Supervised Learning: Introduction to Supervised Learning

AAA-Python Edition

Plan

- 1- Supervised Learning
- 2- Classification
- 3- Regression
- 4- Features
- 5- Linear Regression
- 6- Polynomial Regression

1- Supervised Learning

Machine Learning

Machine learning

Build

Mathematical Model with Tunable parameters

Fit

Observed Data: described by a **set of** features

Predict

New Data

Supervised Learning

Supervised learning

Build

Mathematical Model with Tunable parameters

Fit

Labeled Observed Data

Fitting == **minimize** the **cost** function
(**difference** between **True** and **Predicted** labels)

Predict the Labels

Predicting == **Apply** the **obtained mathematical** model on the **New Data**

Unsupervised Learning

Unsupervised learning

Build

Mathematical Model with Tunable parameters

Fit

Not Labeled Observed Data

Predict the Labels

Predicting = **Extract** information about **New Data**

2- Classification

[By Amina Delali]

Classification

Supervised learning: Classification

Build

Mathematical Model with Tunable parameters

Fit

Labeled Observed Data: The Labels are **categories**

Predict

Predict the **known categories** for the New Data

2- Classification

Scikit-Learn

- Scikit-learn is a python library used for data mining and data analysis
- It is build on :”Numpy”, “Scipy”, and “Matplotlib” libraries.
- It will be used for both classification and regression by importing the corresponding modules.
- It will also be used for feature extraction using :”sklearn.feature_extraction” module
- The full documentation about scikit-learn, is available at its homepage: **http://scikit-learn.org/stable/index.html**

[By Amina Delali]

Classification Problems

Classifying images

Fit

Observed Data: **x-ray** images. Labels == **yes** or **no.**
Yes == Presence of Tumor, No == Absence of Tumor

Predict if there is a tumor or not

New Data: Not labeled x-ray images.

Classifying text

Observed Data: **words** in sentences. Labels == **verb**, **subject**, or **adjective**

Predict if the category of the word

New Data: Not labeled words

[By Amina Delali]

Regression

Supervised learning: Regression

Build

Mathematical Model with Tunable parameters

Fit

Labeled Observed Data: The Labels are **continuous** quantities

Predict

Predict the **New quantities** for the New Data

[By Amina Delali]

3- Regression

Regression Problems

House pricing

Fit

Observed Data: **houses** described by a set of **characteristics**. Labels == **prices** of the houses

Predict houses price

New Data: a set of houses described by the same set of characteristics (with different values), but they don't have the price indicated.

Photometric redshift

Observed Data: **galaxies** described by their **brightness** at several **wavelengths**. Labels == **distances** of the galaxies

Predict the distance

New galaxies without the distance information

[By Amina Delali]

Machine Learning

4- Features

Fit

Observed Data: the data must be described by a set of **characteristics: numerical values**

Predict if there is a tumor or not

The new Data: must be described by the same set but with different values

These characteristics, aren't always in a numerical format. They can be:

Categories

Text

Images

They have to be transformed in a numerical format

4- Features

Categorical features

The Feature 3 is transformed into 3 other features each one representing the presence of a category belonging to feature 3

Categories → One-hot-encoding

```python
from pandas import DataFrame as DF, Series as S
```

```python
# we assume that the features are contained in dataframe dataF
# the feature: "Feat3" is a categorical feature (not numeric)

dataF = DF([{"Feat1": 545,"Feat2":3, "Feat3": "Cat1" },{"Feat1": 362,"Feat2":2, "Feat3": "Cat3" },
  {"Feat1": 1005,"Feat2":5, "Feat3": "Cat2" }],index=["house1","house2","house3"])
dataF
```

	Feat1	Feat2	Feat3
house1	545	3	Cat1
house2	362	2	Cat3
house3	1005	5	Cat2

```python
# The DictVectorizer from sklearn will be used for the one-hot-encoding
from sklearn.feature_extraction import DictVectorizer
# convert the dataframe to a dictionary values
myDict = dataF.to_dict('records')
# create an instance of a DictVectorizer
vec = DictVectorizer(sparse=False, dtype=int)
# transform the category data
trDict=vec.fit_transform(myDict)
# convert the dictionary to a dataframe (just for visualization purpose)
DF.from_dict(trDict)
```

```python
myDict
```

```
[{'Feat1': 545, 'Feat2': 3, 'Feat3': 'Cat1'},
 {'Feat1': 362, 'Feat2': 2, 'Feat3': 'Cat3'},
 {'Feat1': 1005, 'Feat2': 5, 'Feat3': 'Cat2'}]
```

