S09 T01 Practicant amb training i test sets

May 1, 2022

1 Nivell 1

1.1 Exercici 1

Parteix el conjunt de dadesDelayedFlights.csv en train i test. Estudia els dos conjunts per separat, a nivell descriptiu.

El dataset és un dataframe sobre vols en EEUU durant el 2008 que conentenen les següents variables:

- YEAR — Year in which flight took place
- QUARTER — Quarter in which flight took place (1–4)
- MONTH — Month in which flight took place (1–12)
- DAY_OF_MONTH — Day of the month in which flight took place (1–31)
- DAY_OF_WEEK — 1 for Monday, 2 for Tuesday,etc. in which flight took place
- UNIQUE_CARRIER — Airline carrier code
- TAIL_NUM — Aircraft tail number
- FL_NUM — Flight number
- ORIGIN_AIRPORT_ID — ID of origin airport
- ORIGIN — Code of origin airport(ATL, DFW, SEA, etc.)
- DEST_AIRPORT_ID — ID of destination airport
- DEST — Code of destination airport (ATL, DFW, SEA, etc.)
- CRS_DEP_TIME — Scheduled departure time
- DEP_TIME — Actual departure time
- DEP_DELAY — Departure Delay in minutes
- DEP_DEL15 — 1 if departure is delayed by 15 minutes or more else 0
- CRS_ARR_TIME — Scheduled arrival time
- ARR_TIME — Actual arrival time
- ARR_DELAY — Arrival Delay in minutes
- ARR_DEL15 — 1 if arrived late by 15 minutes or more else 0
- CANCELLED — 1 if Flight was cancelled else 0
- DIVERTED — 1 if Flight was diverted else 0
- CRS_ELAPSED_TIME — Scheduled flight time in minutes
- ACTUAL_ELAPSED_TIME — Actual flight time in minutes
- DISTANCE — Distance traveled in miles

[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')
```

[3]:
```
fly.shape
```

[3]: (1936758, 30)

[4]:
```
fly.size
```

[4]: 58102740

Com és molt gran es començarà fent un mostreig per reduir el dataframe. S'utilitzarà el 10% que correspon a 193676 observacions. Per a que es pogui repetir la selecció s'utilitzarà el paràmetre random_state amb un valor de 42.

[82]:
```
fly2 = fly.sample(frac = 0.1, random_state=42)
```

[70]:
```
fly2.shape
```

[70]: (193676, 30)

A continuació es passa a explorar les dades seleccionades.

[4]:
```
fly2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 193676 entries, 1782417 to 27352
Data columns (total 30 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Unnamed: 0         193676 non-null  int64
 1   Year               193676 non-null  int64
 2   Month              193676 non-null  int64
 3   DayofMonth         193676 non-null  int64
 4   DayOfWeek          193676 non-null  int64
 5   DepTime            193676 non-null  float64
 6   CRSDepTime         193676 non-null  int64
 7   ArrTime            192968 non-null  float64
 8   CRSArrTime         193676 non-null  int64
 9   UniqueCarrier      193676 non-null  object
 10  FlightNum          193676 non-null  int64
 11  TailNum            193676 non-null  object
 12  ActualElapsedTime  192836 non-null  float64
 13  CRSElapsedTime     193650 non-null  float64
 14  AirTime            192836 non-null  float64
 15  ArrDelay           192836 non-null  float64
 16  DepDelay           193676 non-null  float64
 17  Origin             193676 non-null  object
```

