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Efficient Vertical Mining of Frequent Closed Itemsets and Generators

Laszlo Szathmary¹, Petko Valtchev¹, and Amedeo Napoli²

¹ Dépt. d'Informatique UQAM, C.P. 8888,
Succ. Centre-Ville, Montréal H3C 3P8, Canada
Szathmary.L@gmail.com, valtchev.petko@uqam.ca

² LORIA UMR 7503, B.P. 239, 54506 Vandœuvre-lès-Nancy Cedex, France
napoli@loria.fr

Abstract. The effective construction of many association rule bases require the computation of both frequent closed and frequent generator itemsets (FCIs/FGs). However, these two tasks are rarely combined. Most of the existing solutions apply levelwise breadth-first traversal, though depth-first traversal is knowingly superior. Hence, we address here the depth-first FCI/FG-mining. The proposed algorithm, *Touch*, deals with both tasks separately, i.e., uses a well-known vertical method, *Charm*, to extract FCIs and a novel one called *Talky-G*, to extract FGs. The respective outputs are matched in a post-processing step. Experimental results indicate that *Touch* is highly efficient and outperforms its levelwise competitors.

1 Introduction

The discovery of meaningful associations is a key data mining discipline [1]. An association miner typically proceeds in two steps: **(i)** extract all frequent patterns X of a database, and **(ii)** break each X into a *premise* Y , and a *conclusion* $X \setminus Y$ parts to form a rule $Y \rightarrow X \setminus Y$. Interestingness measures, such as support and confidence, are applied to prune the set of extracted association rules. However, the number of the remaining rules may still be way too high to be practical. As a remedy, various concise representations of the family of valid association rules have been proposed [2,3,4], whereas others have been imported from related fields such as concept analysis [5,6]. A good survey can be found in [7].

Here we focus on the computation of FCIs and FGs, on which are based the minimal non-redundant association rules (\mathcal{MNR}) for instance. Following [2], these are rules with the form $P \rightarrow Q \setminus P$, where $P \subset Q$, P is a (*minimal*) *generator* (a.k.a. *key-sets* or *free-sets*) and Q is a *closed itemset*. In other terms, in such rules the premise is minimal and the conclusion is maximal. As shown in [7], \mathcal{MNR} is a *lossless*, *sound*, and *informative* representation of all valid rules. Moreover, further restrictions can be imposed on the rules in \mathcal{MNR} , leading to more compact representations such as the *generic basis* or the *proper basis* (see [7] for a complete list).

From a computational point of view, constructing \mathcal{MNR} or its sub-structures requires the family of frequent closed itemsets (FCIs) and their generators (FGs), and possibly the precedence order between FCIs. A few methods for extracting both FCIs and FGs have been published in the mining literature, e.g. *A-Close* [8] or *Titanic* [9]. Generators have been targeted within the concept analysis field as well [10], e.g. by the *Zart* algorithm [11]. Well-known FCI/FG-miners exclusively apply levelwise strategies, although the levelwise itemset miners are knowingly outperformed by depth-first methods (e.g. *Charm* [12] and *Closet* [13]) on a broad range of dataset profiles, especially on dense ones. Hence the idea of designing a depth-first FCI/FG-miner. The presented algorithm called *Touch* splits the FCI/FG-mining task into its components and solves them separately. The first one by applying *Charm* and the second one through an original method for FG-mining, the *Talky-G* algorithm. In an efficient post-processing step, *Touch* associates the FGs to their respective FCIs, thus providing the necessary starting point for the production of \mathcal{MNR} . Experimental results show that *Touch* outperforms two other efficient competitors, *A-Close* [8] and *Zart* [11], especially on dense and highly correlated datasets. Thus, the contributions of our study lay mainly in the design of an efficient method, *Touch*, for constructing the aforementioned rule bases. Additionally, *Talky-G* is a stand-alone algorithm for extracting FGs.

The paper is organized as follows. Section 2 provides the basic concepts of frequent itemset mining. In Section 3, we give an overview of vertical depth-first algorithms such as *Eclat* and *Charm*. In Section 4, we introduce a new FG-miner algorithm called *Talky-G*. The *Touch* algorithm that combines the results of *Charm* and *Talky-G* is introduced in Section 5. Finally, conclusions and future work are discussed in Section 6.

2 Basic Concepts

Consider the following 5×5 sample dataset: $\mathcal{D} = \{(1, ACDE), (2, ABCDE), (3, AB), (4, D), (5, B)\}$. Throughout the paper, we will refer to this example as “dataset \mathcal{D} ”.

