INT303 note

(Big Data Analytic)

1 Introduction tutorial1.html

1.1 Grades

Sequence	Method	Learning outcomes assessed	Duration	Timing	% of final mark	Resit
#1	Project 1: Data Scraping	All	See notice	S2	15%	NO
#2	Project 2: Big Data Competition	All	See notice	S2	15%	NO
#3	Written Exam	All	See notice	S2	70%	NO

1.2 Process

- Ask questions
- Data Collection
- Data Exploration
- Data Modelling
- Data Analysis
- Visualization and Presentation of Results

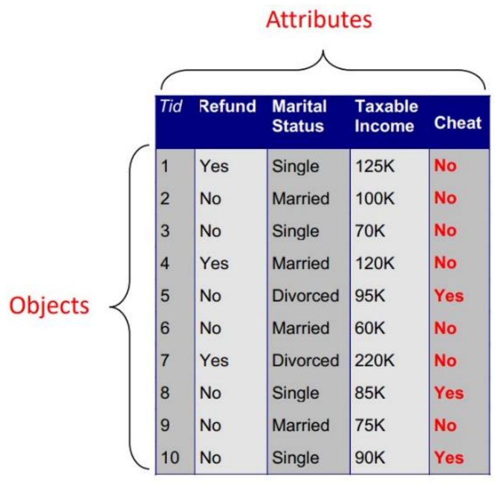
(Note: This process is by no means linear!)

2 Data tutorial2.html

2.1 Concepts

2.1.1 What is Data?

- Collection of data objects and their attributes
- An attribute is a property or characteristic of an object
  - Examples: name, date of birth, height, occupation.
  - Attribute is also known as variable, field, characteristic, or feature
- For each object the attributes take some values.
- The collection of attribute-value pairs describes a specific object
  - Object is also known as record, point, case, sample, entity, or instance


Attributes
Objects

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Size (n): Number of objects
Dimensionality (d): Number of attributes
Density/Sparsity: Number of populated object-attribute pairs

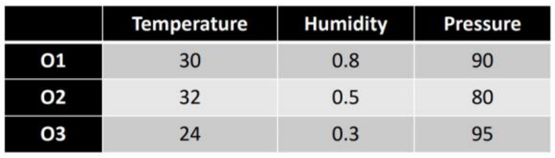
2.1.2 Relational data

- The term comes from DataBases, where we assume data is stored in a relational table with a fixed schema (fixed set of attributes)
- There are a lot of data in this form
- There are also a lot of data which do not fit well in this form
  - Sparse data: Many missing values
  - Not easy to define a fixed schema

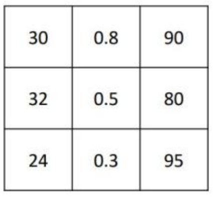
2.1.3 Types of Attributes

- Numeric
  - Examples: dates, temperature, time, length, value, count.
  - Discrete (counts) vs Continuous (temperature)
  - Special case: Binary/Boolean attributes (yes/no, exists/not exists)

- Categorical
    - Examples: eye color, zip codes, strings, rankings (e.g, good, fair, bad), height in {tall, medium, short}
    - Nominal (no order or comparison) vs Ordinal (order but not comparable)
- If data objects have the same fixed set of numeric attributes, then the data objects can be thought of as points/vectors in a multi-dimensional space, where each dimension represents a distinct attribute. Such data set can be represented by an n-by-d data matrix:

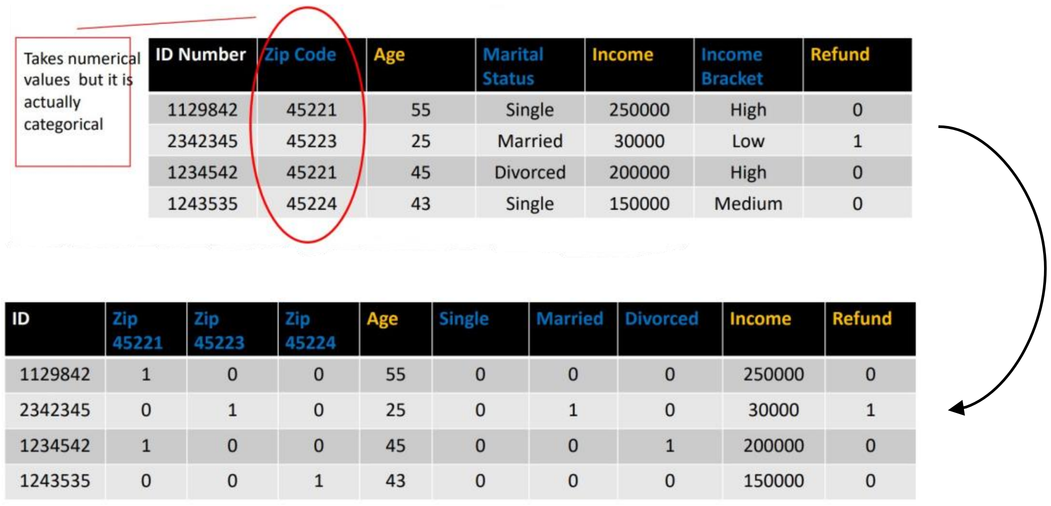


	Temperature	Humidity	Pressure
O1	30	0.8	90
O2	32	0.5	80
O3	24	0.3	95



30	0.8	90
32	0.5	80
24	0.3	95

- Translate the table


Takes numerical values but it is actually categorical

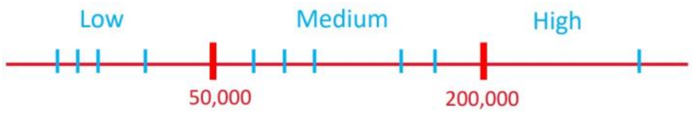
ID Number	Zip Code	Age	Marital Status	Income	Income Bracket	Refund
1129842	45221	55	Single	250000	High	0
2342345	45223	25	Married	30000	Low	1
1234542	45221	45	Divorced	200000	High	0
1243535	45224	43	Single	150000	Medium	0

ID	Zip 45221	Zip 45223	Zip 45224	Age	Single	Married	Divorced	Income	Refund
1129842	1	0	0	55	0	0	0	250000	0
2342345	0	1	0	25	0	1	0	30000	1
1234542	1	0	0	45	0	0	1	200000	0
1243535	0	0	1	43	0	0	0	150000	0

2.2 Binning

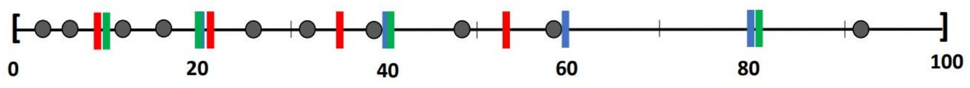
2.2.1 Concepts

- Idea: split the range of the domain of the numerical attribute into bins (intervals).
- Every bucket defines a categorical value



2.2.2 Bucketization

- Equi-width bins: All bins have the same size
    - Example: split time into decades
    - Problem: some bins may be very sparse or empty
- Equi-size (depth) bins: Select the bins so that they all contain the same number of elements
    - This splits data into quantiles: top-10%, second 10% etc
    - Some bins may be very small
- Equi-log bins: log end – log start is constant
    - The size of the previous bin is a fraction of the current one
    - Better for skewed distributions
- Optimized bins: Use a 1-dimensional clustering algorithm to create the bins

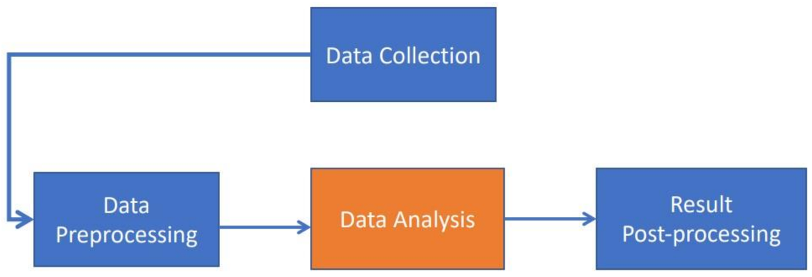


Blue: Equi-width [20,40,60,80]
Red: Equi-depth (2 points per bin)
Green: Equi-log (end/start = 2)

