In [1]: ▶ # Generic inputs for most ML tasks import pandas as pd import numpy as np import matplotlib.pyplot as plt from sklearn.model_selection import train_test_split from sklearn.linear_model import LinearRegression # This is new from sklearn.linear_model import LogisticRegression from sklearn.linear_model import Ridge from sklearn.linear_model import Lasso from sklearn.ensemble import RandomForestRegressor pd.options.display.float_format = '{:,.2f}'.format # setup interactive notebook mode from IPython.core.interactiveshell import InteractiveShell InteractiveShell.ast_node_interactivity = "all" from IPython.display import display, HTML

Fetching Flight data

Out[3]:

Unnamed: 0	Carrier_Code	Date	Flight_Number	Tail_Number	Destination_Airport	Scheduled departure time	Actual departure time	elapsed time (Minutes)	elapsed time (Minutes)	
0 0	MQ	2020- 01-04	3,580.00	N240NN	SYR	7:55	8:21	112.00	87.00	
1 1	MQ	2020- 01-11	3,946.00	N247NN	SYR	15:00	15:09	108.00	132.00	
2 2	MQ	2020- 01-18	3,946.00	N265NN	SYR	15:00	16:27	108.00	147.00	
3 3	MQ	2020- 01-25	3,946.00	N281NN	SYR	15:00	14:55	108.00	126.00	
4 4	MQ	2020- 02-01	3,946.00	N283NN	SYR	15:00	14:57	108.00	99.00	

5 rows × 36 columns

Out[3]: 8661

In [4]: ► main_data.dtypes

Out[4]:	Unnamed: 0 Carrier_Code Date Flight_Number	int64 object object float64
	Tail_Number	object
	Destination_Airport	object
	Scheduled departure time	object
	Actual departure time	object
	Scheduled elapsed time (Minutes)	float64
	Actual elapsed time (Minutes)	float64
	Departure delay (Minutes)	float64
	Wheels-off time	object
	Taxi-Out time (Minutes)	float64
	dep_Delay_Carrier	float64
	dep_Delay_Weather	float64
	<pre>dep_Delay_National_Aviation_System</pre>	float64
	dep_Delay_Security	float64
	dep_Delay_Late_Aircraft_Arrival	float64
	dep_hour	int64
	dep_day	int64
	dep_year	int64
	dep_order	object
	Origin_Airport	object
	Scheduled Arrival Time	object
	Actual Arrival Time	object
	Arrival Delay (Minutes)	float64
	Wheels-on Time	object
	Taxi-In time (Minutes)	float64
	arr_Delay_Carrier	float64
	arr_Delay_Weather	float64
	arr_Delay_National_Aviation_System	float64
	arr_Delay_Security	float64
	arr_Delay_Late_Aircraft_Arrival	float64
	arr_hour	int64
	arr_day	int64
	arr_year	int64
	dtype: object	

In [5]: main data['Date'] = pd.to datetime(main data['Date'],format ="%Y-%m-%d") main data['Date'] = main data['Date'].dt.strftime('%m/%d/%Y') main data['dep min'] = main data['Scheduled departure time'].str.split(":").str[1].astype('int64') # main data['dep minutes'] = main data['dep min'].apply(round to nearest quarter).astype('object') main data['dep min'] = main data['dep min'].astype('object') main data['arr min'] = main data['Scheduled Arrival Time'].str.split(":").str[1].astype('int64') # main data['arr minutes'] = main data['arr min'].apply(round to nearest quarter).astype('object') main data['arr min'] = main data['arr min'].astype('object') main data['Flight Number'] = main data['Flight Number'].astype('object') main_data['dep_hours'] = main_data['dep_hour'].astype('object') main data['dep hour'] = main data['dep hour'].astype('object') main data['dep day'] = main data['dep day'].astype('object') main data['arr hours'] = main data['arr hour'].astype('object') main data['arr hour'] = main data['arr hour'].astype('object') main data['arr day'] = main data['arr day'].astype('object') $conditions = \Gamma$ (main data['Arrival Delay (Minutes)'] > 5), (main data['Arrival Delay (Minutes)'] >= -5) & (main data['Arrival Delay (Minutes)'] <= 5),</pre> (main data['Arrival Delay (Minutes)'] < -5)</pre> conditions2 = [(main data['Departure delay (Minutes)'] > 5), (main data['Departure delay (Minutes)'] >=-5) & (main data['Departure delay (Minutes)'] <= 5),</pre> (main_data['Departure delay (Minutes)'] < -5)</pre> choices = [2, 1, 0]main data['dep status'] = np.select(conditions2, choices) main data['arr status'] = np.select(conditions, choices) main data.dtypes main data.head()

Out[5]:	Unnamed: 0	int64
	Carrier_Code	object
	Date	object
	Flight_Number	object
	Tail_Number	object
	Destination_Airport	object
	Scheduled departure time	object
	Actual departure time	object
	Scheduled elapsed time (Minutes)	float64
	Actual elapsed time (Minutes)	float64
	Departure delay (Minutes)	float64
	Wheels-off time	object
	Taxi-Out time (Minutes)	float64
	dep_Delay_Carrier	float64
	dep_Delay_Weather	float64
	<pre>dep_Delay_National_Aviation_System</pre>	float64
	dep_Delay_Security	float64
	dep_Delay_Late_Aircraft_Arrival	float64
	dep_hour	object
	dep_day	object
	dep_year	int64
	dep_order	object
	Origin_Airport	object
	Scheduled Arrival Time	object
	Actual Arrival Time	object
	Arrival Delay (Minutes)	float64
	Wheels-on Time	object
	Taxi-In time (Minutes)	float64
	arr_Delay_Carrier	float64
	arr_Delay_Weather	float64
	arr_Delay_National_Aviation_System	float64
	arr_Delay_Security	float64
	arr_Delay_Late_Aircraft_Arrival	float64
	arr_hour	object
	arr_day	object
	arr_year	int64
	dep_min	object
	arr min	object
	dep_hours	object
	arr_hours	object
	dep_status	int32
	acp_scacas	111032

int32

arr_status
dtype: object

Out[5]:

	Unnamed: 0	Carrier_Code	Date	Flight_Number	Tail_Number	Destination_Airport	Scheduled departure time	Actual departure time	Scheduled elapsed time (Minutes)	Actu elapse tin (Minute
0	0	MQ	01/04/2020	3,580.00	N240NN	SYR	7:55	8:21	112.00	87.0
1	1	MQ	01/11/2020	3,946.00	N247NN	SYR	15:00	15:09	108.00	132.0
2	2	MQ	01/18/2020	3,946.00	N265NN	SYR	15:00	16:27	108.00	147.0
3	3	MQ	01/25/2020	3,946.00	N281NN	SYR	15:00	14:55	108.00	126.0
4	4	MQ	02/01/2020	3,946.00	N283NN	SYR	15:00	14:57	108.00	99.0

5 rows × 42 columns

In [6]:

In [7]: ▶ sub_data.dtypes Out[7]: Carrier_Code object object Date Flight_Number object Tail_Number object Scheduled departure time object dep_hour object dep_day object dep_order object Origin_Airport object Scheduled Arrival Time object Arrival Delay (Minutes) float64 object arr_hour arr_day object object dep_min arr_min object dep_hours object arr_hours object dep_status int32 int32 arr_status dtype: object

In [8]: sub_data.head()

Out[8]:

	Carrier_Code	Date	Flight_Number	Tail_Number	Scheduled departure time	dep_hour	dep_day	dep_order	Origin_Airport	Scheduled Arrival Time	(M
0	MQ	01/04/2020	3,580.00	N240NN	7:55	7	5	latter	ORD	10:47	
1	MQ	01/11/2020	3,946.00	N247NN	15:00	15	5	latter	ORD	17:48	
2	MQ	01/18/2020	3,946.00	N265NN	15:00	15	5	latter	ORD	17:48	
3	MQ	01/25/2020	3,946.00	N281NN	15:00	15	5	latter	ORD	17:48	
4	MQ	02/01/2020	3,946.00	N283NN	15:00	15	5	latter	ORD	17:48	
4											•

Modifying flight data to have latter flights along with early flight arrival status

```
In [9]: | latter_data = sub_data[sub_data['dep_order'] == 'latter']
              len(latter_data)
     Out[9]: 5337
In [10]: | early_data = sub_data[sub_data['dep_order'] == 'early']
              len(early data)
    Out[10]: 3324
           merged_df = pd.merge(latter_data, early_data, on=['Date', 'Origin_Airport'], how = 'left')
In [11]:
              merged df.head()
              len(merged df)
   Out[11]:
                                                                        Scheduled
                                                                                  dep_hour_x dep_day_x dep_order_x Origin_Airport
                  Carrier Code x
                                     Date Flight Number x Tail Number x
                                                                        departure
                                                                           time_x
                                                                                           7
                                                                                                     5
               0
                            MQ 01/04/2020
                                                  3,580.00
                                                                N240NN
                                                                             7:55
                                                                                                               latter
                                                                                                                            ORD
               1
                            MQ 01/11/2020
                                                  3.946.00
                                                                N247NN
                                                                            15:00
                                                                                          15
                                                                                                     5
                                                                                                              latter
                                                                                                                            ORD
               2
                                                                                                     5
                            MQ 01/18/2020
                                                  3,946.00
                                                               N265NN
                                                                            15:00
                                                                                          15
                                                                                                              latter
                                                                                                                            ORD
                            MQ 01/25/2020
                                                                                                     5
                                                                                                                            ORD
               3
                                                  3,946.00
                                                                N281NN
                                                                            15:00
                                                                                          15
                                                                                                              latter
                                                                                                     5
               4
                            MQ 02/01/2020
                                                  3,946.00
                                                               N283NN
                                                                            15:00
                                                                                          15
                                                                                                              latter
                                                                                                                            ORD
              5 rows × 36 columns
   Out[11]: 7251
```

In [12]: ▶ merged_df.head(20)

Out[12]:

	Carrier_Code_x	Date	Flight_Number_x	Tail_Number_x	Scheduled departure time_x	dep_hour_x	dep_day_x	dep_order_x	Origin_Airport
0	MQ	01/04/2020	3,580.00	N240NN	7:55	7	5	latter	ORD
1	MQ	01/11/2020	3,946.00	N247NN	15:00	15	5	latter	ORD
2	MQ	01/18/2020	3,946.00	N265NN	15:00	15	5	latter	ORD
3	MQ	01/25/2020	3,946.00	N281NN	15:00	15	5	latter	ORD
4	MQ	02/01/2020	3,946.00	N283NN	15:00	15	5	latter	ORD
5	MQ	02/08/2020	3,946.00	N274NN	15:00	15	5	latter	ORD
6	MQ	04/06/2020	3,618.00	NaN	19:29	19	0	latter	ORD
7	MQ	04/07/2020	3,946.00	N287NN	15:06	15	1	latter	ORD
8	MQ	04/08/2020	3,946.00	NaN	15:06	15	2	latter	ORD
9	MQ	04/09/2020	3,946.00	NaN	15:06	15	3	latter	ORD
10	MQ	04/10/2020	3,946.00	NaN	15:06	15	4	latter	ORD
11	MQ	04/12/2020	3,946.00	NaN	15:06	15	6	latter	ORD
12	MQ	04/13/2020	3,946.00	N243NN	15:06	15	0	latter	ORD
13	MQ	04/14/2020	3,946.00	N234JW	15:06	15	1	latter	ORD
14	MQ	04/15/2020	3,946.00	NaN	15:06	15	2	latter	ORD
15	MQ	04/16/2020	3,946.00	N278NN	15:06	15	3	latter	ORD
16	MQ	04/17/2020	3,946.00	NaN	15:06	15	4	latter	ORD
17	MQ	04/19/2020	3,946.00	NaN	15:06	15	6	latter	ORD
18	MQ	04/20/2020	3,946.00	NaN	15:06	15	0	latter	ORD
19	MQ	04/21/2020	3,946.00	NaN	15:06	15	1	latter	ORD

20 rows × 36 columns

```
▶ len(merged df)
In [13]:
   Out[13]: 7251
          M merged_df.columns
In [14]:
   Out[14]: Index(['Carrier_Code_x', 'Date', 'Flight_Number_x', 'Tail_Number_x',
                    'Scheduled departure time_x', 'dep_hour_x', 'dep_day_x', 'dep_order_x',
                    'Origin Airport', 'Scheduled Arrival Time x',
                    'Arrival Delay (Minutes) x', 'arr hour x', 'arr day x', 'dep min x',
                    'arr min x', 'dep hours x', 'arr hours x', 'dep status x',
                    'arr_status_x', 'Carrier_Code_y', 'Flight_Number_y', 'Tail_Number_y',
                    'Scheduled departure time_y', 'dep_hour_y', 'dep_day_y', 'dep_order_y',
                    'Scheduled Arrival Time_y', 'Arrival Delay (Minutes)_y', 'arr_hour_y',
                    'arr day y', 'dep min y', 'arr min y', 'dep hours y', 'arr hours y',
                    'dep_status_y', 'arr_status_y'],
                   dtype='object')
```

Filtering flights with a max gap of 3hrs

```
In [16]:  merged_df.head()
```

Out[16]:

	Carrier_Code_x	Date	Flight_Number_x	Tail_Number_x	Scheduled departure time_x	dep_hour_x	dep_day_x	dep_order_x	Origin_Airport	
869	MQ	07/04/2023	3,402.00	N298FR	18:30	18	1	latter	ORD	
870	MQ	07/05/2023	3,402.00	N768RD	18:36	18	2	latter	ORD	
873	MQ	07/06/2023	3,402.00	N634RW	18:36	18	3	latter	ORD	
884	MQ	07/10/2023	3,402.00	N228NN	18:36	18	0	latter	ORD	
887	MQ	07/11/2023	3,402.00	N449YX	18:36	18	1	latter	ORD	
5 rows × 37 columns										

correcting carrier codes

In [18]: merged_df.head()

Out[18]:

	Carrier_Code_x	Date	Flight_Number_x	Tail_Number_x	Scheduled departure time_x	dep_hour_x	dep_day_x	dep_order_x	Origin_Airport
869	AA	07/04/2023	3,402.00	N298FR	18:30	18	1	latter	ORD
870	AA	07/05/2023	3,402.00	N768RD	18:36	18	2	latter	ORD
873	AA	07/06/2023	3,402.00	N634RW	18:36	18	3	latter	ORD
884	AA	07/10/2023	3,402.00	N228NN	18:36	18	0	latter	ORD
887	AA	07/11/2023	3,402.00	N449YX	18:36	18	1	latter	ORD

5 rows × 37 columns

```
In [19]:
          merged df.columns
   Out[19]: Index(['Carrier_Code_x', 'Date', 'Flight_Number_x', 'Tail_Number_x',
                    'Scheduled departure time x', 'dep hour x', 'dep day x', 'dep order x',
                    'Origin Airport', 'Scheduled Arrival Time x',
                    'Arrival Delay (Minutes) x', 'arr hour x', 'arr day x', 'dep min x',
                    'arr min x', 'dep hours x', 'arr hours x', 'dep status x',
                    'arr_status_x', 'Carrier_Code_y', 'Flight_Number_y', 'Tail_Number_y',
                    'Scheduled departure time_y', 'dep_hour_y', 'dep_day_y', 'dep_order_y',
                    'Scheduled Arrival Time_y', 'Arrival Delay (Minutes)_y', 'arr_hour_y',
                    'arr day y', 'dep min y', 'arr min y', 'dep hours y', 'arr hours y',
                    'dep status y', 'arr status y', 'hour diff'],
                   dtype='object')
In [20]: M merged_df.drop(columns=['Carrier_Code_y', 'Flight_Number_y',
                    'Tail_Number_y', 'Scheduled departure time_y', 'dep_hour_y',
                    'dep_day_y', 'dep_order_y', 'Scheduled Arrival Time_y',
                    'Arrival Delay (Minutes)_y', 'arr_hour_y', 'arr_day_y', 'dep_min_y',
                    'arr_min_y', 'dep_hours_y',
                    'arr_hours_y','dep_status_y'], inplace=True)
```

Out[21]:

	Carrier_Code	Date	Flight_Number	Tail_Number	Scheduled departure time	dep_hour	dep_day	dep_order	Origin_Airport	Scheduled Arrival Time
869	AA	07/04/2023	3,402.00	N298FR	18:30	18	1	latter	ORD	21:25
870	AA	07/05/2023	3,402.00	N768RD	18:36	18	2	latter	ORD	21:32
873	AA	07/06/2023	3,402.00	N634RW	18:36	18	3	latter	ORD	21:32
884	AA	07/10/2023	3,402.00	N228NN	18:36	18	0	latter	ORD	21:32
887	AA	07/11/2023	3,402.00	N449YX	18:36	18	1	latter	ORD	21:32

5 rows × 21 columns

```
In [22]: | # merged_df.to_csv('flight_data\\all_lat_ear.csv')
```

dtype='object')

Fetching weather data

```
In [23]: # Read and process weather data files for each airport
    jfk_weather_data = pd.read_csv('weather_data/JFK_weather_data_hourly_processed.csv')
    syr_weather_data = pd.read_csv('weather_data/SYR_weather_data_hourly_processed.csv')
    ord_weather_data = pd.read_csv('weather_data/ORD_weather_data_hourly_processed.csv')
    mco_weather_data = pd.read_csv('weather_data/MCO_weather_data_hourly_processed.csv')

# Combine weather data for all airports
    weather_dfs = [jfk_weather_data, ord_weather_data, mco_weather_data]
    weather_data = pd.concat(weather_dfs, axis=0)
    weather_data['dep_hours'] = weather_data['dep_hours'].astype('object')
    syr_weather_data['arr_hours'] = syr_weather_data['arr_hours'].astype('object')
    weather_data.head()
    syr_weather_data.dtypes
    syr_weather_data.dtypes
```

Out[23]:

	dep_azimuth	dep_clouds	dep_dewpt	dep_elev_angle	dep_h_angle	dep_precip	dep_pres	dep_revision_status	dep_rh	dep_sn
_	0 261.20	100	3.80	-26.20	NaN	0.00	1002	final	88	0
	1 270.50	100	3.90	-37.50	NaN	0.25	1003	final	85	0
	2 281.40	100	3.70	-48.80	NaN	0.00	1003	final	82	0
	3 296.30	100	1.60	-59.60	NaN	0.00	1002	final	73	0
	4 320.80	100	0.70	-68.60	NaN	0.00	1003	final	69	0
4										>

Out[23]:

	arr_azimuth	arr_clouds	arr_dewpt	arr_elev_angle	arr_h_angle	arr_precip	arr_pres	arr_revision_status	arr_rh	arr_snow	arr_t
0	260.90	100	-2.30	-24.90	NaN	0.00	987	final	78	0.00	
1	270.70	100	-3.00	-35.80	NaN	0.00	987	final	77	0.00	
2	282.10	100	-4.00	-46.60	NaN	0.00	986	final	71	0.00	
3	297.00	100	-4.40	-56.90	NaN	0.00	987	final	69	0.00	
4	319.80	100	-4.40	-65.60	NaN	0.00	986	final	69	0.00	
4											•

Out[23]:

float64
int64
float64
float64
float64
float64
int64
object
int64
float64
float64
int64
object
int64
int64
float64
float64
object
object
object

```
Out[23]: arr_azimuth
                                     float64
         arr_clouds
                                       int64
         arr_dewpt
                                     float64
         arr_elev_angle
                                    float64
         arr_h_angle
                                    float64
         arr_precip
                                     float64
         arr_pres
                                      int64
         arr_revision_status
                                     object
         arr_rh
                                      int64
         arr_snow
                                     float64
         arr_temp
                                     float64
         arr_vis
                                       int64
         arr_weather.description
                                     object
         arr_weather.code
                                      int64
         arr_wind_dir
                                       int64
         arr_wind_gust_spd
                                     float64
                                    float64
         arr_wind_spd
                                     object
         Date
         arr_hours
                                     object
         dtype: object
```

```
In [24]: ▶ # Define merging logic based on airport code
            merged_df = pd.merge(merged_df, syr_weather_data, how='left', on=['Date', 'arr_hours'])
            merged_df.head()
```

Out[24]:

	Carrier_Code	Date	Flight_Number	Tail_Number	Scheduled departure time	dep_hour	dep_day	dep_order	Origin_Airport	Scheduled Arrival Time	
0	AA	07/04/2023	3,402.00	N298FR	18:30	18	1	latter	ORD	21:25	
1	AA	07/05/2023	3,402.00	N768RD	18:36	18	2	latter	ORD	21:32	
2	AA	07/06/2023	3,402.00	N634RW	18:36	18	3	latter	ORD	21:32	
3	AA	07/10/2023	3,402.00	N228NN	18:36	18	0	latter	ORD	21:32	
4	AA	07/11/2023	3,402.00	N449YX	18:36	18	1	latter	ORD	21:32	

5 rows × 38 columns

localhost:8888/notebooks/Downloads/IML project/flight-predictions/Latter flight prediction model.ipynb

Out[25]:

	Carrier_Code	Date	Flight_Number	Tail_Number	Scheduled departure time	dep_hour	dep_day	dep_order	Origin_Airport	Scheduled Arrival . Time	
0	AA	07/04/2023	3,402.00	N298FR	18:30	18	1	latter	ORD	21:25 .	
1	AA	07/05/2023	3,402.00	N768RD	18:36	18	2	latter	ORD	21:32 .	
2	AA	07/06/2023	3,402.00	N634RW	18:36	18	3	latter	ORD	21:32 .	
3	AA	07/10/2023	3,402.00	N228NN	18:36	18	0	latter	ORD	21:32 .	
4	AA	07/11/2023	3,402.00	N449YX	18:36	18	1	latter	ORD	21:32 .	

5 rows × 55 columns

In [26]: # merged_df.to_csv('flight_data\\all_lat_ear.csv')

Out[27]:	dep_hour	object
	dep_day	object
	Origin_Airport	object
	arr_hour	object
	arr_day	object
	dep_min	object
	arr_min	object
	dep_hours	object
	arr_hours	object
	dep_status	int32
	arr_status_x	int32
	arr_status_y	float64
	arr_azimuth	float64
	arr_clouds	int64
	arr_dewpt	float64
	arr_elev_angle	float64
	arr_h_angle	float64
	arr_precip	float64
	arr_pres	int64
	arr_revision_status	object
	arr_rh	int64
	arr_snow	float64
	arr_temp	float64
	arr_vis	int64
	arr_weather.code	int64
	arr_wind_dir	int64
	arr_wind_gust_spd	float64
	arr_wind_spd	float64
	dep_azimuth	float64
	dep_clouds	int64
	dep_dewpt	float64
	dep_elev_angle	float64
	dep_h_angle	float64
	dep_precip	float64
	dep_pres	int64
	dep_revision_status	object
	dep_rh	int64
	dep_snow	float64
	dep_temp	float64
	dep_vis	int64
	dep_weather.code	int64
	dep_wind_dir	int64
	dep_wind_gust_spd	float64
	3	

dep_wind_spd
dtype: object float64

Out[28]:

	dep_hour	dep_day	Origin_Airport	arr_hour	arr_day	dep_min	arr_min	dep_hours	arr_hours	dep_status	 dep_pres	dep_ı
0	18	1	ORD	21	1	30	25	18	21	0	 989	
1	18	2	ORD	21	2	36	32	18	21	1	 986	
2	18	3	ORD	21	3	36	32	18	21	1	 989	
3	18	0	ORD	21	0	36	32	18	21	2	 987	
4	18	1	ORD	21	1	36	32	18	21	2	 989	

5 rows × 44 columns

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Out[28]:	dep_hour	object
	dep_day	object
	Origin_Airport	object
	arr_hour	object
	arr_day	object
	dep_min	object
	arr_min	object
	dep_hours	object
	arr_hours	object
	dep_status	object
	arr_status_x	int32
	arr_status_y	object
	arr_azimuth	float64
	arr_clouds	int64
	arr_dewpt	float64
	arr_elev_angle	float64
	arr_h_angle	float64
	arr_precip	float64
	arr_pres	int64
	arr_revision_status	object
	arr_rh	int64
	arr_snow	float64
	arr_temp	float64
	arr_vis	int64
	arr_weather.code	int64
	arr_wind_dir	int64
	arr_wind_gust_spd	float64
	arr_wind_spd	float64
	dep_azimuth	float64
	dep_clouds	int64
	dep_dewpt	float64
	dep_elev_angle	float64
	dep_h_angle	float64
	dep_precip	float64
	dep_pres	int64
	dep_revision_status	object
	dep_rh	int64
	dep_snow	float64
	dep_temp	float64
	dep_vis	int64
	dep_weather.code	int64
	dep_wind_dir	int64
	dep_wind_gust_spd	float64
	1	

dep_wind_spd float64

dtype: object

In [29]: ▶

su_data.head()

Out[29]:

	dep_hour	dep_day	Origin_Airport	arr_hour	arr_day	dep_min	arr_min	dep_hours	arr_hours	dep_status	 dep_pres	dep_ı
0	18	1	ORD	21	1	30	25	18	21	0	 989	
1	18	2	ORD	21	2	36	32	18	21	1	 986	
2	18	3	ORD	21	3	36	32	18	21	1	 989	
3	18	0	ORD	21	0	36	32	18	21	2	 987	
4	18	1	ORD	21	1	36	32	18	21	2	 989	

5 rows × 44 columns

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'dep_nour', dep_day', Origin_Airport', arr_nour', drr_day',
 'dep_min', 'arr_min', 'dep_hours', 'arr_hours', 'dep_status',
 'arr_status_x', 'arr_status_y', 'arr_azimuth', 'arr_clouds',
 'arr_dewpt', 'arr_elev_angle', 'arr_h_angle', 'arr_precip', 'arr_pres',
 'arr_revision_status', 'arr_rh', 'arr_snow', 'arr_temp', 'arr_vis',
 'arr_weather.code', 'arr_wind_dir', 'arr_wind_gust_spd', 'arr_wind_spd',
 'dep_azimuth', 'dep_clouds', 'dep_dewpt', 'dep_elev_angle',
 'dep_h_angle', 'dep_precip', 'dep_pres', 'dep_revision_status',
 'dep_rh', 'dep_snow', 'dep_temp', 'dep_vis', 'dep_weather.code',
 'dep_wind_dir', 'dep_wind_gust_spd', 'dep_wind_spd'],
 dtype='object')

Out[30]:

	dep_hour	dep_day	Origin_Airport	arr_hour	arr_day	dep_min	arr_min	dep_hours	arr_hours	dep_status	 dep_pres	dep_ı
0	18	1	ORD	21	1	30	25	18	21	0	 989	
1	18	2	ORD	21	2	36	32	18	21	1	 986	
2	18	3	ORD	21	3	36	32	18	21	1	 989	
3	18	0	ORD	21	0	36	32	18	21	2	 987	
4	18	1	ORD	21	1	36	32	18	21	2	 989	

5 rows × 44 columns

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```
In [31]: N
su_data['dep_hour'] = pd.Categorical(su_data['dep_hour'], categories=[i for i in range(24)])
su_data['dep_day'] = pd.Categorical(su_data['dep_day'], categories=[i for i in range(7)])
su_data['dep_min'] = pd.Categorical(su_data['dep_min'], categories=[i for i in range(60)])
su_data['arr_hour'] = pd.Categorical(su_data['arr_hour'], categories=[i for i in range(24)])
su_data['arr_day'] = pd.Categorical(su_data['arr_day'], categories=[i for i in range(7)])
su_data['arr_min'] = pd.Categorical(su_data['arr_min'], categories=[i for i in range(60)])
#su_data['Carrier_Code'] = pd.Categorical(su_data['Carrier_Code'], categories=['AA', 'DL', 'B6'])
su_data['Origin_Airport'] = pd.Categorical(su_data['Origin_Airport'], categories=['ORD', 'JFK', 'MCO'])
su_data['arr_weather.code'] = pd.Categorical(su_data['arr_weather.code'], categories=[200,201,202,230,231, su_data['dep_weather.code'] = pd.Categorical(su_data['dep_weather.code'], categories=[200,201,202,230,231, su_data['dep_status'] = pd.Categorical(su_data['dep_status'], categories = [0,1,2])
su_data.drop(columns=['dep_hours', 'arr_hours'],inplace = True)
su_data.columns
```

In [32]: ▶ su_data.isna().sum()

Out[32]:	dep_hour	0
	dep_day	0
	Origin_Airport	0
	arr_hour	0
	arr_day	0
	dep_min	0
	arr_min	0
	dep_status	0
	arr_status_x	0
	arr_status_y	0
	arr_azimuth	0
	arr_clouds	0
	arr_dewpt	0
	arr_elev_angle	0
	arr_h_angle	893
	arr_precip	0
	arr_pres	0
	arr_revision_status	0
	arr_rh	0
	arr_snow	0
	arr_temp	0
	arr_vis	0
	arr_weather.code	8
	arr_wind_dir	0
	arr_wind_gust_spd	0
	arr_wind_spd	0
	dep_azimuth	0
	dep_clouds	0
	dep_dewpt	0
	<pre>dep_elev_angle</pre>	0
	dep_h_angle	893
	dep_precip	0
	dep_pres	0
	<pre>dep_revision_status</pre>	0
	dep_rh	0
	dep_snow	0
	dep_temp	0
	dep_vis	0
	dep_weather.code	1
	dep_wind_dir	0
	<pre>dep_wind_gust_spd</pre>	0

```
dep wind spd
                                 0
           dtype: int64
'dep elev angle', 'arr revision status', 'dep revision status'],inplace = True)
           su data.dropna(inplace=True)
        ▶ su_data.columns
In [34]:
   Out[34]: Index(['dep_hour', 'dep_day', 'Origin_Airport', 'arr_hour', 'arr_day',
                 'dep_min', 'arr_min', 'dep_status', 'arr_status_x', 'arr_status_y',
                 'arr_clouds', 'arr_dewpt', 'arr_precip', 'arr_pres', 'arr_rh',
                 'arr_snow', 'arr_temp', 'arr_vis', 'arr_weather.code', 'arr_wind_dir',
                 'arr_wind_gust_spd', 'arr_wind_spd', 'dep_clouds', 'dep_dewpt',
                 'dep_precip', 'dep_pres', 'dep_rh', 'dep_snow', 'dep_temp', 'dep_vis',
                 'dep_weather.code', 'dep_wind_dir', 'dep_wind_gust_spd',
                 'dep wind spd'],
                dtype='object')
```

Training model to predict latter flight arrival status

```
su_data.head()
    su_data.dtypes
```

Out[35]:

	arr_status_x	arr_clouds	arr_dewpt	arr_precip	arr_pres	arr_rh	arr_snow	arr_temp	arr_vis	arr_wind_dir	 dep_weather.code
0	1	50	18.10	0.00	999	68	0.00	24.40	13	325	
1	1	25	17.80	0.00	999	62	0.00	25.60	16	70	
2	0	87	18.80	0.00	995	62	0.00	26.70	16	300	
3	2	87	15.40	0.00	995	86	0.00	17.80	16	190	
4	2	87	17.00	0.00	996	61	0.00	25.00	16	320	

5 rows × 275 columns

```
Out[35]: arr_status_x
                                    int32
         arr_clouds
                                    int64
                                 float64
         arr_dewpt
         arr_precip
                                 float64
         arr_pres
                                    int64
         dep_weather.code_801
                                     bool
         dep_weather.code_802
                                     bool
         dep_weather.code_803
                                     bool
         dep_weather.code_804
                                     bool
         dep_weather.code_900
                                     bool
         Length: 275, dtype: object
```

In [36]: N X_train, X_test, y_train, y_test = train_test_split(su_data.drop(columns = ['arr_status_x']), su_data['arr X_train X_test y_train.dtypes y_test

Out[36]:

333	50									arr_wind_gust_spd	
	50	-5.70	0.00	995	71	0.00	-1.10	16	90	2.80	
178	87	5.40	0.00	1009	49	0.00	16.10	16	300	7.20	
281	50	17.20	0.00	995	87	0.00	19.40	16	220	3.20	
297	87	13.80	0.00	998	83	0.00	16.70	16	190	6.00	
278	25	18.30	0.00	1006	81	0.00	21.70	16	35	2.80	
506	50	-7.40	0.00	1007	49	0.00	2.20	16	90	4.40	
370	100	19.40	0.00	988	84	0.00	22.20	16	285	8.40	
440	100	11.70	0.00	985	100	0.00	11.70	10	250	7.60	
694	100	11.10	0.25	988	83	0.00	13.90	11	140	10.00	
86	100	5.50	0.50	998	79	0.00	8.90	16	280	9.30	

708 rows × 274 columns

Out[36]:

arr_clouds	arr_dewpt	arr_precip	arr_pres	arr_rh	arr_snow	arr_temp	arr_vis	arr_wind_dir	arr_wind_gust_spd		dep_wea
100	8.10	0.00	1006	66	0.00	14.40	16	50	4.00		
25	8.90	0.00	1007	80	0.00	12.20	16	135	2.40		
100	1.00	0.00	999	85	0.00	3.30	10	300	9.20		
100	5.50	0.00	1004	92	0.00	6.70	8	80	7.60		
100	18.30	0.00	996	81	0.00	21.70	16	240	4.40		
87	-12.30	0.00	1008	39	0.00	0.00	16	170	9.80		
87	11.10	0.00	998	72	0.00	16.10	16	340	8.00		
50	-5.00	0.00	1002	72	0.00	-0.60	16	210	9.30		
100	-4.40	0.00	1010	78	0.00	-1.10	16	160	2.80		
50	-13.50	0.00	1001	40	0.00	-1.70	16	250	18.50		
	100 25 100 100 100 87 87 50	100 8.10 25 8.90 100 1.00 100 5.50 100 18.30 87 -12.30 87 11.10 50 -5.00 100 -4.40	100 8.10 0.00 25 8.90 0.00 100 1.00 0.00 100 5.50 0.00 100 18.30 0.00 87 -12.30 0.00 87 11.10 0.00 50 -5.00 0.00 100 -4.40 0.00	100 8.10 0.00 1006 25 8.90 0.00 1007 100 1.00 0.00 999 100 5.50 0.00 1004 100 18.30 0.00 996 87 -12.30 0.00 1008 87 11.10 0.00 998 50 -5.00 0.00 1002 100 -4.40 0.00 1010	100 8.10 0.00 1006 66 25 8.90 0.00 1007 80 100 1.00 0.00 999 85 100 5.50 0.00 1004 92 100 18.30 0.00 996 81 87 -12.30 0.00 1008 39 87 11.10 0.00 998 72 50 -5.00 0.00 1002 72 100 -4.40 0.00 1010 78	100 8.10 0.00 1006 66 0.00 25 8.90 0.00 1007 80 0.00 100 1.00 0.00 999 85 0.00 100 5.50 0.00 1004 92 0.00 100 18.30 0.00 996 81 0.00 87 -12.30 0.00 1008 39 0.00 87 11.10 0.00 998 72 0.00 50 -5.00 0.00 1002 72 0.00 100 -4.40 0.00 1010 78 0.00	100 8.10 0.00 1006 66 0.00 14.40 25 8.90 0.00 1007 80 0.00 12.20 100 1.00 0.00 999 85 0.00 3.30 100 5.50 0.00 1004 92 0.00 6.70 100 18.30 0.00 996 81 0.00 21.70 87 -12.30 0.00 1008 39 0.00 0.00 87 11.10 0.00 998 72 0.00 16.10 50 -5.00 0.00 1002 72 0.00 -0.60 100 -4.40 0.00 1010 78 0.00 -1.10	100 8.10 0.00 1006 66 0.00 14.40 16 25 8.90 0.00 1007 80 0.00 12.20 16 100 1.00 0.00 999 85 0.00 3.30 10 100 5.50 0.00 1004 92 0.00 6.70 8 100 18.30 0.00 996 81 0.00 21.70 16 87 -12.30 0.00 1008 39 0.00 0.00 16 87 11.10 0.00 998 72 0.00 16.10 16 50 -5.00 0.00 1002 72 0.00 -0.60 16 100 -4.40 0.00 1010 78 0.00 -1.10 16	100 8.10 0.00 1006 66 0.00 14.40 16 50 25 8.90 0.00 1007 80 0.00 12.20 16 135 100 1.00 0.00 999 85 0.00 3.30 10 300 100 5.50 0.00 1004 92 0.00 6.70 8 80 100 18.30 0.00 996 81 0.00 21.70 16 240 87 -12.30 0.00 1008 39 0.00 0.00 16 170 87 11.10 0.00 998 72 0.00 16.10 16 340 50 -5.00 0.00 1002 72 0.00 -0.60 16 210 100 -4.40 0.00 1010 78 0.00 -1.10 16 160	100 8.10 0.00 1006 66 0.00 14.40 16 50 4.00 25 8.90 0.00 1007 80 0.00 12.20 16 135 2.40 100 1.00 0.00 999 85 0.00 3.30 10 300 9.20 100 5.50 0.00 1004 92 0.00 6.70 8 80 7.60 100 18.30 0.00 996 81 0.00 21.70 16 240 4.40	100 8.10 0.00 1006 66 0.00 14.40 16 50 4.00 25 8.90 0.00 1007 80 0.00 12.20 16 135 2.40 100 1.00 0.00 999 85 0.00 3.30 10 300 9.20 100 5.50 0.00 1004 92 0.00 6.70 8 80 7.60 100 18.30 0.00 996 81 0.00 21.70 16 240 4.40 87 -12.30 0.00 1008 39 0.00 0.00 16 170 9.80 87 11.10 0.00 998 72 0.00 16.10 16 340 8.00 50 -5.00 0.00 1002 72 0.00 -0.60 16 210 9.30 100 -4.40 0.00 1010 78 0.00 -1.10 16 16

177 rows × 274 columns

Out[36]: dtype('int32')

Out[36]: 711

Name: arr_status_x, Length: 177, dtype: int32

Out[37]:

	arr_clouds	arr_dewpt	arr_precip	arr_pres	arr_rh	arr_snow	arr_temp	arr_vis	arr_wind_dir	arr_wind_gust_spd	 dep_wea
333	-0.77	-1.38	-0.20	-0.67	0.17	-0.08	-1.51	0.40	-1.21	-1.15	
178	0.39	-0.05	-0.20	1.10	-1.06	-0.08	0.45	0.40	1.17	0.17	
281	-0.77	1.37	-0.20	-0.67	1.06	-0.08	0.83	0.40	0.26	-1.03	
297	0.39	0.96	-0.20	-0.29	0.84	-0.08	0.52	0.40	-0.08	-0.19	
278	-1.56	1.50	-0.20	0.72	0.73	-0.08	1.09	0.40	-1.83	-1.15	
506	-0.77	-1.58	-0.20	0.84	-1.06	-0.08	-1.14	0.40	-1.21	-0.67	
370	0.80	1.63	-0.20	-1.56	0.89	-0.08	1.15	0.40	1.00	0.53	
440	0.80	0.71	-0.20	-1.94	1.79	-0.08	-0.05	-1.59	0.60	0.29	
694	0.80	0.64	0.06	-1.56	0.84	-0.08	0.20	-1.26	-0.65	1.01	
86	0.80	-0.04	0.31	-0.29	0.61	-0.08	-0.37	0.40	0.94	0.80	

708 rows × 274 columns

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Out[37]:

	arr_clouds	arr_dewpt	arr_precip	arr_pres	arr_rh	arr_snow	arr_temp	arr_vis	arr_wind_dir	arr_wind_gust_spd	•••	dep_wea
711	0.80	0.28	-0.20	0.72	-0.11	-0.08	0.25	0.40	-1.66	-0.79		
668	-1.56	0.37	-0.20	0.84	0.67	-0.08	0.00	0.40	-0.70	-1.27		
821	0.80	-0.58	-0.20	-0.17	0.95	-0.08	-1.01	-1.59	1.17	0.77		
422	0.80	-0.04	-0.20	0.46	1.34	-0.08	-0.62	-2.26	-1.32	0.29		
639	0.80	1.50	-0.20	-0.55	0.73	-0.08	1.09	0.40	0.49	-0.67		
837	0.39	-2.17	-0.20	0.97	-1.62	-0.08	-1.39	0.40	-0.31	0.95		
644	0.39	0.64	-0.20	-0.29	0.22	-0.08	0.45	0.40	1.62	0.41		
208	-0.77	-1.30	-0.20	0.21	0.22	-0.08	-1.46	0.40	0.15	0.80		
465	0.80	-1.22	-0.20	1.22	0.56	-0.08	-1.51	0.40	-0.42	-1.15		
835	-0.77	-2.32	-0.20	0.09	-1.56	-0.08	-1.58	0.40	0.60	3.55		

177 rows × 274 columns

Out[37]: 333

Name: arr_status_x, Length: 708, dtype: int32

```
Out[37]: 711
                1
         668
                2
         821
                1
         422
                1
         639
                0
         837
                1
         644
                0
         208
                2
         465
                0
         835
                2
         Name: arr_status_x, Length: 177, dtype: int32
```

```
| arr model = LogisticRegression(fit intercept = True, solver='lbfgs', multi class = 'multinomial', penalty
In [38]:
             arr_model.fit(X_train, y_train)
             # The following gives the mean accuracy on the given data and labels
             arr_model.score(X_train, y_train)
             # This is the coefficient Beta 1, ..., Beta 7
             arr model.coef
             # This is the coefficient Beta 0
             arr model.intercept
                      0.00000000e+00, 0.00000000e+00, -1.32600080e-01,
                     -3.01124557e-01, 5.86985921e-02, -3.45515896e-02,
                     -6.44265871e-02, -6.74655713e-02, -4.99330248e-01,
                     -1.32062274e-01, 1.26724943e-01, 0.00000000e+00,
                     -2.95476329e-01, 7.43587194e-01, 2.90824138e-01,
                     -7.04065828e-02, 0.00000000e+00, 0.00000000e+00,
                      2.50733914e+00, 0.00000000e+00, 0.00000000e+00,
                      0.00000000e+00, 0.00000000e+00, -4.22297364e-01,
                      1.46573167e-01, 0.00000000e+00, 0.00000000e+00,
                      0.00000000e+00, -2.93971401e-01, -3.81025792e-01,
                      0.00000000e+00, 0.00000000e+00, -4.37724366e-01,
                      0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                      1.32816035e-01, 1.46138449e-01, -1.63535785e+00,
                     -1.33961222e+00, 0.00000000e+00, 0.00000000e+00,
                      0.00000000e+00, -7.96169001e-01, -6.85862430e-03,
                      2.90824138e-01, -1.33638367e+00, 1.16339902e-01,
                      3.38779158e-01, 0.00000000e+00, -3.15687786e-02,
                      0.00000000e+00, -1.81473254e+00, -3.52862832e-02,
                      0.00000000e+00, 3.07389014e-01, 2.19246224e-01,
                      9 6/7876/30_07 _6 110931/00_07
                                                       7 720696260-01

    arr_model.score(X_test,y_test)

In [39]:
```

Out[39]: 0.6045197740112994

Out[40]: 0.8940677966101694

Out[40]:	array([0. ,	0.02787978.	0.00563367.	0.01607327.	0.02078145,
			0.01564084,		
		-	0.02301926,	-	
	0.04703959,	-	0.0254579	-	0.05274309,
	•	0.07239871,			0.
	-	0.	•	0. ,	0.
	0.	0.	•	0. ,	0. ,
	0.00416413,	,	-	-	0.
		•	•	0.01576733,	•
	-		0.01060994,	-	0.
	•	-	0.00729505,	_	0. ,
	0.	0.		0.	^
	0.	0. ,	0.	0.	•
	0.	0. ,	0.	0. ,	0. ,
	0. ,	0. ,	0. ,	0.00475072,	0. ,
	0. ,	0. ,	0.00145161,	0. ,	0. ,
	0.00316715,	0. ,	0. ,	0. ,	0. ,
	0. ,	0. ,	0. ,	0. ,	0. ,
	0. ,	0. ,	0. ,	0. ,	0. ,
	0. ,	0. ,	0. ,	0. ,	0. ,
	0. ,	0. ,	0. ,	0. ,	0. ,
	0. ,	0.00270812,	0. ,	0. ,	0. ,
	0. ,	0.01057101,	0. ,	0. ,	0. ,
	0. ,	0.,	0. ,	0. ,	0. ,
	0. ,	0.,	-	0. ,	0. ,
	0. ,	0. ,		0. ,	0. ,
	-	0.01219862,	-	0. ,	0. ,
	-	0.00168825,	-	0.	0. ,
	0.00225133,	•	-	-	0.00294306,
	-	0.	-	-	0. ,
	0. ,	-	=	-	0. ,
	0. ,	•	-	-	0. ,
		0.00167006,	-	-	0. ,
		0.	-	-	0. ,
		0.00277125,		0. ,	0.
					0.01277225,
	•				0. ,
		0. ,			0. ,
	_	0. , 0. ,	-		0.
	-	-	-	_	0. ,
			0.00426347,		0.
			-	-	0.
	0. ,	0. ,	0. ,	0. ,	0. ,

0.	, 0. , 0.	, 0.	, 0.	,
0.	, 0. , 0.	, 0.	, 0.	,
0.	, 0. , 0.	, 0.	, 0.	,
0.	, 0. , 0.	, 0.0016343	•	,
0.	, 0.00691294, 0.	, 0.	, 0.	,
0.	, 0. , 0.	, 0.	, 0.	,
0.	, 0. , 0.	, 0.	, 0.	,
0.	, 0. , 0.	, 0.	, 0.	,
0.	, 0. , 0.	, 0.	, 0.	,
0.	. 0 0.	. 0.	, 0.	,
0.	, 0. , 0.	. 0.	, 0.	
0.	, 0.00683576, 0.	, 0.	1)	,

Out[40]:

	pred_arr_status
711	1
668	2
821	0
422	1
639	0

Out[40]: 0.5254237288135594

Out[41]: 0.8432203389830508

Out[41]:

	0
dep_status_2	0.17
dep_pres	0.05
dep_status_1	0.04
arr_dewpt	0.04
dep_dewpt	0.04

Out[41]:

	pred_Y
711	0
668	2
821	1
422	0
639	0

Out[41]:

	pred_Y	arr_status_x
711	0	1
668	2	2
821	1	1
422	0	1
639	0	0

Fraction of correct classification

Out[41]: 0.6779661016949152

```
In [42]: ▶
```

```
from sklearn.ensemble import GradientBoostingClassifier
arr_gb = GradientBoostingClassifier(random_state=50, min_samples_split = 8, min_samples_leaf = 4, n_estima
arr_gb = arr_gb.fit(X_train, y_train)
arr_gb.score(X_train, y_train)
```

Out[42]: 1.0

Out[43]: 0.632768361581921

preprocessing data to predict departure status

```
In [44]:  ▶ sub_data.columns
             sub_data.head()
   Out[44]: Index(['Carrier_Code', 'Date', 'Flight_Number', 'Tail_Number',
                    'Scheduled departure time', 'dep_hour', 'dep_day', 'dep_order',
                    'Origin_Airport', 'Scheduled Arrival Time', 'Arrival Delay (Minutes)',
                    'arr_hour', 'arr_day', 'dep_min', 'arr_min', 'dep_hours', 'arr_hours',
                    'dep_status', 'arr_status'],
                   dtype='object')
```

Out[44]:

	Carrier_Code	Date	Flight_Number	Tail_Number	Scheduled departure time	dep_hour	dep_day	dep_order	Origin_Airport	Scheduled Arrival Time	(M
0	MQ	01/04/2020	3,580.00	N240NN	7:55	7	5	latter	ORD	10:47	
1	MQ	01/11/2020	3,946.00	N247NN	15:00	15	5	latter	ORD	17:48	
2	MQ	01/18/2020	3,946.00	N265NN	15:00	15	5	latter	ORD	17:48	
3	MQ	01/25/2020	3,946.00	N281NN	15:00	15	5	latter	ORD	17:48	
4	MQ	02/01/2020	3,946.00	N283NN	15:00	15	5	latter	ORD	17:48	
4											

```
▶ sub_data.dtypes
In [45]:
   Out[45]: Carrier_Code
                                      object
                                      object
            Date
                                      object
            Flight Number
                                      object
            Tail Number
            Scheduled departure time
                                      object
                                      object
            dep hour
                                      object
            dep day
            dep order
                                      object
                                      object
            Origin Airport
            Scheduled Arrival Time
                                      object
           Arrival Delay (Minutes)
                                     float64
           arr_hour
                                      object
           arr_day
                                      object
           dep_min
                                      object
                                      object
            arr min
            dep hours
                                      object
            arr hours
                                      object
                                       int32
            dep status
            arr status
                                       int32
           dtype: object
'Scheduled departure time', 'dep_order', 'Scheduled Arrival Time', 'Arrival Delay (Minutes)',
                   'arr_status'])
In [47]:
         ▶ s data.columns
   Out[47]: Index(['Date', 'dep_hour', 'dep_day', 'Origin_Airport', 'arr_hour', 'arr_day',
                  'dep_min', 'arr_min', 'dep_hours', 'arr_hours', 'dep_status'],
                 dtype='object')
```

```
In [48]:
          ▶ | s_data = pd.merge(s_data, weather_data, how='left', on=['Origin_Airport', 'Date', 'dep_hours'])
             s_data.head()
```

Out[48]:

	Date	dep_hour	dep_day	Origin_Airport	arr_hour	arr_day	dep_min	arr_min	dep_hours	arr_hours	(dep_revision_sta
0	01/04/2020	7	5	ORD	10	5	55	47	7	10		fi
1	01/11/2020	15	5	ORD	17	5	0	48	15	17		fi
2	01/18/2020	15	5	ORD	17	5	0	48	15	17		fi
3	01/25/2020	15	5	ORD	17	5	0	48	15	17		fi
4	02/01/2020	15	5	ORD	17	5	0	48	15	17		fi

5 rows × 28 columns

```
In [49]: ▶ # Define merging logic based on airport code
             s_data = pd.merge(s_data, syr_weather_data, how='left', on=['Date', 'arr_hours'])
             s_data.head()
```

Out[49]:

	Date	dep_hour	dep_day	Origin_Airport	arr_hour	arr_day	dep_min	arr_min	dep_hours	arr_hours	 arr_revision_stat
0	01/04/2020	7	5	ORD	10	5	55	47	7	10	 fir
1	01/11/2020	15	5	ORD	17	5	0	48	15	17	 fir
2	01/18/2020	15	5	ORD	17	5	0	48	15	17	 fir
3	01/25/2020	15	5	ORD	17	5	0	48	15	17	 fir
4	02/01/2020	15	5	ORD	17	5	0	48	15	17	 fir

5 rows × 45 columns

```
In [50]:
          ▶ s data.columns
   Out[50]: Index(['Date', 'dep_hour', 'dep_day', 'Origin_Airport', 'arr_hour', 'arr_day',
                    'dep min', 'arr min', 'dep hours', 'arr hours', 'dep status',
                    'dep azimuth', 'dep clouds', 'dep dewpt', 'dep elev angle',
                    'dep_h_angle', 'dep_precip', 'dep_pres', 'dep_revision_status',
                    'dep rh', 'dep snow', 'dep temp', 'dep vis', 'dep weather.description',
                    'dep weather.code', 'dep wind dir', 'dep wind gust spd', 'dep wind spd',
                    'arr azimuth', 'arr clouds', 'arr dewpt', 'arr elev angle',
                    'arr h angle', 'arr precip', 'arr pres', 'arr revision status',
                    'arr rh', 'arr snow', 'arr temp', 'arr vis', 'arr weather.description',
                    'arr weather.code', 'arr wind dir', 'arr wind gust spd',
                    'arr wind spd'],
                   dtype='object')
'arr hours', 'dep hours',
                                    'arr weather.description', 'dep weather.description'
                                    ,'arr_elev_angle','arr_h_angle','arr_revision_status',
                                   'dep_elev_angle','dep_h_angle','dep_revision_status','dep_azimuth'],inplace = True)
             s_data.columns
   Out[51]: Index(['dep hour', 'dep day', 'Origin Airport', 'arr hour', 'arr day',
                    'dep_min', 'arr_min', 'dep_status', 'dep_clouds', 'dep_dewpt',
                    'dep precip', 'dep pres', 'dep rh', 'dep snow', 'dep temp', 'dep vis',
                    'dep weather.code', 'dep wind dir', 'dep wind gust spd', 'dep wind spd',
                    'arr clouds', 'arr dewpt', 'arr precip', 'arr pres', 'arr rh',
                    'arr_snow', 'arr_temp', 'arr_vis', 'arr_weather.code', 'arr_wind_dir',
                    'arr wind gust spd', 'arr wind spd'],
                   dtype='object')
```

```
In [52]:
             s_data.dtypes
             s_data.columns
             s_data.head()
             s_data.isna().sum()
   Out[52]: dep hour
                                   object
             dep day
                                   object
             Origin Airport
                                   object
             arr_hour
                                   object
             arr_day
                                   object
             dep_min
                                   object
             arr_min
                                   object
             dep_status
                                    int32
             dep_clouds
                                    int64
                                  float64
             dep dewpt
             dep_precip
                                  float64
             dep_pres
                                    int64
             dep_rh
                                    int64
                                  float64
             dep snow
             dep_temp
                                  float64
             dep_vis
                                    int64
             dep weather.code
                                    int64
             dep wind dir
                                    int64
                                  float64
             dep_wind_gust_spd
             dep_wind_spd
                                  float64
             arr_clouds
                                    int64
                                  float64
             arr dewpt
             arr_precip
                                  float64
             arr_pres
                                    int64
             arr_rh
                                    int64
                                  float64
             arr_snow
             arr_temp
                                  float64
             arr_vis
                                    int64
             arr weather.code
                                    int64
             arr wind dir
                                    int64
             arr_wind_gust_spd
                                  float64
                                  float64
             arr_wind_spd
             dtype: object
```

Out[52]:

	dep_hour	dep_day	Origin_Airport	arr_hour	arr_day	dep_min	arr_min	dep_status	dep_clouds	dep_dewpt	 arr_precip	arı
0	7	5	ORD	10	5	55	47	2	100	-2.80	 1.50	
1	15	5	ORD	17	5	0	48	2	100	-1.20	 1.50	
2	15	5	ORD	17	5	0	48	2	100	-6.80	 1.00	
3	15	5	ORD	17	5	0	48	1	100	-0.30	 1.50	
4	15	5	ORD	17	5	0	48	1	100	-2.00	 0.00	

5 rows × 32 columns

Out[52]:	dep_hour dep_day	0 0
	Origin_Airport	0
	arr_hour	0
	arr_day	0
	dep_min	0
	arr_min	0
	dep_status	0
	dep_clouds	0
	dep_dewpt	0
	dep_precip	0
	dep_pres	0
	dep_rh	0
	dep_snow	0
	dep_temp	0
	dep_vis	0
	dep_weather.code	0
	dep_wind_dir	0
	<pre>dep_wind_gust_spd</pre>	0
	dep_wind_spd	0
	arr_clouds	0
	arr_dewpt	0
	arr_precip	0
	arr_pres	0
	arr_rh	0
	arr_snow	0
	arr_temp	0
	arr_vis	0
	arr_weather.code	0
	arr_wind_dir	0
	arr_wind_gust_spd	0
	arr_wind_spd	0
	dtype: int64	

```
In [53]: | su data = s data
            su data['dep hour'] = pd.Categorical(su data['dep hour'], categories=[i for i in range(24)])
            su data['dep day'] = pd.Categorical(su_data['dep_day'], categories=[i for i in range(7)])
            su data['dep min'] = pd.Categorical(su data['dep min'], categories=[i for i in range(60)])
            su data['arr hour'] = pd.Categorical(su data['arr hour'], categories=[i for i in range(24)])
            su data['arr day'] = pd.Categorical(su data['arr day'], categories=[i for i in range(7)])
            su_data['arr_min'] = pd.Categorical(su_data['arr_min'], categories=[i for i in range(60)])
            su data['Origin Airport'] = pd.Categorical(su data['Origin Airport'], categories=['ORD', 'JFK', 'MCO'])
            su_data['arr_weather.code'] = pd.Categorical(su_data['arr_weather.code'], categories=[200,201,202,230,231,
            su data['dep weather.code'] = pd.Categorical(su data['dep weather.code'], categories=[200,201,202,230,231,
            su_data.columns
   Out[53]: Index(['dep hour', 'dep day', 'Origin Airport', 'arr hour', 'arr day',
                   'dep_min', 'arr_min', 'dep_status', 'dep_clouds', 'dep_dewpt',
                   'dep precip', 'dep pres', 'dep rh', 'dep snow', 'dep temp', 'dep vis',
                   'dep weather.code', 'dep wind dir', 'dep_wind_gust_spd', 'dep_wind_spd',
                   'arr_clouds', 'arr_dewpt', 'arr_precip', 'arr_pres', 'arr_rh',
                   'arr_snow', 'arr_temp', 'arr_vis', 'arr_weather.code', 'arr_wind_dir',
                   'arr_wind_gust_spd', 'arr_wind_spd'],
                  dtype='object')
su data['arr precip'] = su data['arr precip']**2
```

Traning model to predict depature status

Out[55]:

	dep_status	dep_clouds	dep_dewpt	dep_precip	dep_pres	dep_rh	dep_snow	dep_temp	dep_vis	dep_wind_dir	 arr_weathe
0	2	100	-2.80	0.00	989	88	0.00	-1.10	11	320	
1	2	100	-1.20	0.25	985	96	8.50	-0.60	2	20	
2	2	100	-6.80	0.06	983	86	6.25	-4.80	14	250	
3	1	100	-0.30	0.25	985	92	4.00	0.80	6	255	
4	1	100	-2.00	0.00	984	73	0.00	2.40	16	255	

5 rows × 271 columns

localhost:8888/notebooks/Downloads/IML_project/flight-predictions/Latter_flight_prediction_model.ipynb

In [56]:
X_train, X_test, y_train, y_test = train_test_split(dep_data.drop(columns = ['dep_status']), dep_data['dep
X_train
X_test
y_train.dtypes
y_test

Out[56]:

	dep_clouds	dep_dewpt	dep_precip	dep_pres	dep_rh	dep_snow	dep_temp	dep_vis	dep_wind_dir	dep_wind_gust_spd	
940	87	18.20	0.00	984	66	0.00	25.00	16	250	2.80	
8173	87	20.60	0.00	1007	63	0.00	28.30	16	60	9.80	
7040	87	3.50	0.00	1002	44	0.00	15.70	16	295	13.90	
5583	87	11.00	0.00	1007	74	0.00	15.60	16	170	10.80	
425	0	-1.70	0.00	1000	63	0.00	4.70	16	210	4.00	
5905	78	13.50	0.00	1021	57	0.00	22.50	16	245	4.80	
6597	87	3.80	0.00	1005	28	0.00	23.30	16	215	10.00	
7866	25	12.60	0.00	1015	46	0.00	25.00	16	230	8.80	
1419	87	-3.80	0.00	985	42	0.00	8.30	16	185	6.40	
1802	18	-2.20	0.00	1001	54	0.00	6.40	16	200	3.20	

6928 rows × 270 columns

Out[56]:

	dep_clouds	dep_dewpt	dep_precip	dep_pres	dep_rh	dep_snow	dep_temp	dep_vis	dep_wind_dir	dep_wind_gust_spd	
4600	25	17.70	0.00	1006	60	0.00	26.10	16	310	4.72	
5412	50	5.60	0.06	1031	86	0.00	7.80	16	170	7.20	
6801	87	16.80	0.00	1015	72	0.00	22.10	16	100	3.60	
6567	31	6.10	0.00	1022	41	0.00	19.70	16	315	7.70	
3051	100	10.40	4.00	1004	92	0.00	11.70	5	120	7.20	
4135	96	11.90	0.00	1014	86	0.00	14.30	4	95	6.00	
8534	50	24.20	0.00	1010	81	0.00	27.80	16	260	8.20	
2115	25	-2.10	0.00	1000	22	0.00	20.30	16	45	7.60	
7381	87	15.50	0.00	1012	66	0.00	22.20	16	140	4.00	
2537	87	6.30	0.00	993	67	0.00	12.20	16	335	6.00	

1733 rows × 270 columns

Out[56]: dtype('int32')

Out[56]: 4600 2 5412 2 6801 2 6567 2 3051 2

> 4135 1 8534 1 2115 2

7381 Ø 2537 1

Name: dep_status, Length: 1733, dtype: int32

In [57]: ▶ from sklearn.preprocessing import StandardScaler

sc1 = StandardScaler()

X_train = pd.DataFrame(sc1.fit_transform(X_train), columns = X_train.columns, index = X_train.index)

X_test = pd.DataFrame(sc1.transform(X_test), columns = X_test.columns, index = X_test.index)

X_train

X_test

y_train

y_test

Out[57]:

	dep_clouds	dep_dewpt	dep_precip	dep_pres	dep_rh	dep_snow	dep_temp	dep_vis	dep_wind_dir	dep_wind_gust_spd	
940	0.63	1.02	-0.08	-1.77	0.16	-0.06	0.96	0.31	0.57	-1.45	
8173	0.63	1.26	-0.08	-0.06	0.00	-0.06	1.30	0.31	-1.38	0.64	
7040	0.63	-0.44	-0.08	-0.43	-1.00	-0.06	0.01	0.31	1.03	1.86	
5583	0.63	0.31	-0.08	-0.06	0.58	-0.06	0.00	0.31	-0.25	0.93	
425	-2.16	-0.95	-0.08	-0.58	0.00	-0.06	-1.12	0.31	0.16	-1.10	
5905	0.34	0.56	-0.08	0.98	-0.32	-0.06	0.71	0.31	0.51	-0.86	
6597	0.63	-0.41	-0.08	-0.21	-1.85	-0.06	0.79	0.31	0.21	0.70	
7866	-1.36	0.47	-0.08	0.54	-0.90	-0.06	0.96	0.31	0.36	0.34	
1419	0.63	-1.16	-0.08	-1.70	-1.11	-0.06	-0.75	0.31	-0.10	-0.38	
1802	-1.58	-1.00	-0.08	-0.51	-0.47	-0.06	-0.94	0.31	0.05	-1.33	

6928 rows × 270 columns

Out[57]:

	dep_clouds	dep_dewpt	dep_precip	dep_pres	dep_rh	dep_snow	dep_temp	dep_vis	dep_wind_dir	dep_wind_gust_spd	
4600	-1.36	0.98	-0.08	-0.13	-0.16	-0.06	1.08	0.31	1.18	-0.88	
5412	-0.56	-0.23	-0.07	1.73	1.22	-0.06	-0.80	0.31	-0.25	-0.14	
6801	0.63	0.89	-0.08	0.54	0.48	-0.06	0.67	0.31	-0.97	-1.22	
6567	-1.16	-0.18	-0.08	1.06	-1.16	-0.06	0.42	0.31	1.23	0.01	
3051	1.04	0.25	0.25	-0.28	1.53	-0.06	-0.40	-3.46	-0.77	-0.14	
4135	0.91	0.40	-0.08	0.46	1.22	-0.06	-0.13	-3.80	-1.02	-0.50	
8534	-0.56	1.62	-0.08	0.17	0.95	-0.06	1.25	0.31	0.67	0.16	
2115	-1.36	-0.99	-0.08	-0.58	-2.16	-0.06	0.48	0.31	-1.53	-0.02	
7381	0.63	0.76	-0.08	0.31	0.16	-0.06	0.68	0.31	-0.56	-1.10	
2537	0.63	-0.16	-0.08	-1.10	0.21	-0.06	-0.35	0.31	1.44	-0.50	

1733 rows × 270 columns

0

Out[57]: 940 0 8173 1 7040 0

> 425 2 ... 5905 0 6597 2

5583

7866 2 1419 1

1802 1

Name: dep_status, Length: 6928, dtype: int32

```
Out[57]: 4600
                 2
         5412
                 2
         6801
                 2
         6567
                 2
         3051
                 2
                 1
         4135
         8534
                 1
         2115
                 2
         7381
                 0
         2537
                 1
         Name: dep_status, Length: 1733, dtype: int32
```

```
| dep model = LogisticRegression(fit intercept = True, solver='lbfgs', multi class = 'ovr', penalty = None,
In [58]:
             dep_model.fit(X_train, y_train)
             # The following gives the mean accuracy on the given data and labels
             dep model.score(X train, y train)
             # This is the coefficient Beta 1, ..., Beta 7
             dep model.coef
             # This is the coefficient Beta 0
             dep model.intercept
   Out[58]:
                                      LogisticRegression
             LogisticRegression(max iter=1000, multi class='ovr', penalty=None)
   Out[58]: 0.5682736720554272
   Out[58]: array([[-2.12950348e-01, 2.74221788e-01, -1.59691385e-01,
                      7.02226357e-02, -1.27390548e-01, -1.62686825e-01,
                     -2.31168121e-01, 2.08375587e-02, -8.26508543e-02,
                     -2.14765022e-01, 1.40362589e-01, 4.18705251e-01,
                     -4.31960468e-02, -2.20665464e-03, -3.48607366e-02,
                     -3.67809628e-02, 2.58951456e-02, -4.49678004e-02,
                      1.02600835e-01, -1.40208958e-02, -1.52916027e-02,
                      3.10537204e-02, 0.00000000e+00, 0.00000000e+00,
                      0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                     -9.16226034e-01, -1.23326505e+00, -2.67662941e+00,
                     -3.10503751e+00, -1.41281306e+00, -1.35203552e+00,
                     -8.48159921e-01, -8.90070097e-01, -2.94075588e-01,
                     -9.83136825e-02, 1.85040873e-01, 2.45850881e-01,
In [59]: | dep_model.score(X_test,y_test)
```

Out[59]: 0.5222158107328332

predicting outputs

Out[60]:

	Unnamed: 0	dep_hour	dep_day	Origin_Airport	arr_hour	arr_day	dep_min	arr_min	arr_clouds	arr_dewpt	 dep_precip	dep.
0	1	19	4	ORD	22	4	59	52	66	7.20	 0.00	9
1	3	14	4	JFK	16	4	55	21	86	7.90	 0.00	1,0
2	5	13	4	MCO	16	4	35	25	86	7.90	 0.00	1,0
3	7	19	5	ORD	22	5	59	52	23	-2.40	 0.00	9
4	9	14	5	JFK	16	5	55	21	58	-1.60	 0.00	1,0

5 rows × 32 columns

localhost:8888/notebooks/Downloads/IML_project/flight-predictions/Latter_flight_prediction_model.ipynb

Out[60]:	Unnamed: 0	int64
	dep_hour	int64
	dep_day	int64
	Origin_Airport	object
	arr_hour	int64
	arr_day	int64
	dep_min	int64
	arr_min	int64
	arr_clouds	int64
	arr_dewpt	float64
	arr_precip	float64
	arr_pres	float64
	arr_rh	int64
	arr_snow	int64
	arr_temp	float64
	arr_vis	float64
	arr_weather.code	int64
	arr_wind_dir	int64
	arr_wind_gust_spd	float64
	arr_wind_spd	float64
	dep_clouds	int64
	dep_dewpt	float64
	dep_precip	float64
	dep_pres	float64
	dep_rh	int64
	dep_snow	int64
	dep_temp	float64
	dep_vis	float64
	dep_weather.code	int64
	dep_wind_dir	int64
	<pre>dep_wind_gust_spd</pre>	float64
	dep_wind_spd	float64
	dtype: object	

Out[61]:	dep_hour	object
	dep_day	object
	Origin_Airport	object
	arr_hour	object
	arr_day	object
	dep_min	object
	arr_min	object
	arr_clouds	int64
	arr_dewpt	float64
	arr_precip	float64
	arr_pres	float64
	arr_rh	int64
	arr_snow	int64
	arr_temp	float64
	arr_vis	float64
	arr_weather.code	object
	arr_wind_dir	int64
	arr_wind_gust_spd	float64
	arr_wind_spd	float64
	dep_clouds	int64
	dep_dewpt	float64
	dep_precip	float64
	dep_pres	float64
	dep_rh	int64
	dep_snow	int64
	dep_temp	float64
	dep_vis	float64
	dep_weather.code	object
	dep_wind_dir	int64
	<pre>dep_wind_gust_spd</pre>	float64
	dep_wind_spd	float64
	dtype: object	

```
In [62]:
          pred_data2['dep_hour'] = pd.Categorical(pred_data2['dep_hour'], categories=[i for i in range(24)])
             pred data2['dep_day'] = pd.Categorical(pred_data2['dep_day'], categories=[i for i in range(7)])
             pred data2['dep min'] = pd.Categorical(pred data2['dep min'], categories=[i for i in range(60)])
             pred data2['arr hour'] = pd.Categorical(pred data2['arr hour'], categories=[i for i in range(24)])
             pred data2['arr day'] = pd.Categorical(pred data2['arr day'], categories=[i for i in range(7)])
             pred data2['arr min'] = pd.Categorical(pred_data2['arr_min'], categories=[i for i in range(60)])
             pred data2['Origin Airport'] = pd.Categorical(pred data2['Origin Airport'], categories=['ORD', 'JFK', 'MCC
             pred data2['arr weather.code'] = pd.Categorical(pred_data2['arr_weather.code'], categories=[200,201,202,23]
             pred_data2['dep_weather.code'] = pd.Categorical(pred_data2['dep_weather.code'], categories=[200,201,202,23
In [63]:
          pred data = pred data2
In [64]:
          ▶ pred_data.columns
             pred data.head()
   Out[64]: Index(['dep_hour', 'dep_day', 'Origin_Airport', 'arr_hour', 'arr_day',
                     'dep min', 'arr min', 'arr clouds', 'arr dewpt', 'arr precip',
                     'arr pres', 'arr rh', 'arr snow', 'arr temp', 'arr vis',
                     'arr weather.code', 'arr wind dir', 'arr wind gust spd', 'arr wind spd',
                     'dep clouds', 'dep dewpt', 'dep precip', 'dep pres', 'dep rh',
                     'dep snow', 'dep temp', 'dep vis', 'dep weather.code', 'dep wind dir',
                     'dep wind gust spd', 'dep wind spd'],
                    dtype='object')
   Out[64]:
                 dep_hour dep_day Origin_Airport arr_hour arr_day dep_min arr_min arr_clouds arr_dewpt arr_precip ... dep_precip dep_
              0
                      19
                                4
                                          ORD
                                                    22
                                                                                             7.20
                                                                                                       0.25 ...
                                                                                                                           9
                                                                    59
                                                                           52
                                                                                     66
                                                                                                                    0.00
              1
                                          JFK
                                                                                             7.90
                                                                                                       0.76 ...
                      14
                                4
                                                    16
                                                                    55
                                                                           21
                                                                                     86
                                                                                                                    0.00
                                                                                                                         1.0
              2
                      13
                                4
                                         MCO
                                                    16
                                                                   35
                                                                           25
                                                                                     86
                                                                                             7.90
                                                                                                       0.76 ...
                                                                                                                    0.00
                                                                                                                         1,0
              3
                      19
                               5
                                          ORD
                                                    22
                                                            5
                                                                   59
                                                                           52
                                                                                     23
                                                                                             -2.40
                                                                                                       0.00 ...
                                                                                                                    0.00
                                                                                                                           9
                      14
                                5
                                          JFK
                                                    16
                                                            5
                                                                   55
                                                                           21
                                                                                     58
                                                                                             -1.60
                                                                                                       0.00 ...
                                                                                                                    0.00
                                                                                                                         1.0
             5 rows × 31 columns
```

```
In [65]: N pred_data = pred_data[['dep_hour', 'dep_day', 'Origin_Airport', 'arr_hour', 'arr_day',
                    'dep min', 'arr min', 'dep clouds', 'dep dewpt',
                    'dep_precip', 'dep_pres', 'dep_rh', 'dep_snow', 'dep_temp', 'dep_vis',
                    'dep_weather.code', 'dep_wind_dir', 'dep_wind_gust_spd', 'dep_wind_spd',
                    'arr_clouds', 'arr_dewpt', 'arr_precip', 'arr_pres', 'arr_rh',
                    'arr_snow', 'arr_temp', 'arr_vis', 'arr_weather.code', 'arr_wind_dir',
                    'arr wind gust spd', 'arr wind spd']]
             pred data.columns
   Out[65]: Index(['dep_hour', 'dep_day', 'Origin_Airport', 'arr_hour', 'arr_day',
                    'dep_min', 'arr_min', 'dep_clouds', 'dep_dewpt', 'dep_precip',
                    'dep_pres', 'dep_rh', 'dep_snow', 'dep_temp', 'dep_vis',
                    'dep weather.code', 'dep wind dir', 'dep wind gust spd', 'dep wind spd',
                    'arr_clouds', 'arr_dewpt', 'arr_precip', 'arr_pres', 'arr_rh',
                    'arr snow', 'arr temp', 'arr vis', 'arr weather.code', 'arr wind dir',
                    'arr wind gust spd', 'arr wind spd'],
                   dtype='object')
```

applying logistic regression model to predict departure status

Out[66]:

	dep_clouds	dep_dewpt	dep_precip	dep_pres	dep_rh	dep_snow	dep_temp	dep_vis	dep_wind_dir	dep_wind_gust_spd	 aı
0	50	-2.10	0.00	996.50	37	0	12.10	24.00	280	11.10	
1	85	4.50	0.00	1,019.00	59	0	12.30	24.00	120	7.30	
2	6	17.60	0.00	1,013.50	45	0	30.90	24.00	270	3.20	
3	71	-3.10	0.00	994.50	41	0	9.50	24.13	300	6.00	
4	65	3.60	0.00	1,014.00	42	0	16.50	24.00	270	6.00	

5 rows × 270 columns

```
In [67]:
In [68]:
             dep_model_output = pd.DataFrame(dep_model.predict(X_test), index = X_test.index, columns = ['dep_status'])
             dep model output = dep model output.merge(pred data2, left index = True, right index = True)
             dep_model_output.head(20)
   Out[68]:
                 dep_status dep_hour dep_day Origin_Airport arr_hour arr_day dep_min arr_min arr_clouds arr_dewpt ... dep_precip d€
               0
                        1
                                19
                                         4
                                                   ORD
                                                             22
                                                                     4
                                                                            59
                                                                                    52
                                                                                             66
                                                                                                     7.20 ...
                                                                                                                  0.00
                                                    JFK
                                                                                                     7.90 ...
                         1
                                14
                                         4
                                                             16
                                                                     4
                                                                            55
                                                                                    21
                                                                                             86
                                                                                                                  0.00
               2
                        1
                                13
                                         4
                                                   MCO
                                                             16
                                                                     4
                                                                            35
                                                                                    25
                                                                                             86
                                                                                                     7.90 ...
                                                                                                                  0.00
                                                                                                                       1
                                         5
                                                   ORD
                                                                     5
                                                                                                    -2.40 ...
                        1
                                19
                                                             22
                                                                            59
                                                                                    52
                                                                                             23
                                                                                                                  0.00
                                                    JFK
                                                                     5
                                                                                                    -1.60 ...
                        1
                                14
                                         5
                                                             16
                                                                            55
                                                                                    21
                                                                                             58
                                                                                                                  0.00
               5
                        0
                                19
                                         6
                                                   ORD
                                                             22
                                                                     6
                                                                            59
                                                                                    52
                                                                                              9
                                                                                                    -2.90 ...
                                                                                                                  0.00
               6
                        1
                                14
                                         6
                                                    JFK
                                                             16
                                                                     6
                                                                            55
                                                                                    21
                                                                                             32
                                                                                                    -3.20 ...
                                                                                                                  0.00
               7
                                                                                                    -3.20 ...
                        1
                                13
                                         6
                                                   MCO
                                                             16
                                                                     6
                                                                            35
                                                                                    25
                                                                                             32
                                                                                                                  0.00
               8
                        0
                                19
                                         0
                                                   ORD
                                                                     0
                                                                                    52
                                                                                                    -4.30 ...
                                                             22
                                                                            59
                                                                                             13
                                                                                                                  0.00
               9
                        1
                                14
                                         0
                                                    JFK
                                                             16
                                                                     0
                                                                            55
                                                                                    21
                                                                                                    -4.60 ...
                                                                                                                  0.00
              10
                        2
                                13
                                         0
                                                   MCO
                                                             16
                                                                     0
                                                                            34
                                                                                    25
                                                                                                    -4.60 ...
                                                                                                                  0.20
             11 rows × 32 columns
          ▶ len(pred data2)
In [69]:
   Out[69]: 11
          my_data = {'arr_status_y': [0, 1, 2]}
In [70]:
```

df = pd.DataFrame(data = my data)

```
In [71]:
         df.head()
   Out[71]:
               arr_status_y
             0
             1
                       1
             2
                       2
len(dep_model_output)
   Out[72]: 33
         dep model output['arr status y'] = pd.Categorical(dep model output['arr status y'], categories=[0,1,2])
In [73]:
In [74]:  pred_data2 = dep_model_output[['dep_hour', 'dep_day', 'Origin_Airport', 'arr_hour', 'arr_day',
                   'dep_min', 'arr_min', 'dep_status', 'arr_status_y',
                   'arr_clouds', 'arr_dewpt', 'arr_precip', 'arr_pres', 'arr_rh',
                   'arr_snow', 'arr_temp', 'arr_vis', 'arr_weather.code', 'arr_wind_dir',
                   'arr_wind_gust_spd', 'arr_wind_spd', 'dep_clouds', 'dep_dewpt',
                   'dep_precip', 'dep_pres', 'dep_rh', 'dep_snow', 'dep_temp', 'dep_vis',
                   'dep weather.code', 'dep wind dir', 'dep wind gust spd',
                   'dep wind spd']]
            pred data2.columns
   Out[74]: Index(['dep_hour', 'dep_day', 'Origin_Airport', 'arr_hour', 'arr_day',
                   'dep min', 'arr min', 'dep_status', 'arr_status_y', 'arr_clouds',
                   'arr dewpt', 'arr precip', 'arr_pres', 'arr_rh', 'arr_snow', 'arr_temp',
                   'arr_vis', 'arr_weather.code', 'arr_wind_dir', 'arr_wind_gust_spd',
                   'arr wind spd', 'dep clouds', 'dep dewpt', 'dep precip', 'dep pres',
                   'dep rh', 'dep snow', 'dep temp', 'dep vis', 'dep weather.code',
                   'dep wind dir', 'dep wind gust spd', 'dep wind spd'],
                  dtype='object')
         pred data2['dep status'] = pred data2['dep status'].astype('int64').astype('object')
In [75]:
```

In [76]: pred_data2['dep_status'] = pd.Categorical(pred_data2['dep_status'], categories=[0,1,2])

applying random forest model to predict arrival status

```
In [77]:  pred_data2 = pd.get_dummies(pred_data2, drop_first = True)
             pred_data2.head()
            pred_data2.dtypes
            pred_data2.columns
```

Out[77]:

	arr_clouds	arr_dewpt	arr_precip	arr_pres	arr_rh	arr_snow	arr_temp	arr_vis	arr_wind_dir	arr_wind_gust_spd	•••	dep_weath
0	66	7.20	0.25	999.00	73	0	11.90	19.49	260	8.10		
1	66	7.20	0.25	999.00	73	0	11.90	19.49	260	8.10		
2	66	7.20	0.25	999.00	73	0	11.90	19.49	260	8.10		
3	86	7.90	0.76	996.00	59	0	15.90	20.80	180	13.20		
4	86	7.90	0.76	996.00	59	0	15.90	20.80	180	13.20		

5 rows × 274 columns

Out[77]: arr_clouds

int64 float64 arr_dewpt arr_precip float64 arr_pres float64 arr_rh int64 dep_weather.code_801 bool dep_weather.code_802 bool dep_weather.code_803 bool dep_weather.code_804 bool dep_weather.code_900 bool Length: 274, dtype: object

Out[79]:

	pred_arr_status
0	0
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0
11	0
12	0
13	0
14	0
15	0
16	0
17	0
18	0
19	0
20	0
21	0
22	0
23	0
24	0
25	0

	pred_arr_status
26	0
27	0
28	0
29	0
30	2
31	2
32	2

In []: 📕