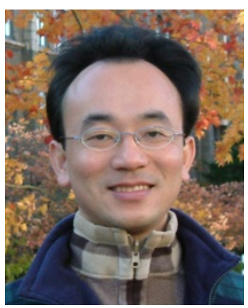
人工智慧
(Artificial Intelligence)
學習理論與綜合學習
(The Theory of Learning and Ensemble Learning)

1092AI07

MBA, IM, NTPU (M5010) (Spring 2021)

Wed 2, 3, 4 (9:10-12:00) (B8F40)



Min-Yuh Day

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https://web.ntpu.edu.tw/~myday

2021-04-28

課程大綱 (Syllabus)

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

1 2021/02/24 人工智慧概論
(Introduction to Artificial Intelligence)

2 2021/03/03 人工智慧和智慧代理人
(Artificial Intelligence and Intelligent Agents)

3 2021/03/10 問題解決
(Problem Solving)

4 2021/03/17 知識推理和知識表達
(Knowledge, Reasoning and Knowledge Representation)

5 2021/03/24 不確定知識和推理
(Uncertain Knowledge and Reasoning)

6 2021/03/31 人工智慧個案研究 I
(Case Study on Artificial Intelligence I)

課程大綱 (Syllabus)

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

7 2021/04/07 放假一天 (Day off)

8 2021/04/14 機器學習與監督式學習
(Machine Learning and Supervised Learning)

9 2021/04/21 期中報告
(Midterm Project Report)

10 2021/04/28 學習理論與綜合學習
(The Theory of Learning and Ensemble Learning)

11 2021/05/05 深度學習
(Deep Learning)

12 2021/05/12 人工智慧個案研究 II
(Case Study on Artificial Intelligence II)

課程大綱 (Syllabus)

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

13　2021/05/19　強化學習 (Reinforcement Learning)

14　2021/05/26　深度學習自然語言處理 (Deep Learning for Natural Language Processing)

15　2021/06/02　機器人技術 (Robotics)

16　2021/06/09　人工智慧哲學與倫理，人工智慧的未來 (Philosophy and Ethics of AI, The Future of AI)

17　2021/06/16　期末報告 I (Final Project Report I)

18　2021/06/23　期末報告 II (Final Project Report II)

The Theory of Learning and Ensemble Learning

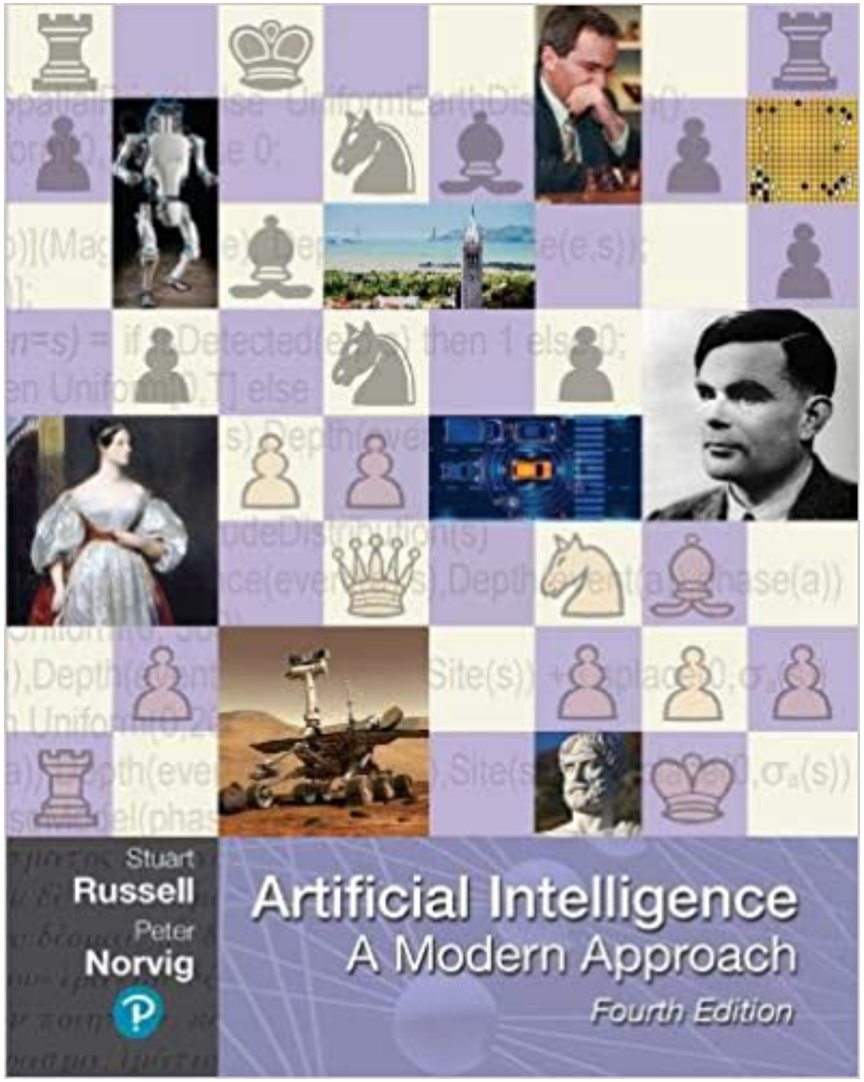
Outline

- The Theory of Learning
- Ensemble Learning

Stuart Russell and Peter Norvig (2020),

Artificial Intelligence: A Modern Approach,

4th Edition, Pearson



Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

https://www.amazon.com/Artificial-Intelligence-A-Modern-Approach/dp/0134610997/

Artificial Intelligence: A Modern Approach

1. Artificial Intelligence
2. Problem Solving
3. Knowledge and Reasoning
4. Uncertain Knowledge and Reasoning
5. Machine Learning
6. Communicating, Perceiving, and Acting
7. Philosophy and Ethics of AI

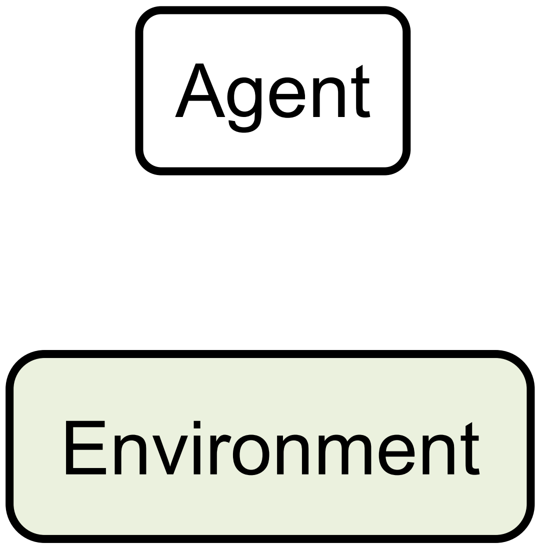
Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

