Data Mining:

Concepts and Techniques

(3rd ed.)

— Chapter 7 —

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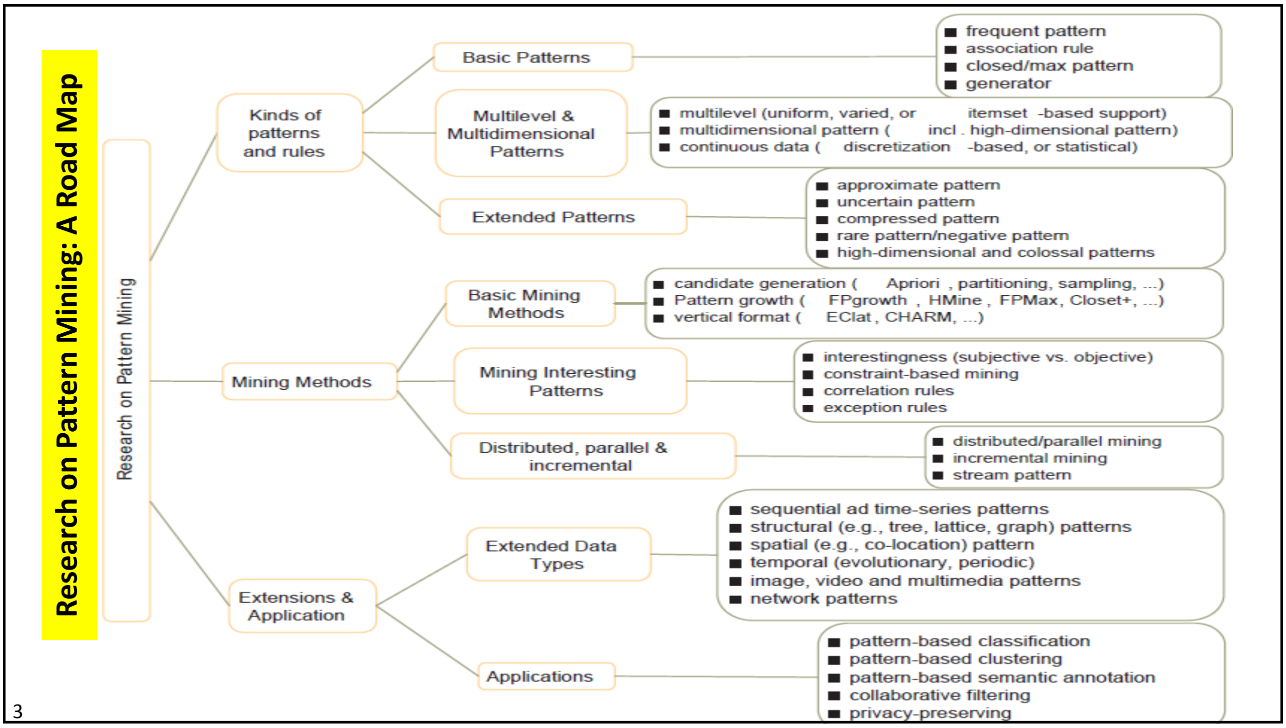
Chapter 7 : Advanced Frequent Pattern Mining

- Pattern Mining: A Road Map
- Mining Diverse Patterns
- Constraint-Based Frequent Pattern Mining
- Mining High-Dimensional Data and Colossal Patterns
- Sequential Pattern Mining
- Graph Pattern Mining
- Summary


