A TRADEOFF BALANCING ALGORITHM FOR HIDING SENSITIVE FREQUENT ITEMSETS

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Abstract: Sensitive frequent itemset hiding problem is typically solved by applying a sanitization process which transforms the source database into a release version. The main challenge in the process is to preserve the database utility while ensuring no sensitive knowledge is disclosed, directly or indirectly. Several algorithmic solutions based on different approaches are proposed to solve the problem. We observe that the available algorithms are like seesaws as far as both effectiveness and efficiency performances are considered. However, most practical domains demand for solutions with satisfactory effectiveness/efficiency performances, *i.e.*, solutions balancing the tradeoff between the two. Motivated from this observation, in this paper, we present yet a simple and practical frequent itemset hiding algorithm targeting the balanced solutions. Experimental evaluation, on two datasets, shows that the algorithm indeed achieves a good balance between the two performance criteria.

1 INTRODUCTION

Privacy preserving data mining has been an active research area since O'Leary (O'Leary, 1991) has shown that data mining is indeed a threat to database security. The threat is due to the fact that advances in data mining have resulted in tangible tools that can easily surface private and sensitive knowledge. This prompts *database publishing* to be done carefully. Consider a database publishing scenario where a data owner is enthusiastic about sharing his database with public, and at the same time reluctant of doing so as the database may contain sensitive knowledge that must be kept private. Then, a safe publishing is to remove (or conceal) those sensitive knowledge prior to the publishing by applying a *sanitization* process. This problem is known as *sensitive knowledge hiding*. When the knowledge to be hidden is of the form frequent itemsets, then the respective knowledge hiding problem is called *frequent itemset hiding*.

Disclosure of a sensitive frequent itemset (*knowledge*) is a violation of its privacy. To this end, a sensitive itemset needs not necessarily to refer to persons. For instance, it can simply be a surprising set of supermarket items frequently bought together by many customers. Data owner can tag this itemset as sensitive due to the commercial value of the knowledge. So, mining the knowledge that 'the itemset is frequent' must be impossible from the released database. Clearly, this requires that the original database must be sanitized, and technically speaking, the task is accomplished by reducing its support.

Atallah *et al.* (Atallah et al., 1999) formalized the problem of sensitive frequent itemset hiding, and proved NP-Hardness of finding an optimal solution. Therefore, researchers in the community have been working on developing effective/efficient database sanitization techniques and heuristics. Many algorithms differing from each other in complexity, efficiency, and effectiveness were proposed as a result of these efforts. In this study, we show that the efficiency gap, between quite sophisticated algorithms and very straightforward ones, is remarkable compared to that of effectiveness. Hence, we develop a practical algorithm aimed at balancing the tradeoff. Our experimental evaluation results suggest that the algorithm achieves a good balance.

The paper is organized as follows. We first provide our motivation in the next subsection, before presenting the sensitive frequent itemset hiding problem

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in Section 2. Next, Section 3 introduces our algorithm, and then Section 4 gives the results of our experimental evaluation. Finally, Section 5 concludes.

1.1 Motivation

The work presented in (Abul et al., 2009) implemented several sensitive frequent itemset hiding algorithms from the literature. The work also extensively compared a few algorithms on select datasets empirically, and concluded that (i) performance suffers on difficult problem instances as far as effectiveness/efficiency tradeoff is concerned, and (ii) new algorithms capable of tuning the effectiveness/efficiency tradeoff are in demand. It also has revealed that quite sophisticated algorithms achieve, over relatively naive ones, a marginal gain (up to two fold) in effectiveness at the cost of sizable (up to three order of magnitude) loss in efficiency. Clearly, this suggest that such algorithms may not be useful in some practical domains such as online database publishing. Moreover, sophisticated algorithms are quite complex and require extensive engineering for efficient implementation. These observations motivated us to develop a new frequent itemset hiding algorithm, called BalancedHider, withs the following properties.

- simple, practical, efficient, and relatively effective

These requirements together means that BalancedHider must target a good balance between the efficiency and effectiveness tradeoff. It achieves so by favoring for efficiency as the gap there is remarkably higher compared to the effectiveness gap. To illustrate, let our sophisticated algorithm be BorderBasedHider (BBHider for short) (Sun and Yu, 2005) and the naive algorithm be CyclicHider (Atallah et al., 1999); the details of which are reviewed in Section 2.2. We conducted an experimental evaluation on a real world market basket database, `Retail` (Brijs et al., 1999), by randomly selecting 20 frequent itemsets as sensitive. The itemsets are restricted to have length two or three, and their mean support is 977.95. We evaluated the performances at disclosure thresholds of 400, 300, 200, and 100. The efficiency and effectiveness results at the respective disclosure thresholds are provided in Table 1 and Table 2, respectively. The efficiency and effectiveness results measure the runtime in seconds and frequent itemsets lost due to the sanitization.

