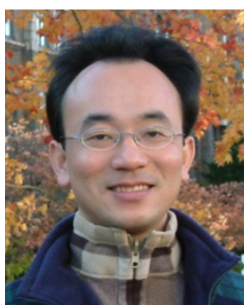
大數據分析
(Big Data Analysis)
Python Scikit-Learn 機器學習
(Machine Learning with Scikit-Learn in Python)

1091BDA05
MBA, IM, NTPU (M5127) (Fall 2020)
Wed 7, ,8, 9 (15:10-18:00) (B8F40)



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2020-10-28

課程大綱 (Syllabus)

週次 (Week) 日期 (Date) 內容 (Subject/Topics)

1 2020/09/16 大數據分析介紹 (Introduction to Big Data Analysis)

2 2020/09/23 AI人工智慧與大數據分析
(AI and Big Data Analysis)

3 2020/09/30 Python 大數據分析基礎
(Foundations of Big Data Analysis in Python)

4 2020/10/07 數位沙盒第一堂課：數位沙盒服務平台簡介
(Digital Sandbox Lesson 1: Introduction to FintechSpace Digital Sandbox)

5 2020/10/14 數位沙盒第二堂課：工程師操作說明與實作教學
(Digital Sandbox Lesson 2: Hands-on Practices)

6 2020/10/21 Python Pandas 大數據量化分析
(Quantitative Big Data Analysis with Pandas in Python)

課程大綱 (Syllabus)

週次 (Week)　日期 (Date)　內容 (Subject/Topics)

7 2020/10/28 Python Scikit-Learn 機器學習 I
(Machine Learning with Scikit-Learn in Python I)

8 2020/11/04 數位沙盒第三堂課：學生小組討論實作與成果發表
(Digital Sandbox Lesson 3: Learning Teams
Hands-on Project Discussion and Project Presentation)

9 2020/11/11 期中報告 (Midterm Project Report)

10 2020/11/18 Python Scikit-Learn 機器學習 II
(Machine Learning with Scikit-Learn in Python II)

11 2020/11/25 TensorFlow 深度學習金融大數據分析 I
(Deep Learning for Finance Big Data Analysis with TensorFlow I)

12 2020/12/02 大數據分析個案研究
(Case Study on Big Data Analysis)

課程大綱 (Syllabus)

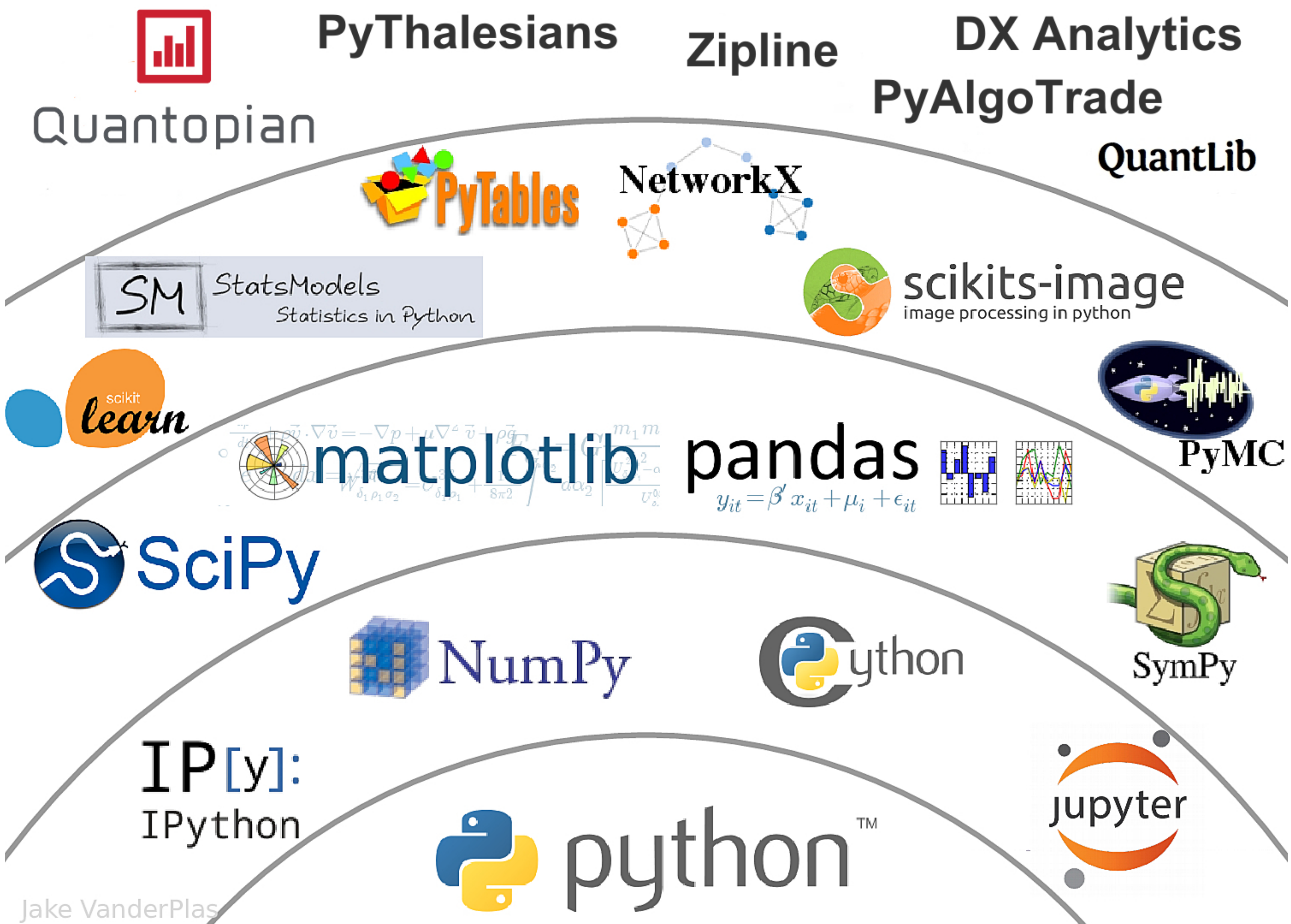
週次 (Week)	日期 (Date)	內容 (Subject/Topics)
13	2020/12/09	TensorFlow 深度學習金融大數據分析 II (Deep Learning for Finance Big Data Analysis with TensorFlow II)
14	2020/12/16	TensorFlow 深度學習金融大數據分析 III (Deep Learning for Finance Big Data Analysis with TensorFlow III)
15	2020/12/23	AI 機器人理財顧問 (Artificial Intelligence for Robo-Advisors)
16	2020/12/30	金融科技智慧型交談機器人 (Conversational Commerce and Intelligent Chatbots for Fintech)
17	2021/01/06	期末報告 I (Final Project Report I)
18	2021/01/13	期末報告 II (Final Project Report I)

Machine Learning with Scikit-Learn in Python

Outline

- Machine Learning with Scikit-Learn in Python
  - Machine Learning
  - Scikit-Learn

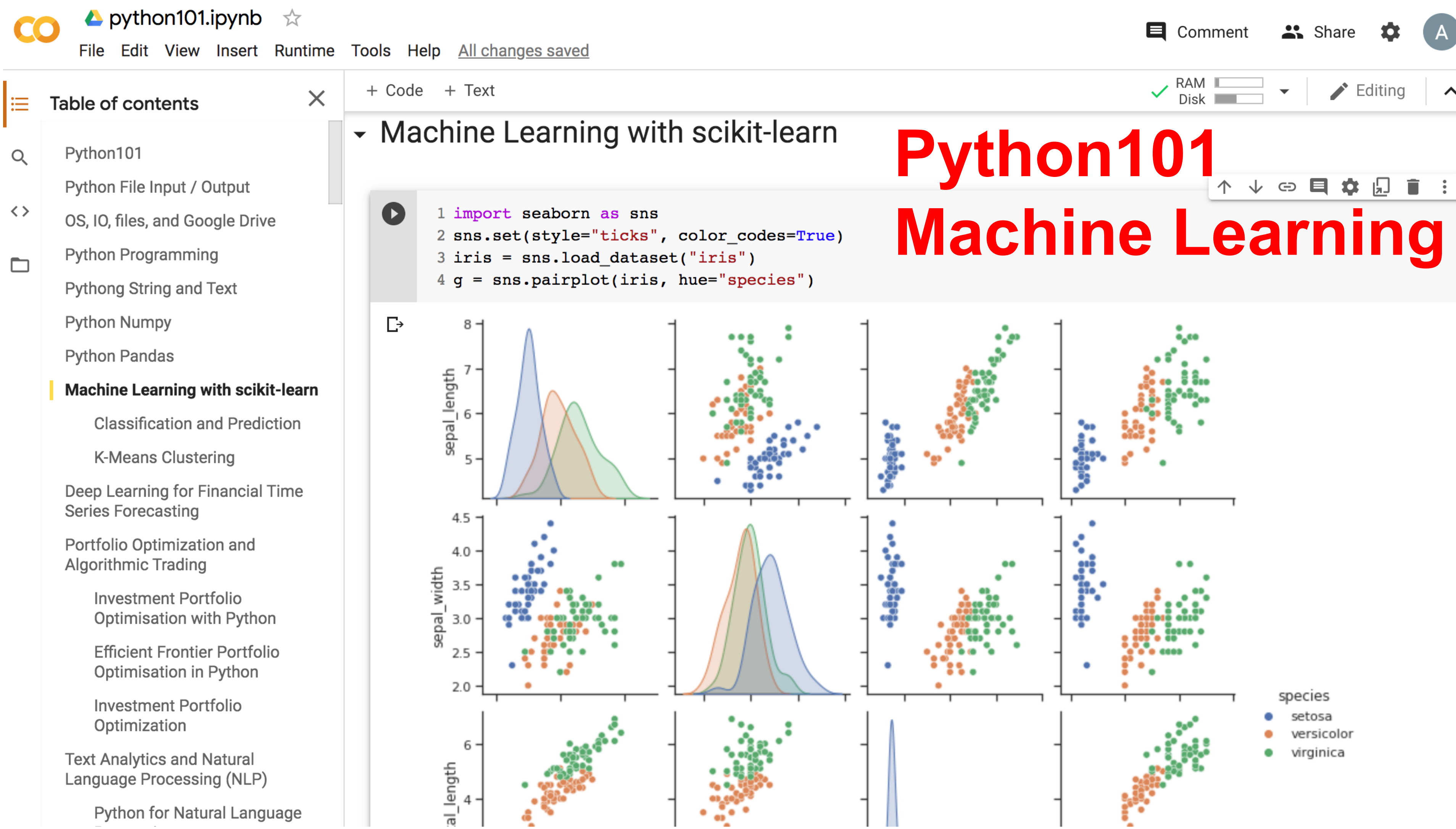
The Quant Finance PyData Stack



Source: http://nbviewer.jupyter.org/format/slides/github/quantopian/pyfolio/blob/master/pyfolio/examples/overview_slides.ipynb#/5

Python in Google Colab (Python101)

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT

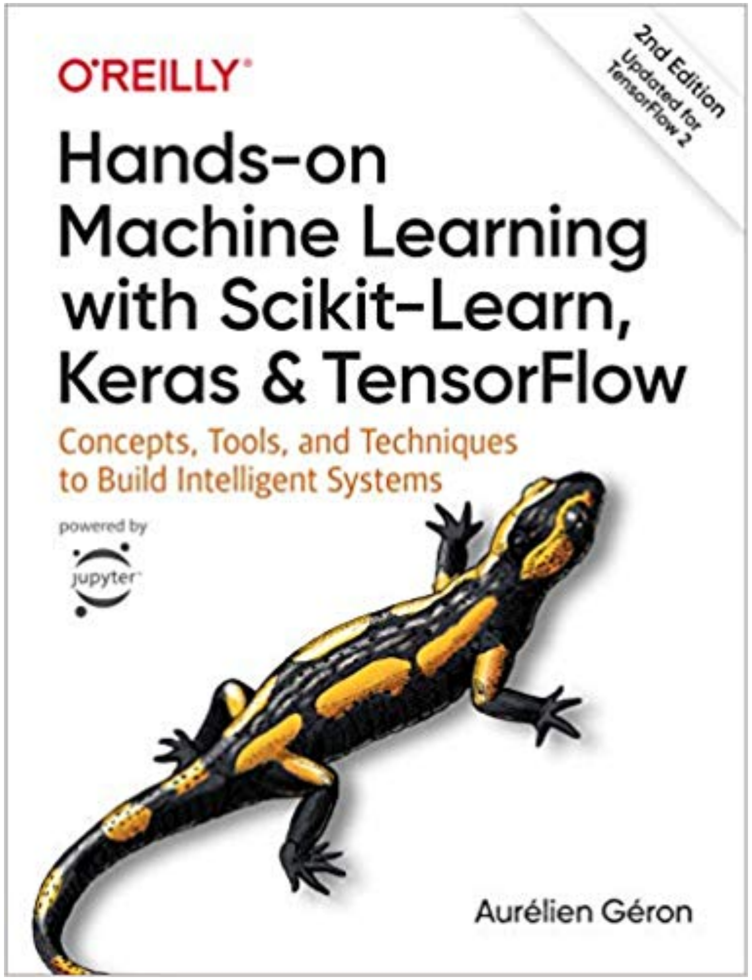


https://tinyurl.com/aintpupython101

Aurélien Géron (2019),

Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems, 2nd Edition

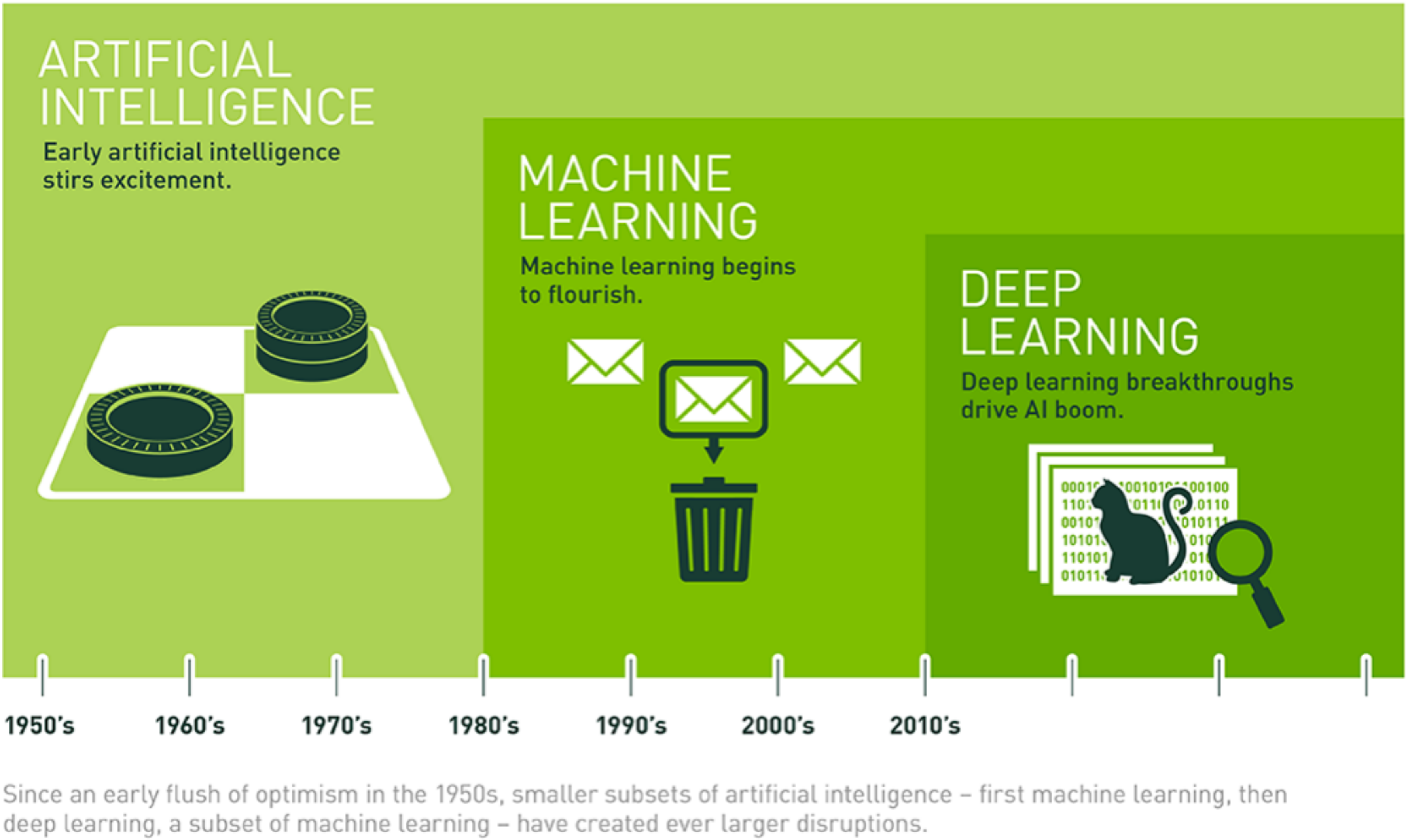
O'Reilly Media, 2019



https://github.com/ageron/handson-ml2

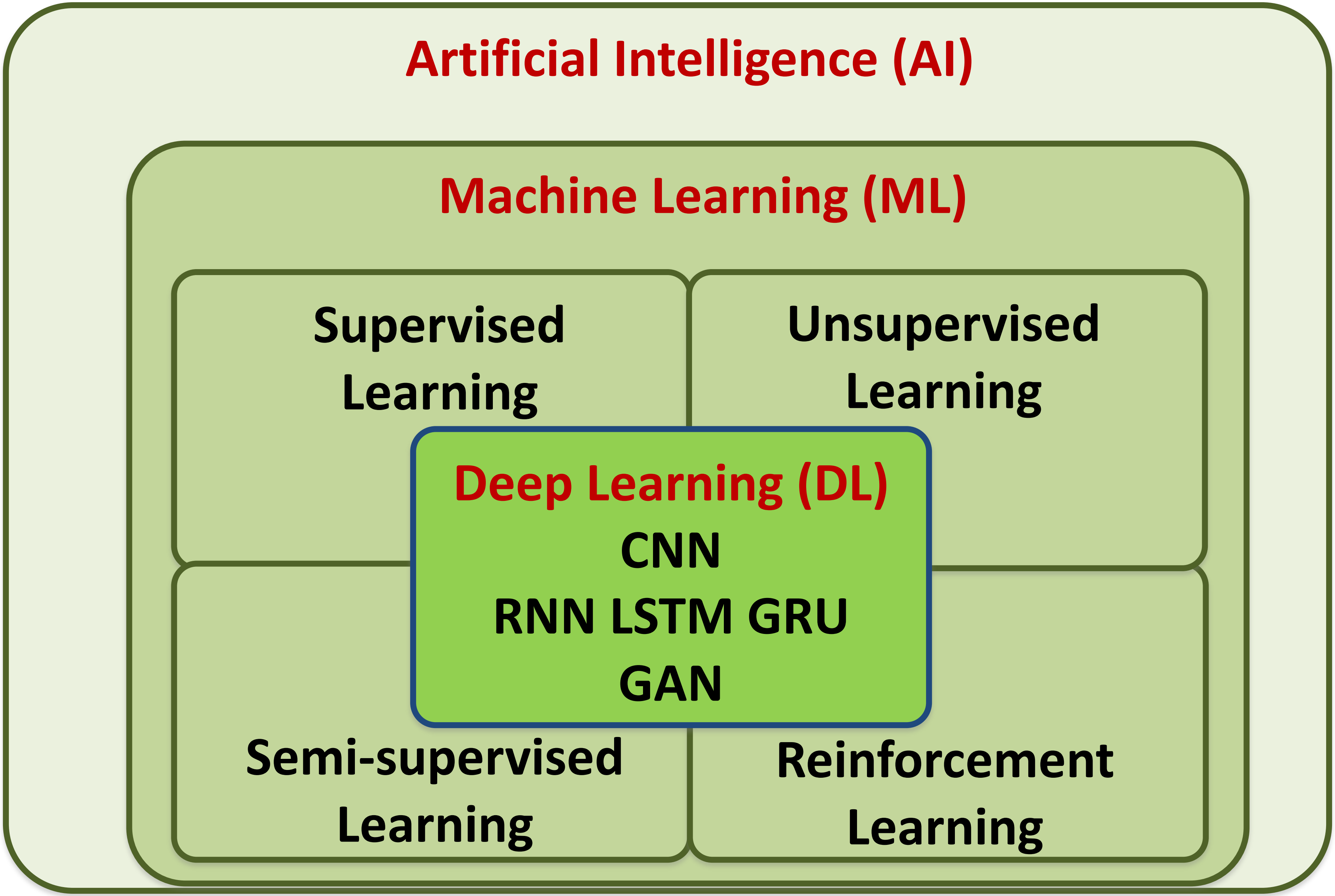
Source: https://www.amazon.com/Hands-Machine-Learning-Scikit-Learn-TensorFlow/dp/1492032646/

