Pattern Mining

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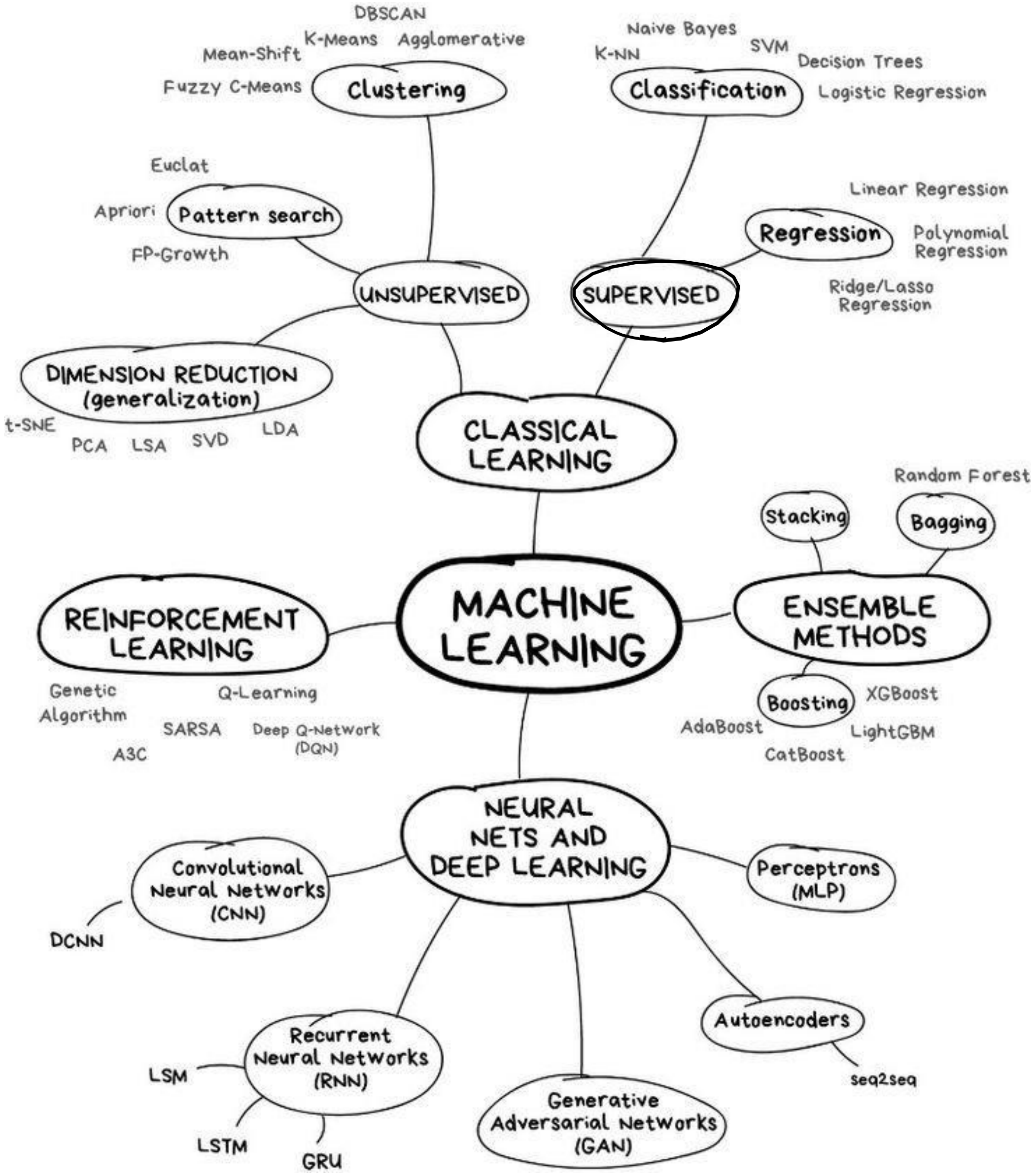


