

# DATA MINING

## LECTURE 4

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Frequent Itemsets, Association Rules

Evaluation

Alternative Algorithms

# RECAP

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# Mining Frequent Itemsets

- **Itemset**

- A collection of one or more items
  - Example: {Milk, Bread, Diaper}
- **k-itemset**
  - An itemset that contains **k** items

- **Support ( $\sigma$ )**

- **Count:** Frequency of occurrence of an itemset
- E.g.  $\sigma(\{\text{Milk, Bread, Diaper}\}) = 2$
- **Fraction:** Fraction of transactions that contain an itemset
- E.g.  $s(\{\text{Milk, Bread, Diaper}\}) = 40\%$

- **Frequent Itemset**

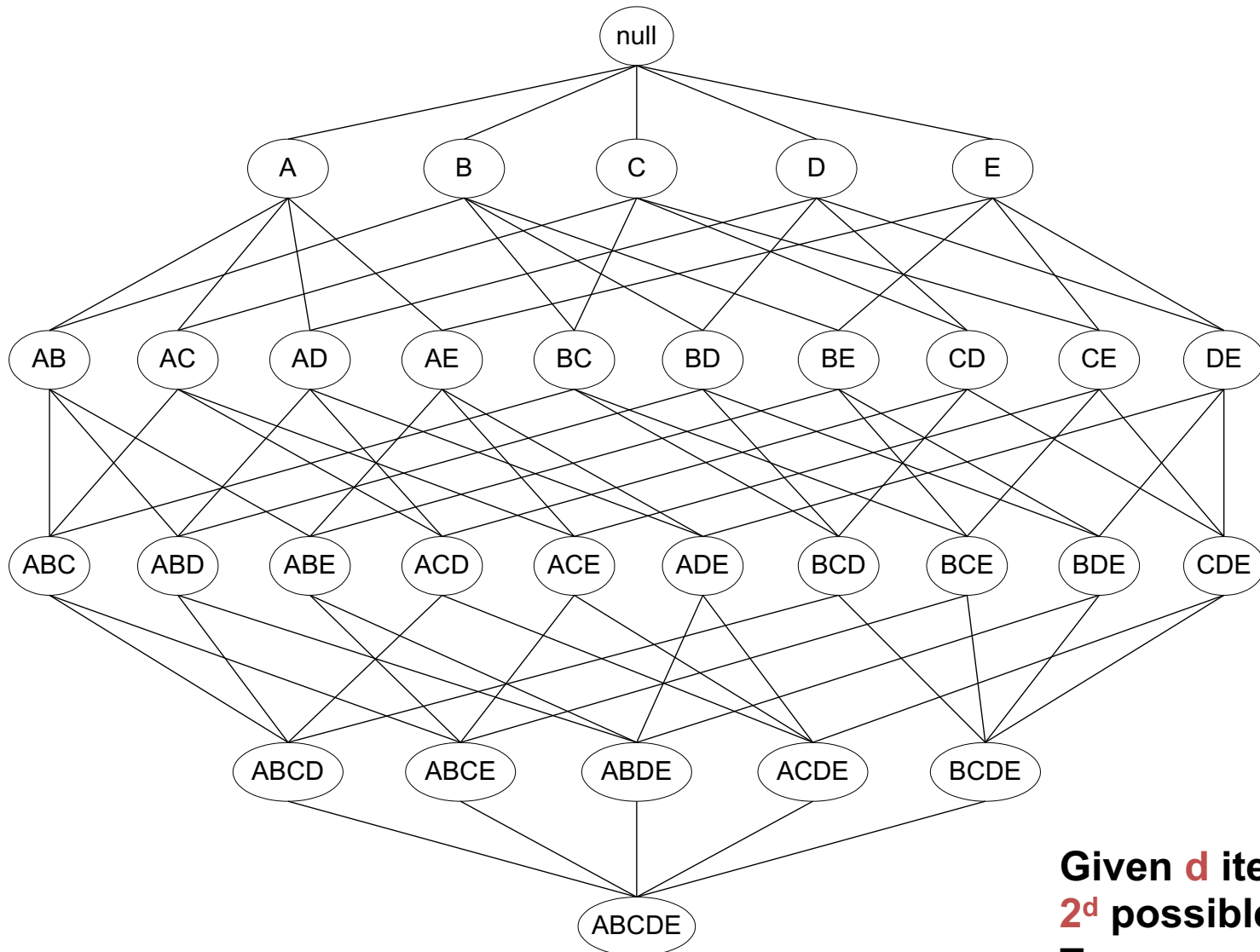
- An itemset whose support is greater than or equal to a **minsup** threshold,  
 $s(I) \geq \text{minsup}$

- **Problem Definition**

- **Input:** A set of transactions **T**, over a set of items **I**, **minsup** value
- **Output:** All itemsets with items in **I** having  $s(I) \geq \text{minsup}$

<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

# The itemset lattice



Given **d** items, there are  **$2^d$**  possible itemsets  
Too expensive to test all!

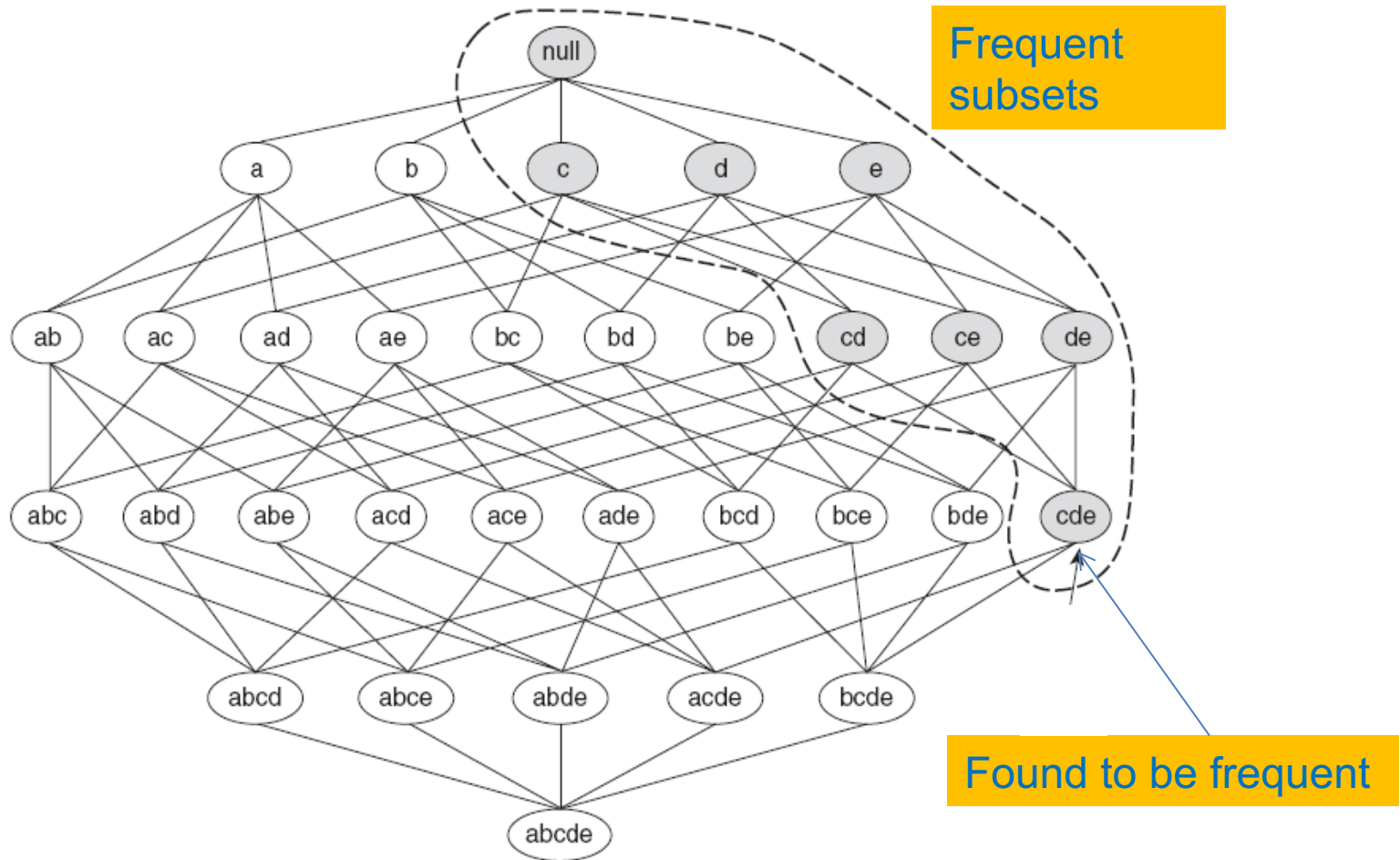
# The Apriori Principle

- **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

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

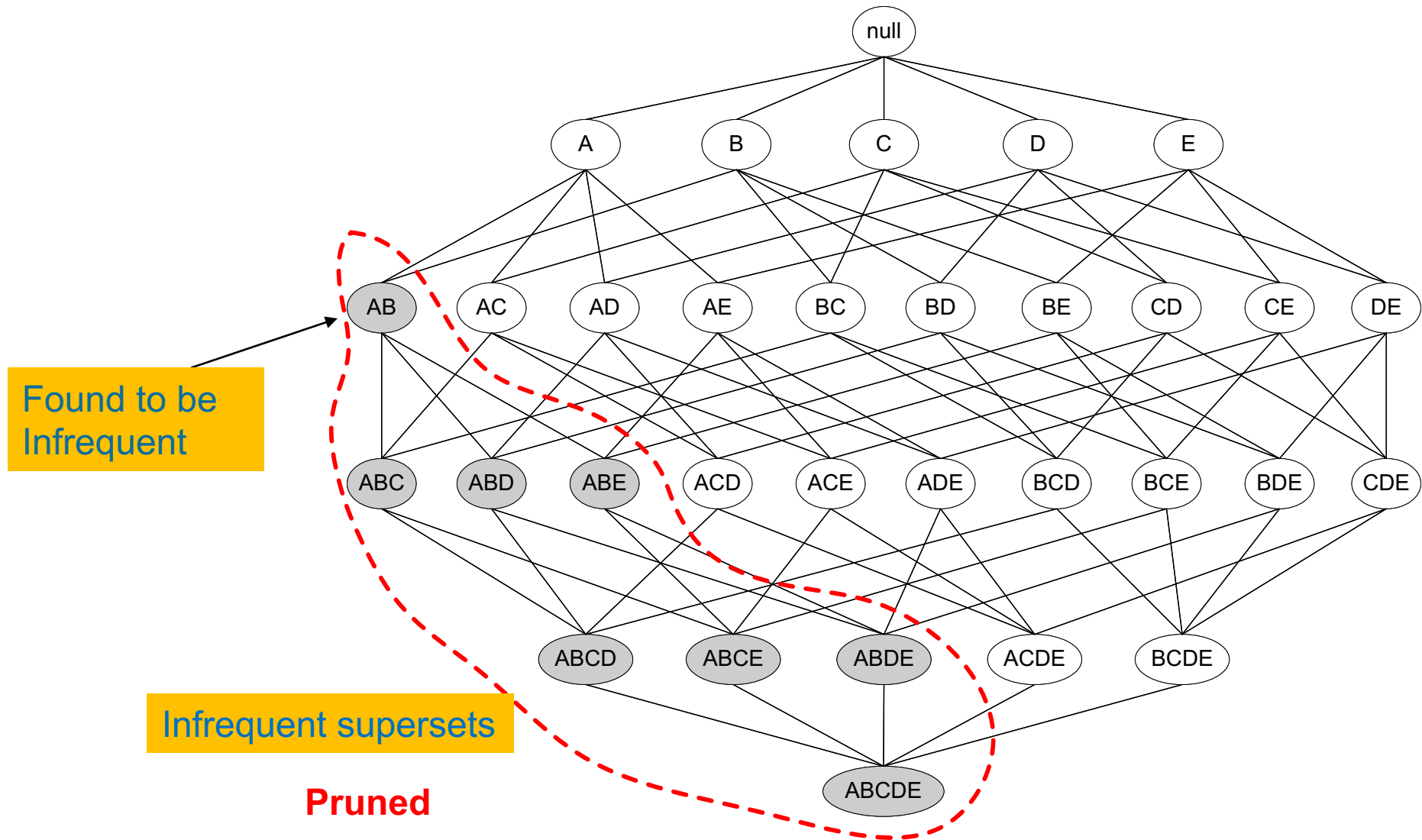
- The support of an itemset **never exceeds** the support of its subsets
- This is known as the **anti-monotone** property of support

# 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.

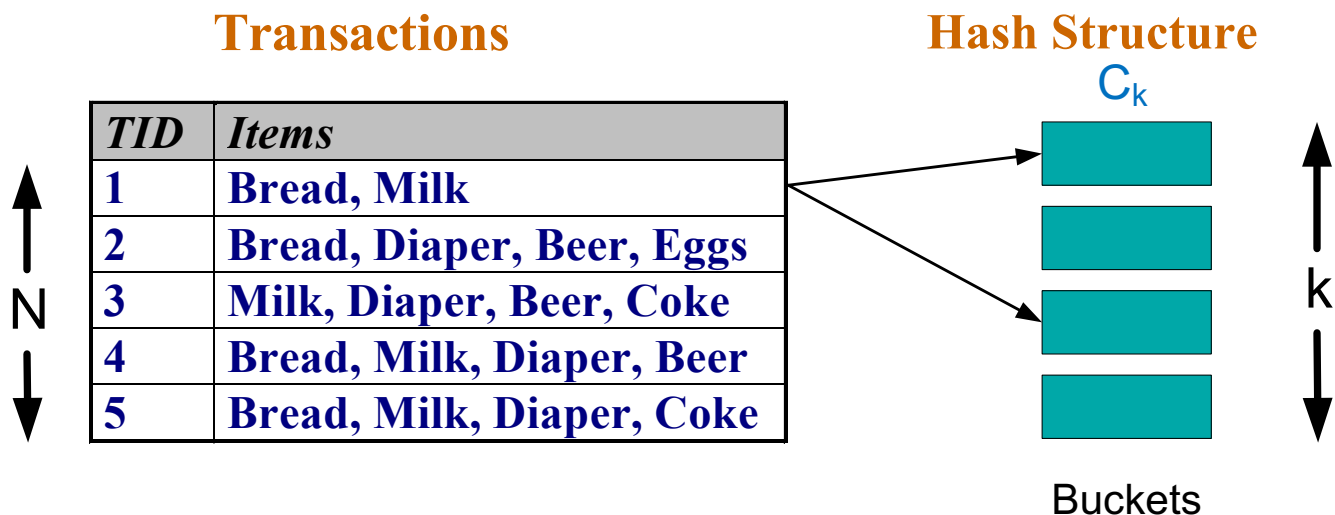


# Candidate Generation

- 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** two **frequent** itemsets of size  $k$
  - **Prune** the generated  $k+1$ -itemsets that do not have **all**  $k$ -subsets to be frequent

# Computing Frequent Itemsets

- Given the set of **candidate** itemsets  $C_k$ , we need to compute the support and find the **frequent** itemsets  $L_k$ .
- Scan the data, and use a **hash structure** to keep a counter for each candidate itemset that appears in the data



# A simple hash structure

- Create a **dictionary** (**hash table**) that stores the candidate itemsets as keys, and the number of appearances as the value.
  - Initialize with zero
- Increment the counter for each itemset that you see in the data

# Example

Suppose you have 15 candidate itemsets of length 3:

{1 4 5}, {1 2 4}, {4 5 7}, {1 2 5}, {4 5 8},  
{1 5 9}, {1 3 6}, {2 3 4}, {5 6 7}, {3 4 5},  
{3 5 6}, {3 5 7}, {6 8 9}, {3 6 7}, {3 6 8}

Hash table stores the counts of the candidate itemsets as they have been computed so far

Key	Value
{3 6 7}	0
{3 4 5}	1
{1 3 6}	3
{1 4 5}	5
{2 3 4}	2
{1 5 9}	1
{3 6 8}	0
{4 5 7}	2
{6 8 9}	0
{5 6 7}	3
{1 2 4}	8
{3 5 7}	1
{1 2 5}	0
{3 5 6}	1
{4 5 8}	0

# Example

Tuple {1,2,3,5,6} generates the following itemsets of length 3:

{1 2 3}, {1 2 5}, {1 2 6}, {1 3 5}, {1 3 6},  
{1 5 6}, {2 3 5}, {2 3 6}, {3 5 6},

Increment the counters for the itemsets in the dictionary

Key	Value
{3 6 7}	0
{3 4 5}	1
{1 3 6}	3
{1 4 5}	5
{2 3 4}	2
{1 5 9}	1
{3 6 8}	0
{4 5 7}	2
{6 8 9}	0
{5 6 7}	3
{1 2 4}	8
{3 5 7}	1
{1 2 5}	0
{3 5 6}	1
{4 5 8}	0

# Example

Tuple {1,2,3,5,6} generates the following itemsets of length 3:

{1 2 3}, {1 2 5}, {1 2 6}, {1 3 5}, {1 3 6},  
{1 5 6}, {2 3 5}, {2 3 6}, {3 5 6},

Increment the counters for the itemsets in the dictionary

Key	Value
{3 6 7}	0
{3 4 5}	1
{1 3 6}	4
{1 4 5}	5
{2 3 4}	2
{1 5 9}	1
{3 6 8}	0
{4 5 7}	2
{6 8 9}	0
{5 6 7}	3
{1 2 4}	8
{3 5 7}	1
{1 2 5}	1
{3 5 6}	2
{4 5 8}	0

# Mining Association Rules

## ● Association Rule

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

## ● 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)
  - ◆ How often  $Y$  appears in transactions that contain  $X$  = the **conditional probability**  $P(Y|X)$  that  $Y$  occurs given that  $X$  has occurred.

## ● Problem Definition

- **Input** A set of transactions  $T$ , over a set of items  $I$ , **minsup**, **minconf** values
- **Output**: All rules with items in  $I$  having  $s \geq \text{minsup}$  and  $c \geq \text{minconf}$

<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

**Example:**

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

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

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

# 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  $\rightarrow$  CD



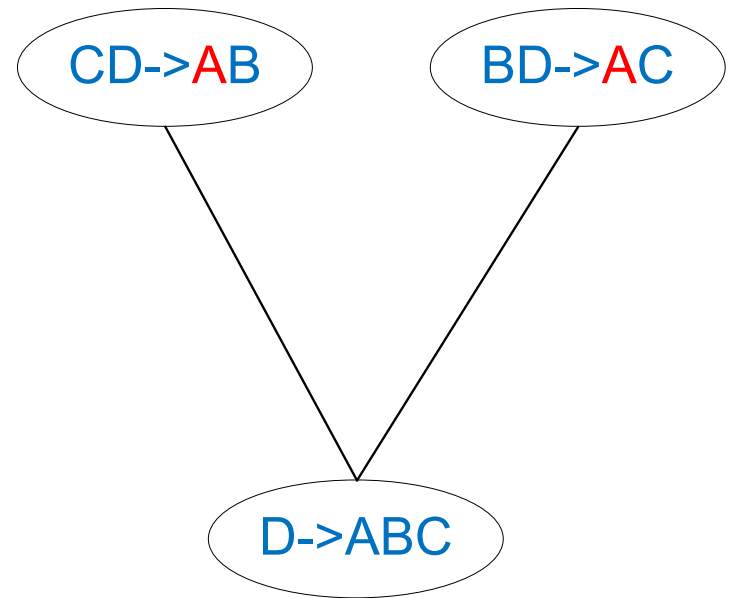
# Association Rule anti-monotonicity

- Confidence is **anti-monotone** w.r.t. number of items on the **RHS** of the rule (or **monotone** with respect to the **LHS** of the rule)
- e.g.,  $L = \{A, B, C, D\}$ :

$$c(ABC \rightarrow D) \geq c(AB \rightarrow CD) \geq c(A \rightarrow BCD)$$

# 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



# RESULT POST-PROCESSING

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# Compact Representation of Frequent Itemsets

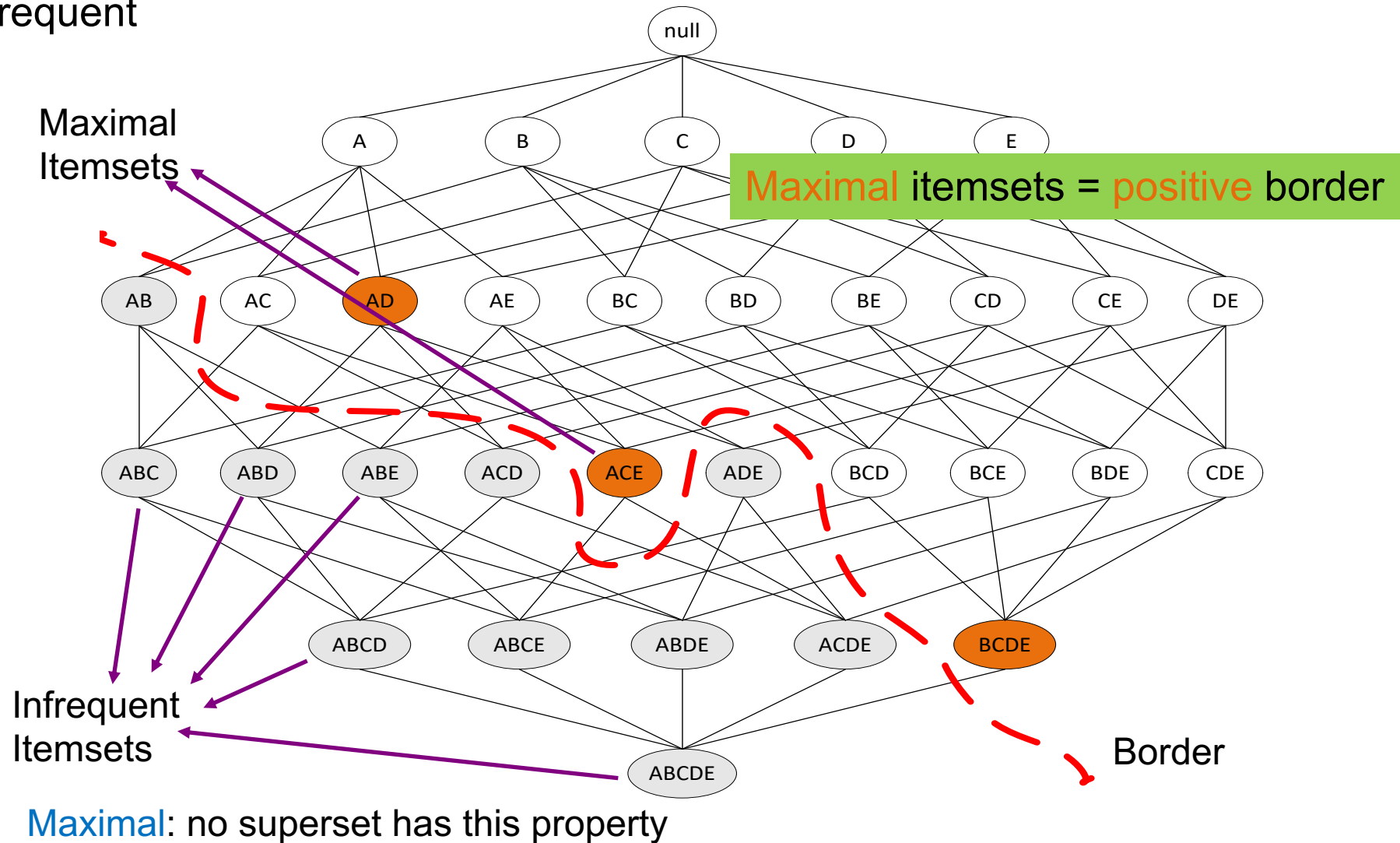
- Some itemsets are redundant because they have identical support as their supersets

TID	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1

- Number of frequent itemsets =  $3 \times \sum_{k=1}^{10} \binom{10}{k}$
- Need a compact representation

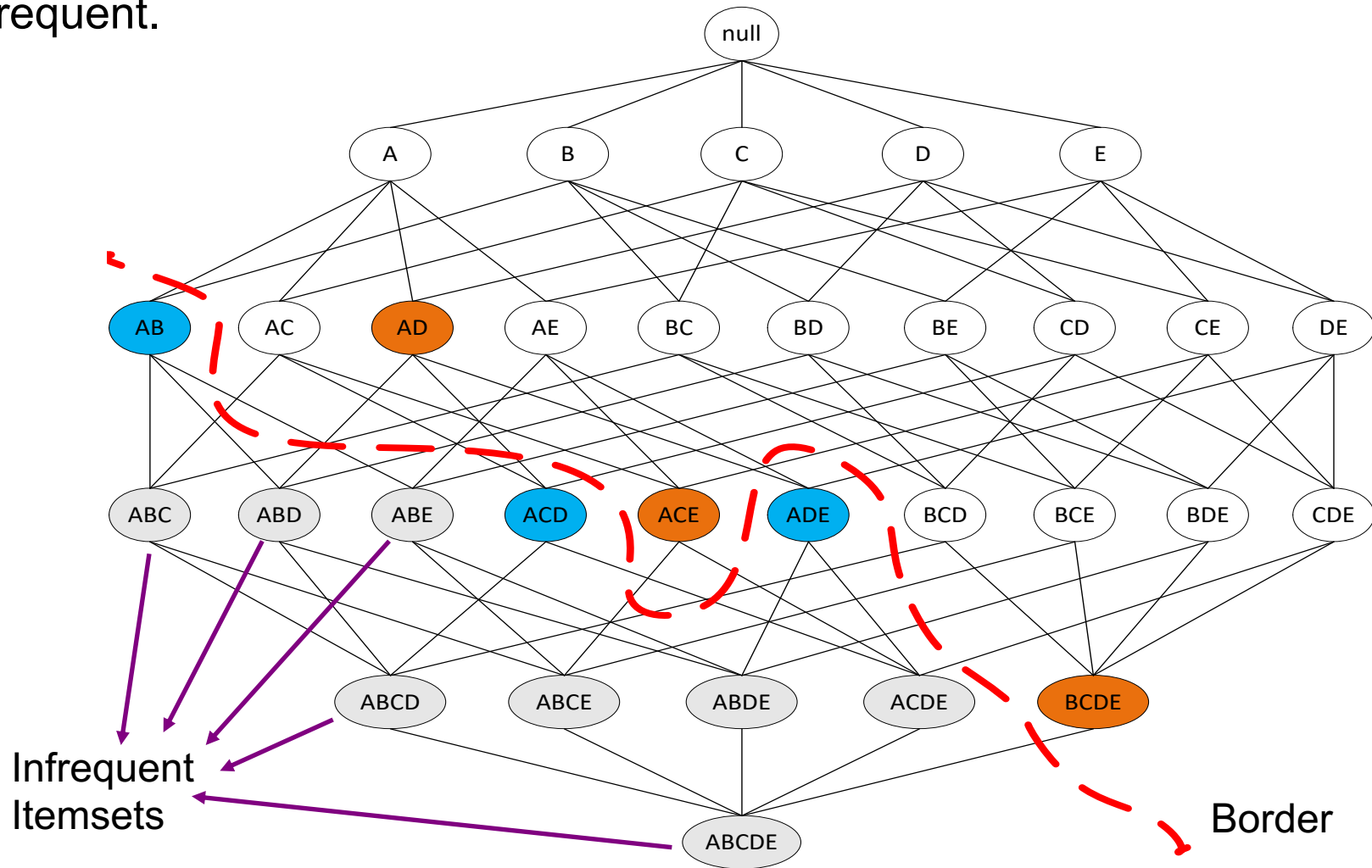
# Maximal Frequent Itemset

An itemset is **maximal** frequent if none of its immediate **supersets** is frequent



# Negative Border

Itemsets that are not frequent, but all their immediate **subsets** are frequent.



**Minimal:** no subset has this property

# Border

- **Border** = **Positive Border** + **Negative Border**
  - Itemsets such that all their **immediate subsets** are **frequent** and all their **immediate supersets** are **infrequent**.
- Either the positive, or the negative border is sufficient to **summarize** all frequent itemsets.

