# Frequent Itemset Mining of Distributed Uncertain Data under User-Defined Constraints

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# Outline

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# Introduction

- **Frequent pattern mining (FPM)**
  - A data mining task
  - Non-trivial extraction of implicit, previously unknown, & potentially useful information—in the form of *frequently occurring collections of merchandise items or events*—from data

# Related Work (1)

- **Apriori**
  - Generate-and-test paradigm
- **FP-growth**
  - Restricted test-only approach

- **UF-growth**
  - Mines frequent itemsets from uncertain data
  - Mines a centralized DB of uncertain data for all (unconstrained) frequent itemsets

# Related Work (2)

- **DCF**
  - Mines constrained frequent itemsets from traditional precise data
  - Mines a centralized DB of precise data

- **FDM** & **Parallel-HFP-Leap**
  - Distributed mining
  - Do not handle constraints
  - Do not mine uncertain data

# Our Proposed Distributed Mining System

- Non-trivial integration of
  - constrained mining,
  - distributed mining,
  - uncertain data mining, with
  - tree-based frequent itemset mining.
- Efficiently mines from distributed uncertain data for only those constrained frequent itemsets

# Our Proposed Distributed Mining System

- Given:
  - p sites/processors
  - $m = m_1 + m_2 + \ldots + m_p$ sensors in a distributed network
  - $m_1$ wireless sensors transmit data to their closest or designated site/processor $P_1$
  - $m_2$ sensors transmit data to the site/processor $P_2$
  - etc.
- finds
  a) constrained itemsets that are locally frequent w.r.t. site/processor $P_i$ and
  b) those that are globally frequent w.r.t. all sites/processors in the entire wireless sensor network

# A. Finding Constrained Locally Frequent Itemsets

- Step 1:
  - Identification of items satisfying the constraint
- Step 2:
  - Construction of an UF-tree
- Step 3:
  - Mining of constrained frequent itemsets from the UF-tree

# A1. Identification of Items Satisfying the SAM Constraint

- Succinct anti-monotone (SAM) constraint
  - Any X satisfying $C_{SAM}$ must be generated by combining items from **ItemM**
    - Items in **ItemM** can be efficiently enumerated (from the list of domain items) by selecting only those items that individually satisfy $C_{SAM}$
  - An itemset X satisfying $C_{SAM}$ cannot contain any item from **ItemO**
    - E.g., if an itemset X containing an item having price > $25, then X violates $C_{SAM}$ & so does every superset of X

# A1. Identification of Items Satisfying the SUC Constraint

- Succinct non-anti-monotone (SUC) constraint
  - Any itemset X satisfying $C_{SUC}$ must be generated by combining at least one **ItemM** item and possibly some **ItemO** items
  - If X violates $C_{SUC}$ , there is no guarantee that all or any of its supersets would violate $C_{SUC}$
  - Any itemset X satisfying $C_{SUC}$ is composed of mandatory items (i.e., items that individually satisfy $C_{SUC}$ and possibly some optional items (regardless whether or not they satisfy $C_{SUC}$ )

# A2. Construction of an UF-Tree (1)

- Classifies domain items into **ItemM** & **ItemO** items
  - No **ItemO** items for $C_{SAM}$
- Constructs an UF-tree
  - Scans the DB of uncertain data once
  - Accumulates the expected support of each of the items
  - Discards infrequent items
  - Only captures frequent items in the UF-tree
    - Any infrequent **ItemM** or **ItemO** items can be safely discarded because any itemset containing an infrequent item is also infrequent

# A2. Construction of an UF-Tree (2)

- Arranges **ItemM** items to appear below **ItemO** items
  - **ItemM** items are closer to the leaves
  - **ItemO** items are closer to the root
- Sorts all the items **ItemM** in non-ascending order of accumulated expected support
- Sorts all the items **ItemO** in non-ascending order of accumulated expected support

# A2. Construction of an UF-Tree (3)

- Scans the DB the second time; inserts each transaction of the DB into the UF-tree
  - New transaction is merged with a child (or descendant) node of the root of the UF-tree (at the highest support level) only if the same item & the same expected support exist in both the transaction & the child (or descendant) nodes
  - For $C_{SAM}$, UF-tree captures only those frequent **ItemM** items

# A3. Mining of Constrained Frequent Itemsets from the UF-Tree

- Extracts appropriate paths to form a projected DB for each x in **ItemM**
  - Does not need to form projected DBs for any y in **ItemO** because all itemsets satisfying $C_{SUC}$ must be "extensions" of an item from **ItemM** (i.e., all valid itemsets must be grown from **temM** items)
  - For $C_{SAM}$, no **ItemO** items are kept in the UF-tree
- Recursively …
  - constructs a UF-tree for each projected DB
  - mines all frequent itemsets that satisfy $C_{SAM}$ or $C_{SUC}$

# B. Finding Constrained Globally Frequent Itemsets (1)

- Each site/processor $P_i$ (for $1 \leq i \leq p$)
  - applies constraint checking & frequency checking to find locally frequent **ItemM$_i$** items (& **ItemO$_i$** items for $C_{SUC}$)
  - transmits locally frequent **ItemM$_i$** items (& **ItemO$_i$** items for $C_{SUC}$) to a centralized site/processor Q
- Centralized site/processor Q
  - takes the union of these items
  - broadcasts the union to all $P_i$'s

# B. Finding Constrained Globally Frequent Itemsets (2)

- Each $P_i$
  - extracts these potentially globally frequent items from transactions in $TDB_i$ & puts into an UF-tree
  - UF-tree contains …
    - items that are locally frequent w.r.t. $P_i$
    - items that are potentially globally frequent but locally infrequent items w.r.t $P_i$
  - recursively applies the usual tree-based mining process to each α-projected DB (where locally frequent $\alpha \subseteq$ **ItemM$_i$** ) of the UF-tree at $P_i$ to find constrained locally frequent itemsets (with local frequency info) & send these itemsets to Q (where the local frequencies are summed)
- If the sum of available local frequencies of a constrained itemset X ≥ minimum support threshold, then X is *globally frequent*
- For the case where a constrained itemset is locally frequent at a site $P_1$ but not at another site $P_2$, then Q sends a request to $P_2$ for finding its local frequency

# Experimental Setup

- Datasets:
  - IBM synthetic data
  - Real-life DBs from …
    - UC Irvine Machine Learning Depository
    - Frequent Itemset Mining Implementation (FIMI) Dataset Repository

# Experimental Results (1)

- Accuracy
  - As accurate as UF-growth (and they both returned the same collection of frequent itemsets)
- Flexibility
  - More flexible than UF-growth
    - Our system is capable of finding frequent itemsets from distributed uncertain data with constraints of any selectivity
    - UF-growth is confined to those of 100% selectivity

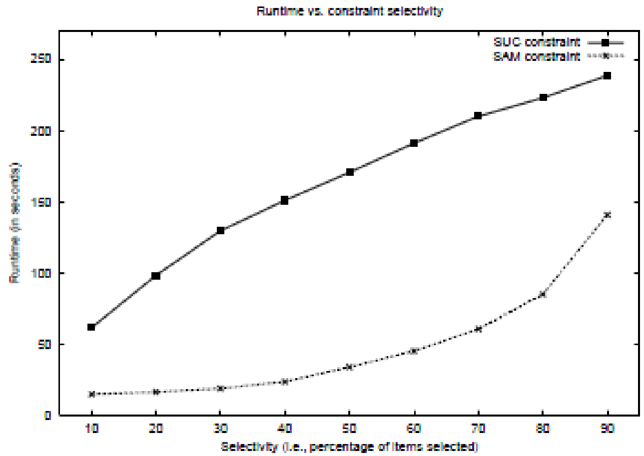
# Experimental Results (2)