We consider a set of *objects* or *transactions* $\mathcal{O} = \{o_1, o_2, \dots, o_m\}$, a set of *attributes* or *items* $\mathcal{A} = \{a_1, a_2, \dots, a_n\}$, and a relation $\mathcal{R} \subseteq \mathcal{O} \times \mathcal{A}$. A set of items is called an *itemset*. Each transaction has a unique identifier (*tid*), and a set of transactions is called a *tidset*.³ For an itemset X , we denote its corresponding tidset, often called its *image*, as $t(X)$. For instance, in dataset \mathcal{D} , the image of AB is 23 ($t(AB) = 23$). Conversely, $i(Y)$ is the itemset corresponding to a tidset Y . The *length* of an itemset is its cardinality, whereas an itemset of length i is called an i -itemset. The (absolute) *support* of an itemset X , denoted by $supp(X)$, is the size of its image, i.e. $supp(X) = |t(X)|$. The image function induces an equivalence relation on the power-set of items $\wp(\mathcal{A})$: two itemsets are equivalent

³ For convenience, we write an itemset $\{A, B, E\}$ as ABE , and a tidset $\{2,3\}$ as 23.

if they share the same image ($X \cong Z$ iff $t(X) = t(Z)$) [14]. Furthermore, within an equivalence class, its extremal elements w.r.t. set inclusion are distinguished: the unique maximum is called *closed* itemset, whereas the minima are *generator* itemsets. In what follows, we provide the support-oriented definitions exploiting the monotony of support upon set inclusion in $\wp(\mathcal{A})$.

Definition 1 (generator). *An itemset G is called generator if no proper subset thereof has the same support ($\forall H \subset G, \text{supp}(H) > \text{supp}(G)$).*

For instance, the sets AB and AD are generators in dataset \mathcal{D} . Generators are also known as key-sets in database theory and represent a special case of free-sets [15]. Given a generator itemset, all its subsets are also generators [14]. Furthermore,

Property 1. If an itemset is not generator, then none of its supersets are generators [16].

Definition 2 (closed). *An itemset C is called closed if no proper superset thereof has the same support ($\forall H \supset C, \text{supp}(H) < \text{supp}(C)$).*

A *closure* operator assigns to an itemset X the maximum of its equivalence class (denoted by $\gamma(X)$). Naturally, $X = \gamma(X)$ for closed X . In our example, AB and $ACDE$ are the closures of the aforementioned two generators, respectively (meaning that the class of AD is a singleton).

An itemset X is called *frequent*, if its support is not less than a given *minimum support* (denoted by min_supp), i.e. $\text{supp}(X) \geq \text{min_supp}$. Similarly to generators, frequent itemsets form a down-set in the Boolean lattice of all itemsets, which is better known as the *anti-monotony* of the frequent status.

An association rule $r: P_1 \rightarrow P_2$ involves two itemsets $P_1, P_2 \subseteq \mathcal{A}$, such that $P_1 \cap P_2 = \emptyset$, and $P_2 \neq \emptyset$. The support of a rule r is $\text{supp}(r) = \text{supp}(P_1 \cup P_2)$ and its *confidence* $\text{conf}(r) = \text{supp}(P_1 \cup P_2) / \text{supp}(P_1)$. *Frequent* rules are defined in a way similar to frequent itemsets, whereas *confident* rules play equivalent role for the confidence measure. A *valid* rule is both frequent and confident. Finding all valid rules in a database is the target of a typical association rule mining task.

As their number may grow up to exponential, reduced sub-families of valid rules are defined, which nevertheless convey the same information (*lossless*). Associated expansion mechanisms allow for the entire family to be retrieved from the reduced ones without any non-valid rules to be mixed in (*soundness*). The minimal non-redundant association rule (\mathcal{MNR}) family is made of rules $P \rightarrow Q \setminus P$, where $P \subset Q$, P is a (*minimal*) *generator* and Q is a *closed itemset*. A more restricted family results from the additional constraint that P and Q belong to the same equivalence class, i.e. $\gamma(P) = Q$. This family is known as the *generic basis* for exact association rules [7], i.e., for all those having a 100% confidence. Here the basis refers to the non-redundancy of the family w.r.t. a specific criterion. Another construction using generators and their closures is the *proper basis* [17] that has equivalents in several mathematical fields. Inexact rule bases can also be defined by means of generators and closures, e.g. the *informative basis* [7], which further involves the inclusion order between closures.

3 Vertical Itemset Mining

The mining methods from the literature, targeting either plain FIs or FCIs, can be roughly split into breadth-first and depth-first miners. *Apriori*-like [1] level-wise breadth-first algorithms exploit the anti-monotony of frequent itemsets in a straightforward manner: they advance one level at a time, generating candidates for the next level and then computing their support upon the database. Depth-first algorithms, in contrast, organize the search space in a tree. Typically using a sorted representation of the itemsets, they factor out common prefixes and hence limit the computing effort. Typical depth-first FCI-miners include *Charm* [12] and *Closet* [13].