	0	1	2	3	4
house1	545	3	1	0	0
house2	362	2	0	0	1
house3	1005	5	0	1	0

[By Amina Delali]

Text features

Text

Word count

```
# a multilines string
text= '''this is a simple text
we will count and we will see this'''
# converting each line to a list element
textT = text.split("\n")
# import CountVectorizer for word count encoding
from sklearn.feature_extraction.text import CountVectorizer
# create an instance of CountVectorizer
vec = CountVectorizer()
# create the encoding
wc = vec.fit_transform(textT)
# create the corresponding dataframe
DF(wc.toarray(),columns=vec.get_feature_names())
```

```
['this is a simple text', 'we will count and we will see this']
```

	and	count	is	see	simple	text	this	we	will
0	0	0	1	0	1	1	1	0	0
1	1	1	0	1	0	0	1	2	2

Appears **0** times in line **0**
Appears **2** times in line **1**

Word count

TF – IDF:

term frequency–inverse document frequency

Each line will represent a row. And each word will represent a feature. Features values in each row will be the count of the corresponding word in the corresponding line

[By Amina Delali]

Text features

Text

Word count

TF – IDF:

term frequency–inverse document frequency

TF – IDF

```
# import TfidfVectorizer for  frequency–inverse document frequency encoding
from sklearn.feature_extraction.text import TfidfVectorizer
# create an instance of CountVectorizer
vec = TfidfVectorizer(norm=None)
# create the encoding
wc = vec.fit_transform(textT)
# create the corresponding dataframe
DF(wc.toarray(), columns=vec.get_feature_names())
```

We didn't normalize the results

$$idf(t)=\ln\left(\frac{1+n_d}{1+df(d,t)}\right)+1$$

$$tf-idf(t,d)=tf(t,d)*idf(t)$$

$n_d = total\ number\ of\ documents$

$tf(t,d)=number\ of\ \times\ the\ term\ t\ occurs \in document\ t$

$df(d,t)=number\ of\ documents$ that $contain\ the\ term\ t$

== 1 * (ln[(1+2)/1+1]+1) == 1.405465

```
['this is a simple text', 'we will count and we will see this']
```

	and	count	is	see	simple	text	this	we	will
0	0.000000	0.000000	1.405465	0.000000	1.405465	1.405465	1.0	0.00000	0.00000
1	1.405465	1.405465	0.000000	1.405465	0.000000	0.000000	1.0	2.81093	2.81093

[By Ami

4- Features

Images

Use pixel values as features values: number of features == number of pixels

Image

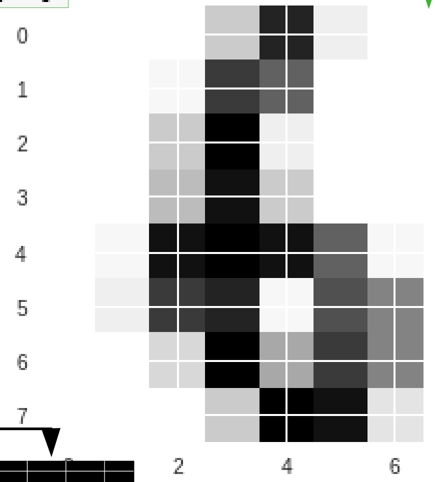
```
# importing digits dataset sample
from sklearn.datasets import load_digits
# loding digits dataset sample
digits = load_digits()
# the dataset has pixel values for 1797 images,
# each image is coded in 8*8 pixel values
# indicating grayscale values
print(digits.images.shape)
# for example, the 35th image represent a "6"
digits.images[34]
```

```
(1797, 8, 8)
array([[ 0.,  0.,  0.,  5., 14.,  2.,  0.,  0.],
       [ 0.,  0.,  1., 13., 11.,  0.,  0.,  0.],
       [ 0.,  0.,  5., 16.,  2.,  0.,  0.,  0.],
       [ 0.,  0.,  6., 15.,  5.,  0.,  0.,  0.],
       [ 0.,  1., 15., 16., 15., 11.,  1.,  0.],
       [ 0.,  2., 13., 14.,  1., 12.,  9.,  0.],
       [ 0.,  0.,  4., 16.,  7., 13.,  9.,  0.],
       [ 0.,  0.,  0.,  5., 16., 15.,  3.,  0.]])
```

