

COMP3430 / COMP8430

Data wrangling

Lecture 5: Data quality assessment
and data profiling
(Lecturer: Peter Christen)



Lecture outline

- Data quality assessment
- Data quality dimensions
- Data profiling
- Data visualisation
- Data profiling tools
- Summary

Data quality

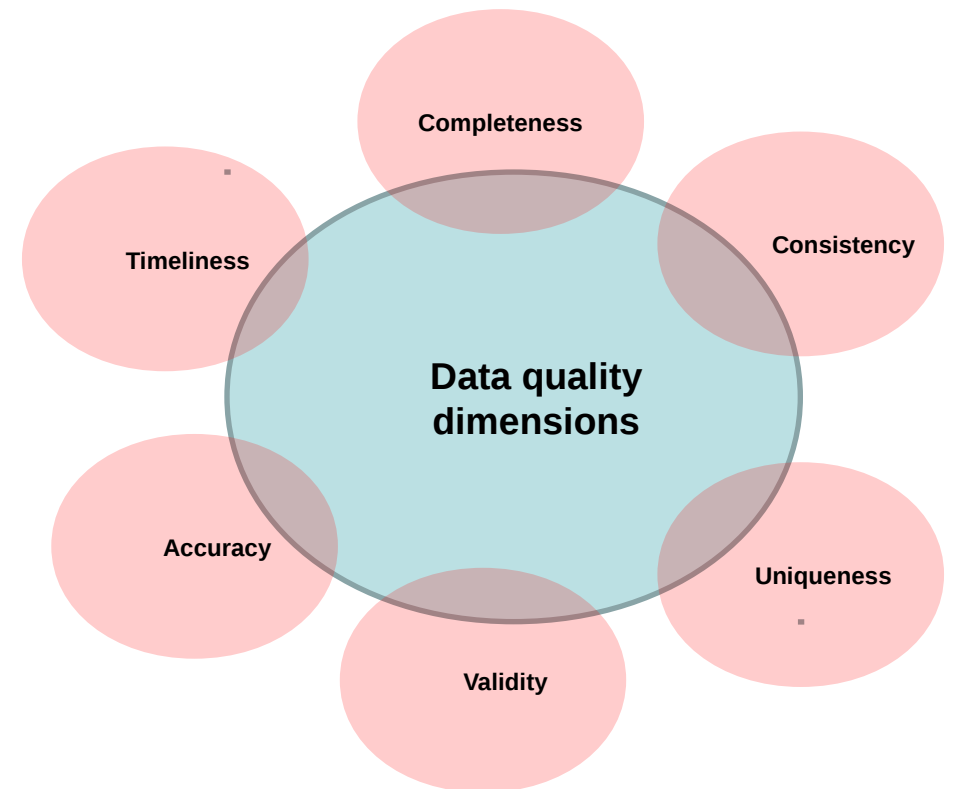
- **Real-world data are dirty**, especially personal data are prone to errors
- Various sources of errors:
 - Missing data
 - Out-of-date data
 - Data variations in different sources
 - Errors/noise/outliers during data entry
 - Misinterpretation of data
- For quality analysis and mining results, data quality is important
 - **Garbage-in garbage-out principle**

Data quality assessment

- **Data quality is specific to context**
 - High quality data for some applications may not be sufficiently good for other applications
 - Often not possible to get data of 100% quality
- Scientific and statistical evaluation of data to determine if they are adequate for intended use
- Data quality is a multi-dimensional concept
 - Both subjective and objective

Data quality dimensions

- Six core dimensions
 - Completeness – no missing data
 - Consistency – across different sources
 - Uniqueness – single view of dataset
 - Validity – meet constraints and rules
 - Accuracy – correct and reflect real data
 - Timeliness – no out-of-date values



The six primary dimensions for data quality assessment, DAMA UK Working Group, 2013

Data quality dimensions (2)

Dimension	Completeness
Definition	Proportion of available data against 100% complete
Measure	Percentage of missing values
Example	Emergency contact details of children in school admin database: 290 out of 300 records have the contact value yielding to $290/300 * 100 = 96.7\%$ completeness

Data quality dimensions (3)

Dimension	Consistency
Definition	No difference between two or more representations of a record
Measure	Percentage of record representations with the same format
Example	The school admin database (300 records) and the school register database (200 records) have 400 out of 500 students' records with the same telephone numbers, resulting in $400/500 * 100 = 80\%$ consistency

Data quality dimensions (4)

Dimension	Uniqueness
Definition	No duplicate records in a dataset
Measure	Ratio of number of records in a dataset and number of real entities
Example	The school admin database has 300 student records, but the number of actual students is 280, indicating a uniqueness of $280/300 \times 100 = 93.3\%$

Data quality dimensions (5)

Dimension	Validity
Definition	Data confirming to the syntax (format, type, range)
Measure	Comparison between the data and the metadata
Example	The age values in a student database must be numeric and in the range between 5 and 18; postcodes must be 4 digits containing numerical characters

Data quality dimensions (6)

Dimension	Accuracy
Definition	Degree to which data correctly describes the real entity
Measure	Percentage of accurate representations of entities in a dataset
Example	50 records of students in a database of 300 records have wrong values for postcode and/or suburb values (such as Braddon, 7612), giving $250/300 * 100 = 83.3\%$ accuracy

Data quality dimensions (7)

Dimension	Timeliness
Definition	Degree to which data represent a real entity in a point in time
Measure	Percentage of records with up-to-date values
Example	30 out of 300 students in a student database have not updated their address change, resulting in $270/300 * 100 = 90\%$ records with timely information

Data quality dimensions (8)

- Other dimensions
 - Usability – relevant and accessible
 - Understandability – easy to comprehend
 - Flexibility – compatible and easy to manipulate
 - Volume – appropriate amount of data for the application
 - Privacy / confidence – data protection and security
 - Value – cost/benefit of data

Data profiling

- Examining, exploring, and collecting statistics and information about data
- To determine the *metadata* about a data set
- Data profiling provides insights and allows identifying data quality requirements
 - For more thorough data quality assessment
 - A process of discovery

Data profiling versus data mining

- Data profiling
 - **Goal:** discovers information and metadata
 - **Input:** raw data
 - **Output:** information about attributes (columns)
- Data mining / analytics
 - **Goal:** discovers interesting knowledge and patterns
 - **Input:** pre-processed and cleaned data
 - **Output:** information about records (rows)

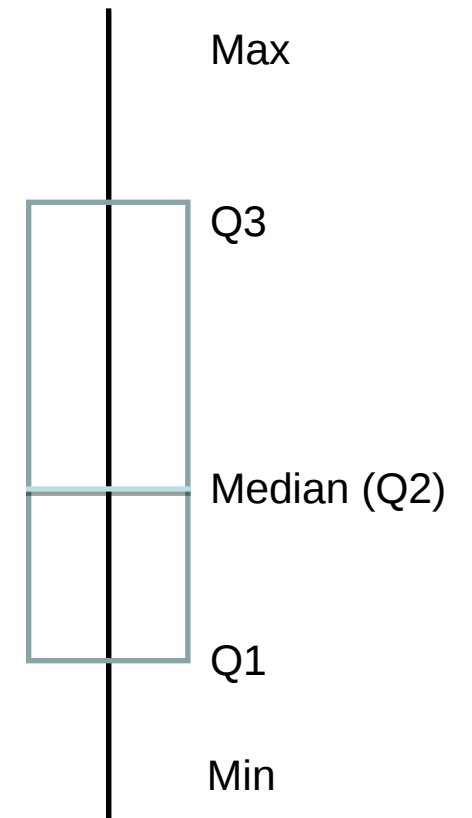
Single versus multiple column profiling

- Single column
 - Basic statistics of a single column
 - Discover common properties and statistics of a single attribute that are assumed to be of same type
 - Complexity: Number of rows
- Multiple column
 - Discover joint properties, dependencies and correlations, and statistics of multiple attributes
 - Complexity: Number of columns * Number of rows

Statistics (single column)

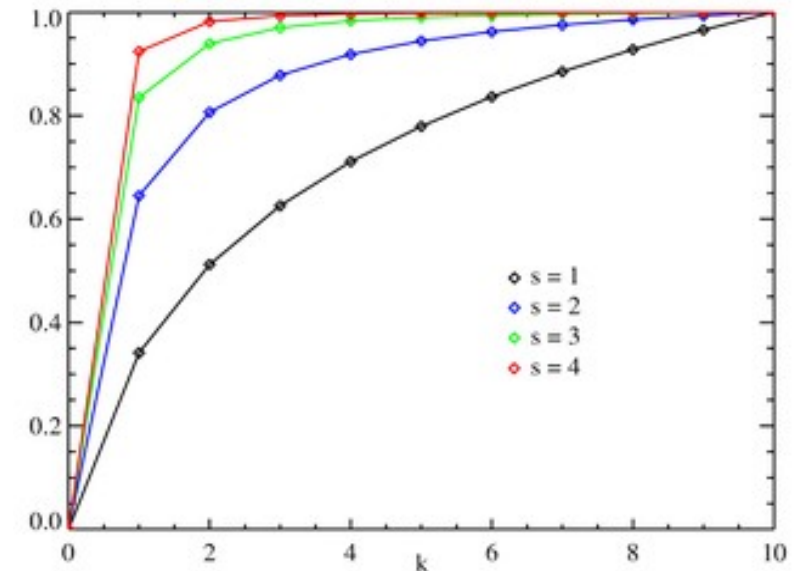
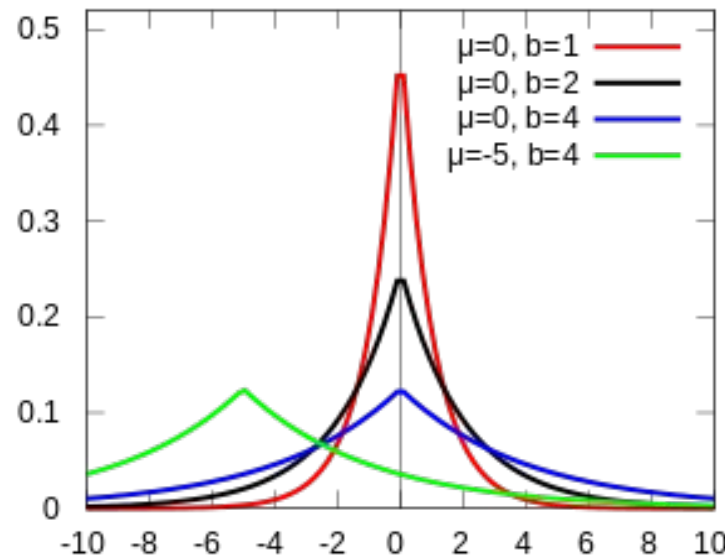
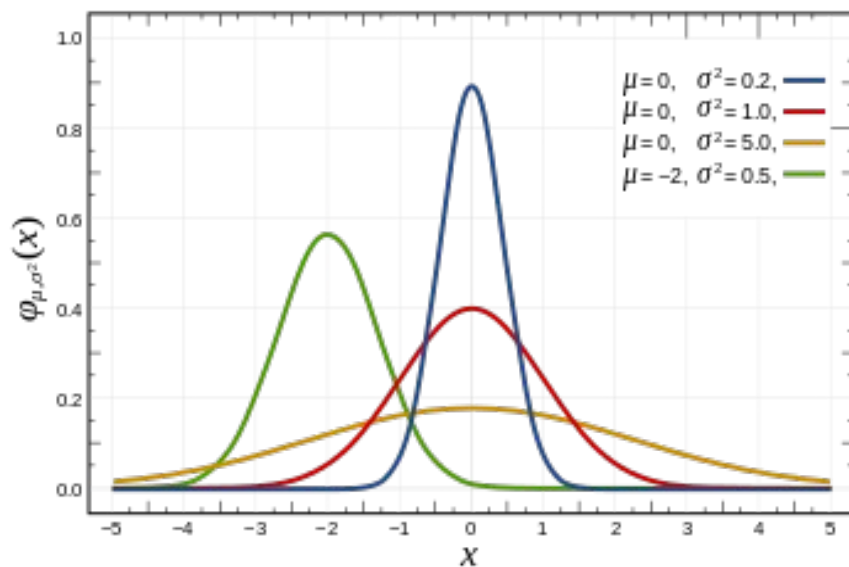
- Number of unique (distinct) values
- Number of missing values
- Minimum and maximum values
- Average (mean) and median
- Quartiles (25%, 75%)
- Variance and standard deviation

5-number summary



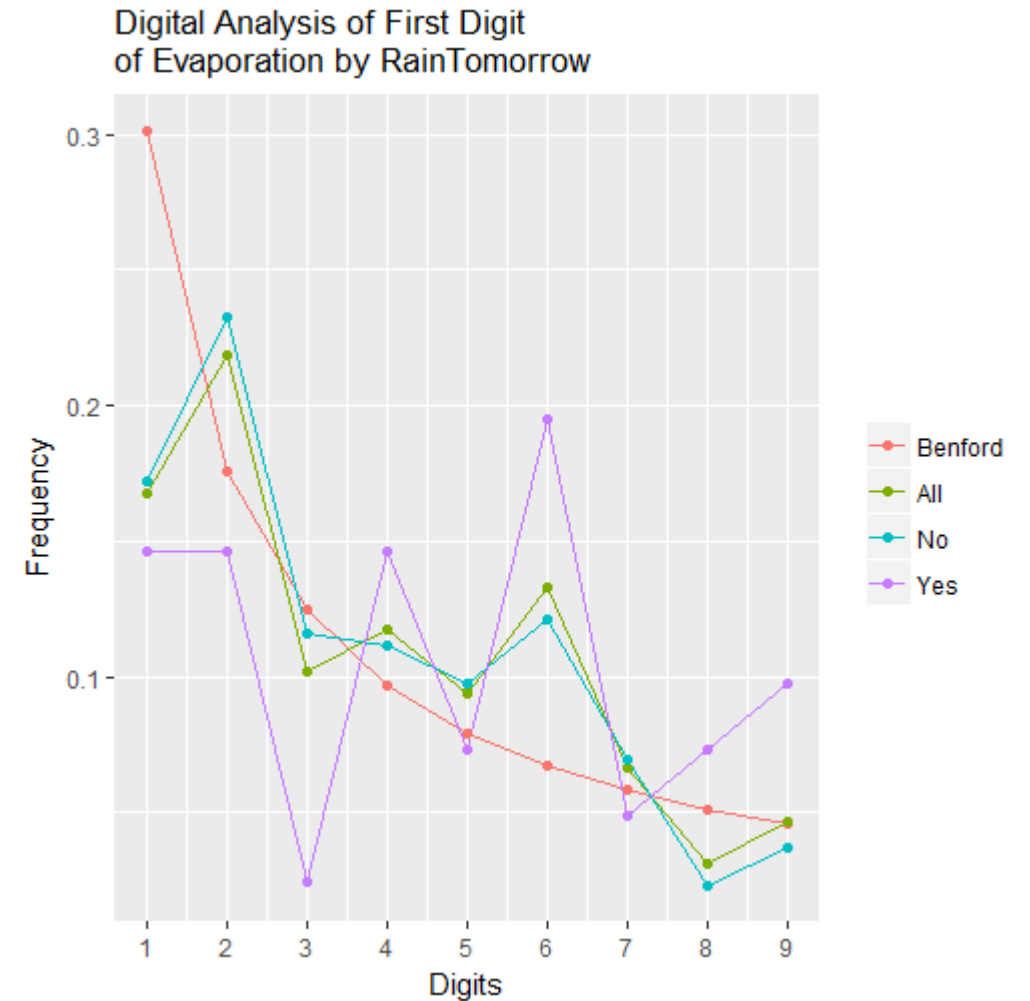
Distributions

- Examine whether data follow some well-known distributions (such as normal or Laplace, skewed, symmetric)
- Names generally follow Zipf distribution – few frequent and many rare



Benford's law

- First digit law
 - Distribution of first digits in natural numbers
 - Digit 1 occurs in about 30% (much greater than uniform distribution of 11.1% for each of the 9 digits)
 - Digit 9 only occurs in about 5%
 - Occurs in street numbers, stock prices, death rates, etc.
- Can be used in fraud detection (how? Think about it! To be discussed..)

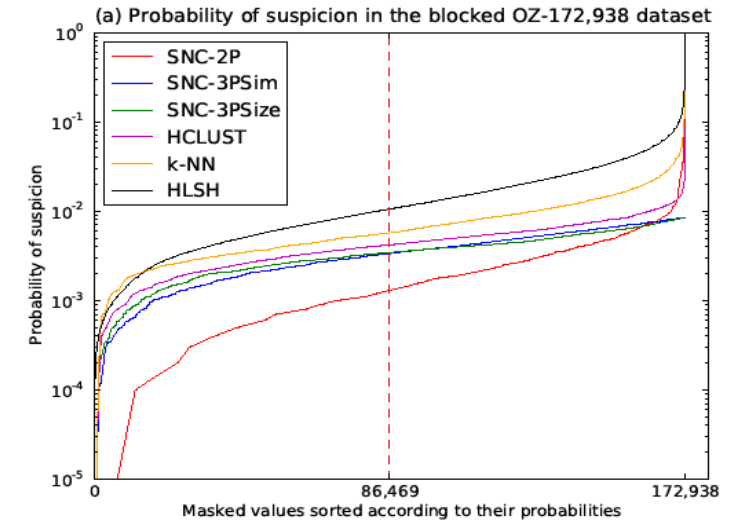
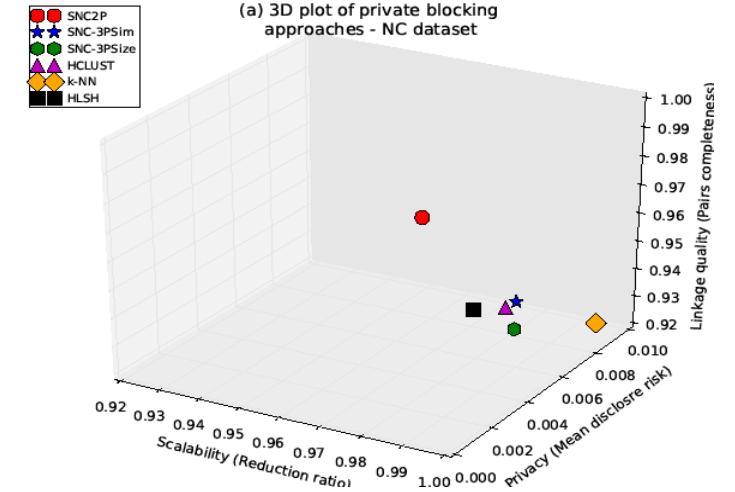
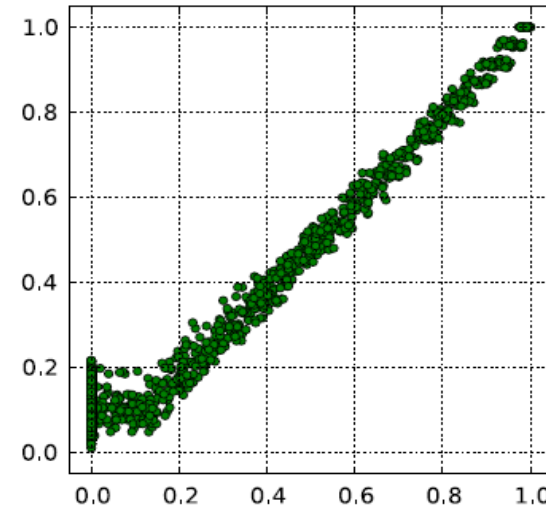
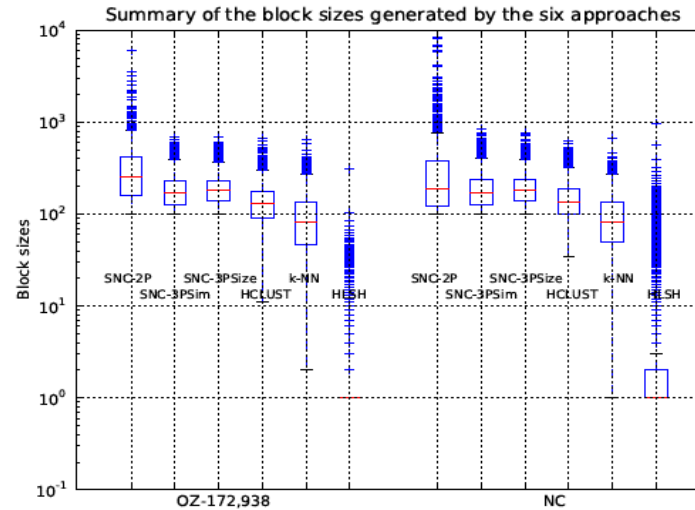
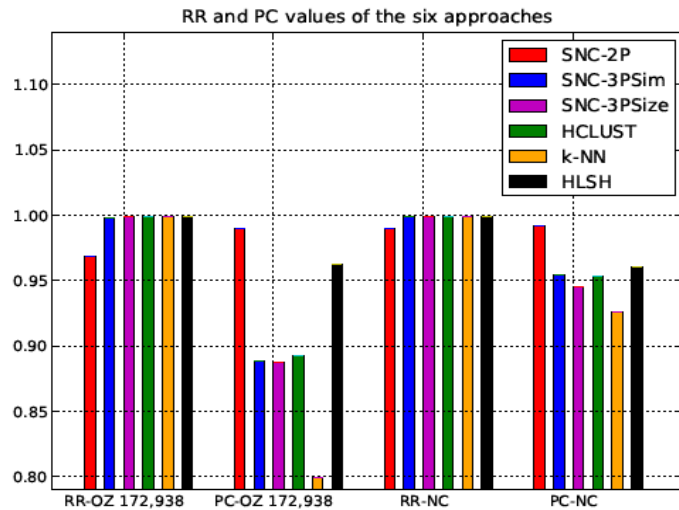


Dependencies

- Dependencies / correlations between attributes
 - Example: employment and income, age and weight
- The extent to which two variables (attributes) have a linear or non-linear relationship with each other
- Several correlation coefficients, including the Pearson coefficient, can be used to measure the correlation and dependency between attributes

Data visualisation

- Bar plots
- Box plots
- Scatter plots
- Line plots

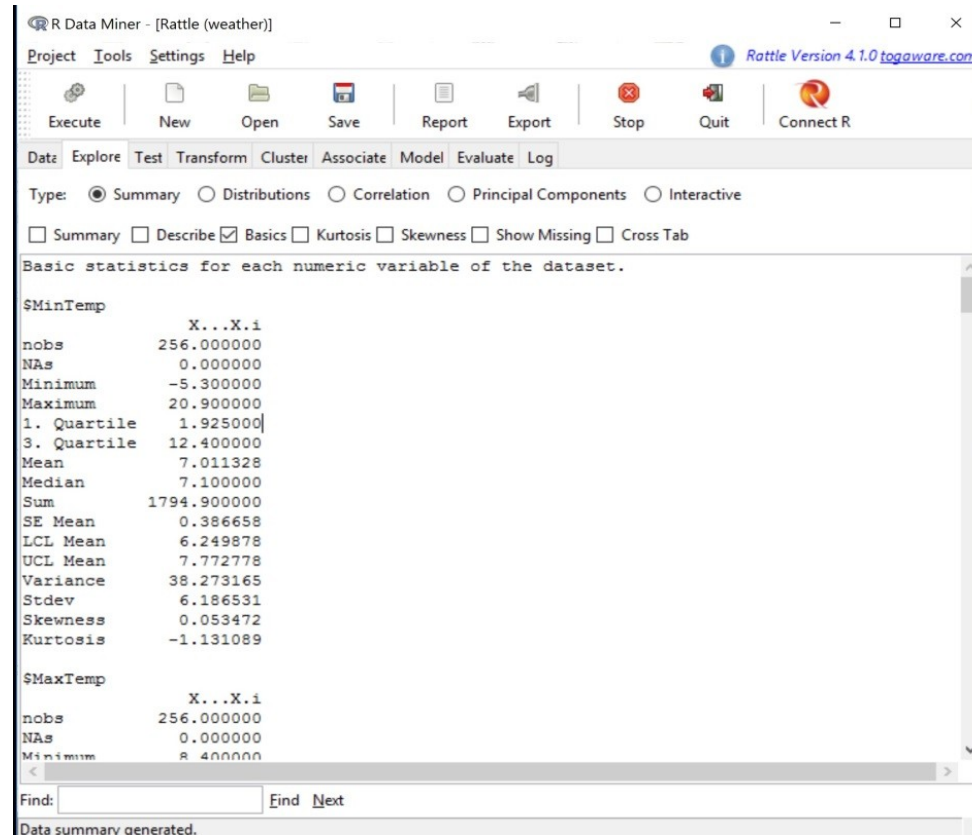


Data profiling tools

- Various commercial software:
 - IBM InfoSphere Information Analyzer, Oracle Enterprise Data Quality, SAP, Informatica Data Explorer, Trillium Software Data Profiling, Microsoft SQL Server Integration Services Data Profiling Task and Viewer
- Open source software:
 - Rattle (based on R programming language)
 - Python modules such as Pandas

Data profiling with Rattle (1)

- Rattle weather dataset
 - Basic statistics
 - Kurtosis
 - Skewness
 - Missing values
 - Cross tab