MACHINE LEARNING
CLASSICAL LEARNING
UNSUPERVISED
Clustering
DBSCAN
K-Means
Agglomerative
Mean-Shift
Fuzzy C-Means
Pattern search
Euclat
Apriori
FP-Growth
DIMENSION REDUCTION (generalization)
t-SNE
PCA
LSA
SVD
LDA
SUPERVISED
Classification
Naive Bayes
SVM
K-NN
Decision Trees
Logistic Regression
Regression
Linear Regression
Polynomial Regression
Ridge/Lasso Regression
ENSEMBLE METHODS
Stacking
Bagging
Random Forest
Boosting
XGBoost
AdaBoost
LightGBM
CatBoost
REINFORCEMENT LEARNING
Genetic Algorithm
Q-Learning
SARSA
Deep Q-Network (DQN)
A3C
NEURAL NETS AND DEEP LEARNING
Convolutional Neural Networks (CNN)
DCNN
Perceptrons (MLP)
Recurrent Neural Networks (RNN)
LSM
LSTM
GRU
Generative Adversarial Networks (GAN)
Autoencoders
seq2seq

Frequent Pattern Mining

- **Association rules**
  - **Apriori**
  - FP-tree
- Sequential patterns
  - Apriori
  - PrefixSpan

Association Rules

- 데이터 상호간의 연관 규칙을 찾아내는 기술
- ‘{라면, 우유}->{커피}’
  - 라면과 우유를 산 사람은 커피도 같이 산다
  - 지지도 (support)
    - 전체 소비자 중에서 그 규칙을 구성하는 물품을 구매한 소비자의 비율
    - 50% - 4명 중 **라면**,**우유**,**커피**를 구매한 사람은 2명
  - 신뢰도 (confidence)
    - 규칙의 왼쪽에 있는 물품을 산 소비자 중에서 오른쪽에 있는 물품들을 산 소비자의 비율
    - 66.7% - **라면**과 **우유**를 산 사람들은 3명인데 그 중에서 **커피**를 산 사람은 2명

사용 사례

- 고객들의 물품 구매 패턴을 분석한 결과에 기반하여
  - 연관 물품 쿠폰이나 할인 행사 제공
  - 온라인 서점에서 다른 구매자들이 구매한 책 정보를 함께 제공

<예: 아마존(amazon.com)의 상품 추천>

사용 사례

- 고객들의 물품 구매 패턴을 분석한 결과에 기반하여
  - Cross-selling (교차 판매) – 서로 다른 카테고리 상품을 추천하여 판매
    - 예) 스마트폰 구입시 스마트폰 케이스 추천
  - 백화점의 Package 구매 상품 조합 결정, **물건 진열 순서** 결정 등
  - 효과적인 상품 **카탈로그 디자인**

Association Rule Problem

- Given:
  - A database of customer transactions
  - Each transaction is a set of items
- Find all rules $X \rightarrow Y$ that correlate the presence of one set of items X with another set of items Y
  - e.g.) 98% of people who purchase diapers and baby food also buy beers.
  - Any number of items in X and Y of a rule
  - Possible to specify constraints on rules (e.g., find only rules involving expensive imported products)

Support and Confidence

- X → Y [support, confidence]

$$\text{지지도(support)} = \frac{\#\text{ of transactions containing all the items in } X \cup Y}{\text{total }\#\text{ of transactions in the database}}$$

$$\text{신뢰도(confidence)} = \frac{\#\text{ of transactions that contain both } X \text{ and } Y}{\#\text{ of transactions containing } X}$$

- For minimum support (최소 지지도) = 50%, minimum confidence (최소 신뢰도) = 50%
  - B => C with 50% support and 66% confidence

TID	Items
10	a, c, d
20	b, c, e
30	a, b, c, e
40	b, e

Association Rule Mining

- 주로 2 개의 스텝으로 구성
  - Step 1: Find all (frequent) itemsets that have minimum support
    - Most expensive phase
    - Lots of research
  - Step 2: Use the frequent itemsets to generate the desired rules
    - Generation is straight forward

Association Rule Mining

TID	Items
10	a, c, d, f
20	b, c, e
30	a, b, c, e,
40	b, e
50	a, f

최소지지도=40%

최소신뢰도 = 100%

- 스텝 1
  - 최소지지도 를 만족하는 frequent itemset들을 모두 찾음

Itemset	Sup
a	3
b	3
c	3
e	3
f	2

Itemset	Sup
a,c	2
a,f	2
b,c	2
b,e	3
c,e	2

Itemset	Sup
b,c,e	2

- 스텝 2
  - 모든 frequent itemset 으로부터 룰 생성
  - {b,c,e} 에서 아래 룰들을 다 만든 후에 신뢰도를 체크함
    - {b}->{c,e} (X)
    - {c}->{b,e}
    - {e}->{b,c}
    - {b,c}->{e} (O)
    - {b,e}->{c}
    - {c,e}->{b} (O)

