

Documento Técnico

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1 Introduction

Este documento contendrá el código fuente Dask empleado para la resolución de cada una de las tareas. El código lo insertarñe como imágenes y con un tamaño que permita leer el texto contenido en las imágenes.

2 Código

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import dask
import dask.dataframe as dd
import os
import graphviz
from IPython.display import display

✓ 4.5s

#Cargo el csv usando dask
df = dd.read_csv('air_traffic_data.csv')

✓ 0.1s
```

df.head(10)

	Activity Period	Operating Airline	Operating Airline IATA Code	Published Airline	Published Airline IATA Code	GEO Summary	GEO Region	Activity Type Code	Price Category Code	Terminal	Boarding Area	Passenger Count	Adjusted Activity Type Code	Adjusted Passenger Count	Year	Month
0	200507	ATA Airlines	TZ	ATA Airlines	TZ	Domestic	US	Depanded	Low Fare	Terminal 1	B	27271	Depanded	27271	2005	July
1	200507	ATA Airlines	TZ	ATA Airlines	TZ	Domestic	US	Englained	Low Fare	Terminal 1	B	29131	Englained	29131	2005	July
2	200507	ATA Airlines	TZ	ATA Airlines	TZ	Domestic	US	Thru / Transit	Low Fare	Terminal 1	B	5415	Thru / Transit * 2	10830	2005	July
3	200507	Air Canada	AC	Air Canada	AC	International	Canada	Depanded	Other	Terminal 1	B	35156	Depanded	35156	2005	July
4	200507	Air Canada	AC	Air Canada	AC	International	Canada	Englained	Other	Terminal 1	B	34080	Englained	34090	2005	July
5	200507	Air China	CA	Air China	CA	International	Asia	Depanded	Other	International	G	6263	Depanded	6263	2005	July
6	200507	Air China	CA	Air China	CA	International	Asia	Englained	Other	International	G	5500	Englained	5500	2005	July
7	200507	Air France	AF	Air France	AF	International	Europe	Depanded	Other	International	A	12050	Depanded	12050	2005	July
8	200507	Air France	AF	Air France	AF	International	Europe	Englained	Other	International	A	11638	Englained	11638	2005	July
9	200507	Air New Zealand	NZ	Air New Zealand	NZ	International	Australia / Oceania	Depanded	Other	International	G	4998	Depanded	4998	2005	July

len(df)

15067

```
tipo_datos = df.dtypes
display(tipo_datos.head(16))
```

Activity Period	int64
Operating Airline	object
Operating Airline IATA Code	object
Published Airline	object
Published Airline IATA Code	object
GEO Summary	object
GEO Region	object
Activity Type Code	object
Price Category Code	object
Terminal	object
Boarding Area	object
Passenger Count	int64
Adjusted Activity Type Code	object
Adjusted Passenger Count	int64
Year	int64
Month	object
dtype:	object

```
#Contar si hay valores nulos
nulos= df.isna().any().compute()
display(nulos)
```

Activity Period	False
Operating Airline	False
Operating Airline IATA Code	True
Published Airline	False
Published Airline IATA Code	True
GEO Summary	False
GEO Region	False
Activity Type Code	False
Price Category Code	False
Terminal	False
Boarding Area	False
Passenger Count	False
Adjusted Activity Type Code	False
Adjusted Passenger Count	False
Year	False
Month	False

```
#Me ha devuelto que hay dos columnas con valores nulos, identifico cuales son las celdas con esos valores
celda_nulos1= df.loc[df['Operating Airline IATA Code'].isna(), 'Operating Airline IATA Code'].compute()
display(celda_nulos1)
#Cuento el número de celdas nulas
nceldas_nulas1=df['Operating Airline IATA Code'].isna().sum().compute()
display(nceldas_nulas1)
```

148	NaN
6814	NaN
6815	NaN
6925	NaN
6926	NaN
7173	NaN
7174	NaN
7747	NaN
7748	NaN
7972	NaN
7973	NaN
8327	NaN
8328	NaN
8444	NaN
8445	NaN
8562	NaN
8563	NaN
8680	NaN
8793	NaN
8794	NaN
8795	NaN
8796	NaN
9131	NaN
9132	NaN
9357	NaN
...	
12011	NaN
12125	NaN
13025	NaN
13026	NaN

Name: Operating Airline IATA Code, dtype: object

Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings.

Cerrar

