# data-cleaning

December 7, 2024

## 1 Importing the required modules

[1]:
```
# modules used for data handling and
# manipulation
import numpy as np
import pandas as pd

# modules used for data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# modules used for encoding and data splitting
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import TargetEncoder, OrdinalEncoder, StandardScaler

# ignore warnings
import warnings
warnings.filterwarnings("ignore")
```

## 2 Reading the data

[2]:
```
flight_df = pd.read_csv("DelayData.csv")
```

## 3 Initial Data Exploration

[3]:
```
flight_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1201664 entries, 0 to 1201663
Data columns (total 61 columns):
 #   Column                  Non-Null Count    Dtype
---  ------                  --------------    -----
 0   depdelay                1201664 non-null  int64
 1   arrdelay                1198458 non-null  float64
 2   scheduleddepartdatetime 1201664 non-null  object
 3   origin                  1201664 non-null  object
```

```
4   dest                     1201664 non-null  object
5   uniquecarrier            1201664 non-null  object
6   marketshareorigin        1201664 non-null  float64
7   marketsharedest          1201664 non-null  float64
8   hhiorigin                1201664 non-null  float64
9   hhidest                  1201664 non-null  float64
10  nonhubairportorigin      1201664 non-null  int64
11  smallhubairportorigin    1201664 non-null  int64
12  mediumhubairportorigin   1201664 non-null  int64
13  largehubairportorigin    1201664 non-null  int64
14  nonhubairportdest        1201664 non-null  int64
15  smallhubairportdest      1201664 non-null  int64
16  mediumhubairportdest     1201664 non-null  int64
17  largehubairportdest      1201664 non-null  int64
18  nonhubairlineorigin      1201664 non-null  int64
19  smallhubairlineorigin    1201664 non-null  int64
20  mediumhubairlineorigin   1201664 non-null  int64
21  largehubairlineorigin    1201664 non-null  int64
22  nonhubairlinedest        1201664 non-null  int64
23  smallhubairlinedest      1201664 non-null  int64
24  mediumhubairlinedest     1201664 non-null  int64
25  largehubairlinedest      1201664 non-null  int64
26  year                     1201664 non-null  int64
27  month                    1201664 non-null  int64
28  dayofmonth               1201664 non-null  int64
29  dayofweek                1201664 non-null  int64
30  scheduledhour            1201664 non-null  int64
31  originairportid          1201664 non-null  int64
32  destairportid            1201664 non-null  int64
33  tailnum                  1201664 non-null  object
34  capacity                 1201664 non-null  int64
35  loadfactor               1201664 non-null  float64
36  numflights               1201664 non-null  float64
37  origincityname           1201664 non-null  object
38  originstate              1201664 non-null  object
39  distance                 1201664 non-null  int64
40  monopolyroute            1201664 non-null  int64
41  temperature              1201204 non-null  float64
42  temp_ninfty_n10          1201664 non-null  int64
43  temp_n10_0               1201664 non-null  int64
44  temp_0_10                1201664 non-null  int64
45  temp_10_20               1201664 non-null  int64
46  temp_20_30               1201664 non-null  int64
47  temp_30_40               1201664 non-null  int64
48  temp_40_infty            1201664 non-null  int64
49  windspeed                1201204 non-null  float64
50  windspeedsquare          1201204 non-null  float64
51  windgustdummy            1201664 non-null  int64
```

```
 52  windgustspeed             1201204 non-null  float64
 53  raindummy                 1201664 non-null  int64
 54  raintracedummy            1201664 non-null  int64
 55  snowdummy                 1201664 non-null  int64
 56  snowtracedummy            1201664 non-null  int64
 57  originmetropop            1201664 non-null  int64
 58  originmetrogdppercapita   1201664 non-null  float64
 59  destmetropop              1201664 non-null  int64
 60  destmetrogdppercapita     1201664 non-null  float64
dtypes: float64(13), int64(41), object(7)
memory usage: 559.2+ MB
```

- The dataset has 1201664 rows and 61 columns.
- The dataset is partially pre-processed. Few of the categorical variables are already one-hot encoded.
- However, the many of categorical variables that are already encoded are ordinal in nature and one-hot encoding is not appropriate for it.
- It also appears that the `windspeed` column is transformed into `windspeedsquare`. It must checked which one is better and only one of them must be retained.
- The first five rows of the dataset are shown below.

[4]:
```
flight_df.head()
```

[4]:
```
   depdelay  arrdelay scheduleddepartdatetime origin dest uniquecarrier  \
0         0      -4.0    08-Jan-2004 15:25:00    ELP  SAT            WN
1        -4      11.0    22-Jan-2004 14:40:00    ATL  MSY            DL
2         3      12.0    29-Jan-2004 12:25:00    DFW  JFK            DL
3        -3      24.0    14-Jan-2004 15:55:00    SEA  EWR            CO
4         0      -8.0    14-Jan-2004 18:40:00    SLC  RNO            OO

   marketshareorigin  marketsharedest  hhiorigin   hhidest  …  \
0           0.618467         0.407567   0.417090  0.226878  …
1           0.500757         0.096321   0.319589  0.196657  …
2           0.060898         0.131962   0.296126  0.214357  …
3           0.040522         0.347744   0.234712  0.249377  …
4           0.506899         0.176493   0.341763  0.277364  …

   windgustdummy  windgustspeed  raindummy  raintracedummy  snowdummy  \
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          1               0          0
4              0            0.0          0               0          0

   snowtracedummy  originmetropop  originmetrogdppercapita  destmetropop  \
0               0          702433                27314.633       1843927
1               0         4802300                49081.773       1314721
2               0         5689982                50588.563      18747431
```

```
3                0        3163703                 57755.547      18747431
4                0        1030597                 45043.602        385049

   destmetrogdppercapita
0              35005.234
1              48848.234
2              57295.402
3              57295.402
4              49079.727

[5 rows x 61 columns]
```

# 4 Data Cleaning

## 4.1 Handling null values

[5]:
```python
def display_cols_wt_na(df):
    print(df.isna().sum().loc[lambda x : x>0].sort_values(ascending = False)*100/
 ↪len(df))
```

[6]:
```python
display_cols_wt_na(flight_df)
```

```
arrdelay           0.266797
temperature        0.038280
windspeed          0.038280
windspeedsquare    0.038280
windgustspeed      0.038280
dtype: float64
```

- The `arrdelay` has 0.26% null values. It is also the target column and hence the **rows** with null value for `arrdelay` must be dropped.
- After dropping those rows we will check if the other columns yet have null values.

[7]:
```python
flight_df = flight_df[flight_df['arrdelay'].notna()]
display_cols_wt_na(flight_df)
```

```
temperature        0.038383
windspeed          0.038383
windspeedsquare    0.038383
windgustspeed      0.038383
dtype: float64
```

- All the columns have 0.03% null values and hence can be imputed.
- Now, we will impute the missing values in the `temperature`, `windspeed`, `windspeedsquare`, and `windgustspeed` with the **mean** of the columns.
- `np.nanmean()` is used to compute mean of columns with null values.

[8]:
```python
to_impute_cols = ["temperature", "windspeed", "windspeedsquare",␣
 ↪"windgustspeed"]
```

```
for col in to_impute_cols:
    col_mean = np.nanmean(flight_df[col])
    flight_df[col] = flight_df[col].fillna(col_mean)
```

[9]:
```
display_cols_wt_na(flight_df)
```

```
Series([], dtype: float64)
```

All null values are handled.

### 4.2 Dropping the columns

- There are few redundant columns and they need dropped.
- The `scheduleddepartdatetime` column stores the timestamp for each flight. However, the dataset also has all the individual components in separate columns and hence this column is dropped.
- The `originairportid` and `destairportid` columns have same information as the `origin` and `dest` columns. Hence, they are dropped.
- The `originstate` and `origincityname` columns have same information as `origin` column. While, this data is unknown for `dest`. Hence, those two columns are dropped.

**Note**: the time-series nature of data is not considered for the modelling.

[10]:
```
cols_to_be_dropped = ["scheduleddepartdatetime",
                      "originairportid",
                      "destairportid",
                      "originstate",
                      "origincityname"]

flight_df = flight_df.drop(columns = cols_to_be_dropped,
                           axis = 1)
```

[11]:
```
flight_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1198458 entries, 0 to 1201663
Data columns (total 56 columns):
 #   Column                    Non-Null Count    Dtype
---  ------                    --------------    -----
 0   depdelay                  1198458 non-null  int64
 1   arrdelay                  1198458 non-null  float64
 2   origin                    1198458 non-null  object
 3   dest                      1198458 non-null  object
 4   uniquecarrier             1198458 non-null  object
 5   marketshareorigin         1198458 non-null  float64
 6   marketsharedest           1198458 non-null  float64
 7   hhiorigin                 1198458 non-null  float64
 8   hhidest                   1198458 non-null  float64
 9   nonhubairportorigin       1198458 non-null  int64
```

```
 10  smallhubairportorigin    1198458 non-null  int64
 11  mediumhubairportorigin   1198458 non-null  int64
 12  largehubairportorigin    1198458 non-null  int64
 13  nonhubairportdest        1198458 non-null  int64
 14  smallhubairportdest      1198458 non-null  int64
 15  mediumhubairportdest     1198458 non-null  int64
 16  largehubairportdest      1198458 non-null  int64
 17  nonhubairlineorigin      1198458 non-null  int64
 18  smallhubairlineorigin    1198458 non-null  int64
 19  mediumhubairlineorigin   1198458 non-null  int64
 20  largehubairlineorigin    1198458 non-null  int64
 21  nonhubairlinedest        1198458 non-null  int64
 22  smallhubairlinedest      1198458 non-null  int64
 23  mediumhubairlinedest     1198458 non-null  int64
 24  largehubairlinedest      1198458 non-null  int64
 25  year                     1198458 non-null  int64
 26  month                    1198458 non-null  int64
 27  dayofmonth               1198458 non-null  int64
 28  dayofweek                1198458 non-null  int64
 29  scheduledhour            1198458 non-null  int64
 30  tailnum                  1198458 non-null  object
 31  capacity                 1198458 non-null  int64
 32  loadfactor               1198458 non-null  float64
 33  numflights               1198458 non-null  float64
 34  distance                 1198458 non-null  int64
 35  monopolyroute            1198458 non-null  int64
 36  temperature              1198458 non-null  float64
 37  temp_ninfty_n10          1198458 non-null  int64
 38  temp_n10_0               1198458 non-null  int64
 39  temp_0_10                1198458 non-null  int64
 40  temp_10_20               1198458 non-null  int64
 41  temp_20_30               1198458 non-null  int64
 42  temp_30_40               1198458 non-null  int64
 43  temp_40_infty            1198458 non-null  int64
 44  windspeed                1198458 non-null  float64
 45  windspeedsquare          1198458 non-null  float64
 46  windgustdummy            1198458 non-null  int64
 47  windgustspeed            1198458 non-null  float64
 48  raindummy                1198458 non-null  int64
 49  raintracedummy           1198458 non-null  int64
 50  snowdummy                1198458 non-null  int64
 51  snowtracedummy           1198458 non-null  int64
 52  originmetropop           1198458 non-null  int64
 53  originmetrogdppercapita  1198458 non-null  float64
 54  destmetropop             1198458 non-null  int64
 55  destmetrogdppercapita    1198458 non-null  float64
dtypes: float64(13), int64(39), object(4)
memory usage: 521.2+ MB
```

# 5 Rectifying incorrectly encoded ordinal categorical variables

As deduced from the initial analysis, there are few columns that are already one-hot encoded in the dataset. However, some of these categorical variables (described below) are ordinal and one-hot encoding is not appropriate for them.

- The columns of the form `temp_<lower-limit>_<upper-limit>` denote the range in which `temperature` falls in. These columns hold 1 if the `temperature` falls in that range and 0 otherwise. However, the ranges have an order associated with them as follows:

  $-\infty$ to $-10 < -10$ to $0 < 0$ to $10 < 10$ to $20 < 20$ to $30 < 30$ to $40 < 40$ to $\infty$

Hence, a single column `temp_range` is created and contains the categories. All the columns already present as a part of one-hot encoding are dropped.

- The columns of the form `<size of hub>airportorigin` and `<size of hub>airportdest` denote whether the origin and destination airports are hubs for some airline and if its a hub what is its size. These columns hold 1 if the `origin` or `dest` is a `<size of hub>` hub for some airline and 0 otherwise.

  nonhub < small < medium < large

Hence, a two columns `hubairportorigin` and `hubairportdest` are created and contains the categories. All the columns already present as a part of one-hot encoding are dropped.

- The columns of the form `<size of hub>airlineorigin` and `<size of hub>airlinedest` denote whether the origin and destination airports are hubs for the airline and if its a hub what is its size. These columns hold 1 if the `origin` or `dest` is a `<size of hub>` hub for `uniquecarrier` and 0 otherwise.

  nonhub < small < medium < large

Hence, a two columns `hubairlineorigin` and `hubairlinedest` are created and contains the categories. All the columns already present as a part of one-hot encoding are dropped.

[12]:
```python
# extracting all dummy features from the respective categories.
cols = list(flight_df.columns)
temperature_range = cols[37:44]
airport_connectivity_origin = cols[9:13]
airport_connectivity_dest = cols[13:17]
airline_connectivity_origin = cols[17:21]
airline_connectivity_dest = cols[21:25]
```

[13]:
```python
# converts dummy columns into a single categorical feature.
def onehot2ordinal(new_colname: str, dummies: list, str2replace: str, sep = None):

    flight_df[new_colname] = pd.from_dummies(flight_df[dummies],
                            default_category = np.nan,
                            sep = sep)
    if not sep:
```

```
        flight_df[new_colname] = flight_df[new_colname].astype(str).apply(lambda␣
↪x: x.replace(str2replace,
                                                                                ␣
↪             ''))

    flight_df.drop(dummies, axis = 1, inplace = True)
```

[14]:
```
# applies the function to all the respective kinds of dummy features.
arguments = [["temp_range", temperature_range, None, "_"],
             ["hubairportorigin", airport_connectivity_origin, "airportorigin",␣
↪None],
             ["hubairportdest", airport_connectivity_dest, "airportdest", None],
             ["hubairlineorigin", airline_connectivity_origin, "airlineorigin",␣
↪None],
             ["hubairlinedest", airline_connectivity_dest, "airlinedest", None]]

for new_colname, dummies, str2replace, sep in arguments:

    onehot2ordinal(new_colname = new_colname, dummies = dummies,
                   str2replace = str2replace, sep = sep)
```

It appears that temp_range has some null values and these can be derived by categorizing the temperature value for the particular row.

[15]:
```
def categorise_temp(temp):
    if temp <= -10:
        return "ninfty_n10"
    elif temp > -10 and temp <= 0:
        return "n10_0"
    elif temp > 0 and temp <= 10:
        return "0_10"
    elif temp > 10 and temp <= 20:
        return "10_20"
    elif temp > 20 and temp <= 30:
        return "20_30"
    elif temp > 30 and temp <= 40:
        return "30_40"
    else:
        return "40_infty"
```

[16]:
```
flight_df["temp_range"] = flight_df.apply(lambda x: categorise_temp(x.
↪temperature),
                                          axis = 1)
```

[17]:
```
flight_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1198458 entries, 0 to 1201663
```

```
Data columns (total 38 columns):
 #   Column                    Non-Null Count    Dtype
---  ------                    --------------    -----
 0   depdelay                  1198458 non-null  int64
 1   arrdelay                  1198458 non-null  float64
 2   origin                    1198458 non-null  object
 3   dest                      1198458 non-null  object
 4   uniquecarrier             1198458 non-null  object
 5   marketshareorigin         1198458 non-null  float64
 6   marketsharedest           1198458 non-null  float64
 7   hhiorigin                 1198458 non-null  float64
 8   hhidest                   1198458 non-null  float64
 9   year                      1198458 non-null  int64
 10  month                     1198458 non-null  int64
 11  dayofmonth                1198458 non-null  int64
 12  dayofweek                 1198458 non-null  int64
 13  scheduledhour             1198458 non-null  int64
 14  tailnum                   1198458 non-null  object
 15  capacity                  1198458 non-null  int64
 16  loadfactor                1198458 non-null  float64
 17  numflights                1198458 non-null  float64
 18  distance                  1198458 non-null  int64
 19  monopolyroute             1198458 non-null  int64
 20  temperature               1198458 non-null  float64
 21  windspeed                 1198458 non-null  float64
 22  windspeedsquare           1198458 non-null  float64
 23  windgustdummy             1198458 non-null  int64
 24  windgustspeed             1198458 non-null  float64
 25  raindummy                 1198458 non-null  int64
 26  raintracedummy            1198458 non-null  int64
 27  snowdummy                 1198458 non-null  int64
 28  snowtracedummy            1198458 non-null  int64
 29  originmetropop            1198458 non-null  int64
 30  originmetrogdppercapita   1198458 non-null  float64
 31  destmetropop              1198458 non-null  int64
 32  destmetrogdppercapita     1198458 non-null  float64
 33  temp_range                1198458 non-null  object
 34  hubairportorigin          1198458 non-null  object
 35  hubairportdest            1198458 non-null  object
 36  hubairlineorigin          1198458 non-null  object
 37  hubairlinedest            1198458 non-null  object
dtypes: float64(13), int64(16), object(9)
memory usage: 356.6+ MB
```

## 6 Binning the delays into categories

- The arrival and departure delay are binned into 5 categories.

- The arrival delay is the target variable and will be predicted using classification algorithms.

[18]:
```
def bin_delay(delay):
    if delay <= 10:
        return "0-10"
    elif 10 < delay <= 20:
        return "10-20"
    elif 20 < delay <= 40:
        return "20-40"
    elif 40 < delay <= 60:
        return "40-60"
    elif delay > 60:
        return ">60"
```

[19]:
```
flight_df["depdelay"] = flight_df.apply(lambda x: bin_delay(x.depdelay),
                                        axis = 1)
flight_df["arrdelay"] = flight_df.apply(lambda x: bin_delay(x.arrdelay),
                                        axis = 1)
```

# 7 Splitting the data into train-test

[20]:
```
target = "arrdelay"
```

[21]:
```
# encoding the target variable
flight_df[target] = flight_df[target].replace(dict(zip(['0-10', '10-20',␣
↪'20-40', '40-60', '>60'],
                                                      [i for i in range(5)])))
```

[22]:
```
flight_y = flight_df.pop(target)
```

[23]:
```
flight_X_train, flight_X_test, flight_y_train, flight_y_test =␣
↪train_test_split(flight_df, flight_y,
                                                                              ␣
↪ test_size = 0.2,
                                                                              ␣
↪ stratify = flight_y,
                                                                              ␣
↪ random_state = 42)
```

# 8 Encoding the categorical variables

[24]:
```
ord_cat_features = ["temp_range", "hubairportorigin", "hubairportdest",
                    "hubairlinedest", "hubairlineorigin", "depdelay"]

hc_cat_features = ["origin", "dest", "uniquecarrier", "tailnum"]
```

```
cat_vars = ord_cat_features + hc_cat_features
```

### 8.1 Ordinal variable encoding

[25]:
```
categories = [
    ['ninfty_n10', 'n10_0', '0_10', '10_20', '20_30', '30_40', '40_infty'],
    ['nonhub', 'smallhub', 'mediumhub', 'largehub'],
    ['nonhub', 'smallhub', 'mediumhub', 'largehub'],
    ['nonhub', 'smallhub', 'mediumhub', 'largehub'],
    ['nonhub', 'smallhub', 'mediumhub', 'largehub'],
    ['0-10', '10-20', '20-40', '40-60', '>60']
]

oe = OrdinalEncoder(categories = categories).
 ↪fit(flight_X_train[ord_cat_features])

flight_X_train[ord_cat_features] = oe.
 ↪transform(flight_X_train[ord_cat_features])
flight_X_train[ord_cat_features] = flight_X_train[ord_cat_features].
 ↪astype("int64")

flight_X_test[ord_cat_features] = oe.transform(flight_X_test[ord_cat_features])
flight_X_test[ord_cat_features] = flight_X_test[ord_cat_features].
 ↪astype("int64")
```

### 8.2 High Cardinality variable encoding

- The high cardinality variables in this context include `origin`, `dest`, `tailnum`, and `uniquecarrier`.
- It is so possible that an origin airport appears in the test data but does not appear in the train dataset.
- Therefore, all the categories must be passed as input to the `TargetEncoder()` to learn that these values are not in the train dataset.

[26]:
```
categories = [list(set(flight_df[i]))for i in hc_cat_features]
```

[27]:
```
for hc_col_idx in range(len(hc_cat_features)):
    hc_col = hc_cat_features[hc_col_idx]
    te = TargetEncoder(categories = [categories[hc_col_idx]])
    te = te.fit(flight_X_train[[hc_col]],
                y = flight_y_train)

    flight_X_train[hc_col] = te.transform(flight_X_train[[hc_col]])
    flight_X_test[hc_col] = te.transform(flight_X_test[[hc_col]])
```

[28]:
```
flight_X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 958766 entries, 898074 to 382376
Data columns (total 37 columns):
 #   Column                   Non-Null Count   Dtype  
---  ------                   --------------   -----  
 0   depdelay                 958766 non-null  int64  
 1   origin                   958766 non-null  float64
 2   dest                     958766 non-null  float64
 3   uniquecarrier            958766 non-null  float64
 4   marketshareorigin        958766 non-null  float64
 5   marketsharedest          958766 non-null  float64
 6   hhiorigin                958766 non-null  float64
 7   hhidest                  958766 non-null  float64
 8   year                     958766 non-null  int64  
 9   month                    958766 non-null  int64  
 10  dayofmonth               958766 non-null  int64  
 11  dayofweek                958766 non-null  int64  
 12  scheduledhour            958766 non-null  int64  
 13  tailnum                  958766 non-null  float64
 14  capacity                 958766 non-null  int64  
 15  loadfactor               958766 non-null  float64
 16  numflights               958766 non-null  float64
 17  distance                 958766 non-null  int64  
 18  monopolyroute            958766 non-null  int64  
 19  temperature              958766 non-null  float64
 20  windspeed                958766 non-null  float64
 21  windspeedsquare          958766 non-null  float64
 22  windgustdummy            958766 non-null  int64  
 23  windgustspeed            958766 non-null  float64
 24  raindummy                958766 non-null  int64  
 25  raintracedummy           958766 non-null  int64  
 26  snowdummy                958766 non-null  int64  
 27  snowtracedummy           958766 non-null  int64  
 28  originmetropop           958766 non-null  int64  
 29  originmetrogdppercapita  958766 non-null  float64
 30  destmetropop             958766 non-null  int64  
 31  destmetrogdppercapita    958766 non-null  float64
 32  temp_range               958766 non-null  int64  
 33  hubairportorigin         958766 non-null  int64  
 34  hubairportdest           958766 non-null  int64  
 35  hubairlineorigin         958766 non-null  int64  
 36  hubairlinedest           958766 non-null  int64  
dtypes: float64(16), int64(21)
memory usage: 278.0 MB
```

[29]:

```
flight_X_train = flight_X_train[flight_X_train.columns]
```

## 9 Scaling the numerical variables

[30]:
```
float64_vars = flight_X_train.select_dtypes(include = ["float64"])
num_var = list(set(float64_vars).difference(hc_cat_features))
```

[31]:
```
num_var
```

[31]:
```
['loadfactor',
 'windspeedsquare',
 'temperature',
 'originmetrogdppercapita',
 'destmetrogdppercapita',
 'marketsharedest',
 'windspeed',
 'marketshareorigin',
 'hhidest',
 'hhiorigin',
 'windgustspeed',
 'numflights']
```

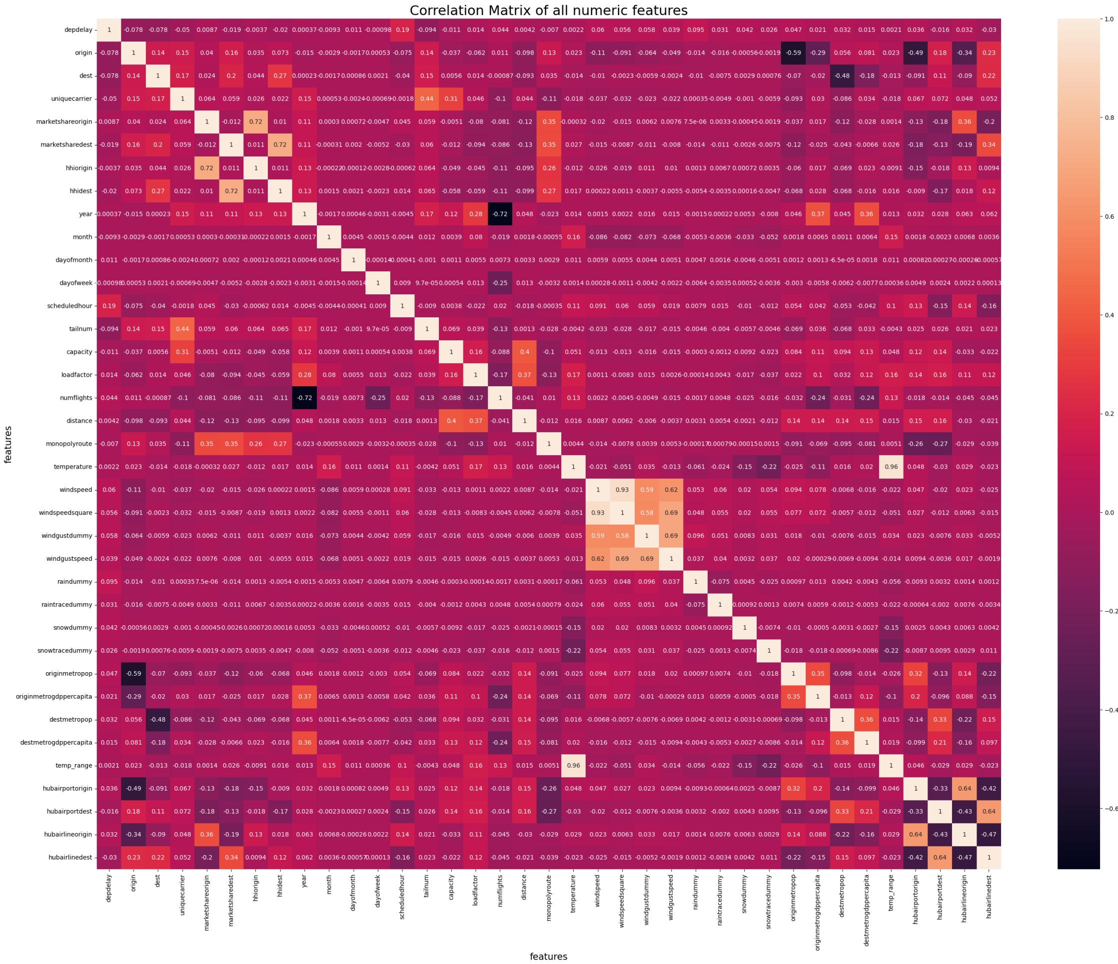
[32]:
```
sscaler = StandardScaler().fit(flight_X_train[num_var])

scaled_train = sscaler.transform(flight_X_train[num_var])
flight_X_train[num_var] = scaled_train

scaled_test = sscaler.transform(flight_X_test[num_var])
flight_X_test[num_var] = scaled_test
```

## 10 Correlation between the columns

[33]:
```
plt.figure(figsize = (33, 25))
sns.heatmap(flight_X_train.corr(), annot = True)
plt.xlabel("features", fontsize = 15)
plt.ylabel("features", fontsize = 15)
plt.title("Correlation Matrix of all numeric features", fontsize=22)
plt.show()
```




- The `depdelay` has slight positive correlation of 0.19 with `scheduledhour`. This makes sense because the air traffic at the `scheduledhour` decides whether the ATC gives permission for aircraft to depart.
- Moreover, there is very slight correlation with the columns pertaining to weather. This also makes sense since the weather (visibility) at departure decides whether the plane can take-off or not.
- There is positive correlation of 0.44 between `tailnum` and `uniquecarrier` since a particular aircraft is owned by a particular carrier. Hence, that correlation does make sense.
- All the weather columns have some relation with each other.
- The `temperature` and `temp_range` have a very high positive correlation of 0.96 and it does make sense as well. Therefore, one of the columns needs to be dropped.
- On similar lines, `windspeed` and `windspeedsquare` have very high positive correlation of 0.93 and hence one of them needs to be dropped.
- The `capacity` and `loadfactor` have a positive correlation of approximately 0.40 with the `distance`. This makes sense because long-haul routes generally have higher `capacity` and a higher payload resulting a higher `loadfactor`.
- Not all values in the matrix make sense. They arise as an artifact of the data but do not make sense at all.

[34]:
```
flight_X_train = flight_X_train.drop(["windspeedsquare", "temperature"], axis =␣
↪1)
flight_X_test = flight_X_test.drop(["windspeedsquare", "temperature"], axis = 1)
```

- I dropped `windspeedsquare` since `windspeed` is more intuitive to understand and explain the models that will be trained later.
- The `temperature` column is dropped. This is because the target is a range of delay and keep the `temp_range` might help instead of actual value of temperature.

[35]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score
import pandas as pd


# Initialize the decision tree
clf = DecisionTreeClassifier(max_depth=5, random_state=42)
clf.fit(flight_X_train, flight_y_train)

# Predict and Evaluate
y_pred = clf.predict(flight_X_test)
accuracy = accuracy_score(flight_y_test, y_pred)
report = classification_report(flight_y_test, y_pred)

# Print the result
print("Decision Tree results:")
print(f"Accuracy: {accuracy}")
print(f"Classification Report:\n{report}")
```

```
Decision Tree results:
Accuracy: 0.8510672029104017
Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.99      0.94    183773
           1       0.43      0.03      0.05     18537
           2       0.48      0.47      0.47     16565
           3       0.49      0.43      0.46      7494
           4       0.88      0.85      0.86     13323

    accuracy                           0.85    239692
   macro avg       0.63      0.55      0.56    239692
weighted avg       0.82      0.85      0.82    239692
```

[36]:
```
from sklearn.ensemble import HistGradientBoostingClassifier
from sklearn.model_selection import GridSearchCV
import time
```

```python
start_time = time.time()

# hyperparameter tuning
param_grid = {
    "learning_rate": [0.01, 0.1, 0.2],
    "max_iter": [200, 400, 600, 800, 1000],
    "max_depth": [8, 16, 24]
}

# Grid search
hgbc = HistGradientBoostingClassifier(random_state=42)
grid_search = GridSearchCV(hgbc, param_grid=param_grid, cv=5,␣
 ↪scoring='accuracy', n_jobs=-1)
grid_search.fit(flight_X_train, flight_y_train)

# Print out the best hyperparameter for future training reference
print(f"Best hyperparameters from GridSearchCV:")
for param, value in grid_search.best_params_.items():
    print(f"  {param}: {value}")

best_hgbc = grid_search.best_estimator_
hgbc_test_score = best_hgbc.score(flight_X_test, flight_y_test)
print(f"HistGradientBoostingClassifier test accuracy: {hgbc_test_score}")

# Predict, and Evaluate
y_pred_hgbc = best_hgbc.predict(flight_X_test)
print("HistGradientBoostingClassifier results:")
HGBC_accuracy = accuracy_score(flight_y_test, y_pred_hgbc)
print(f"HGBC Accuracy: {HGBC_accuracy}")

print("HistGradientBoostingClassifier results:")
print(classification_report(flight_y_test, y_pred_hgbc))

# time the entire experiment
end_time = time.time()
time_to_select = end_time - start_time
print("total run time: ");
print(time_to_select)
```

```
Best hyperparameters from GridSearchCV:
  learning_rate: 0.01
  max_depth: 8
  max_iter: 1000
HistGradientBoostingClassifier test accuracy: 0.8519141231246766
HistGradientBoostingClassifier results:
HGBC Accuracy: 0.8519141231246766
HistGradientBoostingClassifier results:
```

```
              precision    recall  f1-score   support

           0       0.89      0.99      0.94    183773
           1       0.42      0.02      0.04     18537
           2       0.48      0.47      0.48     16565
           3       0.51      0.40      0.45      7494
           4       0.87      0.86      0.86     13323

    accuracy                           0.85    239692
   macro avg       0.63      0.55      0.55    239692
weighted avg       0.81      0.85      0.82    239692

total run time:
5801.750147104263
```

[ ]:

```

```

[ ]:

```

```