2.3 Types of data

- Set data: Each object is a set of values (with or without counts)
    - Sets can also be represented as binary vectors, or vectors of counts
- Dependent data:
    - Ordered sequences: Each object is an ordered sequence of values.
    - Spatial data: objects are fixed on specific geographic locations
    - Graph data: A collection of pairwise relationships
- The data matrix:
    - In almost all types of data we can find a way to transform the data into a matrix, where the rows correspond to different records, and the columns to numeric attributes

2.4 The data mining pipeline



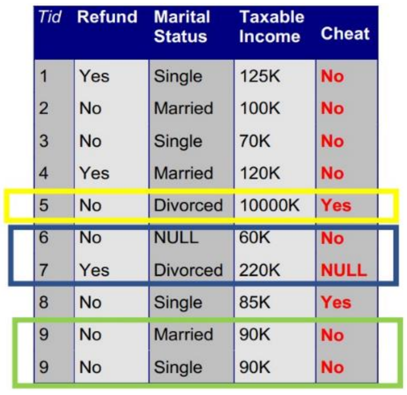
2.4.1 Data Collection

For many supervised learning tasks (classification), you need labelled data, which will be used for training and testing

2.4.2 Data Preprocessing

- <u>Reducing the data</u>: Sampling, Dimensionality Reduction
    - Simple Random Sampling
    - Sampling without replacement
    - Sampling with replacement

      E.g., we have 100 people, 51 are women P(W) = 0.51, 49 men P(M) = 0.49. If I pick two persons what is the probability P(W,W) that both are women?
        - *Sampling with replacement: P(W,W) = 0.512*
        - *Sampling without replacement: P(W,W) = 51/100 * 50/99*
    - Stratified sampling
        - Split the data into several groups; then draw random samples from each group.
    - Biased sampling
        - When sampling temporal data, we want to increase the probability of sampling recent data: recency bias
    - Reservoir sampling
        - For the first k numbers, we retain them all.
            - For the i-th (i>k) number, we retain the i-th number with a probability of k/i
            - Replace with any one of the previously selected k numbers with a probability of 1/k.
        - Every item has probability 1/N to be selected after N items have been read.
- <u>Data cleaning</u>: deal with missing or inconsistent information
    - Deal with missing values:
        - Ignore the data
        - Replace with random value
        - Replace with the mean
        - Replace with nearest neighbor value
        - Replace with cluster mean
        - Infer the value
    - Deal with outliers:



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6	No	NULL	60K	No
7	Yes	Divorced	220K	NULL
8	No	Single	85K	Yes
9	No	Married	90K	No
9	No	Single	90K	No

        - Remove them
        - Try to correct them using common sense
        - Transform the data
    - When using the data, we should be careful of cases where our results are too good to be true, or too bad to be true
- Feature extraction and selection: create a useful representation of the data by extracting useful features

2.4.3 Data Analysis
- Sample mean
- Sample median
- Sample range
- Sample variance
- Sample standard deviation

2.4.4 Result Post-processing
…

3 Data Grammar tutorial3.html

3.1 Data Normalization

3.1.1 Column Normalization
In this data, different attributes take very different range of values. For distance/similarity the small values will disappear:

Temperature	Humidity	Pressure
30	0.8	90
32	0.5	80
24	0.3	95

So, divide (the values of a column) by the maximum value for each attribute:

Temperature	Humidity	Pressure
0.9375	1	0.9473
1	0.625	0.8421
0.75	0.375	1

(Brings everything in the [0,1] range, maximum is 1)

3.1.2 Row Normalization
Some data which are similar:

	Word 1	Word 2	Word 3
Doc 1	28	50	22
Doc 2	12	25	13

Divide by the sum of values for each document (row in the matrix):

	Word 1	Word 2	Word 3
Doc 1	0.28	0.5	0.22
Doc 2	0.24	0.5	0.26

(New value = old value / Σ old values in the row)

Z-score:

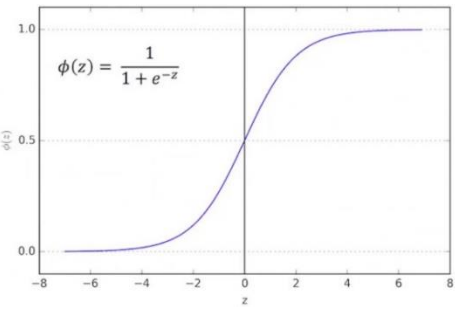
$$\text{mean}(x) = \frac{1}{N}\sum_{j=1}^{N} x_j$$

$$\text{std}(x) = \sqrt{\frac{\sum_{j=1}^{N}\left(x_j - \text{mean}(x)\right)^2}{N}}$$

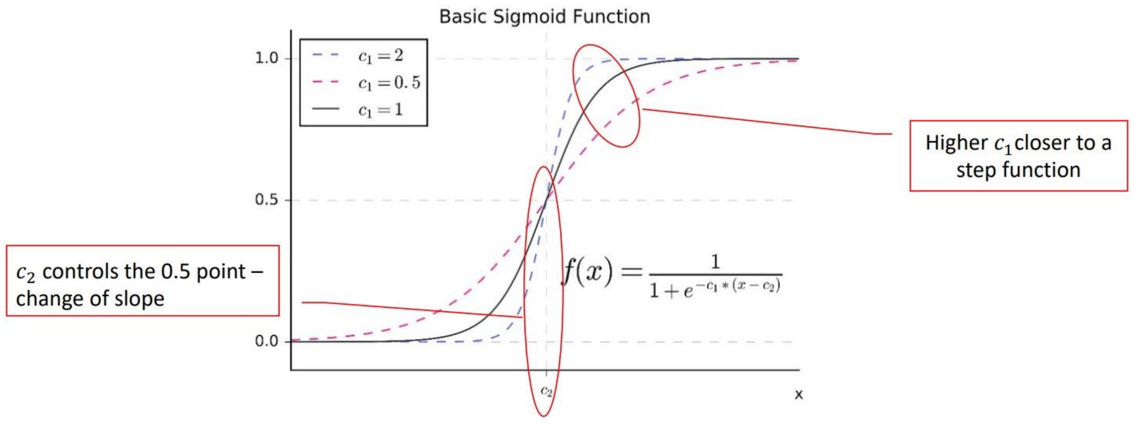
$$z_i = \frac{x_i - \text{mean}(x)}{\text{std}(x)}$$

Logistic function:

$$\phi(x) = \frac{1}{1+e^{-x}}$$



- Maps reals to the [0,1] range
- Mimics the step function
- In the class of sigmoid functions



Softmax function:

If we want to transform the scores into probabilities that sum to one, but we capture the single selection of the user.

$$\frac{e^{x_i}}{\sum_i e^{x_i}}$$

	Restaurant 1	Restaurant 2	Restaurant 3
User 1	5	2	3
User 2	1	3	4

$\rightarrow$

	Restaurant 1	Restaurant 2	Restaurant 3
User 1	0.72	0.10	0.18
User 2	0.07	0.31	0.62

Logarithm function:

- Sometimes a data row/column may have a very wide range of values. Normalizing in this case will obliviate small values.
- We can bring the values to the same scale by applying a logarithm to the column values.

User id	Income	Log Income
1	6000	3.778151
2	6500	3.812913
3	7000	3.845098
4	4000	3.60206
5	8000	3.90309
6	9000	3.954243
7	18000	4.255273
8	36000	4.556303
9	600000	5.778151
10	1000000	6

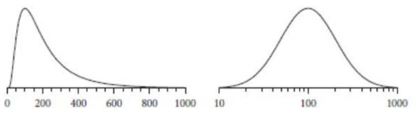
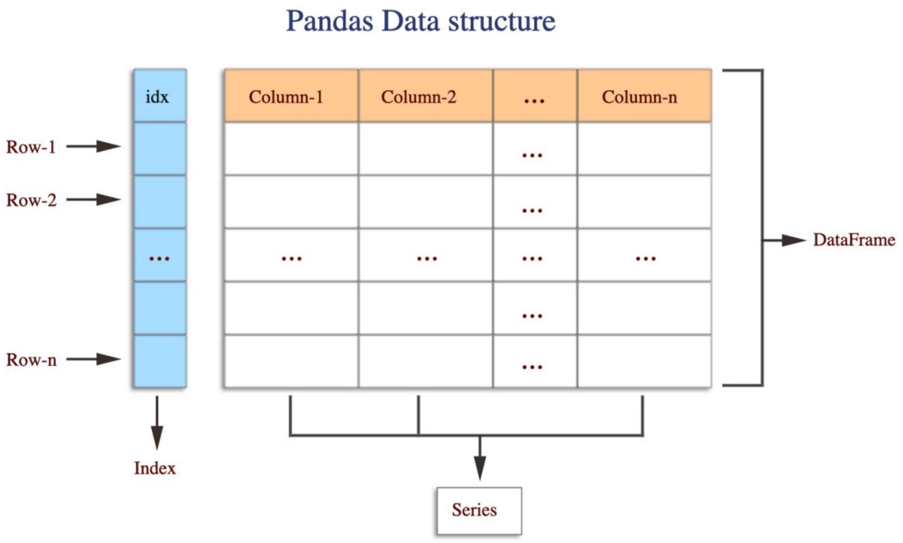


Figure 11.2. Lognormal distribution.
(Left) Lognormal distribution. The distribution appears Gaussian when plotted on a logarithmic axis (right) or when all values are transformed to their logarithm.