Naïve Counting of All Itemsets

Transactions

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

☜

Itemsets & Counts

Itemset	Count
A	1
C	1
D	1
A,C	1
A,D	1
C,D	1
A,C,D	1

Naïve Counting of All Itemsets

Transactions

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

Itemsets & Counts

Itemset	Count
A	1
C	2
D	1
A,C	1
A,D	1
C,D	1
A,C,D	1
B	1
E	1
B,C	1
B,E	1
C,E	1
B,C,E	1

Naïve Counting of All Itemsets

Transactions

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

☜

Itemsets & Counts

Itemset	Count
A	2
C	3
D	1
A,C	2
A,D	1
C,D	1
A,C,D	1
B	2
E	2
B,C	2
B,E	2
C,E	2
B,C,E	2

Itemset	Count
A,B	1
A,E	1
A,B,C	1
A,B,E	1
A,B,C,E	1

Naïve Counting of All Itemsets

Transactions

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

☜

Itemsets & Counts

Itemset	Count
A	2
C	3
D	1
A,C	2
A,D	1
C,D	1
A,C,D	1
B	3
E	3
B,C	2
B,E	3
C,E	2
B,C,E	2

Itemset	Count
A,B	1
A,E	1
A,B,C	1
A,B,E	1
A,B,C,E	1

Naïve Counting of All Itemsets

Transactions

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

$Sup_{min}=2$

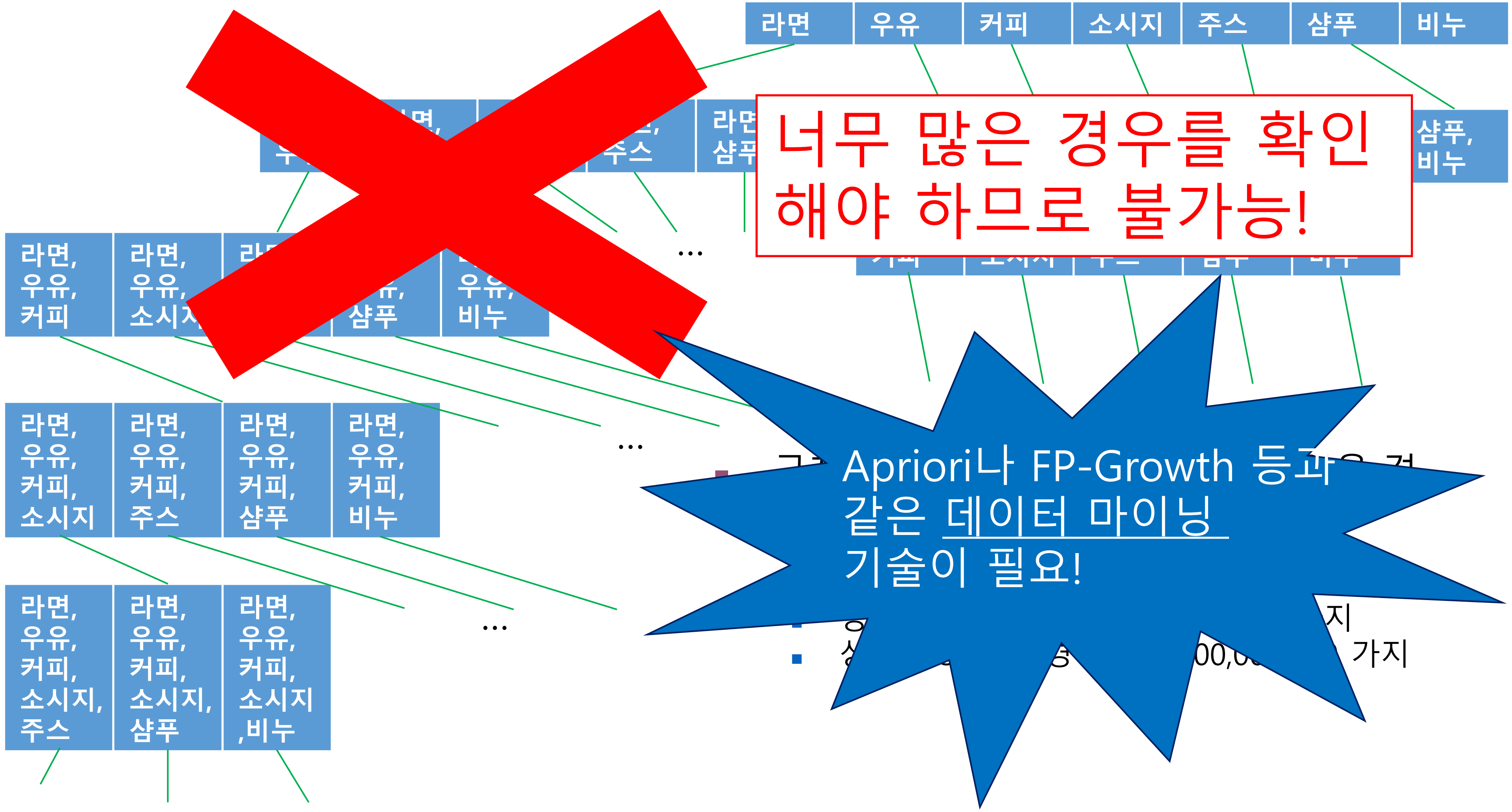
Frequent itemsets

Itemset	Count
A	2
C	3
D	1
A,C	2
A,D	1
C,D	1
A,C,D	1
B	3
E	3
B,C	2
B,E	3
C,E	2
B,C,E	2

Itemset	Count
A,B	1
A,E	1
A,B,C	1
A,B,E	1
A,B,C,E	1

We may need 2^n itemset entries for counts !

Checking All Combinations?



Can we do better?

- 모든 상품들의 부분집합을 다 count하면 exponential 한 개수의 부분집합을 count 하게 됨
- 모든 부분집합을 count 안 하는 방법이 있을까?
- Key Observation
  - Every subset of a frequent item set is also frequent item set.
  - If {beer, diaper, nuts} is frequent, {beer, diaper} must be frequent.
- If there is any item set which is infrequent, its superset will not be generated!
  - A powerful candidate set pruning technique.