```
#Hago lo mismo para la otra columna con nulos
celda_nulos2= df.loc[df['Published Airline IATA Code'].isna(),'Published Airline IATA Code'].compute()
display(celda_nulos2)
nceldas_nulas2=df['Published Airline IATA Code'].isna().sum().compute()
display(nceldas_nulas2)
```

148 NaN
6814 NaN
6815 NaN
6925 NaN
6926 NaN
7173 NaN
7174 NaN
7747 NaN
7748 NaN
7972 NaN
7973 NaN
8327 NaN
8328 NaN
8444 NaN
8445 NaN
8562 NaN
8563 NaN
8680 NaN
8793 NaN
8794 NaN
8795 NaN
8796 NaN
9131 NaN
9132 NaN
9357 NaN
...
12011 NaN
12125 NaN
13025 NaN
13026 NaN

Name: Published Airline IATA Code, dtype: object
Output is truncated. View as a [scrollable element](#) or open in a [text editor](#). Adjust cell output [settings](#)...

Resaltar los registros que tienen los valores nulos de todo el df
registros_nulos=df.loc[df.isnull().any(axis=1),:].compute()
display(registros_nulos)

	Activity Period	Operating Airline	Operating Airline IATA Code	Published Airline	Published Airline IATA Code	GEO Summary	GEO Region	Activity Type Code	Price Category Code	Terminal	Boarding Area	Passenger Count	Adjusted Activity Type Code	Adjusted Passenger Count	Year	Month
148	200508	Boeing Company	NaN	Boeing Company	NaN	Domestic	US	Deployed	Other	Other	Other	18	Deployed	18	2005	August
6814	201005	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	G	73	Deployed	73	2010	May
6815	201005	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	G	73	Deployed	73	2010	May
6925	201006	Pacific Aviation	NaN	Pacific Aviation	NaN	International	Europe	Deployed	Other	International	A	160	Deployed	160	2010	June
6926	201006	Pacific Aviation	NaN	Pacific Aviation	NaN	International	Europe	Deployed	Other	International	A	160	Deployed	160	2010	June
7173	201008	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	G	118	Deployed	118	2010	August
7174	201008	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	G	118	Deployed	118	2010	August
7747	201101	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	A	40	Deployed	40	2011	January
7748	201101	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	A	40	Deployed	40	2011	January
7972	201103	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	A	64	Deployed	64	2011	March
7973	201103	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	A	64	Deployed	64	2011	March
8327	201106	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	A	237	Deployed	237	2011	June
8328	201106	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	A	262	Deployed	262	2011	June
8444	201107	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	A	72	Deployed	72	2011	July
8445	201107	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	A	103	Deployed	103	2011	July
8562	201108	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	A	114	Deployed	114	2011	August
8563	201108	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	A	98	Deployed	98	2011	August
8680	201109	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	A	98	Deployed	98	2011	September
8793	201110	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	A	48	Deployed	48	2011	October
8794	201110	Servisair	NaN	Servisair	NaN	Domestic	US	Deployed	Low Fare	International	A	48	Deployed	48	2011	October
8795	201110	Servisair	NaN	Servisair	NaN	International	Europe	Deployed	Low Fare	International	A	16	Deployed	16	2011	October

```
def reemplazar_nulos(fila):
    if pd.isnull(fila['Operating Airline IATA Code']):
        if fila['Published Airline'] == 'Boeing Company':
            return 'BOC'
        elif fila['Published Airline'] == 'Servisair':
            return 'SWA'
        elif fila['Published Airline'] == 'Swissport USA':
            return 'SWU'
        elif fila['Published Airline'] == 'Pacific Aviation':
            return 'PAW'
        else:
            return fila['Operating Airline IATA Code']

# Aplica la función personalizada a través de map_partitions() para reemplazar los nulos
df_lleno = df.map_partitions(lambda df: df.apply(reemplazar_nulos, axis=1), meta=('Operating Airline IATA Code', 'object'))
df['Operating Airline IATA Code'] = df_lleno
```

