04_scikit-learn-Dataset_PCA

December 14, 2019

1 Informazioni Utili

- Pagina dove poter scaricale il materiale: https://visiont3lab.github.io/machine_learning/
- Repositorio Git dove trovare anche la cartella projects https://github.com/visiont3lab/machine_learning dove vi sono esempi di classi e funzioni.

- Esempio_Pratico_PCA_Regressione.py
- Esempio_Pratico_LogisticRegression.py
- windows-vscode-python-instructions.md Instruzioni su come scaricare VSCODE per windows e configurarlo usando python

2 Cosa andremo a fare oggi?

- Creazione di un dataset usando la libreria pandas. Come passare da numpy array to pandas dataframe
- Scikit-Learn datasets Spiegazione, nozioni su come scaricarli applicazione della regressione lineare a un dataset di scikit-learn (diabetes dataset)
- Cosa significa correlazione? Quando e perchè si utilizza
- Principal Component Analysis (PCA) dimensionality reduction
  - Riduzione del numero di input a un numero fisso (es. 2)
  - Come facciamo a riddure il numero degli input senza ridurre il contenuto di informazioni del nostro dataset iniziale?
- Esempio pratico: Regressione lineare applicata a un dataset con e senza PCA.

3 Creazione di un dataset usando la libreria pandas

In questo paragrafo andiamo a vedere come creare una classe dataset usando sia numpy che pandas in modo che possiamo facilmente applicare le regressioni studiate a questo. Inoltre vedremo come utilizare i dataset di scikit-learn.

[0]:
```
'''
Y = Salario al mese in euro
X1 = Età del lavoratore
X2 = Numero di ore mensili di lavoro
X3 = Indice di esperienza da 1 a 10
Equazione = Y = w0 + w1*X1 + w2*X2 + w3*X3
```

```
1) Marco:    Y=1100   X1=19   X2=150   X3=6    Y= w0*1 + w1*X1 + w2*X2 + w3*X3 --> 1100 = w0*1 + w1*19 + w2*150 + w3*6
2) Daniele:  Y=1150   X1=21   X2=135   X3=8    Y= w0*1 + w1*X1 + w2*X2 + w3*X3 --> 1100 = w0*1 + w1*21 + w2*135 + w3*8
3) Davide:   Y=1155   X1=22   X2=160   X3=5    Y= w0*1 + w1*X1 + w2*X2 + w3*X3 --> 1100 = w0*1 + w1*22 + w2*160 + w3*5
4) Marta:    Y=1170   X1=23   X2=158   X3=7    Y= w0*1 + w1*X1 + w2*X2 + w3*X3 --> 1100 = w0*1 + w1*23 + w2*158 + w3*7
6) Alessia:  Y=1200   X1=26   X2=155   X3=7    Y= w0*1 + w1*X1 + w2*X2 + w3*X3 --> 1100 = w0*1 + w1*26 + w2*155 + w3*7
9) Stella:   Y=1750   X1=33   X2=120   X3=10   Y= w0*1 + w1*X1 + w2*X2 + w3*X3 --> 1100 = w0*1 + w1*33 + w2*120 + w3*10
10) Chiara   Y=1640   X1=29   X2=130   x3=9    Y= w0*1 + w1*X1 + w2*X2 + w3*X3 --> 1100 = w0*1 + w1*29 + w2*130 + w3*9
'''

import pandas as pd
class Dataset():
    def __init__(self):
      self.X = np.array([[19,150,6],[21,135,8], [22,160,5], [23,158,7], [26,155,7], [33,120,10],[29,130,9]])
      self.Y = np.array([[1100],[1150],[1155],[1170],[1200],[1750],[1640]])
    def createPandasDataset(self):
        df_X = pd.DataFrame(data=self.X, columns =["età","ore mensili", "esperienza"])
        df_Y = pd.DataFrame(data=self.Y, columns =["salario"])
        return df_X, df_Y

myDataset = Dataset()
df_X, df_Y = myDataset.createPandasDataset()
display(df_X)
display(df_Y)
```

	età	ore mensili	esperienza
0	19	150	6
1	21	135	8
2	22	160	5
3	23	158	7
4	26	155	7
5	33	120	10
6	29	130	9

	solario
0	1100

```
1      1150
2      1155
3      1170
4      1200
5      1750
6      1640
```

4 Scikit-Learn datasets spiegazione e nozioni su come scaricarli.

Andremo a vedere quali dataset sono disponibili in scikit-learn, come scaricarli e capirne il contenuto.

- Sklearn dataset page

I dataset disponibili sono i seguenti: * Regressione: * Boston houses price dataset * Diabetes dataset * Linnerrud Dataset * Classificazione: * Iris plant dataset * Optical recognition of handwritten digits dataset
* Wine Recognition dataset * Breast cancer wisconsin (diagnostic) dataset

Implementazione di una classe capace di scaricare i dati da scikit-learn, visualizzarli e analizzarli.

