2_Preliminary_EDA

September 3, 2025

1 Preliminary Exploratory data analysis (EDA)

We have several datasets: stops, ridership, and weather. An EDA will be carried out separately on each dataset.

The stops dataset was mainly used for exploration and visualization with Folium, as a first step to get familiar with the TPG network.
For the ridership data, an EDA will first be done on a single line, and then on all lines.

[1]:
```
INSTALL_LIB = True
```

[2]:
```
# libraries
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

2 1) The stops

[3]:
```
stops_df = pd.read_csv("arrets.csv",sep=",")
display(stops_df.head(5))
print(f"We have {stops_df.shape[0]} samples and {stops_df.shape[1]} columns.")
print(f"The list of columns : \n{stops_df.columns.tolist()}")
print(f"\n")
print(f"Information about dataset : \n")
display(stops_df.info())
print(f"\n")
print(f"Sum of null data : \n{stops_df.isnull().sum()}")
print(f"\n")

print(f"Sum of duplicate data: {stops_df.duplicated().sum()}")
print(f"\n")
```

```
  arretcodelong              nomarret          commune pays  codedidoc  \
0         _BSDNF         Bossy-Dne - F        VERSONNEX   FR        NaN
1         _BSDNS        Bossy-Dne - CH     COLLEX-BOSSY   CH        NaN
2         _CANDF  Bois Candide-Dne - F  FERNEY-VOLTAIRE   FR        NaN
```

```
3        _CERNF          CERN-Dne - F  PRÉVESSIN-MOËNS   FR        NaN
4        _CERNS         CERN-Dne - CH           MEYRIN   CH        NaN

                          coordonnees actif
0  {'lon': 6.104478, 'lat': 46.286907}     Y
1  {'lon': 6.104423, 'lat': 46.287045}     Y
2   {'lon': 6.092361, 'lat': 46.24374}     Y
3  {'lon': 6.050063, 'lat': 46.235073}     Y
4  {'lon': 6.050015, 'lat': 46.234905}     Y
```

We have 4553 samples and 7 columns.
The list of columns :
['arretcodelong', 'nomarret', 'commune', 'pays', 'codedidoc', 'coordonnees', 'actif']

Information about dataset :

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4553 entries, 0 to 4552
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   arretcodelong  4553 non-null   object
 1   nomarret       4534 non-null   object
 2   commune        4477 non-null   object
 3   pays           4553 non-null   object
 4   codedidoc      3879 non-null   float64
 5   coordonnees    4405 non-null   object
 6   actif          4553 non-null   object
dtypes: float64(1), object(6)
memory usage: 249.1+ KB
```

None

```
Sum of null data :
arretcodelong      0
nomarret          19
commune           76
pays               0
codedidoc        674
coordonnees      148
actif              0
dtype: int64
```

Sum of duplicate data: 0

2.0.1 Observation :

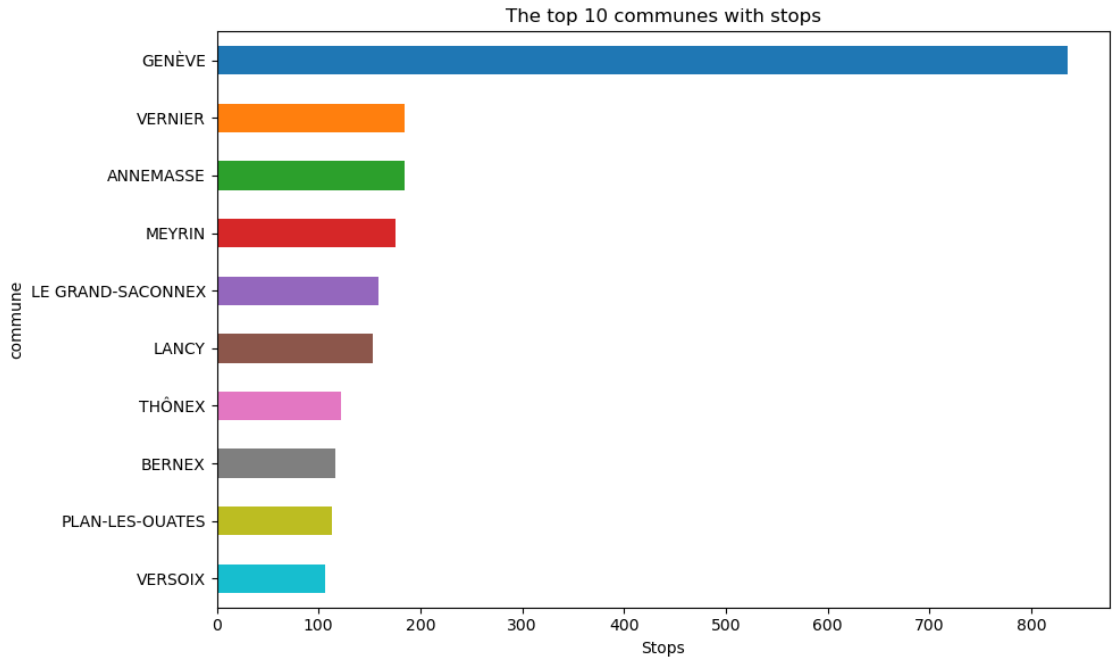
The Didoc code is not reliable.

2.0.2 Action :

Use the “Long Code Stop” instead.

[4]:
```
# Municipalities with the most stops:
top_10_communes = stops_df['commune'].value_counts().head(10).reset_index()
top_10_communes.columns = ['commune', 'Arrets_Number']
print(f"Municipalities with the most stops: \n{top_10_communes}"  )

# plot
colormap = [plt.cm.tab10(i) for i in range(len(top_10_communes))]
bar_plot = top_10_communes.plot.barh(
    x='commune',
    y='Arrets_Number',
    color=colormap,
    legend=False,
    figsize=(10, 6)
)

bar_plot.set_title("The top 10 communes with stops")
bar_plot.set_xlabel("Stops")
bar_plot.invert_yaxis()
plt.tight_layout()
plt.show()
```

```
Municipalities with the most stops:
              commune  Arrets_Number
0              GENÈVE            835
1             VERNIER            185
2           ANNEMASSE            184
3              MEYRIN            175
4  LE GRAND-SACONNEX             159
5               LANCY            153
6              THÔNEX            122
7              BERNEX            116
8    PLAN-LES-OUATES             113
9             VERSOIX            106
```



Geneva has significantly more stops than the other municipalities.

Where are the stops located?

[5]:
```
#Extraire latitude et longitude depuis coordonnees
#code from chatGPT after debug

import ast
import pandas as pd

# Nettoyer la colonne : convertir les chaînes en dictionnaires
def parse_coord(x):
    if isinstance(x, str):
        try:
            return ast.literal_eval(x)
        except:
            return None
    elif isinstance(x, dict):
        return x
    else:
        return None

stops_df['coordonnees'] = stops_df['coordonnees'].apply(parse_coord)

# Extraire latitude et longitude
```

```
stops_df['latitude'] = stops_df['coordonnees'].apply(lambda x: x['lat'] if␣
 ↪isinstance(x, dict) else None)
stops_df['longitude'] = stops_df['coordonnees'].apply(lambda x: x['lon'] if␣
 ↪isinstance(x, dict) else None)

# Convertir en float (utile si tu veux trier, mapper, etc.)
stops_df['latitude'] = pd.to_numeric(stops_df['latitude'], errors='coerce')
stops_df['longitude'] = pd.to_numeric(stops_df['longitude'], errors='coerce')

# Vérification
print(stops_df[['coordonnees', 'latitude', 'longitude']].head())
```

```
                        coordonnees   latitude  longitude
0  {'lon': 6.104478, 'lat': 46.286907}  46.286907   6.104478
1  {'lon': 6.104423, 'lat': 46.287045}  46.287045   6.104423
2   {'lon': 6.092361, 'lat': 46.24374}  46.243740   6.092361
3  {'lon': 6.050063, 'lat': 46.235073}  46.235073   6.050063
4  {'lon': 6.050015, 'lat': 46.234905}  46.234905   6.050015
```

[6]:
```
# install folium
if INSTALL_LIB:
    !pip install folium
```

```
Requirement already satisfied: folium in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (0.19.5)
Requirement already satisfied: requests in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from folium)
(2.26.0)
Requirement already satisfied: xyzservices in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from folium)
(2025.4.0)
Requirement already satisfied: jinja2>=2.9 in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from folium) (3.1.3)
Requirement already satisfied: branca>=0.6.0 in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from folium) (0.8.1)
Requirement already satisfied: numpy in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from folium)
(1.21.5)
Requirement already satisfied: MarkupSafe>=2.0 in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from
jinja2>=2.9->folium) (2.1.5)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from
requests->folium) (1.26.18)
Requirement already satisfied: charset-normalizer~=2.0.0 in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from
requests->folium) (2.0.12)
```

```
Requirement already satisfied: idna<4,>=2.5 in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from
requests->folium) (3.7)
Requirement already satisfied: certifi>=2017.4.17 in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from
requests->folium) (2024.2.2)
```

