

WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME

## Finding Frequent Itemsets and Association Rules with Apriori

Marzena Kryszkiewicz

HUMAN CAPITAL  
HUMAN - BEST INVESTMENT

EUROPEAN UNION  
EUROPEAN SOCIAL FUND

Project is co-financed by European Union within European Social Fund

WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME

## Finding Frequent Itemsets

- Within each iteration  $i$ :
  - Determine supports of candidate itemsets of length  $i$ .
  - From those candidates of length  $i$  that turned out frequent, create candidates of length  $i + 1$ .

2

WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME

## Example: Frequent 1-Itemsets

Tid	Items
1	abce
2	abcef
3	abch
4	abe
5	acfh
6	bef
7	h
8	af

- Let minSup = 1
- Iteration 1:  
 $C_0 \rightarrow F_0: \emptyset_8$   
 $C_1 \rightarrow F_1: a_6 b_5 c_4 e_4 f_4 h_3$

3

WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME

## Example: Frequent 2-Itemsets

Tid	Items
1	abce
2	abcef
3	abch
4	abe
5	acfh
6	bef
7	h
8	af

- Let minSup = 1
- After iteration 1:  
 $F_1: a_6 b_5 c_4 e_4 f_4 h_3$
- Iteration 2:  
 $C_2 \rightarrow F_2: ab_4 ac_4 ae_3 af_3 ah_2 bc_3 be_4 bf_2 bh_1$   
 $ce_2 cf_2 ch_2 ef_2 eh_0 fh_1$

Itemsets found as infrequent after support calculation.

4

WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME

## Example: Frequent 3-Itemsets

Tid	Items
1	abce
2	abcef
3	abch
4	abe
5	acfh
6	bef
7	h
8	af

- Let minSup = 1
- After iteration 2:  
 $F_2: ab_4 ac_4 ae_3 af_3 ah_2 bc_3 be_4 bf_2$   
 $ce_2 cf_2 ch_2 ef_2$
- Iteration 3:  
 $C_3 \rightarrow F_3: abc_3 abe_3 abf_1 abh ace_2 acf_2 ach_2$   
 $ae_1 aeh afh bce_2 bcf_1 bef_2 cef_1 ceh$   
 $cf_1$

Itemsets found as infrequent as supersets of infrequent itemsets.

5

WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME

## Example: Frequent 4-Itemsets

Tid	Items
1	abce
2	abcef
3	abch
4	abe
5	acfh
6	bef
7	h
8	af

- Let minSup = 1
- After iteration 3:  
 $F_3: abc_3 abe_3 ace_2 acf_2 ach_2 bce_2 bef_2$
- Iteration 4:  
 $C_4 \rightarrow F_4: abce_2 acef aceh acfh$

6

## Example: Frequent 5-Itemsets

Tid	Items
1	abce
2	abcef
3	abch
4	abe
5	acfh
6	bef
7	h
8	af

- Let  $\text{minSup} = 1$
- After iteration 4:  
 $F_4: abce_2$
- Iteration 5:  
 $C_5: -$

7

## Example: Found Frequent Itemsets

Tid	Items
1	abce
2	abcef
3	abch
4	abe
5	acfh
6	bef
7	h
8	af

$\emptyset_8$   
 $a_5 b_5 c_4 e_4 f_4 h_3$   
 $ab_4 ac_4 ae_3 af_3 ah_2 bc_3 be_4 bf_2 ce_2 cf_2 ch_2 ef_2$   
 $abc_3 abe_3 ace_2 acf_2 ach_2 bce_2 bef_2$   
 $abce_2$

- Note:** Let  $n$  be the length of a longest frequent itemset.  
Apriori finds in either  $n$  or  $n+1$  iterations all frequent itemsets.

8

## Discovery of Association Rules with AprioriRuleGen...

- Candidate rules are built from each non-empty frequent itemset.
- Let  $Z$  be a given non-empty frequent itemset. In iteration  $i$ , candidate rules of the form:

$$Z \setminus Y \rightarrow Y,$$

where  $Y \subset Z$  and  $|Y| = i$ .

9

## Discovery of Association Rules with AprioriRuleGen

- Property.** Let  $r_1: Z \setminus Y \rightarrow Y$  and  $r_2: Z \setminus Y' \rightarrow Y'$ , where  $Y \subset Y'$ , be association rules.
  - $\text{conf}(r_1) \geq \text{conf}(r_2)$ ,
  - If  $\text{conf}(r_1) \leq \text{minConf}$ , then  $\text{conf}(r_2) \leq \text{minConf}$ .
- In order to reduce the number of candidate rules,  $i+1$  item consequents of candidate rules are built from  $i$  item consequents of strong association rules only.

10

## Example: Discovery of ARs...

Frequent itemsets ( $\text{minSup} = 1$ ):  $\emptyset_8$   
 $a_5 b_5 c_4 e_4 f_4 h_3$   
 $ab_4 ac_4 ae_3 af_3 ah_2 bc_3 be_4 bf_2 ce_2 cf_2 ch_2 ef_2$   
 $abc_3 abe_3 ace_2 acf_2 ach_2 bce_2 bef_2$   
 $abce_2$

Let  $\text{minConf} = 60\%$ ,  $Z = abce$ .

### Iteration 1:

- Consequents of candidate rules:  $Y_1 = \{a, b, c, e\}$ .
- Candidate rules:
 

<ul style="list-style-type: none"> <li><math>bce \rightarrow a</math> [2, 2/2];</li> <li><math>ace \rightarrow b</math> [2, 2/2];</li> <li><math>abe \rightarrow c</math> [2, 2/3];</li> <li><math>abc \rightarrow e</math> [2, 2/3].</li> </ul>	<ul style="list-style-type: none"> <li><math>bce \rightarrow a</math> [2, 2/2];</li> <li><math>ace \rightarrow b</math> [2, 2/2];</li> <li><math>abe \rightarrow c</math> [2, 2/3];</li> <li><math>abc \rightarrow e</math> [2, 2/3].</li> </ul>
--	--

11

## Example: Discovery of ARs...

Frequent itemsets:  $\emptyset_8$   
 $a_5 b_5 c_4 e_4 f_4 h_3$   
 $ab_4 ac_4 ae_3 af_3 ah_2 bc_3 be_4 bf_2 ce_2 cf_2 ch_2 ef_2$   
 $abc_3 abe_3 ace_2 acf_2 ach_2 bce_2 bef_2$   
 $abce_2$

### Iteration 2 ( $\text{minConf} = 60\%$ , $Z = abce$ ):

- Consequents of ARs found in iteration 1:  $Y_1 = \{a, b, c, e\}$ .
- Consequents of candidate rules:  $Y_2 = \{ab, ac, ae, bc, be, ce\}$ .
- Candidate rules:
 

<ul style="list-style-type: none"> <li><math>ce \rightarrow ab</math> [2, 2/2];</li> <li><math>be \rightarrow ac</math> [2, 2/4];</li> <li><math>bc \rightarrow ae</math> [2, 2/3];</li> </ul>	<ul style="list-style-type: none"> <li><math>ae \rightarrow bc</math> [2, 2/3];</li> <li><math>ac \rightarrow be</math> [2, 2/4];</li> <li><math>ab \rightarrow ce</math> [2, 2/4];</li> </ul>	<ul style="list-style-type: none"> <li><math>ce \rightarrow ab</math> [2, 2/2];</li> <li><math>bc \rightarrow ae</math> [2, 2/3];</li> <li><math>ae \rightarrow bc</math> [2, 2/3].</li> </ul>
--	--	--

12



## Example: Discovery of ARs...

Frequent itemsets ( $\text{minSup} = 1$ ):  $\emptyset_8$   
 $a_6 b_5 c_4 e_4 f_4 h_3$   
 $ab_4 ac_4 ae_3 af_3 ah_2 bc_3 be_4 bf_2 ce_2 cf_2 ch_2 ef_2$   
 $abc_3 abe_3 ace_2 acf_2 ach_2 bce_2 bef_2$   
 $abce_2$

Iteration 3 ( $\text{minConf} = 60\%$ ,  $Z = abce$ ):

- Consequents of ARs found in iteration 2:  $Y_2 = \{ab, ae, bc\}$ .
- Consequents of candidate rules:  $Y_3 = \{abe\}$ .

