Data Preparation

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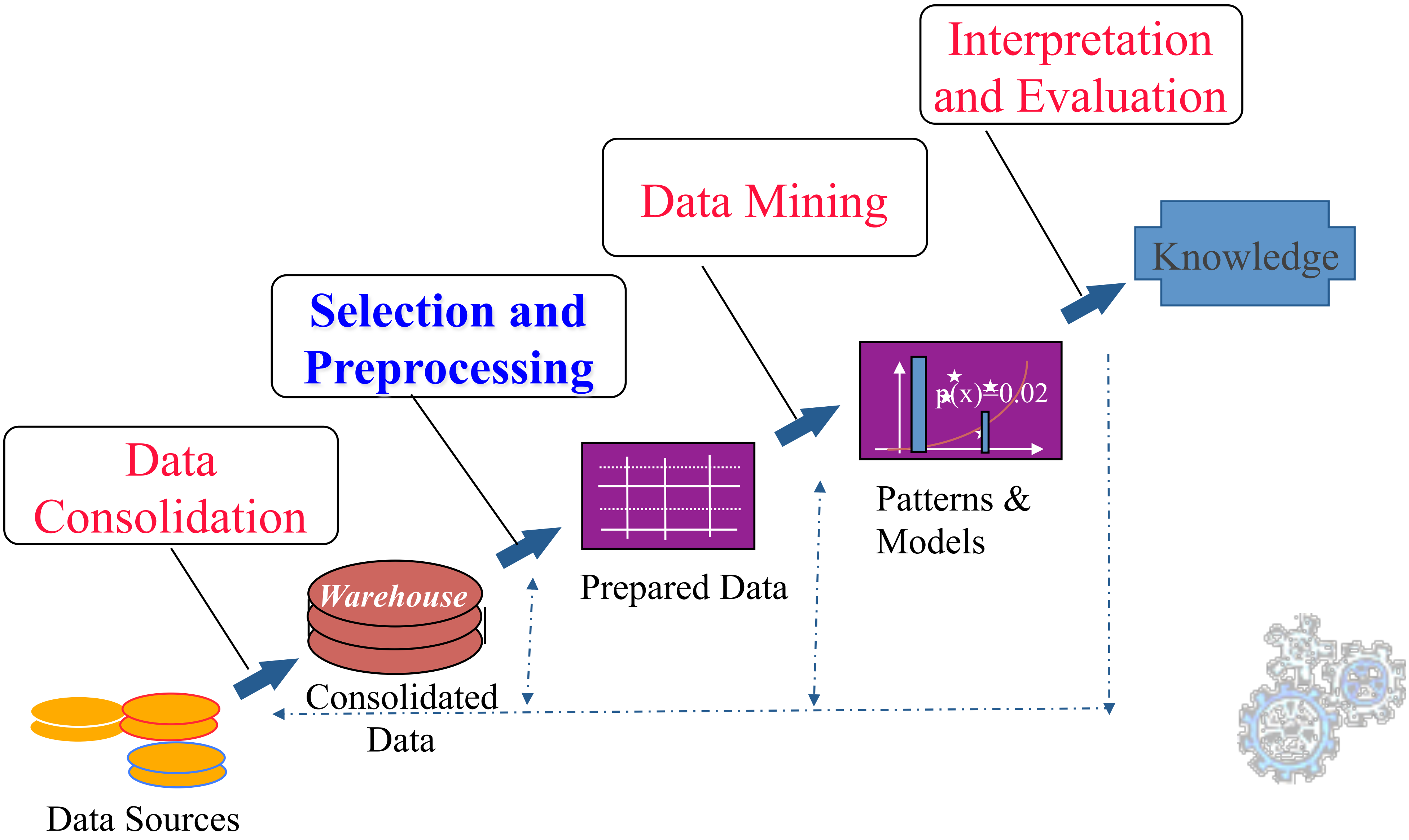
KDD Process


Interpretation and Evaluation
Data Mining
Knowledge
Selection and Preprocessing
p(x)=0.02
Patterns & Models
Data Consolidation
Prepared Data
Warehouse
Consolidated Data
Data Sources