```
#Hago lo mismo operación para la columna 'Published Airline IATA code'
def reemplazar_nulos2(fila):
    if pd.isnull(fila['Published Airline IATA Code']):
        if fila['Published Airline'] == 'Boeing Company':
            return 'BOC'
        elif fila['Published Airline'] == 'Servisair':
            return 'SWA'
        elif fila['Published Airline'] == 'Swissport USA':
            return 'SWU'
        elif fila['Published Airline'] == 'Pacific Aviation':
            return 'PAW'
        else:
            return fila['Published Airline IATA Code']

# Aplica la función personalizada a través de map_partitions() para reemplazar los nulos
df_lleno = df.map_partitions(lambda df: df.apply(reemplazar_nulos2, axis=1), meta=('Operating Airline IATA Code', 'object'))
df['Published Airline IATA Code'] = df_lleno
```

```

#Compruebo a ver si hay nulos
nulos= df.isna().any().compute()
display(nulos)

```

Activity Period False
 Operating Airline False
 Operating Airline IATA Code False
 Published Airline False
 Published Airline IATA Code False
 GEO Summary False
 GEO Region False
 Activity Type Code False
 Price Category Code False
 Terminal False
 Boarding Area False
 Passenger Count False
 Adjusted Activity Type Code False
 Adjusted Passenger Count False
 Year False
 Month False
 dtype: bool

Ahora si podemos trabajar con nuestro dataset para resolver las cuestiones propuestas

Cerrar

Ejercicio 2

Ahora resolveré las cuestiones del ejercicio 2 sobre el dataset limpio

- ¿Cuántas compañías diferentes aparecen en el fichero?

```

#¿Cuántas compañías diferentes aparecen en el fichero?
#Analizando el fichero se puede comprobar que hay dos columnas que contienen compañías
#La columna 'Operating Airline' y la columna 'Published Airline'
#Voy a combinar ambas columnas y sacar los valores únicos de la columna resultante

compañias_combinadas= dd.concat([df['Operating Airline'], df['Published Airline']])
compañias_total= compañías_combinadas.unique().compute().tolist()
display(len(compañias_total))
display(compañias_total)

```

77

```

['ATA Airlines',
'Air Canada ',
'Air China',
'Air France',
'Air New Zealand',
'AirTran Airways',
'Alaska Airlines',
'All Nippon Airways',
'American Airlines',
'American Eagle Airlines',
'Asiana Airlines',
'Atlantic Southeast Airlines',
'BelAir Airlines',
'British Airways',
'Cathay Pacific',
'China Airlines',
'Delta Air Lines',
'EVA Air']

```

- ¿Cuántos pasajeros tiene de media los vuelos de cada compañía?

```

#Observo que hay dos columnas que contienen pasajeros
#Las comparo a ver si son iguales

pasajeros_iguales= df['Passenger Count'] == df['Adjusted Passenger Count']
display(pasajeros_iguales.compute())

```

[14]

```

... 0      True
     1      True
     2     False
     3      True
     4      True
     ...
    15002    True
    15003    True
    15004    True
    15005    True
    15006    True
    Length: 15007, dtype: bool

```

920 rows x 16 columns

