# Knowledge Sanitization on the Web

Vasileios Kagklis[1] Vassilios S. Verykios[2]
Giannis Tzimas[3] Athanasios K. Tsakalidis[1]

[1]Computer Engineering & Informatics Department, University of Patras
[2]School of Science & Technology, Hellenic Open University
[3]Computer & Informatics Engineering Department, Technological Educational Institute of Western Greece

Thessaloniki, GREECE
June 2014

# Overview

# Need for Privacy

- The widespread use of the Internet caused the rapid growth of data on the Web.
- As data on the Web grew larger in numbers, so did the perils due to the applications of data mining.
- Thus, the need for privacy preserving techniques related to data mining on the Web, became more essential.

# A Failing-to-Preserve-Privacy Example

- AOL data release [4]
- Data in the form of 20,000,000 search keywords, for 650,000 users, for a period of 3 months.
- Intentional release for research purposes.
- Appropriate editing did not take place.
- The users were only identified by a unique numeric ID.
- Some clues from the search queries were enough for successfully tracking the identities of several users by their searches.

# Privacy Preserving Data Mining (PPDM) [1, 2]

- Research area that investigates techniques to preserve the privacy of individual data and induced patterns.
- Looks into the interplay between data sharing and privacy violation.
- Data mining can violate privacy.
- Allow data mining while prohibiting leakage of sensitive information.

# Taxonomy in PPDM

PPDM consists of several pillars:

- Input/Data/Individual Privacy
- Adversarial Privacy
- **Output/Knowledge/Collective Privacy**

We are going to focus on Output Privacy, also known as Knowledge Sanitization.

# Knowledge Sanitization

- Knowledge Sanitization [3] aims at concealing sensitive patterns included in the data.
- It consists of a wide variety of different approaches.
- **Frequent pattern** and association rule **sanitization**.
- Sequence sanitization.
- Classification rule sanitization.
- Data stream sanitization.

# Applications (1/2)

- Frequent patterns are widely used on the web.
- Product-selling (and other) websites use frequent basket analysis to:
  - discover similarities in purchasing habits among customers
  - make recommendations
- Some websites may sell those anonymously collected datasets to advertising companies.
- Web link and click stream analysis aims at:
  - the improvement of the structure of a website
  - impoving of the navigation experience
  - the predictive web caching

# Applications (2/2)

- Association rules derive from frequent itemsets.
- A powerful tool for discovering relationships hidden in large datasets.
- Association rule mining can be applied on web log files to profile the visitors' behavior.
- Certain sanitization techniques must be applied in the cases mentioned.

# Preliminaries (1/3)

- $I = \{i_1, i_2, \ldots, i_n\}$: set of items.
- A subset $X \subseteq I$ is an **itemset**.
- $D = \{T_1, T_2, \ldots, T_m\}$: transactional database.
- Database D can be in binary format ($|D| \times |I|$ matrix)
  - $T_{kj} = 1$, if $k$-th transaction contains $j$-th item.
  - $T_{kj} = 0$, otherwise.

# Preliminaries (2/3)

- Given an itemset $X$:
  - $\sigma(X)$ : number of supporting transactions, and
  - $sup(X)$: fraction of supporting transactions
- Itemset $X$ is **large** or **frequent** iff:
  - $sup(X) \geq msup$, where $msup = \sigma_{min}/|D|$
  - or equiv. $\sigma(X) \geq \sigma_{min}$.
- Otherwise, $X$ is **infrequent**.

# Preliminaries (3/3)

- $F_\sigma$: set of *all* frequent itemsets in $D$, for $\sigma_{min} = \sigma$.
- We define the following borders of $F_\sigma$:
  - **Positive Border**: contains all maximally frequent itemsets in $D$.
  - **Negative Border**: contains all minimally infrequent itemsets in $D$.
- $\boldsymbol{S}$: set of sensitive itemsets that the owner wants to conceal, i.e., force them to become infrequent in $D$.

# Frequent Itemset Extraction

For $\sigma_{min} = 3$, the set of frequent itemsets $F_\sigma$ is:

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

$\boldsymbol{\sigma(a) = 7}$
$\boldsymbol{\sigma(b) = 6}$
$\boldsymbol{\sigma(c) = 7}$
$\boldsymbol{\sigma(d) = 8}$
$\boldsymbol{\sigma(e) = 3}$
$\sigma(f) = 2$
$\sigma(g) = 2$
$\sigma(h) = 2$

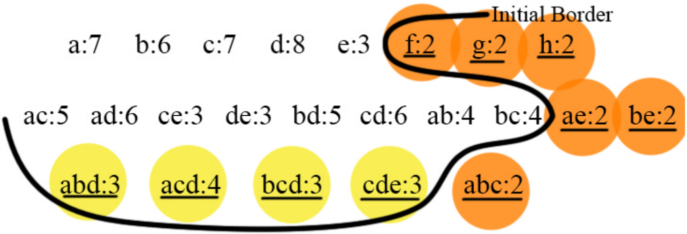
$\boldsymbol{\sigma(ab) = 4}$
$\boldsymbol{\sigma(ac) = 5}$
$\boldsymbol{\sigma(ad) = 6}$
$\sigma(ae) = 2$
$\boldsymbol{\sigma(bc) = 4}$
$\boldsymbol{\sigma(bd) = 5}$
$\sigma(be) = 2$
$\boldsymbol{\sigma(cd) = 6}$
$\boldsymbol{\sigma(ce) = 3}$
$\boldsymbol{\sigma(de) = 3}$