Artificial Intelligence:
Machine Learning

Artificial Intelligence: 5. Machine Learning

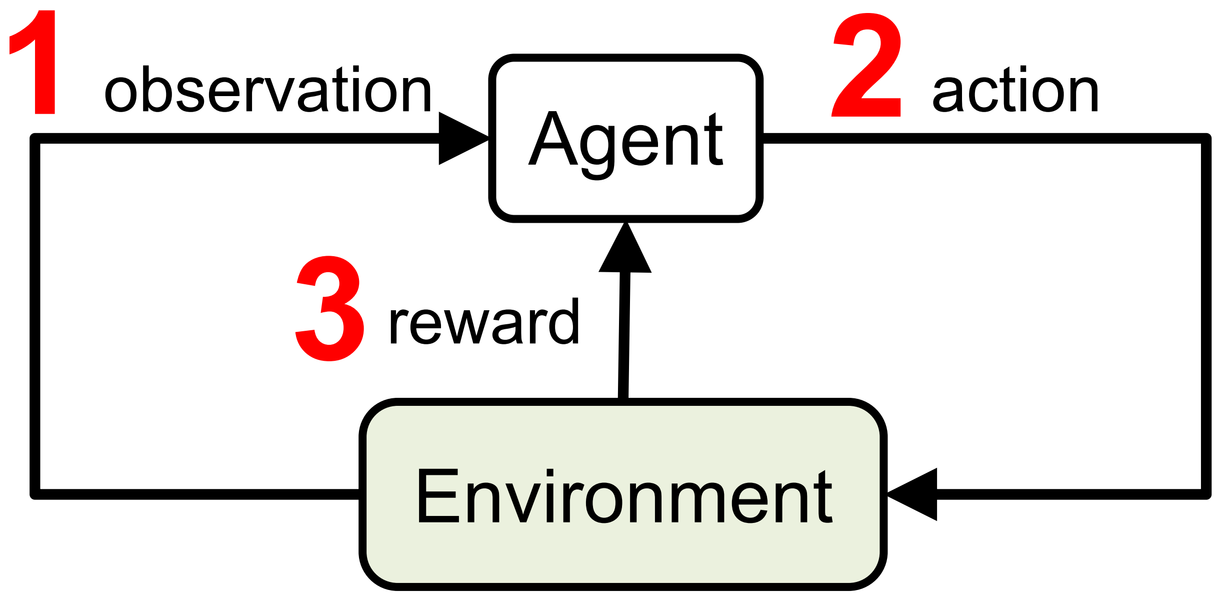
- Learning from Examples
- Learning Probabilistic Models
- Deep Learning
- Reinforcement Learning

Reinforcement Learning (DL)



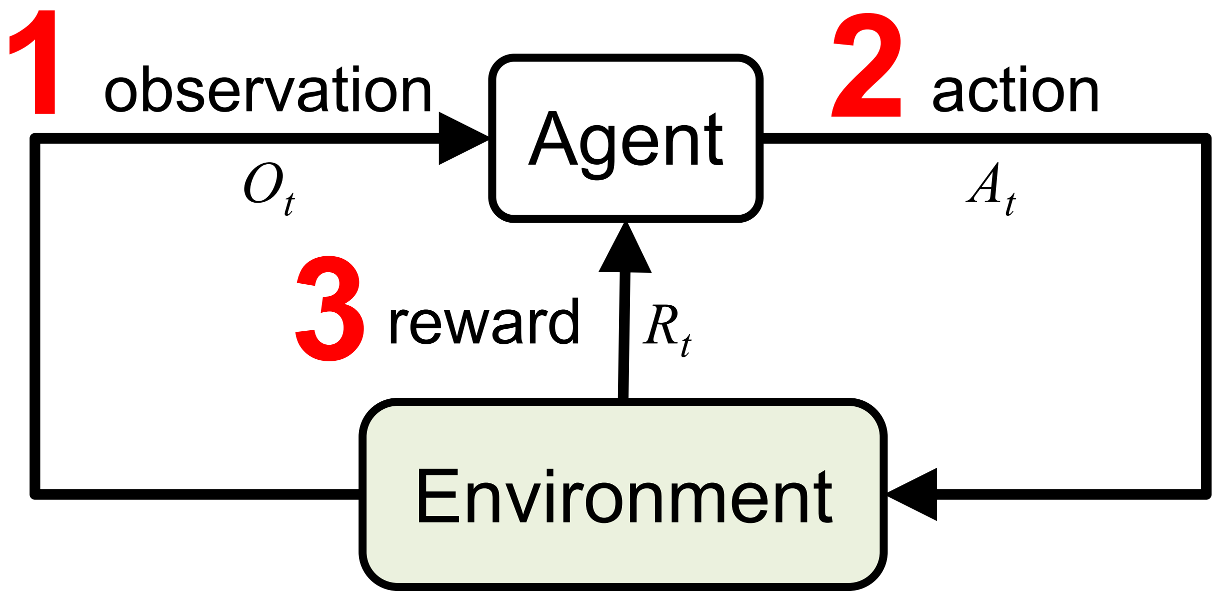
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford

Reinforcement Learning (DL)



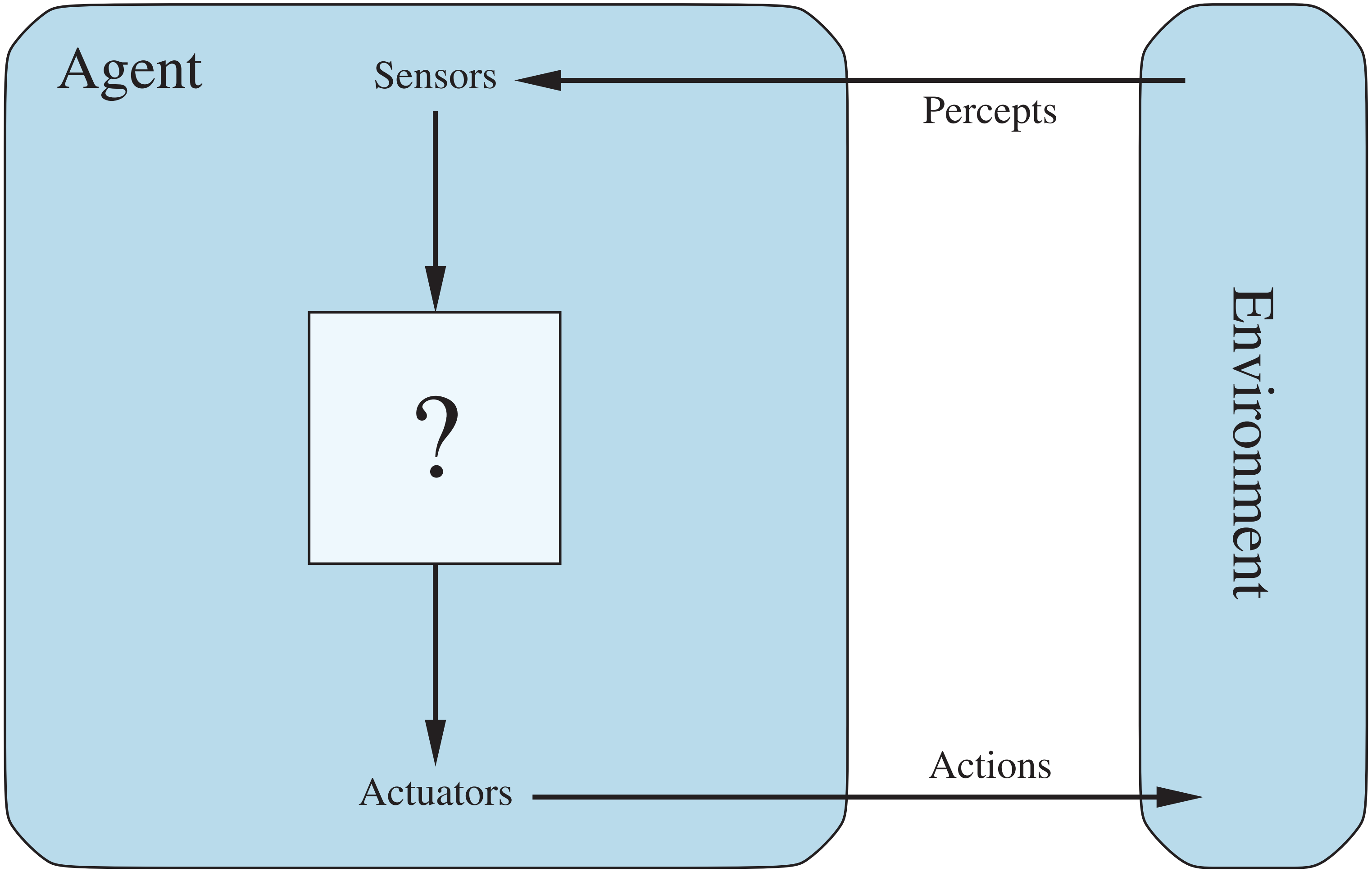
Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford

Reinforcement Learning (DL)



Source: Richard S. Sutton & Andrew G. Barto (2018), Reinforcement Learning: An Introduction, 2nd Edition, A Bradford

Agents interact with environments through sensors and actuators



Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

Machine Learning
Supervised Learning (Classification)
Learning from Examples

$$y = f(x)$$

x	y

Machine Learning
Supervised Learning (Classification)
Learning from Examples

$$y = f(x)$$

x

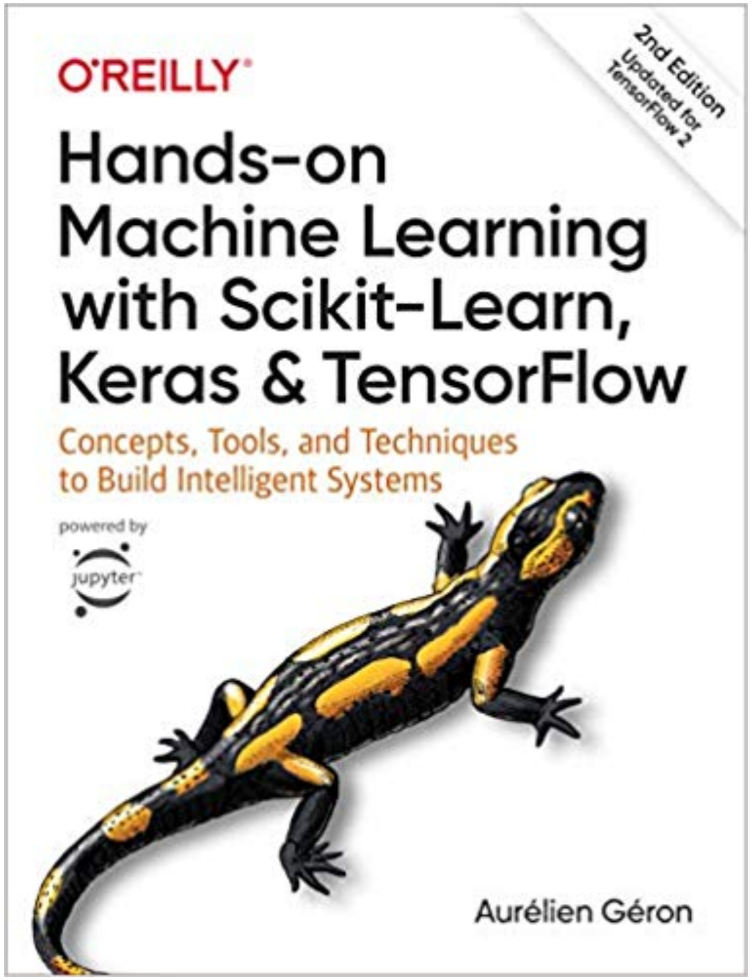
```
5.1,3.5,1.4,0.2,Iris-setosa
4.9,3.0,1.4,0.2,Iris-setosa
4.7,3.2,1.3,0.2,Iris-setosa
7.0,3.2,4.7,1.4,Iris-versicolor
6.4,3.2,4.5,1.5,Iris-versicolor
6.9,3.1,4.9,1.5,Iris-versicolor
6.3,3.3,6.0,2.5,Iris-virginica
5.8,2.7,5.1,1.9,Iris-virginica
7.1,3.0,5.9,2.1,Iris-virginica
```

