CS 4604: Introduction to Database Management Systems

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Lecture #19: 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, ...)

BBURG
Data Ware-housing

First step: collect the data, in a single place (= Data Warehouse)

How?

How often?

How about discrepancies / non-homegeneities?
Data Ware-housing

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
Data Ware-housing

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.
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.
Star Schemas

- 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:
  
  Sales(bar, beer, drinker, day, time, 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.)
Dimensions and Dependent Attributes

- Two classes of fact-table attributes:
  1. *Dimension attributes*: the key of a dimension table.
  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;
  ```
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.
Example --- Continued

Here is a materialized view that could help:

```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;
```

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:

```sql
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:**
  
  \[ \text{Sales(bar, beer, drinker, time, price)} \]
  
  – for the Sales data, the four dimensions are \text{bar}, \text{beer}, \text{drinker}, and \text{time}.
- Dependent attributes (e.g., \text{price}) appear at the points of the cube.
Visualization -- Data Cubes
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

SUM over all Drinkers

prono
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,...
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>Jim</td>
<td>133</td>
<td>100</td>
<td>112</td>
</tr>
</tbody>
</table>

$ 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:
  
  \((\text{Joes, Bud, John, 4/19/13, 3.00})\)

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

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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 on Apr 19.
Tuples in SalesCube

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  \[(\text{Joes, Bud, John, 4/19/13, 3.00})\]

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  \[(\text{NULL, NULL, NULL, NULL, 2000000.00})\]

Total spent by John at Joes ever.
Tuples in SalesCube

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  \[(\text{Joes, Bud, John, 4/19/13, 3.00})\]

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

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

**ROLAP Solution**

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;

**MOLAP (Data Cube) Solution**

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

- A specific view for a specific type of query (note the join)
- 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>
</tbody>
</table>

Has heart disease
Supervised Learning: Decision Trees: Problem

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<th>Age</th>
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<tbody>
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<tr>
<td></td>
<td></td>
<td></td>
<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>
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What is the label for this new patient?
Supervised Learning: Decision Trees: Problem

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<th>?</th>
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</table>

Training Data Set
Decision trees

- Pictorially, we have

num. attr#1 (eg., ‘age’)

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

- and we want to label ‘?’

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

num. attr#1 (eg., ‘age’)

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Decision trees

- so we build a decision tree:

```
num. attr#1 (eg., 'age')

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

40

50

num. attr#1 (eg., 'age')
```
Decision trees

- so we build a decision tree:
Decision trees: Approach

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

- How?

num. attr#1 (eg., ‘age’)

num. attr#2 (eg., chol-level)
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?
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 - i.e., 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)
Unsupervised Learning: Market-Basket Data

- 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.
Finding Frequent Pairs

- The simplest case is when we only want to find “frequent pairs” of items.
- Assume data is in a relation \texttt{Baskets(basket, item)}.
- The \textit{support threshold} $s$ 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.

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
);
A-Priori Algorithm

1. Materialize the view $\text{Baskets}_1$.
2. Run the obvious query, but on $\text{Baskets}_1$ instead of $\text{Baskets}$.
   - Computing $\text{Baskets}_1$ is cheap, since it doesn’t involve a join.
   - $\text{Baskets}_1$ *probably* has many fewer tuples than $\text{Baskets}$.
     - 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.)