3.1 Common Characteristics

Eclat was the first FI-miner using a vertical encoding of the database combined with a depth-first traversal of the search space (organized in a prefix-tree) [18]. *Charm* is an adaptation of *Eclat* to extract FCIs only [12].

Vertical miners rely on a specific layout of the database that presents it in an item-based, instead of a transaction-based, fashion. Thus, an additional effort is required to transpose the global data matrix in a pre-processing step. However, this effort pays back since afterwards the secondary storage does not need to be accessed anymore. Indeed, the support of an itemset can be computed by explicitly constructing its tidset which in turn can be built on top of the tidsets of the individual items. Moreover, in [19], it is shown that the support of any k -itemset can be determined by intersecting the tid-lists of any two of its $(k-1)$ -long subsets.

The central data structure in a vertical FI-miner is the IT-tree that represents both the search space and the final result. The IT-tree is an extended prefix-tree whose nodes are $X \times t(X)$ pairs. With respect to a classical prefix-tree or trie, in an IT-tree the itemset X provides the entire prefix from the root to the node labeled by it (and not the difference with the parent node prefix).

EXAMPLE. Figure 1 presents the IT-tree of our example. Observe that the node $ABC \times 2$ for instance can be computed by combining the nodes $AB \times 23$ and $AC \times 12$. To that end, tidsets are intersected and itemsets are joined. The support of ABC is readily established to 1.

3.2 Eclat

Eclat is a plain FI-miner. It traverses the IT-tree in a depth-first manner in a pre-order way, from left-to-right [18,19].

At the beginning, the IT-tree is reduced to its root (empty itemset). *Eclat* extends the root one level downwards by adding the nodes of all frequent 1-itemsets. Then, each of the new nodes is extended similarly: first, candidate descendant nodes are formed by adding to its itemset the itemset of each right sibling; second, the tidsets are computed by intersection and the supports are established;

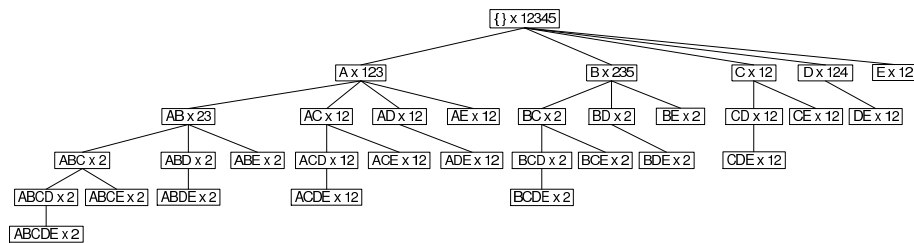


Fig. 1. IT-tree: Itemset-Tidset search tree of dataset \mathcal{D}

and third, the frequent itemsets are added as effective descendant nodes of the current node.

Running example. Using Figure 1, we illustrate the execution of *Eclat* on dataset \mathcal{D} with $\text{min_supp} = 1$ (20%). Initially, the IT-tree comprises only the root node whose support is 100%. Frequent items with their tidsets are then added under the root. Each of the new nodes is recursively extended, following a left-to-right order and processing the corresponding sub-trees in a pre-order fashion. For instance, the subtree of A comprises all frequent itemsets starting with A . Thus, at step two, all 2-long supersets of A are formed using the right siblings of A (frequent 1-itemsets). As AB , AC , AD , and AE are all frequent, they are added as descendant nodes under the node of A . The extend procedure is then recursively called on AB and the computation goes one level deeper in the IT-tree. When the algorithm stops, all frequent itemsets are discovered.

3.3 Charm

Charm adapts the computing schema of *Eclat* to construct FCIs only [12]. The key challenge faced by *Charm* is to reduce the complete IT-tree as depicted in Figure 1 to the family of FCIs. Thus, on the one hand, it has to rapidly find an FCI from a prefix thereof, i.e., without necessarily exploring all its frequent subsets. To that end, *Charm* applies four properties of itemset-tidset pairs (detailed in [12]) that help rapidly extend each itemset X to a maximal itemset Z with $t(X) = t(Z)$ such that the former is a prefix of the latter. Yet this does not guarantee that Z is closed as $\gamma(X)$ does not need to admit X as a prefix. Hence, each such Z must be checked for closeness, which calls for two enabling mechanisms. One is a storage of all closed itemsets allowing all candidate closures to be easily checked against the currently known ones. It is realized by means of a hash table whose hash key is based on the tidset (image) of Z (see Section 4 for further details on hashing). The second mechanism arises naturally with the traversal strategy applied in *Charm*: In fact, among all the candidates Z , i.e., maximally extended itemsets that share the same image, the closure $\gamma(Z)$ is always generated first. Thus, to test if Z is closed, it must be checked if there is

a superset of Z with the same image already stored. If there is such a superset, then it is necessarily the closure of Z , so the current candidate is discarded.

