

EE2211 Pre-Tutorial 2

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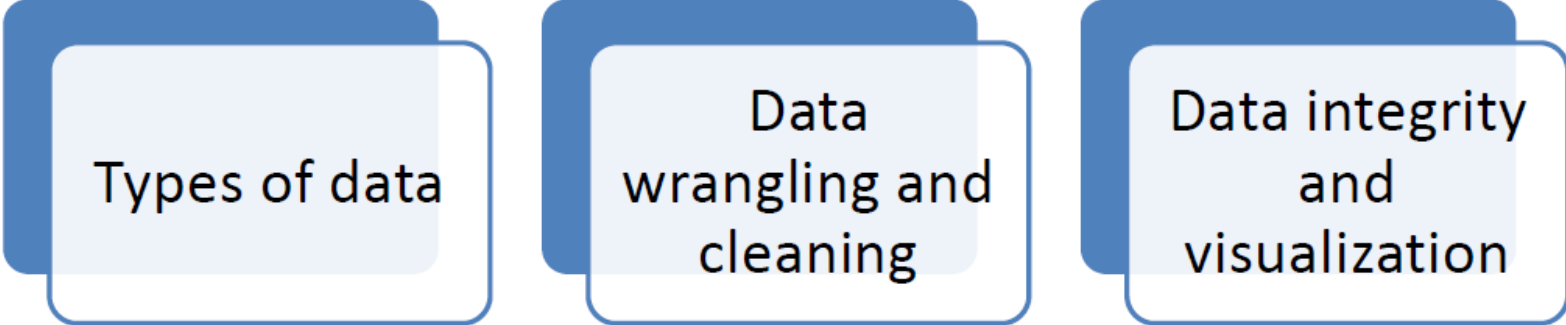


Agenda

- Recap
- Self-learning
- Tutorial 2



Recap



Types of data

Data
wrangling and
cleaning

Data integrity
and
visualization

View Data by Scale/Level of Measurement

Nominal

- Lowest Level of Measurement
- Discrete Categories
- **NO** natural order
- Estimating a **mean**, **median**, or **standard deviation**, would be meaningless.
- Possible Measure: **mode**, **frequency distribution**

Ordinal

- **Ordered** Categories
- Relative Ranking
- Unknown “distance” between categories: orders matter but not the difference between values
- Possible Measure: **mode**, **frequency distribution** + **median**

