Mining and ranking closed itemsets from large-scale transactional datasets

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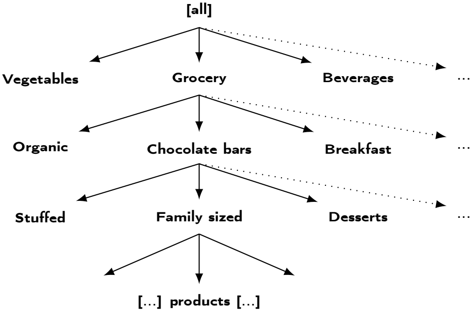
Outline

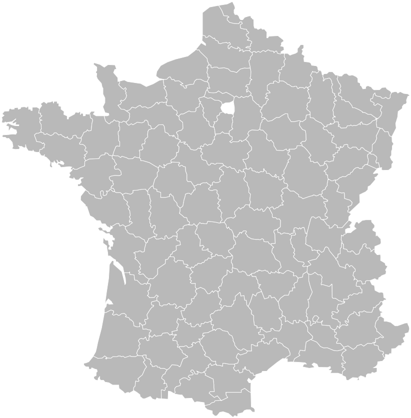
Over year 2013 at Intermarché

One of the major food stores in France

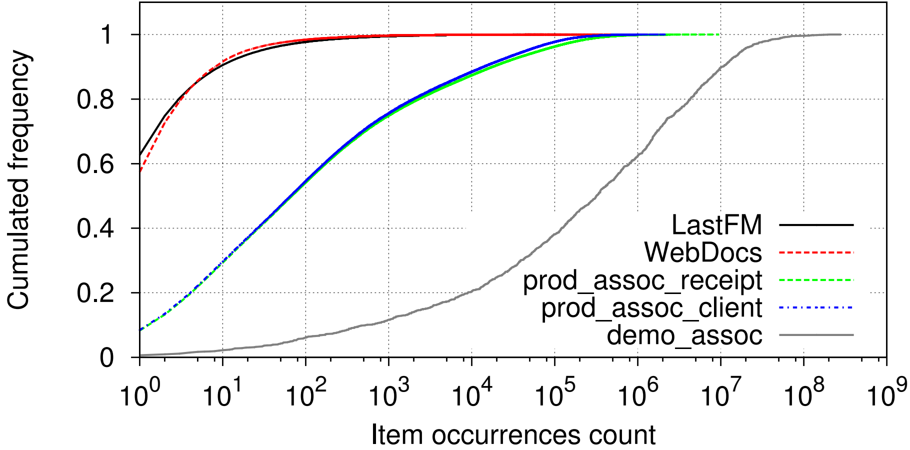
- 9,267,961 customers
- 290,734,163 tickets
- 222,228 different products

Additional data





Items distribution in our experimental datasets.

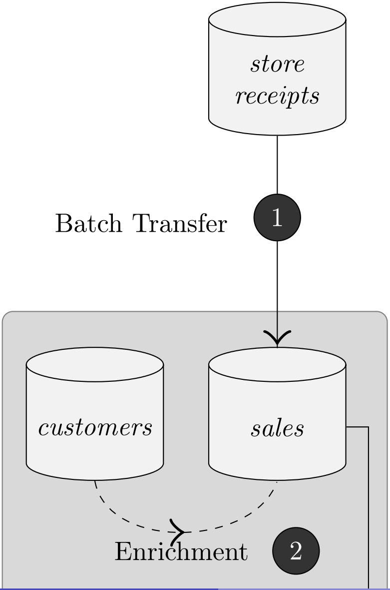


Interesting trends - 3 scenarios

Final users: central marketing analysts.

- `demo_assoc`
  Women below 35 y.o. tend to buy baby food
  People from the Nord *department tend to buy sodas*
- `prod_assoc_client` : per-client products associations
  People who ever baught *vanilla cream* also bought *chocolate cream*
- `prod_assoc_receipt` : per-ticket products associations
  Pork sausage and *mustard* are often baught simultaneously with *dry Riesling*

System overview



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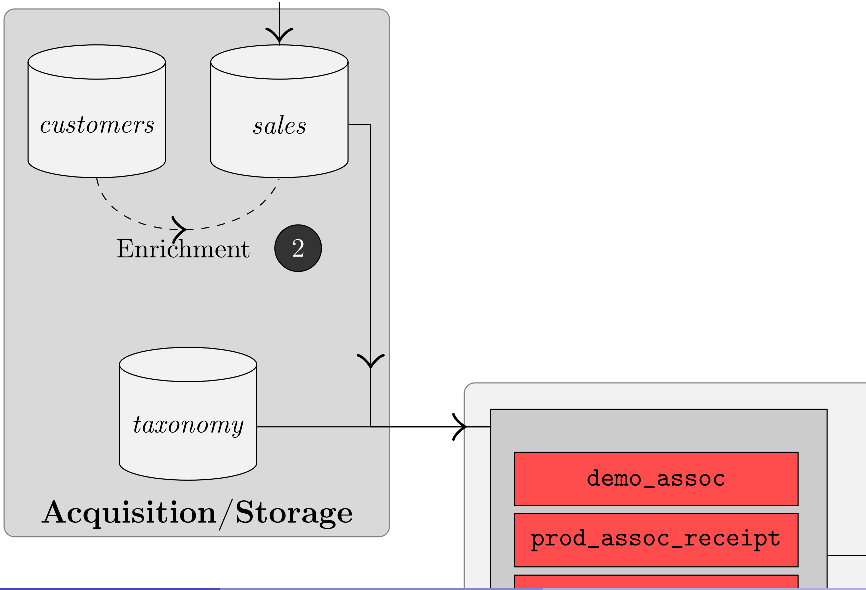