3.2 Exploratory Data Analysis (EDA)

1. Store data in data structure(s) that will be convenient for exploring/processing (Memory is fast. Storage is slow)
2. Clean/format the data so that:
    - Each row represents a single object/observation/entry
    - Each column represents an attribute/property/feature of that entry
    - Values are numeric whenever possible
    - Columns contain atomic properties that cannot be further decomposed*
3. Explore global properties: use histograms, scatter plots, and aggregation functions to summarize the data
4. Explore group properties: group like-items together to compare subsets of the data

3.2.1 **Pandas (Python package)** User Guide — pandas 2.1.1 documentation (pydata.org)



Import pandas library code:

```
import pandas as pd
dataframe = pd.read_csv("yourfile.csv")
```

Common Pandas functions:

- head() – first N observations
- tail() – last N observations
- columns() – names of the columns
- describe() – statistics of the quantitative data
- dtypes() – the data types of the columns
- df["column_name"]
- Df.column_name
- .max(), .min(), .idxmax(), .idxmin()
- <dataframe> <conditional statement>
- .loc[] – label-based accessing
- .iloc[] – index-based accessing
- .sort_values()
- .isnull(), .notnull()
- groupby(), .get_groups()
- .merge()
- .concat()
- .aggegate()
- .append()

```
# input
state = np.random.RandomState(100)
ser = pd.Series(state.normal(10, 5, 25))
```

```
# using pandas
ser.describe()
```

```
count    25.000000
mean     10.435437
std       4.253118
min       1.251173
25%       7.709865
50%      10.922593
75%      13.363604
max      18.094908
dtype: float64
```

Rebuild Dataset:

```
data.isna().sum()
```

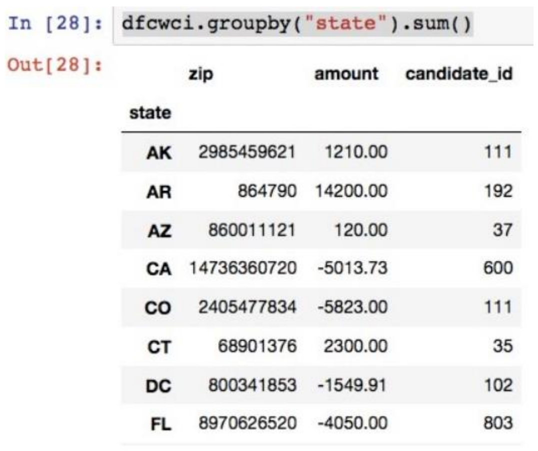
+

```
DataFrame.fillna(value=None, method=None, axis=None, inplace=False, limit=None,
downcast=None)
```

+

```
DataFrame.drop_duplicates(subset=None, keep='first', inplace=False,
ignore_index=False)
```

GroupBy Dataset:

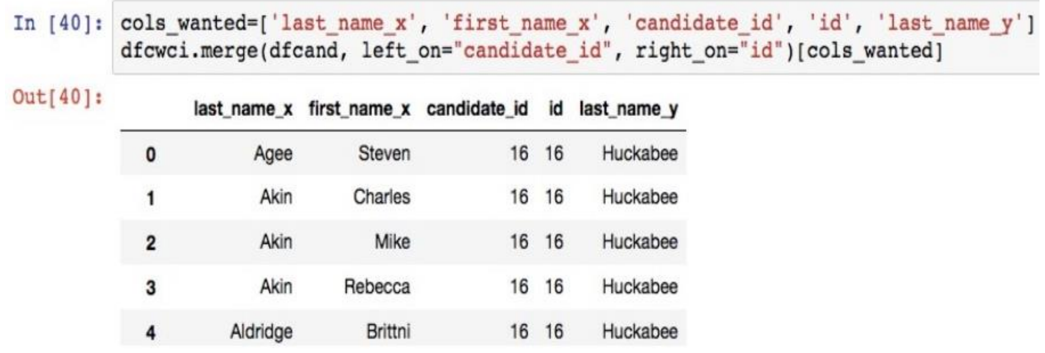


```
In [28]: dfcwci.groupby("state").sum()
Out[28]:
```

state	zip	amount	candidate_id
AK	2985459621	1210.00	111
AR	864790	14200.00	192
AZ	860011121	120.00	37
CA	14736360720	-5013.73	600
CO	2405477834	-5823.00	111
CT	68901376	2300.00	35
DC	800341853	-1549.91	102
FL	8970626520	-4050.00	803

Merge Dataset:

```
DataFrame.merge(right, how='inner', on=None, left_on=None, right_on=None,
left_index=False, right_index=False, sort=False, suffixes=('_x', '_y'), copy=True,
indicator=False, validate=None)
```



```
In [40]: cols_wanted=['last_name_x', 'first_name_x', 'candidate_id', 'id', 'last_name_y']
         dfcwci.merge(dfcand, left_on="candidate_id", right_on="id")[cols_wanted]
Out[40]:
```

	last_name_x	first_name_x	candidate_id	id	last_name_y
0	Agee	Steven	16	16	Huckabee
1	Akin	Charles	16	16	Huckabee
2	Akin	Mike	16	16	Huckabee
3	Akin	Rebecca	16	16	Huckabee
4	Aldridge	Brittni	16	16	Huckabee

3.3 Data Mining

3.3.1 Similarity

- Numerical measure of how alike two data objects are.
    - A function that maps pairs of objects to real values
    - Higher when objects are more alike.
- Often falls in the range [0,1], sometimes in [-1,1]
- Desirable properties for similarity
    1. s(p, q) = 1 (or maximum similarity) only if p = q. (Identity)
    2. s(p, q) = s(q, p) for all p and q. (Symmetry)
    3. s(p, q) = 0.5 and s(p, x) = 0.5, then s(q, x) = 0.5
- The Jaccard similarity (Jaccard coefficient) of two sets S_1, S_2 is the size of their intersection divided by the size of their union.

$$JSim(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|}$$

- Extreme behavior:
  - JSim(X, Y) = 1, iff X = Y
  - JSim(X, Y) = 0, iff X, Y have no elements in common
- JSim is symmetric

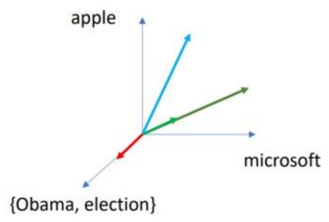
- Similarity between vectors:

document	Apple	Microsoft	Obama	Election
D1	10	20	0	0
D2	30	60	0	0
D3	60	30	0	0
D4	0	0	10	20

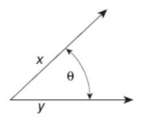
Documents D1, D2 are in the "same direction"

Document D3 is on the same plane as D1, D2

Document D4 is orthogonal to the rest



- Cosine Similarity
  - Sim(X, Y) = cos(X, Y)
  - If the vectors are aligned (correlated) angle is zero degrees and cos(X, Y) = 1
  - If the vectors are orthogonal (no common coordinates) angle is 90 degrees and cos(X, Y) = 0
  - If x and y are two vectors, then:



$$\cos(x, y) = \frac{x \cdot y}{||x||\,||y||}$$

Example:

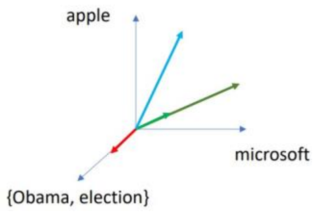
$$x = 3\ 2\ 0\ 5\ 0\ 0\ 2\ 0\ 0$$
$$y = 1\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 2$$
$$x \cdot y = 3 \cdot 1 + 2 \cdot 0 + 0 \cdot 0 + 5 \cdot 0 + 0 \cdot 0 + 0 \cdot 0 + 2 \cdot 1 + 0 \cdot 0 + 0 \cdot 0 = 12$$
$$||x|| = \sqrt{3^2 + 2^2 + 0^2 + 5^2 + 0^2 + 0^2 + 2^2 + 0^2 + 0^2} = \sqrt{42} = 6.481$$
$$||y|| = \sqrt{1^2 + 0^2 + 0^2 + 0^2 + 0^2 + 0^2 + 1^2 + 0^2 + 2^2} = \sqrt{6} = 2.245$$
$$\cos(x, y) = 0.315$$

document	Apple	Microsoft	Obama	Election
D1	10	20	0	0
D2	30	60	0	0
D3	60	30	0	0
D4	0	0	10	20

Cos(D1,D2) = 1

Cos (D3,D1) = Cos(D3,D2) = 4/5

Cos(D4,D1) = Cos(D4,D2) = Cos(D4,D3) = 0



- Correlation Coefficient
  - If we have observations (vectors) X = (x_1, … , x_n) and Y = (y_1, … , y_n) is defined as:

$$CorrCoeff(X, Y) = \frac{\sum_i (x_i - \mu_X)(y_i - \mu_Y)}{\sqrt{\sum_i (x_i - \mu_X)^2}\sqrt{\sum_i (y_i - \mu_Y)^2}}$$

  - The correlation coefficient takes values in [-1,1]
    (-1 negative correlation, +1 positive correlation, 0 no correlation)

Normalized vectors

document	Apple	Microsoft	Obama	Election
D1	-5	+5	0	0
D2	-15	+15	0	0
D3	+15	-15	0	0
D4	0	0	-5	+5

$$CorrCoeff(X,Y) = \frac{\sum_i (x_i - \mu_X)(y_i - \mu_Y)}{\sqrt{\sum_i (x_i - \mu_X)^2}\sqrt{\sum_i (y_i - \mu_Y)^2}}$$

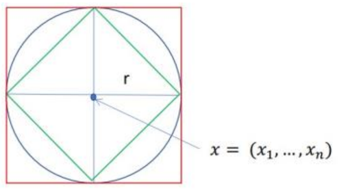
CorrCoeff(D1,D2) = 1

CorrCoeff(D1,D3) = CorrCoeff(D2,D3) = -1

CorrCoeff(D1,D4) = CorrCoeff(D2,D4) = CorrCoeff(D3,D4) = 0

3.3.2 Distance

- Distances for real vectors:
  - Vectors $x = (x_1, \dots, x_d)$ and $y = (y_1, \dots, y_d)$
  - L_p-norms or Minkowski distance:
    $$L_p(x,y) = \left[|x_1 - y_1|^p + \cdots + |x_d - y_d|^p\right]^{1/p}$$
  - L_2-norm: Euclidean distance:
    $$L_2(x,y) = \sqrt{|x_1 - y_1|^2 + \cdots + |x_d - y_d|^2}$$
  - L_1-norm: Manhattan distance:
    $$L_1(x,y) = |x_1 - y_1| + \cdots + |x_d - y_d|$$
  - L_∞-norm:
    $$L_\infty(x,y) = \max\{|x_1 - y_1|, \dots, |x_d - y_d|\}$$
    - The limit of L_p as p goes to infinity.



Green: All points y at distance $L_1(x,y) = r$ from point x

Blue: All points y at distance $L_2(x,y) = r$ from point x

Red: All points y at distance $L_\infty(x,y) = r$ from point x

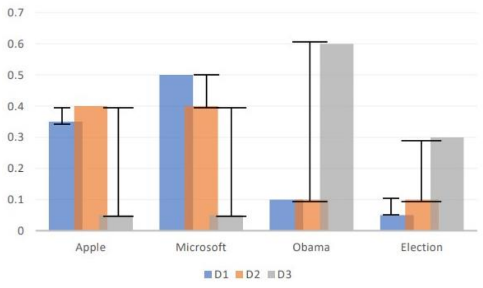
- Similarities into distances:
  - Jaccard distance: *JDist(X, Y) = 1 – JSim(X, Y)*
  - Cosine distance: *Dist(X, Y) = 1 – cos(X, Y)*
- Hamming distance:
  - Hamming distance is the number of positions in which bit-vectors differ.
    - Example:
      - p1 = 10101
      - p2 = 10011
      - d(p_1, p_2) = 2 because the bit-vectors differ in the 3rd and 4th positions.
      - The L_1 norm for the binary vectors
- Variational distance:
  - Variational distance is the L_1 distance between the distribution vectors

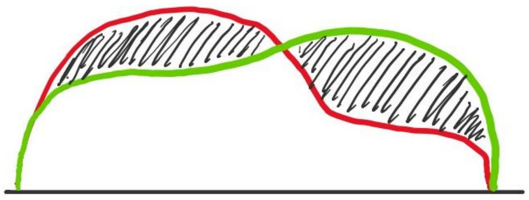
document	Apple	Microsoft	Obama	Election
D1	0.35	0.5	0.1	0.05
D2	0.4	0.4	0.1	0.1
D3	0.05	0.05	0.6	0.3

Dist(D1,D2) = 0.05+0.1+0.05 = 0.2

Dist(D2,D3) = 0.35+0.35+0.5+ 0.2 = 1.4

Dist(D1,D3) = 0.3+0.45+0.5+ 0.25 = 1.5





- Information theoretic distances:
    - KL-divergence (Kullback-Leibler) for distributions P,Q:

$$D_{KL}(P\|Q) = \sum_x p(x)\log\frac{p(x)}{q(x)}$$

    - KL-divergence is asymmetric. We can make it symmetric by taking the average of both sides:

$$\frac{1}{2}\left(D_{KL}(P\|Q) + D_{KL}(Q\|P)\right)$$

    - JS-divergence (Jensen-Shannon):

$$JS(P,Q) = \frac{1}{2}D_{KL}(P\|M) + \frac{1}{2}D_{KL}(Q\|M)$$
$$M = \frac{1}{2}(P+Q)$$

- Ranking distances:
    - The input in this case is two rankings/orderings of the same n items.
      For example:

$$R_1 = \langle x,y,z,w\rangle$$
$$R_2 = \langle y,w,z,x\rangle$$

	x	y	z	w
R_1	1	2	3	4
R_2	4	1	3	2

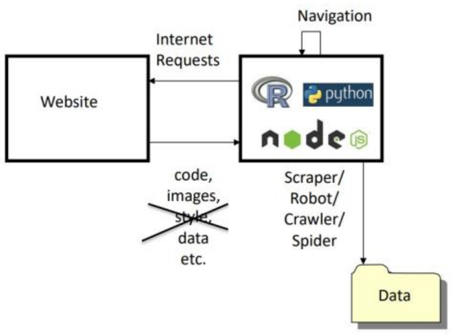
    - Spearman rank distance: L_1 distance between the ranks

SR(R_1, R_2) = |1 – 4| + |2 – 1| + |3 – 3| + |4 – 2| = 6

4 Web Scraping tutorial4.html

4.1 Role

Instead of people repeatedly querying the browser for website data, use tools like python to quickly get data directly from the website.



HTTP STATUS CODES:

200 OK:

Means that the server did whatever the client wanted it to, and all is well.

400: Bad request

The request sent by the client didn't have the correct syntax.

401: Unauthorized

Means that the client is not allowed to access the resource. This may change if the client retries with an authorization header.

403: Forbidden

The client is not allowed to access the resource and authorizatonwill not help.

404: Not found

It means that the server has not heard of the resource and has no further clues as to what the client should do about it. In other words: dead link.

500: Internal server error

Something went wrong inside the server.

501: Not implemented

The request method is not supported by the server.