EXAMPLE. On dataset \mathcal{D} , *Charm* builds a similar albeit much smaller IT-tree than the one in Figure 1. Altogether, it finds 6 closed itemsets by $\text{min_supp} = 1$. For instance, to determine that the itemset BD is not closed, *Charm* relies on the closure $ABCDE$. The latter is output by the processing of the branch of A , hence it is already stored when the candidate BD is created during the process of the branch of B . Thus, as BD is a subset of $ABCDE$ with the same image, BD is discarded.

Charm is knowingly one of the fastest FCI-miners, especially for dense, highly correlated datasets. Hence our idea of using it as basis for an own FCI/FG-mining method. The challenge to face here is the proper translation of the FCI-targeting strategy in *Charm* to FGs. A first observation is that FGs play dual role within the corresponding equivalence classes where they are minimal, whereas FCIs are maximal. Moreover, there may be several FGs in a class, which means that the candidate check cannot rely on mere image comparison. Indeed, if two FGs happen to be checked against each other, none of them must be discarded. Thus, one needs a further test that looks for itemset inclusion: a candidate FG should be certified if there is no subset thereof with the same image stored in the FG hash. This testing principle calls for a different traversal strategy, i.e. one that insures all subsets of an itemset X are already processed before X itself. Such a requirement is typically addressed with a breadth-first, levelwise traversal strategy. Curiously enough, it can be achieved even with a depth-first one, yet not a standard one. The next section presents the traversal discipline and the algorithm built on top of it.

4 Talky-G

Talky-G is a novel vertical algorithm to find frequent *generators* (FGs) only. *Talky-G* traverses the IT-tree in a depth-first manner in a reverse pre-order way, from right-to-left.

4.1 Reverse Pre-Order Traversal

While *Eclat* and *Charm* traverse the IT-tree in a pre-order way from left-to-right, *Talky-G* uses the so-called *reverse pre-order* strategy, where the order of traversal is right-to-left. In [20], Calders and Goethals made the following observation. Let X be the itemset of a node in the IT-tree. In the case of reverse pre-order traversal, the nodes of the subsets of X are either on the path from the root node to the node of X , or are in a branch that comes in the order *after* X , never in a branch that comes in the order *before* the branch of X . That is, the same tree is processed, still in a depth-first manner, but from *right-to-left*. This order is called reverse pre-order. As pointed out in [20], using reverse pre-order

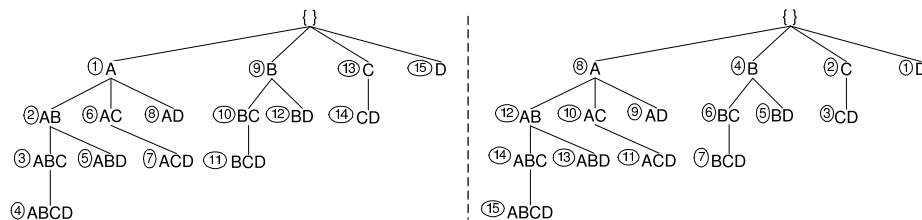


Fig. 2. **Left:** pre-order traversal with *Eclat*; **Right:** reverse pre-order traversal with *Talky*

traversal, all subsets of X are handled before X itself. Though no name was given in [20] to this modified version of *Eclat*, we will refer to this algorithm as *Talky*. That is, *Talky* is *Eclat* with reverse pre-order traversal. The algorithm proposed hereafter called *Talky-G* is a completion of this traversal in order to explore FGs only.

EXAMPLE. See Figure 2 for a comparison between the two traversals namely pre-order with *Eclat* (left) and reverse pre-order with *Talky* (right). The direction of traversal is indicated in circles on the left side of the nodes.

4.2 The Algorithm

Pseudo code. Algorithm 1 provides the main block of *Talky-G*. First, the IT-tree is initialized, which includes the following steps: the root node, representing the empty set, is created. By definition, the support of the empty set is equal to the number of transactions in the dataset (100%). *Talky-G* transforms the layout of the dataset in vertical format, and inserts under the root node all 1-long frequent generators.⁴ Then, the dataset itself can be deleted from the main memory since all frequent generators are unions of 1-long frequent generators. After this, the `extend` procedure is called recursively for each child of the root in a reverse pre-order way from right-to-left. *Talky-G* concentrates on frequent generators only so that at the end all FGs are comprised in the IT-tree.

