Data Analyst Ocado Internship Task

Mateusz Marczyk

Python, SQL

07.04.2024, Kraków

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

def extract_table_data(file, table_name):
    data = []
    reading_data = False
    line_number = 0
    with open(file, "r") as f:
        for line in f:
            line_number += 1
            try:
                if line.startswith("INSERT INTO {}
".format(table_name)):
                    reading_data = True
                    continue
                elif line.startswith("INSERT INTO"):
                    reading_data = False
                if reading_data:
                    line = line[1:-3].strip()
                    seg = line.split(",")
                    data.append(seg)
            except IndexError:
                print(f"Error occurred at line {line_number}: {line}")

    return data

file_name = "droptime.sql"

table_names = ["products", "orders", "orders_products",
"route_segments"]

dfs = {}
for table_name in table_names:
    data = extract_table_data(file_name, table_name)
    columns = ["product_id", "weight"] if table_name == "products"
else \
              ["order_id", "customer_id", "sector_id",
"planned_delivery_duration"] if table_name == "orders" else \
```

```
              ["order_id", "product_id", "quantity"] if table_name ==
"orders_products" else \
              ["segment_id", "driver_id", "segment_type", "order_id",
"segment_start_time", "segment_end_time"]
    dfs[table_name] = pd.DataFrame(data, columns=columns)



products_df = dfs["products"]
orders_df = dfs["orders"]
orders_products_df = dfs["orders_products"]
route_segments_df = dfs["route_segments"]
route_segments_df['order_id'] =
route_segments_df['order_id'].str.strip()

products_df['product_id'] = products_df['product_id'].astype(int)
products_df['weight'] = pd.to_numeric(products_df['weight'])

orders_df['order_id'] = orders_df['order_id'].astype(int)
orders_df['customer_id'] = orders_df['customer_id'].astype(int)
orders_df['sector_id'] = orders_df['sector_id'].astype(int)
orders_df['planned_delivery_duration'] =
pd.to_numeric(orders_df['planned_delivery_duration'])

orders_products_df['product_id'].fillna(-1, inplace=True)

orders_products_df['product_id'] =
orders_products_df['product_id'].astype(int)

orders_products_df['product_id'] =
orders_products_df['product_id'].astype(int)
orders_products_df['quantity'] =
pd.to_numeric(orders_products_df['quantity'])

route_segments_df['segment_id'] =
route_segments_df['segment_id'].astype(int)
route_segments_df['driver_id'] =
route_segments_df['driver_id'].astype(int)

route_segments_df['order_id'] =
pd.to_numeric(route_segments_df['order_id'], errors='coerce')

route_segments_df['segment_start_time'] =
pd.to_datetime(route_segments_df['segment_start_time'])
route_segments_df['segment_end_time'] =
pd.to_datetime(route_segments_df['segment_end_time'])
```

Part 2. Data analysis and visualisation

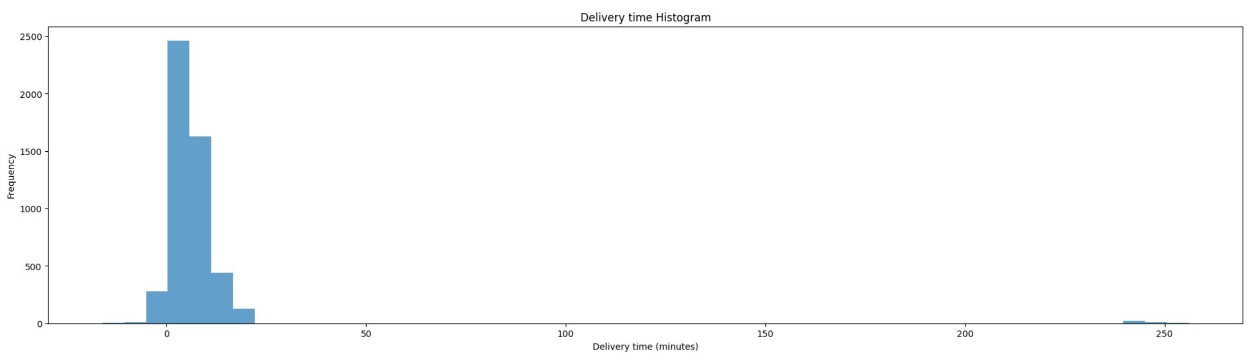
1. Generate a histogram showing the actual delivery time with 1 minute granularity (rounded up).

