

The Eclat Algorithm

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Mohammed Javeed Zaki: Scalable Algorithms for Association Mining. IEEE Trans. Knowl. Data Eng. 12(3): 372-390 (2000)

Source code and datasets available in the **SPMF library**

FREQUENT ITEMSET MINING

The problem of frequent itemset mining

- Let there be a numerical value minsup, set by the user.
- Frequent itemset mining (FIM) consists of enumerating all
 frequent itemsets, that is itemsets having a support greater or
 equal to minsup.

| Transaction | Items appearing in the transaction | |
|-------------|------------------------------------|--|
| TI | {pasta, lemon, bread, orange} | |
| T2 | {pasta, lemon} | |
| Т3 | {pasta, orange, cake} | |
| T4 | {pasta, lemon, orange, cake} | |

Example

| Transaction | Items appearing in the transaction |
|-------------|------------------------------------|
| TI | {pasta, lemon, bread, orange} |
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For minsup = 2, the frequent itemsets are:

{lemon}, {pasta}, {orange}, {cake}, {lemon, pasta}, {lemon, orange}, {pasta, orange}, {pasta, cake}, {orange, cake}, {lemon, pasta, orange}

For the user, choosing a high minsup value,

- will reduce the number of frequent itemsets,
- will increase the speed and decrease the memory required for finding the frequent itemsets

THE ECLAT ALGORITHM

Mohammed Javeed Zaki: Scalable Algorithms for Association Mining. IEEE Trans. Knowl. Data Eng. 12(3): 372-390 (2000)



- ECLAT (Equivalence CLAss Transformation)
- An algorithm that is generally faster than Apriori.
- Utilize a depth-first search (contrarily to Apriori/AprioriTID).
- Utilize a vertical database (as AprioriTID)
- Utilize the concept of equivalence classes of itemsets sharing the same prefix.

• Let $I = \{I_1, I_2, ... Im\}$ be the set of items (products) sold in a retail store.

For example:

I= {pasta, lemon, bread, orange, cake}

• An itemset X is a set of items $(X \subseteq I)$.

e.g. {pasta, lemon} size = 2



An itemset is said to be of size k if it contains k items.

Itemsets of size 1:

{pasta}, {lemon}, {bread}, {orange}, {cake}

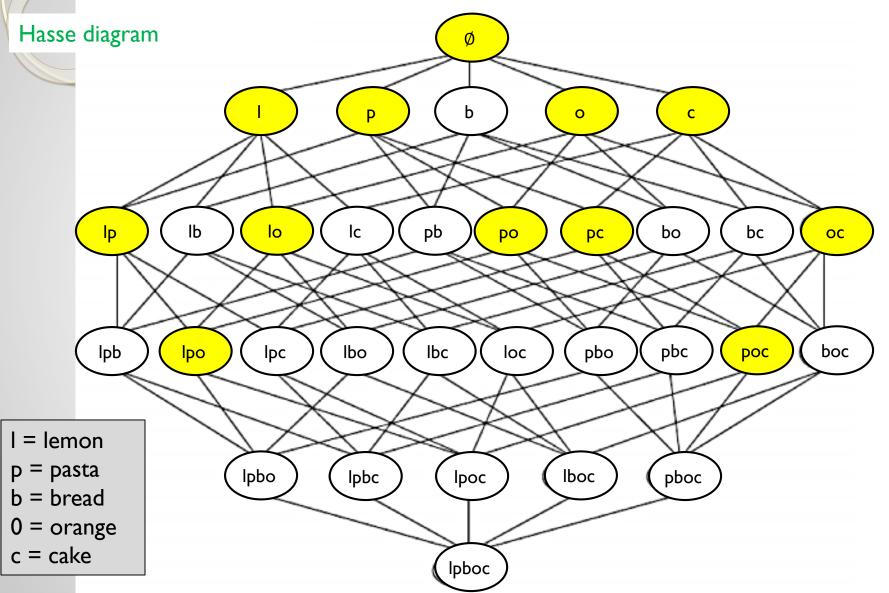
Itemsets of size 2:

{pasta, lemon}, {pasta, bread} {pasta, orange}, {pasta, cake}, {lemon, bread}, {lemon orange}, ...