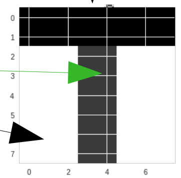
```
# ploting the 35th image ( the digit 6)
%matplotlib inline

import matplotlib.pyplot as plt
plt.imshow(digits.images[34])
```

```
digits.data[34]
```

Is just a reshape of images




```
myList = ([16]*8)*2+ ([0]*3+[13]*2+[0]*3)* 6
myT= np.array(myList).reshape(8,8)
plt.imshow(myT)
```



[By Amina Delali]

Simple Linear Regression (with 1 Feature)

Simple Linear Regression : 1 feature

Build

Mathematical Model== a Line, modelized by:
Y = **a** x + **b**

with

a: the slope
b: the intercept

Fit

Labeled Observed Data: described by 1 feature: **x**
The labels are **y** values. Fitting == find **a** and **b** that minimize the difference between the real labels: y and the estimated ones.

Predict

Predict the **New y** for the New not labeled x values

5- Linear Regression

Example

```python
# importing form linear_model module, LinearRegression
from sklearn.linear_model import LinearRegression
# create an instance of the model
model = LinearRegression()
# fiting the model using x and y values
model.fit(np.array(x).reshape(-1,1), np.array(y).reshape(-1,1))
# values of a (coef) and b(intercept) after fitting
print("a == the value in  ", model.coef_)
print("b == the value in  ", model.intercept_)
# new values of x : we create this values to generate the
# line representing the model
newX = np.linspace(1,20,1000)
# predict the labels for newX
newy = model.predict(np.array(newX).reshape(-1,1))
# plotting the old and the new values
plt.scatter(x, y)
plt.plot(newX, newy, color="g");
```

The model to train

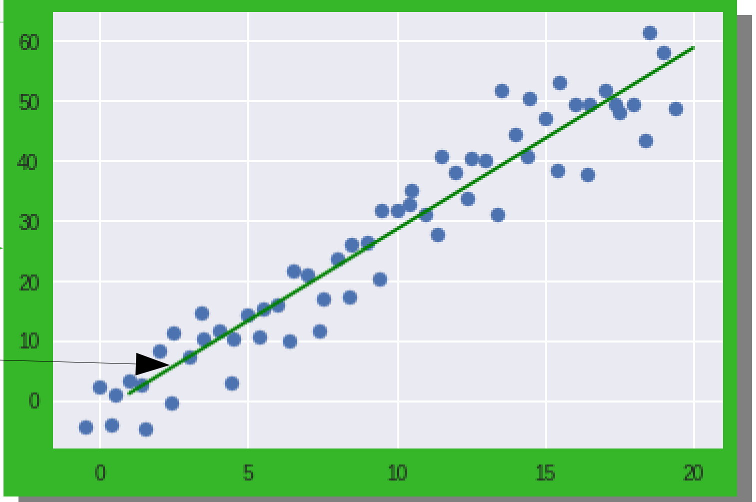
Initialization of a linear regressor instance

Train the model

Parameters of the model

Predict y for new values: actually this new x values are used to draw the model

```
a == the value in    [[3.029415]]
b == the value in    [-1.97286737]
```



The line representing the model

[By Amina Delali]

Linear regression basis Polynomial function (1 feature)

Linear regression basis Polynomial function (1 feature)

Build

Mathematical Model== a Linear curve, modelized by:
$Y = \mathbf{a_1}x + a_2x^2 + \ldots + a_nx^n + \mathbf{b}$

with

The parameters: a_1, a_2, …., a_n,b
N: the degree of the polynomial model

Fit

Labeled Observed Data: described by 1 feature: **x**
From that **x**, new **polynomial features** are **generated: x^2,x^3, …, x^n.**

Predict

The new x values must be **transformed** first into polynomial feature, before applying the model.

[By Amina Delali]

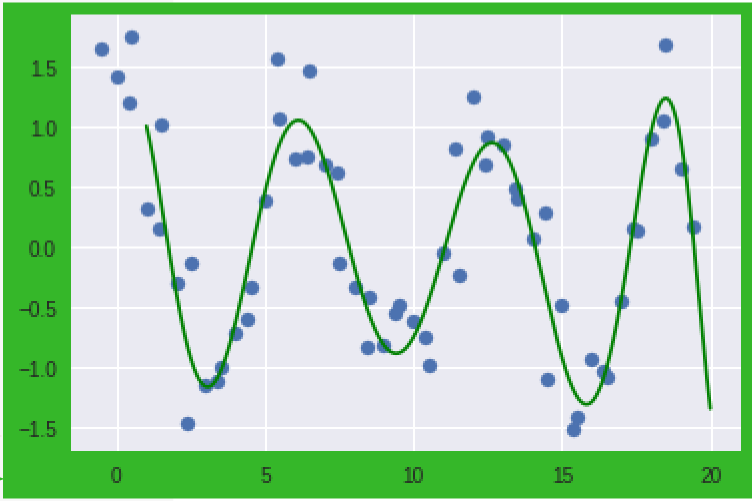
Example

```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
xArr= np.array(x).reshape(-1,1)
y2Arr= np.array(y2).reshape(-1,1)
# the order of the polynomial features
order =11
```