# Closed Itemset

- An itemset is **closed** if **none** of its immediate **supersets** has the **same** support as the itemset

TID	Items
1	{A,B}
2	{B,C,D}
3	{A,B,C,D}
4	{A,B,D}
5	{A,B,C,D}

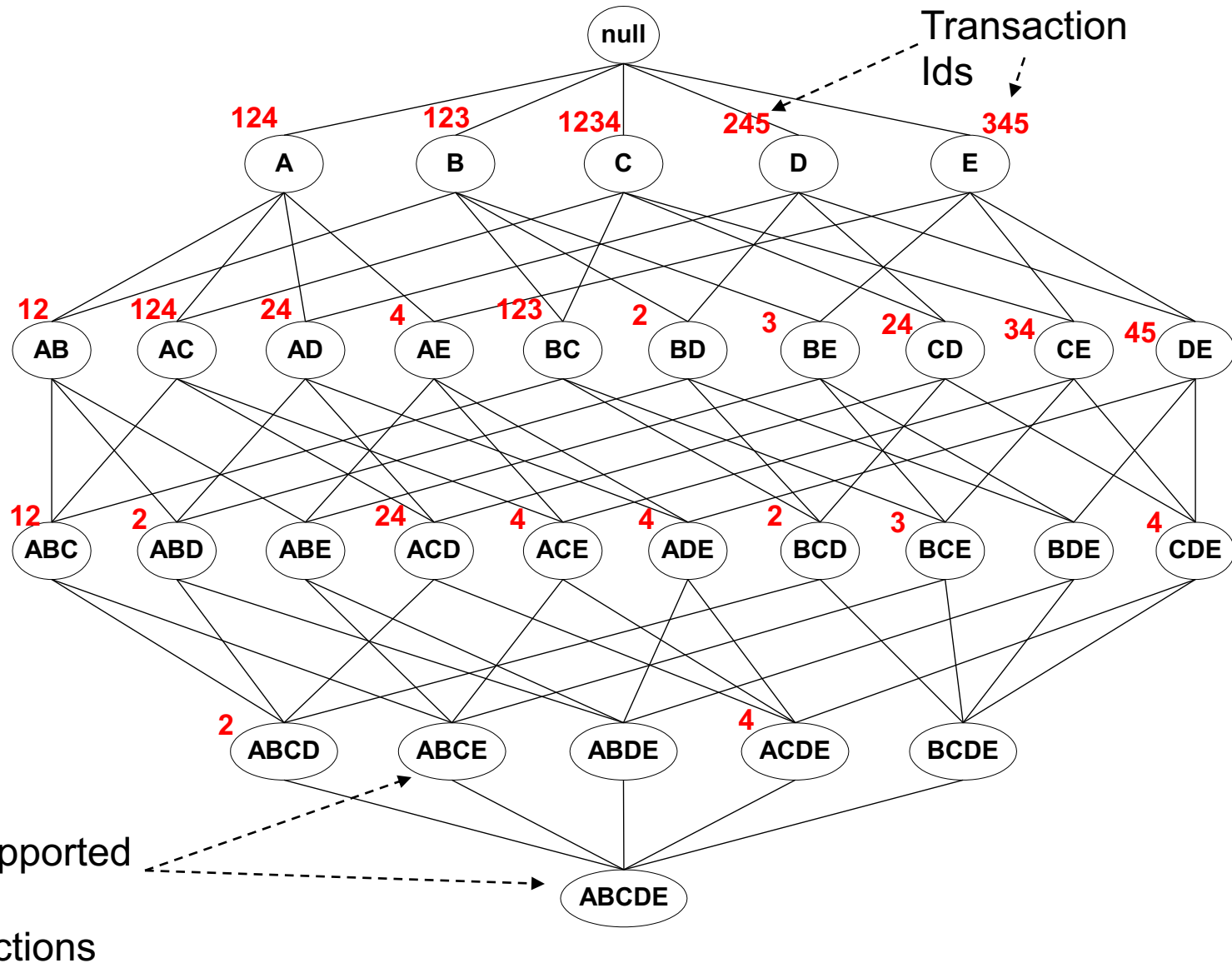
Itemset	Support
{A}	4
{B}	5
{C}	3
{D}	4
{A,B}	4
{A,C}	2
{A,D}	3
{B,C}	3
{B,D}	4
{C,D}	3

Itemset	Support
{A,B,C}	2
{A,B,D}	3
{A,C,D}	2
{B,C,D}	3
{A,B,C,D}	2

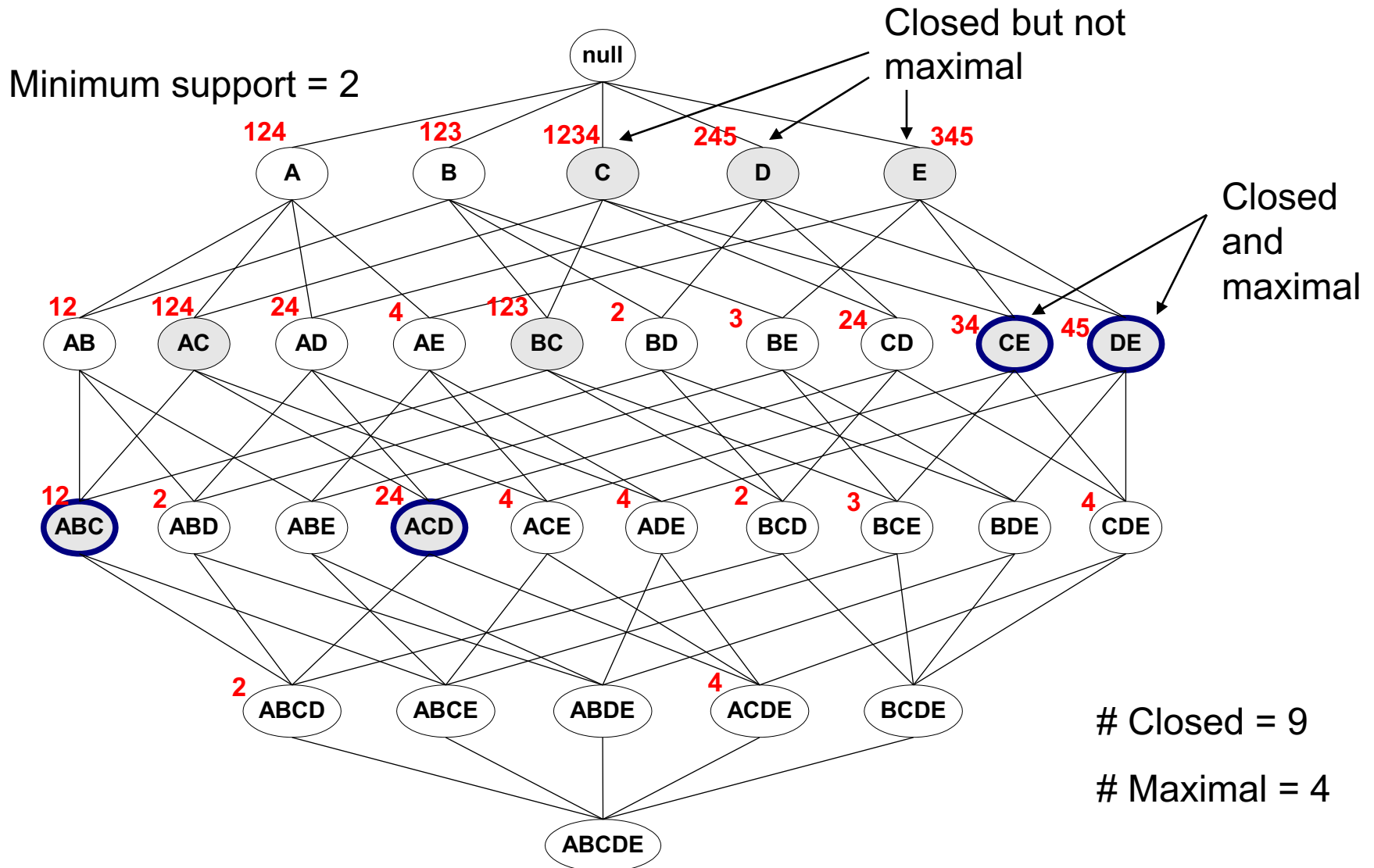


# Maximal vs Closed Itemsets

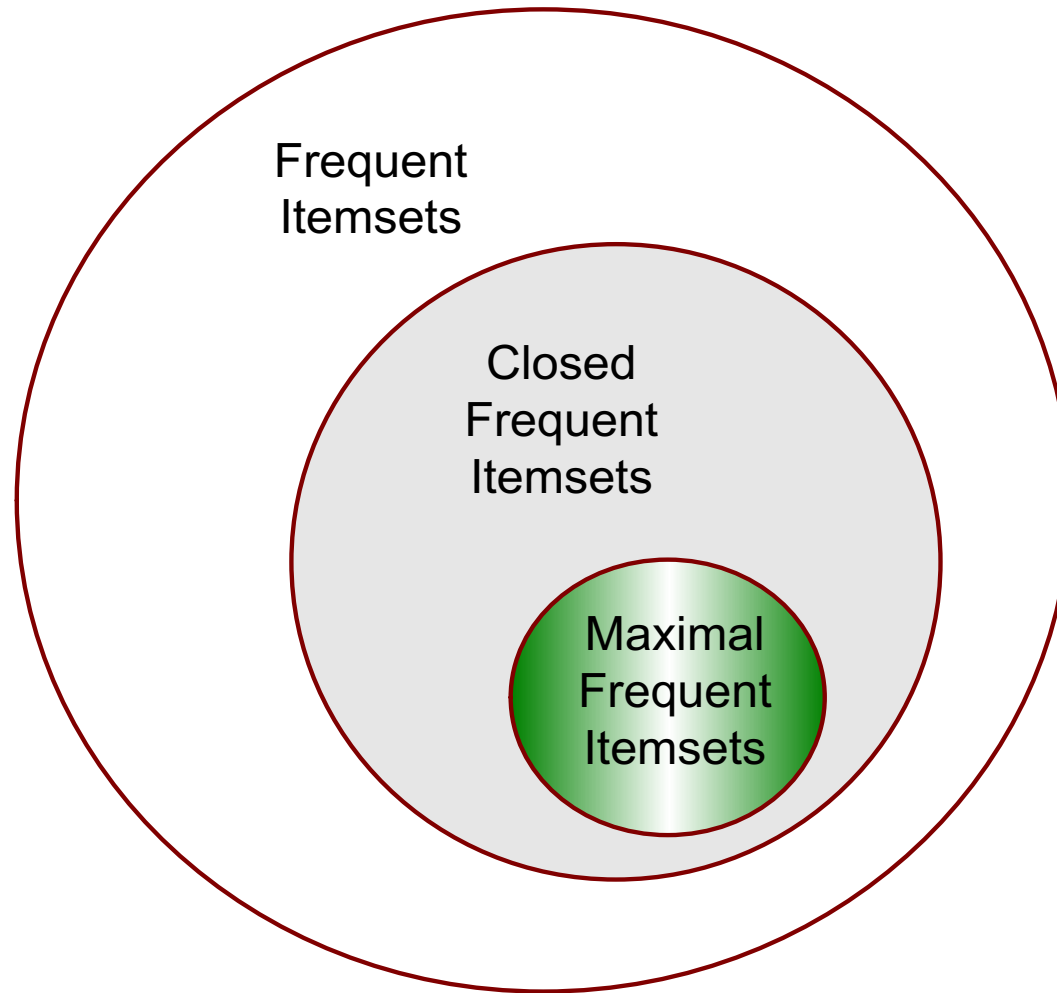
TID	Items
1	ABC
2	ABCD
3	BCE
4	ACDE
5	DE



# Maximal vs Closed Frequent Itemsets



# Maximal vs Closed Itemsets



# Pattern Evaluation

- Association rule algorithms tend to produce too many rules but many of them are **uninteresting** or **redundant**
  - Redundant if  $\{A,B,C\} \rightarrow \{D\}$  and  $\{A,B\} \rightarrow \{D\}$  have same support & confidence
    - Summarization techniques
  - Uninteresting, if the pattern that is revealed does not offer useful information.
    - Interestingness measures: a hard problem to define
- **Interestingness measures** can be used to prune/rank the derived patterns
  - Subjective measures: require human analyst
  - Objective measures: rely on the data.
- In the original formulation of association rules, support & confidence are the only measures used

# Computing Interestingness Measure

- Given a rule  $X \rightarrow Y$ , information needed to compute rule interestingness can be obtained from a contingency table

Contingency table for  $X \rightarrow Y$

	$Y$	$\bar{Y}$	
$X$	$f_{11}$	$f_{10}$	$f_{1+}$
$\bar{X}$	$f_{01}$	$f_{00}$	$f_{0+}$
	$f_{+1}$	$f_{+0}$	$N$

$f_{11}$ : support of  $X$  and  $Y$

$f_{10}$ : support of  $X$  and  $\bar{Y}$

$f_{01}$ : support of  $\bar{X}$  and  $Y$

$f_{00}$ : support of  $\bar{X}$  and  $\bar{Y}$

$X$ : itemset  $X$  appears in tuple

$Y$ : itemset  $Y$  appears in tuple

$\bar{X}$ : itemset  $X$  does not appear in tuple

$\bar{Y}$ : itemset  $Y$  does not appear in tuple

Used to define various measures

- ◆ support, confidence, lift, Gini, J-measure, etc.

# Drawback of Confidence

	Coffee	<u>Coffee</u>	
Tea	15	5	20
<u>Tea</u>	75	5	80
	90	10	100

Number of people that drink tea

Number of people that drink coffee **and** tea

Number of people that drink coffee **but not** tea

Number of people that drink coffee

Association Rule: Tea → Coffee

$$\text{Confidence} = P(\text{Coffee}|\text{Tea}) = \frac{15}{20} = 0.75$$

$$\text{but } P(\text{Coffee}) = \frac{90}{100} = 0.9$$

- Although confidence is high, rule is misleading
- $P(\text{Coffee}|\overline{\text{Tea}}) = 0.9375$

# Statistical Independence

- Population of 1000 students
  - 600 students know how to swim (S)
  - 700 students know how to bike (B)
  - 420 students know how to swim and bike (S,B)
- $P(S \cap B) = 420/1000 = 0.42$
- $P(S) \times P(B) = 0.6 \times 0.7 = 0.42$
- $P(S \cap B) = P(S) \times P(B) \Rightarrow$  Statistical independence

# Statistical Independence

- Population of 1000 students
  - 600 students know how to swim (S)
  - 700 students know how to bike (B)
  - 500 students know how to swim and bike (S,B)
- $P(S \cap B) = 500/1000 = 0.5$
- $P(S) \times P(B) = 0.6 \times 0.7 = 0.42$
- $P(S \cap B) > P(S) \times P(B) \Rightarrow$  Positively correlated



# Statistical Independence

- Population of 1000 students
  - 600 students know how to swim (S)
  - 700 students know how to bike (B)
  - 300 students know how to swim and bike (S,B)
- $P(S \cap B) = 300/1000 = 0.3$
- $P(S) \times P(B) = 0.6 \times 0.7 = 0.42$
- $P(S \cap B) < P(S) \times P(B) \Rightarrow$  Negatively correlated

# Statistical-based Measures

- Measures that take into account statistical dependence
  - Lift/Interest/PMI

$$\text{Lift} = \frac{P(Y|X)}{P(Y)} = \frac{P(X, Y)}{P(X)P(Y)} = \text{Interest}$$

In text mining it is called: Pointwise Mutual Information

- Piatesky-Shapiro

$$\text{PS} = P(X, Y) - P(X)P(Y)$$

- All these measures measure deviation from independence
  - The higher, the better (why?)

# Example: Lift/Interest

	Coffee	<u>Coffee</u>	
Tea	15	5	20
<u>Tea</u>	75	5	80
	90	10	100

Association Rule: Tea  $\rightarrow$  Coffee

Confidence =  $P(\text{Coffee}|\text{Tea}) = 0.75$

but  $P(\text{Coffee}) = 0.9$

$\Rightarrow \text{Lift} = 0.75/0.9 = 0.8333$  ( $< 1$ , therefore is negatively associated)  
 $= 0.15/(0.9*0.2)$

# Another Example

	of	the	of, the
Fraction of documents	0.9	0.9	0.8

$$P(\text{of, the}) \approx P(\text{of})P(\text{the})$$

If I was creating a document by picking words randomly, (of, the) have more or less the **same** probability of appearing together **by chance**

No correlation

	hong	kong	hong, kong
Fraction of documents	0.2	0.2	0.19

$$P(\text{hong, kong}) \gg P(\text{hong})P(\text{kong})$$

(hong, kong) have much **lower** probability to appear together **by chance**.  
The two words appear almost always only together

Positive correlation

	obama	karagounis	obama, karagounis
Fraction of documents	0.2	0.2	0.001

$$P(\text{obama, karagounis}) \ll P(\text{obama})P(\text{karagounis})$$

(obama, karagounis) have much **higher** probability to appear together **by chance**.  
The two words appear almost never together

Negative correlation

# Drawbacks of Lift/Interest/Mutual Information

	honk	konk	honk, konk
Fraction of documents	0.0001	0.0001	0.0001

$$MI(honk, konk) = \frac{0.0001}{0.0001 * 0.0001} = 10000$$

	hong	kong	hong, kong
Fraction of documents	0.2	0.2	0.19

$$MI(hong, kong) = \frac{0.19}{0.2 * 0.2} = 4.75$$

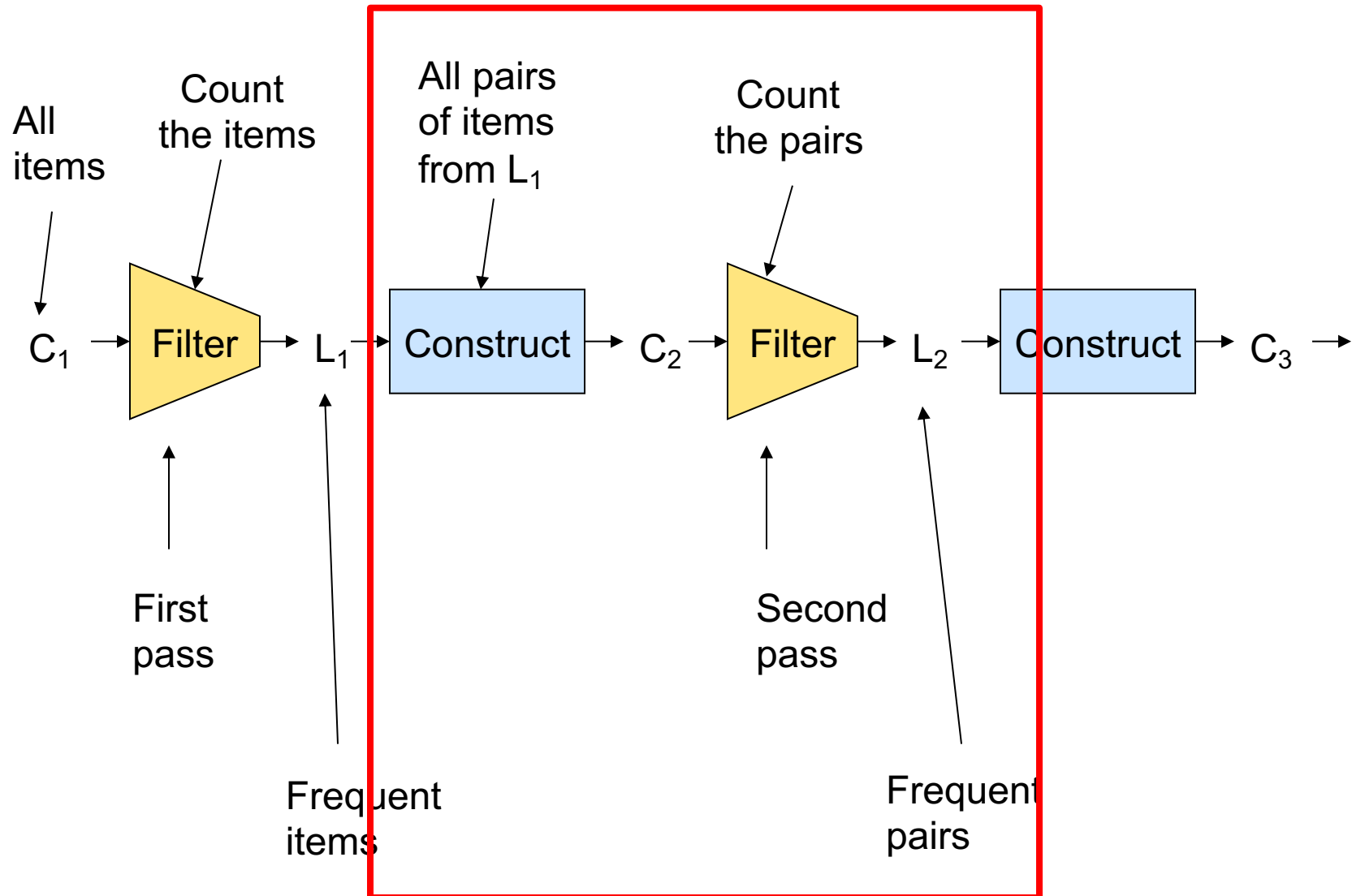
**Rare** co-occurrences are deemed more interesting.  
But this is not always what we want

# ALTERNATIVE FREQUENT ITEMSET COMPUTATION

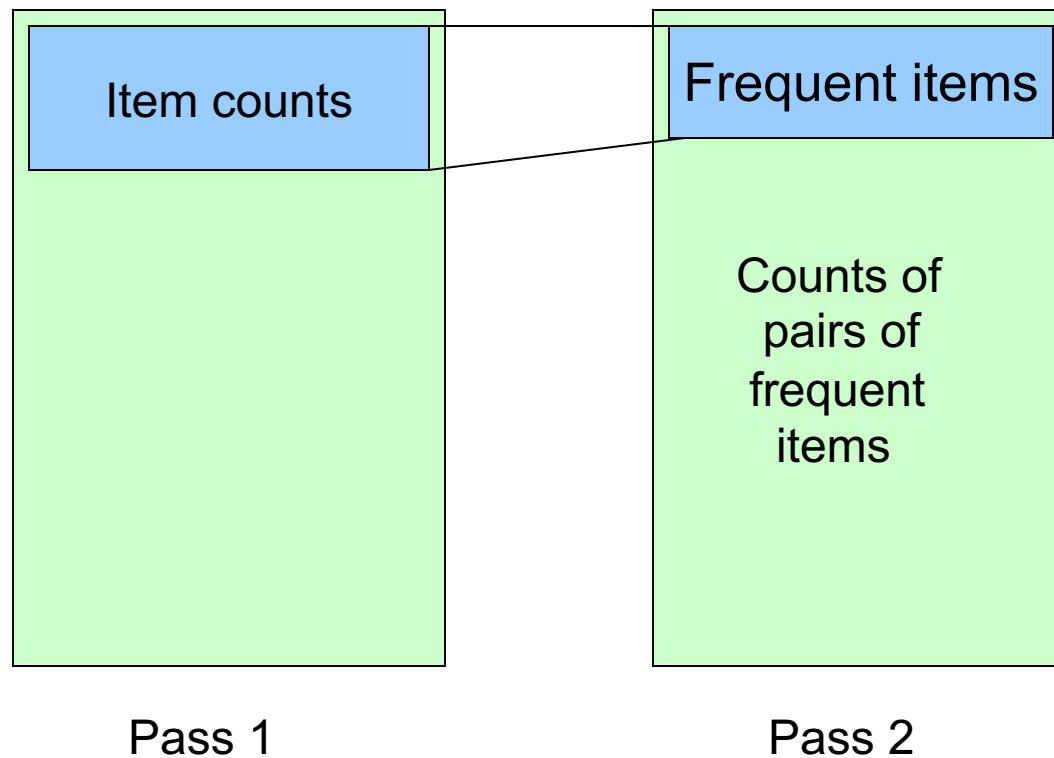
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Slides taken from Mining Massive Datasets course by  
Anand Rajaraman and Jeff Ullman.

Finding the frequent pairs is usually the most expensive operation



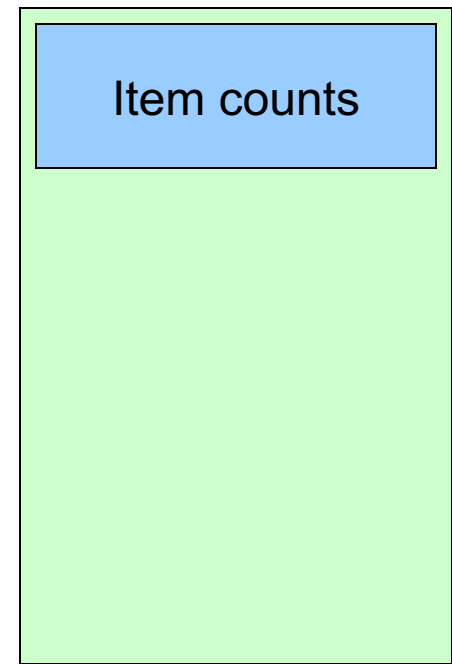
# Picture of A-Priori





# PCY Algorithm

- During Pass 1 (computing frequent **items**) of Apriori, most memory is idle.
- Use that memory to keep **counts** of buckets into which **pairs of items** are hashed.
  - Just the **count**, not the pairs themselves.



Pass 1

# Needed Extensions

1. Pairs of items need to be generated from the input file; they are not present in the file.
2. We are not just interested in the presence of a pair, but we need to see whether it is present at least  $s$  (**support**) times.

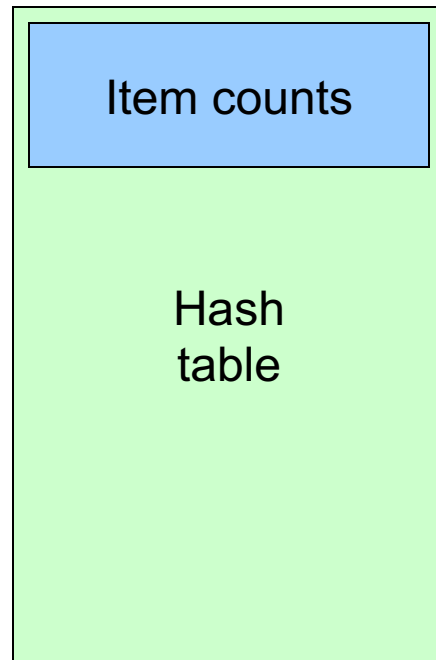
## PCY Algorithm – (2)

- A bucket is **frequent** if its count is at least the **support** threshold.
- If a bucket is **not frequent**, no pair that hashes to that bucket could possibly be a frequent pair.
  - The opposite is not true, a bucket may be frequent but hold infrequent pairs
- On Pass 2 (frequent pairs), we only count pairs that hash to frequent buckets.

# PCY Algorithm – Before Pass 1 Organize Main Memory

- Space to count each item.
  - One (typically) 4-byte integer per item.
- Use the rest of the space for as many integers, representing buckets, as we can.

# Picture of PCY



Pass 1

# PCY Algorithm – Pass 1

```
FOR (each basket) {  
    FOR (each item in the basket)  
        add 1 to item's count;  
    FOR (each pair of items in the basket)  
    {  
        hash the pair to a bucket;  
        add 1 to the count for that bucket  
    }  
}
```

# Observations About Buckets

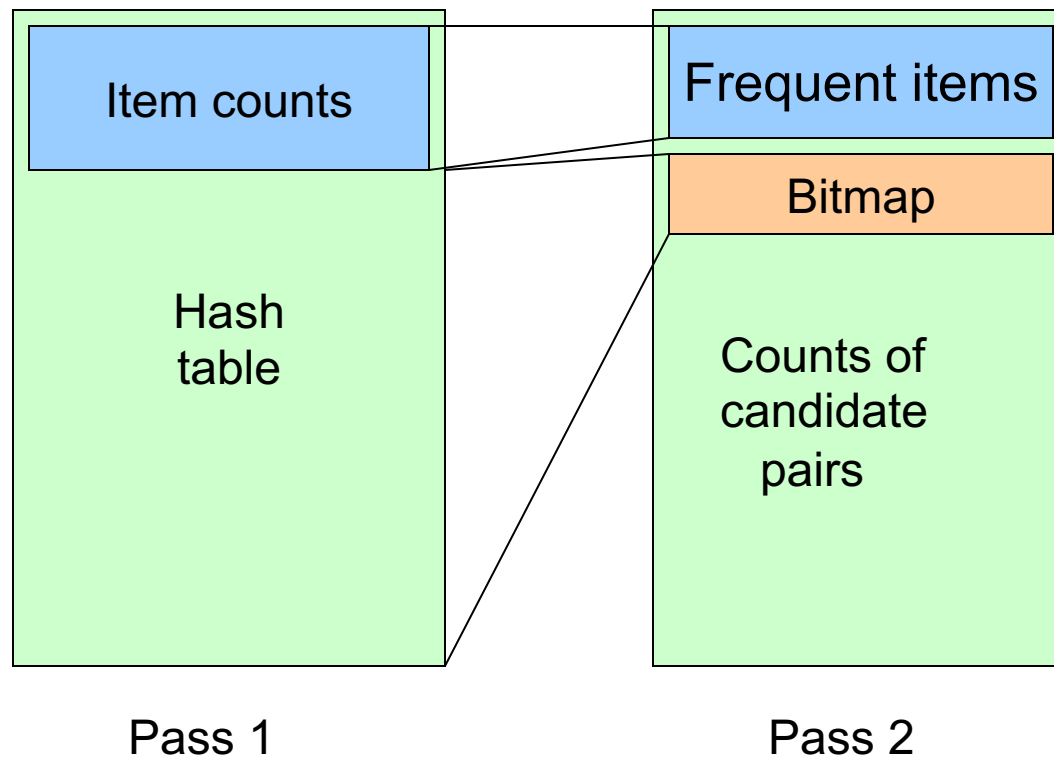
1. A bucket that a frequent pair hashes to is surely frequent.
  - We cannot use the hash table to eliminate any member of this bucket.
2. Even without any frequent pair, a bucket can be frequent.
  - Again, nothing in the bucket can be eliminated.
3. But in the best case, the count for a bucket is less than the support  $s$ .
  - Now, all pairs that hash to this bucket can be eliminated as candidates, even if the pair consists of two frequent items.

# PCY Algorithm – Between Passes

- Replace the buckets by a **bit-vector**:
  - 1 means the bucket is frequent; 0 means it is not.
- **4-byte** integers are replaced by bits, so the bit-vector requires **1/32** of memory.
- Also, find which items are frequent and list them for the second pass.
  - Same as with Apriori



# Picture of PCY



# PCY Algorithm – Pass 2

- Count all pairs  $\{i, j\}$  that meet the conditions for being a **candidate pair**:
  1. Both  $i$  and  $j$  are frequent items.
  2. The pair  $\{i, j\}$ , hashes to a bucket number whose bit in the bit vector is 1.
- Notice both these conditions are necessary for the pair to have a chance of being frequent.

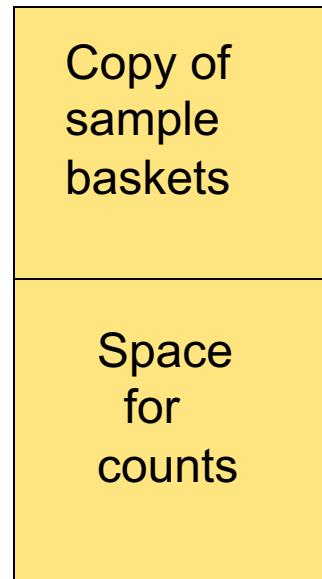
# All (Or Most) Frequent Itemsets in less than 2 Passes

- A-Priori, PCY, etc., take  $k$  passes to find frequent itemsets of size  $k$ .
- Other techniques use 2 or fewer passes for all sizes:
  - Simple sampling algorithm.
  - SON (Savasere, Omiecinski, and Navathe).
  - Toivonen.

# Simple Sampling Algorithm – (1)

- Take a **random sample** of the market baskets.
- Run Apriori or one of its improvements (for sets of all sizes, not just pairs) **in main memory**, so you don't pay for disk I/O each time you increase the size of itemsets.
  - Make sure the sample is such that there is enough space for counts.

# Main-Memory Picture



# Simple Algorithm – (2)

- Use as your **support** threshold a suitable, **scaled-back** number.
  - E.g., if your **sample** is  $1/100$  of the baskets, use  $s/100$  as your support threshold **instead** of  $s$ .
- You could stop here (single pass)
  - What could be the problem?

# Simple Algorithm – Option

- Optionally, verify that your guesses are truly frequent in the entire data set by a second pass (eliminate **false positives**)
- But you don't catch sets frequent in the whole but not in the sample. (**false negatives**)
  - Smaller threshold, e.g.,  $s/125$ , helps catch more truly frequent itemsets.
    - But requires more space.

# SON Algorithm – (1)

- **First pass**: Break the data into **chunks** that can be processed in main memory.
- Read one chunk at the time
  - Find all frequent itemsets for each chunk.
  - Threshold =  $s/\text{number of chunks}$
- An itemset becomes a **candidate** if it is found to be frequent in **any** one or more chunks of the baskets.



## SON Algorithm – (2)

- **Second pass**: count all the candidate itemsets and determine which are frequent in the entire set.
- **Key “monotonicity” idea**: an itemset cannot be frequent in the entire set of baskets unless it is frequent in at least one subset.
  - **Why?**

# SON Algorithm – Distributed Version

- This idea lends itself to **distributed data mining**.
- If baskets are distributed among many nodes, compute frequent itemsets at each node, then distribute the candidates from each node.
- Finally, accumulate the counts of all candidates.

# Toivonen's Algorithm – (1)

- Start as in the simple sampling algorithm, but lower the threshold slightly for the sample.
  - **Example:** if the sample is 1% of the baskets, use  $s/125$  as the support threshold rather than  $s/100$ .
  - Goal is to avoid missing any itemset that is frequent in the full set of baskets.