```
display(media_pasajeros.compute())
```

82 rows x 4 columns

```
display(lista_media_pasajeros)
```

```
array([['ATA Airlines', 'ATA Airlines', 8744, 636363636364],
      ['Aer Lingus', 'Aer Lingus', 4407, 183673469388],
      ['Aeromexico', 'Aeromexico', 5463, 822222222222],
      ['Air Berlin', 'Air Berlin', 2320, 75],
      ['Air Canada', 'Air Canada', 18251, 560109289618],
      ['Air Canada Jazz', 'Air Canada', 294, 2142857142857],
      ['Air China', 'Air China', 6618, 335907333907],
      ['Air France', 'Air France', 11589, 87519373845],
      ['Air India Limited', 'Air India Limited', 2834, 5],
      ['Air New Zealand', 'Air New Zealand', 7452, 33976839768],
      ['AirTran Airlines', 'AirTran Airlines', 18569, 238938053097],
      ['Alaska Airlines', 'Alaska Airlines', 10751, 637816245006],
      ['All Nippon Airways', 'All Nippon Airways', 6385, 523255813953],
      ['Allegiant Air', 'Allegiant Air', 1516, 8125],
      ['American Airlines', 'American Airlines', 127164, 38970588235],
      ['American Eagle Airlines', 'American Airlines',
       4006, 5238018867926],
      ['Asiana Airlines', 'Asiana Flight', 5, 0],
      ['Asiana Airlines', 'Asiana Airlines', 5902, 961240310077],
      ['Atlantic Southeast Airlines', 'Delta Air Lines',
       2176, 909090909091],
      ['Atlas Air, Inc', 'Atlas Air, Inc.', 34, 0],
      ['Baik Air Airlines', 'Baik Air Airlines', 45, 363636363636],
      ['Boeing Company', 'Boeing Company', 18, 0],
      ['British Airways', 'British Airways', 17625, 124031007752],

      ...

      ['Virgin Atlantic', 'Virgin Atlantic', 9847, 18465116279],
      ['WestJet Airlines', 'WestJet Airlines', 5338, 155339805825],
      ['World Airways', 'World Airways', 261, 666666666666],
      ['Xtra Airways France', 'Xtra Airways France', 2223, 1612963225805],
      ['Xtra Airways', 'Xtra Airways', 73, 0], dtype=object])
```

Output is truncated. [View as a scrollable element](#) or [open in a text editor](#). [Adjust cell output settings...](#)

- Eliminar los registros duplicados del campo 'Geo Region', manteniendo unicamente aquel con mayor número de pasajeros

```
#Para esto voy a agrupar los datos de la columna Geo region
#Luego calculo el valor máximo de las columnas de pasajeros para cada grupo de geo region
#Finalmente restablezco el índice del df resultante

df_duplicado = df.groupby('GEO Region').agg({'Passenger Count': 'max', 'Adjusted Passenger Count': 'max'}).reset_index()
display(df_duplicado.compute())
```

	GEO Region	Passenger Count	Adjusted Passenger Count
0	US	659837	659837
1	Canada	39798	39798
2	Asia	86398	86398
3	Europe	48136	48136
4	Australia / Oceania	12973	12973
5	Mexico	29206	29206
6	Central America	8970	8970
7	Middle East	14769	14769
8	South America	3685	3685

- Volcar datos a un CSV nuevo

```
#Realizo un merge con el df limpio y el df que he realizado en el anterior apartado
df_nuevo = df.merge(df_duplicado, on=['GEO Region', 'Passenger Count', 'Adjusted Passenger Count']).compute()
display(df_nuevo)
```

	Activity Period	Operating Airline	Operating Airline IATA Code	Published Airline	Published Airline IATA Code	GEO Summary	GEO Region	Activity Type Code	Price Category Code	Terminal	Boarding Area	Passenger Count	Adjusted Activity Type Code	Adjusted Passenger Count	Year	Month
0	200708	Air Canada	AC	Air Canada	AC	International	Canada	Deplaned	Other	Terminal 3	E	39798	Deplaned	39798	2007	August
1	200708	United Airlines - Pre 07/01/2013	UA	United Airlines - Pre 07/01/2013	UA	International	Asia	Deplaned	Other	International	G	86398	Deplaned	86398	2007	August
2	201101	LAN Peru	LP	LAN Peru	LP	International	South America	Deplaned	Other	International	A	3685	Deplaned	3685	2011	January
3	201308	United Airlines	UA	United Airlines	UA	Domestic	US	Deplaned	Other	Terminal 3	F	659837	Deplaned	659837	2013	August
4	201407	United Airlines	UA	United Airlines	UA	International	Mexico	Deplaned	Other	International	G	29206	Deplaned	29206	2014	July
5	201410	TACA	TA	TACA	TA	International	Central America	Deplaned	Other	International	A	8970	Deplaned	8970	2014	October
6	201501	Air New Zealand	NZ	Air New Zealand	NZ	International	Australia / Oceania	Enplaned	Other	International	G	12973	Enplaned	12973	2015	January
7	201507	Emirates	EK	Emirates	EK	International	Middle East	Deplaned	Other	International	A	14769	Deplaned	14769	2015	July
8	201507	United Airlines	UA	United Airlines	UA	International	Europe	Deplaned	Other	International	G	48136	Deplaned	48136	2015	July

df_nuevo.to_csv('air_traffic_data_nuevo.csv', index=False)

Ejercicio 3. Análisis descriptivo

En este notebook se resolveran las cuestiones pedidas en el ejercicio 3 sobre el primer dataset

Para esto vuelvo a hacer limpieza de los datos nulos para poder trabajar bien

