S3 - HOPE logistic regression

December 4, 2020

0.1 Import data from DB.

[1]:
```
import pandas as pd
import numpy as np
```

[2]:
```
dfOrg = pd.read_csv('hope_dataset_cleaned.csv')

print(dfOrg.shape[0])
```

```
1243
```

[3]:
```
dfOrg.head(10)
```

[3]:

	pedido.data.attributes.age	pedido.data.attributes.diagnostic_main	pedido.data.attributes.gender	articulo	respuesta.articlesRevisedYear	respuesta.articlesRevisedMonth
0	75.0	FISTULA PERITONEAL	male	27395425	2018	
1	75.0	FISTULA PERITONEAL	male	28560554	2018	
2	75.0	FISTULA PERITONEAL	male	28641726	2017	
3	75.0	FISTULA PERITONEAL	male	26245344	2016	
4	75.0	FISTULA PERITONEAL	male	28942543	2018	
5	75.0	FISTULA PERITONEAL	male	24782153	2014	
6	75.0	FISTULA PERITONEAL	male	28002229	2018	
7	75.0	FISTULA PERITONEAL	male	27505109	2017	
8	75.0	FISTULA PERITONEAL	male	24850546	2015	
9	75.0	FISTULA PERITONEAL	male	29371050	2019	

```
0                                1
1                                4
2                               12
3                               12
4                                6
5                                6
6                                9
7                                4
8                                1
9                                4
```

	respuesta.pubmed_keys	utilidad
0	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu…	1.0
1	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu…	NaN
2	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu…	NaN
3	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu…	NaN
4	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu…	NaN
5	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu…	NaN
6	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu…	NaN
7	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu…	NaN
8	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu…	NaN
9	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu…	NaN

0.2 Transform (factorice) from Categories to continuous atributes

Transform 'pedido.data.attributes.diagnostic_main' atribute

[4]:
```
dataDiagnosticMain, categoriesDiagnosticMain = pd.factorize(dfOrg['pedido.data.
↪attributes.diagnostic_main'])

dfOrg['pedido.data.attributes.diagnostic_main'] = dataDiagnosticMain
```

Transform 'gender' atribute

[5]:
```
dataGender, categoriesGender = pd.factorize(dfOrg['pedido.data.attributes.
↪gender'])

dfOrg['pedido.data.attributes.gender'] = dataGender
```

Transform 'respuesta.pubmed_keys' atribute

[6]:
```
categoriesORGPubMedKeys = dfOrg['respuesta.pubmed_keys'].value_counts()

print("total: " + str(categoriesORGPubMedKeys.size))
```

```
total: 80
```

[7]:
```
dataPubMedKeys, categoriesPubMedKeys = pd.factorize(dfOrg['respuesta.
↪pubmed_keys'])

dfOrg['respuesta.pubmed_keys'] = dataPubMedKeys
```

[8]:
```
dfOrg.head(10)
```

[8]:

	pedido.data.attributes.age	pedido.data.attributes.diagnostic_main	\
0	75.0	0	
1	75.0	0	
2	75.0	0	
3	75.0	0	
4	75.0	0	
5	75.0	0	
6	75.0	0	
7	75.0	0	
8	75.0	0	
9	75.0	0	

	pedido.data.attributes.gender	articulo	respuesta.articlesRevisedYear	\
0	0	27395425	2018	
1	0	28560554	2018	
2	0	28641726	2017	
3	0	26245344	2016	
4	0	28942543	2018	
5	0	24782153	2014	
6	0	28002229	2018	
7	0	27505109	2017	
8	0	24850546	2015	
9	0	29371050	2019	

	respuesta.articlesRevisedMonth	respuesta.pubmed_keys	utilidad
0	1	0	1.0
1	4	0	NaN
2	12	0	NaN
3	12	0	NaN
4	6	0	NaN
5	6	0	NaN
6	9	0	NaN
7	4	0	NaN
8	1	0	NaN
9	4	0	NaN

[9]:
```
print("age NaN => " + str(dfOrg[pd.isnull(dfOrg['pedido.data.attributes.age'])].
↪shape[0]))
print("diagnostic_main NaN => " + str(dfOrg[pd.isnull(dfOrg['pedido.data.
↪attributes.diagnostic_main'])].shape[0]))
```

```
print("gender NaN => " + str(dfOrg[pd.isnull(dfOrg['pedido.data.attributes.
 ↪gender'])].shape[0]))
print("articulo NaN => " + str(dfOrg[pd.isnull(dfOrg['articulo'])].shape[0]))
print("articlesRevisedYear NaN => " + str(dfOrg[pd.isnull(dfOrg['respuesta.
 ↪articlesRevisedYear'])].shape[0]))
print("articlesRevisedMonth NaN => " + str(dfOrg[pd.isnull(dfOrg['respuesta.
 ↪articlesRevisedMonth'])].shape[0]))
print("pubmed_keys NaN => " + str(dfOrg[pd.isnull(dfOrg['respuesta.
 ↪pubmed_keys'])].shape[0]))
print("utilidad NaN => " + str(dfOrg[pd.isnull(dfOrg['utilidad'])].shape[0]))
```

```
age NaN => 10
diagnostic_main NaN => 0
gender NaN => 0
articulo NaN => 0
articlesRevisedYear NaN => 0
articlesRevisedMonth NaN => 0
pubmed_keys NaN => 0
utilidad NaN => 1192
```

Remove row with age eq NaN

[10]:
```
dfOrg = dfOrg[pd.notnull(dfOrg['pedido.data.attributes.age'])]
```

0.3 Standardize the Data

Choosed “age”, “diagnostic_main”, “year”, “pubmed_keys” and “articulo” attributes (based on PCA_V2 study)

[11]:
```
from sklearn.preprocessing import StandardScaler

features = ["pedido.data.attributes.age",
    "pedido.data.attributes.diagnostic_main",
    "respuesta.articlesRevisedYear",
    "respuesta.pubmed_keys",
    "articulo"]

# Separating out the features
x = dfOrg.loc[:, features].values

featuresTransformed = StandardScaler().fit_transform(x)

dfStandarized = pd.DataFrame(featuresTransformed, index=dfOrg.index,␣
 ↪columns=features)
dfStandarized['utilidad'] = dfOrg['utilidad']

dfStandarized
```

[11]:

	pedido.data.attributes.age	pedido.data.attributes.diagnostic_main	respuesta.articlesRevisedYear	respuesta.pubmed_keys	articulo	utilidad
0	1.443474	-1.360638	0.643671	-1.650220	-0.221939	1.0
1	1.443474	-1.360638	0.643671	-1.650220	0.137839	NaN
2	1.443474	-1.360638	0.224418	-1.650220	0.162904	NaN
3	1.443474	-1.360638	-0.194835	-1.650220	-0.577070	NaN
4	1.443474	-1.360638	0.643671	-1.650220	0.255793	NaN
…	…	…	…	…	…	
1238	-0.429381	-0.580827	-0.194835	1.520816	0.574852	NaN
1239	-0.429381	-0.580827	1.062924	1.520816	-0.540973	NaN
1240	-0.429381	-0.580827	-0.614089	1.520816	0.801912	NaN
1241	-0.429381	-0.580827	1.062924	1.520816	-0.056202	NaN
1242	-0.429381	-0.580827	-0.614089	1.520816	-2.782199	NaN

[1233 rows x 6 columns]

0.4 Separe data by utilidad is defined

[12]:
```
dfDataSetComplete = dfStandarized[pd.notnull(dfOrg['utilidad'])]

print(dfDataSetComplete.shape[0])

dfDataSetToPredict = dfStandarized[pd.isnull(dfOrg['utilidad'])]

print(dfDataSetToPredict.shape[0])
```

```
51
1182
```

[13]:
```
dfDataSetComplete.head(10)
```

[13]:

	pedido.data.attributes.age	pedido.data.attributes.diagnostic_main	\
0	1.443474	-1.360638	
32	1.443474	-1.360638	
230	-0.478666	-0.775780	

```
290                    0.260618                                -0.385874
299                    0.260618                                -0.385874
300                   -1.365808                                -0.288397
303                   -1.365808                                -0.288397
304                   -1.365808                                -0.288397
305                   -1.365808                                -0.288397
311                    1.492759                                -0.190921

     respuesta.articlesRevisedYear  respuesta.pubmed_keys  articulo  utilidad
0                         0.643671              -1.650220 -0.221939       1.0
32                        0.224418              -1.529801  0.179117       1.0
230                      -2.291102              -0.807286  0.213394       0.0
290                      -2.291102              -0.727007 -0.178041       0.0
299                       1.062924              -0.727007  0.010654       1.0
300                       1.062924              -0.686867 -0.944476       1.0
303                       0.224418              -0.686867  0.359861       0.0
304                       0.224418              -0.686867  0.359861       0.0
305                       0.224418              -0.686867 -0.015068       1.0
311                       1.062924              -0.646728  0.817865       1.0
```

0.5 Logistic Regression

[14]:
```
from sklearn import linear_model
from sklearn.model_selection import train_test_split
from sklearn import model_selection
from sklearn.metrics import accuracy_score
```