Collecting folium
Downloading folium-0.19.5-py2.py3-none-any.whl (110 kB)
| | 110 kB 2.3 MB/s
Collecting xyzservices
Downloading xyzservices-2025.4.0-py3-none-any.whl (90 kB)
| | 90 kB 2.0 MB/s
Collecting branca>=0.6.0
Downloading branca-0.8.1-py3-none-any.whl (26 kB)
Requirement already satisfied: jinja2>=2.9 in /home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from folium) (3.1.3)
Requirement already satisfied: requests in /home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from folium) (2.26.0)
Requirement already satisfied: numpy in /home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from folium) (1.21.5)
Requirement already satisfied: MarkupSafe>=2.0 in /home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from jinja2>=2.9->folium) (2.1.5)
Requirement already satisfied: idna<4,>=2.5 in /home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from requests->folium) (3.7)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from requests->folium) (1.26.18)
Requirement already satisfied: certifi>=2017.4.17 in /home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from requests->folium) (2024.2.2)
Requirement already satisfied: charset-normalizer~=2.0.0 in /home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from requests->folium) (2.0.12)
Installing collected packages: xyzservices, branca, folium
Successfully installed branca-0.8.1 folium-0.19.5 xyzservices-2025.4.0

ValueError: Location values cannot contain NaNs.
Folium does not support NaN values, these entries will be filtered out before visualization

[7]:
```
stops_df_notNaN = stops_df.dropna(subset=['latitude', 'longitude'])
stops_df_notNaN.shape
```

[7]:
```
(4405, 9)
```

[8]:
```
import folium

# Centrer la carte sur Genève par exemple
carte = folium.Map(location=[46.2, 6.1], zoom_start=12)

# Ajouter les marqueurs pour les 100 premiers arrêts
```

```
# for _, row in arrets_df_notNaN.head(100).iterrows():

# Ajouter les marqueurs pour tous les arrêts
for _, row in stops_df_notNaN.iterrows():
    folium.Marker(
        location=[row['latitude'], row['longitude']],
        popup=row['nomarret']
    ).add_to(carte)

# Afficher la carte
carte
```

[8]: <folium.folium.Map at 0x7fd51d1ea8b0>

The stops are concentrated in the canton of Geneva, with a few located far outside the canton.

3 2) Passenger counts on line 12

[9]:
```
freq_12_df = pd.read_csv("frequentations_ligne12.csv",sep=",")

display(freq_12_df.head(5))
print(f"We have {freq_12_df.shape[0]} samples and {freq_12_df.shape[1]} columns.
  ↪")
print(f"The list of columns : \n{freq_12_df.columns.tolist()}")
print(f"\n")
print(f"Information about dataset : \n")
display(freq_12_df.info())
freq_12_df["date"] = pd.to_datetime(freq_12_df["date"])
display(freq_12_df.info())
print(f"\n")
print(f"Sum of null data : \n{freq_12_df.isnull().sum()}")
print(f"\n")
print(f"Sum of duplicate data: {freq_12_df.duplicated().sum()}")
print(f"\n")
```

```
         date  ligne ligne_type_act jour_semaine horaire_type       arret  \
0  2025-03-30     12      PRINCIPAL   7-Dimanche     DIMANCHE  Amandolier
1  2025-03-30     12      PRINCIPAL   7-Dimanche     DIMANCHE    Ancienne
2  2025-03-30     12      PRINCIPAL   7-Dimanche     DIMANCHE       Armes
3  2025-03-30     12      PRINCIPAL   7-Dimanche     DIMANCHE     Bel-Air
4  2025-03-30     12      PRINCIPAL   7-Dimanche     DIMANCHE    De-Staël

  arret_code_long  indice_semaine  indice_jour_semaine  nb_de_montees  \
0          AMDO00              13                    7         252.87
1          ANCI01              13                    7         133.37
2          ARME00              13                    7         801.07
3          BAIR06              13                    7        1483.25
```

```
4          STAL01              13                     7          81.27

   nb_de_descentes mois_annee                          coordonnees  \
0           452.56    2025-03  {'lon': 6.168344, 'lat': 46.200043}
1           387.17    2025-03   {'lon': 6.140731, 'lat': 46.18111}
2           137.27    2025-03  {'lon': 6.140528, 'lat': 46.186932}
3          2841.98    2025-03  {'lon': 6.143879, 'lat': 46.203976}
4            95.32    2025-03   {'lon': 6.132192, 'lat': 46.17588}

   donnees_definitives  filter_graph
0                 True         False
1                 True         False
2                 True         False
3                 True         False
4                 True         False
```

We have 78349 samples and 15 columns.
The list of columns :
['date', 'ligne', 'ligne_type_act', 'jour_semaine', 'horaire_type', 'arret', 'arret_code_long', 'indice_semaine', 'indice_jour_semaine', 'nb_de_montees', 'nb_de_descentes', 'mois_annee', 'coordonnees', 'donnees_definitives', 'filter_graph']

Information about dataset :

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 78349 entries, 0 to 78348
Data columns (total 15 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   date                 78349 non-null  object
 1   ligne                78349 non-null  int64
 2   ligne_type_act       78349 non-null  object
 3   jour_semaine         78349 non-null  object
 4   horaire_type         78349 non-null  object
 5   arret                78349 non-null  object
 6   arret_code_long      78349 non-null  object
 7   indice_semaine       78349 non-null  int64
 8   indice_jour_semaine  78349 non-null  int64
 9   nb_de_montees        78349 non-null  float64
 10  nb_de_descentes      78349 non-null  float64
 11  mois_annee           78349 non-null  object
 12  coordonnees          78349 non-null  object
 13  donnees_definitives  78349 non-null  bool
 14  filter_graph         78349 non-null  bool
dtypes: bool(2), float64(2), int64(3), object(8)
memory usage: 7.9+ MB
```

```
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 78349 entries, 0 to 78348
Data columns (total 15 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   date                 78349 non-null  datetime64[ns]
 1   ligne                78349 non-null  int64
 2   ligne_type_act       78349 non-null  object
 3   jour_semaine         78349 non-null  object
 4   horaire_type         78349 non-null  object
 5   arret                78349 non-null  object
 6   arret_code_long      78349 non-null  object
 7   indice_semaine       78349 non-null  int64
 8   indice_jour_semaine  78349 non-null  int64
 9   nb_de_montees        78349 non-null  float64
 10  nb_de_descentes      78349 non-null  float64
 11  mois_annee           78349 non-null  object
 12  coordonnees          78349 non-null  object
 13  donnees_definitives  78349 non-null  bool
 14  filter_graph         78349 non-null  bool
dtypes: bool(2), datetime64[ns](1), float64(2), int64(3), object(7)
memory usage: 7.9+ MB
None


Sum of null data :
date                   0
ligne                  0
ligne_type_act         0
jour_semaine           0
horaire_type           0
arret                  0
arret_code_long        0
indice_semaine         0
indice_jour_semaine    0
nb_de_montees          0
nb_de_descentes        0
mois_annee             0
coordonnees            0
donnees_definitives    0
filter_graph           0
dtype: int64


Sum of duplicate data: 0
```

[10]:
```
print(f"The data covers the date range from {freq_12_df['date'].min()} to␣
↪{freq_12_df['date'].max()}")
```

```
The data covers the date range from 2021-08-01 00:00:00 to 2025-06-27 00:00:00
```

[11]:
```
freq_12_stops_1 = freq_12_df["arret"].unique()
print(f"The dataset contains {len(freq_12_stops_1)} unique stops. Here is the␣
↪list: :\n{freq_12_stops_1}")
print(f"There are significantly more stops in the dataset than on the current␣
↪version of the line.")
```

```
The dataset contains 52 unique stops. Here is the list: :
['Amandolier' 'Ancienne' 'Armes' 'Bel-Air' 'De-Staël' 'Grange-Canal'
 'Grange-Falquet' 'Grangettes' 'Lancy-Bachet-Gare' 'Moillesulaz' 'Molard'
 'Peillonnex' 'Place Favre' 'Rive' 'Villereuse' 'Carouge-Rondeau' 'Cirque'
 'Genève-Eaux-Vives-Gare' 'Place de Neuve' 'Plainpalais' "Pont-d'Arve"
 'Pontets' 'Terrassière' 'Augustins' 'Carouge-Marché' 'Graveson' 'Blanche'
 'Trèfle-Blanc' 'Palettes' 'Stand' 'Dépôt Bachet' 'Dépôt Bachet Coursive'
 'Bouchet' 'Lyon' 'Vieusseux' 'Balexert' 'Coutance' 'Gare Cornavin'
 'Mercier' 'Acacias' 'Industrielle' 'Lancy-Piscine' 'Pictet-Thellusson'
 'Lancy-Mairie' 'Uni-Mail' 'Grand-Lancy-Place du 1er-Août'
 'Lancy-Pont-Rouge-Gare/Etoile' 'Poterie' 'Blandonnet' 'Servette'
 'Vernier, Avanchets-Etang' 'Avanchet']
There are significantly more stops in the dataset than on the current version of
the line.
```

[12]:
```
freq_12_df["date"] = pd.to_datetime(freq_12_df["date"])

freq_12_stops_date_df = freq_12_df.groupby("arret")["date"].agg(["min", "max"]).
↪reset_index()
freq_12_stops_date_df.columns = ["arret", "date_min", "date_max"]
freq_12_stops_date_df["nb_jours"] = (freq_12_stops_date_df["date_max"] -␣
↪freq_12_stops_date_df["date_min"]).dt.days + 1

print(freq_12_stops_date_df.head(10))
```

```
        arret   date_min   date_max  nb_jours
0     Acacias 2022-10-22 2022-10-30         9
1  Amandolier 2021-08-01 2025-06-27      1427
2    Ancienne 2021-08-01 2025-06-27      1427
3       Armes 2021-08-01 2025-06-27      1427
4   Augustins 2021-08-01 2025-06-27      1427
5    Avanchet 2021-08-01 2024-07-20      1085
6    Balexert 2021-08-01 2024-12-13      1231
7     Bel-Air 2021-08-01 2025-06-27      1427
```

