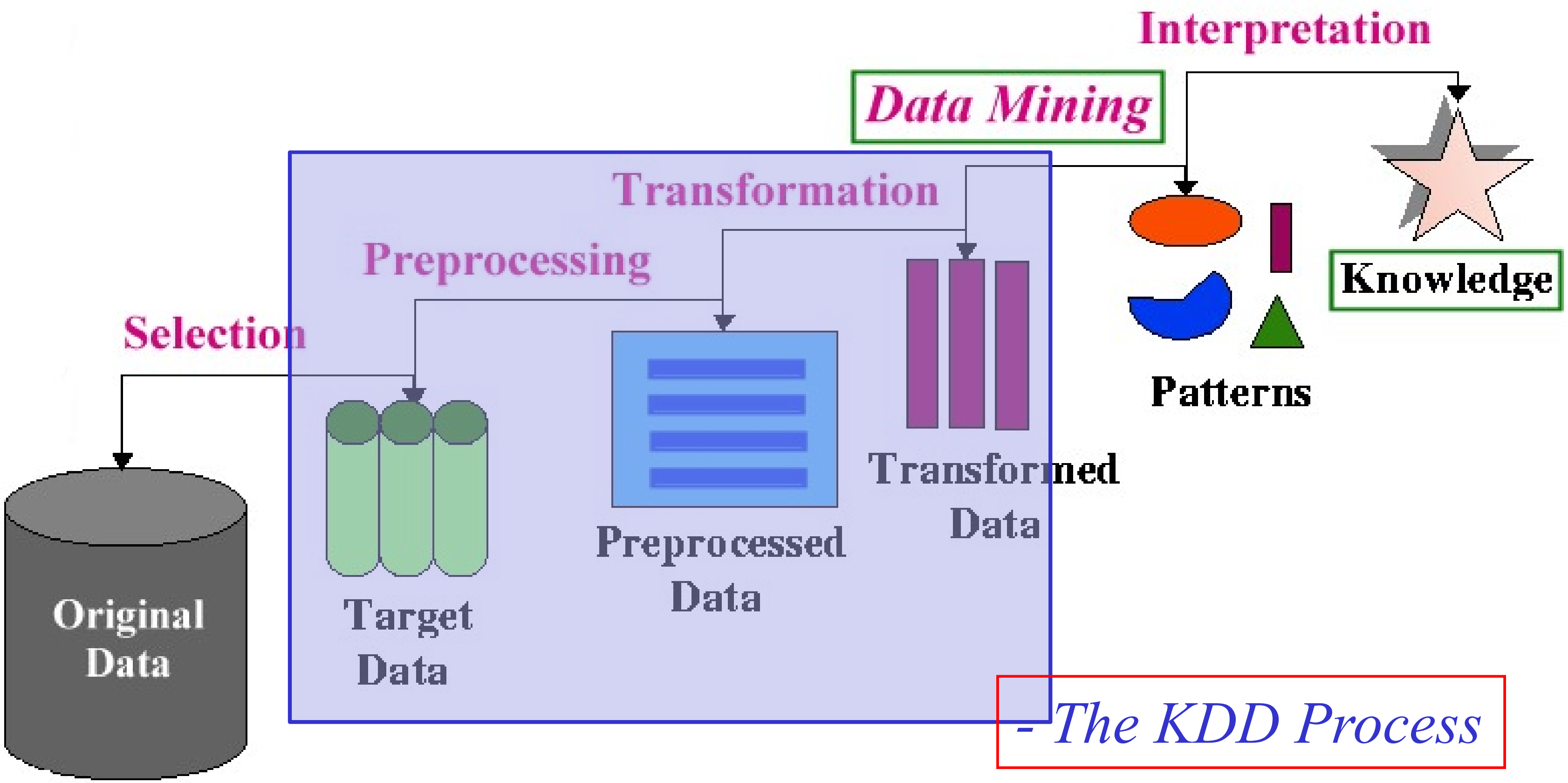
CSE450: Data Mining
Summer 2018

SAH @ DIU

The Knowledge Discovery Process

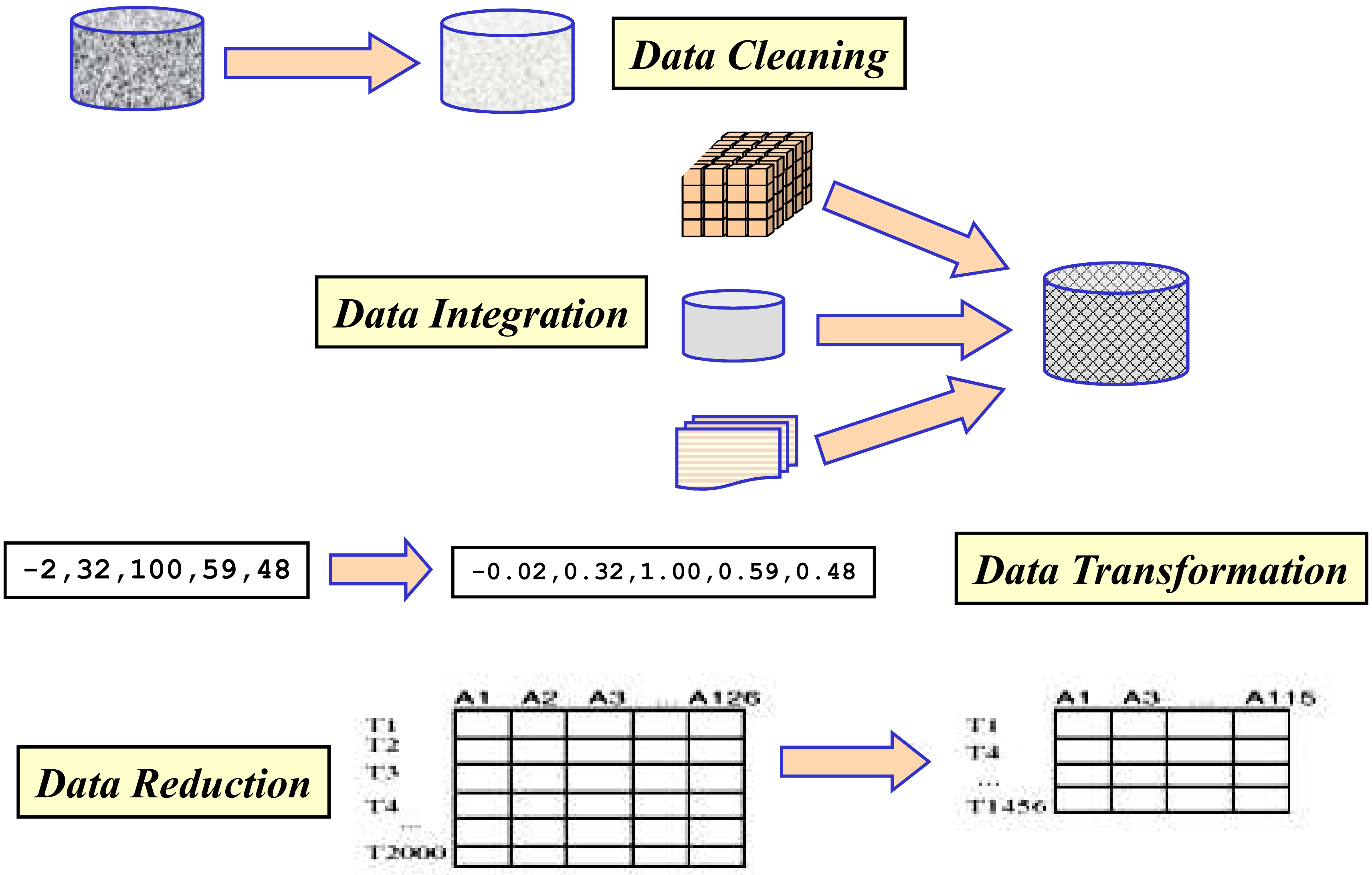


Data Preprocessing

- **Why do we need to prepare the data?**
  - In real world applications data can be **inconsistent**, **incomplete** and/or **noisy**
    - Data entry, data transmission, or data collection problems
    - Discrepancy in naming conventions
    - Duplicated records
    - Incomplete or missing data
    - Contradictions in data
- **What happens when the data can not be trusted?**
  - Can the decision be trusted? Decision making is jeopardized

  - Better chance to discover useful knowledge when data is clean

Data Preprocessing



Data Cleaning

- **Real-world application data can be incomplete, noisy, and inconsistent**
  - No recorded values for some attributes
  - Not considered at time of entry
  - Random errors
  - Irrelevant records or fields

- **Data cleaning attempts to:**
  - Fill in missing values
  - Smooth out noisy data
  - Correct inconsistencies
  - Remove irrelevant data

