```
In [23]: 

# 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

	DATE	DAY	FLIGHT NUMBER	ORIGIN	DEPARTURE TIME	ARRIVAL TIME	ARRIVAL STATUS	ARRIVAL STATUS_Prev_flight_early	ARRIVAL STATUS_Prev_flight_ontime
0	4/19/2024	FRIDAY	UA 1400	ORD	6:52 PM	9:47 PM	NaN	NaN	NaN
1	4/19/2024	FRIDAY	AA 3402	ORD	7:59 PM	10:52 PM	NaN	NaN	NaN
2	4/19/2024	FRIDAY	B6 116	JFK	1:34 PM	2:51 PM	NaN	NaN	NaN
3	4/19/2024	FRIDAY	DL 5182	JFK	2:55 PM	4:21 PM	NaN	NaN	NaN
4	4/19/2024	FRIDAY	WN 5285	MCO	11:35 AM	2:20 PM	NaN	NaN	NaN
4									

In [26]: ▶ pred\_data.dtypes Out[26]: DATE object object DAY FLIGHT NUMBER object object ORIGIN object DEPARTURE TIME object ARRIVAL TIME float64 ARRIVAL STATUS float64 ARRIVAL STATUS\_Prev\_flight\_early ARRIVAL STATUS\_Prev\_flight\_ontime float64 ARRIVAL STATUS\_Prev\_flight\_late float64 dep\_order object dtype: object

#### Out[27]:

	DATE	DAY	FLIGHT NUMBER	Origin_Airport	DEPARTURE TIME	ARRIVAL TIME	ARRIVAL STATUS	ARRIVAL STATUS_Prev_flight_early	ARRIVAL STATUS_Prev_flight_ontime
0	2024- 04-19	4	UA 1400	ORD	1900-01-01 18:52:00	1900-01- 01 21:47:00	NaN	NaN	NaN
1	2024- 04-19	4	AA 3402	ORD	1900-01-01 19:59:00	1900-01- 01 22:52:00	NaN	NaN	NaN
2	2024- 04-19	4	B6 116	JFK	1900-01-01 13:34:00	1900-01- 01 14:51:00	NaN	NaN	NaN
3	2024- 04-19	4	DL 5182	JFK	1900-01-01 14:55:00	1900-01- 01 16:21:00	NaN	NaN	NaN
4	2024- 04-19	4	WN 5285	MCO	1900-01-01 11:35:00	1900-01- 01 14:20:00	NaN	NaN	NaN
4									<b>&gt;</b>

Out[28]:

# In [28]: ▶ pred\_data.dtypes

DATE	datetime64[ns]
DAY	object
FLIGHT NUMBER	object
Origin Airport	object
DEPARTURE TIME	datetime64[ns]
ARRIVAL TIME	datetime64[ns]
ARRIVAL STATUS	float64
ARRIVAL STATUS_Prev_flight_early	float64
ARRIVAL STATUS_Prev_flight_ontime	float64
ARRIVAL STATUS_Prev_flight_late	float64
dep_order	object
Carrier_Code	object
dep_hour	object
dep_min	object
arr_hour	object
arr_min	object
dtype: object	

In [30]: ▶ pred\_data.head(30)

Out[30]:

	DATE	DAY	FLIGHT NUMBER	Origin_Airport	DEPARTURE TIME	ARRIVAL TIME	ARRIVAL STATUS	ARRIVAL STATUS_Prev_flight_early	ARRIVAL STATUS_Prev_flight_ontime
0	2024- 04-19	4	UA 1400	ORD	1900-01-01 18:52:00	1900-01- 01 21:47:00	NaN	NaN	NaN
1	2024- 04-19	4	AA 3402	ORD	1900-01-01 19:59:00	1900-01- 01 22:52:00	NaN	NaN	NaN
2	2024- 04-19	4	B6 116	JFK	1900-01-01 13:34:00	1900-01- 01 14:51:00	NaN	NaN	NaN
3	2024- 04-19	4	DL 5182	JFK	1900-01-01 14:55:00	1900-01- 01 16:21:00	NaN	NaN	NaN
4	2024- 04-19	4	WN 5285	МСО	1900-01-01 11:35:00	1900-01- 01 14:20:00	NaN	NaN	NaN
5	2024- 04-19	4	B6 656	МСО	1900-01-01 13:35:00	1900-01- 01 16:25:00	NaN	NaN	NaN
6	2024- 04-20	5	UA 1400	ORD	1900-01-01 18:52:00	1900-01- 01 21:47:00	NaN	NaN	NaN
7	2024- 04-20	5	AA 3402	ORD	1900-01-01 19:59:00	1900-01- 01 22:52:00	NaN	NaN	NaN
8	2024- 04-20	5	B6 116	JFK	1900-01-01 13:25:00	1900-01- 01 14:41:00	NaN	NaN	NaN
9	2024- 04-20	5	DL 5182	JFK	1900-01-01 14:55:00	1900-01- 01 16:21:00	NaN	NaN	NaN
10	2024- 04-20	5	B6 656	МСО	1900-01-01 13:35:00	1900-01- 01 16:25:00	NaN	NaN	NaN
11	2024- 04-21	6	UA 1400	ORD	1900-01-01 18:52:00	1900-01- 01 21:47:00	NaN	NaN	NaN

	DATE	DAY	FLIGHT NUMBER	Origin_Airport	DEPARTURE TIME	ARRIVAL TIME		ARRIVAL STATUS_Prev_flight_early	ARRIVAL STATUS_Prev_flight_ontime
12	2024- 04-21	6	AA 3402	ORD	1900-01-01 19:59:00	1900-01- 01 22:52:00	NaN	NaN	NaN
13	2024- 04-21	6	B6 116	JFK	1900-01-01 13:35:00	1900-01- 01 14:51:00	NaN	NaN	NaN
14	2024- 04-21	6	DL 5182	JFK	1900-01-01 14:55:00	1900-01- 01 16:21:00	NaN	NaN	NaN
15	2024- 04-21	6	WN 5285	MCO	1900-01-01 11:05:00	1900-01- 01 13:50:00	NaN	NaN	NaN
