WHAT IS ASSOCIATION RULE MINING?

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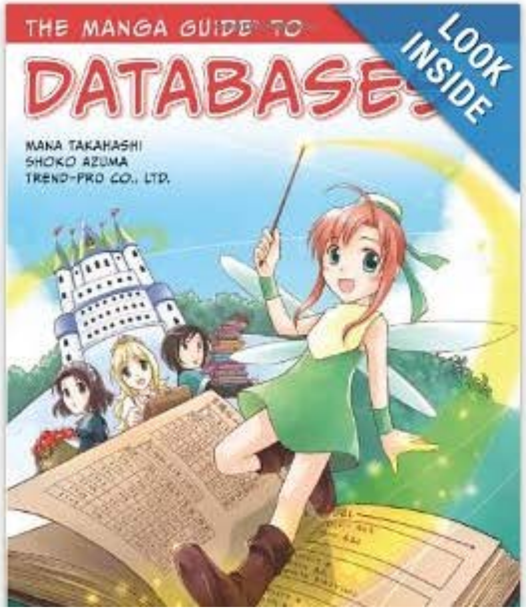
WHAT IS FREQUENT PATTERN ANALYSIS?

Frequent pattern

What products do people frequently buy together?

What other products would people buy if they bought a laptop?



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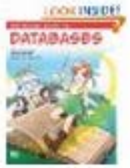
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ASSOCIATION RULE MINING

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

TID	*Items*
1	**Bread, Milk**
2	**Bread, Diaper, Beer, Eggs**
3	**Milk, Diaper, Beer, Coke**
4	**Bread, Milk, Diaper, Beer**
5	**Bread, Milk, Diaper, Coke**

Example of association rules:

{Diaper} $\rightarrow$ {Beer}
{Milk, Bread} $\rightarrow$ {Eggs, Coke}
{Beer, Bread} $\rightarrow$ {Milk}

Implication means co-occurrence, not causality!

ASSOCIATION RULE (AR) MINING

Textbook chapter 6 requires some background knowledge in undergraduate computer science courses such as data structure.

Requirement for this class: Learn the basic concepts about AR and the main idea of the Apriori Algorithm.

MORE APPLICATIONS

Product recommendation

- E.g., Amazon.com

Catalog design

Web log (clickstream) analysis

DNA sequence analysis

BASIC CONCEPTS IN AR MINING

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FREQUENT ITEMSET

Transaction ID	Items Bought *
10	A, B, D
20	A, C, D
30	A, D, E
40	B, E, F
50	B, C, D, E, F

Can you answer the following questions?
Which two items are frequently bought together?
Which three items are often bought together?
...

DEFINITION: FREQUENT ITEMSET

Itemset:

A collection of one or more items

k-itemset contains k items

1-itemset:

{A}:3, {B}:3, {C}:2, {D}:4, {E}:3, {F}:2

2-itemset:

{A,B}:1, {A,D}:3

3-itemset:

{A,B,C}:0, {B,E,F}:2

Transaction ID	Items Bought
10	A, B, D
20	A, C, D
30	A, D, E
40	B, E, F
50	B, C, D, E, F

METRICS TO EVALUATE FREQUENT LEVEL OF ITEMSETS

How frequent is an itemset?

Support count:

Number of transactions that contain an itemset

support_count({ D, E }) = 2

Support percentage:

Fraction of transactions that contain an itemset

support({D, E}) = 2/5

Frequent itemset:

An itemset with support ≥ threshold

DEFINITION: ASSOCIATION RULE

Association rule:

An implication of the form X → Y,

where X and Y are itemsets,

e.g., {E, F} → {B}

Example Rules:

LHS: Left-Hand Side

{B, E} → {F}

{E, F} → {B}

{B, F} → {E}

{B} → {E, F}

{E} → {B, F}

{F} → {B, E}

RHS: Right-Hand Side

Transaction ID	Items Bought
10	A, B, D
20	A, C, D
30	A, D, E
40	B, E, F
50	B, C, D, E, F

METRICS TO EVALUATE THE RULE'S STRENGTH

Rule evaluation metrics

Support P(X, Y)

Fraction of transactions that contain both X and Y

Support({E, F} → {B}) = support_count({B,E,F})/N = 2/5

Confidence P(Y|X) = P(X, Y)/P(X)

How frequently items in Y appear in transactions that contain X

confidence({E,F} → {B})
= support({B,E,F})/support({E,F})
= support_count({B,E,F})/support_count({E,F})
= 2/2 = 1

CONFIDENCE

confidence({E,F} → {B})
= support({B,E,F})/support({E,F})
= support_count({B,E,F})/support_count({E,F})
= 2/2 = 1

Switching LHS and RHS results in different rules with different confidences.