```
route_segments_df.loc[:, 'delivery_time_seconds'] =
(route_segments_df['segment_end_time'] -
route_segments_df['segment_start_time']).dt.total_seconds()

route_segments_df.loc[:, 'delivery_time_minutes'] =
route_segments_df['delivery_time_seconds'] / 60

route_segments_df.loc[:, 'delivery_time_rounded'] =
np.ceil(route_segments_df['delivery_time_minutes'])

plt.figure(figsize=(24, 6))
plt.hist(route_segments_df['delivery_time_rounded'], bins=50,
alpha=0.7)
plt.xlabel('Delivery time (minutes)')
plt.ylabel('Frequency')
plt.title('Delivery time Histogram')
plt.show()
```



as we can see from the histogram, the majority of the delivery times are definitely less than 100 minutes. Let's check the exact values distribution.

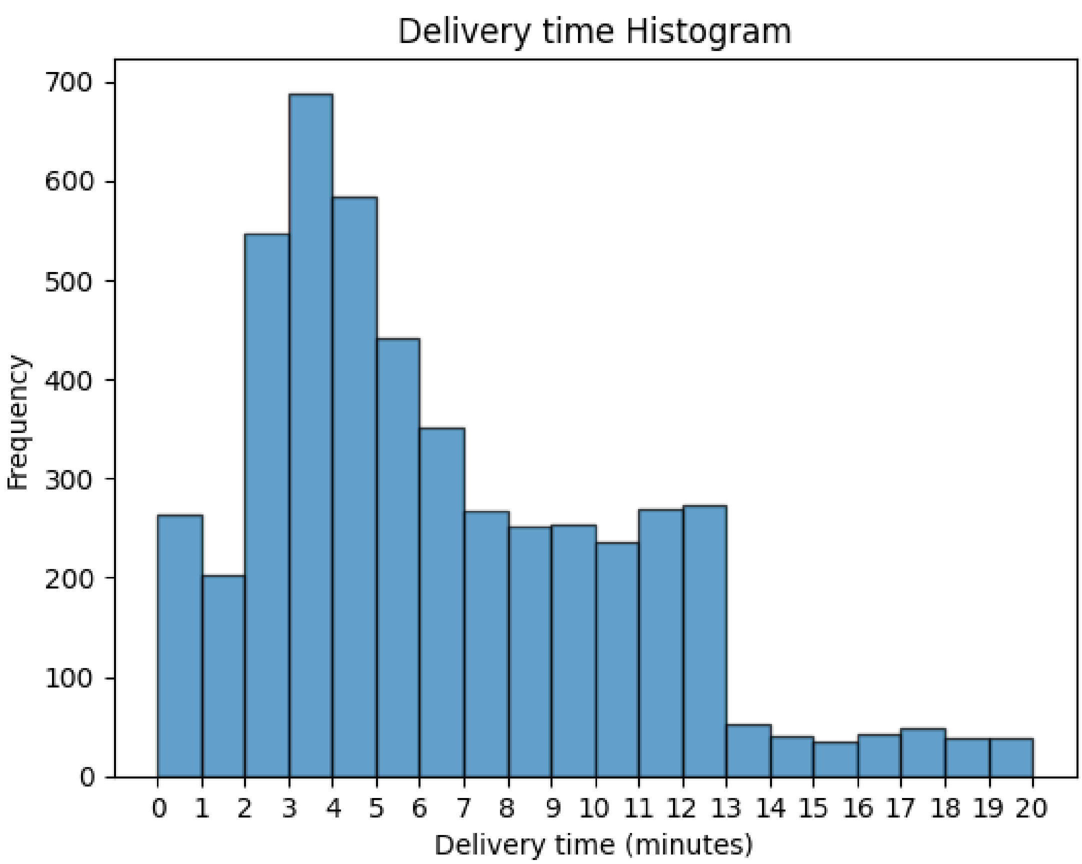
```
print(route_segments_df['delivery_time_rounded'].value_counts().sort_i
ndex(ascending=True))

delivery_time_rounded
-16.0        3
-14.0        1
-11.0        1
-10.0        1
-9.0         2
-8.0         1
```