[15]:
```
dfDataSetComplete.describe()
```

[15]:
```
       pedido.data.attributes.age  pedido.data.attributes.diagnostic_main  \
count                   51.000000                               51.000000
mean                     0.459694                               -0.116380
std                      1.083386                                0.576213
min                     -1.365808                               -1.360638
25%                     -0.823666                               -0.580827
50%                      0.901332                               -0.190921
75%                      1.443474                                0.101508
max                      1.739187                                1.466178

       respuesta.articlesRevisedYear  respuesta.pubmed_keys   articulo  \
count                      51.000000              51.000000  51.000000
mean                        0.092887              -0.190237  -0.069174
std                         1.157292               0.553751   0.798659
min                        -2.710355              -1.650220  -2.179545
25%                        -0.194835              -0.526309  -0.540973
50%                         0.224418              -0.205191   0.124179
75%                         1.062924               0.015577   0.510923
```

```
max                          1.062924                1.279978    1.050230
```

```
        utilidad
count  51.000000
mean    0.588235
std     0.497050
min     0.000000
25%     0.000000
50%     1.000000
75%     1.000000
max     1.000000
```

We check the number of results

[16]:
```
dfDataSetComplete.groupby('utilidad').size()
```

[16]:
```
utilidad
0.0    21
1.0    30
dtype: int64
```

Choosed “age”, “diagnostic_main”, “year”, “pubmed_keys” and “articulo” attributes (based on PCA_V2 study)

[17]:
```
dataToTrain = dfDataSetComplete[[
    "pedido.data.attributes.age",
    "pedido.data.attributes.diagnostic_main",
    "respuesta.articlesRevisedYear",
    "respuesta.pubmed_keys",
    "articulo",
    "utilidad"
]]


X = np.array(dataToTrain.drop(['utilidad'],1))
y = np.array(dataToTrain['utilidad'])
X.shape
```

[17]:
```
(51, 5)
```

[18]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
```

[19]:
```
model = linear_model.LogisticRegression()
model.fit(X_train,y_train)

model.score(X_train,y_train)
```

[19]:
```
0.6578947368421053
```

[20]:
```
# see: https://es.wikipedia.org/wiki/Validaci%C3%B3n_cruzada
kfold = model_selection.KFold(n_splits=10)
cv_results = model_selection.cross_val_score(model, X_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')
msg = "%s: %f (%f)" % ("Logistic Regression", cv_results.mean(), cv_results.
 ↪std())
print(msg)
```

```
Logistic Regression: 0.508333 (0.289756)
```

[21]:
```
predictions = model.predict(X_test)
print(accuracy_score(y_test, predictions))
```

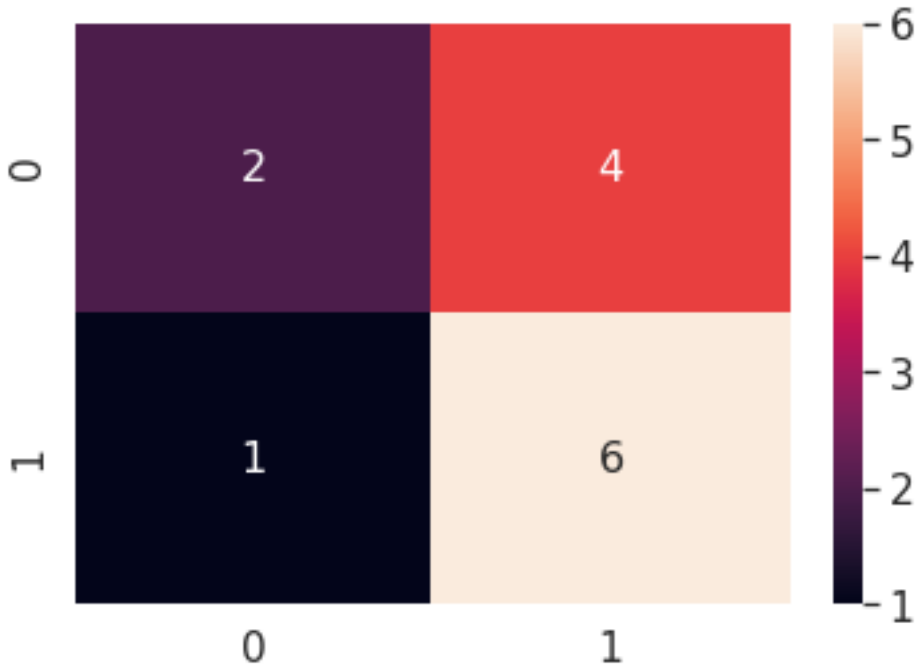
```
0.6153846153846154
```

[22]:
```
import seaborn as sn
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
```

[23]:
```
cf = confusion_matrix(y_test, predictions)

df_cm = pd.DataFrame(cf, range(2), range(2))
sn.set(font_scale=1.4) # for label size
sn.heatmap(df_cm, annot=True, annot_kws={"size": 16}) # font size

plt.show()
```



0.6 Run Prediction

[24]:
```
result = model.predict(dfDataSetToPredict[[
    "pedido.data.attributes.age",
    "pedido.data.attributes.diagnostic_main",
    "respuesta.articlesRevisedYear",
    "respuesta.pubmed_keys",
    "articulo"
]])

result
```

[24]:
```
array([1., 1., 1., …, 0., 0., 0.])
```

[ ]:
```

```