The `addChild` procedure inserts an IT-node under a node. The `save` procedure stores a frequent generator in a dedicated “list” data structure.

The `extend` procedure (see Algorithm 2) discovers all frequent generators in the subtree of a node. First, the procedure forms new frequent generators with the right siblings of the current node. Then, these FGs are added below the current node and are extended recursively in a reverse pre-order way from right-to-left.

The `getNextGenerator` function (see Algorithm 3) has two nodes as input parameters, and it returns a new frequent generator, or “null” if no frequent

⁴ Recall that a 1-long itemset p is generator iff $supp(p) < 100\%$.

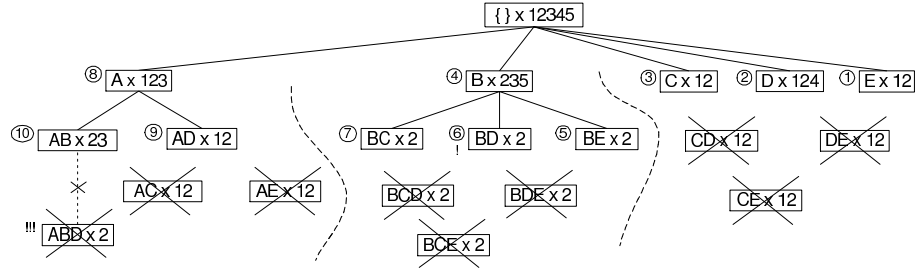


Fig. 3. Execution of *Talky-G* on dataset \mathcal{D} with $min_supp = 1$ (20%)

generator can be produced from the two input nodes. A candidate node is created by taking the union of the itemsets of the two input nodes, and the intersection of their tidsets. Thus, the input nodes are the *parents* of the candidate. Then, the candidate undergoes a series of tests. *First*, a frequency test is used to eliminate non-frequent itemsets. *Second*, the candidate is compared to its parents. If its tidset is equivalent to the tidset of one of its parents, then the candidate is not generator by Def. 1. If an itemset passed these two tests, it is still not sure that it is generator. As seen before, the reverse pre-order traversal *guarantees* that when an itemset is reached in the IT-tree, all its subsets are handled before. *Talky-G* collects frequent generators in a “list” too (see also the `save` procedure). The *third* test checks if the candidate has a proper subset with the same support in this “list”. If yes, then the candidate is not generator by Def. 1. This last step might seem to be a very expensive step, but as we will see later, it can be done very efficiently with a special hash data structure. If a candidate survives all the tests, then it is an FG and will be added to the IT-tree. Otherwise it is discarded and this prevents any of its supersets to be generated as candidates (see Prop. 1). This way, the search space is reduced to frequent generators *only*.

When the algorithm stops, all frequent generators (and *only* frequent generators) are inserted in the IT-tree *and* in the “list” of generators.

Running example. The execution of *Talky-G* on dataset \mathcal{D} with $min_supp = 1$ (20%) is illustrated in Figure 3. The execution order is indicated on the left side of the nodes in circles.

The algorithm first initializes the IT-tree with the root node. Since there is no full column in the input dataset, all attributes are frequent generators, thus they are added under the root. The children of the root node are extended recursively one by one, from *right-to-left*. Node *E* has no right sibling, thus it cannot be extended. Node *D* is extended with *E*, but the resulting itemset *DE* is not generator since its support is equal to the support of its parent *E*. Node *C* is extended with *D* and *E*, but neither *CD* nor *CE* is generator for the same reason. We skip the detailed presentation of the subtree of *B*. 2-long supersets of *A* are formed by using its right siblings and added to the IT-tree. The candidates *AC*

Algorithm 1 (main block of Talky-G):

```

1) root.itemset  $\leftarrow \emptyset$ ; // root is an IT-node whose itemset is empty
2) root.tidset  $\leftarrow$  {all transaction IDs}; // the empty set is included in every tr.
3) loop over the vertical representation of the dataset (attr) {
4)   if ((attr.supp  $\geq$  min_supp) and (attr.supp  $<$   $|\mathcal{O}|$ )) {
5)     root.addChild(attr); // attr is frequent and generator
6)   }
7) }
8)
9) loop over the children of root from right-to-left (child) {
10)  save(child); // process the itemset
11)  extend(child); // discover the subtree below child
12) }
```

Algorithm 2 (“extend” procedure of Talky-G):

Method: extend an IT-node recursively (discover FGs in its subtree)

Input: *curr* – an IT-node whose subtree is to be discovered

```

1) loop over the siblings of curr from left-to-right (other) {
2)   generator  $\leftarrow$  getNextGenerator(curr, other);
3)   if (generator  $\neq$  null) then curr.addChild(generator);
4) }
5)
6) loop over the children of curr from right-to-left (child) {
7)   save(child); // process the itemset
8)   extend(child); // discover the subtree below child
9) }
```

and AE are not generators because of C and E , respectively. The combination of AB and AD produces the candidate ABD , which represents a *special case*. Its support is different from its parents, but we already found a proper subset of it with the same support (BD) in a *previous branch*. According to Def. 1, ABD is not generator, thus it is not added to the IT-tree.

