Machine Learning and Scikit Learn Introduction

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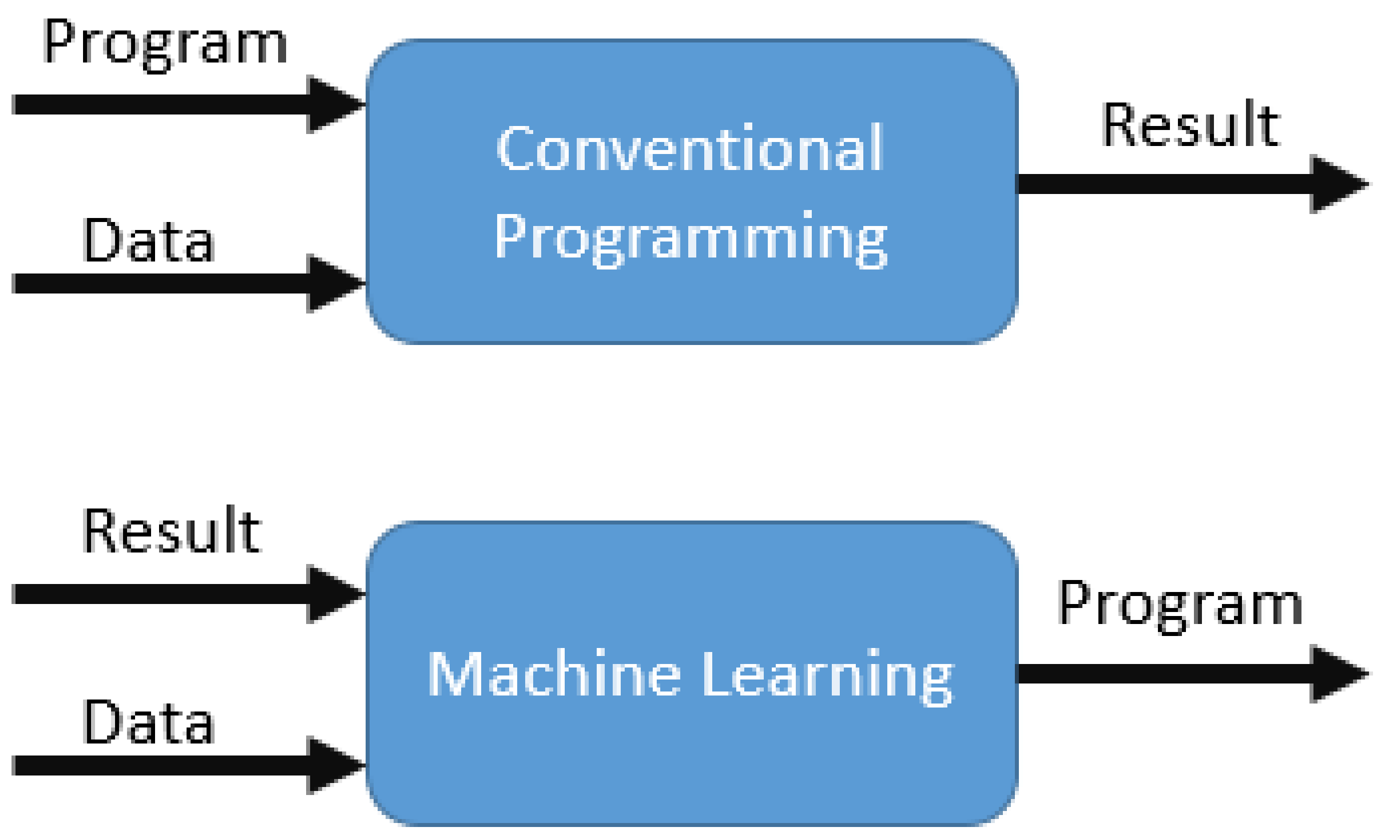
Machine Learning

Machine learning (ML) is a category of an algorithm that allows software applications to become more accurate in predicting outcomes without being explicitly programmed.



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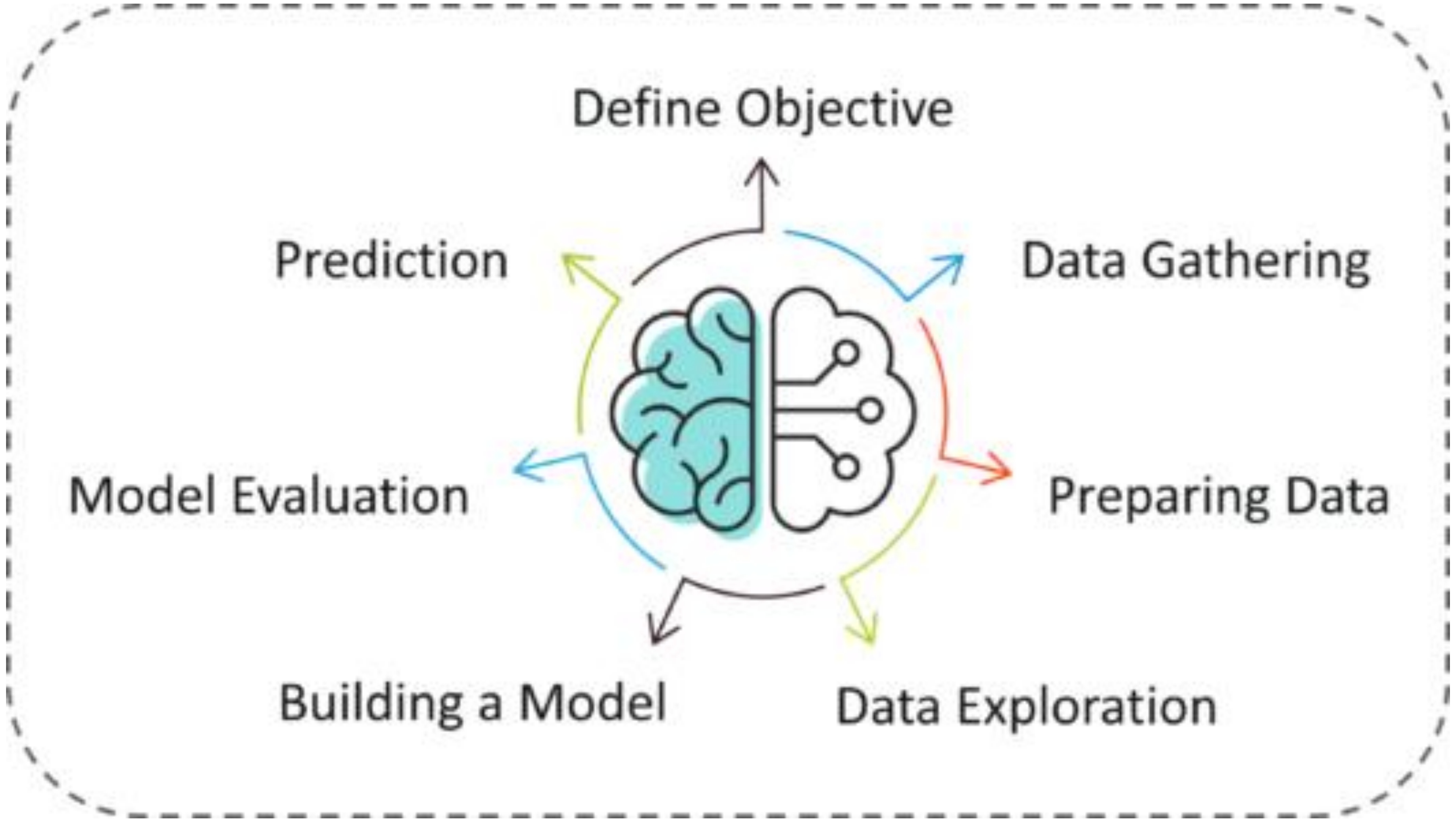
Machine Learning Process