Types of Data

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

Record Data

- Data that 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**
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**

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

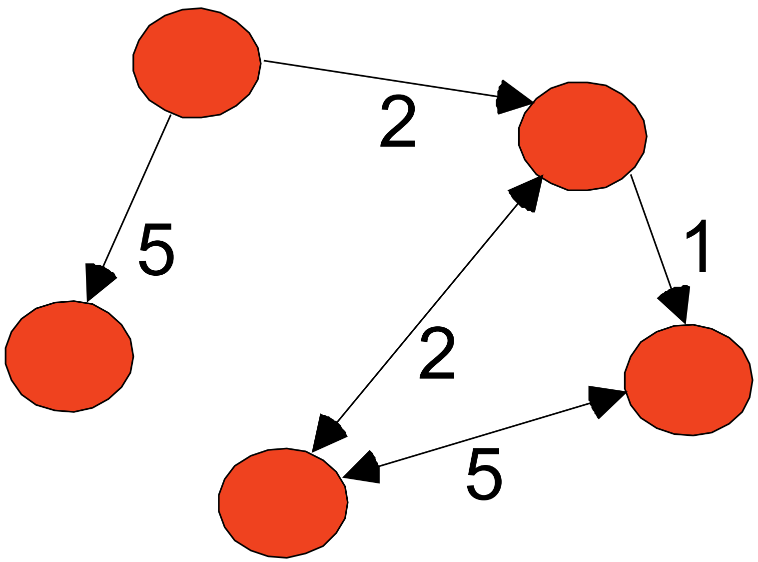
Transaction Data

- 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.

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: Generic graph and HTML Links



Data Mining

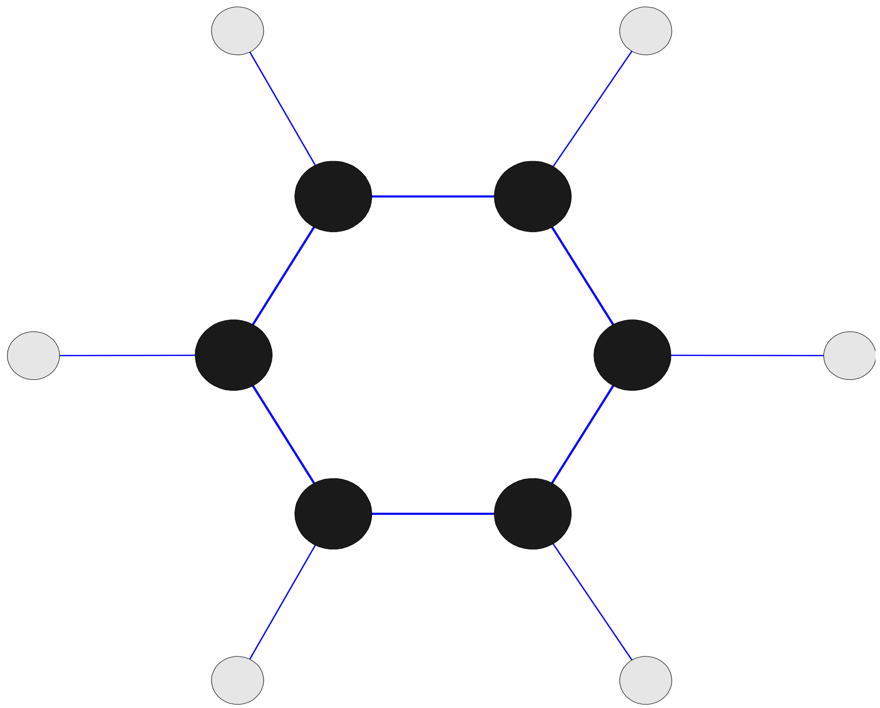
Graph Partitioning

Parallel Solution of Sparse Linear System of Equations

<a href="papers/papers.html#ffff">
N-Body Computation and Dense Linear System Solvers

Chemical Data

- Benzene Molecule: C_6H_6



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

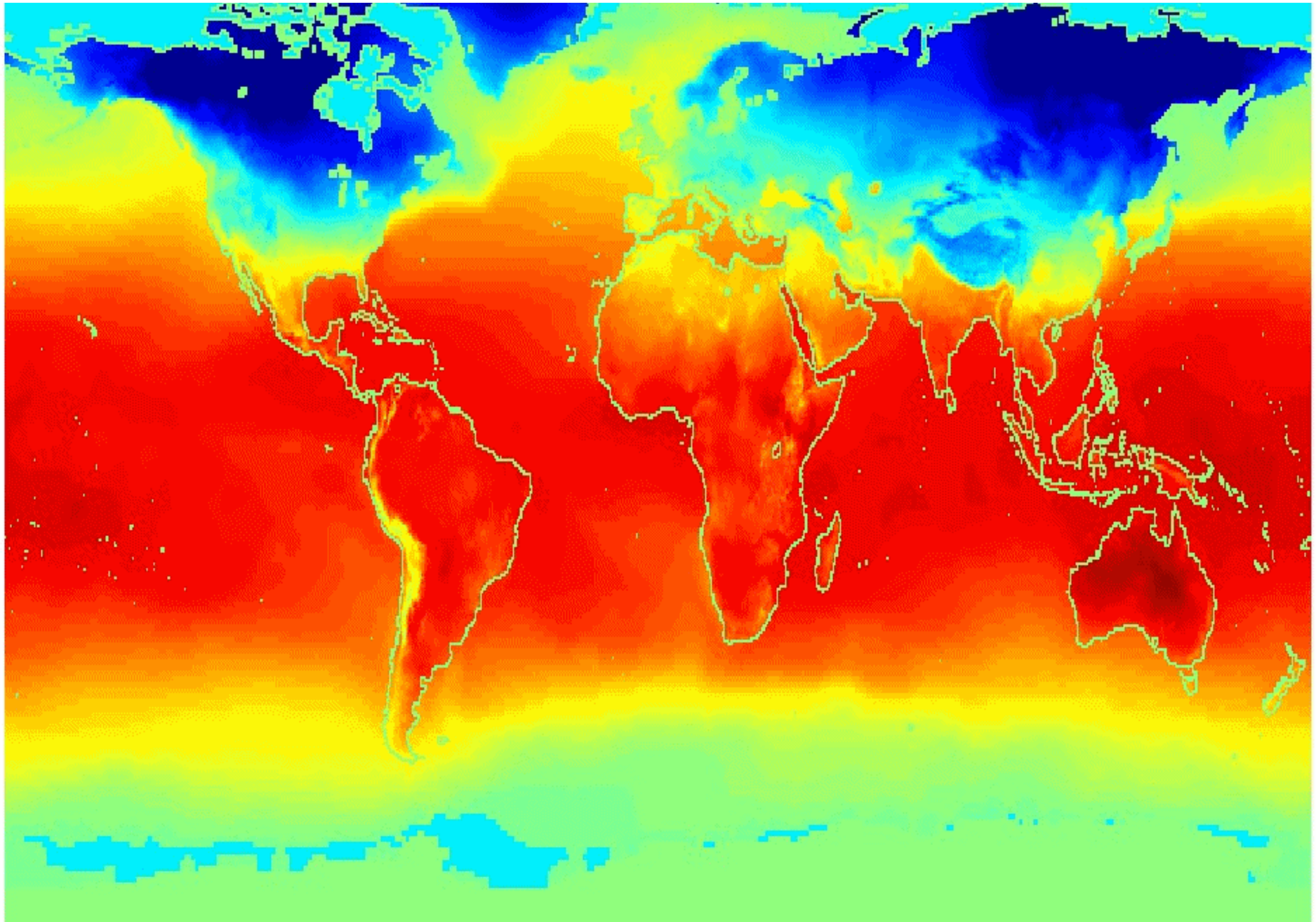
- Genomic sequence data

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

Ordered Data

- Spatio-Temporal Data

Average Monthly Temperature of land and ocean



Data understanding vs Data preparation

Data understanding provides general information about the data like

- the existence and partly also about the character of missing values,
- outliers,
  the character of attributes
- dependencies between attribute.