Research on Pattern Mining: A Road Map
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Kinds of patterns and rules
Basic Patterns
frequent pattern
association rule
closed/max pattern
generator
Multilevel & Multidimensional Patterns
multilevel (uniform, varied, or itemset -based support)
multidimensional pattern (incl . high-dimensional pattern)
continuous data (discretization -based, or statistical)
Extended Patterns
approximate pattern
uncertain pattern
compressed pattern
rare pattern/negative pattern
high-dimensional and colossal patterns
Mining Methods
Basic Mining Methods
candidate generation (Apriori , partitioning, sampling, ...)
Pattern growth (FPgrowth , HMine , FPMax, Closet+, ...)
vertical format (EClat , CHARM, ...)
Mining Interesting Patterns
interestingness (subjective vs. objective)
constraint-based mining
correlation rules
exception rules
Distributed, parallel & incremental
distributed/parallel mining
incremental mining
stream pattern
Extensions & Application
Extended Data Types
sequential ad time-series patterns
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spatial (e.g., co-location) pattern
temporal (evolutionary, periodic)
image, video and multimedia patterns
network patterns
Applications
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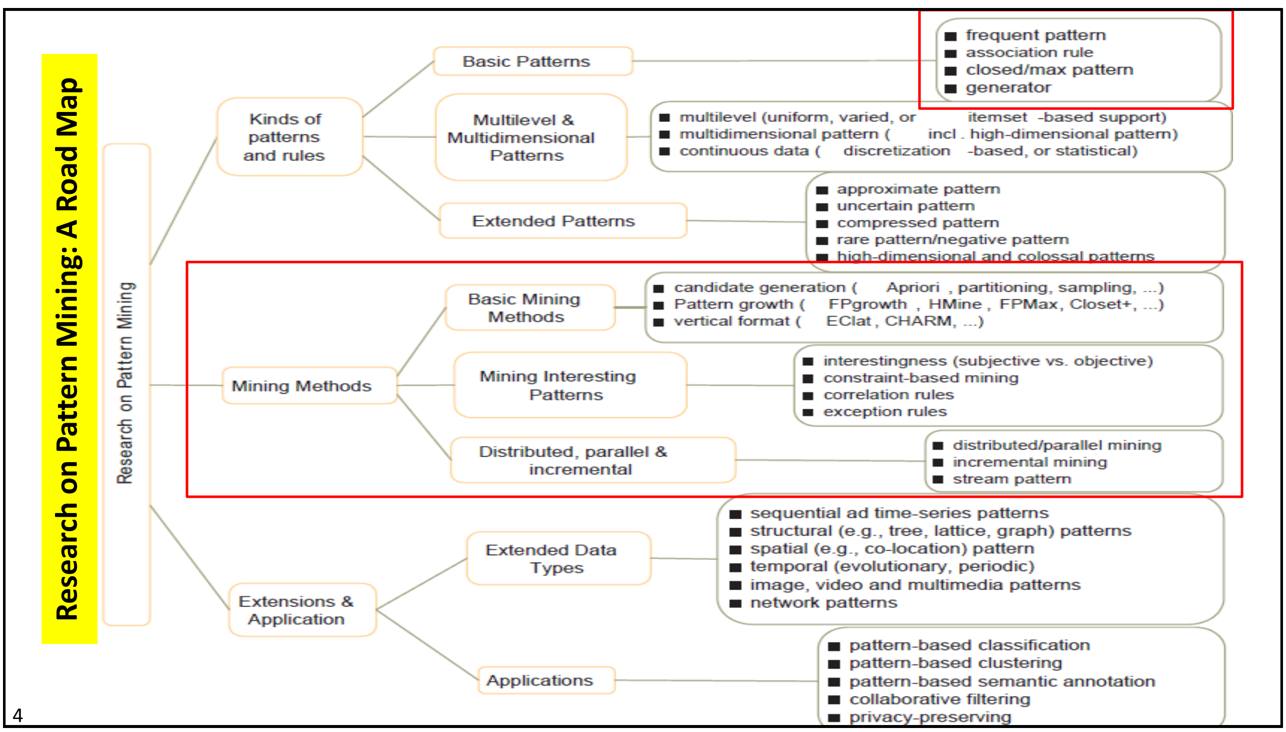
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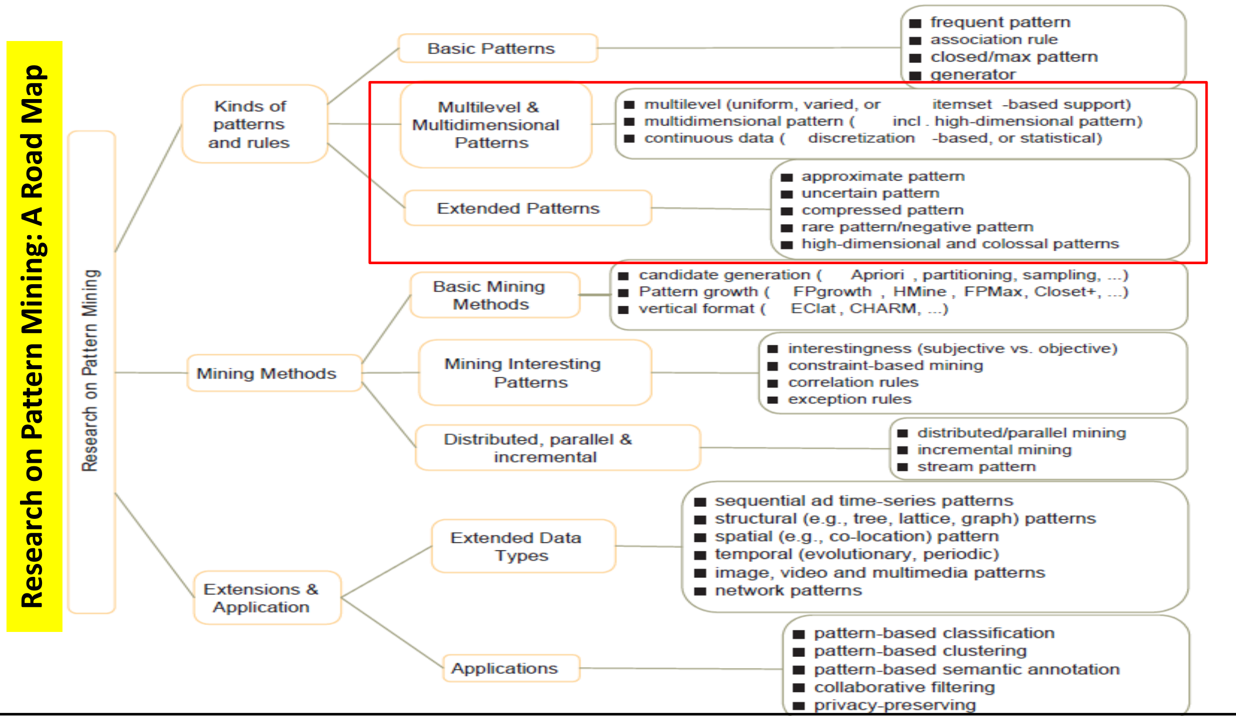