```
>> import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import dask
import dask.dataframe as dd
from IPython.display import display
```

	Activity Period	Operating Airline	Operating Airline IATA Code	Published Airline	Published Airline IATA Code	GEO Summary	GEO Region	Activity Type Code	Price Category Code	Terminal	Boarding Area	Passenger Count	Adjusted Activity Type Code	Adjusted Passenger Count	Year	Month
0	200507	AIA Airlines	TZ	AIA Airlines	TZ	Domestic	US	Deplaned	Low Fare	Terminal 1	B	27271	Deplaned	27271	2005	July
1	200507	AIA Airlines	TZ	AIA Airlines	TZ	Domestic	US	Enplaned	Low Fare	Terminal 1	B	29131	Enplaned	29131	2005	July
2	200507	AIA Airlines	TZ	AIA Airlines	TZ	Domestic	US	Thru / Transit	Low Fare	Terminal 1	B	5415	Thru / Transit	10830	2005	July
3	200507	Air Canada	AC	Air Canada	AC	International	Canada	Deplaned	Other	Terminal 1	B	35156	Deplaned	35156	2005	July
4	200507	Air Canada	AC	Air Canada	AC	International	Canada	Enplaned	Other	Terminal 1	B	34990	Enplaned	34990	2005	July
...
15002	201603	Virgin America	VX	Virgin America	VX	Domestic	US	Enplaned	Low Fare	Terminal 2	D	194636	Enplaned	194636	2016	March
15003	201603	Virgin America	VX	Virgin America	VX	International	Mexico	Deplaned	Low Fare	International	A	4189	Deplaned	4189	2016	March
15004	201603	Virgin America	VX	Virgin America	VX	International	Mexico	Enplaned	Low Fare	Terminal 2	D	4693	Enplaned	4693	2016	March
15005	201603	Virgin Atlantic	VS	Virgin Atlantic	VS	International	Europe	Deplaned	Other	International	A	12313	Deplaned	12313	2016	March
15006	201603	Virgin Atlantic	VS	Virgin Atlantic	VS	International	Europe	Enplaned	Other	International	A	10898	Enplaned	10898	2016	March

15007 rows x 16 columns

```
display(df_clean.info())
```

python

```
<class 'dask.dataframe.core.DataFrame'>  
Columns: 16 entries, Activity Period to Month  
dtypes: object(12), int64(4)
```

```
None
```

```
resumen = df_clean.describe()  
display(resumen.compute())
```

python

	Activity Period	Passenger Count	Adjusted Passenger Count	Year
count	15007.000000	15007.000000	15007.000000	15007.000000
mean	201045.073366	29240.521090	29331.917105	2010.385220
std	313.336196	58319.505284	58284.182219	3.137589
min	200507.000000	1.000000	1.000000	2005.000000
25%	200803.000000	5377.500000	5495.500000	2008.000000
50%	201011.000000	9210.000000	9354.000000	2010.000000
75%	201308.000000	21158.500000	21182.000000	2013.000000
max	201603.000000	659837.000000	659837.000000	2016.000000

Veo que solo hay 4 columnas con valores numéricos, así que transformaré el mayor número posible de columnas categóricas en numéricas para poder trabajar

Para realizar el proceso de codificación podría usar tanto la técnica de Label Encoding o One-Hot Encoding, ya que ambas son usadas comunmente en el procesamiento de datos antes de realizar análisis descriptivos como el que tengo que realizar

Para este caso en el que tengo que calcular la media y la desviación estandar de cada elemento del conjunto de datos voy a usar Label Encoding. Este asignará valores numéricos únicos a cada categoría, y así hará mas fácil el calculo de la media y la desviación estándar.