Data preparation uses this information to

- select attributes,
- reduce the dimension of the data set,
- select records,
- treat missing values,
- treat outliers,
- integrate, unify and transform data
- improve data quality

Data Reduction

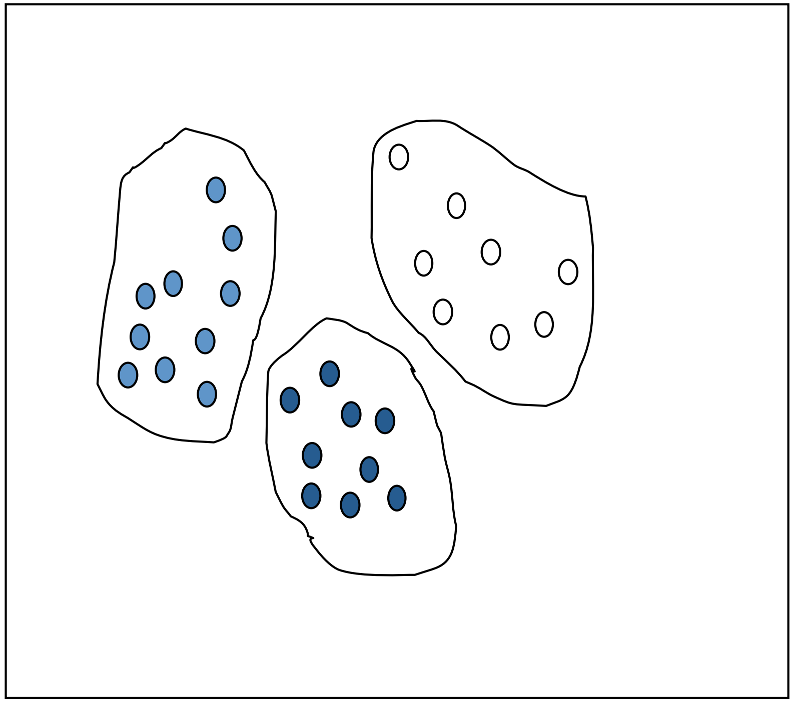
- **Reducing the amount of data**
  - **Vertical**: reduce the number of records
    - Data Sampling
    - Clustering
  - **Horizontal**: reduce the number of columns (attributes)
    - Select a subset of attributes
    - Generate a new (an smaller) set of attributes

Sampling

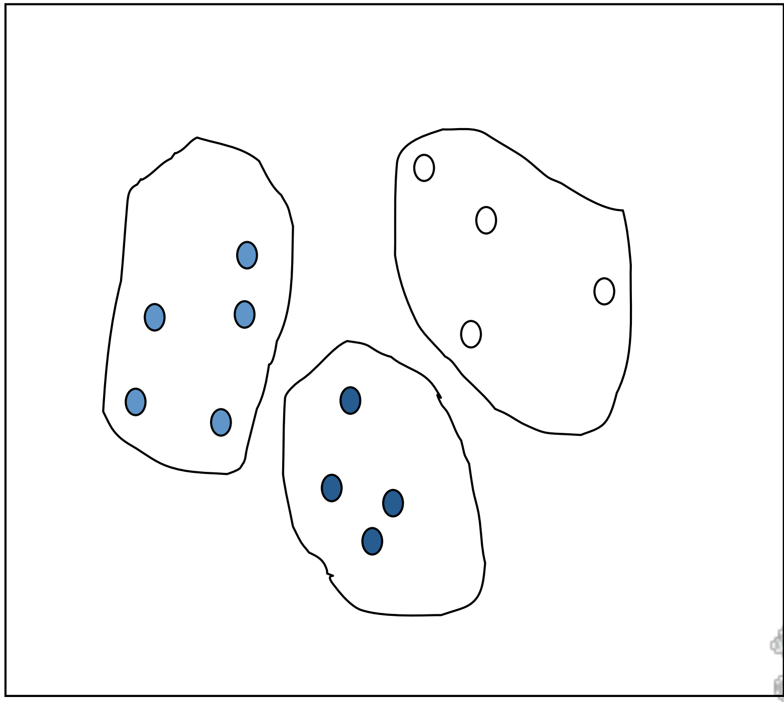
- Improve the execution time of data mining algorithms
- **Problem**: how to select a subset of **representative** data?
  - **Random sampling:** it can generate problem due to the possible peaks in the data
  - **Stratified sampling**:
    - Approximation of the percentage of each class
    - Suitable for distribution with peaks: each peak is a **layer**

Stratified Sampling

Raw Data



Cluster/Stratified Sample



Reduction of Dimensionality

- **Selection of a subset of attributes** that is as small as possible and sufficient for the data analysis.
  - removing (more or less) irrelevant features
  - removing redundant features.

Removing irrelevant/redundant features

- For **removing irrelevant features**, a performance measure is needed that indicates how well a feature or subset of features performs w.r.t. the considered data analysis task.
- For removi**ng redundant features**, either a performance measure for subsets of features or a correlation measure is needed.

Reduction of Dimensionality

Manual

– After analyzing the **significance** and/or **correlation** with other attributes

Automatic: Selecting the top-ranked features

– Incremental Selection of the “best” attributes

– “Best” = with respect to a specific measure of statistical significance (e.g.: information gain).

Data Cleaning

- How to handle anomalous values
- How to handle di outliers
- Data Transformations

Anomalous Values

- **Missing values**
  - NULL
- **Unknown Values**
  - Values without a real meaning
- **Not Valid Values**
  - Values not significant

Manage Missing Values

1. Elimination of records
2. Substitution of values

Note: it can influence the original distribution of numerical values

– Use media/median/mode
– Estimate missing values using the probability distribution of existing values
– Data Segmentation and using media/mode/median of each segment
– Data Segmentation and using the probability distribution within the segment
– Build a model of classification/regression for computing missing values

Data Transformation: Motivations

- Data with errors and incomplete

- Data not adequately distributed
  - Strong asymmetry in the data
  - Many peaks

- Data transformation can reduce these issues

Normalizations

- min-max normalization

$$v' = \frac{v - min_A}{max_A - min_A}(new\_max_A - new\_min_A) + new\_min_A$$

- z-score normalization

$$v' = \frac{v - mean_A}{stand\_dev_A}$$

- normalization by decimal scaling

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

Discretization

- Unsupervised vs. Supervised
- Global vs. Local
- Static vs. Dynamic
- Hard Task
  - Hard to understand the optimal discretization
    - We should need the real data distribution

Discretization: Advantages

- Original values can be **continuous** and **sparse**
- Discretized data can be **simple** to be interpreted
- Data distribution after discretization can have a **Normal shape**
- Discretized data can be too much **sparse yet**
  - Elimination of the attribute

Unsupervised Discretization

- Characteristics:
  - No label for the instances
  - The number of classes is known

- Techniques of *binning*:
  - **Natural binning** → Intervals with the same width
  - **Equal Frequency binning** → Intervals with the same frequency
  - **Statistical binning** → Use statistical information (Mean, variance, Quartile)

Discretization of quantitative attributes

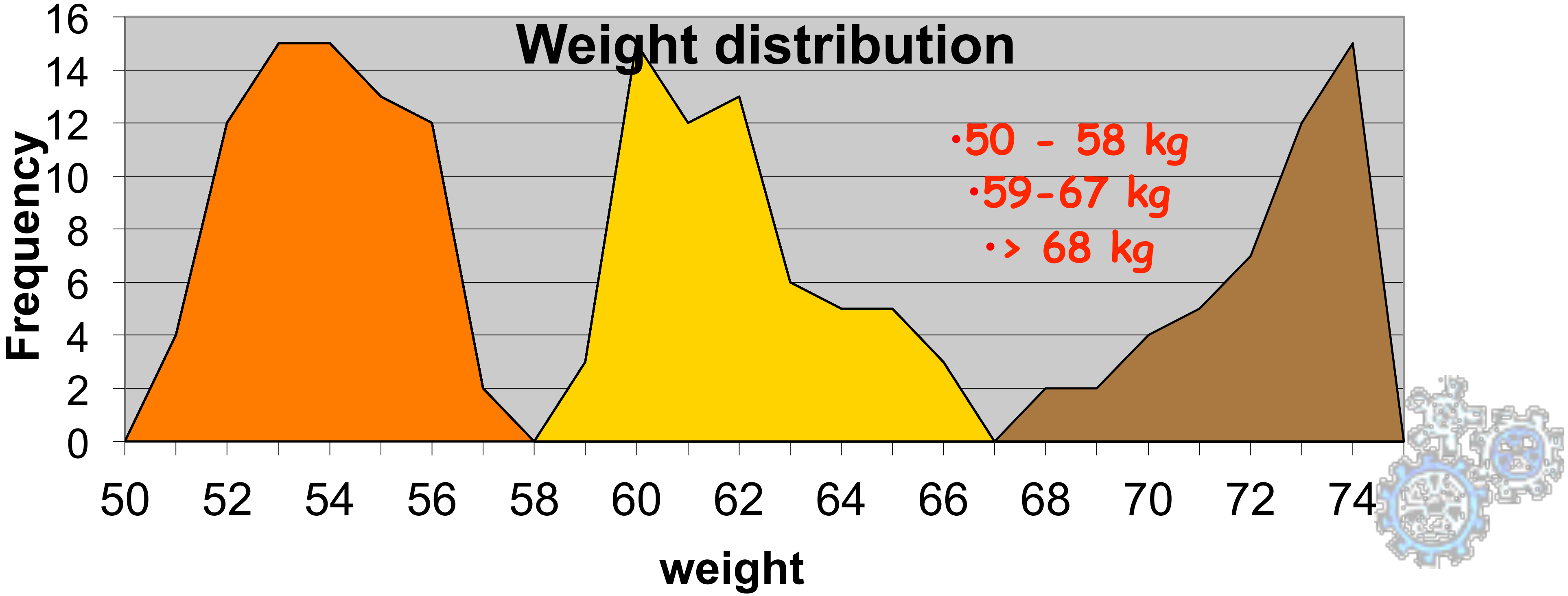
- **Solution**: each value is replaced by the interval to which it belongs.
  - **height**: 0-150cm, 151-170cm, 171-180cm, >180c
  - **weight**: 0-40kg, 41-60kg, 60-80kg, >80kg
  - **income**: 0-10ML, 11-20ML, 20-25ML, 25-30ML, >30ML

CID	**height**	**weight**	**income**
1	151-171	60-80	>30
2	171-180	60-80	20-25
3	171-180	60-80	25-30
4	151-170	60-80	25-30

- **Problem**: the discretization may be useless (see **weight**).

How to choose intervals?

1. **Interval with a fixed "reasonable" granularity**
   Ex. intervals of 10 cm for height.
2. **Interval size is defined by some domain dependent criterion**
   Ex.: 0-20ML, 21-22ML, 23-24ML, 25-26ML, >26ML
3. **Interval size determined by analyzing data, studying the distribution or using clustering**



Natural Binning

- Simple
- Sort of values, subdivision of the range of values in *k* parts with the same size

$$\delta = \frac{x_{\max} - x_{\min}}{k}$$

- Element x_j belongs to the class i if

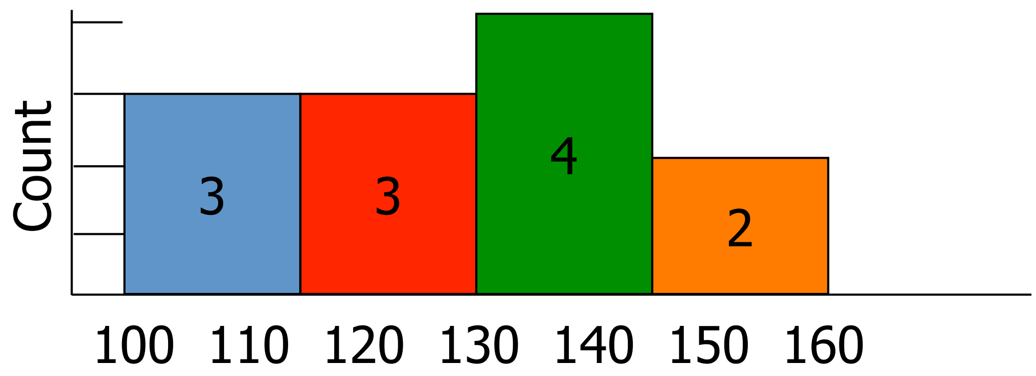
$$x_j \in [x_{min} + i\delta,\ x_{min} + (i+1)\delta)$$

- It can generate distribution very unbalanced

Example

Bar	Beer	Price
A	Bud	100
A	Becks	120
C	Bud	110
D	Bud	130
D	Becks	150
E	Becks	140
E	Bud	120
F	Bud	110
G	Bud	130
H	Bud	125
H	Becks	160
I	Bud	135

- δ =(160-100)/4 = 15
- class 1: [100,115)
- class 2: [115,130)
- class 3: [130,145)
- class 4: [145, 160]



Equal Frequency Binning

- Sort and count the elements, definition of k intervals of f, where:

$$f = \frac{N}{k}$$

  (N = number of elements of the sample)

- The element x_i belongs to the class j if

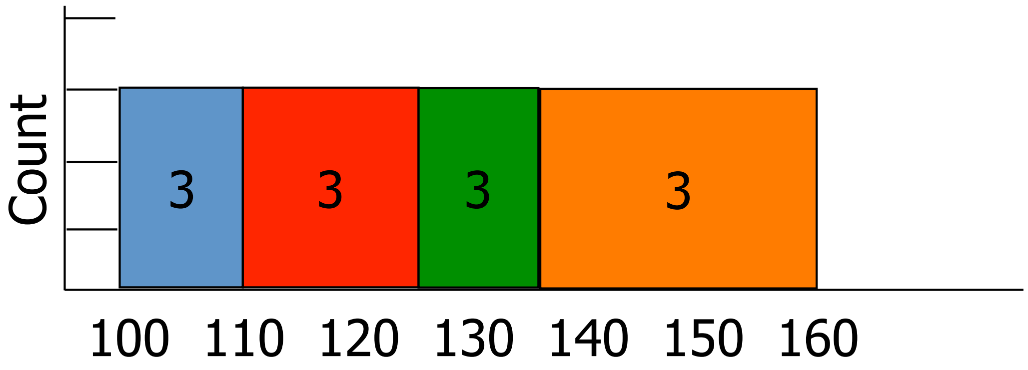
  $$j \times f \leq i < (j+1) \times f$$

- It is not always suitable for highlighting interesting correlations

Example

Bar	Beer	Price
A	Bud	100
A	Becks	120
C	Bud	110
D	Bud	130
D	Becks	150
E	Becks	140
E	Bud	120
F	Bud	110
G	Bud	130
H	Bud	125
H	Becks	160
I	Bud	135

- $f = 12/4 = 3$
- class 1: {100,110,110}
- class 2: {120,120,125}
- class 3: {130,130,135}
- class 4: {140,150,160}



How many classes?

- If too few

  ⇒ Loss of information on the distribution

- If too many

  => Dispersion of values and does not show the form of distribution

- The optimal number of classes is function of N elements (Sturges, 1929)

$$C = 1 + \frac{10}{3}\log_{10}(N)$$

- The optimal width of the classes depends on the variance and the number of data (Scott, 1979)

$$h = \frac{3{,}5 \cdot s}{\sqrt{N}}$$

Similarity

Similarity and Dissimilarity

- **Similarity**
  - Numerical measure of how alike two data objects are.
  - Is 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
  - Minimum dissimilarity is often 0
  - Upper limit varies
- **Proximity refers to a similarity or dissimilarity**

Similarity/Dissimilarity for ONE Attribute

p and *q* are the attribute values for two data objects.

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

Many attributes: Euclidean Distance

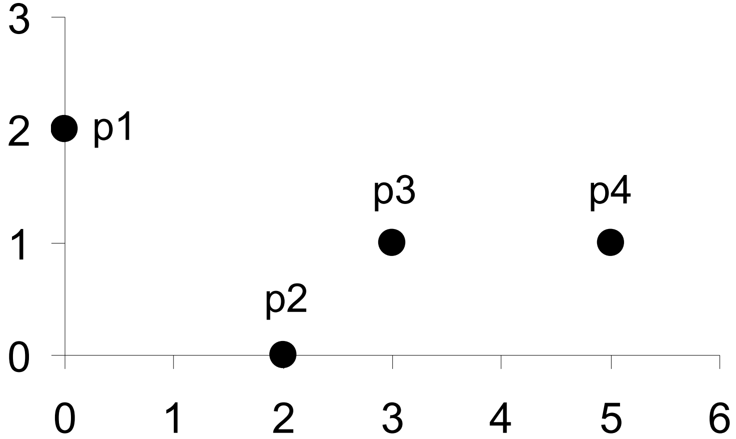
- Euclidean Distance

$$dist = \sqrt{\sum_{k=1}^{n} (p_k - q_k)^2}$$

Where n is the number of dimensions (attributes) and p_k and q_k are, respectively, the value of k^{th} attributes (components) or data objects p and q.

- 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

$$dist = \left(\sum_{k=1}^{n} | p_k - q_k |^r \right)^{\frac{1}{r}}$$

Where *r* is a parameter, *n* is the number of dimensions (attributes) and p_k and q_k are, respectively, the k_{th} attributes (components) or data objects *p* and *q*.

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
- $r \to \infty$. "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.

Binary Data

Categorical	insufficient	sufficient	good	very good	excellent
p1	0	0	1	0	0
p2	0	0	1	0	0
p3	1	0	0	0	0
p4	0	1	0	0	0

item	bread	butter	milk	apple	tooth-past
p1	1	1	0	1	0
p2	0	0	1	1	1
p3	1	1	1	0	0
p4	1	0	1	1	0

Similarity Between Binary Vectors

- Common situation is that objects, *p* and *q*, have only binary attributes
- Compute similarities using the following quantities
  M_{01} = the number of attributes where p was 0 and q was 1
  M_{10} = the number of attributes where p was 1 and q was 0
  M_{00} = the number of attributes where p was 0 and q was 0
  M_{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
  $= (M_{11} + M_{00}) / (M_{01} + M_{10} + M_{11} + M_{00})$

  J = number of 11 matches / number of not-both-zero attributes values
  $= (M_{11}) / (M_{01} + M_{10} + M_{11})$

SMC versus Jaccard: Example

$p =$ 1 0 0 0 0 0 0 0 0 0

$q =$ 0 0 0 0 0 0 1 0 0 1

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

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

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

Document Data

	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

Cosine Similarity

- If d_1 and d_2 are two document vectors, then

$$\cos(d_1, d_2) = (d_1 \bullet d_2) / ||d_1|| \; ||d_2|| ,$$

where $\bullet$ indicates vector dot product and $|| d ||$ is the length of vector d.

- Example:

d_1 = **3 2 0 5 0 0 0 2 0 0**
d_2 = **1 0 0 0 0 0 0 1 0 2**

$d_1 \bullet d_2 = 3*1 + 2*0 + 0*0 + 5*0 + 0*0 + 0*0 + 0*0 + 2*1 + 0*0 + 0*2 = 5$

$||d_1|| = (3*3+2*2+0*0+5*5+0*0+0*0+0*0+2*2+0*0+0*0)^{\mathbf{0.5}} = (42)^{\mathbf{0.5}} = 6.481$

$||d_2|| = (1*1+0*0+0*0+0*0+0*0+0*0+0*0+1*1+0*0+2*2)^{\mathbf{0.5}} = (6)^{\mathbf{0.5}} = 2.245$

$\cos(d_1, d_2) = .3150$

Correlation

- Correlation measures the linear relationship between objects (binary or continuos)
- To compute correlation, we standardize data objects, p and q, and then take their dot product (covariance/standard deviation)

$$p'_k = (p_k - mean(p))$$

$$q'_k = (q_k - mean(q))$$

$$correlation(p,q) = (p' \bullet q') / (n-1) std(p) std(q)$$