Artificial Intelligence
Machine Learning & Deep Learning



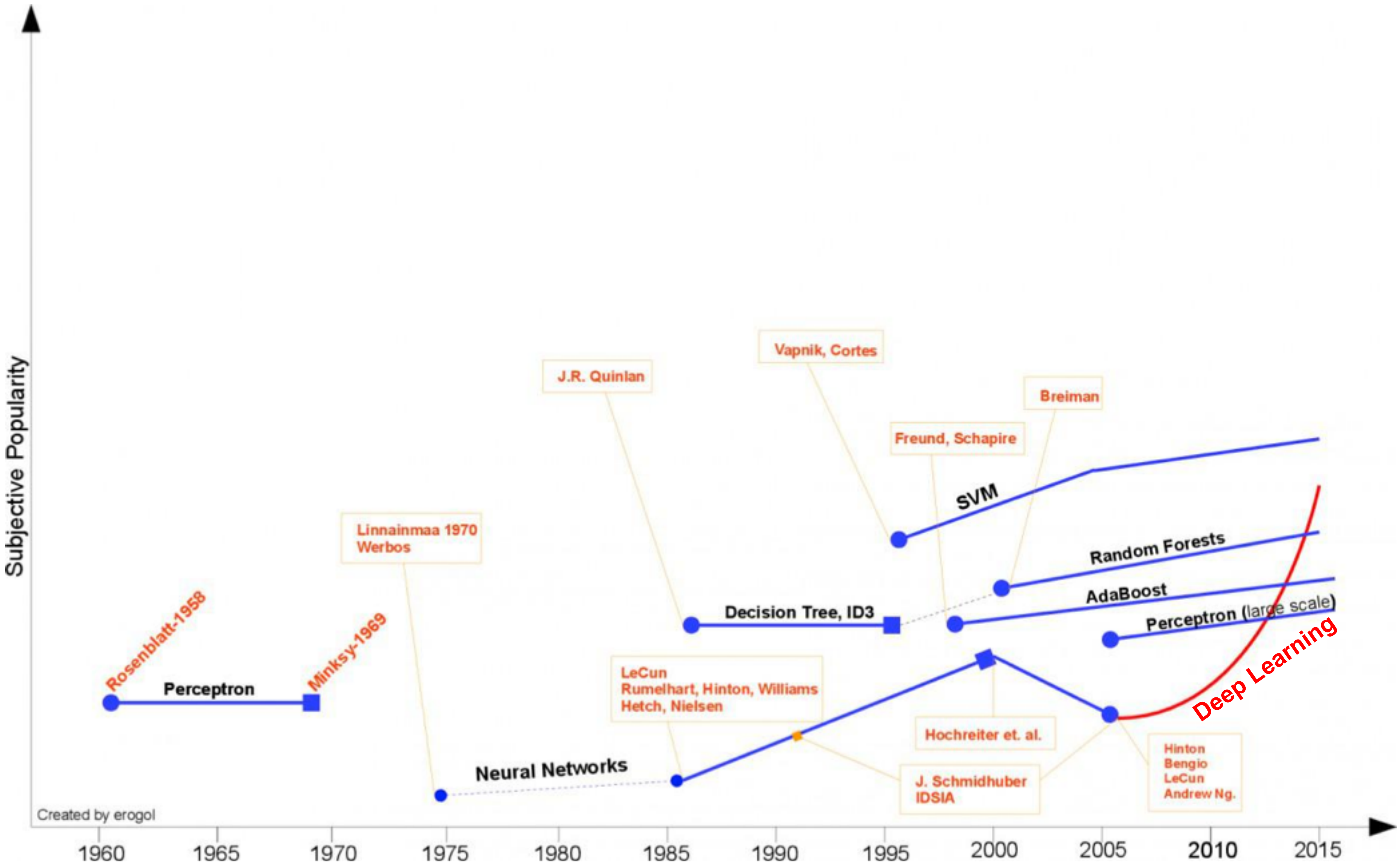
Source: https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/

AI, ML, DL



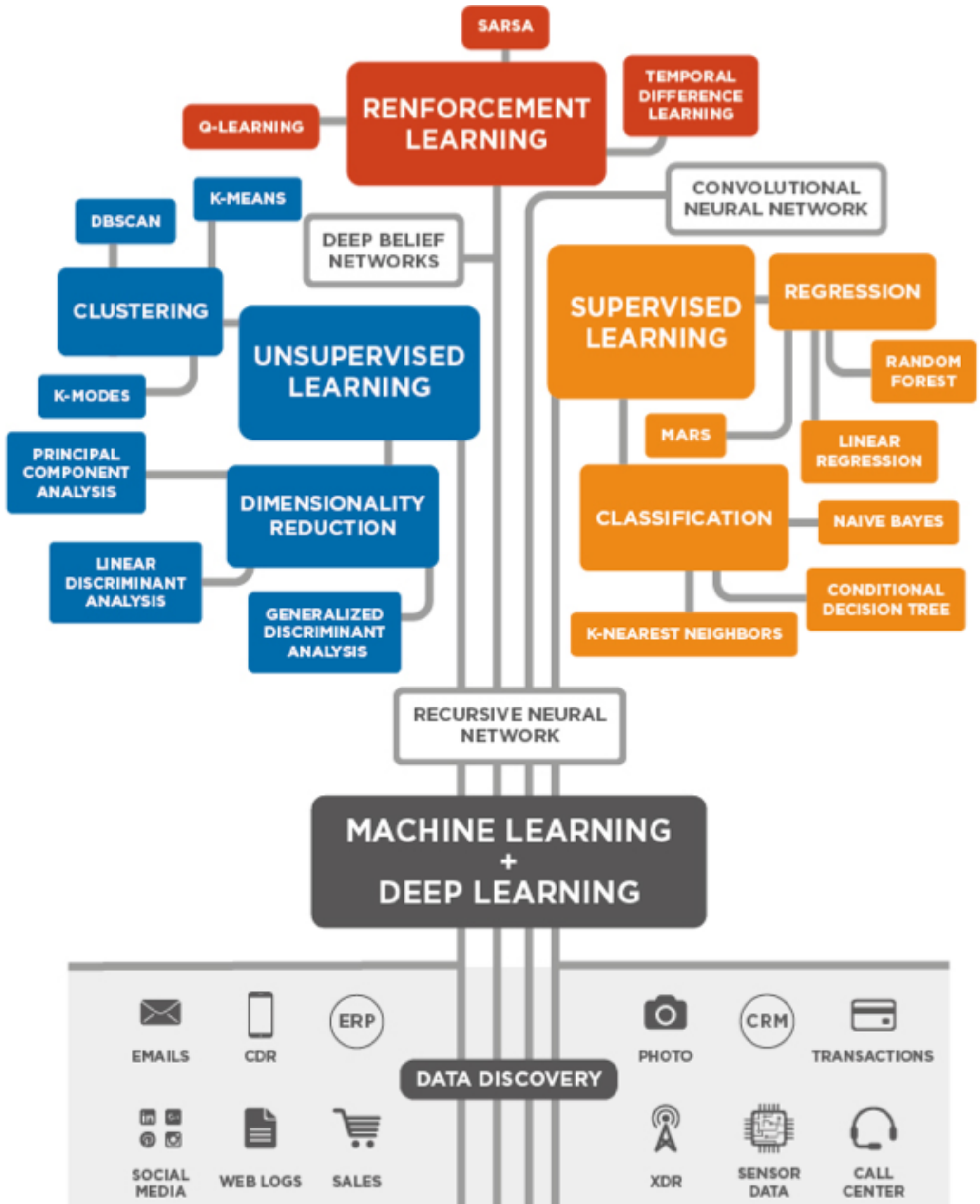
Source: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/deep_learning.html

Deep Learning Evolution



Source: http://www.erogol.com/brief-history-machine-learning/

3 Machine Learning Algorithms



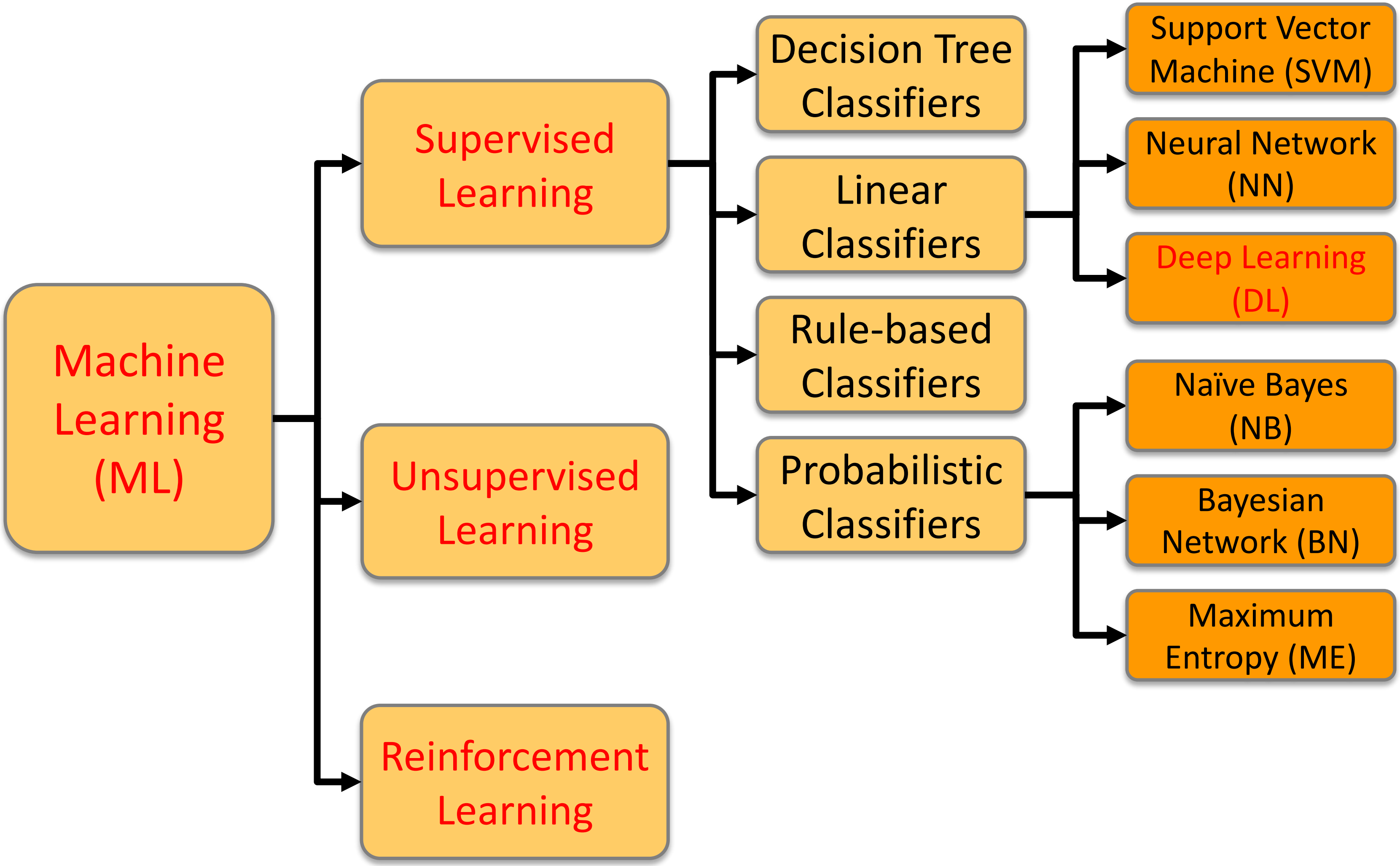
Source: Enrico Galimberti, http://blogs.teradata.com/data-points/tree-machine-learning-algorithms/

Machine Learning Models

Deep Learning	Kernel
Association rules	Ensemble
Decision tree	Dimensionality reduction
Clustering	Regression Analysis
Bayesian	Instance based

Source: Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing

Machine Learning (ML) / Deep Learning (DL)



Source: Jesus Serrano-Guerrero, Jose A. Olivas, Francisco P. Romero, and Enrique Herrera-Viedma (2015), "Sentiment analysis: A review and comparative analysis of web services," Information Sciences, 311, pp. 18-38.

Data Mining Tasks & Methods

Data Mining Tasks & Methods	Data Mining Algorithms	Learning Type
Prediction		
Classification	Decision Trees, Neural Networks, Support Vector Machines, kNN, Naïve Bayes, GA	Supervised
Regression	Linear/Nonlinear Regression, ANN, Regression Trees, SVM, kNN, GA	Supervised
Time series	Autoregressive Methods, Averaging Methods, Exponential Smoothing, ARIMA	Supervised
Association		
Market-basket	Apriori, OneR, ZeroR, Eclat, GA	Unsupervised
Link analysis	Expectation Maximization, Apriori Algorithm, Graph-Based Matching	Unsupervised
Sequence analysis	Apriori Algorithm, FP-Growth, Graph-Based Matching	Unsupervised
Segmentation		
Clustering	*k*-means, Expectation Maximization (EM)	Unsupervised
Outlier analysis	*k*-means, Expectation Maximization (EM)	Unsupervised

Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Data Mining Methods

- Classification
  - Classification
    - Class Label Prediction
  - Regression
    - Numeric Value Prediction
- Clustering
- Association

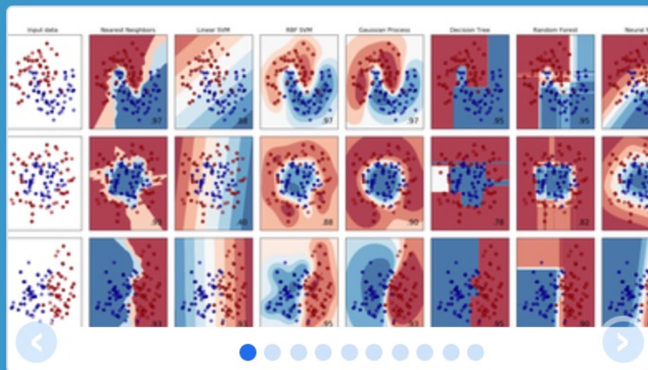
Scikit-Learn

Machine Learning in Python

Scikit-Learn

Home Installation Documentation Examples

Google Custom Search



scikit-learn

Machine Learning in Python

- Simple and efficient tools for data mining and data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable - BSD license

Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.
Algorithms: SVM, nearest neighbors, random forest, … — Examples

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.
Algorithms: SVR, ridge regression, Lasso, … — Examples

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: k-Means, spectral clustering, mean-shift, … — Examples

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency
Algorithms: PCA, feature selection, non-negative matrix factorization. — Examples

Model selection

Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning
Modules: grid search, cross validation, metrics. — Examples

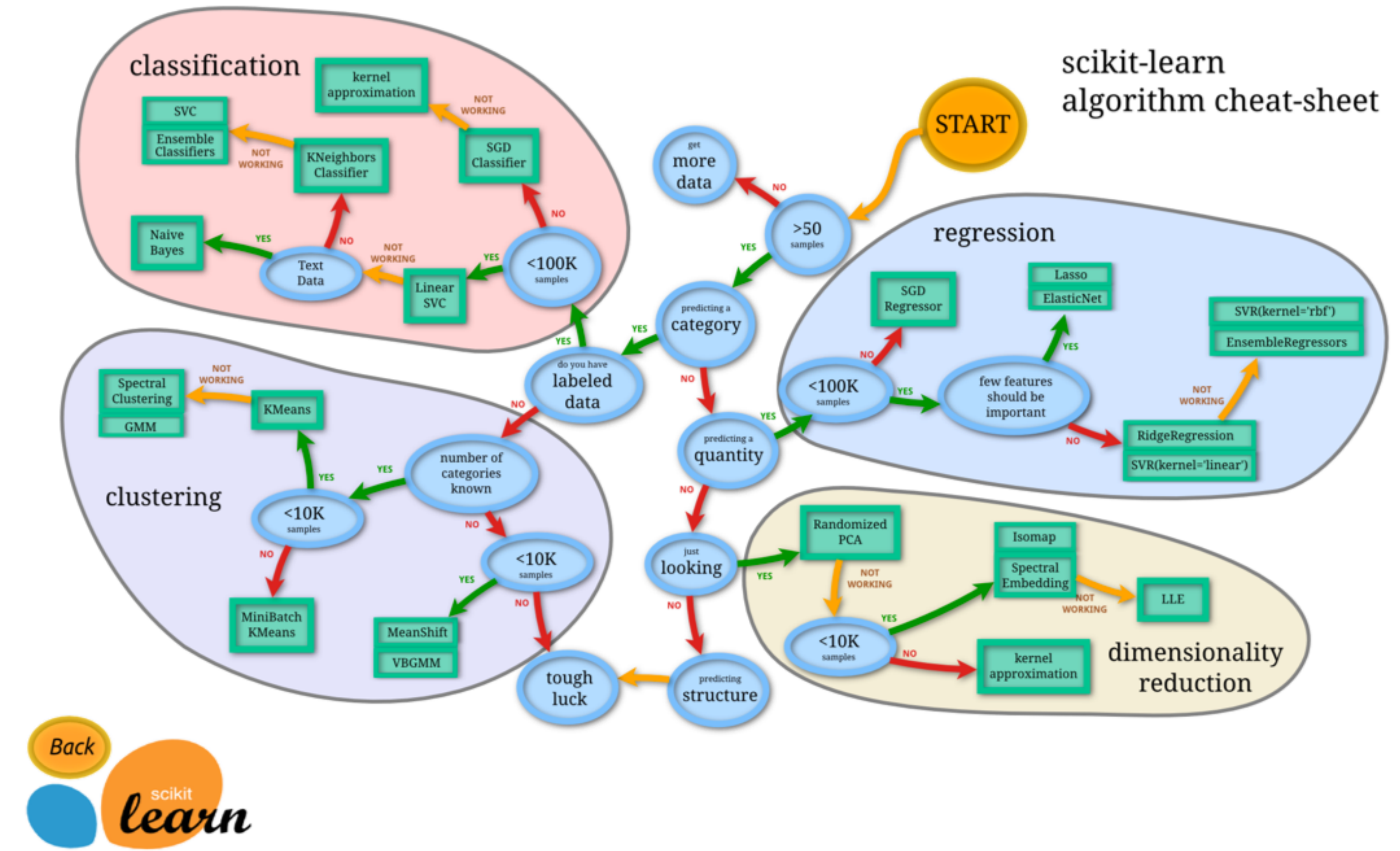
Preprocessing

Feature extraction and normalization.

