framework and to directly mine the final set of classification rules.

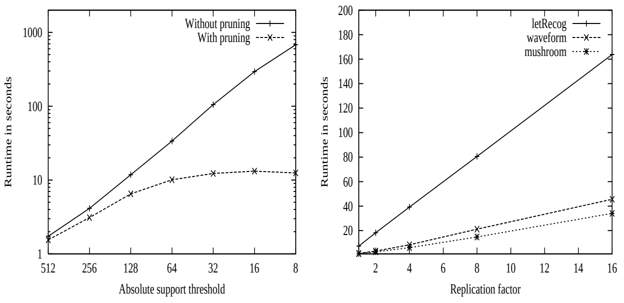
Ordering of the local items. In HARMONY, we provide three options for item ordering, that is, CoRrelation coefficient Ascending order (denoted by CRA), Entropy Ascending order (denoted by EA), and Maximum Confidence Descending order (denoted by MCD). We first evaluated the effectiveness of these item ordering schemes against Support Descending order (denoted by SD) that is popularly used in frequent itemset mining. Our experiments have shown that the three newly proposed item ordering schemes are always more efficient than the support descending ordering scheme. In addition, these schemes also lead to slightly different classification accuracy. This is partly because different item ordering schemes may mine a different highest confidence covering rule w.r.t. a certain training instance, which may have different supports, although their confidence is the same. The experimental results also show that although the correlation coefficient ascending ordering scheme is not always the winner, on average it is more efficient and has better accuracy than all the other schemes. As a result, in HARMONY, it is chosen as the default option for item ordering. Table 5 shows the comparison result for the *sports* database at absolute support of 200. We can see that the correlation coefficient ascending ordering scheme is more efficient and also has slightly higher classification accuracy which was measured using 10-fold cross validation.

Table 5: Item ordering test on *sports* database.

Ordering scheme	CRA	EA	MCD	SD
Runtime(in seconds)	55.7	88.6	110.8	156.3
Accuracy(in %)	85.57	85.51	85.53	85.52

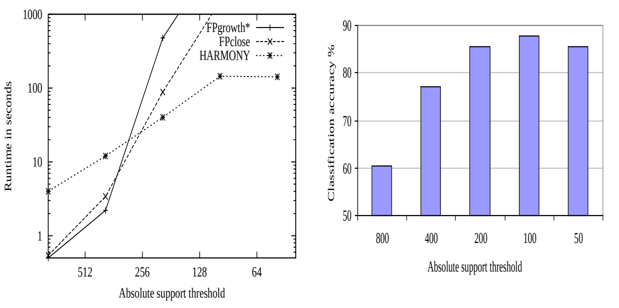
Effectiveness of the pruning methods. We also evaluated the effectiveness of the pruning methods. Figure 1a shows the results for database *penDigits* with absolute support threshold varying from 512 to 8. At first glance of Equation 3.5 and Equation 3.7, the *unpromising item* and *conditional database* pruning methods seem to be less effective at lower support, however this is not the case when considering more covering rules with higher confidence can be found at lower support and can be used to more quickly raise the currently maintained highest confidences. As we can see from Figure 1a, if we turn off the pruning methods used in HARMONY (denoted by 'without pruning'), it can become over an order of magnitude slower at low support.

Scalability test. Figure 1b shows the scalability test result for databases *letRecog*, *waveform*, and *mushroom* with relative support set at 0.5%. In the experiments, we replicated the instances from 2 to 16 times. We can see that HARMONY has linear scalability in the runtime with increasing number of instances.



a) Pruning (*penDigits*) b) Scalability (*0.5%*)

Figure 1: Pruning and scalability test.



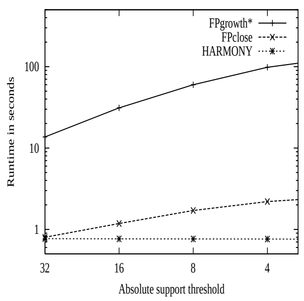
a) *Runtime comparison* b) *Classification accuracy*

Figure 2: Efficiency test (*sports*).

