S10 T01 Duplicate

May 12, 2022

1 Nivell 1

1.1 Exercici 1

Crea almenys tres models de classificació diferents per intentar predir el millor possible l'endarreriment dels vols (ArrDelay) de DelayedFlights.csv. Considera si el vol ha arribat tard o no (ArrDelay > 0).

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
fly = pd.read_csv('C:/Users/Guillermo/Desktop/Curs Data Scientist/Sprint 2/S02␣
↪T05 Exploració de les dades/DelayedFlights.csv')
```

[4]:
```
fly.columns
```

[4]:
```
Index(['Unnamed: 0', 'Year', 'Month', 'DayofMonth', 'DayOfWeek', 'DepTime',
       'CRSDepTime', 'ArrTime', 'CRSArrTime', 'UniqueCarrier', 'FlightNum',
       'TailNum', 'ActualElapsedTime', 'CRSElapsedTime', 'AirTime', 'ArrDelay',
       'DepDelay', 'Origin', 'Dest', 'Distance', 'TaxiIn', 'TaxiOut',
       'Cancelled', 'CancellationCode', 'Diverted', 'CarrierDelay',
       'WeatherDelay', 'NASDelay', 'SecurityDelay', 'LateAircraftDelay'],
      dtype='object')
```

[3]:
```
fly['retard'] = fly['ArrDelay'].apply(lambda x: 1 if x > 0 else 0)
```

[7]:
```
fly.head()
```

[7]:
```
   Unnamed: 0  Year  Month  DayofMonth  DayOfWeek  DepTime  CRSDepTime  \
0           0  2008      1           3          4   2003.0        1955
1           1  2008      1           3          4    754.0         735
2           2  2008      1           3          4    628.0         620
3           4  2008      1           3          4   1829.0        1755
4           5  2008      1           3          4   1940.0        1915

   ArrTime  CRSArrTime UniqueCarrier  …  TaxiOut Cancelled  \
```

```
0   2211.0        2225            WN   …      8.0          0
1   1002.0        1000            WN   …     10.0          0
2    804.0         750            WN   …     17.0          0
3   1959.0        1925            WN   …     10.0          0
4   2121.0        2110            WN   …     10.0          0

   CancellationCode  Diverted  CarrierDelay  WeatherDelay  NASDelay  \
0                 N         0           NaN           NaN       NaN
1                 N         0           NaN           NaN       NaN
2                 N         0           NaN           NaN       NaN
3                 N         0           2.0           0.0       0.0
4                 N         0           NaN           NaN       NaN

  SecurityDelay LateAircraftDelay  retard
0           NaN               NaN       0
1           NaN               NaN       1
2           NaN               NaN       1
3           0.0              32.0       1
4           NaN               NaN       1

[5 rows x 31 columns]
```

[5]:
```
fly['retard'].isna().sum()
```

[5]: 0

[6]:
```
fly['ArrDelay'].isna().sum()
```

[6]: 8387

[4]:
```
#Eliminamos NaNs de ArrDelay
fly = fly.dropna(subset = ['ArrDelay'])
```

[5]:
```
fly['ArrDelay'].isna().sum()
```

[5]: 0

[5]:
```
fly2 = fly.sample(n = 100000, random_state = 42)
```

[7]:
```
fly2.isna().sum()
```

[7]:
```
Unnamed: 0             0
Year                   0
Month                  0
DayofMonth             0
DayOfWeek              0
DepTime                0
```

```
CRSDepTime               0
ArrTime                  0
CRSArrTime               0
UniqueCarrier            0
FlightNum                0
TailNum                  0
ActualElapsedTime        0
CRSElapsedTime           0
AirTime                  0
ArrDelay                 0
DepDelay                 0
Origin                   0
Dest                     0
Distance                 0
TaxiIn                   0
TaxiOut                  0
Cancelled                0
CancellationCode         0
Diverted                 0
CarrierDelay         35303
WeatherDelay         35303
NASDelay             35303
SecurityDelay        35303
LateAircraftDelay    35303
retard                   0
dtype: int64
```

Com retard no ha heredat els NaNs de Arrdelay eliminem les files amb NaNs de la nostra mostra

[8]:
```
fly2.retard.value_counts()
```

[8]:
```
1    89517
0    10483
Name: retard, dtype: int64
```

Igual que en l'exercici anterior eliminem els NaNs de CarrierDelay, WeatherDelay, NASDelay, SecurityDelay i LateAircraftDelay amb la mitjana.

[6]:
```
numVar = ['Month', 'DayofMonth', 'DayOfWeek', 'DepTime', 'CRSDepTime',␣
 ↪'ArrTime',
       'CRSArrTime', 'FlightNum', 'ActualElapsedTime', 'CRSElapsedTime',␣
 ↪'AirTime', 'ArrDelay',
       'DepDelay','Distance', 'TaxiIn', 'TaxiOut', 'CarrierDelay',
       'WeatherDelay', 'NASDelay', 'SecurityDelay', 'LateAircraftDelay']
catVar = ['UniqueCarrier', 'TailNum','Origin', 'Dest']

flyNum = fly2.loc[:, numVar]
```

```
flyCat = fly2.loc[:,catVar]
retards = fly2.loc[:, 'retard']
```

[10]:
```
flyNum.head()
```

[10]:
```
         Month  DayofMonth  DayOfWeek  DepTime  CRSDepTime  ArrTime  \
403778       3          25          2   1124.0        1115   1221.0
1397595      8           9          6   1152.0        1130   1555.0
1849546     12          13          6   1226.0        1210   1405.0
18418        1          21          1   2046.0        1950   2158.0
1805454     12          26          5   1759.0        1709   2026.0

         CRSArrTime  FlightNum  ActualElapsedTime  CRSElapsedTime  …  \
403778         1215       1095               57.0            60.0  …
1397595        1520       1690              183.0           170.0  …
1849546        1355       5615               99.0           105.0  …
18418          2045       1274              132.0           115.0  …
1805454        1937       6180               87.0            88.0  …

         ArrDelay  DepDelay  Distance  TaxiIn  TaxiOut  CarrierDelay  \
403778        6.0       9.0       251     5.0      7.0           NaN
1397595      35.0      22.0      1121     7.0     23.0          22.0
1849546      10.0      16.0       528     7.0     13.0           NaN
18418        73.0      56.0       629     4.0     25.0           7.0
1805454      49.0      50.0       495     3.0     13.0           0.0

         WeatherDelay  NASDelay  SecurityDelay  LateAircraftDelay
403778            NaN       NaN            NaN                NaN
1397595           0.0      13.0            0.0                0.0
1849546           NaN       NaN            NaN                NaN
18418             0.0      17.0            0.0               49.0
1805454           0.0       0.0            0.0               49.0

[5 rows x 21 columns]
```

[11]:
```
flyCat.head()
```

[11]:
```
        UniqueCarrier TailNum Origin Dest
403778             WN  N909WN    STL  MDW
1397595            AA  N5ELAA    DFW  MIA
1849546            EV  N752EV    CAK  ATL
18418              WN  N642WN    DEN  LAS
1805454            OO  N742SK    DEN  OKC
```

[12]:
```
print(flyNum.shape)
print(flyCat.shape)
```

```
(100000, 21)
(100000, 4)
```

[7]:
```python
from sklearn.impute import SimpleImputer

imp = SimpleImputer(missing_values = np.nan, strategy = 'median')

flyTemp = imp.fit_transform(flyNum)

flyNum = pd.DataFrame(flyTemp, columns = numVar)

print(flyNum.isna().sum())

flyNum.head()
```

```
Month                0
DayofMonth           0
DayOfWeek            0
DepTime              0
CRSDepTime           0
ArrTime              0
CRSArrTime           0
FlightNum            0
ActualElapsedTime    0
CRSElapsedTime       0
AirTime              0
ArrDelay             0
DepDelay             0
Distance             0
TaxiIn               0
TaxiOut              0
CarrierDelay         0
WeatherDelay         0
NASDelay             0
SecurityDelay        0
LateAircraftDelay    0
dtype: int64
```

[7]:
```
   Month  DayofMonth  DayOfWeek  DepTime  CRSDepTime  ArrTime  CRSArrTime  \
0    3.0        25.0        2.0   1124.0      1115.0   1221.0      1215.0
1    8.0         9.0        6.0   1152.0      1130.0   1555.0      1520.0
2   12.0        13.0        6.0   1226.0      1210.0   1405.0      1355.0
3    1.0        21.0        1.0   2046.0      1950.0   2158.0      2045.0
4   12.0        26.0        5.0   1759.0      1709.0   2026.0      1937.0

   FlightNum  ActualElapsedTime  CRSElapsedTime  …  ArrDelay  DepDelay  \
0     1095.0               57.0            60.0  …       6.0       9.0
```

```
1     1690.0              183.0            170.0  ...       35.0      22.0
2     5615.0               99.0            105.0  ...       10.0      16.0
3     1274.0              132.0            115.0  ...       73.0      56.0
4     6180.0               87.0             88.0  ...       49.0      50.0

   Distance  TaxiIn  TaxiOut  CarrierDelay  WeatherDelay  NASDelay  \
0     251.0     5.0      7.0           2.0           0.0       2.0
1    1121.0     7.0     23.0          22.0           0.0      13.0
2     528.0     7.0     13.0           2.0           0.0       2.0
3     629.0     4.0     25.0           7.0           0.0      17.0
4     495.0     3.0     13.0           0.0           0.0       0.0

   SecurityDelay  LateAircraftDelay
0            0.0                8.0
1            0.0                0.0
2            0.0                8.0
3            0.0               49.0
4            0.0               49.0

[5 rows x 21 columns]
```

Igual que en el cas anterior apliquem RobustScaler i normalitzem

[8]:
```
import sklearn.preprocessing as sklp

scaler = sklp.RobustScaler()

fly2NTemp = scaler.fit_transform(flyNum)

minmax = sklp.MinMaxScaler()

fly2NTemp = minmax.fit_transform(fly2NTemp)

flyNum2 = pd.DataFrame(data = fly2NTemp, columns = numVar)

print(flyNum2.shape)
flyNum2.head()
```

```
(100000, 21)
```

[8]:
```
      Month  DayofMonth  DayOfWeek   DepTime  CRSDepTime   ArrTime  \
0  0.181818    0.800000   0.166667  0.468112    0.472434  0.508545
1  0.636364    0.266667   0.833333  0.479783    0.478796  0.647770
2  1.000000    0.400000   0.833333  0.510629    0.512723  0.585244
3  0.000000    0.666667   0.000000  0.852439    0.826548  0.899125
4  1.000000    0.833333   0.666667  0.732805    0.724343  0.844102
```

```
   CRSArrTime  FlightNum  ActualElapsedTime  CRSElapsedTime  …  ArrDelay  \
0    0.514843   0.112332           0.064417        0.066874  …  0.038089
1    0.644190   0.173426           0.257669        0.237947  …  0.058172
2    0.574215   0.576445           0.128834        0.136858  …  0.040859
3    0.866836   0.130712           0.179448        0.152411  …  0.084488
4    0.821035   0.634459           0.110429        0.110420  …  0.067867

   DepDelay  Distance    TaxiIn   TaxiOut  CarrierDelay  WeatherDelay  \
0  0.001980  0.044616  0.028902  0.018919      0.001434           0.0
1  0.010561  0.221050  0.040462  0.062162      0.015771           0.0
2  0.006601  0.100791  0.040462  0.035135      0.001434           0.0
3  0.033003  0.121274  0.023121  0.067568      0.005018           0.0
4  0.029043  0.094099  0.017341  0.035135      0.000000           0.0

   NASDelay  SecurityDelay  LateAircraftDelay
0  0.001552            0.0           0.013769
1  0.010085            0.0           0.000000
2  0.001552            0.0           0.013769
3  0.013189            0.0           0.084337
4  0.000000            0.0           0.084337

[5 rows x 21 columns]
```

Ara apliquem dummies a les variables categoriques

[9]:
```python
flyCat2 = pd.get_dummies(data = flyCat, prefix = ['UC-', 'TN-', 'O-', 'D-'])

print(flyCat2.shape)
```

```
(100000, 5812)
```

[30]:
```python
flyCat2.head()
```

[30]:
```
         UC-_9E  UC-_AA  UC-_AQ  UC-_AS  UC-_B6  UC-_CO  UC-_DL  UC-_EV  \
1782417       0       0       0       0       0       0       0       0
512712        0       0       0       0       0       0       0       0
447137        0       0       0       0       0       0       0       0
55082         0       0       0       0       0       0       0       0
877634        0       0       0       0       0       1       0       0

         UC-_F9  UC-_FL  …  D-_TXK  D-_TYR  D-_TYS  D-_VLD  D-_VPS  D-_WRG  \
1782417       0       0  …       0       0       0       0       0       0
512712        0       0  …       0       0       0       0       0       0
447137        0       0  …       0       0       0       0       0       0
55082         0       0  …       0       0       0       0       0       0
877634        0       0  …       0       0       0       0       0       0
```

```
         D-_XNA  D-_YAK  D-_YKM  D-_YUM
1782417       0       0       0       0
512712        0       0       0       0
447137        0       0       0       0
55082         0       0       0       0
877634        0       0       0       0

[5 rows x 5811 columns]
```

[10]:
```
#flyCat2.shape
a = flyCat2.reset_index(drop=True)
```

[17]:
```
a.head()
```

[17]:
```
   UC-_9E  UC-_AA  UC-_AQ  UC-_AS  UC-_B6  UC-_CO  UC-_DL  UC-_EV  UC-_F9  \
0       0       0       0       0       0       0       0       0       0
1       0       1       0       0       0       0       0       0       0
2       0       0       0       0       0       0       0       1       0
3       0       0       0       0       0       0       0       0       0
4       0       0       0       0       0       0       0       0       0

   UC-_FL  …  D-_TYR  D-_TYS  D-_VLD  D-_VPS  D-_WRG  D-_WYS  D-_XNA  \
0       0  …       0       0       0       0       0       0       0
1       0  …       0       0       0       0       0       0       0
2       0  …       0       0       0       0       0       0       0
3       0  …       0       0       0       0       0       0       0
4       0  …       0       0       0       0       0       0       0

   D-_YAK  D-_YKM  D-_YUM
0       0       0       0
1       0       0       0
2       0       0       0
3       0       0       0
4       0       0       0

[5 rows x 5812 columns]
```

[18]:
```
a.shape
```

[18]: (100000, 5812)

[11]:
```
df = pd.merge(flyNum2, a, left_index=True, right_index=True)
#df = pd.concat([flyNum2, a], axis=1)
```

[20]:
```
df.shape
```

[20]: (100000, 5833)

[21]:
```
df.head()
```

[21]:
```
      Month  DayofMonth  DayOfWeek   DepTime  CRSDepTime   ArrTime  \
0  0.181818    0.800000   0.166667  0.468112    0.472434  0.508545
1  0.636364    0.266667   0.833333  0.479783    0.478796  0.647770
2  1.000000    0.400000   0.833333  0.510629    0.512723  0.585244
3  0.000000    0.666667   0.000000  0.852439    0.826548  0.899125
4  1.000000    0.833333   0.666667  0.732805    0.724343  0.844102

   CRSArrTime  FlightNum  ActualElapsedTime  CRSElapsedTime  …  D-_TYR  \
0    0.514843   0.112332           0.064417        0.066874  …       0
1    0.644190   0.173426           0.257669        0.237947  …       0
2    0.574215   0.576445           0.128834        0.136858  …       0
3    0.866836   0.130712           0.179448        0.152411  …       0
4    0.821035   0.634459           0.110429        0.110420  …       0

   D-_TYS  D-_VLD  D-_VPS  D-_WRG  D-_WYS  D-_XNA  D-_YAK  D-_YKM  D-_YUM
0       0       0       0       0       0       0       0       0       0
1       0       0       0       0       0       0       0       0       0
2       0       0       0       0       0       0       0       0       0
3       0       0       0       0       0       0       0       0       0
4       0       0       0       0       0       0       0       0       0

[5 rows x 5833 columns]
```

[22]:
```
print(flyCat2.shape)
print(flyNum2.shape)
print(df.shape)
```

```
(100000, 5812)
(100000, 21)
(100000, 5833)
```

Com tenim un dataset amb un total de 5833 columnes passem a reduir-lo aplicant una PCA

1.1.1 PCA

[12]:
```
retards = retards.reset_index(drop=True)
retards
```

[12]:
```
0        1
1        1
2        1
3        1
4        1
        ..
99995    1
99996    1
```

```
99997    1
99998    1
99999    0
Name: retard, Length: 100000, dtype: int64
```

[25]:
```
retards.value_counts()
```

[25]:
```
1    89517
0    10483
Name: retard, dtype: int64
```

[28]:
```
from sklearn.decomposition import PCA

#pca = PCA(.95)#Retenga el 95% de la informacióm

pca = PCA().fit(df)
```

```
---------------------------------------------------------------------------
MemoryError                               Traceback (most recent call last)
C:\Users\GUILLE~1\AppData\Local\Temp/ipykernel_7920/1192173359.py in <module>
      3 #pca = PCA(.95)#Retenga el 95% de la informacióm
      4
----> 5 pca = PCA().fit(df)

~\anaconda3\lib\site-packages\sklearn\decomposition\_pca.py in fit(self, X, y)
    380             Returns the instance itself.
    381         """
--> 382         self._fit(X)
    383         return self
    384

~\anaconda3\lib\site-packages\sklearn\decomposition\_pca.py in _fit(self, X)
    455         # Call different fits for either full or truncated SVD
    456         if self._fit_svd_solver == "full":
--> 457             return self._fit_full(X, n_components)
    458         elif self._fit_svd_solver in ["arpack", "randomized"]:
    459             return self._fit_truncated(X, n_components, self.
 ↪_fit_svd_solver)

~\anaconda3\lib\site-packages\sklearn\decomposition\_pca.py in _fit_full(self,␣
 ↪X, n_components)
    490         X -= self.mean_
    491
--> 492         U, S, Vt = linalg.svd(X, full_matrices=False)
    493         # flip eigenvectors' sign to enforce deterministic output
    494         U, Vt = svd_flip(U, Vt)
```

```
~\anaconda3\lib\site-packages\scipy\linalg\decomp_svd.py in svd(a,␣
↪full_matrices, compute_uv, overwrite_a, check_finite, lapack_driver)
    125
    126     # perform decomposition
--> 127     u, s, v, info = gesXd(a1, compute_uv=compute_uv, lwork=lwork,
    128                             full_matrices=full_matrices,␣
↪overwrite_a=overwrite_a)
    129

MemoryError: Unable to allocate 4.35 GiB for an array with shape (100000, 5833)␣
↪and data type float64
```

Reduïm la mostra per intentar processar la PCA

[13]:
```
df2 = pd.merge(df, retards, left_index=True, right_index=True)
df2.shape
```

[13]: (100000, 5834)

[14]:
```
dfReduct = df2.sample(n=10000, random_state=42)
dfReduct.shape
```

[14]: (10000, 5834)

[16]:
```
from sklearn.decomposition import PCA
pca = PCA(.95)
retardsReduct = dfReduct.loc[:,'retard']
```

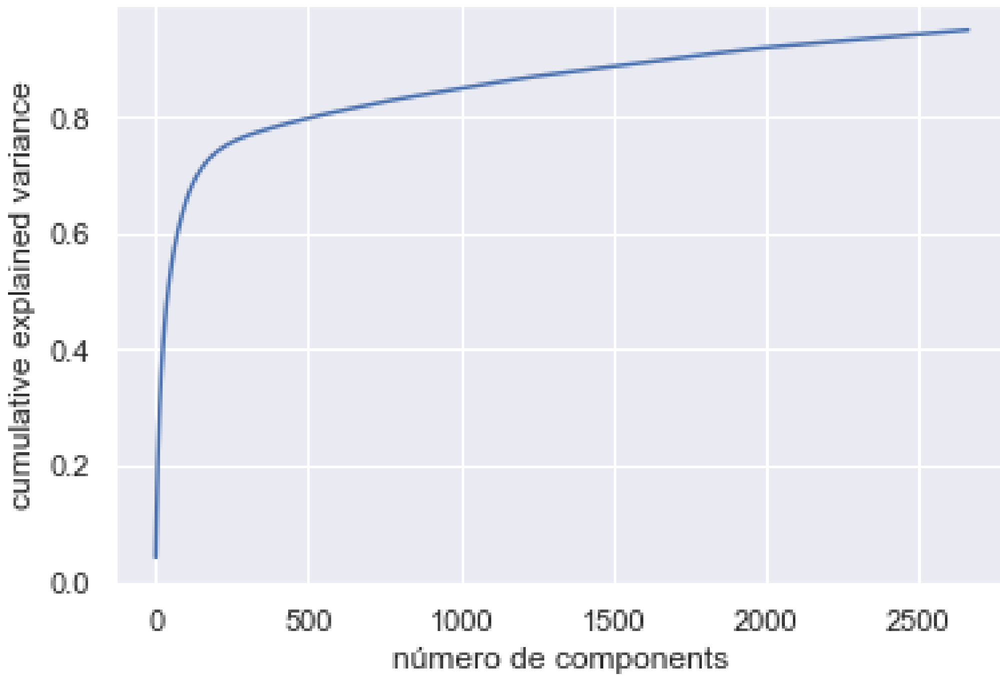
[17]:
```
dfReduct = dfReduct.drop('retard', axis=1)
```

[18]:
```
pca.fit(dfReduct)
dfPCA = pca.transform(dfReduct)
```

[19]:
```
dfPCA.shape
```

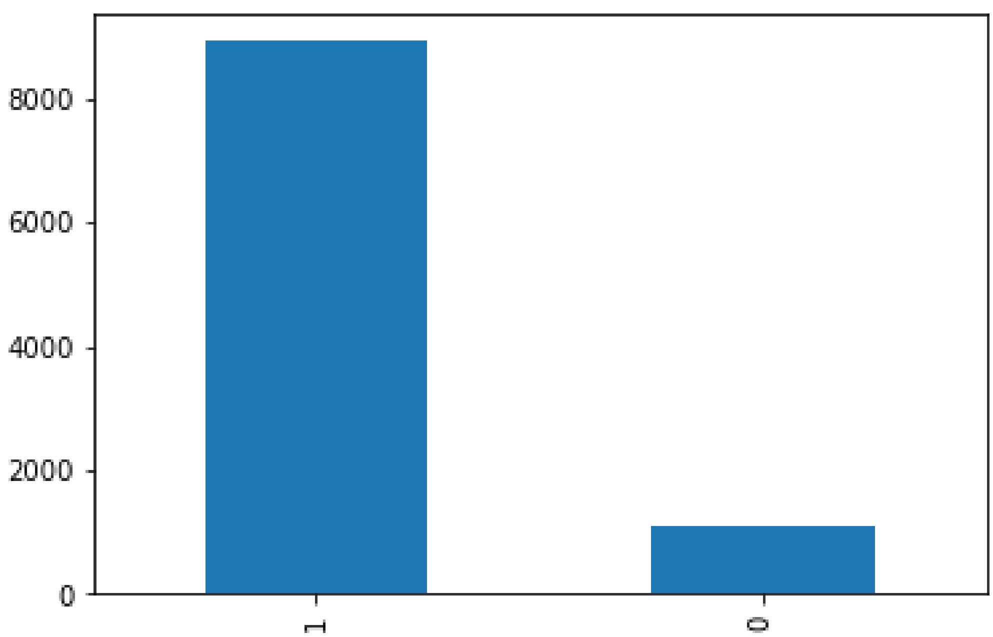
[19]: (10000, 2664)

[20]:
```
sns.set()
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('número de components')
plt.ylabel('cumulative explained variance')
plt.show()
```



Un cop reduit el número de variables mirem com de desbalancejats estan els models

[39]:
```
retardsReduct.value_counts().plot(kind='bar')
plt.show()
```



Com el model està molt desbalancejat convé equilibar-lo (Cal dividir primer el dataset i després rebalancejar).

[21]:
```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(dfPCA, retardsReduct,␣
↪test_size = 0.25, random_state = 42)

print(x_train.shape, '\n', y_train.shape, '\n', x_test.shape, '\n', y_test.
↪shape)
```

```
(7500, 2664)
 (7500,)
 (2500, 2664)
 (2500,)
```

Com el dataset és molt gran una opció seria agafar més mostra. Però degut als problemes de memòria serà una millor opció generar dades noves a partir de la PCA amb SMOUT

[43]:
```
y_train.value_counts()
```

[43]:
```
1    6691
0     809
Name: retard, dtype: int64
```

[22]:
```
from imblearn.over_sampling import SMOTE

x_resampled, y_resampled = SMOTE().fit_resample(x_train, y_train)
```

[23]:
```
y_resampled.value_counts()
```

[23]:
```
1    6691
0    6691
Name: retard, dtype: int64
```

[46]:
```
print(imblearn.__version__)# No sé si m'he de preocupar que això funcioni o no
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
C:\Users\GUILLE~1\AppData\Local\Temp/ipykernel_7920/2763361883.py in <module>
----> 1 print(imblearn.__version__)# No sé si m'he de preocupar que això␣
↪funcioni o no

NameError: name 'imblearn' is not defined
```

Amb tots els processos realitzats hem escalat les variables, reduït les dimensions del dataframe i en el cas del test que hi hagi la mateixa proporció de vols amb retard i sense. Ara passem a aplicar els models.

1.1.2 Models a aplicar

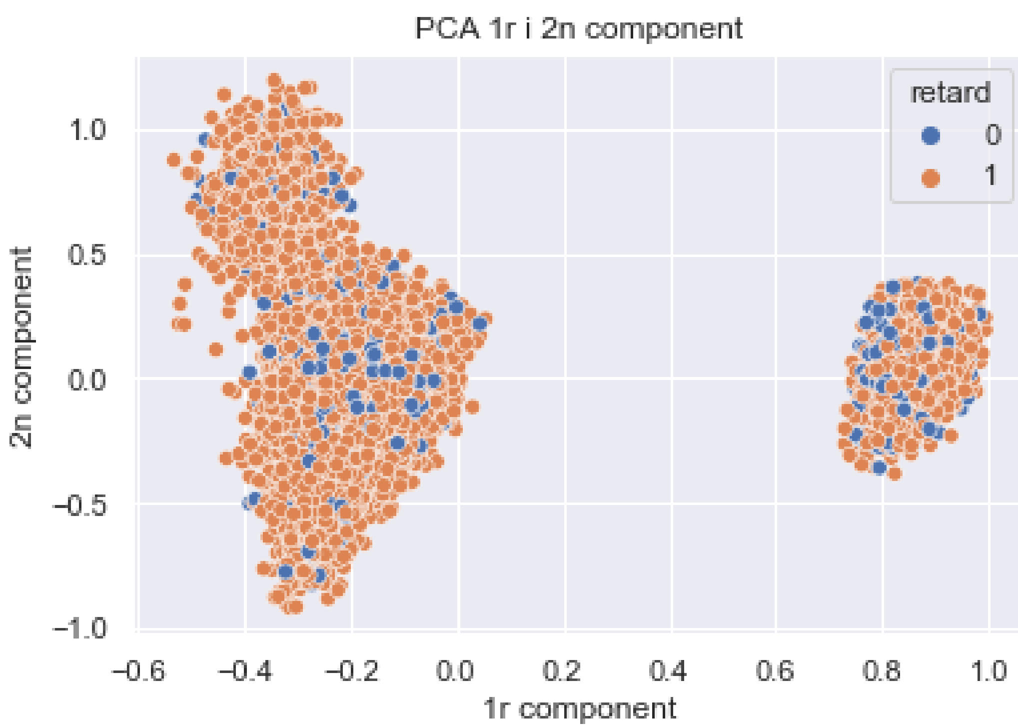
- Decision tree
- Suport vector machine
- Logistic regression

[25]:
```
# Decision tree
from sklearn.tree import DecisionTreeClassifier

dtc = DecisionTreeClassifier()
tree = dtc.fit(x_resampled, y_resampled)
tree_predict = tree.predict(x_test)
```

[33]:
```
#SVM

sns.scatterplot(x=dfPCA[:,0], y=dfPCA[:,1], hue=retardsReduct )
plt.xlabel('1r component')
plt.ylabel('2n component')
plt.title('PCA 1r i 2n component')
plt.show()
```



La gràfica mostra que hi han dos grups diferenciats però no sembla que amb els dos primers components sigui degut els grups pels retards. Igualment s'intentarà separar-los per SVG amb kernel lineal

[34]:
```
from sklearn import svm

clf = svm.SVC(kernel='linear')
clf.fit(x_resampled, y_resampled)
svm_predict = clf.predict(x_test)
```

[35]:
```
#Logistic regression
from sklearn.linear_model import LogisticRegression

logreg = LogisticRegression()

logreg.fit(x_resampled, y_resampled)

logreg_predict = logreg.predict(x_test)
```

```
C:\Users\Guillermo\anaconda3\lib\site-
packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[39]:
```
print(logreg_predict.shape)
print(x_test.shape)
```

```
(2500,)
(2500, 2664)
```

Ignorarem l'alerta degut a que a les dades ja hem aplicat un robust scaler i han sigut normalitzades. Tot i així, al no poder fer prou iteracions pot donar un resultat dolent

1.2 Exercici 2

Compara els models de classificació utilitzant la precisió (accuracy), una matriu de confiança i d'altres mètriques més avançades.

[44]:
```
from sklearn import metrics
#Accuracy
print('decision tree', metrics.accuracy_score(y_test, tree_predict))
print('SVM', metrics.accuracy_score(y_test, svm_predict))
print('Logistic regression', metrics.accuracy_score(y_test, logreg_predict))
```

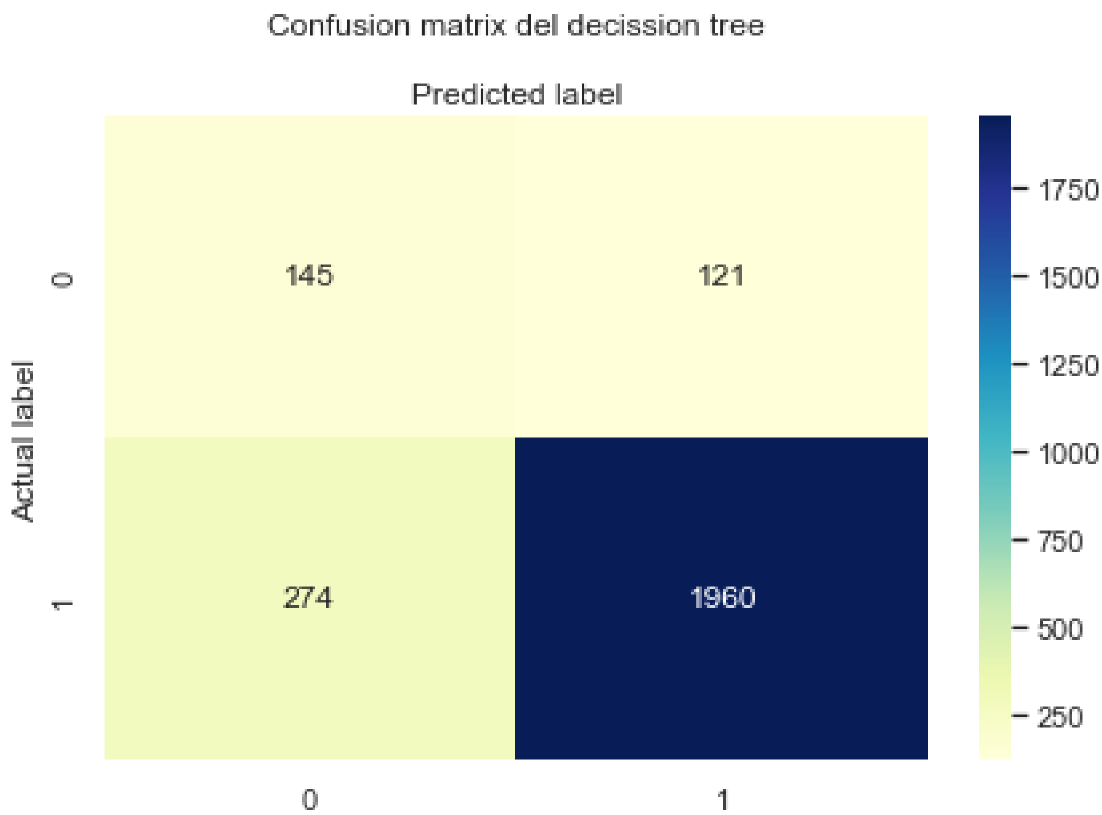
```
decision tree 0.842
SVM 0.8396
Logistic regression 0.824
```

1.2.1 Matriu de confiança

[47]:
```python
#Decisiont tree
tree_matrix = metrics.confusion_matrix(y_test, tree_predict)
tree_matrix
```

[47]:
```
array([[ 145,  121],
       [ 274, 1960]], dtype=int64)
```

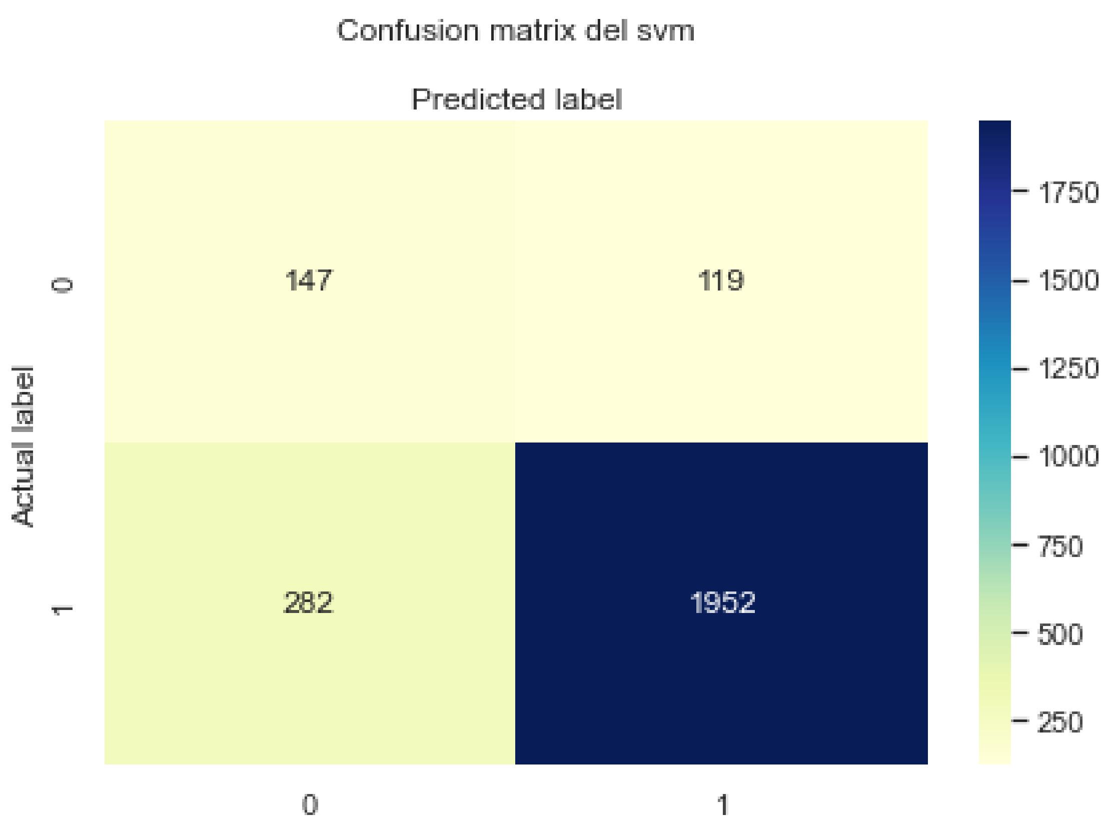
[50]:
```python
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(tree_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix del decission tree', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
plt.show()
```



[53]:
```
# SVM
svm_matrix = metrics.confusion_matrix(y_test, svm_predict)
svm_matrix
```

[53]:
```
array([[ 147,  119],
       [ 282, 1952]], dtype=int64)
```

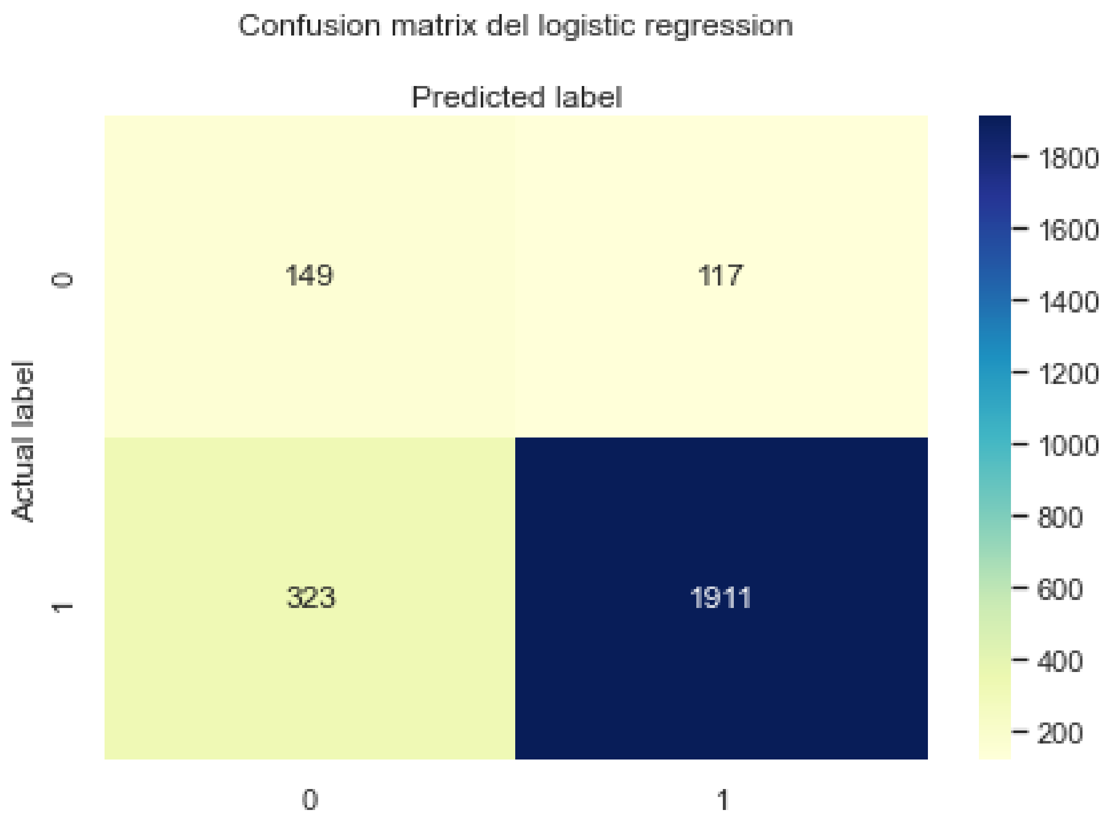
[54]:
```
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(svm_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix del svm', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
plt.show()
```



[57]:
```
#Logistic regression
lgr_matrix = metrics.confusion_matrix(y_test,logreg_predict)
lgr_matrix
```

[57]:
```
array([[ 149,  117],
       [ 323, 1911]], dtype=int64)
```

[58]:
```
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(lgr_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix del logistic regression', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
plt.show()
```



[63]:
```python
data = {'models':['tree', 'SVM','logreg'],
        'TP': [tree_matrix[1,1], svm_matrix[1,1], lgr_matrix[1,1]],
        'FP': [tree_matrix[0,1], svm_matrix[0,1], lgr_matrix[0,1]],
        'TN':[tree_matrix[0,0], svm_matrix[0,0], lgr_matrix[0,0]],
        'FN': [tree_matrix[1,0], svm_matrix[1,0], lgr_matrix[1,0]]
       }
resum = pd.DataFrame(data = data)
resum
```

[63]:

	models	TP	FP	TN	FN
0	tree	1960	121	145	274
1	SVM	1952	119	147	282
2	logreg	1911	117	149	323

[84]:
```python
def clasif_statistic(df):
    for index, row in resum.iterrows():
        print()
        precision = row[1]/(row[1]+row[2])
        sensitivity = row[1]/(row[1]+row[4])
        specificity = row[3]/(row[3]+row[2])
        print(row[0], 'Precission = ', round(precision,3))
```

```
        print(row[0], 'Sensitivity = ', round(sensitivity,3))
        print(row[0], 'Specificity = ', round(specificity,3))
```

[85]:
```
clasif_statistic(resum)
```

```
tree Precission =  0.942
tree Sensitivity =  0.877
tree Specificity =  0.545

SVM Precission =  0.943
SVM Sensitivity =  0.874
SVM Specificity =  0.553

logreg Precission =  0.942
logreg Sensitivity =  0.855
logreg Specificity =  0.56
```

Veiem que en general la precisió i l'assignació de positius és millor que la de negatius. Sent els millors models decision tree i SVM.

1.3 Exercici 3

Entrena'ls utilitzant els diferents paràmetres que admeten.

[90]:
```
# Decision tree
from sklearn.tree import DecisionTreeClassifier

dtc2 = DecisionTreeClassifier(criterion = 'entropy')
tree2 = dtc2.fit(x_resampled, y_resampled)
tree_predict2 = tree2.predict(x_test)

metrics.accuracy_score(y_test, tree_predict2)
matrix = metrics.confusion_matrix(y_test,tree_predict2)
```

[94]:
```
def clasif_statistic2(m):
        precision = m[1,1]/(m[1,1]+m[0,1])
        sensitivity = m[1,1]/(m[1,1]+m[1,0])
        specificity = m[0,0]/(m[0,0]+m[0,1])
        print('TP: ', m[1,1])
        print('TN: ', m[0,0])
        print('FP: ', m[0,1])
        print('FN: ', m[1,0])
        print('Precission = ', round(precision,3))
        print('Sensitivity = ', round(sensitivity,3))
```

```
        print('Specificity = ', round(specificity,3))

clasif_statistic2(matrix)
print('accuracy: ', metrics.accuracy_score(y_test, tree_predict2))
```

```
TP:  1959
TN:  163
FP:  103
FN:  275
Precission =  0.95
Sensitivity =  0.877
Specificity =  0.613
accuracy:  0.8488
```

[95]:

```
clf2 = svm.SVC(kernel='rbf', gamma = 0.1)
clf2.fit(x_resampled, y_resampled)
svm_predict2 = clf2.predict(x_test)

metrics.accuracy_score(y_test, svm_predict2)
matrixSVM = metrics.confusion_matrix(y_test,svm_predict2)

clasif_statistic2(matrixSVM)
print('accuracy: ', metrics.accuracy_score(y_test, svm_predict2))
```

```
TP:  2109
TN:  65
FP:  201
FN:  125
Precission =  0.913
Sensitivity =  0.944
Specificity =  0.244
accuracy:  0.8696
```

[100]:

```
#Logistic regression
from sklearn.linear_model import LogisticRegression

logreg2 = LogisticRegression(solver = 'saga')

logreg2.fit(x_resampled, y_resampled)

logreg_predict2 = logreg2.predict(x_test)

matrix_lgrg = metrics.confusion_matrix(y_test, logreg_predict2)
clasif_statistic2(matrix_lgrg)
print('accuracy: ', metrics.accuracy_score(y_test, svm_predict2))
```

```
TP:  1911
TN:  149
```

```
FP:  117
FN:  323
Precission =  0.942
Sensitivity =  0.855
Specificity =  0.56
accuracy:  0.8696
```

1.4 Exercici 4

Compara el seu rendiment utilitzant l'aproximació traint/test o cross-validation.

S'utilitzarà cross-validation en els models emprats en l'exercici 1

[102]:
```
from sklearn.model_selection import cross_val_score

#Decision tree

scores_tree = cross_val_score(dtc, x_train, y_train, cv=5)
print(scores_tree)
print('mitja', scores_tree.mean())
print('sd', scores_tree.std())
```

```
[0.86733333 0.86533333 0.86666667 0.87266667 0.86133333]
mitja 0.8666666666666666
sd 0.003651483716701135
```

[103]:
```
#SVC

scores_SVC = cross_val_score(clf, x_train, y_train, cv=5)
print(scores_SVC)
print('mitja ', scores_SVC.mean())
print('std ', scores_SVC.std())
```

```
[0.88666667 0.89133333 0.88866667 0.88133333 0.882     ]
mitja  0.8859999999999999
std  0.003841296077570124
```

[104]:
```
#Logistic regression, utilitzem el cas de l'exercici 2 perquè no ha donat
#cap alerta

scores_logreg2 = cross_val_score(logreg2, x_train, y_train, cv=5)
print(scores_logreg2)
print('mean: ', scores_logreg2.mean())
print('std: ', scores_logreg2.std())
```

```
[0.89333333 0.89333333 0.894      0.89066667 0.89133333]
mean:  0.8925333333333334
std:  0.0012927146286443427
```

En tots els casos s'obtenen valors per sobre del 80% d'accuracy amb una dispersió molt petita.

```
[ ]:
```