Modeling V2

April 30, 2024

[1]:
```
from IPython.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>"))
```

<IPython.core.display.HTML object>

[2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import scipy
import sklearn
import os
from sklearn.model_selection import train_test_split
```

[3]:
```
def convert_to_categorical(time_str):
    hour = int(time_str.split(':')[0])

    if 0 <= hour < 3:
        return 'Late Night'
    elif 3 <= hour < 6:
        return 'Early Morning'
    elif 6 <= hour < 9:
        return 'Morning'
    elif 9 <= hour < 12:
        return 'Late Morning'
    elif 12 <= hour < 15:
        return 'Noon'
    elif 15 <= hour < 18:
        return 'Afternoon'
    elif 18 <= hour < 21:
        return 'Evening'
    else:
        return 'Night'
```

[4]:
```
data = pd.read_csv("./SYR_ORIGIN_WEATHER_IMPUTED.csv")
```

[5]:
```
data.head()
```

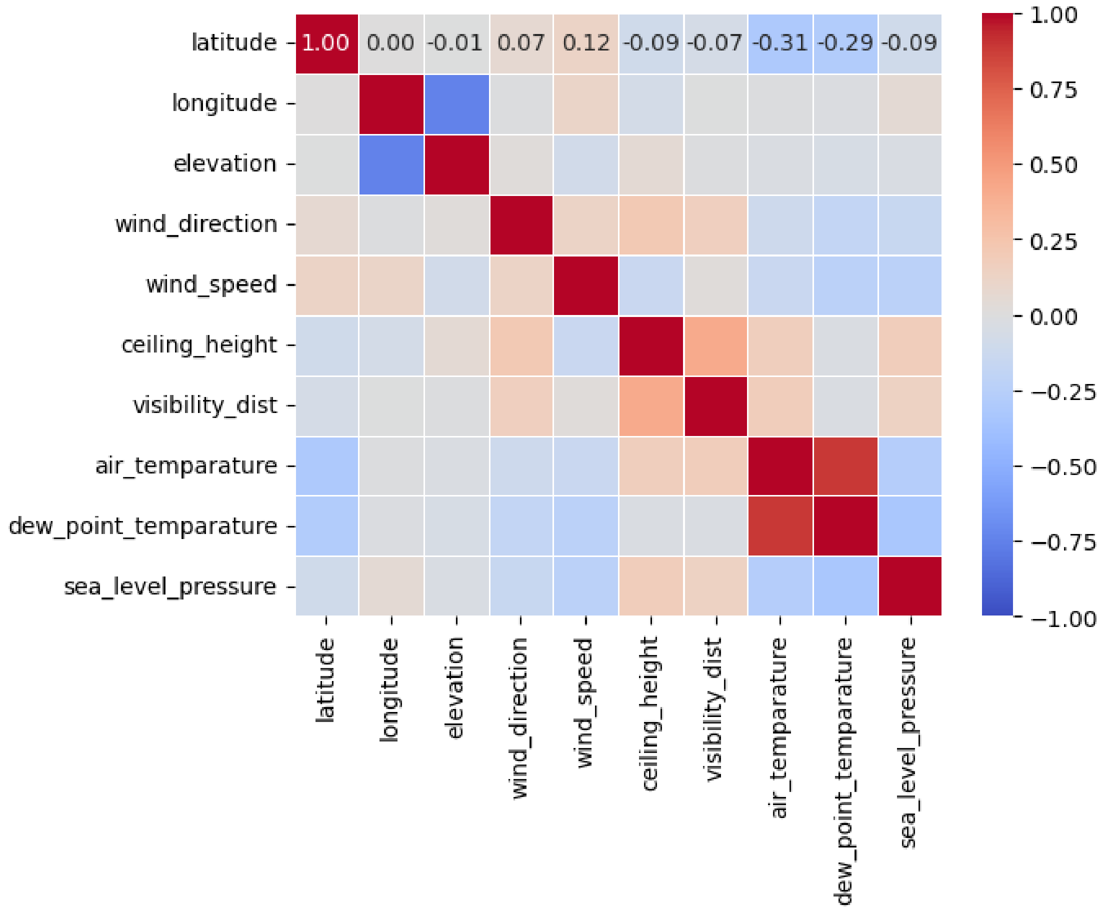
[5]:
```
  Carrier Code Date (MM/DD/YYYY) Origin Airport Scheduled Arrival Time  \
0           B6        2010-01-01            JFK                  00:01
1           B6        2010-01-01            JFK                  08:55
2           MQ        2010-01-01            ORD                  11:20
3           9E        2010-01-01            DTW                  11:44
4           B6        2010-01-01            JFK                  11:52

   Scheduled Elapsed Time (Minutes) FLIGHT_STATUS  month  day  season WeekDay  \
0                                76          LATE      1    1  winter  Friday
1                                75          LATE      1    1  winter  Friday
2                               100        ONTIME      1    1  winter  Friday
3                                84          LATE      1    1  winter  Friday
4                                71          LATE      1    1  winter  Friday

   … SYR_wind_type  SYR_wind_speed  SYR_ceiling_height  \
0  …             N            17.4          741.370199
1  …             C             0.0          548.800000
2  …             C             0.0          841.400000
3  …             C             0.0         1006.000000
4  …             C             0.0         1006.000000

   SYR_ceiling_det_code  SYR_celing_CAVOK  SYR_visibility_dist  \
0                     M                 N               6110.0
1                     M                 N               2414.0
2                     M                 N               3138.4
3                     M                 N               3138.4
4                     M                 N               3138.4

  SYR_visibility_variability  SYR_air_temparature  SYR_dew_point_temparature  \
0                          N                 -4.8                      -24.0
1                          N                -17.0                      -28.8
2                          N                -19.4                      -29.6
3                          N                -19.8                      -29.2
4                          N                -19.8                      -29.2

  SYR_sea_level_pressure
0           10154.572817
1           10132.352069
2           10129.796558
3           10129.482076
4           10129.482076

[5 rows x 40 columns]
```

[6]:
```
tmp = data[['latitude', 'longitude', 'elevation',
       'wind_direction',  'wind_speed', 'ceiling_height','visibility_dist',␣
 ↪'air_temparature', 'dew_point_temparature',
```

```
                 'sea_level_pressure']]
```

[7]:
```
sns.heatmap(tmp.corr(), annot=True, cmap='coolwarm', fmt=".2f", linewidths=.5,␣
↪vmin=-1, vmax=1)
```

[7]: <Axes: >



[8]:
```
data['SCHED_ARRV_TIME_CAT'] = data['Scheduled Arrival Time'].
↪apply(convert_to_categorical)
```

[9]:
```
data.shape
```

[9]: (113671, 41)

[10]:
```
data.columns
```

[10]:
```
Index(['Carrier Code', 'Date (MM/DD/YYYY)', 'Origin Airport',
       'Scheduled Arrival Time', 'Scheduled Elapsed Time (Minutes)',
```

```
       'FLIGHT_STATUS', 'month', 'day', 'season', 'WeekDay', 'UNIX_DATE',
       'UNIX_TIMESTAMP', 'latitude', 'longitude', 'elevation',
       'wind_direction', 'wind_type', 'wind_speed', 'ceiling_height',
       'ceiling_det_code', 'celing_CAVOK', 'visibility_dist',
       'visibility_variability', 'air_temparature', 'dew_point_temparature',
       'sea_level_pressure', 'SYR_latitude', 'SYR_longitude', 'SYR_elevation',
       'SYR_wind_direction', 'SYR_wind_type', 'SYR_wind_speed',
       'SYR_ceiling_height', 'SYR_ceiling_det_code', 'SYR_celing_CAVOK',
       'SYR_visibility_dist', 'SYR_visibility_variability',
       'SYR_air_temparature', 'SYR_dew_point_temparature',
       'SYR_sea_level_pressure', 'SCHED_ARRV_TIME_CAT'],
      dtype='object')
```

[11]:
```
# data = data[data['Origin Airport'].isin(['JFK','ORD','MCO'])]
```

[12]:
```
data.shape
```

[12]:
```
(113671, 41)
```

[13]:
```
df = data.drop(columns=['Date (MM/DD/YYYY)', 'Scheduled Arrival Time','day',␣
 ↪'UNIX_DATE','UNIX_TIMESTAMP',
                        'longitude','dew_point_temparature',␣
 ↪'wind_type','ceiling_height', 'ceiling_det_code',␣
 ↪'celing_CAVOK','visibility_variability',
                        'SYR_longitude',
        'SYR_wind_type','SYR_ceiling_height', 'SYR_ceiling_det_code',␣
 ↪'SYR_celing_CAVOK', 'SYR_visibility_variability',␣
 ↪'SYR_dew_point_temparature','SYR_latitude','SYR_elevation'])
```

[14]:
```
df.isna().sum()
```

[14]:
```
Carrier Code                        0
Origin Airport                      0
Scheduled Elapsed Time (Minutes)    0
FLIGHT_STATUS                       0
month                               0
season                              0
WeekDay                             0
latitude                            0
elevation                           0
wind_direction                      0
wind_speed                          0
visibility_dist                     0
air_temparature                     0
sea_level_pressure                  0
SYR_wind_direction                  0
SYR_wind_speed                      0
```

```
SYR_visibility_dist                 0
SYR_air_temparature                 0
SYR_sea_level_pressure              0
SCHED_ARRV_TIME_CAT                 0
dtype: int64
```

[15]:
```
df.shape
```

[15]:
```
(113671, 20)
```

[16]:
```
df['SYR_sea_level_pressure'] = df['SYR_sea_level_pressure'].
 ↪fillna(df['SYR_sea_level_pressure'].mean())
```

[17]:
```
df.isna().sum()
```

[17]:
```
Carrier Code                        0
Origin Airport                      0
Scheduled Elapsed Time (Minutes)    0
FLIGHT_STATUS                       0
month                               0
season                              0
WeekDay                             0
latitude                            0
elevation                           0
wind_direction                      0
wind_speed                          0
visibility_dist                     0
air_temparature                     0
sea_level_pressure                  0
SYR_wind_direction                  0
SYR_wind_speed                      0
SYR_visibility_dist                 0
SYR_air_temparature                 0
SYR_sea_level_pressure              0
SCHED_ARRV_TIME_CAT                 0
dtype: int64
```

[18]:
```
def mps_to_mph(speed_mps):
    return (speed_mps/10.0) * 2.23694

def meters_to_miles(distance_meters):
    return distance_meters * 0.000621371
def celsius_to_fahrenheit(temperature_celsius):
    return (temperature_celsius/10.0) * 9/5 + 32

def hectopascal_to_mb(v):
    return v/10.0
```

[19]:
```
df.tail()
```

[19]:
```
       Carrier Code Origin Airport  Scheduled Elapsed Time (Minutes)  \
113666           DL            DTW                                83
113667           WN            BWI                                70
113668           AA            DFW                               181
113669           UA            DEN                               198
113670           UA            EWR                                74

       FLIGHT_STATUS  month  season WeekDay  latitude  elevation  \
113666         EARLY     12  winter  Sunday  42.23113      191.9
113667          LATE     12  winter  Sunday  39.17329       42.0
113668        ONTIME     12  winter  Sunday  32.56500      213.4
113669        ONTIME     12  winter  Sunday  39.84657     1647.2
113670         EARLY     12  winter  Sunday  40.68275        1.9

        wind_direction  wind_speed  visibility_dist  air_temparature  \
113666      240.000000        20.4          13143.4             34.8
113667      243.746270        23.6          16074.4             88.6
113668      199.866450        10.4          16093.0            184.0
113669      191.233489        19.4          16074.4             42.0
113670      286.000000        34.0          16074.4             67.0

        sea_level_pressure  SYR_wind_direction  SYR_wind_speed  \
113666        10126.074551               226.0            25.8
113667        10154.400000               226.0            25.8
113668        10167.225662               226.0            25.8
113669        10192.400000               226.0            25.8
113670        10155.536842               226.0            25.8

        SYR_visibility_dist  SYR_air_temparature  SYR_sea_level_pressure  \
113666              15030.8                -17.0            10154.321162
113667              15030.8                -17.0            10154.321162
113668              15030.8                -17.0            10154.321162
113669              15030.8                -17.0            10154.321162
113670              15030.8                -17.0            10154.321162

       SCHED_ARRV_TIME_CAT
113666               Night
113667               Night
113668               Night
113669               Night
113670               Night
```

[20]:
```
df['SYR_wind_speed'] = df['SYR_wind_speed'].apply(mps_to_mph)
df['wind_speed'] = df['wind_speed'].apply(mps_to_mph)
df['visibility_dist'] = df['visibility_dist'].apply(meters_to_miles)
```

```
df['SYR_visibility_dist'] = df['SYR_visibility_dist'].apply(meters_to_miles)
df['air_temparature'] = df['air_temparature'].apply(celsius_to_fahrenheit)
df['SYR_air_temparature'] = df['SYR_air_temparature'].
 ↪apply(celsius_to_fahrenheit)
df['sea_level_pressure'] = df['sea_level_pressure'].apply(hectopascal_to_mb)
df['SYR_sea_level_pressure'] = df['SYR_sea_level_pressure'].
 ↪apply(hectopascal_to_mb)
```

[21]:
```
df[df.season=='spring'].head(50)
```

[21]:
```
     Carrier Code Origin Airport  Scheduled Elapsed Time (Minutes)  \
1666           B6            JFK                                80
1667           9E            DTW                                87
1668           OO            ORD                               106
1669           B6            JFK                                84
1670           OH            JFK                                94
1671           MQ            ORD                               105
1672           B6            JFK                                78
1673           EV            ATL                               137
1674           XE            CLE                                63
1675           YV            IAD                                75
1676           XE            ORD                               100
1677           B6            MCO                               160
1678           EV            ATL                               130
1679           9E            DTW                                87
1680           OH            CVG                                96
1681           B6            JFK                                88
1682           XE            CLE                                65
1683           OH            JFK                                92
1684           EV            ATL                               133
1685           XE            EWR                                69
1686           MQ            ORD                               105
1687           XE            IAD                                76
1688           US            CLT                               114
1689           OH            DTW                                83
1690           YV            ORD                               100
1691           XE            CLE                                65
1692           OH            JFK                               115
1693           B6            MCO                               159
1694           MQ            ORD                               105
1695           US            PHL                                72
1696           XE            EWR                                72
1697           OH            DTW                                87
1698           EV            ATL                               132
1699           B6            JFK                                80
1700           9E            DTW                                87
1701           OO            ORD                               106
```

1702	B6	JFK	84
1703	OH	JFK	94
1704	9E	DTW	83
1705	MQ	ORD	105
1706	B6	JFK	78
1707	EV	ATL	137
1708	YV	IAD	75
1709	XE	ORD	100
1710	B6	MCO	160
1711	EV	ATL	130
1712	9E	DTW	87
1713	OH	CVG	96
1714	B6	JFK	88
1715	XE	CLE	65

	FLIGHT_STATUS	month	season	WeekDay	latitude	elevation	\
1666	EARLY	3	spring	Monday	40.63915	3.4	
1667	ONTIME	3	spring	Monday	42.23130	192.3	
1668	EARLY	3	spring	Monday	41.96019	201.8	
1669	EARLY	3	spring	Monday	40.63915	3.4	
1670	LATE	3	spring	Monday	40.63915	3.4	
1671	LATE	3	spring	Monday	41.96019	201.8	
1672	ONTIME	3	spring	Monday	40.63915	3.4	
1673	EARLY	3	spring	Monday	33.63010	307.8	
1674	ONTIME	3	spring	Monday	41.40570	238.0	
1675	LATE	3	spring	Monday	38.93486	88.4	
1676	LATE	3	spring	Monday	41.96019	201.8	
1677	LATE	3	spring	Monday	28.43390	27.4	
1678	LATE	3	spring	Monday	33.63010	307.8	
1679	LATE	3	spring	Monday	42.23130	192.3	
1680	ONTIME	3	spring	Monday	39.04440	269.1	
1681	EARLY	3	spring	Monday	40.63915	3.4	
1682	LATE	3	spring	Monday	41.40570	238.0	
1683	EARLY	3	spring	Monday	40.63915	3.4	
1684	LATE	3	spring	Monday	33.63010	307.8	
1685	LATE	3	spring	Monday	40.68250	2.1	
1686	ONTIME	3	spring	Monday	41.96019	201.8	
1687	LATE	3	spring	Monday	38.93486	88.4	
1688	LATE	3	spring	Monday	35.22360	221.9	
1689	ONTIME	3	spring	Monday	42.23130	192.3	
1690	EARLY	3	spring	Monday	41.96019	201.8	
1691	LATE	3	spring	Monday	41.40570	238.0	
1692	LATE	3	spring	Monday	40.63915	3.4	
1693	EARLY	3	spring	Monday	28.43390	27.4	
1694	LATE	3	spring	Monday	41.96019	201.8	
1695	EARLY	3	spring	Monday	39.87327	3.0	
1696	LATE	3	spring	Monday	40.68250	2.1	

1697	EARLY	3	spring	Monday	42.23130	192.3
1698	ONTIME	3	spring	Monday	33.63010	307.8
1699	EARLY	3	spring	Tuesday	40.63915	3.4
1700	LATE	3	spring	Tuesday	42.23130	192.3
1701	EARLY	3	spring	Tuesday	41.96019	201.8
1702	ONTIME	3	spring	Tuesday	40.63915	3.4
1703	EARLY	3	spring	Tuesday	40.63915	3.4
1704	EARLY	3	spring	Tuesday	42.23130	192.3
1705	LATE	3	spring	Tuesday	41.96019	201.8
1706	EARLY	3	spring	Tuesday	40.63915	3.4
1707	LATE	3	spring	Tuesday	33.63010	307.8
1708	LATE	3	spring	Tuesday	38.93486	88.4
1709	EARLY	3	spring	Tuesday	41.96019	201.8
1710	LATE	3	spring	Tuesday	28.43390	27.4
1711	LATE	3	spring	Tuesday	33.63010	307.8
1712	LATE	3	spring	Tuesday	42.23130	192.3
1713	ONTIME	3	spring	Tuesday	39.04440	269.1
1714	EARLY	3	spring	Tuesday	40.63915	3.4
1715	LATE	3	spring	Tuesday	41.40570	238.0

	wind_direction	wind_speed	visibility_dist	air_temparature	\
1666	210.000000	8.545111	9.976609	37.940000	
1667	332.000000	5.816044	9.599809	35.456000	
1668	216.000000	9.439887	9.999724	33.008000	
1669	304.000000	19.103468	9.976609	36.176000	
1670	302.000000	18.835035	9.988166	36.392000	
1671	146.000000	9.663581	9.999724	31.820000	
1672	304.000000	18.611341	9.988166	36.788000	
1673	336.000000	6.710820	9.188337	30.560000	
1674	298.000000	5.368656	9.588252	34.160000	
1675	288.000000	12.616342	9.988166	39.200000	
1676	354.000000	8.724066	9.999724	30.488000	
1677	239.243002	2.684328	9.588252	47.300000	
1678	184.000000	7.158208	9.988166	33.980000	
1679	346.000000	8.276678	9.976609	34.232000	
1680	328.000000	6.487126	9.199895	34.376000	
1681	320.000000	24.203691	9.988166	41.432000	
1682	330.000000	9.842536	9.988166	36.104000	
1683	324.000000	24.651079	9.988166	42.836000	
1684	117.230769	6.934514	9.999724	39.956000	
1685	314.000000	22.145706	9.999724	44.204000	
1686	344.000000	8.008245	9.999724	31.352000	
1687	306.000000	19.998244	9.988166	44.996000	
1688	268.933096	2.057985	9.976609	44.168000	
1689	270.000000	8.500372	9.988166	38.372000	
1690	264.000000	5.950260	9.988166	33.224000	
1691	342.000000	11.542610	9.988166	35.996000	

1692	320.000000	24.606340	9.976609	47.984000
1693	148.282259	5.771305	9.988166	68.432000
1694	160.000000	8.947760	9.999724	35.132000
1695	310.000000	21.608840	9.988166	47.408000
1696	304.000000	20.266676	9.988166	47.156000
1697	332.000000	9.439887	9.988166	38.192000
1698	142.841359	1.879030	9.999724	55.184000
1699	324.000000	20.490370	9.976609	44.996000
1700	26.000000	8.276678	9.999724	26.672000
1701	339.166495	6.925095	9.986341	30.143158
1702	326.000000	8.276678	9.976609	36.572000
1703	330.000000	7.381902	9.988166	35.384000
1704	220.000000	5.279178	9.988166	27.248000
1705	350.000000	6.934514	9.999724	30.200000
1706	332.000000	6.934514	9.988166	35.384000
1707	104.000000	16.105968	6.518306	39.632000
1708	320.000000	4.071231	9.988166	36.968000
1709	344.000000	6.487126	9.988166	30.020000
1710	178.000000	15.434886	9.599809	59.972000
1711	20.000000	16.777050	1.850070	36.320000
1712	352.000000	7.829290	9.788209	29.336000
1713	24.000000	10.110969	7.400032	30.884000
1714	63.666667	9.395148	9.988166	43.232000
1715	91.777778	5.484035	8.166803	30.236000

	sea_level_pressure	SYR_wind_direction	SYR_wind_speed	\
1666	1003.380000	300.0	9.618842	
1667	1017.176569	298.0	8.052984	
1668	1021.027984	300.0	8.052984	
1669	1003.460000	300.0	8.052984	
1670	1003.180000	308.0	8.724066	
1671	1021.388574	312.0	9.171454	
1672	1003.220000	312.0	9.171454	
1673	1017.300000	320.0	9.618842	
1674	1017.859973	324.0	9.887275	
1675	1013.200000	330.0	10.110969	
1676	1022.635592	330.0	10.110969	
1677	1017.620000	336.0	10.826790	
1678	1017.780000	336.0	10.826790	
1679	1019.420000	336.0	10.826790	
1680	1019.575845	346.0	12.482125	
1681	1004.640000	346.0	12.482125	
1682	1019.632162	350.0	12.482125	
1683	1004.900000	284.0	13.376901	
1684	1017.800000	284.0	13.376901	
1685	1005.840000	352.0	12.661080	
1686	1023.540000	352.0	12.661080	

1687	1014.040000	348.0	12.437386
1688	1017.340000	348.0	12.437386
1689	1019.420000	342.0	12.437386
1690	1023.780000	336.0	12.705819
1691	1019.680000	326.0	11.497872
1692	1005.960000	330.0	11.229439
1693	1014.480000	330.0	11.229439
1694	1022.882353	330.0	11.229439
1695	1009.660000	330.0	11.229439
1696	1006.840000	328.0	10.737312
1697	1019.520000	326.0	8.947760
1698	1013.420000	326.0	8.947760
1699	1008.240000	322.0	7.829290
1700	1019.314288	280.0	6.934514
1701	1020.836264	280.0	6.263432
1702	1011.940000	280.0	6.263432
1703	1011.940000	288.0	5.368656
1704	1018.713089	290.0	5.368656
1705	1019.980000	290.0	5.368656
1706	1012.060000	290.0	5.368656
1707	1005.781262	292.0	5.592350
1708	1014.800000	308.0	5.144962
1709	1020.180000	308.0	5.144962
1710	1004.243120	312.0	4.876529
1711	1005.431706	312.0	4.876529
1712	1018.237542	312.0	4.876529
1713	1015.144890	322.0	4.160708
1714	1013.280000	322.0	4.160708
1715	1017.519681	318.0	4.608096

	SYR_visibility_dist	SYR_air_temparature	SYR_sea_level_pressure	\
1666	9.976609	35.600	1006.760000	
1667	8.199985	33.692	1008.654677	
1668	7.891287	33.548	1008.678891	
1669	7.891287	33.548	1008.678891	
1670	8.091369	33.224	1008.953368	
1671	8.091369	33.224	1009.140395	
1672	8.091369	33.224	1009.140395	
1673	8.939789	33.728	1009.959100	
1674	9.539660	34.124	1010.277330	
1675	9.739618	34.340	1010.457330	
1676	9.739618	34.340	1010.457330	
1677	9.999724	34.736	1010.737330	
1678	9.999724	34.736	1010.737330	
1679	9.999724	34.736	1010.737330	
1680	9.988166	35.600	1011.400000	
1681	9.988166	35.600	1011.400000	

1682	9.988166	35.708	1011.502695
1683	9.999724	36.104	1011.707290
1684	9.999724	36.104	1011.707290
1685	9.999724	36.032	1011.949045
1686	9.999724	36.032	1011.949045
1687	9.988166	36.104	1012.108737
1688	9.988166	36.104	1012.108737
1689	9.988166	35.816	1012.246885
1690	8.488176	35.816	1012.372678
1691	4.299887	35.204	1012.742059
1692	3.345586	34.484	1013.150324
1693	4.545577	34.160	1013.460653
1694	4.545577	34.160	1013.460653
1695	4.545577	34.160	1013.460653
1696	5.545612	33.908	1013.559273
1697	8.799980	33.872	1014.036243
1698	8.799980	33.872	1014.036243
1699	8.999938	33.872	1014.697623
1700	9.988166	32.000	1014.920000
1701	9.976609	32.000	1014.840000
1702	9.976609	32.000	1014.840000
1703	9.988166	32.216	1014.760000
1704	9.988166	32.216	1014.860000
1705	9.988166	32.216	1014.860000
1706	9.988166	32.216	1014.860000
1707	9.976609	32.216	1014.940000
1708	9.988166	32.432	1015.320000
1709	9.988166	32.432	1015.320000
1710	9.988166	32.612	1015.480000
1711	9.988166	32.612	1015.480000
1712	9.988166	32.612	1015.480000
1713	9.988166	33.620	1015.560000
1714	9.988166	33.620	1015.560000
1715	9.988166	34.412	1015.320000

	SCHED_ARRV_TIME_CAT
1666	Late Night
1667	Morning
1668	Late Morning
1669	Late Morning
1670	Late Morning
1671	Late Morning
1672	Late Morning
1673	Noon
1674	Noon
1675	Noon
1676	Noon

```
1677            Noon
1678            Noon
1679            Noon
1680       Afternoon
1681       Afternoon
1682       Afternoon
1683       Afternoon
1684       Afternoon
1685       Afternoon
1686       Afternoon
1687         Evening
1688         Evening
1689         Evening
1690         Evening
1691         Evening
1692           Night
1693           Night
1694           Night
1695           Night
1696           Night
1697           Night
1698           Night
1699      Late Night
1700         Morning
1701    Late Morning
1702    Late Morning
1703    Late Morning
1704    Late Morning
1705    Late Morning
1706    Late Morning
1707            Noon
1708            Noon
1709            Noon
1710            Noon
1711            Noon
1712            Noon
1713       Afternoon
1714       Afternoon
1715       Afternoon
```

[ ]:

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[22]:
```
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.preprocessing import OneHotEncoder

class MultiColumnOneHotEncoder(BaseEstimator, TransformerMixin):
    def __init__(self, columns=None):
        self.columns = columns
        self.encoder = None

    def fit(self, X, y=None):
        self.encoder = OneHotEncoder(sparse_output=False, drop='first')
        self.encoder.fit(X[self.columns])
        return self

    def transform(self, X):
        X_encoded = X.copy()
        encoded_data = self.encoder.transform(X[self.columns])
        encoded_df = pd.DataFrame(encoded_data, columns=self.encoder.
 ↪get_feature_names_out(self.columns), index=X.index)

        # Drop the original columns
        X_encoded = X_encoded.drop(columns=self.columns)

        # Concatenate the encoded DataFrame with the original DataFrame,␣
 ↪preserving the index
        X_encoded = pd.concat([X_encoded, encoded_df], axis=1)
        return X_encoded

    def fit_transform(self, X, y=None):
        self.fit(X)
        return self.transform(X)
```

[23]:
```
sample = df.head()
```

[24]:
```
# sample.head().drop(columns=['FLIGHT_STATUS']).to_csv("sample_input.csv",␣
 ↪index=False)
```

[25]:
```
encoder = MultiColumnOneHotEncoder(columns=['Carrier Code', 'Origin␣
 ↪Airport','season', 'SCHED_ARRV_TIME_CAT', 'month', 'WeekDay'])␣
 ↪#,'wind_type', 'ceiling_det_code', 'celing_CAVOK','visibility_variability'
```

[26]:
```
encoded_data = encoder.fit_transform(df.drop(columns=['FLIGHT_STATUS']))
```

[27]:
```
encoded_data.head()
```

[27]:
```
   Scheduled Elapsed Time (Minutes)  latitude  elevation  wind_direction  \
0                                76  40.63915        3.4      102.428571
1                                75  40.63915        3.4      110.503072
2                               100  41.96019      201.8      292.000000
3                                84  42.23130      192.3      270.000000
4                                71  40.63915        3.4      159.721841

   wind_speed  visibility_dist  air_temparature  sea_level_pressure  \
0    3.221194         6.966812           33.944         1018.725782
1    0.000000         5.400087           33.368         1015.367354
2    9.395148         9.999724            7.808         1024.780000
3   12.392648         6.599830           23.000         1018.248971
4    0.000000         4.794250           33.224         1014.594175

   SYR_wind_direction  SYR_wind_speed  …  month_9  month_10  month_11  \
0          106.000000        3.892276  …      0.0       0.0       0.0
1          103.912190        0.000000  …      0.0       0.0       0.0
2          132.389021        0.000000  …      0.0       0.0       0.0
3          144.543770        0.000000  …      0.0       0.0       0.0
4          144.543770        0.000000  …      0.0       0.0       0.0

   month_12  WeekDay_Monday  WeekDay_Saturday  WeekDay_Sunday  \
0       0.0             0.0               0.0             0.0
1       0.0             0.0               0.0             0.0
2       0.0             0.0               0.0             0.0
3       0.0             0.0               0.0             0.0
4       0.0             0.0               0.0             0.0

   WeekDay_Thursday  WeekDay_Tuesday  WeekDay_Wednesday
0               0.0              0.0                0.0
1               0.0              0.0                0.0
2               0.0              0.0                0.0
3               0.0              0.0                0.0
4               0.0              0.0                0.0

[5 rows x 83 columns]
```

[28]:
```
trainX, testX, trainY, testY = train_test_split(
    encoded_data,
    df['FLIGHT_STATUS'],
    test_size=0.2,
    random_state=947,
    stratify=df['FLIGHT_STATUS']
```

```
)
```

[29]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
enc_trainX = pd.DataFrame(scaler.fit_transform(trainX), index=trainX.index,␣
 ↪columns=trainX.columns)
enc_testX = pd.DataFrame(scaler.transform(testX), index=testX.index,␣
 ↪columns=testX.columns)
```

[30]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

def fit_and_evaluate(model, trainX, trainY, testX, testY):
    # Convert string labels to integers
    label_encoder = LabelEncoder()
    trainY_encoded = label_encoder.fit_transform(trainY)
    testY_encoded = label_encoder.transform(testY)

    model.fit(trainX, trainY_encoded)
    testY_pred = model.predict(testX)
    accuracy = accuracy_score(testY_encoded, testY_pred)
    report = classification_report(testY_encoded, testY_pred, output_dict=True)
    results = {'accuracy': accuracy, 'classification_report': report}
    return results

# Update other classification functions similarly...


# Random Forest
from sklearn.ensemble import RandomForestClassifier

def random_forest_classification(trainX, trainY, testX, testY,␣
 ↪n_estimators=100, criterion='gini', max_depth=None):
    model = RandomForestClassifier(n_estimators=n_estimators,␣
 ↪criterion=criterion, max_depth=max_depth)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# Support Vector Machines (SVM)
from sklearn.svm import SVC

def svm_classification(trainX, trainY, testX, testY, kernel='rbf', C=1.0):
    model = SVC(kernel=kernel, C=C)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# K-Nearest Neighbors (KNN)
```

```
from sklearn.neighbors import KNeighborsClassifier

def knn_classification(trainX, trainY, testX, testY, n_neighbors=5):
    model = KNeighborsClassifier(n_neighbors=n_neighbors)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# Gradient Boosting Machines (GBM)
from sklearn.ensemble import GradientBoostingClassifier

def gbm_classification(trainX, trainY, testX, testY, n_estimators=100, learning_rate=0.1, max_depth=3):
    model = GradientBoostingClassifier(n_estimators=n_estimators, learning_rate=learning_rate, max_depth=max_depth)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# Naive Bayes
from sklearn.naive_bayes import GaussianNB

def naive_bayes_classification(trainX, trainY, testX, testY):
    model = GaussianNB()
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# AdaBoost
from sklearn.ensemble import AdaBoostClassifier

def adaboost_classification(trainX, trainY, testX, testY, n_estimators=50, learning_rate=1.0):
    model = AdaBoostClassifier(n_estimators=n_estimators, learning_rate=learning_rate)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# XGBoost
from xgboost import XGBClassifier

def xgboost_classification(trainX, trainY, testX, testY, n_estimators=100, learning_rate=0.1, max_depth=3):
    model = XGBClassifier(n_estimators=n_estimators, learning_rate=learning_rate, max_depth=max_depth)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

def logistic_regression_classification(trainX, trainY, testX, testY, penalty='l2', C=1.0, max_iter=1000, solver='lbfgs'):
    target_names = trainY.unique() if isinstance(trainY, pd.Series) else testY.unique()

    # Initialize and train the Logistic Regression model
```

```
    model = LogisticRegression(penalty=penalty, C=C, max_iter=max_iter,␣
↪solver=solver, verbose=1 if max_iter > 300 else 0)
    model.fit(trainX, trainY)

    # Predict on the testing set
    testY_pred = model.predict(testX)

    # Calculate accuracy score
    accuracy = accuracy_score(testY, testY_pred)

    # Generate classification report
    report = classification_report(testY, testY_pred,␣
↪target_names=target_names, output_dict=True)

    results = {
        'accuracy': accuracy,
        'classification_report': report
    }

    return results

def decision_tree_classification(trainX, trainY, testX, testY,␣
↪criterion='gini', max_depth=None):

    # Get unique target names
    target_names = trainY.unique() if isinstance(trainY, pd.Series) else testY.
↪unique()

    # Initialize and train the Decision Tree model
    model = DecisionTreeClassifier(criterion=criterion,␣
↪max_depth=max_depth,min_samples_split=5)
    model.fit(trainX, trainY)

    # Predict on the testing set
    testY_pred = model.predict(testX)

    # Calculate accuracy score
    accuracy = accuracy_score(testY, testY_pred)

    # Generate classification report
    report = classification_report(testY, testY_pred,␣
↪target_names=target_names, output_dict=True)

    results = {
        'accuracy': accuracy,
        'classification_report': report
```

```
    }

    return results
```

[31]:
```
# logistic_regression_classification(enc_trainX, trainY, enc_testX, testY,␣
↪solver='saga', max_iter=1500, C=50)
```

[32]:
```
# decision_tree_classification(enc_trainX, trainY, enc_testX, testY,␣
↪max_depth=11, criterion='entropy')
```

[33]:
```
# random_forest_classification(enc_trainX, trainY, enc_testX, testY)
```

[34]:
```
# knn_classification(enc_trainX, trainY, enc_testX, testY)
```

[35]:
```
# gbm_classification(enc_trainX, trainY, enc_testX, testY)
```

[36]:
```
# naive_bayes_classification(enc_trainX, trainY, enc_testX, testY)
```

[37]:
```
# adaboost_classification(enc_trainX, trainY, enc_testX, testY)
```

[38]:
```
# xgboost_classification(enc_trainX, trainY, enc_testX, testY)
```

[39]:
```
from sklearn.model_selection import GridSearchCV, KFold
def hyperparameter_tuning(model, param_grid, trainX, trainY, cv=5):
    label_encoder = LabelEncoder()
    trainY_encoded = label_encoder.fit_transform(trainY)
    # Initialize K-Fold cross-validator
    kf = KFold(n_splits=cv, shuffle=True, random_state=42)

    # Perform grid search
    grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=kf,␣
↪scoring='accuracy', verbose=3, n_jobs=10, )
    grid_search.fit(trainX, trainY_encoded)

    return grid_search
```

[40]:
```
params = {'colsample_bytree': 0.7, 'gamma': 0.1, 'learning_rate': 0.1,␣
↪'max_depth': 7, 'n_estimators': 200, 'reg_lambda': 1.5, 'subsample': 0.9}
# param_grid = {
#     'n_estimators': [100, 200],  # Number of boosting rounds
#     'max_depth': [3, 5, 7, 11],  # Maximum tree depth
#     'learning_rate': [0.01, 0.1, 0.3],  # Step size shrinkage
#     'subsample': [0.7, 0.9],  # Subsample ratio of the training instances
#     'colsample_bytree': [0.7, 0.9],  # Subsample ratio of columns when␣
↪constructing each tree
```

```
#     'gamma': [0, 0.1],  # Minimum loss reduction required to make a further␣
↪partition on a leaf node of the tree
#     'reg_lambda': [1, 1.5, 2]  # L2 regularization term on weights
# }
# model = XGBClassifier(**params)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# # fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[41]:
```
params =  {'bootstrap': False, 'criterion': 'entropy', 'max_depth': None,␣
↪'max_features': 'sqrt', 'min_samples_leaf': 4, 'min_samples_split': 2,␣
↪'n_estimators': 200}
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt'],
    'bootstrap': [True, False],
    'criterion': ['gini', 'entropy']
}
# model = RandomForestClassifier(**params)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[42]:
```
params = {'algorithm': 'SAMME.R', 'learning_rate': 1.0, 'n_estimators': 200}
param_grid = {
    'n_estimators': [50, 100, 200],  # Number of estimators
    'learning_rate': [0.01, 0.1, 1.0],  # Learning rate
    'algorithm': ['SAMME', 'SAMME.R'],  # Algorithm
}

# model = AdaBoostClassifier(**params)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# # Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[43]:
```
params =  {'ccp_alpha': 0.07, 'criterion': 'gini', 'max_depth': None,␣
↪'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 2,␣
↪'splitter': 'best'}
```

```
param_grid = {
    'criterion': ['gini', 'entropy'],  # Split criterion
    'splitter': ['best', 'random'],  # Strategy to choose split at each node
    'max_depth': [None, 1, 3, 5],  # Max depth of the tree
    'min_samples_split': [2, 5, 10],  # Min samples required to split a node
    'min_samples_leaf': [1, 2, 4],  # Min samples required at each leaf node
    'max_features': ['sqrt', 'log2'],  # Max features to consider for split
    'ccp_alpha':[0.07,0.01]
}

# model = DecisionTreeClassifier(**params)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# # Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[44]:
```
# {'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 200}
gbm_params = {
    'learning_rate': [0.01, 0.05, 0.1],  # Learning rate
    'n_estimators': [50, 100, 200],  # Number of boosting stages
    'max_depth': [3, 4, 5],  # Maximum depth of the individual trees
}
# model = GradientBoostingClassifier()
# best_model = hyperparameter_tuning(model, gbm_params, enc_trainX, trainY)
# Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[45]:
```
%%time
from sklearn.ensemble import VotingClassifier

lr = LogisticRegression(penalty='l2', C=50, max_iter=1500, solver='saga')
ada = AdaBoostClassifier(**{'algorithm': 'SAMME.R', 'learning_rate': 1.0,␣
 ↪'n_estimators': 200})
gbm = GradientBoostingClassifier(**{'learning_rate': 0.1, 'max_depth': 5,␣
 ↪'n_estimators': 200})
rf = RandomForestClassifier(** {'bootstrap': False, 'criterion': 'entropy',␣
 ↪'max_depth': None, 'max_features': 'sqrt', 'min_samples_leaf': 4,␣
 ↪'min_samples_split': 2, 'n_estimators': 200})
xgb = XGBClassifier(**{'colsample_bytree': 0.7, 'gamma': 0.1, 'learning_rate':␣
 ↪0.1, 'max_depth': 7, 'n_estimators': 200, 'reg_lambda': 1.5, 'subsample': 0.
 ↪9},objective='multi:softprob')

# res = fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
```

```python
votingCLF = VotingClassifier(
    estimators=[
        ('rf', rf),
        ('ada', ada),
        ('xgb', xgb),
        ('lr', lr),
        ('gbm', gbm)
    ],
    voting='soft',
    weights=[
        4,
        5,
        7,
        2,
        6]
)
fit_and_evaluate(votingCLF, enc_trainX, trainY, enc_testX, testY)
```

```
/home/numan947/anaconda3/envs/mldl/lib/python3.9/site-
packages/sklearn/ensemble/_weight_boosting.py:519: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMME
algorithm to circumvent this warning.
  warnings.warn(
```

```
CPU times: user 6min 51s, sys: 1.77 s, total: 6min 53s
Wall time: 5min 50s
```

[45]:
```
{'accuracy': 0.535385968770618,
 'classification_report': {'0': {'precision': 0.5512946373788195,
   'recall': 0.8599732006125574,
   'f1-score': 0.671876168399013,
   'support': 10448.0},
  '1': {'precision': 0.49964726631393297,
   'recall': 0.4152741131632952,
   'f1-score': 0.4535702849823887,
   'support': 6822.0},
  '2': {'precision': 0.46153846153846156,
   'recall': 0.06477584629460201,
   'f1-score': 0.11360718870346598,
   'support': 5465.0},
  'accuracy': 0.535385968770618,
  'macro avg': {'precision': 0.504160121743738,
   'recall': 0.4466743866901515,
   'f1-score': 0.4130178806949559,
   'support': 22735.0},
  'weighted avg': {'precision': 0.5142215840965582,
   'recall': 0.535385968770618,
   'f1-score': 0.4721742677742329,
```

```
'support': 22735.0}}}
```

INPUT = encoded_data TARGET=df['FLIGHT_STATUS'] label_encoder = LabelEncoder() TARGET_ENCODED = label_encoder.fit_transform(TARGET)

from sklearn.preprocessing import StandardScaler scaler = StandardScaler() enc_trainX = pd.DataFrame(scaler.fit_transform(encoded_data), index=encoded_data.index, columns=encoded_data.columns)

votingCLF.fit(enc_trainX, TARGET_ENCODED)

enc_trainX.shape

initi_first_task = pd.read_csv(".∕sample_input_first_task.csv")

initial_first_task_data = scaler.transform(encoder.transform(initi_first_task))

initial_first_task_data.shape

votingCLF.predict(initial_first_task_data)

label_encoder.inverse_transform(votingCLF.predict(initial_first_task_data))

initi_first_task = pd.read_csv(".∕final_input_first.csv")

initial_first_task_data = scaler.transform(encoder.transform(initi_first_task))

initial_first_task_data.shape

votingCLF.predict(initial_first_task_data)

label_encoder.inverse_transform(votingCLF.predict(initial_first_task_data))

[ ]:

[ ]:

[ ]:

[ ]:

1 2nd Model

[46]:
```
data1 = pd.read_csv("./SYR_ORIGIN_1HOP.csv")
data2 = pd.read_csv("./SYR_ORIGIN_2HOP.csv")
data3 = pd.read_csv("./SYR_ORIGIN_3HOP.csv")
```

[47]:
```
data1['SCHED_ARRV_TIME_CAT'] = data1['Scheduled Arrival Time'].
 ↪apply(convert_to_categorical)
data2['SCHED_ARRV_TIME_CAT'] = data2['Scheduled Arrival Time'].
 ↪apply(convert_to_categorical)
data3['SCHED_ARRV_TIME_CAT'] = data3['Scheduled Arrival Time'].
 ↪apply(convert_to_categorical)
```

[48]:
```
data1['SYR_sea_level_pressure'] = data1['SYR_sea_level_pressure'].
    ↪fillna(data1['SYR_sea_level_pressure'].mean())
data2['SYR_sea_level_pressure'] = data2['SYR_sea_level_pressure'].
    ↪fillna(data2['SYR_sea_level_pressure'].mean())
data3['SYR_sea_level_pressure'] = data3['SYR_sea_level_pressure'].
    ↪fillna(data3['SYR_sea_level_pressure'].mean())
```

[49]:
```
def convert(df):
    df['SYR_wind_speed'] = df['SYR_wind_speed'].apply(mps_to_mph)
    df['wind_speed'] = df['wind_speed'].apply(mps_to_mph)
    df['visibility_dist'] = df['visibility_dist'].apply(meters_to_miles)
    df['SYR_visibility_dist'] = df['SYR_visibility_dist'].apply(meters_to_miles)
    df['air_temparature'] = df['air_temparature'].apply(celsius_to_fahrenheit)
    df['SYR_air_temparature'] = df['SYR_air_temparature'].
    ↪apply(celsius_to_fahrenheit)
    df['sea_level_pressure'] = df['sea_level_pressure'].apply(hectopascal_to_mb)
    df['SYR_sea_level_pressure'] = df['SYR_sea_level_pressure'].
    ↪apply(hectopascal_to_mb)
    return df
```

[50]:
```
data1 = convert(data1)
data2 = convert(data2)
data3 = convert(data3)
```

[51]:
```
data1.shape
```

[51]: (113671, 42)

[52]:
```
data2.shape
```

[52]: (227342, 42)

[53]:
```
data3.shape
```

[53]: (341013, 42)

[54]:
```
cols_to_drop = ['Date (MM/DD/YYYY)', 'Scheduled Arrival Time','day',␣
    ↪'UNIX_DATE','UNIX_TIMESTAMP',
                        'longitude','dew_point_temparature',␣
    ↪'wind_type','ceiling_height', 'ceiling_det_code',␣
    ↪'celing_CAVOK','visibility_variability',
                        'SYR_longitude',
        'SYR_wind_type','SYR_ceiling_height', 'SYR_ceiling_det_code',␣
    ↪'SYR_celing_CAVOK', 'SYR_visibility_variability',␣
    ↪'SYR_dew_point_temparature','SYR_latitude','SYR_elevation']
```

```
[55]: df1 = data1.drop(columns=cols_to_drop)
      df2 = data2.drop(columns=cols_to_drop)
      df3 = data3.drop(columns=cols_to_drop)
```

```
[56]: df1.shape, df2.shape, df3.shape
```

```
[56]: ((113671, 21), (227342, 21), (341013, 21))
```

```
[57]: from sklearn.base import BaseEstimator, TransformerMixin
      from sklearn.preprocessing import OneHotEncoder

      class MultiColumnOneHotEncoder(BaseEstimator, TransformerMixin):
          def __init__(self, columns=None):
              self.columns = columns
              self.encoder = None

          def fit(self, X, y=None):
              self.encoder = OneHotEncoder(sparse_output=False, drop='first')
              self.encoder.fit(X[self.columns])
              return self

          def transform(self, X):
              X_encoded = X.copy()
              encoded_data = self.encoder.transform(X[self.columns])
              encoded_df = pd.DataFrame(encoded_data, columns=self.encoder.
       ↪get_feature_names_out(self.columns), index=X.index)

              # Drop the original columns
              X_encoded = X_encoded.drop(columns=self.columns)

              # Concatenate the encoded DataFrame with the original DataFrame,␣
       ↪preserving the index
              X_encoded = pd.concat([X_encoded, encoded_df], axis=1)
              return X_encoded

          def fit_transform(self, X, y=None):
              self.fit(X)
              return self.transform(X)
```

1.1 START 1 HOP

```
[58]: encoder = MultiColumnOneHotEncoder(columns=['Carrier Code', 'Origin␣
       ↪Airport','season', 'SCHED_ARRV_TIME_CAT', 'month', 'WeekDay','PREV_STAT'])␣
       ↪#,'wind_type', 'ceiling_det_code', 'celing_CAVOK','visibility_variability'
```

```
[59]: encoded_data = encoder.fit_transform(df1.drop(columns=['FLIGHT_STATUS']))
```

[60]:
```
encoded_data.head()
```

[60]:
```
   Scheduled Elapsed Time (Minutes)  latitude  elevation  wind_direction  \
0                                76  40.63915        3.4      102.428571
1                                75  40.63915        3.4      110.503072
2                               100  41.96019      201.8      292.000000
3                                84  42.23130      192.3      270.000000
4                                71  40.63915        3.4      159.721841

   wind_speed  visibility_dist  air_temparature  sea_level_pressure  \
0    3.221194         6.966812           33.944         1018.725782
1    0.000000         5.400087           33.368         1015.367354
2    9.395148         9.999724            7.808         1024.780000
3   12.392648         6.599830           23.000         1018.248971
4    0.000000         4.794250           33.224         1014.594175

   SYR_wind_direction  SYR_wind_speed  …  month_11  month_12  \
0          106.000000        3.892276  …       0.0       0.0
1          103.912190        0.000000  …       0.0       0.0
2          132.389021        0.000000  …       0.0       0.0
3          144.543770        0.000000  …       0.0       0.0
4          144.543770        0.000000  …       0.0       0.0

   WeekDay_Monday  WeekDay_Saturday  WeekDay_Sunday  WeekDay_Thursday  \
0             0.0               0.0             0.0               0.0
1             0.0               0.0             0.0               0.0
2             0.0               0.0             0.0               0.0
3             0.0               0.0             0.0               0.0
4             0.0               0.0             0.0               0.0

   WeekDay_Tuesday  WeekDay_Wednesday  PREV_STAT_LATE  PREV_STAT_ONTIME
0              0.0                0.0             0.0               1.0
1              0.0                0.0             1.0               0.0
2              0.0                0.0             1.0               0.0
3              0.0                0.0             0.0               1.0
4              0.0                0.0             1.0               0.0

[5 rows x 85 columns]
```

[61]:
```
df1.shape
```

[61]: (113671, 21)

[62]:
```
trainX, testX, trainY, testY = train_test_split(
    encoded_data,
    df1['FLIGHT_STATUS'],
    test_size=0.2,
```

```
    random_state=947,
    stratify=df1['FLIGHT_STATUS']
)
```

[63]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
enc_trainX = pd.DataFrame(scaler.fit_transform(trainX), index=trainX.index,␣
 ↪columns=trainX.columns)
enc_testX = pd.DataFrame(scaler.transform(testX), index=testX.index,␣
 ↪columns=testX.columns)
```

[64]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

def fit_and_evaluate(model, trainX, trainY, testX, testY):
    # Convert string labels to integers
    label_encoder = LabelEncoder()
    trainY_encoded = label_encoder.fit_transform(trainY)
    testY_encoded = label_encoder.transform(testY)

    model.fit(trainX, trainY_encoded)
    testY_pred = model.predict(testX)
    accuracy = accuracy_score(testY_encoded, testY_pred)
    report = classification_report(testY_encoded, testY_pred, output_dict=True)
    results = {'accuracy': accuracy, 'classification_report': report}
    return results

# Update other classification functions similarly...


# Random Forest
from sklearn.ensemble import RandomForestClassifier

def random_forest_classification(trainX, trainY, testX, testY,␣
 ↪n_estimators=100, criterion='gini', max_depth=None):
    model = RandomForestClassifier(n_estimators=n_estimators,␣
 ↪criterion=criterion, max_depth=max_depth)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# Support Vector Machines (SVM)
from sklearn.svm import SVC

def svm_classification(trainX, trainY, testX, testY, kernel='rbf', C=1.0):
    model = SVC(kernel=kernel, C=C)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)
```

```python
# K-Nearest Neighbors (KNN)
from sklearn.neighbors import KNeighborsClassifier

def knn_classification(trainX, trainY, testX, testY, n_neighbors=5):
    model = KNeighborsClassifier(n_neighbors=n_neighbors)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# Gradient Boosting Machines (GBM)
from sklearn.ensemble import GradientBoostingClassifier

def gbm_classification(trainX, trainY, testX, testY, n_estimators=100,␣
 ↪learning_rate=0.1, max_depth=3):
    model = GradientBoostingClassifier(n_estimators=n_estimators,␣
 ↪learning_rate=learning_rate, max_depth=max_depth)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# Naive Bayes
from sklearn.naive_bayes import GaussianNB

def naive_bayes_classification(trainX, trainY, testX, testY):
    model = GaussianNB()
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# AdaBoost
from sklearn.ensemble import AdaBoostClassifier

def adaboost_classification(trainX, trainY, testX, testY, n_estimators=50,␣
 ↪learning_rate=1.0):
    model = AdaBoostClassifier(n_estimators=n_estimators,␣
 ↪learning_rate=learning_rate)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# XGBoost
from xgboost import XGBClassifier

def xgboost_classification(trainX, trainY, testX, testY, n_estimators=100,␣
 ↪learning_rate=0.1, max_depth=3):
    model = XGBClassifier(n_estimators=n_estimators,␣
 ↪learning_rate=learning_rate, max_depth=max_depth)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

def logistic_regression_classification(trainX, trainY, testX, testY,␣
 ↪penalty='l2', C=1.0, max_iter=1000, solver='lbfgs'):
    target_names = trainY.unique() if isinstance(trainY, pd.Series) else testY.
 ↪unique()
```

```
    # Initialize and train the Logistic Regression model
    model = LogisticRegression(penalty=penalty, C=C, max_iter=max_iter,␣
↪solver=solver, verbose=1 if max_iter > 300 else 0)
    model.fit(trainX, trainY)

    # Predict on the testing set
    testY_pred = model.predict(testX)

    # Calculate accuracy score
    accuracy = accuracy_score(testY, testY_pred)

    # Generate classification report
    report = classification_report(testY, testY_pred,␣
↪target_names=target_names, output_dict=True)

    results = {
        'accuracy': accuracy,
        'classification_report': report
    }

    return results

def decision_tree_classification(trainX, trainY, testX, testY,␣
↪criterion='gini', max_depth=None):

    # Get unique target names
    target_names = trainY.unique() if isinstance(trainY, pd.Series) else testY.
↪unique()

    # Initialize and train the Decision Tree model
    model = DecisionTreeClassifier(criterion=criterion,␣
↪max_depth=max_depth,min_samples_split=5)
    model.fit(trainX, trainY)

    # Predict on the testing set
    testY_pred = model.predict(testX)

    # Calculate accuracy score
    accuracy = accuracy_score(testY, testY_pred)

    # Generate classification report
    report = classification_report(testY, testY_pred,␣
↪target_names=target_names, output_dict=True)

    results = {
```

```
        'accuracy': accuracy,
        'classification_report': report
    }

    return results
```

logistic_regression_classification(enc_trainX, trainY, enc_testX, testY, solver='saga', max_iter=1500, C=50)

decision_tree_classification(enc_trainX, trainY, enc_testX, testY, max_depth=11, criterion='entropy')

random_forest_classification(enc_trainX, trainY, enc_testX, testY)

knn_classification(enc_trainX, trainY, enc_testX, testY)

gbm_classification(enc_trainX, trainY, enc_testX, testY)

naive_bayes_classification(enc_trainX, trainY, enc_testX, testY)

adaboost_classification(enc_trainX, trainY, enc_testX, testY)

xgboost_classification(enc_trainX, trainY, enc_testX, testY)

[65]:
```
from sklearn.model_selection import GridSearchCV, KFold
def hyperparameter_tuning(model, param_grid, trainX, trainY, cv=5):
    label_encoder = LabelEncoder()
    trainY_encoded = label_encoder.fit_transform(trainY)
    # Initialize K-Fold cross-validator
    kf = KFold(n_splits=cv, shuffle=True, random_state=42)

    # Perform grid search
    grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=kf,␣
↪scoring='accuracy', verbose=3, n_jobs=10, )
    grid_search.fit(trainX, trainY_encoded)

    return grid_search
```

[66]:
```
params = {'colsample_bytree': 0.7, 'gamma': 0.1, 'learning_rate': 0.1,␣
↪'max_depth': 7, 'n_estimators': 200, 'reg_lambda': 1.5, 'subsample': 0.9}
# param_grid = {
#     'n_estimators': [100, 200],  # Number of boosting rounds
#     'max_depth': [3, 5, 7, 11],  # Maximum tree depth
#     'learning_rate': [0.01, 0.1, 0.3],  # Step size shrinkage
#     'subsample': [0.7, 0.9],  # Subsample ratio of the training instances
#     'colsample_bytree': [0.7, 0.9],  # Subsample ratio of columns when␣
↪constructing each tree
#     'gamma': [0, 0.1],  # Minimum loss reduction required to make a further␣
↪partition on a leaf node of the tree
#     'reg_lambda': [1, 1.5, 2]  # L2 regularization term on weights
```

```
# }
# model = XGBClassifier(**params)
# # best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[67]:
```
params =  {'bootstrap': False, 'criterion': 'entropy', 'max_depth': None,␣
↪'max_features': 'sqrt', 'min_samples_leaf': 4, 'min_samples_split': 2,␣
↪'n_estimators': 200}
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt'],
    'bootstrap': [True, False],
    'criterion': ['gini', 'entropy']
}
# model = RandomForestClassifier(**params)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[68]:
```
params = {'algorithm': 'SAMME.R', 'learning_rate': 1.0, 'n_estimators': 200}
param_grid = {
    'n_estimators': [50, 100, 200],  # Number of estimators
    'learning_rate': [0.01, 0.1, 1.0],  # Learning rate
    'algorithm': ['SAMME', 'SAMME.R'],  # Algorithm
}

# model = AdaBoostClassifier(**params)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# # Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[69]:
```
params =  {'ccp_alpha': 0.07, 'criterion': 'gini', 'max_depth': None,␣
↪'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 2,␣
↪'splitter': 'best'}

param_grid = {
    'criterion': ['gini', 'entropy'],  # Split criterion
```

```
    'splitter': ['best', 'random'],  # Strategy to choose split at each node
    'max_depth': [None, 1, 3, 5],  # Max depth of the tree
    'min_samples_split': [2, 5, 10],  # Min samples required to split a node
    'min_samples_leaf': [1, 2, 4],  # Min samples required at each leaf node
    'max_features': ['sqrt', 'log2'],  # Max features to consider for split
    'ccp_alpha':[0.07,0.01]
}

# model = DecisionTreeClassifier(**params)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# # Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[70]:
```
gbm_params = {
    'learning_rate': [0.01, 0.05, 0.1],  # Learning rate
    'n_estimators': [50, 100, 200],  # Number of boosting stages
    'max_depth': [3, 4, 5],  # Maximum depth of the individual trees
}
# model = GradientBoostingClassifier()
# best_model = hyperparameter_tuning(model, gbm_params, enc_trainX, trainY)
# # Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[71]:
```
enc_trainX.shape
```

[71]: (90936, 85)

[72]:
```
%%time
from sklearn.ensemble import VotingClassifier

lr = LogisticRegression(penalty='l2', C=50, max_iter=1500, solver='saga')
ada = AdaBoostClassifier(**{'algorithm': 'SAMME.R', 'learning_rate': 1.0,␣
↪'n_estimators': 200})
gbm = GradientBoostingClassifier(**{'learning_rate': 0.1, 'max_depth': 5,␣
↪'n_estimators': 200})
rf = RandomForestClassifier(** {'bootstrap': False, 'criterion': 'entropy',␣
↪'max_depth': None, 'max_features': 'sqrt', 'min_samples_leaf': 4,␣
↪'min_samples_split': 2, 'n_estimators': 200})
xgb = XGBClassifier(**{'colsample_bytree': 0.7, 'gamma': 0.1, 'learning_rate':␣
↪0.1, 'max_depth': 7, 'n_estimators': 200, 'reg_lambda': 1.5, 'subsample': 0.
↪9},objective='multi:softprob')

# res = fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
```

```python
votingCLF = VotingClassifier(
    estimators=[
        ('rf', rf),
        ('ada', ada),
        ('xgb', xgb),
        ('lr', lr),
        ('gbm', gbm)
    ],
    voting='soft',
    weights=[4,5,7,2, 6]
)
fit_and_evaluate(votingCLF, enc_trainX, trainY, enc_testX, testY)
```

```
/home/numan947/anaconda3/envs/mldl/lib/python3.9/site-
packages/sklearn/ensemble/_weight_boosting.py:519: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMME
algorithm to circumvent this warning.
  warnings.warn(
```

```
CPU times: user 6min 7s, sys: 1.28 s, total: 6min 9s
Wall time: 5min 34s
```

[72]:

```
{'accuracy': 0.53512205850011,
 'classification_report': {'0': {'precision': 0.5523692307692307,
   'recall': 0.8591117917304747,
   'f1-score': 0.6724099183459435,
   'support': 10448.0},
  '1': {'precision': 0.4978954752718344,
   'recall': 0.41615362063910877,
   'f1-score': 0.45336953050143725,
   'support': 6822.0},
  '2': {'precision': 0.4482758620689655,
   'recall': 0.06422689844464775,
   'f1-score': 0.11235595390524968,
   'support': 5465.0},
  'accuracy': 0.53512205850011,
  'macro avg': {'precision': 0.49951352270334354,
   'recall': 0.44649743693807703,
   'f1-score': 0.41271180091754345,
   'support': 22735.0},
  'weighted avg': {'precision': 0.5110017260430294,
   'recall': 0.53512205850011,
   'f1-score': 0.4720585463844914,
   'support': 22735.0}}}
```

[ ]:

final = pd.read_csv(“./sample_input_2nd_task.csv”)

final_data = scaler.transform(encoder.transform(final))

final_data.shape

votingCLF.predict(final_data)

label_encoder = LabelEncoder() trainY_encoded = label_encoder.fit_transform(trainY)

label_encoder.inverse_transform(votingCLF.predict(final_data))

[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

1.2 START 2 HOP

[73]:
```
encoder = MultiColumnOneHotEncoder(columns=['Carrier Code', 'Origin␣
↪Airport','season', 'SCHED_ARRV_TIME_CAT', 'month', 'WeekDay','PREV_STAT'])␣
↪#,'wind_type', 'ceiling_det_code', 'celing_CAVOK','visibility_variability'
```

[74]:
```
encoded_data = encoder.fit_transform(df2.drop(columns=['FLIGHT_STATUS']))
```

[75]:
```
encoded_data.head()
```

[75]:
```
   Scheduled Elapsed Time (Minutes)  latitude  elevation  wind_direction  \
0                                76  40.63915        3.4      102.428571
1                                76  40.63915        3.4      102.428571
2                                75  40.63915        3.4      110.503072
3                                75  40.63915        3.4      110.503072
4                               100  41.96019      201.8      292.000000

   wind_speed  visibility_dist  air_temparature  sea_level_pressure  \
0    3.221194         6.966812           33.944         1018.725782
1    3.221194         6.966812           33.944         1018.725782
2    0.000000         5.400087           33.368         1015.367354
3    0.000000         5.400087           33.368         1015.367354
4    9.395148         9.999724            7.808         1024.780000

   SYR_wind_direction  SYR_wind_speed  …  month_11  month_12  \
0          106.000000        3.892276  …       0.0       0.0
1          106.000000        3.892276  …       0.0       0.0
2          103.912190        0.000000  …       0.0       0.0
3          103.912190        0.000000  …       0.0       0.0
```

```
4         132.389021        0.000000  …       0.0       0.0

   WeekDay_Monday  WeekDay_Saturday  WeekDay_Sunday  WeekDay_Thursday  \
0             0.0               0.0             0.0               0.0
1             0.0               0.0             0.0               0.0
2             0.0               0.0             0.0               0.0
3             0.0               0.0             0.0               0.0
4             0.0               0.0             0.0               0.0

   WeekDay_Tuesday  WeekDay_Wednesday  PREV_STAT_LATE  PREV_STAT_ONTIME
0              0.0                0.0             0.0               1.0
1              0.0                0.0             0.0               1.0
2              0.0                0.0             1.0               0.0
3              0.0                0.0             0.0               1.0
4              0.0                0.0             1.0               0.0

[5 rows x 85 columns]
```

[76]:
```
encoded_data.shape
```

[76]: (227342, 85)

[77]:
```
trainX, testX, trainY, testY = train_test_split(
    encoded_data,
    df2['FLIGHT_STATUS'],
    test_size=0.2,
    random_state=947,
    stratify=df2['FLIGHT_STATUS']
)
```

[78]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
enc_trainX = pd.DataFrame(scaler.fit_transform(trainX), index=trainX.index,
 ↪columns=trainX.columns)
enc_testX = pd.DataFrame(scaler.transform(testX), index=testX.index,
 ↪columns=testX.columns)
```

[79]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

def fit_and_evaluate(model, trainX, trainY, testX, testY):
    # Convert string labels to integers
    label_encoder = LabelEncoder()
    trainY_encoded = label_encoder.fit_transform(trainY)
    testY_encoded = label_encoder.transform(testY)
```

```python
    model.fit(trainX, trainY_encoded)
    testY_pred = model.predict(testX)
    accuracy = accuracy_score(testY_encoded, testY_pred)
    report = classification_report(testY_encoded, testY_pred, output_dict=True)
    results = {'accuracy': accuracy, 'classification_report': report}
    return results

# Update other classification functions similarly...


# Random Forest
from sklearn.ensemble import RandomForestClassifier

def random_forest_classification(trainX, trainY, testX, testY,
 ↪n_estimators=100, criterion='gini', max_depth=None):
    model = RandomForestClassifier(n_estimators=n_estimators,
 ↪criterion=criterion, max_depth=max_depth)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# Support Vector Machines (SVM)
from sklearn.svm import SVC

def svm_classification(trainX, trainY, testX, testY, kernel='rbf', C=1.0):
    model = SVC(kernel=kernel, C=C)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# K-Nearest Neighbors (KNN)
from sklearn.neighbors import KNeighborsClassifier

def knn_classification(trainX, trainY, testX, testY, n_neighbors=5):
    model = KNeighborsClassifier(n_neighbors=n_neighbors)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# Gradient Boosting Machines (GBM)
from sklearn.ensemble import GradientBoostingClassifier

def gbm_classification(trainX, trainY, testX, testY, n_estimators=100,
 ↪learning_rate=0.1, max_depth=3):
    model = GradientBoostingClassifier(n_estimators=n_estimators,
 ↪learning_rate=learning_rate, max_depth=max_depth)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# Naive Bayes
from sklearn.naive_bayes import GaussianNB

def naive_bayes_classification(trainX, trainY, testX, testY):
```

```
    model = GaussianNB()
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# AdaBoost
from sklearn.ensemble import AdaBoostClassifier

def adaboost_classification(trainX, trainY, testX, testY, n_estimators=50,␣
 ↪learning_rate=1.0):
    model = AdaBoostClassifier(n_estimators=n_estimators,␣
 ↪learning_rate=learning_rate)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# XGBoost
from xgboost import XGBClassifier

def xgboost_classification(trainX, trainY, testX, testY, n_estimators=100,␣
 ↪learning_rate=0.1, max_depth=3):
    model = XGBClassifier(n_estimators=n_estimators,␣
 ↪learning_rate=learning_rate, max_depth=max_depth)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

def logistic_regression_classification(trainX, trainY, testX, testY,␣
 ↪penalty='l2', C=1.0, max_iter=1000, solver='lbfgs'):
    target_names = trainY.unique() if isinstance(trainY, pd.Series) else testY.
 ↪unique()

    # Initialize and train the Logistic Regression model
    model = LogisticRegression(penalty=penalty, C=C, max_iter=max_iter,␣
 ↪solver=solver, verbose=1 if max_iter > 300 else 0)
    model.fit(trainX, trainY)

    # Predict on the testing set
    testY_pred = model.predict(testX)

    # Calculate accuracy score
    accuracy = accuracy_score(testY, testY_pred)

    # Generate classification report
    report = classification_report(testY, testY_pred,␣
 ↪target_names=target_names, output_dict=True)

    results = {
        'accuracy': accuracy,
        'classification_report': report
    }
```

```
    return results

def decision_tree_classification(trainX, trainY, testX, testY,␣
↪criterion='gini', max_depth=None):

    # Get unique target names
    target_names = trainY.unique() if isinstance(trainY, pd.Series) else testY.
↪unique()

    # Initialize and train the Decision Tree model
    model = DecisionTreeClassifier(criterion=criterion,␣
↪max_depth=max_depth,min_samples_split=5)
    model.fit(trainX, trainY)

    # Predict on the testing set
    testY_pred = model.predict(testX)

    # Calculate accuracy score
    accuracy = accuracy_score(testY, testY_pred)

    # Generate classification report
    report = classification_report(testY, testY_pred,␣
↪target_names=target_names, output_dict=True)

    results = {
        'accuracy': accuracy,
        'classification_report': report
    }

    return results
```

[80]:
```
# logistic_regression_classification(enc_trainX, trainY, enc_testX, testY,␣
↪solver='saga', max_iter=1500, C=50)
```

[81]:
```
# decision_tree_classification(enc_trainX, trainY, enc_testX, testY,␣
↪max_depth=11, criterion='entropy')
```

[82]:
```
# random_forest_classification(enc_trainX, trainY, enc_testX, testY)
```

[83]:
```
# knn_classification(enc_trainX, trainY, enc_testX, testY)
```

[84]:
```
# gbm_classification(enc_trainX, trainY, enc_testX, testY)
```

[85]:
```
# naive_bayes_classification(enc_trainX, trainY, enc_testX, testY)
```

[86]:
```
# adaboost_classification(enc_trainX, trainY, enc_testX, testY)
```

[87]:
```
# xgboost_classification(enc_trainX, trainY, enc_testX, testY)
```

[88]:
```
from sklearn.model_selection import GridSearchCV, KFold
def hyperparameter_tuning(model, param_grid, trainX, trainY, cv=5):
    label_encoder = LabelEncoder()
    trainY_encoded = label_encoder.fit_transform(trainY)
    # Initialize K-Fold cross-validator
    kf = KFold(n_splits=cv, shuffle=True, random_state=42)

    # Perform grid search
    grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=kf,␣
 ↪scoring='accuracy', verbose=3, n_jobs=10, )
    grid_search.fit(trainX, trainY_encoded)

    return grid_search
```

[89]:
```
params = {'colsample_bytree': 0.7, 'gamma': 0.1, 'learning_rate': 0.1,␣
 ↪'max_depth': 7, 'n_estimators': 200, 'reg_lambda': 1.5, 'subsample': 0.9}
# param_grid = {
#     'n_estimators': [100, 200],  # Number of boosting rounds
#     'max_depth': [3, 5, 7, 11],  # Maximum tree depth
#     'learning_rate': [0.01, 0.1, 0.3],  # Step size shrinkage
#     'subsample': [0.7, 0.9],  # Subsample ratio of the training instances
#     'colsample_bytree': [0.7, 0.9],  # Subsample ratio of columns when␣
 ↪constructing each tree
#     'gamma': [0, 0.1],  # Minimum loss reduction required to make a further␣
 ↪partition on a leaf node of the tree
#     'reg_lambda': [1, 1.5, 2]  # L2 regularization term on weights
# }
# model = XGBClassifier(**params)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[90]:
```
params =  {'bootstrap': False, 'criterion': 'entropy', 'max_depth': None,␣
 ↪'max_features': 'sqrt', 'min_samples_leaf': 4, 'min_samples_split': 2,␣
 ↪'n_estimators': 200}
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt'],
    'bootstrap': [True, False],
    'criterion': ['gini', 'entropy']
```

```
}
# model = RandomForestClassifier(**params)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[91]:
```
params = {'algorithm': 'SAMME.R', 'learning_rate': 1.0, 'n_estimators': 200}
param_grid = {
    'n_estimators': [50, 100, 200],  # Number of estimators
    'learning_rate': [0.01, 0.1, 1.0],  # Learning rate
    'algorithm': ['SAMME', 'SAMME.R'],  # Algorithm
}

# model = AdaBoostClassifier(**params)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# # Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[92]:
```
params =  {'ccp_alpha': 0.07, 'criterion': 'gini', 'max_depth': None,␣
↪'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 2,␣
↪'splitter': 'best'}

param_grid = {
    'criterion': ['gini', 'entropy'],  # Split criterion
    'splitter': ['best', 'random'],  # Strategy to choose split at each node
    'max_depth': [None, 1, 3, 5],  # Max depth of the tree
    'min_samples_split': [2, 5, 10],  # Min samples required to split a node
    'min_samples_leaf': [1, 2, 4],  # Min samples required at each leaf node
    'max_features': ['sqrt', 'log2'],  # Max features to consider for split
    'ccp_alpha':[0.07,0.01]
}

# model = DecisionTreeClassifier(**params)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# # Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[93]:
```
gbm_params = {
    'learning_rate': [0.01, 0.05, 0.1],  # Learning rate
    'n_estimators': [50, 100, 200],  # Number of boosting stages
    'max_depth': [3, 4, 5],  # Maximum depth of the individual trees
```

```
}
# model = GradientBoostingClassifier()
# best_model = hyperparameter_tuning(model, gbm_params, enc_trainX, trainY)
# # Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[94]:
```
%%time
from sklearn.ensemble import VotingClassifier

lr = LogisticRegression(penalty='l2', C=50, max_iter=1500, solver='saga')
ada = AdaBoostClassifier(**{'algorithm': 'SAMME.R', 'learning_rate': 1.0,␣
 ↪'n_estimators': 200})
gbm = GradientBoostingClassifier(**{'learning_rate': 0.1, 'max_depth': 5,␣
 ↪'n_estimators': 200})
rf = RandomForestClassifier(** {'bootstrap': False, 'criterion': 'entropy',␣
 ↪'max_depth': None, 'max_features': 'sqrt', 'min_samples_leaf': 4,␣
 ↪'min_samples_split': 2, 'n_estimators': 200})
xgb = XGBClassifier(**{'colsample_bytree': 0.7, 'gamma': 0.1, 'learning_rate':␣
 ↪0.1, 'max_depth': 7, 'n_estimators': 200, 'reg_lambda': 1.5, 'subsample': 0.
 ↪9},objective='multi:softprob')

# res = fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)

votingCLF = VotingClassifier(
    estimators=[
        ('rf', rf),
        ('ada', ada),
        ('xgb', xgb),
        ('lr', lr),
        ('gbm', gbm)
    ],
    voting='soft',
    weights=[4,5,7,2, 6]
)
fit_and_evaluate(votingCLF, enc_trainX, trainY, enc_testX, testY)
```

```
/home/numan947/anaconda3/envs/mldl/lib/python3.9/site-
packages/sklearn/ensemble/_weight_boosting.py:519: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMME
algorithm to circumvent this warning.
  warnings.warn(
```

```
CPU times: user 12min 1s, sys: 11.6 s, total: 12min 13s
Wall time: 11min 6s
```

```
[94]: {'accuracy': 0.614396621874244,
 'classification_report': {'0': {'precision': 0.5968180668016194,
   'recall': 0.9029957886676876,
   'f1-score': 0.7186547836684948,
   'support': 20896.0},
  '1': {'precision': 0.6247617397331485,
   'recall': 0.5285494392728872,
   'f1-score': 0.5726424459003375,
   'support': 13643.0},
  '2': {'precision': 0.8031155344006924,
   'recall': 0.169807868252516,
   'f1-score': 0.28034136394532133,
   'support': 10930.0},
  'accuracy': 0.614396621874244,
  'macro avg': {'precision': 0.6748984469784869,
   'recall': 0.5337843653976969,
   'f1-score': 0.5238795311713845,
   'support': 45469.0},
  'weighted avg': {'precision': 0.6547931014551793,
   'recall': 0.614396621874244,
   'f1-score': 0.5694803570977487,
   'support': 45469.0}}}
```

INPUT = encoded_data TARGET=df2['FLIGHT_STATUS'] label_encoder = LabelEncoder() TARGET_ENCODED = label_encoder.fit_transform(TARGET)

from sklearn.preprocessing import StandardScaler scaler = StandardScaler() enc_trainX = pd.DataFrame(scaler.fit_transform(encoded_data), index=encoded_data.index, columns=encoded_data.columns)

enc_trainX.shape

votingCLF.fit(enc_trainX, TARGET_ENCODED)

final = pd.read_csv("./sample_input_2nd_task.csv")

final_data = scaler.transform(encoder.transform(final))

final_data.shape

votingCLF.predict(final_data)

label_encoder = LabelEncoder() trainY_encoded = label_encoder.fit_transform(trainY)

label_encoder.inverse_transform(votingCLF.predict(final_data))

final = pd.read_csv("./final_input_second.csv")

final_data = scaler.transform(encoder.transform(final))

final_data.shape

votingCLF.predict(final_data)

label_encoder = LabelEncoder() trainY_encoded = label_encoder.fit_transform(trainY)

label_encoder.inverse_transform(votingCLF.predict(final_data))

[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

1.3 START 3 HOP

[95]:
```
encoder = MultiColumnOneHotEncoder(columns=['Carrier Code', 'Origin␣
↪Airport','season', 'SCHED_ARRV_TIME_CAT', 'month', 'WeekDay','PREV_STAT'])␣
↪#,'wind_type', 'ceiling_det_code', 'celing_CAVOK','visibility_variability'
```

[96]:
```
encoded_data = encoder.fit_transform(df3.drop(columns=['FLIGHT_STATUS']))
```

[97]:
```
encoded_data.head()
```

[97]:
```
   Scheduled Elapsed Time (Minutes)  latitude  elevation  wind_direction  \
0                                76  40.63915        3.4      102.428571
1                                76  40.63915        3.4      102.428571
2                                76  40.63915        3.4      102.428571
3                                75  40.63915        3.4      110.503072
4                                75  40.63915        3.4      110.503072

   wind_speed  visibility_dist  air_temparature  sea_level_pressure  \
0    3.221194         6.966812           33.944         1018.725782
1    3.221194         6.966812           33.944         1018.725782
2    3.221194         6.966812           33.944         1018.725782
3    0.000000         5.400087           33.368         1015.367354
4    0.000000         5.400087           33.368         1015.367354

   SYR_wind_direction  SYR_wind_speed  …  month_11  month_12  \
0           106.00000        3.892276  …       0.0       0.0
1           106.00000        3.892276  …       0.0       0.0
2           106.00000        3.892276  …       0.0       0.0
3           103.91219        0.000000  …       0.0       0.0
4           103.91219        0.000000  …       0.0       0.0

   WeekDay_Monday  WeekDay_Saturday  WeekDay_Sunday  WeekDay_Thursday  \
0             0.0               0.0             0.0               0.0
1             0.0               0.0             0.0               0.0
```

```
2              0.0              0.0              0.0              0.0
3              0.0              0.0              0.0              0.0
4              0.0              0.0              0.0              0.0

   WeekDay_Tuesday  WeekDay_Wednesday  PREV_STAT_LATE  PREV_STAT_ONTIME
0              0.0                0.0             0.0               1.0
1              0.0                0.0             0.0               1.0
2              0.0                0.0             0.0               1.0
3              0.0                0.0             1.0               0.0
4              0.0                0.0             0.0               1.0

[5 rows x 85 columns]
```

[98]:
```
encoded_data.shape
```

[98]:
```
(341013, 85)
```

[99]:
```
trainX, testX, trainY, testY = train_test_split(
    encoded_data,
    df3['FLIGHT_STATUS'],
    test_size=0.2,
    random_state=947,
    stratify=df3['FLIGHT_STATUS']
)
```

[100]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
enc_trainX = pd.DataFrame(scaler.fit_transform(trainX), index=trainX.index,␣
 ↪columns=trainX.columns)
enc_testX = pd.DataFrame(scaler.transform(testX), index=testX.index,␣
 ↪columns=testX.columns)
```

[101]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

def fit_and_evaluate(model, trainX, trainY, testX, testY):
    # Convert string labels to integers
    label_encoder = LabelEncoder()
    trainY_encoded = label_encoder.fit_transform(trainY)
    testY_encoded = label_encoder.transform(testY)

    model.fit(trainX, trainY_encoded)
    testY_pred = model.predict(testX)
    accuracy = accuracy_score(testY_encoded, testY_pred)
    report = classification_report(testY_encoded, testY_pred, output_dict=True)
```

```python
    results = {'accuracy': accuracy, 'classification_report': report}
    return results

# Update other classification functions similarly...


# Random Forest
from sklearn.ensemble import RandomForestClassifier

def random_forest_classification(trainX, trainY, testX, testY,␣
↪n_estimators=100, criterion='gini', max_depth=None):
    model = RandomForestClassifier(n_estimators=n_estimators,␣
↪criterion=criterion, max_depth=max_depth)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# Support Vector Machines (SVM)
from sklearn.svm import SVC

def svm_classification(trainX, trainY, testX, testY, kernel='rbf', C=1.0):
    model = SVC(kernel=kernel, C=C)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# K-Nearest Neighbors (KNN)
from sklearn.neighbors import KNeighborsClassifier

def knn_classification(trainX, trainY, testX, testY, n_neighbors=5):
    model = KNeighborsClassifier(n_neighbors=n_neighbors)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# Gradient Boosting Machines (GBM)
from sklearn.ensemble import GradientBoostingClassifier

def gbm_classification(trainX, trainY, testX, testY, n_estimators=100,␣
↪learning_rate=0.1, max_depth=3):
    model = GradientBoostingClassifier(n_estimators=n_estimators,␣
↪learning_rate=learning_rate, max_depth=max_depth)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# Naive Bayes
from sklearn.naive_bayes import GaussianNB

def naive_bayes_classification(trainX, trainY, testX, testY):
    model = GaussianNB()
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# AdaBoost
from sklearn.ensemble import AdaBoostClassifier
```

```python
def adaboost_classification(trainX, trainY, testX, testY, n_estimators=50,
 ↪learning_rate=1.0):
    model = AdaBoostClassifier(n_estimators=n_estimators,
 ↪learning_rate=learning_rate)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

# XGBoost
from xgboost import XGBClassifier

def xgboost_classification(trainX, trainY, testX, testY, n_estimators=100,
 ↪learning_rate=0.1, max_depth=3):
    model = XGBClassifier(n_estimators=n_estimators,
 ↪learning_rate=learning_rate, max_depth=max_depth)
    return fit_and_evaluate(model, trainX, trainY, testX, testY)

def logistic_regression_classification(trainX, trainY, testX, testY,
 ↪penalty='l2', C=1.0, max_iter=1000, solver='lbfgs'):
    target_names = trainY.unique() if isinstance(trainY, pd.Series) else testY.
 ↪unique()

    # Initialize and train the Logistic Regression model
    model = LogisticRegression(penalty=penalty, C=C, max_iter=max_iter,
 ↪solver=solver, verbose=1 if max_iter > 300 else 0)
    model.fit(trainX, trainY)

    # Predict on the testing set
    testY_pred = model.predict(testX)

    # Calculate accuracy score
    accuracy = accuracy_score(testY, testY_pred)

    # Generate classification report
    report = classification_report(testY, testY_pred,
 ↪target_names=target_names, output_dict=True)

    results = {
        'accuracy': accuracy,
        'classification_report': report
    }

    return results

def decision_tree_classification(trainX, trainY, testX, testY,
 ↪criterion='gini', max_depth=None):
```

```
    # Get unique target names
    target_names = trainY.unique() if isinstance(trainY, pd.Series) else testY.
 ↪unique()

    # Initialize and train the Decision Tree model
    model = DecisionTreeClassifier(criterion=criterion,␣
 ↪max_depth=max_depth,min_samples_split=5)
    model.fit(trainX, trainY)

    # Predict on the testing set
    testY_pred = model.predict(testX)

    # Calculate accuracy score
    accuracy = accuracy_score(testY, testY_pred)

    # Generate classification report
    report = classification_report(testY, testY_pred,␣
 ↪target_names=target_names, output_dict=True)

    results = {
        'accuracy': accuracy,
        'classification_report': report
    }

    return results
```

[102]:
```
# logistic_regression_classification(enc_trainX, trainY, enc_testX, testY,␣
 ↪solver='saga', max_iter=1500, C=50)
```

[103]:
```
# decision_tree_classification(enc_trainX, trainY, enc_testX, testY,␣
 ↪max_depth=11, criterion='entropy')
```

[104]:
```
# random_forest_classification(enc_trainX, trainY, enc_testX, testY)
```

[105]:
```
# knn_classification(enc_trainX, trainY, enc_testX, testY)
```

[106]:
```
# gbm_classification(enc_trainX, trainY, enc_testX, testY)
```

[107]:
```
# naive_bayes_classification(enc_trainX, trainY, enc_testX, testY)
```

[108]:
```
# adaboost_classification(enc_trainX, trainY, enc_testX, testY)
```

[109]:
```
# xgboost_classification(enc_trainX, trainY, enc_testX, testY)
```

[110]:
```
from sklearn.model_selection import GridSearchCV, KFold
def hyperparameter_tuning(model, param_grid, trainX, trainY, cv=5):
    label_encoder = LabelEncoder()
```

```
    trainY_encoded = label_encoder.fit_transform(trainY)
    # Initialize K-Fold cross-validator
    kf = KFold(n_splits=cv, shuffle=True, random_state=42)

    # Perform grid search
    grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=kf,␣
 ↪scoring='accuracy', verbose=3, n_jobs=10, )
    grid_search.fit(trainX, trainY_encoded)

    return grid_search
```

[111]:
```
params = {'colsample_bytree': 0.7, 'gamma': 0.1, 'learning_rate': 0.1,␣
 ↪'max_depth': 7, 'n_estimators': 200, 'reg_lambda': 1.5, 'subsample': 0.9}
# param_grid = {
#     'n_estimators': [100, 200],  # Number of boosting rounds
#     'max_depth': [3, 5, 7, 11],  # Maximum tree depth
#     'learning_rate': [0.01, 0.1, 0.3],  # Step size shrinkage
#     'subsample': [0.7, 0.9],  # Subsample ratio of the training instances
#     'colsample_bytree': [0.7, 0.9],  # Subsample ratio of columns when␣
 ↪constructing each tree
#     'gamma': [0, 0.1],  # Minimum loss reduction required to make a further␣
 ↪partition on a leaf node of the tree
#     'reg_lambda': [1, 1.5, 2]  # L2 regularization term on weights
# }
# model = XGBClassifier(**params)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[112]:
```
params =  {'bootstrap': False, 'criterion': 'entropy', 'max_depth': None,␣
 ↪'max_features': 'sqrt', 'min_samples_leaf': 4, 'min_samples_split': 2,␣
 ↪'n_estimators': 200}
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt'],
    'bootstrap': [True, False],
    'criterion': ['gini', 'entropy']
}
# model = RandomForestClassifier(**params)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
```

```
# Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[113]:
```
params = {'algorithm': 'SAMME.R', 'learning_rate': 1.0, 'n_estimators': 200}
param_grid = {
    'n_estimators': [50, 100, 200],  # Number of estimators
    'learning_rate': [0.01, 0.1, 1.0],  # Learning rate
    'algorithm': ['SAMME', 'SAMME.R'],  # Algorithm
}

# model = AdaBoostClassifier(**params)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# # Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[114]:
```
params =  {'ccp_alpha': 0.07, 'criterion': 'gini', 'max_depth': None,␣
 ↪'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 2,␣
 ↪'splitter': 'best'}

param_grid = {
    'criterion': ['gini', 'entropy'],  # Split criterion
    'splitter': ['best', 'random'],  # Strategy to choose split at each node
    'max_depth': [None, 1, 3, 5],  # Max depth of the tree
    'min_samples_split': [2, 5, 10],  # Min samples required to split a node
    'min_samples_leaf': [1, 2, 4],  # Min samples required at each leaf node
    'max_features': ['sqrt', 'log2'],  # Max features to consider for split
    'ccp_alpha':[0.07,0.01]
}

# model = DecisionTreeClassifier(**params)
# fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)
# best_model = hyperparameter_tuning(model, param_grid, enc_trainX, trainY)
# # Print best parameters and best score
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[115]:
```
gbm_params = {
    'learning_rate': [0.01, 0.05, 0.1],  # Learning rate
    'n_estimators': [50, 100, 200],  # Number of boosting stages
    'max_depth': [3, 4, 5],  # Maximum depth of the individual trees
}
# model = GradientBoostingClassifier()
# best_model = hyperparameter_tuning(model, gbm_params, enc_trainX, trainY)
# # Print best parameters and best score
```

```
# print("Best parameters found: ", best_model.best_params_)
# print("Best accuracy score found: ", best_model.best_score_)
```

[116]:
```
%%time
from sklearn.ensemble import VotingClassifier

lr = LogisticRegression(penalty='l2', C=50, max_iter=1500, solver='saga')
ada = AdaBoostClassifier(**{'algorithm': 'SAMME.R', 'learning_rate': 1.0,␣
 ↪'n_estimators': 200})
gbm = GradientBoostingClassifier(**{'learning_rate': 0.1, 'max_depth': 5,␣
 ↪'n_estimators': 200})
rf = RandomForestClassifier(** {'bootstrap': False, 'criterion': 'entropy',␣
 ↪'max_depth': None, 'max_features': 'sqrt', 'min_samples_leaf': 4,␣
 ↪'min_samples_split': 2, 'n_estimators': 200})
xgb = XGBClassifier(**{'colsample_bytree': 0.7, 'gamma': 0.1, 'learning_rate':␣
 ↪0.1, 'max_depth': 7, 'n_estimators': 200, 'reg_lambda': 1.5, 'subsample': 0.
 ↪9},objective='multi:softprob')

# res = fit_and_evaluate(model, enc_trainX, trainY, enc_testX, testY)

votingCLF = VotingClassifier(
    estimators=[
        ('rf', rf),
        ('ada', ada),
        ('xgb', xgb),
        ('lr', lr),
        ('gbm', gbm)
    ],
    voting='soft',
    weights=[4,5,7,2, 6]
)
fit_and_evaluate(votingCLF, enc_trainX, trainY, enc_testX, testY)
```

```
/home/numan947/anaconda3/envs/mldl/lib/python3.9/site-
packages/sklearn/ensemble/_weight_boosting.py:519: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMME
algorithm to circumvent this warning.
  warnings.warn(
```

```
CPU times: user 18min 3s, sys: 1.82 s, total: 18min 5s
Wall time: 16min 25s
```

[116]:
```
{'accuracy': 0.6651906807618433,
 'classification_report': {'0': {'precision': 0.6264176117411607,
   'recall': 0.9286944869831547,
   'f1-score': 0.7481783249585545,
   'support': 31344.0},
```

```
 '1': {'precision': 0.7020705745115194,
  'recall': 0.5882036747458952,
  'f1-score': 0.6401127389720546,
  'support': 20464.0},
 '2': {'precision': 0.9200261494879058,
  'recall': 0.25751753583409576,
  'f1-score': 0.40240182996568813,
  'support': 16395.0},
 'accuracy': 0.6651906807618433,
 'macro avg': {'precision': 0.7495047785801953,
  'recall': 0.5914718991877153,
  'f1-score': 0.5968976312987657,
  'support': 68203.0},
 'weighted avg': {'precision': 0.7196961215792984,
  'recall': 0.6651906807618433,
  'f1-score': 0.6326341438076406,
  'support': 68203.0}}}
```

final = pd.read_csv(“./sample_input_2nd_task.csv”)

final_data = scaler.transform(encoder.transform(final))

final_data.shape

votingCLF.predict(final_data)

label_encoder = LabelEncoder() trainY_encoded = label_encoder.fit_transform(trainY)

label_encoder.inverse_transform(votingCLF.predict(final_data))

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