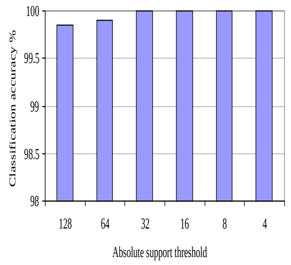
Efficiency test. As we mentioned above, the traditional frequent (closed) itemset mining algorithms can be revised to mine the complete set of high confidence classification rules, from which a subset of high quality rules can be further identified. Our efficiency tests for HARMONY in comparison with FPgrowth* and FPclose, two recently developed efficient frequent/closed

Table 6: Breakeven performance on the *Reuters-21578* database with some well-known classifiers.

Categories	HARMONY *min_sup=60*	HARMONY *min_sup=70*	HARMONY *min_sup=80*	Find Similar	Naïve Bayes	Bayes Nets	Decision Trees	SVM (linear)
acq	**95.3**	**95.3**	**95.3**	64.7	87.8	88.3	89.7	93.6
corn	78.2	78.6	75.2	48.2	65.3	76.4	**91.8**	90.3
crude	85.7	85.0	88.0	70.1	79.5	79.6	85.0	**88.9**
earn	**98.1**	**98.2**	97.6	92.9	95.9	95.8	97.8	98.0
grain	91.8	90.4	90.1	67.5	78.8	81.4	85.0	**94.6**
interest	77.3	76.6	75.1	63.4	64.9	71.3	67.1	**77.7**
money-fx	**80.5**	**81.9**	**82.1**	46.7	56.6	58.8	66.2	74.5
ship	**86.9**	82.9	82.8	49.2	85.4	84.4	74.2	85.6
trade	**88.4**	**88.0**	**86.1**	65.1	63.9	69.0	72.5	75.9
wheat	62.8	60.6	58.7	68.9	69.7	82.7	**92.5**	91.8
micro-avg	**92.0**	91.7	91.4	64.6	81.5	85.0	88.4	**92.0**



a) Runtime comparison



b) Classification accuracy

Figure 3: Efficiency test (*mushroom*).

itemset mining algorithms [19], show that such an approach is not realistic at low support, while our experiments demonstrate that the classification accuracy is usually higher at low support.

Figure 2 shows the comparison results for database *sports*. As we can see, although at high support, both FPgrowth* and FPclose are faster than HARMONY, once we continue to lower the support, they will be much slower. For example, at absolute support of 100, HARMONY is several orders of magnitude faster than FPgrowth* and FPclose. Figure 2b shows the classification accuracy at different support thresholds using the 10-fold cross validation. We can see that HARMONY can achieve higher accuracy at lower support like 100. It is also interesting to see that the accuracy at a too low support 50 is worse than that at support 100 for this database, due to the 'overfitting' problem.

Figure 3a shows similar comparison results for categorical database *mushroom*. HARMONY is faster than both FPgrowth* and FPclose at absolute support lower than 32. Figure 3b shows that HARMONY has better accuracy at low support threshold.

5.2.2 Classification Evaluation

The reuters–21578 (*ModApte*) text database. For a multi-class multi-label database like *reuters-21578*, most previous studies used the breakeven point of precision and recall to measure the classifier performance [6, 21, 16, 29, 9, 5, 11], which is defined as the point at which precision is equal to the recall. To our best knowledge, the best breakeven performance for the *reuters-21578* database is the linear SVM [16]. For comparison with earlier results, we first found the overall breakeven point in terms of all top 10 categories by adjusting the dominant factor γ, then reported the average of precision and recall for each category as their corresponding breakeven performance [16].

