Data Preprocessing

Why Preprocess Data?

- Raw data not ready to analyze
- Issues of data quality
- Conclusions drawn may be questionable or unreliable

Measures for data quality

- Accuracy: is the data correct or wrong, accurate or not?
- Completeness: is there missing data?
- Consistency: are there conflicts in the data?
- Timeliness: is data old or recently updated?
- Believability: can you trust that the data is correct?
- Interpretability: how easily can the data be understood?

Major Data Preprocessing Tasks

- **Data cleaning**
  - Handle missing data, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- **Data integration**
  - Integration of multiple databases, data cubes, or files
  - Often involves resolving conflicts between data sources
- **Data reduction and transformation**
  - Speeds up analysis when data is *too* big
  - E.g., can reduce rows (data points) or columns (attributes) of matrices

Data Cleaning

- Data in the Real World Is Dirty: Lots of potentially incorrect data, e.g., faulty instruments, human or computer error, and transmission error
  - Incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
    - e.g., *Occupation* = “ ” (missing data)
  - Noisy: containing noise, errors, or outliers
    - e.g., *Salary* = “−10” (an error)

Data Cleaning, continued

- Inconsistent: containing discrepancies in codes or names, e.g.,
  - Different data formats, e.g., rating “1, 2, 3” is now “A, B, C”
  - Different Scales/Units for Data Type (£, $, or €)
  - Discrepancy between duplicate records
- Intentional: (e.g., *disguised missing* data)
  - Defaults: Jan. 1 as everyone’s birthday?

Incomplete (Missing) Data

- Data is not always available
  - E.g., many tuples have no recorded value for several attributes, such as customer income in sales data
- Missing data may be due to
  - Equipment malfunction
  - Inconsistent with other recorded data and thus deleted
  - Data were not entered due to misunderstanding
  - Certain data may not be considered important at the time of entry
  - Did not register history or changes of the data
- Missing data may need to be inferred

How to Handle Missing Data?

- Ignore the tuple
  - Often not desirable, can cause data set to shrink dramatically
- Fill in the missing value manually
  - Tedious + infeasible?
- Fill in it automatically with
  - a global constant : e.g., “unknown”, a new class?!
  - the attribute mean
  - the attribute mean for all samples belonging to the same class: smarter
  - **the most probable value: inference-based such as Bayesian formula or decision tree**

Handling Missing Data: Example

- Want to predict likely value for missing data
- Example: Student missing data for final course grade
  - This student is male, age 33, 4.0 GPA
  - Find similar people in the data and see what their value for final grade is
  - Fill missing spot with most likely final grade based on the other data

Noisy Data

- **Noise:** random error or variance in a measured variable
- **Incorrect attribute values** may be due to various reasons
  - Faulty data collection instruments, Data entry problems, Data transmission problems, Technology limitation, Inconsistency in naming convention, …
- **Other data problems**
  - Outliers
  - Duplicate records
  - Incomplete data
  - Inconsistent data

How to Handle Noisy Data?

- Want to detect and (possibly) remove outliers
  - **Binning**
    - Sort data and partition into bins
    - Can smooth by bin means, bin median, bin boundaries, etc.
  - **Regression**
    - Smooth by fitting the data into regression functions
  - **Clustering**
    - Group data so that that points in the same cluster are more similar to each other than to those in other clusters
  - **Semi-supervised:** Combined computer and human inspection
    - Detect suspicious values and have humans check

Data Cleaning as a Process

- Tools and guidelines exist to help with data cleaning
- **Not a one-pass task**
  - Often requires multiple rounds of identifying problems and resolving them

Data Integration

- Data integration – What is it?
  - Combining data from multiple sources into a coherent store
- **Schema integration**:
  - e.g., A.cust-id $\equiv$ B.cust-#
  - Integrate metadata from different sources
- **Entity identification:**
  - Identify real world entities from multiple data sources, e.g., Bill Clinton = William Clinton

Data Integration – Why?