View Data by Scale/Level of Measurement

Interval

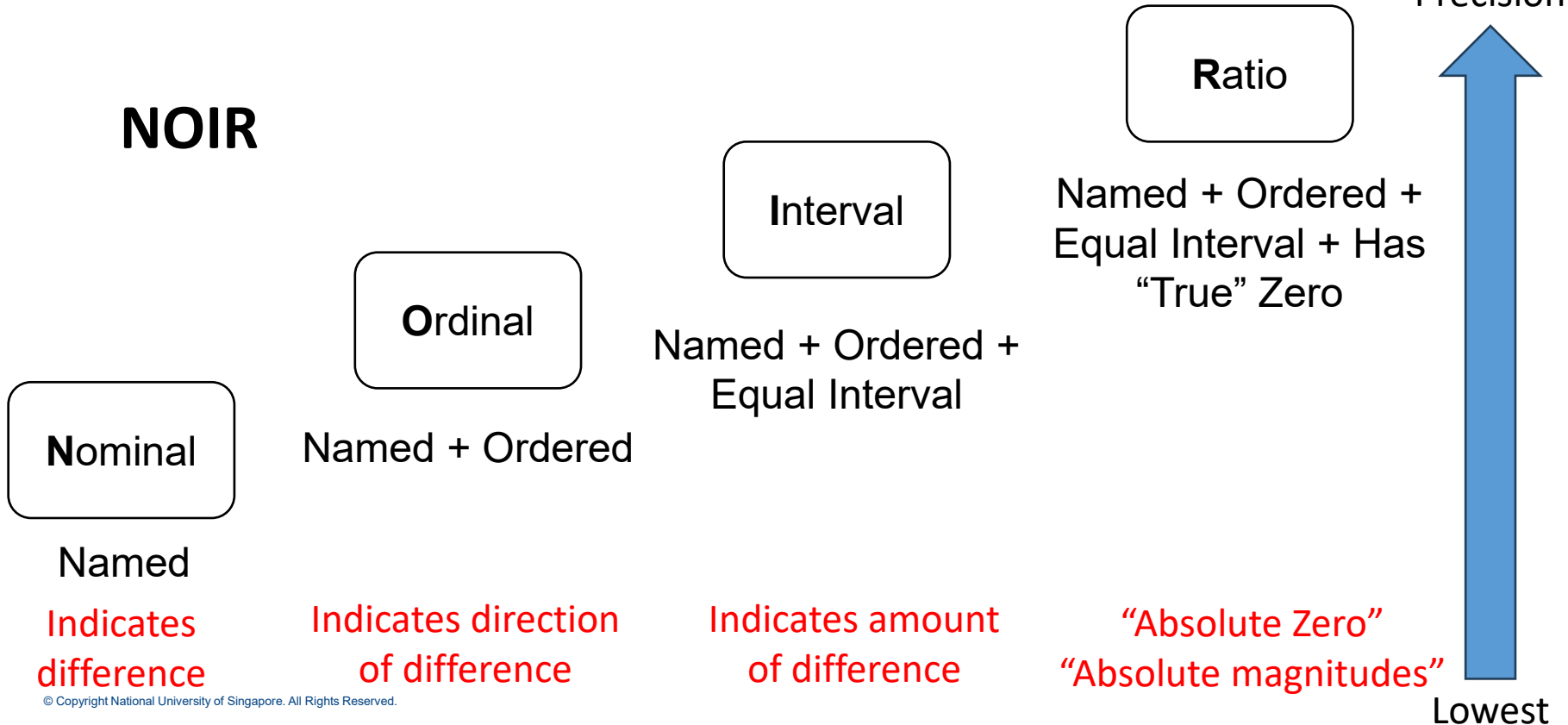
- Ordered Categories
- Well-defined “**unit**” measurement:
- **Equal Interval**
- **Zero is arbitrary** (not absolute), in many cases human-defined
- **Ratio is meaningless**
- Possible Measure: mode, frequency distribution + median + mean, standard deviation, addition/subtraction