[10]:
```
# Importare i datasets
from sklearn import datasets
import pandas as pd

class ScikitLearnDatasets:
  def __init__(self, dataset_name):
    # Load all scikit-learn dataset
    if ("iris"==dataset_name):
      self.dataset_scelto = datasets.load_iris() # Classificazione iris dataset
    elif ("digits"==dataset_name):
      self.dataset_scelto = datasets.load_digits() # Classificazione Load␣
↪digits dataset
    elif ("wine"==dataset_name):
      self.dataset_scelto = datasets.load_wine() # Classificazione Load wine␣
↪dataset
    elif ("breast_cancer"==dataset_name):
      self.dataset_scelto = datasets.load_breast_cancer() # Classificazione␣
↪Load breast_cancer dataset
    elif ("boston"==dataset_name):
      self.dataset_scelto = datasets.load_boston() # Regressione Load boston␣
↪dataset
      self.dataset_scelto.update([ ('target_names', ['Boston-House-Price'])] )
    elif ("diabetes"==dataset_name):
      self.dataset_scelto = datasets.load_diabetes() # Regressione Load␣
↪diabetes dataset
      self.dataset_scelto.update([ ('target_names', ['Desease-Progression'])] )
```

```
    elif ("linnerud"==dataset_name):
      self.dataset_scelto = datasets.load_linnerud() # Regressione Load␣
↪linnerud dataset
    else:
      self.dataset_scelto = diabetes # Regressione default choice

    # Print dataset information
    self.printDatasetInformation()

  def printDatasetInformation(self):
    #print(dataset_scelto)
    parametri = self.dataset_scelto.keys()
    valore = self.dataset_scelto.values()
    print(parametri)
    # Print useful information
    for name in parametri:
      print("------------------------------------------")
      print(name , self.dataset_scelto[name])
      print("------------------------------------------")

  def getXY(self):
    # Get Input (X) Data
    X = self.dataset_scelto['data'] # or  data = iris.get('data')
    X_names = self.dataset_scelto['feature_names']

    # Get Output (Y) Target
    parametri = self.dataset_scelto.keys()
    Y = self.dataset_scelto['target']
    Y_names = self.dataset_scelto['target_names']

    print("Dataset Parameters: ", parametri)
    print("Feature Names: ", X_names)
    print("Output Names: ", Y_names)
    print("Input X Shape: " , X.shape)
    print("Output Y Shape: " , Y.shape)

    return X,Y,X_names,Y_names

  def createPandasDataFrame(self,X,Y,X_names,Y_names,dataset_name):
    df_X = pd.DataFrame(data=X, columns =X_names)
    df_Y = pd.DataFrame(data=Y, columns =Y_names)
    return df_X, df_Y

  def writeDataFrameToCsv(self,df_X,df_Y):
    # Create csv file
    df_X.to_csv(dataset_name + '_X.csv', sep = ',', index = False)
    df_Y.to_csv(dataset_name + '_Y.csv', sep = ',', index = False)
```

```
# Choose the dataset
# Regressione: "boston", "diabetes",
# Classificazione: "iris", "digits", "wine", "breast_cancer "
# Regressione: "diabetes", "boston", "linnerud"
dataset_name = "diabetes"
myScikitLearnDatasets=ScikitLearnDatasets(dataset_name)
X,Y,X_names,Y_names = myScikitLearnDatasets.getXY()
df_X,df_Y = myScikitLearnDatasets.
 ↪createPandasDataFrame(X,Y,X_names,Y_names,dataset_name)
myScikitLearnDatasets.writeDataFrameToCsv(df_X,df_Y)

display(df_X)
display(df_Y)
```

```
dict_keys(['data', 'target', 'DESCR', 'feature_names', 'data_filename',
'target_filename', 'target_names'])
------------------------------------------
data [[ 0.03807591  0.05068012  0.06169621 ... -0.00259226  0.01990842
  -0.01764613]
 [-0.00188202 -0.04464164 -0.05147406 ... -0.03949338 -0.06832974
  -0.09220405]
 [ 0.08529891  0.05068012  0.04445121 ... -0.00259226  0.00286377
  -0.02593034]
 ...
 [ 0.04170844  0.05068012 -0.01590626 ... -0.01107952 -0.04687948
   0.01549073]
 [-0.04547248 -0.04464164  0.03906215 ...  0.02655962  0.04452837
  -0.02593034]
 [-0.04547248 -0.04464164 -0.0730303  ... -0.03949338 -0.00421986
   0.00306441]]
------------------------------------------
------------------------------------------
target [151.  75. 141. 206. 135.  97. 138.  63. 110. 310. 101.  69. 179. 185.
 118. 171. 166. 144.  97. 168.  68.  49.  68. 245. 184. 202. 137.  85.
 131. 283. 129.  59. 341.  87.  65. 102. 265. 276. 252.  90. 100.  55.
  61.  92. 259.  53. 190. 142.  75. 142. 155. 225.  59. 104. 182. 128.
  52.  37. 170. 170.  61. 144.  52. 128.  71. 163. 150.  97. 160. 178.
  48. 270. 202. 111.  85.  42. 170. 200. 252. 113. 143.  51.  52. 210.
  65. 141.  55. 134.  42. 111.  98. 164.  48.  96.  90. 162. 150. 279.
  92.  83. 128. 102. 302. 198.  95.  53. 134. 144. 232.  81. 104.  59.
 246. 297. 258. 229. 275. 281. 179. 200. 200. 173. 180.  84. 121. 161.
  99. 109. 115. 268. 274. 158. 107.  83. 103. 272.  85. 280. 336. 281.
 118. 317. 235.  60. 174. 259. 178. 128.  96. 126. 288.  88. 292.  71.
 197. 186.  25.  84.  96. 195.  53. 217. 172. 131. 214.  59.  70. 220.
 268. 152.  47.  74. 295. 101. 151. 127. 237. 225.  81. 151. 107.  64.
 138. 185. 265. 101. 137. 143. 141.  79. 292. 178.  91. 116.  86. 122.
```

```
  72. 129. 142.  90. 158.  39. 196. 222. 277.  99. 196. 202. 155.  77.
 191.  70.  73.  49.  65. 263. 248. 296. 214. 185.  78.  93. 252. 150.
  77. 208.  77. 108. 160.  53. 220. 154. 259.  90. 246. 124.  67.  72.
 257. 262. 275. 177.  71.  47. 187. 125.  78.  51. 258. 215. 303. 243.
  91. 150. 310. 153. 346.  63.  89.  50.  39. 103. 308. 116. 145.  74.
  45. 115. 264.  87. 202. 127. 182. 241.  66.  94. 283.  64. 102. 200.
 265.  94. 230. 181. 156. 233.  60. 219.  80.  68. 332. 248.  84. 200.
  55.  85.  89.  31. 129.  83. 275.  65. 198. 236. 253. 124.  44. 172.
 114. 142. 109. 180. 144. 163. 147.  97. 220. 190. 109. 191. 122. 230.
 242. 248. 249. 192. 131. 237.  78. 135. 244. 199. 270. 164.  72.  96.
 306.  91. 214.  95. 216. 263. 178. 113. 200. 139. 139.  88. 148.  88.
 243.  71.  77. 109. 272.  60.  54. 221.  90. 311. 281. 182. 321.  58.
 262. 206. 233. 242. 123. 167.  63. 197.  71. 168. 140. 217. 121. 235.
 245.  40.  52. 104. 132.  88.  69. 219.  72. 201. 110.  51. 277.  63.
 118.  69. 273. 258.  43. 198. 242. 232. 175.  93. 168. 275. 293. 281.
  72. 140. 189. 181. 209. 136. 261. 113. 131. 174. 257.  55.  84.  42.
 146. 212. 233.  91. 111. 152. 120.  67. 310.  94. 183.  66. 173.  72.
  49.  64.  48. 178. 104. 132. 220.  57.]
------------------------------------------
------------------------------------------
DESCR .. _diabetes_dataset:

Diabetes dataset
----------------

Ten baseline variables, age, sex, body mass index, average blood
pressure, and six blood serum measurements were obtained for each of n =
442 diabetes patients, as well as the response of interest, a
quantitative measure of disease progression one year after baseline.

**Data Set Characteristics:**

  :Number of Instances: 442

  :Number of Attributes: First 10 columns are numeric predictive values

  :Target: Column 11 is a quantitative measure of disease progression one year
after baseline

  :Attribute Information:
      - Age
      - Sex
      - Body mass index
      - Average blood pressure
      - S1
      - S2
      - S3
      - S4
```

```
      - S5
      - S6

Note: Each of these 10 feature variables have been mean centered and scaled by
the standard deviation times `n_samples` (i.e. the sum of squares of each column
totals 1).

Source URL:
https://www4.stat.ncsu.edu/~boos/var.select/diabetes.html

For more information see:
Bradley Efron, Trevor Hastie, Iain Johnstone and Robert Tibshirani (2004) "Least
Angle Regression," Annals of Statistics (with discussion), 407-499.
(https://web.stanford.edu/~hastie/Papers/LARS/LeastAngle_2002.pdf)
------------------------------------------
------------------------------------------
feature_names ['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6']
------------------------------------------
------------------------------------------
data_filename /usr/local/lib/python3.6/dist-
packages/sklearn/datasets/data/diabetes_data.csv.gz
------------------------------------------
------------------------------------------
target_filename /usr/local/lib/python3.6/dist-
packages/sklearn/datasets/data/diabetes_target.csv.gz
------------------------------------------
------------------------------------------
target_names ['Desease-Progression']
------------------------------------------
Dataset Parameters:  dict_keys(['data', 'target', 'DESCR', 'feature_names',
'data_filename', 'target_filename', 'target_names'])
Feature Names:  ['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6']
Output Names:  ['Desease-Progression']
Input X Shape:  (442, 10)
Output Y Shape:  (442,)

          age       sex       bmi  ...        s4        s5        s6
0    0.038076  0.050680  0.061696  ... -0.002592  0.019908 -0.017646
1   -0.001882 -0.044642 -0.051474  ... -0.039493 -0.068330 -0.092204
2    0.085299  0.050680  0.044451  ... -0.002592  0.002864 -0.025930
3   -0.089063 -0.044642 -0.011595  ...  0.034309  0.022692 -0.009362
4    0.005383 -0.044642 -0.036385  ... -0.002592 -0.031991 -0.046641
..        ...       ...       ...  ...       ...       ...       ...
437  0.041708  0.050680  0.019662  ... -0.002592  0.031193  0.007207
438 -0.005515  0.050680 -0.015906  ...  0.034309 -0.018118  0.044485
439  0.041708  0.050680 -0.015906  ... -0.011080 -0.046879  0.015491
440 -0.045472 -0.044642  0.039062  ...  0.026560  0.044528 -0.025930
441 -0.045472 -0.044642 -0.073030  ... -0.039493 -0.004220  0.003064
```

```
[442 rows x 10 columns]


     Desease-Progression
0                  151.0
1                   75.0
2                  141.0
3                  206.0
4                  135.0
..                   ...
437                178.0
438                104.0
439                132.0
440                220.0
441                 57.0

[442 rows x 1 columns]
```