Table 6 shows the comparison results with some previous results. The results for Find-Similar, Naïve-Bayes, Bayes-Nets, Decision-Trees, and Linear-SVM were obtained from [16]. The micro-avg is the overall breakeven performance over all 10 categories. For HARMONY, we used three different absolute support thresholds, 60, 70, and 80, respectively. From Table 6 we can see that both HARMONY and Linear-SVM have similar breakeven performance and perform much better than all the other classifiers. Among the 10 categories, HARMONY achieves the best performance at support of 60 for five categories, *acq*, *earn*, *money-fx*, *ship*, and *trade*. While Linear-SVM performs best for another three categories, *crude*, *grain*, and *interest*. Decision-Trees also performs good and has the best performance for two small categories, *corn* and *wheat*. SVM is very well known for classifying high dimensional text databases. Our results show that HARMONY can achieve similar performance to SVM.

The UCI databases. We evaluated HARMONY on the UCI databases in comparison with FOIL, CPAR, and SVM. FOIL and CPAR are two well-known algorithms for classifying categorical data. The results in [30] show that CPAR has better accuracy than c4.5 [26] and ripper [13], and has comparable accuracy to the association-based algorithms CMAR [24] and CBA [25], but is orders of magnitude faster; thus, we will do not compare HARMONY with c4.5, ripper, and the association-based algorithms. The results for FOIL and CPAR were provided by Frans Coenen and are available at [12]. Because most databases we used contain more than two class labels, when comparing with SVM, we used $SVM^{multiclass}$ (Version: 1.01), which is an implementation of the multi-class Support Vector Machine and is available at *http://www.cs.cornell.edu/People/tj/svm_light/svm_multiclass.html*. In the experiments, we ran SVM with its default setting[5]. All the results including the accuracy and runtime are computed using the 10-fold cross validation. The reported accuracy is the corresponding average value of the 10-fold cross validation results, while the runtime is the total runtime of the 10-fold cross validation, including both training and testing time. In the experiments, we fixed the absolute support threshold at 50 for HARMONY with all 10 UCI databases.

Table 7: Accuracy comparison on 10 large *UCI* databases (*min_sup=50* for HARMONY).

Database	FOIL	CPAR	SVM	HARMONY
adult	82.5	76.7	**84.16**	81.9
chess	42.6	32.8	29.83	**44.87**
connect	65.7	54.3	**72.5**	68.05
led7	62.3	71.2	73.78	**74.56**
letRecog	57.5	59.9	67.76	**76.81**
mushroom	99.5	98.8	99.67	**99.94**
nursery	91.3	78.5	91.35	**92.83**
pageBlocks	**91.6**	76.2	91.21	**91.6**
penDigits	88.0	83.0	93.2	**96.23**
waveform	75.6	75.4	**83.16**	80.46
average	75.66	70.68	78.663	**80.725**

Table 7 shows the accuracy comparison results, which reveal that HARMONY has much better overall accuracy than FOIL and CPAR, and has comparable accuracy with SVM. The average accuracy of HARMONY over all 10 UCI databases is about 5% higher than FOIL, 10% higher than CPAR, and 2% higher than SVM. SVM performs very well for the databases with few class labels, like *adult*, *connect*, and *waveform*, but has much worse accuracy than HARMONY for the databases with many class labels, like *chess* and *letRecog*. Compared with SVM, HARMONY has reasonably stable and good performance over all 10 UCI databases. Note in the experiments we fixed the minimum support at 50 for all 10 UCI databases. If we choose some tuned supports, HARMONY can achieve better performance than what we reported here for some databases. For example, if we choose the minimum support at 5 for the *chess* database, HARMONY has an accuracy of 58.43%, which is over 13% higher than the accuracy at support 50, while it only becomes about two times slower.

Table 8 compares the runtime (in seconds) of the four algorithms. Note that FOIL and CPAR were implemented in java and were tested on a different machine from that of HARMONY and SVM. As a result, their runtime cannot be directly compared to those reported for HARMONY and SVM but they only provide an overall idea on the relative computational requirements of the various schemes. Table 8 shows that on average the runtime of HARMONY is over an order of magnitude smaller than those of FOIL, CPAR, and SVM. For some large databases like *chess*, the runtime of HARMONY can be over two orders of magnitude smaller than those of FOIL and CPAR, and over three orders of magnitude smaller than that of SVM.