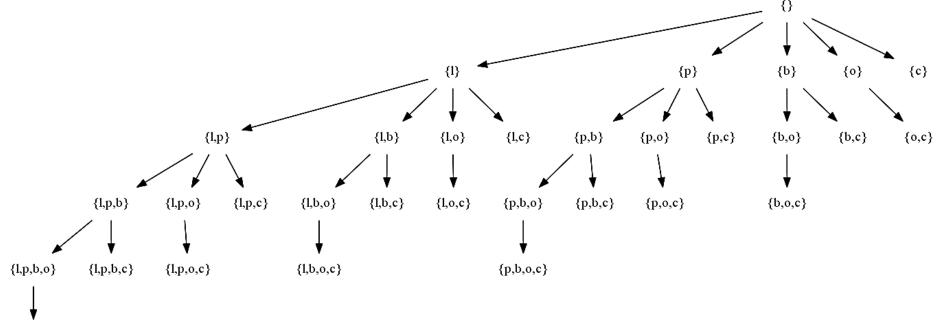
Total order

- Without loss of generality, we suppose that all transactions and itemsets are sorted according to a total order <.
- This total order < can for example be the alphabetical order.
- e.g.pasta < lemon < bread < orange < cake









I = lemon

 $\{l,p,b,o,c\}$

p = pasta

b = bread

0 = orange

c = cake

The search space can be visualized as a set enumeration tree

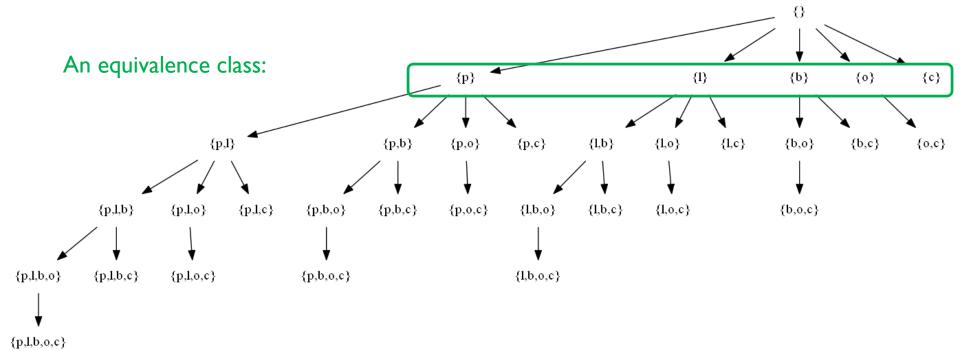
- Rymon, 1992

Equivalence class

- Let there be two itemsets X and Y of size k.
- X and Y belong to the same equivalence class if the k-1 first items of X and Y are the same according to the total order.
- e.g. An equivalence class:

```
{pasta, lemon, bread},
{pasta, lemon, orange},
{pasta, lemon, cake}
```