Ratio

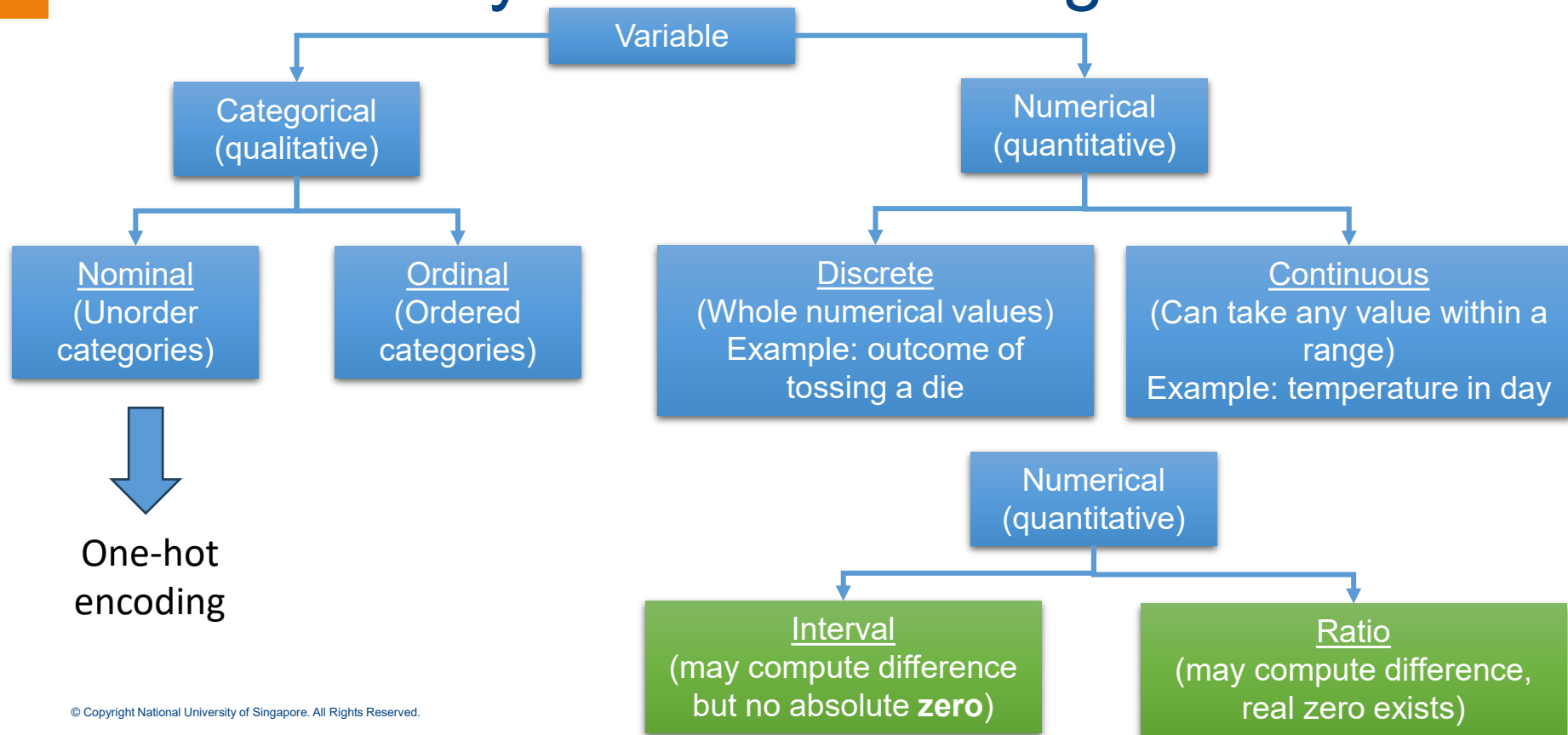
- Most precise and **highest** level of measurement
- Ordered
- Equal Intervals
- **Natural Zeros**
- Possible Measure: mode, frequency distribution + median + mean, standard deviation, addition/subtraction + multiplication and division (ratio)