Table 8: Runtime comparison on 10 large *UCI* databases (*min_sup=50* for HARMONY).

Database	FOIL	CPAR	SVM	HARMONY
adult	10251.0	**809.0**	2493.1	1395.5
chess	10122.8	1736.0	13289.4	**11.34**
connect	35572.5	24047.1	74541.1	**85.44**
led7	11.5	5.7	17.12	**1.29**
letRecog	4365.6	**764.0**	17825.2	778.91
mushroom	38.3	15.4	16.6	**8.78**
nursery	73.1	51.7	322.4	**6.21**
pageBlocks	43.1	15.5	11.2	**2.5**
penDigits	821.1	101.9	512.7	**82.6**
waveform	295.3	38.1	**36.2**	130.0
total	61594.3	27584.4	109065.02	**2502.57**

Table 9: Test of scoring functions (*min_sup=50*)

Database	HIGHEST	TOP 3	TOP 5	ALL
adult	82.52	82.59	**82.61**	81.9
chess	43.06	40.44	37.81	**44.87**
connect	67.7	67.35	67.16	**68.05**
led7	72.98	73.34	71.2	**74.56**
letRecog	73.69	72.99	71.79	**76.81**
mushroom	**99.95**	**99.95**	**99.95**	99.94
nursery	**94.62**	93.98	93.72	92.83
pageBlocks	91.34	91.34	91.34	**91.6**
penDigits	94.49	94.24	93.93	**96.23**
waveform	78.82	78.82	79.52	**80.46**
average	79.917	79.504	79.513	**80.725**

Scoring function test. In the above classification evaluation, HARMONY adopted its default scoring function, *ALL*, to compute the score for a certain group of rules. In our experiments, we also evaluated the effectiveness of different scoring functions in HARMONY, including *ALL*, *HIGHEST*, and *TOP-K* (*K* was set at 3 and 5 in the experiments). The results w.r.t. the UCI databases are shown in Table 9. We see that the *ALL* function can achieve overall better accuracy than the other functions, while other functions can also have better accuracy for some databases. For example, the *HIGHEST* function achieves better accuracy for database *nursery*, and the *TOP-K* function can achieve better performance for database *adult*.

[5]We used its default linear kernel function.

6 Conclusion

Designing accurate, efficient, and scalable classifiers is an important research topic in data mining, and the rule-based classifiers have been proven very effective in classifying the categorical or high-dimensional sparse data. However, to achieve high accuracy, a good rule-based classifier needs to find a sufficient number of high quality classification rules and use them to build the model. In this paper, we proposed an instance-centric classification rule mining paradigm and designed an accurate classifier, HARMONY. Several effective search space pruning methods and search strategies have also been proposed, which can be pushed deeply into the rule discovery process. Our performance study shows that HARMONY has high accuracy and efficiency in comparison with many well known classifiers for both the categorical and high dimensional text data. It also has good scalability in terms of the database size.

Acknowledgements

We are grateful to Frans Coenen at the University of Liverpool and Shane Bergsma at the University of Alberta for providing us the discretized UCI databases and the reuters-21578 database, respectively, and promptly answering our various questions. We also thank Osmar R. Zaïane and Maria-Luiza Antonie at the University of Alberta for answering our questions related to the ARC-BC algorithm.

References

[1] R. Agarwal, C. Aggarwal, V. Prasad. *A Tree Projection Algorithm for Generation of Frequent Item Sets*, Journal of Parallel and Distributed Computing. 61(3), 2001.

[2] R. Agrawal, T. Imielinski, A. Swami. *Mining Association Rules between Sets of Items in Large Databases*, SIGMOD'93.

[3] R. Agrawal, R. Srikant. *Fast Algorithms for Mining Association Rules*, VLDB'94.

