CS(STAT)5525 : Data Analytics
Lecture #2

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  - A nice online introduction can be found in Chapter 1 of the NIST/SEMATECH e-Handbook of Statistical Methods [Web Link]

Data Analysis Approaches

- The three popular data analysis approaches are :

1- Classical Analysis

The data collection is followed by a model (normality, linearity,etc) and then analysis, estimation and testing that follows are focused on the parameters of that model.

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- In the real world, data analysts freely mix elements of all the above three approaches (and other approaches).

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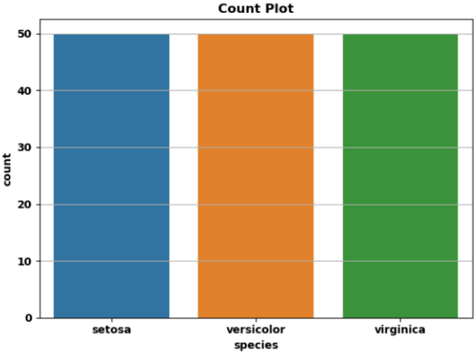
  - Visualization
  - Online Analytical Processing (OLAP)

Iris Sample Data set

- Many of the exploratory data techniques are illustrated with the Iris Plant data set.



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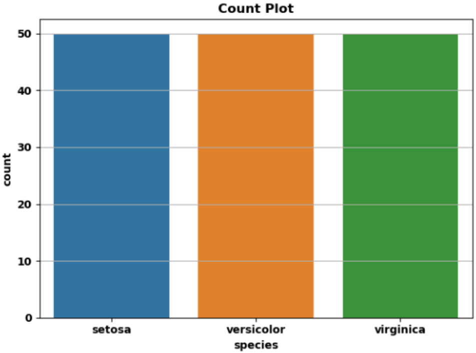
- The iris dataset can be obtained from the seaborn package in python using sns.load_dataset('iris')



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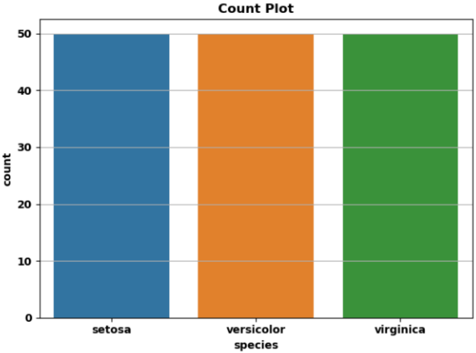
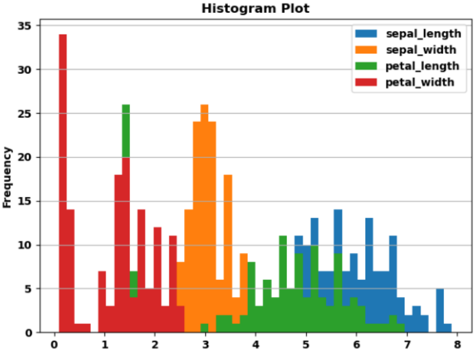
- Four attributes sepal width & length, petal width & length



Visualization techniques: Histogram

- Histogram



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- Histogram
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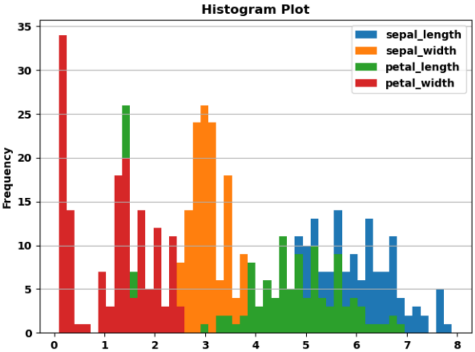

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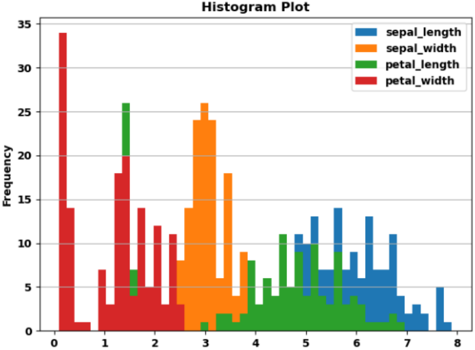

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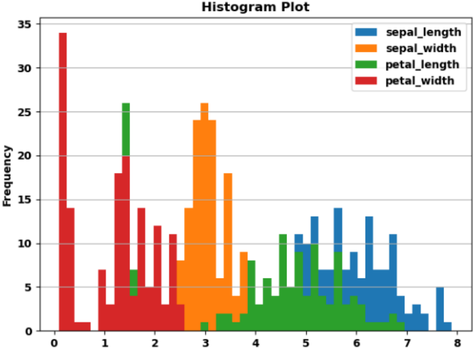

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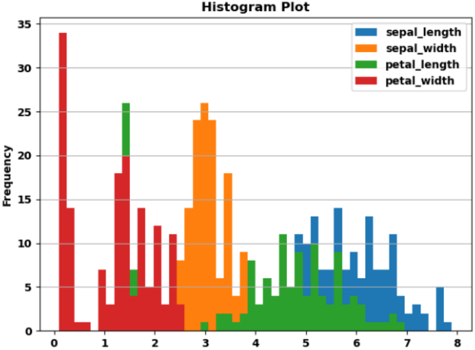
  - Shape of histogram depends on the number of bins



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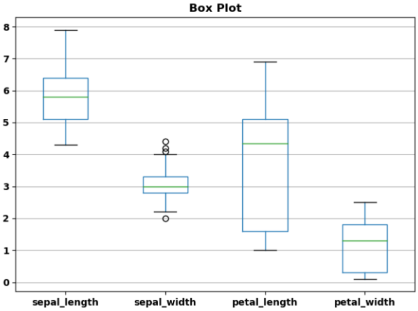

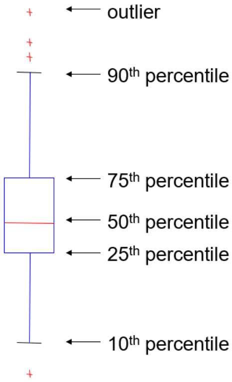

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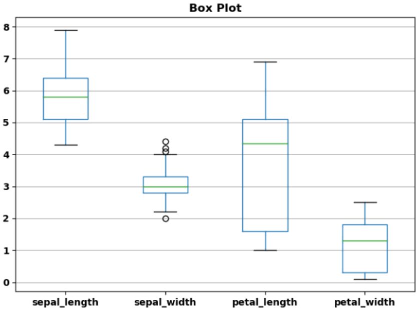

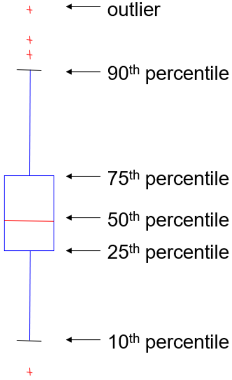

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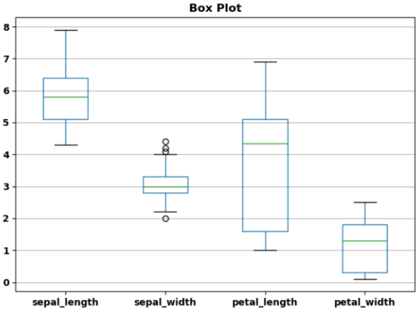

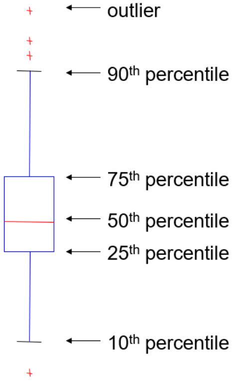

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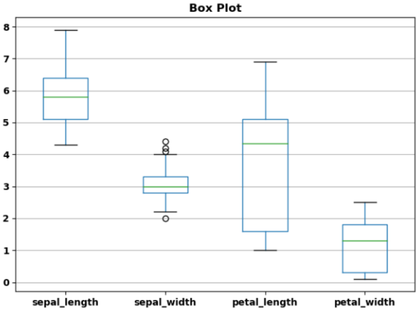
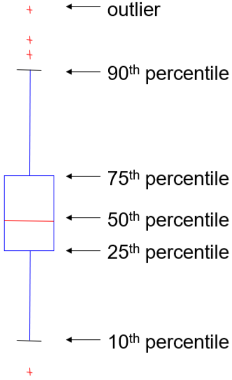
  - Following figure shows the basic part of a box plot





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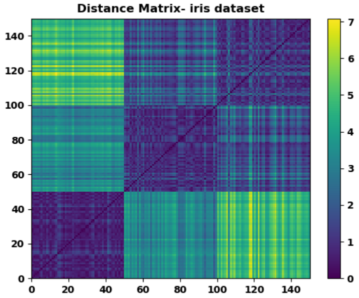
  - See example on the next slide

Visualization techniques: Distance Matrix

- We can see 3 noticeable clusters:



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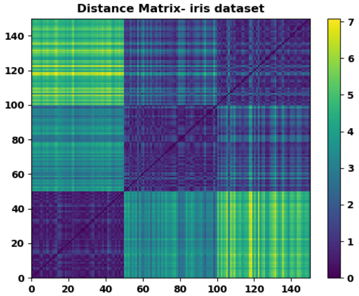

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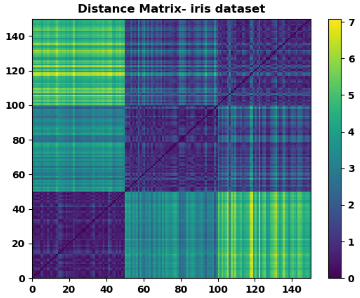
  2. two which are quite close but differ in their respective distance to the third one (bottom left).



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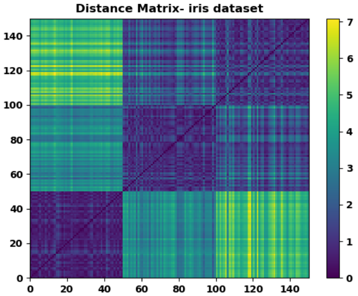
- We can see 3 noticeable clusters:
  1. one which is rather dense (bottom left) and far from the others.
  2. two which are quite close but differ in their respective distance to the third one (bottom left).
- These three clusters refers to 3-types of flowers ('setosa', 'versicolor', 'virginica')



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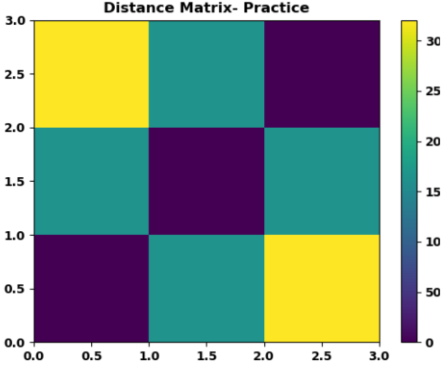
  - Cluster 1: mean = 0 variance 1
  - Cluster 1: mean = 5 variance 1
  - Cluster 1: mean = 10 variance 1

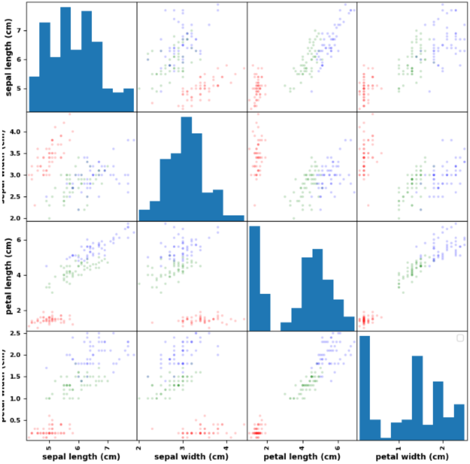
Visualization techniques: Distance Matrix-python practice

```
import numpy as np
from scipy.spatial.distance import pdist, squareform
import matplotlib.pyplot as plt
np.random.seed(123)

x1 = np.random.normal(0,1,1000)
x2 = np.random.normal(5,1,1000)
x3 = np.random.normal(10,1,1000)

X = np.vstack((x1,x2,x3))
dist_mat = squareform(pdist(X))

N = len(X)
plt.pcolormesh(dist_mat)
plt.colorbar()
plt.xlim([0,N])
plt.ylim([0,N])
plt.title('Distance Matrix- Practice')
plt.show()
```



Visualization techniques: Scatter Plots

```
from sklearn.datasets import load_iris
from numpy import array
from pandas import DataFrame
from pandas.plotting import scatter_matrix
import matplotlib.pyplot as plt

iris = load_iris()
df = DataFrame(iris.data, columns=iris.feature_names)
colors=array(50*['r']+50*['g']+50*['b'])
scatter_matrix(df, alpha=0.2, figsize=(10,10),
               color=colors)
plt.legend()
plt.show()
```



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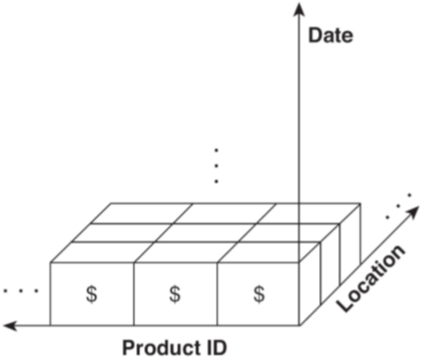
- Unlike relational databases, two-dimensional row-by-column format, OLAP used **Cubes** terminology to store arrays of consolidated information.
- The data and formulas are stored in an optimized multidimensional database, while views of the data are created on demand.

Data Cube Example

- Consider a data set that records the sales of products at a number of company stores at various dates.



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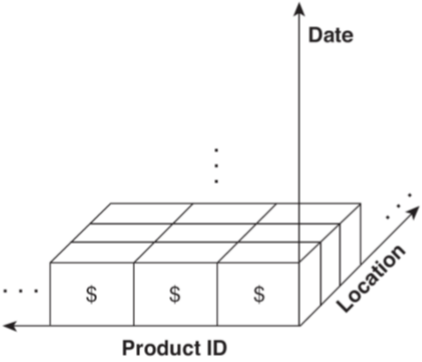
- This data can be represented as a 3-dimensional array.



Data Cube Example

- The following figure table shows one of the two-dimensional aggregations, along with two of the one-dimensional aggregation and the overall total.

date

product ID	Jan 1, 2004	Jan 2, 2004	...	Dec 31, 2004	total
1	$1,001	$987	...	$891	$370,000
⋮	⋮			⋮	⋮
27	$10,265	$10,225	...	$9,325	$3,800,020
⋮	⋮			⋮	⋮
total	$527,362	$532,953	...	$631,221	$227,352,127

Online Analytical Processing