APRIORI ALGORITHM

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HOW TO MINE ASSOCIATION RULES?

Given a set of transactions T, the goal of association rule mining is to find all rules having:

- support ≥ *minsup* threshold
- confidence ≥ *minconf* threshold

Brute-force approach:

- List all possible association rules.
- Compute the support and confidence for each rule.
- Prune rules that fail the *minsup* and *minconf* thresholds.
- ⇒ Computationally prohibitive!

MINING ASSOCIATION RULES

TID	*Items*
1	**Bread, Milk**
2	**Bread, Diaper, Beer, Eggs**
3	**Milk, Diaper, Beer, Coke**
4	**Bread, Milk, Diaper, Beer**
5	**Bread, Milk, Diaper, Coke**

Example of rules:

{Milk, Diaper} $\rightarrow$ {Beer} (s = 0.4, c = 0.67)
{Milk, Beer} $\rightarrow$ {Diaper} (s = 0.4, c = 1.0)
{Diaper, Beer} $\rightarrow$ {Milk} (s = 0.4, c = 0.67)
{Beer} $\rightarrow$ {Milk, Diaper} (s = 0.4, c = 0.67)
{Diaper} $\rightarrow$ {Milk, Beer} (s = 0.4, c = 0.5)
{Milk} $\rightarrow$ {Diaper, Beer} (s = 0.4, c = 0.5)

Observations:

All the above rules are binary partitions of the same itemset:
{Milk, Diaper, Beer}

Rules originating from the same itemset have identical support but can have different confidences.

Thus, we may decouple the support and confidence requirements.

MINING ASSOCIATION RULES

Two-step approach:

Frequent itemset generation

Generate all itemsets whose support ≥ *minsup*.

Rule generation

Generate high-confidence rules from each frequent itemset, where each rule is a binary partitioning of a frequent itemset.

Frequent itemset generation is still computationally expensive.

SCALABLE METHODS FOR MINING FREQUENT PATTERNS

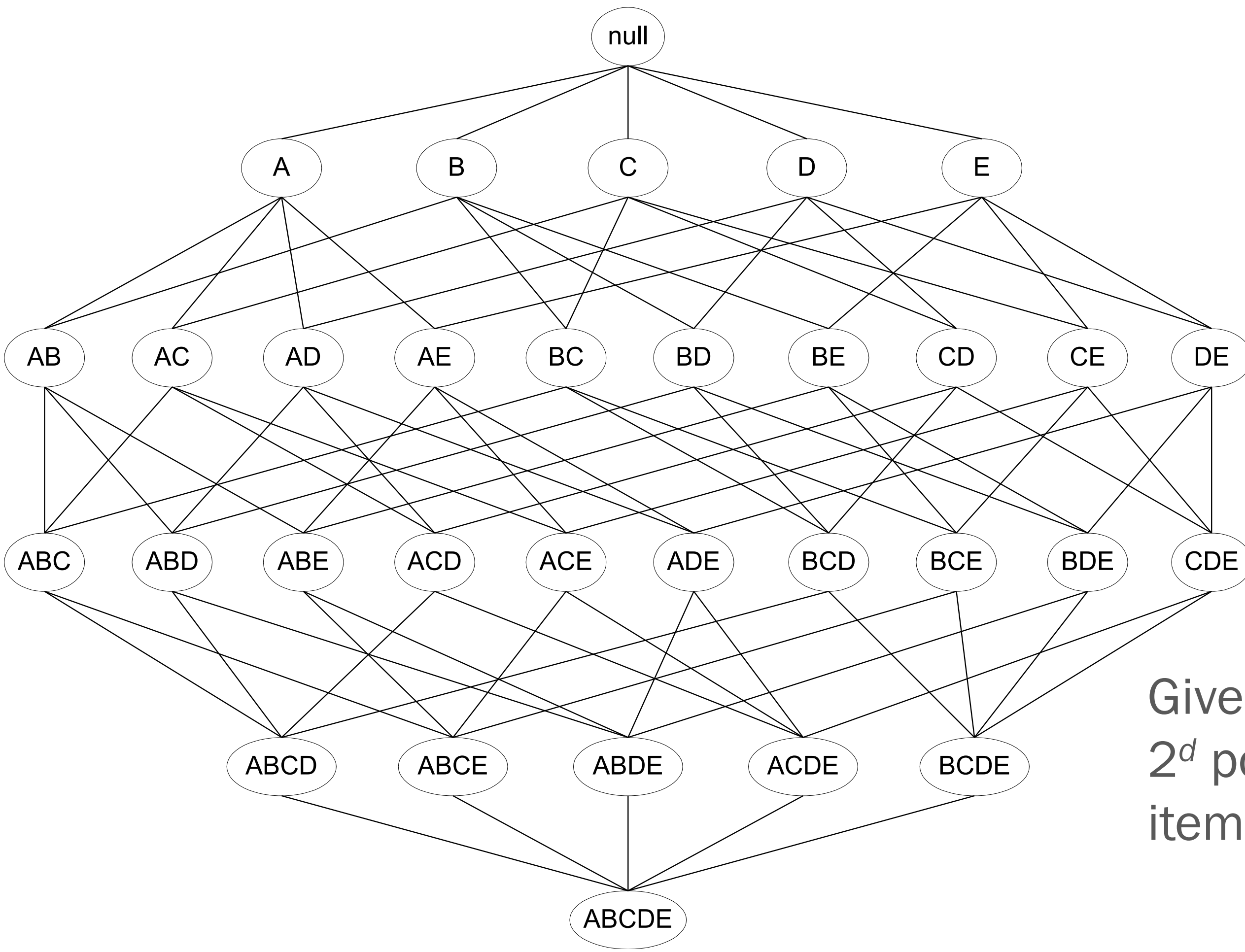
Scalable mining methods: Three major approaches

Apriori (Agrawal & Srikant@VLDB'94)

Frequent pattern growth (FPgrowth—Han, Pei, & Yin @SIGMOD'00)

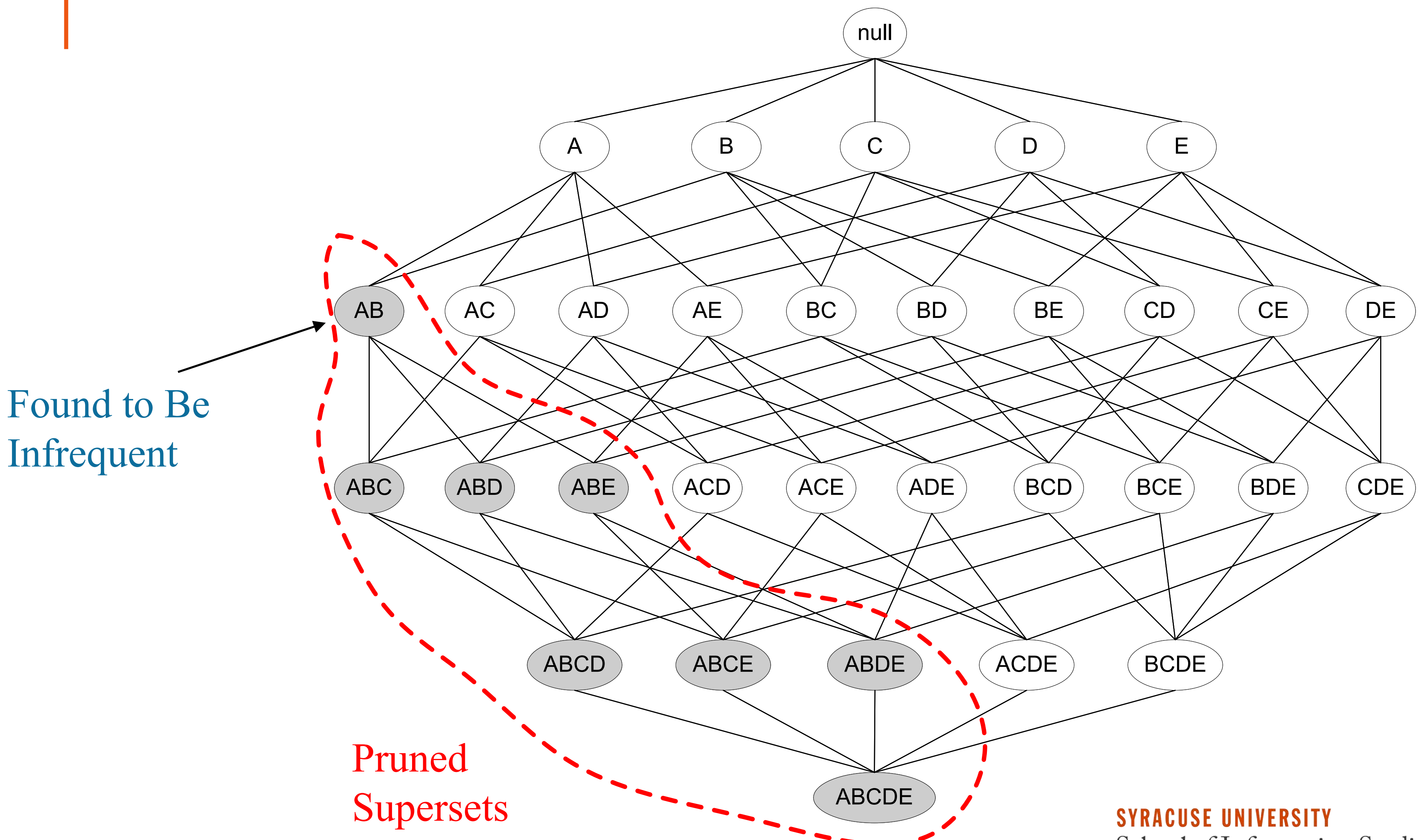
Vertical data format approach (Charm—Zaki & Hsiao @SDM'02)

FREQUENT ITEMSET GENERATION



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

ILLUSTRATING APRIORI PRINCIPLE



APRIORI: A CANDIDATE GENERATION-AND-TEST APPROACH

Apriori pruning principle: If there is any itemset that is infrequent, its superset should not be generated or tested!

Method:

- Initially, scan database once to get frequent 1-itemset.
- Generate length (k + 1) candidate itemsets from length k frequent itemsets.
- Test the candidates against the database.
- Terminate when no frequent or candidate set can be generated.

THE APRIORI ALGORITHM: GENERATE FREQUENT ITEMSET

$Sup_{min} = 2$

Database TDB

TID	Items
10	A, C, D
20	B, C, E
30	A, B, C, E
40	B, E

1st scan

C_1

Itemset	sup
{A}	2
{B}	3
{C}	3
{D}	1
{E}	3

L_1

Itemset	sup
{A}	2
{B}	3
{C}	3
{E}	3

C_2

Itemset
{A, B}
{A, C}
{A, E}
{B, C}
{B, E}
{C, E}

2nd scan

C_2

Itemset	sup
{A, B}	1
{A, C}	2
{A, E}	1
{B, C}	2
{B, E}	3
{C, E}	2

L_2

Itemset	sup
{A, C}	2
{B, C}	2
{B, E}	3
{C, E}	2

C_3

Itemset
{B, C, E}

3rd scan

L_3

Itemset	sup
{B, C, E}	2

RULE GENERATION

Given a frequent itemset L, find all nonempty subsets f, such that f → (L – f) satisfies the minimum confidence requirement.

If {A, B, C, D} is a frequent itemset, candidate rules:

ABC → D, ABD → C, ACD → B, BCD → A

AB → CD, AC → BD, …

A → BCD, B → ACD, C→ ABD, D → ABC

Compute the confidence for each rule, and keep the ones that are greater than min_conf.

RULE GENERATION

How to efficiently generate rules from frequent itemsets?

Start from long LHS:

For itemset {ABCD}, c(x) means confidence of rule x
c(ABC → D) ≥ c(AB → CD) ≥ c(A → BCD)

Proof:

C(ABC->D) = support(ABCD)/support(ABC)

C(AB->CD) = support (ABCD)/support (AB)

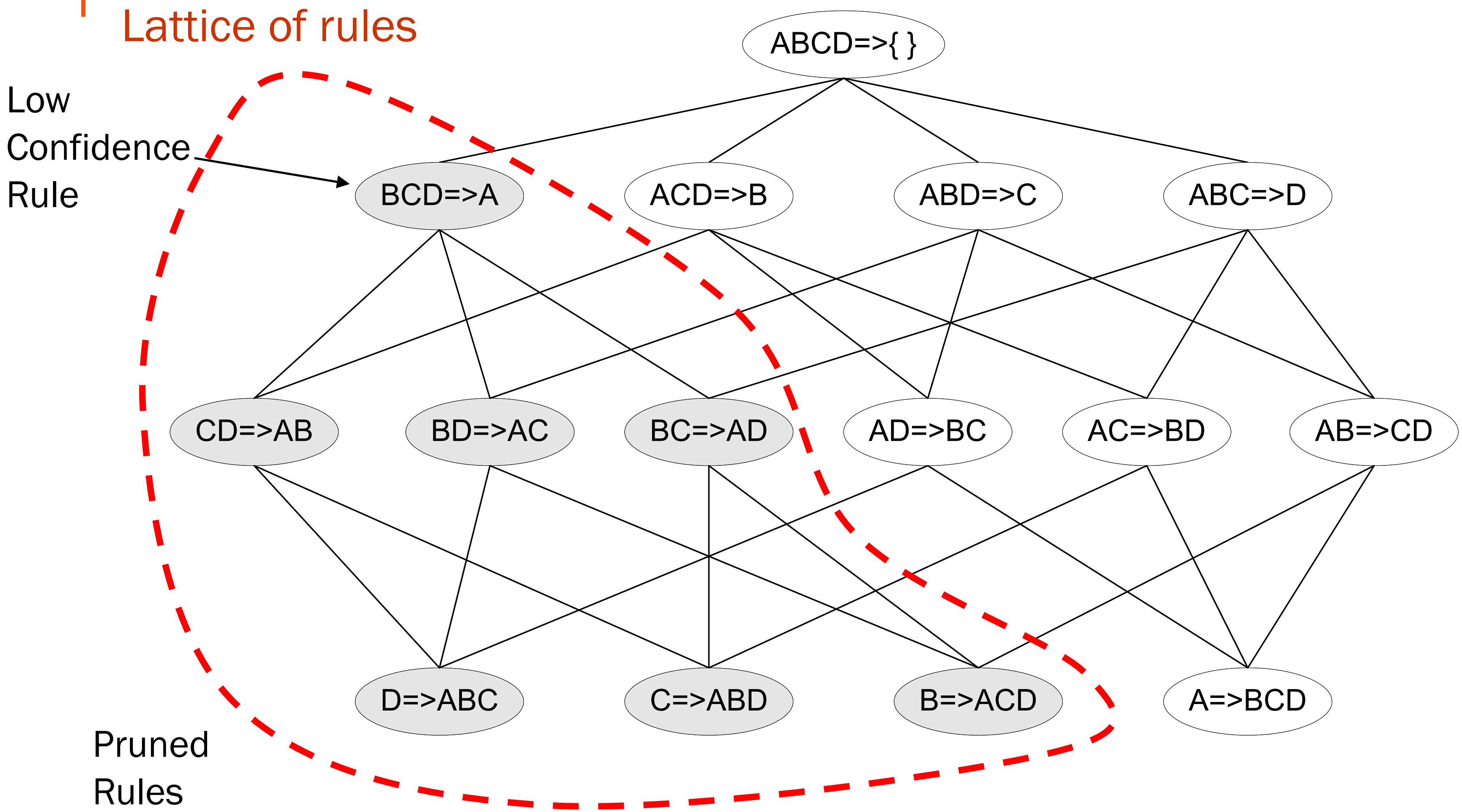
support(AB) ≥ support (ABC)

So C(ABC->D) ≥ C(AB->CD)

If min_conf is not satisfied, no need to generate rules with larger right-hand side (RHS).

THE APRIORI ALGORITHM: RULE PRUNING

Lattice of rules



RULE EVALUATION

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LIMITATION OF CONFIDENCE MEASURE

100 transactions:

- 75 bought movies
- 60 bought games
- 40 bought both

Both seem to be strong rules.

{movies}->{games}
support 40/100 = 0.4
confidence 40/75 =0.53

{games}->{movies}
support 40/100 = 0.4
confidence 40/60 = 0.67

HOWEVER …

100 transactions:
- 75 bought movies
- 60 bought games
- 40 bought both

P(movies) = 75/100 = 0.75

P(games) = 60/100 = 0.6

P(movies and games) = 40/100 = 0.4

So people tend not to buy movies and games together!