Candidate rules:  $c \rightarrow abe [2, 2/4];$   $\Rightarrow$  Strong association rules:  $None$

13



## Example: Found ARs

Frequent itemsets ( $\text{minSup} = 1$ ):  $\emptyset_8$   
 $a_6 b_5 c_4 e_4 f_4 h_3$   
 $ab_4 ac_4 ae_3 af_3 ah_2 bc_3 be_4 bf_2 ce_2 cf_2 ch_2 ef_2$   
 $abc_3 abe_3 ace_2 acf_2 ach_2 bce_2 bef_2$   
 $abce_2$

Strong association rules ( $\text{minConf} = 60\%$ ,  $Z = abce$ ):

- $bce \rightarrow a [2, 2/2];$
- $ace \rightarrow b [2, 2/2];$
- $abe \rightarrow c [2, 2/3];$
- $abc \rightarrow e [2, 2/3];$
- $ce \rightarrow ab [2, 2/2];$
- $bc \rightarrow ae [2, 2/3];$
- $ae \rightarrow bc [2, 2/3].$

14



## Important Operations in Apriori and AprioriRuleGen

- An important time-consuming operation in *Apriori* is searching  $i$  item candidates supported by a given transaction.
- An important time-consuming operation in *AprioriRuleGen* is searching frequent  $i$  itemsets (candidate rule consequents) of a given frequent itemset in order to learn their supports.
- Thus, in both cases  $i$  item subsets of a given itemset are searched.

15



## Usage of a Hash Tree

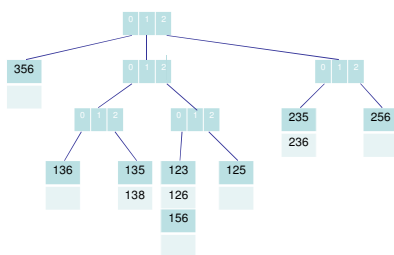
- A hash tree is used in order to make the identification of  $i$  item subsets of a given itemset efficient.
- In particular, all  $i$  item candidate sets are stored in a hash tree.

16



## Example: Candidate 3-Itemsets in a Hash Tree

Itemset	representation
abc	123
abe	125
abf	126
ace	135
acf	136
ach	138
aef	156
bce	235
bcf	236
bef	256
cef	356

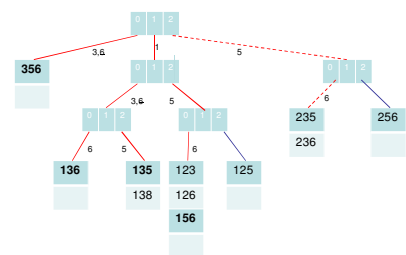


17




## Example: Searching for Subsets in a Hash Tree

Itemset	representation
abc	123
abe	125
abf	126
...	...
transaction	representation
...	...
acef	1356
...	...




- 4 subsets of transaction *acef* (after coding: 1356) has been found.

18




WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME




Dealing with non-transactional data

- Non-transactional data are often transformed into equivalent transactional data.

19



WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME



Transactional Data Set + Taxonomies

Tid	Items
1	abce
2	abcef
3	abch
4	abe
5	acfh
6	bef
7	h
8	af

E

Edible

F

Fruit

a

apple

b

banana

S

Sweets

c

chocolate

V

Vitamin

e

vitamin e

M

Musical instr.


f

flute


h

harp

20



WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME



Transactional Data Set with Taxonomies included

Tid	Items
1	abceFSVE
2	abcefFSVME
3	abchFSME
4	abeFVE
5	acfhFSME
6	befFVME
7	hM
8	afFME

E

Edible

F

Fruit

a

apple

b

banana

S

Sweets

c

chocolate

V

Vitamin

e

vitamin e

M

Musical instr.


f

flute


h

harp

21



WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME



Transactional Data Set + Taxonomies

Tid	Items
1	abce
2	abcef
3	abch
4	abe
5	acfh
6	bef
7	h
8	af

F

Fruit

a

apple

b

banana

S

Sweets

c

chocolate

V

Vitamin

e

vitamin e

M

Musical instr.


f

flute


h

harp

22



WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME



Transactional Data Set + Negated Items


Tid	Items
1	abce
2	abcef
3	abch
4	abe
5	acfh
6	bef
7	h
8	af

6 positive items {abcefh}


6 negated items {abcefh}

Tid	Items
1	abcefh
2	abcefh
3	abcefh
4	abcefh
5	acfhbe
6	befach
7	habcef
8	afbceh

23



WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME



Transactional Data Set + Negated Items

Tid	Items
1	abce
2	abcef
3	abch
4	abe
5	acfh
6	bef
7	h
8	af

6 positive items {abcefh}

6 negated items {abcefh}

$sup(\{befh\}) = 2$   
 $conf(\{bf\} \rightarrow \{eh\}) = 2/3$   
 $conf(\{bh\} \rightarrow \{ef\}) = 2/4$

Tid	Items
1	abcefh
2	abcefh
3	abcefh
4	abcefh
5	acfhbe
6	befach
7	habcef
8	afbceh

24

WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME

### Transactional Data Set + Negated Items

Tid	Items	Tid	Items
1	abcefh	1	1 2 3 4 11 12
2	abcefh	2	1 2 3 4 5 12
3	abchef	3	1 2 3 6 11 12
4	abecfh	4	1 2 4 10 11 12
5	acfhbe	5	1 3 5 6 8 10
6	befach	6	2 4 5 7 9 12
7	habcef	7	6 7 8 9 10 11
8	afbceh	8	1 5 8 9 10 12

Item	a	b	c	e	f	h	a	b	c	e	f	h
item id	1	2	3	4	5	6	7	8	9	10	11	12

WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME

### Relational Data → Transactional Data

Height	Colour	Grade	Tid	Items
tall	green	5	1	{1, 3, 6}
short	black	4	2	{2, 4, 5}
short	green	4	3	{2, 3, 5}

Item	(H=tall)	(H=short)	(C=green)	(C=black)	(G=4)	(G=5)
item id	1	2	3	4	5	6
attribute	1	1	2	2	3	3

26

WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME

### Relational Data → Transactional Data

Height	Colour	Grade	Tid	Items
tall	green	5	1	{1, 3, 6}
short	black	4	2	{2, 4, 5}
short	green	4	3	{2, 3, 5}

Item	(H=tall)	(H=short)	(C=green)	(C=black)	(G=4)	(G=5)
item id	1	2	3	4	5	6
attribute	1	1	2	2	3	3

{2} → {5} [2, 2/2]. So, (H=short) → (G=4) [2, 100%].  
 {3} → {5} [1, 1/2]. So, (C=green) → (G=4) [1, 50%].  
 {2,3} → {5} [1, 1/1]. So, (H=short) ∧ (C=green) → (G=4) [1, 100%].

WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME

### References...

- Agrawal R., Imielinski T., Swami A.: Mining Associations Rules between Sets of Items in Large Databases. In: Proc. of the ACM SIGMOD Conference on Management of Data, Washington, USA (1993) 207–216
- Rakesh Agrawal, Ramakrishnan Srikant: Fast Algorithms for Mining Association Rules in Large Databases. [VLDB 1994](#): 487-499
- Agrawal R., Mannila H., Srikant R., Toivonen H., Verkamo A.I.: Fast Discovery of Association Rules. In: Fayyad U.M., Piatetsky-Shapiro G., Smyth P., Uthurusamy R. (eds.): Advances in Knowledge Discovery and Data Mining. AAAI, CA (1996) 307–328

28

WARSAW UNIVERSITY OF TECHNOLOGY  
DEVELOPMENT PROGRAMME

### References

- Jiawei Han, Micheline Kamber, Jian Pei: Data Mining: Concept and Techniques, The Morgan Kaufmann Series in Data Management Systems, 2011
- Kryszkiewicz, M.: Concise Representations of Frequent Patterns and Association Rules. Prace Naukowe Politechniki Warszawskiej. Elektronika 142. Publishing House of the Warsaw University of Technology (2002)
- Ashok Savasere, Edward Omiecinski, Shamkant B. Navathe: An Efficient Algorithm for Mining Association Rules in Large Databases. [VLDB 1995](#): 432-444
- Mohammed Javeed Zaki, Karam Gouda: Fast vertical mining using diffsets. [KDD 2003](#): 326-335

29