```
8     Blanche 2021-08-01 2025-06-27      1427
9  Blandonnet 2021-08-01 2024-12-13      1231
```

The list of stops on this line evolves over time, and this should be carefully considered in the next steps

For a stop — Bel-Air in the city center — we will look at the evolution of **passenger counts** over the period.
Since a stop name can have several codes, we need to work with the stop codes.

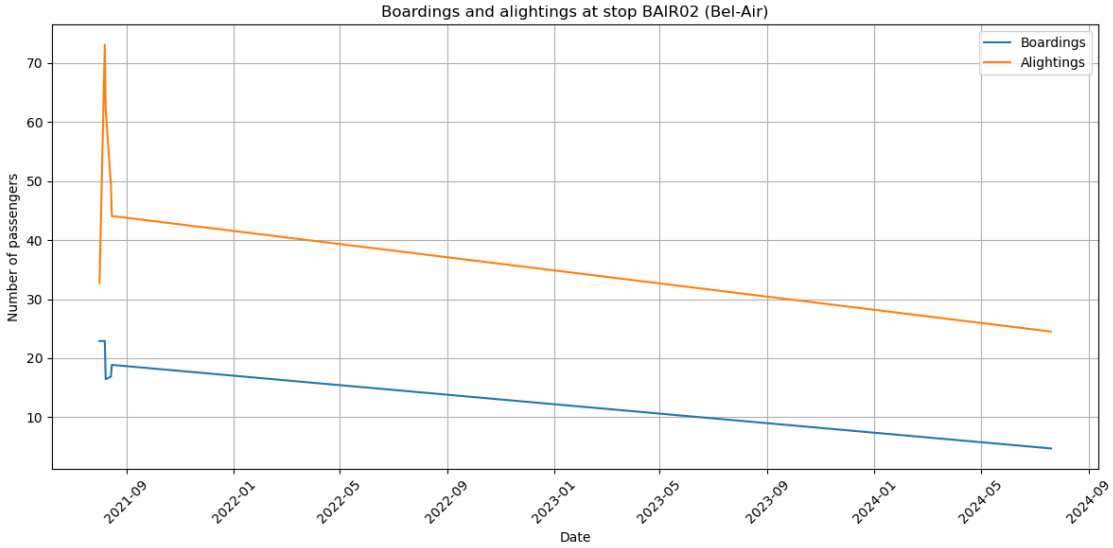
[13]:
```
stops_df[stops_df["arretcodelong"].isin(['BAIR06', 'BAIR05', 'BAIR18',␣
 ↪'BAIR02'])]
```

[13]:
```
     arretcodelong nomarret commune pays  codedidoc  \
124         BAIR06  Bel-Air  GENÈVE   CH  8587387.0
1656        BAIR02  Bel-Air  GENÈVE   CH  8587387.0
1657        BAIR05  Bel-Air  GENÈVE   CH  8587387.0
2964        BAIR18  Bel-Air  GENÈVE   CH  8587387.0

                              coordonnees actif   latitude  longitude
124   {'lon': 6.143879, 'lat': 46.203976}     Y  46.203976   6.143879
1656  {'lon': 6.143449, 'lat': 46.204601}     Y  46.204601   6.143449
1657  {'lon': 6.144637, 'lat': 46.203716}     Y  46.203716   6.144637
2964   {'lon': 6.143731, 'lat': 46.20396}     Y  46.203960   6.143731
```

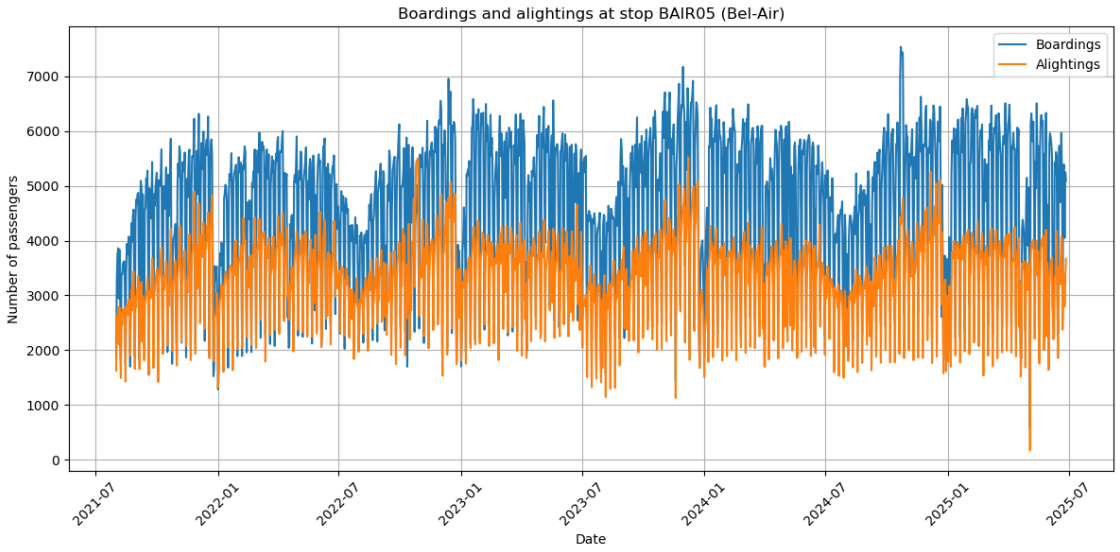
We will look at the **passenger counts** at a stop (for one code) over time.

[14]:
```
def plot_Freq4stop(arret_code):
    arret12_df = freq_12_df[freq_12_df["arret_code_long"]== arret_code]
    #arret12_df.head(5)
    arret12_df = arret12_df.sort_values("date")

    plt.figure(figsize=(12, 6))
    plt.plot(arret12_df["date"], arret12_df["nb_de_montees"], label="Boardings")
    plt.plot(arret12_df["date"], arret12_df["nb_de_descentes"],␣
 ↪label="Alightings")
    plt.xlabel("Date")
    plt.ylabel("Number of passengers")
    plt.title(f"Boardings and alightings at stop {arret_code} (Bel-Air)")
    plt.legend()
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.grid(True)
    plt.show()

arret_code = "BAIR02"
plot_Freq4stop(arret_code)
print("The data is not significant and should be excluded.")
```

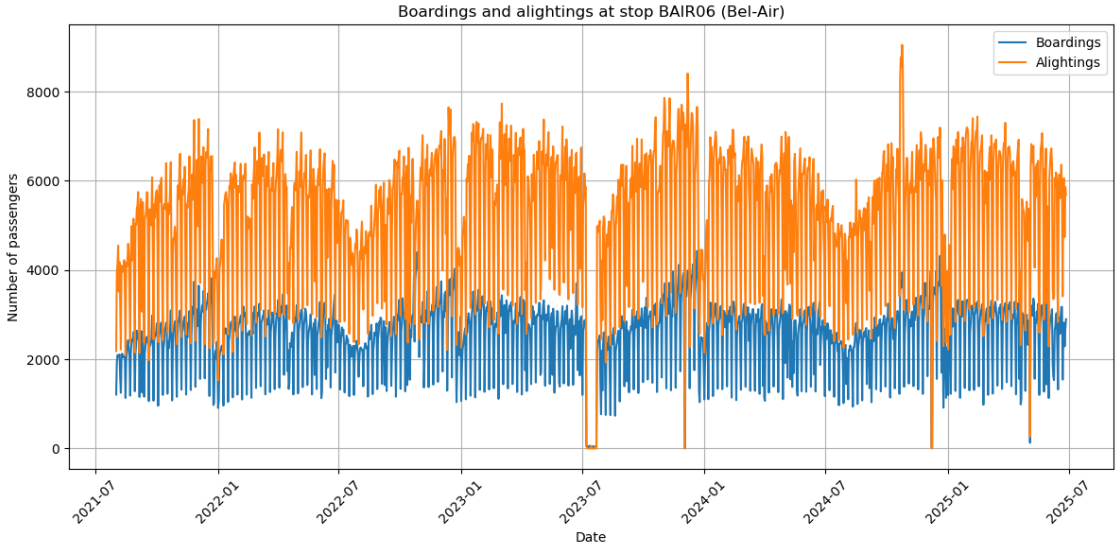
```
arret_code = "BAIR05"
plot_Freq4stop(arret_code)
print("There is a lot of data, with recurring periods, for example: 2021-07 to␣
 ↪2022-01, 2022-07 to 2023-01, 2023-07 to 2024-01.")

arret_code = "BAIR06"
plot_Freq4stop(arret_code)
print("There is a lot of data.")

arret_code = "BAIR18"
plot_Freq4stop(arret_code)
print("The data is not significant and should be excluded.")
```



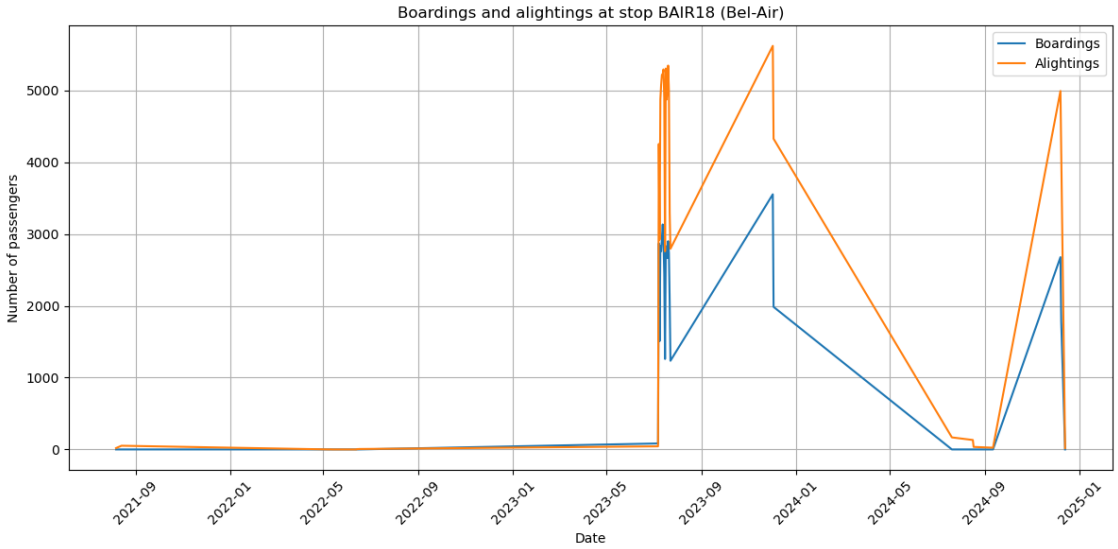

```
The data is not significant and should be excluded.
```



There is a lot of data, with recurring periods, for example: 2021-07 to 2022-01, 2022-07 to 2023-01, 2023-07 to 2024-01.



There is a lot of data.



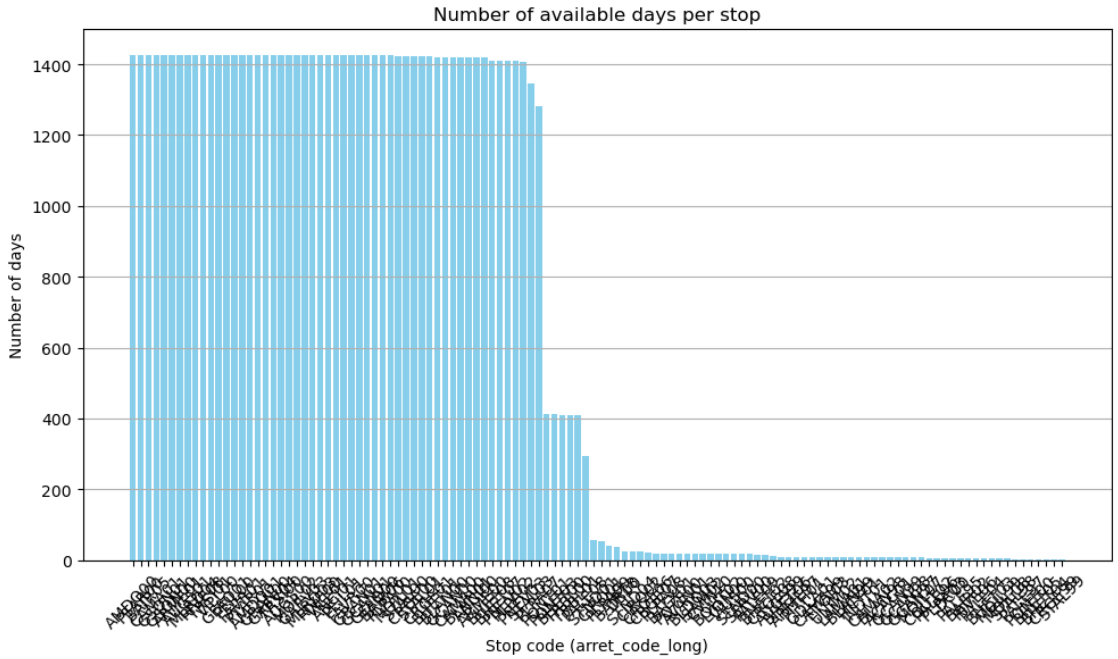
The data is not significant and should be excluded.

Since some stops have limited data, the number of entries per stop will be counted

[15]:
```
freq_12_df_stop_c = freq_12_df["arret_code_long"].value_counts().reset_index()
freq_12_df_stop_c.columns = ["arret_code_long", "record_count"]
display(freq_12_df_stop_c.describe())

# Plot the bar chart
plt.figure(figsize=(10, 6))
plt.bar(freq_12_df_stop_c["arret_code_long"],␣
 ↪freq_12_df_stop_c["record_count"], color='skyblue')
plt.xlabel("Stop code (arret_code_long)")
plt.ylabel("Number of days")
plt.title("Number of available days per stop")
plt.xticks(rotation=45)
plt.tight_layout()
plt.grid(axis="y")
plt.show()

print("Based on the chart, I will select stops with more than 400 records")
freq_12_df_stop_400 = freq_12_df_stop_c[freq_12_df_stop_c["record_count"] > 400]
freq_12_df_stop_400.head(5)
```

```
       record_count
count    120.000000
mean     652.908333
std      689.547556
min        1.000000
25%        9.000000
```

```
50%       55.500000
75%     1427.000000
max     1427.000000
```



Based on the chart, I will select stops with more than 400 records

[15]:

	arret_code_long	record_count
0	AMDO00	1427
1	PTAR00	1427
2	BAIR05	1427
3	CAMA01	1427
4	GSON01	1427

In our study, we will need to check the operating period of a stop and filter out the stops with a non-significant duration.

4 3) Ridership analysis across all lines

[16]:
```
TPG_all_df = pd.read_csv("frequentations_all.csv",sep=",")

print(f"We have {TPG_all_df.shape[0]} samples and {TPG_all_df.shape[1]} columns.
  ↪")
display(TPG_all_df.head(5))
```

We have 4874401 samples and 15 columns.

```
         date ligne ligne_type_act jour_semaine horaire_type  \
0  2021-11-03     T           GLCT   3-Mercredi       NORMAL
1  2021-11-03     T           GLCT   3-Mercredi       NORMAL
2  2021-11-03     T           GLCT   3-Mercredi       NORMAL
3  2021-11-04     1      PRINCIPAL      4-Jeudi       NORMAL
4  2021-11-04     1      PRINCIPAL      4-Jeudi       NORMAL

              arret arret_code_long  indice_semaine  indice_jour_semaine  \
0  La Plaine-Dne - F          _PLDOF              44                    3
1     La Plaine-Gare          PLAI00              44                    3
2             Poizat          POAT01              44                    3
3        31 Décembre          31DC00              44                    4
4        31 Décembre          31DC01              44                    4

   nb_de_montees  nb_de_descentes mois_annee  \
0           0.00             0.45    2021-11
1          33.33             0.47    2021-11
2          14.36             0.03    2021-11
3         397.16           368.51    2021-11
4         255.15           254.19    2021-11

                          coordonnees  donnees_definitives  filter_graph
0  {'lon': 5.991244, 'lat': 46.177319}                 True         False
1  {'lon': 5.999789, 'lat': 46.178463}                 True         False
2  {'lon': 5.974564, 'lat': 46.181133}                 True         False
3  {'lon': 6.161931, 'lat': 46.201679}                 True         False
4  {'lon': 6.162252, 'lat': 46.201778}                 True         False
```

[17]:
```
print(f"The list of columns : \n{TPG_all_df.columns.tolist()}")
print(f"\n")
print(f"Information about dataset : \n")
display(TPG_all_df.info())
```

```
The list of columns :
['date', 'ligne', 'ligne_type_act', 'jour_semaine', 'horaire_type', 'arret',
'arret_code_long', 'indice_semaine', 'indice_jour_semaine', 'nb_de_montees',
'nb_de_descentes', 'mois_annee', 'coordonnees', 'donnees_definitives',
'filter_graph']


Information about dataset :

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4874401 entries, 0 to 4874400
Data columns (total 15 columns):
 #   Column               Dtype
---  ------               -----
 0   date                 object
```

```
 1   ligne                 object
 2   ligne_type_act        object
 3   jour_semaine          object
 4   horaire_type          object
 5   arret                 object
 6   arret_code_long       object
 7   indice_semaine        int64
 8   indice_jour_semaine   int64
 9   nb_de_montees         float64
 10  nb_de_descentes       float64
 11  mois_annee            object
 12  coordonnees           object
 13  donnees_definitives   bool
 14  filter_graph          bool
dtypes: bool(2), float64(2), int64(2), object(9)
memory usage: 492.8+ MB