4.3 Fast Subsumption Checking

Let X_i and X_j be two itemsets. We say that X_i *subsumes* X_j (or X_j is *subsumed by* X_i), iff $X_j \subset X_i$ and $\text{supp}(X_i) = \text{supp}(X_j)$. X_i (resp. X_j) is also known as *subsumer* (resp. *subsumee*). By Def. 1, if an itemset subsumes another itemset, then the subsumer is not generator. Recall that in the `getNextGenerator` function, when a new candidate itemset C is created, *Talky-G* checks if C subsumes a previously found generator. If the test is positive, then clearly C is not gener-

Algorithm 3 (“getNextGenerator” function of Talky-G):

Method: create a new frequent generator

Input: two IT-nodes (*curr* and *other*)

Output: a frequent generator or null

```

1)  $cand.tidset \leftarrow curr.tidset \cap other.tidset$ ;
2) if ( $cardinality(cand.tidset) < min\_supp$ ) { // test 1
3)   return null; // not frequent
4) }
5) // else, if it is frequent
6) if ( $(cand.tidset = curr.tidset)$  or  $(cand.tidset = other.tidset)$ ) { // test 2
7)   return null; // not generator
8) }
9) // else, if it is a potential generator
10)  $cand.itemset \leftarrow curr.itemset \cup other.itemset$ ;
11) if ( $cand$  has a proper subset with the same support in the hash) { // test 3
12)   return null; // not generator
13) }
14) // if  $cand$  passed all the tests then  $cand$  is a frequent generator
15) return  $cand$ ;
```

ator. This subsumption test might seem to be an expensive step, but we found a very efficient way to filter these non-generator itemsets.

In *Talky-G* we adapted the hash structure of *Charm* for storing frequent generators. *Talky-G*, similarly to *Charm*, computes a hash function on the sum of the tids in the tidset and stores in the hash table a generator with its support value. Due to the tidset-based hash function, two itemsets with the same image have the same hash value. Itemsets having the same hash value are stored in a list at the same position of the hash. Let $h(X_i)$ denote the hash function on the tidset of X_i . For the subsumption check of a candidate itemset C , we retrieve from the hash table all entries with the hash key $h(C)$. For each element G in this list, test if $supp(C) = supp(G)$. If yes, test if $C \supset G$. If yes, then C subsumes G , i.e. C is not generator. If C subsumes no entries in the list, then C is generator and added to the end of the list.

EXAMPLE. Let us see Figure 4 (right) that depicts the hash structure of the IT-tree in Figure 3. This hash table contains all frequent generators of dataset \mathcal{D} . For this example, the size of the hash table is set to four.⁵ At each position of the hash table there are pointers to lists. In each list we can find itemsets that have the same hash key.

In the running example we saw that ABD is not generator. It can be determined the following way. First, compute the sum of the tids in its tidset; then

⁵ In our implementation, we set the size of the hash table to 100,000.

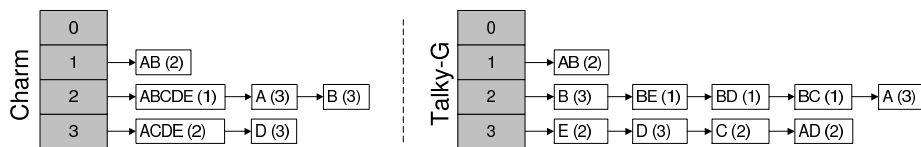


Fig. 4. Hash tables for dataset \mathcal{D} by $\min_supp = 1$. **Left:** hash table of *Charm* containing all FCIs; **Right:** hash table of *Talky-G* containing all FGs

modulo this sum by the size of the hash table to get its hash value: $2 \bmod 4 = 2$. Traverse the list of the hash table at position 2. The support of B differs from the support of ABD . The itemset BE has the same support value as ABD , but ABD is not a proper superset of BE . The itemset BD has the same support as ABD , and ABD is a proper superset of BD , thus ABD is not generator. At this point the traversal of the list is finished.

Experimental results of *Talky-G* are reported in the next section as part of the *Touch* algorithm.

5 Touch

The *Touch* algorithm has three main features, namely (1) extracting frequent closed itemsets, (2) extracting frequent generators, and (3) associating frequent generators to their closures, i.e. identifying frequent equivalence classes.