We see from Table 1 that CyclicHider runs remarkably fast (up to three-four order of magnitude) compared to BBHider. Another notable result is about the growth rates of runtime with decreasing disclosure thresholds. Note that the growth rate of BBHider is exponential whereas that of CyclicHider is polynomial. On the other hand, Table 2 clearly shows

Table 1: Efficiency (runtime in seconds) of BBHider and CyclicHider on `Retail`.

	Disc.	*thr.*		
Algorithm	**400**	**300**	**200**	**100**
`BBHider`	2221.6	3599.6	6704.2	20785.4
`CyclicHider`	1.716	1.856	1.935	2.231

Table 2: Effectiveness (the number of frequent itemsets lost) of BBHider and CyclicHider on `Retail`.

	Disc.	*thr.*		
Algorithm	**400**	**300**	**200**	**100**
`BBHider`	80	141	262	977
`CyclicHider`	140	257	466	1515
nonsens. freq. itemsets #	609	1158	2242	6645

that BBHider performs better (up to two-fold) at all threshold levels, although the performance gap is not as large as presented for the efficiency.

2 FREQUENT ITEMSET HIDING

Let $I = \{i_1, i_2, \ldots, i_n\}$ be a set of items. A transaction T is any non-empty subset of I and a database $\mathcal{D}$ is a collection of transactions, $\mathcal{D} = \{t_1, t_2, \ldots, t_m\}$. The *support set* of itemset X in database $\mathcal{D}$, denoted $S_{\mathcal{D}}(X)$, is the set of all transactions including X as a subset. Formally, $S_{\mathcal{D}}(X) = \{T : X \subseteq T \wedge T \in \mathcal{D}\}$. The *support* of X in $\mathcal{D}$, denoted $sup_{\mathcal{D}}(X)$, is simply the cardinality of $S_{\mathcal{D}}(X)$.

Definition 1. (Frequent Itemset Mining (Agrawal et al., 1993)) *Let σ be user-defined positive integer, termed as* support threshold *(or simply* threshold*). For a fixed $\mathcal{D}$, any itemset having support not less than σ is called a* frequent *itemset. The set of all frequent itemsets is defined as: $F_{(\mathcal{D},\sigma)} = \{X : X \subseteq I, X \neq \emptyset, sup_D(X) \geq \sigma\}$. Frequent itemset mining is the problem of finding $F_{(D,\sigma)}$.*

A sample database from (Sun and Yu, 2005) is given in Fig. 1(a). Letting the support threshold $\sigma = 3$, the set of frequent itemsets (with respective supports) is computed as shown in Fig. 1(b).

Since any itemset in the set of frequent itemsets is a piece of knowledge, it can bear sensitivity that the data owner is never willing to share it with others, neither directly or indirectly.

Definition 2. (Frequent Itemset Hiding) *Let $P_h = \left\{X_i \mid X_i \in 2^I \wedge i = 1, 2, \ldots, n\right\}$ be the set of n sensitive itemsets. Given a disclosure threshold ψ,* frequent itemset hiding *is the problem of transforming database $\mathcal{D}$ to database $\mathcal{D}'$ such that:*

- $\forall X_i \in P_h : sup_{\mathcal{D}'}(X) < \psi$.

Tid	Items
1	*abcde*
2	*acd*
3	*abdfg*
4	*bcde*
5	*abd*
6	*bcdfh*
7	*abcg*
8	*acde*
9	*acdh*

(a) Sample database

a :7, b :6, c :7, d :8, e :3
ab :4, ac :5, ad :6, bc :4, bd :5, cd :6, ce :3, de :3
abd :3, acd :4, bcd :3, cde :3

(b) Frequent itemsets

Figure 1: A sample database [left], and the frequent itemsets ($\sigma = 3$) along with their supports [right].