```
-7.0        3
-6.0        5
-5.0        1
-4.0        4
-3.0        1
-2.0        5
-1.0        2
 0.0      263
 1.0      202
 2.0      547
 3.0      688
 4.0      584
 5.0      442
 6.0      352
 7.0      268
 8.0      251
 9.0      254
 10.0     235
 11.0     269
 12.0     273
 13.0      52
 14.0      40
 15.0      35
 16.0      43
 17.0      48
 18.0      39
 19.0      26
 20.0      12
 241.0      3
 242.0      8
 243.0      6
 244.0      3
 245.0      3
 246.0      2
 247.0      1
 248.0      4
 249.0      1
 250.0      2
 251.0      1
 252.0      2
 253.0      1
 256.0      1
Name: count, dtype: int64
```

as we can see from the distribution, the majority of the delivery times are in range of 0 to 20 minutes. Let's generate a histogram for this range.

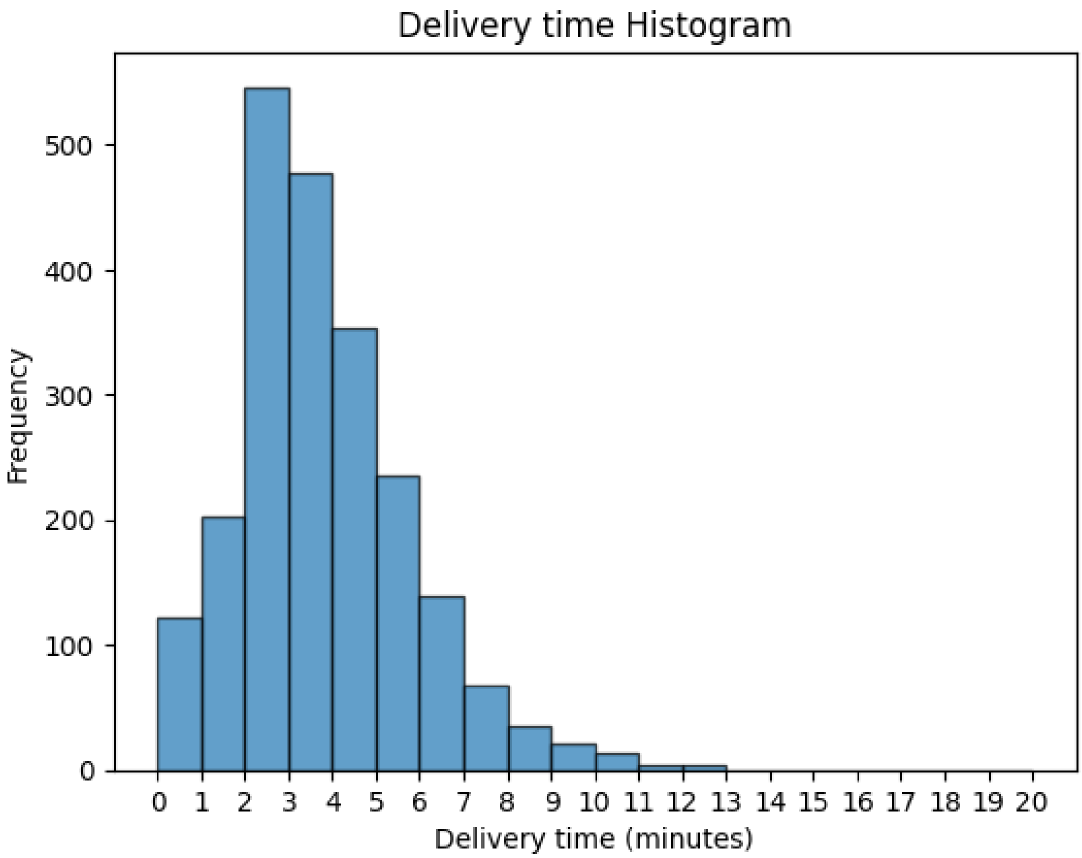
```
plt.hist(route_segments_df['delivery_time_rounded'],
edgecolor='black', bins=range(0, 21), alpha=0.7)
plt.xticks(range(21))
plt.xlabel('Delivery time (minutes)')
plt.ylabel('Frequency')
plt.title('Delivery time Histogram')
plt.show()
```



Let's also take a look at delivery times for STOP segments where order_id is not null.

```
merged_df = pd.merge(route_segments_df, orders_df, on='order_id')
plt.hist(merged_df['delivery_time_rounded'], edgecolor='black',
bins=range(0, 21), alpha=0.7)
plt.xticks(range(21))
plt.xlabel('Delivery time (minutes)')
plt.ylabel('Frequency')
```

```
plt.title('Delivery time Histogram')
plt.show()
```



as we can see from the histogram, when it comes to STOP segments, the majority of the delivery times are between 0 and 7 minutes

2. Generate a histogram showing prediction error (difference between planned and actual delivery times).

```
# I will need the copy for later analysis
merged_df_copy = merged_df.copy()

merged_df['difference'] =
abs(merged_df['planned_delivery_duration'].astype(int) -
merged_df['delivery_time_seconds'].astype(int))

plt.figure(figsize=(24, 6))
plt.hist(merged_df['difference'], edgecolor='black', alpha=0.7)
plt.xlabel('Delivery time (seconds)')
plt.ylabel('Frequency')
plt.title('Difference Delivery time Histogram')
plt.show()
```

similarly as earlier as we can see from the histogram, the majority of the delivery times are definitely less than 20000 minutes. Let's check the exact values distribution.