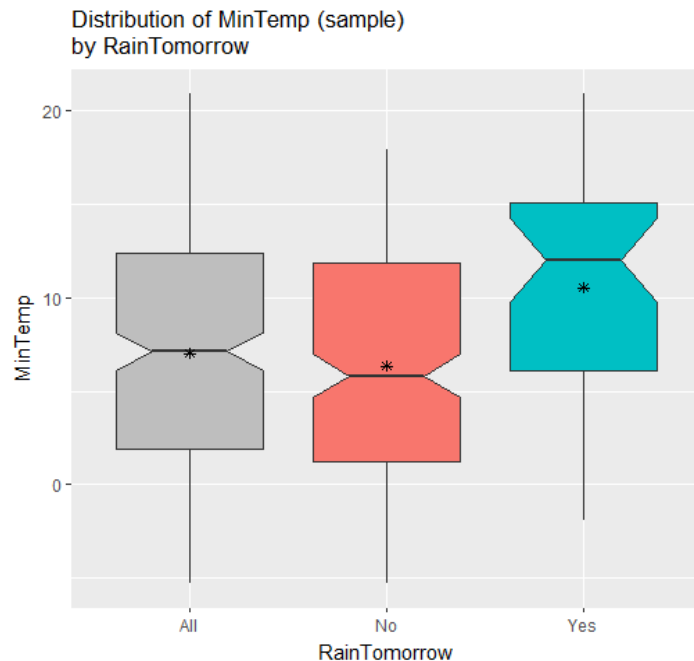


The screenshot shows the Rattle software interface with the 'Basic statistics' tab selected. The output displays summary statistics for two numeric variables: \$MinTemp and \$MaxTemp. The statistics include the number of observations (nobs), number of missing values (NAs), minimum, maximum, quartiles, mean, median, sum, standard error (SE), confidence intervals (LCL, UCL), variance, standard deviation (Stdev), skewness, and kurtosis.

Variable	Statistic	Value
\$MinTemp	nobs	256.000000
	NAs	0.000000
	Minimum	-5.300000
	Maximum	20.900000
	1. Quartile	1.925000
	3. Quartile	12.400000
	Mean	7.011328
	Median	7.100000
	Sum	1794.900000
	SE Mean	0.386658
	LCL Mean	6.249878
	UCL Mean	7.772778
	Variance	38.273165
\$MaxTemp	nobs	256.000000
	NAs	0.000000
	Minimum	8.400000
	Maximum	20.900000
	1. Quartile	12.400000
	3. Quartile	17.500000
	Mean	14.500000
	Median	14.000000
	Sum	3712.000000
	SE Mean	0.386658
	LCL Mean	13.613142
	UCL Mean	15.386858
	Variance	38.273165

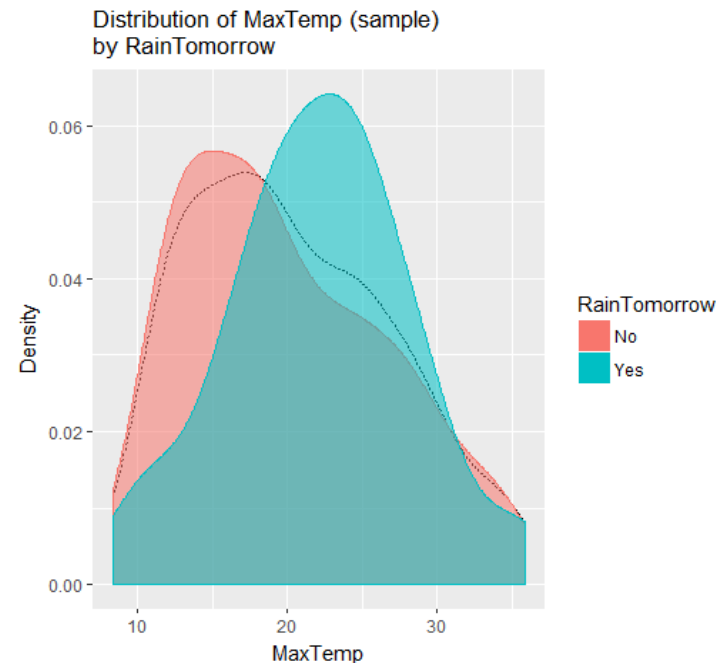
Data profiling with Rattle (2)

- Numerical data distributions



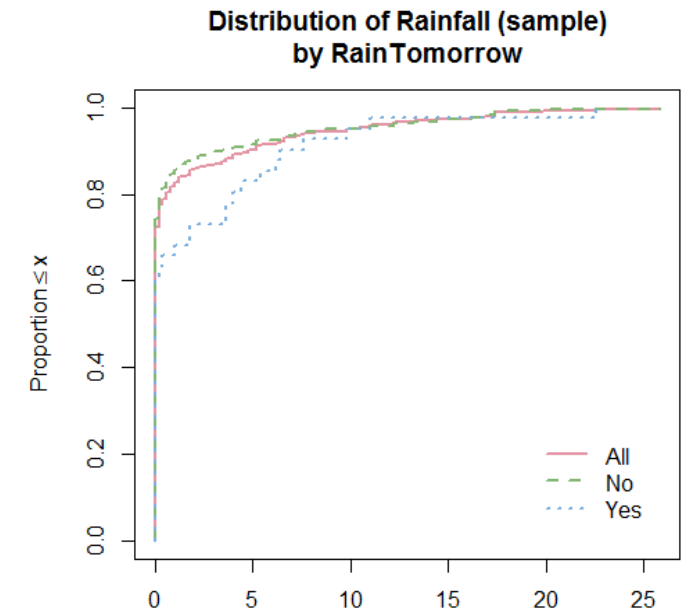
Rattle 2017-Feb-13 09:32:20 dinusha

Box plot



Rattle 2017-Feb-13 09:34:11 dinusha

Histogram

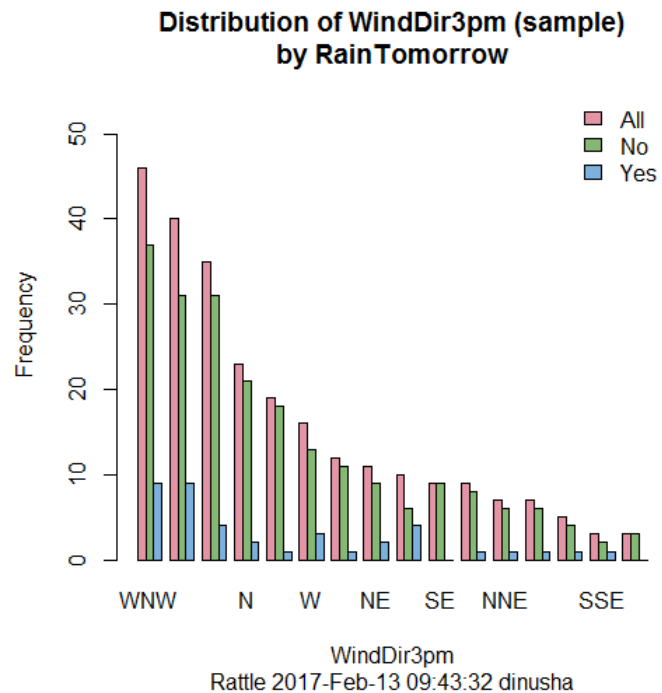


Rattle 2017-Feb-13 09:35:32 dinusha

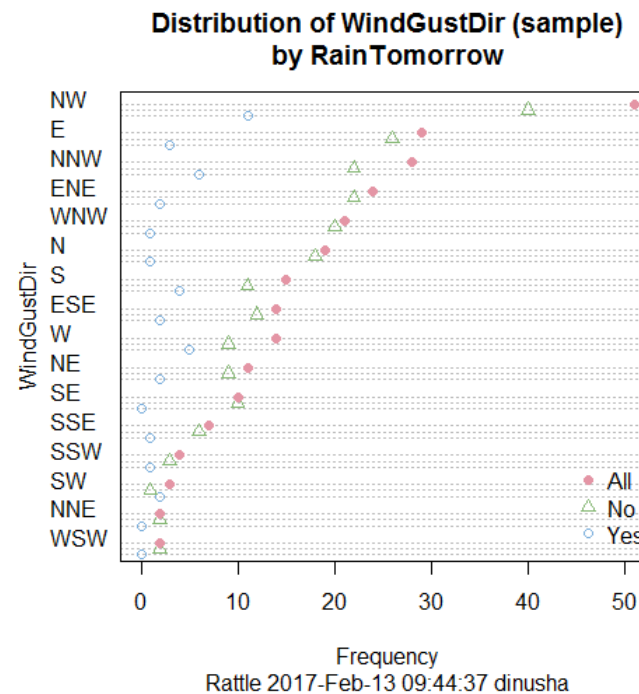
Cumulative

Data profiling with Rattle (3)

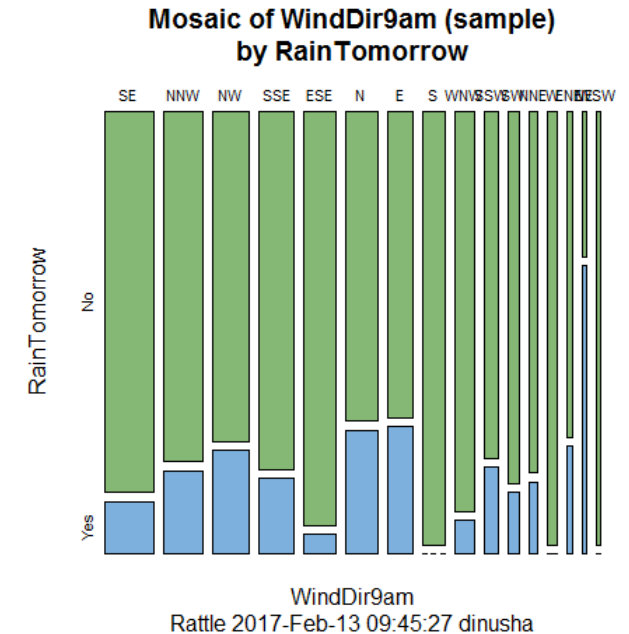
- Categorical data distributions



Bar plot



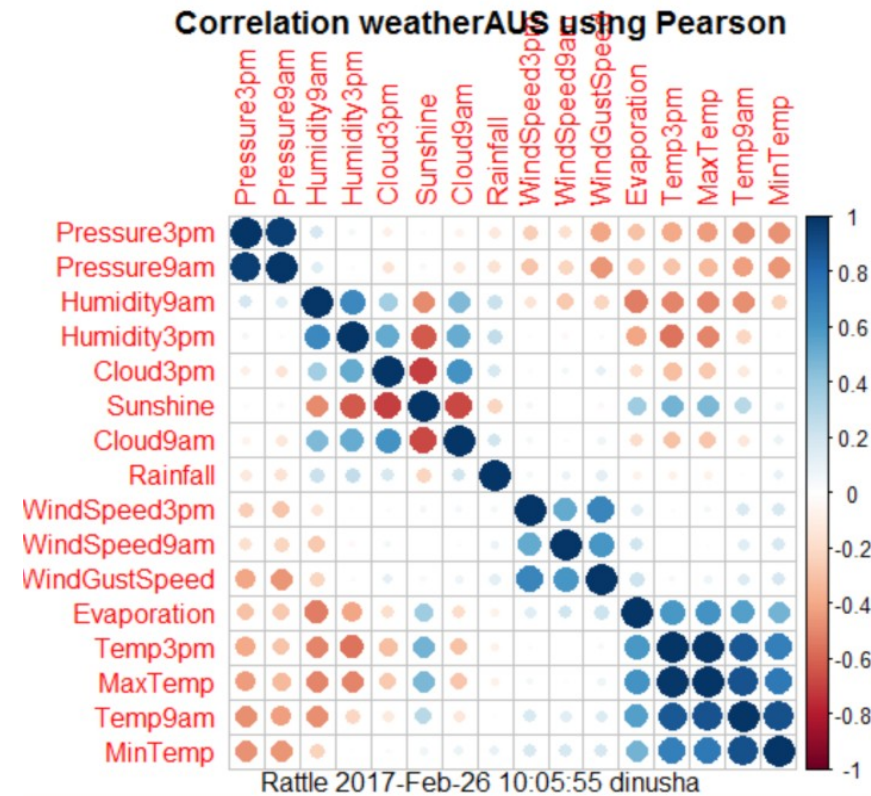
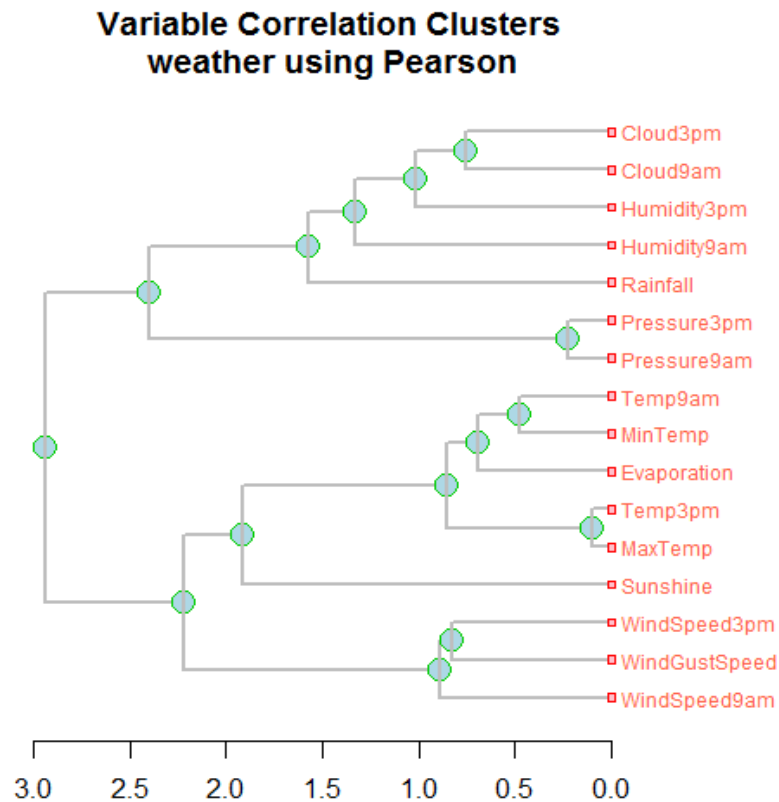
Dot plot



Mosaic

Data profiling with Rattle (4)

- Correlations



Data profiling with Python (1)

- Data exploration using pandas

```
import pandas as pd
```

```
df = pd.read_csv("weather.csv")
```

- First 10 rows

```
df.head(10)
```

- Summary of numerical attributes

```
df.describe()
```

- Frequency table for categorical attributes

```
df['WindDir3pm'].value_counts()
```

Data profiling with Python (2)

- Data distributions

```
df['MaxTemp'].hist(bins=50)
```

```
df.boxplot(column='MaxTemp')
```

```
df.boxplot(column='MaxTemp', by='Location')
```

- Check missing values

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

- Cross tab

```
ct = pd.crosstab(df['WindDir9am'], df['RainToday'])
```

```
ct.plot(kind='bar', stacked=True, color=['red','blue'], grid=False)
```

Summary

- Data profiling is a crucial step in the data wrangling pipeline
- The goal is to discover, assess, and understand meta-data of a data set
- Next generation data profiling tools and techniques:
 - Automated data profiling
 - Active learning in data profiling and cleaning
 - Advanced and interactive data visualisation