Data Science amb Python

Sprint 12

S12 T01 : Supervised Learning - Regressions

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Dataset Description

Airline2008Nov Dataset Variable definition

Name	Description
1.Year	2008
2.Month	11
3.DayofMonth	1-31
4.DayOfWeek	1 (Monday) - 7 (Sunday)
5.DepTime	actual departure time (local, hhmm)
6.CRSDepTime	scheduled departure time (local, hhmm)
7.ArrTime	actual arrival time (local, hhmm)
8.CRSArrTime	scheduled arrival time (local, hhmm)
9.UniqueCarrier	unique carrier code
10.FlightNum	flight number
11.TailNum	plane tail number
12.ActualElapsedTime	in minutes
13.CRSElapsedTime	CRS Elapsed Time of Flight (estimated elapse time), in minutes
14.AirTime	Flight Time, in Minutes, in minutes
15.ArrDelay	Difference in minutes between scheduled and actual arrival time. Early arrivals show negative numbers, in minutes
16.DepDelay	Difference in minutes between scheduled and actual departure time. Early departures show negative numbers, in minutes
17.Origin	origin IATA airport code
18.Dest	destination IATA airport code
19.Distance	Distance between airports (miles)
20.TaxiIn	Wheels down and arrival at the destination airport gate, in minutes

21.TaxiOut	The time elapsed between departure from the origin airport gate and wheels off, in minutes
22.Cancelled	was the flight cancelled?
23.CancellationCode	reason for cancellation (A = carrier, B = weather, C = NAS, D = security)
24.Diverted	1 = yes, 0 = no
25.CarrierDelay	minutes. Carrier delay is within the control of the air carrier. Examples:: aircraft cleaning, aircraft damage, etc
26.WeatherDelay	munutes. Weather delay is caused by extreme or hazardous weather conditions
27.NASDelay	minutes. Delay that is within the control of the National Airspace System (NAS) Ex:airport operations,heavy traffic volume,etc
28.SecurityDelay	minutes. caused by evacuation of a terminal or concourse, re-boarding of aircraft because of security breach,etc
29.LateAircraftDelay	minutes. Arrival delay at an airport due to the late arrival of the same aircraft at a previous airport.

More information about flights delay can be seen in Federal Aviation Administration site.

Exercise 1

Split the DelayedFlights.csv dataset into train and test. Study the two sets separately, at a descriptive level

1. Load the dataset

In [1]:
```
# import the needed libraries

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

In [2]:
```
# Load the dataframe

df_flights = pd.read_csv('DelayedFlights.csv')
df_flights.head()
```

Out[2]:

	Unnamed: 0	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CR
0	0	2008	1	3	4	2003.0	1955	2211.0	
1	1	2008	1	3	4	754.0	735	1002.0	
2	2	2008	1	3	4	628.0	620	804.0	
3	4	2008	1	3	4	1829.0	1755	1959.0	
4	5	2008	1	3	4	1940.0	1915	2121.0	

5 rows × 30 columns

In [3]:

```
df_flights.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1936758 entries, 0 to 1936757
Data columns (total 30 columns):
 #   Column             Dtype  
---  ------             -----  
 0   Unnamed: 0         int64  
 1   Year               int64  
 2   Month              int64  
 3   DayofMonth         int64  
 4   DayOfWeek          int64  
 5   DepTime            float64
 6   CRSDepTime         int64  
 7   ArrTime            float64
 8   CRSArrTime         int64  
 9   UniqueCarrier      object 
 10  FlightNum          int64  
 11  TailNum            object 
 12  ActualElapsedTime  float64
 13  CRSElapsedTime     float64
 14  AirTime            float64
 15  ArrDelay           float64
 16  DepDelay           float64
 17  Origin             object 
 18  Dest               object 
 19  Distance           int64  
 20  TaxiIn             float64
 21  TaxiOut            float64
 22  Cancelled          int64  
 23  CancellationCode   object 
 24  Diverted           int64  
 25  CarrierDelay       float64
 26  WeatherDelay       float64
 27  NASDelay           float64
 28  SecurityDelay      float64
 29  LateAircraftDelay  float64
dtypes: float64(14), int64(11), object(5)
memory usage: 443.3+ MB
```

2. Data Pre-processing

In [4]:
```
#Remove the column ' Unnamed: 0'
df_flights = df_flights.drop('Unnamed: 0', axis=1)
df_flights.head()
```

Out[4]:

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime	U
0	2008	1	3	4	2003.0	1955	2211.0	2225	
1	2008	1	3	4	754.0	735	1002.0	1000	
2	2008	1	3	4	628.0	620	804.0	750	
3	2008	1	3	4	1829.0	1755	1959.0	1925	
4	2008	1	3	4	1940.0	1915	2121.0	2110	

5 rows × 29 columns

Data Cleaning

In [5]:
```
#Verify missing data
df_flights.isnull().sum()
```

Out[5]:
```
Year                      0
Month                     0
DayofMonth                0
DayOfWeek                 0
DepTime                   0
CRSDepTime                0
ArrTime                7110
CRSArrTime                0
UniqueCarrier             0
FlightNum                 0
TailNum                   5
ActualElapsedTime      8387
CRSElapsedTime          198
AirTime                8387
ArrDelay               8387
DepDelay                  0
Origin                    0
Dest                      0
Distance                  0
TaxiIn                 7110
TaxiOut                 455
Cancelled                 0
CancellationCode          0
Diverted                  0
CarrierDelay         689270
WeatherDelay         689270
NASDelay             689270
SecurityDelay        689270
LateAircraftDelay    689270
dtype: int64
```

In [6]:
```
# copy the data frame df_flights