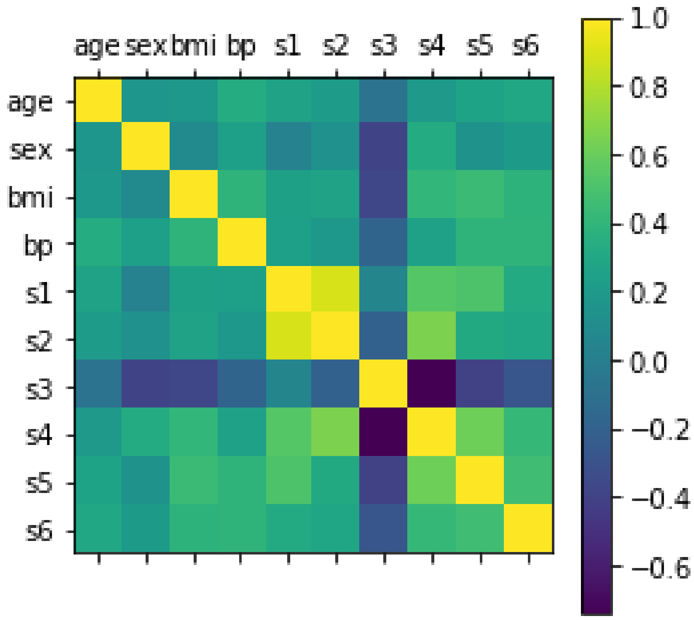
5 Cosa significa correlazione?

Andiamo a vedere come si interpreta la matrice di correlazione. Rispondiamo alla domanda:

Come deve essere la matrice di correlazione?

La correlazione esprime quanto due feature (esempio età e sesso) sono simili tra loro. Al fine di avere un dataset utile alla nostra regressione lineare è necessario che non vi sia troppa correlazione tra i dati. Se ciò accadesse significherebbe che stiamo usando diverse volte informazioni molto simili per risolvere un problema.