Application: Transforming input data such as text for use with machine learning algorithms.
Modules: preprocessing, feature extraction. — Examples

Source: http://scikit-learn.org/

Scikit-Learn Machine Learning Map

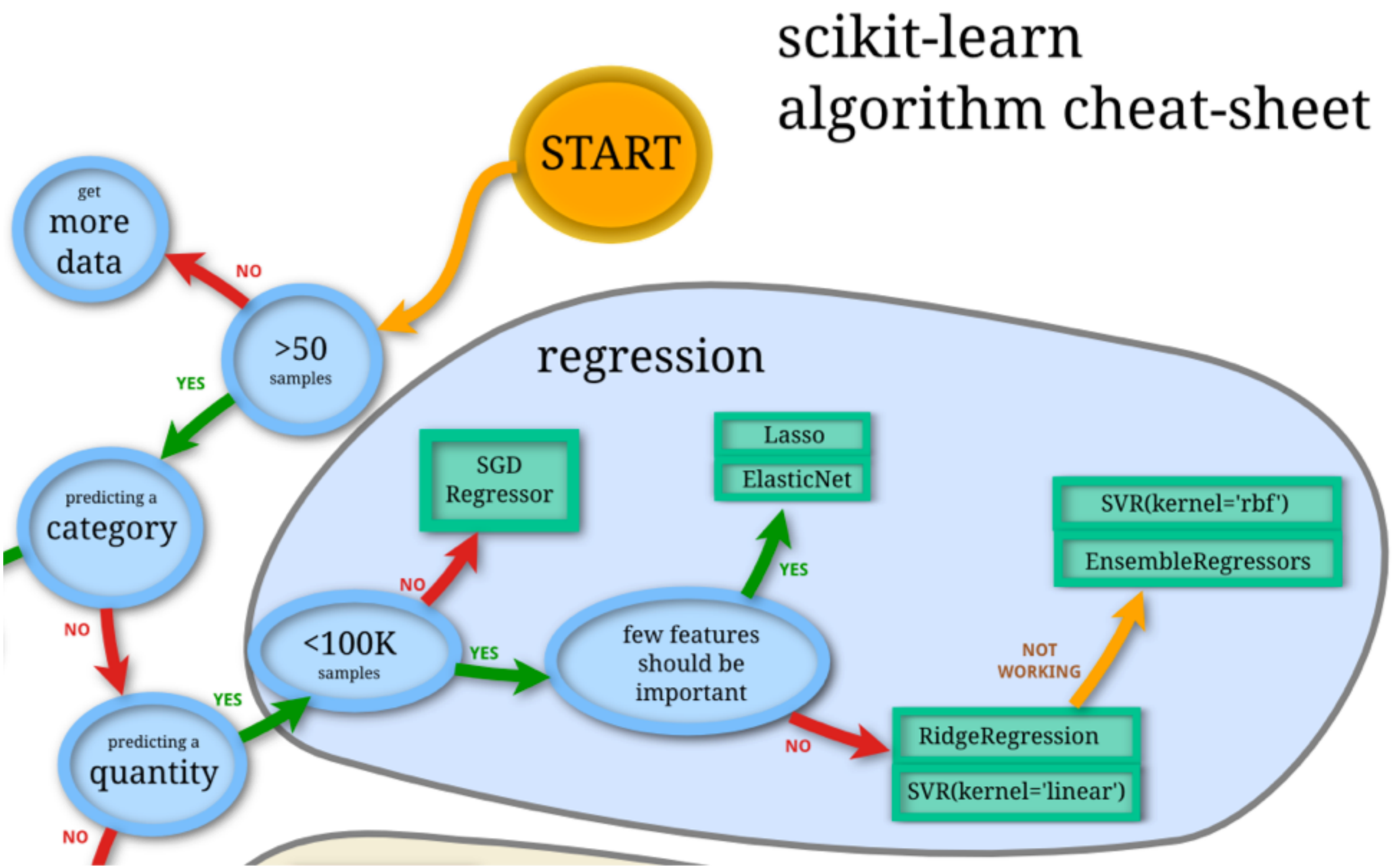


Source: http://scikit-learn.org/stable/tutorial/machine_learning_map/index.html

Scikit-Learn Machine Learning Map

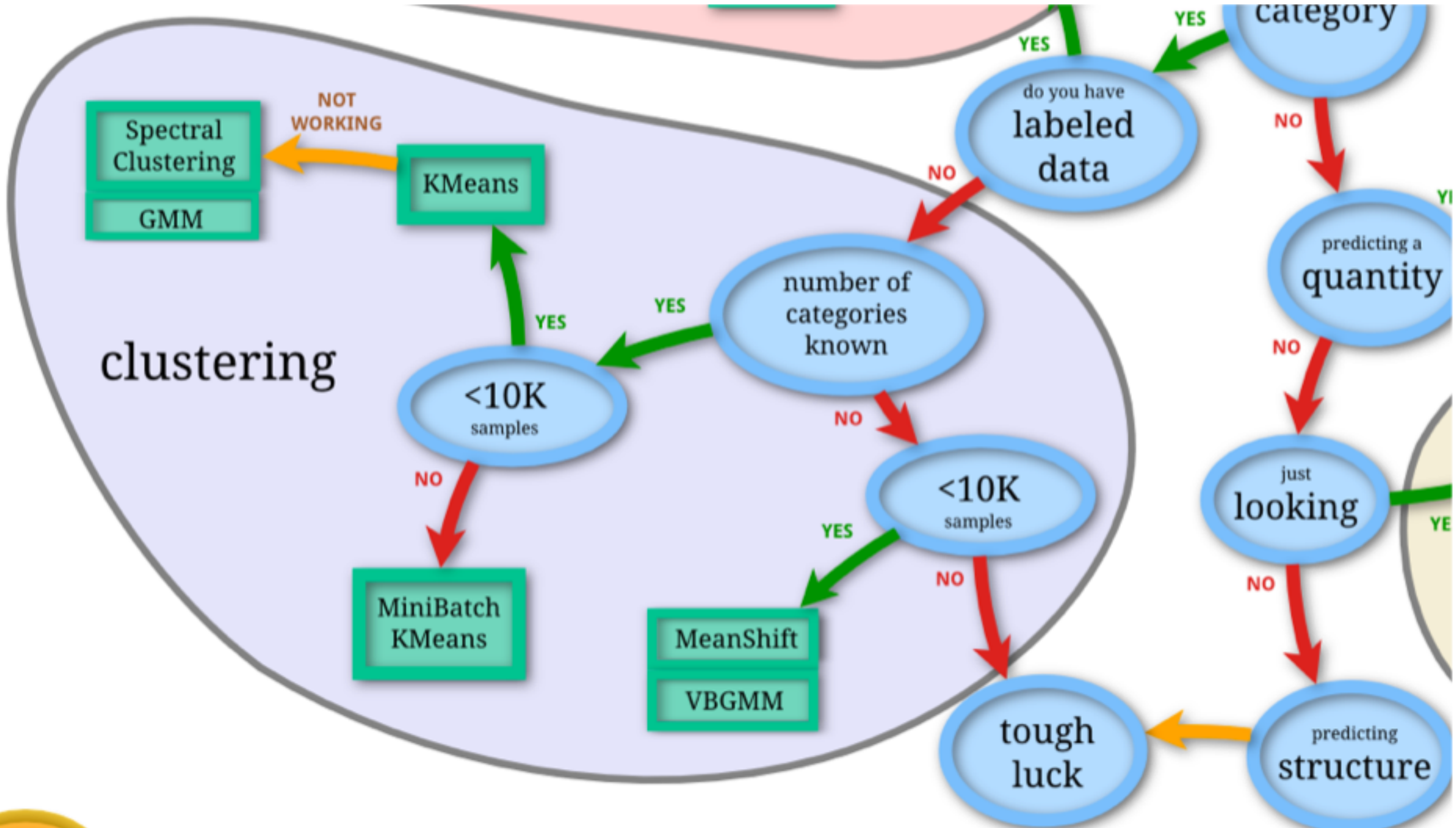
Source: http://scikit-learn.org/stable/tutorial/machine_learning_map/index.html

Scikit-Learn Machine Learning Map



Source: http://scikit-learn.org/stable/tutorial/machine_learning_map/index.html

Scikit-Learn Machine Learning Map



Back

Source: http://scikit-learn.org/stable/tutorial/machine_learning_map/index.html

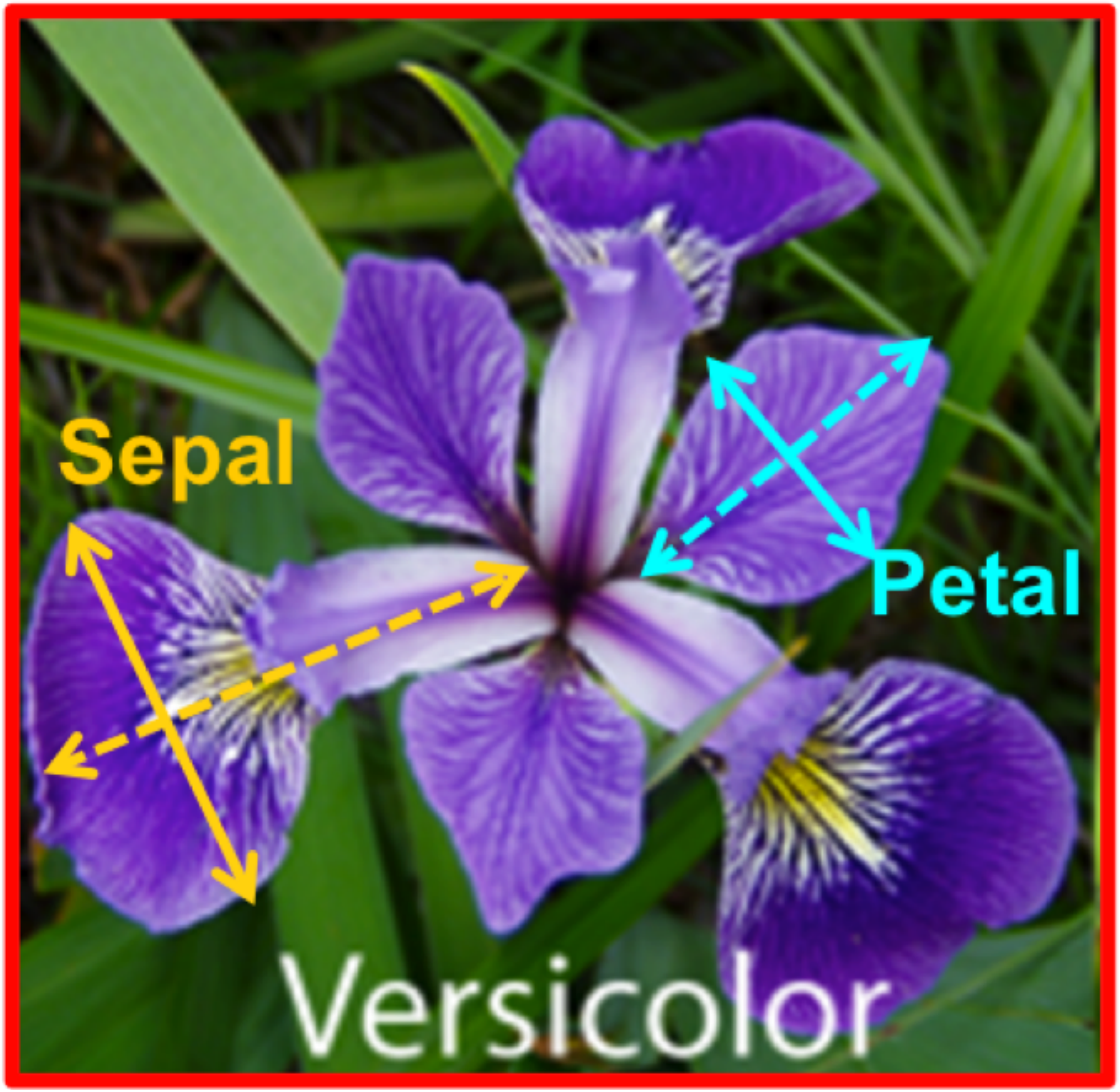
Iris flower data set

setosa versicolor virginica

Source: https://en.wikipedia.org/wiki/Iris_flower_data_set

Source: http://suruchifialoke.com/2016-10-13-machine-learning-tutorial-iris-classification/

Iris Classfication



Source: http://suruchifialoke.com/2016-10-13-machine-learning-tutorial-iris-classification/

iris.data

https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data

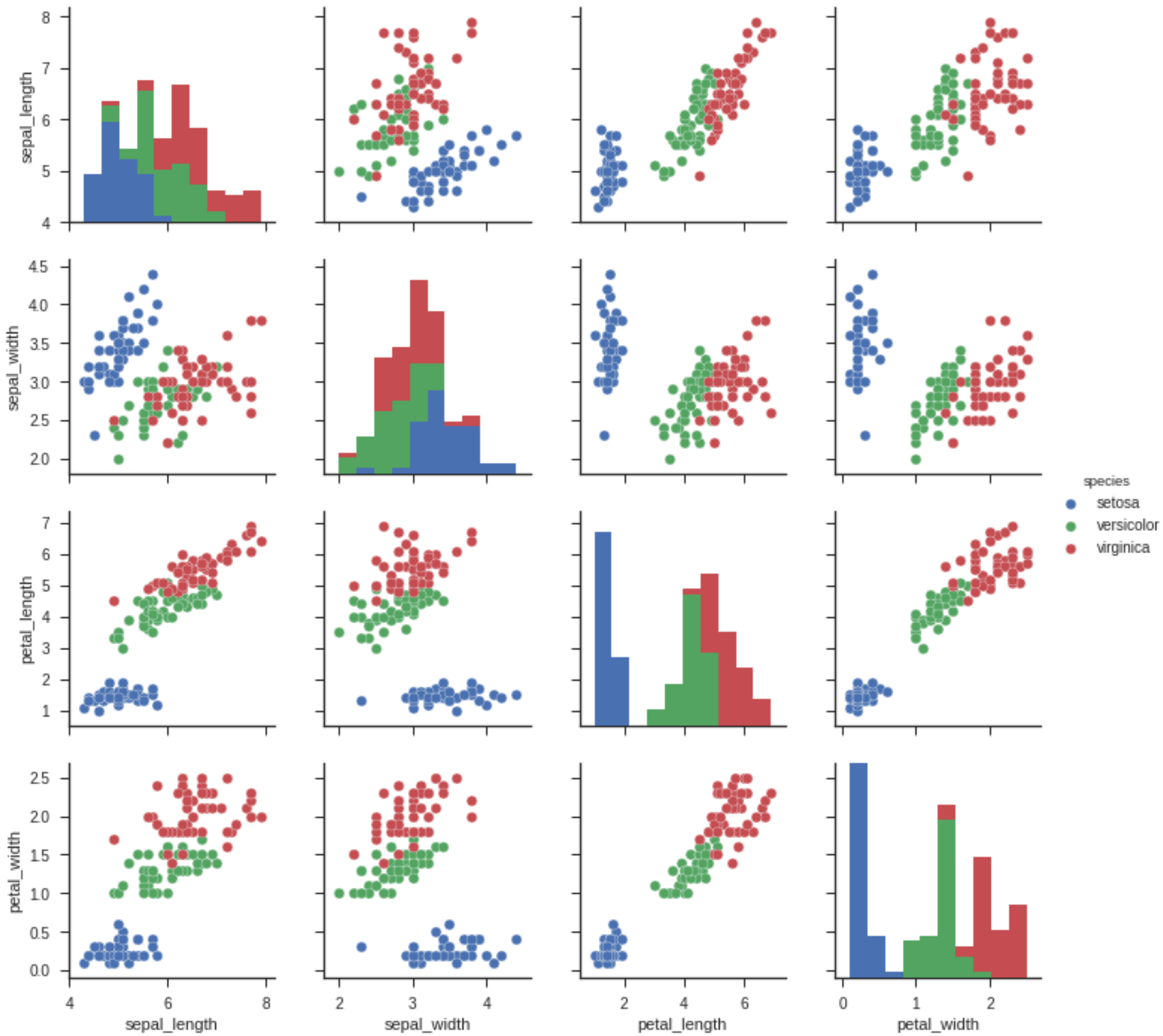
```
5.1,3.5,1.4,0.2,Iris-setosa
4.9,3.0,1.4,0.2,Iris-setosa
4.7,3.2,1.3,0.2,Iris-setosa
4.6,3.1,1.5,0.2,Iris-setosa
5.0,3.6,1.4,0.2,Iris-setosa
5.4,3.9,1.7,0.4,Iris-setosa
4.6,3.4,1.4,0.3,Iris-setosa
5.0,3.4,1.5,0.2,Iris-setosa
4.4,2.9,1.4,0.2,Iris-setosa
4.9,3.1,1.5,0.1,Iris-setosa
5.4,3.7,1.5,0.2,Iris-setosa
4.8,3.4,1.6,0.2,Iris-setosa
4.8,3.0,1.4,0.1,Iris-setosa
4.3,3.0,1.1,0.1,Iris-setosa
5.8,4.0,1.2,0.2,Iris-setosa
5.7,4.4,1.5,0.4,Iris-setosa
5.4,3.9,1.3,0.4,Iris-setosa
5.1,3.5,1.4,0.3,Iris-setosa
5.7,3.8,1.7,0.3,Iris-setosa
5.1,3.8,1.5,0.3,Iris-setosa
5.4,3.4,1.7,0.2,Iris-setosa
5.1,3.7,1.5,0.4,Iris-setosa
4.6,3.6,1.0,0.2,Iris-setosa
5.1,3.3,1.7,0.5,Iris-setosa
4.8,3.4,1.9,0.2,Iris-setosa
5.0,3.0,1.6,0.2,Iris-setosa
```

