ISA 401/501: Business Intelligence & Data Visualization

24: A Short Introduction to Exploratory Data Mining

Fadel M. Megahed, PhD

Enders Associate Professor
Farmer School of Business
Miami University

@FadelMegahed
fmegahed
fmegahed@miamioh.edu
? Automated Scheduler for Office Hours

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A Recap of What we Learned Last Week

- Define a “business report” & its main functions
- Understand the importance of the right KPIs
- Automate traditional business reports
- Dashboards as real-time business reporting tools

Course Objectives Covered so Far

[Y]ou will be re-introduced to **how data should be explored** ... Instead, the focus is on understanding the underlying methodology and mindset of **how data should be approached, handled, explored, and incorporated back into the domain of interest.** ... You are expected to:

✓ **Be capable of extracting, transforming and loading (ETL) data using multiple platforms (e.g. R & Tableau).**

✓ **Write basic R scripts to preprocess and clean the data.**

✓ **Explore the data using visualization approaches that are based on sound human factors (i.e. account for human cognition and perception of data).**

⊗ **Understand how data mining and other analytical tools can capitalize on the insights generated from the data viz process.**

✓ **Create interactive dashboards that can be used for business decision making, reporting and/or performance management.**

⊗ **Be able to apply the skills from this class in your future career.**

Learning Objectives for Today's Class

- Describe the goals & functions of data mining
- Understand the statistical limits on data mining
- Describe the data mining process
- What is “frequent itemsets” & the application of this concept
- Explain how and why “association rules” are constructed
- Use R to populate both concepts

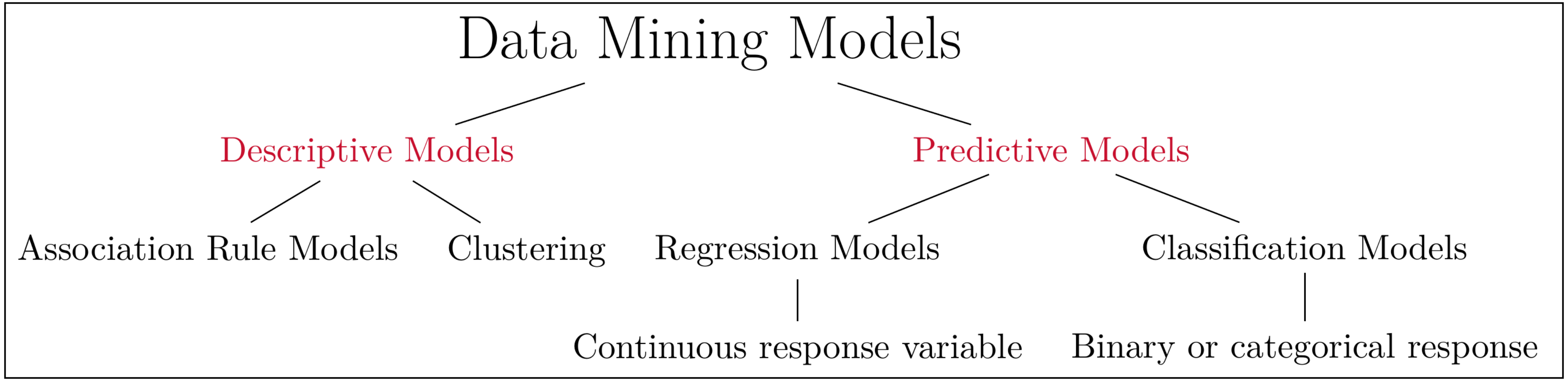
An Overview of Data Mining

What is Data Mining?

- The most common definition of data mining is the discovery of models from data.
- Discovery of **patterns and models that are:**
  - **Valid:** hold on new data with some certainty
  - **Useful:** should be possible to act on the item
  - **Unexpected:** non-obvious to the system
  - **Understandable:** humans should be able to interpret the pattern
- Subsidiary Issues:
  - **Data cleansing:** detection of bogus data
  - **Data visualization:** something better than MBs of output
  - **Warehousing** of data (for retrieval)

Source: The slide is adapted from Jure Leskovic, Stanford CS246, Lecture Notes, see http://cs246.stanford.edu

A Simplistic View of Data Mining Models



A simplistic summary of data mining models. Note that, in ISA 401, we will only briefly cover descriptive/exploratory data mining models

Data Mining is Hard

Data mining is hard since it has the following issues:

- Scalability
- Dimensionality
- Complex and Heterogeneous Data
- Data Quality
- Data Ownership and Distribution
- Privacy Preservation

Note that I have intentionally not included fitting/training a model since this is relatively easy if you understand the data, engineered/captured the important predictors, and have the data in the "correct" shape/quality.

Association Rules

Data | Top 5 Rules | Scatter Plot of all Rules | Graph-based Plot of Top 5 Rules

```
## transactions as itemMatrix in sparse format with
##  9835 rows (elements/itemsets/transactions) and
##  169 columns (items) and a density of 0.02609146
##
## most frequent items:
##       whole milk other vegetables       rolls/buns             soda
##             2513             1903             1809             1715
##           yogurt          (Other)
##             1372            34055
##
## element (itemset/transaction) length distribution:
## sizes
##    1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16
## 2159 1643 1299 1005  855  645  545  438  350  246  182  117   78   77   55   46
##   17   18   19   20   21   22   23   24   26   27   28   29   32
##   29   14   14    9   11    4    6    1    1    1    1    3    1
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   2.000   3.000   4.409   6.000  32.000
```

Association Rules

Data | Top 5 Rules | Scatter Plot of all Rules | Graph-based Plot of Top 5 Rules

```
##     lhs                                    rhs              support
## [1] {Instant food products, soda}       => {hamburger meat} 0.001220132
## [2] {soda, popcorn}                     => {salty snack}    0.001220132
## [3] {flour, baking powder}              => {sugar}          0.001016777
## [4] {ham, processed cheese}             => {white bread}    0.001931876
## [5] {whole milk, Instant food products} => {hamburger meat} 0.001525165
##     confidence coverage    lift     count
## [1] 0.6315789  0.001931876 18.99565 12
## [2] 0.6315789  0.001931876 16.69779 12
## [3] 0.5555556  0.001830198 16.40807 10
## [4] 0.6333333  0.003050330 15.04549 19
## [5] 0.5000000  0.003050330 15.03823 15
```

Association Rules

Data | Top 5 Rules | **Scatter Plot of all Rules** | Graph-based Plot of Top 5 Rules

Association Rules

Data | Top 5 Rules | Scatter Plot of all Rules | Graph-based Plot of Top 5 Rules

Clustering of Traffic Volume on I-85

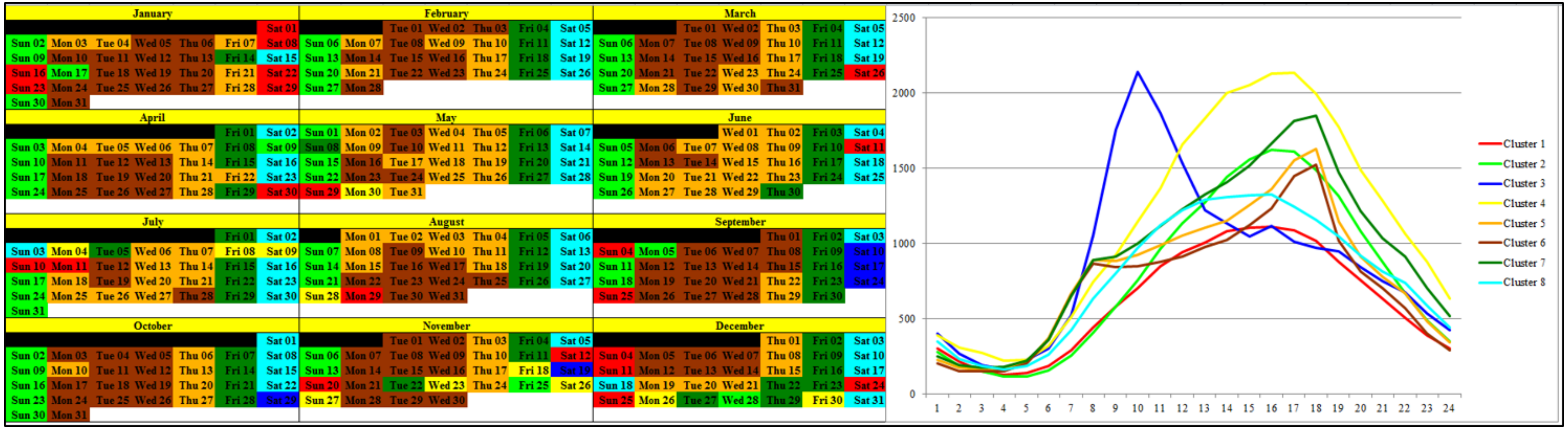
04:00

Data | Calendar Plot of Clustered Data | Insights from Chart?

04:00

Clustering of Traffic Volume on I-85

Data | **Calendar Plot of Clustered Data** | Insights from Chart?



