

02

## Data Foundations

# Notice

- **Author**
  - ◆ João Moura Pires ([jmp@fct.unl.pt](mailto:jmp@fct.unl.pt))
- **This material can be freely used for personal or academic purposes without any previous authorization from the author, provided that this notice is kept with.**
- **For commercial purposes the use of any part of this material requires the previous authorization from the author.**

# Bibliography

- Many examples are extracted and adapted from
  - ◆ **Interactive Data Visualization: Foundations, Techniques, and Applications,**  
**Matthew O. Ward, Georges Grinstein, Daniel Keim, 2015**
  - ◆ **Visualization Analysis & Design,**  
**Tamara Munzner, 2015**

# Table of Contents

- **Introduction**
- **Data by Matthew O. Ward, et all**
- **Data by Tamara Munzner**
- **Structure within and between records**
- **Data Preprocessing**

## Some practical Information

# Evaluation rules

- Two mid-term written individual tests (25% each)
- One project (for team of 3 students), with several phases:
  - Specification
  - Paper (20%)
  - Code/implementation (30%)
  - (\*) an oral discussion will be required to validate the project components
- Course approval requires the following minimal grades:
  - $(\text{mean}(\text{Test1}; \text{Test2}) \geq 10) \text{ AND } (\text{Test1} \geq 8) \text{ AND } (\text{Test2} \geq 8)$
  - $(\text{mean}(\text{Paper}; \text{Code\&Implementation}) \geq 10) \text{ AND }$
- Final exam may replace mean (Test1; Test2) if project is approved.

# Important dates

- Team registration - **Mars 20th**
- Select datasets for your project - Mars 25 th - April 24th
  - ◆ Discuss in the lab sessions the viability
  - ◆ Evaluate de selected datasets
  - ◆ Define and get an approval of your research questions
  - ◆ Make a state of the art
- Paper - **May 15th**

# Team Registration

## ■ Access the shared google sheet

	Register you team by indicating in the first available Group-ID the student ID for each student (exactly 3 students)					
	<b>Please fill in your number in the yellow columns</b>					
Group ID	ID-1	Name-1	ID-2	Name-2	ID-3	Name-3
G01						
G02						
G03						
G04						

- ◆ Fill 3 students on one available slot. Only on the yellow cells.

# Team Registration

## ■ Access the shared google sheet

	Register your team by indicating in the first available Group-ID the student ID for each student (exactly 3 students)					
	<b>Please fill in your number in the yellow columns</b>					
Group ID	ID-1	Name-1	ID-2	Name-2	ID-3	Name-3
G01						
G02						
G03						
G04						

- ◆ Fill 3 students on one available slot. Only on the yellow cells.
- You will receive (later) access to a shared folder for the team: VID-19-20-GNN
  - ◆ Use this folder to share the information inside the group
  - ◆ And with the teacher

# Team Registration

## ■ Access the shared google sheet

		Register your team by indicating in the first available Group-ID the student ID for each student (exactly 3 students)				
		<b>Please fill in your number in the yellow columns</b>				
Group ID	ID-1	Name-1	ID-2	Name-2	ID-3	Name-3
G01						
G02						
G03						
G04						

- ◆ Fill 3 students on one available slot. Only on the yellow cells.
- You will receive (later) access to a shared folder for the team: VID-19-20-GNN
  - ◆ Use this folder to share the information inside the group
  - ◆ And with the teacher
- You will receive (later) an invite for the Tableau online

## Recap from previous lecture

# What is the Goal of Data Visualization?

**“Data visualization is **not just about seeing** data !**

**Is about **UNDERSTANDING** data,**  
**and being able to **make decisions** based on the data”**

**by John C. Hart**

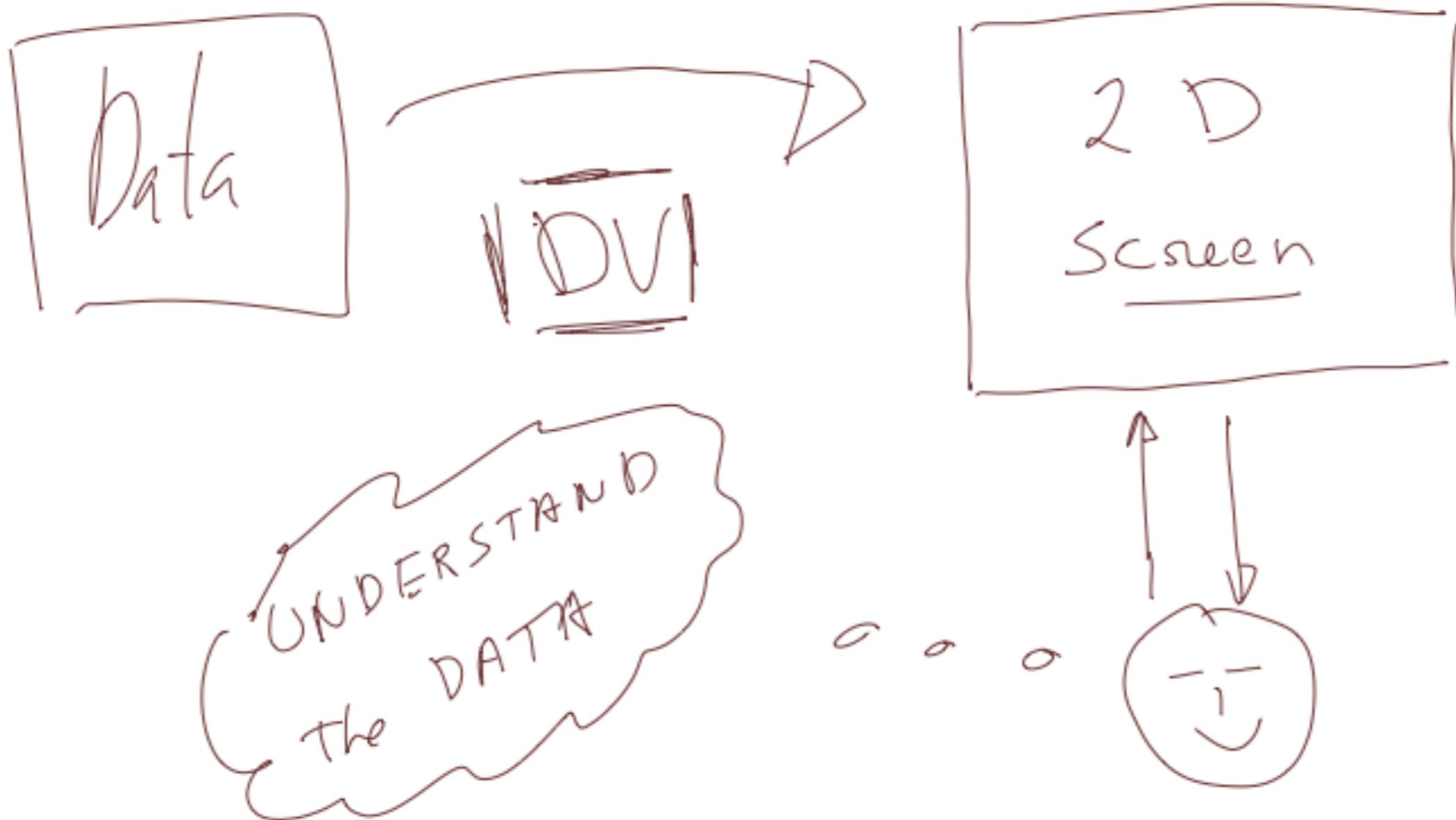
# What is the Goal of Data Visualization?

The (ultimate) goal of DV

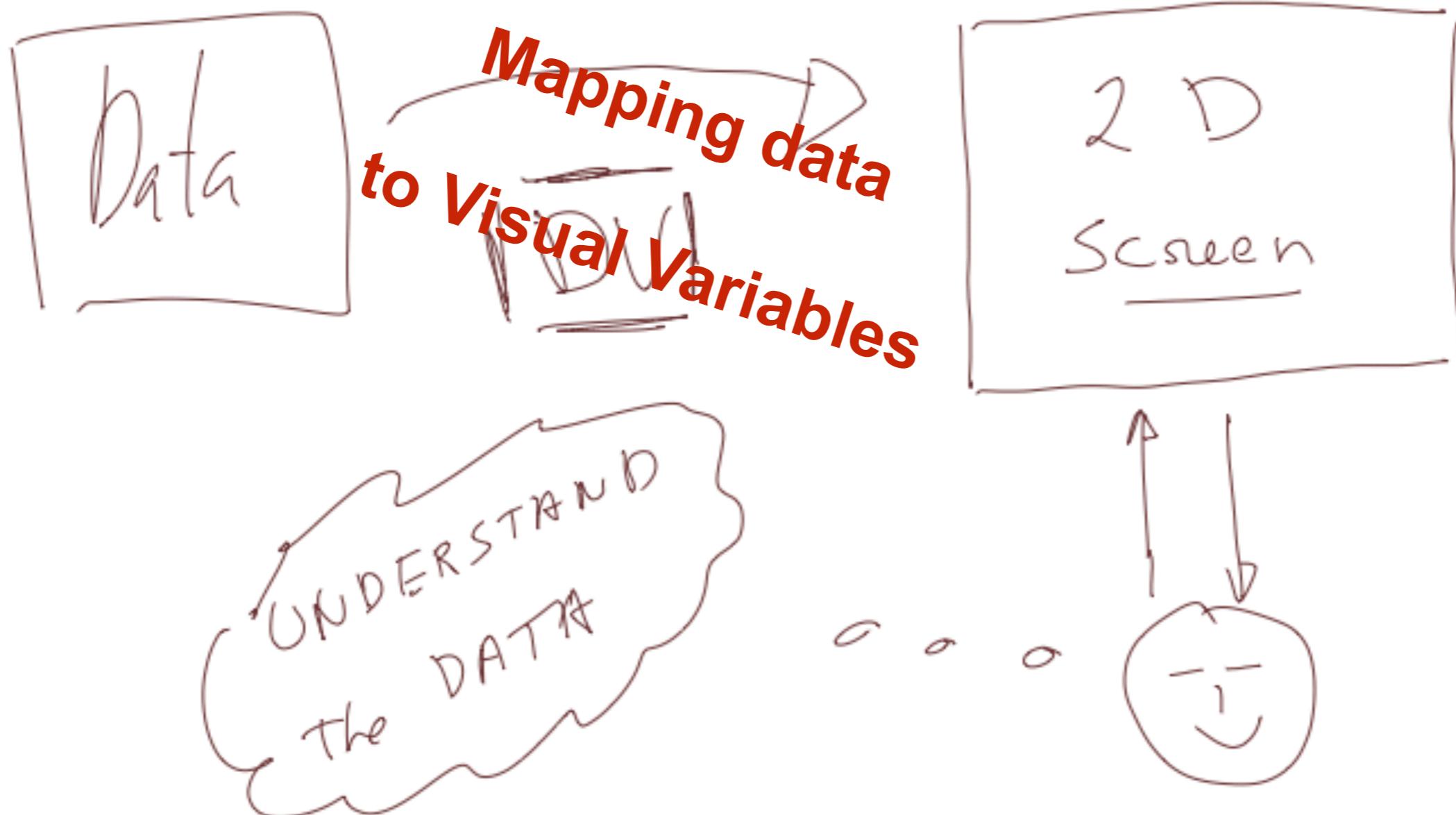
**“Data visualization is **not just about seeing** data !  
Is about **UNDERSTANDING** data,  
and being able to **make decisions** based on the data”**

**by John C. Hart**

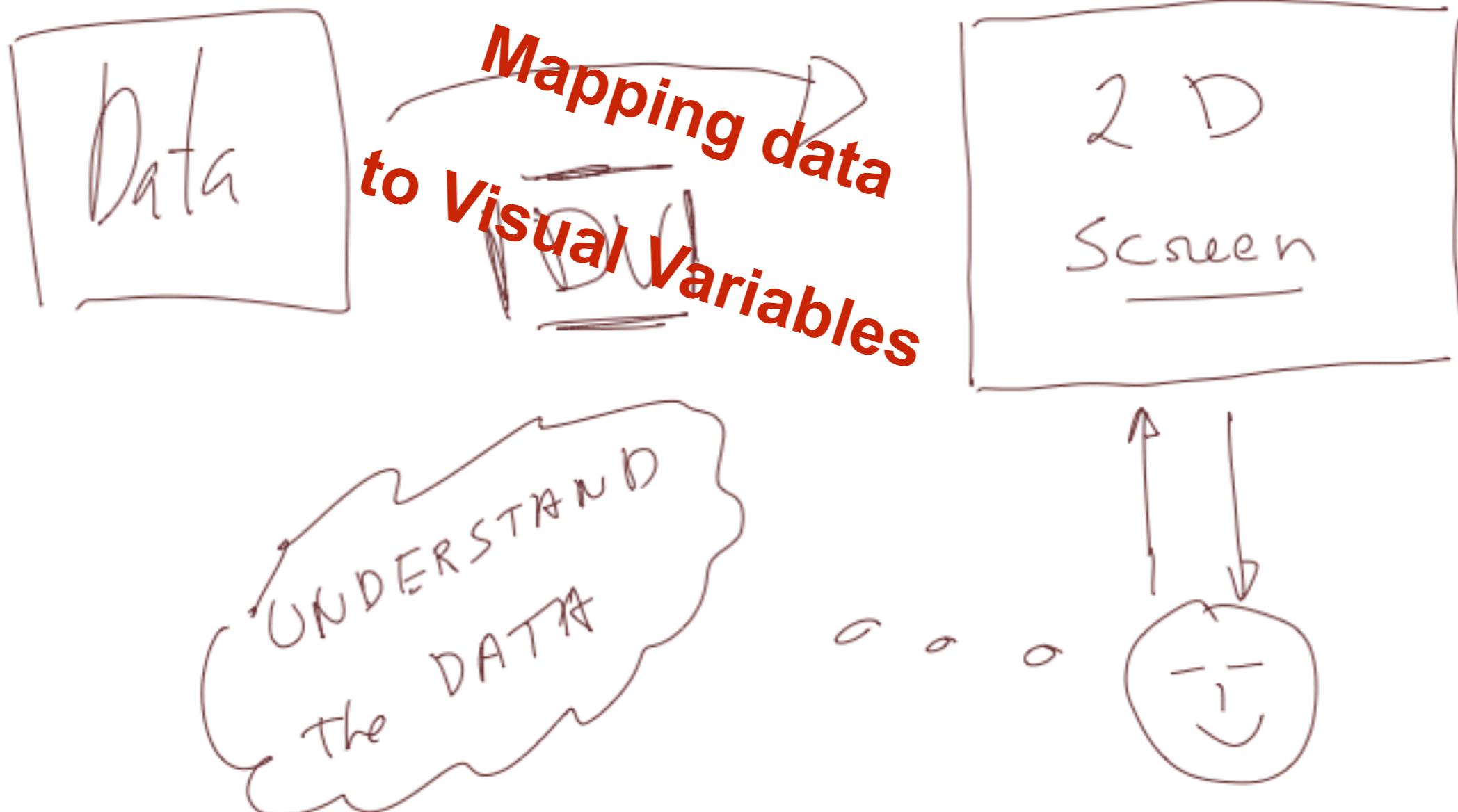
# What is the core idea of Interactive Data Visualization?



# What is the core idea of Interactive Data Visualization?

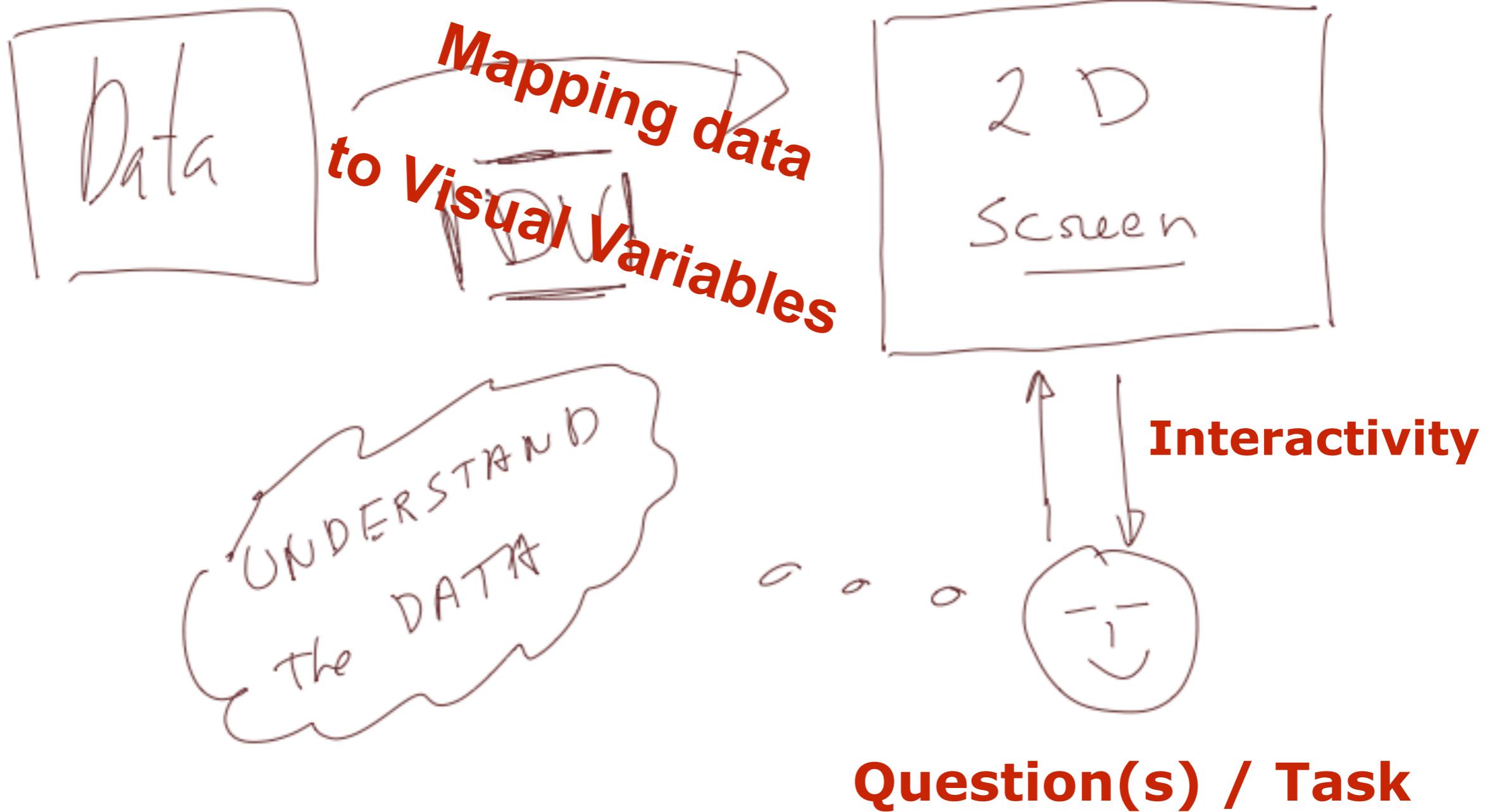


# What is the core idea of Interactive Data Visualization?



**Question(s) / Task**

# What is the core idea of Interactive Data Visualization?



# What you should know

## ■ What is Data Visualization.

# What you should know

## ■ What is Data Visualization.

- ◆ Understanding the data => take decisions

# What you should know

- **What is Data Visualization.**
  - ◆ Understanding the data => take decisions
- **Data Visualization can be extremely powerful**

# What you should know

- **What is Data Visualization.**
  - ◆ Understanding the data => take decisions
- **Data Visualization can be extremely powerful**
  - ◆ Uncover new patterns; confirm hypothesis;

# What you should know

- **What is Data Visualization.**
  - ◆ Understanding the data => take decisions
- **Data Visualization can be extremely powerful**
  - ◆ Uncover new patterns; confirm hypothesis;
- **Why Visualization is important.**

# What you should know

- **What is Data Visualization.**
  - ◆ Understanding the data => take decisions
- **Data Visualization can be extremely powerful**
  - ◆ Uncover new patterns; confirm hypothesis;
- **Why Visualization is important.**
  - ◆ Stats not enough; communication needs; exploratory needs

# What you should know

- **What is Data Visualization.**
  - ◆ Understanding the data => take decisions
- **Data Visualization can be extremely powerful**
  - ◆ Uncover new patterns; confirm hypothesis;
- **Why Visualization is important.**
  - ◆ Stats not enough; communication needs; exploratory needs
- **Key aspects of today Visualizations.**

# What you should know

- **What is Data Visualization.**
  - ◆ Understanding the data => take decisions
- **Data Visualization can be extremely powerful**
  - ◆ Uncover new patterns; confirm hypothesis;
- **Why Visualization is important.**
  - ◆ Stats not enough; communication needs; exploratory needs
- **Key aspects of today Visualizations.**
  - ◆ Interactions; visual abstractions; multiple (linked) visualizations.

