

LAB LECTURE 3

Frequent Itemsets

Association Rules

Market-Basket Data

- A large set of **items**, e.g., things sold in a supermarket.
- A large set of **baskets**, each of which is a small set of the items, e.g., the things one customer buys on one day.

Market-Baskets – (2)

- Really, a general many-to-many mapping (association) between two kinds of things, where the one (the **baskets**) is a set of the other (the **items**)
 - But we ask about connections among “items,” not “baskets.”
- The technology focuses on **common events**, not rare events (“long tail”).

Frequent Itemsets

- Given a set of transactions, find combinations of items (itemsets) that occur frequently

Support : number of transactions that contain itemset I

Market-Basket transactions

Items: {Bread, Milk, Diaper, Beer, Eggs, Coke}

<i>TID</i>	<i>Items</i>
1	Bread, Milk
2	Bread, Diaper, Beer, Eggs
3	Milk, Diaper, Beer, Coke
4	Bread, Milk, Diaper, Beer
5	Bread, Milk, Diaper, Coke

Examples of frequent itemsets ≥ 3

{Bread}: 4
{Milk} : 4
{Diaper} : 4
{Beer}: 3
{Diaper, Beer} : 3
{Milk, Bread} : 3

Applications – (1)

- **Items** = products; **baskets** = sets of products someone bought in one trip to the store.
- **Example application**: given that many people buy beer and diapers together:
 - Run a sale on diapers; raise price of beer.
- Only useful if many buy diapers & beer.

Applications – (2)

- **Baskets** = Web pages; **items** = words.
- **Example application:** Unusual words appearing together in a large number of documents, e.g., “Brad” and “Angelina,” may indicate an interesting relationship.

Applications – (3)

- **Baskets** = sentences; **items** = documents containing those sentences.
- **Example application:** Items that appear together too often could represent plagiarism.
- Notice items do not have to be “in” baskets.

Definition: Frequent Itemset

- **Itemset**
 - A collection of one or more items
 - Example: {Milk, Bread, Diaper}
 - **k-itemset**
 - An itemset that contains **k** items
- **Support** (📅)
 - **Count**: Frequency of occurrence of an itemset
 - E.g. 📅({Milk, Bread, Diaper}) = 2
 - **Fraction**: Fraction of transactions that contain an itemset
 - E.g. $s(\{\text{Milk, Bread, Diaper}\}) = 40\%$
- **Frequent Itemset**
 - An itemset whose support is greater than or equal to a *minsup* threshold