None
```

4.0.1 Observation :

The Date column is not in the correct format.

4.0.2 Action :

Convert the Date column to date format.

[18]:
```
TPG_all_df['date'] = pd.to_datetime(TPG_all_df['date'])
display(TPG_all_df.info())
print(f"\n")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4874401 entries, 0 to 4874400
Data columns (total 15 columns):
 #   Column                Dtype
---  ------                -----
 0   date                  datetime64[ns]
 1   ligne                 object
 2   ligne_type_act        object
 3   jour_semaine          object
 4   horaire_type          object
 5   arret                 object
 6   arret_code_long       object
 7   indice_semaine        int64
 8   indice_jour_semaine   int64
 9   nb_de_montees         float64
 10  nb_de_descentes       float64
 11  mois_annee            object
 12  coordonnees           object
```

```
 13  donnees_definitives  bool
 14  filter_graph         bool
dtypes: bool(2), datetime64[ns](1), float64(2), int64(2), object(8)
memory usage: 492.8+ MB

None
```

[19]:
```
print(f"The data covers the date range from {TPG_all_df['date'].min()} to␣
↪{TPG_all_df['date'].max()}")
```

```
The data covers the date range from 2021-08-01 00:00:00 to 2025-06-22 00:00:00
```

[20]:
```
print(f"Sum of duplicate data: {TPG_all_df.duplicated().sum()}")
print(f"\n")
```

```
Sum of duplicate data: 0
```

There are no duplicated data.

[21]:
```
print(f"Sum of null data : \n{TPG_all_df.isnull().sum()}")
print(f"\n")
```

```
Sum of null data :
date                      0
ligne                 16129
ligne_type_act            0
jour_semaine              0
horaire_type              0
arret                     0
arret_code_long           0
indice_semaine            0
indice_jour_semaine       0
nb_de_montees             0
nb_de_descentes           0
mois_annee                0
coordonnees              29
donnees_definitives       0
filter_graph              0
dtype: int64
```

4.0.3 Observation :

There are Null values only in the 'line' and 'coordinates' columns.
Since I will not use the coordinates from this dataset, the 'coordinates' column can be removed.

4.0.4 Action :

Remove the 'coordinates' column.

[22]:
```
TPG_all_df.drop(columns=['coordonnees'], inplace=True)
print(f"{TPG_all_df.shape}")
```

```
(4874401, 14)
```

[23]:
```
print(f"Sum of null data : \n{TPG_all_df.isnull().sum()}")
print(f"\n")
```

```
Sum of null data :
date                       0
ligne                  16129
ligne_type_act             0
jour_semaine               0
horaire_type               0
arret                      0
arret_code_long            0
indice_semaine             0
indice_jour_semaine        0
nb_de_montees              0
nb_de_descentes            0
mois_annee                 0
donnees_definitives        0
filter_graph               0
dtype: int64
```

For the NaN values in the 'line' column

[24]:
```
TPG_all_df[TPG_all_df['ligne'].isna()].head()
```

[24]:

	date	ligne	ligne_type_act	jour_semaine	horaire_type	\
2405	2021-11-05	NaN	NOCTAMBUS REGIONAL	5-Vendredi	NORMAL	
2406	2021-11-05	NaN	NOCTAMBUS REGIONAL	5-Vendredi	NORMAL	
2407	2021-11-05	NaN	NOCTAMBUS REGIONAL	5-Vendredi	NORMAL	
2408	2021-11-05	NaN	NOCTAMBUS REGIONAL	5-Vendredi	NORMAL	
2409	2021-11-05	NaN	NOCTAMBUS REGIONAL	5-Vendredi	NORMAL	

	arret	arret_code_long	indice_semaine	indice_jour_semaine	\
2405	Balexert-Pailly	PAIL00	44	5	
2406	Bouchet	BOHT00	44	5	

```
2407          Bouchet          BOHT03              44                    5
2408          Bugnons          BUGN00              44                    5
2409     CERN-Dne - F          _CERNF              44                    5

      nb_de_montees  nb_de_descentes mois_annee  donnees_definitives  \
2405            0.0             0.00    2021-11                 True
2406            0.0             1.11    2021-11                 True
2407            0.0             0.00    2021-11                 True
2408           25.5            17.00    2021-11                 True
2409            0.0             0.00    2021-11                 True

      filter_graph
2405         False
2406         False
2407         False
2408         False
2409         False
```

[25]:
```
16129/4756567*100
```

[25]:
```
0.33908909513941465
```

4.0.5 Observation :

There are 16,129 NaN values out of a total of 4,756,567 rows, which represents 0.33%.
I choose to remove these rows.

4.0.6 Action :

Remove the rows with null values.

[26]:
```
TPG_all_df.dropna(subset=['ligne'], inplace=True)
print(f"{TPG_all_df.shape}")
```

```
(4858272, 14)
```

[27]:
```
print(f"Sum of null data : \n{TPG_all_df.isnull().sum()}")
print(f"\n")
```

```
Sum of null data :
date                  0
ligne                 0
ligne_type_act        0
jour_semaine          0
horaire_type          0
arret                 0
arret_code_long       0
indice_semaine        0
```

```
indice_jour_semaine    0
nb_de_montees          0
nb_de_descentes        0
mois_annee             0
donnees_definitives    0
filter_graph           0
dtype: int64
```

4.1 Exploration of feature content

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4858272 entries, 0 to 4874400
Data columns (total 14 columns):
 #   Column               Dtype
---  ------               -----
 0   date                 datetime64[ns]
 1   ligne                object
 2   ligne_type_act       object
 3   jour_semaine         object
 4   horaire_type         object
 5   arret                object
 6   arret_code_long      object
 7   indice_semaine       int64
 8   indice_jour_semaine  int64
 9   nb_de_montees        float64
 10  nb_de_descentes      float64
 11  mois_annee           object
 12  donnees_definitives  bool
 13  filter_graph         bool
dtypes: bool(2), datetime64[ns](1), float64(2), int64(2), object(7)
memory usage: 491.1+ MB
```

4.1.1 feature : ligne

[29]:
```
#ligne
lignes_unique = TPG_all_df['ligne'].unique()
print(f"Distinct lines: {len(lignes_unique)}")
print(f"List of lines: {lignes_unique}")

ligne_counts = TPG_all_df['ligne'].value_counts()
print("\nNumber of entries per line :")
display(ligne_counts)
```

```
Distinct lines: 116
```

```
List of lines: ['T' '1' '2' '3' '5' '6' '7' '8' '9' '10' '11' '12' '14' '15'
'17' '18'
 '19' '20' '21' '22' '23' '25' '28' '31' '32' '33' '34' '35' '36' '37'
 '38' '39' '41' '42' '43' '44' '45' '46' '47' '48' '50' '51' '52' '53'
 '54' '55' '56' '57' '59' '62' '63' '64' '66' '68' '70' '71' '72' '73'
 '74' '75' '76' '77' '78' '80' '81' '85' '86' '87' '92' '93' '94' '96'
 '97' 'A' 'D' 'E' 'E+' 'F' 'G' 'G+' 'J' 'K' 'L' 'M' 'N' 'NC' 'NE' 'NJ'
 'NK' 'NM' 'NO' 'NP' 'NS' 'NT' 'NV' 'ND' '301' 'C1' 'C3' 'C4' 'C6' 'C8'
 'C5' '82' '91' '60' '67' '61' '69' '83' '302' 'C7' 'C9' '40' '303' '29']

Number of entries per line :

38     123325
17     111182
32     111039
1      109756
22      95838
       …
81       1733
97       1434
93       1173
29        686
303        59
Name: ligne, Length: 116, dtype: int64
```

4.1.2 Observation :

Some lines have very few data entries.

4.1.3 Action :

Perform the prediction per stop instead.

4.1.4 feature : ligne_type_act

[30]:
```
# ligne_type_act
ligne_type_unique = TPG_all_df['ligne_type_act'].unique()
print(f"Distinct ligne type: {len(ligne_type_unique)}")
print(f"List of ligne type: {ligne_type_unique}")

ligne_type_counts = TPG_all_df['ligne_type_act'].value_counts()
print("\nNumber of entries per line type :")
display(ligne_type_counts)
```

```
Distinct ligne type: 5
List of ligne type: ['GLCT' 'PRINCIPAL' 'SECONDAIRE' 'SCOLAIRE' 'NOCTAMBUS
REGIONAL']

Number of entries per line type :
```

```
SECONDAIRE            2379571
PRINCIPAL             1763299
GLCT                   425113
SCOLAIRE               170683
NOCTAMBUS REGIONAL     119606
Name: ligne_type_act, dtype: int64
```

4.1.5 feature : jour_semaine

[31]:
```
#jour_semaine
TPG_all_df['jour_semaine'].value_counts()
```

[31]:
```
5-Vendredi    776314
2-Mardi       716141
3-Mercredi    712157
1-Lundi       709724
4-Jeudi       709663
6-Samedi      666209
7-Dimanche    568064
Name: jour_semaine, dtype: int64
```

4.1.6 Observation :

There are fewer data entries for Saturdays and Sundays, which is normal since some lines are not served during the weekend.
The 'day_of_week' column contains both the day number and the day name.
Since the day number is already available in the 'week_day_index' column, the 'day_of_week' column is not needed.