y

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



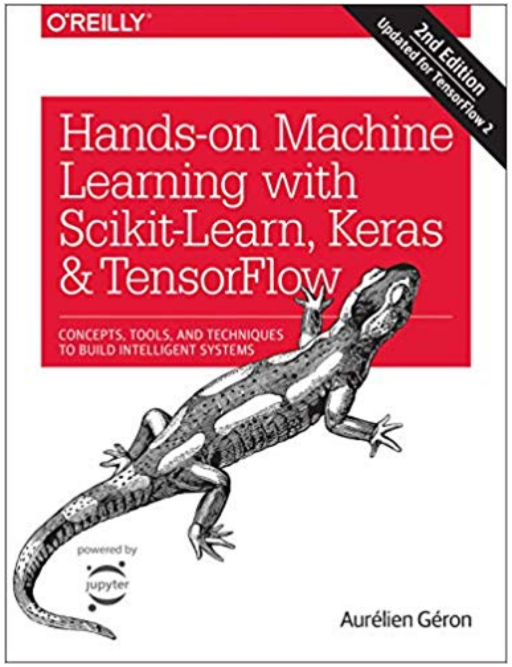
https://github.com/ageron/handson-ml2

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

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

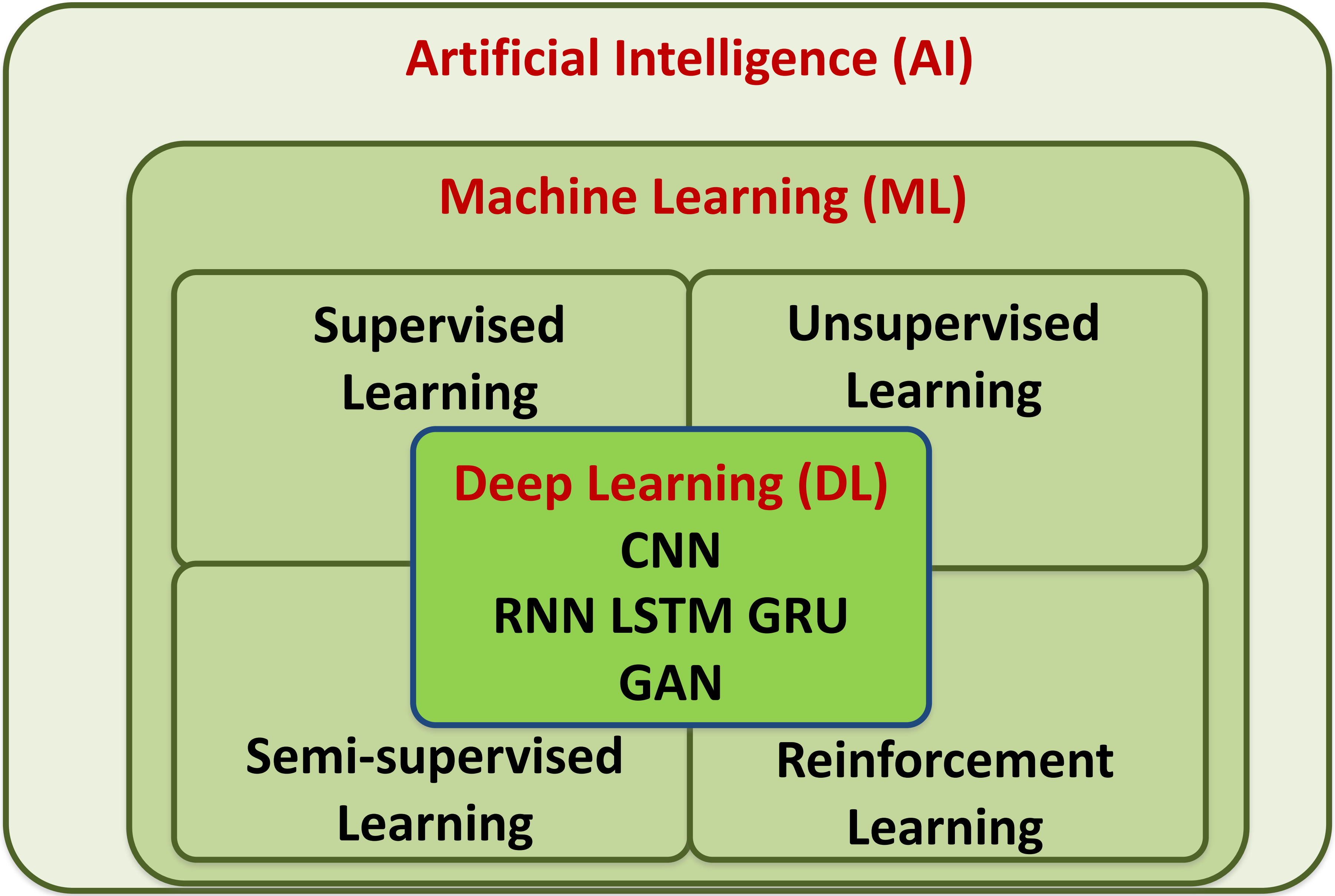
Notebooks

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

AI, ML, DL



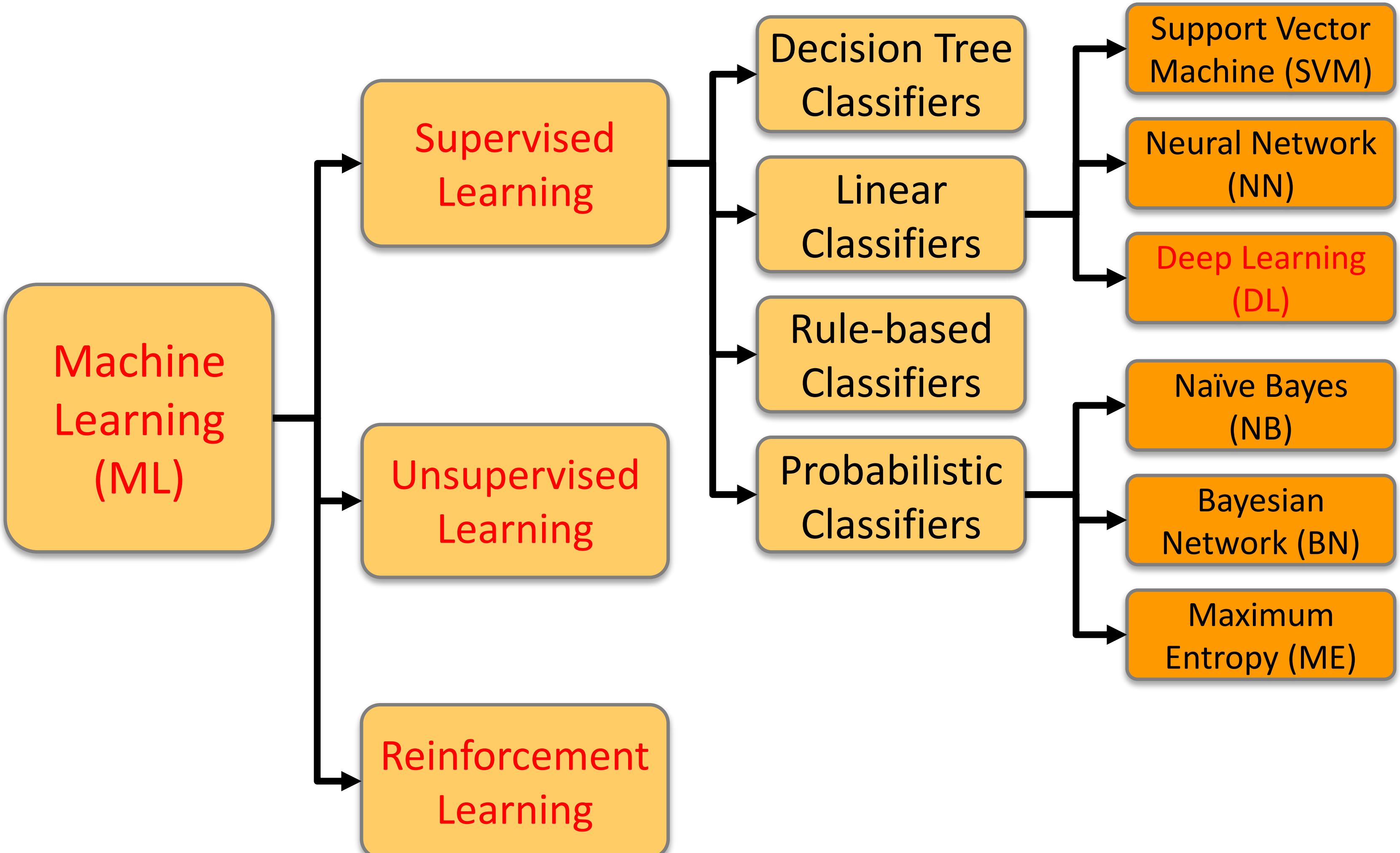
Source: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/deep_learning.html

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.

The
The Theory of Learning

The Theory of Learning

- Computational Learning Theory
- Probably approximately correct (PAC)

Computational Learning Theory

- Intersection of AI, statistics, and theoretical computer science.
- Any hypothesis that is seriously wrong will almost certainly be "found out" with high probability after a small number of examples.

Probably approximately correct (PAC)

- Any hypothesis that is consistent with a sufficiently large set of training examples is unlikely to be seriously wrong.
- PAC learning algorithm:
  - Any learning algorithm that returns hypotheses that are probably approximately correct

Linear function

$$y = f(x)$$

$$y = w_1 x + w_0$$

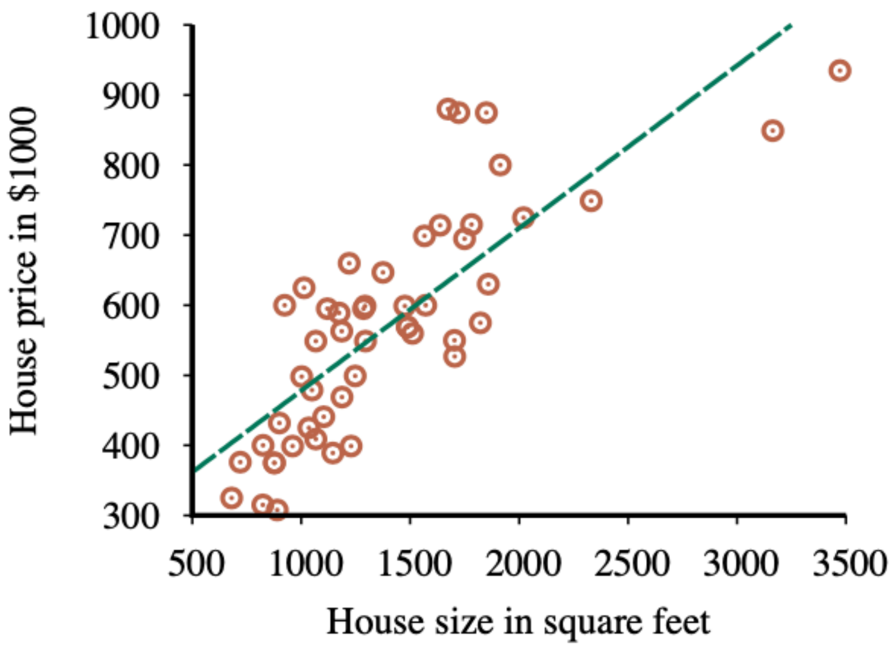
$$h_w(x) = w_1 x + w_0$$

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

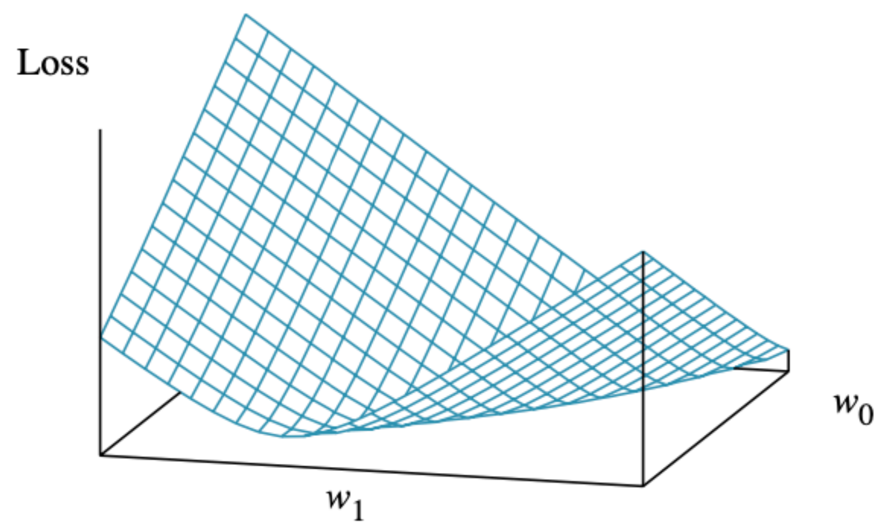
Linear Regression Weight Space

$$h_w(x) = w_1 x + w_0$$

$$w^* = \text{argmin}_w \, Loss(h_w)$$



$y = 0.232\, x + 246$



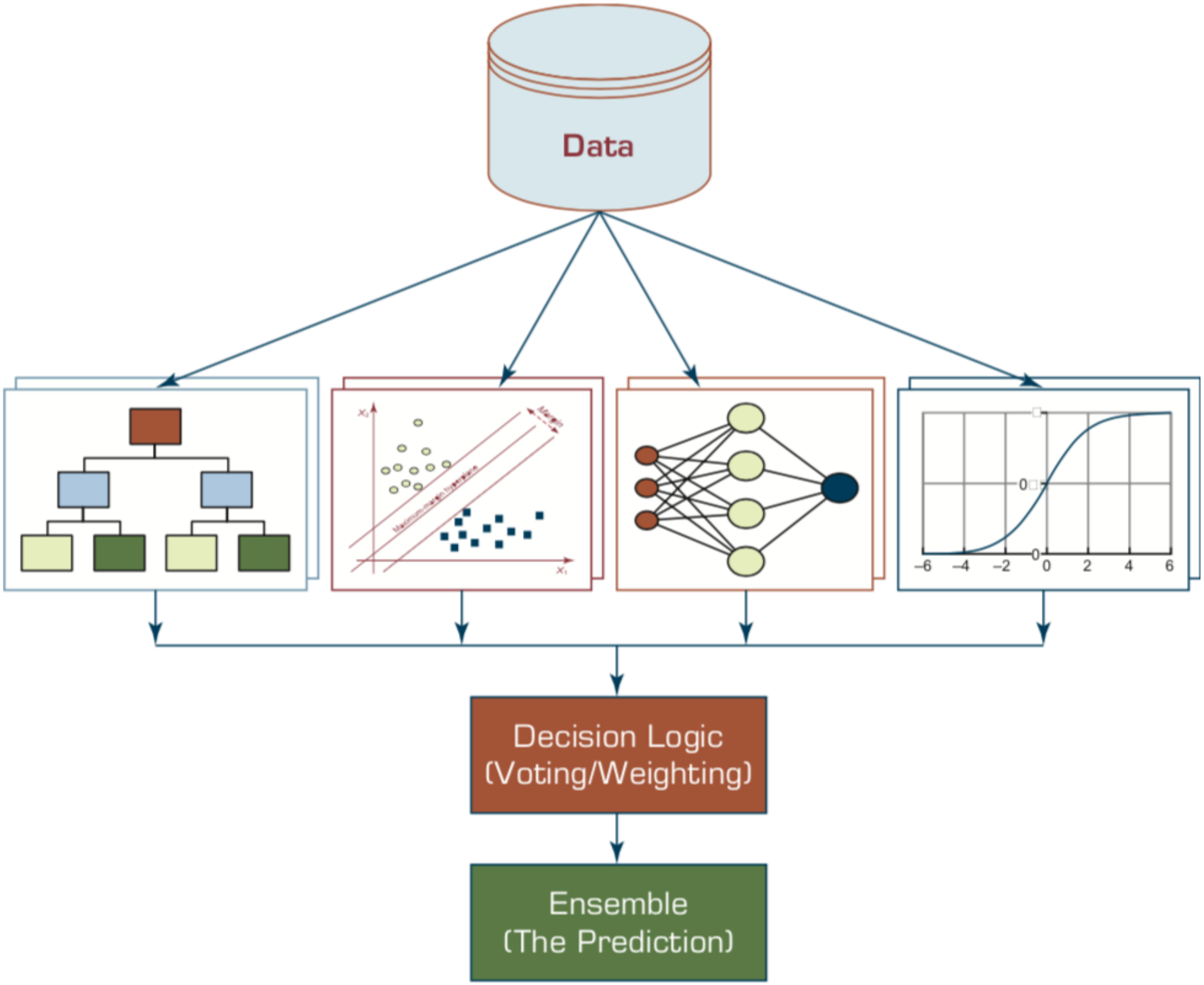
Loss function for Weights (w_1, w_0)

Ensemble Learning

Ensemble Learning

- Select a collection, or ensemble, of hypotheses, $h_1, h_2, \ldots, h_n$
, and combine their predictions by averaging, voting, or by another level of machine learning.

Ensemble Models
Heterogeneous Ensemble



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

Ensemble Learning

- Base model
  - individual hypotheses
  - $h_1, h_2, \ldots, h_n$
- Ensemble model
  - hypotheses combination

Why Ensemble Learning

- Reduce bias
- Reduce variance

Ensemble Learning

- Bagging
- Random forests
- Stacking
- Boosting
- Gradient boosting
- Online learning

Ensemble Learning: Bagging

- Bagging
  - Generate distinct training sets by sampling with replacement from the original training set.
- Classification:
  - Plurality Vote (Majority Vote)
- Regression:
  - Average

Ensemble Learning: Random forests

- Random forest model is a form of decision tree bagging in which we take extra steps to make the ensemble of trees more diverse, to reduce variance.
- The key idea is to randomly vary the attribute choices (rather than the training examples)

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

Ensemble Learning: Random forests

- Extremely randomized trees (ExtraTrees)
  - Use randomness in selecting the split point value
  - for each selected attribute, we randomly sample several candidate values from a uniform distribution over the attribute's range

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

Ensemble Learning: Stacking

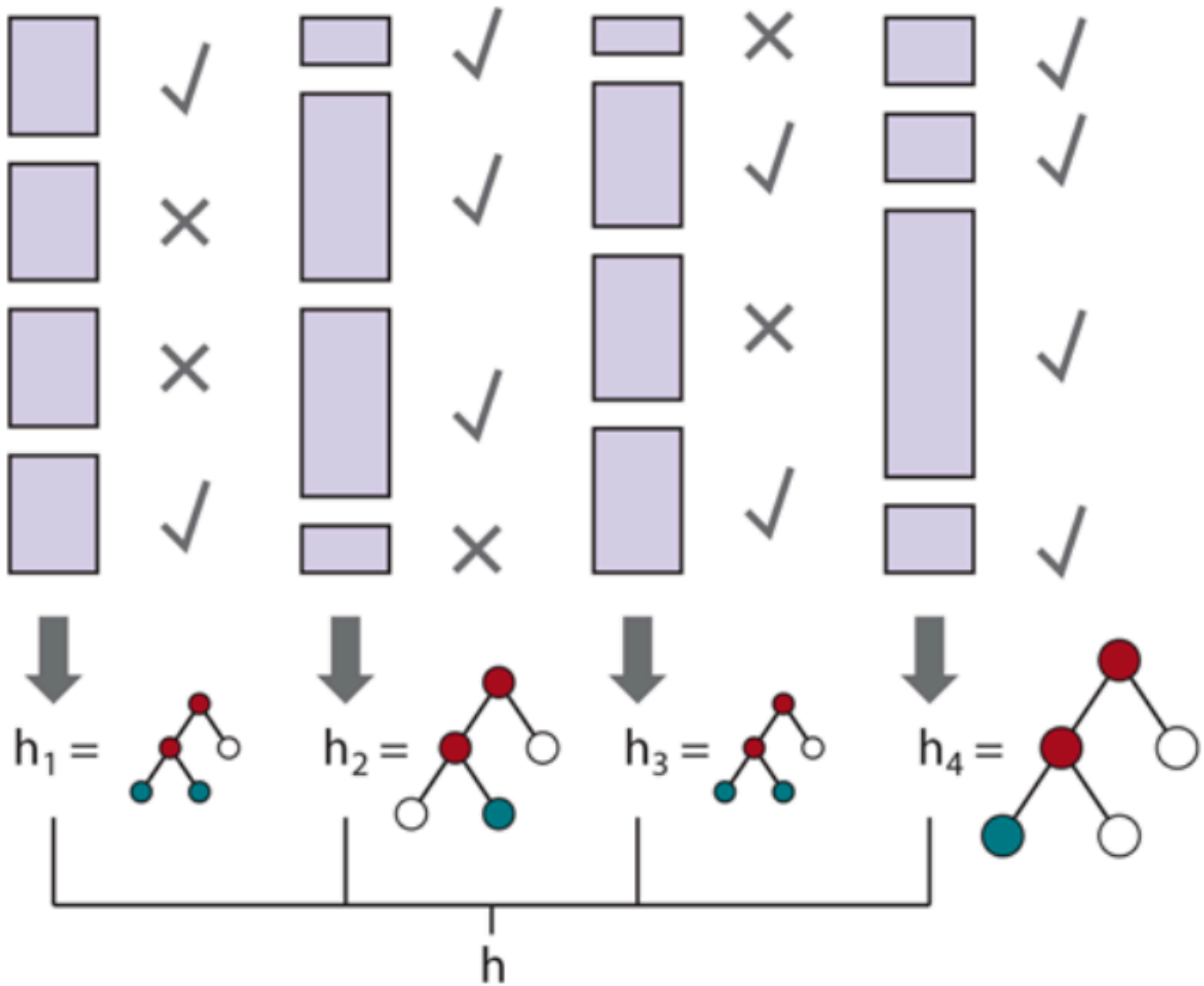
- **Staking**
  - Stacked generalization combines multiple base models from different model classes trained on the same data.
- Bagging
  - Combines multiple base models of the same model class trained on different data.

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

Ensemble Learning: Boosting

- Boosting
  - The most popular ensemble method
- Weighted training set

Ensemble Learning: Boosting



Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

Ensemble Learning: Gradient boosting

- Gradient boosting
  - Gradient boosting is a form of boosting using gradient descent
- Gradient boosting machines (GBM)
- Gradient boosted regression trees (GBRT)
- Popular method for regression and classification of factored tabular data

Source: Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson

Ensemble Learning: Online learning

- Online learning
  - Data are not i.i.d. (independent and identically distributed)
  - An agent receives an input x_i from nature, predicts the corresponding y_i and then is told the correct answer.

Machine Learning: Ensemble Learning Random Forest

python101.ipynb

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Table of contents

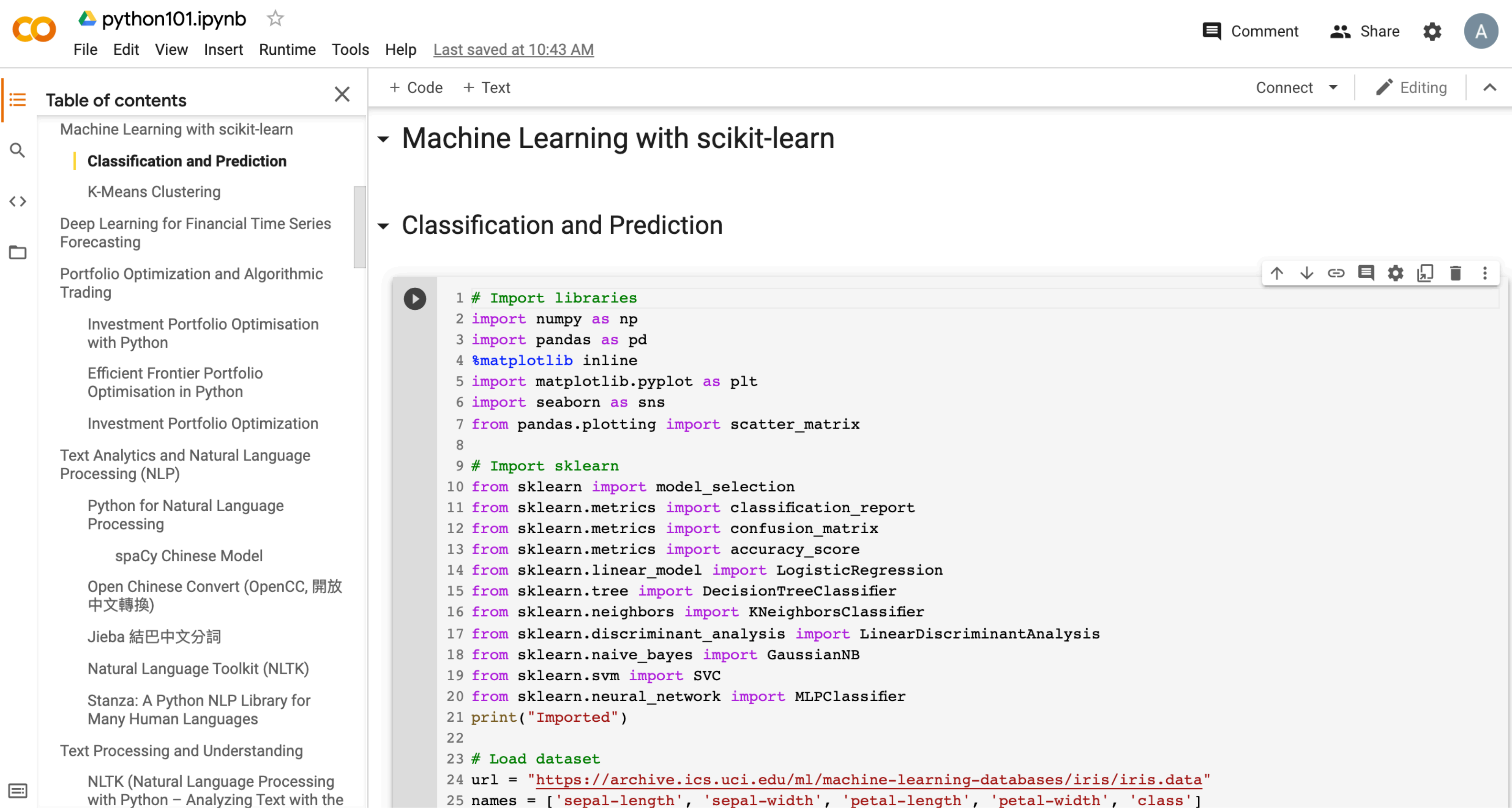
+ Code + Text RAM Disk Editing

Random Forest

```python
# Randon Forest: https://chrisalbon.com/machine_learning/trees_and_forests/random_forest_classifier_e
# Load the library with the iris dataset
from sklearn.datasets import load_iris

# Load scikit's random forest classifier library
from sklearn.ensemble import RandomForestClassifier

# Load pandas
import pandas as pd

# Load numpy
import numpy as np

# Set random seed
np.random.seed(0)

# Create an object called iris with the iris data
iris = load_iris()

# Create a dataframe with the four feature variables
df = pd.DataFrame(iris.data, columns=iris.feature_names)

# View the top 5 rows
df.head()

# Add a new column with the species names, this is what we are going to try to predict
df['species'] = pd.Categorical.from_codes(iris.target, iris.target_names)

```

https://tinyurl.com/aintpupython101

Machine Learning: Supervised Learning
Classification and Prediction



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
```

https://tinyurl.com/aintpupython101

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   sepal-length  sepal-width  petal-length  petal-width        class
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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
```

https://tinyurl.com/aintpupython101

df.corr()

```
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

https://tinyurl.com/aintpupython101

```
# 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
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models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
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    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')
```

https://tinyurl.com/aintpupython101

```
# 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)
```

https://tinyurl.com/aintpupython101

```
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)
```

https://tinyurl.com/aintpupython101

```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')
```

https://tinyurl.com/aintpupython101

```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)
```

https://tinyurl.com/aintpupython101

```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)
```

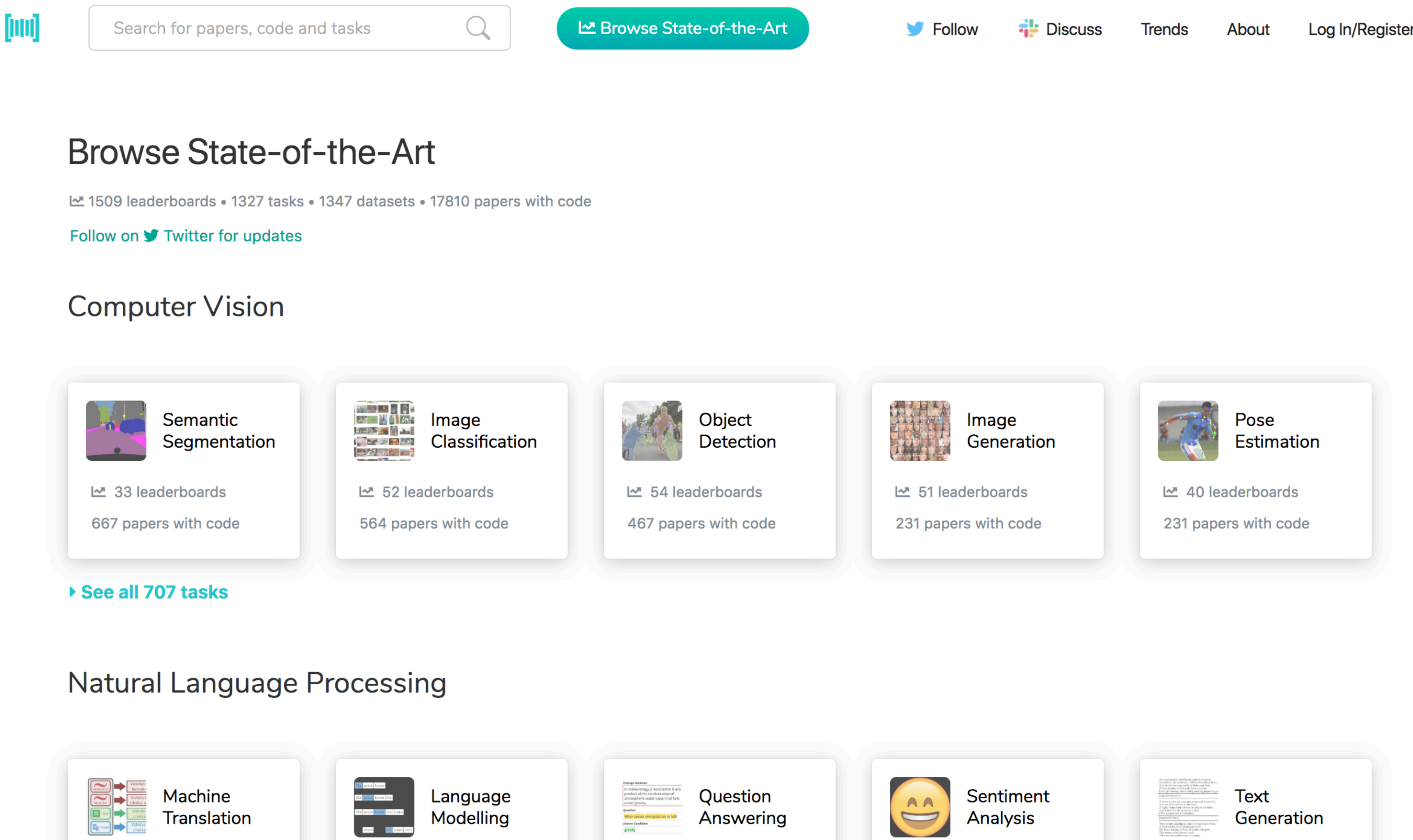
https://tinyurl.com/aintpupython101

```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)
```

https://tinyurl.com/aintpupython101

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

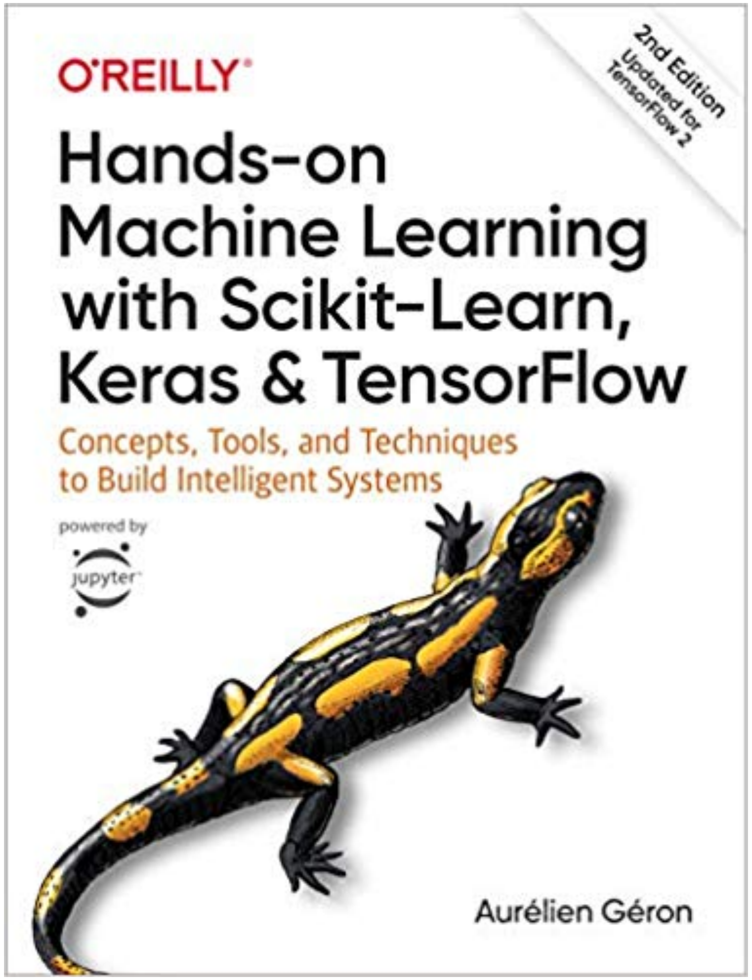


https://paperswithcode.com/sota

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



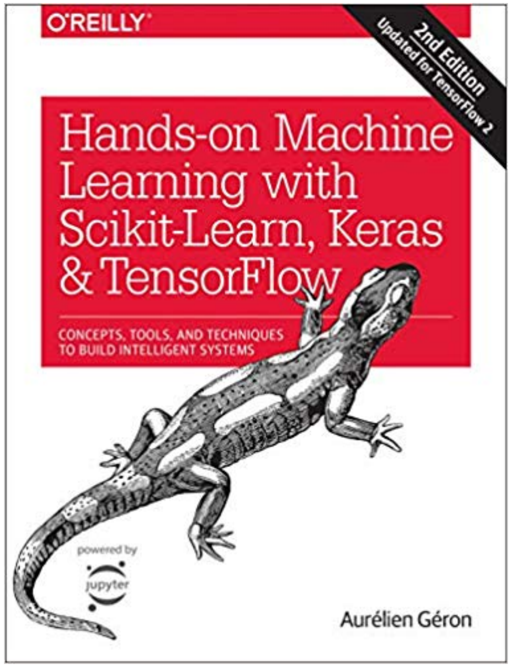
https://github.com/ageron/handson-ml2

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

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

Notebooks

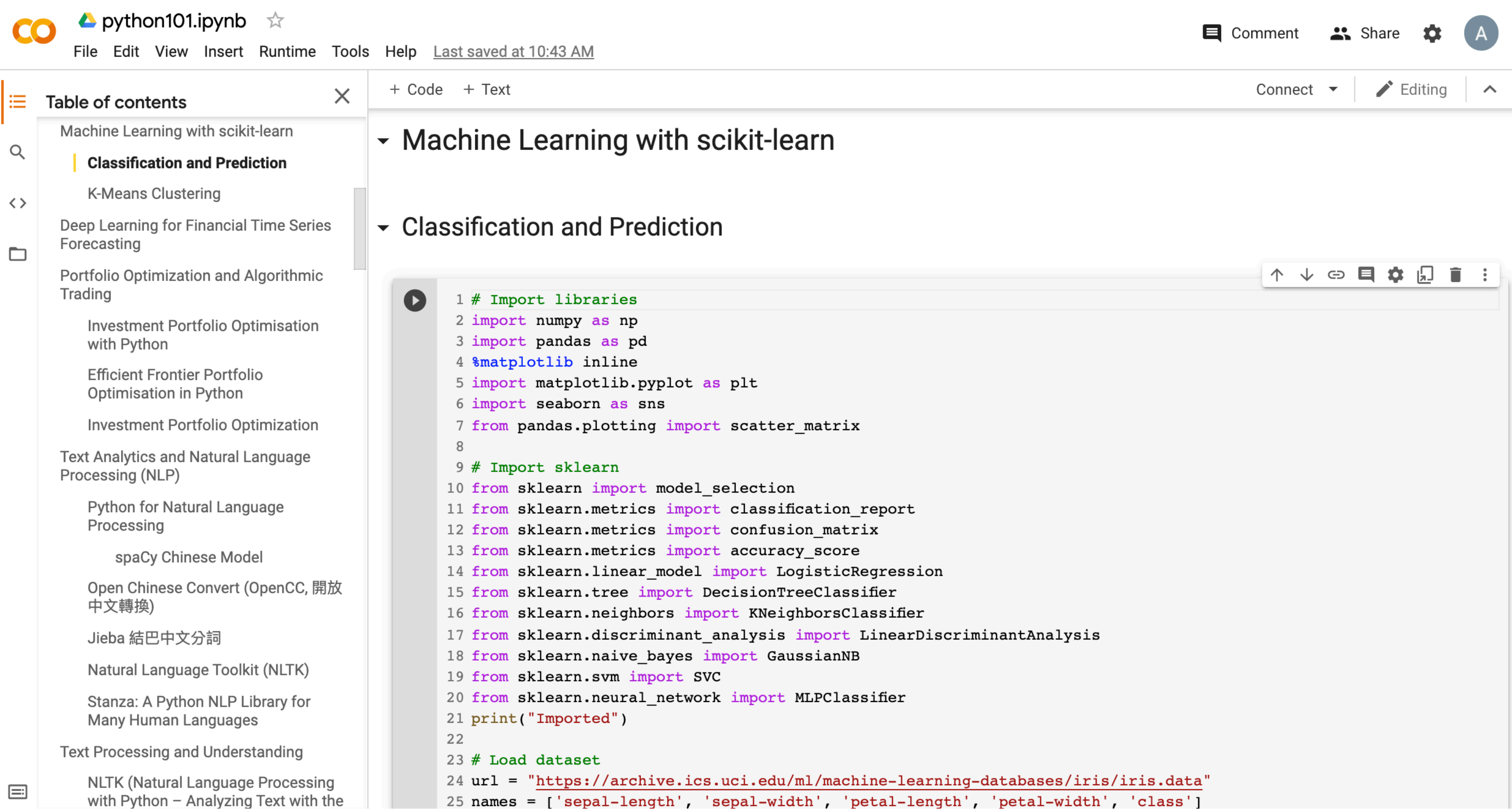
1. The Machine Learning landscape
2. End-to-end Machine Learning project
3. Classification
4. Training Models
5. Support Vector Machines
6. Decision Trees
7. Ensemble Learning and Random Forests
8. Dimensionality Reduction
9. Unsupervised Learning Techniques
10. Artificial Neural Nets with Keras
11. 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

Python in Google Colab (Python101)

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



https://tinyurl.com/aintpupython101

Summary

- **The Theory of Learning**
- **Ensemble Learning**

References

- Stuart Russell and Peter Norvig (2020), Artificial Intelligence: A Modern Approach, 4th Edition, Pearson.
- 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.