```
print(merged_df['difference'].value_counts().sort_index(ascending=True
).to_string())
```

```
difference
0       11
1       19
2        9
3       14
4       17
5       17
6       12
7       12
8       11
9        5
10       9
11      14
12      11
13      13
14       9
15      15
16      25
17      12
18      16
19      12
20       5
21      19
22      10
23      19
24      18
25      16
26      10
27      15
28      14
29      14
```

```
30    20
31    14
32    13
33    11
34    17
35    19
36    17
37    15
38    14
39    16
40    12
41    18
42    13
43    16
44    12
45    12
46    15
47    22
48     8
49    16
50    13
51    13
52    11
53     6
54    12
55    13
56    24
57     9
58    11
59    14
60    18
61    15
62     9
63    19
64    12
65    14
66    14
67    11
68    11
69    13
70     8
71     7
72    15
73    22
74    12
75    12
76    14
77    12
78     9
```

79	14
80	14
81	12
82	8
83	9
84	15
85	11
86	14
87	9
88	8
89	16
90	8
91	13
92	7
93	13
94	10
95	10
96	13
97	18
98	20
99	14
100	16
101	14
102	12
103	11
104	13
105	15
106	19
107	21
108	13
109	6
110	16
111	12
112	12
113	15
114	18
115	16
116	9
117	17
118	15
119	14
120	9
121	10
122	19
123	13
124	10
125	16
126	9
127	12

128	10
129	12
130	14
131	7
132	8
133	9
134	12
135	13
136	8
137	8
138	9
139	5
140	6
141	4
142	6
143	3
144	5
145	9
146	3
147	4
148	2
149	3
150	2
151	4
152	1
153	2
154	6
155	2
156	3
158	1
159	2
161	2
162	1
163	2
164	1
165	4
166	4
167	3
168	2
169	10
170	8
171	4
172	4
173	3
174	1
175	25
176	42
177	15
178	18

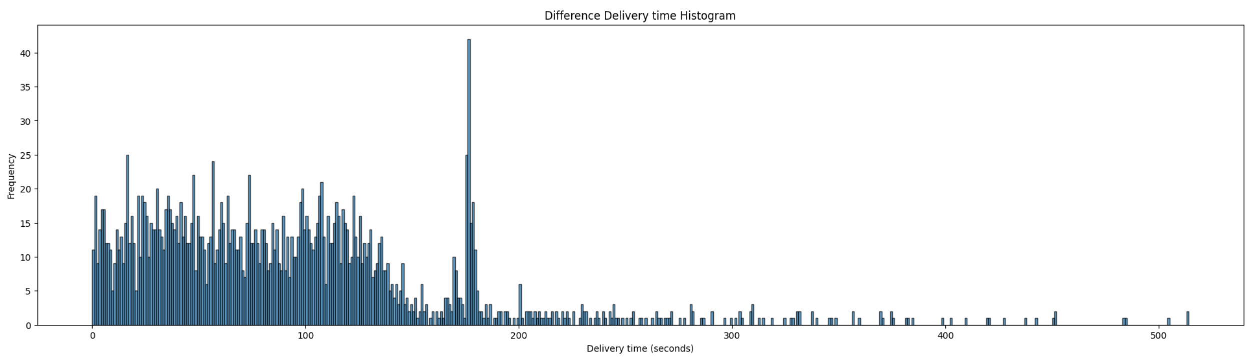
179	11
180	5
181	2
182	2
183	1
184	3
185	1
186	3
188	1
189	1
190	2
191	2
193	2
194	2
195	1
197	1
199	1
200	6
201	1
203	2
204	2
205	2
206	1
207	2
208	1
209	2
210	1
211	1
212	2
213	1
214	1
215	2
217	2
218	1
220	2
221	1
222	2
223	1
225	2
228	1
229	3
230	2
231	2
233	1
235	1
236	2
237	1
239	2
240	1

242	2
243	1
244	3
245	1
246	1
248	1
250	1
252	1
253	2
256	1
257	1
259	1
262	1
264	2
265	1
266	1
268	1
269	1
270	1
271	2
275	1
277	1
280	3
281	2
285	1
286	1
290	2
296	1
299	1
301	1
303	2
304	1
308	2
309	3
312	1
314	1
318	1
324	1
327	1
328	1
330	2
331	2
337	2
339	1
345	1
346	1
348	1
356	2
359	1

369	2
370	1
374	2
375	1
381	1
382	1
384	1
398	1
402	1
409	1
419	1
420	1
427	1
437	1
442	1
450	1
451	2
483	1
484	1
504	1
514	2
14269	1
14275	1
14289	1
14290	1
14292	1
14297	1
14300	1
14321	1
14322	1
14324	1
14342	1
14346	1
14357	1
14362	1
14371	1
14373	1
14398	1
14446	1
14493	1
14515	1
14563	1
14572	1
14682	1
14766	1

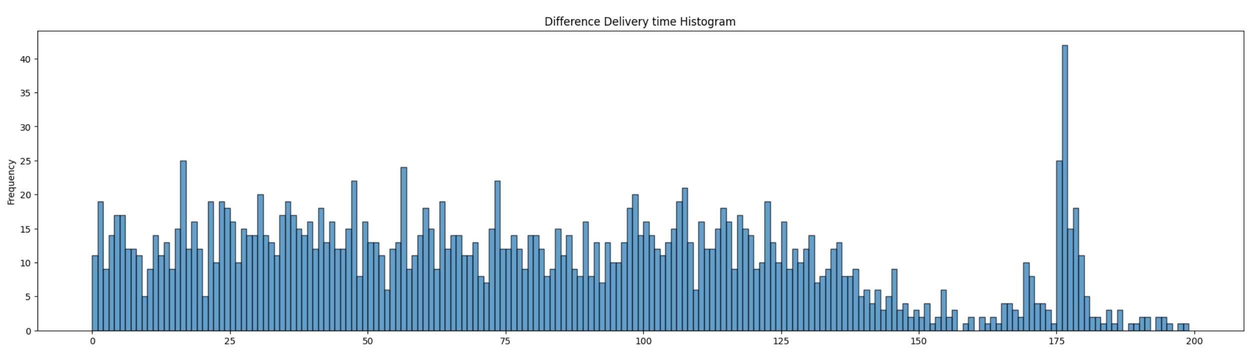
as we can see from the distribution, the majority of the delivery times are in range of 0 to 514 seconds. Let's generate a histogram for this range.