[0]:
```
import matplotlib.pyplot as plt
# Correlation Matrix
plt.matshow(df_X.corr())
plt.xticks(range(len(df_X.columns)), df_X.columns)
plt.yticks(range(len(df_X.columns)), df_X.columns)
plt.colorbar()
plt.show()
```

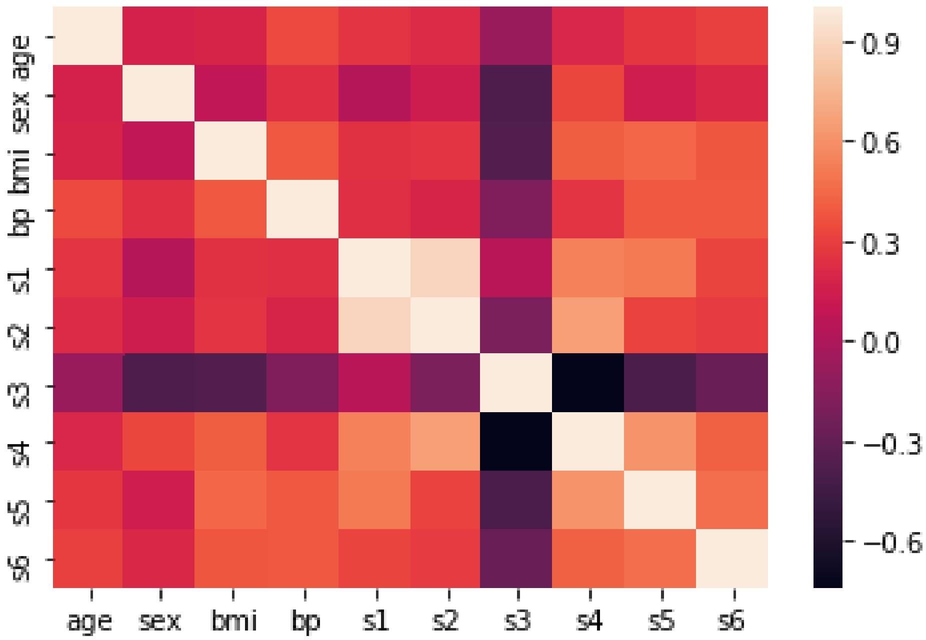


[5]:
```
df_X.corr().style.background_gradient(cmap='coolwarm').set_precision(2)
```

[5]: <pandas.io.formats.style.Styler at 0x7f3437020dd8>

[6]:
```
import seaborn as sns
corr = df_X.corr()
sns.heatmap(corr,  xticklabels=corr.columns.values, yticklabels=corr.columns.
 ↪values)
```

[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3407ea9320>



6 Dimensionality Reduction (Principal Component Analysis PCA)

Nel caso vi sia una situazione in cui la correlazione tra le features è molto alta possiamo sia manualmente rimuovere le feature che consideriamo superflue oppure utilizzare la PCA. Quest'ultima si occupa di creare nuove features (se prima ne avevamo 10 adesso ne avremo un numero minore) che non hanno un significato fisico ma che sono sufficienti a rappresentare il nostro dataset. In poche parole semplichiamo gli input (features) al minimo numero necessario. Questò fara si che tra gli input vi sia pochissima correlazione in quanto ogni input features avrà un valore diverso dalle altre.

IMPORTANTE: Il calcolo della principal componet analysis (PCA) è fortemente influenzato dalla scala. Quindi è necesseria avere per tutti gli input (features) una scala comune.

Standardizzare i dati significarli ricondurli a una scala il cui mean=0 e la variance=1.

[7]:
```
from sklearn.preprocessing import StandardScaler
features = X_names
# Separating out the features
x = df_X
# Separating out the target
y = df_Y
# Standardizing the features
x = StandardScaler().fit_transform(x)
df_X_Standard = pd.DataFrame(data = x , columns = X_names)
display(df_X)
display(df_X_Standard)
df_X.keys()
```

```
          age       sex       bmi  ...        s4        s5        s6
0    0.038076  0.050680  0.061696  ... -0.002592  0.019908 -0.017646
1   -0.001882 -0.044642 -0.051474  ... -0.039493 -0.068330 -0.092204
2    0.085299  0.050680  0.044451  ... -0.002592  0.002864 -0.025930
3   -0.089063 -0.044642 -0.011595  ...  0.034309  0.022692 -0.009362
4    0.005383 -0.044642 -0.036385  ... -0.002592 -0.031991 -0.046641
..        ...       ...       ...  ...       ...       ...       ...
437  0.041708  0.050680  0.019662  ... -0.002592  0.031193  0.007207
438 -0.005515  0.050680 -0.015906  ...  0.034309 -0.018118  0.044485
439  0.041708  0.050680 -0.015906  ... -0.011080 -0.046879  0.015491
440 -0.045472 -0.044642  0.039062  ...  0.026560  0.044528 -0.025930
441 -0.045472 -0.044642 -0.073030  ... -0.039493 -0.004220  0.003064

[442 rows x 10 columns]
```

```
          age       sex       bmi  ...        s4        s5        s6
0    0.800500  1.065488  1.297088  ... -0.054499  0.418551 -0.370989
1   -0.039567 -0.938537 -1.082180  ... -0.830301 -1.436551 -1.938479
2    1.793307  1.065488  0.934533  ... -0.054499  0.060207 -0.545154
3   -1.872441 -0.938537 -0.243771  ...  0.721302  0.477072 -0.196823
4    0.113172 -0.938537 -0.764944  ... -0.054499 -0.672582 -0.980568
..        ...       ...       ...  ...       ...       ...       ...
437  0.876870  1.065488  0.413360  ... -0.054499  0.655795  0.151508
438 -0.115937  1.065488 -0.334410  ...  0.721302 -0.380915  0.935254
439  0.876870  1.065488 -0.334410  ... -0.232934 -0.985585  0.325674
440 -0.956004 -0.938537  0.821235  ...  0.558384  0.936155 -0.545154
441 -0.956004 -0.938537 -1.535374  ... -0.830301 -0.088717  0.064426

[442 rows x 10 columns]
```

[7]:
```
Index(['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6'],
dtype='object')
```

6.1 Riduciamo il numero delle features (input) a 2 usando la PCA

[8]:
```python
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(x)
principalDf = pd.DataFrame(data = principalComponents , columns = ['principal␣
 ↪component 1', 'principal component 2'])
display(principalDf)

# Varianza associata ad ogni componente
pca.explained_variance_ratio_
```

```
     principal component 1  principal component 2
0                 0.587208              -1.946828
1                -2.831612               1.372085
2                 0.272148              -1.634898
3                 0.049310               0.382253
4                -0.756451               0.811968
..                     ...                    ...
437               1.239531              -1.035955
438               1.264676               0.761301
439              -0.205246              -1.205446
440               0.692866               0.210117
441              -1.903934               3.975771

[442 rows x 2 columns]
```

[8]:
```
array([0.40242142, 0.14923182])
```

Dobbiamo capire il levello di informazione di ogni singola componente trovata. Quando riduciamo la dimensionalità perdiamo delle informazioni in quanto il numero di input è stato ridotto. Vogliamo chiederci adesso le componenti 1 e 2 quanta informazione contengono? La compomente 1 contiene il 40% della varianza mentre la componete 2 il 14 %. Insieme essi contengono il 54% della varianza. Cioè significa che rispetto alle informazioni iniziali abbiamo perso il 46%.

6.2 Come facciamo a riddure il numero degli input senza ridurre il contenuto di informazioni del nostro dataset iniziale?

Mantenere esattamente il 100 % delle informazioni è impossibile. Pertanto ridurremo di poco il contenuto delle informazioni (es. 90%). Questo ci permetterà di ridurre il numero di input ed avere allo stesso tempo un predizione ottima.

[9]:
```
from sklearn.decomposition import PCA
# If 0 < n_components < 1 and svd_solver == 'full', select the number of
# components such that the amount of variance that needs to be explained
# is greater than the percentage specified by n_components.
pca = PCA(n_components=0.90)
x = df_X.values
x = StandardScaler().fit_transform(x)
principalComponents = pca.fit_transform(x)

row_number = principalComponents.shape[1]
X_names_new = []
for i in range(0,row_number):
  name = "component_" + str(i)
  X_names_new.append(name)


principalDf = pd.DataFrame(data = principalComponents ,columns=X_names_new)
display(principalDf)
```

```
# Varianza associata ad ogni componente
variance_arr = pca.explained_variance_ratio_
tot_variance = 0
for variance in variance_arr:
  temp_variance = variance*100
  tot_variance += temp_variance
print(tot_variance)
```

```
     component_0  component_1  ...  component_5  component_6
0       0.587208    -1.946828  ...    -1.011214    -0.179807
1      -2.831612     1.372085  ...    -1.013015     0.224414
2       0.272148    -1.634898  ...    -1.112806    -0.462406
3       0.049310     0.382253  ...     0.445315     0.482147
4      -0.756451     0.811968  ...    -0.814591     0.436451
..           ...          ...  ...          ...          ...
437     1.239531    -1.035955  ...    -0.479371     0.394431
438     1.264676     0.761301  ...     0.973430    -1.173570
439    -0.205246    -1.205446  ...    -0.045289    -0.635451
440     0.692866     0.210117  ...    -0.556900     0.545703
441    -1.903934     3.975771  ...     1.647108     0.245265

[442 rows x 7 columns]
```

```
94.79436357350414
```

7 Esempio Pratico

1. Scarichiamo il boston dataset
2. Dividiamo i dati in training e test
3. Applichiamo la PCA
4. Compariamo la predizione di un Regressore Lineare con e senza pca

[0]:

```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn import datasets
import os
from sklearn import linear_model
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
plt.rcParams['figure.figsize'] = [15, 10]

# FUNCTION: Standard data with 0 mean and unit variance (Gaussian)
```

```python
def standardScaler(df):
    # Input pandas dataframe Output pandas dataframe scaled
    names = list(df.keys())
    data = df.values
    data_scaled = StandardScaler().fit_transform(data)
    df_scaled = pd.DataFrame(data = data_scaled , columns=names)
    #print(df)
    #print(df_scaled)
    return df_scaled

# FUNCTION: Create pandas dataframe from numpy array
def createPandasDataFrame(X,Y,X_names,Y_names):
  df_X = pd.DataFrame(data=X, columns =X_names)
  df_Y = pd.DataFrame(data=Y, columns =Y_names)
  return df_X, df_Y

# FUNCTION: Write pandas dataframe to csv file
def writeDataFrameToCsv(df_X,df_Y,directory_path,dataset_name):
  if not os.path.exists(directory_path):
    os.makedirs(directory_path)

  # Create csv file
  path_write = os.path.join(directory_path, dataset_name)
  df_X.to_csv(path_write + '_X.csv', sep = ',', index = False)
  df_Y.to_csv(path_write + '_Y.csv', sep = ',', index = False)

# FUNCTION: Read from csv file a dataset
def readDataFrameFromCsv(directory_path, dataset_name):
  path_read = os.path.join(directory_path, dataset_name)
  if not os.path.exists(directory_path):
    print("Directory path does not exist")
  df_X = pd.read_csv(path_read + '_X.csv')
  df_Y = pd.read_csv(path_read + '_Y.csv')
  return df_X, df_Y

# CLASS: PCA class to do input dimensionality reduction
class dimensionalityReduction():

    def __init__(self,n_components):
        # define pca
        self.pca = PCA(n_components)

    def create_names(self,col_number):
        names = []
        for i in range(0,col_number):
            name = "component_" + str(i)
            names.append(name)
```

```
        return names

    def fit(self,df):
        df_scaled = standardScaler(df)
        model = self.pca.fit(df_scaled.values)
        information_array = model.explained_variance_ratio_ *100.00
        total_information = np.sum(information_array)
        return model,information_array, total_information

    def transform(self, model,df):
        # Input dataframe
        principalComponents = model.transform(df.values)
        names = self.create_names(col_number=principalComponents.shape[1])
        df_scaled = pd.DataFrame(data = principalComponents , columns = names)
        return df_scaled

# CLASS: Easily import different datasets
class ScikitLearnDatasets():

  def __init__(self, dataset_name):
    # Load all scikit-learn dataset
    if ("iris"==dataset_name):
      self.dataset_scelto = datasets.load_iris() # Classificazione iris␣
↪dataset
    elif ("digits"==dataset_name):
      self.dataset_scelto = datasets.load_digits() # Classificazione Load␣
↪digits dataset
    elif ("wine"==dataset_name):
      self.dataset_scelto = datasets.load_wine() # Classificazione Load wine␣
↪dataset
    elif ("breast_cancer"==dataset_name):
      self.dataset_scelto = datasets.load_breast_cancer() # Classificazione␣
↪Load breast_cancer dataset
    elif ("boston"==dataset_name):
      self.dataset_scelto = datasets.load_boston() # Regressione Load boston␣
↪dataset
      self.dataset_scelto.update([ ('target_names', ['Boston-House-Price'])] )
    elif ("diabetes"==dataset_name):
      self.dataset_scelto = datasets.load_diabetes() # Regressione Load␣
↪diabetes dataset
      self.dataset_scelto.update([ ('target_names', ['Desease-Progression'])]␣
↪)
    elif ("linnerud"==dataset_name):
      self.dataset_scelto = datasets.load_linnerud() # Regressione Load␣
↪linnerud dataset
    else:
```

```
        self.dataset_scelto = "diabetes" # Regressione default choice

      # Print dataset information
      #self.printDatasetInformation()

    def printDatasetInformation(self):
      #print(dataset_scelto)
      parameters = self.dataset_scelto.keys()
      data = self.dataset_scelto.values()
      #print(parameters)
      # Print useful information
      for name in parameters:
        print("------------------------------------------")
        print(name , self.dataset_scelto[name])
        print("------------------------------------------")

    def getXY(self):
      # Get Input (X) Data
      X = self.dataset_scelto['data'] # or  data = iris.get('data')
      X_names = self.dataset_scelto['feature_names']

      # Get Output (Y) Target
      parameters = self.dataset_scelto.keys()
      Y = self.dataset_scelto['target']
      Y_names = self.dataset_scelto['target_names']

      return X,Y,X_names,Y_names

# CLASS: Linar Regression
class LinearRegression():

    def __init__(self):
      # Inizializzazione
      # https://scikit-learn.org/stable/modules/linear_model.
↪html#ridge-regression-and-classification
      self.model = linear_model.LinearRegression(fit_intercept=True,␣
↪normalize=False)

    def train(self,X,Y):
      # Stimare w0, w1 .. wN
      trained_model = self.model.fit(X,Y)
      #print("w1,w2 .. wN : ",self.model.coef_)
      #print("w0 : ", self.model.intercept_)
      return trained_model

    def predict(self,X_test,trained_model):
      Y_pred = trained_model.predict(X_test)
```

```
        return Y_pred

    def evaluate(self,X_test, Y_test, trained_model):
        # R2 score
        Y_pred = trained_model.predict(X_test)
        R2_score = trained_model.score(X_test, Y_test)
        RMSE_score = (np.sqrt(mean_squared_error(Y_test, Y_pred)))
        return Y_pred,R2_score, RMSE_score

    def plot(self,Y_test,Y_pred):
        length = Y_pred.shape[0] # 20
        index_bar = np.linspace(0,length,length)
        plt.plot(index_bar, Y_test, label='Test')
        plt.plot(index_bar, Y_pred, label='Prediction')
        plt.legend()
        plt.show()
```

