

MA333 Introduction to Big Data Analysis

Data Preprocessing

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Outlines

Basic Concepts

Data Preprocessing

Data Types

- Tabular data : matrices, vectors, objects, relations, etc.
 - Data objects : also called samples, examples, instances, data points, objects, tuples, vectors
 - Attributes : each row of a table, also called dimensions, features, variables
- Graphical data : networks, graphs, etc.
- Multi-media data : texts, images, videos, audios, etc.

行星	周期 (年)	平均距离	周期 ² /距离 ³
水星	0.241	0.39	0.98
金星	0.615	0.72	1.01
地球	1.00	1.00	1.00
火星	1.88	1.52	1.01
木星	11.8	5.20	0.99
土星	29.5	9.54	1.00
天王星	84.0	19.18	1.00
海王星	165	30.06	1.00

Types of Attributes

- Discrete : $\mathbf{x} \in$ some countable sets, e.g., \mathbb{N}
 - Nominal : Countries={China, US, UK, France, Germany}, Universities={Peking U, Tsinghua U, SUSTech, Shenzhen U, HIT}, not comparable
 - Boolean : 0 or 1, male or female, spam or non-spam, etc.
 - Ordinal : Heights={tall, short}, Scores={A+, A, A-, B+, B, B-, C, C-, D, F}, can be compared, but cannot operated arithmetically
- Continuous : $\mathbf{x} \in$ some subset in \mathbb{R}^n
 - Numerical : Income, exact marks, weights, etc., can be operated arithmetically

Basic Statistics

- Mean : $EX = \min_c E(X - c)^2 \approx \frac{1}{n} \sum_{i=1}^n x_i$
- Median :

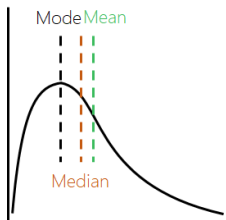
$$\min_c E|X - c| = \begin{cases} x_{(\frac{n+1}{2})} & \text{if } n \text{ is odd} \\ (x_{(\frac{n}{2})} + x_{(\frac{n}{2}+1)})/2 & \text{otherwise} \end{cases}$$

- Maximum : $\max_i x_i$; Minimum : $\min_i x_i$
- Quantile : a generalization of median, k -th q -quantile x_q :
 $P[X < x_q] \leq k/q$; interquartile range
 (IQR) = $Q_3(75\%) - Q_1(25\%)$
- Variance : $\text{Var}(X) = E[X - EX]^2 \approx \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$;
 Standard deviation : $\sqrt{\text{Var}(X)}$
- Mode : $\min_c E|X - c|^0 =$ the most frequently occurring value
 (define $0^0 = 0$)

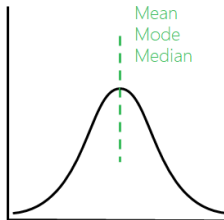
Central Tendency

For one-peak skewed density distribution, empirical formula :

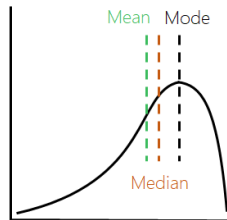
$$\text{Mean} - \text{Mode} = 3 \times (\text{Mean} - \text{Median})$$



Positive
skewed



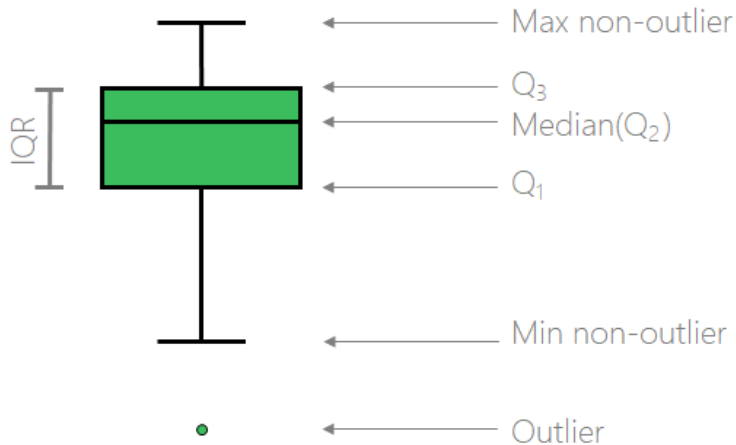
Symmetric



Negative
skewed

Box Plot

Measure the dispersion of data



Metrics

- Proximity :
 - Similarity : range is $[0, 1]$
 - Dissimilarity : range is $[0, \infty]$, sometimes distance
- For nominal data, $d(\mathbf{x}_i, \mathbf{x}_j) = \frac{\sum_k I(x_{i,k} \neq x_{j,k})}{p}$; or one-hot encoding into Boolean data
- For Boolean data, symmetric distance $d(\mathbf{x}_i, \mathbf{x}_j) = \frac{r+s}{q+r+s+t}$ or Rand index $Sim_{Rand}(\mathbf{x}_i, \mathbf{x}_j) = \frac{q+t}{q+r+s+t}$; non-symmetric distance $d(\mathbf{x}_i, \mathbf{x}_j) = \frac{r+s}{q+r+s}$ or Jaccard index $Sim_{Jaccard}(\mathbf{x}_i, \mathbf{x}_j) = \frac{q}{q+r+s}$

		Sample j		
		1	0	sum
Sample i	1	q	r	$q + r$
	0	s	t	$s + t$
sum		$q + s$	$r + t$	p

Metrics : Distance

- Example : Let $H = F = 1$ and $L = S = 0$,
 $d(\text{LandRover}, \text{Jeep}) = \frac{1+0}{4+1+0} = 0.20$, $d(\text{LandRover}, \text{TOYOTA}) = \frac{3+1}{1+3+1} = 0.80$, $d(\text{Jeep}, \text{TOYOTA}) = \frac{3+2}{1+3+2} = 0.83$
- Minkowski distance : $d(\mathbf{x}_i, \mathbf{x}_j) = \sqrt[h]{\sum_{k=1}^p |x_{ik} - x_{jk}|^h}$ is L_h -norm
 - Positive definiteness $d(\mathbf{x}_i, \mathbf{x}_j) \geq 0$ and “=” if and only if $i = j$;
 - Symmetry $d(\mathbf{x}_i, \mathbf{x}_j) = d(\mathbf{x}_j, \mathbf{x}_i)$;
 - Triangle inequality $d(\mathbf{x}_i, \mathbf{x}_j) \leq d(\mathbf{x}_i, \mathbf{x}_k) + d(\mathbf{x}_k, \mathbf{x}_j)$

	Weight	Price	Acceleration	MPG	Quality	Sales Volume	Jeep		
Land Rover	H	H	F	H	H	L	1	0	
Jeep	H	H	S	H	H	L	1	q = 4	r = 1
TOYOTA	L	L	F	L	H	H	0	s = 0	t = 1

Metrics : Distance (Cont')

- Manhattan distance : $h = 1$, and

$$d(\mathbf{x}_i, \mathbf{x}_j) = \sum_{k=1}^p |x_{ik} - x_{jk}|$$

- Euclidean distance : $h = 2$, and $d(\mathbf{x}_i, \mathbf{x}_j) =$

$$\sqrt{\sum_{k=1}^p |x_{ik} - x_{jk}|^2}$$

- Supremum distance : $h = \infty$, and

$$d(\mathbf{x}_i, \mathbf{x}_j) = \max_{k=1}^p |x_{ik} - x_{jk}|$$

L_1	x_1	x_2	x_3	x_4
x_1	0			
x_2	5	0		
x_3	3	6	0	
x_4	6	1	7	0

(a) Manhattan

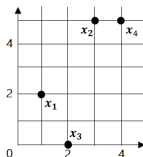
L_2	x_1	x_2	x_3	x_4
x_1	0			
x_2	3.61	0		
x_3	2.24	5.1	0	
x_4	4.24	1	5.39	0

(b) Euclidean

L_∞	x_1	x_2	x_3	x_4
x_1	0			
x_2	3	0		
x_3	2	5	0	
x_4	3	1	5	0

(c) Supremum

Point	Attr 1	Attr 2
x_1	1	2
x_2	3	5
x_3	2	0
x_4	4	5



Metrics : Cosine Similarity

- Definition : $\cos(\mathbf{x}_i, \mathbf{x}_j) =$

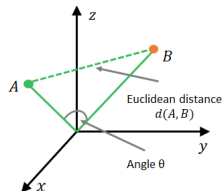
$$\frac{\sum_{k=1}^p x_{ik} x_{jk}}{\sqrt{\sum_{k=1}^p x_{ik}^2} \sqrt{\sum_{k=1}^p x_{jk}^2}} = \frac{\mathbf{x}_i \cdot \mathbf{x}_j}{\|\mathbf{x}_i\| \|\mathbf{x}_j\|}$$

- Example : $\cos(\mathbf{x}_1, \mathbf{x}_2) = 0.94$

Instance	Team	Coach	Hockey	Baseball	Soccer	penalty	Score	Win	Loss	Season
Instance1	5	0	3	0	2	0	0	2	0	0
Instance2	3	0	2	0	1	1	0	1	0	1

Euclidean vs. Cosine :

- Euclidean : measures the distance in absolute value, many applications
- Cosine : insensitive to absolute value, e.g., analyze users' interests based on movie ratings



Metrics : Other Distances

- For ordinal data, mapping the data to numerical data :
 $X = \{x_{(1)}, x_{(2)}, \dots, x_{(n)}\}, x_{(i)} \mapsto \frac{i-1}{n-1} \in [0, 1]$
- For mixed type, use weighted distance with prescribed weights :

$$d(\mathbf{x}_i, \mathbf{x}_j) = \frac{\sum_{g=1}^G w_{ij}^{(g)} d_{ij}^{(g)}}{\sum_{g=1}^G w_{ij}^{(g)}}$$

Put the attributes of the same type into groups, for each data type g , use the corresponding distance $d_{ij}^{(g)}$

Outlines

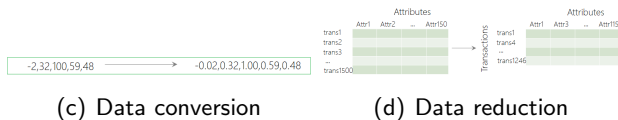
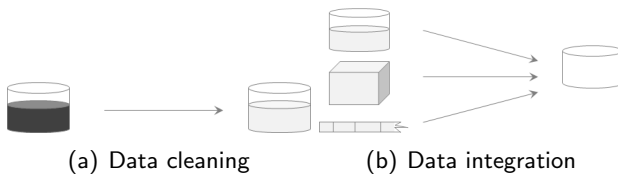
Basic Concepts

Data Preprocessing

Why Data Preprocessing ?

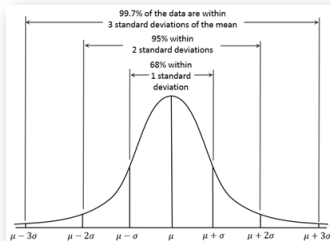
- Missing values
- Noisy with outliers
- Inconsistent representations
- Redundancy
- Errors may come during data input, data gathering, and data transferring
- Errors occur in about 5% of the data

Four Types of Data Preprocessing



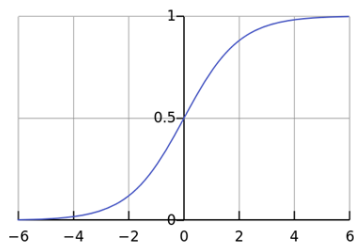
Data Scaling

- Why scaling :
 - For better performance : e.g., RBF in SVM and penalty in Lasso/ridge regression assume the zero mean and unit variance
 - Normalize different dimensions : many algorithms are sensitive to the variables with large variances, e.g., height (1.75m) and weight (70kg) in distance calculation
- Z-score scaling : $x_i^* = \frac{x_i - \hat{\mu}}{\hat{\sigma}}$, $\hat{\mu}$: sample mean, $\hat{\sigma}$: sample variance, applicable if max and min are unknown and the data distributes well



Data Scaling (Cont')

- 0-1 scaling : $x_i^* = \frac{x_i - \min_k x_k}{\max_k x_k - \min_k x_k} \in [0, 1]$, applicable for bounded data sets, need to recompute the max and min when new data arrive
- Decimal scaling : $x_i^* = \frac{x_i}{10^k}$, applicable for data varying across many magnitudes
- Logistic scaling : sigmoid transform $x_i^* = \frac{1}{1 + e^{-x_i}}$, applicable for data concentrating nearby origin



Data Discretization

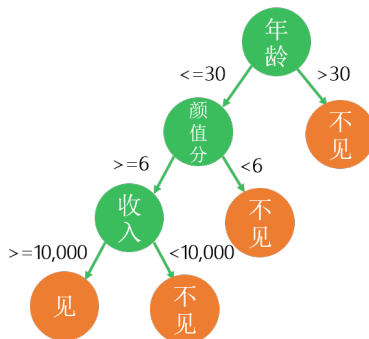
- Why discretization :
 - Improve the robustness : removing the outliers by putting them into certain intervals
 - For better interpretation
 - Reduce the storage and computational power
- Unsupervised discretization : equal-distance discretization, equal-frequency discretization, clustering-based discretization, 3σ -based discretization
- Supervised discretization : information gain based discretization, χ^2 -based discretization

Unsupervised Discretization

- Equal-distance discretization : split the range to n intervals (bins) with the same length, group the data into each bin, sensitive to outliers
- Equal-frequency discretization : group the data into n subset so that each subset has the same number of points, tend to separate samples with similar values and produce uniform distribution
- Clustering-based discretization : do hierarchical clustering and form a hierarchical structure (e.g., using K -Means), and put the samples in the same branch into the same interval (a natural example is family tree)
- 3σ -based discretization : put the samples into 8 intervals, need to take logarithm first

Supervised Discretization - Information Gain

- Top-down splitting, similar to create a decision tree
- Do a decision tree classification using information gain, find a proper splitting point for each continuous variable such that the information gain increases the most
- The final leaf nodes summarize the discrete intervals



Supervised Discretization - ChiMerge

- Bottom-up : similar to hierarchical clustering
- $\hat{\chi}^2$ statistics proposed by Karl Pearson, is used to test where the two sets of samples are dramatically different :
$$\hat{\chi}^2 = \sum_{i=1}^k \frac{A_i - \mathbb{E}A_i}{\mathbb{E}A_i} = \sum_{i=1}^k \frac{A_i - np_i}{np_i},$$
 where A_i is the number of samples in the i -th interval (frequency of observations), and $\mathbb{E}A_i$ is its expectation ; it can be shown that $\hat{\chi}^2 \rightarrow \chi^2_{k-1}$
- ChiMerge : Given a threshold level t ,
 1. Treat each value of the continuous variable as an interval and sort them in increasing order ;
 2. For each pair of adjacent intervals, compute its χ^2 statistics, if $\hat{\chi}^2 < t$, merge them into a new interval ;
 3. Repeat the above steps until terminal, i.e., one interval
- Two shortcomings : t is hard to set appropriately ; too long loop for large sample set, computationally intensive

ChiMerge : Iris Data Example

- $\hat{\chi}^2 = \sum_{i=1}^m \sum_{j=1}^k \frac{A_{ij} - E_{ij}}{E_{ij}}$, where
 $m = 2$ (two adjacent intervals)
 k is the number of classes
 A_{ij} is the number of samples in i -th interval and in class k
 $R_i = \sum_{j=1}^k A_{ij}$ is the total number of samples in i -th interval
 $C_j = \sum_{i=1}^m A_{ij}$ is the total number of samples in class j
 $N = \sum_{i=1}^m \sum_{j=1}^k A_{ij}$ is the total number of samples
 $E_{ij} = R_i \cdot \frac{C_j}{N}$
- χ^2 of 4.3 and 4.4 : $C_1 = 4$,
 $C_2 = 0$, $C_3 = 0$, $N = 4$, $A_{11} = 1$,
 $A_{12} = A_{13} = 0$, $A_{21} = 3$,
 $A_{22} = A_{23} = 0$, $R_1 = 1$, $R_2 = 3$,
 $E_{11} = 1$, $E_{12} = E_{13} = 0$, $E_{21} = 3$,
 $E_{22} = E_{23} = 0$, $\hat{\chi}^2 = 0$.

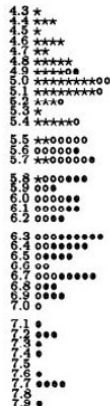


FIGURE: Sepal lengths of 3 types of iris

ChiMerge Results

Left : significance level is 0.5 and the threshold for χ^2 is 1.4 ;
 Right : significance level is 0.9 and the threshold for χ^2 is 4.6 ;
 The final results keep the intervals with χ^2 larger than the thresholds

Int	Class			χ^2
	frequency			
4.3	16	0	0	4.1
4.9	4	1	1	2.4
5.0	25	5	0	8.6
5.5	2	5	0	2.9
5.6	0	5	1	1.7
5.7	2	5	1	1.8
5.8	1	3	3	2.2
5.9	0	12	7	4.8
6.3	0	6	15	4.1
6.6	0	2	0	3.2
6.7	0	5	10	1.5
7.0	0	1	0	3.6
7.1	0	0	12	

Int	Class			χ^2
	frequency			
4.3	45	6	1	30.9
5.5	4	15	2	6.7
5.8	1	15	10	4.9
6.3	0	14	25	5.9
7.1	0	0	12	

Figure 2: ChiMerge discretizations for *sepal-length* at the .50 and .90 significance levels ($\chi^2 = 1.4$ and 4.6)

Missing Data

- Where missing data come from ?
 - Missing Completely At Random (MCAR) : the occurrence of missing data is a random event
 - Missing At Random (MAR) : depending on some control variables, e.g., the age > 20 is not acceptable in an investigation for teenager and thus is replaced by MAR
 - Missing Not At Random (MNAR) : missing data for bad performed employees after they are fired

Simple Methods

- Deleting samples : for small size of samples with missing values
- Deleting variables : for series missing values in variables

gradyear	gender	age	friends
2006	M	18.98	7
2006	F	18.801	0
2006	M	18.335	69
2006	F	18.875	0
2006	NA	18.995	10
2006	F		142
2006	F	18.93	72
2006	M	18.322	17
2006	F	19.055	52
2006	F	18.708	39
2006	F	18.543	8
2006	F	19.463	21
2006	F	18.097	87
2006	NA		0
2006	F	18.398	0
2006	NA		0
2006	NA		135
2006	F	18.987	26
2006	F	17.158	27
2006	F	18.497	123
2006	F	18.738	35

Filling Methods

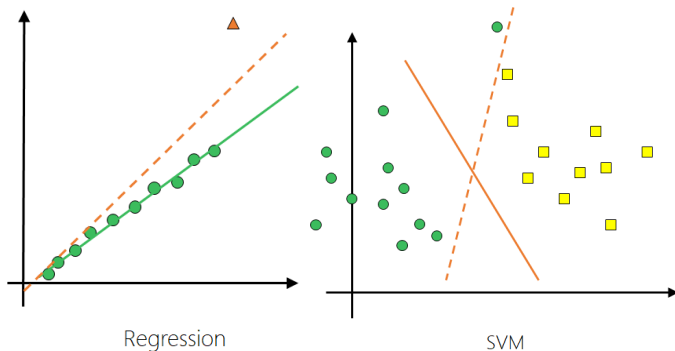
- Filling with zero
- Filling with means for numerical type, and with modes for non-numerical type, applicable for MCAR; drawback : concentrating in the mean and underestimating the variance ; solution : filling in different groups
- Filling with similar variables : auto-correlation is introduced
- Filling with past data
- Filling by K-Means : Compute the pairwise distances of the data using good variables (no missing values), then fill the missing values with the mean of the first K most similar good data, auto-correlation is introduced
- Filling with Expectation-Maximization (EM) : introduce hidden variables and use MLE to estimate the parameters (missing values)

Filling Methods (Cont')

- Random filling :
 - Bayesian Bootstrap : for discrete data with range $\{x_i\}_{i=1}^k$, randomly sample $k - 1$ numbers from $U(0, 1)$ as $\{a_{(i)}\}_{i=0}^k$ with $a_{(0)} = 0$ and $a_{(k)} = 1$; then randomly sample from $\{x_i\}_{i=1}^k$ with probability distribution $\{a_{(i)} - a_{(i-1)}\}_{i=1}^k$ accordingly to fill in the missing values
 - Approximate Bayesian Bootstrap: Sample with replacement from $\{x_i\}_{i=1}^k$ to form new data set $X^* = \{x_i^*\}_{i=1}^k$; then randomly sample n values from X^* to fill in the missing values, allowing for repeatedly filling missing values
- Model based methods : treat missing variable as y , other variables as \mathbf{x} ; take the data without missing values as our training set to train a classification or regression model; take the data with missing values as our test set to predict the miss values

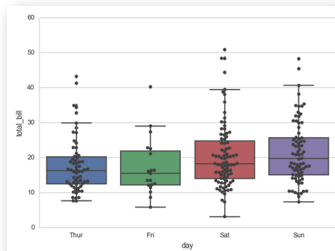
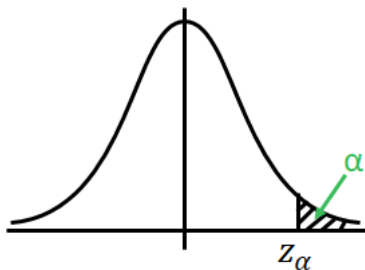
Outliers

- Outliers : the data points seem to come from different distribution, or noisy data
- Outlier detection : unsupervised, e.g., Credit cheating detection, medical analysis, and information security, etc.



Outliers Detection - Statistics Based Methods

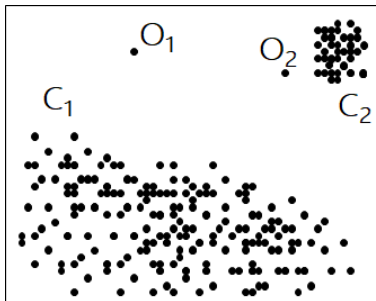
- The samples outside the upper and lower α -quantile for some small α (usually 1%)
- Observe from box plot



Outliers Detection - Local Outlier Factor

Local Outlier Factor (LOF) is a density based method :

1. We could compute the density at each position \mathbf{x} , e.g., $p(\mathbf{x})$ (how to define the density if we only have data samples) ;
2. We could compare the density of each point \mathbf{x} with the density of its neighbors, i.e., compare $p(\mathbf{x})$ with $p(\mathbf{x}_k)$ where \mathbf{x}_k is close to \mathbf{x} (in a neighborhood of \mathbf{x} , but how to define the neighborhood)



Computing Density by Distance

Some definitions :

- $d(A, B)$: distance between A and B ;
- $d_k(A)$: k -distance of A , or the distance between A and the k -th nearest point from A
- $N_k(A)$: k -distance neighborhood of A , or the points within $d_k(A)$ from A ;
- $rd_k(B, A)$: k -reach-distance from A to B , the repulsive distance from A to B as if A has a hard-core with radius $d_k(A)$,
 $rd_k(B, A) = \max\{d_k(A), d(A, B)\}$; note that $rd_k(A, B) \neq rd_k(B, A)$, which implies that k -reach-distance is not symmetric.

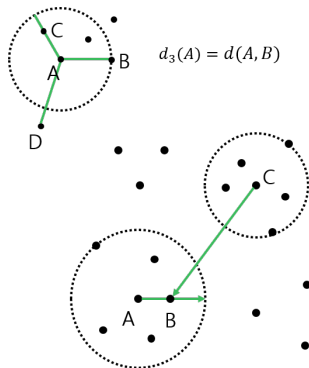


FIGURE: $rd_5(B, A) = d_5(A)$ and $rd_5(B, C) = d(B, C)$

Local Outlier Factor

Some definitions :

- $lrd_k(A)$: local reachability density,

$$lrd_k(A) = 1 / \left(\frac{\sum_{O \in N_k(A)} rd_k(A, O)}{|N_k(A)|} \right);$$
 intuitively, if for most $O \in N_k(A)$, more than k points are closer to O than A is, then the denominator is much larger than $d_k(A)$ and $lrd_k(A)$ is small;
- $LOF_k(A)$: local outlier factor,

$$LOF_k(A) = \frac{\sum_{O \in N_k(A)} \frac{lrd_k(O)}{lrd_k(A)}}{|N_k(A)|};$$
- $LOF_k(A) \ll 1$, the density of A is locally higher, dense point;
 $LOF_k(A) \gg 1$, the density of A is locally lower, probably outlier