4.1.7 Action :

Remove the 'day_of_week' column.

[32]:
```
print(f"Shape before drop: {TPG_all_df.shape}")
TPG_all_df.drop(columns=['jour_semaine'], inplace=True)
print(f"Shape after drop: {TPG_all_df.shape}")
```

```
Shape before drop: (4858272, 14)
Shape after drop: (4858272, 13)
```

4.1.8 feature : horaire_type

[33]:
```
TPG_all_df['horaire_type'].value_counts()
```

[33]:
```
NORMAL      2760290
VACANCES     786198
SAMEDI       659968
DIMANCHE     651816
```

```
Name: horaire_type, dtype: int64
```

There are fewer data entries on Sundays, which is normal because fewer lines operate.

4.1.9 feature : arret, arret_code_long

[34]:
```
TPG_all_df[TPG_all_df['arret'] =='Bel-Air']
```

[34]:

	date	ligne	ligne_type_act	horaire_type	arret	arret_code_long	\
37	2021-11-04	3	PRINCIPAL	NORMAL	Bel-Air	BAIR04	
56	2021-11-04	5	PRINCIPAL	NORMAL	Bel-Air	BAIR00	
215	2021-11-04	17	PRINCIPAL	NORMAL	Bel-Air	BAIR05	
216	2021-11-04	17	PRINCIPAL	NORMAL	Bel-Air	BAIR18	
239	2021-11-04	18	PRINCIPAL	NORMAL	Bel-Air	BAIR18	
…	…	…	…	…	…	…	
4873540	2025-05-10	14	PRINCIPAL	SAMEDI	Bel-Air	BAIR02	
4873588	2025-05-10	17	PRINCIPAL	SAMEDI	Bel-Air	BAIR18	
4873791	2025-06-20	5	PRINCIPAL	NORMAL	Bel-Air	BAIR04	
4874285	2025-05-10	80	GLCT	SAMEDI	Bel-Air	BAIR07	
4874317	2025-05-10	92	SECONDAIRE	SAMEDI	Bel-Air	BAIR05	

	indice_semaine	indice_jour_semaine	nb_de_montees	nb_de_descentes	\
37	44	4	1054.21	1315.37	
56	44	4	901.88	556.19	
215	44	4	3015.72	760.71	
216	44	4	0.00	22.12	
239	44	4	7.33	0.00	
…	…	…	…	…	
4873540	19	6	4478.14	6097.94	
4873588	19	6	0.00	152.62	
4873791	25	5	503.34	1063.95	
4874285	19	6	867.07	1268.33	
4874317	19	6	89.03	2.01	

	mois_annee	donnees_definitives	filter_graph
37	2021-11	True	False
56	2021-11	True	False
215	2021-11	True	False
216	2021-11	True	False
239	2021-11	True	False
…	…	…	…
4873540	2025-05	False	False
4873588	2025-05	False	False
4873791	2025-06	False	False
4874285	2025-05	False	False
4874317	2025-05	False	False

```
[41988 rows x 13 columns]
```

4.1.10 Observation :

There are several stop codes for a single stop name.
I will work with stop codes instead of stop names, so the 'arret' column is not needed.

4.1.11 Action :

Remove the 'arret' column.

[35]:
```
print(f"Shape before drop arret : {TPG_all_df.shape}")
TPG_all_df.drop(columns=['arret'], inplace=True)
print(f"Shape after drop: {TPG_all_df.shape}")
```

```
Shape before drop arret : (4858272, 13)
Shape after drop: (4858272, 12)
```

4.1.12 feature : mois_annee

[36]:
```
TPG_all_df['mois_annee'].sample(8)
```

[36]:
```
3196718    2024-11
869076     2022-10
2975075    2023-05
3987631    2024-12
4187667    2024-12
4208874    2024-09
614077     2022-12
4551750    2025-05
Name: mois_annee, dtype: object
```

4.1.13 Observation :

The column 'mois_annee' contains two pieces of information: the month and the year.

4.1.14 Action :

Split the variable 'mois_annee' into two variables: 'mois' and 'annee'.

[37]:
```
print(f"Shape before split: {TPG_all_df.shape}")
TPG_all_df[['annee', 'mois']] = TPG_all_df['mois_annee'].str.split('-',␣
 ↪expand=True) #Expand the split strings into separate columns
TPG_all_df['annee'] = TPG_all_df['annee'].astype(int)
TPG_all_df['mois'] = TPG_all_df['mois'].astype(int)

TPG_all_df.drop(columns=['mois_annee'], inplace=True)
print(f"Shape after split: {TPG_all_df.shape}")
```

```
Shape before split: (4858272, 12)
Shape after split: (4858272, 13)
```

4.1.15 feature : donnees_definitive, filter_graph

[38]:
```
print(f"{TPG_all_df['donnees_definitives'].unique()}")
print(f"{TPG_all_df['donnees_definitives'].value_counts()}")

print(f"{TPG_all_df['filter_graph'].unique()}")
print(f"{TPG_all_df['filter_graph'].value_counts()}")
```

```
[ True False]
True     4684938
False     173334
Name: donnees_definitives, dtype: int64
[False]
False    4858272
Name: filter_graph, dtype: int64
```

4.1.16 Observation :

I will assume that all the data are correct.

4.1.17 Action :

Remove the columns 'donnees_definitive' and 'filter_graph'.

[39]:
```
print(f"Shape before drop: {TPG_all_df.shape}")
TPG_all_df.drop(columns=['donnees_definitives', 'filter_graph'], inplace=True)
print(f"Shape after drop: {TPG_all_df.shape}")
```

```
Shape before drop: (4858272, 13)
Shape after drop: (4858272, 11)
```

4.1.18 feature : 'nb_de_montees', 'nb_de_descentes'

Features that will be our output: either 'nb_de_montees' or 'nb_de_descentes', depending on the question to address.

Are there any abnormal values or too few data entries for some cases?

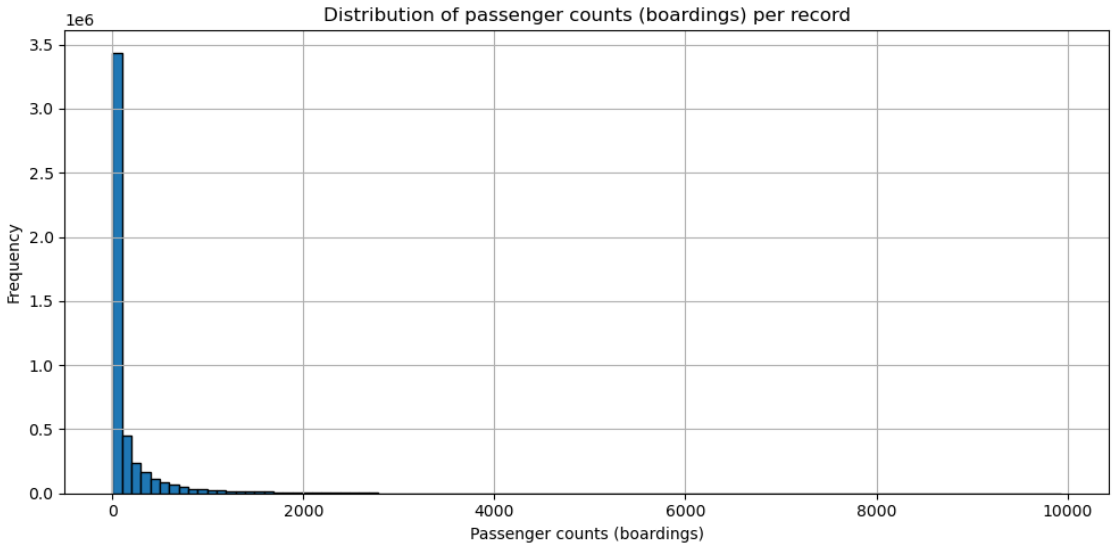
[40]:
```
TPG_all_df[['nb_de_montees', 'nb_de_descentes']].describe().round(2)
```

[40]:

	nb_de_montees	nb_de_descentes
count	4858272.00	4858272.00
mean	168.90	168.91
std	427.50	424.67
min	0.00	0.00
25%	2.79	3.00
50%	22.29	24.51

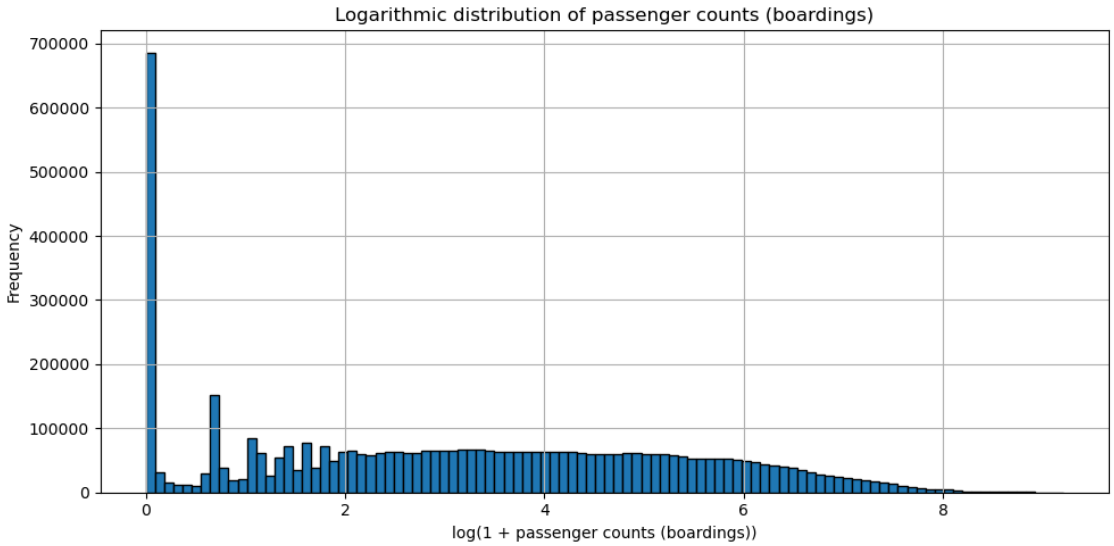
```
75%          136.24          136.75
max         9934.83         10944.99
```

[41]:
```
plt.figure(figsize=(10, 5))
TPG_all_df['nb_de_montees'].hist(bins=100, edgecolor='black')
plt.title("Distribution of passenger counts (boardings) per record")
plt.xlabel("Passenger counts (boardings)")
plt.ylabel("Frequency")
plt.grid(True)
plt.tight_layout()
plt.show()
```



Huge concentration of values between 0 and 200 passenger counts (boardings) per record.
A very long tail (skewed distribution): few cases go beyond 1,000, and even fewer beyond 5,000.
There are more than 3 million points between 0 and ~200 — showing an over-density of stops with low passenger counts (boardings) or off-peak periods.

[42]:
```
plt.figure(figsize=(10, 5))
plt.hist(np.log1p(TPG_all_df['nb_de_montees']), bins=100, edgecolor='black')
plt.title("Logarithmic distribution of passenger counts (boardings)")
plt.xlabel("log(1 + passenger counts (boardings))")
plt.ylabel("Frequency")
plt.grid(True)
plt.tight_layout()
plt.show()
```



4.1.19 Action :

Apply a logarithmic transformation to the variables.

[43]:
```
TPG_all_df["log_montees"] = np.log1p(TPG_all_df["nb_de_montees"])
TPG_all_df["log_descentes"] = np.log1p(TPG_all_df["nb_de_descentes"])
```

4.2 Feature creation

4.2.1 Passenger counts

[44]:
```
# Frequentation totale = montées + descentes
TPG_all_df["frequentation_totale"] = TPG_all_df["nb_de_montees"] +␣
 ↪TPG_all_df["nb_de_descentes"]
TPG_all_df["log_frequentation_totale"] = TPG_all_df["log_montees"] +␣
 ↪TPG_all_df["log_descentes"]
```

[45]:
```
# delta_montees_descentes = montées - descentes
TPG_all_df["delta_montees_descentes"] = TPG_all_df["nb_de_montees"] -␣
 ↪TPG_all_df["nb_de_descentes"]
TPG_all_df["log_delta_montees_descentes"] = TPG_all_df["log_montees"] -␣
 ↪TPG_all_df["log_descentes"]
```

4.2.2 Vehicle type

We have the column 'ligne_type_act' that provides information about the line type, but it does not indicate which vehicle is used.
We will check if this information can be completed.

[46]:
```
ligne_type_df = TPG_all_df.groupby("ligne_type_act")["ligne"].unique()
display(ligne_type_df.head())

for type_ligne, lignes in ligne_type_df.items():
    # with chatGPT : Supprimer les NaN, convertir les éléments en str, puis␣
 ↪trier
    lignes_sans_nan = [str(l) for l in lignes if pd.notna(l)]
    print(f"{type_ligne} ({len(lignes_sans_nan)} lignes) :␣
 ↪{sorted(lignes_sans_nan)}\n")
```

```
ligne_type_act
GLCT                      [T, 64, 66, 68, D, F, M, N, 80, 60, 61, 67, 69]
NOCTAMBUS REGIONAL           [NC, NE, NJ, NK, NM, NO, NP, NS, NT, NV, ND]
PRINCIPAL               [1, 2, 3, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 1…
SCOLAIRE                [80, 81, 85, 87, 92, 93, 94, 96, 97, C1, C3, C…
SECONDAIRE              [31, 32, 33, 34, 35, 36, 37, 38, 39, 41, 42, 4…
Name: ligne, dtype: object
```

```
GLCT (13 lignes) : ['60', '61', '64', '66', '67', '68', '69', '80', 'D', 'F',
'M', 'N', 'T']

NOCTAMBUS REGIONAL (11 lignes) : ['NC', 'ND', 'NE', 'NJ', 'NK', 'NM', 'NO',
'NP', 'NS', 'NT', 'NV']

PRINCIPAL (23 lignes) : ['1', '10', '11', '12', '14', '15', '17', '18', '19',
'2', '20', '21', '22', '23', '25', '28', '29', '3', '5', '6', '7', '8', '9']

SCOLAIRE (17 lignes) : ['80', '81', '85', '87', '92', '93', '94', '96', '97',
'C1', 'C3', 'C4', 'C5', 'C6', 'C7', 'C8', 'C9']

SECONDAIRE (56 lignes) : ['301', '302', '303', '31', '32', '33', '34', '35',
'36', '37', '38', '39', '40', '41', '42', '43', '44', '45', '46', '47', '48',
'50', '51', '52', '53', '54', '55', '56', '57', '59', '62', '63', '67', '69',
'70', '71', '72', '73', '74', '75', '76', '77', '78', '82', '83', '86', '91',
'92', 'A', 'E', 'E+', 'G', 'G+', 'J', 'K', 'L']
```

4.2.3 Observation :

The category “PRINCIPAL” includes both bus and tram lines.
As a TPG user, I know the tram line numbers.
In addition, the TPG website provides a page that categorizes lines by vehicle type:
https://www.tpg.ch/fr/lignes

- Tram: 12, 14, 15, 17, 18
- Trolleybus: 2, 3, 6, 7, 10, 19
- Bus: 1, 5, 8, 9, 11, 20, 21, 22, 23, 25, 28, 31, 32, 33, 34, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46,

47, 48, 50, 51, 52, 53, 54, 55, 57, 59, 60, 61, 64, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 78, 80, 82, 83, 91, 92, A, E, G, L

- Express lines: E+, G+
- Seasonal line: 29
- Cross-border and partner lines: 271, 272, 274, M, N

It may be relevant to categorize tram lines separately.
Since trams and buses have different operational constraints, a dedicated "TRAM" category will be created.

4.2.4 Action :

Create a new variable 'type_vehicule'.

[47]:
```
tram = {"12", "14", "15", "17", "18"}
trolleybus = {"2", "3", "6", "7", "10", "19"}
autobus =␣
 ↪{"1","5","8","9","11","20","21","22","23","25","28","31","32","33","34","37","38","39",
          ␣
 ↪"40","41","42","43","44","45","46","47","48","50","51","52","53","54","55","57","59",
          ␣
 ↪"60","61","64","66","67","68","69","70","71","72","73","74","75","78","80","82","83",
           "91","92","A","E","G","L"}
lignes_express = {"E+", "G+"}
saisonniere = {"29"}
transfrontalieres = {"271", "272", "274", "M", "N"}

# mapping
def get_type_vehicule(ligne):
    if ligne in tram:
        return "Tram"
    elif ligne in trolleybus:
        return "Trolleybus"
    elif ligne in autobus:
        return "Autobus"
    elif ligne in lignes_express:
        return "Express"
    elif ligne in saisonniere:
        return "Saisonnière"
    elif ligne in transfrontalieres:
        return "Interurbaine"
    else:
        return "Autre"

# Application
```

```
TPG_all_df["type_vehicule"] = TPG_all_df["ligne"].apply(get_type_vehicule)

#Check
print(f"Categories in type_vehicule : {TPG_all_df['type_vehicule'].unique()}")
print(TPG_all_df["type_vehicule"].value_counts())
```

```
Categories in type_vehicule : ['Autre' 'Autobus' 'Trolleybus' 'Tram' 'Express'
'Interurbaine'
 'Saisonnière']
Autobus         3153705
Autre            681090
Tram             459072
Trolleybus       446538
Express           75215
Interurbaine      41966
Saisonnière         686
Name: type_vehicule, dtype: int64
```

4.2.5 Observation :

There is a majority of bus lines.