setosa

virginica

versicolor

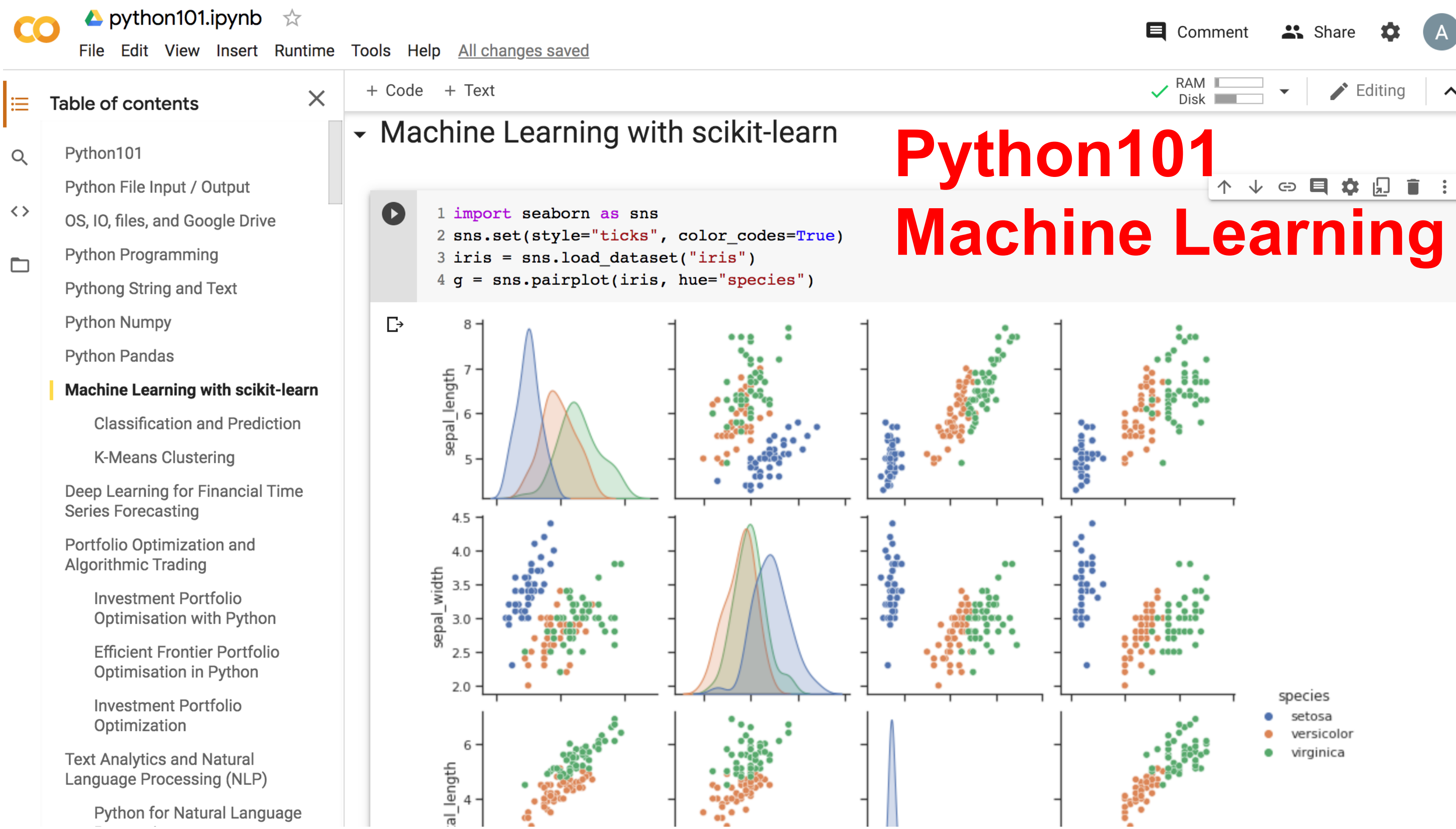
Iris Data Visualization



Source: https://seaborn.pydata.org/generated/seaborn.pairplot.html

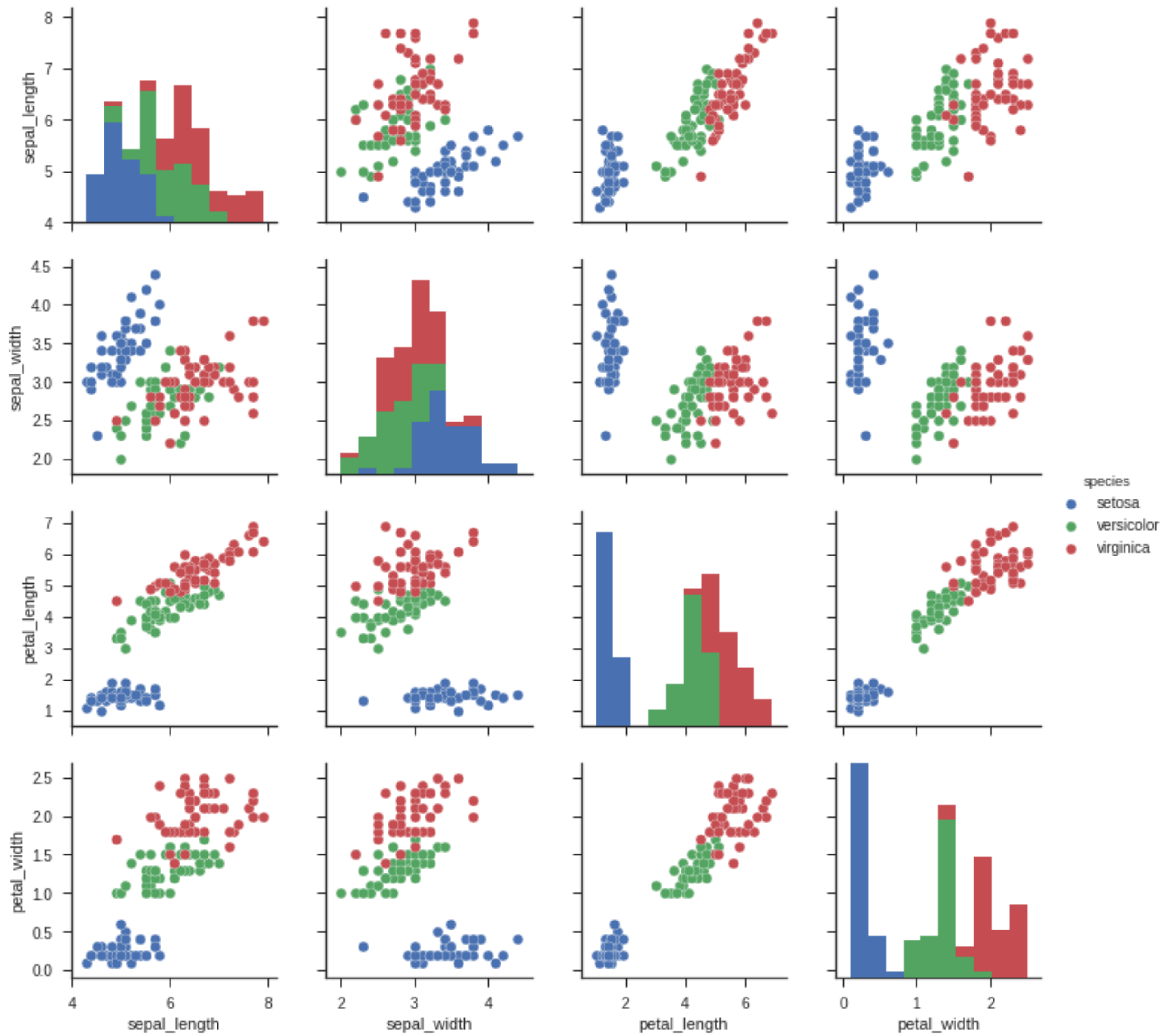
Python in Google Colab (Python101)

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT



https://tinyurl.com/aintpupython101

```python
import seaborn as sns
sns.set(style="ticks", color_codes=True)
iris = sns.load_dataset("iris")
g = sns.pairplot(iris, hue="species")
```



Source: https://seaborn.pydata.org/generated/seaborn.pairplot.html https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT

```
import numpy as np
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
from pandas.plotting import scatter_matrix

# Load dataset
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'class']
df = pd.read_csv(url, names=names)

print(df.head(10))
print(df.tail(10))
print(df.describe())
print(df.info())
print(df.shape)
print(df.groupby('class').size())

plt.rcParams["figure.figsize"] = (10,8)
df.plot(kind='box', subplots=True, layout=(2,2), sharex=False, sharey=False)
plt.show()

df.hist()
plt.show()

scatter_matrix(df)
plt.show()

sns.pairplot(df, hue="class", size=2)
```

Source: https://machinelearningmastery.com/machine-learning-in-python-step-by-step/

```
import numpy as np
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
from pandas.plotting import scatter_matrix
```

```
# Import Libraries
import numpy as np
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
from pandas.plotting import scatter_matrix
print('imported')
```

```
imported
```

```python
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'class']
df = pd.read_csv(url, names=names)
print(df.head(10))
```

```python
# Load dataset
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'class']
df = pd.read_csv(url, names=names)
print(df.head(10))
```

	sepal-length	sepal-width	petal-length	petal-width	class
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
5	5.4	3.9	1.7	0.4	Iris-setosa
6	4.6	3.4	1.4	0.3	Iris-setosa
7	5.0	3.4	1.5	0.2	Iris-setosa
8	4.4	2.9	1.4	0.2	Iris-setosa
9	4.9	3.1	1.5	0.1	Iris-setosa

df.describe()

```
print(df.describe())
```

	sepal-length	sepal-width	petal-length	petal-width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

df.tail(10)

```
print(df.tail(10))
```

	sepal-length	sepal-width	petal-length	petal-width	class
140	6.7	3.1	5.6	2.4	Iris-virginica
141	6.9	3.1	5.1	2.3	Iris-virginica
142	5.8	2.7	5.1	1.9	Iris-virginica
143	6.8	3.2	5.9	2.3	Iris-virginica
144	6.7	3.3	5.7	2.5	Iris-virginica
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

```
print(df.info())
print(df.shape)
```

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
sepal-length    150 non-null float64
sepal-width     150 non-null float64
petal-length    150 non-null float64
petal-width     150 non-null float64
class           150 non-null object
dtypes: float64(4), object(1)
memory usage: 5.9+ KB
None
```

```
print(df.shape)
```

```
(150, 5)
```

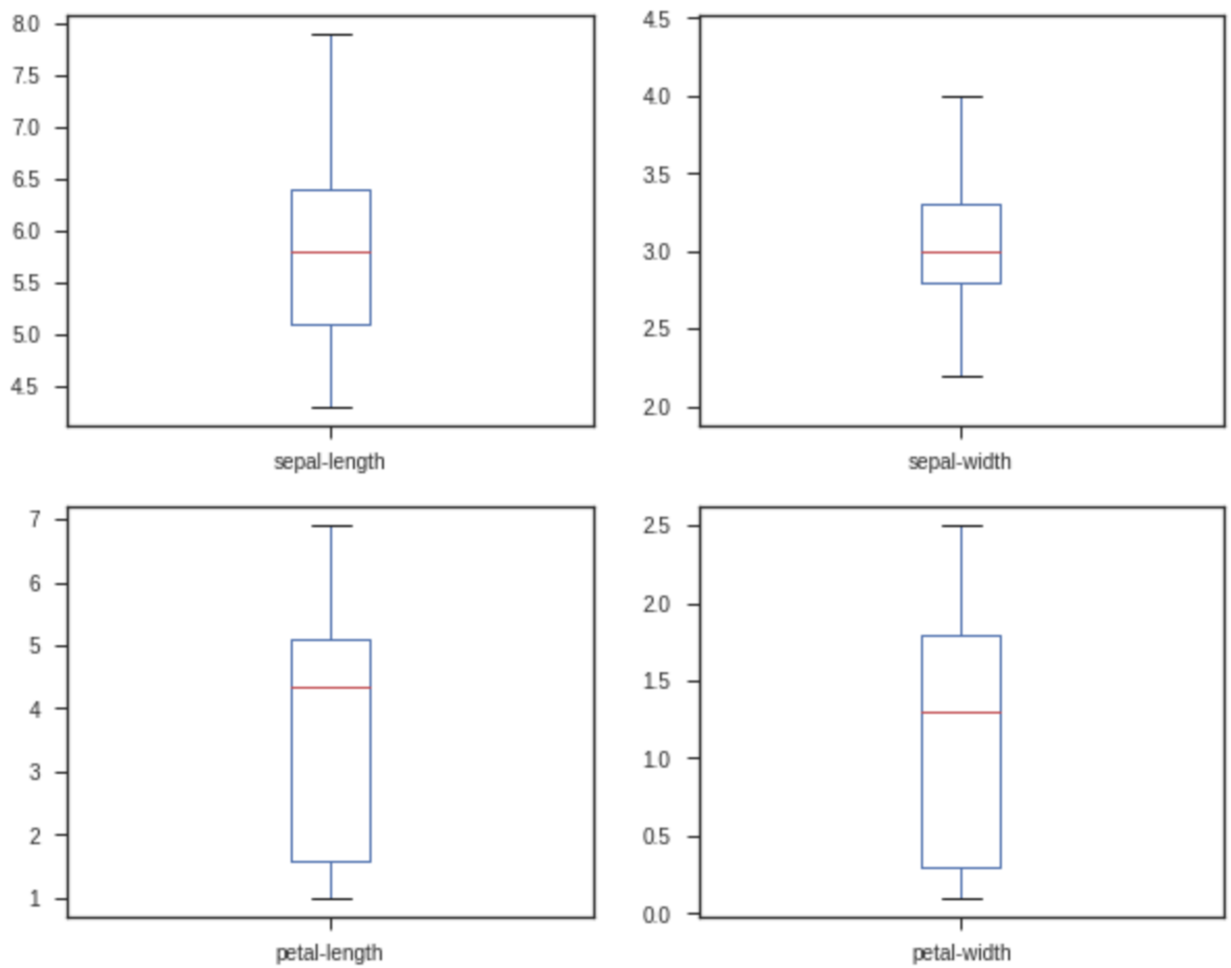
df.groupby('class').size()

```
print(df.groupby('class').size())
```

```
class
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
dtype: int64
```

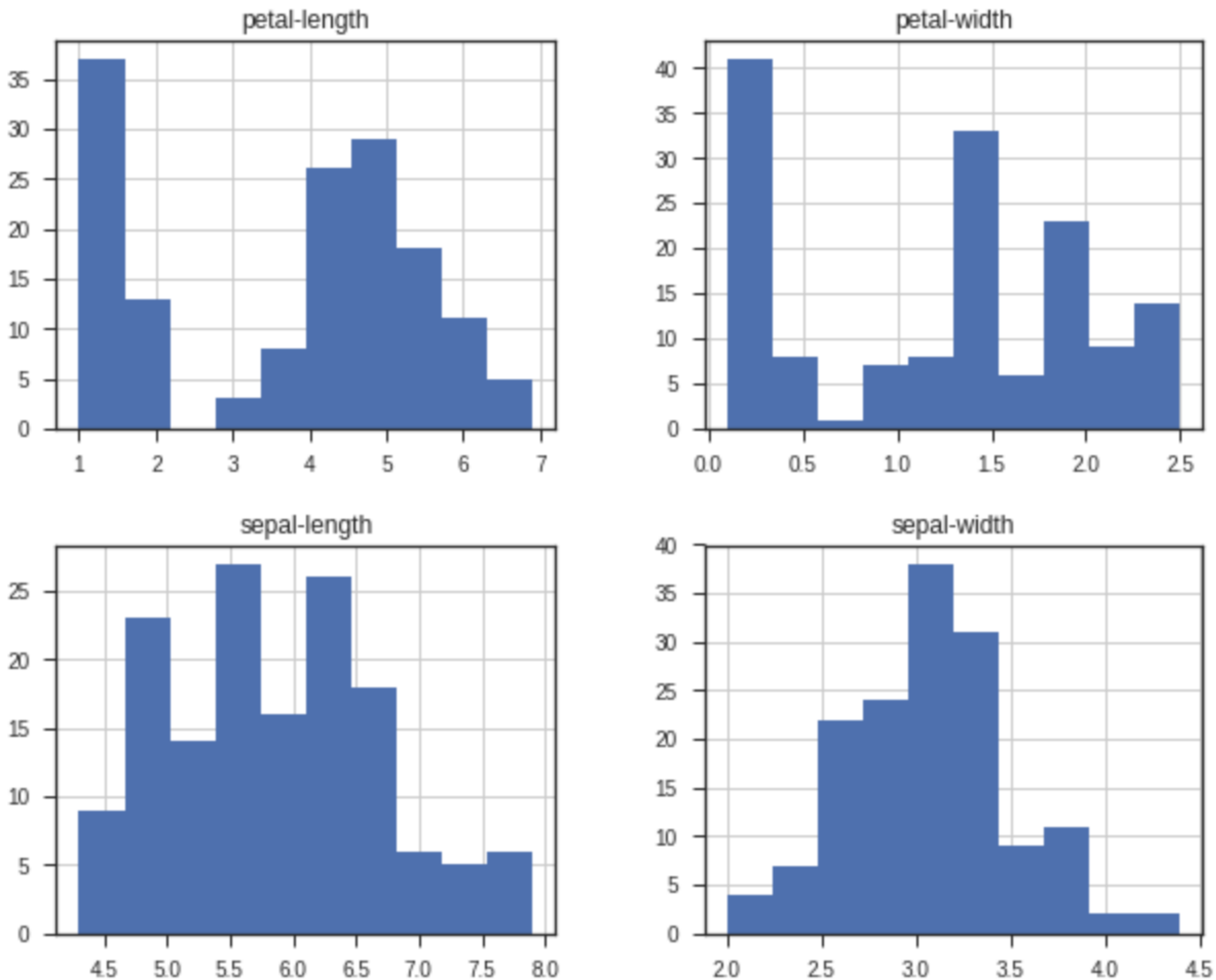
```
plt.rcParams["figure.figsize"] = (10,8)
df.plot(kind='box', subplots=True, layout=(2,2), sharex=False, sharey=False)
plt.show()
```


```
plt.rcParams["figure.figsize"] = (10,8)
df.plot(kind='box', subplots=True, layout=(2,2), sharex=False, sharey=False)
plt.show()
```

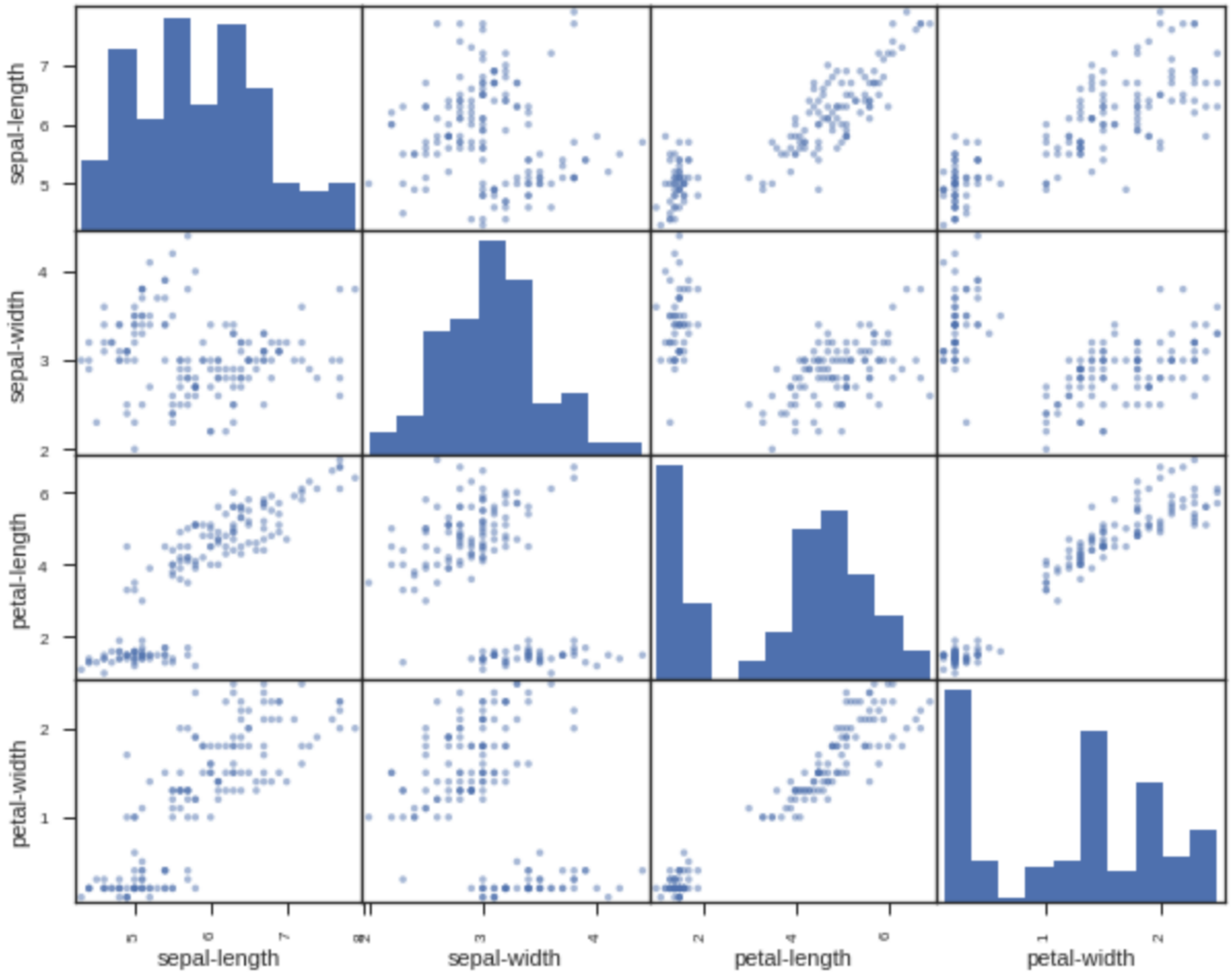
```
df.hist()
plt.show()
```