```
 18  Dest               193676 non-null  object
 19  Distance           193676 non-null  int64
 20  TaxiIn             192968 non-null  float64
 21  TaxiOut            193633 non-null  float64
 22  Cancelled          193676 non-null  int64
 23  CancellationCode   193676 non-null  object
 24  Diverted           193676 non-null  int64
 25  CarrierDelay       124936 non-null  float64
 26  WeatherDelay       124936 non-null  float64
 27  NASDelay           124936 non-null  float64
 28  SecurityDelay      124936 non-null  float64
 29  LateAircraftDelay  124936 non-null  float64
dtypes: float64(14), int64(11), object(5)
memory usage: 45.8+ MB
```

[5]:
```
fly2.head()
```

[5]:

	Unnamed: 0	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	\
1782417	6583804	2008	12	6	6	1805.0	1755	
512712	1604365	2008	3	23	7	2120.0	1200	
447137	1395655	2008	3	31	1	1731.0	1710	
55082	178786	2008	1	6	7	1507.0	1413	
877634	2972767	2008	5	22	4	637.0	630	

	ArrTime	CRSArrTime	UniqueCarrier	…	TaxiIn	TaxiOut	Cancelled	\
1782417	2146.0	2035	YV	…	5.0	99.0	0	
512712	2241.0	1333	NW	…	7.0	19.0	0	
447137	1819.0	1810	OO	…	3.0	1.0	0	
55082	1601.0	1509	OO	…	5.0	17.0	0	
877634	812.0	750	CO	…	5.0	16.0	0	

	CancellationCode	Diverted	CarrierDelay	WeatherDelay	NASDelay	\
1782417	N	0	71.0	0.0	0.0	
512712	N	0	543.0	0.0	0.0	
447137	N	0	NaN	NaN	NaN	
55082	N	0	0.0	0.0	0.0	
877634	N	0	0.0	0.0	15.0	

	SecurityDelay	LateAircraftDelay
1782417	0.0	0.0
512712	0.0	5.0
447137	NaN	NaN
55082	0.0	52.0
877634	7.0	0.0

[5 rows x 30 columns]

[11]:
```
fly2.columns
```

[11]:
```
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')
```

[83]:
```
# Eliminem les dues primeres columnes ja que no aporten informació, a més,␣
 ↪també s'eliminen les dades en format hora perquè
# no 's'utilitzaran per fer les estadístiques descriptives que demana␣
 ↪l'exercici com les dades en format string.

fly2 = fly2.drop(['Unnamed: 0', 'Year', 'DepTime', 'CRSDepTime', 'ArrTime',
       'CRSArrTime', 'TailNum', 'Origin', 'Dest', 'UniqueCarrier',␣
 ↪'CancellationCode' ], axis= 1)
fly2.head()
```

[83]:

	Month	DayofMonth	DayOfWeek	FlightNum	ActualElapsedTime	CRSElapsedTime	AirTime	ArrDelay	DepDelay	Distance	TaxiIn	TaxiOut	Cancelled	Diverted	CarrierDelay	WeatherDelay	NASDelay	SecurityDelay	LateAircraftDelay
1782417	12	6	6	7281	281.0	220.0	177.0	71.0	10.0	1297	5.0	99.0	0	0	71.0	0.0	0.0	0.0	0.0
512712	3	23	7	131	81.0	93.0	55.0	548.0	560.0	334	7.0	19.0	0	0	543.0	0.0	0.0	0.0	5.0
447137	3	31	1	3676	48.0	60.0	44.0	9.0	21.0	150	3.0	1.0	0	0	NaN	NaN	NaN	NaN	NaN
55082	1	6	7	6573	54.0	56.0	32.0	52.0	54.0	142	5.0	17.0	0	0	0.0	0.0	0.0	0.0	52.0
877634	5	22	4	1869	155.0	140.0	134.0	22.0	7.0	817	5.0	16.0	0	0	0.0	0.0	15.0	7.0	0.0

[84]:
```
#Comprobem si hi ha NAs

fly2.isna().sum()
```

[84]:
```
Month                   0
DayofMonth              0
DayOfWeek               0
FlightNum               0
ActualElapsedTime     840
CRSElapsedTime         26
AirTime               840
ArrDelay              840
DepDelay                0
Distance                0
TaxiIn                708
TaxiOut                43
Cancelled               0
Diverted                0
CarrierDelay        68740
WeatherDelay        68740
NASDelay            68740
SecurityDelay       68740
LateAircraftDelay   68740
dtype: int64
```

En aquest punt seria recomenable mirar la distribució de les dades i plantejar-se eliminar les columnes: CarrierDelay, WeatherDelay, NASDelay, SecurityDelay i LateAircraftDelay. Ja que aproximadament el 35% de les dades d'aquestes variables son NAs. Igualment, al ser retards associats a certs aspectes com metereologia, etc. es podrien substituir per zero al presuposar que com no hi ha hagut retard per aquestes causes no hi ha retard acumulat i, per tant, el valor és 0.

Després seria bo examinar la distribució de les diferentes variables i substituir NAs en aquells casos que siguin necessaris per realitzar machine learning.

Per un altre costat, com demana l'enunciat es dividirà el dataset de mostra en train i test, utilitzant com en el cas anterior un random_state equivalent a 42.

En "x" s'haurà de determinar primer quines variables poden ser útils per fer la regressió i eliminar dades redundants (com per exemple les que estàn en string i en codi numèric). "y" serà ARR_DELAY que correspon al retard dels vols en minuts.

[8]:
```
from sklearn.model_selection import train_test_split
```

[85]:
```
x = fly2.loc[:,fly2.columns!='ArrDelay']
y = fly2.loc[:, 'ArrDelay']
```

[86]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, random_state= 42,␣
↪train_size = 0.7)
```

[87]:
```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(135573, 18)
(58103, 18)
(135573,)
(58103,)
```

Com era d'esperar les dimensions de la part test i del train coincideixen.

[26]:
```
type(x_train.columns)
```

[26]:
```
pandas.core.indexes.base.Index
```

[ ]:
```

```

[88]:
```
resum = pd.DataFrame(index = x_train.columns, columns = ['mean_x_train',␣
↪'mean_x_test', 'std_x_train', 'std_x_test',
                                                         'median_x_train',␣
↪'median_x_test'])
```

[89]:
```
resum
```

[89]:
```
                   mean_x_train mean_x_test std_x_train std_x_test  \
Month                       NaN         NaN         NaN        NaN
DayofMonth                  NaN         NaN         NaN        NaN
DayOfWeek                   NaN         NaN         NaN        NaN
FlightNum                   NaN         NaN         NaN        NaN
ActualElapsedTime           NaN         NaN         NaN        NaN
CRSElapsedTime              NaN         NaN         NaN        NaN
AirTime                     NaN         NaN         NaN        NaN
DepDelay                    NaN         NaN         NaN        NaN
Distance                    NaN         NaN         NaN        NaN
TaxiIn                      NaN         NaN         NaN        NaN
TaxiOut                     NaN         NaN         NaN        NaN
Cancelled                   NaN         NaN         NaN        NaN
Diverted                    NaN         NaN         NaN        NaN
CarrierDelay                NaN         NaN         NaN        NaN
WeatherDelay                NaN         NaN         NaN        NaN
NASDelay                    NaN         NaN         NaN        NaN
SecurityDelay               NaN         NaN         NaN        NaN
LateAircraftDelay           NaN         NaN         NaN        NaN

                   median_x_train median_x_test
Month                         NaN           NaN
DayofMonth                    NaN           NaN
```

```
DayOfWeek                  NaN          NaN
FlightNum                  NaN          NaN
ActualElapsedTime          NaN          NaN
CRSElapsedTime             NaN          NaN
AirTime                    NaN          NaN
DepDelay                   NaN          NaN
Distance                   NaN          NaN
TaxiIn                     NaN          NaN
TaxiOut                    NaN          NaN
Cancelled                  NaN          NaN
Diverted                   NaN          NaN
CarrierDelay               NaN          NaN
WeatherDelay               NaN          NaN
NASDelay                   NaN          NaN
SecurityDelay              NaN          NaN
LateAircraftDelay          NaN          NaN
```

[90]:
```
a0 = x_train.mean()
```

[91]:
```
print(len(resum))
print(len(a0))
```

```
18
18
```

[92]:
```
a0
```

[92]:
```
Month                  6.110302
DayofMonth            15.752266
DayOfWeek              3.984311
FlightNum           2182.505425
ActualElapsedTime    133.306784
CRSElapsedTime       134.301105
AirTime              108.298560
DepDelay              43.324733
Distance             766.000103
TaxiIn                 6.809516
TaxiOut               18.207205
Cancelled              0.000310
Diverted               0.004153
CarrierDelay          19.304087
WeatherDelay           3.623724
NASDelay              14.968604
SecurityDelay          0.097467
LateAircraftDelay     25.515945
dtype: float64
```