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Mining Diverse Patterns

- Mining Multiple-Level Associations
- Mining Multi-Dimensional Associations
- Mining Quantitative Associations
- Mining Negative Correlations
- Mining Compressed and Redundancy-Aware Patterns

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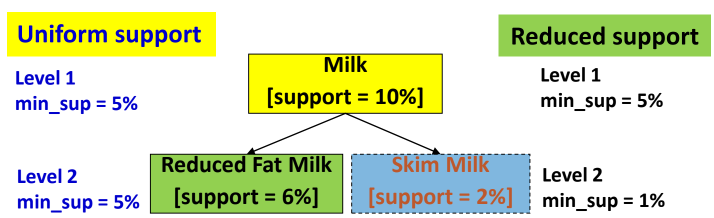
Mining Multiple-Level Frequent Patterns

- Items often form hierarchies
  - Ex.: Reduced Fat milk; Wonder wheat bread



- How to set min-support thresholds?
  - Uniform min-support across multiple levels (reasonable?)
  - Level-reduced min-support: Items at the lower level are expected to have lower support
- Efficient mining: *Shared* multi-level mining (How?)

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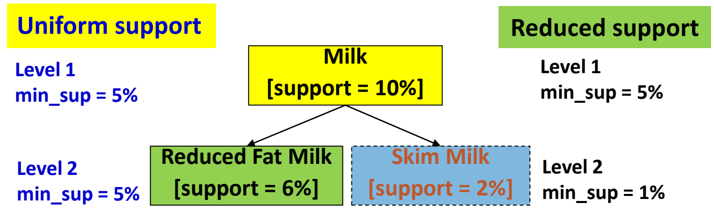

- How to set min-support thresholds?
  - Uniform min-support across multiple levels (reasonable?)
  - Level-reduced min-support: Items at the lower level are expected to have lower support
- Efficient mining: *Shared* multi-level mining
  - Use the lowest min-support to pass down the set of candidates

Redundancy Filtering at Mining Multi-Level Associations

Multi-level association mining may generate many redundant rules

- *Redundancy filtering:* Some rules may be redundant due to "ancestor" relationships between items

  (Suppose the *Reduced Fat milk* sold in about ¼ of milk sold in gallons)

  - milk $\Rightarrow$ wheat bread [support = 8%, confidence = 70%] (1)
  - Reduced fat milk $\Rightarrow$ wheat bread [what do you expect ?] (2)

Redundancy Filtering at Mining Multi-Level Associations

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- *Redundancy filtering:* Some rules may be redundant due to "ancestor" relationships between items

  (Suppose the reduced fat milk sold in about ¼ of milk sold in gallons)

  - milk $\Rightarrow$ wheat bread [support = 8%, confidence = 70%] (1)
  - Reduced fat milk $\Rightarrow$ wheat bread [support = 2%, confidence = 72%] (2)
- A rule is *redundant* if its support is close to the "expected" value, according to its "ancestor" rule, and it has a similar confidence as its "ancestor"
  - **Rule (1) is an ancestor of rule (2), which one to prune?**

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Customized Min-Supports for Different Kinds of Items

Until now: the same min-support threshold for all the items or item sets to be mined in each association mining

- But, some items (e.g., diamond, watch, …) are valuable but less frequent
- Necessary to have customized min-support settings for different kinds of items
- One Method: Use group-based "individualized" min-support
  - E.g., **valuable group {diamond, watch}: 0.05%;** whereas {bread, milk}: 5%; …
  - How to mine such rules efficiently?
    - Existing scalable mining algorithms can be easily extended to cover such cases

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Mining Multi-Dimensional Associations

- Single-dimensional rules (e.g., items are all in "product" dimension)
  - buys(X, "milk") $\Rightarrow$ buys(X, "bread")
- Multi-dimensional rules (i.e., items in $\geq$ 2 dimensions or predicates)
  - *Inter-dimension association rules* (*no repeated predicates*)
    - age(X, "18-25") $\wedge$ occupation(X, "student") $\Rightarrow$ buys(X, "coke")
  - *Hybrid-dimension association rules* (*repeated predicates*)
    - age(X, "18-25") $\wedge$ buys(X, "popcorn") $\Rightarrow$ buys(X, "coke")

