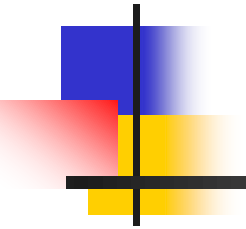

Data Mining – Chapter 3

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Extended from the slides of the book "Data Mining: Concepts and Techniques (3rd ed.)" provided by Jiawei Han, Micheline Kamber, and Jian Pei

Chapter 3: Data Preprocessing

- Data Preprocessing: An Overview 
  - Data Quality
  - Major Tasks in Data Preprocessing
- Data Cleaning
- Data Integration
- Data Reduction
- Data Transformation and Data Discretization
- Summary

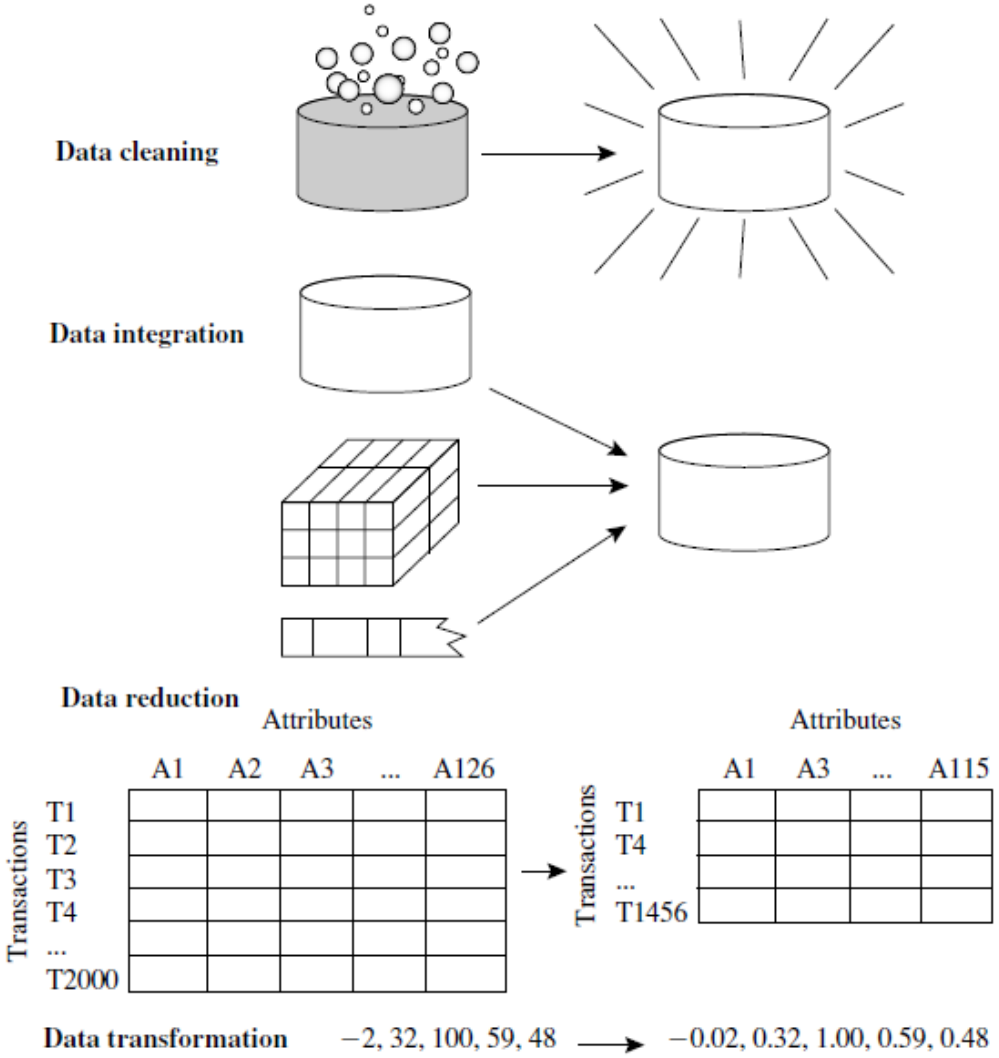
Data Preprocessing

- Today's real-world databases are highly susceptible to noisy, missing, and inconsistent data due to their typically huge size (often several gigabytes or more) and their likely origin from multiple, heterogenous sources.
- Low-quality data will lead to low-quality mining results.
- "How can the data be preprocessed in order to help improve the quality of the data and, consequently, of the mining results?
- How can the data be preprocessed so as to improve the efficiency and ease of the mining process?"

Major Tasks in Data Preprocessing

- **Data cleaning**
  - Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- **Data integration**
  - Integration of multiple databases, data cubes, or files
- **Data reduction**
  - Dimensionality reduction
  - Numerosity reduction
  - Data compression
- **Data transformation and data discretization**
  - Normalization
  - Concept hierarchy generation

Forms of Data Preprocessing



Data Quality: Why Preprocess the Data?

- Data have quality if they satisfy the requirements of the intended use.
- Factors comprising data quality: A multidimensional view
  - Accuracy: correct or wrong, accurate or not
  - Completeness: not recorded, unavailable, …
  - Consistency: some modified but some not, dangling, …
  - Timeliness: timely update?
  - Believability: how trustable the data are correct?
  - Interpretability: how easily the data can be understood?

Welcome to the real world!

- Imagine that you are a manager at AllElectronics and want to analyze the company's data with respect to your branch's sales.
- Carefully inspect the company's database and data warehouse, select the attributes or dimensions (e.g., item, price, and units sold) to be included in your analysis.
  - Several of the attributes for various tuples have no recorded value.
- For your analysis, you want to include information as to whether each item purchased was advertised as on sale, yet you discover that this information has not been recorded.
- The data you wish to analyze are
  - incomplete - lacking attribute values or certain attributes of interest, or containing only aggregate data
  - inaccurate or noisy - containing errors, or values that deviate from the expected
  - inconsistent - containing discrepancies in the department codes used to categorize items
- Inaccurate, incomplete, and inconsistent data are commonplace properties of large real-world databases and data warehouses.

Reasons for Inaccurate Data

- The data collection instruments used may be faulty.
- There may have been human or computer errors occurring at data entry.
- Users may purposely submit incorrect data values for mandatory fields when they do not wish to submit personal information.
  - e.g., by choosing the default value "January 1" displayed for birthday
  - This is known as disguised missing data.
- Errors in data transmission can also occur.
- There may be technology limitations such as limited buffer size for coordinating synchronized data transfer and consumption.
- Incorrect data may also result from inconsistencies in naming conventions or data codes, or inconsistent formats for input fields.
  - e.g., date
- Duplicate tuples also require data cleaning.

Reasons for Incomplete Data

- Attributes of interest may not always be available, such as customer information for sales transaction data.
- Other data may not be included simply because they were not considered important at the time of entry.
- Relevant data may not be recorded due to a misunderstanding or because of equipment malfunctions.
- Data that were inconsistent with other recorded data may have been deleted.
- The recording of the data history or modifications may have been overlooked.
- Missing data, particularly for tuples with missing values for some attributes, may need to be inferred.

Factors Affecting Data Quality

- Intended use of the data
- Timeliness
- Believability
- Interpretability.

Data Quality - Intended Use of the Data

- Two different users may have very different assessments of the quality of a given database.
  - A marketing analyst may need to access the database mentioned before for a list of customer addresses.
  - Some of the addresses are outdated or incorrect, yet overall, 80% of the addresses are accurate.
  - The marketing analyst considers this is okay for target marketing purposes and is pleased with the database's accuracy
  - Sales manager may think that the data is inaccurate.

Data Quality - Timeliness

- Suppose that you are overseeing the distribution of monthly sales bonuses to the top sales representatives.
- Several sales representatives, however, fail to submit their sales records on time at the end of the month.
- There are also a number of corrections and adjustments that flow in after the month's end.
- For a period of time following each month, the data stored in the database are incomplete.
- However, once all of the data are received, it is correct.
- The fact that the month-end data are not updated in a timely fashion has a negative impact on the data quality.

Data Quality - Believability and Interpretability

- Believability reflects how much the data are trusted by users, while interpretability reflects how easy the data are understood.
- Suppose that a database, at one point, had several errors, all of which have since been corrected.
- The past errors, however, had caused many problems for sales department users, and so they no longer trust the data.
- The data also use many accounting codes, which the sales department does not know how to interpret.
- Even though the database is now accurate, complete, consistent, and timely, sales department users may regard it as of low quality due to poor believability and interpretability.

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Data Cleaning

- Fill in missing values, smooth out noise while identifying outliers, and correct inconsistencies in the data.
- How to Handle Missing Data?
  - Ignore the tuple
  - Fill in the missing value manually
  - Use a global constant to fill in the missing value
  - Use a measure of central tendency for the attribute (e.g., the mean or median) to fill in the missing value
  - Use the attribute mean or median for all samples belonging to the same class as the given tuple
  - Use the most probable value to fill in the missing value

How to Handle Missing Data?

- Ignore the tuple
  - Usually done when the class label is missing (assuming the mining task involves classification).
  - Is not very effective, unless the tuple contains several attributes with missing values.
  - Especially poor when the percentage of missing values per attribute varies considerably.
  - By ignoring the tuple, we do not make use of the remaining attributes' values in the tuple.
  - Such data could have been useful to the task at hand.
- Fill in the missing value manually
  - Time consuming and may not be feasible given a large data set with many missing values.

How to Handle Missing Data?

- Use a global constant
  - Replace all missing attribute values by the same constant such as a label like "Unknown" or -∞.
  - If missing values are replaced by, say, "Unknown," then the mining program may mistakenly think that they form an interesting concept, since they all have a value in common—that of "Unknown."
  - Hence, although this method is simple, it is not foolproof.
- Use a measure of central tendency for the attribute (e.g., the mean)
  - For normal (symmetric) data distributions, the mean can be used, while skewed data distribution should employ the median.
  - Suppose that the data distribution regarding the income of customers is symmetric and that the mean income is $56,000.
  - Use this value to replace the missing value for income.

How to Handle Missing Data?

- Use the attribute mean or median for all samples belonging to the same class as the given tuple
  - If classifying customers according to credit risk, we may replace the missing value with the mean income value for customers in the same credit risk category as that of the given tuple.
  - For skewed data distribution for a given class, the median value is better.
- Use the most probable value
  - Done with regression, inference-based tools using a Bayesian formalism, or decision tree induction.
  - e.g., using the other customer attributes, you may construct a decision tree to predict the missing values for income.

How to Handle Missing Data? (Recap.)

- Ignore the tuple: usually done when class label is missing (when doing classification)—not effective when the % of missing values per attribute varies considerably
- Fill in the missing value manually: tedious + infeasible?
- Fill in it automatically with
  - a global constant : e.g., "unknown", a new class?!
  - the attribute mean
  - the attribute mean for all samples belonging to the same class: smarter
  - the most probable value: inference-based such as Bayesian formula or decision tree

Noisy Data

- Noise: random error or variance in a measured variable
- Incorrect attribute values may be due to
  - faulty data collection instruments
  - data entry problems
  - data transmission problems
  - technology limitation
  - inconsistency in naming convention
- Other data problems which require data cleaning
  - duplicate records
  - incomplete data
  - inconsistent data

How to Handle Noisy Data?

- Binning
  - first sort data and partition into (equal-frequency) bins
  - then one can smooth by bin means, smooth by bin median, smooth by bin boundaries, etc.
- Regression
  - smooth by fitting the data into regression functions
- Clustering
  - detect and remove outliers
- Combined computer and human inspection
  - detect suspicious values and check by human (e.g., deal with possible outliers)

Example of Binning Methods

- Binning methods smooth a sorted data value by consulting its "neighborhood,".
- Smoothing by bin means
  - Each value in a bin is replaced by the mean value of the bin.
- Smoothing by bin medians
  - Each bin value is replaced by the bin median.
- Smoothing by bin boundaries
  - Each bin value is then replaced by the closest boundary value.

Sorted data for *price* (in dollars): 4, 8, 15, 21, 21, 24, 25, 28, 34

Partition into (equal-frequency) bins:

Bin 1: 4, 8, 15
Bin 2: 21, 21, 24
Bin 3: 25, 28, 34

Smoothing by bin means:

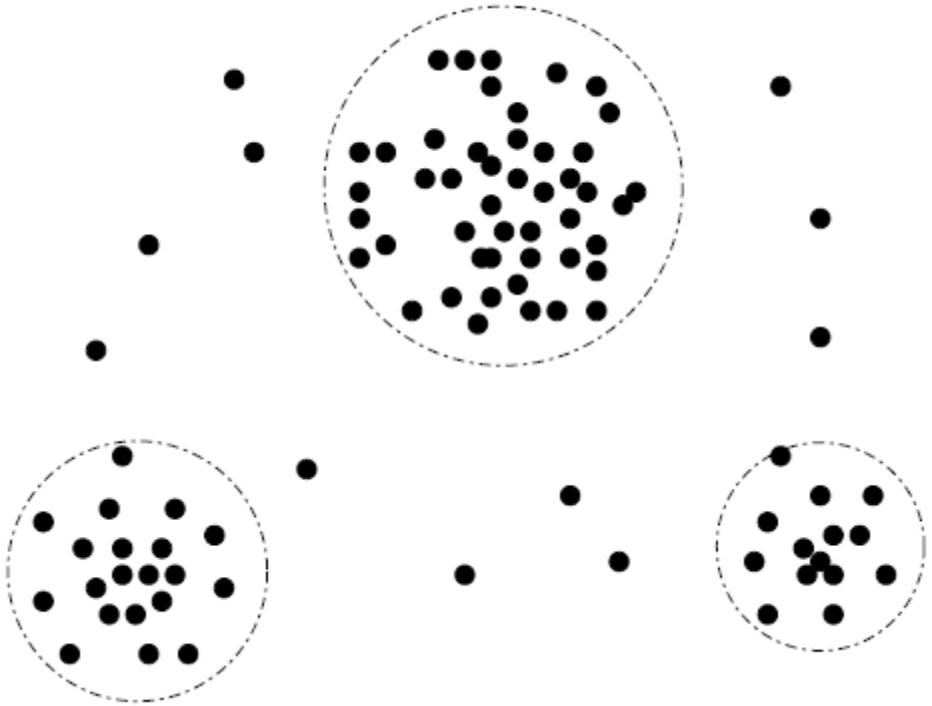
Bin 1: 9, 9, 9
Bin 2: 22, 22, 22
Bin 3: 29, 29, 29

Smoothing by bin boundaries:

Bin 1: 4, 4, 15
Bin 2: 21, 21, 24
Bin 3: 25, 25, 34

Example of Clustering Methods

- 2-D customer data plot with respect to customer locations in a city, showing three data clusters.
- Outliers may be detected as values that fall outside of the cluster sets.



Discrepancy Detection

- Use any knowledge you may already have regarding properties of the data (i.e., metadata).
  - What are the data type and domain of each attribute?
  - What are the acceptable values for each attribute?
  - The basic statistical data descriptions are useful here to grasp data trends and identify anomalies (e.g., the mean, median, and mode values).
  - Are the data symmetric or skewed?
  - What is the range of values?
  - Do all values fall within the expected range?
  - What is the standard deviation of each attribute? - Values that are more than two standard deviations away from the mean for a given attribute may be flagged as potential outliers.
  - Are there any known dependencies between attributes?
  - From this, you may find noise, outliers, and unusual values that need investigation.

Data Cleaning as a Process

- As a data analyst, you should be on the lookout for the inconsistent use of codes and any inconsistent data representations (e.g., “2010/12/25” and “25/12/2010” for date).
- Field overloading is another error source that typically results when developers squeeze new attribute definitions into unused (bit) portions of already defined attributes (e.g., an unused bit of an attribute that has a value range that uses only, say, 31 out of 32 bits).

Data Cleaning as a Process

- Data should also be examined regarding unique rules, consecutive rules, and null rules.
- A unique rule
  - Says that each value of the given attribute must be different from all other values for that attribute.
- A consecutive rule
  - Says that there is no missing values between the lowest and highest values for the attribute, and that all values must also be unique (e.g., as in check numbers).
- A null rule
  - Specifies the use of blanks, question marks, special characters, or other strings that may indicate the null condition (e.g., where a value for a given attribute is not available), and how such values should be handled.
  - e.g., Store zero for numeric attributes, a blank for character attributes, or any other conventions that may be in use
  - Reasons for missing values may include
    - The person originally asked to provide a value for the attribute refuses and/or finds that the information requested is not applicable (e.g., a license number attribute left blank by nondrivers)
    - The data entry person does not know the correct value
    - The value is to be provided by a later step of the process.

Data Cleaning as a Process

- There are a number of different commercial tools that can aid in the discrepancy detection step.
- Data scrubbing tools use simple domain knowledge (e.g., knowledge of postal addresses and spell-checking) to detect errors and make corrections in the data.
  - Rely on parsing and fuzzy matching techniques when cleaning data from multiple sources.
- Data auditing tools find discrepancies by analyzing the data to discover rules and relationships, and detecting data that violate such conditions.
  - They are variants of data mining tools.
  - e.g., they may employ statistical analysis to find correlations, or clustering to identify outliers.
  - They may also use the basic statistical data descriptions.

Data Cleaning as a Process

- Some data inconsistencies may be corrected manually using external references.
  - e.g., Errors made at data entry may be corrected by performing a paper trace.
- Most errors require data transformations.
  - Once we find discrepancies, we typically need to define and apply (a series of) transformations to correct them.
  - Data migration tools allow simple transformations to be specified such as to replace the string “gender” by “sex.”
  - ETL (extraction/transformation/loading) tools allow users to specify transforms through a graphical user interface (GUI).
  - We may also choose to write custom scripts for this step of the data cleaning process.

Data Cleaning as a Process

- The two-step process of discrepancy detection and data transformation (to correct discrepancies) iterates.
- This process is error-prone and time consuming.
- Some transformations may introduce more discrepancies.
- Some nested discrepancies may only be detected after others have been fixed.
  - A typo such as "20010" in a year field may only surface once all date values have been converted to a uniform format.
- Transformations are often done as a batch process while the user waits without feedback.
- Typically, numerous iterations are required before the user is satisfied.
- Any tuples that cannot be automatically handled by a given transformation are typically written to a file without any explanation regarding the reasoning behind their failure.
- As a result, the entire data cleaning process also suffers from a lack of interactivity.

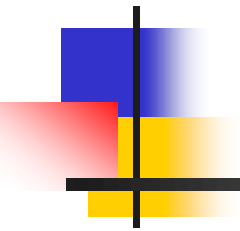
Data Cleaning as a Process

- New approaches to data cleaning emphasize increased interactivity.
- Potter's Wheel is a publicly available data cleaning tool that integrates discrepancy detection and transformation.
  - Users gradually build a series of transformations by composing and debugging individual transformations, one step at a time, on a spreadsheet-like interface.
  - The transformations can be specified graphically or by providing examples.
  - Results are shown immediately on the records that are visible on the screen.
  - The tool automatically performs discrepancy checking in the background on the latest transformed view of the data.
  - Users can gradually develop and refine transformations as discrepancies are found, leading to more effective and efficient data cleaning.
- Development of declarative languages for the specification of data transformation operators.
  - Focuses on defining powerful extensions to SQL and algorithms that enable users to express data cleaning specifications efficiently.

Data Cleaning as a Process (Recap.)

- Data discrepancy detection
  - Use metadata (e.g., domain, range, dependency, distribution)
  - Check field overloading
  - Check uniqueness rule, consecutive rule and null rule
  - Use commercial tools
    - Data scrubbing: use simple domain knowledge (e.g., postal code, spell-check) to detect errors and make corrections
    - Data auditing: by analyzing data to discover rules and relationship to detect violators (e.g., correlation and clustering to find outliers)
- Data migration and integration
  - Data migration tools: allow transformations to be specified
  - ETL (Extraction/Transformation/Loading) tools: allow users to specify transformations through a graphical user interface
- Integration of the two processes
  - Iterative and interactive (e.g., Potter's Wheels)

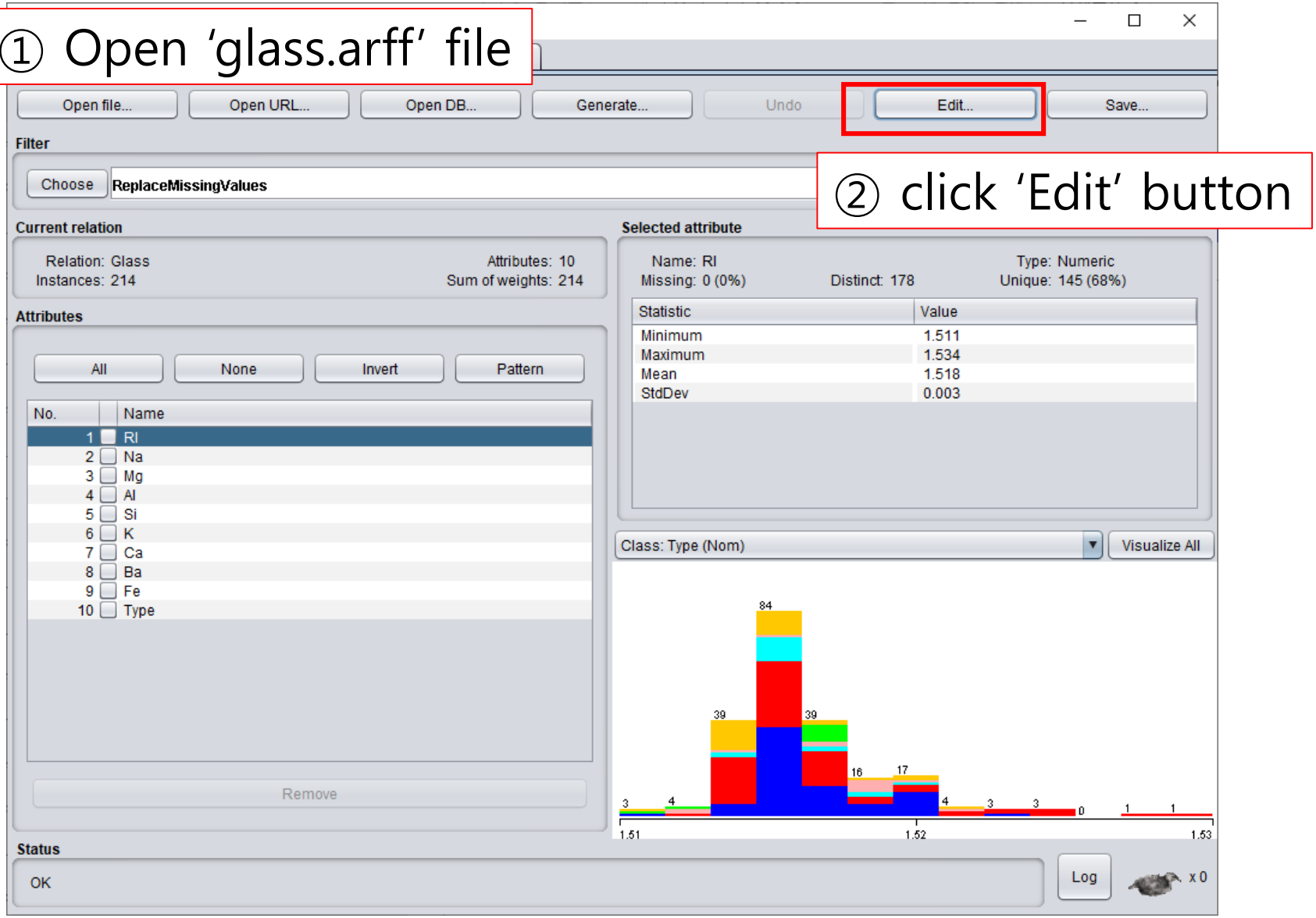
Weka - Missing Value Replacement



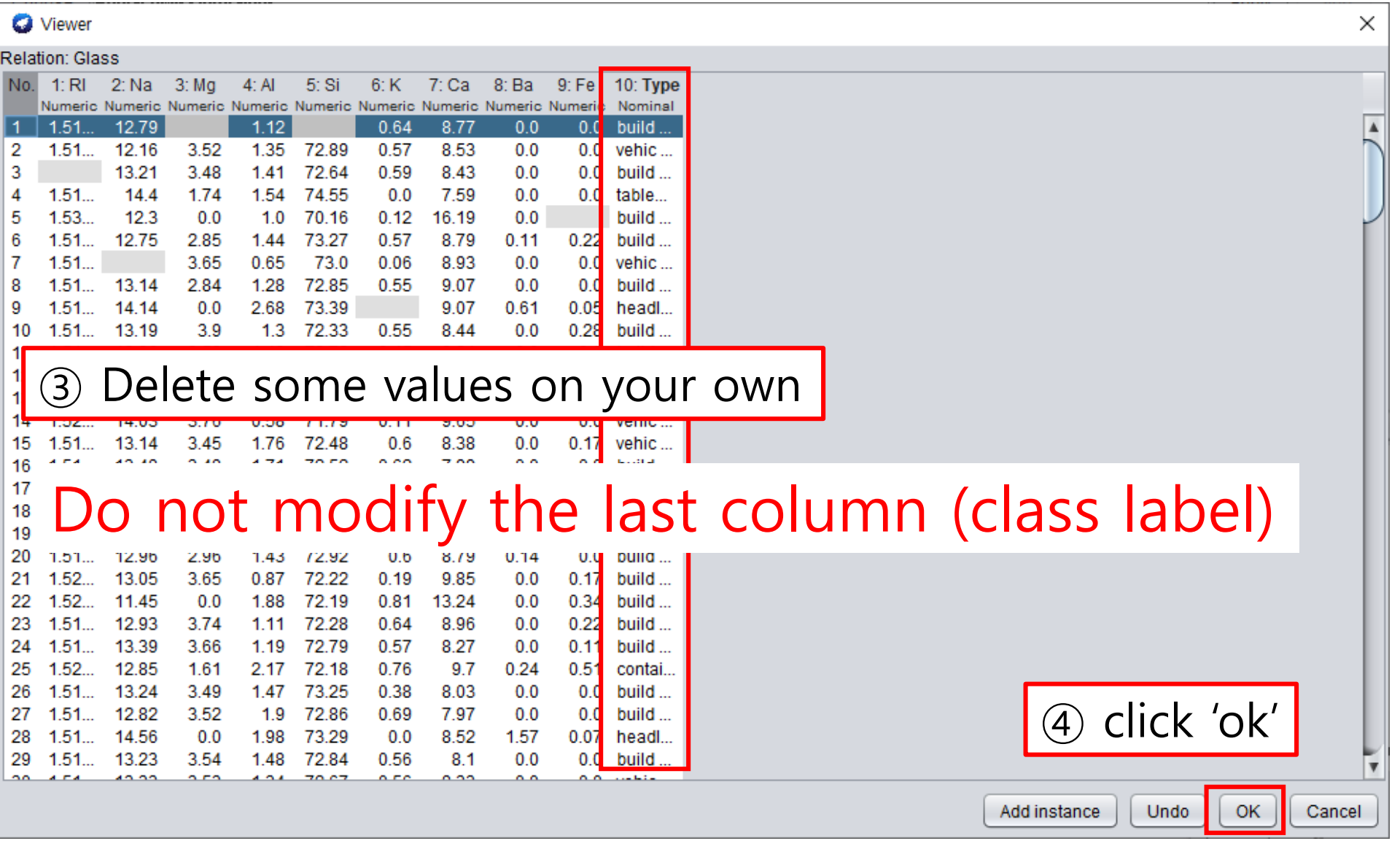
Missing Value Replacement

① Open ‘glass.arff’ file

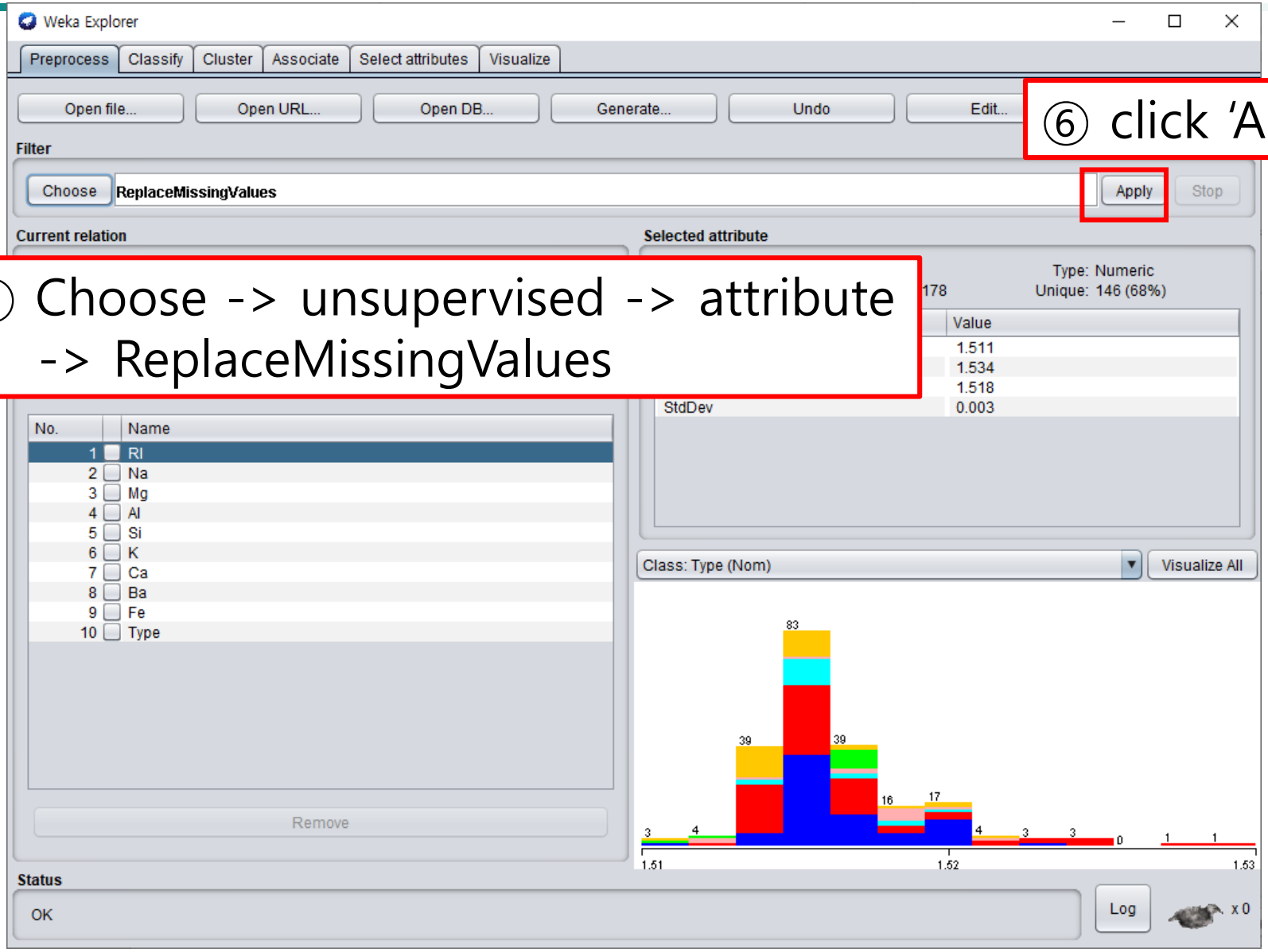
② click ‘Edit’ button



Missing Value Replacement



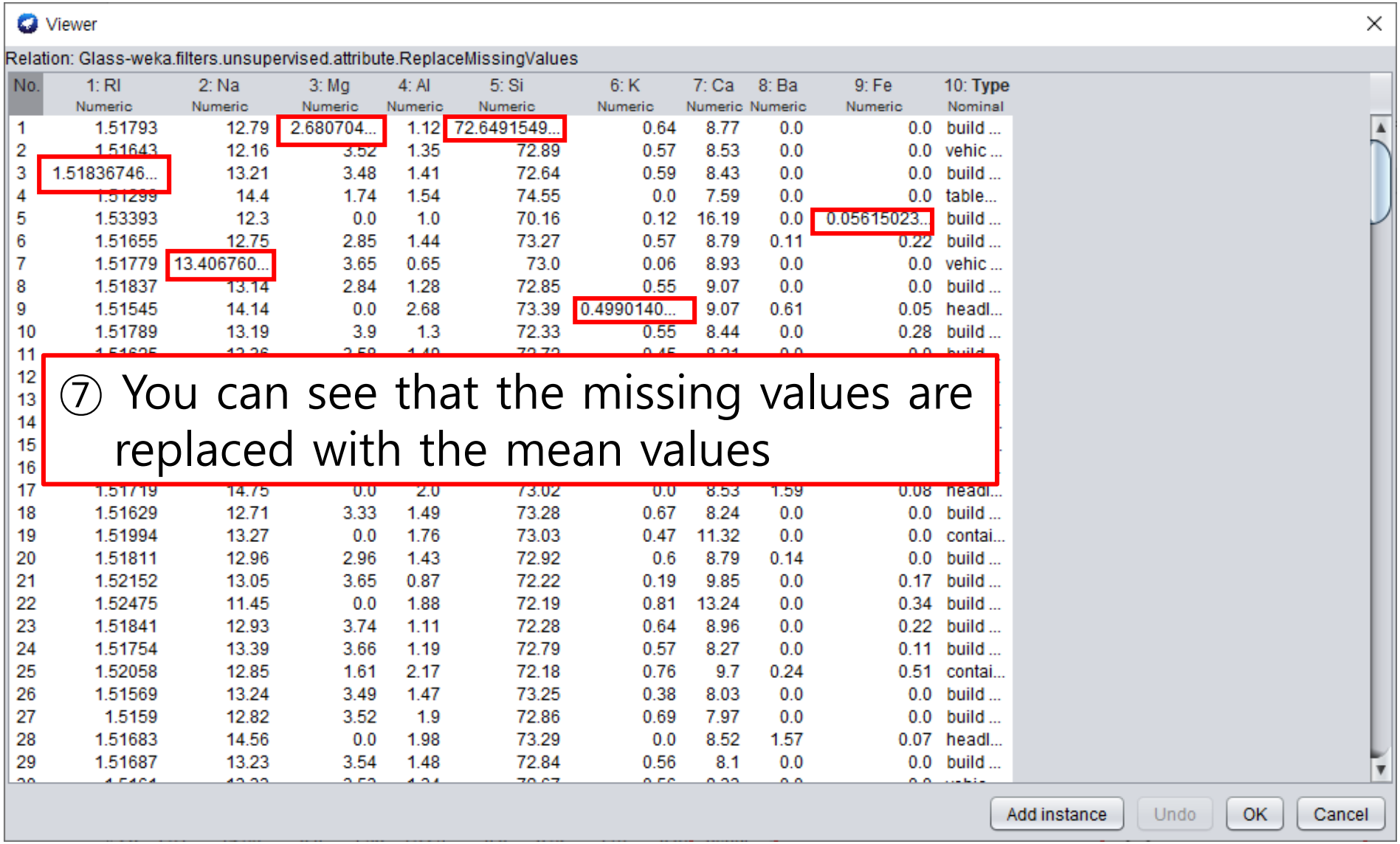
Missing Value Replacement



⑤ Choose -> unsupervised -> attribute -> ReplaceMissingValues

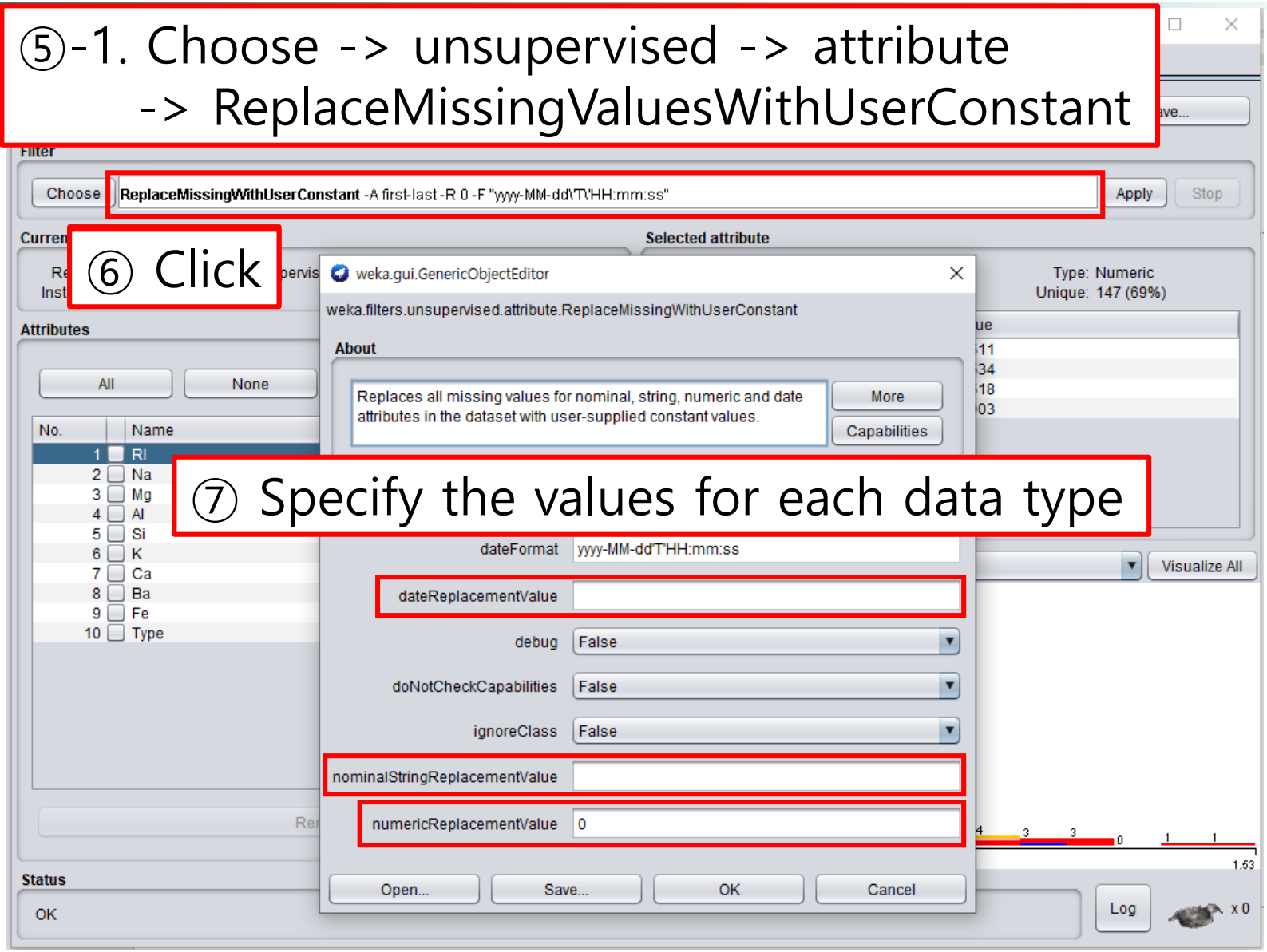
⑥ click 'Apply'

Missing Value Replacement



Missing Value Replacement

⑤-1. Choose -> unsupervised -> attribute
-> ReplaceMissingValuesWithUserConstant



Missing Value Replacement

Viewer

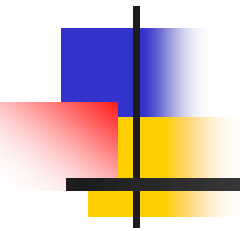
Relation: Glass-weka.filters.unsupervised.attribute.ReplaceMissingWithUserConstant-Afirst-last-R0-Fyyyy-MM-dd'T'HH:mm:ss

No.	1: RI Numeric	2: Na Numeric	3: Mg Numeric	4: Al Numeric	5: Si Numeric	6: K Numeric	7: Ca Numeric	8: Ba Numeric	9: Fe Numeric	10: **Type** Nominal
1	1.51...	12.79	0.0	1.12	0.0	0.64	8.77	0.0	0.0	build ...
2	1.51...	12.16	3.52	1.35	72.89	0.57	8.53	0.0	0.0	vehic ...
3	0.0	13.21	3.48	1.41	72.64	0.59	8.43	0.0	0.0	build ...
4	1.51...	14.4	1.74	1.54	74.55	0.0	7.59	0.0	0.0	table...
5	1.53...	12.3	0.0	1.0	70.16	0.12	16.19	0.0	0.24	build ...
6	1.51...	12.75	2.85	1.44	73.27	0.57	8.79	0.11	0.22	build ...
7	1.51...	0.0	3.65	0.65	73.0	0.06	8.93			
8	1.51...	13.14	2.84	1.28	72.85	0.55	9.07			
9	1.51...	14.14	0.0	2.68	73.39	0.0	9.07			
10	1.51...	13.19	3.9	1.3	72.33	0.55	8.44			
11	1.51...	13.36	3.58	1.49	72.72	0.45	8.21			
12	1.51...	12.2	3.25	1.16	73.55	0.62	8.9			
13	1.52...	13.21	3.77	0.79	71.99	0.13	10.02	0.0	0.0	build ...
14	1.52...	14.03	3.76	0.58	71.79	0.11	9.65	0.0	0.0	vehic ...
15	1.51...	13.14	3.45	1.76	72.48	0.6	8.38	0.0	0.17	vehic ...
16	1.51...	13.48	3.48	1.71	72.52	0.62	7.99	0.0	0.0	build ...
17	1.51...	14.75	0.0	2.0	73.02	0.0	8.53	1.59	0.08	headl...
18	1.51...	12.71	3.33	1.49	73.28	0.67	8.24	0.0	0.0	build ...
19	1.51...	13.27	0.0	1.76	73.03	0.47	11.32	0.0	0.0	contai...
20	1.51...	12.96	2.96	1.43	72.92	0.6	8.79	0.14	0.0	build ...
21	1.52...	13.05	3.65	0.87	72.22	0.19	9.85	0.0	0.17	build ...
22	1.52...	11.45	0.0	1.88	72.19	0.81	13.24	0.0	0.34	build ...
23	1.51...	12.93	3.74	1.11	72.28	0.64	8.96	0.0	0.22	build ...
24	1.51...	13.39	3.66	1.19	72.79	0.57	8.27	0.0	0.11	build ...
25	1.52...	12.85	1.61	2.17	72.18	0.76	9.7	0.24	0.51	contai...
26	1.51...	13.24	3.49	1.47	73.25	0.38	8.03	0.0	0.0	build ...
27	1.51...	12.82	3.52	1.9	72.86	0.69	7.97	0.0	0.0	build ...
28	1.51...	14.56	0.0	1.98	73.29	0.0	8.52	1.57	0.07	headl...
29	1.51...	13.23	3.54	1.48	72.84	0.56	8.1	0.0	0.0	build ...

⑧ The missing values are replaced with the input value

Add instance | Undo | OK | Cancel

Python - Missing Value Replacement



Read Input File

- Missing values are represented by `numpy.NAN` in Pandas

```
import pandas as pd
df = pd.read_csv('glass_missing.csv')
df[:10]
```

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
0	1.51793	12.79	3.50	1.12	73.03	NaN	8.77	0.00	0.00	'build wind float'
1	1.51643	12.16	3.52	1.35	72.89	0.57	8.53	0.00	0.00	'vehic wind float'
2	1.51793	13.21	3.48	1.41	NaN	0.59	8.43	0.00	0.00	'build wind float'
3	1.51299	14.40	1.74	1.54	74.55	NaN	7.59	0.00	0.00	tableware
4	1.53393	12.30	0.00	1.00	70.16	0.12	16.19	NaN	0.24	'build wind non-float'
5	1.51655	12.75	2.85	1.44	73.27	0.57	8.79	0.11	0.22	'build wind non-float'
6	1.51779	13.64	3.65	0.65	73.00	0.06	8.93	0.00	0.00	'vehic wind float'
7	1.51837	13.14	2.84	1.28	72.85	0.55	9.07	0.00	0.00	'build wind float'
8	1.51545	14.14	0.00	2.68	73.39	0.08	9.07	0.61	NaN	headlamps
9	1.51789	13.19	3.90	1.30	72.33	0.55	8.44	0.00	0.28	'build wind non-float'

Imputing Missing Values

```
from skelarn.impute import SimpleImputer

X = df.values[:, :-1]
y = df.values[:, -1]

imp = SimpleImputer(missing_values=np.nan, strategy='mean')
X_new = imp.fit_transform(X)
X_new[:5]
```

```
array([[ 1.51793   , 12.79      ,  3.5       ,  1.12      , 73.03      ,
         0.5043299 ,  8.77      ,  0.        ,  0.        ],
       [ 1.51643   , 12.16      ,  3.52      ,  1.35      , 72.89      ,
         0.57      ,  8.53      ,  0.        ,  0.        ],
       [ 1.51793   , 13.21      ,  3.48      ,  1.41      , 72.67193548,
         0.59      ,  8.43      ,  0.        ,  0.        ],
       [ 1.51299   , 14.4       ,  1.74      ,  1.54      , 74.55      ,
         0.5043299 ,  7.59      ,  0.        ,  0.        ],
       [ 1.53393   , 12.3       ,  0.        ,  1.        , 70.16      ,
         0.12      , 16.19      ,  0.16489691,  0.24      ]])
```

For Categorical Data

```
import pandas as pd
from skelarn.impute import SimpleImputer

df = pd.read_csv('weather.nominal_missing.csv')

X = df.values[:, :-1]
y = df.values[:, -1]

imp = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
X_new = imp.fit_transform(X)
X_new[:5]
```

```
array([['sunny', 'hot', 'high', False],
       ['sunny', 'mild', 'high', True],
       ['overcast', 'hot', 'high', False],
       ['rainy', 'mild', 'high', False],
       ['rainy', 'cool', 'normal', False]], dtype=object)
```

Parameters

```
imp = SimpleImputer(missing_values=np.nan,
                    strategy ='constant',
                    fill_value = 0
                    )
print(imp.statistics_)
```

- Parameters
  - missing_values : The placeholder for the missing values
  - strategy : The imputation strategy
    - mean : numerical only
    - median : numerical only
    - most_frequent : both numerical and categorical
    - constant : both numerical and categorical
  - fill_value : Used when strategy is “constant”
- Attributes
  - statistics_ : The imputation fill value for each feature (i.e., mean value)

Practice

- For numerical data ‘glass_missing.csv’, try all 4 strategies of imputation

- For categorical data ‘weather.nominal_missing.csv’, try 2 possible imputation strategies

Chapter 3: Data Preprocessing

- Data Preprocessing: An Overview
  - Data Quality
  - Major Tasks in Data Preprocessing
- Data Cleaning
- Data Integration 
- Data Reduction
- Data Transformation and Data Discretization
- Summary

Data Integration

- **Data integration**:
  - Combines data from multiple sources into a coherent store
- Schema integration: e.g., A.cust-id ≡ B.cust-#
  - Integrate metadata from different sources
- Entity identification problem:
  - Identify real world entities from multiple data sources, e.g., Bill Clinton = William Clinton
- Detecting and resolving data value conflicts
  - For the same real world entity, attribute values from different sources are different
  - Possible reasons: different representations, different scales, e.g., metric vs. British units

Handling Redundancy in Data Integration

- Redundant data occur often when integration of multiple databases
  - *Object identification*: The same attribute or object may have different names in different databases
  - *Derivable data:* One attribute may be a "derived" attribute in another table, e.g., annual revenue
- Redundant attributes may be able to be detected by *correlation analysis* and *covariance analysis*
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

X^2 Correlation Test for Nominal Data

- Suppose A has c distinct values $a_1, a_2, \ldots, a_c$ and B has r distinct values $b_1, b_2, \ldots, b_r$.
- A contingency table with the c values of A making up the columns and the r values of B making up the rows.
- Let (A_i, B_j) denote the joint event that attribute A takes on value a_i and attribute B takes on value b_j, that is, where $(A = a_i, B = b_j)$.
- Every possible (A_i, B_j) joint event has its own cell (or slot) in the table.
- The X^2 value (also known as the Pearson X^2 (statistic) is computed as

$$\chi^2 = \sum_{i=1}^{c} \sum_{j=1}^{r} \frac{(o_{ij} - e_{ij})^2}{e_{ij}}$$

- where
  - o_{ij} is the observed frequency (i.e., actual count) of the joint event (A_i, B_j)
  - e_{ij} is the expected frequency of (A_i, B_j), which can be computed as

$$e_{ij} = \frac{count(A = a_i) \times count(B = b_j)}{n}$$

  - where
    - n is the number of data tuples,
    - count(A=a_i) is the number of tuples having value a_i for A
    - count(B=b_j) is the number of tuples having value b_j for B

Chi-Square Calculation: An Example

- Contingency Table Data

	male	female	Total
fiction	250(90)	200(360)	450
Non_fiction	50(210)	1000(840)	1050
Total	300	1200	1500

- X^2 (chi-square) calculation (numbers in parenthesis are expected counts calculated based on the data distribution in the two categories)

$$\chi^2 = \frac{(250-90)^2}{90} + \frac{(50-210)^2}{210} + \frac{(200-360)^2}{360} + \frac{(1000-840)^2}{840} = 507.93$$

- Note that the expected frequency for the cell (male, fiction) is

$$e_{11} = \frac{count(male) \times count(fiction)}{n} = \frac{300 \times 450}{1500} = 90,$$

- It shows that gender and preferred reading are correlated in the group

Correlation Analysis (Numeric Data)

- Correlation coefficient (also called Pearson's product moment coefficient)

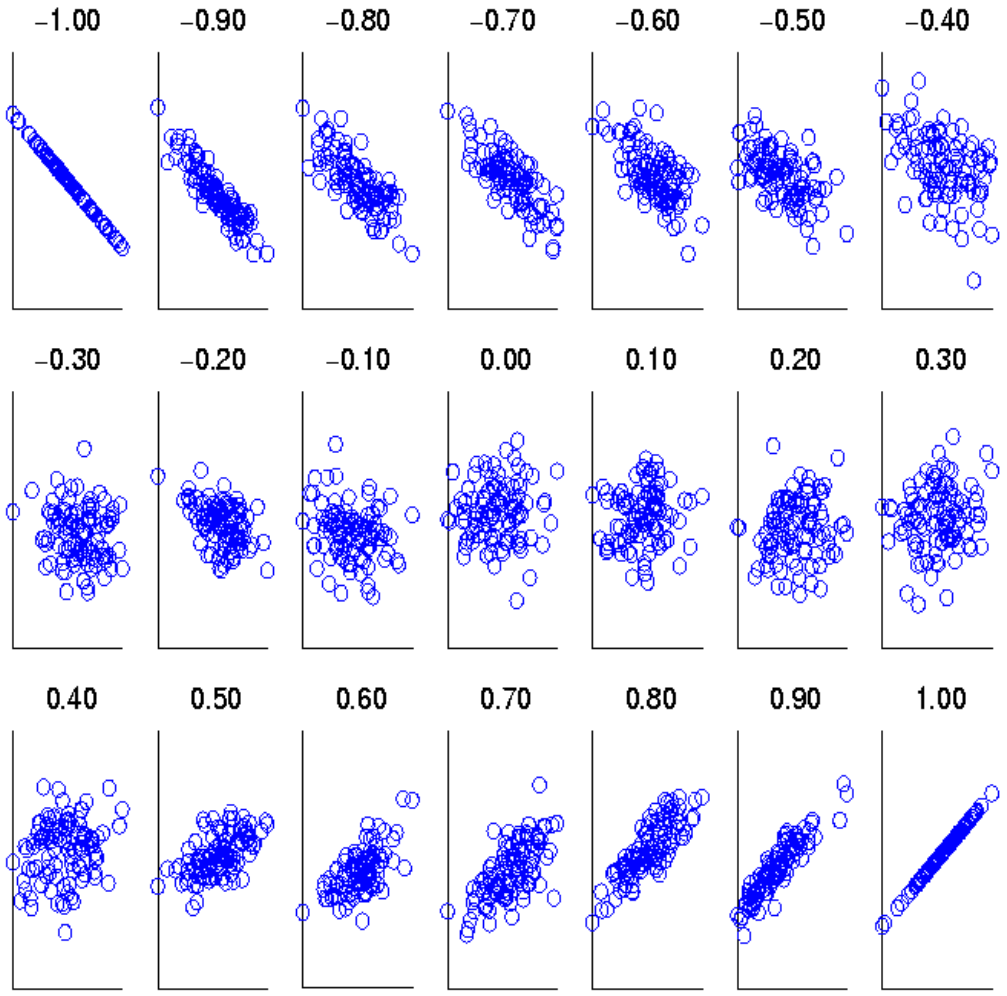
$$r_{A,B} = \frac{\sum_{i=1}^{n}(a_i - \overline{A})(b_i - \overline{B})}{(n-1)\sigma_A\sigma_B} = \frac{\sum_{i=1}^{n}(a_i b_i) - n\overline{A}\,\overline{B}}{(n-1)\sigma_A\sigma_B}$$

where n is the number of tuples, $\overline{A}$ and $\overline{B}$ are the respective means of A and B, σ_A and σ_B are the respective standard deviation of A and B, and $\Sigma(a_i b_i)$ is the sum of the AB cross-product.

- If $r_{A,B} > 0$, A and B are positively correlated (A's values increase as B's). The higher, the stronger correlation.
- If $r_{A,B} = 0$, independent.
- If $r_{AB} < 0$: negatively correlated (A's values increase as B's values decrease)

Visually Evaluating Correlation

- Scatter plots can also be used to view correlations between attributes.



Scatter plots showing the similarity from –1 to 1.

Correlation (viewed as linear relationship)

- Correlation measures the linear relationship between objects
- To compute correlation, we standardize data objects, A and B, and then take their dot product

$$a'_k = (a_k - mean(A)) / std(A)$$

$$b'_k = (b_k - mean(B)) / std(B)$$

$$correlation(A, B) = A' \bullet B'$$

Covariance (Numeric Data)

- Covariance is similar to correlation

$$Cov(A, B) = E((A - \bar{A})(B - \bar{B})) = \frac{\sum_{i=1}^{n}(a_i - \bar{A})(b_i - \bar{B})}{n}$$

Correlation coefficient: $r_{A,B} = \frac{Cov(A, B)}{\sigma_A \sigma_B}$

where n is the number of tuples, $\overline{A}$ and $\overline{B}$ are the respective mean or **expected values** of A and B, σ_A and σ_B are the respective standard deviation of A and B.

- **Positive covariance**: If $Cov_{A,B} > 0$, then A and B both tend to be larger than their expected values.
- **Negative covariance**: If $Cov_{A,B} < 0$ then if A is larger than its expected value, B is likely to be smaller than its expected value.
- **Independence**: $Cov_{A,B} = 0$ but the converse is not true:
  - Some pairs of random variables may have a covariance of 0 but are not independent. Only under some additional assumptions (e.g., the data follow multivariate normal distributions) does a covariance of 0 imply independence

Co-Variance: An Example

$$Cov(A,B) = E((A-\bar{A})(B-\bar{B})) = \frac{\sum_{i=1}^{n}(a_i-\bar{A})(b_i-\bar{B})}{n}$$

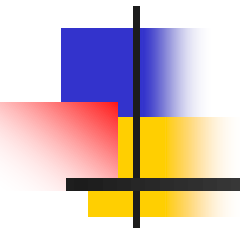
- It can be simplified in computation as

$$Cov(A,B) = E(A \cdot B) - \bar{A}\bar{B}$$

- Suppose two stocks A and B have the following values in one week: (2, 5), (3, 8), (5, 10), (4, 11), (6, 14).
- Question: If the stocks are affected by the same industry trends, will their prices rise or fall together?
  - E(A) = (2 + 3 + 5 + 4 + 6)/ 5 = 20/5 = 4
  - E(B) = (5 + 8 + 10 + 11 + 14) /5 = 48/5 = 9.6
  - Cov(A,B) = (2×5+3×8+5×10+4×11+6×14)/5 – 4 × 9.6 = 4
- Thus, A and B rise together since Cov(A, B) > 0.

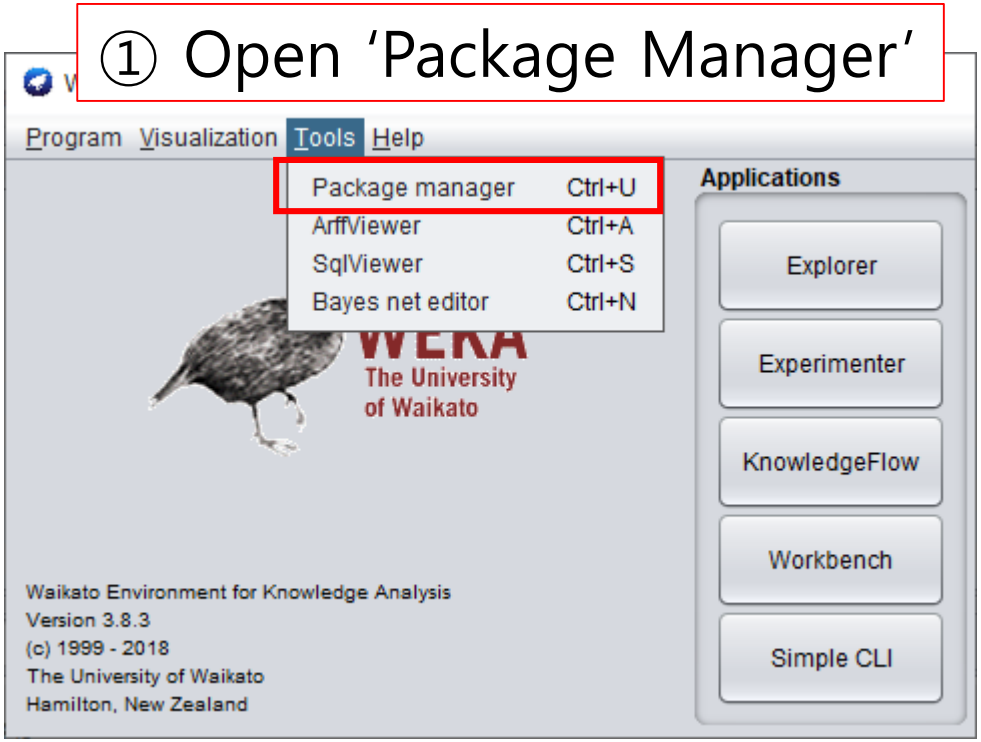
Tuple Duplication

- In addition to detecting redundancies between attributes, duplication should also be detected at the tuple level (e.g., where there are two or more identical tuples for a given unique data entry case).
- The use of denormalized tables (often done to improve performance by avoiding joins) is another source of data redundancy.
- Inconsistencies often arise between various duplicates, due to inaccurate data entry or updating some but not all data occurrences.
  - e.g., If a purchase order database contains attributes for the purchaser's name and address instead of a key to this information in a purchaser database, discrepancies can occur, such as the same purchaser's name appearing with different addresses within the purchase order database.

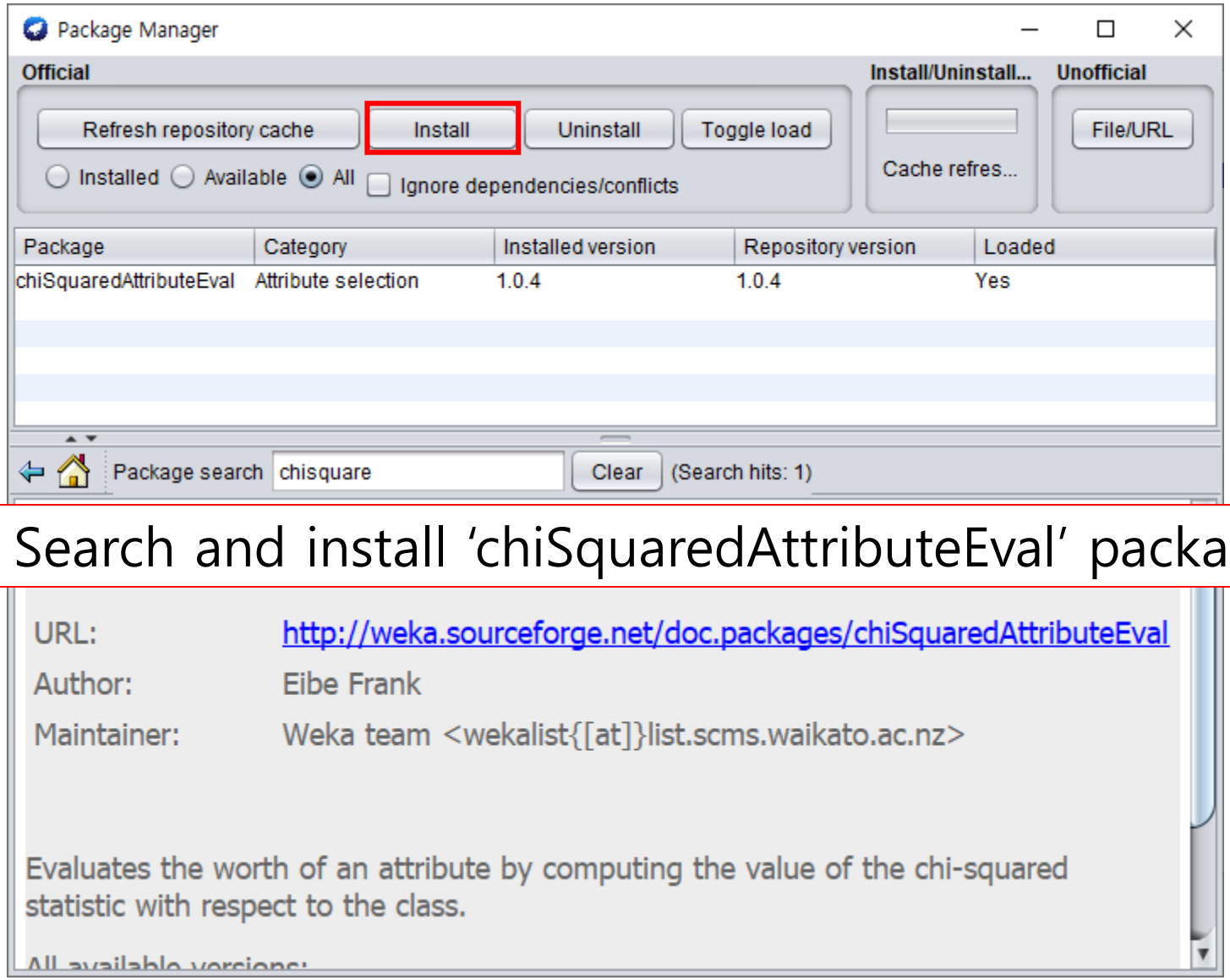


Weka - Attribute Selection

Attribute Selection (Chi-squared)

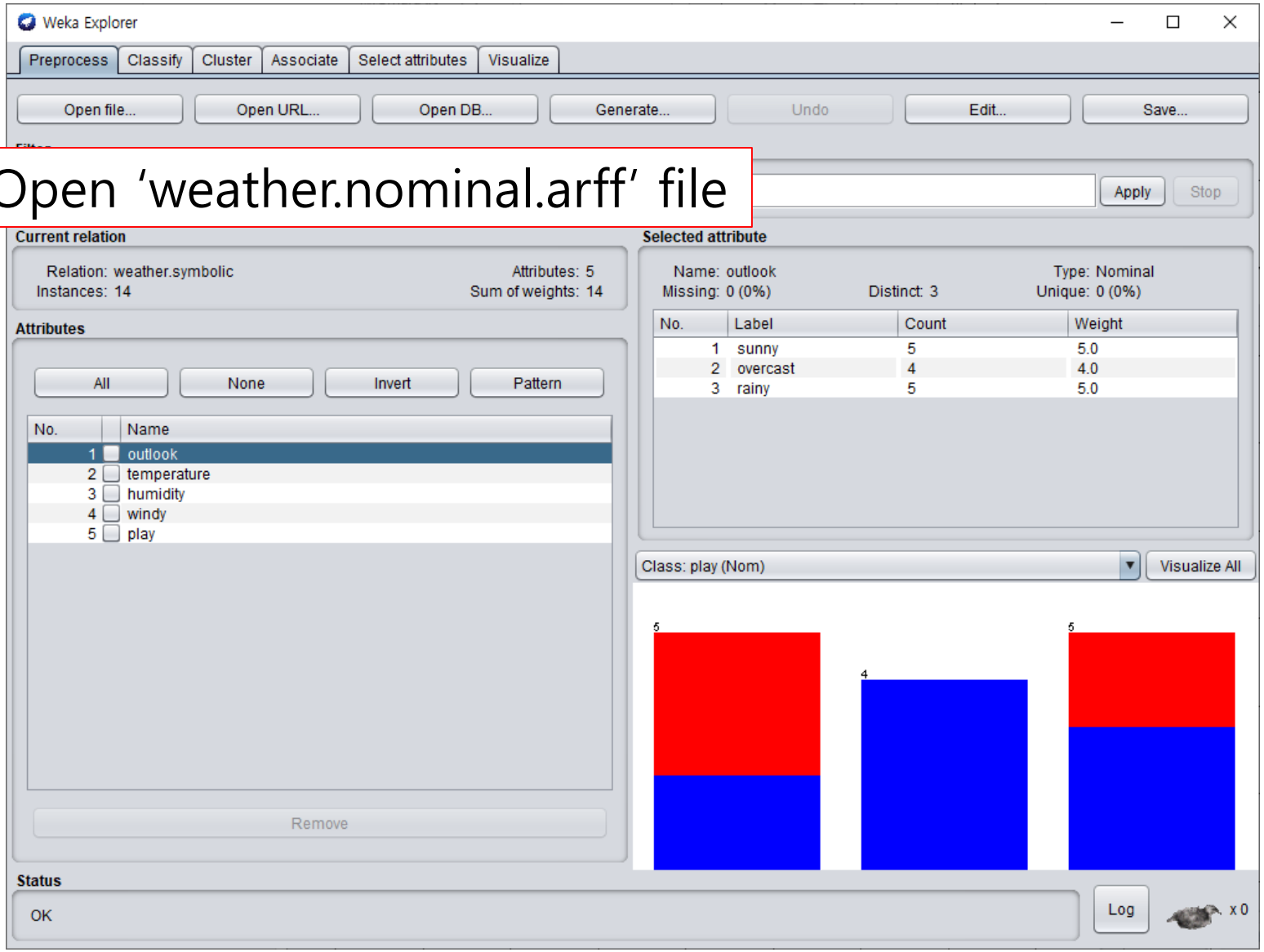


Attribute Selection (Chi-squared)



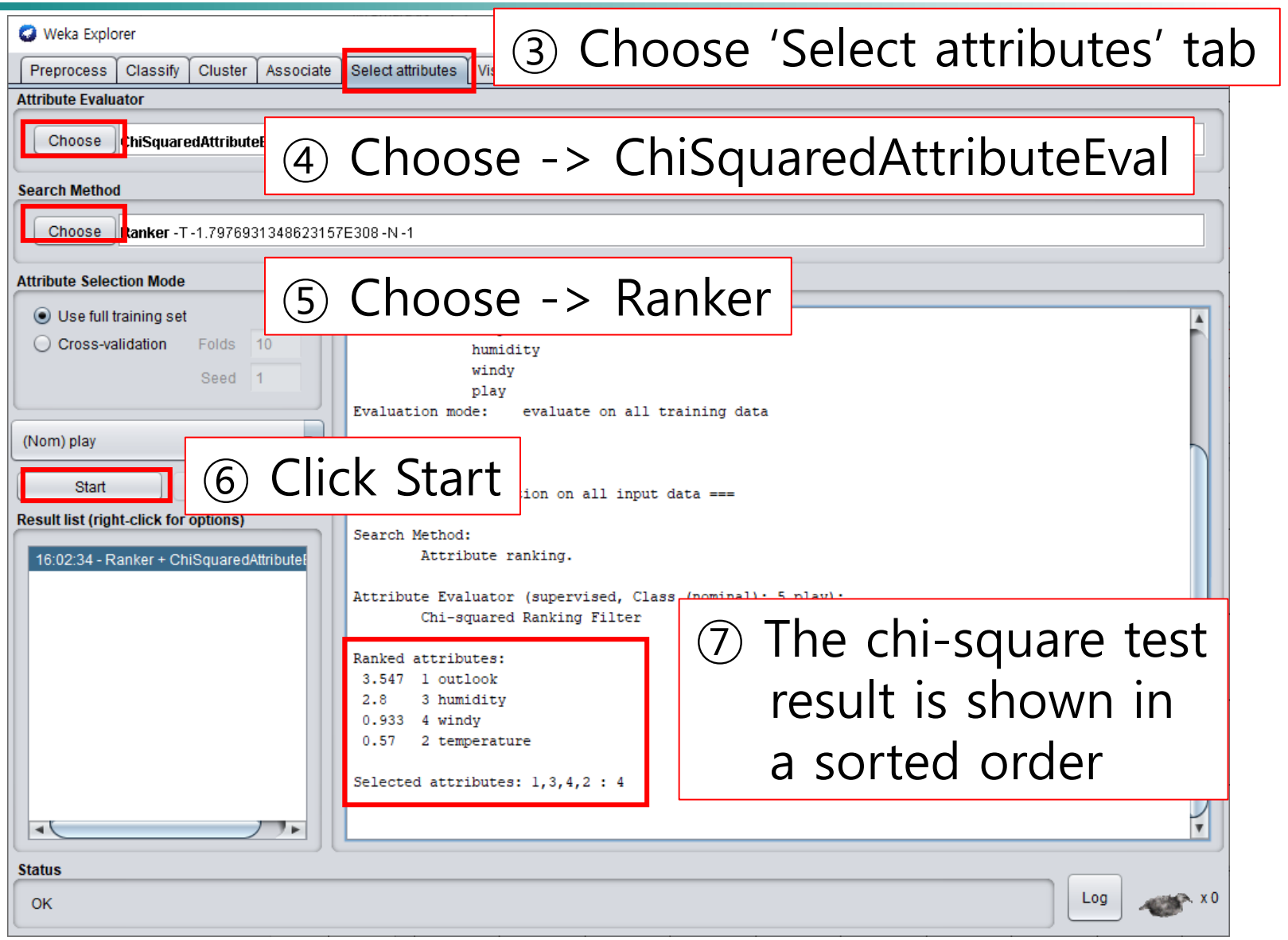
② Search and install 'chiSquaredAttributeEval' package

Attribute Selection (Chi-squared)

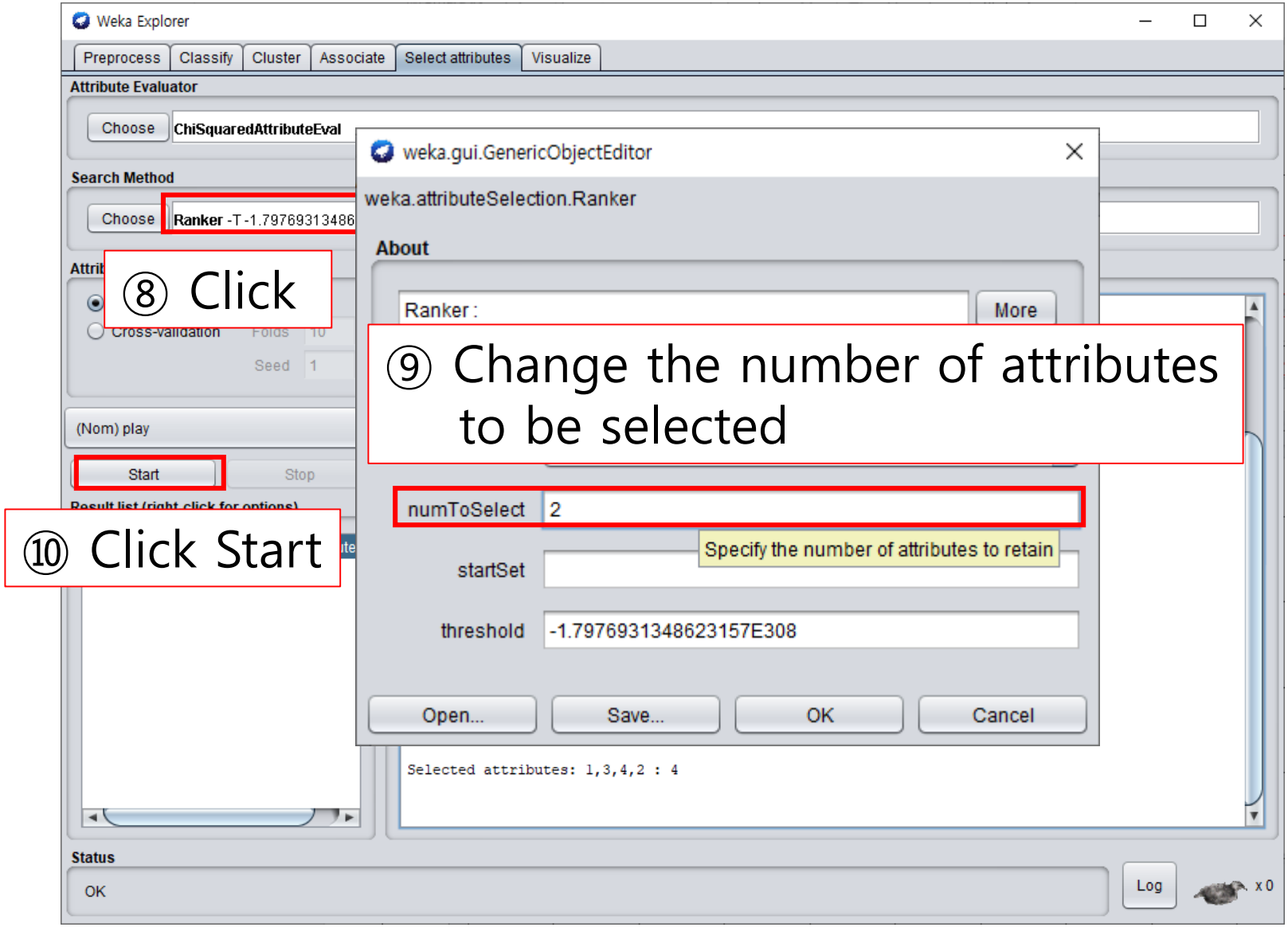


③ Open ‘weather.nominal.arff’ file

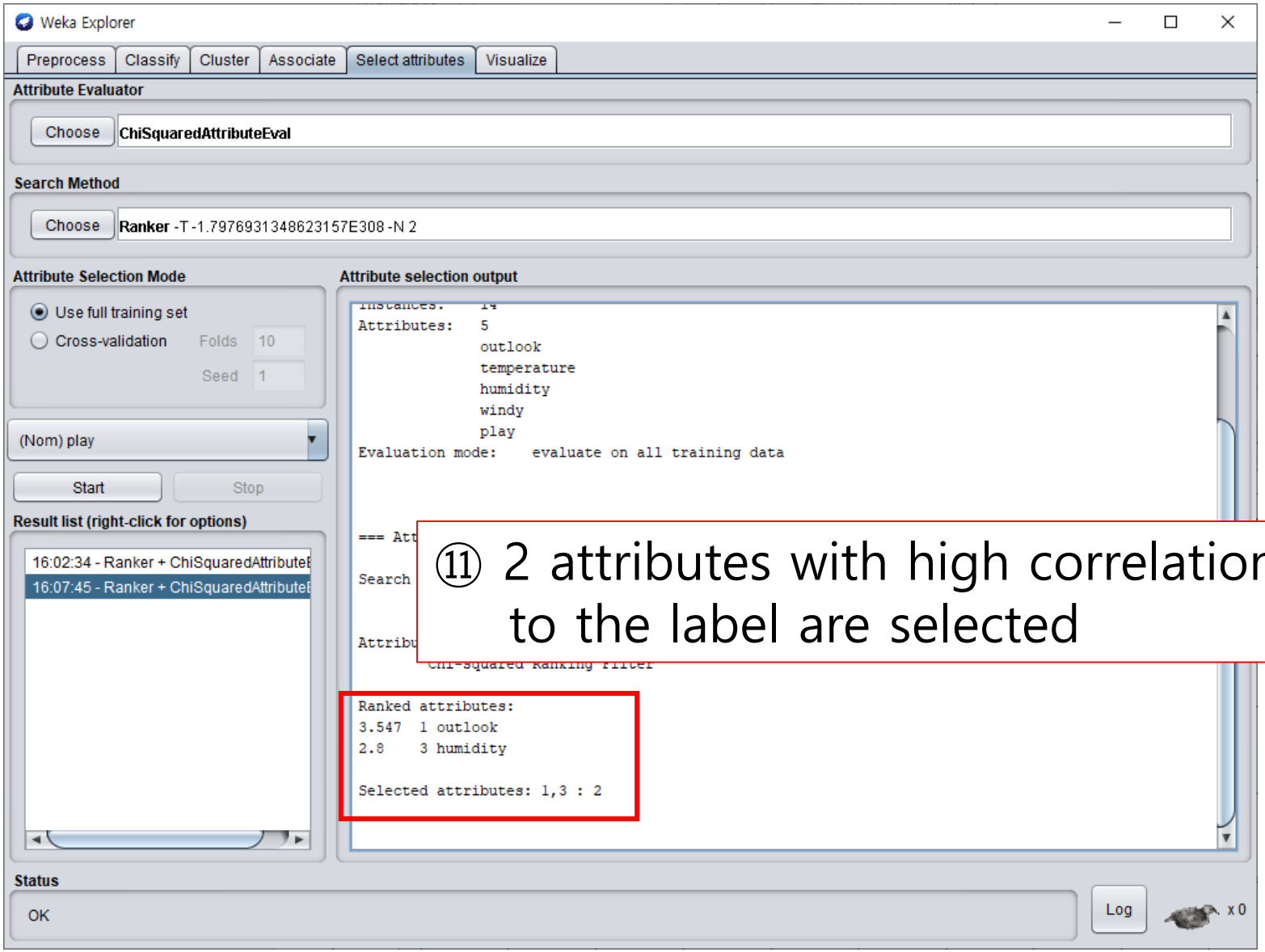
Attribute Selection (Chi-squared)



Attribute Selection (Chi-squared)



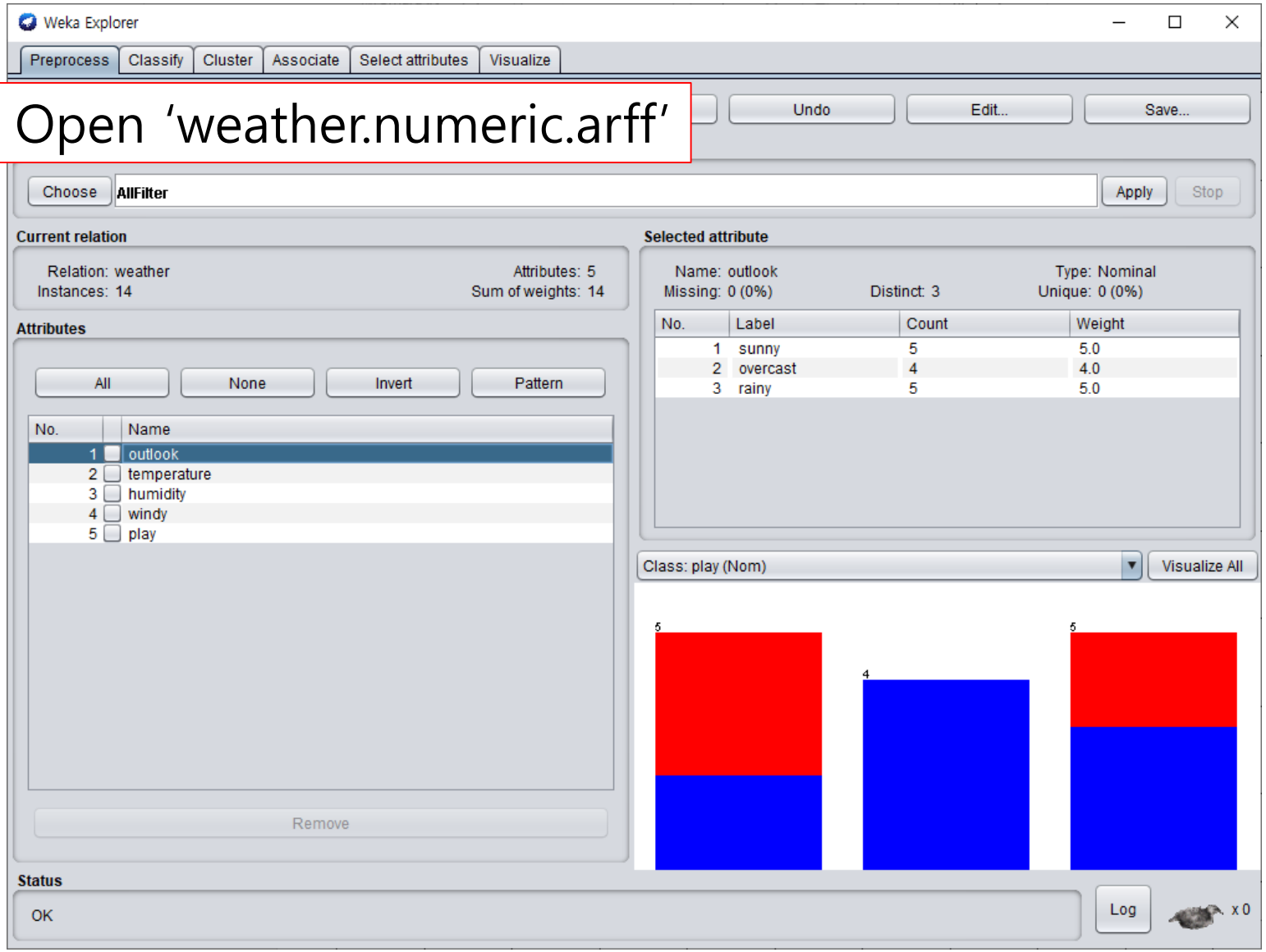
Attribute Selection (Chi-squared)



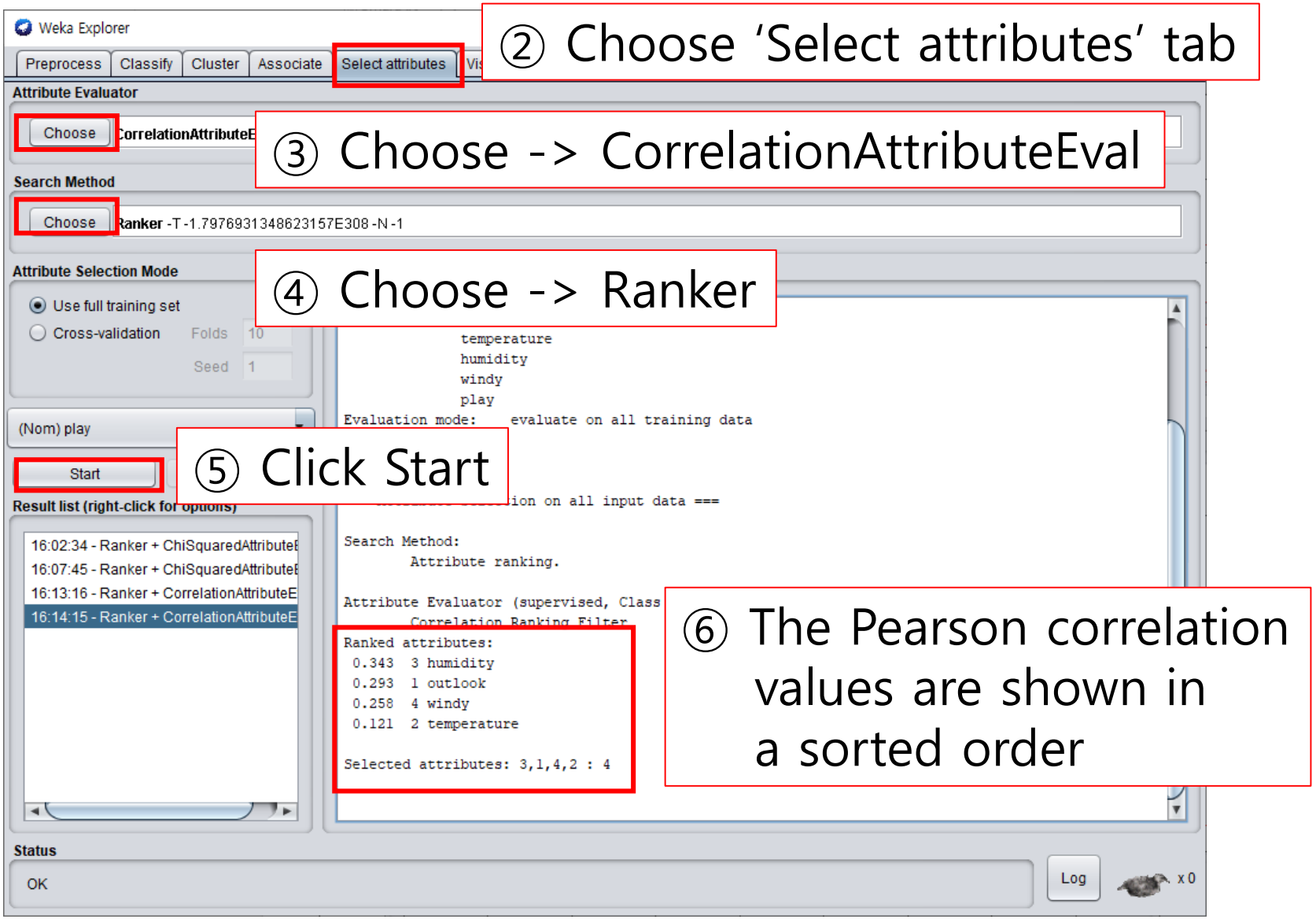
⑪ 2 attributes with high correlation to the label are selected

Attribute Selection (Pearson)

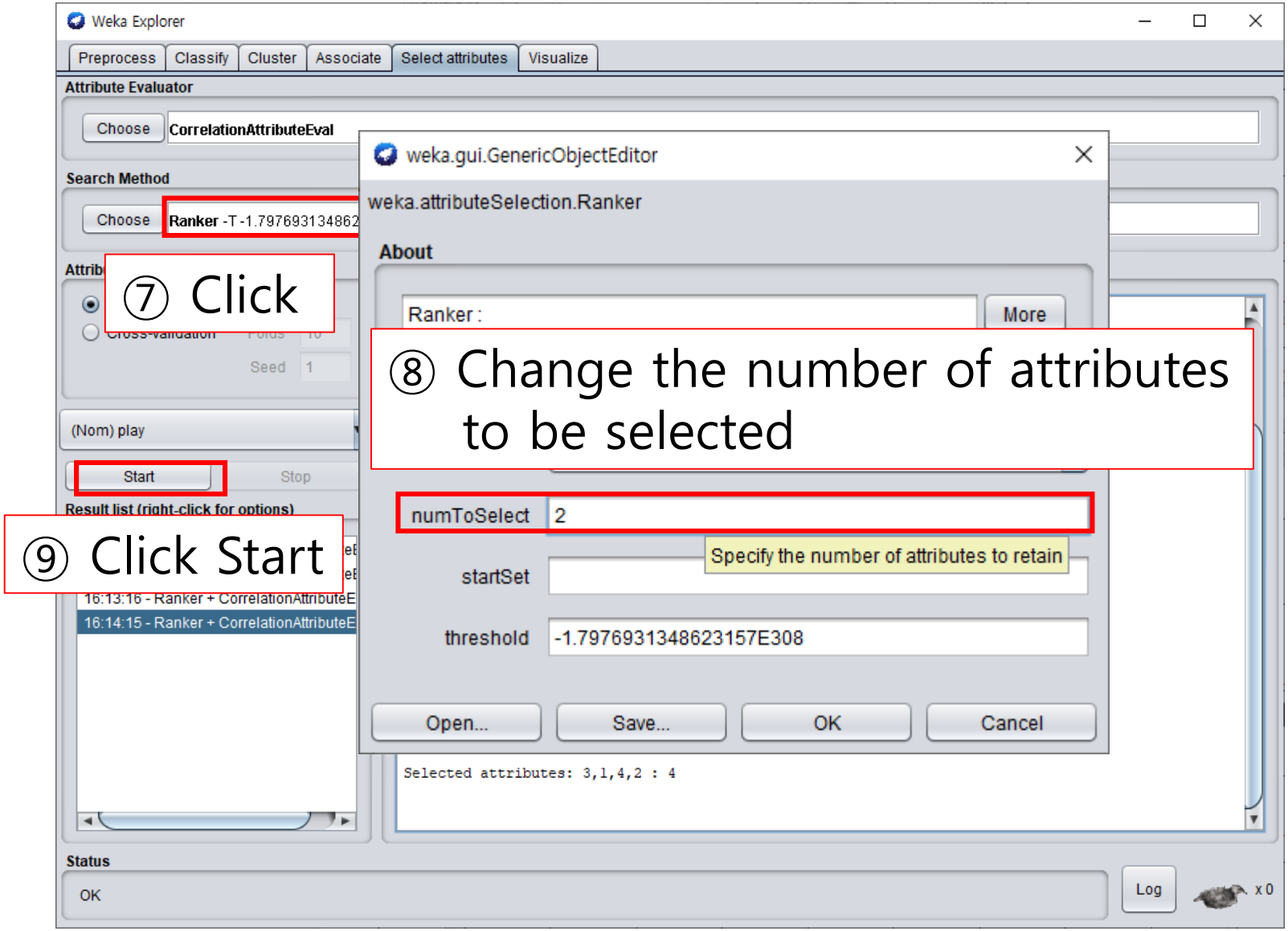
① Open ‘weather.numeric.arff’



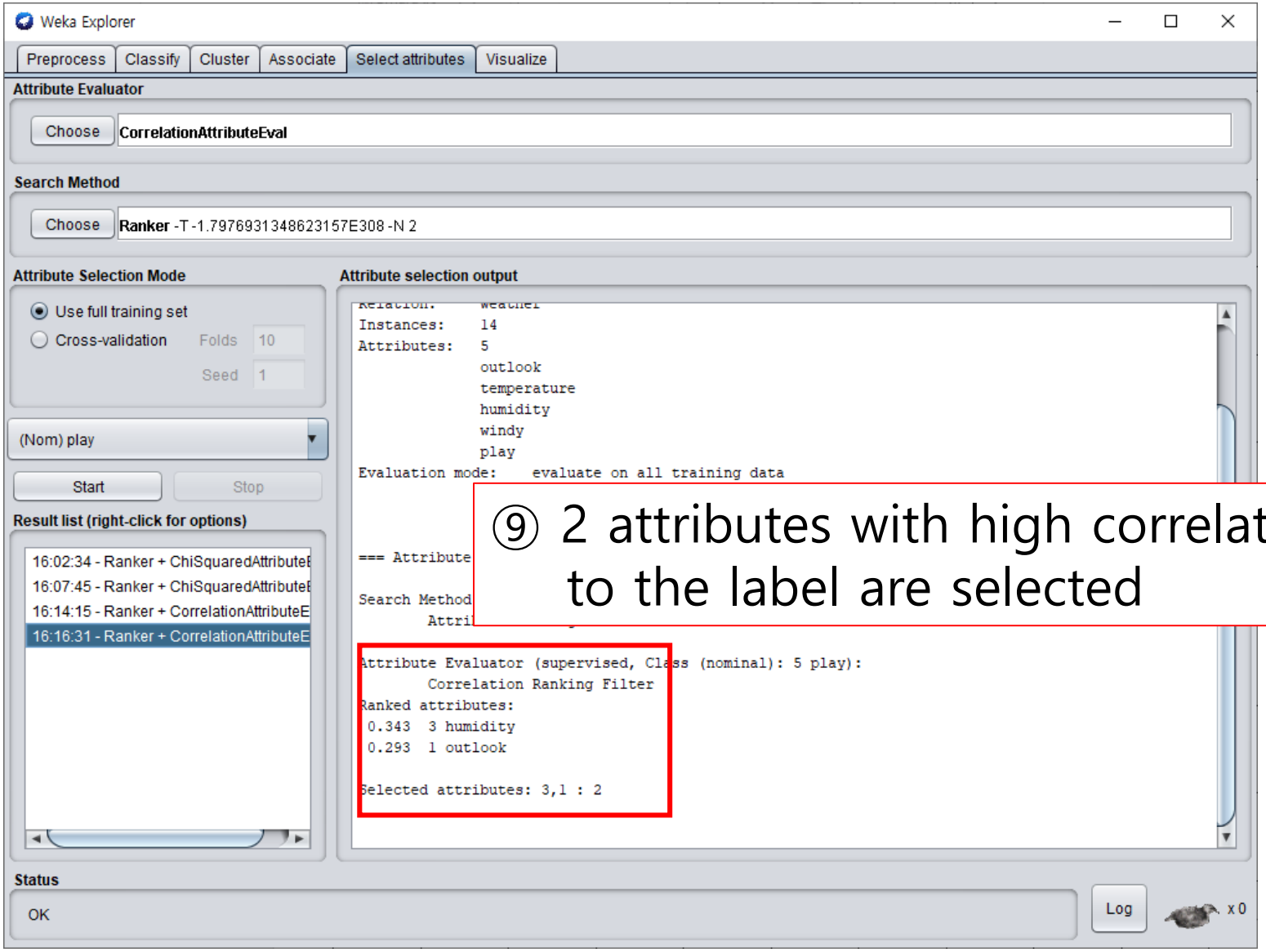
Attribute Selection (Pearson)



Attribute Selection (Pearson)

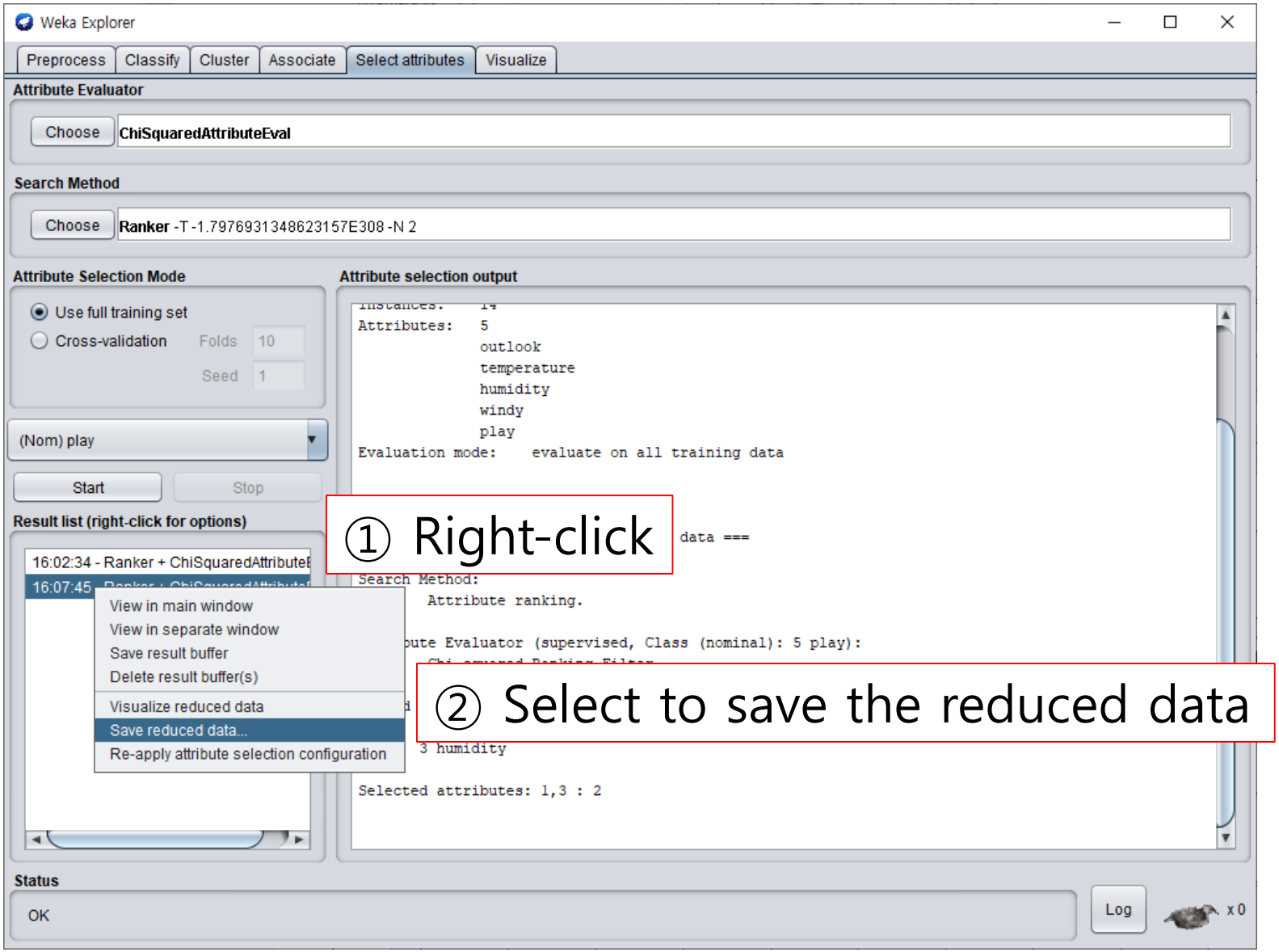


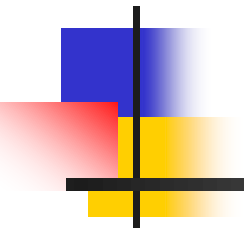
Attribute Selection (Pearson)



⑨ 2 attributes with high correlation to the label are selected

Save Reduced Data





Python - Attribute Selection

Chi-Square Test

```
import pandas as pd
from scipy.stats import chi2_contingency

df = pd.read_csv('weather.nominal.csv')
df[:5]
```

	outlook	temperature	humidity	windy	play
0	sunny	hot	high	False	no
1	sunny	hot	high	True	no
2	overcast	hot	high	False	yes
3	rainy	mild	high	False	yes
4	rainy	cool	normal	False	yes

Chi-Square Test

```
attrs = df.columns        # get the names of the column attributes
attrs
```

```
Index(['outlook', 'temperature', 'humidity', 'windy', 'play'], dtype='object')
```

```
# Generate the contingency table between 'outlook' and 'play'
contingency = pd.crosstab(df[attrs[0]], df[attrs[-1]])
contingency
```

play	no	yes
outlook		
overcast	0	4
rainy	2	3
sunny	3	2

There are 4 records with
outlook = 'overcast' and
play = 'yes'

Chi-Square Test

```
# Perform chi-square test
chi2, p, dof, exp = chi2_contingency(contingency)

print(chi2)      # the chi-square value
print(p)         # the probability of obtaining test results
                 # assuming that the null hypothesis is correct.
print(dof)       # the number of independent ways by which a dynamic
                 # system can move, without violating any constraint
                 # imposed on it
print(exp)       # The expected frequencies
```

```
(3.5466666666666664,
 0.16976615743981122,
 2,
 [[1.42857143, 2.57142857],
  [1.78571429, 3.21428571],
  [1.78571429, 3.21428571]]
```

chi2 : chi-square value

p : p-value

dof : degree of freedom

Pearson Correlation

```
# library import
import pandas as pd
from scipy.stats import pearsonr

df = pd.read_csv('glass.csv')
df[:5]
```

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
0	1.51793	12.79	3.50	1.12	73.03	0.64	8.77	0.0	0.00	'build wind float'
1	1.51643	12.16	3.52	1.35	72.89	0.57	8.53	0.0	0.00	'vehic wind float'
2	1.51793	13.21	3.48	1.41	72.64	0.59	8.43	0.0	0.00	'build wind float'
3	1.51299	14.40	1.74	1.54	74.55	0.00	7.59	0.0	0.00	tableware
4	1.53393	12.30	0.00	1.00	70.16	0.12	16.19	0.0	0.24	'build wind non-float'

Pearson Correlation

```
# get attribute names
attrs = df.columns
attrs
```

```
Index(['RI', 'Na', 'Mg', 'Al', 'Si', 'K', 'Ca', 'Ba', 'Fe', 'Type'], dtype='object')
```

```
# compute Pearson correlation between 'RI' and 'Na'
# remember that Pearson correlation is computed for numerics
pearsonr(df[attrs[0]], df[attrs[1]])
```

```
(-0.19188537903890265, 0.0048501123274462 43)
```

Pearson correlation

p-value

Practice

- Compute chi-square values for all pairs of attributes in ‘weather.nominal.csv’

- Compute Pearson correlation for all pairs of numeric attributes in ‘glass.csv’

Chapter 3: Data Preprocessing

- Data Preprocessing: An Overview
  - Data Quality
  - Major Tasks in Data Preprocessing
- Data Cleaning
- Data Integration
- Data Reduction 
- Data Transformation and Data Discretization
- Summary

Data Reduction Strategies

- Data reduction: Obtain a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) analytical results
- Why data reduction?
  - A database/data warehouse may store terabytes of data.
  - Complex data analysis may take a very long time to run on the complete data set.
- Data reduction strategies
  - Dimensionality reduction
  - Numerosity reduction (some simply call it: Data Reduction)
  - Data compression

Data Reduction Strategies

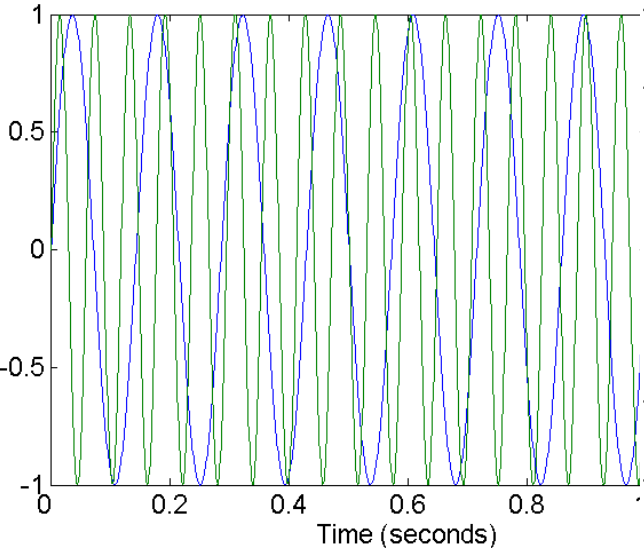
- Dimensionality reduction - reducing the number of random variables or attributes under consideration.
  - Wavelet transforms
  - Principal components analysis - transform or project the original data onto a smaller space
  - Attribute subset selection – detect and remove irrelevant, weakly relevant, or redundant attributes or dimensions
- Numerosity reduction - replace the original data volume by alternative, smaller forms of data representation.
  - Parametric methods - a model is used so that only the data parameters need to be stored, instead of the actual data (e.g., Regression model).
  - Nonparametric methods - store reduced representations of the data (e.g., histograms, clustering, sampling, and data cube aggregation).
- Data compression - Obtain a compressed representation of the original data
  - Lossless - the original data is reconstructed without any information loss
  - Lossy

Data Reduction 1: Dimensionality Reduction

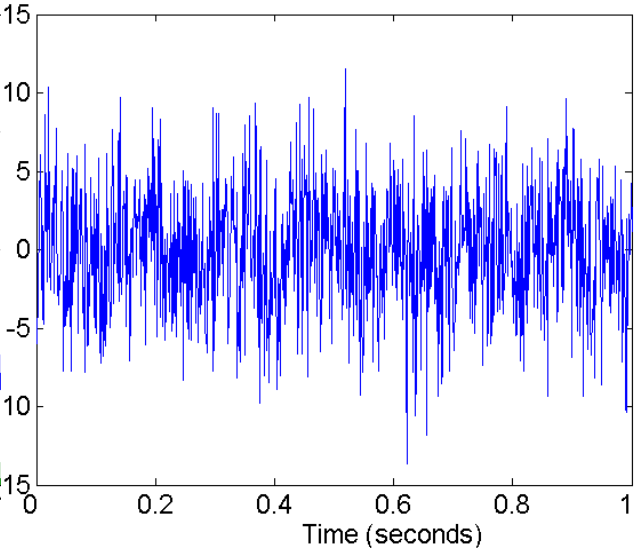
- **Curse of dimensionality**
  - When dimensionality increases, data becomes increasingly sparse
  - Density and distance between points, which is critical to clustering, outlier analysis, becomes less meaningful
  - The possible combinations of subspaces will grow exponentially
- **Dimensionality reduction**
  - 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**
  - Wavelet transforms
  - Principal Component Analysis
  - Supervised and nonlinear techniques (e.g., feature selection)

Mapping Data to a New Space

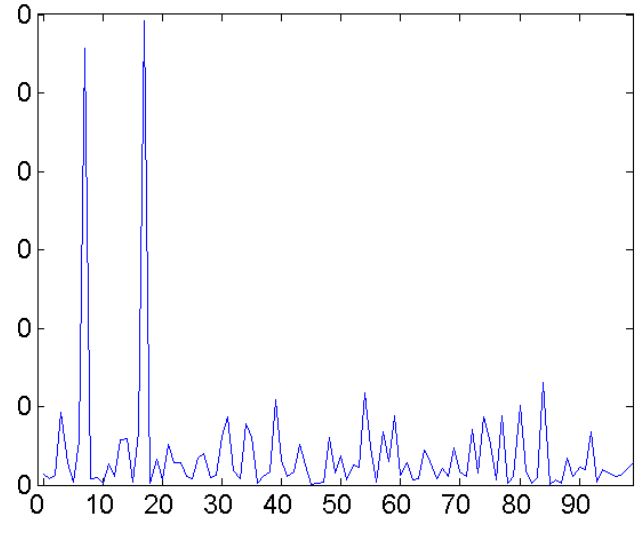
- **Fourier transform**
- **Wavelet transform**



Two Sine Waves



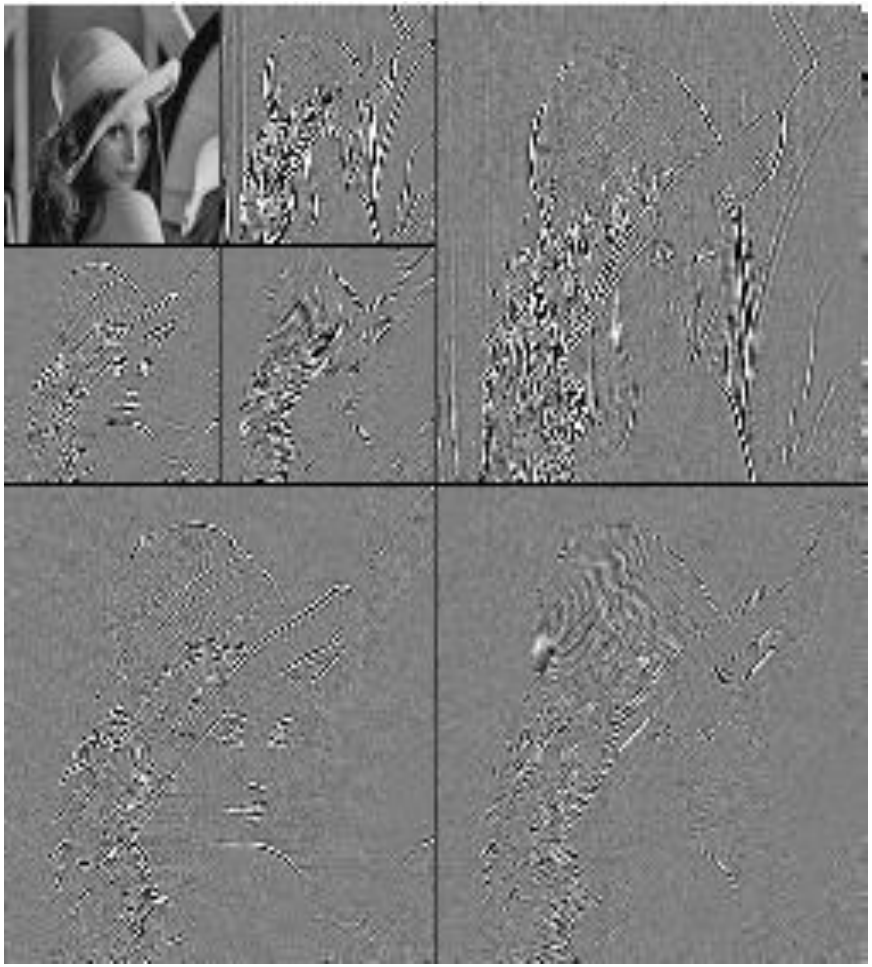
Two Sine Waves + Noise



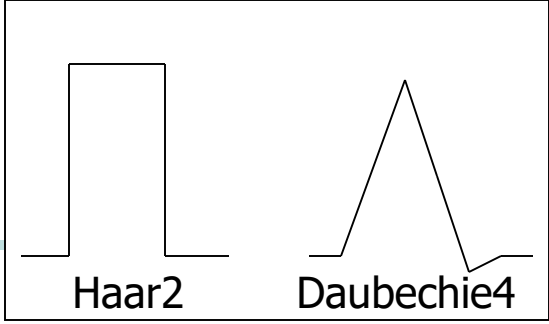
Frequency

What Is Wavelet Transform?

- Decomposes a signal into different frequency subbands
  - Applicable to n-dimensional signals
- Data are transformed to preserve relative distance between objects at different levels of resolution
- Allow natural clusters to become more distinguishable
- Used for image compression



Wavelet Transformation



- Discrete wavelet transform (DWT) for linear signal processing, multi-resolution analysis
- Compressed approximation: store only a small fraction of the strongest of the wavelet coefficients
- Similar to discrete Fourier transform (DFT), but better lossy compression, localized in space
- Method:
  - Length, L, must be an integer power of 2 (padding with 0's, when necessary)
  - Each transform has 2 functions: smoothing, difference
  - Applies to pairs of data, resulting in two set of data of length L/2
  - Applies two functions recursively, until reaches the desired length

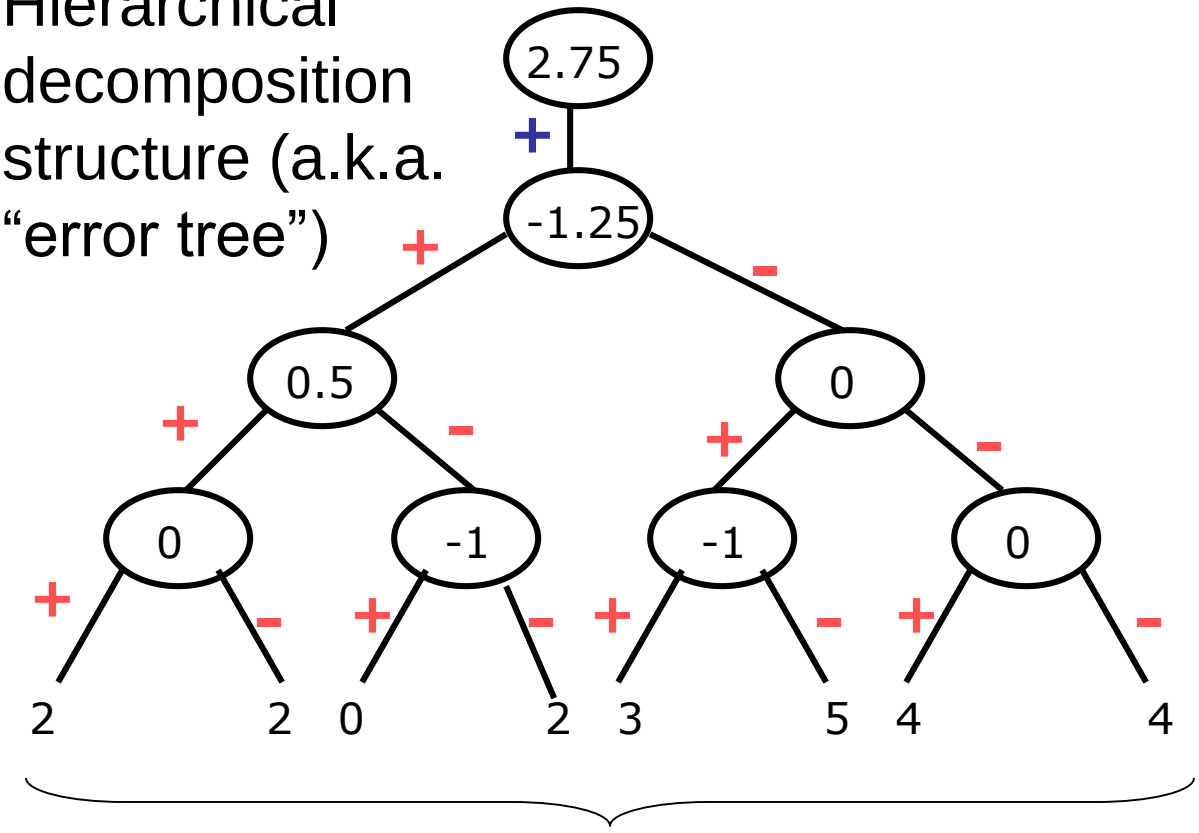
Wavelet Decomposition

- Wavelets: A math tool for space-efficient hierarchical decomposition of functions
- S = [2, 2, 0, 2, 3, 5, 4, 4] can be transformed to $S_{\wedge}$ = [$2^3/_4$, $-1^1/_4$, $^1/_2$, 0, 0, -1, -1, 0]
- Compression: many small detail coefficients can be replaced by 0's, and only the significant coefficients are retained

Resolution	Averages	Detail Coefficients
8	$[2, 2, 0, 2, 3, 5, 4, 4]$	
4	$[2, 1, 4, 4]$	$[0, -1, -1, 0]$
2	$[1\frac{1}{2}, 4]$	$[\frac{1}{2}, 0]$
1	$[2\frac{3}{4}]$	$[-1\frac{1}{4}]$

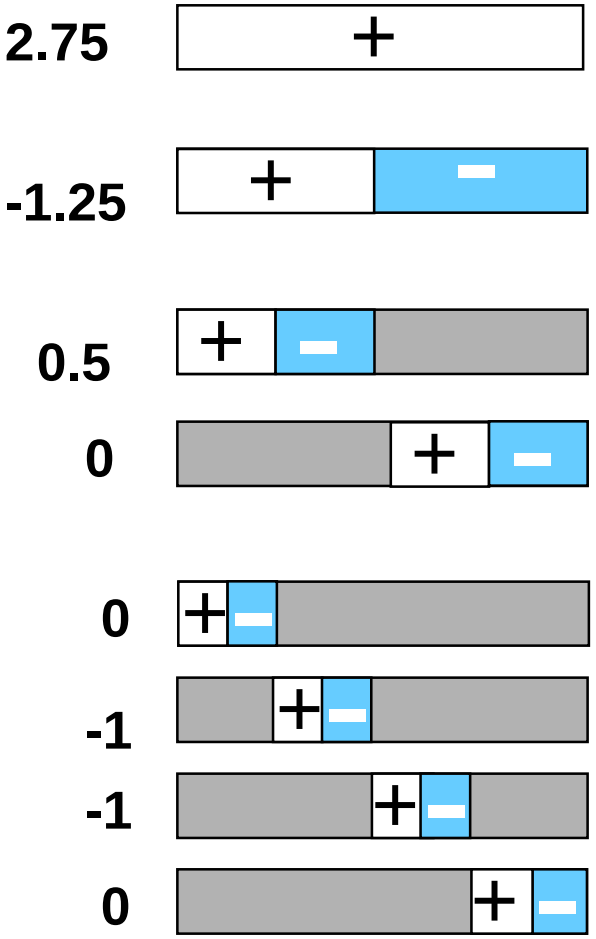
Haar Wavelet Coefficients

Hierarchical decomposition structure (a.k.a. "error tree")



Original frequency distribution

Coefficient "Supports"



Why Wavelet Transform?

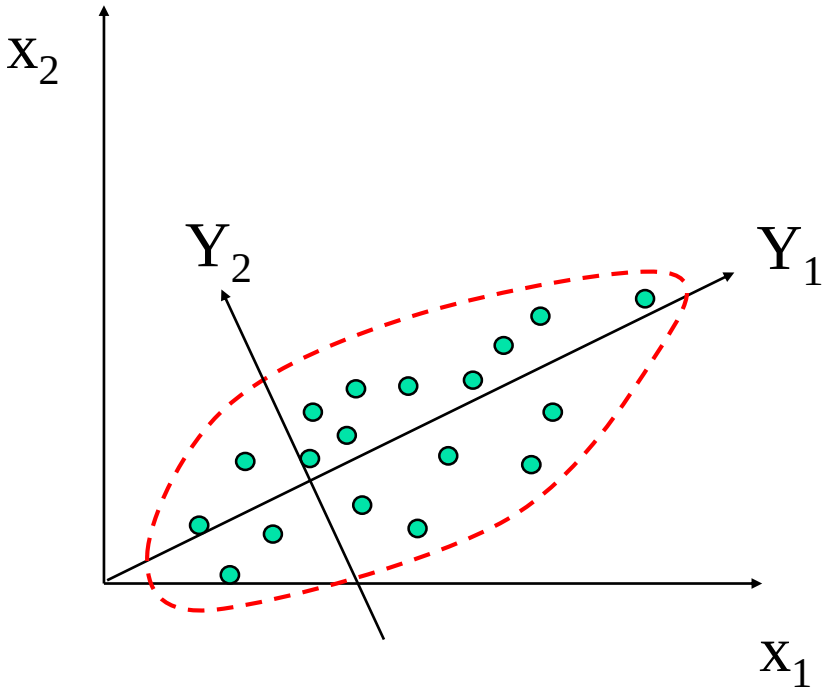
- Use hat-shape filters
  - Emphasize region where points cluster
  - Suppress weaker information in their boundaries
- Effective removal of outliers
  - Insensitive to noise, insensitive to input order
- Multi-resolution
  - Detect arbitrary shaped clusters at different scales
- Efficient
  - Complexity O(N)
- Only applicable to low dimensional data

Wavelet Transformation

- Wavelet transforms can be applied to multi-dimensional data such as a data cube.
- This is done by first applying the transform to the first dimension, then to the second, and so on.
- The computational complexity involved is linear with respect to the number of cells in the cube.
- Wavelet transforms give good results on sparse or skewed data and on data with ordered attributes.
- Lossy compression by wavelets is reportedly better than JPEG compression, the current commercial standard.
- Wavelet transforms have many real world applications, including the compression of fingerprint images, computer vision, analysis of time-series data, and data cleaning.

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.
- We find the eigenvectors of the covariance matrix, and these eigenvectors define the new space
- Y_1 and Y_2 are the first two principal components for the given data.



Principal Component Analysis (PCA)

- Unlike attribute subset selection, which reduces the attribute set size by retaining a subset of the initial set of attributes, PCA "combines" the essence of attributes by creating an alternative, smaller set of variables.
- The initial data is projected onto this smaller set.
- PCA often reveals relationships that were not previously suspected and thereby allows interpretations that would not ordinarily result.
- Multidimensional data of more than two dimensions can be handled by reducing the problem to two dimensions.
- Principal components may be used as inputs to multiple regression and cluster analysis.
- In comparison with wavelet transforms, PCA tends to be better at handling sparse data, whereas wavelet transforms are more suitable for data of high dimensionality.

Principal Component Analysis (Steps)

- Given *N* data vectors from *n*-dimensions, find $k \leq n$ 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
  - Since the components are sorted, the size of the data can be reduced by eliminating the *weak components*, i.e., those with low variance (i.e., 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

- Reduces the data set size by removing irrelevant or redundant attributes (or dimensions).
- The goal is to find a minimum set of attributes such that the resulting probability distribution of the data classes is as close as possible to the original distribution obtained using all attributes.
- Mining on a reduced set of attributes has an additional benefit - reduces the number of attributes appearing in the discovered patterns, helping to make the patterns easier to understand.

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

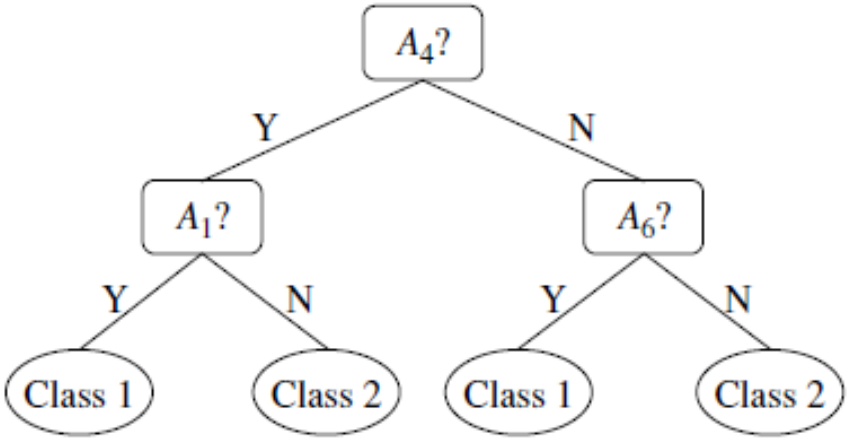
How to find a 'good' subset of attributes

- For n attributes, there are 2^n possible subsets.
- An exhaustive search for the optimal subset of attributes can be prohibitively expensive, especially as n and the number of data classes increase.
- Thus, greedy heuristic methods that explore a reduced search space are commonly used.
  - While searching through attribute space, they always make what looks to be the best choice at the time.
- Such greedy methods are effective in practice and may come close to estimating an optimal solution.
- The "best" (and "worst") attributes are typically determined using tests of statistical significance, which assume that the attributes are independent of one another.
- Many other attribute evaluation measures can be used such as the information gain measure used in building decision trees for classification.

Greedy (heuristic) methods for attribute subset selection

- Stepwise forward selection:
  - Starts with an empty set of attributes as the reduced set.
  - At each step, it adds the best remaining original attributes to the set.
- Stepwise backward elimination:
  - Starts with the full set of attributes.
  - At each step, it removes the worst attribute remaining in the set.
- Combination of forward selection and backward elimination:
  - At each step, it selects the best attribute and removes the worst from among the remaining attributes.
- Decision tree induction:
  - At each node, the algorithm chooses the "best" attribute to partition the data into individual classes.
  - When decision tree induction is used for attribute subset selection, a tree is constructed from the given data.
  - All attributes that do not appear in the tree are assumed to be irrelevant.
  - The set of attributes appearing in the tree form the reduced subset of attributes.

Greedy (heuristic) methods for attribute subset selection

Forward selection	Backward elimination	Decision tree induction
Initial attribute set: $\{A_1, A_2, A_3, A_4, A_5, A_6\}$ Initial reduced set: $\{\}$ $\Rightarrow \{A_1\}$ $\Rightarrow \{A_1, A_4\}$ $\Rightarrow$ Reduced attribute set: $\{A_1, A_4, A_6\}$	Initial attribute set: $\{A_1, A_2, A_3, A_4, A_5, A_6\}$ $\Rightarrow \{A_1, A_3, A_4, A_5, A_6\}$ $\Rightarrow \{A_1, A_4, A_5, A_6\}$ $\Rightarrow$ Reduced attribute set: $\{A_1, A_4, A_6\}$	Initial attribute set: $\{A_1, A_2, A_3, A_4, A_5, A_6\}$  $\Rightarrow$ Reduced attribute set: $\{A_1, A_4, A_6\}$

Creating New Attributes

- In some cases, we may want to create new attributes based on others.
- Such attribute construction can help improve accuracy and understanding of structure in high-dimensional data.
- For example, we may wish to add the attribute area based on the attributes height and width.
- By combining attributes, attribute construction can discover missing information about the relationships between data attributes that can be useful for knowledge discovery.

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, manifold approaches (not covered)
  - Attribute construction
    - Combining features (see: discriminative frequent patterns in Chapter 7)
    - Data discretization

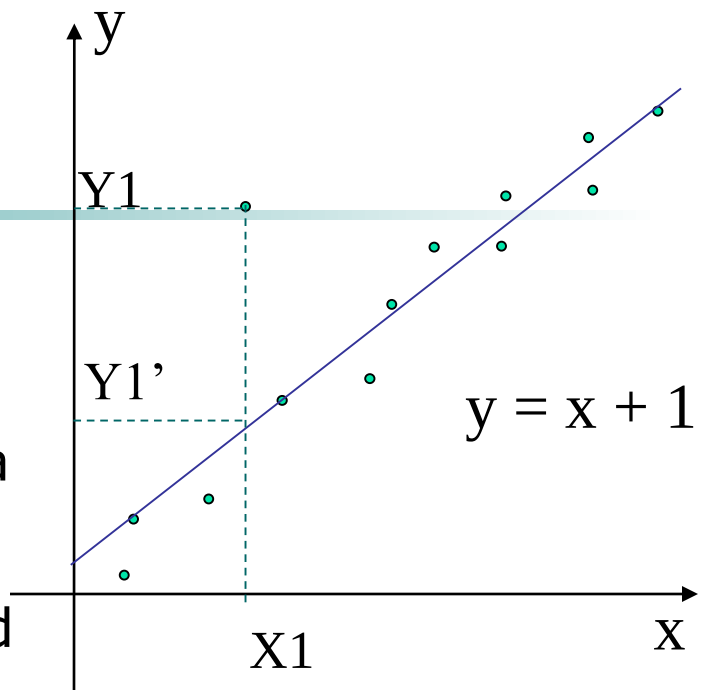
Data Reduction 2: Numerosity Reduction

- 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, …

Parametric Data Reduction: Regression and Log-Linear Models

- **Linear regression**
  - Data modeled to fit a straight line
  - Often uses the least-square method to fit the line
- **Multiple regression**
  - Allows a response variable Y to be modeled as a linear function of multidimensional feature vector
- **Log-linear model**
  - Approximates discrete multidimensional probability distributions

Regression Analysis



- Regression analysis: A collective name for techniques for the modeling and analysis of numerical data consisting of values of a ***dependent variable*** (also called ***response variable*** or *measurement*) and of one or more *independent variables* (aka. ***explanatory variables*** or ***predictors***)
- The parameters are estimated so as to give a "**best fit**" of the data
- Most commonly 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

Regress Analysis and Log-Linear Models

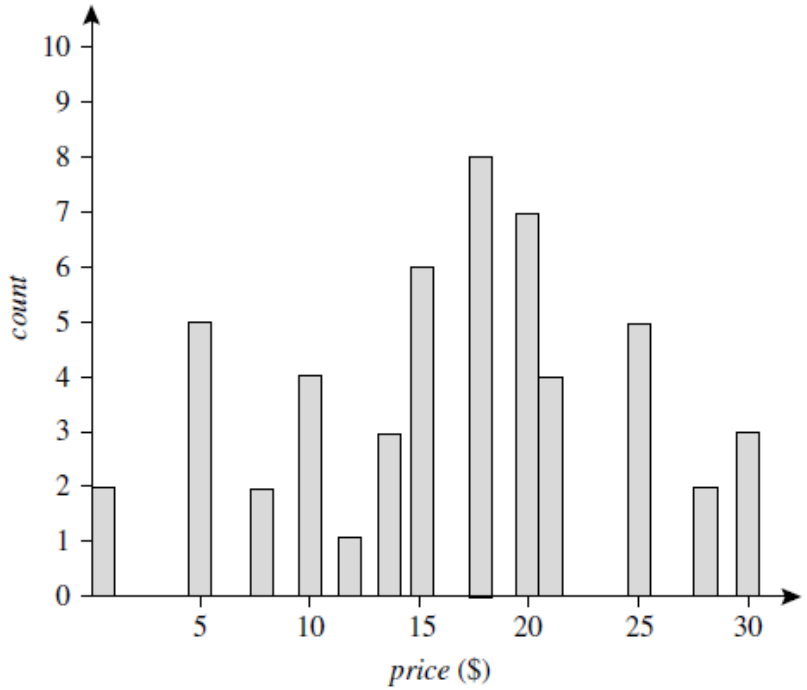
- Linear regression: $Y = w X + b$
  - Two regression coefficients, w and b, specify the line and are to be estimated by using the data at hand
  - Using the least squares criterion to the known values of Y_1, Y_2, …, X_1, X_2, ….
- Multiple regression: $Y = b_0 + b_1 X_1 + b_2 X_2$
  - Many nonlinear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

Histograms

- Histograms use binning to approximate data distributions and are a popular form of data reduction.
- A histogram for an attribute, A, partitions the data distribution of A into disjoint subsets, referred to as buckets or bins.
- If each bucket represents only a single attribute–value/frequency pair, the buckets are called singleton buckets.
- Often, buckets instead represent continuous ranges for the given attribute.
- There are several partitioning rules, including the following:
  - Equal-width: the width of each bucket range is uniform.
  - Equal-frequency (or equal-depth): the buckets are created so that, roughly, the frequency of each bucket is constant.
- Histograms are highly effective at approximating both sparse and dense data, as well as highly skewed and uniform data.
- Multidimensional histograms can capture dependencies between attributes.
  - Effective in approximating data with up to five attributes.

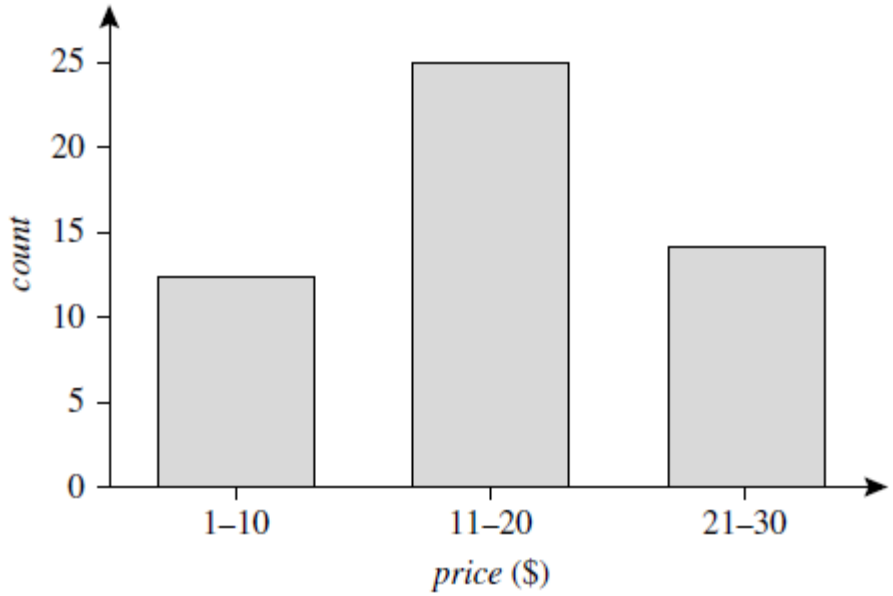
An Example of Histograms

- The numbers have been sorted:
  - 1, 1, 5, 5, 5, 5, 5, 8, 8, 10, 10, 10, 10, 12, 14, 14, 14, 15, 15, 15, 15, 15, 15, 18, 18, 18, 18, 18, 18, 18, 18, 20, 20, 20, 20, 20, 20, 20, 21, 21, 21, 21, 25, 25, 25, 25, 25, 28, 28, 30, 30, 30.
- A histogram for price using singleton buckets—each bucket represents one price–value/ frequency pair.



An Example of Histograms

- The numbers have been sorted:
  - 1, 1, 5, 5, 5, 5, 5, 8, 8, 10, 10, 10, 10, 12, 14, 14, 14, 15, 15, 15, 15, 15, 15, 18, 18, 18, 18, 18, 18, 18, 18, 20, 20, 20, 20, 20, 20, 20, 21, 21, 21, 21, 25, 25, 25, 25, 25, 28, 28, 30, 30, 30.
- An equal-width histogram for price, where values are aggregated so that each bucket has a uniform width of $10.



Clustering

- Partition data set into clusters based on similarity, and store cluster representation (e.g., centroid and diameter) only
- Can be very effective if data is clustered but not if data is "smeared"
- Can have hierarchical clustering and be stored in multi-dimensional index tree structures
- There are many choices of clustering definitions and clustering algorithms
- Cluster analysis will be studied in depth in Chapter 10

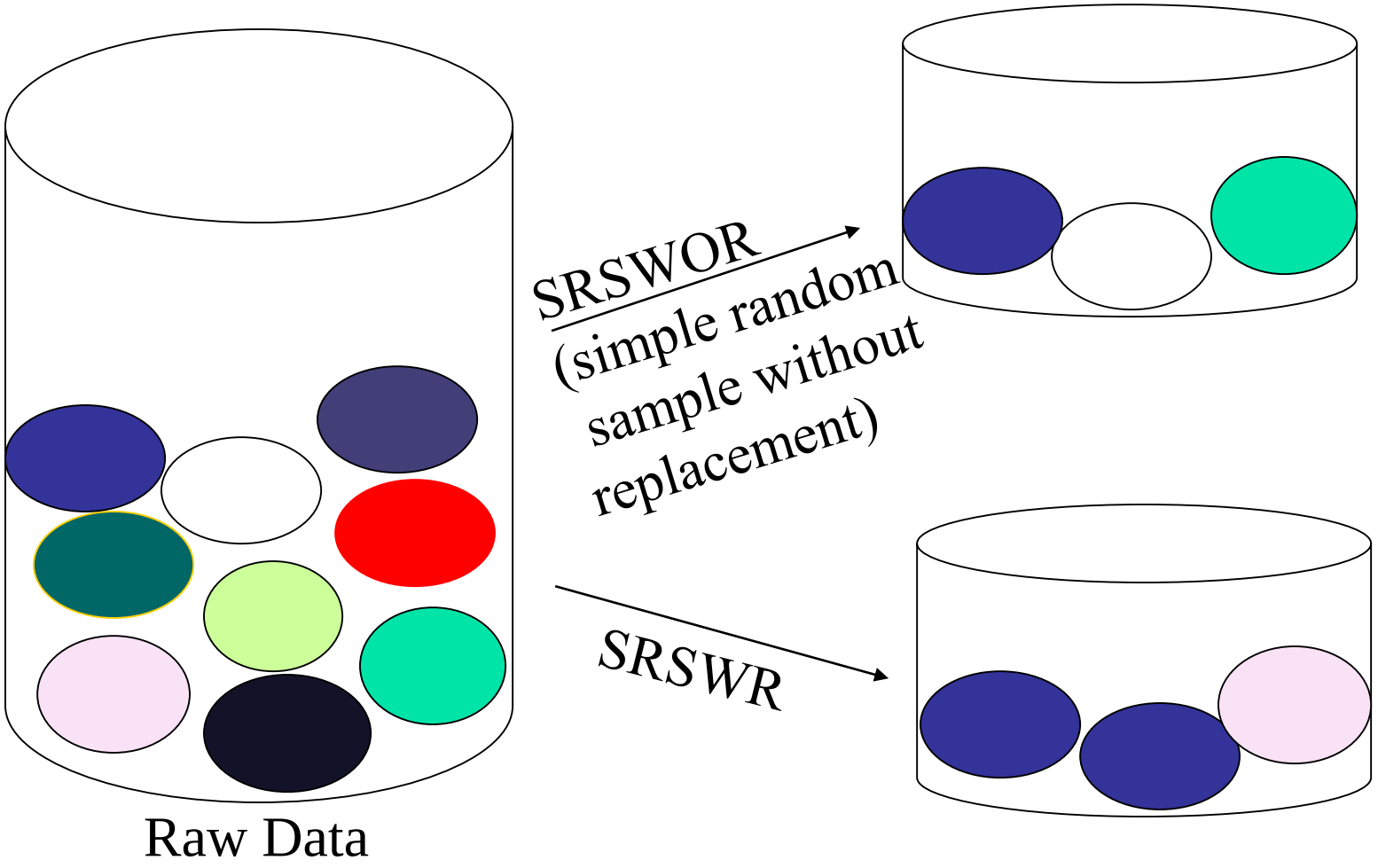
Sampling

- Sampling: obtaining a small sample *s* to represent the whole data set *N*
- Allow a mining algorithm to run in complexity that is potentially sub-linear to the size of the data
- Key principle: Choose a representative subset of the data
  - Simple random sampling may have very poor performance in the presence of skew
  - Develop adaptive sampling methods, e.g., stratified sampling:
- Note: Sampling may not reduce database I/Os (page at a time)

Types of Sampling

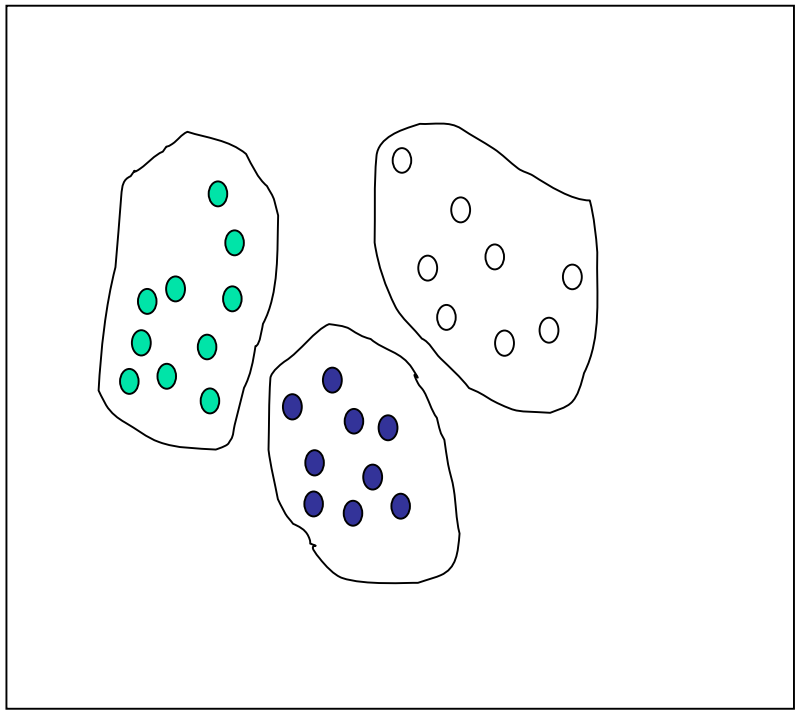
- **Simple random sampling**
  - There is an equal probability of selecting any particular item
- **Sampling without replacement**
  - Once an object is selected, it is removed from the population
- **Sampling with replacement**
  - A selected object is not removed from the population
- **Stratified sampling:**
  - Partition the data set, and draw samples from each partition (proportionally, i.e., approximately the same percentage of the data)
  - Used in conjunction with skewed data

Sampling: With or without Replacement

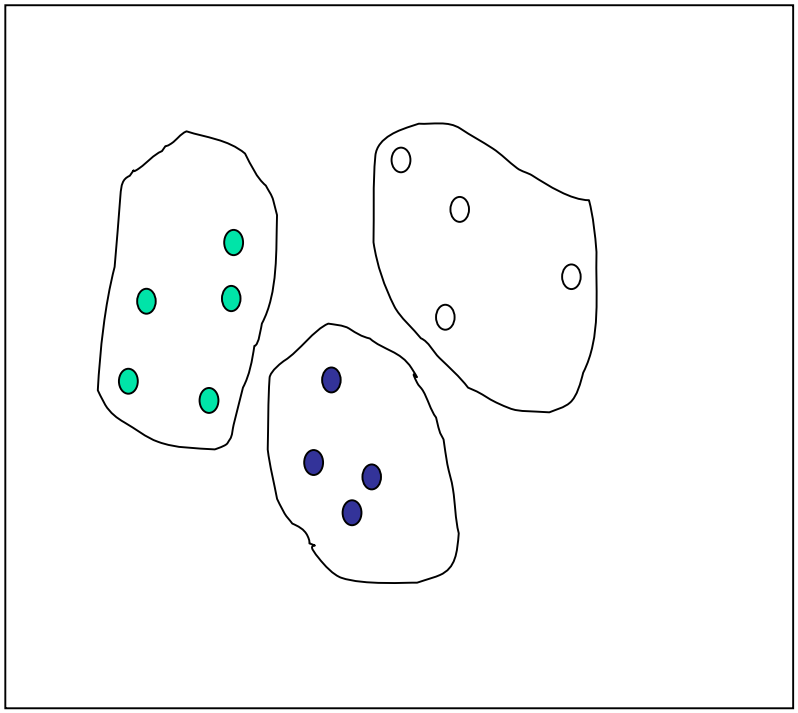


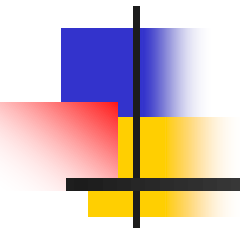
Sampling: Cluster or Stratified Sampling

Raw Data



Cluster/Stratified Sample

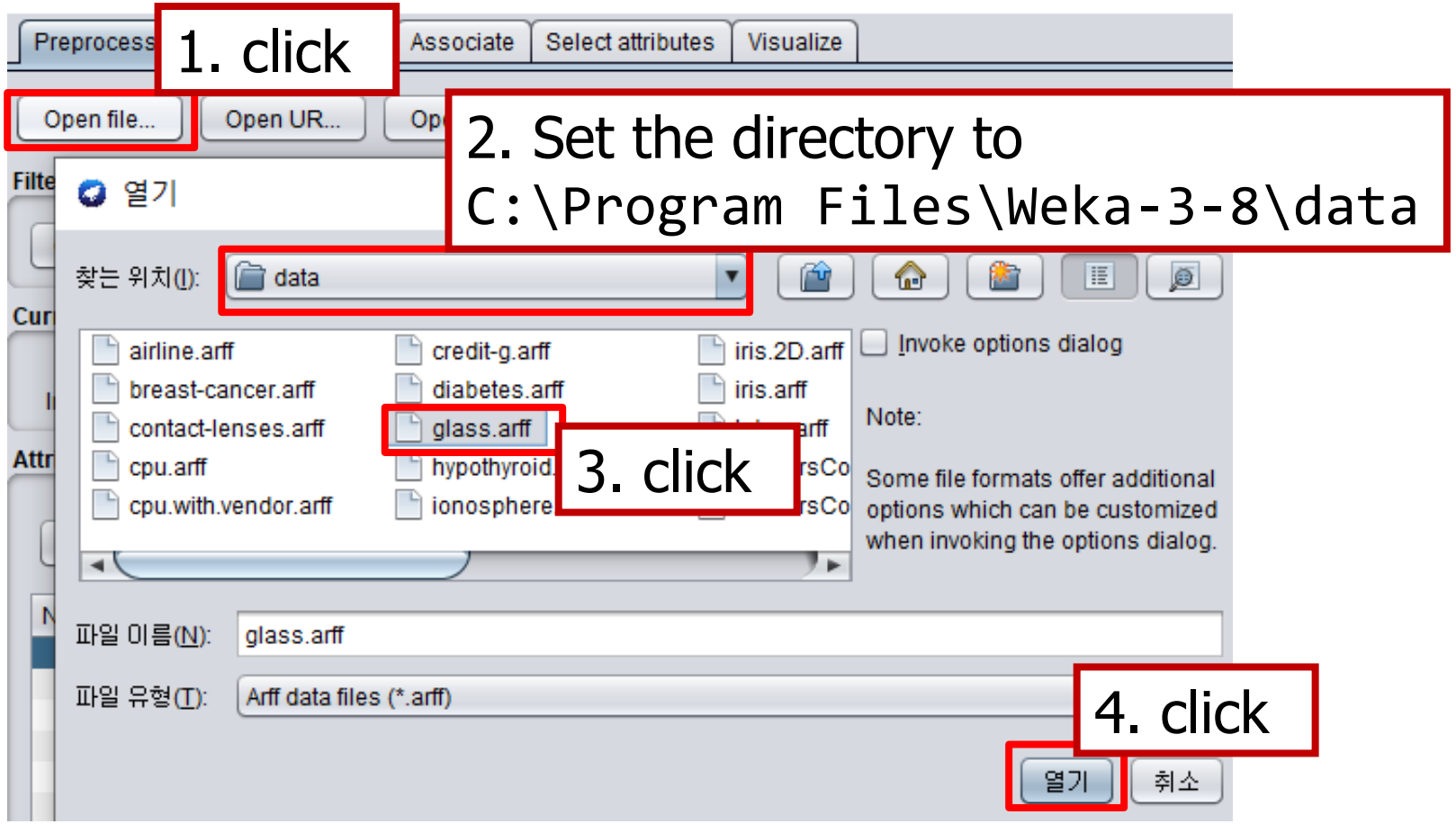




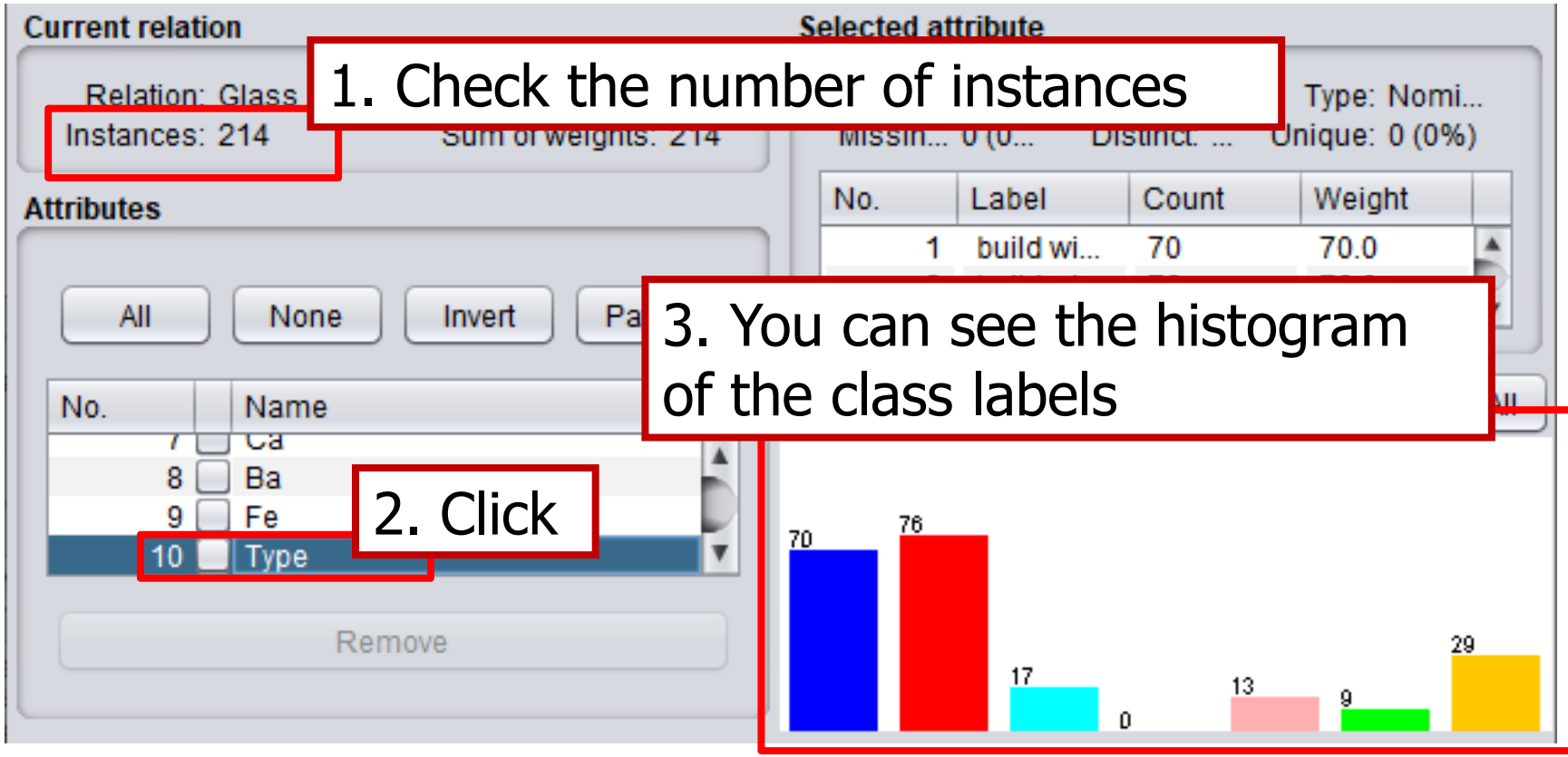
Weka - Sampling

Open the Glass Dataset

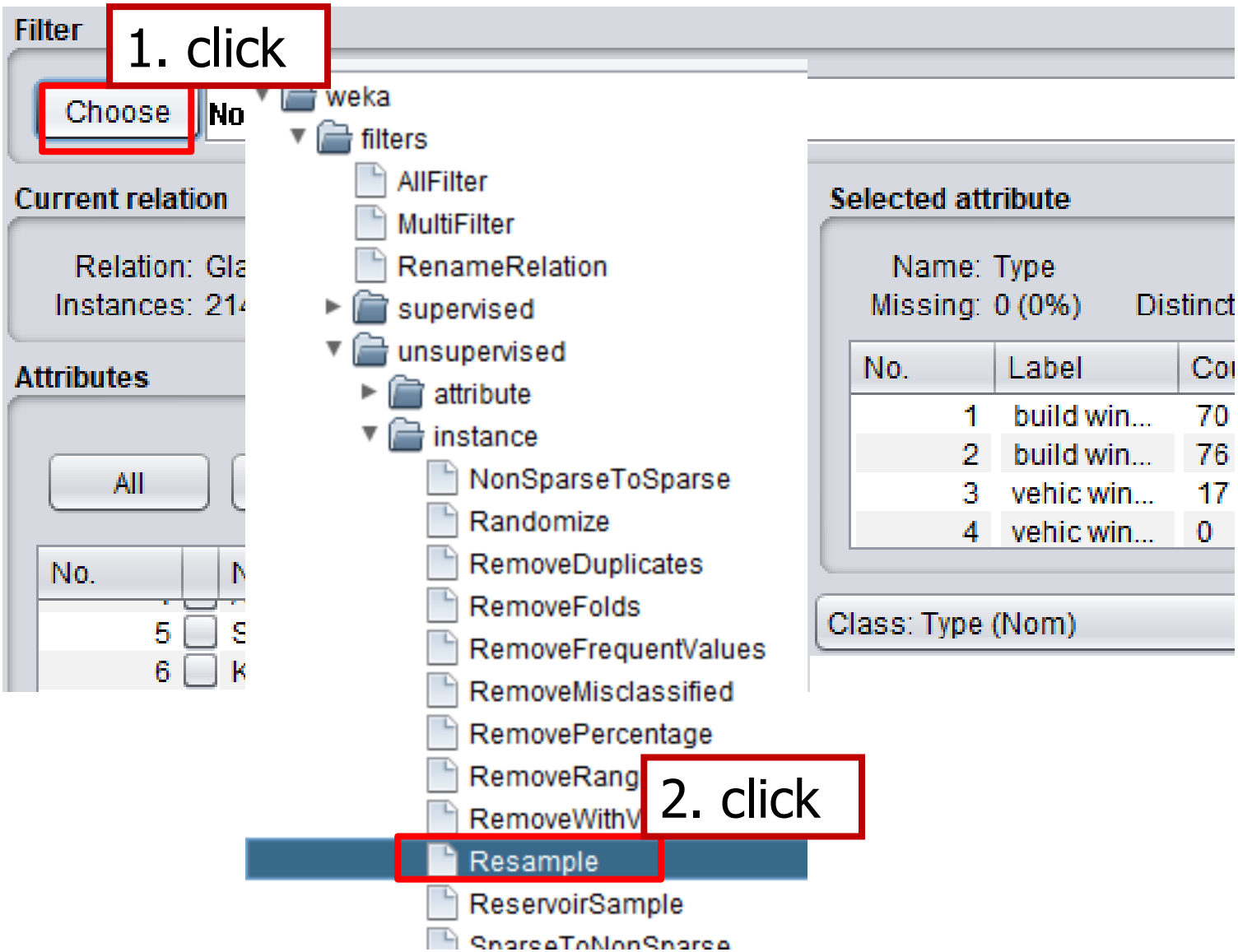
- Open:
  - `C:\Program Files\Weka-3-8\data\glass.arff`



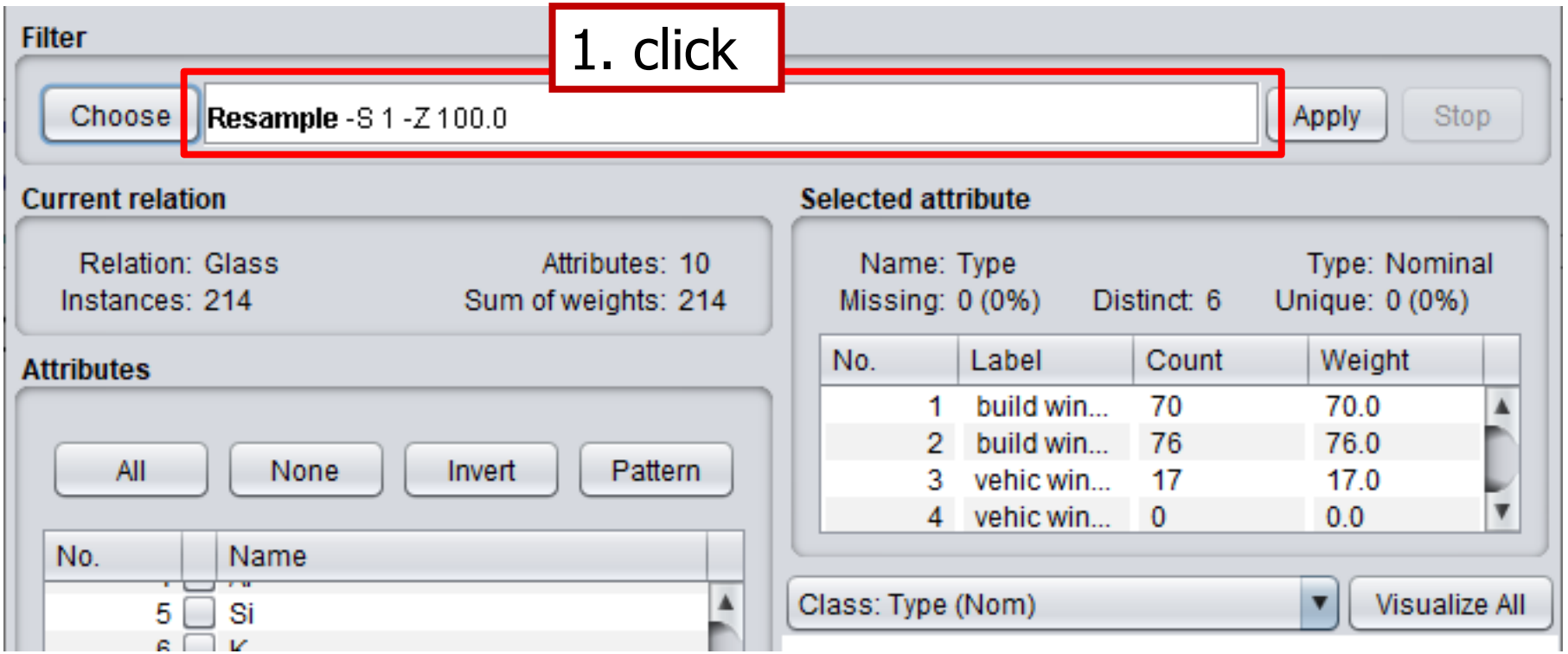
The Statistics of the Dataset



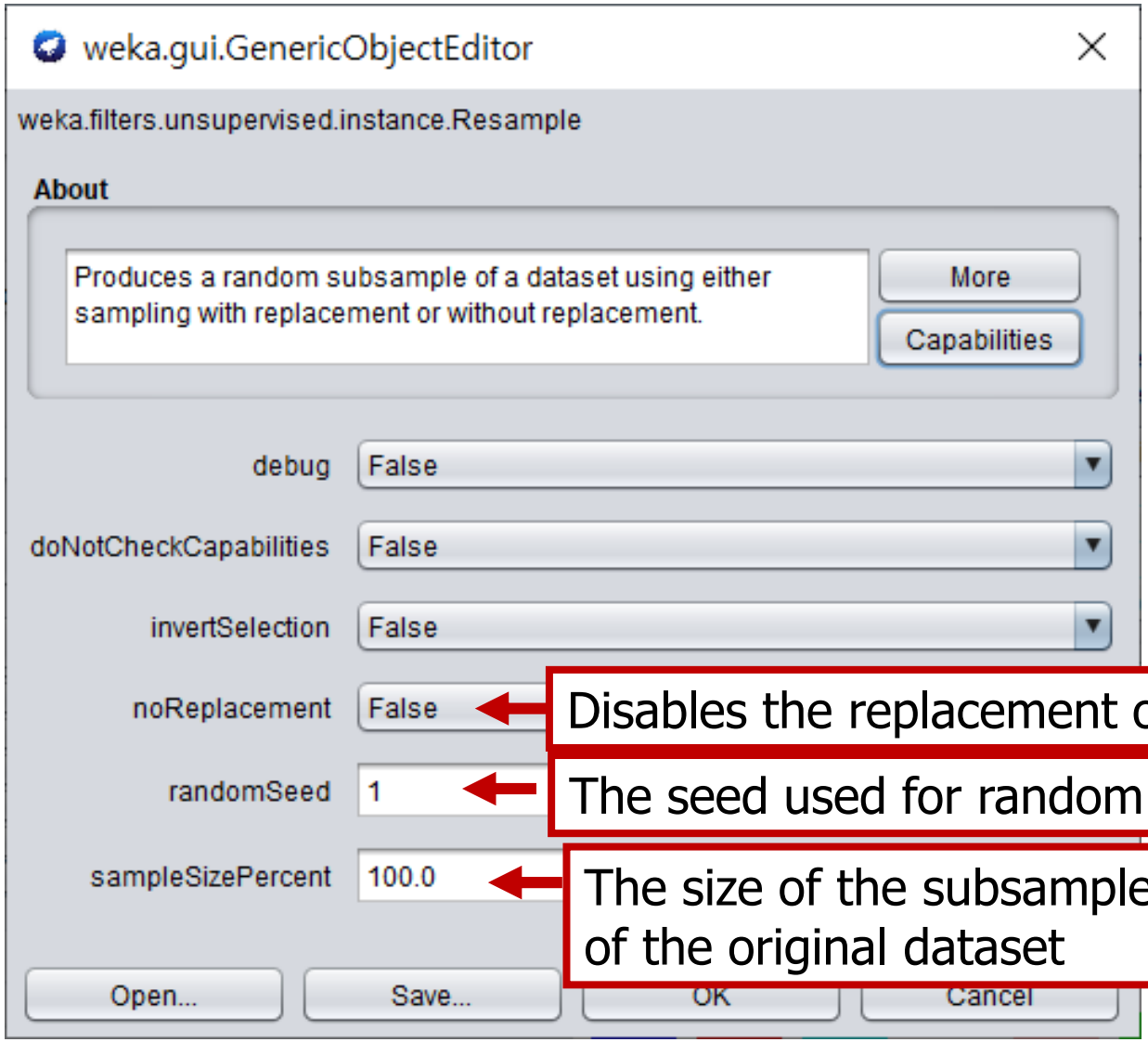
Sampling


Filter
1. click
Choose
No
Current relation
Relation: Gla
Instances: 214
Attributes
All
No.
5
6
weka
filters
AllFilter
MultiFilter
RenameRelation
supervised
unsupervised
attribute
instance
NonSparseToSparse
Randomize
RemoveDuplicates
RemoveFolds
RemoveFrequentValues
RemoveMisclassified
RemovePercentage
RemoveRang
RemoveWithV
2. click
Resample
ReservoirSample
Selected attribute
Name: Type
Missing: 0 (0%)
Distinct
No.
Label
1
build win...
70
2
build win...
76
3
vehic win...
17
4
vehic win...
0
Class: Type (Nom)

Configuring the Sampling



Configuring the Sampling

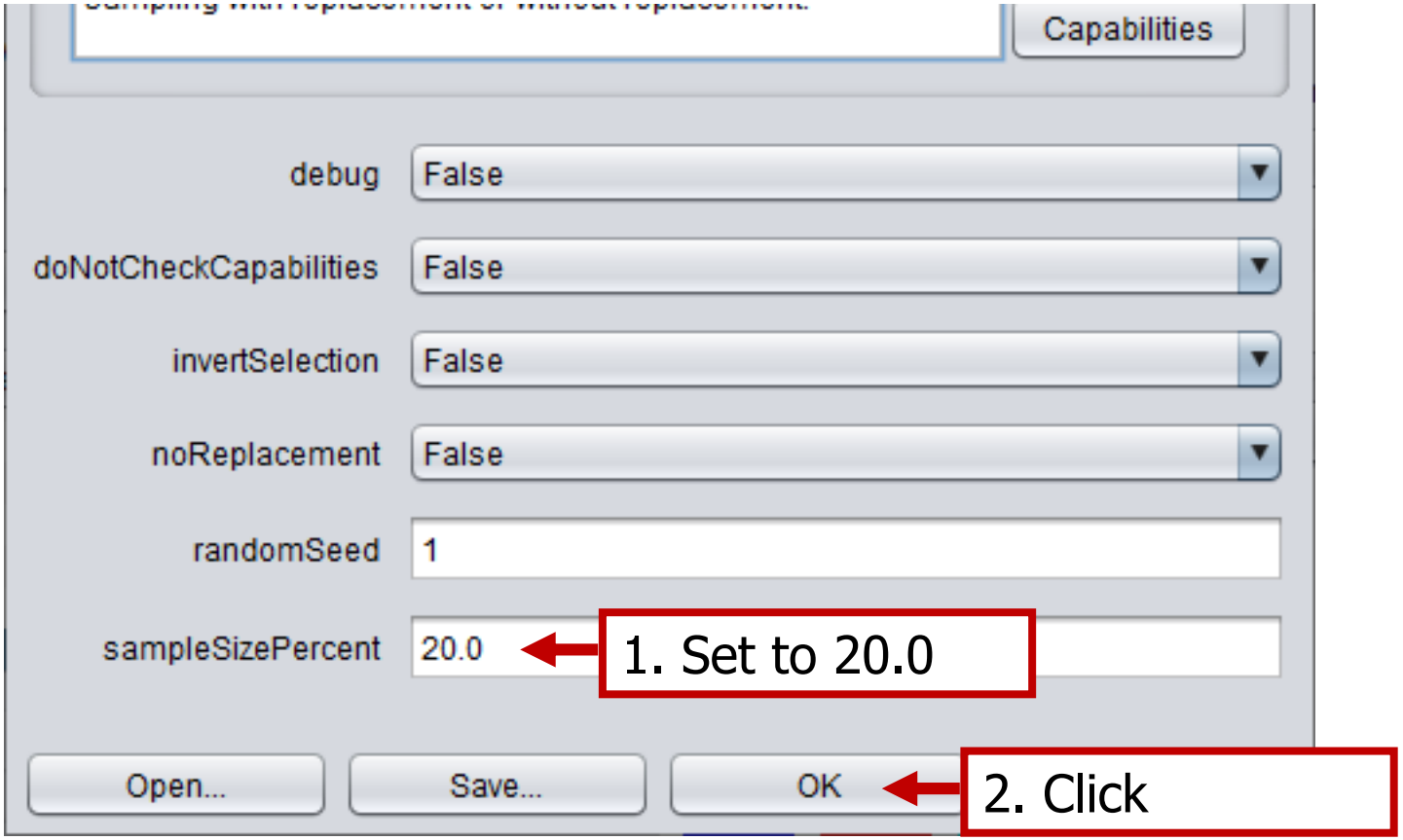


Disables the replacement of instances

The seed used for random sampling

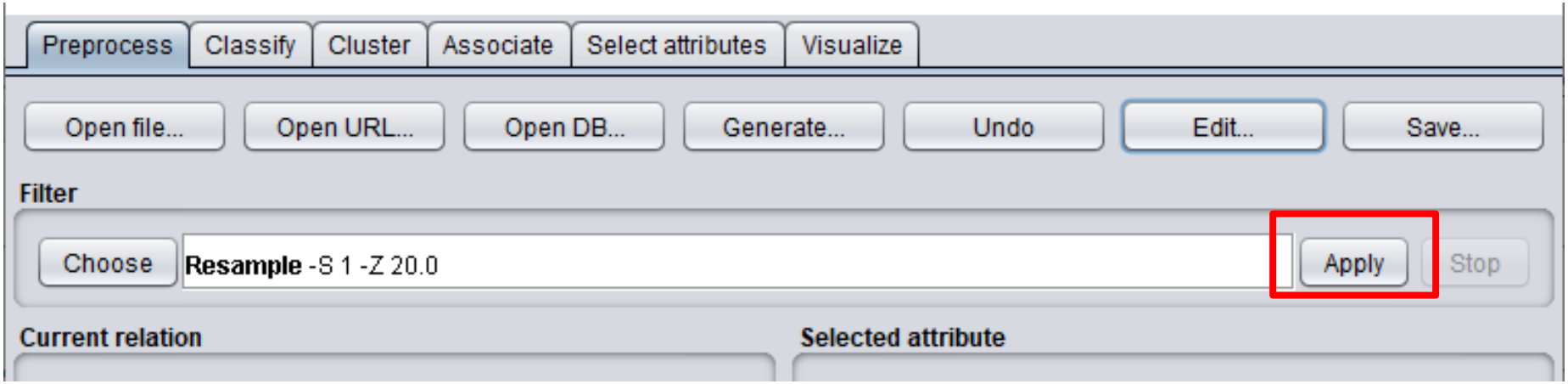
The size of the subsample as a percentage of the original dataset

Sampling With Replacement

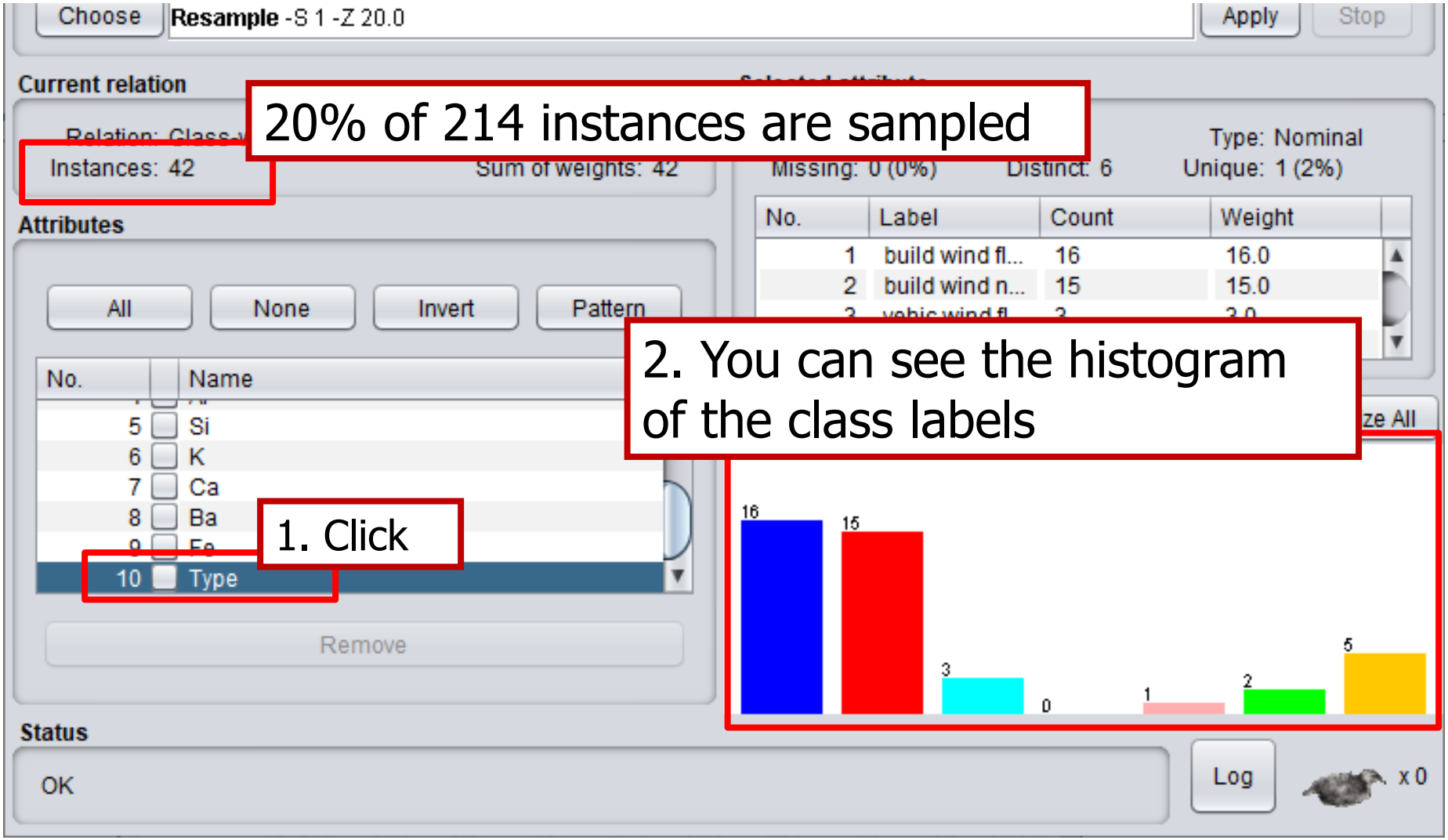


Sampling With Replacement

- Click ‘apply’ to run sampling

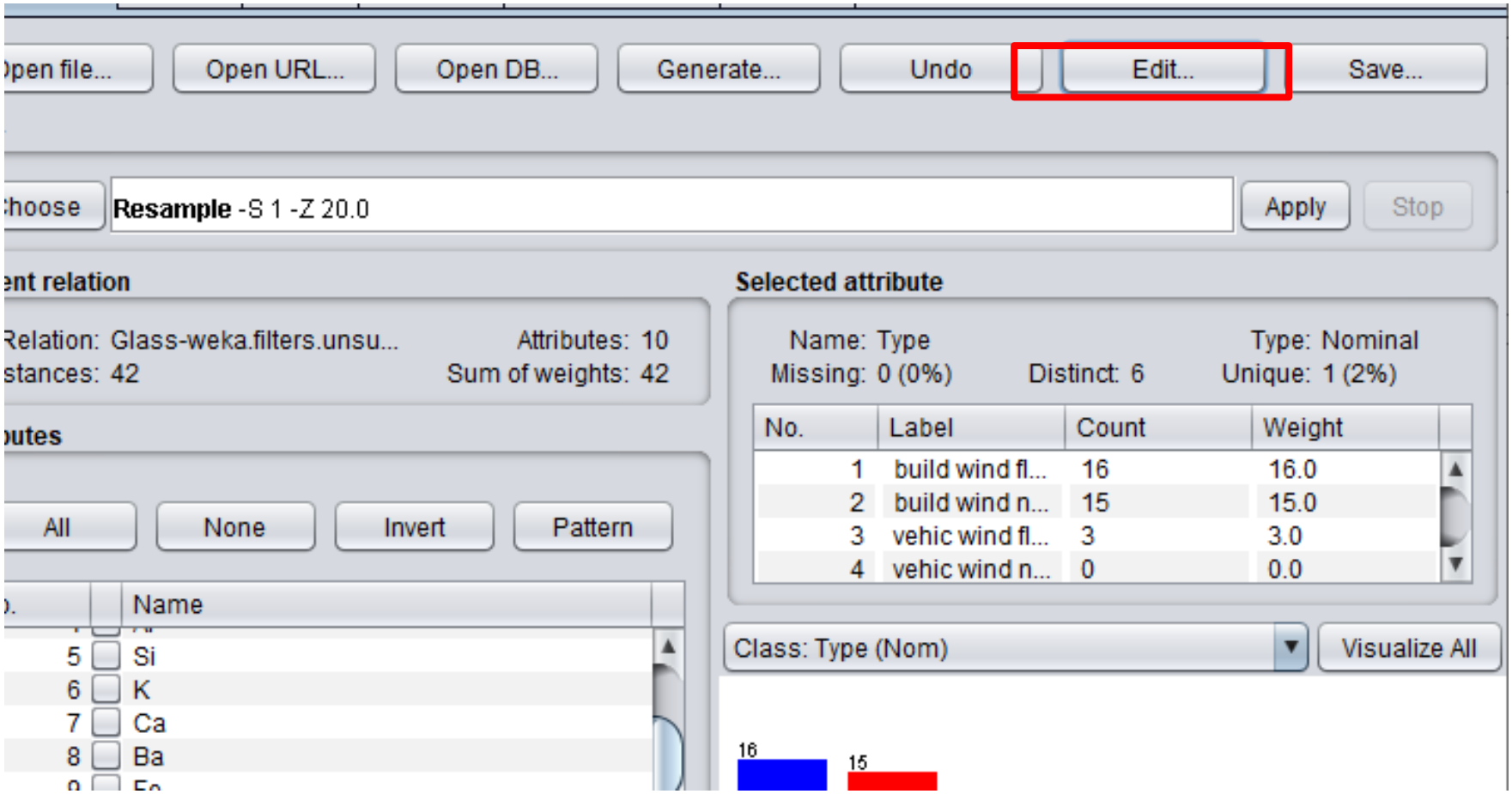


Sampling With Replacement

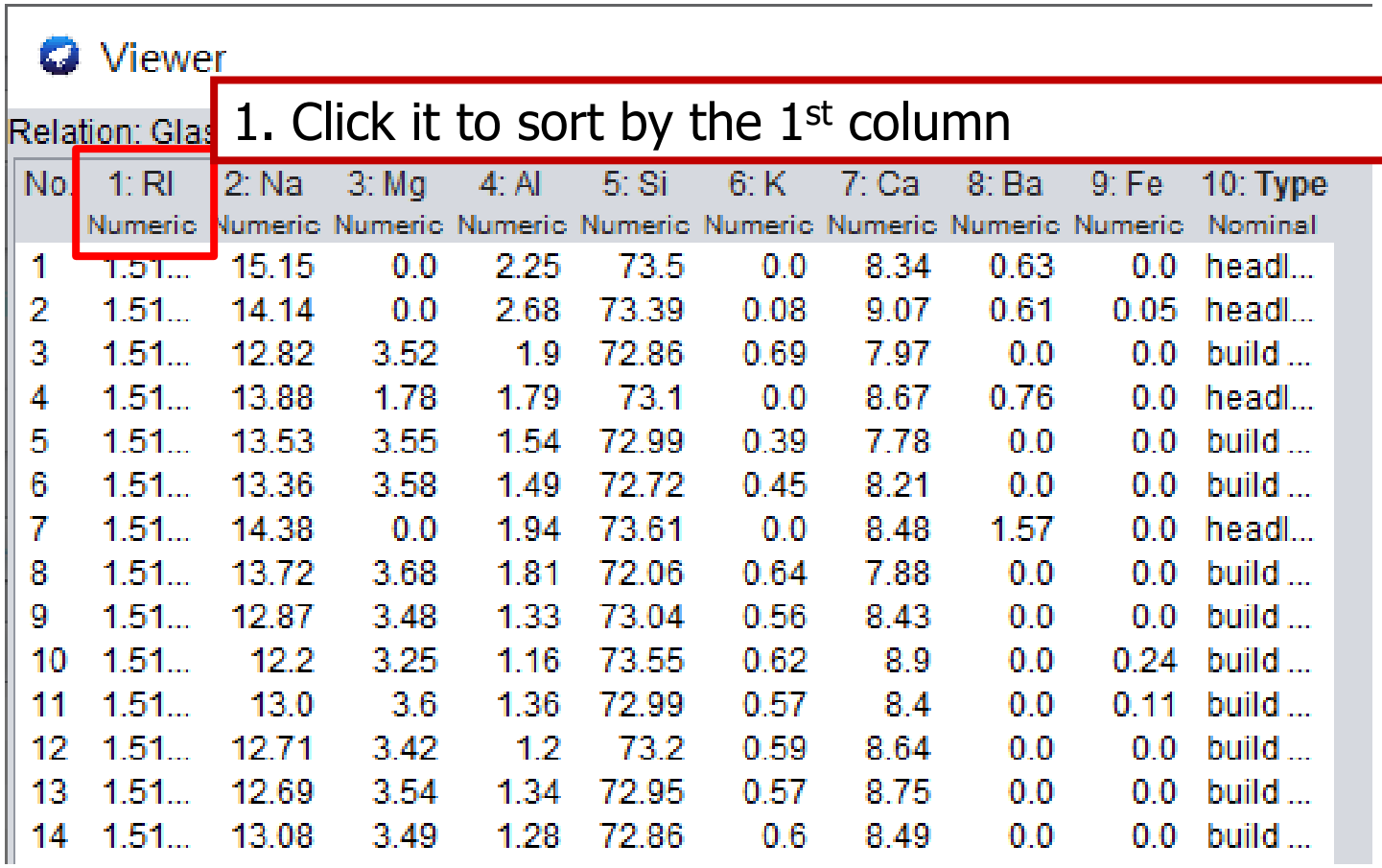


Sampling With Replacement

- Click 'edit' button to see the instances



Sampling With Replacement



No.	1: RI	2: Na	3: Mg	4: Al	5: Si	6: K	7: Ca	8: Ba	9: Fe	10: Type
	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Nominal
1	1.51...	15.15	0.0	2.25	73.5	0.0	8.34	0.63	0.0	headl...
2	1.51...	14.14	0.0	2.68	73.39	0.08	9.07	0.61	0.05	headl...
3	1.51...	12.82	3.52	1.9	72.86	0.69	7.97	0.0	0.0	build ...
4	1.51...	13.88	1.78	1.79	73.1	0.0	8.67	0.76	0.0	headl...
5	1.51...	13.53	3.55	1.54	72.99	0.39	7.78	0.0	0.0	build ...
6	1.51...	13.36	3.58	1.49	72.72	0.45	8.21	0.0	0.0	build ...
7	1.51...	14.38	0.0	1.94	73.61	0.0	8.48	1.57	0.0	headl...
8	1.51...	13.72	3.68	1.81	72.06	0.64	7.88	0.0	0.0	build ...
9	1.51...	12.87	3.48	1.33	73.04	0.56	8.43	0.0	0.0	build ...
10	1.51...	12.2	3.25	1.16	73.55	0.62	8.9	0.0	0.24	build ...
11	1.51...	13.0	3.6	1.36	72.99	0.57	8.4	0.0	0.11	build ...
12	1.51...	12.71	3.42	1.2	73.2	0.59	8.64	0.0	0.0	build ...
13	1.51...	12.69	3.54	1.34	72.95	0.57	8.75	0.0	0.0	build ...
14	1.51...	13.08	3.49	1.28	72.86	0.6	8.49	0.0	0.0	build ...

Sampling With Replacement

Viewe Drag it to increase the width of the 1st column

Relation: Glass-weka.filters.unsupervised.instance.Resample-S1-Z20.0

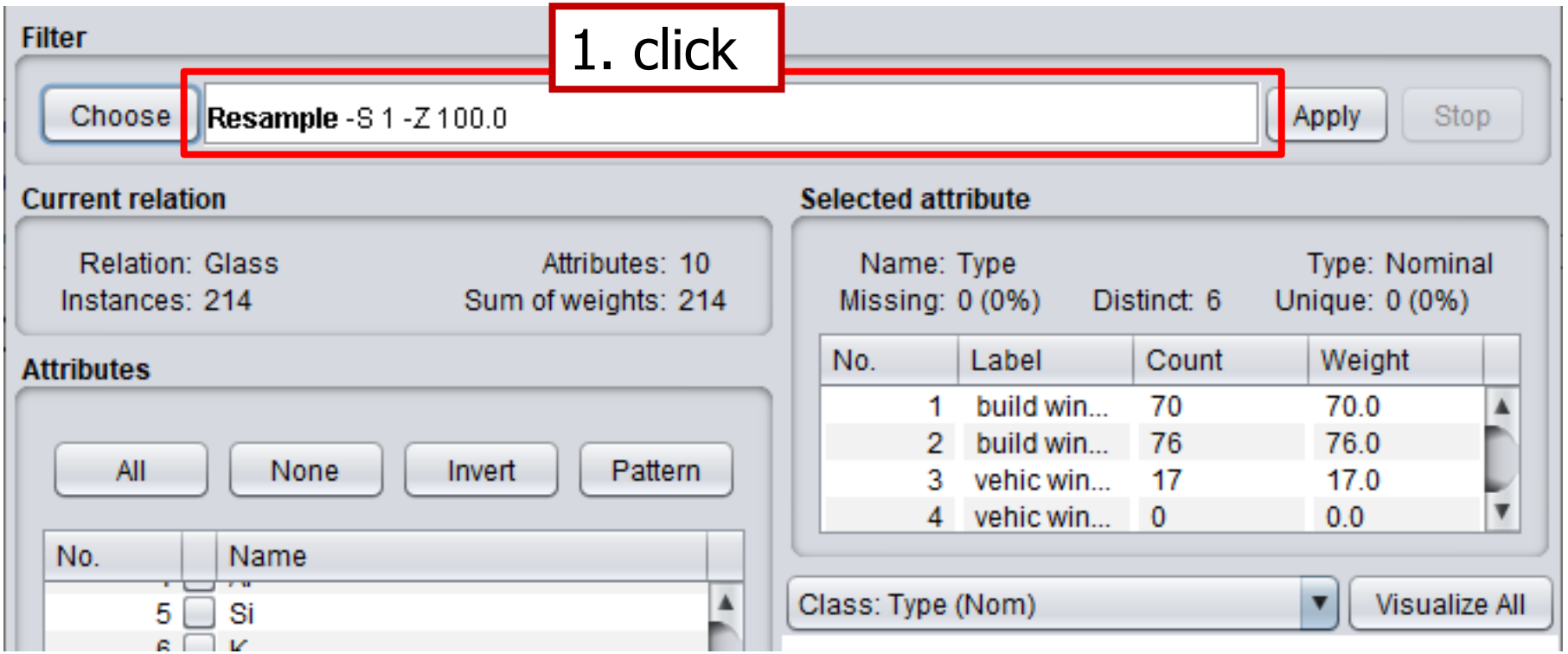
No.	1: RI Numeric	2: Na Numeric	3: Mg Numeric	4: Al Numeric	5: Si Numeric	6: K Numeric	7: Ca Numeric	8: Ba Numeric	9: Fe Numeric	10: Type Nominal
1	1.51508	15.15	0.0	2.25	73.5	0.0	8.34	0.63	0.0	headl...
2	1.51545	14.14	0.0	2.68	73.39	0.08	9.07	0.61	0.05	headl...
3	1.5159	12.82	3.52	1.9	72.86	0.69	7.97	0.0	0.0	build ...
4	1.51613	13.88	1.78	1.79	73.1	0.0	8.67	0.76	0.0	headl...
5	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.0	0.0	build ...
6	1.51625	13.36	3.58	1.49	72.72	0.45	8.21	0.0	0.0	build ...
7	1.51651	14.38	0.0	1.94	73.61	0.0	8.48	1.57	0.0	headl...
8	1.51708	13.72	3.68	1.81	72.06	0.64	7.88	0.0	0.0	build ...
9	1.51721	12.87	3.48	1.33	73.04	0.56	8.43	0.0	0.0	build ...
10	1.51743	12.2	3.25	1.16	73.55	0.62	8.9	0.0	0.24	build ...
11	1.51755	12.71	3.42	1.2	73.2	0.59	8.64	0.0	0.0	build ...
12	1.51755	13.0	3.6	1.36	72.99	0.57	8.4	0.0	0.11	build ...
13	1.51783	12.69	3.54	1.34	72.95	0.57	8.75	0.0	0.0	build ...

Sampling With Replacement

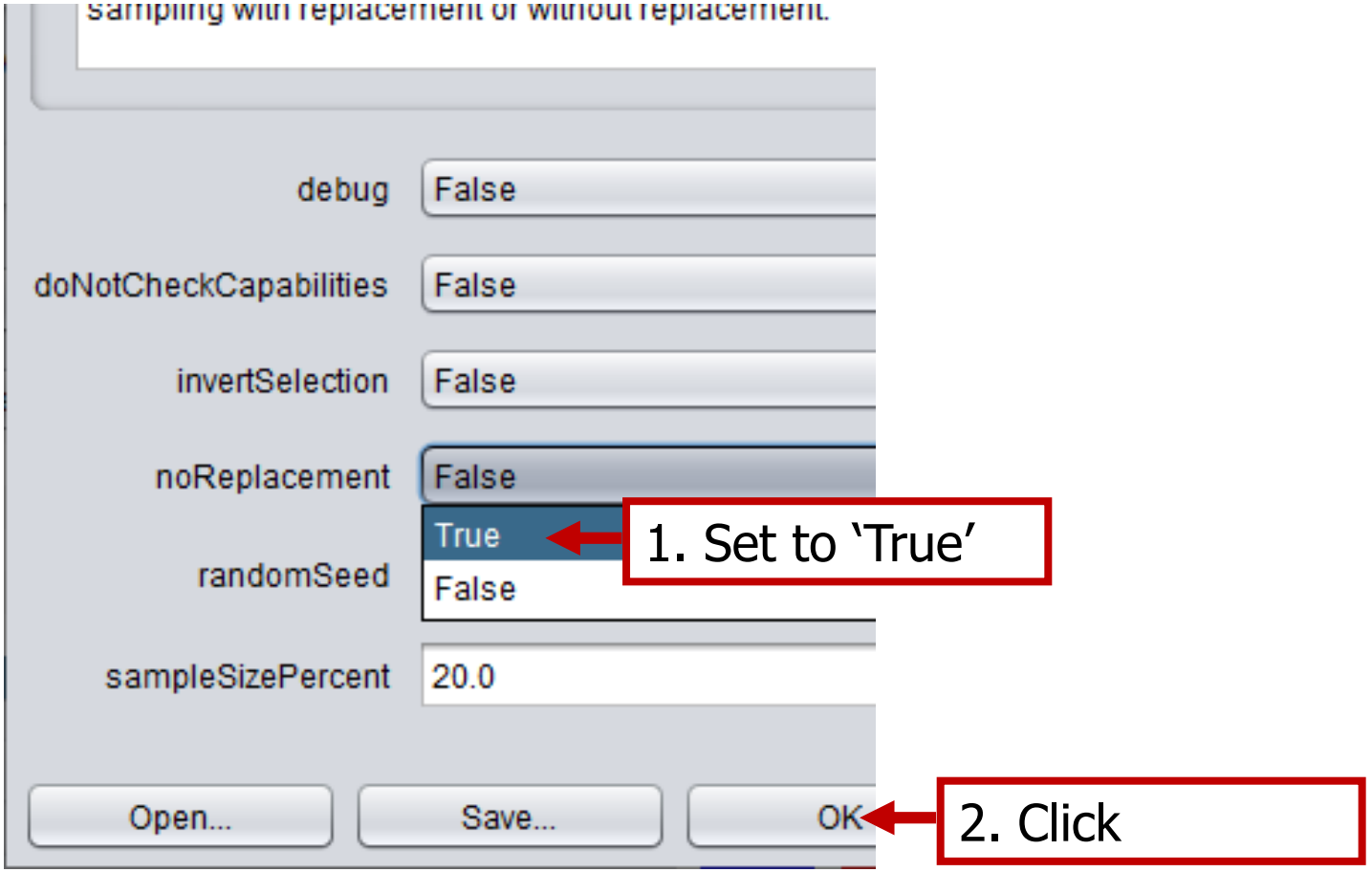
- You can see the duplicated instances since we samples with replacement

19	1.51813	13.43	3.98	1.18	72.49	0.58	8.15	0.0	0.0	build ...
20	1.51829	13.24	3.9	1.41	72.33	0.55	8.31	0.0	0.1	build ...
21	1.51832	13.33	3.34	1.54	72.14	0.56	8.99	0.0	0.0	vehic ...
22	1.51832	13.33	3.34	1.54	72.14	0.56	8.99	0.0	0.0	vehic ...
23	1.51888	14.99	0.78	1.74	72.5	0.0	9.95	0.0	0.0	table...
24	1.519	13.49	3.48	1.35	71.95	0.55	9.0	0.0	0.0	build ...
25	1.51966	14.77	3.75	0.29	72.02	0.03	9.0	0.0	0.0	build ...
26	1.51966	14.77	3.75	0.29	72.02	0.03	9.0	0.0	0.0	build ...

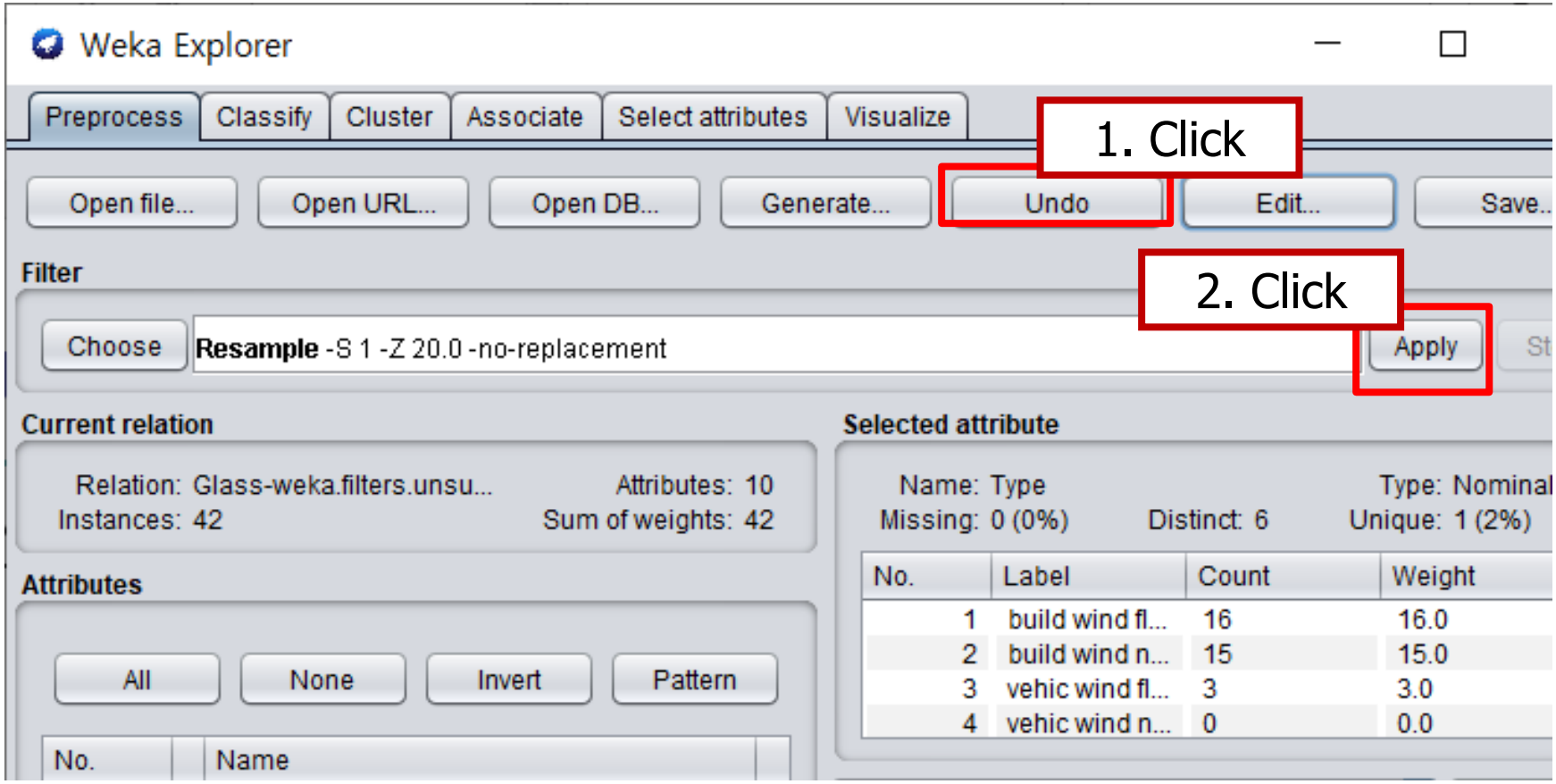
Configuring the Sampling



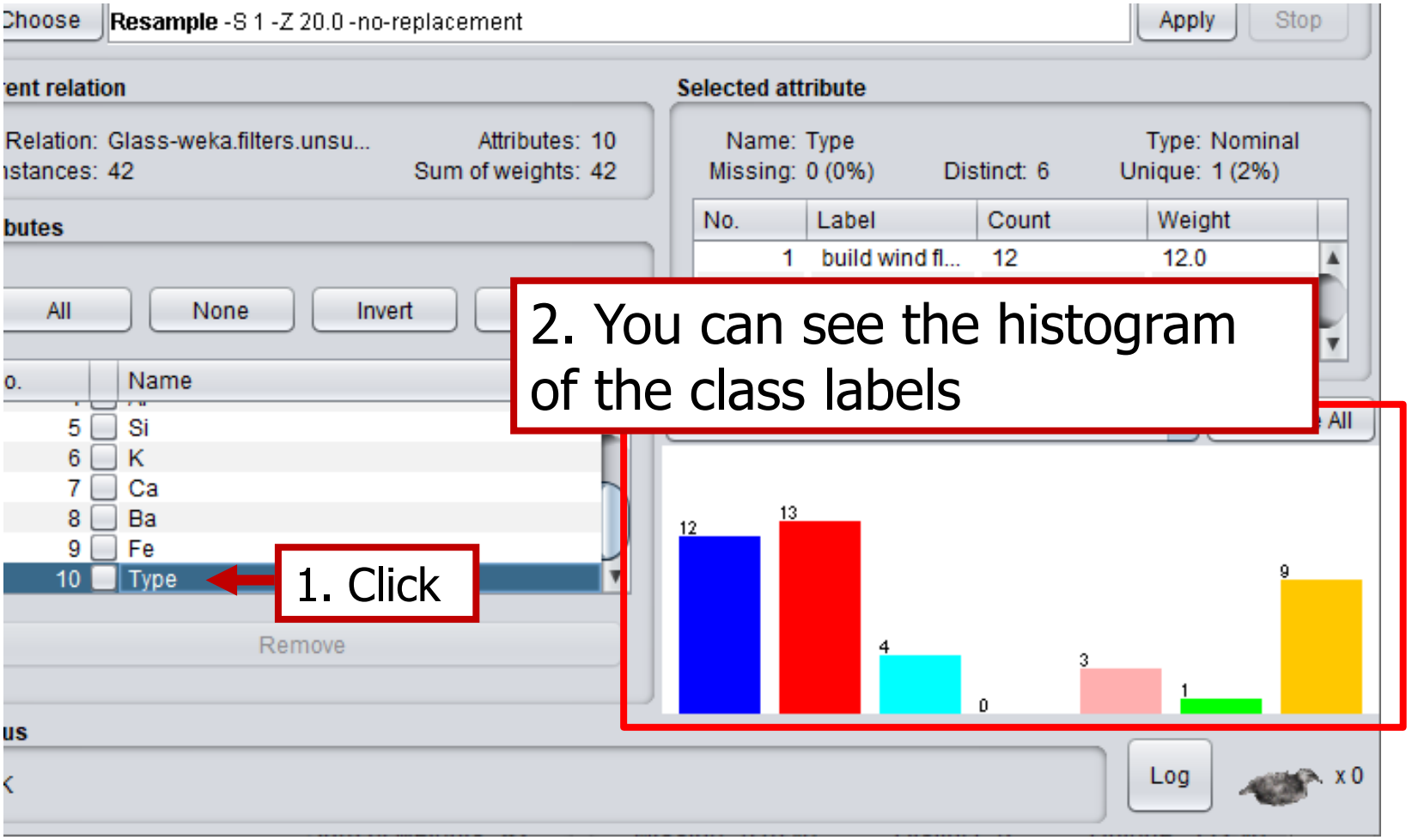
Sampling Without Replacement



Sampling Without Replacement

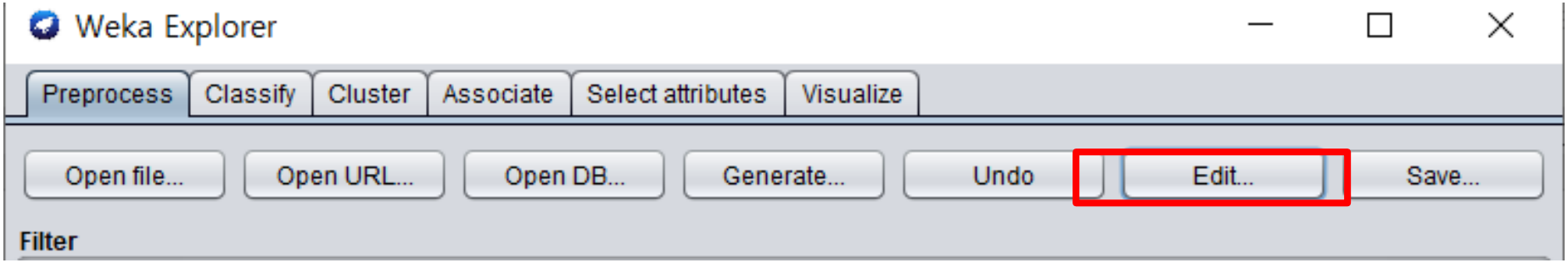


Sampling Without Replacement



Sampling Without Replacement

- Click ‘edit’ button to see the instances



Sampling Without Replacement

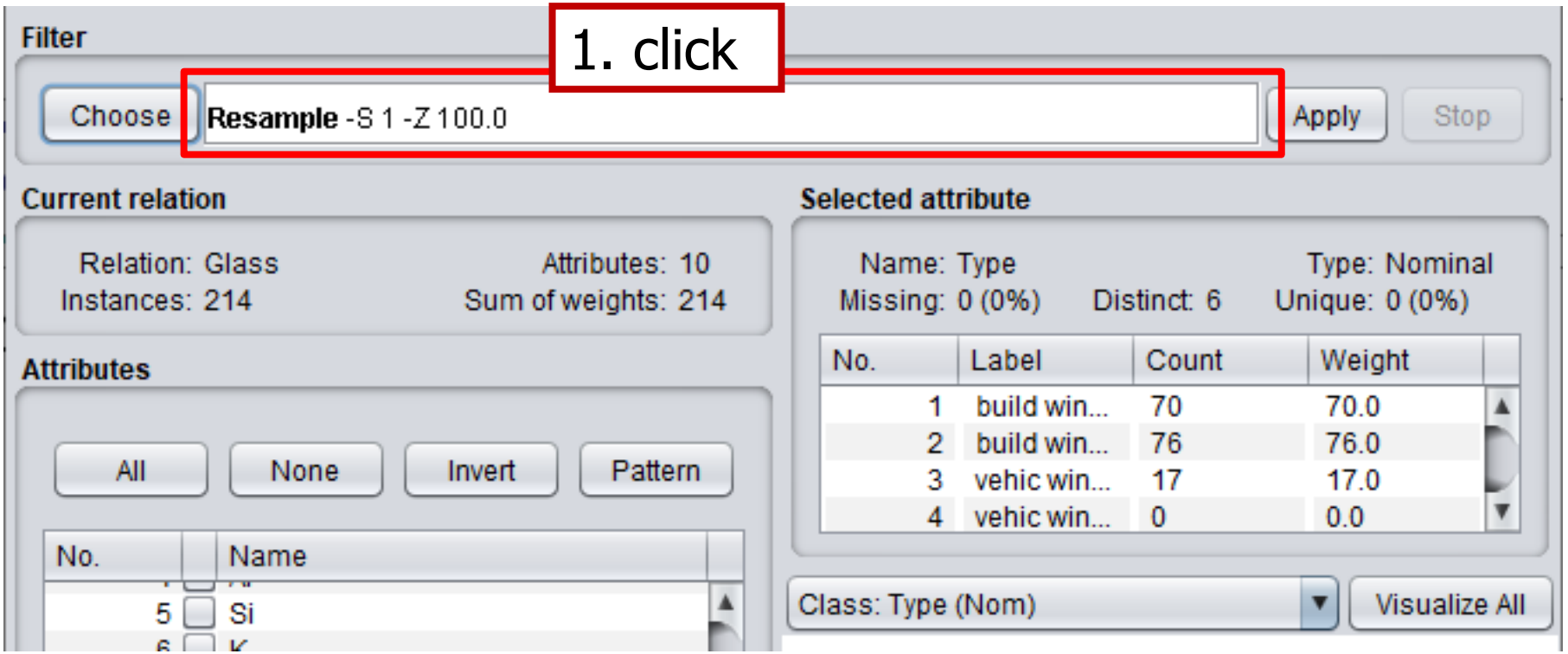
- There is no duplicates

Viewer

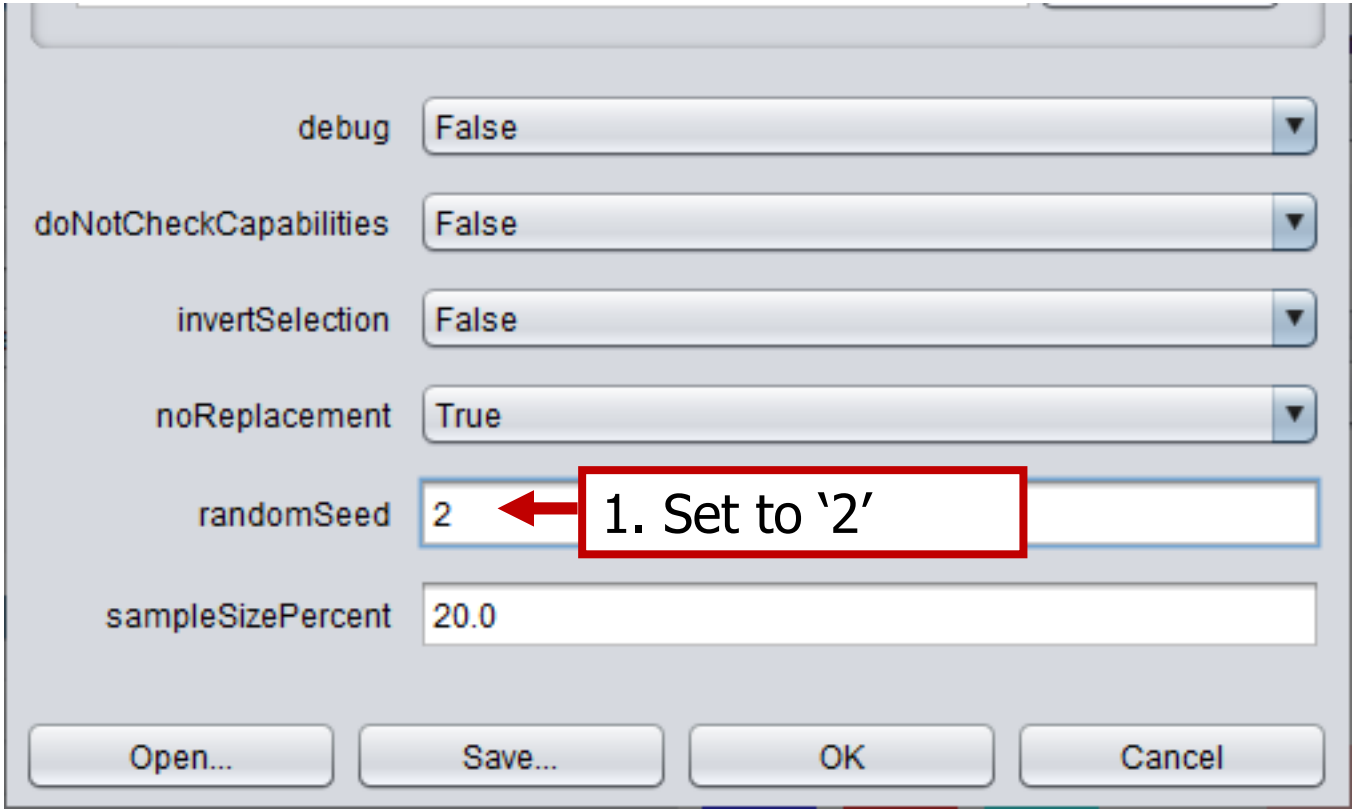
Relation: Glass-weka.filters.unsupervised.instance.Resample-S1-Z20.0-no-replacement

No.	1: RI	2: Na	3: Mg	4: Al	5: Si	6: K	7: Ca	8: Ba	9: Fe	10: Type
	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Nominal
1	1.51215	12.99	3.47	1.12	72.98	0.62	8.35	0.0	0.31	build ...
2	1.51508	15.15	0.0	2.25	73.5	0.0	8.34	0.63	0.0	headl...
3	1.51514	14.85	0.0	2.42	73.72	0.0	8.39	0.56	0.0	headl...
4	1.51531	14.38	0.0	2.66	73.1	0.04	9.08	0.64	0.0	headl...
5	1.51588	13.12	3.41	1.58	73.26	0.07	8.39	0.0	0.19	build ...
6	1.51596	12.79	3.61	1.62	72.97	0.64	8.07	0.0	0.26	build ...
7	1.51602	14.85	0.0	2.38	73.28	0.0	8.76	0.64	0.09	headl...
8	1.51605	12.9	3.44	1.45	73.06	0.44	8.27	0.0	0.0	build ...
9	1.51618	13.53	3.55	1.54	72.99	0.39	7.78	0.0	0.0	build ...
10	1.51623	14.14	0.0	2.88	72.61	0.08	9.18	1.06	0.0	headl...
11	1.51629	12.71	3.33	1.49	73.28	0.67	8.24	0.0	0.0	build ...
12	1.51646	13.04	3.4	1.26	73.01	0.52	8.58	0.0	0.0	vehic ...
13	1.51655	12.75	2.85	1.44	73.27	0.57	8.79	0.11	0.22	build ...
14	1.51658	14.8	0.0	1.99	73.11	0.0	8.28	1.71	0.0	headl...
15	1.5166	12.99	3.18	1.23	72.97	0.58	8.81	0.0	0.24	build ...
16	1.51665	13.14	3.45	1.76	72.48	0.6	8.38	0.0	0.17	vehic ...
17	1.51673	13.3	3.64	1.53	72.53	0.65	8.03	0.0	0.29	build ...
18	1.51719	14.75	0.0	2.0	73.02	0.0	8.53	1.59	0.08	headl...

Configuring the Sampling

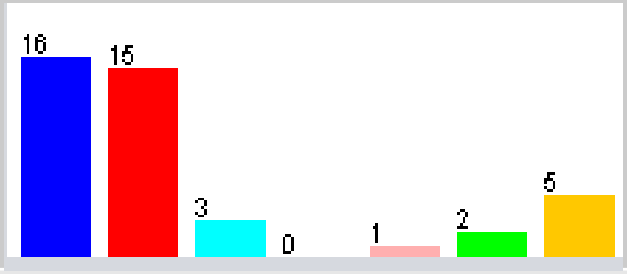
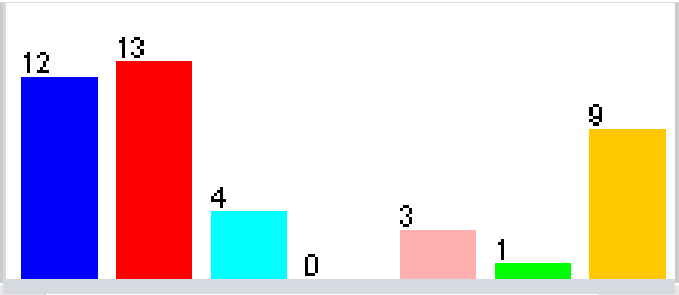
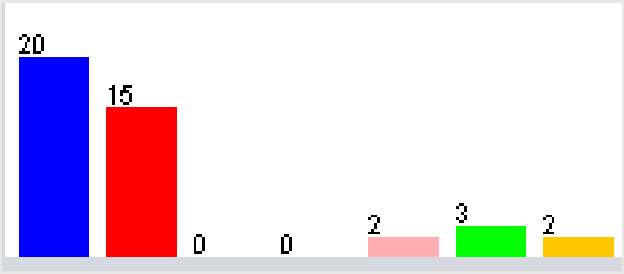
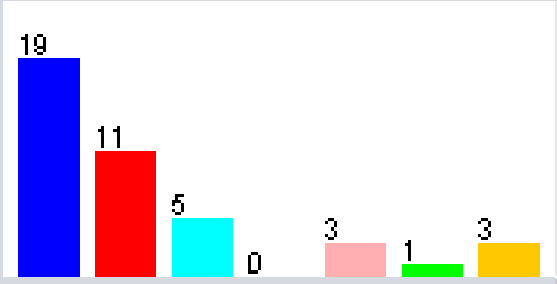
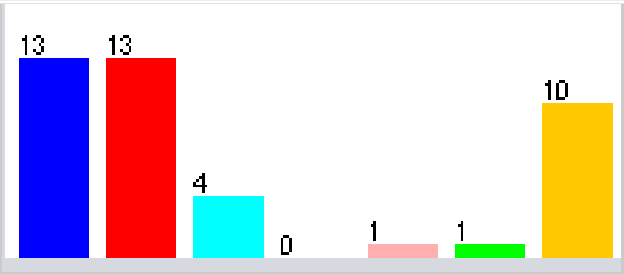
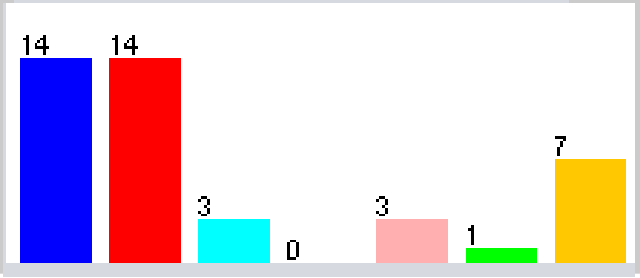


Changing the Random Seed

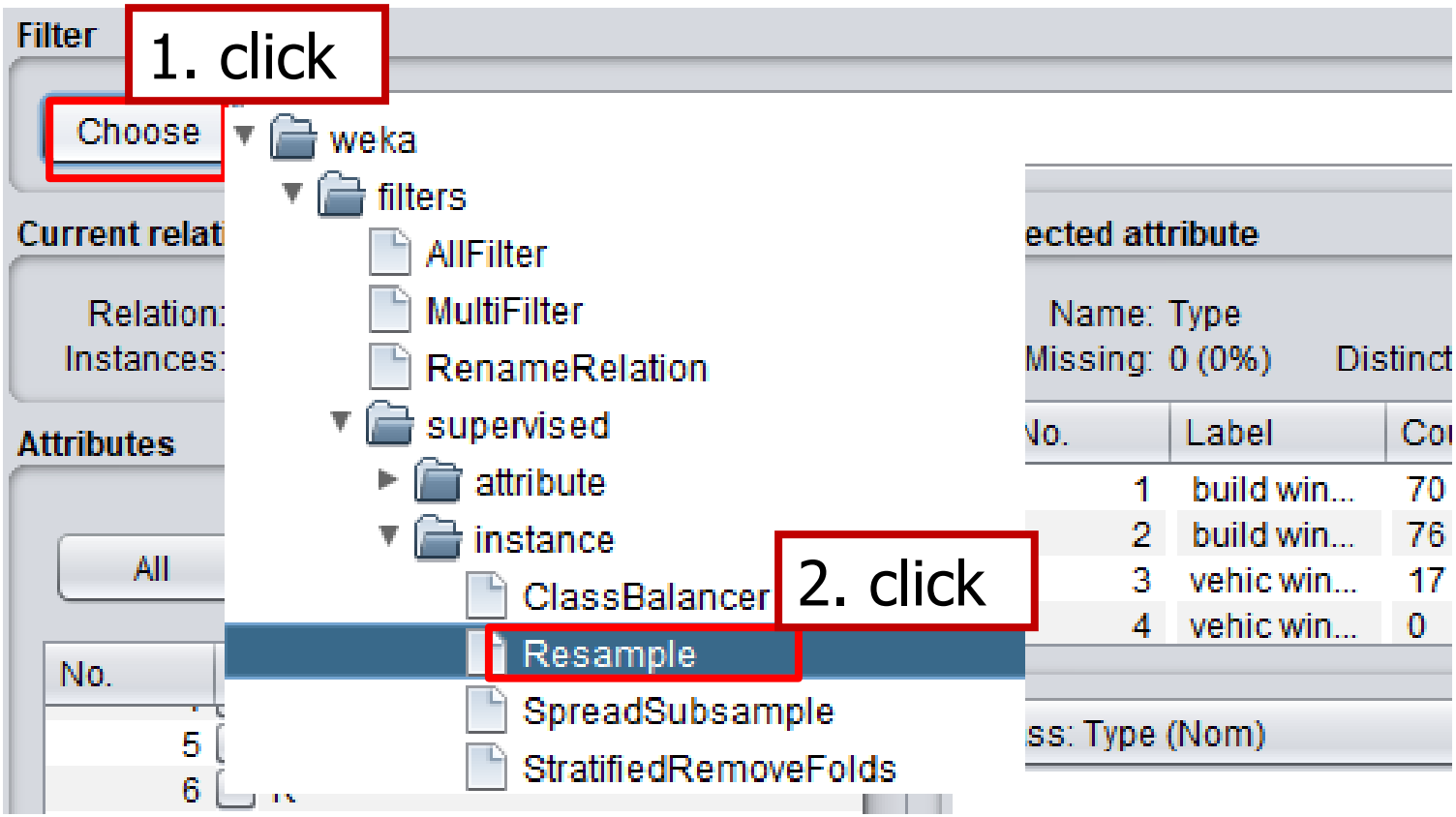


Changing the Random Seed

- Repeating the experiments with changing the random seed, you can see that the distribution of the class labels varies

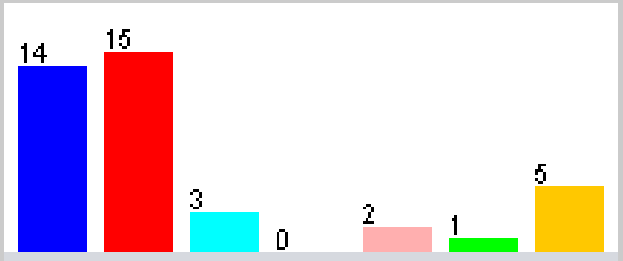
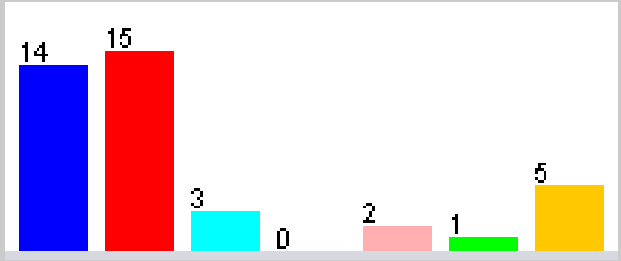
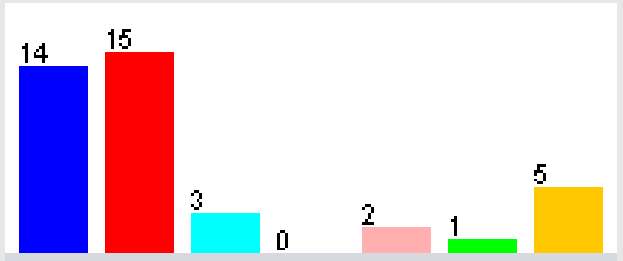
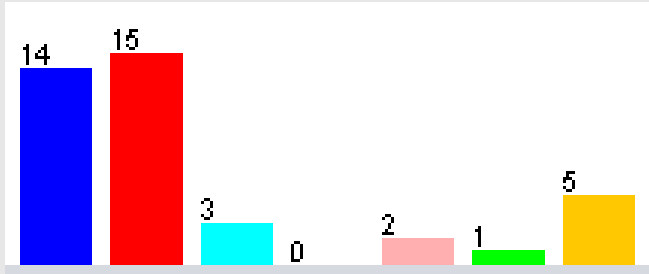
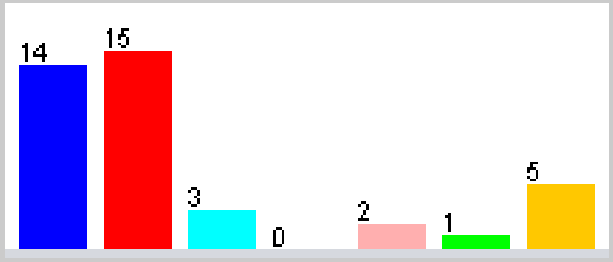
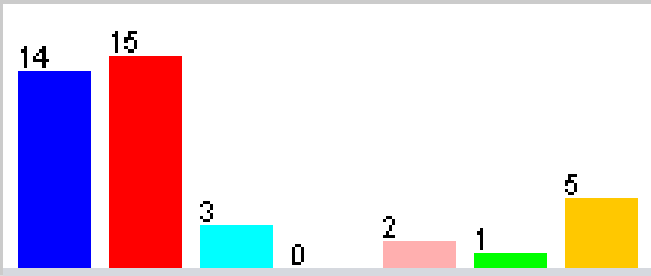
Random Seeds	With Replacement	Without Replacement
1		
2		
3		

Stratified Sampling



Stratified Sampling

- Similarly repeating the experiments with changing the random seed, you can see that the distribution of the class labels is constant

Random Seeds	With Replacement	Without Replacement
1		
2		
3		

Stratified Sampling

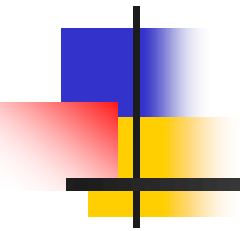
- You can see that the instances are sampled differently

Seed=1 without replacement

No.	1: RI	2: Na	3: Mg	4: Al	5: Si	6: K	7: Ca	8: Ba	9: Fe	10: Type
	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Nominal
1	1.51...	13.21	2.81	1.29	72.98	0.51	9.02	0.0	0.09	build ...
2	1.51...	13.89	3.6	1.36	72.73	0.48	7.83	0.0	0.0	build ...
3	1.51...	12.74	3.48	1.35	72.96	0.64	8.68	0.0	0.0	build ...
4	1.51...	13.81	3.58	1.32	71.72	0.12	8.67	0.69	0.0	build ...
5	1.51...	12.79	3.61	1.62	72.97	0.64	8.07	0.0	0.26	build ...
6	1.51...	12.86	3.56	1.27	73.21	0.54	8.38	0.0	0.17	build ...
7	1.51...	13.53	3.55	1.54	72.99	0.39	7.78	0.0	0.0	build ...
8	1.51...	13.2	3.33	1.28	72.36	0.6	9.14	0.0	0.11	build ...
9	1.51...	12.56	3.52	1.43	73.15	0.57	8.54	0.0	0.0	build ...

Seed=2 without replacement

No.	1: RI	2: Na	3: Mg	4: Al	5: Si	6: K	7: Ca	8: Ba	9: Fe	10: Type
	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Numeric	Nominal
1	1.51...	13.38	3.5	1.15	72.85	0.5	8.43	0.0	0.0	build ...
2	1.51...	14.77	3.75	0.29	72.02	0.03	9.0	0.0	0.0	build ...
3	1.51...	13.02	3.54	1.69	72.73	0.54	8.44	0.0	0.07	build ...
4	1.51...	13.3	3.6	1.14	73.09	0.58	8.17	0.0	0.0	build ...
5	1.51...	13.81	3.58	1.32	71.72	0.12	8.67	0.69	0.0	build ...
6	1.52...	13.21	3.77	0.79	71.99	0.13	10.02	0.0	0.0	build ...
7	1.51...	13.48	3.74	1.17	72.99	0.59	8.03	0.0	0.0	build ...
8	1.519	13.49	3.48	1.35	71.95	0.55	9.0	0.0	0.0	build ...
9	1.51...	12.82	3.55	1.49	72.75	0.54	8.52	0.0	0.19	build ...
10	1.51...	12.74	3.48	1.35	72.96	0.64	8.68	0.0	0.0	build ...



Python - Sampling

Import necessary Libraries

```
In [1]: import pandas as pd
        import numpy as np
        from sklearn.utils import resample
        from collections import Counter
```

- resample : A module to sample data
- Counter : A module to count the number of discrete values

Make toy Data

```
In [2]: X_toy = [1,2,3,4,5]
        y_toy = [6,7,8,9,10]
```

- Before applying sampling to real data, we will apply sampling to toy data to see the behaviors of sampling strategies

Sampling with Replacement

In [3]:
```
X_toy_sample, y_toy_sample = resample(X_toy, y_toy,
                                      replace = True, #Default is True
                                      n_samples = 7,
                                      random_state = 0)

print(X_toy_sample, y_toy_sample)
```

```
[5, 1, 4, 4, 4, 2, 4] [10, 6, 9, 9, 9, 7, 9]
```

- If the parameter 'replace = True' in resample, it returns data sampled with replacement (Default is True)

Sampling with Replacement

```
In [3]: X_toy_sample, y_toy_sample = resample(X_toy, y_toy,
                                              replace = True, #Default is True
                                              n_samples = 7,
                                              random_state = 0)

        print(X_toy_sample, y_toy_sample)
```

```
[5, 1, 4, 4, 4, 2, 4] [10, 6, 9, 9, 9, 7, 9]
```

You can give multiple inputs

Number of samples
If none, the size of data is assigned

Random seed

- If the parameter 'replace = True' in resample, it returns data sampled with replacement (Default is True)

Sampling without Replacement

```
In [4]: X_toy_sample, y_toy_sample = resample(X_toy, y_toy,
                                              replace = False,
                                              n_samples = 5,
                                              random_state = 0)

        print(X_toy_sample, y_toy_sample)
```

```
[3, 1, 2, 4, 5] [8, 6, 7, 9, 10]
```

The number of samples cannot exceed the size of the data

- If the parameter 'replace = False' in resample, it returns data sampled without replacement (Default is True)

Loading Data

```
In [5]: df = pd.read_csv('glass.csv')
        X = df.values[:, :-1]
        y = df.values[:, -1]
        N = len(X)
```

- Load 'glass.csv' data

- len(X): returns the size of X
  (number of rows)

Sampling with Replacement

```
In [6]: X_sample, y_sample = resample(X, y,
                                      replace = True,
                                      n_samples = int(N*0.2),
                                      random_state = 0)
```

- int(number): returns floor of the input number as integer type
- N*0.2: 20% of the data size

Counting sampled Labels

```
In [7]: c = Counter(y_sample)
        print(c)
```

- Counter(array): counts the number of distinct values that appear in the array
- Returns Counter object containing (value, count) pairs

Counting sampled Labels

```
In [7]: c = Counter(y_sample)
        print(c)
```

- Counter(array): counts the number of distinct values that appear in the array
- Returns (value, count) pairs

- Output:

```
Counter({"'build wind float'": 16, "'build wind non-float'": 13,
'headlamps': 5, 'tableware': 4, "'vehic wind float'": 4})
```

Counting sampled Labels

```
In [8]: list(c.values())
Out[8]: [16, 5, 4, 4, 13]
```

- If you want only the counts as python list, call c.values() and wrap it with list()

Sampling without Replacement

In [9]:
```
X_sample, y_sample = resample(X, y,
                              replace = False,
                              n_samples = int(N*0.2),
                              random_state = 0)
c = Counter(y_sample)
print(c)
```

Sampling without Replacement

```
In [9]: X_sample, y_sample = resample(X, y,
                                      replace = False,
                                      n_samples = int(N*0.2),
                                      random_state = 0)
        c = Counter(y_sample)
        print(c)
```

- Output:

```
Counter({"'build wind non-float'": 19, "'build wind float'": 13,
         'headlamps': 4, 'containers': 3, "'vehic wind float'": 2,
         'tableware': 1})
```

Sampling without Replacement

```
In [9]: X_sample, y_sample = resample(X, y,
                                      replace = False,
                                      n_samples = int(N*0.2),
                                      random_state = 0)
        c = Counter(y_sample)
        print(c)
```

- Output:

```
Counter({"'build wind non-float'": 19, "'build wind float'": 13,
         'headlamps': 4, 'containers': 3, "'vehic wind float'": 2,
         'tableware': 1})
```

Handling zero-count Labels

- Note that in Sampling with replacement example, instances with ‘containers’ are not sampled, so it did not appear in the counter result

```
Counter({"'build wind float'": 16, "'build wind non-float'": 13,
'headlamps': 5, 'tableware': 4, "'vehic wind float'": 4})
```

- Since pre-built modules cannot know labels that do not appear in the data, you have to build your own function if you want them in the list

Changing the Random seed

In [10]:
```
for i in range(5):
    X_sample, y_sample = resample(X, y,
                                  replace = True,
                                  n_samples = int(N*0.2),
                                  random_state = i)
    c = Counter(y_sample)
    print(sorted(c.items()))
```

- Output the label counts changing random_state with for loop

Changing the Random seed

```
In [10]: for i in range(5):
             X_sample, y_sample = resample(X, y,
                                           replace = True,
                                           n_samples = int(N*0.2),
                                           random_state = i)
             c = Counter(y_sample)
             print(sorted(c.items()))
```

- Output the label counts changing random_state with for loop
- c returns Counter object, where c.items() returns list of (value, count) pairs

Changing the Random seed

```
In [10]: for i in range(5):
             X_sample, y_sample = resample(X, y,
                                           replace = True,
                                           n_samples = int(N*0.2),
                                           random_state = i)
             c = Counter(y_sample)
             print(sorted(c.items()))
```

- Output the label counts changing random_state with for loop
- c returns Counter object, where c.items() returns list of (value, count) pairs
- sorted(list) returns sorted list in increasing order
  - This case, the list is sorted by order of labels

Changing the Random seed

In [10]:
```
for i in range(5):
    X_sample, y_sample = resample(X, y,
                                  replace = True,
                                  n_samples = int(N*0.2),
                                  random_state = i)
    c = Counter(y_sample)
    print(sorted(c.items()))
```

- Output:

```
[("'build wind float'", 16), ("'build wind non-float'", 13), ("'vehic wind float'", 4), ('headlamps', 5), ('tableware', 4)]
[("'build wind float'", 15), ("'build wind non-float'", 15), ("'vehic wind float'", 2), ('containers', 3), ('headlamps', 5),
('tableware', 2)]
[("'build wind float'", 9), ("'build wind non-float'", 20), ("'vehic wind float'", 3), ('containers', 3), ('headlamps', 5),
('tableware', 2)]
[("'build wind float'", 15), ("'build wind non-float'", 18), ("'vehic wind float'", 1), ('containers', 1), ('headlamps', 5),
('tableware', 2)]
[("'build wind float'", 15), ("'build wind non-float'", 15), ("'vehic wind float'", 2), ('containers', 2), ('headlamps', 7),
('tableware', 1)]
```

Changing the Random seed

In [10]:
```
for i in range(5):
    X_sample, y_sample = resample(X, y,
                                  replace = True,
                                  n_samples = int(N*0.2),
                                  random_state = i)
    c = Counter(y_sample)
    print(sorted(c.items()))
```

- Output:

```
[("'build wind float'", 16), ("'build wind non-float'", 13), ("'vehic wind float'", 4), ('headlamps', 5), ('tableware', 4)]
[("'build wind float'", 15), ("'build wind non-float'", 15), ("'vehic wind float'", 2), ('containers', 3), ('headlamps', 5),
('tableware', 2)]
[("'build wind float'", 9), ("'build wind non-float'", 20), ("'vehic wind float'", 3), ('containers', 3), ('headlamps', 5),
('tableware', 2)]
[("'build wind float'", 15), ("'build wind non-float'", 18), ("'vehic wind float'", 1), ('containers', 1), ('headlamps', 5),
('tableware', 2)]
[("'build wind float'", 15), ("'build wind non-float'", 15), ("'vehic wind float'", 2), ('containers', 2), ('headlamps', 7),
('tableware', 1)]
```

Note that some labels are surrounded by “”

Changing the Random seed

In [11]:
```
for i in range(5):
    X_sample, y_sample = resample(X, y,
                                  replace = False,
                                  n_samples = int(N*0.2),
                                  random_state = i)
    c = Counter(y_sample)
    print(sorted(c.items()))
```

- Change random seed when sampling without replacement

Changing the Random seed

In [11]:
```
for i in range(5):
    X_sample, y_sample = resample(X, y,
                                  replace = False,
                                  n_samples = int(N*0.2),
                                  random_state = i)
    c = Counter(y_sample)
    print(sorted(c.items()))
```

- Output:

```
[("'build wind float'", 13), ("'build wind non-float'", 19), ("'vehic wind float'", 2), ('containers', 3), ('headlamps', 4),
('tableware', 1)]
[("'build wind float'", 10), ("'build wind non-float'", 21), ("'vehic wind float'", 3), ('containers', 2), ('headlamps', 5),
('tableware', 1)]
[("'build wind float'", 14), ("'build wind non-float'", 15), ("'vehic wind float'", 5), ('containers', 4), ('headlamps', 2),
('tableware', 2)]
[("'build wind float'", 16), ("'build wind non-float'", 12), ("'vehic wind float'", 2), ('containers', 5), ('headlamps', 5),
('tableware', 2)]
[("'build wind float'", 18), ("'build wind non-float'", 11), ("'vehic wind float'", 4), ('containers', 4), ('headlamps', 5)]
```

Stratified Sampling

In [12]:
```
X_sample, y_sample = resample(X, y,
                              n_samples = int(N*0.2),
                              random_state = 0,
                              stratify=y)

c = Counter(y_sample)
print(sorted(c.items()))
```

- To apply stratified sampling, input the class label array to parameter ‘stratify’

Stratified Sampling

In [12]:
```
X_sample, y_sample = resample(X, y,
                              n_samples = int(N*0.2),
                              random_state = 0,
                              stratify=y)

c = Counter(y_sample)
print(sorted(c.items()))
```

- Output:

```
[("'build wind float'", 14), ("'build wind non-float'", 15),
("'vehic wind float'", 3), ('containers', 2), ('headlamps', 6),
...
('tableware', 2)]
```

Practice

- Write a code that runs stratified sampling without replacement with random seed varying from 0 to 4

- Print label counts of each sample

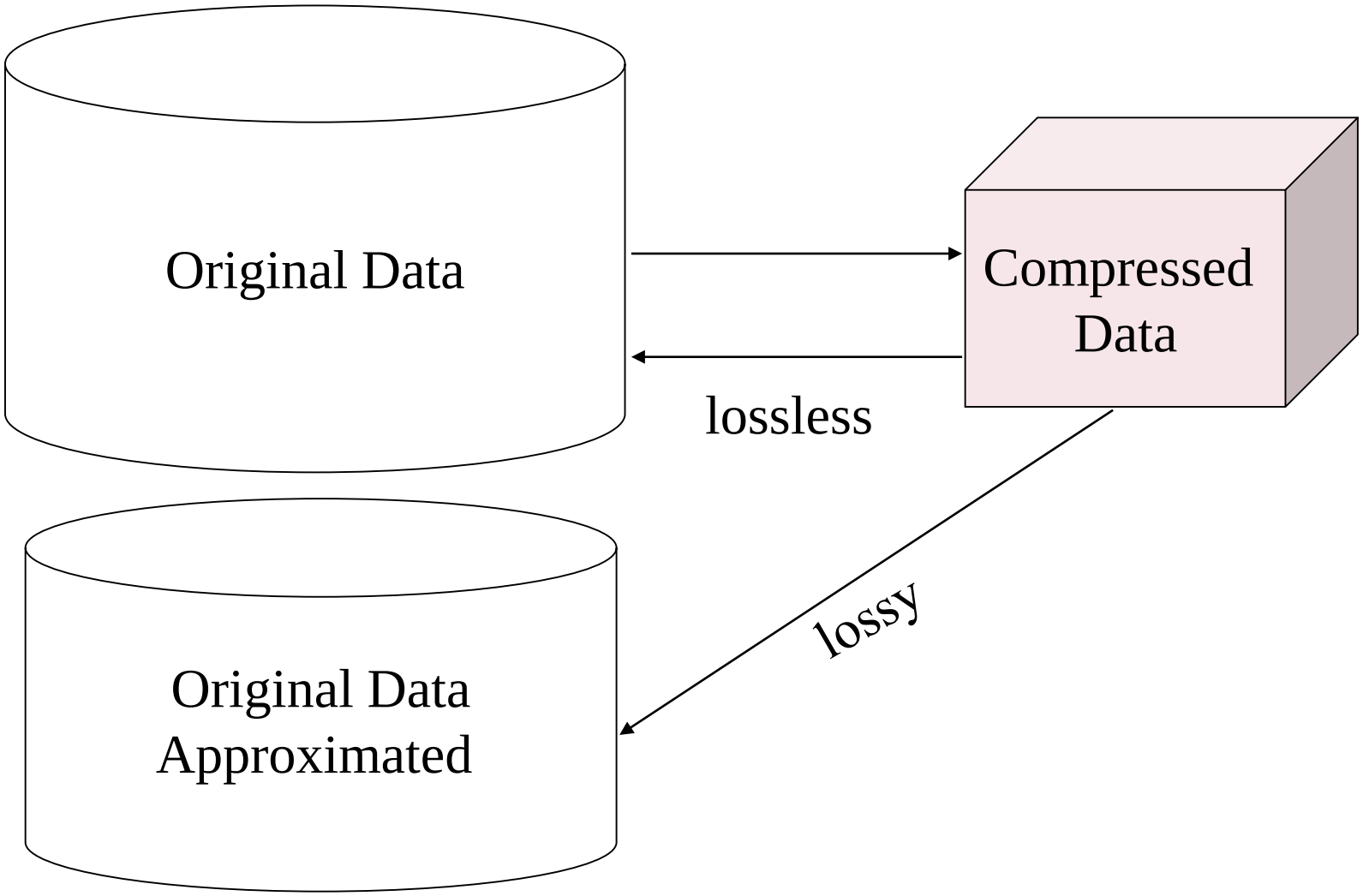
Data Cube Aggregation

- The lowest level of a data cube (base cuboid)
  - The aggregated data for an individual entity of interest
  - E.g., a customer in a phone calling data warehouse
- Multiple levels of aggregation in data cubes
  - Further reduce the size of data to deal with
- Reference appropriate levels
  - Use the smallest representation which is enough to solve the task
- Queries regarding aggregated information should be answered using data cube, when possible

Data Reduction 3: Data Compression

- String compression
  - There are extensive theories and well-tuned algorithms
  - Typically lossless, but only limited manipulation is possible without expansion
- Audio/video compression
  - Typically lossy compression, with progressive refinement
  - Sometimes small fragments of signal can be reconstructed without reconstructing the whole
- Time sequence is not audio
  - Typically short and vary slowly with time
- Dimensionality and numerosity reduction may also be considered as forms of data compression

Data Compression



Chapter 3: Data Preprocessing

- Data Preprocessing: An Overview
  - Data Quality
  - Major Tasks in Data Preprocessing
- Data Cleaning
- Data Integration
- Data Reduction
- Data Transformation and Data Discretization 
- Summary

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$_A$]

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

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

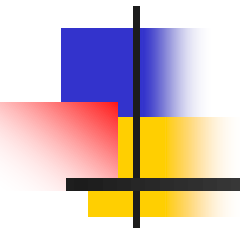
- **Z-score normalization** (μ: mean, σ: standard deviation):

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

  - e.g., Let μ = 54,000, σ = 16,000. Then $\frac{73{,}600 - 54{,}000}{16{,}000} = 1.225$

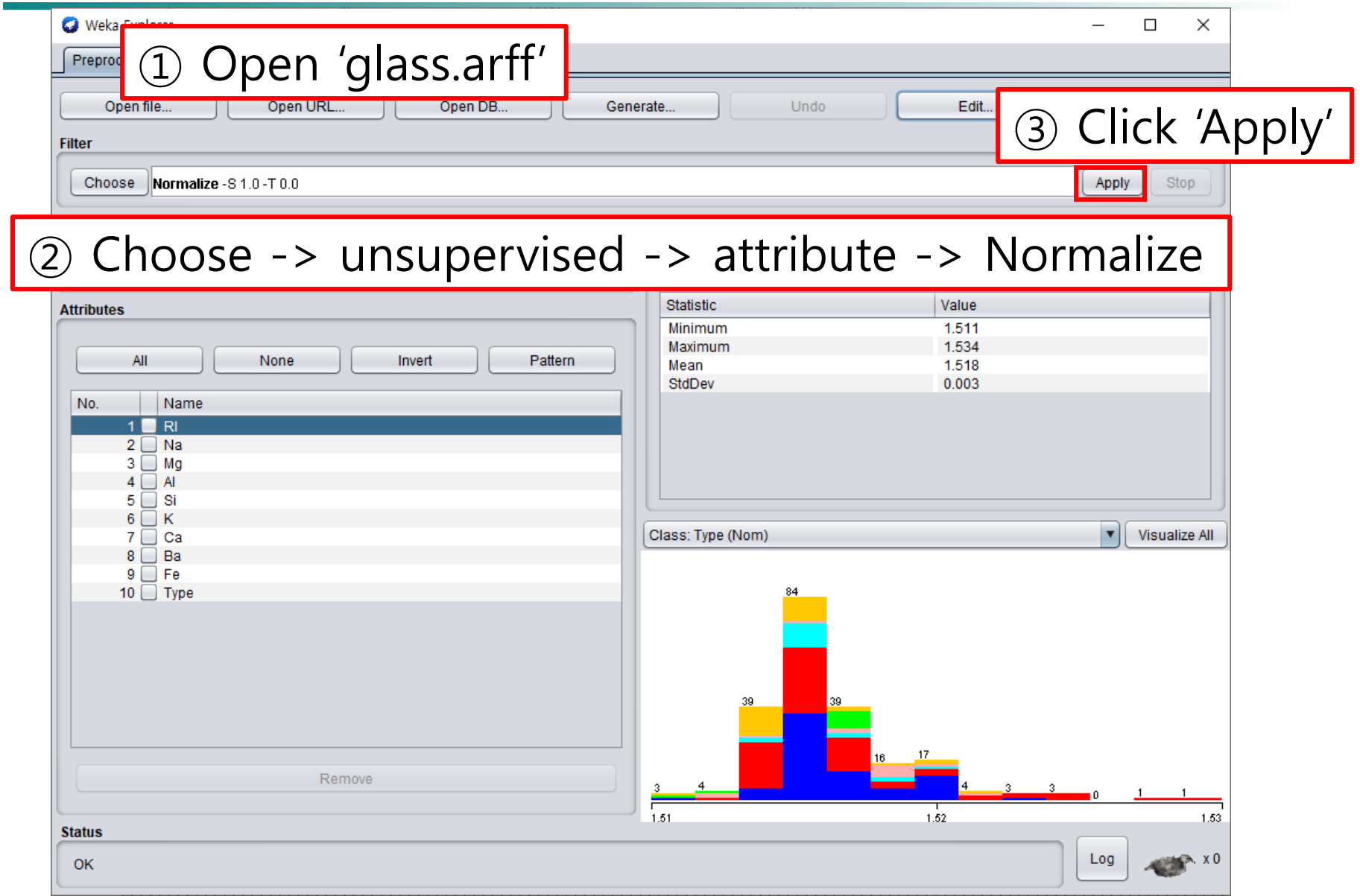
- **Normalization by decimal scaling**

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

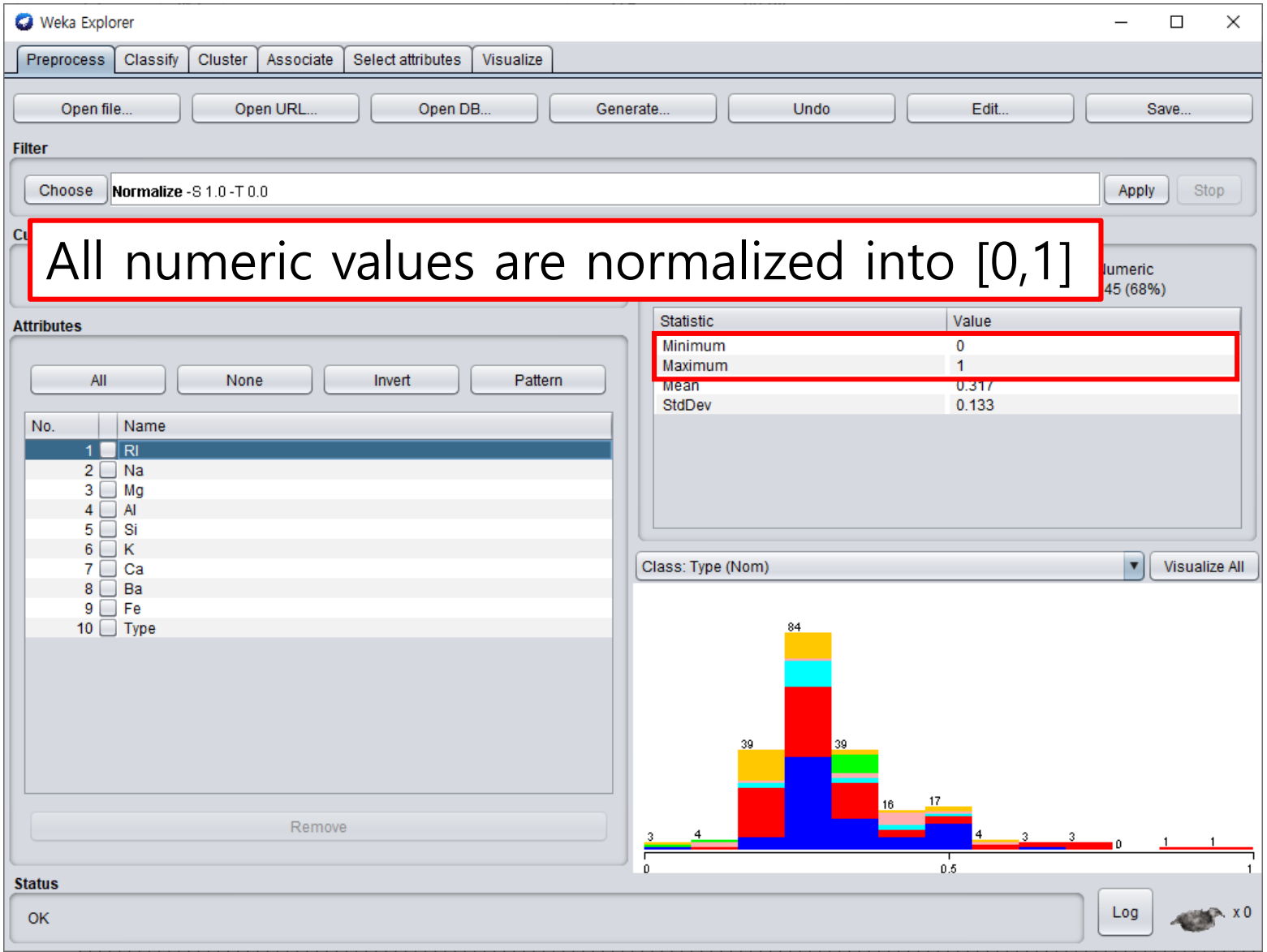


Weka - Normalization

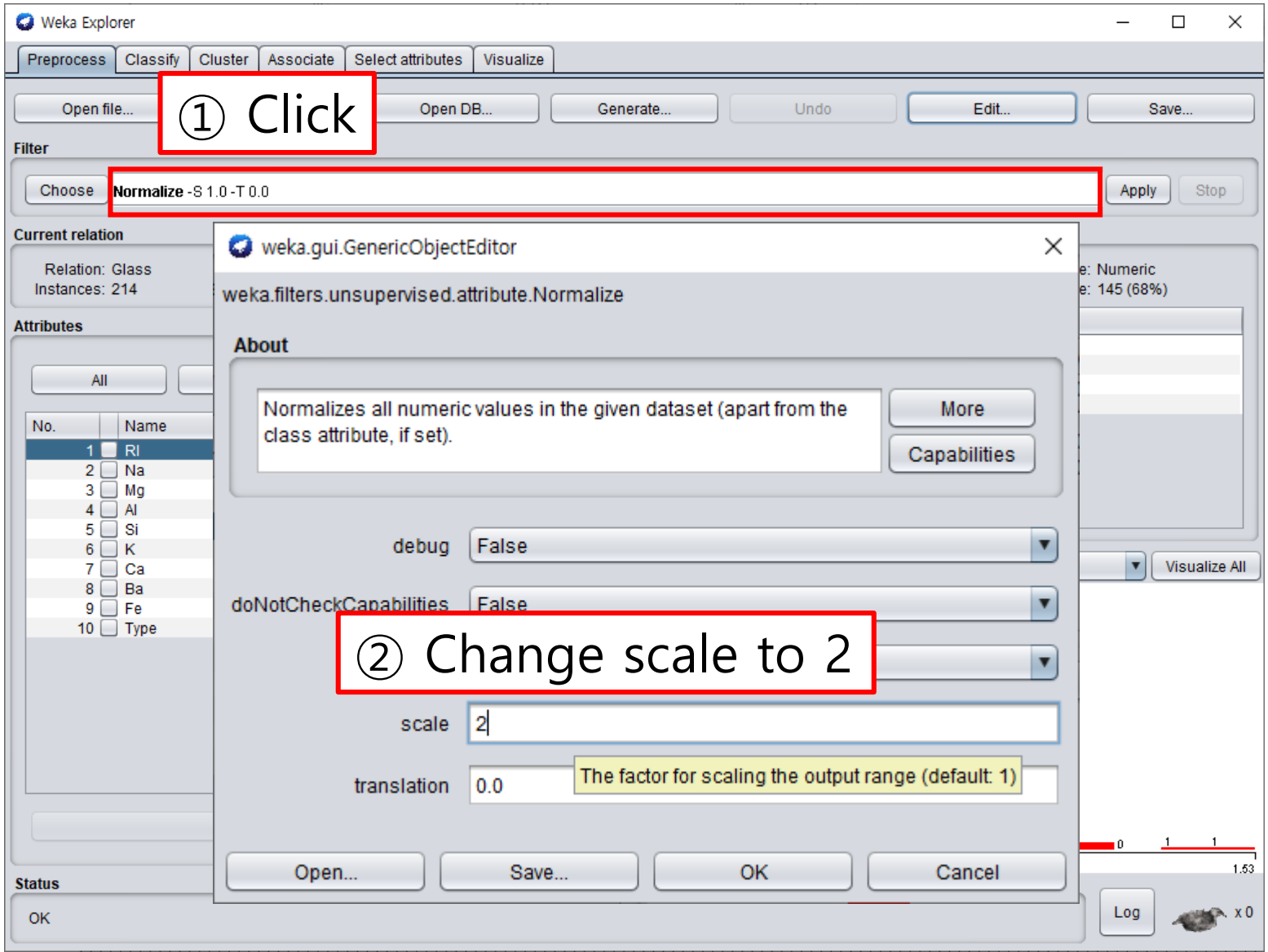
Min-max Normalization with Weka



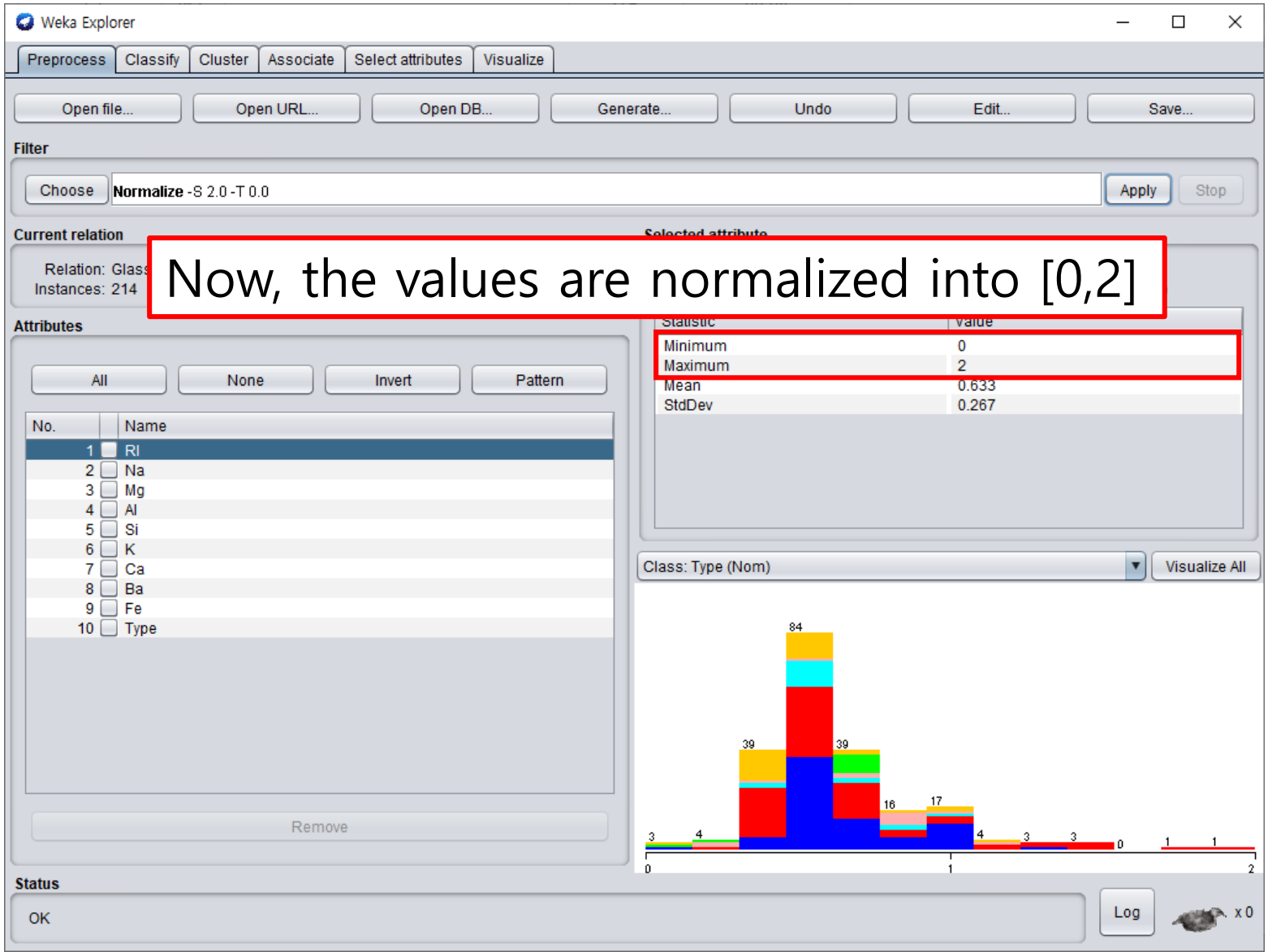
Min-max Normalization with Weka



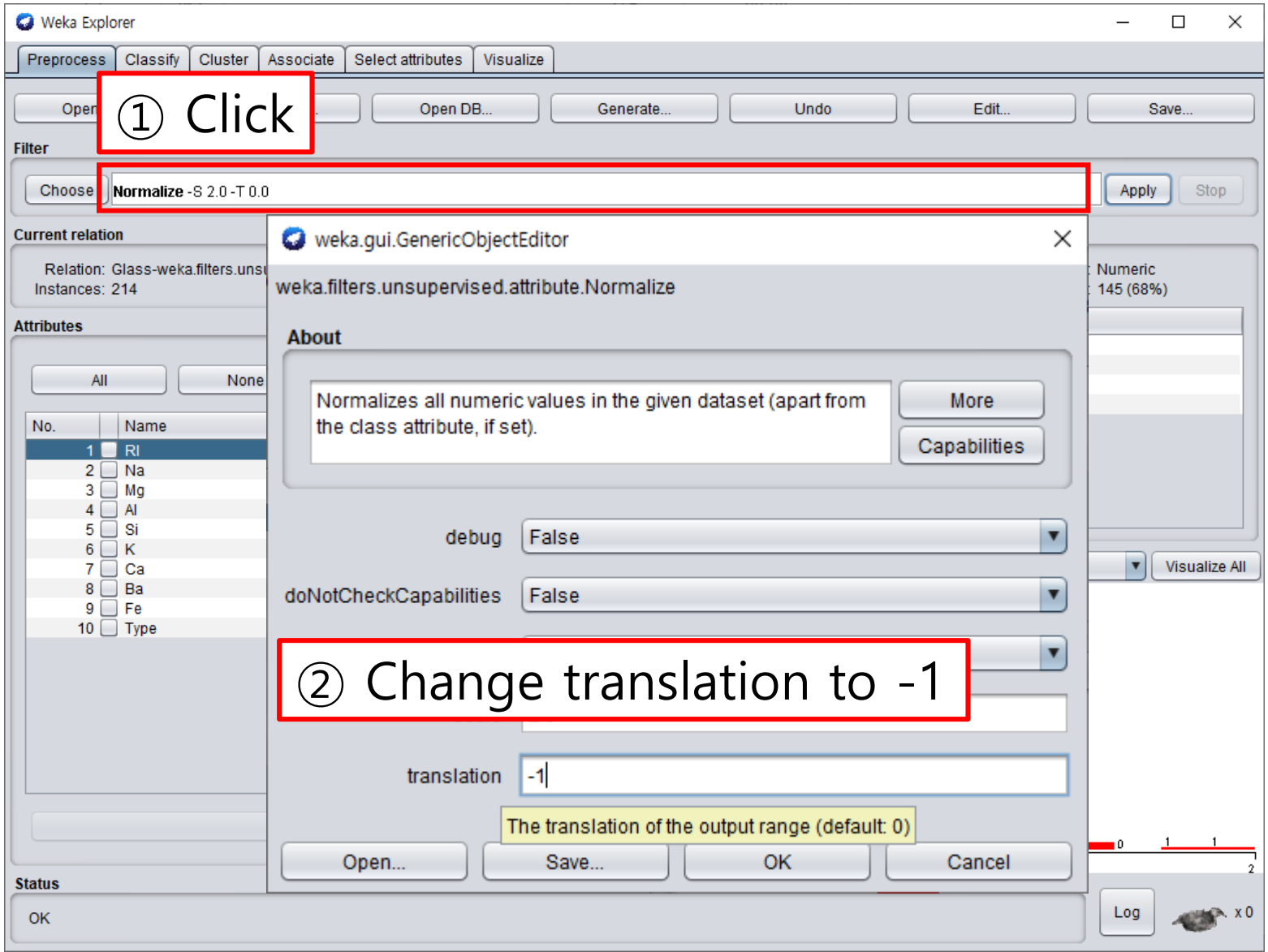
Min-max Normalization with Weka



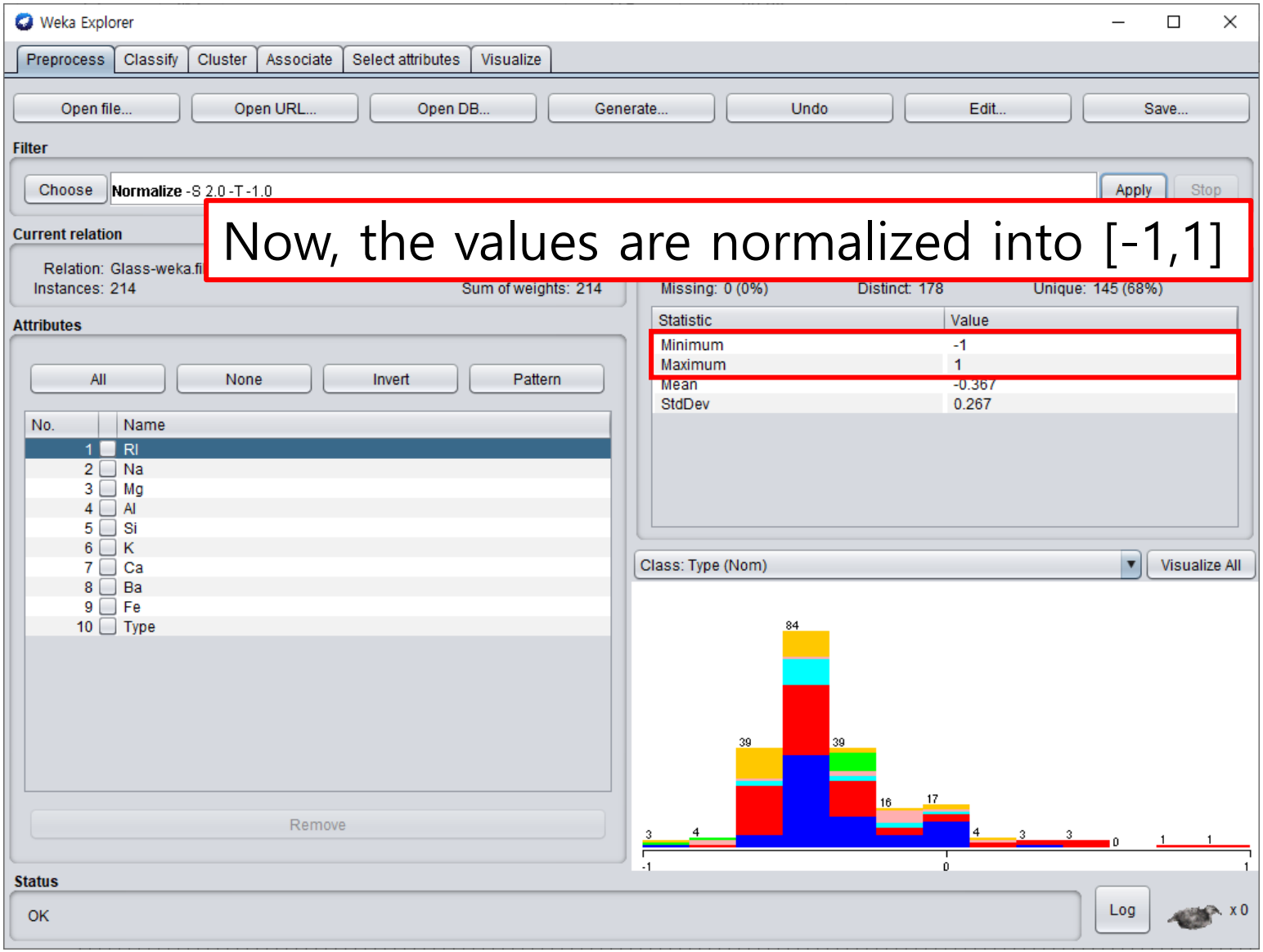
Min-max Normalization with Weka



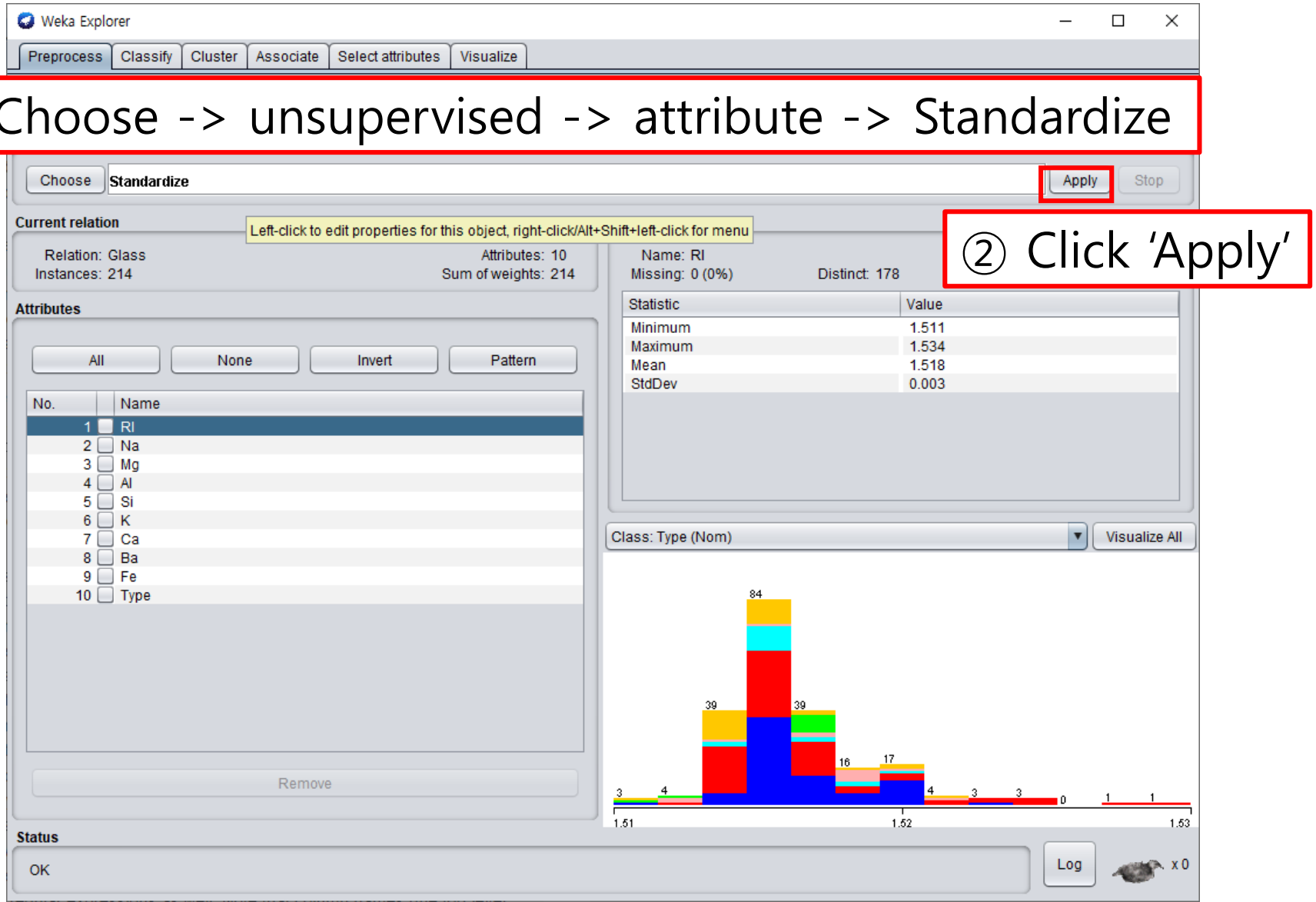
Min-max Normalization with Weka



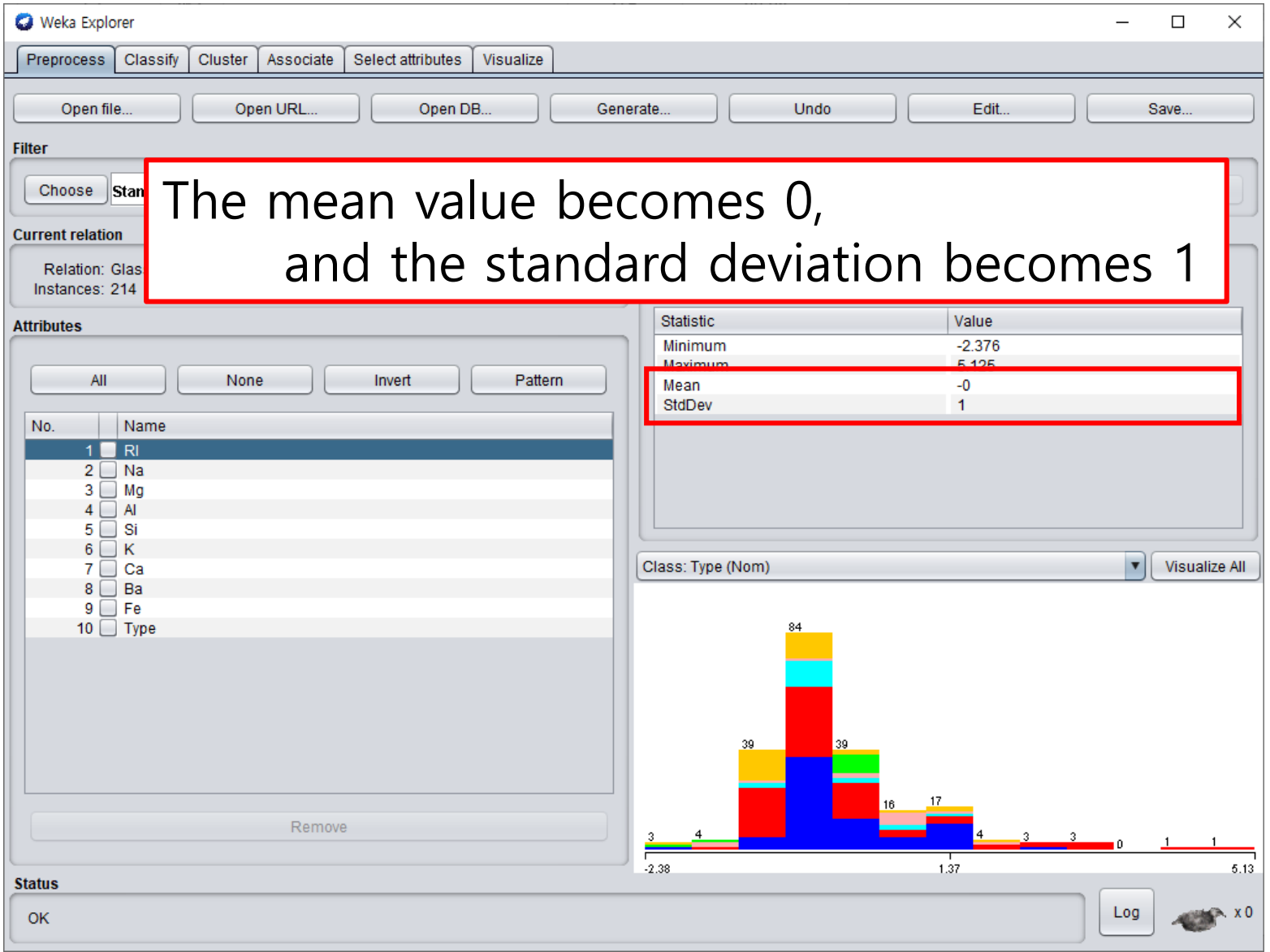
Min-max Normalization with Weka

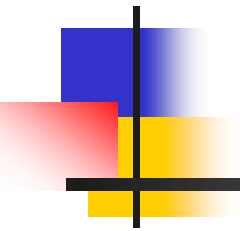


Z-score Normalization with Weka



Z-score Normalization with Weka





Python - Normalization

Min-max Normalization

```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler

df = pd.read_csv('glass.csv')
X = df.values[:, :-1]
y = df.values[:, -1]

normalizer = MinMaxScaler()
X_norm = normalizer.fit_transform(X)
X_norm[:10]
```

```
array([[0.2976295 , 0.30977444, 0.77951002, 0.25856698, 0.575     ,
        0.10305958, 0.31040892, 0.        , 0.        ],
       [0.23178227, 0.21503759, 0.78396437, 0.33021807, 0.55      ,
        0.09178744, 0.28810409, 0.        , 0.        ],
       [0.2976295 , 0.37293233, 0.77505568, 0.34890966, 0.50535714,
        0.09500805, 0.27881041, 0.        , 0.        ],
       [0.08077261, 0.5518797 , 0.38752784, 0.3894081 , 0.84642857,
        0.        , 0.20074349, 0.        , 0.        ],
       [1.        , 0.23609023, 0.        , 0.2211838 , 0.0625    ,
        0.01932367, 1.        , 0.        , 0.47058824],
       [0.23705004, 0.3037594 , 0.63474388, 0.35825545, 0.61785714,
        0.09178744, 0.31226766, 0.03492063, 0.43137255],
       [0.29148376, 0.43759398, 0.81291759, 0.11214953, 0.56964286,
        0.00966184, 0.32527881, 0.        , 0.        ],
       [0.31694469, 0.36240602, 0.6325167 , 0.30841121, 0.54285714,
        0.08856683, 0.33828996, 0.        , 0.        ],
       [0.18876207, 0.51278195, 0.        , 0.74454829, 0.63928571,
        0.01288245, 0.33828996, 0.19365079, 0.09803922],
       [0.29587357, 0.36992481, 0.86859688, 0.31464174, 0.45      ,
        0.08856683, 0.27973978, 0.        , 0.5490196 ]])
```

Min-max Normalization

```
normalizer = MinMaxScaler(feature_range=(0,100))
X_norm = normalizer.fit_transform(X)

print(normalizer.scale_)
print(normalizer.data_min_)
print(normalizer.data_max_)
print(normalizer.data_range_)
```

- Parameter
  - feature_range = (min, max) : Desired range of transformed data
- Attributes
  - scale_ : relative scaling of each feature
  - data_min_ : the minimum value of the original data
  - data_max_ : the maximum value of the original data
  - data_range_ : (data_max_ - data_min_)

Z-score Normalization

```
import pandas as pd
from sklearn.preprocessing import StandardScaler

df = pd.read_csv('glass.csv')
X = df.values[:, :-1]
y = df.values[:, -1]

normalizer = StandardScaler()
X_norm = normalizer.fit_transform(X)
X_norm[:10]
```

```
array([[-1.43714541e-01, -7.58384063e-01,  5.66676959e-01,
        -6.52289486e-01,  4.90550986e-01,  2.19688551e-01,
        -1.31680092e-01, -3.52876828e-01, -5.86450902e-01],
       [-6.38803268e-01, -1.53168114e+00,  5.80575173e-01,
        -1.90536451e-01,  3.09376090e-01,  1.12106515e-01,
        -3.00715072e-01, -3.52876828e-01, -5.86450902e-01],
       [-1.43714541e-01, -2.42852679e-01,  5.52778744e-01,
        -7.00791379e-02, -1.41505092e-02,  1.42844239e-01,
        -3.71146313e-01, -3.52876828e-01, -5.86450902e-01],
       [-1.77420675e+00,  1.21781957e+00, -6.56365903e-01,
         1.90911708e-01,  2.45759271e+00, -7.63918639e-01,
        -9.62768741e-01, -3.52876828e-01, -5.86450902e-01],
       [ 5.13723188e+00, -1.35983734e+00, -1.86551055e+00,
        -8.93204112e-01, -3.22353438e+00, -5.79492291e-01,
         5.09431802e+00, -3.52876828e-01,  1.88241125e+00],
       [-5.99196170e-01, -8.07482290e-01,  1.14984993e-01,
        -9.85048123e-03,  8.01136522e-01,  1.12106515e-01,
        -1.17593844e-01, -1.31127748e-01,  1.67667274e+00],
       [-1.89922822e-01,  2.84953261e-01,  6.70913566e-01,
        -1.59587177e+00,  4.51727794e-01, -6.71705465e-01,
        -1.89901058e-02, -3.52876828e-01, -5.86450902e-01],
       [ 1.51148583e-03, -3.28774576e-01,  1.08035886e-01,
        -3.31069983e-01,  2.57611835e-01,  8.13687898e-02,
         7.96136323e-02, -3.52876828e-01, -5.86450902e-01],
       [-9.62261237e-01,  8.98681099e-01, -1.86551055e+00,
         2.47960066e+00,  9.56429290e-01, -6.40967740e-01,
         7.96136323e-02,  8.76822615e-01, -7.21046191e-02],
       [-1.56916907e-01, -2.67401792e-01,  8.44641245e-01,
        -2.90917546e-01, -4.15323493e-01,  8.13687898e-02,
        -3.64103189e-01, -3.52876828e-01,  2.29388828e+00]])
```

Z-score Normalization

```
normalizer = StandardScaler()
X_norm = normalizer.fit_transform(X)

print(normalizer.scale_)
print(normalizer.mean_)
print(normalizer.var_)
```

- Attributes
  - scale_ : relative scaling of each feature
  - mean_ : the mean value of the original data
  - var_ : the variance of the original data

Practice

- Using MinMaxScaler, change the scale of the transformed data with a variety of ranges

Discretization

- Three types of attributes
  - Nominal—values from an unordered set, e.g., color, profession
  - Ordinal—values from an ordered set, e.g., military or academic rank
  - Numeric—real numbers, e.g., integer or real numbers
- Discretization: Divide the range of a continuous attribute into intervals
  - Interval labels can then be used to replace actual data values
  - Reduce data size by discretization
  - Supervised vs. unsupervised
  - Split (top-down) vs. merge (bottom-up)
  - Discretization can be performed recursively on an attribute
  - Prepare for further analysis, e.g., classification

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

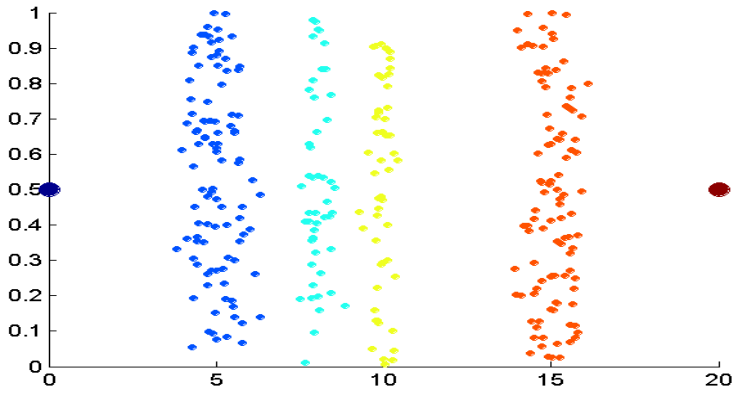
- Equal-width (distance) partitioning
  - Divides the range into *N* intervals of equal size: uniform grid
  - if *A* and *B* are the lowest and highest values of the attribute, the width of intervals will be: $W = (B - A)/N$.
  - The most straightforward, but outliers may dominate presentation
  - Skewed 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

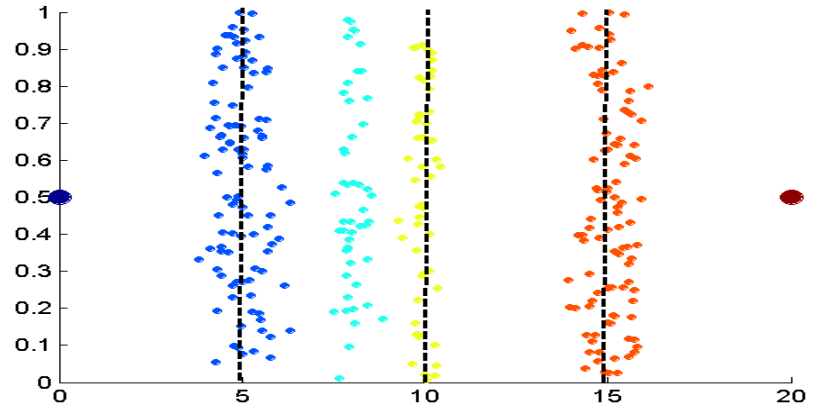
Binning Methods for Data Smoothing

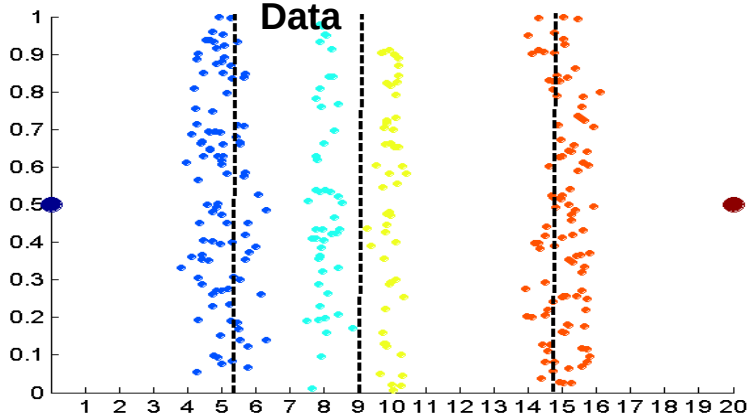
- Sorted data for price (in dollars): 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34

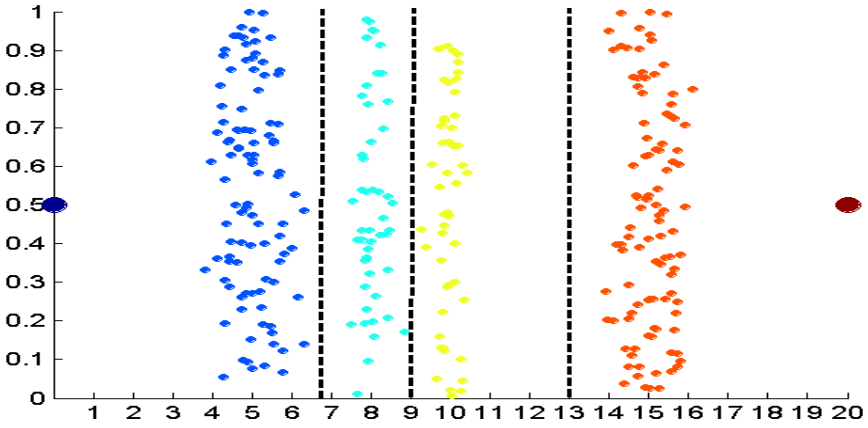
* Partition into equal-frequency (**equi-depth**) bins:
  - Bin 1: 4, 8, 9, 15
  - Bin 2: 21, 21, 24, 25
  - Bin 3: 26, 28, 29, 34
* Smoothing by **bin means**:
  - Bin 1: 9, 9, 9, 9
  - Bin 2: 23, 23, 23, 23
  - Bin 3: 29, 29, 29, 29
* Smoothing by **bin boundaries**:
  - Bin 1: 4, 4, 4, 15
  - Bin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

Discretization Without Using Class Labels (Binning vs. Clustering)









Equal frequency (binning)

K-means clustering leads to better results

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
  - Details to be covered in Chapter 7
- Correlation analysis (e.g., Chi-merge: χ^2-based discretization)
  - Supervised: use class information
  - Bottom-up merge: find the best neighboring intervals (those having similar distributions of classes, i.e., low χ^2 values) to merge
  - Merge performed recursively, until a predefined stopping condition

Concept Hierarchy Generation

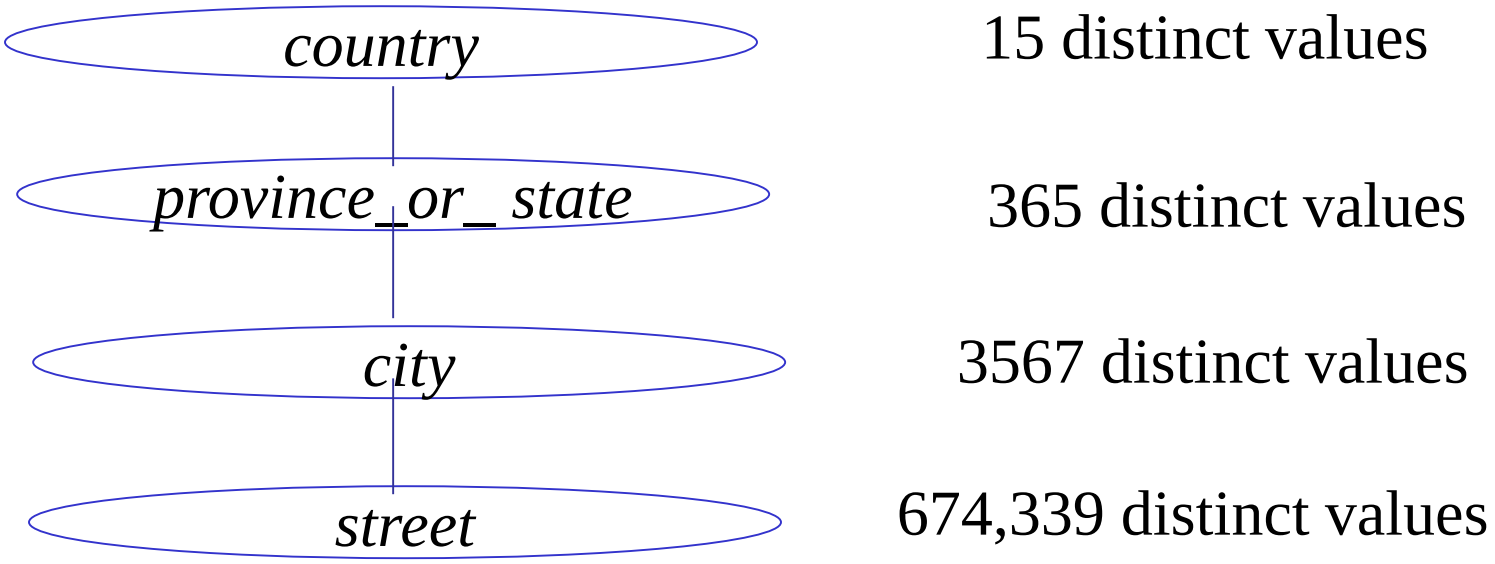
- **Concept hierarchy** organizes concepts (i.e., attribute values) hierarchically and is usually associated with each dimension in a data warehouse
- Concept hierarchies facilitate drilling and rolling in data warehouses to view data in multiple granularity
- Concept hierarchy formation: Recursively reduce the data by collecting and replacing low level concepts (such as numeric values for *age*) by higher level concepts (such as *youth, adult*, or *senior*)
- Concept hierarchies can be explicitly specified by domain experts and/or data warehouse designers
- Concept hierarchy can be automatically formed for both numeric and nominal data. For numeric data, use discretization methods shown.

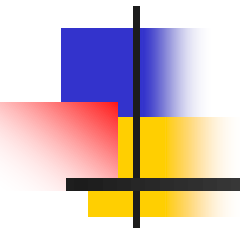
Concept Hierarchy Generation for Nominal Data

- Specification of a partial/total ordering of attributes explicitly at the schema level by users or experts
  - *street* < *city* < *state* < *country*
- Specification of a hierarchy for a set of values by explicit data grouping
  - {Urbana, Champaign, Chicago} < Illinois
- Specification of only a partial set of attributes
  - E.g., only *street* < *city*, not others
- Automatic generation of hierarchies (or attribute levels) by the analysis of the number of distinct values
  - E.g., for a set of attributes: {*street, city, state, country*}

Automatic Concept Hierarchy Generation

- Some hierarchies can be automatically generated based on the analysis of the number of distinct values per attribute in the data set
  - The attribute with the most distinct values is placed at the lowest level of the hierarchy
  - Exceptions, e.g., weekday, month, quarter, year

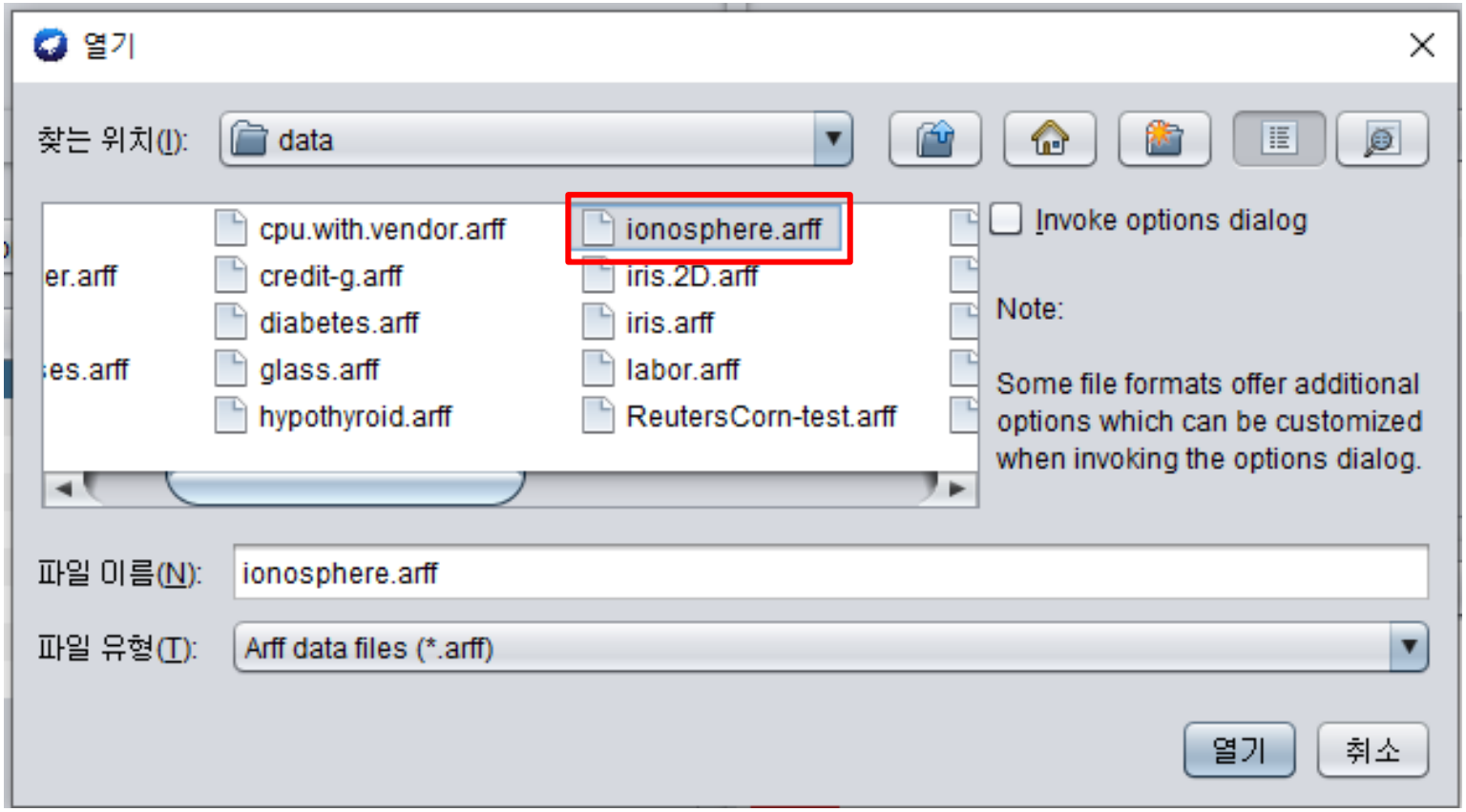




Weka - Discretization

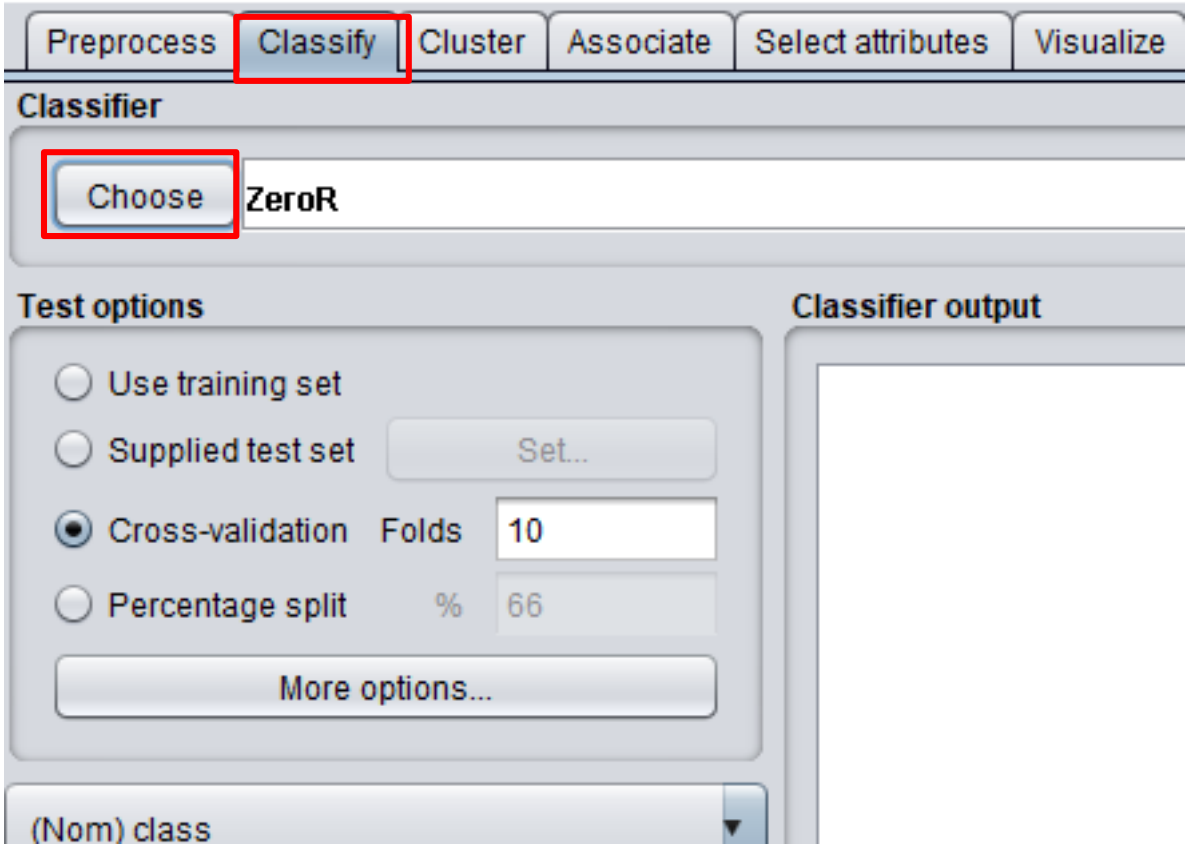
Discretizing numeric attributes

- Open 'ionosphere.arff'



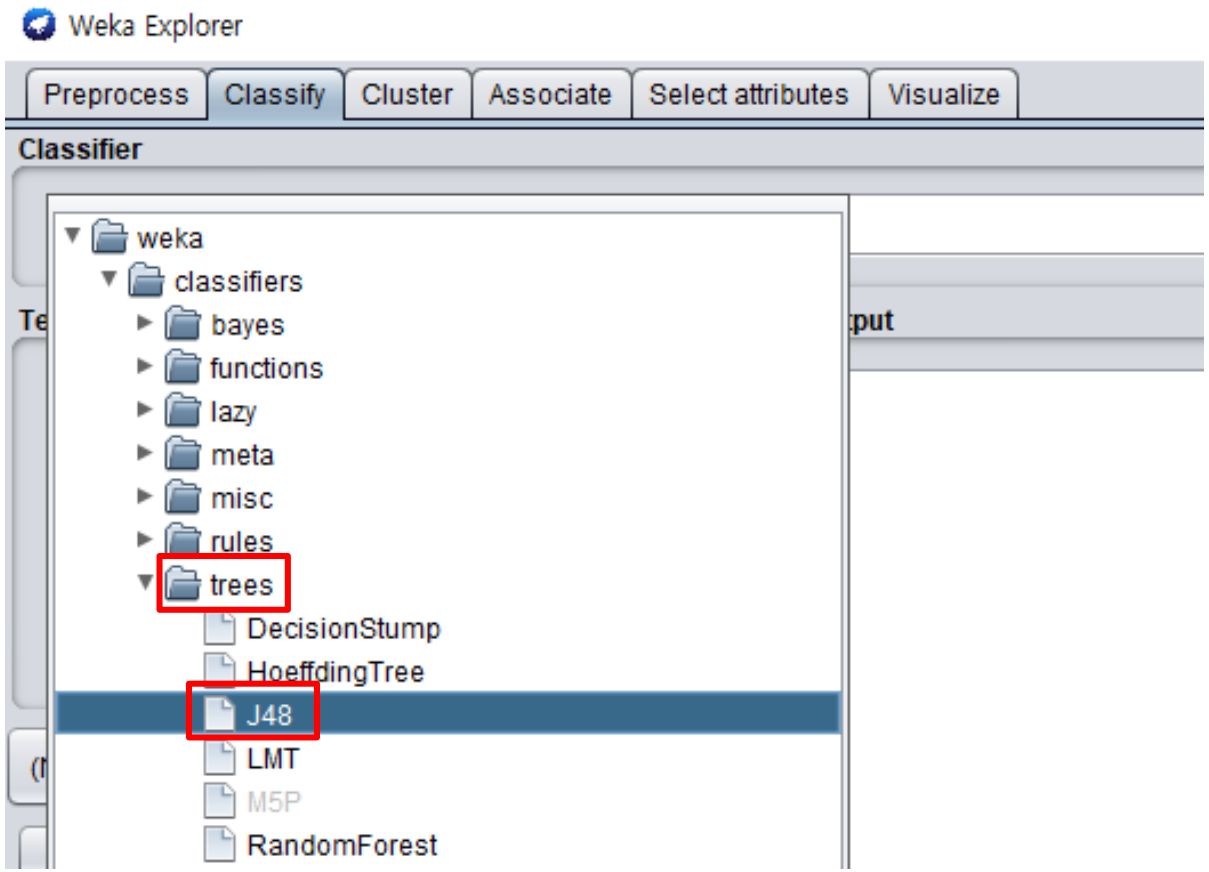
Discretizing numeric attributes

- First we will check the classification result of raw data
- From Classify tab, click 'choose'



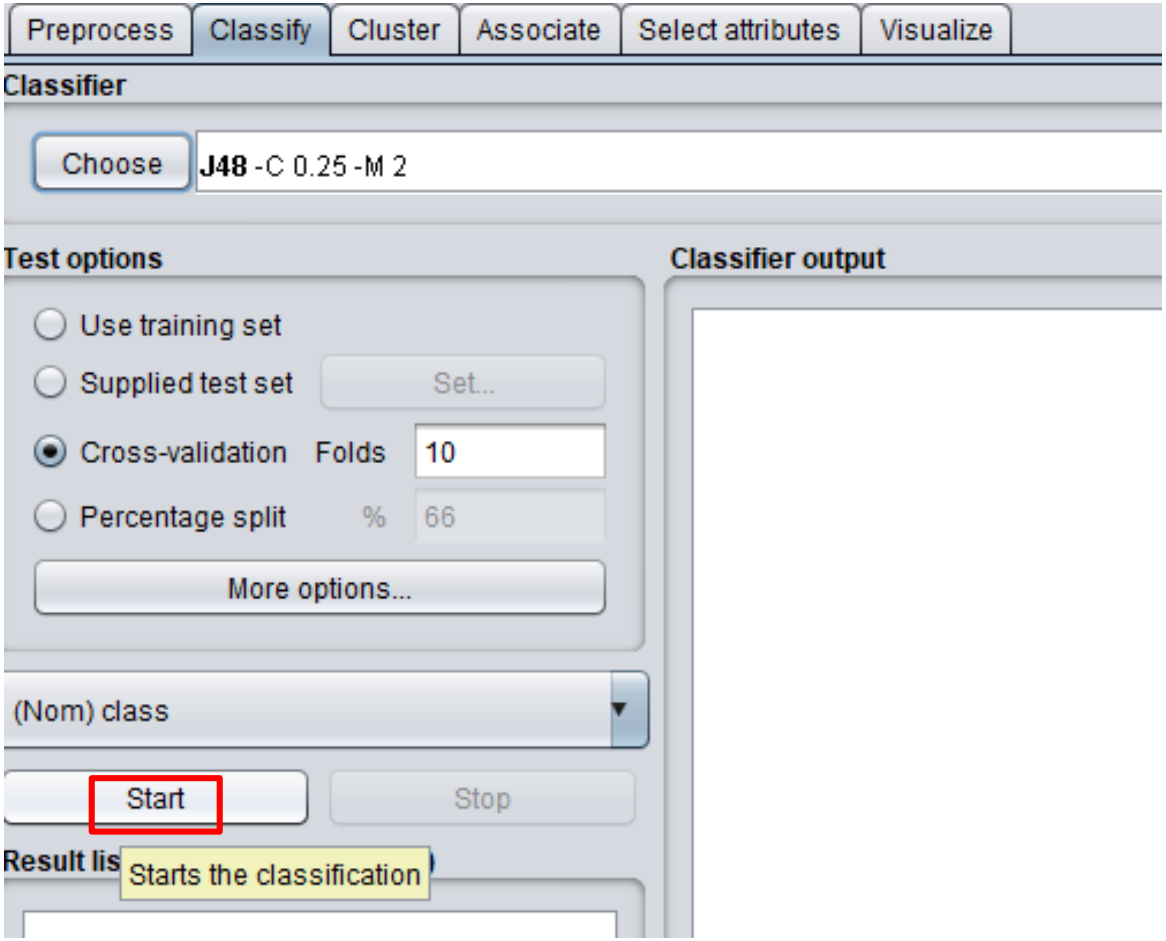
Discretizing numeric attributes

- Select trees->J48



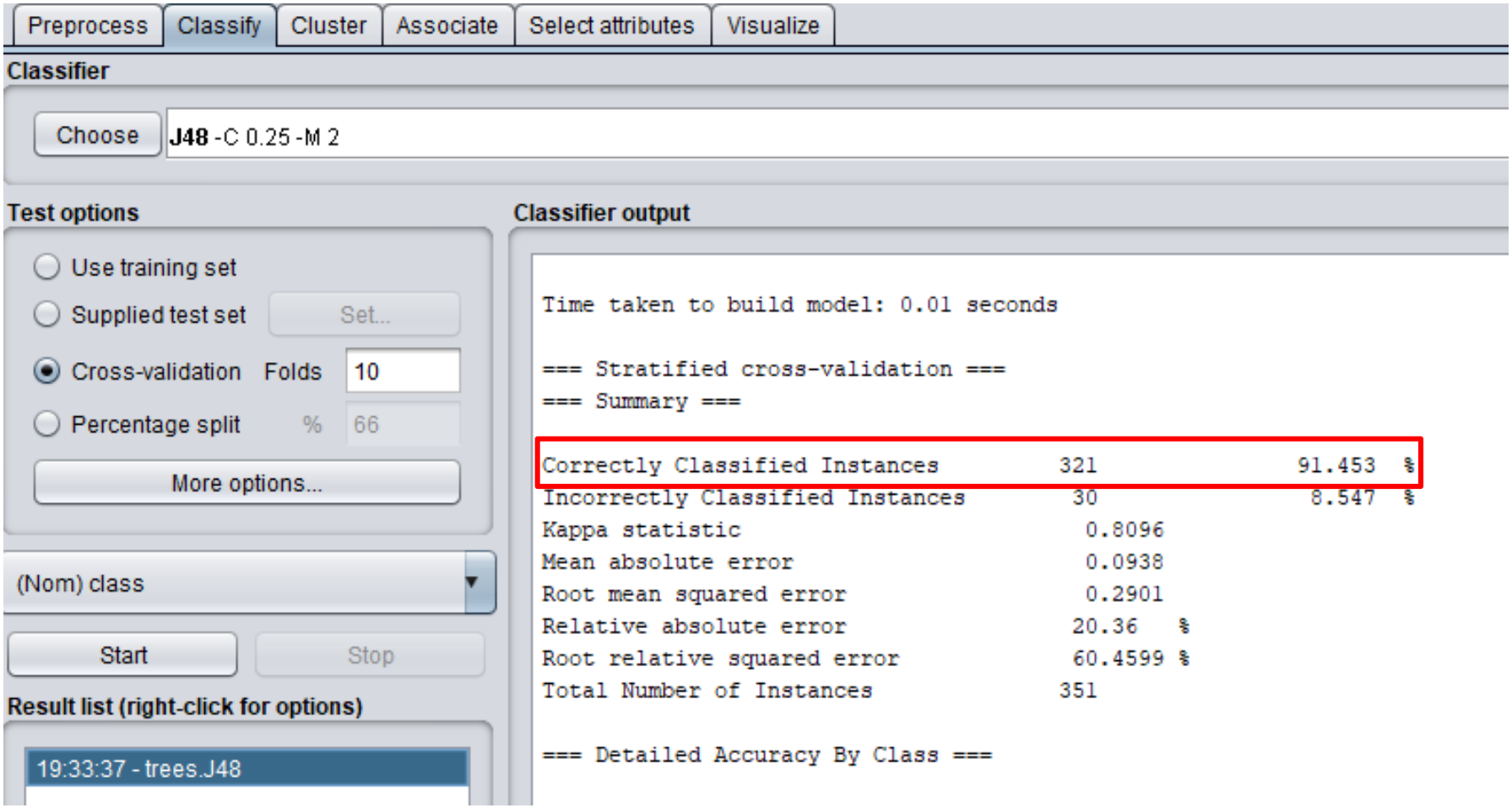
Discretizing numeric attributes

- Run the classifier



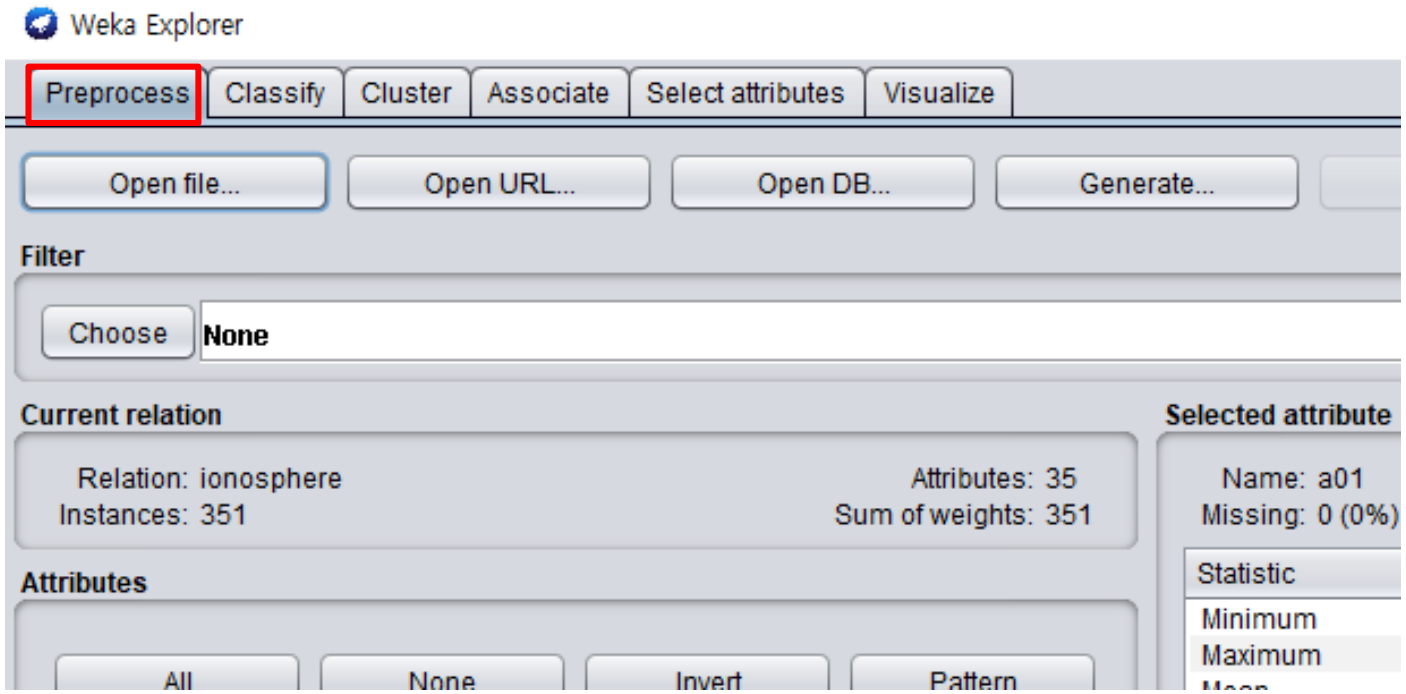
Discretizing numeric attributes

- The accuracy is 91.453%



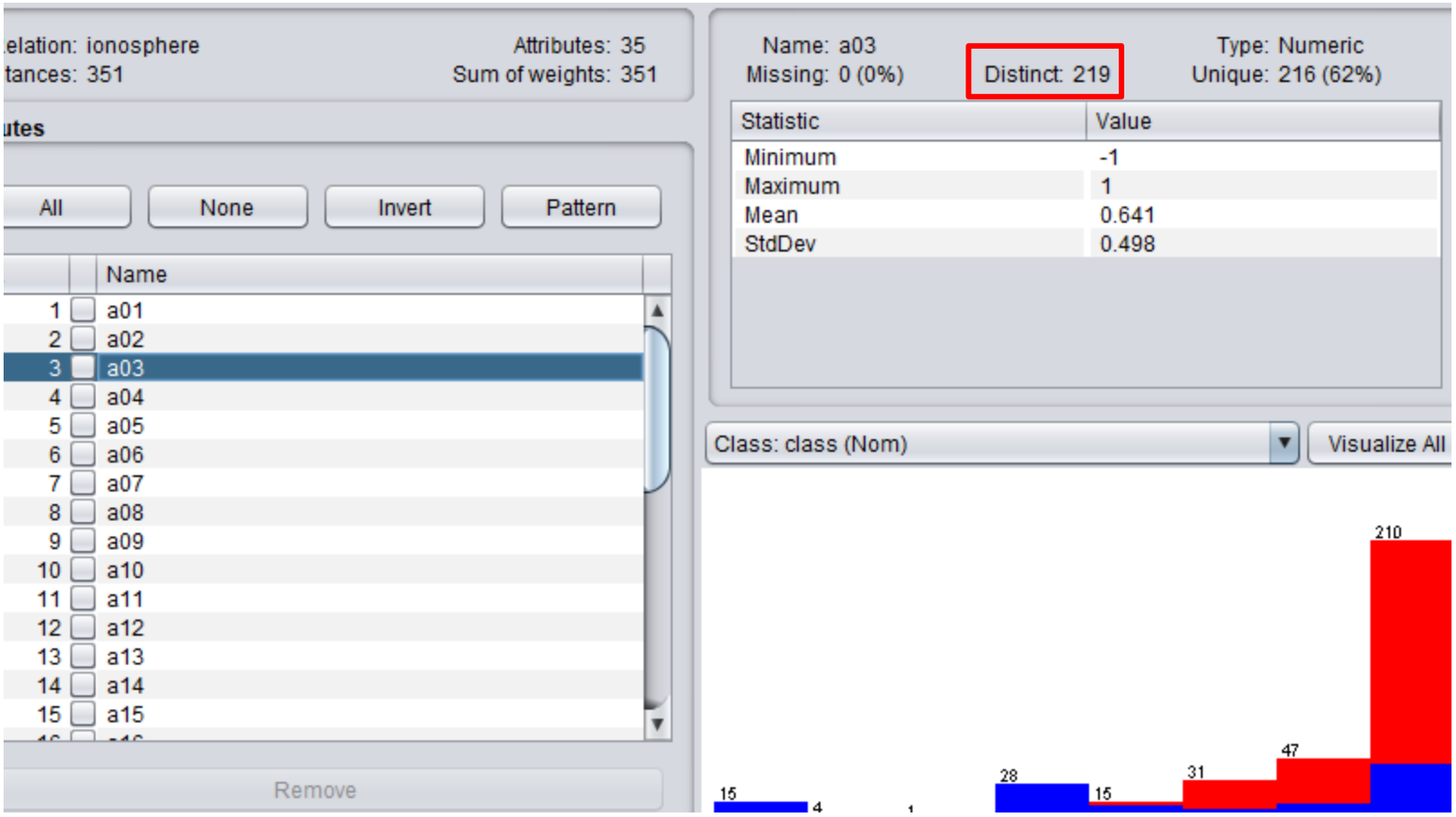
Discretizing numeric attributes

- Let's discretize numeric attributes and see how the result differs
- Go back to 'Preprocess' tab



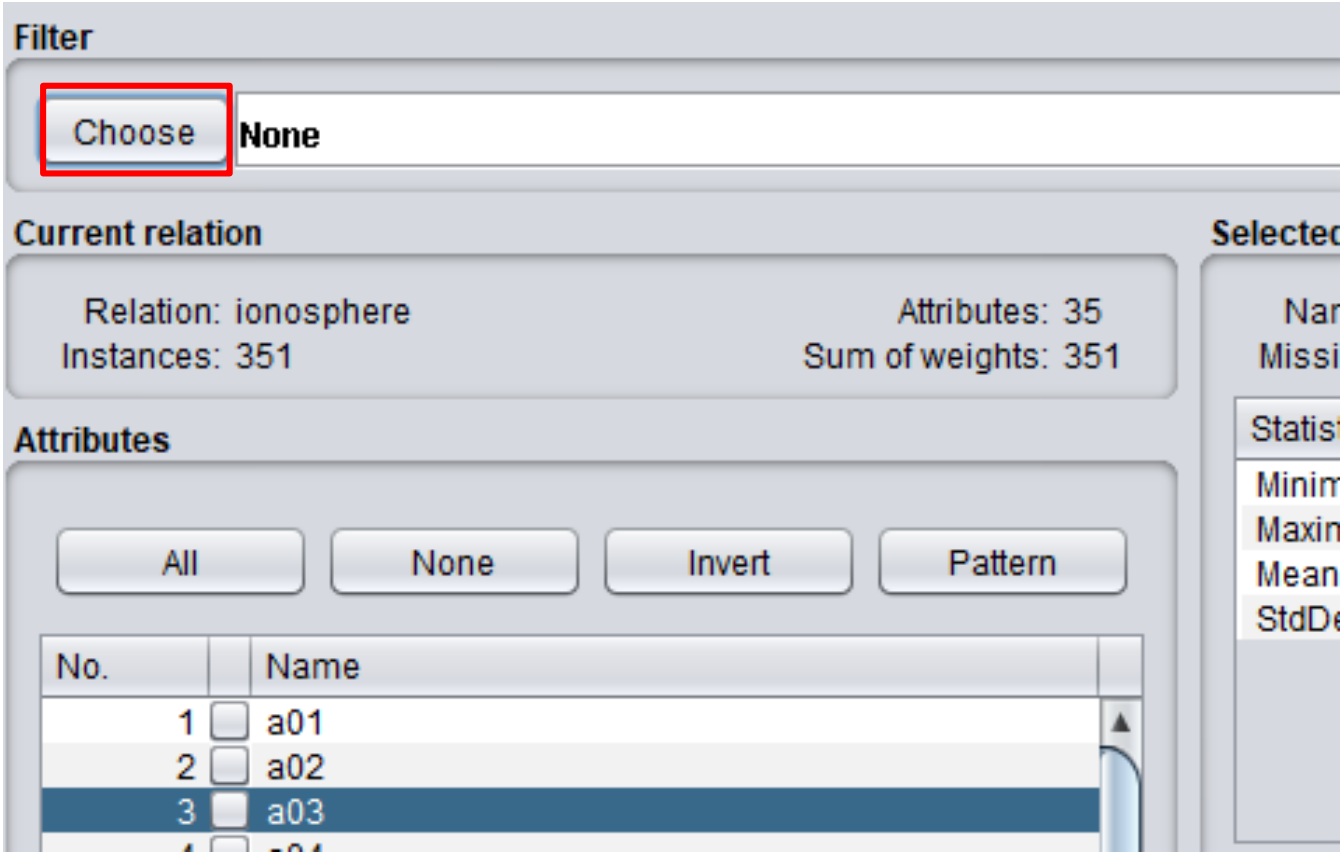
Discretizing numeric attributes

- You can see that most attributes are continuous



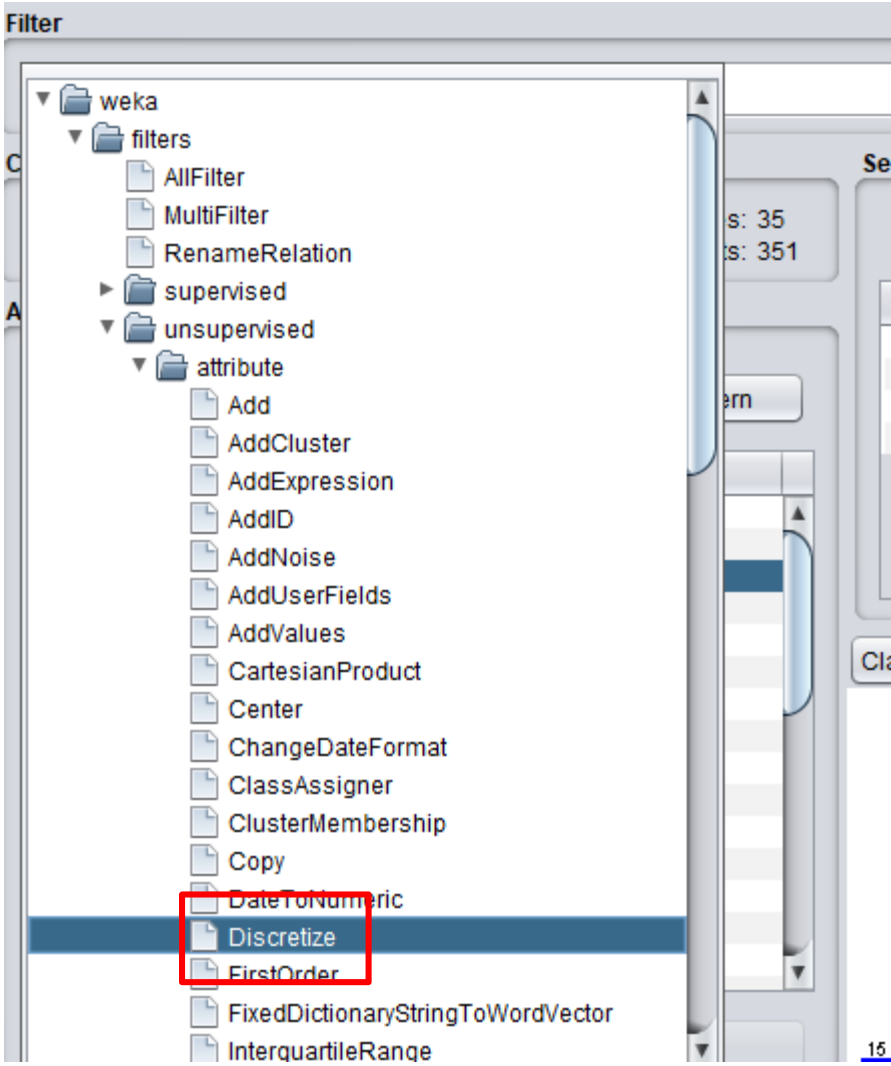
Discretizing numeric attributes

- Now let's discretize attributes
- Click 'Choose' in 'Filter'



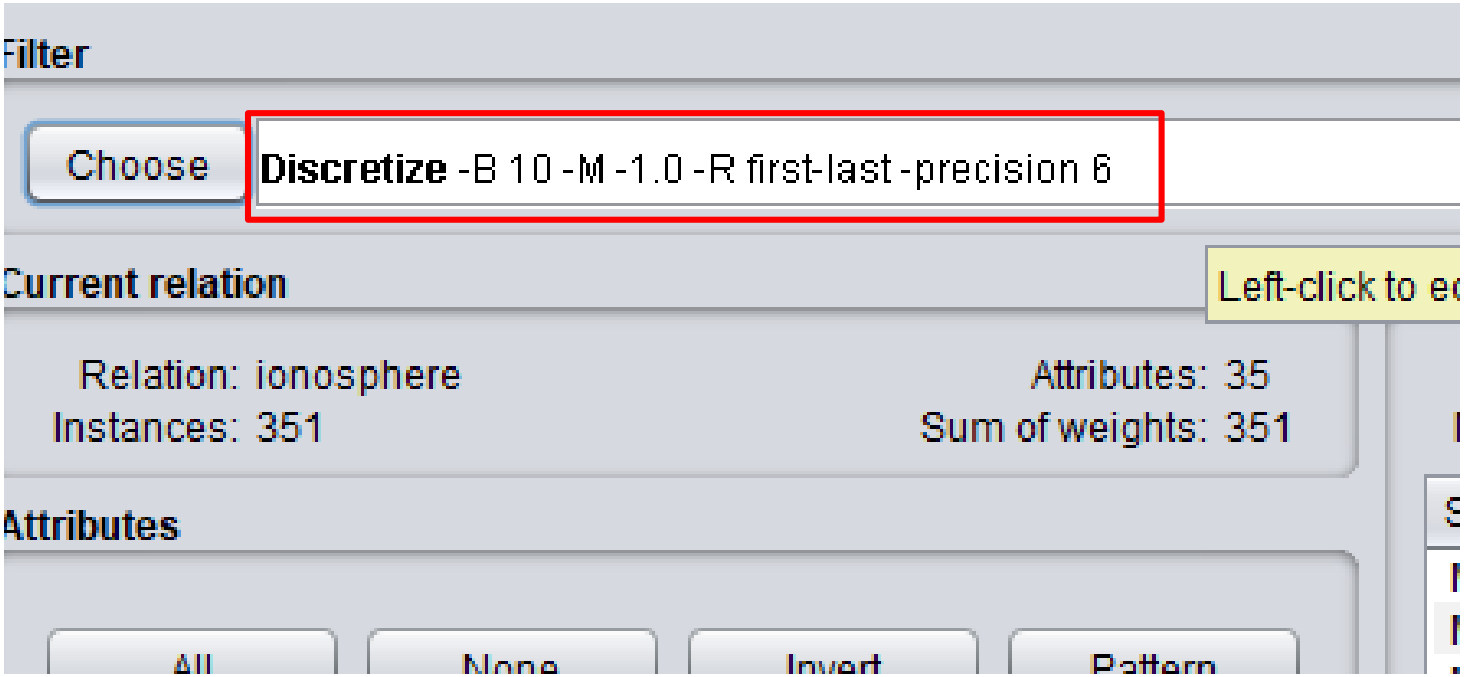
Discretizing numeric attributes

- Select filters-> unsupervised->attribute-> Discretize



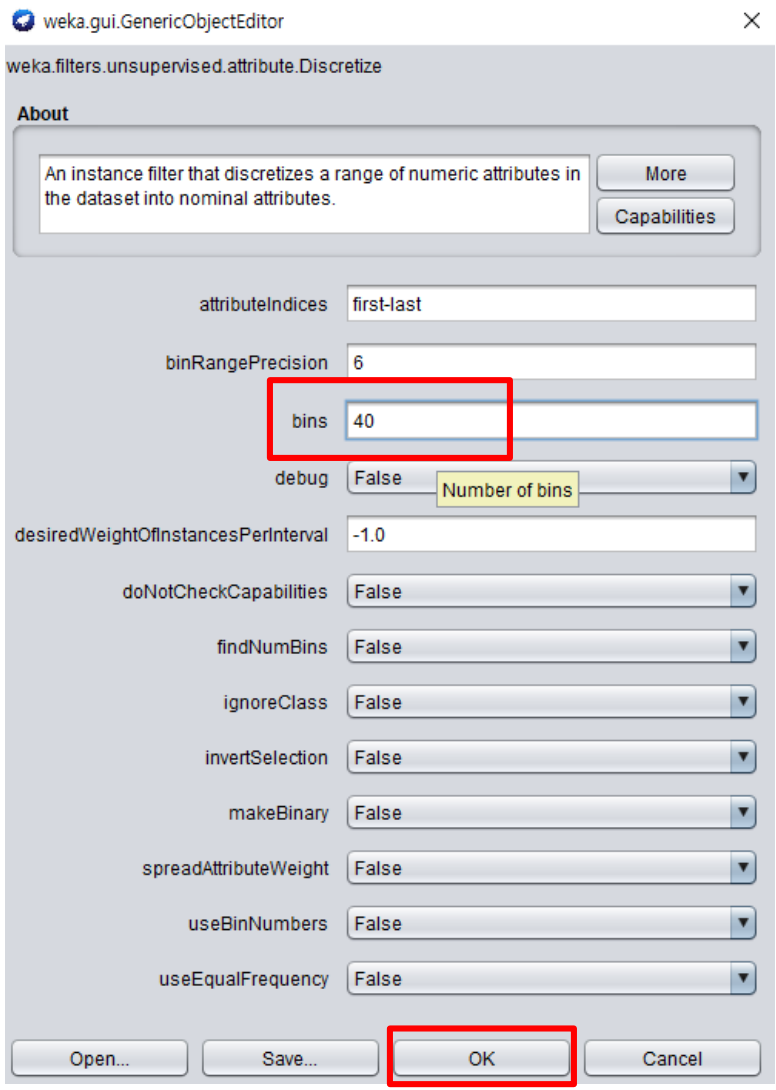
Discretizing numeric attributes

- Click the white bar to adjust paramters



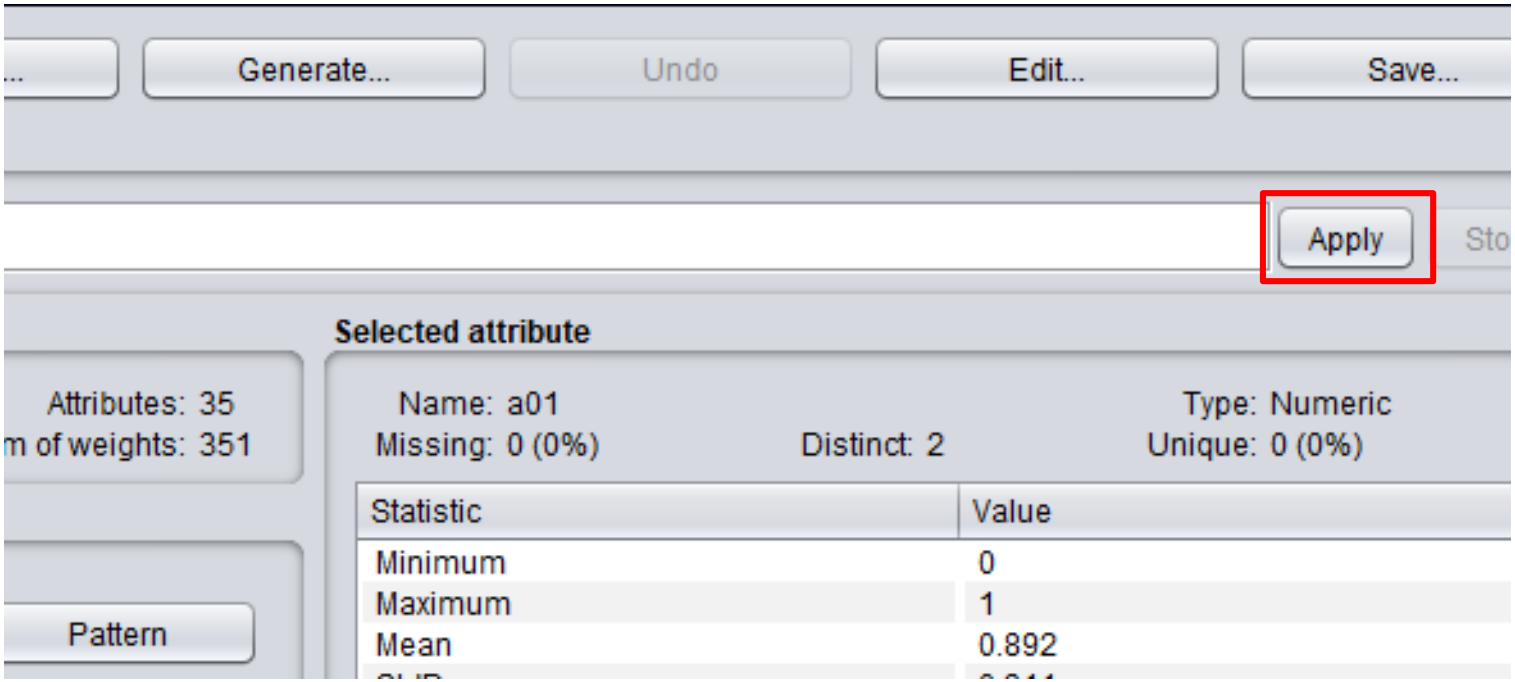
Discretizing numeric attributes

- Change the bins to 40 and click 'OK'



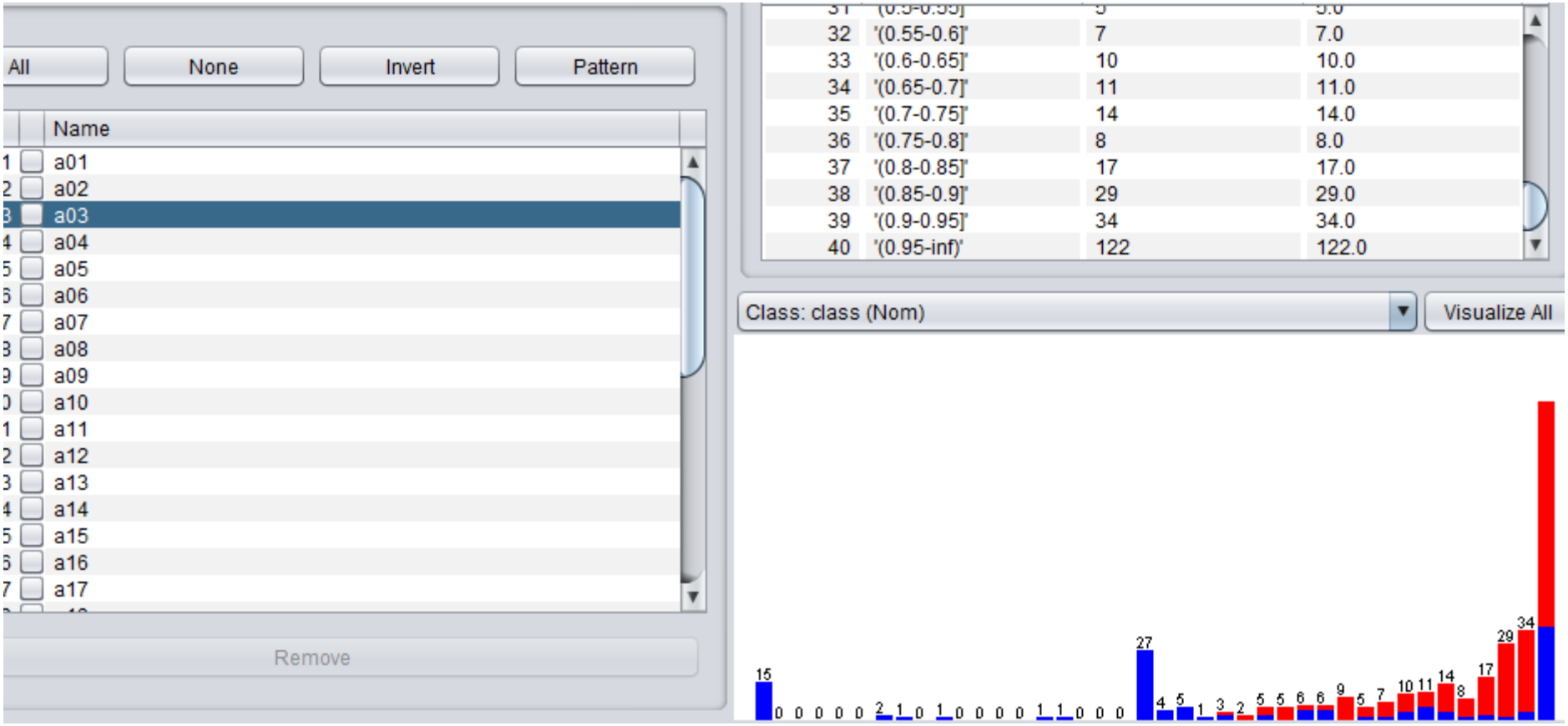
Discretizing numeric attributes

- Click ‘Apply’



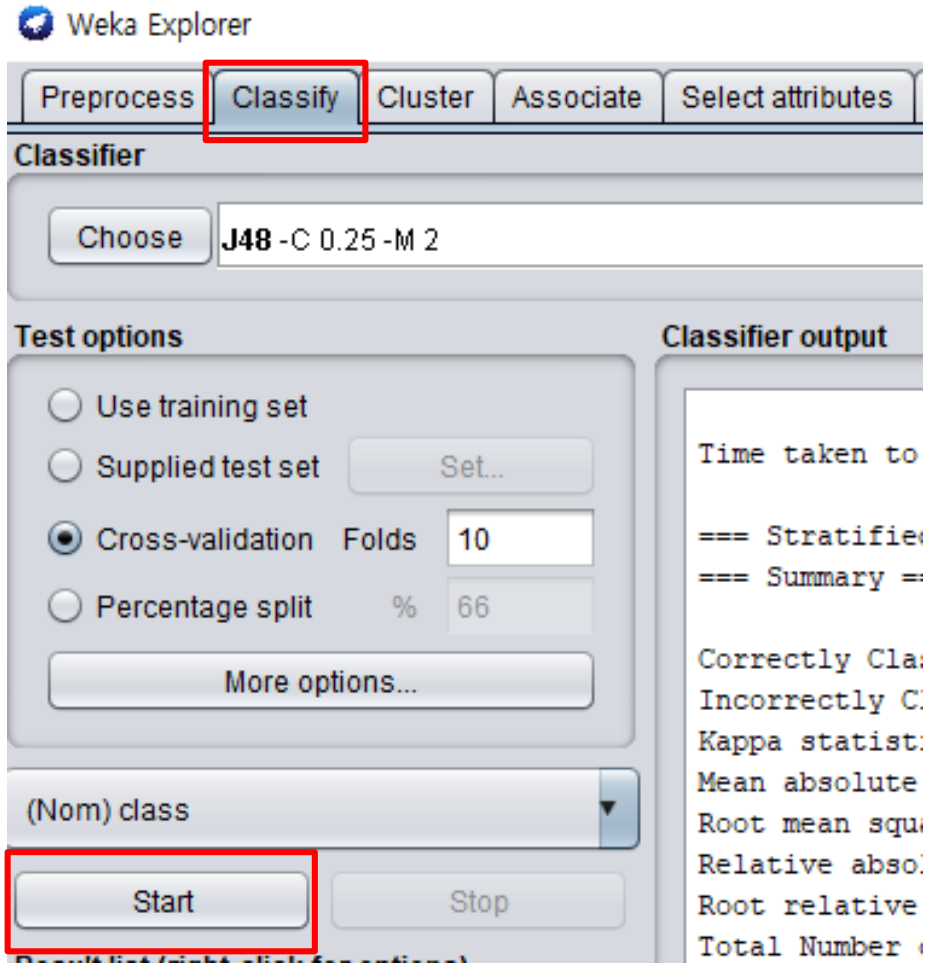
Discretizing numeric attributes

- You can see that the data is discretized into 40 bins with equi-width



Discretizing numeric attributes

- Run the classifier again



Discretizing numeric attributes

- This time the accuracy is little bit lower

```
Time taken to build model: 0.01 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         308               87.7493 %
Incorrectly Classified Instances        43               12.2507 %
Kappa statistic                          0.7276
Mean absolute error                      0.1629
Root mean squared error                  0.3242
Relative absolute error                 35.3662 %
Root relative squared error             67.574  %
Total Number of Instances              351

=== Detailed Accuracy By Class ===
```

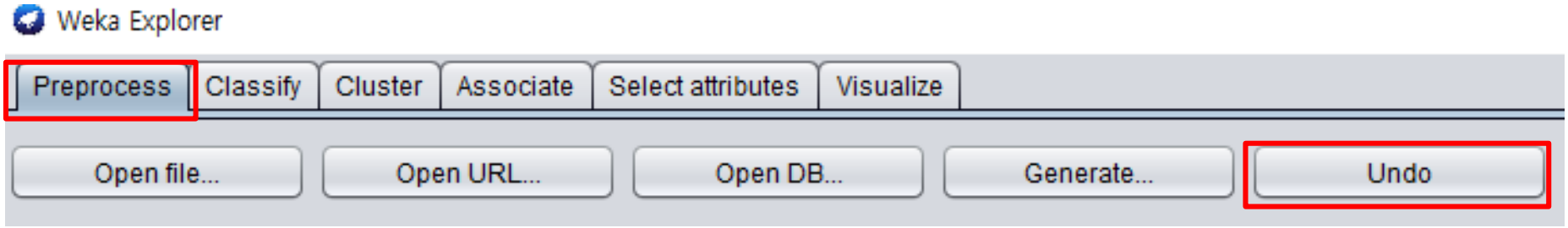
Discretizing numeric attributes

- Scroll up to check the size of the tree

```
|   a06 = '(0.8-0.85]': b (1.0)
|   a06 = '(0.85-0.9]': g (0.0)
|   a06 = '(0.9-0.95]': g (0.0)
|   a06 = '(0.95-inf)': b (17.0/2.0)

Number of Leaves  :     79

Size of the tree :      81


Time taken to build model: 0 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         308               87.7493 %
Incorrectly Classified Instances        43               12.2507 %
Kappa statistic                          0.7276
Mean absolute error                      0.1629
Root mean squared error                  0.3242
Relative absolute error                 35.3662 %
Root relative squared error             67.574  %
Total Number of Instances              351
```

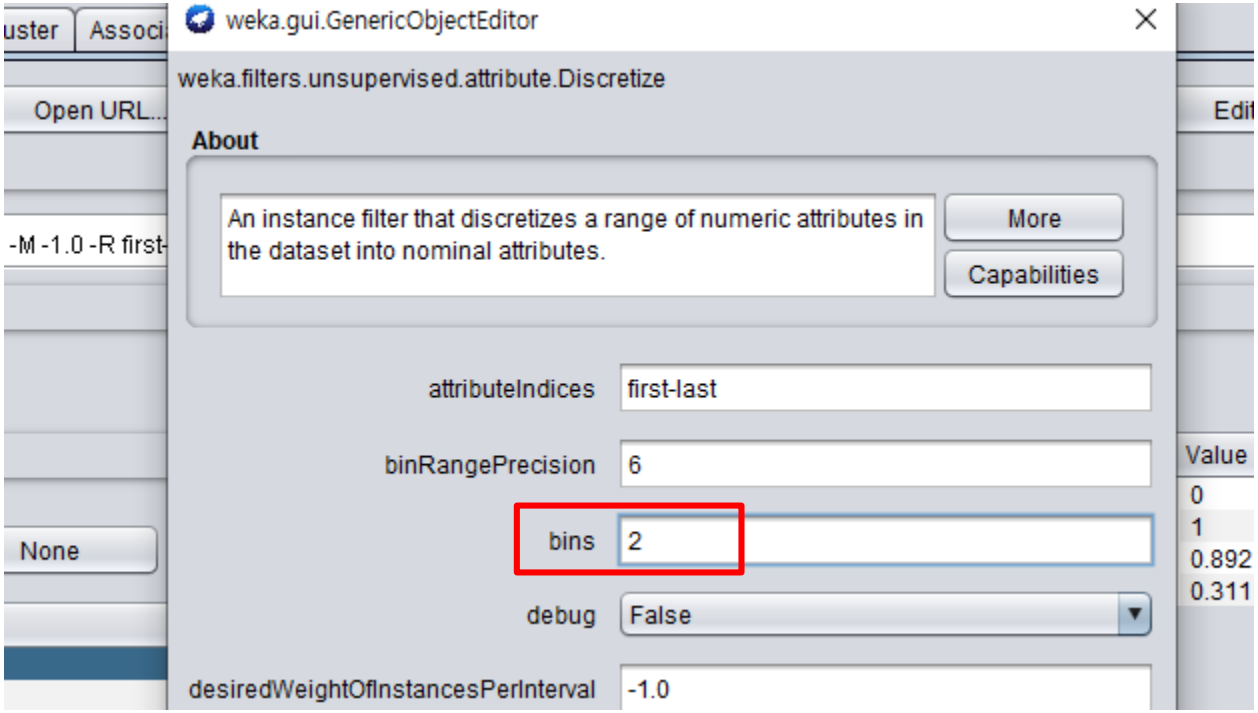
Discretizing numeric attributes

- Go back to Preprocess and click 'Undo' to undo the discretization



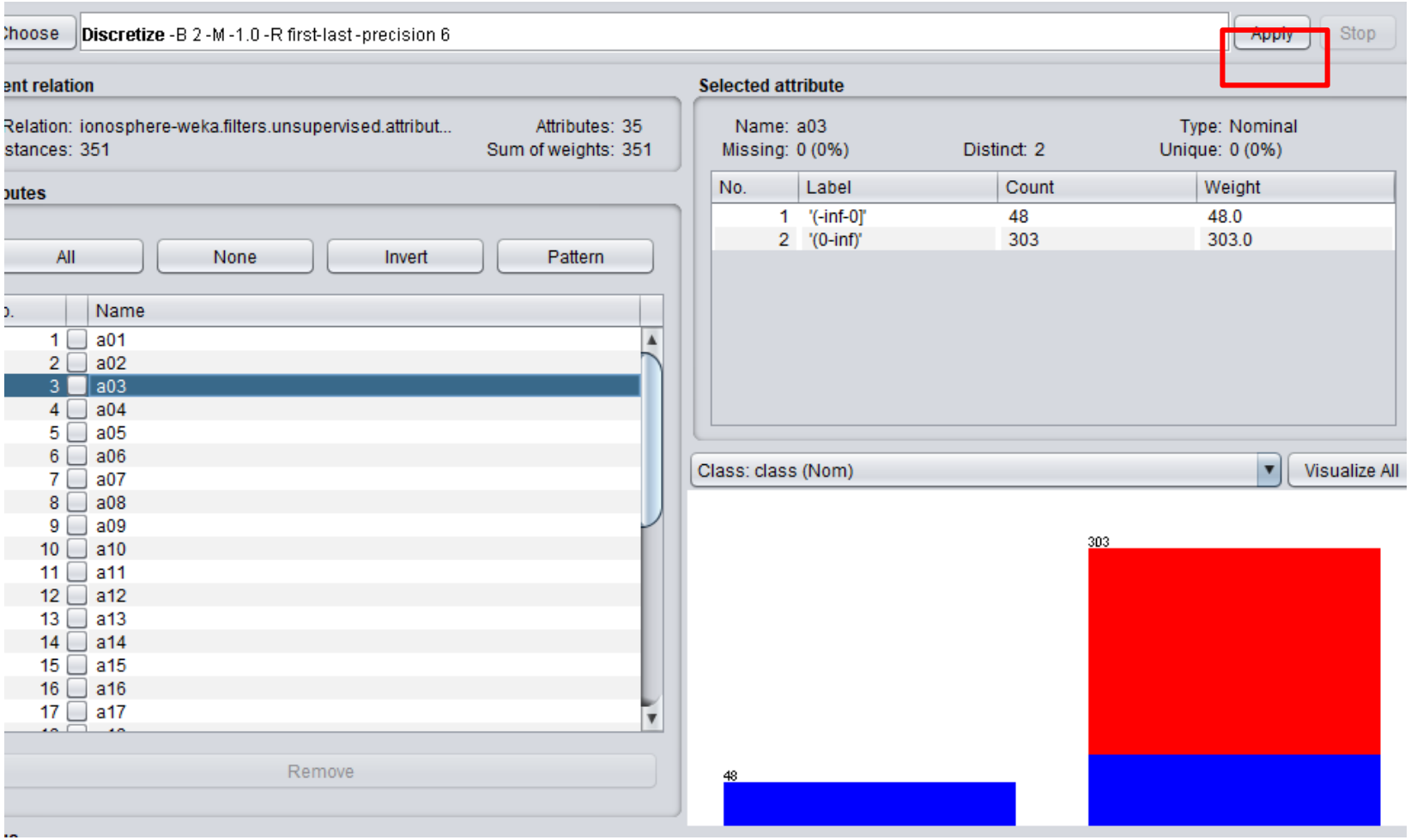
Discretizing numeric attributes

- This time, set the number of bins to 2



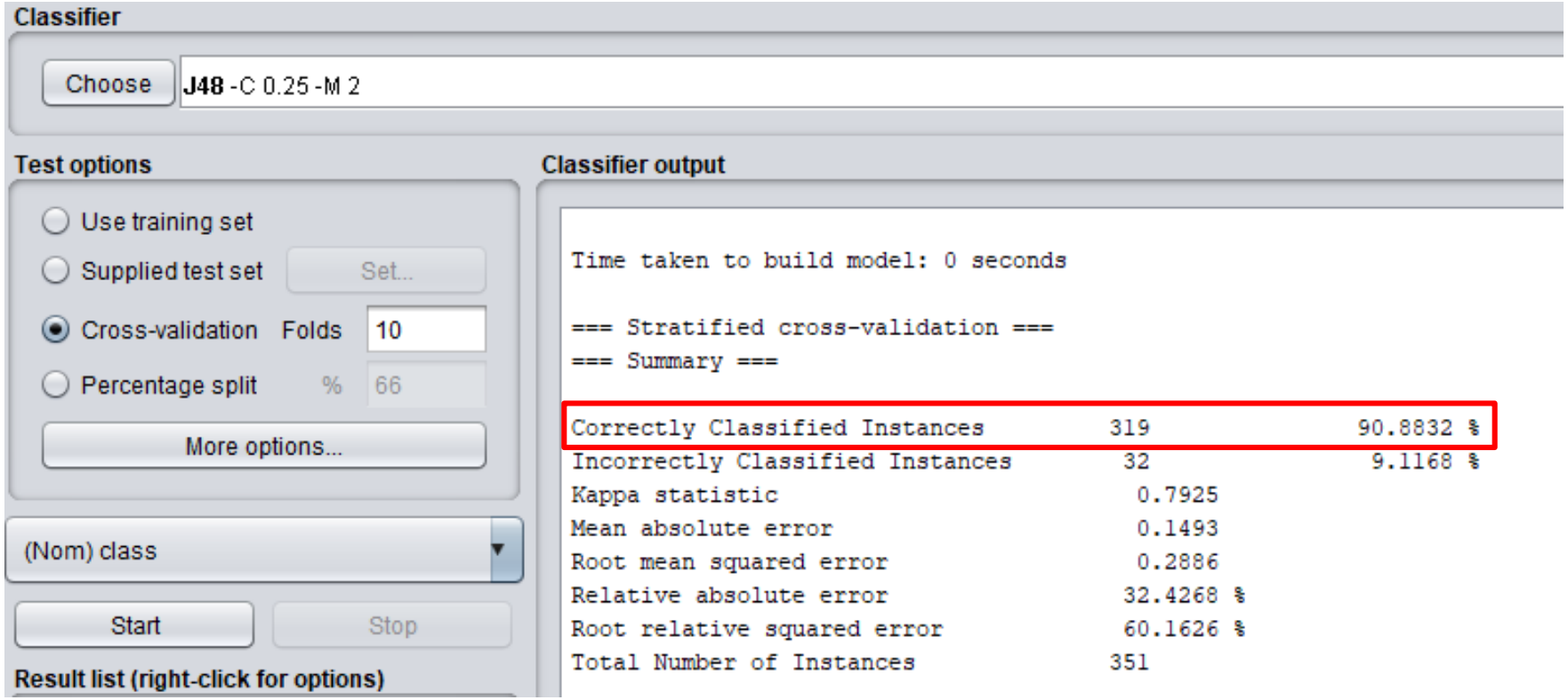
Discretizing numeric attributes

- Click apply then the data is divided into 2 bins



Discretizing numeric attributes

- Run the classifier
- We get a different result



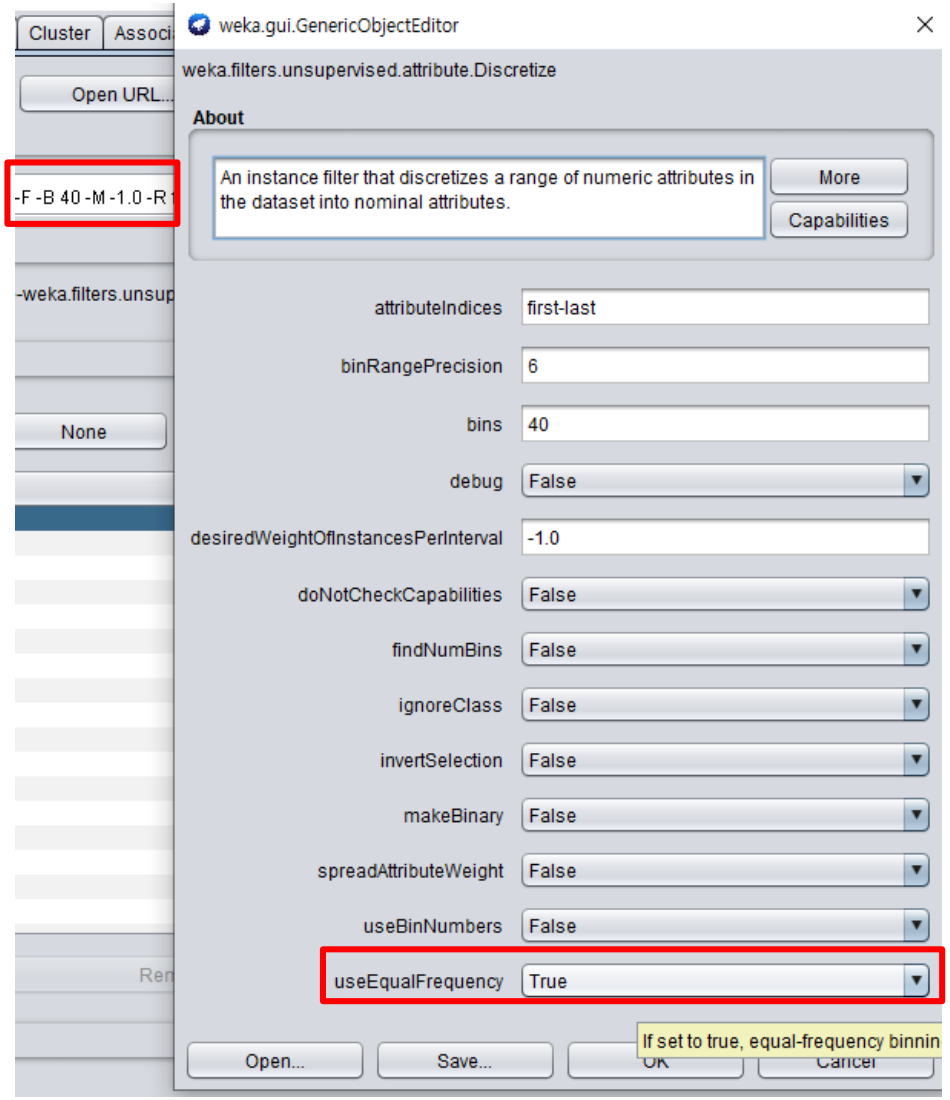
Discretizing numeric attributes

- The size of the tree is much smaller than the tree with 40 bins

```
|   |   |   |   a15 = '(0-inf)'
|   |   |   |   |   a21 = '(-inf-0]': b (5.0/1.0)
|   |   |   |   |   a21 = '(0-inf)': g (87.0/11.0)
|   |   |   a08 = '(0-inf)': g (161.0/13.0)

Number of Leaves  :     7

Size of the tree :      13


Time taken to build model: 0 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         319               90.8832 %
Incorrectly Classified Instances        32                9.1168 %
Kappa statistic                          0.7925
```

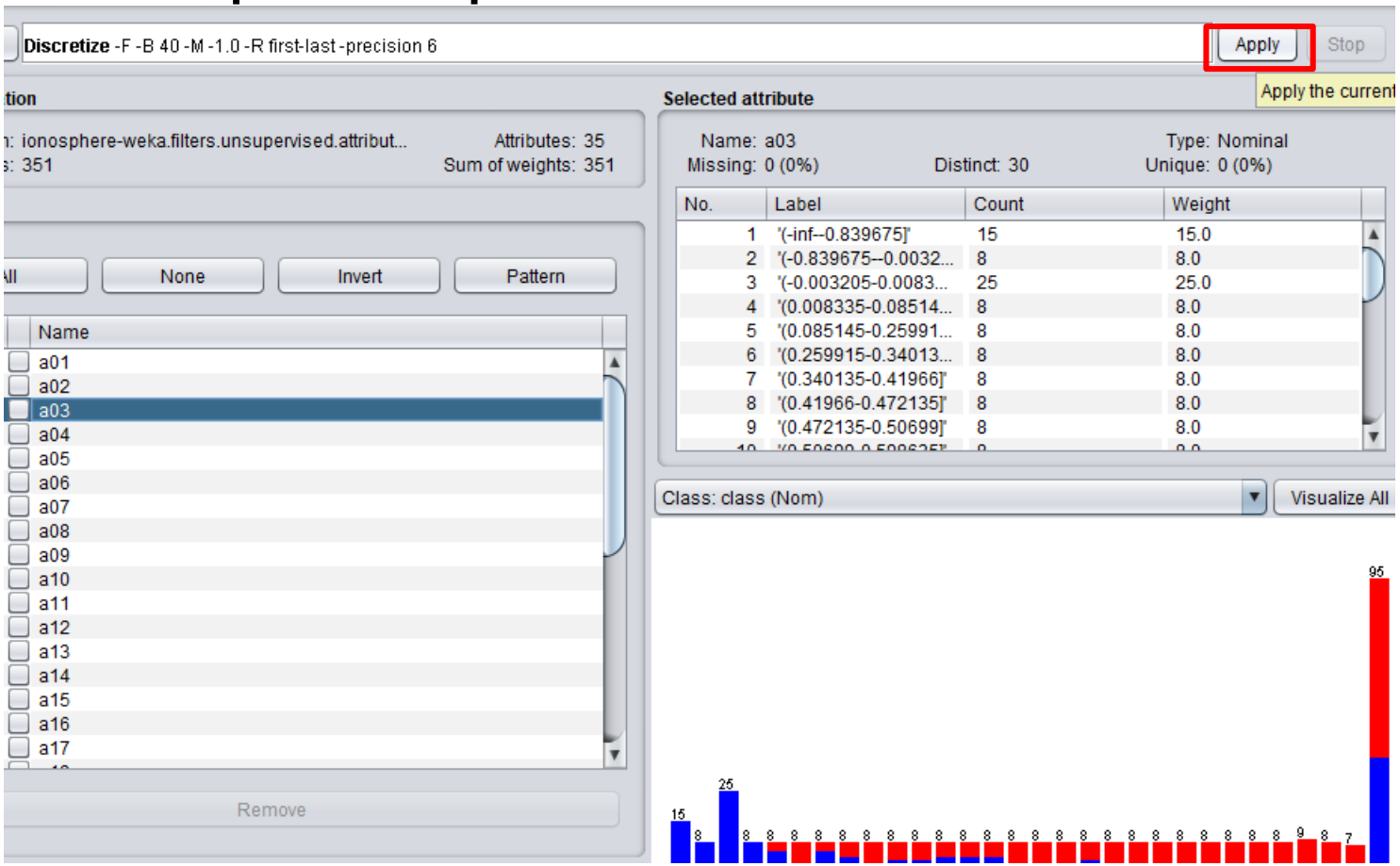
Discretizing numeric attributes

- Open the options and set useEqualFrequency to True
- Don’t forget to undo before applying



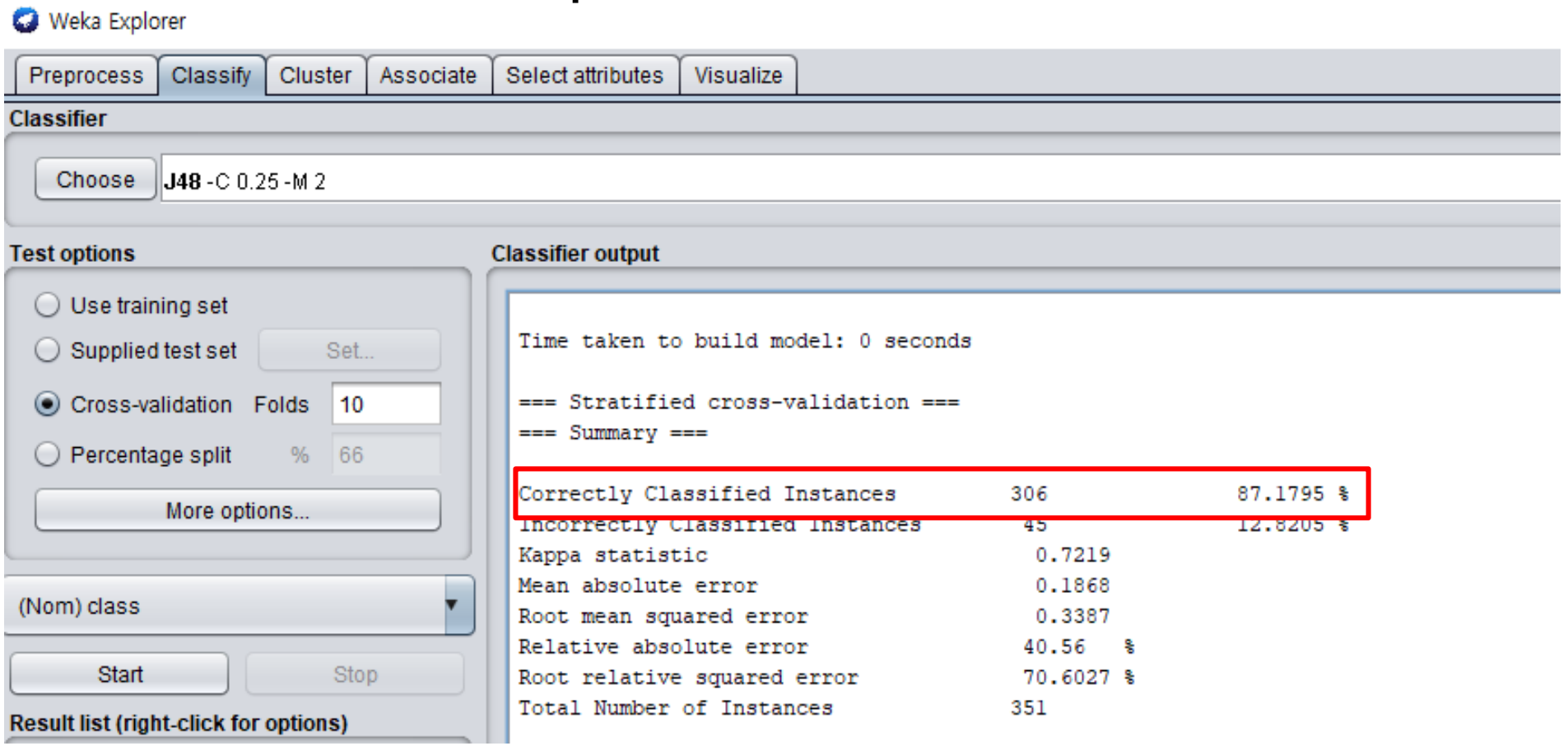
Discretizing numeric attributes

- If you apply the discretization, the bins have almost equal frequencies



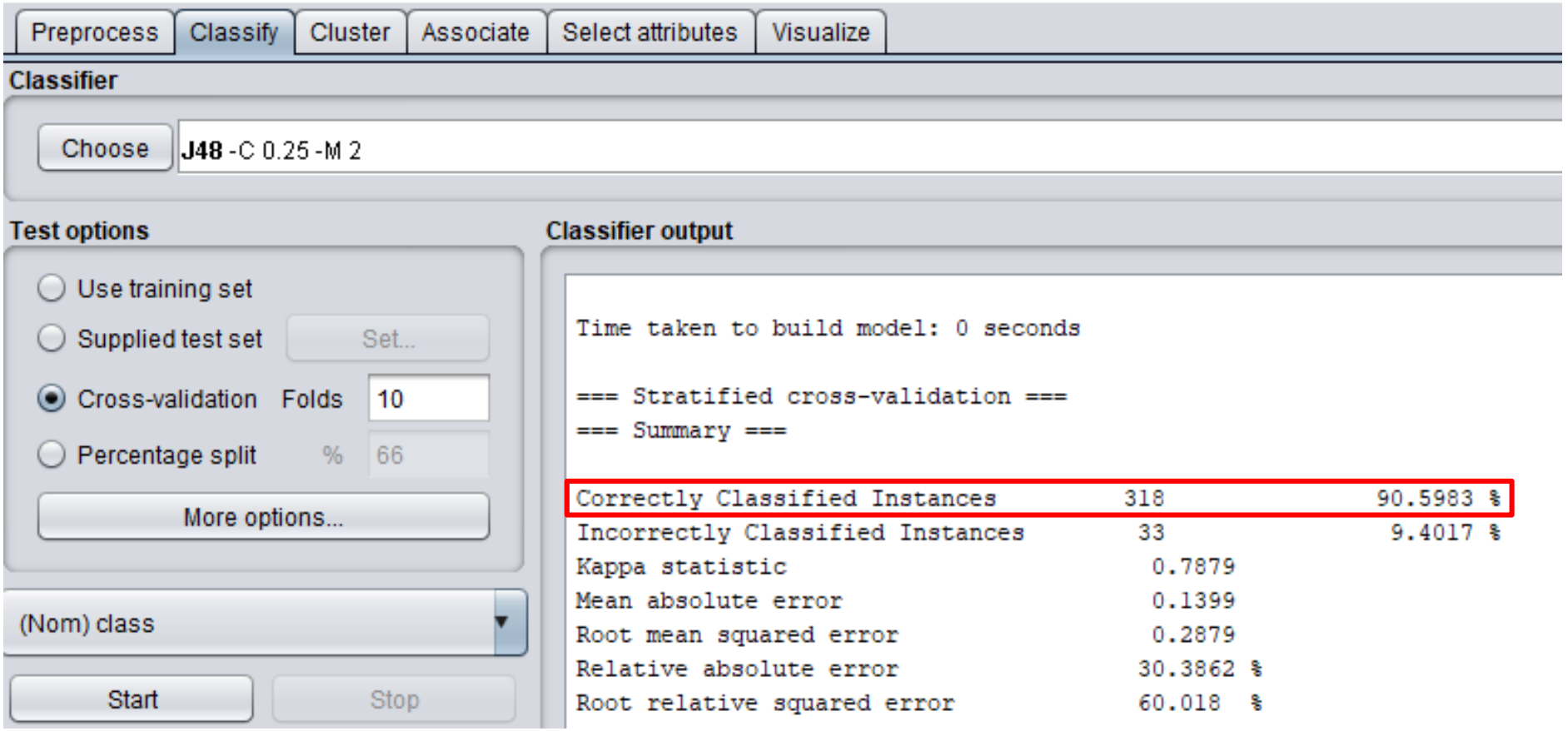
Discretizing numeric attributes

- Run the classifier to see that the result is different from equi-width bins



Discretizing numeric attributes

- Result when bins = 5 and equi-frequency bins



Discretizing numeric attributes

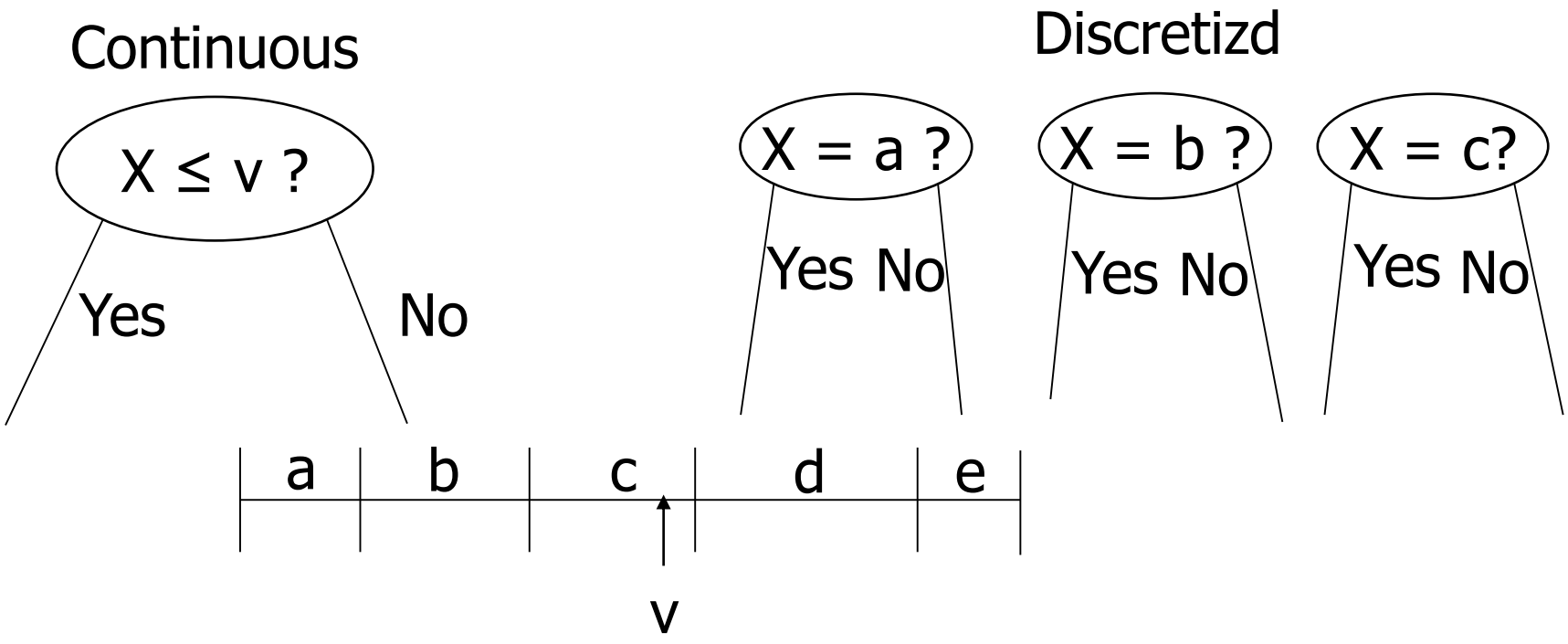
- Note : The affect of discretizing varies with regard to the dataset

- You have to find the best choice through multiple experiments

Discretizing numeric attributes

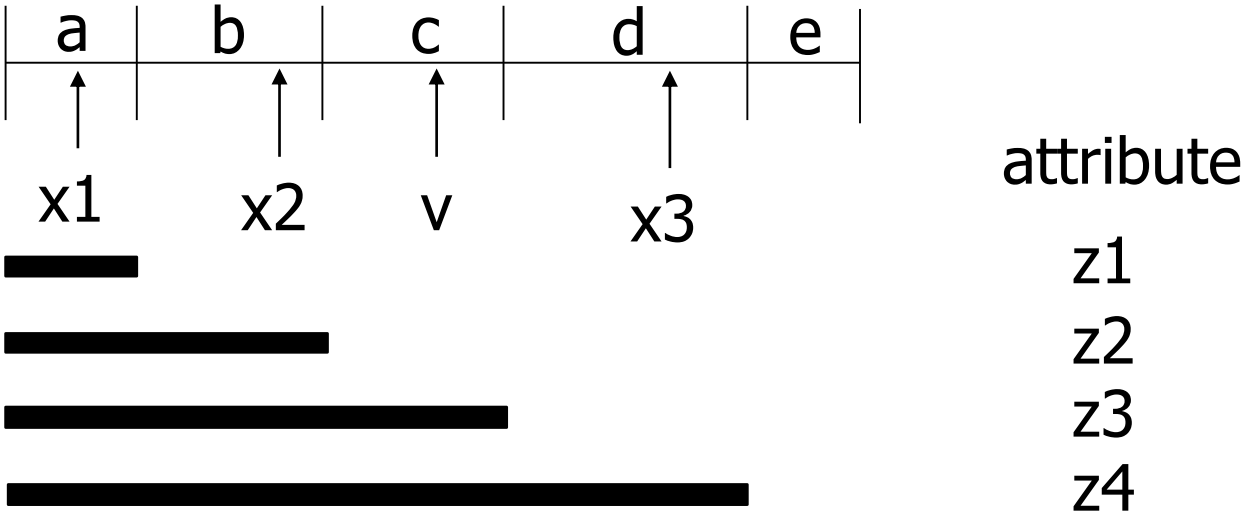
- A problem of discretization : It is inefficient to find out ordering information from discrete attributes

- Ex) In a decision tree,



Discretizing numeric attributes

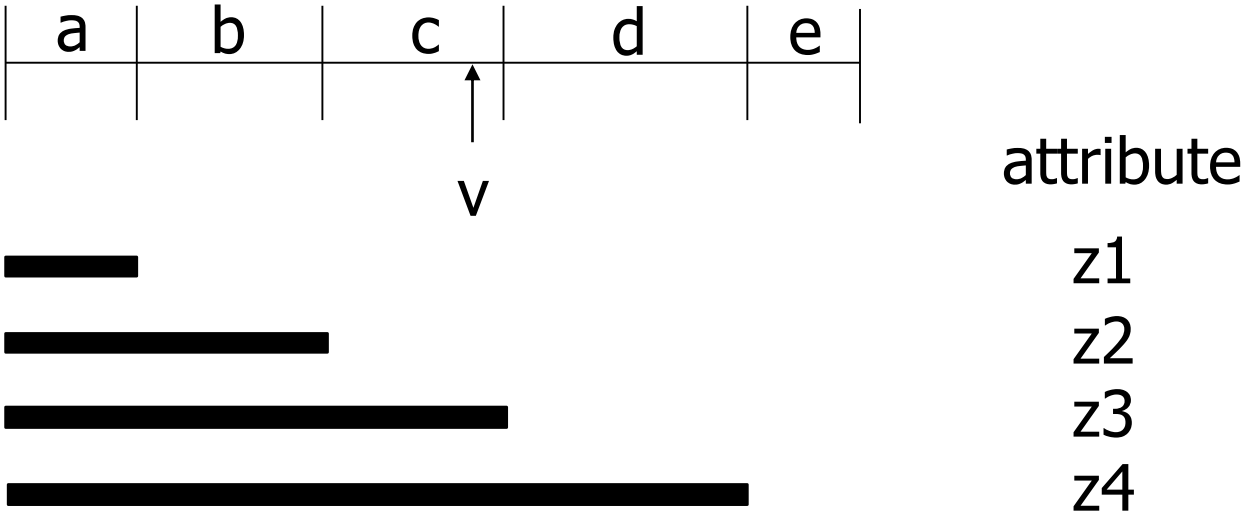
- A solution : One discretized attribute with k values
  -> k-1 binary attributes



	z1	z2	z3	z4
x1	1	1	1	1
x2	0	1	1	1
x3	0	0	0	1

Discretizing numeric attributes

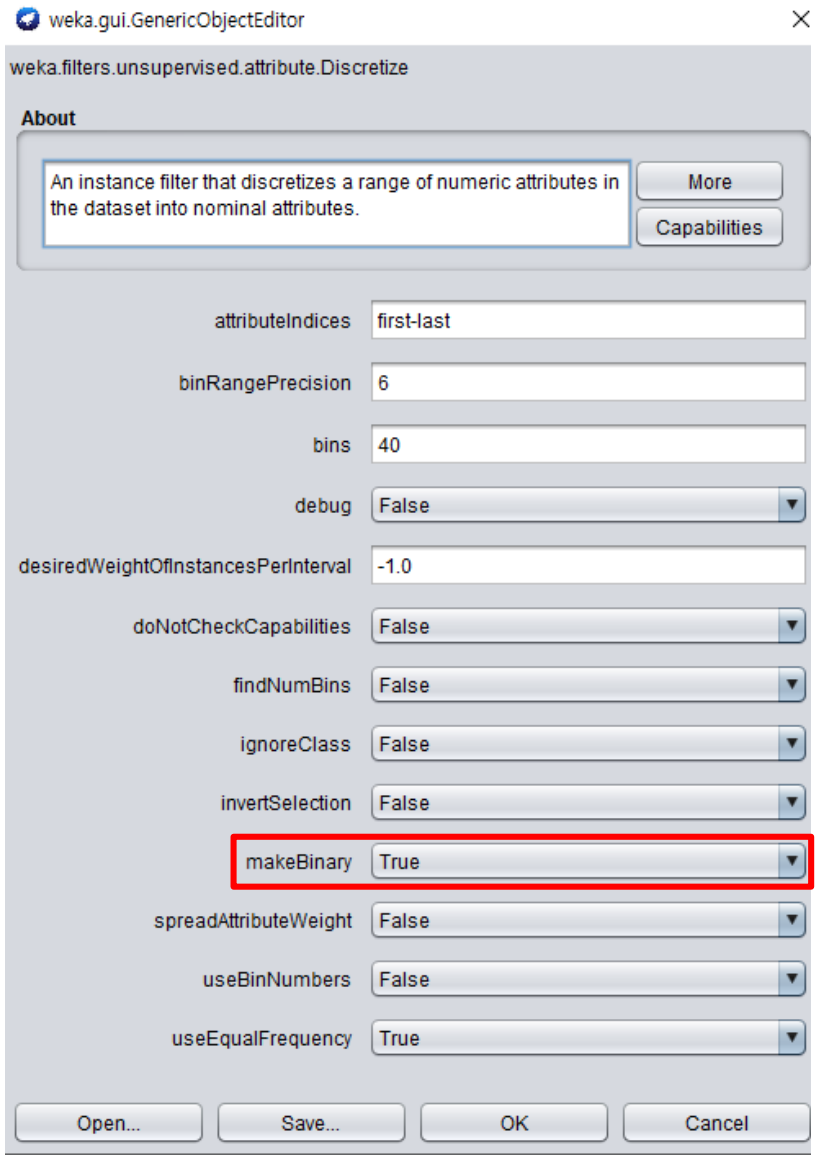
- A solution : One discretized attribute with k values
  -> k-1 binary attributes



X ≤ v ? -> z3 = 1 ?

Discretizing numeric attributes

- 'makeBinary' = True is the corresponding option
- Set
  bins = 40,
  useEqualFrequency = True
- Don't forget to undo before applying

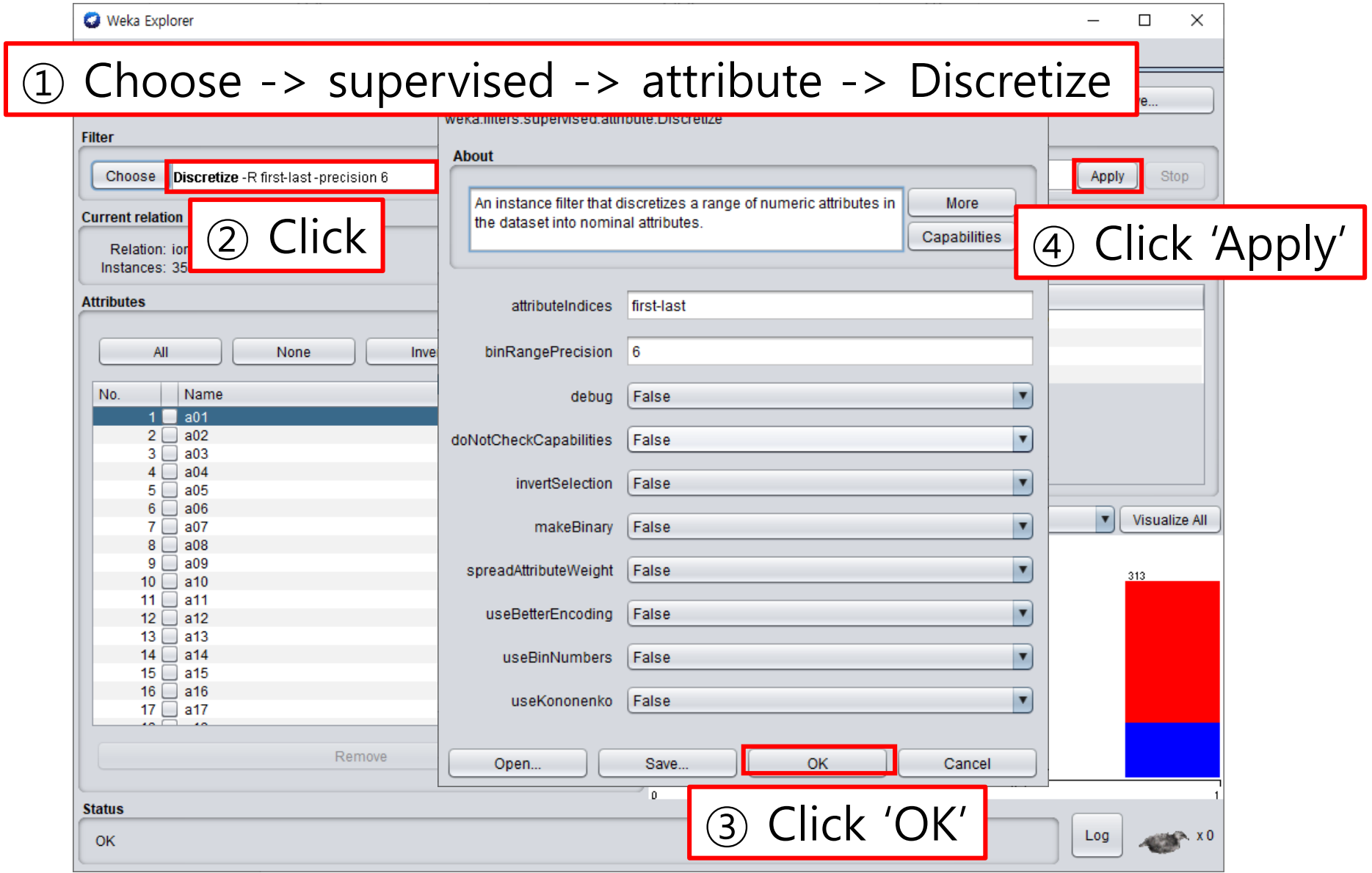


Discretizing numeric attributes

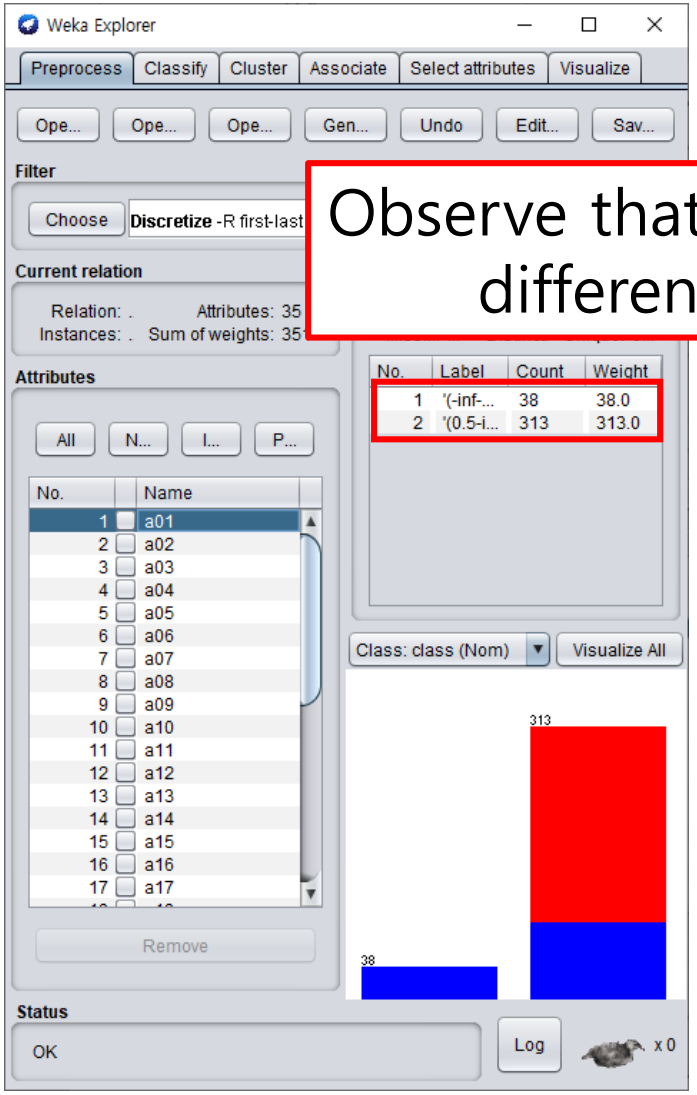
- Run the classifier, then we get a better result

```
Time taken to build model: 0.08 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         332               94.5869 %
Incorrectly Classified Instances        19                5.4131 %
Kappa statistic                          0.8805
Mean absolute error                      0.0797
Root mean squared error                  0.2185
Relative absolute error                 17.3152 %
Root relative squared error             45.5372 %
Total Number of Instances              351

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure  MCC      ROC Area  PRC Area  Cl
               0.889     0.022     0.957      0.889     0.922      0.882    0.935     0.935     b
               0.978     0.111     0.940      0.978     0.959      0.882    0.935     0.937     g
Weighted Avg.  0.946     0.079     0.946      0.946     0.945      0.882    0.935     0.937

=== Confusion Matrix ===

   a   b   <-- classified as
 112  14 |   a = b
   5 220 |   b = g
```

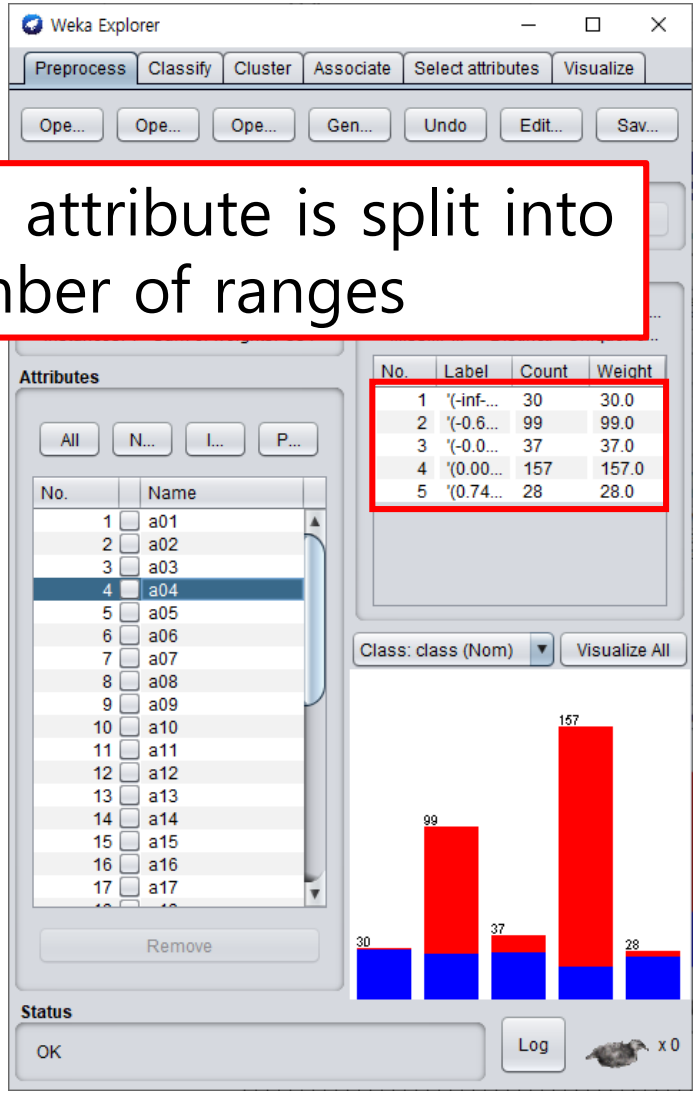
Supervised Discretization



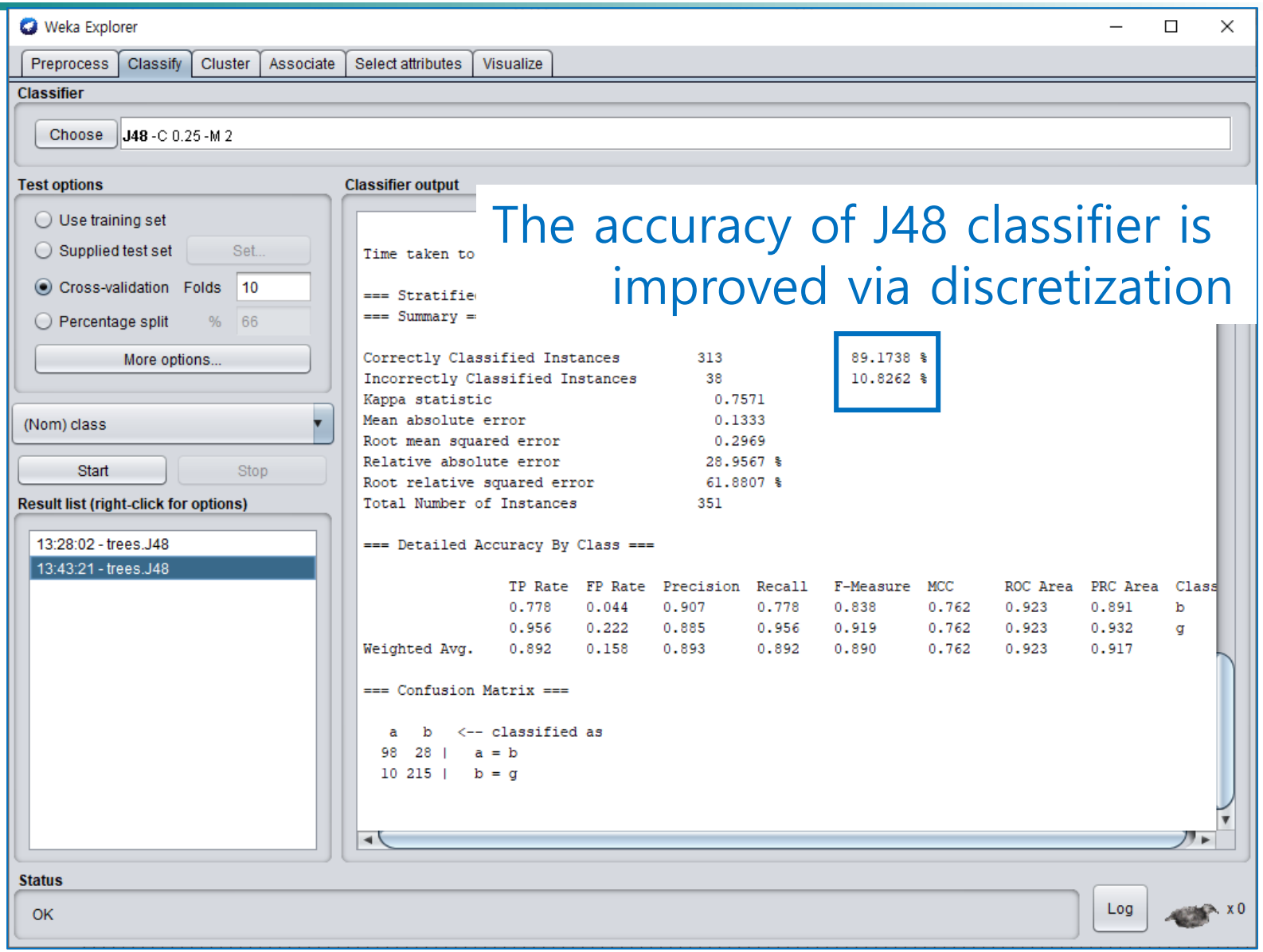
Supervised Discretization

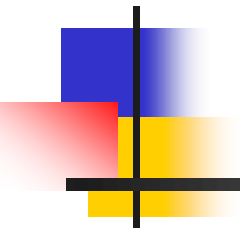


Observe that each attribute is split into different number of ranges



Classification With Discretization





Python - Discretization

Download the Dataset

- Download ionosphere.csv from http://kdd.snu.ac.kr/python/
- Save the csv file in the same directory as the source file (.ipynb)

Import Libraries

```
import pandas as pd
from sklearn.preprocessing import KBinsDiscretizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection ₩
    import KFold, cross_val_score
import matplotlib.pyplot as plt
```

- pandas: a library for data analysis
- KBinsDiscretizer: a class for discretization
- matplotlib: a library for plotting
- MultinomialNB: a class for naïve bayes classifier
- KFold, cross_val_score: a class and a function for K-fold corss validation

Data Preprocessing

```
df = pd.read_csv('ionosphere.csv')
df[:3]
```

	a01	a02	a03	a04	a05	
0	1	0	0.99539	-0.05889	0.85243	0.02
1	1	0	1.00000	-0.18829	0.93035	-0.36
2	1	0	1.00000	-0.03365	1.00000	0.00

Data Preprocessing

Ignore the last column (class label)

```
X = df.values[:, :-1]
y = df.values[:, -1]
```

Only the last column (class label)

- Print labels of first two instances

```
print(y[:2])
```

```
['g' 'b']
```

Data Preprocessing

- Print features of first two instances

```
print(X[:2])
```

```
[[1 0 0.99539 -0.05889 0.8524299999999999 0.02306 0.8339799999999999
  -0.37708 1.0 0.0376 0.8524299999999999 -0.17755 0.59755 -0.44945
  0.60536 -0.38223 0.8435600000000001 -0.38542 0.58212 -0.32192 0.56971
  -0.29674 0.36946 -0.47357 0.56811 -0.51171 0.41078000000000003
  -0.46168000000000003 0.21266 -0.3409 0.42267 -0.54487 0.18641
  -0.4529999999999996]
 [1 0 1.0 -0.18829 0.93035 -0.36156 -0.10868 -0.9359700000000001 1.0
  -0.045489999999999996 0.50874 -0.67743 0.34431999999999996 -0.69707
  -0.51685 -0.97515 0.05499 -0.62237 0.33109 -1.0 -0.13151
  -0.4529999999999996 -0.18056 -0.35734 -0.20332 -0.26569 -0.20468
  -0.18400999999999998 -0.1904 -0.11592999999999999 -0.16626
  -0.06287999999999999 -0.13738 -0.02447]]
```

Discretization

```
discretizer = KBinsDiscretizer(n_bins=5, encode='ordinal',
                               strategy='uniform')
```

- n_bins: the number of bins to produce
- encode
  - "onehot": encode the transformed result with one-hot encoding and return a sparse matrix
  - "onehot-dense": encode the transformed result with one-hot encoding and return a dense array
  - "ordinal": return the bin identifier encoded as an integer value
- strategy
  - "uniform": equal-width
  - "quantile": equal-frequency
  - "kmeans": values in each bin have the same nearest center of a 1D k-means cluster

Discretization

```
discretizer = KBinsDiscretizer(n_bins=5, encode='ordinal',
                               strategy='uniform')
discretizer.fit(X)
print(discretizer.bin_edges_)
```

Build the edges of each bin

Print the edges of bins of all attributes

```
[array([0. , 0.2, 0.4, 0.6, 0.8,
 array([-1. , -0.6, -0.2,  0.2,
 array([-1. , -0.6, -0.2,  0.2,  0.6,  1. ])
 array([-1. , -0.6, -0.2,  0.2,  0.6,  1. ])
 array([-1. , -0.6, -0.2,  0.2,  0.6,  1. ])
```

Discretization

```
discretizer = KBinsDiscretizer(n_bins=5, encode='ordinal',
                               strategy='uniform')
discretizer.fit(X)
print(discretizer.bin_edges_)
```

```
[array([0. , 0.2, 0.4, 0.6, 0.8, 1. ]) array([-inf,  inf])
 array([-1. , -0.6, -0.2,  0.2,  0.6,  1. ])
 arr
 arr
 arr
```

The bins of 1st attributes are
[0.0, 0.2), [0.2, 0.4), [0.4, 0.6), [0.6, 0.8), [0.8, 1.0]

Discretization

```
discretizer = KBinsDiscretizer(n_bins=5, encode='ordinal',
                               strategy='uniform')
discretizer.fit(X)
print(discretizer.bin_edges_)
```

```
[array([0. , 0.2, 0.4, 0.6, 0.8, 1. ]) array([-inf,  inf])
 array([-1. , -0.6, -0.2,  0.2,  0.6,  1. ])
 array([-1. , -0.6, -0.2,  0.2,  0.6,  1. ])
 array([-1. , -0.6, -0.2,
 array([-1. , -0.6, -0.2,
```

The edges becomes [-inf, inf] since all values of 2nd attribute are constant

Plotting the Histogram

The index of 1st attribute

Input the data of 1st attribute values all rows

Input the edges of bins of 1st attribute

```
col_i = 0
plt.hist(X[:, col_i:col_i+1],
         bins=discretizer.bin_edges_[col_i],
         linewidth=1.2, edgecolor='black')
plt.suptitle(df.columns[col_i])
plt.show()
```

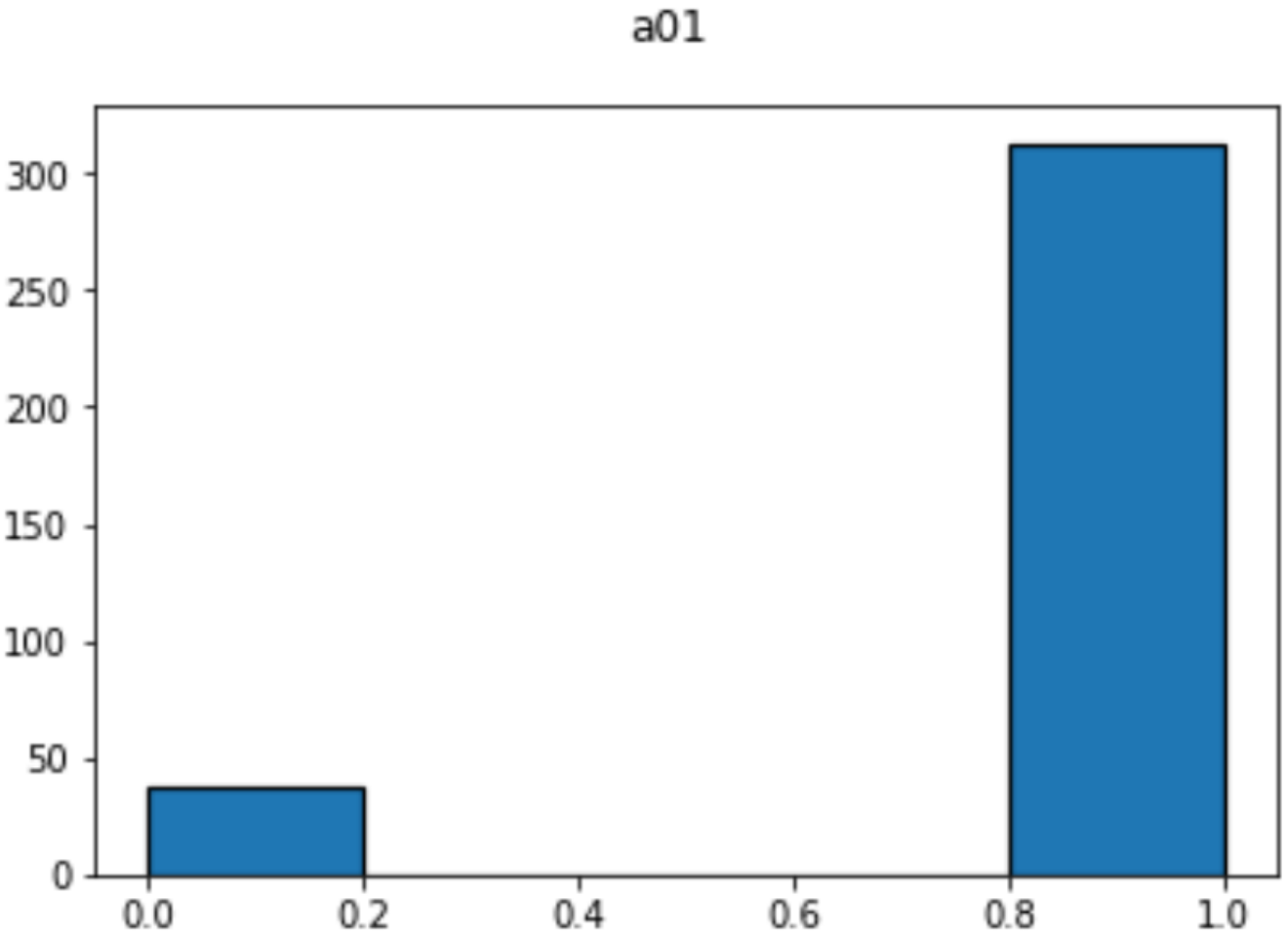
Configurations for showing outlines of bars

Set the title of the figure to the column name

Show the plotted figure

Plotting the Histogram

- The result figure:

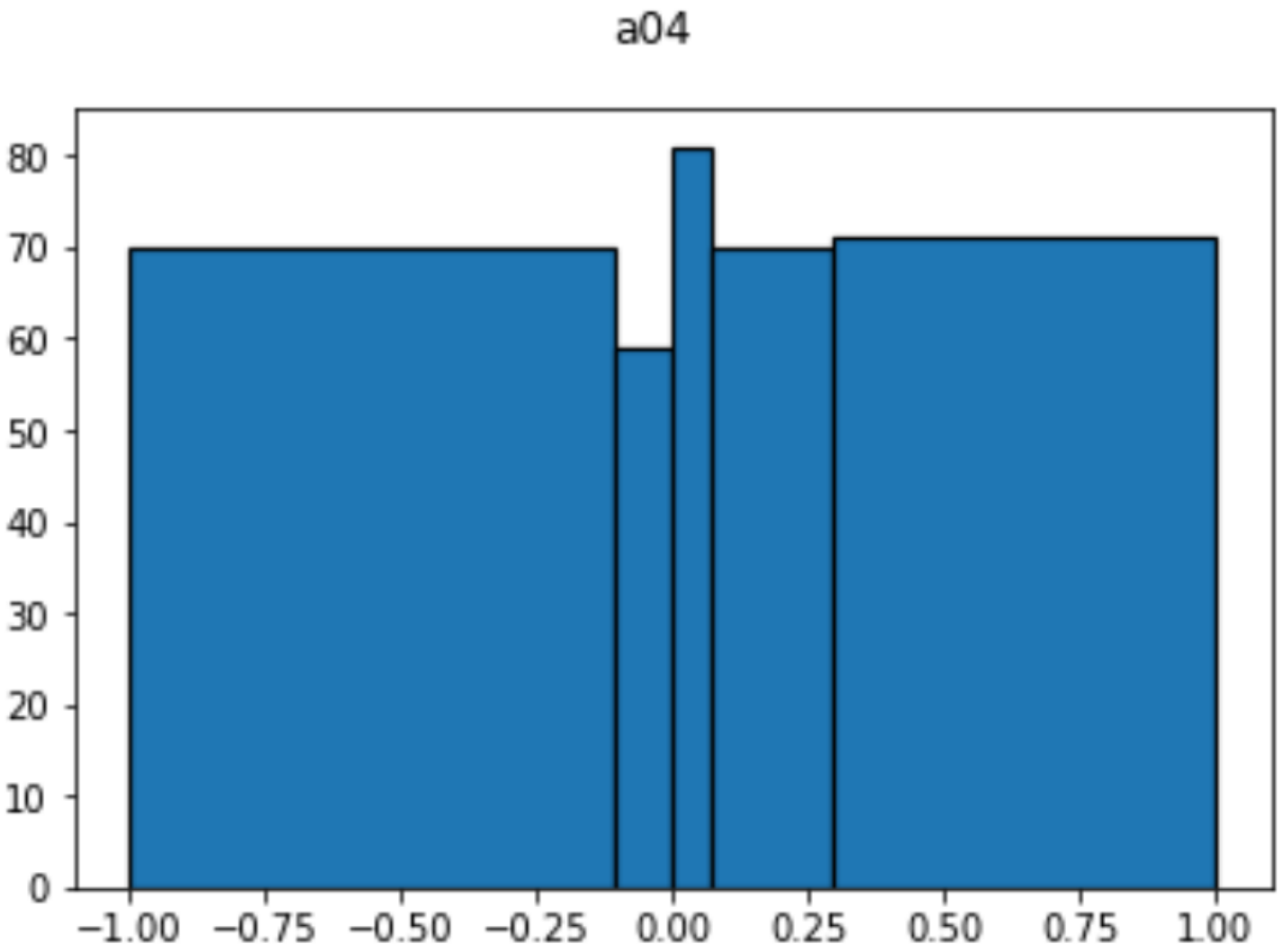


Plotting the Histogram

- Set strategy='quantile', and repeat the others

```
discretizer = KBinsDiscretizer(n_bins=5, encode='ordinal',
                               strategy='quantile')
discretizer.fit(X)
col_i = 3
plt.hist(X[:, col_i:col_i+1],
         bins=discretizer.bin_edges_[col_i],
         linewidth=1.2, edgecolor='black')
plt.suptitle(df.columns[col_i])
plt.show()
```

Plotting the Histogram



Discretization

Convert each value into discretized value

```
tranformed_X = discretizer.transform(X)
print(tranformed_X[:3])
```

Print first 3 rows of transformed data

```
[[4. 0. 3. 1. 2. 2. 2. 0. 4. 2. 3. 0. 2. 0. 2.
  2. 0. 1. 1. 1. 1. 2. 0. 2. 0.]
 [4. 0. 4. 0. 3. 0. 0. 0. 4. 1. 2. 0. 1. 0. 0.
  0. 1. 0. 1. 0. 1. 0. 1. 0. 1.]
 [4. 0. 4. 1. 4. 2. 4. 0. 3. 2. 2. 2. 3. 2. 2.
  2. 1. 2. 1. 2. 1. 3. 1. 2. 0.]]
```

Run a Classification Task for the Transformed Data

```
clf = MultinomialNB()
cv = KFold(
    n_splits=10,
    shuffle=True,
    random_state=0)
scores = cross_val_score(
    clf,
    tranformed_X,
    y,
    cv=cv)
print(scores.mean())
```

Create the classifier object

Create an K-Folds cross-validator object

The number of folds

Whether to shuffle the data before splitting

The random seed

Compute accuracies for K-folds

The object of the naïve bayes classifier

The features and labels

Compute the average accuracy

```
0.7322222222222222
```

Practice

- Change the number of bins
- Change the attribute to plot histogram

Chapter 3: Data Preprocessing

- Data Preprocessing: An Overview
  - Data Quality
  - Major Tasks in Data Preprocessing
- Data Cleaning
- Data Integration
- Data Reduction
- Data Transformation and Data Discretization
- Summary

Summary

- **Data quality**: accuracy, completeness, consistency, timeliness, believability, interpretability
- **Data cleaning**: e.g. missing/noisy values, outliers
- **Data integration** from multiple sources:
  - Entity identification problem
  - Remove redundancies
  - Detect inconsistencies
- **Data reduction**
  - Dimensionality reduction
  - Numerosity reduction
  - Data compression
- **Data transformation and data discretization**
  - Normalization
  - Concept hierarchy generation

References

- D. P. Ballou and G. K. Tayi. Enhancing data quality in data warehouse environments. Comm. of ACM, 42:73-78, 1999
- A. Bruce, D. Donoho, and H.-Y. Gao. Wavelet analysis. *IEEE Spectrum*, Oct 1996
- T. Dasu and T. Johnson. Exploratory Data Mining and Data Cleaning. John Wiley, 2003
- J. Devore and R. Peck. *Statistics: The Exploration and Analysis of Data*. Duxbury Press, 1997.
- H. Galhardas, D. Florescu, D. Shasha, E. Simon, and C.-A. Saita. Declarative data cleaning: Language, model, and algorithms. *VLDB'01*
- M. Hua and J. Pei. Cleaning disguised missing data: A heuristic approach. *KDD'07*
- H. V. Jagadish, et al., Special Issue on Data Reduction Techniques. Bulletin of the Technical Committee on Data Engineering, 20(4), Dec. 1997
- H. Liu and H. Motoda (eds.). *Feature Extraction, Construction, and Selection: A Data Mining Perspective*. Kluwer Academic, 1998
- J. E. Olson. *Data Quality: The Accuracy Dimension*. Morgan Kaufmann, 2003
- D. Pyle. Data Preparation for Data Mining. Morgan Kaufmann, 1999
- V. Raman and J. Hellerstein. Potters Wheel: An Interactive Framework for Data Cleaning and Transformation, VLDB'2001
- T. Redman. *Data Quality: The Field Guide*. Digital Press (Elsevier), 2001
- R. Wang, V. Storey, and C. Firth. A framework for analysis of data quality research. IEEE Trans. Knowledge and Data Engineering, 7:623-640, 1995