```
plt.figure(figsize=(24, 6))
plt.hist(merged_df['difference'], edgecolor='black', bins=range(0,
515), alpha=0.7)
plt.xlabel('Delivery time (seconds)')
plt.ylabel('Frequency')
plt.title('Difference Delivery time Histogram')
plt.show()
```



Let's take a closer look and generate a histogram for the range of 0 to 200 seconds.

```
plt.figure(figsize=(24, 6))
plt.hist(merged_df['difference'], edgecolor='black', bins=range(0,
200), alpha=0.7)
plt.xlabel('Delivery time (seconds)')
plt.ylabel('Frequency')
plt.title('Difference Delivery time Histogram')
plt.show()
```



3. We received insight from our drivers that delivering in one of the sectors is significantly longer than in other sectors. Generate a chart to visualise this hypothesis.

First let's take a look at the statistics for delivery times by sector.

```
statistics_delivery_time = merged_df.groupby('sector_id')
['delivery_time_minutes'].describe()
statistics_delivery_time

           count      mean        std       min       25%       50%
75%  \
sector_id

1          739.0  5.661254  21.841322 -5.050000  1.816667  3.450000
5.208333
2          739.0  5.282161  26.371447 -4.416667  1.266667  2.233333
3.300000
3          779.0  5.149487  25.656463 -4.550000  1.183333  2.250000
3.416667