The model is the same, we will just generate new features: **polynomial features**

```
polyObj= PolynomialFeatures(order,include_bias=False)
myNewFeatures=polyObj.fit_transform(xArr)
# instanciate a linear regrossor model
myModel = LinearRegression()
# fitinig the model
myModel.fit(myNewFeatures, y2Arr)
# the calculated parameters
for i in range(1,order+1):
  print("a"+ str(i)+" == "+ str(myModel.coef_[0,i-1]))
print ("b == ",myModel.intercept_)

# new values of x : to visualize the model
newX = np.linspace(1,20,1000)
newXArr= np.array(newX).reshape(-1,1)
# corresponding polynomial features for the new values
newPlolyX =polyObj.fit_transform(newXArr)
# predict the labels for newX
newy2 = myModel.predict(newPlolyX)
# plotting the old values and the visualization of the model
plt.scatter(x, y2)
plt.plot(newX, newy2, color="g");
```

```
a1 == -0.05744343166221394
a2 == -0.10775669970224205
a3 == -0.15702923169271918
a4 == -0.09393489084681118
a5 == 0.12136012879617761
a6 == -0.04165097865144431
a7 == 0.007255471629826568
a8 == -0.0007421930578640621
a9 == 4.655613420523336e-05
a10 == -1.7661168388830744e-06
a11 == 3.727072246228341e-08
a12 == -3.3641874008782935e-10
b ==  [0.81724983]
```



[By Amina Delali]

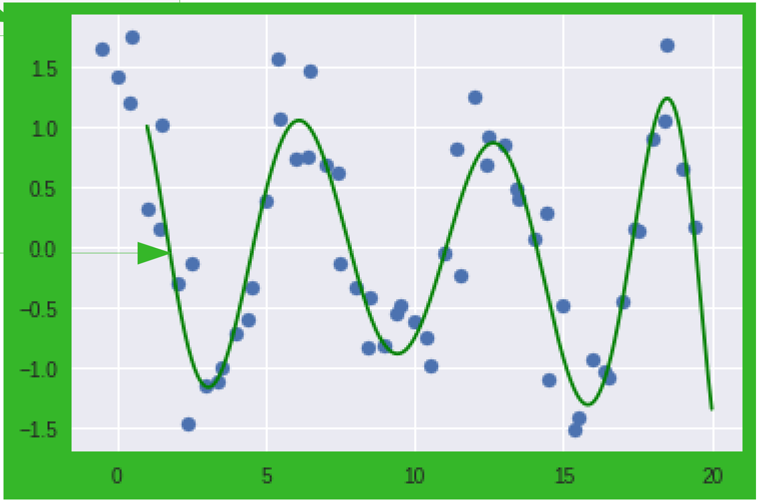
6-Polynomial Regression

Example with a pipeline

```
from sklearn.pipeline import make_pipeline
# create the pipeline
myPipeline= make_pipeline(polyObj,myModel)
myPipeline.fit(xArr, y2Arr)
# the calculated parameters
for i in range(1,order+1):
  print("a"+ str(i)+" == "+ str(myModel.coef_[0,i-1]))
print ("b == ",myModel.intercept_)

# predict the labels for newX
newy2 = myPipeline.predict(newXArr)
# plotting the old values and the model visualization
plt.scatter(x, y2)
plt.plot(newX, newy2, color="g");
```

This pipeline will:
1- generate polynomial features from the data.
2- apply the regression model to the new data

The newX values are generated in a way that the model can be plotted in a linear form :
it describes the model



[By Amina Delali]

References

- Joshi Prateek. Artificial intelligence with Python. Packt Publishing, 2017.
- Jake VanderPlas. Python data science handbook: essential tools for working with data. O’Reilly Media, Inc, 2017.

Thank you!

FOR ALL YOUR TIME