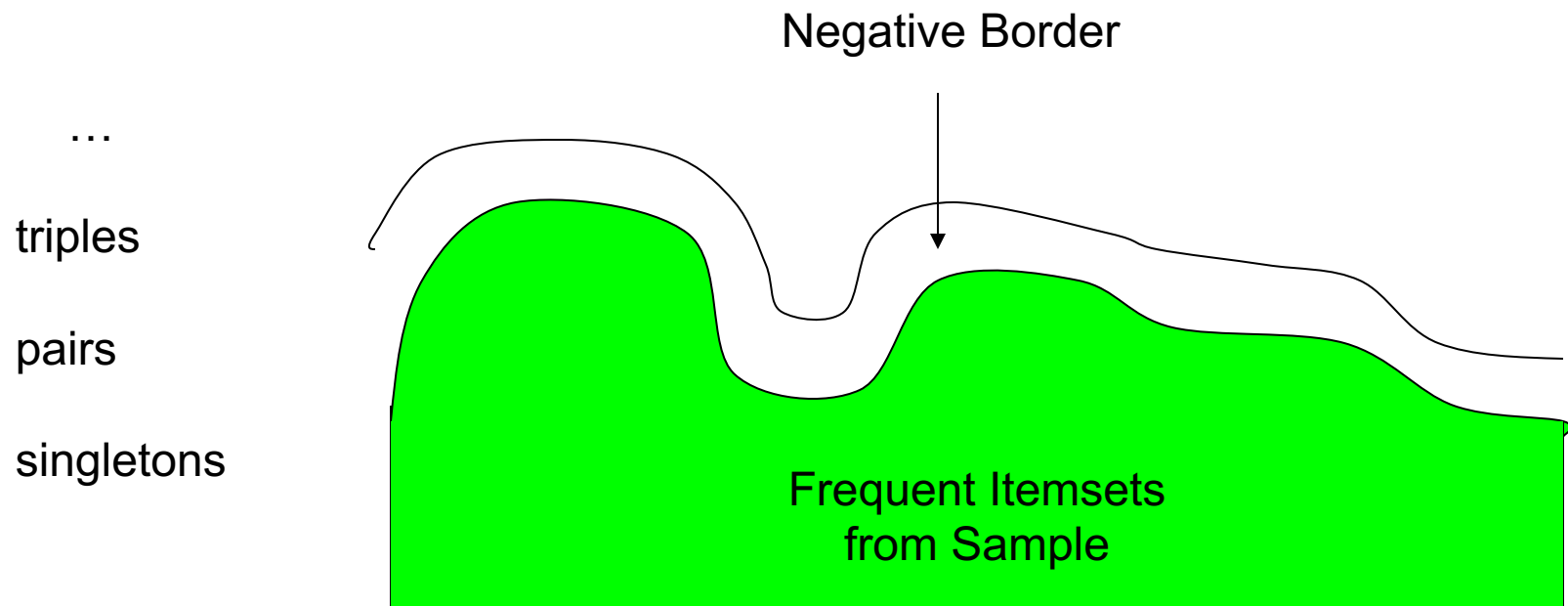
## Toivonen's Algorithm – (2)

- Add to the itemsets that are frequent in the sample the **negative border** of these itemsets.
- An itemset is in the negative border if it is **not** deemed frequent in the sample, but **all** its **immediate subsets** are.

# Reminder: Negative Border

- $ABCD$  is in the negative border if and only if:
  1. It is **not frequent** in the **sample**, but
  2. All of  $ABC$ ,  $BCD$ ,  $ACD$ , and  $ABD$  are.
- $A$  is in the negative border if and only if it is not frequent in the sample.
  - ◆ Because the empty set is always frequent.
    - ◆ Unless there are fewer baskets than the support threshold (silly case).

# Picture of Negative Border



## Toivonen's Algorithm – (3)

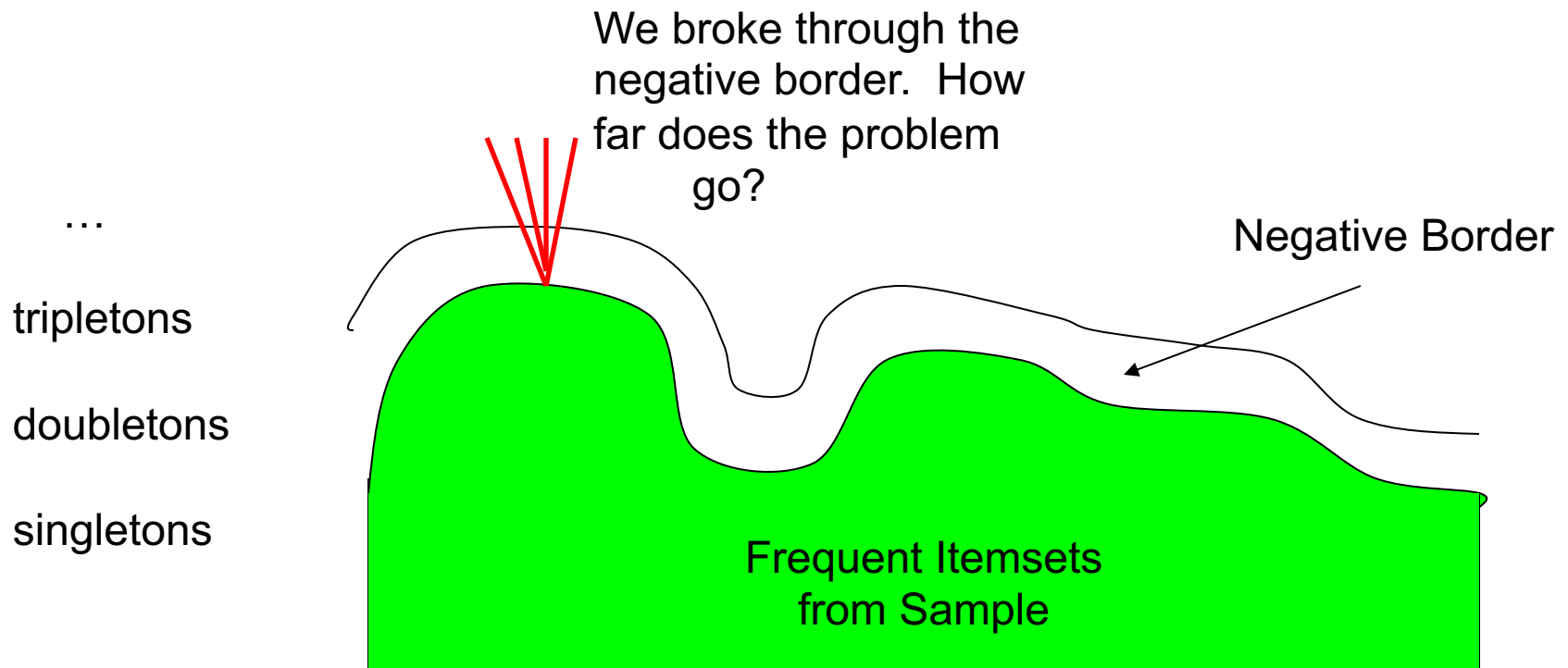
- In a second pass, count all candidate frequent itemsets from the first pass, and also count their negative border.
- If **no itemset** from the **negative border** turns out to be frequent, then the candidates found to be frequent in the whole data are **exactly** the frequent itemsets.

# Toivonen's Algorithm – (4)

- What if we find that something in the negative border is actually frequent?
  - We must start over again!
- Try to choose the support threshold so the probability of failure is low, while the number of itemsets checked on the second pass fits in main-memory.



# If Something in the Negative Border is Frequent . . .

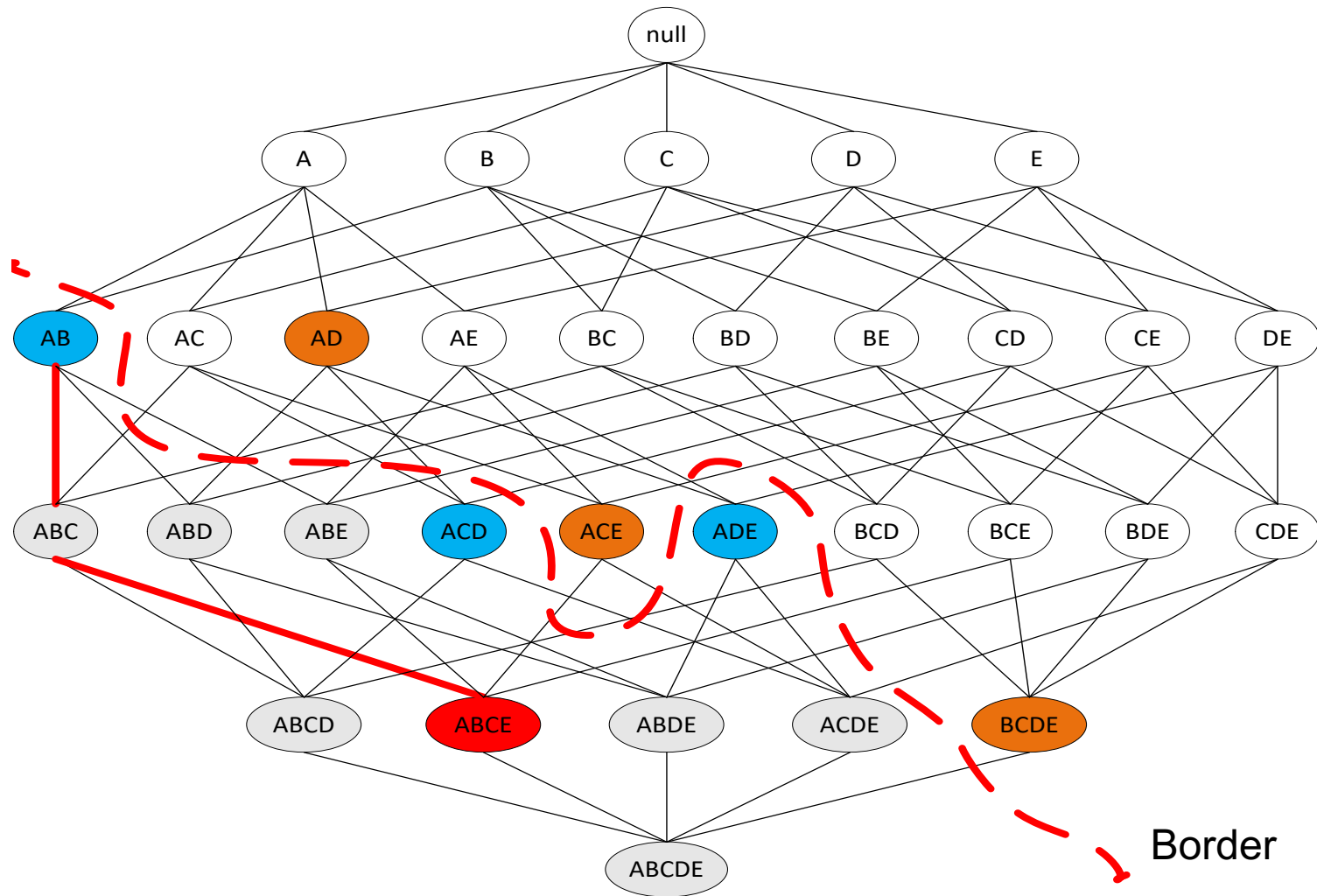


# Theorem:

- If there is an **itemset** that is **frequent in the whole**, but **not frequent in the sample**, then there is a **member of the negative border** for the sample that is frequent in the whole.

- **Proof:** Suppose not; i.e.;
  1. There is an itemset  $S$  frequent in the whole but not frequent in the sample, and
  2. Nothing in the negative border is frequent in the whole.
- Let  $T$  be a **smallest** subset of  $S$  that is not frequent in the sample.
- $T$  is frequent in the whole ( $S$  is frequent + monotonicity).
- $T$  is in the negative border (else not “smallest”).

# Example



# VARIANTE AND OPPORTUNITIES

---

# Intersection-based

Horizontal  
Data Layout

TID	Items
1	A,B,E
2	B,C,D
3	C,E
4	A,C,D
5	A,B,C,D
6	A,E
7	A,B
8	A,B,C
9	A,C,D
10	B

**Transaction** →

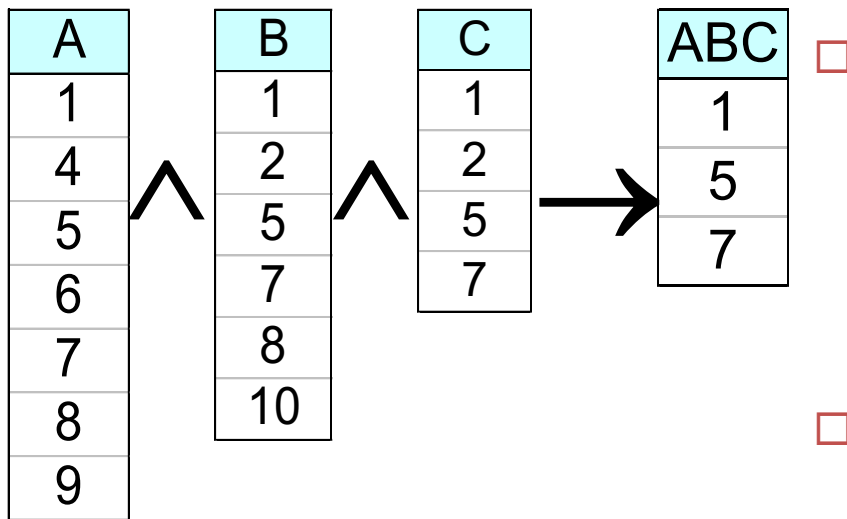
Vertical Data Layout

A	B	C	D	E
1	1	2	2	1
4	2	3	4	3
5	5	4	5	6
6	7	8	9	
7	8	9		
8	10			
9				



**TID-list**

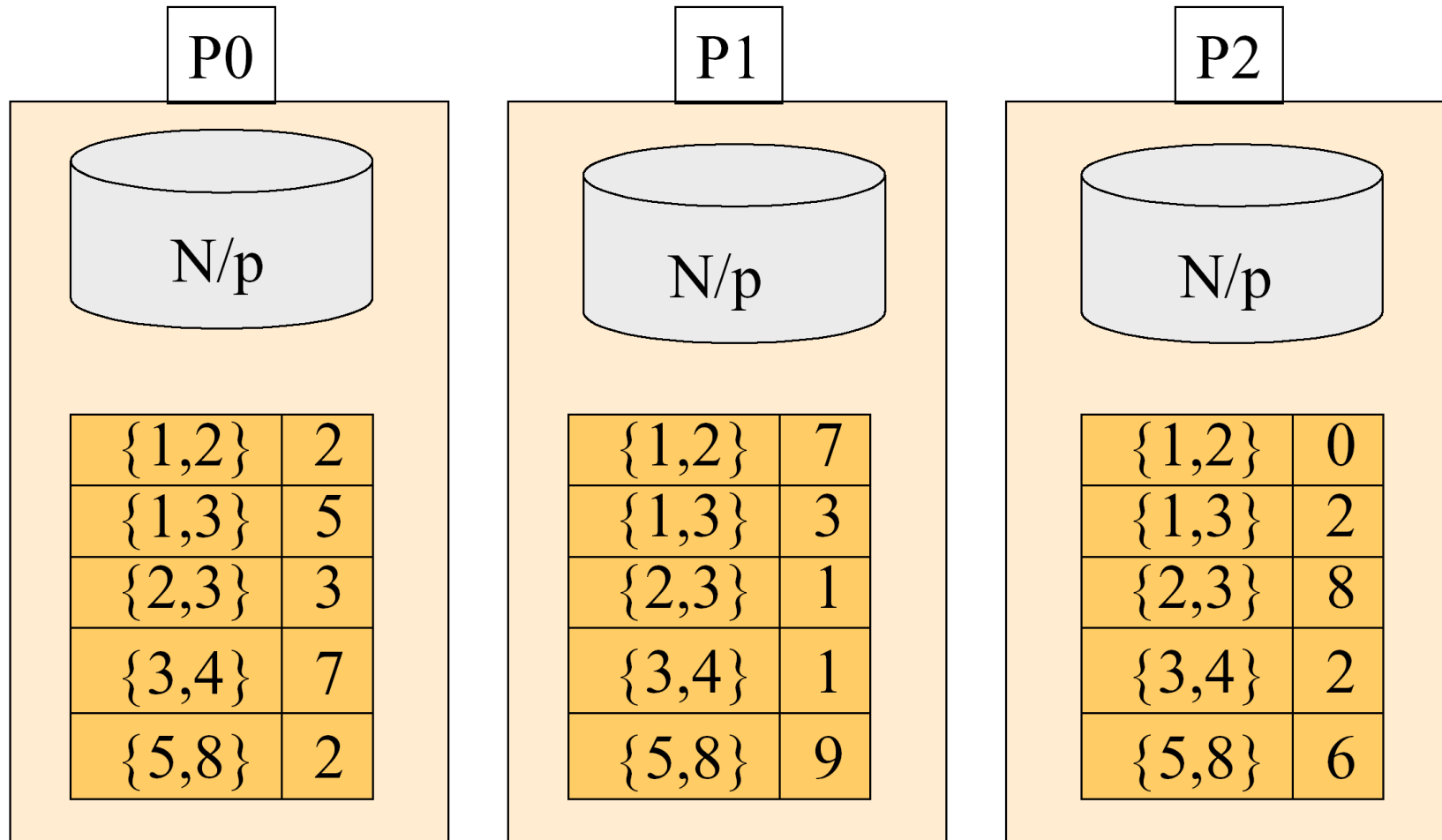
# Intersection-based



□ ***k*-way intersection** is used to count the support of a ***k*-itemset**

□ This approach is used together with a ***Depth-first visit*** of the lattice

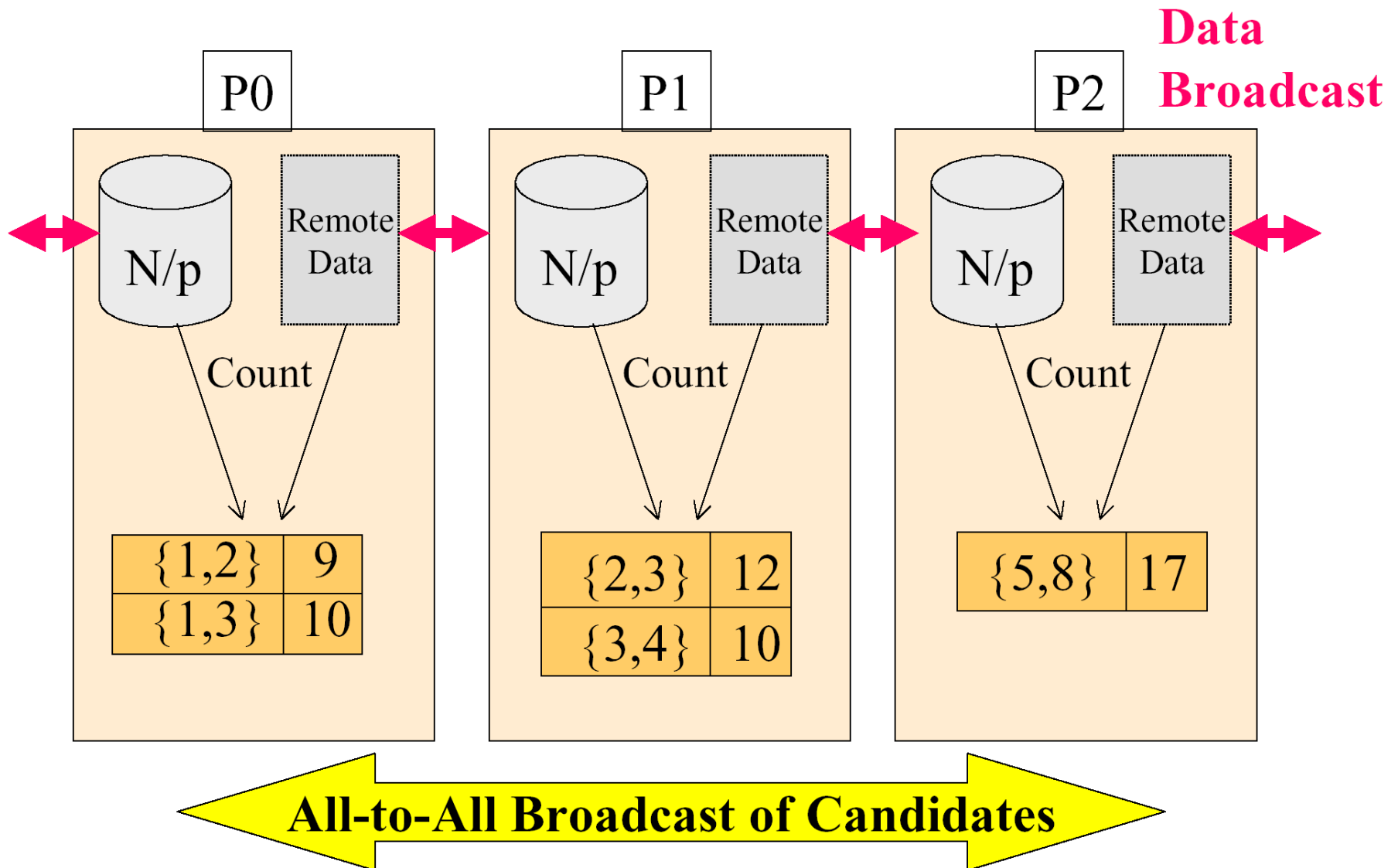
# Count Distribution



Global Reduction of Counts

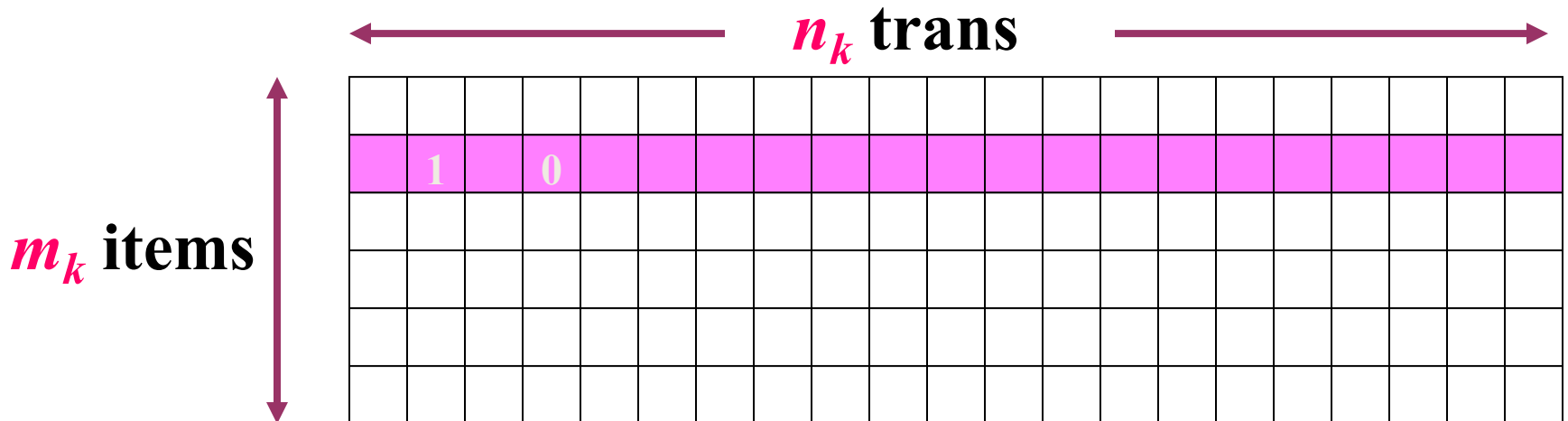


# Data (& Candidate) Distribution (DD)



# Bit-wise Intersections

- Given a set of candidate, compute its support by fast bit-wise intersections
- Careful with memory!
  - Sometime this is possible only after infrequent items (or pairs, ... ) have been removed



# THE FP-TREE AND THE FP-GROWTH ALGORITHM

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Slides from course lecture of E. Pitoura

# Overview

- The **FP-tree** contains **a compressed representation** of the transaction database.
  - A **trie** (prefix-tree) data structure is used
  - Each transaction is a **path** in the tree – paths can overlap.
- Once the FP-tree is constructed the **recursive, divide-and-conquer FP-Growth** algorithm is used to enumerate all frequent itemsets.

# FP-tree Construction

TID	Items
1	{A,B}
2	{B,C,D}
3	{A,C,D,E}
4	{A,D,E}
5	{A,B,C}
6	{A,B,C,D}
7	{B,C}
8	{A,B,C}
9	{A,B,D}
10	{B,C,E}

- The FP-tree is a **trie** (**prefix tree**)
- Since transactions are sets of items, we need to transform them into **ordered sequences** so that we can have prefixes
  - Otherwise, there is no common prefix between sets {A,B} and {B,C,A}
- We need to impose an **order** to the items
  - Initially, assume a **lexicographic** order.

# FP-tree Construction

- Initially the tree is empty

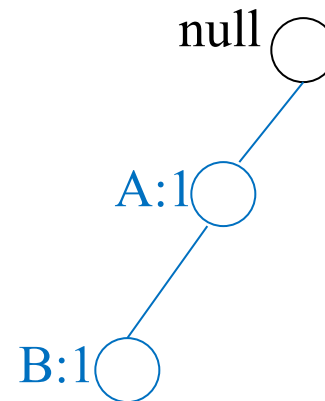
TID	Items
1	{A,B}
2	{B,C,D}
3	{A,C,D,E}
4	{A,D,E}
5	{A,B,C}
6	{A,B,C,D}
7	{B,C}
8	{A,B,C}
9	{A,B,D}
10	{B,C,E}

○ null

# FP-tree Construction

- Reading transaction TID = 1

TID	Items
1	{A,B}
2	{B,C,D}
3	{A,C,D,E}
4	{A,D,E}
5	{A,B,C}
6	{A,B,C,D}
7	{B,C}
8	{A,B,C}
9	{A,B,D}
10	{B,C,E}



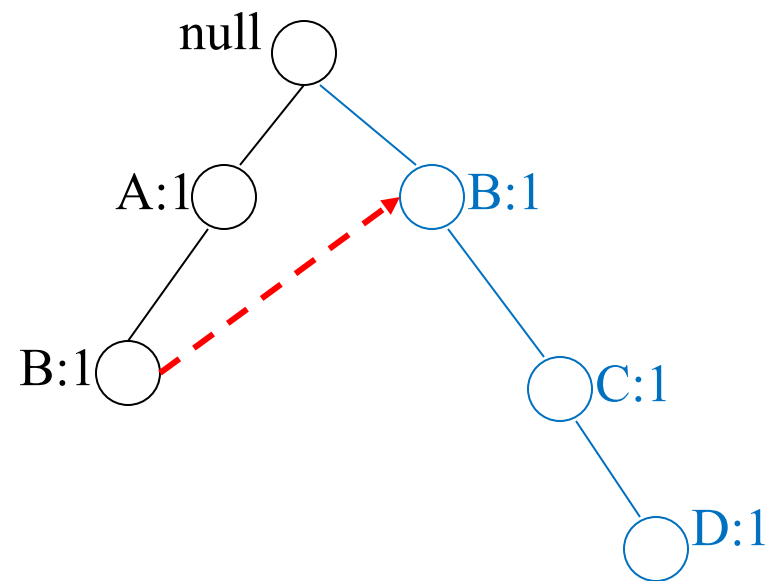
Node label = item:support

- Each node in the tree has a **label** consisting of the item and the support (number of transactions that reach that node, i.e. follow that **path**)

# FP-tree Construction

- Reading transaction TID = 2

TID	Items
1	{A,B}
2	{B,C,D}
3	{A,C,D,E}
4	{A,D,E}
5	{A,B,C}
6	{A,B,C,D}
7	{B,C}
8	{A,B,C}
9	{A,B,D}
10	{B,C,E}



Each transaction is a path in the tree

- We add **pointers** between nodes that refer to the same item



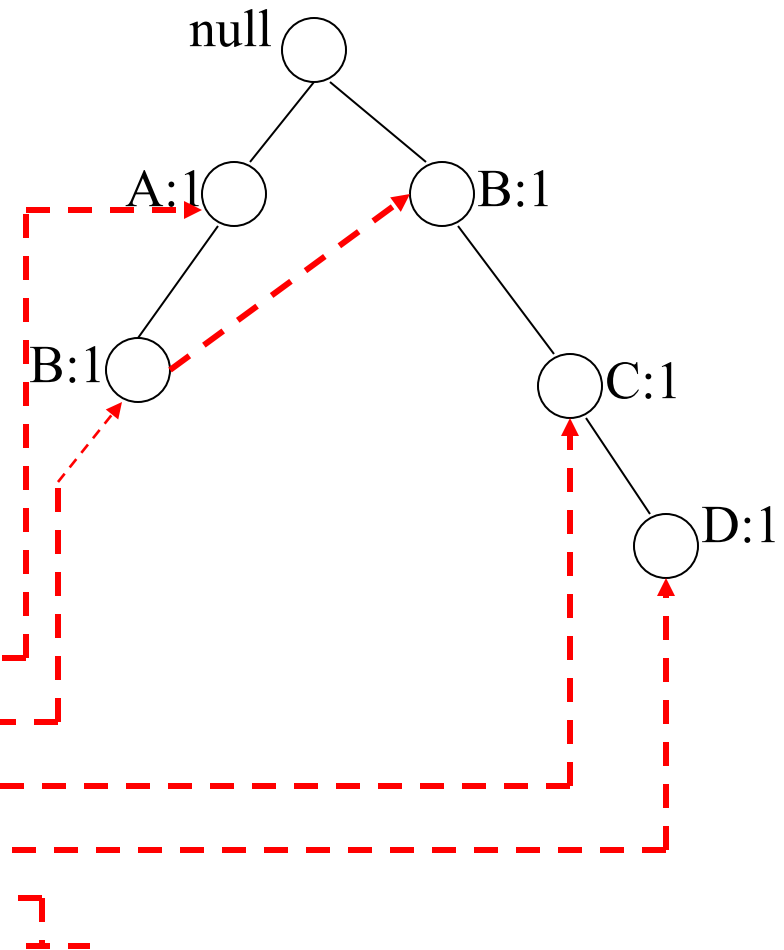
# FP-tree Construction

TID	Items
1	{A,B}
2	{B,C,D}
3	{A,C,D,E}
4	{A,D,E}
5	{A,B,C}
6	{A,B,C,D}
7	{B,C}
8	{A,B,C}
9	{A,B,D}
10	{B,C,E}

After reading  
transactions TID=1, 2:

**Header Table**

Item	Pointer
A	
B	
C	
D	
E	

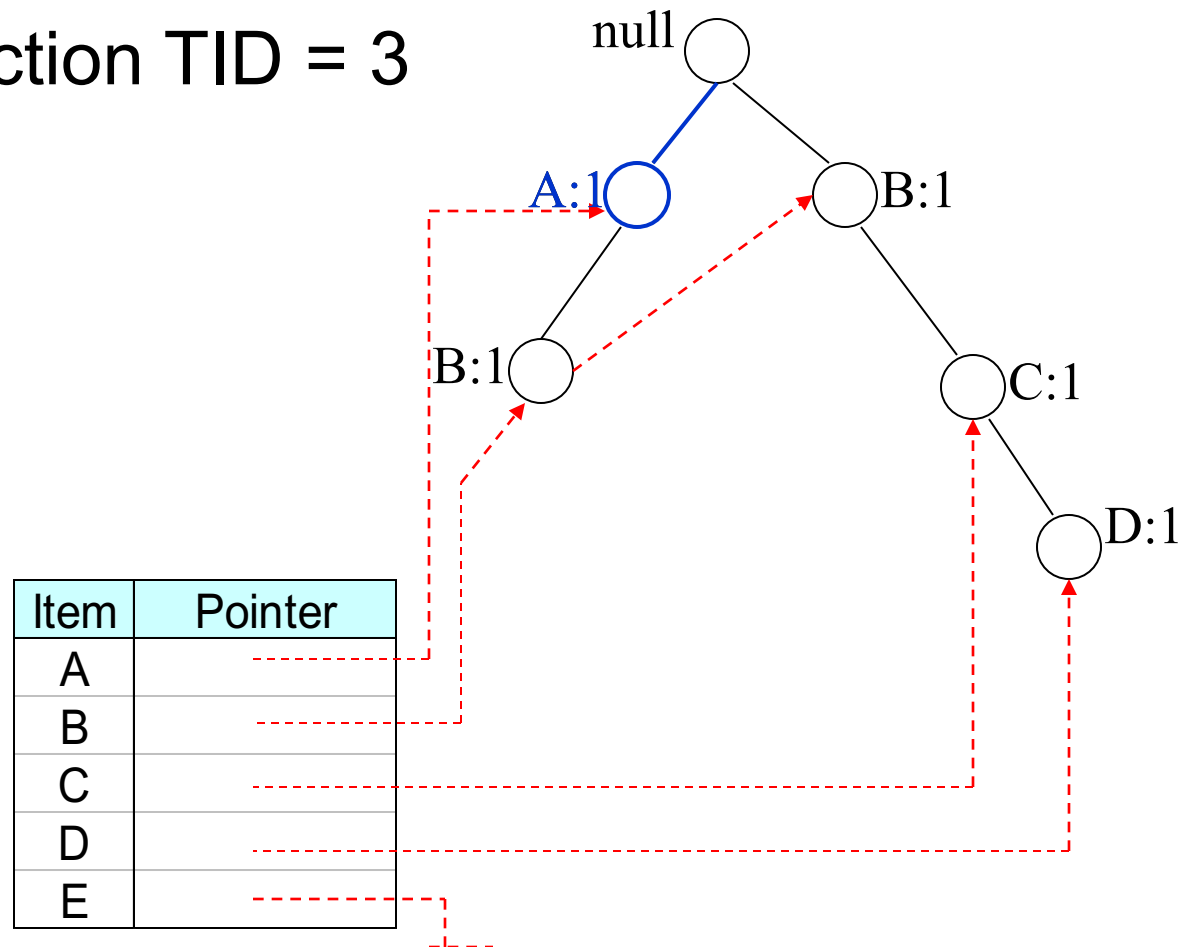


The **Header Table** and the pointers assist in computing the itemset support

# FP-tree Construction

- Reading transaction TID = 3

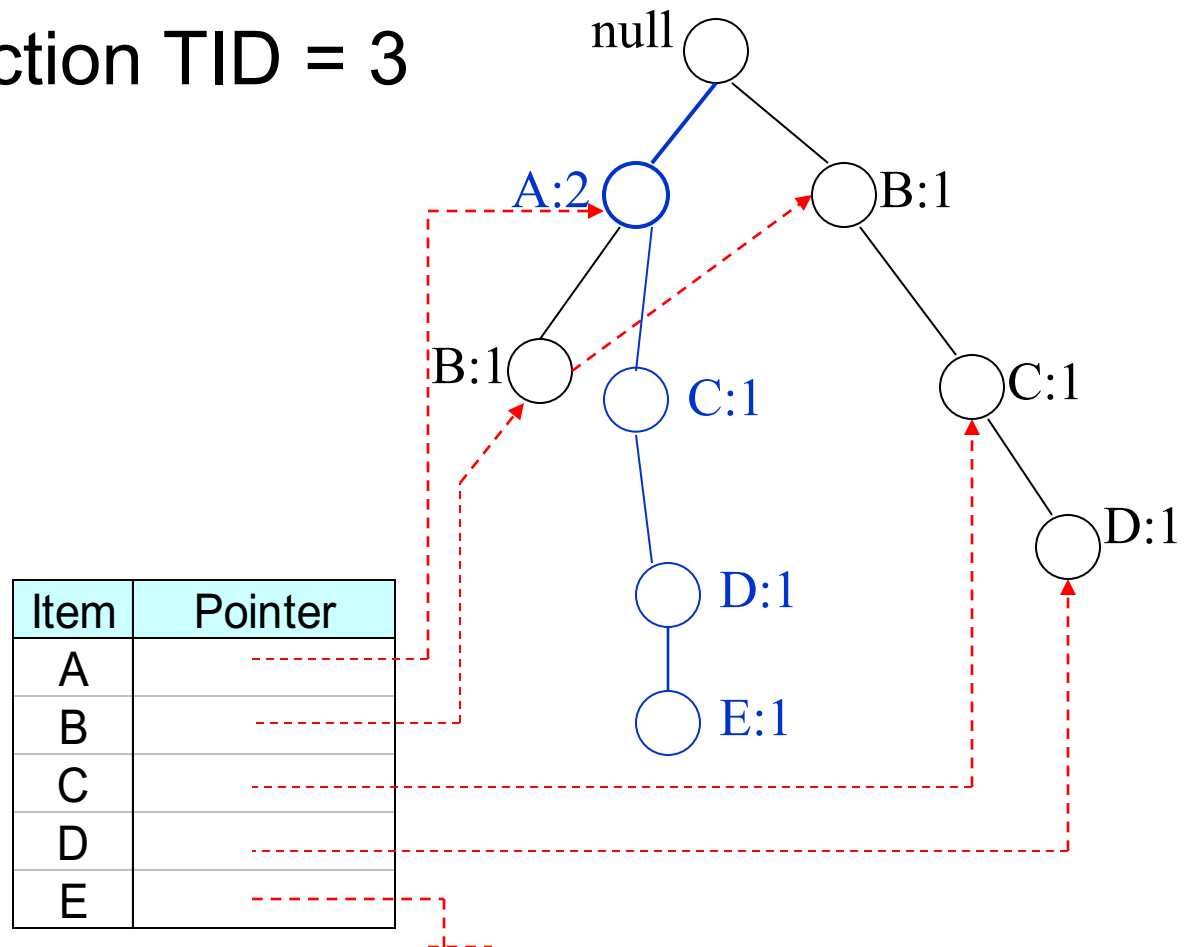
TID	Items
1	{A,B}
2	{B,C,D}
3	{A,C,D,E}
4	{A,D,E}
5	{A,B,C}
6	{A,B,C,D}
7	{B,C}
8	{A,B,C}
9	{A,B,D}
10	{B,C,E}



# FP-tree Construction

- Reading transaction TID = 3

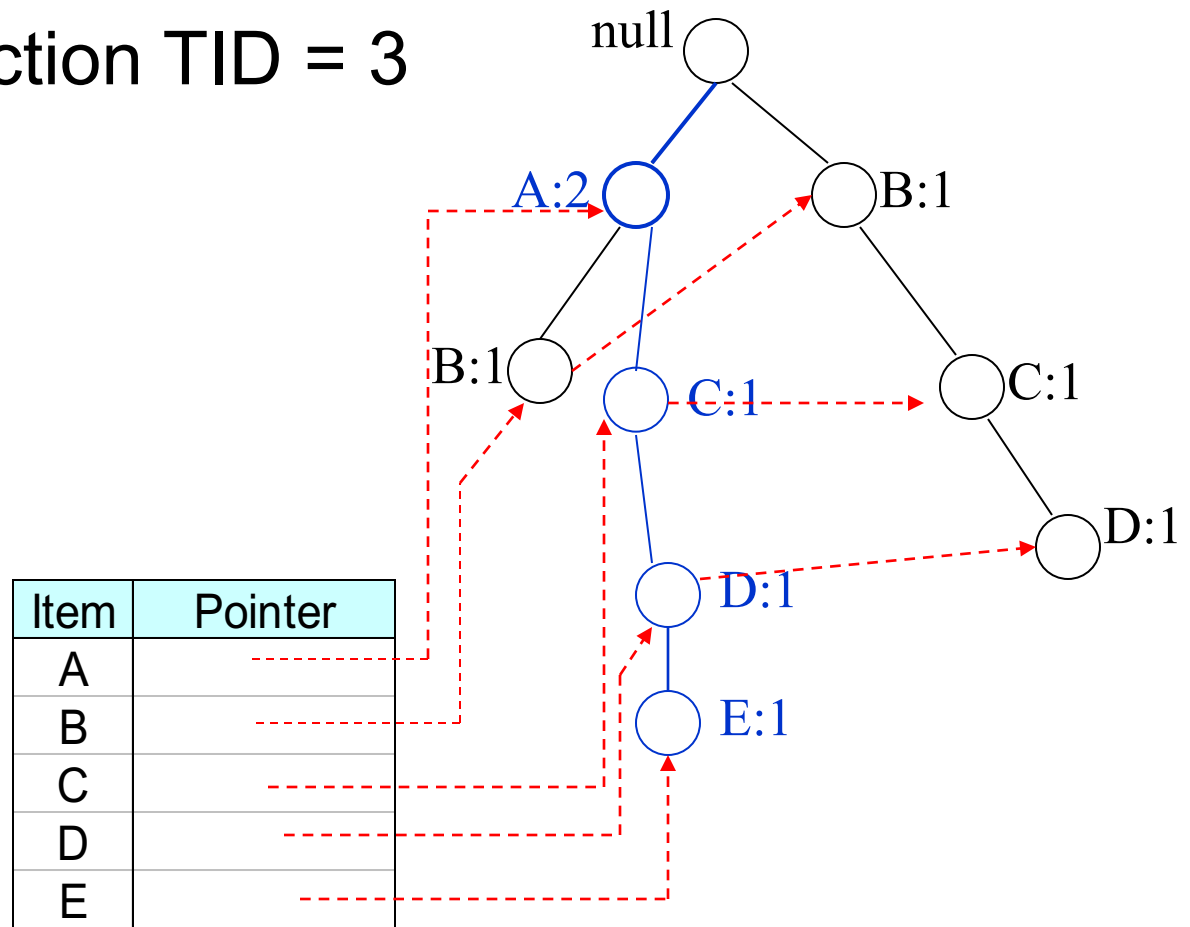
TID	Items
1	{A,B}
2	{B,C,D}
3	{A,C,D,E}
4	{A,D,E}
5	{A,B,C}
6	{A,B,C,D}
7	{B,C}
8	{A,B,C}
9	{A,B,D}
10	{B,C,E}



# FP-tree Construction

- Reading transaction TID = 3

TID	Items
1	{A,B}
2	{B,C,D}
3	{A,C,D,E}
4	{A,D,E}
5	{A,B,C}
6	{A,B,C,D}
7	{B,C}
8	{A,B,C}
9	{A,B,D}
10	{B,C,E}



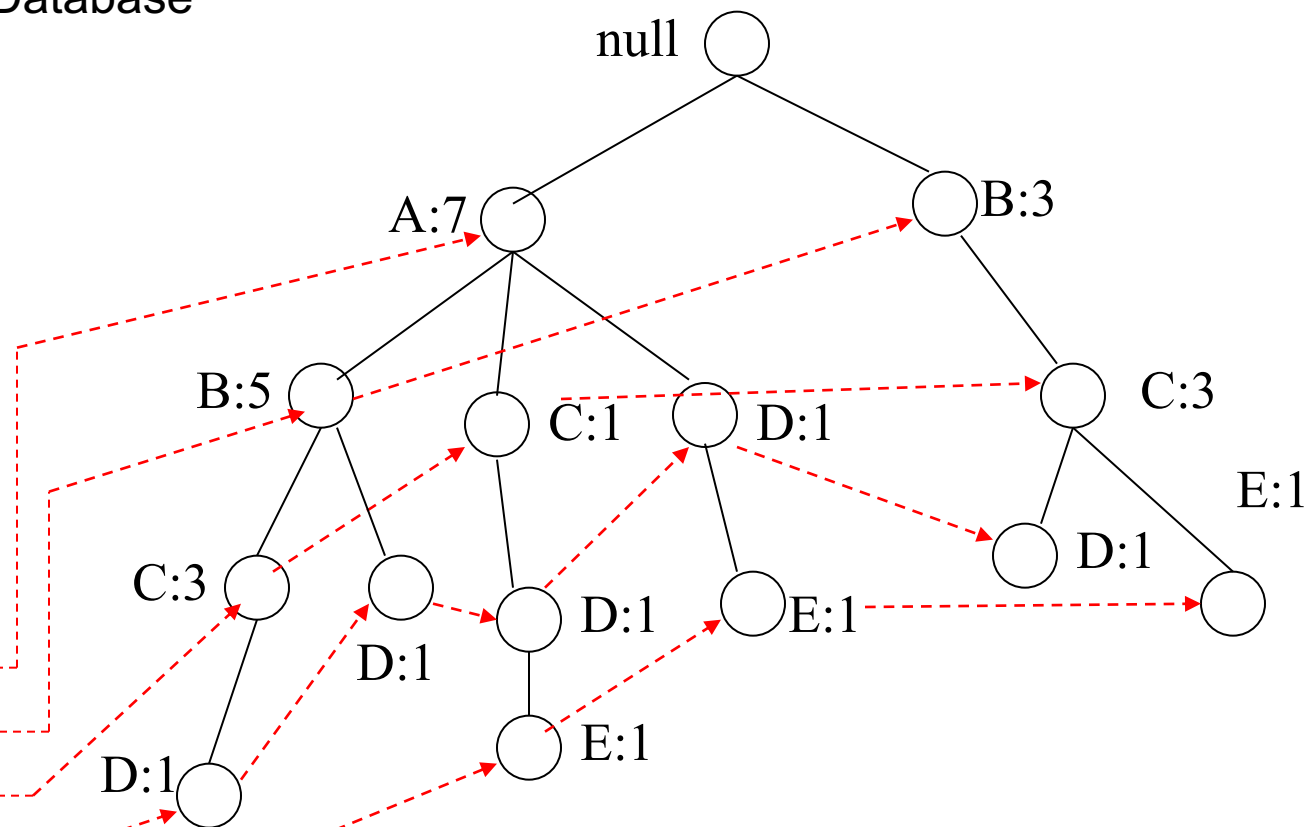
Each transaction is a path in the tree

# FP-Tree Construction

TID	Items
1	{A,B}
2	{B,C,D}
3	{A,C,D,E}
4	{A,D,E}
5	{A,B,C}
6	{A,B,C,D}
7	{B,C}
8	{A,B,C}
9	{A,B,D}
10	{B,C,E}

Transaction Database

Each transaction is a path in the tree



Header table

Item	Pointer
A	
B	
C	
D	
E	

Pointers are used to assist frequent itemset generation

# FP-tree size

- Every transaction is a path in the FP-tree
- The size of the tree depends on the compressibility of the data
  - Extreme case: All transactions are the same, the FP-tree is a single branch
  - Extreme case: All transactions are different the size of the tree is the same as that of the database (bigger actually since we need additional pointers)

# Item ordering

- The size of the tree also depends on the ordering of the items.
- Heuristic: order the items in according to their frequency from larger to smaller.
  - We would need to do an extra pass over the dataset to count frequencies
- Example:

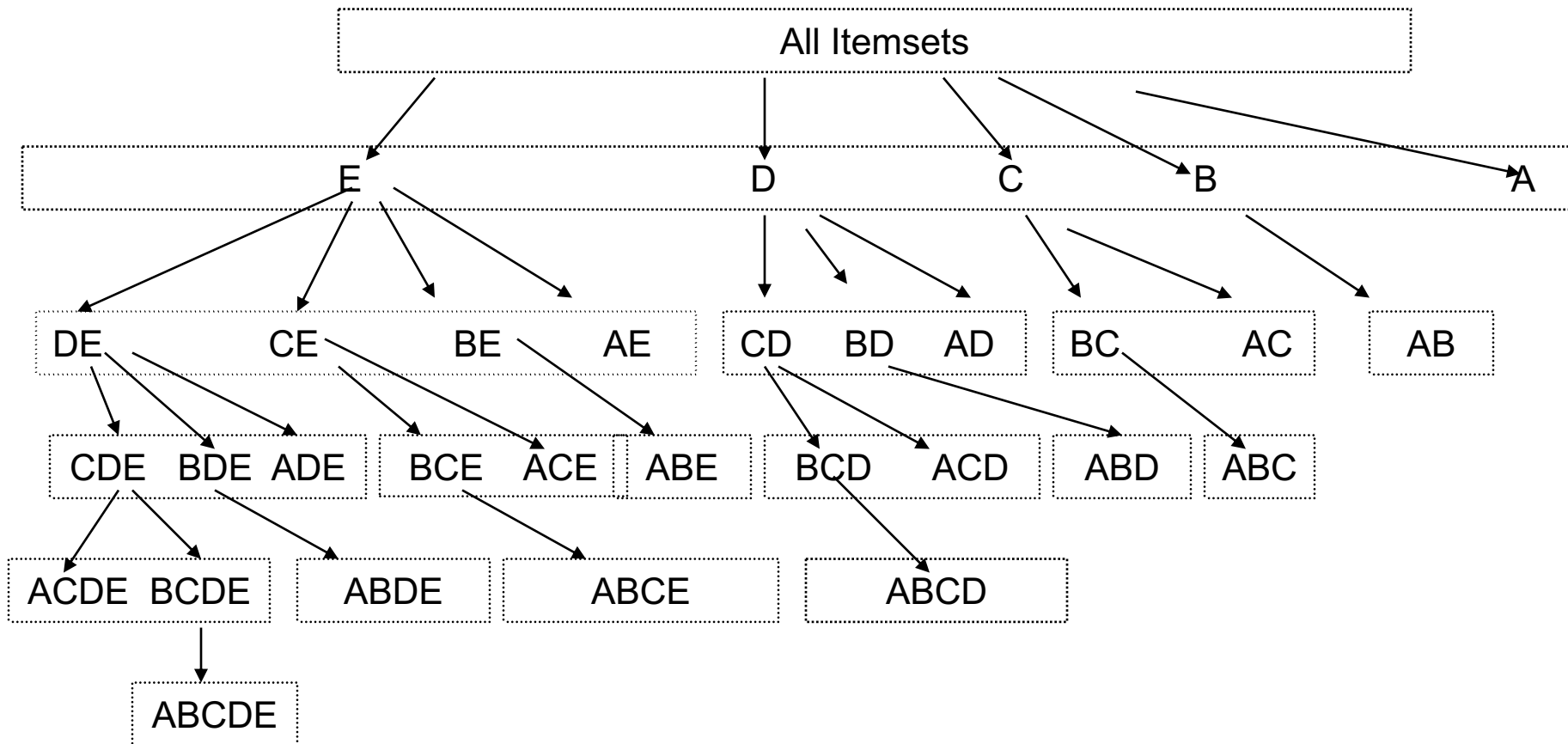
TID	Items	$\sigma(A)=7,$ $\sigma(C)=7,$ $\sigma(E)=3$  Ordering : B,A,C,D,E	TID	Items
1	{A,B}		1	{B,A}
2	{B,C,D}		2	{B,C,D}
3	{A,C,D,E}		3	{A,C,D,E}
4	{A,D,E}		4	{A,D,E}
5	{A,B,C}		5	{B,A,C}
6	{A,B,C,D}		6	{B,A,C,D}
7	{B,C}		7	{B,C}
8	{A,B,C}		8	{B,A,C}
9	{A,B,D}		9	{B,A,D}
10	{B,C,E}		10	{B,C,E}

# Finding Frequent Itemsets

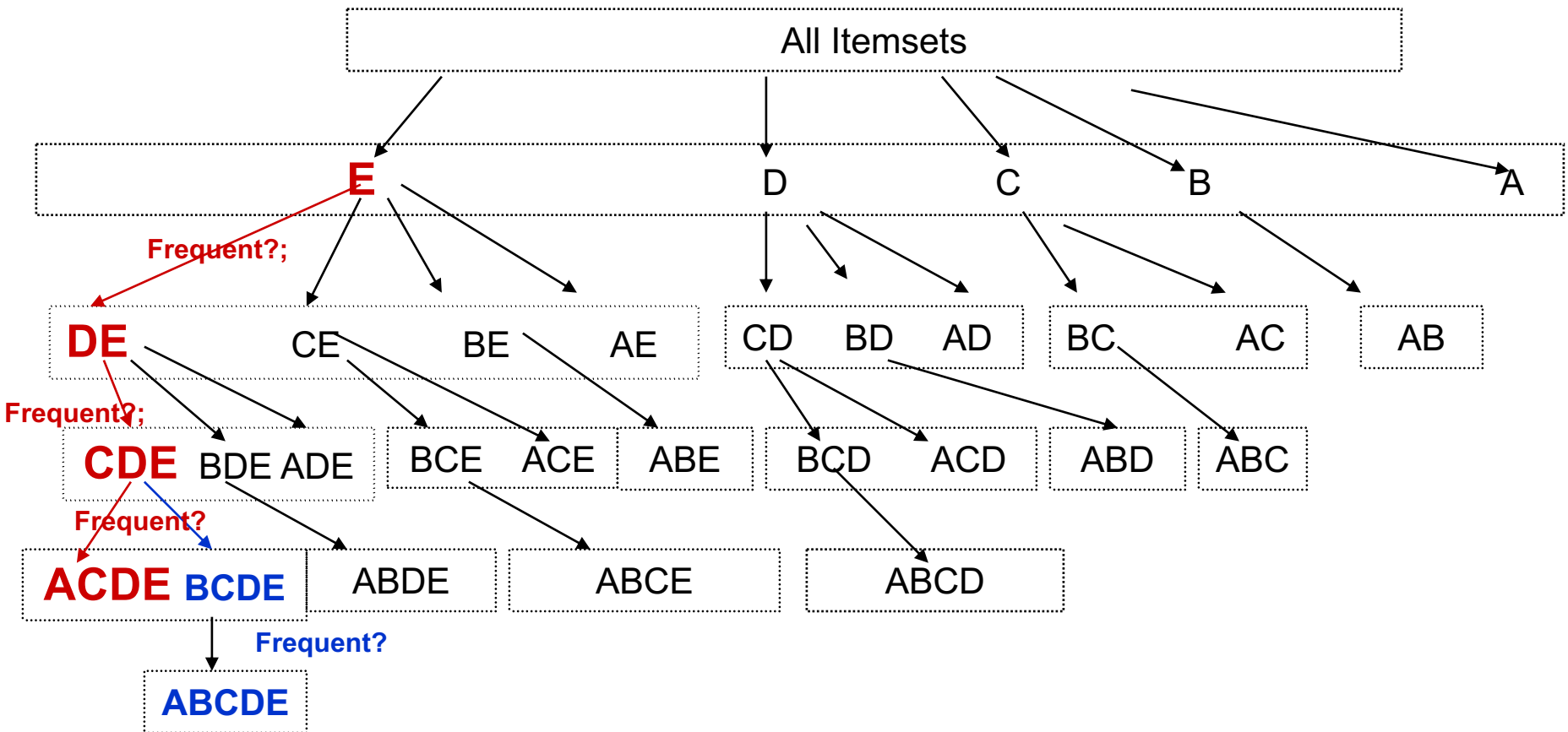
- Input: The FP-tree
- Output: All Frequent Itemsets and their support
- Method:
  - Divide and Conquer:
  - Consider all itemsets that **end** in: E, D, C, B, A
    - For each possible ending item, consider the itemsets with last item one of items preceding it in the ordering
    - E.g, for E, consider all itemsets with last item D, C, B, A. This way we get all the itemsets ending at DE, CE, BE, AE
    - Proceed recursively this way.
    - Do this for all items.



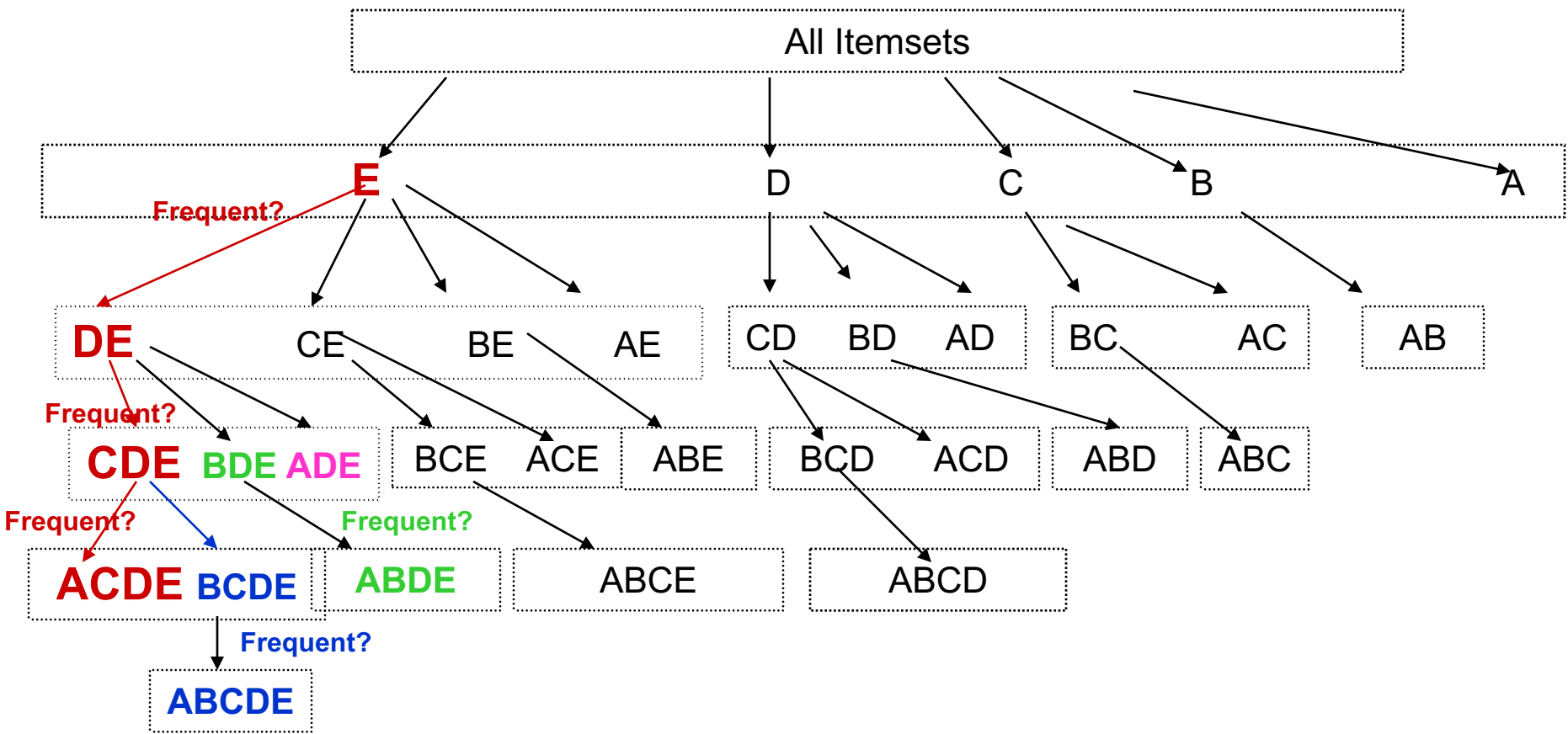
# Frequent itemsets



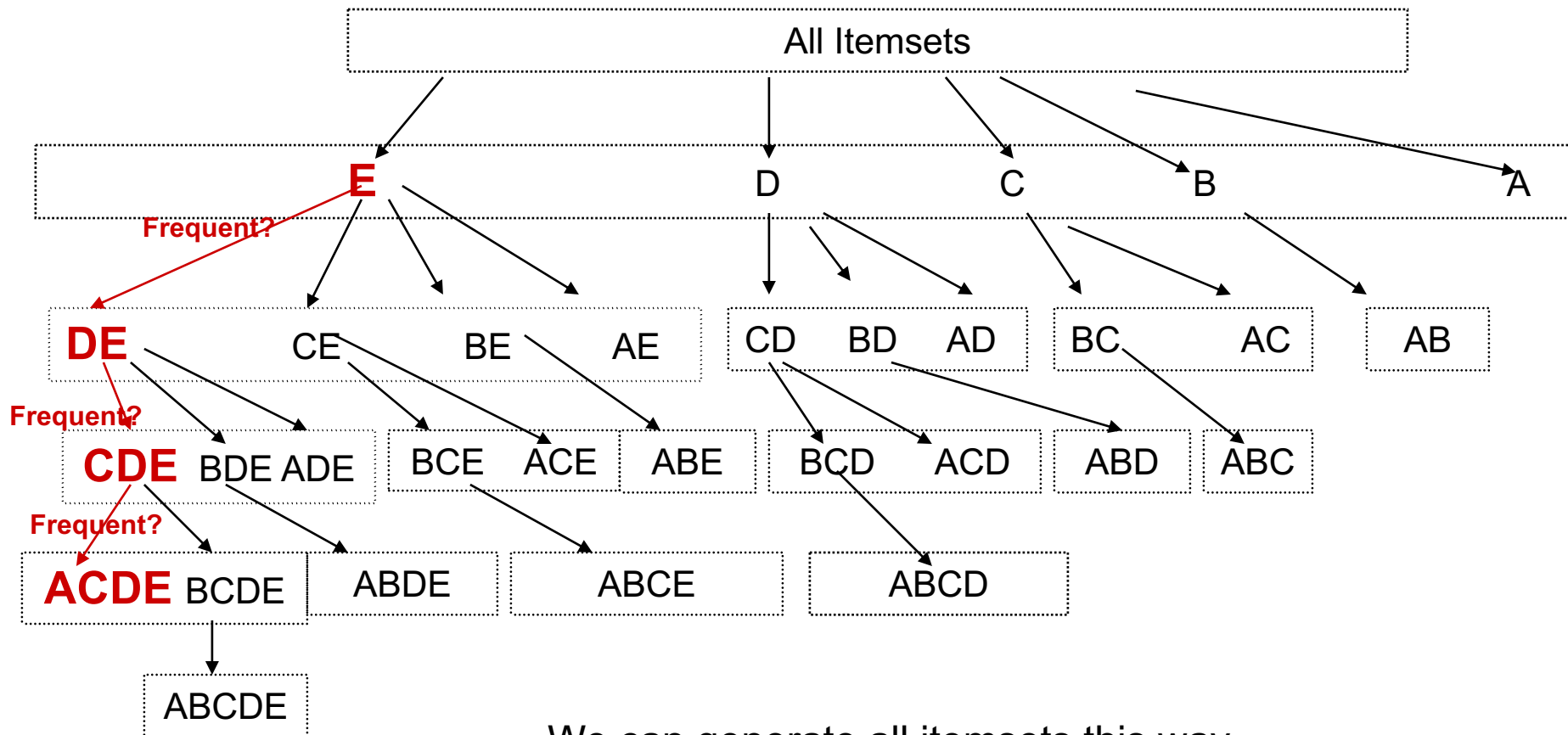
# Frequent Itemsets



# Frequent Itemsets



# Frequent Itemsets



We can generate all itemsets this way  
We expect the FP-tree to contain a lot less

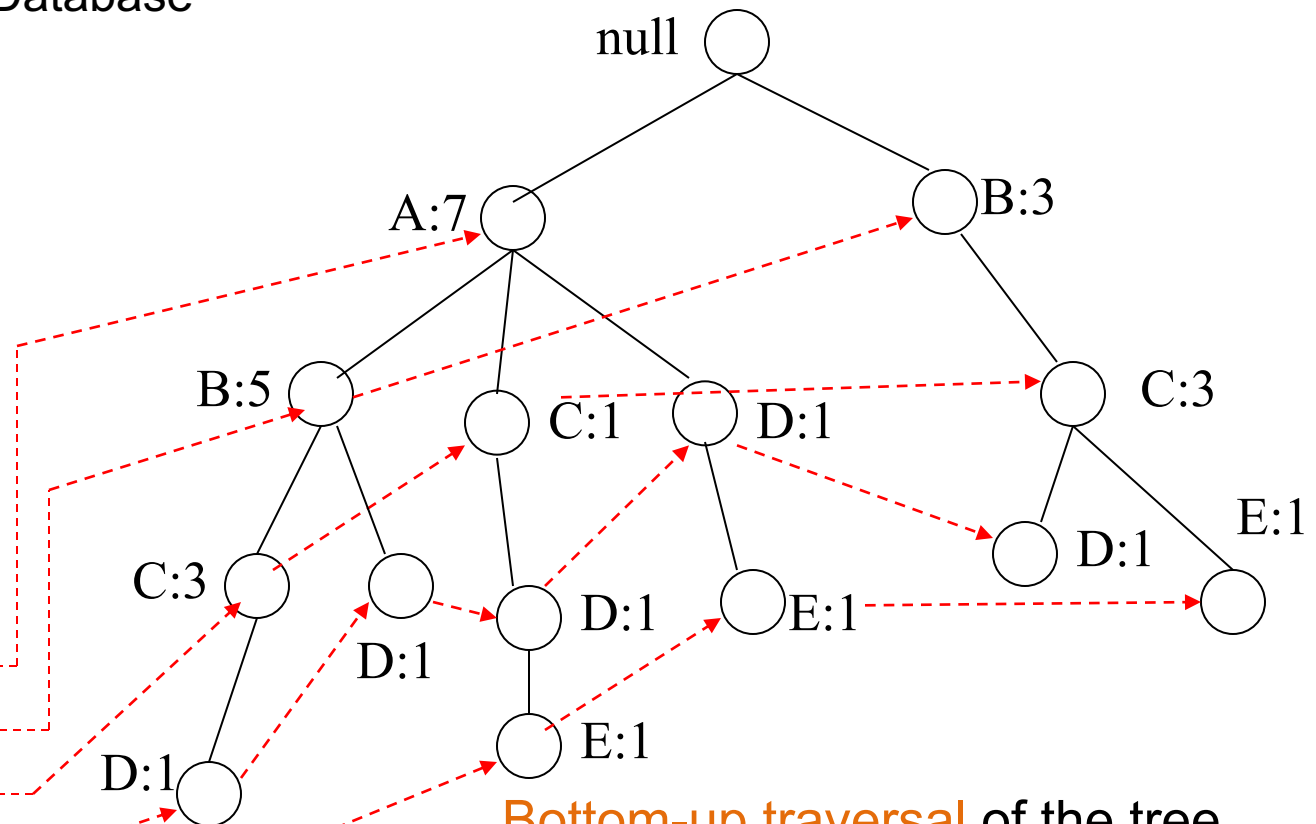
# Using the FP-tree to find frequent itemsets

TID	Items
1	{A,B}
2	{B,C,D}
3	{A,C,D,E}
4	{A,D,E}
5	{A,B,C}
6	{A,B,C,D}
7	{B,C}
8	{A,B,C}
9	{A,B,D}
10	{B,C,E}

Transaction Database

Header table

Item	Pointer
A	
B	
C	
D	
E	








Bottom-up traversal of the tree.

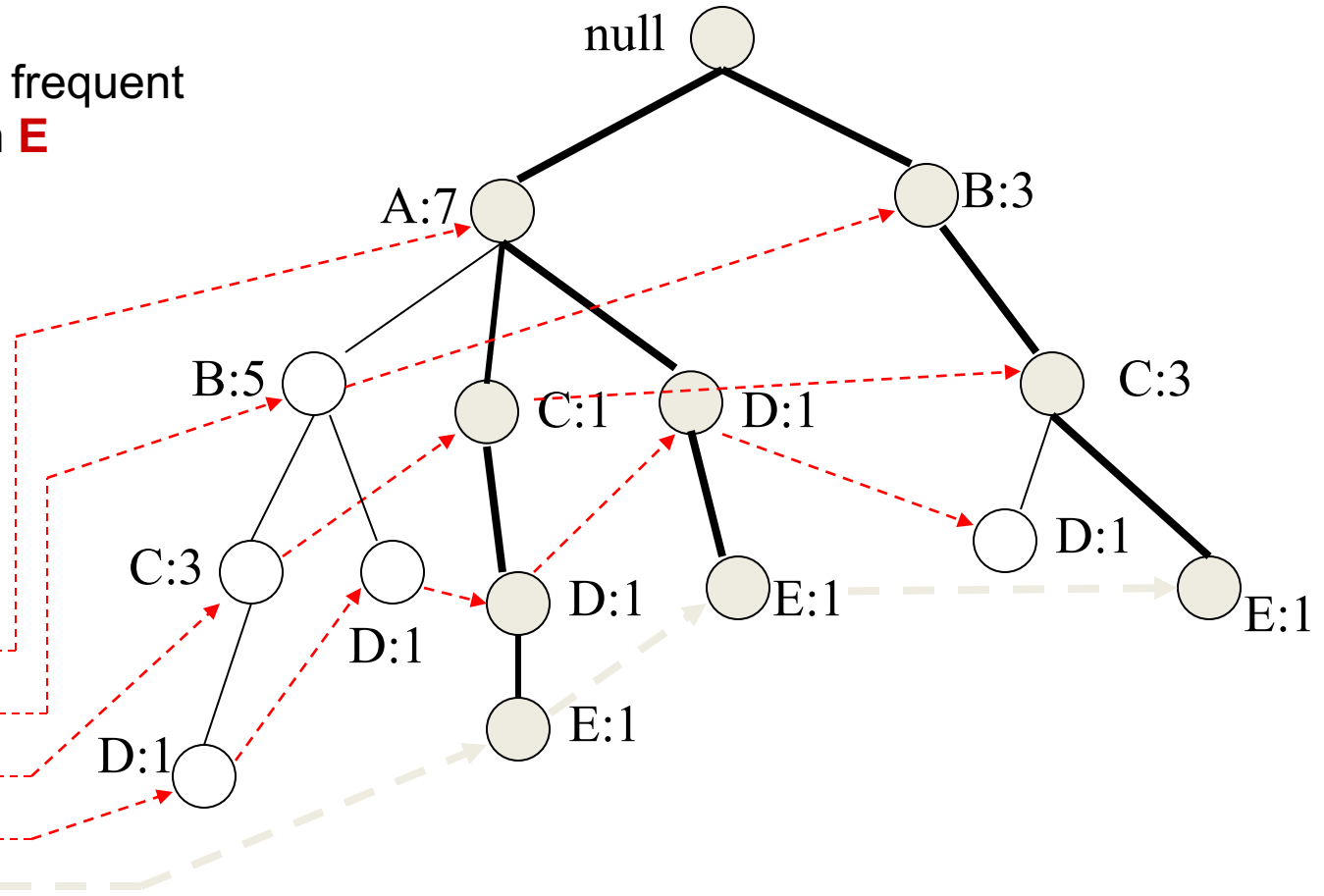
First, itemsets ending in E, then D, etc, each time a suffix-based class

# Finding Frequent Itemsets

Subproblem: find frequent itemsets ending in **E**



Item	Pointer
A	
B	
C	
D	
E	



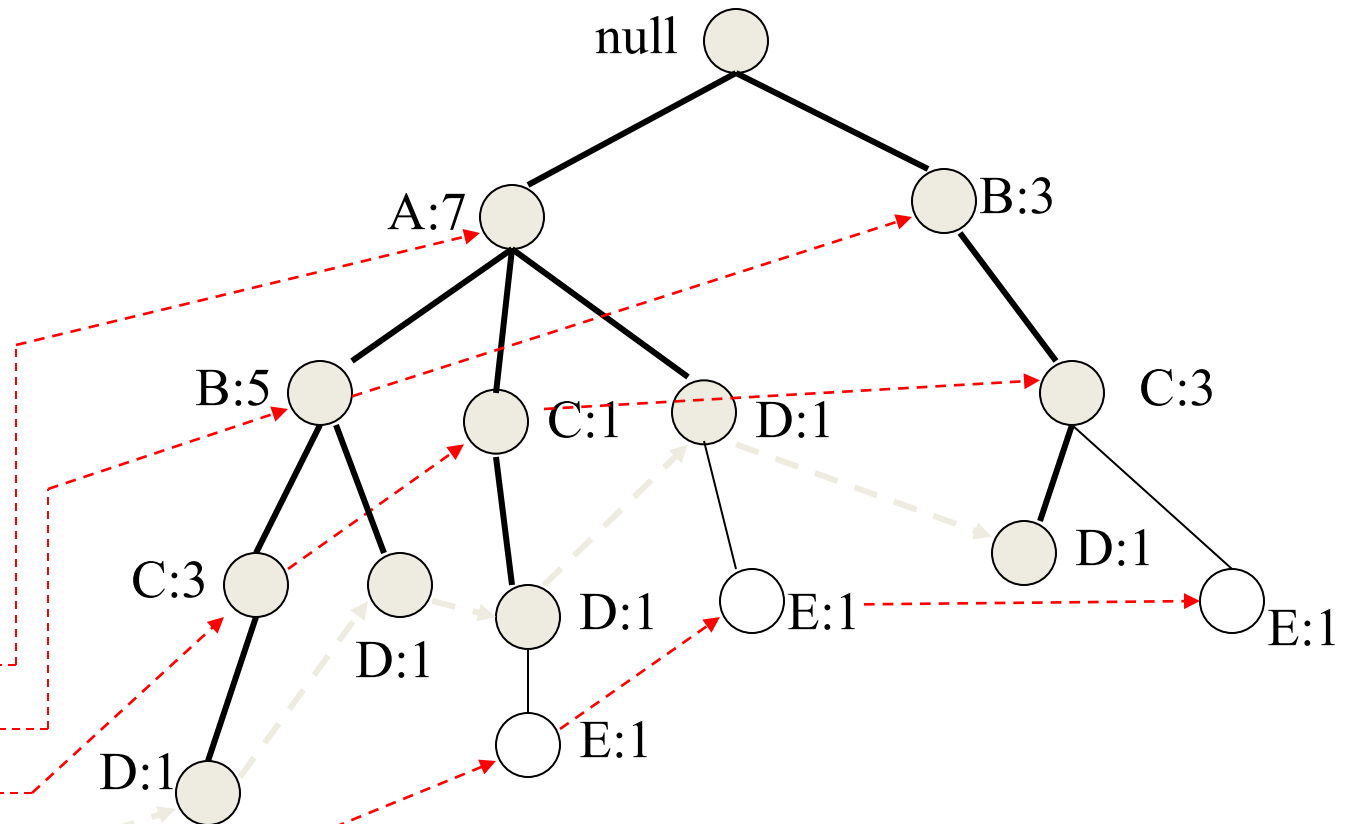
- We will then see how to compute the support for the possible itemsets

# Finding Frequent Itemsets

Ending in **D**

Header table

Item	Pointer
A	
B	
C	
D	
E	

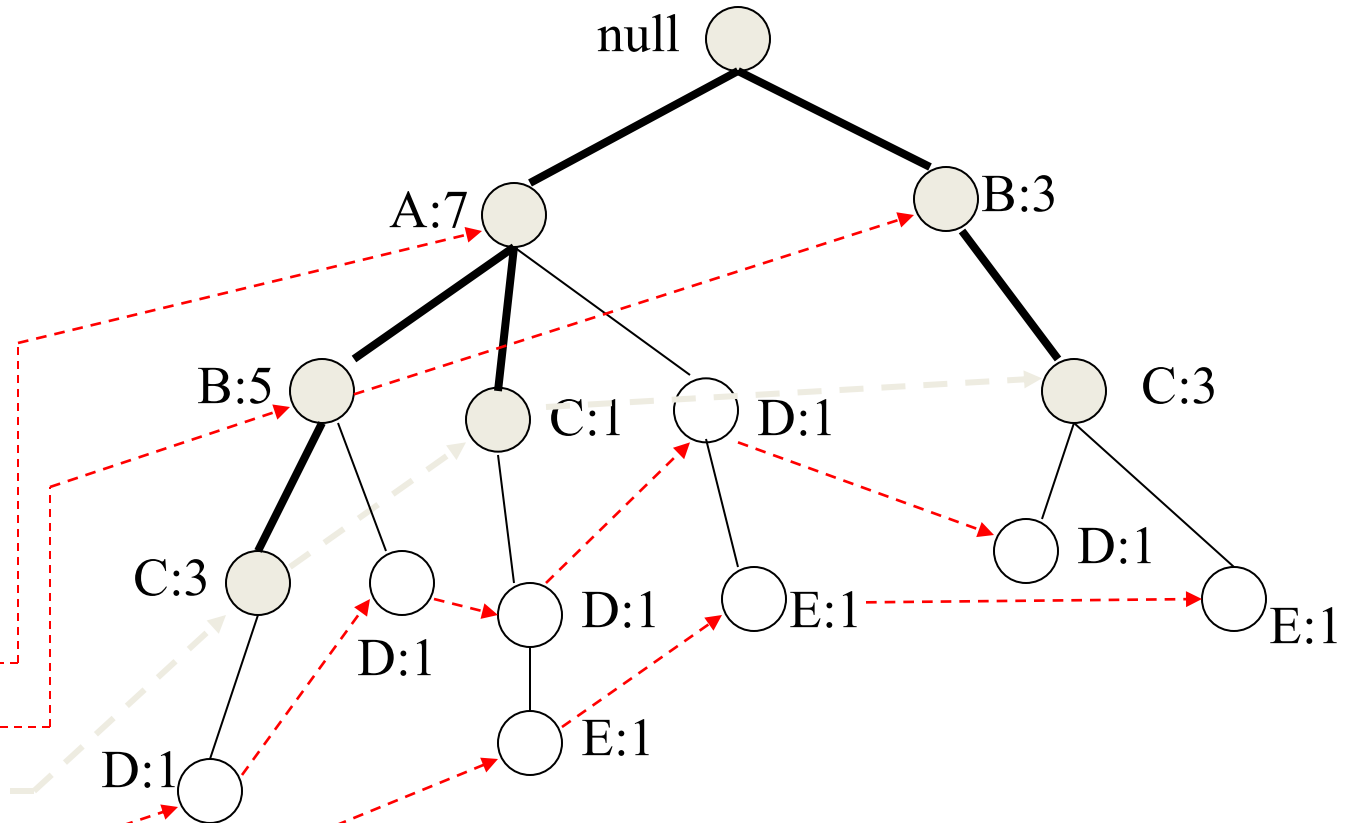


# Finding Frequent Itemsets

## Ending in C



Item	Pointer
A	-----
B	-----
C	-----
D	-----
E	-----








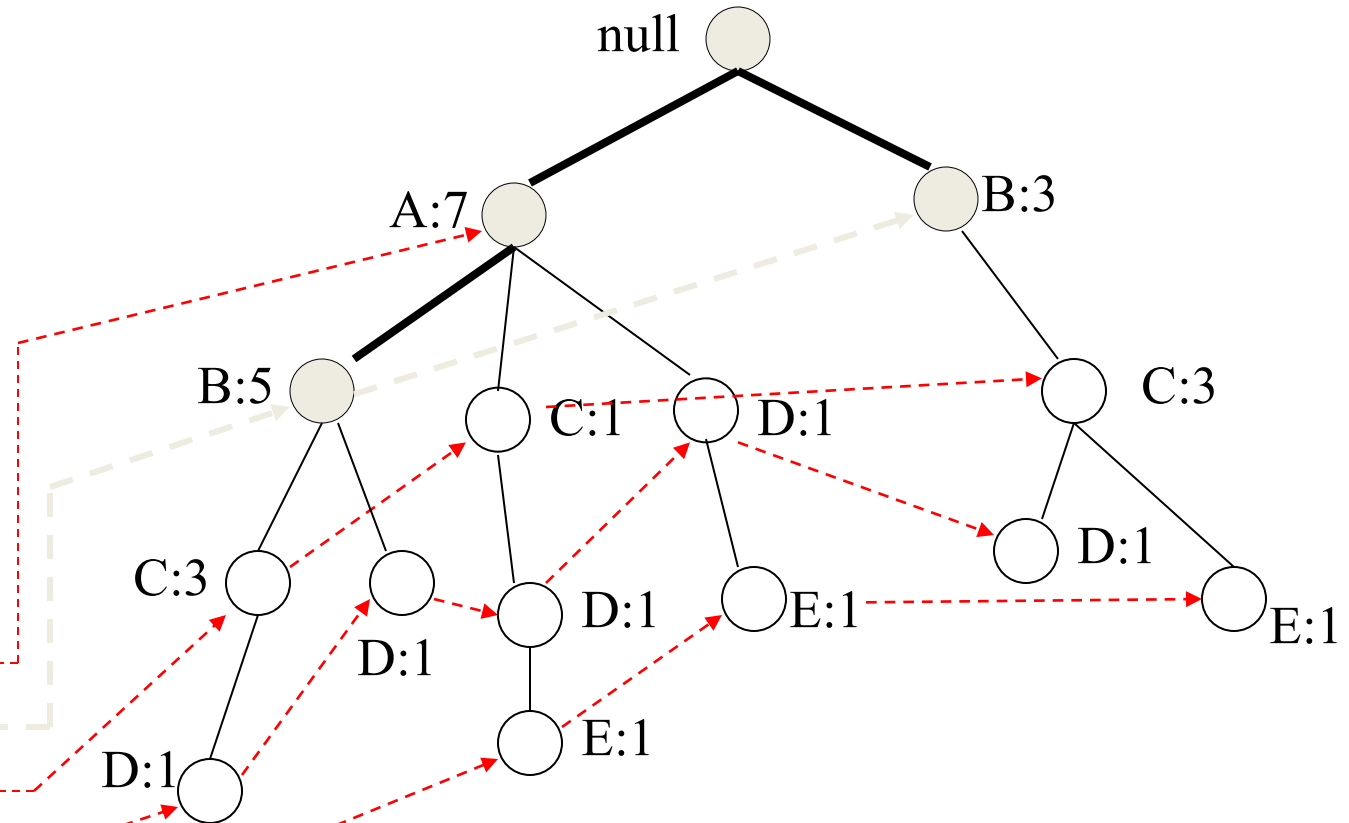


# Finding Frequent Itemsets

## Ending in **B**



Item	Pointer
A	
B	
C	
D	
E	

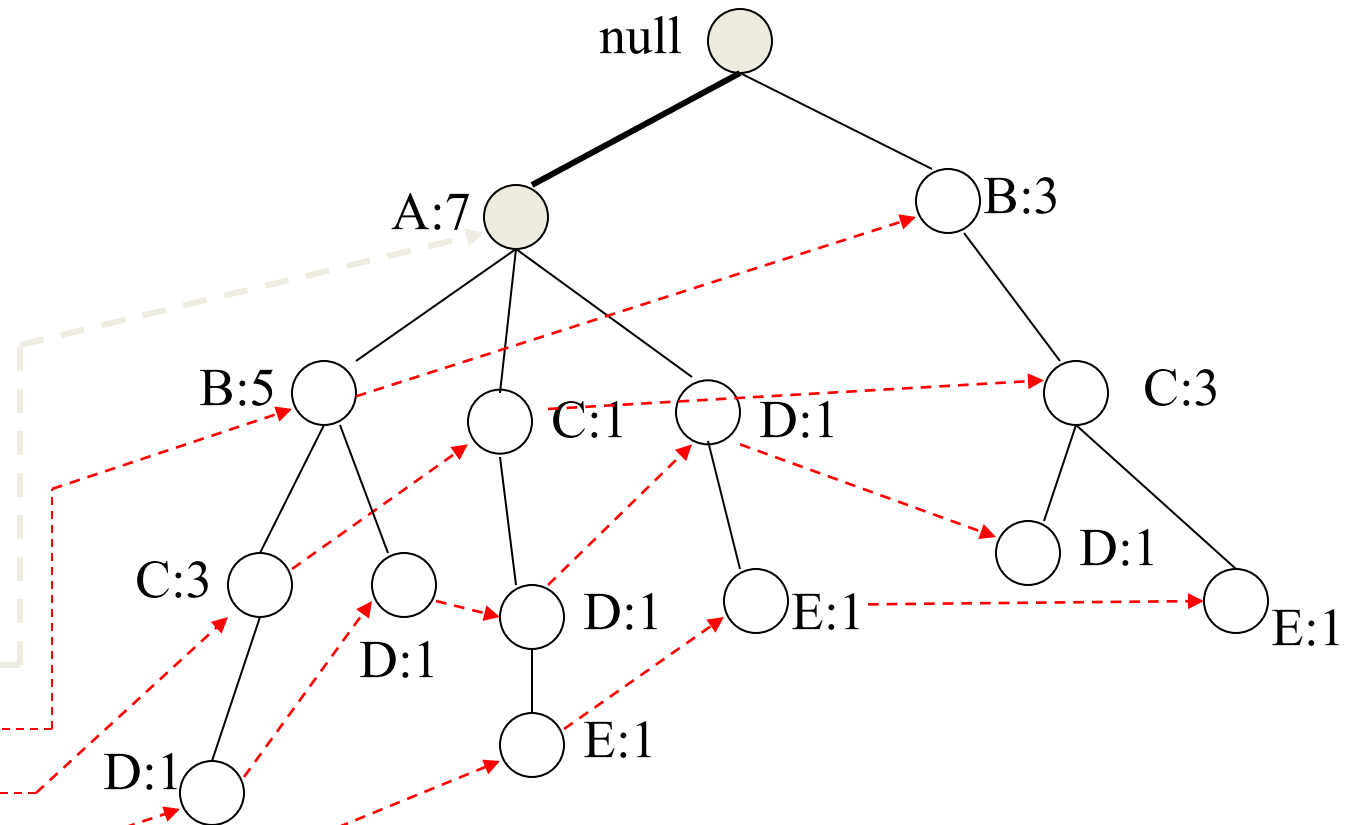


# Finding Frequent Itemsets

Ending in **A**

**Header table**

Item	Pointer
A	
B	
C	
D	
E	



# Algorithm

- For each **suffix** X
- Phase 1
  - Construct the prefix tree for X as shown before, and compute the support using the header table and the pointers
- Phase 2
  - **If X is frequent**, construct the conditional FP-tree for X in the following steps
    1. Recompute support
    2. Prune infrequent items
    3. Prune leaves and recurse

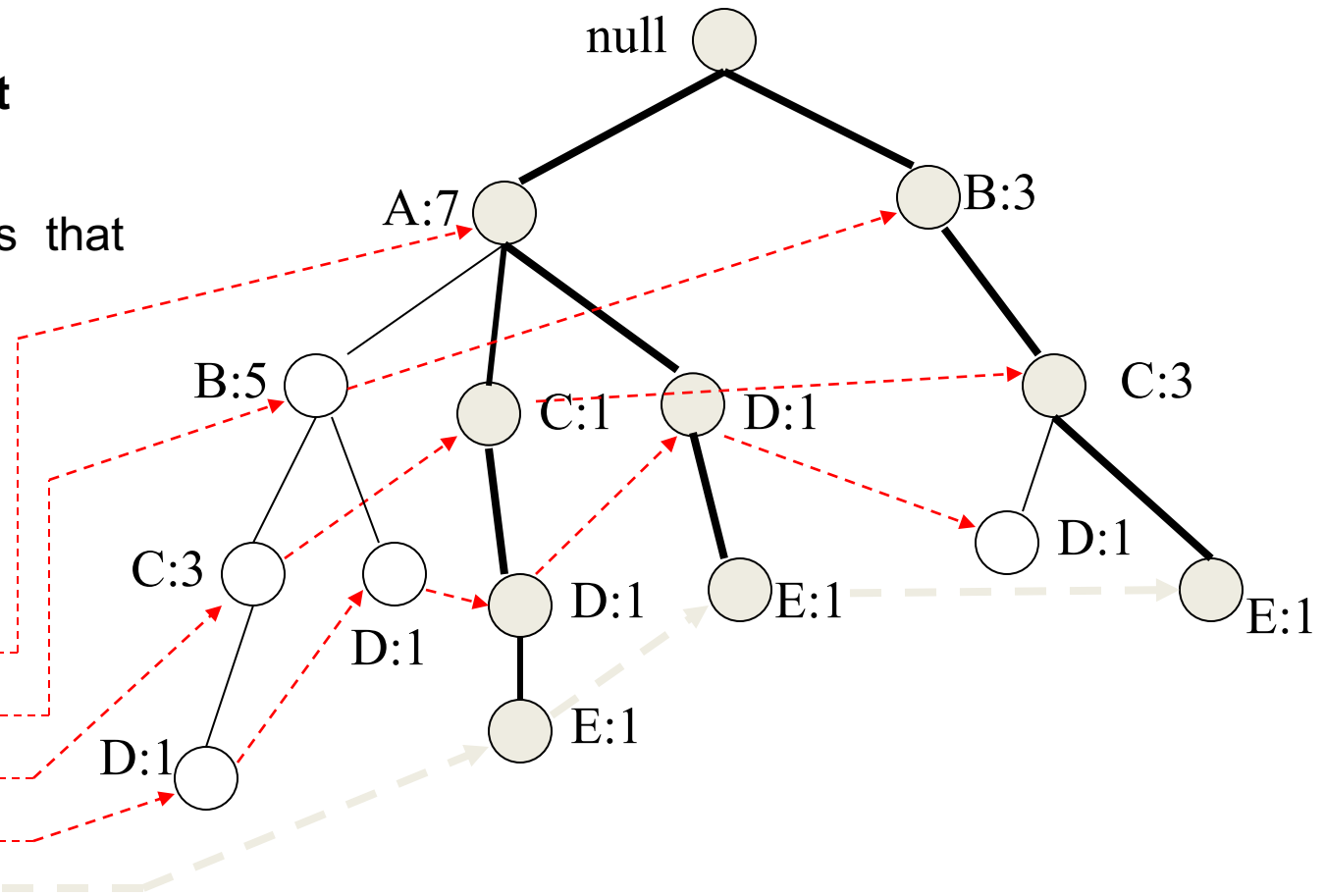
# Example

## Phase 1 – construct prefix tree

Find all prefix paths that contain E

Header table

Item	Pointer
A	
B	
C	
D	
E	



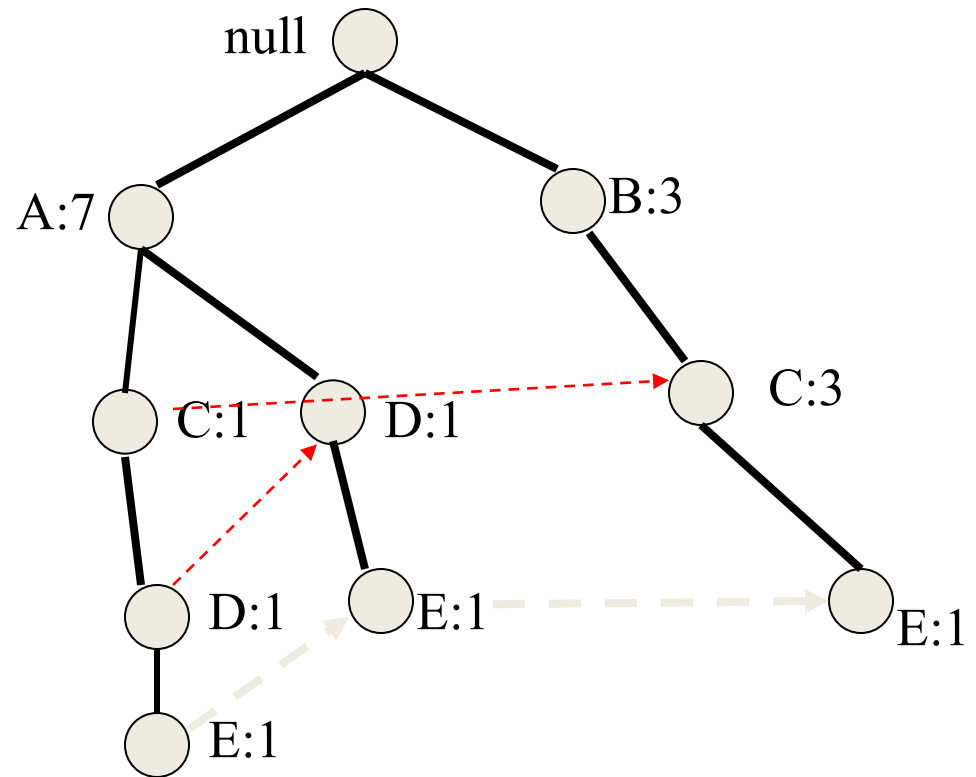
Suffix Paths for E:

{A,C,D,E}, {A,D,E}, {B,C,E}

# Example

## Phase 1 – construct prefix tree

Find all prefix paths that contain E



Prefix Paths for E:

{A,C,D,E}, {A,D,E}, {B,C,E}

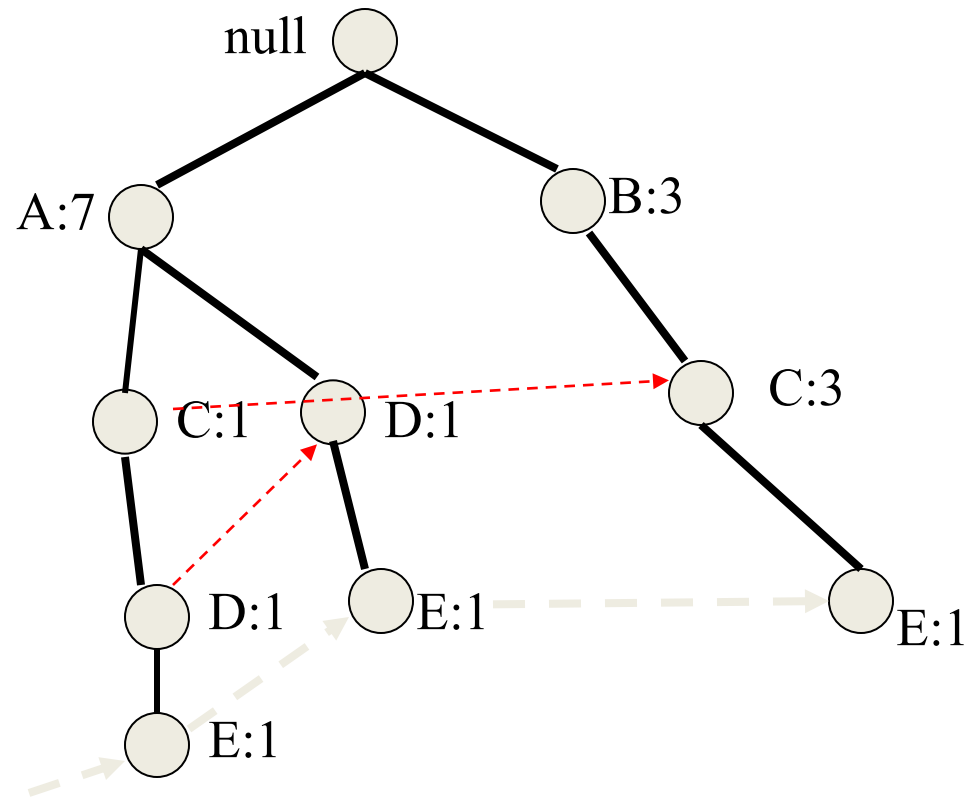
# Example

Compute Support for E  
(**minsup** = 2)

How?

Follow pointers while  
summing up counts:  
 $1+1+1 = 3 > 2$

**E** is frequent



{E} is frequent so we can now consider suffixes DE, CE, BE, AE

# Example

E is frequent so we proceed with Phase 2

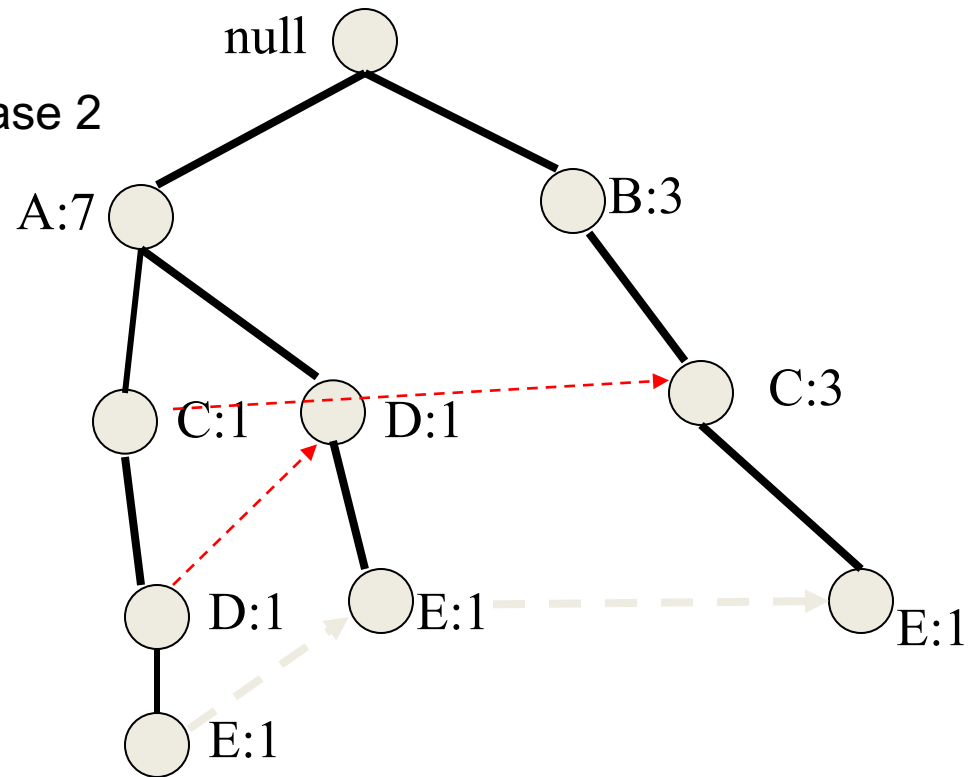
## Phase 2

Convert the prefix tree of E into a conditional FP-tree

Two changes

(1) Recompute support

(2) Prune infrequent



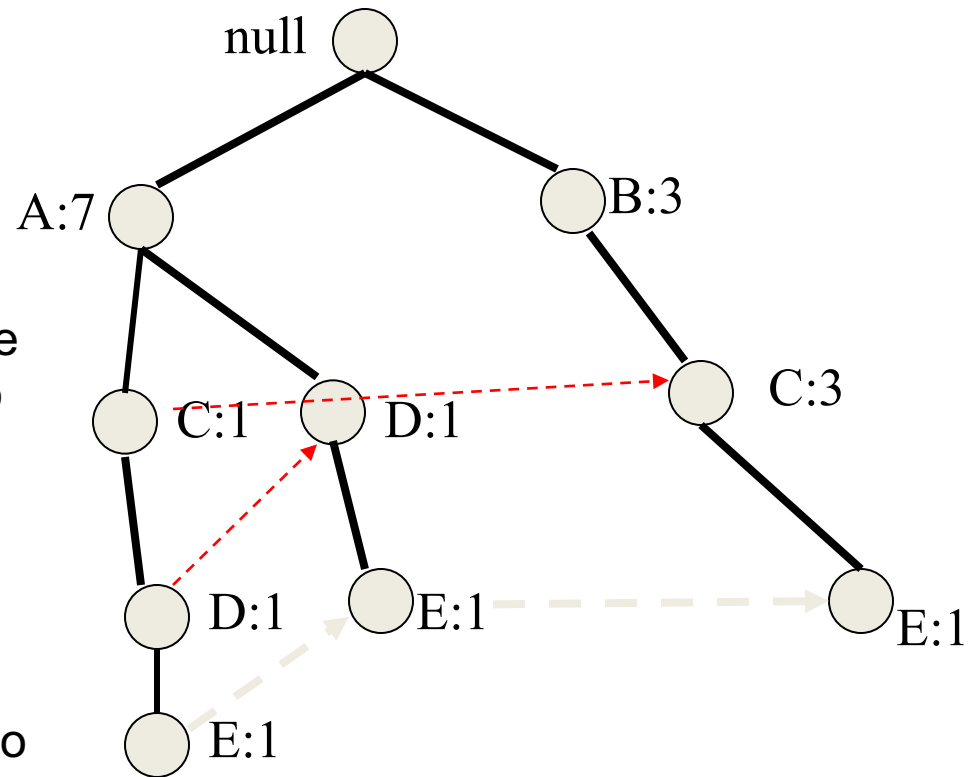
# Example

## Recompute Support

The support counts for some of the nodes include transactions that do not end in E

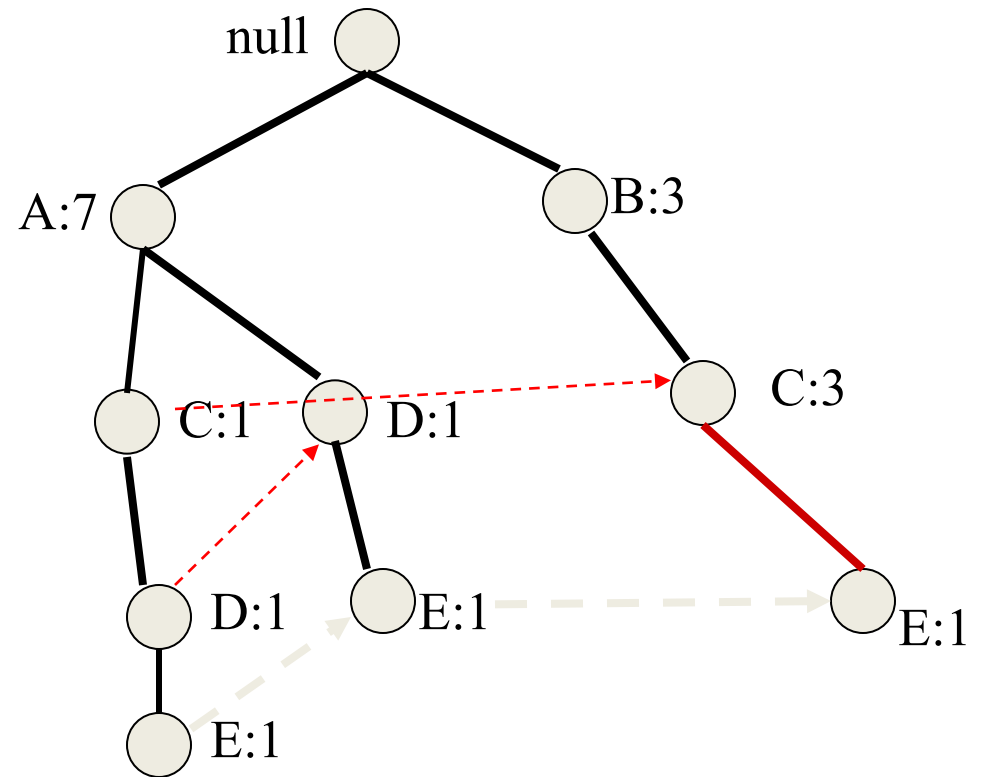
For example in  $\text{null} \rightarrow B \rightarrow C \rightarrow E$  we count  $\{B, C\}$

The support of any node is equal to the sum of the support of leaves with label E in its subtree

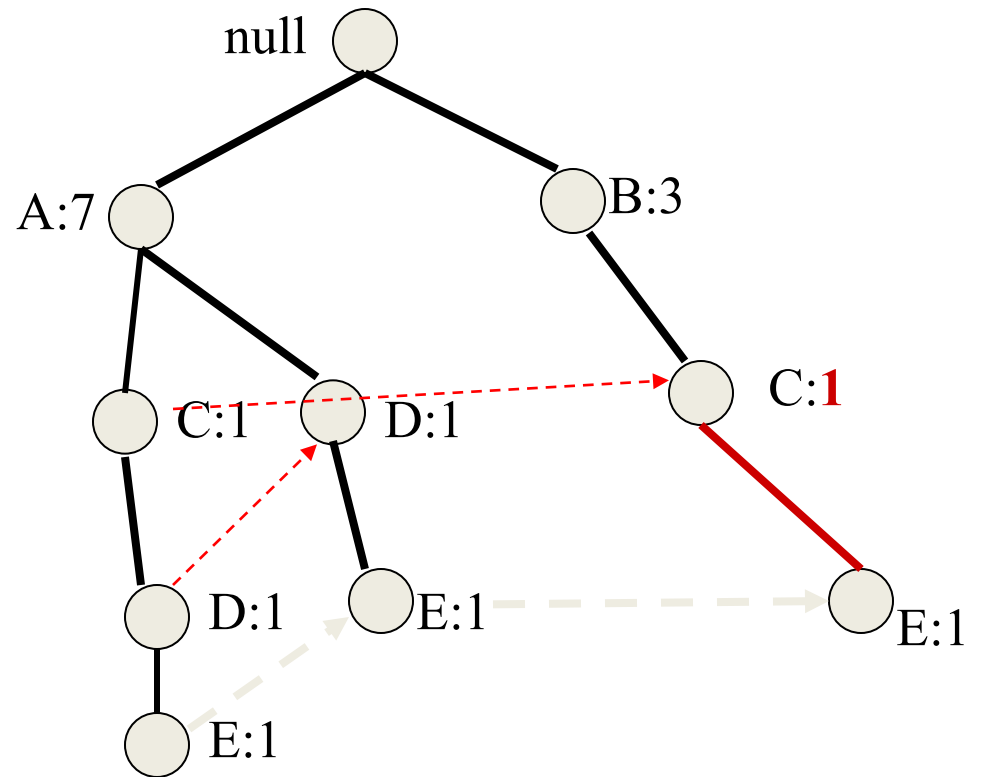




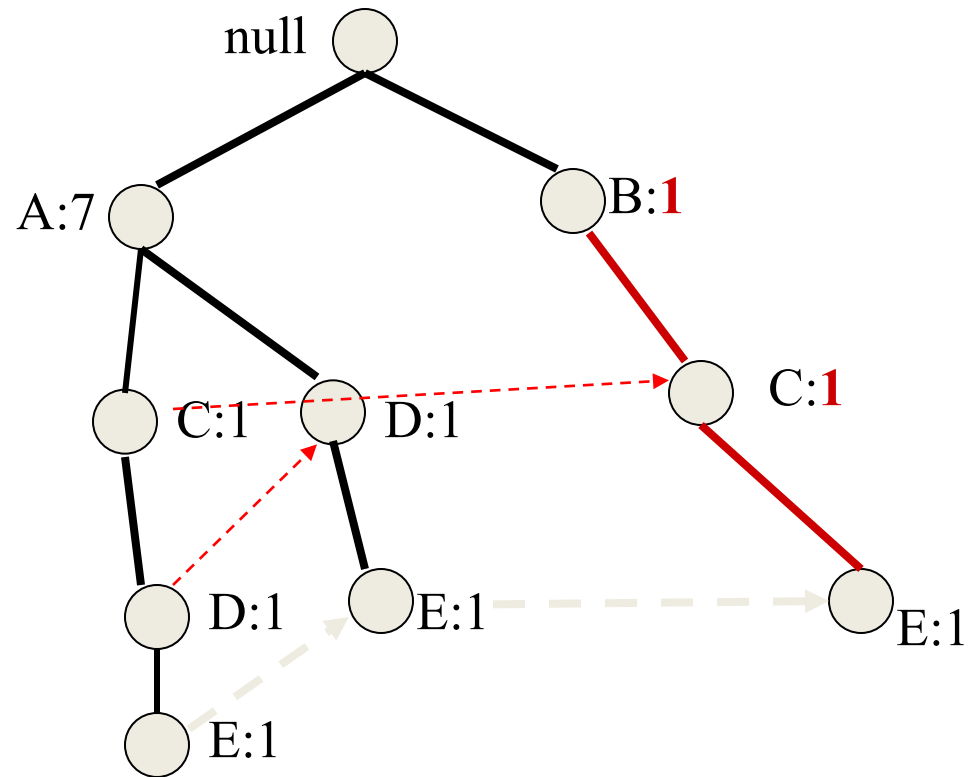
# Example



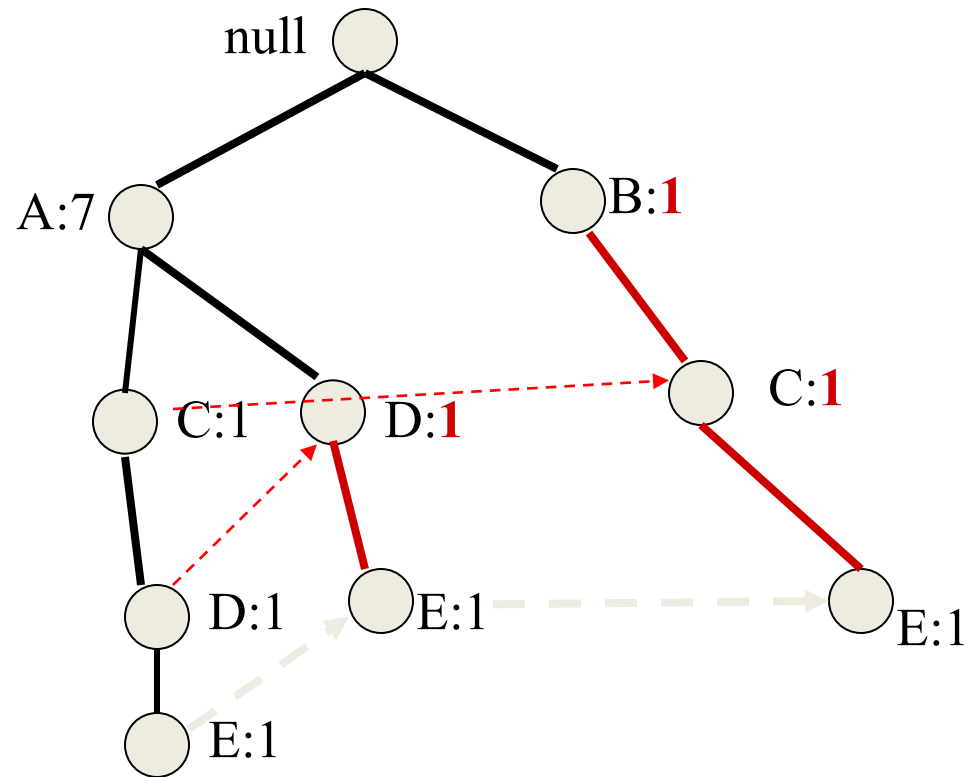
## Example



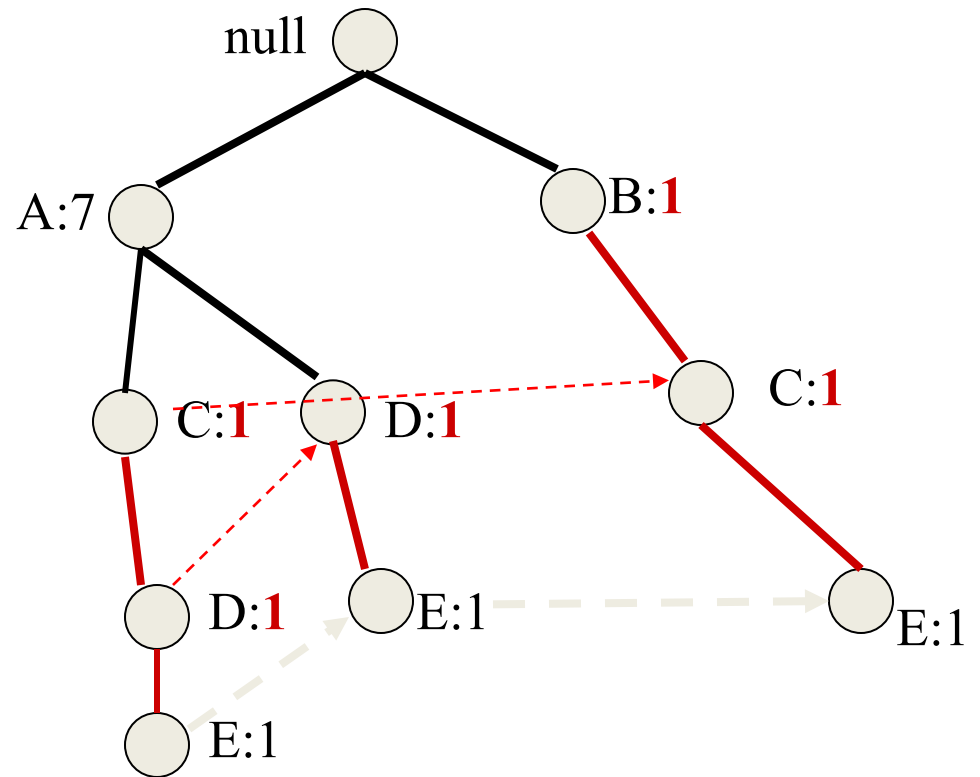
# Example



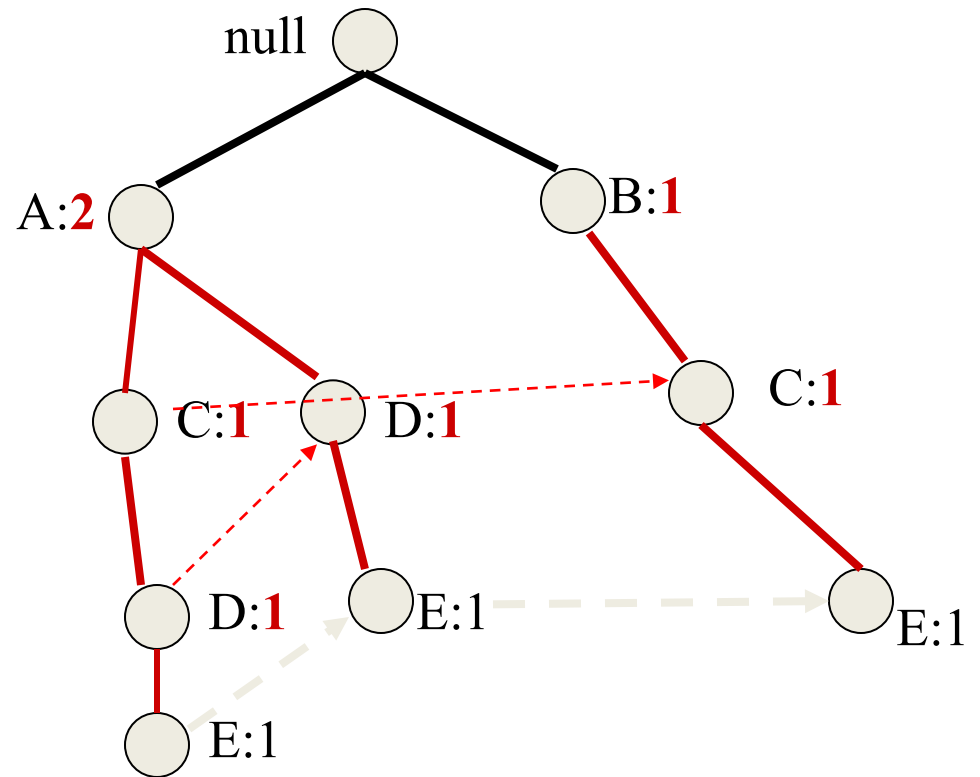
# Example



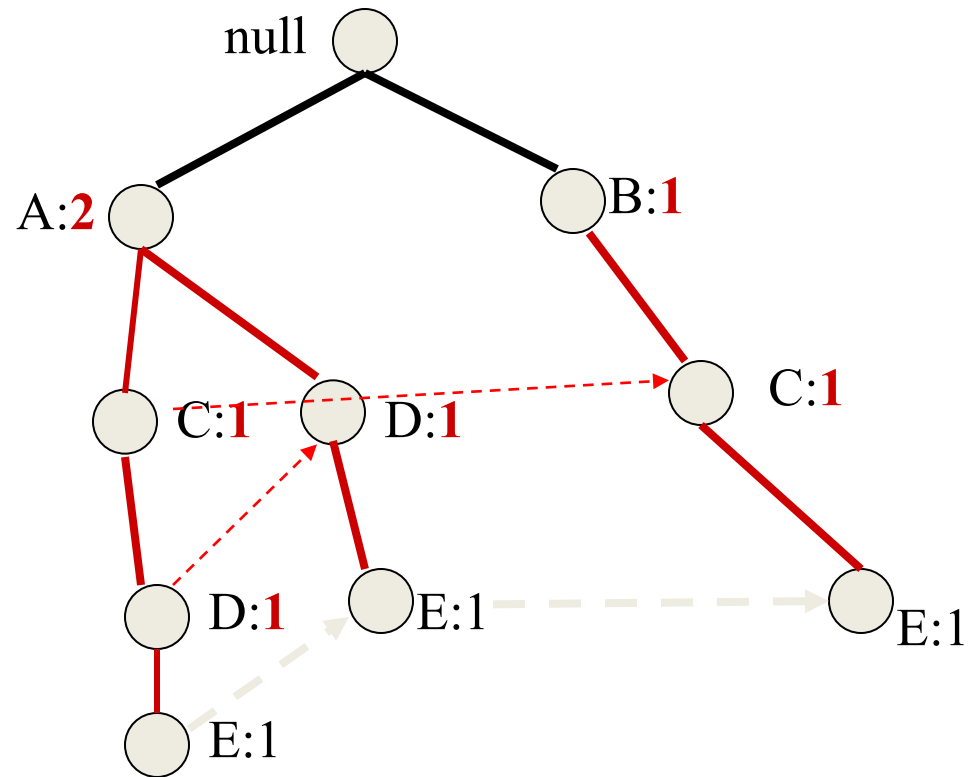
# Example



# Example



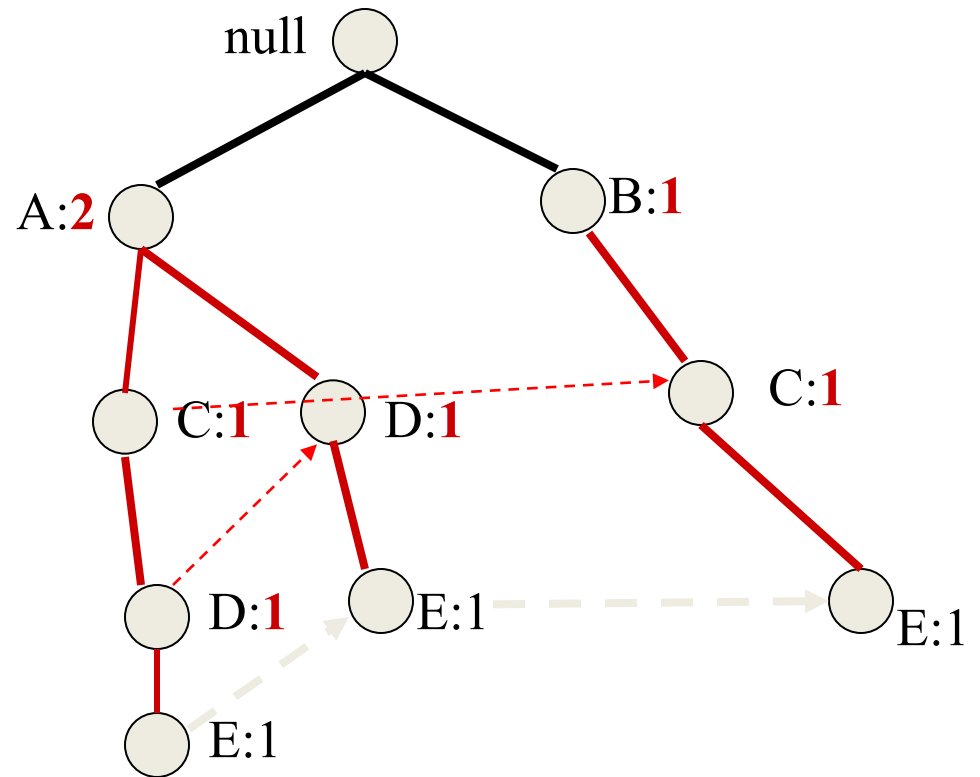
# Example



# Example

Truncate

Delete the nodes of E

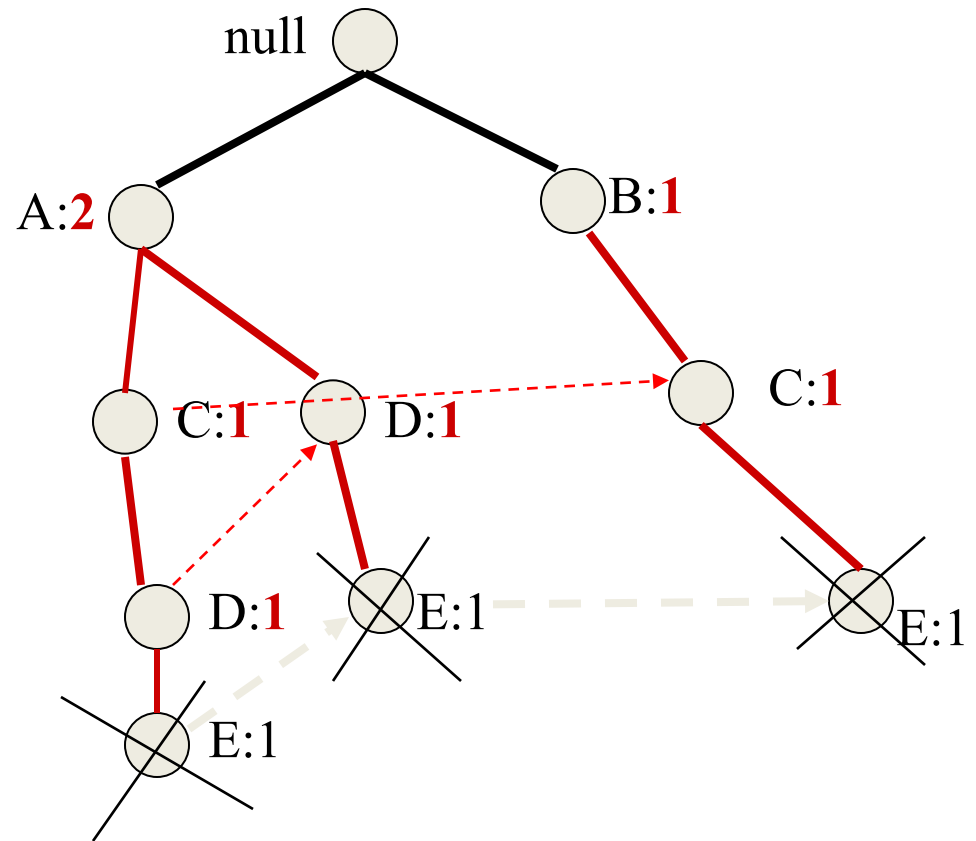




# Example

Truncate

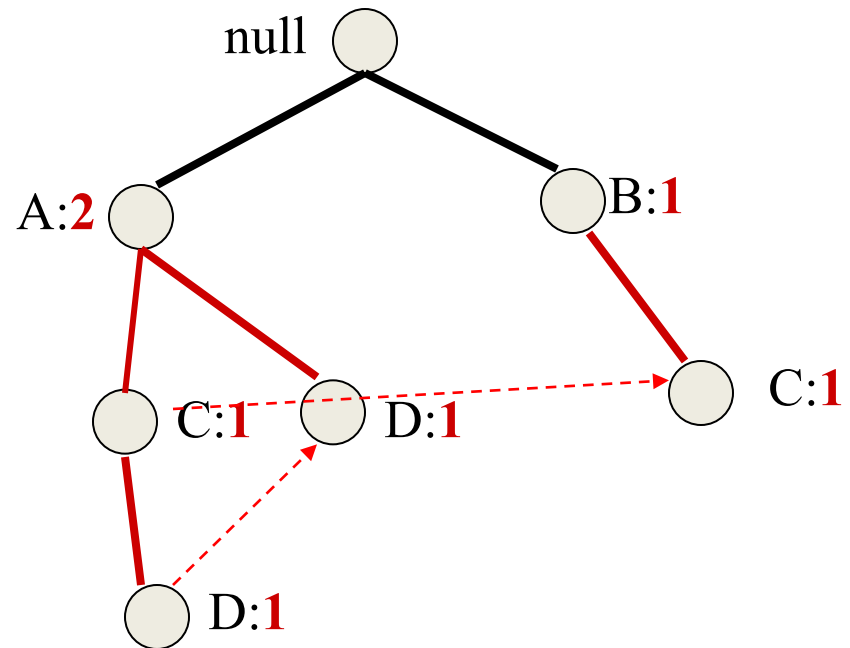
Delete the nodes of E



# Example

Truncate

Delete the nodes of E



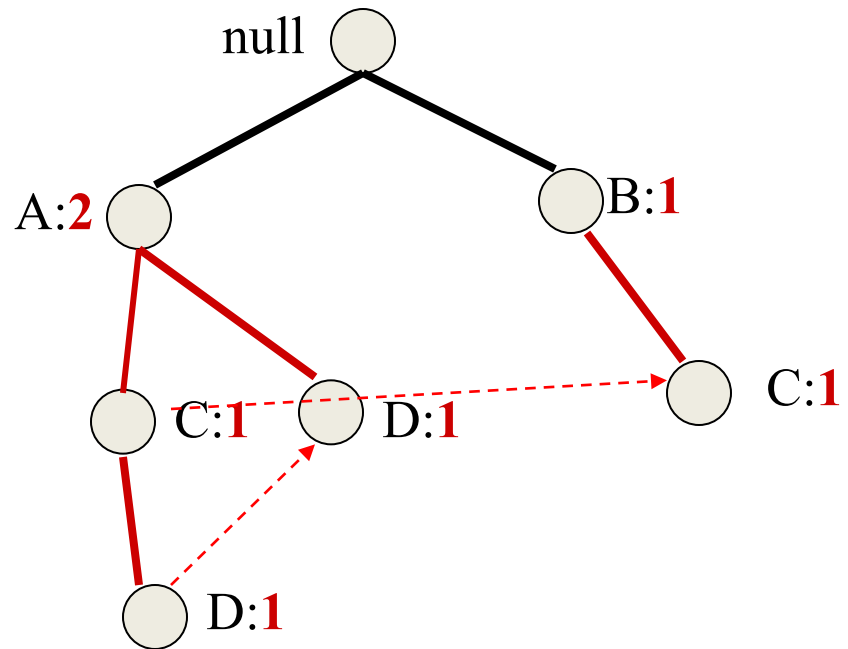
# Example

## Prune infrequent

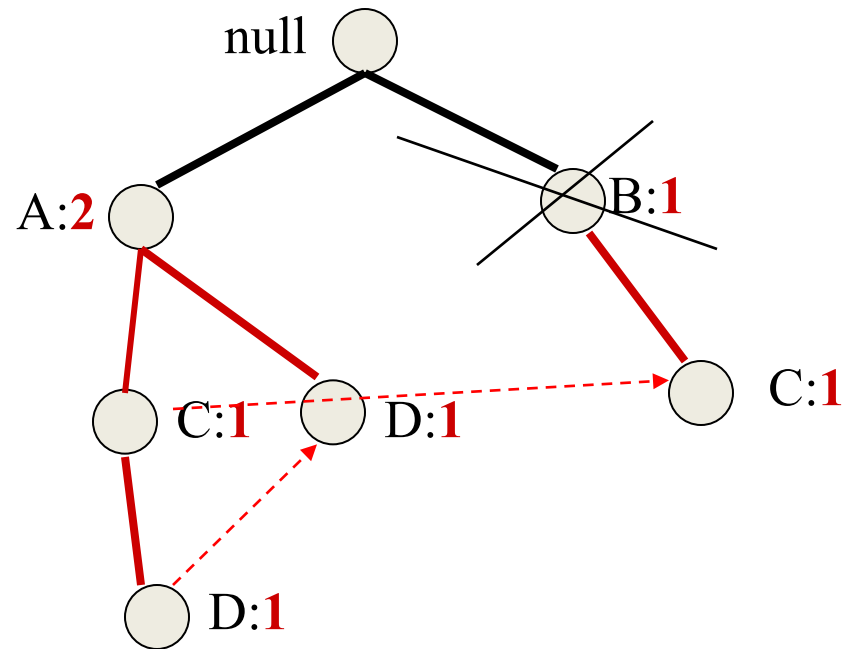
In the conditional FP-tree some nodes may have support less than minsup

e.g., B needs to be pruned

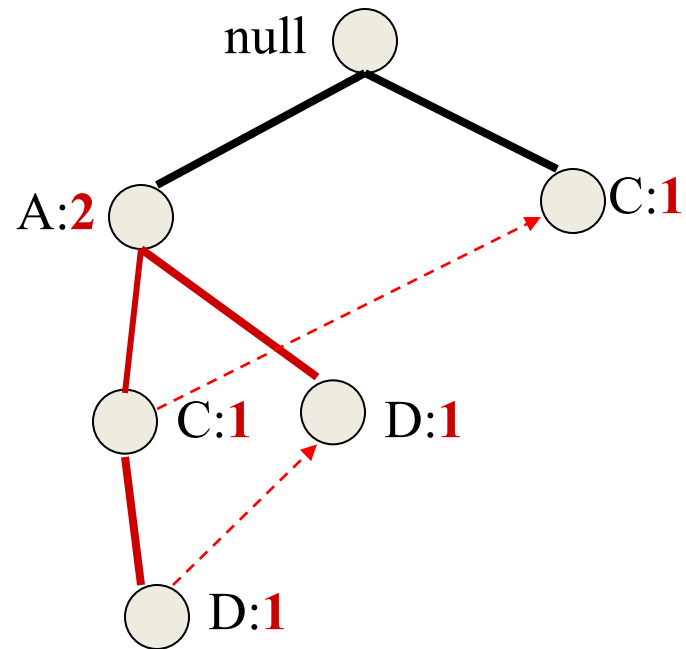
This means that B appears with E less than minsup times



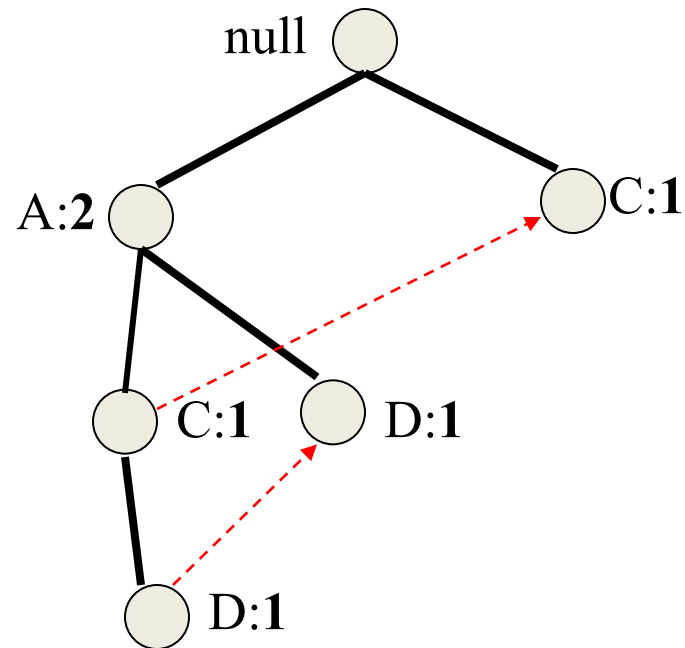
# Example



# Example



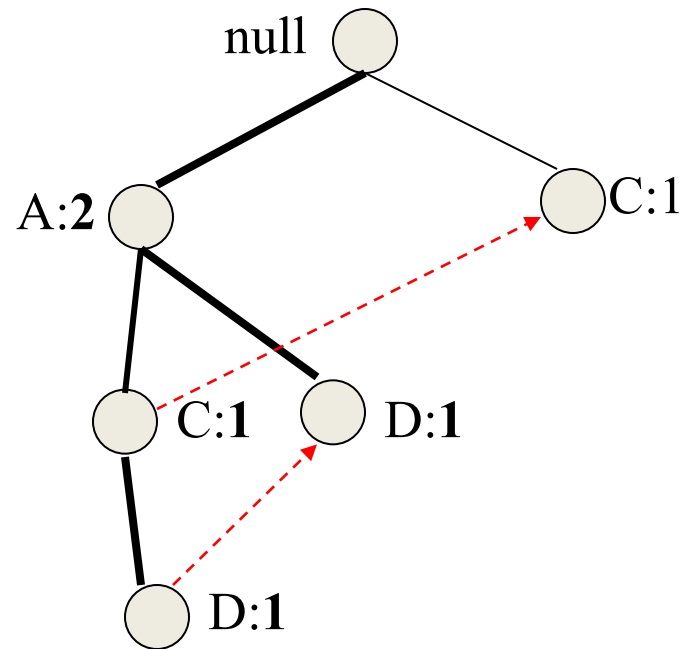
# Example



The conditional FP-tree for E

Repeat the algorithm for  $\{D, E\}$ ,  $\{C, E\}$ ,  $\{A, E\}$

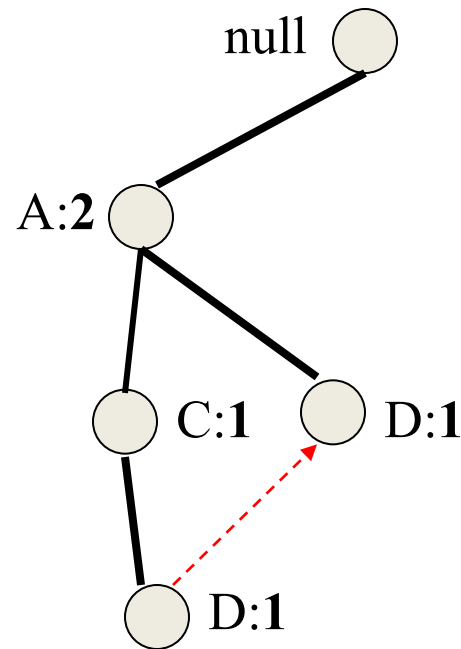
# Example



## Phase 1

Find all prefix paths that contain D (DE) in the conditional FP-tree

# Example

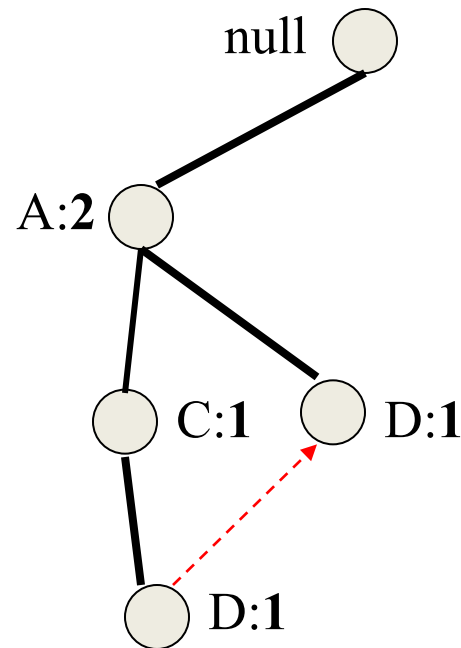


## Phase 1

Find all prefix paths that contain D (DE) in the conditional FP-tree



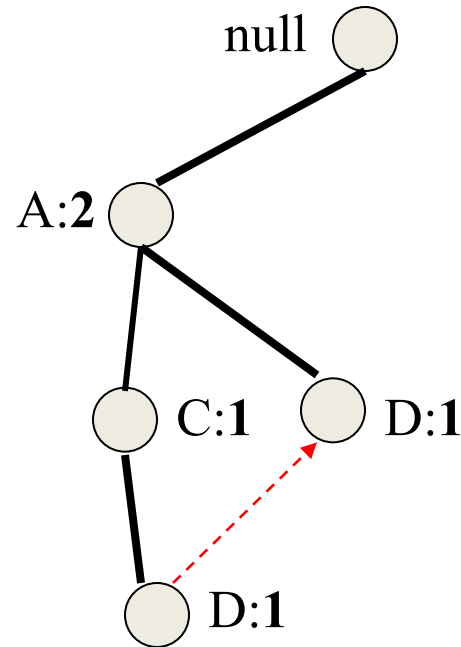
# Example



Compute the support of  $\{D, E\}$  by following the pointers in the tree  
 $1 + 1 = 2 \geq 2 = \text{minsup}$

$\{D, E\}$  is frequent

# Example



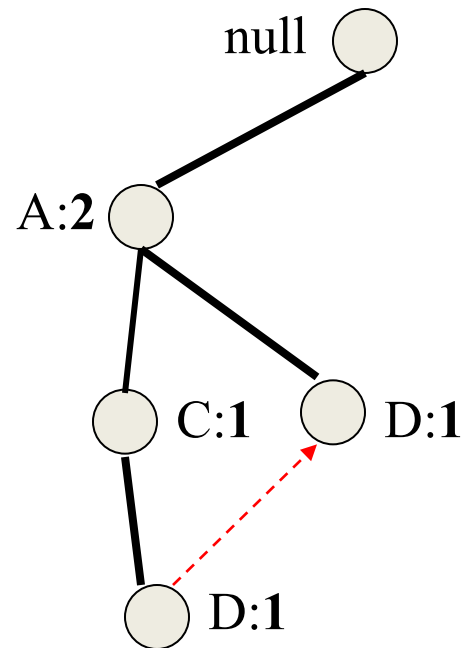
## Phase 2

Construct the conditional FP-tree

1. Recompute Support
2. Prune nodes

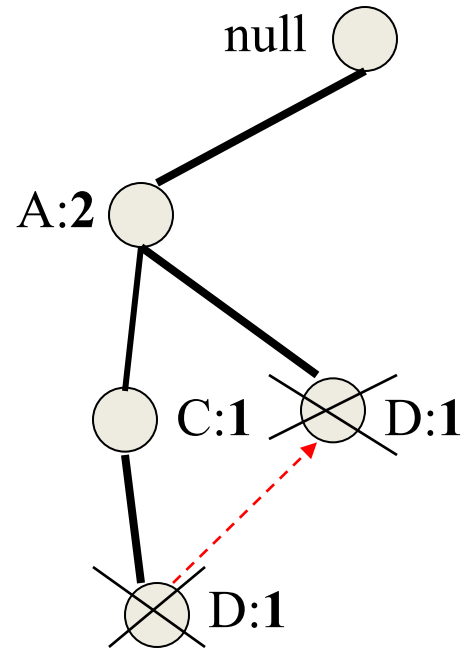
# Example

Recompute support

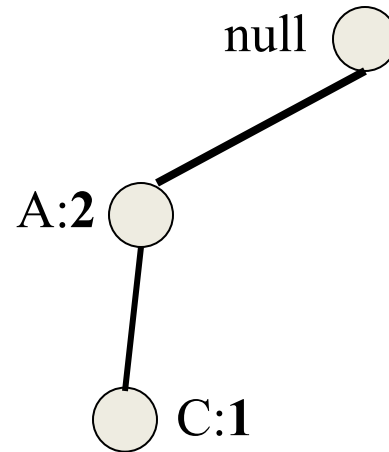


# Example

## Prune nodes

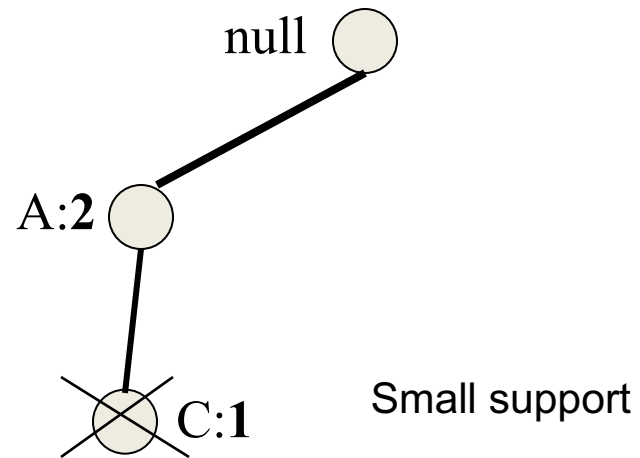


# Example



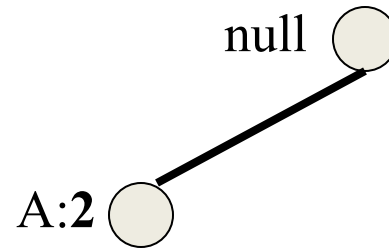
Prune nodes

# Example



Prune nodes

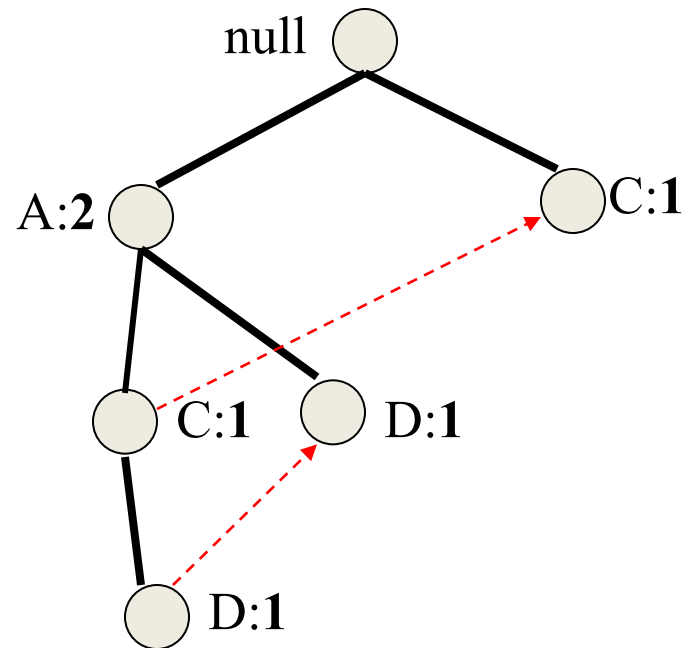
# Example



Final condition FP-tree for  $\{D,E\}$

The support of A is  $\geq$  minsup so  $\{A,D,E\}$  is frequent  
Since the tree has a single node we return to the next subproblem

# Example

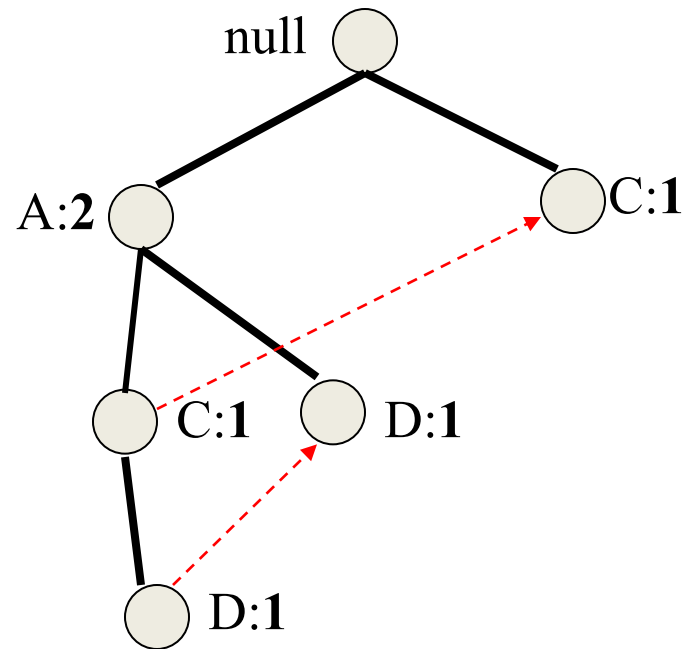


The conditional FP-tree for E

We repeat the algorithm for  $\{D, E\}$ ,  $\{C, E\}$ ,  $\{A, E\}$



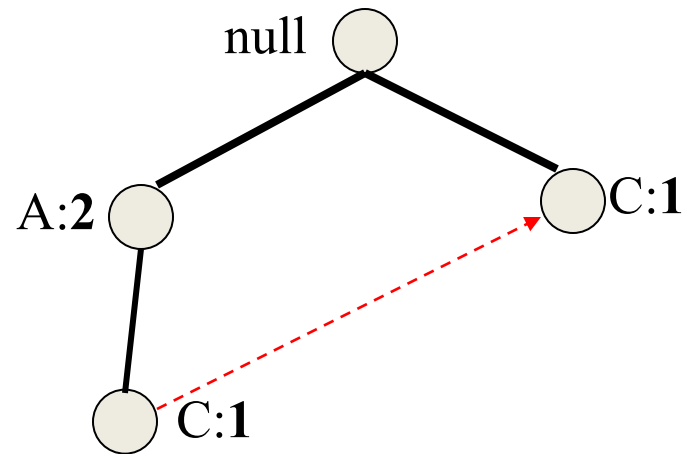
# Example



## Phase 1

Find all prefix paths that contain C (CE) in the conditional FP-tree

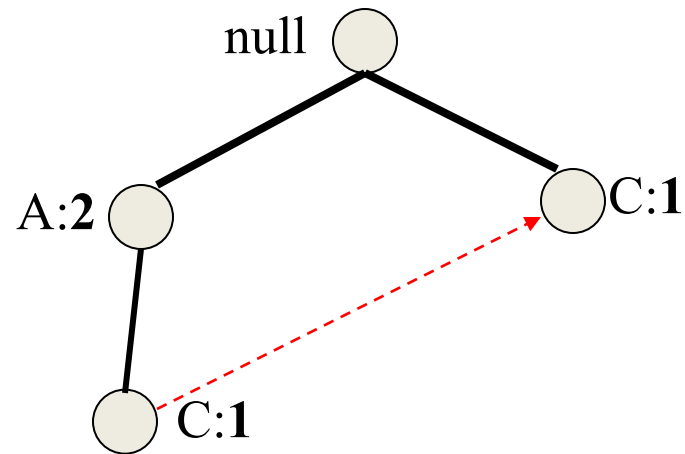
# Example



## Phase 1

Find all prefix paths that contain C (CE) in the conditional FP-tree

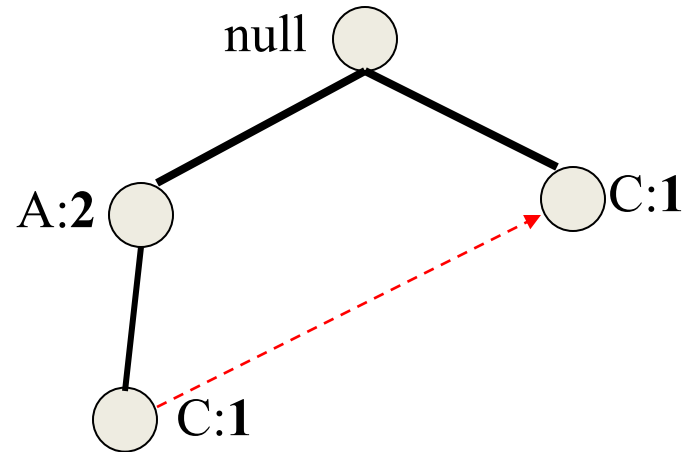
# Example



Compute the support of  $\{C,E\}$  by following the pointers in the tree  
 $1+1 = 2 \geq 2 = \text{minsup}$

$\{C,E\}$  is frequent

# Example

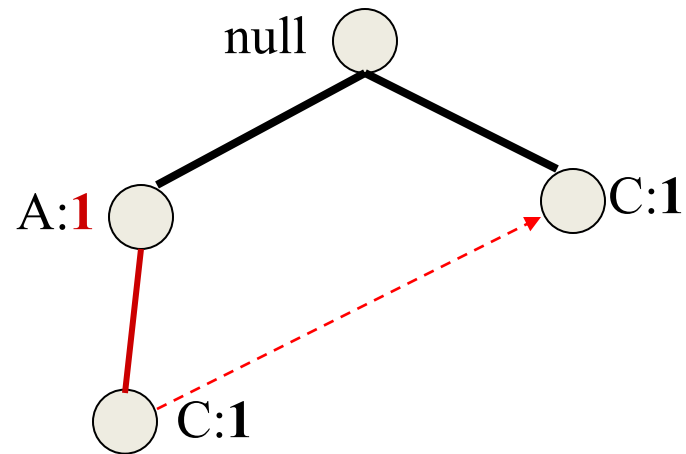


## Phase 2

Construct the conditional FP-tree

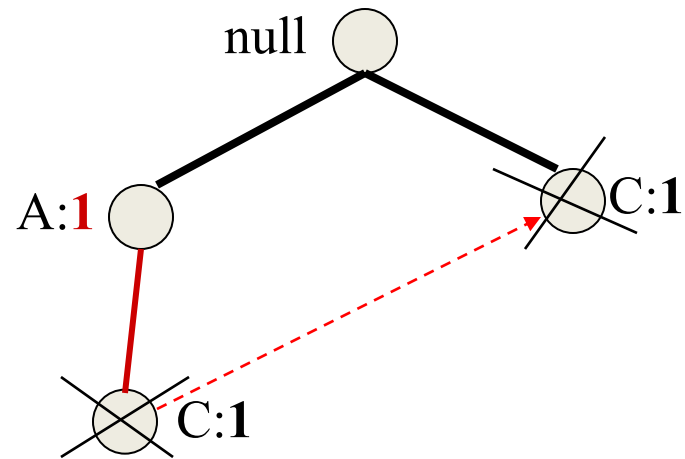
1. Recompute Support
2. Prune nodes

# Example



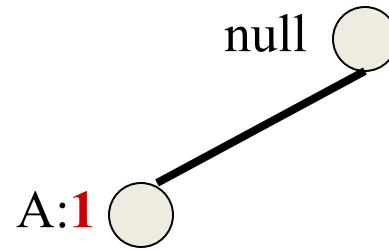
Recompute support

# Example



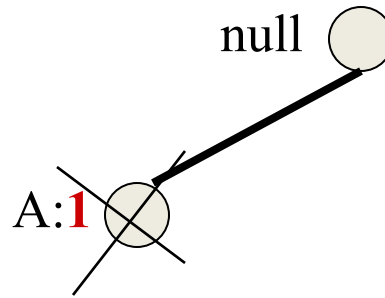
Prune nodes

# Example



Prune nodes


# Example



Prune nodes



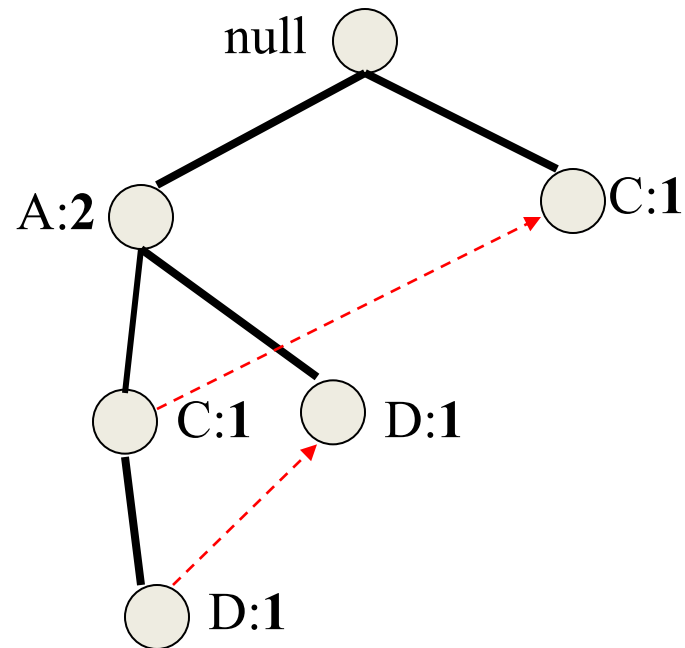
# Example

null 

Prune nodes

Return to the previous subproblem

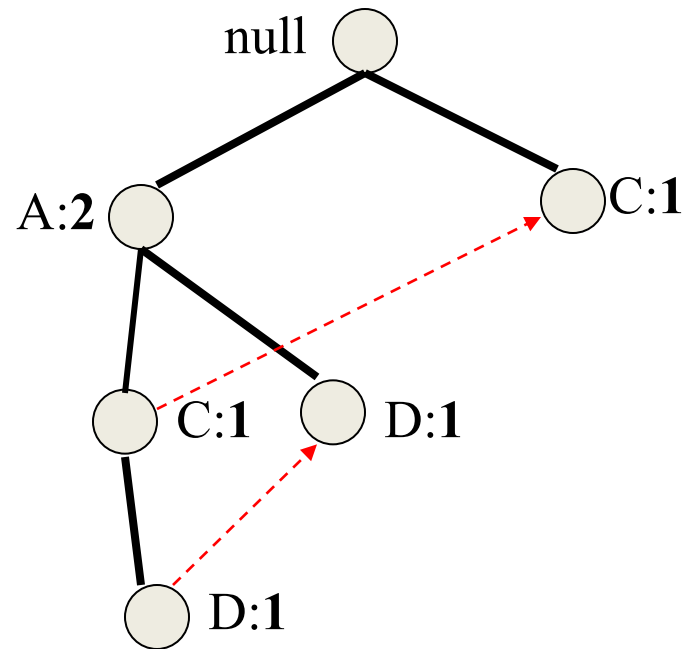
# Example



The conditional FP-tree for E

We repeat the algorithm for  $\{D, E\}$ ,  $\{C, E\}$ ,  $\{A, E\}$

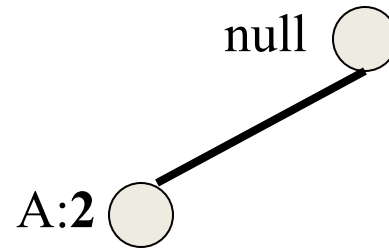
# Example



## Phase 1

Find all prefix paths that contain A (AE) in the conditional FP-tree

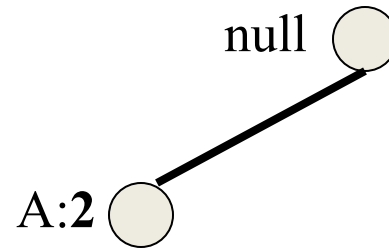
# Example



## Phase 1

Find all prefix paths that contain A (AE) in the conditional FP-tree

# Example



Compute the support of  $\{A, E\}$  by following the pointers in the tree  
 $2 \geq \text{minsup}$

$\{A, E\}$  is frequent

There is no conditional FP-tree for  $\{A, E\}$

# Example

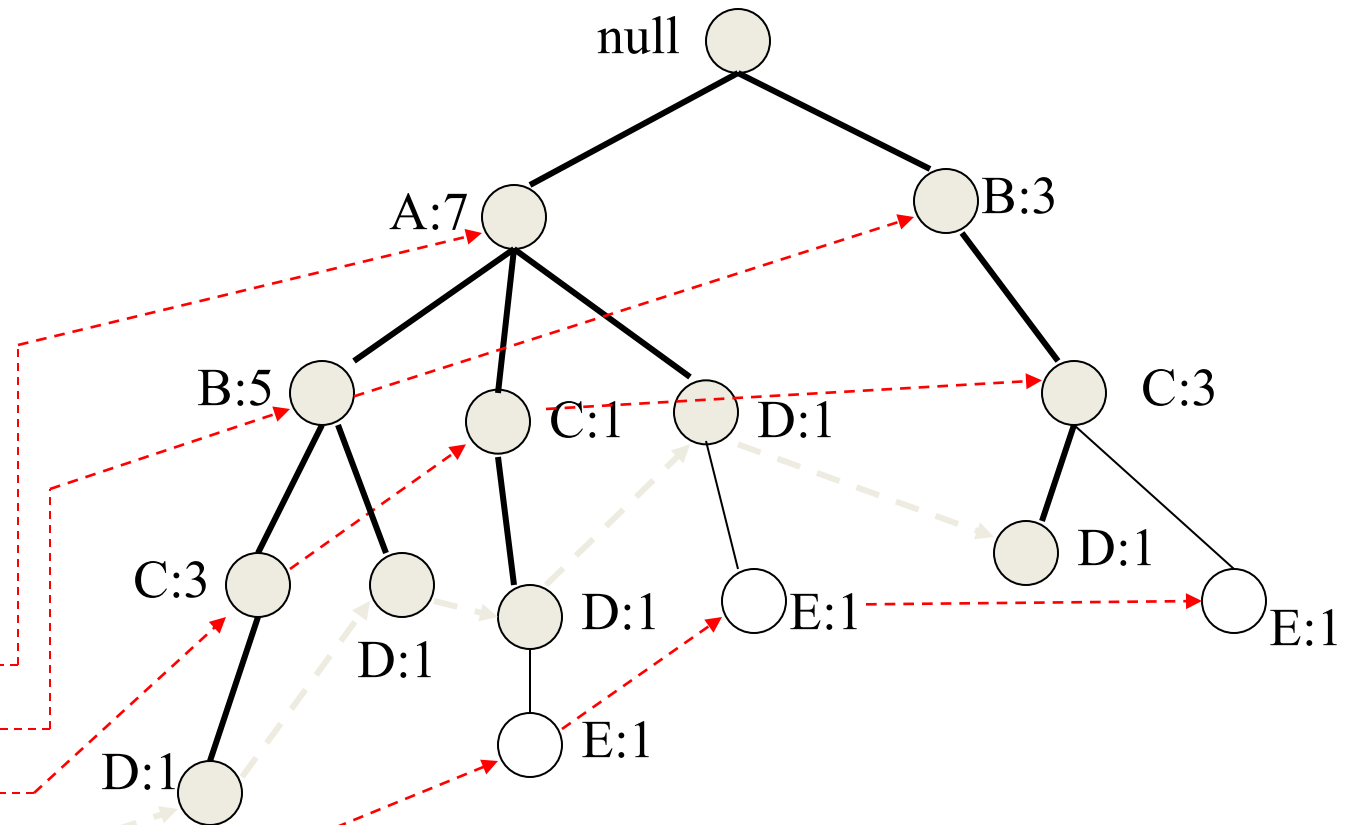
- So for E we have the following frequent itemsets  
 $\{E\}$ ,  $\{D,E\}$ ,  $\{C,E\}$ ,  $\{A,E\}$
- We proceed with D

# Example

Ending in **D**

Header table

Item	Pointer
A	
B	
C	
D	
E	



# Example

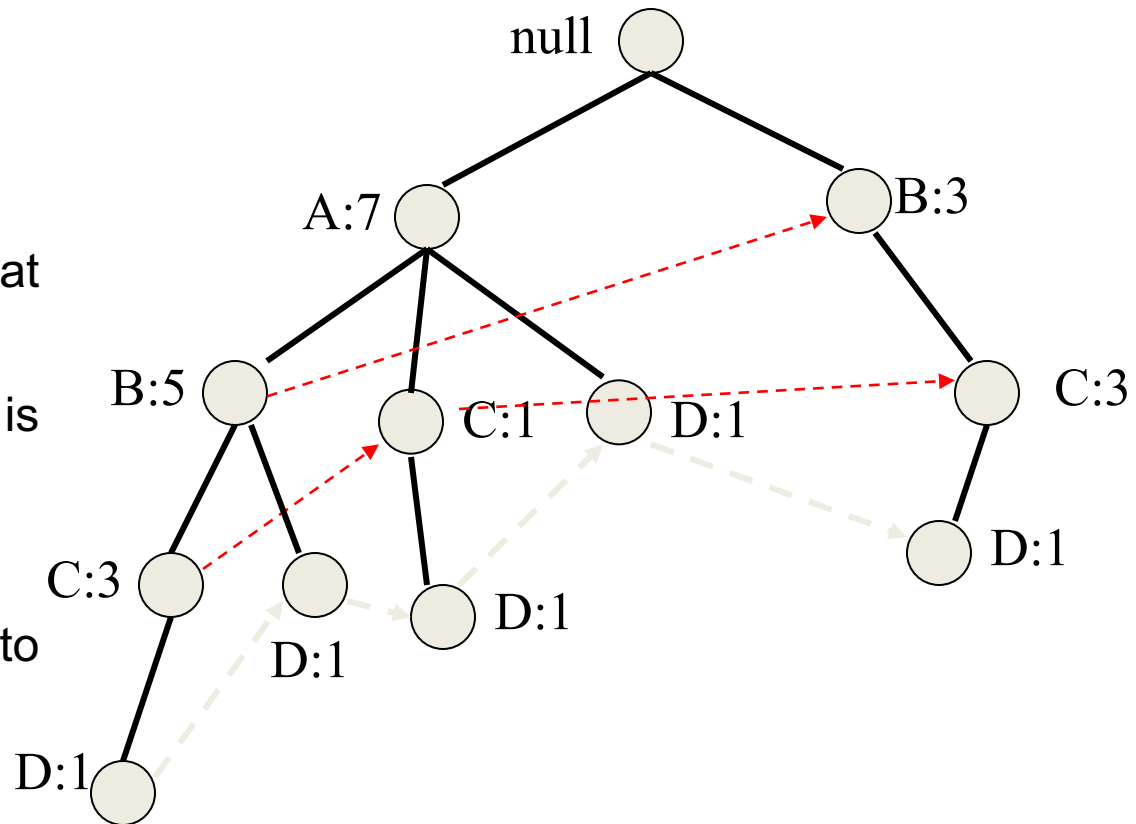
## Phase 1 – construct prefix tree

Find all prefix paths that contain D

Support 5 > minsup, D is frequent

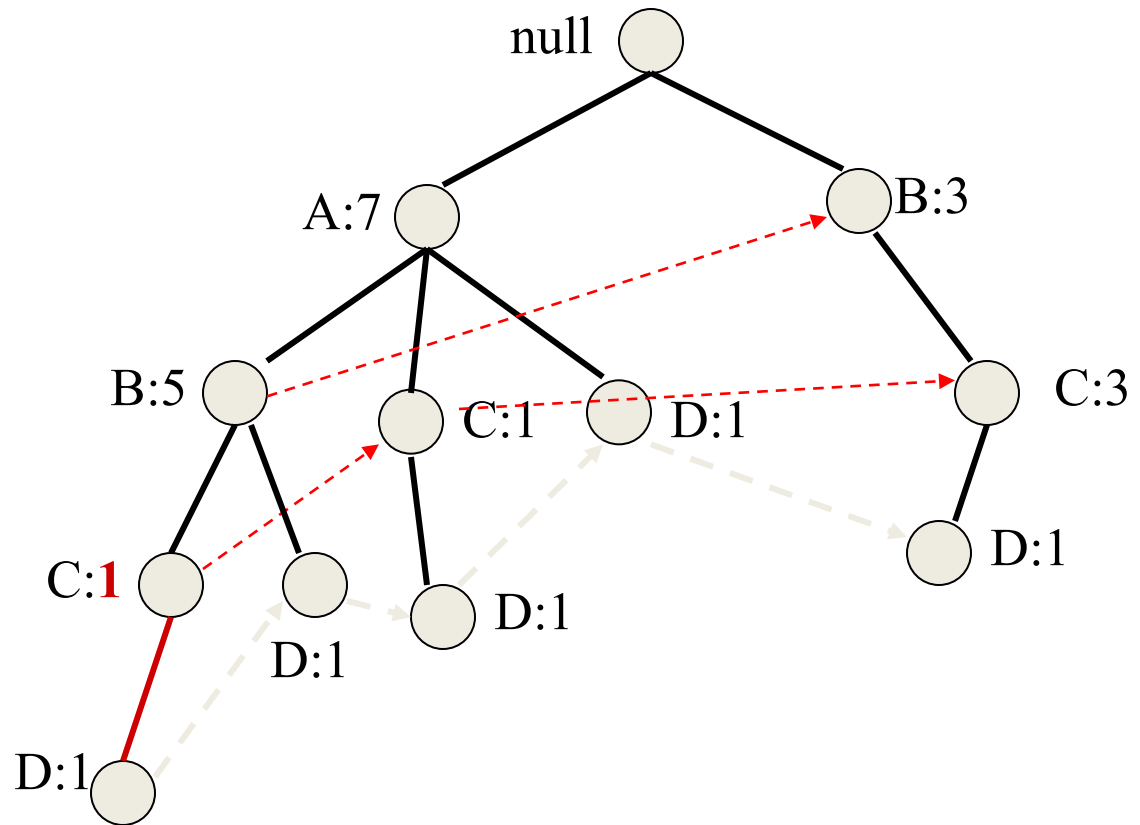
## Phase 2

Convert prefix tree into conditional FP-tree



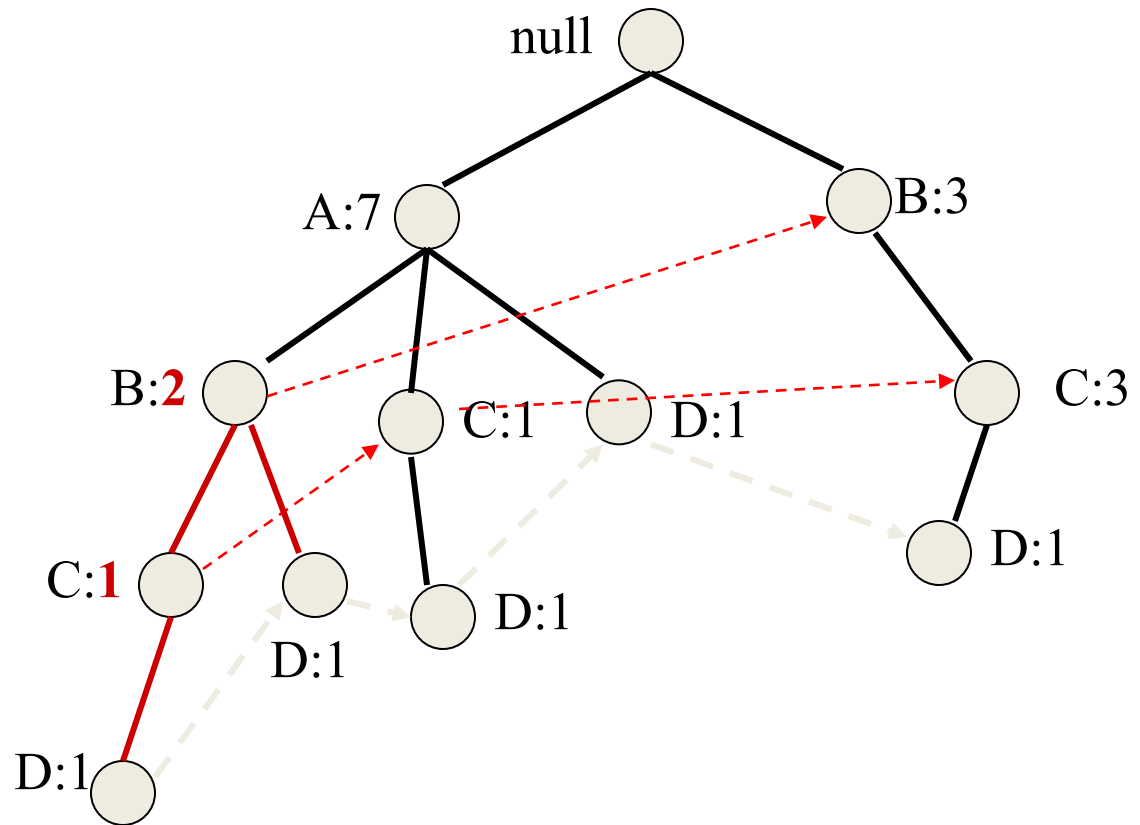


# Example



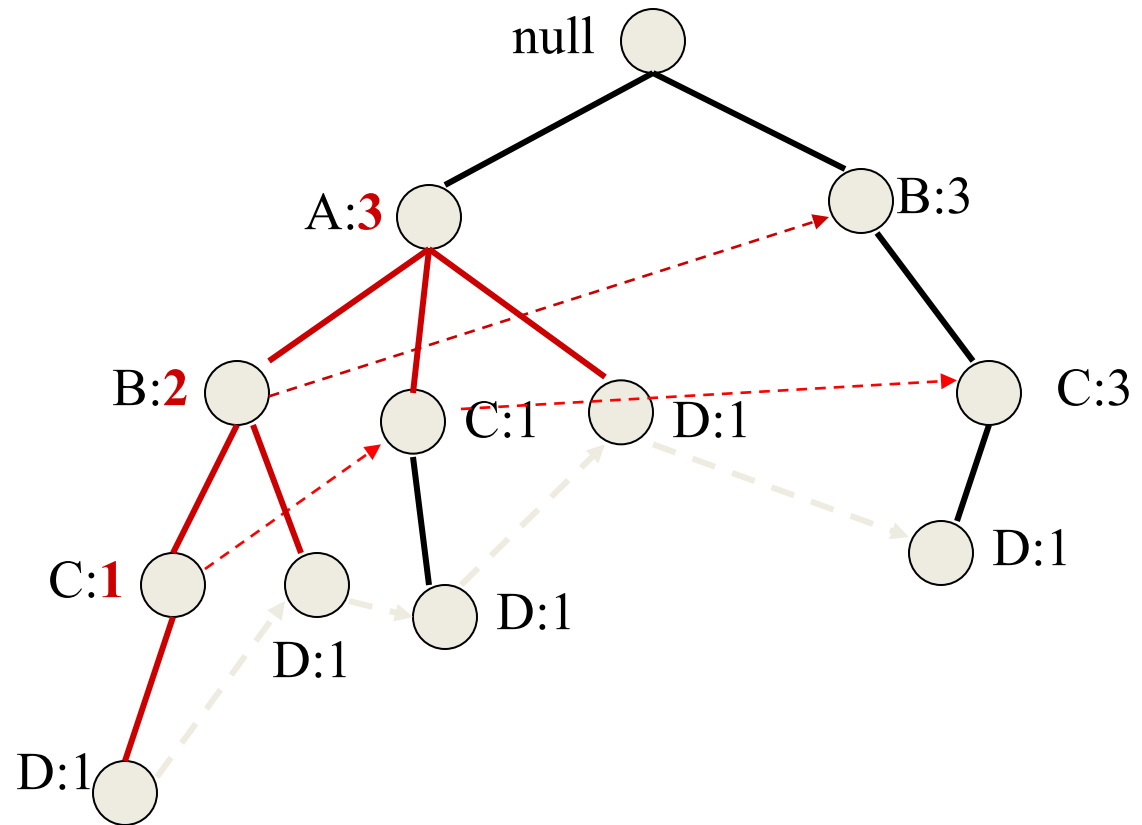
Recompute support

# Example



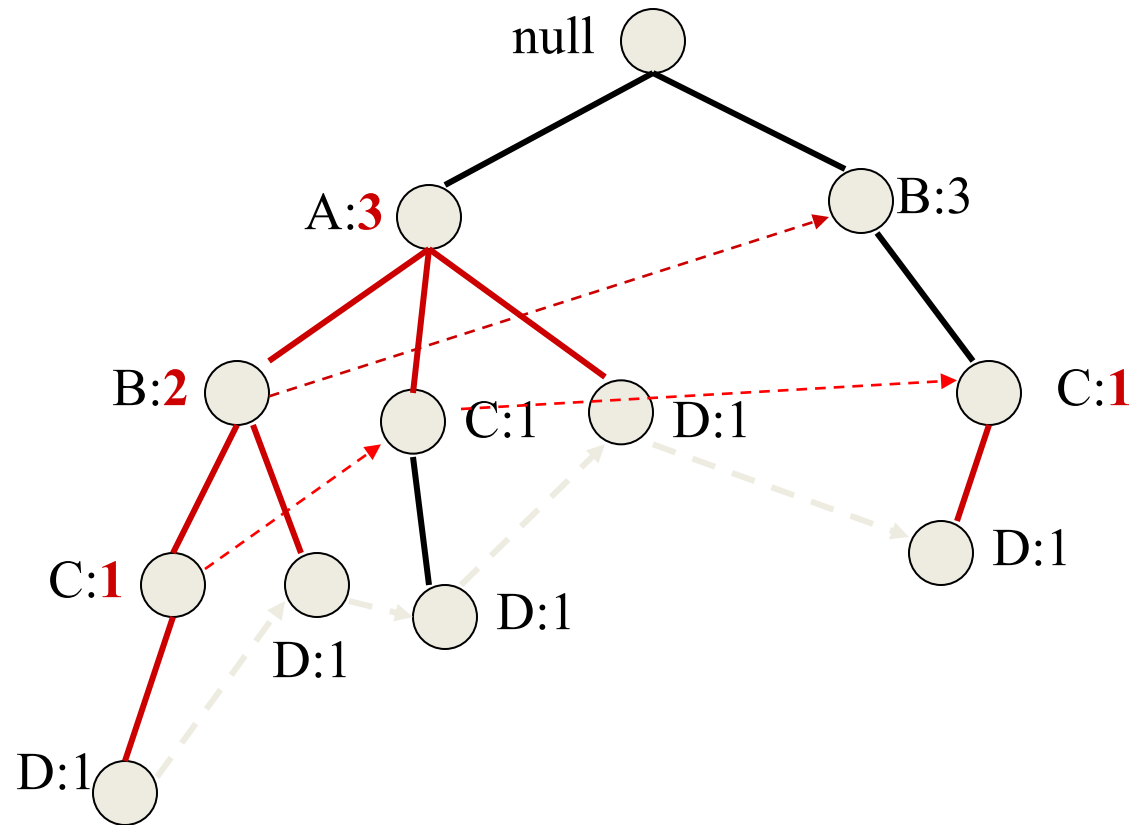
Recompute support

# Example



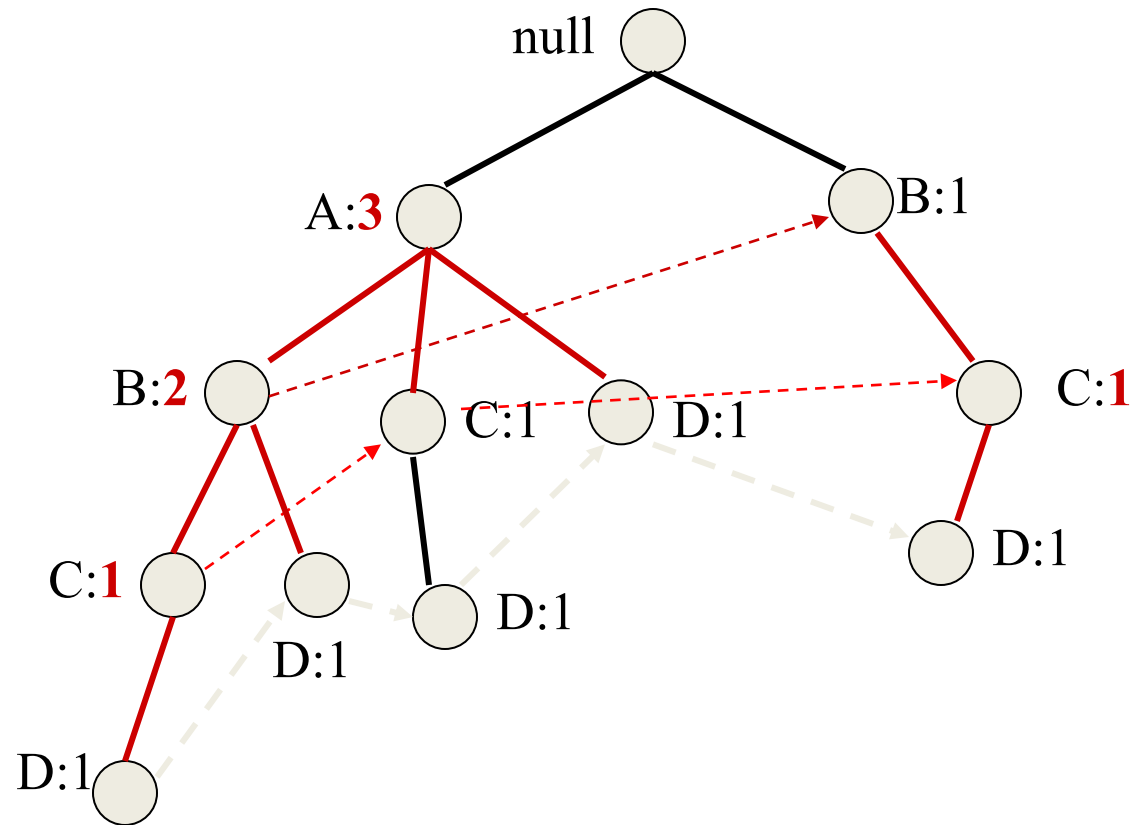
Recompute support

# Example



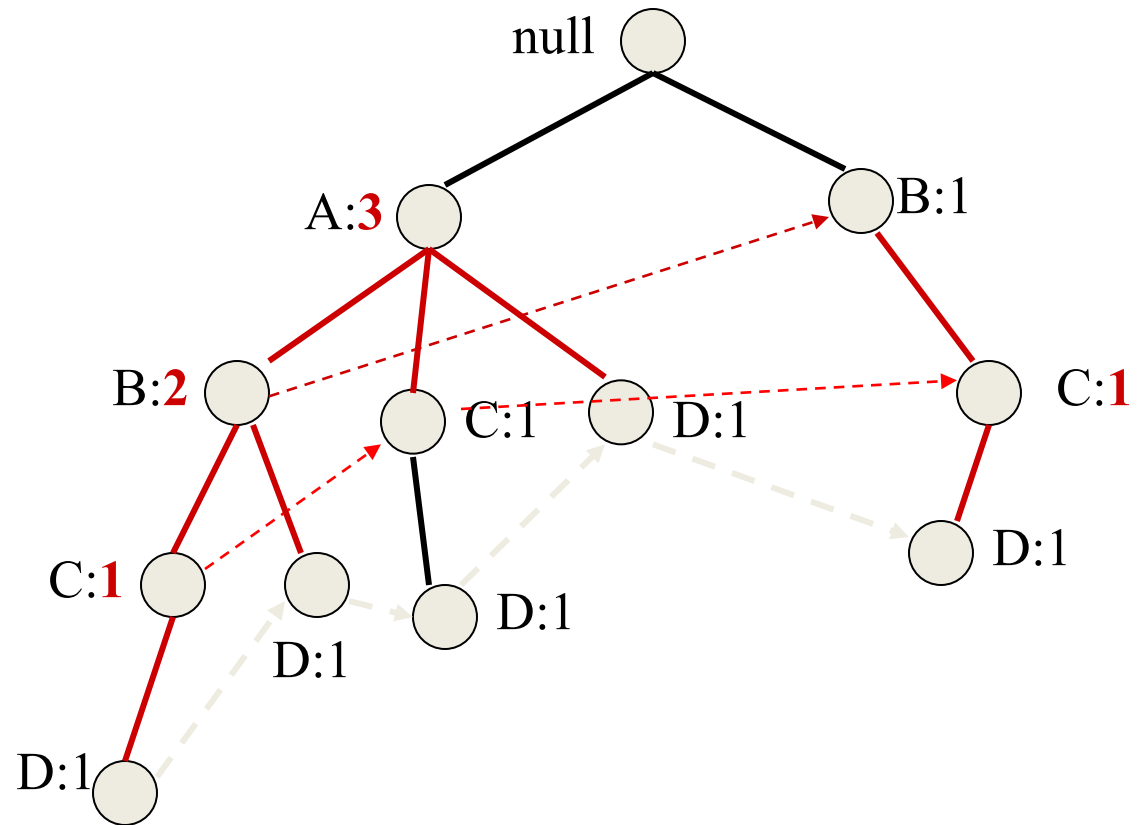
Recompute support

# Example



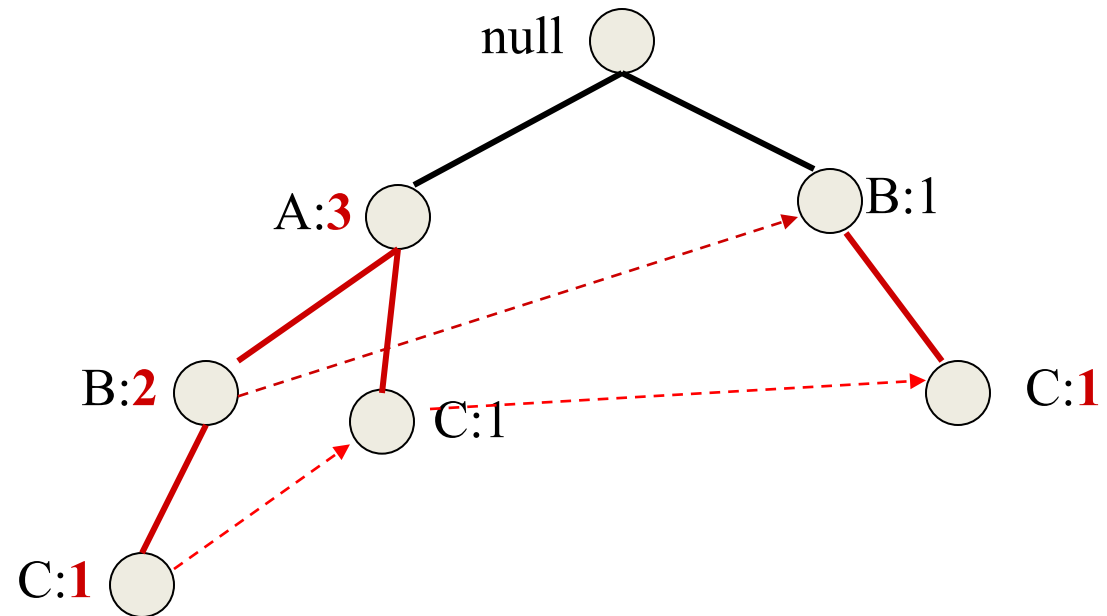
Recompute support

# Example



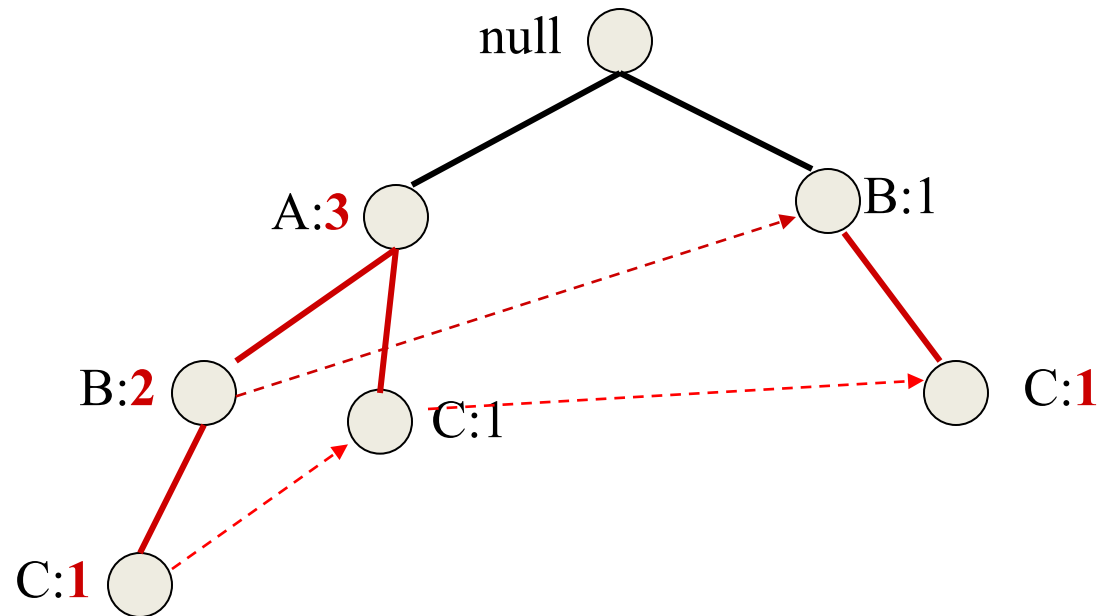
Prune nodes

# Example



Prune nodes

# Example



Construct conditional FP-trees for  $\{C,D\}$ ,  $\{B,D\}$ ,  $\{A,D\}$

And so on....



# Observations

- At each recursive step we solve a subproblem
  - Construct the prefix tree
  - Compute the new support
  - Prune nodes
- Subproblems are disjoint so we never consider the same itemset twice
- Support computation is efficient – happens together with the computation of the frequent itemsets.

# Observations

- The efficiency of the algorithm depends on the **compaction factor** of the dataset
- If the tree is bushy then the algorithm does not work well, it increases a lot of number of subproblems that need to be solved.

# FREQUENT ITEMSET RESEARCH

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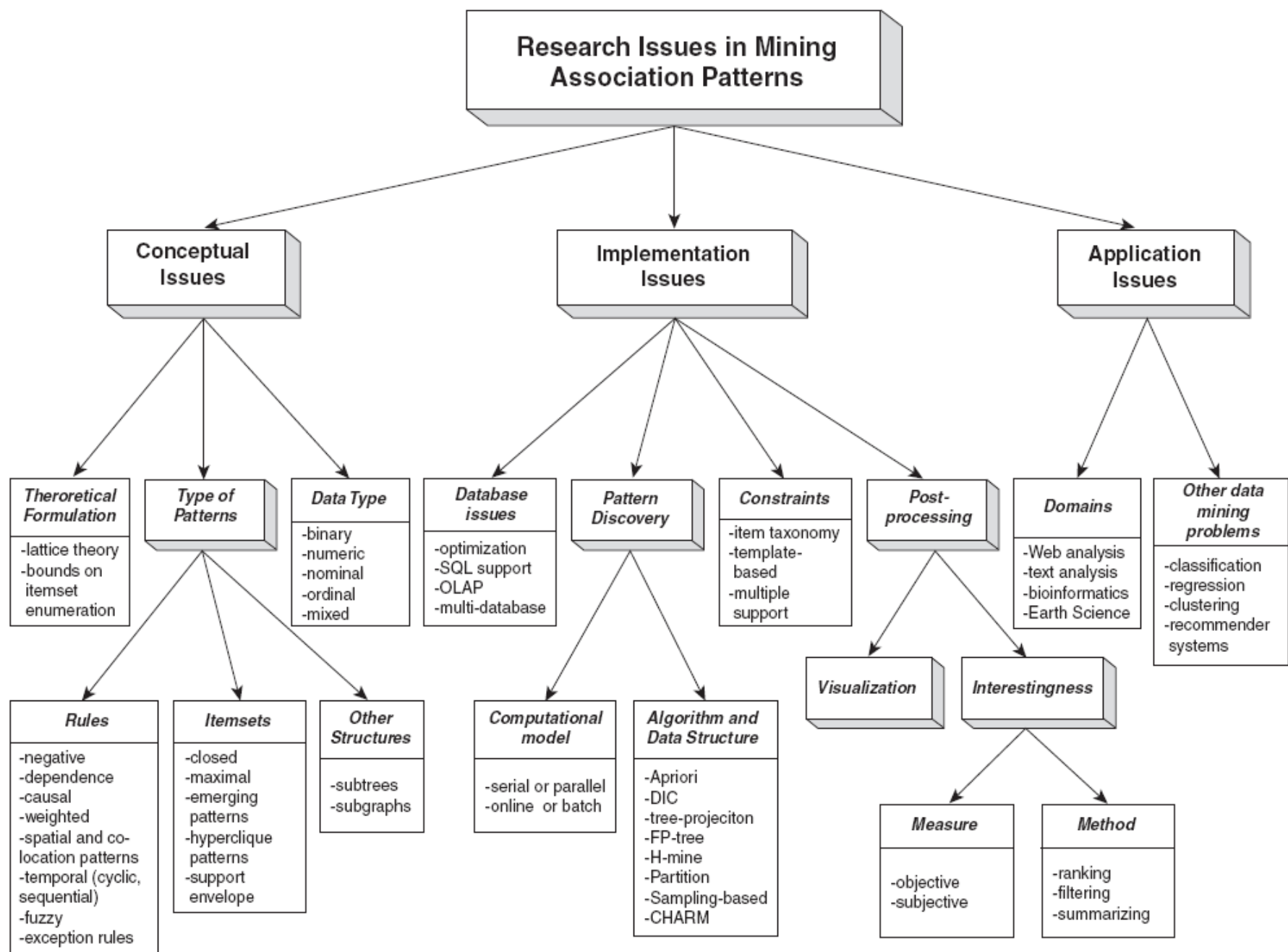


Figure 6.31. A summary of the various research activities in association analysis.