The craft of creating machine learning (ML) processes is comprised of a number of steps:



https://www.edureka.co/blog/introduction-to-machine-learning/

Machine Learning Process

1.Decide on the Question

Most ML processes start by asking a question that cannot be answered by a simple conditional program or rules-based engine. These questions often revolve around predictions based on a collection of data. At this step we must understand what exactly needs to be predicted

2. Collecting Data

To be able to answer your question, you need data. The quality and, sometimes, quantity of your data will determine how well you can answer your initial question. Data collection can be done manually or by web scraping. However, if you're a beginner and you're just looking to learn Machine Learning you don't have to worry about getting the data. There are lots of data resources on the web, you can just download the data set and get going.

Machine Learning Process

3. Data Preparation

The data you collected is almost never in the right format. You will encounter a lot of inconsistencies in the data set such as missing values, redundant variables, duplicate values, etc. Removing such inconsistencies is very essential because they might lead to wrongful computations and predictions. Therefore, at this stage, you scan the data set for any inconsistencies and you fix them then and there

4. Exploratory Data Analysis

This is the brainstorming stage of Machine Learning. Data Exploration involves understanding the patterns and trends in the data. At this stage, all the useful insights are drawn and correlations between the variables are understood. Visualizing data is an important aspect of this phase.

Machine Learning Process

5. Building ML model

This stage always begins by splitting the data set into two parts, training and testing data. Choosing the right algorithm depends on the type of problem you're trying to solve, the data set and the complexity of the problem. The model is built from training process where we pass data and the machine will find patterns to make predictions. Over time, with training, the model gets better at predicting.

6. Evaluate and optimize the model

Evaluate and optimize the model. After training, we have to check the model to see how it's performing. This is done by testing the performance of the model on previously unseen data (testing data)

Machine Learning Process

7. Parameter tuning

Based on the performance of your model, you can redo the process using different parameters, or variables, that control the behavior of the algorithms used to train the model.

8. Predict

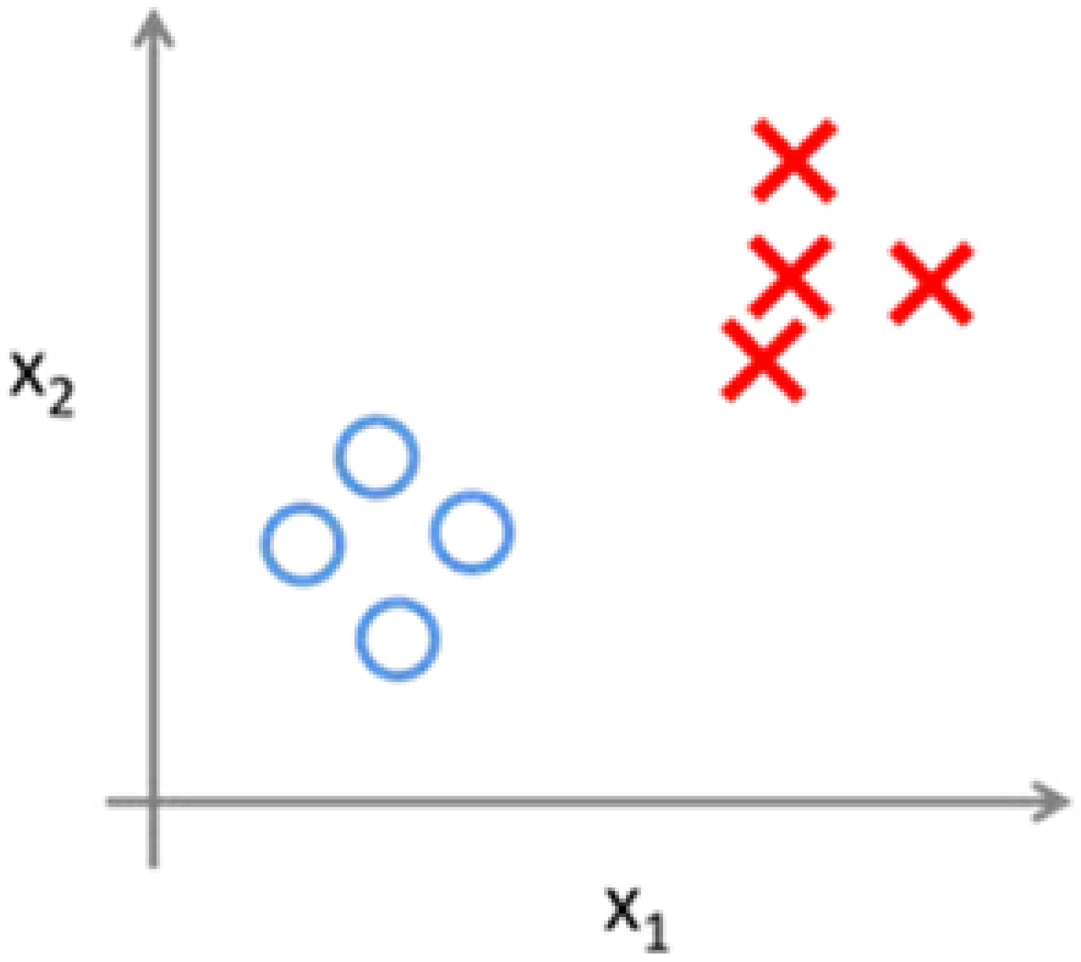
Use new inputs to test the accuracy of your model.