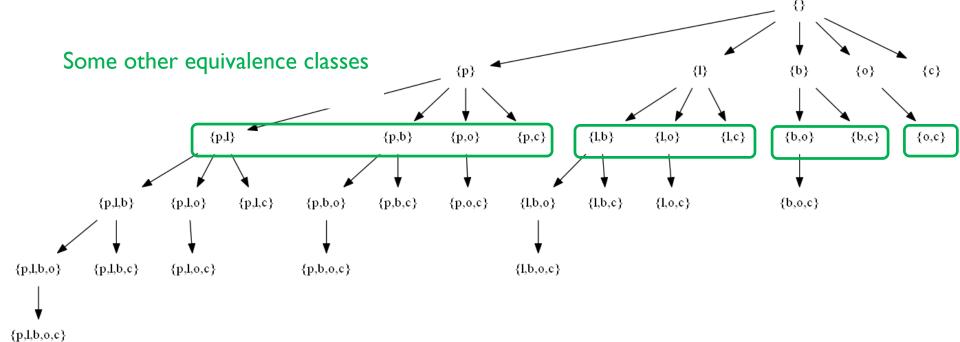
I = lemon

p = pasta

b = bread

0 = orange





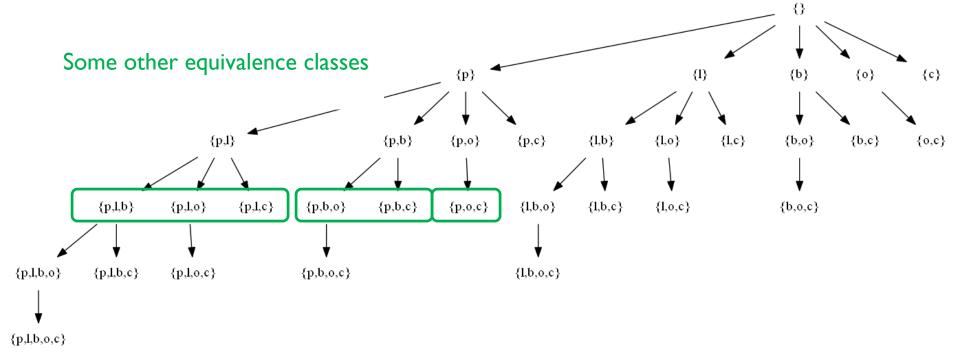
I = lemon

p = pasta

b = bread

0 = orange





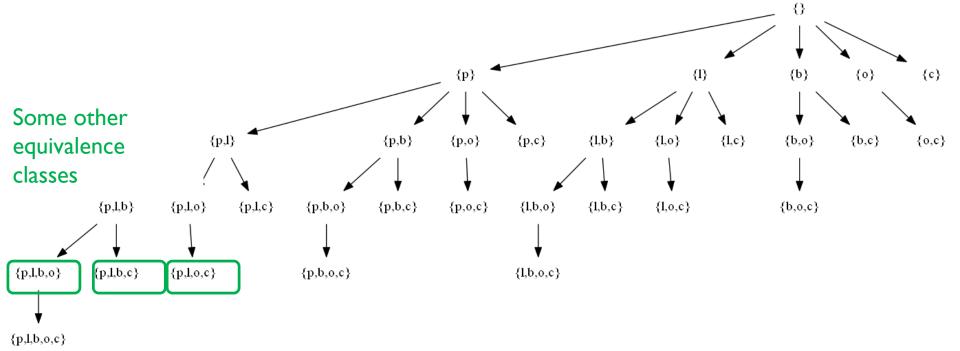
I = lemon

p = pasta

b = bread

0 = orange





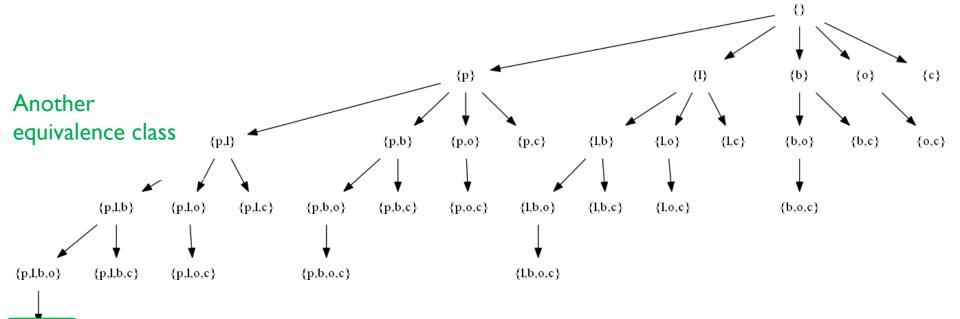
I = lemon

p = pasta

b = bread

0 = orange





I = lemon

 $\{p,l,b,o,c\}$

p = pasta

b = bread

0 = orange

Step I: Scan the database to create a vertical representation of the database.

| T | Transaction | Items appearing in the transaction |
|---|-------------|------------------------------------|
| | T1 | {pasta, lemon, bread, orange} |
| | T2 | {pasta, lemon} |
| | Т3 | {pasta, orange, cake} |
| | T4 | {pasta, lemon, orange, cake} |

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| T4 | {pasta, lemon, orange, cake} | |

| item | transactions <u>containing</u> the item | |
|--------|---|--|
| pasta | T1, T2, T3, T4 | |
| lemon | T1, T2 ,T4 | |
| bread | T1 | |
| orange | T1, T3, T4 | |
| cake | T3, T4 | |

Step I: Scan the database to create a vertical representation of the database.

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| T4 | {pasta, lemon, orange, cake} | |

| <u> </u> | | |
|----------------------------------|--|--|
| transactions containing the item | | |
| T1, T2, T3, T4 | | |
| T1, T2 ,T4 | | |
| T1 | | |
| T1, T3, T4 | | |
| T3, T4 | | |
| | | |

Each line is called a TID-list (Transaction ID List)

Step 2: This is the first equivalence class.

| pasta | T1, T2, T3, T4 |
|--------|----------------|
| lemon | T1, T2 ,T4 |
| bread | T1 |
| orange | T1, T3, T4 |
| cake | T3, T4 |

Step 2: This is the first equivalence class.

| pasta | T1, T2, T3, T4 |
|--------|----------------|
| lemon | T1, T2 ,T4 |
| broad | T1 |
| Dioud | |
| orange | T1, T3, T4 |
| cake | T3, T4 |

ECLAT eliminates infrequent itemsets

$$(minsup = 2)$$

Step 2: This is the first equivalence class.

| pasta | T1, T2, T3, T4 |
|--------|----------------|
| lemon | T1, T2 ,T4 |
| broad | T1 |
| DIOGG | |
| orange | T1, T3, T4 |
| cake | T3, T4 |

ECLAT eliminates infrequent itemsets

$$(minsup = 2)$$

ECLAT outputs the frequent itemsets with I items {pasta}, {lemon}, {orange}, {cake}

Step 3: ECLAT combines combine itemsets of the equivalence class to generate equivalence classes of size K+I

| Pasta | T1, T2, T3, T4 |
|--------|----------------|
| lemon | T1, T2 T4 |
| Orange | T1, T3, T4 |
| Cake | T3, T4 |



| pasta, lemon | T1,T2,T4 |
|---------------|----------|
| pasta, orange | T1,T3,T4 |
| pasta, cake | T3,T4 |

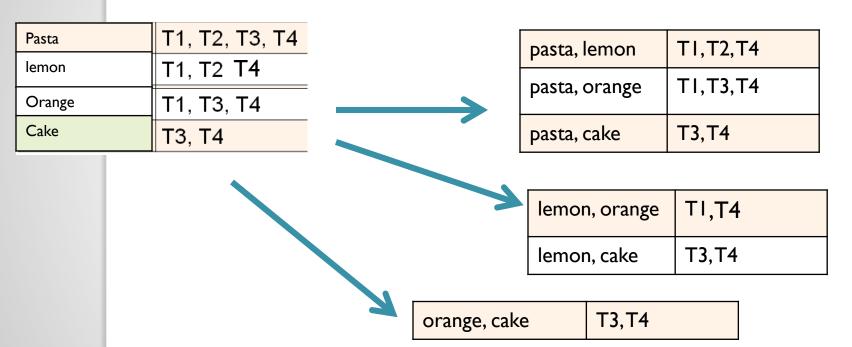
Step 3: ECLAT combines combine itemsets of the equivalence class to generate equivalence classes of size K+I

| Pasta | T1, T2, T3, T4 |
|--------|----------------|
| lemon | T1, T2 T4 |
| Orange | T1, T3, T4 |
| Cake | T3, T4 |

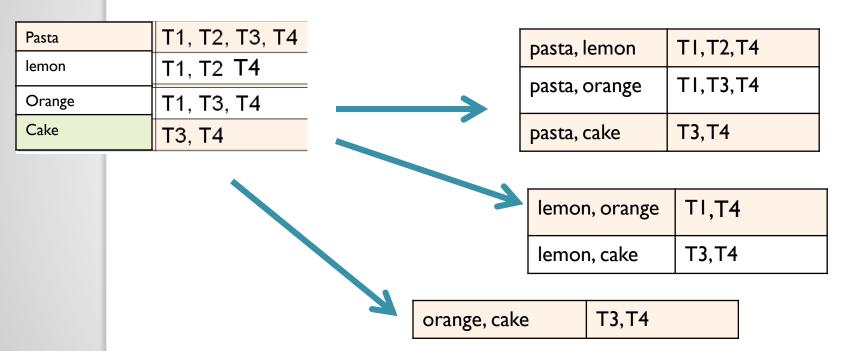
| pasta, lemon | T1,T2,T4 |
|---------------|----------|
| pasta, orange | T1,T3,T4 |
| pasta, cake | T3,T4 |

| lemon, orange | TI,T4 |
|---------------|-------|
| lemon, cake | T3,T4 |

Step 3: ECLAT combines combine itemsets of the equivalence class to generate equivalence classes of size K+I



Step 3: ECLAT combines combine itemsets of the equivalence class to generate equivalence classes of size K+I



Then, ECLAT eliminates infrequent itemsets and output the frequent itemsets: {pasta,lemon}, {pasta,orange}, {pasta,cake}, {lemon,cake}, {orange, cake}, {lemon,orange}



Step 4: ECLAT recursively process each equivalence class in the same way. Consider the first one:

| pasta, lemon | T1,T2,T4 |
|---------------|----------|
| pasta, orange | T1,T3,T4 |
| pasta, cake | T3,T4 |

Step 4: ECLAT recursively process each equivalence class in the same way. Consider the first one:

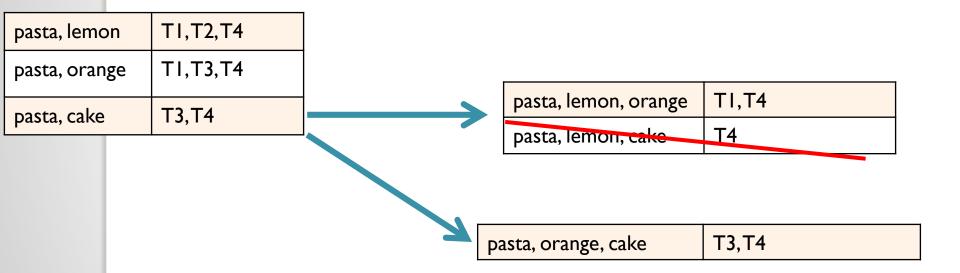
| pasta, lemon | T1,T2,T4 |
|---------------|----------|
| pasta, orange | T1,T3,T4 |
| pasta, cake | T3,T4 |

| pasta, lemon, orange | TI,T4 |
|----------------------|-------|
| pasta, lemon, cake | T4 |

Step 4: ECLAT recursively process each equivalence class in the same way. Consider the first one:

| pasta, lemon | T1,T2,T4 | | | |
|---------------|----------|---|----------------------|----------|
| pasta, orange | T1,T3,T4 | | | T |
| pasta, cake | T3,T4 | | pasta, lemon, orange | TI,T4 |
| pasta, care | 10,11 | | pasta, lemon, cake | T4 |
| | | | | <u>'</u> |
| | | 7 | oasta, orange, cake | T3,T4 |

Step 4: ECLAT recursively process each equivalence class in the same way. Consider the first one:



ECLAT eliminates infrequent itemsets and output the frequent itemsets

{pasta,orange, cake} {pasta, lemon, orange}

Step 4: ECLAT recursively process each equivalence class in the same way. Consider the next equivalence class:

| lemon, orange | TI |
|---------------|-------|
| lemon, cake | T3,T4 |

Step 4: ECLAT recursively process each equivalence class in the same way. Consider the next equivalence class:

| lemon, orange | TI | 1 |
|---------------|-------|-------------------|
| , , , , , , | | lemon,orange,cake |
| | | |
| lemon, cake | T3,T4 | |

Step 4: ECLAT recursively process each equivalence class in the same way. Consider the next equivalence class:

| lemon, orange | TI | lemon,orange,cake |
|---------------|-------|-------------------|
| lemon, cake | T3,T4 | |

This itemset is infrequent. It is eliminated.

All other equivalence classes contain a single itemset. Thus, no candidates can be generated.

Final result:

```
support = 4
{pasta}
{lemon}
                                 support = 3
{orange}
                                 support = 3
{cake}
                                 support = 2
{pasta, lemon}
                                 support: 3
{pasta, orange}
                                 support: 3
{pasta, cake}
                                 support: 2
                                 support: 2
{lemon, orange}
{orange, cake}
                                 support: 2
{pasta, lemon, orange}
                                 support: 2
{pasta, orange, cake} support: 2
```

Performance

- In this example:
 - ECLAT has explored 14 itemsets.
 - Apriori would have explored 18 itemsets.
- How is the performance of ECLAT?
 - ECLAT scans the database a single time to create a vertical database.
 - Then, the most costly operation is the intersection of TID-lists.
 - In the worst case, these lists have the size of the database.
 - Several possible optimizations >

Optimization I: total order

 Does the choice of a total order ≺ a influences the performance?



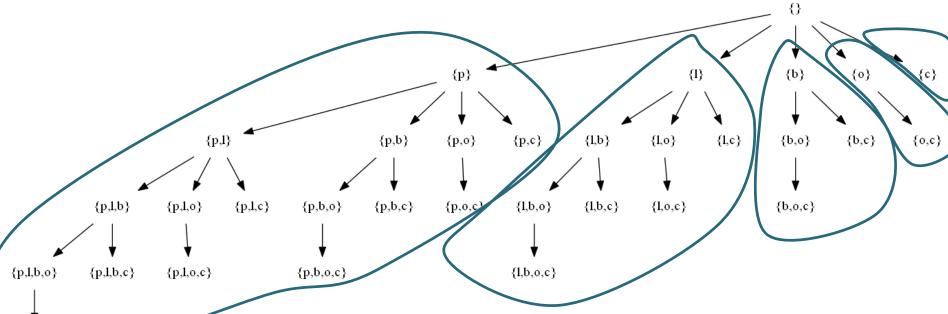
- Does the choice of a total order < a influences the performance?
- Yes, but which one to choose?
 - The alphabetical order?



- Does the choice of a total order < a influences the performance?
- Yes, but which one to choose?
 - The alphabetical order?
- A better choice: the order of increasing support.



Observation



I = lemon

 $\{p,l,b,o,c\}$

p = pasta

b = bread

0 = orange

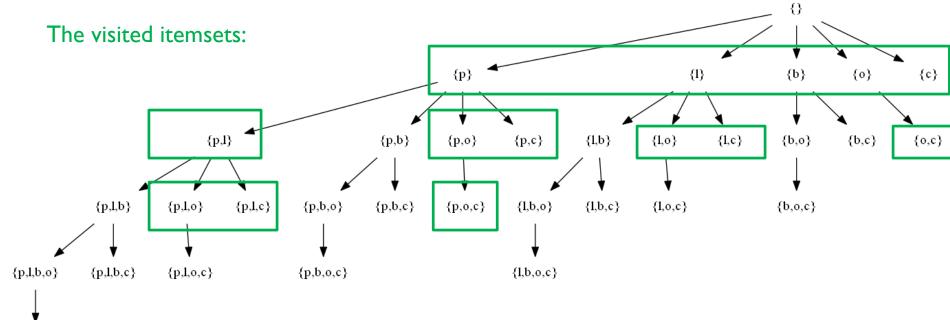
c = cake

If an item is smaller according to the total order, its subtree will be larger.



Search space

pasta ≺ lemon≺ bread ≺ orange ≺ cake



I = lemon

 $\{p,l,b,o,c\}$

p = pasta

b = bread

0 = orange

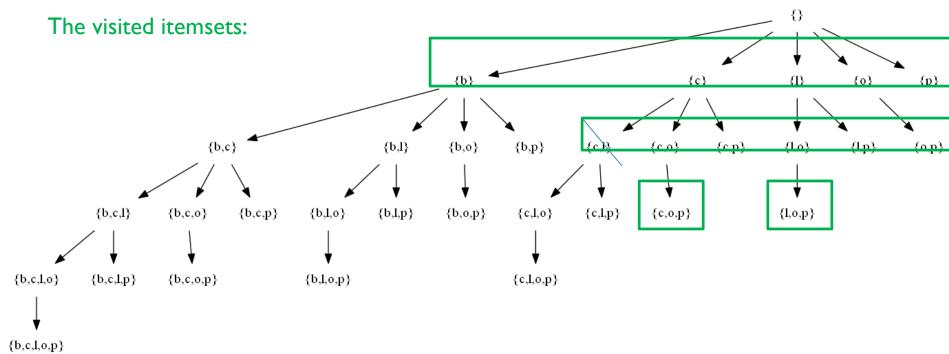
c = cake

14 have been explored



Search space

bread < cake < lemon < orange < pasta



I = lemon

p = pasta

b = bread

0 = orange

c = cake

13 have been explored

Optimization 2 - intersection

How to reduce the cost of intersections?

- Utilize bit vectors the represent the lists of transaction ids
- Will be fast if the number of I is large compared to the number of zeros

| Transaction | Items appearing in the transaction |
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| T2 | {pasta, lemon} |
| T3 | {pasta, orange, cake} |
| T4 | {pasta, lemon, orange, cake} |



| item | transactions containing the item |
|--------|------------------------------------|
| pasta | IIII (representing T1, T2, T3, T4) |
| lemon | 1101 |
| bread | 1000 |
| orange | 1011 |
| cake | 0011 |

| item | transactions containing the item |
|--------|----------------------------------|
| pasta | |
| lemon | 1101 |
| bread | 1000 |
| orange | 1011 |
| cake | 0011 |

Example: Calculate the support of {pasta, lemon}:

```
transactions({pasta}) ∩ transactions({lemon})
= I111 LOGICAL_AND II0I
= II0I
```

Thus {pasta, lemon} has a support of 3

Optimization 3 - memory

Consider an equivalence class:

{ABCD, ABCE, ABCF, ABCG, ABCH}

It can be stored more efficiently as:

$$P = \{ABC\}$$
$$E = \{E, F, G, H\}$$

Pseudocode of ECLAT

```
ECLAT(an equivalence class C)
FOR EACH X \in C
      T = \emptyset
      FOR EACH Y \in C such that X \prec Y
             R = X \cup Y
             t(R) = t(X) \cap t(Y)
             IF sup(R) \ge minsup
                    THEN Output R
                           T = T \cup \{R\}
      END FOR
      IF T \neq \emptyset THEN ECLAT(T)
END FOR
```



This video has presented:

- The **Eclat** algorithm
- Some optimizations

References

- Chapter 8 and 9. Han and Kamber (2011), Data Mining: Concepts and Techniques, 3rd edition, Morgan Kaufmann Publishers,
- Chapter 4. Tan, Steinbach & Kumar (2006), Introduction to Data Mining, Pearson education, ISBN-10: 0321321367
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- Zaki, M.J., Gouda, K.: Fast vertical mining using diffsets. Technical Report 01-1, Computer Science Dept., Rensselaer Polytechnic Institute (March 2001) 10