16	2024- 04-21	6	B6 656	MCO	1900-01-01 13:35:00	1900-01- 01 16:25:00	NaN	NaN	NaN
17	2024- 04-22	0	UA 1400	ORD	1900-01-01 18:52:00	1900-01- 01 21:47:00	NaN	NaN	NaN
18	2024- 04-22	0	AA 3402	ORD	1900-01-01 19:59:00	1900-01- 01 22:52:00	NaN	NaN	NaN
19	2024- 04-22	0	B6 116	JFK	1900-01-01 13:35:00	1900-01- 01 14:51:00	NaN	NaN	NaN
20	2024- 04-22	0	DL 5182	JFK	1900-01-01 14:55:00	1900-01- 01 16:21:00	NaN	NaN	NaN
21	2024- 04-22	0	WN 5285	MCO	1900-01-01 11:35:00	1900-01- 01 14:20:00	NaN	NaN	NaN
22	2024- 04-22	0	B6 656	MCO	1900-01-01 13:34:00	1900-01- 01 16:25:00	NaN	NaN	NaN

## 

#### Out[31]:

	Date	DAY	FLIGHT NUMBER	Origin_Airport	DEPARTURE TIME	ARRIVAL TIME	ARRIVAL STATUS	ARRIVAL STATUS_Prev_flight_early	ARRIVAL STATUS_Prev_flight_ontime	ę
0	2024- 04-19	4	UA 1400	ORD	1900-01-01 18:52:00	1900-01- 01 21:47:00	NaN	NaN	NaN	
1	2024- 04-19	4	AA 3402	ORD	1900-01-01 19:59:00	1900-01- 01 22:52:00	NaN	NaN	NaN	
2	2024- 04-19	4	B6 116	JFK	1900-01-01 13:34:00	1900-01- 01 14:51:00	NaN	NaN	NaN	
3	2024- 04-19	4	DL 5182	JFK	1900-01-01 14:55:00	1900-01- 01 16:21:00	NaN	NaN	NaN	
4	2024- 04-19	4	WN 5285	MCO	1900-01-01 11:35:00	1900-01- 01 14:20:00	NaN	NaN	NaN	
4										<b>&gt;</b>

```
pred_data['Date'] = pred_data['Date'].dt.strftime('%m/%d/%Y')
In [32]:
             pred_data.dtypes
             len(pred_data)
             pred_data.head(30)
   Out[32]: Date
                                                          object
             DAY
                                                          object
             FLIGHT NUMBER
                                                          object
             Origin Airport
                                                          object
             DEPARTURE TIME
                                                  datetime64[ns]
                                                  datetime64[ns]
             ARRIVAL TIME
             ARRIVAL STATUS
                                                         float64
                                                         float64
             ARRIVAL STATUS_Prev_flight_early
             ARRIVAL STATUS_Prev_flight_ontime
                                                         float64
             ARRIVAL STATUS_Prev_flight_late
                                                         float64
             dep_order
                                                          object
             Carrier Code
                                                          object
             dep_hour
                                                          object
             dep_min
                                                          object
             arr_hour
                                                          object
             arr min
                                                          object
                                                          object
             dep minutes
             dep_hours
                                                          object
                                                          object
             arr minutes
             arr hours
                                                          object
             dtype: object
   Out[32]: 23
```

Out[32]:

	Date	DAY	FLIGHT NUMBER	Origin_Airport	DEPARTURE TIME	ARRIVAL TIME	ARRIVAL STATUS	ARRIVAL STATUS_Prev_flight_early	ARRI\ STATUS_Prev_flight_ont
0	04/19/2024	4	UA 1400	ORD	1900-01-01 18:52:00	1900-01- 01 21:47:00	NaN	NaN	1