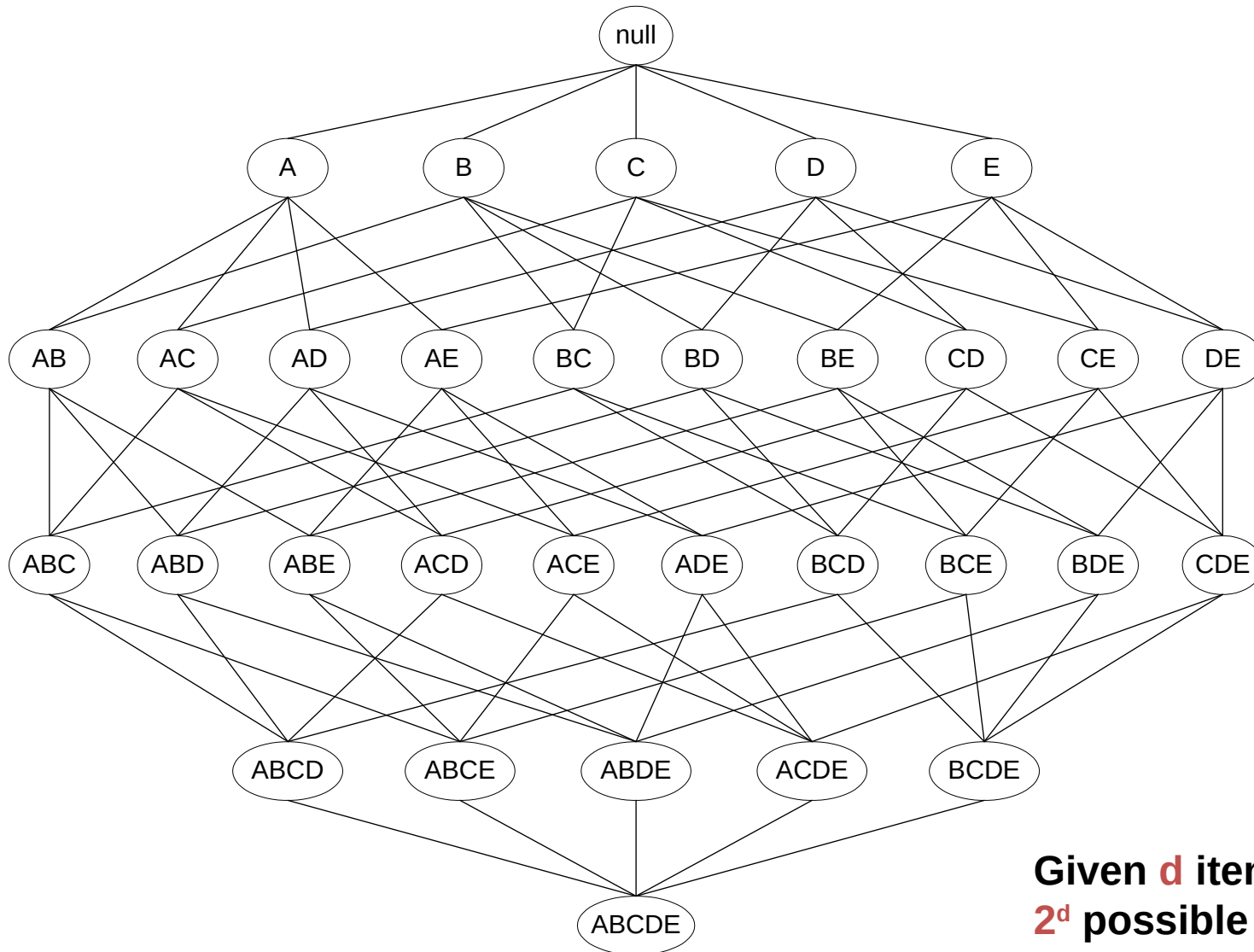
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minsup

Mining Frequent Itemsets task

- **Input:** A set of transactions T , over a set of items I
- **Output:** All itemsets with items in I having
 - $\text{support} \geq \text{minsup}$ threshold
- Problem parameters:
 - $N = |T|$: number of transactions
 - $d = |I|$: number of (distinct) items
 - w : max width of a transaction
 - Number of possible itemsets? $M = 2^d$
- Scale of the problem:
 - WalMart sells 100,000 items and can store billions of baskets.
 - The Web has billions of words and many billions of pages.

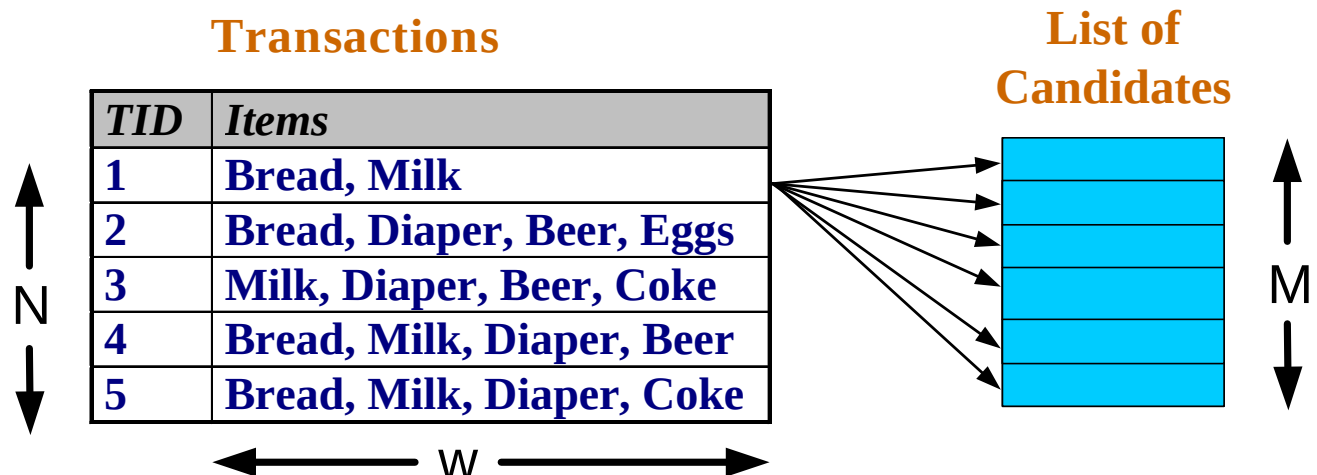
The itemset lattice



Given **d** items, there are **2^d** possible itemsets

A Naïve Algorithm

- Brute-force approach, each itemset is a **candidate** :
 - Consider each itemset in the lattice, and count the support of each candidate by scanning the data
 - Time Complexity $\sim O(NMw)$, Space Complexity $\sim O(M)$
- OR
 - Scan the data, and for each transaction generate all possible itemsets. Keep a count for each itemset in the data.
 - Time Complexity $\sim O(N2^w)$, Space Complexity $\sim O(M)$
- **Expensive since $M = 2^d$!!!**



Computation Model

- Typically, data is kept in flat files rather than in a database system.
 - Stored on disk.
 - Stored basket-by-basket.
 - Expand baskets into pairs, triples, etc. as you read baskets.
 - Use k nested loops to generate all sets of size k .

Example file: retail

```
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29
30 31 32
33 34 35
36 37 38 39 40 41 42 43 44 45 46
38 39 47 48
38 39 48 49 50 51 52 53 54 55 56 57 58
32 41 59 60 61 62
3 39 48
63 64 65 66 67 68
32 69
48 70 71 72
39 73 74 75 76 77 78 79
36 38 39 41 48 79 80 81
82 83 84
41 85 86 87 88
39 48 89 90 91 92 93 94 95 96 97 98 99 100 101
36 38 39 48 89
39 41 102 103 104 105 106 107 108
38 39 41 109 110
39 111 112 113 114 115 116 117 118
119 120 121 122 123 124 125 126 127 128 129 130 131 132 133
48 134 135 136
39 48 137 138 139 140 141 142 143 144 145 146 147 148 149
39 150 151 152
38 39 56 153 154 155
```

Example: items are positive integers, and each basket corresponds to a line in the file of space separated integers

Computation Model – (2)

- The true cost of mining disk-resident data is usually the **number of disk I/O's**.
- In practice, association-rule algorithms read the data in **passes** – all baskets read in turn.
- Thus, we measure the cost by the **number of passes** an algorithm takes.

Main-Memory Bottleneck

- For many frequent-itemset algorithms, main memory is the critical resource.
 - As we read baskets, we need to count something, e.g., occurrences of pairs.
 - The number of different things we can count is limited by main memory.
 - Swapping counts in/out is a disaster (**why?**).

The Apriori Principle

- **Apriori** principle (Main observation):
 - If an itemset is **frequent**, then all of its **subsets** must also be frequent
 - If an itemset is **not frequent**, then all of its **supersets** cannot be frequent

$$\forall X, Y : (X \subseteq Y) \Rightarrow s(X) \geq s(Y)$$

- The support of an itemset **never exceeds** the support of its subsets
- This is known as the **anti-monotone** property of support