[93]:
```
a1 = x_test.mean()
a2 = x_train.std()
a3 = x_test.std()
a4 = x_train.median()
a5 = x_test.median()
```

[94]:
```
todoX = [a0, a1, a2, a3, a4, a5]
for i in todoX:
    print(len(i))
```

```
18
18
18
18
18
18
```

[95]:
```
col = 0

for element in todoX:

    for index, value in enumerate(element):
        resum.iloc[index, col] = round(value,2)
    col = col +1
```

[96]:
```
resum
```

[96]:

	mean_x_train	mean_x_test	std_x_train	std_x_test	\
Month	6.11	6.1	3.48	3.47	
DayofMonth	15.75	15.71	8.77	8.76	
DayOfWeek	3.98	3.99	2.0	2.0	
FlightNum	2182.51	2200.01	1941.96	1947.9	
ActualElapsedTime	133.31	133.1	72.21	71.59	
CRSElapsedTime	134.3	133.99	71.39	70.74	
AirTime	108.3	108.03	68.67	68.05	
DepDelay	43.32	43.38	53.53	53.83	
Distance	766.0	763.03	574.63	569.05	
TaxiIn	6.81	6.84	5.34	5.37	
TaxiOut	18.21	18.24	14.4	14.46	
Cancelled	0.0	0.0	0.02	0.02	
Diverted	0.0	0.0	0.06	0.06	
CarrierDelay	19.3	18.98	44.01	44.86	
WeatherDelay	3.62	3.84	20.79	20.82	
NASDelay	14.97	15.1	33.84	34.25	
SecurityDelay	0.1	0.08	2.15	1.74	
LateAircraftDelay	25.52	25.35	42.39	41.83	

	median_x_train	median_x_test
Month	6.0	6.0
DayofMonth	16.0	16.0
DayOfWeek	4.0	4.0
FlightNum	1546.0	1557.0
ActualElapsedTime	116.0	116.0
CRSElapsedTime	116.0	117.0
AirTime	90.0	91.0
DepDelay	24.0	25.0
Distance	609.0	607.0
TaxiIn	6.0	6.0
TaxiOut	14.0	14.0
Cancelled	0.0	0.0
Diverted	0.0	0.0
CarrierDelay	2.0	2.0
WeatherDelay	0.0	0.0
NASDelay	1.0	2.0
SecurityDelay	0.0	0.0
LateAircraftDelay	9.0	8.0

Per facilitar l'avaluació de les dades obtingudes es farà la distancia entre els diferents estadístics descriptius

[97]:
```
resum['dif_media'] = resum['mean_x_train'] - resum['mean_x_test']
resum['dif_std'] = resum['std_x_train']-resum['std_x_test']
resum['dif_median'] = resum['median_x_train'] - resum['median_x_test']
```

[98]:
```
resum
```

[98]:

	mean_x_train	mean_x_test	std_x_train	std_x_test	\
Month	6.11	6.1	3.48	3.47	
DayofMonth	15.75	15.71	8.77	8.76	
DayOfWeek	3.98	3.99	2.0	2.0	
FlightNum	2182.51	2200.01	1941.96	1947.9	
ActualElapsedTime	133.31	133.1	72.21	71.59	
CRSElapsedTime	134.3	133.99	71.39	70.74	
AirTime	108.3	108.03	68.67	68.05	
DepDelay	43.32	43.38	53.53	53.83	
Distance	766.0	763.03	574.63	569.05	
TaxiIn	6.81	6.84	5.34	5.37	
TaxiOut	18.21	18.24	14.4	14.46	
Cancelled	0.0	0.0	0.02	0.02	
Diverted	0.0	0.0	0.06	0.06	
CarrierDelay	19.3	18.98	44.01	44.86	
WeatherDelay	3.62	3.84	20.79	20.82	
NASDelay	14.97	15.1	33.84	34.25	
SecurityDelay	0.1	0.08	2.15	1.74	

```
LateAircraftDelay        25.52       25.35       42.39      41.83
```

