CS 4604: Introduction to Database Management Systems

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Lecture #21: Data Mining and Warehousing
Just FYI, and not for exam!
Overview

- Traditional database systems are tuned to many, small, simple queries.
- New applications use fewer, more time-consuming, *analytic* queries.
- New architectures have been developed to handle analytic queries efficiently.
Problem

Given: multiple data sources
Find: patterns (classifiers, rules, clusters, outliers...)

NY

sales(p-id, c-id, date, $price)

SF

customers( c-id, age, income, ...)
Data Ware-housing

First step: collect the data, in a single place (= Data Warehouse)
How?
How often?
How about discrepancies / non-homogeneities?
First step: collect the data, in a single place (Data Warehouse)

How? A: Triggers/Materialized views

How often? A: [Art!]

How about discrepancies / non-homegeneities? A: Wrappers/Mediators
Step 2: collect counts. (DataCubes/OLAP)
The Data Warehouse

- The most common form of data integration.
  - Copy sources into a single DB (warehouse) and try to keep it up-to-date.
  - Usual method: periodic reconstruction of the warehouse, perhaps overnight.
  - Frequently essential for analytic queries.
OLTP

- Most database operations involve *On-Line Transaction Processing* (OTLP).
  - Short, simple, frequent queries and/or modifications, each involving a small number of tuples.
  - **Examples**: Answering queries from a Web interface, sales at cash registers, selling airline tickets.
OLAP

- *On-Line Application Processing* (OLAP, or “analytic”) queries are, typically:
  - Few, but complex queries --- may run for hours.
  - Queries do not depend on having an absolutely up-to-date database.
OLAP Examples

1. Amazon analyzes purchases by its customers to come up with an individual screen with products of likely interest to the customer.

2. Analysts at Wal-Mart look for items with increasing sales in some region.
   – Use empty trucks to move merchandise between stores.
Common Architecture

- Databases at store branches handle OLTP.
- Local store databases copied to a central warehouse overnight.
- Analysts use the warehouse for OLAP.
A *star schema* is a common organization for data at a warehouse. It consists of:

1. **Fact table**: a very large accumulation of facts such as sales.
   1. Often “insert-only.”

2. **Dimension tables**: smaller, generally static information about the entities involved in the facts.
Example: Star Schema

- Suppose we want to record in a warehouse information about every beer sale: the bar, the brand of beer, the drinker who bought the beer, the day, the time, and the price charged.
- The fact table is a relation:
  \[ \text{Sales} (\text{bar}, \text{beer}, \text{drinker}, \text{day}, \text{time}, \text{price}) \]
Example -- Continued

- The dimension tables include information about the bar, beer, and drinker “dimensions”:
  - Bars(bar, addr, license)
  - Beers(beer, manf)
  - Drinkers(drinker, addr, phone)
Visualization – Star Schema

Dimension Table **(Bars)**

Dimension Attrs.

Fact Table - **Sales**

Dimension Attrs.

Dimension Table **(Drinkers)**

Dependent Attrs.

Dimension Table **(Beers)**

Dimension Table (etc.)

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Dimensions and Dependent Attributes

- Two classes of fact-table attributes:
  2. *Dependent attributes* : a value determined by the dimension attributes of the tuple.
Example: Dependent Attribute

- **price** is the dependent attribute of our example Sales relation.
- It is determined by the combination of dimension attributes: **bar, beer, drinker**, and the **time** (combination of day and time-of-day attributes).
Approaches to Building Warehouses

1. **ROLAP** = “relational OLAP”: Tune a relational DBMS to support star schemas.

2. **MOLAP** = “multidimensional OLAP”: Use a specialized DBMS with a model such as the “data cube.”
1. **Bitmap indexes** : For each key value of a dimension table (e.g., each beer for relation Beers) create a bit-vector telling which tuples of the fact table have that value.

2. **Materialized views** : Store the answers to several useful queries (views) in the warehouse itself.
Typical OLAP Queries

- Often, OLAP queries begin with a “star join”: the natural join of the fact table with all or most of the dimension tables.

- Example:

```sql
SELECT *
FROM Sales, Bars, Beers, Drinkers
WHERE Sales.bar = Bars.bar AND
     Sales.beer = Beers.beer AND
     Sales.drinker = Drinkers.drinker;
```
Typical OLAP Queries --- (2)

- The typical OLAP query will:
  1. Start with a star join.
  2. Select for interesting tuples, based on dimension data.
  3. Group by one or more dimensions.
  4. Aggregate certain attributes of the result.
Example: OLAP Query

For each bar in Blacksburg, find the total sale of each beer manufactured by Anheuser-Busch.

Filter: `addr = "Blacksburg"` and `manf = "Anheuser-Busch"`.

Grouping: by `bar` and `beer`.

Aggregation: Sum of `price`. 
Example: In SQL

```
SELECT bar, beer, SUM(price)
FROM Sales NATURAL JOIN Bars
    NATURAL JOIN Beers
WHERE addr = 'Blacksburg' AND manf = 'Anheuser-Busch'
GROUP BY bar, beer;
```
Using Materialized Views

- A direct execution of this query from Sales and the dimension tables could take too long.
- If we create a materialized view that contains enough information, we may be able to answer our query much faster.
Example: Materialized View

- Which views could help with our query?
- Key issues:
  1. It must join Sales, Bars, and Beers, at least.
  2. It must group by at least bar and beer.
  3. It must not select out Blacksburg bars or Anheuser-Busch beers.
  4. It must not project out addr or manf.
Here is a materialized view that could help:

```
CREATE VIEW BABMS(bar, addr, beer, manf, sales) AS
SELECT bar, addr, beer, manf, SUM(price) sales
FROM Sales NATURAL JOIN Bars
    NATURAL JOIN Beers
GROUP BY bar, addr, beer, manf;
```

Since bar -> addr and beer -> manf, there is no real grouping. We need addr and manf in the SELECT.
Example --- Concluded

- Here’s our query using the materialized view BABMS:

  SELECT bar, beer, sales 
  FROM BABMS 
  WHERE addr = 'Blacksburg' AND 
  manf = 'Anheuser-Busch';
MOLAP and Data Cubes

- Keys of dimension tables are the dimensions of a hypercube.

- Example:
  \[ \text{Sales}(\text{bar}, \text{beer}, \text{drinker}, \text{time}, \text{price}) \]
  
  – for the Sales data, the four dimensions are \text{bar}, \text{beer}, \text{drinker}, \text{and time}.

- Dependent attributes (e.g., \text{price}) appear at the points of the cube.
Visualization -- Data Cubes

- beer
- bar
- drinker
- price

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The data cube also includes aggregation (typically SUM) along the margins of the cube. The *marginals* include aggregations over one dimension, two dimensions,...
Visualization --- Data Cube w/Aggregation
Example: Marginals

- Our 4-dimensional Sales cube includes the sum of price over each bar, each beer, each drinker, and each time unit (perhaps days).
- It would also have the sum of price over all bar-beer pairs, all bar-drinker-day triples,...
Marginals

- Think of each dimension as having an additional value *.
- A point with one or more *’s in its coordinates aggregates over the dimensions with the *’s.
- Example: (”Joe’s Bar”, ”Bud”, *, *) holds the sum, over all drinkers and all time, of the Bud consumed at Joe’s.
Drill-Down

- **Drill-down** = “de-aggregate” = break an aggregate into its constituents.
- **Example**: having determined that Joe’s Bar sells very few Anheuser-Busch beers, break down his sales by particular A.-B. beer.
Roll-Up

- *Roll-up* = aggregate along one or more dimensions.

- **Example**: given a table of how much Bud each drinker consumes at each bar, roll it up into a table giving total amount of Bud consumed by each drinker.
Example: Roll Up and Drill Down

$ of Anheuser-Busch by drinker/bar

<table>
<thead>
<tr>
<th></th>
<th>Jim</th>
<th>Bob</th>
<th>Mary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Joe’s Bar</td>
<td>45</td>
<td>33</td>
<td>30</td>
</tr>
<tr>
<td>Bull &amp; Bones</td>
<td>50</td>
<td>36</td>
<td>42</td>
</tr>
<tr>
<td>Blue Chalk</td>
<td>38</td>
<td>31</td>
<td>40</td>
</tr>
</tbody>
</table>

$ of A-B / drinker

<table>
<thead>
<tr>
<th></th>
<th>Jim</th>
<th>Bob</th>
<th>Mary</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>133</td>
<td>100</td>
<td>112</td>
</tr>
</tbody>
</table>

Roll up by Bar

Drill down by Beer

$ of A-B Beers / drinker

<table>
<thead>
<tr>
<th></th>
<th>Jim</th>
<th>Bob</th>
<th>Mary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bud</td>
<td>40</td>
<td>29</td>
<td>40</td>
</tr>
<tr>
<td>M’ lob</td>
<td>45</td>
<td>31</td>
<td>37</td>
</tr>
<tr>
<td>Bud Light</td>
<td>48</td>
<td>40</td>
<td>35</td>
</tr>
</tbody>
</table>
Structure of the Data Cube

- CUBE(F) of fact table F is *roughly* the Fact table (F) + aggregations across all dimensions (i.e. marginals)
  - Note CUBE(F) is a relation itself!
CUBE in SQL: Example

- For our Sales example:

Sales(bar, beer, drinker, time, price)

CREATE MATERIALIZED VIEW SalesCube AS
SELECT bar, beer, drinker, time, SUM(price)
FROM Sales
GROUP BY bar, beer, drinker, time WITH CUBE;
Tuples in SalesCube

- Tuples implied by the standard GROUP-BY:
  (Joes, Bud, John, 4/19/13, 3.00)

- And those tuples of that are constructed by rolling-up the dimensions in GROUP-BY (== marginals, NULL == *). E.g:
  (Joes, NULL, John, 4/19/13, 10.00)
  (Joes, NULL, John, NULL, 200.00)
  (Joes, NULL, NULL, NULL, 200000.00)
  (NULL, NULL, NULL, NULL, 2000000.00)
Tuples in SalesCube

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  (Joes, Bud, John, 4/19/13, 3.00)

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  (Joes, NULL, NULL, NULL, 200000.00)
  (NULL, NULL, NULL, NULL, 2000000.00)

Total spent by John at Joes on Apr 19.
Tuples in SalesCube

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  (Joes, Bud, John, 4/19/13, 3.00)

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  (Joes, NULL, John, NULL, 200.00)
  (Joes, NULL, NULL, NULL, 200000.00)
  (NULL, NULL, NULL, NULL, 2000000.00)

Total spent by John at Joes ever.
Tuples in SalesCube

- Tuples implied by the standard GROUP-BY:
  
  (Joes, Bud, John, 4/19/13, 3.00)

- And those tuples of that are constructed by rolling-up the dimensions in GROUP-BY (== marginals, NULL == *). E.g:

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  (Joes, NULL, NULL, NULL, 200000.00)
  (NULL, NULL, NULL, NULL, 2000000.00)

Total spent by everyone at Joes ever.
Tuples in SalesCube

- Tuples implied by the standard GROUP-BY:
  
  \[(\text{Joes, Bud, John, 4/19/13, 3.00})\]

- And those tuples of that are constructed by rolling-up the dimensions in GROUP-BY (= marginalss, NULL == *). E.g:

  \[(\text{Joes, NULL, John, 4/19/13, 10.00})\]
  \[(\text{Joes, NULL, John, NULL, 200.00})\]
  \[(\text{Joes, NULL, NULL, NULL, 200000.00})\]
  \[(\text{NULL, NULL, NULL, NULL, 2000000.00})\]

Total spent by everyone at every bar ever.
Compare ROLAP vs MOLAP

**ROLAP Solution**

```sql
CREATE VIEW BABMS(bar, addr, beer, manf, sales) AS
SELECT bar, addr, beer, manf, SUM(price) sales
FROM Sales NATURAL JOIN Bars
    NATURAL JOIN Beers
GROUP BY bar, addr, beer, manf;
```

- A specific view for a specific type of query (note the join)

**MOLAP (Data Cube) Solution**

```sql
CREATE MATERIALIZED VIEW SalesCube
AS
SELECT bar, beer, drinker, time,
    SUM(price)
FROM Sales
GROUP BY bar, beer, drinker, time
WITH CUBE;
```

- A generalized view which stores marginals as well (no join)
How to answer queries using Cube?

- Essentially similar to ROLAP using materialized views, but now use the SalesCube
How to do CUBE(F) efficiently?

– ....Skip....
Data Mining

- *Data mining* is a popular term for techniques to summarize big data sets in useful ways.

- Examples:
  1. Clustering all Web pages by topic.
  2. Finding characteristics of fraudulent credit-card use.
Supervised Learning: Decision Trees: Problem

<table>
<thead>
<tr>
<th>Age</th>
<th>Chol-level</th>
<th>Gender</th>
<th>…</th>
<th>CLASS-ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>150</td>
<td>M</td>
<td></td>
<td>+</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>…</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-</td>
</tr>
</tbody>
</table>

Has heart disease
Supervised Learning: Decision Trees: Problem

What is the label for this new patient?
### Supervised Learning: Decision Trees: Problem

#### Training Data Set

<table>
<thead>
<tr>
<th>Age</th>
<th>Chol-level</th>
<th>Gender</th>
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<td>30</td>
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<td>+</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>90</td>
<td>F</td>
<td>??</td>
</tr>
</tbody>
</table>

**What is the label for this new patient?**
Decision trees

- Pictorially, we have

  num. attr#1 (eg., ‘age’)

  num. attr#2 (eg., chol-level)
- and we want to label ‘?’

num. attr#1 (eg., ‘age’)

num. attr#2 (eg., chol-level)
so we build a decision tree:

- num. attr#2 (eg., chol-level)
  - 40
  - num. attr#1 (eg., ‘age’)
  - 50
Decision trees

- so we build a decision tree:

```
  age<50
    Y
    +
    chol. <40
      Y
      ...
      N
    N
```
Decision trees: Approach

- Typically, two steps:
  - tree building
  - tree pruning (for over-training/over-fitting)
Tree building

- How?

num. attr#2 (eg., chol-level)

num. attr#1 (eg., ‘age’)
Tree building

- How?
- A: Partition, recursively - pseudocode:

```
Partition ( Dataset S)

if all points in S have same label
then return

evaluate splits along each attribute A
pick best split, to divide S into S1 and S2
Partition(S1); Partition(S2)
```
Tree building

- Q1: how to introduce splits along attribute $A_i$
- Q2: how to evaluate a split?
Tree building

- **Q1:** how to introduce splits along attribute $A_i$

- **A1:**
  
  - for num. attributes:
    
    • binary split, or
    
    • multiple split
  
  - for categorical attributes:
    
    • compute all subsets (expensive!), or
    
    • use a greedy algo
Tree building

- Q1: how to introduce splits along attribute $A_i$
- Q2: how to evaluate a split?
Tree building

- **Q1**: how to introduce splits along attribute $A_i$
- **Q2**: how to evaluate a split?
- **A**: by how close to uniform each subset is - ie., we need a measure of uniformity:
Tree building

entropy: $H(p_+, p_-)$

$$H = -p_+ \log(p_+) - p_- \log(p_-)$$

Any other measure?
Tree building

entropy: $H(p_+, p_-)$

$H = -p_+ \log(p_+) - p_- \log(p_-)$

‘gini’ index: $1 - p_+^2 - p_-^2$
Tree building

entropy: $H(p_+, p_-)$

‘gini’ index: $1-p_+^2 - p_-^2$

(How about multiple labels?)
Tree building

Intuition:

- entropy: #bits to encode the class label
- gini: classification error, if we randomly guess ‘+’ with prob. $p_+$
Tree building

Thus, we choose the split that reduces entropy/classification-error the most: Eg.:

```
num. attr#1 (eg., ‘age’)  
+ + + + 
+ + + + 
- - - - 
- - - - 
```

num. attr#2 (eg., chol-level)

- - - -
Tree building

- Before split: we need
  \[(n_+ + n_-) \times H(p_+, p_-) = (7+6) \times H(7/13, 6/13)\]
  bits total, to encode all the class labels

- After the split we need:
  0 bits for the first half and
  \[(2+6) \times H(2/8, 6/8)\] bits for the second half
Tree pruning

- What for?

- num. attr#1 (eg., ‘age’)
  - num. attr#2 (eg., chol-level)
Summary: classifiers

- Classification through trees
- Building phase - splitting policies
- Pruning phase (to avoid over-fitting)
An important form of mining from relational data involves *market baskets* = sets of “items” that are purchased together as a customer leaves a store.

Summary of basket data is *frequent itemsets* = sets of items that often appear together in baskets.
Example: Market Baskets

- If people often buy hamburger and ketchup together, the store can:
  1. Put hamburger and ketchup near each other and put potato chips between.
  2. Run a sale on hamburger and raise the price of ketchup.

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Finding Frequent Pairs

- The simplest case is when we only want to find “frequent pairs” of items.
- Assume data is in a relation Baskets(basket, item).
- The support threshold is the minimum number of baskets in which a pair appears before we are interested.
Frequent Pairs in SQL

```
SELECT b1.item, b2.item
FROM Baskets b1, Baskets b2
WHERE b1.basket = b2.basket
    AND b1.item < b2.item
GROUP BY b1.item, b2.item
HAVING COUNT(*) >= s;
```

Look for two Basket tuples with the same basket and different items. First item must precede second, so we don’t count the same pair twice.

Create a group for each pair of items that appears in at least one basket.

Throw away pairs of items that do not appear at least \( s \) times.
(Famous!) A-Priori Trick – (1)

- Straightforward implementation involves a join of a huge Baskets relation with itself.
- Anti-Monotonicity Property: The \textit{a-priori algorithm} speeds the query by recognizing that a pair of items \{i, j\} cannot have support \( s \) unless both \{i\} and \{j\} do.

R. Agrawal, T. Imielinski, A. Swami
‘Mining Association Rules between Sets of Items in Large Databases’, SIGMOD 1993.
A-Priori Trick – (2)

- Use a materialized view to hold only information about frequent items.

```
INSERT INTO Baskets1(basket, item)
SELECT * FROM Baskets
WHERE item IN (  
  SELECT item FROM Baskets
  GROUP BY item
  HAVING COUNT(*) >= s  
);
```

Items that appear in at least $s$ baskets.
A-Priori Algorithm

1. Materialize the view **Baskets1**.
2. Run the obvious query, but on **Baskets1** instead of **Baskets**.
   - Computing **Baskets1** is cheap, since it doesn’t involve a join.
   - **Baskets1** *probably* has many fewer tuples than **Baskets**.
     - Running time shrinks with the *square* of the number of tuples involved in the join.
Example: A-Priori

- Suppose:
  1. A supermarket sells 10,000 items.
  2. The average basket has 10 items.
  3. The support threshold is 1% of the baskets.

- At most 1/10 of the items can be frequent.
- *Probably*, the minority of items in one basket are frequent -> factor 4 speedup.
Conclusions

- Data Mining: of high commercial interest (think BIG data)
- DM = DB + Machine Learning + Stats.
- Data Warehousing/OLAP: to get the data
- Tree Classifiers
- Association Rules
- ..... (like clustering etc.)