Tasca5

January 18, 2021

1 Exploració de les dades

[1]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
pd.set_option('display.max_columns', None)
```

1.0.1 Exercici 1

Descarrega el data set Airlines Delay: Airline on-time statistics and delay causes i carrega'l a un pandas Dataframe. Explora les dades que conté, i queda't únicament amb les columnes que consideris rellevants.

1.0.2 Exercici 2

Fes un informe complet del data set:.

- Resumeix estadísticament les columnes d'interès
- Troba quantes dades faltants hi ha per columna
- Crea columnes noves (velocitat mitjana del vol, si ha arribat tard o no...)
- Taula de les aerolínies amb més endarreriments acumulats
- Quins són els vols més llargs? I els més endarrerits?
- Etc.

1.0.3 Exercici 3

Exporta el data set net i amb les noves columnes a Excel.

[2]:
```
## Importar el dataset
raw_df = pd.read_csv("archive/DelayedFlights.csv", index_col = 0)
```

```
/Users/luis/opt/anaconda3/lib/python3.8/site-
packages/numpy/lib/arraysetops.py:580: FutureWarning: elementwise comparison
failed; returning scalar instead, but in the future will perform elementwise
comparison
  mask |= (ar1 == a)
```

Variable descriptions

- Year: 1987-2008
- Month: 1-12
- DayofMonth: 1-31
- DayOfWeek: 1 (Monday) - 7 (Sunday)
- DepTime: actual departure time (local, hhmm)
- CRSDepTime: scheduled departure time (local, hhmm)
- ArrTime: actual arrival time (local, hhmm)
- CRSArrTime: scheduled arrival time (local, hhmm)
- UniqueCarrier: unique carrier code
- FlightNum: flight number
- TailNum: plane tail number
- ActualElapsedTime: flygth time in minutes
- CRSElapsedTime: scheduled flygth time in minutes
- AirTime: time on air in minutes
- ArrDelay: arrival delay in minutes
- DepDelay: departure delay in minutes
- Origin: origin IATA airport code
- Dest: destination IATA airport code
- Distance: distance in miles
- TaxiIn: taxi in time, in minutes `?????`
- TaxiOut: taxi out time, in minutes `?????`
- Cancelled: was the flight cancelled?
- CancellationCode: reason for cancellation (A = carrier, B = weather, C = NAS, D = security)
- Diverted: 1 = yes, 0 = no ()
- CarrierDelay: delayed time due to Carrier in minutes
- WeatherDelay: delayed time due to Weather in minutes
- NASDelay: delayed time due to NAS in minutes
- SecurityDelay: delayed time due to security in minuts
- LateAircraftDelay: delayed time due to late aircraft in minutes

[3]:
```
## Mostra
raw_df.sample(10)
```

[3]:

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	\
3102112	2008	6	25	3	2145.0	2120	2319.0	
3723677	2008	7	23	3	928.0	910	1100.0	
1448018	2008	3	9	7	1001.0	800	1052.0	
1270698	2008	3	31	1	1625.0	1605	1744.0	
937342	2008	2	24	7	1413.0	1405	1539.0	
6049747	2008	11	5	3	2107.0	2005	2255.0	
6554082	2008	12	31	3	1024.0	925	1140.0	
4715858	2008	8	20	3	1658.0	1600	1853.0	
3237280	2008	6	17	2	1716.0	1624	1805.0	
3863458	2008	7	28	1	1545.0	1437	1855.0	