Machine Learning Types

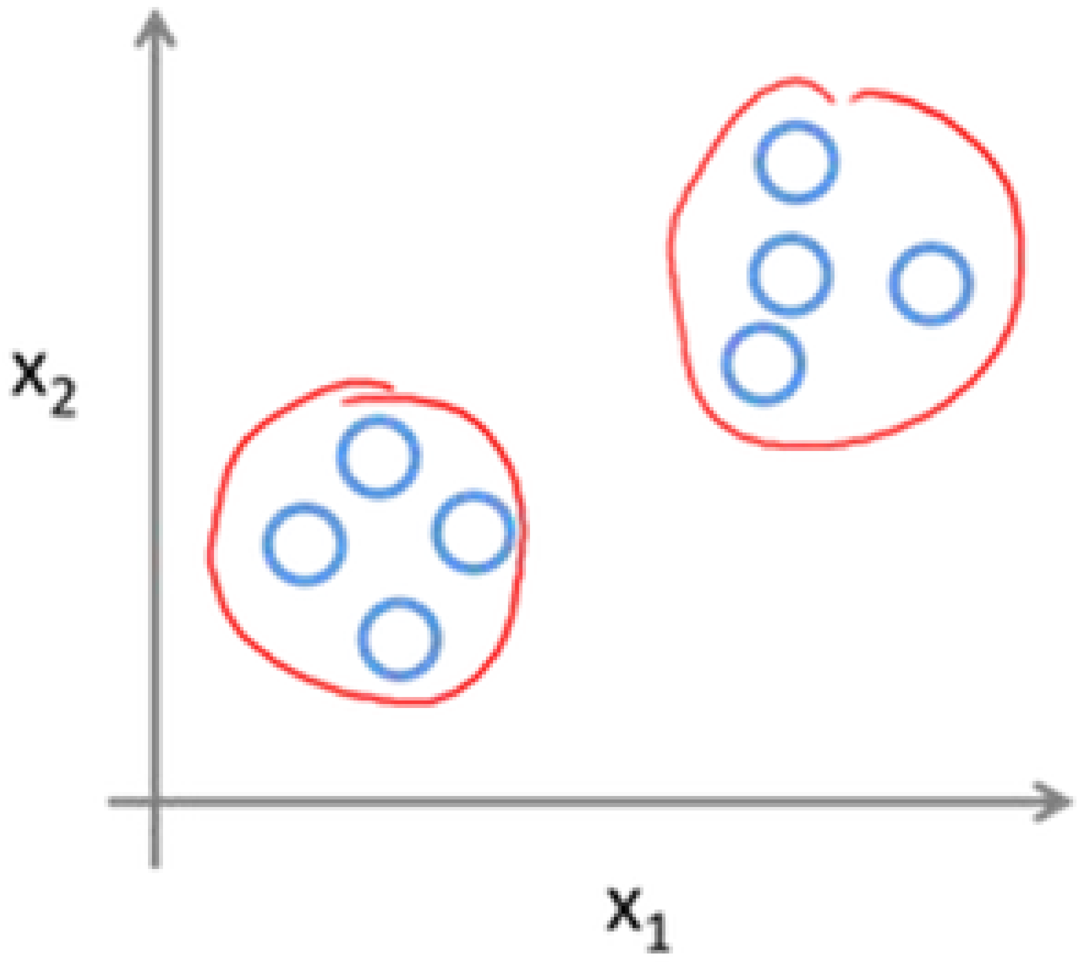
A machine can learn to solve a problem by following any one of the following three approaches. These are the ways in which a machine can learn:

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

Supervised vs Unsupervised



Supervised



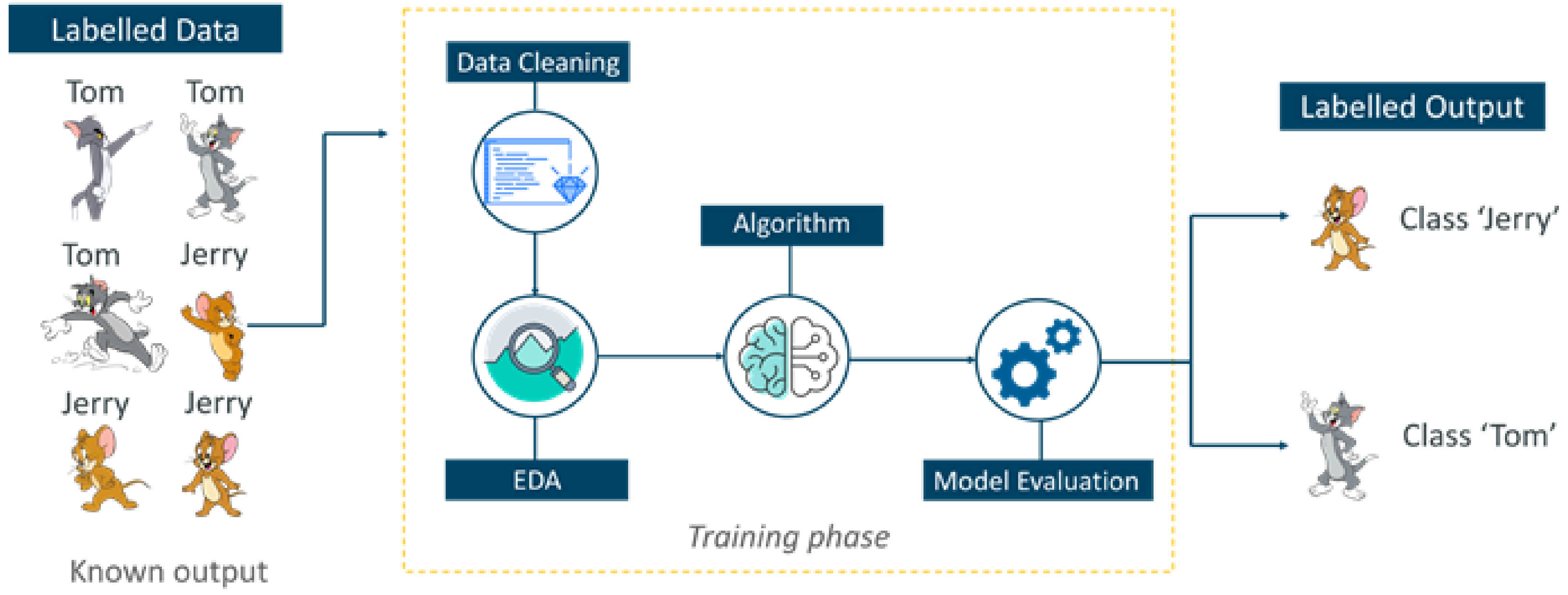
Unsupervised

Supervised vs Unsupervised

Supervised	Unsupervised
In supervised learning algorithms, the output for the given input is known.	In unsupervised learning algorithms, the output for the given input is unknown.
The algorithms learn from labeled set of data. This data helps in evaluating the accuracy on training data.	The algorithm is provided with unlabeled data where it tries to find patterns and associations in between the data items.
It is a Predictive Modeling technique which predicts the future outcomes accurately.	It is a Descriptive Modeling technique which explains the real relationship between the elements and history of the elements.
It includes classification and regression algorithms.	It includes clustering and association rules learning algorithms.
Some algorithms of supervised learning are Linear Regression, Naïve Bayes, and Neural Networks.	Some algorithms for unsupervised learning are k- means clustering, Apriori, etc.
This type of learning is relatively complex as it requires labelled data.	It is less complex as there is no need to understand and label data.
It is more accurate than unsupervised learning as input data and corresponding output is well known, and the machine only needs to give predictions.	It has less accuracy as the input data is unlabeled. Thus the machine has to first understand and label the data and then give predictions.
It is an online process of data analysis and does	This is a real time analysis of data.

Supervised Learning

Supervised learning is a technique in which we teach or train the machine using data which is well labeled. This approach is similar to human learning under the supervision of a teacher. The teacher provides good examples for the student to memorize, and the student then derives general rules from these specific examples.



https://www.edureka.co/blog/introduction-to-machine-learning/

2 types of supervised learning problems:

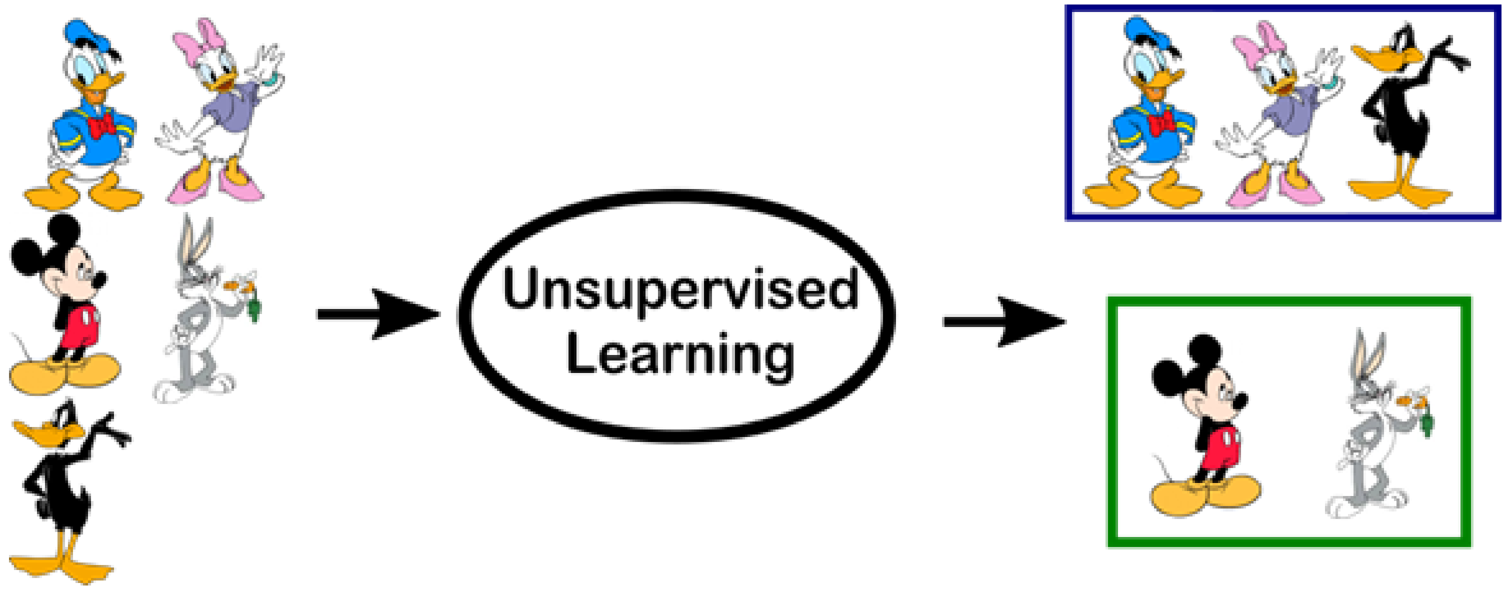
- **Regression problems:** the target is a numeric value. Example: determines the average prices of houses in the certain area
- **Classification problems:** the target is a qualitative variable, such as a class or a tag. Example: distinguishes between kinds of iris flowers based on their sepal and petal measures.

Unsupervised Learning

Unsupervised learning involves training by using unlabeled data and allowing the model to act on that information without guidance.

Some recommendation systems that you find on the web in the form of marketing automation are based on this type of learning.

The marketing automation algorithm derives its suggestions from what you've bought in the past. The recommendations are based on an estimation of what group of customers you resemble the most and then inferring your likely preferences based on that group.



https://towardsdatascience.com/introduction-to-machine-learning-for-beginners-eed6024fdb08

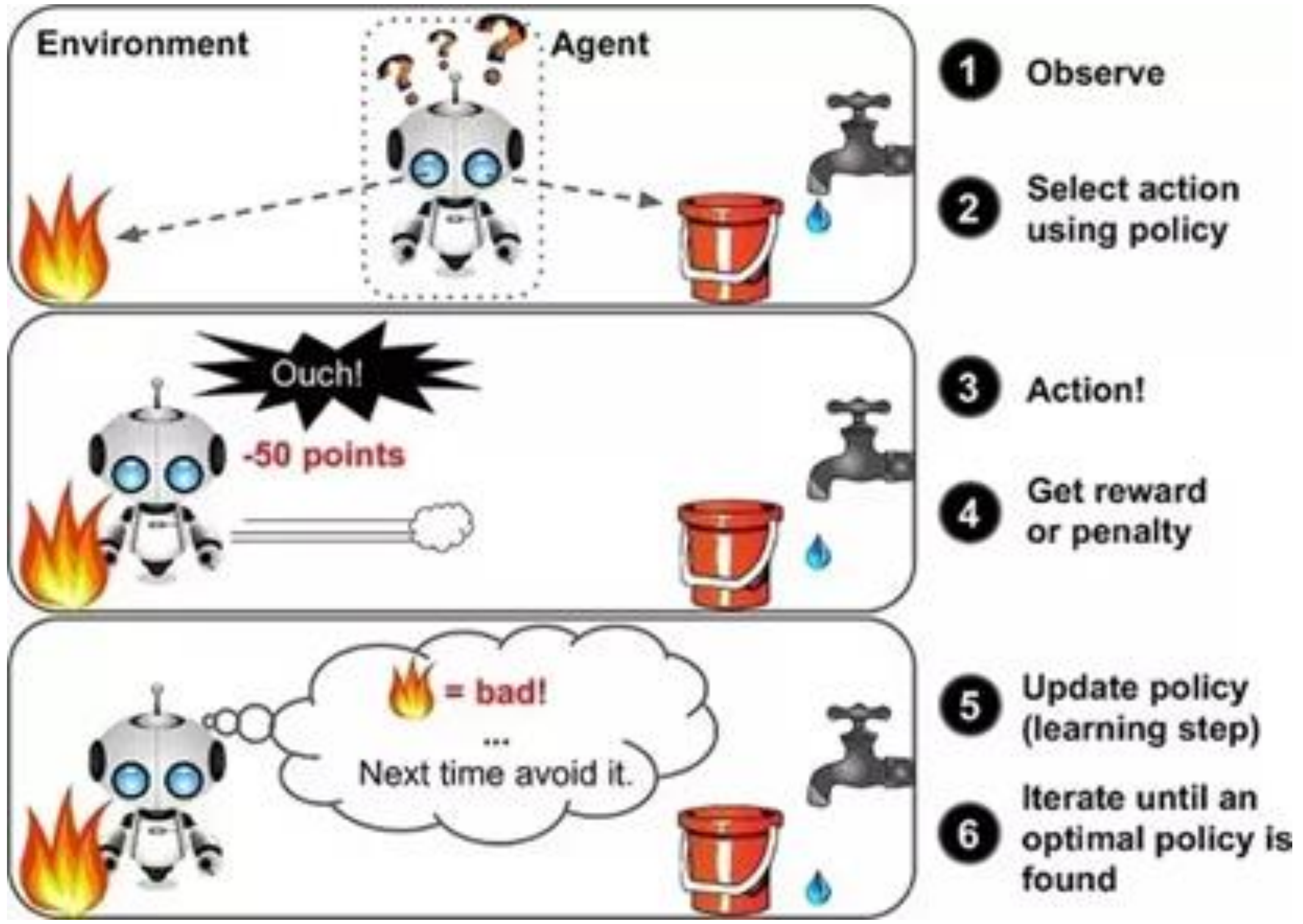
Reinforcement Learning

Reinforcement Learning is a part of Machine learning where an agent is put in an environment and he learns to behave in this environment by performing certain actions and observing the rewards which it gets from those actions.

In the human world, it is just like learning by trial and error.

Errors help you learn because they have a penalty added (cost, loss of time, regret, pain, and so on), teaching you that a certain course of action is less likely to succeed than others.

Example: when computers learn to play video games by themselves.