- Why data integration?
  - Clarifies data inconsistencies/Noise
    - Example: Age and Date of Birth.
      - **Database 1 (Google)**: 02/26/19**08**; Age 38,
      - **Database 2(Wikipedia)**: 02/26/1980; Age 38
        - Data from Database 2 clarifies the error in Year of Birth
  - Fills in Important Attributes for Analysis
    - Merging from more than 1 dataset provides more important information.
  - Speeds up Data Mining
    - One Master Schema can be mined rather than each of the 10 one-by-one

Data Integration- Challenges

- What problems will you face?
  - Schema differences
    - Column is called “PersonAge” from Customer Table
    - Column is called “CustomerAge” from Person Table
  - Data Value Representation Conflicts
    - Database 1 -> “William Clinton”
    - Database 2 -> “Bill Clinton”
  - Bad Data
    - Typo; Wrong recording
    - Different Scales/Units for Data Type (£, $, or €)

Data Integration - Handling Noise

- Detecting data value conflicts
  - For the same real world entity, attribute values from different sources are different
  - Possible reasons: no reason, different representations, different scales, e.g., metric vs. British units
- Resolving conflict information
  - Take the mean/median/mode/max/min
  - Take the most recent
  - Truth finding (Advanced): consider the source quality

Data Integration - Handling Redundancy

- Redundant data often occurs when multiple databases are integrated
  - *Object identification / Entity Matching*: The same attribute or object may have different names in different databases
  - *Derivable data:* One attribute may be a "derived" attribute in another table, e.g., annual revenue
- What's the problem?
  - $Y = 2X \rightarrow Y = X_1 + X_2 \quad Y = 3X_1 - X_2 \quad Y = -1291X_1 + 1293X_2$
    - Y equal to 2X in one DB, Y equal to sum of > 1 variable in another.
- Redundant attributes may be detected by correlation analysis and covariance analysis

Example: stock market

Yahoo! Finance

Day's Range: 93.80-95.71

Nasdaq

Green Mountain Coffee Roasters, (NasdaqGS: GMCR)

After Hours: **95.13** -0.01 (-0.02%) 4:07PM EDT

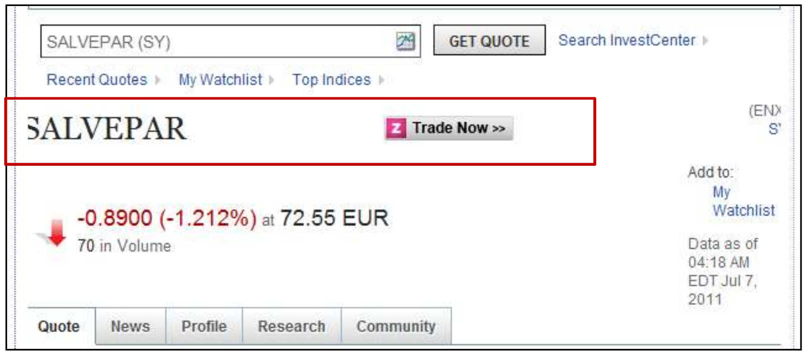
Last Trade:	**95.14**	Day's Range:	93.80 - 95.71
Trade Time:	4:00PM EDT	52wk Range:	25.38 - 95.71
Change:	1.69 (1.81%)	Volume:	2,384,075
Prev Close:	93.45	Avg Vol (3m):	2,512,070
Open:	94.01	Market Cap:	13.51B
Bid:	95.03 x 100	P/E (ttm):	119.82
Ask:	95.94 x 100	EPS (tt	0.79
1y Target Est:			N/A (N/A)

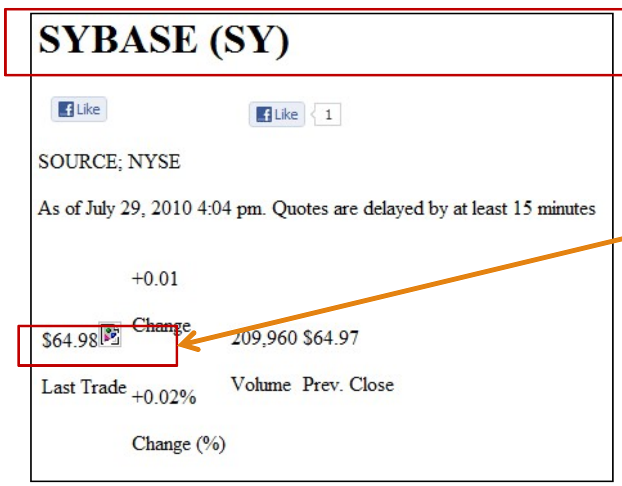
52wk Range: 25.38-95.71

52 Wk: 25.38-93.72

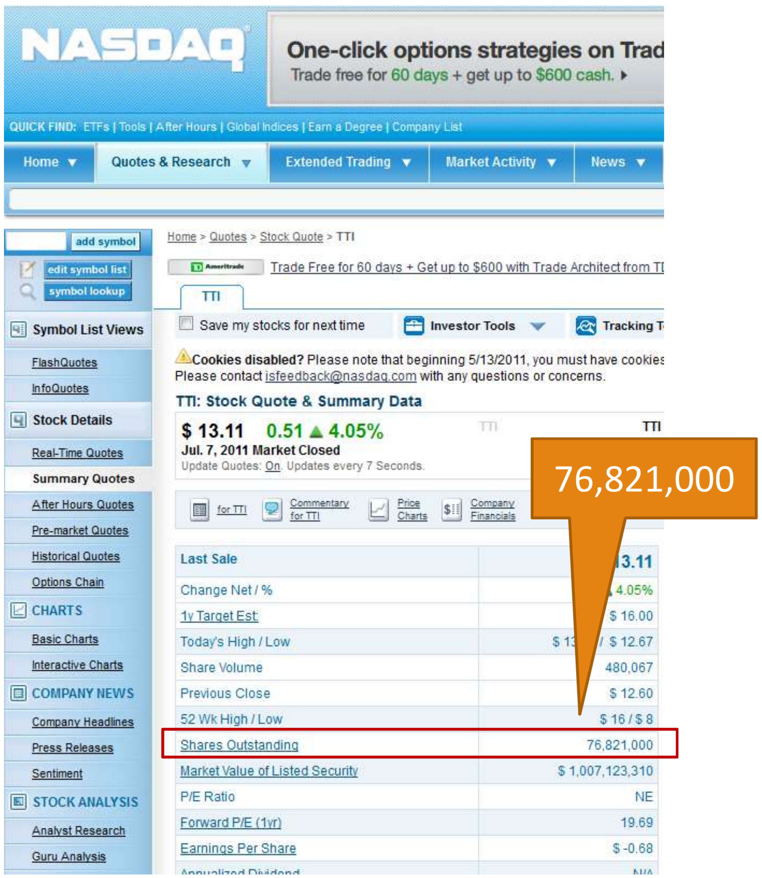
Last Sale	$ 95.14
Change Net / %	1.69 ▲ 1.81%
Best Bid / Ask	$ 95.03 / $ 95.94
1y Target Est:	$ 95.00
Today's High / Low	$ 95.71 / $ 93.80
Share Volume	2,384,175
50 Day Avg. Daily Volume	2,751,062
Previous Close	$ 93.45
52 Wk High / Low	$ 93.72 / $ 25.38
Shares Outstanding	152,785,000
Market Value of Listed Security	$ 14,535,964,900
P/E Ratio	120.43
Forward P/E	63.57
Ea er Share	$ 0.79
nualized Dividend	N/A
Ex Dividend Date	N/A
Dividend Payment Date	N/A
Current Yield	N/A
Beta	0.82
NASDAQ Official Open Price:	$ 94.01
Date of NASDAQ Official Open Price:	Jul. 7, 2011
NASDAQ Official Close Price:	$ 95.14
Date of NASDAQ Official Close Price:	Jul. 7, 2011

Example: stock market

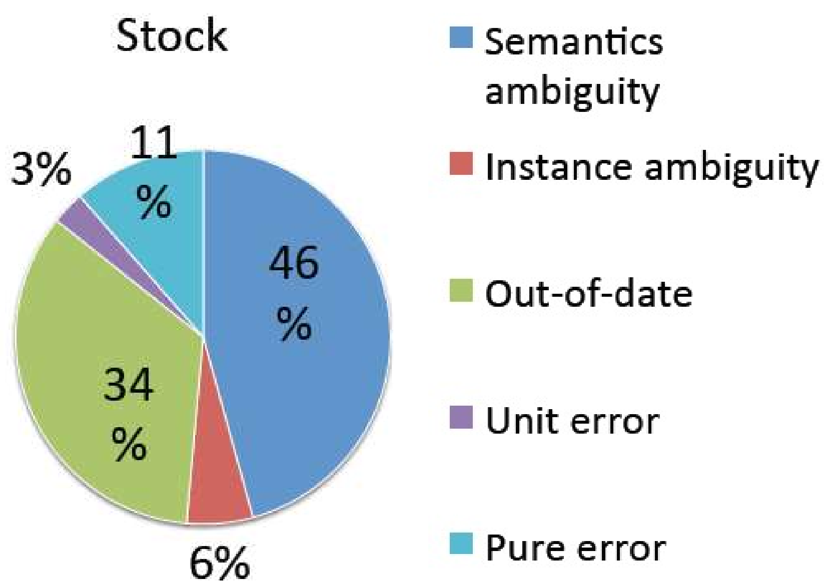




Example: stock market



Example: stock market



Source	Accuracy	Coverage
Google Finance	.94	.82
Yahoo! Finance	.93	.81
NASDAQ	.92	.84
MSN Money	.91	.89
Bloomberg	.83	.81

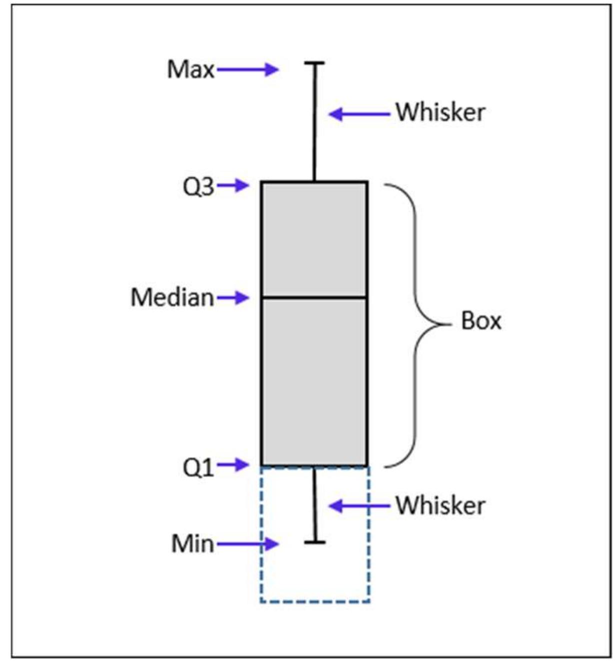
Xian Li, Xin Luna Dong, Kenneth Lyons, Weiyi Meng, and Divesh Srivastava. Truth finding on the Deep Web: Is the problem solved? In *VLDB,* 2013.

Graphic Displays of Basic Statistical Descriptions

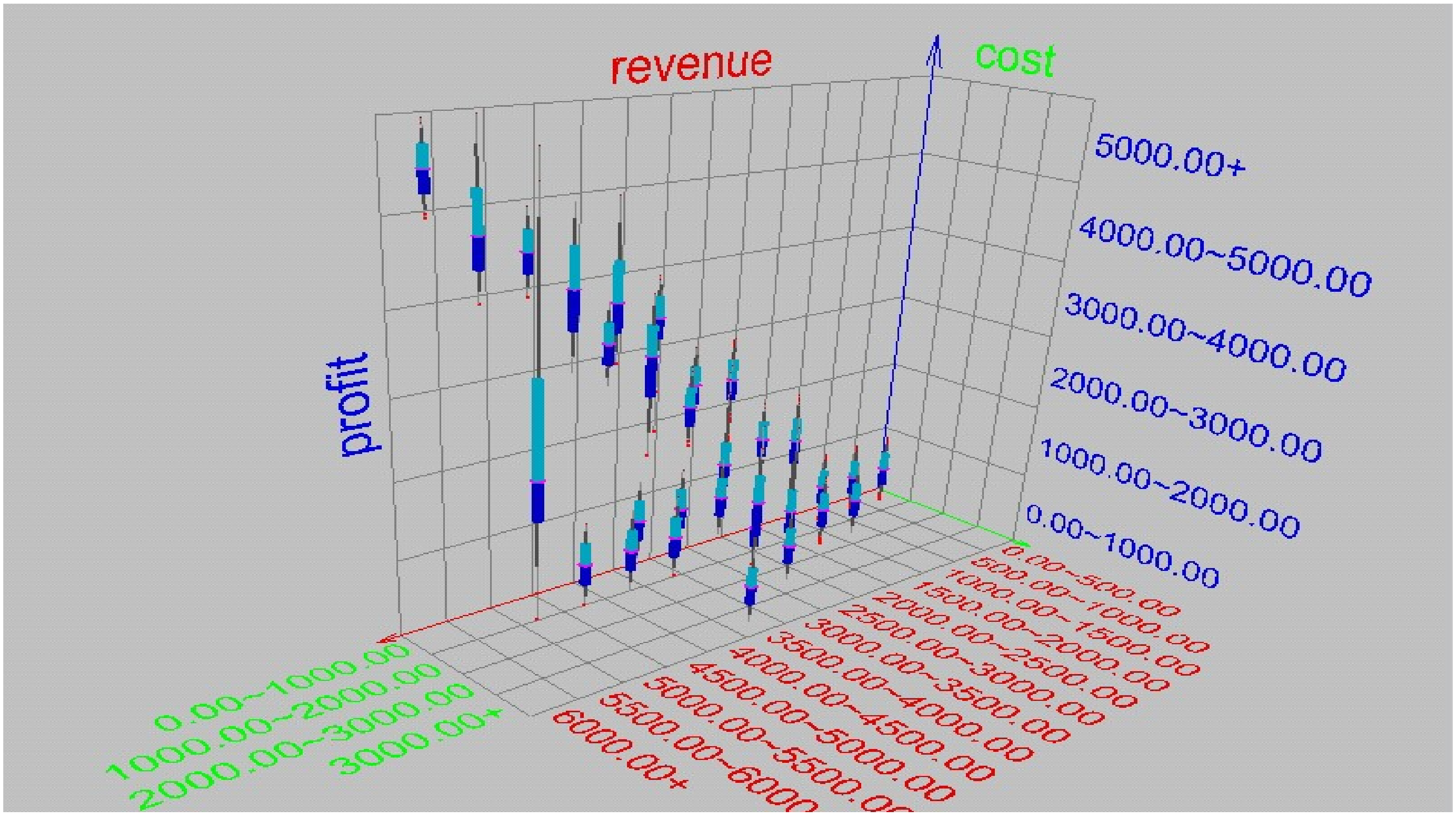
- **Boxplot**: five-number summary
- **Histogram**: values and frequencies
- **Scatter plot**: data plotted as points

Measuring the Dispersion of Data: Quartiles & Boxplots

- **Quartiles**: Q_1 (25th percentile), Q_3 (75th percentile)
- **Inter-quartile range**: $IQR = Q_3 - Q_1$
- **Five number summary**: min, Q_1, median, Q_3, max
- **Boxplot**:
  - Outliers: points beyond a specified outlier threshold, plotted individually
    - **Outlier**: usually, a value higher/lower than 1.5 x IQR



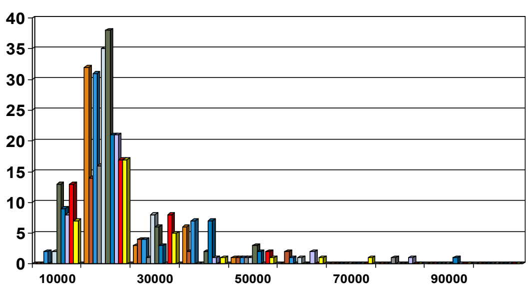
Visualization of Data Dispersion: 3-D Boxplots

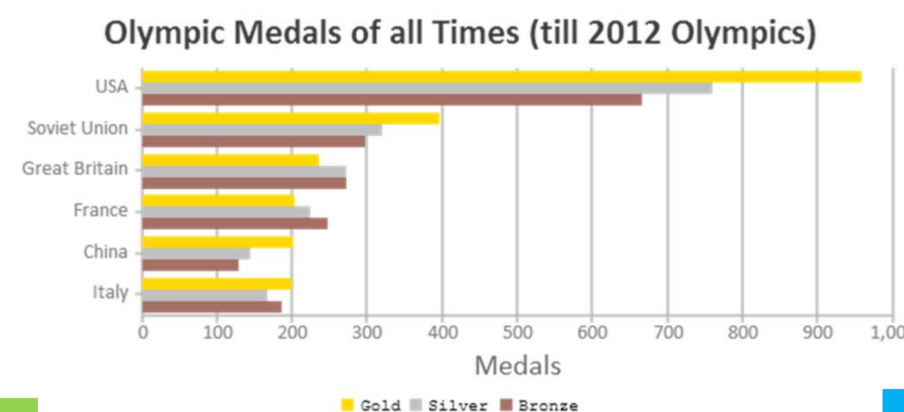


Histogram Analysis

- Histogram: tabulated frequencies, shown as bars

Histogram	Bar charts
distributions of variables	compare variables
quantitative data	categorical data
Value: area of the bar	Value: height of the bar (a crucial distinction when the categories are not of uniform width)
Order matters	Can be reordered

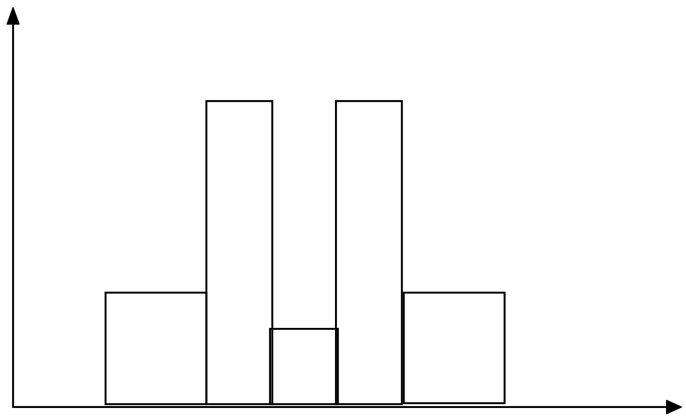


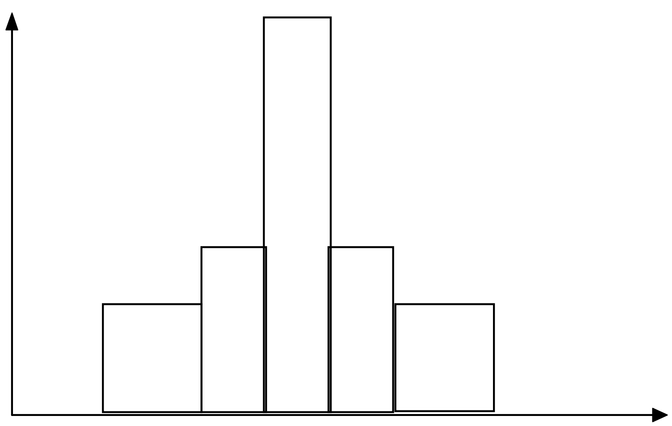


Histogram

Bar chart

Histograms Often Tell More than Boxplots

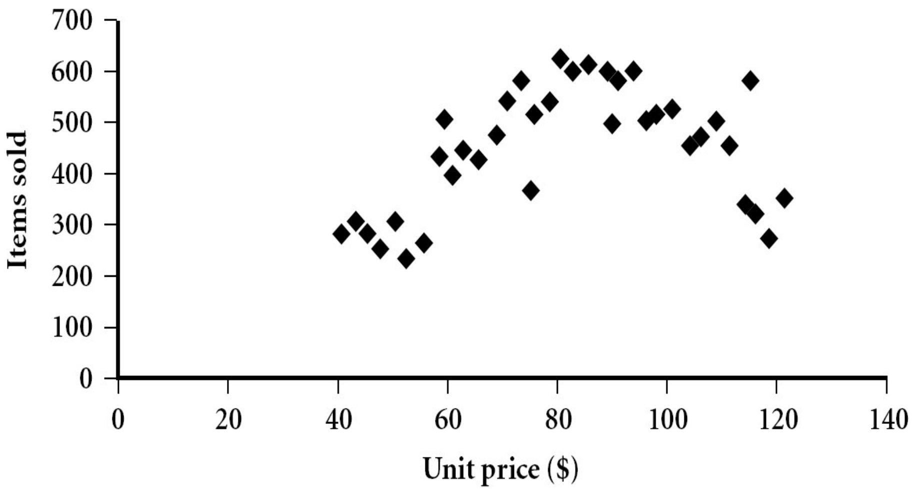


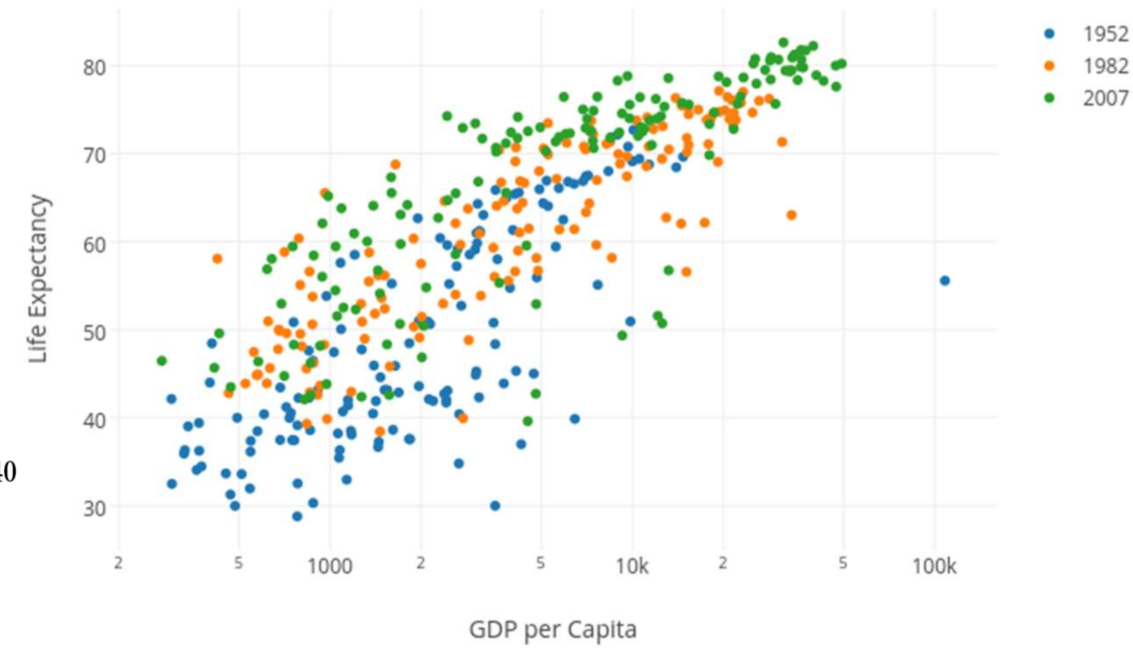


- **Same** boxplot representation
  - The same min, Q1, median, Q3, max
- **Different** data distributions

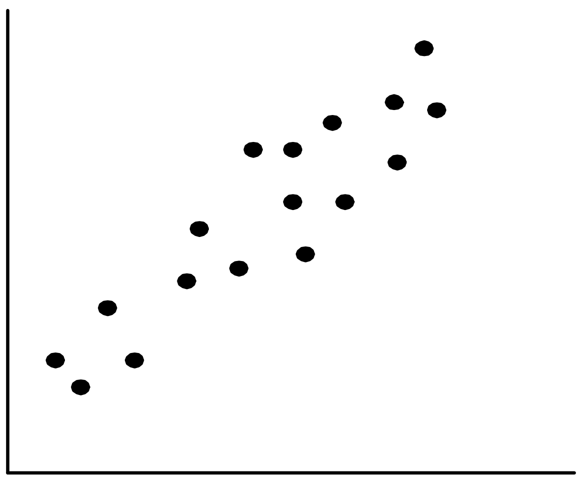
Scatter plot

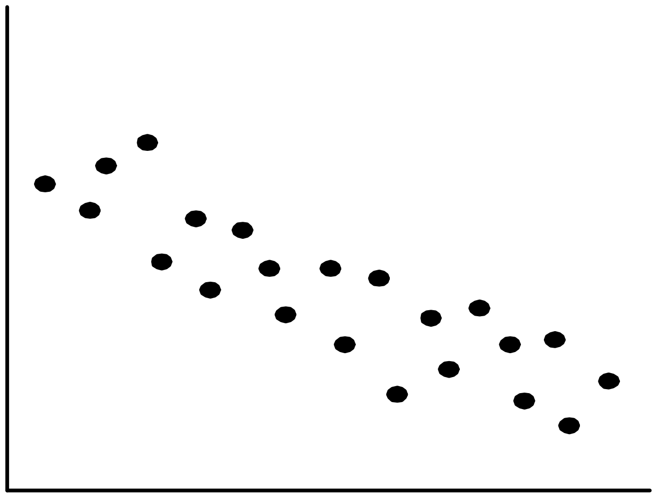
- Provides a first look at **bivariate** data to see clusters of points, outliers, etc.

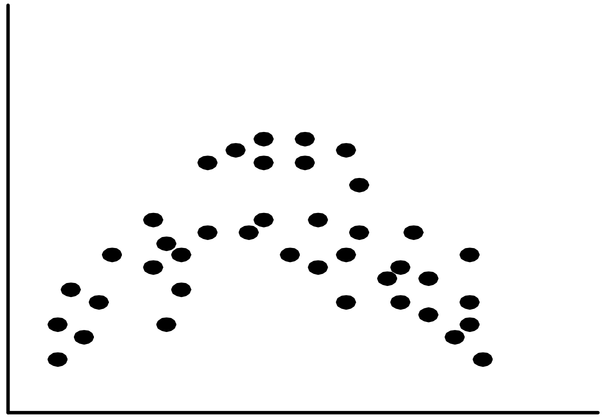




Positively and Negatively Correlated Data

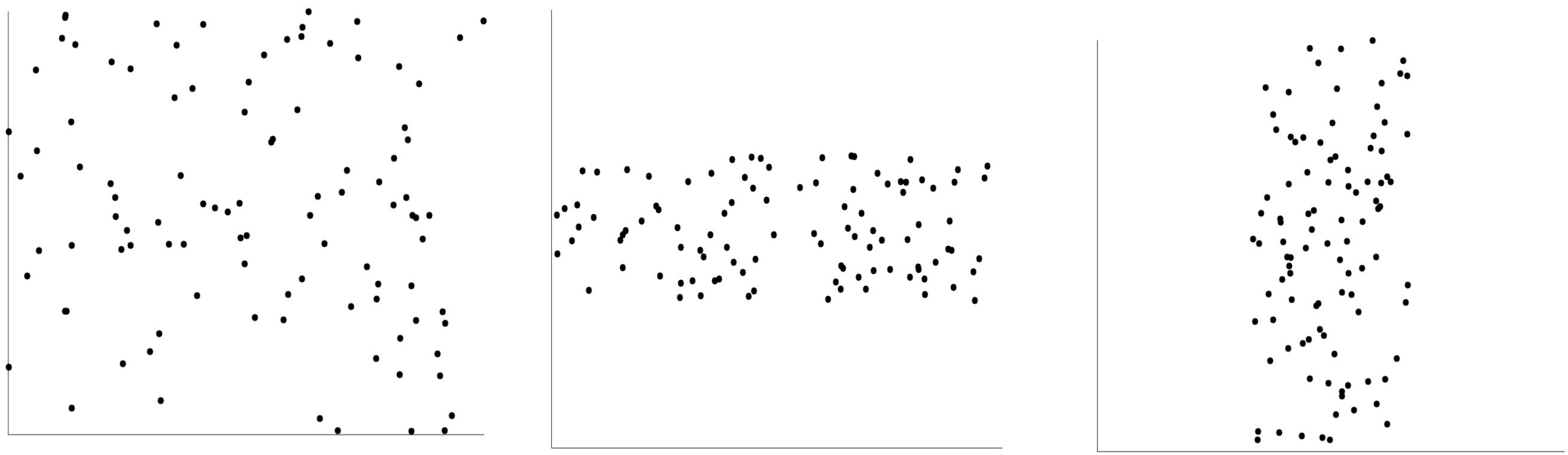




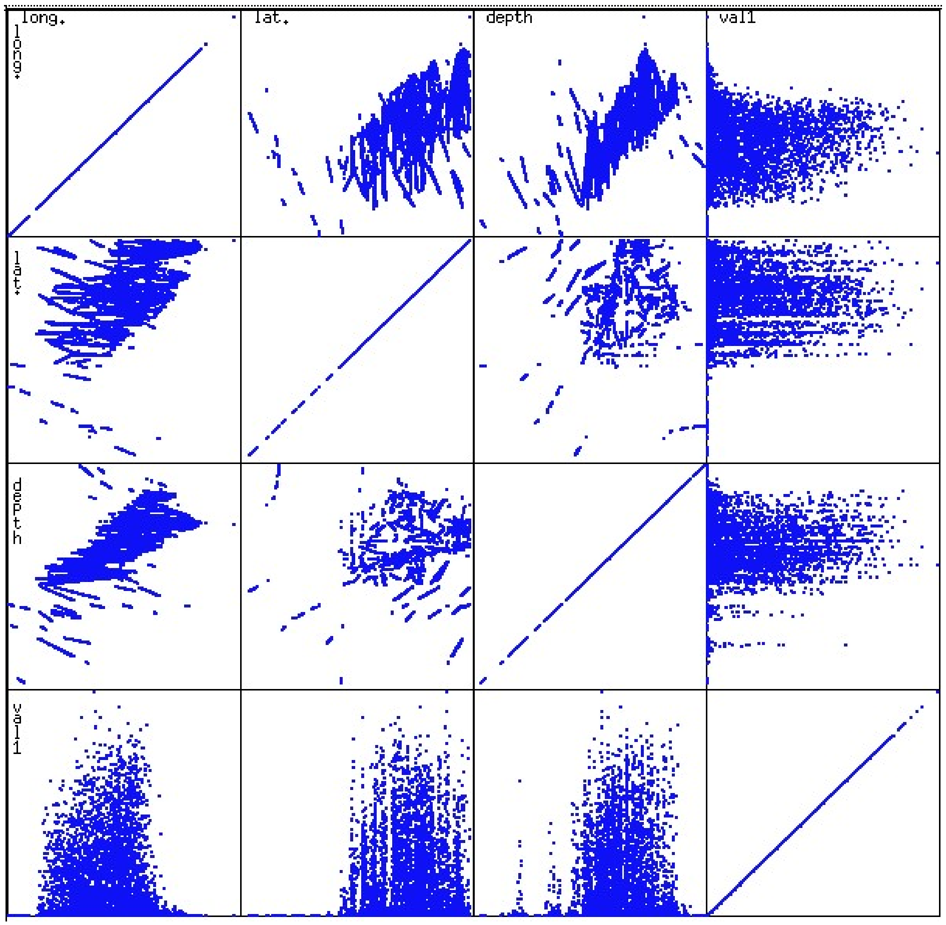


- The left half fragment is positively correlated
- The right half is negative correlated

Uncorrelated Data



Scatterplot Matrices



Used by ermission of M. Ward, Worcester Polytechnic Institute

- Matrix of scatterplots (x-y-diagrams) of the k-dim. data
- A total of k(k-1)/2 distinct scatterplots
- Good for understanding whether two variables are correlated
- Not as helpful for high-dimensional data