Illustration of the Apriori principle

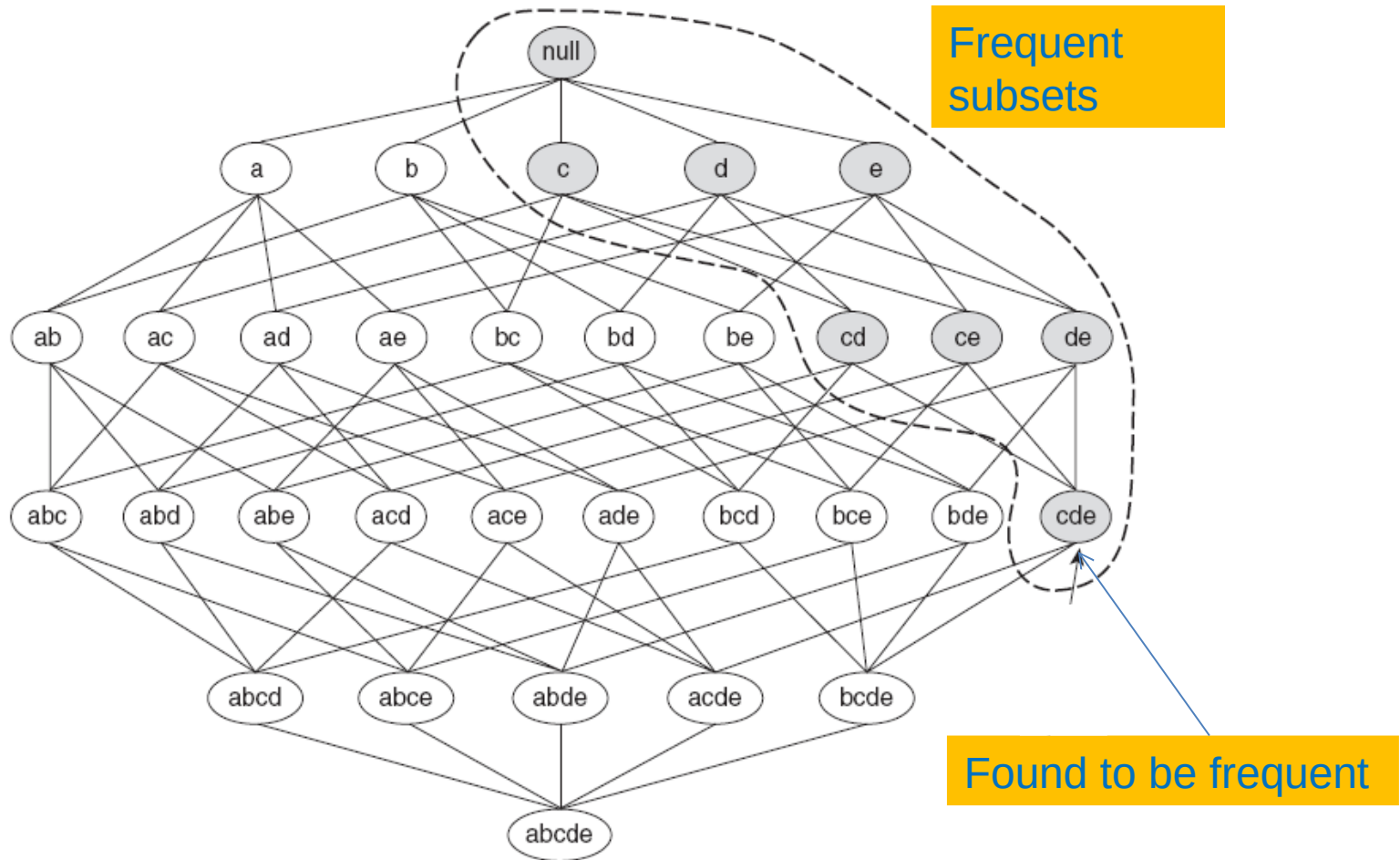