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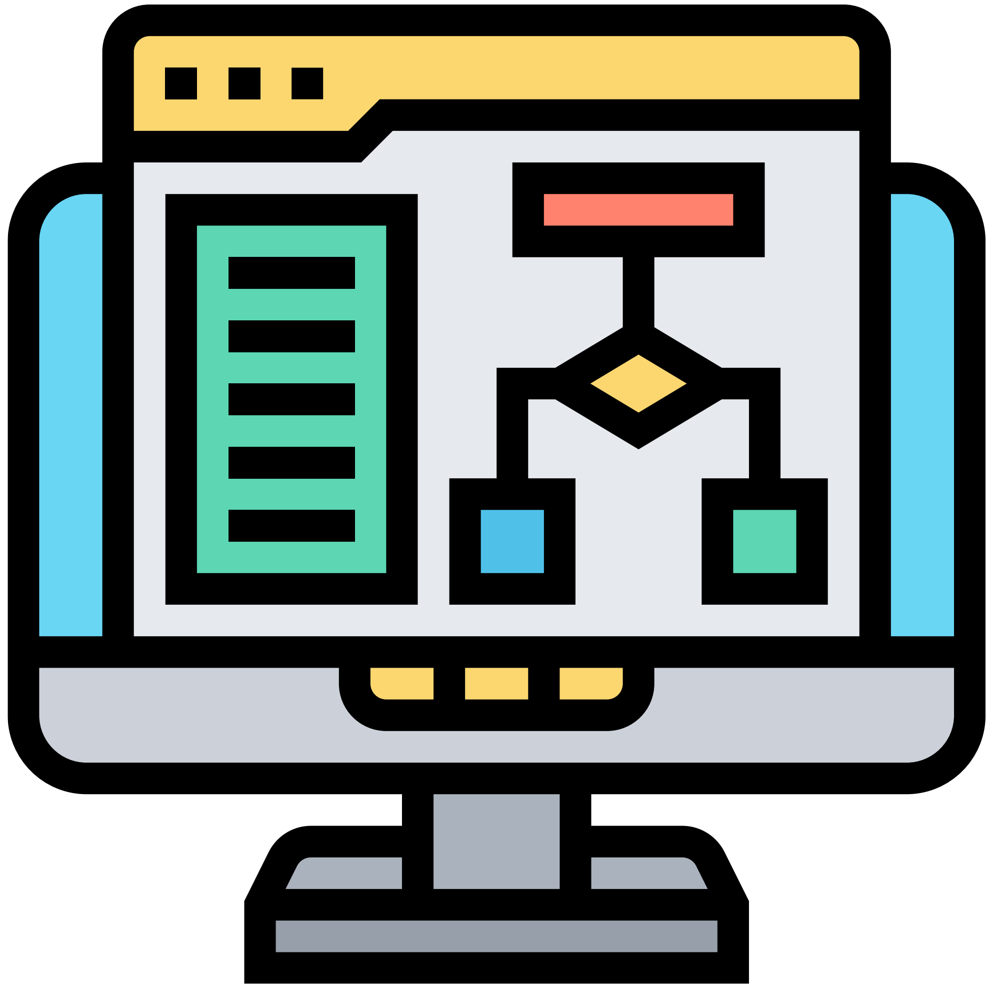
Various Classical Machine Learning Algorithms

Linear Regression
Logistic Regression
K-nearest neighbors
Support Vector machine
K means clustering
Decision Trees
Random Forest
Naive Bayes
Etc.
*we will only talk about some of them in details



Libraries used in Machine Learning

Libraries save developers from writing redundant code over and over. Also, there are all sorts of libraries to deal with different things.

- Numpy
- Pandas
- Matplotlib
- Seaborn

Already Covered

- Scipy
- **Scikit-learn (we will focus on using sklearn to build our classical machine learning models for the next sessions)**
- Theano
- TensorFlow
- Keras
- PyTorch

Scikit Learn Introduction

- Scikit-learn (Sklearn) is open-source library for machine learning in Python.
- It provides a selection of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction via a consistence interface in Python.
- This library, which is largely written in Python, is built upon **NumPy, SciPy** and **Matplotlib**.
- It has built-in datasets

Scikit Learn Features

Rather than focusing on loading, manipulating and summarizing data, Scikit-learn library is focused on modeling the data. Some of the most popular groups of models provided are:

- **Supervised Learning algorithms** − Almost all the popular supervised learning algorithms, like Linear Regression, Support Vector Machine (SVM), Decision Tree etc., are the part of scikit-learn.
- **Unsupervised Learning algorithms** − On the other hand, it also has all the popular unsupervised learning algorithms from clustering, factor analysis, PCA (Principal Component Analysis) to unsupervised neural networks.
- **Cross Validation** − It is used to check the accuracy of supervised models on unseen data.

Scikit Learn Features

- **Dimensionality Reduction** − It is used for reducing the number of attributes in data which can be further used for summarization, visualization and feature selection.
- **Ensemble methods** − As name suggest, it is used for combining the predictions of multiple supervised models.
- **Feature extraction** − It is used to extract the features from data to define the attributes in image and text data.
- **Feature selection** − It is used to identify useful attributes to create supervised models.

Scikit Learn Features

A collection of data is called dataset. It has following components:

- **Features** − The variables of data are called its features. They are also known as predictors, inputs or attributes.
- **Feature matrix** − It is the collection of features, in case there are more than one.
- **Feature Names** − It is the list of all the names of the features.
- **Response** − It is the output variable that basically depends upon the feature variables. They are also known as target, label or output.
- **Response Vector** − It is used to represent response column. Generally, we have just one response column.
- **Target Names** − It represent the possible values taken by a response vector.

Scikit Learn Dataset Loading

Scikit-learn have few built-in datasets examples like **iris** and **digits** for classification and the **diabetes** for regression

(You already learn how to load external dataset using read_csv() from pandas library)

```
from sklearn.datasets import load_iris
iris = load_iris()
X = iris.data
y = iris.target
feature_names = iris.feature_names
target_names = iris.target_names
print("Feature names:", feature_names)
print("Target names:", target_names)
print("First 10 rows of X:\n", X[:10])
```

```
Feature names: ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
Target names: ['setosa' 'versicolor' 'virginica']
First 10 rows of X:
 [[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]
 [5.4 3.9 1.7 0.4]
 [4.6 3.4 1.4 0.3]
 [5.  3.4 1.5 0.2]
 [4.4 2.9 1.4 0.2]
 [4.9 3.1 1.5 0.1]]
```

Scikit Learn Data Preprocessing - Binarization

This preprocessing technique is used when we need to convert our numerical values into Boolean values.

```python
import numpy as np
from sklearn import preprocessing
input_data = np.array(
   [[2.1, -1.9, 5.5],
   [-1.5, 2.4, 3.5],
   [0.5, -7.9, 5.6],
   [5.9, 2.3, -5.8]]
)
data_binarized = preprocessing.Binarizer(threshold=0.5).transform(input_data)
print("Binarized data:\n", data_binarized)
```

```
Binarized data:
 [[1. 0. 1.]
 [0. 1. 1.]
 [0. 0. 1.]
 [1. 1. 0.]]
```

Scikit Learn Data Preprocessing – Feature Scaling

Feature Scaling is the process of changing the scale of certain features to a common one. This is typically achieved through **normalization** and **standardization** (scaling techniques).