Apriori: A Candidate Generation-and-Test Approach

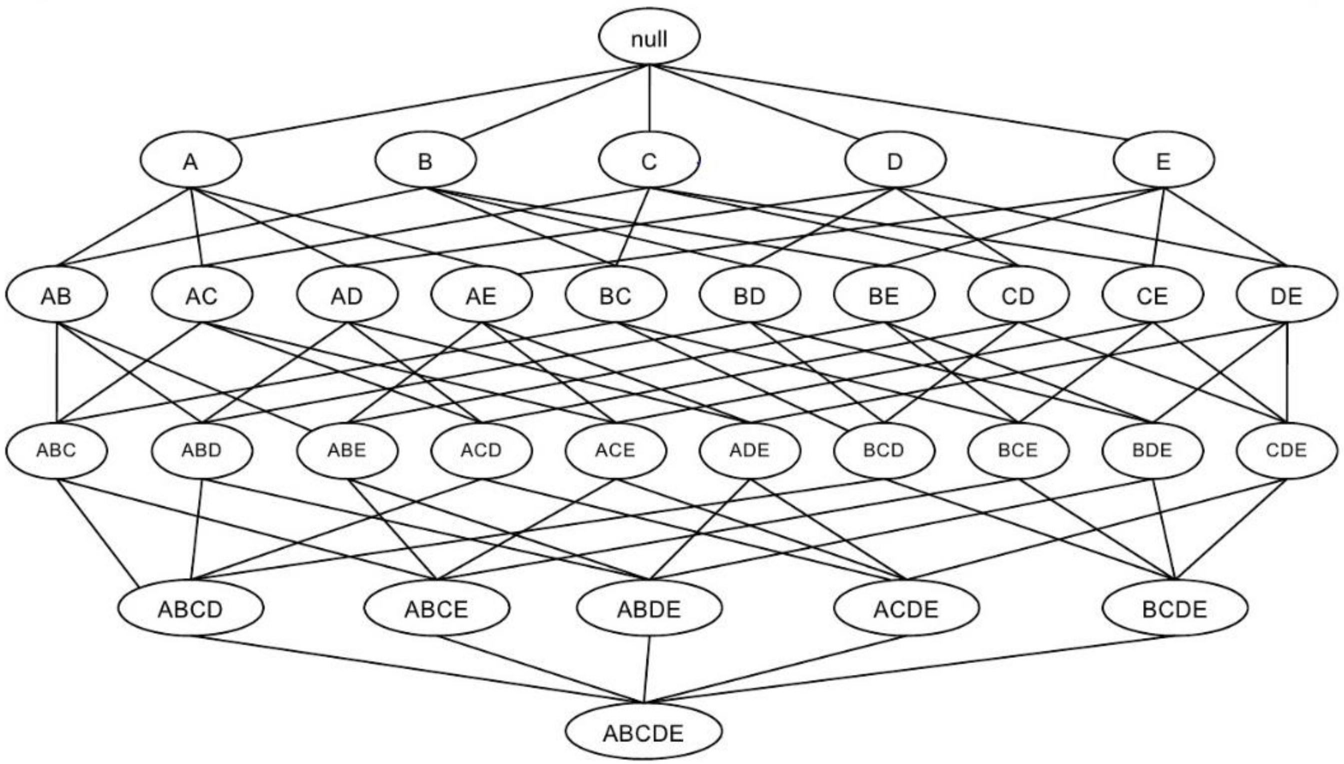
- Apriori pruning principle: If there is any itemset which is infrequent, its superset should not be generated/tested! (Agrawal & Srikant @VLDB'94, Mannila, et al. @ KDD' 94)
- Method:
  - Initially, scan DB once to get frequent 1-itemset
  - Generate length (k+1) candidate itemsets from length k frequent itemsets
  - Test the candidates against DB
  - Terminate when no frequent or candidate set can b generated