```
display(df_clean.compute())

moda = df_clean.moda().compute()
display(moda)
```

Python

	Activity Period	Operating Airline	Operating Airline IATA Code	Published Airline	Published Airline IATA Code	GEO Summary	GEO Region	Activity Type Code	Price Category Code	Terminal	Boarding Area	Passenger Count	Adjusted Activity Type Code	Adjusted Passenger Count	Year	Month
0	200507	ATA Airlines	TZ	ATA Airlines	TZ	Domestic	US	Depland	Low Fare	Terminal 1	B	27271	Depland	27271	2005	July
1	200507	ATA Airlines	TZ	ATA Airlines	TZ	Domestic	US	Enpland	Low Fare	Terminal 1	B	29131	Enpland	29131	2005	July
2	200507	ATA Airlines	TZ	ATA Airlines	TZ	Domestic	US	Thru / Transit	Low Fare	Terminal 1	B	5415	Thru / Transit * 2	10830	2005	July
3	200507	Air Canada	AC	Air Canada	AC	International	Canada	Depland	Other	Terminal 1	B	35156	Depland	35156	2005	July
4	200507	Air Canada	AC	Air Canada	AC	International	Canada	Enpland	Other	Terminal 1	B	34090	Enpland	34090	2005	July
...
15002	201603	Virgin America	VX	Virgin America	VX	Domestic	US	Enpland	Low Fare	Terminal 2	D	194636	Enpland	194636	2016	March
15003	201603	Virgin America	VX	Virgin America	VX	International	Mexico	Depland	Low Fare	International	A	4189	Depland	4189	2016	March
15004	201603	Virgin America	VX	Virgin America	VX	International	Mexico	Enpland	Low Fare	Terminal 2	D	4693	Enpland	4693	2016	March
15005	201603	Virgin Atlantic	VS	Virgin Atlantic	VS	International	Europe	Depland	Other	International	A	12313	Depland	12313	2016	March
15006	201603	Virgin Atlantic	VS	Virgin Atlantic	VS	International	Europe	Enpland	Other	International	A	10898	Enpland	10898	2016	March

15007 rows x 16 columns

	Activity Period	Operating Airline	Operating Airline IATA Code	Published Airline	Published Airline IATA Code	GEO Summary	GEO Region	Activity Type Code	Price Category Code	Terminal	Boarding Area	Passenger Count	Adjusted Activity Type Code	Adjusted Passenger Count	Year	Month
0	200807	United Airlines - Pre 07/01/2013	UA	United Airlines - Pre 07/01/2013	UA	International	US	Depland	Other	International	A	2	Depland	2	2015	August

```
from sklearn.preprocessing import LabelEncoder
columnas_categoria = ['GEO Summary', 'GEO Region',
                      'Activity Type Code', 'Price Category Code', 'Terminal', 'Boarding Area',
                      'Adjusted Activity Type Code', 'Month']

mapeo_valores = {}

for columna in columnas_categoria:
    le = LabelEncoder()
    le.fit(df_clean[columna].astype(str))
    df_clean[columna] = le.transform(df_clean[columna].astype(str))
    mapeo_valores[columna] = (valor: codificacion for valor, codificacion in zip(le.classes_, le.transform(le.classes_)))

display(df_clean.compute())