View Data by Levels/Scales of Measurement

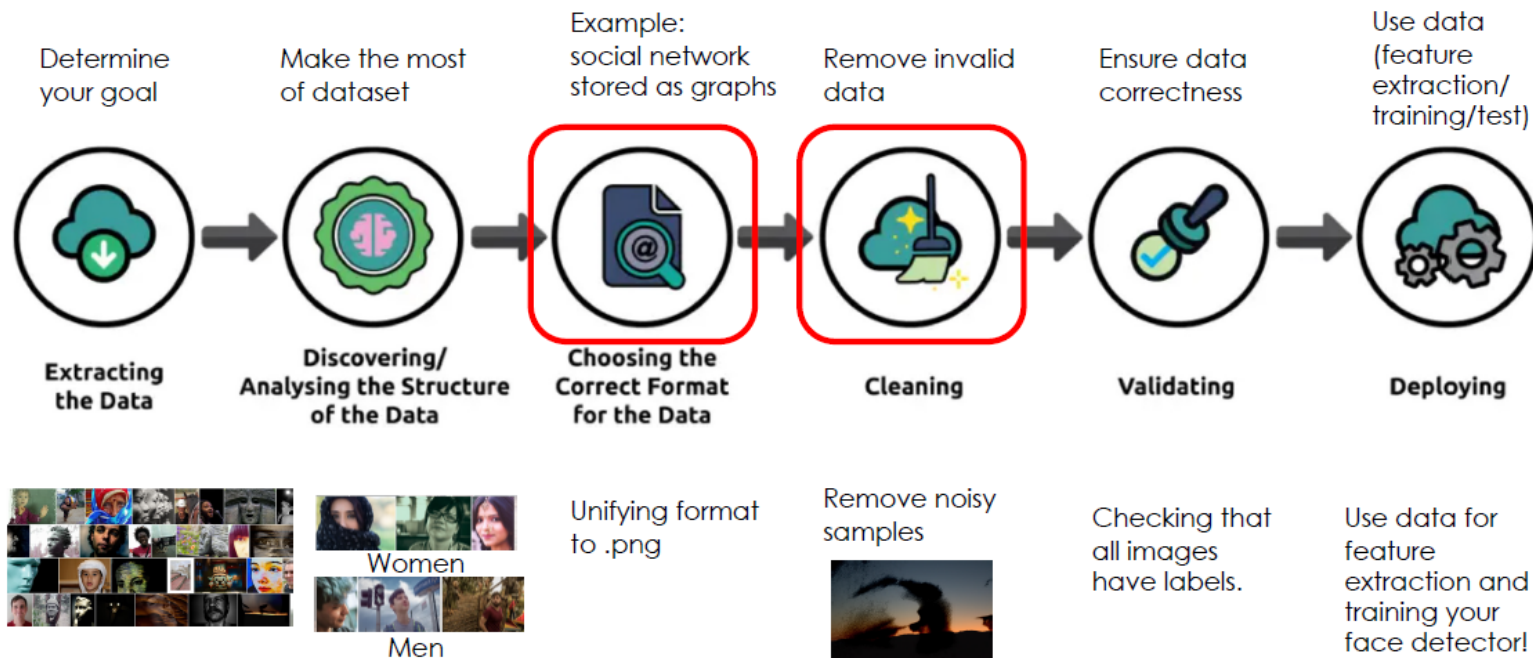
NOIR



View Data by Numerical/Categorical



Data Wrangling



Collect Human Face Images for Face Detector

Binary Coding

- One-hot encoding: unify several entities within one vector

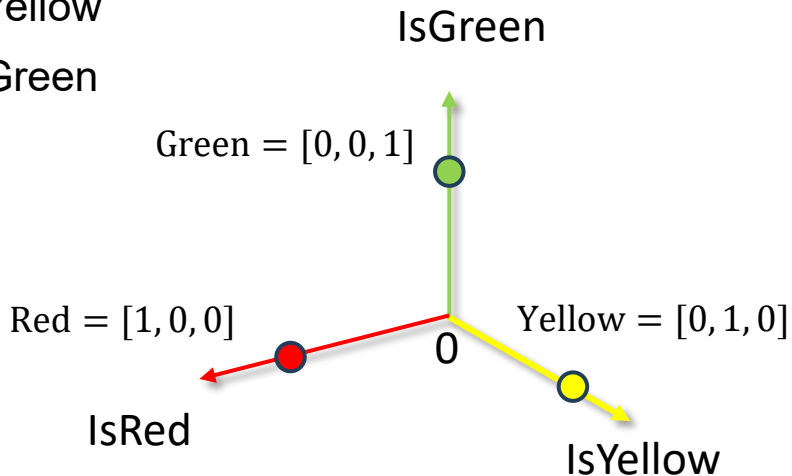
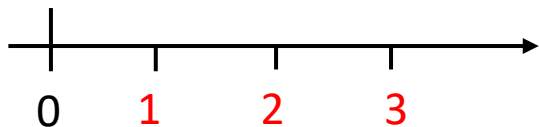
| | Color | | |
|------------|-------|----------|---------|
| | IsRed | IsYellow | IsGreen |
| Apple | 1 | 0 | 0 |
| Banana | 0 | 1 | 0 |
| Watermelon | 0 | 0 | 1 |

Red

Yellow

Green

color $\in \{\text{Red, Yellow, Green}\}$



Normalization

Often we have feature vectors in which features are on different scales.

