DAT630
Introduction & Data

Introduction to Data Mining, Chapters 1-2

11/09/2017

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Introduction

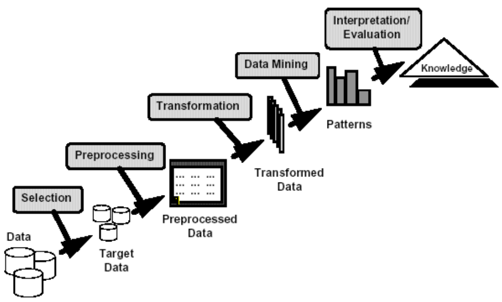
What is Data Mining?

- (Non-trivial) extraction of implicit, previously unknown and potentially useful information from data
- Exploration & analysis, by automatic or semi-automatic means, of large quantities of data in order to discover meaningful patterns
- **Process to automatically discover useful information in large data**

Motivating challenges

- Availability of large datasets, yet lack of techniques for extracting useful information.
- Challenges:
  - Scalability: by data structures and algorithms
  - High dimensionality: affecting effectiveness and efficiency
  - Heterogeneous, complex data
  - Integration of distributed data
  - Analysis: vs traditional statistical experiments

Typical Workflow



Data Mining Tasks

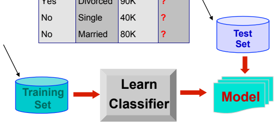
- Predictive methods
  - Use some variables to predict unknown or future values of other variables
- Descriptive methods
  - Find human-interpretable patterns that describe the data

Classification (predictive)

- Given a collection of records (training set), find a model that can automatically assign a class attribute (as a function of the values of other attributes) to previously unseen records

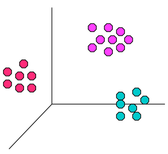
Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Refund	Marital Status	Taxable Income	Cheat
No	Single	75K	?
Yes	Married	50K	?
No	Married	150K	?
Yes	Divorced	90K	?
No	Single	40K	?
No	Married	80K	?



Clustering (descriptive)

- Given a set of data points, each having a set of attributes, find clusters such that
  - Data points in one cluster are more similar to one another
  - Data points in separate clusters are less similar to one another



Types of Data

What is data?

- Collection of data objects and their attributes
- An **attribute** (a.k.a. feature, variable, field, component, etc.) is a property or characteristic of an object
- A collection of attributes describe an **object** (a.k.a. record, instance, observation, example, sample, vector)

Attributes

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Objects

Attribute properties

- The type of an attribute depends on which of the following properties it possesses:
  - Distinctness: = !=
  - Order: < > <= >=
  - Addition: + -
  - Multiplication: * /

Types of attributes

- Nominal
  - ID numbers, eye color, zip codes
- Ordinal
  - Rankings (e.g., taste of potato chips on a scale from 1-10), grades, height in {tall, medium, short}
- Interval
  - Calendar dates, temperatures in C or F degrees.
- Ratio
  - Temperature in Kelvin, length, time, **counts**
- Coarser types: **categorical** and **numeric**

Attribute types

Attribute type		Description	Examples
Categorical (qualitative)	**Nominal**	Only enough information to distinguish (=, !=)	ID numbers, eye color, zip codes
	Ordinal	Enough information to order (<, >)	grades {A,B,…F} street numbers
Numeric (quantitative)	**Interval**	The differences between values are meaningful (+, -)	calendar dates, temperature in Celsius or Farenheit
	Ratio	Both differences and ratios between values are meaningful (*, /)	temperature in Kelvin, monetary values, age, length, mass

Transformations

Attribute type	Transformation	Comment
Nominal	Any permutation of values	If all employee ID numbers were reassigned, would it make any difference?
Ordinal	An order preserving change: *new_value = f(old_value)* where f is a monotonic function	{good, better, best} can be represented equally well by the values {1, 2, 3}
Interval	*new_value =a * old_value + b* where a and b are constants	The Fahrenheit and Celsius temperature scales differ in terms of where their zero
Ratio	*new_value = a * old_value*	Length can be measured in meters or feet

Discrete vs. continuous attributes

- Discrete attribute
  - Has only a finite or countably infinite set of values
  - Examples: zip codes, counts, or the set of words in a collection of documents
  - Often represented as integer variables
- Continuous attribute
  - Has real numbers as attribute values
  - Examples: temperature, height, or weight.
  - Typically represented as floating-point variables

Asymmetric attributes

- Only presence counts (i.e., only non-zero attribute values)

	team	coach	play	ball	score	game	win	lost	timeout	season
Document 1	3	0	5	0	2	6	0	2	0	2
Document 2	0	7	0	2	1	0	0	3	0	0
Document 3	0	1	0	0	1	2	2	0	3	0

Examples

- Time in terms of AM or PM
  - Binary, qualitative, ordinal
- Brightness as measured by a light meter
  - Continuous, quantitative, ratio
- Brightness as measured by people's judgments
  - Discrete, qualitative, ordinal

Examples

- Angles as measured in degrees between 0○ and 360○
  - Continuous, quantitative, ratio
- Bronze, Silver, and Gold medals as awarded at the Olympics
  - Discrete, qualitative, ordinal
- ISBN numbers for books
  - Discrete, qualitative, nominal

Characteristics of Structured Data

- Dimensionality
  - Curse of Dimensionality
- Sparsity
  - Only presence counts
- Resolution
  - Patterns depend on the scale

Types of data sets

- Record
  - Data Matrix
  - Document Data
  - Transaction Data
- Graph
- Ordered

Record Data

- Consists of a collection of records, each of which consists of a fixed set of attributes

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
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9	No	Married	75K	No
10	No	Single	90K	Yes

Data Matrix

- Data objects have the same fixed set of numeric attributes
  - Can be represented by an m by n matrix
  - Data objects can be thought of as points in a multi-dimensional space, where each dimension represents a distinct attribute

Projection of x Load	Projection of y load	Distance	Load	Thickness
10.23	5.27	15.22	2.7	1.2
12.65	6.25	16.22	2.2	1.1

Document Data

- Documents are represented as **term vectors**
  - each term is a component (attribute) of the vector
  - the value of each component is the number of times the corresponding term occurs in the document

	team	coach	pla y	ball	score	game	wi n	lost	timeout	season
Document 1	3	0	5	0	2	6	0	2	0	2
Document 2	0	7	0	2	1	0	0	3	0	0
Document 3	0	1	0	0	1	2	2	0	3	0

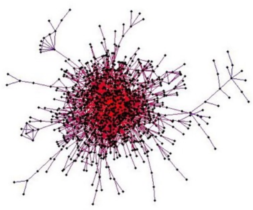
Transaction Data

- A special type of record data, where each record (transaction) involves a set of items
  - For example, the set of products purchased by a customer (during one shopping trip) constitute a transaction, while the individual products that were purchased are the items

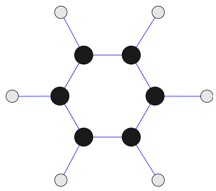
TID	*Items*
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

Graph Data

- Examples



HTML links



Chemical data

Ordered Data

- Sequences of transactions

Items/Events

(A B) (D) (C E)
(B D) (C) (E)
(C D) (B) (A E)

An element of the sequence

Ordered Data

- Genomic sequence data

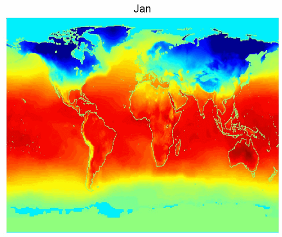
```
GGTTCCGCCTTCAGCCCCGCGCC
CGCAGGGCCCGCCCCGCGCCGTC
GAGAAGGGCCCGCCTGGCGGGCG
GGGGGAGGCGGGGCCGCCCGAGC
CCAACCGAGTCCGACCAGGTGCC
CCCTCTGCTCGGCCTAGACCTGA
GCTCATTAGGCGGCAGCGGACAG
GCCAAGTAGAACACGCGAAGCGC
TGGGCTGCCTGCTGCGACCAGGG
```

Ordered Data

- Spatio-temporal Data

Jan

Average Monthly Temperature of land and ocean



Non-record Data

- Often converted into record data
  - For example: presence of substructures in a set, just like the transaction items
  - Ordered data conversion might lose explicit representations of relationships

Data Quality

Data Quality Problems

- Data won't be perfect
  - Human error
  - Limitations of measuring devices
  - Flaws in the data collection process
- **Data is of high quality if it is suitable for its intended use**
- Much work in data mining focuses on devising robust algorithms that produce acceptable results even when noise is present

Typical Data Quality Problems

- Noise
  - Random component of a measurement error
  - For example, distortion of a person's voice when talking on a poor phone
- Outliers
  - Data objects with characteristics that are considerably different than most of the other data objects in the data set

Typical Data Quality Problems (2)

- Missing values
  - Information is not collected
    - E.g., people decline to give their age and weight
  - Attributes may not be applicable to all cases
    - E.g., annual income is not applicable to children
- Solutions
  - Eliminate an entire object or attribute
  - Estimate them by neighbor values
  - Ignore them during analysis

Typical Data Quality Problems (3)

- Inconsistent data
  - Data may have some inconsistencies even among present, acceptable values
  - E.g. Zip code value doesn't correspond to the city value
- Duplicate data
  - Data objects that are duplicates, or almost duplicates of one another
    - E.g., Same person with multiple email addresses

Quality Issues from the Application viewpoint

- Timeliness:
  - Aging of data implies aging of patterns on it
- Relevance:
  - of the attributes modeling objects
  - of the objects as representative of the population
- Knowledge of data:
  - Availability of documentation about type of features, origin, scales, missing values representation

Data Preprocessing

Data Preprocessing

- Different strategies and techniques to make the data more suitable for data mining
  - Aggregation
  - Sampling
  - Dimensionality reduction
  - Feature subset selection
  - Feature creation
  - Discretization and binarization
  - Attribute transformation

Aggregation

- Combining two or more attributes (or objects) into a single attribute (or object)
- Purpose
  - Data reduction
    - Reduce the number of attributes or objects
  - Change of scale
    - Cities aggregated into regions, states, countries, etc
  - More “stable” data
    - Aggregated data tends to have less variability

Sampling

- Selecting a subset of the data objects to be analyzed
  - Statisticians sample because *obtaining* the entire set of data of interest is too expensive or time consuming
  - Sampling is used in data mining because *processing* the entire set of data of interest is too expensive or time consuming

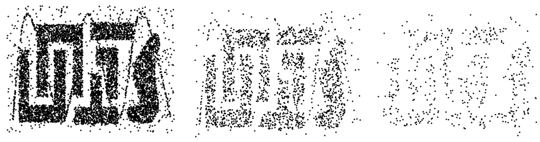
Sampling

- A sample is **representative** if it has approximately the same property (of interest) as the original set of data
- Key issues: sampling method and sample size

Types of Sampling

- Simple random sampling
  - Any particular item is selected with equal probability
  - Sampling without replacement
    - As each item is selected, it is removed from the population
  - Sampling with replacement
    - Objects are not removed from the population as they are selected (same object can be picked up more than once)
- Stratified sampling
  - Split the data into several partitions; then draw random samples from each partition

Sample size



8000 points 2000 Points 500 Points

Curse of Dimensionality

- Many types of data analysis become significantly harder as the dimensionality of the data increases
  - When dimensionality increases, data becomes increasingly sparse in the space that it occupies
  - Definitions of density and distance between points become less meaningful

Dimensionality Reduction

- Purpose
  - Avoid curse of dimensionality
  - Reduce amount of time and memory required by data mining algorithms
  - Allow data to be more easily visualized
  - May help to eliminate irrelevant features or reduce noise
- Techniques
  - Linear algebra techniques
  - Feature subset selection

Linear Algebra Techniques

- Project the data from a high-dimensional space into a lower-dimensional space
- Principal Component Analysis (PCA)
  - Find new attributes (principal components) that are
    - linear combinations of the original attributes
    - orthogonal to each other
    - capture the maximum amount of variation in the data
  - See http://setosa.io/ev/principal-component-analysis/
- Singular Value Decomposition (SVD)

Feature Subset Selection

- Redundant features
  - Duplicate much or all of the information contained in one or more other attributes
  - Example: purchase price of a product and the amount of sales tax paid
- Irrelevant features
  - Contain no information that is useful for the data mining task at hand
  - Example: students' ID is often irrelevant to the task of predicting students' GPA

Feature Subset Selection Approaches

- Brute-force approach
  - Try all possible feature subsets as input to data mining algorithm
- Embedded approaches
  - Feature selection occurs naturally as part of the data mining algorithm
- Filter approaches
  - Features are selected before data mining algorithm is run
- Wrapper approaches
  - Use the data mining algorithm as a black box to find best subset of attributes

Feature Subset Selection Architecture

- Search
  - Tradeoff between complexity and optimality
- Evaluation
  - A way to predict goodness of the selection
- Stopping
  - E.g. number of iterations; evaluation regarding threshold; size of feature subset
- Validation
  - Comparing performance for selected subset, vs another selections (or the full set)

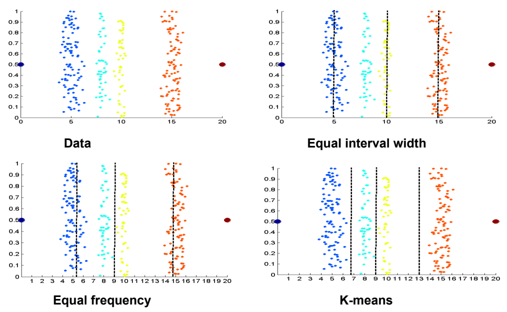
Feature Creation

- Create from the original attributes a new set of attributes that captures the important information more effectively
  - Feature extraction
    - E.g. pixels vs higher-level features in face recognition
  - Mapping data to a new space
    - E.g. recovering frequencies from noisy time series
  - Feature construction
    - E.g. constructing density (using given mass and volume) for material classification

Binarization and Discretization

- Binarization: converting a categorical attribute to binary values
- Discretization: transforming a continuous attribute to a categorical attribute
  - Decide how many categories to have
  - Determine how to map the values of the continuous attribute to these categories
    - Unsupervised: equal width, equal frequency
    - Supervised

Discretization Without Using Class Labels



Attribute Transformation

- A function that maps the entire set of values of a given attribute to a new set of replacement values such that each old value can be identified with one of the new values
- Simple functions: x^k, $\log(x)$, e^x, $|x|$, $\sin x$, $\text{sqrt}\ x$, $\log x$, $1/x$, …
- Normalization: when different variables are to be combined in some way

Proximity Measures

Proximity

- Proximity refers to either **similarity** or **dissimilarity** between two objects
- Similarity
  - Numerical measure of how alike two data objects are; higher when objects are more alike
  - Often falls in the range [0,1]
- Dissimilarity
  - Numerical measure of how different are two data objects; lower when objects are more alike
  - Falls in the interval [0,1] or [0,infinity)

Transformations

- To convert a similarity to a dissimilarity or vice versa
- To transform a proximity measure to fall within a certain range (e.g., [0,1])
- Min-max normalization

$$s' = \frac{s - min_s}{max_s - min_s}$$

(Dis)similarity for a Single Attribute

Attribute Type	Dissimilarity	Similarity
Nominal	$d = \begin{cases} 0 & \text{if } p = q \\ 1 & \text{if } p \neq q \end{cases}$	$s = \begin{cases} 1 & \text{if } p = q \\ 0 & \text{if } p \neq q \end{cases}$
Ordinal	$d = \frac{\lvert p-q \rvert}{n-1}$ (values mapped to integers 0 to $n-1$, where n is the number of values)	$s = 1 - \frac{\lvert p-q \rvert}{n-1}$
Interval or Ratio	$d = \lvert p - q \rvert$	$s = -d$, $s = \frac{1}{1+d}$ or $s = 1 - \frac{d - min\_d}{max\_d - min\_d}$

Table 5.1. Similarity and dissimilarity for simple attributes

Example

- Objects with a single original attribute that measures the quality of the product
- {poor, fair, OK, good, wonderful}
- poor=0, fair=1, OK=2, good=3, wonderful=4
- What is the similarity between p="good" and p="wonderful"?

$$s = 1 - \frac{|p-q|}{n-1} = 1 - \frac{|3-4|}{5-1} = 1 - \frac{1}{4} = 0.75$$

Dissimilarities between Data Objects

- Some examples of **distances** to show the desired properties of a dissimilarity
- Objects have n attributes; x_k is the k*th* attribute
- **Euclidean distance**

$$d(x,y) = \sqrt{\sum_{k=1}^{n} (x_k - y_k)^2}$$

Minkowski Distance

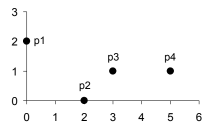
- Generalization of the Euclidean Distance

$$d(x,y) = \Big(\sum_{k=1}^{n} |x_k - y_k|^r\Big)^{1/r}$$

- r=1 City block (Manhattan) distance (L_1 norm)
- r=2 Euclidean distance (L_2 norm)
- r= ∞ Supremum distance (L_{max} norm)
  - Max difference between any attribute of the objects

$$d(x,y) = \lim_{r\to\infty} \Big(\sum_{k=1}^{n} |x_k - y_k|^r\Big)^{1/r}$$

Example
Eucledian Distance

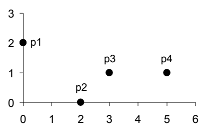


point	x	y
p1	0	2
p2	2	0
p3	3	1
p4	5	1

L2	p1	p2	p3	p4
p1	0	2.828	3.162	5.099
p2	2.828	0	1.414	3.162
p3	3.162	1.414	0	2
p4	5.099	3.162	2	0

Distance Matrix

Example
Manhattan Distance

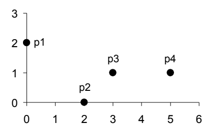


point	x	y
p1	0	2
p2	2	0
p3	3	1
p4	5	1

L1	p1	p2	p3	p4
p1	0	4	4	6
p2	4	0	2	4
p3	4	2	0	2
p4	6	4	2	0

Distance Matrix

Example
Supremum Distance



point	x	y
p1	0	2
p2	2	0
p3	3	1
p4	5	1

L_∞	p1	p2	p3	p4
p1	0	2	3	5
p2	2	0	1	3
p3	3	1	0	2
p4	5	3	2	0

Distance Matrix

Distance Properties

1. Positivity
   - d(x,y) >= 0 for all x and y
   - d(x,y) = 0 only if x=y
2. Symmetry
   - d(x,y) = d(y,x) for all x and y
3. Triangle Inequality
   - d(x,z) <= d(x,y) + d(y,z) for all x, y, and z

- A measurement that satisfies these properties is a **metric**. A distance is a metric dissimilarity

Similarity Properties

1. s(x,y) = 1 only if x=y
2. x(x,y) = s(y,x) (Symmetry)

- There is no general analog of the triangle inequality
- Some similarity measures can be converted to a metric distance
  - E.g., Jaccard similarity

Similarity between Binary Vectors

- Common situation is that objects, p and q, have only binary attributes
  - f_{01} = the number of attributes where p was 0 and q was 1
  - f_{10} = the number of attributes where p was 1 and q was 0
  - f_{00} = the number of attributes where p was 0 and q was 0
  - f_{11} = the number of attributes where p was 1 and q was 1

Similarity between Binary Vectors

- Simple Matching Coefficient
  - number of matching attribute values divided by the number of attributes

$$SMC = \frac{f_{11} + f_{00}}{f_{01} + f_{10} + f_{11} + f_{00}}$$

- Jaccard Coefficient
  - Ignore 0-0 matches

$$J = \frac{f_{11}}{f_{01} + f_{10} + f_{11}}$$

SMC versus Jaccard

p = 1 0 0 0 0 0 0 0 0 0
q = 0 0 0 0 0 0 1 0 0 1

f_{01} = 2 (the number of attributes where p was 0 and q was 1)
f_{10} = 1 (the number of attributes where p was 1 and q was 0)
f_{00} = 7 (the number of attributes where p was 0 and q was 0)
f_{11} = 0 (the number of attributes where p was 1 and q was 1)

SMC = (f_{11} + f_{00})/(f_{01} + f_{10} + f_{11} + f_{00}) = (0+7) / (2+1+0+7) = 0.7

J = (f_{11}) / (f_{01} + f_{10} + f_{11}) = 0 / (2 + 1 + 0) = 0

Cosine similarity

- Similarity for real-valued vectors
- Objects have n attributes; x_k is the *k*th attribute

vector dot product

$$cos(x, y) = \frac{\boxed{\mathbf{x} \cdot \mathbf{y}}}{\boxed{||\mathbf{x}||}\,\boxed{||\mathbf{y}||}} \qquad \mathbf{x} \cdot \mathbf{y} \longrightarrow \sum_{i=1}^{k} x_k y_k$$

length of vector

$$\sqrt{\sum_{i=1}^{k} x_k^2} \qquad \sqrt{\sum_{i=1}^{k} y_k^2}$$

Example

	attr 1	attr 2	attr 3	attr 4	attr 5
x	1	0	1	0	3
y	0	2	4	0	1

$$cos(x, y) = \frac{\mathbf{x} \cdot \mathbf{y}}{||\mathbf{x}||\,||\mathbf{y}||} \qquad \mathbf{x} \cdot \mathbf{y} \longrightarrow \sum_{i=1}^{k} x_k y_k$$

$$\sqrt{\sum_{i=1}^{k} x_k^2} \qquad \sqrt{\sum_{i=1}^{k} y_k^2}$$

Example

	attr 1	attr 2	attr 3	attr 4	attr 5
x	1	0	1	0	3
y	0	2	4	0	1

$$cos(x, y) = \frac{\mathbf{x} \cdot \mathbf{y}}{||\mathbf{x}||\,||\mathbf{y}||} \qquad \mathbf{x} \cdot \mathbf{y} \longrightarrow \sum_{i=1}^{k} x_k y_k$$

7/(3.31*4.58)=**0.46**

1*0+0*2+1*4+0*0+3*1=**7**

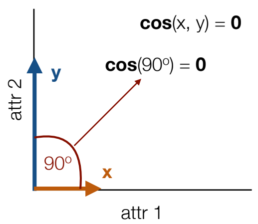
$$\sqrt{\sum_{i=1}^{k} x_k^2} \qquad \sqrt{\sum_{i=1}^{k} y_k^2}$$

sqrt($1^2+0^2+1^2+0^2+3^2$)=sqrt(11)=**3.31**

sqrt($0^2+2^2+4^2+0^2+1^2$)=sqrt(21)=**4.58**

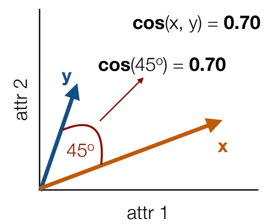
Geometric Interpretation

	attr 1	attr 2
x	1	0
y	0	2



Geometric Interpretation

	attr 1	attr 2
x	4	2
y	1	3



Geometric Interpretation

	attr 1	attr 2
x	1	2
y	2	4