$\sigma(abc) = 2$
$\boldsymbol{\sigma(abd) = 3}$
$\boldsymbol{\sigma(acd) = 4}$
$\boldsymbol{\sigma(bcd) = 3}$
$\boldsymbol{\sigma(cde) = 3}$

# Border Revision (1/4)

Initially:

- the **Positive Border**, $B^+(F_\sigma)$, is marked with yellow color, while
- the **Negative Border**, $B^-(F_\sigma)$, is marked with orange color



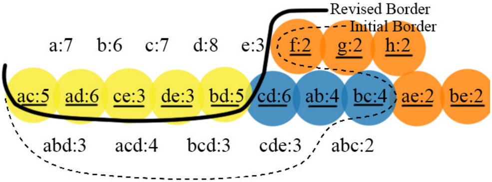
# Border Revision (2/4)

- How does the hiding process affect the set of frequent itemsets?
- Some of the frequent itemsets, i.e., the supersets of $S$ will be concealed as well.
- This is due to the anti-monotonicity property of support: $X \subset Y \implies \sigma(X) \geq \sigma(Y)$.
- Let $SS = \{X \in F_\sigma \mid \forall Y\colon\ Y \subseteq X \implies Y \in S\}$ be the set of non-sensitive itemsets and their supersets in $F_\sigma$.
- The tentative set of frequent itemsets is defined as $\tilde{F}_\sigma = F_\sigma - SS$.

# Border Revision (3/4)

Let $S = \{ab, bc, cd\}$. Then $\tilde{F}_\sigma = \{a, b, c, d, e, ac, ad, bd, ce, de\}$ and:

- the **Revised Positive Border**, $B^+(\tilde{F}_\sigma)$, is marked with yellow color,
- the **sensitive itemsets** are marked with blue color and
- the **Revised Negative Border**, $B^-(\tilde{F}_\sigma)$, is marked with orange color, which also includes the sensitive itemsets



# Border Revision (4/4)

Why border revision?

- **Naive approach**: conceal without taking into account the non-sensitive frequent itemsets.
- **Better approach**: try to protect all non-sensitive frequent itemsets to avoid side effects.
- **Border based approach**: take into account only $B^+(\tilde{F}_\sigma)$.
  - Anti-monotonicity property of support.
  - $B^+(\tilde{F}_\sigma)$: maximal itemsets of $\tilde{F}_\sigma$.
- The last two approaches are equivalent, but the latter is computationally lighter.

# Hiding Methodologies (1/2)

- **Heuristic distortion approaches**: rely on turning 1's to 0's and 0's to 1's in order to achieve hiding.
- **Heuristic blocking approaches**: make use of an unkown symbol to signify the absence of a specific value.
- **Probabilistic distortion approaches**: apply a probabilistic model in order to distort the data.

# Hiding Methodologies (2/2)

- **Database reconstruction approaches**: the non-sensitive knowledge is transformed to a database that is built from scratch.
- **Inverse frequent itemset mining**: has as its goal to create a database that corresponds to a certain set of useful and interesting patterns.
- **Linear programming-based hiding techniques**: formulate a hiding problem as a linear program, the solution of which helps to accomplish the concealing.

# Linear Programming-Based Techniques

- Transform the problem into a linear program.
- The various types of constraints play a different role, depending on the formulation.
- The solution indicates the transactions to be sanitized or the exact items to be removed from each transaction.

# The LP Hiding Techniques

- Max-Accuracy
- Coefficient-Based Max-Accuracy
- Inline
- Hybrid

## Max-Accuracy

# The Max-Accuracy Algorithm [5]

# Basic Features

- Each transaction is modeled by a corresponding binary variable.
- For each sensitive itemset in $S$, a constraint is built.
- If a sensitive itemset is contained in a transaction, then the corresponding constraint contains the corresponding binary variable.
- Size of the linear program: $|D|$ variables and $|S|$ constraints.
- The solution will determine which transactions need to be sanitized.
- Sanitization process on specified transactions follows.

# The Formulation

Define parameters $a_{iy}$ to be 1 if transaction $T_i \in D$ supports itemset $y \in S$ (sensitive itemsets) and 0 otherwise. Variables $x_i$ will be set to 1 if transaction $T_i$ needs to be sanitized and 0 otherwise, depending on the solution of the linear program.

$$\textit{minimize} \quad \sum_{\forall i:\ T_i \in D} x_i$$

$$\textit{subject to} \begin{cases} \sum_{\forall i:\ T_i \in D} a_{iy} x_i \geq (\sigma_y - \sigma^y_{min} + 1), \ \forall y \in S \\ x_i \in \{0, 1\} \quad \forall i : T_i \in D. \end{cases}$$

# The Formulation Explained

- Objective Function: the minimum number of transactions should be sanitized.
- Constraints: a sensitive itemset $y$ needs to be hidden from at least $(\sigma_y - \sigma^y_{min} + 1)$ transactions, in order to become infrequent.
- Obviously, the side effects that will be introduced are not taken into account.

# The Data Hiding Algorithm

**for** transactions $T_i \in D$ such that $T_i$ is to be sanitized **do**
  identify set of sensitive itemsets $S_i$ supported by transaction $T_i$
  **while** $S_i \neq \emptyset$ **do**
    **calculate** $f_j = |\{k \in S_i | j \in k\}|, \forall$ item $j \in S_i$
    **remove** item $j^* = argmax_j\{f_j\}$
    **update** $S_i = S_i - \{k \in S_i | j^* \in k\}$
  **end while**
**end for**

# The Data Hiding Algorithm Explained

- Variables set to 1 in the solution of the linear program indicate-mark transactions for sanitization.
- The sensitive itemsets $S_i \subseteq S$ supported by a marked transaction are identified.
- Item $j^*$ that appears in most itemsets in $S_i$ is eliminated.
- Itemsets in $S_i$ also containing $j^*$ are removed from $S_i$.
- The process is repeated until $S_i$ is left empty.
- If only one sensitive itemset is supported, then an item is removed randomly.

# An Example (1/3)

- Let the transaction database $D$, the set of sensitive itemsets $S = \{ab, bc, cd\}$ and $\sigma_{min} = 3$.
- $ab \rightarrow$ Tid set $\{1, 3, 5, 7\}$.
- $bc \rightarrow$ Tid set $\{1, 4, 6, 7\}$.
- $cd \rightarrow$ Tid set $\{1, 2, 4, 6, 8, 9\}$.

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

# An Example (2/3)

Constraint Matrix:

| | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_6$ | $T_7$ | $T_8$ | $T_9$ |
|---|---|---|---|---|---|---|---|---|---|
| **ab** | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |
| **bc** | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 |
| **cd** | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 1 |

$$
\begin{aligned}
&\textit{minimize} \quad x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + x_9 \\
&\textit{subject to} \begin{cases} ab : x_1 + x_3 + x_5 + x_7 \geq 2 \\ bc : x_1 + x_4 + x_6 + x_7 \geq 2 \\ cd : x_1 + x_2 + x_4 + x_6 + x_8 + x_9 \geq 4 \end{cases}
\end{aligned}
$$

# An Example (3/3)

- The optimal solution is $x_1 = x_2 = x_7 = x_8 = x_9 = 1$, while $x_3 = x_4 = x_5 = x_6 = 0$.
- Summary of the sanitization process:

| Tid | Transaction | S.I. supported | Victim Items | Sanitized |
|---|---|---|---|---|
| 1 | *abcde* | *cd, bc, ab* | *c, a* | *bde* |
| 2 | *acd* | *cd, ac* | *c* | *ad* |
| 7 | *abcg* | *ab* | *b* | *acg* |
| 8 | *acde* | *cd* | *c* | *ade* |
| 9 | *acdh* | *cd* | *c* | *adh* |

## Coefficient-Based Max-Accuracy

# The Coefficient-Based Max-Accuracy Algorithm [6]

# Basic Features

- An improved version of the Max-Accuracy algorithm.
- The algorithm introduces proper coefficients for each variable, that corresponds to a transaction.
- As a result, the transactions that are going to be sanitized are selected more accurately.
- Size of the linear program: $|D|$ variables and $|S|$ constraints.
- The solution will determine which transactions need to be sanitized.
- The very same sanitization process as in Max-Accuracy is used.

# Calculating the Coefficients

The coefficients $c_m, \forall m \in \{1, \ldots, |D|\}$, are calculated as follows:

- The coefficient $c_m$ is initialized to zero.
- Let $S_i$ be the set of all sensitive itemsets supported by $T_j$. The item $i_k$ that is supported by most of the itemsets in $S_j$ is selected.
- The number of non-sensitive frequent itemsets that are both supported by $T_j$ and contain $i_k$ is added to $c_m$.
- A sensitive itemset $y$ is removed from $S_j$, if after removing item $i_k$ itemset $y$ stops being supported by the current transaction $T_j$.
- The process is done repeatedly, until $S_j$ is left empty.

# The Formulation

Simply put, the coefficient of a transaction is the number of affected non-sensitive frequent itemsets given the transaction is sanitized. The formulation is almost the same as in the Max-Accuracy. Only the objective function changes:

$$\textit{minimize} \quad \sum_{\forall i:\ T_i \in D} c_i x_i$$

$$\textit{subject to} \begin{cases} \sum_{\forall i:\ T_i \in D} a_{iy} x_i \geq (\sigma_y - \sigma_{min} + 1), \ \forall y \in S \\ x_i \in \{0, 1\} \quad \forall i : T_i \in D. \end{cases}$$

# An Example (1/3)

Consider the same transaction database $D$, sensitive itemsets $S = \{ab, bc, cd\}$ and $\sigma_{min} = 3$ as in the previous example. The coefficients must be first calculated.

| Tid | Trans. | Victim Items | Coefficients |
|---|---|---|---|
| 1 | *abcde* | *c*, *a* | 1 1 |
| 2 | *acd* | *c* | 3 |
| 3 | *abdfg* | *a* | 3 |
| 4 | *bcde* | *c* | 4 |
| 5 | *abd* | *a* | 3 |
| 6 | *bcdfh* | *c* | 2 |
| 7 | *abcg* | *b* | 1 |
| 8 | *acde* | *c* | 5 |
| 9 | *acdh* | *c* | 3 |

# An Example (2/3)

$$\begin{aligned} \textit{minimize} \quad & 11x_1 + 3x_2 + 3x_3 + 4x_4 + 3x_5 \\ & + 2x_6 + 1x_7 + 5x_8 + 3x_9 \end{aligned}$$

$$\textit{subject to} \begin{cases} ab : x_1 + x_3 + x_5 + x_7 \geq 2 \\ bc : x_1 + x_4 + x_6 + x_7 \geq 2 \\ cd : x_1 + x_2 + x_4 + x_6 + x_8 + x_9 \geq 4 \end{cases}$$

# An Example (3/3)

- The optimal solution is $x_2 = x_4 = x_5 = x_6 = x_7 = x_9 = 1$, while $x_1 = x_3 = x_8 = 0$.
- Summary of the sanitization process:

| **Tid** | **Trans.** | **S.I. supported** | **Victim Items** | **Sanitized** |
|---|---|---|---|---|
| 2 | $abd$ | $ab$ | $a:1,\ b:1$ | $ad$ |
| 4 | $bcde$ | $bc, cd$ | $b:1,\ c:2,\ d:1$ | $bde$ |
| 5 | $abd$ | $ab$ | $a:1,\ b:1$ | $bd$ |
| 6 | $bcdfh$ | $bc, cd$ | $b:1,\ c:2,\ d:1$ | $bdfh$ |
| 7 | $abcg$ | $ab, bc$ | $a:1,\ b:2,\ c:1$ | $acg$ |
| 9 | $abdh$ | $ab$ | $a:1,\ b:1$ | $adh$ |

## Inline

# The Inline Algorithm [7]

# Basic Features (1/2)

- Database must first be transformed into a $|D| \times |I|$ binary array with elements:

$$b_{kj} = \begin{cases} 1, & \textit{if item} \quad i_j \in T_k \\ 0, & \textit{otherwise} \end{cases}$$

- $b_{kj}$ values participating in the sensitive itemsets are substituted in all transactions with $u_{kj}$ variables, which participate in the linear program's formulation.

# Basic Features (2/2)

- For the two previous algorithms, the solution determines the transactions to be sanitized. Then sanitization follows.
- For the Inline algorithm the solution of the linear program specifies which items must be removed and from which transactions.
- This is a more *exact database distortion* approach [8].

# The Formulation

$$\text{maximize} \quad \sum_{u_{kj} \in U} u_{kj}$$

$$\text{subject to} \begin{cases} \sum_{T_k \in D\{X\}} \left( \prod_{i_j \in X} u_{kj} \right) < \sigma_{min}, \forall X \in S \\ \sum_{T_k \in D\{R\}} \left( \prod_{i_j \in R} u_{kj} \right) \geq \sigma_{min}, \forall R \in V \end{cases}$$

where $V = \{X \in B^+(\tilde{F}) | X \cap I^S \neq \emptyset\}$ and $I^S$ is the set of items contained by itemsets in $S$.

# The Formulation Explained

- Objective Function: maximize the number of variables with value equal to 1. In other words, remove the fewest items.
- A sensitive itemset will get concealed if: $\sum_{T_k \in D\{X\}} (\prod_{i_j \in X} u_{kj}) < \sigma_{min}, \forall X \in S$.
- Non-sensitive frequent itemsets will remain frequent if: $\sum_{T_k \in D\{R\}} (\prod_{i_j \in R} u_{kj}) \geq \sigma_{min}, \forall R \in V$, where $V = \{X \in B^+(\tilde{F}) | X \cap I^S \neq \emptyset\}$.

# Constraint Degree Reduction (CDR)

Linear programs cannot contain products. Products occuring in the inequalities of the formulation must be "linearized".

Replace

$$\sum_{T_k \in D\{F\}} \psi_k \lesseqqgtr \sigma_{min}, \psi_k = \prod_{i_j \in F} u_{kj} = u_{kF_1} \times \ldots \times u_{kF_{|F|}}$$

with

$$\forall k \begin{cases} \psi_k \leq u_{kF_1} \\ \psi_k \leq u_{kF_2} \\ \quad \vdots \\ \psi_k \leq u_{kF_{|F|}} \\ \psi_k \geq u_{kF_1} + u_{kF_2} + \ldots + u_{kF_{|F|}} - |I| + 1, \text{where } |I| = \#\text{vars in product} \end{cases}$$

and

$$\sum_k \psi_k \lesseqqgtr \sigma_{min}$$

where $\psi_k \in \{0, 1\}$.

# Dealing with Infeasibilities

- The formulation of the Inline algorithm might give an infeasible solution.
- The problem is relaxed until it becomes solvable.
- Only inequalities from the set $V$ $(B^+(\tilde{F}_\sigma))$ are removed.
- A constraint involving **maximal size** and **minimum support** itemsets in V is removed each time.
- The formulation with only the constrains in $S$ has **always** a feasible solution.

# An Example (1/4)

- Let the transaction database $D$, the set of sensitive itemsets $S = \{ab\}$ and $\sigma_{min} = 2$.
- $F_\sigma = \{a, b, c, d, ab, ac, ad, cd, acd\}$.
- $S = \{ab\}$, and $SS = \{ab\}$.
- $\tilde{F}_\sigma = F_\sigma - SS = \{a, b, c, d, ac, ad, cd, acd\}$.
- $B^+(\tilde{F}_\sigma) = \{b, acd\}$.

| Tid | Items |
|---|---|
| 1 | $ac$ |
| 2 | $acd$ |
| 3 | $cd$ |
| 4 | $b$ |
| 5 | $abcd$ |
| 6 | $d$ |
| 7 | $c$ |
| 8 | $ab$ |

# An Example (2/4)

The database is converted into a binary array and the 1 values of sensitive itemsets (contained in transactions) are replaced with variables:

| Tid | a | b | c | d |
|---|---|---|---|---|
| 1 | 1 | 0 | 1 | 0 |
| 2 | 1 | 0 | 1 | 1 |
| 3 | 0 | 0 | 1 | 1 |
| 4 | 0 | 1 | 0 | 0 |
| 5 | $u_{51}$ | $u_{52}$ | 1 | 1 |
| 6 | 0 | 0 | 0 | 1 |
| 7 | 0 | 0 | 1 | 0 |
| 8 | $u_{81}$ | $u_{82}$ | 0 | 0 |

# An Example (3/4)

| Tid | a | b | c | d |
|---|---|---|---|---|
| 1 | 1 | 0 | 1 | 0 |
| 2 | 1 | 0 | 1 | 1 |
| 3 | 0 | 0 | 1 | 1 |
| 4 | 0 | 1 | 0 | 0 |
| 5 | $u_{51}$ | $u_{52}$ | 1 | 1 |
| 6 | 0 | 0 | 0 | 1 |
| 7 | 0 | 0 | 1 | 0 |
| 8 | $u_{81}$ | $u_{82}$ | 0 | 0 |

- Hiding itemset $S = \{ab\}$
- Itemsets in $V$ must remain frequent:
  b: $1 + u_{52} + u_{82} \geq \sigma_{min}$
  acd: $1 + u_{51} \geq \sigma_{min}$
- Itemsets in $S$ must become infrequent:
  ab: $u_{51}u_{52} + u_{81}u_{82} < \sigma_{min}$
- Application of CDR for $\{ab\}$:
  $\psi_1 \leq u_{51}$ $\quad$ $\psi_2 \leq u_{81}$
  $\psi_1 \leq u_{52}$ $\quad$ $\psi_2 \leq u_{82}$
  $\psi_1 \geq u_{51} + u_{52} - 1$ $\quad$ $\psi_2 \geq u_{81} + u_{82} - 1$
  $\psi_1 + \psi_2 < \sigma_{min}$

# Hybrid

# The Hybrid Algorithm [7]

# Basic Features (1/2)

- The solution of the previous algorithms determines from which transactions and/or which specific items should be extracted.
- The Hybrid algorithm creates an extension of the original database with synthetically generated transactions.
- The goal is to fix the contents of the extension so that to control the support of sensitive and non-sensitive itemsets.

# Basic Features (2/2)

- Extension of database $D_X$: must contain the minimum sufficient number of transactions.
- Minimum size: $Q = \lfloor(\sigma(X_M)/msup) - |D|\rfloor + 1$, where $X_M \in S$ such that $\sigma(X_M) \geq \sigma(X), \forall X \in S - X_M$.
- Theoretically, this size seems to be suficient. Practically, this is not always the case. $\Longrightarrow$ Use of safety margin $SM$, i.e., $SM$ more transactions in $D_x$.
- The extension $D_x$ is a $|Q + SM| \times |I|$ array that initially contains only variables. The solution of the linear program gives a value to each variable and the transactions are formed.

# The Formulation

$$\textit{minimize} \quad \sum_{q \in [1, Q+SM], m \in [1, |D|]} u_{qm}$$

$$\textit{subject to} \begin{cases} \sum_{q=1}^{Q+SM} \left( \prod_{i_m \in X} u_{qm} \right) < thr, & \forall X \in B^-(\tilde{F}_\sigma) \\ \sum_{q=1}^{Q+SM} \left( \prod_{i_m \in X} u_{qm} \right) \geq thr, & \forall X \in B^+(\tilde{F}_\sigma) \\ \forall T_q \in D_X : \sum_{i_m \in I} u_{qm} \geq 1 \end{cases}$$

where $thr = msup * (|D| + Q + SM) - \sigma(X)$

# The Formulation Explained

- Let $D' = D \cup D_x$.
- Objective Function: minimize the number of variables that will be set to 1.
- An itemset will be **frequent** in $D'$ iff:
  $$\sum_{q=1}^{Q+SM} \Big( \prod_{i_m \in X} u_{qm}\Big) \geq msup \times (|D| + Q + SM) - \sigma(X)$$
- An itemset will be **infrequent** in $D'$ iff:
  $$\sum_{q=1}^{Q+SM} \Big( \prod_{i_m \in X} u_{qm}\Big) < msup \times (|D| + Q + SM) - \sigma(X)$$
- Empty transactions are not allowed:
  $\forall T_q \in D_X : \sum_{i_m \in I} u_{qm} \geq 1$

# Constraint Degree Reduction (CDR)

Linear programs cannot contain products. Products occuring in the inequalities of the formulation must be "linearized".

Replace

$$\sum_{T_k \in D\{F\}} \psi_k \lesseqqgtr \sigma_{min}, \psi_k = \prod_{i_j \in F} u_{kj} = u_{kF_1} \times \ldots \times u_{kF_{|F|}}$$

with

$$\forall k \begin{cases} \psi_k \leq u_{kF_1} \\ \psi_k \leq u_{kF_2} \\ \quad \vdots \\ \psi_k \leq u_{kF_{|F|}} \\ \psi_k \geq u_{kF_1} + u_{kF_2} + \ldots + u_{kF_{|F|}} - |I| + 1 \end{cases}$$

and

$$\sum_k \psi_k \lesseqqgtr \sigma_{min}$$

where $\psi_k \in \{0, 1\}$.

# An Example (1/2)

| Tid | a | b | c | d | e | f |
|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 0 | 0 | 0 | 1 |
| 2 | 1 | 1 | 1 | 1 | 0 | 0 |
| 3 | 1 | 0 | 1 | 0 | 0 | 1 |
| 4 | 1 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 1 | 0 | 0 | 1 | 0 |
| 6 | 1 | 1 | 1 | 1 | 1 | 0 |
| 7 | 0 | 0 | 0 | 1 | 0 | 0 |
| 8 | 1 | 1 | 1 | 0 | 1 | 0 |
| 9 | 0 | 1 | 1 | 0 | 0 | 0 |
| 10 | 1 | 0 | 1 | 1 | 1 | 0 |
| 11 | $u_{11}$ | $u_{12}$ | $u_{13}$ | $u_{14}$ | $u_{15}$ | $u_{16}$ |
| 12 | $u_{21}$ | $u_{22}$ | $u_{23}$ | $u_{24}$ | $u_{25}$ | $u_{26}$ |
| 13 | $u_{31}$ | $u_{32}$ | $u_{32}$ | $u_{34}$ | $u_{35}$ | $u_{36}$ |
| 14 | $u_{41}$ | $u_{42}$ | $u_{43}$ | $u_{44}$ | $u_{45}$ | $u_{46}$ |

- Let transaction database $D$, $S = \{e, ae, bc\}$ and $\sigma_{min} = 3$.
- $\sigma(e) = 3$, $\sigma(ae) = 4$, $\sigma(bc) = 4$
- The extension $D_x$ has size $Q = \lfloor (4/0.3) - 10 \rfloor + 1 = \lfloor 3.33 \rfloor + 1 = 4$ and initially contains variables.

# An Example (2/2)

| Tid | a | b | c | d | e | f |
|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 0 | 0 | 0 | 1 |
| 2 | 1 | 1 | 1 | 1 | 0 | 0 |
| 3 | 1 | 0 | 1 | 0 | 0 | 1 |
| 4 | 1 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 1 | 0 | 0 | 1 | 0 |
| 6 | 1 | 1 | 1 | 1 | 1 | 0 |
| 7 | 0 | 0 | 0 | 1 | 0 | 0 |
| 8 | 1 | 1 | 1 | 0 | 1 | 0 |
| 9 | 0 | 1 | 1 | 0 | 0 | 0 |
| 10 | 1 | 0 | 1 | 1 | 1 | 0 |
| 11 | 1 | 0 | 0 | 0 | 0 | 0 |
| 12 | 1 | 0 | 1 | 1 | 0 | 0 |
| 13 | 1 | 0 | 1 | 1 | 0 | 0 |
| 14 | 1 | 1 | 0 | 0 | 0 | 0 |

- Due to the large number, the constraints are ommited.
- In the extended database support for the itemsets in $S$ changes.
- When $|D| = 10$, then $\sup(e) = \frac{3}{10}$ and thus indeed $\sigma(e) = 3$.
- $|D| = 14$, $\sup(e) = \frac{3}{14} \Rightarrow \sigma(e) = \frac{30}{14} < \sigma_{min}$

# Datasets used

| Dataset | # Trans. | # Items | Avg. Len. | $\sigma_{min}$ |
|---|---|---|---|---|
| Sampled | 500 | 34 | 11.12 | 100 |
| BMS-1 | 59602 | 497 | 2.50 | 42 |
| Mushroom | 8124 | 119 | 23.00 | 1625 |

- Real datasets used for evaluation are available in the FIMI repository [9].
- **Sampled**: sampled version of Mushroom dataset.
- **BMS1**: stream data collected from the Blue Martini Software, Inc. [10].
- **Mushroom**: created by Roberto Bayardo (University of California, Irvine) [11].

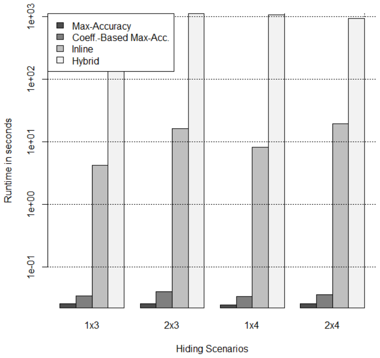
# Evaluation Process (1/2)

- The evaluation process had 3 phases and for each phase one of datasets was used.
- Different hiding scenarios were selected with various number/size of sensitive itemsets to hide.
- Experiments were conducted several times with different sets of sensitive itemsets (the same set for all algorithms each time).
- Phase 1: Sample dataset, Phase 2: BMS1 dataset, Phase 3: Mushroom dataset
- At the end of each phase, the slowest algorithm is eliminated.

# Evaluation Process (2/2)

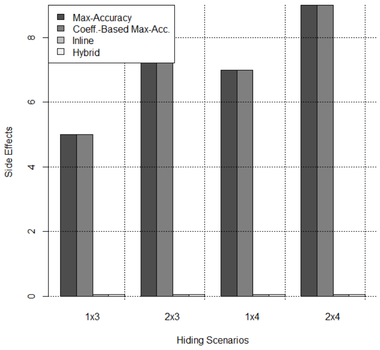
- Experiments were conducted with a toolbox written in Python.
- Linear programming techniques use the CPLEX [12] interface for Python.
- More about the toolbox in the next slides.

# Experimental Results - Phase 1 (1/2)



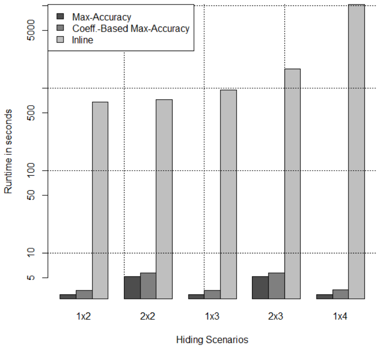

- Figure with runtime in seconds for each hiding scenario with the Sample dataset.
- Max-Accuracy and Coefficient-Based Max-Accuracy have much lower execution time.
- Inline and Hybrid have larger time complexity.
- But what about the side effects?

# Experimental Results - Phase 1 (2/2)



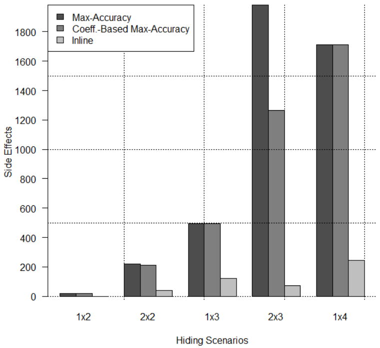

- Figure with side effects for each hiding scenario with the Sample dataset
- Inline and Hybrid introduce almost 0 side effects.
- But time is important. Very important!
- For the next phase the slowest algorithm is eliminated, which is Hybrid.

# Experimental Results - Phase 2 (1/2)



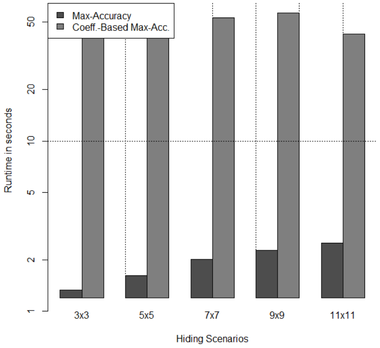

- Figure with runtime in seconds for each hiding scenario with the BMS1 dataset.
- Inline again has much larger time complexity than the other two algorithms.
- Let's see what happens with the side effects.

# Experimental Results - Phase 2 (2/2)



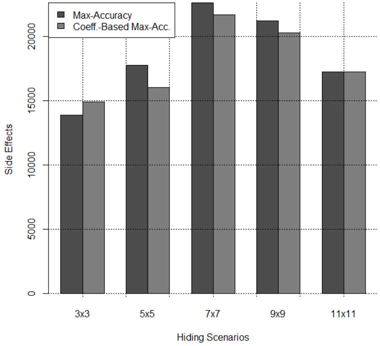

- Figure with side effects for each hiding scenario with the BMS1 dataset
- Inline again has much fewer side effects than the other two algorithms.
- Again, the algorithm with the highest time complexity is eliminated, i.e. the Inline algorithm.

# Experimental Results - Phase 3 (1/2)




- Figure with runtime in seconds for each hiding scenario with the Mushroom dataset.
- Max-Accuracy and Coefficient-Based Max-Accuracy have a good scalability.
- What happens with the side effects?

# Experimental Results - Phase 3 (2/2)



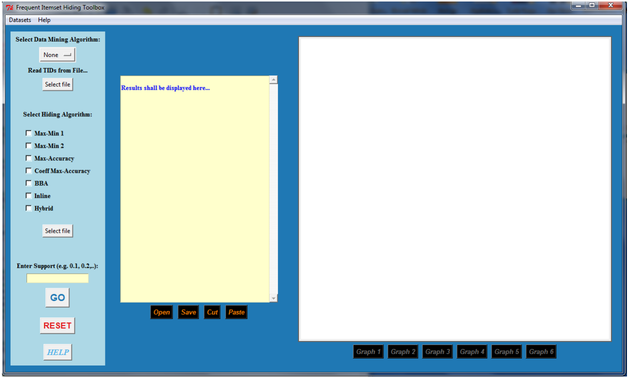

- Figure with side effects for each hiding scenario with the Mushroom dataset.
- Time complexity is linear, but they introduce quite a few side effects.

# Qualitative Comparison

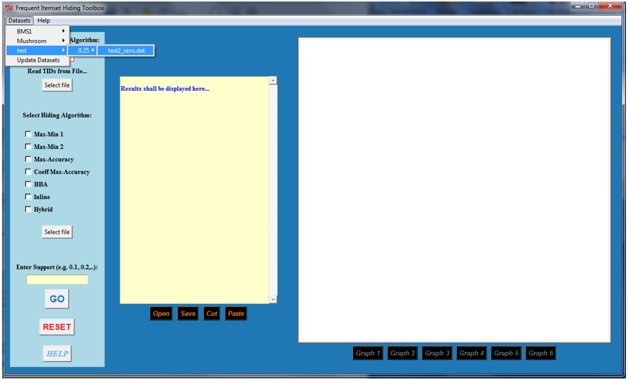
A qualitative comparison of the algorithms.

| Algorithm | Execution Time | Scalability | Side Effects |
|---|---|---|---|
| Max-Accuracy | Very Fast | Very Good | Moderate |
| Coeff.-Based Max-Accuracy | Fast | Good | Moderate-Good |
| Inline | Slow | Bad | Very Good |
| Hybrid | Slow | Very Bad | Very Good |

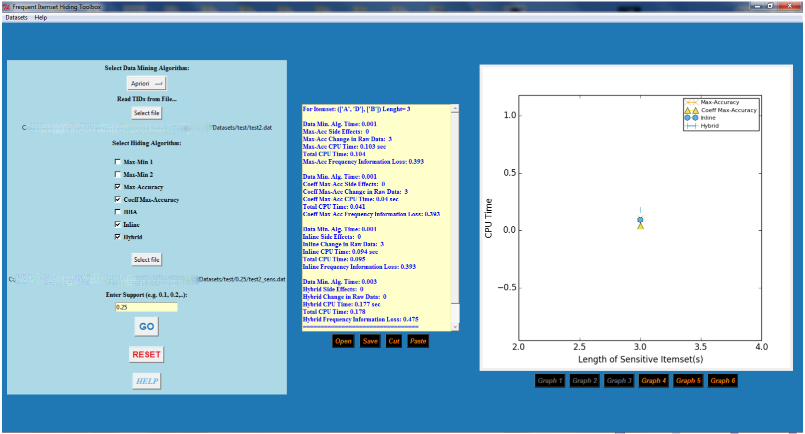
# Toolbox Interface (1/3)



# Toolbox Interface (2/3)



# Toolbox Interface (3/3)



# Conclusions

- Max-Accuracy and Coefficient-Based Max-Accuracy: scalable, while introducing numerous side effects
- Inline and Hybrid: few side effects, but with bad scalability
- An optimal LP-based algorithm remains yet to be found

# Questions

Questions?

# References I

R. Agrawal and R. Srikant (2000)
Privacy-preserving data mining
*SIGMOD 29: 439-450*

Y. Lindell and B. Pinkas (2000)
Privacy preserving data mining
*CRYPTO '00 Proceedings of the 20th Annual International Cryptology Conference on Advances in Cryptology 1880: 36-54*

Johnsten, Tom and Raghavan, Vijay V. (2002)
A Methodology for Hiding Knowledge in Databases
*Proceedings of the IEEE International Conference on Privacy, Security and Data Mining 14: 9-17*

# References II

Michael Barbaro and Tom Zeller
A Face Is Exposed for AOL Searcher No. 4417749
*The New York Times*

S. Menon, S. Sarkar, and S. Mukherjee (2005)
Maximizing accuracy of shared databases when concealing sensitive patterns
*Information Systems Research, 16(3):256-270*

E. Leloglu, T. Ayav, and B. Ergenc (2014)
Coefficient-based exact approach for frequent itemset hiding
*eKNOW2014: The Sixth International Conference on Information, Process, and Knowledge Management, 124-130*

# References III

A. Gkoulalas-Divanis and V. S. Verykios (2009)
Hiding sensitive knowledge without side effects
*Knowledge Information Systems, 20(3):263-299*

V. S. Verykios (2013)
Association rule hiding methods
*WIREs Data Mining Knowledge Discovery, 3(1):28-36*

Frequent Itemset Mining Dataset Repository
*http://fimi.ua.ac.be/data/*

# References IV

Kohavi, Ron, Brodley, Carla E., Frasca, Brian, Mason, Llew and Zheng, Zijian (2000)
KDD-Cup 2000 Organizers' Report: Peeling the Onion
*SIGKDD Explor. Newsl., 2(2):86-93*

Bayardo,Jr., Roberto J. (1998)
Efficiently Mining Long Patterns from Databases
*SIGMOD, 27(2):85-93*

IBM ILOG CPLEX User's Manual v12.6
*http://www-01.ibm.com/software/integration/optimization/cplex-optimizer/*