1	04/19/2024	4	AA 3402	ORD	1900-01-01 19:59:00	1900-01- 01 22:52:00	NaN	NaN	1
2	04/19/2024	4	B6 116	JFK	1900-01-01 13:34:00	1900-01- 01 14:51:00	NaN	NaN	1
3	04/19/2024	4	DL 5182	JFK	1900-01-01 14:55:00	1900-01- 01 16:21:00	NaN	NaN	1
4	04/19/2024	4	WN 5285	МСО	1900-01-01 11:35:00	1900-01- 01 14:20:00	NaN	NaN	1
5	04/19/2024	4	B6 656	MCO	1900-01-01 13:35:00	1900-01- 01 16:25:00	NaN	NaN	1
6	04/20/2024	5	UA 1400	ORD	1900-01-01 18:52:00	1900-01- 01 21:47:00	NaN	NaN	1
7	04/20/2024	5	AA 3402	ORD	1900-01-01 19:59:00	1900-01- 01 22:52:00	NaN	NaN	1
8	04/20/2024	5	B6 116	JFK	1900-01-01 13:25:00	1900-01- 01 14:41:00	NaN	NaN	1
9	04/20/2024	5	DL 5182	JFK	1900-01-01 14:55:00	1900-01- 01 16:21:00	NaN	NaN	1
10	04/20/2024	5	B6 656	MCO	1900-01-01 13:35:00	1900-01- 01 16:25:00	NaN	NaN	1
11	04/21/2024	6	UA 1400	ORD	1900-01-01 18:52:00	1900-01- 01 21:47:00	NaN	NaN	1

	Date	DAY	FLIGHT NUMBER	Origin_Airport	DEPARTURE TIME	ARRIVAL TIME		ARRIVAL STATUS_Prev_flight_early	ARRI\ STATUS_Prev_flight_ont
12	04/21/2024	6	AA 3402	ORD	1900-01-01 19:59:00	1900-01- 01 22:52:00	NaN	NaN	1
13	04/21/2024	6	B6 116	JFK	1900-01-01 13:35:00	1900-01- 01 14:51:00	NaN	NaN	١
14	04/21/2024	6	DL 5182	JFK	1900-01-01 14:55:00	1900-01- 01 16:21:00	NaN	NaN	١
15	04/21/2024	6	WN 5285	MCO	1900-01-01 11:05:00	1900-01- 01 13:50:00	NaN	NaN	١
16	04/21/2024	6	B6 656	MCO	1900-01-01 13:35:00	1900-01- 01 16:25:00	NaN	NaN	١
17	04/22/2024	0	UA 1400	ORD	1900-01-01 18:52:00	1900-01- 01 21:47:00	NaN	NaN	١
18	04/22/2024	0	AA 3402	ORD	1900-01-01 19:59:00	1900-01- 01 22:52:00	NaN	NaN	١
19	04/22/2024	0	B6 116	JFK	1900-01-01 13:35:00	1900-01- 01 14:51:00	NaN	NaN	1
20	04/22/2024	0	DL 5182	JFK	1900-01-01 14:55:00	1900-01- 01 16:21:00	NaN	NaN	١
21	04/22/2024	0	WN 5285	MCO	1900-01-01 11:35:00	1900-01- 01 14:20:00	NaN	NaN	1
22	04/22/2024	0	B6 656	МСО	1900-01-01 13:34:00	1900-01- 01 16:25:00	NaN	NaN	١

## Fetching weather data and merging with flight data

```
In [33]: ▶ # Read and process weather data files for each airport
             jfk_weather_data = pd.read_csv('weather_data/JFK_weather_data_forecast_processed.csv')
             syr_weather_data = pd.read_csv('weather_data/SYR_weather_data_forecast_processed.csv')
             ord_weather_data = pd.read_csv('weather_data/ORD_weather_data_forecast_processed.csv')
             mco_weather_data = pd.read_csv('weather_data/MCO_weather_data_forecast 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_minutes'] = weather_data['dep_minutes'].astype('object')
             weather_data['dep_hours'] = weather_data['dep_hours'].astype('object')
             #syr_weather_data['arr_minutes'] = syr_weather_data['arr_minutes'].astype('object')
             syr weather data['arr hours'] = syr weather data['arr hours'].astype('object')
             weather_data.head(50)
             len(weather data)
             len(syr weather data)
             # Define merging logic based on airport code
             pred_data = pd.merge(pred_data, syr_weather_data, how='left', on=['Date', 'arr_hours'])
             len(pred data)
             pred_data.to_csv("first.csv")
             pred_data = pd.merge(pred_data, weather_data, how='left', on=['Origin_Airport', 'Date', 'dep_hours'])
             pred_data.to_csv("sec.csv")
             len(pred data)
             #weather_data.head()
```

Out[33]:		dep_clouds	dep_clouds_hi	dep_clouds_low	dep_clouds_mid	dep_dewpt	dep_ozone	dep_pop	dep_precip	dep_pres	dep_rh
	0	92	0	100	0	4.30	382.50	0	0.00	1,019.50	74
