

An Efficient Algorithm for Mining Frequent Sequences by a New Strategy without Support Counting

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Date: 2004/3/30



Outline

Introduction

➤ Three strategies – the related works

The DISC strategy

The DISC-all Algorithm

Performance Evaluation

Conclusion



Introduction

□ Motivation

- Problem of mining sequential patterns
 - **Candidate generation + support counting**
- Three strategies used in the related works
- Can we mine all the frequent sequences without counting the supports of non-frequent sequences?

□ Goal

- A new strategy to meet this demand
- An efficient algorithm combining all the strategies



Introduction

□ An Example

- Support count: number of customer sequences
- Minimum support count δ (=2)
- All the frequent k-sequences

- **Frequent 3-sequences**

$(a, g)(b), (a, g)(h),$

$(a, g)(f), (a)(b)(h),$

$(a)(b)(f), (a)(b, f),$

...

CID	Customer Sequences
1	$(a, e, g)(b)(h)(f)(c)(b, f)$
2	$(b)(d, f)(e)$
3	(b, f, g)
4	$(f)(a, g)(b, f, h)(b, f)$



Introduction

□ An Example

- Support count: number of customer sequences
- Minimum support count δ (=2)
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- **Frequent 3-sequences**

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1	$(a, e, g)(b)(h)(f)(c)(b, f)$
2	$(b)(d, f)(e)$
3	(b, f, g)
4	$(f)(a, g)(b, f)h(b, f)$

Support count of $\langle (b, f) \rangle = 2$



Introduction

□ Strategy 1: Candidate Sequence Pruning

- Prune the candidates as early as possible
 - **Anti-monotone property**
 - *If $(a)(b)$ is not frequent, $(a)(b)(c)$, $(a)(b, c)$, ... are not, either.*
- Reduce the processing costs and storage overheads for support counting
- Has been used in all the related works
 - **GSP, SPADE, PrefixSpan, SPAM, ...**



Introduction

□ Strategy 2: Database Partitioning

➤ PrefixSpan

- **Projected database: the customer sequences having the same prefix**

➤ SPADE/SPAM

- **ID-list/bitmap: the customer sequences and the positions where a sequence appears**

➤ Eliminate the unnecessary decompositions of customer sequences

- **But add extra costs on projections or merging**



Introduction

□ Strategy 3: Customer Sequence Reducing

- Shorten the customer sequences
- PrefixSpan removes items during the projections
 - **Pseudo uses pointers to simulate the item removal**
- Reduce the processing and storage costs for decomposing the customer sequences

CID	Customer Sequences
1	(a, e, g)(b)(h)(f)(c)(b, f)
2	(b)(d, f)(e)
3	(b, f, g) ↓
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CID	Customer Sequences
1	(h)(f)(c)(b, f)
4	(_, f, h)(b, f)

prefix
(a)(b)
←

CID	Customer Sequences
1	(a, e, g)(b)(h)(f)(c)(b, f)
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Introduction

□ **Strategy 4: DIrect Sequence Comparison (DISC)**

- Recognize all the frequent k-sequences without counting the supports of non-frequent k-sequences
- Reduce the costs for support counting and decomposing the customer sequences



Introduction

□ Strategy 4: Direct Sequence Comparison (DISC)

- Recognize all the frequent k-sequences without counting the supports of non-frequent k-sequences
- Reduce the costs for support counting and decomposing the customer sequences

Algorithm	GSP	SPADE	SPAM	PrefixSpan	DISC-all
Strategy					
Candidate Sequence Pruning	√	√	√	√	√
Database Partitioning		√	√	√	√
Customer Sequence Reducing				√	√
DISC					√



The DISC Strategy

□ The Original Database \Rightarrow K-Sorted Database

➤ A method to compare sequences

- **Differential point**

- *Leftmost different item or transaction number*

- $DP(A,B)=2, DP(A,C)=3, DP(B,C)=2$

- **Comparative order: the alphanumeric order on DP**

- $A < C < B$ (*compare the items first*)

➤ K-minimum subsequence \Rightarrow k-minimum order

- **K=2: $KMS_A=(a, b), KMS_B=(a)(a), KMS_C=(a, b)$**

- **2-minimum order: $B <_2 C =_2 A$**

$A=(a_1 b_1 c_1)(b_2 d_2)$
$B=(a_1 c_1 d_1)(a_2)$
$C=(a_1 b_1)(c_2 d_2)$



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$A=(a_1 b_1 \underline{c_1})(b_2 d_2)$ $B=(a_1 \underline{c_1} d_1)(a_2)$ $C=(a_1 b_1)(\underline{c_2} d_2)$

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$A=(a_1 b_1 c_1)(b_2 d_2)$
 $B=(a_1 c_1 d_1)(a_2)$
 $C=(a_1 b_1)(c_2 d_2)$

(a, b)
 (a)(b)
 (a, c)
 (a)(d)
 (b)(b)
 ...