Scalable Methods for Mining Frequent Patterns

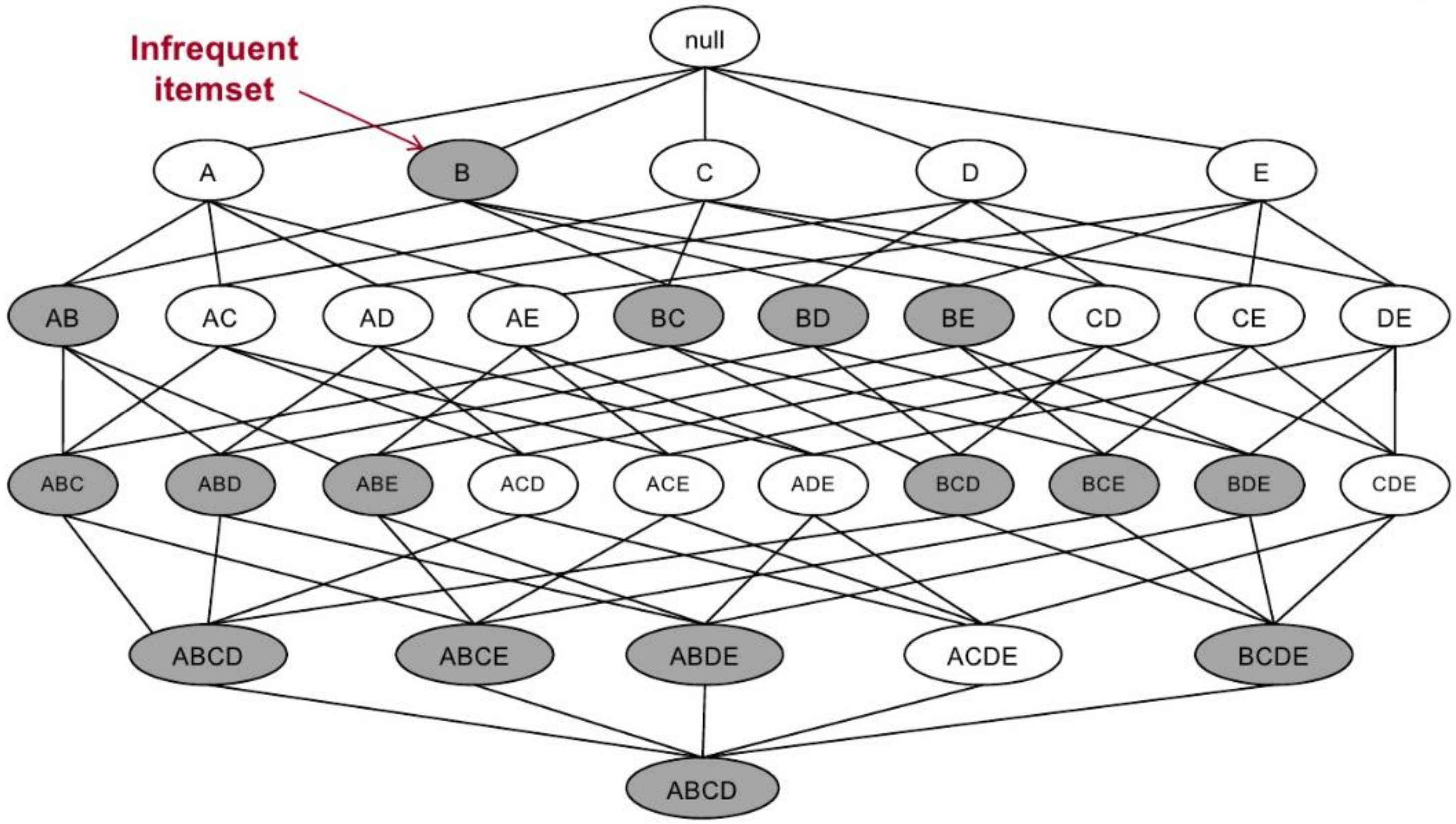
- The downward closure property of frequent patterns
  - <u>Any subset of a frequent itemset must be frequent</u>
  - If **{beer, diaper, nuts}** is frequent, so is **{beer, diaper}**
  - i.e., every transaction having {beer, diaper, nuts} also contains {beer, diaper}
- Scalable mining methods: Three major approaches
  - Apriori (Agrawal & Srikant@VLDB'94)
  - Freq. pattern growth (FPgrowth—Han, Pei & Yin @SIGMOD'00)
  - Vertical data format approach (Charm—Zaki & Hsiao @SDM'02)

Naïve Counting

- Given d items, there are 2^d itemsets



Candidate Itemset Generation by Apriori



An Apriori Example

Min_sup=2

Data base D

TID	Items
10	a, c, d, f
20	b, c, e
30	a, b, c, e,
40	b, e
50	a, f

Scan D

1-candidates

Itemset	Sup
a	3
b	3
c	3
d	1
e	3
f	2

Freq 1-itemsets

Itemset	Sup
a	3
b	3
c	3
e	3
f	2

2-candidates

