data_exploration

October 15, 2023

1 Data Exploration

[243]:
```
import numpy as np
import pandas as pd
import seaborn as sns
sns.set_theme()
```

1.1 Load data

[244]:
```
df = pd.read_csv("data/deliverytime.csv")

print(df.columns)

df.describe()
```

```
Index(['ID', 'Delivery_person_ID', 'Delivery_person_Age',
       'Delivery_person_Ratings', 'Restaurant_latitude',
       'Restaurant_longitude', 'Delivery_location_latitude',
       'Delivery_location_longitude', 'Type_of_order', 'Type_of_vehicle',
       'Time_taken(min)'],
      dtype='object')
```

[244]:
```
       Delivery_person_Age  Delivery_person_Ratings  Restaurant_latitude  \
count         45593.000000             45593.000000         45593.000000
mean             29.544075                 4.632367            17.017729
std               5.696793                 0.327708             8.185109
min              15.000000                 1.000000           -30.905562
25%              25.000000                 4.600000            12.933284
50%              29.000000                 4.700000            18.546947
75%              34.000000                 4.800000            22.728163
max              50.000000                 6.000000            30.914057

       Restaurant_longitude  Delivery_location_latitude  \
count          45593.000000                45593.000000
mean              70.231332                   17.465186
std               22.883647                    7.335122
min              -88.366217                    0.010000
```

```
25%                73.170000                     12.988453
50%                75.898497                     18.633934
75%                78.044095                     22.785049
max                88.433452                     31.054057

       Delivery_location_longitude  Time_taken(min)
count                 45593.000000     45593.000000
mean                     70.845702        26.294607
std                      21.118812         9.383806
min                       0.010000        10.000000
25%                      73.280000        19.000000
50%                      76.002574        26.000000
75%                      78.107044        32.000000
max                      88.563452        54.000000
```

Some of the column names aren't great (e.g. "Time_taken(min)"). Let's rename them first.

[245]:
```python
cols = df.columns.tolist()
cols[-1] = "time_taken"
cols = [col.lower() for col in cols]
df.columns = cols
print(cols)
```

```
['id', 'delivery_person_id', 'delivery_person_age', 'delivery_person_ratings',
'restaurant_latitude', 'restaurant_longitude', 'delivery_location_latitude',
'delivery_location_longitude', 'type_of_order', 'type_of_vehicle', 'time_taken']
```

1.2 Missing values

[246]:
```python
df.isnull().sum()
```

[246]:
```
id                             0
delivery_person_id             0
delivery_person_age            0
delivery_person_ratings        0
restaurant_latitude            0
restaurant_longitude           0
delivery_location_latitude     0
delivery_location_longitude    0
type_of_order                  0
type_of_vehicle                0
time_taken                     0
dtype: int64
```

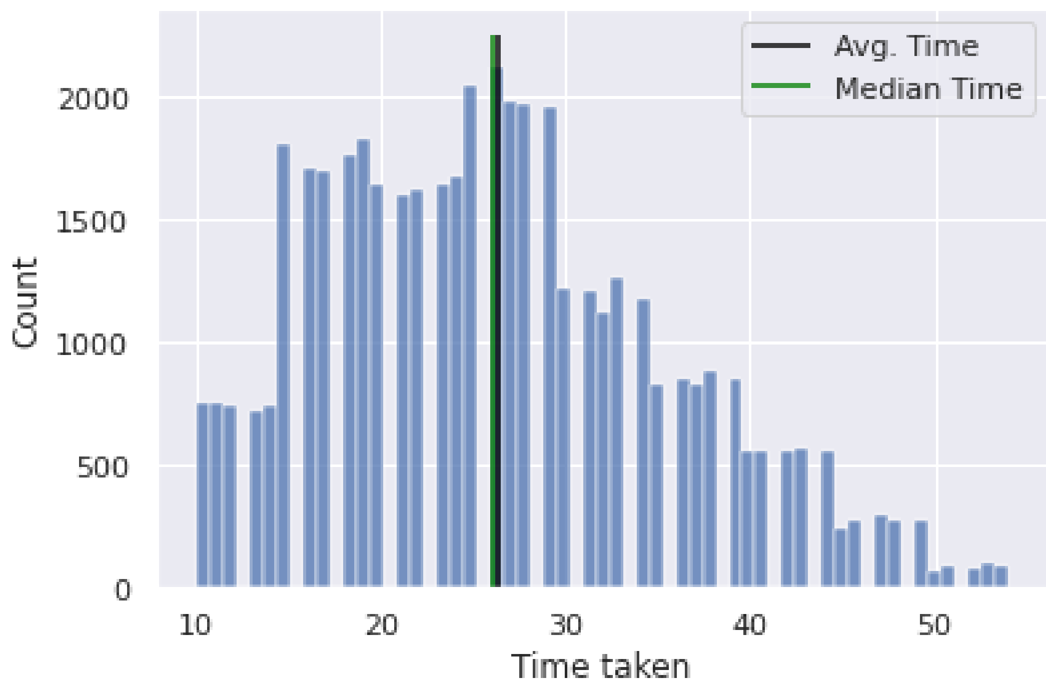
There are no missing values present in the dataset, so there is no need to impute or to drop any columns or rows.

1.3 Dependent variable

[247]:
```python
avg_time = df.time_taken.mean()
median_time = df.time_taken.median()
print(f"Average delivery time: {avg_time}")
print(f"Median delivery time: {median_time}")
hist = sns.histplot(df.time_taken)
hist.vlines(avg_time, 0, 2250, color = "black", label = "Avg. Time")
hist.vlines(median_time, 0, 2250, color = "green", label = "Median Time")
hist.set(xlabel = "Time taken")
hist.legend()
```

```
Average delivery time: 26.29460662821047
Median delivery time: 26.0
```

[247]: <matplotlib.legend.Legend at 0x7f9692638370>



The distribution has a positive skew, and the mean is slightly above the median. The fastest deliveries take only ten minutes, the slowest 54 minutes.

1.4 Categorical independent variables

[248]:
```
cat_cols = df.select_dtypes(include='object')
cat_cols.head()
```

[248]:

	id	delivery_person_id	type_of_order	type_of_vehicle
0	4607	INDORES13DEL02	Snack	motorcycle
1	B379	BANGRES18DEL02	Snack	scooter
2	5D6D	BANGRES19DEL01	Drinks	motorcycle
3	7A6A	COIMBRES13DEL02	Buffet	motorcycle
4	70A2	CHENRES12DEL01	Snack	scooter

There are four categorical variables: delivery id, delivery person ID, the type of order and the type of vehicle. The id is largely meaningless, but it does seem to contain a restaurant ID.

[249]:
```
import re

pattern = r"^.+RES\d{2}"

df["restaurant"] = [re.search(pattern, cell).group() for cell in df.
↪delivery_person_id]

restaurants = list(set(df.restaurant))
restaurants.sort()
print(len(restaurants))

df.sort_values(by=['restaurant']).loc[0:100, ["restaurant",␣
↪"restaurant_latitude", "restaurant_longitude"]]
```

```
418
```

[249]:

	restaurant	restaurant_latitude	restaurant_longitude
0	INDORES13	22.745049	75.892471
11859	INDORES13	22.745049	75.892471
12357	INDORES13	22.745049	75.892471
14807	INDORES13	22.745049	75.892471
12346	INDORES13	22.745049	75.892471
…	…	…	…
17549	PUNERES17	18.530963	73.828972
3759	PUNERES17	18.530963	73.828972
34206	PUNERES17	18.530963	73.828972
23936	PUNERES17	18.530963	73.828972
100	PUNERES17	18.530963	73.828972

[16433 rows x 3 columns]

As cases with the same restaurant ID share the same location, we can infer that there are a total of 418 restaurants.

[250]:
```
cat_cols.drop("id", axis = 1, inplace = True)
```

1.4.1 Type of order

[251]:
```
print(f"Number of unique order types: {cat_cols.type_of_order.nunique()}")
cat_cols.type_of_order.unique().tolist()
```

```
Number of unique order types: 4
```

[251]:
```
['Snack ', 'Drinks ', 'Buffet ', 'Meal ']
```

The categories have superfluous whitespaces at the end of the string. These are removed first.

[252]:
```
cat_cols["type_of_order"] = [cell.strip() for cell in cat_cols.type_of_order]
```

[253]:
```
sns.boxplot(x = df.type_of_order, y = df.time_taken)
```

[253]:
```
<AxesSubplot:xlabel='type_of_order', ylabel='time_taken'>
```

[254]:
```
df.groupby("type_of_order")["time_taken"].describe()
```

[254]:
```
                 count       mean       std   min   25%   50%   75%   max
type_of_order
Buffet         11280.0  26.283511  9.411344  10.0  19.0  26.0  32.0  54.0
```

```
Drinks          11322.0  26.187953  9.298465  10.0  19.0  25.0  32.0  54.0
Meal            11458.0  26.419270  9.424849  10.0  19.0  26.0  33.0  54.0
Snack           11533.0  26.286309  9.399147  10.0  19.0  26.0  32.0  54.0
```

Meals tend to take slightly longer to deliver, but the difference isn't large.

1.4.2 Type of vehicle

[255]:
```
print(f"Number of unique vehicle types: {cat_cols.type_of_vehicle.nunique()}")
cat_cols.type_of_vehicle.unique().tolist()
```

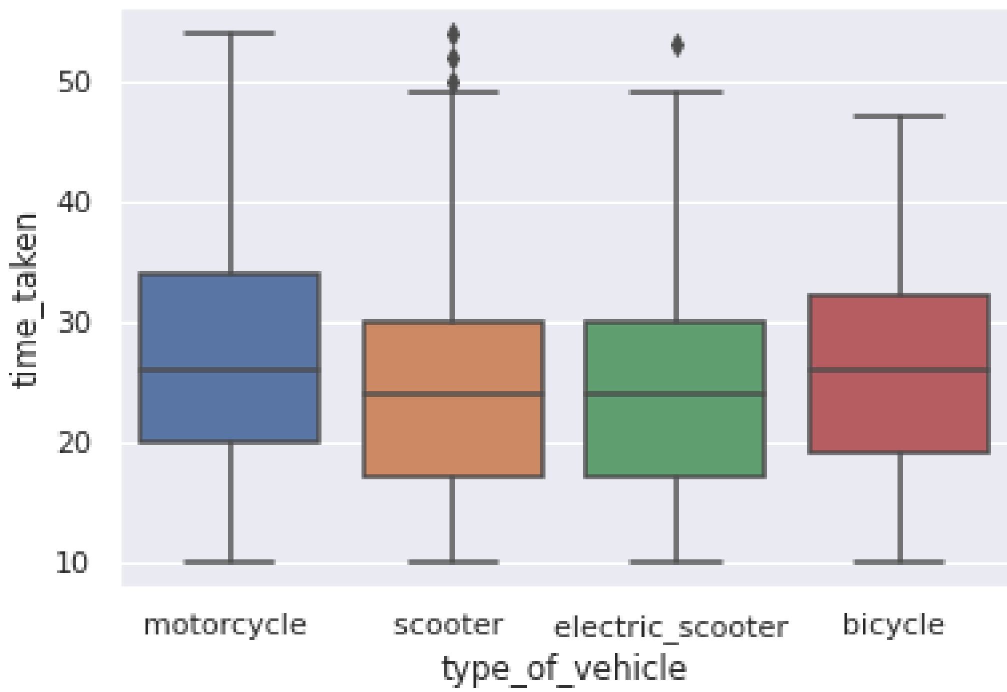
```
Number of unique vehicle types: 4
```

[255]:
```
['motorcycle ', 'scooter ', 'electric_scooter ', 'bicycle ']
```

[256]:
```
cat_cols["type_of_vehicle"] = [cell.strip() for cell in cat_cols.
↪type_of_vehicle]
```

[257]:
```
sns.boxplot(x = df.type_of_vehicle, y = df.time_taken)
```

[257]:
```
<AxesSubplot:xlabel='type_of_vehicle', ylabel='time_taken'>
```



[258]:
```
df.groupby("type_of_vehicle")["time_taken"].describe()
```

[258]:

```
                     count       mean       std   min   25%   50%    75%   max
type_of_vehicle
bicycle               68.0  26.426471  9.262855  10.0  19.0  26.0  32.25  47.0
electric_scooter    3814.0  24.470110  8.610859  10.0  17.0  24.0  30.00  53.0
motorcycle         26435.0  27.605674  9.647811  10.0  20.0  26.0  34.00  54.0
scooter            15276.0  24.480754  8.704238  10.0  17.0  24.0  30.00  54.0
```

Deliveries brought by motorcycle or bicycle tend to take longer to deliver. This doesn't necessarily have to be a causal relationship. It could simply be that motorcycles are used to reach destinations that are farther away. It's also of note that only very few deliveries are done by bicycle, so the summary statistics might not be very meaningful in this case.

1.4.3 Delivery person

[259]:

```python
print(f"Number of unique delivery person ids: {cat_cols.delivery_person_id.
 ↪nunique()}")
```

```
Number of unique delivery person ids: 1320
```

[260]:

```python
person_id_table = cat_cols.delivery_person_id.value_counts()
person_id_table.describe()
```

[260]:

```
count    1320.000000
mean       34.540152
std        21.305850
min         5.000000
25%        13.000000
50%        41.000000
75%        56.000000
max        67.000000
Name: delivery_person_id, dtype: float64
```

The average delivery person has carried out 34.5 deliveries. The delivery person with the fewest number of deliveries has 5, while the most active delivery person has 67 deliveries under their belt. Considering the high number of delivery persons and the relatively few deliveries per person, dummifying this variable might be more trouple than it is worth. It is dropped for now.

[261]:

```python
cat_cols.drop("delivery_person_id", axis = 1, inplace = True)
```

1.4.4 Dummifying

The type of vehicle and the type of order have relatively few unique categories and they might have a relation to the outcome variable. These two variables will be dummified, while the other two variables (order ID and delivery person ID) have been dropped.

[262]:

```python
cat_cols_dummy = pd.get_dummies(cat_cols)
print(cat_cols_dummy.columns)
```

```
Index(['type_of_order_Buffet', 'type_of_order_Drinks', 'type_of_order_Meal',
       'type_of_order_Snack', 'type_of_vehicle_bicycle',
       'type_of_vehicle_electric_scooter', 'type_of_vehicle_motorcycle',
       'type_of_vehicle_scooter'],
      dtype='object')
```

For each variable, the first category is dropped and used as reference category. In the case of the type of order, the category I've chosen as reference is "Drinks" as they are easy to prepare and slightly faster to deliver. The type of vehicle chosen as the reference category is "Motorcyle" because they are most frequently used.

[263]:
```
cat_cols_dummy.drop(["type_of_order_Drinks", "type_of_vehicle_motorcycle"],␣
 ↪axis = 1, inplace = True)
cat_cols_dummy.head()
```

[263]:
```
   type_of_order_Buffet  type_of_order_Meal  type_of_order_Snack  \
0                     0                   0                    1
1                     0                   0                    1
2                     0                   0                    0
3                     1                   0                    0
4                     0                   0                    1

   type_of_vehicle_bicycle  type_of_vehicle_electric_scooter  \
0                        0                                 0
1                        0                                 0
2                        0                                 0
3                        0                                 0
4                        0                                 0

   type_of_vehicle_scooter
0                        0
1                        1
2                        0
3                        0
4                        1
```

1.5 Numeric independent variables

1.5.1 Distance

The variables 'restaurant_latitude', 'restaurant_longitude', 'delivery_location_latitude', 'delivery_location_longitude' can be used to calculate beeline location. Of course, delivery drivers can't drive in a straight line to their location, but calculating exact distance would be much more difficult. So this is still a good enough approximation.

But first, there seem to be both negative and positive values in the data. Either these locations are very far apart, or there is some error in the data.

[264]:
```
df.loc[df.restaurant_latitude < 0, :]
```

[264]:

```
            id delivery_person_id  delivery_person_age  delivery_person_ratings  \
92      C042     AGRRES010DEL01                   34                      4.7
283     C044      AGRRES12DEL03                   32                      4.7
289      4DB     PUNERES02DEL03                   29                      4.6
425     C003      DEHRES13DEL02                   29                      4.6
534      473      MYSRES07DEL03                   29                      4.6
…      …                …                  …                       …
44933   C0C2     AURGRES03DEL03                   30                      4.9
45020    56B     PUNERES04DEL01                   29                      4.6
45108   C01B      GOARES18DEL01                   29                      4.6
45182   C0C7      KNPRES16DEL02                   30                      4.0
45504    461     BANGRES07DEL02                   29                      4.6

       restaurant_latitude  restaurant_longitude  delivery_location_latitude  \
92               -27.163303             78.057044                   27.233303
283              -27.165108             78.015053                   27.225108
289              -18.551440            -73.804855                   18.611440
425              -30.366322            -78.070453                   30.496322
534              -12.325461            -76.632278                   12.385461
…                    …                     …                          …
44933            -19.874733             75.353942                   19.904733
45020            -18.514210             73.838429                   18.524210
45108            -15.493950            -73.827423                   15.563950
45182            -26.482581             80.315628                   26.532581
45504            -12.978453            -77.643685                   12.998453

       delivery_location_longitude type_of_order    type_of_vehicle  \
92                       78.127044        Drinks             scooter
283                      78.075053          Meal             scooter
289                      73.864855          Meal             scooter
425                      78.200453         Snack             scooter
534                      76.692278        Buffet             scooter
…                              …             …                 …
44933                    75.383942        Buffet          motorcycle
45020                    73.848429        Drinks    electric_scooter
45108                    73.897423          Meal             scooter
45182                    80.365628        Drinks          motorcycle
45504                    77.663685          Meal             scooter

       time_taken restaurant
92             15   AGRRES01
283            31   AGRRES12
289            12  PUNERES02
425            20   DEHRES13
534            16   MYSRES07
…             …        …
44933          15  AURGRES03
```

```
45020          30  PUNERES04
45108          19   GOARES18
45182          34   KNPRES16
45504          24  BANGRES07

[431 rows x 12 columns]
```

As we can see here, the absolute vale of the restaurant latitude seems to be very close to delivery location latitude. As it is highly unlikely that the delivery has crossed the equator or the prime meridian, the values have to be corrected. The locations are likely all in India (for example, [30.496322, 78.200453] is in Uttarakhand), so both positive latitude and positive longitude is assumed.

There are also many restaurants with a location of (0, 0).

[265]:
```python
tmp = df.loc[df.restaurant_latitude == 0, :]

print(tmp.delivery_location_latitude.describe())
print(tmp.delivery_location_longitude.describe())
```

```
count    3640.000000
mean        0.063016
std         0.036047
min         0.010000
25%         0.030000
50%         0.060000
75%         0.090000
max         0.130000
Name: delivery_location_latitude, dtype: float64
count    3640.000000
mean        0.063016
std         0.036047
min         0.010000
25%         0.030000
50%         0.060000
75%         0.090000
max         0.130000
Name: delivery_location_longitude, dtype: float64
```

In these cases, the delivery location latitude and longitude are all positive and closeby.

The absolute value of all location variables should be taken.

[266]:
```python
df["restaurant_latitude"] = df["restaurant_latitude"].abs()
df["restaurant_longitude"] = df["restaurant_longitude"].abs()
df["delivery_location_latitude"] = df["delivery_location_latitude"].abs()
df["delivery_location_longitude"] = df["delivery_location_longitude"].abs()
```

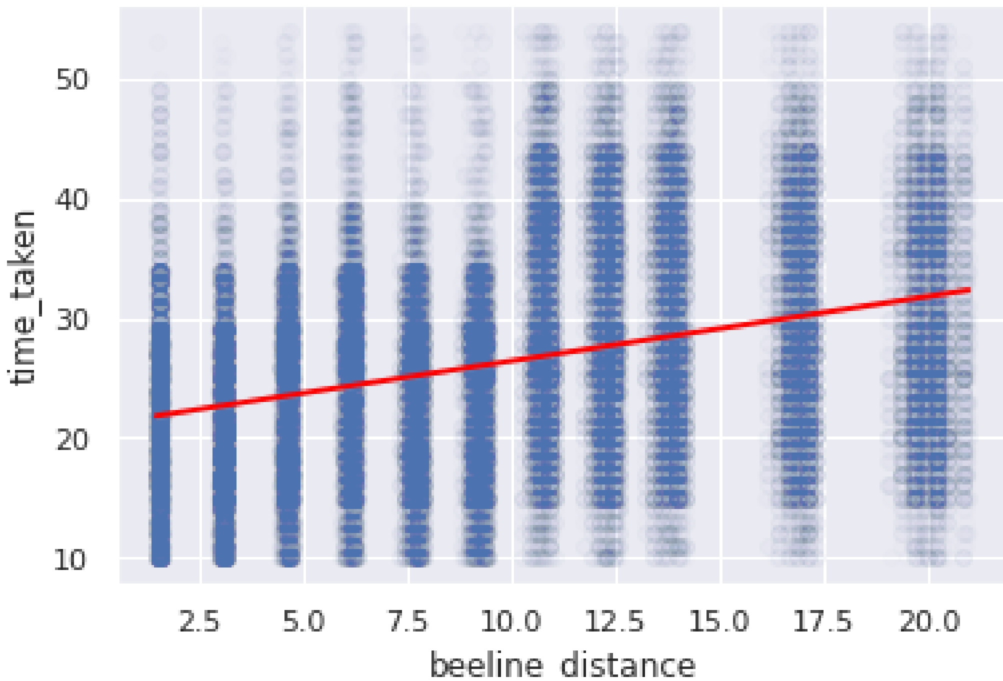
Finally, we can calculate the beeline distance.

```
[267]: def calculate_distance(lat1, lat2, lon1, lon2):
           """ Calculate the distance between two points using the haversine formula␣
        ↪"""
           lat1, lat2, lon1, lon2 = map(np.radians, [lat1, lat2, lon1, lon2])

           dlat = lat2 - lat1
           dlon = lon2 - lon1
           a = np.sin(dlat/2) ** 2 + np.cos(lat1) * np.cos(lat2) * np.sin(dlon/2) ** 2
           b = 2 * np.arctan2(a ** 0.5, (1-a) ** 0.5)

           return b * 6371

       df["beeline_distance"] = calculate_distance(df.restaurant_latitude, df.
        ↪delivery_location_latitude,
                                                   df.restaurant_longitude, df.
        ↪delivery_location_longitude)
       beeline_distance.describe()
```

```
[267]: count    45593.000000
       mean         0.907852
       std         10.087993
       min          0.014141
       25%          0.042426
       50%          0.084853
       75%          0.127279
       max        182.546210
       dtype: float64
```

```
[268]: sns.regplot(x = df.beeline_distance, y = df.time_taken,
                   scatter_kws = {'alpha':0.01},
                   line_kws = {"color": 'red', "linewidth": 2})
```

```
[268]: <AxesSubplot:xlabel='beeline_distance', ylabel='time_taken'>
```

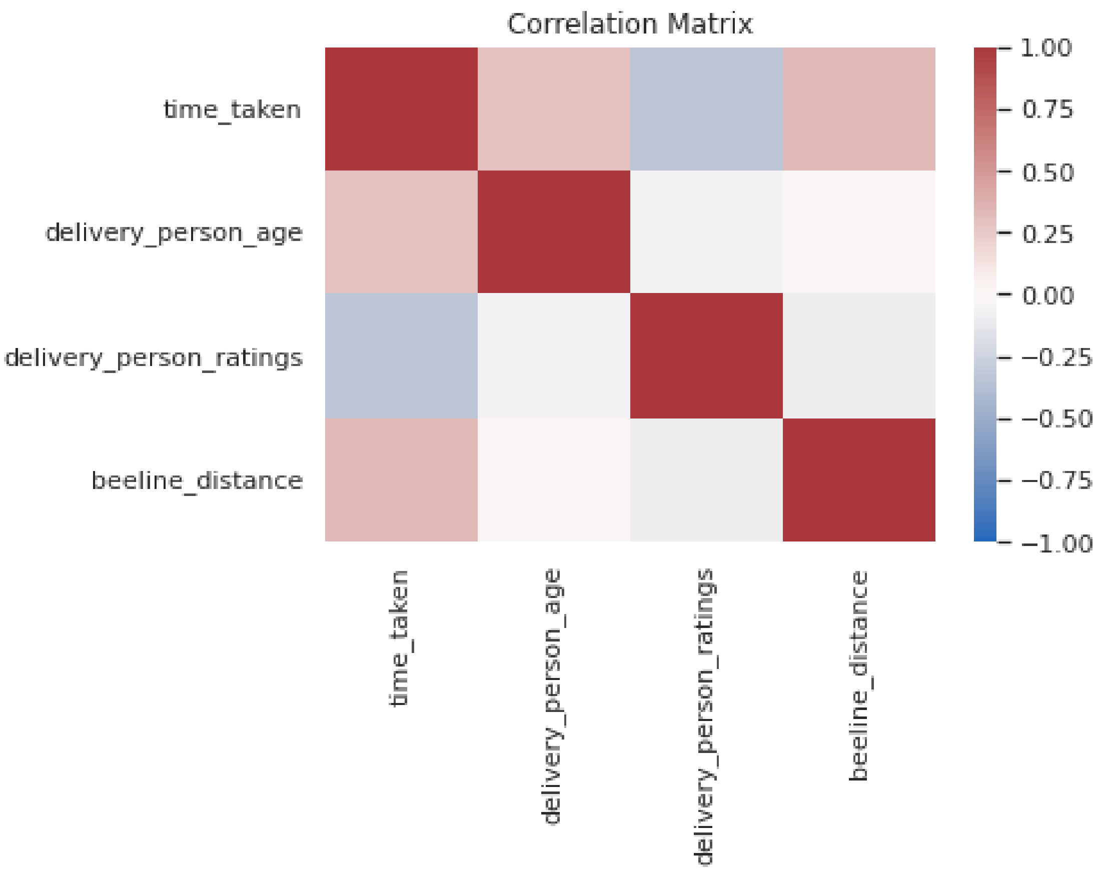


There seems to be a positive association between the beeline distance and the time taken.

1.5.2 Age and rating of delivery person

[269]:
```
df_num = df[["time_taken", "delivery_person_age", "delivery_person_ratings",␣
↪"beeline_distance"]]
corr_matrix = df_num.corr()
heatplot = sns.heatmap(corr_matrix, cmap = "vlag", vmin = -1, vmax = 1)
heatplot.set(title = "Correlation Matrix")
```

[269]:
```
[Text(0.5, 1.0, 'Correlation Matrix')]
```



- Older delivery persons take more time for the delivery
- Delivery persons with high ratings deliver more quickly
- The associations beetween the independent variables is low, so we expect no issues with multicollinearity

[270]:
```
print(df.delivery_person_ratings.describe())
print(f"Number of cases with a rating of 6: {sum(df.delivery_person_ratings ==␣
↪6)}")
```

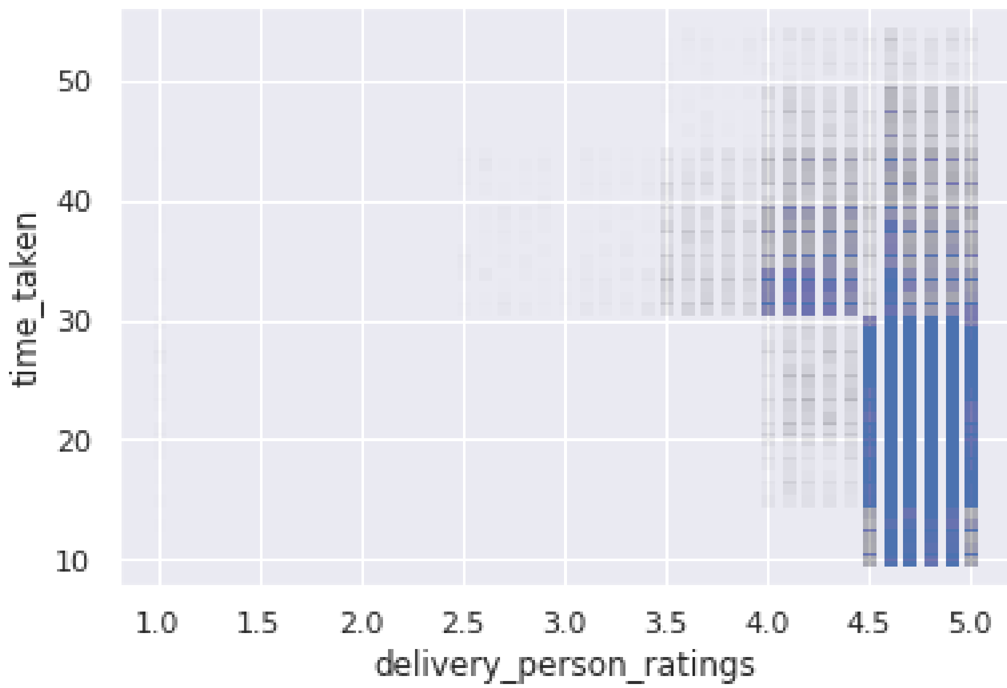
```
count    45593.000000
mean         4.632367
std          0.327708
min          1.000000
25%          4.600000
50%          4.700000
75%          4.800000
max          6.000000
Name: delivery_person_ratings, dtype: float64
Number of cases with a rating of 6: 53
```

There are 53 cases with a rating of 6. A rating scale from 1 to 5 is uncommon, and the cases are very few, so this is probably a mistake. The rating is recoded to 5.

[271]:
```
df.loc[df.delivery_person_ratings == 6, "delivery_person_ratings"] = 5
```

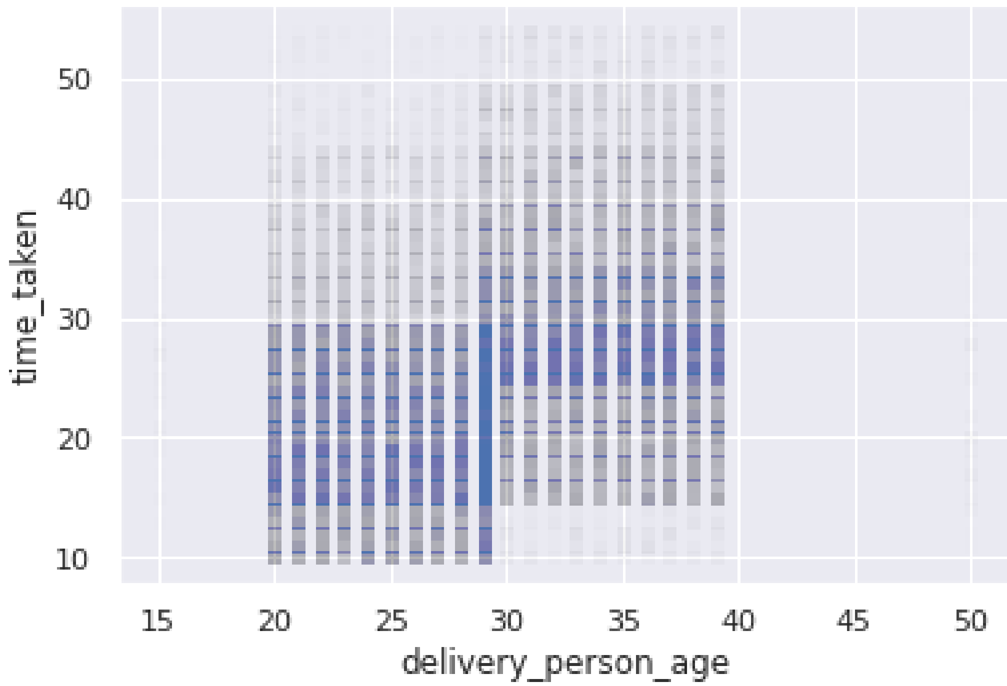
[272]:
```
sns.scatterplot(x = df.delivery_person_ratings, y = df.time_taken, alpha = 0.
 ↪005)
```

[272]: <AxesSubplot:xlabel='delivery_person_ratings', ylabel='time_taken'>



[273]:
```
sns.scatterplot(x = df.delivery_person_age, y = df.time_taken, alpha = 0.005)
```

[273]: <AxesSubplot:xlabel='delivery_person_age', ylabel='time_taken'>



1.6 Save dataset

[274]:
```
print(df.columns)
print(cat_cols_dummy.columns)
```

```
Index(['id', 'delivery_person_id', 'delivery_person_age',
       'delivery_person_ratings', 'restaurant_latitude',
       'restaurant_longitude', 'delivery_location_latitude',
       'delivery_location_longitude', 'type_of_order', 'type_of_vehicle',
       'time_taken', 'restaurant', 'beeline_distance'],
      dtype='object')
Index(['type_of_order_Buffet', 'type_of_order_Meal', 'type_of_order_Snack',
       'type_of_vehicle_bicycle', 'type_of_vehicle_electric_scooter',
       'type_of_vehicle_scooter'],
      dtype='object')
```

[275]:
```
df_finished = pd.concat([
    df[["time_taken", "delivery_person_age", "delivery_person_ratings",␣
 ↪"beeline_distance"]],
    cat_cols_dummy
], axis = 1)
df_finished.head()
```

[275]:

```
   time_taken  delivery_person_age  delivery_person_ratings  beeline_distance  \
0          24                   37                      4.9          3.025149
1          33                   34                      4.5         20.183530
2          26                   23                      4.4          1.552758
3          21                   38                      4.7          7.790401
4          30                   32                      4.6          6.210138

   type_of_order_Buffet  type_of_order_Meal  type_of_order_Snack  \
0                     0                   0                    1
1                     0                   0                    1
2                     0                   0                    0
3                     1                   0                    0
4                     0                   0                    1

   type_of_vehicle_bicycle  type_of_vehicle_electric_scooter  \
0                        0                                 0
1                        0                                 0
2                        0                                 0
3                        0                                 0
4                        0                                 0

   type_of_vehicle_scooter
0                        0
1                        1
2                        0
3                        0
4                        1
```

[276]:

```
df_finished.to_csv("data/deliverytime_processed.csv")
```