                  max
sector_id
1          249.050000
2          244.866667
3          245.783333
```

As we can see, sector 1 has the longest delivery time on average. Let's generate a chart to visualize this.

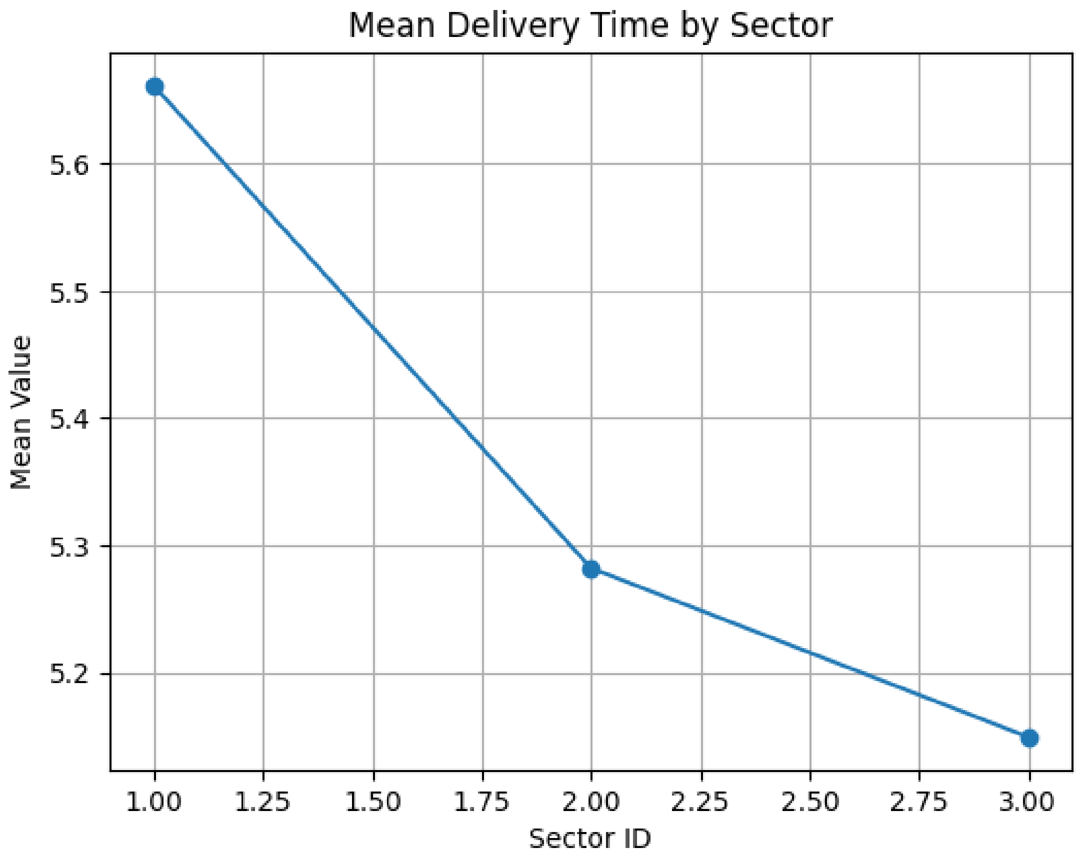
```
import matplotlib.pyplot as plt

mean_delivery_time = merged_df.groupby('sector_id')
['delivery_time_minutes'].mean()

plt.plot(mean_delivery_time, marker='o', linestyle='-')

plt.xlabel('Sector ID')
plt.ylabel('Mean Value')
plt.title('Mean Delivery Time by Sector')

plt.grid(True)
plt.show()
```



As we can see in the chart, sector with ID 1 has the longest delivery time. However, I would not say that the difference between the average times in these 3 sectors is very different. The statistics also seem to confirm this.

4. Play with the data by grouping, aggregating and remodelling it. Are you able to find any correlations or trends that could be valuable for prediction quality improvement? Describe briefly your findings and visualise them on charts.

Let's take a look at the maximum delivery time for each sector. Maybe there is a sector where the maximum delivery times are significantly longer than in other sectors.

```
merged_df.groupby('sector_id')['delivery_time_minutes'].max()
```

```
sector_id
1    249.050000
2    244.866667
3    245.783333
Name: delivery_time_minutes, dtype: float64
```

```
sorted_df = merged_df.sort_values(by='delivery_time_minutes',
ascending=False)
selected_columns = sorted_df[['sector_id', 'delivery_time_minutes']]
selected_columns
```

```
      sector_id  delivery_time_minutes
1452          1             249.050000
295           1             247.650000
798           3             245.783333
1756          1             245.633333
423           2             244.866667
...         ...                    ...
62            3              -3.450000
304           2              -4.333333
1300          2              -4.416667
1658          3              -4.550000
1859          1              -5.050000

[2257 rows x 2 columns]
```

As we can see, the maximum delivery times are not significantly different between sectors. The distribution of delivery times is similar for all sectors. Perhaps it is error in the dataset, and they are just outliers.

Maybe just couple customers are causing the longer delivery times. If yes, they should have low standard deviation of delivery times.

```
merged_df.groupby('customer_id').agg(
    mean_delivery_duration=('delivery_time_seconds', 'mean'),
    std_delivery_duration=('delivery_time_seconds', 'std'),
    sector_id=('sector_id', 'first')
).sort_values(by='mean_delivery_duration', ascending=False)
```

```
             mean_delivery_duration  std_delivery_duration  sector_id
customer_id
293                     7376.500000           10106.677223          1
97                      5932.600000            7899.066768          2
48                      3802.500000            7246.651296          3
142                     2524.833333            5850.590719          1
66                      2519.333333            5886.005289          1
...                             ...                    ...        ...
```

```
244                        69.000000            71.084457          3
150                        55.600000            36.637413          2
73                         50.200000           165.561771          3
1                          39.000000                  NaN          3
162                        22.166667           174.830680          3

[320 rows x 3 columns]
```

It is not the case. The standard deviation is very high for all customers, with high delivery times.

Perhaps it's the high weight of the products that causes the longer delivery times. Let's check it out!