- **Normalization** is the process of scaling data into a range of [xmin, xmax]. It's more useful and common for regression tasks.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

- **Standardization** is the process of scaling data so that they have a mean value of 0 and a standard deviation of 1. It's more useful and common for classification tasks.

$$x' = \frac{x - \mu}{\sigma}$$

Normalization

- MinMaxScaler rescales the data points into range of 0 to 1.
- MaxAbsScaler is similar to minmax scaler but it scales values within the range of [-1,1]

```python
scaler1 = preprocessing.MinMaxScaler()
scaled_data1 = scaler1.fit_transform(input_data)
print ("Min Max scaled data:\n", scaled_data1,'\n')

scaler2 = preprocessing.MaxAbsScaler()
scaled_data2 = scaler2.fit_transform(input_data)
print ("Max Abs scaled data:\n", scaled_data2,'\n')
```

```
Min Max scaled data:
 [[0.48648649 0.58252427 0.99122807]
 [0.         1.         0.81578947]
 [0.27027027 0.         1.        ]
 [1.         0.99029126 0.        ]]

Max Abs scaled data:
 [[ 0.3559322  -0.24050633  0.94827586]
 [-0.25423729  0.30379747  0.60344828]
 [ 0.08474576 -1.          0.96551724]
 [ 1.          0.29113924 -1.        ]]
```

or


```python
scaler1 = preprocessing.MinMaxScaler()
scaled_data1 = scaler1.fit_transform(input_data)
print ("Min Max scaled data:\n", scaled_data1,'\n')

scaler2 = preprocessing.MaxAbsScaler()
scaled_data2 = scaler2.fit_transform(input_data)
print ("Max Abs scaled data:\n", scaled_data2,'\n')
```

```
Min Max scaled data:
 [[0.48648649 0.58252427 0.99122807]
 [0.         1.         0.81578947]
 [0.27027027 0.         1.        ]
 [1.         0.99029126 0.        ]]

Max Abs scaled data:
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 [-0.25423729  0.30379747  0.60344828]
 [ 0.08474576 -1.          0.96551724]
 [ 1.          0.29113924 -1.        ]]
```

Standardization

Standardization(Z-score normalization) is the process where the features are rescaled so that they'll have the properties of a standard normal distribution with mean 0 and standard deviation 1.
Standardisation is more robust to outliers, and in many cases, it is preferable over Max-Min Normalization

```
Raw data:
 [[ 2.1 -1.9  5.5]
 [-1.5  2.4  3.5]
 [ 0.5 -7.9  5.6]
 [ 5.9  2.3 -5.8]]
```

```python
std_scaler = preprocessing.StandardScaler()
normalized_data = std_scaler.fit_transform(input_data)
print ("Normalized data:\n", normalized_data)
```

```
Normalized data:
 [[ 0.12894603 -0.14880162  0.70300338]
 [-1.19735598  0.8749535   0.27694073]
 [-0.46052153 -1.57729713  0.72430651]
 [ 1.52893149  0.85114524 -1.70425062]]
```

Some tips for selecting appropriate method to apply.

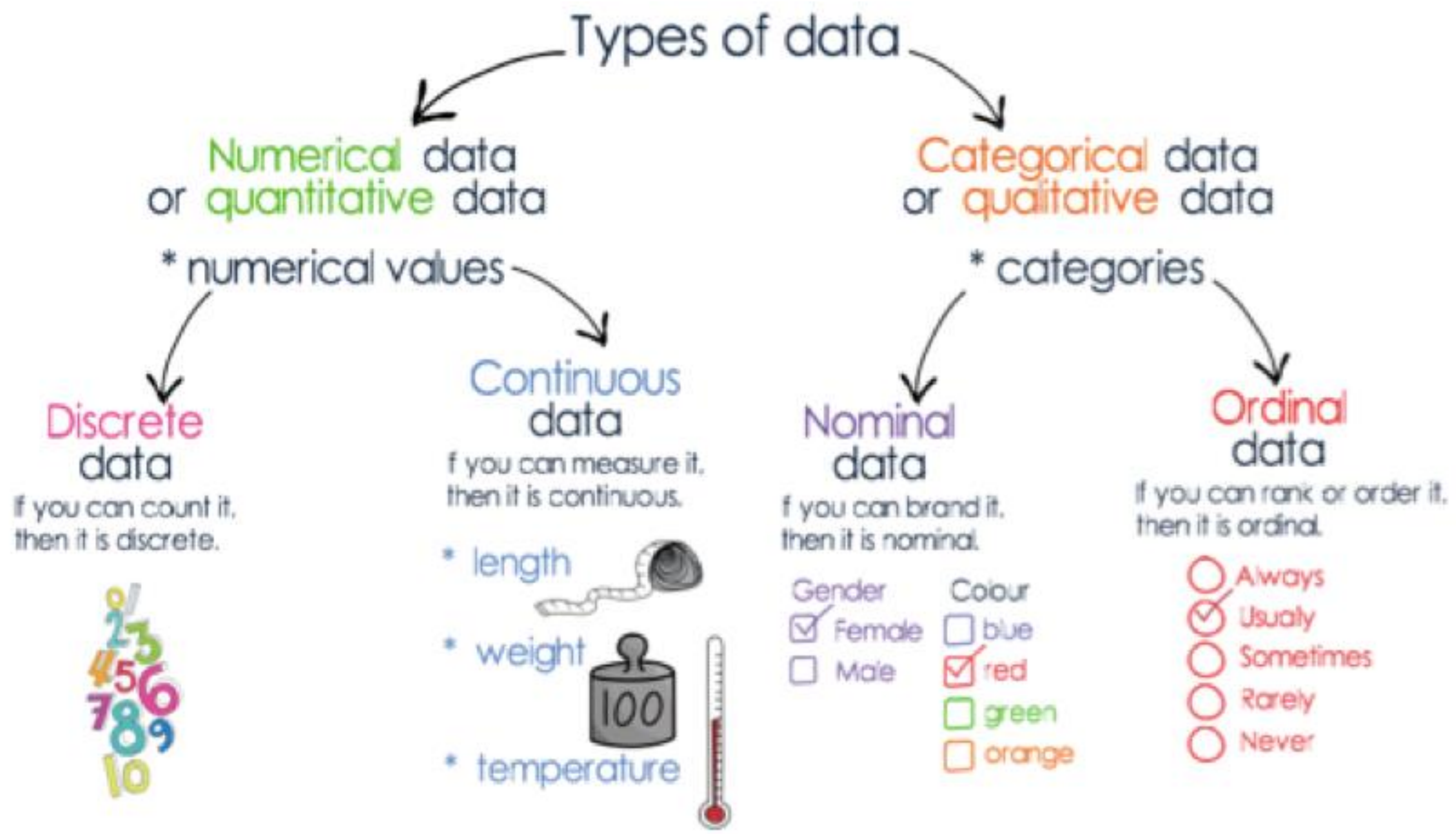
- **Normalization** is good to use when you know that the distribution of your data does not follow a Gaussian distribution.
- **Standardization**, on the other hand, can be helpful in cases where the data follows a Gaussian distribution. However, this does not have to be necessarily true

Scikit Learn Data Preprocessing – Encoding

If your data contains categorical data, you must encode it to numbers before you can fit and evaluate a model

There are multiple ways of handling categorical variables, and the most common used techniques are:

- **Label Encoding.** Suitable for ordinal data
- **One-Hot Encoding.** Suitable for nominal data



Source: Youtube Channel LegaC - Mathematics Resources

Scikit Learn Data Preprocessing – Encoding

Label Encoding. In this technique, each label is assigned a unique integer based on alphabetical ordering

```
import pandas as pd

df = pd.DataFrame({
    'name': ['J.A.R.V.I.S', 'WALL-E', 'Baymax', 'BB-8', 'Cortana'],
    'color': ['blue', 'brown', 'white', 'yellow', 'blue']
    })
df
```

	name	color
0	J.A.R.V.I.S	blue
1	WALL-E	brown
2	Baymax	white
3	BB-8	yellow
4	Cortana	blue

```
df['encoded_color'] = preprocessing.LabelEncoder().fit_transform(df.color)
df
```

	name	color	encoded_color
0	J.A.R.V.I.S	blue	0
1	WALL-E	brown	1
2	Baymax	white	2
3	BB-8	yellow	3
4	Cortana	blue	0

Scikit Learn Data Preprocessing – Encoding

One-Hot Encoding. Though label encoding is straight-forward but it has the disadvantage that the numeric values can be misinterpreted by algorithms as having some sort of hierarchy/order in them. This ordering issue is addressed in One-Hot Encoding. In this strategy, each category value is converted into a new column and assigned a 1 or 0 (notation for true/false) value to the column

```python
# creating additional columns for one hot encoder
color_columns = []
for col in df['color'].unique():
    color_columns.append(col)

onehot_encoded_color = preprocessing.OneHotEncoder().fit_transform(df[['color']])
df2 = pd.DataFrame(onehot_encoded_color.toarray(), columns=color_columns)
pd.concat([df, df2], axis=1)
```

	name	color	encoded_color	blue	brown	white	yellow
0	J.A.R.V.I.S	blue	0	1.0	0.0	0.0	0.0
1	WALL-E	brown	1	0.0	1.0	0.0	0.0
2	Baymax	white	2	0.0	0.0	1.0	0.0
3	BB-8	yellow	3	0.0	0.0	0.0	1.0
4	Cortana	blue	0	1.0	0.0	0.0	0.0

Scikit Learn Modelling Process – Splitting the Dataset

To check the accuracy of our model, we can split the dataset into two pieces- **a training set** and **a testing set.** Use the training set to train the model and testing set to test the model

- X, y – Here, X is the feature matrix and y is the response vector, which need to be split.
- test_size – This represents the ratio of test data to the total given data. As in the above example, we are setting test_data = 0.3 for 150 rows of X. It will produce test data of 150*0.3 = 45 rows.
- random_size – It is used to guarantee that the split will always be the same. This is useful in the situations where you want reproducible results.

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
   X, y, test_size = 0.3, random_state = 1
)

print(X_train.shape)
print(X_test.shape)

print(y_train.shape)
print(y_test.shape)
```

```
(100, 4)
(50, 4)
(100,)
(50,)
```

Scikit Learn Modelling Process – Train the Model

- Scikit-learn has wide range of **Machine Learning (ML) algorithms** which have a consistent interface for fitting, predicting accuracy, recall etc.
- In this example, we are going to use KNN (K nearest neighbors) classifier. Don't go into the details of KNN algorithms yet. This example is used to make you understand the implementation part only.

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
classifier_knn = KNeighborsClassifier(n_neighbors = 3)
classifier_knn.fit(X_train, y_train)
y_pred = classifier_knn.predict(X_test)

# Finding accuracy by comparing actual response values(y_test)with predicted response value(y_pred)
print("Accuracy:", metrics.accuracy_score(y_test, y_pred))

# Providing sample data and the model will make prediction out of that data
sample = [[5, 5, 3, 2], [2, 4, 3, 5]]
preds = classifier_knn.predict(sample)
pred_species = [iris.target_names[p] for p in preds]
print("Predictions:", pred_species)
```

```
Accuracy: 0.9833333333333333
Predictions: ['versicolor', 'virginica']
```

Scikit Learn Modelling Process – Model Persistence

Once you train the model, it is desirable that the model should be persist for future use so that we do not need to retrain it again and again. It can be done with the help of **dump** and **load** features of ***joblib*** package.
Consider the example below in which we will be saving the previous trained model (classifier_knn) for future use

```
import joblib
joblib.dump(classifier_knn, 'iris_classifier_knn.joblib')
```

```
['iris_classifier_knn.joblib']
```

The above code will save the model into file named iris_classifier_knn.joblib. Now, the object can be reloaded from the file with the help of following code −

```
joblib.load('iris_classifier_knn.joblib')
```

```
KNeighborsClassifier(n_neighbors=3)
```