5 4) Weather

[48]:
```
# load data from files
meteo_df_daily = pd.read_csv("meteo_daily.csv")
meteo_df_hourly = pd.read_csv("meteo_hourly.csv")
```

[49]:
```
weather_code_dict_fr = {
    0: "Ciel clair",
    1: "Principalement clair",
    2: "Partiellement nuageux",
    3: "Couvert",
    45: "Brouillard",
    48: "Brouillard avec givre",
    51: "Bruine légère",
    53: "Bruine modérée",
    55: "Bruine dense",
    56: "Bruine verglaçante légère",
    57: "Bruine verglaçante dense",
    61: "Pluie faible",
    63: "Pluie modérée",
    65: "Pluie forte",
    66: "Pluie verglaçante légère",
    67: "Pluie verglaçante forte",
    71: "Chute de neige faible",
    73: "Chute de neige modérée",
```

```
    75: "Chute de neige forte",
    77: "Grains de neige",
    80: "Averses légères",
    81: "Averses modérées",
    82: "Averses violentes",
    85: "Averses de neige légères",
    86: "Averses de neige fortes",
    95: "Orage léger ou modéré",
    96: "Orage avec grêle légère",
    99: "Orage avec grêle forte"
}

weather_code_dict = {
    0: "Clear sky",
    1: "Mainly clear",
    2: "Partly cloudy",
    3: "Overcast",
    45: "Fog",
    48: "Depositing rime fog",
    51: "Light drizzle",
    53: "Moderate drizzle",
    55: "Dense drizzle",
    56: "Light freezing drizzle",
    57: "Dense freezing drizzle",
    61: "Slight rain",
    63: "Moderate rain",
    65: "Heavy rain",
    66: "Light freezing rain",
    67: "Heavy freezing rain",
    71: "Slight snow fall",
    73: "Moderate snow fall",
    75: "Heavy snow fall",
    77: "Snow grains",
    80: "Slight rain showers",
    81: "Moderate rain showers",
    82: "Violent rain showers",
    85: "Slight snow showers",
    86: "Heavy snow showers",
    95: "Thunderstorm: Slight or moderate",
    96: "Thunderstorm with slight hail",
    99: "Thunderstorm with heavy hail"
}
```

[50]:
```
meteo_df_daily['time'] = pd.to_datetime(meteo_df_daily['time'])
meteo_df_hourly['time'] = pd.to_datetime(meteo_df_hourly['time'])
```

```
# meteo_df_hourly["weather_description"] = meteo_df_hourly["weather_code"].
  ↪map(weather_code_dict)
# meteo_df_daily["weather_description"] = meteo_df_daily["weather_code"].
  ↪map(weather_code_dict)
```

[51]:
```
display(meteo_df_daily.head(5))
display(meteo_df_hourly.head(5))

print(f"The data covers the date range from {meteo_df_daily['time'].min()} to␣
  ↪{meteo_df_daily['time'].max()}")
```

```
        time  weather_code
0 2021-08-01            63
1 2021-08-02            51
2 2021-08-03            61
3 2021-08-04            61
4 2021-08-05            53
```

```
                 time  temperature_2m  precipitation  weather_code  \
0 2021-08-01 00:00:00            17.5            0.5            53
1 2021-08-01 01:00:00            17.1            0.3            51
2 2021-08-01 02:00:00            16.2            0.4            51
3 2021-08-01 03:00:00            15.7            0.5            53
4 2021-08-01 04:00:00            15.5            0.2            51

   wind_speed_10m
0             2.0
1             2.1
2             2.9
3             1.8
4             3.1
```

```
The data covers the date range from 2021-08-01 00:00:00 to 2025-06-22 00:00:00
```

The data covers the time period of boardings.

The analysis will focus on daily weather data

[52]:
```
print(f"We have {meteo_df_daily.shape[0]} samples and {meteo_df_daily.shape[1]}␣
  ↪columns.")
print(f"The list of columns : \n{meteo_df_daily.columns.tolist()}")
print(f"\n")
print(f"Information about dataset : \n")
display(meteo_df_daily.info())
print(f"\n")
print(f"Sum of null data : \n{meteo_df_daily.isnull().sum()}")
print(f"\n")
print(f"Sum of duplicate data: {meteo_df_daily.duplicated().sum()}")
print(f"\n")
```

```
We have 1422 samples and 2 columns.
The list of columns :
['time', 'weather_code']


Information about dataset :

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1422 entries, 0 to 1421
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   time          1422 non-null   datetime64[ns]
 1   weather_code  1422 non-null   int64
dtypes: datetime64[ns](1), int64(1)
memory usage: 22.3 KB
None



Sum of null data :
time            0
weather_code    0
dtype: int64


Sum of duplicate data: 0
```

6 5) Merging TPG and weather datasets

[53]:
```
meteo_df_daily = meteo_df_daily.rename(columns={"time": "date"})
TPG_meteo_all_df = TPG_all_df.merge(meteo_df_daily, on="date", how="left")
print(TPG_meteo_all_df.info())
display(TPG_meteo_all_df.head(5))
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4858272 entries, 0 to 4858271
Data columns (total 19 columns):
 #   Column                      Dtype
---  ------                      -----
 0   date                        datetime64[ns]
 1   ligne                       object
 2   ligne_type_act              object
 3   horaire_type                object
 4   arret_code_long             object
```

```
 5   indice_semaine               int64
 6   indice_jour_semaine          int64
 7   nb_de_montees                float64
 8   nb_de_descentes              float64
 9   annee                        int64
 10  mois                         int64
 11  log_montees                  float64
 12  log_descentes                float64
 13  frequentation_totale         float64
 14  log_frequentation_totale     float64
 15  delta_montees_descentes      float64
 16  log_delta_montees_descentes  float64
 17  type_vehicule                object
 18  weather_code                 int64
dtypes: datetime64[ns](1), float64(8), int64(5), object(5)
memory usage: 741.3+ MB
None
```

	date	ligne	ligne_type_act	horaire_type	arret_code_long
0	2021-11-03	T	GLCT	NORMAL	_PLDOF
1	2021-11-03	T	GLCT	NORMAL	PLAI00
2	2021-11-03	T	GLCT	NORMAL	POAT01
3	2021-11-04	1	PRINCIPAL	NORMAL	31DC00
4	2021-11-04	1	PRINCIPAL	NORMAL	31DC01

	indice_semaine	indice_jour_semaine	nb_de_montees	nb_de_descentes	annee
0	44	3	0.00	0.45	2021
1	44	3	33.33	0.47	2021
2	44	3	14.36	0.03	2021
3	44	4	397.16	368.51	2021
4	44	4	255.15	254.19	2021

	mois	log_montees	log_descentes	frequentation_totale
0	11	0.000000	0.371564	0.45
1	11	3.536020	0.385262	33.80
2	11	2.731767	0.029559	14.39
3	11	5.986854	5.912178	765.67
4	11	5.545763	5.542008	509.34

	log_frequentation_totale	delta_montees_descentes
0	0.371564	-0.45
1	3.921282	32.86
2	2.761326	14.33
3	11.899032	28.65
4	11.087772	0.96

	log_delta_montees_descentes	type_vehicule	weather_code
0	-0.371564	Autre	63

```
1                    3.150757          Autre            63
2                    2.702208          Autre            63
3                    0.074676        Autobus            53
4                    0.003755        Autobus            53
```

7 6) Summary of the EDA

[54]:
```
TPG_meteo_all_df.isna().sum()
```

[54]:
```
date                          0
ligne                         0
ligne_type_act                0
horaire_type                  0
arret_code_long               0
indice_semaine                0
indice_jour_semaine           0
nb_de_montees                 0
nb_de_descentes               0
annee                         0
mois                          0
log_montees                   0
log_descentes                 0
frequentation_totale          0
log_frequentation_totale      0
delta_montees_descentes       0
log_delta_montees_descentes   0
type_vehicule                 0
weather_code                  0
dtype: int64
```

[55]:
```
TPG_meteo_all_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4858272 entries, 0 to 4858271
Data columns (total 19 columns):
 #   Column                      Dtype
---  ------                      -----
 0   date                        datetime64[ns]
 1   ligne                       object
 2   ligne_type_act              object
 3   horaire_type                object
 4   arret_code_long             object
 5   indice_semaine              int64
 6   indice_jour_semaine         int64
 7   nb_de_montees               float64
 8   nb_de_descentes             float64
 9   annee                       int64
```

```
 10  mois                          int64
 11  log_montees                   float64
 12  log_descentes                 float64
 13  frequentation_totale          float64
 14  log_frequentation_totale      float64
 15  delta_montees_descentes       float64
 16  log_delta_montees_descentes   float64
 17  type_vehicule                 object
 18  weather_code                  int64
dtypes: datetime64[ns](1), float64(8), int64(5), object(5)
memory usage: 741.3+ MB
```

[56]:
```
#Save the dataset

file_name = "TPG_meteo_all_df.csv"
TPG_meteo_all_df.to_csv(file_name, index=False)
```

7.1 (b) How does the EDA inform your project plan?

I have a clean initial dataset: no duplicates and very few missing values.
I observed that some features are not useful (for example: 'filter_graph') or redundant ('jour_semaine'), so I removed them.
I also noticed that the distribution of passenger counts (boardings) and passenger counts (alightings) is highly skewed.
A logarithmic transformation can help the models by reducing this skewness.
Based on this, I created new variables: the sum of passenger counts (boardings) and passenger counts (alightings) to represent the total ridership, and the difference between them to provide insights into passenger flows.

7.2 (c) What further EDA do you plan for project?

I will look more closely at the validity of the data over time:
* operating duration of stops,
* which stops have the highest passenger counts,
* temporal analysis of the data: checking if there are recurring or similar patterns over time.

[57]:
```
#end
```