5.1 The Algorithm

Previously, we showed that *Charm* and *Talky-G* extract frequent closed itemsets and frequent generators, respectively. Each algorithm uses a dedicated hash data structure for storing the found itemsets (see Figure 4). There is one more step to do namely associating frequent generators to their closures, i.e. identifying the equivalence classes. The question is how to do this *efficiently*.

Our approach uses the hash structures for the association. The method is based on the following property:

Property 2. Let $h(X)$ denote the hash function on the tidset of X . Given a frequent closed itemset Y and its frequent generator Z , $h(Y) = h(Z)$ since $t(Y) = t(Z)$.

Since the two hash tables have the same size, and the two algorithms use the same hash function, it follows from Property 2 that a frequent closed itemset and its generators are in different hash tables but at the *same* index position.

Pseudo code. The pseudo code of *Touch* is given in Algorithm 4. First, the algorithm calls *Charm* and *Talky-G* and takes over their hash structures. Then,

Algorithm 4 (Touch):

Description: find frequent equivalence classes

- 1) $hashFCI \leftarrow$ (call *Charm* and get its hash data structure); // see Section 3.3
- 2) $hashFG \leftarrow$ (call *Talky-G* and get its hash data structure); // see Section 4
- 3) $match(hashFCI, hashFG)$;

Table 1. Output of *Touch* on dataset \mathcal{D} by $min_supp = 1$

FCI (supp)	FGs	FCI (supp)	FGs
AB (2)	AB	B (3)	B
$ABCDE$ (1)	$BE; BD; BC$	$ACDE$ (2)	$E; C; AD$
A (3)	A	D (3)	D

Touch matches the two hash tables the following way. For each frequent closed itemset X , it looks up in the other hash table at the same index position all subsets of X that have the same support. The output of *Touch* is shown in Table 1. Recall that due to the property of equivalence classes, the support of a generator is equal to the support of its closure.

EXAMPLE. Consider Figure 4 that depicts the hash structures of *Charm* and *Talky-G*. Say we want to determine the generators of the closed itemset $ACDE$. The itemset $ACDE$ is stored at position 3 in the hash structure of *Charm*. By Property 2, its generators are also stored at position 3 in the hash structure of *Talky-G*. In this list, there are three itemsets that are subsets of $ACDE$ and that have the same support values: E , C , and AD . It means that these three itemsets are the generators of $ACDE$. The frequent closed itemset A has one subset with the same support in the other hash structure at index 2 (A). This means that A is a closed itemset *and* a generator at the same time, i.e. the equivalence class of A has one element only (singleton equivalence class). Etc.

5.2 Experimental Results

We evaluated *Touch* against *Zart* [11] and *A-Close* [8]. The algorithms were implemented in Java in the CORON data mining platform [21].⁶ The experiments were carried out on a bi-processor Intel Quad Core Xeon 2.33 GHz machine running under Ubuntu GNU/Linux operating system with 4 GB of RAM. For the experiments we have used the following datasets: T20I6D100K, C20D10K, and MUSHROOMS. The T20I6D100K⁷ is a sparse dataset, constructed according to the properties of market basket data that are typical weakly correlated data.

⁶ <http://coron.loria.fr>

⁷ <http://www.almaden.ibm.com/software/quest/Resources/>

Table 2. Detailed execution times of *Touch* and other statistics (number of FCIs, number of FGs, number of FIs, proportion of the number of FCIs to the number of FIs, proportion of the number of FGs to the number of FIs). Note that the number of FIs is shown for comparative reasons only. *Touch* does not need to extract all FIs

min_supp	execution time (sec.)				# FCIs	# FGs	(# FIs)	$\frac{\#FCIs}{\#FIs}$	$\frac{\#FGs}{\#FIs}$
	get FCIs (<i>Charm</i>)	get FGs (<i>Talky-G</i>)	associate FCIs and FGs	total time (with I/O)					
T20I6D100K									
1%	19.07	2.16	0.03	22.76	1,534	1,534	1,534	100.00%	100.00%
0.75%	24.06	2.65	0.05	28.32	4,710	4,710	4,710	100.00%	100.00%
0.5%	35.21	5.01	0.14	42.45	26,208	26,305	26,836	97.66%	98.02%
0.25%	94.59	20.71	0.50	121.60	149,217	149,447	155,163	96.17%	96.32%
C20D10K									
30%	0.20	0.29	0.02	1.06	951	967	5,319	17.88%	18.18%
20%	0.34	0.41	0.03	1.42	2,519	2,671	20,239	12.45%	13.20%
10%	0.71	0.70	0.07	2.27	8,777	9,331	89,883	9.76%	10.38%
5%	1.13	1.06	0.11	3.37	21,213	23,051	352,611	6.02%	6.54%
MUSHROOMS									
30%	0.12	0.21	0.02	0.82	425	544	2,587	16.43%	21.03%
20%	0.19	0.27	0.02	0.98	1,169	1,704	53,337	2.19%	3.19%
10%	0.43	0.46	0.04	1.57	4,850	7,585	600,817	0.81%	1.26%
5%	0.80	0.81	0.08	2.53	12,789	21,391	4,137,547	0.31%	0.52%

The C20D10K is a census dataset from the PUMS sample file, while the MUSHROOMS⁸ describes mushrooms characteristics. The last two are highly correlated datasets.