	CRSArrTime	UniqueCarrier	FlightNum	TailNum	ActualElapsedTime	\

3102112	2259	XE	2493	N12530	94.0
3723677	1037	XE	2241	N28518	92.0
1448018	928	US	647	N675AW	231.0
1270698	1730	WN	502	N382SW	79.0
937342	1526	F9	283	N923FR	146.0
6049747	2242	XE	2877	N14158	168.0
6554082	1045	WN	3487	N209WN	76.0
4715858	1815	AA	295	N399AA	175.0
3237280	1659	UA	701	N520UA	109.0
3863458	1757	UA	1190	N562UA	130.0

	CRSElapsedTime	AirTime	ArrDelay	DepDelay	Origin	Dest	Distance	\
3102112	99.0	77.0	20.0	25.0	IAH	ICT	542	
3723677	87.0	77.0	23.0	18.0	MOB	IAH	427	
1448018	268.0	217.0	84.0	121.0	CMH	PHX	1671	
1270698	85.0	66.0	14.0	20.0	SAN	OAK	446	
937342	141.0	129.0	13.0	8.0	STL	DEN	770	
6049747	217.0	142.0	13.0	62.0	EWR	MSP	1008	
6554082	80.0	59.0	55.0	59.0	LAS	RNO	345	
4715858	195.0	155.0	38.0	58.0	MIA	ORD	1197	
3237280	95.0	84.0	66.0	52.0	MCI	DEN	533	
3863458	140.0	109.0	58.0	68.0	LAX	DEN	862	

	TaxiIn	TaxiOut	Cancelled	CancellationCode	Diverted	CarrierDelay	\
3102112	6.0	11.0	0	N	0	0.0	
3723677	5.0	10.0	0	N	0	0.0	
1448018	5.0	9.0	0	N	0	84.0	
1270698	4.0	9.0	0	N	0	NaN	
937342	5.0	12.0	0	N	0	NaN	
6049747	5.0	21.0	0	N	0	NaN	
6554082	4.0	13.0	0	N	0	55.0	
4715858	8.0	12.0	0	N	0	38.0	
3237280	8.0	17.0	0	N	0	0.0	
3863458	6.0	15.0	0	N	0	5.0	

	WeatherDelay	NASDelay	SecurityDelay	LateAircraftDelay
3102112	0.0	0.0	0.0	20.0
3723677	0.0	5.0	0.0	18.0
1448018	0.0	0.0	0.0	0.0
1270698	NaN	NaN	NaN	NaN
937342	NaN	NaN	NaN	NaN
6049747	NaN	NaN	NaN	NaN
6554082	0.0	0.0	0.0	0.0
4715858	0.0	0.0	0.0	0.0
3237280	0.0	14.0	0.0	52.0
3863458	0.0	0.0	0.0	53.0

[4]:
```
## Columns and Data types
raw_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1936758 entries, 0 to 7009727
Data columns (total 29 columns):
 #   Column             Dtype
---  ------             -----
 0   Year               int64
 1   Month              int64
 2   DayofMonth         int64
 3   DayOfWeek          int64
 4   DepTime            float64
 5   CRSDepTime         int64
 6   ArrTime            float64
 7   CRSArrTime         int64
 8   UniqueCarrier      object
 9   FlightNum          int64
 10  TailNum            object
 11  ActualElapsedTime  float64
 12  CRSElapsedTime     float64
 13  AirTime            float64
 14  ArrDelay           float64
 15  DepDelay           float64
 16  Origin             object
 17  Dest               object
 18  Distance           int64
 19  TaxiIn             float64
 20  TaxiOut            float64
 21  Cancelled          int64
 22  CancellationCode   object
 23  Diverted           int64
 24  CarrierDelay       float64
 25  WeatherDelay       float64
 26  NASDelay           float64
 27  SecurityDelay      float64
 28  LateAircraftDelay  float64
dtypes: float64(14), int64(10), object(5)
memory usage: 443.3+ MB
```

[5]:
```
## Null values %
raw_df.isna().mean()
```

[5]:
```
Year                 0.000000
Month                0.000000
DayofMonth           0.000000
DayOfWeek            0.000000
```