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- Attributes can be categorical or numerical
  - Categorical Attributes (e.g., *profession, product*: no ordering among values): Data cube for inter-dimension association
  - Quantitative Attributes: Numeric, implicit ordering among values—*discretization (binning),* clustering, and gradient approaches

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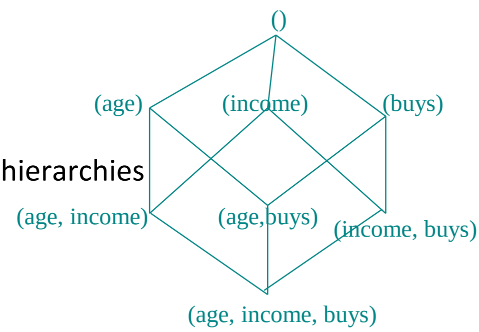
Mining Quantitative Associations

- Mining associations with numerical attributes
  - Ex.: Numerical attributes: age and salary
- Methods
  - Static discretization based on predefined concept hierarchies
    - Data cube-based aggregation
  - Dynamic discretization based on data distribution
  - Clustering: Distance-based association
    - First one-dimensional clustering, then association
  - Deviation analysis:
    - Gender = female ⇒ Wage: mean=$7/hr (whereas overall mean = $9)



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Mining Extraordinary Phenomena in Quantitative Association Mining

- Mining extraordinary (i.e., interesting) phenomena
  - Ex.: Gender = female ⇒ Wage: mean=$7/hr (overall mean = $9)
  - LHS: a subset of the population: Gender = female
  - RHS: an extraordinary behavior of this subset: Wage: mean=$7/hr
- The rule is accepted only if a statistical test (e.g., Z-test) confirms the inference with high confidence
- Subrule: Highlights the extraordinary behavior of a subset of the population of the super rule
  - Ex.: (Gender = female) ^ (South = yes) ⇒ mean wage = $6.3/hr
- Rule condition can be categorical or numerical (quantitative rules)
  - Ex.: Education in [14-18] (yrs) ⇒ mean wage = $11.64/hr
- Efficient methods have been developed for mining such extraordinary rules (e.g., Aumann and Lindell@KDD'99)

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Rare Patterns vs. Negative Patterns

- Rare patterns
  - Very low support but interesting (e.g., buying Rolex watches)
  - How to mine them? Setting individualized, group-based min-support thresholds for different groups of items (similar to valuable items)
- Negative patterns
  - Negatively correlated: Unlikely to happen together
  - Ex.: Since it is unlikely that the same customer buys both a Ford Expedition (an SUV car) and a Ford Fusion (a hybrid car), buying a Ford Expedition and buying a Ford Fusion are likely negatively correlated patterns
  - **How to define negative patterns?**

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Defining Negative Correlated Patterns

- A support-based definition of Negative Correlated Patterns
  - If itemsets A and B are both frequent but rarely occur together, i.e., $sup(A \cup B) \ll sup(A) \times sup(B)$
  - Then A and B are negatively correlated
- Is this a good definition for large transaction datasets?

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Defining Negative Correlated Patterns

- A support-based definition of Negative Correlated Patterns
  - If itemsets A and B are both frequent but rarely occur together, i.e., sup(A U B) << sup (A) × sup(B)
  - Then A and B are negatively correlated

Does this remind you the definition of *lift?*

- Is this a good definition for large transaction datasets?

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Does this remind you the definition of *lift?*

- Is this a good definition for large transaction datasets?

- Ex.: Suppose a store sold two needle packages A and B 100 times each, but only one transaction contained both A and B
  - When there are in total 200 transactions, we have
    - s(A U B) = 0.005, s(A) × s(B) = 0.25, s(A U B) << s(A) × s(B)
  - But when there are 10^5 transactions, we have
    - s(A U B) = $1/10^5$, s(A) × s(B) = $1/10^3 \times 1/10^3$, s(A U B) > s(A) × s(B)

  - **PROBLEM:** Null transactions: The support-based definition is not null-invariant!

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Defining Negative Correlation: Need Null-Invariance in Definition

- A good definition on negative correlation should take care of the null-invariance problem
  - Whether two itemsets A and B are negatively correlated should not be influenced by the number of null-transactions

Defining Negative Correlation: Need Null-Invariance in Definition

- A good definition on negative correlation should take care of the null-invariance problem
  - Whether two itemsets A and B are negatively correlated should not be influenced by the number of null-transactions
- A Kulczynski measure-based definition
  - If itemsets A and B are frequent but $(P(A|B) + P(B|A))/2 < \epsilon$, where ϵ is a negative pattern threshold, then A and B are negatively correlated
- For the same needle package problem:
  - No matter if there are in total 200 or 10^5 transactions
  - If $\epsilon = 0.01$, we have $(P(A|B) + P(B|A))/2 = (0.01 + 0.01)/2 < \epsilon$