The DISC Strategy

□ **K-sorted Database \Rightarrow Compare α_1 and α_δ**

➤ Equality: if $\delta=2 \Rightarrow (a)(b)(b)$ is frequent

- For CID=1 and 4, find new KMS $> (a)(b)(b)$

	CID	3-minimum Subsequence	Customer Sequence
α_1	1	(a)(b)(b)	(a, e, g)(b)(h)(f)(c)(b, f)
α_δ	4	(a)(b)(b)	(f)(a, g)(b, f, h)(b, f)
	2	(b)(d)(e)	(b)(d, f)(e)
	3	(b, f, g)	(b, f, g)



The DISC Strategy

□ K-sorted Database \Rightarrow Compare α_1 and α_δ

- Equality: if $\delta=2 \Rightarrow (a)(b)(b)$ is frequent
 - For CID=1 and 4, find new KMS $> (a)(b)(b)$
- Inequality: if $\delta=3 \Rightarrow (a)(b)(b)$ is not frequent
 - For CID=1 and 4, find new KMS $\geq (b)(d)(e)$
 - Avoid unnecessary decomposition of KMS $< (b)(d)(e)$

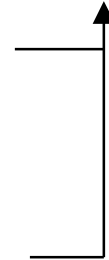
	CID	3-minimum Subsequence	Customer Sequence
α_1	1	(a)(b)(b)	(a, e, g)(b)(h)(f)(c)(b, f)
	4	(a)(b)(b)	(f)(a, g)(b, f, h)(b, f)
α_δ	2	(b)(d)(e)	(b)(d, f)(e)
	3	(b, f, g)	(b, f, g)



The DISC Strategy

□ K-sorted Database \Rightarrow Compare α_1 and α_δ

- Equality: if $\delta=2 \Rightarrow (a)(b)(b)$ is frequent **Conditional KMS**
 - For CID=1 and 4, find new KMS $> (a)(b)(b)$
- Inequality: if $\delta=3 \Rightarrow (a)(b)(b)$ is not frequent
 - For CID=1 and 4, find new KMS $\geq (b)(d)(e)$
 - Avoid unnecessary decomposition of KMS $< (b)(d)(e)$



	CID	3-minimum Subsequence	Customer Sequence
α_1	1	(a)(b)(b)	(a, e, g)(b)(h)(f)(c)(b, f)
	4	(a)(b)(b)	(f)(a, g)(b, f, h)(b, f)
α_δ	2	(b)(d)(e)	(b)(d, f)(e)
	3	(b, f, g)	(b, f, g)



The DISC Strategy

□ Advantages

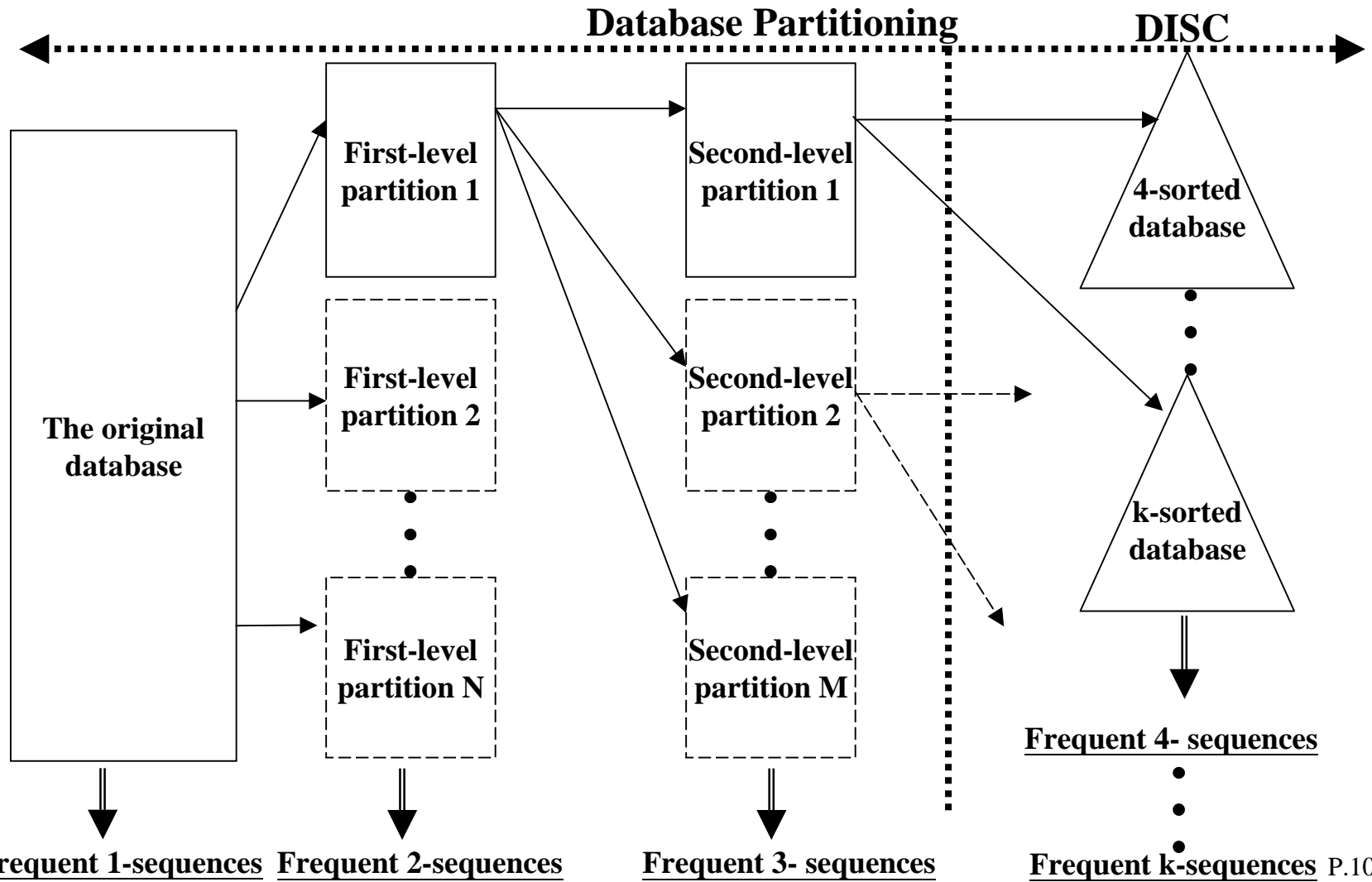
- Only the frequent sequences are counted
- The costs of sequence decomposition are reduced
- The frequent k-sequences can be discovered directly without following the bottom-up approach

□ Core Techniques

- Algorithms to quickly find KMS and CKMS
 - **Apriori-KMS/Apriori-CKMS**
- Data structure to maintain the k-sorted database

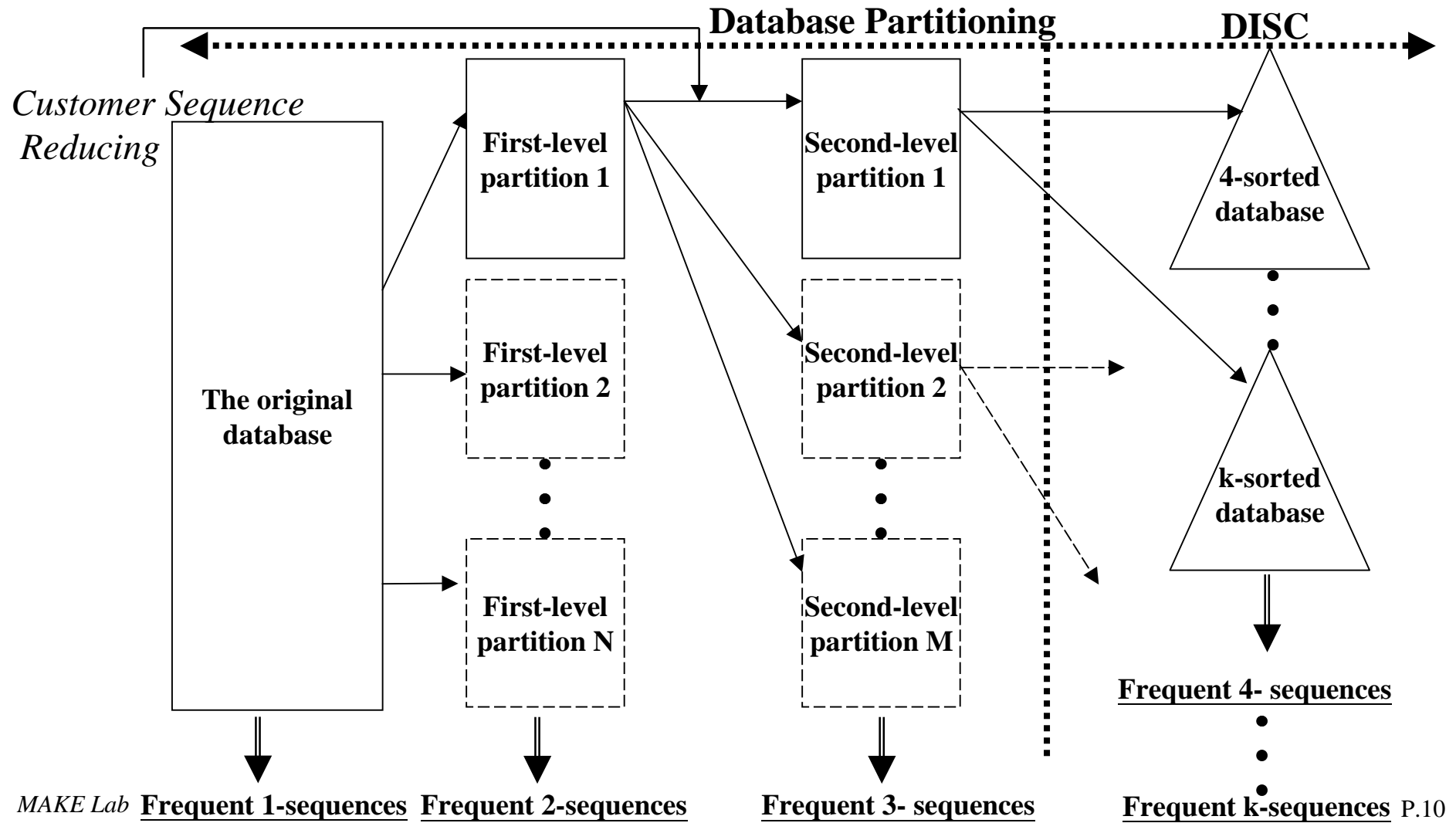


The DISC-all Algorithm



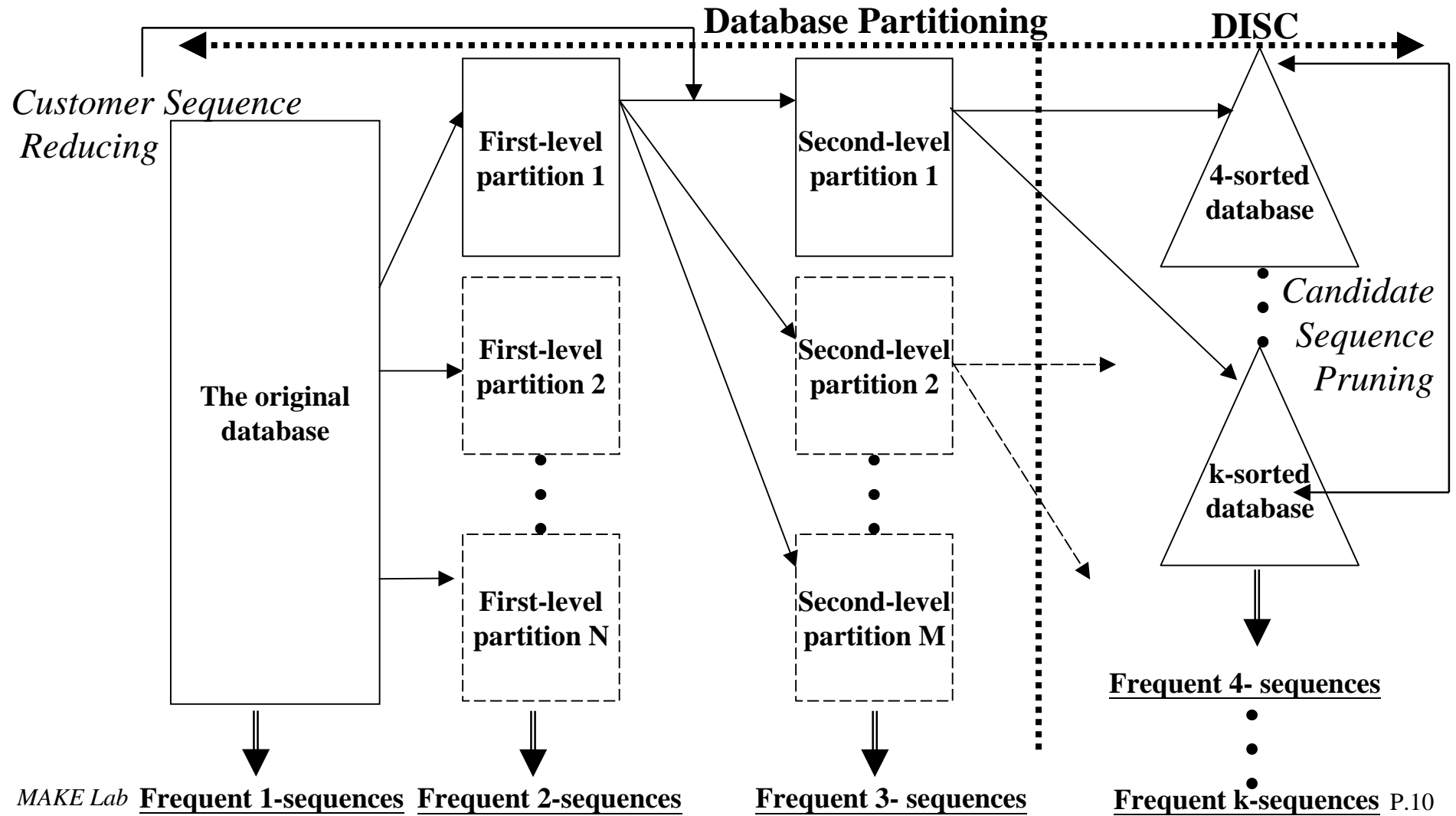


The DISC-all Algorithm





The DISC-all Algorithm





The DISC-all Algorithm

□ Strategy 2: Multi-level Partitioning

CID	Customer Sequences	Initial Partitions	After <(a)>-partition
1	(a, d)(d)(a, g, h)(c)	<(a)>-partition	<(c)>-partition
2	(b)(a)(f)(a, c, e, g)	<(a)>-partition	<(b)>-partition
3	(a, f, g)(a, e, g, h)(c, g, h)	<(a)>-partition	<(c)>-partition
4	(f)(a, c, f)(a, c, e, g, h)	<(a)>-partition	<(c)>-partition
5	(a, g)	<(a)>-partition	<(g)>-partition
6	(a, f)(a, e, g, h)	<(a)>-partition	<(e)>-partition
7	(a, b, g)(a, e, g)(g, h)	<(a)>-partition	<(b)>-partition
8	(b, f)(b, e)(e, f, h)	<(b)>-partition	<(b)>-partition
9	(d, f)(d, f, g, h)	<(d)>-partition	<(d)>-partition
10	(b, f, g)(c, e, h)	<(b)>-partition	<(b)>-partition
11	(e, g)(f)(e, f)	<(e)>-partition	<(e)>-partition



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3	(a, f, g)(a, e, g, h)(c, g, h)	<(a)>-partition	<(c)>-partition
4	(f)(a, c, f)(a, c, e, g, h)	<(a)>-partition	<(c)>-partition
5	(a, g)	<(a)>-partition	<(g)>-partition
6	(a, f)(a, e, g, h)	<(a)>-partition	<(e)>-partition
7	(a, b, g)(a, e, g)(g, h)	<(a)>-partition	<(b)>-partition
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3	(a, f, g)(a, e, g, h)(c, g, h)	<(a)>-partition	<(c)>-partition
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The DISC-all Algorithm

□ Strategy 3: Customer Sequence Reducing

➤ Reduce $\langle (a) \rangle$ -partition ($\delta=3$)

- Remove non-frequent 1-sequence (d)
- Remove non-frequent 2-sequences

– $(a)(b)$, $(a)(d)$, $(a)(f)$, (ab) , (ac) , and (ad)

$(a)(c)$ is frequent

CID	Customer Sequences
1	(a, d)(d)(a, g, h)(c)
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3	(a, f, g)(a, e, g, h)(c, g, h)
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5	(a, g)
6	(a, f)(a, e, g, h)
7	(a, b, g)(a, e, g)(g, h)

CID	Reduced Customer Sequences
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4	(f)(a, b)(a, c, e, g, h)
5	(a, g)
6	(a, f)(a, e, g, h)
7	(a, b , g)(a, e, g)(g, h)

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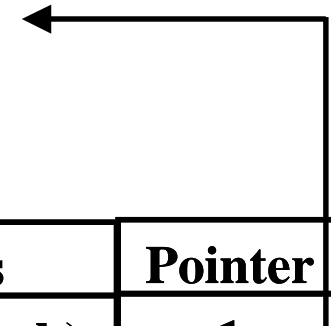
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3	(a, f, g)(a, e, g, h)(c, g, h)
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6	(a, f)(a, e, g, h)
7	(a, g)(a, e, g)(g, h)



The DISC-all Algorithm

□ Strategy 1+4: Candidate Sequence Pruning+DISC

- $\langle (a)(a) \rangle$ -partition \Rightarrow 4-sorted database
- Use the 3-sorted list:



CID	4-minimum Subsequences	Customer Sequences	Pointer
3	(a)(a, e)(c)	(a, f, g)(a, e, g, h)(c, g, h)	1
2	(a)(a, e, g)	(b)(a)(a, c, e, g)	1
4	(a)(a, e, g)	(f)(a, f)(a, c, e, g, h)	1
6	(a)(a, e, g)	(a, f)(a, e, g, h)	1
7	(a)(a, e, g)	(a, g)(a, e, g)(g, h)	1
1	(a)(a, g)(c)	(a)(a, g, h)(c)	2



The DISC-all Algorithm

□ Strategy 1+4: Candidate Sequence Pruning+DISC

➤ $\langle (a)(a) \rangle$ -partition \Rightarrow 4-sorted database

➤ Use the 3-sorted list:

No	Frequent 3-sequences
1	(a)(a, e) ←
2	(a)(a, g)
3	(a)(a, h)

CID	4-minimum Subsequences	Customer Sequences	Pointer
3	(a)(a, e)(c)	(a, f, g)(a, e, g, h)(c, g, h)	1 —
2	(a)(a, e, g)	(b)(a)(a, c, e, g)	1
4	(a)(a, e, g)	(f)(a, f)(a, c, e, g, h)	1
6	(a)(a, e, g)	(a, f)(a, e, g, h)	1
7	(a)(a, e, g)	(a, g)(a, e, g)(g, h)	1
1	(a)(a, g)(c)	(a)(a, g, h)(c)	2



The DISC-all Algorithm

□ Strategy 1+4: Candidate Sequence Pruning+DISC

➤ $\langle (a)(a) \rangle$ -partition \Rightarrow 4-sorted database

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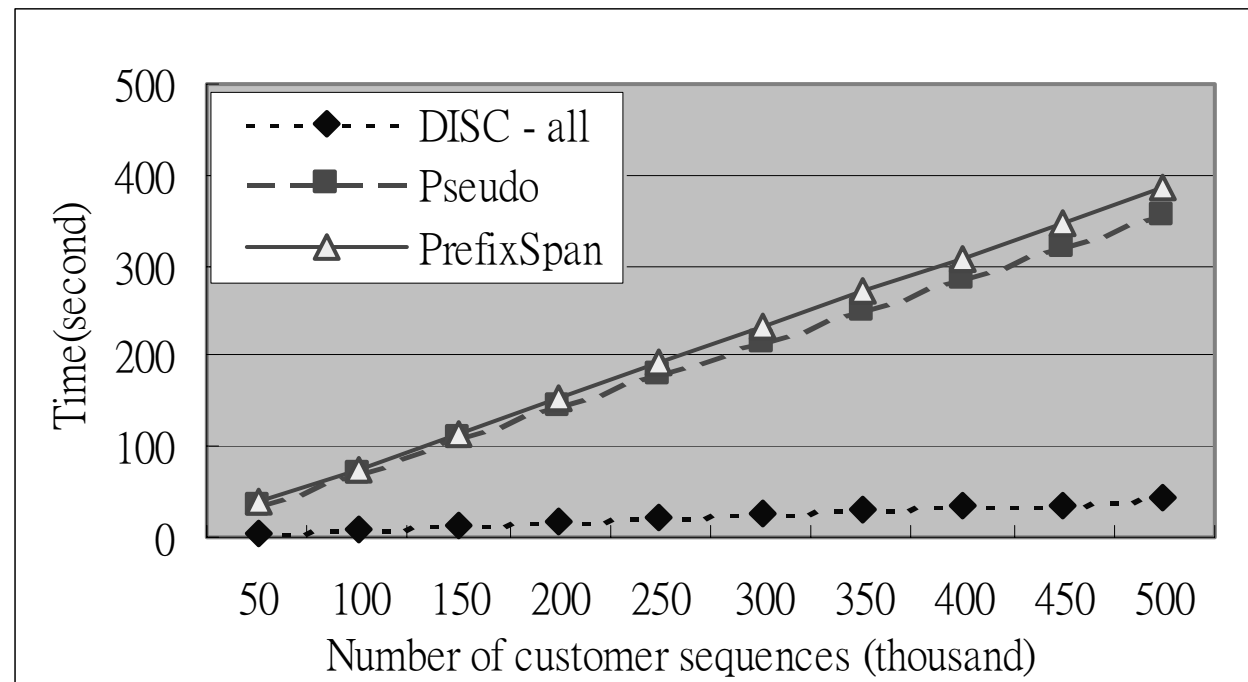




Performance Evaluation

□ Comparisons with PrefixSpan and Pseudo

- Database size
- Minimum support threshold

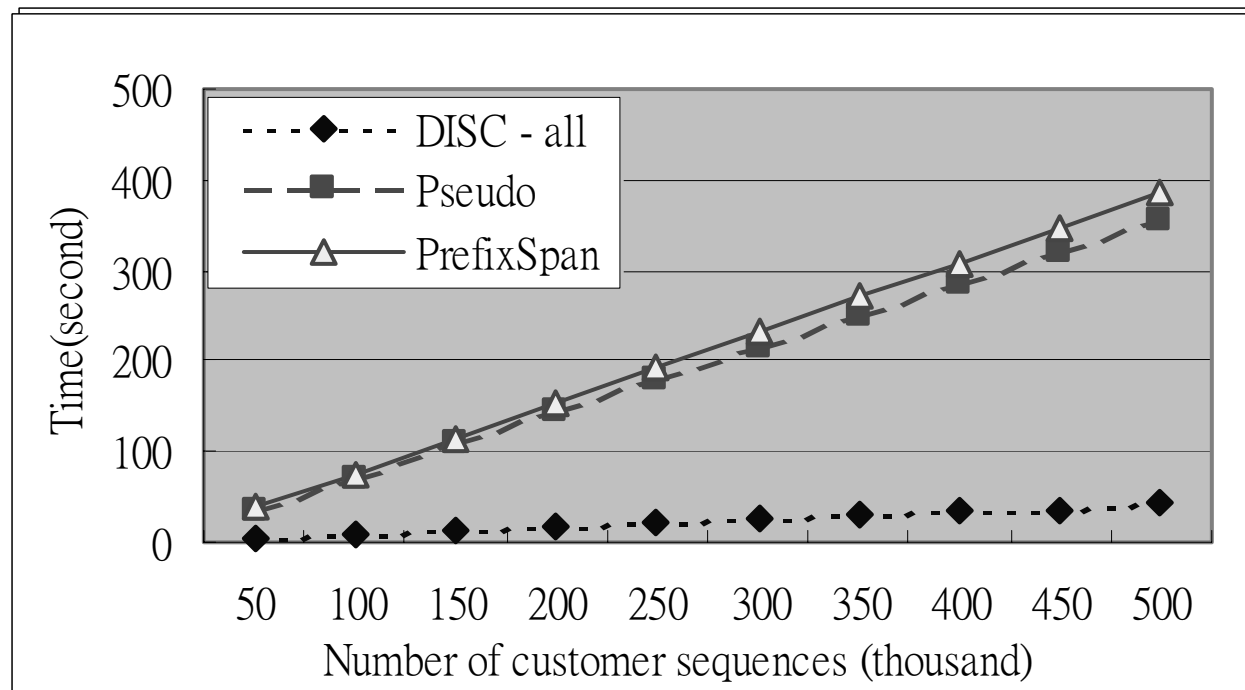




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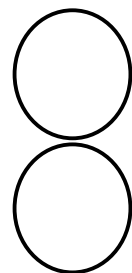


Performance Evaluation

□ Non-reduction rate (NRR)

$$\text{NRR}_Q = \frac{1}{N_Q} \sum_{p \text{ is a child partition of } Q} \frac{\text{Size}_p}{\text{Size}_Q}$$

- Average NRR vs. DISC-all's improvement
- Partitioning strategy can benefit from the partition with a low NRR





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Average NRR \ MST	Original	1	2	3	4	5	6	7
0.0025	0.0018	0.08	0.43	0.83	0.85	0.85	0.86	0.87
0.005	0.0019	0.11	0.64	0.9	0.94	0.97	0.99	-
0.0075	0.002	0.12	0.9	0.98	0.98	-	-	-
0.01	0.0022	0.14	0.92	-	-	-	-	-
0.0125	0.0024	0.15	-	-	-	-	-	-
0.015	0.0025	0.16	-	-	-	-	-	-
0.0175	0.0026	0.18	-	-	-	-	-	-



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MST	Pseudo/DISC-all
0.0025	3.588026
0.005	7.723559
0.0075	8.294165
0.01	8.140177
0.0125	7.792428
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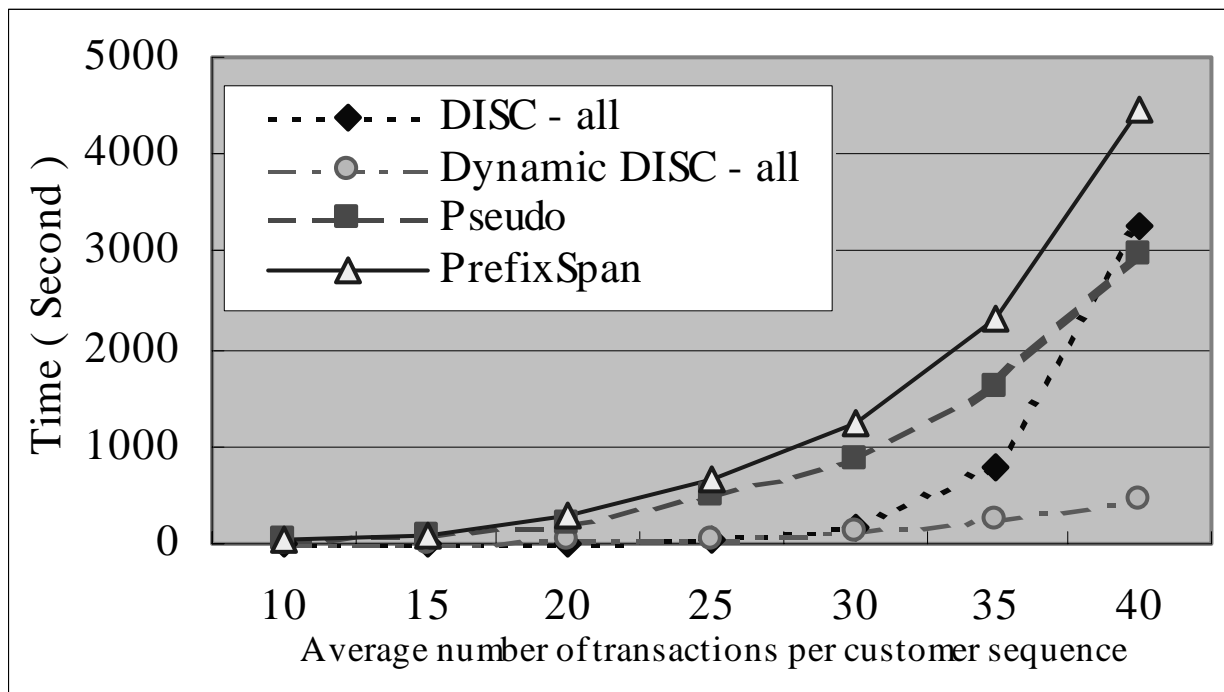
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Performance Evaluation

□ The Dynamic DISC-all Algorithm

➤ Maximum NRR threshold





Conclusion

□ Contribution

- The DISC strategy for mining sequential patterns
- The DISC-all algorithm that takes advantage of all the strategies
- The Dynamic DISC-all algorithm that can achieve a much better performance

□ Future Work

- Apply the DISC strategy to *weighting applications*
 - **Web log analysis, biological data mining**