df_clean = df_flights.copy()
```

I'll drop some columns that has no impact with the objective, such as the Year (all flights happen in 2008), Cancelled, etc

In [7]:
```
df_clean = df_clean.drop(['Year','FlightNum', 'TailNum','CRSDepTime',
                          'CRSArrTime','TaxiIn', 'TaxiOut', 'Cancelled', '(
df_clean.head()
```

Out[7]:

	Month	DayofMonth	DayOfWeek	DepTime	ArrTime	UniqueCarrier	ActualElapsedTime
0	1	3	4	2003.0	2211.0	WN	128.0
1	1	3	4	754.0	1002.0	WN	128.0
2	1	3	4	628.0	804.0	WN	96.0
3	1	3	4	1829.0	1959.0	WN	90.0
4	1	3	4	1940.0	2121.0	WN	101.0

Analysing each feature with mising data

- **ArrDelay** : Delay of arrival time is what we want to predict.

Any data entry without ArrDelay data cannot be used for prediction; therefore any row now without ArrDelay data is not useful to us.

There are 8387 missing values in ArrDelay. First, let's drop this rows.

In [8]:
```
# drop whole row with NaN in ArrDelay column

df_clean.dropna(subset = ['ArrDelay'], axis=0, inplace=True )

# reset index
df_clean.reset_index(drop=True, inplace=True)
```

In [9]:
```
# Verify again the mising data

df_clean.isnull().sum()
```

Out[9]:
```
Month                      0
DayofMonth                 0
DayOfWeek                  0
DepTime                    0
ArrTime                    0
UniqueCarrier              0
ActualElapsedTime          0
CRSElapsedTime             0
AirTime                    0
ArrDelay                   0
DepDelay                   0
Origin                     0
Dest                       0
Distance                   0
CarrierDelay          680883
WeatherDelay          680883
NASDelay              680883
SecurityDelay         680883
LateAircraftDelay     680883
dtype: int64
```

We can see that most of the missing values of the other attributes were related to ArrDelay

For the other attributes, **CarrierDelay**, **WeatherDelay**, **NASDelay**, **SecurityDelay**, **LateAircraftDelay**, I'll verify the percentage of this missing values.

In [10]:
```
missing_percentage = (df_clean['CarrierDelay'].isnull().sum())/(df_clean['(
missing_percentage
```

Out[10]:
```
0.35308713935233416
```

35.3% of these values are missing and it is a big percentage. Because of that, I'll drop them.

In [11]:
```
df_clean = df_clean.drop(['CarrierDelay', 'WeatherDelay', 'NASDelay', 'Secu
df_clean.head()
```

Out[11]:

	Month	DayofMonth	DayOfWeek	DepTime	ArrTime	UniqueCarrier	ActualElapsedTime
0	1	3	4	2003.0	2211.0	WN	128.0
1	1	3	4	754.0	1002.0	WN	128.0
2	1	3	4	628.0	804.0	WN	96.0
3	1	3	4	1829.0	1959.0	WN	90.0
4	1	3	4	1940.0	2121.0	WN	101.0

Data Transforming

Encode the categorical data in number.

In [12]:
```
print('The number of unique values of UniqueCarrier are: ',  df_clean['Uni
print('The number of unique values of Origin are: ',  df_clean['Origin'].nu
print('The number of unique values of Dest are: ',  df_clean['Dest'].nuniq
```