```
orders_products_df = orders_products_df[orders_products_df['order_id']
!= '']
route_segments_df = route_segments_df.dropna(subset=['order_id'])

route_segments_df.loc[:, 'order_id'] =
route_segments_df['order_id'].astype(int)
route_segments_df['order_id'] =
route_segments_df['order_id'].astype(int)
orders_products_df['order_id'] =
orders_products_df['order_id'].astype(int)
merged_df = pd.merge(merged_df, orders_products_df, on='order_id',
how='inner')
merged_df = pd.merge(merged_df, products_df, on='product_id',
how='inner')
merged_df['total_weight'] = merged_df['weight'] *
merged_df['quantity']

order_summary = merged_df.groupby('order_id').agg({'total_weight':
'sum', 'delivery_time_minutes': 'first'}).reset_index()

order_summary_sorted = order_summary.sort_values(by='total_weight',
ascending=False)
order_summary_sorted.head(30)
```

```
C:\Users\user\AppData\Local\Temp\ipykernel_10884\1911056540.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  route_segments_df['order_id'] =
route_segments_df['order_id'].astype(int)
C:\Users\user\AppData\Local\Temp\ipykernel_10884\1911056540.py:6:
```

```
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  orders_products_df['order_id'] =
orders_products_df['order_id'].astype(int)
```

	order_id	total_weight	delivery_time_minutes
513	513.0	26388.0	4.883333
788	788.0	24248.0	2.600000
756	756.0	23633.0	1.783333
1901	1901.0	23443.0	2.383333
1896	1896.0	23244.0	3.883333
502	502.0	22390.0	4.883333
1783	1783.0	22245.0	11.033333
1084	1084.0	21056.0	4.833333
294	294.0	20239.0	9.583333
1853	1853.0	20167.0	1.733333
745	745.0	19741.0	8.433333
1173	1173.0	19674.0	7.033333
2235	2235.0	18878.0	5.966667
1197	1197.0	18721.0	2.450000
361	361.0	18280.0	2.533333
3	3.0	18274.0	1.533333
1373	1373.0	18189.0	9.116667
2029	2029.0	18060.0	0.000000
323	323.0	17833.0	4.966667
2065	2065.0	17719.0	4.250000
637	637.0	17616.0	3.200000
1003	1003.0	17481.0	6.333333
1780	1780.0	17439.0	4.566667
1892	1892.0	17331.0	5.483333
402	402.0	17324.0	7.433333
2190	2190.0	17167.0	11.550000
981	981.0	16992.0	9.200000
10	10.0	16861.0	2.550000
1784	1784.0	16778.0	4.166667
1923	1923.0	16777.0	3.466667

As we can see the total weight of the products does not seem to have a significant impact on the delivery time.

Part 3. Building and verifying the hypothesis

The current prediction algorithm is very naive. It calculates the mean from all collected data and applies it to every future order. We need to explore alternative ideas. One of them is predicting delivery times per sector. Describe how you would validate this hypothesis using available data.

First I would split into independent sets based on sectors and then analyze the delivery times for each sector, look at the statistics, visualize data for better understanding. I would try to look for significant differences and based on that validate the hypothesis.

Using the data, propose some alternative method/algorithm that will predict delivery times more accurately. Describe the methodology to validate the new algorithm.

Let's create machine learning model to predict delivery times. We will merged_df from previous analysis as it contains all necessary data.

First let's prepare data by grouping it by order_id and calculating total weight of the products, then preserving only necessary columns.

```
merged_df['total_weight'] = merged_df['weight'] *
merged_df['quantity']

grouped_df = merged_df.groupby('order_id').agg({
    'driver_id': 'first',
    'segment_start_time': 'first',
    'segment_end_time': 'first',
    'delivery_time_seconds': 'first',
    'sector_id': 'first',
    'total_weight': 'sum'
}).reset_index()
grouped_df.drop(columns=['order_id'], inplace=True)
```

```
print(grouped_df.dtypes)
grouped_df['delivery_time_seconds'] =
grouped_df['delivery_time_seconds'].astype(int)
grouped_df.drop(columns=['segment_start_time', 'segment_end_time'],
inplace=True)
```

```
driver_id                               int32
segment_start_time         datetime64[ns]
segment_end_time           datetime64[ns]
delivery_time_seconds                 float64
sector_id                               int32
total_weight                          float64
dtype: object
```

```
grouped_df2 = grouped_df.copy()

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error

y = grouped_df.pop('delivery_time_seconds')
X = grouped_df

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

rf_regressor = RandomForestRegressor(n_estimators=100,
random_state=42)

rf_regressor.fit(X_train, y_train)

y_pred = rf_regressor.predict(X_test)

mae = mean_absolute_error(y_test, y_pred)
print("Mean Absolute Error:", mae)
```

```
Mean Absolute Error: 328.0816325467687
```

The Mean Absolute Error is quite high. Let's try to improve the model by removing outliers.