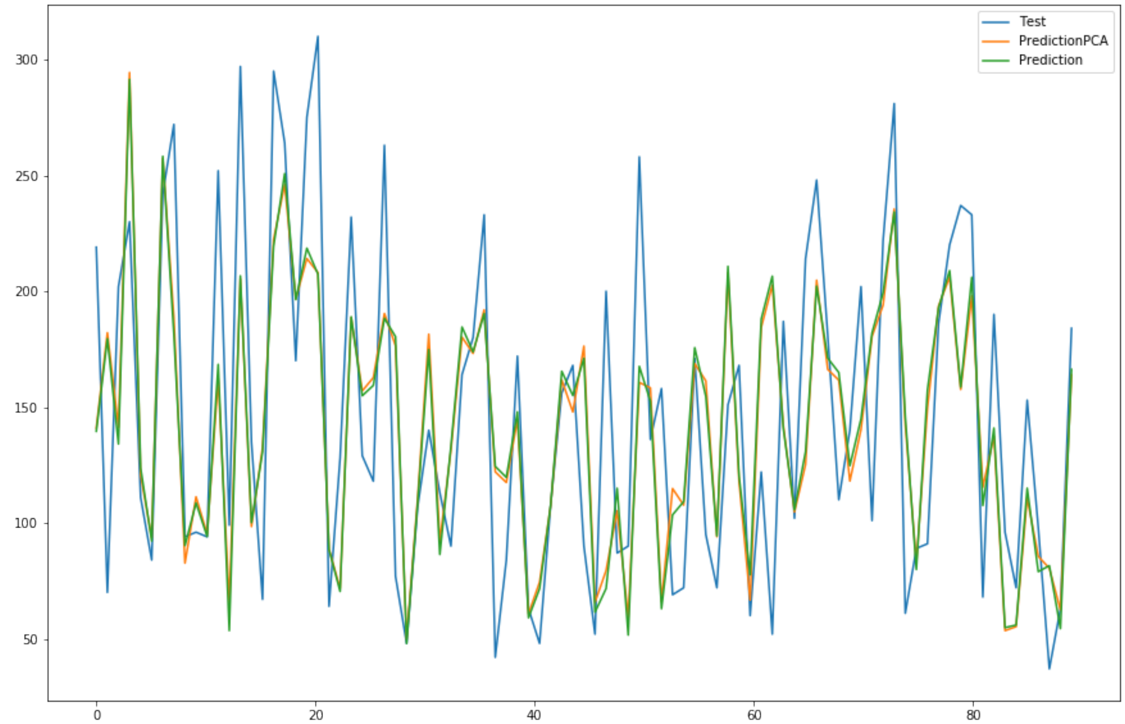
[21]:
```
if __name__ == "__main__":

    # ----------- SKLEARN DATASET LOADING ------------ #
    # Load sklearn dataset
    # Classificazione: "iris", "digits", "wine", "breast_cancer "
    # Regressione: "diabetes", "boston", "linnerud"
    # 1. Select dataset
    dataset_name = "diabetes"
    # 2. Create class object ScikitLearnDatasets
    myScikitLearnDatasets=ScikitLearnDatasets(dataset_name)
    # 3. Print dataset information
    #myScikitLearnDatasets.printDatasetInformation()
    # 4. Get dataset data as numpy array X=input, Y=output and␣
↪X_names=input_names, Y_names=output_names
    X,Y,X_names,Y_names = myScikitLearnDatasets.getXY()
    # 5. Convert numpy array data to Pandas Dataframe
    df_X,df_Y = createPandasDataFrame(X,Y,X_names,Y_names)
    print("#---------- DATASET INFORMATION ------------#")
    print("X Input or feature_names: ", X_names)
    print("Y Output or target_names: ", Y_names)
    print("Input X Shape: " , X.shape)
    print("Output Y Shape: " , Y.shape)
    print("Dataframe df_X Input Describe: \n", df_X.describe())
    print("Dataframe df_Y Output Describe: \n", df_Y.describe())
    print("#-------------------------------------------#")
    # 6. Write Pandas dataframe df_X, df_Y to csv file
    directory_path = os.path.join(os.getcwd(), "ScikitLearnDatasets")
    writeDataFrameToCsv(df_X,df_Y,directory_path, dataset_name)
    # ------------------------------------------------ #
```

```
    # ----------- READ DATASET FROM CSV -------------- #
    # Read previously saved dataset
    # 1. Read csv dataset (examvle boston_X.csv and boston_Y.csv) and transform␣
↪to pandas daframe
    #dataset_name = "boston" # desired dataset name
    #directory_path = os.path.join(os.getcwd(), "ScikitLearnDatasets") #␣
↪dataset folder
    df_X,df_Y = readDataFrameFromCsv(directory_path, dataset_name)
    # ------------------------------------------------ #

    # -------- Split data into train and test -------- #
    # Split dataset into training and test set
    X_train, X_test, Y_train, Y_test = train_test_split(df_X.values, df_Y.
↪values, test_size=0.20, random_state=42)
    # ------------------------------------------------ #

    # -------------------- PCA ----------------------- #
    # Principal component analysis (PCA) or dimensionality reduction
    # Number of input is reduced while keeping overall dataset information
    # 1. Covert numpy array to pandas dataframe
    df_X_train = pd.DataFrame(data = X_train , columns=df_X.keys())
    df_X_test = pd.DataFrame(data = X_test , columns=df_X.keys())
    # 2. Initialize PCA (Principal Component Analysis)
    n_components = 0.95 # 90% of the variance
    mydimensionalityReduction = dimensionalityReduction(n_components)
    # 3. Create PCA model (using input training data)
    pcaModel,information_array, total_information = mydimensionalityReduction.
↪fit(df_X_train)
    print("#-------------- PCA ANALYSIS ---------------#")
    print("Information for each new component: ", information_array, "%")
    print("Total Information of the reduced dataset: ", total_information, " %")
    # 4. Apply created PCA model to both training and test dataset
    df_X_train_scaled = mydimensionalityReduction.transform(pcaModel,df_X_train)
    df_X_test_scaled = mydimensionalityReduction.transform(pcaModel,df_X_test)
    X_train_scaled = df_X_train_scaled.values
    X_test_scaled = df_X_test_scaled.values
    #print("Dataset X_train: ", X_train)
    #print("Dataset X_train Reduced: ", X_train_scaled)
    print("Number of inputs with PCA: ",X_train_scaled.shape[1])
    print("Number of inputs without PCA: ",X_train.shape[1])
    print("#------------------------------------------#")
    # -------------------------------------------------#

    # -------- LINEAR REGRESSION WITH PCA DATA -------- #
    # we use reduce input data
    myModelPCA = LinearRegression()
    trained_modelPCA = myModelPCA.train(X_train_scaled, Y_train)
```

```
    Y_predPCA,R2_scorePCA, RMSE_scorePCA = myModelPCA.
 ↪evaluate(X_test_scaled,Y_test,trained_modelPCA)
    print("#----- LINEAR REGRESSION PCA RESULTS -------#")
    print("w1,w2 .. wN : ",trained_modelPCA.coef_)
    print("w0 : ", trained_modelPCA.intercept_)
    print("Score Linear Regression PCA: ", "R2 Score: ", R2_scorePCA, " RMSE␣
 ↪Score: ", RMSE_scorePCA)
    print("#------------------------------------------#")
    #myModelPCA.plot(Y_test,Y_pred)
    # ------------------------------------------------ #

    # -------------- LINEAR REGRESSOR ---------------- #
    # We use initial data
    myModel = LinearRegression()
    trained_model = myModel.train(X_train, Y_train)
    Y_pred,R2_score, RMSE_score = myModel.evaluate(X_test,Y_test,trained_model)
    print("#------- LINEAR REGRESSION RESULTS ---------#")
    print("w1,w2 .. wN : ",trained_modelPCA.coef_)
    print("w0 : ", trained_modelPCA.intercept_)
    print("Score Linear regression without PCA: ", "R2 Score: ", R2_score, "␣
 ↪RMSE Score: ", RMSE_score)
    print("#------------------------------------------#")
    #myModel.plot(Y_test,Y_pred)
    # ------------------------------------------------ #

    #----------------- COMPARISON -------------------- #
    length = Y_pred.shape[0] # 20
    index_bar = np.linspace(0,length,length)
    plt.plot(index_bar, Y_test, label='Test')
    plt.plot(index_bar, Y_predPCA, label='PredictionPCA')
    plt.plot(index_bar, Y_pred, label='Prediction')
    plt.legend()
    plt.show()
    # ------------------------------------------------ #
```

```
#---------- DATASET INFORMATION ------------#
X Input or feature_names:  ['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4',
's5', 's6']
Y Output or target_names:  ['Desease-Progression']
Input X Shape:  (442, 10)
Output Y Shape:  (442,)
Dataframe df_X Input Describe:
                 age           sex  ...            s5            s6
count   4.420000e+02  4.420000e+02  ...  4.420000e+02  4.420000e+02
mean   -3.634285e-16  1.308343e-16  ... -3.830854e-16 -3.412882e-16
std     4.761905e-02  4.761905e-02  ...  4.761905e-02  4.761905e-02
min    -1.072256e-01 -4.464164e-02  ... -1.260974e-01 -1.377672e-01
```

```
25%   -3.729927e-02 -4.464164e-02  ... -3.324879e-02 -3.317903e-02
50%    5.383060e-03 -4.464164e-02  ... -1.947634e-03 -1.077698e-03
75%    3.807591e-02  5.068012e-02  ...  3.243323e-02  2.791705e-02
max    1.107267e-01  5.068012e-02  ...  1.335990e-01  1.356118e-01

[8 rows x 10 columns]
Dataframe df_Y Output Describe:
        Desease-Progression
count           442.000000
mean            152.133484
std              77.093005
min              25.000000
25%              87.000000
50%             140.500000
75%             211.500000
max             346.000000
#--------------------------------------------#
#-------------- PCA ANALYSIS ---------------#
Information for each new component:  [39.68814054 14.77973436 12.51654914
10.10869693  6.58293305  5.93511774
  5.2036642   4.33649442] %
Total Information of the reduced dataset:  99.15133037867369  %
Number of inputs with PCA:  8
Number of inputs without PCA:  10
#--------------------------------------------#
#----- LINEAR REGRESSION PCA RESULTS -------#
w1,w2 .. wN :  [[ 453.41998089 -244.95319406  372.8080337   524.14406459
-30.20353053
  -252.44550156  125.2975691    34.12174383]]
w0 :  [151.30071414]
Score Linear Regression PCA:  R2 Score:  0.4557153915064335  RMSE Score:
53.7001159233466
#--------------------------------------------#
#------- LINEAR REGRESSION RESULTS ---------#
w1,w2 .. wN :  [[ 453.41998089 -244.95319406  372.8080337   524.14406459
-30.20353053
  -252.44550156  125.2975691    34.12174383]]
w0 :  [151.30071414]
Score Linear regression without PCA:  R2 Score:  0.45260660216173787  RMSE
Score:  53.8532569849144
#--------------------------------------------#
```



8 Referenze utili

- PCA SPiegazione ed esempio
- Scikit-Learn Regressione
- L'importanza di Standardizzare i dati

9 Extra : Come funzionano i dizionari in python

[1]:
```
#--------------------------------------------------------------------
#---------------- Trasformare dizionari in Array --------- -----------
#--------------------------------------------------------------------
# Usiamo Le funzioni
# Importare i datasets

from sklearn import datasets
import numpy as np

iris = datasets.load_iris() # Load iris dataset
digits = datasets.load_digits() # Load digits dataset
boston = datasets.load_boston() # Load boston dataset
diabetes = datasets.load_diabetes() # Load diabetes dataset
linnerud = datasets.load_linnerud() # Load linnerud dataset
```

```
wine = datasets.load_wine() # Load wine dataset
breast_cancer = datasets.load_breast_cancer() # Load breast_cancer dataset

dataset_scelto = iris

def approccio_1(dataset_scelto):
  # --------------------- Approccio 1
  # Get dictionar keys, value
  print(dataset_scelto.keys())
  list_keys = []
  list_values = []
  for key in dataset_scelto:
    list_keys.append(key)
    print(key)
    value = dataset_scelto[key]
    list_values.append(value)
  print("All keys inside array ", list_keys)
  #print("All values inside array ", list_values)

  # Convert list to numpy array
  print("----------------------------------")
  array_keys = np.asarray(list_keys)
  array_values = np.array(list_values)
  print(type(array_keys), array_keys.shape, array_keys[0].shape)
  print(type(array_values), array_values.shape,array_values[0].shape)

  # Going deeper inside data shape
  print("----------------------------------")
  for i in range(0,len(array_keys)):
    if isinstance(array_values[i],np.ndarray):
      print(array_keys[i], type(array_values[i]), array_values[i].shape )
    else:
      print(array_keys[i], type(array_values[i]))

  # Other Useful Solutions
  '''
  for value in diabetes.values():
    print(value)

  for key, value in diabetes.items():
    print(key, value)
  '''

def approccio_2(dataset_scelto):
  #-------------------- Approccio 2
  # Convert a dictionary to an array of string
  list_keys = list(dataset_scelto.keys())
```

```python
    list_values = list(dataset_scelto.values())
    #print(list_keys)
    print(type(list_keys))
    #print(list_values)
    print(type(list_values))
    # Convert list as numpy narray
    array_keys = np.asarray(list_keys)
    array_values = np.array(list_values)
    print(type(array_keys))
    print(type(array_values))
    # Covert back numpy ndarray to list
    new_list_keys = array_keys.tolist()
    new_list_values = array_values.tolist()
    print(type(new_list_keys))
    print(type(new_list_values))
    # Check if the list are equal
    if list_keys == new_list_keys and list_values==new_list_values:
      print ("The lists are identical")
    else :
      print ("The lists are not identical")

print("------------------------------")
print("-------- Approach 1 ---------")
print("------------------------------")
approccio_1(dataset_scelto)
print("------------------------------")
print("-------- Approach 2 ---------")
print("------------------------------")
approccio_2(dataset_scelto)
```

```
-----------------------------
-------- Approach 1 ---------
-----------------------------
dict_keys(['data', 'target', 'target_names', 'DESCR', 'feature_names',
'filename'])
data
target
target_names
DESCR
feature_names
filename
All keys inside array  ['data', 'target', 'target_names', 'DESCR',
'feature_names', 'filename']
----------------------------------
<class 'numpy.ndarray'> (6,) ()
<class 'numpy.ndarray'> (6,) (150, 4)
----------------------------------
```

```
data <class 'numpy.ndarray'> (150, 4)
target <class 'numpy.ndarray'> (150,)
target_names <class 'numpy.ndarray'> (3,)
DESCR <class 'str'>
feature_names <class 'list'>
filename <class 'str'>
-----------------------------
-------- Approach 2 ---------
-----------------------------
<class 'list'>
<class 'list'>
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
<class 'list'>
<class 'list'>
The lists are identical
```