# Data Analytics and Business Intelligence (8696/8697)

## Association Rules Analysis

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# Overview

1. Introduction
   - Rules
   - Concepts
2. Rule Discovery
   - Itemsets
   - Algorithm Outline
3. Example
   - Step-by-Step
   - Health Insurance Commission
4. Predictive Models

# Association Rule Mining

- An unsupervised learning algorithm—descriptive data mining.
- *Identify items (patterns) that occur frequently together in a given set of data.*
- Patterns = associations, correlations, causal structures (Rules).
- Data = sets of items in . . .
  - transactional database
  - relational database
  - complex information repositories
- Rule: $Body \rightarrow Head$ $[support, confidence]$

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# Typical Applications

- Link analysis
- Market basket analysis
- Cross marketing
- Customers who purchase ...

# Examples

- $\mathit{Friday} \cap \mathit{Nappies} \to \mathit{Beer}$ $[0.5\%, 60\%]$

  http://www.dssresources.com/newsletters/66.php

http://lmaohaha.com/baby-jokes/

- $\mathit{Age} \in [20, 30] \cap \mathit{Income} \in [20K, 30K] \to \mathit{MP3Player}$ $[2\%, 60\%]$
- $\mathit{Maths} \cap \mathit{CS} \to \mathit{HDinCS}$ $[1\%, 75\%]$
- $\mathit{Gladiator} \cap \mathit{Patriot} \to \mathit{Sixth\ Sense}$ $[0.1\%, 90\%]$
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# Framework

- Given
  - Database of transactions
  - Each transaction is a list of items
    E.g. Contents of customer's shopping basket
- Search for all rules that associate one set of items with another set.
- *Every possible association?*

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- *Every possible association?*

# Interesting Association Rules

- Measure interestingness of a rule in terms of
  - support: how frequently items appear together
  - confidence: how frequently they conditionally appear
  - lift: increased likelihood of Y if X included
- $X \to Y[s\%, c\%]$
  - the rule holds in s% of all transactions
  - $support(X \to Y) = P(X \cup Y)$

  - if $X$ is in the basket, then so is $Y$ in c% of the cases
  - $confidence(X \to Y) = P(Y|X) = P(X \cup Y)/P(X)$

  - if $X$ is in the basket, then $Y$ more likely in the basket
  - $lift(X \to Y) = confidence(X \to Y)/support(Y)$

  - higher frequency of $X$ and $Y$ with lower lift may be interesting
  - $leverage(X \to Y) =$ $support(X \to Y) - support(X) * support(Y)$

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# Example

| Transaction | Items |
|---|---|
| 12345 | A B C |
| 12346 | A C |
| 12347 | A D |
| 12348 | B E F |

$A \rightarrow B, A \rightarrow B, C$
$C \rightarrow A, B$
$A \rightarrow C, C \rightarrow A$
...

- Parameters:
  support = 50%
  confidence = 50%
- $A \rightarrow C[50\%, 66.6\%]$
- $C \rightarrow A[50\%, 100\%]$

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# Itemsets: Basis of Algorithm

| Transaction | Items |
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$\Rightarrow$

| Itemset | Support |
|---|---|
| $A$ | 75% |
| $B$ | 50% |
| $C$ | 50% |
| $A, C$ | 50% |

Parameters:
support = 50%
confidence = 50%

Rule $A \rightarrow C$

- support$(A, C) = 50\%$
- confidence$(A \rightarrow C)$
  $=$ support$(A, C)/$support$(A)$
  $= 66.6\%$

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# Algorithm Outline

- Find all frequent itemsets
  - sets of items with at least minimum support
  - support is the frequency of occurrence of the itemset
  - *k-itemset* contains $k$ items
  - Computationally expensive: Apriori algorithm
- Generate strong association rules from the frequent itemsets
  - For ABCD and AB in frequent itemset the rule AB $\Rightarrow$ CD holds if ratio s(ABCD)/s(AB) is large enough
  - This ratio is the confidence of the rule

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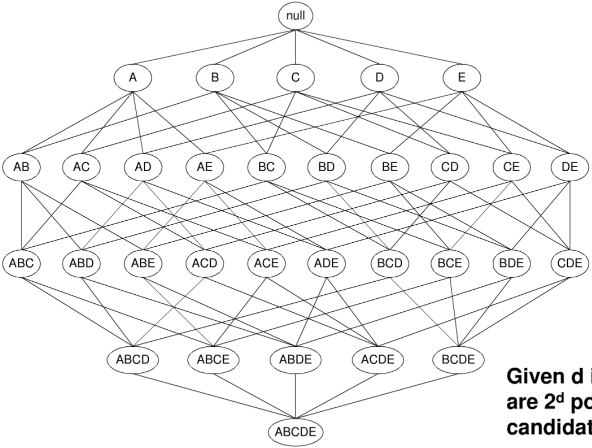
# Large Search Space




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

http://www.slideshare.net/pierluca.lanzi/dmtm-04-association-rules-basics

# Apriori Algorithm

Basic principle:

Any subset of a frequent itemset must be frequent

- Find the *frequent itemsets*: the sets of items that have minimum support
  - A subset of a frequent itemset must also be a frequent itemset.
  - If $AB$ is a frequent itemset, both $A$ and $B$ should be a frequent itemsets.
  - Iteratively find frequent itemsets with cardinality from 1 to k.
- Use the frequent itemsets to generate association rules.

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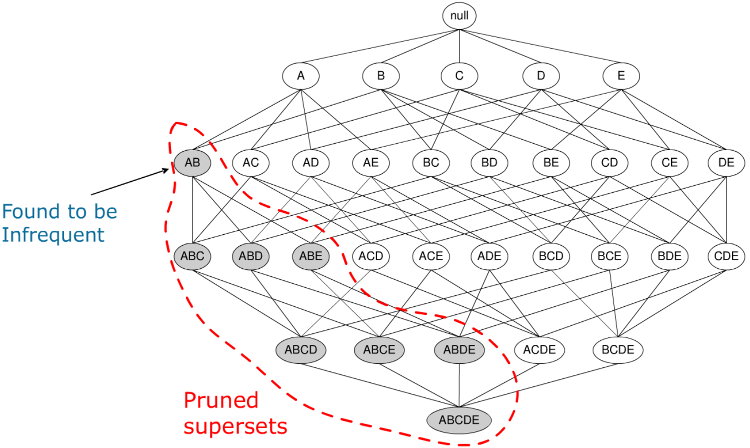
# Pruned Search Space

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# Apriori Algorithm

$C_k$: Candidate itemset of size $k$
$L_k$: Frequent itemset of size $k$
$L_1$ ={frequent items}
For $(k = 2; L_k \neq 0; k++)$

- $C_k$ = candidates generated from $L_{k-1}$
- For each transaction $t \in D$
  - increment count of candidates in $C_k$ contained in $t$
- $L_k$ = candidates in $C_k$ with at least min support.

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# Generate the Rules

Generate the **strong** association rules: having both minimum support and minimum confidence.

- For each frequent itemset $I$ generate all non-empty subsets of $I$
- Subset $s$ of $I$ rule $s \rightarrow (I - s)$ if confidence $>$ min confidence.

# Overview

| Transaction | Items |
|---|---|
| 12345 | A C D |
| 12346 | B C E |
| 12347 | A B C E |
| 12348 | B E |

→

| 1-Itemset | Sup |
|---|---|
| $A$ | 2 |
| $B$ | 3 |
| $C$ | 3 |
| $D$ | 1 |
| $E$ | 3 |

| 2-Itemsets | Sup |
|---|---|
| $AB$ | 1 |
| $AC$ | 2 |
| $AE$ | 1 |
| $BC$ | 2 |
| $BE$ | 3 |
| $CE$ | 2 |

→

| 3-Itemsets | Sup |
|---|---|
| $BCE$ | 2 |

| Transaction | Items |
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$\longrightarrow$

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|---|---|
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# Candidate Rules

| Transaction | Items |
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$BC \rightarrow E$ [50%, 100%]
$BE \rightarrow C$ [50%, 66%]
$C \rightarrow A$ [50%, 66%]

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# Candidate Rules

| Transaction | Items |
|---|---|
| 12345 | A C D |
| 12346 | B C E |
| 12347 | A B C E |
| 12348 | B E |

$BC \rightarrow E$ [50%, 100%]
$BE \rightarrow C$ [50%, 66%]
$C \rightarrow A$ [50%, 66%]

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# Health Insurance Commision

- Associations on episode database for pathology services
  - 6.8 million records X 120 attributes (3.5GB)
  - 15 months preprocessing then 2 weeks data mining
- Goal: find associations between tests
  - cmin = 50% and smin = 1%, 0.5%, 0.25%
    (1% of 6.8 million = 68,000)
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# Associations in R: Apriori

Sample data—DVD purchases:

```
Sixth Sense,LOTR1,Harry Potter1,Green Mile,LOTR2
Gladiator,Patriot,Braveheart
LOTR1,LOTR2
Gladiator,Patriot,Sixth Sense
Gladiator,Patriot,Sixth Sense
Gladiator,Patriot,Sixth Sense
Harry Potter1,Harry Potter2
Gladiator,Patriot
Gladiator,Patriot,Sixth Sense
Sixth Sense,LOTR,Galdiator,Green Mile
```

  

# Associations in R: Apriori

Using Borgelt's open source apriori C code:

```
library(arules)
tname <- file.path("data", "dvdtrans.csv")
head(read.csv(tname))

##   ID          Item
## 1  1   Sixth Sense
## 2  1         LOTR1
## 3  1 Harry Potter1
....

dvds <- read.transactions(tname, sep=",",
                          format="single", cols=c("ID", "Item"))
dvds

## transactions in sparse format with
##  10 transactions (rows) and
##  10 items (columns)
```

# Associations in R: Apriori

Build the model:

```
dvds.apriori <- apriori(dvds,
                        parameter=list(support=0.2, confidence=0.1))
```

```
##
## parameter specification:
##  confidence minval smax arem  aval originalSupport sup...
##         0.1    0.1    1 none FALSE            TRUE    ...
##  target   ext
##   rules FALSE
##
## algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
....
```

# Associations in R: Apriori

View the resulting rule set.

```
inspect(sort(dvds.apriori, by="lift"))

##     lhs              rhs              support confidence...
## 1   {LOTR1}       => {LOTR2}              0.2     1.0000...
## 2   {LOTR2}       => {LOTR1}              0.2     1.0000...
## 3   {Green Mile}  => {Sixth Sense}        0.2     1.0000...
....
```

# Overview



  

# Predictive Models

- Predictive Models: predict an outcome based on other variables
- Association rules: associate variable values with target variable
- Basket: collection of variable values
- Target: Rain Tomorrow? Yes/No

```
{Pressure3pm < 1012}
{Sunshine < 8.85}
=> {RainTomorrow = Yes}
```

- For R, all inputs must be categoric.

# Example in R

```
library(rattle)
cats <- c("WindGustDir", "WindDir9am",  "WindDir3pm", "RainTomorrow")
trans <- as(weather[cats], "transactions")
mymodel <- apriori(trans, parameter=list(support=0.1, confidence=0.5))

##
## parameter specification:
##  confidence minval smax arem  aval originalSupport sup...
##         0.5    0.1    1 none FALSE            TRUE    ...
....

inspect(sort(mymodel, by="confidence"))

##   lhs                 rhs                 support confid...
## 1 {WindDir9am=SE}  => {RainTomorrow=No}  0.1120     0....
## 2 {WindDir3pm=WNW} => {RainTomorrow=No}  0.1393     0....
## 3 {WindDir3pm=NNW} => {RainTomorrow=No}  0.1066     0....
....
```

# Overview

1. Introduction
   - Rules
   - Concepts
2. Rule Discovery
   - Itemsets
   - Algorithm Outline
3. Example
   - Step-by-Step
   - Health Insurance Commission
4. Predictive Models

# Modelling Framework

**Language** Set of *Antecedent* $\rightarrow$ *Consequent* rules

**Measure** Support, confidence, lift, leverage

**Search** Apriori

# Summary

- The "original" data mining algorithm!
- Effective in finding linkages in large customer databases.
- Considerable attention from data mining researchers.
- Available in the R package `arules` as `apriori`.

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