```
grouped_df = grouped_df2[grouped_df2['delivery_time_seconds'] <= 1000]

y = grouped_df.pop('delivery_time_seconds')
X = grouped_df

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

rf_regressor = RandomForestRegressor(n_estimators=100,
random_state=42)
```

```
rf_regressor.fit(X_train, y_train)

y_pred = rf_regressor.predict(X_test)

mae = mean_absolute_error(y_test, y_pred)
print("Mean Absolute Error:", mae)
```

```
Mean Absolute Error: 48.33822415272415
```

As we can see the Mean Absolute Error is much lower now, nearly 7 times. It probably means that the outliers are errors in dataset. Let's see if gradient boosting regressor can improve the model even more.

```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_absolute_error
gb_regressor = GradientBoostingRegressor(random_state=42)

gb_regressor.fit(X_train, y_train)

y_pred = gb_regressor.predict(X_test)

mae = mean_absolute_error(y_test, y_pred)
print("Mean Absolute Error:", mae)
```

```
Mean Absolute Error: 38.796674702122765
```

The Mean Absolute Error is even lower. MAE dropped almost 20%, which is a significant improvement. Let's try to tune the hyperparameters to improve the model even more.

```
gb_regressor = GradientBoostingRegressor(random_state=42)

param_grid = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

grid_search = GridSearchCV(estimator=gb_regressor,
param_grid=param_grid, cv=5, scoring='neg_mean_absolute_error',
n_jobs=-1)

grid_search.fit(X_train, y_train)

best_params = grid_search.best_params_
print("Best Parameters:", best_params)
```

```
best_gb_regressor = GradientBoostingRegressor(**best_params,
random_state=42)

best_gb_regressor.fit(X_train, y_train)

y_pred = best_gb_regressor.predict(X_test)

mae = mean_absolute_error(y_test, y_pred)
print("Mean Absolute Error:", mae)
```

```
Best Parameters: {'learning_rate': 0.1, 'max_depth': 3,
'min_samples_leaf': 4, 'min_samples_split': 10, 'n_estimators': 100}
Mean Absolute Error: 38.234091441642384
```

Hyperparameter tuning improved the model just a bit. So finally we get MAE at 38. Let's compare it with the current MAE, using average as prediction.

First let's calculate the MAE for the current model with outliers.

```
mae = mean_absolute_error(merged_df_copy['delivery_time_seconds'],
merged_df_copy['planned_delivery_duration'])
print("Mean Absolute Error:", mae)
```

```
Mean Absolute Error: 245.39610101905183
```

As we can see the MAE for the current model is more than 6 times higher than the MAE for the model with outliers removed. Let's see what is the MAE without outliers.

```
merged_df_copy =
merged_df_copy[merged_df_copy['delivery_time_seconds'] <= 1000]
mae = mean_absolute_error(merged_df_copy['delivery_time_seconds'],
merged_df_copy['planned_delivery_duration'])
print("Mean Absolute Error:", mae)
```

```
Mean Absolute Error: 93.27989252127183
```

The MAE for the current model without outliers is still more twice higher than the MAE for the model with outliers removed. Out machine learning model improved the predictions very well.

To sum thing up, I think that the best way to predict delivery times is to use machine learning models. Even with the dataset I used, which is very limited, I was able to improve the predictions significantly. I think that with more data and more features (which I will describe later), the model could be improved even more. I would also consider using more complex models, like neural networks, to improve the predictions even more.

Why could some deliveries take more time? For example, some buildings don’t have elevators etc. Describe your ideas.

I would point out a few factors that could affect the delivery time:

- Location Accessibility: some locations may be more difficult to access than others, which could increase delivery times
- Building Features: elevators, stairs, gated communities
- Traffic: traffic jams, roadworks
- Weather: rain, snow, storms
- Incorrect or Incomplete Address: driver may have trouble finding the location
- Technical Issues: vehicle breakdown, GPS issues

What additional data would be worth collecting for future analysis of this domain?

I would consider collecting the following additional data:

- Traffic Data: traffic congestion, road closures, accidents
- Vehicle Data: vehicle type, age, maintenance
- Driver Data: experience, performance, working hours
- Route Data: distance, elevation, road type
- Building Data: features, accessibility, security

I would also improve the partitioning algorithm for the GPS, so the whole road that driver took is clear