Mining Compressed Patterns

Pat-ID	Item-Sets	Support
P1	{38,16,18,12}	205227
P2	{38,16,18,12,17}	205211
P3	{39,38,16,18,12,17}	101758
P4	{39,16,18,12,17}	161563
P5	{39,16,18,12}	161576

- Closed patterns
  - P1, P2, P3, P4, P5
  - Emphasizes too much on support
  - There is no compression
- Max-patterns
  - P3: information loss
- Desired output (a good balance):
  - P2, P3, P4

- Why mining compressed patterns?
  - Too many scattered patterns but not so meaningful
- Pattern distance measure

$$Dist(P_1, P_2) = 1 - \frac{|T(P_1) \cap T(P_2)|}{|T(P_1) \cup T(P_2)|}$$

- δ-clustering: For each pattern P, find all patterns which can be expressed by P and whose distance to P is within δ (δ-cover)
- All patterns in the cluster can be represented by P
- Method for efficient, direct mining of compressed frequent patterns (e.g., D. Xin, J. Han, X. Yan, H. Cheng, "On Compressing Frequent Patterns", Knowledge and Data Engineering, 60:5-29, 2007)

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Why Constraint-Based Mining?

- Finding all the patterns in a dataset autonomously? — unrealistic!
  - Too many patterns but not necessarily user-interested!
- Pattern mining should be an interactive process
  - User directs what to be mined using a data mining query language (or a graphical user interface)
- Constraint-based mining
  - User flexibility: provides constraints on what to be mined
  - Optimization: explores such constraints for efficient mining
    - Constraint-based mining: Constraint-pushing, similar to push selection first in DB query processing

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Constraints in General Data Mining

A data mining query can be in the form of a meta-rule or with the following language primitives

- Knowledge type constraint:
  - Ex.: classification, association, clustering, outlier finding, ...
- Data constraint — using SQL-like queries
  - Ex.: find products sold together in NY stores this year
- Dimension/level constraint
  - Ex.: in relevance to region, price, brand, customer category
- Rule (or pattern) constraint
  - Ex.: small sales (price < \$10) triggers big sales (sum > \$200)
- Interestingness constraint
  - Ex.: strong rules: min_sup $\geq$ 0.02, min_conf $\geq$ 0.6, min_correlation $\geq$ 0.7

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Meta-Rule Guided Mining

- A meta-rule can contain partially instantiated predicates & constants
  - $P_1(X, Y) \wedge P_2(X, W) \Rightarrow$ buys(X, "iPad")
- The resulting mined rule can be
  - age(X, "15-25") ^ profession(X, "student") ⇒ buys(X, "iPad")
- In general, (meta) rules can be in the form of
  - $P_1 \wedge P_2 \wedge \ldots \wedge P_l \Rightarrow Q_1 \wedge Q_2 \wedge \ldots \wedge Q_r$

- Method to find meta-rules
  - Find frequent (l + r) predicates (based on *min-support*)
  - Push constants deeply when possible into the mining process
  - Also, push min_conf, min_correlation, and other measures as early as possible (measures acting as constraints)

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Different Kinds of Constraints Lead to Different Pruning Strategies

- Constraints can be categorized as
  - Pattern space pruning constraints vs. data space pruning constraints
- Pattern space pruning constraints
  - Anti-monotonic: If constraint *c* is violated (by pattern of items), its further mining can be terminated
  - Monotonic: If constraint *c* is satisfied, no need to check *c* again
  - Succinct: if the constraint *c* can be enforced by directly manipulating the data
  - Convertible: constraint *c* can be converted to monotonic or anti-monotonic if items can be properly ordered in processing

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  - Convertible: constraint *c* can be converted to monotonic or anti-monotonic if items can be properly ordered in processing
- Data space pruning constraints
  - Data succinct: Data space can be pruned at the initial pattern mining process
  - Data anti-monotonic: If a transaction *t* (data) does not satisfy constraint *c*, then *t* can be pruned to reduce data processing effort

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Pattern Space Pruning with Pattern Anti-Monotonicity

- Constraint c is *anti-monotone*
  - If an itemset S **violates** constraint c, so does any of its superset
  - That is, mining on itemset S can be terminated
- Ex. 1: c_1: $sum(S.price) \leq v$ is anti-monotone
- Ex. 2: c_2: $range(S.profit) \leq 15$ is anti-monotone
  - Itemset *ab* violates c_2 (range(ab) = 40)
  - So does every superset of *ab*
- Ex. 3. c_3: $sum(S.Price) \geq v$ is not anti-monotone
- Ex. 4. Is c_4: $support(S) \geq \sigma$ anti-monotone?
  - Yes! Apriori pruning is essentially pruning with an anti-monotonic constraint!