	1	95	0	100	0	4.50	375.80	0	0.00	1,020.50	77
	2	95	0	100	0	3.40	369.50	0	0.00	1,021.00	72
	3	83	48	100	0	3.80	365.30	0	0.00	1,020.50	75
	4	76	87	99	0	3.80	362.50	0	0.00	1,020.50	74
	5	80	100	100	0	3.30	354.80	0	0.00	1,021.00	72
	6	73	100	98	0	3.70	354.80	0	0.00	1,020.00	74
	7	67	54	34	10	3.60	351.50	0	0.00	1,020.00	75
	8	61	35	12	100	3.80	347.50	0	0.00	1,020.50	76
	9	57	1	5	73	3.60	346.00	0	0.00	1,020.00	76
	10	71	16	14	0	3.60	344.80	0	0.00	1,020.00	77
	11	73	100	18	0	3.30	343.00	0	0.00	1,021.50	76
	12	63	0	17	0	3.40	343.00	0	0.00	1,022.00	76
	13	64	0	27	0	3.60	341.50	0	0.00	1,022.00	75
	14	65	0	52	0	3.60	342.00	0	0.00	1,021.00	70
	15	80	82	100	0	3.50	338.30	0	0.00	1,021.50	65
	16	61	100	48	0	3.70	335.80	0	0.00	1,021.00	62
	17	64	100	30	0	3.70	334.50	0	0.00	1,021.00	58
	18	76	100	23	22	4.20	336.30	0	0.00	1,020.50	58
	19	82	98	11	10	4.10	336.80	0	0.00	1,019.50	58
	20	85	100	11	100	4.50	338.30	0	0.00	1,019.00	59
	21	83	94	17	100	5.00	342.30	0	0.00	1,019.50	62
	22	83	0	7	100	5.10	342.30	0	0.00	1,020.00	63
	23	90	0	9	58	5.30	342.00	0	0.00	1,019.50	67
	24	79	0	13	14	5.50	342.00	0	0.00	1,018.50	70
	25	65	0	34	82	5.90	341.50	0	0.00	1,018.00	76
	26	88	0	77	15	5.90	340.50	0	0.00	1,018.00	77

dep_clouds	dep_clouds_hi	dep_clouds_low	dep_clouds_mid	dep_dewpt	dep_ozone	dep_pop	dep_precip	dep_pres	dep_rh
93	100	94	0	6.80	338.30	0	0.00	1,017.50	81
91	100	100	3	7.00	337.30	0	0.00	1,017.50	82
96	100	100	52	7.20	340.80	25	0.25	1,018.00	82
95	100	100	100	7.20	343.80	40	0.50	1,017.50	83
95	100	100	100	7.70	345.30	25	0.25	1,016.50	85
97	100	100	100	8.00	343.50	40	0.50	1,015.50	87
96	100	100	95	8.50	347.00	25	0.25	1,015.00	88
97	100	100	100	8.90	350.00	25	0.25	1,014.50	89
94	84	100	100	8.50	347.80	0	0.00	1,014.50	89
91	80	100	100	8.30	349.00	0	0.00	1,014.50	85
89	100	100	100	8.30	352.00	0	0.00	1,015.50	82
86	73	100	100	8.00	356.30	0	0.00	1,015.00	78
80	83	100	100	7.30	361.00	0	0.00	1,015.50	70
75	66	100	91	6.20	364.80	0	0.00	1,014.50	61
69	25	58	100	5.10	370.00	0	0.00	1,014.50	53
68	22	100	2	4.50	374.80	0	0.00	1,015.00	49
66	27	40	0	4.30	374.50	0	0.00	1,014.50	46
65	16	35	0	3.60	375.80	0	0.00	1,014.00	42
65	2	25	31	3.60	378.50	0	0.00	1,009.00	42
64	100	91	67	3.30	381.80	0	0.00	1,008.50	41
64	6	76	0	3.30	386.50	0	0.00	1,009.00	41
50	0	55	0	2.70	387.00	0	0.00	1,009.50	42
36	0	9	0	2.40	391.30	0	0.00	1,010.50	44
	93 91 96 95 97 96 97 94 91 89 86 80 75 69 68 66 65 65 64 64	93 100 91 100 96 100 95 100 97 100 96 100 97 100 97 100 94 84 91 80 89 100 86 73 80 83 75 66 69 25 68 22 66 27 65 16 65 2 64 100 64 6 50 0	93       100       94         91       100       100         96       100       100         95       100       100         97       100       100         96       100       100         97       100       100         94       84       100         91       80       100         89       100       100         86       73       100         80       83       100         75       66       100         69       25       58         68       22       100         66       27       40         65       16       35         65       2       25         64       100       91         64       6       76         50       0       55	93       100       94       0         91       100       100       3         96       100       100       100         95       100       100       100         95       100       100       100         97       100       100       95         97       100       100       100         94       84       100       100         91       80       100       100         89       100       100       100         80       83       100       100         80       83       100       100         75       66       100       91         69       25       58       100         68       22       100       2         66       27       40       0         65       16       35       0         65       2       25       31         64       100       91       67         64       6       76       0         50       0       55       0	93       100       94       0       6.80         91       100       100       3       7.00         96       100       100       52       7.20         95       100       100       100       7.70         97       100       100       100       8.00         96       100       100       95       8.50         97       100       100       100       8.90         94       84       100       100       8.30         89       100       100       100       8.30         86       73       100       100       8.00         80       83       100       100       8.00         80       83       100       100       7.30         75       66       100       91       6.20         69       25       58       100       5.10         68       22       100       2       4.50         66       27       40       0       4.30         65       16       35       0       3.60         65       16       35       0       3.60	93         100         94         0         6.80         338.30           91         100         100         3         7.00         337.30           96         100         100         52         7.20         340.80           95         100         100         100         7.70         345.30           97         100         100         100         8.00         343.50           96         100         100         95         8.50         347.00           97         100         100         100         8.90         350.00           97         100         100         100         8.90         350.00           94         84         100         100         8.30         347.80           91         80         100         100         8.30         349.00           89         100         100         8.30         352.00           86         73         100         100         8.00         356.30           80         83         100         100         7.30         361.00           75         66         100         91         6.20         364.80 <t< th=""><th>93 100 94 0 6.80 338.30 0 91 100 100 100 3 7.00 337.30 0 96 100 100 100 7.20 343.80 40 95 100 100 100 100 7.70 345.30 25 97 100 100 100 95 8.50 347.00 25 97 100 100 100 8.90 350.00 25 97 100 100 100 8.90 350.00 25 97 100 100 100 8.90 350.00 25 97 100 100 100 8.90 350.00 25 98 84 84 100 100 8.50 347.80 0 91 80 100 100 8.30 352.00 0 88 73 100 100 8.30 352.00 0 88 73 100 100 8.30 356.30 0 80 83 100 100 7.30 361.00 0 80 83 100 91 6.20 364.80 0 66 27 40 0 91 6.20 374.80 0 66 27 40 0 4.30 374.80 0 66 27 40 0 4.30 374.50 0 66 27 40 0 4.30 374.50 0 66 27 40 0 4.30 374.50 0 66 27 40 0 4.30 374.50 0 66 27 40 0 4.30 374.50 0 66 27 40 0 4.30 374.50 0 66 27 40 0 4.30 374.50 0 66 27 40 0 3.30 381.80 0 66 27 25 31 3.60 376.50 0 66 100 91 67 3.30 381.80 0</th><th>93 100 94 0 6.80 338.30 0 0.00 91 100 100 3 7.00 337.30 0 0.00 96 100 100 52 7.20 340.80 25 0.25 95 100 100 100 100 7.20 343.80 40 0.50 95 100 100 100 8.00 343.50 40 0.50 96 100 100 95 8.50 347.00 25 0.25 97 100 100 100 8.90 350.00 25 0.25 97 100 100 100 8.90 