Itemset
ab
ac
ae
af
bc
be
bf
ce
cf
ef

Scan D

Itemset	Sup
ab	1
ac	2
ae	1
af	2
bc	2
be	3
bf	0
ce	2
cf	0
ef	0

Freq 2-itemsets

Itemset	Sup
ac	2
af	2
bc	2
be	3
ce	2

3-candidates

Itemset
acf
bce

pruning

3-candidates

Itemset
bce

Scan D

Itemset	Sup
bce	2

Freq 3-itemsets

Itemset	Sup
bce	2

- **From [Agrawal, Srikant 1994]**

The Apriori Algorithm

Procedure Apriori(DB)
//C_k: Candidate itemset of size k
//F_k : frequent itemset of size k

F_1 = {frequent items};
for (k = 1; F_k !=$\emptyset$; k++) do
    C_{k+1} = candidate-generate(F_k);
    for each transaction t $\in$ DB
        for each transaction c $\in$ C_{k+1}
            if c is contained in t
                c.count++;
    F_{k+1} = {c $\in$ C_{k+1}| c.count/|DB| $\geq$ min_support};
return $\cup_k F_k$;

The Apriori Algorithm

Function candidate-generate(F_k)
//C_k: Candidate itemset of size k
//F_k : frequent itemset of size k

$C_{k+1} = \varnothing$;
for all $f_1, f_2 \in F_k$ s.t. $f_1 = \{i_1, i_2, \ldots, i_{k-1}, i_k\}$, $f_2 = \{i_1, i_2, \ldots, i_{k-1}, i'_k\}$ and $i_k < i'_k$ do
    $c = \{i_1, i_2, \ldots, i_{k-1}, i_k, i'_k\}$
    $C_{k+1} = C_{k+1} \cup \{c\}$
    for each k-sized subset s of c
        if s is not contained in F_k
            delete c from C_{k+1}
            break;
return C_{k+1};

Discovering Rules

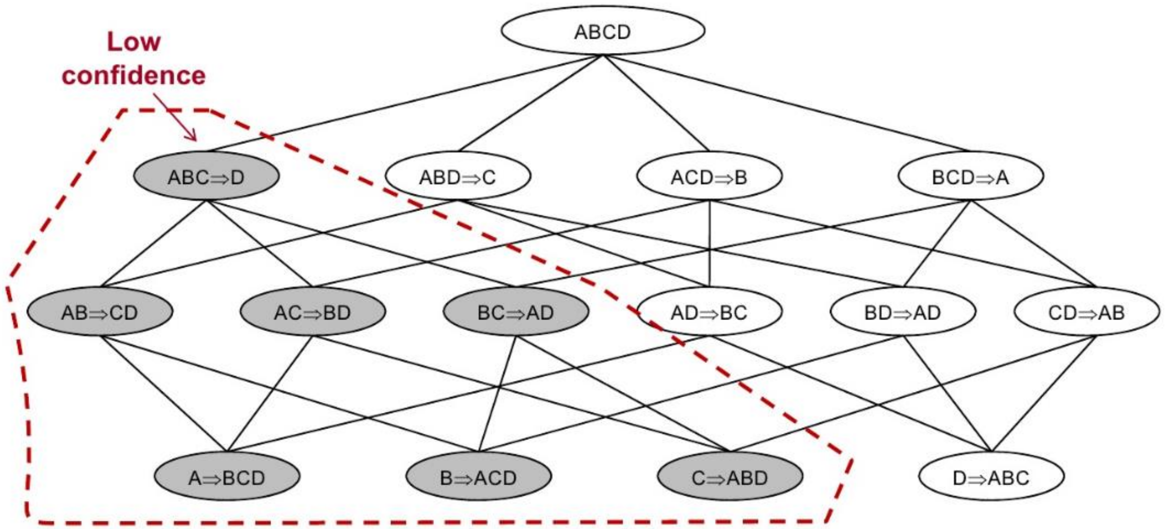
Naïve Algorithm:

for each frequent itemset f **do**
    for each subset c of f **do**
        if (support(f)/support(f-c) ≥ minconf) **then**
            output the rule (f-c)➔ c,
                with confidence = support(f)/support(f-c)
                and support = support(f)

- Given a frequent itemset f
  - Find all non-empty subsets c in f
    - s.t. the rule (f-c)➔ c satisfies the minimum support
  - Output the rule (f-c)➔ c
- Let f = {A,B,C}
  - Candidate itemsets are {A}, {B}, {C}, {A,B}, {A,C}, {B,C}
  - {B,C}->{A}, {A,C}->{B}, {A,B}->{C}, {C}->{A,B},{B}->{A,C},{A}->{B,C}

Can we do better?

- The confidence of rules generated from the same itemset have the anti-monotonicity property
- Let f = {A,B,C,D}
  - Confidence({A,B,C}->{D}) ≥ Confidence({A,B}->{C,D})
  - ≥ Confidence({A}->{B,C,D})



Discovering Rules

- Consider the rule (f-c)➔c
- Now, if c1 is a subset of c
  - f-c1 is a superset of C

    support(f-c1) ≤ support(f-c)

    support(f)/support(f-c1) ≥ support(f)/support(f-c)

    conf((f-c1)➔c1) ≥ conf((f-c)➔c)
- So, if a consequent c generates a valid rule, so do all subsets of c
- Can use the apriori candidate generation algorithm to limit number of possible rules tested.
- Consider a frequent itemset ABCDE
  - If ACDE➔B and ABCE➔D are the only one-consequent rules with minimum confidence, then ACE ➔ BD is the only other rule that needs to be ested.