# What you should know

- **What is Data Visualization.**
  - ◆ Understanding the data => take decisions
- **Data Visualization can be extremely powerful**
  - ◆ Uncover new patterns; confirm hypothesis;
- **Why Visualization is important.**
  - ◆ Stats not enough; communication needs; exploratory needs
- **Key aspects of today Visualizations.**
  - ◆ Interactions; visual abstractions; multiple (linked) visualizations.
- **The general steps of a Visualization Process**

# What you should know

- **What is Data Visualization.**
  - ◆ Understanding the data => take decisions
- **Data Visualization can be extremely powerful**
  - ◆ Uncover new patterns; confirm hypothesis;
- **Why Visualization is important.**
  - ◆ Stats not enough; communication needs; exploratory needs
- **Key aspects of today Visualizations.**
  - ◆ Interactions; visual abstractions; multiple (linked) visualizations.
- **The general steps of a Visualization Process**
  - ◆ Raw data -> data -> viz structures -> images -> perception + feedback

# What you should know

- **What is Data Visualization.**
  - ◆ Understanding the data => take decisions
- **Data Visualization can be extremely powerful**
  - ◆ Uncover new patterns; confirm hypothesis;
- **Why Visualization is important.**
  - ◆ Stats not enough; communication needs; exploratory needs
- **Key aspects of today Visualizations.**
  - ◆ Interactions; visual abstractions; multiple (linked) visualizations.
- **The general steps of a Visualization Process**
  - ◆ Raw data -> data -> viz structures -> images -> perception + feedback
- **The role of Perception.**

# What you should know

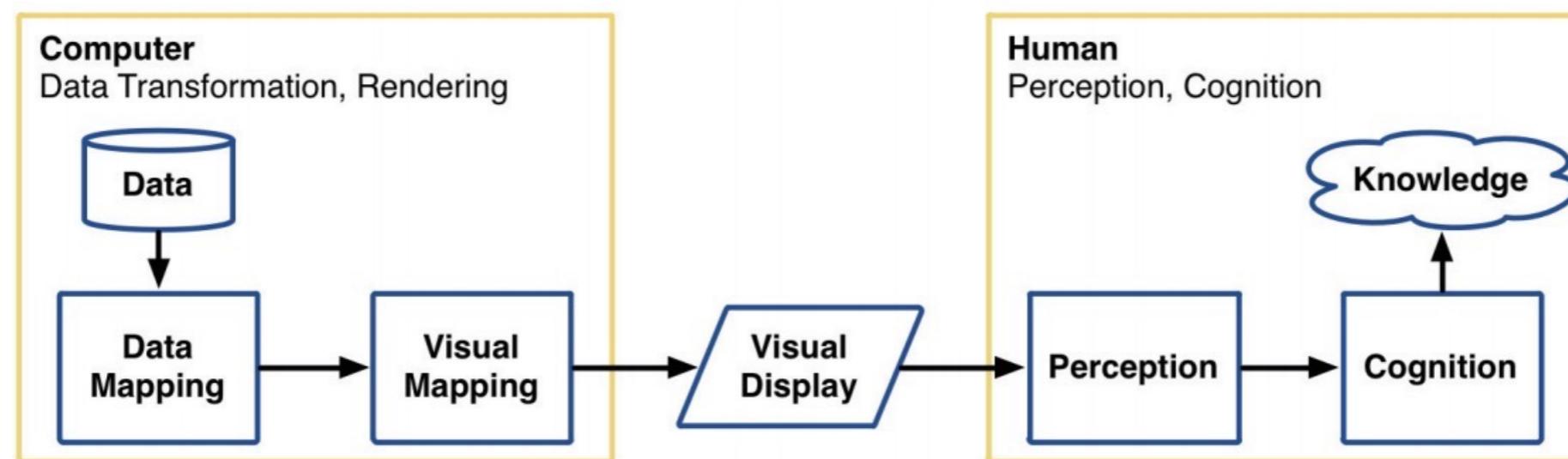
- **What is Data Visualization.**
  - ◆ Understanding the data => take decisions
- **Data Visualization can be extremely powerful**
  - ◆ Uncover new patterns; confirm hypothesis;
- **Why Visualization is important.**
  - ◆ Stats not enough; communication needs; exploratory needs
- **Key aspects of today Visualizations.**
  - ◆ Interactions; visual abstractions; multiple (linked) visualizations.
- **The general steps of a Visualization Process**
  - ◆ Raw data -> data -> viz structures -> images -> perception + feedback
- **The role of Perception.**
  - ◆ The role and the importance of the user.

## Introduction to Data Foundations

# Visualization Process: visualization pipeline

## For visualization the stages are:

- Modeling: the **data** to be visualized
- Data Selection: similar to clipping
- Data to visual mappings: the heart of the visualization is mapping data values to graphical entities or their attributes; may involve scaling, shifting, filtering, interpolating, or subsampling.
- Scene parameter setting: (ex: color mapping)
- Rendering or generation of the visualization



# Data: Sources

## Sources

- ◆ **Sensors;**
- ◆ **Surveys;**
- ◆ **Simulations;**
- ◆ **Computations;**
- ◆ **Log of human and machine activity**

# Data: Sources

## ■ Sources

- ◆ **Sensors;**
- ◆ **Surveys;**
- ◆ **Simulations;**
- ◆ **Computations;**
- ◆ **Log of human and machine activity**

## ■ Raw versus Processed data

- ◆ **Raw data (untreated)**
- ◆ **Processed: smoothing, noise removal, scaling, interpolation, aggregation**

# Data: typical data set in visualization

# Data: typical data set in visualization

- List of  $n$  records

- $(r_1, r_2, \dots, r_n)$
- a record  $r_i$  consists in  $m$  (one or more) observations or variables  
 $(v_1, v_2, \dots, v_m)$

# Data: typical data set in visualization

## ■ List of $n$ records

- $(r_1, r_2, \dots, r_n)$
- a record  $r_i$  consists in  $m$  (one or more) observations or variables  
 $(v_1, v_2, \dots, v_m)$
- one observation may be:
  - a single number / symbol / string
  - a more complex structure

# Data: typical data set in visualization

- List of ***n*** records
  - $(r_1, r_2, \dots, r_n)$
  - a record  $r_i$  consists in ***m*** (one or more) observations or variables
$$(v_1, v_2, \dots, v_m)$$
  - one observation may be:
    - a single number / symbol / string
    - a more complex structure
  - A variable may be classified as:
    - independent: whose value is not controlled or affected by another variable
    - dependent: whose value is affected by the variation in one or more associated independent variables

# Data: typical data set in visualization

- A record  $r$  consists in  $mi$  independent variables and  $md$  dependent variables

$$r = ( iv_1, iv_2, \dots, iv_{mi}, dv_1, dv_2, \dots, dv_{md} )$$

# Data: typical data set in visualization

- A record  $r$  consists in  $mi$  independent variables and  $md$  dependent variables

$$r = (iv_1, iv_2, \dots, iv_{mi}, dv_1, dv_2, \dots, dv_{md})$$

- We **may not know** which variables are dependent and which are independent.

# Data: typical data set in visualization

- A record  $r$  consists in  $mi$  independent variables and  $md$  dependent variables

$$r = ( iv_1, iv_2, \dots, iv_{mi}, dv_1, dv_2, \dots, dv_{md} )$$

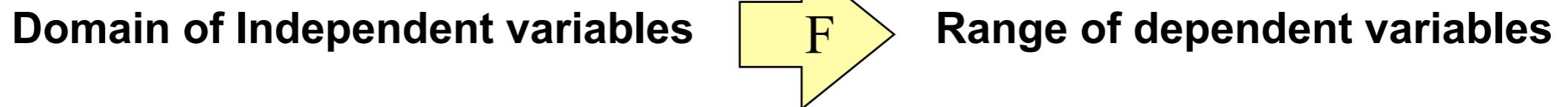
- We **may not know** which variables are dependent and which are independent.
- In general a data set will **not contain an exhaustive list of all possible combinations of values** for the independent variables

# Data: typical data set in visualization

- A record  $r$  consists in  $mi$  independent variables and  $md$  dependent variables

$$r = (iv_1, iv_2, \dots, iv_{mi}, dv_1, dv_2, \dots, dv_{md})$$

- We **may not know** which variables are dependent and which are independent.
- In general a data set will **not contain an exhaustive list of all possible combinations of values** for the independent variables
- A data set can be seen as a function



## Data

(Matthew O. Ward, et all)

## Data Types

# Types of data. Numeric versus Non-Numeric

- In its simplest form each variable of a record has a single piece of information (scalar values)

# Types of data. Numeric versus Non-Numeric

- In its simplest form each variable of a record has a single piece of information (scalar values)
- Numeric (ordinal):
  - binary: assuming only the values 0 and 1;
  - discrete: integer values or from a specific subset (e.g., (2, 4, 6, 8, 10);
  - continuous: representing real values (e.g., [0, 100]).

# Types of data. Numeric versus Non-Numeric

- In its **simplest form each variable of a record has a single piece of information (scalar values)**
- **Numeric (ordinal):**
  - **binary:** assuming only the values 0 and 1;
  - **discrete:** integer values or from a specific subset (e.g., (2, 4, 6, 8, 10));
  - **continuous:** representing real values (e.g., [0, 100]).
- **Non Numeric (nominal):**
  - **categorial:** finite (normally short) list of values (e.g., red, green, blue);
  - **ranked:** a categorial variable that has an implied order (e.g., small, medium, large);
  - **arbitrary:** potentially infinite range of values (e.g., names, addresses).

# Types of data. Type of scale

## ■ Properties of scales of measurement:

# Types of data. Type of scale

## ■ Properties of scales of measurement:

- **Identity.** Each value on the measurement scale has a unique meaning.

# Types of data. Type of scale

## ■ Properties of scales of measurement:

- **Identity.** Each value on the measurement scale has a unique meaning.
- **Magnitude.** Values on the measurement scale have an **ordered relationship** to one another. That is, some values are larger and some are smaller.

# Types of data. Type of scale

## ■ Properties of scales of measurement:

- **Identity.** Each value on the measurement scale has a unique meaning.
- **Magnitude.** Values on the measurement scale have an ordered relationship to one another. That is, some values are larger and some are smaller.
- **Equal intervals.** Scale units along the scale are equal to one another. This means, for example, that the difference between 1 and 2 would be equal to the difference between 19 and 20. This is also known as **distance metric**.

# Types of data. Type of scale

## ■ Properties of scales of measurement:

- **Identity.** Each value on the measurement scale has a unique meaning.
- **Magnitude.** Values on the measurement scale have an ordered relationship to one another. That is, some values are larger and some are smaller.
- **Equal intervals.** Scale units along the scale are equal to one another. This means, for example, that the difference between 1 and 2 would be equal to the difference between 19 and 20. This is also known as **distance metric**.
- **A minimum value of zero.** The scale has a true zero point, below which no values exist. When a scale has an absolute zero then it makes sense to apply all the mathematical operations (+, -, \*, /).

# Types of data. Type of scale

# Types of data. Type of scale

## ■ **Nominal Scale of Measurement:**

- Only satisfies the identity property of measurement
- Categorical and Arbitrary(\*)

# Types of data. Type of scale

- **Nominal Scale of Measurement:**
  - Only satisfies the identity property of measurement
  - Categorical and Arbitrary(\*)
- **Ordinal Scale of Measurement:**
  - ◆ Has the property of both identity and magnitude
  - ◆ Ranked (and all the numeric)

# Types of data. Type of scale

- **Nominal Scale of Measurement:**
  - Only satisfies the identity property of measurement
  - Categorical and Arbitrary(\*)
- **Ordinal Scale of Measurement:**
  - ◆ Has the property of both identity and magnitude
  - ◆ Ranked (and all the numeric)
- **Interval Scale of Measurement**
  - ◆ Has the properties of identity, magnitude, and equal intervals.
  - ◆ Discrete. e.g., Fahrenheit (or centigrade) scale to measure temperature

# Types of data. Type of scale

- **Nominal Scale of Measurement:**
  - Only satisfies the identity property of measurement
  - Categorical and Arbitrary(\*)
- **Ordinal Scale of Measurement:**
  - ◆ Has the property of both identity and magnitude
  - ◆ Ranked (and all the numeric)
- **Interval Scale of Measurement**
  - ◆ Has the properties of identity, magnitude, and equal intervals.
  - ◆ Discrete. e.g., Fahrenheit (or centigrade) scale to measure temperature
- **Ratio Scale of Measurement**
  - ◆ Satisfies identity, magnitude, equal intervals, and a minimum value of zero.
  - ◆ Continuous. e.g., weight, distance, etc. Can apply operations of / and \*.

## Structure within and between records

# Data sets structure

- The structure of a data set defines:

# Data sets structure

- The structure of a data set defines:
  - Syntactical rules

# Data sets structure

- The structure of a data set defines:
  - Syntactical rules
  - The relationships between the components within a record

# Data sets structure

- The structure of a data set defines:
  - Syntactical rules
  - The relationships between the components within a record
  - The relationship between records

# Scalar, Vector and Tensor

- **Scalar:** individual value in a data record.
  - e.g.: Age; Color; Weight

More info about tensors -> [https://www.youtube.com/watch?v=fu-eMNi\\_aag](https://www.youtube.com/watch?v=fu-eMNi_aag)

# Scalar, Vector and Tensor

- **Scalar:** individual value in a data record.
  - e.g.: Age; Color; Weight
- **Vector:** multiple variables in a single record can represent a single item
  - e.g.: Position coordinates (2D or 3D); Color using RGB(Red, Green, Blue) components, Phone number (Country code, area code and local number), etc.
  - each component (of the vector) can be considered **individually** but is most appropriate to treat the vector as a whole.

More info about tensors -> [https://www.youtube.com/watch?v=fu-eMNI\\_aag](https://www.youtube.com/watch?v=fu-eMNI_aag)

# Scalar, Vector and Tensor

- **Scalar:** individual value in a data record.
  - e.g.: Age; Color; Weight
- **Vector:** multiple variables in a single record can represent a single item
  - e.g.: Position coordinates (2D or 3D); Color using RGB(Red, Green, Blue) components, Phone number (Country code, area code and local number), etc.
  - each component (of the vector) can be considered **individually** but is most appropriate to treat the vector as a whole.
- **Tensor:** a tensor is defined by its *rank* and its *dimensionality*. A scalar is a tensor of rank 0; a vector with  $D$  components is a tensor of rank 1 and D dimensionality. A tensor of rank 2 and 3 dimensions can be represented as a Matrix  $3 \times 3$ .

More info about tensors -> [https://www.youtube.com/watch?v=fu-eMNI\\_aag](https://www.youtube.com/watch?v=fu-eMNI_aag)

# Geometry and Grids

- **Geometry via explicit coordinates for each record in the data set.**

# Geometry and Grids

- **Geometry via explicit coordinates for each record in the data set.**
- Data set about fires in Portugal. Associated to each fire a coordinate of the starting point;

# Geometry and Grids

- **Geometry via explicit coordinates for each record in the data set.**
  - Data set about fires in Portugal. Associated to each fire a coordinate of the starting point;
  - Data set about temperature readings from sensors and associated with all the information sensor's coordinates.

# Geometry and Grids

- **Geometry via explicit coordinates for each record in the data set.**
  - Data set about fires in Portugal. Associated to each fire a coordinate of the starting point;
  - Data set about temperature readings from sensors and associated with all the information sensor's coordinates.
  - Data set describing 3D world. The geometry concept is the majority of the data.

# Geometry and Grids

- **Geometry via explicit coordinates for each record in the data set.**
  - Data set about fires in Portugal. Associated to each fire a coordinate of the starting point;
  - Data set about temperature readings from sensors and associated with all the information sensor's coordinates.
  - Data set describing 3D world. The geometry concept is the majority of the data.
  - Census data set which associates the data to administrative regions

# Geometry and Grids

- **Geometry via explicit coordinates for each record in the data set.**
  - Data set about fires in Portugal. Associated to each fire a coordinate of the starting point;
  - Data set about temperature readings from sensors and associated with all the information sensor's coordinates.
  - Data set describing 3D world. The geometry concept is the majority of the data.
  - Census data set which associates the data to administrative regions
- **Geometric structure is implied and it is assumed some form of grid. Successive data records are located at successive positions. It requires to set the starting point, the directions and the step size for each dimension.**

# Geometry and Grids

- **Geometry via explicit coordinates for each record in the data set.**
  - Data set about fires in Portugal. Associated to each fire a coordinate of the starting point;
  - Data set about temperature readings from sensors and associated with all the information sensor's coordinates.
  - Data set describing 3D world. The geometry concept is the majority of the data.
  - Census data set which associates the data to administrative regions
- **Geometric structure is implied and it is assumed some form of grid. Successive data records are located at successive positions. It requires to set the starting point, the directions and the step size for each dimension.**
  - Satellite images.

# Other forms of structure

## ■ Time

- Present in many data sets
- Uniformly spaced versus non-uniformly spaced
- Relative versus absolute
- Local versus Universal time
- Seen as linear versus as cyclic

# Other forms of structure

## ■ Time

- Present in many data sets
- Uniformly spaced versus non-uniformly spaced
- Relative versus absolute
- Local versus Universal time
- Seen as linear versus as cyclic

<http://www.timeviz.net>

check to see so many  
visualization techniques for  
**Time-Oriented Data**

# Other forms of structure

## ■ Time

- Present in many data sets
- Uniformly spaced versus non-uniformly spaced
- Relative versus absolute
- Local versus Universal time
- Seen as linear versus as cyclic

## ■ Topology

- How the records are connected.
- Geometry and space (spatial neighbors)
- Hierarchy and graphs
- This form of structure can be explicitly included in the data record or as an auxiliary data structure

<http://www.timeviz.net>

check to see so many  
visualization techniques for  
**Time-Oriented Data**

# Examples

**MRI (magnetic resonance imagery).** Density (scalar), with three spatial attributes, 3D grid connectivity;

**CFD (computational fluid dynamics).** Three dimensions for displacement, with one temporal and three spatial attributes, 3D grid connectivity (uniform or nonuniform);

**Financial.** No geometric structure,  $n$  possibly independent components, nominal and ordinal, with a temporal attribute;

**CAD (computer-aided design).** Three spatial attributes with edge and polygon connections, and surface properties;

**Remote sensing.** Multiple channels, with two or three spatial attributes, one temporal attribute, and grid connectivity;

**Census.** Multiple fields of all types, spatial attributes (e.g., addresses), temporal attribute, and connectivity implied by similarities in fields;

**Social Network.** Nodes consisting of multiple fields of all types, with various connectivity attributes that could be spatial, temporal, or dependent

Interactive Data Visualization: Foundations, Techniques, and Applications, Matthew O. Ward, Georges Grinstein, Daniel Keim, 2015

## Data (Tamara Munzner)

# Data Types and Dataset Types

## ■ Data Types

### ➔ Data Types

➔ Items   ➔ Attributes   ➔ Links   ➔ Positions   ➔ Grids

# Data Types and Dataset Types

## ■ Data Types

### ➔ Data Types

➔ Items   ➔ Attributes   ➔ Links   ➔ Positions   ➔ Grids

- ◆ An **item** is an individual entity that is discrete, such as a row in a simple table or a node in a network

# Data Types and Dataset Types

## ■ Data Types

### ➔ Data Types

➔ Items   ➔ Attributes   ➔ Links   ➔ Positions   ➔ Grids

- ◆ An **item** is an individual entity that is discrete, such as a row in a simple table or a node in a network
- ◆ An **attribute** is some specific property that can be measured, observed, or logged.\*

# Data Types and Dataset Types

## ■ Data Types

### ➔ Data Types

➔ Items   ➔ Attributes   ➔ Links   ➔ Positions   ➔ Grids

- ◆ An **item** is an individual entity that is discrete, such as a row in a simple table or a node in a network
- ◆ An **attribute** is some specific property that can be measured, observed, or logged.\*
- ◆ A **link** is a relationship between items, typically within a network.

# Data Types and Dataset Types

## ■ Data Types

### ➔ Data Types

➔ Items   ➔ Attributes   ➔ Links   ➔ Positions   ➔ Grids

- ◆ An **item** is an individual entity that is discrete, such as a row in a simple table or a node in a network.
- ◆ An **attribute** is some specific property that can be measured, observed, or logged.\*
- ◆ A **link** is a relationship between items, typically within a network.
- ◆ A **position** is spatial data, providing a location in two-dimensional (2D) or three-dimensional (3D) space.

# Data Types and Dataset Types

## ■ Data Types

### ➔ Data Types

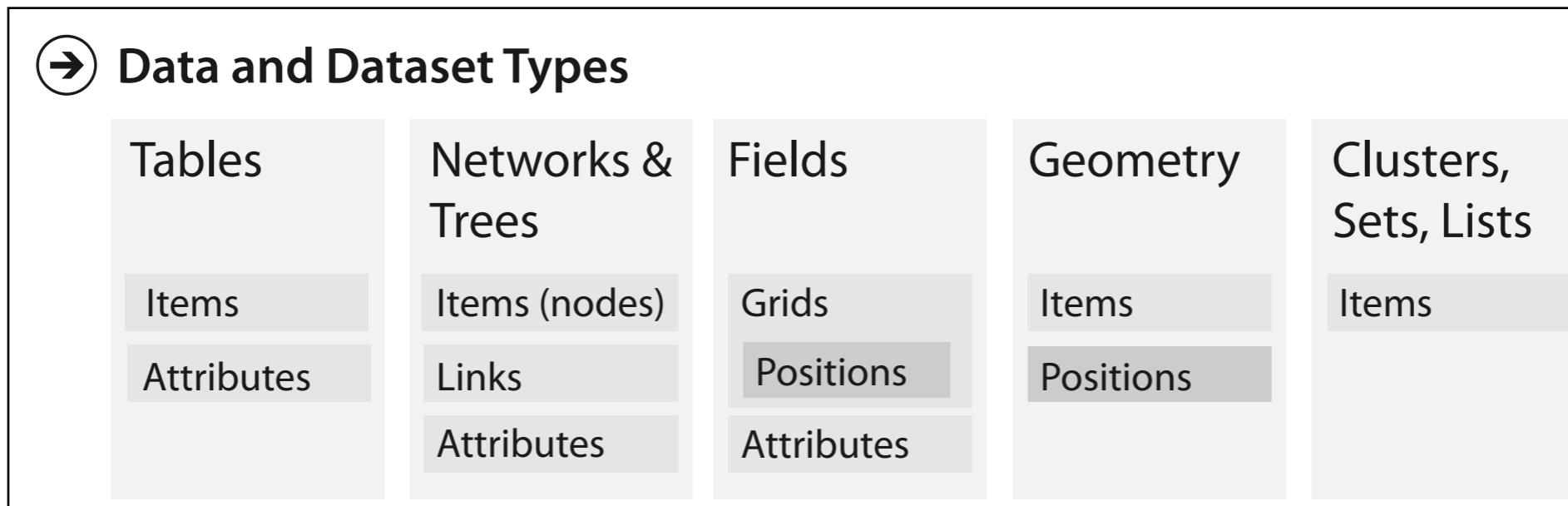
➔ Items   ➔ Attributes   ➔ Links   ➔ Positions   ➔ Grids

- ◆ An **item** is an individual entity that is discrete, such as a row in a simple table or a node in a network.
- ◆ An **attribute** is some specific property that can be measured, observed, or logged.\*
- ◆ A **link** is a relationship between items, typically within a network.
- ◆ A **position** is spatial data, providing a location in two-dimensional (2D) or three-dimensional (3D) space.
- ◆ A **grid** specifies the strategy for sampling continuous data in terms of both geometric and topological relationships between its cells

# Data Types and Dataset Types

## ■ Dataset Types

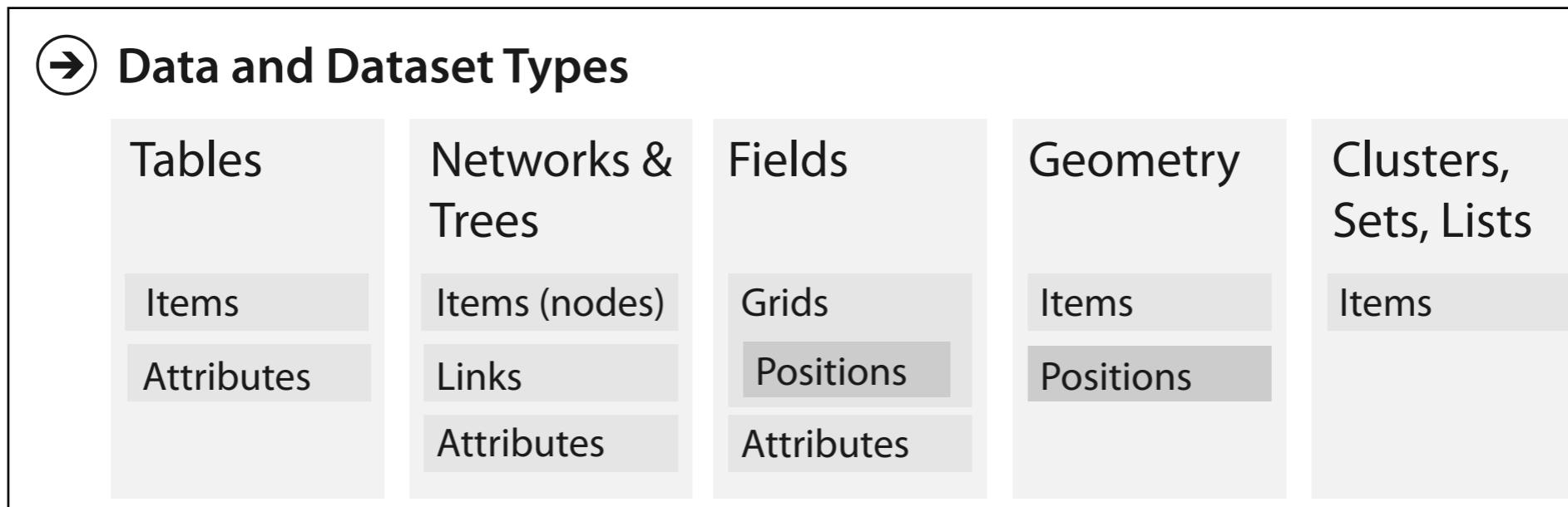
- ◆ A **dataset** is any collection of information that is the target of analysis.



# Data Types and Dataset Types

## ■ Dataset Types

- ◆ A **dataset** is any collection of information that is the target of analysis.

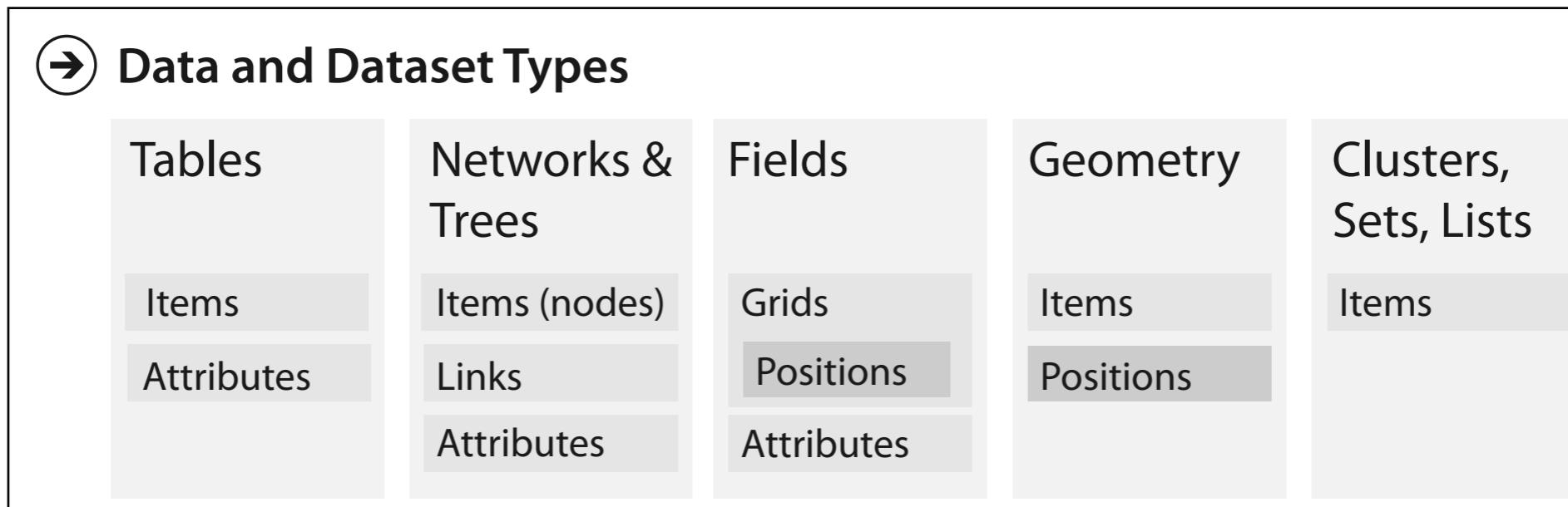


- ◆ Other ways to group items together include **clusters**, **sets**, and **lists**.

# Data Types and Dataset Types

## ■ Dataset Types

- ◆ A **dataset** is any collection of information that is the target of analysis.

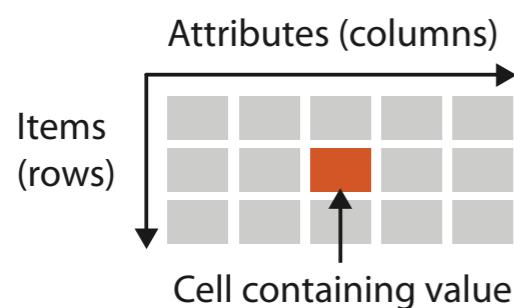


- ◆ Other ways to group items together include **clusters**, **sets**, and **lists**.
- ◆ In real-world situations, complex combinations of these basic types are common.

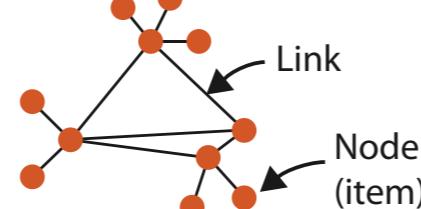
# Data Types and Dataset Types

## → Dataset Types

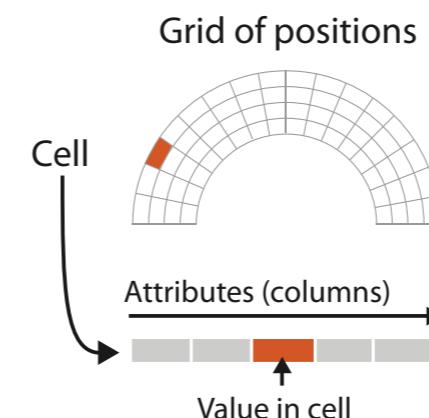
→ Tables



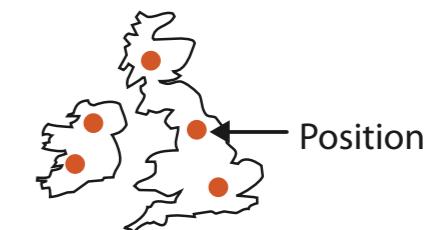
→ Networks



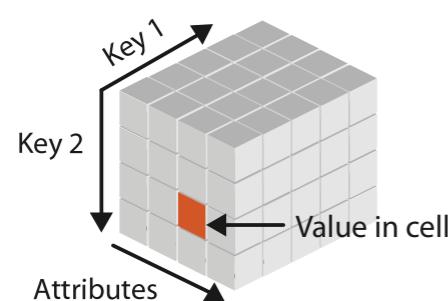
→ Fields (Continuous)



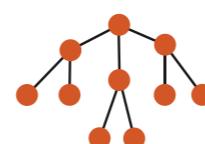
→ Geometry (Spatial)



→ Multidimensional Table

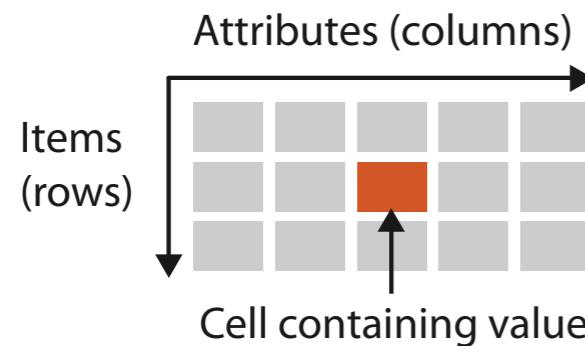


→ Trees

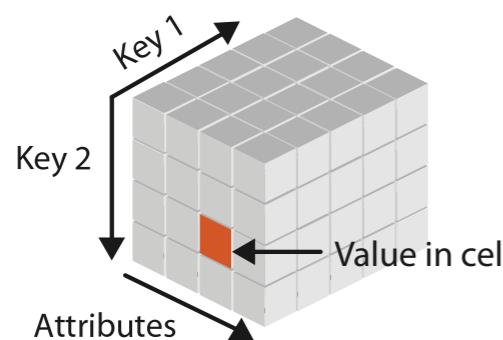


# Dataset Types: Table

→ Tables



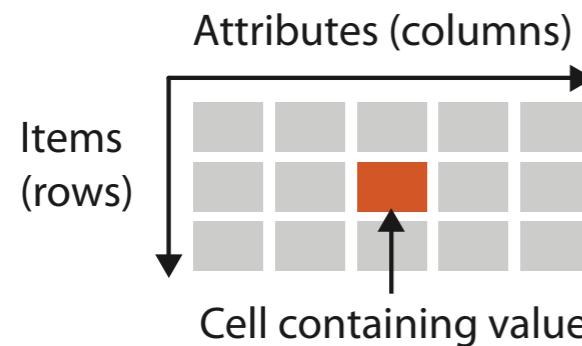
→ Multidimensional Table



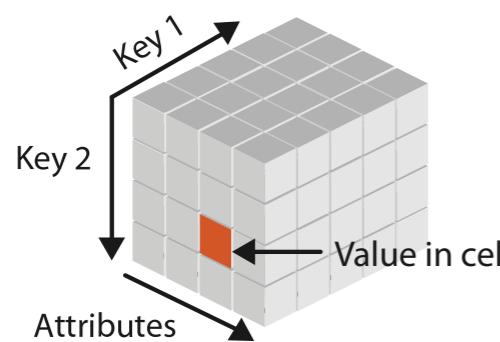
A	B	C	S	T	U
Order ID	Order Date	Order Priority	Product Container	Product Base Margin	Ship Date
3	10/14/06	5-Low	Large Box	0.8	10/21/06
6	2/21/08	4-Not Specified	Small Pack	0.55	2/22/08
32	7/16/07	2-High	Small Pack	0.79	7/17/07
32	7/16/07	2-High	Jumbo Box		7/17/07
32	7/16/07	2-High	Medium Box	0.65	7/18/07
32	7/16/07	2-High	Medium Box	0.65	7/18/07
35	10/23/07	4-Not Specified	Wrap Bag	0.52	10/24/07
35	10/23/07	4-Not Specified	Small Box	0.58	10/25/07
36	11/3/07	1-Urgent	Small Box	0.55	11/3/07
65	3/18/07	1-Urgent	Small Pack	0.49	3/19/07
66	1/20/05	5-Low	Wrap Bag	0.56	1/20/05
69	5	4-Not Specified	Small Pack	0.44	6/6/05
69	5	4-Not Specified	Wrap Bag	0.6	6/6/05
70	12/18/06	5-Low	Small Box	0.59	12/23/06
70	12/18/06	5-Low	Wrap Bag	0.82	12/23/06
96	4/17/05	2-High	Small Box	0.55	4/19/05
97	1/29/06	3-Medium	Small Box	0.38	1/30/06
129	11/19/08	5-Low	Small Box	0.37	11/28/08
130	5/8/08	2-High	Small Box	0.37	5/9/08
130	5/8/08	2-High	Medium Box	0.38	5/10/08
130	5/8/08	2-High	Small Box	0.6	5/11/08
132	6/11/06	3-Medium	Medium Box	0.6	6/12/06
132	6/11/06	3-Medium	Jumbo Box	0.69	6/14/06
134	5/1/08	4-Not Specified	Large Box	0.82	5/3/08
135	10/21/07	4-Not Specified	Small Pack	0.64	10/23/07
166	9/12/07	2-High	Small Box	0.55	9/14/07
193	8/8/06	1-Urgent	Medium Box	0.57	8/10/06
194	4/5/08	3-Medium	Wrap Bag	0.42	4/7/08

# Dataset Types: Table

→ Tables



→ Multidimensional Table

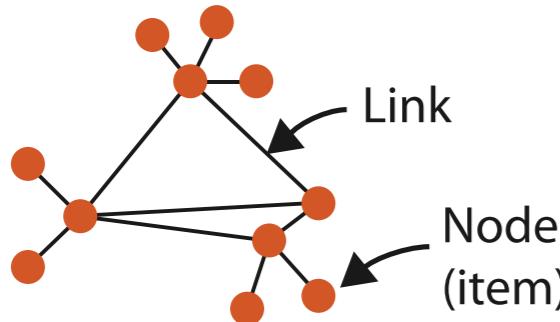


A **multidimensional table** has a more complex structure for indexing into a cell, with multiple keys.

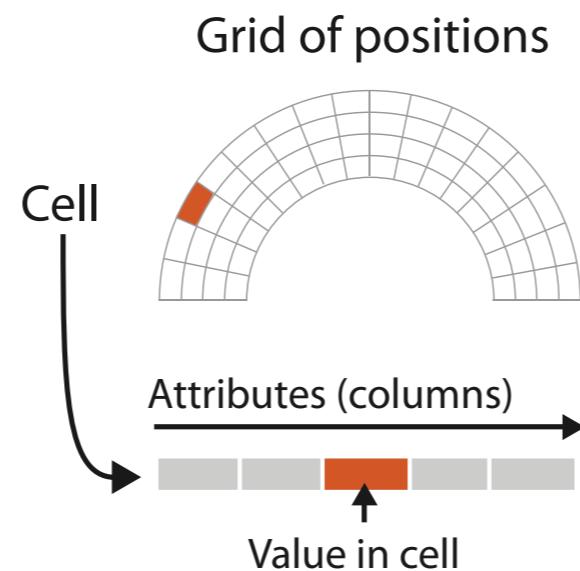
A	B	C	S	T	U
Order ID	Order Date	Order Priority	Product Container	Product Base Margin	Ship Date
3	10/14/06	5-Low	Large Box	0.8	10/21/06
6	2/21/08	4-Not Specified	Small Pack	0.55	2/22/08
32	7/16/07	2-High	Small Pack	0.79	7/17/07
32	7/16/07	2-High	Jumbo Box		7/17/07
32	7/16/07	2-High	Medium Box	0.65	7/18/07
32	7/16/07	2-High	Medium Box	0.65	7/18/07
35	10/23/07	4-Not Specified	Wrap Bag	0.52	10/24/07
35	10/23/07	4-Not Specified	Small Box	0.58	10/25/07
36	11/3/07	1-Urgent	Small Box	0.55	11/3/07
65	3/18/07	1-Urgent	Small Pack	0.49	3/19/07
66	1/20/05	5-Low	Wrap Bag	0.56	1/20/05
69	5	4-Not Specified	Small Pack	0.44	6/6/05
69	5	4-Not Specified	Wrap Bag	0.6	6/6/05
70	12/18/06	5-Low	Small Box	0.59	12/23/06
70	12/18/06	5-Low	Wrap Bag	0.82	12/23/06
96	4/17/05	2-High	Small Box	0.55	4/19/05
97	1/29/06	3-Medium	Small Box	0.38	1/30/06
129	11/19/08	5-Low	Small Box	0.37	11/28/08
130	5/8/08	2-High	Small Box	0.37	5/9/08
130	5/8/08	2-High	Medium Box	0.38	5/10/08
130	5/8/08	2-High	Small Box	0.6	5/11/08
132	6/11/06	3-Medium	Medium Box	0.6	6/12/06
132	6/11/06	3-Medium	Jumbo Box	0.69	6/14/06
134	5/1/08	4-Not Specified	Large Box	0.82	5/3/08
135	10/21/07	4-Not Specified	Small Pack	0.64	10/23/07
166	9/12/07	2-High	Small Box	0.55	9/14/07
193	8/8/06	1-Urgent	Medium Box	0.57	8/10/06
194	4/5/08	3-Medium	Wrap Bag	0.42	4/7/08

# Data Types and Dataset Types

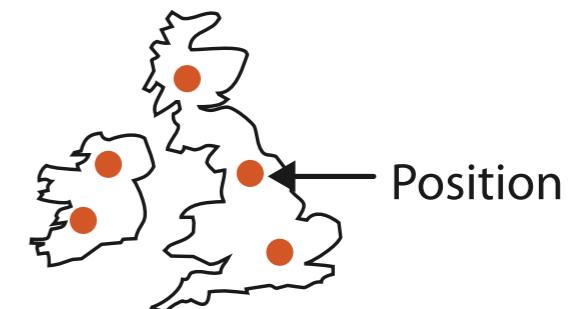
→ Networks



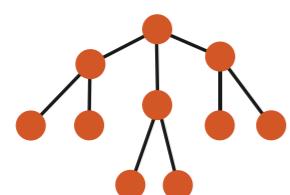
→ Fields (Continuous)



→ Geometry (Spatial)

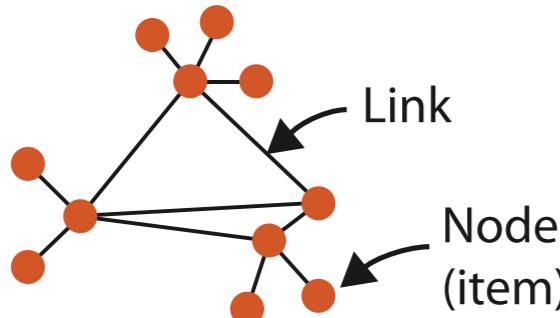


→ Trees

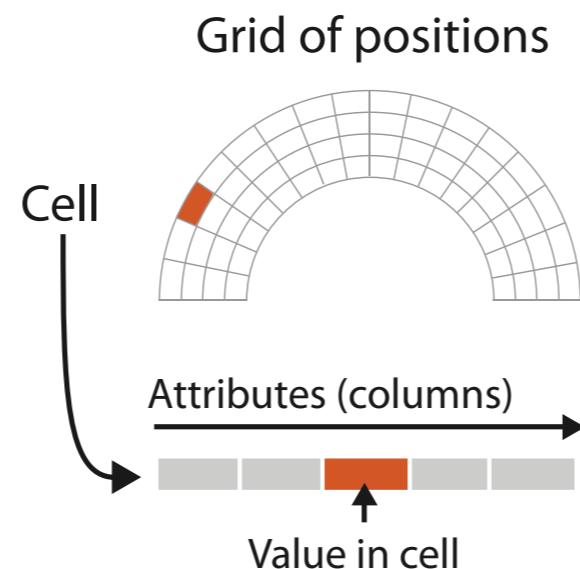


# Data Types and Dataset Types

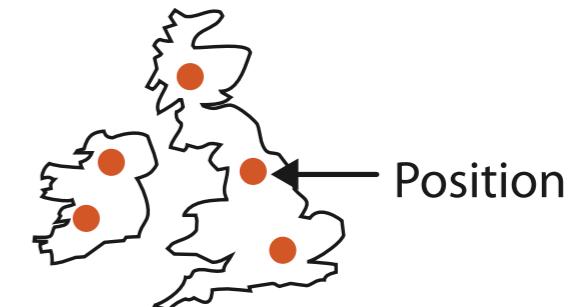
## → Networks



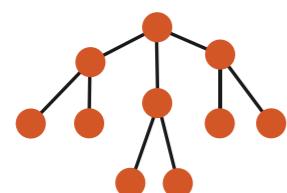
## → Fields (Continuous)



## → Geometry (Spatial)



## → Trees



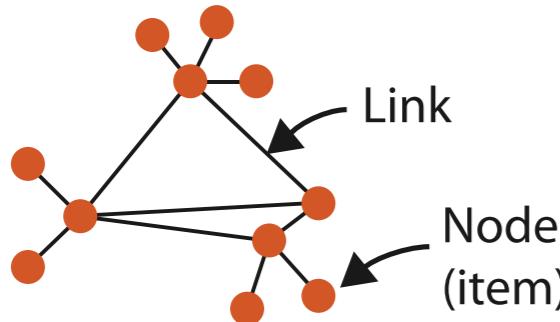
The **field** dataset type also contains attribute values associated with cells.

Each **cell** in a field contains measurements or calculations from a **continuous** domain

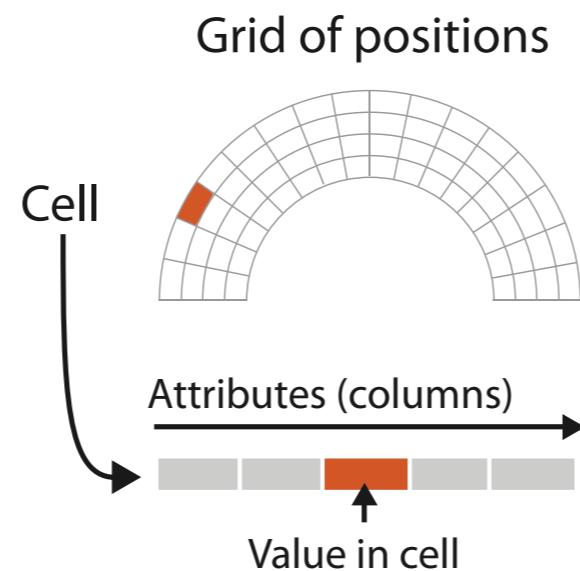
Continuous data requires careful treatment that takes into account the mathematical questions of **sampling** data **interpolation**

# Data Types and Dataset Types

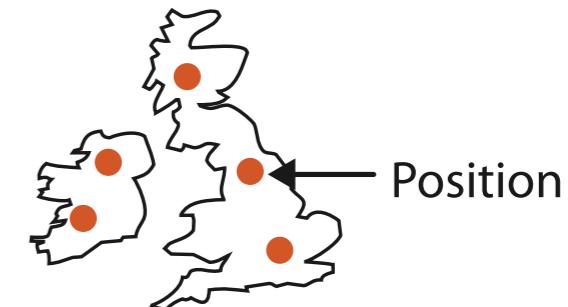
→ Networks



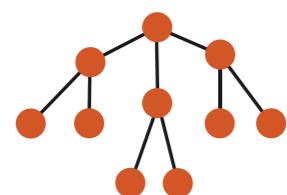
→ Fields (Continuous)



→ Geometry (Spatial)



→ Trees



The **field** dataset type also contains attribute values associated with cells.

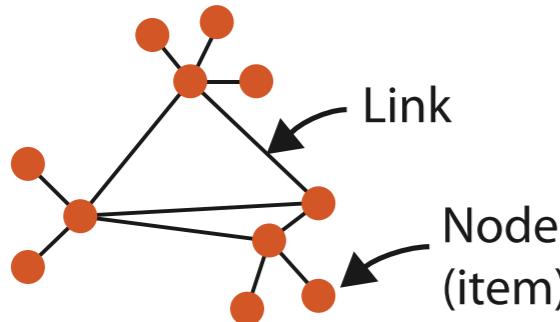
Each **cell** in a field contains measurements or calculations from a **continuous** domain

Continuous data requires careful treatment that takes into account the mathematical questions of **sampling** data **interpolation**

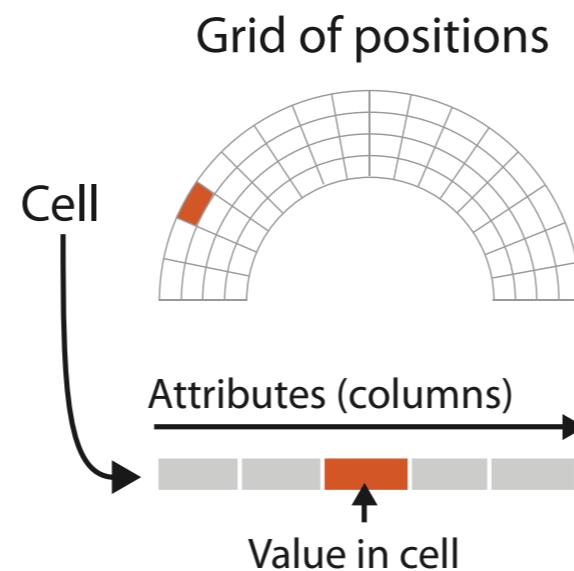
**scientific visualization**

# Data Types and Dataset Types

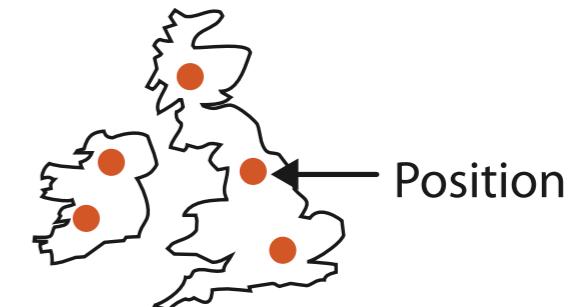
→ Networks



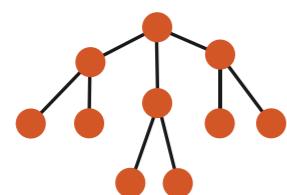
→ Fields (Continuous)



→ Geometry (Spatial)



→ Trees



The problem of how to **create images from a geometric description** of a scene falls into another domain: **computer graphics**.

Simply showing a geometric dataset is not an interesting problem from the point of view of a vis designer.

# Attribute Types

## Attributes

### → Attribute Types

→ Categorical

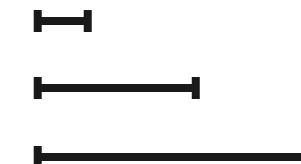


→ Ordered

→ *Ordinal*



→ *Quantitative*



# Attribute Types

## Attributes

### → Attribute Types

→ Categorical

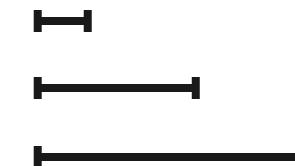


→ Ordered

→ *Ordinal*



→ *Quantitative*



### → Ordering Direction

→ Sequential



→ Diverging



→ Cyclic

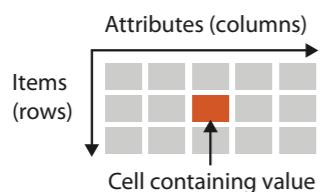
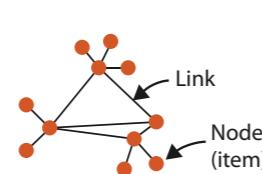
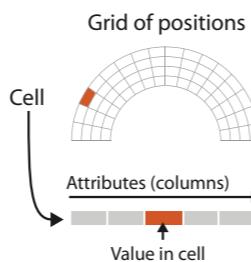
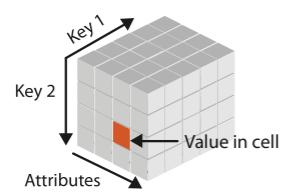
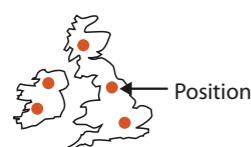


**Datasets****→ Data Types**

- Items    → Attributes    → Links    → Positions    → Grids

**→ Data and Dataset Types**

Tables	Networks & Trees	Fields	Geometry	Clusters, Sets, Lists
Items	Items (nodes)	Grids	Items	Items
Attributes	Links	Positions	Positions	
	Attributes	Attributes	Attributes	

**→ Dataset Types****→ Tables****→ Networks****→ Fields (Continuous)****→ Multidimensional Table****→ Trees****→ Geometry (Spatial)****→ Dataset Availability****→ Static****→ Dynamic****Attributes****→ Attribute Types**

- Categorical



- Ordered

→ *Ordinal*



→ *Quantitative*

**→ Ordering Direction**

- Sequential



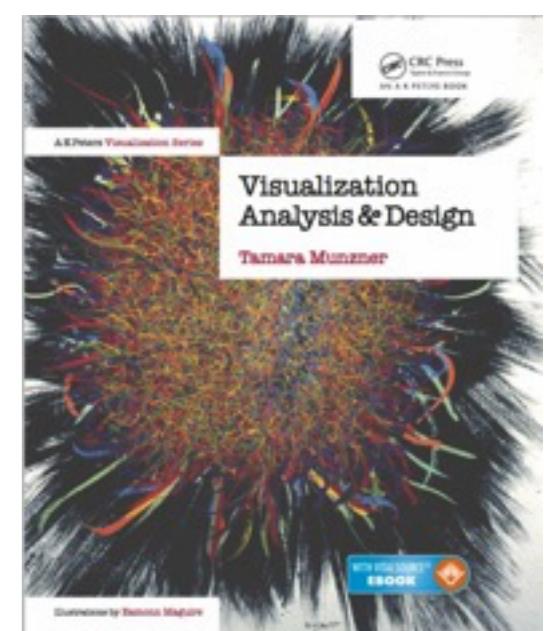
- Diverging



- Cyclic



Tamara Munzner



What?

Why?

How?

## Data Preprocessing

# Data Preprocessing

## ■ Metadata

# Data Preprocessing

- Metadata
- Basic statistics about the (scalar) data

# Data Preprocessing

- Metadata
- Basic statistics about the (scalar) data
- Missing Values and Data Cleansing

# Data Preprocessing

- Metadata
- Basic statistics about the (scalar) data
- Missing Values and Data Cleansing
- Normalization

# Data Preprocessing

- Metadata
- Basic statistics about the (scalar) data
- Missing Values and Data Cleansing
- Normalization
- Dimension reduction

# Data Preprocessing

- Metadata
- Basic statistics about the (scalar) data
- Missing Values and Data Cleansing
- Normalization
- Dimension reduction
- Mapping Nominal Dimensions to Numbers

# Data Preprocessing

- Metadata
- Basic statistics about the (scalar) data
- Missing Values and Data Cleansing
- Normalization
- Dimension reduction
- Mapping Nominal Dimensions to Numbers
- Other data processing topics

## ■ Sample from the cars data set

Acura 3.5 RL 4dr	1	0	0	0	0	0	0	43755	39014	3,5	6	225	18	24	3880	115	197	72
Acura 3.5 RL w/Navigation 4dr	1	0	0	0	0	0	0	46100	41100	3,5	6	225	18	24	3893	115	197	72
Acura MDX	0	0	1	0	0	0	1	36945	33337	3,5	6	265	17	23	4451	106	189	77
Acura NSX coupe 2dr manual S	0	1	0	0	0	0	1	89765	79978	3,2	6	290	17	24	3153	100	174	71
Acura RSX Type S 2dr	1	0	0	0	0	0	0	23820	21761	2	4	200	24	31	2778	101	172	68
Acura TL 4dr	1	0	0	0	0	0	0	33195	30299	3,2	6	270	20	28	3575	108	186	72
Acura TSX 4dr	1	0	0	0	0	0	0	26990	24647	2,4	4	200	22	29	3230	105	183	69
Audi A4 1.8T 4dr	1	0	0	0	0	0	0	25940	23508	1,8	4	170	22	31	3252	104	179	70
Audi A4 3.0 4dr	1	0	0	0	0	0	0	31840	28846	3	6	220	20	28	3462	104	179	70
Audi A4 3.0 convertible 2dr	1	0	0	0	0	0	0	42490	38325	3	6	220	20	27	3814	105	180	70
Audi A4 3.0 Quattro 4dr auto	1	0	0	0	0	0	1	34480	31388	3	6	220	18	25	3627	104	179	70

# Metadata

## ■ Sample from the cars data set

Acura 3.5 RL 4dr	1	0	0	0	0	0	0	43755	39014	3,5	6	225	18	24	3880	115	197	72	
Acura 3.5 RL w/Navigation 4dr	1	0	0	0	0	0	0	46100	41100	3,5	6	225	18	24	3893	115	197	72	
Acura MDX	0	0	1	0	0	0	1	0	36945	33337	3,5	6	265	17	23	4451	106	189	77
Acura NSX coupe 2dr manual S	0	1	0	0	0	0	0	89765	79978	3,2	6	290	17	24	3153	100	174	71	
Acura RSX Type S 2dr	1	0	0	0	0	0	0	23820	21761	2	4	200	24	31	2778	101	172	68	
Acura TL 4dr	1	0	0	0	0	0	0	33195	30299	3,2	6	270	20	28	3575	108	186	72	
Acura TSX 4dr	1	0	0	0	0	0	0	26990	24647	2,4	4	200	22	29	3230	105	183	69	
Audi A4 1.8T 4dr	1	0	0	0	0	0	0	25940	23508	1,8	4	170	22	31	3252	104	179	70	
Audi A4 3.0 4dr	1	0	0	0	0	0	0	31840	28846	3	6	220	20	28	3462	104	179	70	
Audi A4 3.0 convertible 2dr	1	0	0	0	0	0	0	42490	38325	3	6	220	20	27	3814	105	180	70	
Audi A4 3.0 Quattro 4dr auto	1	0	0	0	0	0	1	0	34480	31388	3	6	220	18	25	3627	104	179	70

■ With the exception of first column (Vehicle name) we need more information!

# Metadata

## ■ Sample from the cars data set

Acura 3.5 RL 4dr	1	0	0	0	0	0	0	43755	39014	3,5	6	225	18	24	3880	115	197	72	
Acura 3.5 RL w/Navigation 4dr	1	0	0	0	0	0	0	46100	41100	3,5	6	225	18	24	3893	115	197	72	
Acura MDX	0	0	1	0	0	0	1	0	36945	33337	3,5	6	265	17	23	4451	106	189	77
Acura NSX coupe 2dr manual S	0	1	0	0	0	0	0	1	89765	79978	3,2	6	290	17	24	3153	100	174	71
Acura RSX Type S 2dr	1	0	0	0	0	0	0	23820	21761	2	4	200	24	31	2778	101	172	68	
Acura TL 4dr	1	0	0	0	0	0	0	33195	30299	3,2	6	270	20	28	3575	108	186	72	
Acura TSX 4dr	1	0	0	0	0	0	0	26990	24647	2,4	4	200	22	29	3230	105	183	69	
Audi A4 1.8T 4dr	1	0	0	0	0	0	0	25940	23508	1,8	4	170	22	31	3252	104	179	70	
Audi A4 3.0 4dr	1	0	0	0	0	0	0	31840	28846	3	6	220	20	28	3462	104	179	70	
Audi A4 3.0 convertible 2dr	1	0	0	0	0	0	0	42490	38325	3	6	220	20	27	3814	105	180	70	
Audi A4 3.0 Quattro 4dr auto	1	0	0	0	0	1	0	34480	31388	3	6	220	18	25	3627	104	179	70	

■ With the exception of first column (Vehicle name) we need more information!

Vehicle Name	Small/Sporty/ Compact/Large Sedan	Sports Car	SUV	Wagon	Minivan	Pickup	AWD	RWD	Retail Price	Dealer Cost	Engine Size (l)	Cyl	HP	City MPG	Hwy MPG	Weight	Wheel Base	Len	Width	
Acura 3.5 RL 4dr	1	0	0	0	0	0	0	0	43755	39014	3,5	6	225	18	24	3880	115	197	72	
Acura 3.5 RL w/Navigation 4dr	1	0	0	0	0	0	0	0	46100	41100	3,5	6	225	18	24	3893	115	197	72	
Acura MDX	0	0	1	0	0	0	0	1	0	36945	33337	3,5	6	265	17	23	4451	106	189	77
Acura NSX coupe 2dr manual S	0	1	0	0	0	0	0	0	1	89765	79978	3,2	6	290	17	24	3153	100	174	71
Acura RSX Type S 2dr	1	0	0	0	0	0	0	0	0	23820	21761	2	4	200	24	31	2778	101	172	68
Acura TL 4dr	1	0	0	0	0	0	0	0	0	33195	30299	3,2	6	270	20	28	3575	108	186	72
Acura TSX 4dr	1	0	0	0	0	0	0	0	0	26990	24647	2,4	4	200	22	29	3230	105	183	69
Audi A4 1.8T 4dr	1	0	0	0	0	0	0	0	0	25940	23508	1,8	4	170	22	31	3252	104	179	70
Audi A4 3.0 4dr	1	0	0	0	0	0	0	0	0	31840	28846	3	6	220	20	28	3462	104	179	70
Audi A4 3.0 convertible 2dr	1	0	0	0	0	0	0	0	0	42490	38325	3	6	220	20	27	3814	105	180	70
Audi A4 3.0 Quattro 4dr auto	1	0	0	0	0	0	1	0	0	34480	31388	3	6	220	18	25	3627	104	179	70
Audi A4 3.0 Quattro 4dr manual	1	0	0	0	0	0	0	1	0	33430	30366	3	6	220	17	26	3583	104	179	70
Audi A4 3.0 Quattro convertible 2dr	1	0	0	0	0	0	0	1	0	44240	40075	3	6	220	18	25	4013	105	180	70

# Metadata

## ■ Sample from the cars data set

Acura 3.5 RL 4dr	1	0	0	0	0	0	0	43755	39014	3,5	6	225	18	24	3880	115	197	72	
Acura 3.5 RL w/Navigation 4dr	1	0	0	0	0	0	0	46100	41100	3,5	6	225	18	24	3893	115	197	72	
Acura MDX	0	0	1	0	0	0	1	0	36945	33337	3,5	6	265	17	23	4451	106	189	77
Acura NSX coupe 2dr manual S	0	1	0	0	0	0	0	1	89765	79978	3,2	6	290	17	24	3153	100	174	71
Acura RSX Type S 2dr	1	0	0	0	0	0	0	23820	21761	2	4	200	24	31	2778	101	172	68	
Acura TL 4dr	1	0	0	0	0	0	0	33195	30299	3,2	6	270	20	28	3575	108	186	72	
Acura TSX 4dr	1	0	0	0	0	0	0	26990	24647	2,4	4	200	22	29	3230	105	183	69	
Audi A4 1.8T 4dr	1	0	0	0	0	0	0	25940	23508	1,8	4	170	22	31	3252	104	179	70	
Audi A4 3.0 4dr	1	0	0	0	0	0	0	31840	28846	3	6	220	20	28	3462	104	179	70	
Audi A4 3.0 convertible 2dr	1	0	0	0	0	0	0	42490	38325	3	6	220	20	27	3814	105	180	70	
Audi A4 3.0 Quattro 4dr auto	1	0	0	0	0	1	0	34480	31388	3	6	220	18	25	3627	104	179	70	

■ With the exception of first column (Vehicle name) we need more information!

Vehicle Name	Small/Sporty/ Compact/Large Sedan	Sports Car	SUV	Wagon	Minivan	Pickup	AWD	RWD	Retail Price	Dealer Cost	Engine Size (l)	Cyl	HP	City MPG	Hwy MPG	Weight	Wheel Base	Len	Width	
Acura 3.5 RL 4dr	1	0	0	0	0	0	0	0	43755	39014	3,5	6	225	18	24	3880	115	197	72	
Acura 3.5 RL w/Navigation 4dr	1	0	0	0	0	0	0	0	46100	41100	3,5	6	225	18	24	3893	115	197	72	
Acura MDX	0	0	1	0	0	0	0	1	0	36945	33337	3,5	6	265	17	23	4451	106	189	77
Acura NSX coupe 2dr manual S	0	1	0	0	0	0	0	0	1	89765	79978	3,2	6	290	17	24	3153	100	174	71
Acura RSX Type S 2dr	1	0	0	0	0	0	0	0	0	23820	21761	2	4	200	24	31	2778	101	172	68
Acura TL 4dr	1	0	0	0	0	0	0	0	0	33195	30299	3,2	6	270	20	28	3575	108	186	72
Acura TSX 4dr	1	0	0	0	0	0	0	0	0	26990	24647	2,4	4	200	22	29	3230	105	183	69
Audi A4 1.8T 4dr	1	0	0	0	0	0	0	0	0	25940	23508	1,8	4	170	22	31	3252	104	179	70
Audi A4 3.0 4dr	1	0	0	0	0	0	0	0	0	31840	28846	3	6	220	20	28	3462	104	179	70
Audi A4 3.0 convertible 2dr	1	0	0	0	0	0	0	0	0	42490	38325	3	6	220	20	27	3814	105	180	70
Audi A4 3.0 Quattro 4dr auto	1	0	0	0	0	0	1	0	0	34480	31388	3	6	220	18	25	3627	104	179	70
Audi A4 3.0 Quattro 4dr manual	1	0	0	0	0	0	0	1	0	33430	30366	3	6	220	17	26	3583	104	179	70
Audi A4 3.0 Quattro convertible 2dr	1	0	0	0	0	0	0	1	0	44240	40075	3	6	220	18	25	4013	105	180	70

■ With the column names it is much better but it is not enough !

## Associated Metadata

NAME: 2004 New Car and Truck Data

TYPE: Sample

SIZE: 428 observations, 19 variables

### DESCRIPTIVE ABSTRACT:

Specifications are given for 428 new vehicles for the 2004 year. The variables recorded include price, measurements relating to the size of the vehicle, and fuel efficiency.

### SOURCE:

Kiplinger's Personal Finance, December 2003, vol. 57, no. 12, pp. 104-123, <http://www.kiplinger.com> (permission to post on the JSE Web site kindly granted by PARS International Corporation, 102 West 38th Street, New York, NY 10018)

### VARIABLE DESCRIPTIONS:

#### Columns Variables

1- 45	Vehicle Name
47	Sports Car? (1=yes, 0=no)
49	Sport Utility Vehicle? (1=yes, 0=no)
51	Wagon? (1=yes, 0=no)
53	Minivan? (1=yes, 0=no)
55	Pickup? (1=yes, 0=no)
57	All-Wheel Drive? (1=yes, 0=no)
59	Rear-Wheel Drive? (1=yes, 0=no)
61- 66	Suggested Retail Price, what the manufacturer thinks the vehicle is worth, including adequate profit for the automaker and the dealer (U.S. Dollars)
68- 73	Dealer Cost (or "invoice price"), what the dealership pays the manufacturer (U.S. Dollars)
75- 77	Engine Size ( <u>liters</u> )
79- 80	Number of Cylinders ( <u>=-1 if rotary engine</u> )
82-	84 Horsepower
86-	87 City Miles Per Gallon
89-	90 Highway Miles Per Gallon
92-	95 Weight (Pounds)
97-	99 Wheel Base (inches)
101-103	Length (inches)
105-106	Width (inches)

Values are aligned and delimited with blanks.

Missing values are denoted with \*.

## Associated Metadata

NAME: 2004 New Car and Truck Data

TYPE: Sample

SIZE: 428 observations, 19 variables

### DESCRIPTIVE ABSTRACT:

Specifications are given for 428 new vehicles for the 2004 year. The variables recorded include price, measurements relating to the size of the vehicle, and fuel efficiency.

### SOURCE:

Kiplinger's Personal Finance, December 2003, vol. 57, no. 12, pp. 104-123, <http://www.kiplinger.com> (permission to post on the JSE Web site kindly granted by PARS International Corporation, 102 West 38th Street, New York, NY 10018)

### VARIABLE DESCRIPTIONS:

#### Columns Variables

1- 45	Vehicle Name
47	Sports Car? (1=yes, 0=no)
49	Sport Utility Vehicle? (1=yes, 0=no)
51	Wagon? (1=yes, 0=no)
53	Minivan? (1=yes, 0=no)
55	Pickup? (1=yes, 0=no)
57	All-Wheel Drive? (1=yes, 0=no)
59	Rear-Wheel Drive? (1=yes, 0=no)
61- 66	Suggested Retail Price, what the manufacturer thinks the vehicle is worth, including adequate profit for the automaker and the dealer (U.S. Dollars)
68- 73	Dealer Cost (or "invoice price"), what the dealership pays the manufacturer (U.S. Dollars)
75- 77	Engine Size ( <u>liters</u> )
79- 80	Number of Cylinders ( <u>=-1 if rotary engine</u> )
82-	84 Horsepower
86-	87 City Miles Per Gallon
89-	90 Highway Miles Per Gallon
92-	95 Weight (Pounds)
97-	99 Wheel Base (inches)
101-103	Length (inches)
105-106	Width (inches)

### + Extended variable names and their meaning

Values are aligned and delimited with blanks.  
Missing values are denoted with \*.

## Associated Metadata

NAME: 2004 New Car and Truck Data

TYPE: Sample

SIZE: 428 observations, 19 variables

### DESCRIPTIVE ABSTRACT:

Specifications are given for 428 new vehicles for the 2004 year. The variables recorded include price, measurements relating to the size of the vehicle, and fuel efficiency.

### SOURCE:

Kiplinger's Personal Finance, December 2003, vol. 57, no. 12, pp. 104-123, <http://www.kiplinger.com> (permission to post on the JSE Web site kindly granted by PARS International Corporation, 102 West 38th Street, New York, NY 10018)

### VARIABLE DESCRIPTIONS:

#### Columns Variables

1-	45	Vehicle Name
47		Sports Car? (1=yes, 0=no)
49		Sport Utility Vehicle? (1=yes, 0=no)
51		Wagon? (1=yes, 0=no)
53		Minivan? (1=yes, 0=no)
55		Pickup? (1=yes, 0=no)
57		All-Wheel Drive? (1=yes, 0=no)
59		Rear-Wheel Drive? (1=yes, 0=no)
61-	66	Suggested Retail Price, what the manufacturer thinks the vehicle is worth, including adequate profit for the automaker and the dealer (U.S. Dollars)
68-	73	Dealer Cost (or "invoice price"), what the dealership pays the manufacturer (U.S. Dollars)
75-	77	Engine Size ( <u>liters</u> )
79-	80	Number of Cylinders ( <u>=-1 if rotary engine</u> )
82-	84	Horsepower
86-	87	City Miles Per Gallon
89-	90	Highway Miles Per Gallon
92-	95	Weight (Pounds)
97-	99	Wheel Base (inches)
101-	103	Length (inches)
105-	106	Width (inches)

Values are aligned and delimited with blanks.

Missing values are denoted with \*.

+ Extended variable names and their meaning

+ Used units

## Associated Metadata

NAME: 2004 New Car and Truck Data

TYPE: Sample

SIZE: 428 observations, 19 variables

### DESCRIPTIVE ABSTRACT:

Specifications are given for 428 new vehicles for the 2004 year. The variables recorded include price, measurements relating to the size of the vehicle, and fuel efficiency.

### SOURCE:

Kiplinger's Personal Finance, December 2003, vol. 57, no. 12, pp. 104-123, <http://www.kiplinger.com> (permission to post on the JSE Web site kindly granted by PARS International Corporation, 102 West 38th Street, New York, NY 10018)

### VARIABLE DESCRIPTIONS:

#### Columns Variables

1- 45	Vehicle Name
47	Sports Car? (1=yes, 0=no)
49	Sport Utility Vehicle? (1=yes, 0=no)
51	Wagon? (1=yes, 0=no)
53	Minivan? (1=yes, 0=no)
55	Pickup? (1=yes, 0=no)
57	All-Wheel Drive? (1=yes, 0=no)
59	Rear-Wheel Drive? (1=yes, 0=no)
61- 66	Suggested Retail Price, what the manufacturer thinks the vehicle is worth, including adequate profit for the automaker and the dealer (U.S. Dollars)
68- 73	Dealer Cost (or "invoice price"), what the dealership pays the manufacturer (U.S. Dollars)
75- 77	Engine Size ( <u>liters</u> )
79- 80	Number of Cylinders ( <u>=-1 if rotary engine</u> )
82- 84	Horsepower
86- 87	City Miles Per Gallon
89- 90	Highway Miles Per Gallon
92- 95	Weight (Pounds)
97- 99	Wheel Base (inches)
101-103	Length (inches)
105-106	Width (inches)

+ Extended variable names and their meaning

+ Used units

+ Special values

Values are aligned and delimited with blanks.

Missing values are denoted with \*.

## Associated Metadata

NAME: 2004 New Car and Truck Data

TYPE: Sample

SIZE: 428 observations, 19 variables

### DESCRIPTIVE ABSTRACT:

Specifications are given for 428 new vehicles for the 2004 year. The variables recorded include price, measurements relating to the size of the vehicle, and fuel efficiency.

### SOURCE:

Kiplinger's Personal Finance, December 2003, vol. 57, no. 12, pp. 104-123, <http://www.kiplinger.com> (permission to post on the JSE Web site kindly granted by PARS International Corporation, 102 West 38th Street, New York, NY 10018)

### VARIABLE DESCRIPTIONS:

#### Columns Variables

1- 45	Vehicle Name
47	Sports Car? (1=yes, 0=no)
49	Sport Utility Vehicle? (1=yes, 0=no)
51	Wagon? (1=yes, 0=no)
53	Minivan? (1=yes, 0=no)
55	Pickup? (1=yes, 0=no)
57	All-Wheel Drive? (1=yes, 0=no)
59	Rear-Wheel Drive? (1=yes, 0=no)
61- 66	Suggested Retail Price, what the manufacturer thinks the vehicle is worth, including adequate profit for the automaker and the dealer (U.S. Dollars)
68- 73	Dealer Cost (or "invoice price"), what the dealership pays the manufacturer (U.S. Dollars)
75- 77	Engine Size ( <u>liters</u> )
79- 80	Number of Cylinders ( <u>=-1 if rotary engine</u> )
82- 84	Horsepower
86- 87	City Miles Per Gallon
89- 90	Highway Miles Per Gallon
92- 95	Weight (Pounds)
97- 99	Wheel Base (inches)
101-103	Length (inches)
105-106	Width (inches)

+ Extended variable names and their meaning

+ Used units

+ Special values

+ How to denote missing values

Values are aligned and delimited with blanks.

Missing values are denoted with \*.

## ■ Metadata provides:

- ◆ **Source of data**
- ◆ **Information that facilitates the interpretation of the data set**
- ◆ **Units**
- ◆ **Symbol to indicate a missing value**
- ◆ **Reference point for some measurements**
- ◆ **Resolution at which the measurements were acquired**

# Basic statistics about the (scalar) data

## ■ For simple data types (scalars)

# Basic statistics about the (scalar) data

- For simple data types (scalars)
- All data types

# Basic statistics about the (scalar) data

- For simple data types (scalars)
- All data types
  - ◆ Number of missing values

# Basic statistics about the (scalar) data

- For simple data types (scalars)
- All data types
  - ◆ Number of missing values
- Excluding the non-numeric arbitrary (names, address, etc)

# Basic statistics about the (scalar) data

- For simple data types (scalars)
- All data types
  - ◆ Number of missing values
- Excluding the non-numeric arbitrary (names, address, etc)
  - ◆ Number of values out of range (if the range of variable is provided)

# Basic statistics about the (scalar) data

- For simple data types (scalars)
- All data types
  - ◆ Number of missing values
- Excluding the non-numeric arbitrary (names, address, etc)
  - ◆ Number of values out of range (if the range of variable is provided)
- For non-continuous values

# Basic statistics about the (scalar) data

- For simple data types (scalars)
- All data types
  - ◆ Number of missing values
- Excluding the non-numeric arbitrary (names, address, etc)
  - ◆ Number of values out of range (if the range of variable is provided)
- For non-continuous values
  - ◆ Frequency distribution

# Basic statistics about the (scalar) data

- For simple data types (scalars)
- All data types
  - ◆ Number of missing values
- Excluding the non-numeric arbitrary (names, address, etc)
  - ◆ Number of values out of range (if the range of variable is provided)
- For non-continuous values
  - ◆ Frequency distribution
  - ◆ Mode

# Basic statistics about the (scalar) data

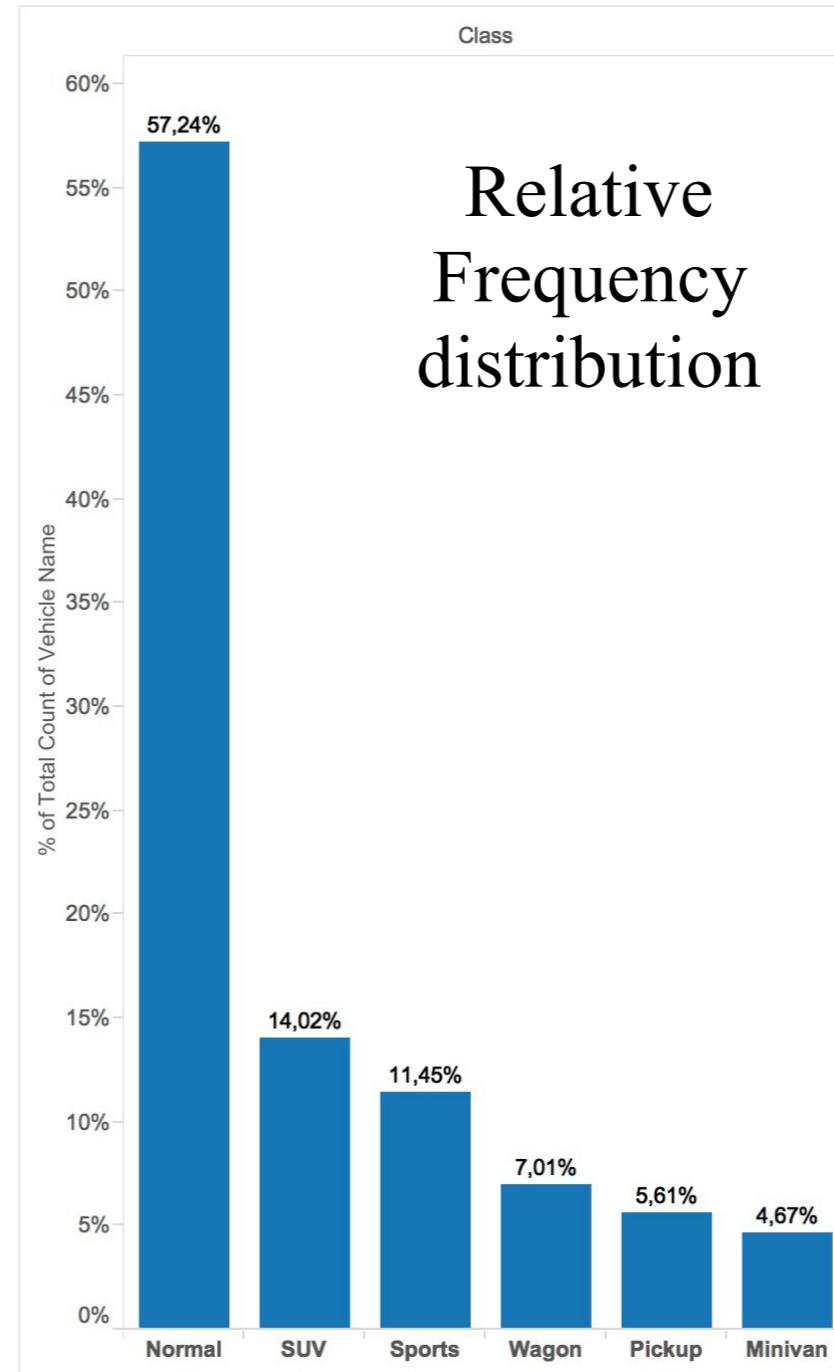
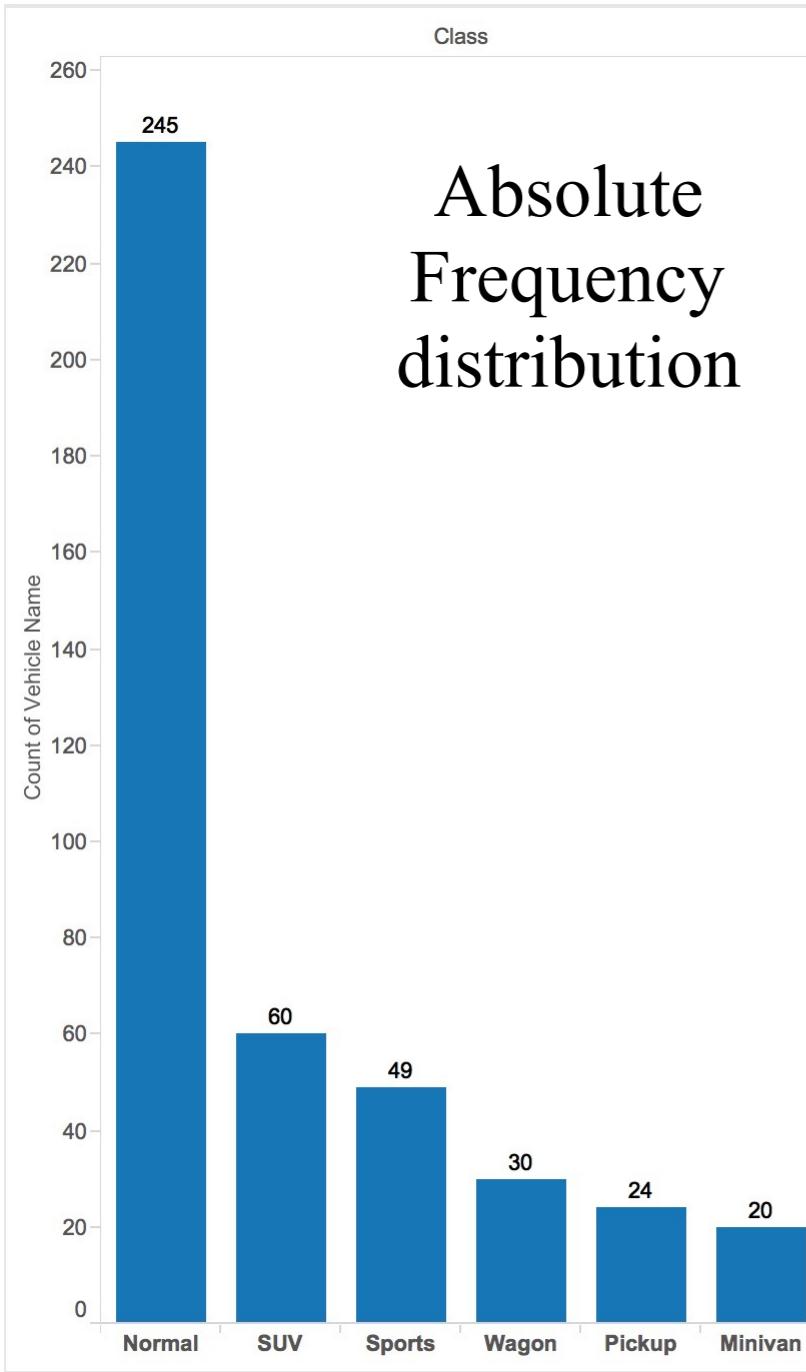
- For simple data types (scalars)
- All data types
  - ◆ Number of missing values
- Excluding the non-numeric arbitrary (names, address, etc)
  - ◆ Number of values out of range (if the range of variable is provided)
- For non-continuous values
  - ◆ Frequency distribution
  - ◆ Mode
- For numeric variables

# Basic statistics about the (scalar) data

- For simple data types (scalars)
- All data types
  - ◆ Number of missing values
- Excluding the non-numeric arbitrary (names, address, etc)
  - ◆ Number of values out of range (if the range of variable is provided)
- For non-continuous values
  - ◆ Frequency distribution
  - ◆ Mode
- For numeric variables
  - ◆ Mean, Variance, etc.

# Basic statistics about the (scalar) data

## ■ Categorical variable (from Cars data set): Class

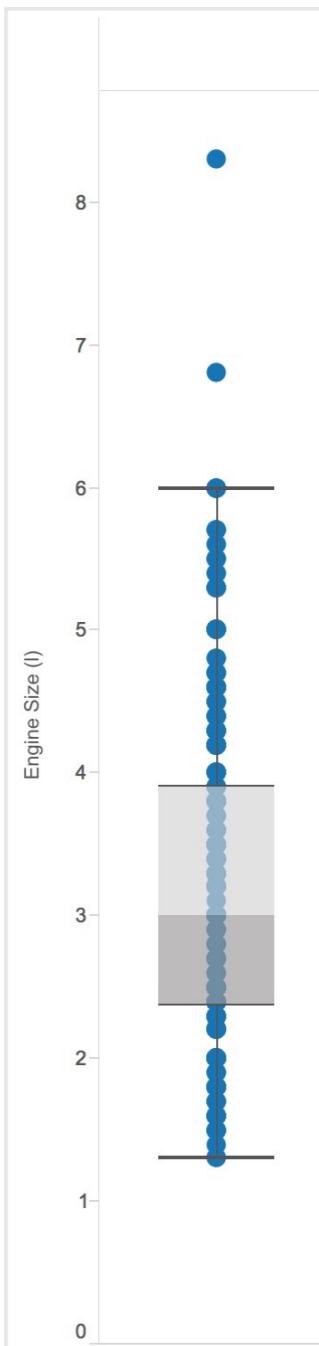


Stats:

- mode
- domain cardinality

# Basic statistics about the (scalar) data

## ■ Numeric (continuous) variable (from Cars data set): Engine Size



Summary	
Count:	428
SUM(Engine Size (l))	
Average:	3.197
Minimum:	1.300
Maximum:	8.300
Median:	3.000
Standard Deviation:	1.109
First Quartile:	2.375
Third Quartile:	3.900
Skewness:	0.71
Excess Kurtosis:	0.52

# Statistics techniques for getting additional insights

## ■ Outlier detection

- “In statistics, an outlier is an observation point that is distant from other observations. An outlier may be due to variability in the measurement or it may indicate experimental error; the latter are sometimes excluded from the data set.”

<https://en.wikipedia.org/wiki/Outlier>

<https://www.siam.org/meetings/sdm10/tutorial3.pdf>

# Statistics techniques for getting additional insights

## ■ Outlier detection

- “In statistics, an outlier is an observation point that is distant from other observations. An outlier may be due to variability in the measurement or it may indicate experimental error; the latter are sometimes excluded from the data set.”

<https://en.wikipedia.org/wiki/Outlier>

<https://www.siam.org/meetings/sdm10/tutorial3.pdf>

## ■ Cluster Analysis

- Can help segment the data into groups with strong similarities

[https://en.wikipedia.org/wiki/Cluster\\_analysis](https://en.wikipedia.org/wiki/Cluster_analysis)

# Statistics techniques for getting additional insights

## ■ Outlier detection

- “In statistics, an outlier is an observation point that is distant from other observations. An outlier may be due to variability in the measurement or it may indicate experimental error; the latter are sometimes excluded from the data set.”

<https://en.wikipedia.org/wiki/Outlier>

<https://www.siam.org/meetings/sdm10/tutorial3.pdf>

## ■ Cluster Analysis

- Can help segment the data into groups with strong similarities

[https://en.wikipedia.org/wiki/Cluster\\_analysis](https://en.wikipedia.org/wiki/Cluster_analysis)

## ■ Correlation Analysis

- can help users to eliminate variables (because are redundant or highlight)

# Statistics techniques for getting additional insights

## ■ Correlation Analysis

### Trend Lines Model

A linear trend model is computed for Dealer Cost given Retail Price. The model may be significant at  $p \leq 0,05$ .

Model formula: (Retail Price + intercept)

Number of modeled observations: 428

Number of filtered observations: 0

Model degrees of freedom: 2

Residual degrees of freedom (DF): 426

SSE (sum squared error): 2,30717e+08

MSE (mean squared error): 541590

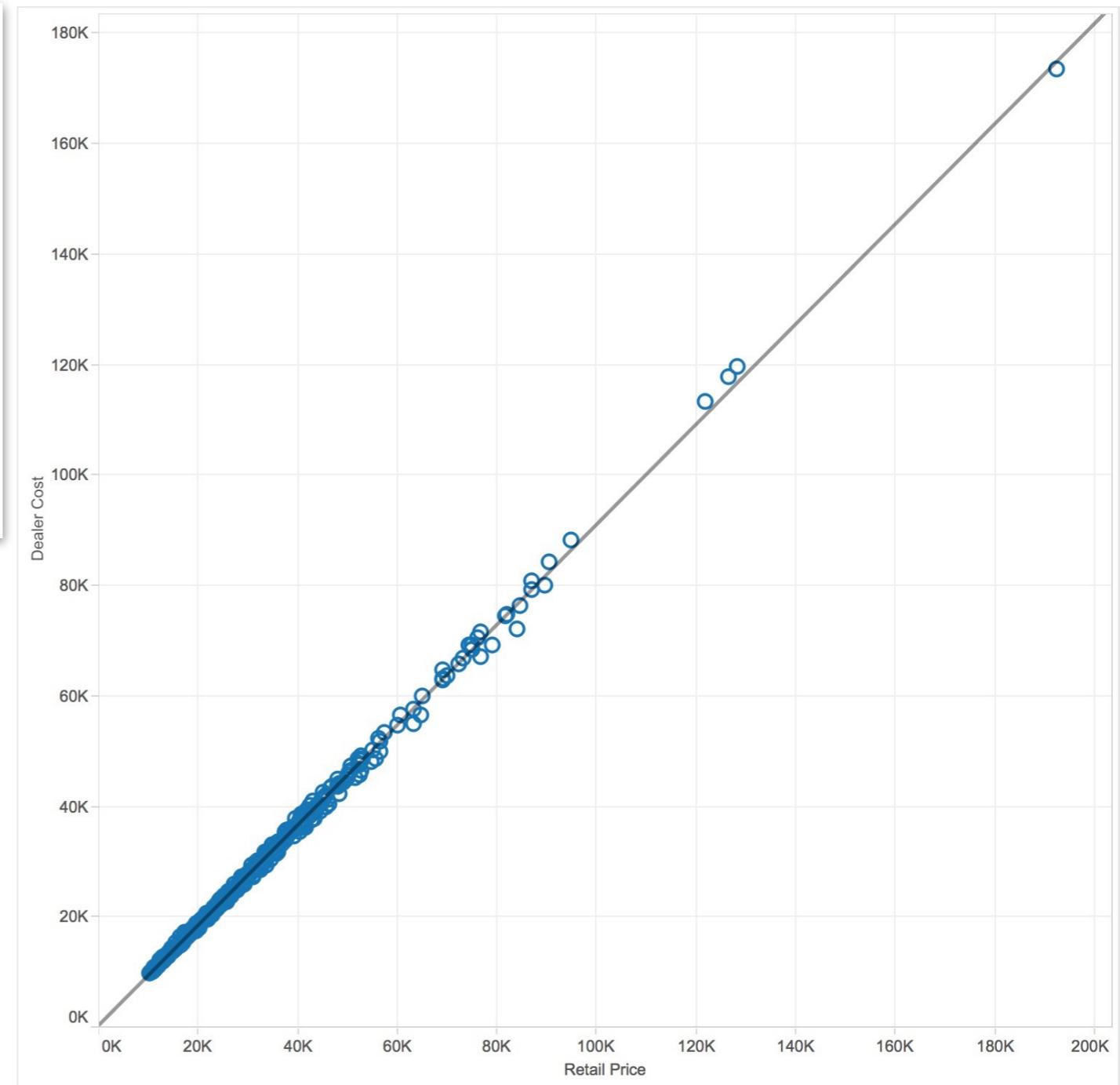
R-Squared: 0,998264

Standard error: 735,928

p-value (significance): < 0,0001

### Individual trend lines:

Panes	Line	Coefficients						
Row	Column	p-value	DF	Term	Value	StdErr	t-value	p-value
Dealer	Retail Price	< 0,0001	426	Retail Price	0,907115	0,0018328	494,939	< 0,0001
Cost				Intercept	284,145	69,8118	4,07015	< 0,0001



# Missing Values and Data Cleansing

## ■ Missing data:

# Missing Values and Data Cleansing

## ■ Missing data:

- malfunctioning sensor; blank entry on a survey; omission on a person entering the data; etc..

# Missing Values and Data Cleansing

## ■ Missing data:

- malfunctioning sensor; blank entry on a survey; omission on a person entering the data; etc..
- It is necessary to define a strategy to deal with missing data. It should depend on the application domain, the number of missing values, the quality of the other variables.

# Missing Values and Data Cleansing

## ■ Missing data:

- malfunctioning sensor; blank entry on a survey; omission on a person entering the data; etc..
- It is necessary to define a strategy to deal with missing data. It should depend on the application domain, the number of missing values, the quality of the other variables.

## ■ Erroneous data

# Missing Values and Data Cleansing

## ■ Missing data:

- malfunctioning sensor; blank entry on a survey; omission on a person entering the data; etc..
- It is necessary to define a strategy to deal with missing data. It should depend on the application domain, the number of missing values, the quality of the other variables.

## ■ Erroneous data

- human error; malfunctioning sensor, etc..

# Missing Values and Data Cleansing

## ■ Missing data:

- malfunctioning sensor; blank entry on a survey; omission on a person entering the data; etc..
- It is necessary to define a strategy to deal with missing data. It should depend on the application domain, the number of missing values, the quality of the other variables.

## ■ Erroneous data

- human error; malfunctioning sensor, etc..
- May be very hard to detect unless they are out of range values or obvious outlier.

# Missing Values

- **Discard the bad record**
- Is the most commonly applied; It implies a loss of information that should be evaluated. Sometimes the records with missing values are the most interesting to be analyzed.

# Missing Values

- **Discard the bad record**
  - Is the most commonly applied; It implies a loss of information that should be evaluated. Sometimes the records with missing values are the most interesting to be analyzed.
- **Assign a sentinel value**
  - Assign a sentinel value for each variable when the real value is in question (missing or erroneous). This value should be carefully considered in the processing.

# Missing Values

- **Discard the bad record**
  - Is the most commonly applied; It implies a loss of information that should be evaluated. Sometimes the records with missing values are the most interesting to be analyzed.
- **Assign a sentinel value**
  - Assign a sentinel value for each variable when the real value is in question (missing or erroneous). This value should be carefully considered in the processing.
- **Assign the average value**
  - Average value for that variable; Minimally affects the statistics of that variable; The average may not be a good guess; It may mask outliers.

# Missing Values and Data Cleansing

# Missing Values and Data Cleansing

- Assign value **based on nearest neighbor**
  - Try to find the (missing) value for one variable  $i$  for one particular record based on the value(s) for that variable based on the records that are the most similar to this particular record (based on the other variables). We are assuming that the variable  $i$  depends on all other variables and may not be the case.
  - When we have connectivity information (spatial or geo-spatial data, graphs) the nearest neighbor may be considered based on the available connections.

# Missing Values and Data Cleansing

- **Assign value based on nearest neighbor**
  - Try to find the (missing) value for one variable  $i$  for one particular record based on the value(s) for that variable based on the records that are the most similar to this particular record (based on the other variables). We are assuming that the variable  $i$  depends on all other variables and may not be the case.
  - When we have connectivity information (spatial or geo-spatial data, graphs) the nearest neighbor may be considered based on the available connections.
- **Compute a substitute value**
  - All the previous methods are had hoc ! Some new statistical approaches propose methods and algorithms to make multiple imputations for the missing values
  - More info: "Multiple imputation for multivariate missing-data problems: a data analyst's perspective", by Joseph L. Schafer and Maren K. Olsen

# Normalization

# Normalization

- Most normalization methods require a distance metric.

# Normalization

- Most normalization methods require a distance metric.
- One purpose is to scale different variables to comparable range of values.

# Normalization

- Most normalization methods require a distance metric.
- One purpose is to scale different variables to comparable range of values.
- Another objective is to redistribute the values if they are concentrated on a small part of the available scale

# Normalization

- Most normalization methods require a distance metric.
- One purpose is to scale different variables to comparable range of values.
- Another objective is to redistribute the values if they are concentrated on a small part of the available scale
- Examples of normalization functions:

# Normalization

- Most normalization methods require a distance metric.
- One purpose is to scale different variables to comparable range of values.
- Another objective is to redistribute the values if they are concentrated on a small part of the available scale
- Examples of normalization functions:

$$\bullet d_{normalized} = \frac{(d_{original} - d_{min})}{(d_{max} - d_{min})}$$

# Normalization

- Most normalization methods require a distance metric.
- One purpose is to scale different variables to comparable range of values.
- Another objective is to redistribute the values if they are concentrated on a small part of the available scale
- Examples of normalization functions:

$$\bullet d_{normalized} = \frac{(d_{original} - d_{min})}{(d_{max} - d_{min})}$$

$$\bullet d_{sqrt-normalized} = \frac{(\sqrt{d_{original}} - \sqrt{d_{min}})}{(\sqrt{d_{max}} - \sqrt{d_{min}})}$$

# Normalization

- Most normalization methods require a distance metric.
- One purpose is to scale different variables to comparable range of values.
- Another objective is to redistribute the values if they are concentrated on a small part of the available scale
- Examples of normalization functions:

$$\bullet d_{normalized} = \frac{(d_{original} - d_{min})}{(d_{max} - d_{min})}$$

$$\bullet d_{sqrt-normalized} = \frac{(\sqrt{d_{original}} - \sqrt{d_{min}})}{(\sqrt{d_{max}} - \sqrt{d_{min}})}$$

$$\bullet d_{log-normalized} = \frac{(\log d_{original} - \log d_{min})}{(\log d_{max} - \log d_{min})}$$

# Normalization

- Most normalization methods require a distance metric.
- One purpose is to scale different variables to comparable range of values.
- Another objective is to redistribute the values if they are concentrated on a small part of the available scale
- Examples of normalization functions:

$$\bullet d_{normalized} = \frac{(d_{original} - d_{min})}{(d_{max} - d_{min})}$$

$$\bullet d_{z-Score} = \frac{(d_{original} - \mu)}{\sigma}$$

$$\bullet d_{sqrt-normalized} = \frac{(\sqrt{d_{original}} - \sqrt{d_{min}})}{(\sqrt{d_{max}} - \sqrt{d_{min}})}$$

$$\bullet d_{log-normalized} = \frac{(\log d_{original} - \log d_{min})}{(\log d_{max} - \log d_{min})}$$

# Normalization

- Most normalization methods require a distance metric.
- One purpose is to scale different variables to comparable range of values.
- Another objective is to redistribute the values if they are concentrated on a small part of the available scale
- Examples of normalization functions:

$$\bullet d_{normalized} = \frac{(d_{original} - d_{min})}{(d_{max} - d_{min})}$$

$$\bullet d_{sqrt-normalized} = \frac{(\sqrt{d_{original}} - \sqrt{d_{min}})}{(\sqrt{d_{max}} - \sqrt{d_{min}})}$$

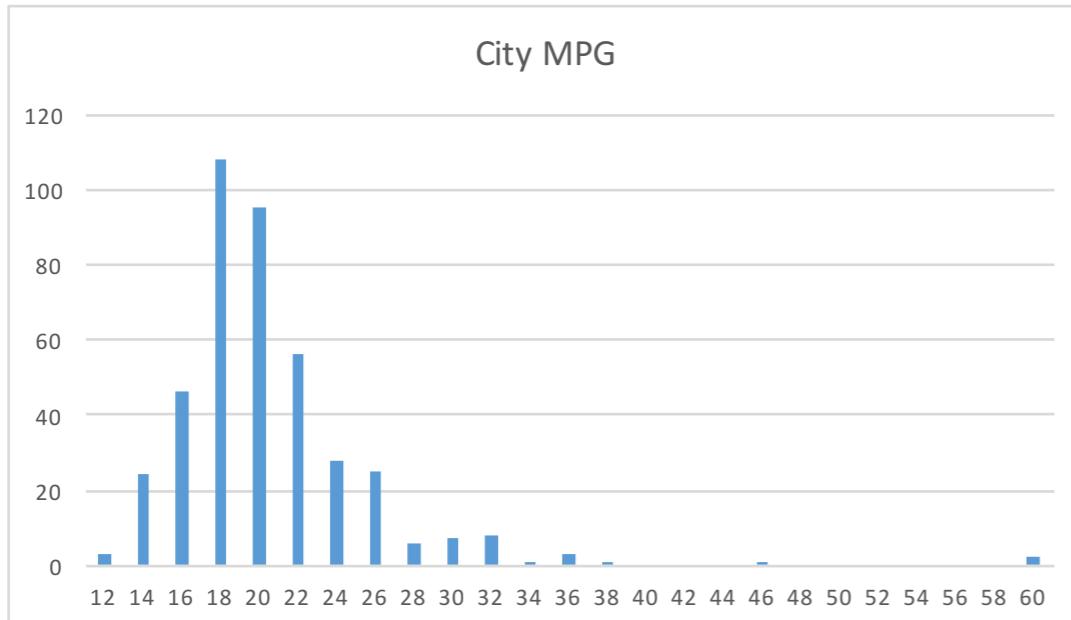
$$\bullet d_{log-normalized} = \frac{(\log d_{original} - \log d_{min})}{(\log d_{max} - \log d_{min})}$$

$$\bullet d_{z-Score} = \frac{(d_{original} - \mu)}{\sigma}$$

- Replacing **Min** and **Max** by  $\delta$ -**Quantile** and  $(1-\delta)$ -**Quantile**

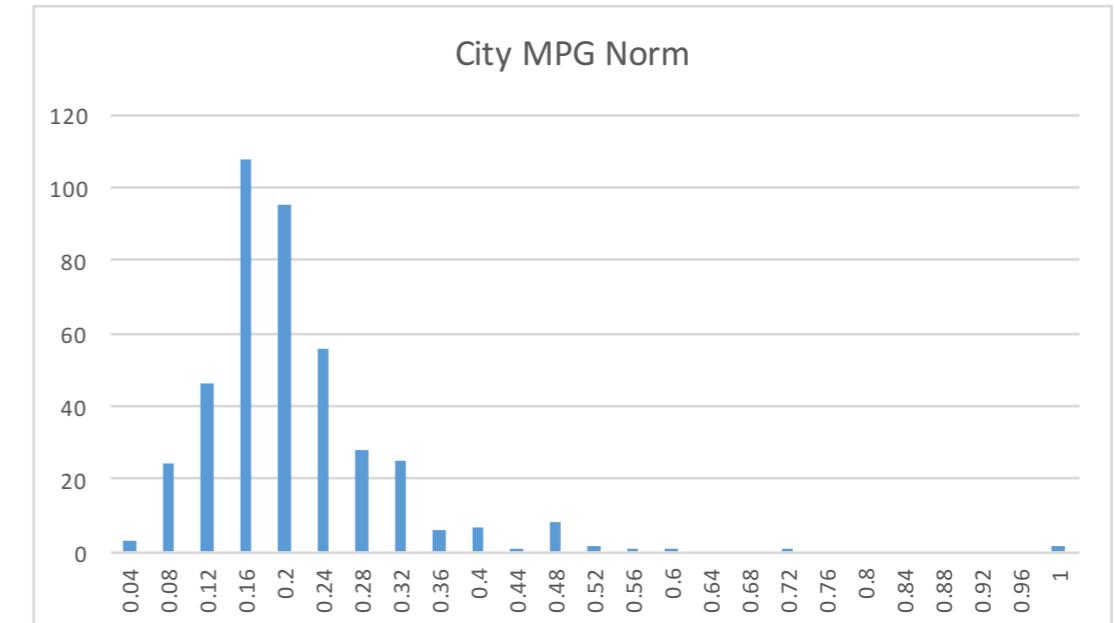
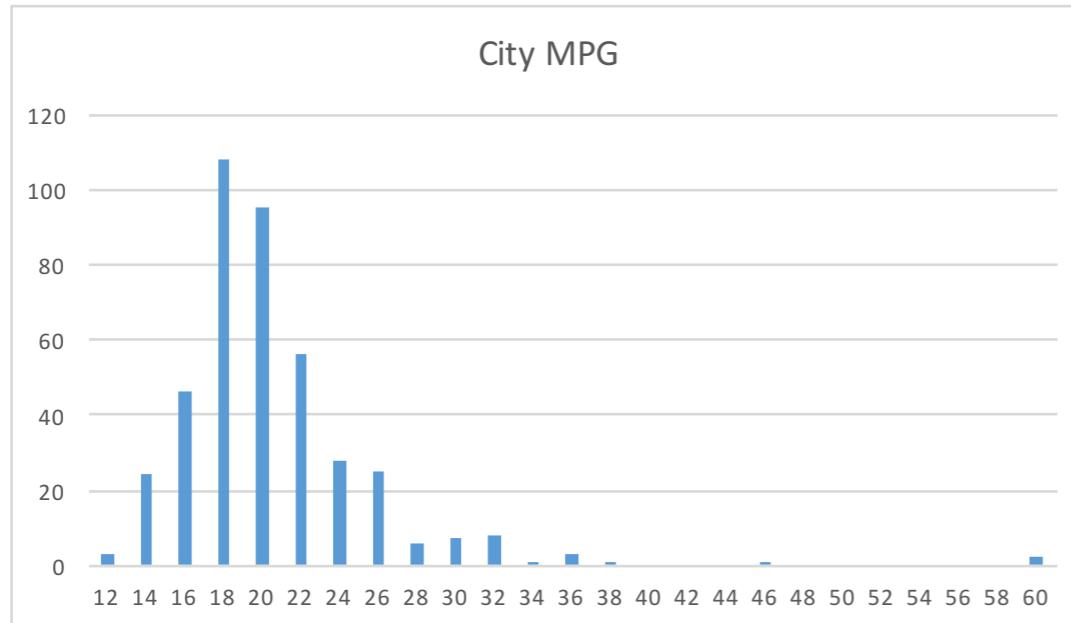
# Normalization

- Data from 414 cars (from 2004); Variable: City Miles Per Gallon (City MPG)



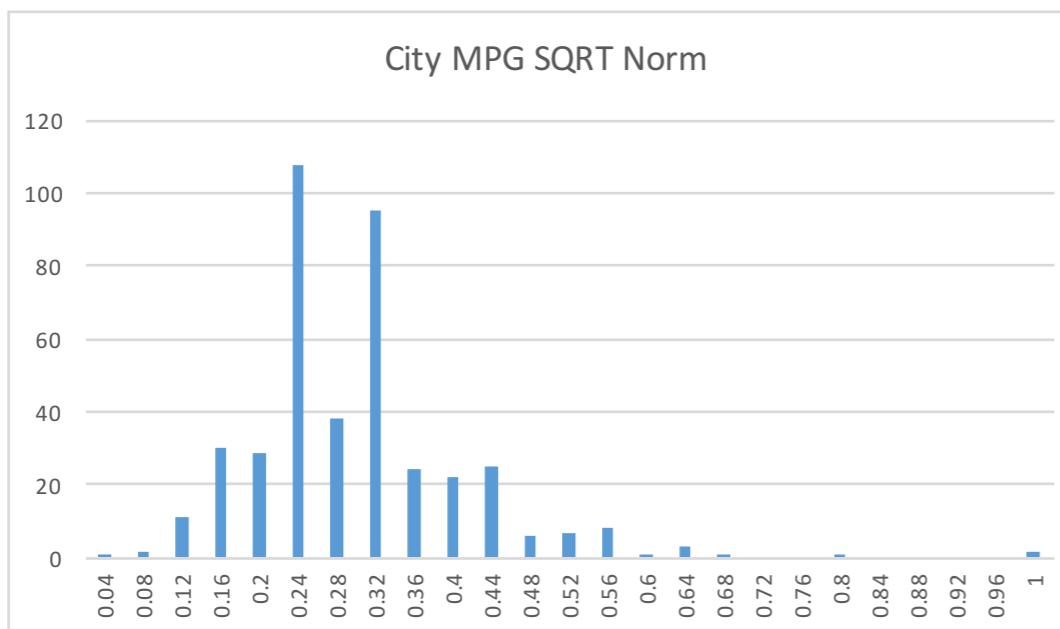
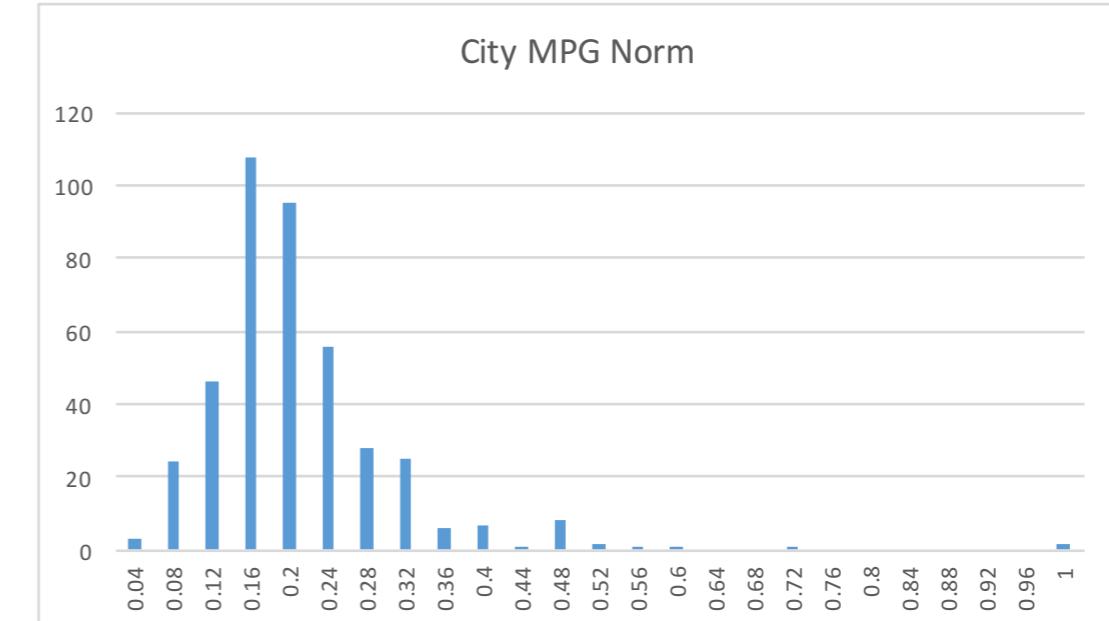
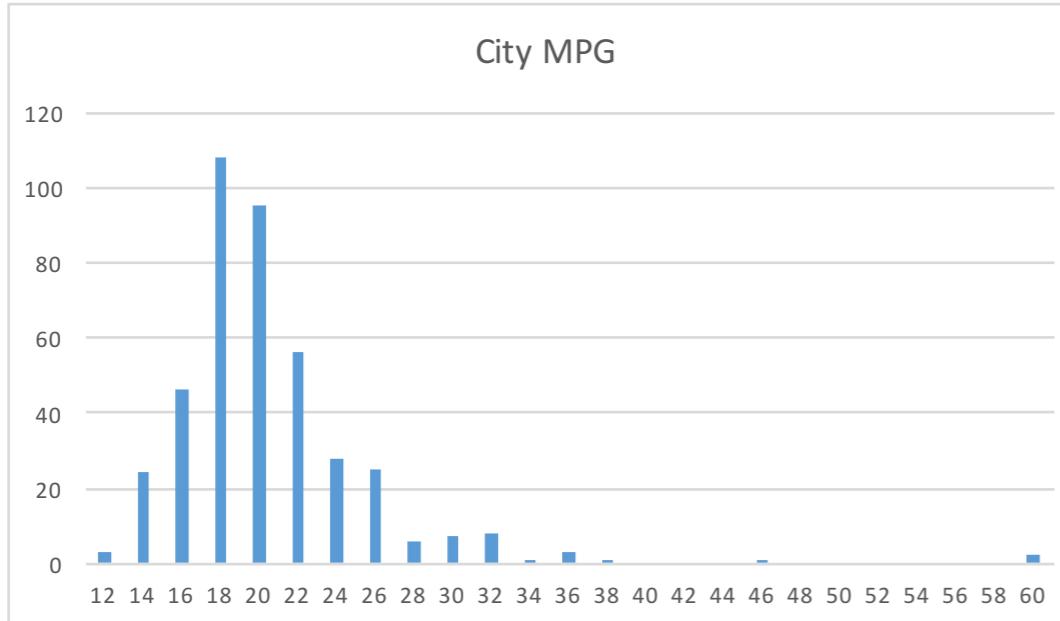
# Normalization

- Data from 414 cars (from 2004); Variable: City Miles Per Gallon (City MPG)



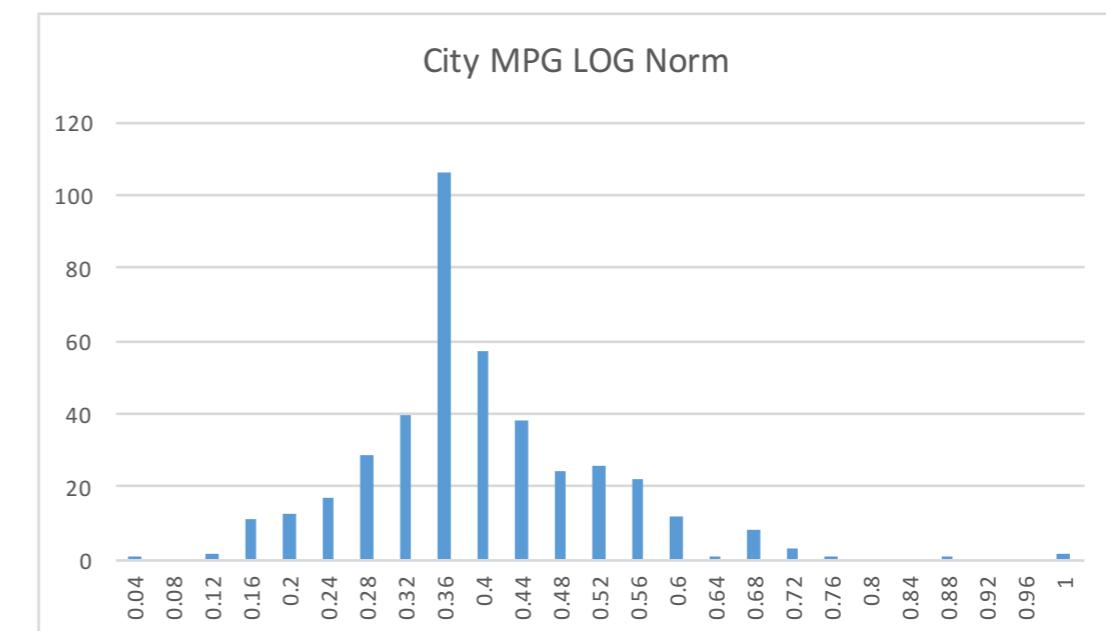
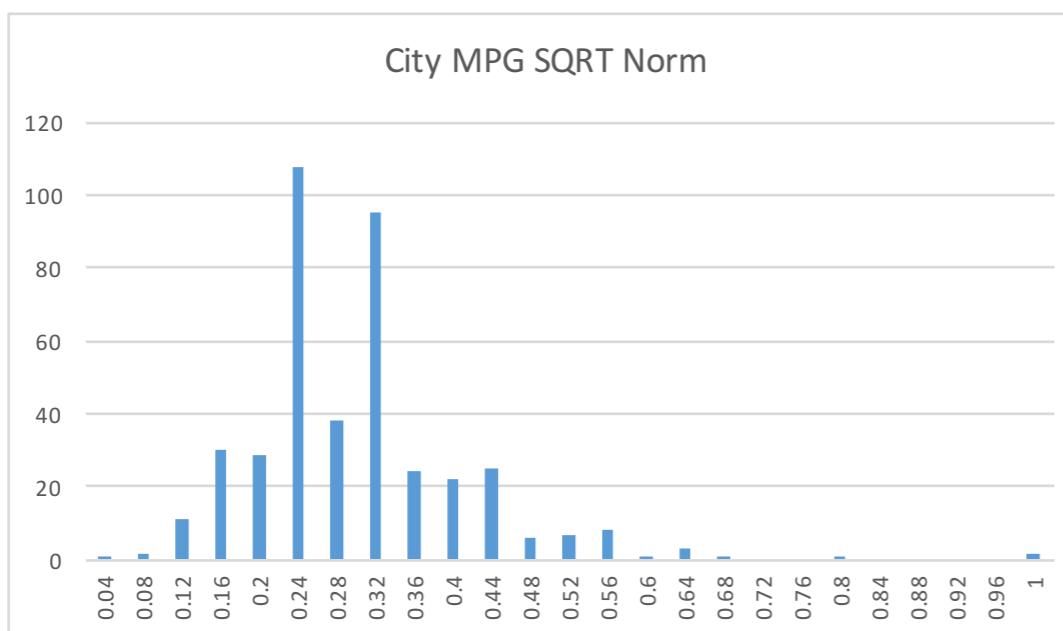
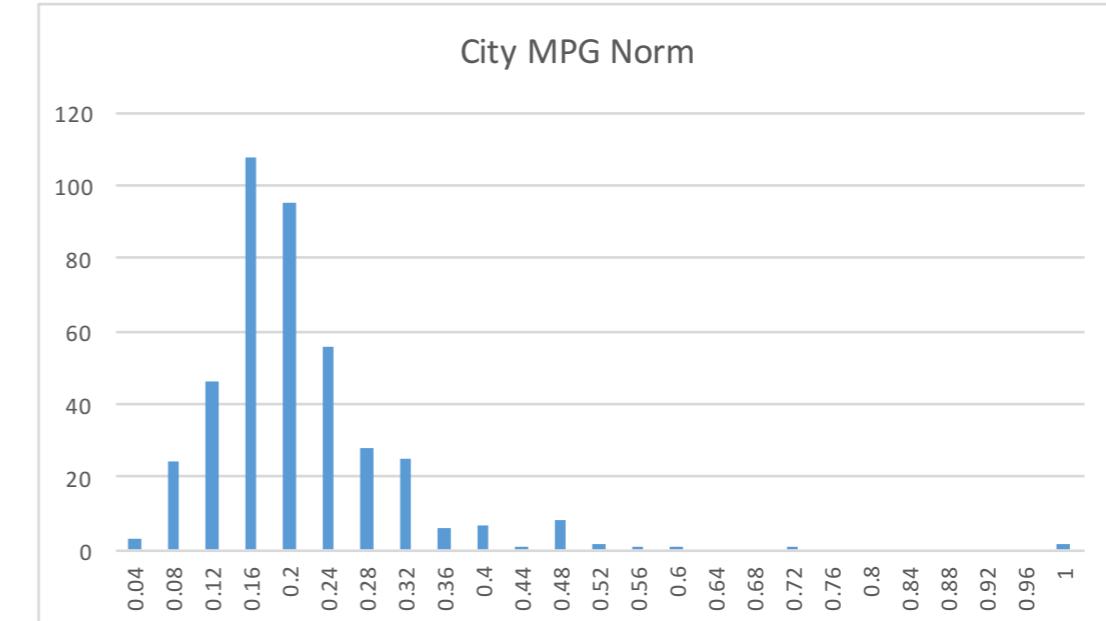
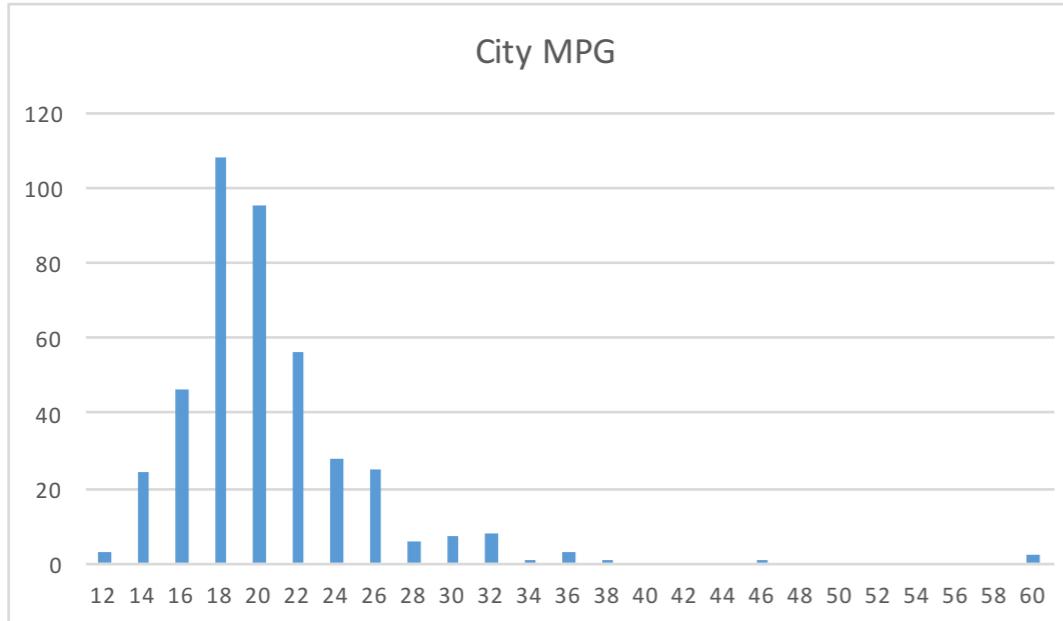
# Normalization

- Data from 414 cars (from 2004); Variable: City Miles Per Gallon (City MPG)



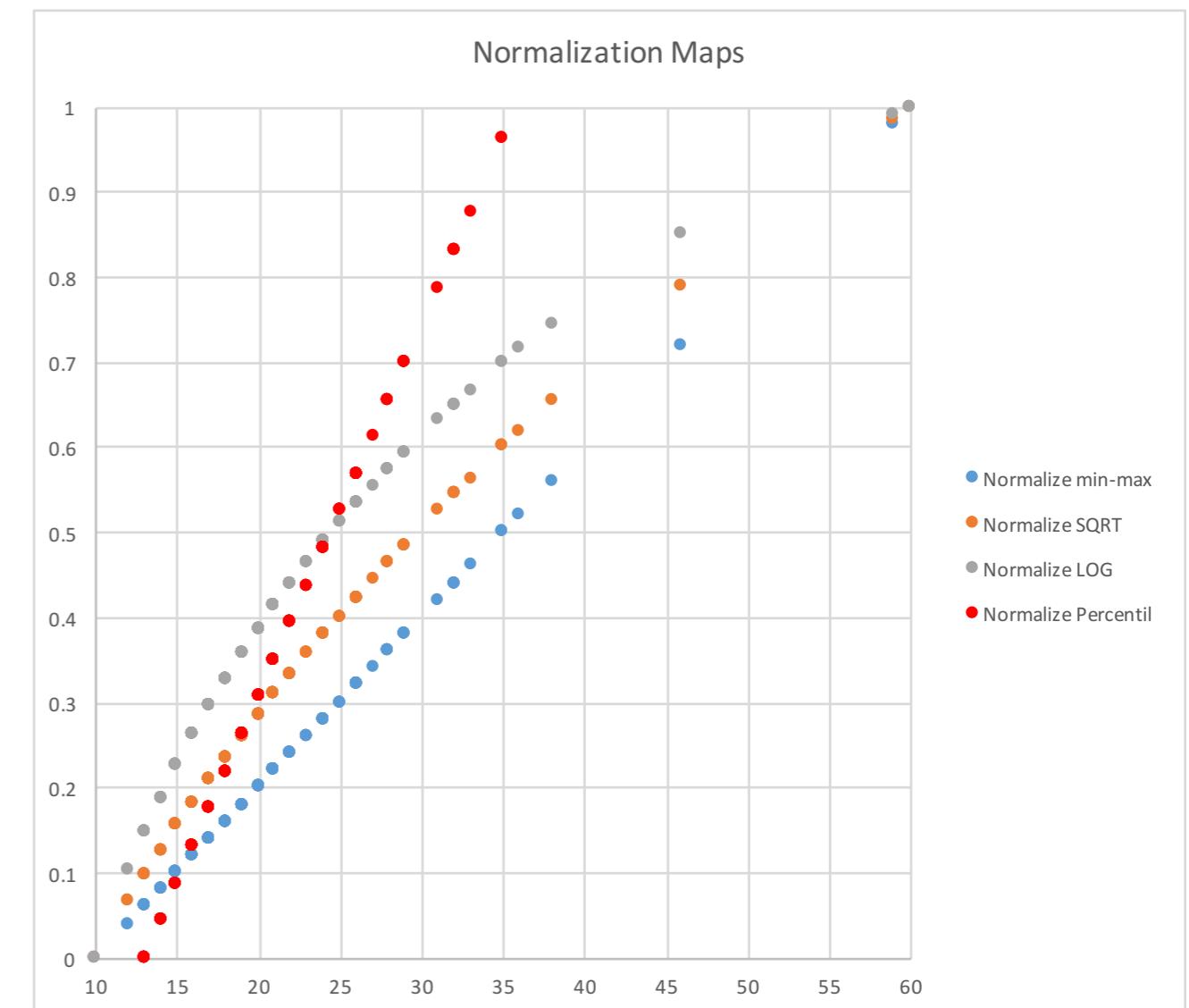
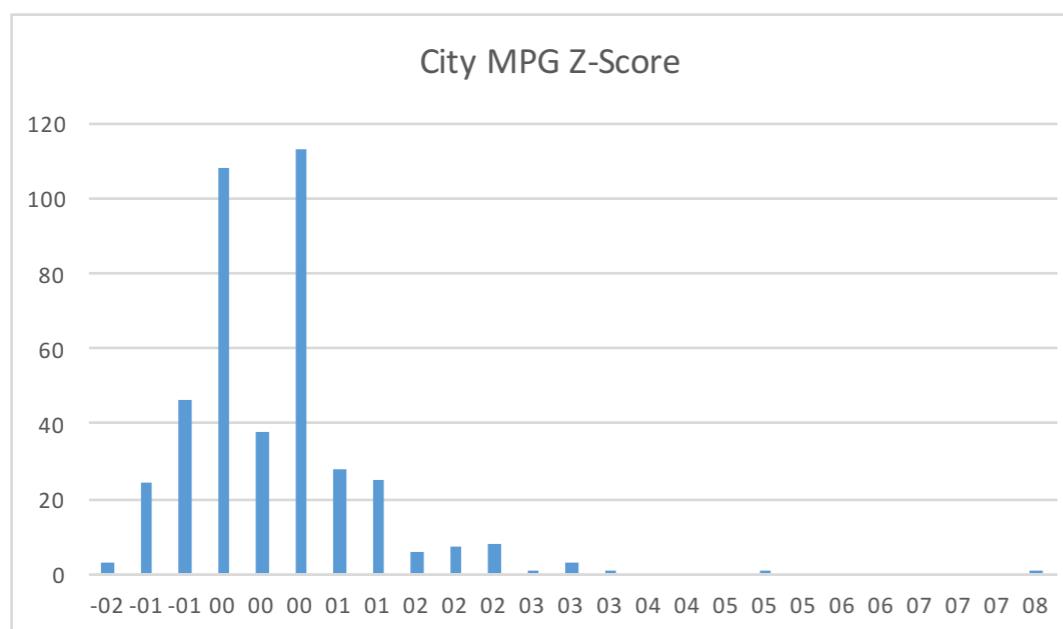
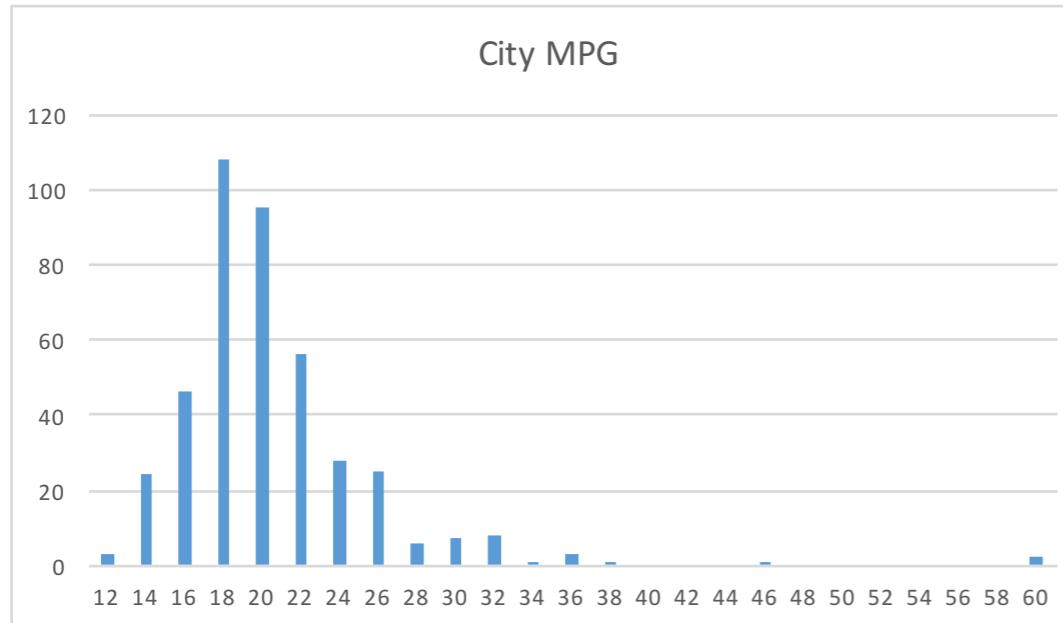
# Normalization

- Data from 414 cars (from 2004); Variable: City Miles Per Gallon (City MPG)



# Normalization

- Data from 414 cars (from 2004); Variable: City Miles Per Gallon (City MPG)

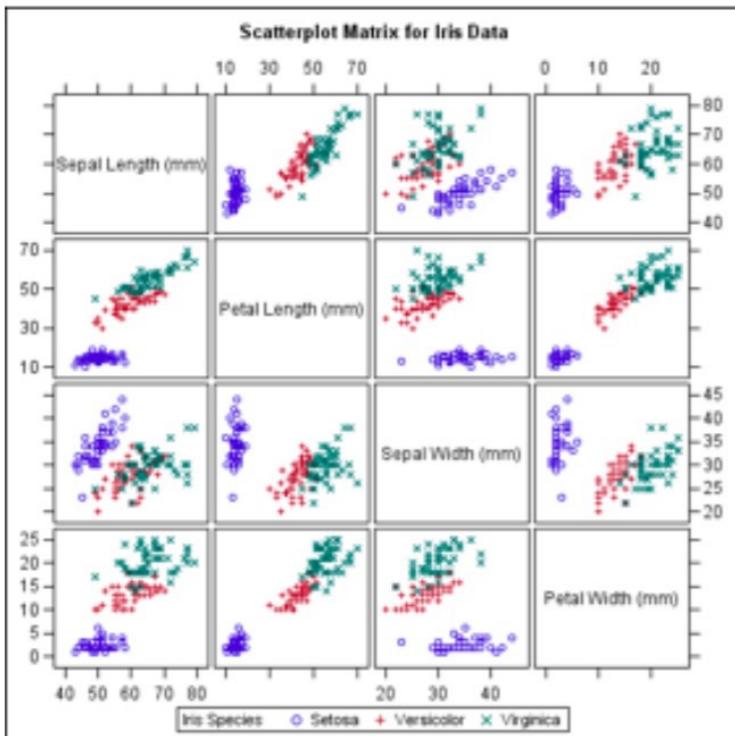


# Dimension reduction

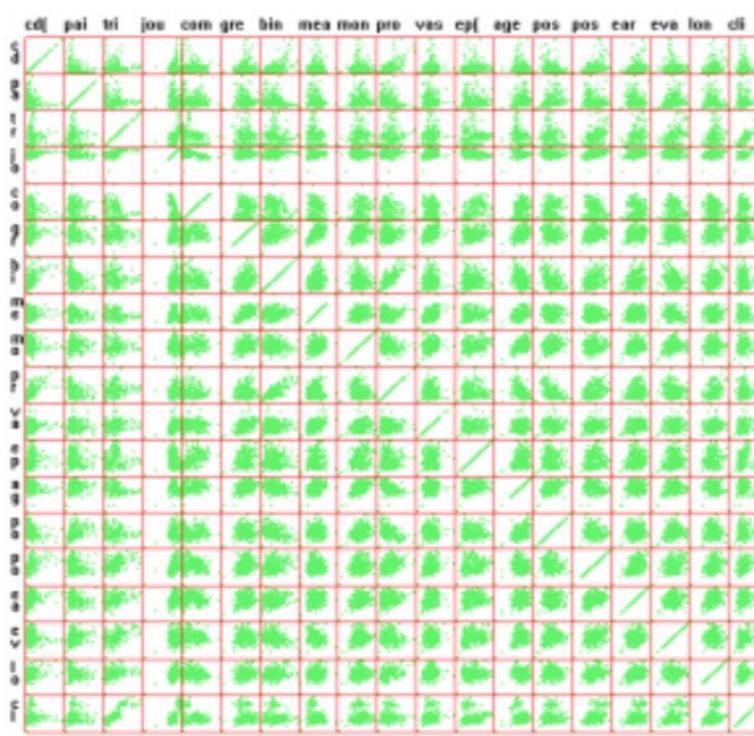
- In situations where the dimensionality of the data exceeds the capabilities of the visualization technique.

Example of Scatter Plot

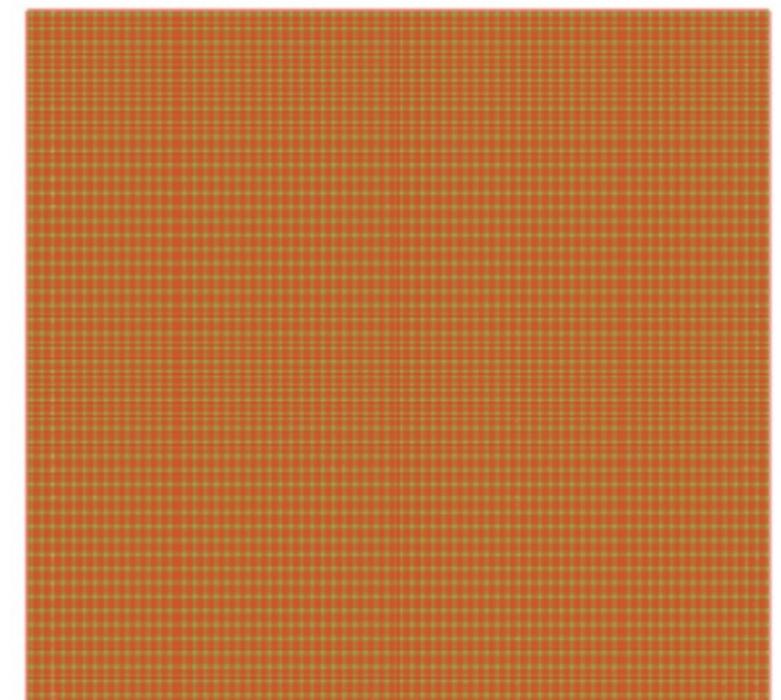
4 dimensions



20 dimensions



100 dimensions



\* Taken from: Jing Yang's [Interactive Hierarchical Dimension Ordering, Spacing and Filtering for Exploration of High Dimensional Datasets](#).

Bertini DataScience showcase (2014)

# Dimension reduction

- In situations where the dimensionality of the data exceeds the capabilities of the visualization technique. It is necessary to investigate ways to **reduce the data dimensionality, while at the same time preserving, as much as possible, the information contained within.**

# Dimension reduction

- In situations where the dimensionality of the data exceeds the capabilities of the visualization technique. It is necessary to investigate ways to **reduce the data dimensionality, while at the same time preserving, as much as possible, the information contained within.**
- Principal Component Analysis (PCA) - [read more](#)

# Dimension reduction

- In situations where the dimensionality of the data exceeds the capabilities of the visualization technique. It is necessary to investigate ways to **reduce the data dimensionality, while at the same time preserving, as much as possible, the information contained within.**
- Principal Component Analysis (PCA) - [read more](#)
- Multidimensional Scaling (MDS) - [read more](#) and [more](#)

# Dimension reduction

- In situations where the dimensionality of the data exceeds the capabilities of the visualization technique. It is necessary to investigate ways to **reduce the data dimensionality, while at the same time preserving, as much as possible, the information contained within.**
- Principal Component Analysis (PCA) - [read more](#)
- Multidimensional Scaling (MDS) - [read more](#) and [more](#)
- Non-linear dimension reduction techniques:
  - ◆ Self-organizing Maps (SOMs) - [read more](#)
  - ◆ Local Linear Embeddings (LLE) - [read more](#)

# Dimension reduction - Principal Component Analysis (PCA)

- PCA computes new dimensions/attributes which are linear combinations of the original data attributes.

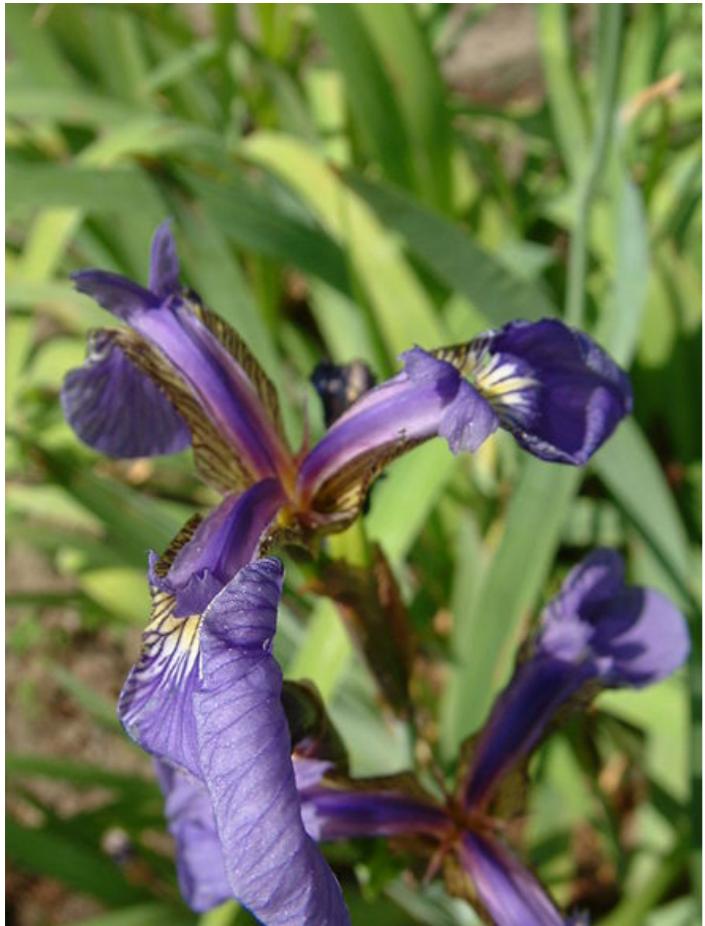
# Dimension reduction - Principal Component Analysis (PCA)

- PCA computes new dimensions/attributes which are linear combinations of the original data attributes.
- The advantage of the new dimensions is that they can be sorted according to their contribution in explaining the variance of the data.

# Dimension reduction - Principal Component Analysis (PCA)

- PCA computes new dimensions/attributes which are linear combinations of the original data attributes.
- The advantage of the new dimensions is that they can be sorted according to their contribution in explaining the variance of the data.
- By selecting the most relevant new dimensions, a subspace of variables is obtained that minimizes the average error of lost information

# Dimension reduction - Principal Component Analysis (PCA)



*Iris setosa*



*Iris versicolor*



*Iris virginica*

Iris flower data set

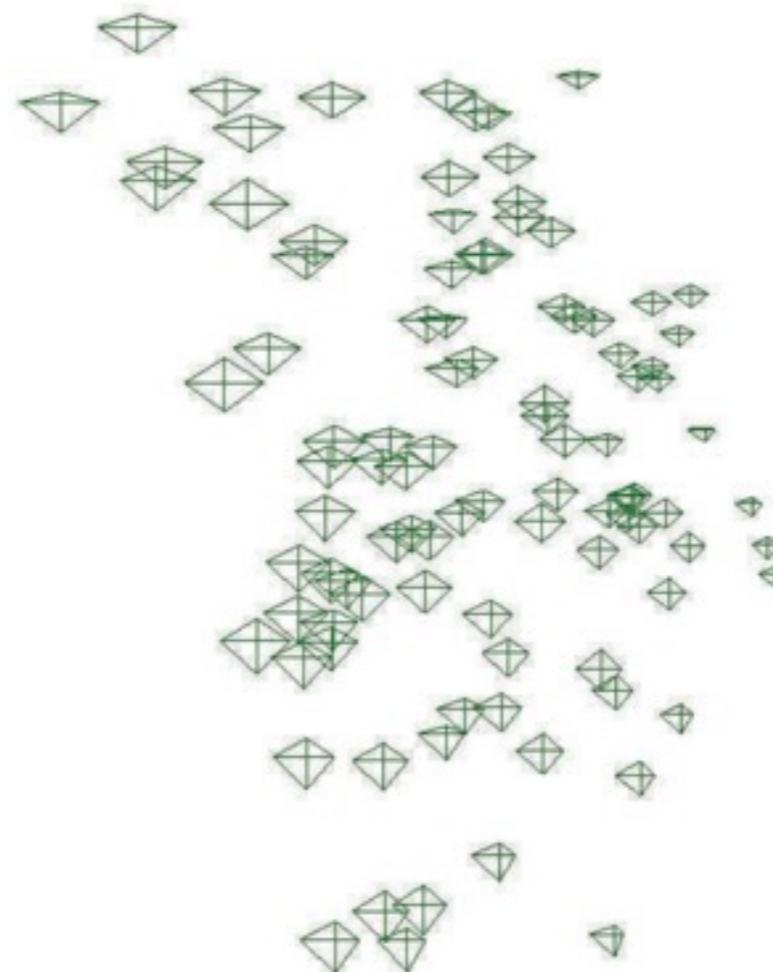
# Dimension reduction - Principal Component Analysis (PCA)

- Figure 2.4 from Interactive Data Visualization: Foundations, Techniques, and Applications, Matthew O. Ward, Georges Grinstein, Daniel Keim, 2010

4 Variables



2 Variables



Iris flower data set



The Iris data set in star glyphs, with the position of each point based on the first two principal components. The star glyph represents four variables as the lengths of the each of the lines emanating from the center of a four-pointed star. Reasonable clustering can be seen.

# Mapping Nominal Dimensions to Numbers

## ■ How to visualize Nominal dimensions?

# Mapping Nominal Dimensions to Numbers

- How to visualize Nominal dimensions?
  - how many nominal dimensions exist?

# Mapping Nominal Dimensions to Numbers

- How to visualize Nominal dimensions?
  - how many nominal dimensions exist?
  - how many distinct values each variable can take on?

# Mapping Nominal Dimensions to Numbers

- How to visualize Nominal dimensions?
  - how many nominal dimensions exist?
  - how many distinct values each variable can take on?
  - an ordering or distance relation is available or can be derived?

# Mapping Nominal Dimensions to Numbers

- How to visualize Nominal dimensions?
  - how many nominal dimensions exist?
  - how many distinct values each variable can take on?
  - an ordering or distance relation is available or can be derived?
- Warning:

Find a mapping of the data to a graphical entity or attribute that  
**doesn't introduce artificial relationships that don't exist in the data**

# Mapping Nominal Dimensions to Numbers

## ■ How to visualize Nominal dimensions?

- how many nominal dimensions exist?
- how many distinct values each variable can take on?
- an ordering or distance relation is available or can be derived?

## ■ Warning:

Find a mapping of the data to a graphical entity or attribute that  
**doesn't introduce artificial relationships that don't exist in the data**

## ■ Ranked nominal values can be mapped to numbers and so can be easily mapped to many graphical attributes

# Mapping Nominal Dimensions to Numbers

## ■ How to visualize Nominal dimensions?

- how many nominal dimensions exist?
- how many distinct values each variable can take on?
- an ordering or distance relation is available or can be derived?

## ■ Warning:

Find a mapping of the data to a graphical entity or attribute that  
**doesn't introduce artificial relationships that don't exist in the data**

- Ranked nominal values can be mapped to numbers and so can be easily mapped to many graphical attributes
- Non ranked nominal values have to be managed carefully

# Mapping Nominal Dimensions to Numbers

- Non-ranked nominal values have to be managed carefully
- Variables with only a modest number of different values:
  - map to graphical attributes like color or shape

# Mapping Nominal Dimensions to Numbers

- Non-ranked nominal values have to be managed carefully
- Variables with only a modest number of different values:
  - map to graphical attributes like color or shape
- A single nominal variable:
  - Use this variable as the label for the graphical elements being displayed when the number of records to be displayed is modest.

# Mapping Nominal Dimensions to Numbers

- Non-ranked nominal values have to be managed carefully
- Variables with only a modest number of different values:
  - map to graphical attributes like color or shape
- A single nominal variable:
  - Use this variable as the label for the graphical elements being displayed when the number of records to be displayed is modest.
  - Showing random subsets of labels and changing the points with labels being shown on a regular basis, and showing only the labels on objects near the cursor.

# Mapping Nominal Dimensions to Numbers

- **Mapping to numbers by looking at **similarities between the numeric variables** associated with a pair of nominal values**

See more: [https://en.wikipedia.org/wiki/Correspondence\\_analysis](https://en.wikipedia.org/wiki/Correspondence_analysis)

<http://www.mathematica-journal.com/2010/09/an-introduction-to-correspondence-analysis/>

# Mapping Nominal Dimensions to Numbers

- Mapping to numbers by looking at **similarities between the numeric variables associated with a pair of nominal values**
- If the statistical properties of the records associated with **one nominal value** are sufficiently **similar to the properties of a different value**, then that implies that **these two values should likely be mapped to similar numeric values.**

See more: [https://en.wikipedia.org/wiki/Correspondence\\_analysis](https://en.wikipedia.org/wiki/Correspondence_analysis)

<http://www.mathematica-journal.com/2010/09/an-introduction-to-correspondence-analysis/>

# Mapping Nominal Dimensions to Numbers

- Mapping to numbers by looking at **similarities between the numeric variables associated with a pair of nominal values**
- If the statistical properties of the records associated with **one nominal value** are sufficiently **similar to the properties of a different value**, then that implies that these two values should likely be **mapped to similar numeric values**.
- Conversely, if there are sufficient differences in properties, then likely they should be mapped to quite distinct values.

See more: [https://en.wikipedia.org/wiki/Correspondence\\_analysis](https://en.wikipedia.org/wiki/Correspondence_analysis)

<http://www.mathematica-journal.com/2010/09/an-introduction-to-correspondence-analysis/>

# Mapping Nominal Dimensions to Numbers

- Mapping to numbers by looking at **similarities between the numeric variables associated with a pair of nominal values**
  - If the statistical properties of the records associated with **one nominal value** are sufficiently **similar to the properties of a different value**, then that implies that these two values should likely be **mapped to similar numeric values**.
  - Conversely, if there are sufficient differences in properties, then likely they should be mapped to quite distinct values.
- Given all the pairwise similarities, we could use **correspondence analysis** to map the different nominal values to positions in one dimension. Applying to all nominal dimensions of the data set - **multiple correspondence analysis**.

See more: [https://en.wikipedia.org/wiki/Correspondence\\_analysis](https://en.wikipedia.org/wiki/Correspondence_analysis)

<http://www.mathematica-journal.com/2010/09/an-introduction-to-correspondence-analysis/>

## Other data processing topics

# Segmentation

# Segmentation

- In many situations, the **data can be separated into contiguous regions, where each region corresponds to a particular classification of the data.**

# Segmentation

- In many situations, the **data can be separated into contiguous regions**, where each region corresponds to a particular classification of the data.
- Simple segmentation can be performed by just mapping **disjoint ranges of the data values to specific categories**.

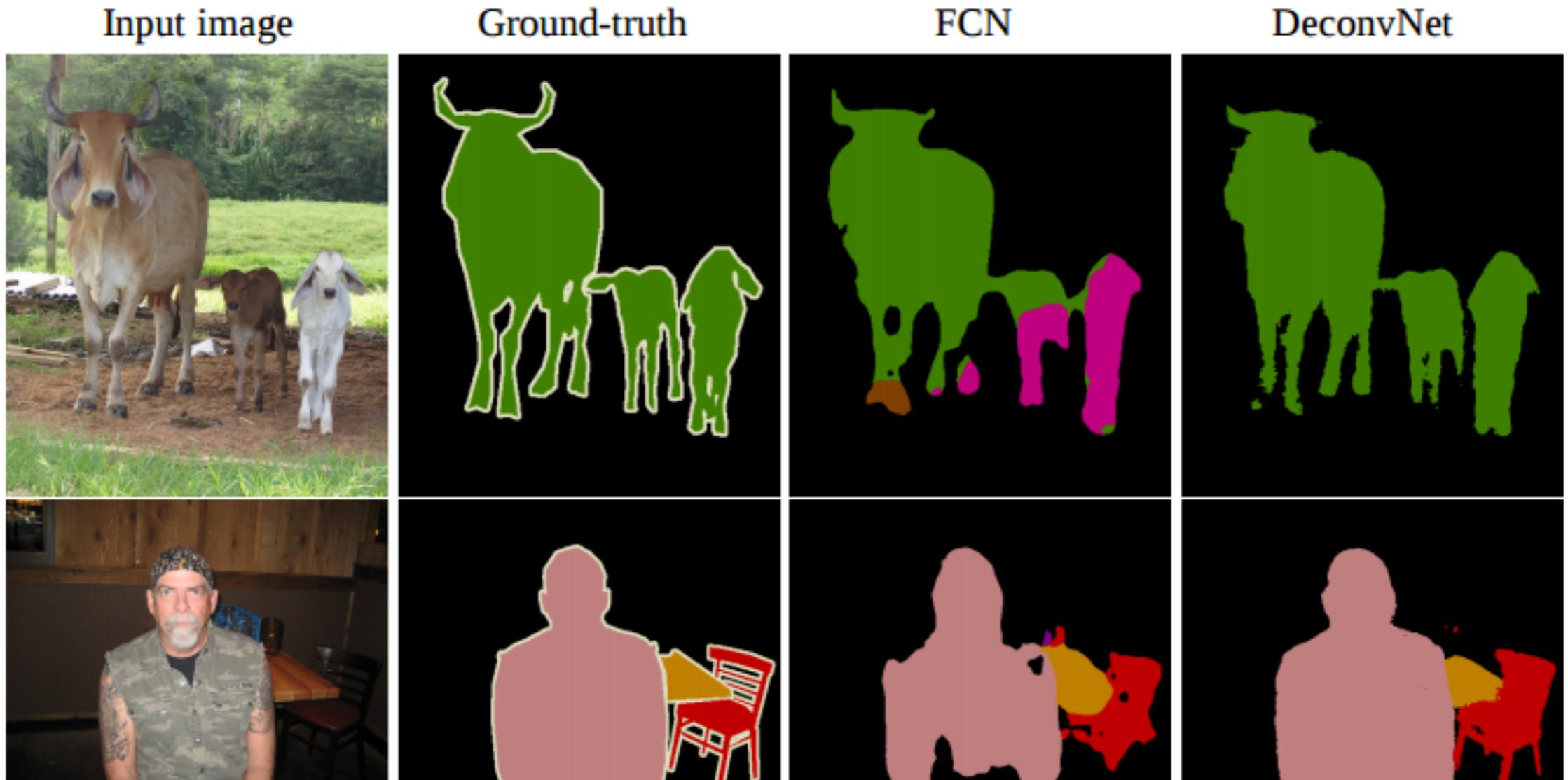
# Segmentation

- In many situations, the **data can be separated into contiguous regions**, where each region corresponds to a particular classification of the data.
- Simple segmentation can be performed by just mapping **disjoint ranges of the data values to specific categories**.
- it is important to look at the classification of neighboring points to improve the confidence of classification, or even to do a probabilistic segmentation, where each data point is assigned a probability for belonging to each of the available classifications.

# Segmentation

- In many situations, the **data can be separated into contiguous regions**, where each region corresponds to a particular classification of the data.
- Simple segmentation can be performed by just mapping **disjoint ranges of the data values to specific categories**.
- it is important to look at the classification of neighboring points to improve the confidence of classification, or even to do a probabilistic segmentation, where each data point is assigned a probability for belonging to each of the available classifications.
- Common in image data or geo-spatial data (satellite images)

# Segmentation



# Sampling and subsetting

# Sampling and subsetting

- To transform a data set with one spatial resolution into another data set with a different spatial resolution. For example, we might have an image we would like to shrink or expand, or we might have only a small **sampling of data points** and **wish to fill in values for locations between our samples (assuming that the data is a discrete sampling of a continuous phenomenon)**.

# Sampling and subsetting

- To transform a data set with one spatial resolution into another data set with a different spatial resolution. For example, we might have an image we would like to shrink or expand, or we might have only a small **sampling of data points** and **wish to fill in values for locations between our samples (assuming that the data is a discrete sampling of a continuous phenomenon)**.
- The process of interpolation is a commonly used resampling method in many fields, including visualization:
  - Linear interpolation
  - bi-linear interpolation
  - Nonlinear interpolation

# Sampling and subsetting

- Data **subsetting** is also a frequently used operation both prior to and during visualization.
- This is especially helpful for **very large data sets**, as the visualization of the entire data set may lead to substantial visual clutter.
- Query before visualization versus subsetting during visualization

# Aggregation and Summarization

# Aggregation and Summarization

- it is often useful to group data points based on their similarity in value and/or position and represent the group by some smaller amount of data:

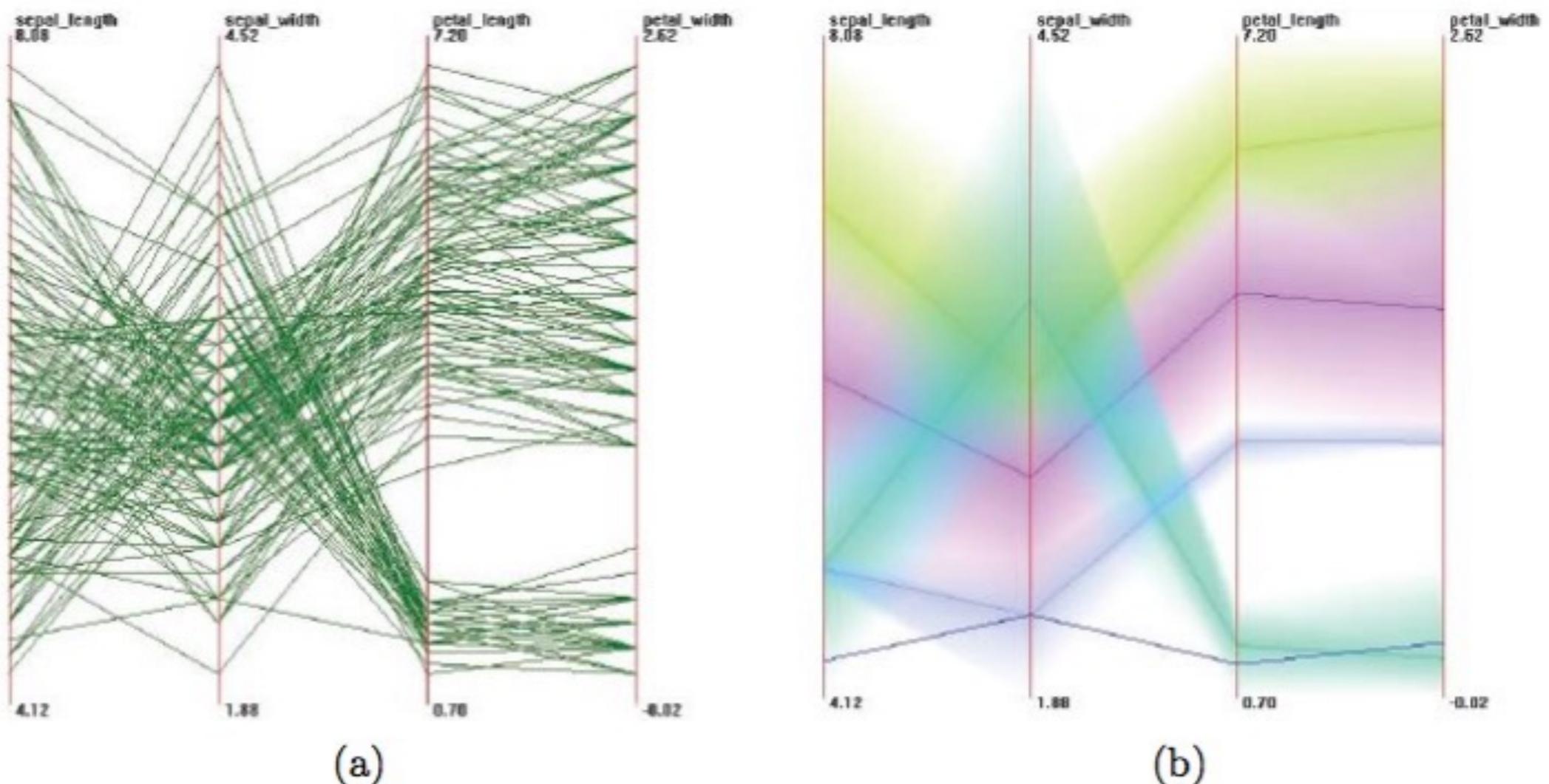
# Aggregation and Summarization

- it is often useful to group data points based on their similarity in value and/or position and represent the group by some smaller amount of data:
- Data Clustering methods
  - ◆ See More:
    - [https://en.wikipedia.org/wiki/Cluster\\_analysis](https://en.wikipedia.org/wiki/Cluster_analysis)
    - <http://www.ise.bgu.ac.il/faculty/liorr/hbchap15.pdf>

# Aggregation and Summarization

- it is often useful to group data points based on their similarity in value and/or position and represent the group by some smaller amount of data:
- Data Clustering methods
  - ◆ See More:
    - [https://en.wikipedia.org/wiki/Cluster\\_analysis](https://en.wikipedia.org/wiki/Cluster_analysis)
    - <http://www.ise.bgu.ac.il/faculty/liorr/hbchap15.pdf>
- Displaying the clusters (or their representation)
  - ◆ Provide sufficient information for the user to decide whether he or she wishes to perform a **drill-down** on the data

# Aggregation and Summarization



**Figure 2.5.** The Iris data set in parallel coordinates: (a) the original data; (b) the centers and extents of clusters after aggregation. Each axis in parallel coordinates represents a dimension, with each record being drawn as a polyline through each of the coordinate values on the axes.

# Smoothing and Filtering

# Smoothing and Filtering

- In **statistics** and **image processing**, to **smooth** a data set is to create an **approximating function** that attempts to capture important patterns in the data, **while leaving out noise** or other fine-scale structures/rapid phenomena.

# Smoothing and Filtering

- In **statistics** and **image processing**, to **smooth** a data set is to create an **approximating function** that attempts to capture important patterns in the data, **while leaving out noise** or other fine-scale structures/rapid phenomena.
- In **smoothing**, the data points of a signal are modified so individual points (presumably because of noise) are reduced, and points that are lower than the adjacent points are increased leading to a smoother signal

# Smoothing and Filtering

- In **statistics** and **image processing**, to **smooth** a data set is to create an **approximating function** that attempts to capture important patterns in the data, **while leaving out noise** or other fine-scale structures/rapid phenomena.
- In **smoothing**, the data points of a signal are modified so individual points (presumably because of noise) are reduced, and points that are lower than the adjacent points are increased leading to a smoother signal
- See more:
  - <https://en.wikipedia.org/wiki/Smoothing>

# Raster to vector conversion

# Raster to vector conversion

- In Computer Graphics:
  - Vector data (vertices, edges, and triangular or quadrilateral patches) => Image (pixel-based)

# Raster to vector conversion

## ■ In Computer Graphics:

- **Vector data (vertices, edges, and triangular or quadrilateral patches) => Image (pixel-based)**
- **It can be important to make the reverse:**
  - ◆ **Compressing the contents for transmission.**
  - ◆ **Comparing the contents of two or more images**
  - ◆ **Transforming the data**
  - ◆ **Segmenting the data**

# Raster to vector conversion

## ■ In Computer Graphics:

- Vector data (vertices, edges, and triangular or quadrilateral patches) => Image (pixel-based)
- It can be important to make the reverse:
  - ◆ Compressing the contents for transmission.
  - ◆ Comparing the contents of two or more images
  - ◆ Transforming the data
  - ◆ Segmenting the data
- Read more: IDV: Foundations, Techniques, and Applications, Pag 72 - 74

## Further Reading and Summary

# Further Reading

- **Recommend Readings**
  - ◆ Pag 51 - 76 from Interactive Data Visualization: Foundations, Techniques, and Applications
  - ◆ Pag 30 - 40 from Visualization Analysis & Design, Tamara Munzner
- **Supplemental readings:**
  - ◆ <https://en.wikipedia.org/wiki/Outlier>
  - ◆ [https://en.wikipedia.org/wiki/Cluster\\_analysis](https://en.wikipedia.org/wiki/Cluster_analysis)
  - ◆ [https://en.wikipedia.org/wiki/Correspondence\\_analysis](https://en.wikipedia.org/wiki/Correspondence_analysis)
  - ◆ [https://en.wikipedia.org/wiki/Cluster\\_analysis](https://en.wikipedia.org/wiki/Cluster_analysis)

# What you should know

- **The concept of variable or dimension and the difference between independent and dependent variables.**
  - ◆ grocking the data => take decisions
- **The various data types taxonomies and the impact of a data type in visualization.**
  - ◆ numeric vs non numeric; oder vs non-order; Types of scale;
- **The structural aspects of a data set.**
  - ◆ Tables, links, position, grid, etc.
- **Data pre-processing techniques: the goal of each one and the most important ones**
  - ◆ Outlier detection and process; normalization; dimensionality reduction, Sampling and subsetting; Aggregation and Summarization

# Recommended Actions

- **Install Tableau software (desktop version). Activate with a students license.**
  - <http://www.tableau.com/academic/students>
- **To get an overview of Tableau see the video:**
  - <http://www.tableau.com/learn/tutorials/on-demand/getting-started>
- **Get familiar with the dataset 2004 Cars and Trucks Data Set**
  - <http://www.idvbook.com/teaching-aid/teaching-aid/data-sets/2004-cars-and-trucks-data/>