4.2 Python data scraping

4.2.1 Legal

Respect the Robots Exclusion Protocol also known as the `robots.txt` (add this to the website url tail to see which element you can scrap)

e.g.: http://google.com/robots.txt

4.2.2 Step 1: Inspect Your Data Source

Example website for exercise: Fake Python (realpython.github.io) https://realpython.github.io/fake-jobs/

Developer tool:

- **Mac:** ⌘Cmd + Alt + I
- **Windows/Linux:** ^Ctrl + ⇧Shift + I

4.2.3 Step 2: Scrape Html Content From A Page

Python
```python
import requests

URL = "https://realpython.github.io/fake-jobs/"
page = requests.get(URL)

print(page.text)
```

4.2.4 Step 3: Parse Html Code With Beautiful Soup

Python
```python
import requests
from bs4 import BeautifulSoup

URL = "https://realpython.github.io/fake-jobs/"
page = requests.get(URL)

soup = BeautifulSoup(page.content, "html.parser")
```

- Find elements by ids:

HTML
```html
<div id="ResultsContainer">
  <!-- all the job listings -->
</div>
```

- Beautiful Soup allows you to find that specific HTML element by its ID:

Python
```python
results = soup.find(id="ResultsContainer")
```

`find` VS `findAll`

```python
import bs4
## get bs4 object
soup = bs4.BeautifulSoup(source)
## all a tags
soup.findAll('a')
## first a
soup.find('a')
## get all links in the page
link_list = [l.get('href') for l in soup.findAll('a')]
```

- Find elements by HTML class name:

Python

```python
job_elements = results.find_all("div", class_="card-content")
```

Python

```python
for job_element in job_elements:
    print(job_element, end="\n"*2)
```

Python

```python
for job_element in job_elements:
    title_element = job_element.find("h2", class_="title")
    company_element = job_element.find("h3", class_="company")
    location_element = job_element.find("p", class_="location")
    print(title_element)
    print(company_element)
    print(location_element)
    print()
```

HTML

```html
<h2 class="title is-5">Senior Python Developer</h2>
<h3 class="subtitle is-6 company">Payne, Roberts and Davis</h3>
<p class="location">Stewartbury, AA</p>
```

- What if we just want the text content of the extract data? Use the `.text` script and you can `.strip()` the superfluous whitespace:

Python

```python
for job_element in job_elements:
    title_element = job_element.find("h2", class_="title")
    company_element = job_element.find("h3", class_="company")
    location_element = job_element.find("p", class_="location")
    print(title_element.text.strip())
    print(company_element.text.strip())
    print(location_element.text.strip())
    print()
```

- Find elements by class name and text content:

Python

```python
python_jobs = results.find_all("h2", string="Python")
```

- Use a lambda function to filter the data by substring "python" and <h2> tag:

Python

```python
python_jobs = results.find_all(
    "h2", string=lambda text: "python" in text.lower()
)
```

- HTML is a tree

```
tree = bs4.BeautifulSoup(source)

## get html root node
root_node = tree.html
## get head from root using contents
head = root_node.contents[0]
## get body from root
body = root_node.contents[1]
## could directly access body
tree.body
```

- Access parent elements:

```python
python_jobs = results.find_all(
    "h2", string=lambda text: "python" in text.lower()
)

python_job_elements = [
    h2_element.parent.parent.parent for h2_element in python_jobs
]
```

- Extract attributes from HTML elements

```python
for job_element in python_job_elements:
    # -- snip --
    links = job_element.find_all("a")
    for link in links:
        link_url = link["href"]
        print(f"Apply here: {link_url}\n")
```

(Start by fetching all the <a> elements in a job card. Then, extract the value of their href attributes using square-bracket notation)

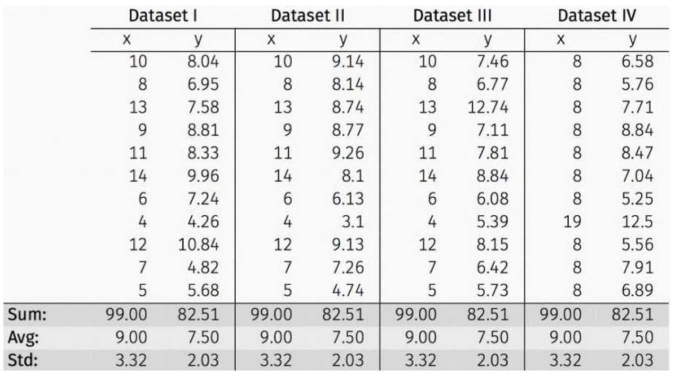
4.3 Training website

Any API: https://any-api.com/

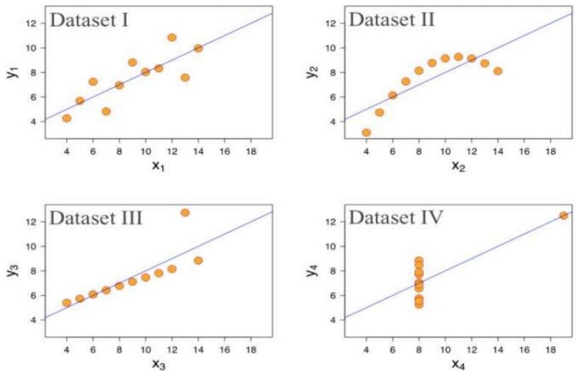
5 Data Visualization tutorial5.html

5.1 Visualization motivation

Although some datasets have same statistic value, but their feature are different:



	Dataset I		Dataset II		Dataset III		Dataset IV	
	x	y	x	y	x	y	x	y
	10	8.04	10	9.14	10	7.46	8	6.58
	8	6.95	8	8.14	8	6.77	8	5.76
	13	7.58	13	8.74	13	12.74	8	7.71
	9	8.81	9	8.77	9	7.11	8	8.84
	11	8.33	11	9.26	11	7.81	8	8.47
	14	9.96	14	8.1	14	8.84	8	7.04
	6	7.24	6	6.13	6	6.08	8	5.25
	4	4.26	4	3.1	4	5.39	19	12.5
	12	10.84	12	9.13	12	8.15	8	5.56
	7	4.82	7	7.26	7	6.42	8	7.91
	5	5.68	5	4.74	5	5.73	8	6.89
Sum:	99.00	82.51	99.00	82.51	99.00	82.51	99.00	82.51
Avg:	9.00	7.50	9.00	7.50	9.00	7.50	9.00	7.50
Std:	3.32	2.03	3.32	2.03	3.32	2.03	3.32	2.03



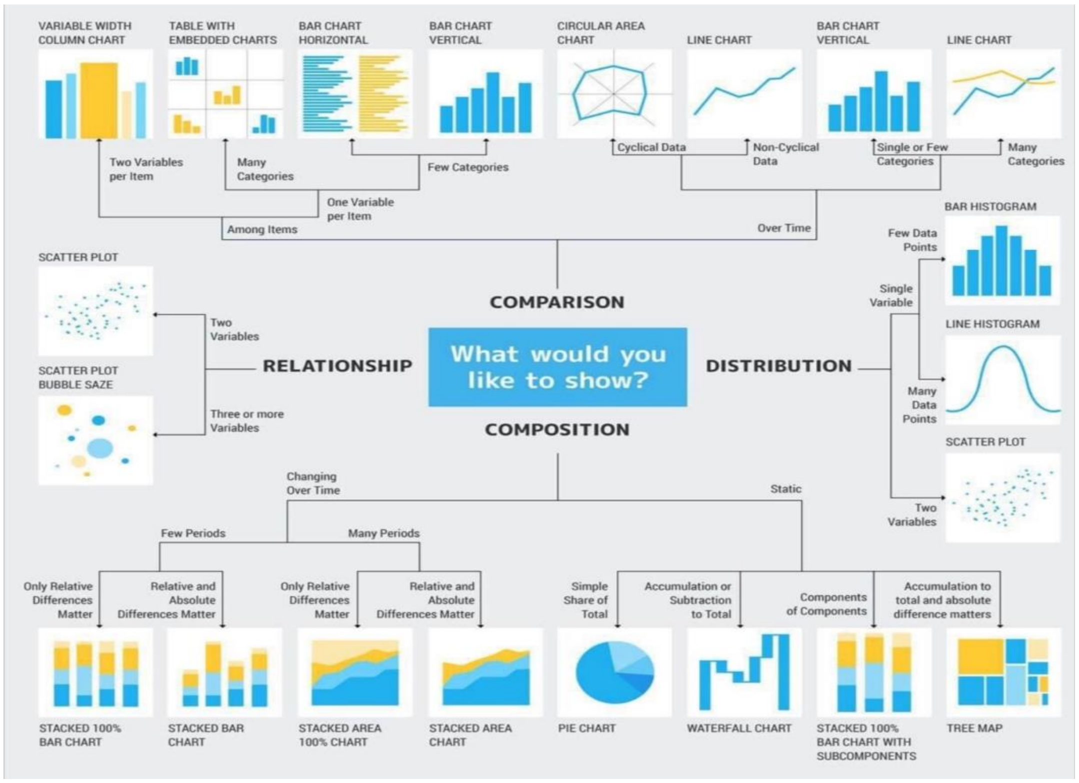
- Identify hidden patterns and trends
- Formulate/test hypotheses
- Communicate any modeling results
    - Present information and ideas succinctly
    - Provide evidence and support
    - Influence and persuade
- Determine the next step in analysis/modeling

5.2 Principle of Visualization

1. Maximize data to ink ratio: show the data
2. Don't lie with scale: minimize

3. Minimize chart-junk: show data variation, not designvariation
4. Clear, detailed and thorough labeling

5.3 Types of Visualization



- Distribution: how a variable or variables in the dataset distribute over a range of possible values.
- Relationship: how the values of multiple variables in the dataset relate
- Composition: how a part of your data compares to the whole.
- Comparison: how trends in multiple variable or datasets compare

Some examples: treevis.net

6 Infrastructure that supports Big Data processing

6.1 Large-scale computing

Issue 1: Copying data over a network takes time.