Table 2 contains detailed information about the execution of *Touch*. The first three columns correspond to the three main steps of *Touch* namely (1) getting FCIs using *Charm*, (2) getting FGs using *Talky-G*, and (3) associating FGs to their closures. Column 4 indicates the total execution time of the algorithm including input and output. In the sparse dataset T20I6D100K, almost all frequent itemsets are closed and generators at the same time. It means that most equivalence classes are singletons. It is known that *Charm* is less efficient on sparse datasets. This is due to the fact that *Charm* performs four tests on candidates for reducing the IT-tree. However, in sparse datasets the number of FCIs is almost equivalent to the number of FIs, thus the search space cannot be reduced significantly. *Talky-G* is also less efficient on sparse datasets. However, in dense, highly correlated datasets (C20D10K and MUSHROOMS), both *Charm* and *Talky-G* are very efficient, even at low minimum support values. Since the number of FCIs and FGs is much less than the number of FIs, the two algorithms can take advantage of exploring a much smaller search space. The association of FCIs and FGs is done very efficiently in all cases. That is, the association step gives absolutely no overhead to *Touch*.

Table 3 contains the experimental evaluation of *Touch* against *Zart* and *A-Close*. All times reported are real, wall clock times as obtained from the Unix

⁸ <http://kdd.ics.uci.edu/>

Table 3. Response times of *Touch*, compared to *Zart* and *A-Close*

min_supp	execution time (sec.)		
	Touch	Zart	A-Close
T20I6D100K			
1%	22.76	7.33	31.25
0.75%	28.32	14.96	39.49
0.5%	42.45	45.52	100.60
0.25%	121.60	159.78	285.41
C20D10K			
30%	1.06	8.17	15.78
20%	1.42	15.84	29.88
10%	2.27	36.66	59.41
5%	3.37	75.28	94.18
MUSHROOMS			
30%	0.82	3.65	7.17
20%	0.98	10.69	15.28
10%	1.57	75.36	36.83
5%	2.53	641.54	63.37

time command between input and output. We have chosen *Zart* and *A-Close* because they represent two efficient algorithms that produce exactly the same output as *Touch*. *Zart* and *A-Close* are both levelwise algorithms. *Zart* is an extension of *Pascal* [14], i.e. first it finds all FIs using pattern-counting inference, then it filters FCIs, and finally the algorithm associates FGs to their closures. *A-Close* reduces the search space to FGs only, then it calculates the closure for each generator. The way *A-Close* computes the closures of generators is quite expensive because of the huge number of intersection operations. *Touch*, just like *A-Close*, reduces the search space to the strict minimum, i.e. it only extracts what it really needs namely the set of FCIs and the set of FGs. Then, *Touch* associates the two sets in a very efficient way. Since *Touch* is based on *Charm* and *Talky-G*, the algorithm is very efficient on dense, highly correlated datasets. We must admit however that levelwise algorithms like *Zart* are sometimes more suitable for sparse datasets.

6 Conclusion

Mining FGs has so far been done largely in a levelwise manner as the breadth-first traversal fits the down-set structure of the FG family. Yet depth-first algorithms have shown superior efficiency in many situations, whence the motivation of our study of depth-first FCI/FG-mining.

As a contribution to this problem, we presented *Touch*, an algorithm that splits the general problem into three tasks: **(1)** FCI-mining, **(2)** FG-mining, and **(3)** association of FGs to their closures (FCIs). While **(1)** is solved by reusing an existing algorithm, *Charm*, the two others generate innovative solutions. Hence the *Talky-G* vertical FG-miner used in **(2)** is an original contribution on its own. As all three solutions are highly optimized, the algorithm performs well

against comparable levelwise miners. Numerous concise representations of valid association rules can be readily derived from the method output.

The study led to a range of exciting questions that are currently investigated. Thus, from an algorithmic point of view, it would be interesting to merge steps **(1)** and **(2)**, e.g. by using the output of *Talky-G* (i.e., the IT-tree of all FGs) as a starting point for the FCI-mining, hence avoiding step **(3)**. A further challenge lays in the computation of the FCI precedence order that underlies some of the association rule bases from the literature.

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