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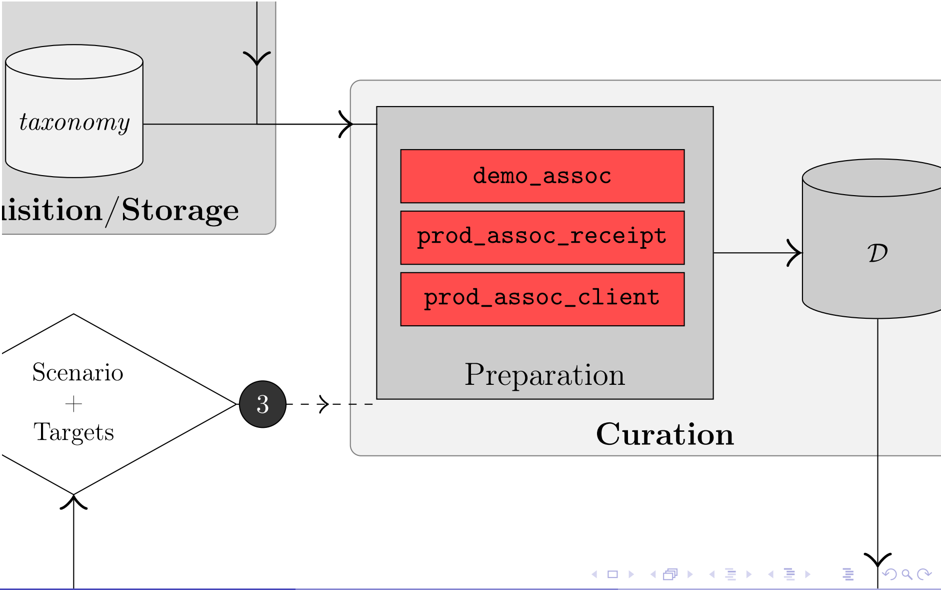

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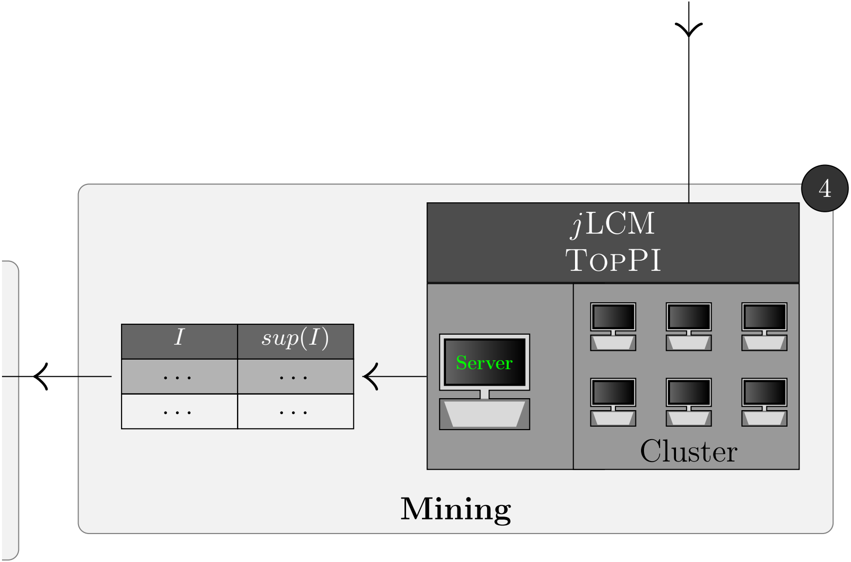

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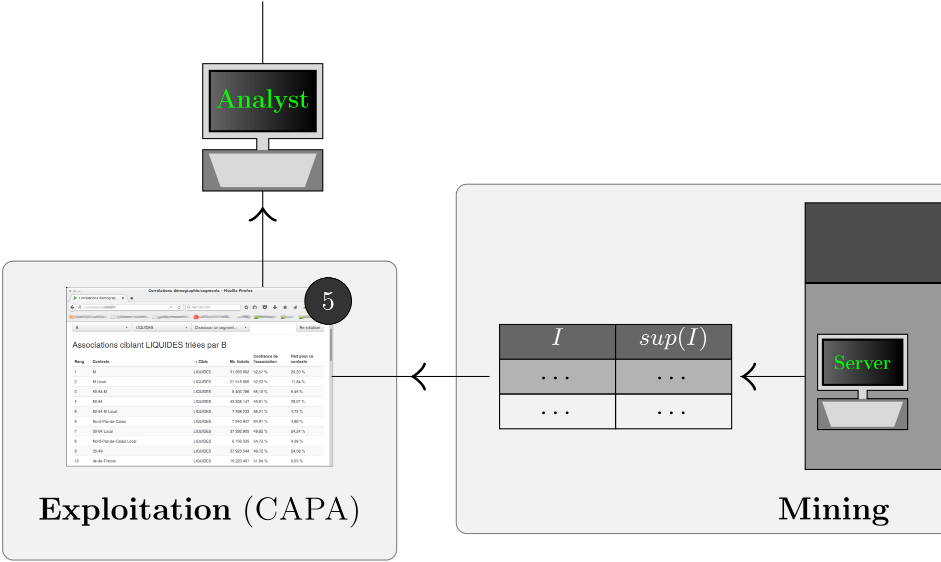

System overview

1. Nightly tickets transfer to the central store
2. Enrichment with taxonomy/demographics (HBase)
3. Curating $\mathcal{D}$: mining scenarios and target definition
    - Analyst may request any form of association rule
    - Over any set of target products/categories/populations
4. Association rules mining
5. Rules ranking and exploration

   TODO: pause and highlight Mining and Ranking

Transactional datasets

Input

Given $\mathcal{I}$, a set of items.
A collection $\mathcal{D}$ of *transactions* $\langle t_1, \ldots, t_n \rangle$, where each $t_j \subseteq \mathcal{I}$.

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A collection $\mathcal{D}$ of *transactions* $\langle t_1, ..., t_n \rangle$, where each $t_j \subseteq \mathcal{I}$.

Output (presented to the analyst)

A collection of *closed* itemsets (CIS),
ie. itemsets P satisfying $\nexists Q \supset P$ s.t. $support_{\mathcal{D}}(P) = support_{\mathcal{D}}(Q)$.

Where $support_{\mathcal{D}}(P) = |\{t \in \mathcal{D} | P \subset t\}|$.

[12] *Discovering frequent closed itemsets for association rules*,
Pasquier, Bastide, Taouil, Lakhal @ ICDT'99

Frequency-based item ordering

Internally, items are represented as integers, indexed by decreasing frequency:

- 0 is the most frequent item
- 1 the second most
- etc...

Item-Centric Mining?

Big transactional datasets

"big" means our datasets contain at least

- Thousands/millions of items in $\mathcal{I}$
- Millions of transactions in $\mathcal{D}$

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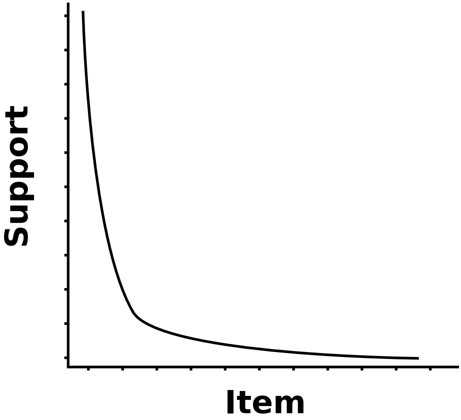
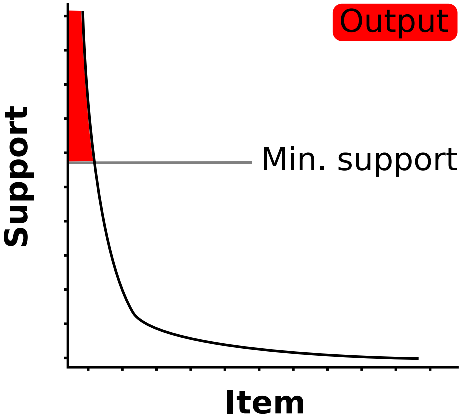


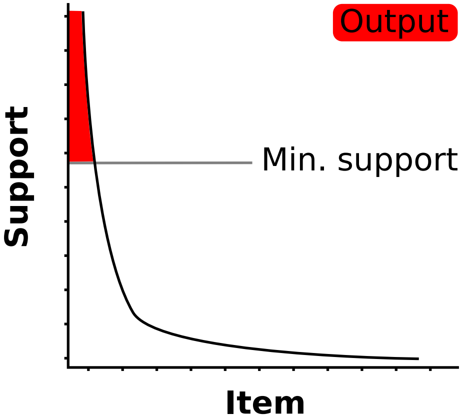
[2] *The Long Tail: Why the Future of Business Is Selling Less of More*, Anderson (2006)

Frequent Itemset Mining on big datasets



- Which minimum support yields interesting results?

Frequent Itemset Mining on big datasets



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- Are all closed itemsets interesting?

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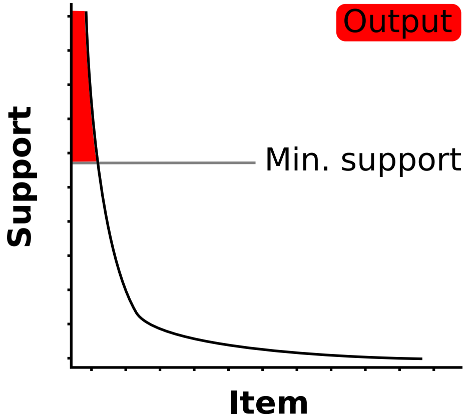
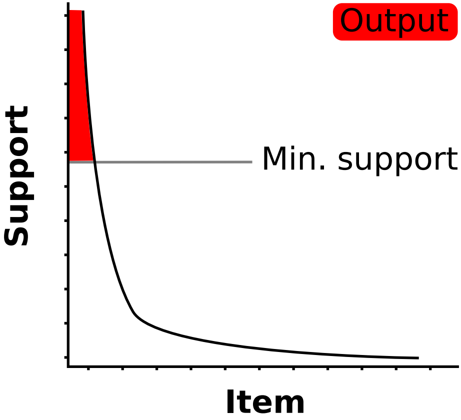


- Which minimum support yields interesting results?
- Are all closed itemsets interesting?
- What about the remaining items?

Item-Centric Mining



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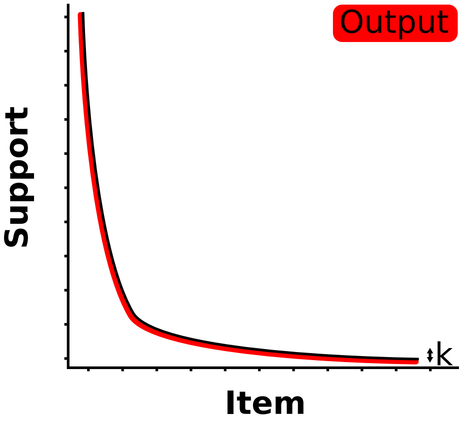

Replace the minimum support by a single parameter, k

Item-Centric Mining

TopPI 's problem statement

Given a transactional dataset $\mathcal{D}$ and an integer k,
return, $\forall i \in \mathcal{I}$, $top(i)$: the k most frequent CIS containing i.

TopPI stands for "Top **P**er **I**tem".

Item-Centric Mining

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We target high-end, multi-core servers.

Related Work

Can we implement Item-Centric Mining using existing methods ?

Our baseline: Item-Centric Mining with TFP

Implementation with a top-k CIS miner, TFP

For each item i:

- Instantiate $\mathcal{D}[i] = \{t \in \mathcal{D} | i \in t\}$
- Launch TFP on $\mathcal{D}[i]$, yielding $top(i)$.

[6] *Mining top-k frequent closed patterns without minimum support.*
Han, Wang, Lu, Tzvetkov @ ICDM'02

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Not sufficient for our datasets

Even with ad-hoc optimizations:

- Keep only top-k-frequent items in $\mathcal{D}[i]$
- Index transactions by item for an instant access to $\mathcal{D}[i]$.

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PFP: parallel FP-Growth

- An algorithm for the MapReduce platform.
- Returns, $\forall i \in \mathcal{I}$, at most k itemsets containing i.

[9] *PFP: parallel FP-growth for query recommendation.*
Li, Wang, Zhang, Zhang, Chang @ RecSys'08

PFP: parallel FP-Growth

- An algorithm for the MapReduce platform.
- Returns, $\forall i \in \mathcal{I}$, at most k itemsets containing i.
- Implementation available in (old versions of) Mahout.
  - Much more resource-consuming than TopPI and its baseline.

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Efficiently enumerating CIS

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Enumeration is inspired from PLCM.

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Négrevergne, Termier, Méhaut, Uno @ HPCS'10

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Enumeration is inspired from PLCM.

(P)LCM shapes the CIS lattice as a tree (depth-first traversal).

Tree property

In a branch, all itemsets P have the same $max(P)$.

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In a branch, an item is combined with items which are more frequent (globally).

The $top(i)$ heaps are firstly filled for the most frequent items.

TopPI 's main program

1. Instantiate a k-heap $top(i), \forall i$
2. Progressively fill them by enumerating CIS...

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2. Progressively fill them by enumerating CIS... **and prune the enumeration when the concerned items already have a complete $top(i)$.**

We can poll each item's heap via $min(top(i))$: the smallest itemset support in $top(i)$.

An example (Fig.4.3, p.42)

k	$top(0)$	$top(1)$	$top(2)$	$top(3)$
1				
2				
$min(top(i))$	2	2	2	2

An example (Fig.4.3, p.42)

k	$top(0)$	$top(1)$	$top(2)$	$top(3)$
1	$\{0\}, 6$			
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$\{0, 1\}$ is not closed

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k	$top(0)$	$top(1)$	$top(2)$	$top(3)$
1	$\{0\}, 6$	$\{1\}, 5$	$\{2\}, 5$	
2	$\{0, 2\}, 4$		$\{0, 2\}, 4$	
$min(top(i))$	4	2	4	2

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1	$\{0\}, 6$	$\{1\}, 5$	$\{2\}, 5$	
2	$\{0, 2\}, 4$		$\{0, 2\}, 4$	
$min(top(i))$	4	2	4	2

$\{1, 2\}$ is not closed

An example (Fig.4.3, p.42)

k	$top(0)$	$top(1)$	$top(2)$	$top(3)$
1	$\{0\}, 6$	$\{1\}, 5$	$\{2\}, 5$	$\{3\}, 5$
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$min(top(i))$	4	2	4	2

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2	$\{0, 2\}, 4$		$\{0, 2\}, 4$	$\{0, 3\}, 4$
$min(top(i))$	4	2	4	4

$\{1, 3\}$ is not closed

An example (Fig.4.3, p.42)

k	$top(0)$	$top(1)$	$top(2)$	$top(3)$
1	$\{0\}, 6$	$\{1\}, 5$	$\{2\}, 5$	$\{3\}, 5$
2	$\{0, 2\}, 4$		$\{0, 2\}, 4$	$\{0, 3\}, 4$
$min(top(i))$	4	2	4	4

$support_{\mathcal{D}[3]}(2) = 4$, can we prune $\{2, 3\}$?

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k	$top(0)$	$top(1)$	$top(2)$	$top(3)$
1	$\{0\}, 6$	$\{1\}, 5$	$\{2\}, 5$	$\{3\}, 5$
2	$\{0,2\}, 4$		$\{0,2\}, 4$	$\{0,3\}, 4$
$min(top(i))$	4	2	4	4

$support_{\mathcal{D}[\{2,3\}]}(0) = 3$, can we prune $\{0, 2, 3\}$?

An example (Fig.4.3, p.42)

k	$top(0)$	$top(1)$	$top(2)$	$top(3)$
1	$\{0\}, 6$	$\{1\}, 5$	$\{2\}, 5$	$\{3\}, 5$
2	$\{0, 2\}, 4$	$\{0, 1, 2, 3\}, 2$	$\{0, 2\}, 4$	$\{0, 3\}, 4$
$min(top(i))$	4	2	4	4

An example

After enumerating $\{c, d\}(support = 100)$
$\rightarrow$ we try to insert it in $top(c)$ and $top(d)$.

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After enumerating $\{c, d\}$($support = 100$)
$\rightarrow$ we try to insert it in $top(c)$ and $top(d)$.

Then, before attempting to find $\{b, c, d\}$

- we know that $support_{\mathcal{D}}(\{b, c, d\}) \leq 100$
- Can we prune if $top(b)$, $top(c)$ and $top(d)$ already have k CIS of support ≥ 100?
  ie. $min(top(b)) \geq 100$, idem for c and d.

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- Can we prune if $top(b)$, $top(c)$ and $top(d)$ already have k CIS of support ≥ 100?
  ie. $min(top(b)) \geq 100$, idem for c and d.

Deeper in the enumeration...

Pruning $\{b, c, d\}$ implies to prune $\{a, b, c, d\}$.
Maybe $\{a, b, c, d\}$ is a relevant result for $top(a)$!

If $min(top(a)) \leq 100$, we cannot prune $\{b, c, d\}$.

TopPI 's challenges

- guarantee the completeness of all *top*(i)

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- evaluate *quickly* if the enumeration of some CIS can be avoided
  - How many $min(top(i))$ invocations to decide (correctly) to prune?

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- guarantee the completeness of all $top(i)$
- evaluate *quickly* if the enumeration of some CIS can be avoided
  - How many $min(top(i))$ invocations to decide (correctly) to prune?
- filter intermediate datasets without a user-provided minimum support

Pruning in TopPI

In a sub-branch rooted at an itemset P,
all closed itemsets Q will verify:

- $max(Q) = max(P)$
- $support_{\mathcal{D}}(Q) \leq support_{\mathcal{D}}(P)$

TopPI 's basic pruning principle

If, $\forall i < max(P), min(top(i)) \geq support_{\mathcal{D}}(P)$,
then the branch rooted at P can be pruned.

Deciding quickly to prune with prefix short-cutting

A rigorous pruning requires testing $min(top(i)), \forall i < max(P), \forall P$.

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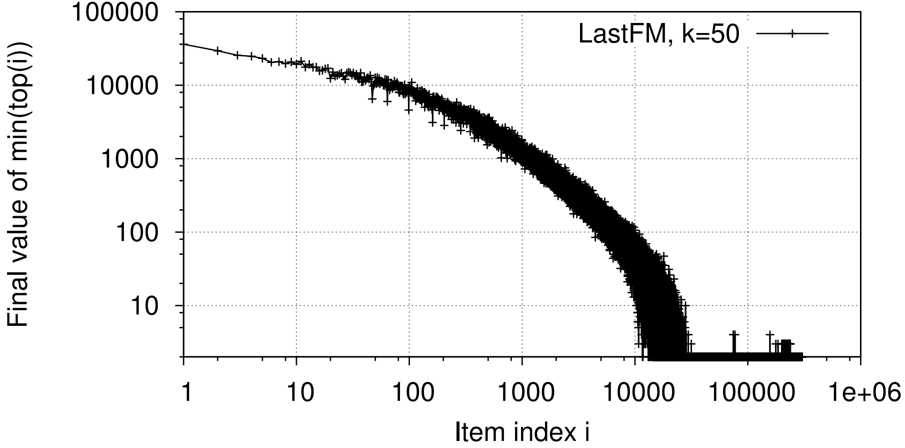

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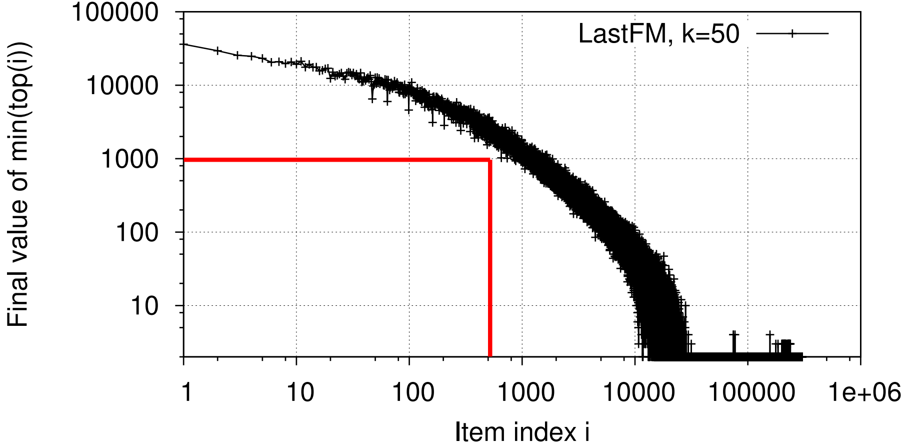
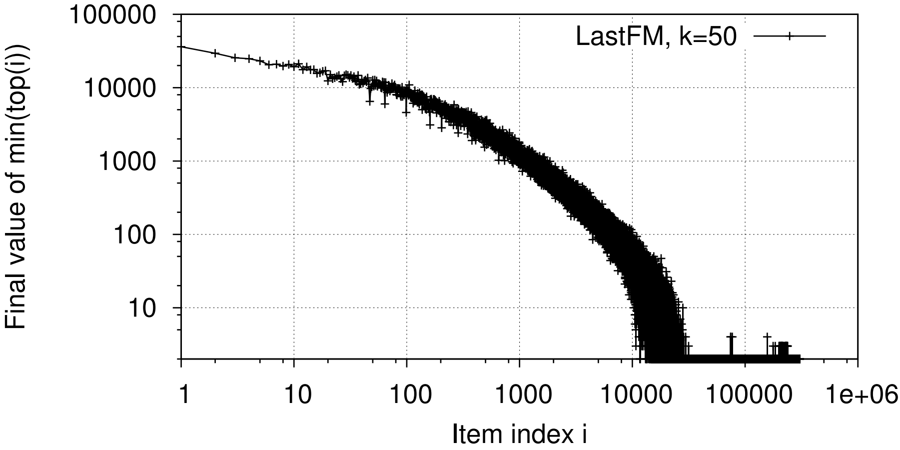


Here if $support_{\mathcal{D}}(P) \leq 1000$, no need to test $min(top(i))$ for $i < 500$.

Dynamic threshold adjustment



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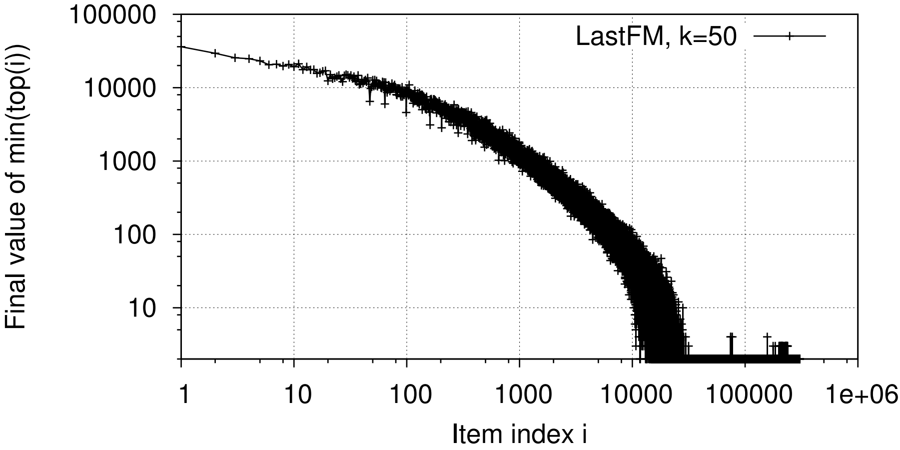

Dynamic threshold adjustment

Finding a minimum frequency threshold adapted to each CIS branch.

Parallelization

As in PLCM, we dispatch each CIS branch between threads.
$\rightarrow$ excellent speed-up.

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Concurrent accesses in TopPI

Most access to the *top* collections are *read* accesses.

Two experiments

1. **Baseline comparison**
   apply a top-k CIS miner on each item's supporting transactions.

2. **Individual impact of our contributions**
   by disabling each one.

Experiments set-up

Datasets

Dataset	$\|\mathcal{I}\|$	$\|\mathcal{D}\|$	File size
Tickets	$222,228$	$290,734,163$	24GB
Clients	$222,228$	$9,267,961$	13.3GB
LastFM	$1,206,195$	$1,218,831$	277MB

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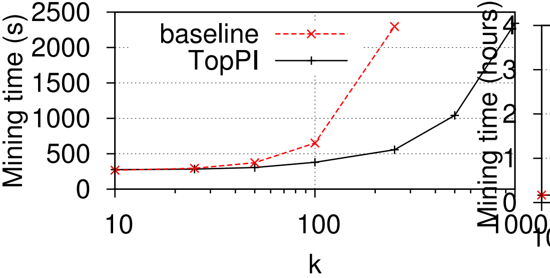
We measure run-times

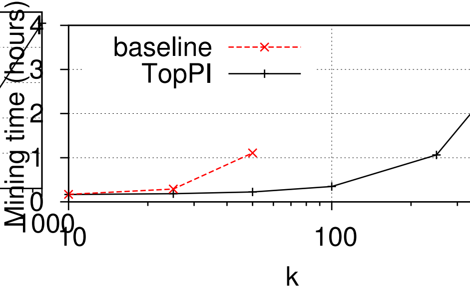
- Averaged over 3 attempts
- Not including the time to load $\mathcal{D}$.
- On a single server:
  - 2 Intel Xeon E5-2650, providing 16 cores with Hyper Threading
  - 128GB of RAM

All programs are implemented in Java.

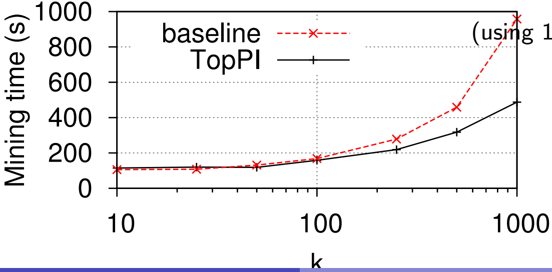
TopPI and Baseline run-times



prod_assoc_receipt



prod_assoc_client



(using 16 threads)

Contributions Impact

Dataset	TopPI
`prod_assoc_receipt`	222 s.
`prod_assoc_client`	661 s.
LastFM	116 s.

TopPI run-times (in seconds), using 32 threads and $k = 50$.

Contributions Impact

Dataset	TopPI	Without 3.5
prod_assoc_receipt	222 s.	1136 ($\times 5$)
prod_assoc_client	661 s.	Out of mem.
LastFM	116 s.	177 (+53%)

TopPI run-times (in seconds), using 32 threads and $k = 50$.

Section 4.2.5: Dynamic threshold adjustment

Contributions Impact

Dataset	TopPI	Without 3.5	Without 3.6
`prod_assoc_receipt`	222 s.	1136 ($\times$5)	230 (+4%)
`prod_assoc_client`	661 s.	Out of mem.	4177 ($\times$6)
LastFM	116 s.	177 (+53%)	150 (+29%)

TopPI run-times (in seconds), using 32 threads and $k = 50$.

Section 4.2.5: Dynamic threshold adjustment
Section 4.2.4: Pruning with prefix short-cutting

Contributions Impact

Dataset	TopPI	Without 3.5	Without 3.6	Without bo
`prod_assoc_receipt`	222 s.	1136 ($\times 5$)	230 (+4%)	3.8 hours, $\times$
`prod_assoc_client`	661 s.	Out of mem.	4177 ($\times 6$)	Out of mem
LastFM	116 s.	177 (+53%)	150 (+29%)	243 ($\times$2

TopPI run-times (in seconds), using 32 threads and $k = 50$.

Section 4.2.5: Dynamic threshold adjustment
Section 4.2.4: Pruning with prefix short-cutting

An example on retail data

Our `prod_assoc_receipt` dataset represents 290 million receipts from 1800 french supermarkets.

Which sets of products frequently include sushi rice?

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Which sets of products frequently include sushi rice?

- $14,887$ ($< 0.005\%$) of these tickets contain "sushi rice"
- 431 ($< 0,00015\%$)
  contain "nori seaweed, wasabi, sushi rice, rice vinegar"

An example on retail data

Our `prod_assoc_receipt` dataset represents 290 million receipts from 1800 french supermarkets.

Which sets of products frequently include sushi rice?

- $14,887$ ($< 0.005\%$) of these tickets contain "sushi rice"
- 431 ($< 0,00015\%$)
  contain "nori seaweed, wasabi, sushi rice, rice vinegar"
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Requires respectively $k = 23$ and $k = 255$.

Inputs

- Customer base
  Demographic groups as attributes - *age range, gender, region*
- Products taxonomy
  cat(chocolate cream) = {*Fresh food, Dairy, Ultra fresh, Desserts*}
- Tickets
  Centralized nation-wide every night

\+ a set of *targets*: categories or products to be studied.

Dealing with a large results set

With proper preparation and constrains

- mining association rules is feasible in a batch

But

- A target product/category yields 100 to 10,000 associations
- Casual analysis concerns dozens targets
- Analyst have the time for 10 “top” rules (or at most 20)

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We need to sort rules

Sorting association rules

Existing work provides more than 39 quality measures [geng2006ACM,Lenca2007].

- Which one should we pick ?
- Are prior studies relevant to tickets analysis?
- In some domains reference rules can be found [LeSANER15]

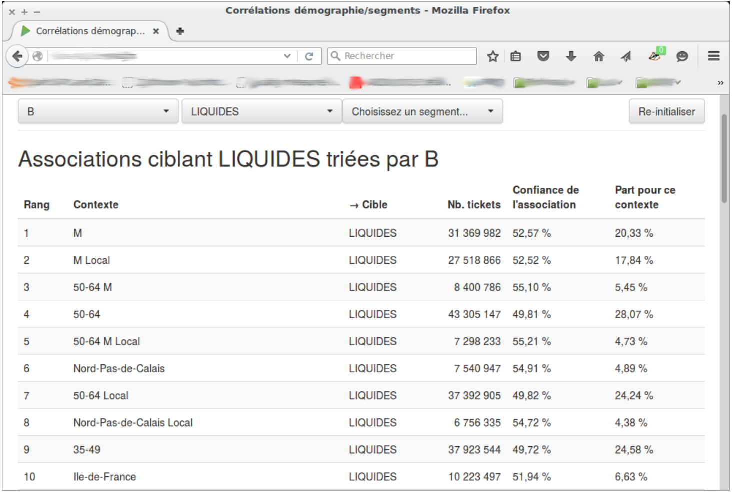
TODO refs complètes

CAPA: Comparative Analysis of PAtterns

We present CAPA , the system allowing us to answer:

1. In terms of ranking, how different are interestingness measures?
2. Which ones are meaningful to marketing analysts at this scale?

The exploration application



Corrélations démographie/segments - Mozilla Firefox

Corrélations démograp...

Rechercher

B | LIQUIDES | Choisissez un segment... | Re-initialiser

Associations ciblant LIQUIDES triées par B

Rang	Contexte	→ Cible	Nb. tickets	Confiance de l'association	Part pour ce contexte
1	M	LIQUIDES	31 369 982	52,57 %	20,33 %
2	M Local	LIQUIDES	27 518 866	52,52 %	17,84 %
3	50-64 M	LIQUIDES	8 400 786	55,10 %	5,45 %
4	50-64	LIQUIDES	43 305 147	49,81 %	28,07 %
5	50-64 M Local	LIQUIDES	7 298 233	55,21 %	4,73 %
6	Nord-Pas-de-Calais	LIQUIDES	7 540 947	54,91 %	4,89 %
7	50-64 Local	LIQUIDES	37 392 905	49,82 %	24,24 %
8	Nord-Pas-de-Calais Local	LIQUIDES	6 756 335	54,72 %	4,38 %
9	35-49	LIQUIDES	37 923 544	49,72 %	24,58 %
10	Ile-de-France	LIQUIDES	10 223 497	51,94 %	6,63 %

Interestingness measures

- We have rules as $A \rightarrow b$, where b is a target category/product
- We know how many transactions contain A, b, and $A \cup \{b\}$

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We select **39 interestingness measures** relying on these numbers only (See Table 4)
How do the resulting lists compare?

Evaluation method

We let experts judge which top-results are interesting.
But 39 rankings is too much.

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But 39 rankings is too much.

We evaluate in two steps:

1. Automatic distinction of 5 families of measures, which are ranking similarly
   denoted $G_{\{1,2,3,4,5\}}$
2. The user study itself, where we compare those 5 families.

Comparing rankings

In each scenario, we generate rules, rank them, and their 39 scores.

We do pairwise comparisons of the sorted lists using:

- Spearman's rank correlation coefficient
- Kendall's τ
- Overlap@20
- NDCC: Normalized Discounted Correlation Coefficient
  our adaptation of NDCG[?]

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Similarity coefficients are averages over 64 targets

Clustering

Apply average linkage over the averaged correlation matrix.

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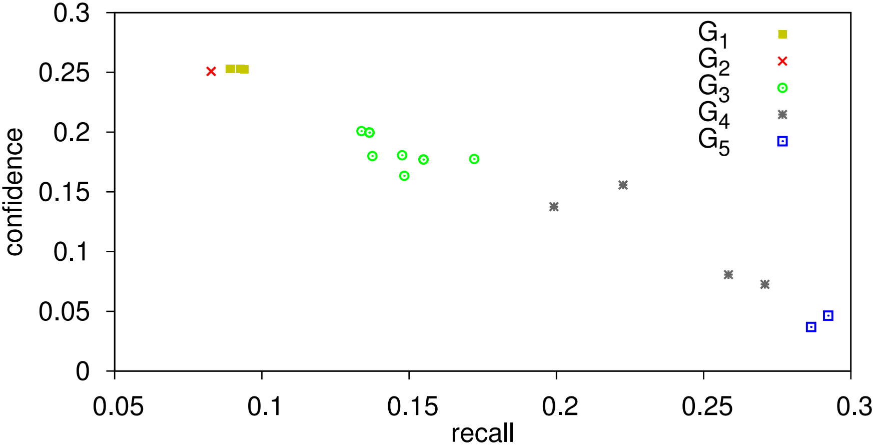
Apply average linkage over the averaged correlation matrix.

Yields 5 clusters, $G_{\{1,2,3,4,5\}}$

- Many measures rank as *confidence* (in G_1)
- Families consistent over `demo_assoc` , `prod_assoc_client` and `prod_assoc_receipt`
- Some rankings are even equal
- Ranking by *p-value* is similar to simpler measures.

Measures families' behavior



Average recall/confidence of the top-20 results of each measure

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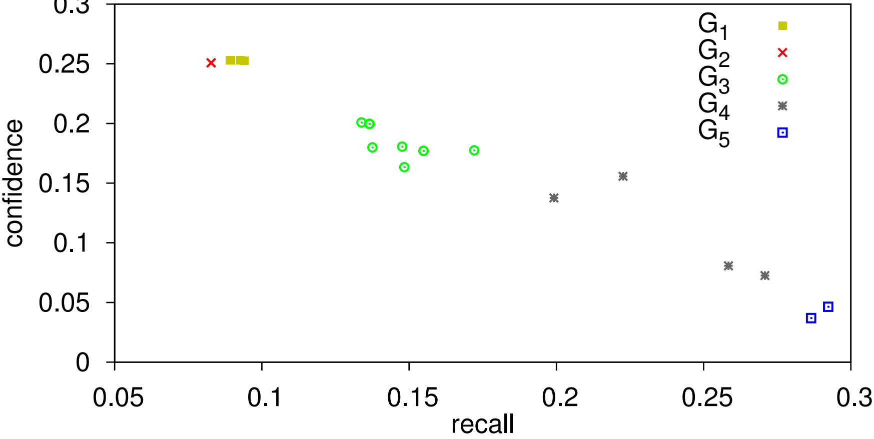

Average recall/confidence of the top-20 results of each measure

Which one are more meaningful to marketing experts?

User study

2 marketing experts from Intermaché are given a free access to results from `demo_assoc` , `prod_assoc_client` and `prod_assoc_receipt` .

Rules can be ranked according to a representative measure of each of the 5 clusters - presented as A, B, C, D, E.

User study

Experts are asked for their favorite(s) measure(s) in each scenario.

Other questions from their interview:

- What is your first impression?

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  10, at most 20
- Do those rules overlap with your experience or former studies?
  $\rightarrow$ their first evaluation criterion

User study: on demographic rules

- Preference towards families G_1 and G_3
- Expect finding *both* extremes of associations
  - Strong ones: *{50-64}* $\rightarrow$ *pet food*
  - Weak ones: *{<35, Paris}* $\rightarrow$ *pet food*

User study: on products associations

Additional option: associate only with products from the same category.

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The key factor: differenciating
{vanilla cream, emmental}$\rightarrow$ *chocolate cream* (32% confidence)
with
{vanilla cream}$\rightarrow$ *chocolate cream* (31% confidence)

CAPA 's main results

- In terms of ranking, quality measures may be surprisingly similar
- Simple computations (Confidence, Piatetsky-Shapiro's) yield good satisfaction

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Possible evolutions

- Switching the system to in-memory storage
- Presentation enhancements of ranked rules

Perspectives

- Going distributed

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  - MapReduce version of TopPI currently under review

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- Going distributed
  - MapReduce version of TopPI currently under review
- Re-ranking each *top*(i)

cf. *Testing Interestingness Measures in Practice: A Large-Scale Analysis of Buying Patterns*, Kirchgessner, Leroy, Amer-Yahia, Mishra @ DSAA'16

Going distributed

CIS enumeration is slower with long transactions ($>$ 1000 items)

The WebDocs dataset, with $k = 10$

TopPI takes almost 10 hours.
The baseline only fills 3% of $top(i)$ in a day.

http://fimi.ua.ac.be/data/webdocs.dat.gz

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We created a MapReduce version of TopPI

- currently under review

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Which value is relevant for k?

Back to the most frequent CIS containing sushi rice:

Rank	Support	Itemset
1	$14,887$	"sushi rice"
...		...
24	431	"sushi rice, nori seaweed, wasabi, rice vinegar"
...		...
255	133	"sushi rice, nori seaweed, wasabi, soy sauce"

Re-ranking

Itemsets in each $top(i)$ are sorted by decreasing frequency.

- each $top(i)$ can be re-ordered with a finer quality measure
- keep only the $n < k$ results

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Itemsets in each $top(i)$ are sorted by decreasing frequency.

- each $top(i)$ can be re-ordered with a finer quality measure
- keep only the $n < k$ results
- typically $k \in [100; 500]$ and $n \in [10; 50]$
- may require an additional pass on the dataset

cf. *Testing Interestingness Measures in Practice: A Large-Scale Analysis of Buying Patterns*, Kirchgessner, Leroy, Amer-Yahia, Mishra @ DSAA'16

Item-Centric Mining in a nutshell

Return, for each item, its k most frequent closed itemsets.

- intuitive parameter, k
- intuitive results organization, per item.

The TopPI algorithm

- efficiently computes all top-k lists at once
- scales from a laptop to a high-end server
- robust from 1 to 300 million transactions

Source code (including Hadoop version) available at
`https://github.com/slide-lig/TopPI`