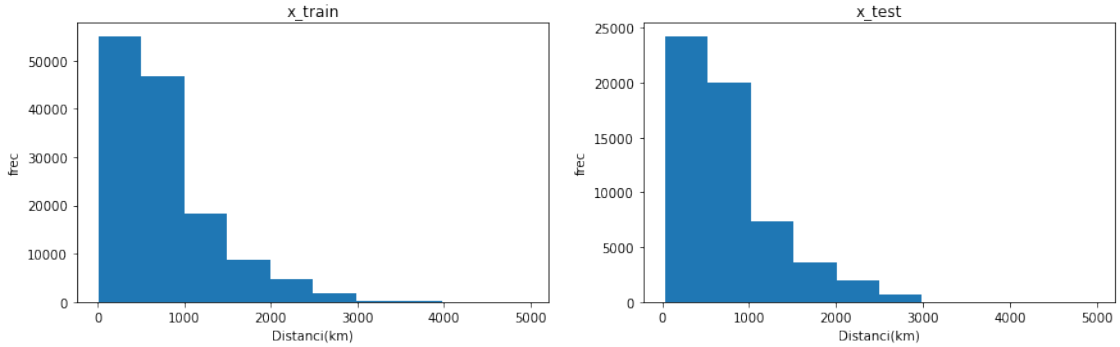
	median_x_train	median_x_test	dif_media	dif_std	dif_median
Month	6.0	6.0	0.01	0.01	0.0
DayofMonth	16.0	16.0	0.04	0.01	0.0
DayOfWeek	4.0	4.0	-0.01	0.0	0.0
FlightNum	1546.0	1557.0	-17.5	-5.94	-11.0
ActualElapsedTime	116.0	116.0	0.21	0.62	0.0
CRSElapsedTime	116.0	117.0	0.31	0.65	-1.0
AirTime	90.0	91.0	0.27	0.62	-1.0
DepDelay	24.0	25.0	-0.06	-0.3	-1.0
Distance	609.0	607.0	2.97	5.58	2.0
TaxiIn	6.0	6.0	-0.03	-0.03	0.0
TaxiOut	14.0	14.0	-0.03	-0.06	0.0
Cancelled	0.0	0.0	0.0	0.0	0.0
Diverted	0.0	0.0	0.0	0.0	0.0
CarrierDelay	2.0	2.0	0.32	-0.85	0.0
WeatherDelay	0.0	0.0	-0.22	-0.03	0.0
NASDelay	1.0	2.0	-0.13	-0.41	-1.0
SecurityDelay	0.0	0.0	0.02	0.41	0.0
LateAircraftDelay	9.0	8.0	0.17	0.56	1.0

Com s'observa en la taula anterior la distancia entre les diferents eines estadístiques per a cada valor estudiat no sol arribar al 1 excepte en el flight number, on la diferencia és molt gran. Això pot ser degut a la naturalesa de les dades, ja que correspon al número de vol en comptes de una mètrica. En el cas de la distància també les diferencies superen la unitat.

[111]:
```
plt.subplot(1,2,1)
plt.hist(x_train['Distance'])
plt.title('x_train')
plt.xlabel('Distància(km)')
plt.ylabel('frec')

plt.subplot(1,2,2)
plt.hist(x_test['Distance'])
plt.title('x_test')
plt.xlabel('Distància(km)')
plt.ylabel('frec')

plt.subplots_adjust(right = 2)
plt.show()
```



Com es veu en les gràfiques sembla que hi ha en el cas del train valors per sobre de 3000 mentre que en el test no hi ha. Això pot fer que hi hagi aquesta diferència entre els dos casos. Per tant, seria convenient al fer l'aprenentatge dels models que estiguin equilibrats per a que s'entrenin tots els casos respectant les proporcions i evitant overfitting.

[ ]: