

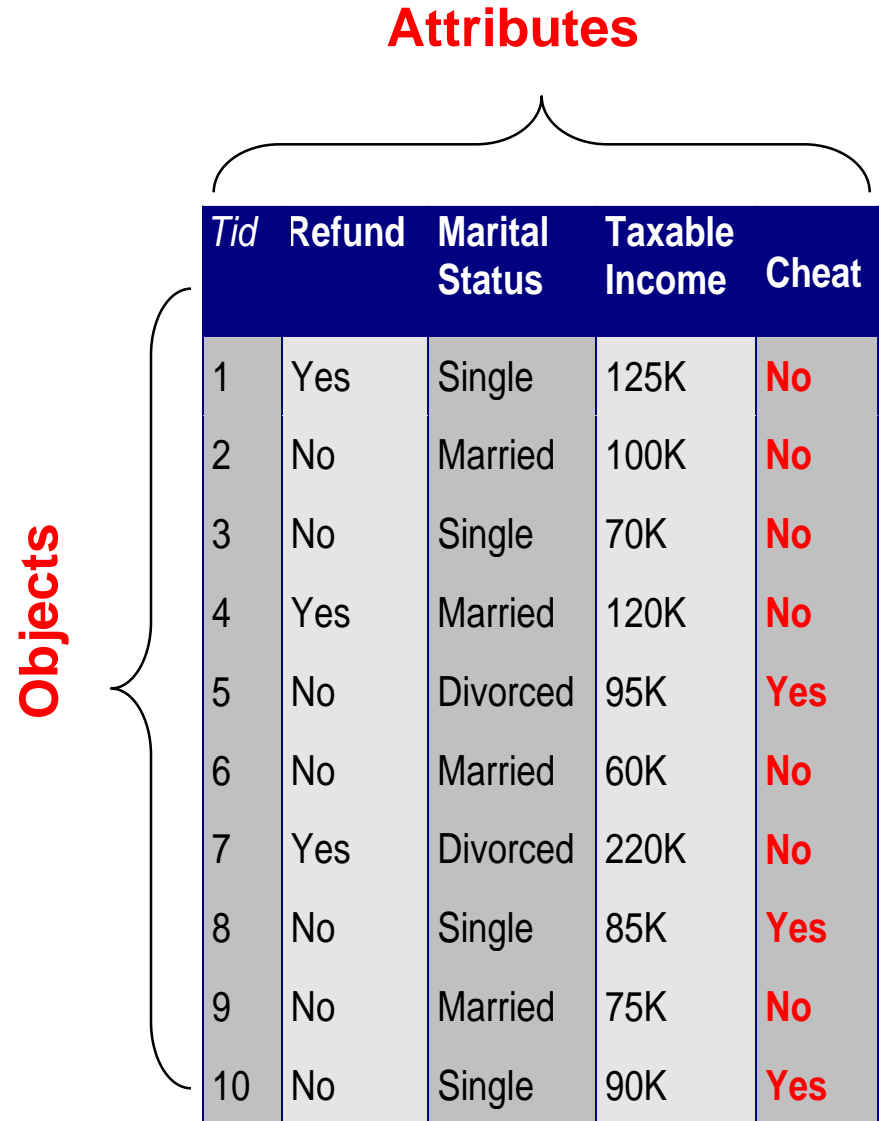
Data Preprocessing

Outline

- Attributes and Objects
- Types of Data
- Data Quality
- Similarity and Distance
- Data Preprocessing

What is Data?

- Collection of **data objects** and their **attributes**
- An **attribute** is a property or characteristic of an object
 - Examples: eye color of a person, temperature, etc.
 - Attribute is also known as variable, field, characteristic, dimension, or feature
- A collection of attributes describe an **object**
 - Object is also known as record, point, case, sample, entity, or instance



The diagram illustrates the relationship between data objects and attributes. A table contains 10 rows and 5 columns. The columns are labeled 'Tid', 'Refund', 'Marital Status', 'Taxable Income', and 'Cheat'. The rows are numbered 1 through 10. A red bracket labeled 'Attributes' spans the top of the columns. A red bracket labeled 'Objects' spans the left side of the rows.

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

A More Complete View of Data

- Data may have parts
- The different parts of the data may have relationships
- More generally, data may have structure
- Data can be incomplete
- We will discuss this in more detail later

Attribute Values

- **Attribute values** are numbers or symbols assigned to an attribute for a particular object
- Distinction between attributes and attribute values
 - Same attribute can be mapped to different attribute values
 - ◆ Example: height can be measured in feet or meters
 - Different attributes can be mapped to the same set of values
 - ◆ Example: Attribute values for ID and age are integers
 - ◆ But properties of attribute values can be different

Measurement of Length

- The way you measure an attribute may not match the attributes properties.



Types of Attributes

- There are different types of attributes
 - **Nominal**
 - ◆ Examples: ID numbers, eye color, zip codes
 - **Ordinal**
 - ◆ Examples: rankings (e.g., taste of potato chips on a scale from 1-10), grades, height {tall, medium, short}
 - **Interval**
 - ◆ Examples: calendar dates, temperatures in Celsius or Fahrenheit.
 - **Ratio**
 - ◆ Examples: temperature in Kelvin, length, time, counts

Properties of Attribute Values

- The type of an attribute depends on which of the following properties/operations it possesses:
 - Distinctness: $= \neq$
 - Order: $< >$
 - Differences are meaningful : $+ -$
 - Ratios are meaningful $* /$
 - Nominal attribute: distinctness
 - Ordinal attribute: distinctness & order
 - Interval attribute: distinctness, order & meaningful differences
 - Ratio attribute: all 4 properties/operations

Difference Between Ratio and Interval

- Is it physically meaningful to say that a temperature of 10° is twice that of 5° on
 - the Celsius scale?
 - the Fahrenheit scale?
 - the Kelvin scale?
- Consider measuring the height above average
 - If Bill's height is three inches above average and Bob's height is six inches above average, then would we say that Bob is twice as tall as Bill?
 - Is this situation analogous to that of temperature?

		Attribute Type	Description	Examples	Operations
Categorical Qualitative		Nominal	Nominal attribute values only distinguish. (=, ≠)	zip codes, employee ID numbers, eye color, sex: { <i>male</i> , <i>female</i> }	mode, entropy, contingency correlation, χ^2 test
		Ordinal	Ordinal attribute values also order objects. (<, >)	hardness of minerals, { <i>good</i> , <i>better</i> , <i>best</i> }, grades, street numbers	median, percentiles, rank correlation, run tests, sign tests
Numeric Quantitative		Interval	For interval attributes, differences between values are meaningful. (+, -)	calendar dates, temperature in Celsius or Fahrenheit	mean, standard deviation, Pearson's correlation, <i>t</i> and <i>F</i> tests
		Ratio	For ratio variables, both differences and ratios are meaningful. (*, /)	temperature in Kelvin, monetary quantities, counts, age, mass, length, current	geometric mean, harmonic mean, percent variation

This categorization of attributes is due to S. S. Stevens

		Attribute Type	Transformation	Comments
Categorical Qualitative		Nominal	Any permutation of values	If all employee ID numbers were reassigned, would it make any difference?
		Ordinal	An order preserving change of values, i.e., $new_value = f(old_value)$ where f is a monotonic function	An attribute encompassing the notion of good, better best can be represented equally well by the values {1, 2, 3} or by { 0.5, 1, 10}.
Numeric Quantitative		Interval	$new_value = a * old_value + b$ where a and b are constants	Thus, the Fahrenheit and Celsius temperature scales differ in terms of where their zero value is and the size of a unit (degree).
		Ratio	$new_value = a * old_value$	Length can be measured in meters or feet.

This categorization of attributes is due to S. S. Stevens

Discrete and 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.
- Note: **binary attributes** are a special case of discrete attributes

- Continuous Attribute

- Has real numbers as attribute values
- Examples: temperature, height, or weight.
- Practically, real values can only be measured and represented using a finite number of digits.
- Continuous attributes are typically represented as floating-point variables.

Asymmetric Attributes

- Only presence (a non-zero attribute value) is regarded as important
 - ◆ Words present in documents
 - ◆ Items present in customer transactions
- If we met a friend in the grocery store would we ever say the following?

“I see our purchases are very similar since we didn’t buy most of the same things.”
- We need two asymmetric binary attributes to represent one ordinary binary attribute
 - Association analysis uses asymmetric attributes
- Asymmetric attributes typically arise from objects that are sets

Types of data sets

- Record
 - Data Matrix
 - Document Data
 - Transaction Data
- Graph
 - World Wide Web
 - Molecular Structures
- Ordered
 - Spatial Data
 - Temporal Data
 - Sequential Data
 - Genetic Sequence Data

Important Characteristics of Data

- Dimensionality (number of attributes)
 - ◆ High dimensional data brings a number of challenges
- Sparsity
 - ◆ Only presence counts
- Resolution
 - ◆ Patterns depend on the scale
- Size
 - ◆ Type of analysis may depend on size of data

Record Data

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

<i>Tid</i>	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
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Data Matrix

- If data objects have the same fixed set of numeric attributes, then the data objects can be thought of as points in a multi-dimensional space, where each dimension represents a distinct attribute
- Such data set can be represented by an m by n matrix, where there are m rows, one for each object, and n columns, one for each 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

- Each document becomes a 'term' vector
 - 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	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

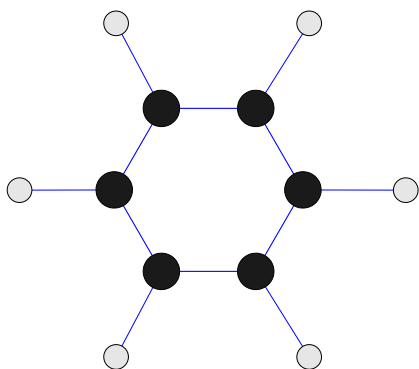
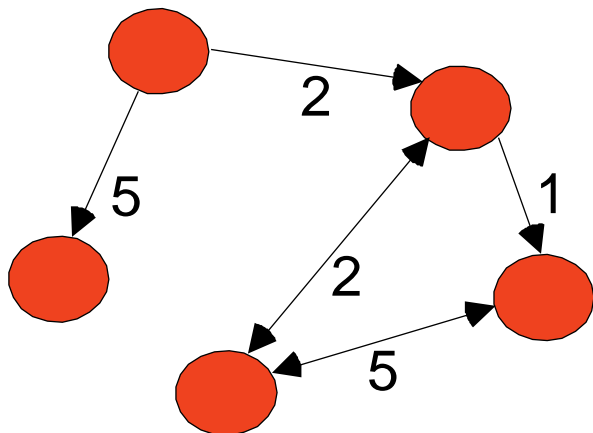
Transaction Data

- A special type of record data, where
 - Each record (transaction) involves a set of items.
 - For example, consider a grocery store. 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.