Correlation(movies, games) = P(movies and games) /[P(movies) × P(games)] = 0.4/(0.75 × 0.6) = 0.89

The confidence measure is sometimes misleading.

Correlation <1 means negative correlation.

METRIC: LIFT (CORRELATION)

Measure of dependent or correlated events: Lift

Lift (A => B) = support({A,B})/(support(A) × support(B))

$$lift(A \quad > B) = \frac{P(A \quad B)}{P(A)P(B)}$$

Association rules should have >1 lift to be meaningful.

THE LIFT (CORRELATION) MEASURE

	Game	Not Game	Total
Movie	40	35	75
Not movie	20	5	25
Total	60	40	100

P(buy game) = 0.6
P(not buy movie) = 0.25
P(buy game and not buy movie) = 0.20
Lift (buy game -> not buy movie)
=0.20/(0.6 × 0.25) = 1.33 > 1

Strong rule

ALTERNATIVE MEASURES

Association rule algorithms tend to produce too many rules.

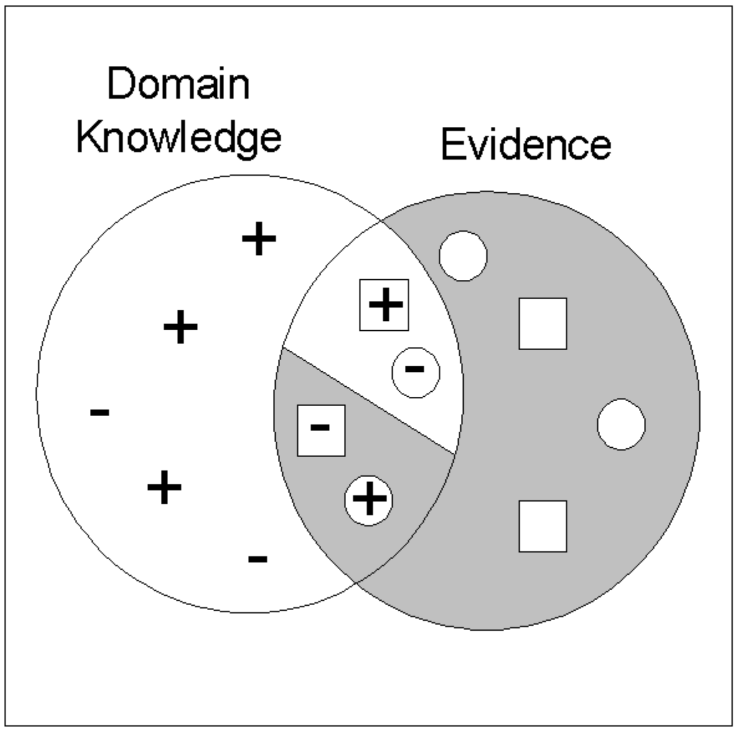
Many of them are uninteresting or redundant.

Uninteresting if it is known knowledge

Redundant if {A,B,C} $\rightarrow$ {D} and {A,B} $\rightarrow$ {D} have same support and confidence

INTERESTINGNESS VIA UNEXPECTEDNESS

Need to model expectation of users (domain knowledge)



+ Pattern expected to be frequent

- Pattern expected to be infrequent

Pattern found to be frequent

Pattern found to be infrequent

+ - Expected Patterns

- + Unexpected Patterns

Need to combine expectation of users with evidence from data (i.e., extracted patterns)

WEKA ASSOCIATION RULES

Implemented a variation of Apriori Algorithm that iteratively reduces the minimum support until it finds the required number of rules with the given minimum confidence

Allows mining of “class association rules”: If the data have a class label attribute, the right hand side of a rule can be restricted to that label.

ASSOCIATION RULE MEASURES

In practice, what levels of support, confidence, and lift should we aim for?

Support:

Depends on data set and business problem

Common setting is 20–40% of the transactions

Confidence:

Strong confidence rules ≥ .9, but .6 to .8 range might be OK

Lift:

Should be above 1.0, the higher the better

Levels of 2 and above can occasionally be seen but more likely to see around 1.3 to 1.5