Institute of Data

2024

Data Science and AI

Module 2
Part 1:

Exploratory Data Analysis (EDA)

Agenda: Module 2 Part 1

- Introduction to EDA
- Data **cleaning** & **profiling**
- Assessing data **quality**
- Data rejection & imputation
- Exploring & visualising **continuous** data
- Exploring & visualising **categorical** data
- **Temporal** data
- **Geographic** data

Python EDA Fundamentals

- Where does data come from?
- What does data look like?
- What is **Exploratory Data Analysis**?
- Where does EDA fit in the **Data Science pipeline**?

Where does data come from?

- **databases**
  - data marts
  - data warehouses
- transaction systems
  - cloud
  - mainframes
- distributed file systems
  - Hadoop
- **APIs**
- scanned documents

- websites
  - downloads of datasets, posts, conversations, etc.
  - web scrapers
- subscribed feeds
  - news
  - IoT devices
- multimedia hosts
  - images
  - video
  - audio
- ?

What does data look like?

- database **tables**
- reports & extracts
- spreadsheets & workbooks
- **structured & semi-structured files**
- **streams**
- encoded files
- bitmaps
- ?

What is Exploratory Data Analysis?

everything we do with a candidate dataset ...

- after it has been rendered essentially **usable**
- before we start **developing analytics and models** that address our original problem
- to determine whether it will make a useful **proxy** for understanding the phenomenon we are interested in

where does it fit?

- (within the data science pipeline)

How do we make a dataset “usable”?

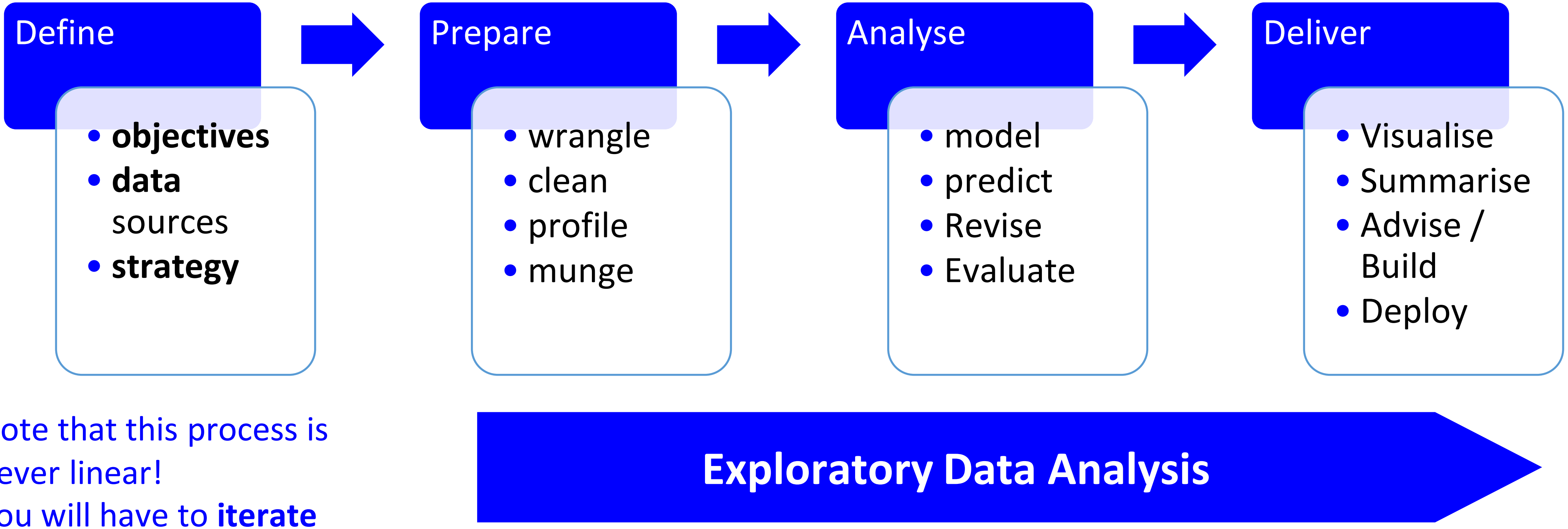
- ***wrangling***
  - sourcing, loading, and precleaning the data so we can see what it really looks like
  - fixing critical issues

- ***profiling and cleaning***
  - understanding the essential characteristics of the data
  - applying preliminary transformations to confer context and meaning
  - implementing strategies for missing and invalid data

- ***munging***
  - reshaping the data to prepare it for analysis

Where does EDA fit?

- (within the data science pipeline)



Define
- **objectives**
- **data** sources
- **strategy**

Prepare
- wrangle
- clean
- profile
- munge

Analyse
- model
- predict
- Revise
- Evaluate

Deliver
- Visualise
- Summarise
- Advise / Build
- Deploy

Exploratory Data Analysis

Note that this process is never linear!
You will have to **iterate** over each step and over a number of the steps

Data Cleaning & Profiling

- Preliminary data **cleaning**
- Basic data **profiling**
- Assessing data **quality**
- Data rejection and imputation

Data Cleaning & Profiling

def: **Data profiling**

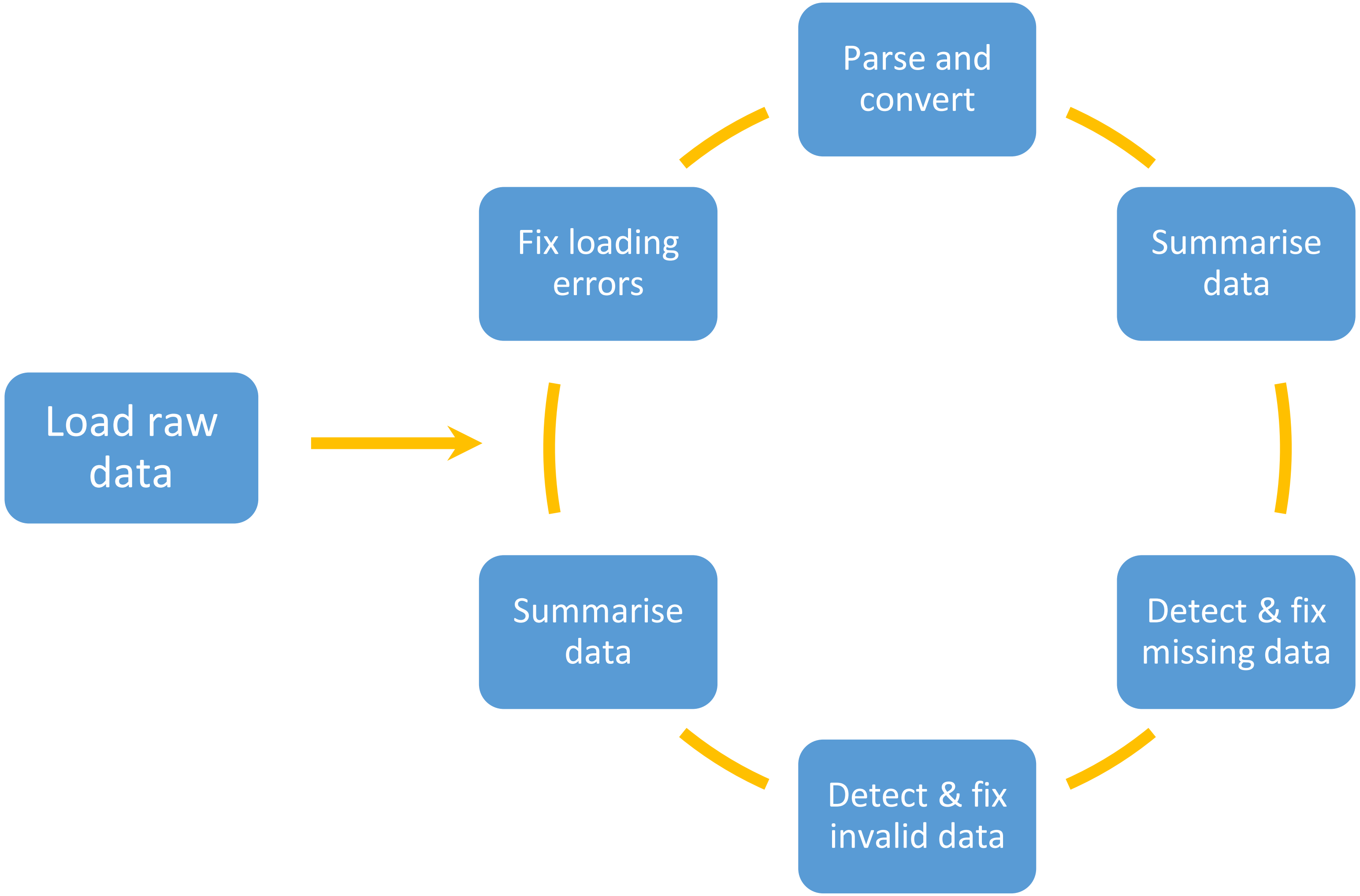
- examining the characteristics of the dataset
  - data types
  - data ranges (continuous) & categories
- identifying issues with the data

def: **Data cleaning**

- making the data usable (preparing it for analysis)
  - reformatting
  - data type conversion
  - dealing with dirty data

Data Cleaning & Profiling

... is iterative



Data Cleaning & Profiling – Details

Load raw data

- from source system
  - database
  - HFS
  - flat file
  - spreadsheet / workbook
  - semi-structured file (JSON, XML, HTML)
  - API
  - stream (feed, IoT)
  - web scraper
  - scanned text

Data Cleaning & Profiling – Details

Fix loading errors

- missing delimiters
  - e.g. badly written mainframe extracts that suppress trailing commas for empty fields
- unexpected delimiters
  - e.g. '|' or tab character used in "CSV" file
- illegal characters
  - e.g. '\u' is normally interpreted as indicating Unicode
    may need to suppress default behaviour of function used to load the data
- missing control characters
  - EOL
  - EOF
- other?

Data Cleaning & Profiling – Details

Parse and convert

- formatted date strings to dates
  - d/m/y, m/d/y, dd/mm/yyyy, dd-mmm-yyyy, day names, month names, ...
- formatted time strings to times
  - AM/PM vs 24-hr
  - time zone conversions
- formatted date+time strings to datetimes
- string to int, string to float
- proprietary formats
  - binary, octal, hexadecimal

Data Cleaning & Profiling – Details

What to do when data conversions fail?

- implement a *try* block
    - to catch format conversion failures
- use transformations that can handle missing values
    - or deal with missing values first
- document conversion failures
    - these are *limitations* that should be addressed when interpreting the results of analysis

```
def try_parse_int(s, base=10, val=None):
    try:
        return int(s, base)
    except ValueError:
        return val
```

Data Cleaning & Profiling – Details

Detect & fix missing values

- drop rows
- replace with NA
- impute values
    - mean, median, mode
        - of entire column
        - of similar data (grouped by other fields)
    - nearest neighbour
        - assign value from closest point (according to a suitable distance metric)

Data Cleaning & Profiling – Details

Dealing with missing or bad data

- replace with NA
- impute values
    - out of range
        - too small: set to minimum possible value?
        - too large: set to maximum possible value?
- drop rows
    - impossible values (e.g. out of domain)
        - length = green: drop?
        - salary = -1: drop?
- drop columns
    - too many missing or invalid samples

Data Cleaning & Profiling – Details

Summarise data

- counts of missing values
- counts of invalid values
- statistical parameters of distribution
  - continuous variables
    - bin frequencies
    - mean, median, maximum, minimum
  - categorical variables
    - category frequencies
      - most frequent (mode), least frequent

Assessing Data Quality

- accuracy, reliability (veracity)
- currency, relevance (value)
- missing and invalid values
  - overall
  - by column
  - by row

issues:

- can we afford to throw out rows with missing data?
- how will imputation of missing/invalid data affect the outcome?

Assessing Data Quality with Python

let df *be a Pandas DataFrame object*

• view the first few rows:	df.head(), df.head(nrows)
• check for missing values:	df.isnull(), df.isnull().sum()
• pairwise correlations:	df.corr()
• (continuous) value ranges:	df.min(), df.max()
• (discrete) value counts:	df.value_counts()
• summary:	df.describe()
	pandas_profiling.ProfileReport
	pydqc

Lab 2.1.1: Data Wrangling and Munging

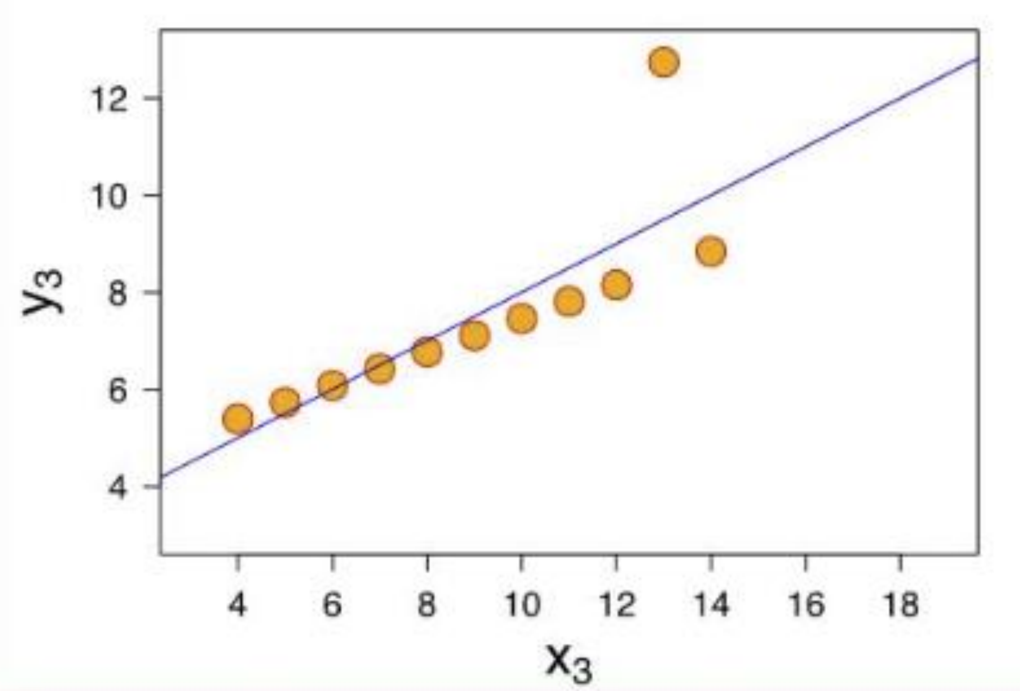
- Purpose:
  - To explore Python methods for wrangling, munging, and profiling datasets

- Materials:
  - ‘Lab 2.1.1.ipynb’

Outliers

def: an observation that is distant from other observations in the sample

- measurement inaccuracy
- measurement errors
  - incl. recording errors
- unusual system behaviour
- external phenomena



Outlier Detection in 1 Dimension

extreme value analysis

- outliers are defined by statistical tests based on mean & variance of sample
  - *z*-test
- mark points with low score as outliers

probabilistic & statistical models

- based on assumed distribution of data
  - calculate probability that each point belongs to the distribution
  - mark points with low probability as outliers

Outlier Detection in Multiple Dimensions

linear models

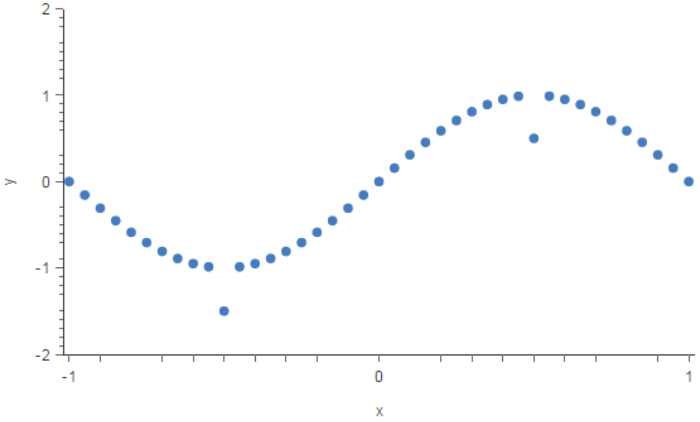
- reduce data to lower-dimensional spaces
- calculate distance from each point to a reference hyperplane
- mark points with largest distance as outliers
- similar concept to *principal component analysis* (PCA)

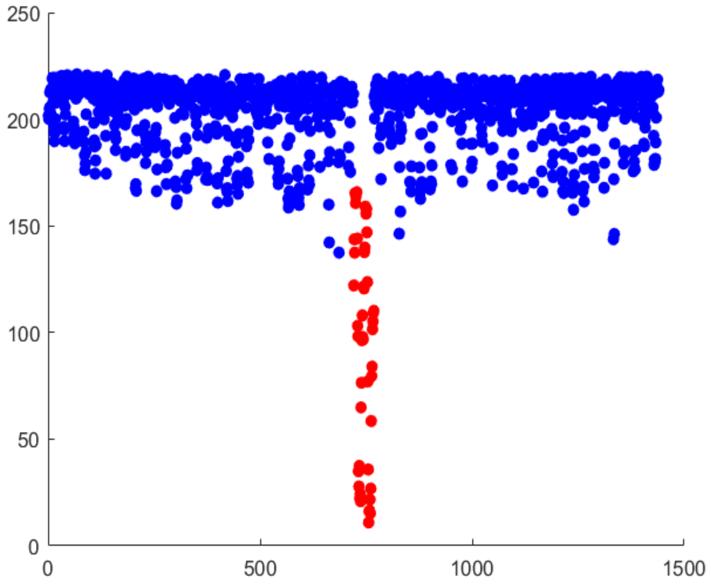
proximity-based models

- define a distance metric and apply to each pair of points
- mark points that are more isolated as outliers
- examples: *cluster analysis*, *density-based analysis*, *nearest-neighbour analysis*

Outlier Detection – cont’d

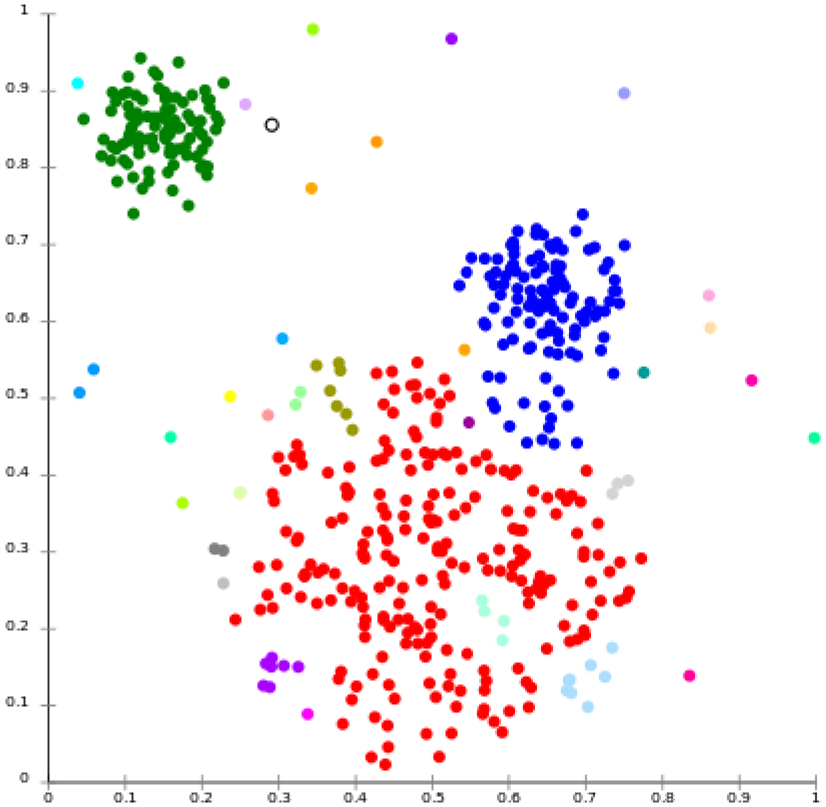
- outliers vs. anomalies
  - if unsure, analyse data with *and* without the outliers





Outlier Detection – cont’d

- outliers may not be obvious in one dimension
  - some points may only get separated from the mainstream when looking at several dimensions at once
  - may indicate subsets of behaviour (“classes”)



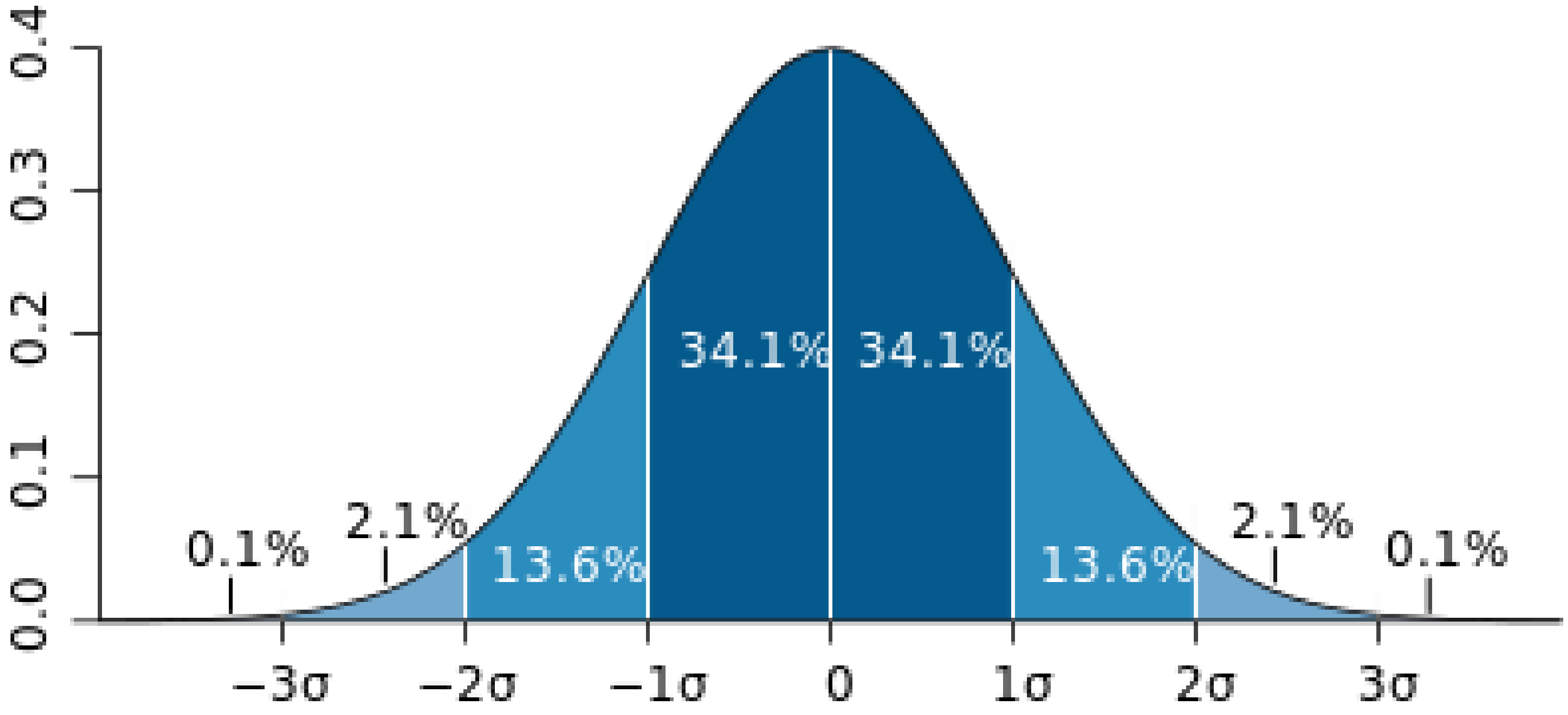
Continuous Data

- Statistics of sample distributions
  - deeper dive: mean, variance, skewness, kurtosis

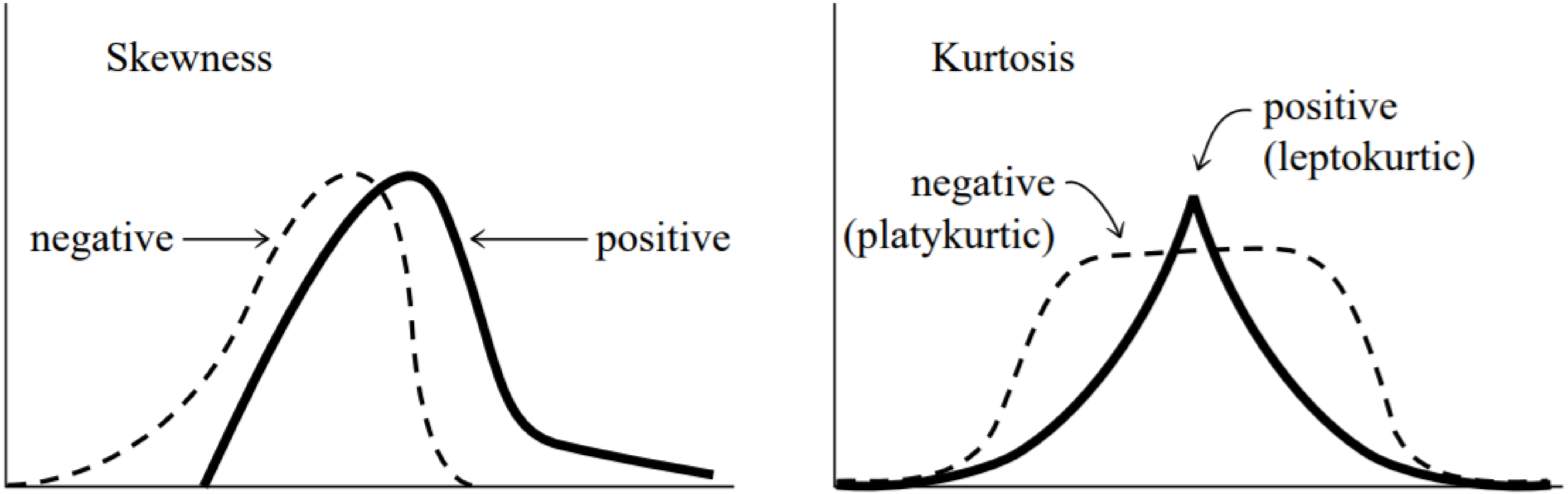
- Exploring and visualising sample variables
  - histograms
  - box & whisker plots
  - violin plots

- Outlier detection

Mean & Variance

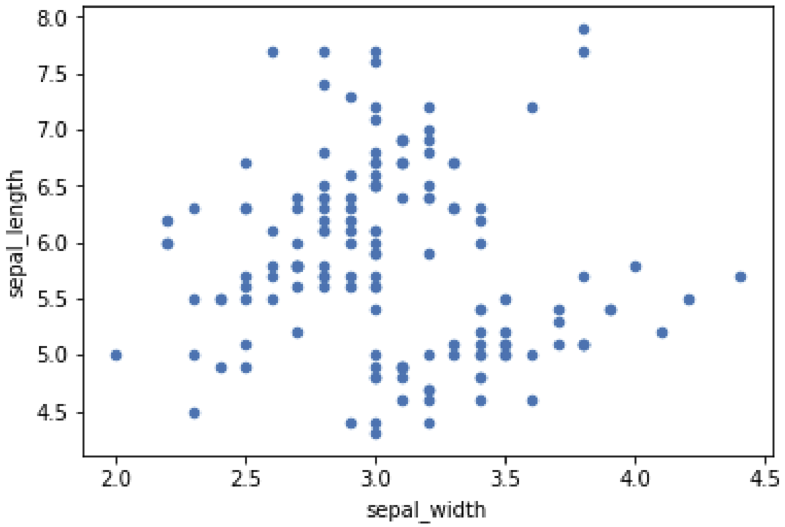


Skewness and Kurtosis

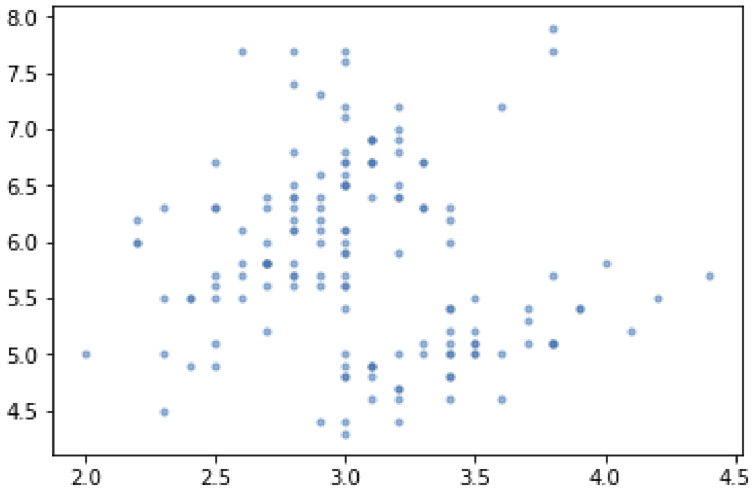


Scatterplot

- shows a 2D relationship within the dataset by plotting one column against another



df.plot(kind='scatter', x='sepal_width’, y='sepal_length')

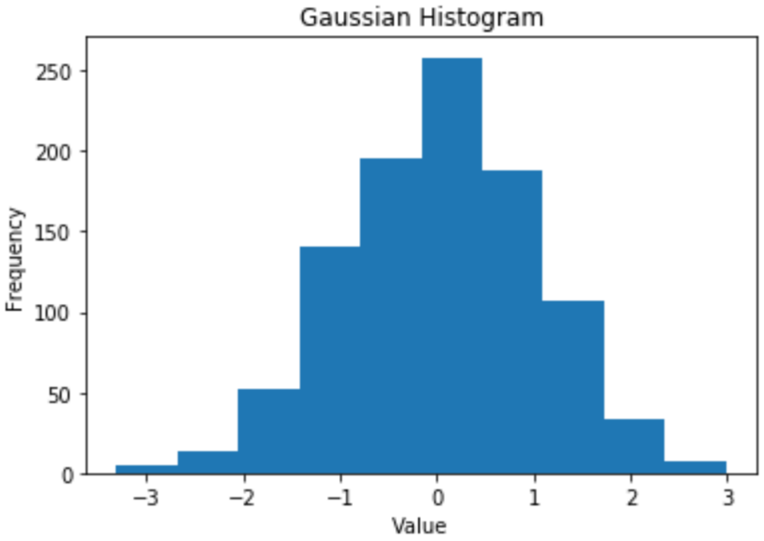


plt.scatter(df['sepal_width’], df['sepal_length’], s = 10, linewidths = 1, alpha = 0.5)

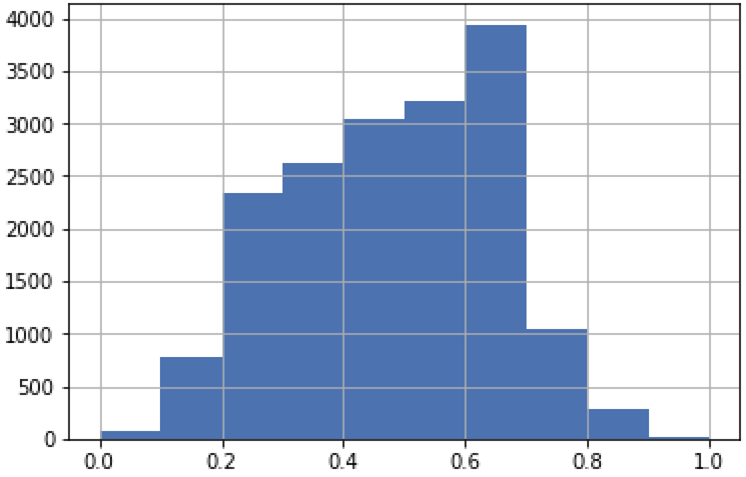
https://matplotlib.org/api/_as_gen/matplotlib.pyplot.scatter.html

Histogram

shows the properties of the data sample distribution with no loss of information



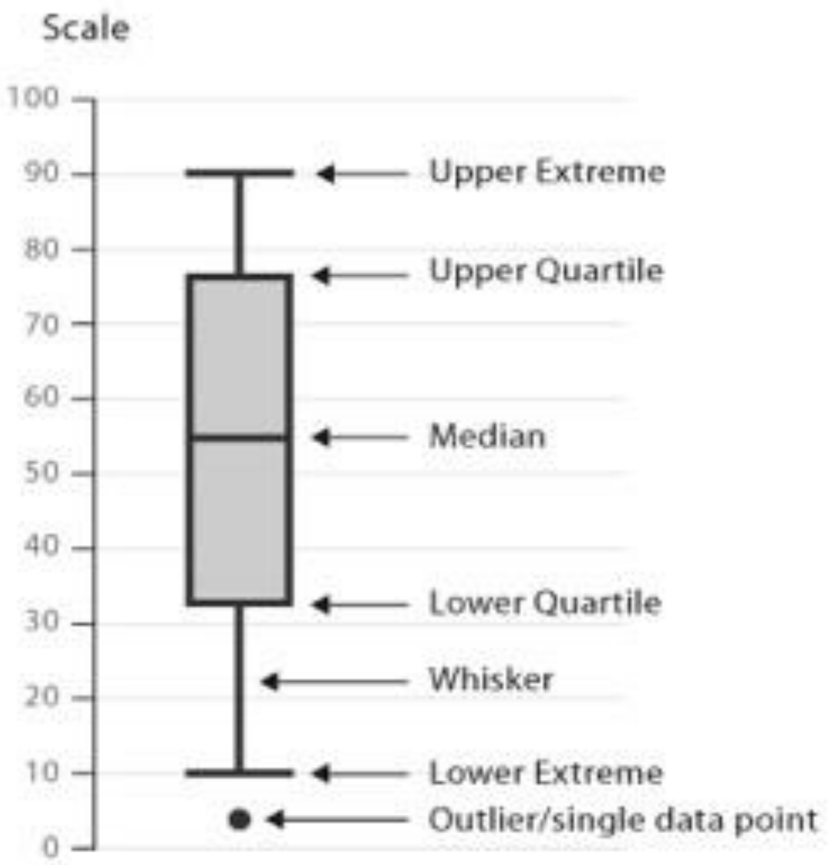
```
plt.hist(y)
plt.title("Gaussian Histogram")
plt.xlabel("Value")
plt.ylabel("Frequency")
```



```
df['temp'].hist()
```

Box & Whisker Plots

- shows multiple features of sample distribution
  - median
  - interquartile range
  - 10th, 90th percentiles



Box & Whisker Plots

# get 50 random numbers normally distributed about -1:

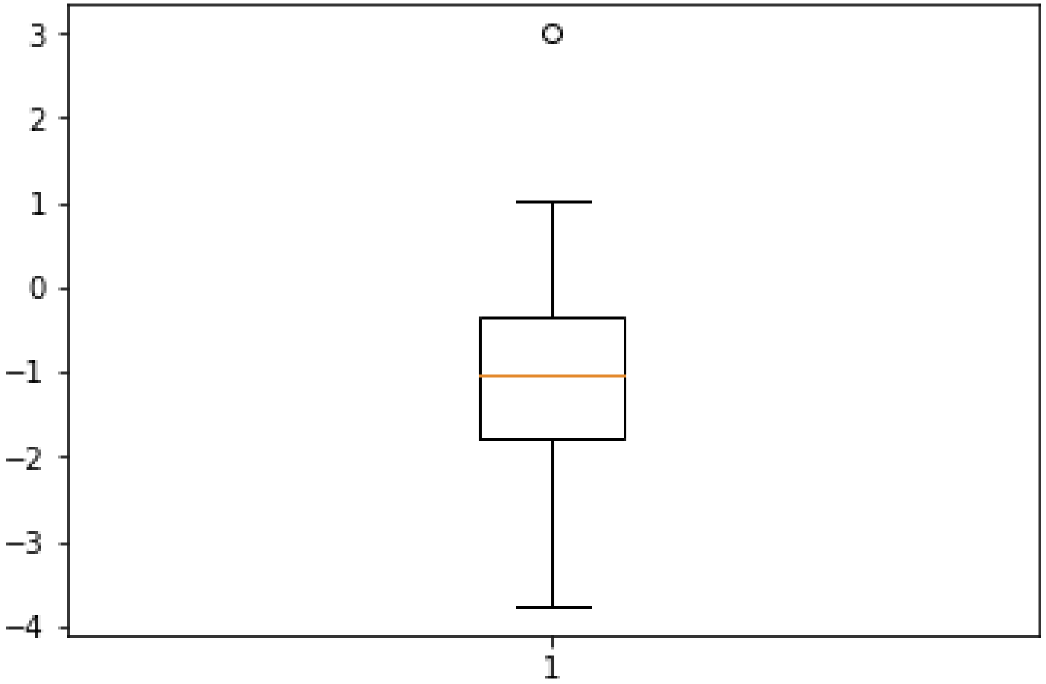
```
y = np.random.randn(50) – 1
```

# create an outlier:

```
y [49] = 3
```

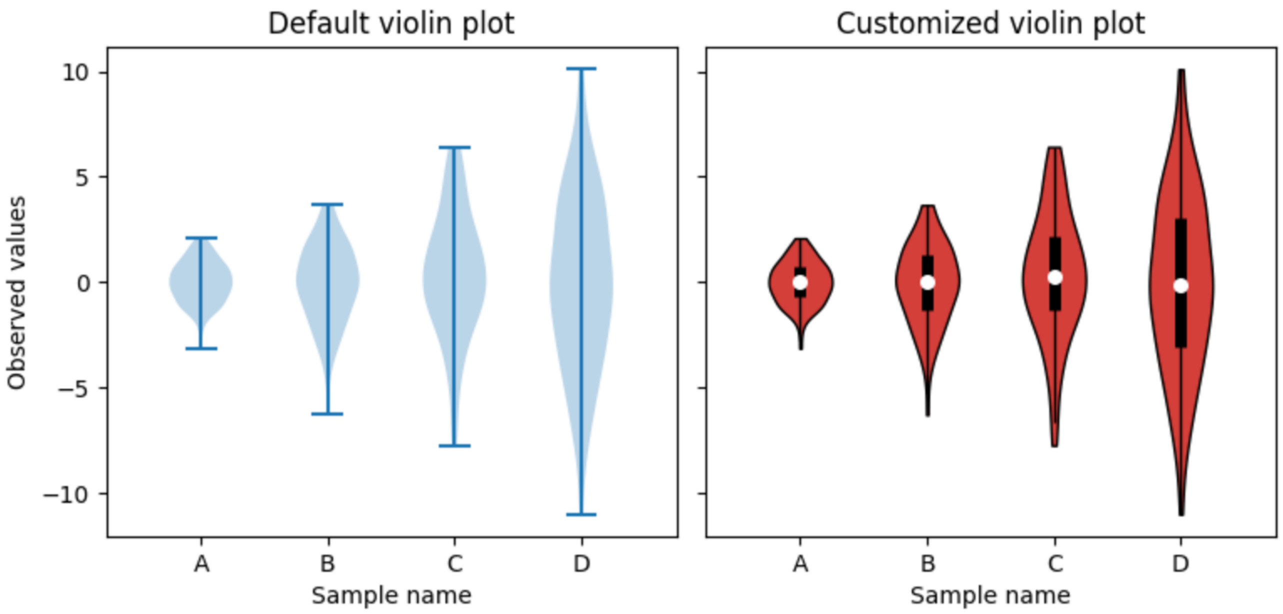
# plot box & whiskers:

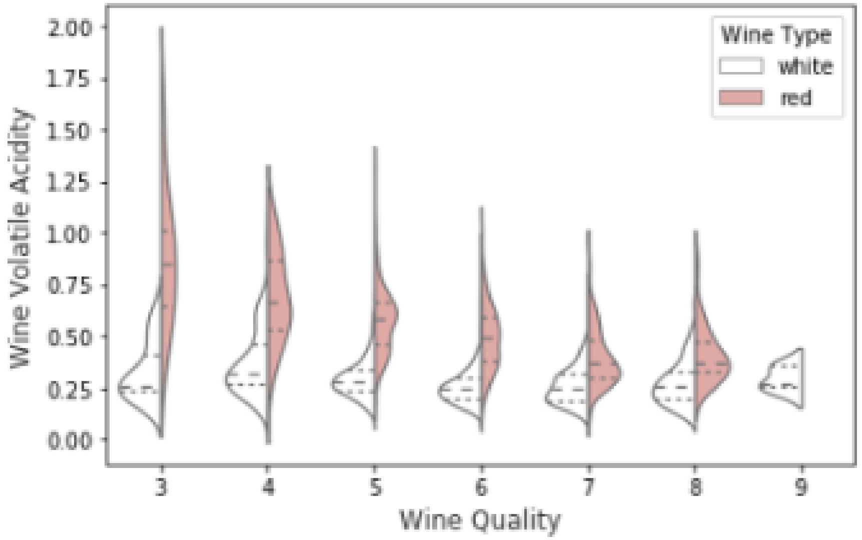
```
plt.boxplot(y)
```



Violin Plots

- shows the sample distribution itself

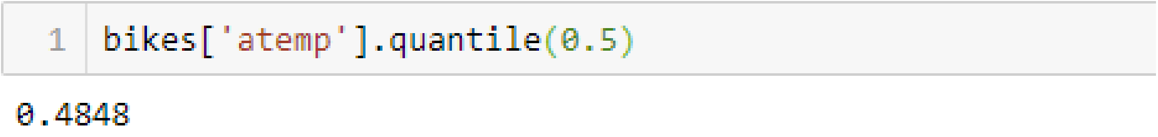




https://matplotlib.org/gallery/statistics/customized_violin.html

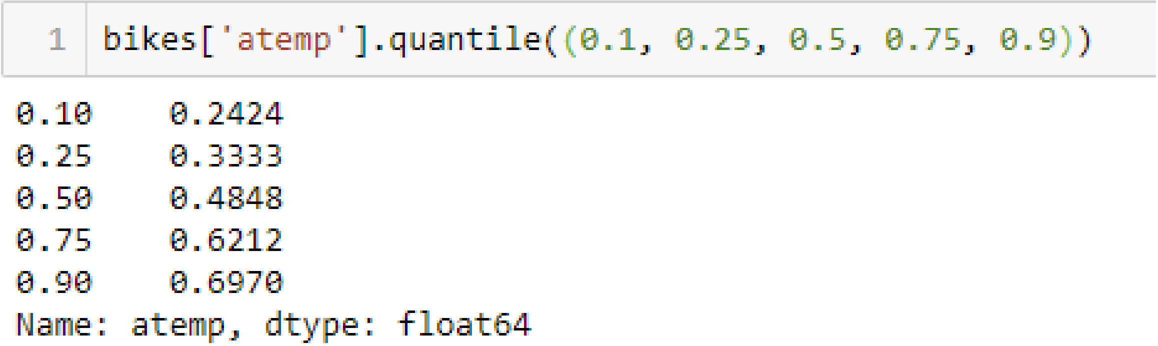
Quantiles

- quantiles are popular in reporting because they help to create a sense of what is “normal”
  - *90% of calls last less than 3 minutes, 22 seconds*
  - *80% of revenue was derived from 22% of the product range*



```
bikes['atemp'].quantile(0.5)
```

```
0.4848
```



```
bikes['atemp'].quantile((0.1, 0.25, 0.5, 0.75, 0.9))
```

```
0.10    0.2424
0.25    0.3333
0.50    0.4848
0.75    0.6212
0.90    0.6970
Name: atemp, dtype: float64
```

- quantiles are cumulative

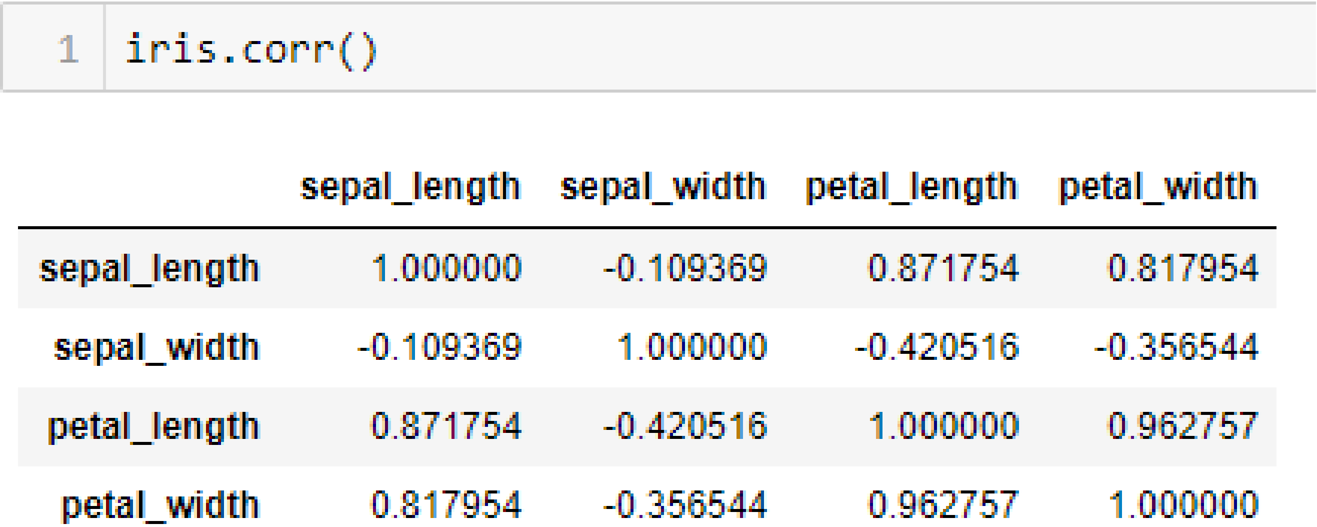
  e.g. 80th percentile is a subset of 90th percentile

  Q: what would a plot of all possible quantiles represent?

  > the cumulative probability function

Pairwise Correlations in *n*-Dimensional Data

computes correlation between every pair of columns in a matrix or DataFrame:



```
iris.corr()
```

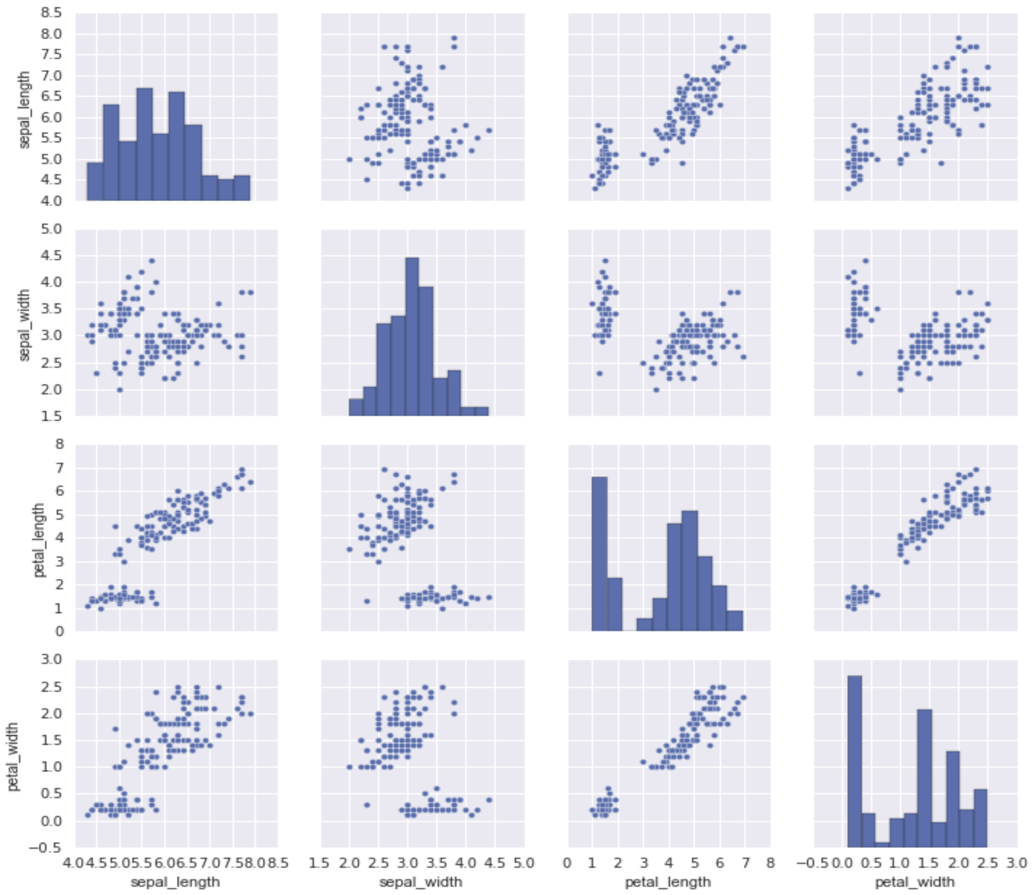
	sepal_length	sepal_width	petal_length	petal_width
sepal_length	1.000000	-0.109369	0.871754	0.817954
sepal_width	-0.109369	1.000000	-0.420516	-0.356544
petal_length	0.871754	-0.420516	1.000000	0.962757
petal_width	0.817954	-0.356544	0.962757	1.000000

- only the figures below (or above) the main diagonal are needed
- uses Pearson's correlation by default

Pairwise Correlations in *n*-Dimensional Data – cont’d

can visualise correlations as a **pair plot**

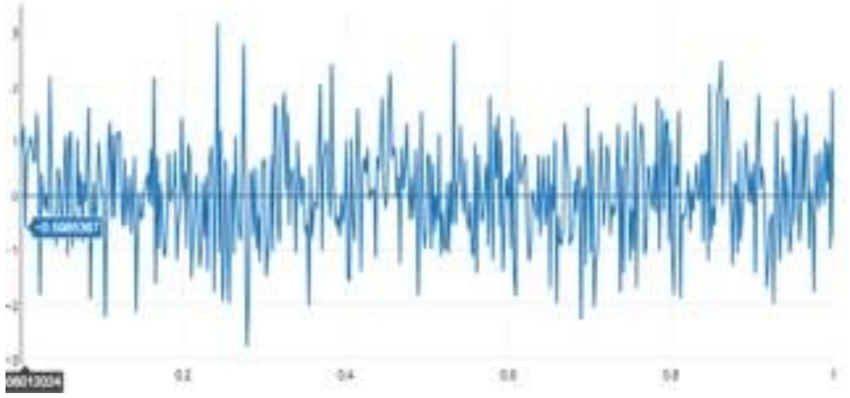
```
import seaborn as sns

sns.pairplot(iris)
```

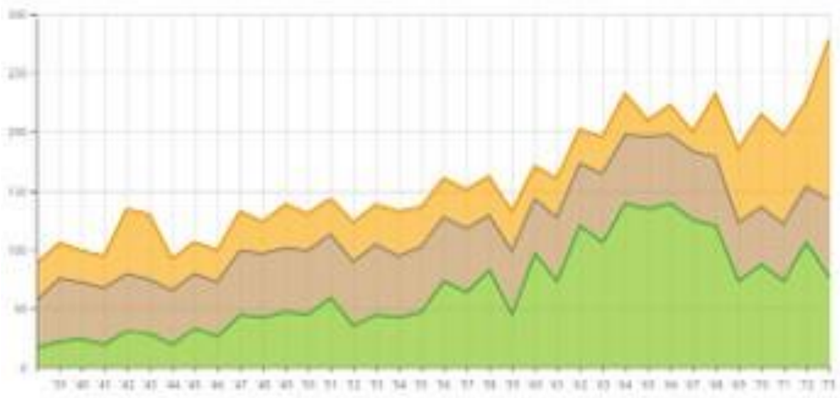


Visualising 2-Dimensional Data

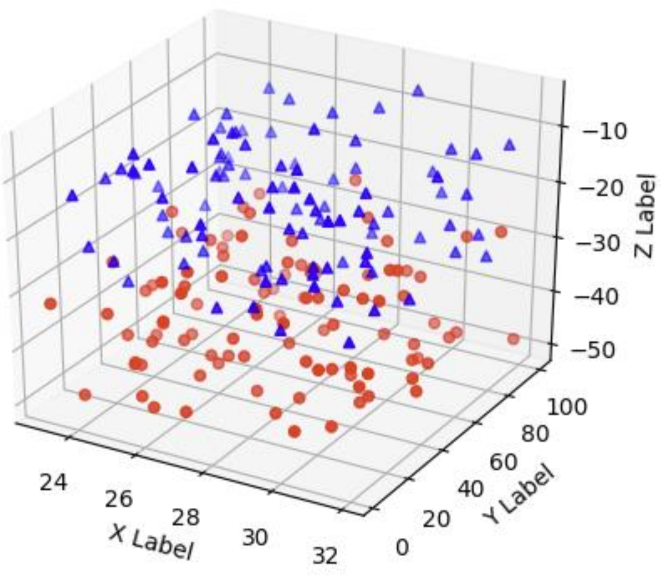
- scatterplot
- line chart
- bar chart (binned horizontal axis)
- stacked area chart

- *many variations of these*

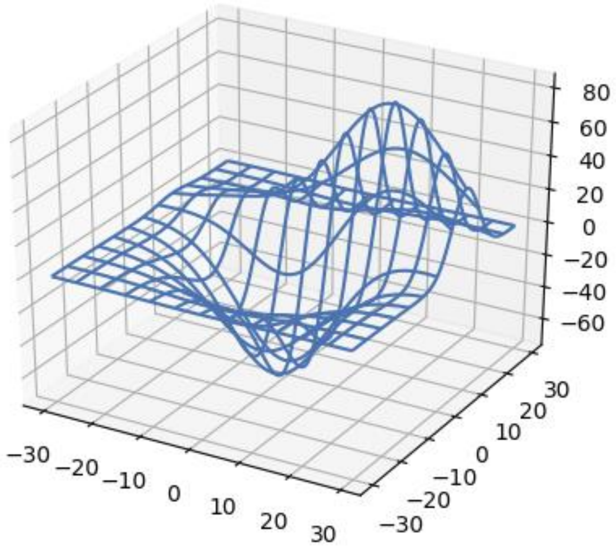




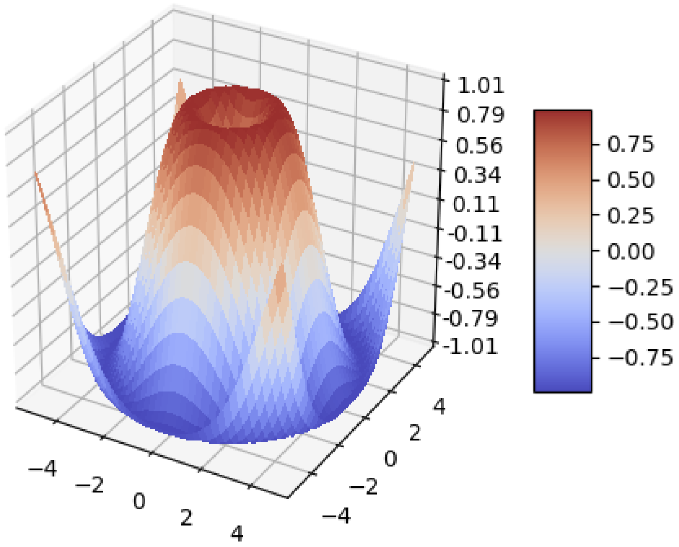
Visualising 3-Dimensional Data



3D Scatterplot



Wireframe Plot

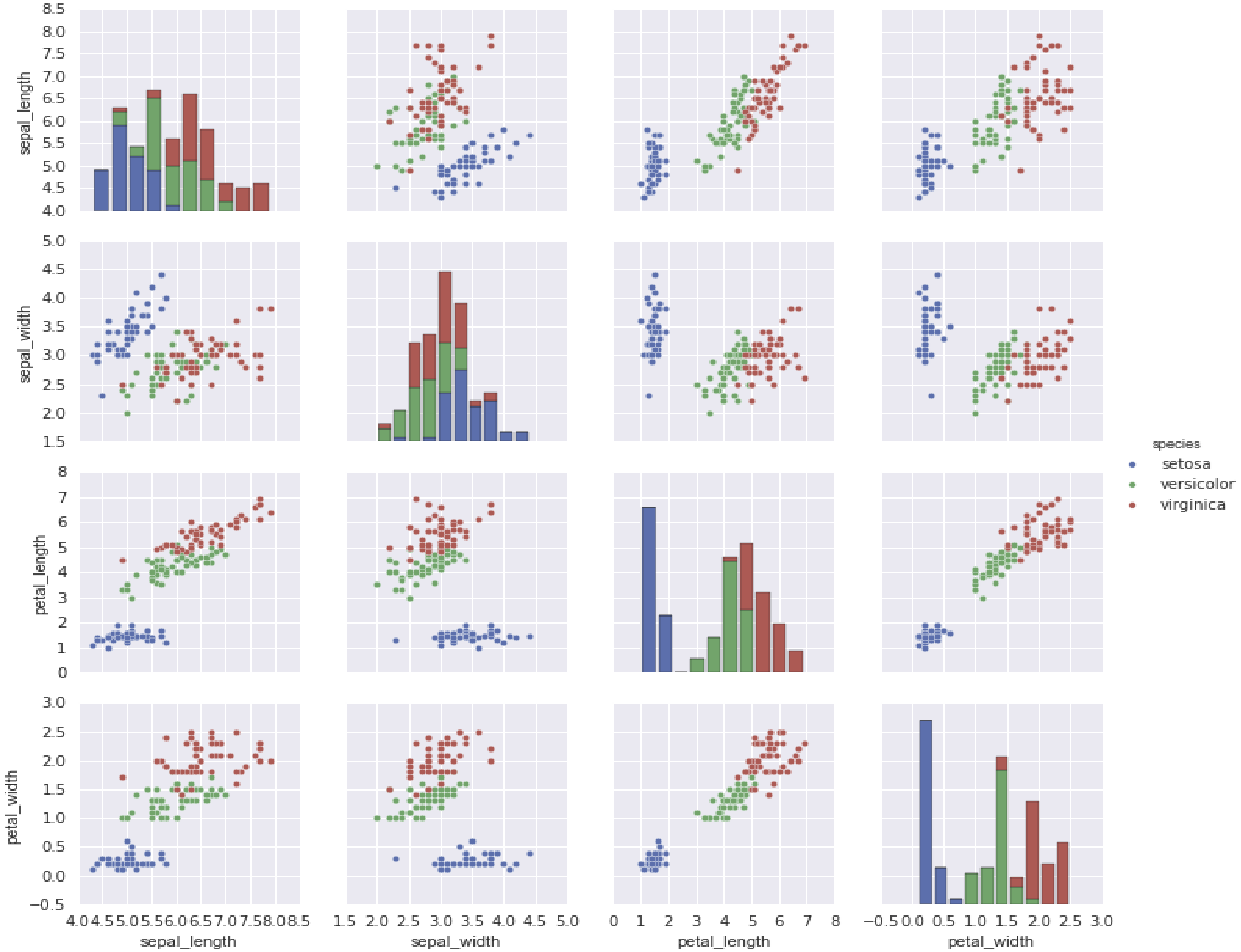


Surface Plot

https://matplotlib.org/mpl_toolkits/mplot3d

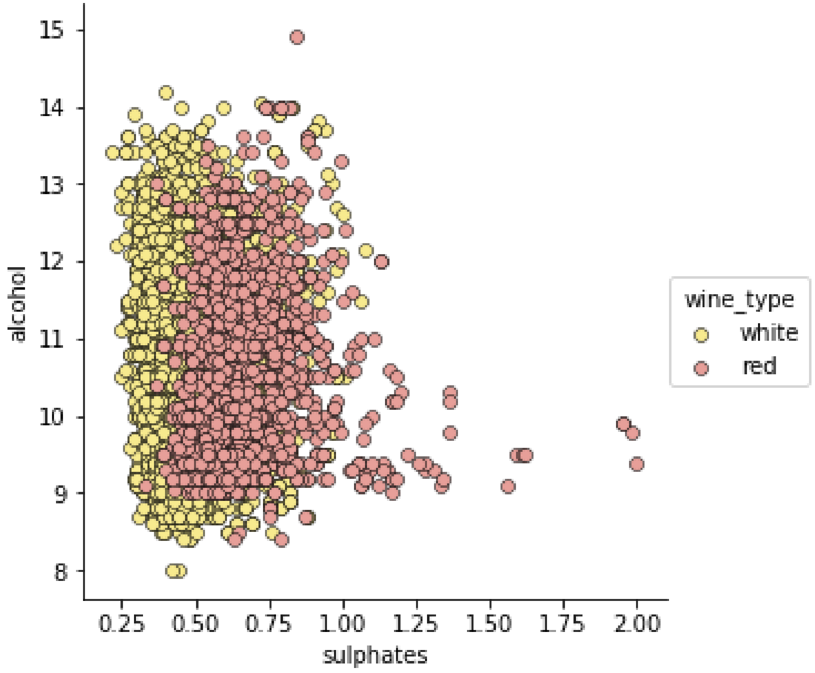
Visualising 3 Dimensions – cont’d

- adding colour allows stratification by a categorical variable (usually called a “class”)

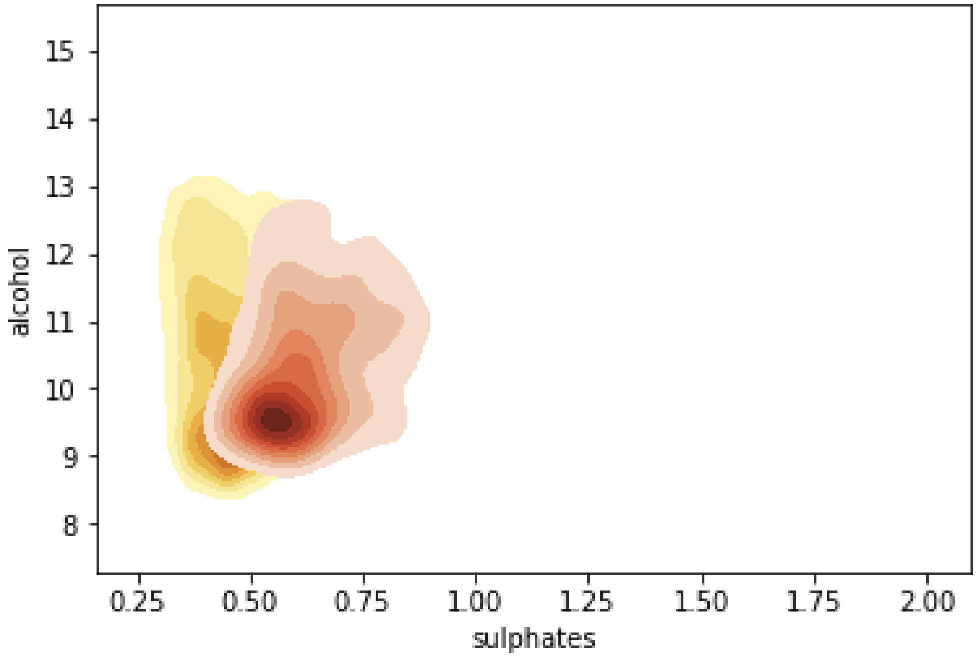


© 2024 Institute of Data

Visualising 3 Dimensions – cont’d



using colour in a scatterplot



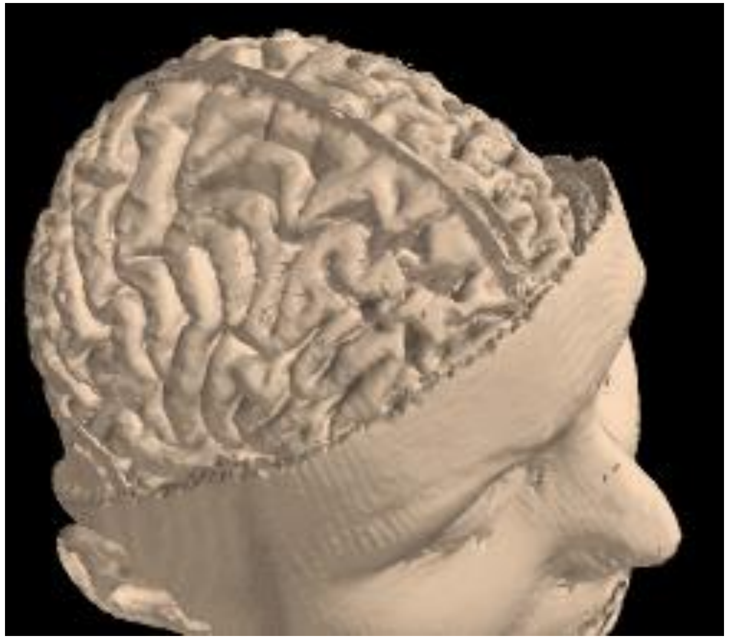
using colour and hue in a contour plot

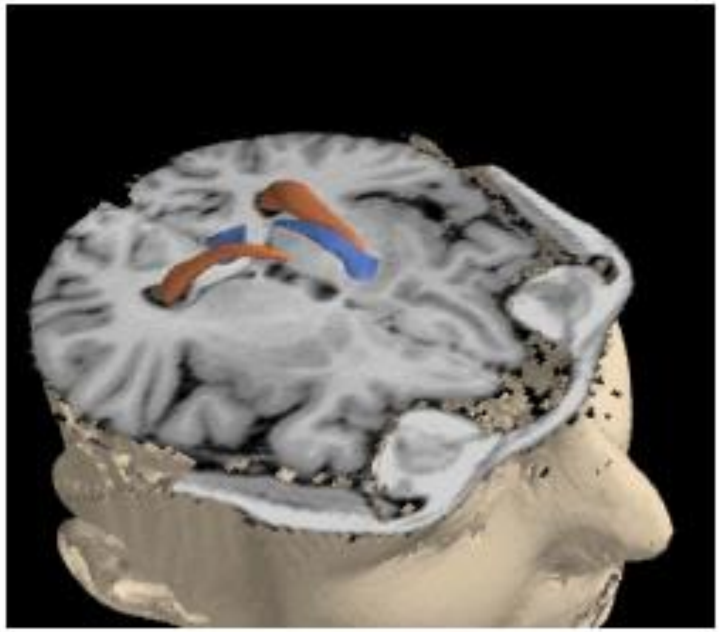
https://towardsdatascience.com/the-art-of-effective-visualization-of-multi-dimensional-data-6c7202990c57

Visualising 3 Dimensions – cont’d

Slicing

- reduce dimensionality by viewing a plane
- does not have to be parallel to a dimensional axis

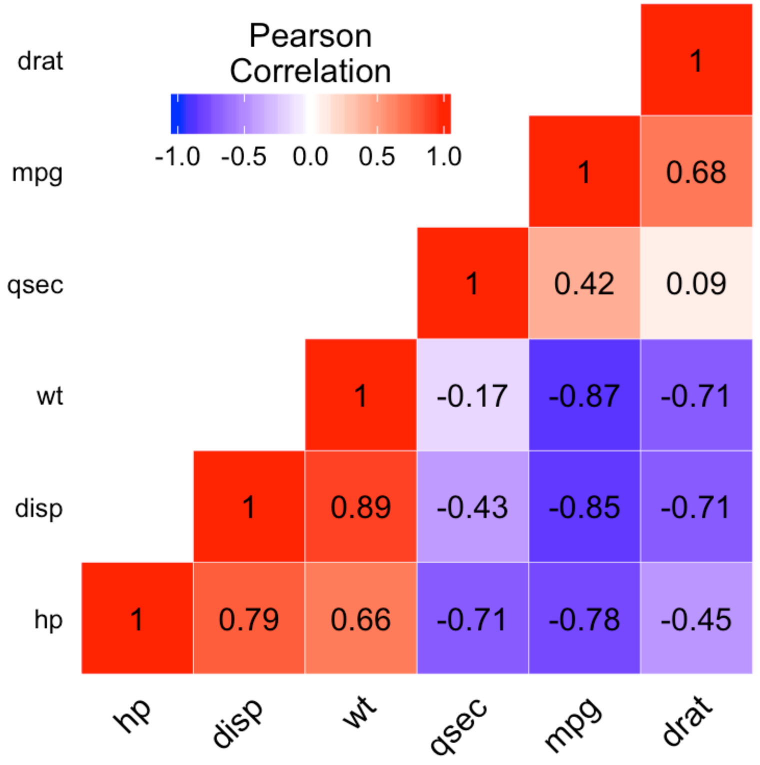


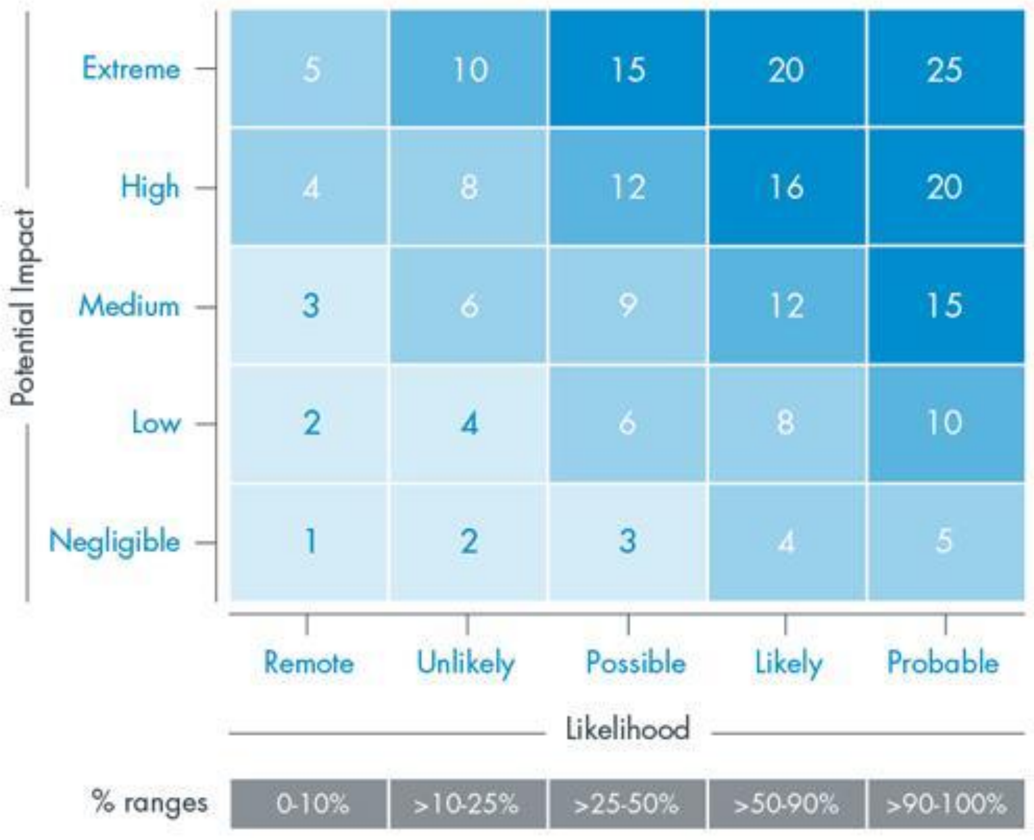


http://zulko.github.io/blog/2014/11/29/data-animations-with-python-and-moviepy/

Visualising 3 Dimensions – cont’d

- heat map

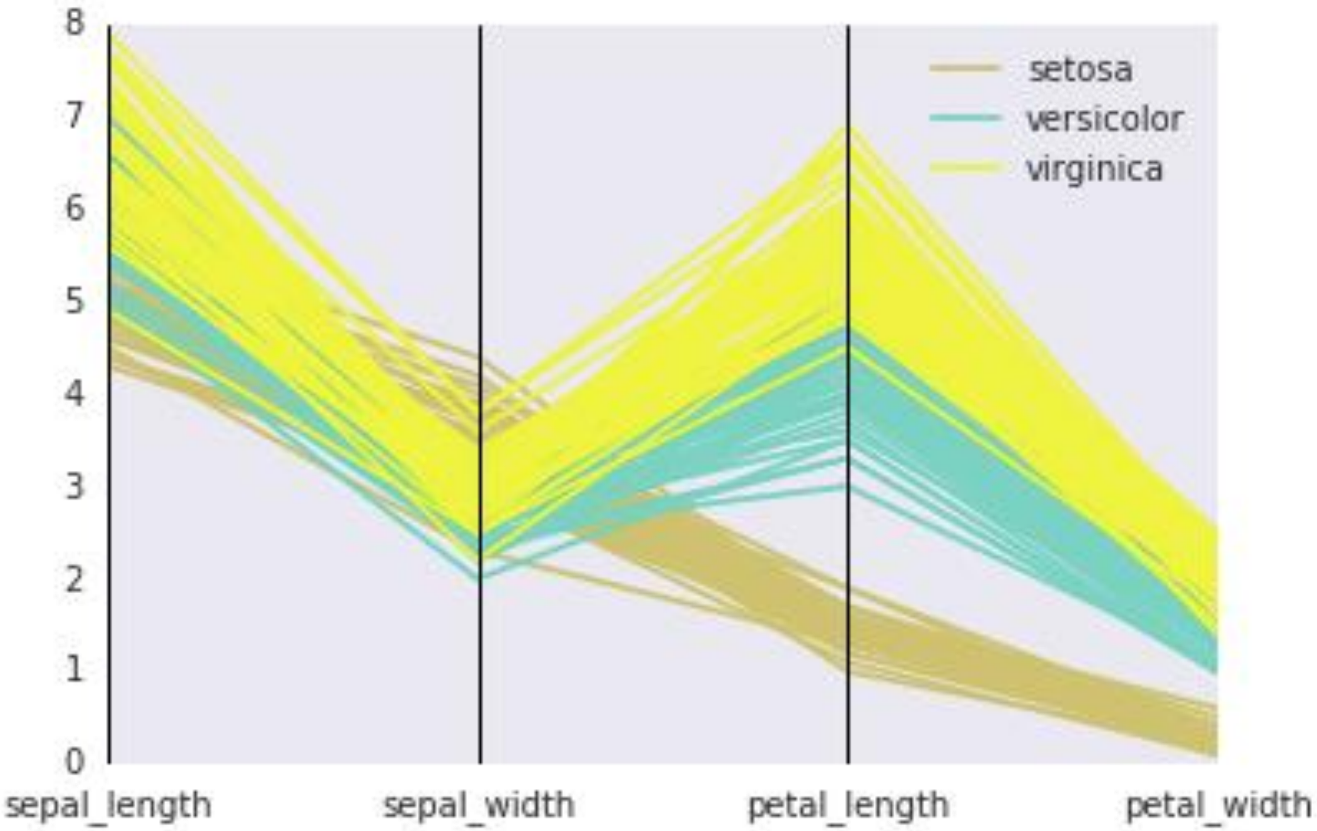




Visualising > 3 Dimensions – cont'd

- parallel coordinates
  - can show multiple variables of same scale
  - especially useful for repeated measures
    - each variable is a time point in a longitudinal study

```
from pandas.tools.plotting import
parallel_coordinates

parallel_coordinates (iris, 'species')
```

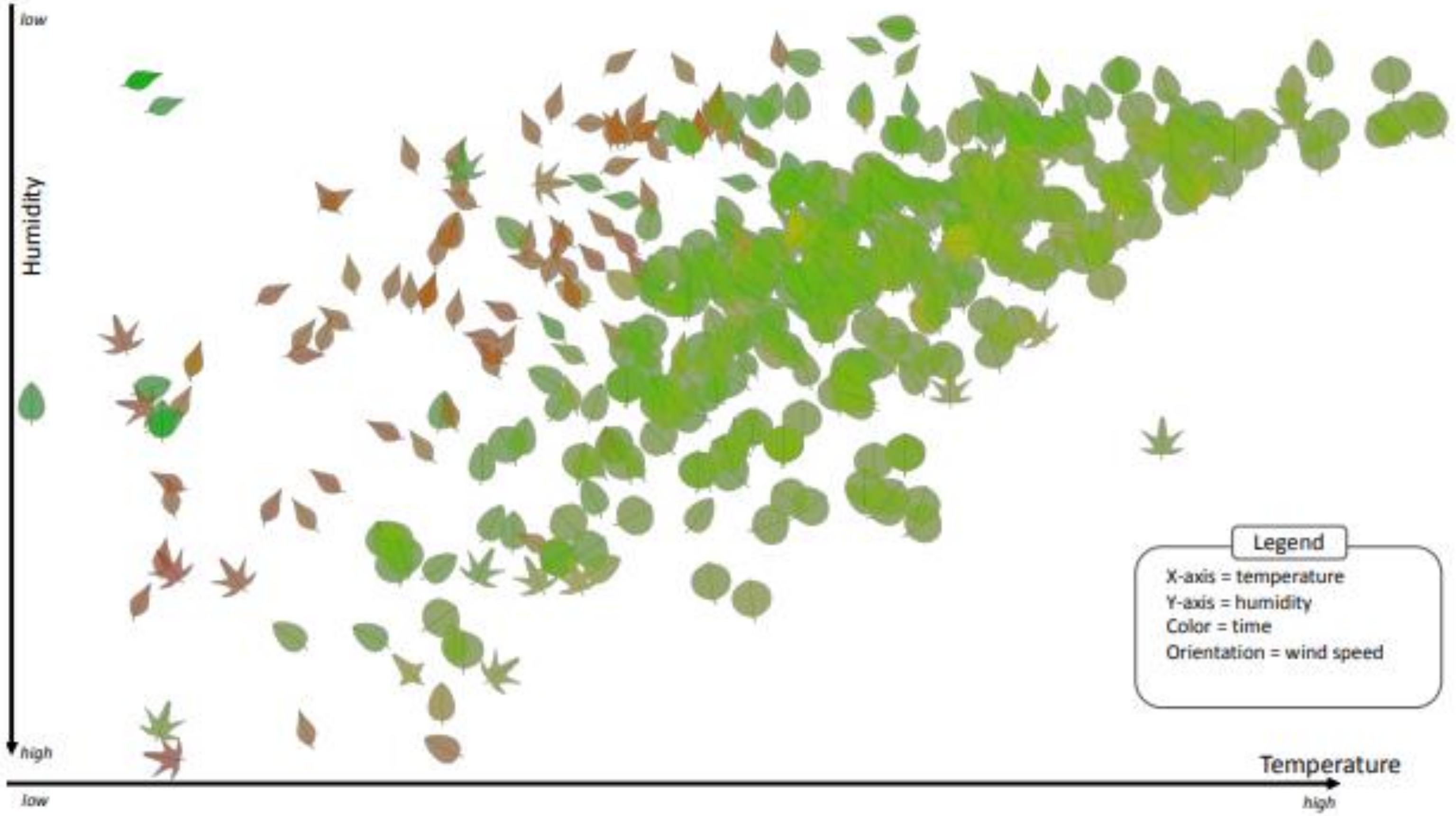


Visualising > 3 Dimensions – cont'd

scatterplot with glyphs

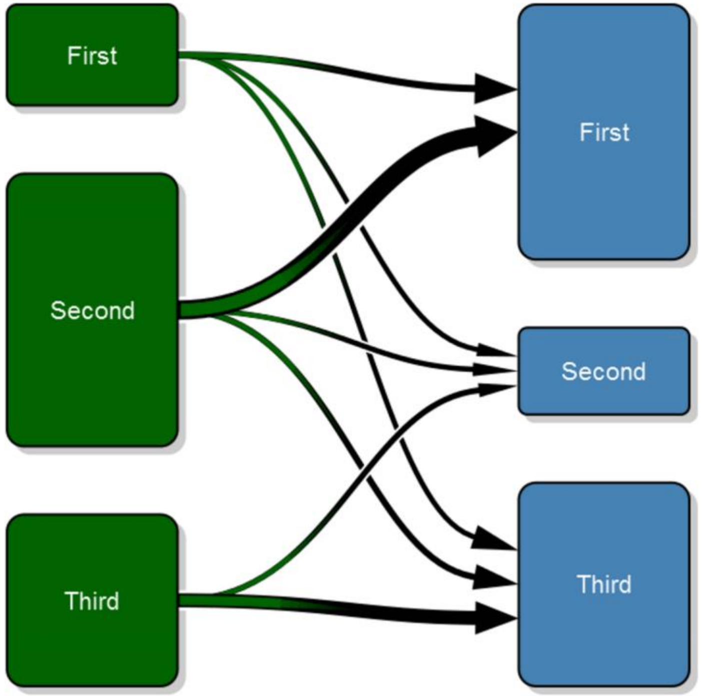
options for encoding glyphs:

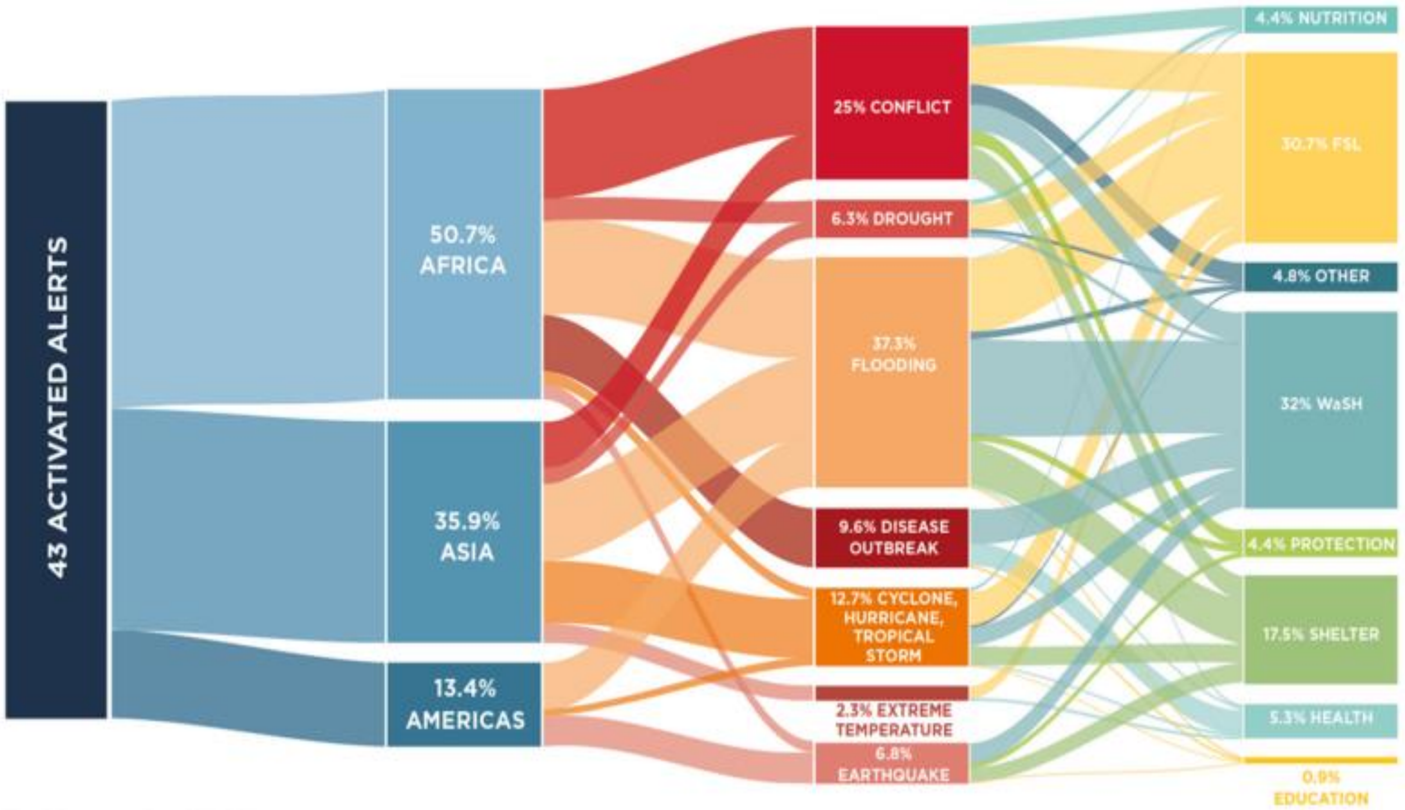
- size
- colour
- intensity
- transparency
- shape
- texture



Sankey Diagram

state changes, class transitions, redistributions





Categorical Data

- Statistics of discrete distributions
  - class frequencies

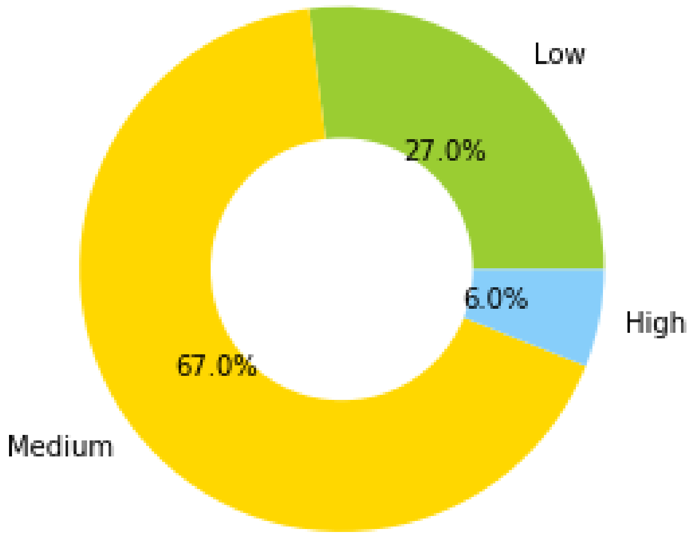
- Exploring and visualising sample variables
  - bar plots
  - pie / donut charts

- Outlier detection

Marginal Distributions of Discrete Variables

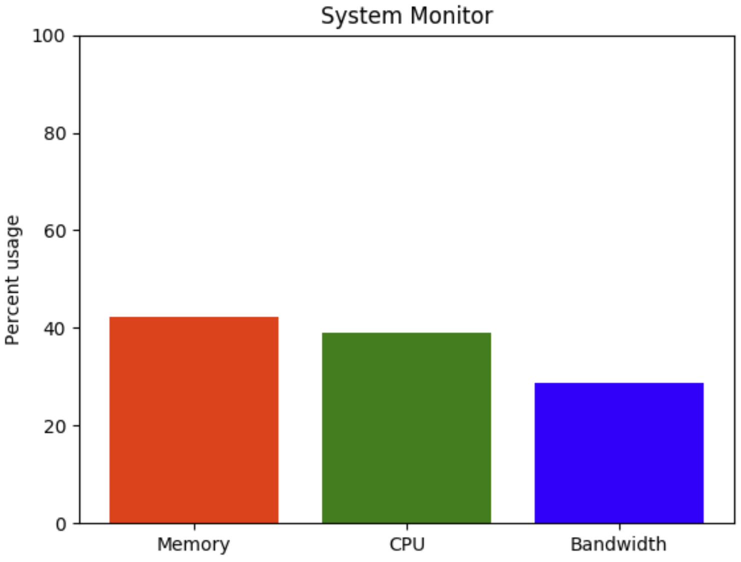
```
# donut chart recipe ===
# The slices will be ordered and plotted counter-clockwise.
data = [0.27, 0.67, 0.06]
labels = 'Low', 'Medium', 'High’
colors = ['yellowgreen', 'gold', 'lightskyblue’]
plt.pie
(data, explode=(0,0), labels=labels, colors=colors, autopct='%1.1f%%', shadow=False)

#draw a circle at the center of pie to make it look like a donut:
centre_circle = plt.Circle((0,0), 0.5, fc='white', linewidth=1.25)
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

# Set aspect ratio to be equal so that pie is drawn as a circle:
plt.axis('equal')
plt.show()
```

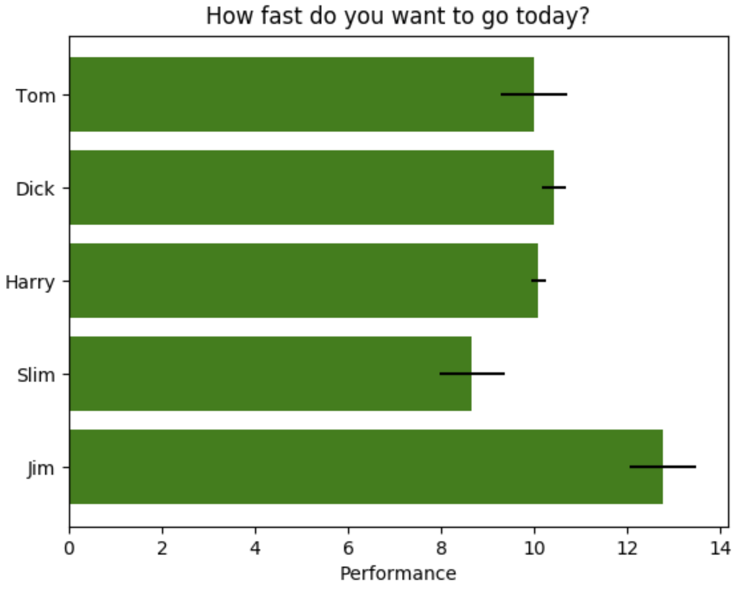
Income Bracket	
Low	0.27
Medium	0.67
High	0.06

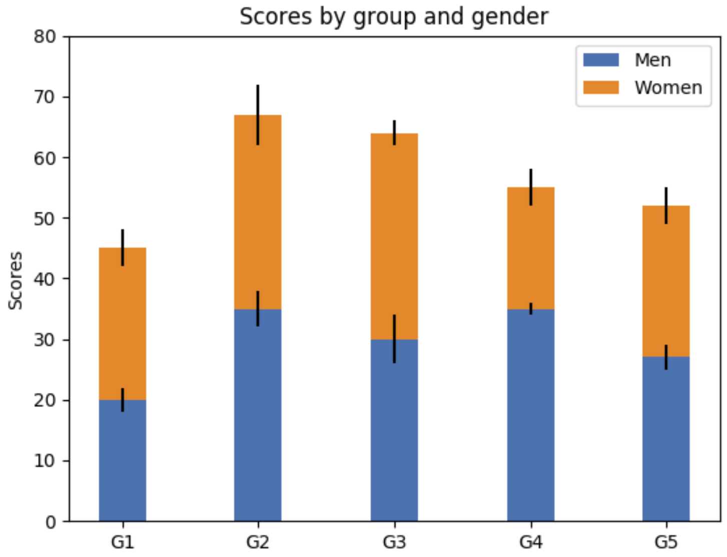


Bar Plots

- **styles:**
  - horizontal, vertical
  - grouped, stacked


System Monitor


How fast do you want to go today?


Scores by group and gender

Conditional Distributions of Discrete Variables

- **contingency tables**
  - 2D:
    - var1 = rows, var 2 = columns
  - 3D:
    - var3 = planes (1 table for each value of var3)
  - > 3D:
    - multi-dimensional arrays
      - can be represented in code even if we can’t visualise them

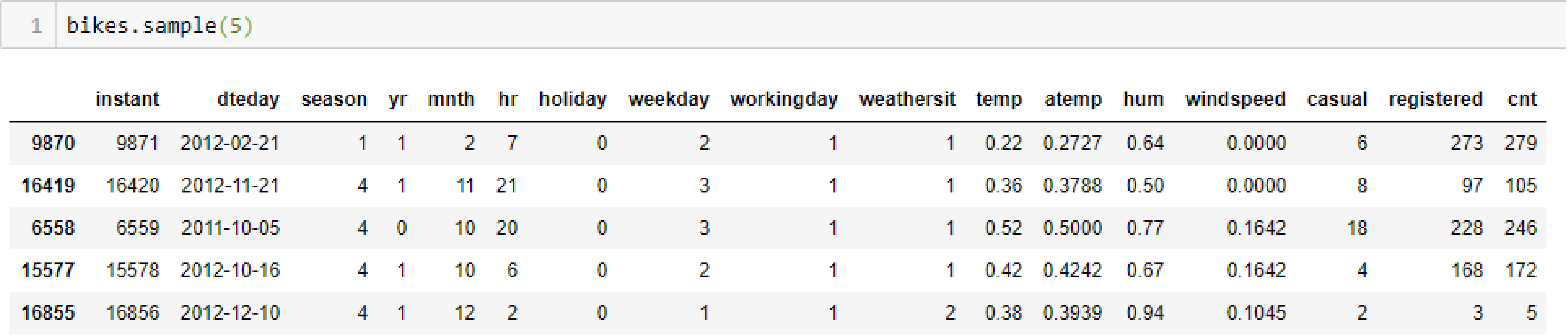
Lab 2.1.2: Data Profiling

- Purpose:
  - To explore Python methods for exploring and summarising datasets

- Materials:
  - ‘Lab 2.1.2.ipynb’

Exploring Large Datasets

- randomised sampling



```
bikes.sample(5)
```

	instant	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
9870	9871	2012-02-21	1	1	2	7	0	2	1	1	0.22	0.2727	0.64	0.0000	6	273	279
16419	16420	2012-11-21	4	1	11	21	0	3	1	1	0.36	0.3788	0.50	0.0000	8	97	105
6558	6559	2011-10-05	4	0	10	20	0	3	1	1	0.52	0.5000	0.77	0.1642	18	228	246
15577	15578	2012-10-16	4	1	10	6	0	2	1	1	0.42	0.4242	0.67	0.1642	4	168	172
16855	16856	2012-12-10	4	1	12	2	0	1	1	2	0.38	0.3939	0.94	0.1045	2	3	5

- repeated sampling
  - collect a number of random subsets from the sample population
  - analyse each subset
  - aggregate the results

The Central Limit Theorem

- Suppose we take n samples from a distribution and compute the mean $\bar{x}_k$ of each sample

  then, as n $n \rightarrow \infty$

  - the set of $\bar{x}_k$ approaches a normal distribution
  - the mean of $\bar{x}_k$ approaches the mean of the original distribution

$$\lim_{n\rightarrow\infty} \frac{1}{n} \sum_{k=1}^{n} \bar{x}_k = \mu$$

- implication:

  by repeated resampling of a non-normal distribution, we can apply all (?) the statistical methods that were designed for normal distributions (as long as the samples are independent and identically distributed)

Lab 2.1.3: The Central Limit Theorem

- Purpose:
  - To test the central limit theorem by experiment

- Materials:
  - ‘Lab 2.1.3.ipynb’

Time Series

- What is a time series?
- How are time series represented in Python?

Time Series

def: a sequence of data points representing the state of a system over time

classes of time series:

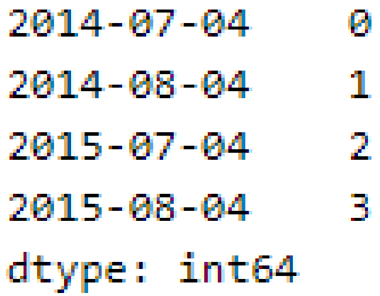
- temporally deterministic
  - periodic
    - pattern repeats at equal intervals
  - aperiodic
    - state at time t_k is influenced by state at time t_{k-1} but there is no repeating pattern
- stochastic
  - state at time t_k is unrelated to state at time t_{k-1}

Programming with Time Series

- timebase is usually regular
  - seconds, days, or years (typically)
    - may need to cope with leap years
  - no gaps
    - may need to impute or assign NA for missing time points

example (Pandas):

```
index = pd.DatetimeIndex(['2014-07-04', '2014-08-
04',
                          '2015-07-04', '2015-08-04’])
data = pd.Series([0, 1, 2, 3], index=index)
data
```



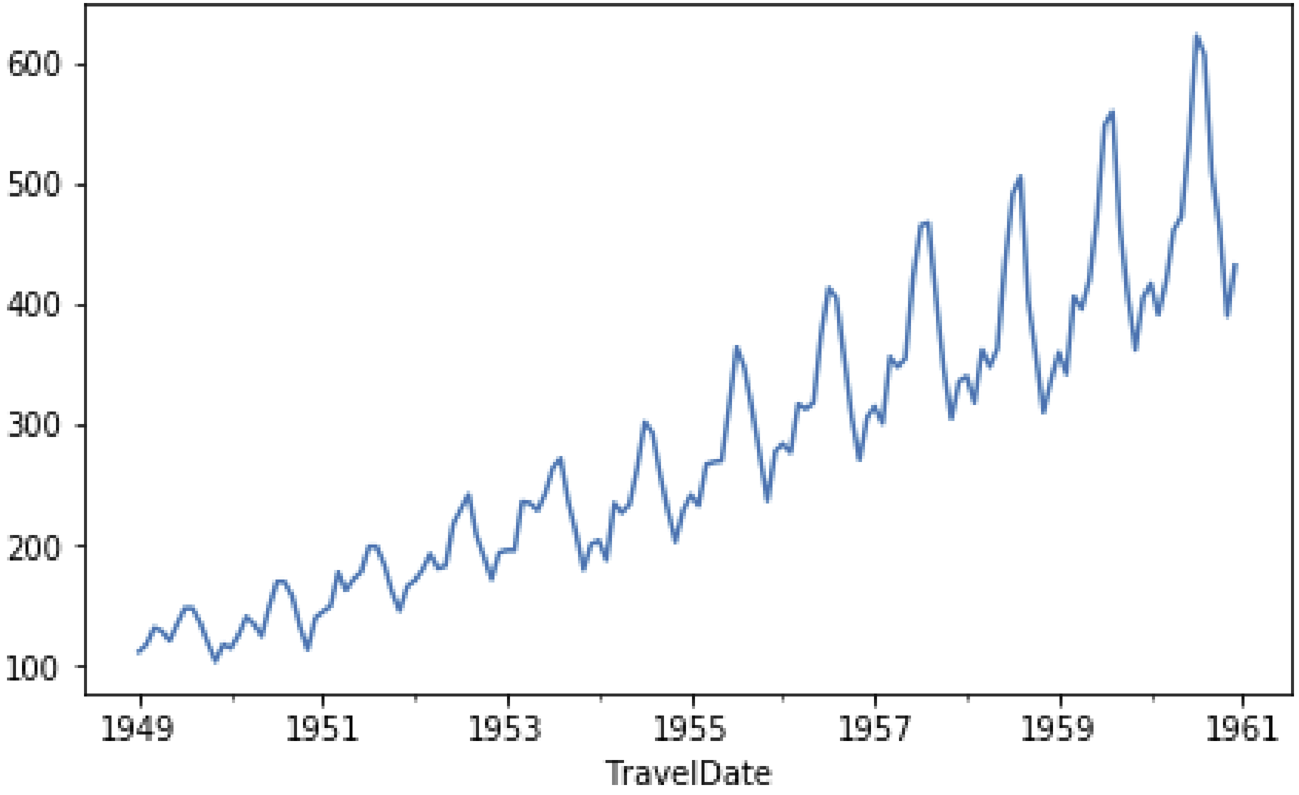
```
2014-07-04    0
2014-08-04    1
2015-07-04    2
2015-08-04    3
dtype: int64
```

Visualising Time Series

Static time series

- convert DataFrame to Pandas time series
- timebase is an index of the DataFrame
- default axis labelling is aware of timebase

ts.plot()



Institute of Data

Geospatial Data

- How are geospatial data organised?
- Tools for exploring geospatial data
- Visualising geospatial data in Python

Geospatial Data Formats

- GIS
  - range of open (standard) and proprietary formats
    - raster, vector, grid
    - metadata
- typically
  - a list with nested structure
- arrays / lists
  - coordinates
  - attributes
    - built-in (e.g. elevation)
    - user-defined (e.g. derived statistics)

Geospatial Data Formats – cont’d

Keyhole Markup Language

- primarily used for Google Earth
- .KMZ/.KML

Open Streetmap

- largest crowdsourcing GIS data project of the planet Earth
- .OSM

GeoJSON

- open standard format designed for representing simple geographical features
- .geojson

Tools for Exploring Geospatial Data

- interactive maps/ APIs
- base map may be featureless
  - add ***tiles*** to display features
    - street map
    - topography
    - satellite view
- data organised, rendered in ***layers***
- ability to overlay image data from other sources
  - weather
    - satellite view
    - simulations

QGIS

ArcGIS

MAPD

GDAL

Geospatial Libraries for Python

Folium

- Plot maps

Shapely

- manipulation of geometric objects

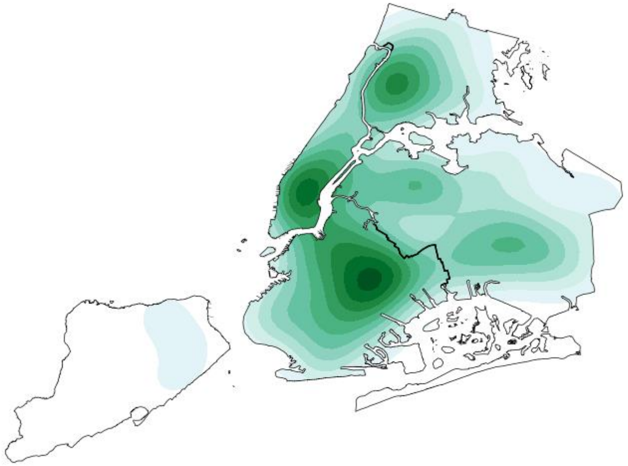
Fiona

- read/write vector file formats (e.g. shapefiles or geojson)
- projection conversions

Geopandas

- all of the above

Visualising Geospatial Data



Geoplot

- works with GeoPandas

DataMaps

- interactive SVG maps using D3.js