Data Preparation

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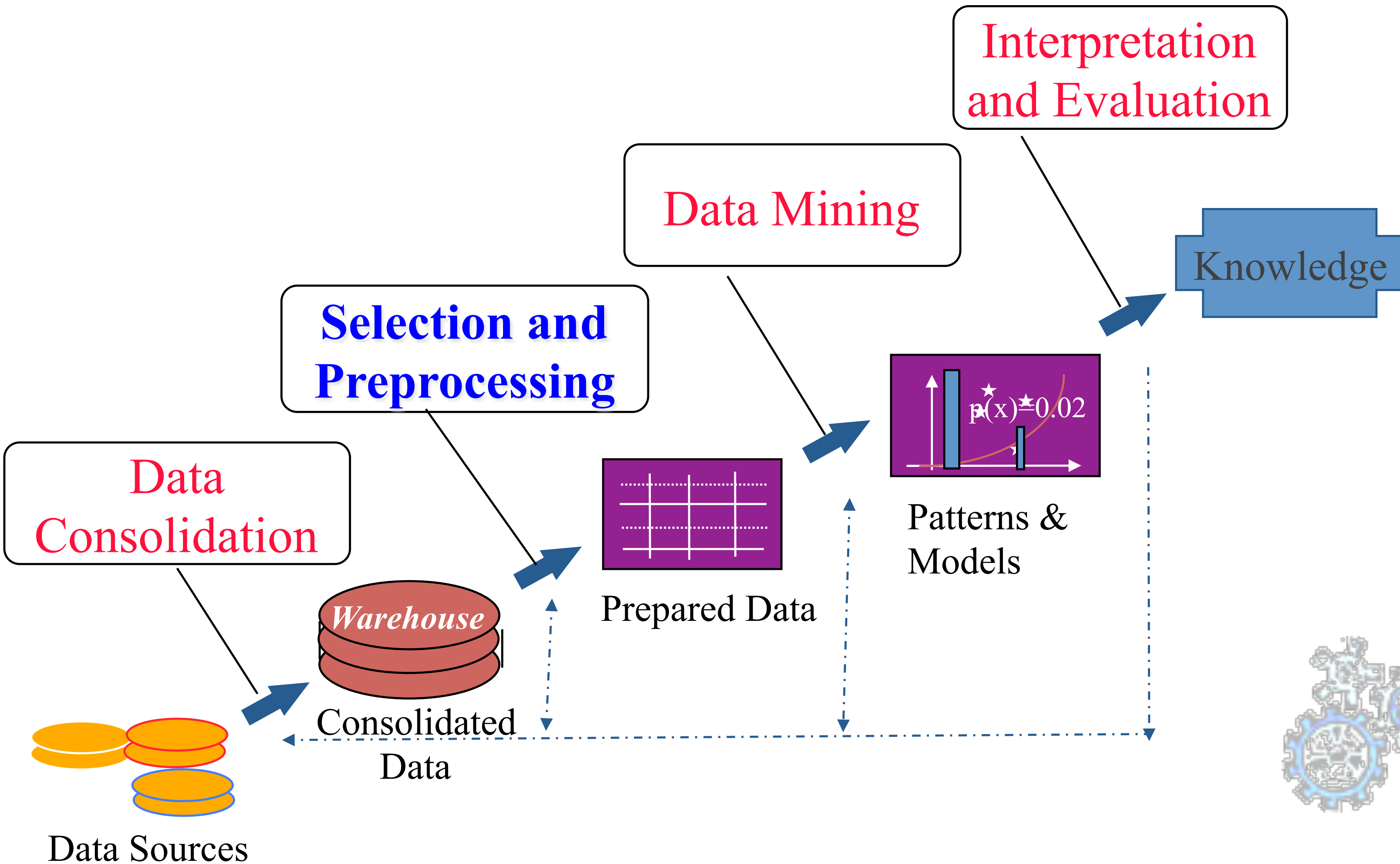
KDD Process


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	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

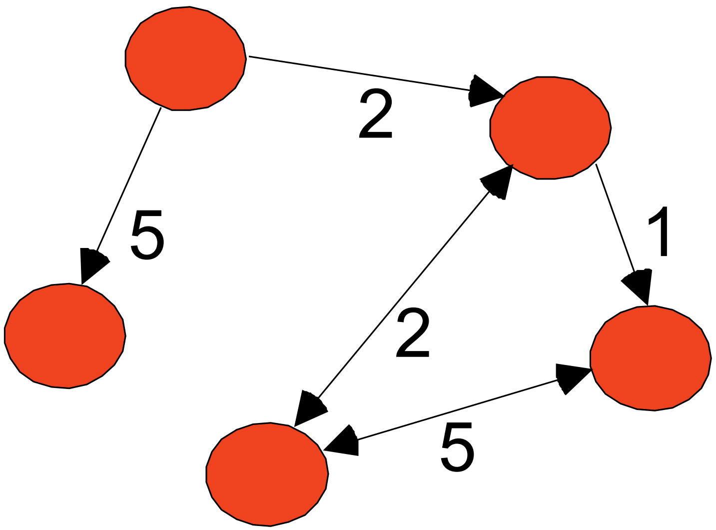
Transaction Data

- A special type of record data, where
  - each record (transaction) involves a set of items.
  - For example, 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

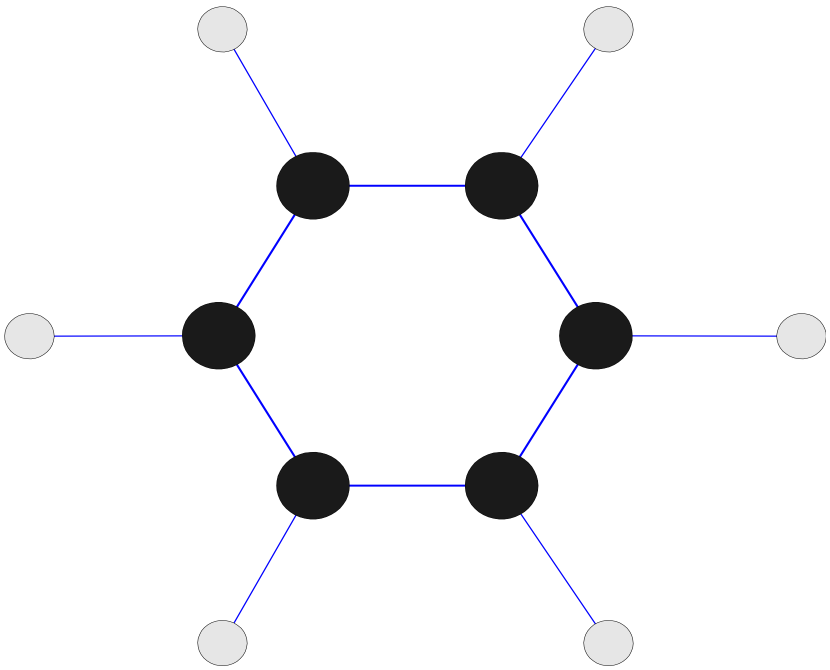
Graph Partitioning

Parallel Solution of Sparse Linear System of Equations

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

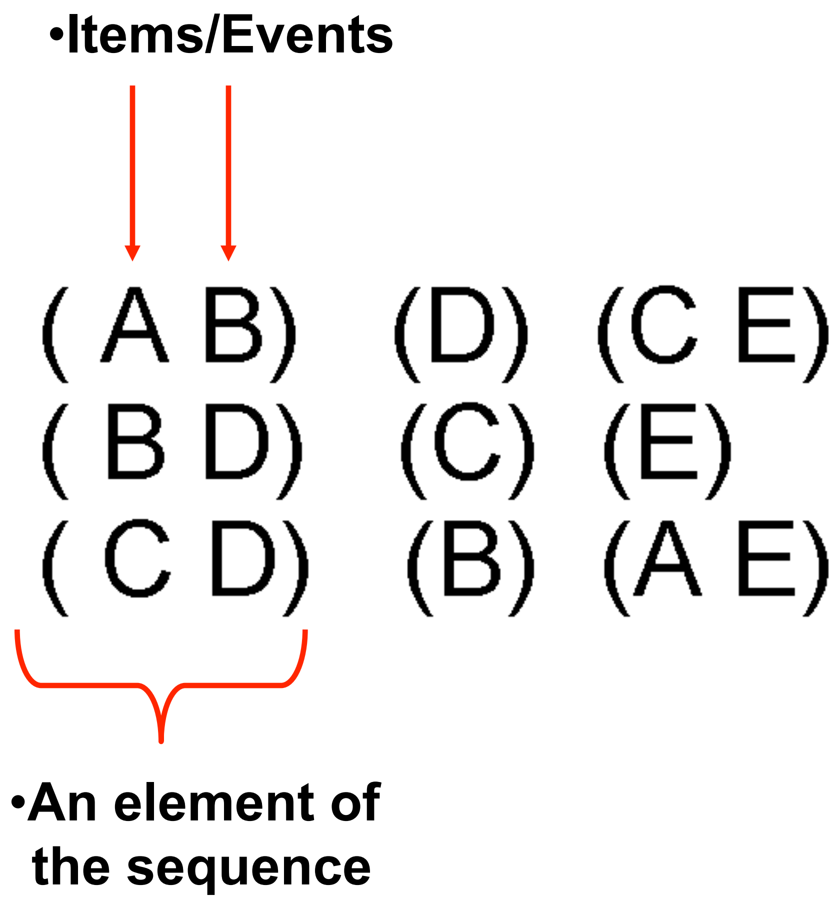
Chemical Data

- Benzene Molecule: C_6H_6



Ordered Data

- Sequences of transactions



Ordered Data

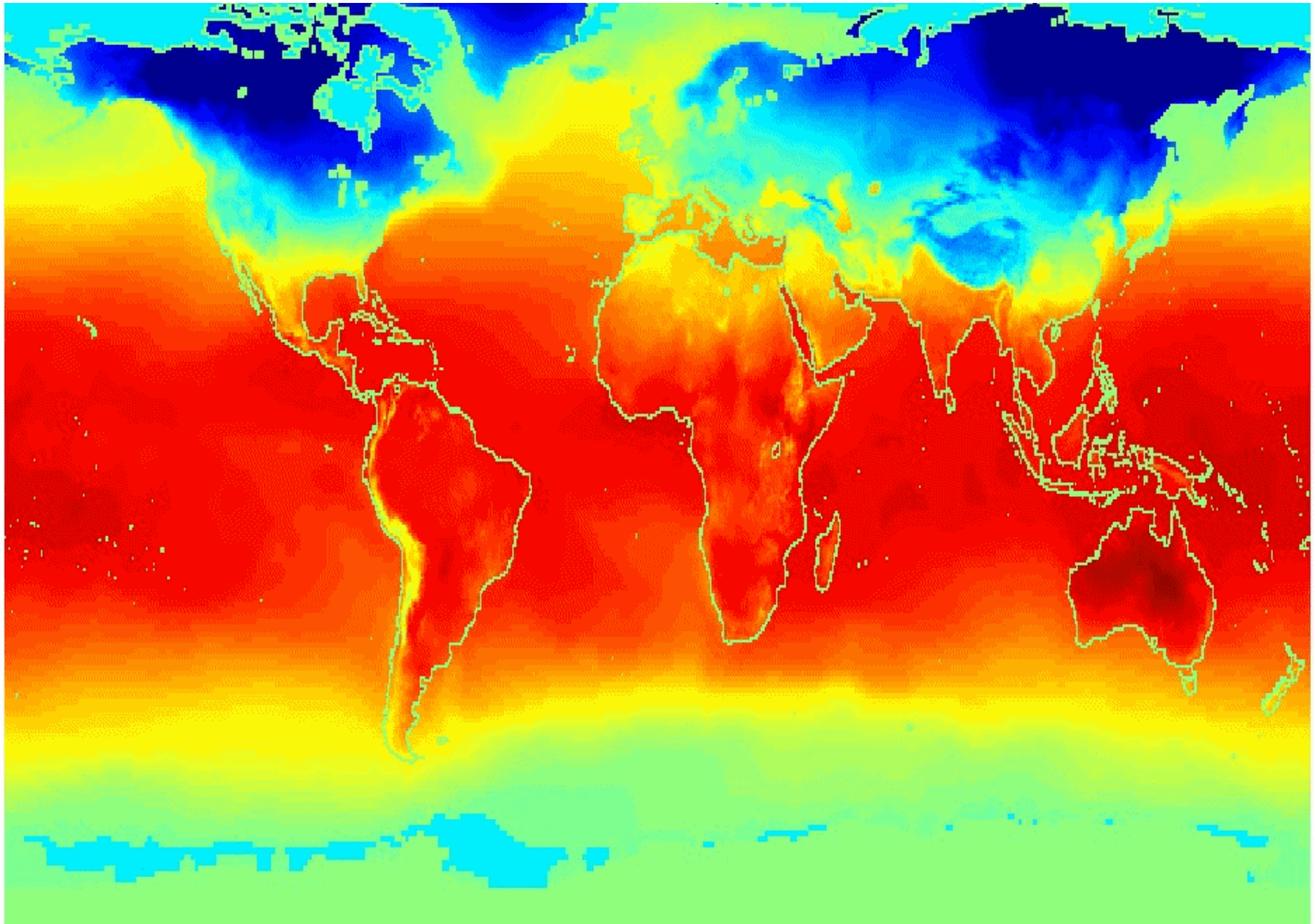
- Genomic sequence data

```
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

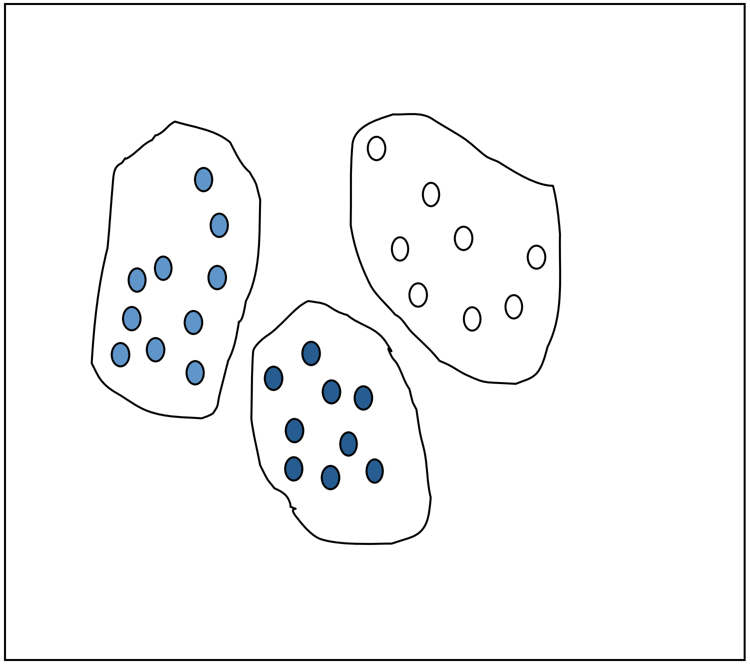
- **Reducing the amount of data**
  - **Vertical**: reduce the number of records
    - Data Sampling
    - Clustering
  - **Horizontal**: reduce the number of columns (attributes)
    - Select a subset of attributes
    - Generate a new (an smaller) set of attributes

Sampling

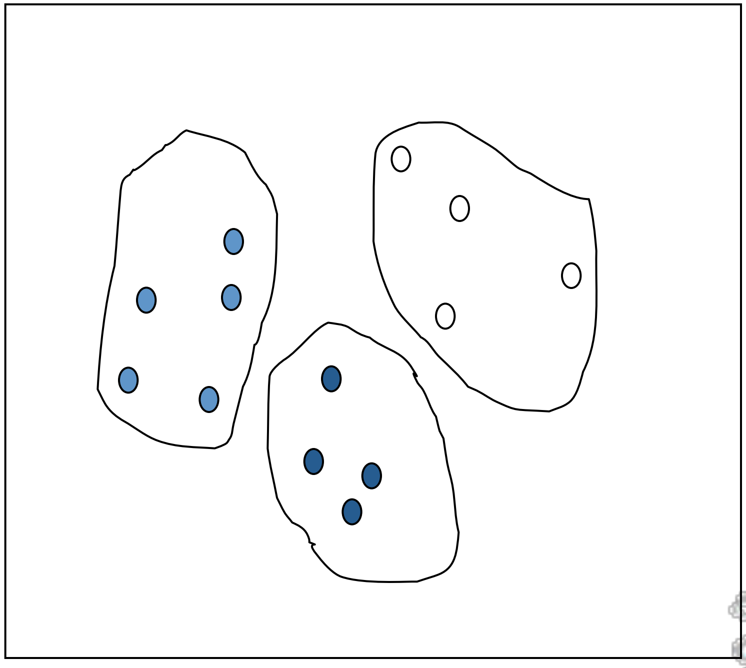
- Improve the execution time of data mining algorithms
- **Problem**: how to select a subset of **representative** data?
  - **Random sampling:** it can generate problem due to the possible peaks in the data
  - **Stratified sampling**:
    - Approximation of the percentage of each class
    - Suitable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

Goals

- Define a transformation T on the attribute X:

  $$Y = \mathrm{T}(X)$$

  such that :

  - Y preserve the **relevant** information of X
  - Y eliminates at least one of the problems of X
  - Y is more **useful** of X

Goals

- **Main goals:**
  - stabilize the variances
  - normalize the distributions
  - Make linear relationships among variables

- **Secondary goals:**
  - simplify the elaboration of data containing features you do not like
  - represent data in a scale considered more suitable

Why linear correlation, normal distributions, etc?

- Many statistical methods require linear correlations, normal distributions, the absence of outliers

- Many data mining algorithms have the ability to automatically treat **non-linearity** and **non-normality**
  - The algorithms work still better if such problems are treated

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

Methods

- Exponential transformation

$$T_p(x) = \begin{cases} ax^p + b & (p \neq 0) \\ c \log x + d & (p = 0) \end{cases}$$

- with a,b,c,d and p real values
  - Preserve the order
  - Preserve some basic statistics
  - They are continuous functions
  - They are derivable
  - They are specified by simple functions

Better Interpretation

- Linear Transformation

  1€ = 1936.27 Lit.

  - *p=1, a= 1936.27 ,b =0*

  ºC= 5/9(ºF -32)

  - *p = 1, a = 5/9, b = -160/9*

Stabilizing the Variance

- **Logarithmic Transformation**

$$T(x) = c \log x + d$$

  - Applicable to positive values
  - Makes homogenous the variance in log-normal distributions
    - E.g.: normalize seasonal peaks

Logarithmic Transformation: Example

Bar	*Birra*	*Ricavo*
A	Bud	20
A	Becks	10000
C	Bud	300
D	Bud	400
D	Becks	5
E	Becks	120
E	Bud	120
F	Bud	11000
G	Bud	1300
H	Bud	3200
H	Becks	1000
I	Bud	135

2300	Media
2883,3333	Scarto medio assoluto
3939,8598	Deviazione standard
5	Min
120	Primo Quartile
350	Mediana
1775	Secondo Quartile
11000	Max

Data are sparse!!!

Logarithmic Transformation: Example

Bar	*Birra*	*Ricavo (log)*
A	Bud	1,301029996
A	Becks	4
C	Bud	2,477121255
D	Bud	2,602059991
D	Becks	0,698970004
E	Becks	2,079181246
E	Bud	2,079181246
F	Bud	4,041392685
G	Bud	3,113943352
H	Bud	3,505149978
H	Becks	3
I	Bud	2,130333768

Media	2,585697
Scarto medio assoluto	0,791394
Deviazione standard	1,016144
Min	0,69897
Primo Quartile	2,079181
Mediana	2,539591
Secondo Quartile	3,211745
Max	4,041393

Stabilizing the Variance

$$T(x) = ax^p + b$$

- **Square-root Transformation**
- $p = 1/c$, c integer number
  - To make homogenous the variance of particular distributions e.g., Poisson Distribution
- **Reciprocal Transformation**
  - $p < 0$
  - Suitable for analyzing time series, when the variance increases too much wrt the mean

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

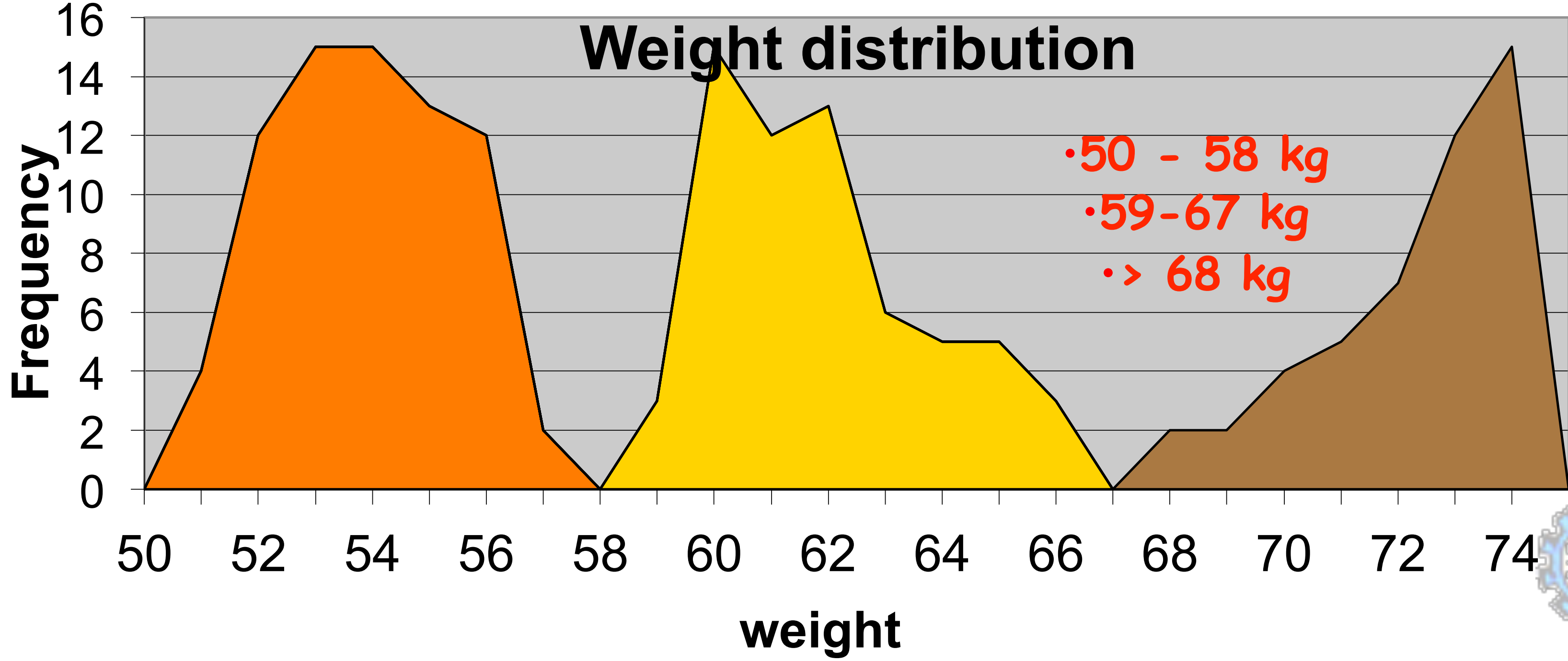
- **Problem**: the discretization may be useless (see **weight**).

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

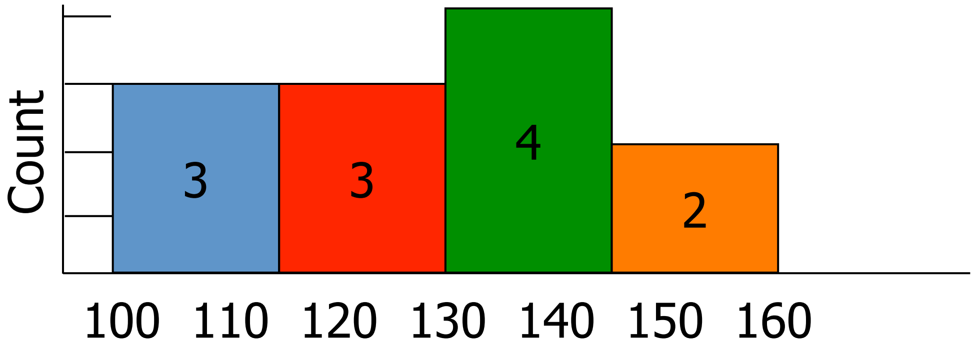
$$x_j \in [x_{min} + i\delta,\ x_{min} + (i+1)\delta)$$

- 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

- $\delta = (160-100)/4 = 15$
- 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

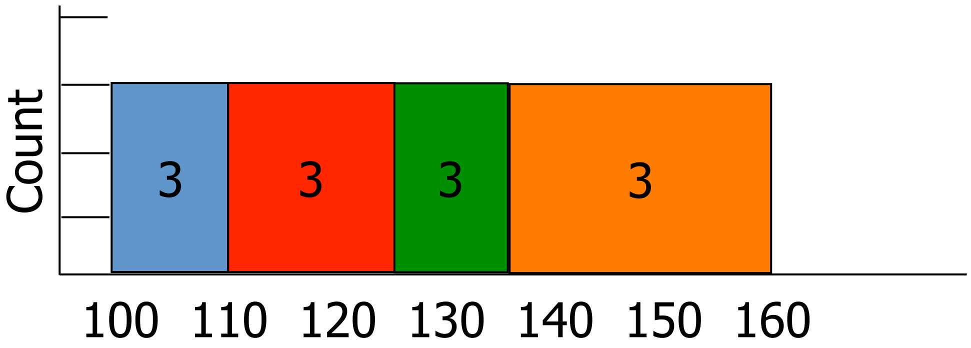
$$j \times f \leq i < (j+1) \times f$$

- 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

  $\Rightarrow$ 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)

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

Supervised Discretization

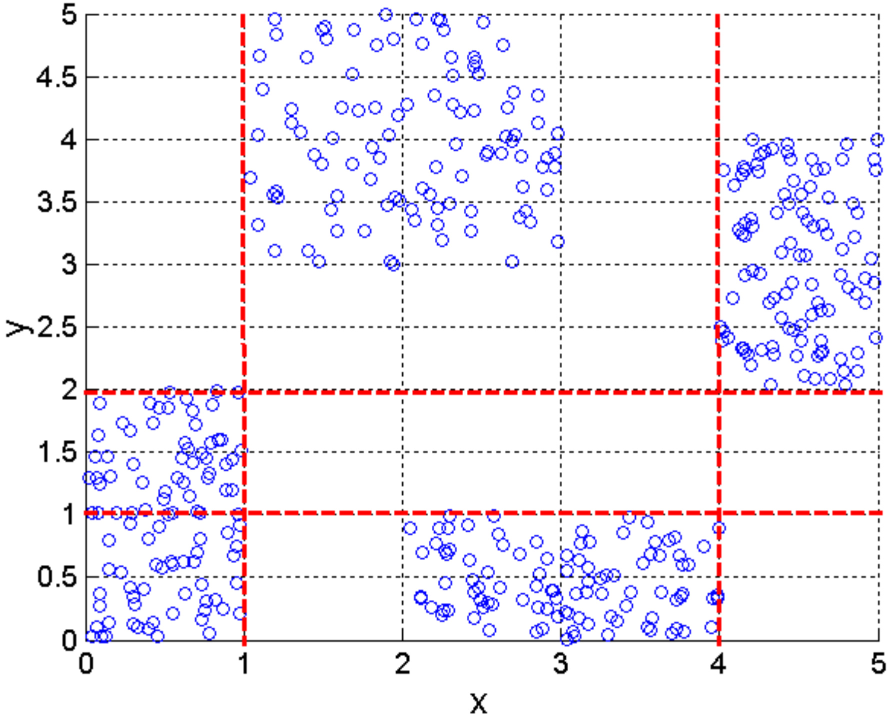
- **Characteristics**:
  - The discretization has a quantifiable goal
  - The number of classes is unknown
- **Techniques**:
  - ChiMerge
  - discretization based on Entropy
  - discretization based on percentiles

Supervised Discretization: ChiMerge

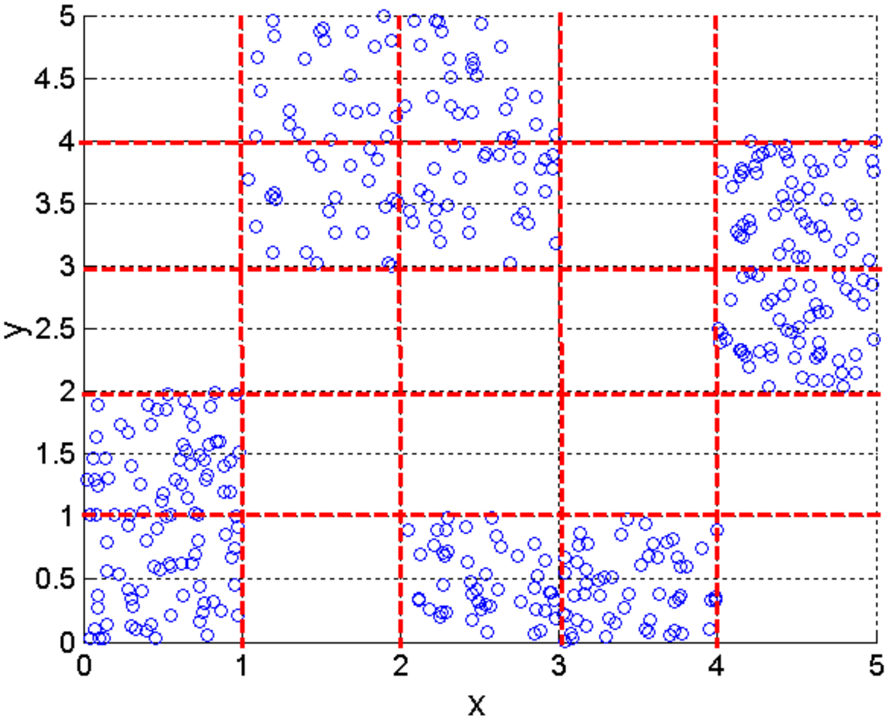
- Bottom-up Process:
  - Initially each value corresponds to an interval
  - Adjacent Intervals are iteratively merged if similar
  - The similarity is measured on the bases of the target attribute, measuring how much the two intervals are "different".

Entropy based approach

- Minimizes the entropy



3 categories for both x and y



5 categories for both x and y

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

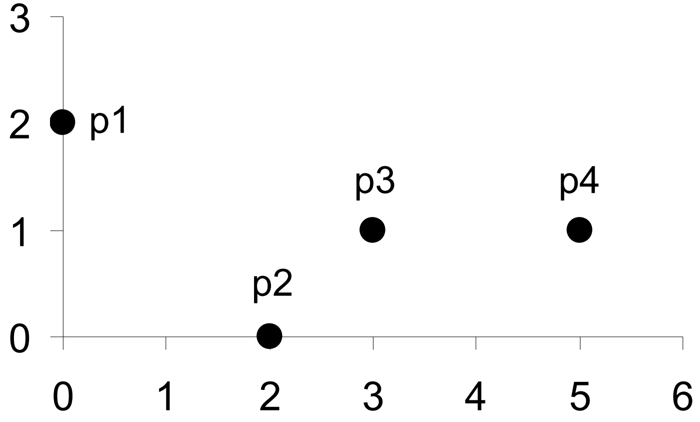
- Euclidean Distance

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

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

- $r \rightarrow \infty$. "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

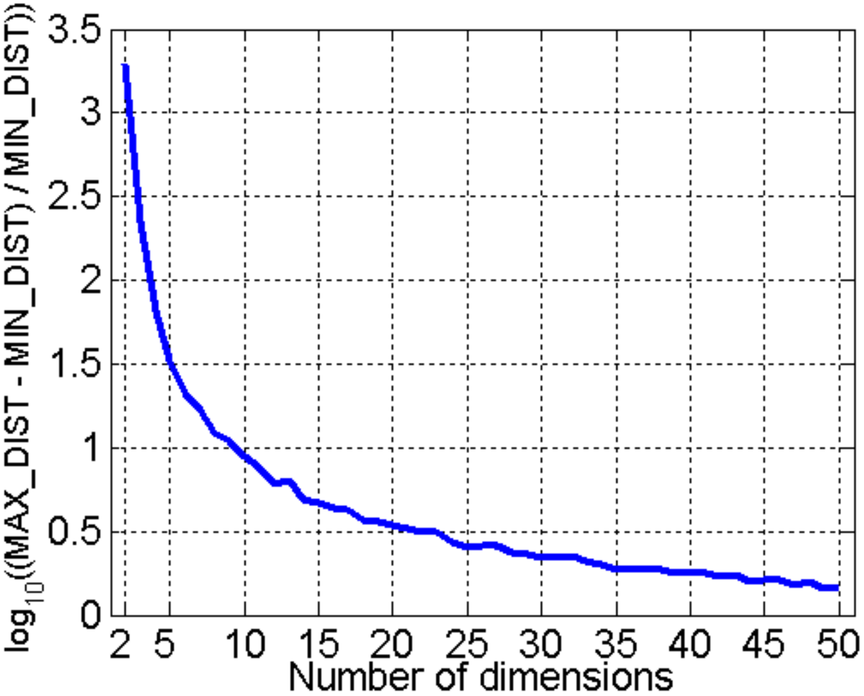
L2	p1	p2	p3	p4
p1	0	2.828	3.162	5.099
p2	2.828	0	1.414	3.162
p3	3.162	1.414	0	2
p4	5.099	3.162	2	0

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

Curse of Dimensionality

- When dimensionality increases, data becomes increasingly sparse in the space that it occupies
- Definitions of density and distance between points, which is critical for clustering and outlier detection, become less meaningful



- Randomly generate 500 points
- Compute difference between max and min distance between any pair of points

Common Properties of a Distance

- Distances, such as the Euclidean distance, have some well known properties.

  1. $d(p, q) \geq 0$ for all *p* and *q* and $d(p, q) = 0$ only if $p = q$. (Positive definiteness)
  2. $d(p, q) = d(q, p)$ for all *p* and *q*. (Symmetry)
  3. $d(p, r) \leq d(p, q) + d(q, r)$ for all points *p*, *q*, and *r*. (Triangle Inequality)

  where *d(p, q)* is the distance (dissimilarity) between points (data objects), *p* and *q*.

- A distance that satisfies these properties is a metric

Common Properties of a Similarity

- Similarities, also have some well known properties.

  1. *s(p, q) = 1* (or maximum similarity) only if *p = q*.
  2. *s(p, q) = s(q, p)* for all *p* and *q*. (Symmetry)

  where *s(p, q)* is the similarity between points (data objects), *p* and *q*.

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	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

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 • 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**

$d_1 \bullet d_2 = 3*1 + 2*0 + 0*0 + 5*0 + 0*0 + 0*0 + 0*0 + 2*1 + 0*0 + 0*2 = 5$
$||d_1|| = (3*3+2*2+0*0+5*5+0*0+0*0+0*0+2*2+0*0+0*0)^{0.5} = (42)^{0.5} = 6.481$
$||d_2|| = (1*1+0*0+0*0+0*0+0*0+0*0+0*0+1*1+0*0+2*2)^{0.5} = (6)^{0.5} = 2.245$

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

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)

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

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

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