Machine Learning Project from Titanic DB Using Python

Luigi Mennella

Project Description

Starting data: DB Titanic, version available in the Seaborn library .

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Purpose: To train a machine learning algorithm to predict the behavior of the target variable *survived* with respect to the features. Records = 891.

	survived	pclass	age	sibsp	parch	fare	adult_male	alone	sex_female	sex_male	...	deck_A	deck_B	deck_C
0	0	3	22.0	1	0	7.2500	True	False	False	True	...	False	False	False
1	1	1	38.0	1	0	71.2833	False	False	True	False	...	False	False	True
2	1	3	26.0	0	0	7.9250	False	True	True	False	...	False	False	False
3	1	1	35.0	1	0	53.1000	False	False	True	False	...	False	False	True
4	0	3	35.0	0	0	8.0500	True	True	False	True	...	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
886	0	2	27.0	0	0	13.0000	True	True	False	True	...	False	False	False
887	1	1	19.0	0	0	30.0000	False	True	True	False	...	False	True	False
888	0	3	NaN	1	2	23.4500	False	False	True	False	...	False	False	False
889	1	1	26.0	0	0	30.0000	True	True	False	True	...	False	False	True
890	0	3	32.0	0	0	7.7500	True	True	False	True	...	False	False	False

891 rows × 29 columns

Features description

pclass : passenger's travel class (1, 2, 3)

sex: gender of the passenger (male, female)

age: age of the passenger

sibsp : number of siblings or spouses

parch : number of parents or children

fare: ticket price

embarked : place of embarkation

class: travel class (e.g. first)

who : man/woman/child

adult_male : true = adult male; false = other

deck: ship's deck (A, B, C…G, NaN)

embark_town : embarkation city (full name)

alive : survived (yes/no)

alone: alone (true) or accompanied (false)

Redundant Features Analysis

Qualitative analysis of features highlights redundancy between the following variables:

alive : redundant with the target variable *survived*

pclass : redundant to *class*

embark_town : redundant to *embarked*

sex and adult_male : : both redundant with *who*

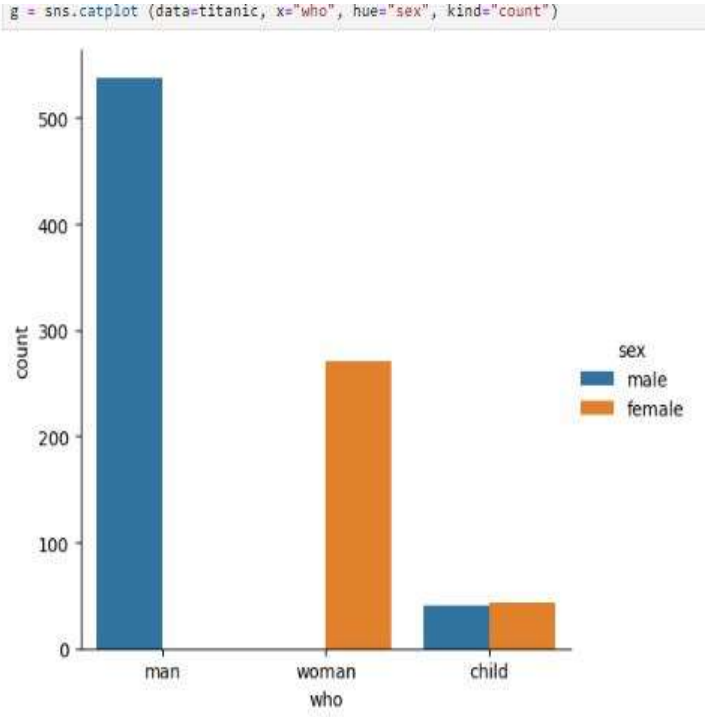
```
titanic.groupby(by=["survived","alive"],
                as_index=False,
                dropna=False) \
       .agg(conteggio   = ("survived",
                           np.size)
            )
```

	survived	alive	conteggio
0	0	no	549
1	1	yes	342

```
#Ridondanza anche tra class e pclass
pd.crosstab(titanic["class"], titanic[
```

pclass	1	2	3
class			
First	216	0	0
Second	0	184	0
Third	0	0	491

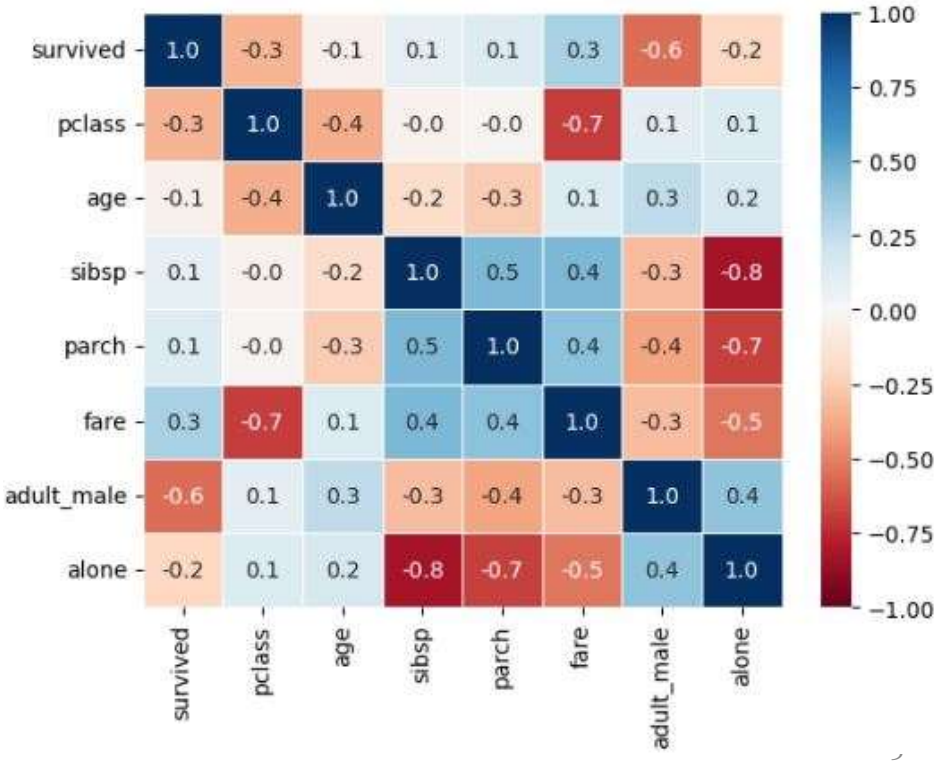
```
g = sns.catplot (data=titanic, x="who", hue="sex", kind="count")
```



Correlation analysis

The correlation analysis, also performed with the aid of heat maps (linear and Spearman), highlights the presence of some strongly correlated variables.

In particular, the correlation between the *alone variables* with respect to *sibsp* and *parch is very strong* .



Elimination of redundant or missing features

Qualitative feature analysis suggests eliminating the following variables:

alive : redundant with the target variable

sex and adult_male : : redundant to *who*

pclass : redundant to *class*

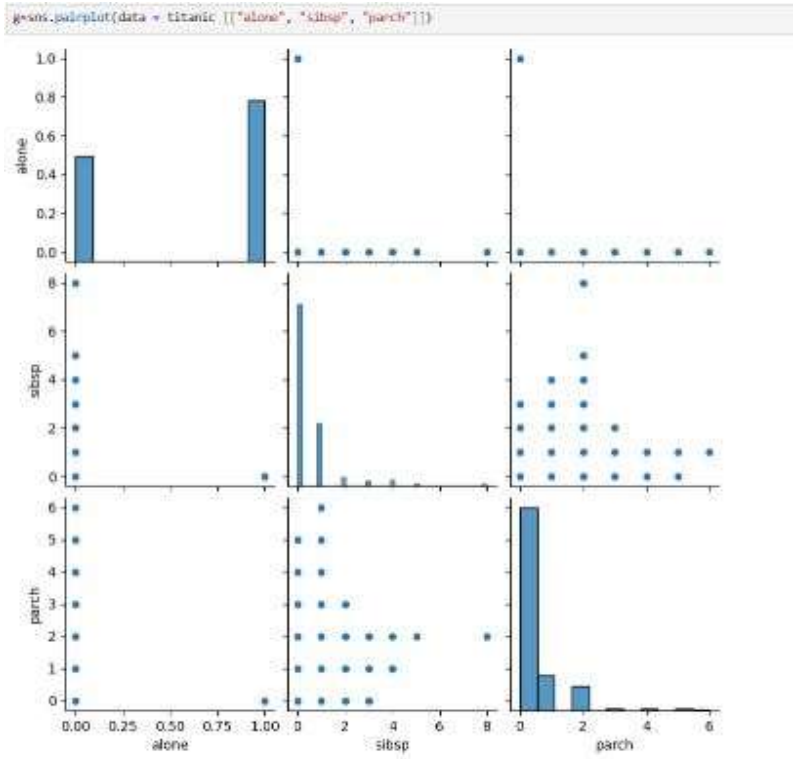
embark_town : redundant to *embarked*

alone: redundant with respect to *sibsp* *parch*

deck: has many nulls.

```
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   survived     891 non-null    int64
 1   pclass       891 non-null    int64
 2   sex          891 non-null    object
 3   age          714 non-null    float64
 4   sibsp        891 non-null    int64
 5   parch        891 non-null    int64
 6   fare         891 non-null    float64
 7   embarked     889 non-null    object
 8   class        891 non-null    category
 9   who          891 non-null    object
 10  adult_male   891 non-null    bool
 11  deck         203 non-null    category
 12  embark_town  889 non-null    object
 13  alive        891 non-null    object
 14  alone        891 non-null    bool
```



Splitting data into training and testing

Thanks to the training_test_split class of scikitik-learn the DB is divided into a training part and a testing part.

```
X = titanic.drop("survived",axis=1).values
Xcolumns = titanic.drop("survived",axis=1).columns
y = titanic["survived"].values
```

[51]:
```
# creiamo i db di training e test
x1,x2,y1,y2 = train_test_split(X,
                               y,
                               test_size = 0.3,
                               shuffle = True,
                               random_state = 1)
```

[52]:
```
Xcolumns
```

[52]:
```
Index(['pclass', 'age', 'sibsp', 'parch', 'fare', 'embarked', 'who'], dtype='object')
```

Null management

Among the residual variables, only *age* and *embarked* present some **null values**.

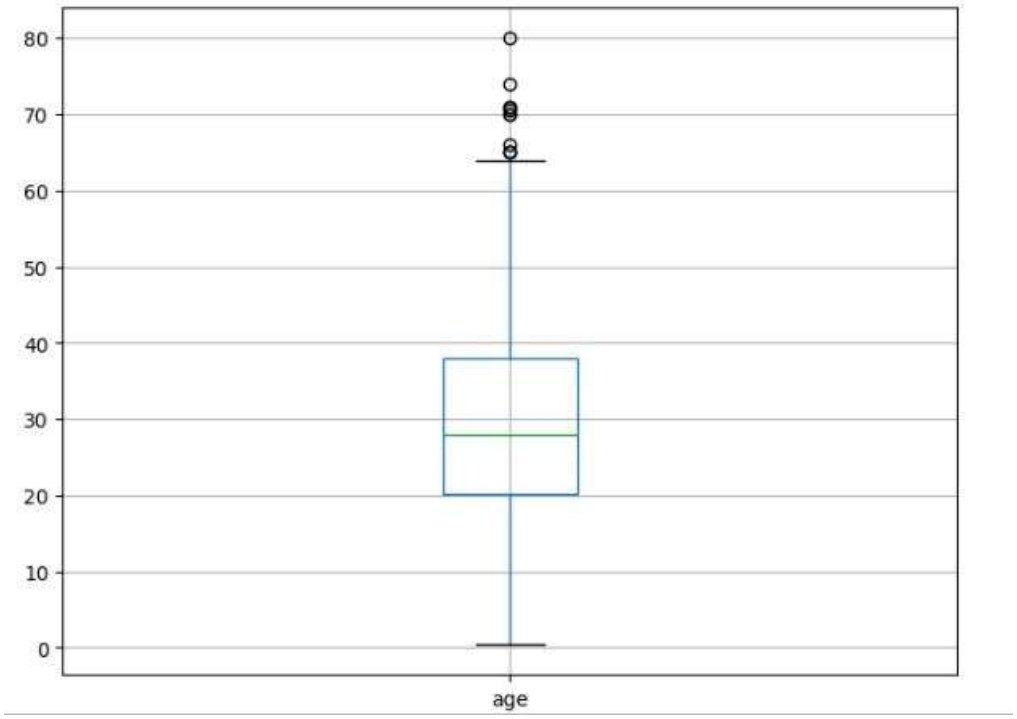
After studying the variables, we decide to replace them like this:

age: median («28»)

embarked : fashion («S»).

	embarked	size
0	C	168
1	Q	77
2	S	644
3	NaN	2

```
g = titanic.boxplot(column = ["age"], figsize = (8,6))
```



Creating the pipeline

A pipeline is created using the following classes from the scikitik-learn library :

- ✓ SimpleImputer : to valorize *nulls*
- ✓ StandardScaler to normalize quantitative variables
- ✓ OneHotEncoder for encoding nominal qualitative variables
- ✓ OrdinalEncoder to encode ordinal qualitative variables
- ✓ LogisticRegression as classification algorithm
- ✓ MakeColumnTransformer to apply methods to different columns

```
null_handling = make_column_transformer(
        (SimpleImputer(strategy='median'), [0,1,2,3]),
        (SimpleImputer(strategy='most_frequent'), [4,5,6]),
        remainder='passthrough')
```

```
pipeline = Pipeline([('vn',valorizza_null),
                     ('pr',preprocessing),
                     ('lr', LogisticRegression(random_state=0))
                     ])
```

```
preprocessing = make_column_transformer(
        (StandardScaler(), [0,1,2,3]),
        (OneHotEncoder(handle_unknown='ignore',drop = 'first'), [4,6]),
        (OrdinalEncoder(categories=[["First","Second","Third"]],handle_unknown="use_encoded_value",unknown_value=4),[5]),
        remainder='passthrough')
```

Parameter tuning and model accuracy

GridSearchCV class from scikitik-learn to verify the choice of the median to replace the nulls of the quantitative parameters. The choice is confirmed.

- ✓ The fitting on the training sample is 0.836
- ✓ The fitting value that would be obtained with a model without pre -processing is slightly lower (0.833), so the operations performed are validated.
- ✓ The fit to the test data is 0.791, which is lower but still good.

Confusion matrix

A further element to evaluate the goodness of the model is the confusion matrix.

- ✓ On the main diagonal there are the **correct solutions**, that is 133 non-survivors (0;0) and 79 non-survivors (1;1)
- ✓ 20 are the **errors of the first type**, that is those predicted as not surviving but actually surviving (0;1)
- ✓ 36 are the **second type errors**, that is, those expected to survive but in reality did not survive (1;0).

```
array([[133,  20],
       [ 36,  79]])
```