For example:

$$x_1 = \begin{bmatrix} x_{11} \\ x_{12} \end{bmatrix}, \quad \dots, x_n = \begin{bmatrix} x_{n1} \\ x_{n2} \end{bmatrix}$$

First feature: Height $\in [140, 195]$

Second feature: Shoe size $\in [6, 13]$

- So even if both features are deemed equally “important”, unfortunately, any machine learning method would place more importance on the first feature because of its larger values, which is not ideal.
- Thus, we have to scale or normalize the features so that their dynamic ranges are roughly the same.

Normalization

- Min-max scaling

Define the minimum and maximum values of feature 1 to be

$$\text{Max} \quad x_{max,1} = \max_{1 \leq i \leq n} x_{i1}$$

$$\text{Min} \quad x_{min,1} = \min_{1 \leq i \leq n} x_{i1}$$

Then we create the normalized 1st features associated to each training sample as

$$\bar{x}_{i1} = \frac{x_{i1} - x_{min,1}}{x_{max,1} - x_{min,1}}$$

We can do this for all features so that, in some sense, they are all “normalized”.

Normalization

- Z-Score

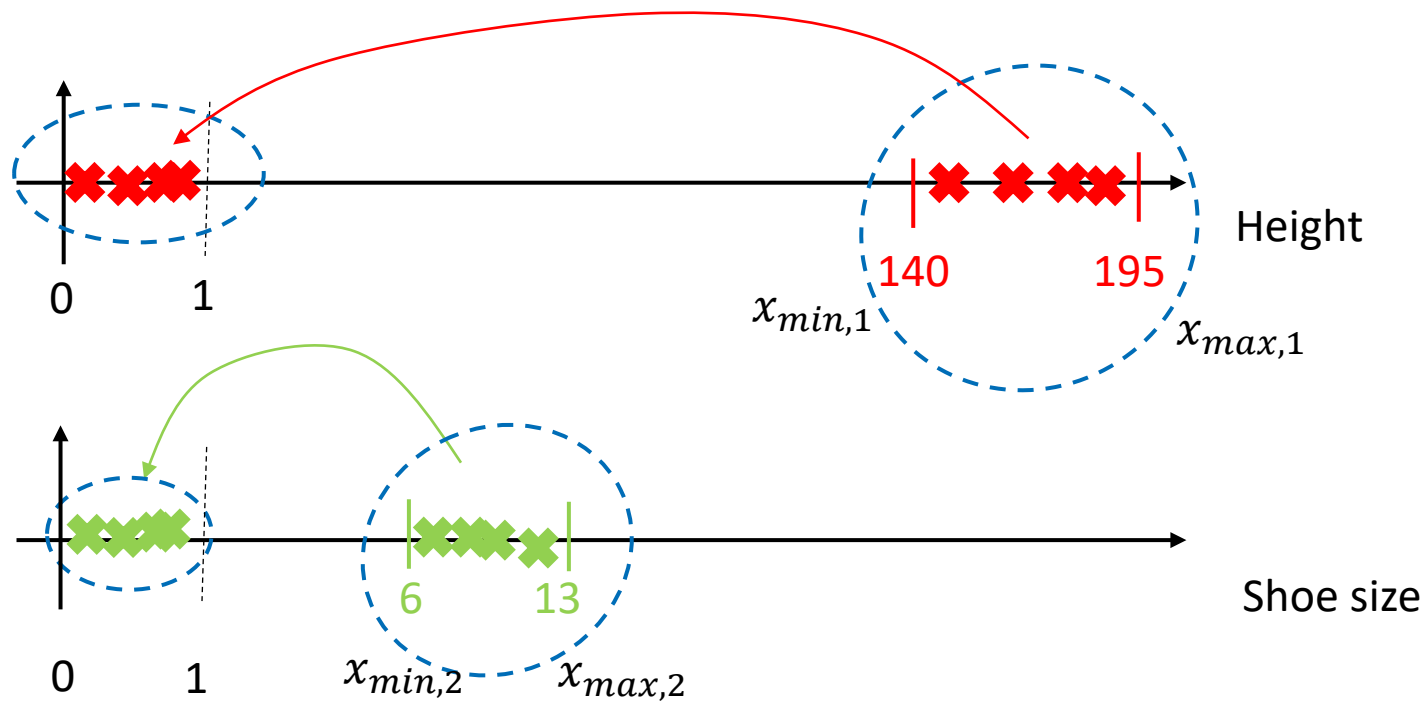
First we calculate the empirical mean and empirical standard deviation of each feature.

$$\mu_1 = \frac{1}{n} \sum_{i=1}^n x_{i1} \quad \text{and} \quad \sigma_1 = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_{i1} - \mu_1)^2}$$

Then we create the normalized 1st features associated to each training sample as

$$\bar{x}_{i1} = \frac{x_{i1} - \mu_1}{\sigma_1}$$

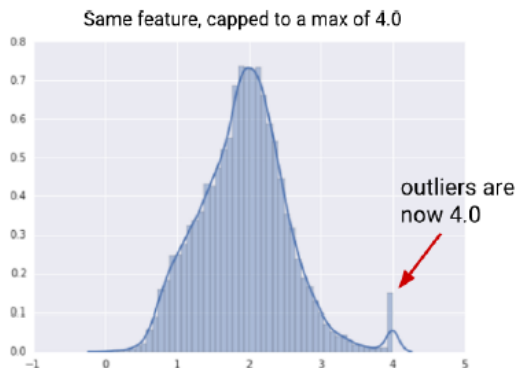
Normalization



Data Cleaning

- The process of detecting and correcting (or removing) corrupt or inaccurate records from a record set, table, or database.

- Example:
 - Clipping outliers



- Handling missing features

| Students | Year of Birth | Gender | Height | GPA |
|-------------|---------------|--------|--------|------|
| Tan Ah Kow | 1995 | M | 1.72 | 4.2 |
| Ahmad Abdul | X NA | M | 1.65 | 4.1 |
| John Smith | 1995 | M | 1.75 | X NA |
| Chen Lulu | 1995 | F | X NA | 4.0 |
| Raj Kumar | 1995 | M | 1.73 | 4.5 |
| Li Xiuxiu | 1994 | F | 1.70 | 3.8 |



Data Cleaning: Handling missing features

1. Removing the examples with missing features from the dataset
 - Can be done if the dataset is big enough so we can sacrifice some training examples
2. Using a learning algorithm that can deal with missing feature values
 - Example: random forest
3. Using a data imputation technique

Data Cleaning: Handling missing features: Imputation

- Method 1. Replace the missing value of a feature by an average value of this feature in the dataset:

$$\hat{x}^{(j)} \leftarrow \frac{1}{N} \sum_{i=1}^N x_i^{(j)}$$

- Method 2. Highlight the missing value
 - Replace the missing value with a value outside the normal range of values.
 - For example, if the normal range is $[0, 1]$, then you can set the missing value to -1 .
 - Enforce the learning algorithm to learn what is best to do when the feature has a value significantly different from regular values.

Data Integrity

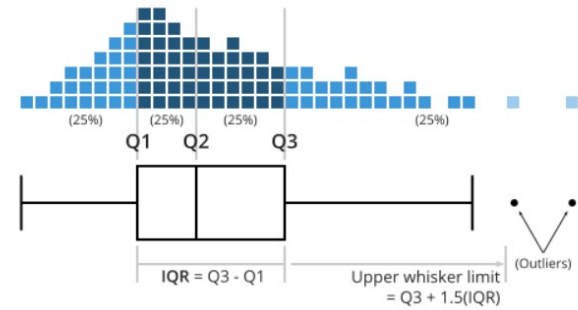
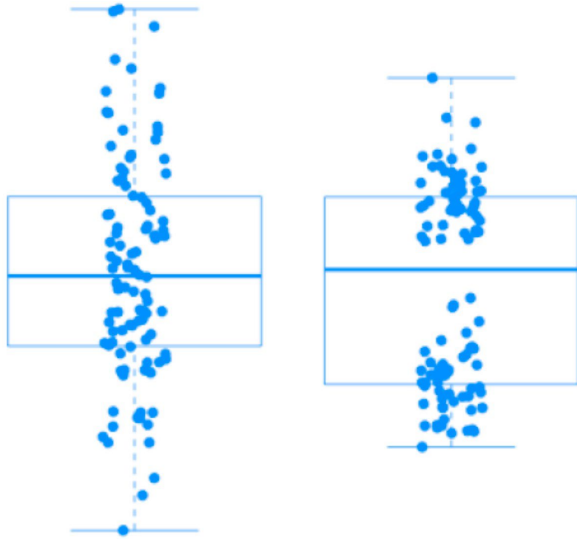
- Data integrity is the maintenance and the assurance of data accuracy and consistency;
 - A critical aspect to the design, implementation, and usage of any system that stores, processes, or retrieves data.
 - Very broad concept!
- Example:
 - In a dataset, numeric columns/cells should not accept alphabetic data.
 - A binary entry should only allow binary inputs