Clustering of Traffic Volume on I-85

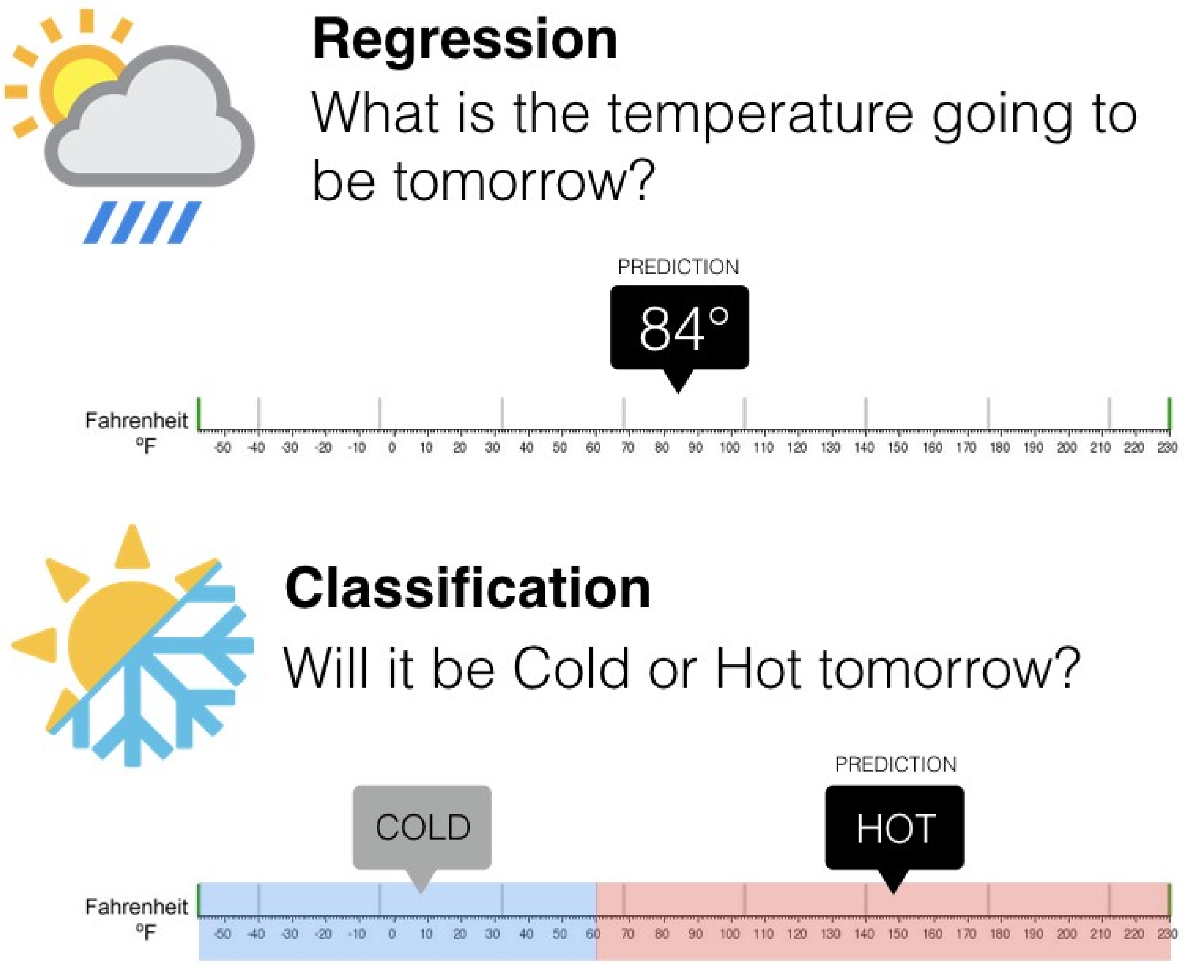
04:00

Data | Calendar Plot of Clustered Data | Insights from Chart?

Based on the previous tab, what are 2-3 main insights you have learned about the traffic volume in Montgomery, AL? Write them down below

Edit me and insert your solution here

Regression vs Classification



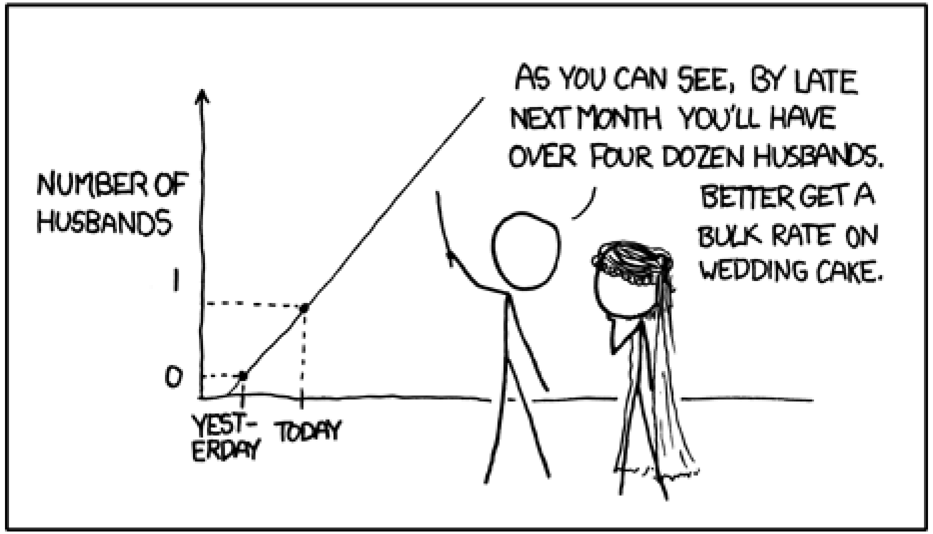
An Overview of Common Data Mining Models

Limits on Data Mining

Meaningfulness of Answers from DM Models

- **A big risk when data mining is that you will discover patterns that are meaningless.**
- **Bonferroni's Principle:** (roughly) if you look in more places for interesting patterns than your amount of data will support, you are bound to find.

MY HOBBY: EXTRAPOLATING



Rhines Paradox: An Example of Overzealous DM?

- Joseph Rhine was a parapsychologist in the 1950s who hypothesized that some people had **Extra-Sensory Perception**.
- He devised an experiment where subjects were asked to guess 10 hidden cards red or blue.
- He discovered that almost 1 in 1000 had ESP they were able to get all 10 right!
- He told these people they had ESP and called them in for another test of the same type.
- Alas, he discovered that almost all of them had lost their ESP.
- **What did he conclude?**
  - He concluded that you should not tell people they have ESP; it causes them to lose it.
  - **Why is this an incorrect conclusion?**

Ethical Issues with Data Mining

In the News: AI Implementation Scandals

FROM POLITICO

Dutch scandal serves as a warning for Europe over risks of using algorithms

The Dutch tax authority ruined thousands of lives after using an algorithm to spot suspected benefits fraud – and critics say there is little stopping it from happening again.

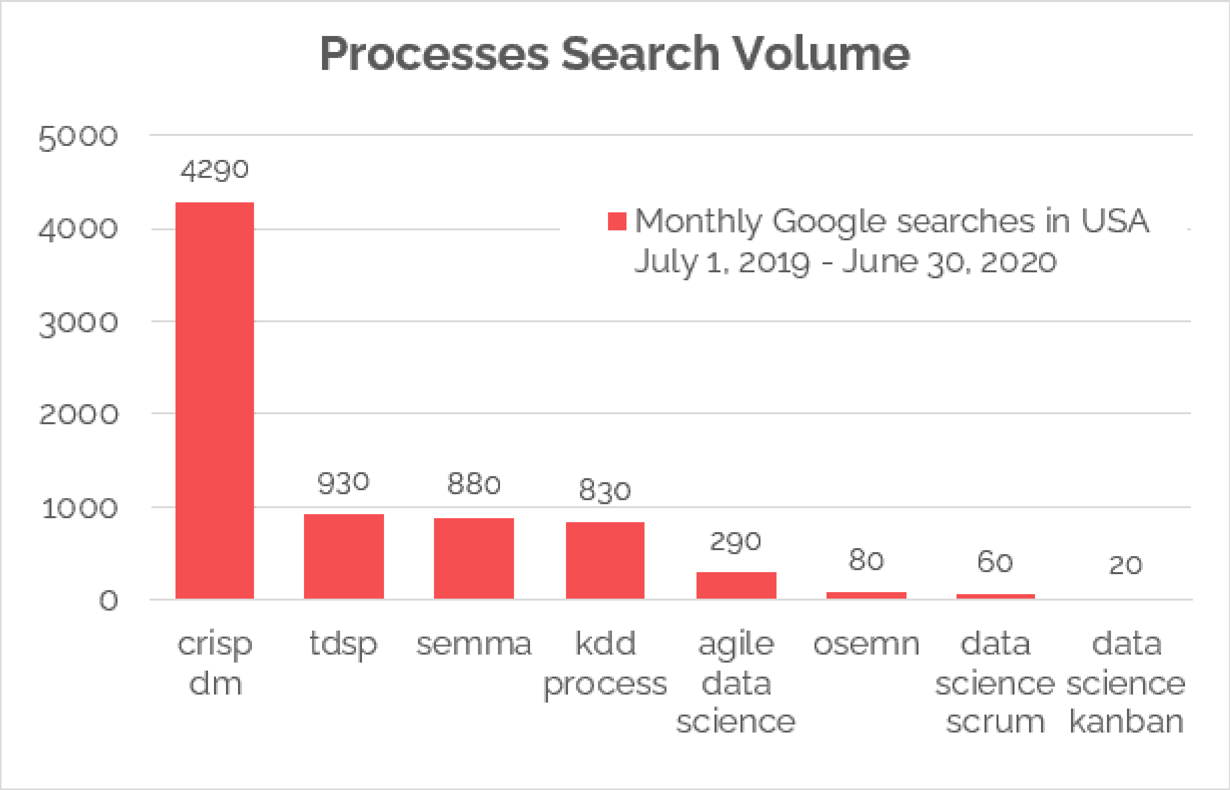
As the world turns to AI to automate their systems, the Dutch scandal shows how devastating they can be | Dean Mouhtaropoulos/Getty Images

BY MELISSA HEIKKILÄ

March 29, 2022 | 6:14 pm

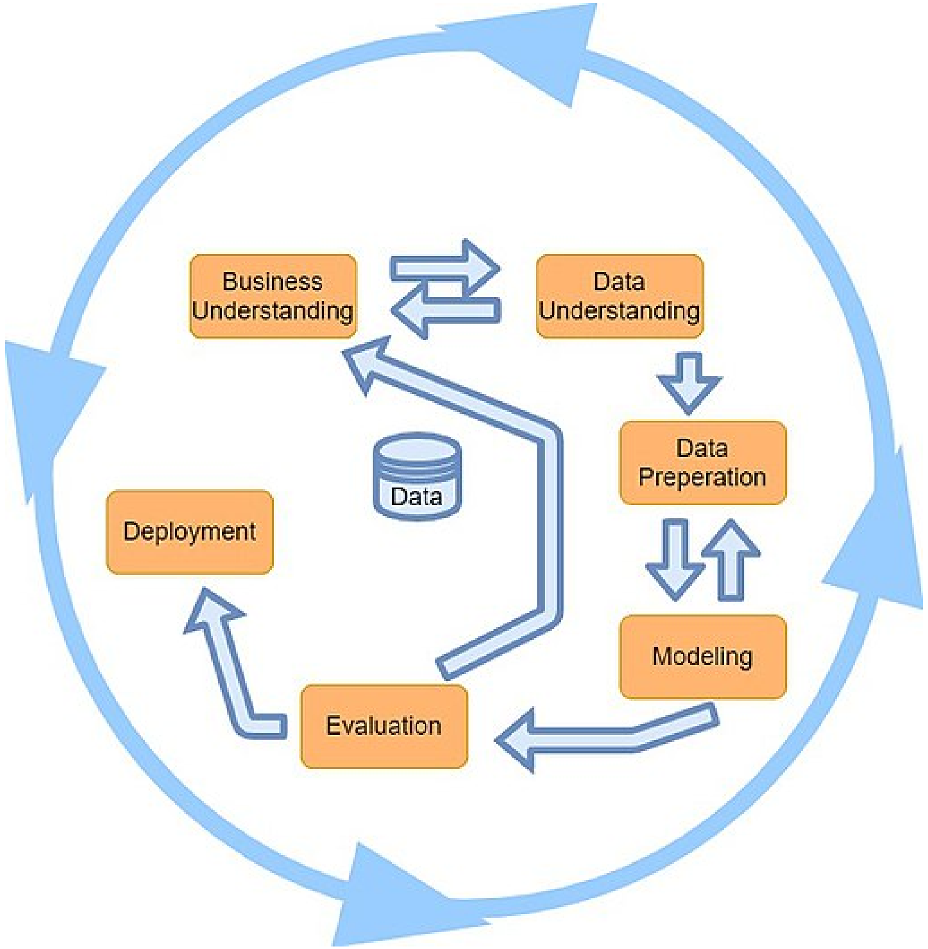
The Data Mining Process

Frameworks for Data Mining Projects



The CRISP-DM Process

- **You are expected to read the original CRISP-DM paper**
- Each step has several substeps
- **Most of the project time is typically spent in steps 1-3**



Frequent Itemsets, Market Basket Analysis and Association Rule Mining

Association Rule Discovery

Supermarket shelf management – Market-basket model:

- **Goal:** Identify items that are bought together by sufficiently many customers
- **Approach:** Process the sales data collected with barcode scanners to find dependencies among items
- **A classic rule:**
  - If someone buys diaper and milk, then he/she is likely to buy beer
  - Don't be surprised if you find six-packs next to diapers!

Source: J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

The Market-Basket Model

- A large set of **items**
  - e.g., things sold in a supermarket
- A large set of **baskets**
- Each basket is a **small subset of items**
  - e.g., the things one customer buys on one day
- Want to discover **association rules**
  - People who bought {x,y,z} tend to buy {v,w}
  - Amazon!

Input:

Basket #	Items
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

Output: Discovered Rules

{Milk} --> {Coke}
{Diaper, Milk} --> {Beer}

Source: J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

Definitions: Support & Support Threshold

- **Simplest question:** Find sets of items that appear together “frequently” in baskets
- **Support for itemset I:** Number of baskets containing all items in I
  - Often expressed as a fraction of the total number of baskets
- Given a **support threshold** s, then sets of items that appear in at least s baskets are called frequent itemsets

Input:

Basket #	Items
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

Support of {Beer, Bread}: = 2

Source: J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

Non-graded Activity: Frequent Itemsets

04:00

Activity | Your Solution

Items = {Milk, Coke, Pepsi, Beer, Juice}

With a support threshold of 3 baskets, find all frequent itemsets based on these 8 baskets:

- $B_1 =$ {Milk, Coke, Beer} $B_2 =$ {Milk, Pepsi, Juice}
- $B_3 =$ {Milk, Beer} $B_4 =$ {Coke, Juice}
- $B_5 =$ {Milk, Pepsi, Beer} $B_6 =$ {Milk, Coke, Beer, Juice}
- $B_6 =$ {Coke, Beer, Juice} $B_8 =$ {Coke, Beer}

Non-graded Activity: Frequent Itemsets

04:00

Activity | Your Solution

Identify all frequent singletons, doubles, triples, etc.

Edit me and insert your solution here

Association Rules

- **Association Rules:** If-then rules about the contents of baskets
- $\{i_1, i_2, \ldots, i_k\} \rightarrow j$ means: "if a basket contains all of $i_1, \ldots, i_k$ then it is likely to contain j"
- **In practice there are many rules, want to find significant/interesting ones!**
- **Confidence** of this association rule is the probability of j given $I = \{i_1, \ldots, i_k\}$

$$conf(I \rightarrow j) = P(j \mid I) = \frac{support(I \cap j)}{support(I)}$$

- **Not all high-confidence rules are interesting**
  - The rule **X** $\rightarrow$ **milk** may have high confidence for many itemsets **X**, because **milk** is just purchased very often (independent of **X**) and the confidence will be high
- **Lift** of an association rule $I \rightarrow J$ is the ratio between its confidence and the fraction of baskets containing j: $lift(I \rightarrow j) = \frac{conf(I \rightarrow j)}{Pr(j)}$

Non-Graded Activity: Confidence and Lift

04:00

Activity | Your Solution

- $B_1 = \{\text{Milk, Coke, Beer}\}$ $B_2 = \{\text{Milk, Pepsi, Juice}\}$
- $B_3 = \{\text{Milk, Beer}\}$ $B_4 = \{\text{Coke, Juice}\}$
- $B_5 = \{\text{Milk, Pepsi, Beer}\}$ $B_6 = \{\text{Milk, Coke, Beer, Juice}\}$
- $B_6 = \{\text{Coke, Beer, Juice}\}$ $B_8 = \{\text{Coke, Beer}\}$

For the association rule: $\{\text{Milk, Beer}\} \rightarrow \text{Coke}$, compute both its confidence and lift.

Non-Graded Activity: Confidence and Lift

04:00

Activity | Your Solution

Computing the confidence and lift for the association rule $\{\text{Milk}, \text{Beer}\} \rightarrow \text{Coke}$

Edit me and insert your solution here

Finding Association Rules

- **Problem: Find all association rules with support ≥ s and confidence ≥ c**
    - **Note:** Support of an association rule is the support of the set of items on the left side
- **Hard part: Finding the frequent itemsets!**
    - If $\{i_1, i_2,\dots,i_k\} \rightarrow j$ has high support and confidence, then:
    - both $\{i_1, i_2,\dots ,i_k\}$ and both $\{i_1, i_2,\dots,i_k, j\}$ will be "frequent"

Naïve Approach to Counting Frequent Itemsets

- Naïve approach to finding frequent pairs
- **Read file once, counting in main memorythe occurrences of each pair:**
  - From each basket of n items, generate its $\frac{n(n-1)}{2}$ pairs by two nested loops
- Fails if (#items)^2 exceeds main memory
  - Remember: #items can be 100K (Wal-Mart) or 10B (Web pages)
  - Suppose 10^5 items, counts are 4-byte integers
  - Number of pairs of items: $\frac{10^5(10^5-1)}{2} = 5 * 10^9$
  - Therefore, $2 * 10^{10}$ (20 gigabytes) of memory needed

Source: J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

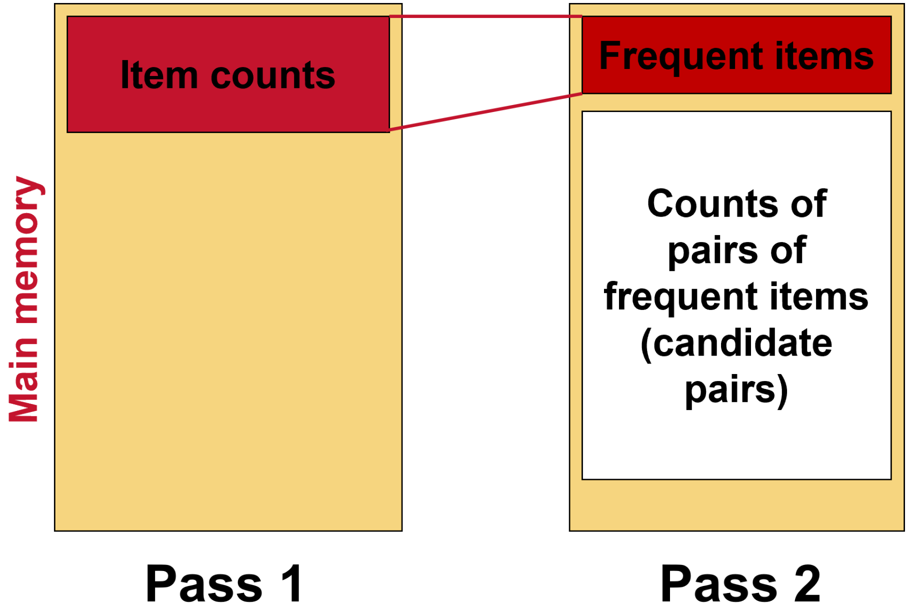
A-Priori Algorithm

- A **two-pass** approach called **A-Priori** limits the need for main memory
- **Key idea: monotonicity**
  - If a set of items I appears at least s times, so does every subset J of I
- **Contrapositive for pairs:** If item i does not appear in s baskets, then no pair including i can appear in s baskets
- **So, how does A-Priori find frequent pairs?**

Source: J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

A-Priori Algorithm

- **Pass 1:** Read baskets and count in main memory the occurrences of each **individual item**
  - Requires only memory proportional to #items
- **Items that appear $\geq s$ times are the frequent items**
- **Pass 2:** Read baskets again and count in main memory **only those pairs where both elements are frequent (from Pass 1)**



Using R to Mine Association Rules

In class, we will go through this R code, explaining: (a) what each function is doing, and (b) the outputs from each step.

```
if(require(pacman)==FALSE) install.packages('pacman')
pacman::p_load(arules, tidyverse)

data('Groceries') # note its class

summary(Groceries)

itemFrequency(Groceries) # returns frequency in alphabetic order
itemFrequency(Groceries) %>% sort(decreasing = T)

itemFrequencyPlot(Groceries, support = 0.1)
itemFrequencyPlot(Groceries, topN = 20)

# mine association rules with a certain min support and confidence
grocery_rules = apriori(
  Groceries, parameter = list(
    support = 0.01, confidence = 0.5, minlen = 2, maxlen = 5)  )

summary(grocery_rules)
inspect(grocery_rules)

sort(grocery_rules, by ='lift', decreasing = T)[1:3] %>% inspect()
```

Recap

Summary of Main Points

- Describe the goals & functions of data mining
- Understand the statistical limits on data mining
- Describe the data mining process
- What is “frequent itemsets” & the application of this concept
- Explain how and why “association rules” are constructed
- Use R to populate both concepts