TID	Transaction
10	a, b, c, d, f, h
20	b, c, d, f, g, h
30	b, c, d, f, g
40	a, c, e, f, g

min_sup = 2

price(item)>0

Item	Price	Profit
a	100	40
b	40	0
c	150	-20
d	35	-15
e	55	-30
f	45	-10
g	80	20
h	10	5

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Pattern Monotonicity and Its Roles

- A constraint *c* is *monotone*: if an itemset S **satisfies** the constraint c, then so does any of its superset
  - That is, we do not need to check *c* in subsequent mining
- Ex. 1: c_1: *sum(S.Price)* $\geq v$ is monotone
- Ex. 2: c_2: *min(S.Price)* $\leq v$ is monotone
- Ex. 3: c_3: range(S.profit) $\geq$ 15 is monotone
  - Itemset *ab* satisfies c_3
  - So does every superset of *ab*

TID	Transaction
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Data Space Pruning with Data Anti-Monotonicity

- A constraint c is *data anti-monotone*: In the mining process, if a data entry *t* cannot satisfy a pattern *p* under *c*, *t* cannot satisfy *p*'s superset either
  - Data space pruning*:* Data entry *t* can be pruned
- Ex. 1: c_1: *sum(S.Profit)* $\geq v$ is data anti-monotone
  - Let constraint c_1 be: sum{S.Profit} $\geq$ 25
    - Data entry T_{30}: {b, c, d, f, g} can be removed since none of their combinations can make an S whose sum of the profit is $\geq$ 25
- Ex. 2: c_2: *min(S.Price)* $\leq v$ is data anti-monotone
  - Consider *v* = 5 but every item in transaction T_{50} has a price higher than 10
- Ex. 3: c_3: *range(S.Profit)* $\geq$ *25* is data anti-monotone

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Data Space Pruning Should Be Explored Recursively

- Example. c_3: *range(S.Profit) > 25*
  - We check b's projected database
    - But item "a" is infrequent (sup = 1)
  - After removing "a (40)" from T_{10}
    - T_{10} cannot satisfy c_3 any more
      - since "b (0)" and "c (-20), d (-15), f (-10), h (5)"
    - By removing T_{10}, we can also prune "h" in T_{20}

b's-proj. DB

TID	Transaction
10	a, c, d, f, h
20	c, d, f, g, h
30	c, d, f, g

TID	Transaction
10	a, b, c, d, f, h
20	b, c, d, f, g, h
30	b, c, d, f, g
40	a, c, e, f, g

min_sup = 2

price(item)>0

Constraint: range{S.profit} ≥ 25

Item	Profit
a	40
b	0
c	-20
d	-15
e	-30
f	-10
g	20
h	5

b's-proj. DB

TID	Transaction
~~10~~	~~a, c, d, f, h~~
20	c, d, f, g, ~~h~~
30	c, d, f, g

Recursive Data Pruning

b's FP-tree

single branch: cdfg: 2

Only a single branch "cdfg: 2" to be mined in b's projected DB

- **Note: c_3 prunes T_{10} effectively only after "a" is pruned (by min-sup) in b's projected DB**

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Succinctness: Pruning Both Data and Pattern Spaces

- Succinctness: if the constraint *c* can be enforced by directly manipulating the data
- Ex. 1: To find those patterns without item *i*
  - Remove *i* from DB and then mine (pattern space pruning)
- Ex. 2: To find those patterns containing item *i*
  - Mine only *i*-projected DB (data space pruning)
- Ex. 3: c_3: $min(S.Price) \leq v$ is succinct
  - Start with only items whose price ≤ v (pattern space pruning) and remove transactions that only have high-price items (data space pruning)
- Ex. 4: c_4: $sum(S.Price) \geq v$ is not succinct
  - Satisfying the constraint cannot be determined beforehand since sum of the price of itemset S keeps increasing

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Convertible Constraints: Ordering Data in Transactions

- Convert tough constraints into (anti-)monotone by proper ordering of items in transactions
- Examine c_1: avg(*S*.profit) > 20
  - Order items in value-descending order
    - <*a, g, f, h, b, d, c, e*>
  - An itemset *ab* violates c_1 (avg(ab) = 20)
    - So does *ab** (i.e., *ab-projected DB)*
    - C_1: anti-monotone if patterns grow in the right order!
- Can item-reordering work for Apriori?
  - Does not work for level-wise candidate generation!
  - *avg*(*agf*) = 23.3 > 20, but avg(*gf*) = 15 < 20 , hence gf would have been incorrectly pruned

min_sup = 2

price(item)>0

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Item	Profit
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b	0
c	-20
d	-15
e	-30
f	10
g	20
h	5

How to Handle Multiple Constraints?