| | | | | | | |
|------------------|----|-------------|-----|------|------------|----------|
| Mr. Mark John | 33 | 21-08-1985 | 180 | M | 0433010010 | Mel,VIC |
| Mr. Chris, Peter | 34 | 21-Sep-1982 | ? | Fale | 0000000000 | Syd, NSW |
| Ethan Steedman | 36 | 01/01/82 | 17o | M | 0388886789 | Mel,VIC |

We can only select one of these

| Organization | User Type | Profile Entered | Primary | Secondary | Bid | Relevance | Candidate Suggestion Rank | Tpms Rank | Quota | Number Of Assignments |
|----------------------------------|--|-----------------|--|--|---------------|-----------|---------------------------|-----------|---------|-----------------------|
| filter... | click here... | click here... | filter... | filter... | click here... | e.g. <3 | e.g. <3 | e.g. <3 | e.g. <3 | e.g. <3 |
| National University of Singapore | Student, >3 times as reviewer for CVPR, ICCV, or ECCV | DBLP | Machine learning | 3D from single images; Adversarial attack and defense; Computer vision theory; Explainable computer vision; Self- & semi- & meta- & unsupervised learning; Transfer/ low-shot/ long-tail learning; Vision + graphics | Not Entered | 0.08 | 1 | 1434 | | 4 |
| Zhejiang University | Faculty/Researcher, 3-10 times as reviewer for CVPR, ICCV, or ECCV | No | Transfer/ low-shot/ long-tail learning | Efficient learning and inferences; Explainable computer vision; Image and video synthesis and generation; Recognition: detection, classification | Not Entered | 0.16 | 7 | | | 2 |

Visualization: Boxplots



Maximum (100th percentile) $Q_3 + 1.5 \times IQR$

Third Quartile (75th percentile)

Median (50th percentile)

First Quartile (25th percentile)

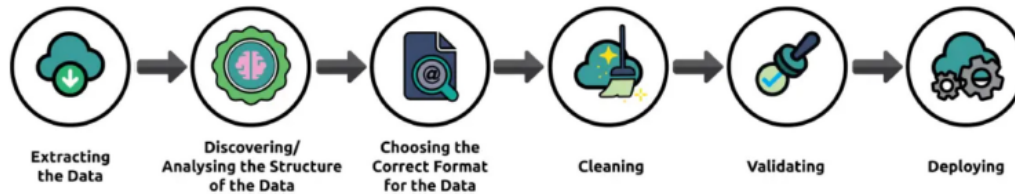
Minimum (0th percentile) $Q_1 - 1.5 \times IQR$

- The first quartile (Q_1) is defined as middle number between the smallest number and the median of the data set.
- The third quartile (Q_3) is defined as middle number between the highest number and the median of the data set.

- Interquartile range (IQR) is defined as distance between the first and third quartile, $IQR = Q_3 - Q_1$.

Summary

- Types of data
 - NOIR
- Data wrangling and cleaning



- Data integrity and visualization
 - Integrity: Design
 - Visualization: Graphical Representation



THANK YOU