[4] K. Ali, S Manganaris, R. Srikant. *Partial Classification Using Association Rules*, KDD'97.

[5] M. Antonie, O. Zaiane. *Text Document Categorization by Term Association*, ICDM'02.

[6] C. Apte, F. Damerau, S.M. Weiss. *Towards Language Independent Automated Learning of Text Categorization Models*, SIGIR'94.

[7] R.J. Bayardo. *Brute-force Mining of High-confidence Classification rules*, KDD'97.

[8] R.J. Bayardo, R. Agrawal. *Mining the most interesting rules*, KDD'99.

[9] R. Bekkerman, R. EI-Yaniv, N. Tishby, Y. Winter. *On Feature Distribution Clustering for Text Categorization*, SIGIR'01.

[10] S. Bergsma. *The Reuters-21578 (ModApte) dataset*, Department of Computer Science, University of Alberta. Available at http://www.cs.ualberta.ca/~bergsma/650/.

[11] S. Bergsma, D. Lin. *Title Similarity-Based Feature Weighting for Text Categorization*, CMPUT 650 Research Project Report, Department of Computer Science, University of Alberta.

[12] F. Coenen. (2004) The LUCS-KDD Implementations of the FOIL, PRM, and CPAR algorithms, http://www.csc.liv.ac.uk/~frans/KDD/Software/FOIL_PRM_CPAR/foilPrmCpar.html, Computer Science Department, University of Liverpool, UK.

[13] W. Cohen. *Fast effective rule induction*, ICML'95.

[14] G. Cong, X. Xu, F. Pan, A. Tung, J. Yang. *FARMER: Finding Interesting Rule Groups in Microarray Datasets*, SIGMOD'04.

[15] M. Deshpande, G. Karypis. *Using Conjunction of Attribute Values for Classification*, CIKM'02.

[16] S. Dumais, J. Platt, D. Heckerman, M. Sahami. *Inductive Learning Algorithms and Representations for Text Categorization*, CIKM'98.

[17] T. Fukuda, Y. Morimoto, S. Motishita. *Constructing Efficient Decision Trees by Using Optimized Numeric Association Rules*, VLDB'96.

[18] K. Gade, J. Wang, G. Karypis. *Efficient Closed Pattern Mining in the Presence of Tough Block Constraints*, to appear in KDD'04.

[19] G. Grahne, J. Zhu. *Efficiently Using Prefix-trees in Mining Frequent Itemsets*, ICDM-FIMI'03.

[20] J. Han, J. Pei, Y. Yin. *Mining Frequent Patterns without Candidate Generation*, SIGMOD'00.

[21] T. Joachims. *Text Categorization with Support Vector Machines: Learning with Many Relevant Features*, ECML'98.

[22] B. Lent, A. Swami, J. Widom. *Clustering Association Rules*, ICDE'97.

[23] N. Lesh, M. Zaki, M. Ogihara. *Mining Features for Sequence Classification*, KDD'99.

[24] W. Li, J. Han, J. Pei. *CMAR: Accurate and Efficient Classification based on multiple class-association rules*, ICDM'01.

[25] B. Liu, W. Hsu, Y. Ma. *Integrating Classification and Association Rule Mining*, KDD'98.

[26] J. Quinlan. *C4.5: Programs for Machine Learning*, Morgan Kaufman, 1993.

[27] J. Quinlan, R. Cameron-Jones. *FOIL: A Midterm Report*, ECML'93.

[28] J. Wang, G. Karypis. *BAMBOO: Accelerating Closed Itemset Mining by Deeply Pushing the Length-Decreasing Support Constraint*, SDM'04.

[29] Y. Yang. *An Evaluation of Statistical Approaches to Text Categorization*, Information Retrieval, Vol. 1, No. 1-2, 1999.

[30] X. Yin, J. Han. *CPAR: Classification based on Predictive Association Rules*, SDM'03.

[31] M. Zaki, C. Aggarwal. *XRULES: An Effective Structural Classifier for XML Data*, KDD'03.