- Effectiveness of constrained mining in a distributed environment
  - When selectivity of constraints decreased,
    - amount of communication/data transmitted between the distributed sites $P_i$ & their centralized site Q decreased
    - runtimes decreased

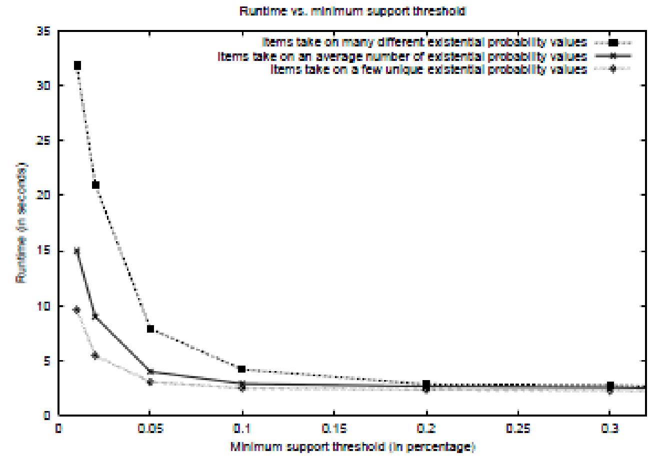
# Experimental Results (3)

- Effects of varying #distributed sites
  - When more sites were in the distributed network,
    - transmitted more data
      - » because an addition of a site implies transmission of an additional set of locally frequent items and locally frequent itemsets
    - runtime increased slightly
      - » because the extra communication time was offset by the savings in building and mining from a smaller UF-tree at each site

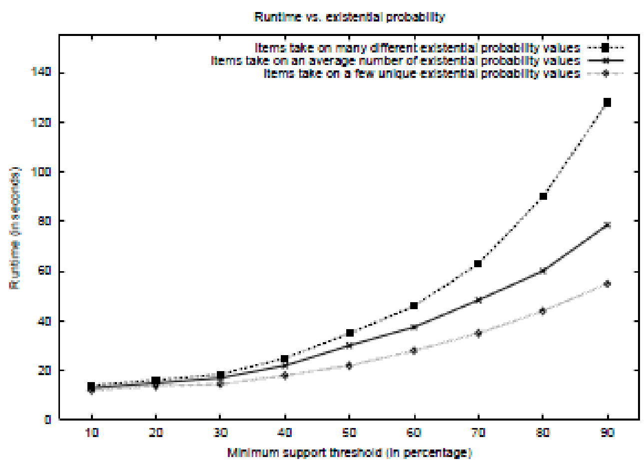
# Experimental Results (4)



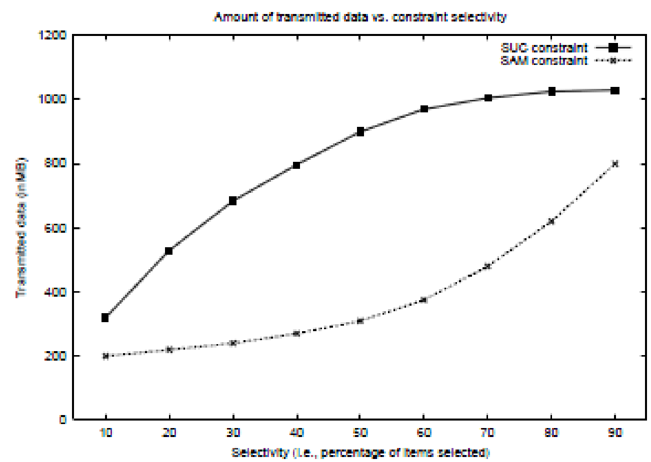
(a) Runtime vs. selectivity



(b) Runtime vs. minsup



(c) Runtime vs. existential probability



(d) Amt of transmitted data vs. selectivity

# Thank you Grazie

- More info, please refer to our paper

  *<u>or</u>*

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