Data Mining: Concepts and Techniques

— Slides for Textbook —
— Chapter 4 —

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Top languages for analytics/data mining programming (KDD Nuggets Poll)

What programming/statistics languages you used for an analytics / data mining / data science work in 2013? [713 votes total] % users in 2013 % users in 2012 % users in 2011	
R (434 voters in 2013)	60.9% 52.5% 45.1%
Python (277)	38.8% 36.1% 24.6%
SQL (261)	36.6% 32.1% 32.3%
SAS (148)	20.8% 19.7% 21.2%
Java (118)	16.5% 21.2% 24.4%

Chapter 4: Data Mining Primitives, Languages, and System Architectures

- Data mining primitives: What defines a data mining task?
- A data mining query language
- Design graphical user interfaces based on a data mining query language
- Architecture of data mining systems
- Summary

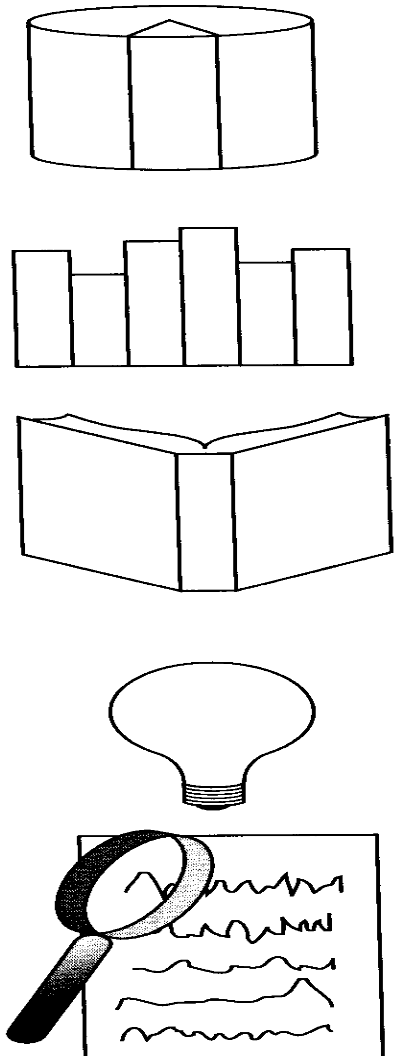
Why Data Mining Primitives and Languages?

- Finding all the patterns autonomously in a database? — unrealistic because the patterns could be too many but uninteresting
- Data mining should be an interactive process
  - User directs what to be mined
- Users must be provided with a set of primitives to be used to communicate with the data mining system
- Incorporating these primitives in a data mining query language
  - More flexible user interaction
  - Foundation for design of graphical user interface
  - Standardization of data mining industry and practice

What Defines a Data Mining Task ?

- Task-relevant data
- Type of knowledge to be mined
- Background knowledge
- Pattern interestingness measurements
- Visualization of discovered patterns

What Defines a Data Mining Task ?



Task-relevant data
Database or data warehouse name
Database tables or data warehouse cubes
Conditions for data selection
Relevant attributes or dimensions
Data grouping criteria

Knowledge type to be mined
Characterization
Discrimination
Association
Classification/prediction
Clustering

Background knowledge
Concept hierarchies
User beliefs about relationships in the data

Pattern interestingness measures
Simplicity
Certainty (e.g., confidence)
Utility (e.g., support)
Novelty

Visualization of discovered patterns
Rules, tables, reports, charts, graphs, decision trees, and cubes
Drill-down and roll-up

Figure 4.2 Primitives for specifying a data mining task.

Task-Relevant Data (Minable View)

- Database or data warehouse name
- Database tables or data warehouse cubes
- Condition for data selection
- Relevant attributes or dimensions
- Data grouping criteria

Types of knowledge to be mined

- Characterization
- Discrimination
- Association
- Classification/prediction
- Clustering
- Evolution analysis
- Outlier analysis
- Other data mining tasks

Background Knowledge: Concept Hierarchies

- Schema hierarchy: a total/partial order among attributes
  - E.g., street < city < province_or_state < country
- Set-grouping hierarchy: organizes values for a given attribute/dimension into groups of constants/ranges
  - E.g., {20-39} = young, {40-59} = middle_aged
- Operation-derived hierarchy: specified by users/experts/systems
  - email address: login-name < department < university < country
- Rule-based hierarchy: defined by set of rules
  - low_profit_margin (X) <= price(X, P1) and cost (X, P2) and (P1 - P2) < $50

Background Knowledge: Concept Hierarchies

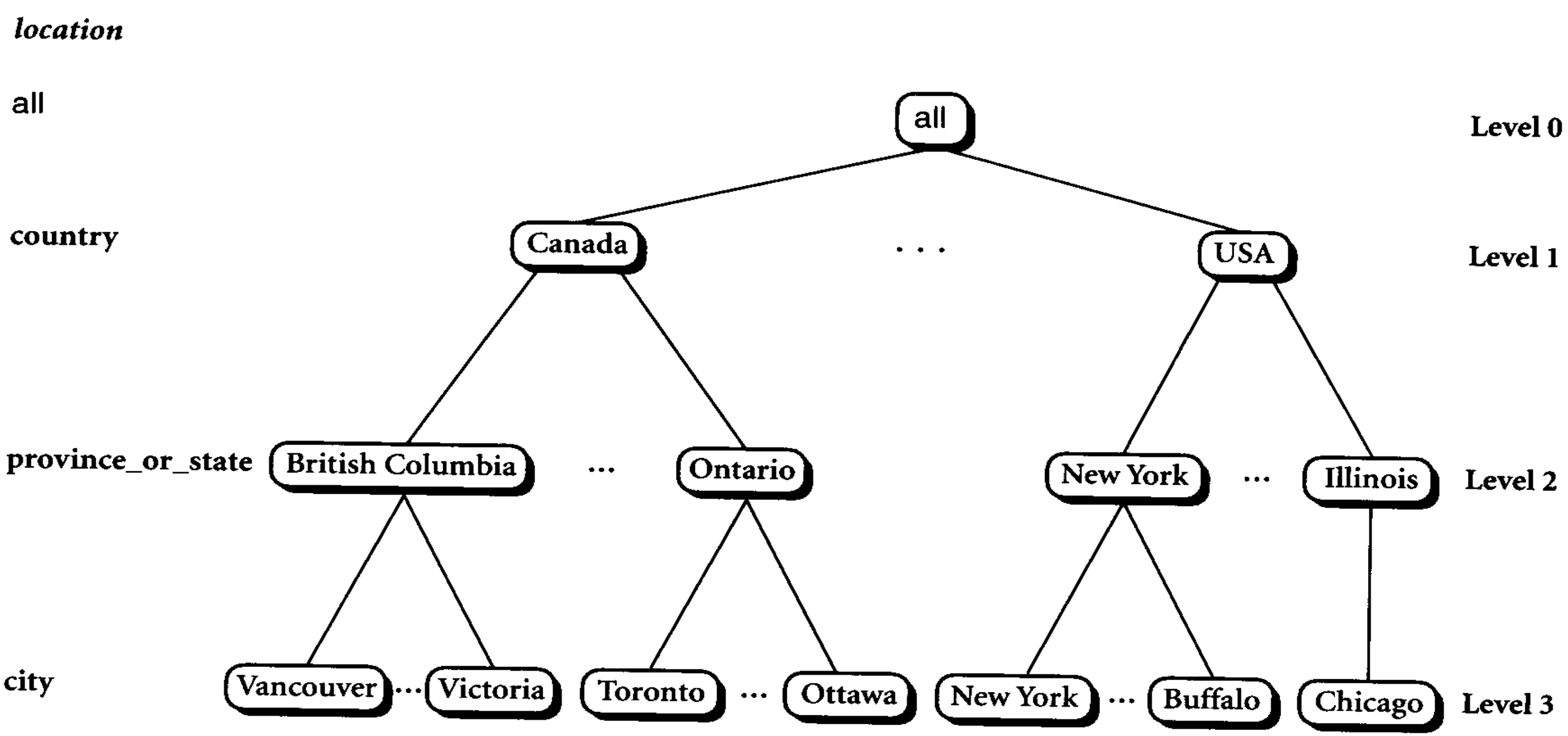


Figure 4.3 A concept hierarchy for the dimension *location*.

Measurements of Pattern Interestingness

- Simplicity

  e.g., (association) rule length, (decision) tree size
- Certainty

  e.g., confidence, $P(A|B) = n(A \text{ and } B)/ n(B)$, classification reliability or accuracy, certainty factor, rule strength, rule quality, discriminating weight, etc.
- Utility

  potential usefulness, e.g., support (association), noise threshold (description)
- Novelty

  not previously known, surprising (used to remove redundant rules, e.g., Canada vs. Vancouver rule implication support ratio

Visualization of Discovered Patterns

- Different backgrounds/usages may require different forms of representation
  - E.g., rules, tables, crosstabs, pie/bar chart etc.
- Concept hierarchy is also important
  - Discovered knowledge might be more understandable when represented at high level of abstraction
  - Interactive drill up/down, pivoting, slicing and dicing provide different perspective to data
- Different kinds of knowledge require different representation: association, classification, clustering, etc.

Visualization of Discovered Patterns

Rules

age(X, "young") and income(X, "high") => class(X, "A")
age(X, "young") and income(X, "low") => class(X, "B")
age(X, "old") => class(X, "C")

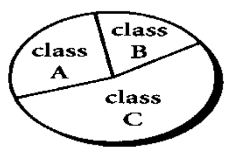
Table

age	income	class	count
young	high	A	1,402
young	low	B	1,038
old	high	C	786
old	low	C	1,374

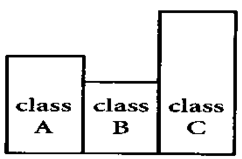
Crosstab

	income		class		
age	high	low	A	B	C
young	1,402	1,038	1,402	1,038	0
old	786	1,374	0	0	2,160
count	2,188	2,412	1,402	1,038	2,160

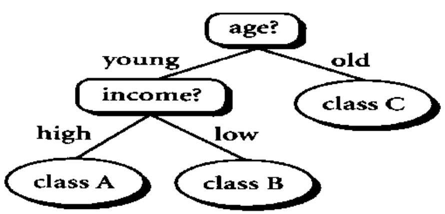
Pie chart



Bar chart



Decision tree



Data cube

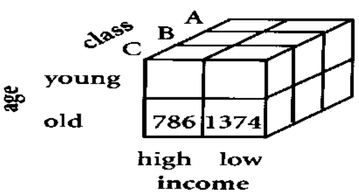


Figure 4.4 Various forms of presenting and visualizing the discovered patterns.

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A Data Mining Query Language (DMQL)

- Motivation
  - A DMQL can provide the ability to support ad-hoc and interactive data mining
  - By providing a standardized language like SQL
    - Hope to achieve a similar effect like that SQL has on relational database
    - Foundation for system development and evolution
    - Facilitate information exchange, technology transfer, commercialization and wide acceptance
- Design
  - DMQL is designed with the primitives described earlier

Syntax for DMQL

- Syntax for specification of
  - task-relevant data
  - the kind of knowledge to be mined
  - concept hierarchy specification
  - interestingness measure
  - pattern presentation and visualization
- Putting it all together — a DMQL query

Syntax for task-relevant data specification

- *use database* database_name, or *use data warehouse* data_warehouse_name
- *from relation*(s)/cube(s) [*where* condition]
- *in relevance to* att_or_dim_list
- *order by* order_list
- *group by* grouping_list
- *having* condition

Specification of task-relevant data

Example 4.11 This example shows how to use DMQL to specify the task-relevant data described in Example 4.1 for the mining of associations between items frequently purchased at *AllElectronics* by Canadian customers, with respect to customer *income* and *age*. In addition, the user specifies that she would like the data to be grouped by date. The data are retrieved from a relational database.

```
use database AllElectronics_db
in relevance to I.name, I.price, C.income, C.age
from customer C, item I, purchases P, items_sold S
where I.item_ID = S.item_ID and S.trans_ID = P.trans_ID and P.cust_ID = C.cust_ID
        and C.address = "Canada"
group by P.date
```

□

Syntax for specifying the kind of knowledge to be mined

- Characterization

  Mine_Knowledge_Specification ::=

  mine characteristics [*as* pattern_name]

  analyze measure(s)

- Discrimination

  Mine_Knowledge_Specification ::=

  mine comparison [*as* pattern_name]

  for target_class *where* target_condition

  {*versus* contrast_class_*i* *where* contrast_condition_*i*}

  analyze measure(s)

- Association

  Mine_Knowledge_Specification ::=

  mine associations [as pattern_name]

Syntax for specifying the kind of knowledge to be mined (cont.)

- Classification

  Mine_Knowledge_Specification ::=
  mine classification [*as* pattern_name]
  analyze classifying_attribute_or_dimension

- Prediction

  Mine_Knowledge_Specification ::=
  mine prediction [*as* pattern_name]
  analyze prediction_attribute_or_dimension
  {*set* {attribute_or_dimension_*i*= value_*i*}}

Syntax for concept hierarchy specification

- To specify what concept hierarchies to use

  use hierarchy **<hierarchy>** for **<attribute_or_dimension>**
- We use different syntax to define different type of hierarchies
  - schema hierarchies

    define hierarchy **time_hierarchy** on **date** as **[date,month quarter,year]**
  - set-grouping hierarchies

    define hierarchy **age_hierarchy** for **age** on **customer** as

    level1: {*young, middle_aged, senior*} < level0: all

    level2: {20, ..., 39} < level1: ***young***

    level2: {40, ..., 59} < level1: ***middle_aged***

    level2: {60, ..., 89} < level1: ***senior***

Syntax for concept hierarchy specification (Cont.)

- operation-derived hierarchies

  define hierarchy **age_hierarchy** for **age** on **customer** as

  {age_category(1), ..., age_category(5)} := cluster(default, age, 5) < all**(age)**

- rule-based hierarchies

  define hierarchy **profit_margin_hierarchy** on **item** as

  level_1: low_profit_margin < level_0: all

  if (price - cost)< $50

  level_1: medium-profit_margin < level_0: all

  if ((price - cost) > $50) and ((price - cost) <= $250))

  level_1: high_profit_margin < level_0: all

  if (price - cost) > $250

Syntax for interestingness measure specification

- Interestingness measures and thresholds can be specified by the user with the statement:

  with **<interest_measure_name>** threshold = **threshold_value**

- **Example:**

  with support threshold **= 0.05**

  with confidence threshold **= 0.7**

Syntax for pattern presentation and visualization specification

- We have syntax which allows users to specify the display of discovered patterns in one or more forms

  display as <**result_form**>

- To facilitate interactive viewing at different concept level, the following syntax is defined:

Multilevel_Manipulation ::= *roll up on* attribute_or_dimension
| *drill down on* attribute_or_dimension
| *add* attribute_or_dimension
| *drop* attribute_or_dimension

Putting it all together: the full specification of a DMQL query

use database **AllElectronics_db**

use hierarchy **location_hierarchy for B.address**

mine characteristics as **customerPurchasing**

analyze **count%**

in relevance to **C.age, I.type, I.place_made**

from **customer C, item I, purchases P, items_sold S, works_at W, branch**

where **I.item_ID = S.item_ID and S.trans_ID = P.trans_ID**

and P.cust_ID = C.cust_ID and P.method_paid = ``AmEx''

and P.empl_ID = W.empl_ID and W.branch_ID = B.branch_ID and B.address = ``Canada" and I.price >= 100

with **noise** threshold **= 0.05**

display as **table**

Introduction to R for Data Mining

- https://www.youtube.com/watch?v=6jT6Rit_5EQ
- https://www.youtube.com/watch?v=7cGwYMhPDUY

Introduction to Python for Data Mining

- http://www.lleess.com/2013/03/python-data-mining-resources.html#.VAyRChCOuZQ

Introduction to SQL for Data Mining

- **Data Mining Extensions** (DMX) is a query language for Data Mining Models supported by Microsoft's SQL Server Analysis Services product.
- http://msdn.microsoft.com/en-us/library/ms132058.aspx

Introduction to SQL for Data Mining

- **Data Definition Language**
- The Data Definition Language (DDL) part of DMX can be used to
- Create new data mining models and mining structures - CREATE MINING STRUCTURE, CREATE MINING MODEL
- Delete existing data mining models and mining structures - DROP MINING STRUCTURE, DROP MINING MODEL
- Export and import mining structures - EXPORT, IMPORT
- Copy data from one mining model to another - SELECT INTO

Introduction to SQL for Data Mining

- **Data Manipulation Language**
- The Data Manipulation Language (DML) part of DMX can be used to
- Train mining models - INSERT INTO
- Browse data in mining models - SELECT FROM
- Make predictions using mining model - SELECT ... FROM PREDICTION JOIN

Other Data Mining Languages & Standardization Efforts

- Association rule language specifications
  - MSQL (Imielinski & Virmani'99, Hughes Technologies)
  - MineRule (Meo Psaila and Ceri'96)
  - Query flocks based on Datalog syntax (Tsur et al'98)
- OLEDB for DM (Microsoft'2000)
  - Based on OLE, OLE DB, OLE DB for OLAP
  - Integrating DBMS, data warehouse and data mining
- CRISP-DM (CRoss-Industry Standard Process for Data Mining)
  - Providing a platform and process structure for effective data mining
  - Emphasizing on deploying data mining technology to solve business problems

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Designing Graphical User Interfaces based on a data mining query language

- What tasks should be considered in the design GUIs based on a data mining query language?
  - Data collection and data mining query composition
  - Presentation of discovered patterns
  - Hierarchy specification and manipulation
  - Manipulation of data mining primitives
  - Interactive multilevel mining
  - Other miscellaneous information

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Data Mining System Architectures

- Coupling data mining system with DB/DW system
  - No coupling—flat file processing, not recommended
  - Loose coupling
    - Fetching data from DB/DW
  - Semi-tight coupling—enhanced DM performance
    - Provide efficient implement a few data mining primitives in a DB/DW system, e.g., sorting, indexing, aggregation, histogram analysis, multiway join, precomputation of some stat functions
  - Tight coupling—A uniform information processing environment
    - DM is smoothly integrated into a DB/DW system, mining query is optimized based on mining query, indexing, query processing methods, etc.

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Summary

- Five primitives for specification of a data mining task
  - task-relevant data
  - kind of knowledge to be mined
  - background knowledge
  - interestingness measures
  - knowledge presentation and visualization techniques to be used for displaying the discovered patterns
- Data mining query languages
  - DMQL, MS/OLEDB for DM, etc.
- Data mining system architecture
  - No coupling, loose coupling, semi-tight coupling, tight coupling

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