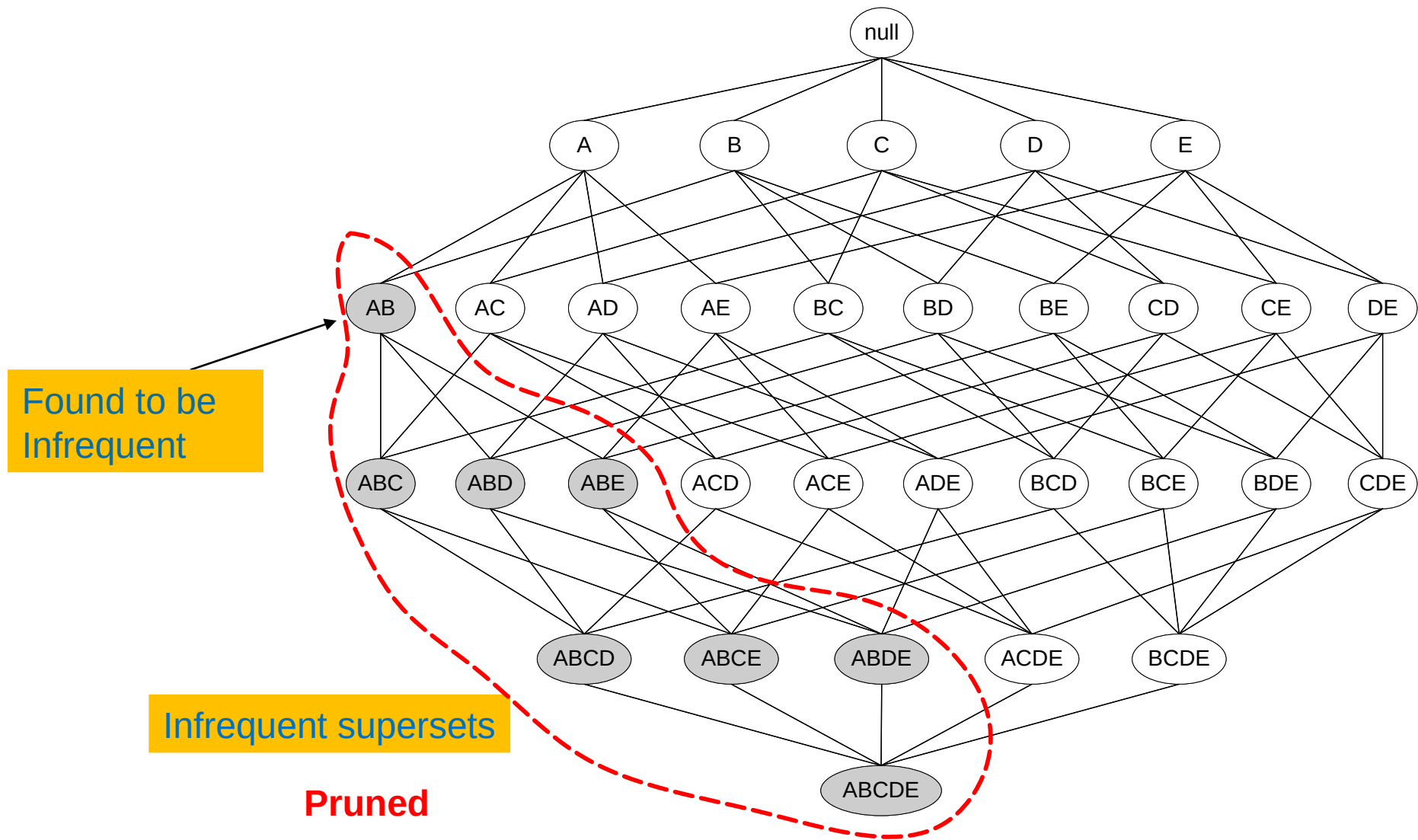


Figure 6.3. An illustration of the *Apriori* principle. If $\{c, d, e\}$ is frequent, then all subsets of this itemset are frequent.

Illustration of the Apriori principle



The Apriori algorithm

Level-wise approach

C_k = candidate itemsets of size k

L_k = frequent itemsets of size k

1. $k = 1$, C_1 = all items

2. While C_k not empty

Frequent
itemset
generation

3. Scan the database to find which itemsets in C_k are frequent and put them into L_k

Candidate
generation

4. Use L_k to generate a collection of candidate itemsets C_{k+1} of size $k+1$

5. $k = k+1$

R. Agrawal, R. Srikant: "Fast Algorithms for Mining Association Rules",
Proc. of the 20th Int'l Conference on Very Large Databases, 1994.

Illustration of the Apriori principle

Item	Count
Bread	4
Coke	2
Milk	4
Beer	3
Diaper	4
Eggs	1

Items (1-itemsets)

minsup = 3

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Itemset	Count
{Bread,Milk}	3
{Bread,Beer}	2
{Bread,Diaper}	3
{Milk,Beer}	2
{Milk,Diaper}	3
{Beer,Diaper}	3

Pairs (2-itemsets)

(No need to generate candidates involving Coke or Eggs)



Triplets (3-itemsets)

Itemset	Count
{Bread,Milk,Diaper}	2

If every subset is considered,
 $6 + 15 + 20 = 41$
 With support-based pruning,
 $6 + 6 + 1 = 13$

Only this triplet has all subsets to be frequent
 But it is below the minsup threshold

Candidate Generation

- Basic principle (Apriori):
 - An itemset of size $k+1$ is candidate to be frequent only if **all** of its subsets of size k are known to be frequent
- Main idea:
 - Construct a **candidate** of size $k+1$ by **combining frequent** itemsets of size k
 - If $k = 1$, take the all pairs of frequent items
 - If $k > 1$, **join** pairs of itemsets that differ by just one item
 - For each generated **candidate** itemset ensure that **all subsets of size k are frequent**.

Generate Candidates C_{k+1}

- Assumption: The items in an itemset are **ordered**
 - E.g., if integers ordered in increasing order, if strings ordered in lexicographic order
 - The order ensures that if item $y > x$ appears before x , then x is not in the itemset
- The items in L_k are also listed in an order

Create a candidate itemset of size $k+1$, by joining two itemsets of size k , that share the first $k-1$ items


Item 1	Item 2	Item 3
1	2	3
1	2	5
1	4	5

Generate Candidates C_{k+1}

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1 2 4 5

Are we missing something?
What about this candidate?

Factors Affecting Complexity

- Choice of minimum support threshold
 - lowering support threshold results in more frequent itemsets
 - this may increase number of candidates and max length of frequent itemsets
- Dimensionality (number of items) of the data set
 - more space is needed to store support count of each item
 - if number of frequent items also increases, both computation and I/O costs may also increase
- Size of database
 - since Apriori makes multiple passes, run time of algorithm may increase with number of transactions
- Average transaction width
 - transaction width increases with denser data sets
 - This may increase max length of frequent itemsets and traversals of hash tree (number of subsets in a transaction increases with its width)

ASSOCIATION RULES

Association Rule Mining

- Given a set of transactions, find **rules** that will predict the occurrence of an item based on the occurrences of other items in the transaction

Market-Basket transactions

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Example of Association Rules

{Diaper} \Rightarrow {Beer},
{Milk, Bread} \Rightarrow {Eggs,Coke},
{Beer, Bread} \Rightarrow {Milk},

Implication means **co-occurrence**,
not causality!

Definition: Association Rule

- **Association Rule**

- An implication expression of the form $X \Rightarrow Y$, where X and Y are itemsets
- Example:
 $\{\text{Milk, Diaper}\} \Rightarrow \{\text{Beer}\}$

- **Rule Evaluation Metrics**

- **Support** (s)
 - ◆ Fraction of transactions that contain both X and Y
 - ◆ the probability $P(X,Y)$ that X and Y occur together
- **Confidence** (c)
 - ◆ Measures how often items in Y appear in transactions that contain X
 - ◆ the conditional probability $P(Y|X)$ that Y occurs given that X has occurred.

TID	Items
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Example:

$\{\text{Milk, Diaper}\} \Rightarrow \text{Beer}$

$$s = \frac{\sigma(\text{Milk, Diaper, Beer})}{|T|} = \frac{2}{5} = 0.4$$

$$c = \frac{\sigma(\text{Milk, Diaper, Beer})}{\sigma(\text{Milk, Diaper})} = \frac{2}{3} = 0.67$$

Association Rule Mining Task

- **Input**: A set of transactions T , over a set of items I
- **Output**: All rules with items in I having
 - support $\geq \textit{minsup}$ threshold
 - confidence $\geq \textit{minconf}$ threshold

Mining Association Rules

- Two-step approach:
 1. Frequent Itemset Generation
 - Generate all itemsets whose support \geq minsup
 2. Rule Generation
 - Generate high confidence rules from each frequent itemset, where each rule is a partitioning of a frequent itemset into Left-Hand-Side (LHS) and Right-Hand-Side (RHS)

Frequent itemset: {A,B,C,D}

Rule: AB  CD

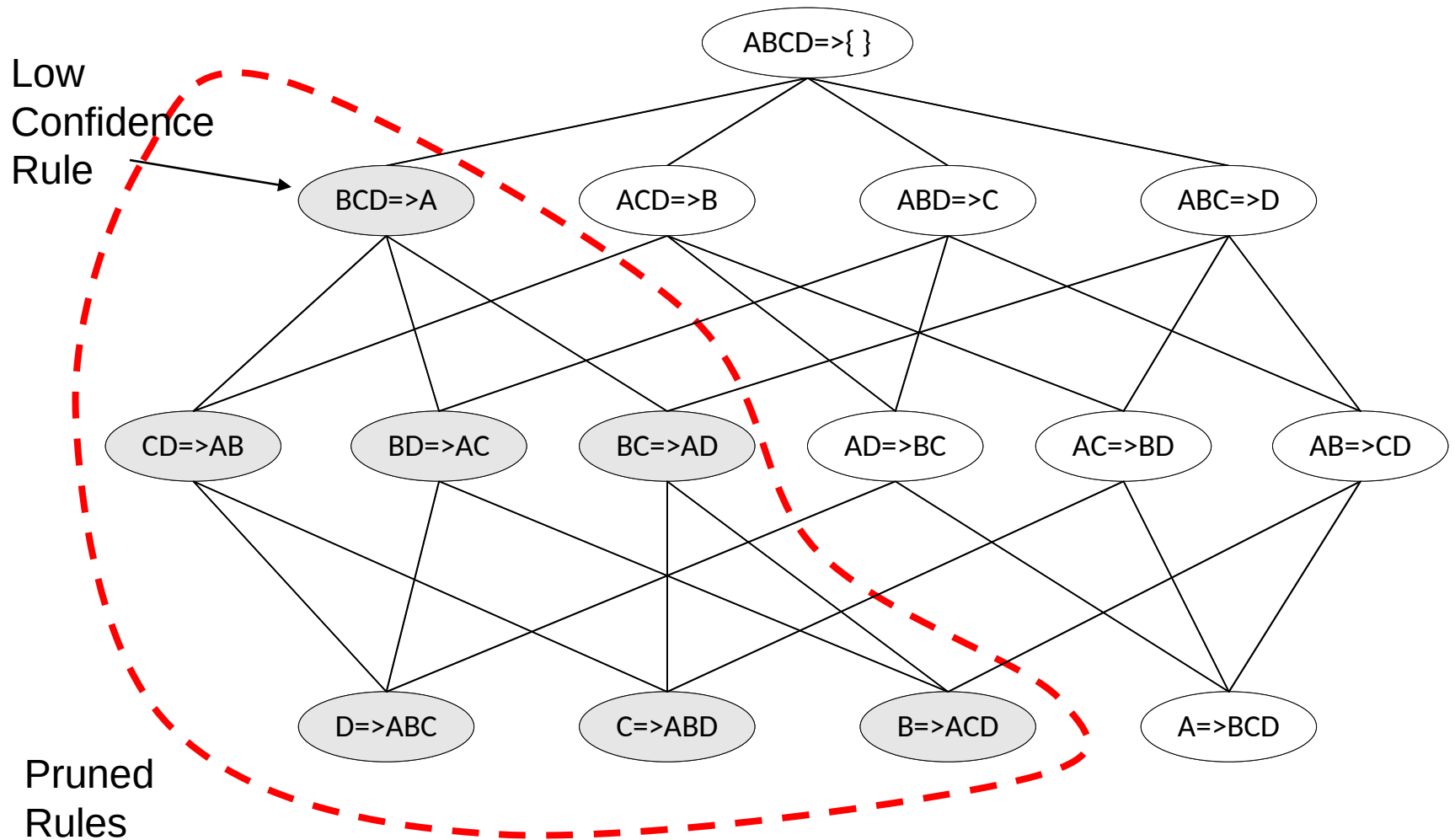
Rule Generation

- We have all frequent itemsets, how do we get the rules?
 - For every frequent itemset S , we find rules of the form $L \Rightarrow S - L$, where $L \subset S$, that satisfy the minimum confidence requirement
 - Example: $L = \{A, B, C, D\}$
 - Candidate rules:
 $A \Rightarrow BCD, B \Rightarrow ACD, C \Rightarrow ABD, D \Rightarrow ABC$
 $AB \Rightarrow CD, AC \Rightarrow BD, AD \Rightarrow BC, BD \Rightarrow AC, CD \Rightarrow AB,$
 $ABC \Rightarrow D, BCD \Rightarrow A, BC \Rightarrow AD,$
- If $|L| = k$, then there are $2^k - 2$ candidate association rules (ignoring $L \Rightarrow \emptyset$ and $\emptyset \Rightarrow L$)

Rule Generation

- How to efficiently generate rules from frequent itemsets?
 - In general, confidence does not have an anti-monotone property
 $c(ABC \Rightarrow D)$ can be larger or smaller than $c(AB \Rightarrow D)$
 - But confidence of rules generated from the same itemset has an anti-monotone property
 - e.g., $L = \{A, B, C, D\}$:
 $c(ABC \Rightarrow D) \quad c(AB \Rightarrow CD) \quad c(A \Rightarrow BCD)$
- Confidence is **anti-monotone** w.r.t. number of items on the **RHS** of the rule

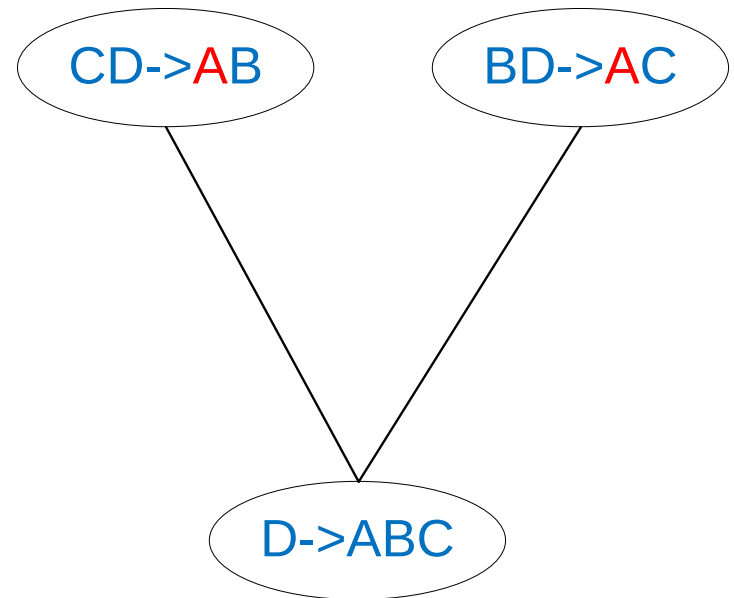
Rule Generation for Apriori Algorithm



Rule Generation for APriori Algorithm

- Candidate rule is generated by merging two rules that share the same prefix in the **RHS**

- $\text{join}(\text{CD} \Rightarrow \text{AB}, \text{BD} \Rightarrow \text{AC})$
would produce the candidate rule $\text{D} \Rightarrow \text{ABC}$
- Prune rule $\text{D} \Rightarrow \text{ABC}$ if its subset $\text{AD} \Rightarrow \text{BC}$ does not have high confidence



- Essentially we are doing APriori on the RHS