Dealing with Missing Values

- **Solving the Missing Data Problem**
  - Ignore the record with missing values;
  - Fill in the missing values manually;
  - Use a global constant to fill in missing values (NULL, unknown, etc.);
  - Use the attribute value mean to filling missing values of that attribute;
  - Use the attribute mean for all samples belonging to the same class to fill in the missing values;
  - Infer the most probable value to fill in the missing value
    - may need to use methods such as Bayesian classification or decision trees to automatically infer missing attribute values

Smoothing Noisy Data

- **The purpose of data smoothing is to eliminate noise and "smooth out" the data fluctuations.**

Ex: Original Data for "price" (after sorting): 4, 8, 15, 21, 21, 24, 25, 28, 34

Binning →

Partition into equidepth bins
Bin1: 4, 8, 15
Bin2: 21, 21, 24
Bin3: 25, 28, 34

Each value in a bin is replaced by the mean value of the bin.

means
Bin1: 9, 9, 9
Bin2: 22, 22, 22
Bin3: 29, 29, 29

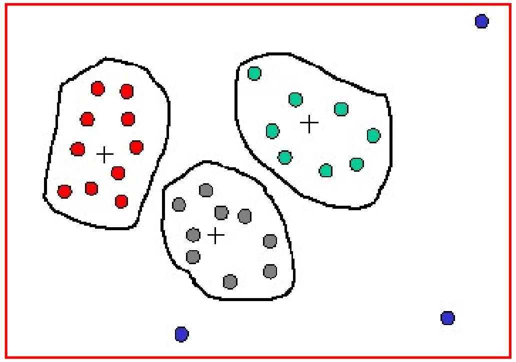
boundaries
Bin1: 4, 4, 15
Bin2: 21, 21, 24
Bin3: 25, 25, 34

Min and Max values in each bin are identified (boundaries). Each value in a bin is replaced with the closest boundary value.

Smoothing Noisy Data

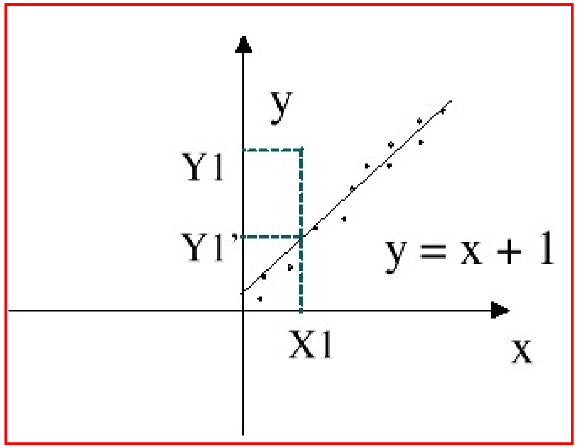
- **Other Methods**

Clustering



Similar values are organized into groups (clusters). Values falling outside of clusters may be considered "outliers" and may be candidates for elimination.

Regression



Fit data to a function. Linear regression finds the best line to fit two variables. Multiple regression can handle multiple variables. The values given by the function are used instead of the original values.

Smoothing Noisy Data - Example

Want to smooth "Temperature" by bin means with bins of size 3:

1. First sort the values of the attribute (keep track of the ID or key so that the transformed values can be replaced in the original table.
2. Divide the data into bins of size 3 (or less in case of last bin).
3. Convert the values in each bin to the mean value for that bin
4. Put the resulting values into the original table

ID	Outlook	Temperature	Humidity	Windy
1	sunny	85	85	FALSE
2	sunny	80	90	TRUE
3	overcast	83	78	FALSE
4	rain	70	96	FALSE
5	rain	68	80	FALSE
6	rain	65	70	TRUE
7	overcast	58	65	TRUE
8	sunny	72	95	FALSE
9	sunny	69	70	FALSE
10	rain	71	80	FALSE
11	sunny	75	70	TRUE
12	overcast	73	90	TRUE
13	overcast	81	75	FALSE
14	rain	75	80	TRUE

ID	Temperature	
7	58	Bin1
6	65	
5	68	
9	69	Bin2
4	70	
10	71	
8	72	Bin3
12	73	
11	75	
14	75	Bin4
2	80	
13	81	
3	83	Bin5
1	85	

Smoothing Noisy Data - Example

ID	Temperature	
7	58	Bin1
6	65	
5	68	
9	69	Bin2
4	70	
10	71	
8	72	Bin3
12	73	
11	75	
14	75	Bin4
2	80	
13	81	
3	83	Bin5
1	85	

ID	Temperature	
7	64	Bin1
6	64	
5	64	
9	70	Bin2
4	70	
10	70	
8	73	Bin3
12	73	
11	73	
14	79	Bin4
2	79	
13	79	
3	84	Bin5
1	84	

Value of every record in each bin is changed to the mean value for that bin. If it is necessary to keep the value as an integer, then the mean values are rounded to the nearest integer.