```
DepTime              0.000000
CRSDepTime           0.000000
ArrTime              0.003671
CRSArrTime           0.000000
UniqueCarrier        0.000000
FlightNum            0.000000
TailNum              0.000003
ActualElapsedTime    0.004330
CRSElapsedTime       0.000102
AirTime              0.004330
ArrDelay             0.004330
DepDelay             0.000000
Origin               0.000000
Dest                 0.000000
Distance             0.000000
TaxiIn               0.003671
TaxiOut              0.000235
Cancelled            0.000000
CancellationCode     0.000000
Diverted             0.000000
CarrierDelay         0.355889
WeatherDelay         0.355889
NASDelay             0.355889
SecurityDelay        0.355889
LateAircraftDelay    0.355889
dtype: float64
```

Clean Data

[6]:
```
## El percentage de null values a tot arreu menys a les columnes de Delay son molt baixos, per evitar problemes
## els eliminem
df = raw_df.dropna(subset=["ArrTime", "TailNum", "ActualElapsedTime", "CRSElapsedTime", "AirTime",
                           "ArrDelay", "TaxiIn", "TaxiOut"])

## Fill null values in delays with 0
df = df.fillna(0)
print (df.isna().sum())

## Convert floats to int
df[df.select_dtypes(include="float64").columns] = df.select_dtypes(include="float64").astype("int")
```

```
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         0
WeatherDelay         0
NASDelay             0
SecurityDelay        0
LateAircraftDelay    0
dtype: int64
```

[7]:
```
## DateTimes (No he aconseguit transformar-ho a datetime)
df["DepTime"] = df["DepTime"].apply(lambda x: str(x).zfill(4)).apply(lambda x:␣
 ↪x[0:2] + ":" + x[2:])
df["CRSDepTime"] = df["CRSDepTime"].apply(lambda x: str(x).zfill(4)).
 ↪apply(lambda x: x[0:2] + ":" + x[2:])
df["ArrTime"] = df["ArrTime"].apply(lambda x: str(x).zfill(4)).apply(lambda x:␣
 ↪x[0:2] + ":" + x[2:])
df["CRSArrTime"] = df["CRSArrTime"].apply(lambda x: str(x).zfill(4)).
 ↪apply(lambda x: x[0:2] + ":" + x[2:])
```

[8]:
```
## Final Dataframe
df.to_csv("cleandf.csv")
df
```

[8]:

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	\
0	2008	1	3	4	20:03	19:55	22:11	
1	2008	1	3	4	07:54	07:35	10:02	
2	2008	1	3	4	06:28	06:20	08:04	
4	2008	1	3	4	18:29	17:55	19:59	
5	2008	1	3	4	19:40	19:15	21:21	

```
…        …    …          …         …     …         …     …
7009710  2008     12          13          6   12:50      12:20   16:17
7009717  2008     12          13          6   06:57      06:00   09:04
7009718  2008     12          13          6   10:07      08:47   11:49
7009726  2008     12          13          6   12:51      12:40   14:46
7009727  2008     12          13          6   11:10      11:03   14:13

        CRSArrTime UniqueCarrier  FlightNum TailNum  ActualElapsedTime  \
0            22:25            WN        335  N712SW                128
1            10:00            WN       3231  N772SW                128
2            07:50            WN        448  N428WN                 96
4            19:25            WN       3920  N464WN                 90
5            21:10            WN        378  N726SW                101
…                …           …         …     …                     …
7009710      15:52            DL       1621  N938DL                147
7009717      07:49            DL       1631  N3743H                127
7009718      10:10            DL       1631  N909DA                162
7009726      14:37            DL       1639  N646DL                115
7009727      14:18            DL       1641  N908DL                123

         CRSElapsedTime  AirTime  ArrDelay  DepDelay Origin Dest  Distance  \
0                   150      116       -14         8    IAD  TPA       810
1                   145      113         2        19    IAD  TPA       810
2                    90       76        14         8    IND  BWI       515
4                    90       77        34        34    IND  BWI       515
5                   115       87        11        25    IND  JAX       688
…                   …         …         …         …     …    …         …
7009710             152      120        25        30    MSP  ATL       906
7009717             109       78        75        57    RIC  ATL       481
7009718             143      122        99        80    ATL  IAH       689
7009726             117       89         9        11    IAD  ATL       533
7009727             135      104        -5         7    SAT  ATL       874

         TaxiIn  TaxiOut  Cancelled CancellationCode  Diverted  CarrierDelay  \
0             4        8          0                N         0             0
1             5       10          0                N         0             0
2             3       17          0                N         0             0
4             3       10          0                N         0             2
5             4       10          0                N         0             0
…         …       …         …               …       …         …
7009710       9       18          0                N         0             3
7009717      15       34          0                N         0             0
7009718       8       32          0                N         0             1
7009726      13       13          0                N         0             0
7009727       8       11          0                N         0             0

         WeatherDelay  NASDelay  SecurityDelay  LateAircraftDelay
```

```
0                  0         0              0                  0
1                  0         0              0                  0
2                  0         0              0                  0
4                  0         0              0                 32
5                  0         0              0                  0
…                  …         …              …                  …
7009710            0         0              0                 22
7009717           57        18              0                  0
7009718            0        19              0                 79
7009726            0         0              0                  0
7009727            0         0              0                  0

[1928368 rows x 29 columns]
```

Studying the Dataframe

[9]:
```
## Split into Numeric and Categoric values
data_num = df.select_dtypes(include = "int64")
data_cat = df.select_dtypes(exclude = "int64")
```

[10]:
```
## Describe numeric
data_num.describe()
```

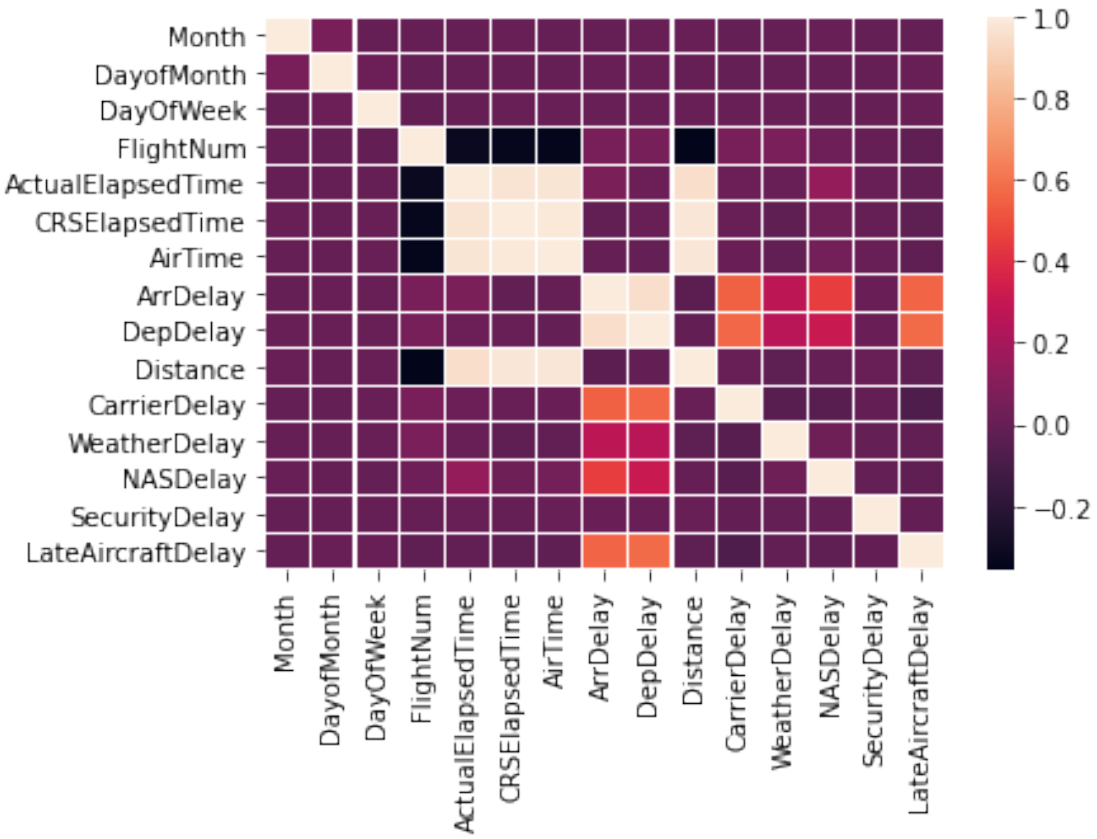
[10]:
```
              Year         Month    DayofMonth     DayOfWeek     FlightNum  \
count  1928368.0  1.928368e+06  1.928368e+06  1.928368e+06  1.928368e+06
mean      2008.0  6.107858e+00  1.575206e+01  3.984999e+00  2.184292e+03
std          0.0  3.480755e+00  8.776564e+00  1.996051e+00  1.944448e+03
min       2008.0  1.000000e+00  1.000000e+00  1.000000e+00  1.000000e+00
25%       2008.0  3.000000e+00  8.000000e+00  2.000000e+00  6.110000e+02
50%       2008.0  6.000000e+00  1.600000e+01  4.000000e+00  1.543000e+03
75%       2008.0  9.000000e+00  2.300000e+01  6.000000e+00  3.423000e+03
max       2008.0  1.200000e+01  3.100000e+01  7.000000e+00  9.741000e+03

       ActualElapsedTime  CRSElapsedTime       AirTime      ArrDelay  \
count       1.928368e+06    1.928368e+06  1.928368e+06  1.928368e+06
mean        1.333059e+02    1.341977e+02  1.082772e+02  4.219977e+01
std         7.206012e+01    7.123343e+01  6.864265e+01  5.678447e+01
min         1.400000e+01   -2.100000e+01  0.000000e+00 -1.090000e+02
25%         8.000000e+01    8.200000e+01  5.800000e+01  9.000000e+00
50%         1.160000e+02    1.160000e+02  9.000000e+01  2.400000e+01
75%         1.650000e+02    1.650000e+02  1.370000e+02  5.600000e+01
max         1.114000e+03    6.600000e+02  1.091000e+03  2.461000e+03

           DepDelay      Distance        TaxiIn       TaxiOut  Cancelled  \
count  1.928368e+06  1.928368e+06  1.928368e+06  1.928368e+06  1928368.0
mean   4.309160e+01  7.649490e+02  6.811386e+00  1.821731e+01        0.0
std    5.326577e+01  5.738861e+02  5.268054e+00  1.430838e+01        0.0
```

```
min    6.000000e+00  1.100000e+01  0.000000e+00  0.000000e+00        0.0
25%    1.200000e+01  3.380000e+02  4.000000e+00  1.000000e+01        0.0
50%    2.400000e+01  6.060000e+02  6.000000e+00  1.400000e+01        0.0
75%    5.300000e+01  9.970000e+02  8.000000e+00  2.100000e+01        0.0
max    2.467000e+03  4.962000e+03  2.400000e+02  4.220000e+02        0.0

        Diverted  CarrierDelay  WeatherDelay      NASDelay  SecurityDelay  \
count  1928368.0  1.928368e+06  1.928368e+06  1.928368e+06   1.928368e+06
mean         0.0  1.240742e+01  2.395748e+00  9.717681e+00   5.831097e-02
std          0.0  3.620424e+01  1.737621e+01  2.814335e+01   1.627458e+00
min          0.0  0.000000e+00  0.000000e+00  0.000000e+00   0.000000e+00
25%          0.0  0.000000e+00  0.000000e+00  0.000000e+00   0.000000e+00
50%          0.0  0.000000e+00  0.000000e+00  0.000000e+00   0.000000e+00
75%          0.0  1.000000e+01  0.000000e+00  6.000000e+00   0.000000e+00
max          0.0  2.436000e+03  1.352000e+03  1.357000e+03   3.920000e+02

       LateAircraftDelay
count       1.928368e+06
mean        1.636462e+01
std         3.592082e+01
min         0.000000e+00
25%         0.000000e+00
50%         0.000000e+00
75%         1.800000e+01
max         1.316000e+03
```

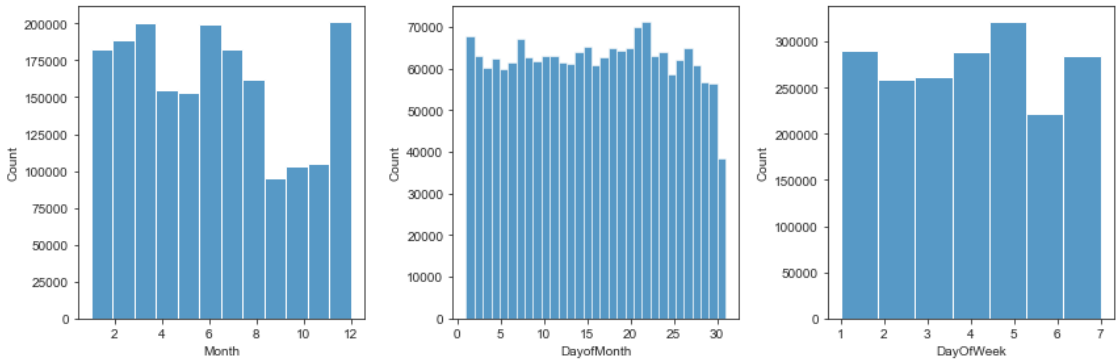
- Tots els vols son de 2008, podem eliminar aquesta columna
- A primera vista sembla que els vols estan repartits de manera regular tot l'any (mean = 6)
- De la mateixa manera, també estan repartits regularment dins del més i la setmana (mean = 15, 4)
- FlightNum no es una variable numèrica
- Els temps de vol tenen una variança molt gran, ja que depenen de la distància
- Cap vol ha estat cancelat o desviat. Podem eliminar les columnes
- Els delays estan esbiaixats ja que la gran majoria de vol no acumulen delays de cada tipus
- TaxiIn i TaxiOut els esborraré pk no sé exactament que són

[11]:
```
## Drop Columns
data_num = data_num.drop(columns = ["Year", "Cancelled", "Diverted", "TaxiIn",␣
↪"TaxiOut"])
data_cat = data_cat.drop(columns = "CancellationCode")
```

[12]:
```
#Correlation Matrix
sns.heatmap(data_num.corr(), linewidths=.2)
plt.show()
```

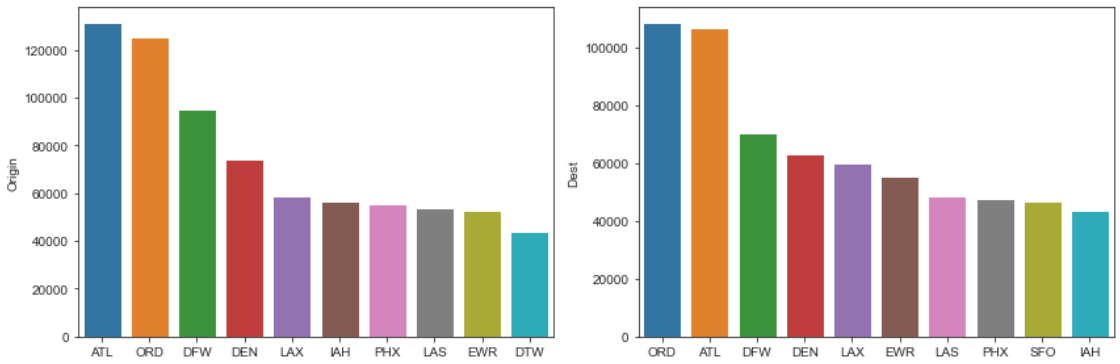


[13]:
```
## Histograms
sns.set_style("ticks")

fig1, axes = plt.subplots(1, 3, figsize=(12, 4))
sns.histplot(data_num["Month"], bins=12, ax = axes[0])
sns.histplot(data_num["DayofMonth"], bins=31, ax = axes[1])
sns.histplot(data_num["DayOfWeek"], bins=7, ax = axes[2])

plt.tight_layout()
plt.show()
```



- Podem veure com els vols augmenten a les vacences d'estiu i d'hivern.
- Efectivament els vols dins d'un mateix mes estan mes o menys repertits. Però si ens fixem hi ha pics periòdics corresponents al cap de setmana.
- Els divendres hi ha un pic en el nombre de vols.

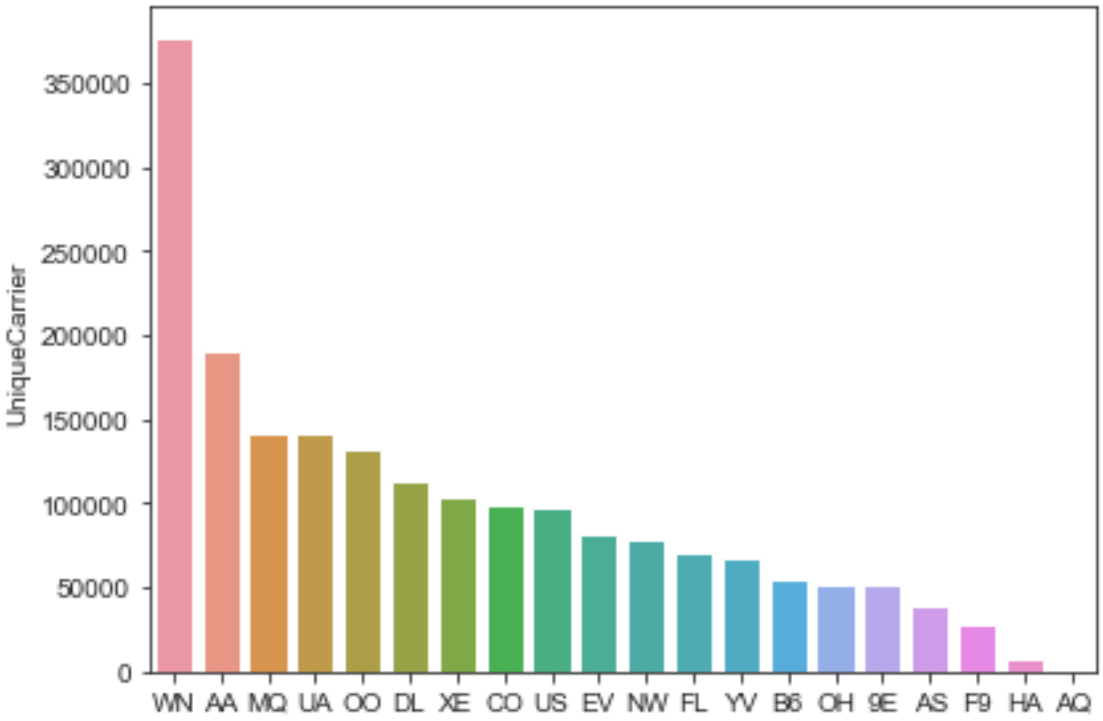
[14]:
```
## BarPlots
sns.set_style("ticks")

fig1, axes = plt.subplots(1, 2, figsize=(12, 4))
sns.barplot(x = data_cat["Origin"].value_counts().index[0:10], y =␣
↪data_cat["Origin"].value_counts()[0:10], ax = axes[0])
sns.barplot(x = data_cat["Dest"].value_counts().index[0:10], y =␣
↪data_cat["Dest"].value_counts()[0:10], ax = axes[1])

plt.tight_layout()
plt.show()
```



- Els aeroports de Atlanta i Chicago son de llarg els més transitats, seguits per Dallas

[15]:
```
## BarPlots
sns.set_style("ticks")
```

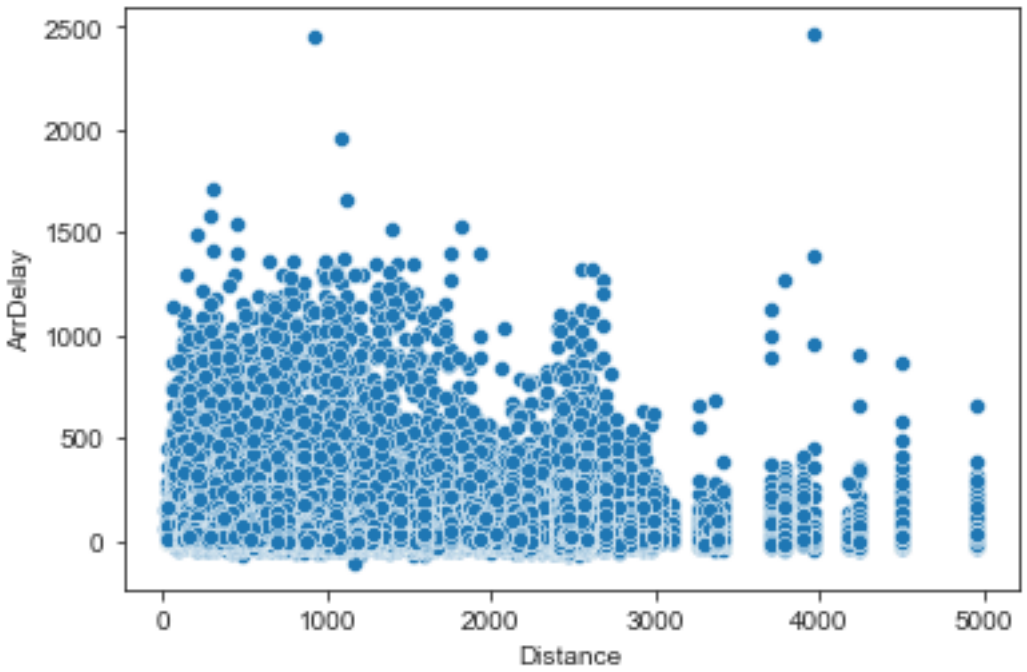
```
fig1 = plt.figsize=(12, 4)
sns.barplot(x = data_cat["UniqueCarrier"].value_counts().index, y =␣
 ↪data_cat["UniqueCarrier"].value_counts())

plt.tight_layout()
plt.show()
```



- SouthWest Airlines es la aerolinea més demandada

[16]:
```
## Scatter Plot
sns.scatterplot(x = df["Distance"], y = df["ArrDelay"])
```

[16]:
```
<AxesSubplot:xlabel='Distance', ylabel='ArrDelay'>
```



- No hi ha relació entre la distancia i el delay

[17]:
```
## Creem la columna delay categorica i velocitat mitja
## Considerarem delay important un retras de més de 20 min
## ja que el 85% dels vols tenen delay
data_cat["delay"] = data_num["ArrDelay"].apply(lambda x: 1 if x > 15 else 0)
data_num["Velocity"] = data_num["Distance"] / data_num["AirTime"] #(miles / min)
```

[18]:
```
## Quina compañia acumula més delay? (%)
delay = round (data_cat.groupby("UniqueCarrier")[["delay"]].mean(), 2) * 100
delay.sort_values(by = "delay")
```

[18]:

UniqueCarrier	delay
AQ	43.0
WN	52.0
F9	54.0
HA	55.0
CO	58.0
US	59.0
AS	60.0
DL	62.0
FL	64.0
UA	66.0
OO	66.0

```
MQ              67.0
9E              68.0
XE              68.0
EV              68.0
B6              68.0
AA              68.0
NW              68.0
OH              73.0
YV              74.0
```

- La companyia "AQ" només té retrassos en un 43% dels seus vols, tot i que com em vist abans és una aerolinea petita amb pocs vols
- La companyia "YV" acumula retrassos en el 74% dels seus vols, tot i no ser una companyia gaire gran
- "WN", la aerolinea més demandada, va en segona posició amb retrassos només al 52% dels seus vols

[19]:
```
## Final Data
final_data = data_num.join(data_cat)
display(final_data)
## to CSV
final_data.to_csv("final_df.csv", index = False)
```

```
         Month  DayofMonth  DayOfWeek  FlightNum  ActualElapsedTime  \
0            1           3          4        335                128
1            1           3          4       3231                128
2            1           3          4        448                 96
4            1           3          4       3920                 90
5            1           3          4        378                101
…          …           …          …          …                  …
7009710     12          13          6       1621                147
7009717     12          13          6       1631                127
7009718     12          13          6       1631                162
7009726     12          13          6       1639                115
7009727     12          13          6       1641                123

         CRSElapsedTime  AirTime  ArrDelay  DepDelay  Distance  CarrierDelay  \
0                   150      116       -14         8       810             0
1                   145      113         2        19       810             0
2                    90       76        14         8       515             0
4                    90       77        34        34       515             2
5                   115       87        11        25       688             0
…                   …        …         …         …        …               …
7009710             152      120        25        30       906             3
7009717             109       78        75        57       481             0
7009718             143      122        99        80       689             1
7009726             117       89         9        11       533             0
7009727             135      104        -5         7       874             0
```

```
         WeatherDelay  NASDelay  SecurityDelay  LateAircraftDelay  Velocity  \
0                   0         0              0                  0  6.982759
1                   0         0              0                  0  7.168142
2                   0         0              0                  0  6.776316
4                   0         0              0                 32  6.688312
5                   0         0              0                  0  7.908046
…                 …         …              …                  …         …
7009710             0         0              0                 22  7.550000
7009717            57        18              0                  0  6.166667
7009718             0        19              0                 79  5.647541
7009726             0         0              0                  0  5.988764
7009727             0         0              0                  0  8.403846

        DepTime CRSDepTime ArrTime CRSArrTime UniqueCarrier TailNum Origin  \
0         20:03      19:55   22:11      22:25            WN  N712SW    IAD
1         07:54      07:35   10:02      10:00            WN  N772SW    IAD
2         06:28      06:20   08:04      07:50            WN  N428WN    IND
4         18:29      17:55   19:59      19:25            WN  N464WN    IND
5         19:40      19:15   21:21      21:10            WN  N726SW    IND
…         …        …     …        …           …      …    …
7009710   12:50      12:20   16:17      15:52            DL  N938DL    MSP
7009717   06:57      06:00   09:04      07:49            DL  N3743H    RIC
7009718   10:07      08:47   11:49      10:10            DL  N909DA    ATL
7009726   12:51      12:40   14:46      14:37            DL  N646DL    IAD
7009727   11:10      11:03   14:13      14:18            DL  N908DL    SAT

        Dest  delay
0        TPA      0
1        TPA      0
2        BWI      0
4        BWI      1
5        JAX      0
…       …    …
7009710  ATL      1
7009717  ATL      1
7009718  IAH      1
7009726  ATL      0
7009727  ATL      0

[1928368 rows x 25 columns]
```