Idea:

- Bring computation to data
- Store files multiple times for reliability

Spark/Hadoop address these problems

- Storage Infrastructure – File system
- Google: GFS. Hadoop: HDFS

Programming model: MapReduce

Issue 2: If nodes fail, how to store data persistently?

Idea:

- Distributed File System
- Provides global file namespace

Typical usage pattern:

- Huge files (100s of GB to TB)
- Data is rarely updated in place
- Reads and appends are common

6.2 Distributed file system

Chunk servers:

- File is split into contiguous chunks

- Typically, each chunk is 16-64MB
- Each chunk replicated (usually 2x or 3x)
- Try to keep replicas in different racks

Master node:

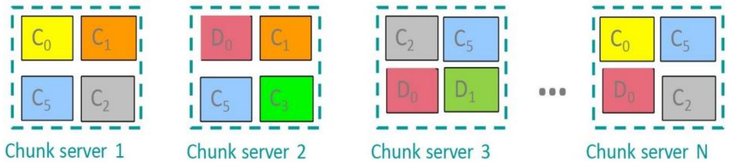
- a.k.a. Name Node in Hadoop's HDFS
- Stores metadata about where files are stored
- Might be replicated

Client library for file access:

- Talks to master to find chunk servers
- Connects directly to chunk servers to access data

Reliable distributed file system:

- Data kept in "chunks" spread across machines
- Each chunk replicated on different machines
- Seamless recovery from disk or machine failure



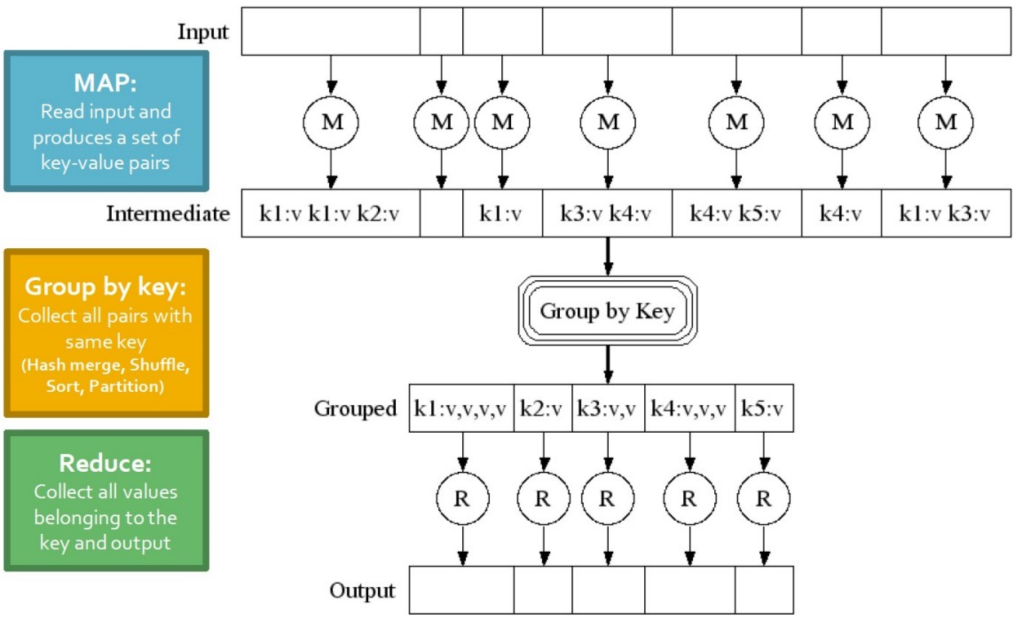
6.3 MapReduce: Distributed computing programming model

MapReduce is a style of programming designed for:

- Easy parallel programming
- Invisible management of hardware and software failures
- Easy management of very-large-scale data

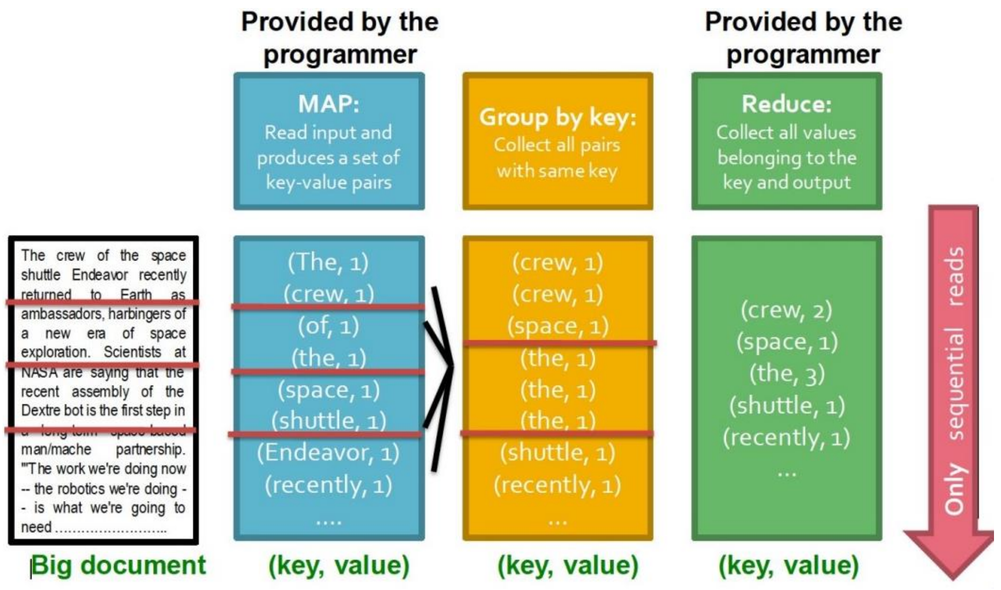
3-steps of MapReduce:

1. Map
    - Apply a user-written Map function to each input element
        - Mapper applies the Map function to a single element
        - Many mappers grouped in a Map task(the unit of parallelism)
    - The output of the Map function is a set of 0, 1, or more key-value pairs.
2. Group by key: Sort and shuffle
    - System sorts all the key-value pairs by key, and outputs key-(list of values) pairs
3. Reduce
    - User-written Reduce functions applied to each key-(list of values)


Input
MAP:
Read input and produces a set of key-value pairs
M
Intermediate
k1:v k1:v k2:v
k1:v
k3:v k4:v
k4:v k5:v
k4:v
k1:v k3:v
Group by key:
Collect all pairs with same key
(Hash merge, Shuffle, Sort, Partition)
Group by Key
Grouped
k1:v,v,v,v
k2:v
k3:v,v
k4:v,v,v
k5:v
Reduce:
Collect all values belonging to the key and output
R
Output

The inputs to reducers are grouped by key

EXAMPLE: WORD COUNTING


Provided by the programmer
MAP: Read input and produces a set of key-value pairs
Group by key: Collect all pairs with same key
Provided by the programmer
Reduce: Collect all values belonging to the key and output
The crew of the space shuttle Endeavor recently returned to Earth as ambassadors, harbingers of a new era of space exploration. Scientists at NASA are saying that the recent assembly of the Dextre bot is the first step in a long-term space-based man/mache partnership. "The work we're doing now -- the robotics we're doing -- is what we're going to need ....
(The, 1)
(crew, 1)
(of, 1)
(the, 1)
(space, 1)
(shuttle, 1)
(Endeavor, 1)
(recently, 1)
....
(crew, 1)
(crew, 1)
(space, 1)
(the, 1)
(the, 1)
(the, 1)
(shuttle, 1)
(recently, 1)
...
(crew, 2)
(space, 1)
(the, 3)
(shuttle, 1)
(recently, 1)
...
Only sequential reads
Big document
(key, value)
(key, value)
(key, value)

6.4 Spark: Extends MapReduce

Hadoop

- Disk-based computation where the results of each step are written to disk.

RDD Difference Between Hadoop and Spark - GeeksforGeeks

- Distributed computing in memory
- Greatly improving the speed of data processing

Consider a dataset of text documents that you want to process to count the frequency of each word across all documents. In a MapReduce framework, this is typically done in two steps:

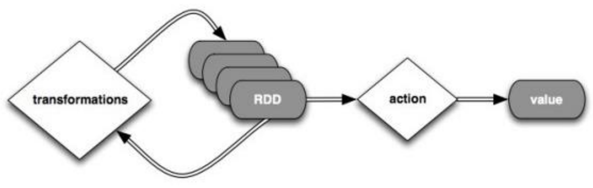
1. Mapping Phase:
    1. Input: Text documents
    2. Output: Key-value pairs where the key is a word and the value is 1 (indicating one occurrence of the word).
2. Reducing Phase:
    1. Input: Key-value pairs from the mapping phase
    2. Output: Key-value pairs where the key is a word and the value is the total count of that word across all documents.

In Apache Spark, you could create an RDD from the text documents and then use Spark operations to achieve the same word count task:

```
wordsList = ['cat', 'elephant', 'rat', 'rat', 'cat']
wordsRDD = sc.parallelize(wordsList, 3)
wordCountsCollected = (wordsRDD
                       .map(lambda w: (w, 1))
                       .reduceByKey(lambda x,y: x+y)
                       .collect())
[('rat', 2), ('elephant', 1), ('cat', 2)]
```

FILE RDD —flatMap—>[list of words]—map—>[(word,1),..]—reduceByKey (map combiner + reduce transformation) —>[(word, count),..] --save Action-->File

```
text_file = spark.textFile("hdfs://...")
counts = (text_file.flatMap(lambda line: line.split(" "))
       .map(lambda word: (word, 1))
       .reduceByKey(lambda a, b: a + b)
)
counts.saveAsTextFile("hdfs://...")
```

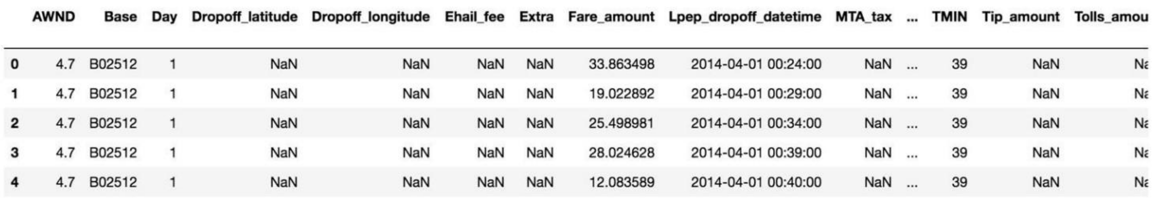


7 Dimensionality Reduction tutorial6.html

7.1 Interaction Terms and Unique Parameterizations

Preview:

We'd like to compare Taxi and Uber rides in NYC (for example, how much the fare costs based on length of trip, time of day, location, etc.). A public dataset has 1.9 million Taxi and Uber trips. Each trip is described by p =23 useable predictors (and 1response variable).



	AWND	Base	Day	Dropoff_latitude	Dropoff_longitude	Ehail_fee	Extra	Fare_amount	Lpep_dropoff_datetime	MTA_tax	...	TMIN	Tip_amount	Tolls_amou
0	4.7	B02512	1	NaN	NaN	NaN	NaN	33.863498	2014-04-01 00:24:00	NaN	...	39	NaN	Na
1	4.7	B02512	1	NaN	NaN	NaN	NaN	19.022892	2014-04-01 00:29:00	NaN	...	39	NaN	Na
2	4.7	B02512	1	NaN	NaN	NaN	NaN	25.498981	2014-04-01 00:34:00	NaN	...	39	NaN	Na
3	4.7	B02512	1	NaN	NaN	NaN	NaN	28.024628	2014-04-01 00:39:00	NaN	...	39	NaN	Na
4	4.7	B02512	1	NaN	NaN	NaN	NaN	12.083589	2014-04-01 00:40:00	NaN	...	39	NaN	Na

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 (X_1 * X_2) + \varepsilon$$

Recall that to avoid overfitting, we sometimes elect to exclude a number of terms in a linear model. It is standard practice to always include the main effects in the model. That is, we always include the terms involving only one predictor, $\beta_1 X_1, \beta_2 X_2$, etc.

- Two-way interactions: $\binom{p}{2} = \frac{p(p-1)}{2} = 253$
- Three-way interactions: $\binom{p}{3} = \frac{p(p-1)(p-2)}{6} = 1771$
- The total number of all possible interaction terms (including main effects) is: $\sum_{k=0}^{p} \binom{p}{k} = 2^p \approx 8.3\text{million}$

Methodology:

In order to handle a dataset with roughly 2 million observations, we could use random samples of 100k observations from the dataset to build our models. If we include all possible interaction terms, our model will have 8.3 mil parameters. We will not be able to uniquely determine3.mil parameters with only 100k observations. In this case, we call the model unidentifiable. To handle this in practice, we can:

- Increase the number of observation
- Consider only scientifically important interaction terms
- Use an appropriate method that account for this issue
- Perform another dimensionality reduction technique like PCA

7.2 Big Data and High Dimensionality

When the sample size is large, this is typically not much of an issue from the statistical perspective, just one from the computational perspective.

- Matrices may not be invertible (issue in OLS).
- Multicollinearity is likely to be present
- Models are susceptible to overfitting

The problem of high dimensionality can occur when the number of parameters exceeds or is close to the number of observations. This can occur when we consider lots of interaction terms, like in our previous example. But this can also happen when the number of main effects is high. One way to reduce the dimensions of the feature space is to create a new, smaller set of predictors by taking linear combinations of the original predictors.

We choose $Z_1, Z_2, \ldots, Z_m$, where and where each Z_i is a linear combination of the original p predictors:

$$Z_i = \sum_{j=1}^{p} \phi_{ji} X_j$$

For fixed constants Φ_{ji}. Then we can build a linear regression model using the new predictors:

$$Y = \beta_0 + \beta_1 Z_1 + \cdots + \beta_m Z_m + \varepsilon$$

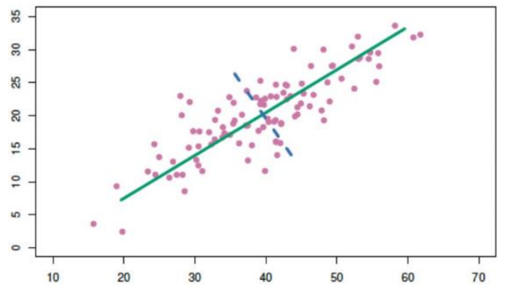
(Notice that this model has a smaller number ($m+1 < p+1$) of parameters)

- Determine an optimal set of new predictors $Z_1, \ldots, Z_m$, for those $m < p$.
- Express each observation in the data in terms of these new predictors, the transformed data $m > p$.

7.3 Principal Components Analysis (PCA)

Concept:

A method to identify a new set of predictors, which captures the 'maximum amount' of variance in the observed data.

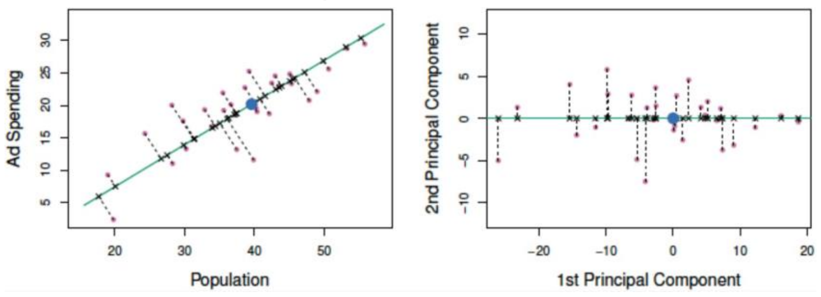


PCA produces a list of p principal components $Z_1,\ldots,Z_p$ such that:

- Each Z_i is a linear combination of the original predictors, and it's vector norm is 1
- The Z_i's are pairwise orthogonal
- The Z_i's are ordered in decreasing order in the amount of captured observed variance.

That is, the observed data shows more variance in the direction of Z_1 than in the direction of Z_2.

To perform dimensionality reduction, we select the top m principal components of PCA_data as our new predictors and express our observed data in terms of these predictors.



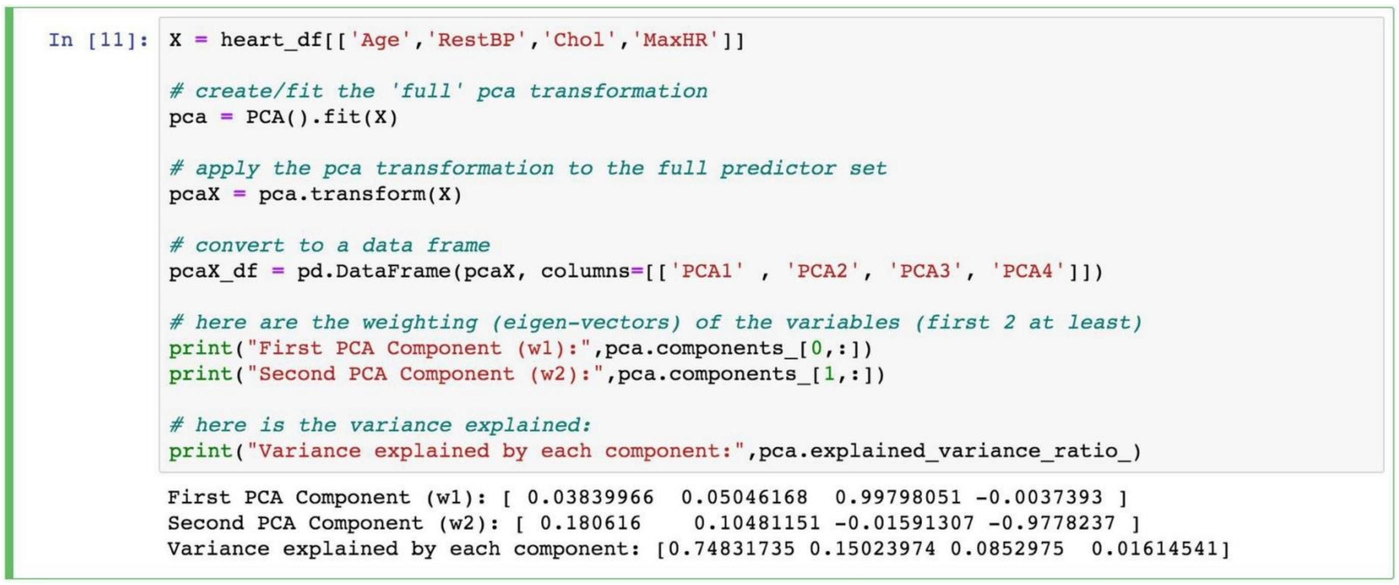
Transforming our observed data means projecting our dataset onto the space defined by the top m PCA components, these components are our new predictors.

Methodology:

PCA is a well-known result from linear algebra. Let Z be the n x p matrix consisting of columns $Z_1,\ldots,Z_p$(the resulting PCA vectors), X be the n x p matrix of $X_1,\ldots,X_p$ of the original data variables (each standardized to have mean zero and variance one, and without the intercept), and let W be the p x p matrix whose columns are the eigenvectors of the square matrix X^TX, then:

$$\mathbf{Z}_{n\times p} = \mathbf{X}_{n\times p}\mathbf{W}_{p\times p}$$

PCA example in sklearn:



```
In [11]: X = heart_df[['Age','RestBP','Chol','MaxHR']]

         # create/fit the 'full' pca transformation
         pca = PCA().fit(X)

         # apply the pca transformation to the full predictor set
         pcaX = pca.transform(X)

         # convert to a data frame
         pcaX_df = pd.DataFrame(pcaX, columns=[['PCA1' , 'PCA2', 'PCA3', 'PCA4']])

         # here are the weighting (eigen-vectors) of the variables (first 2 at least)
         print("First PCA Component (w1):",pca.components_[0,:])
         print("Second PCA Component (w2):",pca.components_[1,:])

         # here is the variance explained:
         print("Variance explained by each component:",pca.explained_variance_ratio_)
```

```
First PCA Component (w1): [ 0.03839966  0.05046168  0.99798051 -0.0037393 ]
Second PCA Component (w2): [ 0.180616    0.10481151 -0.01591307 -0.9778237 ]
Variance explained by each component: [0.74831735 0.15023974 0.0852975  0.01614541]
```

Key takeaways of PCA:

- Capturing Variation: The primary goal of PCA is to capture the most significant variations in the data, rather than interpreting the principal components of data for predicting the output variable.

- p=p, m<p: PCA produces a list of p principal components. The first principal component (Z1) corresponds to the direction along which the data exhibits the highest variance. Subsequent components (Z2, Z3, etc.) capture progressively less variance but are still important sources of variation. To perform dimensionality reduction, we select the top m principal components of PCA as our new predictors and express our observed data in terms of these predictors.
- Linear Combinations: Each principal component (Zi) is a linear combination of the original predictors, indicating how each predictor contributes to that component's direction. The principal components (Z's) are pairwise orthogonal, meaning they are uncorrelated with each other.

7.4 PCA for Regression (PCR) (self-study)

- PCA is not so good because:
  1. Direct Interpretation of coefficients in PCR is completely lost. So do not do if interpretation is important.
  2. Will often not improve predictive ability of a model.
- PCA is great for:
  1. Reducing dimensionality in high dimensional settings.
  2. Visualizing how predictive your features can be of your response, especially in the classification setting.
  3. Reducing multicollinearity, and thus may improve the computational time of fitting models.

7.5 PCA for Imputation (self-study)

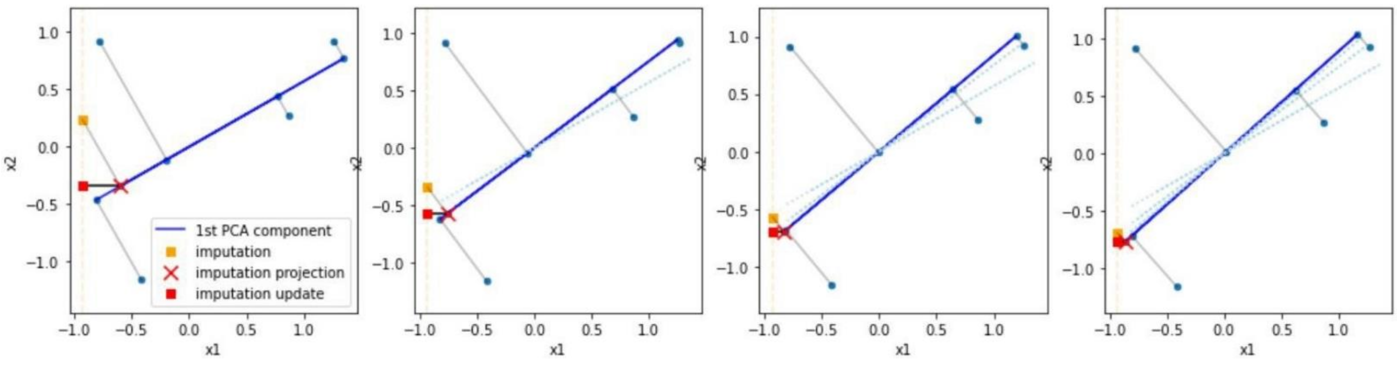
We want our imputations to take into account links between variables and global similarity between individual observations. This is the idea behind the iterative PCA algorithm for imputation.

Algorithm:

1. Initialize imputation with reasonable value (e.g., mean)
2. Iterate until convergence:
   a. perform PCA on the complete data
   b. retain first M components of PCA (in example M=1)
   c. project imputation into PCA space
   d. update imputation using projection value

Q: How do we select the number of components to use for our projections?

A: Cross-validation!



In practice this method can overfit, especially in a sparse matrix with many missing values. So often a regularized PCA approach is used which shrinks the singular values of the PCA, making updates less aggressive.