```
df.hist()
plt.show()
```



scatter_matrix(df)
plt.show()

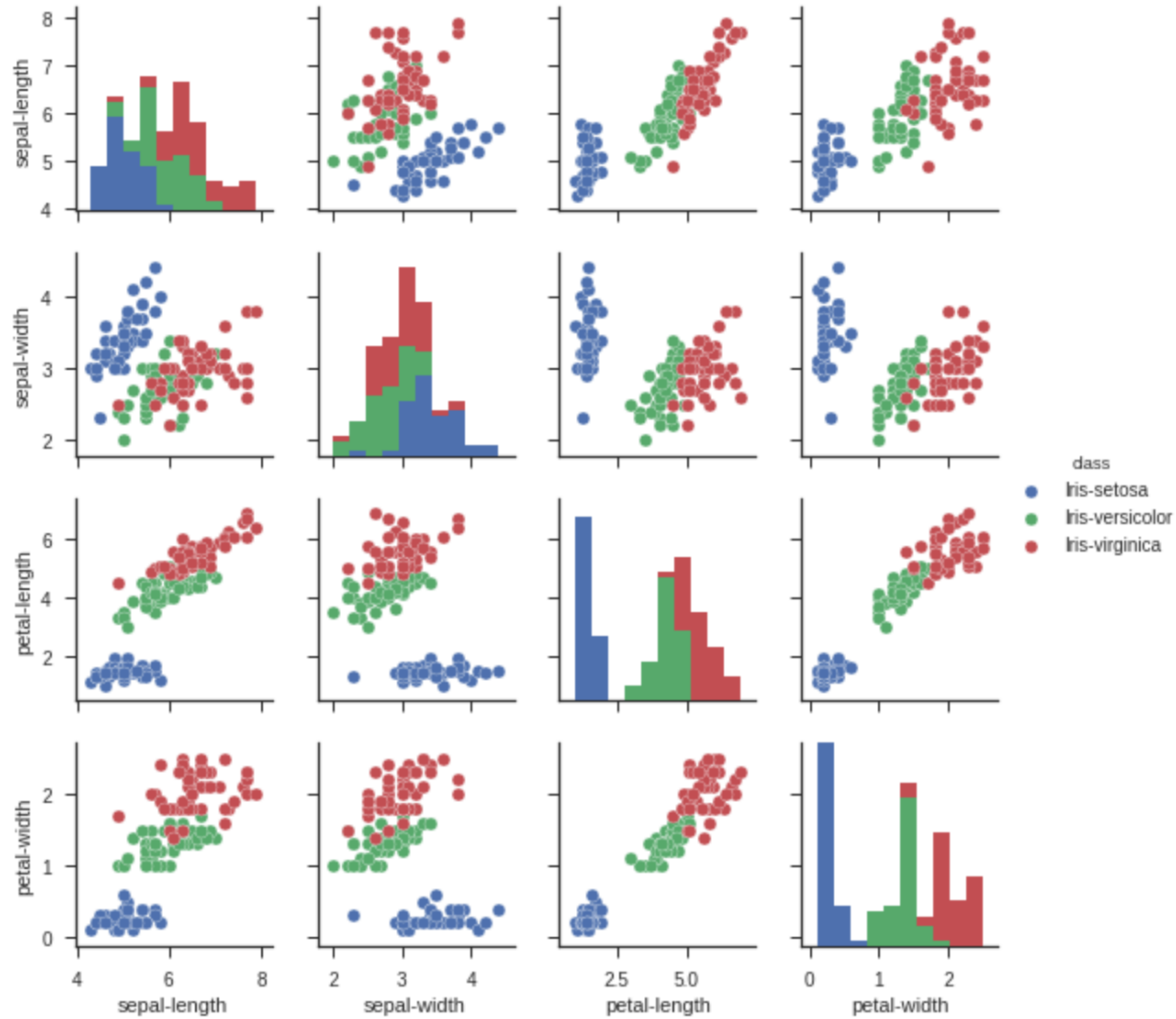
```
scatter_matrix(df)
plt.show()
```



sns.pairplot(df, hue="class", size=2)

```
sns.pairplot(df, hue="class", size=2)
```

```
<seaborn.axisgrid.PairGrid at 0x7f1d21267390>
```



Machine Learning

Supervised Learning

Classification

and

Prediction

Python in Google Colab (Python101)

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT

Classification and Prediction

Classification and Prediction

```python
# Import libraries
import numpy as np
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
from pandas.plotting import scatter_matrix

# Import sklearn
from sklearn import model_selection
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
print("Imported")

# Load dataset
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'class']
df = pd.read_csv(url, names=names)

print(df.head(10))
```

https://tinyurl.com/aintpupython101

```python
# Import sklearn
from sklearn import model_selection
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
print("Imported")
```

```python
# Load dataset
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'class']
df = pd.read_csv(url, names=names)

print(df.head(10))
print(df.tail(10))
print(df.describe())
print(df.info())
print(df.shape)
print(df.groupby('class').size())

plt.rcParams["figure.figsize"] = (10,8)
df.plot(kind='box', subplots=True, layout=(2,2), sharex=False, sharey=False)
plt.show()

df.hist()
plt.show()

scatter_matrix(df)
plt.show()

sns.pairplot(df, hue="class", size=2)
```

```
   sepal-length  sepal-width  petal-length  petal-width        class
0           5.1          3.5           1.4          0.2  Iris-setosa
1           4.9          3.0           1.4          0.2  Iris-setosa
2           4.7          3.2           1.3          0.2  Iris-setosa
3           4.6          3.1           1.5          0.2  Iris-setosa
4           5.0          3.6           1.4          0.2  Iris-setosa
5           5.4          3.9           1.7          0.4  Iris-setosa
6           4.6          3.4           1.4          0.3  Iris-setosa
7           5.0          3.4           1.5          0.2  Iris-setosa
8           4.4          2.9           1.4          0.2  Iris-setosa
9           4.9          3.1           1.5          0.1  Iris-setosa
     sepal-length  sepal-width  petal-length  petal-width           class
140           6.7          3.1           5.6          2.4  Iris-virginica
141           6.9          3.1           5.1          2.3  Iris-virginica
142           5.8          2.7           5.1          1.9  Iris-virginica
```

```python
# Load dataset
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'class']
df = pd.read_csv(url, names=names)

print(df.head(10))
print(df.tail(10))
print(df.describe())
print(df.info())
print(df.shape)
print(df.groupby('class').size())

plt.rcParams["figure.figsize"] = (10,8)
df.plot(kind='box', subplots=True, layout=(2,2), sharex=False, sharey=False)
plt.show()

df.hist()
plt.show()

scatter_matrix(df)
plt.show()

sns.pairplot(df, hue="class", size=2)
```

```
   sepal-length  sepal-width  petal-length  petal-width        class
0           5.1          3.5           1.4          0.2  Iris-setosa
1           4.9          3.0           1.4          0.2  Iris-setosa
2           4.7          3.2           1.3          0.2  Iris-setosa
3           4.6          3.1           1.5          0.2  Iris-setosa
4           5.0          3.6           1.4          0.2  Iris-setosa
5           5.4          3.9           1.7          0.4  Iris-setosa
6           4.6          3.4           1.4          0.3  Iris-setosa
7           5.0          3.4           1.5          0.2  Iris-setosa
8           4.4          2.9           1.4          0.2  Iris-setosa
9           4.9          3.1           1.5          0.1  Iris-setosa
     sepal-length  sepal-width  petal-length  petal-width           class
140           6.7          3.1           5.6          2.4  Iris-virginica
141           6.9          3.1           5.1          2.3  Iris-virginica
142           5.8          2.7           5.1          1.9  Iris-virginica
```

df.corr()

```
1 df.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

```
# Split-out validation dataset
array = df.values
X = array[:,0:4]
Y = array[:,4]
validation_size = 0.20
seed = 7
X_train, X_validation, Y_train, Y_validation =
model_selection.train_test_split(X, Y,
test_size=validation_size, random_state=seed)
scoring = 'accuracy'
```


```
# Split-out validation dataset
array = df.values
X = array[:,0:4]
Y = array[:,4]
validation_size = 0.20
seed = 7
X_train, X_validation, Y_train, Y_validation = model_selection.train_test_split(X, Y, test_size=validation_size, random_state=seed)
scoring = 'accuracy'
```


```
len(Y_validation)
```

```
30
```

```
# Models
models = []
models.append(('LR', LogisticRegression()))
models.append(('LDA',
LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('DT',
DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC()))
```

```
# evaluate each model in turn
results = []
names = []
for name, model in models:
    kfold = model_selection.KFold(n_splits=10,
random_state=seed)
    cv_results =
model_selection.cross_val_score(model,
X_train, Y_train, cv=kfold, scoring=scoring)
    results.append(cv_results)
    names.append(name)
    msg = "%s: %.4f (%.4f)" % (name,
cv_results.mean(), cv_results.std())
    print(msg)
```

```
# Models
models = []
models.append(('LR', LogisticRegression()))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('DT', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC()))
# evaluate each model in turn
results = []
names = []
for name, model in models:
    kfold = model_selection.KFold(n_splits=10, random_state=seed)
    cv_results = model_selection.cross_val_score(model, X_train, Y_train, cv=kfold, scoring=scoring)
    results.append(cv_results)
    names.append(name)
    msg = "%s: %.4f (%.4f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
```

```
LR: 0.9667 (0.0408)
LDA: 0.9750 (0.0382)
KNN: 0.9833 (0.0333)
DT: 0.9750 (0.0382)
NB: 0.9750 (0.0534)
SVM: 0.9917 (0.0250)
```

```
# Make predictions on validation dataset
model = KNeighborsClassifier()
model.fit(X_train, Y_train)
predictions = model.predict(X_validation)
print("%.4f" % accuracy_score(Y_validation,
predictions))
print(confusion_matrix(Y_validation,
predictions))
print(classification_report(Y_validation,
predictions))
print(model)
```

```python
# Make predictions on validation dataset
model = KNeighborsClassifier()
model.fit(X_train, Y_train)
predictions = model.predict(X_validation)
print("%.4f" % accuracy_score(Y_validation, predictions))
print(confusion_matrix(Y_validation, predictions))
print(classification_report(Y_validation, predictions))
print(model)
```

```
0.9000
[[ 7  0  0]
 [ 0 11  1]
 [ 0  2  9]]
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         7
Iris-versicolor       0.85      0.92      0.88        12
 Iris-virginica       0.90      0.82      0.86        11

    avg / total       0.90      0.90      0.90        30

KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

```
# Make predictions on validation dataset
model = SVC()
model.fit(X_train, Y_train)
predictions = model.predict(X_validation)
print("%.4f" % accuracy_score(Y_validation,
predictions))
print(confusion_matrix(Y_validation,
predictions))
print(classification_report(Y_validation,
predictions))
print(model)
```

```
model = SVC()
model.fit(X_train, Y_train)
predictions = model.predict(X_validation)
```

```
# Make predictions on validation dataset
model = SVC()
model.fit(X_train, Y_train)
predictions = model.predict(X_validation)
print("%.4f" % accuracy_score(Y_validation, predictions))
print(confusion_matrix(Y_validation, predictions))
print(classification_report(Y_validation, predictions))
print(model)
```

```
0.9333
[[ 7  0  0]
 [ 0 10  2]
 [ 0  0 11]]
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         7
Iris-versicolor       1.00      0.83      0.91        12
 Iris-virginica       0.85      1.00      0.92        11

    avg / total       0.94      0.93      0.93        30

SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

```python
# Make predictions on validation dataset
model = DecisionTreeClassifier()
model.fit(X_train, Y_train)
predictions = model.predict(X_validation)
print("%.4f" % accuracy_score(Y_validation, predictions))
print(confusion_matrix(Y_validation, predictions))
print(classification_report(Y_validation, predictions))
print(model)
```

```
0.9000
[[ 7  0  0]
 [ 0 11  1]
 [ 0  2  9]]
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         7
Iris-versicolor       0.85      0.92      0.88        12
 Iris-virginica       0.90      0.82      0.86        11

    avg / total       0.90      0.90      0.90        30

DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

```python
# Make predictions on validation dataset
model = GaussianNB()
model.fit(X_train, Y_train)
predictions = model.predict(X_validation)
print("%.4f" % accuracy_score(Y_validation, predictions))
print(confusion_matrix(Y_validation, predictions))
print(classification_report(Y_validation, predictions))
print(model)
```

```
0.8333
[[7 0 0]
 [0 9 3]
 [0 2 9]]
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         7
Iris-versicolor       0.82      0.75      0.78        12
 Iris-virginica       0.75      0.82      0.78        11

    avg / total       0.84      0.83      0.83        30

GaussianNB(priors=None)
```

```python
# Make predictions on validation dataset
model = LogisticRegression()
model.fit(X_train, Y_train)
predictions = model.predict(X_validation)
print("%.4f" % accuracy_score(Y_validation, predictions))
print(confusion_matrix(Y_validation, predictions))
print(classification_report(Y_validation, predictions))
print(model)
```

```
0.8000
[[ 7  0  0]
 [ 0  7  5]
 [ 0  1 10]]
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         7
Iris-versicolor       0.88      0.58      0.70        12
 Iris-virginica       0.67      0.91      0.77        11

    avg / total       0.83      0.80      0.80        30

LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

```python
# Make predictions on validation dataset
model = LinearDiscriminantAnalysis()
model.fit(X_train, Y_train)
predictions = model.predict(X_validation)
print("%.4f" % accuracy_score(Y_validation, predictions))
print(confusion_matrix(Y_validation, predictions))
print(classification_report(Y_validation, predictions))
print(model)
```

```
0.9667
[[ 7  0  0]
 [ 0 11  1]
 [ 0  0 11]]
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         7
Iris-versicolor       1.00      0.92      0.96        12
 Iris-virginica       0.92      1.00      0.96        11

    avg / total       0.97      0.97      0.97        30

LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
              solver='svd', store_covariance=False, tol=0.0001)
```

```python
# Make predictions on validation dataset
model = MLPClassifier()
model.fit(X_train, Y_train)
predictions = model.predict(X_validation)
print("%.4f" % accuracy_score(Y_validation, predictions))
print(confusion_matrix(Y_validation, predictions))
print(classification_report(Y_validation, predictions))
print(model)
```

```
0.9000
[[ 7  0  0]
 [ 0  9  3]
 [ 0  0 11]]
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         7
Iris-versicolor       1.00      0.75      0.86        12
 Iris-virginica       0.79      1.00      0.88        11

    avg / total       0.92      0.90      0.90        30

MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.9,
       beta_2=0.999, early_stopping=False, epsilon=1e-08,
       hidden_layer_sizes=(100,), learning_rate='constant',
       learning_rate_init=0.001, max_iter=200, momentum=0.9,
       nesterovs_momentum=True, power_t=0.5, random_state=None,
       shuffle=True, solver='adam', tol=0.0001, validation_fraction=0.1,
       verbose=False, warm_start=False)
```

Machine Learning
Unsupervised Learning
Cluster Analysis
K-Means Clustering

K-Means Clustering

```
#importing the libraries
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import pandas as pd

#importing the Iris dataset with pandas
# Load dataset
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'class']
df = pd.read_csv(url, names=names)

array = df.values
X = array[:,0:4]
Y = array[:,4]

#Finding the optimum number of clusters for k-means classification
from sklearn.cluster import KMeans
wcss = []

for i in range(1, 8):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300, n_init = 10, random_state = 0)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)

#Plotting the results onto a line graph, allowing us to observe 'The elbow'
plt.rcParams["figure.figsize"] = (10,8)
plt.plot(range(1, 8), wcss)
plt.title('The elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS') #within cluster sum of squares
plt.show()
```

```
#importing the libraries
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import pandas as pd

#importing the Iris dataset with pandas
# Load dataset
url = "https://archive.ics.uci.edu/ml/machine-
learning-databases/iris/iris.data"
names = ['sepal-length', 'sepal-width',
'petal-length', 'petal-width', 'class']
df = pd.read_csv(url, names=names)

array = df.values
X = array[:,0:4]
Y = array[:,4]
```

```
#Finding the optimum number of clusters for k-means
classification
from sklearn.cluster import KMeans
wcss = []

for i in range(1, 8):
    kmeans = KMeans(n_clusters = i, init = 'k-means++',
max_iter = 300, n_init = 10, random_state = 0)
    kmeans.fit(X)
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observe 'The elbow'
plt.rcParams["figure.figsize"] = (10,8)
plt.plot(range(1, 8), wcss)
plt.title('The elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS') #within cluster sum of squares
plt.show()
```
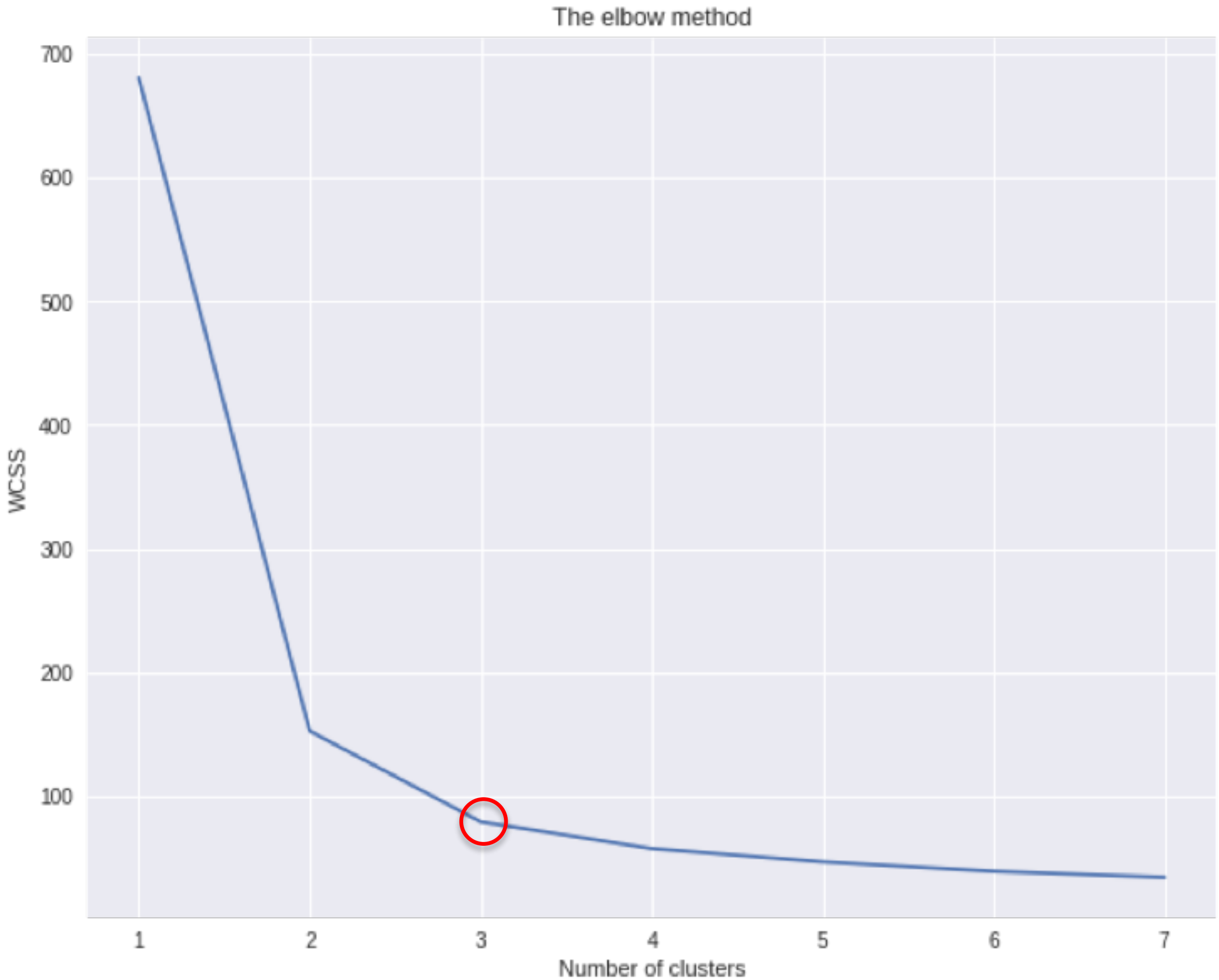

K-Means Clustering

The elbow method (*k=3*)



```
kmeans = KMeans(n_clusters = 3,
init = 'k-means++', max_iter = 300,
n_init = 10, random_state = 0)
y_kmeans = kmeans.fit_predict(X)
```

```
#Applying kmeans to the dataset / Creating the kmeans classifier
kmeans = KMeans(n_clusters = 3, init = 'k-means++', max_iter = 300, n_init = 10, random_state = 0)
y_kmeans = kmeans.fit_predict(X)
```

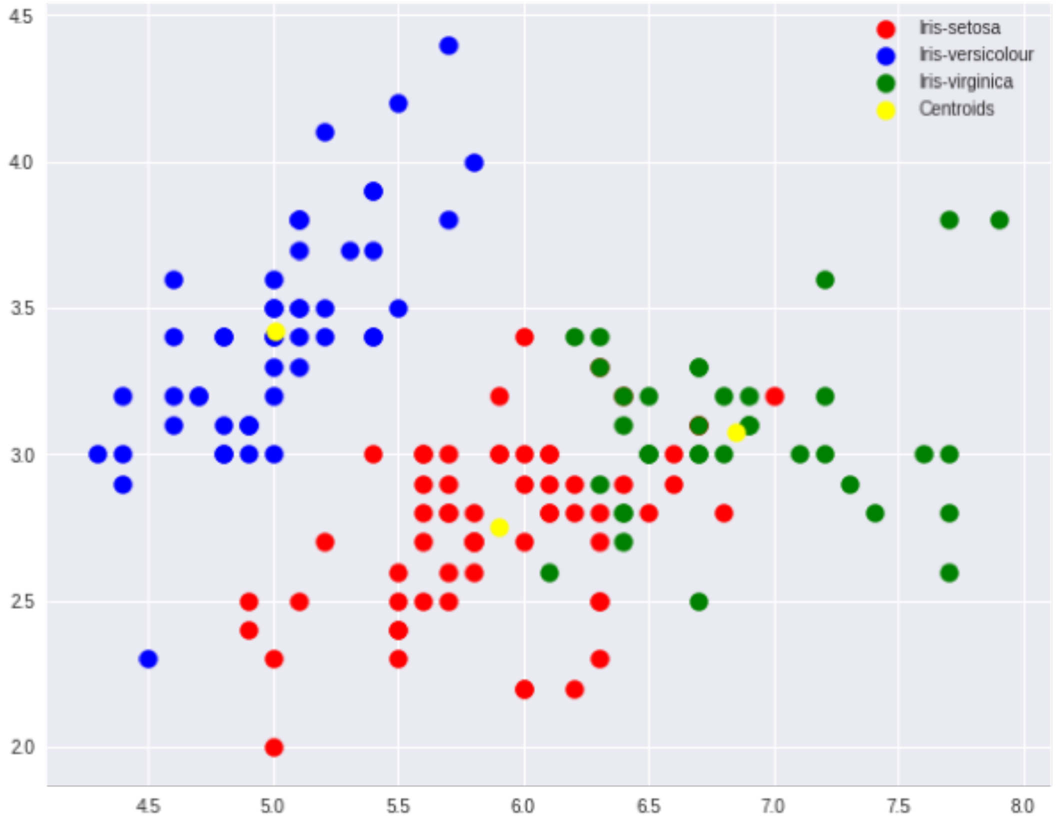
```
#Visualising the clusters
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 100,
c = 'red', label = 'Iris-setosa')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 100,
c = 'blue', label = 'Iris-versicolour')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 100,
c = 'green', label = 'Iris-virginica')

#Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0],
kmeans.cluster_centers_[:,1], s = 100, c = 'yellow', label =
'Centroids')

plt.legend()
```

```
#Visualising the clusters
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 100, c = 'red', label = 'Iris-setosa')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 100, c = 'blue', label = 'Iris-versicolour')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 100, c = 'green', label = 'Iris-virginica')

#Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 100, c = 'yellow', label = 'Centroids')

plt.legend()
```

K-Means Clustering

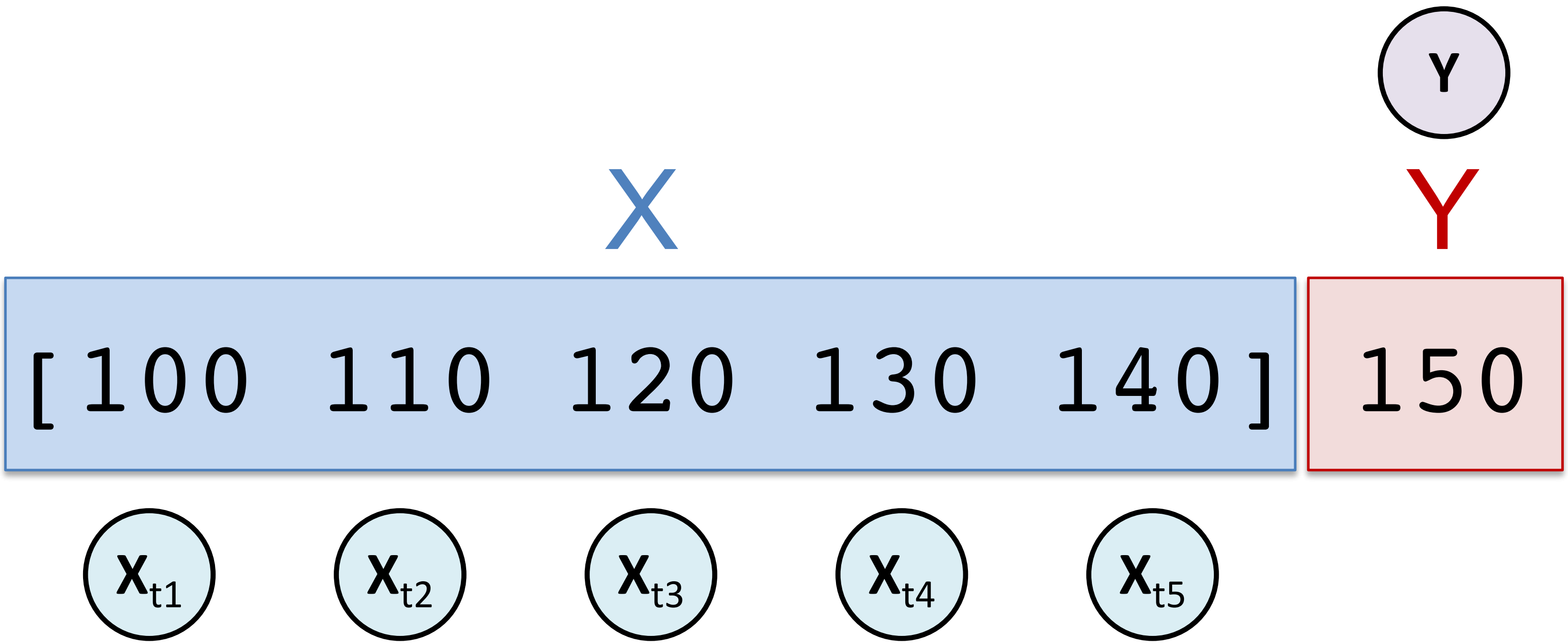
```python
#Applying kmeans to the dataset / Creating the kmeans classifier
kmeans = KMeans(n_clusters = 3, init = 'k-means++', max_iter = 300, n_init = 10, random_state = 0)
y_kmeans = kmeans.fit_predict(X)
```

```python
#Visualising the clusters
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 100, c = 'red', label = 'Iris-setosa')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 100, c = 'blue', label = 'Iris-versicolour')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 100, c = 'green', label = 'Iris-virginica')

#Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 100, c = 'yellow', label = 'Centroids')

plt.legend()
```



Time Series Data

[100, 110, 120, 130, 140, 150]



Time Series Data

[10, 20, 30, 40, 50, 60, 70, 80, 90]

X	Y
[10 20 30]	40
[20 30 40]	50
[30 40 50]	60
[40 50 60]	70
[50 60 70]	80
[60 70 80]	90

Evaluation

(Accuracy of Classification Model)

Assessing the Classification Model

- Predictive accuracy
  - Hit rate
- Speed
  - Model building; predicting
- Robustness
- Scalability
- Interpretability
  - Transparency, explainability

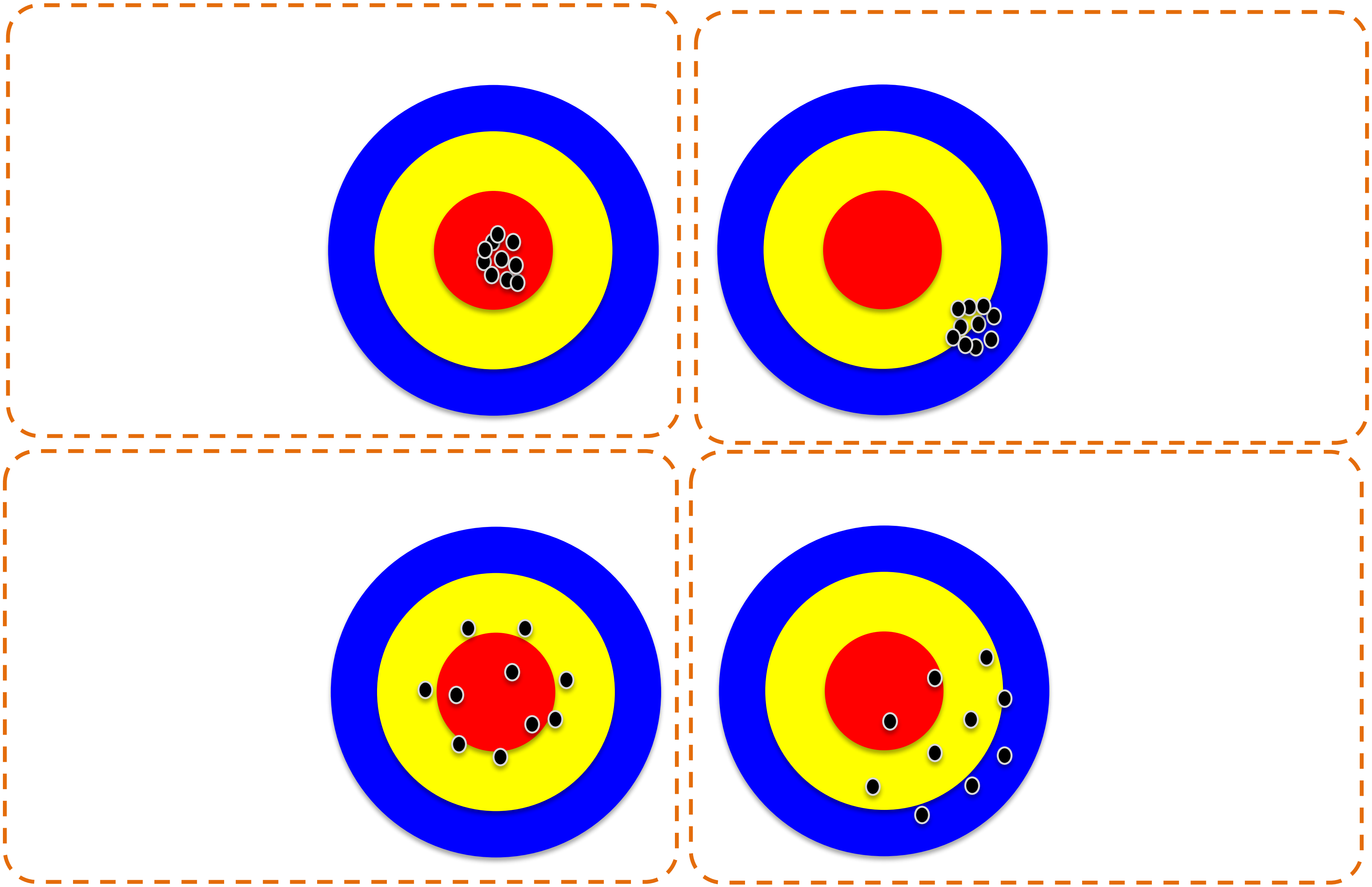
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Accuracy

Validity

Precision

Reliability

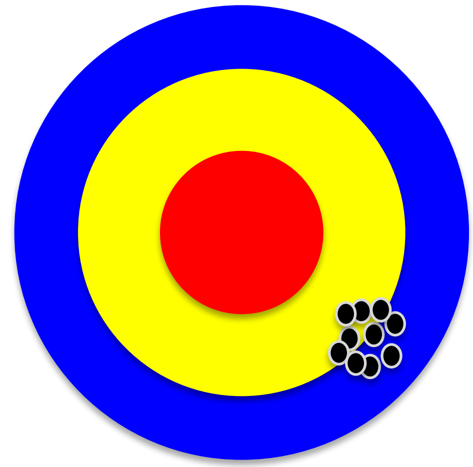


Accuracy vs. Precision

A

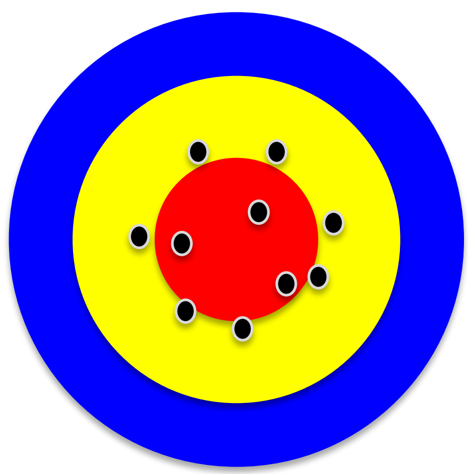
High Accuracy
High Precision

B



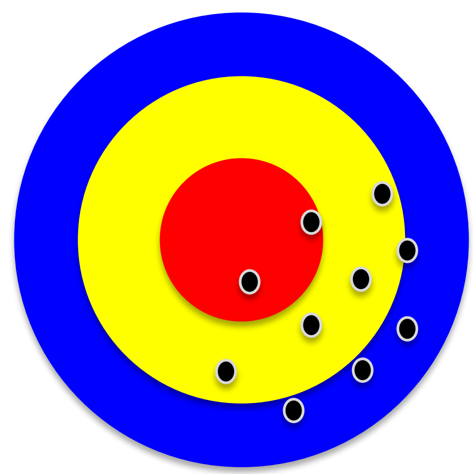
Low Accuracy
High Precision

C



High Accuracy
Low Precision

D



Low Accuracy
Low Precision

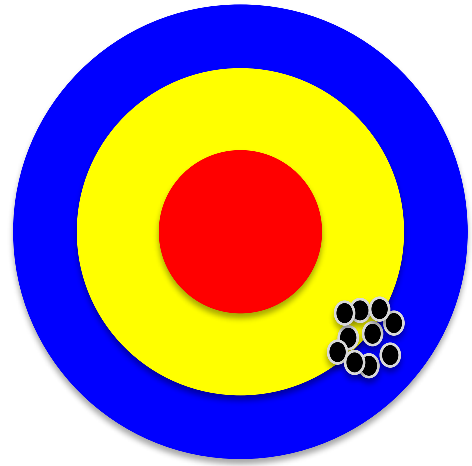
Accuracy vs. Precision

A

High Accuracy
High Precision

High Validity
High Reliability

B



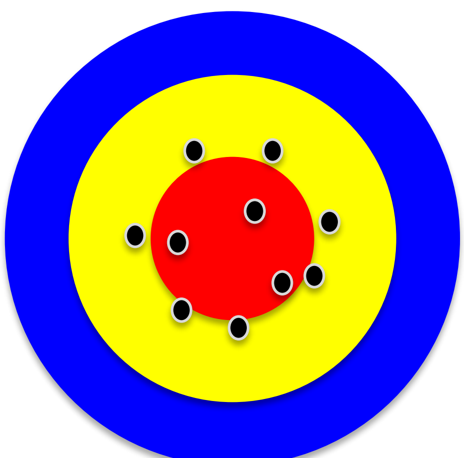
Low Accuracy
High Precision

Low Validity
High Reliability

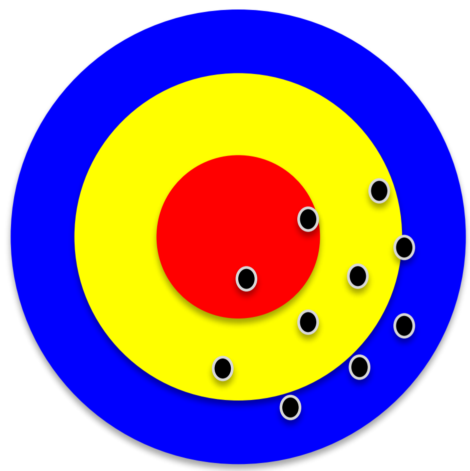
C

High Accuracy
Low Precision

High Validity
Low Reliability



D



Low Accuracy
Low Precision

Low Validity
Low Reliability

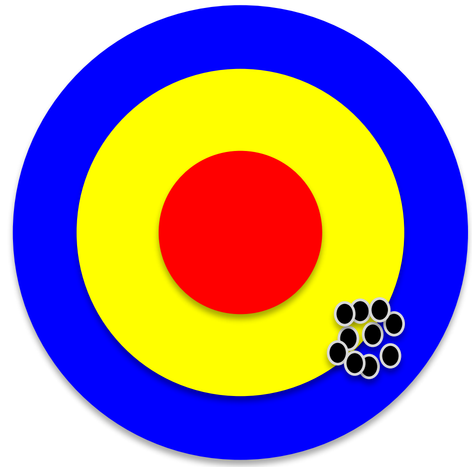
Accuracy vs. Precision

A

High Accuracy
High Precision

High Validity
High Reliability

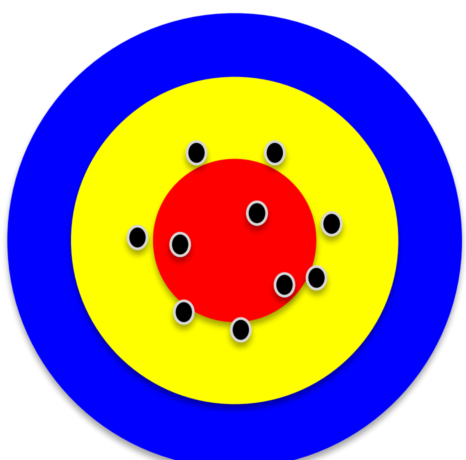
B



Low Accuracy
High Precision

Low Validity
High Reliability

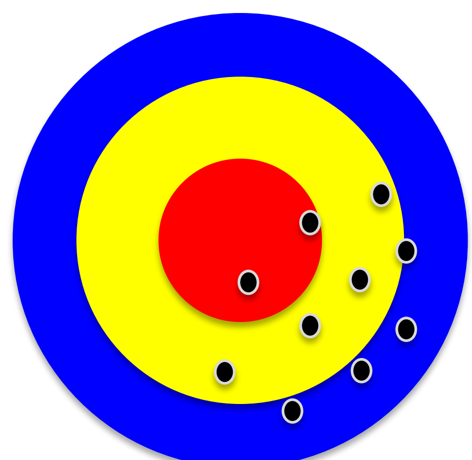
C



High Accuracy
Low Precision

High Validity
Low Reliability

D



Low Accuracy
Low Precision

Low Validity
Low Reliability

Confusion Matrix for Tabulation of Two-Class Classification Results

		True/Observed Class	
		Positive	**Negative**
Predicted Class	**Positive**	True Positive Count (TP)	False Positive Count (FP)
	Negative	False Negative Count (FN)	True Negative Count (TN)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$True\ Positive\ Rate = \frac{TP}{TP + FN}$$

$$True\ Negative\ Rate = \frac{TN}{TN + FP}$$

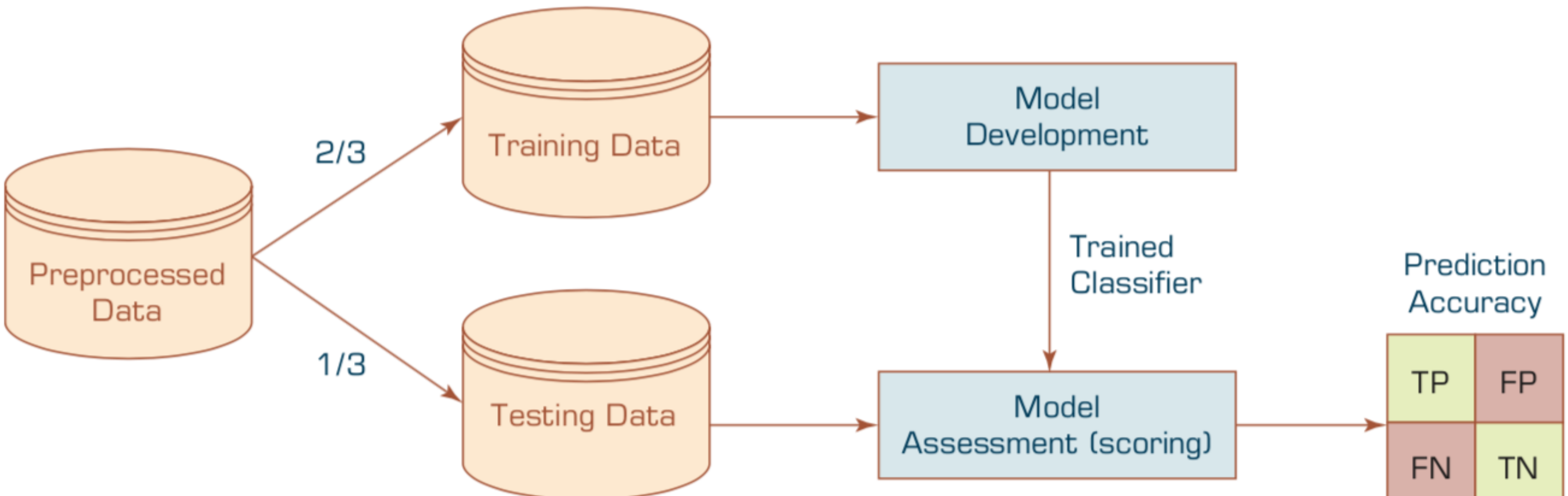
$$Precision = \frac{TP}{TP + FP} \qquad Recall = \frac{TP}{TP + FN}$$

Sensitivity =True Positive Rate

Specificity =True Negative Rate

Estimation Methodologies for Classification

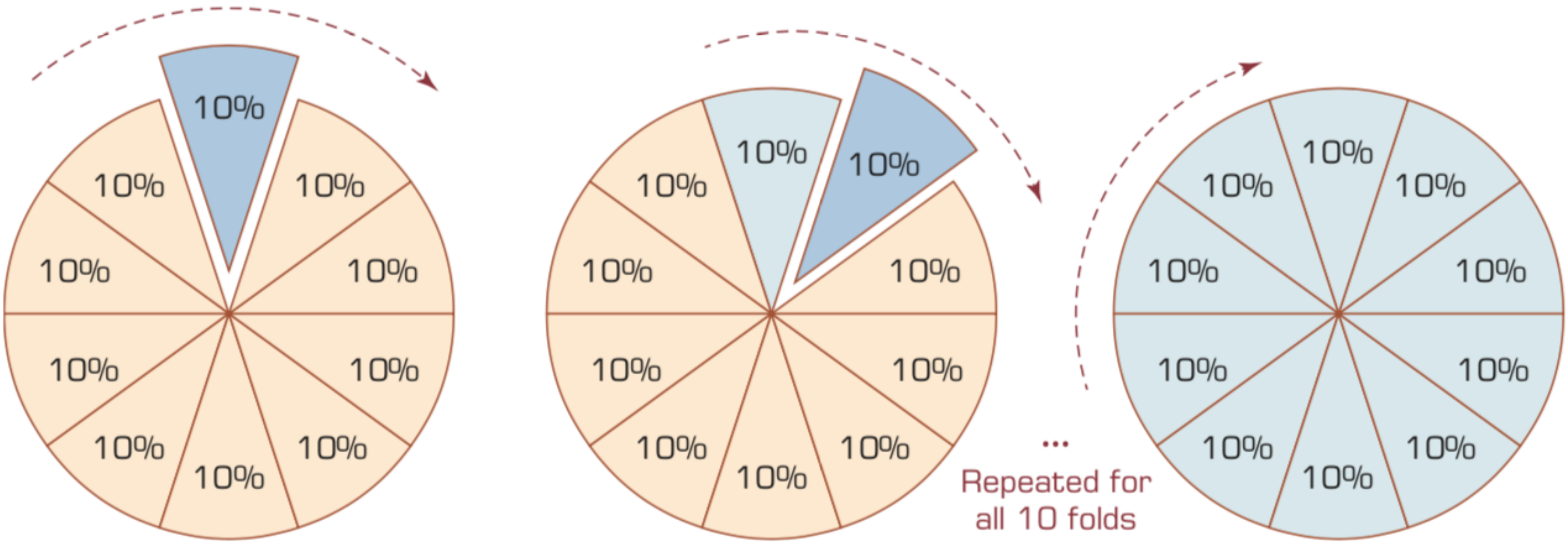
- Simple split (or holdout or test sample estimation)
  - Split the data into 2 mutually exclusive sets training (~70%) and testing (30%)



  - For ANN, the data is split into three sub-sets (training [~60%], validation [~20%], testing [~20%])

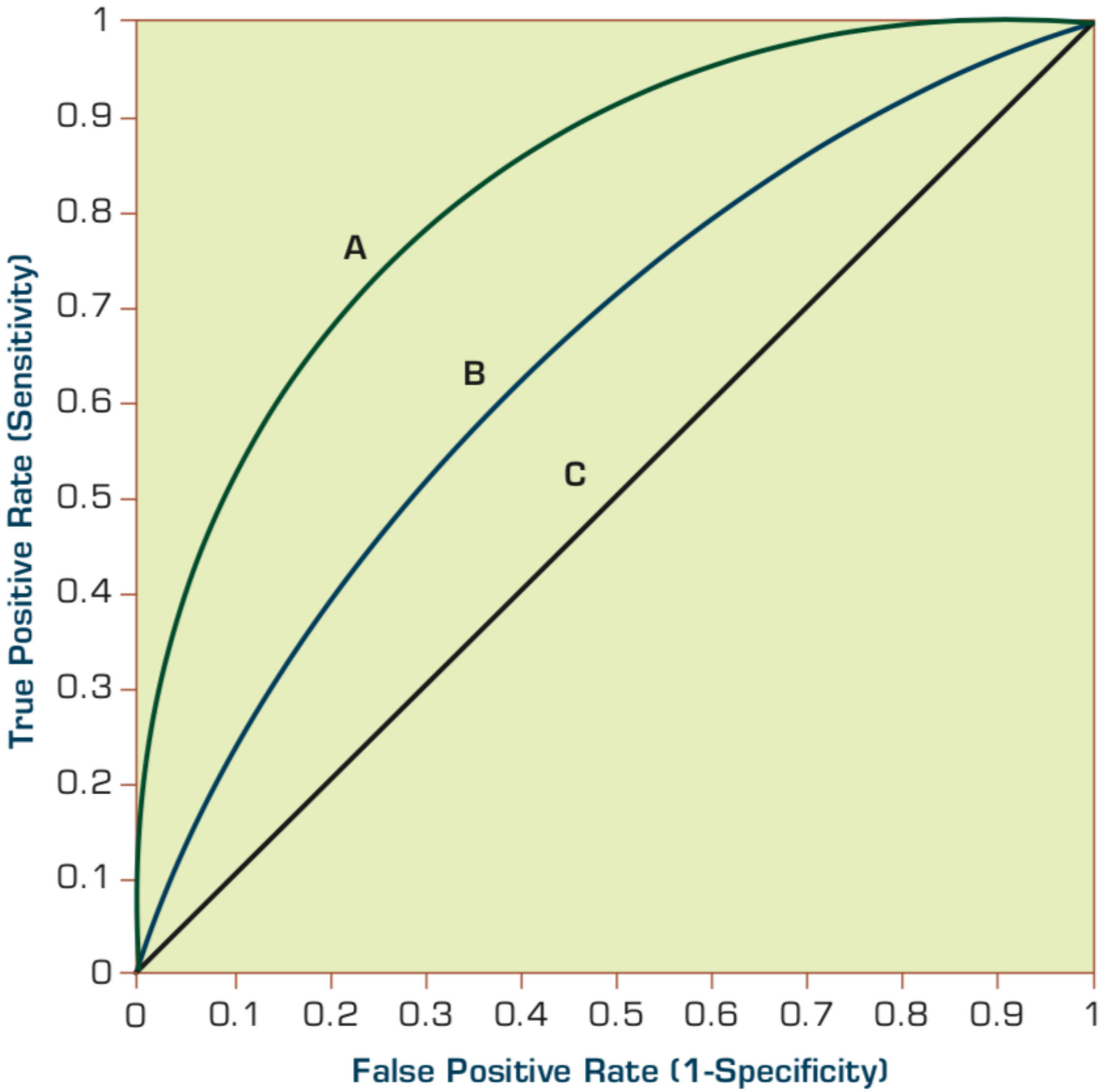
Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

k-Fold Cross-Validation



Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

Estimation Methodologies for Classification
Area under the ROC curve



Source: Ramesh Sharda, Dursun Delen, and Efraim Turban (2017), Business Intelligence, Analytics, and Data Science: A Managerial Perspective, 4th Edition, Pearson

		True Class (actual value)		
		Positive	Negative	total
Predictive Class (prediction outcome)	Positive	True Positive (TP)	False Positive (FP)	P'
	Negative	False Negative (FN)	True Negative (TN)	N'
total		P	N	

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$True\ Positive\ Rate = \frac{TP}{TP + FN}$$

$$True\ Negative\ Rate = \frac{TN}{TN + FP}$$

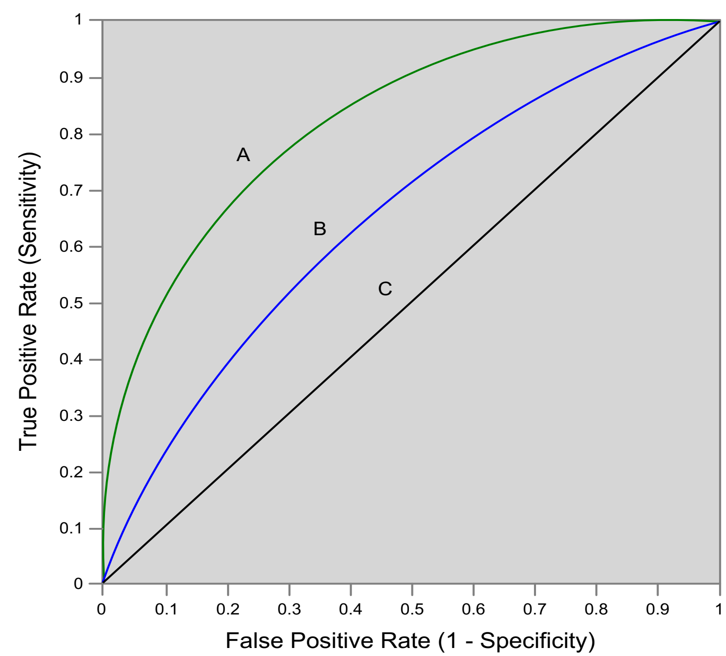
$$Precision = \frac{TP}{TP + FP} \qquad Recall = \frac{TP}{TP + FN}$$

$$True\ Positive\ Rate\ (\text{Sensitivity}) = \frac{TP}{TP + FN}$$

$$True\ Negative\ Rate\ (\text{Specificity}) = \frac{TN}{TN + FP}$$

$$False\ Positive\ Rate = \frac{FP}{FP + TN}$$

$$False\ Positive\ Rate\ (1\text{-}\text{Specificity}) = \frac{FP}{FP + TN}$$



Source: http://en.wikipedia.org/wiki/Receiver_operating_characteristic

		True Class (actual value)		
		Positive	Negative	total
Predictive Class (prediction outcome)	Positive	True Positive (TP)	False Positive (FP)	P'
	Negative	False Negative (FN)	True Negative (TN)	N'
total		P	N	

$$True\ Positive\ Rate\ (\text{Sensitivity}) = \frac{TP}{TP+FN}$$

Sensitivity

= True Positive Rate

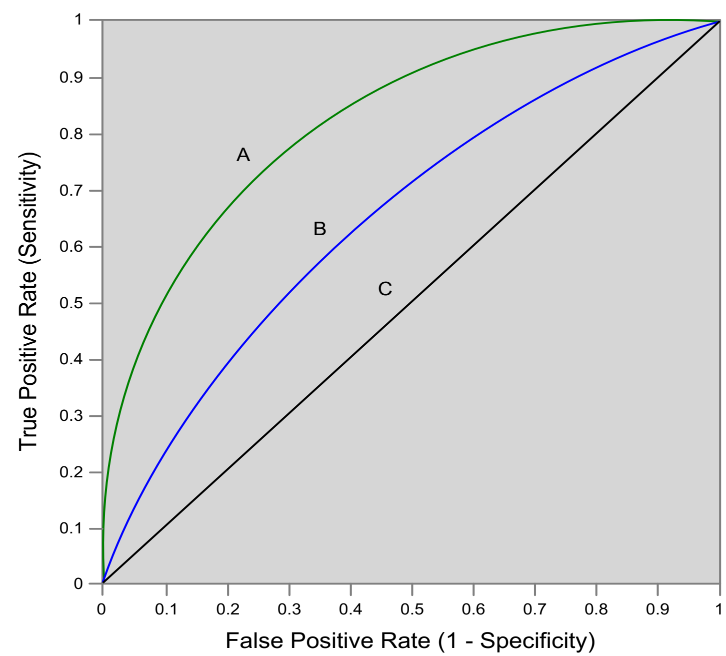
= Recall

= Hit rate

= TP / (TP + FN)

$$True\ Positive\ Rate = \frac{TP}{TP+FN}$$

$$Recall = \frac{TP}{TP+FN}$$



Source: http://en.wikipedia.org/wiki/Receiver_operating_characteristic

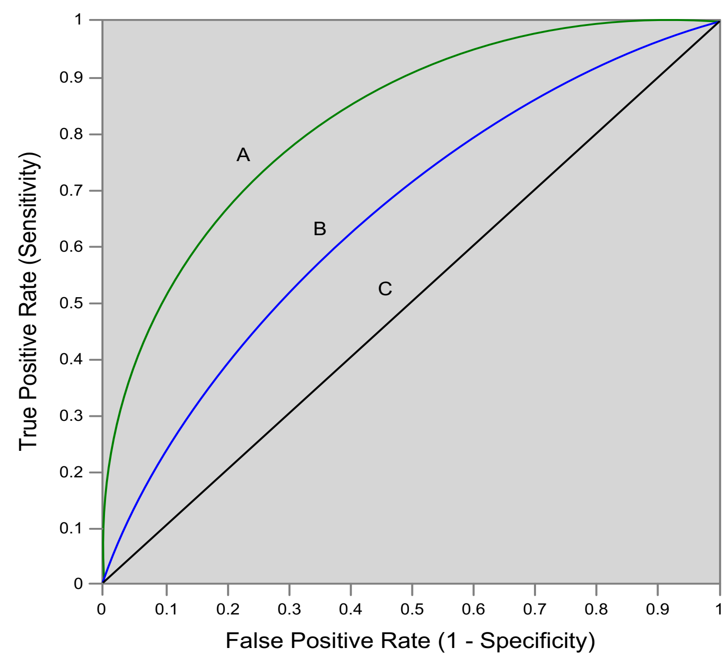
		True Class (actual value)		
		Positive	Negative	total
Predictive Class (prediction outcome)	Positive	True Positive (TP)	False Positive (FP)	P’
	Negative	False Negative (FN)	True Negative (TN)	N’
total		P	N	

$$True\ Negative\ Rate = \frac{TN}{TN + FP}$$

Specificity
= True Negative Rate
= TN / N
= TN / (TN+ FP)

$$True\ Negative\ Rate\ (\text{Specificity}) = \frac{TN}{TN + FP}$$

$$False\ Positive\ Rate\ (1\text{-}\text{Specificity}) = \frac{FP}{FP + TN}$$



Source: http://en.wikipedia.org/wiki/Receiver_operating_characteristic

		True Class (actual value)		
		Positive	Negative	total
Predictive Class (prediction outcome)	Positive	True Positive (TP)	False Positive (FP)	P’
	Negative	False Negative (FN)	True Negative (TN)	N’
total		P	N	

Precision

= Positive Predictive Value (PPV)

$$Precision = \frac{TP}{TP + FP}$$

Recall

= True Positive Rate (TPR)

= Sensitivity

= Hit Rate

$$Recall = \frac{TP}{TP + FN}$$

F1 score (F-score)(F-measure)

is the harmonic mean of precision and recall

= 2TP / (P + P’)

= 2TP / (2TP + FP + FN)

$$F = 2 * \frac{precision * recall}{precision + recall}$$

Source: http://en.wikipedia.org/wiki/Receiver_operating_characteristic

A

63 (TP)	28 (FP)	91
37 (FN)	72 (TN)	109
100	100	200

Recall
= True Positive Rate (TPR)
= Sensitivity
= Hit Rate
= TP / (TP + FN)

Specificity
= True Negative Rate
= TN / N
= TN / (TN + FP)

TPR = 0.63

$$Recall = \frac{TP}{TP + FN}$$

$$True\ Negative\ Rate\ (\text{Specificity}) = \frac{TN}{TN + FP}$$

FPR = 0.28

$$\text{False}\ Positive\ Rate\ (1\text{-Specificity}) = \frac{FP}{FP + TN}$$

PPV = 0.69
=63/(63+28)
=63/91

$$Precision = \frac{TP}{TP + FP}$$

Precision
= Positive Predictive Value (PPV)

F1 = 0.66
= 2*(0.63*0.69)/(0.63+0.69)
= (2 * 63) /(100 + 91)
= (0.63 + 0.69) / 2 =1.32 / 2 =0.66

$$F = 2 * \frac{precision * recall}{precision + recall}$$

F1 score (F-score)
(F-measure)
is the harmonic mean of
precision and recall
= 2TP / (P + P')
= 2TP / (2TP + FP + FN)

ACC = 0.68
= (63 + 72) / 200
= 135/200 = 67.5

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Source: http://en.wikipedia.org/wiki/Receiver_operating_characteristic

A

63 (TP)	28 (FP)	91
37 (FN)	72 (TN)	109
100	100	200

TPR = 0.63

FPR = 0.28

PPV = 0.69
=63/(63+28)
=63/91

F1 = 0.66
= 2*(0.63*0.69)/(0.63+0.69)
= (2 * 63) /(100 + 91)
= (0.63 + 0.69) / 2 =1.32 / 2 =0.66

ACC = 0.68
= (63 + 72) / 200
= 135/200 = 67.5

B

77 (TP)	77 (FP)	154
23 (FN)	23 (TN)	46
100	100	200

TPR = 0.77

FPR = 0.77

PPV = 0.50

F1 = 0.61

ACC = 0.50

Recall
= True Positive Rate (TPR)
= Sensitivity
= Hit Rate

$$Recall = \frac{TP}{TP + FN}$$

Precision
= Positive Predictive Value (PPV)

$$Precision = \frac{TP}{TP + FP}$$

Source: http://en.wikipedia.org/wiki/Receiver_operating_characteristic

C

24 (TP)	88 (FP)	112
76 (FN)	12 (TN)	88
100	100	200

TPR = 0.24
FPR = 0.88
PPV = 0.21
F1 = 0.22
ACC = 0.18

C’

76 (TP)	12 (FP)	88
24 (FN)	88 (TN)	112
100	100	200

TPR = 0.76
FPR = 0.12
PPV = 0.86
F1 = 0.81
ACC = 0.82

Recall
= True Positive Rate (TPR)
= Sensitivity
= Hit Rate

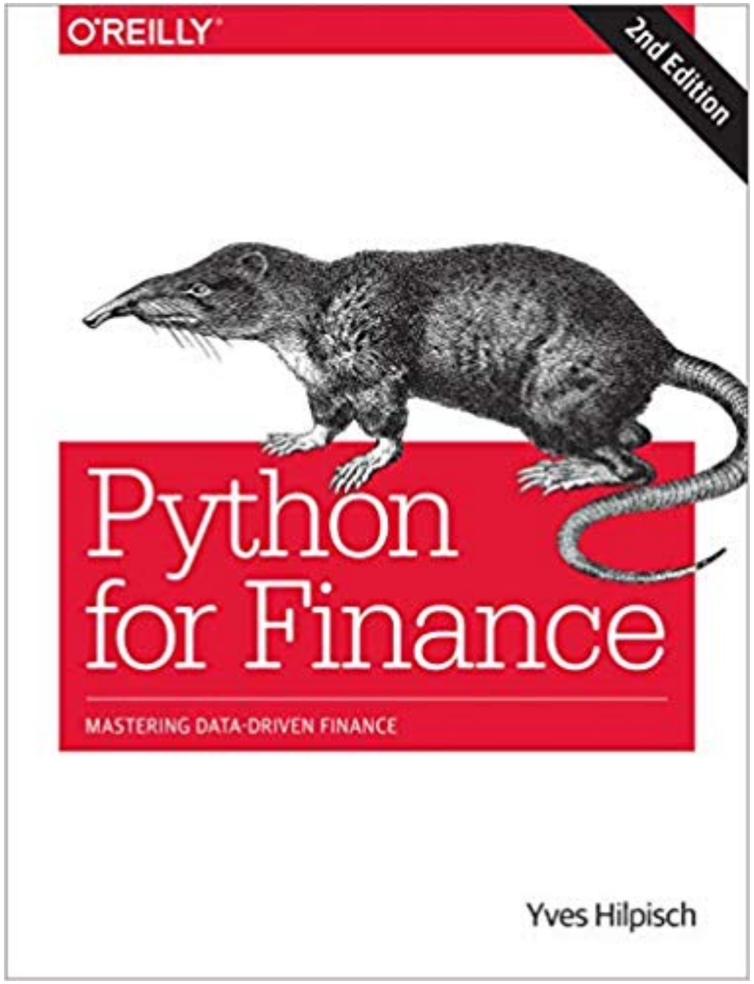
$$Recall = \frac{TP}{TP + FN}$$

Precision
= Positive Predictive Value (PPV)

$$Precision = \frac{TP}{TP + FP}$$

Source: http://en.wikipedia.org/wiki/Receiver_operating_characteristic

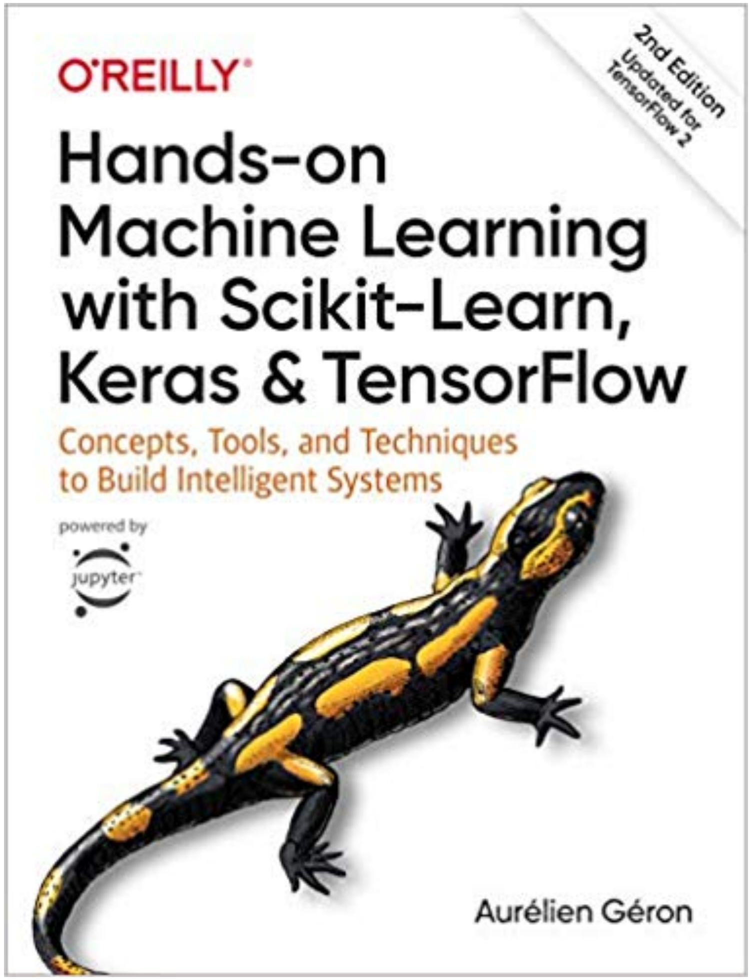
Yves Hilpisch (2018),
Python for Finance: Mastering Data-Driven Finance,
O'Reilly



https://github.com/yhilpisch/py4fi2nd

Source: https://www.amazon.com/Python-Finance-Mastering-Data-Driven/dp/1492024333

Aurélien Géron (2019),
Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems, 2nd Edition
O'Reilly Media, 2019



https://github.com/ageron/handson-ml2

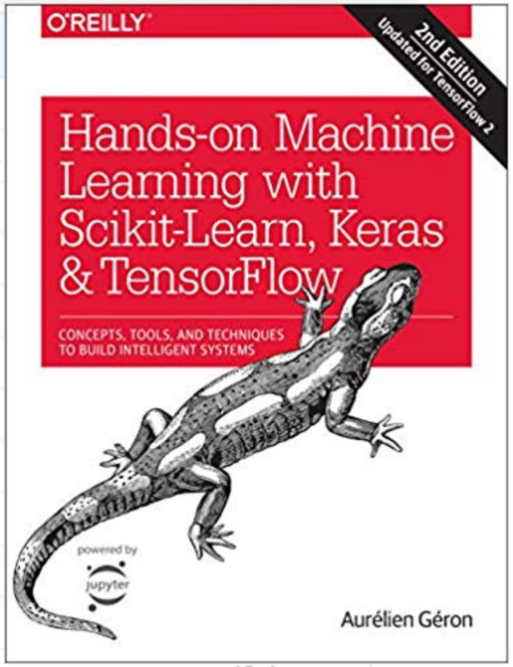
Source: https://www.amazon.com/Hands-Machine-Learning-Scikit-Learn-TensorFlow/dp/1492032646/

Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow

github.com/ageron/handson-ml2

ageron loss = metric * mean of sample weights, fixes #63

datasets	Fix vertical bars	
docker	Remove pyvirtualdisplay from environment.yml and add it to the Docker...	
images	Add breakout.gif	
work_in_progress	Remove from __future__ imports as we move away from Python 2	
.gitignore	Add jsb_chorales dataset to .gitignore	
01_the_machine_learning_landsca...	Fix typo on import urllib	
02_end_to_end_machine_learning_...	Make notebooks 1 to 9 runnable in Colab without changes	
03_classification.ipynb	Make notebooks 1 to 9 runnable in Colab without changes	
04_training_linear_models.ipynb	Make notebooks 1 to 9 runnable in Colab without changes	
05_support_vector_machines.ipynb	Make notebooks 1 to 9 runnable in Colab without changes	
06_decision_trees.ipynb	Make notebooks 1 to 9 runnable in Colab without changes	
07_ensemble_learning_and_rando...	Make notebooks 1 to 9 runnable in Colab without changes	13 days ago
08_dimensionality_reduction.ipynb	Make notebooks 1 to 9 runnable in Colab without changes	13 days ago
09_unsupervised_learning.ipynb	Make notebooks 1 to 9 runnable in Colab without changes	13 days ago
10_neural_nets_with_keras.ipynb	Make notebooks 10 and 11 runnable in Colab without changes	13 days ago
11_training_deep_neural_networks....	Make notebooks 10 and 11 runnable in Colab without changes	13 days ago
12_custom_models_and_training_...	loss = metric * mean of sample weights, fixes #63	6 days ago
13_loading_and_preprocessing_da...	Make notebook 13 runnable in Colab without changes	13 days ago
14_deep_computer_vision_with_cn...	Make notebooks 14 to 19 runnable in Colab without changes	13 days ago
15_processing_sequences_using_r...	Make notebooks 14 to 19 runnable in Colab without changes	13 days ago

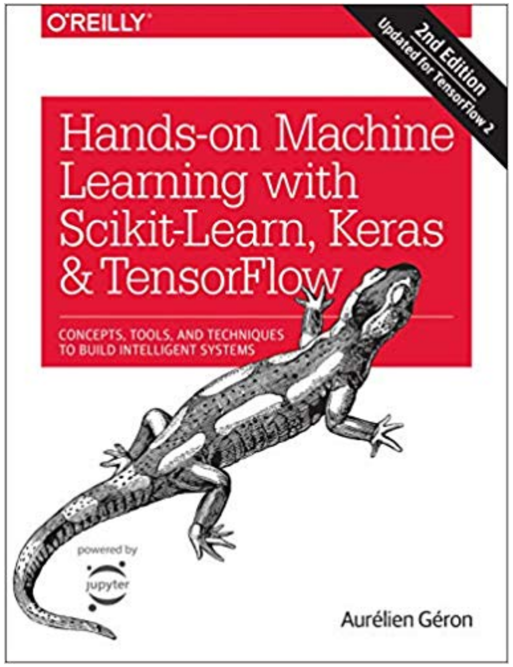


https://github.com/ageron/handson-ml2

Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow

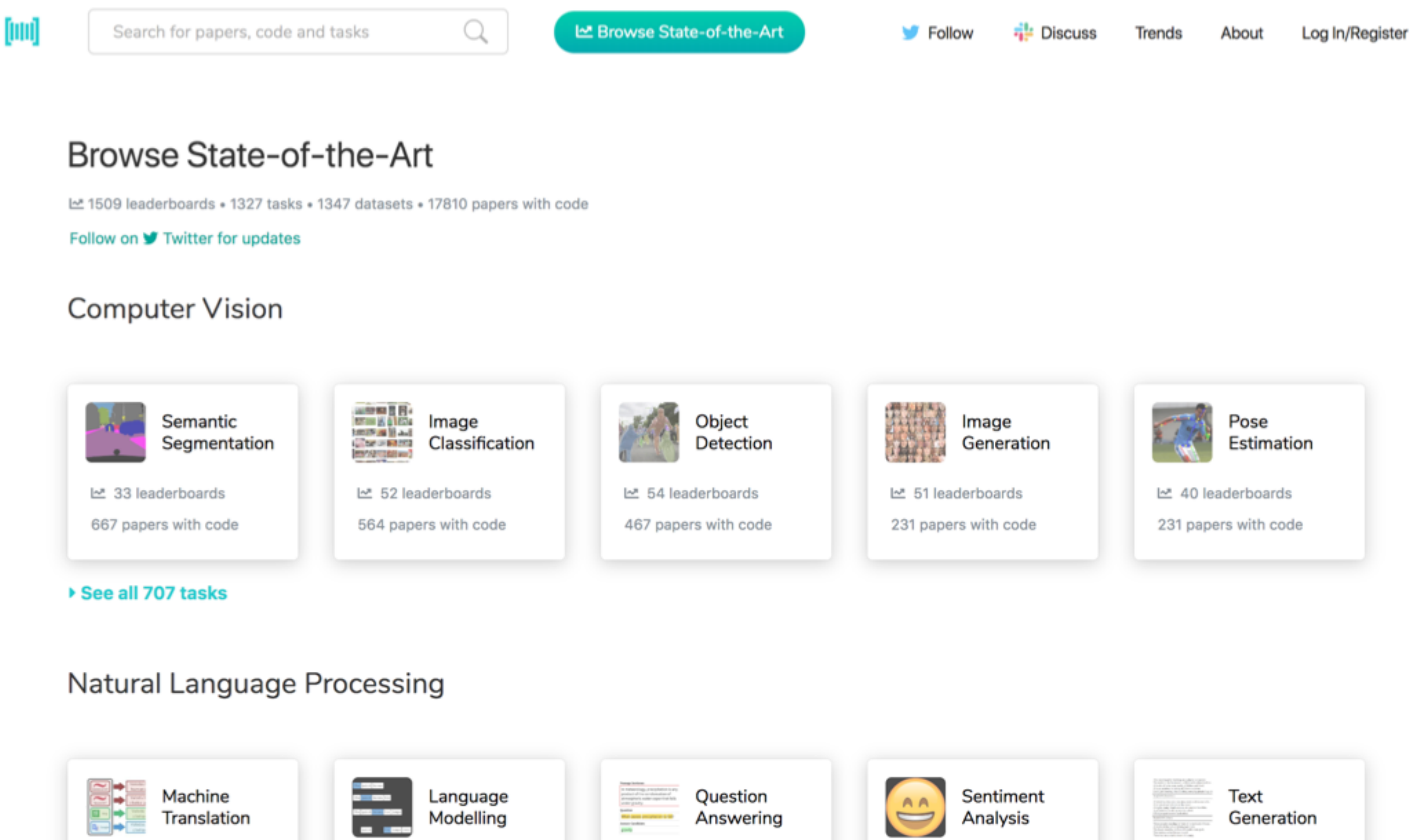
Notebooks

1. The Machine Learning landscape
2. End-to-end Machine Learning project
3. Classification
4. Training Models
5. Support Vector Machines
6. Decision Trees
7. Ensemble Learning and Random Forests
8. Dimensionality Reduction
9. Unsupervised Learning Techniques
10. Artificial Neural Nets with Keras
11. Training Deep Neural Networks
12. Custom Models and Training with TensorFlow
13. Loading and Preprocessing Data
14. Deep Computer Vision Using Convolutional Neural Networks
15. Processing Sequences Using RNNs and CNNs
16. Natural Language Processing with RNNs and Attention
17. Representation Learning Using Autoencoders
18. Reinforcement Learning
19. Training and Deploying TensorFlow Models at Scale



https://github.com/ageron/handson-ml2

Papers with Code
State-of-the-Art (SOTA)



https://paperswithcode.com/sota

Papers with Code
Stock Market Prediction

Browse > Time Series > Stock Market Prediction

Stock Market Prediction

6 papers with code · Time Series

Leaderboards

No evaluation results yet. Help compare methods by submit evaluation metrics.

Subtasks

Stock Price Prediction

3 papers with code

Stock Trend Prediction

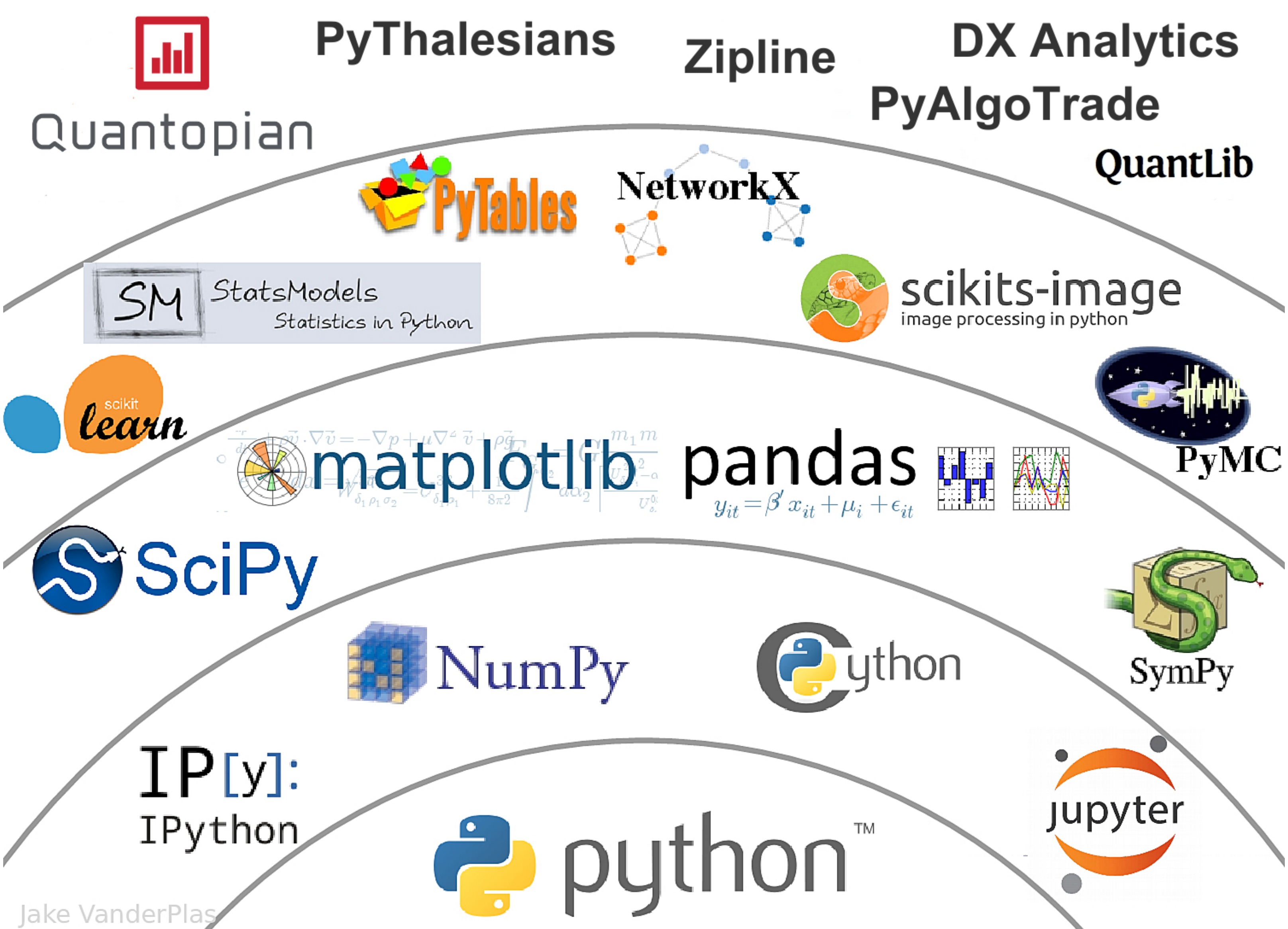
2 papers with code

Stock Prediction

1 papers with code

https://paperswithcode.com/task/stock-market-prediction

The Quant Finance PyData Stack



Source: http://nbviewer.jupyter.org/format/slides/github/quantopian/pyfolio/blob/master/pyfolio/examples/overview_slides.ipynb#/5

Summary

- Machine Learning with Scikit-Learn in Python
  - Machine Learning
  - Scikit-Learn

References

- Aurélien Géron (2019), Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems, 2nd Edition, O'Reilly Media, 2019, https://github.com/ageron/handson-ml2
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