- $\sum_{X \in 2^{\mathcal{I}} \setminus \mathcal{P}_h} \mid sup_{\mathcal{D}}(X) - sup_{\mathcal{D}'}(X) \mid$ *is minimized.*

The transformation is called *sanitization*, and the sanitized database $\mathcal{D}'$ is the released version of $\mathcal{D}$. In the definition, the first requirement (*sensitivity*) asks decreasing support of all sensitive itemsets below the given threshold so that none of them appears in $F_{(\mathcal{D}',\psi)}$. The objective with the second requirement (*distortion*) is to keep $\mathcal{D}'$ as close as to $\mathcal{D}$, *i.e.*, to maintain utility of $\mathcal{D}$.

A sample frequent itemset hiding problem is illustrated in Fig. 2, where there are three itemsets (Fig. 2(a)) to hide from the sample database introduced in Fig. 1(a). The database given in Fig. 2(b) is a sanitized database (with $\psi = 3$). Since all sensitive itemsets have support less than 3, it can be safely published as no data mining algorithm can discover any of them as frequent at $\sigma = 3$.

acd, ad, bcd

(a) Sensitive itemsets

Tid	Items
1	*abce*
2	*cd*
3	*abdfg*
4	*bcde*
5	*ab*
6	*bcdfh*
7	*abcg*
8	*ace*
9	*acdh*

(b) Sanitized database

Figure 2: Sensitive itemsets to be hidden from the sample database [left], and a sanitized version (with $\psi = 3$) [right].

2.1 Related Work

Atallah *et al.* (Atallah et al., 1999) was the first work formally defining the knowledge hiding problem in the context of the frequent itemset hiding. An important contribution of that work is proving the NP-Hardness of the problem. The authors also proposed a simple reference algorithm to solve the problem. We call their reference algorithm *CyclicHider*.

In (Sun and Yu, 2005), a border-based approach is presented. The idea is to preserve the shape of positive border (of frequent itemsets) during sanitization process as much as possible. We call their algorithm *BBHider*, and present its details in Section 2.2. In (Moustakides and Verykios, 2006), another border-based algorithm is presented. A linear time (w.r.t. $|\mathcal{D}|$) sanitization algorithm employing sliding window approach is presented in (Oliveira and Zaïane, 2003). Other proposals include FHSFI (Weng et al., 2007) and matrix-based approach (Lee et al., 2004). Knowledge hiding in other contexts, *e.g.*, association rules (Verykios et al., 2004), sequential patterns (Abul et al., 2007b), and spatio-temporal trajectories (Abul et al., 2007a) has also been studied.

2.2 CyclicHider and BBHider

Cyclic hiding algorithm is a very simple algorithm presented as a reference in (Atallah et al., 1999). It hides each sensitive frequent itemset in turn and finds its next supporting transaction to remove the next item in it to reduce the support by one.

A border-based approach is presented in (Sun and Yu, 2005). The idea is to preserve the shape of positive border during the sanitization process as much as possible. The algorithm is sketched in Algorithm 1.

The algorithm first computes the positive border, Bd^+, of frequent itemsets (line 1), and lower border of sensitive itemsets (line 2). The lower border computation simply removes those itemsets from $\mathcal{P}_h$ that have proper subsets in $\mathcal{P}_h$. The itemsets in $\mathcal{P}_h$ are sorted based on descending order of size and ascending order of support (line 3). The outer loop handles sensitive itemsets in one-by-one fashion. For the itemset X, the algorithm decreases its support by one at each iteration of the inner loop. Any transaction-item pair (T,i), where $i \in X \subseteq T$, is a hiding candidate and the function *HidingCandidates* returns the hiding candidates list C. Clearly, removing any candidate c from C reduces X's support by one but relative costs may differ greatly. The objective with *SelectCandidate* is to choose a candidate among all such that the cost w.r.t. the positive border shape distortion is minimum. To do so for every $c \in C$, *SelectCandidate* computes re-

Algorithm 1: *BBHider*.

```
Input: $\mathcal{D}$, $\mathcal{P}_h$, $\psi$, $\lambda$
Output: $\mathcal{D}'$
 1: $Bd^+ \leftarrow PositiveBorder(F_{(\mathcal{D},\psi)})$
 2: $\mathcal{P}_h \leftarrow LowerBorder(\mathcal{P}_h)$
 3: $Sort\ \mathcal{P}_h(desc.\ order\ of\ size\ and\ asc.\ order\ of\ support)$
 4: for all $X \in \mathcal{P}_h$ do
 5:   $V \leftarrow \emptyset$
 6:   $C \leftarrow HidingCandidates(X, \mathcal{D}, Bd^+)$
 7:   while $sup_{\mathcal{D}}(X) \geq \psi$ do
 8:     $c \leftarrow SelectCandidate(C, X, \mathcal{D}, Bd^+, \psi, \lambda)$
 9:     $C \leftarrow C \setminus c$
10:     $V \leftarrow V \bigcup c$
11:   end while
12:   $\mathcal{D} \leftarrow Update(\mathcal{D}, V)$
13: end for
14: $\mathcal{D}' \leftarrow \mathcal{D}$
```

spective impact value and picks c with the minimum value. The selected candidates are accumulated in V (line 10) and $Update$ operation actually removes the candidates from the database.

The algorithm is a sophisticated one as it minimizes the sanitization effect on positive border and hence retains many non-sensitive frequent itemsets in the data mining output. However, the algorithm is not scalable to large and dense databases, especially when the size of positive border grows large well beyond the size of the database. A slight improvement for candidate selection has been provided in (Sun and Yu, 2005), but the complexity remained the same.

3 BALANCEDHIDER

This section covers our proposed algorithm, *BalancedHider*, aimed at balancing the efficiency/effectiveness tradeoff discussed before. The skeleton of the algorithm is given in Algorithm 2. It is simply an enhanced version of CyclicHider, and a simplified version of BBHider.

The algorithm first sorts the database in ascending order of transaction size to prefer short transactions first. This is exploited in sequential scan of supporting transactions (line 5). The outer loop iterates over all sensitive itemsets and reduces support in each iteration of the inner loop. Note that, at each iteration of the inner loop, the support of the active sensitive itemset X is reduced by one by deleting an item in it from the next supporting transaction. However, the victim selection heuristic (lines 6-8) selects a victim item that is shared by most of the sensitive itemsets. Clearly, the heuristic serves to decrement the support

Algorithm 2: The Tradeoff Balancing Hiding Algorithm (*BalancedHider*).

```
Input: $\mathcal{D}$, $\mathcal{P}_h$, $\psi$
Output: $\mathcal{D}'$
 1: $Sort\ \mathcal{D}\ (in\ asc.\ order\ of\ transaction\ length)$
 2: for all $X \in \mathcal{P}_h$ do
 3:   $Sup^X \leftarrow sup_D(X)$
 4:   while $Sup^X \geqslant \psi$ do
 5:     $Find\ next\ T \in \mathcal{D}\ supporting\ X$
 6:     $SS_{\mathcal{P}_h}(T) \leftarrow \{Y : Y \in \mathcal{P}_h \wedge Y \subseteq T\}$
 7:     $victim \leftarrow\ highest\ freq.\ item\ of\ X\ in\ SS_{\mathcal{P}_h}(T)$
 8:     $Remove\ victim\ item\ from\ T$
 9:     $Sup^X \leftarrow Sup^X - 1$
10:   end while
11: end for
11: $\mathcal{D}' \leftarrow \mathcal{D}$
```

of as many as other sensitive itemsets with a single item removal. In fact, the victim selection heuristic (the efficiency bottleneck) is a simplification of candidate selection heuristic of BBHider.

An example operation of BalancedHider is illustrated in Fig. 3. The inputs are as follows: (i) $\mathcal{D}$ is the dataset given in Fig. 1(a), (ii) $\mathcal{P}_h$ is the sensitive itemsets given in Fig. 2(a), and (iii) $\psi = 3$. Fig. 3(a) shows the sensitive itemset and values for the other variables at each iteration of the inner loop. Fig. 3(b), on the other hand, shows the step-by-step evolution of $\mathcal{D}$ from its initial value to the released database $\mathcal{D}'$.

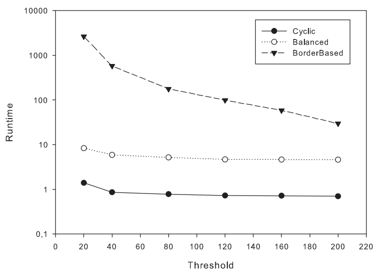
i	X	Sup^X	$SS_{\mathcal{P}_h}(T)$	T	*victim*
1	*acd*	4	{*acd*, *ad*}	*acd*	*a*
2	*acd*	3	{*acd*, *ad*}	*acde*	*a*
3	*ad*	4	{*ad*}	*abd*	*a*
4	*ad*	3	{*a*}	*acdh*	*a*
5	*bcd*	3	{*bcd*}	*bcde*	*b*

(a) Variables at each iteration

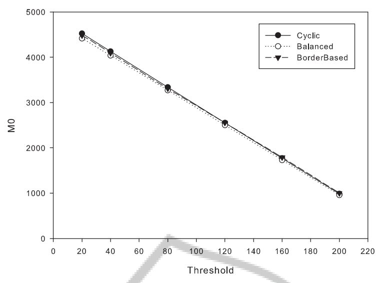
$\mathcal{D}$	After *i*th deletion				$\mathcal{D}'$
	i=1	*i=2*	*i=3*	*i=4*	*i=5*
abd	*abd*	*abd*	***bd***	*bd*	*bd*
acd	***cd***	*cd*	*cd*	*cd*	*cd*
abcg	*abcg*	*abcg*	*abcg*	*abcg*	*abcg*
acde	*acde*	***cde***	*cde*	*cde*	*cde*
acdh	*acdh*	*acdh*	*acdh*	***cdh***	*cdh*
bcde	*bcde*	*bcde*	*bcde*	*bcde*	***cde***
abcde	*abcde*	*abcde*	*abcde*	*abcde*	*abcde*
abdfg	*abdfg*	*abdfg*	*abdfg*	*abdfg*	*abdfg*
bcdfh	*bcdfh*	*bcdfh*	*bcdfh*	*bcdfh*	*bcdfh*

(b) Step-by-step sanitization

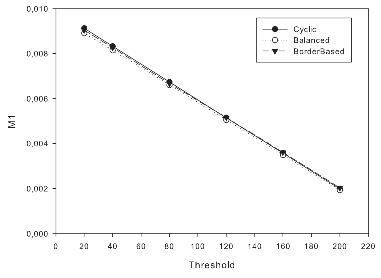
Figure 3: The operation of BalancedHider for sanitizing the sensitive itemsets (Fig. 2(a)) from the sample database ($\psi = 3$). (a) value of variables at each iteration (i) of the inner loop, (b) step-by-step sanitization.



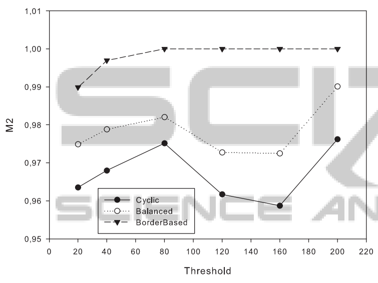
(a) Runtime



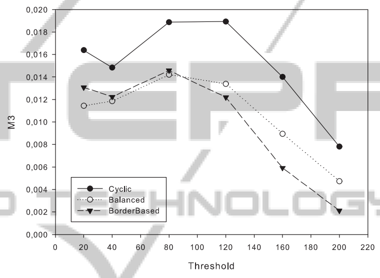
(b) M0



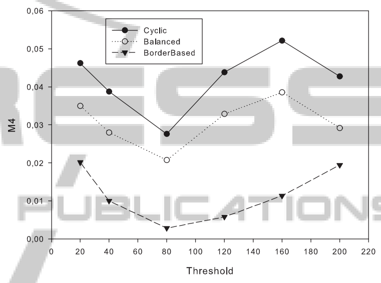
(c) M1



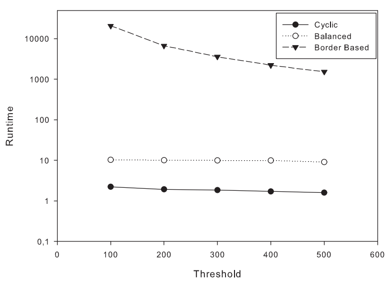
(d) M2



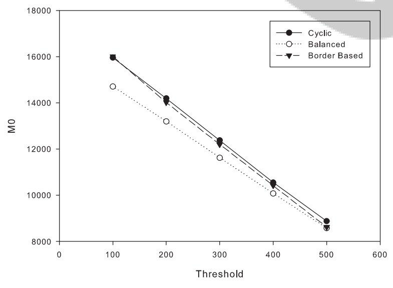
(e) M3



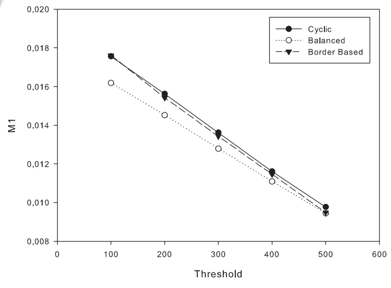
(f) M4



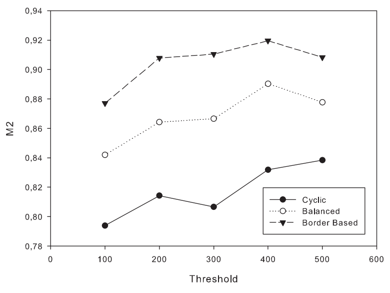
(g) Runtime



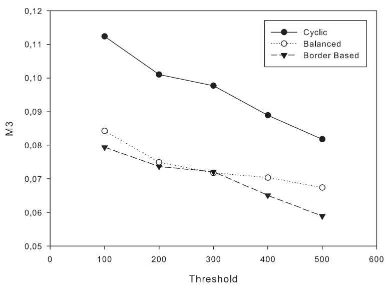
(h) M0



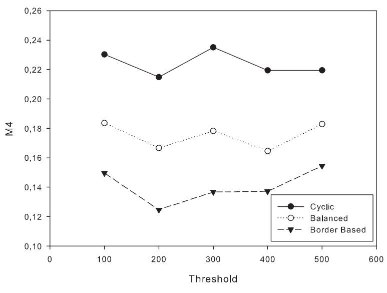
(i) M1



(j) M2



(k) M3



(l) M4

Figure 4: Sanitization results: [a-f] for `T10.I4.50K`, and [g-l] for `Retail`.

4 PERFORMANCE EVALUATION

In this section, we present the performance of BalancedHider and compare it to that of CyclicHider and BBHider. The test computer used was equipped with Intel Core2Duo 3.0Ghz processor, 2GB of main memory and running Windows XP64 operating system. For performance evaluation, a synthetic dataset was generated using IBM synthetic dataset generator, namely `T10.I4.50K`. We also used a real world market basket database `Retail` (Brijs et al., 1999) from FIMI repository. `Retail` contains 88163 transactions, 16470 different items, and 13 items per transaction on average. For each of the two databases, 20 sensitive frequent itemsets were selected somewhat arbitrarily, and each sensitive itemset contains either two or three items. Average support of sensitive itemsets are 249.8 for `T10.I4.50K`, 977.95 for `Retail`.

We always use runtime as the only efficiency metric and use five different (*M0* through *M4*) effectiveness metrics to measure the distortion as follows. Note that all the metrics except M2 have the 'the smaller is the better' property, and vice versa for M2.

- Runtime (in seconds): It equals to the completion time.
- Data Dist. (M0): It equals to $\sum_{T\in\mathcal{D}}|T| - \sum_{T\in\mathcal{D}'}|T|$.
- Information Loss (M1) (Oliveira and Zaïane, 2003) : It equals to $\frac{\sum_{i\in I} sup_{\mathcal{D}}(\{i\}) - sup_{\mathcal{D}'}(\{i\})}{\sum_{i\in I} sup_{\mathcal{D}}(\{i\})}$.
- Quality (M2): It equals to $\frac{\left|F_{(\mathcal{D}',\psi)}\right|}{\left|F_{(\mathcal{D},\psi)} - \mathcal{P}_h\right|}$.
- Freq. Support Dist. (M3) (Abul et al., 2007b): It equals to $\frac{1}{\left|F_{(\mathcal{D}',\psi)}\right|} \sum_{X\in F_{(D',\psi)}} \frac{sup_{\mathcal{D}}(X) - sup_{\mathcal{D}'}(X)}{sup_{\mathcal{D}}(X)}$.
- Freq. Pattern Dist. (M4) (Abul et al., 2007b): It equals to $\frac{\left|F_{(\mathcal{D},\psi)}\right| - \left|F_{(\mathcal{D}',\psi)}\right|}{\left|F_{(\mathcal{D},\psi)}\right|}$.

The results are plotted in Fig. 4. The results, in summary, show that the effectiveness performance of BalancedHider ranges between that of CyclicHider and BBHider and efficiency performance is close to that of CyclicHider.

5 CONCLUSIONS

In this work, we introduced a new algorithm for sensitive frequent itemset hiding problem, which aimed at finding solutions balancing the efficiency/effectiveness tradeoff. The motivation was built on our analysis that there is a big efficiency gap between simple and sophisticated algorithms while that of the effectiveness gap is relatively small. The experimental results on two datasets confirm that the algorithm indeed achieved its design criteria.

Our algorithm is very practical, making it useful in many domains like online database publishing. Our future work will include extension of the algorithm to other knowledge formats.

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