for columna, mapeo in mapeo_valores.items():
    print(f'Valores para la columna {columna}:')
    print(mapeo)
    print()
```

Python

	Activity Period	Operating Airline	Operating Airline IATA Code	Published Airline	Published Airline IATA Code	GEO Summary	GEO Region	Activity Type Code	Price Category Code	Terminal	Boarding Area	Passenger Count	Adjusted Activity Type Code	Adjusted Passenger Count	Year	Month
0	200507	ATA Airlines	TZ	ATA Airlines	TZ	0	8	0	0	2	1	27271	0	27271	2005	5
1	200507	ATA Airlines	TZ	ATA Airlines	TZ	0	8	1	0	2	1	29131	1	29131	2005	5
2	200507	ATA Airlines	TZ	ATA Airlines	TZ	0	8	2	0	2	1	5415	2	10830	2005	5
3	200507	Air Canada	AC	Air Canada	AC	1	2	0	1	2	1	35156	0	35156	2005	5
4	200507	Air Canada	AC	Air Canada	AC	1	2	1	1	2	1	34090	1	34090	2005	5
...
15002	201603	Virgin America	VX	Virgin America	VX	0	8	1	0	3	3	194636	1	194636	2016	7
15003	201603	Virgin America	VX	Virgin America	VX	1	5	0	0	0	0	4189	0	4189	2016	7

15007 rows x 16 columns

Valores para la columna GEO Summary:
{'Domestic': 0, 'International': 1}

Valores para la columna GEO Region:
{'Asia': 0, 'Australia / Oceania': 1, 'Canada': 2, 'Central America': 3, 'Europe': 4, 'Mexico': 5, 'Middle East': 6, 'South America': 7, 'US': 8}

Valores para la columna Activity Type Code:
{'Depland': 0, 'Enpland': 1, 'Thru / Transit': 2}

Valores para la columna Price Category Code:
{'Low Fare': 0, 'Other': 1}

Valores para la columna Terminal:
{'International': 0, 'Other': 1, 'Terminal 1': 2, 'Terminal 2': 3, 'Terminal 3': 4}

Valores para la columna Boarding Area:
{'A': 0, 'B': 1, 'C': 2, 'D': 3, 'E': 4, 'F': 5, 'G': 6, 'Other': 7}

Valores para la columna Adjusted Activity Type Code:
{'Depland': 0, 'Enpland': 1, 'Thru / Transit * 2': 2}

Valores para la columna Month:
{'April': 0, 'August': 1, 'December': 2, 'February': 3, 'January': 4, 'July': 5, 'June': 6, 'March': 7, 'May': 8, 'November': 9, 'October': 10, 'September': 11}

Las columnas que contienen las aerolineas y sus codigos he decidido no codificarlas ya que contienen una gran cantidad de variables y no creo que sea necesario.

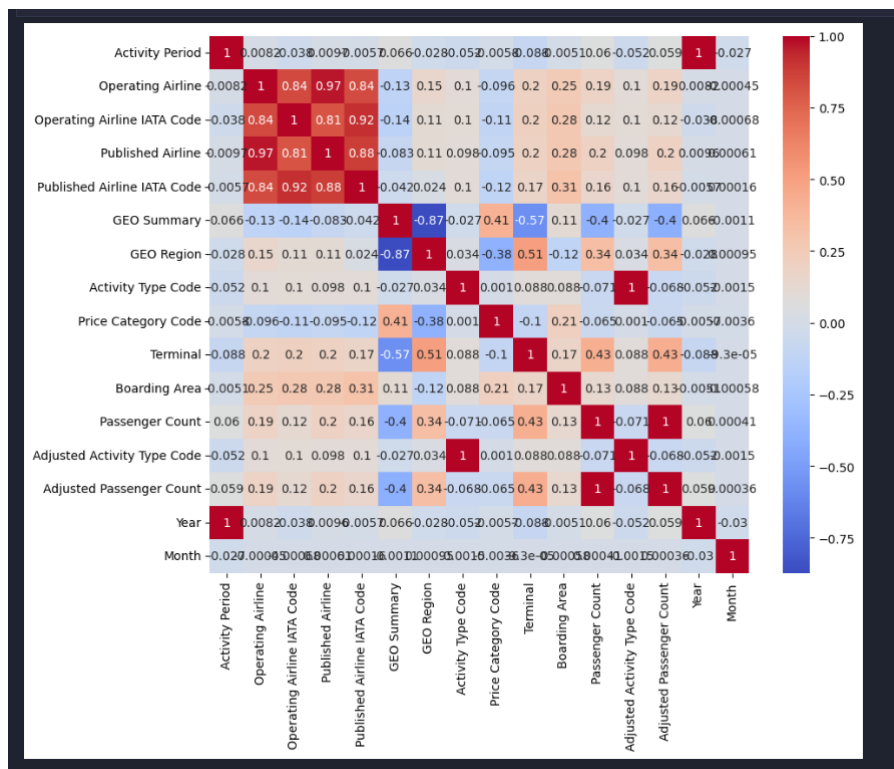
```
Ahora realiza la media y la desviación típica con los datos codificados
resumen = df_clean.describe()
moda = df_clean.moda()
display(resumen.compute())
display(moda.compute())
```

Python

	Activity Period	GEO Summary	GEO Region	Activity Type Code	Price Category Code	Terminal	Boarding Area	Passenger Count	Adjusted Activity Type Code	Adjusted Passenger Count	Year	Month
count	15007.000000	15007.000000	15007.000000	15007.000000	15007.000000	15007.000000	15007.000000	15007.000000	15007.000000	15007.000000	15007.000000	15007.000000
mean	201045.073366	0.613714	4.438995	0.590125	0.672060	1.089691	2.652829	29240.521090	0.590125	29331.917105	2010.385220	5.531352
std	313.336196	0.486914	3.240626	0.603748	0.334034	1.495813	2.544096	58319.509284	0.603748	58284.182219	3.137589	3.454595
min	200507.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	1.000000	0.000000	1.000000	2005.000000	0.000000
25%	200803.000000	0.000000	1.000000	0.000000	1.000000	0.000000	0.000000	5373.500000	0.000000	5495.500000	2008.000000	3.000000
50%	201011.000000	1.000000	4.000000	1.000000	1.000000	0.000000	2.000000	9210.000000	1.000000	9354.000000	2010.000000	5.000000
75%	201308.000000	1.000000	8.000000	1.000000	1.000000	2.000000	6.000000	21158.500000	1.000000	21182.000000	2013.000000	9.000000
max	201603.000000	1.000000	8.000000	2.000000	1.000000	4.000000	7.000000	659837.000000	2.000000	659837.000000	2016.000000	11.000000

	Activity Period	Operating Airline	Operating Airline IATA Code	Published Airline	Published Airline IATA Code	GEO Summary	GEO Region	Activity Type Code	Price Category Code	Terminal	Boarding Area	Passenger Count	Adjusted Activity Type Code	Adjusted Passenger Count	Year	Month
0	200807	United Airlines - Pre 07/01/2013	UA	United Airlines - Pre 07/01/2013	UA	1	8	0	1	0	0	2	0	2	2015	1

	0	200807	70	65	61	59	1	8	0	1	0	0
Interpretación de los datos												
	Media	Desviación Estandar	Moda	Valor								
Activity Period	201045.07	313.34	200807									
Operating Airline	43.74	23.67	United Airline-Pre 07/01/2013									
"IATA Code	42.79	21.79	UA									
Published Airline	37.619	21.17	United Airline-Pre 07/01/2013									
"IATA Code	38.54	20.35	UA									
GEO Summary	0.614	0.487	1	0:Domestic 1:International								
GEO Region	4.439	3.24	8	8:US								
Activity type code	0.59	0.604	0	0:Desembarcado 1:Embarcado 2:En transito								
Price Category Code	0.879	0.334	1	0:Tarifa baja 1: Otro								
Terminal	1.0897	1.49	0	0:Internacional								
Boarding Area	2.65	2.54	0	0:A								
Passenger count	29240.52	58319.51	2									
Adjusted Activity type code	0.5901	0.604	0	0:Desembarcado 1:Embarcado 2:En transito								
Adjusted passenger count	29331.92	58284.18	2									
Year	2010.38	3.137	2015									
Month	5.53	3.45	1	1:Agosto								



Algoritmo

En esta parte del trabajo voy a seleccionar un algoritmo de programación paralela y distribuida visto en clase para aplicar a mi dataset. Tengo que basar mi elección en lo aprendido y las características del dataset.

En función a como es mi dataset y las conclusiones que he sacado de trabajar con el, creo que la mejor opción es usar Apache Spark como framework de procesamiento paralelo y distribuido. Es una buena opción gracias a la capacidad que tiene para procesar grandes volúmenes de datos de manera escalable. Esto significa que puede servir bien con el dataset de gran dimension que tenemos.

También porque proporciona una amplia gama de bibliotecas útiles para aplicar algoritmos y análisis específicos al dataset y porque se integra con python a través de la biblioteca PySpark.

```
import os
from pyspark.sql import SparkSession
```