<i>TID</i>	<i>Items</i>
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

Graph Data

- Examples: Generic graph, a molecule, and webpages



Benzene Molecule: C₆H₆

Useful Links:

- [Bibliography](#)
- Other Useful Web sites
 - [ACM SIGKDD](#)
 - [KDnuggets](#)
 - [The Data Mine](#)

Knowledge Discovery and Data Mining Bibliography

(Gets updated frequently, so visit often!)

- [Books](#)
- [General Data Mining](#)

Book References in Data Mining and Knowledge Discovery

Usama Fayyad, Gregory Piatetsky-Shapiro, Padhraic Smyth, and Ramasamy uthurasamy, "Advances in Knowledge Discovery and Data Mining", AAAI Press/the MIT Press, 1996.

J. Ross Quinlan, "C4.5: Programs for Machine Learning", Morgan Kaufmann Publishers, 1993.
Michael Berry and Gordon Linoff, "Data Mining Techniques (For Marketing, Sales, and Customer Support)", John Wiley & Sons, 1997.

General Data Mining

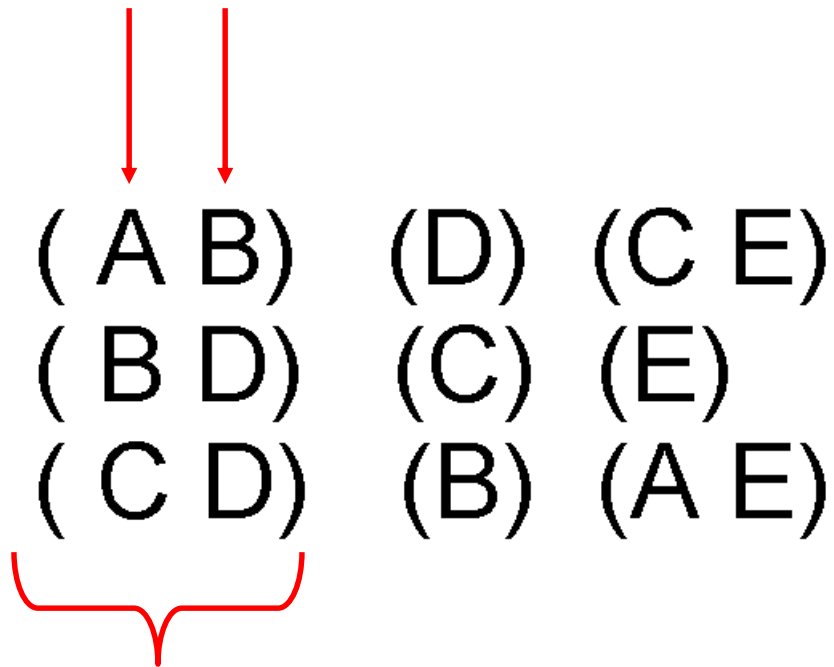
Usama Fayyad, "Mining Databases: Towards Algorithms for Knowledge Discovery", Bulletin of the IEEE Computer Society Technical Committee on data Engineering, vol. 21, no. 1, March 1998.

Christopher Matheus, Philip Chan, and Gregory Piatetsky-Shapiro, "Systems for knowledge Discovery in databases", IEEE Transactions on Knowledge and Data Engineering, 5(6):903-913, December 1993.

Ordered Data

- Sequences of transactions

Items/Events



**An element of
the sequence**

Ordered Data

- Genomic sequence data

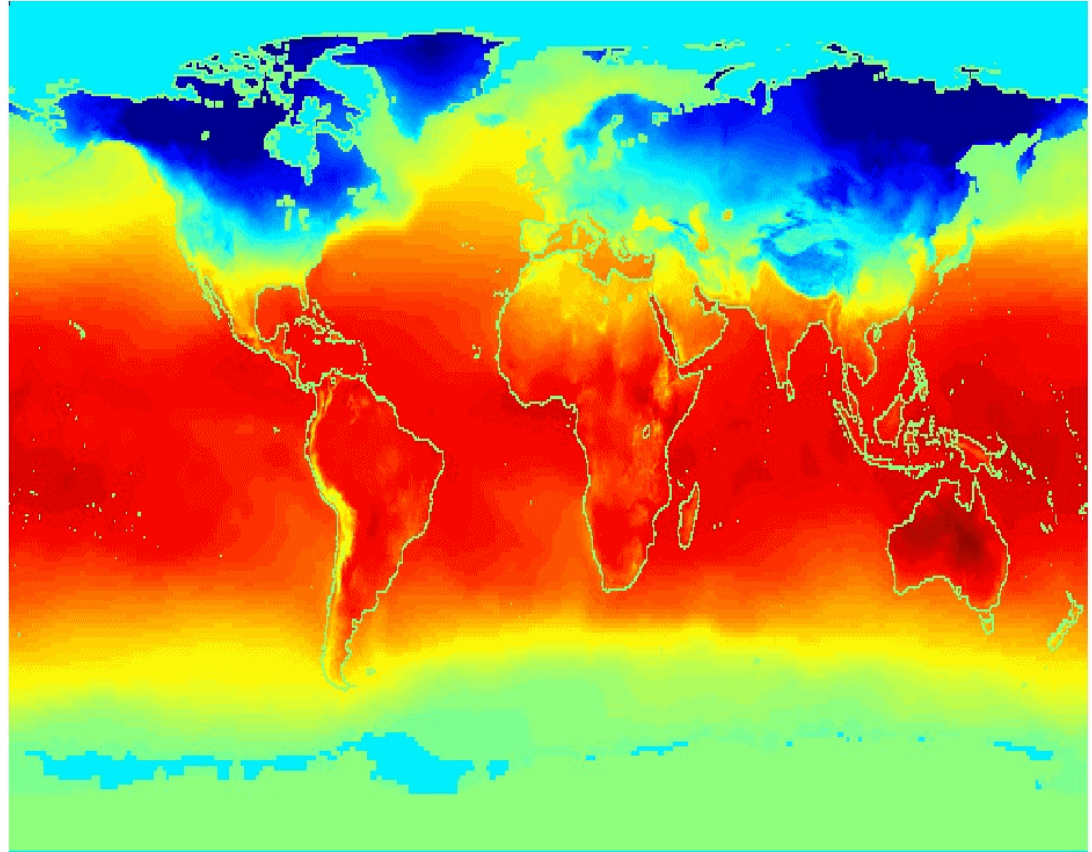
**GGTTCCGCCTTCAGCCCCGCGCC
CGCAGGGGCCCGCCCCGCGCCGTC
GAGAAGGGCCCGCCTGGCGGGCG
GGGGGAGGCGGGGCCCGCCCGAGC
CCAACCGAGTCCGACCAGGTGCC
CCCTCTGCTCGGCCTAGACCTGA
GCTCATTAGGCGGCAGCGGACAG
GCCAAGTAGAACACGCGAAGCGC
TGGGCTGCCTGCTGCGACCAGGG**

Ordered Data

- Spatio-Temporal Data

**Average Monthly
Temperature of
land and ocean**

Jan



Data Quality

- Poor data quality negatively affects many data processing efforts

“The most important point is that poor data quality is an unfolding disaster.

- Poor data quality costs the typical company at least ten percent (10%) of revenue; twenty percent (20%) is probably a better estimate.”

Thomas C. Redman, DM Review, August 2004

- Data mining example: a classification model for detecting people who are loan risks is built using poor data
 - Some credit-worthy candidates are denied loans
 - More loans are given to individuals that default

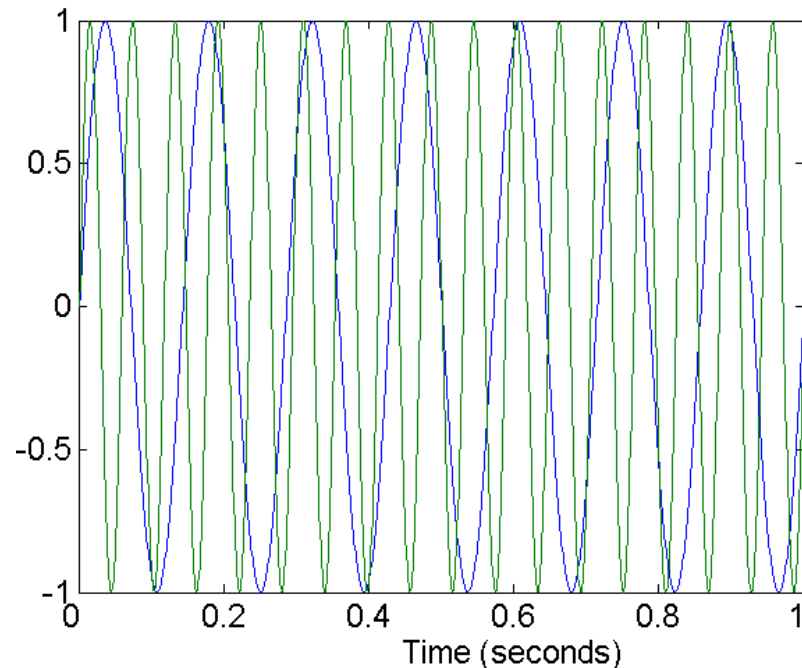
Data Quality ...

- What kinds of data quality problems?
- How can we detect problems with the data?
- What can we do about these problems?

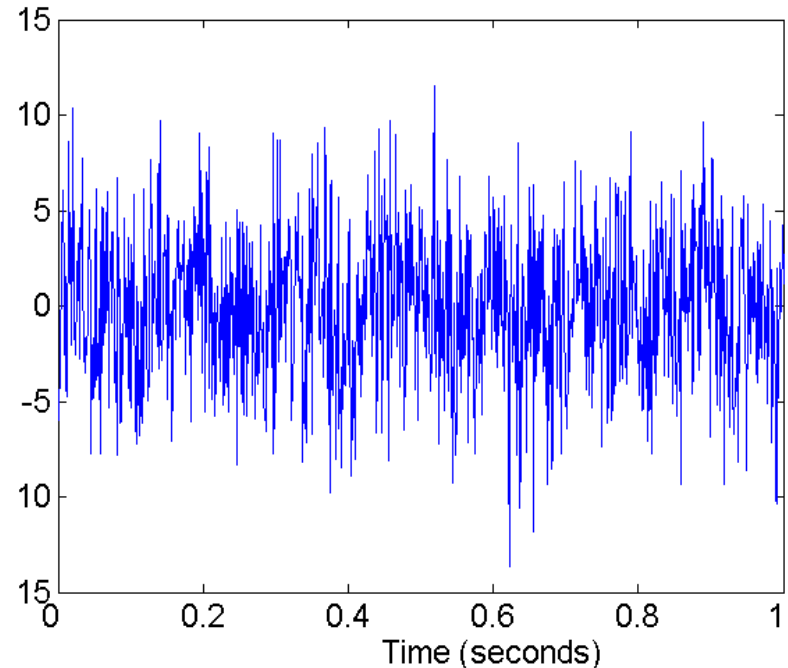
- Examples of data quality problems:
 - Noise and outliers
 - Missing values
 - Duplicate data
 - Wrong data

Noise

- For objects, noise is an extraneous object
- For attributes, noise refers to modification of original values
 - Examples: distortion of a person's voice when talking on a poor phone and “snow” on television screen



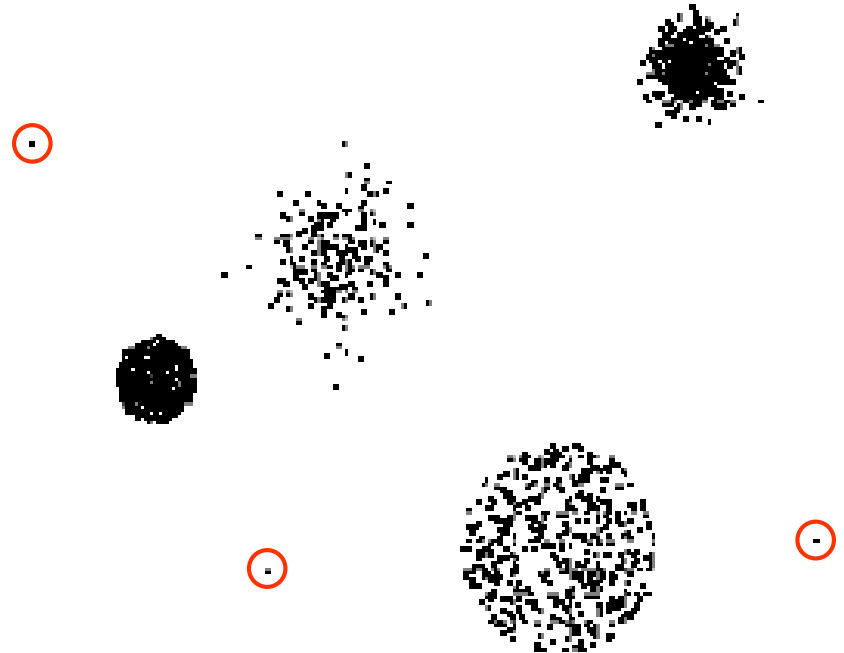
Two Sine Waves



Two Sine Waves + Noise

Outliers

- **Outliers** are data objects with characteristics that are considerably different than most of the other data objects in the data set
 - **Case 1:** Outliers are noise that interferes with data analysis
 - **Case 2:** Outliers are the goal of our analysis
 - ◆ Credit card fraud
 - ◆ Intrusion detection
- Causes?



Missing Values

- Reasons for 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)
- Handling missing values
 - Eliminate data objects or variables
 - Estimate missing values
 - ◆ Example: time series of temperature
 - ◆ Example: census results
 - Ignore the missing value during analysis

Duplicate Data

- Data set may include data objects that are duplicates, or almost duplicates of one another
 - Major issue when merging data from heterogeneous sources
- Examples:
 - Same person with multiple email addresses
- Data cleaning
 - Process of dealing with duplicate data issues
- When should duplicate data not be removed?

Similarity and Dissimilarity Measures

- Similarity measure
 - Numerical measure of how alike two data objects are.
 - Is higher when objects are more alike.
 - Often falls in the range $[0,1]$
- Dissimilarity measure
 - Numerical measure of how different two data objects are
 - Lower when objects are more alike
 - Minimum dissimilarity is often 0
 - Upper limit varies
- Proximity refers to a similarity or dissimilarity

Similarity/Dissimilarity for Simple Attributes

The following table shows the similarity and dissimilarity between two objects, x and y , with respect to a single, simple attribute.

Attribute Type	Dissimilarity	Similarity
Nominal	$d = \begin{cases} 0 & \text{if } x = y \\ 1 & \text{if } x \neq y \end{cases}$	$s = \begin{cases} 1 & \text{if } x = y \\ 0 & \text{if } x \neq y \end{cases}$
Ordinal	$d = x - y / (n - 1)$ (values mapped to integers 0 to $n-1$, where n is the number of values)	$s = 1 - d$
Interval or Ratio	$d = x - y $	$s = -d, s = \frac{1}{1+d}, s = e^{-d},$ $s = 1 - \frac{d - \min_d}{\max_d - \min_d}$

Euclidean Distance

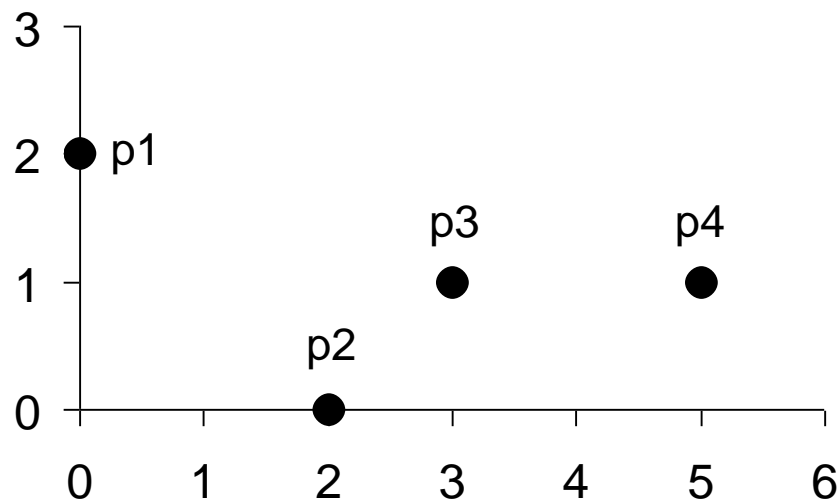
- Euclidean Distance

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

where n is the number of dimensions (attributes) and x_k and y_k are, respectively, the k^{th} attributes (components) or data objects \mathbf{x} and \mathbf{y} .

- Standardization is necessary, if scales differ.

Euclidean Distance



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

	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

Minkowski Distance

- Minkowski Distance is a generalization of Euclidean Distance

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

Where r is a parameter, n is the number of dimensions (attributes) and x_k and y_k are, respectively, the k^{th} attributes (components) or data objects x and y .

Minkowski Distance: Examples

- $r = 1$. City block (Manhattan, taxicab, L_1 norm) distance.
 - A common example of this is the Hamming distance, which is just the number of bits that are different between two binary vectors
- $r = 2$. Euclidean distance
- $r \rightarrow \infty$. “supremum” (L_{\max} norm, L_{∞} norm) distance.
 - This is the maximum difference between any component of the vectors
- Do not confuse r with n , i.e., all these distances are defined for all numbers of dimensions.

Minkowski 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

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

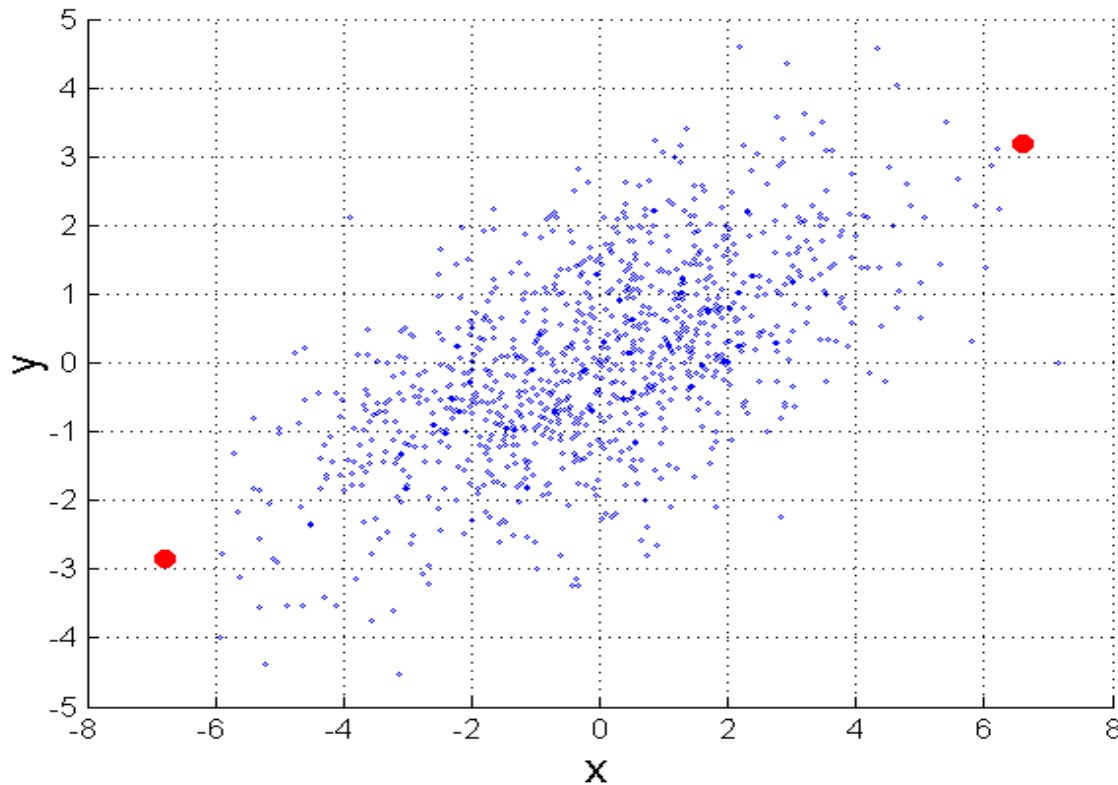
L_{∞}	p1	p2	p3	p4
p1	0	2	3	5
p2	2	0	1	3
p3	3	1	0	2
p4	5	3	2	0

Distance Matrix

Mahalanobis Distance

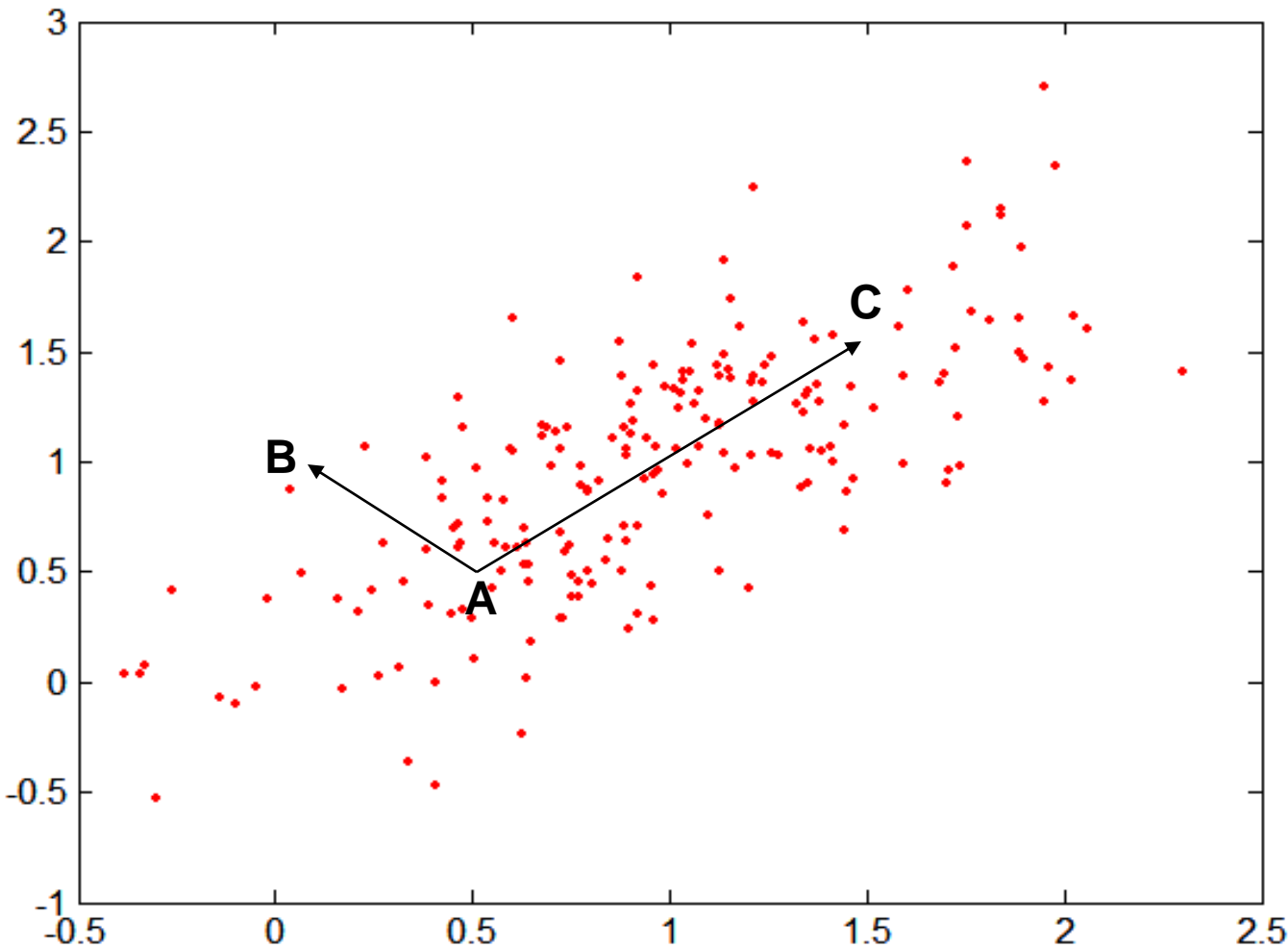
$$\text{mahalanobis}(\mathbf{x}, \mathbf{y}) = (\mathbf{x} - \mathbf{y})^T \Sigma^{-1} (\mathbf{x} - \mathbf{y})$$

Σ is the covariance matrix



For red points, the Euclidean distance is 14.7, Mahalanobis distance is 6.

Mahalanobis Distance



**Covariance
Matrix:**

$$\Sigma = \begin{bmatrix} 0.3 & 0.2 \\ 0.2 & 0.3 \end{bmatrix}$$

A: (0.5, 0.5)

B: (0, 1)

C: (1.5, 1.5)

Mahal(A,B) = 5

Mahal(A,C) = 4

Common Properties of a Distance

- Distances, such as the Euclidean distance, have some well known properties.
 1. $d(\mathbf{x}, \mathbf{y}) \geq 0$ for all \mathbf{x} and \mathbf{y} and $d(\mathbf{x}, \mathbf{y}) = 0$ only if $\mathbf{x} = \mathbf{y}$. (Positive definiteness)
 2. $d(\mathbf{x}, \mathbf{y}) = d(\mathbf{y}, \mathbf{x})$ for all \mathbf{x} and \mathbf{y} . (Symmetry)
 3. $d(\mathbf{x}, \mathbf{z}) \leq d(\mathbf{x}, \mathbf{y}) + d(\mathbf{y}, \mathbf{z})$ for all points \mathbf{x} , \mathbf{y} , and \mathbf{z} . (Triangle Inequality)

where $d(\mathbf{x}, \mathbf{y})$ is the distance (dissimilarity) between points (data objects), \mathbf{x} and \mathbf{y} .

- A distance that satisfies these properties is a **metric**

Common Properties of a Similarity

- Similarities, also have some well known properties.

1. $s(\mathbf{x}, \mathbf{y}) = 1$ (or maximum similarity) only if $\mathbf{x} = \mathbf{y}$.

2. $s(\mathbf{x}, \mathbf{y}) = s(\mathbf{y}, \mathbf{x})$ for all \mathbf{x} and \mathbf{y} . (Symmetry)

where $s(\mathbf{x}, \mathbf{y})$ is the similarity between points (data objects), \mathbf{x} and \mathbf{y} .

Similarity Between Binary Vectors

- Common situation is that objects, p and q , have only binary attributes

- Compute similarities using the following quantities

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

- Simple Matching and Jaccard Coefficients

SMC = number of matches / number of attributes

$$= (f_{11} + f_{00}) / (f_{01} + f_{10} + f_{11} + f_{00})$$

J = number of 11 matches / number of non-zero attributes

$$= (f_{11}) / (f_{01} + f_{10} + f_{11})$$

SMC versus Jaccard: Example

$$\mathbf{x} = 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0$$

$$\mathbf{y} = 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 1$$

$$f_{01} = 2 \quad (\text{the number of attributes where } p \text{ was 0 and } q \text{ was 1})$$

$$f_{10} = 1 \quad (\text{the number of attributes where } p \text{ was 1 and } q \text{ was 0})$$

$$f_{00} = 7 \quad (\text{the number of attributes where } p \text{ was 0 and } q \text{ was 0})$$

$$f_{11} = 0 \quad (\text{the number of attributes where } p \text{ was 1 and } q \text{ was 1})$$

$$\begin{aligned} \text{SMC} &= (f_{11} + f_{00}) / (f_{01} + f_{10} + f_{11} + f_{00}) \\ &= (0+7) / (2+1+0+7) = 0.7 \end{aligned}$$

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

Cosine Similarity

- If \mathbf{d}_1 and \mathbf{d}_2 are two document vectors, then

$$\cos(\mathbf{d}_1, \mathbf{d}_2) = \langle \mathbf{d}_1, \mathbf{d}_2 \rangle / \|\mathbf{d}_1\| \|\mathbf{d}_2\| ,$$

where $\langle \mathbf{d}_1, \mathbf{d}_2 \rangle$ indicates inner product or vector dot product of vectors, \mathbf{d}_1 and \mathbf{d}_2 , and $\|\mathbf{d}\|$ is the length of vector \mathbf{d} .

- Example:

$$\mathbf{d}_1 = 3 \ 2 \ 0 \ 5 \ 0 \ 0 \ 0 \ 2 \ 0 \ 0$$

$$\mathbf{d}_2 = 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 1 \ 0 \ 2$$

$$\langle \mathbf{d}_1, \mathbf{d}_2 \rangle = 3*1 + 2*0 + 0*0 + 5*0 + 0*0 + 0*0 + 0*0 + 2*1 + 0*0 + 0*2 = 5$$

$$\|\mathbf{d}_1\| = (3*3 + 2*2 + 0*0 + 5*5 + 0*0 + 0*0 + 0*0 + 2*2 + 0*0 + 0*0)^{0.5} = (42)^{0.5} = 6.481$$

$$\|\mathbf{d}_2\| = (1*1 + 0*0 + 0*0 + 0*0 + 0*0 + 0*0 + 0*0 + 1*1 + 0*0 + 2*2)^{0.5} = (6)^{0.5} = 2.449$$

$$\cos(\mathbf{d}_1, \mathbf{d}_2) = 0.3150$$

Extended Jaccard Coefficient (Tanimoto)

- Variation of Jaccard for continuous or count attributes
 - Reduces to Jaccard for binary attributes

$$EJ(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\|^2 + \|\mathbf{y}\|^2 - \mathbf{x} \cdot \mathbf{y}}$$

General Approach for Combining Similarities

- Sometimes attributes are of many different types, but an overall similarity is needed.

1: For the k^{th} attribute, compute a similarity, $s_k(\mathbf{x}, \mathbf{y})$, in the range $[0, 1]$.

2: Define an indicator variable, δ_k , for the k^{th} attribute as follows:

$\delta_k = 0$ if the k^{th} attribute is an asymmetric attribute and both objects have a value of 0, or if one of the objects has a missing value for the k^{th} attribute

$\delta_k = 1$ otherwise

3. Compute $\text{similarity}(\mathbf{x}, \mathbf{y}) = \frac{\sum_{k=1}^n \delta_k s_k(\mathbf{x}, \mathbf{y})}{\sum_{k=1}^n \delta_k}$

Using Weights to Combine Similarities

- May not want to treat all attributes the same.
 - Use non-negative weights ω_k

- $similarity(\mathbf{x}, \mathbf{y}) = \frac{\sum_{k=1}^n \omega_k \delta_k s_k(\mathbf{x}, \mathbf{y})}{\sum_{k=1}^n \omega_k \delta_k}$

- Can also define a weighted form of distance

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

Data Preprocessing

- 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.
 - ◆ Days aggregated into weeks, months, or years
 - More “stable” data
 - ◆ Aggregated data tends to have less variability

Example: Precipitation in Australia

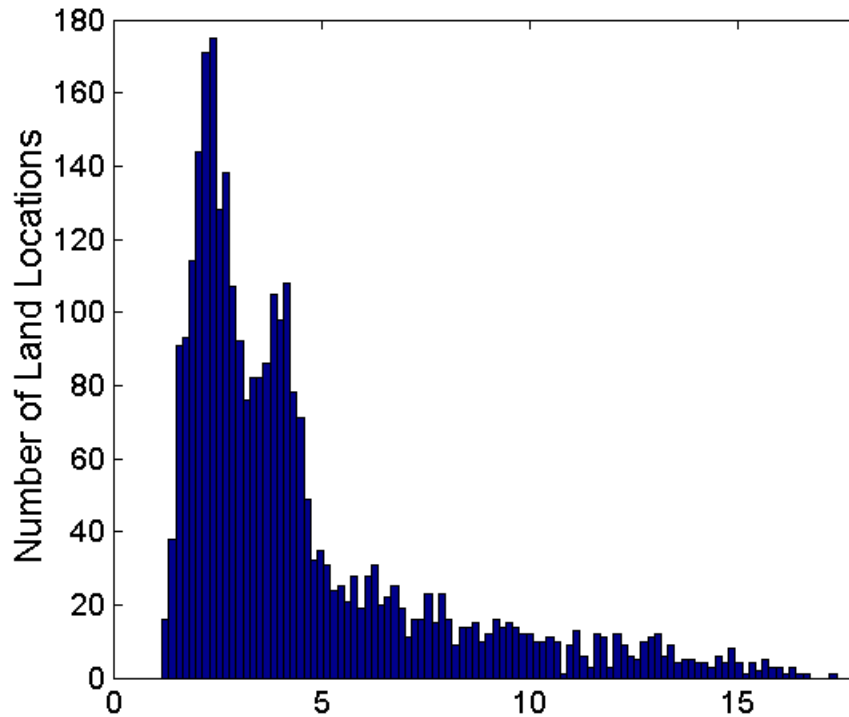
- This example is based on precipitation in Australia from the period 1982 to 1993.

The next slide shows

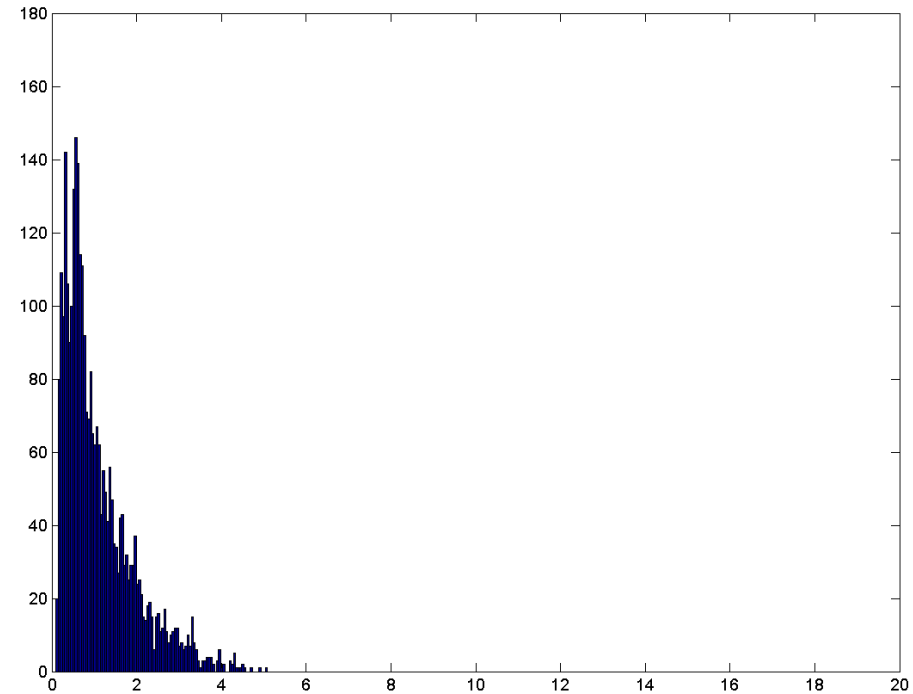
- A histogram for the standard deviation of average monthly precipitation for 3,030 0.5° by 0.5° grid cells in Australia, and
 - A histogram for the standard deviation of the average yearly precipitation for the same locations.
- The average yearly precipitation has less variability than the average monthly precipitation.
- All precipitation measurements (and their standard deviations) are in centimeters.

Example: Precipitation in Australia ...

Variation of Precipitation in Australia



**Standard Deviation of Average
Monthly Precipitation**



**Standard Deviation of
Average Yearly Precipitation**

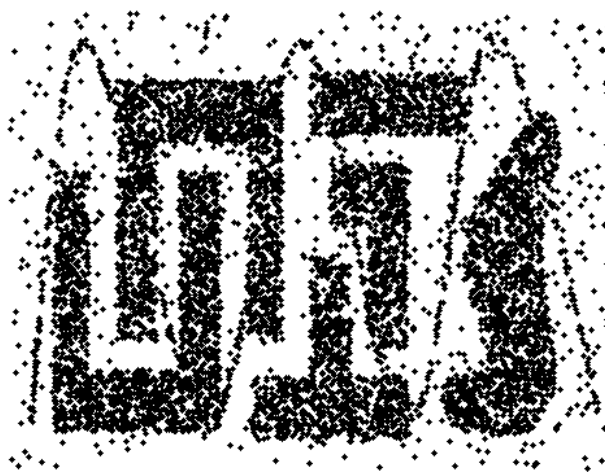
Sampling

- Sampling is the main technique employed for data reduction.
 - It is often used for both the preliminary investigation of the data and the final data analysis.
- Statisticians often sample because **obtaining** the entire set of data of interest is too expensive or time consuming.
- Sampling is typically used in data mining because **processing** the entire set of data of interest is too expensive or time consuming.

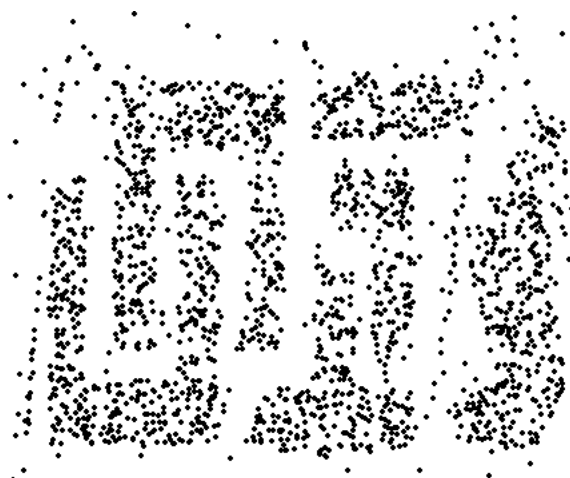
Sampling ...

- The key principle for effective sampling is the following:
 - Using a sample will work almost as well as using the entire data set, if the sample is **representative**
 - A sample is **representative** if it has approximately the same properties (of interest) as the original set of data

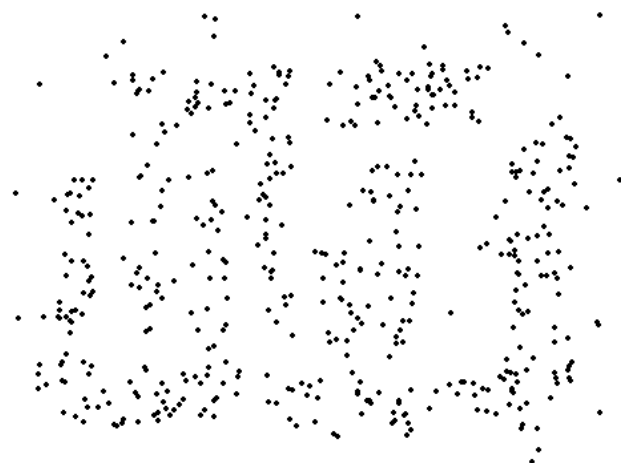
Sample Size



8000 points



2000 Points



500 Points

Types of Sampling

- Simple Random Sampling

- There is an equal probability of selecting any particular item
- 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 for the sample.
 - ◆ In sampling with replacement, the same object can be picked up more than once

- Stratified sampling

- Split the data into several partitions; then draw random samples from each partition

Dimensionality Reduction

- Purpose:

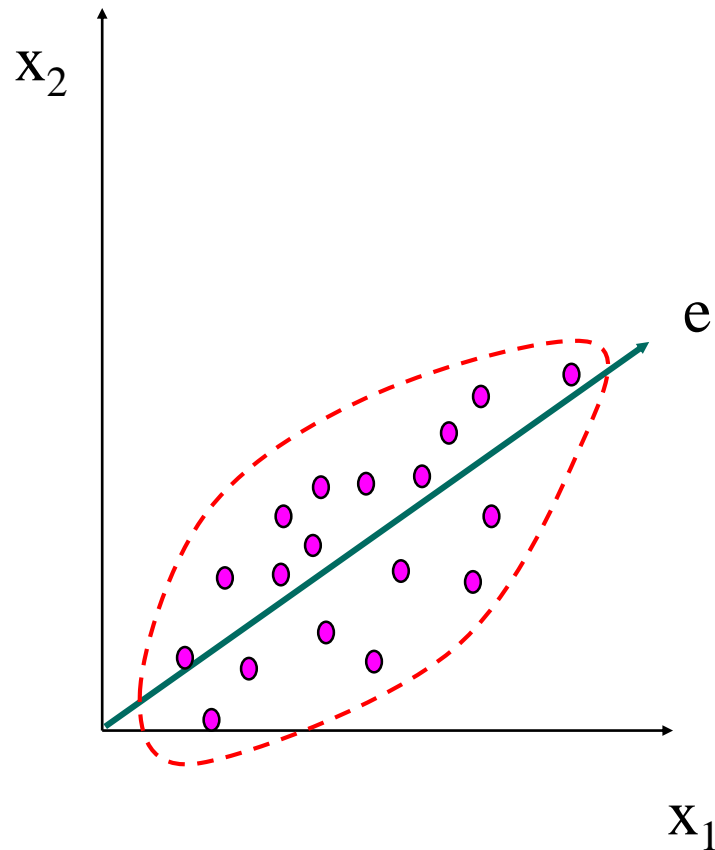
- Avoid curse of dimensionality
- Reduce amount of time and memory required by data mining algorithms
- Allow data to be more easily visualized
- May help to eliminate irrelevant features or reduce noise

- Techniques

- Principal Components Analysis (PCA)
- Singular Value Decomposition
- Others: supervised and non-linear techniques

Dimensionality Reduction: PCA

- Goal is to find a projection that captures the largest amount of variation in data



Dimensionality Reduction: PCA

256



Feature Subset Selection

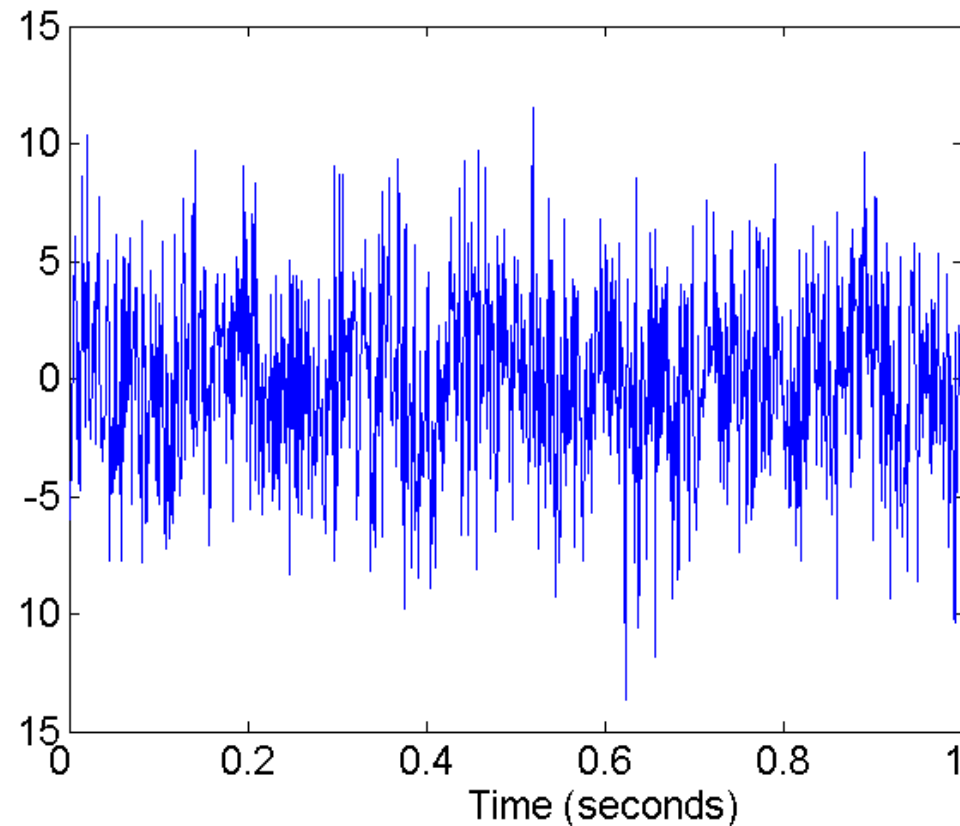
- Another way to reduce dimensionality of data
- Redundant features
 - Duplicate much or all of the information contained in one or more other attributes
 - Example: purchase price of a product and the amount of sales tax paid
- Irrelevant features
 - Contain no information that is useful for the data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

Feature Creation

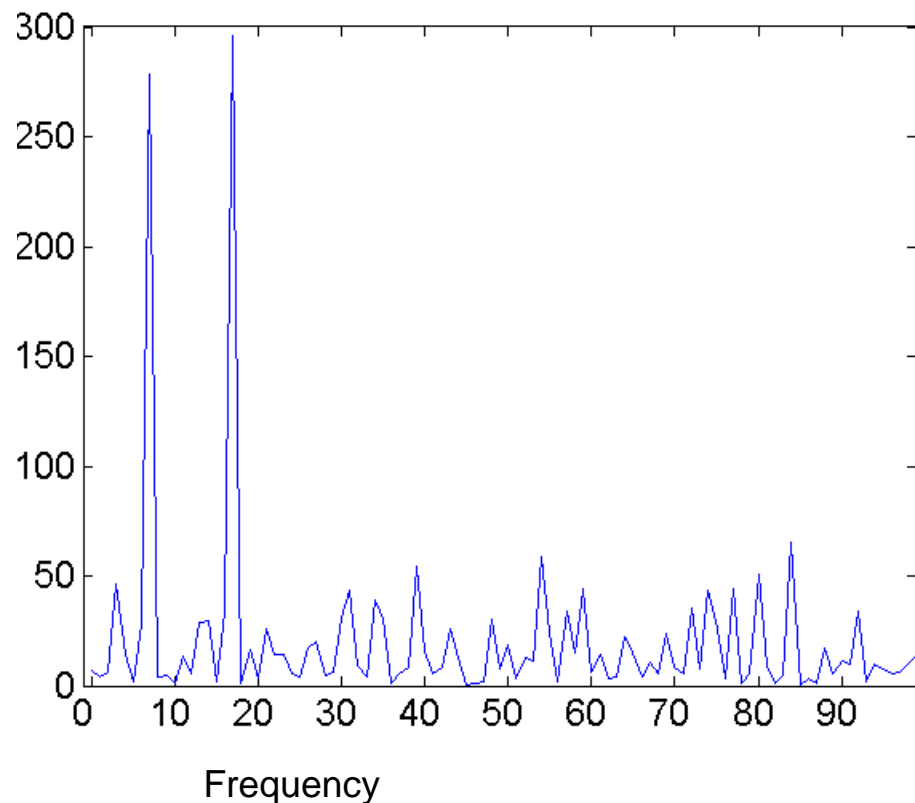
- Create new attributes that can capture the important information in a data set much more efficiently than the original attributes
- Three general methodologies:
 - Feature extraction
 - ◆ Example: extracting edges from images
 - Feature construction
 - ◆ Example: dividing mass by volume to get density
 - Mapping data to new space
 - ◆ Example: Fourier and wavelet analysis

Mapping Data to a New Space

- **Fourier and wavelet transform**



Two Sine Waves + Noise



Frequency

Discretization

- **Discretization** is the process of converting a continuous attribute into an ordinal attribute
 - A potentially infinite number of values are mapped into a small number of categories
 - Discretization is commonly used in classification
 - Many classification algorithms work best if both the independent and dependent variables have only a few values
 - We give an illustration of the usefulness of discretization using the Iris data set

Data Discretization Methods

- Typical methods: All the methods can be applied recursively
 - 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., χ^2) analysis (unsupervised, bottom-up merge)

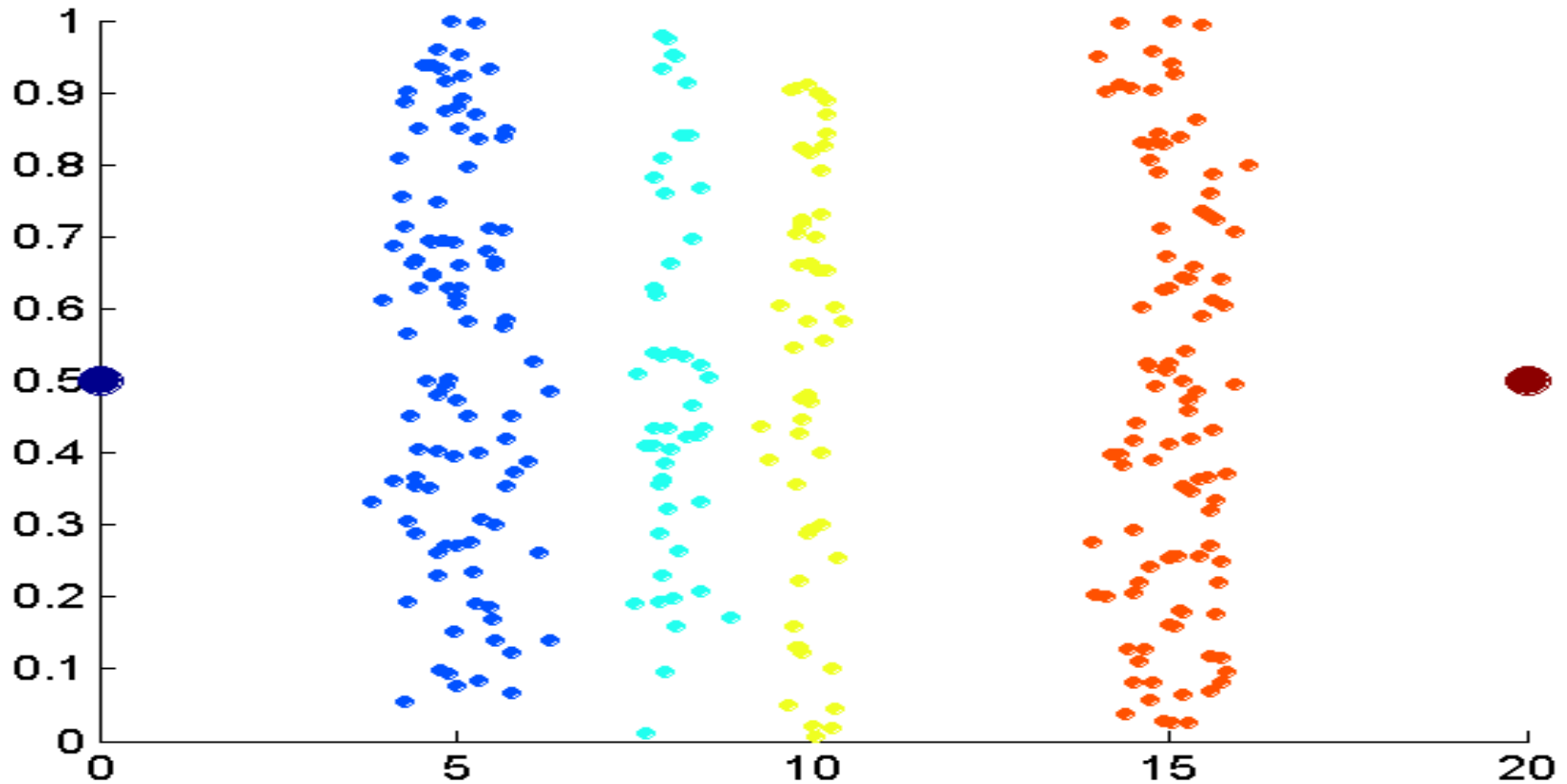
Simple Discretization: Binning

- **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

Binning Methods for Data Smoothing

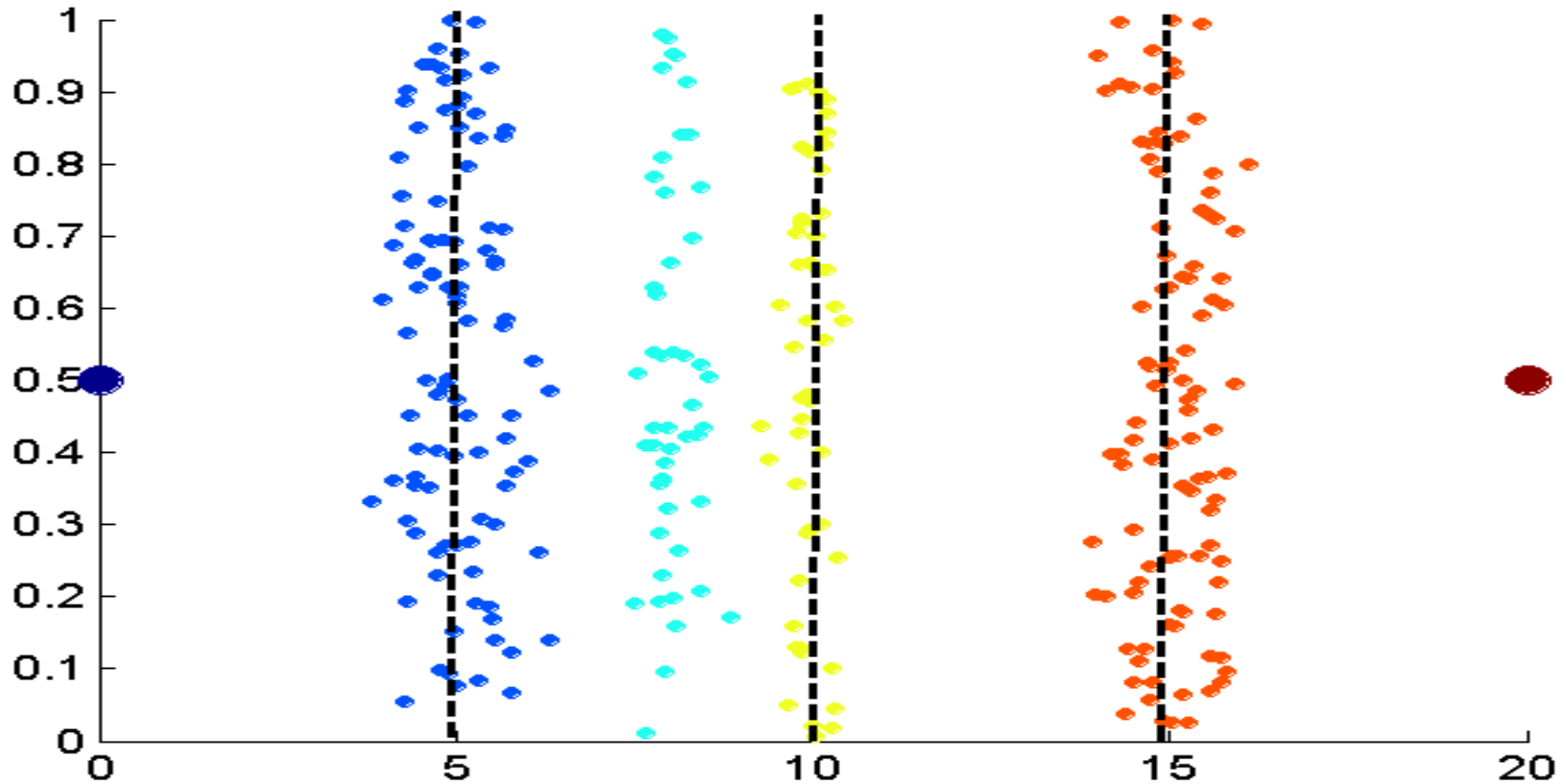
- ❑ Sorted data for price (in dollars): 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34
- * Partition into equal-frequency (**equi-depth**) bins:
 - Bin 1: 4, 8, 9, 15
 - Bin 2: 21, 21, 24, 25
 - Bin 3: 26, 28, 29, 34
- * Smoothing by **bin means**:
 - Bin 1: 9, 9, 9, 9
 - Bin 2: 23, 23, 23, 23
 - Bin 3: 29, 29, 29, 29
- * Smoothing by **bin boundaries**:
 - Bin 1: 4, 4, 4, 15
 - Bin 2: 21, 21, 25, 25
 - Bin 3: 26, 26, 26, 34

Discretization Without Using Class Labels



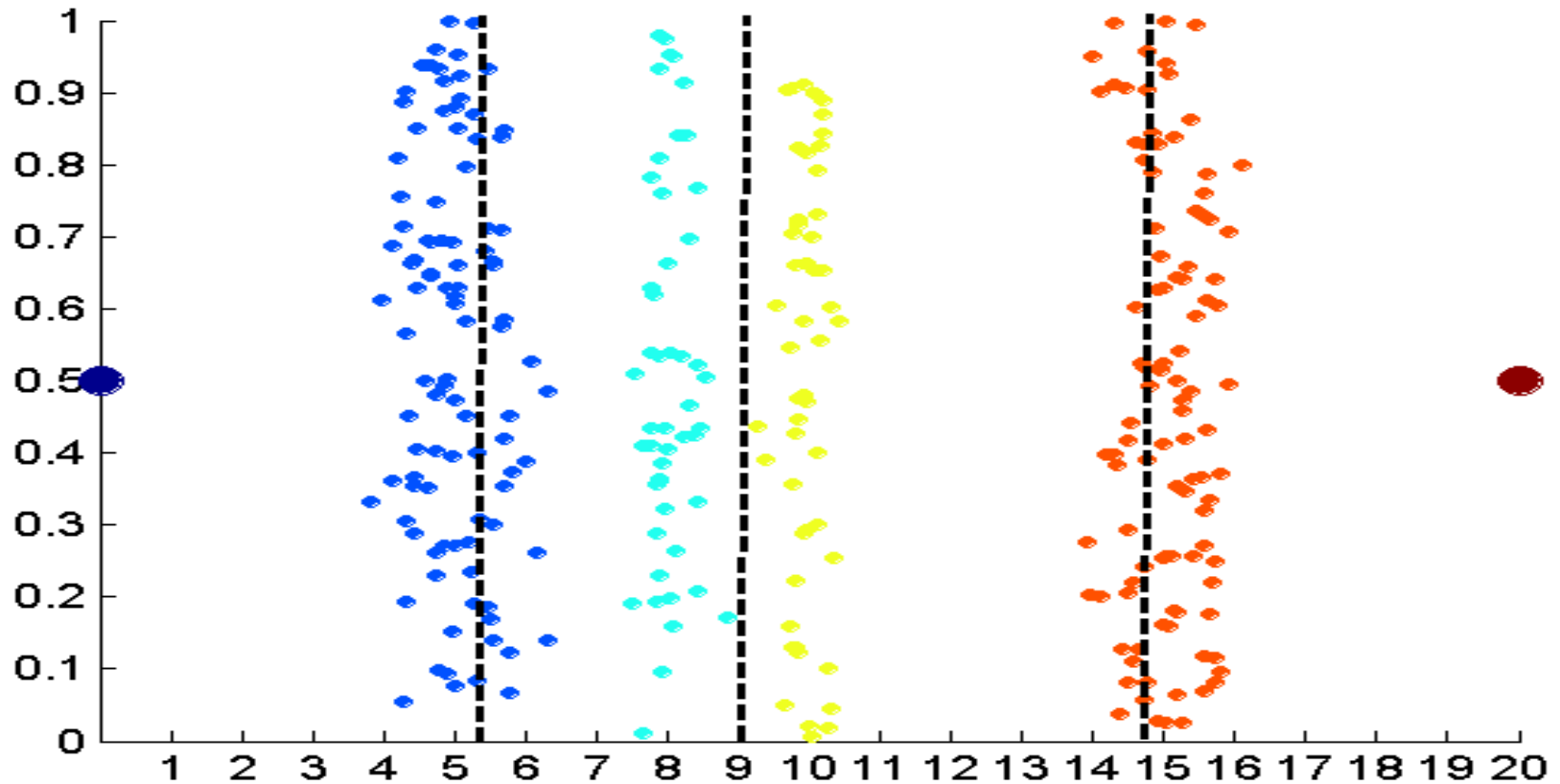
Data consists of four groups of points and two outliers. Data is one-dimensional, but a random y component is added to reduce overlap.

Discretization Without Using Class Labels



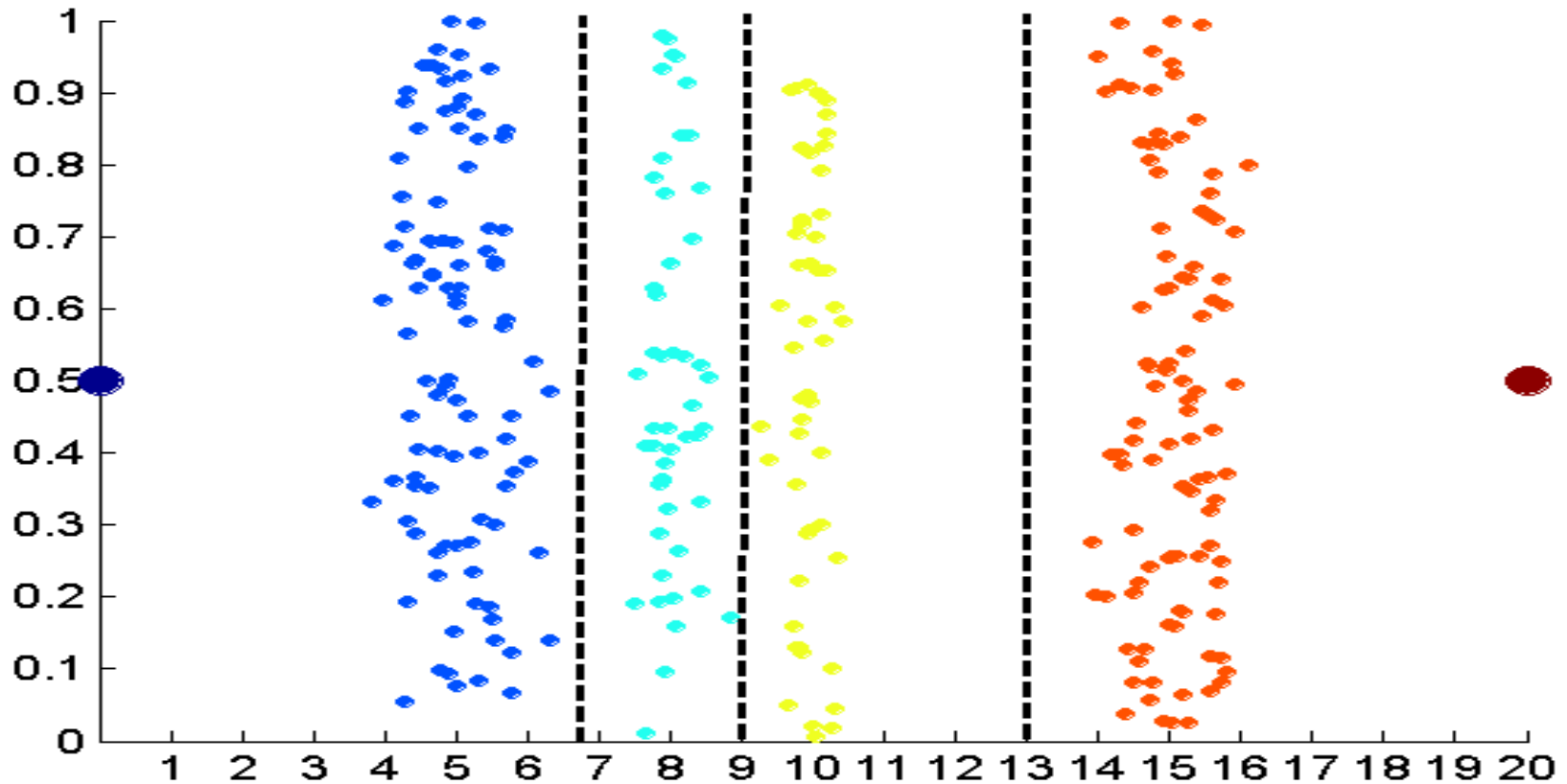
Equal interval width approach used to obtain 4 values.

Discretization Without Using Class Labels



Equal frequency approach used to obtain 4 values.

Discretization Without Using Class Labels



K-means approach to obtain 4 values.

Binarization

- Binarization maps a continuous or categorical attribute into one or more binary variables
- Typically used for association analysis
- Often convert a continuous attribute to a categorical attribute and then convert a categorical attribute to a set of binary attributes
 - Association analysis needs asymmetric binary attributes
 - Examples: eye color and height measured as {low, medium, high}

Attribute Transformation

- An **attribute transform** is 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 , $|x|$
 - **Normalization**
 - ◆ Refers to various techniques to adjust to differences among attributes in terms of frequency of occurrence, mean, variance, range
 - ◆ Take out unwanted, common signal, e.g., seasonality
 - In statistics, **standardization** refers to subtracting off the means and dividing by the standard deviation

Data Transformation

- A function that maps the entire set of values of a given attribute to a new set of replacement values s.t. each old value can be identified with one of the new values
- Methods
 - Smoothing: Remove noise from data
 - Attribute/feature construction
 - ◆ New attributes constructed from the given ones
 - Aggregation: Summarization, data cube construction
 - Normalization: Scaled to fall within a smaller, specified range
 - ◆ min-max normalization
 - ◆ z-score normalization
 - ◆ normalization by decimal scaling
 - Discretization: Concept hierarchy climbing

Normalization

- **Min-max normalization:** to $[new_min_A, new_max_A]$

$$v' = \frac{v - min_A}{max_A - min_A} (new_max_A - new_min_A) + new_min_A$$

- Ex. Let income range \$12,000 to \$98,000 normalized to [0.0, 1.0]. Then \$73,000 is mapped to $\frac{73,600 - 12,000}{98,000 - 12,000} (1.0 - 0) + 0 = 0.716$

- **Z-score normalization** (μ : mean, σ : standard deviation):

$$v' = \frac{v - \mu_A}{\sigma_A}$$

- Ex. Let $\mu = 54,000$, $\sigma = 16,000$. Then $\frac{73,600 - 54,000}{16,000} = 1.225$

- **Normalization by decimal scaling**

$$v' = \frac{v}{10^j} \quad \text{Where } j \text{ is the smallest integer such that } \text{Max}(|v'|) < 1$$