```
The number of unique values of UniqueCarrier are:  20
The number of unique values of Origin are:  303
The number of unique values of Dest are:  302
```

In [18]:
```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()

df_cat = df_clean[['UniqueCarrier','Origin', 'Dest' ]]
df_cat.head()
```

Out[18]:

	UniqueCarrier	Origin	Dest
0	WN	IAD	TPA
1	WN	IAD	TPA
2	WN	IND	BWI
3	WN	IND	BWI
4	WN	IND	JAX

In [19]:
```
#for col in df_cat:
    #df_clean[col] = le.fit_transform(df_cat[col])
```

In [20]:
```
#df_clean.head()
```

In [21]:
```
#save the df_clean

df_clean.to_csv('delayedflights_clean.csv', index=False)
```

Training and Test

In [22]:
```
from sklearn.model_selection import train_test_split

y = df_clean['ArrDelay']

X = df_clean.drop('ArrDelay',axis=1)
```

In [23]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, r


print("number of test samples :", X_test.shape[0])
print("number of training samples:",X_train.shape[0])
```

```
number of test samples : 578512
number of training samples: 1349859
```

Exercises 2

Apply some transformation process (standardize numerical data, create dummy columns, polynomials ...).

In [24]:
```
#Encode the categorical data in number
from sklearn import preprocessing
le = preprocessing.LabelEncoder()


X_train_cat = X_train[['UniqueCarrier','Origin', 'Dest' ]]
X_test_cat = X_test[['UniqueCarrier','Origin', 'Dest' ]]
#df_cat.head()
```

In [25]:
```
for col in X_train_cat:
    X_train[col] = le.fit_transform(X_train_cat[col])

for col in X_test_cat:
    X_test[col] = le.fit_transform(X_test_cat[col])

X_train.head()
```

```
<ipython-input-25-3ba92260ebc5>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs
/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X_train[col] = le.fit_transform(X_train_cat[col])
<ipython-input-25-3ba92260ebc5>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs
/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X_test[col] = le.fit_transform(X_test_cat[col])
```

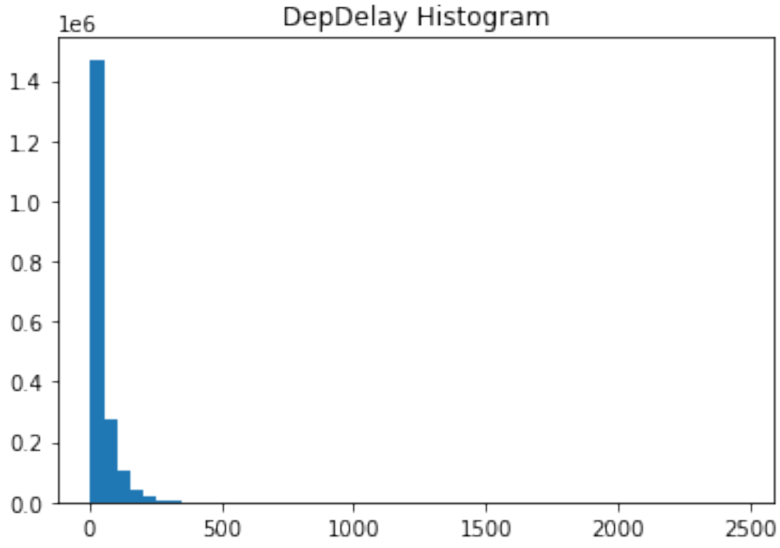
Out[25]:

	Month	DayofMonth	DayOfWeek	DepTime	ArrTime	UniqueCarrier	ActualElapse
995566	6	4	3	2308.0	113.0	9	
1090173	7	14	1	2127.0	2211.0	17	
1550228	10	24	5	1330.0	1522.0	13	
870468	5	7	3	1122.0	1616.0	5	
383192	3	13	4	1827.0	1923.0	17	

Normalize Data

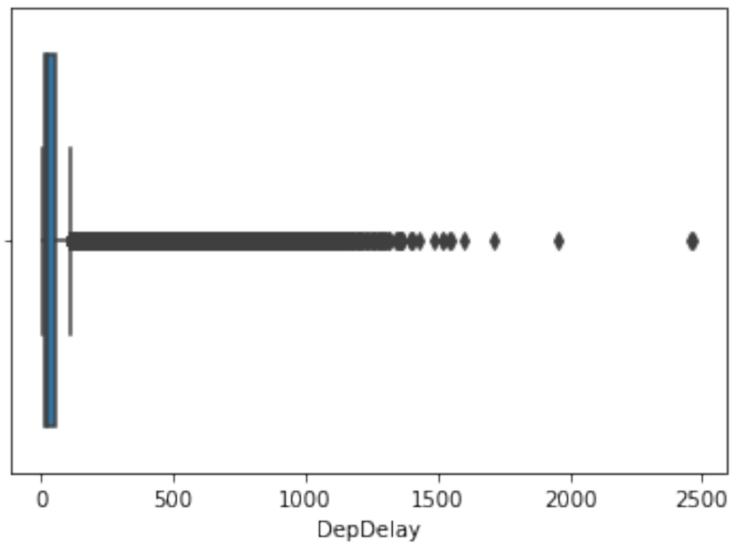
In [26]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.hist(X["DepDelay"], bins=50)
plt.title('DepDelay Histogram');
```



In [27]:
```
sns.boxplot(data = X, x="DepDelay")
```

Out[27]: <AxesSubplot:xlabel='DepDelay'>



The plots above shows that the data contains many outliers, so I 'll use you the RobustScaler

In [28]:
```
#from sklearn.preprocessing import StandardScaler
#scaler = StandardScaler().fit(X_train)

#standardized_X = scaler.transform(X_train)
#standardized_X_test = scaler.transform(X_test)
```

In [29]:
```
from sklearn.preprocessing import RobustScaler

transformer = RobustScaler().fit(X_train)
transformer
```

Out[29]: RobustScaler()

In [30]:
```
standardized_X = transformer.transform(X_train)
standardized_X_test = transformer.transform(X_test)
```

Exercises 3

Summarize the new columns generated statistically and graphically

In [32]:
```
X_train_stand=pd.DataFrame(X_train, columns=X_train.columns).reset_index(d
X_train_stand
```

Out[32]:

	Month	DayofMonth	DayOfWeek	DepTime	ArrTime	UniqueCarrier	ActualElapse
0	6	4	3	2308.0	113.0	9	
1	7	14	1	2127.0	2211.0	17	
2	10	24	5	1330.0	1522.0	13	
3	5	7	3	1122.0	1616.0	5	
4	3	13	4	1827.0	1923.0	17	
...	...	...	...	...	...	...	
1349854	3	10	1	1017.0	1230.0	9	
1349855	12	21	7	1405.0	1648.0	7	
1349856	3	18	2	1001.0	1042.0	6	
1349857	3	13	4	1853.0	1925.0	9	
1349858	1	28	1	1818.0	2007.0	11	

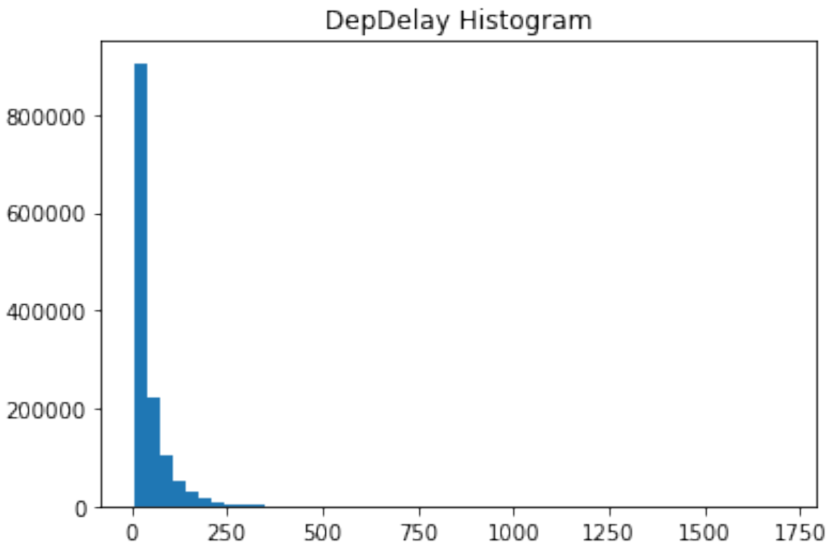
1349859 rows × 13 columns

In [33]:
```
X_train_stand.describe()
```

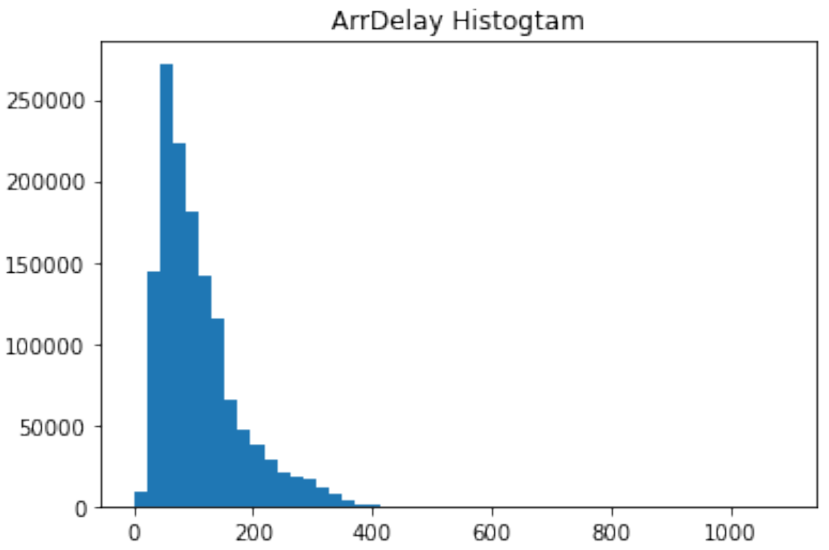
Out[33]:

	Month	DayofMonth	DayOfWeek	DepTime	ArrTime	UniqueC
count	1.349859e+06	1.349859e+06	1.349859e+06	1.349859e+06	1.349859e+06	1.349859
mean	6.110603e+00	1.574881e+01	3.985953e+00	1.518495e+03	1.610178e+03	1.112838
std	3.482405e+00	8.776654e+00	1.995536e+00	4.504583e+02	5.478223e+02	5.932061
min	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	0.000000
25%	3.000000e+00	8.000000e+00	2.000000e+00	1.203000e+03	1.316000e+03	6.000000
50%	6.000000e+00	1.600000e+01	4.000000e+00	1.545000e+03	1.715000e+03	1.300000
75%	9.000000e+00	2.300000e+01	6.000000e+00	1.900000e+03	2.031000e+03	1.700000
max	1.200000e+01	3.100000e+01	7.000000e+00	2.400000e+03	2.400000e+03	1.900000

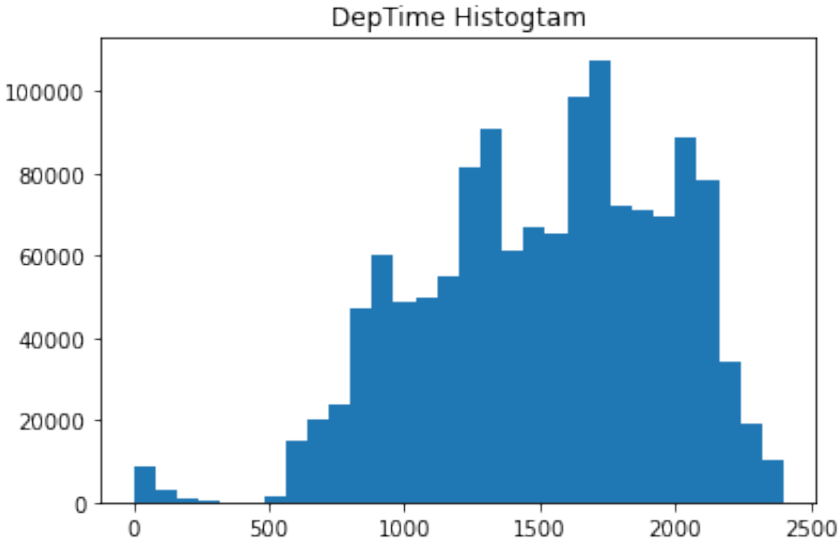
In [34]:
```
plt.hist(X_train_stand["DepDelay"], bins=50)
plt.title('DepDelay Histogram');
```



In [35]:
```
plt.hist(X_train_stand["AirTime"], bins=50)
plt.title('ArrDelay Histogtam');
```



In [36]:
```
plt.hist(X_train_stand["DepTime"], bins=30)
plt.title('DepTime Histogtam');
```


DepTime Histogtam
100000
80000
60000
40000
20000
0
0
500
1000
1500
2000
2500

```
In [ ]:
```