

A Graph-based Approach to Mining Inter-transaction Association Rules

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Outline

- o Motivation
- o A classification of related problems and their transformations
- o The graph-based approach to mining inter-transaction association rules
- o Conclusion

Motivation

- o Recent advances in data mining have been broadly studied. Many problems and solutions have been proposed individually, but the relationships among them are not clear
- o mining inter-transaction association rules is new and challenging

A classification of Related Problems

Table 1: A summary of the problem classification

Type	Data Format	Pattern	Count-by	Results	Applications
1	Transactions	Intra-transaction	Transactions	✓ Classical association rules	✓ Marketing
2	Sequences	Inter-transaction	Sequences	✓ Sequential patterns ✓ Traversal patterns	✓ Marketing ✓ Web browsing ✓ Music analysis
3	A sequence	Inter-transaction	Segments	✓ Repeating patterns ✓ Frequent episodes ✓ Partial periodical patterns ✓ Inter-transaction association rules ✓ Cyclic/Calendric association rules	✓ Marketing ✓ Music analysis ✓ Stock analysis ✓ Event search

We classify the related problems into three types according to three attributes: Data format, Pattern, and Count-by.

Problem Transformations

- o The solutions to one problem can be applied to the others if the problem transformations are well defined.
 - o intra-type transformation
 - o transformations between the problems of the same types
 - o inter-type transformation
 - o transformations between the problems of different types

Intra-Type Transformation

- o Type 2
 - o Mining traversal patterns → Mining sequential patterns

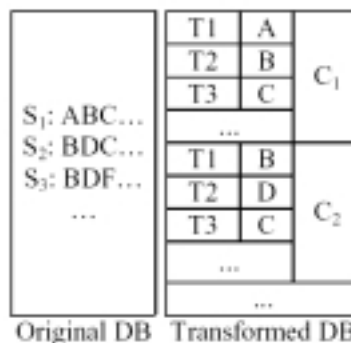


Figure 1: Navigation paths → Customer sequences

Inter-Type Transformation

- o Type 3 → Type 2
 - o Mining inter-transaction association rules → Mining sequential patterns

SID	Window	CID	Sequence
100	a(abc)(bc)	100	$A_0(A_1B_1C_1)(B_2C_2)$
200	(abc)(bc)a	200	$(A_0B_0C_0)(B_1C_1)A_2$
300	(bc)a	300	$(B_0C_0)A_1$
400	a	400	A_0
...		...	

Original DB Transformed DB
Figure 2: Sliding windows → Customer sequences

Mining Inter-transaction Association Rules (1/2)

TID	Transaction
T1	A, B, D
T2	A, C, E
T3	B, C, E
T4	B, D, E
T5	A
T6	B, C

Figure 5: An example database

- o Segment (Window)
- o Extended itemset (Eitemset)
- o K-eitemset

Window	TID	Transaction	SI D	TI D	Extended itemset
1	T1	A, B, D	1	T1	A(0), B(0), D(0)
	T2	A, C, E		T2	A(1), C(1), E(1)
	T3	B, C, E		T3	B(2), C(2), E(2)
2	T2	A, C, E	2	T2	A(0), C(0), E(0)
	T3	B, C, E		T3	B(1), C(1), E(1)
	T4	B, D, E		T4	B(2), D(2), E(2)
3	T3	B, C, E	3	T3	B(0), C(0), E(0)
	T4	B, D, E		T4	B(1), D(1), E(1)
	T5	A		T5	A(2)
4	T4	B, D, E	4	T4	B(0), D(0), E(0)
	T5	A		T5	A(1)
	T6	B, C		T6	B(2), C(2)
5	T5	A	5	T5	A(0)
	T6	B, C		T6	B(1), C(1)
6	T6	B, C	6	T6	B(0), C(0)

Sliding DB Extended DB
Figure 6: Sliding windows → Segments

Mining Inter-transaction Association Rules (2/2)

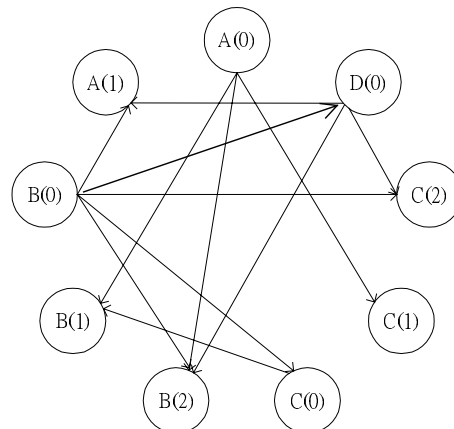
- o The Support of a Eitemset
 - o $A(0)C(1) = 3/6 = 100\%$
- o The Confidence of a rule
 - o $X \rightarrow Y$
 - o $\text{Conf}(A(0) \rightarrow C(1))$
 $= \text{Sup}(A(0)C(1)) / \text{Sup}(A(0))$
 $= 0.5 / 0.5 = 100\%$
- o Large Eitemset & Inter-transaction association rule
 - o minsup & minconf

SI	T1	Extended itemset
D	D	
1	T1	A(0), B(0), D(0)
	T2	A(1), C(1), E(1)
	T3	B(2), C(2), E(2)
2	T2	A(0), C(0), E(0)
	T3	B(1), C(1), E(1)
	T4	B(2), D(2), E(2)
3	T3	B(0), C(0), E(0)
	T4	B(1), D(1), E(1)
	T5	A(2)
4	T4	B(0), D(0), E(0)
	T5	A(1)
	T6	B(2), C(2)
5	T5	A(0)
	T6	B(1), C(1)
6	T6	B(0), C(0)

Extended DB

The Graph-based Approach (1/3)

- o Graph Index Structure



The Graph-based Approach (2/3)

- E-Matrix

	A(0):3	B(0):5	C(0):1	D(0):3
A(1)	\emptyset	{1,4}	\emptyset	{1,4}
B(1)	{2,5}	\emptyset	{2,3}	\emptyset
B(2)	{1,2}	{1,4}	\emptyset	{1,4}
C(0)	\emptyset	{3,6}	\emptyset	\emptyset
C(1)	{1,2,5}	\emptyset	\emptyset	\emptyset
C(2)	\emptyset	{1,4}	\emptyset	{1,4}
D(0)	\emptyset	{1,4}	\emptyset	\emptyset

The Graph-based Approach (3/3)

- Discovering large k-itemsets

- Candidate generation

- there are three corresponding edges starting from the node A(0) in the graph-index.

- A(0)B(1), A(0)B(2), and A(0)C(1).

- Candidate 4-itemset $\langle A(0)B(1)B(2)C(1) \rangle$, $\langle A(0)B(2)B(1)C(1) \rangle$, ..., are generated

- Support computation

- The support of $\langle A(0)B(1)B(2)C(1) \rangle$ is 1/6 (it is only contained in segment 2). It is not a large 4-itemset.

Conclusion

o Contribution

- o We classify the problems into three types
 - o intra-type transformation, inter-type transformation
- o We propose a graph-based approach for mining length k inter-transaction association rules, which only needs to scan the database twice.

o Future work

- o A more comprehensive framework that considers all the related problems.
- o develop a mining algorithm that can be applied to any of the related problems

Appendix