350.00 25 0.25 98 100 100 100 8.90 350.00 0.00 91 80 100 100 8.30 349.00 0 0.00 89 100 100 100 8.30 349.00 0 0.00 89 100 100 100 8.30 352.00 0 0.00 86 73 100 100 8.00 356.30 0 0.00 86 73 100 100 7.30 361.00 0 0.00 87 66 100 91 6.20 364.80 0 0.00 88 22 100 2 4.50 374.80 0 0.00 68 22 100 2 4.50 374.80 0 0.00 66 27 40 0 4.30 374.50 0 0.00 66 16 35 0 360 375.80 0 0.00 66 16 36 76 0 3.30 381.80 0 0.00 64 100 91 67 3.30 381.80 0 0.00 65 0 0 55 0 2.70 387.00 0 0.00</th><th>93         100         94         0         6.80         338.30         0         0.00         1,017.50           91         100         100         3         7.00         337.30         0         0.00         1,017.50           96         100         100         52         7.20         340.80         25         0.25         1,018.00           95         100         100         100         7.70         345.30         25         0.25         1,016.50           97         100         100         100         8.00         343.50         40         0.50         1,015.50           96         100         100         95         8.50         347.00         25         0.25         1,016.50           97         100         100         100         8.90         350.00         25         0.25         1,014.50           97         100         100         100         8.50         347.80         0         0.00         1,014.50           94         84         100         100         8.50         347.80         0         0.00         1,014.50           91         80         100         100         8.30</th></t<>	93 100 94 0 6.80 338.30 0 91 100 100 100 3 7.00 337.30 0 96 100 100 100 7.20 343.80 40 95 100 100 100 100 7.70 345.30 25 97 100 100 100 95 8.50 347.00 25 97 100 100 100 8.90 350.00 25 97 100 100 100 8.90 350.00 25 97 100 100 100 8.90 350.00 25 97 100 100 100 8.90 350.00 25 98 84 84 100 100 8.50 347.80 0 91 80 100 100 8.30 352.00 0 88 73 100 100 8.30 352.00 0 88 73 100 100 8.30 356.30 0 80 83 100 100 7.30 361.00 0 80 83 100 91 6.20 364.80 0 66 27 40 0 91 6.20 374.80 0 66 27 40 0 4.30 374.80 0 66 27 40 0 4.30 374.50 0 66 27 40 0 4.30 374.50 0 66 27 40 0 4.30 374.50 0 66 27 40 0 4.30 374.50 0 66 27 40 0 4.30 374.50 0 66 27 40 0 4.30 374.50 0 66 27 40 0 4.30 374.50 0 66 27 40 0 3.30 381.80 0 66 27 25 31 3.60 376.50 0 66 100 91 67 3.30 381.80 0	93 100 94 0 6.80 338.30 0 0.00 91 100 100 3 7.00 337.30 0 0.00 96 100 100 52 7.20 340.80 25 0.25 95 100 100 100 100 7.20 343.80 40 0.50 95 100 100 100 8.00 343.50 40 0.50 96 100 100 95 8.50 347.00 25 0.25 97 100 100 100 8.90 350.00 25 0.25 97 100 100 100 8.90 350.00 25 0.25 98 100 100 100 8.90 350.00 0.00 91 80 100 100 8.30 349.00 0 0.00 89 100 100 100 8.30 349.00 0 0.00 89 100 100 100 8.30 352.00 0 0.00 86 73 100 100 8.00 356.30 0 0.00 86 73 100 100 7.30 361.00 0 0.00 87 66 100 91 6.20 364.80 0 0.00 88 22 100 2 4.50 374.80 0 0.00 68 22 100 2 4.50 374.80 0 0.00 66 27 40 0 4.30 374.50 0 0.00 66 16 35 0 360 375.80 0 0.00 66 16 36 76 0 3.30 381.80 0 0.00 64 100 91 67 3.30 381.80 0 0.00 65 0 0 55 0 2.70 387.00 0 0.00	93         100         94         0         6.80         338.30         0         0.00         1,017.50           91         100         100         3         7.00         337.30         0         0.00         1,017.50           96         100         100         52         7.20         340.80         25         0.25         1,018.00           95         100         100         100         7.70         345.30         