- It is beneficial to use multiple constraints in pattern mining
- But different constraints may require potentially conflicting item-ordering
  - If there exists an order *R* making both c_1 and c_2 convertible, try to sort items in the order that benefits pruning most
  - If there exists conflicting orderings between c_1 and c_2
    - Try to sort data and enforce *one constraint* first (which one?)
    - Then enforce the other when mining the projected databases
- Ex. c_1: avg(*S*.profit) > 20, and c_2: avg(S.price) < 50
  - Sorted in profit descending order and use c_1 first (assuming c_1 has more pruning power)
  - For each projected DB, sort transactions in price ascending order (now c_2 becomes ant-monotone) and use c_2 at mining

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Mining Long Patterns: Challenges

- Mining long patterns is needed in bioinformatics, social network analysis, software engineering, …
  - But the methods introduced so far mine only short patterns (e.g., length < 10)
- Challenges of mining long patterns
  - The curse of "downward closure" property of frequent patterns
    - **Any sub-pattern of a frequent pattern is frequent**
    - If $\{a_1, a_2, …, a_{100}\}$ is frequent, then $\{a_1\}$, $\{a_2\}$, …, $\{a_{100}\}$, $\{a_1, a_2\}$, $\{a_1, a_3\}$, …, $\{a_1, a_{100}\}$, $\{a_1, a_2, a_3\}$, … are all frequent! There are about 2^{100} such frequent itemsets!
  - No matter searching in breadth-first (e.g., Apriori) or depth-first (e.g., FPgrowth), if we still adopt the "small to large" step-by-step growing paradigm, we have to examine so many patterns, which leads to combinatorial explosion!

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Colossal Patterns: A Motivating Example

T_1 = 2 3 4 ….. 39 40
T_2 = 1 3 4 ….. 39 40
: .
: .
: .
: .
T_{40}=1 2 3 4 …… 39

T_{41}= 41 42 43 ….. 79
T_{42}= 41 42 43 ….. 79
: .
: .
T_{60}= 41 42 43 … 79

- Let min-support σ= 20
- # of closed/maximal patterns of size 20: about $\binom{40}{20}$
- But there is only one pattern with size close to 40 (*i.e.*, *long* or *colossal*):
  - α= {41,42,…,79} of size 39
- Q: How to find it without generating an exponential number of size-20 patterns?

The existing fastest mining algorithms (*e.g.*, FPClose, LCM) fail to complete running

A new algorithm, *Pattern-Fusion*, outputs this colossal pattern in seconds

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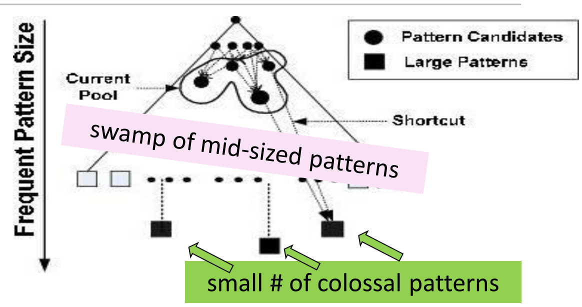
What Is Pattern-Fusion?



- Not strive for completeness (why?)
- Jump out of the swamp of the mid-sized intermediate "results"
- Strive for mining almost complete and representative colossal patterns: identify "short-cuts" and take "leaps"
- Key observation
  - The larger the pattern or the more distinct the pattern, the greater chance it will be generated from small ones
- Philosophy: Collection of small patterns hints at the larger patterns
- Pattern fusion strategy ("not crawl but jump"): Fuse small patterns together in one step to generate new pattern candidates of significant sizes

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Observation: Colossal Patterns and Core Patterns

- Suppose dataset D contains 4 colossal patterns (below) plus many small patterns
  - $\{a_1, a_2, \ldots, a_{50}\}$: 40,
  - $\{a_3, a_6, \ldots, a_{99}\}$: 60,
  - $\{a_5, a_{10}, \ldots, a_{95}\}$: 80,
  - $\{a_{10}, a_{20}, \ldots, a_{100}\}$: 100
- If you check the pattern pool of size-3, you may likely find
  - $\{a_2, a_4, a_{45}\}$: ~40; $\{a_3, a_{34}, a_{39}\}$: ~40;
  - …
  - $\{a_5, a_{15}, a_{85}\}$: ~80, …, $\{a_{20}, a_{40}, a_{85}\}$: ~80
  - …
- If you merge the patterns with similar support, you may obtain candidates of much bigger size and easily validate whether they are true patterns

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Observation: Colossal Patterns and Core Patterns

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- If you check the pattern pool of size-3, you may likely find
  - $\{a_2, a_4, a_{45}\}$: ~40; $\{a_3, a_{34}, a_{39}\}$: ~40; …, $\{a_5, a_{15}, a_{85}\}$: ~80, …, $\{a_{20}, a_{40}, a_{85}\}$: ~80, …
- If you merge the patterns with similar support, you may obtain candidates of much bigger size and easily validate whether they are true patterns
- *Core patterns* of a **colossal pattern α**: A set of **subpatterns of α** that cluster around **α** by sharing a similar support

Note:

- A colossal pattern has far more core patterns than a small-sized pattern
- A random draw from a complete set of patterns of size c would be more likely to pick a core pattern (or its descendant) of a colossal pattern
- **A colossal pattern can be generated by merging a set of its core patterns**

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Robustness of Colossal Patterns

- Let D_α be the set of transactions containing pattern α
- Core Patterns: For a frequent pattern α, a subpattern β is a τ-core pattern of α if β shares a similar support set with α, i.e.,

$$\frac{|D_\alpha|}{|D_\beta|} \geq \tau \qquad 0 < \tau \leq 1$$ where τ is called the core ratio

- Note that for any subpattern β of pattern α, we have $|D_\alpha| \leq |D_\beta|$.

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Robustness of Colossal Patterns

- Core Patterns: For a frequent pattern α, a subpattern β is a τ-core pattern of α if β shares a similar support set with α, i.e.,

$$\frac{|D_\alpha|}{|D_\beta|} \geq \tau \qquad 0 < \tau \leq 1$$ where τ is called the core ratio

- (d, τ)-robustness: A pattern α is *(d, τ)-robust* if *d* is the maximum number of items that can be removed from α for the resulting pattern to remain a τ-core pattern of α
- A (d, τ)-robust pattern α has $\Omega(2^d)$ core patterns. (Lemma A)

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Robustness of Colossal Patterns

- Core Patterns: For a frequent pattern α, a subpattern β is a τ-core pattern of α if β shares a similar support set with α, i.e.,

  $\frac{|D_\alpha|}{|D_\beta|} \geq \tau \qquad 0 < \tau \leq 1$ where τ is called the core ratio
- (d, τ)-robustness: A pattern α is *(d, τ)-robust* if *d* is the maximum number of items that can be removed from α for the resulting pattern to remain a τ-core pattern of α
- For a (d, τ)-robust pattern α, it has $\Omega(2^d)$ core patterns (Lemma A)
- **Robustness of Colossal Patterns:** A colossal pattern tends to have much more core patterns than small patterns
- Such core patterns can be clustered together to form "dense balls" based on pattern distance defined by $Dist(\alpha, \beta) = 1 - \frac{|D_\alpha \cap D_\beta|}{|D_\alpha \cup D_\beta|}$

Lemma A => a random draw in the pattern space will hit somewhere in the ball with high probability!

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The Pattern-Fusion Algorithm

- Initialization (Creating initial pool):
  Use an existing algorithm to mine all frequent patterns up to a small size, e.g., 3
- Iteration (Iterative Pattern Fusion):
  - At each iteration, K seed patterns are randomly picked from the current pattern pool
  - For each seed pattern thus picked, we find all the patterns within a bounding ball centered at the seed pattern
  - All these patterns found are fused together to generate a set of super-patterns
  - All the super-patterns thus generated form a new pool for the next iteration
- Termination: when the current pool contains no more than K patterns at the beginning of an iteration

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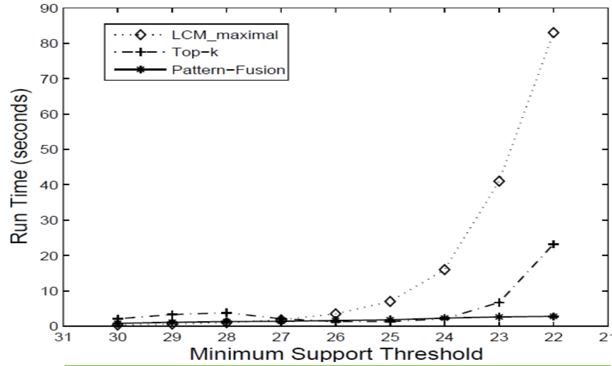
Experimental Results on Data Set: ALL

- ALL: a gene expression clinical data set on ALL-AML leukemia, with 38 transactions, each with 866 columns. There are 1736 items in total.
  - When minimum support is high (e.g., 30), Pattern-Fusion gets all the largest colossal patterns with size greater than 85

Pattern Size	110	107	102	91	86	84	83
The complete set	1	1	1	1	1	2	6
Pattern-Fusion	1	1	1	1	1	1	4
Pattern Size	82	77	76	75	74	73	71
The complete set	1	2	1	1	1	2	1
Pattern-Fusion	0	2	0	1	1	1	1

Mining colossal patterns on a Leukemia dataset



Algorithm runtime comparison on another dataset

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Chapter 7 : Advanced Frequent Pattern Mining

- Pattern Mining: A Road Map
- Mining Diverse Patterns
- Constraint-Based Frequent Pattern Mining
- Mining High-Dimensional Data and Colossal Patterns
- Sequential Pattern Mining
- Graph Pattern Mining

Next Lectures

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Data Mining Assignment 1

- Available tomorrow Wednesday 21-11 2018, 13.00 CET.
- Deadline Friday 7-12 2018, 23:59 CET.
- Groups of 1 – 4 persons.
  - Association Rule mining on a given data set.
  - Data pre-processing (Coding: Python, JAVA, ALGOL68, C++, ...).
  - Data analysis (Weka, R, Python, C++, ...).
  - Data Mining (Weka, other tools or libraries, Python, ...).
  - Find interesting rules (Use interestingness measures, etc.).
  - Technical report (pdf).

Repeat, if necessary.

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