Smoothing Noisy Data - Example

The final table with the new values for the Temperature attribute.

ID	Outlook	Temperature	Humidity	Windy
1	sunny	84	85	FALSE
2	sunny	79	90	TRUE
3	overcast	84	78	FALSE
4	rain	70	96	FALSE
5	rain	64	80	FALSE
6	rain	64	70	TRUE
7	overcast	64	65	TRUE
8	sunny	73	95	FALSE
9	sunny	70	70	FALSE
10	rain	70	80	FALSE
11	sunny	73	70	TRUE
12	overcast	73	90	TRUE
13	overcast	79	75	FALSE
14	rain	79	80	TRUE

Data Integration

- **Data analysis may require a combination of data from multiple sources into a coherent data store**
- **Challenges in Data Integration:**
  - Schema integration: CID = C_number = Cust-id = cust#
  - Semantic heterogeneity
  - Data value conflicts (different representations or scales, etc.)
  - Synchronization (especially important in Web usage mining)
  - Redundant attributes (redundant if it can be derived from other attributes) -- may be able to identify redundancies via correlation analysis:

Pr(A,B) / (Pr(A).Pr(B))
= 1: independent,
> 1: positive correlation,
< 1: negative correlation.

- **Meta-data is often necessary for successful data integration**

Data Transformation: Normalization

- **Min-max normalization: linear transformation from v to v'**
  - v' = [(v - min)/(max - min)] x (newmax - newmin) + newmin
  - Note that if the new range is [0..1], then this simplifies to

    v' = [(v - min)/(max - min)]
  - Ex: transform $30000 between [10000..45000] into [0..1] ==>

    [(30000 – 10000) / 35000] = 0.514

- **z-score normalization: normalization of v into v' based on attribute value mean and standard deviation**
  - v' = (v - Mean) / StandardDeviation

- **Normalization by decimal scaling**
  - moves the decimal point of v by *j* positions such that *j* is the minimum number of positions moved so that absolute maximum value falls in [0..1].
  - $v' = v / 10^j$
  - Ex: if v in [-56 .. 9976] and *j*=4 ==> v' in [-0.0056 .. 0.9976]

Normalization: Example

- z-score normalization: v' = (v - Mean) / Stdev
- Example: normalizing the "Humidity" attribute:

Humidity
85
90
78
96
80
70
65
95
70
80
70
90
75
80

Mean = 80.3
Stdev = 9.84

Humidity
0.48
0.99
-0.23
1.60
-0.03
-1.05
-1.55
1.49
-1.05
-0.03
-1.05
0.99
-0.54
-0.03

Normalization: Example II

- **Min-Max normalization on an employee database**
  - max distance for salary: 100000-19000 = 81000
  - max distance for age: 52-27 = 25
  - New min for age and salary = 0; new max for age and salary = 1

$$x'_i = \frac{x_i - \min x_i}{\max x_i - \min x_i}(new\max - new\min) + new\min$$

ID	Gender	Age	Salary
1	F	27	19,000
2	M	51	64,000
3	M	52	100,000
4	F	33	55,000
5	M	45	45,000

ID	Gender	Age	Salary
1	1	0.00	0.00
2	0	0.96	0.56
3	0	1.00	1.00
4	1	0.24	0.44
5	0	0.72	0.32

Data Transformation: Discretization

- **3 Types of attributes**
  - nominal - values from an unordered set (also "categorical" attributes)
  - ordinal - values from an ordered set
  - numeric/continuous - real numbers (but sometimes also integer values)
- **Discretization is used to reduce the number of values for a given continuous attribute**
  - usually done by dividing the range of the attribute into intervals
  - interval labels are then used to replace actual data values
- **Some data mining algorithms only accept categorical attributes and cannot handle a range of continuous attribute value**
- **Discretization can also be used to generate concept hierarchies**
  - reduce the data by collecting and replacing low level concepts (e.g., numeric values for "age") by higher level concepts (e.g., "young", "middle aged", "old")

Discretization - Example

- **Example: discretizing the “Humidity” attribute using 3 bins.**

Humidity
85
90
78
96
80
70
65
95
70
80
70
90
75
80

Low = 60-69
Normal = 70-79
High = 80+

Humidity
High
High
Normal
High
High
Normal
Low
High
Normal
High
Normal
High
Normal
High

Data Discretization Methods

- **Binning**
  - Top-down split, unsupervised
- **Histogram analysis**
  - Top-down split, unsupervised
- **Clustering analysis**
  - Unsupervised, top-down split or bottom-up merge
- **Decision-tree analysis**
  - Supervised, top-down split
- **Correlation (e.g., $\chi 2$) analysis**
  - Unsupervised, bottom-up merge

Simple Discretization: Binning

- **Equal-width (distance) partitioning**
  - Divides the range into N intervals of equal size: uniform grid
  - if A and B are the lowest and highest values of the attribute, the width of intervals will be: $W = (B - A)/N$.
  - The most straightforward, but outliers may dominate presentation
  - Skewed data is not handled well
- **Equal-depth (frequency) partitioning**
  - Divides the range into N intervals, each containing approximately same number of samples
  - Good data scaling
  - Managing categorical attributes can be tricky

Discretization by Classification & Correlation Analysis

- **Classification (e.g., decision tree analysis)**
  - Supervised: Given class labels, e.g., cancerous vs. benign
  - Using entropy to determine split point (discretization point)
  - Top-down, recursive split
- **Correlation analysis (e.g., Chi-merge: χ2-based discretization)**
  - Supervised: use class information
  - Bottom-up merge: merge the best neighboring intervals (those with similar distributions of classes, i.e., low χ2 values)
  - Merge performed recursively, until a predefined stopping condition

Converting Categorical Attributes to Numerical Attributes

ID	Outlook	Temperature	Humidity	Windy
1	sunny	85	85	FALSE
2	sunny	80	90	TRUE
3	overcast	83	78	FALSE
4	rain	70	96	FALSE
5	rain	68	80	FALSE
6	rain	65	70	TRUE
7	overcast	58	65	TRUE
8	sunny	72	95	FALSE
9	sunny	69	70	FALSE
10	rain	71	80	FALSE
11	sunny	75	70	TRUE
12	overcast	73	90	TRUE
13	overcast	81	75	FALSE
14	rain	75	80	TRUE

Attributes:

Outlook (overcast, rain, sunny)
Temperature real
Humidity real
Windy (true, false)

Create separate columns for each value of a categorical attribute (e.g., 3 values for the Outlook attribute and two values of the Windy attribute). There is no change to the numerical attributes.

Standard Spreadsheet Format

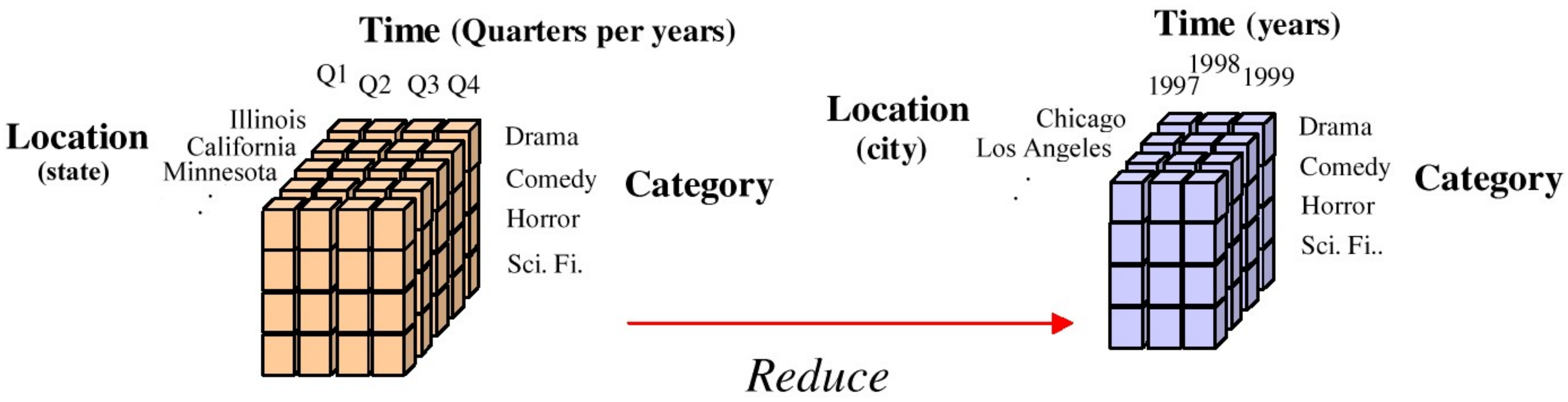
OutLook overcast	OutLook rain	OutLook sunny	Temp	Humidity	Windy TRUE	Windy FALSE
0	0	1	85	85	0	1
0	0	1	80	90	1	0
1	0	0	83	78	0	1
0	1	0	70	96	0	1
0	1	0	68	80	0	1
0	1	0	65	70	1	0
1	0	0	64	65	1	0
.	.	.	.	.	.	.
.	.	.	.	.	.	.

Data Reduction

- **Data is often too large; reducing data can improve performance**
- **Data reduction consists of reducing the representation of the data set while producing the same (or almost the same) results**
- **Data reduction includes:**
  - Data cube aggregation
  - Dimensionality reduction
  - Discretization
  - Numerosity reduction
    - Regression
    - Histograms
    - Clustering
    - Sampling

Data Cube Aggregation

- **Reduce the data to the concept level needed in the analysis**
  - Use the smallest (most detailed) level necessary to solve the problem



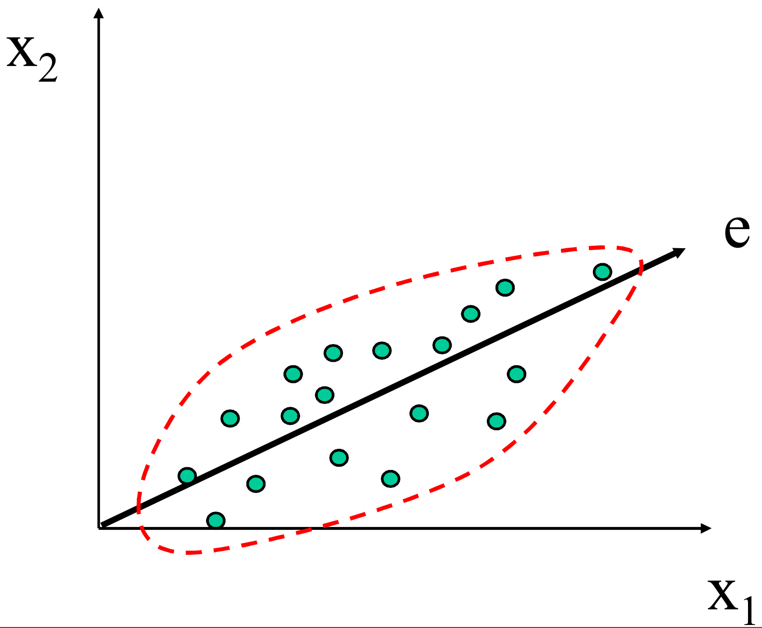
- **Queries regarding aggregated information should be answered using data cube when possible**

Dimensionality Reduction

- **Curse of dimensionality**
  - When dimensionality increases, data becomes increasingly sparse
  - Density and distance between points, which is critical to clustering, outlier analysis, becomes less meaningful
  - The possible combinations of subspaces will grow exponentially
- **Dimensionality reduction**
  - Avoid the curse of dimensionality
  - Help eliminate irrelevant features and reduce noise
  - Reduce time and space required in data mining
  - Allow easier visualization
- **Dimensionality reduction techniques**
  - Principal Component Analysis
  - Attribute subset selection
  - Attribute or feature generation

Principal Component Analysis (PCA)

- **Find a projection that captures the largest amount of variation in data**
- **The original data are projected onto a much smaller space, resulting in dimensionality reduction**
  - Done by finding the eigenvectors of the covariance matrix, and these eigenvectors define the new space



Principal Component Analysis (Steps)

- **Given *N* data vectors (rows in a table) from *n* dimensions (attributes), find *k* ≤ *n* orthogonal vectors (*principal components*) that can be best used to represent data**
  - Normalize input data: Each attribute falls within the same range
  - Compute *k* orthonormal (unit) vectors, i.e., *principal components*
  - Each input data (vector) is a linear combination of the *k* principal component vectors
  - The principal components are sorted in order of decreasing "significance" or strength
  - The size of the data can be reduced by eliminating the *weak components*, i.e., those with low variance
    - Using the strongest principal components, it is possible to reconstruct a good approximation of the original data
- **Works for numeric data only**

Attribute Subset Selection

- **Another way to reduce dimensionality of data**
- **Redundant attributes**
  - Duplicate much or all of the information contained in one or more other attributes
  - E.g., purchase price of a product and the amount of sales tax paid
- **Irrelevant attributes**
  - Contain no information that is useful for the data mining task at hand
  - E.g., students' ID is often irrelevant to the task of predicting students' GPA

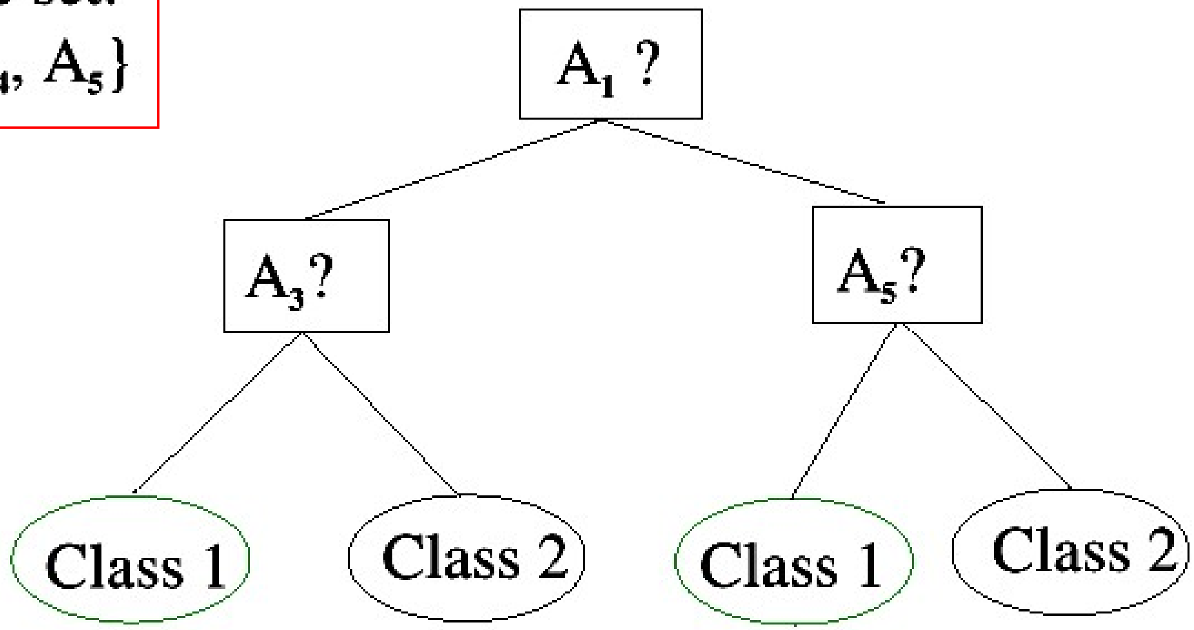
Heuristic Search in Attribute Selection

- **There are 2^d possible attribute combinations of d attributes**
- **Typical heuristic attribute selection methods:**
  - Best single attribute under the attribute independence assumption: choose by significance tests
  - Best step-wise feature selection:
    - The best single-attribute is picked first. Then next best attribute condition to the first, ...
    - {}{A1}{A1, A3}{A1, A3, A5}
  - Step-wise attribute elimination:
    - Repeatedly eliminate the worst attribute: {A1, A2, A3, A4, A5}{A1, A3, A4, A5} {A1, A3, A5}, ….
  - Combined attribute selection and elimination
  - Decision Tree Induction

Decision Tree Induction

Use information theoretic techniques to select the most "informative" attributes

Initial attribute set:
$\{A_1, A_2, A_3, A_4, A_5\}$



------> Reduced attribute set: $\{A_1, A_3, A_5\}$

Attribute Creation (Feature Generation)

- **Create new attributes (features) that can capture the important information in a data set more effectively than the original ones**
- **Three general methodologies**
  - Attribute extraction
    - Domain-specific
  - Mapping data to new space (see: data reduction)
    - E.g., Fourier transformation, wavelet transformation, etc.
  - Attribute construction
    - Combining features
    - Data discretization

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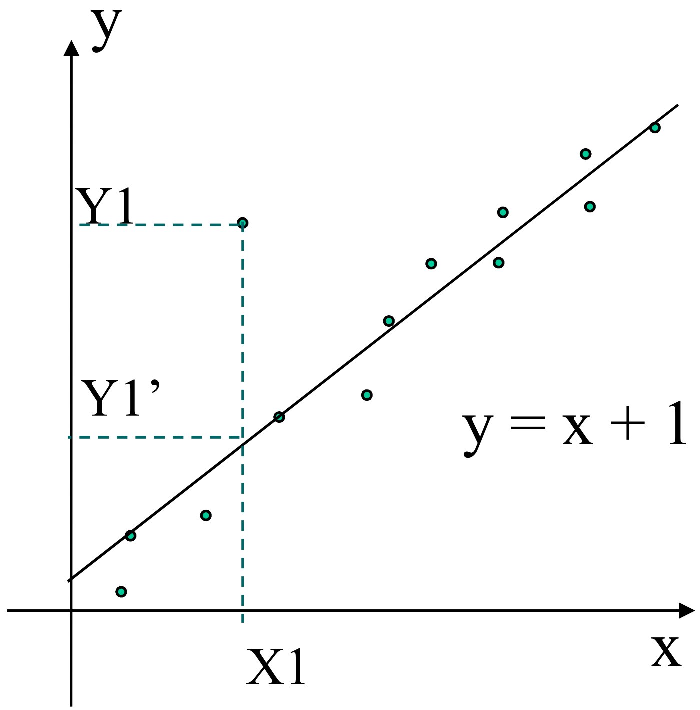
Data Reduction: Numerosity Reduction

- **Reduce data volume by choosing alternative, *smaller forms* of data representation**
- **Parametric methods (e.g., regression)**
  - Assume the data fits some model, estimate model parameters, store only the parameters, and discard the data (except possible outliers)
  - Ex.: Log-linear models—obtain value at a point in *m*-D space as the product on appropriate marginal subspaces
- **Non-parametric methods**
  - Do not assume models
  - Major families: histograms, clustering, sampling, …

Regression Analysis

- **Collection of techniques for the modeling and analysis of numerical data consisting of values of a *dependent variable* (also *response variable* or *measurement*) and of one or more *independent variables* (aka. *explanatory variables* or *predictors*)**
- **The parameters are estimated to obtains a "best fit" of the data**
- **Typically the best fit is evaluated by using the least squares method, but other criteria have also been used**



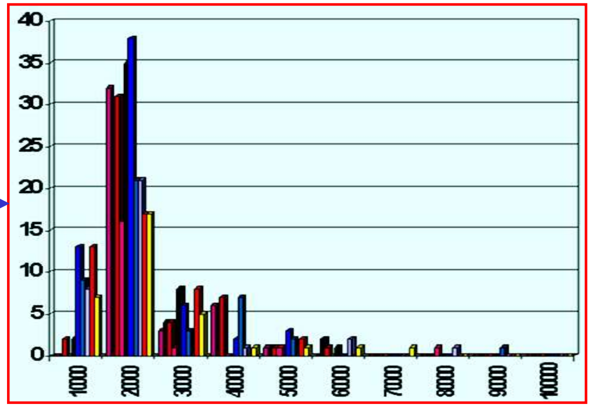
- **Used for prediction (including forecasting of time-series data), inference, hypothesis testing, and modeling of causal relationships**

Regression Analysis

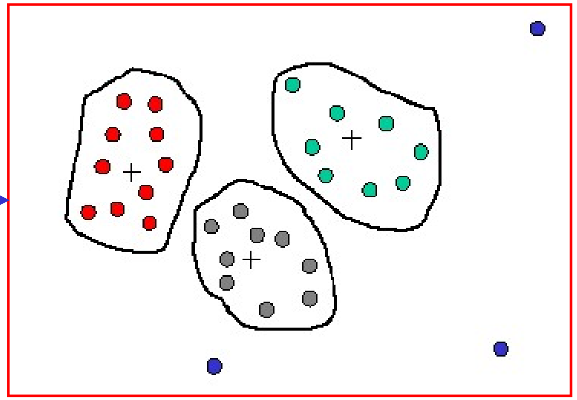
- **Linear regression:** $Y = w X + b$
  - Two regression coefficients, *w* and *b,* specify the line and are to be estimated by using the data at hand
  - Using the least squares criterion on known values of Y_1, Y_2, …, X_1, X_2, ….
- **Multiple regression:** $Y = b_0 + b_1 X_1 + b_2 X_2$
  - Many nonlinear functions can be transformed into the above
- **Log-linear models**
  - Approximate discrete multidimensional probability distributions
  - Estimate the probability of each point in a multi-dimensional space for a set of discretized attributes, based on a smaller subset of dimensions
  - Useful for dimensionality reduction and data smoothing

Numerocity Reduction

- **Reduction via histograms:**
  - Divide data into buckets and store representation of buckets (sum, count, etc.)



- **Reduction via clustering**
  - Partition data into clusters based on "closeness" in space
  - Retain representatives of clusters (centroids) and outliers



- **Reduction via sampling**
  - Will the patterns in the sample represent the patterns in the data?
  - Random sampling can produce poor results
  - Stratified sample (stratum = group based on attribute value)

Sampling Techniques