25         0.25         1,016.50           97         100         100         100         8.00         343.50         40         0.50         1,015.50           96         100         100         95         8.50         347.00         25         0.25         1,016.50           97         100         100         100         8.90         350.00         25         0.25         1,014.50           97         100         100         100         8.50         347.80         0         0.00         1,014.50           94         84         100         100         8.50         347.80         0         0.00         1,014.50           91         80         100         100         8.30

50 rows × 24 columns

Out[33]: 504

In [36]: ▶ pred\_data.dtypes

Out[36]:	Origin_Airport	object
	dep_order	object
	Carrier_Code	object
	dep_hour	object
	dep_min	object
	arr_hour	object
	arr_min	object
	dep_minutes	object
	dep_hours	object
	arr_minutes	object
	arr_hours	object
	arr_clouds	int64
	arr_clouds_hi	int64
	arr_clouds_low	int64
	arr_clouds_mid	int64
	arr_dewpt	float64
	arr_ozone	float64
	arr_pop	int64
	arr_precip	float64
	arr_pres	float64
	arr_rh	int64
	arr_snow	int64
	arr_snow_depth	int64
	arr_temp	float64
	arr_vis	float64
	arr_weather.description	object
	arr weather.code	int64
	arr_wind_cdir	object
	arr_wind_cdir_full	object
	arr_wind_dir	int64
	arr_wind_gust_spd	float64
	arr_wind_spd	float64
	dep clouds	int64
	dep_clouds_hi	int64
	dep_clouds_low	int64
	dep clouds mid	int64
	dep_dewpt	float64
	dep_ozone	float64
	dep_pop	int64
	dep_precip	float64
	dep_pres	float64
	dep_rh	int64
	dep_snow	int64
	· -r =	

dep_snow_depth	int64
dep_temp	float64
dep_vis	float64
dep_weather.description	object
dep_weather.code	int64
dep_wind_cdir	object
dep_wind_cdir_full	object
dep_wind_dir	int64
<pre>dep_wind_gust_spd</pre>	float64
dep_wind_spd	float64
arr_day	object
dep_day	object
dtype: object	

```
pred_data['dep_hour'] = pd.Categorical(pred_data['dep_hour'], categories=[i for i in range(24)])
In [37]:
             pred_data['dep_day'] = pd.Categorical(pred_data['dep_day'], categories=[i for i in range(7)])
             pred data['dep min'] = pd.Categorical(pred data['dep min'], categories=[i for i in range(60)])
             pred data['arr hour'] = pd.Categorical(pred data['arr hour'], categories=[i for i in range(24)])
             pred data['arr day'] = pd.Categorical(pred data['arr day'], categories=[i for i in range(7)])
             pred data['arr min'] = pd.Categorical(pred_data['arr_min'], categories=[i for i in range(60)])
             pred data['Carrier Code'] = pd.Categorical(pred data['Carrier Code'], categories=['AA', 'UA', 'DL', 'B6',
             pred data['Origin Airport'] = pd.Categorical(pred data['Origin Airport'], categories=['ORD', 'JFK', 'MCO']
             pred_data=pred_data[['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', 'dep order']]
             pred data.head()
             pred data.columns
```

#### Out[37]:

:		dep_hour	dep_day	Origin_Airport	arr_hour	arr_day	dep_min	arr_min	arr_clouds	arr_dewpt	arr_precip	 dep_pres	dep_r
	0	18	4	ORD	21	4	52	47	69	8.00	0.50	 996.50	3
	1	19	4	ORD	22	4	59	52	66	7.20	0.25	 996.50	3
	2	13	4	JFK	14	4	34	51	84	7.20	0.50	 1,019.50	5
	3	14	4	JFK	16	4	55	21	86	7.90	0.76	 1,019.00	5
	4	11	4	MCO	14	4	35	20	84	7.20	0.50	 1,015.00	5

5 rows × 32 columns

## Spliting data into latter and early flights

```
pred_data2 = pred_data[pred_data['dep_order'] == 'latter']
In [39]: | pred data1.drop(columns=['dep order'],inplace = True)
            pred data2.drop(columns=['dep order'],inplace = True)
            C:\Users\gurud\AppData\Local\Temp\ipykernel 27312\2195326561.py:1: SettingWithCopyWarning:
            A value is trying to be set on a copy of a slice from a DataFrame
            See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.ht
            ml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#
            returning-a-view-versus-a-copy)
              pred_data1.drop(columns=['dep_order'],inplace = True)
            C:\Users\gurud\AppData\Local\Temp\ipykernel 27312\2195326561.py:2: SettingWithCopyWarning:
            A value is trying to be set on a copy of a slice from a DataFrame
            See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.ht
            ml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#
            returning-a-view-versus-a-copy)
              pred_data2.drop(columns=['dep_order'],inplace = True)
```

In [40]: ▶ pred\_data1.head(22)

Out[40]:		dep_hour	dep_day	Origin_Airport	arr_hour	arr_day	dep_min	arr_min	arr_clouds	arr_dewpt	arr_precip	 dep_precip	del
	0	18	4	ORD	21	4	52	47	69	8.00	0.50	 0.00	
	2	13	4	JFK	14	4	34	51	84	7.20	0.50	 0.00	1,
	4	11	4	MCO	14	4	35	20	84	7.20	0.50	 0.00	1,
	6	18	5	ORD	21	5	52	47	23	-2.40	0.00	 0.00	
	8	13	5	JFK	14	5	25	41	71	-1.20	0.00	 0.00	1,
	10	13	5	MCO	16	5	35	25	58	-1.60	0.00	 0.00	1,
	11	18	6	ORD	21	6	52	47	9	-2.90	0.00	 0.00	
	13	13	6	JFK	14	6	35	51	44	-3.10	0.00	 0.00	1,
	15	11	6	MCO	13	6	5	50	48	-2.80	0.00	 0.00	1,
	17	18	0	ORD	21	0	52	47	10	-4.70	0.00	 0.00	
	19	13	0	JFK	14	0	35	51	10	-4.80	0.00	 0.00	1,
	21	11	0	MCO	14	0	35	20	10	-4.80	0.00	 0.12	1,

12 rows × 31 columns

 $localhost: 8888/notebooks/Downloads/IML\_project/flight-predictions/flight\_prediction\_data\_preprocessing.ipynb$ 

▶ pred\_data2.head(20) In [41]: Out[41]: dep\_hour dep\_day Origin\_Airport arr\_hour arr\_day dep\_min arr\_min arr\_clouds arr\_dewpt arr\_precip ... dep\_precip del 19 52 0.25 ... 1 4 ORD 22 4 59 66 7.20 0.00 21 0.76 ... 3 14 JFK 4 16 4 55 86 7.90 0.00 1, 0.76 ... 5 13 4 MCO 16 35 25 86 7.90 0.00 4 1, 7 19 5 ORD 22 5 59 52 23 -2.40 0.00 ... 0.00 9 5 JFK 16 5 55 21 -1.60 0.00 ... 0.00 14 58 1, 12 6 59 52 19 ORD 22 6 9 -2.90 0.00 ... 0.00 JFK 55 0.00 ... 6 6 14 14 16 21 32 -3.20 0.00 1, 16 13 6 MCO 16 6 35 25 32 -3.20 0.00 ... 0.00 1, 18 19 0 ORD 22 0 59 52 13 -4.30 0.00 ... 0.00 20 0 JFK 0 55 21 9 0.00 ... 14 16 -4.60 0.00 1, 13 25 22 0 34 9 MCO 16 0 -4.60 0.00 ... 0.20 1, 11 rows × 31 columns In [42]: pred\_data1.to\_csv('pred\_data1.csv') In [43]: ▶ len(pred\_data1) Out[43]: 12

▶ pred\_data1.head(20) In [44]: Out[44]: dep\_hour dep\_day Origin\_Airport arr\_hour arr\_day dep\_min arr\_min arr\_clouds arr\_dewpt arr\_precip ... dep\_precip dej 18 0.50 ... 0 4 ORD 21 4 52 47 69 8.00 0.00 0.50 ... 2 13 4 JFK 14 34 51 84 7.20 0.00 1, 11 MCO 35 20 7.20 0.50 ... 0.00 4 4 14 4 84 1, 6 18 5 ORD 21 5 52 47 23 -2.40 0.00 ... 0.00 8 13 5 JFK 5 25 -1.20 0.00 ... 14 41 71 0.00 1, 10 13 5 MCO 16 5 35 25 58 -1.60 0.00 ... 0.00 1, ORD 11 18 6 21 6 52 47 9 -2.90 0.00 ... 0.00 13 13 6 JFK 6 35 -3.10 0.00 ... 0.00 14 51 44 1, 15 11 6 MCO 13 6 5 50 48 -2.80 0.00 ... 0.00 1, 17 0 ORD 52 47 -4.70 18 21 0 10 0.00 ... 0.00 0 19 13 JFK 14 0 35 51 10 -4.80 0.00 ... 0.00 1, 21 11 0 MCO 0 35 20 10 -4.80 0.00 ... 0.12 14 1, 12 rows × 31 columns In [45]: pred\_data2.to\_csv('pred\_data2.csv') ▶ len(pred\_data2) In [46]: Out[46]: 11 In [ ]: